A PROSPECT ON HOW TO FIND THE POLARITY OF A FINANCIAL NEWS BY KEEPING AN OBJECTIVE STANDPOINT. (POSITION PAPER)

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Abstract: This paper raises the question on how we can keep an independent standpoint regarding the finding of a polarity in a news document. As we know, an usefulness/relevance of a text news may be seen differently by a group of evaluators, among others, it depends on their interests, their knowledge, and/or their ability to understand. Recent research in literature mostly follow a top-down approach, which is either a context-based solution or a dictionary-based approach. With respect to the perspectives (standpoints) of an evaluator, we therefore come up with an alternative approach, which is bottom-up and which tends to overcome the power of a single evaluator. The idea is to introduce a collection of theme-related *Artificial Companions* (financial, economic, or political, ...), which are able to vote. A decision regarding the polarity of a financial news bases on the interplay of a social collection of agents (a swarm), which serve and assist the Artificial Companion while fulfilling simple (linguistic, statistical) tasks.

1 MOTIVATION

The European Financial Crisis has emerged within the last years, with many Ups and Downs, with many consequences and decisions for politics and economy. For example, Eurobonds have been suggested, attracting a great deal of attention while financial news appeared in a Tsunami-style of eruptively flowing pace. Besides, financial and political activities have taken place, political communities have emerged, and coalitions established. Also, a certain number of states have been down-rated, Greece (and potentially other European states) are close to insolvency. All these information has been well-noted in financial news.

We concern with such *financial text news* (Thomson Reuters), which represent a reflection of momentary political, economical, and financial incidents. *Financial text news* can influence decisions, expose realistically and unaltered current events, and/or contribute to the formation of an opinion. And a subjectiveness, therefore, is of course inherent. Our concern therefore is: assuming that we have financial texts as a pure medium with an exclusive concentration on facts and objectivity, without a disposedness to persuasion and without an inducement to think a matter over, can we then find indications regarding financial, political, or economic decisions, for example with respect to the European crisis? Can we identify a relationship to the financial market (stock market and others) given, observe a composition of like-minded people? Can we be proactive and illustrate the emergence of the crisis as well as a future recurrence?

In Computer Science research, several directions regarding the analysis of texts have evolved. One of them is *sentiment analysis* of texts and with it the finding of an inherent polarity of the document. A sentiment classification refers to identify and extract subjective information that appears in source materials and to determine the attitude of a person concerning an overall contextual polarity of a document. The sentiment may be a judgement or an evaluation, an affective state, or the intended emotional communication. Following this, a finding of answers to the questions as given above might be rather simple in a way that a certain number of existing techniques may be applied. More easily, we could argue that we only have analyse the documents linguistically, statistically, and from a Machine Learning point of view, and that we then may come up with a sentiment decision. However, this is not as easy as it seems.

A crucial argument is that we must guarantee a neutral perspective (or standpoint), with almost no apriori expectations. The reason is that a financial news may be interpreted in a different way, depending on what a evaluator thinks, believes, and/or knows. As an example, let us consider the following financial text news:

> "Juncker suggested to introduce Eurobonds. This is a good sign for the new Europe."

Here, the interpretation is ambiguous and may cause - because of the evaluator's position - different conclusions as well as a misunderstanding. If the a-priori perspective of the evaluator is somehow positive with respect to Eurobonds, then the content is very appreciated and the document classified as to be positive. If it is not, then the document becomes a negative polarity and with it, possibly a negative signal for financial markets. Therefore, the argument of having a neutral perspective is essential with respect to a classification of the polarity.

In the following, we will concern the polarity/sentiment of a document and present a collection of research works that has been made recently (Chapter 2). We will target the problem of having independent perspectives (standpoints) and claim that a fair, stable, and reliable decision can only be made by a voting of emancipated artificial entities (Chapter 3). We will suggest an imaginary concept, which includes several theories of 'Wisdom of Crowd' [Surowiecki, 2004], Inside/Outside [Clark, 2001], and Artificial Companions [Wilks, 2006]. We conclude with some prospects (Chapter 4).

2 SELECTED RESEARCH

2.1 Feature Spaces

A first idea on how to discover a polarity of a news texts are geometric models that are often used in the field of *Information Retrieval*. Given a set of (predefined) features F=$\{f_1,\ldots,f_n\}$, where for example the features represent financial terms, locations, interests, et cetera, then each financial news can be represented itself as a vector in the space. We take the frequency of a feature f_i in a financial news document as a coordinate of the vector F and normalise F to the unit circle. Financial news documents are then more similar, if the cosine between associated financial news documents is less.

Regarding the polarity of financial news documents, we may start with a set of training documents, whose polarity is already known (supervised approach). Their position in the space then gives a first hint on whether new documents, which are close enough, are becoming even more positive-polar or negative-polar. However, the assignment of a new financial news to the polarity feature space is like taking a risk. The features (dimensions) may be too weak or less appropriate or their relevance has changed over time. There is also a big uncertainty regarding financial news with regard to contents: two such documents can certainly be neighboured (similar), but the presence of a negation or an antonym may force a different polarity. Moreover, the perspective (standpoint) of an individual is not sufficiently respected, since the fixing of the dimension and/or the supervised polarity assignment of the training documents are subjective.

The reason why we mention this is caused (among others) by a work of [C. Scheible, 2012], who present a novel graph-theoretic method for the initial annotation of high-confidence training data for bootstrapping sentiment classification. Here, the polarity is estimated here by a theme-specific 'PageRank' algorithm. The authors argue that basically sentiment information is propagated from an initial seed lexicon through a joint graph representation of words and documents. They show that their approach outperforms a baseline classifier and that its performance can be further improved by a bootstrapping method that can take advantage of the entire feature space available.

2.2 Polarity in Text Documents

In literature, a conscious discussion on perspectives (standpoints) is rarely made. Almost any research work concerns a concrete application or a technical how-to-do, accomplished with arguments describing its need. Some applications use a dictionary-based solution, others a context-based solution. As some examples, [Hassan and Radev, 2010] propose a method to automatically identify the polarity of words by taking advantage of a Markov random walk model to a large word relatedness graph and producing a polarity estimate for any given word. The authors say that a key advantage of their model is its ability to accurately and quickly assign a polarity sign and magnitude to any word. [Richter et al., 2010] describe a new method for extracting negative polarity item candidates (called NPI candidates) from dependency-parsed German text corpora focusing on target multiword expressions. [Schumaker et al., 2012] raise the question whether the choice of words and tone used by the authors of financial news articles can correlate to measurable stock price movements. If yes, so the authors, can then the magnitude of price movement be predicted using these same variables? The authors answer these questions by using the Arizona financial Text (AZfinText) system, a financial news article prediction system, and pair it with a sentiment analysis tool. [Mizumoto et al., 2012] determine sentimental polarities of the stock market news using a polarity dictionary, which consists of terms and their polarities, respectively. The authors construct the polarity dictionary automatically but establish a small polarity dictionary, which a word polarity, manually first. They apply many stock market news to add new words, whose polarity is unknown, to the polarity dictionary. [Devitt and Ahmad, 2007] aim to explore a computable metric of positive or negative polarity in financial news text, which is consistent with human judgments. The authors say that this can be used in a quantitative analysis of news sentiment impact on financial markets. [Sakai and Masuyama, 2009] propose a method of assigning polarity to causal information extracted from Japanese financial articles concerning business performance of companies. The authors assign a polarity (positive or negative) to causal information in accordance with business performance. [Drury et al., 2011] propose a strategy to segment quotations inside a text by an inferred "opinion maker" role and then apply individual polarity classification strategies to each group of the segmented quotations. They have modelled a contextual information with Random Forests based on a vector of unigrams. [Heerschop et al., 2011] propose a system called *Pathos*, which is a framework to perform document sentiment analysis. *Pathos* is partially based on a discourse structure of the document. The authors hypothesize that - by splitting a text into important and less important text spans and by subsequently making use of this information by weighting the sentiment conveyed by distinct text spans in accordance with their importance - they improve the performance of a sentiment classifier. A document's discourse structure is obtained by applying Rhetorical Structure Theory on sentence level. [Kaji and Kitsuregawa, 2006] propose a novel fully-automated method of building polarity-tagged corpus from HTML documents to utilize certain layout structures and linguistic pattern.

In general, Polarity Dictionaries are not less devoid from being subject to subjectiveness. The approach of [Mizumoto et al., 2012], for example, essentially call upon a financial expert, who initially defines a seed of words, whose polarity is either positive or negative. From an engineering point of view, the approach is surely disputable as only 'clean' co-ocurrences of verbs and adjectives are considered, but neither negations, adversative conjunctions, or any kind of contextual pertinence. Also, the receive of an error rate of more than 50% for two independent tests does not bear witness to a promising approach. However, the generation of a dictionary is principally acceptable, bearing good prospects. [Paulo-Santos et al., 2011], for example, argue that most approaches in finding polarity dictionaries rely on linguistic works concerning part-of-speech tagging or rich lexical resources such as WordNet. The authors show and examine the viability to create a polarity lexicon using only a common online dictionary with five positive and five negative words, a set of highly accurate extraction rules, and a simple yet effective polarity propagation algorithm. The algorithm evaluation results show an accuracy of 84.86% for a lexicon of 3034 words.

3 A PROSPECTIVE APPROACH

The term *Artificial Companion* has originally been introduced by [Wilks, 2006] as *an intelligent and helpful cognitive companion which appears to know its owner and their habits, chats to them and diverts them, assists them with simple tasks*. The most important characteristics of an *Artificial Companion* are the absence of a central task, a sustained discourse over a long time period, a capability to serve interests of the user, and a lot of personal knowledge about the main user [Wilks, 2010]. As referenced in [Danilava et al., 2012], [Adam et al., 2010] define companions as to be *intelligent, and built to interact naturally [...] with their user over a prolonged period of time, personalising the interaction to them and developing a relationship with them.* [Ståhl et al., 2009] refer *Artificial Companion*s to a *computational companion that acts as a conversational partner to its user, builds a long-term relationship to the user, and learns about the user's needs and preferences.* [Webb et al., 2010] emphasise that *Artificial companions are targeted as persistent, collaborative, conversational partners that can have a range of tasks*. [Pulman et al., 2010] see a conversation with an Artificial Companion as *not necessarily connected to any immediate task*. [Benyon and Mival, 2008] describe an Artificial Companion as a *personalised conversational, multimodal interface, one that knows its owner.* They see a companionship as *an accessible, pleasing relationship with an interactive source in which there has been placed a social and emotional investment* [Benyon and Mival, 2010].

3.1 Demands

Regarding the polarity finding, we demand for adaptive *Artificial Companion* ([Wilks, 2006], [Danilava et al., 2012]), which is able to represent and acquire knowledge, to learn from internal and external information (Inside/Outside and Extended Mind Theory, [Clark, 2001]), and to take advandage of the Wisdom of Crowds ([Surowiecki, 2004]). An *Artificial companion* is able to classify documents based on its internal *knowledge base*. With this, it owns an *aptitude*, which is a competency regarding a field of application, for example *finance*, *politics*, *economics*, and others. An *Artificial companion* can either represent a natural person (Merkel, Sarkozy, ...), a country (Greece, Germany, ...), or another individual. Each *companion* owns a standpoint and is able to vote, classifying a financial news individually to a polarity, which is either positive, negative, or neutral. Using a set-based operation like the *intersection* can be applied to prove a stable, reliable, and plausible polarity decision, where a financial news is then positive (negative, neutral), if the majority of the *companions* vote for positive (negative, neutral), respectively. We demand the following as to be a fundamental character of an *Artificial Companion*:

- Holding a *Perspective*: since there exist much more than one perspective (there are often many truths), an *Artificial Companion* must have have a adaptive knowledge base.
- Able to take a *decision*: An *Artificial companion* must be able to operate on text, to find associative structures, co-occurrences, or other forms of patterns.
- *Independence* of voting: An *Artificial companion* must state his/her polarity decision independently and has only then the right to vote.
- Presence of a *theme*: A companion can only decide a document polarity, if an evaluation theme exists. Otherwise, a voting may become directionless.

Then,

$$polarity(d, r_n) = \begin{cases} +1, & \Delta(r_{i+}, r_{j-}) > \varepsilon \\ -1, & \Delta(r_{i+}, r_{j-}) < -\varepsilon \\ 0, & -\varepsilon \leq \Delta(r_{i+}, r_{j-}) \leq \varepsilon \end{cases} \quad (1)$$

with $|d| = n = i + j$ and where r_{i+} (r_{j-}) refer to a positive (negative) vote regarding the document. ε is a slope, which only classifies a financial news to -1 or +1 if Δ is not too narrow to ε. Only in case that the voting is equal, the document is seen to be neutral. This follows the concept of [Surowiecki, 2004], who argues that decisions are taken by a large group, even if the individuals within the group are not smart; but these decisions are always better than decisions made by small numbers of 'experts'.

3.2 Companions and Agents

An alternative idea is to understand the polarity as a decision, which is taken by a majority (or a weighted sum of) of very small entities. These share a small capacity, are assigned a simple task, and collaborate as a part of a social system. One consequence of such an architectural framework is a small amount of apriori knowledge, because the participating entities have to do a little task requiring less of it. Also, a plausibility of the polarity decision will be inherently given. All entities' decision, being either 'positive', 'negative', or 'neutral' can be identified and arguments for the final decision retrieved. As the decision is made by many collaborating entities, the decision is more fault-tolerant, more resistant against temporal changes, and less vulnerable to a wrong document classification. A single change of the knowledge landscape (for example 'Sarkozy' is no longer president but 'Hollande' is now) will not have such a big effect. Moreover, the social system might work autonomous and organises itself, reducing the number of investigated efforts. And finally, an independent perspective is maintained. With that, we may understand an *Artificial Companion* as an artificial entity, which knows its user (reviewer of the financial news), but which is served by even small entities, i.e., agents.

Assume that we have a certain number of European key players, country names, locations, and other *facts*. In an intelligent environment, the social system could detect such *facts* by itself and neglect such *facts* in case of inactivity over a certain period of time, but we keep it more simple here and assume that a certain number of *fact agents* (for example, focusing on the key players in Europe, countries, locations, etc.), whose task is to serve the artificial companion and to check a document for occurrences and frequencies of assigned terms. If the frequency is sufficient, possibly above a given threshold, then each *fact agent* contributes to the polarity decision.

We also may consider k-ary operations like *agrees(X)*, *brings(X,Y)*, *has(X,Y)*, or *gives(X,Y,Z)*, which are addressed by *action agents* aiming at instantiating the arguments or even word polarities like *war (-)*, *Eurobond (+/-)*, or *good (+)*, where we assign an individual *polarity companion*, whose task is to control the presence of predefined words. Of course, many other types of companions may be used, for example a *negation companion*, whose task could be to convert an *action companion*'s decision; or an *uncertainty companion*, whose task is to reduce a certainty of the companion's decision, for example by a multiplicative compensation. *Warehouse companions* may have the task to put all these information together, bringing the whole information landscape to a consistent and reasonable decision. Finally, *statistical companions* and *linguistic companions* may be taken as well, for example to deliver statistical and linguistic numbers/values.

But which role do the *warehouse agents* play? Do they just compute weights and relation between action companions and polarity companions or should they perform more than that? Moreover, which are the role of the linguistic agents? Is a linguistic analysis not yet incorporated by the *action agents*? Which is the role of the *statistical agents*, especially, are they not yet incorporated by the *polarity companions*? To give a more precise answer, we suggest the following:

- A *Fact agent* can be either a *subject agent* or an *object agent*. Each of these agents can have sub-hierarchies of their own, for example a *subject agent* may have subcategories like 'politician', 'company', et cetera, a *object agent* categories 'location', 'event', et cetera. As an example, 'Merkel is the chancellor' is a subcategory of 'politician', and with that, a subcategory of the *subject agent*. 'Madrid is a city' is a subcategory of a country, and with it, a subcategory of a 'location'. 'Summit G-20' is subcategory of 'event', which is a subcategory of an *object agent*.
- *Action agents* can be, as mentioned above, k-ary. But we think that using *action agents* with ≥ 3 parameters burdens the relation extraction too intensively. Assuming to determine one term would be as good as 90%, then we probably get an accuracy of almost 72% for three terms.
- *Polarity agents* can be applied for the subcategories 'verb', 'noun', and 'adjective'. Some verbs and adjective may have a given standard polarity (Example 'good' polarity is positive, 'hates' polarity is negative), whereas a polarity of nouns may differ over time (Example: 'war' is constantly, but the polarity of 'Eurobond' is probably not).
- *Linguistic agents* would perform some linguistic analysis deciding for the polarity of the sentence based on some predefined policy. E.g., when the verb has a negative or positive polarity the sentence takes the polarity of the verb. If the verb has an objective polarity, then the polarity of the sentence is the polarity of the nouns, the adjectives, or the adverbs (Example: "Merkel supports Eurobonds."). Thus, the polarity of the sentence is taken by the polarity of Eurobonds. Linguistic agents capture negations as well reversing the polarity of a sentence as well. E.g."Merkel does not agree on Eurobonds".
- *Uncertainty agents* are responsible for decreasing the polarity volume of the sentence by capturing the uncertainty word.
- *Warehouse agents* are basically responsible for the decision, because they integrate the information coming from the other agents. However, they are not allowed to vote.

3.3 How to find a decision?

A companion is composed of many agents, which perform a simple task. The working together of these agents, specifically the construction of a associative polarity dictionary, will then become the fundament with respect to the polarity. In the simplest case, a voting of all companions with equal rights can be taken into account. But before the decision on the polarity of a document is taken, it must be considered whether alternative types of voting can be applied (or not), especially plurality voting systems, single-winner voting systems, or multiple-winner voting systems. For example, whether there exist the word 'Eurobond' or not can be subject to a plurality voting system. But, which countries are pro 'Eurobond' or against 'Eurobond' it is a multiple-winner one.

Regarding the voting decision, there are numerous paths in theory and application, which can be applied. These theories have their roots in the fields of Game Theory, Auction theory, and multi-agent systems. Examples for the field of Game theory are *Nash equilibrium* and the *revelation principle of economics*; examples for the field of *Auction Theory* are *English auction*, *Dutch auction*, *Wickrey auction*, and *sealed first-prive auction*. It is important to keep this in mind, because such a system takes into consideration an application, such as the increase of utility functions, the prediction of some economical phenomena, et cetera. Without this, a system would sound nothing more than a data collection system with no direct application.

3.4 How to represent the polarity dictionary

We have described in [Poray and Schommer, 2010] the idea of an *Explorative Mindmap*, which is basically a connectionist framework on the natural principle on sensations and the corresponding propagation of stimuli. Explorative mindmaps share a principle through an associative architecture that incrementally processes accepted symbolic stimuli to a consistent informational structure. This is similar to a variety of connectionist approaches, but on contrast to a verifying processing of a user's thoughts, the explorative mindmap is built from bottom up, meaning that a mindmap exclusively depend on the presence of incoming signals. Explorative mindmaps share a subsymbolic architecture that is composed of interacting entity cells. As mentioned above for the natural principle, these cells foster on a processing of symbolic data streams and a stimulation/inhibition-principle of adjacent connections. The activation of such a connectionist architecture bases on a dynamic construction of cell structures during the processing of the input stream.

In Figure 1, Explorative Mindmaps have been drafted regarding a conversation between two conversing partners, Alice and Bob. Both share a mindmap, which has evolved over time, and which consists of connectionist cells, each representing a word with a temporary activity. However, both also share a mindmap about the conversing partner as well, which may have been established during their conversation. The more often words appear together (co-occurrence) within a conversation, the more stronger their relationship will be. For example and with respect to a polarity of texts, such an associative structures corresponds to the polarity dictionary as given in [Mizumoto et al., 2012]. The principle of *Explorative Mindmaps* are based on the theory of the *Extended Mind* given by [Clark, 2001], who argues that an internal decision making basically depends on internal (inside) and external (outside) signals.

Interestingly, co-occurrences of words in a financial news and already known polar words like 'good' or 'worse' (as mentioned in [Mizumoto et al., 2012]) may become represented as associative structures in a mind-graph. Also, the more a co-occurrence appears, the stronger the connection of the adjacent words will be. Moreover, a merge of the mind-graphs can be done if two mind-graphs share a polar-word in common.

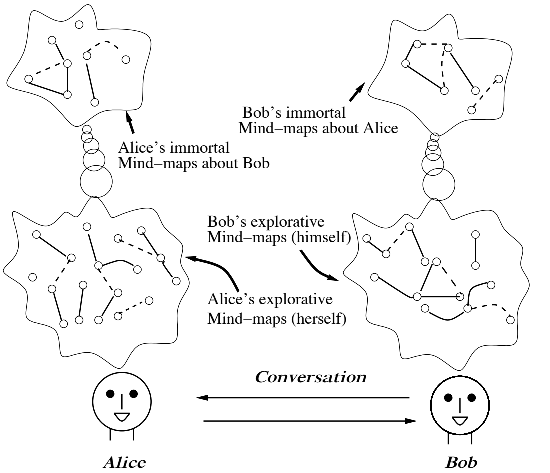

Figure 1: The Figure shows the construction of mindmaps for two conversing partners, Alice and Bob. Both share an *own* associative mindmap as well as an associative mindmap *about the other*, respectively. Understanding Alice and Bob, however, as individual *Artificial Companions*, the *own* associative mindmaps may correspond to the polarity dictionary. The *about the other* mindmap would not be needed, since we consider each companion as to be independent.

4 CONCLUSIONS

The given idea is a visionary and prototypically try to overcome the problem of having a subjective perspective (standpoint) regarding the polarity finding of a document. It targets several theories that are present in research, for example Andy Clarke's theory on the Inside and Outside ('Supersizing the mind'), Surowiecki's theory on the 'Wisdom of Crowd', and Wilk's theory on 'Artificial Companions'.

As mentioned in Chapter 1, the interpretation of a financial news may depend on a reviewer's knowledge, interest, and much more. Having designed Artificial Companions of different thematic directions, being assisted by many self-organising and self-evaluating types of agents, then this may overcome the given problem. Regarding the voting, which is only allowed for the Companions, an independent voting is recommended. With that, we believe to fulfill the given demands of holding a perspective, an ability to take a decision, an independence of voting, and a presence of a theme. Our aim is now to follow this idea and to come up with a more detailed concept. An implementation is planned.

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