BEYOND WORD-LEVEL TO SENTENCE-LEVEL SENTIMENT ANALYSIS FOR FINANCIAL REPORTS

Chi-Han Du,† Ming-Feng Tsai,‡ Chuan-Ju Wang†

†Academia Sinica, Taiwan
‡National Chengchi University, Taiwan

What is sentiment analysis for financial reports?

Labeled in word-level by financial sentiment word lexicon (Loughran, 2011)

> In addition, revenues increased due to fee income on growing variable COLI account values, partially offset by declines in fees on leveraged COLI as that block of business continues to decline due to the HIPA Act of 1996. Benefits, claims and expenses increased $593, or 63%, to $1.5 billion in 1998 from $938 in 1997 due primarily to the MBL Recapture discussed previously.

Labeled in sentence-level by multiple financial experts (high risk)

> In addition, revenues increased due to fee income on growing variable COLI account values, partially offset by declines in fees on leveraged COLI as that block of business continues to decline due to the HIPA Act of 1996. Benefits, claims and expenses increased $593, or 63%, to $1.5 billion in 1998 from $938 in 1997 due primarily to the MBL Recapture discussed previously.

Motivation

→ Use existing knowledge (financial sentiment lexicon) to improve sentence-level classification performance of deep learning models.

→ Extend boundary of financial sentiment out of word range by semantics, for each sentiment (positive, negative, litigious, and uncertain) shown in sentence.

> In addition, revenues increased due to fee income on growing variable COLI account values, partially offset by declines in fees on leveraged COLI as that block of business continues to decline due to the HIPA Act of 1996. Benefits, claims and expenses increased $593, or 63%, to $1.5 billion in 1998 from $938 in 1997 due primarily to the MBL Recapture discussed previously.

→ Examine **applicability of the proposed approach across models**, including traditional method, naive DL models, and more complicated models.

Sub-phrase Algorithm

function Sub-Phrase (T_M, k, ℓ);

Input : A frequency table T_M including the top k most frequent sentiment n-grams and their frequencies, for $n = 2, \ldots, M$; the number of iterations, ℓ

Output: A reference table, W

$W \leftarrow \{\}$;

for $e \leftarrow 1$ **to** ℓ **do**

- Find the most frequent word pair w_i and w_j in T_M;
- Find all n-grams containing w_i and w_j within T_M;
- Merge these two words into a new "word";
- Add the merged new "word" $w_i\_w_j$ to the reference table W;
- Delete the most frequent word pair w_i and w_j in T_M;
- Update the frequency table T_M by replacing (w_i, w_j) as $(w_i\_w_j)$;

end

return W;

1st run	2nd run	3rd run
net loss (250) adverse impact (211) net loss of (196) offset by (180) adverse impact on (166) …	**adverse impact (211)** net_loss of (196) offset by (180) adverse impact on (166) …	**net_loss of (196)** offset by (180) adverse_impact on(166) …
↓	↓	↓
net_loss	net_loss adverse_impact	net_loss adverse_impact net_locs_of

→ **The time spent is primarily proportional to k**, which means that it is fast to implement.

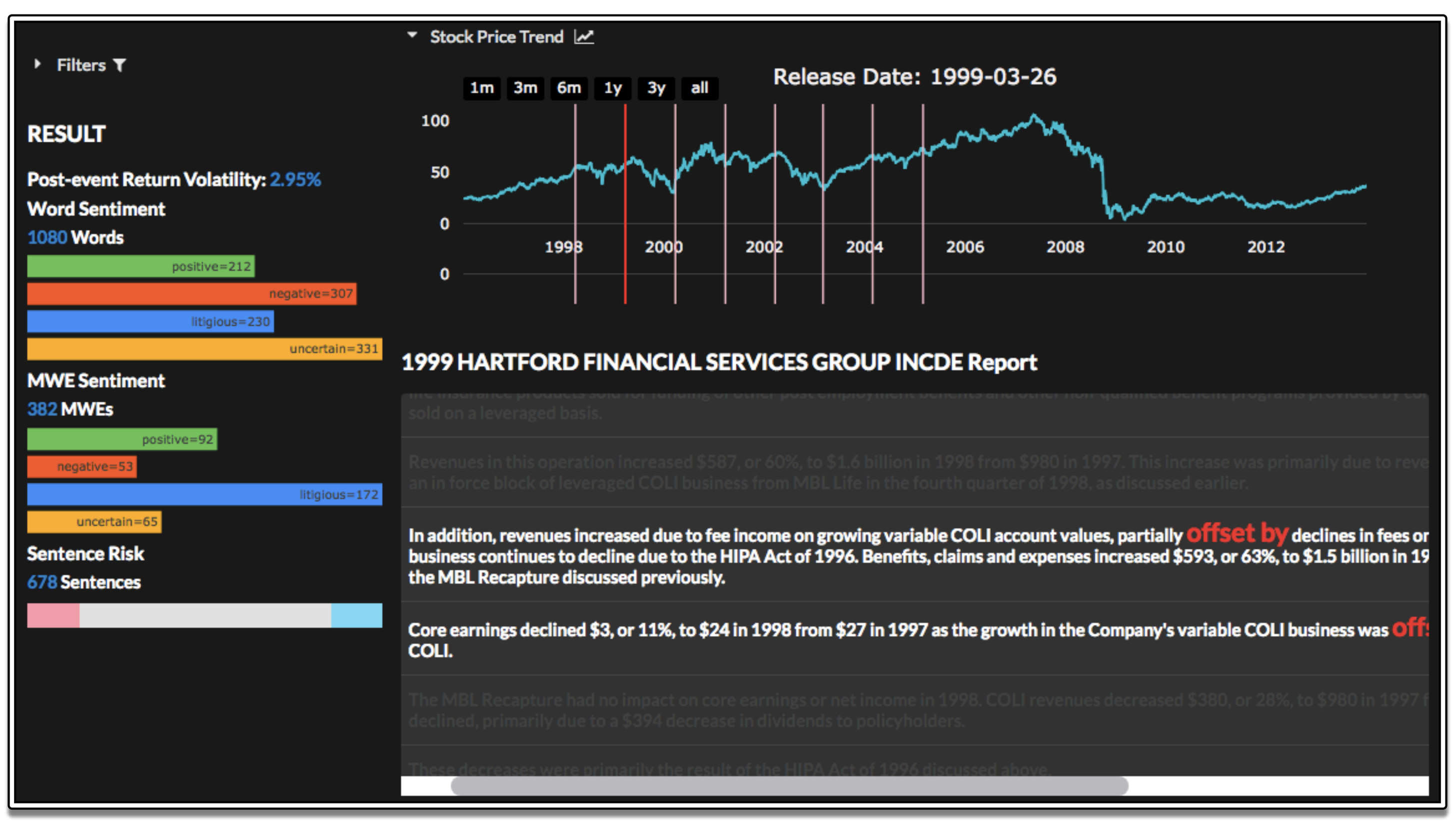
Main Results

	Accuracy	F1 score High-risk	F1 score Neutral
tf-idf	**88.27**	**0.889**	0.876
tf-idf+senti-phrases	87.15	0.883	**0.880**
LSTM [8]	86.96	**0.893**	0.851
LSTM+senti-phrases	**87.14**	0.889	**0.857**
CNN [9]	86.33	0.852	0.891
CNN+senti-phrases	**86.35**	**0.861**	**0.915**
fastText [10]	87.76	0.858	0.895
fastText+senti-phrases	**88.03**	**0.922**	**0.901**
SiameseCBOW [11]	87.92	0.890	**0.902**
SiameseCBOW+senti-phrases	**88.79**	**0.927**	0.888

→ Combining words to generate senti-phrases is not beneficial to the traditional bag-of-word model.

→ **Complicated DL models achieve better performance than naive models**, but all DL models perform better when using senti-phrases.

An application



→ Our new developed tool: **Financial Risk Information Detecting and analYzing System (FRIDAYS) (AAAI'19)**

https://cfda.csie.org/FRIDAYS/

→ The proposed algorithm is fast to compress data and even improve the semantics of NLP models for financial texts.

→ As a result, in the future it could be applied for **summarization of financial corpus**, or even **automatic generation (NLU) for financial reports**.