

ECONOMIC EVENT DETECTION FOR COMPANY-SPECIFIC NEWS TEXT

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OUTLINE

1. Introduction
2. Dataset description
3. Experiments
4. Error analysis
5. Conclusion
6. Limitations & future work



INTRODUCTION

- Task: Event mention detection and typing for economic events in company-specific news.
- Event conceptualization: “*textually reported real-world occurrences, actions, situations involving companies*”

“However, revenues from voice and text fell in the period.”

→ Turn-over event

“So far, free cash flow has been used to finance share buybacks and dividend increases.”

→ Share buyback event

“It will increase the number of Barclays’ customers in France by 25 per cent.”

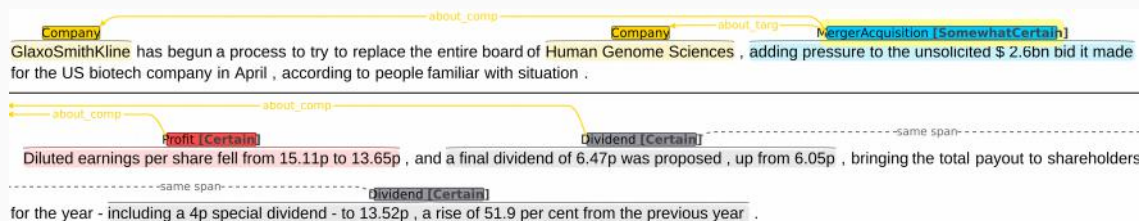
→ Sales Volume event

INTRODUCTION

- Applications:
 - Economics (academic): event studies (MacKinlay, 1997); assessing impact of news events (Boudoukh et al., 2016)
 - Security price prediction, business intelligence, trading strategies, etc.
- Current methods are pattern- or knowledge-based (Feldman et al., 2011; Arendarenko and Kakkonen, 2012; Hogenboom et al., 2013; Du et al., 2016): largely handmade ontologies.
- Supervised, data-driven methods: potential to generalize over lexical variation.
- → requires annotated **gold-standard dataset**.
- Currently no resources exist for supervised event detection in economic domain.
 - In general-domain event detection: large amount of resources (e.g. ACE/ERE (TAC-KBP) (Aguilar et al., 2014)).

DATASET DESCRIPTION

- Our SentiFM dataset enables event mention detection and typing (!= event extraction with argument slots).
- **7 companies** selected for sector diversification.
- **497 news articles** from the Financial Times (2004-2013) in English.
- **2522 event mentions.**
- Annotations:
 - Token-level annotation: Discontinuous and multi-token span.
 - “about_company” relation on each event.



DATASET DESCRIPTION

- Dutch counterpart available (Lefever and Hoste, 2016).
- Validity of the annotation scheme was evaluated on Dutch subset:
 - 78.41% Inter-annotator F1-score.
- Event types:
 - 10 event types, typology constructed iteratively on corpus subsample.
 - Type overlap with StockSonar (Feldman et al., 2011) and SPEED ontology (Hogenboom, 2013).

Event type	Type ratio	# mentions
BuyRating	9.00%	227
Debt	2.38%	60
Dividend	7.22%	182
MergerAcquisition	10.03%	253
Profit	25.81%	651
QuarterlyResults	10.59%	267
SalesVolume	19.31%	487
ShareRepurchase	2.42%	61
TargetPrice	3.73%	94
Turnover	9.52%	240
total	100%	2522

Event type distribution and mention count.

EXPERIMENTS

- Goal: provide a baseline for the dataset.
- Task: Sentence-level event typing, multi-label classification.
- **Feature-engineering + SVM.**
 - Lexical features: bag-of-n-gram (token, char, lemma), special token presence.
 - Syntactic features: PoS and NER-tags.
 - Kernels: linear and RBF.
- **wvec + LSTM:**
 - Pre-trained, hold-in set GloVe.
 - Pre-trained, 6B corpus GloVe.
 - No pre-trained, token-sequence input.
- Pre-trained vectors chosen from multiple candidates by quality evaluation on analogy task.

EXPERIMENTAL SET-UP

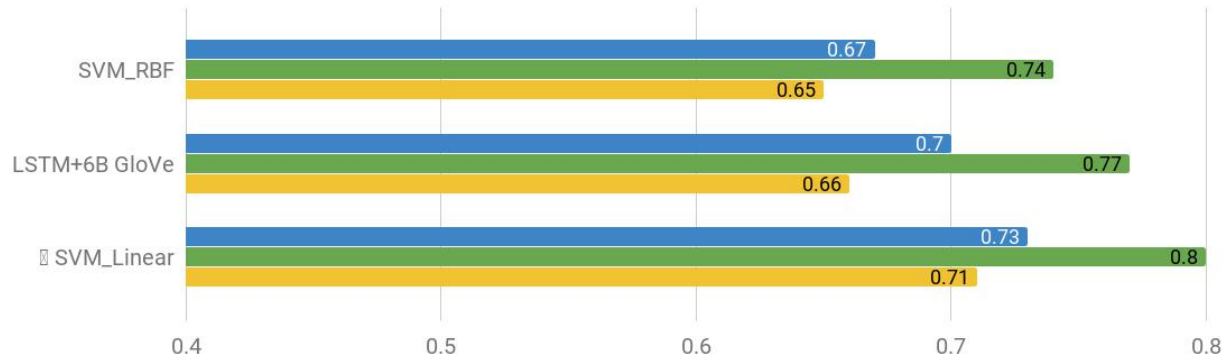
- Evaluation: support-weighted macro-F1 on 10% random hold-out test.
- Hyper-parameter optimization:
 - SVM-RBF: 5-fold cross-validation, grid-search.
 - SVM-Linear: No optimization, default LibSVM hyper-parameters.
 - LSTM: 3-fold cross-validation, randomized-search (32 it.).
- SVM: one-vs-rest.
- LSTM: multi-label & one-vs-rest (for best input).

RESULTS: ALL SYSTEMS

Multi-label



One-vs-rest



RESULTS: BEST SVM & LSTM SYSTEM, SCORES BY TYPE

Event type	Precision	Recall	F_1 -score
Linear kernel one-vs-rest			
BuyRating	<u>0.95</u>	<u>0.91</u>	<u>0.93</u>
Debt	<u>0.50</u>	<u>1.00</u>	<u>0.67</u>
Dividend	<u>0.62</u>	<u>0.73</u>	<u>0.67</u>
MergerAcquisition	<u>0.56</u>	<u>0.40</u>	<u>0.47</u>
Profit	0.75	0.74	0.75
QuarterlyResults	0.82	0.53	0.64
SalesVolume	0.88	<u>0.75</u>	<u>0.81</u>
ShareRepurchase	<u>1.00</u>	<u>0.50</u>	<u>0.67</u>
TargetPrice	<u>1.00</u>	<u>0.75</u>	<u>0.86</u>
Turnover	<u>0.91</u>	<u>0.77</u>	<u>0.83</u>
avg	<u>0.80</u>	<u>0.71</u>	<u>0.73</u>

Event type	Precision	Recall	F_1 -score
6B corpus GloVe one-vs-rest			
BuyRating	0.88	<u>0.95</u>	0.91
Debt	0.50	0.50	0.50
Dividend	0.55	0.55	0.55
MergerAcquisition	<u>0.58</u>	<u>0.44</u>	<u>0.50</u>
Profit	0.81	0.74	0.77
QuarterlyResults	0.84	0.47	0.60
SalesVolume	0.81	<u>0.76</u>	0.79
ShareRepurchase	0.75	0.50	0.60
TargetPrice	<u>1.00</u>	<u>1.00</u>	<u>1.00</u>
Turnover	0.94	0.65	0.77
avg	0.77	0.66	0.70

ERROR ANALYSIS

- We performed qualitative error analysis on best system prediction (SVM_Linear).
- Some event types have highly indicative lexical clues for some events:
 - “Home-serve, which also reports on Friday, rose 2.8% to pound(s) 17.54 after RBS upgraded from ”hold” to ”buy”.
→ BuyRating: often triggered by upgraded, hold, buy.
- Most types show strong lexical variation.
 - “This could raise doubts about Vodafone’s target of reaching 10m subscribers by the end of the current financial year.”
 - “It will increase the number of Barclays’ customers in France by 25 per cent.”
- → SalesVolume: different lexical trigger item for each possible product or service (e.g., customers, viewers, drivers).
- Ambiguous lexical clues occur in several event categories.
 - E.g., “buy”: informs MergerAcquisition and Buyrating categories.
- Classifier did not pick up on some strong lexical clues:
 - Add semantic knowledge from structured resources for semantic generalization.

CONCLUSION

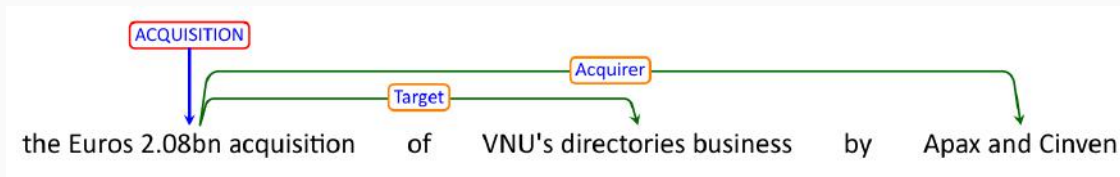
- 1st gold-standard event detection dataset for micro-economic domain.
- Baseline experiments on sentence-level event typing:
Satisfactory performance with straight-forward one-vs-rest classification method:
SVM_Linear: 73% F1-score.
LSTM_6B-Glove: 70% F1-score.

LIMITATIONS

- Corpus collection:
 - Keyword-search to retrieve articles per event type: introduces lexical bias.
 - Type coverage could be improved: 18 event types in Boudhouk et al. (2016) vs. our 10 types.
- Baseline classification too elementary:
 - Task: Our data-set allows for token-span event mention detection instead of sentence-level.
 - Straight-forward classifiers: much room for improvement and more advanced approaches.

FUTURE WORK

- Collect more data: New SENTiVENT dataset for ERE-like event extraction currently being annotated.
 - Randomly crawled for 30 companies (vs. SentiFM keyword-search collection).
 - Larger type and subtype coverage.
 - Enables multi-task approach using the current SentiFM dataset.
- Task: Token-span mention detection and event subtype detection.
- Cross-lingual experiments with English and Dutch dataset.



THANK YOU! QUESTIONS?

- English SentiFM dataset and experiment replication data available here:
<https://osf.io/enu2k/>

- Dutch + English SentiFM dataset: available upon request.

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