Learning Word Representations by Jointly Modeling Syntagmatic and Paradigmatic Relations

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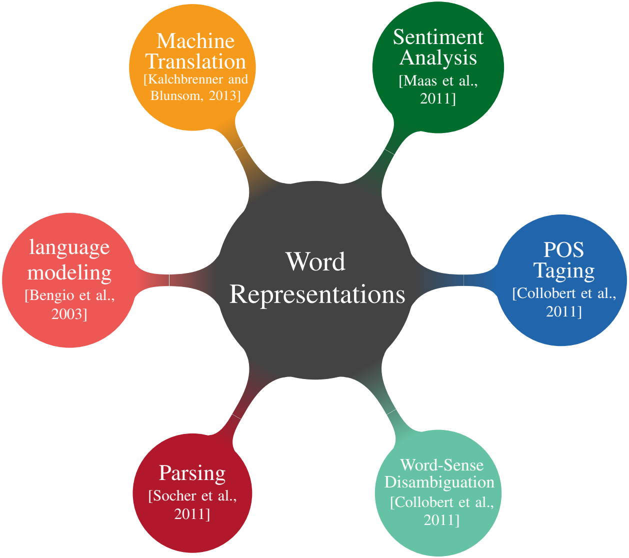
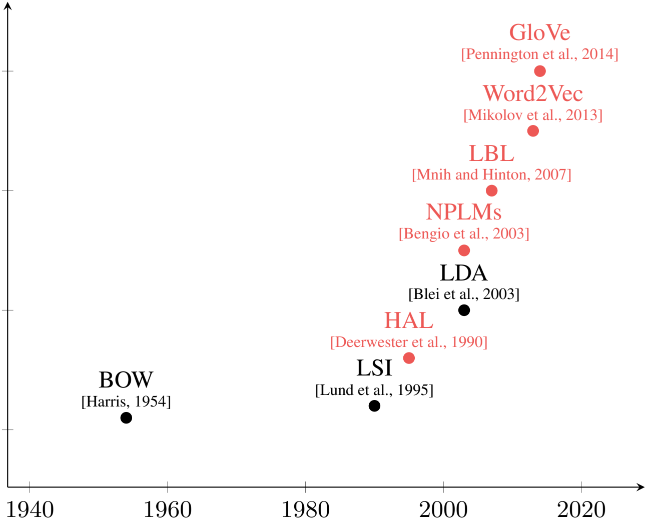
Word Representations



Word Representations Models



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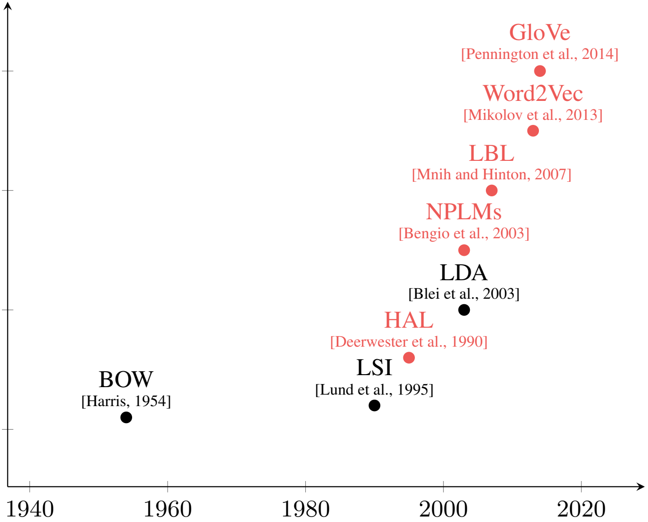


Relations?

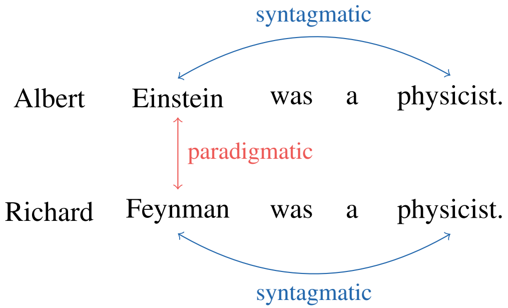
One Hypothesis
Two Interpretation

The Distributional Hypothesis [Harris, 1954, Firth, 1957]

"*You shall know a word by the company it keeps*."

—J.R. Firth

Syntagmatic and Paradigmatic Relations [Gabrilovich and Markovitch, 2007]



- Syntagmatic: words co-occur in the same text region
- Paradigmatic: words occur in the same context, may not at the same time

Syntagmatic

syntagmatic

Albert Einstein was a physicist.

Richard Feynman was a physicist.

syntagmatic

Syntagmatic

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Albert Einstein was a physicist.

Richard Feynman was a physicist.

syntagmatic

	d_1	d_2
Einstein	1	0
Feynman	0	1
physicist	1	1

Syntagmatic

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Albert **Einstein** was a **physicist**.

Richard **Feynman** was a **physicist**.

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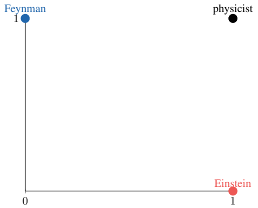

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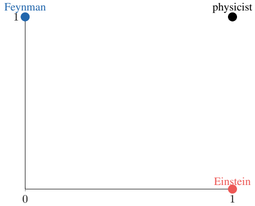

LSI, LDA, PV-DBOW $\cdots$

Paradigmatic

Albert	Einstein	was	a	physicist.
	↕ paradigmatic			
Richard	Feynman	was	a	physicist.

Paradigmatic

Albert **Einstein** was a physicist.

$\updownarrow$ paradigmatic

Richard **Feynman** was a physicist.

	Einstein	Feynman	physicist
Einstein	0	0	1
Feynman	0	0	1
physicist	1	1	0

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Albert **Einstein** was a **physicist**.

$\updownarrow$ paradigmatic

Richard **Feynman** was a **physicist**.

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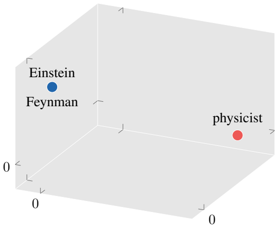

Paradigmatic

Albert Einstein was a physicist.

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	Einstein	Feynman	physicist
Einstein	0	0	1
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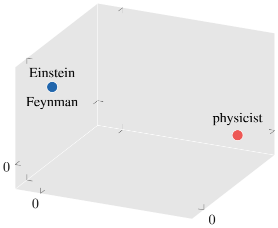


NLMs, Word2Vec, GloVe $\cdots$

Motivation

syntagmatic

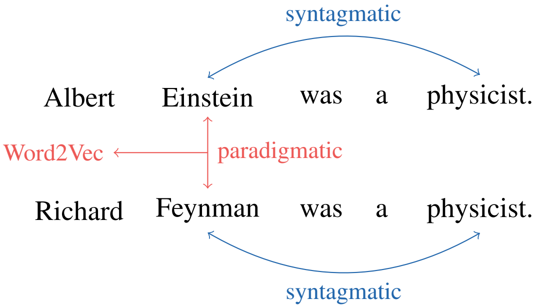
Albert Einstein was a physicist.

paradigmatic

Richard Feynman was a physicist.

syntagmatic

Motivation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Albert Einstein was a physicist.
Word2Vec
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Richard Feynman was a physicist.
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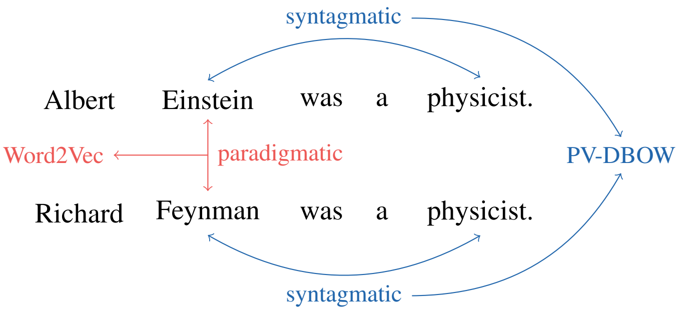
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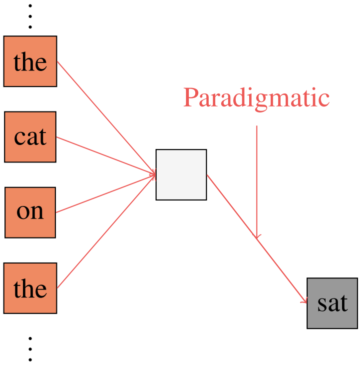
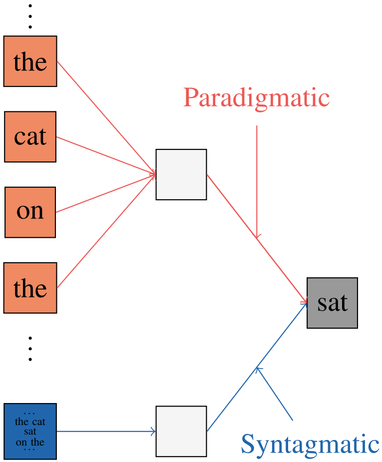
Model

Parallel Document Context Model (PDC)



$$\ell = \sum_{n=1}^{N} \sum_{w_i^n \in d_n} \log p(w_i^n | h_i^n)$$

Parallel Document Context Model (PDC)



$$\ell = \sum_{n=1}^{N} \sum_{w_i^n \in d_n} \left(\log p(w_i^n | h_i^n) + \log p(w_i^n | d_n) \right)$$

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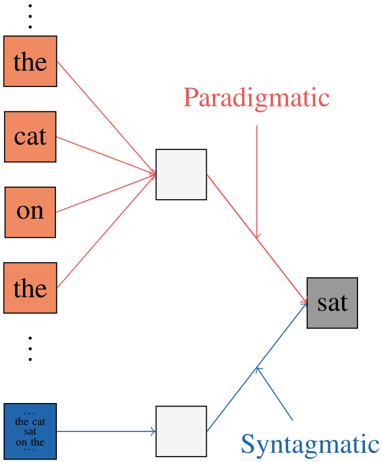


$$\ell = \sum_{n=1}^{N} \sum_{w_i^n \in d_n} \left(\log p(w_i^n | h_i^n) + \log p(w_i^n | d_n) \right)$$

Negative Sampling

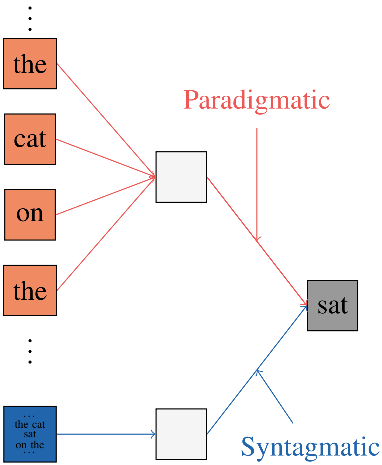
$$\ell = \sum_{n=1}^{N} \sum_{w_i^n \in d_n} \Big(\log \sigma(\vec{w_i^n} \cdot \vec{h_i^n}) + \log \sigma(\vec{w_i^n} \cdot \vec{d_n})$$

$$+ k \cdot \mathbb{E}_{w' \sim P_{\mathrm{nw}}} \log \sigma(-\vec{w'} \cdot \vec{h_i^n})$$

$$+ k \cdot \mathbb{E}_{w' \sim P_{\mathrm{nw}}} \log \sigma(-\vec{w'} \cdot \vec{d_n}) \Big)$$

$$\sigma(x) = \frac{1}{1 + \exp(-x)}$$

Parallel Document Context Model (PDC)



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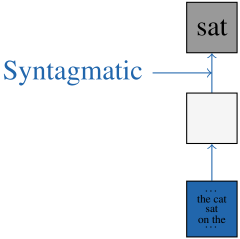
PDC	PV-DM
MF for W-D + W-C [Levy and Goldberg, 2014]	not clear

Hierarchical Document Context Model (HDC)

$$\ell = \sum_{n=1}^{N} \sum_{w_i^n \in d_n} \log p(w_i^n | d_n)$$



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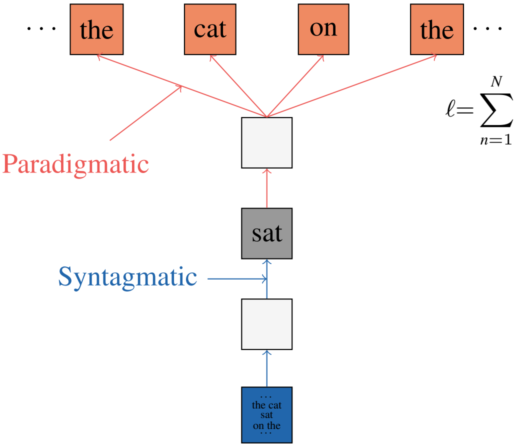
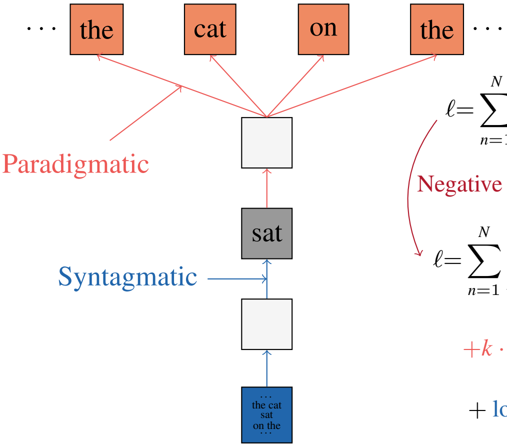


$$\ell = \sum_{n=1}^{N} \sum_{w_i^n \in d_n} \left(\log p(w_i^n | d_n) + \sum_{\substack{j=i-L \\ j \neq i}}^{i+L} \log p(c_j^n | w_i^n) \right)$$

Hierarchical Document Context Model (HDC)



$$\ell = \sum_{n=1}^{N} \sum_{w_i^n \in d_n} \left(\log p(w_i^n | d_n) + \sum_{\substack{j=i-L \\ j \neq i}}^{i+L} \log p(c_j^n | w_i^n) \right)$$

Negative Sampling

$$\ell = \sum_{n=1}^{N} \sum_{w_i^n \in d_n} \Bigg(\sum_{\substack{j=i-L \\ j \neq i}}^{i+L} \Big(\log \sigma(\vec{c_j^n} \cdot \vec{w_i^n}) + k \cdot \mathbb{E}_{c' \sim P_{\text{nc}}} \log \sigma(-\vec{c'} \cdot \vec{w_i^n}) \Big) + \log \sigma(\vec{w_i^n} \cdot \vec{d_n}) + k \cdot \mathbb{E}_{w' \sim P_{\text{nw}}} \log \sigma(-\vec{w'} \cdot \vec{d_n}) \Bigg)$$

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Relation with Existing Models

- CBOW, SG, PV-DBOW
  - Sub-model
- Global Context-Aware Neural Language Model [Huang et al., 2012]
  - neural language model
  - weighted average of all word vectors

Experiments

Experiments Plan

- Qualitative Evaluations
  - Verify word representations learned by different relations
- Quantitative Evaluations
  - Word Analogy Task
  - Word Similarity Task

Experimental Settings

Corpus:

model	corpus	size
C&W [Collobert et al., 2011]	Wikipedia 2007 + Reuters RCV1	0.85B
HPCA [Lebret and Collobert, 2014]	Wikipedia 2012	1.6B
GloVe	Wikipedia 2014+ Gigaword5	6B
GCANLM, CBOW, SG PV-DBOW, PV-DM, PDC, HDC	Wikipedia 2010	1B

Parameters Setting:

window	negative	iteration	learning rate		noise distribution
10	10	20	0.025[1]	0.05[2]	$\propto \#(w)^{0.75}$

[1] SG, PV-DBOW, HDC [2] CBOW, PV-DM, PDC

Qualitative Evaluations

Top 5 similar words to **Feynman**

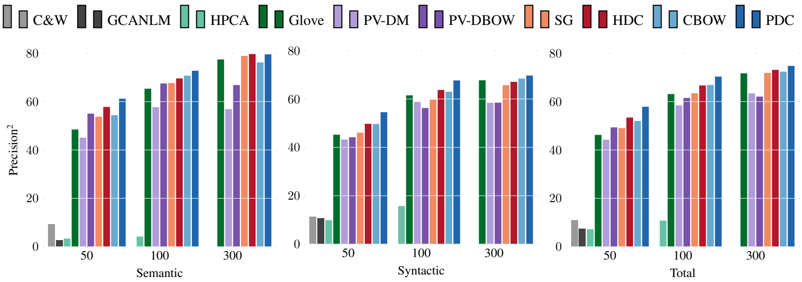
CBOW	SG	PDC	HDC	PV-DBOW
einstein	schwinger	geometrodynamics	schwinger	physicists
schwinger	quantum	bethe	electrodynamics	spacetime
bohm	bethe	semiclassical	bethe	geometrodynamics
bethe	einstein	schwinger	semiclassical	tachyons
relativity	semiclassical	perturbative	quantum	einstein

Paradigmatic Syntagmatic

Word Analogy

- Test Set
  - Google [Mikolov et al., 2013]
    - Semantic: "Beijing is to China as Paris is to _____"
    - Syntactic: "big is to bigger as deep is to _____"
- Solution:
  - $\arg \max_{\substack{x \in W, x \neq a \\ x \neq b,\ x \neq c}} (\vec{b} + \vec{c} - \vec{a}) \cdot \vec{x}$
- Metric:
  - percentage of questions answered correctly

Word Analogy

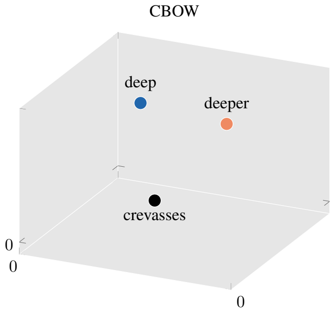


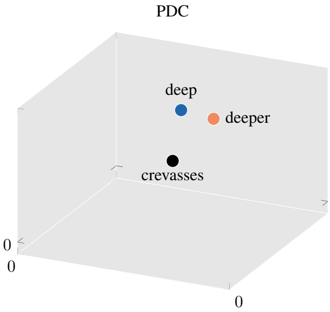
- Word2Vec and GloVe are very strong baselines.
- PDC and HDC outperform CBOW and SG respectively.

[2] percentage of questions answered correctly

Case Study

big: bigger $\sim$ deep: deeper





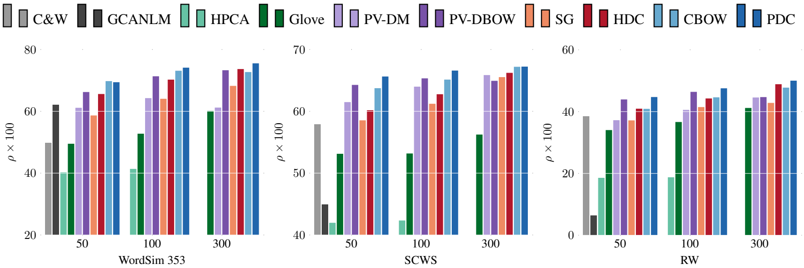
CBOW: shallower ×

PDC: deeper √

Word Similarity

- Test Set
  - WordSim-353 [Finkelstein et al., 2002]
  - Stanford's Contextual Word Similarities (SCWS) [Huang et al., 2012]
  - Rare Word (RW) [Luong et al., 2013]
- Detail:
  - Word pair with similarity score assigned by human
  - (tiger cat 7.35)
- Evaluation Metric:
  - spearman rank correlation

Word Similarity



- PV-DBOW does well.
- PDC and HDC outperform CBOW and SG respectively.

Summary

- Revisit word representation models through syntagmatic and paradigmatic relations.
- Two novel models modeling syntagmatic and paradigmatic relations simultaneously.
- State-of-the-art results.

Thanks

Q & A

More Infomration:

http://ofey.me/projects/wordrep

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