Introduction to Human Language Technologies
6. Word Sense Disambiguation

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Outline

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1. Word Sense Disambiguation
   - Goal and Motivation
   - Resources
2. WSD Approaches

Goal

- Semantic resources provide the possible senses for each word (polisemy)

lema	**PoS**	**sense**
dog	NN	1. animal
		2. (colloquial) wicked person
	VB	1. to follow
		...

- **Goal**: automatically select the right sense for an occurrence of a word in a sentence (for NN, JJ, VB and maybe ADV)

Motivation

- WSD is potentially useful for many NLP applications:
  - Speech Synthesis and Recognition
  - Acquisition of Lexical Knowledge
  - Semantic Parsing
  - Sentiment Analysis
  - IR, IE, QA, MT
  - ...
- WSD has been defined as AI-complete (Ide & Véronis, 1998)
- Unfortunately, this usefulness has not been proven yet

Motivation

- Ex.: Semantic parsing: selecting the right word sense is needed to build the meaning of the sentence

sense	**gloss from WordNet 1.5**
age 1	the length of time something (or someone) has existed
age 2	a historic period

He was mad about stars at the age of nine .

Motivation

- P.e.: MT: selecting the right word sense is needed to translate a word into the target language.

NOUN

1. (animal)

a. **el perro (m)**, **la perra (f)**

My dog is a German Shepherd. — Mi perro es un pastor alemán.

2. (colloquial) (wicked person)

a. **el bribón (m)**, **la bribona (f)**

My coworker is a lazy dog; I'm always having to do his work. — Mi colega es un bribón perezoso; siempre le tengo que estar haciendo el trabajo.

b. **el canalla (m)**, **la canalla (f)** (colloquial)

That dog started cheating on his girlfriend almost as soon as they started going out. — Ese canalla le pegó cuernos a su novia prácticamente tan pronto empezaron a salir.

3. (pejorative) (unattractive woman)

TRANSITIVE VERB

4. (to follow)

a. **seguir**

The neighborhood bullies dogged him all the way to his house. — Los matones del vecindario lo siguieron el camino entero hasta llegar a su casa.

5. (to plague)

a. **perseguir**

He has been dogged by scandal his entire career. — El escándalo lo ha perseguido durante su carrera entera.

Source: `http://www.spanishdict.com`.

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Resources

- Sense Definitions
  - Machine Readable Dictionaries
  - WordNets

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  - WordNets
- Corpora
  - Samples with only one word labeled for each sample
    - SemEval Lexical Sample Task (training/Test corpus)
    - mainly for supervised Machine Learning algorithms

800004
Mr Purves is tight-lipped about what happens then.
He vexed rumour-mongers, who <tag '520051'>bet</> on a bid for Midlan sooner.
800005
Mr Jones loses his <tag '519914'>bet</>:1,000 people attended Cowley pools last year.

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  - Samples with all the words labeled
    - Semcor, SemEval All Words Task (Test corpus)
    - mainly for unsupervised algorithms

Outline

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Types of WSD Algorithms

- **Based on corpus**:
  - **Supervised approaches**:
    - Occurrences of a particular word in text annotated with their correct senses
    - Ex.: Naïve Bayes, kNN or SVM
    - word embeddings + deep learning, sense embeddings (to see in AHLT)

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    - Ex.: Yarowsky Algorithm (Bootstrapping)
- **Knowledge-based**: from a external knowledge source
  - **Unsupervised approaches**
  - They use lexical knowledge (WordNets, machine readable dictionaries)
  - Ex.: Lesk Algorithm (available at NLTK),
UKB (available via TextServer)

Outline

Based on Corpus: Supervised ML Approaches

WSD as a classification problem: learn a model useful to disambiguate occurrences of **a particular word** in text

veo	un	banco	de	peces	desde	el	banco

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veo	un	banco	de	peces	desde	el	banco

$$\begin{array}{c} \downarrow \\ M_{ver} \\ \downarrow \\ ver_1 \\ ver_2 \\ ver_3 \end{array}$$

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veo	un	banco	de	peces	desde	el	banco
$\downarrow$		$\downarrow$					
M_{ver}		M_{banco}					
$\downarrow$		$\downarrow$					
ver_3		$banco_1$					
		$banco_2$					
		$banco_3$					
		$banco_4$					
		$banco_5$					
		...					

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veo	un	banco	de	peces	desde	el	banco
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M_{ver}		M_{banco}		M_{pez}			
$\downarrow$		$\downarrow$		$\downarrow$			
ver_3		$banco_4$		pez_1			
				pez_2			
				pez_3			
				pez_4			

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ver_3		$banco_4$		pez_1			$banco_1$
							$banco_2$
							$banco_3$
							$banco_4$
							$banco_5$
							$\ldots$

Based on Corpus: Supervised ML Approaches

WSD as a classification problem: learn a model useful to disambiguate occurrences of **a particular word** in text

- **Set of categories**:

  $\{\text{sense}_1 \ldots, \text{sense}_k\}$

  Ex.:

  44 different senses of word *bajo* in Spanish (NN, JJ, VB)

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- **Annotated corpus** :

  $\{<\mathrm{occurrence}_i, \mathrm{context}_i, \mathrm{right\_sense}_i >\}$

  Ex.:

			e_1^+			e_2^+
text:	el	niño	bajo	toca	el	bajo
POS:	DT	NN	JJ	VB	DT	NN
			01206474-a			02803349-n

Based on Corpus: Supervised ML Approaches

WSD as a classification problem: learn a model useful to disambiguate occurrences of **a particular word** in text

- Examples:

  $\{e^+\}$: $\{<$occurence$_i$, context$_i$, correct_sense$_i$ $>\}$

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- Representation with feature vectors:
  - Local context: word+position, lemma+position, POS+position
    Ex.: *come up with* → `w+1_up, w+2_with`

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  - Global context: bag of words, lemmas, bigrams or collocations
    Ex.: *I was studing at U.P.C. in Barcelona for 2 years* →
    `l+_year, co+_U.P.C._Barcelona.`

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  - Syntax: syntactic functions
    Ex.: *cats eat fish.* → `subj_cat, obj_fish`

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  - Syntax: syntactic functions
    Ex.: *cats eat fish.* → `subj_cat, obj_fish`
  - Semantics: domain, senses of previous words
    p.e.: the example is about *history* → `topic_history`

Exercise

We want the sentence below to be represented by local and topical features and be supplied as example for a ML algorithm:

Example He was mad about stars at the age of nine .
age.01

+ PoS ('He', 'PRP'), ('was', 'VBD'), ('mad', 'JJ'), ('about', 'IN'), ('stars', 'NNS'), ('at', 'IN'), ('the', 'DT'), ('age', 'NN'), ('of', 'IN'), ('nine', 'CD'), ('.', '.')

1. Give the bag of open-class words of the left context.
2. Give the local features in a ± 2 word window of the word forms.
3. Give two other possible local or topical features

Based on Corpus: Supervised ML Approaches

WSD as a classification problem: learn a model useful to disambiguate occurrences of **a particular word** in text

Bottleneck:

- The lack of models for all the words of a given language
- The difficulty of acquiring annotated corpora for learning models

Based on Corpus: Supervised ML Approaches

WSD as a classification problem: learn a model useful to disambiguate occurrences of **a particular word** in text

Bottleneck:

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Alternatives:

- Semisupervised methods (few annotated examples and lots of unannotated ones -ex.: bootstrapping-)
- Knowledge-based methods

Outline

Based on Knowledge: Lesk Algorithm

Lesk algorithm
Disambiguates just one word within a context

$$\mathrm{Lesk}(w) = \underset{s_i \in S(L(w))}{\operatorname{argmax}} \; \forall_{s_j \in S(C(w))} |\mathrm{Def}(s_i) \cap \mathrm{Def}(s_j)|$$

$L(w)$: set of lemmas of word w

$C(w)$: set of lemmas of open-class words in the context of w

$S(X)$: set of senses for all lemmas in X

$\mathrm{Def}(s)$: set of lemmas in the definition of sense s

Based on Knowledge: Lesk Algorithm

Example

Input: "pine cone"

PINE

1. kinds of evergreen tree with needle-shaped leaves
2. waste away through sorrow or illness

CONE

1. solid body which narrows to a point
2. something of this shape whether solid or hollow
3. fruit of certain evergreen trees

Based on Knowledge: Lesk Algorithm

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Solution (sin contar las *stopwords*)

Mejor intersección: $Pine\#1 \cap Cone\#3 = 2$.

sense for "pine": $Pine\#1$

Based on Knowledge: Lesk Algorithm

Example

Input: "pine cone"

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Solution (sin contar las *stopwords*)
Mejor intersección: $Pine\#1 \cap Cone\#3 = 2$.
sense for "cone": $Cone\#3$

Based on Knowledge: Lesk Algorithm Simplification

Simplified Lesk algorithm

$$\mathrm{Lesk}(w) = \underset{s_i \in S(\mathrm{L}(w))}{\operatorname{argmax}} |\mathrm{Def}(s_i) \cap \mathrm{C}(w)|$$

$\mathrm{L}(w)$: set of lemmas of word w

$\mathrm{C}(w)$: set of lemmas of open-class words in the context of w.

$S(X)$: set of senses for all lemmas in X

$\mathrm{Def}(s)$: set of lemmas in the definition of sense s.

In general, better performance than the general Lesk algorithm

Based on Knowledge: Lesk Algorithm Exercise

Given the sentence:

- `I went to the bank to deposit money.`

and the definitions of the two first senses of the word *bank*:

1. `sloping land (especially the slope beside a body of water)`
2. `a financial institution that accepts deposits and channels the money into lending activities`

apply simplified Lesk algorithm to find the most appropriate sense among them.

Based on Knowledge: Lesk's Algorithm Extensions

Lesk algorithm suffers from low recall

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Lesk algorithm suffers from low recall

Variants:

- Changing the similarity measure: Cosine
- Use of WordNet instead of a dictionary
- Enrichment with WordNet (Adapted/Extended Lesk) (Banerjee and Pederson, 2002/2003)
  - Use examples of Wordnet Synsets
  - Use the data of hypernyms and/or hyponyms
- Enrichment with WordNet and Wikipedia (Enhanced Lesk) (Basile et al. 2014)

Based on Knowledge: UKB

- Methods to disambiguate one word or all the words at the same time
- Based on **PageRank** algorithm from Google
  input: net of linked webpages
  output: relevance of each webpage included in the net

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- Methods to disambiguate one word or all the words at the same time
- Based on **PageRank** algorithm from Google
  - **input**: net of linked webpages
  - **output**: relevance of each webpage included in the net
- Analogy:
  - **input**: text to disambiguate and graph of word senses defined by their relations (ex. WordNet)
  - **output**: relevance of each sense of each word occurrence included in the text

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1. PRELIMINARY: How does **PageRank** perform?

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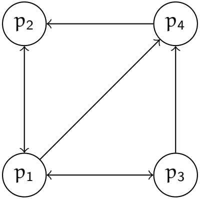

transition matrix

$$H = \begin{bmatrix} 0 & 1 & 1/2 & 0 \\ 1/3 & 0 & 0 & 1 \\ 1/3 & 0 & 0 & 0 \\ 1/3 & 0 & 1/2 & 0 \end{bmatrix}$$

Based on Knowledge: UKB

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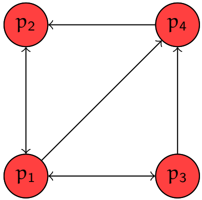
$$v_{(i+1)} = H \cdot v_i \qquad v_0 = [1/n]_n$$



transition matrix

$$H = \begin{bmatrix} 0 & 1 & 1/2 & 0 \\ 1/3 & 0 & 0 & 1 \\ 1/3 & 0 & 0 & 0 \\ 1/3 & 0 & 1/2 & 0 \end{bmatrix}$$

initial relevance vector

$$v_0 = \begin{bmatrix} 1/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{bmatrix}$$

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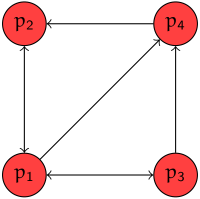

$$v_1 = \begin{bmatrix} - \\ - \\ - \\ - \end{bmatrix} = \begin{bmatrix} 0 & 1 & 1/2 & 0 \\ 1/3 & 0 & 0 & 1 \\ 1/3 & 0 & 0 & 0 \\ 1/3 & 0 & 1/2 & 0 \end{bmatrix} \cdot \begin{bmatrix} 1/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{bmatrix}$$

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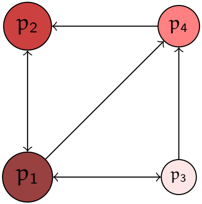

$$v_1 = \begin{bmatrix} 0.375 \\ 0.333 \\ 0.083 \\ 0.208 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 1/2 & 0 \\ 1/3 & 0 & 0 & 1 \\ 1/3 & 0 & 0 & 0 \\ 1/3 & 0 & 1/2 & 0 \end{bmatrix} \cdot \begin{bmatrix} 1/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{bmatrix}$$

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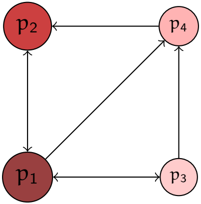

$$v_2 = \begin{bmatrix} 0.374 \\ 0.333 \\ 0.125 \\ 0.166 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 1/2 & 0 \\ 1/3 & 0 & 0 & 1 \\ 1/3 & 0 & 0 & 0 \\ 1/3 & 0 & 1/2 & 0 \end{bmatrix} \cdot \begin{bmatrix} 0.375 \\ 0.333 \\ 0.083 \\ 0.208 \end{bmatrix}$$

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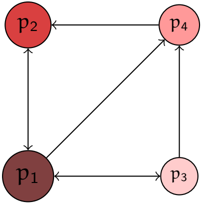

$$v_3 = \begin{bmatrix} 0.395 \\ 0.291 \\ 0.125 \\ 0.187 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 1/2 & 0 \\ 1/3 & 0 & 0 & 1 \\ 1/3 & 0 & 0 & 0 \\ 1/3 & 0 & 1/2 & 0 \end{bmatrix} \cdot \begin{bmatrix} 0.374 \\ 0.333 \\ 0.125 \\ 0.166 \end{bmatrix}$$

Based on Knowledge: UKB

1. PRELIMINARY: How does **PageRank** perform?

DRAWBACK: webpages without outcoming links and disconnected graphs

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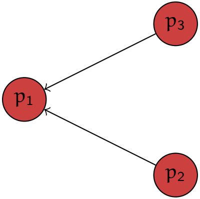

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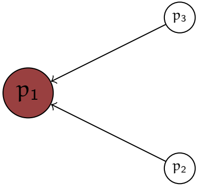

$$v_1 = \begin{bmatrix} 0.66 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix}$$

Based on Knowledge: UKB

1. PRELIMINARY: How does **PagеRank** perform?

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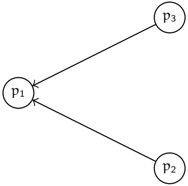
$$v_{(i+1)} = H \cdot v_i \qquad v_0 = [1/n]_n$$



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Based on Knowledge: UKB

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SOLUTION: select a webpage randomly

$$v_{(i+1)} = H \cdot v_i \quad v_0 = [1/n]_n$$

Based on Knowledge: UKB

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DRAWBACK: webpages without outcoming links and disconnected graphs
SOLUTION: select a webpage randomly

$$v_{(i+1)} = M \cdot v_i \qquad v_0 = [1/n]_n$$

$$M = (1 - \alpha) \cdot H + \alpha \cdot B$$

M: PageRank matrix

H: transition matrix

α: probability of random selection (default 0.15)

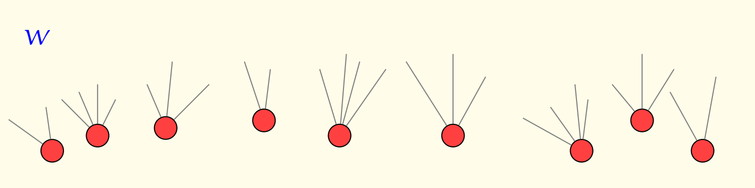
B: matrix $[1/n]_n^n$

Based on Knowledge: UKB

2. WSD using PageRank

* Use of WordNet as graph

$$v_{(i+1)} = M_W \cdot v_i \qquad v_0 = [1/|W|]_{|W|}$$



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2. WSD using PageRank

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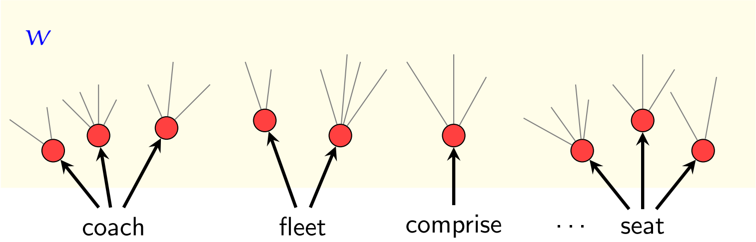
- Focused on the synsets of the input words



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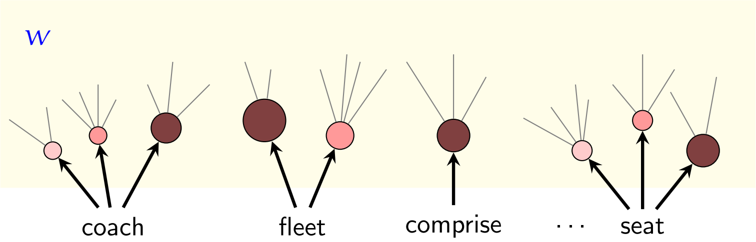
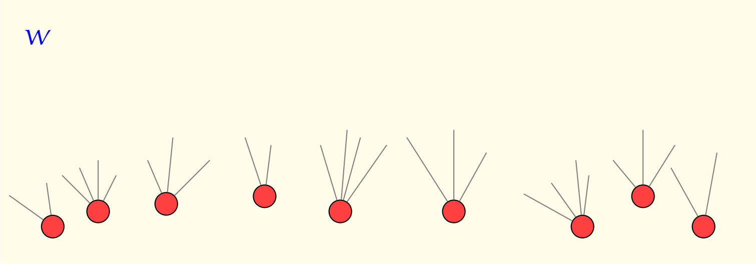


Based on Knowledge: UKB

2. WSD using PageRank

How does it focus on the synsets of the k input words?

$$v_{(i+1)} = M_W \cdot v_i \qquad v_0 = [1/|W|]_{|W|}$$



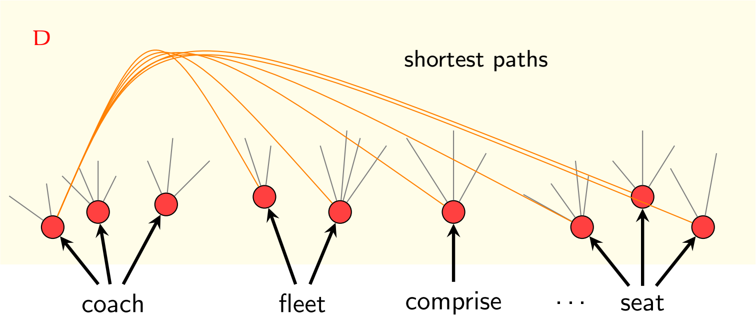
Based on Knowledge: UKB

2. WSD using PageRank

How does it focus on the synsets of the k input words?

OPTION 1. Restrict W to the disambiguation graph D

$$v_{(i+1)} = M_D \cdot v_i \qquad v_0 = [1/|D|]_{|D|}$$



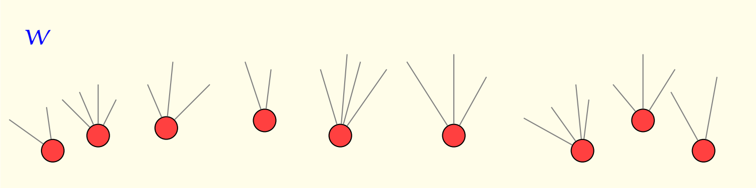
Based on Knowledge: UKB

2. WSD using PageRank

How does it focus on the synsets of the k input words?

OPTION 2. Personalize B to the k input words

$$v_{(i+1)} = M_W \cdot v_i \qquad v_0 = [1/|W|]_{|W|}$$



Based on Knowledge: UKB

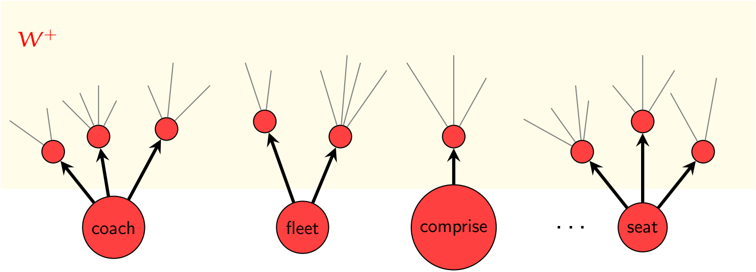
2. WSD using PageRank

How does it focus on the synsets of the k input words?

OPTION 2. Personalize B to the k input words

$$v_{(i+1)} = M_{W^+} \cdot v_i \qquad v_0 = [1/(|W| + k)]_{|W|+k}$$

- Add the k words as new nodes linked to their synsets



Based on Knowledge: UKB

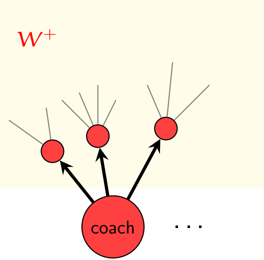
2. WSD using PageRank

How does it focus on the synsets of the k input words?

OPTION 2. Personalize B to the k input words

$$M_{W^+} = (1-\alpha) \cdot H_{W^+} + \alpha \cdot B_{W^+}$$

- Add the k words as new nodes linked to their synsets



$$H_{W^+} = \begin{array}{cc} \begin{array}{cc} \overbrace{\qquad\quad}^{|W|} & \overbrace{\quad\quad}^{k} \end{array} & \\ \left[\begin{array}{c:cc} & 0 & \dots \\ & 1/3 & \dots \\ & 1/3 & \dots \\ H_W & 0 & \dots \\ & \dots & \\ & 0 & \dots \\ & 1/3 & \dots \\ \hdashline 0 & 0 & \end{array}\right] & \begin{array}{l} \left.\begin{array}{c} \\ \\ \\ \\ \\ \\ \\ \end{array}\right\} |W| \\ \left.\begin{array}{c} \\ \end{array}\right\} k \end{array} \end{array}$$

Based on Knowledge: UKB

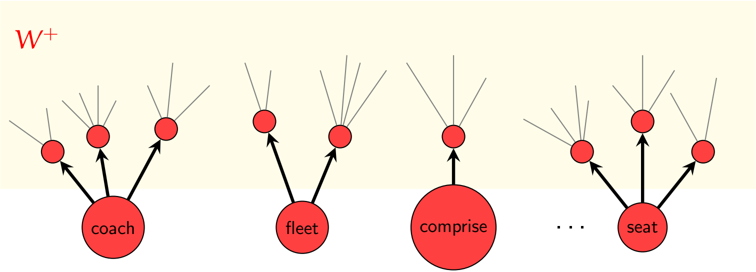
2. WSD using PageRank

How does it focus on the synsets of the k input words?

OPTION 2. Personalize B to the k input words

$$M_{W^+} = (1 - \alpha) \cdot H_{W^+} + \alpha \cdot B_{W^+}$$

- Concentrate the random selection prob. on the k words



Based on Knowledge: UKB

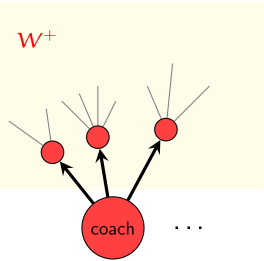
2. WSD using PageRank

How does it focus on the synsets of the k input words?

OPTION 2. Personalize B to the k input words

$$M_{W^+} = (1-\alpha) \cdot H_{W^+} + \alpha \cdot B_{W^+}$$

- Concentrate the random selection prob. on the k words



$$B_{W^+} = \begin{array}{cc} \begin{array}{cc} \overbrace{\hphantom{xxxxxxxxxxxxxxxx}}^{|W|} & \overbrace{\hphantom{xxxxx}}^{k} \end{array} & \\ \left[\begin{array}{ccc|cc} & 0 & & & 0 \\ & n = |W| + k & & & \\ \hline 1/n & & \cdots & \cdots & 1/n \\ \cdots & & \cdots & \cdots & \cdots \\ 1/n & & \cdots & \cdots & 1/n \end{array}\right] & \begin{array}{l} \left.\vphantom{\begin{array}{c}0\\0\end{array}}\right\} |W| \\ \left.\vphantom{\begin{array}{c}0\\0\\0\end{array}}\right\} k \end{array} \end{array}$$