Stockholm School of Economics
Department of Management and Organization
Master of Science in Business and Economics
Master Thesis (30 ECTS)

Twitter Emotional Profile Improves The Stock Market Values Forecast

Do emotions derived from Twitter have prediction power on the stock market index?

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Abstract

The vast expansion of online social platforms and increasing openness of their users created a great opportunity for researchers to obtain more detailed information about such complicated phenomena as public opinions and emotions. And since it was proven by behavioral economist long time ago that emotions take part in decision-making process, the researchers have initiated a new series of exciting studies that can be combined under the title "emotions derived from online social platforms predict the future" The author of this thesis joins this large group of researchers by investigating whether 7 emotions, namely Surprise, Happiness, Comfort, Calm, Frustration, Anger, and Sadness expressed by Twitter users from Singapore can influence SIMSCI closing values index over the time. The analysis was based on hourly values of all 8 variables obtained for the period from 12 September 2011 to 12 November 2011. With a help of Multilayer Perceptron network it was discovered that combination of all 7 emotions expressed within an hour T have predictive power on SIMSCI closing price of the hour T, the conclusion drawn from the fact that Relative Error has decreased by more than 40%. The historical values of each of the emotions taken separately or in combination with others didn't show any consistency in generating lower errors.

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Submission: January 9, 2012

1. Introduction

1.1 Thesis background

As a child of the century, when the Internet has become inseparable part of the everyday life, the author of this thesis spends more than ¾ th of a day in the Internet, not only working, but studying, communicating, entertaining, and even relaxing, and she is not alone, most of the people nowadays do the same. During all these activities they are bombarding by the information that is spread by huge network of social media sources, where Facebook and Twitter are on the top. But social media is not only a source of external information, but also unique space to expose oneself through expressing opinions and emotions.

Opinion is something that is possible to explain, control, i.e. keep unrevealed or announce it at every corner. While emotions are far from being sensibly explained and controlled, at least without special long and regular training.

What do you feel? Why did you react like this? And many other questions that require thorough analysis of emotional state to give at least approximate answer. Very often people have very hard time to give any answer, because emotions lie beneath consciousness and can influence mental and body reactions without awareness and control.

And it is well known, the more mysterious the subject the more interesting to investigate it. A lot of researchers devoted, and still keeping doing so, their works to examining the way emotions influences certain human behavior, decision-making process. The first challenge the researchers face is collection of emotional states of analyzed group of people. For this purpose such tools as public polls and live experiments were frequently used and are still in demand. But these kinds of research instruments require a lot of resources, especially time and money. Thus the development and penetration in everyday life of the Internet as well as social media was very welcomed by academic and business world, because they created a unique opportunity to complement and sometimes even substitute public polls.

This new source allowed to observe in more details how emotions participated in decision-making, buying, selling, and other everyday life processes. Moreover it enabled to go further and investigate whether emotions were correlated or even predictive of certain future events, the practice that has attracted a lot of attention in scientific and business worlds.

1.2 Research question

The success of some researchers as well as innovativeness of the research area inspired to dedicate this paper to answer the question whether *emotions extracted from Twitter can positively impact effectiveness of stock values forecast*. The choice of stock market can be explained by importance of this industry for well-being of not only national but also the world economy. This fact was clearly illustrated by the events in 2008. Hence any prediction of what can happen with stock values at least within nearest future is priceless, and there is a hope that this work can make an important contribution in creating mechanism to avoid critical situations in the world economy. Moreover, from practical point of view stock market historical data is much easier to get than of any other industry.

Regarding selection of online platform, Twitter was chosen due to its increasing popularity worldwide, by the 1 April 2011 it had over 175 million registered users (Golijan, 2011). Though not all of the registered users are active, there are still enough to collect sufficient data set for analysis. Another factor in favor of Twitter is openness of its data, which means that it is easy to search, derive any information, and apply it in the analysis without any legal restrictions. Finally, Twitter messages are very short (140 characters maximum) and hence present any information in concise and clear form, which makes it easy to process and analyze.

The other specifications of the study will be given in Methodology part.

So the goal of this thesis is to answer the following research question:

Does emotional profile of Twitter messages improve performance of stock index forecasting model?

1.3 Definitions and terminology

There are two main terms that are essential to understand prior to designing further analysis to answer the research question.

Emotions are part of the mechanism of biological regulation that represents physiological and mental reactions towards interaction between internal and external influencers. Such reactions can be unconscious and conscious, but both kinds are responsible for "physiological arousal, expressive behaviors, and conscious experience" (Myers, 2004). From medical point of view emotion is "a state of arousal characterized by alteration of feeling tone and by physiologic behavioral changes" (Emotion. Miller-Keane Encyclopedia and Dictionary of Medicine, Nursing, and Allied Health, 2007). There are many classifications defined by various theorists. The most popular are basic vs. complex emotions. However there is no consensus among these theorists regarding the way to define whether emotion is basic or complex. As the result many of them created their own lists of basic emotions, the careful consideration of which revealed that there are 5 most frequently mentioned emotions, namely happiness/joy, surprise/wonder/amusement, fear, anger, sadness.

Twitter is a social network that was launched in 2006, providing the service of sending short 140 character length messages through public or private message agents. Twitter messages (tweets) can serve as a way to stay connected with friends, family, or professional contacts. Twitter is also a way to keep being updated about celebrities, companies, experts and other people/organizations of interest by subscribing to, or using Twitter terminology, following their accounts.

As it was mentioned Twitter has become one of the most popular online social platforms, and its popularity is still growing. One of the many reasons of upwards trend in the number of registered users is that Twitter appeared to be a unique tool for "anonymous voyeurism" through process of constant updates of a circle of followers with anything on one's minds and in one's heart (Kaplan & Haenlein, 2011).

The magnetism of "anonymous voyeurism" through Twitter is even more irresistible when it became known that the size of potential audience could easily reach six-digit number due to the "one to many" feature of interaction (Fischer & Reuber, 2010).

In addition to everything said above, Twitter provides with unique information dissemination mechanism, which is carried out mostly through retweeting[1] within time span that can last only few minutes (Kwak, Lee, Park, & Moon, 2010). Such speed can be explained by the finding that users tend to follow many various groups of people, and average path length between two users appears to be just over four, creating potential for any retweeted message to reach in average 1000 users at once (Kwak et al., 2010).

Statsit – is a marketing research company that is the first to combine techniques of research industry with analysis of real-time consumer messages available on social media platforms Statsit is the company this thesis is written in cooperation with.

1.4 Structure of the Thesis

Chapter 2 will build a logical platform for the following empirical study by reviewing related literature and research papers.

Chapter 3 will give all details of every instrument, data set, techniques, tests and models to be applied in the study.

Chapter 4 will describe the process of study design and results it has generated, and then present outcome of careful comparison of the results.

Chapter 5 will concentrate on final conclusions, results implementation, study contribution, finalizing by describing its limitations and suggesting directions of further research.

2. Theoretical framework

1 Nature of Emotions and their influence on decision-making process.

Emotions play indisputably important role in human's life. And this fact made many researchers to question what exactly this role was, which areas of life it touched, how strong its influence.

And for the purpose of this thesis it is vital to understand the essence of this phenomenon.

[1] "forwarding a tweet by posting it again" (Thelwall, Buckley, & Paltoglou, 2011)

The analysis of the existed literature show that it's very difficult to clearly define the nature of emotions due to several theoretical perspectives on this subject.

There are two main theories that give their interpretation of the nature of emotions: James-Lange theory and two-factor theory.

William James, pioneering American psychologist and philosopher, denoted emotions as physiological reaction to the environment stimuli. His contemporary Carl Lange advanced the theory by suggesting that such physiological reactions are the product of our autonomic nervous system, expressed by stomach contractions, blood rushes to our skin, changes in the heart rate, etc. This theory is known as James-Lange theory of emotions. And according to it, if there were no body responses, there was no reaction, and as the physiological experience is quite similar among all human beings, the emotions are quite universal phenomenon.

The contemporaries that didn’t agree with James stated that all the emotions couldn’t be just a product of body reactions, which is a slow nervous system; instead this school proposed that emotions were interpretation of those body reactions. This means that emotional expressions are shaped not only by our physiological basis, but also by our background, belief systems. This theory was named two-factor theory of emotions. (Bradford Titchener, 2001).

To make it clear from the very beginning, the two-factor theory was accepted as the base for further theoretical and empirical analyses of the thesis. The reason is that this theory allows examination of the emotions without actually seeing an individual expressing them, since it is possible to learn about the factors lying behind certain emotion such as belief system through various sources, the largest of which are academic studies. Another important argument in favor of the two-factor theory of emotions is that this paper aims to analyze emotions derived from online platforms, which makes it impossible to study physiological experience of specific individuals.

In addition to the to the differentiation in the understanding of the emotions’ origin, there are also two different schools of emotions classifications by their dimensions.

Russel (1980, 1989) introduced circumplex model of emotions, in accordance with which there are “two bipolar dimensions of emotion, pleasantness and arousal, where the former ranges from very positive to very negative, and the latter describes the level of intensity of the emotion". This model in contrast to basic, which will be described below, says that emotions arise from linear combination of the two dimensions, i.e., quoting Posner, Russell, and Peterson (2005), "each and every affective experience is the consequence of a linear combination of valence and arousal independent systems, which is then interpreted as representing a particular emotion". Hence emotions can be interpreted as a final product of complicated cooperation between cognitions and neurophysiological changes associated with valence and arousal systems (Posner et al., 2005)

Whereas basic model, or dominant theory of emotions (Ekman, 1992) states that humans have been provided with "discreet and limited set of basic emotions". And each of these basic emotions is independent from the others and have its own "unique neural pathways of the central nervous system" (Ekman, 1992).

Even though the basic model has some valuable inputs, it didn't get wide application among academics and has been challenged by various affective neuroscience studies. For example, there are studies of facial expressions, the aim of which is to show that each emotion, being unique in its own nature, associates with certain unique facial expression.

As the result of these studies it was discovered that not all emotions are associated with facial expression (Ekman, 1993), besides, certain facial expressions relate to several emotions (smile – happiness, sarcasm, pride). Moreover none of the studies provided with justification of neural foundation of the basic emotions, and with foundation of peripheral physiological correlates of these emotions. All these drawbacks resulted in the dominant theory being left behind due to the lack of adequate foundation, which would allow to define what kinds of emotions are indeed basic (Ortony & Turner, 1990).

Thus circumplex model or in other sources two-dimensional (2-D) model (Pozner et al., 2005) became the most widespread model in emotional analysis.

To illustrate how 2-D model is applied, consider the following example. Due to the fact, which was discovered by many clinicians and researchers, that people themselves can hardly evaluate and describe their own emotions (Saarne, 1999), researchers had to turn to the complex statistics methods, usually factor analysis or multidimensional scaling, to figure out what prevents people from reporting clearly their emotions. As it was later noted the main reason lies in the high intercorrelation among the emotions both within and between the individuals (Russel & Carroll, 1999). And through those complex techniques and two-dimensional model application it was possible to conduct thorough and detailed analysis of correlation among emotional reactions (Larsen & Diener, 1992).

Additionally to breakdown of emotions by their dimensions, it's worth to look at them at macro level scale. Such kind of examination shows that it is possible to define emotions by their core appraisal themes. Appraisal themes are "thought to provide a convenient summary of specific harms or benefits that arise in the individual's ongoing interaction with the social environment" (Han, Lerner & Keltner, 2007). What interesting is that each emotion-specific appraisal theme affects the probability of further sequence of actions (Lazarus, 1991).

This discovery raises very interesting and relevant question, namely: **Have the emotions an ability to influence decision-making process and subsequent actions of individuals?**

Today as never before it is vital to find the answer due to the fact that our society has turned to the "reputation society" , bringing alone the time of strong emotions (Pizzorno, 2004, Luoma-aho, 2005), the time when even gigantic organizations, their prosperity and survival have started to be dependent on the emotional state of their stakeholders (Luoma-aho, 2009). Today public doesn't want just simply participate; it expresses all gradient of emotions, and today it has as many tools to do this as never before through thousands of social networks just under fingertips.

With discovery of such phenomenon as appraisal themes it became possible to learn how emotions can actually impact the decisions and judgment formation process, and thus built at least approximate picture of possible outcomes.

The study of these appraisal themes put the beginning of a new theory - Appraisal-Tendency Framework (ATF) suggested by Lerner and Keltner (2000, 2001). According to this framework, emotions can provoke cognitive inclination to evaluate future events through the prism of appraisal themes (Han & Lerner, 2006). ATF is used as a basis to study the effect of emotions on the decision-making process and judgments.

ATF identifies two groups of emotions that differ in their way of affective influence on mental conclusions.

Integral emotions include those emotions that effect subjective experience applicable to present decisions and judgments (Loewenstein & Lerner, 2003).

As an example Larrick and Boles (1995) and Loewenstein and Lerner (2003) show that feelings of fear and anticipated regret while gambling affect the sum of money one is inclined to gamble.

Another group is incidental emotions that include sometimes very mysterious influence of subjective emotional experience on the choices and judgments not directly connected to this experience. For example, bad weather, stressful events, relaxing music can impact the decisions you make later during the day (Bodenhausen, Kramer, & Susser, 1994). And this impact can remain unnoticed even when certain financial results are at stake (Lerner, Small, & Loewenstein, 2004).

Though it might be very interesting to analyze how certain incidental emotions, especially weather, affect decisions and actions relying on already existing research, for example, a study by Hirshleifer and Shumway (2003), which examines influence of weather on the stock market; it was chosen to focus only on integral emotions. The main reason is time and size restriction. Besides, the technology that will be applied in the study is well trained to work with integral emotions.

Hence with a help of integral emotions it is possible to estimate the future, i.e. knowing emotion state of a person it's possible to predict his/her reaction to a certain experience.

To summarize, at the beginning of this chapter two main theories of the emotions' origin - James-Lunge and two-factor theories of emotions were introduced, followed by selection of one of them, namely two-factor theory, as a basis of the thesis study. Then further academic literature review acknowledged that there were also difference in views on emotions' dimensions: either emotions are already existing set of unique and independent basic emotions or each emotion is a result of cooperation between pleasantness and arousal systems (two-dimension model). Due to the empirical findings contradicting basic emotions model, the two-dimension model is the one that received the widest recognition among academics, and thus is adopted in this research as a working model. Deeper investigation in emotion theoretical literature revealed that emotions at macro level can be triggered by appraisal themes, in alignment with which emotions induce “cognitive predisposition” to evaluate future events (Han & Lerner, 2006). Between the two groups that classify the emotions by the way they influence decisions and judgments, it was decided to study integral emotions due to the available technology for the analysis, and sources limits.

So as a conclusion it can be said that by analyzing how integral emotions affect people’s choices it is possible to build approximation of the future events.

But before looking into the existing research devoted to the emotions’ ability to predict future decisions and actions, it’s important to investigate whether the idea of predicting anything makes sense in the today’s rapidly changing world.

2.2 Is it possible to predict anything in the modern world?

The “forecasting” fever has become so widely spread during the last few decades among academics and business people, that there were just a few who dared to question whether it was rational practice and worth spending valuable resources to build any complicated forecasting model.

Among these few brave ones was Makridakis, Chatfield, Hibon, Lawrence, Mills, Ord, and Simmons, (1993), who stated that many complex statistical forecasting models were not as successful as they hoped to be.

But such scarcity in criticism of forecasting modeling didn’t last long.

In 2007 Nassim Nicholas Taleb published a book that provoked a wave of doubts in the ability of humanity to forecast anything. The book ‘s title “Black Swan” is used as a term for things and events that can’t be ever predicted due to the “randomness of empirical reality” (Taleb, 2007). It is widely accepted practice to track down all the anomalies and exclude them from the analyzing data set during examination of any phenomena. Taleb argues that such approach is completely wrong. It allows studying only normal “bell-curved” cases, while “life consists of shocks and jumps”. And “despite or maybe because of new inventions, progress, the world will be becoming even more unpredictable” (Taleb, 2007, p.

54). Thus any forecast based on historical data is useless in real life, because “history doesn’t crawl, it jumps” and “every day brings something unforeseen” (Taleb, 2007, p. 67).

“Black Swan” spent 17 weeks in New York Times bestseller list (Wikipedia) and caused a stream of skepticism towards various aspects of forecasting.

In 2009 Goldstein and Gigerenzer published a paper, where they questioned the prediction power of complicated forecasting models, and compare it with the one of simple models that take into account only one or two basic factors – heuristics. They discovered that heuristic based models gave better explanation to people’s behavior, and thus performed better in forecasting various phenomena than complex multifactor models. To support their findings Goldstein and Gigerenzer sited the famous paraphrase of Einstein “make things as simple as possible, but not simpler”. They argued that simple, but not oversimplified input factors in some situations especially with high uncertainty- the usual case in the real world, provided with robust forecasting results.

One of the main barriers for the simple models to be accepted is that for some reasons human psychology doesn’t acknowledge heuristics as sufficient factors to base scientific and business developments on. Thus, according to Goldstein and Gigerenzer (2009), many complicated models are used just because it’s accepted by society that the more complex a model the better results it generates, which is certainly untrue. The undesirable consequence of such tendency is that multiplex models are considered the final goal, behind which stands simple desire to show off, while such important objective as to learn how to get the results that will really make a change to something better are missed (Goldstein & Gigerenzer, 2009).

Makridakis, Hogarthb, and Gabac (2009) concentrated on grouping the events by their uncertainty and creating forecasting strategy depending on the type of uncertainty. The authors defined two main types of uncertainties: “subway uncertainty” and “coconut uncertainty”. The “black swans”, using Taleb terminology, they put as a separate type, as it was very rare and impossible to define beforehand. Events with “subway uncertainty” are possible to predict with fare accuracy with a help of statistical models, since it is not difficult to count their mean and deviation due to their “continuity between the past and the future”. At the same time Makridakis et al. (2009) agree with Taleb that life is full of unpredictability, and there are a lot of rare events with "coconut uncertainty" that are very hard to predict such as earthquakes and financial crisis. However the authors state that *even if it is impossible to predict something, it doesn't mean that it should be neglected in any forecast. On the contrary, "coconut" events create huge distortion of the reality and thus their occurrence even if unpredictable should be always taken into account.*

As to Black Swans, they are unknown unknowns, using the former US Secretary of Defense Donald Rumsfeid terminology, and they are impossible to imagine, unrealistically to foresee. Black Swans "can only be identified after their occurrence, since if we could have anticipated them before, they would not be Black Swans" (Makridakis et al., 2009). Great Depression 1929-1933 is one of the best examples of Black Swans.

It is important to be aware of Black Swans, *but it doesn't mean that there is no sense in making attempts to forecast certain events*. Most of life situations are a combination of "subway" and "coconut" ambiguity, or, returning to Donal Rumsreid way of defining it, known knowns and known unknowns. In other words almost every event has a component, that is known for sure what it will be in the future, and another component, the possible future states of which is known, but which of them will happen is a mystery. And although the unpredictability of "coconuts" can't be eliminated, still it makes sense to build forecasting models preferably as simple as possible that will be undoubtedly of great benefit not only to business and policy planners, but also to an average person in every day choices (Makridakis et al., 2009). Another argument in favor of keeping on trying making predictions is borrowed from the systems approach. It argues that first of all people need to change the type of questions they ask when trying to anticipate coming up events. Instead of attempting to find the future values or probabilities, models should enable to apprehend "**the subtle dynamics of the complex systems in which we are embedded, and find ways to shape and direct them"** (Orrell & McSharry, 2009). One of the suggested methods to create such models is to build it in accordance with the following 3-step strategy: (1) "Accept" the existence of uncertainty; (2) "Assess" its magnitude; (3) "Augment" its range. The last step relates to the typical human behavior shortcoming - the tendency to underestimate effect of uncertainty or in other words to "downgrade or completely ignore the risk that a storm or hurricane can hit [...] during the long periods of calm" (Makridakis et al., 2009).

To conclude it should be said that the nature of many life events makes it clear that none of the forecasts can give 100% accuracy, but by building predictions without expecting them to give absolutely clear picture of the future, and taking into account as many uncertainties as possible, there is a great chance to invent a model that will be applicable to single out the best future choices and decisions.

2.3 Emotions and Predicting the Future

This section will concentrate on examination of emotions ability to predict the future.

The first section of this chapter was devoted to introduction of several theories about the nature of emotions, their components, followed by Appraisal-Tendency Framework, that shows how emotions influence decisions and judgments through appraisal themes. This section will be focused on theories that offer explanation to the process of the future formation with a help of emotions.

Until recently research on forecasting was built with two main purposes, to foresee either the occurrence of future events (e.g., price of a company's shares) or individuals own behavior (e.g., "will I study in this university next year?"). But all this research neglected very important point, namely people's ability to predict their own feelings, because at the end of the day what interests people the most is what they want to know about the future (Wilson & Gilbert, 2005). For example, they want to know if they will be studying in a specific university, since this directly influence their future career and thus many aspects of happiness – money, reputation, relationship, friendship. Actually behind many choices in life lies happiness as it is the root of all drives in human life (Wilson & Gilbert, 2005). Thus individuals choose and follow certain sequence of actions by evaluating whether it will make them happy, and if yes, for how long.

To investigate deeper the above statement researchers began studying affective forecasting, which is about predicting how you will feel in the future (Affective Forecasting. Psychology Today).

The extensive analysis in this field revealed that individuals tend to mispredict the degree of pleasantness of the future events, which in turn leads to pursuing the events that don't maximize their happiness (Wilson & Gilbert, 2005). For example, affective forecasting errors can cause people to make poor medical choices (Riis et al., 2005), buy ice-cream more then they really will be able to eat (Wilson & Gilbert, 2005), misinterpret someone's feelings in a specific future situation that results into interpersonal misunderstanding (Van Boven, Loewenstein, & Dunning, 2003).

Another more detailed illustration of affective forecasting fallacy is offered by Van Dijk. (2009), who demonstrated how athletes were inclined to overestimate the emotional experience they would gain after results of a race. The author discovered that athletes were more biased when they expected negative outcome and that athletes with high expectations of positive consequence would force them training much harder in comparison with those who have negative expectations such as defeat in the race.

After brief acquaintance with the affective forecasting phenomena and its misleading consequences, it became clear that the more positive impression about certain event an individual had, the higher the probability he or she would choose to participate in this event due to his of her high expectations of positive emotion experience during or after this event. So it can be concluded that by creating an emotional chart, consisting of individuals' impressions, expectations, and other emotional experience, it's possible to predict particular future events with a certain degree of accuracy.

This discovery provoked many researchers to question how knowledge of emotional profile of a certain group of people can be applied in practice.

Carroll et al. (1994) conducted very important study using sentiments profile of US population as a main input. They discovered, after fixing all fundamental factors of spending at the same level, that sentiments played a small but valuable role in predicting any alterations of spending. The same connection was found in the United Kingdom (Berry & Davey, 2004), Australia (Bryant & Macri, 2005), and Canada (Kwan & Cotsomitis, 2006). Taking into consideration that there is high degree of integration, at least among developed countries, it is reasonable to assume that this connection between sentiments and spending changes will be expanded to other countries (Chua & Tsiaplias, 2009).

Besides consumer spending public emotional profile might be valuable indicator of GDP due to the significant contribution of consumption to GDP and a "cointegrating relationship" between consumption and GDP (Chua & Tsiaplias, 2009).

To summarize, this chapter helps to see how emotions through process of affective forecasting participate in the future formation, and how misleading the affective forecasting can be in drawing a picture of the future events and outcomes. This chapter ends with review of some practical examples, illustrating how knowledge of public emotions can be applied in forecasting such important economic indicators as consumer spending and GDP.

2.4 Internet, Social Media and their influence on humanity

"*The Internets is the greatest distractor to serious thinking since the invention of television"* (Leo Chalupa, ophthalmologist and neurobiologist, University of California, Davis).

"Filtering, not remembering, is the most important skill for those who use the Internet" (David Dalrymple, eighteen-year-old PhD student; researcher, MIT's Mind Machine Project).

According to some well-known academics and business people the Internet along with positive changes brought in the life of humanity quite considerable negative alterations in the way people receive and digest information. Though it is probably true, but the Internet has achieved something else that outweighs most of the negative effects; that is modifications in the communication process among individuals. And this has impacted all the areas of human's life regardless the attitude one has towards this process. The main channels through which online communication penetrated daily routines are email, message boards, forums, blogs, social networks, and, more recently, microblogs (e.g. Twitter). All these channels are grouped under Social Media conception. And according to many specialists in this field, the society in the modern world no longer consumes and shares information through traditional media sources, instead individuals have become media themselves using social media as their tool (Thevenot, 2007; Comm, 2009). As Gruhl (2004) described it, the Internet and its sub product - social media - have "changed the physics of information diffusion". Using social media platforms people share their experiences, news, insights, perspectives, opinions, and emotions, which makes these platforms an unique channel for expressing the internal world of every human being. Besides, through expressing themselves, individuals are building their social relationship with various people many of who they haven't even met, and this was impossible just around 4 decades ago (O'Dell, 2011). However the empirical studies showed that in reality individuals communicate with only few people listed as "friends" in their social networks. This finding is in alliance with the viewpoints of many professionals (see the quote at the beginning of the chapter), who affirm that the Internet distracts from serious thinking, making attention a scarce resource and forcing people to concentrate on interaction with only few the most important social contacts (Huberman, Romero & Wu, 2008).

The main factor caused this attention distraction is the enormous amount of information and social connections bombarding each and every Internet user every day. So scarce attention is like a shield protecting from brain overload. At the same time this various types of data flow thought the Internet cause rapid growth of sharing activity. This might be a consequence of reciprocity, a social psychology law arguing that the more people get the more they feel like sharing. The peculiarity of this process of sharing is that it includes not only external but also personal information. In addition to reciprocity law the increasing wiliness to share can be explained by such behavioral pattern as self-disclosure, which makes people to desire to (Loinson, 2001). This behavioral pattern makes people desire to publish their emotions statuses, write their emotional statements, talk about their emotional states (Loinson, 2001). This tendency turned sharing from occasional and unplanned to purposeful and regular activity. Nowadays sharing is driving experience, not other way around. Thus this trend makes the Internet, its social platforms in particular, a unique unlocked door to the souls and minds of human beings.

As the volume of news, facts, and messages pouncing daily upon heads of the Internet users is growing rapidly beyond any control, the disclosure of personal information is becoming more habitual and very normal thing to do. This tendency makes the doorway into the society internal world larger enough to make a lot of positive changes in the process of research, and bring a lot of new amazing and valuable discoveries. The realization of this great opportunity made academics investigate with great attention a role of online emotions in the modern world, including its role in forecasting of various phenomena. The evolution of this kind of research rises from the first attempts to see how general online chatter could predict the future.

Everything has started with analysis of how information from search engines, Google in particular, can increase predictive effectiveness of epidemics of flue and other dangerous diseases as well as some important economic trends such as unemployment and private consumption. In the paper "Infodemiology: Tracking Flu-Related Searches on the Web for Syndromic Surveillance" Eysenbach showed that there was very high correlation (r=0.91) between number of clicks on keyword-triggered Google search results and flu epidemiological data from the season 2004/2005 in Canada. As a conclusion he argued that Google trends were more timely, more accurate and cheaper method of tracking flu infectious than traditional reports on clinically observed by physicians flu-like cases. Thus web searches have ability to forecast relevant for health industry topics.

At the same time it was discovered that Google search analysis can reveal some trends and be valuable input for forecasting models not only in health industry, but also in the world economy. A study by Ettredge, Gerdes, and Karuga (2005) demonstrates that even short-term job-related search data can have significant association with official unemployment data. D'Amuri (2009) agrees with this statement arguing that even for quarterly unemployment rate Google index[2] (GI) should be routinely included in forecasting models. But he remarks that GI has limitations to be taken into account, among which the search of jobs when the seeker is still employed is the main one. Nevertheless D'Amuri shows that predicting power of GI is superior to the widely used unemployment indicators such as the employment expectations surveys and the industrial production index. Another interesting finding discovered by D'Amuri is that models built on small set of data but with inclusion of GI has better performance then the ones based on much larger sample even when expanded with other leading indexes.

Besides unemployment Google Trends data were examined for effect on private

[2] number of job-related searches divided by total number of searches (Reid, 2004)

consumption. Shmidt and Vosen (2009) compared Google Trends with survey-based indicators in their forecasting performance of private consumption. The authors state that search queries is a preliminary step before purchase decision, thus it's a good source of measuring future consumption. Further on the comparison the existing forecasting model with the model augmented with survey-based data illustrates that search queries provide with higher increase in the model prediction power than conventional survey-based indicators.

There are many other studies that investigate Google search queries as way to forecast various phenomena, and each of them in their own expand agreed on the value this source of data can be for predicting modeling in any specified area.

The results of the Google search studies provoked next flow of research papers, concentrated on the social media platforms such as blogs, Twitter, and discussions as a next prospect prediction tool. And these online data have much greater disruptive potential in comparison with GI methods (Economist, 2011).

"[…] *those who weave the deliberate acts of listening, predictive analysis, and studying market reactions will learn and demonstrate that markets are indeed defined by conversations*" (Solis, 2010).

There are quite a few studies on utilizing Twitter to predict first signs of disease outbreaks. Ritterman, Osborne, and Klein (2009) and Quincey & Kostkova (2009) analyzed Twitter ability to improve forecasting accuracy of H1N1 epidemic. Another series of research works were devoted to evaluate national influenza rates relying on Twitter messages (Lampos & Cristianini, 2010)

Besides enabling to foresee the time when epidemic may break out, Twitter messages can help to predict other disasters such as earthquakes. One of the most impressive utilizations of Twitter in this field was a system created to monitor real-time tweets in Japan to pinpoint with fairly high accuracy when and where earthquakes occured (Sakaki, Okazaki, & Matsuo, 2010).

Twitter is not the only social media platform that is examined on prediction power of the events. Researchers from IBM Almaden Research analyzed correlation between blog posts about books and Amazon book sales spikes (Gruhl, Guha, Kumar, Novak, & Tomkins, 2005).

As the result it was established that there was quite high correlation between blog posts and book sales spikes. It's worth to emphasize that the authors don't try to prove causality, meaning that they don't argue that blogs can cause growth in sales. On the contrary, they state that most probably blogs are non-causative reflection of some external events that lead to sales spikes. The authors of the study propose also some ideas for further research, the most interesting of which is the idea to test prediction power of online chatter in events such as election and common reaction to various corporate or public policy changes.

And this idea was partly implemented with a help of Twitter by Tumasjan, Sprenger, Sandner, & Welpe (2010), who observed how Twitter chatter served as platform for deliberation regarding German federal election, and how tweets numbers partly reflected the results of this election. There are many other studies, findings of which prove that "social media, such as Facebook and Twitter, were often better predictors of election results than how much money a candidate raised and spent […]" (The Economic Times, 2010).

Finally further prosperity of the social media platforms and increased openness of their users brought to the idea that these platforms stored a lot of consumer insights, which by applying proper processing techniques can draw more or less real emotion chart of the users and amend existing forecasting methods. And this is how the era of series of fascinating research devoted to online emotion as a prediction tool has started. There are already quite a few studies and projects that clearly demonstrate the fantastic perspectives in this field.

In 2006 Mishne and Glance published a study where they showed that blog posts sentiments could predict movie revenue. Later Azur and Huberman from HP Labs (2010) discovered that tweets could outperform market-based indicators such as Hollywood Stock Exchange Values in predicting box-office revenues for movies, and by including tweets' sentiments the prediction power increased even more.

In relation to other industries, Gilbert and Karahalios (2010) found out that daily rates of anxiety, fear, and worry in LiveJournal blogs may show the future direction of the stock market movements.

Moreover strong correlation between Twitter sentiments and public opinion polls suggests that emotion profile of Twitter users can reveal public opinion regarding widely discussed topics (O'Connor, Balasubramanyan, Routledge, & Smith, 2010).

The above-mentioned research papers and many other show that social media platforms have a great potential to become a widely used forecasting instruments. The insightful information they store, emotions in particular, can raise forecasting practice to the next level. This will be beneficial for all industries, but especially for financial markets

2.5 Behavioral finance

As first and second sections of the Theoretical review demonstrate, emotions play crucial part in mental processing operations.

According to some research works (Clore, Schwarz, & Conway, 1994; Forgas, 1995; Isen 2000), good mood provokes more optimistic judgments, even in very abstract areas, where there is usually lack of accurate information, leads to utilization of more clear heuristics, and less critical detailed ways of information processing. Besides, good mood makes people rely on "pre-existing knowledge structures" (Bless et al., 1996*)* part of which is stereotypes, and leads to more positive assessment of future events.

At the same time negative mood usually has negative impact on information perception, future events evaluation, risk consideration.

Taking into account all this effects of the emotions on the mental output of the humans, theorists in various areas have reconsidered many models, which previously served as basis for all the next stage research. Financial theory is not exclusion.

The first signs of todays widely developed and very popular branch of financial analysis– Behavioral Finance – appeared in finance journals in the 1970s, when theorists, though still remaining loyal to Efficient Market Theory, couldn't anymore neglect the anomalies in the stock market (Fama, 1970). By that time Efficient Market Hypothesis (EMH) was firmly established in financial world, and according to it financial markets work "informationally efficient", which denotes that any additional information is immediately reflected in the market prices.

At the end of 1980s it became evident that EMH couldn't explain some substantial noise that caused several considerable changes in the market movements, the direction of which was far from efficient (Shiller, 2002). Theorist cherished a hope to clarify this noise with a help of semi-strong version of EMH, which argues that the Hypothesis works only for publically available information. Hence stock market players can't make any excess profits relying on publically available information (Fama, 1970; Fama, 1991). However the nature of most of the noise sill remained undiscovered.

This fact made researchers turn their academic curiosity towards new alternative theories. During 1990s the academic attention in financial markets gradually shifted from time series analysis of prices, dividends, indices and other financial indicators towards models based on human behavior and sentiments (Shiller, 2002). This is how Behavioral Finance has been developed.

"Behavioral finance – that is, finance from a broader social science perspective including psychology and sociology - is now one of the most vital research programs, and it stands in sharp contradiction to much of efficient markets theory" (Shiller, 2002)

One of the main theories in Behavioral Finance is feedback theory that argues that many financial decisions are based on biased information. This biased information has been received either from successful investors that managed to profit on speculative prices and cause word of mouth buzz, increased expectations, and excitement or from previous experience that is the result of the systematic biases of human judgments (Shiller, 2002). Both kinds of feedback may account for creation of speculative bubbles, which can be either negative (continuous groundless, based only on expectations of price decrease) or positive (continuous groundless, based only on expectations of price growth) (Shiller, 2002).

Some other behavioral economists apply cognitive psychological interpretation of nature of bias that emerges from established preferences, beliefs, decision-making processes in order to explain why people don't follow Bayes's law and SEU while dealing with new information and making decisions. The interpretation includes 6 human behavior patterns that prevents from behaving rationally (Thaler, 2005)

<u>Self-attribution.</u> Individuals have a tendency to attribute the events that are consistent with

their actions to their own capabilities, and the events that controvert their actions to bad luck (Bem, 1965).

Representativeness. People often think that they see certain rules, interdependences in completely random sequence (Kahneman, & Tversky, 1974). In other words, individuals, being unaware of data-generating process are inclined to make certain conclusions, relying on very few data points (Thaler, 2005).

As an illustration consider the following: an investor is considered to be successful and professional only because of 2 or 3 first profitable transactions, even though she or he might be just a lucky amateur.

Overconfidence. People very often overestimate their ability to predict the future. There is statistics that shows that when people are absolutely sure about certain outcome, only in 80% cases it really happens (Fischhoff, Slovic, & Lichtenstein, 1977).

Optimism and Wishful Thinking. Large portion of population have unrealistically optimistic views on their skills, abilities, perspectives. According to some surveys about 90% of participants are sure that their driving, networking skills are above the average, the same is true for sense of humor. Also their time estimation for a task to be fully completed is much shorter than it is in reality (Buehler, Griffin, & Ross, 1994).

Belief Perseverance/Conservatism. A lot of studies show that individuals have strong attachment to opinions, decisions, and things they have for too long. (Lord, Ross, and Lepper 1979). In this case they may disregard any new piece of information that doesn't reconcile with their established opinion. For instance, an individual may neglect earnings or other public announcements relating to a certain subject of evaluation, because s/he believe that the announcement has a temporal effect, and keep sticking to the prior earnings estimation.

Availability Biases. In order to build an estimation of probability that certain things will happen people frequently rely on the recent memories they consider relevant to a subject. For example, if your friend was mugged by a taxi driver in the city you live, it will influence your choice of means of transportation next time you will need to go somewhere. Another illustration given by Thaler (2005) is the nature of expertise. As he argues "expertise, too, is often a hindrance rather than a help: experts, armed with their sophisticated models, have been found to exhibit more overconfidence than laymen, particularly when they receive only limited feedback about their predictions" (Thaler, 2005). This means that if you haven't received any complaints from outside world regarding the things you do, you will tend to overestimate your professionalism in this area.

Awareness of all these behavior patterns enables to recognize not only irrational behavior itself, but also the factors that my cause this manner of behavior way in advance.

One of such factors is underacting in reply to market news that leads to a very slow price adjustment to a new information set and new market environment. This is a clear impact of the conservatism pattern.

Another very common factor is recommendations from stock analysts that are considered industry specialists usually in the number of stocks from 5 to 25 (Michaely & Womack, 1999). Because of the fact that these stock analysts constantly update their reviews of the stocks and recommendations, they are considered "informed investors" as Grossman (1976) would call them and worth to be listened and followed, which is direct result of the representatives' pattern of human behavior. Thus any change in recommendations, any announcements from these stock analysts is considered very valuable piece information, and thus enables these stock analysts influence the prices of individual stocks.

Leading consulting companies McKinsey & Co. has divided all the factors that can cause market deviation from its effective state into three groups: a) irrational behavior; b) systematic patterns of behavior; c) limits to arbitrage in financial markets (The McKinsey Quarterly, 2005). The first two conditions combine the behavioral patterns described above, where irrational behavior caused by belief perseverance/ conservatism and availability biases, and systematic patterns of behavior include overconfidence, self-attribution, and representativeness. As the company's analysts explain in the online business journal The McKinsey Quarterly (The McKinsey Quarterly, 2005), the irrationality in investors' behavior may be caused by putting too much emphasis on recent results and events. And this excess attention leads to unreasonably high stock prices of companies' that happen to show positive performance indicators and receive positive feedback from outside business world. However McKinsey analysts are convinced in short-term nature of market inefficiency, and thus advise corporate managers to use knowledge of this phenomenon only for tactical decisions such as value of a transaction or issue of additional capital, whereas for strategic decisions they should rely on well-known and widely used discounted-cash-flow approach (The McKinsey Quarterly, 2005).

This thorough analysis of behavior patterns has a prime goal to illustrate how emotions touch the most important aspects of the stock market. To make it absolutely clear the relation between emotions and above-mentioned behavioral patterns should be explained. After careful consideration it became obvious that behavioral patterns are the product of emotional reaction to the outside changes. This emotion reaction can be both positive and negative or only positive, or only negative. For example, such pattern as conservatism is a mixture of fear and calm, representativeness bases mostly on trust. Thus behavioral finance is a quite successful attempt to connect emotions of market actors and market inefficiencies. As Orell and McSharry (2009) describe it, behavioral finance is a combination of knowledge of experts from such fields as psychology, neuroscience, economics and its aim is to "understand the emotional biases that govern decision-making".

However the analysts warn that the prices may fluctuate from their market efficient level only when the systematic patterns of behavior *are expressed by a large group of investors at least for some time*. And that is distinctly proven by many academic papers, for example, Samanidoul, Zschischang, Stauffer, & Lux (2007) in their paper, devoted to agent-based modeling and its application in finance, say that "agents learn by adapting to their environment, and their collective actions can produce emergent behavior", meaning that a group of market agents by expressing similar emotions can become a stimulant for abnormal behavior of the market. These collective actions according to Demarzo et al. (2003) are a product of not only quality and accuracy of shared information, but also the strength of ties connecting each individual within a network – source of this information.

To summarize, there are 6 behavior patterns that have emotional determinative factors, responsible for market deviation from its efficient state defined by EMH. This deviation has short-term nature, and is not easily achieved. For the emotions and thus certain behavioral patterns to have an effect on market prices, they should be manifested by considerable group of people. Emotional contamination among market agents depends on not only quality of spreading information, but also on degree, i.e. number of connections, each individual has in a social network, which is the source of the information.

Thus if there is a network that is a perfect transmitter of a certain emotionally rich information among large number of people, then there is high probability that this emotion infection would be large enough to cause short-term effect on financial markets. With high probability such network can be Twitter.

2.6 Twitter sentiments predict stock markets

This chapter has a goal to combine all the findings of the theoretical review in the previous sections. So to briefly summarize, in the first three sections clarified the nature and dimensions of emotions, emphasizing the role of emotions in forming the future, questioned the ability to predict anything in this world and found the prove that by taking specific precautions there was a chance to build an efficient forecasting mechanism, and finally examined how exactly emotions effect forthcoming events and how the knowledge of this process can help in predicting certain phenomena.

Then the theoretical review was advanced by careful analysis of the Internet and social media platforms, focusing later on estimating online chatter prediction power and more importantly prediction abilities of emotions extracted from it. Lastly the previous section carefully considered the Behavioral Finance theory in order to see how emotions participate in financial market decisions and events and build a full theoretical base for an investigation of the question whether emotions extracted from tweets can enhance the efficiency of a stock value forecasting model.

The choice of Twitter as source of emotions was explained in the introduction chapter, to repeat in short, the main reason is that Twitter is a platform of fast, real-time exchange of any kind of short messages that can easily be collected and analyzed. The limited size of the message makes the analysis even easier providing with more precise and concise information.

Besides for stock markets Twitter has started playing very important role. By now many specialists mention that tweets are "the modern version of traders shouting in the pits"

(BusinessWeek (2009). And increasing number of investors argues that many of their successful decisions were made relying on the information from social media; Twitter in particular (Bloomberg, 2010). That won Twitter fame among financiers community as a "Bloomberg for the average guy" (BusinessWeek , 2009).

"Communities of active investors and day traders who are sharing opinions and in some case sophisticated research about stocks, bonds and other financial instruments will actually have the power to move share prices [...] making Twitter-based input as important as any other data to the stock" (TIME, 2009).

And regardless relatively young age in comparison with other social media platforms Twitter has become more preferable source of the stock market information. One of the main reasons is that unlike financial blogs or forums, where readership can be achieved by simply writing opinion posts or comments without worrying about establishing reputation among other blog/forum users, Twitter users care what other users think about them, because it directly impacts the number of their followers and retweets. Thus the quality of tweets, their insightfulness and value are very important to maintain and develop further fellowship and the rate of retweets (Sprenger & Welpe, 2010), and that testify the trustworthiness of tweets in the eyes of investors.

The increasing role of tweets in financial decisions revealed business opportunity that some of entrepreneurs have quite successfully realized, for example, Wall Street Birds that provides online stock signals based on Twitter analysis (PR Newswire, 2011).

The mechanism behind such kind of business projects though is not illustrated explicitly and most probably includes sentiments extracted from tweets as one of the main inputs.

As Zhang, Fuehres, and Gloor (2009) showed in their early work that such emotional words as Happy, Hope, Fear, Worry, Nervous, Anxious, and Upset have significant correlation coefficients with daily values of the three main indices DJIA, S&P 500, and NASDAQ within time period from 30 March 2009 to 7 September 2009. The authors' in their preliminary conclusion state that "just checking on twitter for emotional outbursts of any kind gives a predictor of how the stock market will be doing the next day" (Zhang et al., 2009).

Later next year Sprenger and Welpe (2010) published a working paper, where they analyzed on daily basis roughly 250 000 stock-related tweets and found that tweets' sentiments (bullishness) have strong association with abnormal returns of the stock market. However Sprenger and Welpe (2010) state that due to the transaction costs and rapidness, with which the market absorbs new information, it is very had to exploit market inefficiencies. Though later the authors add that it might be possible to make profit out of these abnormal returns with the help of a more complex and precise emotion extraction technique. And this is quite feasible, taking into account enormous attention towards anything happening in the area of Twitter data implication.

In February 2011, Bollen, Mao, and Zeng illustrated that particular kinds of emotions could improve accuracy of even the most basic, based on only historical values, forecasting models of daily DJIA closing values. They found out that among the 6 emotions only Calm increased prediction accuracy of the DJIA historical values-based model. As the authors explain that strong reaction to unexpected news that cause fluctuation of calm state of human beings keeps being significant factor for stock market results. The remained five emotions covered in their study are Sure, Alert, Vital, Kind, and Happy.

However, existing literature has not addressed some of the limitations in their methodology. For instance, Bollen et al. (2011) investigated the influence of only positive emotions, with one exception – Alert, the polarity of which is a bit unclear. In this research it was considered essential for measuring effect on stock market values to examine a combination of both positive and negative emotions.

Moreover the mentioned papers have based their research on daily data, which maybe too long time period for such rapidly spread pieces of information as tweets. As it was shown in the introduction chapter the speed of diffusion of information in Twitter is very high (Kwak et. al., 2010), thus emotions can affect stock market already the next minute. Also according EMH markets absorbs information within the next moment it became publically available (Fama, 1970; Fama, 1991), and McKinsey analysts are confident that any market inefficiencies can last only very short period of time (The McKinsey Quarterly, 2005). Taking this into account it was decided to build analysis relying not on daily, but hourly values.

In addition, none of the research specifies geographical limits of their Twitter data set. All three research collected English-language tweets to analyze U.S. based stock indices and other events such as Thanksgiving and U.S. presidential election (Bollen et al. 2011). But it is obvious that far from all English-language tweets were posted in the U.S. and thus could have any direct or indirect impact on the dependent variables. Even though US stock values are affected by individuals all around the world, the increasing international usage of Twitter might have caused geographical as well as cultural sampling errors (Bollen et al., 2011). Thus to avoid these possible errors this study relies of specified geographical market for both tweets and stock index values.

The present thesis strives to address these three issues through a more refined methodology. First, it will employ a wide combination of both positive and negative emotions, each of which will be described by a comprehensive list of associative words and phrases. Second, instead of daily data values, the data extracted for this thesis will contained more detailed hourly data that corresponds more accurately to the pulse of the market. Third, the thesis will address the generalizability of previous research by limiting the geographical market for the samples to one country – Singapore.

Therefore, my thesis will address the following hypothesis: **Hourly based emotional profile, consisted of positive and negative emotions, extracted from Twitter messages posted in Singapore, can increase efficiency of Singapore stock market index hourly value forecast.**

The analysis of this hypothesis will be based on MSCI Singapore Index Futures historical tick data and hourly emotional profile of tweets posted in Singapore within time period from 1 of September 2011 till 31 of October 2011. More details regarding the process and tools of the study I will describe in the next part of the paper – Methodology.

3. Methodology

3.1 Research basis

After formulating the working hypothesis, the next step is to specify tools and terms that will be employed to test it.

First of all it was decided to narrow down stock market values to only one aggregated stock index, trading in Singapore, since, as it was stated above, this is the geographical market, where all the data samples will be derived from. The reason is mainly the logic – the less complicated basis the easier it is to see the patterns that lead to an answer.

The choice of Singapore as a target geographical can be reasoned by its economic prosperity, international interest in it, huge flow of investments, international organizations, and Statsit long-term experience in working with Singapore social media platforms. Moreover the country's stock exchange – Singapore Exchange (SGX) – has quite high international reputation and is stated to be gateway between Asian and global markets, as it has the largest representation of international companies listed among Asia's stock exchange. SGX trades many different Asian indices, among which it's own index – MSCI Singapore Index (SIMSCI). SIMSCI is "adjusted market capitalization weighted index that is designed to track the equity market performance of Singapore securities listed on Singapore Stock Exchange" (MSCI, 2011). Thus the choice of SIMSCI was obvious.

Next step was to decide on the source of emotions that will be inserted into the base model to test the working hypothesis. As it was initially asserted all the emotional analysis will be implemented entirely in Twitter. The selection of Twitter has been rationalized already several times. However it can be added that it was decided to base the study only on Twitter, rather than on a combination of several platforms, e.g. Twitter, blogs, and forums, due to the fact that blogs and forums have very different, more complicated for analysis, format of communication from in comparison with the one of Twitter. Thus it would be very challenging to combine all the platforms and less effective due to the higher ambiguity of blog and forum posts.

3.2 Data collection

The main challenge of the study was to understand what emotions to derive from Twitter. But before facing this challenge it was essential to find a way to obtain Twitter conversation. The solution was found by cooperating with Statsit, that has a huge database consisted of historical and current messages posted on social media platforms and collected for each country separately. So the company provided with Twitter messages data sample, compiled from users in Singapore for the time period from the 12 of September 2011 to the 12 of November 2011. The data sample includes 8 531 222 tweets posted within given time span. Further processing of tweets created a new data pool that consists of sum values of each of the emotions per hour per day from the 12 of September 2011 till the 12 of November 2011. So after this operation there were 1464 units of the analysis.

After the question with Twitter data sample was solved, the next step was to decide on what emotions should be derived.

Since the aim of this study is to show that emotional public profile of Twitter messages analyzed on hour basis can improve forecast efficiency of a stock index hourly value, it should be clearly defined what is meant by emotional public profile. This term is used to designate more or less equal combination of positive and negative emotions that cover all the possible basic emotional states. Basic emotional states in turn mean the emotions, the combination of which produces all other possible emotional expressions, feelings, and moods. The reason why this study applies emotional profile is because it is believed that to examine influence of one phenomenon on another it is essential to reproduce their real nature as close to real as possible. Hence the study is built on emotional profile that was created in a way to include as many existing emotional expressions as possible, and in preferably in equal proportions to avoid any distortion. And it is especially important to consider negative emotions, since they have strong influence on decision making process in a way that a person becomes more attentive to details (Luce, Bettman, & Payne 1997, p. 384), relies much less on pre-existing knowledge (Schwarz & Clore, 1996), and displays extreme level of risk averse (Benartzi & Thaler, 1995). The last effect is knows as myopic loss aversion (Benartzi & Thaler, 1995), which is plays very important role is stock markets, for example, it has been prove to be one of the main reasons why a large amount of individuals prefer to invest in bonds when it was historically proven that stocks exhibits much higher rate of return (Narayana, 1996; Siegel & Thaler, 1997).

The reason why importance of negative emotions was emphasized in the previous paragraph is to address the limitation of one of the most reliable related research by Bollen et al. (2011) mentioned in the last section of theoretical review. As it was described there are three main limitations of related studies, one of them is failure to represent full picture of emotional profile. In their study Bollen et al. (2011) based their emotional extraction process on self-created mood analysis tool, GPOMS, the lexicon of which was derived from well-established psychometric method – Profile of Mood States (POMS) and include with one exception only positive emotions, namely Sure, Vital, Calm, Happy, Kind.

To create this emotional profile with balanced polarity, i.e. with equal number of positive and negative emotions, it was important to analyze other research papers dedicated to emotions' influence on various events. In their study Bollen, Mao, and Pepe (2011) rely on POMS-ex, which expanded version of POMS. The authors describe POMS-ex as psychometric instrument with the same six emotions dimensions as initial version POMS, but with expanded list of synonyms and related words constructions from 65 to 793 terms. The emotions dimensions are: Tension, Depression, Anger, Vigor, Fatigue, and Confusion. It is surprising that Morgan (1978) included slightly different number of emotions dimensions in his description of POMS. In addition to the six emotions enumerated above he had Friendliness that was the only positive emotion among all seven (Morgan, 1978; Morgan & Johnson, 1977, 1978). Anyway POMS doesn't satisfy the requirement of equal representation of positive and negative emotions.

Further examination reviled completely different sets of emotions. One of the most frequently applied is named group of basic emotions – surprise, happiness, fear, disgust, and anger (Collet, Vernet-Maury, Delhomme , Dittmar, 1997; Stets, 2005). There are many other classifications, each of which has slight dissimilarities from others. To give more examples, Izard (1977) has created his own set of 10 fundamental emotions – enjoyment, surprise, interest, anger, sadness, disgust, fear, contempt, shame, and guilt. Also Plutchik (1980, p. 138), relying on evolutionary theory, identified eight "primary" emotions – joy, trust, surprise, anticipation, anger, fear, disgust, and sadness. As it is shown there is no agreement in what emotions should be included in the list of basic emotions, thus it was not obvious what should be a final group of emotions to employ in the thesis analysis.

The solution was found through application of findings from few studies that showed how online emotional expressions differed from those used during standard linguistic sentiment analysis (Brill, 1992). The reason is that in the standard method of linguistic analysis words follow language grammar and spelling rules, while in online conversations and in Twitter especially there are many purposeful misspelling and various invented emotional expressions and emoticons (Derks, Bos, & von Grumbkow, 2008). Thus many researchers have created their own sentiment extraction algorithm with suitable for given social media platform list of emotions and associative words and expressions. This list takes into account the style of writing, abbreviations, and all linguistic innovations (Thelwall, Buckley, Paltoglou, Cai, and Kappas, 2010). Fortunately Statsit has already well-vetted emotional filter for Twitter platform that was developed through constant analysis of tweets, and has proved its effectiveness during more than a year of practice within Asian market. Besides reliability Statsit emotional filter solves another issue – the relatively equal representation of positive and negative emotions. It should be explained that the emotional filter represents list of emotions, each of which has a very thorough list of associative words, phrases, and any specific linguistic slang to be used in extraction of all relevant messages. The final list of emotions consists of surprise, happiness, calm, comfort, anger, frustration, and sadness. The actual emotional filter includes also trust, fear and disappointment, but during the analysis of the tweets, it was discovered that these emotions had very few relevant mentions, thus they were excluded from the study. So the final list of the emotions used to process the tweets consists of four positive and three negative emotions, which makes it quite balanced in terms of positive-negative gradation.

The question, how to extract the above emotions wasn't a problem since Statsit has very developed method to derive any mentions of specific keywords. This tool is using every word of expression from emotional filter to collect all the tweets that mention at least on of them. The emotional filter for given list of emotions has been created by Statsit analysts and utilized for impressive amount of research projects. The emotional filter applied in this thesis study can be obtained by contacting Statsit Head of Research Deborah M. Ko.

Next challenge related to finding MSCI hour data for this time period. The problem was twofold: first, all the financial web sites provided only with daily values of the index and secondly, SGX could sell the hour data only till 1 of October since they processed data on quarterly basis. The solution was found by contacting various financial organizations and investigating weather they were selling SIMSCI hour data. This is how tick database company Tickdatamarket was discovered. This company provided me with tick SIMSCI values for the requested time period within a week. By aggregating tick data it was easy to obtain hourly SIMSCI Futures values for the period from 12 of September till 12 of November 2011 that included close, open, maximum, minimum prices, and volumes. Futures value is the value of futures contract, the price and volume of which is agreed today, but the delivery is happening on the specific date in the future The number of observations wasn't as large as the one of Twitter, since SGX works within shortened trading hours during holidays and doesn't trade at all during weekends. Thus after all the processing was completed, there were 767 data points, each of which represented SIMSCI closing price value at the end of every hour.

The reason why closing price was chosen as the only dependent variable is because it is a common practice in stock market research (Bollen J. et al., 2011; Zhang & Wu , 2009)

So the final data pool consists of 767 observations for every of the following time series: SIMSCI hourly based close price and 7 emotions hourly values, within time frame from the 12 of September 2011 till the 12 of November 2011.

3.3 Data validation

Before designing the analysis, it's essential to understand the nature of the data to see what model can be applied to achieve desired result.

One of the most important tests is the verification of data linearity, because if the result of the test is negative then most statistical models will give distorted results due to their linearity assumption.

There are many ways to examine linearity; the easiest one is the graphical analysis. In the case of close price's scatter plot (Figure 1) it's hard to say whether very fluctuating time series reflects any linearity, though it is very tempting to assume already now that the data are far from being linear.

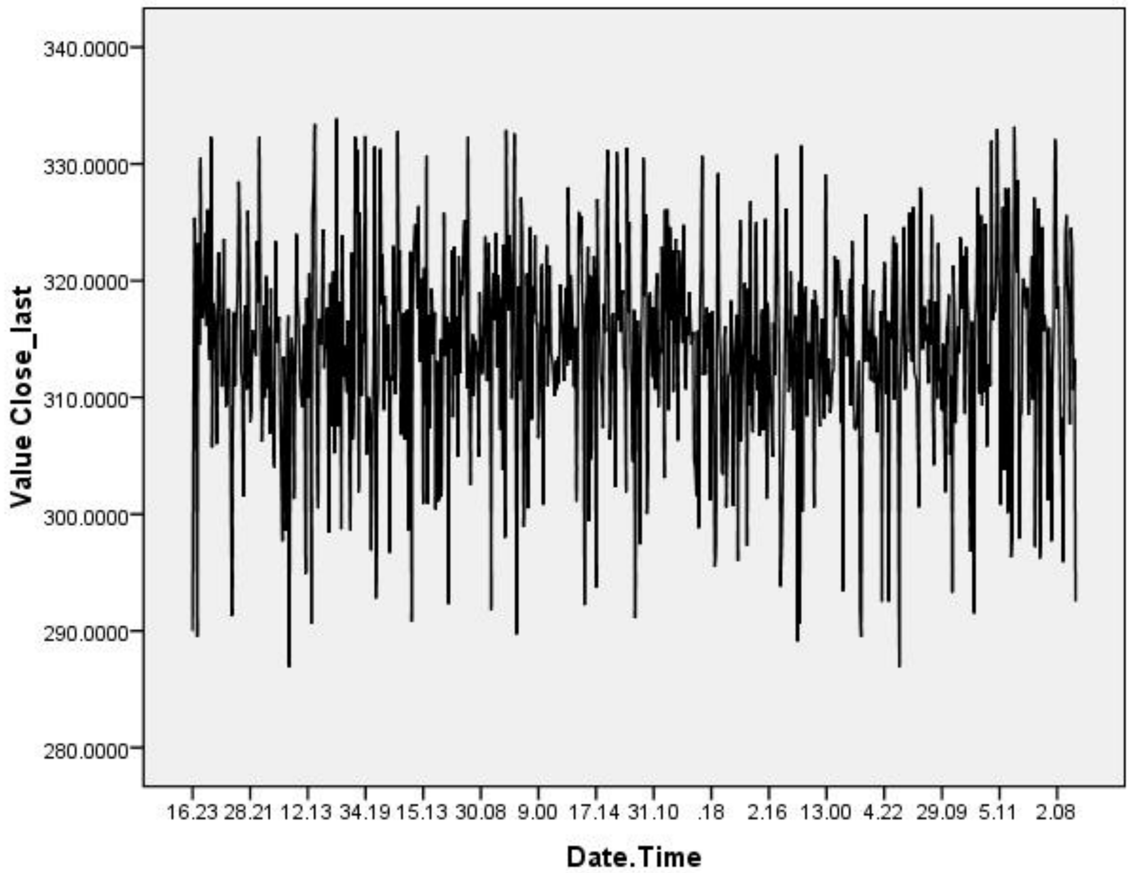

Figure 1. Close price sequence

More statistically reliable way to check linearity is testing the data with a help of various statistics. For this purpose Ramsey's RESET test was applied due to it's appropriateness for time series. The test investigating whether nonlinear transformation of the model is valid, in case it's not, then the data are linear and no power transformation is needed. The result of RESET test of close price showed in the Table 1 below.

SSR0	SSR1	F	Pvalue_F
1104.35	1104.35	0	1

Table 1

The P-value is much bigger than critical value of 0.05, which denotes that the hypothesis that nonlinear transformation is significant, i.e. the data should be described by nonlinear model, has not enough grounds to be denied. Actually with such a big difference between P-value and critical value, it can be argued that the data have very nonlinear fashion.

The next step is to examine stationarity of the data. This characteristic is very important assumption for any linear model. To test it the Augmented Dickey-Fuller statistic (ADF) was applied. This statistic assumes that stationary data have predisposition to return to a constant mean (Dickey & Fuller, 1979). The statistic was calculated several times with different number of time periods included. To choose which variation was the most appropriate it was decided to use the Akaike information criterion that shows which of the variants has highest goodness of fit for given data set. After identifying the best-fit model it was possible to proceed to the final step of the Dickey-Fuller process – comparison of the test t-statistic with the critical values for respective number of parameters and periods included in the model.

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.072[a]	.005	.004	1.20195	.005	3.933	1	764	.048	2.087

a. Predictors: (Constant), lag1_close

b. Dependent Variable: D_close

Table 2

Coefficientsa

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	2.957	1.578		1.874	.061	-.141	6.055
	lag1_close	-.009	.005	-.067	-1.870	.062	-.019	.000

a. Dependent Variable: D_close

Table 3

The t-statstic (Table 3) is higher than -3.45 for 5% critical value and for given number of parameters and time periods. Thus it is reasonable to conclude that there is no stationarity in the data. But before firmly stating this it's essential to check that the model's error terms are not positively autocorrelated, which can negatively influence validity of the results. Verification of positive autocorrelation was implemented with a help of Durbin-Wantson (D-W) statistic. As it can be seen from the table above, the model's D-W statistic is higher than upper critical level, which is 1.88270 for 750 total number of observations and two parameters (constant and lag1_close). This means that there is no positive autocorrelation. Thus the results of the ADF statistic are valid and prove nonstationarity of the data.

Being nonlinear and nonstationary, close price time series can't be examined with commonly used statistical models such as OLS since linearity of data is their main assumption. This indicates that this study should be designed basing on a model that doesn't assume linearity and stationarity of data. It will be shown in the next section that there is the whole family of models that satisfy this requirement.

Regarding emotions variables, it is strongly believed that there is no need to spend time on verifications of linearity and stationarity of emotion data samples since it was already agreed that the model to be used in this study should work with any kind of data (no any requirements on stationarity and linearity of data). However it is still useful to know the nature of all the data to be employed in the analysis. Thus it was decided to run RESET test to verify linearity of the emotions time series. Prior to implementing quite heavy calculations of the RESET test, each of the emotional variable was analyzed with a help of descriptive statistics that showed mean, standard deviation, maximum, range, and other statistical descriptive indicators (Table 4)

	N	Range	Mean	Std. Deviation
surprise_sum	767	17.00	1.2816	1.50247
happy_sum	767	7.00	1.2360	1.34431
comfort_sum	767	8.00	1.3129	1.44024
calm_sum	767	7.00	1.2595	1.27200
frustration_sum	767	7.00	1.2725	1.30577
anger_sum	767	7.00	1.0795	1.22749
sadness_sum	767	4.000	1.19426	1.200724

Table 4

It was discovered that all emotions time series are very similar in nature. Hence it was reasonable to assume that the result of RESET test of one emotion variable will be applicable for the remained six. The result of the test for Surprise time series is in table 5 below.

The result shows that the hypothesis of nonlinearity of the data sample should be rejected.

SSR0	SSR1	F	Pvalue_F
1581.58	1516.47	10.92	0

Table 5

Thus Surprise time series is linear, and with high degree of confidence it can be stated that the rest of emotion time series are linear as well.

3.4 Research design

There are many studies devoted to financial markets and prediction of stock values in particular. The most challenging part of these papers is to choose the right model to for analyzed data. This thesis is not an exclusion. The first glance at the possible options, gave the idea me that ordinary least square (OLS) would be the most suitable model for the given study. The ground of the choice was justified by quite considerable amount of studies that relied on OLS as feasible and less complicated model (Jing Tian, 2007; Yoon Dokko and Robert H. Edelstein, 1989). But this model assumes the linearity and stationarity of the data. Many of the researchers used various transformation technique to change data into linear and stationary sometimes without much improvement in the results.

However the further developments in the field of forecast invented a new way to tackle the nonlinear and nonstationary data not only in financial markets, but also in many other areas such as health, economics, and engineering. This new way is Neural Networks, and the algorithm of these models is actually not so new. Neural Networks (NN) have been widely used in neural science for many years to model human brain processes. In the basis of the algorithm lies a belief that all experience and knowledge are stored in the interconnections between the neurons, and by imitating these connections using knowledge of previous experience it's possible to build future values approximation. In another words, Neural Networks have potential to predict the future by learning behavior from previous experiences. This finding has immediately found its application in many engineering solutions in forecasting. During last decade a considerable amount of research was devoted to comparison of NN with widely used statistical models such as Box-Jenkins, polynomial regression, OLS .

Almost all of them concluded that NN outperformed them in forecasting ability. It should be mentioned that NN have limitations such as overtraining that can lead to biased results, but by following certain precautions, it's possible to reduce considerably the risk of any result distortion. Moreover NN process is a "black box", meaning that there is no way to find out how input and output connection through hidden layers is estimated (Li, 1994). Nevertheless these limitations are outweighed by much better performance in comparison with other statistical models. One of the reasons of NN's superiority is that they are based on learning process that allows to see patterns and predict behavior of any kind of data, even of the data with high structural instability. Moreover they don't make few if any prior assumption about the nature of generating process (Thenmozhi, 2006). And this quality makes NN a unique and quite effective instrument in prediction engineering in many areas, but especially in finance.

Financial industry deals with very unstable and unpredicted data, and there are many assumptions and very little knowledge about real generating process. As Granger (1991) states in financial data non-linear relationships are more probable to happen than linear. Moreover the financial markets are constantly under the influence of huge variety of macro-economic factors such as economic situation, government policy, investors' expectations, etc. (Wang, Y, 2002)

By now NN have found its value in almost every aspects of finance such as predicting financial distress, bond ratings (Hatfield & White, 1996), stock market (Yochanan Shachmurove, 2000), design of trading system (Kusturelis, 1998, Majhi R., Panda G., Sahoo G., Dash P. K., Das D. P., 2007), to name a few.

Many of these papers based their analysis on the most common type of NN - Multilayer Perceptron (MLP). Without going deeper into a long description of the algorithm behind MLP, it should be said that main principle of MLP is backwards learning process, where weights for each input modified according to the previous operation of error minimization (for more details see Leonardo Noriega, 2005). As other types of Neural Networks MLP enables analyzing both linear and nonlinear data (Hong-Choon Ong 1, a and Shin-Yue Chan, 2011), and due to its comparative ease to understand, apply with a help of any available software, and approximate input or output map (Birgul Egeli, Meltem Ozturan, and Bertan Badur, 2003) MLP became widely used in financial institutes. For example, General Electric and American Express use MLP to spot stolen card, to indicated patterns that may lead to fraud and, and to predict stock trading trends, prices (Shandle, 1993), Citibank has successful experience in predicting exchange rate with a help of MLP (Thenmozhi, 2006).

The academic world also seized the opportunity to discover new solutions in financial forecasting by questioning whether MLP had higher prediction power of stock values than commonly used statistical methods. Most of the studies came to positive conclusion – yes, MLP is superior in prediction power to the linear models for predicting stock market values (Shachmurove, Witkowska, 2000)

Thus for the given study MLP is perfectly suitable model. All the training of MLP network was carried out in SPSS MLP analytical tool, which allows full utilization of all the properties and settings of the model. The details of the process will be described in the next chapter of the thesis - Empirical Results.

4. Empirical results

This chapter will describe in all the details the process of designing close price forecasting model based on only historical data (**Model 1**), and then the results of this model. Further sections of the chapter will illustrate the expansion of **Model 1** by adding Surprise, Happiness, Calm, Comfort, Frustration, Anger, and Sadness time series (**Model 2**), with further analyzes of their performance. The set of all 7 emotions is named **emotional profile** following the terminology used in all the previous chapters of the thesis. Finally all the results will be compared and interpreted in last section of the chapter.

4.1 Design of Model 1

As it was discovered in the previous chapter the closing values of SIMSCI are far from being linear and stationary. Thus previously widely used linear statistical models are not applicable for the study even though emotion variables satisfy their requirements of linearity. The solution was found in new wave of studies in financial field that clearly showed that there was much better type of models for such chaotic data as stock values. This new type was Neural Networks (NN). Among all the types of NN this study has employed Multilayer Perceptron as the most common NN model. The software that was exploited to fulfill this task is SPSS MLP builder, which can be found among Analytical tools in the main menu of the application.

The first decision to make related to the order of lag[3] variables to use as input data (independent variables) in Model 1. The best strategy is to analyze partial autocorrelation (PACF) plot of close price time series. The rule of thumb is the following: "To determine tentatively the value of p [order of lag variables], look at the PACF plot and determine the highest lag at which the PACF is significant"[4]. Confident limits lines – two horizontal lines - show the level, above which the PACF is significant. From the PACF plot (Figure 2) below it

[3] An event occurring at time t+k(k>0) is said to lag behind event occurring at time t, the extent of the lag being k (A Dictionary of Statistical Terms, 5th edition, prepared for the International Statistical Institute by F.H.C. Marriott. Published for the International Statistical Institute by Longman Scientific and Technical)
[4] http://computerwranglers.com/Com531/Handouts/Time%20Series%20Analysis.doc

is clear that the optimal order of lag is one.

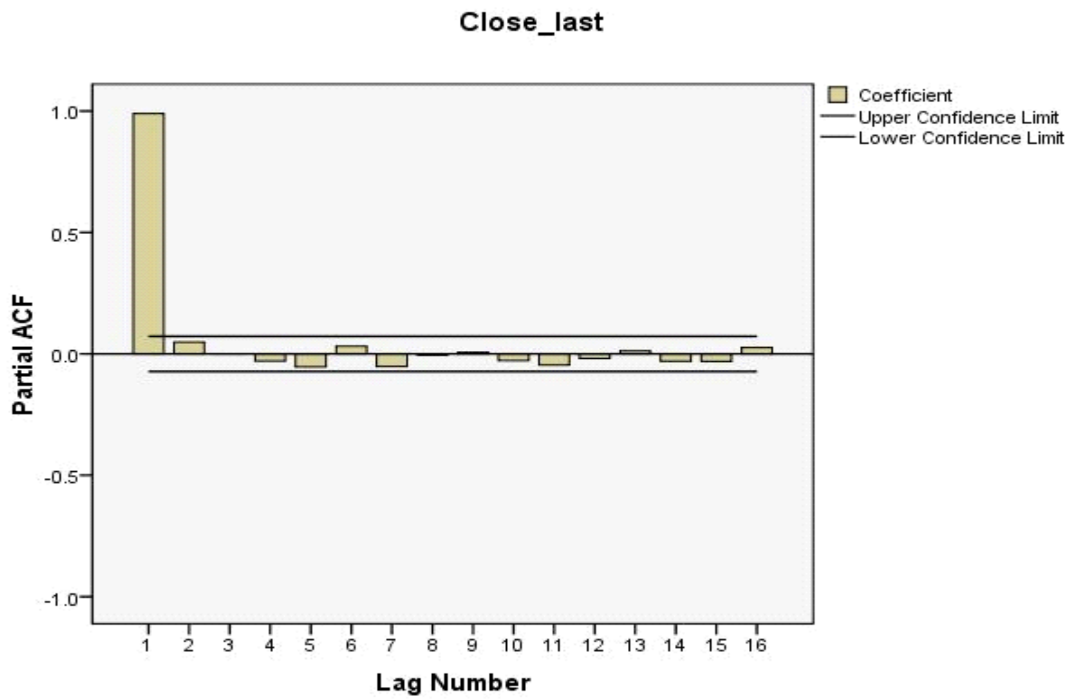

Figure 2

Thus the only input data for the Model 1 is the first order lag of closing price. To verify whether the result of the graph analysis is genuine the network was trained with various number of lags (with a maximum of 7). The outcome proved that the first order was the most optimal, since the network performed the best when there was only first order lag of close price as an input variable.

After the number of historical data point to be included as independent variables was defined, the next step was to design MLP model for SIMSCI close price by deciding on and specifying quite impressive number of parameters and criteria of the network architecture. So the creation process of MLP networks consisted of careful consideration of each of the parameters enumerated below.

Rescaling of input data. MLP offers four options: standardized (subtracts the mean and then divides by the standard deviation), normalized (the scale of the values fall between 0 and 1), adjusted normalized (the scale is between -1 and 1), none. Many researchers as well as

MLP practitioners (Zhang, 1999) used normalized scaling in cases when they have input set that includes variables of different range and standard deviation. This helps to avoid the situation when the larger numbers are considered to be more significant (http://www.faqs.org/faqs/ai-faq/neural-nets/part2/section-16.html). In the given case the Model 1 has only one input variable, thus there is no need in normalization. But it is important to keep in mind that Model 1 and Model 2 should have identical fixed values of all the parameters to track the effect of input variables alterations. And since Model 2 has, besides lag value of close price, emotion variables, the range and standard deviation of which are much lower than the ones of the close price lag value, it is necessary to apply rescaling. Thus it was chosen to apply normalization as rescaling operation in both of the models.

Partitions. With a help of partitioning the data pool is divided into training, testing, and hold samples. The training sample is the one that is actually used to create a MLP model. Basing on this sample MLP is trained until a certain stop criterion is reached. The test sample is an independent data set that is used to verify errors during training process. Through the test sample MLP judges the performance of every set of weights. It is stated that the network training will be more effective if the testing data set is smaller then the training sample. Finally, hold sample is another independent set of observations that provides with the honest estimate of the performance the final model has demonstrated since it doesn't participate in the model design and training at all.

In some research the data set is divided into two groups: training and testing or training and holdout, where training set is usually more than 60% of total ; while other studies use all three samples leaving training sample the biggest part of data records (Atsalakis, Valavanis, 2009)

It was decide to build a network with only training and testing set, then verify the conclusions by another network with training, testing, and hold samples.

Since the data set is quite big, there was no harm to make the testing sample as big as approximately 40% of the total number of observations. The intention was to secure thorough verification of the results through large amount of data points in testing sample. So the sample division of the first network is: 61.5% - training sample and 38.5% - testing sample.

Architecture. By following the practice of many MLP practitioners the chosen architecture of the network is hyperbolic tangent with one hidden layer

Rescaling of dependent variable. Since there is only one dependent variable, there is no need to worry about rescaling as it was with independent variables.

Training function. Batch training was selected as the training function since it "is often preferred because it directly minimizes the total error" (SPSS Neural Networks™ 16.0, Copyright © 2007 by SPSS Inc)

Stopping rules. By default the network stops training, when the error hasn't been decreased after one step of the process, or when the relative change in error in comparison with previous step error is less then 0.0001, or when the ratio of the error to the error of null model (when all predicted values of close price equal its average) is less then 0.001, or when the size of sample used to define the network architecture reaches 1000. By trial and error method it was concluded that nothing should be changed but the number of steps, during which the error can stay at the same level of increase; this number should be raised from 1 to 3 (see Appendix 1 and 2 for the results of each variation)

Output. As soon as all the parameters are defined the MLP runs the training process until one of the stopping rules is satisfied. When it happens the results of the last training are presented in tables. The most important are a table of model summary with Sum of Squares Errors (SSE) and relative errors for all samples (training, testing, hold), which are used to evaluate a network performance, and a table of parameters estimates (weights), using which it is possible to approximate the network to calculate future close price values (forecast).

To summarize, the MLP network design requires consideration of many parameters, which can be sometimes defined by replicating practice of other research, following instructions in MLP manuals, or simply by applying trial and error method (choosing the best model with lowest error value). As soon as all the parameters defined there is no manual work required, the software will carry out the training and reveal results that are ready to be applied in evaluation and forecasting processes.

4.2 Results of Model 1

As it has been stated in the previous section as soon as all the parameters are determined, the software will perform training within few seconds to several hours depending on a size of data set. The training process can be repeated unlimited amount of times. But there is always a risk of overtraining (overfitting) described in the Methodology chapter. After certain number of training sessions MLP network can start memorizing the training set, generating wrong results. Usually overtraining can be noticed, when the network performed quite well working with training set and pretty bad with test set.

For regulation of the network to avoid overfitting many researchers apply early stopping rule (Caruana, Lawrence, & Giles, 2000; Benuskova & Lakshminarayanan, 2005). The rule is to stop the training as soon as the testing error starts increasing (Figure 3)

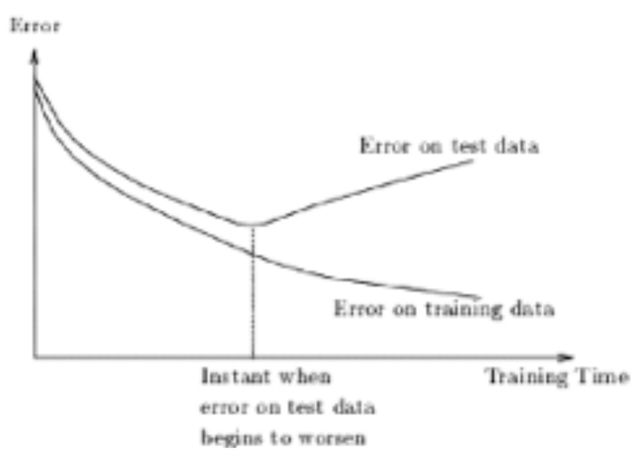

Figure 3

The test sample error of Model 1 starts increasing after third training. Thus the training was stopped after third time, and the best performed, i.e. with the lowest errors, training outcome was chosen as Model 1 (Table 6).

# of	Independent	SSE(training)	Relative	SSE(testing)	Relative

Training	variables		Error(training)		Error(testing)
1	Close price (t-1)	1567.918	0.085	896.676	0.088
2	Close price (t-1)	1494.022	0.081	853.975	0.083
3	**Close price (t-1)**	**772.782**	**0.042**	**443.762**	**0.043**
4	Close price (t-1)	1385.838	0.075	790.078	0.077

Table 6

So the best-performed training that was accepted as the final version of Model 1 is the model with **parameters estimates: 311.7 (constant) and -34.8 (close price lag coefficient)**. Using these parameters and knowing architecture of the network it is possible to approximate the future values of dependent variable, in other words, to build hourly close price forecasting model based on only historical data given per hour.

The next step is to design Model 2 by replicating the architecture of Model 1, changing only the set of independent variables. This new set includes, in addition to first order lag of close price, 7 emotion time series. The design of this process will be explained in the next section.

4.3 Design of Model 2

Architecture of Model 2 is absolutely identical to the one of Model 1, thus there was no any changed made only the list of input variables was expanded by 7 emotion time series.

To test the thesis hypothesis the first step was training Model 2 on the input data set consisted of close price first order lag and current values of 7 emotions: Surprise, Happiness, Calm, Comfort, Frustration, Anger, and Sadness. Then the input set was expanded by first order lag variables of each of the emotions. The aim was to see if the network will perform better, which would signify the influence power of some or all the emotions expressed within not only current hour, but also the previous one.

To examine impact of each emotion separately, the network (Model 2) was trained with various combinations of the emotions, taking each of them independently, or in combination with their lag values. This was done to test whether any of the emotions had significant influence on the close price independently from the others.

All the trainings were carried out using the same network specifications, including sample division. However to be sure that the results are genuine, both of the models were trained based on two new networks, each of which have different sample division. The second variant of sample division consists of 71.3% training, 20.9% testing, and 7.8% hold samples. The third variant of sample division is 84.7% training, 10.8% testing, and 4.4% hold samples.

Both two new networks were trained only employing only those input sets that had achieved better results than the ones of Model 1 during training of the first network (with initial sample division).

4.4 Results of Model 2 and their Comparison with the Result of Model 1

Before describing and interpreting the results, it is important to note that training process of all the Model 2 variations has been run the same number of times as the trainings of Model 1 in order to assure that both Models have the same chances to perform and reach the highest level of effectiveness. Also as was already explained many times the input set of Model 2 consists of various combinations of emotions and the close price first order lag value, and since the close price first lag value is included in each input, it will be omitted every time any input combination is describes and considered to be included by default for a sake of simplicity.

So the first network with every input sample was trained three times, and then the training outcome with the lowest errors was selected and compared with the errors of Model 1. Below the Table 7 represents only those input combinations with their outcomes that outperformed Model 1 in terms of lower errors. The full list of emotion compositions and their training errors are inserted in the Appendix 2.

Training	0.615			
Testing	0.385			

Hold	0			
Independent variables	*SSE(training)*	*Relative Error(training)*	*SSE(testing)*	*Relative Error(testing)*
Close price (t-1)	**772.782**	**0.042**	**443.762**	**0.043**
Close price (t-1)+Emotions (t)	***388.548***	***0.021***	***256.008***	***0.025***
Close price (t-1)+Emotions (t)+Emotions (t-1)	*389.03*	*0.021*	*268.189*	*0.026*
Close price (t-1)+Emotions (t)+Surprise (t-1)	*423.421*	*0.023*	*271.207*	*0.026*
Close price (t-1)+Emotions (t)+Emotions (t-1)+Emotions (t-2)	*423.5*	*0.023*	*289.6*	*0.028*
Close price (t-1)+Emotions (t)+Happiness(t-1)	*450.574*	*0.024*	*315.73*	*0.031*
Close price (t-1)+Emotions (t)+Comfort(t-1)	*466.769*	*0.025*	*295.983*	*0.029*
Close price (t-1)+Emotions (t)+Frustration(t-1)	*577.074*	*0.031*	*344.566*	*0.034*
Close price (t-1)+Emotions (t)+Anger(t-1)	*518.275*	*0.028*	*327.333*	*0.032*
Close price (t-1)+Surprise (t)+Surprise (t-1)+Surprise (t-2)+Surprise (t-3)	*568.661*	*0.031*	*377.505*	*0.037*
Close price (t-1)+Calm(t)+Calm(t-1)	*669.533*	*0.036*	*400.372*	*0.039*
Close price (t-1)+Frustration(t)+Frustration (t-1)+Frustration(t-2)	*614.728*	*0.033*	*371.576*	*0.036*
Close price (t-1)+Sadness(t)+Sadness(t-1)+Sadness(t-2)	*573.376*	*0.031*	*341.425*	*0.033*

Table 7

As it can be seen from the table there are quite a few variations of Model 2 that generated much lower errors than Model 1. The comparison relied on both training and testing errors, but in case of ambiguity the testing error was given higher weights since the test sample was not participating in the network training directly, thus it provided with independent and more reliable appraisal of a model performance.

The lowest testing error was demonstrated by the input set, which included only **current hour emotional profile**. **Both training and testing errors are more than 1.5 times lower than the errors of Model 1**. *Such results suggest that these variations of Model 2 are more efficient than Model 1 in predicting close price hourly values.*

There are 11 other input combinations, the training of which produced lower errors in comparison with the ones of Model 1. The lowest errors were generated from training current and previous hour emotional profile values. The second lowest errors among these 11 combinations were produced by current emotional profile and its two previous values (t-1 and t-2). The other five input combinations include in addition to current hour emotional profile first order lag of either Surprise, or Happiness, or Comfort, or Anger, or Frustration. The first intention is to interpret the above mentioned results as evidence of prediction power demonstrated by past hour expressions of Surprise, Happiness, Comfort, Anger, and Frustration as well as of the past hour emotional profile. However the errors are higher than the ones when only current hour emotional profile is considered. This indicates that the impact on SIMSCI close price of current hour emotional profile is stronger if it's taken independently from any past hour emotions. In other words, **the emotional profile of tweets posted by users from Singapore during the hour T displays predictive power on SIMSCI close price by the end of the hour T. However if to expand the emotional profile of the hour T by any of the seven emotions' value of the hour T-1 or by all seven emotions' values collected within the hour T-1 and T-2 then the predictive power will diminish though will still exist.** The explanation of these findings can be found in the hypothesis that the *any of the past hour emotions may dilute the emotions impact and misdirect the forecast by providing information that is not significant for current close price formation*. Testing of this hypothesis will be implemented further in this section.

Further review of the results revealed that **Surprise up to third order lag, Sadness up to second order lag, Calm up to first order lag, and Frustration up to second order lag if included in the basic forecasting model (Model 1) independently from each other have potential to amend the model efficiency as well.** Nonetheless the difference in errors is quite small and requires further examination before any conclusion can be made.

To summarize everything discovered by now it can be said that the thesis hypothesis has high probability to be accepted since there are quite a few evidences that emotion variables reduce models errors, i.e. improve its performance. However to secure the accuracy of the above outcomes and come to final conclusions it is advised to run training of the network again, but prior to that to change sample division. This way it is possible to avoid risk of overfitting by training once again the same network based on the same sample sets with an idea that further network training can produce clearer evidences that the above findings are authentic and not just a lucky coincidence.

The new data set division consists of 71.3% training, 20.9% testing, and 7.8% hold samples. The training sample has been not only increased (from 471 to 546 data cases) , but also prescribed new mix of observations (with a help of random probability distribution function[5]). This operation ensured that the network was trained on new set of data points of dependent variable to avoid overfitting and at the same time providing with new results to be employed in testing the above conclusions. The same changes were done to testing sample, but its size has been decreased, which means that the network had fewer data points to evaluate performance during training. But to compensate this, the third sample – hold – has been created. This sample is another independent set of observations that is used after the network training has stopped. As soon as the final parameters estimates are known the network applies these weights to predict values of those data cases in hold sample and compare them with actual values by calculating relative error. Thus hold sample gives an opportunity to make independent appraisal of final outcome of network training.

After the new sample division had been defined the network was trained for all the input combinations that had showed superior performance in the previous network trainings, but prior to that the network had been trained for close price first order lag value to obtain the basis for further comparison of the results.

Again it should be noted that to avoid overfitting the early stopping technique was used. Basing on Model 1 results the optimal number of trainings was defined by following the

[5] rv.bernoulli(0.7) (SPSS Neural Networks™ 16.0
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same strategy described above. The table 8 shows that the testing error is rising after third training.

# of Training	Independent variables	SSE(training)	Relative Error(training)	SSE(testing)	Relative Error(testing)	Relative Error(hold)
1	Close price (t-1)	1286.307	0.063	453.797	0.079	0.048
2	Close price (t-1)	1550.444	0.076	494.537	0.086	0.054
3	**Close price (t-1)**	**851.258**	**0.042**	**297.543**	**0.052**	**0.03**
4	Close price (t-1)	1281.521	0.063	438.551	0.076	0.048

Table 8

Hence the optimal number of training for the network based on the new sample division is three. Following the same argumentations described at the beginning of this section, training of all the combinations of independent variables was run three times.

The training of the new network produced very promising results (see 3ix 2). The main conclusion that the current hour emotional profile positively affects Model *1 performance is confirmed*. *However the hypothesis that the emotions expressed within past hour or past two hours dilutes the current emotional profile's prediction power didn't receive any proofs*, on the contrary the combination of current and past hour or current and past two hours emotional public profile generated much better results – testing and hold errors almost 1.4 times lower. At the same time among those combinations of the current emotional profile and one of the five past hour emotion values, namely Surprise, Happiness, Comfort, Frustration, and Anger, only first three generated lower errors than Model 1 did, and only Comfort – lower than current emotional profile. The conclusion is that *the influence of the past hour emotions on the current hour close price of SIMSCI is very ambiguous and requires more thorough investigations*.

Table 9 represents only best-performed combinations among those 12 that were discussed above.

Training	61.50%				
Testing	27.20%				
Hold	11.40%				

Independent variables	SSE(training)	Relative Error(training)	SSE(testing)	Relative Error(testing)	Relative Error(hold)
Close price (t-1)	**851.3**	**0.042**	**297.5**	**0.052**	**0.03**
Close price (t-1)+Emotions (t)	*581.5*	*0.029*	*201.9*	*0.035*	*0.021*
Close price (t-1)+Emotions (t)+Emotions (t-1)	*455.5*	*0.022*	*146.1*	*0.025*	*0.015*
Close price (t-1)+Emotions (t)+Emotions (t-1)+Emotions (t-2)	*414.7*	*0.020*	*149.0*	*0.026*	*0.015*
Close price (t-1)+Emotions (t)+Surprise (t-1)	*720.4*	*0.035*	*249.4*	*0.043*	*0.026*
Close price (t-1)+Emotions (t)+Happiness(t-1)	*799.646*	*0.039*	*286.043*	*0.05*	*0.032*
Close price (t-1)+Emotions (t)+Comfort(t-1)	*507.034*	*0.025*	*156.914*	*0.027*	*0.017*
Close price (t-1)+Frustration(t)+Frustration(t-1)+Frustration(t-2)	*777.214*	*0.038*	*282.948*	*0.049*	*0.028*

Table 9

The consideration of the outcomes generated by four other combinations that outperformed Model 1 in previous network training reveals that only Frustration's current and two previous hour values preserved positive influence on SIMSCI closing price forecast. This may indicate that among all 7 emotions' time series, when considered independently from each other, *Frustration has the strongest impact on the SIMSCI close price*. But the error difference is very small both for this network and for the first one. *This may signal of unstable effect on the hourly SIMSCI close price each of the emotions produces* since further training with other variations of sample divisions of the data set may easily result in the negative difference. Thus no any sound conclusions can be made regarding prediction power of any of the 7 emotions taken individually.

Since the trainings of second network generated some results opposite to the ones from trainings of first network, it is useful to train the network again, changing sample division prior to that.

The process of creating third variation of sample division and all the next steps relating to early stopping technique and training of the network are the same. Thus there is no need to describe in details how the third network was trained. It should be just said that the new division includes 84.7% training, 10.8% testing, and 4.4% hold samples, which means that now the network is trained on even more bigger sample, but is tested on much smaller data sets, which may worsen the performance (this assumption was confirmed, see Appendix 3 for the details). Also the early stopping technique defined that the number of optimal trainings is 3, thus all the following input variables variations were trained three times.

For the sake of conciseness the performance indicators of 12 input sets training are represented in the table, inserted in the Appendix 4. It should be explained that 12 input sets are the same ones that were used in the second network training; and they were chosen to make final conclusion regarding all previously ambiguous results.

To make the final conclusions from all the input combinations training performance, their results were compared with the ones of Model 1 and Model 2 with current emotional profile (Table 10). The intention behind such comparison is to see clearly which combinations constantly outperformed Model 1 and current hour emotional profile, since this combination was a leader during the first network trainings.

1-positive difference	0-equal or negative difference					
	Partition 1		Partition 2		Partition 3	
	Close price (t-1)	Close price (t-1)+Emotions (t)	Close price (t-1)	Close price (t-1)+Emotions (t)	Close price (t-1)	Close price (t-1)+Emotions (t)
Close price (t-1)+Emotions (t)	1	-	1	-	1	-
Close price (t-1)+Emotions (t)+Emotions (t-1)	1	0	1	1	1	1
Close price (t-1)+Emotions (t)+Emotions (t-1)+Emotions (t-2)	1	0	1	1	1	1
Close price (t-1)+Emotions (t)+Surprise (t-1)	1	0	1	0	1	1
Close price (t-1)+Emotions (t)+Happiness(t-1)	1	0	1	0	1	0
Close price (t-1)+Emotions (t)+Comfort(t-1)	1	0	1	1	1	0
Close price (t-1)+Emotions (t)+Frustration(t-1)	1	0	0	0	1	1
Close price (t-1)+Emotions (t)+Anger(t-1)	1	0	0	0	1	1

Close price (t-1)+Surprise (t)+Surprise (t-1)+Surprise (t-2)+Surprise (t-3)	1	0	0	0	0	0
Close price (t-1)+Calm(t)+Calm(t-1)	1	0	0	0	1	0
Close price (t-1)+Frustration(t)+Frustration(t-1)+Frustration(t-2)	1	0	1	0	0	0
Close price (t-1)+Sadness(t)+Sadness(t-1)+Sadness(t-2)	1	0	0	0	1	0

Table 10

The table clearly illustrates that combination of current emotional profile and first lag of the close price has been steadily producing better results than Model 1. The same is true for the combinations of current plus past hour and current plus past two hours emotional profiles, and in two out of three cases the errors are lower than when only current hour emotional profile is considered. It should be noticed the comparison of combinations with one lag value and with two lag values showed that the error has increased when the second lag was added in two cases out of three. The input sets consisted of current emotional profile and one period lag value of one of the five emotions, namely Surprise, Happiness, Comfort, Frustration, and Anger produced very volatile results. The sets with Surprise, Happiness, and Comfort generated lower errors than the ones of Model 1 in all three cases, while Frustration and Anger failed to outperform Model 1 in the second case. However the errors of the sets with Surprise, Happiness, and Comfort were lower at least in two cases out of three than the errors of the set with just current emotional profile included. The remained combinations didn't show any consistency in generating superior results than Model 1.

To compile all the findings from the table # it can be concluded with high degree of confidence that:

- current period emotional public profile extracted from tweets improves predictive abilities of MLP SIMSCI closing price forecasting model;

- past hours Twitter users' emotional profile has high chances to increase the positive effect of current period emotional profile on the model efficiency, but since the difference when lag values are added is not constantly positive, these chances are less than 100%;
- past hour value of any of the seven emotions has tendency to diminish current hour emotional profile predictive power on SIMSCI current hour closing price, sometimes to the degree when forecast efficiency of the model is worse than the one of the model based on only historical close price values;
- none of the emotions, taken independently, has any stable positive effect on SIMSCI close price forecast performance;

The overall conclusion is that **Singaporean's emotional profile extracted from their tweets within current hour influence formation of SIMSCI close price of the current hour**. The inclusion of past hour and especially past two hours emotional profile should be carried out with caution since it may have negative impact on the performance of the model. The analysis of each emotion separately or in combination with next hour emotional profile didn't reveal any constant positive effect, thus there is nothing could be said about each emotion's predictive power on SIMSCI closing price.

However the last statement raised the question whether the exclusion of any of the emotions from current emotional profile would reduce the efficiency of the model. To test this hypothesis it was decided to compare testing errors before and after deduction of one of the emotions for every network . The results are in the Table 11 below.

Testing Relative Error			
	Division 1	Division 2	Division 3
Testing Relative Error (Close price (t))	**0.043**	**0.052**	**0.058**
Testing Relative Error (Close price (t-1)+Emotions (t))	**0.025**	**0.035**	**0.029**
Close price (t-1)+Happiness(t)+Comfort(t)+Calm(t)+Frustratio(t)+Anger(t)+Sadness(t)	**0.057**	**0.073**	**0.062**
Close price (t-1)+Surprise (t)+Comfort(t)+Calm(t)+Frustration(t)+Anger(t)+Sadness(t)	**0.053**	**0.043**	0.026
Close price (t-1)+Surprise (t)+Happiness(t)+Calm(t)+Frustration(t)+Anger(t)+Sadness(t)	**0.047**	0.027	**0.047**
Close price (t-1)+Surprise (t)+Happiness(t)+Comfort(t)+Frustration(t)+Anger(t)+Sadness(t)	**0.063**	**0.061**	**0.067**

Close price (t-1)+Surprise (t)+Happiness(t)+Comfort(t)+Calm(t)+Anger(t)+Sadness(t)	**0.034**	**0.071**	**0.046**
Close price (t-1)+Surprise (t)+Happiness(t)+Comfort(t)+Calm(t)+Frustration(t))+Sadness(t)	**0.034**	**0.091**	**0.085**
Close price (t-1)+Surprise (t)+Happiness(t)+Comfort(t)+Calm(t)+Frustration(t)+Anger(t)	**0.057**	**0.085**	**0.070**

Table 11

By comparing the results it became evident that the above hypothesis could be accepted as valid, since in more than 90% cases the error increases after one of the emotions has been removed from the analysis. Moreover, in more than 70% cases the error became bigger than the one of Model 1. Hence it can be argued with high degree of certainty that *prediction power of the current emotional profile declines or even disappears as soon as one of the components of this emotional profile is removed.*

As the final step in this study, the parameters estimates of the best-performed output combination were selected and presented in the Table 12 below. These parameters estimates can be employed to build a forecasting model during future practice represented It is quite complicated to interpret these parameters without building a model itself, the operation that may take a few pages to illustrate just its final outcome. For the purpose of this paper it is enough to say that the final forecasting model represents network with one hidden layer, where every input variable including constant (Bias) is connected to each of the unit (H) in hidden layer through estimated weights (parameters), and then these units are connected to output layer (close price) through another set of parameters.

Predictor		Predicted							
		Hidden Layer 1							Output Layer
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	Close_last
Input Layer	(Bias)	-5.010	5.551	4.346	4.655	-.477	-4.610	2.875	
	lag1_close	-2.825	3.063	2.076	2.380	1.477	-3.112	1.984	
	surprise_sum	-.885	1.035	.929	.812	.003	-.657	.392	
	happy_sum	-.536	1.117	.505	1.125	-.005	-1.132	.824	
	comfort_sum	-1.288	1.213	.993	.679	-.003	-.664	.835	

Table 12	calm_sum	-.822	1.091	.309	1.009	-.002	-1.172	.949	
	frustration_sum	-.340	.738	.571	1.053	-.014	-.817	.370	
	anger_sum	-.706	.663	.161	.271	.002	-.672	.438	
	sadness_sum	-.280	.257	-.078	-.209	.017	-.723	.148	
Hidden Layer 1	(Bias)								54.680
	H(1:1)								-47.019
	H(1:2)								40.411
	H(1:3)								41.631
	H(1:4)								42.392
	H(1:5)								35.940
	H(1:6)								-41.972
	H(1:7)								33.739

5. Discussion

5.1 Conclusion

Emotions are inseparable from everyday activity of any human being. As it was shown in theoretical review the nature of emotions is connected with both physiological reactions and mental operations. Knowing this it is easy to trace a link between emotional state and decisions and judgments formation, a mental process that accompanies every step in life. The life full of unpredictability and constant changes. Hence any piece of information, any source of insights that may give a hint of future events is priceless and constantly being chased by millions of researchers, business people, any other professionals. Soon it was realized that emotions can serve as such flashlight to guide in darkness of the future.

And as time was passing, and the century of information and technology gave birth to many innovation and developments in many areas especially in communication and information diffusion. Two of the main inventions were Internet and later on various online communication platforms that were grouped under the name social media. Within short period of time these platforms started to be a source of not only searched information, but also new friends and sharing. Sharing of everything: plans, opinions, and feelings. Moreover plans and opinions are expressed with a help of emotional words, and the more users spend time online the less they are afraid to reveal their inner world. This tendency made researchers recognize social media platforms as a unique source of public emotional profile that, as it was already indicated several times, might be very effective instrument in forecasting practice. The last statement has been under constant examination by researchers from various fields including financial industry, since it was proven that financial markets are frequently influenced by emotional status of the society.

The author of this theses has decided to join this group of researchers and make contribution in investigation of the impact online emotions have on financial markets. More specifically the goal of this thesis is to find whether emotional profile of Twitter users has prediction power of stock index values.

Dealing with limitations and implementing further study suggestions of the existing works in this topic, it was decided to include both positive and negative emotions in more or less equal proportion, and consider their aggregated as well as individual influence. Moreover the analysis was based on hourly rather than daily data , as these time period is more suitable for the nature of Twitter and financial markets information diffusion. Finally, to avoid any misleading findings due to the cultural and geographical differences the study was strictly limited to Singapore market by extracting emotions from tweets posted only in Singapore and investigating their impact on Singapore Stock Index - SIMSCI.

All the further calculations were implemented keeping the working hypothesis in mind. The hypothesis formulation is the following: **Hourly based emotional profile, consisted of positive and negative emotions, extracted from Twitter, can increase efficiency of stock index hourly value forecast.**

The analysis was carried out for the period from the 12 September 2011 to 12 November 2011 using a combination of both positive and negative emotions' time series , namely Surprise, Happiness, Comfort, Calm, Frustration, Anger, and Sadness, and the previous hour close price time series. The model that was applied for all input combinations is MLP network, chosen due to the nonlinear and nonstationary nature of close price values. To examine the effect of emotions on the index forecast, the network was trained on only historical data of the close price, i.e. its past hour value. Then input set was extended by seven emotions current hour values, by their combination with the past hour values of all the emotions or one of the emotions, and finally by each emotion's current or current and historical values. All the variations of network input sets were trained for three different close price cases, and after all the results were obtained and compared, a few important conclusions were made.

First of all, *it was clearly shown that emotional profile, i.e. all seven emotions' values, extracted from tweets created within hour T has influence on SIMSCI close value at the end of the hour T*. **This statement proves the working hypothesis.**

Second of all, *each of the seven emotions, derived within the hours T, T-1, ..., T-5, has no any constant effect on the index closing value at the end of the hour T*. This indicates that none of the emotions taken individually has enough power to improve the index forecast.

Finally, *the emotional profiles of the past hours T-1 and T-2 have high degree of probability to improve the index forecast.* However there is a risk to get opposite (negative) effect when one or two lag values are added, and in case of two lag values this risk is higher. Thus it is reasonable to verify the performance every time the forecast is based on lag values of emotional profile. There is another observation that may testify *that the more lags of emotional profile are included the higher the risk of getting negative effect on the model efficiency*. This observation relates to the combinations with one lag T-1 value and with two lag T-1 and T-2 values of emotional profile performance comparison, which revealed that the errors are higher in two out of three cases when the T-2 lag value is added. In other words, this finding may signify that *the predictive power of emotional profile is diminishing with increase of time gap between the close price and tweets this emotional profile was derived.* This statement is in agreement with the assertion that markets absorb information within few moments from the time it has become public and that Twitter is a great help for any information to become public in a seconds. However this finding needs further investigation, about which I'll mention in the Further Research Suggestions section.

Second conclusion raised the question, investigation of which brought to another interesting inference, namely the *current hour emotional profile loses its prediction power to some extent or totally when one of its components is eliminated from the analysis*. This discovery suggests that the initial intention to capture the most complete picture of emotional state in order to secure the authenticity of results is achieved. Also it can be stated that in contrast to Bollen et al. (2011) conclusion, which argues that only Calm is predictive of DJIA closing values, this study shows that only combination of seven emotions produces constant positive effect on the SIMSCI closing values forecast efficiency. It should be noted that this positive effect is guaranteed only when the combination of the seven emotions' values, named emotional profile for simplicity, is withdrawn from tweets posted by Singaporeans within current hour.

5.2 Practical implementation

The findings in this research have very wide application first and foremost in the forecasting engineering field. This research illustrates the efficiency of very unique and at the same time quite easy to acquire predictive instrument - the emotional profile of tweets, i.e. a combination of 7 emotions extracted from Twitter messages. Any practitioner can insert emotional profile in an input set of any kind of forecast and expect to get superior results. It is not guaranteed that the given combination of 7 emotions will provoke better performance of a forecast model, but it gives an opportunity to work further on improvement and requires not as much spending of resources as many other forecasting tools do.

Another area, where this study may be successfully utilized is financial industry. Thousands of investment decisions can be enhanced by creating emotional map of tweets posted within an hour. Again it is not 100% assurance that the investment decisions will yield higher profits if they are based on tweets' emotional analysis, but the investors and financial organization will definitely benefit if emotional profile of Twitter users will be one of the numerous factors to consider during decision-making process.

Finally the results of the study can become one of the factors that lead to development of a new industry, namely Social Media Analytics. This industry will derive knowledge from the social media platforms and employ it in various types of investigation. This idea is partly implemented by marketing research companies, but it is just a small part of their service. Soon it is likely to happen that social media analysis will grow into independent departments and then the whole industry.

5.3 Theoretical implementation

As the study was applied specifically for Singapore market, there are no barriers to carry out the identical study for other geographical markets. This may result not only increase the number of evidences in favor of tweets emotions ability to predict stock values, but also in the great opportunity to examine cultural differences in the emotions salience and emotionality of Twitter.

Moreover implementation of this study in other regions can actually lead to another series of studies devoted to comparison of Twitter's role in the life of the population. In other words negative result of the given study in one of the regions can evidence that emotions expressed in Twitter within that region don't penetrated into the areas of people's life that involve financial decisions, thus don't bear any effect on their formation. However it is reasonable to assume that financial decisions is part of almost every activity in the life of modern human beings, thus absence of correlation between Twitter emotional profile and stock markets in a certain geographical region while it exists in others may indicate that

Twitter is only part of online life and has no relation to offline life processes.

Another question that this research may assist examining timing in decision making among countries or industries. By including different combinations of lag values of emotional profile in forecasting models of stock aggregated indices in various countries or in forecasting models of industry specific indices, and then defining the best-performed lag combination, it is possible to estimate time interval, within which the information is absorbed and becomes obsolete.

Finally, by analyzing influence of Twitter emotions on industry-specific indices it is possible to examine what emotions are more important for what industry, study the differences in the strength of prediction power of the emotional profile, and define which industries are more emotionally driven.

5.4 Contribution

First of all, this study discovered optimal combination of emotions, the positive effect of which on the stock index forecast efficiency is clearly visible.

Secondly, it brought unique opportunities and increased reliability of the results by analyzing only specific geographical market.

Thirdly, it showed the importance of analyzing shorter time intervals to follow the speed of information diffusion in such rapidly changing environment as social media and financial markets.

5.5 Limitations

The main limitation of the given study is reliance on only one type of analytical models. Many other researchers supported their main model with some correlation or other statistical analysis. Due to nonlinear and nonstationary nature of the close price time series, most of the employed supporting methods were not applicable. Thus it was preferred to restrict the analysis to only one model to avoid any misleading and contradicting outcome.

Though the list of associative keywords for each emotion was tested and applied in various projects by Statsit analysts more than 100 times during last two years, there is a risk of missing out some relevant data. The reason is that online language is continually expanding: new slang phrases, intentional misspelled words, and new emoticons[6] are being constantly invented within very short periods of time, thus textual analysis of Twitter messages requires very thorough and regular verifications and update of relative words and phrases. Such process is very time consuming and demands very extensive knowledge base in linguistic research, both of these resources were very limited, hence the analysis was based on already existing lists of associative emotional words and expressions obtained from Statsit. This decision led to another limitation of the study, namely the restricted access to that lists of associative words and phrases due to the intellectual property concerns.

5.6 Suggestions for future research

This study considers the emotional profile that consists of seven emotions, 4 of which are positive and 3 are negative. Such number of various emotions provides with opportunity to create a lot of combinations, the analysis of each of which can generate exciting and useful findings. For example, a researcher may investigate how combination of only negative emotions influence stock market forecast, and compare with the results of only positive emotions. Besides positive and negative, these seven emotions can be divided into groups of high arousal and low arousal (Russell, 1980, 1989), the classification that wasn't touched in this research, but has definitely very wide field of implementation. As an exmample, it can be investigated wheather high arousal emotions have higher prediction power on the stock market value, since this type of emotions is the one that provokes further actions, while low arousal emotions usually have opposite effect – demotivate further actions. To summarize, further research can consider not just a combination of all emotions, but devide them into fourt groups: positive-high arousal, positive-low arousal, negative-high arousal, and negative-low arousal, and compare their effect on the stock values forecast performance.

Also, as it was suggested in the implementation section, the emotional profile may be tested on predictive abilities of each industrial indices. Such study will be useful to understand

[6] a pictorial representation of a facial expression using punctuation marks and letters, usually written to express a person's mood. Emoticons are often used to alert a responder to the tenor or temper of a statement, and can change and improve interpretation of plain text (Wikipedia, http://en.wikipedia.org/wiki/Emoticon)

what emotions are more salient for certain industry, and the findings of this study will be very valuable not only for financial industry, but also for marketing (gives an idea what emotions to touch to attract more attention).

Lastly the same analysis can be carried out for anther geographical market, preferably from other cultural background. And as it was suggested in implementation part, that comparison of results may open the whole new world of opportunities to learn about cultural differences.

Appendix

Appendix 1

Max steps without decrease in error	Minimum relative change in training error.	Minimum relative change in training error ratio	Independent variables	SSE(training)	Relative Error(training)	SSE(testing)	Relative Error(testing)
1	0.0001	0.001	Close price (t-1)	1093.735	0.059	625.281	0.061
2	0.0001	0.001	Close price (t-1)	970.38	0.053	556.014	0.054
3	0.0001	0.001	Close price (t-1)	772.782	0.042	443.762	0.043

Appendix 2

Max steps without decrease in error	Minimum relative change in training error.	Minimum relative change in training error ratio	Independent variables	SSE(training)	Relative Error(training)	SSE(testing)	Relative Error(testing)
3	0.0001	0.0005	Close price (t-1)	948.502	0.052	543.141	0.053
3	0.0001	0.005	Close price (t-1)	794.985	0.043	458.625	0.045
3	0.0001	0.0001	Close price (t-1)	772.782	0.042	443.762	0.043

Appendix 3

Training	0.615			
Testing	0.385			

Hold	0			
Independent variables	*SSE(training)*	*Relative Error(training)*	*SSE(testing)*	*Relative Error(testing)*
Close price (t-1)	**772.782**	**0.042**	**443.762**	**0.043**
Close price (t-1)+Emotions (t)	***388.548***	***0.021***	***256.008***	***0.025***
Close price (t-1)+Emotions (t)+Emotions (t-1)	***389.03***	***0.021***	***268.189***	***0.026***
Close price (t-1)+Emotions (t)+Surprise (t-1)	*423.421*	*0.023*	*271.207*	*0.026*
Close price (t-1)+Emotions (t)+Happiness(t-1)	*450.574*	*0.024*	*315.73*	*0.031*
Close price (t-1)+Emotions (t)+Comfort(t-1)	*466.769*	*0.025*	*295.983*	*0.029*
Close price (t-1)+Emotions (t)+Calm(t-1)	905.223	0.049	537.482	0.052
Close price (t-1)+Emotions (t)+Frustration(t-1)	*577.074*	*0.031*	*344.566*	*0.034*
Close price (t-1)+Emotions (t)+Anger(t-1)	*518.275*	*0.028*	*327.333*	*0.032*
Close price (t-1)+Emotions (t)+Sadness(t-1)	837.59	0.045	486.881	0.048
Close price (t-1)+Surprise (t)	1560.342	0.085	887.919	0.087
Close price (t-1)+Happiness (t)	1011.711	0.055	578.121	0.056
Close price (t-1)+Comfort(t)	956.938	0.052	551.507	0.054
Close price (t-1)+Calm(t)	1397.186	0.076	792.088	0.077
Close price (t-	1458.356	0.079	725.725	0.071

1)+Frustration(t)				
Close price (t-1)+Anger(t)	1209.227	0.066	690.903	0.067
Close price (t-1)+Sadness(t)	1250.691	0.068	712.698	0.07
Close price (t-1)+Surprise (t)+Surprise (t-1)+Surprise (t-2)	812.694	0.044	467.699	0.046
Close price (t-1)+Surprise (t)+Surprise (t-1)+Surprise (t-2)+Surprise (t-3)	*568.661*	*0.031*	*377.505*	*0.037*
Close price (t-1)+Surprise (t)+Surprise (t-1)+Surprise (t-2)+Surprise (t-3)+Surprise (t-4)	862.636	0.047	502.707	0.049
Close price (t-1)+Surprise (t)+Surprise (t-1)+Surprise (t-2)+Surprise (t-3)+Surprise (t-4)+Surprise (t-5)	1195.628	0.065	684.563	0.067
Close price (t-1)+Calm(t)+Calm(t-1)	*669.533*	*0.036*	*400.372*	*0.039*
Close price (t-1)+Calm(t)+Calm(t-1)+Calm(t-2)	1323.031	0.072	770.737	0.075
Close price (t-1)+Calm(t)+Calm(t-1)+Calm(t-2)+Calm(t-3)	799.609	0.043	471.866	0.046
Close price (t-1)+Calm(t)+Calm(t-1)+Calm(t-2)+Calm(t-3)+Calm(t-4)	1224.456	0.066	698.253	0.068

Close price (t-1)+Calm(t)+Calm(t-1)+Calm(t-2)+Calm(t-3)+Calm(t-4)+Calm(t-5)	1364.748	0.074	801.631	0.078
Close price (t-1)+Frustration(t)+Frustration (t-1)	1312.488	0.071	705.363	0.069
Close price (t-1)+Frustration(t)+Frustration(t-1)+Frustration(t-2)	*614.728*	*0.033*	*371.576*	*0.036*
Close price (t-1)+Frustration(t)+Frustration (t-1)+Frustration(t-2)+Frustration(t-3)	1440.295	0.078	866.372	0.085
Close price (t-1)+Frustration(t)+Frustration (t-1)+Frustration(t-2)+Frustration(t-3)+Frustration(t-4)	716.368	0.039	436.129	0.043
Close price (t-1)+Frustration(t)+Frustration (t-1)+Frustration(t-2)+Frustration(t-3)+Frustration(t-4)+Frustration(t-5)	1238.283	0.067	735.648	0.072
Close price (t-1)+Anger(t)+Anger(t-1)	1030.64	0.056	597.971	0.058
Close price (t-1)+Anger(t)+Anger(t-	810.978	0.044	470.313	0.046

1)+Anger(t-2)				
Close price (t-1)+Anger(t)+Anger(t-1)+Anger(t-2)+Anger(t-3)	905.88	0.049	533.904	0.052
Close price (t-1)+Anger(t)+Anger(t-1)+Anger(t-2)+Anger(t-3)+Anger(t-4)	1139.754	0.062	666.704	0.065
Close price (t-1)+Anger(t)+Anger(t-1)+Anger(t-2)+Anger(t-3)+Anger(t-4)+Anger(t-5)	1266.073	0.069	727.249	0.071
Close price (t-1)+Sadness(t)+Sadness(t-1)	841.889	0.046	483.439	0.047
Close price (t-1)+Sadness(t)+Sadness(t-1)+Sadness(t-2)	*573.376*	*0.031*	*341.425*	*0.033*
Close price (t-1)+Sadness(t)+Sadness(t-1)+Sadness(t-2)+Sadness(t-3)	1041.152	0.057	596.409	0.058
Close price (t-1)+Sadness(t)+Sadness(t-1)+Sadness(t-2)+Sadness(t-3)+Sadness(t-4)	764.311	0.042	444.047	0.043
Close price (t-1)+Sadness(t)+Sadness(t-1)+Sadness(t-2)+Sadness(t-3)Sadness(t-4)+Sadness(t-5)	730.79	0.04	430.367	0.042

Appendix 4

Training	546	71.30%			
Testing	160	20.90%			
Hold	60	7.80%			
Independent variables	SSE(training)	Relative Error(training)	SSE(testing)	Relative Error(testing)	Relative Error(hold)
Close price (t-1)	851.258	0.042	297.543	0.052	0.03
Close price (t-1)+Emotions (t)	581.54	0.029	201.931	0.035	0.021
Close price (t-1)+Emotions (t)+Emotions (t-1)	455.469	0.022	146.129	0.025	0.015
Close price (t-1)+Emotions (t)+Emotions (t-1)+Emotions (t-2)	414.7	0.020	149.0	0.026	0.015
Close price (t-1)+Emotions (t)+Surprise (t-1)	720.408	0.035	249.413	0.043	0.026
Close price (t-1)+Emotions (t)+Happiness(t-1)	799.646	0.039	286.043	0.05	0.032
Close price (t-1)+Emotions (t)+Comfort(t-1)	507.034	0.025	156.914	0.027	0.017
Close price (t-1)+Emotions	901.622	0.044	312.583	0.054	0.037

(t)+Frustration(t-1)					
Close price (t-1)+Emotions (t)+Anger(t-1)	888.345	0.044	307.821	0.053	0.036
Close price (t-1)+Surprise (t)+Surprise (t-1)+Surprise (t-2)+Surprise (t-3)	1538.15	0.076	498.105	0.086	0.059
Close price (t-1)+Calm(t)+Calm(t-1)	1641.189	0.081	546.245	0.095	0.062
Close price (t-1)+Frustration(t)+Frustration(t-1)+Frustration(t-2)	777.214	0.038	282.948	0.049	0.028
Close price (t-1)+Sadness(t)+Sadness(t-1)+Sadness(t-2)	1154.945	0.057	410.94	0.071	0.044

Appendix 5

Training	649.0	84.7%			
Testing	83.0	10.8%			
Hold	34.0	4.4%			
Independent variables	SSE(training)	Relative Error(training)	SSE(testing)	Relative Error(testing)	Relative Error(hold)
Close price (t-1)	1449.6	0.058	165.8	0.058	0.054
Close price (t-1)+Emotions (t)	857.0	0.034	81.7	0.029	0.038

Close price (t-1)+Emotions (t)+Emotions (t-1)	685.7	0.027	67.7	0.024	0.041
Close price (t-1)+Emotions (t)+Emotions (t-1)+Emotions (t-2)	618.4	0.025	57.3	0.020	0.039
Close price (t-1)+Emotions (t)+Surprise (t-1)	754.6	0.030	76.9	0.027	0.042
Close price (t-1)+Emotions (t)+Happiness(t-1)	1038.4	0.041	115.2	0.040	0.048
Close price (t-1)+Emotions (t)+Comfort(t-1)	808.6	0.032	82.3	0.029	0.042
Close price (t-1)+Emotions (t)+Frustration(t-1)	566.6	0.023	51.7	0.018	0.038
Close price (t-1)+Emotions (t)+Anger(t-1)	671.2	0.027	65.0	0.023	0.036
Close price (t-1)+Surprise (t)+Surprise (t-1)+Surprise (t-2)+Surprise (t-3)	1904.8	0.076	215.8	0.076	0.070
Close price (t-1)+Calm(t)+Calm(t-1)	1223.1	0.049	138.0	0.048	0.048

Close price (t-1)+Frustration(t)+Frustration(t-1)+Frustration(t-2)	1605.5	0.064	182.5	0.064	0.059
Close price (t-1)+Sadness(t)+Sadness(t-1)+Sadness(t-2)	1366.2	0.054	150.5	0.053	0.053

Reference

Asur S, Huberman B. (2010). Predicting the Future with Social Media. ACM WI, arXiv:1003.5699

Bem, DarylJ. 1965. "AnExperimental Analysis reprintedin Economisch Historisch Jaarboek.1926, ofSelf-Persuasion."JournalofExperimentaSlocial 12:20-43, pp.28-29. Psychology1.,pp.199-218

Ben-Ari, E. (2009). Twitter: What's All the Chirping About? BioScience, 59, (7), 632.

Benhabib, J. & Wen. Y. (2004). Indeterminacy, Aggregate Demand, and the Real Business Cycle. Journal of Monetary Economics, 51(3), 503–30.

Berinato, S (2010). Six ways to find value in Twitter's noise. Harvard Business Review 88 (6), 34–35

Berry, S. & Davey. M. (2004). How Should We Think about Consumer Confidence? Bank of England Quarterly Bulletin, 44(3), 282–90.

Bless, Herbert; Clore, Gerald L.; Schwarz, Norbert; Golisano, Verana; Rabe, Christian and Wolk, Marcus. “Mood and the Use of Scripts: Does a Happy Mood Really Lead to Mindlessness?” Journal of Personality and Social Psychology, October 1996, 71(4), pp. 665–79.

Bodenhausen, G. V., Kramer, G. P., & Süsser, K. (1994). Happiness and stereotypic thinking in social judgment. Journal of Personality & Social Psychology, 66, 621-632.

Bollen, J., Mao, H.; and Zeng, X.-J. (2010). Twitter mood predicts the stock market. Journal of Computational Science 2(1):1–8.

Bradford Titchener, E. A. (2001). Text-Book of Psychology. Adamant Media Corporation

Bram, J. & Ludvigson, S. (1998). Does Consumer Confidence Forecast Household Expenditure? A Sentiment Index Horse Race. ECONOMIC POLICY REVIEW, 4 (2).

Bryant, W. D. A. & Macri. J. (2005). Does Sentiment Explain Consumption? Journal of Economics and Finance, 29(1), 97–111

Buehler, R., McFarland, C., Spyropoulos, V., & Lam, K. C. H. (2007). Motivated prediction of future feelings: Effects of negative mood and mood orientation on affective forecasts. Personality and Social Psychology Bulletin, 33(9), 1265-1278.

doi:10.1177/0146167207303014

Businessweek (2007) Hugging the Tree-huggers. Why so many companies are suddenly linking up with eco groups. Hint: Smart business. Businessweek, maaliskuu 12, 2007.

Cacioppo, JT.; Berntson, GG.; Larsen, JT.; Poehlmann, KM.; Ito, TA. The psychophysiology of emotion. In: Lewis, M.; Haviland–Jones, JM., editors. Handbook of emotions. 2nd. New York: Guilford Press; 2000.

Carroll, C. D., Fuhrer, J. C. & Wilcox, D. W. (1994). Does consumer sentiment forecast household spending? If so, why? American Economic Review, 84 (5), 1397-1408.

Chua, C. L., & Tsiaplias, S. (2009). Can consumer sentiment and its components forecast australian GDP and consumption? Journal of Forecasting, 28(8), 698-711. doi:10.1002/for.1120

Comm, J. (2009). Twitter Power: How to Dominate Your Market One Tweet at a Time. John Wiley & Sons, Hoboken NJ

Cox, B. J, & Swinson, R. P. (1994). Overprediction of fear in panic disorder with agoraphobia. Behaviour Research & Therapy, 32, 735-739.

Dholakia, U.M. & Durham, E., 2010. One café chain's Facebook experiment. Harvard Business Review 88 (3), 26

Dickey, D.A. and W.A. Fuller (1979), “Distribution of the Estimators for Autoregressive Time Series with a Unit Root,” Journal of the American Statistical Association, 74, p. 427–431

Dunn, E. W., Brackett, M. A., Ashton-James, C., Schneiderman, E., & Salovey, P. (2007). On emotionally intelligent time travel: Individual differences in affective forecasting ability. Personality and Social Psychology Bulletin, 33(1), 85-93. doi:10.1177/0146167206294201

Dunning, D., Leuenberger, A., & Sherman, D. A. (1995). Are self- serving theories of success a product of motivational forces? Journal of Personality and Social Psychology, 69, 58-68

economic statistics. Commun ACM 48:87–92.

Ed de Quincey, Patty Kostkova: Early Warning and Outbreak Detection Using Social Networking Websites: The Potential of Twitter. eHealth 2009: 21-24

Egeli, B., M. Ozturan and B. Badur, (2003). Stock market prediction using artificial neural networks. Proceedings of the 3rd International Conference on Business, June 18-21, Hawaii, pp: 1-8.

Ekman P. An argument for basic emotions. Cognition and Emotion 1992;6:169–200

Ekman P. Facial expression and emotion. American Psychologist 1993;48:384–392.

Emotion. (2003). Miller-Keane Encyclopedia and Dictionary of Medicine, Nursing, and Allied Health, Seventh Edition. Retrieved November 18, 2011, from http://medical-dictionary.thefreedictionary.com/emotion

Ettredge M, Gerdes J, Karuga G (2005) Using web-based search data to predict macro-

Eysenbach G. Infodemiology: Tracking Flu-Related Searches on the Web for Syndromic Surveillance. AMIA 2006 Symposium Proceedings; 244-8.

Felton, J., & Kim, J. (2002). Warnings from the Enron Message Board. Journal of Investing, 11(3), 29. Retrieved from EBSCOhost.

Fischer, E., & Reuber, A. R. (2011). Social interaction via new social media: (How) can interactions on Twitter affect effectual thinking and behavior? Journal of Business Venturing, 26, 1-18.

Forecasting and uncertainty in the economic and business world Spyros Makridakisa,∗, Robin M. Hogarthb,1, Anil Gabac,2 Mellers, B. A. & McGraw A. P. (2001). Anticipated Emotions as Guides to Choice. Current Directions in Psychological Science, 10 (6), 210

Forgas, J. P. (2003). Affective influences on attitudes and judgments. In R. J. Davidson, K. R. Scherer & H. H. Goldsmith (Eds.), Handbook of Affective Sciences (pp. 596-218). New York: Oxford University Press.

Freiert, M. (2008, May 15). Twitter traffic explosion: Who's behind it all? Compete. Retrieved May 21, 2008 from //http://blog.compete.com/2008/05/15/twitter-traffic-growth- usage-demographics/

Freiert, M. (2008). Twitter traffic explosion: Who's behind it all? Compete. Retrieved May 21, 2008 from //http://blog.compete.com/2008/05/15/twitter-traffic-growth- usage-demographics/

Frijda, N. H. (1993). Moods, emotion episodes, and emotions. In M. Lewis & J. M. Haviland (Eds.), Handbook of emotions (pp. 381-403). New York: Guilford Press.

Gilbert, D. T., & Wilson, T. D. (2000). Miswanting: Some problems in the forecasting of future states. In J. P. Forgas (Ed.), Feeling and thinking: The role of affect in social cognition (pp. 178-197). Cambridge, UK: Cambridge University Press.

Glance, N., Hurst, M., Nigam, K., Siegler, M., Stockton, R., & Tomokiyo, T. (2005). Deriving marketing intelligence from online discussion. Paper presented at the Proceedings of the Eleventh ACM SIGKDD International Conference on Knowledge Discovery in Data Mining, 419-428. Retrieved from http://dx.doi.org/10.1145/1081870.1081919

Goldstein, D. G. & Gigerenzer G. (2009). Fast and frugal forecasting. International Journal of Forecasting, 25, 760–772

Gruhl, D., Guha, R., Kumar, R., Novak, J., & Tomkins, A. (2005). The predictive power of online chatter. In R. L. Grossman, R. Bayardo, K. Bennett & J. Vaidya (Eds.), Proceedings of the 11th ACM SIGKDD International Conference on Knowledge Discovery in Data Mining (KDD '05) (pp. 78–87). New York: ACM Press.

H. Kwak, C. Lee, H. Park, and S. Moon. What is Twitter, a Social Network or a News Media? In WWW'10: Proceedings of the 19th International World Wide Web Conference, April 2010.

Han, S. & Lerner, J. S. (2006). When the status quo turns sour: Robust effects of incidental disgust on economic transactions. To be presented at the 8th annual meeting of the Society for Personality and Social Psychology, Memphis, Tennessee.

Han, S., Lerner, J. S., & Keltner, D. (2007). Feelings and Consumer Decision Making: The Appraisal-Tendency Framework. Journal of Consumer Psychology, 17(3), 158-168. Lawrence Erlbaum Associates. Retrieved from http://linkinghub.elsevier.com/retrieve/pii/S1057740807700232

International Journal of Forecasting 25 (2009) 794–812

Java, A., Song, X., Finn, T., & Tseng, B. (2006). Why we Twitter: Understanding microblogging usage and communities. Joint 9th WEBKDD and 1st SNA-KDD Work- shop '07, San Jose, CA.

Joinson, A. N. (2001). Self-disclosure in computer-mediated communication: The role of self-awareness and visual anonymity. European Journal of Social Psychology, 31, 177-192

Kaplan, A. M. & Haenlein, M. (2011). The early bird catches the news: Nine things you should know about micro-blogging, Business Horizons, 54(2)

Kozinets, R., de Valck, C., Wojnicki, A. & Wilner, S., 2010. Networked narratives:

understanding word-of-mouth marketing in online communities. Journal of

Kwan, A. & J. Cotsomitis. (2006). The Usefulness of Consumer Confidence in Forecasting Household Spending in Canada: A National and Regional Analysis. Economic Inquiry, 44(1), , 185–97.

Larrick, R. P., & Boles, T. L. (1995). Avoiding regret in decisions with feedback: A negotiation example. Organizational Behavior and Human Decision Processes, 63, 87-97.

Larsen, RJ.; Diener, E. (1992).Promises and problems with the circumplex model of emotion. In: Clark, MS., editor. Review of personality and social psychology. 13. Newbury Park, CA: Sage; p. 25-59.

Larsen, RJ.; Diener, E. Promises and problems with the circumplex model of emotion. In: Clark, MS., editor. Review of personality and social psychology. 13. Newbury Park, CA: Sage; 1992. p. 25-59.

Lazarus, R. S. (1991). Emotion and adaptation. New York: Oxford University Press.

Lerner, J. S., & Keltner, D. (2000). Beyond valence: Toward a model of emotion-specific influences on judgment and choice. Cognition and Emotion, 14(4), 473-493.

Lerner, J. S., & Keltner, D. (2001). Fear, anger, and risk. Journal of Personality and Social Psychology, 81(1), 146-159.

Lerner, J. S., Small, D. A., & Loewenstein, G. (2004). Heart strings and purse strings: Effects of emotions on economic transactions. *Psychological Science, 15*, 337-341.

Loewenstein, G., & Lerner, J. S. (2003). The role of affect in decision making. In R. Davidson, K. Scherer & H. Goldsmith (Eds.), Handbook of affective science (pp. 619-642). New York: Oxford University Press.

Loewenstein, G., & Schkade, D. (1999). Wouldn't it be nice? Predict- ing future feelings. In D. Kahneman, E. Diener, & N. Schwarz (Eds.), Well-being: The foundations of hedonic psychology (pp. 85-105). New York: Russell Sage Foundation.

Ludvigson, S. C. (2004). Consumer Confidence and Consumer Spending. Journal of Economic Perspectives, 18(2), 29–50.

Luoma-aho, V. (2005) Faith-holders as Social Capital of Finnish Public Organisations. Jyväskylä Studies in Humanities 42, University of Jyväskylä.

Luoma-aho, V. (2005). Faith-holders as Social Capital of Finnish Public

Organisations.Jyväskylä Studies in Humanities 42, University of Jyväskylä.

Luoma-aho, V. (2009). Love, hate and surviving stakeholder emotions. A paper presented at the International Public Relations Research Conference, Miami, Florida, March 11th-14th, 2009. Available online: http://www.instituteforpr.org/files/uploads/Love_Hate.pdf

Makridakis, S., & Hibon, M. (1979). Accuracy of forecasting: An empirical investigation (with discussion). Journal of the Royal Statistical Society, Series A, 142(2), 79–145.

Makridakis, S., Andersen, A., Carbone, R., Fildes, R., Hibon, M., Lewandowski, R., Newton, J., Parzen, E., & Winkler, R. (1982). The accuracy of extrapolation (time series) methods: Results of a forecasting competition. Journal of Forecasting, 1, 111–153.

Makridakis, S., Chatfield, C., Hibon, M., Lawrence, M., Mills, T., Ord, K., & Simmons, L. F. (1993). The M-2 competition: A real-time judgmentally based forecasting study. International Journal of Forecasting, 9, 5–23.

Morgan, W. P. (1978). The mind of the marathoner. Psychology Today, 11, 38-49.

Morgan, W. P., & Johnson, R. W. (1977). Psychologic characterization of the elite wrestler: A mental health model. Medicine and Science in Sports, 9, 55-56.

Morgan, W. P., & Johnson, R. W. (1978). Personality characteristics of successful and unsuccessful oarsmen. International Journal of Sport Psychology, 9, 119-133.

Mosby's Medical Dictionary, 8th edition. © 2009, Elsevier

Orrella D. & McSharry P. (2009). System economics: Overcoming the pitfalls of forecasting models via a multidisciplinary approach. International Journal of Forecasting, 25, 734–743

Ortony, A. & Turner, T.J. (1990).What's basic about basic emotions? Psychology Review ;97:315–331.

Pizzorno, A. (2004). Resources of Social Capital: Reputation and Visibility. A presentation given at the ECSR Summer School on Social Capital, Trento Italy.

Posner, J., J. A. Russell, and B. S. Peterson (2005). The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. Development and Psychopathology 17(03), 715–734.

Riis, J., Loewenstein, G., Baron, J., Jepson, C., Fagerlin, A., & Ubel, P. A. (2005). Ignorance of hedonic adaptation to hemo-dialysis: A study using ecological momentary assessment. Journal of Exper- imental Psychology: General, 134, 3-9.

Russell, J. A. (1980). A circumplex model of affect. Journal of Personality and Social Psychology;39:1161– 1178.

Russell, J. A. (1980). A circumplex model of affect. Journal of Person-

Russell, J. A. (1989). Measures of emotion. In R. Plutchik & H. Kellerman (Eds.), Emotion - Theory, research, and experience: Vol. 4. The measurement of emotions (pp. 83-111). New York: Academic Press.

Russell, J.A. (2003). Core affect and the psychological construction of emotion. Psychological Review;110:145–172. [PubMed: 12529060]

Russell, J.A. & Carroll, J.M. (1999). On the bipolarity of positive and negative affect. Psychology Bulletin;125:3–30.

Saarni, C. Development of emotional competence. New York: Guilford Press; 1999.

Samanidoul, E., Zschischang, E., Stauffer, D., & Lux, T. (2007). Agent-based models of financial markets. Reports on Progress in Physics, 70, 409–450.

Schau, H. J. & Gilly, M. C. (2003), "We Are What We Post? Self-Presentation in Personal Web Space," Journal of Consumer Research, 30 (December), 385-404

Shandle, J., (1993), "Neural Networks are Ready for Prime Time", Electronic Design,February 18,1993, pp. 51-58

Small, D. A., & Lerner, J. S. (2005). Emotional politics: Personal sadness and anger shape public welfare preferences. Paper presented at the Society for Personality and Social Psychology, New Orleans, LA.

Solis, B. (2010). A Prediction: Twitter to Predict the Future. Retrieved from http://www.briansolis.com/2010/04/a-prediction-twitter-to-predict-the-future/

Sprenger, T. O. & Welpe, I. M. (2010). Tweets and Trades: The Information Content of Stock Microblogs. Available at SSRN: http://ssrn.com/abstract=1702854

Taleb, (2007). The black swan: The impact of the highly improbable. New York, NY: Random House.

Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., & Kappas, A. (2010). Sentiment strength detection in short informal text. Journal of the American Society for Information Science and Technology, 61(12), 2544–2558.

Thevenot, G. (2007). Blogging as a social media. Tourism and Hospitality Research, 7 (3/4), 282–289.

Tumarkin, R. & Whitelaw R. F. (2001) News or Noise? Internet Postings and Stock Prices. FinancialAnalysts Journal; May/June 2001; 57, 3

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. Science, 185, 1124–1131.

Van Boven, Loewenstein, & Dunning, (2003). Mispredicting the endowment effect: Underestimation of owners' selling prices by buyer's agents. Journal of Economic Behavior & Organization, 51, 351-365.

Vilma Luoma-aho "Love, hate and surviving stakeholder emotions". Standford university

Vincent, Arnaud, and Armstrong Margaret, 2010, Predicting break-points in trading strategies with Twitter, Working paper, École Nationale Supérieure des Mines de Paris..

Wilson, T. D. & Gilbert, D. T. (2005). Affective forecasting: Knowing what to want. Current Directions in Psychological Science, 14, 131-134.

Zarnowitz, V. (1966). How accurate are the forecasts? Challenge, 14 (3), 20-23

Zhang, X., Fuehres, H., & Gloor A.V. (2010). Predicting Stock Market Indicators Through Twitter "I hope it is not as bad as I fear". Procedia Social and Behavioral Sciences