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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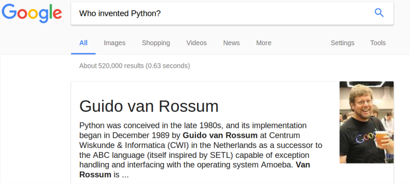
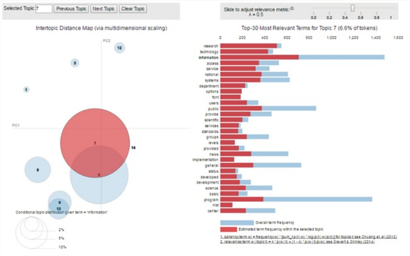
Supervised by Sabine Loudcher and Julien Ah-Pine

February 7th, 2018

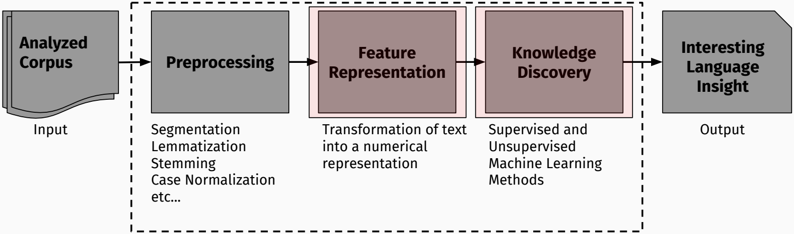
Why it is useful to us to understand text?





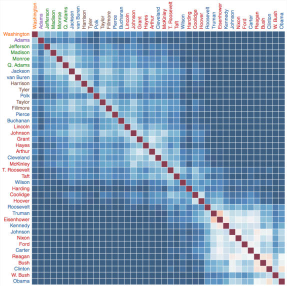
How do we extract meaning from text?

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

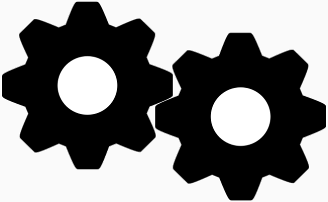


Feature Representation and Knowledge Discovery

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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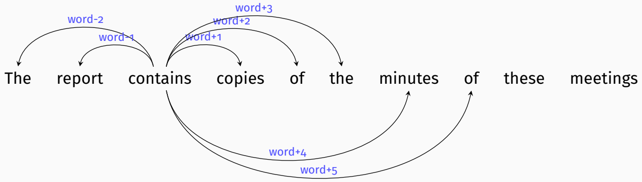

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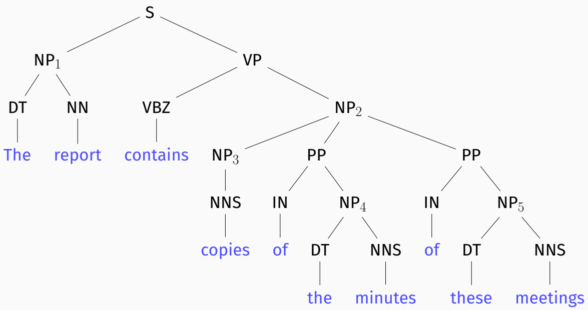

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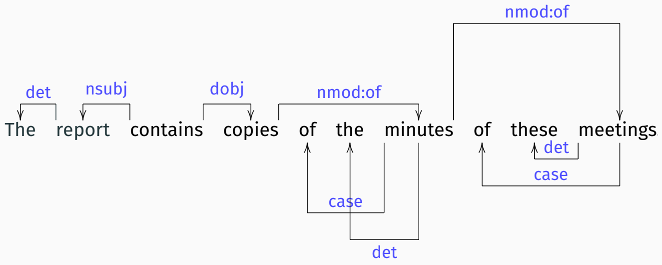

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  - Words and features can be represented by means of graph-based models matrices
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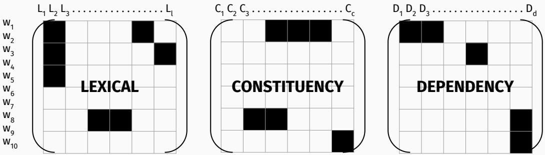

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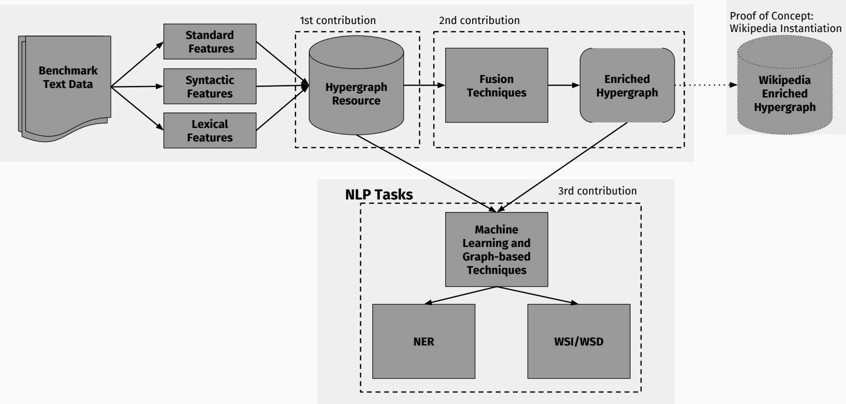
   - *An alternative network-based algorithm to discover semantically related words within a text*

Work Overview



Contributions in Detail

Hypergraph Linguistic Model

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  - Ultimately graphs are transformed to a vectorial representation through the adjacency/incidence matrices

Classic Language Networks

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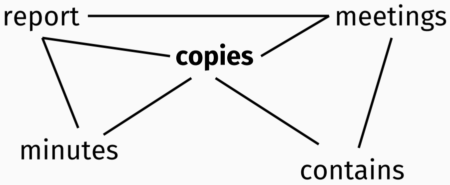
Lexical Networks

Sentence Level



[KM08]

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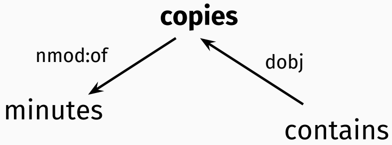
Syntactic Networks

Dependency Tree



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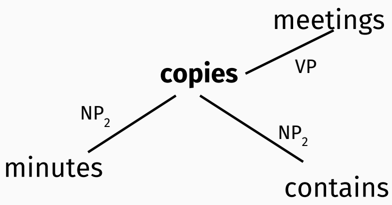
Syntactic Networks

Constituency Tree



Classic Language Networks

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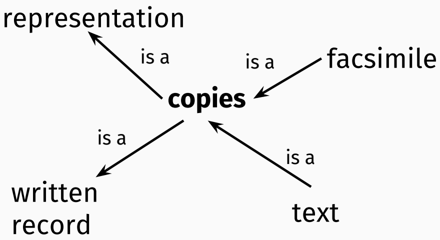
Semantic Networks



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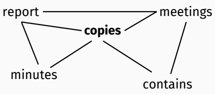
- **Proposition**
  - Represent together linguistic co-occurrences through a hypergraph model
    - Link together three different types of networks, using lexical and syntactic data
    - Get a semantic overview at three different levels: short range (with dependency functions), medium range (phrase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

Proposed Model

Lexical Networks
Sentence Level



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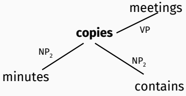
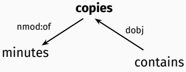


Syntactic Networks
Dependency Tree



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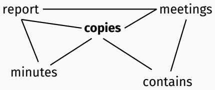

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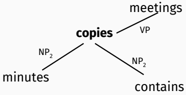

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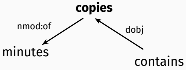

Hypergraph Model

Proposed Model

Lexical Networks
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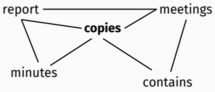

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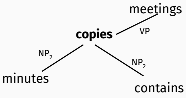

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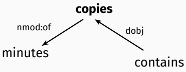

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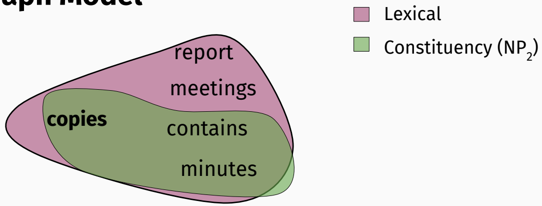

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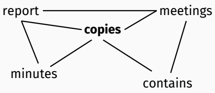

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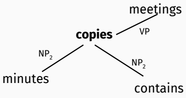

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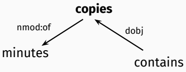

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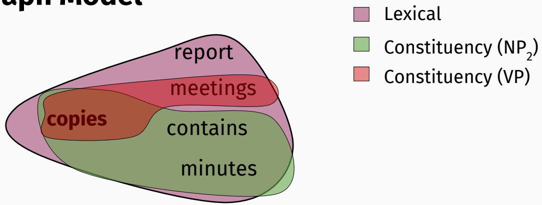

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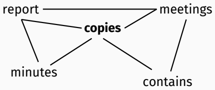

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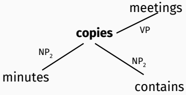

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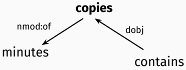

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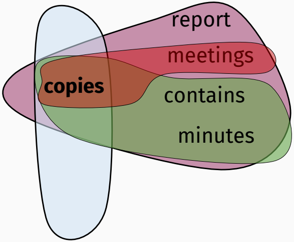

- Lexical
- Constituency (NP_2)
- Constituency (VP)
- Dependency (dobj:contains)

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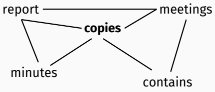
Sentence Level



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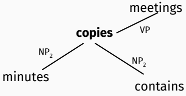

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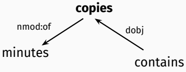

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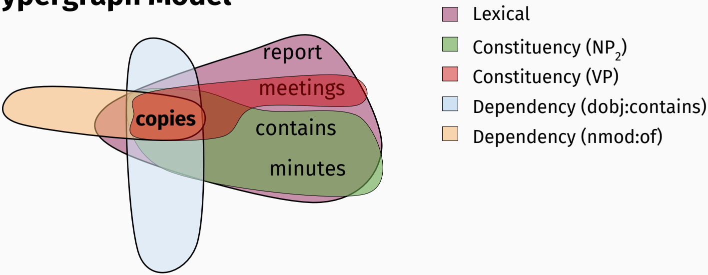

Contributions in Detail

Combining Features and Dealing with Sparsity

Multimedia Fusion Techniques

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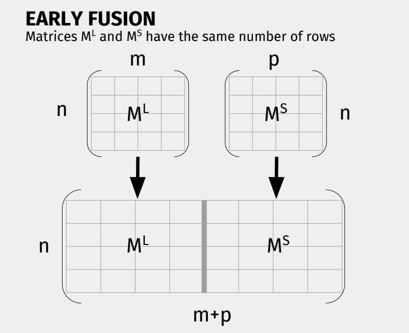
  - Cross Fusion $X_{\gamma}(\cdot), X_{F}(\cdot)$

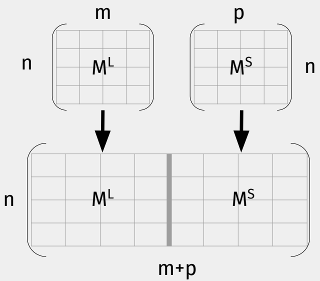
Early and Late Fusion



Early and Late Fusion

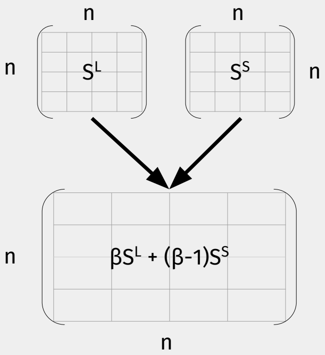
EARLY FUSION

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

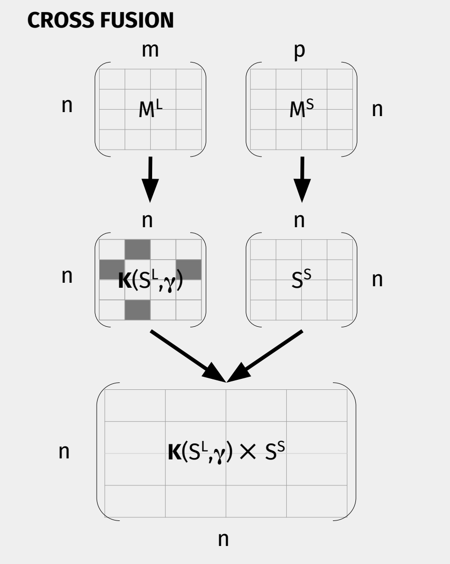


LATE FUSION: SIMILARITY FUSION

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



Cross Fusion



Hybrid Fusion

- We distinguish three levels of fusion operators
  - **First Degree**
    - $E(M^L, M^S)$, $L(S^S, M^L)$
    - Cross Feature Fusion: $X_F(S^S, M^L)$
    - Cross Similarity Fusion: $X_S(S^S, S^L)$
  - **Second Degree**
    - Cross Feature Early Fusion: $X_F(S^T, E(M^L, M^S))$
    - Late Cross Feature Fusion: $L(M^T, X_F(S^T, M^T))$
  - **Higher Degree**
    - Triple Early Double Late Cross Feature Fusion: $E(M_L, E(E(M_T, L(M^T, X_F(S^T, M^T))), L(M^L, X_F(S^S, M^L))))$

Hybrid Fusion

$$E(M_L, E(E(M^T, L(M^T, X_F(S^T, M^T))), L(M^L, X_F(S^S, M^L))))$$

Hybrid Fusion

$$\boxed{E(M_L, \boxed{E(\boxed{E(M^T, \boxed{L(M^T, X_F(S^T, M^T))})}, \boxed{L(M^L, X_F(S^S, M^L))})})}$$

Hybrid Fusion

$$E(M_L, E(E(M^T, L(M^T, X_F(S^T, M^T))), L(M^L, X_F(S^S, M^L))))$$

$$L(M^L, X_F(S^S, M^L))$$

$$\begin{array}{cc} & w_1\ w_2\ w_3 \\ \begin{array}{c}w_1\\w_2\\w_3\end{array} & \begin{pmatrix} S^S \end{pmatrix}\end{array} \times \begin{array}{cc} & f_{L1}\ f_{L2}\ f_{L3} \\ \begin{array}{c}w_1\\w_2\\w_3\end{array} & \begin{pmatrix} M^L \end{pmatrix}\end{array} = \begin{array}{cc} & f_{L1}\ f_{L2}\ f_{L3} \\ \begin{array}{c}w_1\\w_2\\w_3\end{array} & \begin{pmatrix} X_F(S^S, M^L) \end{pmatrix}\end{array}$$

$$\begin{array}{cc} & f_{L1}\ f_{L2}\ f_{L3} \\ \begin{array}{c}w_1\\w_2\\w_3\end{array} & \begin{pmatrix} M^L \end{pmatrix}\end{array} + \begin{array}{cc} & f_{L1}\ f_{L2}\ f_{L3} \\ \begin{array}{c}w_1\\w_2\\w_3\end{array} & \begin{pmatrix} X_F(S^S, M^L) \end{pmatrix}\end{array} = \begin{array}{cc} & f_{L1}\ f_{L2}\ f_{L3} \\ \begin{array}{c}w_1\\w_2\\w_3\end{array} & \begin{pmatrix} L(M^L, X_F(S^S, M^L)) \end{pmatrix}\end{array}$$

Hybrid Fusion

$$E(M_L, E(E(M^T, L(M^T, X_F(S^T, M^T))), L(M^L, X_F(S^S, M^L))))$$

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$$\begin{array}{c|c} & w_1\ w_2\ w_3 \\ \hline \begin{matrix} w_1 \\ w_2 \\ w_3 \end{matrix} & \begin{pmatrix} S^T \end{pmatrix} \end{array} \times \begin{array}{c|c} & f_{T1}\ f_{T2}\ f_{T3} \\ \hline \begin{matrix} w_1 \\ w_2 \\ w_3 \end{matrix} & \begin{pmatrix} M^T \end{pmatrix} \end{array} = \begin{array}{c|c} & f_{T1}\ f_{T2}\ f_{T3} \\ \hline \begin{matrix} w_1 \\ w_2 \\ w_3 \end{matrix} & \begin{pmatrix} X_F(S^T, M^T) \end{pmatrix} \end{array}$$

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$$\boxed{E(M_L, E(E(M^T, L(M^T, X_F(S^T, M^T))), L(M^L, X_F(S^S, M^L))))}$$

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Contributions in Detail

Finding Communities in the Network

Finding Senses in the Network

- **Language networks tend to be scale-free**

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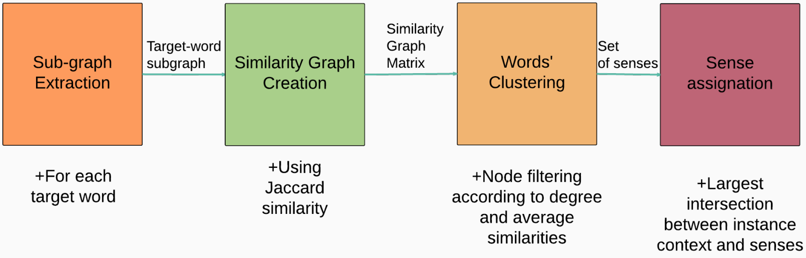
  - Keep the number of parameters low and allow for their automatic adjusting according to the network's nature

Proposed Method



Applications to NLP

Hypergraph Model Instantiation

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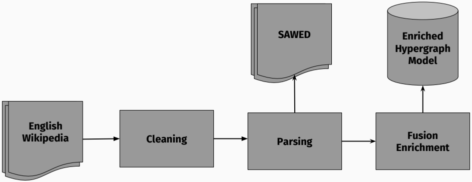

SAEWD: Parsed sample

FILENAME wiki_00.parsed

token	lemma	POS	constituency	head	dependency
%%#PAGE Anarchism					
⋮	⋮	⋮	⋮	⋮	⋮
%%#SEN 25 9					
A	a	DT	NP_22,S_97	3	det
great	great	JJ	NP_22,S_97	3	amod
brigand	brigand	NN	NP_22,S_97	4	nsubj
becomes	become	VBZ	VP_44,S_97	0	root
a	a	DT	NP_18,NP_20,VP_44,S_97	6	det
ruler	ruler	NN	NP_18,NP_20,VP_44,S_97	4	xcomp
of	of	IN	PP_57,NP_20,VP_44,S_97	9	case
a	a	DT	NP_18,PP_57,NP_20,VP_44,S_97	9	det
Nation	nation	NN	NP_18,PP_57,NP_20,VP_44,S_97	6	nmod

Hypergraph Incidence Matrix

		CONSTITUENT			DEPENDENCY		SENTENCE
		NP_1 DT:NN	NP_2 NP:PP:PP	NP_3 NNS	nsubj contains	dobj contains	S_1
NN	report	1			1		1
	copies		1	1		1	1
	minutes		1				1
	meetings		1				1
VB	contains						1

Wikipedia Feature Enriched Space

	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

Introduction

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- **Our goal**
    - We assess the effectiveness of the classic fusion methods and propose new hybrid combinations

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**

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  - Normalize numbers

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  - Precision, Recall, F-measure

Evaluation

A	B	Early Fusion (EF)		
		CONLL	WNER	WGLD
M^L	M^S	72.01	70.59	59.38
M^L	M^T	78.13	79.78	61.96
M^S	M^T	77.70	78.10	60.93
M^L	$E(M^S, M^T)$	**78.90**	**80.04**	**63.20**
		Late Fusion (LF)		
		CONLL	WNER	WGLD
S^L	S^S	**61.65**	58.79	44.29
S^L	S^T	55.64	**67.70**	48.00
S^S	S^T	50.21	58.41	**49.81**

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		Cross Feature Fusion ($X_F F$)		
		CONLL	WNER	WGLD
S^L	M^T	49.90	**70.27**	**62.69**
S^S	M^T	47.27	51.38	48.53
S^T	$b^*_{X_F F}$	**52.89**	62.21	50.15
		Cross Similarity Fusion ($X_S F$)		
		CONLL	WNER	WGLD
S^L	S^T	27.75	**59.12**	38.35
S^S	$b^*_{X_S F}$	36.87	40.92	39.62
S^T	$b^*_{X_S F}$	**41.89**	52.03	**39.92**

$$b^*_{X_F F} \in \{M^L, M^T\}$$
$$b^*_{X_S F} \in \{S^L, S^S\}$$

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$$E(M_L, E(E(M^T, L(M^T, X_F(S^T, M^T))), L(M^L, X_F(S^S, M^L))))$$

Evaluation

$$E(M_L, E(E(M^T, L(M^T, X_F(S^T, M^T))), L(M^L, X_F(S^S, M^L))))$$

		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

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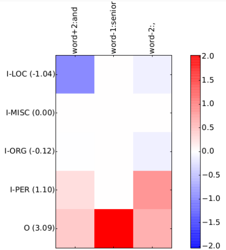
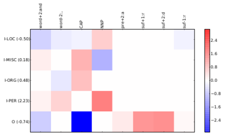
$$\overbrace{\underbrace{\overbrace{E_{\alpha=0.95}(\underbrace{M^L}_{1}, M^T}^{2}, L(M^T, X_F(S^S, M^T))}_{3}, L(M^L, X_F(S^S, M^L)))}^{4}$$

Analyzing the Best Fusion Operator

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



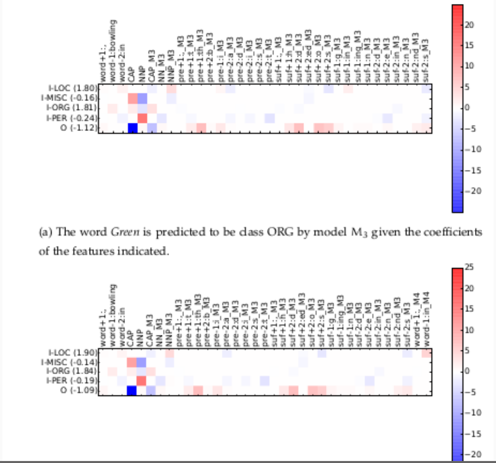
(a) The word *Kory* is predicted to be class O by model M_1 given the coefficients of the features indicated.



(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

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  - Again, to assess the effectiveness of the fusion enriched spaces and to evaluate the pertinence of our community discovering algorithm

Experimental Protocol

- **Preprocessing**
    - Remove very frequent and very infrequent words
- **Test Corpora**
    - Semeval 2007 [SM03]: Train: 219,554 lines. Test: 50,350
- **Clustering Algorithm**
    - Spectral Clustering [SM00]
    - Proposed Community Algorithm
- **Evaluation Metrics**
    - Supervised Recall
    - Unsupervised F-measure
    - Proposed: H-measure

$$\text{H-measure} = \frac{1}{2}\left(2 * \frac{SR * UF}{SR + UF} + \frac{\delta}{\delta + |\#cl - \delta|}\right)$$

δ is the average true number of senses of the words in a test corpus

Spectral Clustering Evaluation

Cross Feature Cross Similarity Fusion ($X_F X_S F$)					
$X_F(X_S(S^L, S^S), M^L)$	78.40	80.40	76.10	3.11	
$X_F(X_S(S^L, S^S), M^S)$	78.90	81.80	75.60	3.16	
Early Cross Feature Fusion ($EX_F F$)					
$E(M^L, X_F(S^L, M^L))$	79.20	82.40	75.70	3.57	**2F**
$E(M^S, X_F(S^L, M^L))$	78.30	80.50	75.80	1.95	
Late Cross Feature Fusion ($LX_F F$)					
$L(M^S, X_F(S^L, M^S))$	78.60	81.10	75.80	4.22	
$L(M^L, X_F(S^L, M^L))$	**79.50**	**82.80**	75.70	3.96	
Early Late Cross Feature Fusion ($ELX_F F$)					
$E(M^L, L(M^S, X_F(S^L, M^S)))$	78.50	81.40	75.40	4.26	**HF**
$E(M^L, L(M^L, X_F(S^L, M^L)))$	**79.50**	82.70	75.90	3.99	
Baseline MFS	78.70	80.90	76.20	1.00	

Figure 1: Supervised Recall

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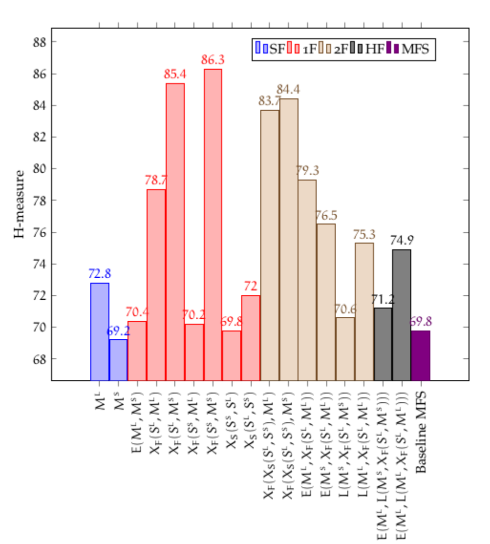
Figure 1: Supervised Recall

Early Fusion (EF)					
$E(M^L, M^S)$	74.00	76.66	71.11	4.46	
Cross Feature Fusion ($X_F F$)					
$X_F(S^L, M^L)$	76.20	79.60	72.50	3.63	
$X_F(S^L, M^S)$	74.60	75.10	73.90	3.08	**1F**
$X_F(S^S, M^L)$	**78.90**	80.70	**76.90**	1.08	
$X_F(S^S, M^S)$	73.70	77.70	70.00	2.72	
Cross Similarity Fusion ($X_S F$)					
$X_S(S^S, S^L)$	**78.90**	**80.80**	76.80	1.01	
$X_S(S^L, S^S)$	78.70	80.50	76.80	1.33	

Figure 2: Unsupervised F-measure

Spectral Clustering Evaluation



Proposed Algorithm Evaluation

	Early Fusion (EF)			
$E(M^L, M^S)$	78.80	81.00	**76.40**	2.43
	Cross Feature Fusion ($X_F F$)			
$X_F(S^L, M^L)$	78.70	80.90	76.20	3.11
$X_F(S^L, M^S)$	78.50	81.10	75.60	1.92
$X_F(S^S, M^L)$	**79.10**	**81.60**	**76.40**	1.73
$X_F(S^S, M^S)$	78.60	80.90	76.00	1.81
	Cross Similarity Fusion ($X_S F$)			
$X_S(S^S, S^L)$	78.60	80.80	76.20	1.44
$X_S(S^L, S^S)$	78.70	80.90	76.20	1.10

1F

Figure 4: Supervised Recall

Proposed Algorithm Evaluation

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	Cross Feature Fusion ($X_F F$)				
$X_F(S^L, M^L)$	78.70	80.90	76.20	3.11	
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$X_F(S^S, M^L)$	**79.10**	**81.60**	**76.40**	1.73	
$X_F(S^S, M^S)$	78.60	80.90	76.00	1.81	
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$X_S(S^S, S^L)$	78.60	80.80	76.20	1.44	
$X_S(S^L, S^S)$	78.70	80.90	76.20	1.10	

Figure 4: Supervised Recall

	Early Fusion (EF)				
$E(M^L, M^S)$	76.90	**80.20**	73.10	2.43	
	Cross Feature Fusion ($X_F F$)				
$X_F(S^L, M^L)$	71.00	68.10	74.20	3.11	
$X_F(S^L, M^S)$	77.70	79.60	75.50	1.92	1F
$X_F(S^S, M^L)$	75.20	75.50	74.90	1.73	
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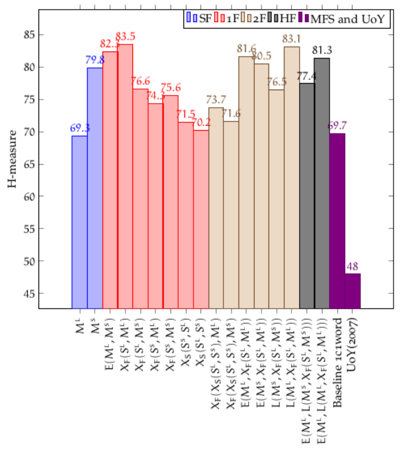

Figure 6: Proposed H-measure

Conclusions

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    - The community finding algorithm improves over similar algorithms while being simpler and allows for heterogeneous features
    - The Wikipedia-based instantiation serves as a NLP system starting

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  - Test more feature weighting schemes, validate findings on more datasets

Publications Produced by Our Research

- Edmundo-Pavel Soriano-Morales, Julien Ah-Pine, Sabine Loudcher: **Fusion Techniques for Named Entity Recognition and Word Sense Induction and Disambiguation.** DS 2017
- Edmundo-Pavel Soriano-Morales, Julien Ah-Pine, Sabine Loudcher: **Using a Heterogeneous Linguistic Network for Word Sense Induction and Disambiguation.** CICLING 2016
- Edmundo-Pavel Soriano-Morales, Julien Ah-Pine, Sabine Loudcher: **Hypergraph Modelization of a Syntactically Annotated English Wikipedia Dump.** LREC 2016
- Adrien Guille, Edmundo-Pavel Soriano-Morales, Ciprian-Octavian Truica: **Topic modeling and hypergraph mining to analyze the EGC conference history.** EGC 2016
- Adrien Guille, Edmundo-Pavel Soriano-Morales: **TOM: A library for topic modeling and browsing.** EGC 2016:

Publications Produced by Our Research

- Julien Ah-Pine, Edmundo-Pavel Soriano-Morales: **A Study of Synthetic Oversampling for Twitter Imbalanced Sentiment Analysis**. DMNLP@PKDD/ECML 2016
- Sabine Loudcher, Wararat Jakawat, Edmundo-Pavel Soriano-Morales, Cécile Favre: **Combining OLAP and information networks for bibliographic data analysis: a survey**. Scientometrics 103(2)

The End

Thank you for your attention

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