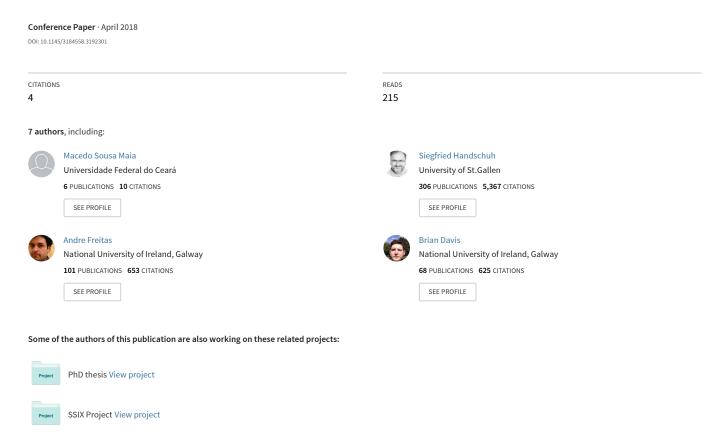
WWW'18 Open Challenge: Financial Opinion Mining and Question Answering



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ABSTRACT

The growing maturity of Natural Language Processing (NLP) techniques and resources is dramatically changing the landscape of many application domains which are dependent on the analysis of unstructured data at scale. The finance domain, with its reliance on the interpretation of multiple unstructured and structured data sources and its demand for fast and comprehensive decision making is already emerging as a primary ground for the experimentation of NLP, Web Mining and Information Retrieval (IR) techniques for the automatic analysis of financial news and opinions online. This challenge focuses on advancing the state-of-the-art of aspect-based sentiment analysis and opinion-based Question Answering for the financial domain.

CCS CONCEPTS

Information systems → Retrieval models and ranking;
 Computing methodologies → Natural language processing;

KEYWORDS

Opinion Mining; Question Answering; Financial Domain

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1 MOTIVATION

The increasing interest and investment around technologies which can support better financial analysis and decision making creates the demand for an increasing dialog between academia and industry. The specificity of the language use and its underlying conceptualizations in the financial and economic domains requires the creation of new fine-grained models and techniques which can capture the particular semantic phenomena of this field.

This challenge aims to provide an experimentation and discussion ground for novel NLP approaches targeting the interpretation of financial data using the tasks of aspect-based sentiment analysis and opinionated Question Answering (QA) as motivational scenarios. The challenge aims at catalyzing theoretical and empirical discussions around principles, methods and resources focused on financial data.

While previous tasks and challenges have focused on multilingual document, message sentence or even entity level sentiment classification, no challenge that we are aware of attempts to analyse to the aspect level. In addition, research in Question Answering (QA) from opinionated datasets is also under-explored.

2 CHALLENGE DESCRIPTION

Two tasks were available to participating systems: *Task 1: Aspect-based Financial Sentiment Analysis* and *Task 2: Opinion-based QA over Financial Data.*

2.1 Task 1: Aspect-based Financial Sentiment Analysis

Given a text instance in the financial domain (microblog message, news statement or headline) in English, detect the target aspects which are mentioned in the text (from a pre-defined list of aspect classes) and predict the sentiment score for each of the mentioned targets. Sentiment scores will be defined using continuous numeric values ranged from -1 (negative) to 1 (positive).

	Aspect category classification model			
Team	headline			
	accuracy	precision	recall	f1-score
CUKG_Tongji	0.2688	0.1512	0.1634	0.1399
IIT-Delhi	0.0537	0.0162	0.0201	0.0149

Table 1: Aspect category classification model results for headlines.

Systems are evaluated with regard to aspect classification, sentiment classification and aspect-sentiment attachment.

The Task 1 datasets include two types of discourse: financial news headlines and financial microblogs, with manually annotated target entities, sentiment scores and aspects. The financial news headlines dataset contains a total 529 annotated headlines samples (436 samples for the training set and 93 samples for the test set) while the financial microblogs contains a total 774 annotated posts samples (675 samples for the training set and 99 samples for the test set).

2.2 Task 2: Opinion-based QA over Financial Data

Given a corpus of structured and unstructured text documents from different financial data sources in English (microblogs, reports, news) build a Question Answering system that answers natural language questions. For this challenge, part of the questions are opinionated, targeting mined opinions and their respective entities, aspects, sentiment polarity and opinion holder.

The challenge takes both an Information Retrieval (IR) and a Question Answering (QA) perspective. Systems can rank relevant documents from the reference knowledge base with regard to a natural language question or generate their own answer. The relevant score information is implicit if you consider the question-doc matches information contained in the training FiQA_question_doc data source.

The Opinion QA test collection is built by crawling Stackexchange posts under the Investment topic in the period between 2009 and 2017. The final dataset contains a KB of 57.640 answer posts with 17.110 question-answer pairs for training and 531 questionanswer pairs for testing.

3 EVALUATION MEASURES

In order to evaluate the sentiment scores models, regression model evaluation measures were used during the experiments, such as: **Mean Squared Error (MSE)**, **R Square** (\mathbb{R}^2) and **Cosine**

To evaluate the financial aspect category models, classification model evaluation measures were used during the experiments: Accuracy, Precision, Recall and F1-Score

To evaluate the opinion question as nwering models, ranking evaluation measures were used during the experiments: Normalized Discounted Cumulative Gain (nDCG) and Mean reciprocal rank (MRR)

	Aspect category classification model			
Team	post			
	accuracy	precision	recall	f1-score
CUKG_Tongji	0.8484	0.5	0.4357	0.4619
NLP301	0.7575	0.3006	0.2678	0.2832
IIT-Delhi	0.2424	0.0274	0.0229	0.0250

Table 2: Aspect category classification model results for posts.

Team	Opinion question answering model		
Tealli	nDCG@10	MRR	
eLabour	0.3052	0.1947	
CUKG_Tongji	0.1682	0.0957	

Table 3: Opinion question answering results.

	Sentiment score prediction model			
Team	headline			
	MSE	\mathbb{R}^2	cosine	
CUKG_Tongji	0.1345	0.4579	0.6768	
IIT-Delhi	0.2039	0.1779	0.4401	
Inf-UFG	0.2067	0.1665	0.4153	

Table 4: Sentiment score prediction results for headlines.

	Sentiment score prediction model			
Team	post			
	MSE	R ²	cosine	
Inf-UFG	0.0958	0.1642	0.5333	
CUKG_Tongji	0.1040	0.0923	0.6063	
IIT-Delhi	0.1049	0.0849	0.3422	
NLP301	0.3058	-1.6669	-0.0685	

Table 5: Sentiment score prediction results for posts.

4 EVALUATION RESULTS

Sentiment-based models were evaluated with regard to aspect category classification and sentiment score prediction. For question answering models, each team sent the output file containing the top 10 most relevant answers.

Tables 4 and 5 show the results for each sentiment score prediction models. Table 1 and 2 show the result for each aspect category models. For opinion question answering, the results were showed in Table 3.

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