

Word vectors

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Outline

1. Why do we need word representations?
2. One-hot encodings
3. What is meaning?
4. word2vec
5. Counting methods and GloVe
6. Evaluation of word vectors

Word representations

Text is a sequence of symbols

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One-hot vectors

text

sequence

symbol

One-hot vectors

text

sequence

symbol

Problems:

- vector size is too large
- vectors don't capture *meaning*, since all vectors have same distances

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Denotational semantics

Meaning (Webster dictionary)

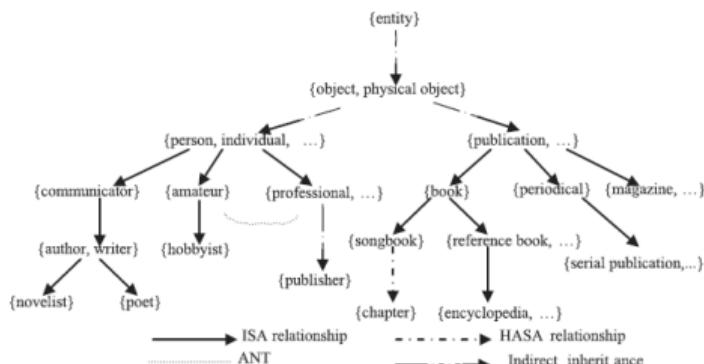
- the idea that is represented by a word, phrase, etc.
- the idea that a person wants to express by using words, signs, etc.
- the idea that is expressed in a work of writing, art, etc.

signifier (symbol) \Leftrightarrow signified (idea or thing)

tree \Leftrightarrow {  ,  ,  }

WordNet

A thesaurus containing lists of synonyms and hypernims (“is a” relations)



WordNet Search - 3.1	
WordNet home page - Glossary - Help	
Word to search for: <input type="text" value="dog"/> <input type="button" value="Search WordNet"/>	
Display Options: <input type="button" value="Select option to change"/> <input type="button" value="Change"/>	
Key: "S" = Show Synset (semantic) relations, "W" = Show Word (lexical) relations Display options for sense: (gloss) "an example sentence"	
Noun	
<ul style="list-style-type: none">• <u>S. (n) dog, domestic_dog, Canis_familiaris</u> (a member of the genus Canis (probably descended from the common wolf) that has been domesticated by man since prehistoric times; occurs in many breeds) "the dog barked all night"<ul style="list-style-type: none">◦ <u>direct hyponym / full hyponym</u>◦ <u>part meronym</u>◦ <u>member holonym</u>◦ <u>direct hyperonym / inherited hyponym / sister term</u><ul style="list-style-type: none">• <u>S. (n) canine, canid</u> (any of various fissiped mammals with nonretractile claws and typically long muzzles)• <u>S. (n) carnivore</u> (a terrestrial or aquatic flesh-eating mammal) "terrestrial carnivores have four or five clawed digits on each limb"<ul style="list-style-type: none">• <u>S. (n) placental, placental mammal, eutherian, eutherian mammal</u> (mammals having a placenta; all mammals except monotremes and marsupials)• <u>S. (n) mammal, mammalian</u> (any warm-blooded vertebrate having the skin more or less covered with hair; young are born alive except for the small subclass of monotremes and nourished with milk)• <u>S. (n) vertebrate, craniate</u> (animals having a bony or cartilaginous skeleton with a segmented spinal column and a large brain enclosed in a skull or cranium)• <u>S. (n) chordate</u> (any animal of the phylum Chordata having a notochord or spinal column)• <u>S. (n) animal, animate_being, beast, brute, creature, fauna</u> (a living organism characterized by voluntary movement)• <u>S. (n) organism, being</u> (a living thing that has (or can develop) the ability to act or function independently)• <u>S. (n) living_thing, animate_thing</u> (a living (or once living) entity)• <u>S. (n) whole, unit</u> (an assemblage of parts that is regarded as a single entity) "how big is that part compared to the whole?"; "the team is a unit"• <u>S. (n) object, physical_object</u> (a tangible and visible entity; an entity that can cast a shadow) "it was full of rackets, balls and other objects"• <u>S. (n) physical_entity</u> (an entity that has physical existence)• <u>S. (n) entity</u> (that which is perceived or known or inferred to have its own distinct existence (living or nonliving))	

Problems with WordNet

Problems with WordNet

- Requires human labour to create and adapt
- Missing nuances, synonyms may be correct only in some contexts
- Missing new meaning of words, impossible to keep up-to-date
- Subjective, i.e. depends on human that collected thesaurus
- Can't be used to accurately compute word similarity

Distributional semantics

Words which frequently appear in similar contexts have similar meaning.
(Harris 1954, Firth 1957)

When a word **w** appears in a text, its context is a set of words that appear nearby (within a fixed-sized window). We have to encode information about contexts into word vectors.

...debt problems turning into **banking** crises as happened in 2009...

...Europe needs unified **banking** regulation to replace the hodgepodge...

...India has just given its **banking** system a shot in the arm...

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Idea

Learn word vectors by teaching them to predict contexts:

1. Take a huge text corpus
2. Go over the text with sliding window:
 - 2.1 For the central word, compute probabilities of context words
 - 2.2 Adjust the vectors to increase these probabilities

... Words are the **primary** building blocks of meaning ...

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... Words are the primary **building** blocks of meaning ...

Objective function

word2vec learns parameters θ that maximize training data likelihood:

$$L(\theta) = \prod_{t=1}^T \prod_{\substack{-m \leq j \leq m, \\ j \neq 0}} P(w_{t+j} | w_t, \theta)$$

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$$L(\theta) = \prod_{t=1}^T \prod_{\substack{-m \leq j \leq m, \\ j \neq 0}} P(w_{t+j} | w_t, \theta)$$

To make optimization simpler, we use negative log-likelihood as loss function:

$$J(\theta) = -\frac{1}{T} \log L(\theta) = -\frac{1}{T} \sum_{t=1}^T \sum_{\substack{-m \leq j \leq m, \\ j \neq 0}} \log P(w_{t+j} | w_t, \theta)$$

How to compute $P(w_{t+j} | w_t, \theta)$?

For each word w we will have two vectors:

- v_w when w is a central word
- u_w when w is a context word
(used only during training)

All v_w and u_w are trained parameters θ

$$P(o | c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in W} \exp(u_w^T v_c)}$$

Training step

$$J(\theta) = -\frac{1}{T} \log L(\theta) = -\frac{1}{T} \sum_{t=1}^T \sum_{\substack{-m \leq j \leq m, \\ j \neq 0}} \log P(w_{t+j} | w_t, \theta)$$

Now we can compute gradient of loss w.r.t. v_{primary} and all u_w and update parameters with gradient descent

Training step

... Words are the **primary** building blocks of meaning ...

$$\begin{aligned}-\log P(\text{blocks} \mid \text{primary}) &= -\log \frac{\exp(u_{\text{blocks}}^T v_{\text{primary}})}{\sum_{w \in W} \exp(u_w^T v_{\text{primary}})} = \\ &= -\underbrace{u_{\text{blocks}}^T v_{\text{primary}}}_{\text{increase}} + \log \sum_{w \in W} \exp\left(\underbrace{u_w^T v_{\text{primary}}}_{\text{decrease}}\right)\end{aligned}$$

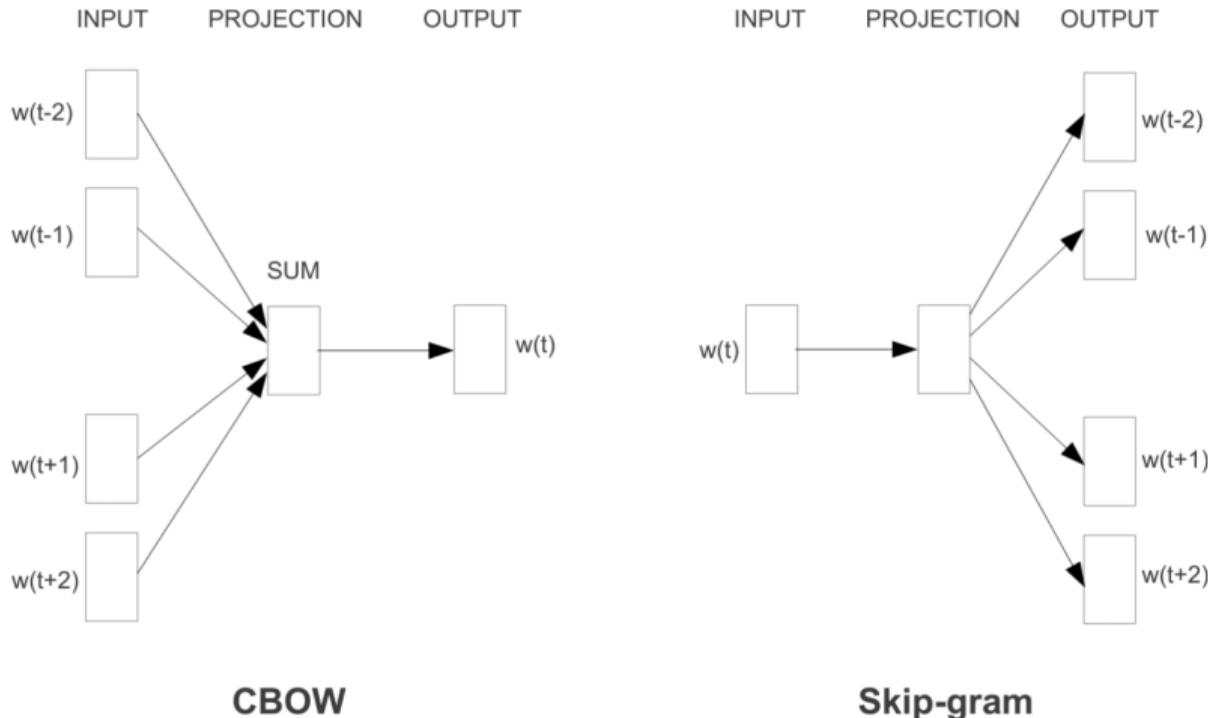
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Faster training with negative sampling

$$-\log P(\text{blocks} \mid \text{primary}) = \underbrace{-u_{\text{blocks}}^T v_{\text{primary}}}_{\text{increase}} + \log \sum_{w \in W} \exp \left(\underbrace{u_w^T v_{\text{primary}}}_{\text{decrease}} \right)$$

Updating $|W| + 2$ vectors is too expensive, use small number (i.e. $K = 10$) of random negative samples

Skip-gram vs CBOW



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Directly counting word occurrence

- I like deep learning
- I like flying
- I enjoy NLP

counts	I	like	enjoy	deep	learning	NLP	flying	.
I	0	2	1	0	0	0	0	0
like	2	0	0	1	0	1	0	0
enjoy	1	0	0	0	0	0	1	0
deep	0	1	0	0	1	0	0	0
learning	0	0	0	1	0	0	0	1
NLP	0	1	0	0	0	0	0	1
flying	0	0	1	0	0	0	0	1
.	0	0	0	0	1	1	1	0

$$N(w, c)$$

Using SVD to obtain word and context vectors

GloVe: Global Vectors for Word Representation

$$J(\theta) = \sum_{w,c \in W} f(N(w,c)) \cdot (u_c^T \tilde{v}_w + b_c + \tilde{b}_w - \log N(w,c))^2$$

Weighting function f to:

- penalize rare events
- not to over-weight frequent events

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Intrinsic and extrinsic evaluation

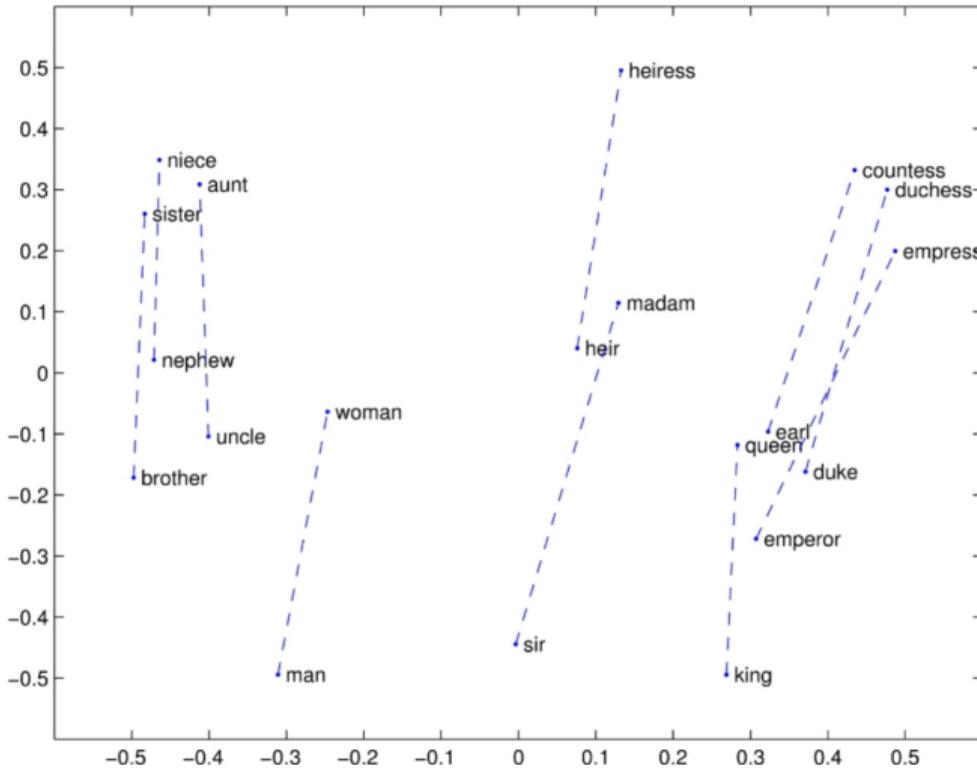
Intrinsic:

- Evaluation on a specific/intermediate subtask
- Fast to compute
- Helps to understand that system
- Not clear if it's helpful unless correlation to real task is established

Extrinsic:

- Evaluation on a real task
- Can take a long time to compute accuracy
- Unclear if the subsystem is the problem or its interaction or other subsystems, have to ablate

Intrinsic evaluation: vector linearity



Intrinsic evaluation: meaning similarity

Word 1	Word 2	Human (mean)
tiger	cat	7.35
tiger	tiger	10
book	paper	7.46
computer	internet	7.58
plane	car	5.77
professor	doctor	6.62
stock	phone	1.62
stock	CD	1.31
stock	jaguar	0.92

Intrinsic evaluation: meaning similarity

Model	Size	WS353	MC	RG	SCWS	RW
SVD	6B	35.3	35.1	42.5	38.3	25.6
SVD-S	6B	56.5	71.5	71.0	53.6	34.7
SVD-L	6B	65.7	<u>72.7</u>	75.1	56.5	37.0
CBOW [†]	6B	57.2	65.6	68.2	57.0	32.5
SG [†]	6B	62.8	65.2	69.7	<u>58.1</u>	37.2
GloVe	6B	<u>65.8</u>	<u>72.7</u>	<u>77.8</u>	53.9	<u>38.1</u>
SVD-L	42B	74.0	76.4	74.1	58.3	39.9
GloVe	42B	75.9	83.6	82.9	59.6	47.8
CBOW*	100B	68.4	79.6	75.4	59.4	45.5

Conclusion

We reviewed following topics:

- why do we need word representations
- denotational and distributional semantics
- word2vec approach
- counting methods and GloVe
- approaches to evaluate quality of obtained embeddings