Qual Presentation

Daniel Khashabi

Outline

- My own line of research
- Papers:
  - Fast Dropout training, ICML, 2013
  - Distributional Semantics Beyond Words: Supervised Learning of Analogy and Paraphrase, TACL, 2013.

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  - For example, SAT test:

Stem:		word:language
Choices:	(1)	paint:portrait
	(2)	poetry:rhythm
	(3)	note:music
	(4)	tale:story
	(5)	week:year
Solution:	(3)	note:music

  - Very important for understanding hierarchies of word semantics

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Search + Engine = Search Engine

Google

YAHOO!

bing

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  - Compositional behavior of the word semantics
  - For example: understanding noun-modifier questions

Stem:		fantasy world
Choices:	(1)	fairyland
	(2)	fantasy
	(3)	world
	(4)	phantasy
	(5)	universe
	(6)	ranter
	(7)	souring
Solution:	(1)	fairyland

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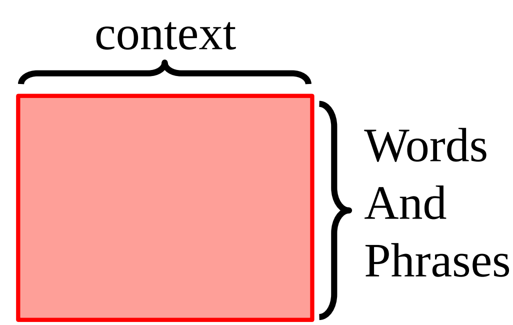
- Three word-context matrices
  - Rows correspond to words/phrases in Wordnet



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- One useful definition for probabilities
  - The ratio of the times a context appears with a words

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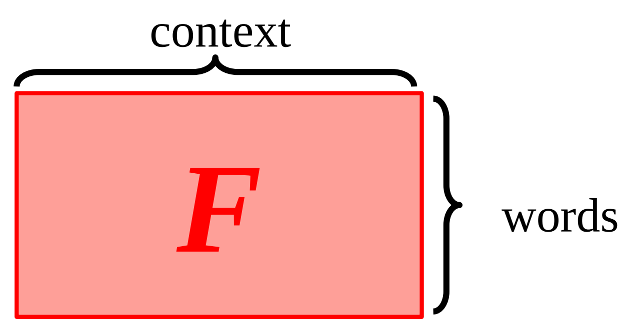

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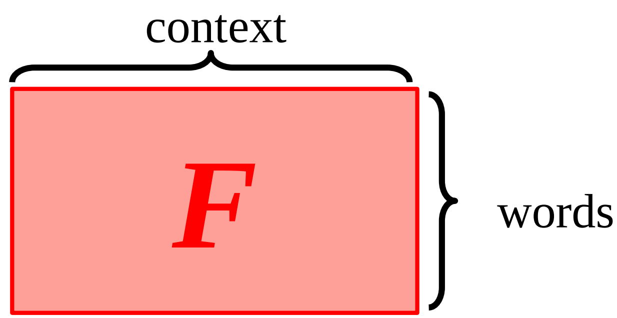

- f_{ij} is the number of times w_i appear in context c_j .

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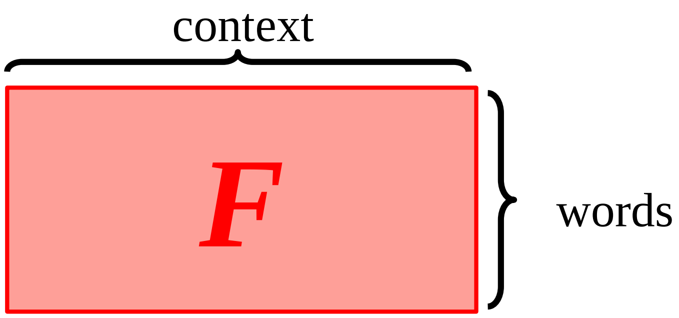

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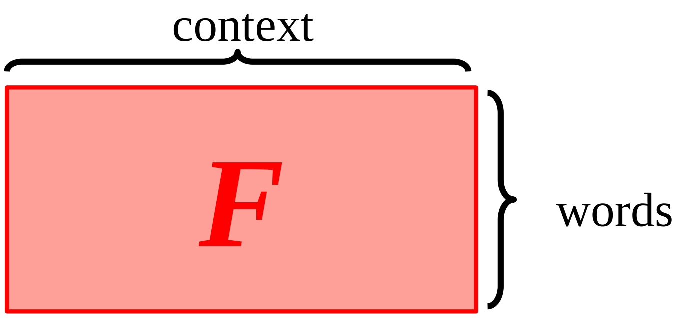

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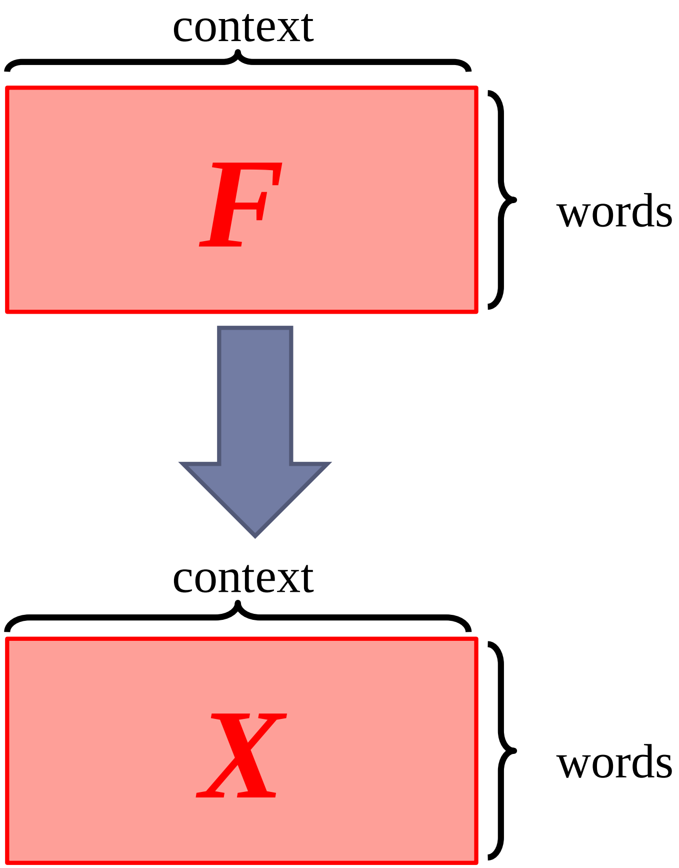

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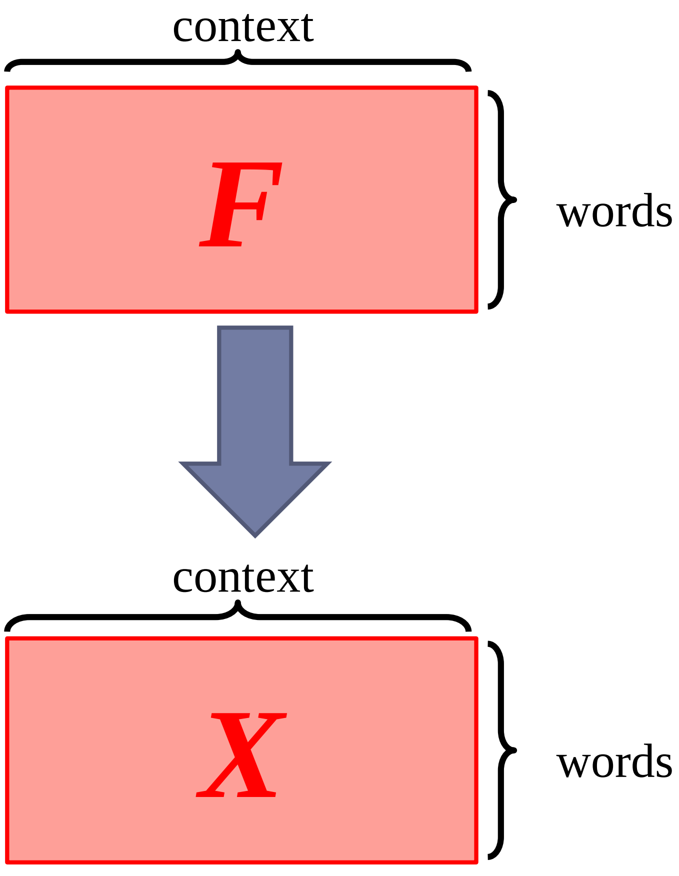
$$p_{ij} = f_{ij} \Big/ \sum_{j=1}^{n_r} \sum_{i=1}^{n_c} f_{ij}$$



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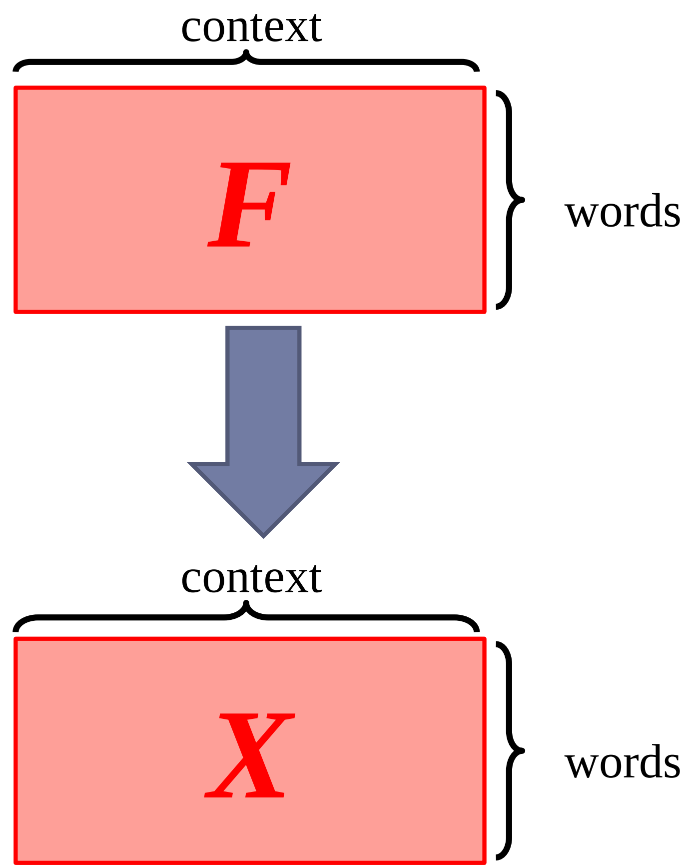

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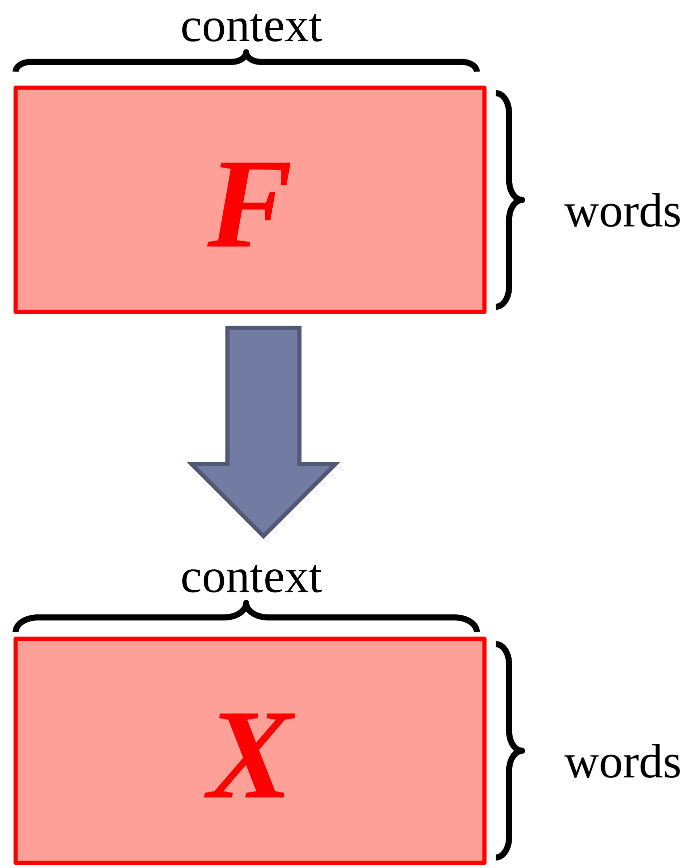

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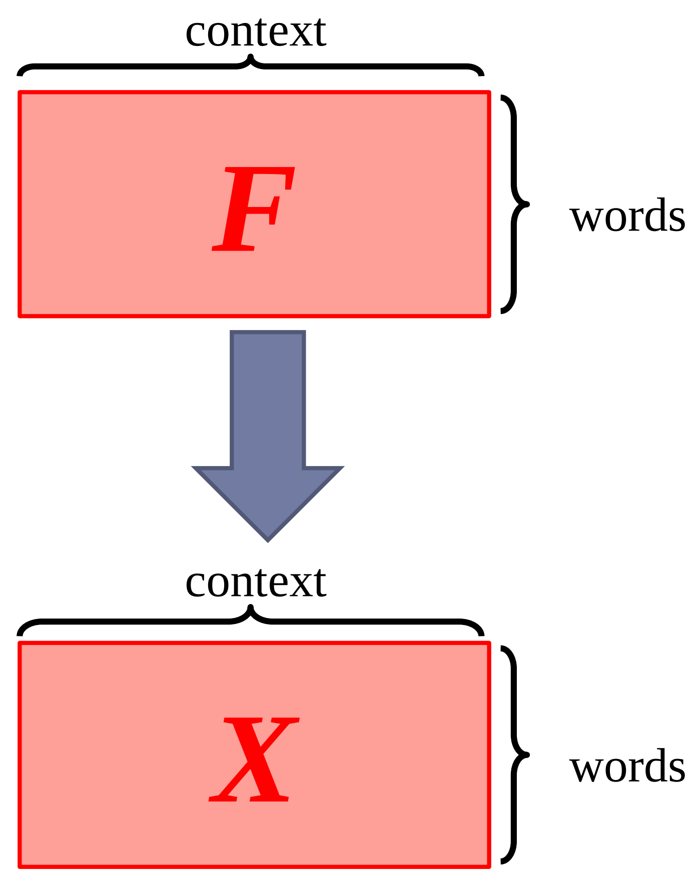
$$x_{ij} = \max\left(\log(\frac{p_{ij}}{p_{i*} p_{*j}}), 0 \right)$$



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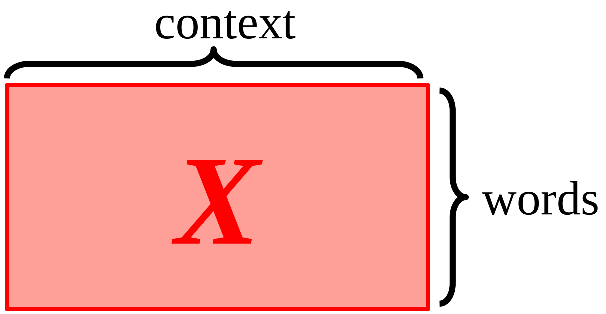

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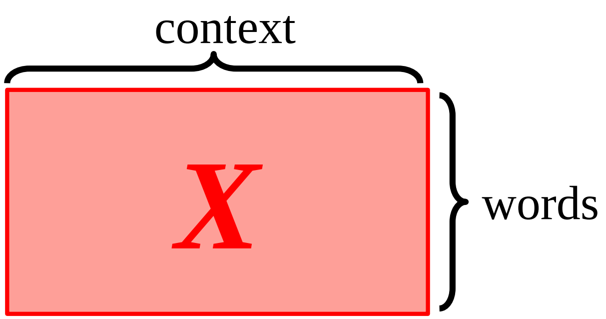

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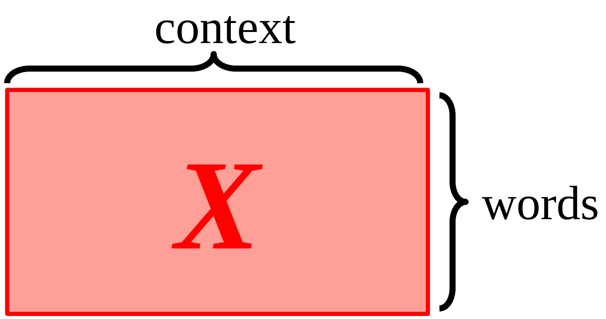

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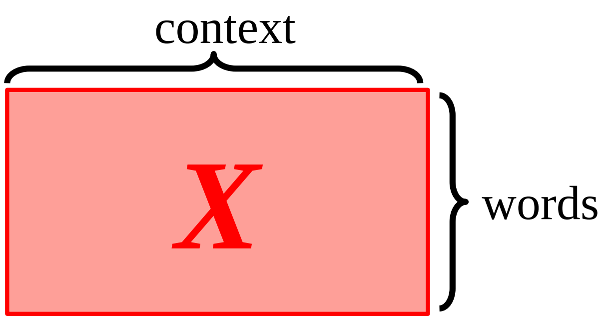

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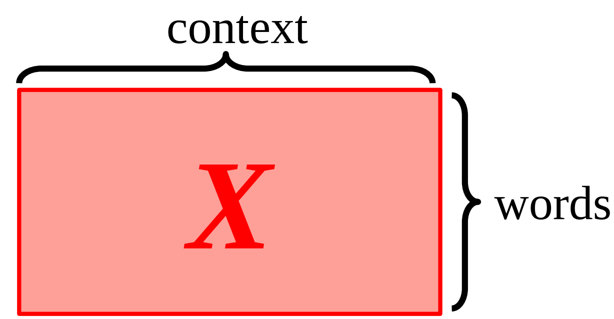

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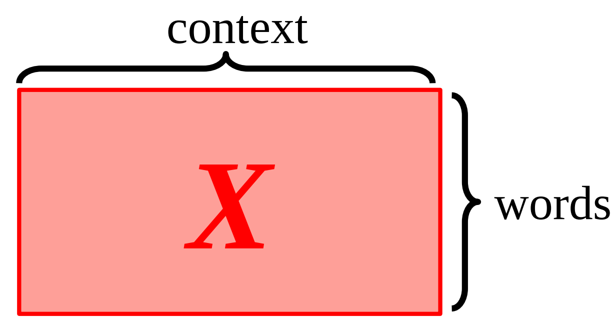

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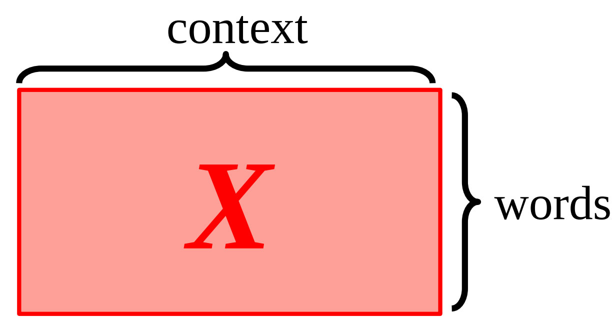

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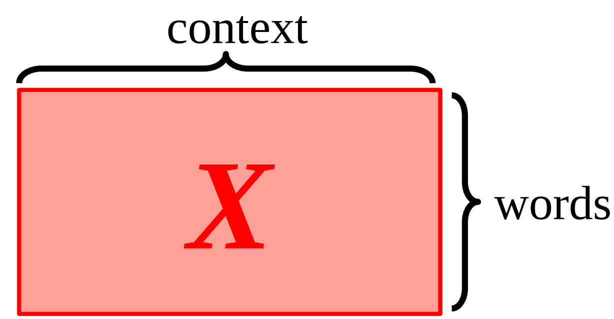

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- For an n-tuple one can generate $2n(n-1)$ PPMI features

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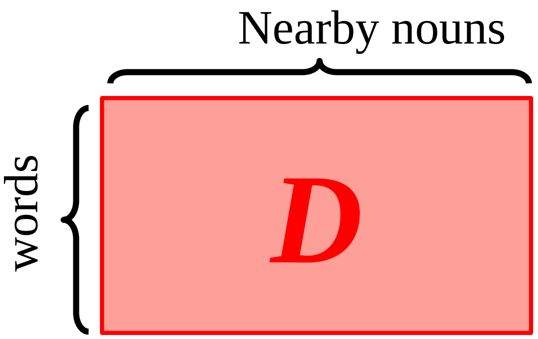

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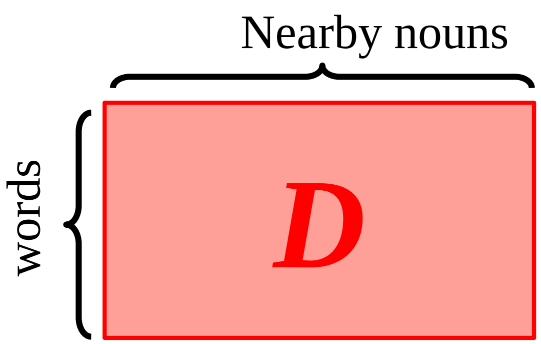

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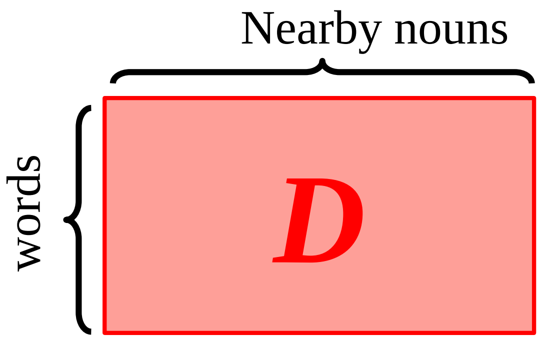

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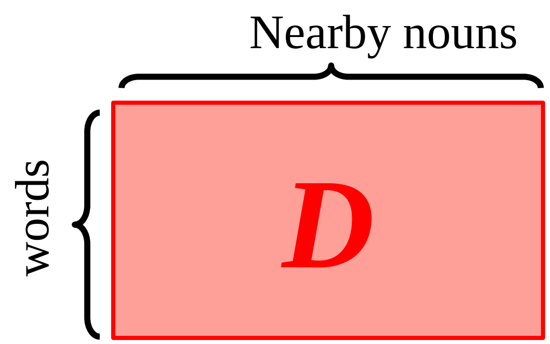

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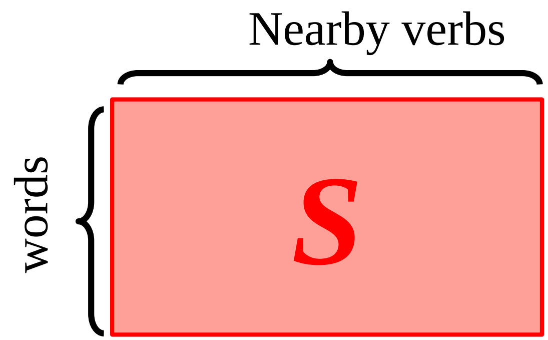

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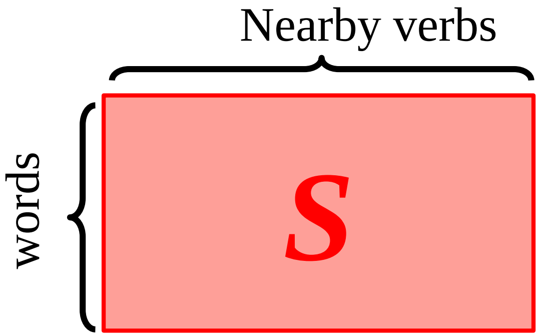

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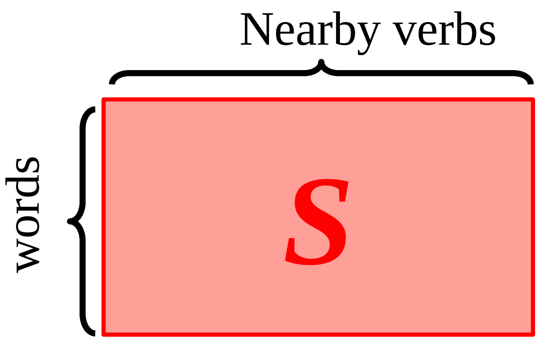

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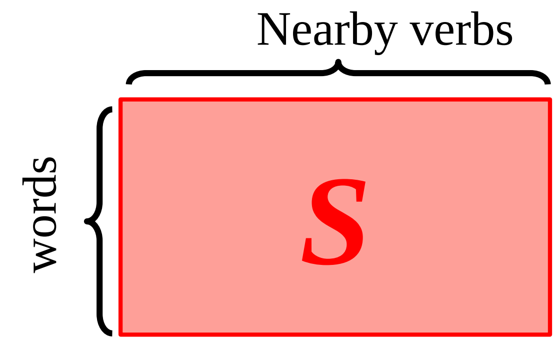

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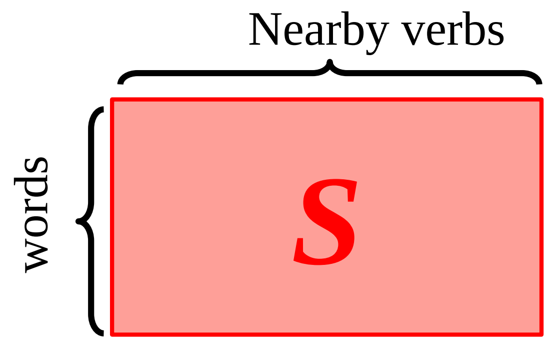

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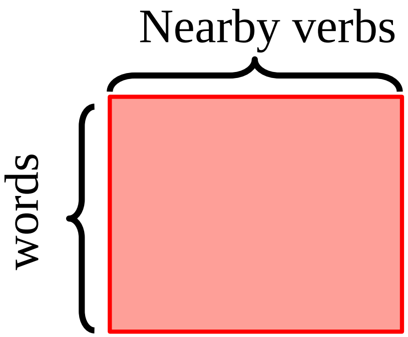

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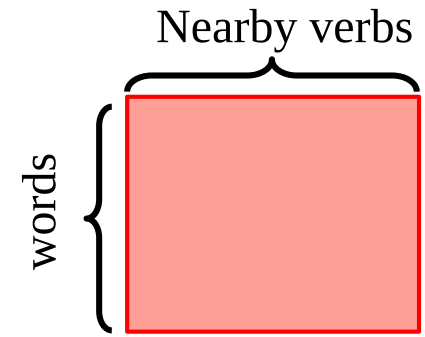
$$F = U\Sigma V$$



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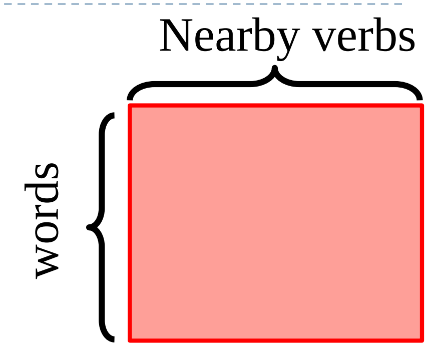

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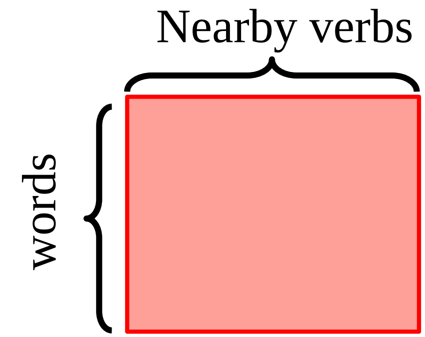

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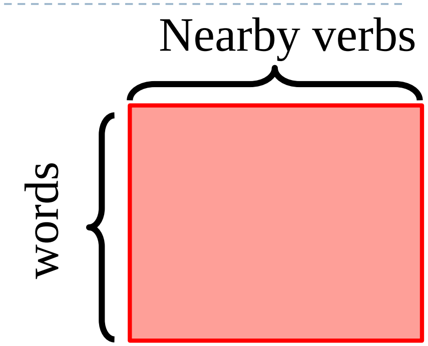
- Given word w_i, $U_k \Sigma_k^p$ is the corresponding vector

Using semantic and functional similarity

- Given the frequency matrix:
- Keep the lower-dimensional representation



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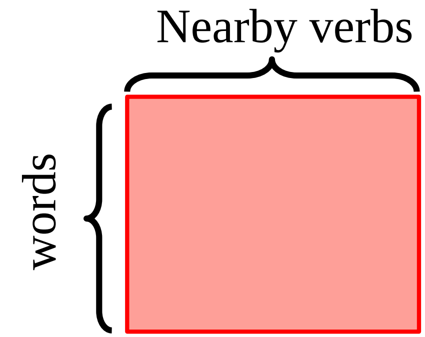

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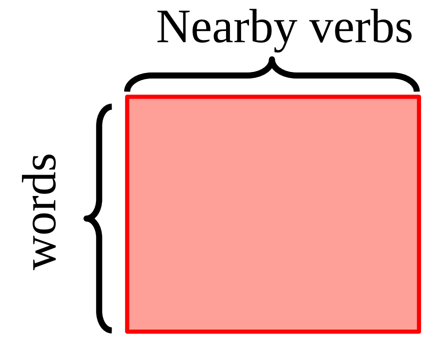

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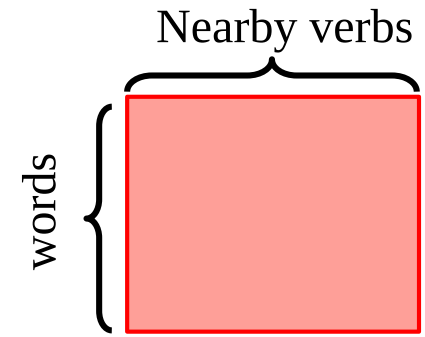

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- Given word w_i, $U_k \Sigma_k^p$ is the corresponding vector
- $p \in [0,1]$ is used to tune sensitivity with respect to eigenvalues
  - Given w_i and w_j to find: $Dom(w_i, w_j, k, p)$
  - *find corresponding vectors*
  - *find cosine distance between the vectors*

5-choice SAT tests

- 374 five-choice SAT questions

Stem:		word:language
Choices:	(1)	paint:portrait
	(2)	poetry:rhythm
	(3)	note:music
	(4)	tale:story
	(5)	week:year
Solution:	(3)	note:music

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- Could be converted into 5 4-tuples:

$$\langle \textit{word, language, note, music} \rangle$$

↓

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- Could be converted into 5 4-tuples:

$$\langle word,\ language,\ note,\ music \rangle$$

- Each positive 4-tuple $\langle a, b, c, d \rangle$ could be converted to:

$$\langle b, a, d, c \rangle,\ \ \langle c, d, a, b \rangle,\ \langle d, c, b, a \rangle$$

Results on 5-choice SAT

- The top ten results with the SAT analogy questions.

Algorithm	Reference	Correct
Know-Best	Veale (2004)	43.0
k-means	Biçici & Yuret (2006)	44.0
BagPack	Herdağdelen & Baroni (2009)	44.1
VSM	Turney & Littman (2005)	47.1
Dual-Space	Turney (2012)	51.1
BMI	Bollegala et al. (2009)	51.1
PairClass	Turney (2008b)	52.1
PERT	Turney (2006a)	53.5
SuperSim	—	54.8
LRA	Turney (2006b)	56.1
Human	Average college applicant	57.0

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not significantly different according to Fisher's exact test at the 95% confidence level

- SuperSim answers the SAT questions in a few minutes
- LRA requires nine days

SAT with 10 choices

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- Adding more negative instances

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- In general if $\langle a, b, c, d \rangle$ is positive $\langle a, d, c, b \rangle$ is negative

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- For example: Positive: $\langle word,\ language,\ note,\ music \rangle$

SAT with 10 choices

- Adding more negative instances
- In general if $\langle a, b, c, d \rangle$ is positive $\langle a, d, c, b \rangle$ is negative
- For example: Positive: $\langle word,\ language,\ note,\ music \rangle$

  Negative: $\langle word,\ music,\ note,\ language \rangle$

SAT with 10 choices

- Adding more negative instances
- In general if $\langle a, b, c, d \rangle$ is positive $\langle a, d, c, b \rangle$ is negative
- For example: Positive: $\langle word,\ language,\ note,\ music \rangle$

  Negative: $\langle word,\ music,\ note,\ language \rangle$
- This generates 5 more negative instances

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- In general if $\langle a, b, c, d \rangle$ is positive $\langle a, d, c, b \rangle$ is negative
- For example: Positive: $\langle word,\ language,\ note,\ music \rangle$
  Negative: $\langle word,\ music,\ note,\ language \rangle$
- This generates 5 more negative instances

	Features				
Algorithm	LF	PPMI	Dom	Fun	Correct
Dual-Space	0	0	1	1	47.9
SuperSim	1	1	1	1	52.7
SuperSim	0	1	1	1	52.7
SuperSim	1	0	1	1	52.7
SuperSim	1	1	0	1	45.7
SuperSim	1	1	1	0	41.7
SuperSim	1	0	0	0	5.6
SuperSim	0	1	0	0	32.4
SuperSim	0	0	1	0	39.6
SuperSim	0	0	0	1	39.3

SemEval-2012 Task 2

- Class and subclasses labels + examples

```
CLASS-INCLUSION,Taxonomic
50.0 "weapon:spear"
...
34.7 "vegetable:carrot"
...
-1.9 "mammal:porpoise"
...
-29.8 "pen:ballpoint"
...
-55.1 "wheat:bread"
```

- Gather using Mechanical Turk:
- 75 subcategories
- Average of 41 word-pairs per subcategories

SemEval-2012 Task 2

- SuperSim Trained on 5-choice SAT and tested on SemEval data
- It gives the best correlation coefficient

Algorithm	Reference	Spearman
BUAP	Tovar et al. (2012)	0.014
Duluth-V2	Pedersen (2012)	0.038
Duluth-V1	Pedersen (2012)	0.039
Duluth-V0	Pedersen (2012)	0.050
UTD-SVM	Rink & Harabagiu (2012)	0.116
UTD-NB	Rink & Harabagiu (2012)	0.229
RNN-1600	Mikolov et al. (2013)	0.275
UTD-LDA	Rink & Harabagiu (2013)	0.334
Com	Zhila et al. (2013)	0.353
SuperSim	—	0.408

Compositional similarity: the data

- Noun-modifier question based on WordNet

Stem:		fantasy world
Choices:	(1)	fairyland
	(2)	fantasy
	(3)	world
	(4)	phantasy
	(5)	universe
	(6)	ranter
	(7)	souring
Solution:	(1)	fairyland

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- Create tuples of the form: $\langle a, b, c \rangle$

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  - Example: $\langle$*fantasy, world, fairyland*$\rangle$

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- Create tuples of the form: $\langle a, b, c \rangle$
  - Example: $\langle \textit{fantasy, world, fairyland} \rangle$
- Any question gives one positive instance and six negative instance

Compositional similarity: 7-choices questions

- 680 questions for training
- 1,500 questions for testing

Total of 2,180 questions

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Algorithm	7-choices
Vector addition	50.1
Element-wise multiplication	57.5
Dual-Space model	58.3
SuperSim	75.9
Holistic model	81.6

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SuperSim	75.9
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- The holistic approach is noncompositional.
  - The stem bigram is represented by a single context vector
  - As if it were a unigram.

Compositional similarity:14-choices questions

Compositional similarity:14-choices questions

- Any question gives one positive instance and six negative instance

Compositional similarity: 14-choices questions

- Any question gives one positive instance and six negative instance
- Positive instance: $\langle a, b, c \rangle$

Compositional similarity: 14-choices questions

- Any question gives one positive instance and six negative instance
- Positive instance: $\langle a, b, c \rangle$
- Negative instance: $\langle b, a, c \rangle$ e.g. word fantasy $\neq$ wonderland

Compositional similarity: 14-choices questions

- Any question gives one positive instance and six negative instance
- Positive instance: $\langle a, b, c \rangle$
- Negative instance: $\langle b, a, c \rangle$ e.g. word fantasy $\neq$ wonderland
- This gives 7 more negative instances (14-choices)

Compositional similarity:14-choices questions

- Any question gives one positive instance and six negative instance
- Positive instance: $\langle a, b, c \rangle$
- Negative instance: $\langle b, a, c \rangle$ e.g. word fantasy $\neq$ wonderland
- This gives 7 more negative instances (14-choices)

	Correct	
Algorithm	7-choices	14-choices
Vector addition	50.1	22.5
Element-wise multiplication	57.5	27.4
Dual-Space model	58.3	41.5
SuperSim	75.9	68.0
Holistic model	81.6	—

Compositional similarity: ablation experiment

- Analyzing effect of each feature type on the 14-choice test

	Features				
Algorithm	LF	PPMI	Dom	Fun	Correct
Dual-Space	0	0	1	1	41.5
SuperSim	1	1	1	1	68.0
SuperSim	0	1	1	1	66.6
SuperSim	1	0	1	1	52.3
SuperSim	1	1	0	1	69.3
SuperSim	1	1	1	0	65.9
SuperSim	1	0	0	0	14.1
SuperSim	0	1	0	0	59.7
SuperSim	0	0	1	0	34.6
SuperSim	0	0	0	1	32.9

- PPMI features are the most important

Compositional similarity: closer look at PPMI

Compositional similarity: closer look at PPMI

- PPMI features for $\langle a, b, c\rangle$ into three subsets:

$$\langle a, b\rangle, \langle a, c\rangle, \langle b, c\rangle$$

Compositional similarity: closer look at PPMI

- PPMI features for $\langle a, b, c\rangle$ into three subsets:

$$\langle a, b\rangle, \langle a, c\rangle, \ \langle b, c\rangle$$

- For example for $\langle a, b\rangle$: $\boxed{\begin{array}{l}\mathrm{PPMI}(a, b, \mathit{left}), \ \mathrm{PPMI}(a, b, \mathit{right}) \\ \mathrm{PPMI}(b, a, \mathit{left}), \ \mathrm{PPMI}(b, a, \mathit{right})\end{array}}$

Compositional similarity: closer look at PPMI

- PPMI features for $\langle a, b, c\rangle$ into three subsets:

$$\langle a, b\rangle, \langle a, c\rangle, \ \langle b, c\rangle$$

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PPMI feature subsets			
$\langle a, b\rangle$	$\langle a, c\rangle$	$\langle b, c\rangle$	Correct
1	1	1	68.0
0	1	1	59.9
1	0	1	65.4
1	1	0	67.5
1	0	0	62.6
0	1	0	58.1
0	0	1	55.6
0	0	0	52.3

Compositional similarity: closer look at PPMI

- PPMI features for $\langle a, b, c\rangle$ into three subsets:

$$\langle a, b\rangle, \langle a, c\rangle, \langle b, c\rangle$$

- For example for $\langle a, b\rangle$: $\mathrm{PPMI}(a, b, \mathit{left})$, $\mathrm{PPMI}(a, b, \mathit{right})$ $\mathrm{PPMI}(b, a, \mathit{left})$, $\mathrm{PPMI}(b, a, \mathit{right})$

- $\langle a, b\rangle$ subset are more important.

PPMI feature subsets			
$\langle a, b\rangle$	$\langle a, c\rangle$	$\langle b, c\rangle$	Correct
1	1	1	68.0
0	1	1	59.9
1	0	1	65.4
1	1	0	67.5
1	0	0	62.6
0	1	0	58.1
0	0	1	55.6
0	0	0	52.3

Compositional similarity: holistic training

Compositional similarity: holistic training

- A holistic training data

Compositional similarity: holistic training

- A holistic training data

Stem:		search engine
Choices:	(1)	search_engine
	(2)	search
	(3)	engine
	(4)	search_language
	(5)	search_warrant
	(6)	diesel_engine
	(7)	steam_engine
Solution:	(1)	search_engine

Compositional similarity: holistic training

- A holistic training data
- Extract noun-modifier pairs from WordNet

Stem:		search engine
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Compositional similarity: holistic training

- A holistic training data
- Extract noun-modifier pairs from WordNet
- Call a_b a pseudo-unigram and treat it as unigram

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Solution:	(1)	search_engine

Compositional similarity: holistic training

- A holistic training data
- Extract noun-modifier pairs from WordNet
- Call a_b a pseudo-unigram and treat it as unigram
- Use the components as distracters

Stem:		search engine
Choices:	(1)	search_engine
	(2)	search
	(3)	engine
	(4)	search_language
	(5)	search_warrant
	(6)	diesel_engine
	(7)	steam_engine
Solution:	(1)	search_engine

Compositional similarity: holistic training(2)

- Training on the holistic questions: "Holistic"
- Compared with the standard training
- Test is the standard testing

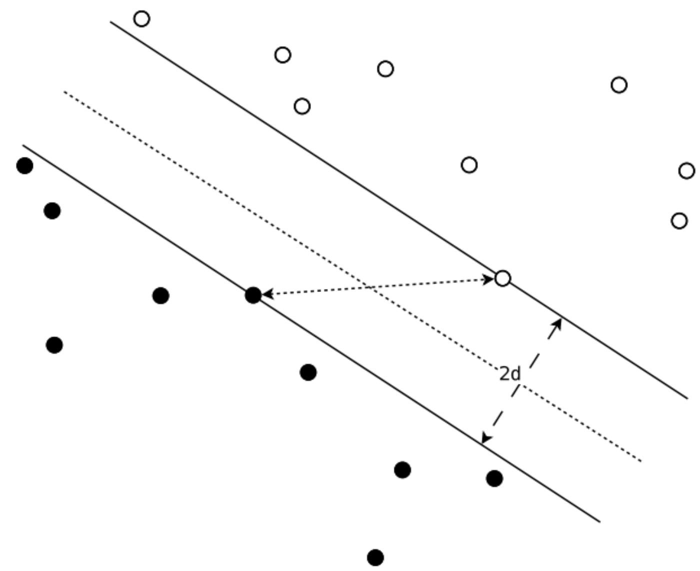
	Correct	
Training	7-choices	14-choices
Holistic	61.8	54.4
Standard	75.9	68.0

- There is a drop when training with the holistic samples
- Not very clear, but seems to be because of the nature of the

References

- Some figures from: http://nlp.cs.berkeley.edu/tutorials/variational-tutorial-slides.pdf
- Hinton, Geoffrey E., et al. "Improving neural networks by preventing co-adaptation of feature detectors." arXiv preprint arXiv:1207.0580 (2012).

SVM



- Primal form:

$$\begin{cases} \min_\beta \frac{1}{2}\|\beta\|^2 \\ y_i\left(\beta.\mathbf{x}_i\right)-1\geq 0 \end{cases}$$

- Relaxed form:

$$\begin{cases} \min_\beta \frac{1}{2}\|\beta\|^2 + C\sum_i \varepsilon_i \\ y_i\left(\beta.\mathbf{x}_i\right)-1\geq -\varepsilon_i \end{cases}$$

- Dual form:

$$\begin{cases} \max_\alpha \sum \alpha_i - \frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j \left(\mathbf{x}_i.\mathbf{x}_j\right) \\ \sum_i \alpha_i y_i = 0, \quad 0\leq \alpha_i \leq C \end{cases}$$

Proof: Hinge regression closed form

- Suppose we want to minimize:

$$\left\|Ax - b\right\|^2 + \left\|\Gamma x\right\|^2$$

$$x = \left(A^T A + \Gamma^T \Gamma\right)^{-1} A^T b$$

Proof: Hinge regression closed form

- Proof:

$$L = \frac{1}{2}\left(Ax - b\right)^T \left(Ax - b\right)$$

$$\frac{dL}{dx} = A^T \left(Ax - b\right) = 0$$

$$x = \left(A^T A\right)^{-1} A^T b$$

Proof: Hinge regression closed form

- Proof:

$$L = \frac{1}{2}\left(Ax - b\right)^T\left(Ax - b\right) + \frac{1}{2}\left(\Gamma x\right)^T\left(\Gamma x\right)$$

$$\frac{dL}{dx} = A^T\left(Ax - b\right) + \Gamma^T\left(\Gamma x\right) = 0$$

$$x = \left(A^T A + \Gamma^T \Gamma\right)^{-1} A^T b$$