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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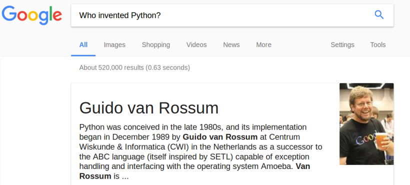
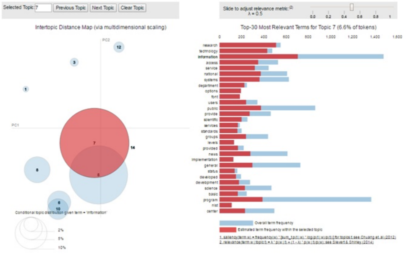
Introduction

Why it is useful to we research written language understanding?

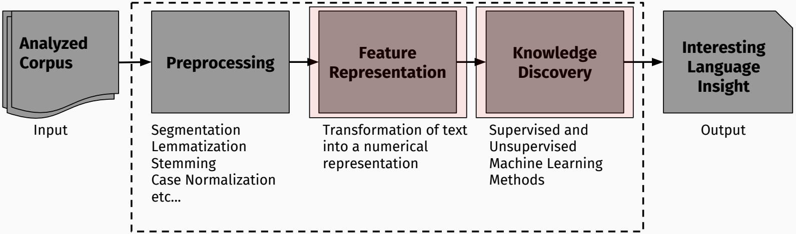




Introduction

How do we extract meaning from written language?

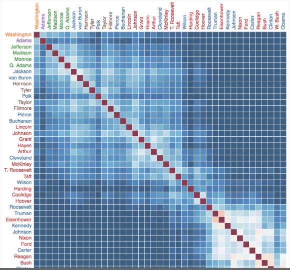
We use **Natural Language Processing** (NLP), a field of computer science interested on making computers extract useful information from text



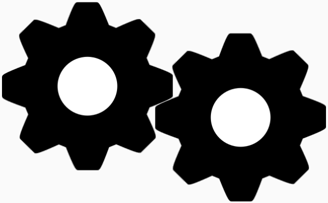
Introduction

In this thesis, we focus on 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?



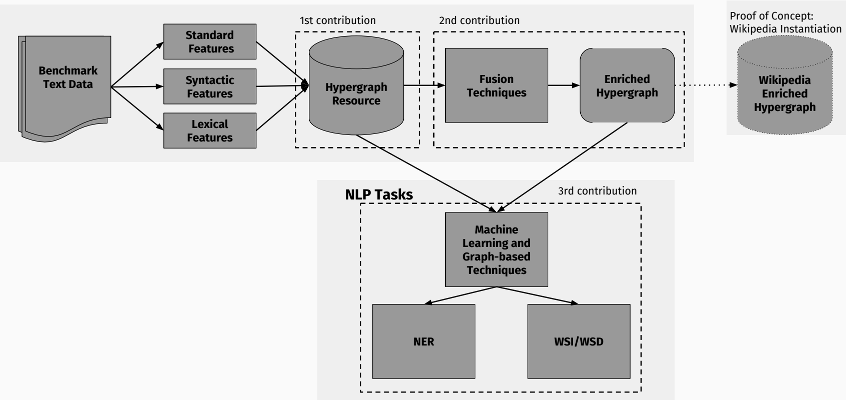
Introduction

Research work carried out in this thesis

- **Main Challenges and Contributions**
  1. What type of model can we employ to represent a corpus using heterogeneous features?
     - *Hypergraph linguistic model to hold different types of linguistic information*
  2. How can we combine these features while dealing with feature sparsity?
     - *Multimedia fusion techniques to combine and densify representation spaces*
  3. How can we find and employ communities existing within the language networks?
     - *An alternative network-based algorithm to discover semantically related words within a text*

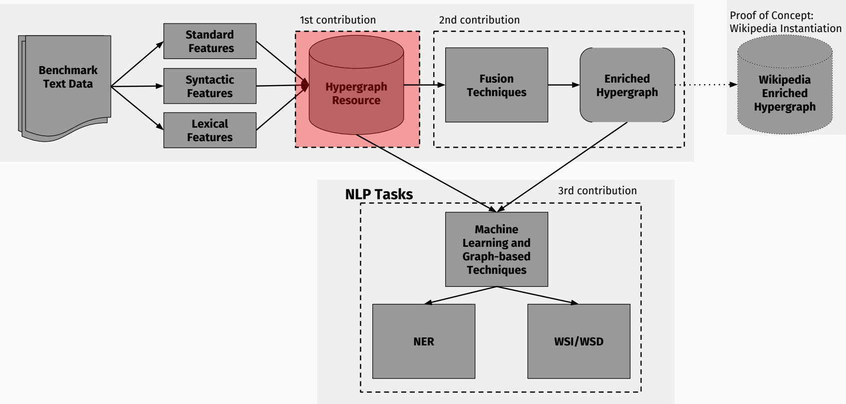
Introduction

Approach Overview



First Contribution: Hypergraph Linguistic Model

Work Overview



Introduction

What type of model can we employ to represent textual features? Which textual features?

- **Models used to represent textual information**
  - Vector Space Models [MS+99]
  - Network Models [MTF04]
- **Generally used types of features**
  - Lexical: words as they appear in the text
  - Syntactic: the role a word plays in the text
  - Semantic: the meaning of the word given the text

First Contribution: Hypergraph Linguistic Model

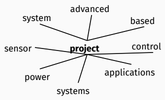
Hypergraph Representation

State of the Art and Proposition

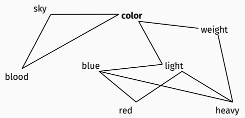
How to represent words in a network according to different language properties?

- **Existing representations**
  - Lexical Co-occurrence Networks [DMN11; Jur11; Qia+14]
  - Syntactic Co-occurrence Networks [BP13]
  - Semantic Networks [SP10; MRN14]
  - Heterogenous Networks [SN13]

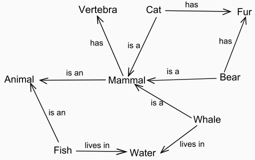
Lexical Networks



Syntactic Networks



Semantic Networks



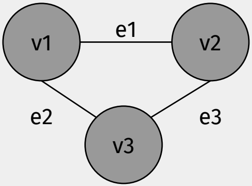
State of the Art and Proposition

- **Limitations of existing representations**
  - Language networks generally employ a single type of textual information
  - The edges of the network may relate maximum two words at each time
- **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)

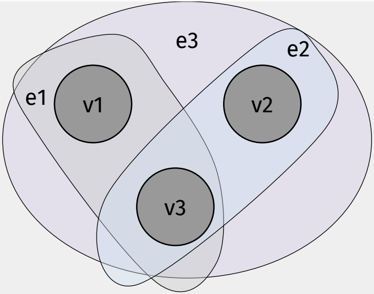
Proposed Model: Definitions

Hypergraph Linguistic Model

- **Hypergraph:**
  - A graph generalization, where edges may link more than 2 nodes at the same time. It can be seen as a set of sets



e1 = {v1, v2}



e1 = {v1, v3}

Proposed Model: Definitions

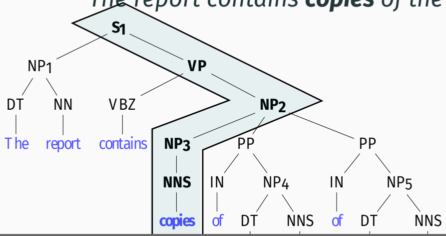
Hypergraph Linguistic Model

- **Linguistic Features:**
  1. **CONSTITUENT (M^N):** noun phrase constituents memberships
  2. **DEPENDENCY** (M^S) dependency relations. We consider all types of dependency functions between nouns and verbs,
  3. **SENTENCE (M^L):** lexical context, in this case the window considered is the whole sentence
- **Show image with the three different levels**

Proposed Model: Working Example

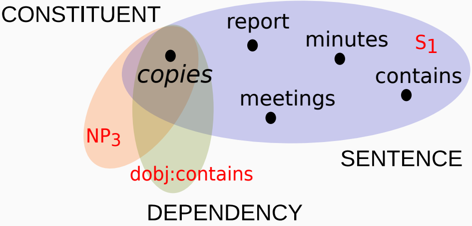
- **Input:** Set of linguistic features from an entry corpus
- **Output:** A network relating words according to the input features. Computationally, a key-value structure holding words and their descriptors for fast retrieval
- **Example sentence S_1:**

*The report contains **copies** of the minutes of these meetings.*



root(root, contains)
det(report, The)
dobj(contains, copies)
case(minutes, of)

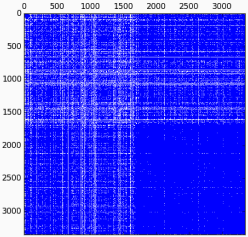
Proposed Model: Working example



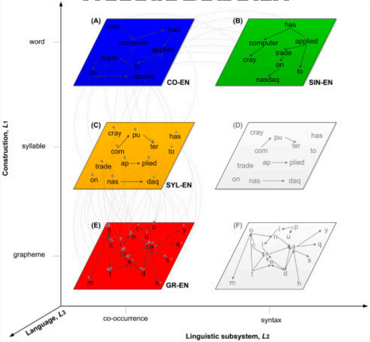
		CONSTITUENT			DEPENDENCY		SENTENCE
		NP_1 DT:NN	NP_2 NP:PP:PP	NP_3 NNS	nsubj contains	dobj contains	S_1
NN	report	1			1		1
	copies		1	1		1	1
	minutes		1				1
	meetings		1				1
VB	contains						1

Challenges of textual representations

Sparsity

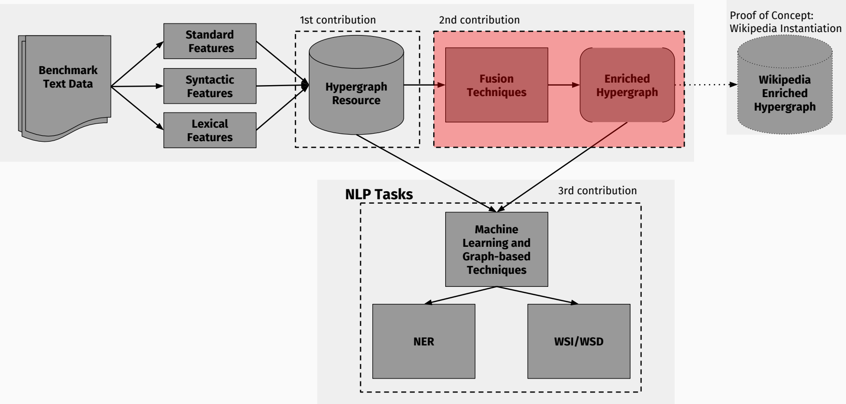


Heterogeneity



Second Contribution: Combining Features and Dealing with Sparsity

Work Overview



Second Contribution: Combining Features and Dealing with Sparsity

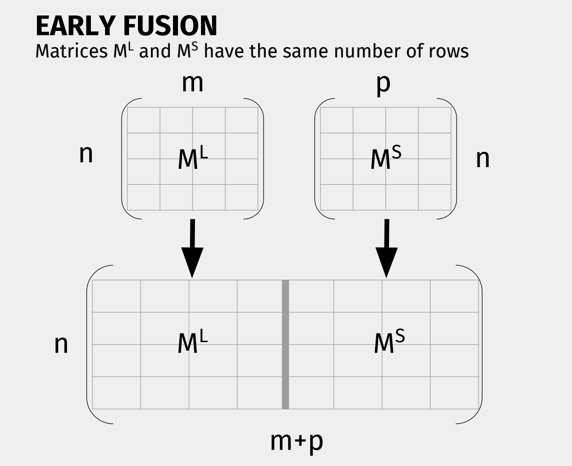
Term Representation Enrichment

Introduction

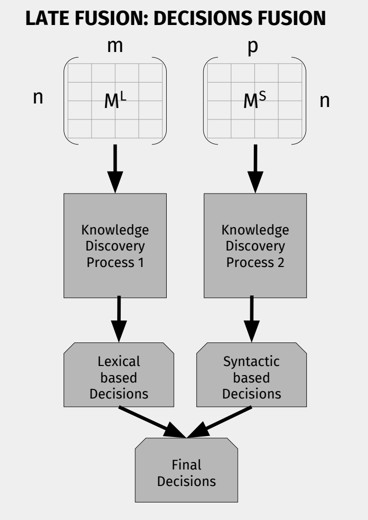
Multimedia Fusion Techniques [Atr+10; ABL10]:

- **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

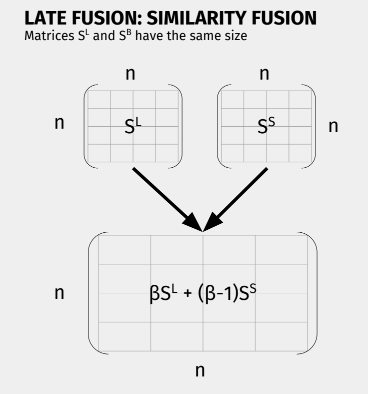
Early Fusion



Late Fusion

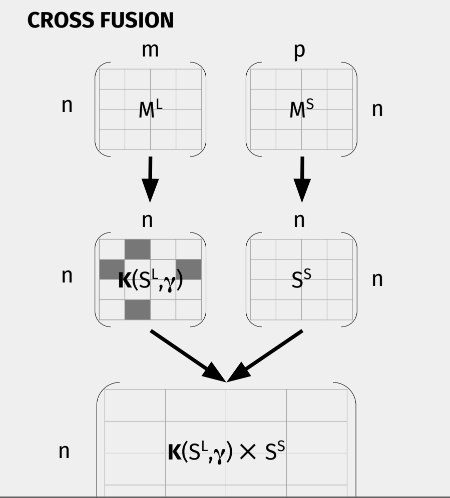


LATE FUSION: DECISIONS FUSION
m
p
n
M^L
M^S
n
Knowledge Discovery Process 1
Knowledge Discovery Process 2
Lexical based Decisions
Syntactic based Decisions
Final Decisions



LATE FUSION: SIMILARITY FUSION
Matrices S^L and S^B have the same size
n
n
n
S^L
S^S
n
n
$\beta S^L + (\beta\text{-}1)S^S$
n

Cross Fusion



Levels of Fusion

In our work we distinguish three levels of fusion operators:

- **First Degree Fusion (1F)**
  - $E(M^L, M^S)$
  - $X_F(S^L, M^S)$
  - $X_S(S^S, S^L)$

Levels of Fusion

In our work we distinguish three levels of fusion operators:

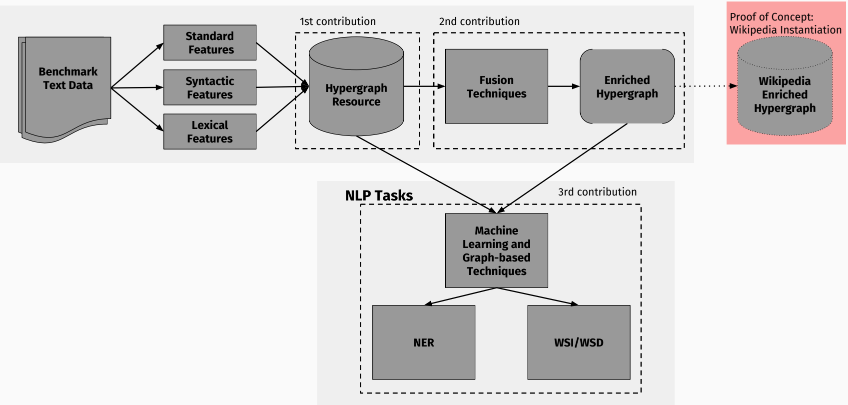
- **Second Degree Fusion (1F)**
  - Cross Feature Early Fusion: $X_F(S^L, E(M^L, M^S))$
  - Cross Feature Cross Similarity Fusion: $X_F(X_S(S^T, S^S), M^T)$
  - Early Cross Feature Fusion: $E(M^T, X_F(S^L, M^T))$
  - Late Cross Feature Fusion: $L(M^T, X_F(S^T, M^T))$

Levels of Fusion

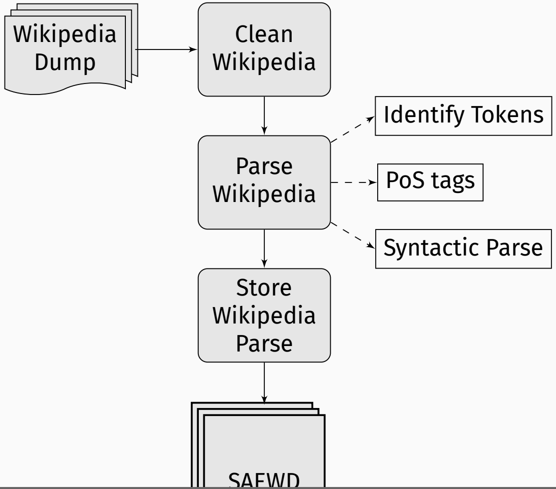
In our work we distinguish three levels of fusion operators:

- **Higher Degree Fusion (HF)**
  - $E(M^L, E(E(M^T, L(M^T, X_F(S^T, M^T))), L(M_L, X_F(S^S, M^L))))$
    - **Show decomposition of operator graphically**

Work Overview



SAEWD: A Wikipedia Enriched Hypergraph



Wikipedia Feature Enriched Spaces

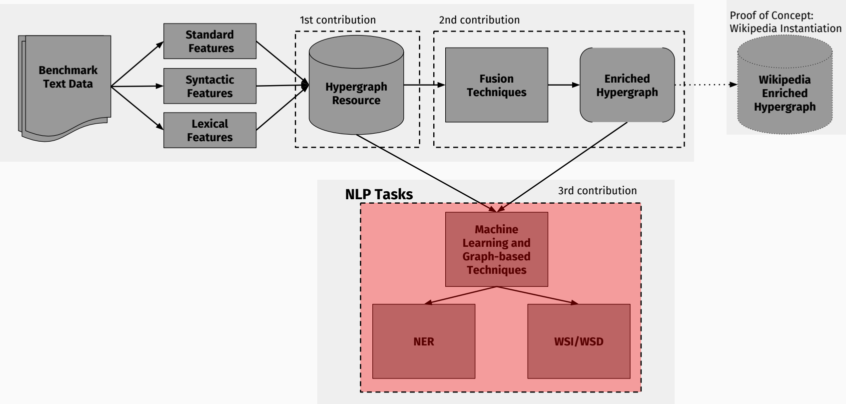
	Lexical Features (5.49%) M^L	Syntactic Features (4.97%) M^S	Early Fusion (5.23%) $E(M^L, M^S)$	X_F Fusion (16.75%) $X_F(S^S, M^L)$	X_F Fusion (13.45%) $X_F(S^L, M^S)$
priest	priests nun canton sailor burial	monk regent aedile seer meek	sailor regent nuclei nun relic	vassal regent nun sailor monk	sailor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

Wikipedia Similarity Enriched Spaces

	Lexical Similarity (75.25%) S^L	**Syntactic Similarity (60.64%)** S^S	**Early Fusion (67.94%)** $E(S^L, S^S)$	**Late Fusion (83.17%)** $L(S^L, S^S)$	X_S **Fusion (87.22%)** $X_S(S^S, S^L)$	X_S **Fusion (79.69%)** $X_S(S^L, S^S)$
priest	wholly burial monk lingua nuclei	regent coach broker dream tailor	regent slang broker rebel tiger	regent slang seer tutor cradle	regent vassal vizier leader result	sailor nuclei nun canton burial

Third Contribution: Applications to Named Entity Recognition and Word Sense Disambiguation

Work Overview



Introduction

Applications

- 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

Third Contribution: Applications to Named Entity Recognition and Word Sense Disambiguation

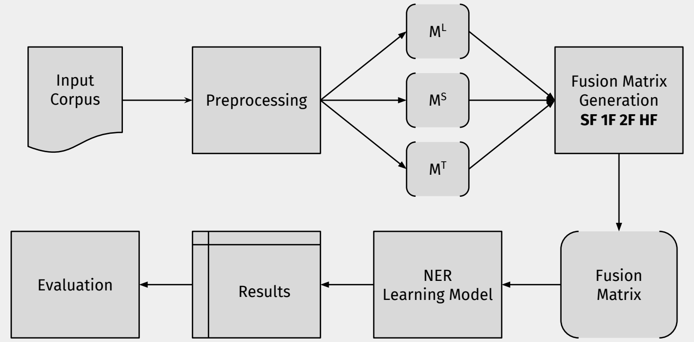
Named Entity Recognition (NER)

Introduction

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**

Experiment Flow Diagram



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

Representation Spaces

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

Representation Spaces

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

F-measure on the three datasets using single features independently with the structured perceptron

A	Single Features		
	CONLL	**WNER**	**WGLD**
M^T	**77.41**	**77.50**	**59.66**
M^L	69.40	69.17	52.34
M^S	32.95	28.47	25.49

Evaluation

F-measure on the three datasets using First Degree (1F) fusion operators

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**

		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**

Evaluation

F-measure on the three datasets using Second Degree (2F) fusion operators

In $X_F X_S F$, $\hat{a}$ corresponds to the best performing matrix in the set $\{X_S(S^T, S^L), X_S(S^L, S^T), X_S(S^T, S^S)\}$

A	B	CONLL	WNER	WGLD
		Cross Feature Cross Similarity Fusion ($X_F X_S F$)		
$\hat{a}$	M^T	37.69	59.44	**41.71**
$\hat{a}$	M^L	**38.31**	**58.73**	41.56
$\hat{a}$	M^S	29.31	52.06	34.91
		Cross Feature Early Fusion ($X_F EF$)		
		CONLL	WNER	WGLD
S^T	$E(M^L, M^T)$	**54.34**	**64.20**	39.59
S^L	$E(M^L, M^T)$	49.71	71.84	**45.14**
S^S	$E(M^L, M^T)$	47.54	53.77	43.32

In $EX_F F$, $b^*_{EX_F F} \in \{X_F(S^S, M^L), X_F(S^L, M^L), X_F(S^L, M^T), X_F(S^S, M^L), X_F(S^S, M^T)\}$

		CONLL	WNER	WGLD
		Early Cross Feature Fusion ($EX_F F$)		
M^T	$b^*_{EX_F F}$	49.58	**77.32**	**61.69**
M^L	$b^*_{EX_F F}$	49.79	66.22	53.54
M^S	$b^*_{EX_F F}$	**51.53**	70.94	53.70
		Late Cross Feature Fusion ($LX_F F$)		
		CONLL	WNER	WGLD
M^T	$\hat{b}_{LX_F F}$	54.82	**75.70**	**54.73**
M^L	$\hat{b}_{LX_F F}$	**56.53**	62.27	52.39

Evaluation

F-measure on the three datasets using Higher Degree (HF) fusion operators

In $EEELX_FLX_F$, $\hat{b}_{EEELX_FLX_F} \in E(E(M^T, L(M^L, X_F(S^S, M^L))),$ $L(M^L, X_F(S^T, M^L))), E(E(M^T, L(M^T, X_F(S^S, M^T))), L(M^L, X_F(S^S, M^L)))$ for CONLL, WNER and WGLD.

A	B	Early Late Cross Feature Fusion (ELX_FF)		
		CONLL	WNER	WGLD
M^T	$L(M^L, X_F(S^S, M^L))$	67.16	79.45	62.37
		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

Third Contribution: Applications to Named Entity Recognition and Word Sense Disambiguation

Fusion Analysis

Analyzing the Best Fusion Operator

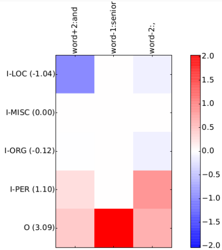
Decompose best fusion in four models:

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

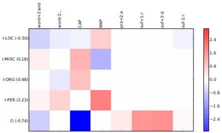
1. M^L used to train model M_1.
2. $E(\alpha_1 M^L, \alpha_2 M^T)$ used to train model M_2, with $\alpha_1 = 0.95, \alpha_2 = 0.05$
3. $E_\alpha(\alpha_1 M^L, \alpha_2 M^T, \alpha_3 L(M^T, X_F(S^S, M^T)))$ used to train model M_3, with $\alpha_1 = 0.95, \alpha_2 = \alpha_3 = 0.05$
4. $E_\alpha(\alpha_1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

Analyzing the Best Fusion Operator

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



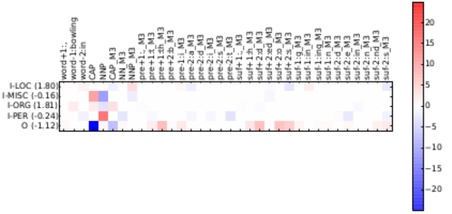
(a) The word *Kory* is predicted to be class O by model M_1 given the coefficients of the features indicated.



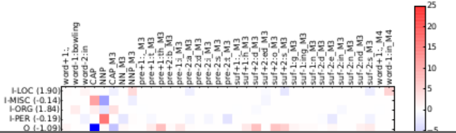
(b) The same word is correctly predicted to be class PER by model M_2 given the new features in the model.

Analyzing the Best Fusion Operator

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



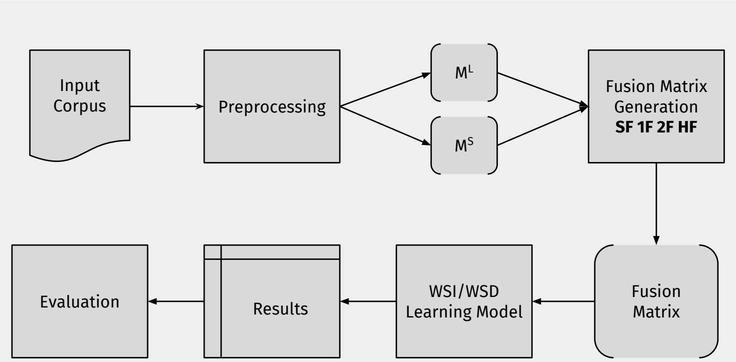
(a) The word *Green* is predicted to be class ORG by model M_3 given the coefficients of the features indicated.



Third Contribution: Applications to Named Entity Recognition and Word Sense Disambiguation

Word Sense Disambiguation

Experiment Flow Diagram



Experimental Protocol

Supevised Evaluation

Unsupevised Evaluation

Proposed Evaluation

Third Contribution: Applications to Named Entity Recognition and Word Sense Disambiguation

Leveraging the Linguistic Network Structure

Introduction and State of the Art

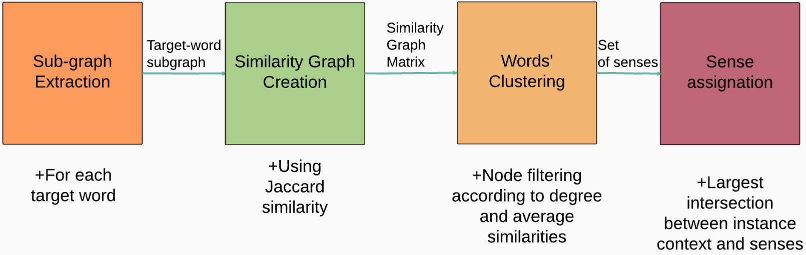
How to exploit a linguistic network to solve word sense induction and disambiguation?

- **Existing graph-based approaches**
  - Hyperlex [V04]
  - University of York (UoY) [KM07]
- **Limitations of existing approaches**
  - Single typed networks
  - Large number of parameters

Proposed Method

- **Features**
  - Automatically group words to induce senses and then assign them
  - 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
  - Use a robust and interpretable similarity measure

Proposed Method



Proposed Method: Step One

- **Creation of the linguistic network**
  - After preprocessing, we build a HLM G_{tw} that contains the co-occurrent (lexically and syntactically) words for a target word tw.

Proposed Method: Step Two

- **Computing the similarity between nodes**
  - G_{tw} is represented as a bipartite graph B_{tw}. Left nodes U represent words and right nodes W correspond to the hyperedges. An edge from a node u to a node w depicts the incidence of node u in hyperedge w.
  - A similarity matrix S_{tw} of dimension $|U| \times |U|$ is calculated using the Jaccard similarity: given $n_{i,j} \in U$, then $Jaccard(i,j) = \frac{|N(i) \cap N(j)|}{|N(i) \cup N(j)|}$.
  - Induce a new incidence matrix F_{tw} from S_{tw} containing only the closest neighbours to each word $n_i \in U$. Each of these hyperedges represent a set of words that are deemed similar between them according to their Jaccard index value, which must be equal or higher than an assigned threshold th_1.

Proposed Method: Step Three

- **Clustering words together**
  - We select the top c-nodes in F_{tw} according to their degree. These nodes are candidate hubs, which must surpass a second threshold th_2 to be considered as proper hubs. We use the average Jaccard measure defined for each node n as:

$$AvgJaccard(n) = \frac{1}{|hedges(n)|} \sum_{h \in hedges(n)} \frac{\sum_{\substack{i \in h \\ j \in h; i \neq j}} Jaccard(i,j)}{|h+1|}$$

    where $hedeges(n)$ is the set of hyperedges n is incident in and its cardinality is defined as $|hedges(n)|$. $|h|$ is the number of nodes in hyperedge h.
  - Accepted hubs represent senses alongside with their co-occurrent words. The final set of senses is called SoS_{tw}.

Proposed Method: Step Four

- **Word Sense Disambiguation**
  - The assignation of a sense consists in looking at each *tw* instance represented by a context *ct* and simply determining which sense *s* in SoS_{tw} shares the highest amount of words with *ct*. The sense *s* is thus assigned to that instance.

Semeval Results

Unsupervised paired F-Score (FS) for Semeval-2007

FS (%)	all	nouns	verbs	#cl
1c1word	78.9	80.7	76.8	1.00
UBC-AS	78.7	80.8	76.3	1.32
DEP	74.9	80.2	69.0	3.27
LEX	61.4	62.6	60.1	4.26
UoY(2007)	56.1	65.8	45.1	9.28
Random	37.9	38.1	37.7	19.7
1c1instance	9.5	6.6	12.7	48.51

Semeval Results

Supervised Recall (SR) for Semeval-2007

SR (%)	all	nouns	verbs	#cl
I2R	81.6	86.8	75.7	3.08
LEX	79.4	82.5	75.9	4.26
DEP	79.1	81.5	76.4	3.27
MFS	78.7	80.9	76.2	1
UoY(2007)	77.7	81.6	73.3	9.28

Semeval Results

- **Discussion**
  - Both **DEP** and **LEX** beat the competition baselines
  - They also beat the most similar approach UoY(2007)
  - Best result for verbs concerning supervised Recall
  - Possibility for features' combination: both seem to complement each other

Conclusions and Future Work

Conclusions

Future Work

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Appendix

Appendix

WSI/D Method in Detail

Proposed Method: Step One

- **Creation of the linguistic network**
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Experiments

- **Implementation Framework**
  - **Systems built and evaluated**: **DEP** and **LEX**.
    - **DEP**: Syntactical dependencies
    - **LEX**: Lexical co-occurrences
  - **Two datasets**: Semeval-2007 Task 2 (100 words: 35 nouns, 65 verbs) and Semeval-2010 Task 14 (100 words: 50 nouns, 50 verbs). For brevity, only the results for the first dataset are discussed in this presentation.
  - **Evaluation metrics**: Unsupervised evaluation (Paired F-Score, V-Measure). Supervised evaluation (Recall).

Results Semeval 2010

VM (%)	all	nouns	verbs	#cl
Hermit	16.2	16.7	15.6	10.78
NMF_{lib}	11.8	13.5	9.4	4.80
LEX	11.6	8.8	11.9	10.5
Random	4.4	4.2	4.6	4.00
DEP	3.5	3.9	2.8	2.75
MFS	0.0	0.0	0.0	1.00

Table 1: Unsupervised V-Measure (VM) on the Semeval 2010 test set

Results Semeval 2010

FS (%)	all	nouns	verbs	#cl
MFS	63.5	57.0	72.4	1.00
Duluth-WSI-SVD-Gap	63.3	57.0	72.4	1.02
DEP	53.6	50.1	58.7	2.75
NMF_{lib}	45.3	42.2	49.8	5.42
LEX	38.4	46.7	28.5	10.5
Random	31.9	30.4	34.1	4.00

Table 2: Unsupervised Paired F-Score (FS) for the Semeval 2010 test set

Results Semeval 2010

SR (%)	all	nouns	verbs
NMF_{lib}	62.6	57.3	70.2
UoY(2010)	62.4	59.4	66.8
LEX	59.8	55.8	67.4
DEP	59.3	53.9	67.2
MFS	58.7	53.2	66.6
Random	57.3	51.5	65.7

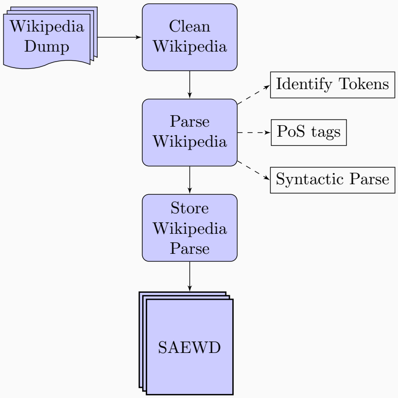
Table 3: Supervised recall (SR) for Semeval 2010 test set (80% mapping, 20% evaluation)

Appendix

SAEWD

SAEWD: Syntactically Annotated English Wikipedia Dump

Building SAEWD



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

Appendix

Ongoing Results

Ongoing Work: Results

- **Combining the hyperedges: cross fusion**

Unsupervised paired F-Score (FS) for the Semeval 2007 test set

FS (%)	**all**	**nouns**	**verbs**	**#cl**
1c1word	78.9	80.7	76.8	1.00
UBC-AS	78.7	80.8	76.3	1.32
CROSS$_{k=75}$	78.6	80.7	76.3	1.70
DEP	74.9	80.2	69.0	3.27
CLUST$_{k=5,th=55}$	72.5	76.0	63.8	5.47
LEX	61.4	62.6	60.1	4.26
UoY(2007)	56.1	65.8	45.1	9.28
Random	37.9	38.1	37.7	19.7
1c1instance	9.5	6.6	12.7	48.51