A Comparison of Stylometric and Lexical Features for Web Genre Classification and Emotion Classification in Blogs

**Elisabeth Lex** 

**Know Center Graz** 

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### Introduction

- Aim of this work and Approach
- 👽 Features
- Experiments and Results
- Lessons Learned
- Future Work



- A lot of content on the Web and in the blogosphere
- New challenges for search engines
- →"finding a needle in a haystack to a process of being presented with a variety of needles and choosing the one you want" [Etzioni2008].
- → providing different facets for the users' different information needs is crucial

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## Agenda

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# Aim of this work

- Support blog retrieval with genre information and facets
- Assign blogs to the news genre and to assess a facet denoting the emotionality in the blogs
- Study which features and algorithms serve best





- Lexical versus stylometric/shallow text features to classify blogs into
  - News related blogs versus rest
  - Emotional versus neutral

# Approach

- Lexical versus stylometric/shallow text features to classify blogs into
  - News related blogs versus rest
  - Emotional versus neutral
- Feature study on lexical features with 3 SOTA classifiers
- Analysis of statistical properties of stylometric features with Mutual Information (MI)





- Supervised classification strategy:
- Binary Problems: News versus Rest, Emotional versus Neutral
  - SVM (LibLinear, LibSVM)
  - K-NN (k=10, both cosine as well as Euclidean)
  - Class Feature Centroid (CFC) (b=1.1)

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# Features – Lexical Features

- Common Bag of Words features:
  - Unigrams, Bigrams, Trigrams
  - Stems (Porter Stemming Algorithm)
  - Nouns, Verbs, Adjectives (OpenNLP)
  - Leading and Trailing Graphems
  - Personal Pronouns

We create one feature space for each type of feature!

# **Features – Stylometric Features**

- Stylistic variations depend on author, genre, context, characteristics of indented audience [Sanders1977]
  - Punctuation, Emoticons
  - Words in sentences, Avg words / sentences
  - Chars in sentences, Avg chars / sentences
  - Noun+verb sentences (complete sentences)
  - Avg number of unique pos tags
  - Lower case/upper case
  - Word length
  - Adjective rate and adverb rate



# **Features – Stylometric Features**

- Stylistic variations depend on author, genre, context, characteristics of intented audience [Sanders1977]
  - Punctuation, Emoticons
  - Words in sentences, Avg words / sentences
  - Chars in sentences, Avg chars / sentences
  - Focus on topic independence: Text classifiers can easily overfit to topics due to natural correlation - Noun+verb sentences (complete sentences)
  - Avg number of unique pos tags between topics and genres
  - Lower case/upper case
  - Word length
  - Adjective rate and adverb rate

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### **Experiments - Dataset**

Manually annotated subset of Blogs08 TREC dataset: 83 annotated blogs (12844 Blog entries)

	News Related	Other
blog level	29%	71%
entry level	30%	70%

(a) News vs. Rest

	Emotional	Neutral
blog level	52%	48%
entry level	40%	60%

(b) Emotion Classification Task

Table I CORPUS DISTRIBUTIONS



## **Results – Lexical Features: News versus Rest**



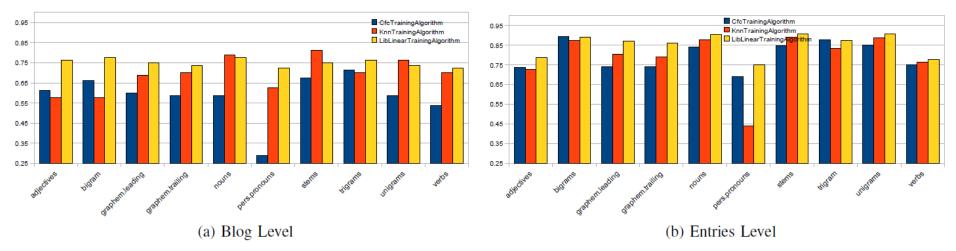


Figure 2. News vs. Rest: Classification Accuracy

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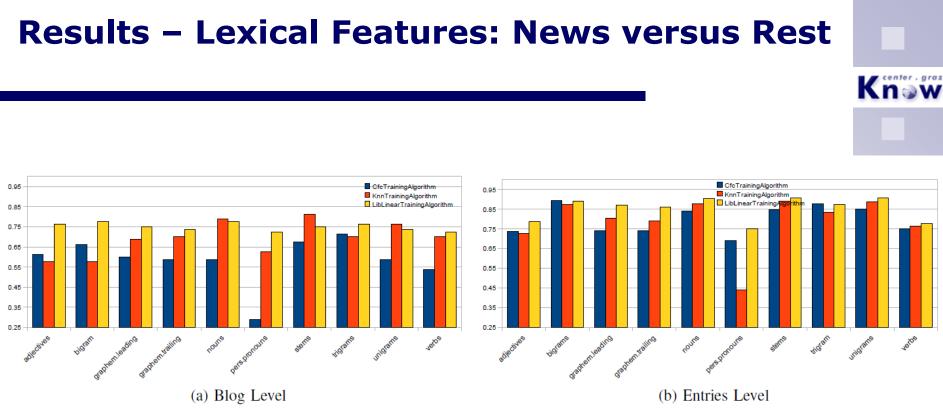


Figure 2. News vs. Rest: Classification Accuracy

 $\rightarrow$  it makes a difference on which level the classification is performed!

- -Best result on entry level: 91.2% (LibLin on stems)
- Best result on blog level: 81.3% (kNN on stems)
- ightarrow Assess genre on entry level and extrapolate to the blog level

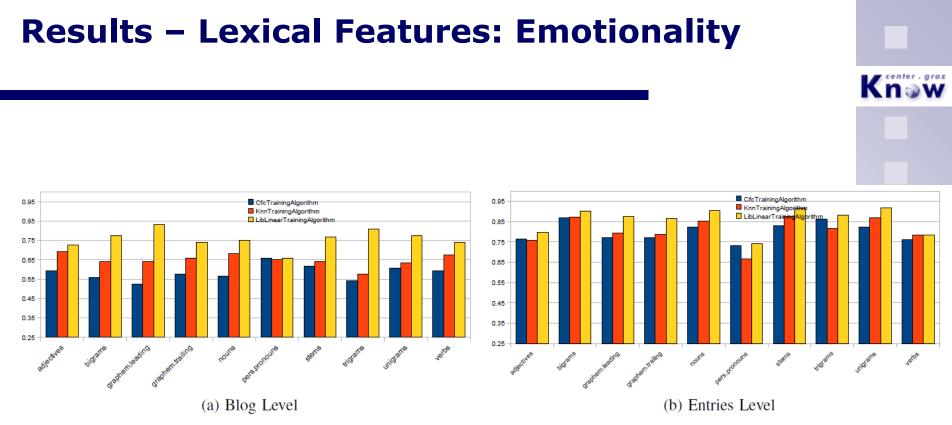
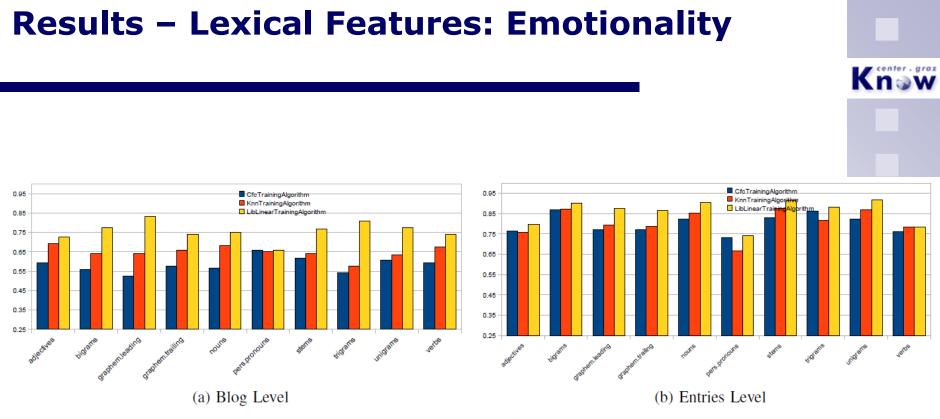
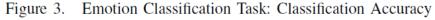


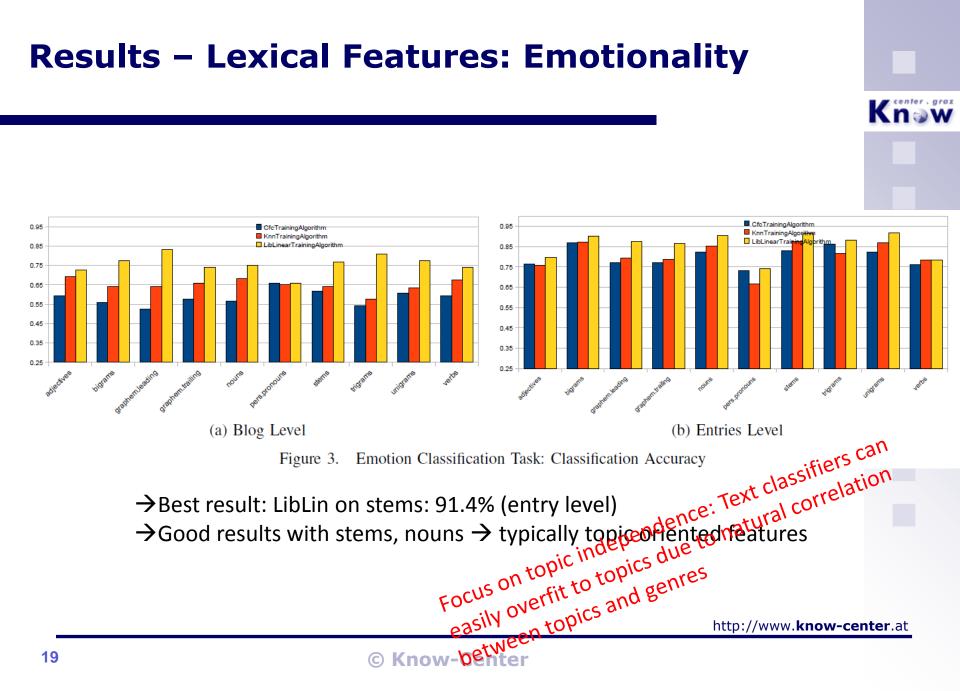
Figure 3. Emotion Classification Task: Classification Accuracy

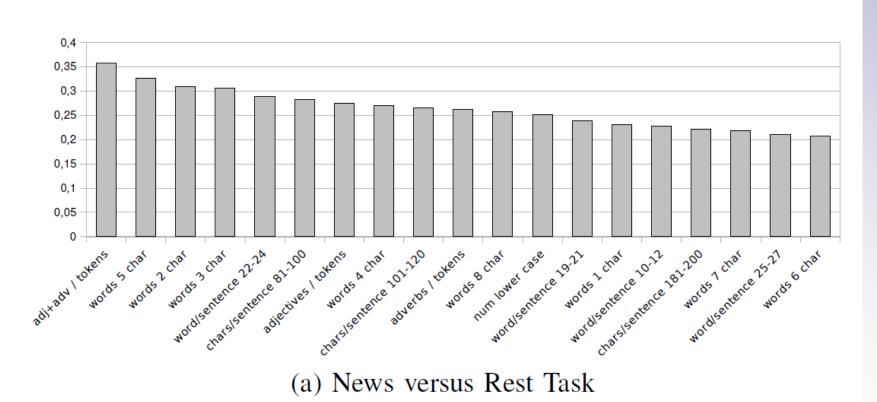




→Best result: LibLin on stems: 91.4% (entry level) →Good results with stems, nouns → typically topic oriented features

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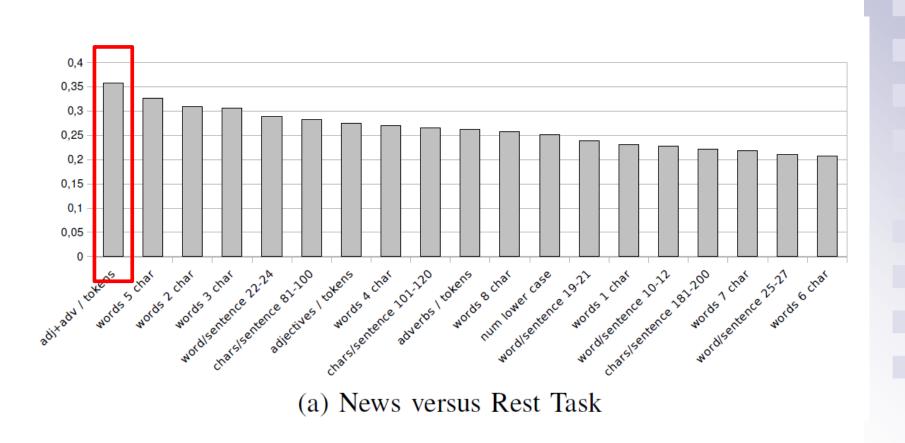


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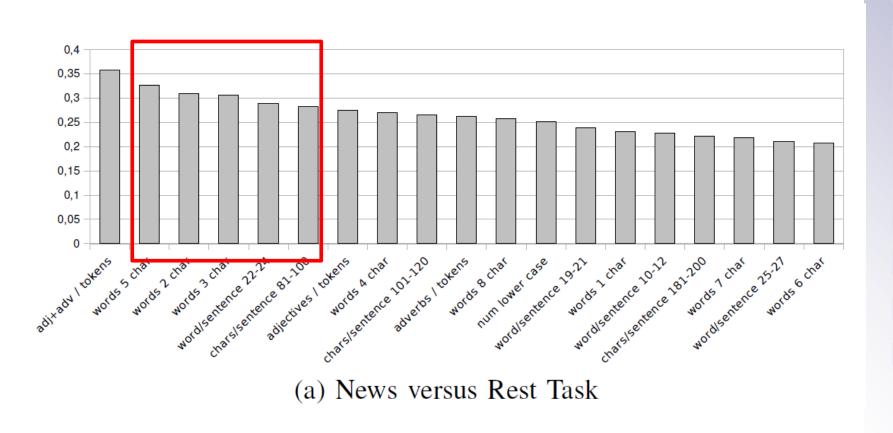
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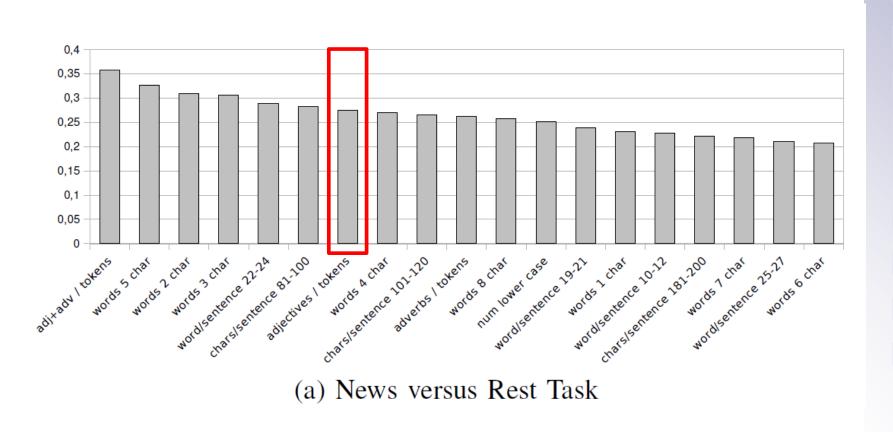
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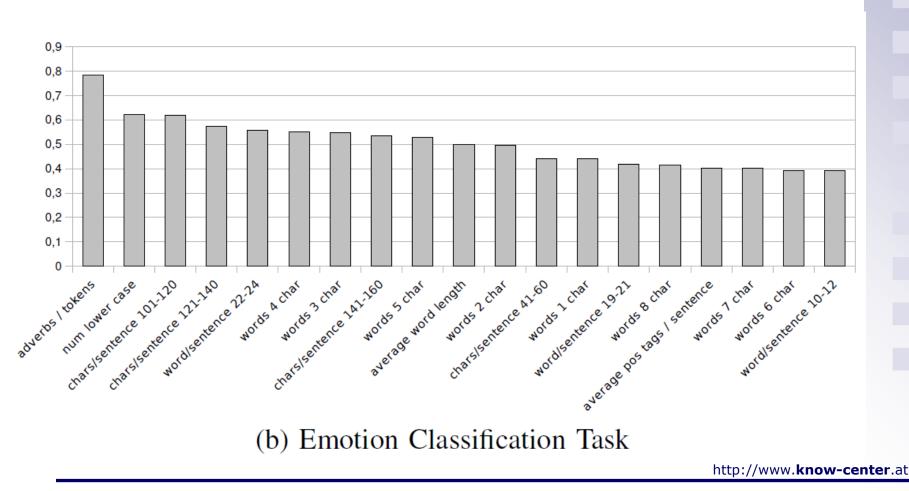
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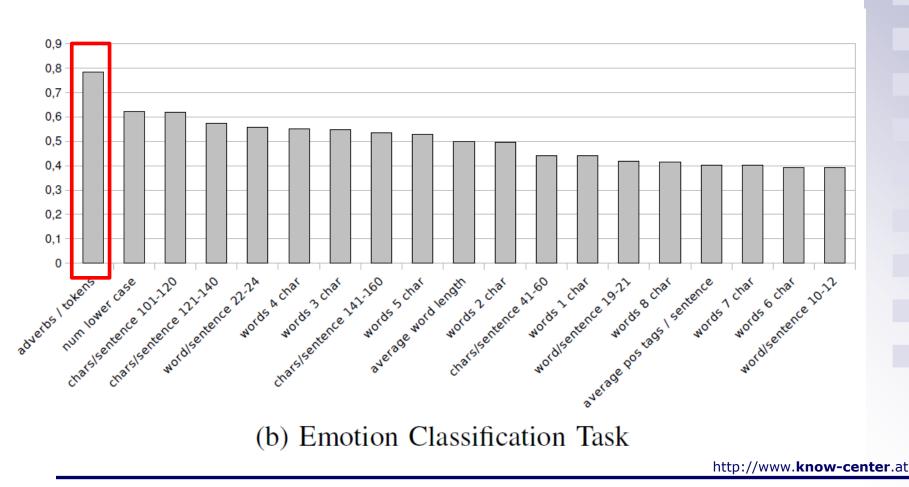
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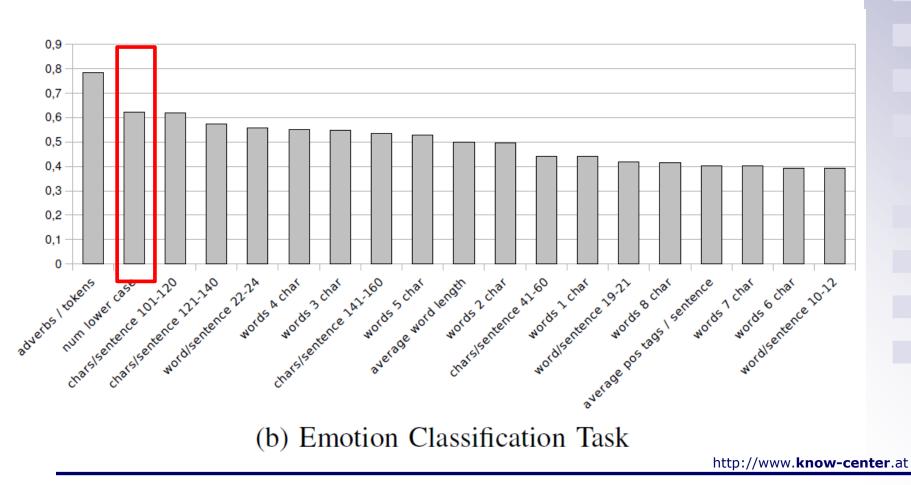


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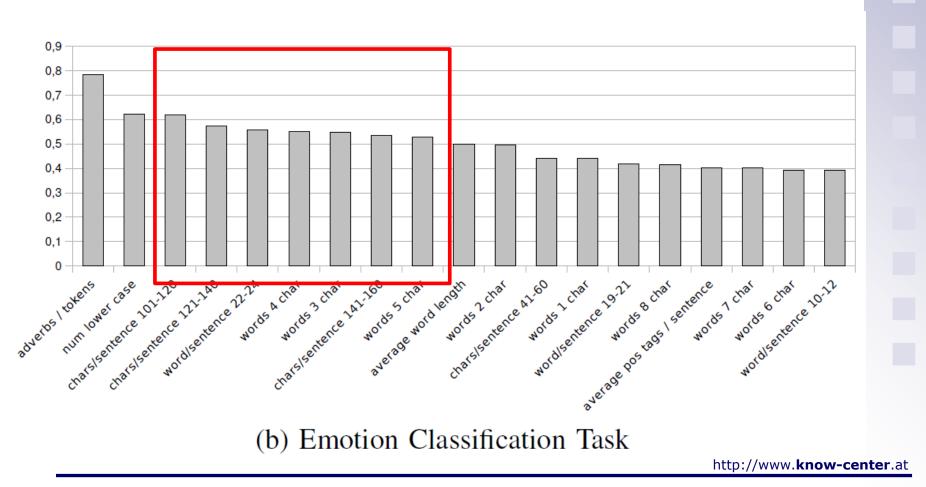
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# **Results – Stylometric Features**

Algorithm	News	Emotionality
CFC	0.69	0.73
LibLinear	0.72	0.78
k-NN10	0.74	0.78
LibSvm	0.69	0.73
NB	0.70	0.76
NB+AdaBoost	0.70	0.77
C45	0.72	0.78
C45+AdaBoost	0.72	0.76

### Table III

CLASSIFICATION ACCURACY OF STYLOMETRIC FEATURES.

- $\rightarrow$  Only the best features, according to their Mutual Information
- $\rightarrow$  No match for lexical features
- → But: Topic independent generalize better [Lex2010]

# **Results: Algorithmic Point of View**

- CFC performs best when size of feature space grows and feature space is sparse
  - Unigram space: 82k dimensions, LibLin wins
  - Bigram space: 680k dimensions, LibLin and CFC same
  - Trigram space: 1.42 Mio dimensions, CFC wins
- CFC fast in terms of training and testing

Algorithm	Train(s)	StdDev.	Test(s)	StdDev.
CFC	5.494	1.061	0.037	0.002
KNN	0.034	0.000	63.448	1.078
LibLinear	38.089	1.411	0.036	0.002

Table II TRAIN AND TEST SPEED FOR TRIGRAMS

In dense stylometric feature space – kNN10 wins

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## **Lessons Learned**

- The news genre and the emotionality must be assessed on a per entry level
- Topic independent stylometric text features can be used to perform the emotion classification task
  - $\rightarrow$  However, their accuracy is lower
  - $\rightarrow$  But: Topic independent
- Classifiers trained on lexical features perform consistently better than classifiers trained on the best stylometric features
- The CFC algorithm performs equally good as SVM in high dimensional spaces (> 1 Mio dimensions), but outperforms LibLinear in terms of time consumption how-center.at

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- Study the genre classification problem as One Class problem
- Combine the best lexical features in one feature space
- Extension to much larger datasets

Please find our annotations of the Blogs08 TREC dataset on our Website:

www.know-center.at/forschung/knowledge\_relationship\_discovery/downloads\_demos/ annotated blog corpus facet annotations on the trec blogs08 test collection

http://www.know-center.at

### Thank you for your attention! Questions?

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