GpKEX: Genetically Programmed Keyphrase Extraction from Croatian Texts

Marko Bekavac and Jan Šnajder

University of Zagreb
Faculty of Electrical Engineering and Computing
Text Analysis and Knowledge Engineering Lab

The Biennial International Workshop on Balto-Slavic Natural Language Processing
Sofia, August 8, 2013
Keyphrases are an effective way to summarize documents
  - *economic crisis, Greece debt crisis, foreign policy, G8 summit*

Useful for text categorization, document management, search

Two approaches:
  - keyphrase assignment: keyphrases chosen from a predefined taxonomy
  - keyphrase extraction: keyphrases chosen from document

Manual keyphrase extraction is tedious and inconsistent

Many supervised and unsupervised machine learning techniques have been proposed

We focus on *supervised keyphrase extraction* for Croatian using genetic programming
Genetic programming (GP)

- Evolutionary optimization technique in which solutions are symbolic expressions represented as syntax trees (Koza and Poli, 1992)

**GP in a nutshell**

1. Start with a random set of initial expressions *(population)*
2. Evaluate the fitness of each expression from the population
3. Randomly select two expressions, so that best-fitted expressions have a higher chance of being selected
4. Cross-over selected expressions and replace them with the cross-over result
5. Occasionally, mutate some expressions by changing them slightly
6. Repeat from step (1) until population fitness converges
Typically done in two steps:

- **Step 1:** Candidate extraction
  E.g.: *economic crisis* vs. *crisis in*

- **Step 2:** Candidate scoring using a keyphrase scoring measure (KSM)
  E.g.: *economic crisis* vs. *recent crisis*

Previous approaches learn KSMs using decision trees (Turney, 1999), naïve Bayes (Witten *et al.*, 1999), and SVM (Zhang *et al.*, 2006)

Work for Croatian: naïve Bayes (Ahel *et al.*, 2009), tf-idf scoring (Mijić *et al.*, 2010), topic clustering (Saratlija *et al.*, 2011)

Unlike previous work, we learn KSMs using GP

GP yields interpretable and efficient KSMs
Step 1: Candidate extraction

- Any sequence of words that
  - does not span over clause boundaries
  - matches any of the predefined POS patterns
- Each candidate is assigned a set of features
  - Frequency-based:
    relative term frequency, idf, tf-idf
  - Position-based:
    first/last occurrence, occurrence in title,
    # occurrences in 1st/2nd/3rd third
  - Surface form:
    length, # discriminative words
Step 2: Genetic programming

- Each genetic expression is a KSM represented as a syntax tree
- Outer nodes: keyphrase features
- Inner nodes: $+, -, \times, \div, \log \cdot, \cdot \times 10, \cdot / 10, 1 / \cdot$
GP parameters

- **Fitness:** Evaluated by comparing top \( k \)-ranked extracted phrases against gold-standard keyphrases.

- ** Parsimony pressure:** To prevent overfitting, we use a regularized fitness function:
  \[
  f_{\text{reg}} = \frac{f}{1 + N/\alpha}
  \]

- **Crossover:** Exchanges subtrees rooted at random nodes.

- **Mutation:** Grows a random subtree rooted at a randomly chosen node.

- **Selection:** Fitness-proportionate with elitist strategy.

- **Population:** 500 expressions, maximum 50 generations.
Evaluation – Dataset

- 1020 newspaper documents annotated by professional documentalists (Mijić et al., 2010)
- Split into:
  - 960 training docs, each annotated by a single annotator
  - 60 testing docs, each independently annotated by eight annotators
- We use the training set to define a set of six POS patterns: \textit{N}, \textit{AN}, \textit{NN}, \textit{NSN}, \textit{V}, \textit{X}
  - cover \textasciitilde70\% of keyphrases, reduce candidates by \textasciitilde80\%
  - keyphrases of at most length 3 (\textasciitilde93\%)
Keyphrase extraction is a highly subjective task
  - average human performance: $\sim65\%$ F1 (Saratlija et al., 2011)

We aggregate human annotations to obtain a ranked list of keyphrases for each document

Evaluation measures:
  - Generalized average precision (GAP) (Kishida, 2005)
  - $P@10$ and $R@10$ at two agreement levels:
    weak (2-annotator agreement) and strong (5-annotator agreement)
**Results**

| Model                  | GAP  | Strong agreement | Weak agreement |
|------------------------|------|------------------|----------------|
|                        |      | P@10   | R@10   | P@10 | R@10 |
| No parsimony           | 13.0 | 8.3    | 28.7   | 28.7 | 8.4  |
| $\alpha = 1000$       | 12.8 | 8.2    | 30.2   | 28.4 | 8.5  |
| $\alpha = 100$        | 12.5 | 7.7    | 27.3   | 27.3 | 7.7  |
| All POS patterns       | 9.9  | 5.1    | 25.9   | 20.4 | 7.3  |
| Baseline: tf-idf       | 7.4  | 5.8    | 22.3   | 21.5 | 12.4 |
| Saratlija et al. (2011)| 6.0  | 5.8    | 32.6   | 15.3 | 15.8 |

- First two models perform best and outperform the baseline (except for weak R@10)
- Parsimony pressure does not help, conservative POS filtering does
- Outperforms unsupervised extraction on GAP and strong F1@10
Tf-idf, First, and Rare positively correlated with keyphraseness
Length negatively correlated with keyphraseness
Summary

- **GpKex** uses genetically programmed keyphrase extraction measures to assign ranking to keyphrase candidates.
- Performs comparable to other machine learning methods developed for Croatian ⇒ efficient alternative to more complex models.
- We use simple features ⇒ easily applicable to other languages.
- Data/source code available from [takelab.fer.hr/gpkex](http://takelab.fer.hr/gpkex).
- Future work:
  - use additional (e.g., syntactic) features.
  - learn keyphrase ranking directly.
Ahel, R., Dalbelo Bašic, B., and Šnajder, J. (2009). Automatic keyphrase extraction from Croatian newspaper articles. *The Future of Information Sciences, Digital Resources and Knowledge Sharing*, pages 207–218.

Kishida, K. (2005). *Property of average precision and its generalization: An examination of evaluation indicator for information retrieval experiments*. National Institute of Informatics.

Koza, J. R. and Poli, R. (1992). *Genetic Programming: On the programming of computers by Means of Natural Selection*. MIT Press.

Mijić, J., Dalbelo Bašic, B., and Šnajder, J. (2010). Robust keyphrase extraction for a large-scale Croatian news production system. In *Proceedings of FASSBL*, pages 59–66.

Saratlija, J., Šnajder, J., and Bašić, B. D. (2011). Unsupervised topic-oriented keyphrase extraction and its application to Croatian. In *Text, Speech and Dialogue*, pages 340–347. Springer.

Turney, P. (1999). Learning to extract keyphrases from text. Technical report, National Research Council, Institute for Information Technology.
Witten, I. H., Paynter, G. W., Frank, E., Gutwin, C., and Nevill-Manning, C. G. (1999). Kea: Practical automatic keyphrase extraction. In *Proceedings of the fourth ACM conference on Digital libraries*, pages 254–255. ACM.

Zhang, K., Xu, H., Tang, J., and Li, J. (2006). Keyword extraction using support vector machine. In *Advances in Web-Age Information Management*, volume 4016 of *LNCS*, pages 85–96. Springer Berlin / Heidelberg.