

# Computing Word Senses by Semantic Mirroring and Spectral Graph Partitioning

Masters Thesis by Martin Fagerlund

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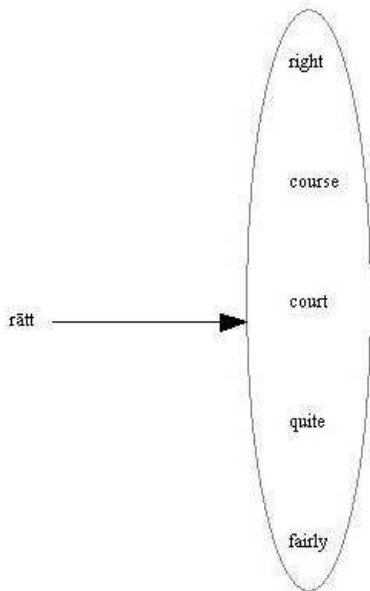
ACL 2010

- 1 Semantic Mirrors
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  - Graph theory
  - Spectral theory
- 3 The Computation of Word Senses
- 4 Evaluation and Results

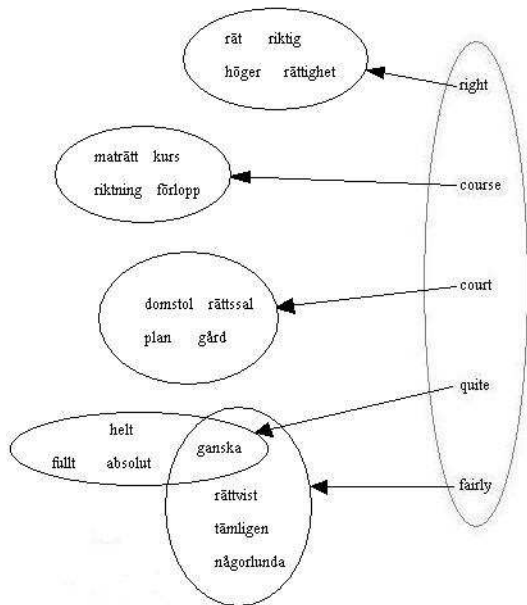
# Semantic Mirrors (Dyvik)

- Use translations to extract information from a bilingual lexicon.
- Semantically closely related words tend to have strongly overlapping sets of translations.
- Words with a wide meaning tend to have a higher number of translations, than words with a more narrow meaning.

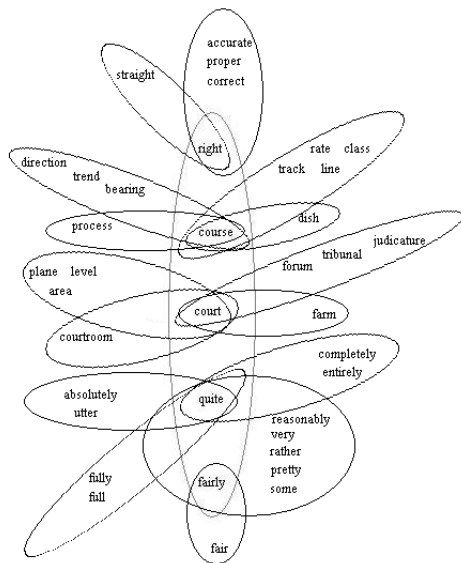
# Semantic Mirrors



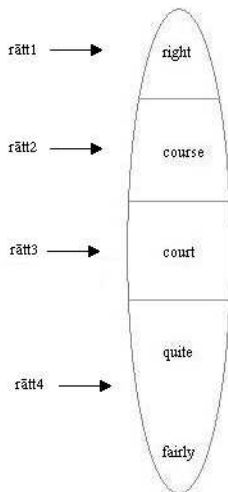
# Semantic Mirrors

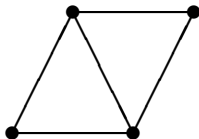


# Semantic Mirrors



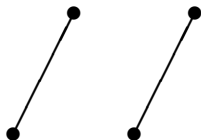
# Semantic Mirrors





- Connected graph with vertex set  $V$  and edge set  $E$ .





- Disconnected graph.

- The weight function.
- $w(v_i, v_j) = w(v_j, v_i)$ .
- $w(v_i, v_j) \geq 0$ .

- The adjacency matrix.

$$A(i, j) = \begin{cases} w(v_i, v_j), & \text{if } v_i \text{ and } v_j \text{ are adjacent,} \\ 0, & \text{otherwise.} \end{cases}$$

- The Laplacian.

$$d(v_i) = \sum_j w(v_i, v_j).$$

$$D(i, j) = \begin{cases} d(v_i), & \text{if } i = j, \\ 0, & \text{otherwise.} \end{cases}$$

- $L = D - A$ .

- The Laplacian.

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- $L = D - A$ .

- The normalised Laplacian.

$$\mathcal{L} = D^{-1/2} L D^{-1/2}.$$

$$\mathcal{L} = \begin{cases} 1 - \frac{w(v_i, v_i)}{d(v_i)}, & \text{if } i = j \text{ and } d(v_i) \neq 0, \\ -\frac{w(v_i, v_j)}{\sqrt{d(v_i)d(v_j)}}, & \text{if } v_i \text{ and } v_j \text{ are adjacent,} \\ 0, & \text{otherwise.} \end{cases}$$

# Spectral graph partitioning

Compute the eigenvalues

$$0 = \lambda_0 \leq \lambda_1 \leq \dots \leq \lambda_{n-1},$$

and the eigenvectors

$$\bar{u}_0, \dots, \bar{u}_{n-1}$$

of  $\mathcal{L}$ .

$\lambda_1$  is called the Fiedler value, and  $\bar{u}_1$  is called the Fiedler vector.

# Spectral graph partitioning

Let  $\bar{u} = (u_1, \dots, u_n)$  be the Fiedler vector.

Divide the vertices into  $S$  and  $\bar{S}$  using a splitting value  $s$ :

$v_i \in S$  if  $u_i > s$

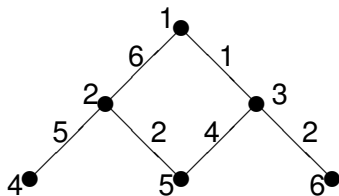
$v_i \in \bar{S}$  if  $u_i \leq s$ .

A few ways of choosing  $s$ :

- bisection:  $s$  is the median of  $\{u_1, \dots, u_n\}$ .
- sign cut:  $s = 0$ .
- gap cut:  $s$  is a value in the largest gap in the sorted Fiedler vector.

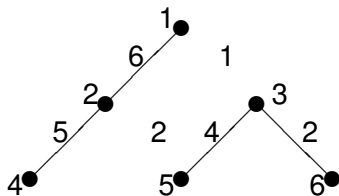


# Spectral graph partitioning - An example



$$\begin{pmatrix} -0.2523 \\ -0.4183 \\ 0.5701 \\ -0.3603 \\ 0.3571 \\ 0.4232 \end{pmatrix}$$

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# Spectral graph partitioning

Measures of the partitioning. Let

$$d(S) = \sum_{v_i \in S} d(v_i),$$

and

$$|E(S, \bar{S})| = \sum_{v_i \in S, v_j \in \bar{S}} w(v_i, v_j).$$

Conductance,

$$\phi(S) = d(V) \frac{|E(S, \bar{S})|}{d(S)d(\bar{S})},$$

# Spectral graph partitioning

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Sparsity,

$$sp(S) = \frac{|E(S, \bar{S})|}{\min(d(S), d(\bar{S}))}$$

# Spectral graph partitioning

The conductance of a graph

$$\phi_G = \min_S \phi(S)$$

The sparsity of a graph

$$sp_G = \min_S sp(S)$$

The Cheeger inequalities

$$2\phi_G > \lambda_1 \geq \frac{\phi_G^2}{8}.$$

$$2sp_G \geq \lambda_1 \geq \frac{sp_G^2}{2}.$$

# Separating word senses - Translation

- English-Swedish lexicon of adjectives.  
Words into two lists.
- Translation matrix **B**.  
Rows correspond to English words.  
Columns correspond to Swedish words.

- English word  $j$  defines a vector  $\bar{e}_j$  by

$$\bar{e}_j(i) = \begin{cases} 1 & \text{if } i = j, \\ 0 & \text{if } i \neq j. \end{cases}$$

- $\mathbf{B}^T \bar{e}_j$  gives translations from English to Swedish.



# Separating word senses - Computation

Start with an English word, called *eng1*.

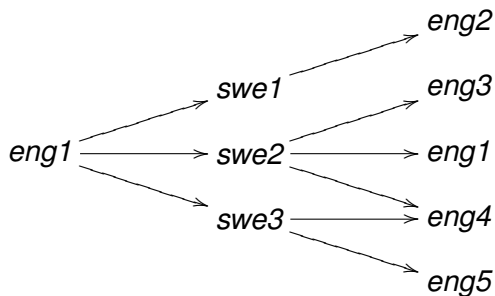
$$\mathbf{BB}^T \bar{e}_{eng1}.$$



# Separating word senses - Computation

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# Separating word senses - Computation

Replace the row in  $\mathbf{B}$  corresponding to *eng1*, with an all-zero row. Call this new matrix  $\mathbf{B}_{mod1}$ .

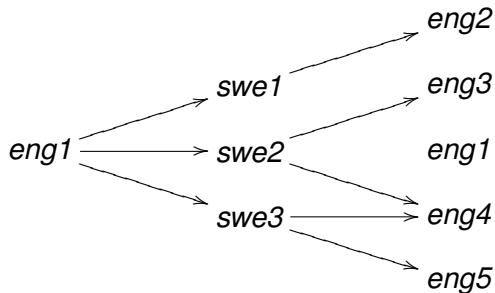
$$\mathbf{B}_{mod1} \mathbf{B}^T \bar{e}_{eng1}.$$



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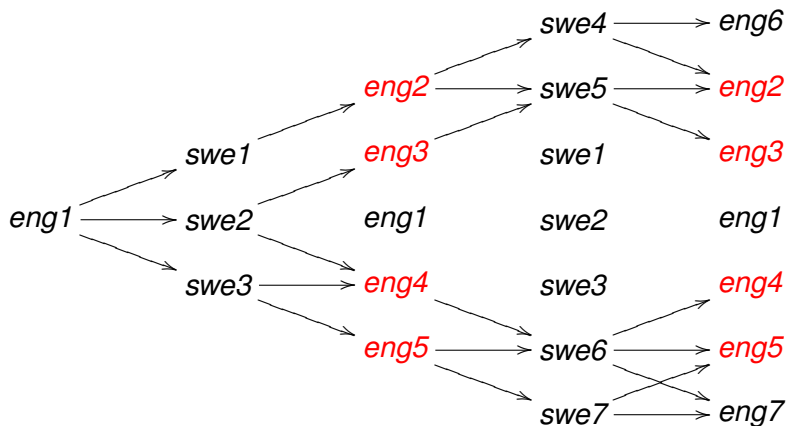
# Separating word senses - Computation

Let  $\mathbf{B}_{mod2}$  be the matrix  $\mathbf{B}$ , with columns corresponding to the Swedish words  $swe1, \dots, swe3$ , replaced with all-zero columns.

Then

$$\mathbf{B}_{mod2} \mathbf{B}_{mod2}^T \mathbf{E}$$

# Separating word senses - Computation



# Separating word senses - Computation

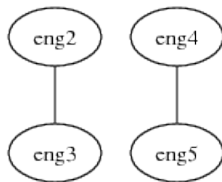
If in

$$\mathbf{B}_{mod2} \mathbf{B}_{mod2}^T \mathbf{E}$$

keeping only the rows corresponding to *eng2*,...*eng5*, we get a symmetric matrix  $\mathbf{A}$ .

$$\mathbf{A} = \begin{pmatrix} 2 & 1 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 1 & 2 \end{pmatrix}$$

# Separating word senses - Computation





# Separating word senses - Computation

- Create  $\mathcal{L}$ , and compute the Fiedler vector.
- Sort the Fiedler vector, and make  $n - 1$  cuts.
- For each cut, compute the conductance and choose the the cut that produce the lowest value.
- Partition the graph.

# Separating word senses - Computation

- Continue and partition the largest of the subgraphs obtained.
- End the iteration when a stopping criterion is fulfilled.

# Separating word senses - Example 1

## Global

absolute	full-scale	round
aggregate	intact	teetotal
all-out	integral	total
clear	integrate	unbroken
complete	international	universal
entire	mondial	utter
full	one-piece	whole
full-length	outright	worldwide

# Separating word senses - Example 1

## Global

intact whole full-length one-piece clear round full	absolute utter complete all-out teetotal outright entire total	integrate unbroken integral	aggregate full-scale
worldwide international	mondial	universal	

## Visiting

adventitious  
alien  
exotic  
foreign  
outlandish  
strange  
unaccustomed  
uncouth  
unfamiliar  
ungenial

## Visiting

alien	unaccustomed
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## Evaluation

- 10 random words with at least 8 vertices in the graph were evaluated.
- Both conductance and sparsity were used as a measure.

## Results

- The sense groups are not always completely synonymous with the seed word.
- The words are often consistent within the sense groups.

## Evaluation

- 10 random words with at least 8 vertices in the graph were evaluated.
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# Conclusions and future work

## Conclusion

Our preliminary results indicate that graph partitioning-based semantic mirroring can be developed into an automatic method for computing word senses.

## Future work

- automatic treatment of homonyms
- Tests on other dictionaries, languages
- Systematic evaluation of the method

To get a copy of Martin Fagerlund's Masters thesis, send me or him a message.