Acquiring Semantic Knowledge using Patterns

Roy Schwartz, NLP Lab, The Hebrew University

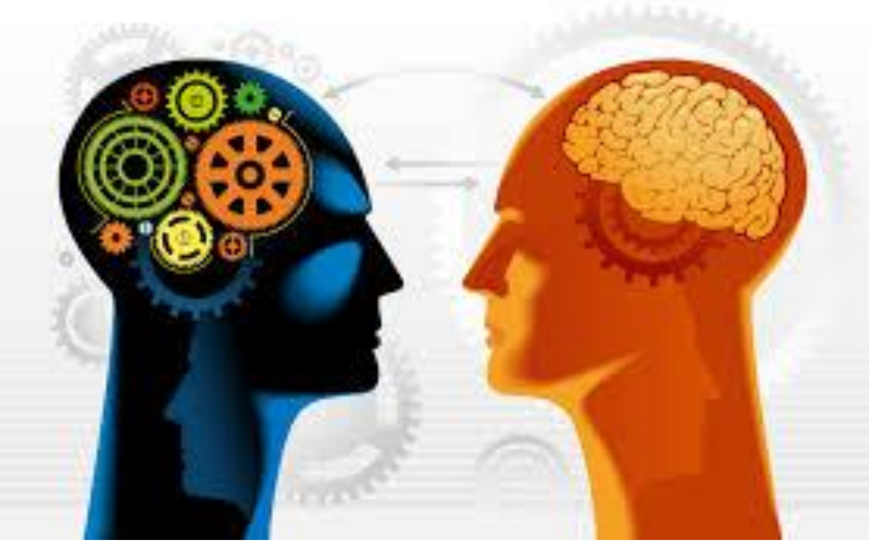
Learning Club, Dec. 4th, 2014

Overview

- NLP
  - Problems and open questions
  - Main approaches
- Lexico-syntactic Patterns
- Latest Results
  - Interpretable Word Embeddings Using Patterns Features (**Schwartz**, Reichart and Rappoport, under review)

NLP

NLP



Text Understanding

NLP

Language Representation

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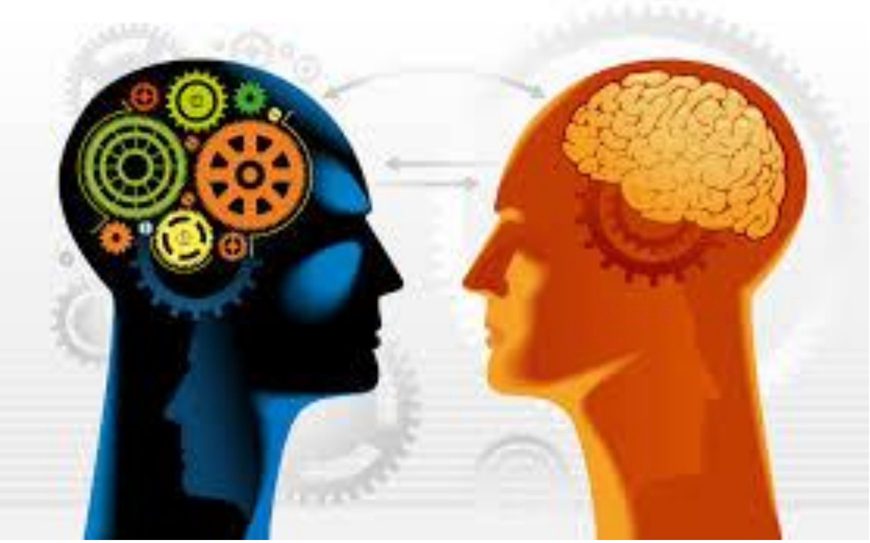

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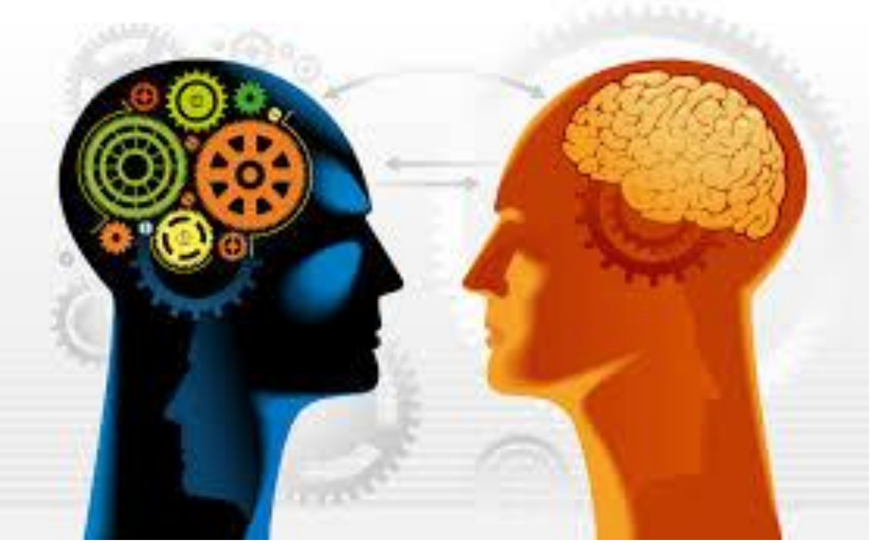

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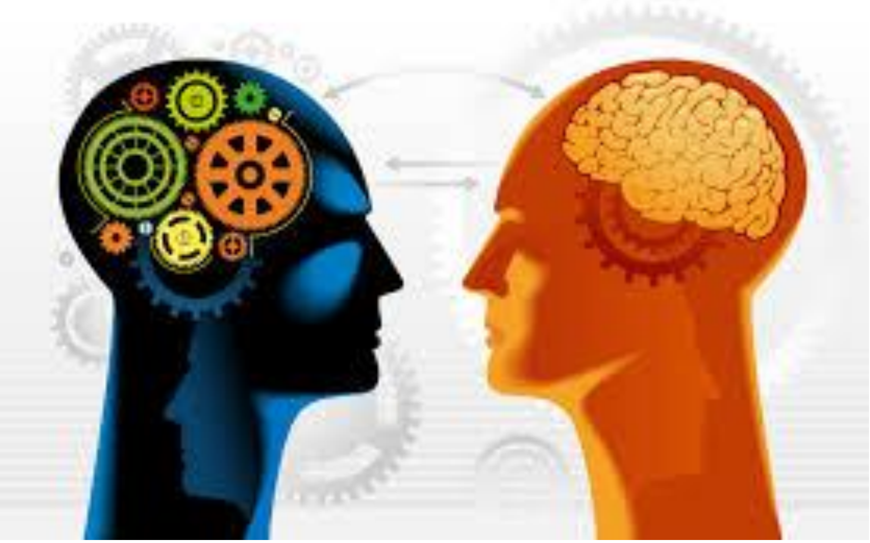

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NLP is Hard

Ambiguity

Noise

Paraphrasing

Complex structures

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Language is Hard!

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  - Search
  - Question Answering
  - Machine Translation
  - Summarization
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  - Required by virtually every high level task (machine translation, questions answering, summarization, speech recognition, etc.)

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- A common solution: Markov independence assumption
  - Formally: compute $p(w_i | w_{i-1}, \ldots, w_{i-n})$
  - *n* usually equals 3 (**trigram** models)

Neuro-probabilistic Language Models

- Address sparsity by building a (dense) vector word representation (aka ***word embeddings***)
  - Replace $p(w_i | \mathbf{w}_{i-1}, \ldots, \mathbf{w}_{i-n})$ with $p(w_i | \mathbf{V}_{i-1}, \ldots, \mathbf{V}_{i-n})$

$$\mathbf{V}_{\mathbf{dog}} = \begin{pmatrix} 0 \\ 0.5 \\ 0.76 \\ -0.12 \\ 0.76 \\ 0 \\ 0 \\ -0.51 \\ . \\ . \\ . \end{pmatrix}$$

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- Use deep neural networks to train language models
  - Bengio, 2003; Collobert, 2008 & 2011, **word2vec** (Mikolov 2013{a,b,c})

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- Use deep neural networks to train language models
  - Bengio, 2003; Collobert, 2008 & 2011, **word2vec** (Mikolov 2013{a,b,c})
- Surprisingly, the word representations turned out to be quite successful on their own

$$\mathbf{V}_{\mathbf{dog}}$$
$$\begin{bmatrix} 0 \\ 0.5 \\ 0.76 \\ -0.12 \\ 0.76 \\ 0 \\ 0 \\ -0.51 \\ . \\ . \\ . \end{bmatrix}$$

Bag of Words Models

- Main type of feature
  - Used in various NLP tasks
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... tokens to date, **friend** lists and recent ...

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... partner, in-laws, relatives or **friends** speak a different ...

... petition to a **friend** Go to the ...

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...images from my **friend** Rory though - ...

... great, and a **friend** as well as a colleague, who, ...

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- For each word w in the vocabulary V, learn both a "target-embedding" v_w and and a "context-embedding" v_c
  – p(c|w) is computed using soft-max:

$$p(c \mid w) = \frac{e^{v_c \cdot v_w}}{\sum_{w' \in V} e^{v_c \cdot v_{w'}}}$$

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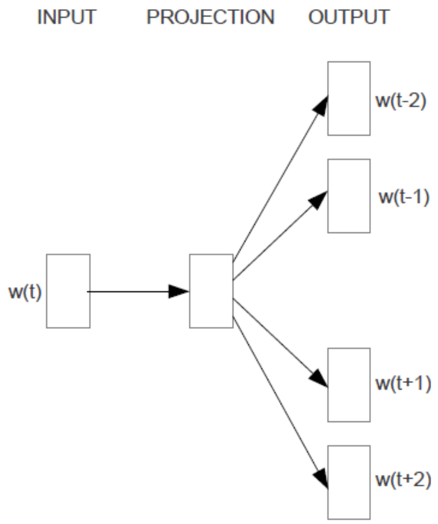
- For each training sentence, treat each word in turn as a target word
  - Sample (word,context) pairs from a window of nearby words

word2vec's Skip-Gram Model (2)

Mikolov et al., 2013



<u>Objective function:</u>

$$\max \sum_{t=1}^{T} \sum_{-c \leq j \leq c, j \neq 0} \log p(w_{t+j} | w_t)$$

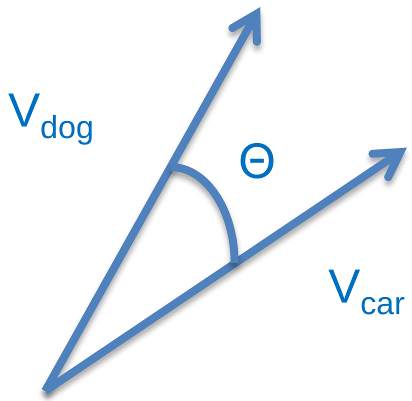
<u>Algorithm:</u>
Stochastic gradient descent

Word Embeddings Applications

- Information Retrieval
- Document Classification
- Question Answering
- Named Entity Recognition
- Parsing
- …

Word Embeddings (Cool!) Properties

- (accurate) Word similarity



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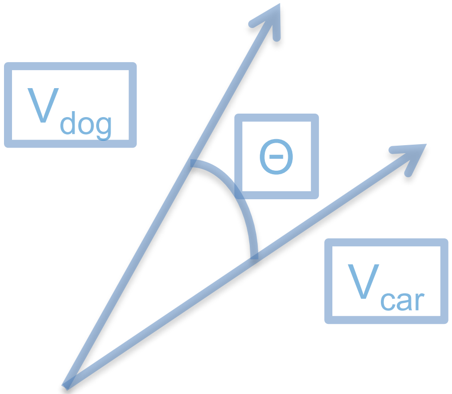
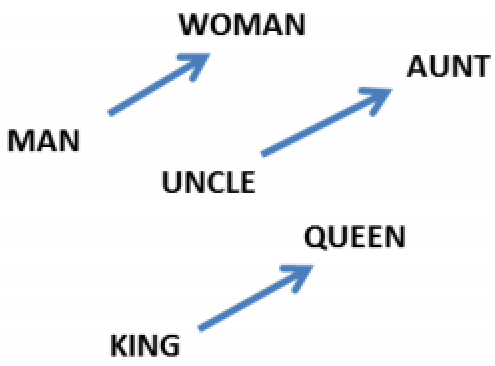


- Word analogy



(Mikolov et al., 2013)

Word Embeddings Limitations

- Resulting vectors are highly **uninterpretable**
  - Sequences of several hundred numbers
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- Restricted to a limited set of relations
  - Similarity/Relatedness, some analogies
  - Other relations are not supported: hyponymy (animal → dog), antonymy (big/tall), etc.

Lexico-syntactic Patterns

Hearst, 1992

- Patterns that contain words and wildcards
  - "***X*** *is a country*", "***X*** *such as* ***Y***", etc.

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Lexico-syntactic Patterns

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- Patterns potentially capture the **context** in which a word participates

- For example:
  - A *dog* participates in patterns (contexts) such as:
  - *"**X** **barks**"*, *"**X** has a **tail**"*, *"**X** and **cats**"*, …

Pattern Applications

- Acquiring the semantics of **relationships** between words
  - Discovering hyponymy (animal → cat) (Hearst, 1992)
  - Discovering meronymy (cat → tail) (Berland & Charniak, 1999)
  - Discovering antonymy (big / small) (Lin, 2003)
- Word clustering and classification
  - Davidov & Rappoport, 2006; **Schwartz**, Reichart & Rappoport, 2014
- Sentence Level Applications
  - Sarcasm Detection (Tsur, Davidov & Rappoport, 2010)
  - Sentiment Analysis (Davidov, Tsur, & Rappoport, 2010)
  - Authorship Attribution (**Schwartz** et al., 2013)

Examples of Patterns

- Extracting antonymy (opposite) relations
  - “***either X or Y***”
  - *John is* ***either tall or short***
  - ***either stay or come*** *with us*

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- Extracting hyponymy (is-a) relations
  - "***X such as Y***"

  - *Cut the stems of boxed **flowers such as roses***
  - *I am responsible for preparing a range of **fruits such as apples***

Word Similarity via Patterns

- Some patterns are useful for identifying words that are **similar***
  - mouse / rat , shirt / sweater, etc.

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  - mouse / rat , shirt / sweater, etc.

- These patterns are **symmetric**
  - Contain exactly two wildcards (***X***,***Y***)
  - Words w_i,w_j that co-occur in these patterns can come in both forms (***X***=w_i,***Y***=w_j) and (***X***=w_j,***Y***=w_i)

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Symmetric Patterns (SPs)

- X *and* Y
  - cats and dogs , dogs and cats
  - France and England, England and France
- X *as well as* Y
  - friends as well as colleagues, colleagues as well as friends
  - apples and oranges , oranges and apples
- ….

Automatically Extracted Symmetric Patterns

The (Davidov and Rappoport, 2006) Algorithm

- A graph-based algorithm
  - Input: a corpus of **plain text**
  - Output: a set of symmetric patterns

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- The idea: search for patterns with **interchangeable** word pairs
  - For each pattern candidate, compute symmetry measure (**M**)
  - Select the N patterns with the highest **M** values

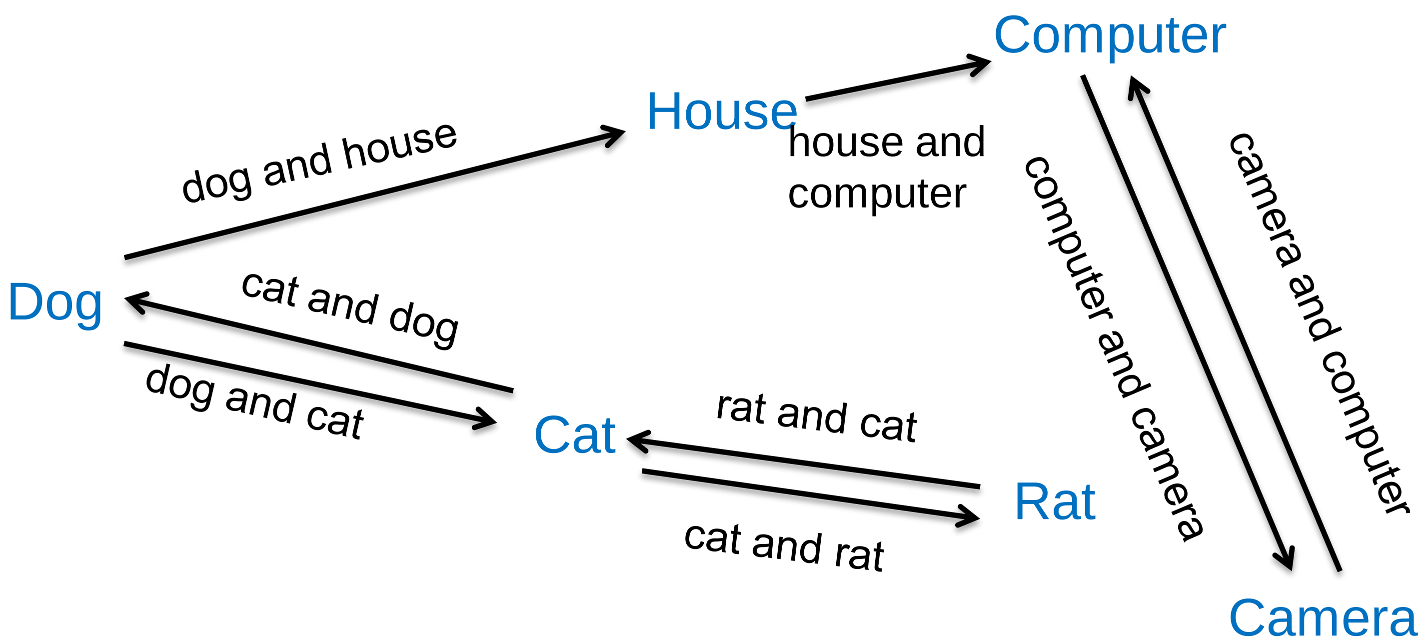
Automatically Extracted Symmetric Patterns (2)

The (Davidov and Rappoport, 2006) Algorithm

- The **M** measure counts the proportion of pattern instances that appear in both directions ("cat and dog" + "dog and cat")
- High **M** value ➔ A symmetric pattern

DR06 Example

X *and* Y



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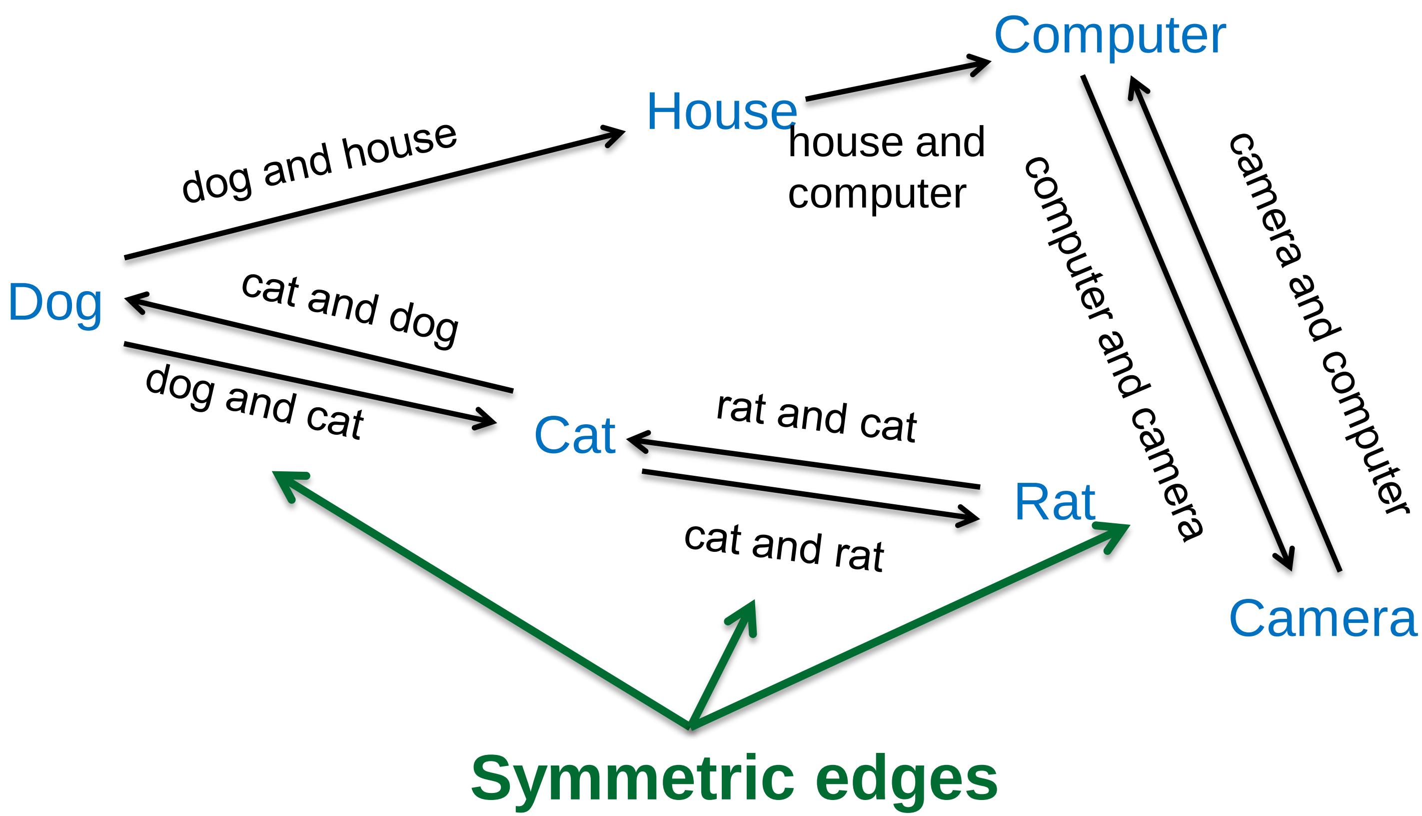

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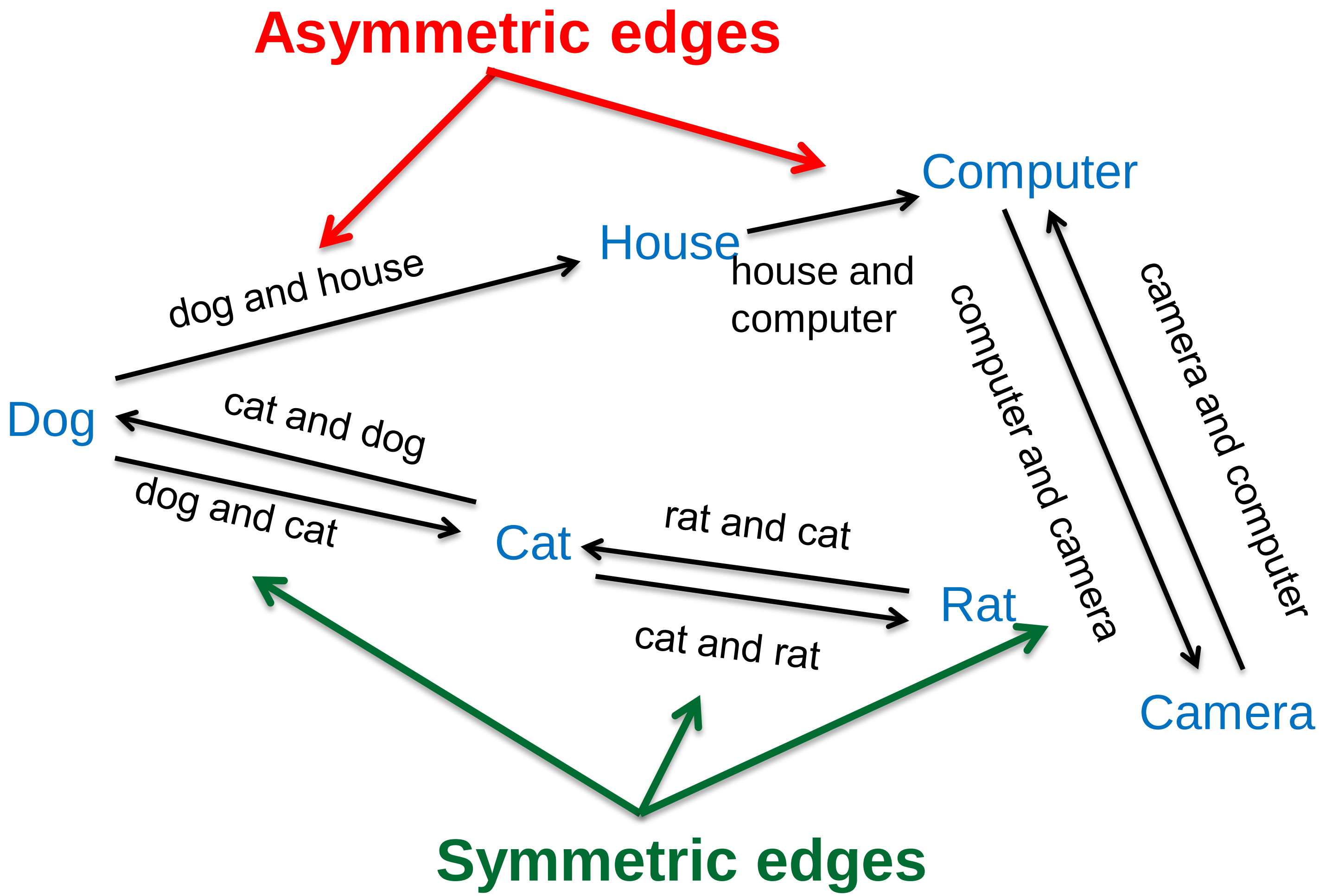

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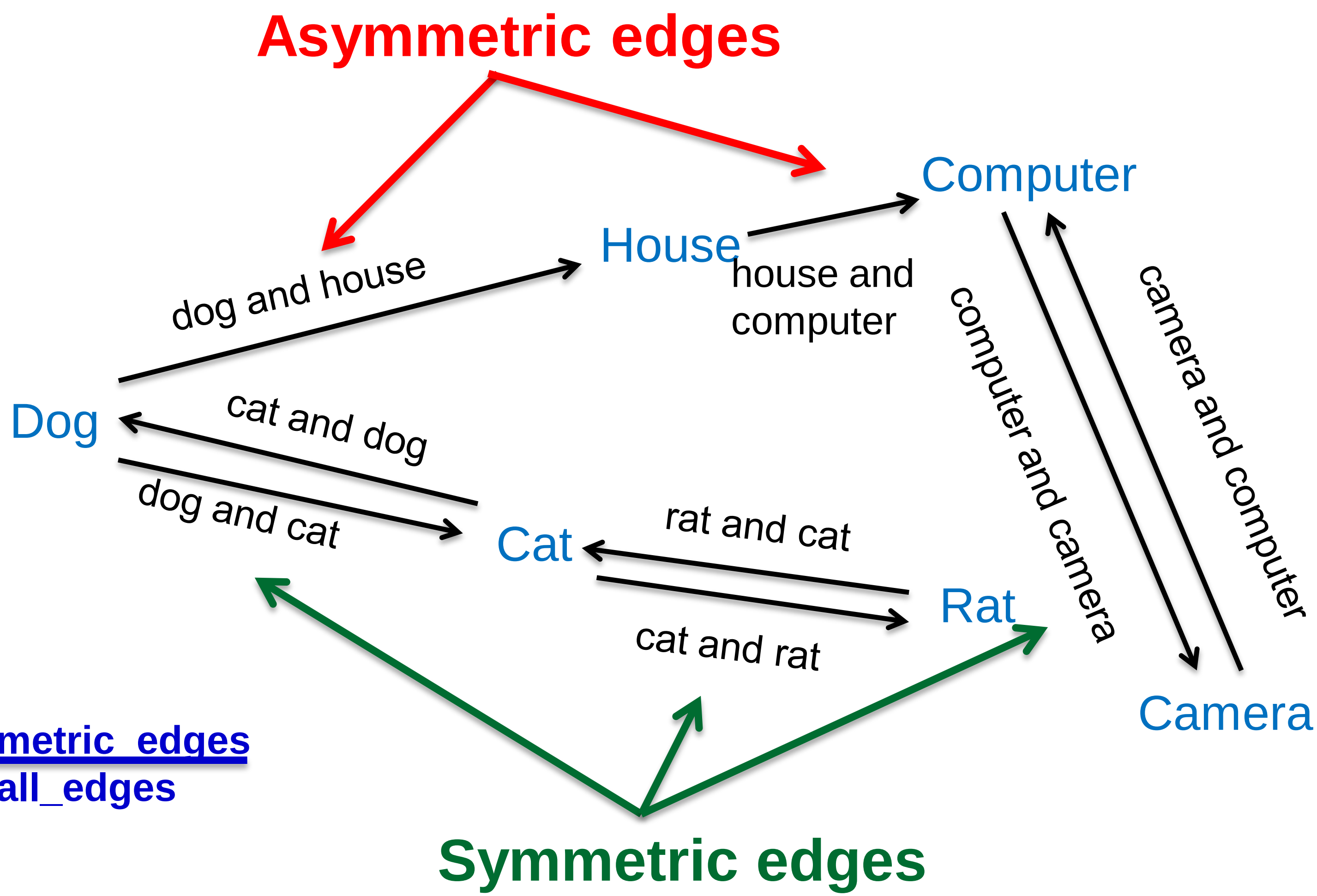

$$M = \frac{\#symmetric\_edges}{\#all\_edges}$$

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- Word embeddings are great
  - Useful for down stream applications
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  - Useful for down stream applications
  - Have cool properties (similarity, word analogies)

- But not perfect
  - Uninterpretable
  - Unable to recognize various relations

Interpretable Word Embeddings Using Pattern Features

Roy Schwartz, Roi Reichart and Ari Rappoport

(Under Revision)

Outline

- Learn **interpretable** and **high quality** word embeddings
  - Substantially outperform state-of-the-art word2vec embeddings
- Show the benefits of interpretability
  - Use our embeddings to assign dissimilar vectors to antonym pairs (big/small)
- Combine our embeddings with state-of-the-art embeddings to get improved expressive power

Symmetric Patterns to Word Similarity

- Input: a large corpus C

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- Extract a set of SPs *P* using the DR06 algorithm
  - *"**X** and **Y**", "**X** or **Y**", "**X** and the **Y**", "from **X** to **Y**", "**X** or the **Y**", "**X** as well as **Y**", "**X** or a **Y**","**X** rather than **Y**", "**X** nor **Y**", "**X** and one **Y**", "either **X** or **Y**"*

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- Traverse C, extract all instances of all *p in P*
  - **cats** *and* **dogs**
  - **House** *and the* **rooms**
  - *from* **France** *to* **England**
  - …

Symmetric Patterns to Word Similarity (2)

- For each word *w* in the lexicon, build a count vector (V_w) of all other words that co-occur with *w* in SPs

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- orange
  1. … apples and oranges …
  2. … oranges as well as grapes

     …

  K. … neither banana nor orange

- China
  1. … Japan or China …
  2. … China rather than Korea

     …

  M. … Vietnam and China …

Symmetric Patterns to Word Similarity (3)

- Compute the Positive Pointwise Mutual Information (PPMI) between each pair of words

$$PMI(w_i, w_j) = \log\left(\frac{p(w_i, w_j)}{p(w_i)\,p(w_j)}\right)$$

$$PPMI(w_i, w_j) = \begin{cases} PMI(w_i, w_j) < 0 : 0 \\ otherwise : PMI(w_i, w_j) \end{cases}$$

The Result: **Interpretable** Word Embeddings based on Symmetric Patterns

$$V^{sp}_{\mathbf{dog}} = \begin{pmatrix} \text{PPMI(dog,house)} \\ \text{PPMI(dog,mouse)} \\ \text{PPMI(dog,zebra)} \\ \text{PPMI(dog,wine)} \\ \text{PPMI(dog,cat)} \\ \text{PPMI(dog,dolphin)} \\ \text{PPMI(dog,bottle)} \\ \text{PPMI(dog,pen)} \\ . \\ . \\ . \end{pmatrix}$$

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$$|V^{SP}_{w}| = \sim 500K$$

$$E_w(|nonzero(V^{SP}_{w})|\ ) = \sim 50$$

Smoothing

- For each word *w*, V^N_w denotes the top N vectors with the smallest cosine distance to V^{SP}_w

$$V_w^{\mathrm{SP'}} = V_w^{\mathrm{SP}} + \alpha \sum_{v \in V_w^N} v$$

- Using N=50: $E_w(|nonzero(V^{SP'}_w)|\ ) = \sim 8K$

❖ α and *N* are tuned using a development set

Antonyms

big / small

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  - Here is a X car
  - I live in a X house

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➔ In typical word embeddings, $\cos(V_{big}, V_{small})$ is high

Antonyms

big / small

- Some symmetric patterns are indicative of antonymy*
  - “*either* X *or* Y” (*either* big *or* small), “*from* X *to* Y” (*from* poverty *to* richness)

* Lin et al. (2003)

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- For each word *w*, compute V_w^{AP} similarly to V_w^{SP}, but using the set of antonym patterns

$$V_w^{\mathrm{AP'}} = V_w^{\mathrm{SP}} - \beta \cdot V_w^{\mathrm{AP}}$$

❖ β is tuned using a development set

Experiments

- Word similarity task
  - Experiments with the SimLex999 dataset (Hill et al., 2014)
  - 999 word pairs, each assigned a similarity score by human annotators
  - $f_{<model>}(w_i,w_j) = \cos(V^{<model>}_{wi},V^{<model>}_{wj})$
  - Evaluation results is the Spearman's ρ score between model and human judgments
  - Numbers are average scores of 10 folds of 25% (dev) / 75 (test) partitions
  - Baselines: 2 interpretable baselines, 3 state-of-the-art, non-interpretable baselines

Interpretable?	Model	Spearman's ρ
Non-interpretable	GloVe	0.426
	CBOW	0.43
	skip-gram	0.462
Interpretable	BOW	0.423
	NNSE	0.455
	$SP^{(+)}$	**0.502**

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Word Pair	*SP*		SG
	+AN	-AN	
new - old	1	6	6
narrow - wide	1	7	8
necessary - unnecessary	2	2	9
bottom - top	3	8	10
absence - presence	4	7	9
receive - send	1	9	8
fail - succeed	1	8	6

Joint Model

$$f_{joint}(w_i, w_j) = \gamma \cdot f_{SP}(w_i, w_j) + (1-\gamma) \cdot f_{skip\text{-}gram}(w_i, w_j)$$

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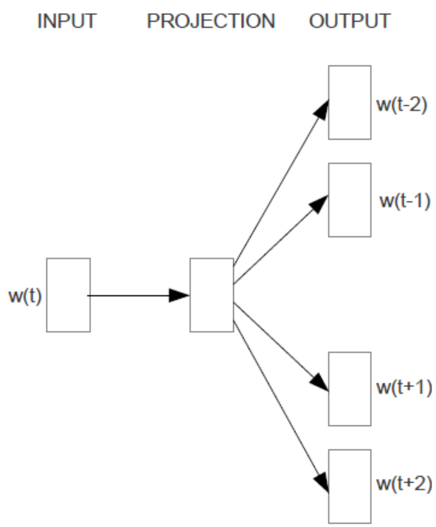
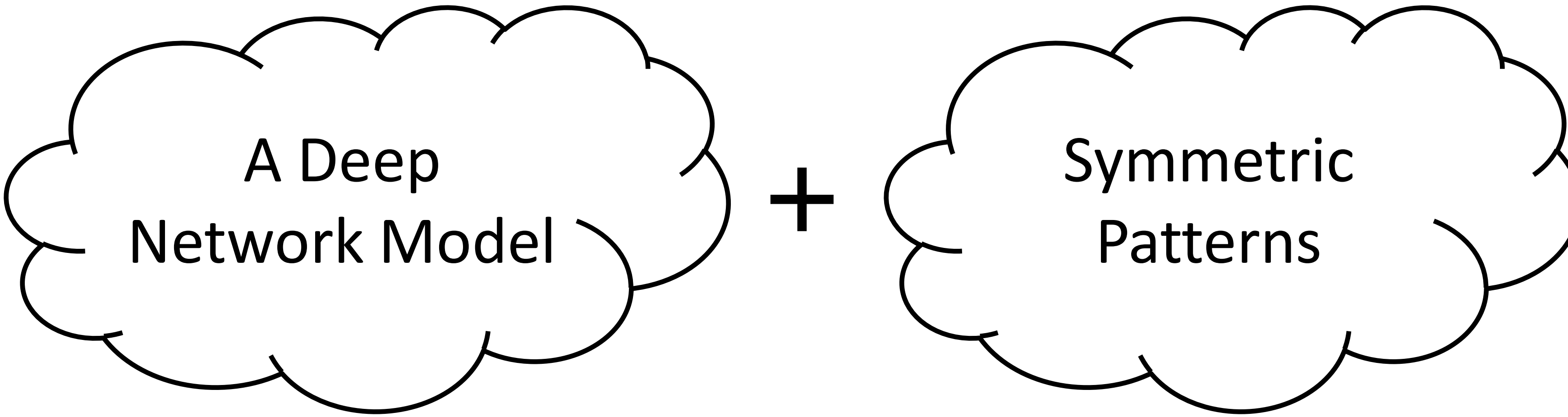
Reminder: word2vec's Skip-Gram Model
(Mikolov et al., 2013)



Objective function:

$$\max \sum_{t=1}^{T} \sum_{-c \le j \le c, j \ne 0} \log p(w_{t+j} | w_t)$$

Integrating Symmetric Patterns into Existing NN Architectures?



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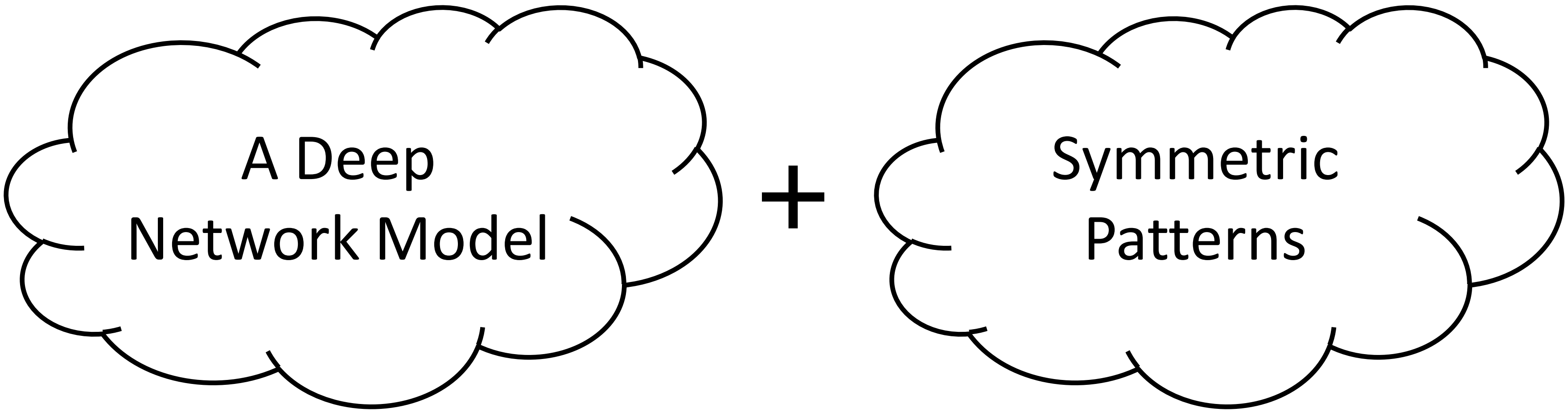

Pre-processing?

Enhance plain text with symmetric pattern information?

Integrating Symmetric Patterns into Existing NN Architectures?

A Deep Network Model

+

Symmetric Patterns

Pre-processing?

Smarter Objective Function?

max $\Sigma\, p(c|w)$ + **constraint**

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Symmetric Patterns

Pre-processing?

Smarter Objective Function?

Summary

- Patterns are useful for extracting semantic information

- Symmetric patterns are as useful (actually more useful) as state-of-the-art word embeddings in modeling word similarity
  - 4–7.9 points gap

- Patterns can capture relations that word embeddings cannot
  - Antonymy

- SPs can be combined along with state-of-the-art embeddings to create an even more accurate representation
  - 6.6 points higher than state-of-the-art

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