Dynamic Analysis of Investor's Community Sentiment: A Hawkes-Process Framework.

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April 2017
(Draft Version)

Abstract

Our work is driven by the need of an unbiased measure of sentiment of investors with optimal explanatory power to asset-classes returns. We represent the membership of agents in financial-community as a self-exciting hawkes-process. Contrary to other studies that consider the financial community on social media as a static entity, our dynamic approach reduces the size of the community at each time-period. We then exctract the sentiment from this community. We show that this approach helps reducing the noise of the sentiment signal exctracted and enhances its predictive power over financial markets movements.

JEL classification: C55, G14
Keywords: Sentiment, Hawkes-Process, Temporal-Network, Twitter.

1 Introduction

Sentiment of investors is a long gone field of financial theory, in fact a very long one. The first sentiment of investors index: Investors-Intelligence's *Bearish Sentiment Index* has been launched in 1963. This index was fairly close to the definition of investors' sentiment as we know it today, since it was formed by surveying the bullish or bearish opinion of 130 investment advisors as described by (Cohen et al. 1973, Solt and Statman 1988). In 1991, (Lee et al. 1991) offered a solution to the *closed-end-fund-puzzle*, claiming that small-investors' sentiment may have an impact on stocks and

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closed-end funds valuation. Their work was based on limits-of-arbitrage theory (De Long et al. 1990 Shleifer and Vishny 1997). It that divergences in asset prices may be explained by divergences of sentiment between a rational investor aiming for price convergence in the long-term, and short-term irrational noise traders causing them to diverge. (Lee et al. 1991) introduce a measure of this small-investors sentiment through the discount on closed-end funds. This measure's interest was later confirmed empirically by (Neal and Wheatley 1998, Qiu and Welch 2004) and strongly contested by (Elton et al. 1998). Following the same philosophy, (Baker and Wurgler 2006) uses a composite sentiment metric including sentiment proxies such as closed-end-fund-discount, turnover, number of IPOs and their first-day return. They find empirical evidences that cross-sectional return of stocks depends on sentiment. This measure of investor sentiment became a standard, widely used for example in (Baker and Wurgler 2007) or (McLean and Zhao 2014) who apply it to model cost of finance for investors in recession periods.

A radically different approach was introduced by (Tetlock 2007) where instead of computing sentiment from market data, they measured the sentiment coming from financial news. In his study, Paul Tetlock used The Wall Street Journal articles to compute a negative sentiment index between 1984 and 1999 and empirically proves that pessimism in news leads to short-term negative returns on equity markets. This study was later reproduced in the very long term (a century, from 1905 to 2005) by (Garcia 2013) using New-York Times financial articles. They confirm Tetlock's findings and underlin the stronger predictive power of pessimism in news to financial markets during NBER recession periods.

The emergence of social networks and easily accessible large datasets lead to conduct such studies on sentiment extracted from news media. In 2011, (Bollen et al. 2011) investigates the predictive power of a *Public-mood index* computed using Twitter content on the DJIA index. (Mao et al. 2014) follows a similar approach on Google Trend data. Complexity and unreliability of the textual measurement of sentiment from social media has been widely addressed to sentiment indices. One pitfall of social-media sentiment is representativeness. As we presented it before, investors-sentiment indices can be divided in two categories depending on the type of data they handle. On the one hand, some indices are based on newspapers, with very few occurrences per day, but accurate, verified, and highly shared amongst the financial community. On the other hand, sentiment indices using twitter data are very noisy. They contain a majority of non-shared entities, withthe problem of reliability of their content. This permanent trade-off (between very large but unreliable data and smaller but more specific and trustworthy one) has also been explicated by (Ozik and Sadka 2013) on a paper relative to hedge-fund returns, where they underline the importance of considering a *specialized* media source instead of a *general* one. Our study's goal will follow these studies by looking for a more robust indicator through a more specific information as opposed to the commonly-used *wisdom of the crowd* approach.

In a quest of a more simple and robust methodology, (Mao et al. 2014) studied the predictive power of a *Google-bullishness* index based on Google trends and compared it to a similar measure coming from Twitter. Their founding was that, despite its complexity, Twitter sentiment provided a better correlation to market returns. Another more successful attempt to increase Twitter's sentiment robustness was provided by Yang et al. 2015. This paper focuses on Twitter sentiment from a graph-theory perspective by considering the *community of investors* instead of Twitter as a whole.The paper proves that the smaller and the more concentrated the network for extracting sentiment, the more significant its predictive power is. The paper nevertheless fails to propose an optimal size of the network and only provides an ex-post construction of the *community of investors.* We expand this literature by providing a sentiment measures that relies on a community of temporally optimal size and structure.

Social networks members interact with each other in various forms by connecting to each other, giving opinion on each other's publications or sharing content. Being able to measure the influence of one user is essential to produce an accurate sentiment calculation. A widely used family of measures of the importance of a user within a network are centralities, which are based on a users number and type of connections to the rest of the network. Among the most used centrality-measures, we can mention (Freeman 1977) *betweenness-centrality* and (Bonacich 1987) *eigenvector-centrality* on which Google's famous PageRank is based. Although these measures are useful for defining users notoriety, they are weak proxies for influence and predictive audience as studied in (Cha et al. 2010[1]). A similar finding is documented in (Romero et al. 2011) who also argue that content sharing and mentioning is a better indicator of audience than user's centrality.

Content shared on social media takes several hours and even days to finally spread to the whole network. An ex-post measure of such spreading thus introduces a strong in-sample bias to the measure of sentiment. In order to use influence measures to compute investor sentiment, it is necessary to first solve the puzzle of an estimation of one publication's audience

[1] Cha et al. 2010, *"We found that indegree represents a user's popularity, but is not related to other important notions of influence such as engaging audience, i.e., retweets and mentions."*.

prior to its publication. In order to do so, we will represent each user of our network as a point-process. The intensity of the process represents the influence of the user and is function of its past activity. Hawkes-process are self-exciting point-processes introduces by (Hawkes 1971). They are self-exciting in the sense that their intensity depends on previous occurrences. They have been widely used to model events whose probably of occuring directly depends on the proximity of past occurences, such as hearthquakes (Kagan and Knopoff 1981). Multivariate Hawkes-process also became quite popular in the recent finance litterature (and more particularly in the High-Frequency-Trading litterature of the past 10 years)or high-frequency finance microstructure(Hewlett 2006; Bowsher 2007; Bacry et al. 2013). Their popularity is mostly due to their simplicity of modeling and interpretation, intensity vector being a linear fit of past events, as well as their versatility since hawkes-Process allow to account for the influence of some intensive factors and non-stationarities. In their study (Crane and Sornette 2008) have proven that online media's interactions follow a self-exciting pattern. Our approach will follow recent literature on social-networks trend detection using point-process (Li and Zha 2013; Pinto et al. 2015).

We will first present the different steps of our methodology, being the sentiment-analysis techniques, the network-analysis process and finally the Hawkes-process modeling of users importance within the network. This first part's final step will be the computing of a sentiment index.In order to prove its predictive power on major financial indices, we will then present the financial data that we used. The results will exhibit in a first time the necessity of using ex-post characteristics of users, then it will present the predictive-power of the sentiment index using ex-ante measure of notoriety. In the last part of this paper we will provide robustness-checks of our results.

This paper will contribute to the existing literature on investor's sentiment by providing a framework for taking into account the dynamic structure of a social-network in the computing of a sentiment index. To our best knowledge, there isn't any work using a dynamic measure of notoriety in the computing of investor's sentiment. We will prove that notoriety of financial community members should be measured dynamicaly. Our results will exhibit that our measure, contrary to previous works on static centrality measures, doesn't present an in-sample bias. Moreover, our *out-of-sample* measure also enhances the explanatory significance over financial assets.

2 Methodology and Data

2.1 Sentiment Analysis

The quality of sentiment extraction is an ongoing topic in computer sciences and many issues remain unsolved. For instance, most of the models currently used ignore word order and grammatical construction of the sentences and models for sentiment analysis taking sentence structure into account is an active field of research (Socher et al. 2013; Poria et al. 2016).

(...Recursive Neural-Networks model might be used in the Final version of this paper...)

We will focus here only on algorithm that takes into account words meaning to evaluate sentiment disregard their position in the sentence or the structure of the sentence per se. This type of algorithm isone of the most popuular in investors' sentiment papers . These techniques can be devided in two groups. The first group accounts for algforithms that count word occurence of negative and positive words defined in a dictionnary. The second one uses features from a dataset of sentences previously labelled as *positive* or *negative*, for training machine-learning algorithms such as Naive-Bayse, SVM or Neural-Networks. Most of the historical papers adopting investor sentiment in finance use dictionary-based methodologies, generally based on one of the Harvard Psychological Dictionary called the Harvard-IV4 TagNeg dictionary (Tetlock 2007; Garcia 2013; Da et al. 2015). In their paper, (Loughran and McDonald 2011) show that sentiment classification in a financial context relies on a specific vocabulary, and should not be interpreted through a general terms dictionary but instead through a financial specific one. They then provide a dictionary of financial words classified into categories such as *positive*, *negative* or *litigious*. Several other studies of sentiment related to stock markets use supervised machine-learning text-mining methods in order to improve the accuracy of the predicted sentiment. They all need to access a dataset of labelled entities already classified and to extract a vector of features from each entity. Then, Machine-Learning algorithms are used to train the model on the dataset. The three types of widely used machine-learning algorithms are, Support-Vector-Machine (Ranco et al. 2015; Schumaker and Chen 2009; Lugmayr and Gossen 2013), Naive-Bayes (Yu et al. 2013) and Random-forrest (Kalyani et al. 2016) and and Maximum-entropy (Zhang 2013). (Kalyani et al. 2016) proves a similar accuracy of Random-forrest to SVM an Naive-Bayes approaches, while maximum-entropy is compared in (Zhang 2013) against SVM and Naive-Bayes techniques, showing very close results. In this paper we decided to use the naive-bayesian approach on labelled data as it is a robust and simlple procedure that none of the more complex algorithms outperform.

2.2 Twitter Data

2.2.1 Tweets Sentiment

Twitter is a social-network where users can exchange content of a maximum length of 140 charaters, called *tweets*. Users can connect to each others on the networks using *follows* directional connections between a *follower* and a *followed* user. User can also interact with each other's content by simply approving it, using *likes*, or by sharing it to their own followers using *retweets*. We will use the *follower/followed* connections to compute our static network of the financial community while we will use *likes* and *retweets* to appreciate user's audience. Twitter data have been extracted through the provided Twitter API. We first follow (Yang et al. 2015) by downloading every followers of 50 seed chosen accounts. These accounts, chosen by their alleged notoriety amongst financial medias, are composed of the 25 most important institutional accounts according to (WSJ 2016) and the most influential finance peoples as defined by (MarketWatch 2016). Although, due to the recursive nature of our approach, the importance of these seed users is very limited. After filtering users that keep their tweets private and users that don't tweet in english, we repeat the previous operation of downloading all of their respective followers to obtain a representation of the financial community of Twitter. This community can be represented as a graph $G(E, V)$, with every user being a node (vertex) V, and every connection between two users being an edge E. Finally, the computed graph is composed of 212,789 nodes and 154.8 million directed edges. Next, we download every available tweet for these users since the creation of Twitter in 2007, for a total of more than 150 million tweets.

We process the tweets in order to apply feature classification following the 5 steps process below:

1. Tokenization: Sentences are transformed into list of tokens using NLTK Python package.

2. Metadata removal:

   (a) Mentions @: Every mention of another user using the @ mention will be removed from tweets and replaced by the generic mention *'USERNAME'*

   (b) Hashtags #: We assume, as it is mentioned in (Palogiannidi et al. 2016) that hashtags have different semantic interpretations depending on their position in the sentence. Hashtags at the end of a tweet are preserved since they generally provide their own meaning while hashtags in the middle of sentences are removed and treated like regular words.

(c) URLs: URLs of any type are removed and replaced by the genereic mention 'URL'

3. Negation: We follow (Potts 2011) methodology and its negation words-list for negation-marking by adding the prefix 'NOT' to every token following a negation word until an ending punctuation mark is found.

4. Lemmatization: We reduced the tokens to their meaning root using the NLTK lemmatizer.

5. Stop-words removal: we then remove every stop word that might occur too often in the frequency distribution of words.

Afterwards, we attribute features to tweets. We used n-grams as features, which are the list of consecutive n words occurring in a sentence. For example the sentence 'I am happy' has three 1-grams ('I', 'am', and 'happy'), two 2-grams ('I am' and 'am happy') and one 3-grams ('I am happy'). We computed the list of n-grams for the whole universe of tweets. We found that a vector of the 3000 most frequent n-grams of our datasets is the most optimal, which is in accordance with the state-of-art in n-grams models.

After processing, tweets are attributed a sentiment label (*postive*, *neutral* or *negative*) using our Naive-Bayes algorithm with features vectors and labels as inputs. To train our algorithm, we used two datasets. The first one using the group of training datasets provided by SemEval, composed of about 19,000 labelled tweets, next we use the Sentiment140 dataset of 1.6 million labeled tweets. Finally, in order to benchmark the accuracy of our model, we test it on the SemEval2013 test dataset. Our algorithm reaches an accuracy of 69.8% which in the upper range of the participants to this international competition.

At every date t the three sentiments measures of *poisitive, negative* and *overall* sentiment are defined by $Spos_t$, $Sneg_t$, $Sall_t$ as:

$$Spos_t = \frac{\sum_{i=1}^{N} \sum_{j,s_{j,t}=1}^{M_i} (s_j)}{\sum_{i=1}^{N} M_i}, \tag{1}$$

$$Sneg_t = \frac{\sum_{i=1}^{N} \sum_{j,s_{j,t}=-1}^{M_i} (s_j)}{\sum_{i=1}^{N} M_i}, \tag{2}$$

$$Sall_t = \frac{\left(\sum_{i=1}^{N} \sum_{j,s_{j,t}=1}^{M_i} s_j\right) + \left(\sum_{i=-1}^{N} \sum_{j,s_{j,t}=1}^{M_i} s_j\right)}{\sum_{i=1}^{N} M_i}, \tag{3}$$

Where M_i represents the number of tweets j of user i, $s_{i,j}$ the individual sentiment of each tweet and N the total number of users.

2.2.2 User audience

In-Sample Audience For every user, we extract a time series of activity characterized by its interactions with other users within and outside the network. For a user i at given time t, we compute the *Audience-features* vector $F_{t,i}$ of size $f = 6$, composed of the 6 following measures:

1. Original-Tweet: 1 if the user tweeted an original content classified as *financial*, 0 otherwise.

2. Retweet: 1 if the user retweeted a content classified as *financial*, 0 otherwise.

3. Likes: The total number of *Likes* of the user's *financial* content.

4. Out-Retweet : The total number of *Retweets* of the user's *financial* content inside and outside of the community.

5. In-Retweet : The total number of *Retweet* of the user's *financial* content within the community.

6. In-Out-Ratio : The ratio between In-Retweet and Out-Retweet of one user's content pourcentage of sharing within the community.

In order to control for extreme values, we consider the log of the four later features while the two first ones are binary. We compute for every of the f features, the sentiment measures *Spos*, *Sneg*, *Sall* where sentiment at a given time t is the weighted average of the sentiment by each user's audience $F_{t,i}$ defined as:

$$Spos_{t,f} = \frac{\sum_{i=1}^{N} F_{t,i,f} \sum_{j,s_{j,t}=1}^{M_{i,t}} (s_{j,t})}{\sum_{i=1}^{N} M_{i,t} \sum_{i=1}^{N} F_{i,t,f}} \tag{4}$$

$$Sneg_{t,f} = \frac{\sum_{i=1}^{N} F_{t,i,f} \sum_{j,s_{j,t}=1}^{M_{i,t}} (s_{j,t})}{\sum_{i=1}^{N} M_{i,t} \sum_{i=1}^{N} F_{i,t,f}} \tag{5}$$

$$Sall_{t,f} = \frac{\left(\sum_{i=1}^{N} F_{t,i,f} \sum_{j,s_{j,t}=1}^{M_{i,t}} (s_{j,t})\right) + \left(\sum_{i=1}^{N} F_{t,i,f} \sum_{j,s_{j,t}=1}^{M_{i,t}} (s_{j,t})\right)}{\sum_{i=1}^{N} M_{i,t} \sum_{i=1}^{N} F_{i,t,f}} \tag{6}$$

For every of the 6 activity measure f, we end up with 3 sentiment indices $(Spos_{t,f}, Sneg_{t,f}, Sall_{t,f})$. We also add 3 unweighted indices, for a total of 21 indices as displayed in Figure 1.

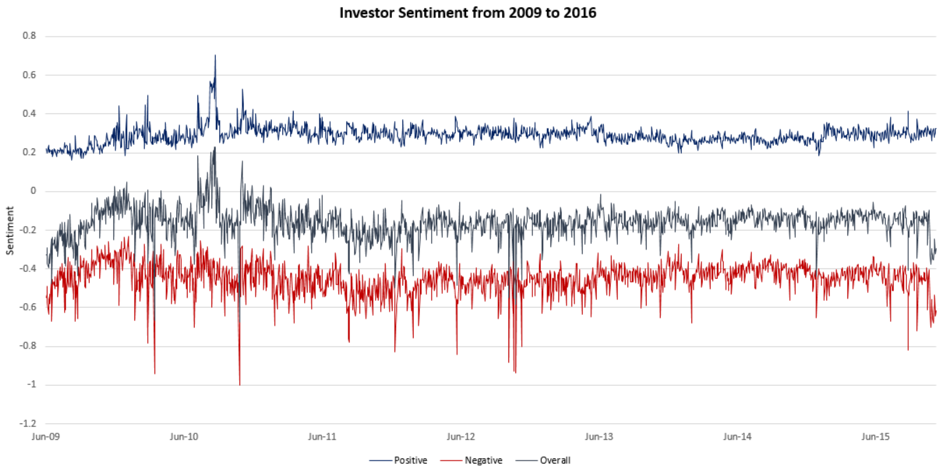

Figure 1: In-sample Features Sentiment-Index between 2010 and 2016 for the considered feature In-Out-Ratio. This figure presents the three sentiment indices (*positive, negative and overall*)

2.3 Hawkes-Process

The univariate Hawkes-Process is a self-exciting point-process defined as a counting process $(N(t) : t > 0)$ with the associated filtration $(\mathcal{F}(t) : t > 0)$ that satisfies:

$$P(N(t+h) - N(t) = m|\mathcal{F}(t)) = \begin{cases} \lambda * (t)h + o(h), & m = 1 \\ o(h), & m > 1 \\ 1 - \lambda * (t)h + o(h), & m = 0 \end{cases}$$

With its intensity following:

$$\lambda(t) = \mu + \int_0^t \alpha(t-u)dN_u \tag{7}$$

As originally used by Hawkes as a usefull simplification for derivations, the excitation function is commonly defined as an exponential decay by applying Ito's lemma to the case $\alpha(t) = \alpha e^{-\beta t}$, leading to:

$$\lambda_t = \mu + \int_{-\inf}^t \alpha e^{-\beta(t-s)} dN_s = \mu + \sum_{t_i < t} \alpha e^{-\beta(t-t_i)} \tag{8}$$

The log-likelihood function L is then defined for a process on [0, T] with $t_1 ... t_N$ the realizations of $(N_t)_{t>0}$ as:

$$L = T - T\mu - \sum_{i=1}^{N} \frac{\alpha}{\beta}(1 - e^{-\beta(T-t_i)}) + \sum_{i=1}^{N} ln(\mu + \alpha R(i)), \tag{9}$$

where $R(i) = \sum_{t_j<t_i} e^{-\beta(t_i-t_j)}$.

We estimate the maximum likelihood using a nonlinear optimization algorithm such as Nelder-Mead. In our case we use the Python package scipy implementation's of Limited-memory-BFGS[2].

Out-of-Sample Audience Modelization using Hawkes-Process We then use Hawkes-process in order to estimate out-of-sample Audience level for each user of the community. To do so we consider only the two most significative Audience-features *'In-Sample-Retweet'* and *'In-Out-Ratio'*. The out-of-sample audience level in t is then defined by the intensity λ_t of the univariate Hawkes-process, with jump N_t equals to the past measures of audiences $F_{t,i,f}$ ocuring above a given threshold θ leading to the process on [0, T] with $t_1 ... t_N$ the realizations of $(N_t)_{t>0}$ when $(F_{t,i,f})_t > \theta$ as: :

$$\lambda_t = \mu + \sum_{t_i<t} \alpha e^{-\beta(t-t_i)} \tag{10}$$

For each user i at a given time t we have his out-of sample audience level $\lambda_{i,t}$. This out of sample measure is then used to compute the *negative-sentiment* $Sneg_{i,t}$ for user i at time t as:

$$Sneg_{t,f} = \frac{\sum_{i=1}^{N} \lambda_{i,t} \sum_{j,s_{j,t}=1}^{M_{i,t}} (s_{j,t})}{\sum_{i=1}^{N} M_{i,t} \sum_{i=1}^{N} \lambda_{i,t}} \tag{11}$$

Out of sample sentiment index' explanatory significance as diplayed in Figure 2 will then be tested against six financial markets data.

2.4 Financial Data

We study the predictive power significance of our Sentiment-Index on 6 financial-data divided in 2 categories: Return-metrics and Risk-metrics. OUr sample period ranges from 2010 to 2016. For return metrics, we consider the daily return R of the time-serie P computed at each period t as $R_t = P_t/P_{t-1} - 1$ while for risk metrics we consider the first difference of the serie P computed as $R_t = P_t - P_{t-1}$. We then use the preceding sentiment measure as an explanatory factor in the following model:

$$R_t = \alpha + \beta S_{t-1} + \epsilon_t, \tag{12}$$

With ϵ_t the error term.

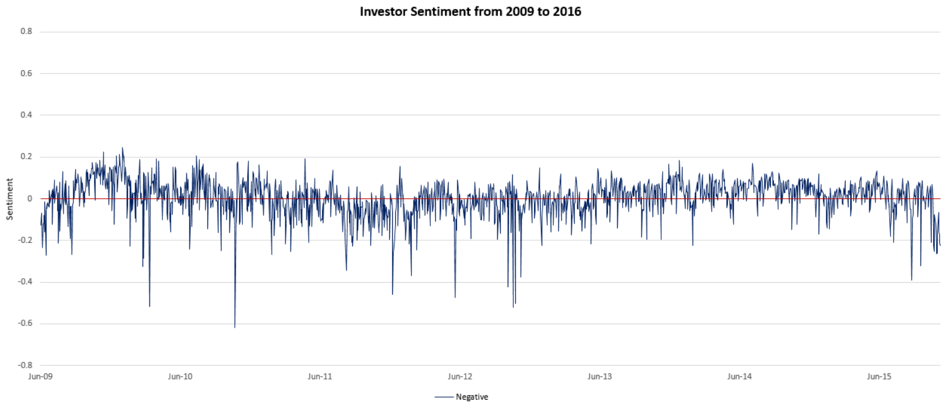

Figure 2: Out-of-Sample Features Sentiment-Index between 2010 and 2016 for the considered feature In-Out-Ratio. This figure exhibits the sentiment-index computed using an out-of-sample audience measure based on the hawkes-process methodology

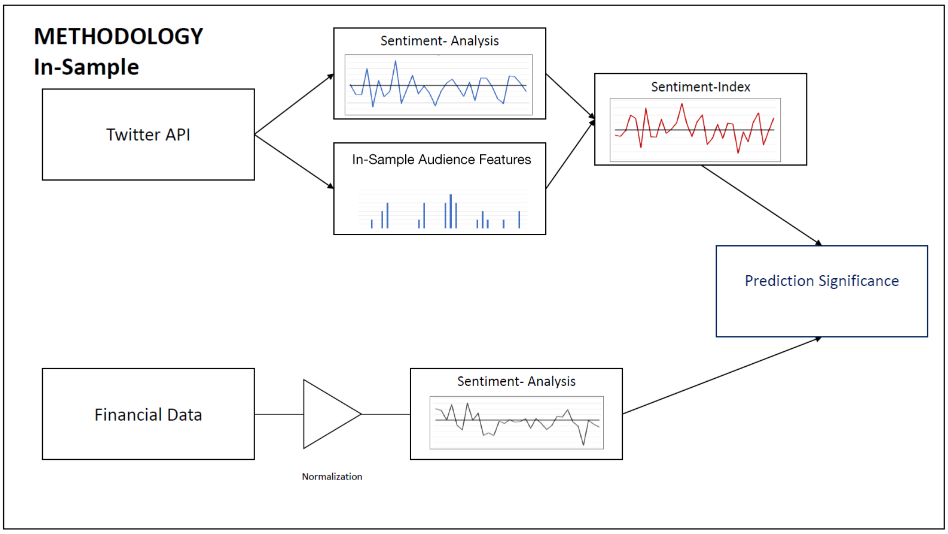

Figure 3: In-Sample Features Methodology. This diagram shows the work-flow that leads to predictive significance tests of our in-sample sentiment index over financial metrics (both return and risk metrics).

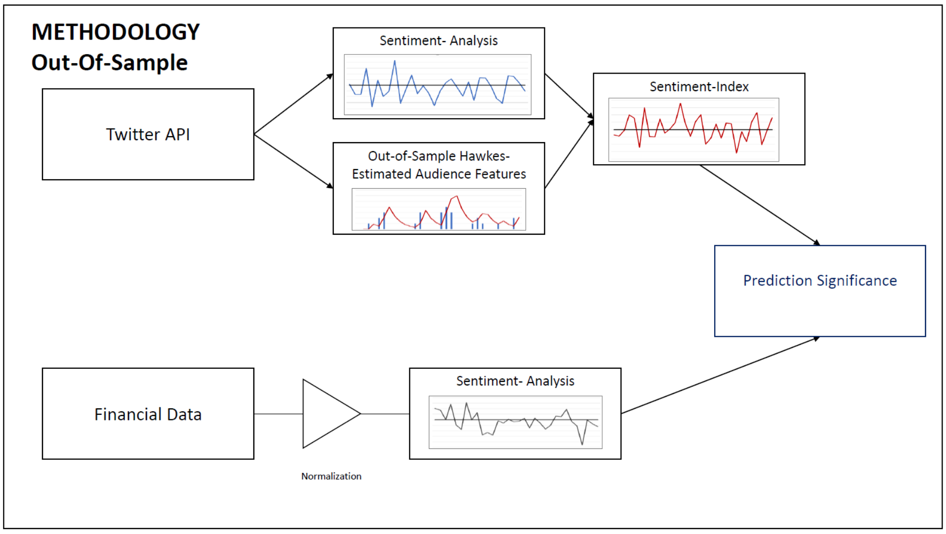

Figure 4: Out-Of-Sample Features Methodology. This diagram shows the workflow that leads to predictive significance tests of our in-sample sentiment index over financial metrics (both return and risk metrics). Contrary to the In-sample methodology, the audience-features are now measured out-of-sample using the Hawkes-process methodology.

The global methodology is described in figure 3 for the in-sample audience modeling and figure 4 for the out-of sample hawkes-process methodology.

3 Results

3.1 In sample results

In-sample results displayed in Table 1 show both the oversignificance of *negative* sentiment over *positive* and *total* ones and the generally more significant audience features which are the *In-Out-Ratio* and the *Retweet-In* features.

Out-of-sample results displayed in Table 2 shows that there is a loss in term of explanatory-power significance over finacial metrics when using our out-of-sample investors' sentiment index compared to the in-sample measure. However, the significance of the out-of-sample measure remains strong and statistically acceptable.

[2] Broyden-Fletcher-Goldfarb-Shanno algorithm (Broyden 1970; Fletcher 1970; Goldfarb 1970; Shanno 1970) is an itterative optimization algorithm in the family of quasi-Newton methods that approximates the stationary point of a function

	SP500			**US10GOV**			**GER10GOV**		
	Pos_Sent	**Neg_Sent**	**Total_Sent**	**Pos_Sent**	**Neg_Sent**	**Total_Sent**	**Pos_Sent**	**Neg_Sent**	**Total_Sent**
All_Tweets	0.972	0.758	0.859	0.335	0.275	0.840	0.366	0.811	0.466
Original_tweet	0.765	0.314	0.364	0.682	0.471	0.876	0.457	0.672	0.759
Retweet	0.905	**0.127**	0.420	0.242	0.229	0.894	0.458	0.380	0.987
Number_Likes	0.870	0.208	0.380	0.334	0.206	0.987	0.388	0.362	0.908
Number_Retweet_Out	0.892	0.203	0.363	0.368	0.357	0.998	0.442	0.468	0.971
Number_Retweet_In	0.854	**0.093**	0.294	0.206	**0.063**	0.702	0.397	0.165	0.736
In_Out_Ratio	0.813	**0.098**	0.202	0.303	**0.058**	0.285	0.676	**0.143**	0.347

	VIX			**USHY**			**USD SWAPTIONS**		
	Pos_Sent	**Neg_Sent**	**Total_Sent**	**Pos_Sent**	**Neg_Sent**	**Total_Sent**	**Pos_Sent**	**Neg_Sent**	**Total_Sent**
All_Tweets	0.222	**0.059**	0.925	0.294	0.706	0.194	0.960	0.569	0.659
Original_tweet	0.568	**0.009**	0.198	0.289	0.656	0.256	0.848	0.639	0.642
Retweet	0.241	**0.001**	0.237	0.318	0.549	0.288	0.994	0.382	0.606
Number_Likes	0.417	**0.001**	0.159	0.298	0.659	0.289	0.848	0.739	0.730
Number_Retweet_Out	0.350	**0.002**	0.171	0.271	0.624	0.300	0.910	0.549	0.645
Number_Retweet_In	0.231	**0.000**	**0.072**	0.295	0.333	**0.147**	0.882	0.198	0.310
In_Out_Ratio	0.207	**0.000**	**0.020**	0.308	0.278	**0.137**	0.640	**0.121**	**0.091**

Table 1: Comparaison of audience measures importance on Sentiment-Index explanatory power (p-values). Considering a significant p-value of 5%, this table shows the generally more significant *negative* and *Total* sentiment over *positive* sentiment for allmost every features and financial-metrics. This table also exhibits that the most significant features for almost all the financial-metrics are the *In-Out-Ratio* and the *Retweet-In* features.

	Investor Sentiment p-values	
	In-sample audience	Out-of sample Hawkes estimation
SP500	**0.10**	**0.11**
US10GOV	**0.06**	**0.06**
GER10GOV	**0.14**	0.17
VIX	**0.00**	**0.00**
USHY	0.28	0.33
USD SWAPTIONS	**0.12**	0.17

Table 2: Comparaison of Sentiment-Index from In-sample and Out-of-Sample network estimations (p-values). This table proves exhibits the fact that despite a a loss of significance of the *Out-of-sample* measure compared to the *In-sample* one, our in-sample sentiment index explanatory power remains significant over most of the financial-metrics.

4 Conclusion

In this paper we:

1. Provided a Framework for taking into account the dynamic structure of a social-network through its user's audience in the computing of sentiment.

2. Proved that audience should be measured dynamicaly instead of statical centrality measures.

3. Showed that sentiment computed using hawkes-process estimation of

audience both provide a real out-of-sample measure and enhances the explanatory significance.

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