Hypergraphs and Information Fusion for Term Representation Enrichment. Applications to Named Entity Recognition and Word Sense Disambiguation

Ph.D. Thesis Defense

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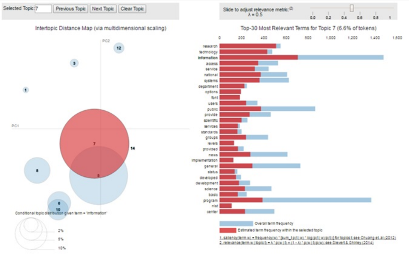
Supervised by Sabine Loudcher and Julien Ah-Pine

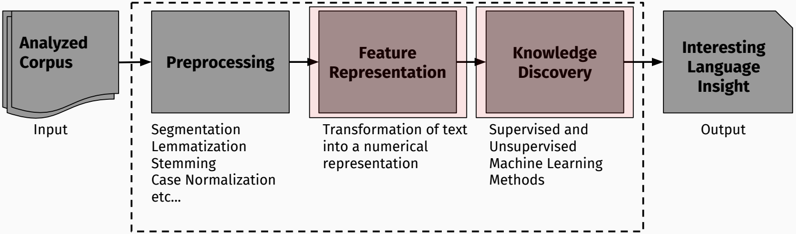
February 7th, 2018

Why it is useful to us to understand text?



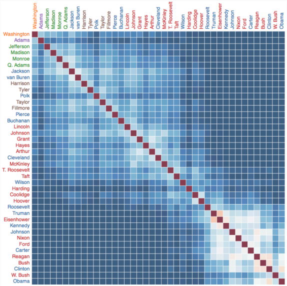
How do we extract meaning from text?

We use **Natural Language Processing** (NLP), a field of computer science interested on making computers extract useful information from text

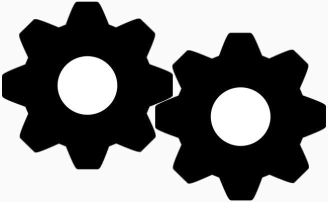


Feature Representation and Knowledge Discovery

How do we represent text for the machine to understand?



What techniques do we use to discover meaning from text?



Representing Text

- **Three common ways to represent text**

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  - Syntactic

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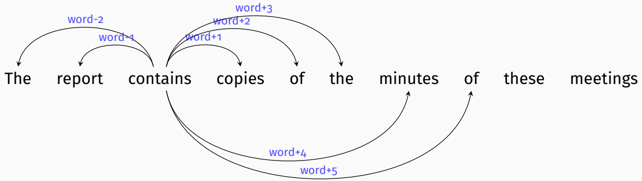

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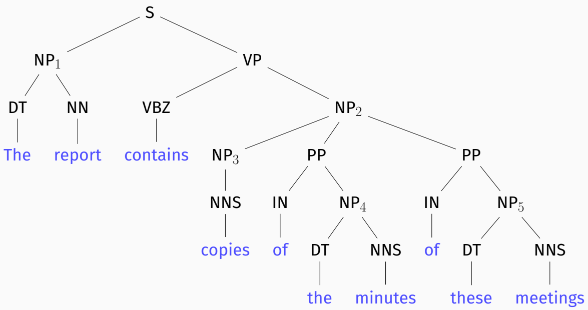

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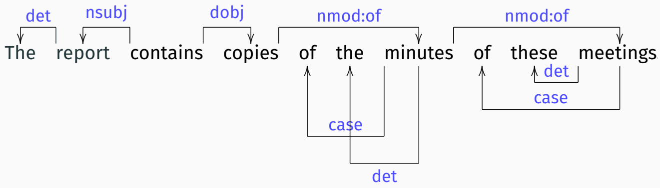

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  - Words and features can be represented by means of graph-based models matrices
  - Or directly with (sparse) matrices
- **Leveraging the Network Structure**
  - We can find communities of similiar words according to their meaning

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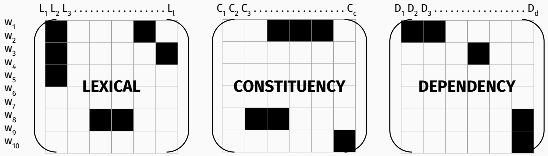

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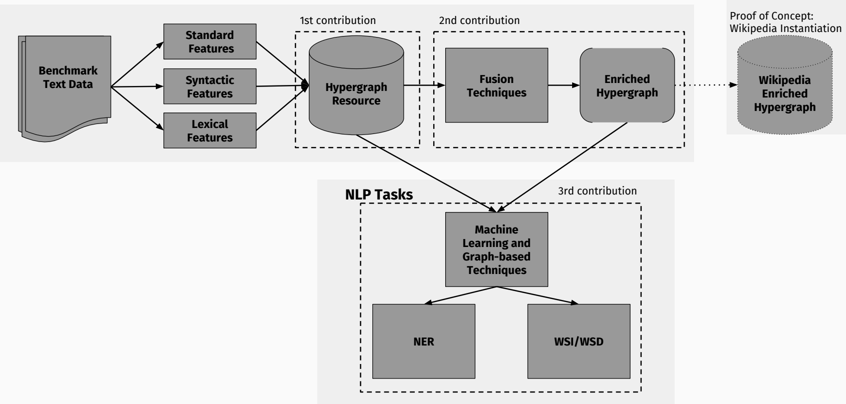
   - *An alternative network-based algorithm to discover semantically related words within a text*

Work Overview



Contributions in Detail

Hypergraph Linguistic Model

Introduction

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  - Graphs structures can give us a clearer view into the relations of words within a text [CM09]
  - Ultimately graphs are transformed to a vectorial representation through the adjacency/incidence matrices

Existing Language Networks

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Lexical Networks

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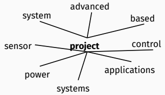

Syntactic Networks

Existing Language Networks

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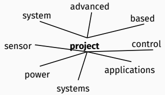

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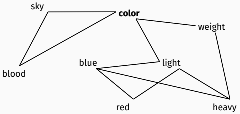

Semantic Networks

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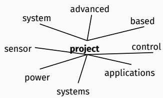

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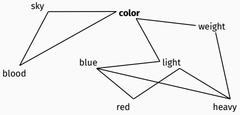

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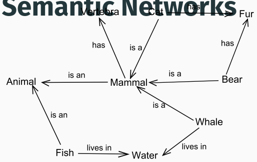

An expert is usually involved.

Limitations and Proposition

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- **Proposition**
  - Represent together linguistic co-occurrences through a hypergraph model
    - Link together three different types of networks, using lexical and syntactic data
    - Get a semantic overview at three different levels: short range (with dependency functions), medium range (phrase constituency membership), and long range (lexical co-occurrence)

Proposed Model

- Explain (grpahically/with the working exampleh) we use lexical and syntactic info and the build a fusion of them with a hypergraph.

Contributions in Detail

Combining Features and Dealing with Sparsity

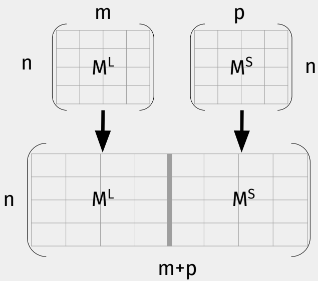
Multimedia Fusion Techniques [Atr+10; ABL10]:

- **Definition**
  - Set of techniques used in multimedia analysis tasks to integrate multiple media
  - The goal is to obtain rich insights about the data being treated
  - We adapt these techniques to our use case: textual information
- **Main fusion operators:**
  - Early Fusion $E_\alpha(\cdot)$,
  - Late Fusion $L_\beta(\cdot)$,
  - Cross Fusion $X_\gamma(\cdot), X_F(\cdot)$
  - α and β: Assign an importance weight to each of their operators
  - γ: number of top similar items to take from the similarity space

Early and Late Fusion

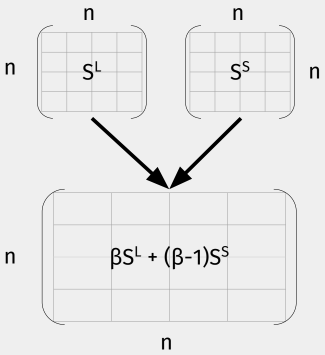
EARLY FUSION

Matrices M^L and M^S have the same number of rows

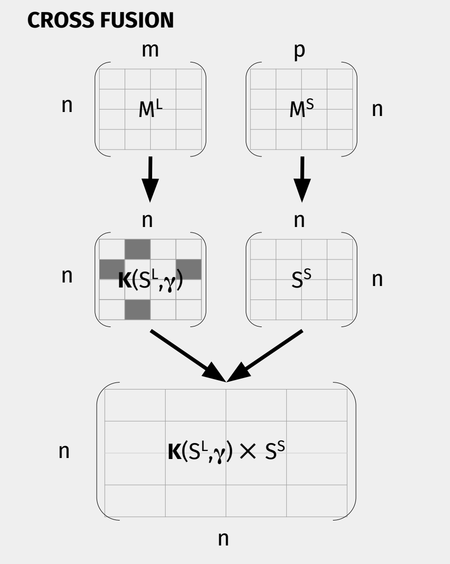


LATE FUSION: SIMILARITY FUSION

Matrices S^L and S^B have the same size



Cross Fusion



Hybrid Fusion 1

Put here some very visual way of representing hybrid fusion.

In fact, early and late fusion should be presented with the working example also.

Hybrid Fusion 2

Put here some very visual way of representing hybrid fusion.

In fact, early and late fusion should be presented with the working example also.

Leveraging the network communities

1. Show a large (with more text than that of my example) image of the hypergraph model

Contributions in Detail

Finding Communities in the Network

Leveraging the network communities 1

1. Link some words together with a color overlay to represent possible communities (clusters/groups) of same sense words.
2. Argue that thanks to the heterogeneous info contained in the structure, we can relate words according to different linguistic properties

Leveraging the network communities 2

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Applications to NLP

Hypergraph Model Instantiation

Applications

- We instantiate our proposed linguistic resource
  - Based on the English Wikipedia corpus
- Use the proposed model to solve two NLP tasks:
  - Named Entity Recognition
  - Word Sense Induction and Disambiguation
- These experiments have two main objectives:
  - Test the effectiveness of fusion enriched representations (heterogeneity + less sparse spaces)
  - Leverage the structure of the network built following our proposed model

Hypergraph Model Instantiation

- Introduction to SAEWD
- Motivation
- Characteristics
- Show small diagram of the process

Hypergraph Model Instantiation

- Image with how the hypergraph corpus is stored in files and how we can access the information via key-value pairs to select nouns or verbs or types of noun phrases etc

Wikipedia Feature Enriched Spaces

	Lexical Features (5.49%) M^L	**Syntactic Features (4.97%)** M^S	**Early Fusion (5.23%)** $E(M^L, M^S)$	X_F **Fusion (16.75%)** $X_F(S^S, M^L)$	X_F **Fusion (13.45%)** $X_F(S^L, M^S)$
	priests	monk	sailor	vassal	sailor
	nun	regent	regent	regent	fluent
priest	canton	aedile	nuclei	nun	dean
	sailor	seer	nun	sailor	nuclei
	burial	meek	relic	monk	chorus

Applications to NLP

Solving Named Entity Recognition

Definition and Objectives

- The goal is to automatically discover mentions that belong to a well-defined semantic category.
- The classic task of NER involves detecting among four types of entities and a non-entity class:
  - Location (LOC)
  - Organization (ORG)
  - Person (PER)
  - Miscellaneous (MISC)
  - None (O)
- We assess the effectiveness of the classic fusion methods and propose new hybrid combinations
- ** Show here graphical presentation of entities**

Representation Spaces

Lexical Space (L)

Word	Features
Australian	word:Australian, word+1:scientist, word+2:discovers
scientist	word-1:Australian, word:scientist, word+1:discovers, word+2:star
discovers	word-2:Australian, word-1:scientist, . . . , word+2:telescope
star	word-2:scientist, word-1:discovers, word:star, . . . , word+2:telescope
with	word-2:discovers, word-1:star, word:with, word+1:telescope
telescope	word-2:star, word-1:with, word:telescope

Syntactic Space (S)

Word	Contexts
Australian	scientist/NN/amod_inv
scientist	Australian/JJ/amod, discovers/VBZ/nsubj_inv
discovers	scientist/NN/nsubj, star/NN/dobj, telescope/NN/nmod:with
star	discovers/VBZ/dobj_inv
telescope	discovers/VBZ/nmod:with_inv

Standard Features Space (T)

- Each word
- Whether it is capitalized
- Prefix and suffix (of each word their surroundings)
- Part of Speech tag

Experimental Protocol

- **Preprocessing**
  - Normalize numbers
- **Test Corpora**
  - CoNLL-2003 (CONLL) [SM03]: Train: 219,554 lines. Test: 50,350
  - Wikiner (WNER) [NMC09]: No Train/Test split. 3.5 million words. Evaluated in a 5-fold CV
  - Wikigold (WGLD) [Bal+09]: No Train/Test split. 41,011 words. Evaluated in a 5-fold CV
- **Annotation Scheme**
  - **B**eginning, **I**nside, **O**utside
- **Learning Algorithm**
  - Structured Perceptron [Col02]
- **Evaluation Metrics**
  - Precision, Recall, F-measure

Evaluation

- Best Fusion operators on the F-measure over the three datasets.
- Achieved using a higher Degree fusion operator
- Notice the comparison with the Early Fusion baseline
- Visually show the best fusion operator, not with the formula.

		Triple Early Double Late Cross Feature Fusion ($EEELX_FLX_F$)		
		CONLL	WNER	WGLD
M^L	$\hat{b}_{EEELX_FLX_F}$	65.01	78.02	62.34
$M^L_{\alpha=0.95}$	$\hat{b}_{EEELX_FLX_F}$	**79.67**	**81.79**	**67.05**
EF Baseline		78.90	80.04	63.20

Analyzing the Best Fusion Operator

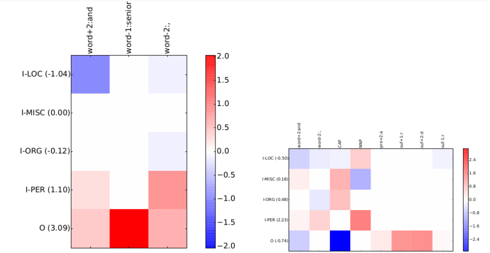
Decompose best fusion in four models:

$$\overbrace{\underbrace{\overbrace{E_{\alpha=0.95}(\underbrace{M^L}_{1}, M^T}^{2}, L(M^T, X_F(S^S, M^T))}_{3}, L(M^L, X_F(S^S, M^L))}^{4})$$

1. M^L used to train model M_1.
2. $E(\alpha_1 M^L, \alpha_2 M^T)$ used to train model M_2, with $\alpha_1 = 0.95, \alpha_2 = 0.05$
3. $E_\alpha(\alpha_1 M^L, \alpha_2 M^T, \alpha_3 L(M^T, X_F(S^S, M^T)))$ used to train model M_3, with $\alpha_1 = 0.95, \alpha_2 = \alpha_3 = 0.05$
4. $E_\alpha(\alpha_1 M^L, \alpha_2 M^T, \alpha_3 L(M^T, X_F(S^S, M^T)), \alpha_4 L(M^L, X_F(S^S, M^L)))$ used to train model M_4, with $\alpha_1 = 0.95, \alpha_2 = \alpha_3 = \alpha_4 = 0.05$

Analyzing the Best Fusion Operator

We focus on the word *Kory*, and its performance from model M_1 to M_2

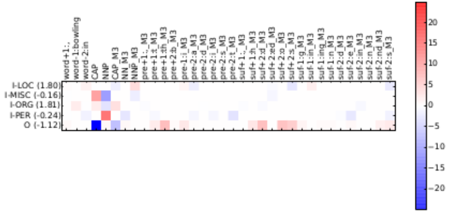


(a) The word *Kory* is predicted to be class O by model M_1 given the coefficients of the features indicated.

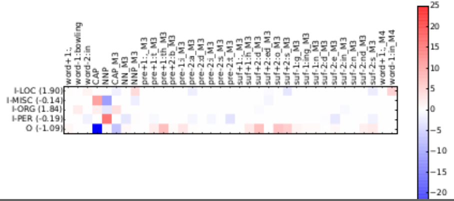
(b) The same word is correctly predicted to be class PER by model M_2 given the new features in the model.

Analyzing the Best Fusion Operator

We focus on the word *Green*, and its performance from model M_3 to M_4



(a) The word *Green* is predicted to be class ORG by model M_3 given the coefficients of the features indicated.



Applications to NLP

Solving Word Sense Induction and Disambiguation

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- Introduction to WSI/WSD

Experimental Protocol

- **Preprocessing**
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- **Test Corpora**
  - Semeval 2007 [SM03]: Train: 219,554 lines. Test: 50,350
- **Clustering Algorithm**
  - Spectral Clustering
- **Evaluation Metrics**
  - Supervised: F-score
  - Unsupervised: Recall
  - Proposed: H-score

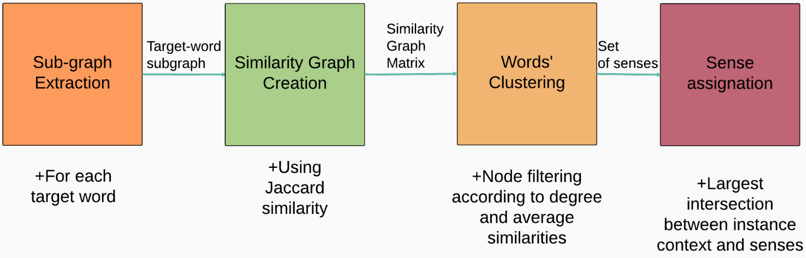
WSI/WSD: Evaluation

- Results for WSI/WSD with spectral clustering

How to exploit a linguistic network to solve word sense induction and disambiguation?

- **Similar approaches**
  - Hyperlex [Vé04]
  - University of York (UoY) [KM07]
- **Limitations of existing approaches**
  - Single typed networks
  - Large number of parameters
- **Features**
  - Be able to exploit different types of linguistic information (lexical or syntactic co-occurrence)
  - Keep the number of parameters low and allow for their automatic adjusting according to the network's nature

Proposed Method



Semeval Results

- Semeval 2007 results table

WSI/WSD: Evaluation

- Verbs and nouns behaviors
- Insight into senses found by the algorithm

Conclusions

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Insights From our Contributions

Future Work

References I

References

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