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#### Exploring the Impact of Lexical and Grammatical Features on Automatic Genre Identification

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# Introduction

• Automatic genre identification = text classification task, focused on genres

- Genres = text categories based on author's purpose, function and form of the document
  - news article, recipe, legal texts, etc.



# Goal



Various information is hidden in words in the running text: meaning, word function, relation with other words ...

Which of these signals are the most

informative for identifying genres?

# Method

- Text classification experiments
  - ML model: linear fastText classifier



- Dataset: <u>Slovene Web genre identification corpus GINCO 1.0</u>
  - 5 largest genre classes used in the experiments
  - 688 texts, 60:20:20 training-dev-test stratified split
  - 6 representations, separate training and testing on each representation

### Genre classes

GINCO	Reduced Set
News/Reporting Opinionated News	News (198)
Information/Explanation Research Article	Information/Explanation (127)
Opinion/Argumentation Review	Opinion/Argumentation (124)
Promotion Promotion of a Product Promotion of Services Invitation	Promotion (191)
Forum	Forum (48)

### Feature sets

- 6 training and test datasets 6 feature sets:
  - 1. baseline text: original running text as extracted from the dataset,
  - 2. preprocessed text: lowercase text without punctuation, digits and stopwords,
  - 3. lemmas: base dictionary forms of words,
  - 4. part-of-speech (PoS) tags: main word types (noun, verb)
  - 5. morphosyntactic descriptors (MSD): extended PoS tags with information on number, case, person ...
  - 6. syntactic dependencies: types of dependency relations between words (subject, object)

Feature Set	Example
Baseline - Running Text	V Laškem se bo v nedeljo, 21.4.2013 odvijal prvi dobrodelni tek Veselih nogic.
Preprocessed Baseline	laškem nedeljo odvijal dobrodelni tek veselih nogic
Lemmas	v Laško se biti v nedelja , 21.4.2013 odvijati prvi dobrodelen tek vesel nogica .
PoS	ADP PROPN PRON AUX ADP NOUN PUNCT NUM VERB ADJ ADJ NOUN ADJ NOUN PUNCT
MSD	Sl Npnsl Px—–y Va-f3s-n Sa Ncfsa Z Mdc Vmpp-sm Mlomsn Agpmsny Ncmsn Agpfpg Ncfpg Z
Dependencies	case nmod expl aux case obl punct nummod root amod amod nsubj amod nmod punct

# Input to the classifier

#### 🔚 upos-fasttext.train 🔣

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- 1 \_\_label\_\_Information/Explanation · NOUN · NOUN · ADJ · NOUN NOUN · VERB · DET · NOUN · AUX · AUX · ADJ · NOUN · NOUN · ADP · NOUN · PUNCT · NOUN · AUX · PRON · VERB · ADP · NOUN · ADJ · NOUN · ADJ · NOUN · ADP · NOUN · PUNCT · CCONJ · ADP · NOUN · CCONJ · NOUN · ADJ · NOUN · CCONJ · CCONJ · ADP · NOUN · ADJ · ADP · ADJ · NOUN · ADP · NOUN · NOUN · PUNCT · NOUN · VERB · DET · NOUN · AUX · ADP · NOUN · NOUN · ADJ · NOUN ADP · ADJ · NOUN · NUM · PUNCT · NUM · VERB · NOUN · ADP · NOUN · CCONJ · NOUN · NOUN · PROPN · PUNCT · NOUN · AUX · VERB · NUM · ADJ · NOUN · PUNCT ·
  - \_\_label\_\_\_Promotion.NOUN.PROPN.CCONJ.NOUN.PROPN.NOUN.PROPN.PRON.AUX.VERB.NOUN.ADJ.NOUN.NOUN.PROPN.PUNCT.SCONJ.AUX.ADP.NOUN.NOUN.PROPN.VERB.NOUN.PUNCT.SCONJ.ADP.ADJ.NOUN.ADP.PROPN.ADP.PROPN.PUNCT.VERB.ADJ.NOUN.ADP.NOUN.NOUN.PUNCT.NOUN.PUNCT.NOUN.PUNCT.NOUN.PUNCT.NOUN.PUNCT.NOUN.PUNCT.NOUN.PUNCT.NOUN.PUNCT.NOUN.PUNCT.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.ADJ.NOUN.PUNCT.ADJ.NOUN.ADJ.NOUN.ADJ.NOUN.ADJ.NOUN.ADJ.NOUN.ADJ.NOUN.ADJ.NOUN.PUNCT.ADJ.NOUN.ADJ.NOUN.PUNCT.ADJ.NOUN.ADJ.NOUN.PUNCT.ADJ.NOUN.ADJ.NOUN.PUNCT.ADJ.NOUN.ADJ.NOUN.PUNCT.ADJ.NOUN.ADJ.NOUN.PUNCT.ADJ.NOUN.ADJ.NOUN.PUNCT.ADJ.NOUN.ADJ.NOUN.PUNCT.ADJ.NOUN.ADJ.NOUN.PUNCT.ADJ.NOUN.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.ADJ.NOUN.PUNCT.VERB.AUX.NOUN.CCONJ.ADJ.NOUN.ADJ.NOUN.ADP.PUNCT.VERB.AUX.NOUN.PUNCT.ADJ.NOUN.ADJ.ADP.DET.NOUN.PUNCT.VERB.

#### 🔚 baseline\_text-fasttext.train 🗵

label Information/Explanation.JEDILNIK.Iskalnik Poglavitni cilj projekta Najdi svojo službo je bil aktivno sodelovanje šole z gospodarstvom, dijaki so se seznanili s smernicami gospodarskega razvoja kraške regije v prihodnosti, ter z razvojem in potrebami obstoječih podjetij in zato k usmerjanju mladih k ciljnemu izobraževanju za potrebe delodajalcev. Projekt Najdi svojo službo je v okviru razpisa Skriti zaklad v šolskem letu 2003/04 odobrilo Ministrstvo za šolstvo in šport Republike Slovenije. Projekt je trajal dve šolski leti. label Promotion Projekt INNOVAge in zavod Oreli Zavod Oreli se je odzval povabilu Razvojnega c entra Srca Slovenije, ki je v okviru projekta INNOVAge imelo nalogo, da na študijski obisk v Helsinke na Finskem, pripelje zunanje strokovnjake na področju oskrbe starostnikov, teleoskrbe, e-zdravja, eko-inovacij v stanovanjih in hišah, prilagojenih starostnikom. V tem projektu sodeluje 13 evropskih partnerjev, med njimi Razvojni center Srca Slovenije kot edini slovenski partner. Glavni cilj.projekta.INNOVage.je.prenos.dobrih.praks.v Evropi na področju aktivnega staranja in

# Experimental setup

- Prepared 6 training and test files (6 feature sets):
  - applied preprocessing methods  $\rightarrow$  preprocessed text
  - o applied linguistic processing with the CLASSLA pipeline → lemmas, POS, MSDs and syntactic dependencies
- Hyperparameter search for fastText (evaluation on dev split):
  - automatic hyperparameter optimization did not yield satisfactory results: very different hyperparameter values, 0.48 micro F1, 0.38 macro F1.
  - manual hyperparameter search: changing one hyperparameter at a time (epochs, learning rates, number of words in n-grams) → much better scores:
    0.63 micro F1, 0.62 macro F1.
- Training and testing with fastText on each of the 6 feature sets.

# Comparison with other models

Classifier	Micro F1	Macro F1
Dummy Classifier	0.24	0.08
Support Vector Machine	0.49	0.33
Decision Tree	0.34	0.35
Logistic Regression	0.52	0.38
<b>Random Forest classifier</b>	0.51	0.41
Naive Bayes classifier	0.54	0.42
FastText	0.56	0.59

# Results: Lexical representations

Representation	Micro F1	Macro F1
<b>Baseline</b> Text	$0.560 \pm 0.00$	$0.589\pm0.00$
Preprocessed Baseline	$0.596 \pm 0.00$	$0.597\pm0.00$
Lemmas	$0.597 \pm 0.01$	$0.601\pm0.00$

- Preprocessing improves results.
- Further improvements when using base dictionary forms of words (lemmas).

### Results: Lexical versus Grammatical Features

Representation	Micro F1	Macro F1
Baseline Text	$0.560\pm0.00$	$0.589 \pm 0.00$
Preprocessed Baseline	$0.596 \pm 0.00$	$0.597\pm0.00$
Lemmas	$0.597 \pm 0.01$	$0.601\pm0.00$
PoS	$0.540\pm0.01$	$0.547 \pm 0.01$
MSD	$0.563 \pm 0.01$	$0.536 \pm 0.02$
Dependencies	$0.610 \pm 0.00$	$0.639 \pm 0.00$

 Syntactic dependencies provide the best results → model learns on the structure of the sentences in the text instead of word meanings (topic).

### Results: Variation between genre classes



- Best feature set for:
- Information/Explanation, Promotion: lemmas
- News, Opinion/Argumentation, Forum: grammatical representations
- Forum best scores, although it is the least frequent.

# Conclusions

- The choice of textual representation does impact the results of automatic genre identification.
- POS tags result in worse performance than lexical features (as in previous work, performed on English).
- The most beneficial textual representation: syntactic dependencies (not studied in previous work).
- Variation between genres: some benefit more from lexical features, other from grammatical.

# Further work



- Combining multiple features sets.
- Analysis of English and Croatian dataset: are characteristics of genres language-independent?
- Transformer-based models significantly outperform fastText (XLM-RoBERTa: 0.22-0.26 micro/macro F1 scores higher):

 $\rightarrow$  adapt classifier's heads so that syntactic information has larger impact on classification.

 $\rightarrow$  experimenting how outputs of different layers effect the classification results.



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