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Deep Approaches to Semantic Text Matching

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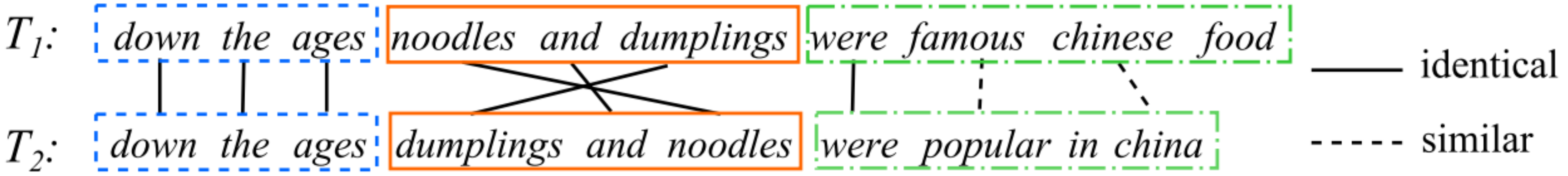
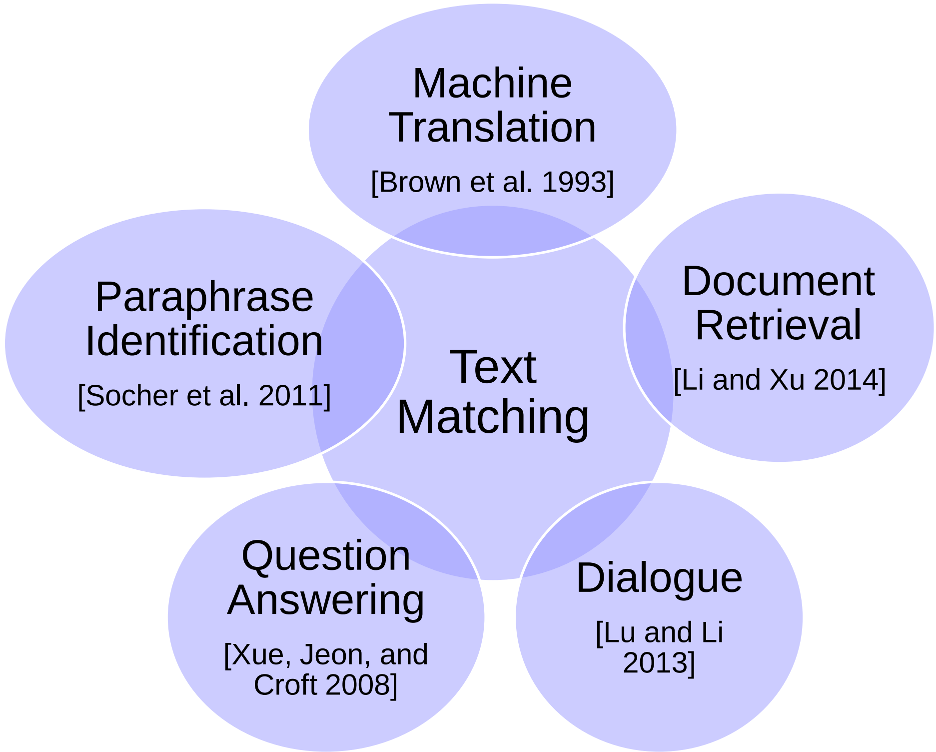
Outline

- Semantic text matching is important
- Word representation: bridging the semantic gap
- Sentence matching: capturing the proximity
- Summary

Semantic Text Matching



Are these two sentences **similar**?



Accuracies of Natural Language Analysis

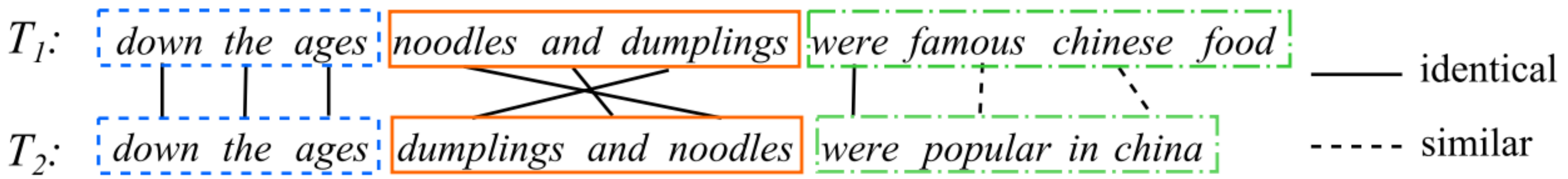
- Lexical Analysis (word segmentation and part-of-speech tagging): practically usable
- Syntactic Analysis: almost usable
- Semantic Analysis: still difficult
- Programmatic Analysis: ?

	English	Chinese
Prgrammatic Analysis	?	?
Semantic Role Labeling	>=87%	>=75%
Syntactic Analysis	>=90%	>=80%
Part of Speech Tagging	>=97%	>=93%
Word Segmentation	NA	>=95%

Slides from Hang Li

Current Approach:
Avoid Understanding and Conduct **Matching**

Text semantic matching challenges



- Word level: semantic gaps between words
  - Two words has similar meanings
  - “popular” ~ “famous”; “china” ~ “chinese"
- Sentence level: proximity matching between sentences
  - The matching positions do matter
  - “noodles and dumpling” – “dumplings and noodles”
- Need to consider them simultaneously

Learning to (semantic) text match

- The problem can be formulized as

$$\text{Match}(T_1, T_2) = F\big(\phi(T_1), \phi(T_2)\big)$$

  - ϕ: mapping text to representation vector
  - F: scoring function based on representation
- Learning the model parameters
  - Learning the representation ϕ
  - Learning the scoring function F

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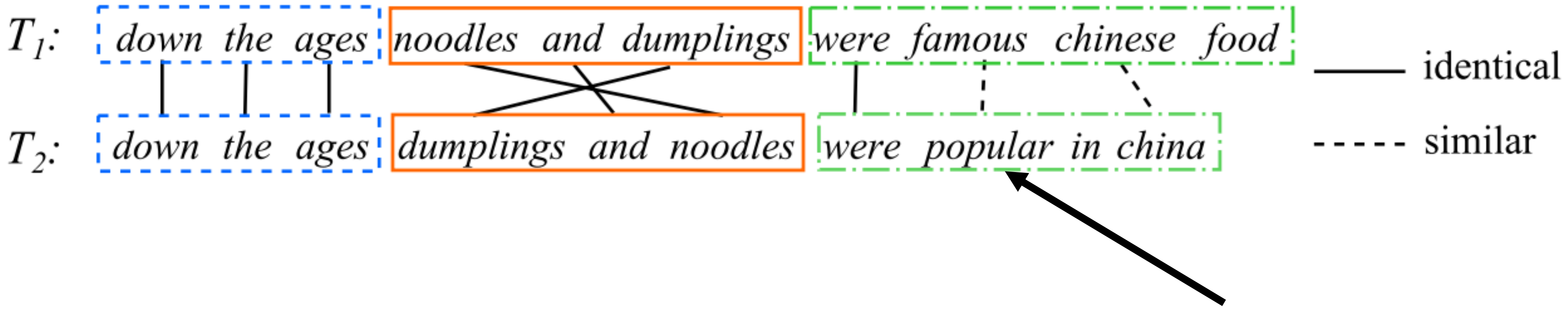


How similar "popular" to "famous"?

Local representation of words

- Words are the building blocks of texts
- NLP treats words mainly (rule-based / statistical approach at least) as atomic symbols:

  Man | Woman | Dog | Computer

- also known as "one-hot" or local representation

One-Hot Representation	
man	[1,0,...,0,0,...,0,0]
woman	[0,1,...,0,0,...,0,0]
dog	[0,0,...,1,0,...,0,0]
computer	[0,0,...,0,0,...,1,0]

- local representation: each word is locally represented by a distinct node.

Limitation of local representations

- Local representation makes a strong independent assumption between words

Local Representation	
man	[1,0,...,0,0,...,0,0]
woman	[0,1,...,0,0,...,0,0]
car	[0,0,...,1,0,...,0,0]
automobile	[0,0,...,0,0,...,1,0]

cos(car, automobile) = 0!

cos(man, women) = cos(man, car)

- Local representation is not efficient
  - require N nodes to represent N words

The distributional hypothesis
[Harris, 1954, Firth, 1957]

"Words that occur in the same contexts tend to have similar meanings."

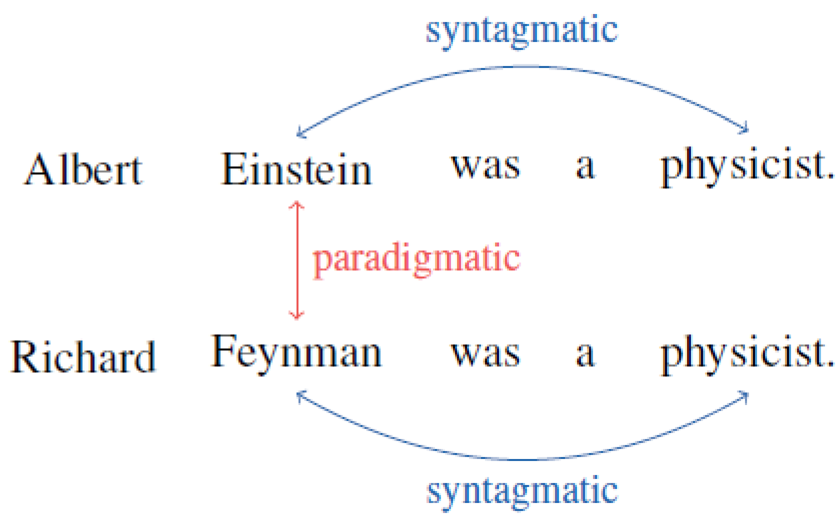
–Zellig Harris [Harris, 1954]

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

—J.R. Firth

- Discover semantic from **external** information
  - A word is just an ID, its meaning depends on other words (company it keeps, or context)
- One Hypothesis, two interpretations

Two interpretations: Syntagmatic and paradigmatic [Sahlgren, 2008]



- Syntagmatic: words co-occur in the same text region (they are related)
- Paradigmatic: words occur in the same context, may not at the same time (they are similar)

Modeling syntagmatic relation

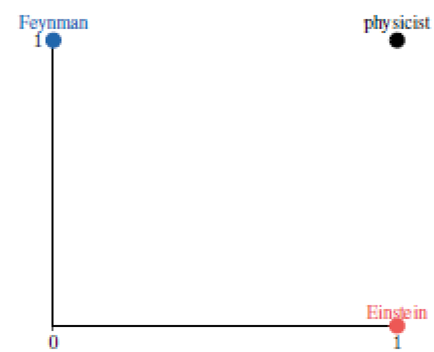
syntagmatic

Albert Einstein was a physicist.

Richard Feynman was a physicist.

syntagmatic

	d_1	d_2
Einstein	1	0
Feynman	0	1
physicist	1	1



LSI, LDA, PV-DBOW $\cdots$

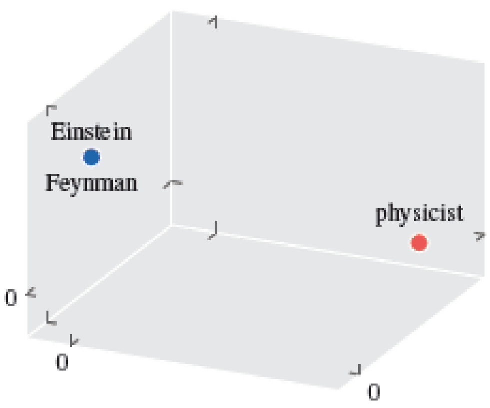
Modeling paradigmatic relation

Albert **Einstein** was a physicist.

↕ paradigmatic

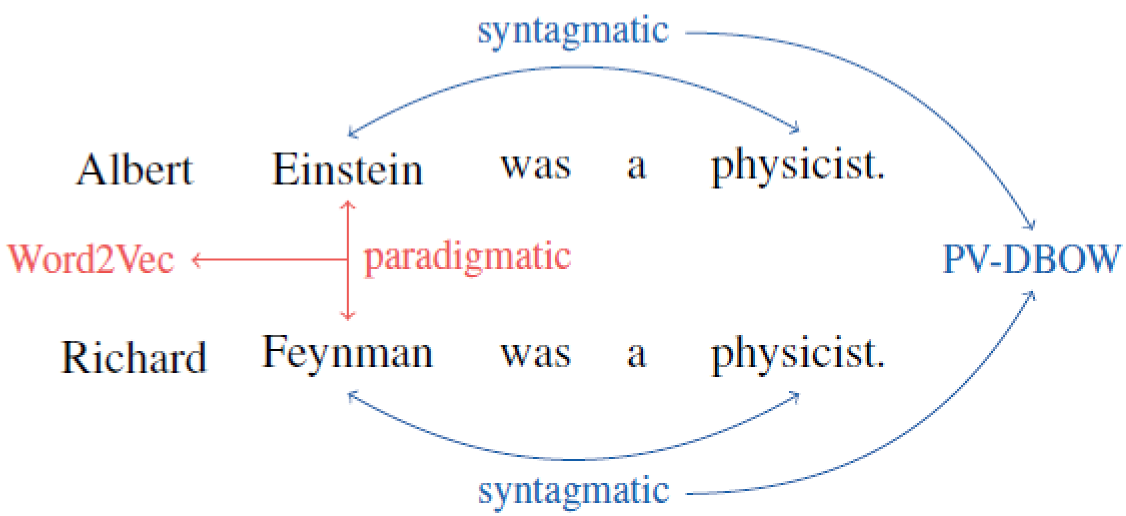
Richard **Feynman** was a physicist.

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



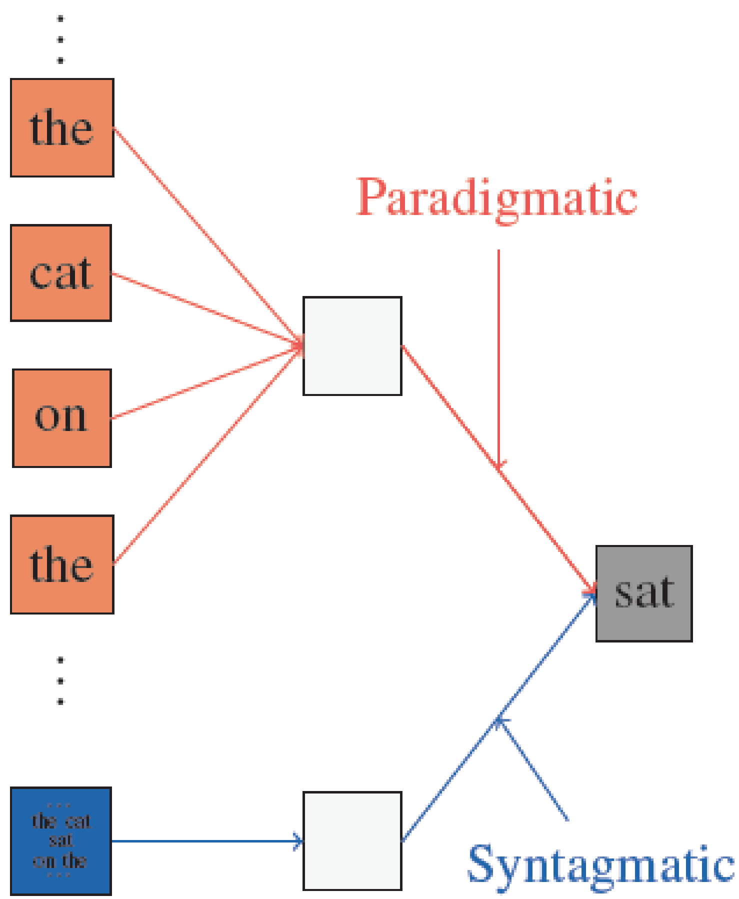
NLMs, Word2Vec, GloVe · · ·

Modeling them jointly



Sun et al., Learning Word Representations by Jointly Modeling Syntagmatic and Paradigmatic Relations. In Proc. ACL 2015.

Parallel document content model (PDC)



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

Negative Sampling

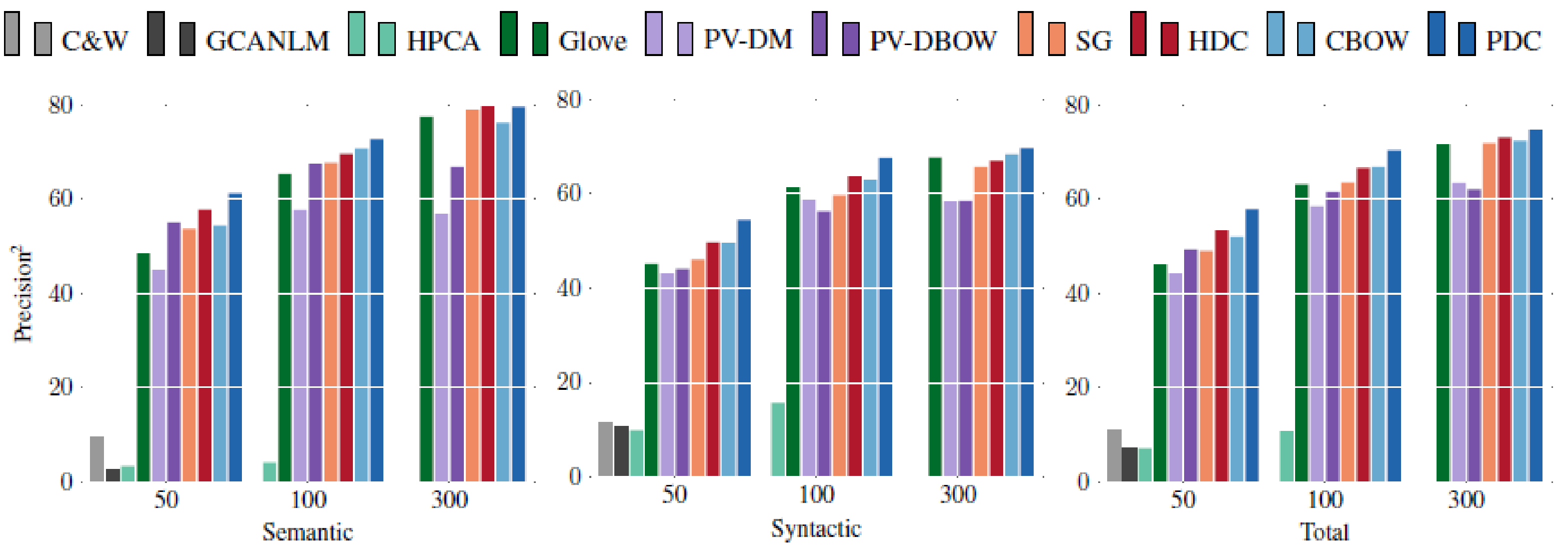
$$\ell = \sum_{n=1}^{N} \sum_{w_i^n \in d_n} \Big(\log \sigma(\vec{w_i^n} \cdot \vec{h_i^n}) + \log \sigma(\vec{w_i^n} \cdot \vec{d_n}) + k \cdot \mathbb{E}_{w' \sim P_{\mathrm{nw}}} \log \sigma(-\vec{w'} \cdot \vec{h_i^n}) + k \cdot \mathbb{E}_{w' \sim P_{\mathrm{nw}}} \log \sigma(-\vec{w'} \cdot \vec{d_n}) \Big)$$

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

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

Empirical evaluation: word analogy

- Google test set [Mikolov et al., 2013]
  - Semantic: "Beijing is to China as Paris is to __"
  - Syntactic: "big is to bigger as deep is to __"



Diversify the results

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

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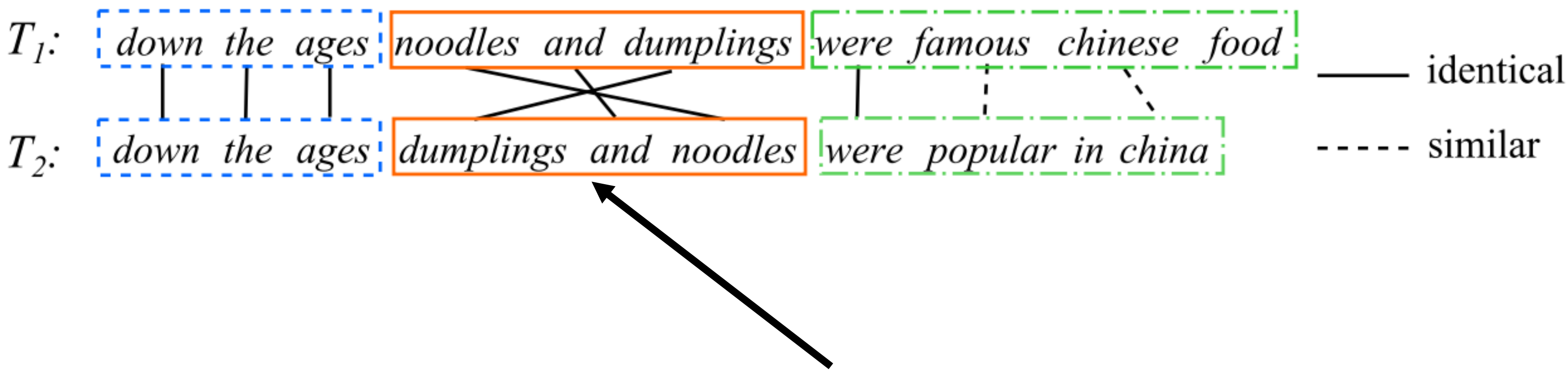
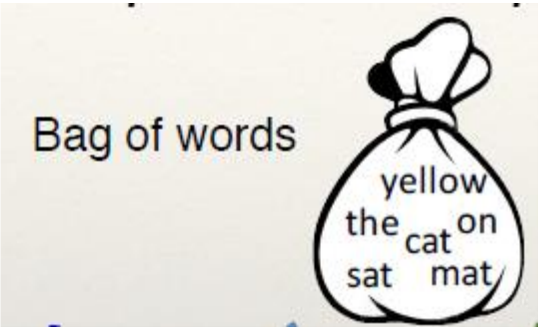
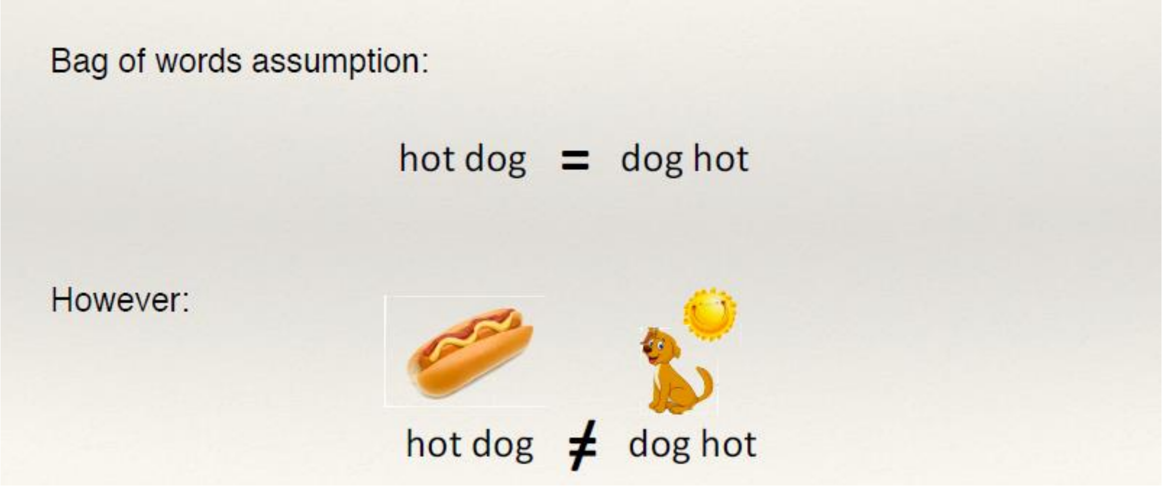


How similar "noodles and dumplings" to "dumplings and noodles"?

Bag of words

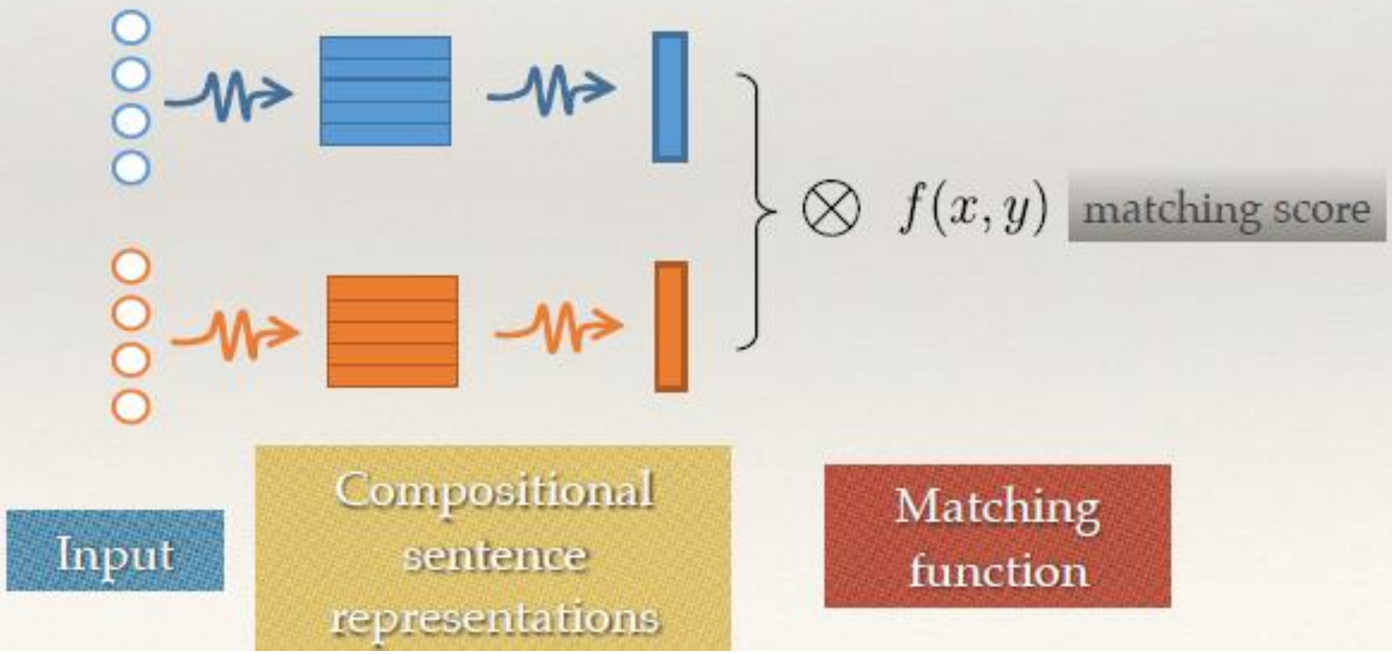
- Bag of words representation of sentences
  - the yellow cat sat on the mat
  - the cat sat on the yellow mat
- Heuristic matching function
  - Cosine similarity, BM25 ……
- However, order of words is important



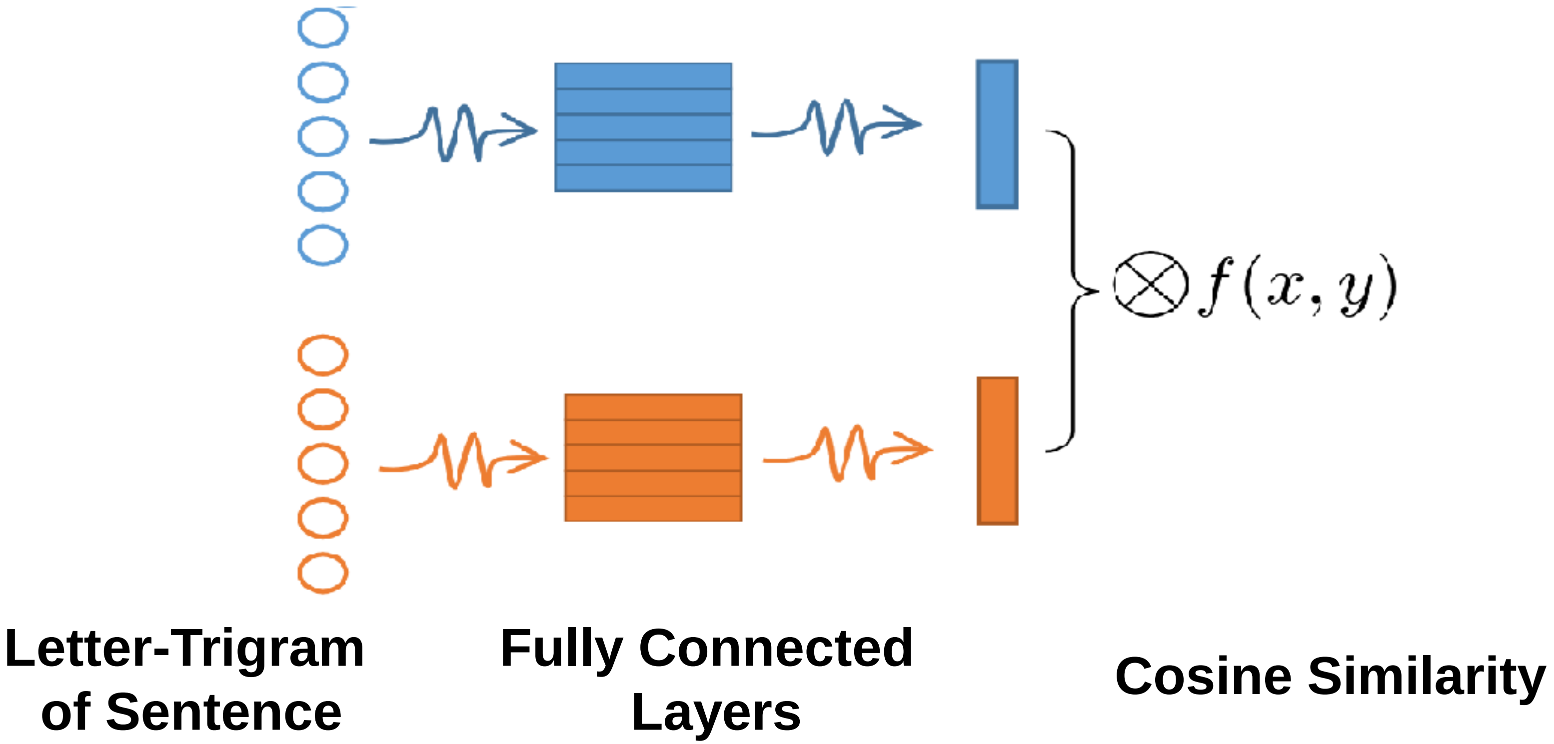


Approach 1: composition focused

- Step 1: Composite sentence representation $\phi(x)$
- Step 2: Matching between the representations $F(\phi(x), \phi(y))$



Composition focused methods example: DSSM



Huang P-S, He X, Gao J, et al. Learning deep structured semantic models for web search using clickthrough data//Proceedings of the 22nd ACM international conference on CIKM, 2013: 2333-2338.

DSSM Input – letter-trigram

- Word One-Hot Representation

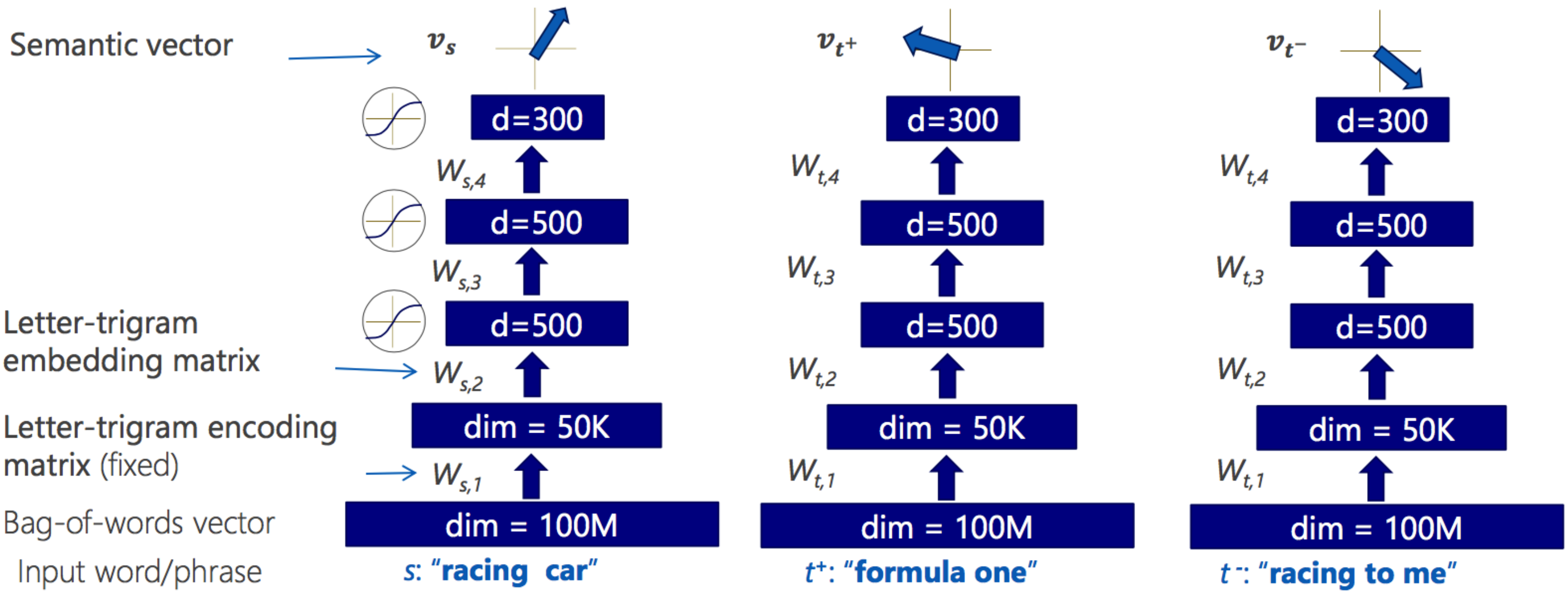
  Candy [o o o o o **1** o o o o o o o o o o o ...]

  Store [o o o o o o o o o o o o o o o **1** o ...]

- Letter-Trigram Representation
  - #candy# | #store#   can split into:
  - #ca | can | and | ndy | dy# | #st | sto | tor | ore | re#
  - [o o 1 o o ... o 1 o 1 ... o o ...]

- Compact representation: |words| (500K) -> |letter-trigrams| (30K)
- Generalize to unseen words
- Robust to misspelling, inflection, etc

DSSM - Composite Embedding



DSSM - Aggregate Matching Score

- Compute Cosine similarity between semantic vectors

$$S = \frac{x^T \cdot y}{|x| \cdot |y|}$$

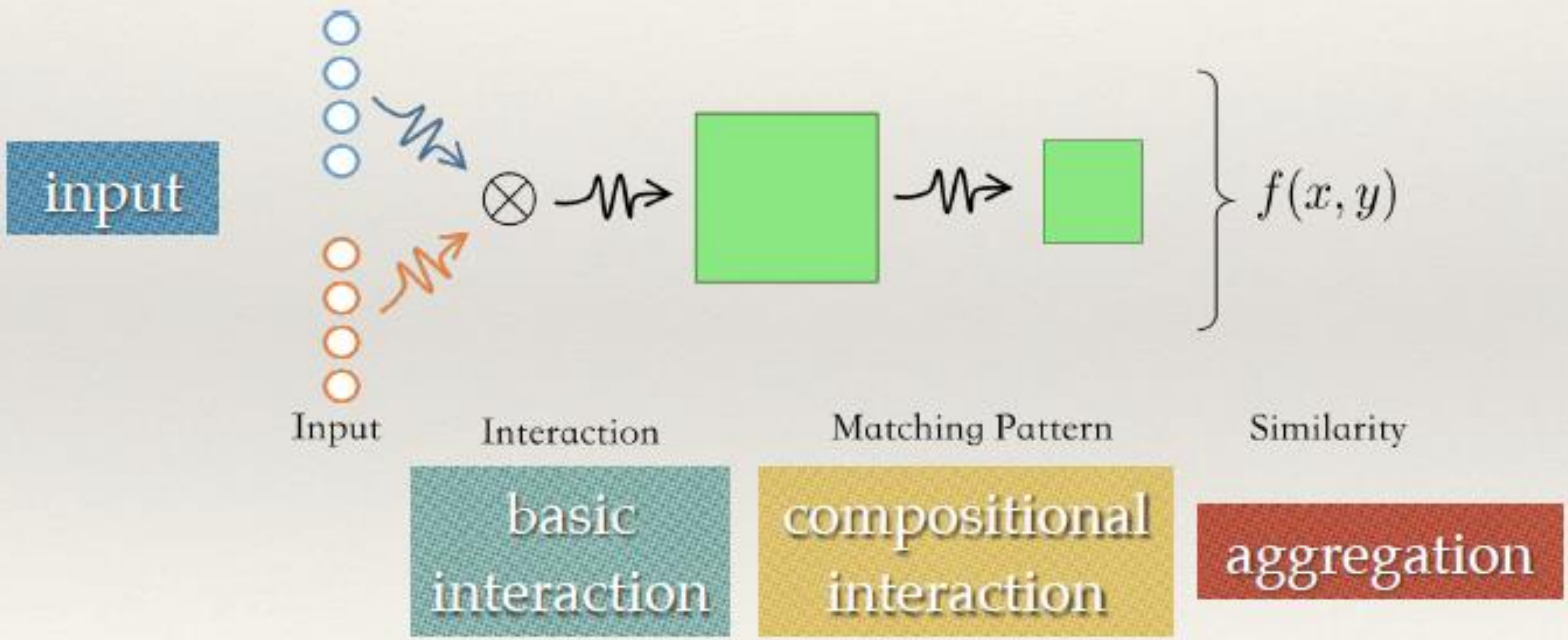
- Training
  - A query q and a list of docs $D = \{d^+, d_1^-, \dots, d_k^-\}$
  - d^+positive doc, $d_1^-, \dots, d_k^-$ negative docs to q
  - Objective:

$$P(d^+|q) = \frac{\exp(\gamma\, cos(q, d^+))}{\sum_{d \in D} \exp(\gamma\, cos(q, d))}$$

  - Optimize to maximize $P(d^+|q)$. SGD Method.

Approach 2: interaction focused

- Step 1: Construct basic low-level interaction signals
- Step 2: Aggregate matching patterns

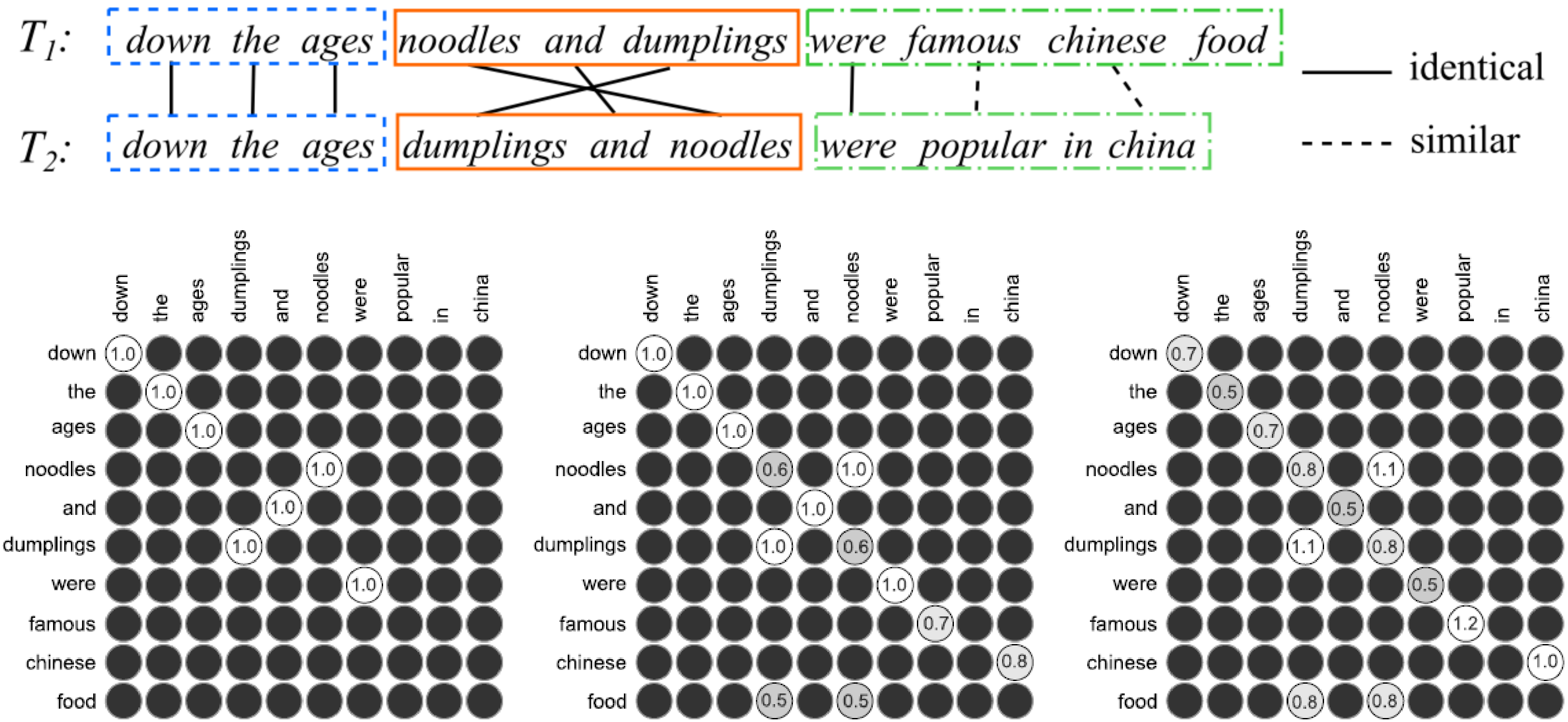


Interaction focused methods example: MatchPyramid

- Challenges
  - Representation: representing the word level **matching signals** as well as the **matching positions**
  - Modeling: discovering the **matching patterns** between two texts
- Our solutions
  - Step 1: representing as matching matrix
  - Step 2: matching as image recognition

Pang et al., Text Matching as Image Recognition. In Proc. AAAI 2016.

Step 1: matching matrix



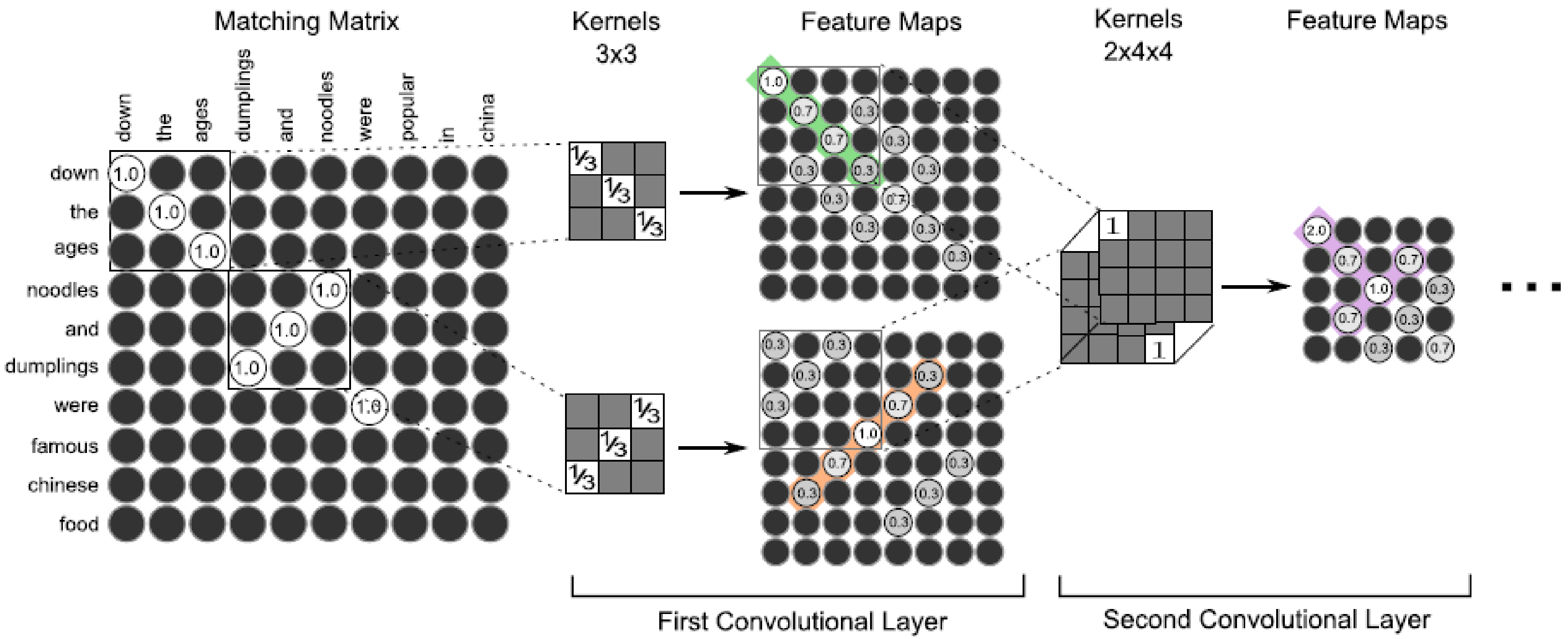
(a) Matching Matrix-Indicator (b) Matching Matrix-Cosine (c) Matching Matrix-Dot Product

$$\mathbf{M}_{ij} = \mathbb{I}_{\{w_i = v_j\}} = \begin{cases} 1, & \text{if } w_i = v_j \\ 0, & \text{otherwise.} \end{cases}$$

$$\mathbf{M}_{ij} = \frac{\vec{\alpha_i}^\top \vec{\beta_j}}{\|\vec{\alpha_i}\| \cdot \|\vec{\beta_j}\|}$$

$$\mathbf{M}_{ij} = \vec{\alpha_i}^\top \vec{\beta_j}.$$

Step 2: matching as image recognition



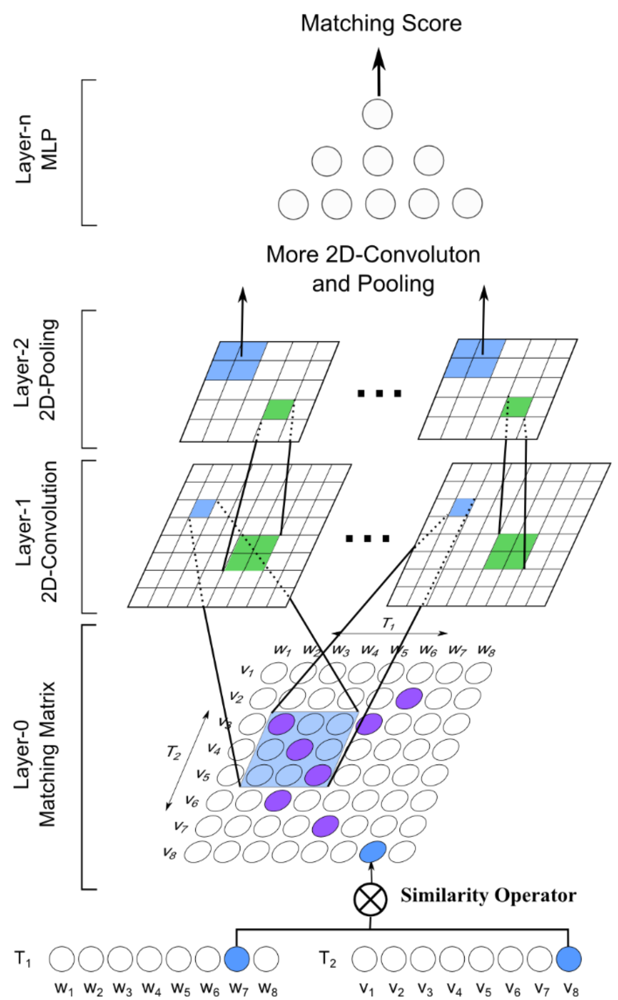
Putting together: MatchPyramid

Hierarchical Convolution

Capturing rich matching patterns

Matching Matrix

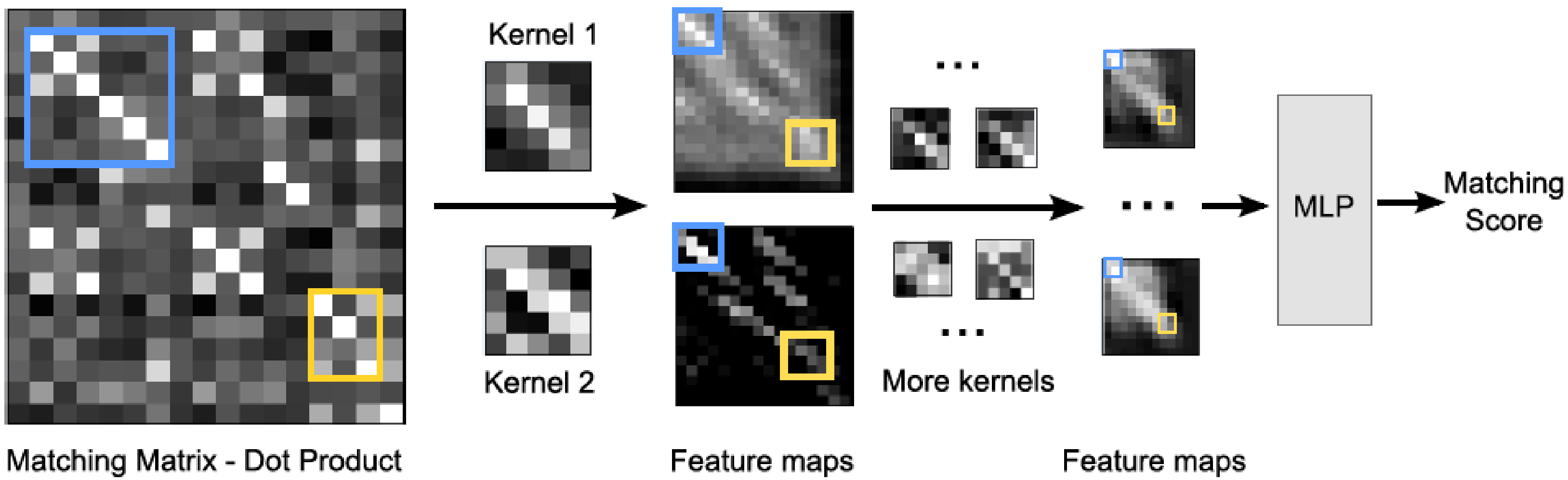
Bridging the semantic gap between words



MatchPyramid discovers text matching patterns

T_1: PCCW's chief operating officer, Mike Butcher, and Alex Arena, the chief financial officer, will report directly to Mr So.

T_2: Current Chief Operating Officer Mike Butcher and Group Chief Financial Officer Alex Arena will report to So.



Empirical evaluation: Paraphrase Identification (MSRP)

	Model	Accuracy(%)	F1(%)
Traditional	TF-IDF	70.31	77.62
Composition Focused	DSSM	70.09	80.96
	CDSSM	69.80	80.42
	ARC-I	69.60	80.27
	uRAE	76.80	83.60
	MultiGranCNN	78.10	84.40
	MV-LSTM	75.40	82.80
Interaction Focused	ARC-II	69.90	80.91
	MatchPyramid	75.94	83.01
	Match-SRNN	74.50	81.70

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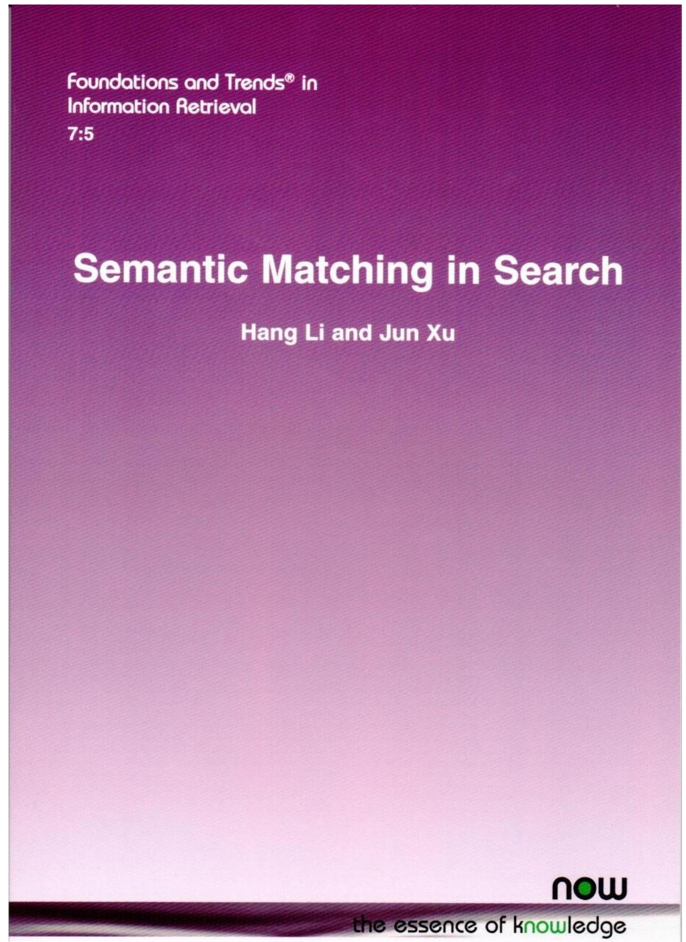
Summary

- Semantic matching in text is fundamental for QA, IR, and paraphrasing etc.
- Semantic matching is challenging
  - Semantic gaps between words
  - Proximity matching between sentences
- Our solutions
  - Semantic: distributed word representation with external (content) information
  - Proximity: Composition focused and interaction focused methods, e.g., MatchPyramid



http://www.bigdatalab.ac.cn/~junxu/publications/SemanticMatchingInSearch_2014.pdf
http://www.nowpublishers.com/articles/foundations-and-trends-in-information-retrieval/INR-035

Thank you!

Q&A

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