The University of Alicante at MultiLing 2015: approach, results and further insights

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MultiLing 2015

GPLSI

Universitat d'Alacant
Universidad de Alicante

Overview

- Motivation & Context
- Multilingual Single-document Summarization
  - UA-DLSI approach
- Experiments & Evaluation
  - Language choice & Datasets
  - Experimental Setup
  - Results & Analysis
- Conclusions & Next Steps

Motivation & Context

redpacientes.com

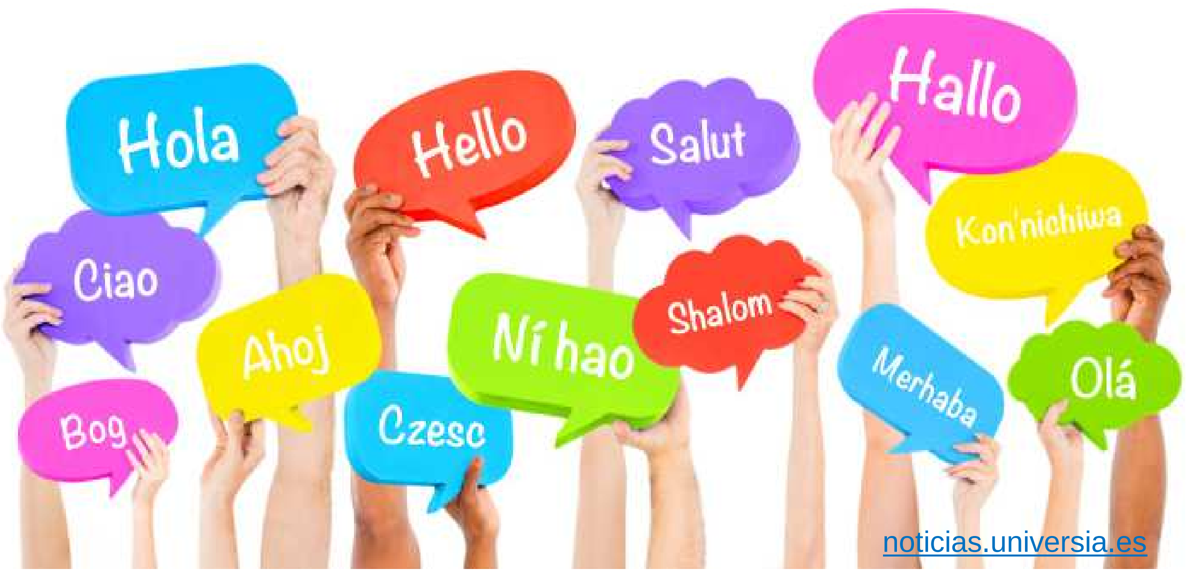
High volumes of information

- Difficult to manage
- What is the relevant information for us?

Motivation & Context

… in multiple languages

- Information lost if we cannot understand all the languages



Motivation & Context

Multilingual Summarization as a key technology

Determines the most relevant information

Deal with multiple languages

Multilingual Single-document Summarization (MSS)

To evaluate performance of systems generating a single document summary from Wikipedia articles in some of the languages provided (at least 3 languages from 38 available languages)

UA-DLSI Approach

- Technique employed
  - PCA: Principal Component Analysis
    - A statistical technique focused on the synthesis of information to compress and interpret the data.
    - Provides a way to determine the most relevant key terms of a document

UA-DLSI Approach

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  - PCA: Principal Component Analysis
    - A statistical technique focused on the synthesis of information to compress and interpret the data.
    - Provides a way to determine the most relevant key terms of a document
- Our **contribution**
  - Incorporation of lexical-semantic knowledge
    - Named Entity Recognition
    - WordNet + EuroWordNet

UA-DLSI Approach

- Summary Generation Process

Interpretation	• Creating the lexical-semantic matrix
Transformation	• PCA in action: determining key concepts
Summary Generation	• Sentence selection and ordering

UA-DLSI Approach

Interpretation

- Creating the lexical-semantic matrix

- Basic linguistic processing: sentence segmentation, tokenization, stopwords removal
- Identification of Named Entities and synonyms
- We group a set of synonyms under the same concept by the most frequent sense approach for each term.

UA-DLSI Approach

Interpretation

- Creating the lexical-semantic matrix

- Basic linguistic processing: sentence segmentation, tokenization, stopwords removal
- Identification of Named Entities and synonyms
- We group a set of synonyms under the same concept by the most frequent sense approach for each term.

Result: an initial lexical-semantic matrix, sentence as rows in the matrix, sense units (concepts, named entities, terms) as columns.

UA-DLSI Approach

Transformation

- PCA in action: determining key concepts

- Applying PCA technique we obtain the principal components (eigenvectors) and its corresponding weight (eigenvalue).
- The first eigenvectors collect the major part of the information extracted from the covariance matrix
  - Eigenvectors are derived in decreasing order of importance

UA-DLSI Approach

Transformation

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- The first eigenvectors collect the major part of the information extracted from the covariance matrix
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Result: relevant concepts are determined

UA-DLSI Approach

Summary Generation	• Sentence selection and ordering

- Two strategies are proposed for building different types of summaries
  - **Generic summaries** → for each relevant concept, select *<u>one sentence</u>* in which it appears
  - **Topic-focused summaries** → for each relevant concept, select *<u>all the sentences</u>* in which it appears

UA-DLSI Approach

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  - **Generic summaries** → for each relevant concept, select *one sentence* in which it appears
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Result: the summary is obtained

Experiments & Evaluation

- Language choice

English	Adding lexical-semantic knowledge requires some resources available for these languages
German	Named Entity Recognition → Standford NER
Spanish	Semantic knowledge → WordNet + EuroWordnet

Experiments & Evaluation

- Datasets provided

Training

- 30 articles/language
- Human-generated summaries
- Character length/target summary

Test

- 30 articles/language
- **NO** human-generated summaries
- Character length/target summary

Experiments & Evaluation

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Concision & precision are required

Lang	Compr. ratio
DE	2.75%
EN	7.19%
ES	5.21%

Experiments & Evaluation

- Experimental Setup

Criteria → **System configurations**

Types of summaries

- **T1** Generic Summary
- **T3** Topic-focused Summary

Types of Knowledge included

- **LI** Language-independent approach
- **LEX** Using Lexical Knowledge (Name Entity Recognition)
- **SEM** Semantic Knowledge (WordNet,…)

Words in the PCA matrix construction

- **OWFH** Only words in Wikipedia headings
- **AW** All words in the document

UA-DLSI 1	T1	LI	AW	
UA-DLSI 2	T3	LEX	SEM	OWFH
UA-DLSI 3	T1	LI	OWFH	
UA-DLSI 4	T1	LEX	SEM	AW
UA-DLSI 5	T3	LI	OWFH	
UA-DLSI 6	T3	LEX	SEM	AW

Experiments & Evaluation

- Experimental Setup
  - Baselines
    - LEAD
      - System that selects the leading substring of the article's body having the same length as the human summary
    - ORACLES
      - Select sentences from the body text that cover the tokens in the human sentences using as few sentences as possible
  - MSS 2015 Participants (5 systems)
    - *"BGU-SCE" – "CCS" – "EXB" – "LCS-IESI" – "UA-DLSI"*

Experiments & Evaluation

- Results & Analysis

ROUGE 1, F-measure

	UA - DLSI 1	UA - DLSI 2	UA - DLSI 3	UA - DLSI 4	UA - DLSI 5	UA - DLSI 6	Lead	Oracles	Best performance
en	0.45605	0.42703	0.40551	**0.45627** (15/22)	0.42419	0.42727	0.42907	0.60983	BGU-SCE 5 0.49361
es	**0.48977** (8/13)	0.47141	0.46979	0.48454	0.47691	0.47193	0.46599	0.61691	CCS 4 0.52126
de	0.34110	0.33725	**0.36236** (7/13)	0.34317	0.33437	0.34553	0.32230	0.52759	CCS 4 0.38803

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Experiments & Evaluation

Results & Analysis

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- When summarizing Wikipedia articles, generic summarization has been shown to be more appropriate.
- Compress ratio values for German are the highest (2.75% against 7.19% for English), which is reflected in the scores obtained for this language.
  - These high values are quite challenging for a summarization task. In this sense, we keep looking into new options to improve our implementation

Conclusions & Next Steps

- Potentials
  - 1st time we participate in a summarization competition
  - Promising results were obtained
  - PCA is a very good technique for language-independent summarization
  - Wikipedia title headings were meaningful enough to build the PCA matrix in our summarization process
- Limitations
  - Lexical and semantic knowledge is dependent on the performance of the existing tools and resources
  - Need for going beyond extractive summarization
  - Compression ratio of Wikipedia articles too high compared with other type of documents

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Future Work → analyze PCA with other types of knowledge in order to advance the generation of abstractive summarization

Thank you for your attention!

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