

Overview of FinNum



Fine-Grained Numeral Understanding in Financial Social Media Data

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Motivation

Numerals on Social Trading Platforms



Apr 26th, 1:39 am

Bullish

\$TSLA 256 Break-out thru 50 & 200- DMA (197-230) upper head res (274-279) Short squeeze in progress Nr term obj: 310 Stop loss:239



Apr 12th, 7:02 pm

Bullish

\$AAPL support identified \$198.8 ... next move to \$215



Apr 12th, 7:02 pm

Bearish

\$TVIX making a new 52 week low.



Introduction

\$TSLA 256 Break-out thru 50 & 200- DMA (197-230) upper head res (274-279) Short squeeze in progress Nr term obj: 310 Stop loss:239. *25 tokens 9 numbers 6 meanings*

We

- propose **fine-grained numeral taxonomy** for financial social media data
- attempt to **leverage the numeral opinions made by the crowd** to mine **additional information** for trading

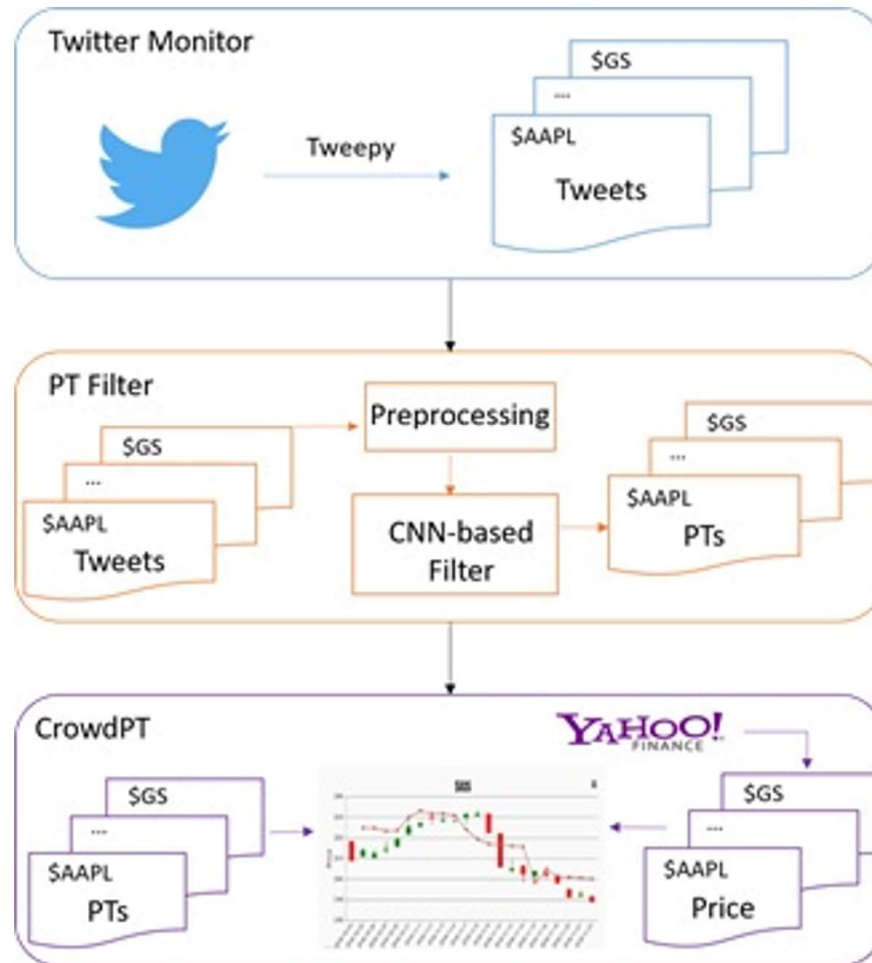
I will introduce the

- application of proposed tasks
- numeral taxonomy
- details of FinNum shared task
- empirical studies of extracted information
- further research direction of the numerals in financial data
- FinNum-2 proposal

Application Scenario

Crowd View: Converting Investors' Opinions into Indicators

System Flowchart



- Monetary
 - price target
 - support or resistance
 - buying
 - selling
 - other
- Percentage
- Temporal
- Option
- Indicator
- Quantity
- Product/ Version Number

Numeral Taxonomy

Numeral Taxonomy

Category	Subcategory	Train	Dev.	Test	Total	Ratio
Monetary		2467	261	459	3187	35.94%
	money	589	52	95	736	8.30%
	quote	792	89	152	1033	11.65%
	change	143	8	25	176	1.98%
	buy price	319	36	60	415	4.68%
	sell price	103	10	22	135	1.52%
	forecast	270	33	52	355	4.00%
	stop loss	25	4	6	35	0.39%
	support or resistance	226	29	47	302	3.41%
Percentage		838	105	170	1113	12.55%
	relative	585	70	112	767	8.65%
	absolute	253	35	58	346	3.90%
Option		169	11	22	202	2.28%
	exercise price	113	5	14	132	1.49%
	maturity date	56	6	8	70	0.79%
Indicator		167	22	27	216	2.44%
Temporal		2364	253	401	3018	34.03%
	date	2079	223	351	2653	29.92%
	time	285	30	50	365	4.12%
Quantity		741	87	154	982	11.07%
Product/Version		114	14	22	150	1.69%
		6860	753	1255	8868	100.00%

Monetary

- The Monetary category contains the following 8 subcategories:
 - “money”, “quote” and “change”
 - **“buy price”, “sell price”, “forecast”, “stop loss” and “support or resistance”**
- The identification of “buy price” and “sell price” can help us understand the performance of the writer.
 - \$SPY Long 1/2 position 137.89
- Some investors “forecast” the price of the instruments depending on their analysis results.
- The concepts of support and resistance are always discussed in technical analysis.

Percentage

- The numeral that indicates the proportion of a certain amount is classified into “absolute”.
- The numeral that stands for the change relative to original amount is classified into “relative”.
- ⚡Den up almost **10%** since Q1 and £áuro up around **7.5%**, much more \$ for \$AAPL pocket. Remember **23%** of Apple revenues comes from this two @jimcramer
 - 10% and 7.5% are annotated as “relative”
 - 23% stands for “absolute”.

Option

- Option is a popular instrument frequently discussed.
- To capture the implications of investors' opinions, we propose two subcategories for Option category, “exercise price” and “maturity date”.
- \$XLU long April \$44 calls
- \$MSFT those APR.22 CALLS were getting hot.

Indicator

- This category captures the parameters of the technical indicators.
- Different investors may use dissimilar parameters for the same indicator. In order to capture the price most investors pay attention to, we should identify the parameters being used.
- \$ATHX riding **5**dma higher, dropping to **13**dma at the dips, sign of a healthy advancing stock that stays above **20**dma

Temporal

- Temporal information is also important in financial domain.
- The day most investor focusing on is the one with high volatility.
- We classify Temporal category into two subcategories, “date” and “time”

Quantity

- Quantity information can help us know the position of an investor, and we can give the large weighting to the opinions held by persons who have large positions.

Product/Version Number

- The version of products may contain numerals. We can use the product information to compare importance of different tweets.
- For example, the tweets discuss of iPhone 7 may be more important than the tweets that discuss iPhone 4.

Dataset

Corpus Creation

- We collected the data from StockTwits.
- Two experts were involved in the annotating process.
- FinNum dataset contains only the numerals in full agreement.

Distribution

Category	Subcategory	Train	Dev.	Test	Total	Ratio
Monetary		2467	261	459	3187	35.94%
	money	589	52	95	736	8.30%
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Task Setting

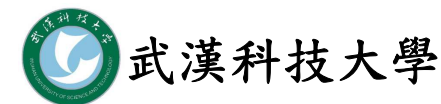
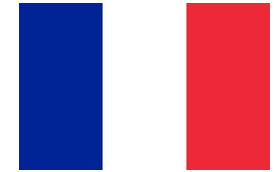
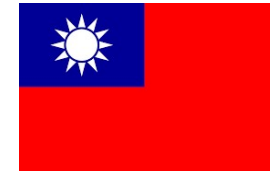
Task Formulation & Evaluation

- The position of a numeral in a tweet is given in advance.
- Participants are asked to disambiguate its category.
- This task is further separated into two subtasks:
 - Classify a numeral into 7 categories, i.e., Monetary, Percentage, Option, Indicator, Temporal, Quantity and Product/Version Number.
 - Extend the classification task to the subcategory level, and classify numerals into 17 classes, including Indicator, Quantity, Product/Version Number, and all subcategories
- Micro-averaged F-score and macro-averaged F-scores are adopted for evaluating the classification performance of participants' runs.

Participants

12 Teams including 15 Institutions from 6 Countries

Participants



Methods

Models

Features

Topic
Format
Position
Keywords
Named Entity
Brown Cluster
Part-of-speech
Term Frequency
Prefixes/ Suffixes
Bag-of-Characters
Numeral Information
Recognizers-Text Type

Task Setting

Classification
Sequential Labeling

Representation

Skip-Gram
GloVe
ELMo
BERT

Models

SVM
MLP
CNN
RNN
RNN + CNN
Attention-based LSTM

Results

Participants Results

Subtask 1			Subtask 2		
Submission ID	Micro F1 (%)	Macro F1 (%)	Submission ID	Micro F1 (%)	Macro F1 (%)
Fortia1 - 1	93.94	90.05	Fortia1 - 2	87.17	82.40
Fortia1 - 2	93.70	88.98	Fortia1 - 1	86.53	80.49
DeepMRT - 1	91.87	87.94	DeepMRT - 1	83.03	77.90
DeepMRT - 2	91.16	84.72	DeepMRT - 2	81.27	75.59
ASNLU - 2	89.72	80.93	aiai - 1	80.24	74.11
ASNLU - 1	89.40	79.96	aiai - 2	80.64	73.43
ZHAW - 2	86.45	79.27	ASNLU - 1	79.12	72.51
Fortia2 - 1	89.88	79.26	ASNLU - 2	77.37	70.09
Fortia2 - 2	87.73	78.59	Fortia2 - 2	77.05	68.86
aiai - 1	86.45	78.09	Fortia2 - 1	79.28	68.33
aiai - 2	87.41	78.04	ZHAW - 2	75.54	66.44
ZHAW - 1	84.78	75.40	ZHAW - 1	72.67	64.84
WUST	74.02	63.71	Stark - 1	69.08	56.83
BRNIR - 1	74.27	63.53	WUST	60.88	52.93
Stark - 1	78.01	61.75	BRNIR - 1	63.67	51.90
BRNIR - 2	72.91	58.54	BRNIR - 2	61.99	47.14
word-based CNN	55.90	51.67	char-based CNN	43.75	31.12

Error Analysis

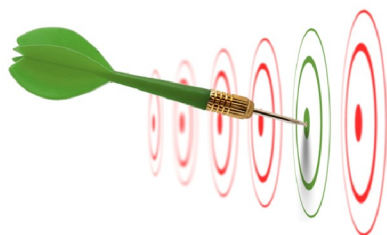
Confusion matrix



Empirical Study

Numerical Understanding in Financial Tweets for Fine-grained Crowd-based Forecasting

Comparable to Professional Analysts



	Crowd	Analyst
Average difference	13.17%	6.75%
Achieving rate	67.03%	74.73%
Achieving duration	3.38 months	2.46 months
Average return	4.86%	2.93%

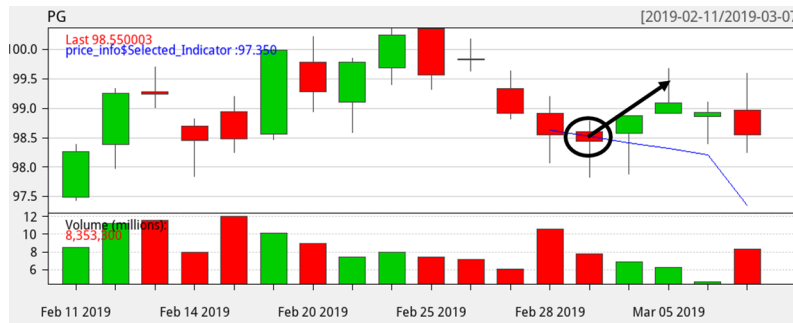
Progressive



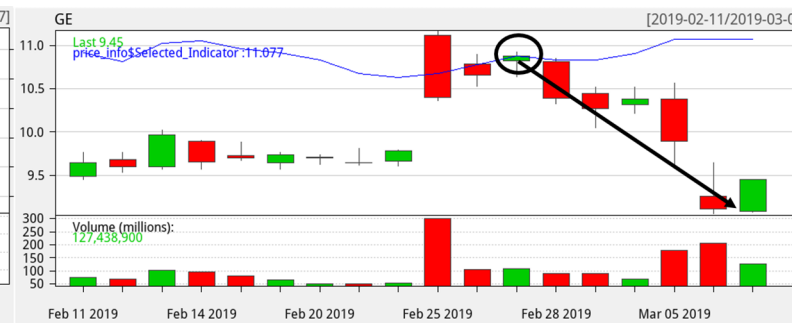
	Crowd	Analyst
Winning ratio	68.13%	71.43%
Max profit	52.17%	17.23%
Max drawdown	-11.82%	-14.10%
Average profit	11.08%	6.42%
Average loss	-8.43%	-8.40%

Profitable

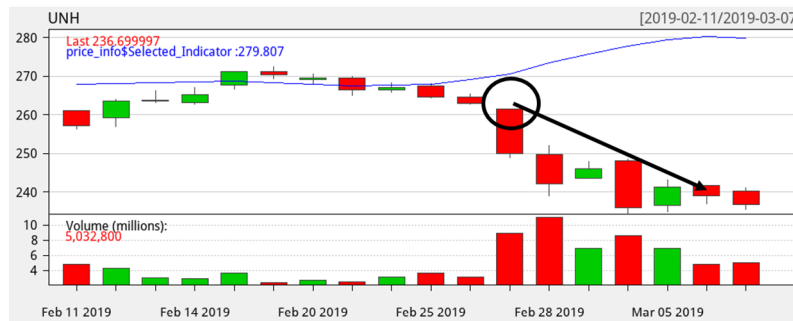
Crowd View: Converting Investors' Opinions into Indicators



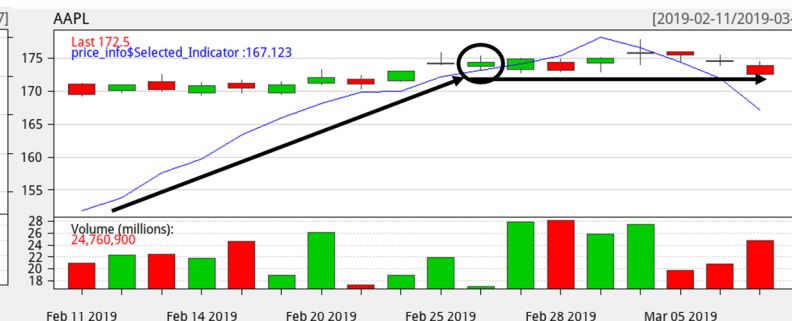
(A)



(B)



(C)



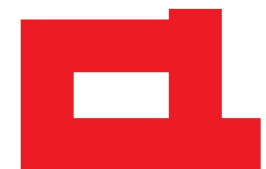
(D)

- The indicators related to the analysis results of crowd investors (**support and resistance** price level) provide the incremental information for short-term (**3- and 5-day**) trading.
- The indicator constructed by **the cost of crowd investors** (buy-side and sell-side cost) furnish trader with additional long-term (**10-day**) information.

Further Research Directions

Numeracy-600K: Learning Numeracy for Detecting Exaggerated Information in Market Comments

- S&P 500 <.SPX> UP 1.53 POINTS, OR 0.08 PERCENT, AT ___ AFTER MARKET OPEN
- DOW JONES <.DJI> UP 8.70 POINTS, OR 0.05 PERCENT, AT ___ AFTER MARKET OPEN
- U.S. Q3 GDP rises _____ pct



Multilingual & Different Domain & Document Level

近5年來京城銀行每股盈餘分別為2.51、4.89、4.17、3.09、4.33元，合併總損益分別為28、56、47、36、51億。除去年外，整體來說獲利向上，本年度光第一季就已經獲利19億，表現十分出色。

去年底，京城銀提列華映呆帳16.4億元，造成每股損失1.42元，也導致去年盈餘只剩2.51元，是近年來新低。若沒此呆帳，京城銀去年獲利應有44億。但據悉，京城銀行對華映六代廠有最高限額抵押權18億，透過該抵押16億債權可望全額受償，且已經獲得抵押物拍賣裁定，即將對華映六代廠做強制執行。也因此去年認列的呆帳損失可能回沖，進一步推升本年度獲利。若獲利與去年水準相同，有44億，在加上呆帳回沖的16億，一年就可獲利60億，每股盈餘突破5元。

【NQNロンドン】25日のフランクフルト株式市場で、ドイツ株式指数(DAX)は10営業日ぶりに反落した。終値は前日と比べて30.56ポイント(0.25%)安の12282.60だった。

オンライン決済サービスのワイヤーカードは、前日に大幅上昇した反動で、3%超下がった。ドイツ銀行の値下がりも目立った。同行とコメルツ銀行が3月から続けていた統合交渉を打ち切る見通しとなった。タイヤのコンチネンタルも売られた。一方で、第1四半期の決算を発表した医薬・農薬大手のバイエルは上昇した。鉄鋼のティッセン・クルップも買われた。

Cette révision à la baisse de la croissance fait suite au brusque ralentissement de l'économie canadienne à la fin de 2018, avec une progression de 0,4 % en rythme annuel au quatrième trimestre, et de chiffres décevants pour le début 2019.

Clinical Geography

Cooperation



Next Step

FinNum-2: Numeral Attachment

- \$NE OK NE, last time oil was over \$65 you were close to \$8.
Giddy-up...
- Given a target numeral and a cashtag, and we formulate the problem as a binary classification to tell if the given numeral is related to the given cashtag.
- Macro-F1 score is adopted for evaluating the experimental results.
- Baseline: CapsNet → Macro-F1 score: 67.14%



THANK YOU