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Sentiment Analysis of Norwegian Financial News

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Agenda

- Motivation
- Background
  - Definitions & Applications
  - Theoretical Background
  - Related Work
- Annotation Study
- Feature Engineering
- Classification & Evaluation
- Conclusion & Further Work
- References

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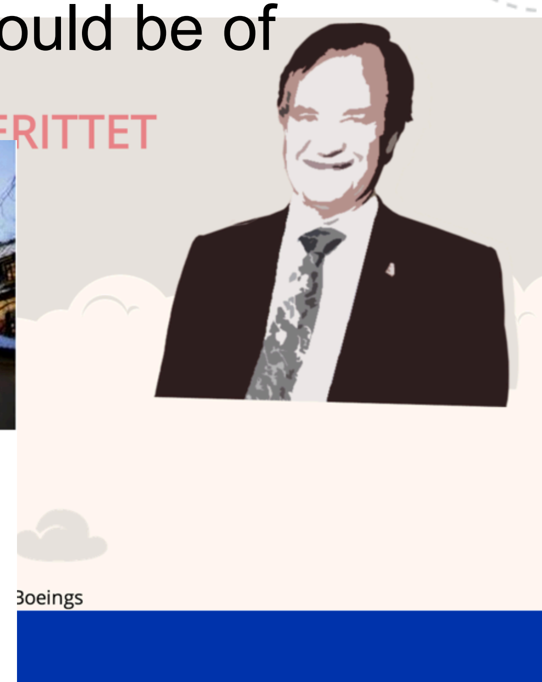
Motivation

- Searching for **explicit content** contained in documents well-researched
- Searching for **implicitly contained content**, like sentiments, in documents much less researched
- For instance: Ability to monitor the **sentiments expressed towards Norwegian** (NAS) could be of much use to day-traders



Motivation (2)

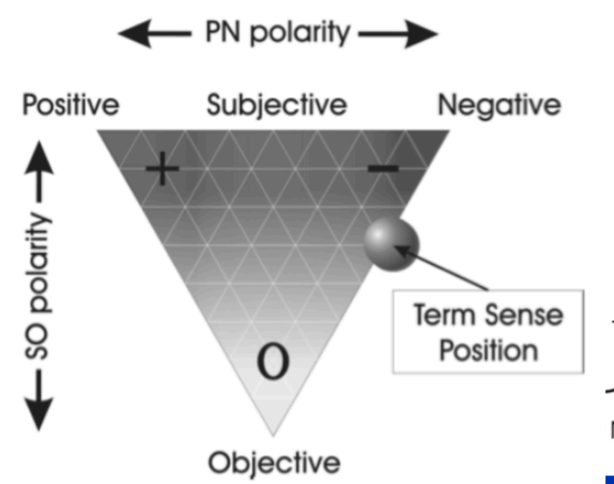
- **Financial news:** sentiment-rich and linked to stocks, financial derivatives and other tradable instruments
- **Norwegian:** most financial News are so-called ‘non-events’ - Oslo Stock Exchange perfect for sentiment analysis given numerous **day-traders**, **non-institutional investors** and **level of psychology**

Background - Definitions & Applications

- Subjectivity = the expression of private states in text and speech
  - Private state = a state not open to objective observation or verification

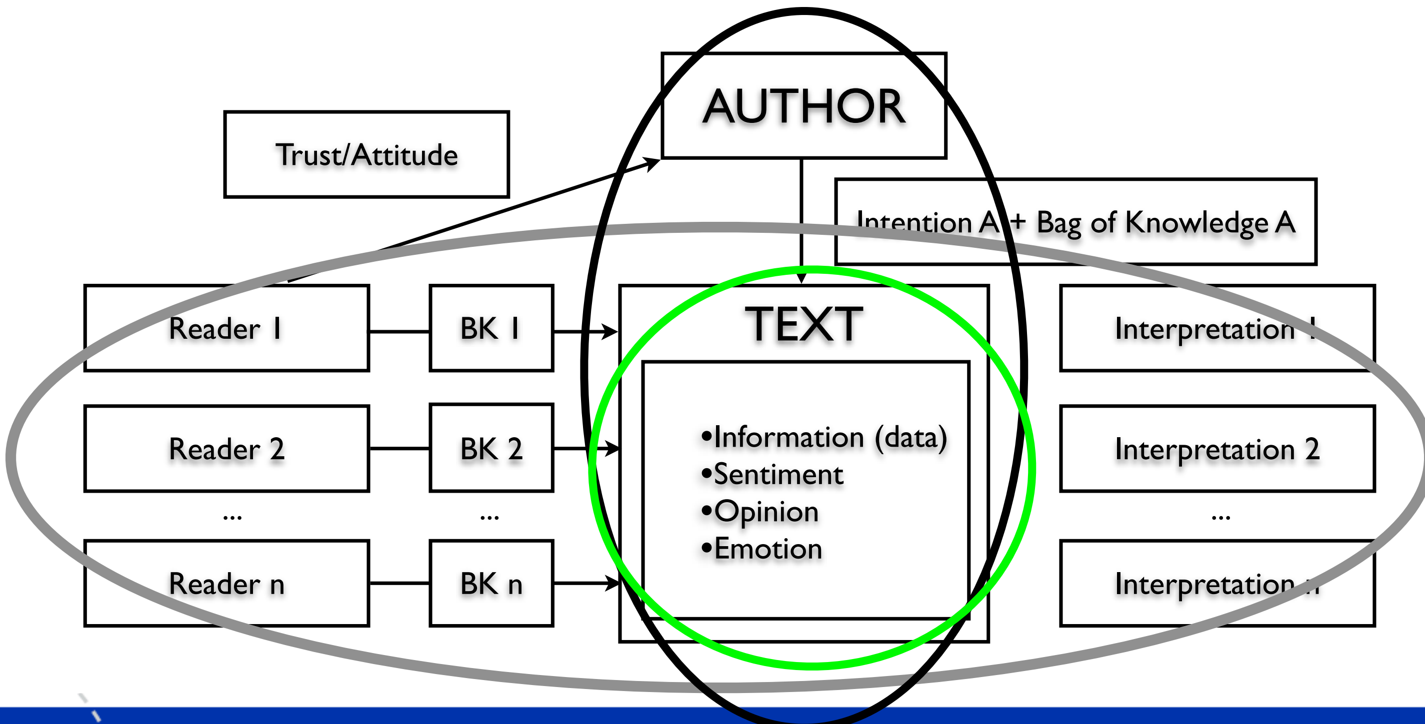
- Sentiment = a view or opinion being expressed in text or speech (≈ subjectivity + polarity)
  - Source, target, opinion

Sentiment analysis	Subjectivity analysis
Positive	Subjective
Negative	
Neutral	Objective

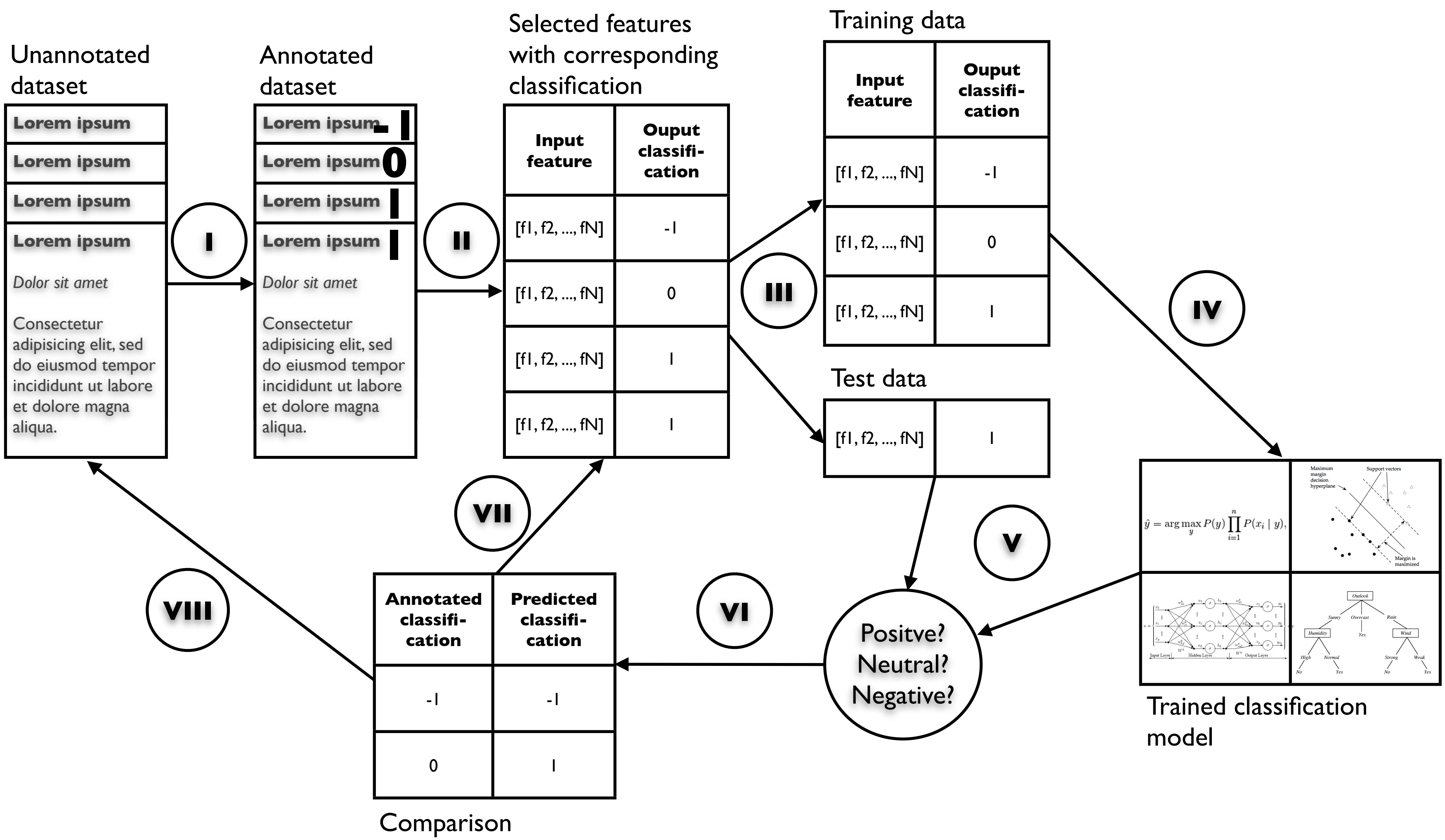


Background - Definitions & Applications (2)

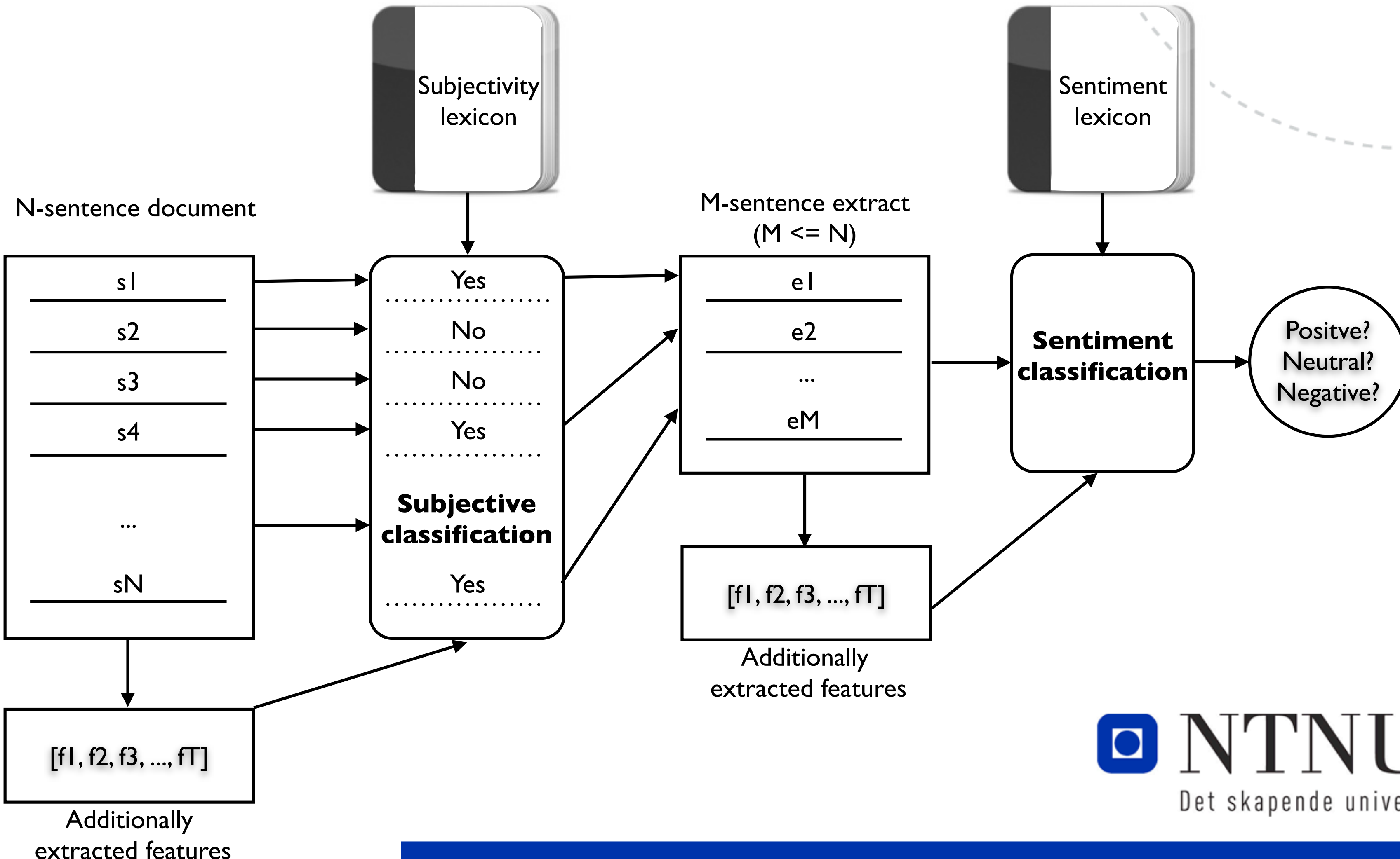
- In the News domain:
  - Definition of **target**, separation of **good/bad news and positive/ negative** sentiment and **textual sentiment veiw**



Background - Theoretical Background



Background - Related Work



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Annotation Study

Article from hegnar.no

Bunnen nådd, sier Hermanrud - REC rett opp

USA-avtale gir ingen børsjubel. I Oslo steg REC-aksje og Norske Skog heftig. Norwegian var også et lyspunkt, mens oljeservice trakk ned (er oppdatert med oljepris og sluttkurser Europa 17.45).

Artikkel av: Odd Steinar Parr (HegnarOnline - 11.12.13 16:30)

Hovedindeksen på Oslo Børs endte onsdag på 530,27, etter en nedgang på 0,64 prosent.

Aksjer og egenkapitalbevis ble omsatt for 2.545 millioner kroner.

Så langt i år har børsen steget 19,4 prosent, mens avkastningen den siste måneden er på minus 1,4 prosent.

Hva vil Fed gjøre?

Wall Street stiger forsiktig fra start, etter at en ny budsjettavtale ble dratt land i USA i går kveld norsk tid.

Avtalen kan forhindre at myndighetene i Washington må stenge kontorene de neste månedene, men fikk ikke ordentlig fart på Europa-børsene.

Relaterte artikler
- Salmar selger alt i Bakkafrost
- Oljelagrene dundrer ned i USA

Aggregate

() x 1000 x

Title 

Lead 

Main 

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Annotation Study (2)

	Joint Probability of Agreement	Spearmann's Correlation	Cohen's Kappa	Krippendorff's Alpha
Title	0.754	0.695	0.581	0.697
Lead	0.735	0.639	0.518	0.635
Main	0.628	0.489	0.317	0.439
Aggregate	0.678	0.687	0.514	0.703
All parts	0.432	-	0.311	0.732

Figure 5.1: Annotation inter-rater reliability results

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Annotation Study (3)

	-1	0	1
-1	142	45	1
0	54	442	80
1	5	61	170

Table 5.1: Confusion matrix title annotations

	-1	0	1
-1	104	47	3
0	74	484	94
1	2	45	147

Table 5.2: Confusion matrix lead annotations

	-1	0	1
-1	83	32	3
0	125	469	198
1	3	11	76

Table 5.3: Confusion matrix main annotations

	-1	0	1
-1	184	38	6
0	97	257	127
1	10	44	237

Table 5.4: Confusion matrix aggregate annotations

Annotation Study (4)

	Title	Lead	Main	Aggre-gate
Title	1.000	0.748	0.599	0.886
Lead	0.748	1.000	0.659	0.826
Main	0.599	0.659	1.000	0.755
Aggregate	0.886	0.826	0.755	1.000

Figure 5.2: Correlation matrix on fully agreed annotations

	Title	Lead	Main	Aggre-gate
Title	1.000	0.666	0.413	0.841
Lead	0.666	1.000	0.484	0.791
Main	0.413	0.484	1.000	0.618
Aggregate	0.841	0.791	0.618	1.000

Figure 5.3: Correlation matrix on annotations by annotator 1

	Title	Lead	Main	Aggre-gate
Title	1.000	0.690	0.585	0.788
Lead	0.690	1.000	0.668	0.780
Main	0.585	0.668	1.00	0.841
Aggregate	0.788	0.780	0.841	1.000

Figure 5.4: Correlation matrix on annotations by annotator 2

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Feature Engineering

- 26 (Candidate) Features
- 4 Categories of Features
  - **Textual**: Length of Title, Length of Lead, Average length of words etc.
  - **Categorical**: Stock exchange, Analysis, Economics
  - **Grammatical** (relying on POS-tagger - OBT): Number of verbs, Number of adjectives, Number of positive adjectives etc.
    - Annotation of adjectives, verbs
  - **Sentiment**: Positive / Negative Title Clues
    - Annotation of positive / negative title clues
- Evaluated with Mutual Information, Chi-squared and Maximum Information Coefficient
- Experiment with **Greedy**, **Local** and **Exhaustive Search** (the latter guided by heuristics)

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Classification & Evaluation

	SVM	ANN
Textual	0.4258024743480563	0.4232137107891745
Textual + Categorical	0.4249791602081111	0.4217086698208013
Textual + Categorical + Gramatical	0.4243037860848316	0.4126256423751963
Textual + Categorical + Gramatical + Sentiment	0.3349914504275205	0.3595937723797976
Best feature composition	0.3161098306669208	0.3421513362243104

Table 7.1: Overview of classifier results

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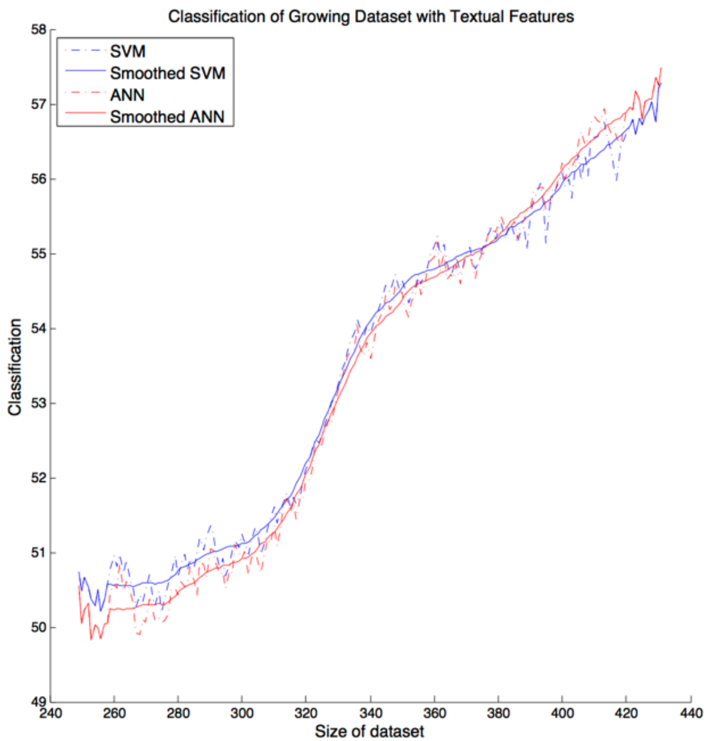
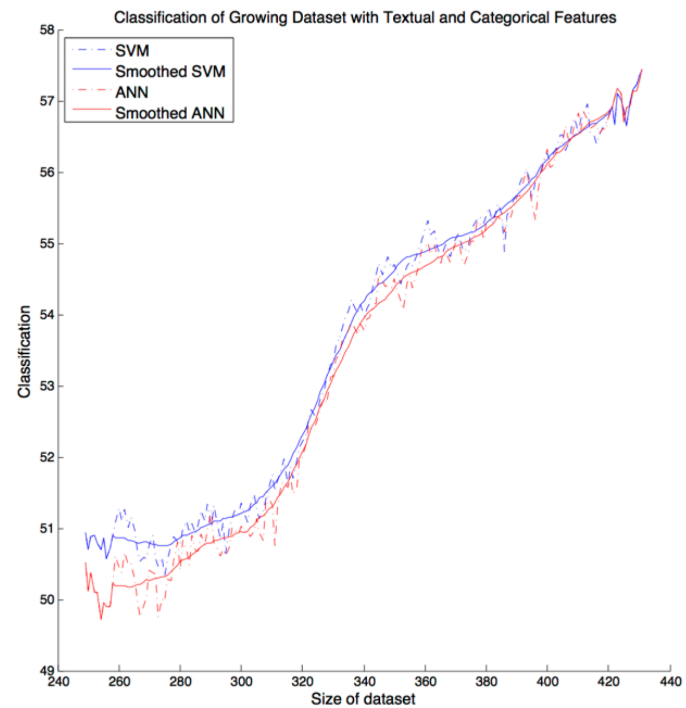
Classification & Evaluation (2)

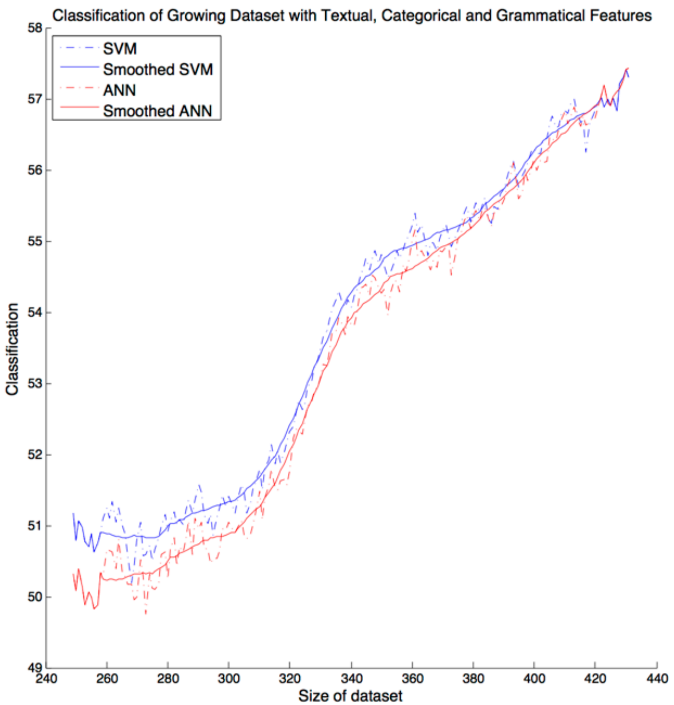


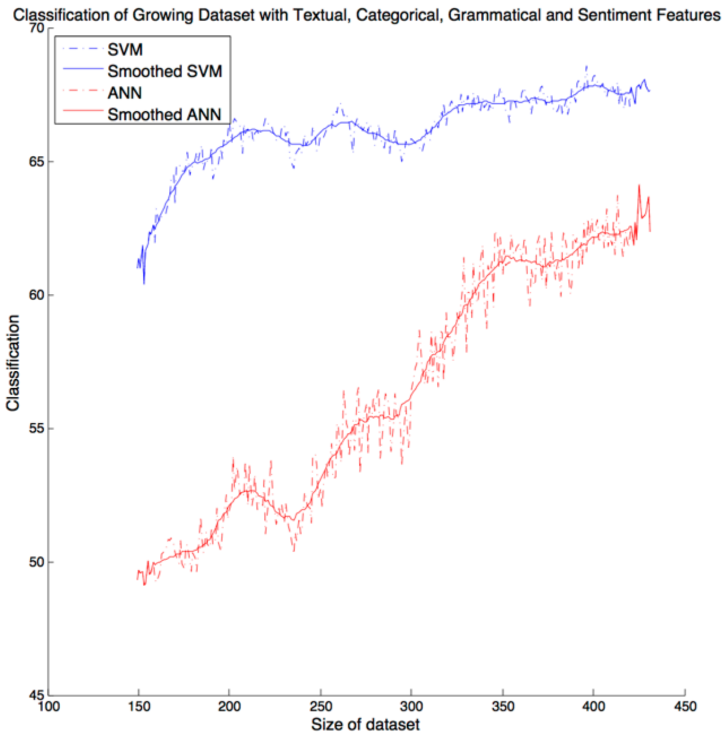
Textual



Textual+Categorical

Classification & Evaluation (3)

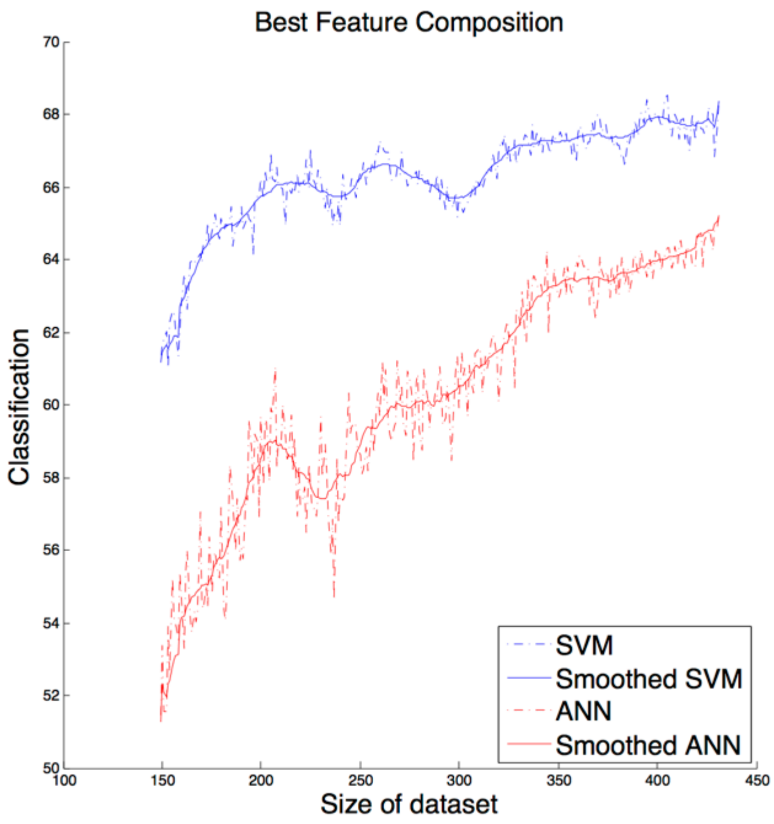




Textual+
Categorical+
Grammatical

Textual+
Categorical+
Grammatical+
Sentiment

Classification & Evaluation (4)



Best Festures

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Conclusion & Further Work

- Have (re)defined sentiment in the context of financial news to achieve satisfactory inter-rater reliability
  - And constructed thorough annotation guide potentially to be used by new annotators in the future
- Established the strong correlation between article title and aggregate sentiment classification...
- ... and that this can be exploited to achieve ~70% percision on machine learned classification model (and still to be improved)
- Textual, Categorical, Grammatical and Sentiment category features contribute to classification - with the strength in that order

et

Conclusion & Further Work (2)

- Further refinement of classification model (binning, feature search, NB, CRF)
- Additional annotations
- More sophisticated features
  - Valence shifters, lexicon of adjective-noun and adverb-verb constructs
- Link to financial entities (like Norwegian or OSEBX) and stock price / index performance

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