The Impact of Attention Mechanism, Context and Genre Information when Classifying Semantic Clause Types with Recurrent Neural Networks

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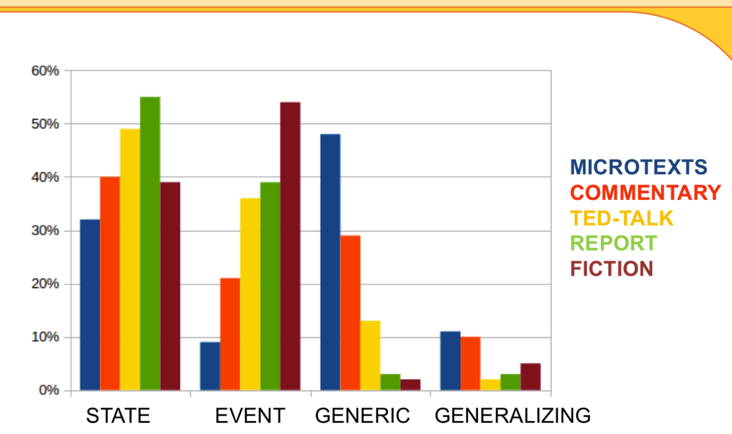
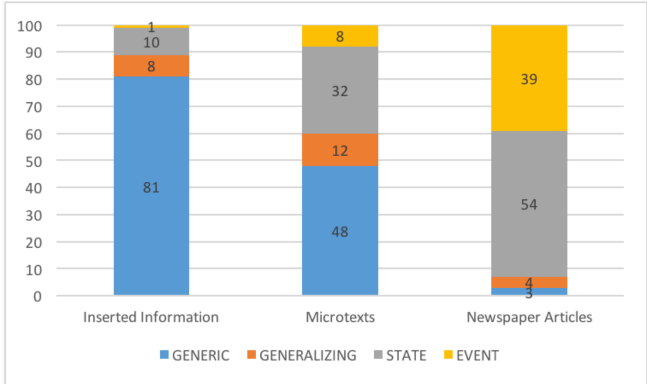
LIMO Empirical Linguistics and Computational Language Modeling

Motivation: Why are Semantic Clause Types Interesting?

The distribution of SCT in text passages correlates with **discourse modes** (Smith 2003) and plays a role in

- **Genre** characterization (Palmer and Friedrich, 2014)
- Detection of **generic and generalizing sentences** (Friedrich and Pinkal, 2015)
- **Argumentation** structure analysis (Becker et al., 2016)
- Characterization of **implicit knowledge** (Becker et al., 2017)





Related Work and Contribution

Automatic Classification of Semantic Clause Types

Prior work. **Feature-based classifiers** (Palmer et al. 2007, Friedrich et al. 2016)

- exploit language-specific and resource-intensive **features**
- **results**: with standard NLP Features – 69.8 accuracy
  with detailed features including external repositories – 71.4 accuracy
  with standard and detailed features used jointly – 74.7 accuracy

→ **Adaptation** to novel languages is **expensive**

Our Aim: Resource-lean **Recurrent Neural Network** model with **attention,** enhanced with **context** and **genre** information which is

- capable of modeling sequences
- capable of focusing on parts of the input
- easy to port to novel languages
- able to exploit context & genre

Data

- **English** Dataset: Friedrich et al. (2016): Wikipedia (10,607 clauses) and MASC (30,333 clauses), 13 genres *(Email, Essay, Letter, Newspaper, TED talk, Wikipedia...)*
- **German** Datasets: Mavridou et al. (2015) and Becker et al. (2016a,b) + self-annotated data (total: 18,194 clauses), 7 genres *(Fiction, Commentary, report...)*
- **Word embeddings**
  - English: 300-dim word2vec, trained on Google News (Mikolov et al. 2013)
  - German: 100-dim word2vec, trained on a web corpus (Reimers et al, 2014)

German annotated dataset: www.cl.uni-heidelberg.de/english/research/downloads/resource_pages/GER_SET/GER_SET_data.shtml

Results

		English Testset		German Testset	
		Accuracy	F1-Score	Accuracy	F1-Score
Local Models	Local model (w/o attention)	66.55	59.14	74.94	67.12
	Local model with attention	69.18	68.31	74.51	74.02
	Local model with attention+genre	**71.12**	69.55	**75.56**	69.98
Context Model: Clauses	1 previous clause/genre	**71.67**	59.19	**74.51**	72.41
Local model with attention	2 previous clauses/genres	71.57	48.12	74.44	72.26
+ previous clauses (tokens, w/o attention)	3 previous clauses/genres	69.76	42.73	73.35	71.79
+ genre label	4 previous clauses/genres	69.29	41.55	73.11	71.12
	5 previous clauses/genres	68.99	30.78	72.89	70.61
Context Model: Labels	1 previous label/genre	69.55	60.21	71.78	52.88
Local model with attention	2 previous labels/genres	71.04	64.54	72.29	52.52
+ previous labels with attention	3 previous labels/genres	71.68	64.42	72.47	52.34
+ genre label	4 previous labels/genres	71.25	65.06	74.33	51.12
	5 previous labels/genres	**72.04**	64.74	**74.92**	50.76
Context Model: Labels + Clauses	1 previous label/clause/genre	**71.35**	70.82	**73.43**	59.51
Local model (w/o attention)	2 previous labels/clauses/genres	70.65	68.62	72.23	57.38
+ previous clauses (tokens, w/o attention)	3 previous labels/clauses/genres	69.90	68.83	71.69	57.99
+ previous labels (w/o attention)	4 previous labels/clauses/genres	69.26	67.47	71.11	56.48
+ genre label of previous labels	5 previous labels/clauses/genres	69.00	64.36	71.09	56.23

Conclusions

- Models that attend to **local clauses, context & genre jointly** perform best
- **Competitive performance** at the level of feature-based classifiers
- Model avoids reproducing linguistic features for **novel languages**

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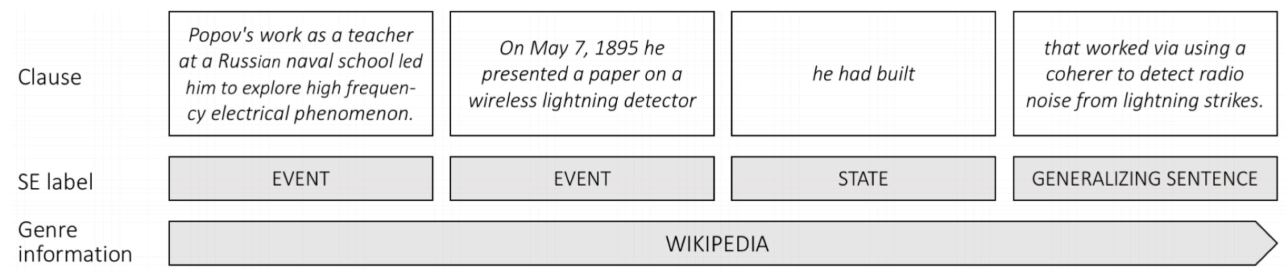
Inventory

Semantic Clause Types (SCT) (Smith 2003, Friedrich et al. 2016) characterize the **aspectual properties** of clauses and their **function** within a **text/discourse**:

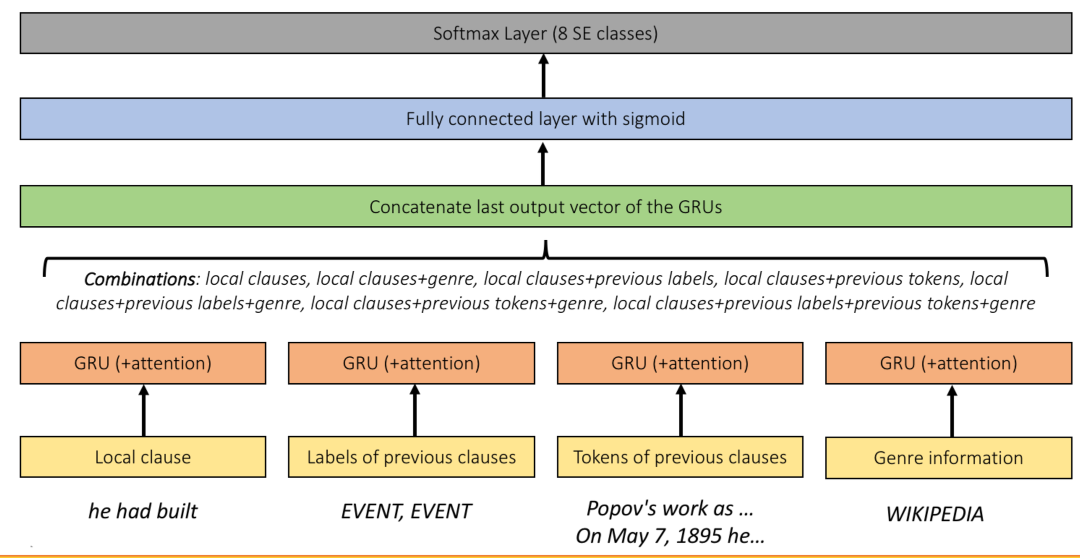
- STATES: John loves cake.
- EVENTS: Mike won the race.
- GENERALIZING SENTENCES: Mary often feeds my cat.
- GENERIC SENTENCES: Lions are carnivores.
- REPORT: John says that he loves cake.
- QUESTION: Why do you torment me so?
- IMPERATIVE: Listen to this.

Model

Modeling Context and Genre Information

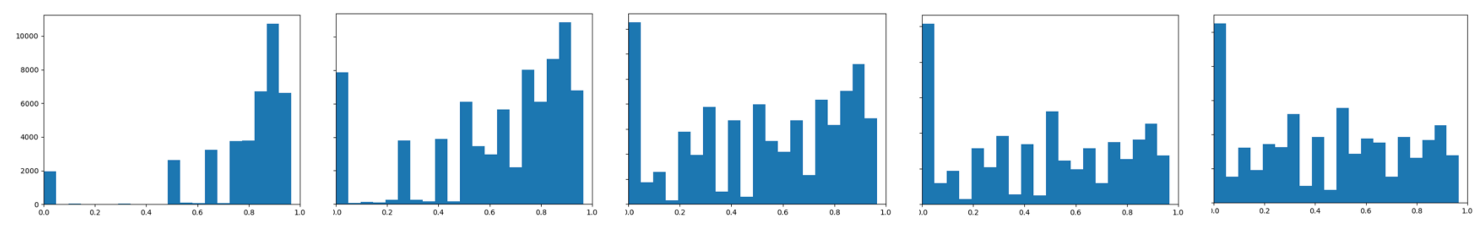


Model Architecture



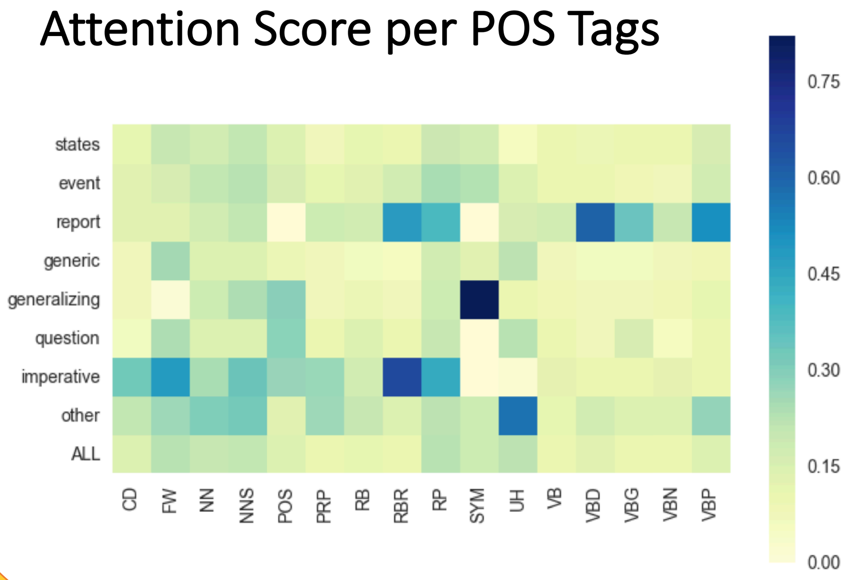
Analysis

Position of Words with High Attention Scores



1 word with highest attention | 2 words with highest attention | 3 words with highest attention | 4 words with highest attention | 5 words with highest attention

Attention Score per POS Tags

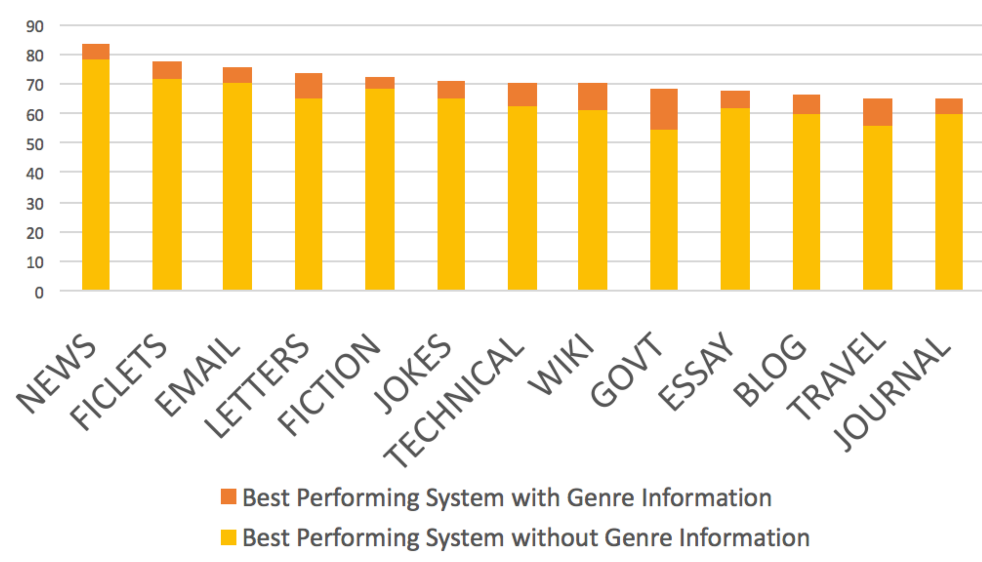


Words With High Attention Scores

- STATE: nouns, personal pronouns, pred. auxiliaries *(editors, I, am)*
- EVENT: gerunds *(thinking, writing)*
- GENERIC: adjectives, adverbs, modal verbs, indef. determiner *(awake, can, an)*
- GENERALIZING: names of official places/people *(York, States...)*

Impact of Genre

- Which genres are **easier** to classify?
- Which genre **helped** classifying correctly?



Similarity of Genres

- (sequences of) **SCT** differ among **genres**: most freq. n-grams per genre:
  - GENERIC → arg. texts, EVENTS → reports
  - STATE-STATE → Journals, GENERIC-GENERIC → Wikipedia
  - EVENT-EVENT-EVENT → Jokes, EVENT-STATE-STATE → gov. documents
- Distributions of SCT and their n-grams measured by **symmetric Kullback-Leibler divergence**