Vector Semantics and Embeddings

Natural Language Processing

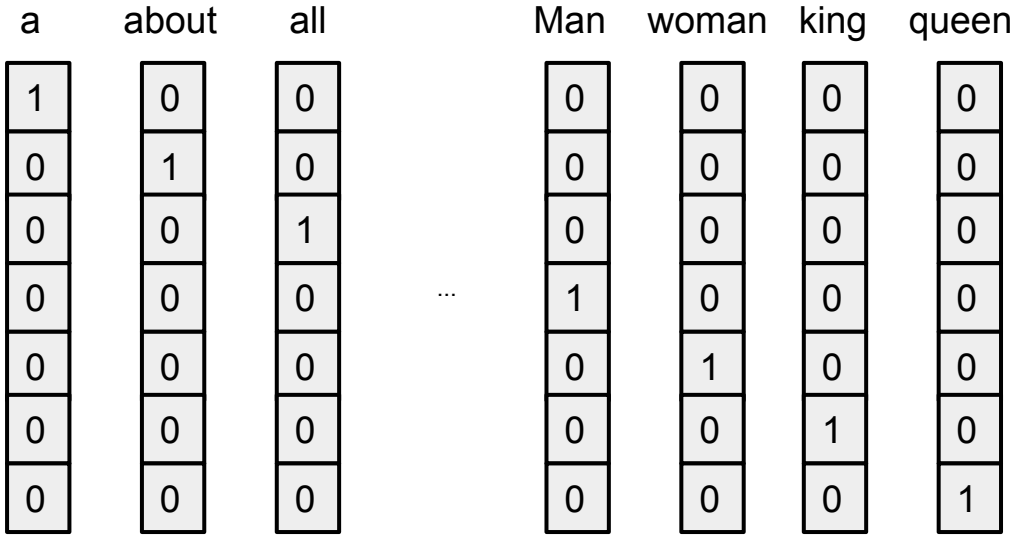
Younes Samih and David Arps

Word Representations in NLP

- Neural Network
- Distributed Word representations
  - Raw text
  - Representing words as low-dimensional vectors
  - These vectors capture Semantics and Syntax
- Word2Vec
- GloVe
- Fasttext

Word Representation

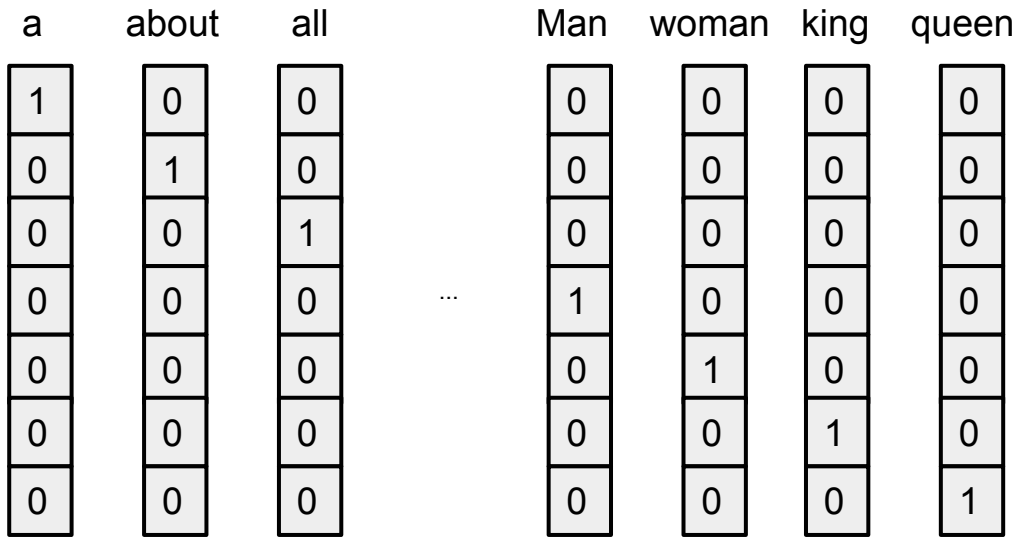
One-hot encoding



Word Representation

Weaknesses One-hot encoding

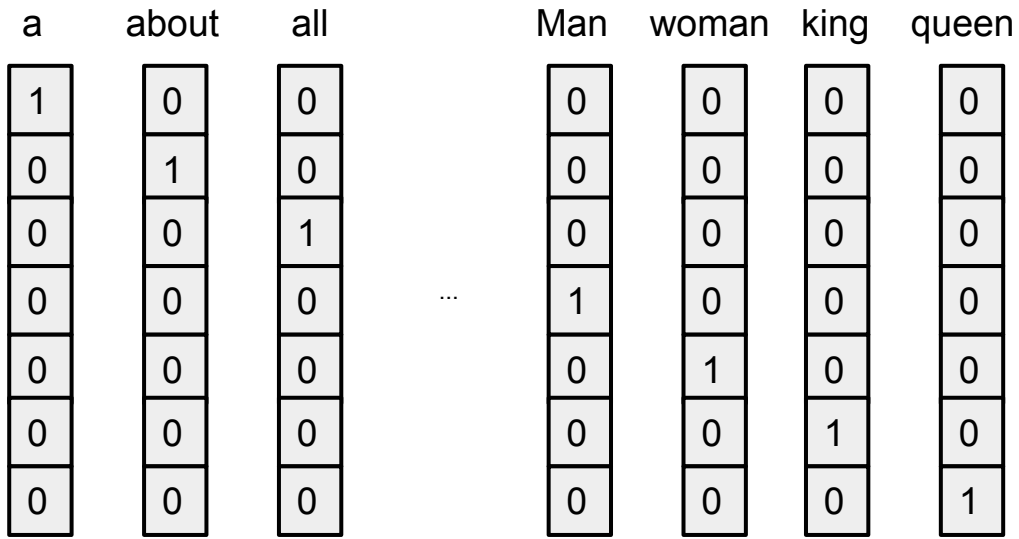
- The **distance** between any pair of words is the same



Word Representation

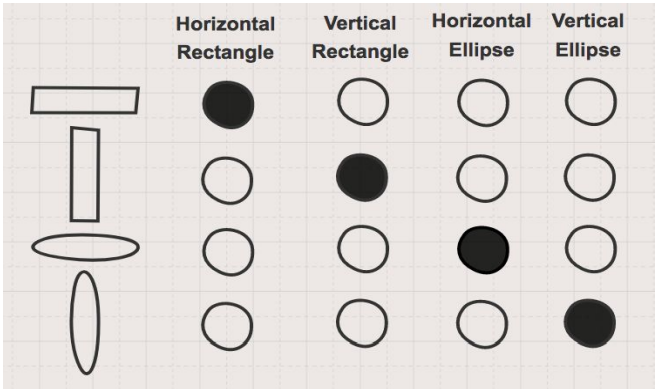
Weaknesses One-hot encoding

- The **distance** between any pair of words is the same
- Can not capture word similarity

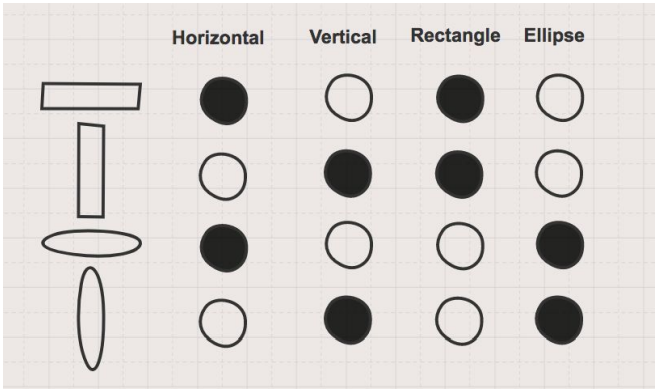


Word Representation

Distributed representation



Non-distributed representation



distributed representation

Image source: https://www.oreilly.com/content/how-neural-networks-learn-distributed-representations/

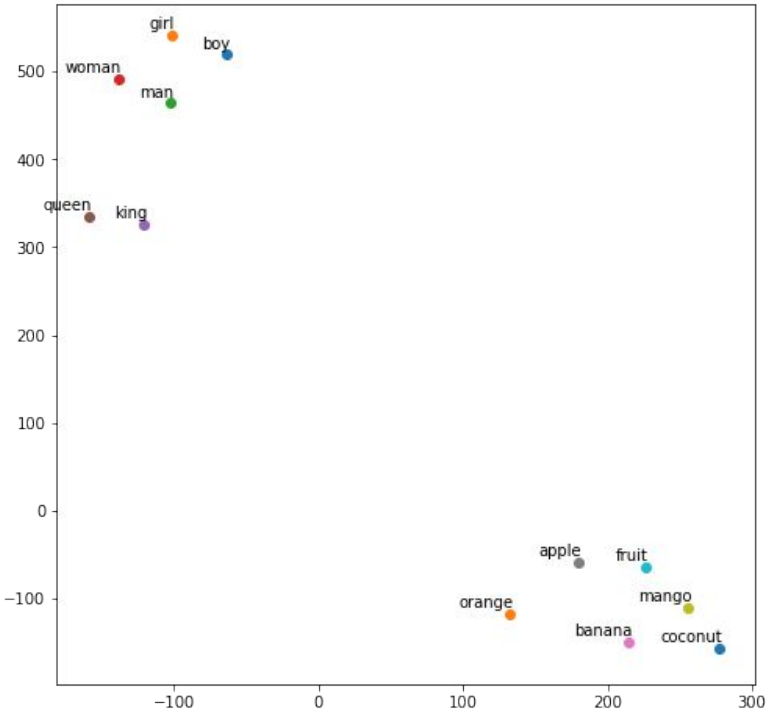
Word Representation

Distributed representation of words

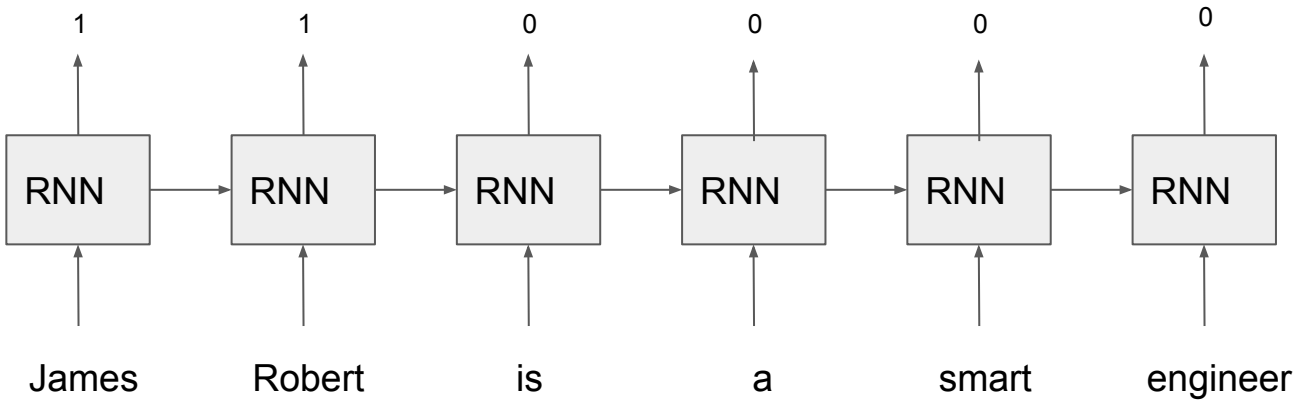
	Man	Women	Knig	Queen	Apple	Orange
Gender	-1	1	-0.98	0.97	0.00	-0.01
Royal	0.01	0.02	0.93	0.98	-0.01	0.00
age	0.03	0.02	0.72	0.56	0.03	0.02
Food	0.00	0.00	0.01	0.02	0.96	0.93

Word Representation

Visualizing word embeddings



Application of Word Embeddings



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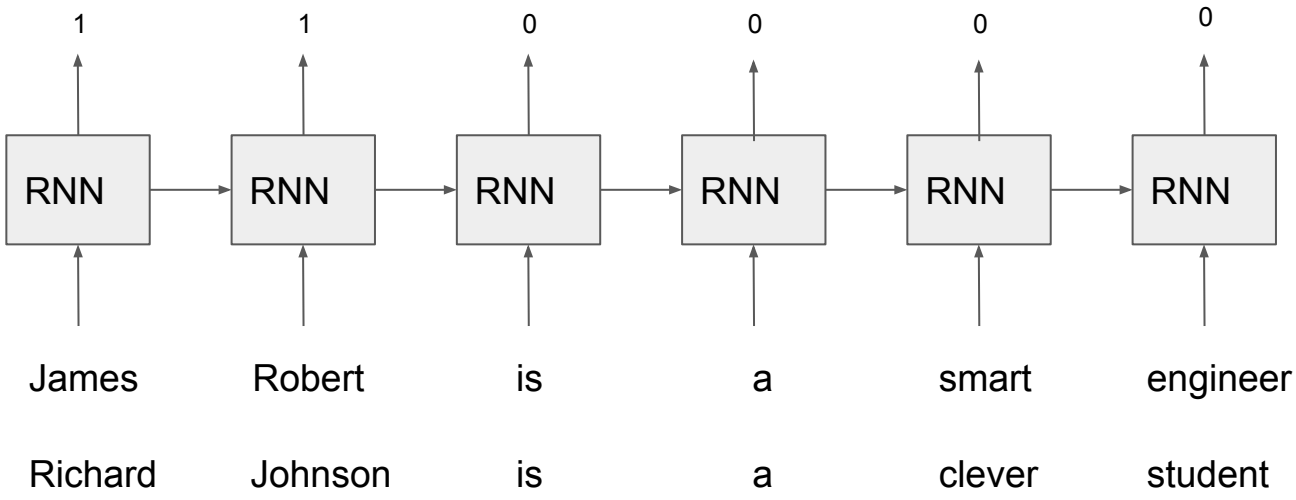

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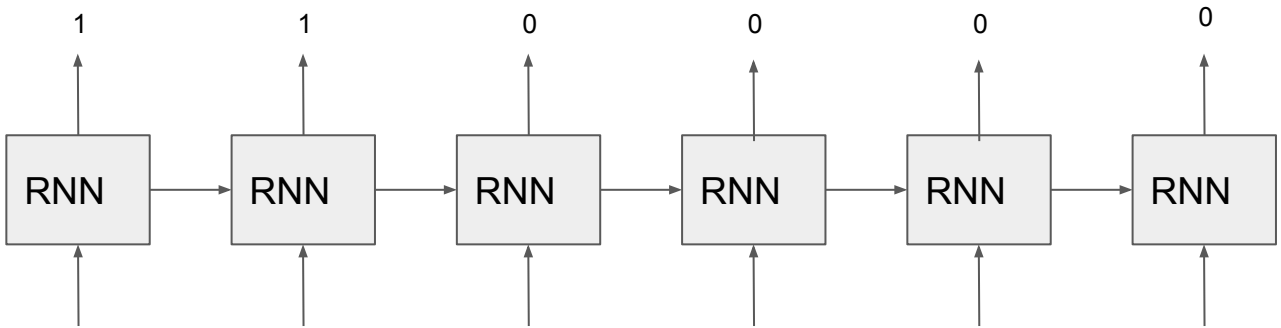

James	Robert	is	a	smart	engineer
Richard	Johnson	is	a	clever	student
Jone	clark	is	a	nuclear	scientist

Transfer Learning

- Train word embeddings using large text corpus

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- Use pre-trained word embeddings

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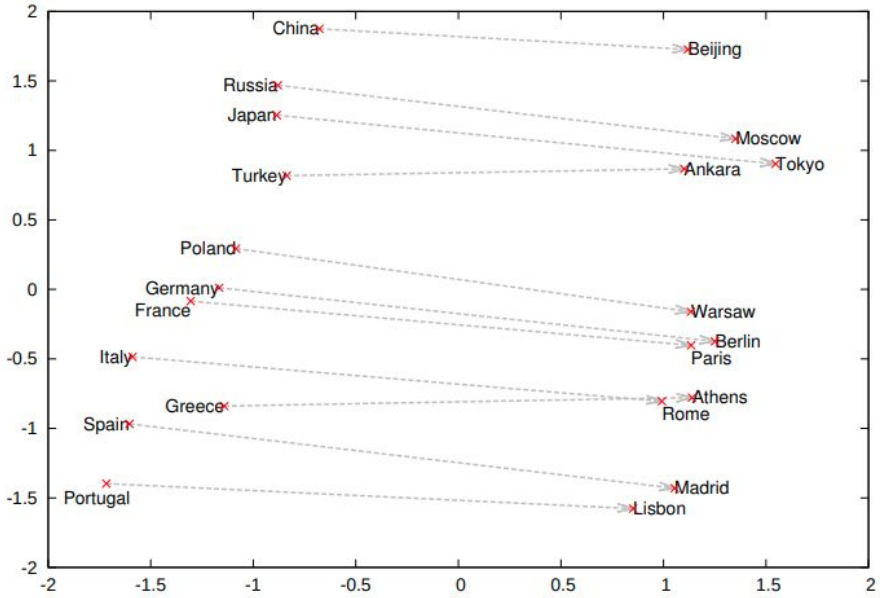
- Use pre-trained word embeddings
- Leverage word embedding for new tasks with smaller training data set

Analogies and Word Embeddings

Analogy Reasoning



Reference: [Mikolov et. al., 2013, Distributed Representations of Words and Phrases and their Compositionality]

Word Embeddings

Word Similarity

- Similarity is calculated using cosine similarity :

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$$\cos\theta = \frac{\vec{a} \cdot \vec{b}}{\|\vec{a}\| \cdot \|\vec{b}\|}$$

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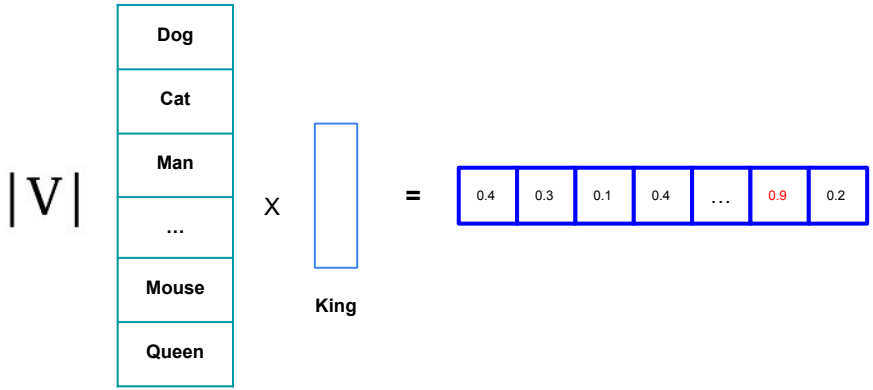
- vectors need to normalised when loading them

Similarity and Word Embeddings

Finding the most similar word to **King**

- Compute the similarity from word **King** to all other words.



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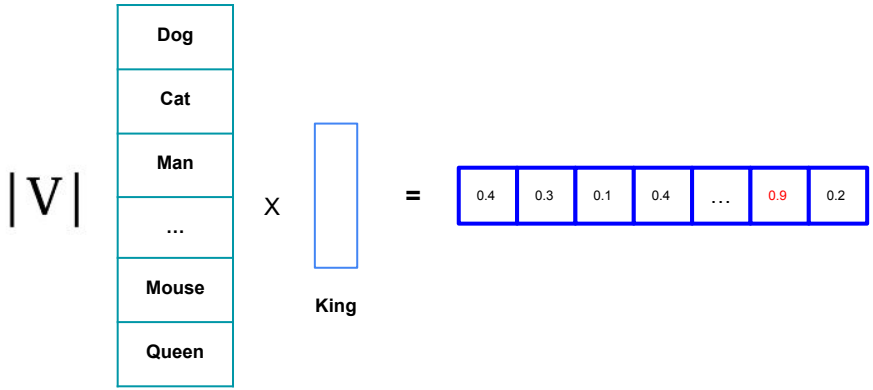

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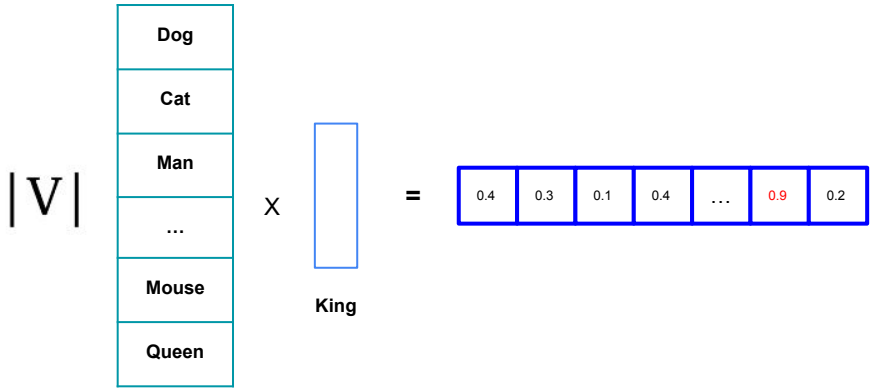

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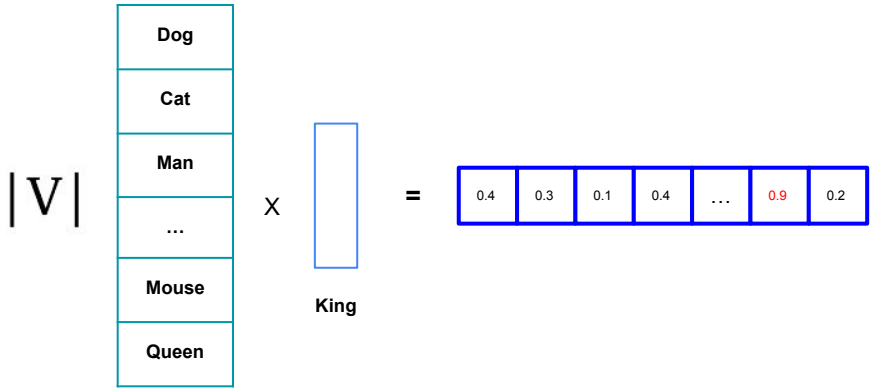


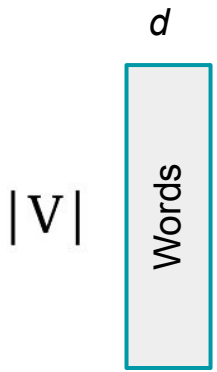
- This is a single matrix-vector product
- Result is a | V | sized vector of similarities
- Get the k -highest values
- But where do these vectors come from?

Word2Vec

Text

word2vec

Cat	=	0.8	0.4	0.3	0.2	…	0.4	0.8	0.2	0.3	0.4
Dog	=	0.5	0.9	0.7	0.3	…	0.5	0.7	0.8	0.4	0.3
King	=	0.4	0.3	0.1	0.4	…	0.4	0.2	0.6	0.3	0.2



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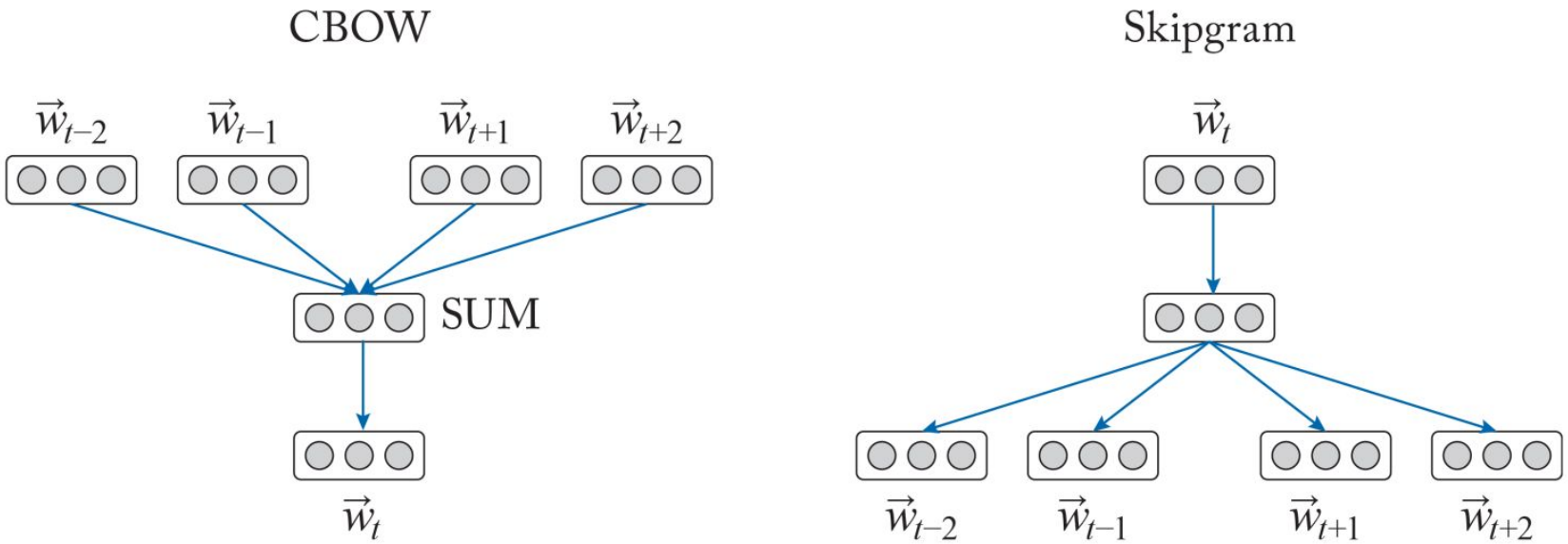

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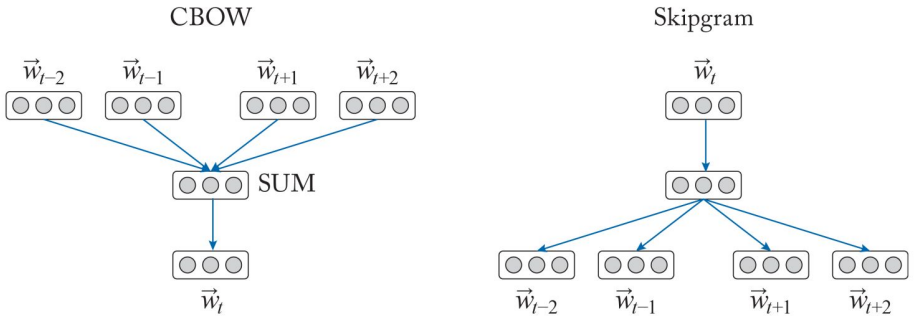
Word2Vec

- Word2vec [Mikolov et al., 2013d]



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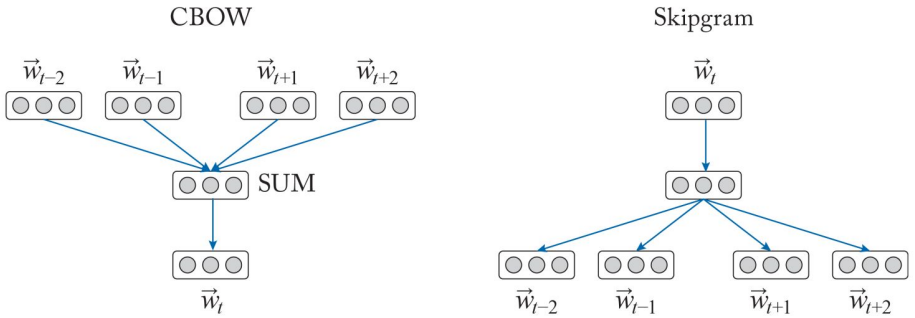
Word2Vec

- Word2vec [Mikolov et al., 2013d]
- FFNN architecture trained with language modeling objective.



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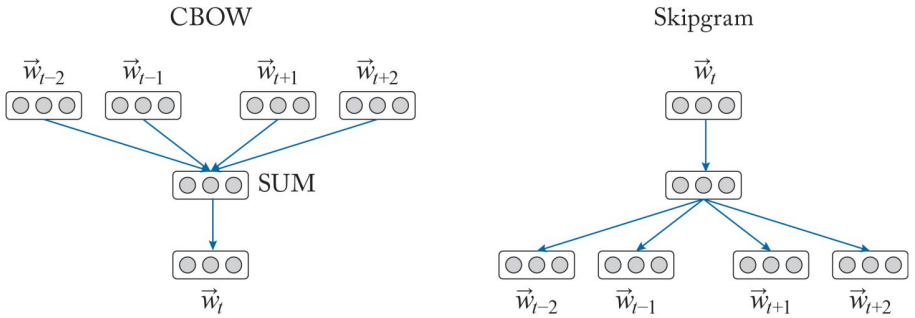
Word2Vec

- Word2vec [Mikolov et al., 2013d]
- FFNN architecture trained with language modeling objective.
- Two different Word2vec models were proposed:
  - Continuous Bag-Of-Words (CBOW)
  - The Skip-gram model



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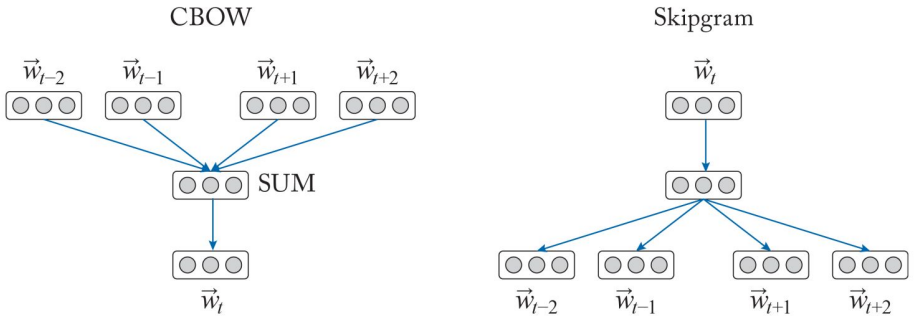
Word2Vec

- The **CBOW** model aims at predicting the current word using its surrounding context
- The **Skip-gram** model aims at predicting the words in the surrounding context given the target word

- Two training methods:
  - Negative sampling
  - Hierarchical Softmax



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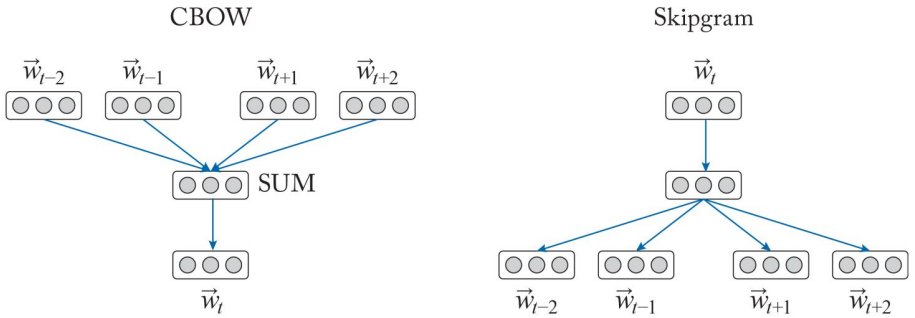

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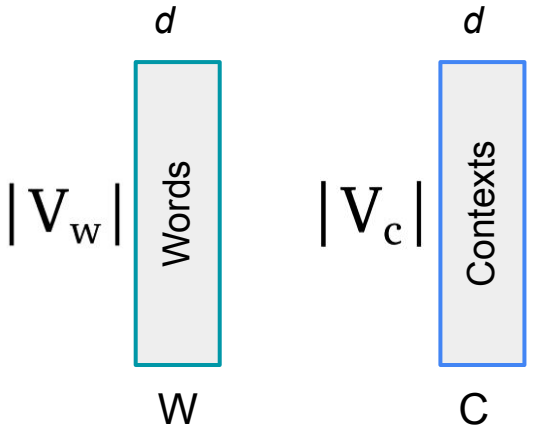
Word2Vec

Training the **Skip-gram** model

1. Each word is represented as a ***d*** dimensional vector.



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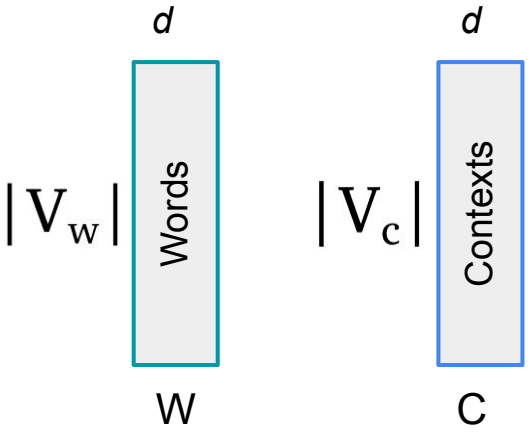

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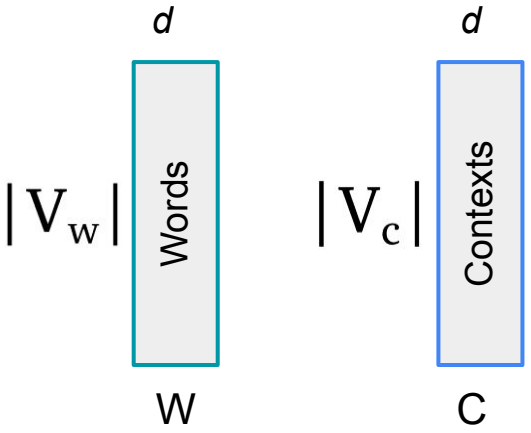
3. All vectors weights are randomly initialized .



Word2Vec

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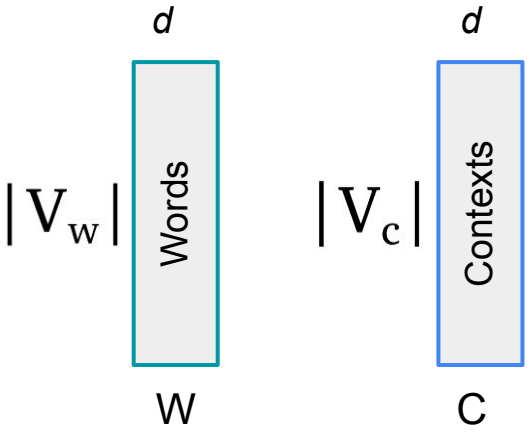
3. All vectors weights are randomly initialized .
4. Arrange vectors in two matrices, *W* and *C*



Word2Vec

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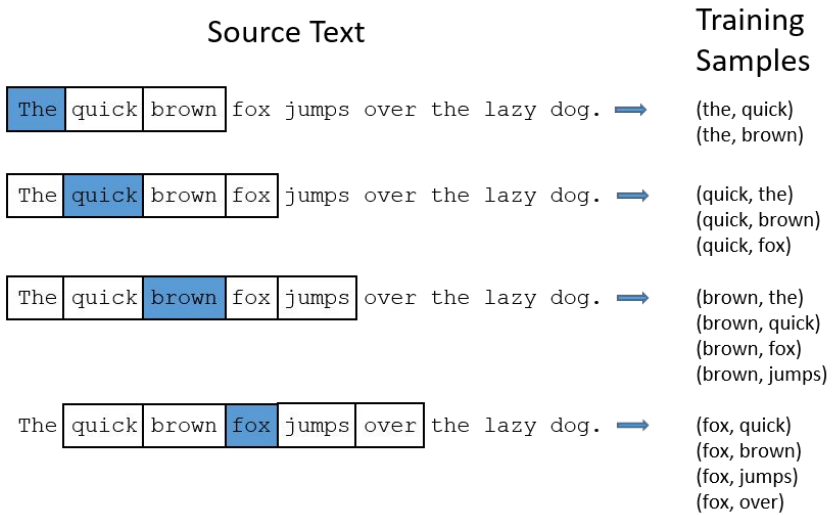
1. Data



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Word2Vec

Training the **Skip-gram** model

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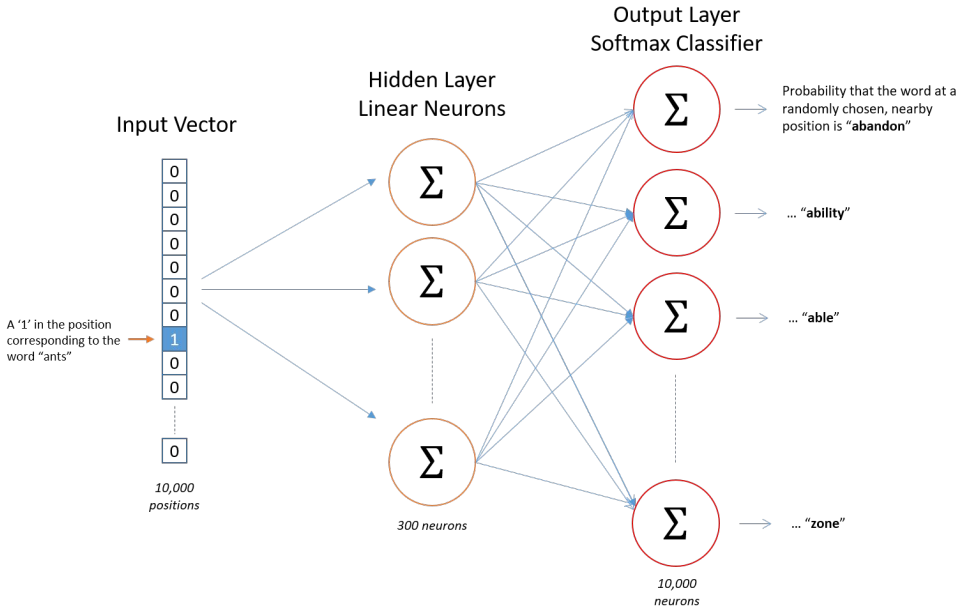
2. Architecture



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Word2Vec

Training the **Skip-gram** model

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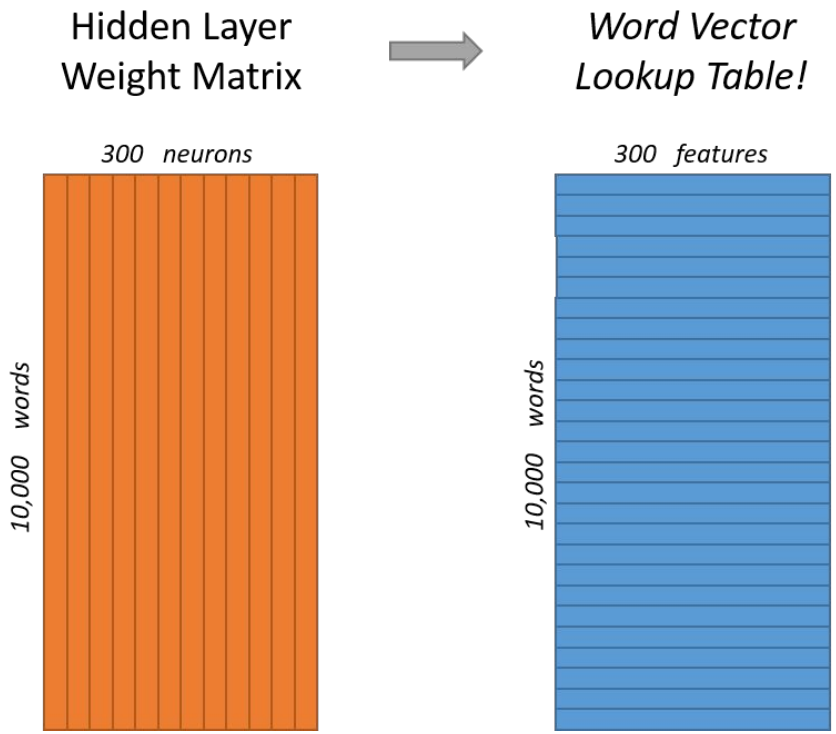
3. The Hidden Layer



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Word2Vec

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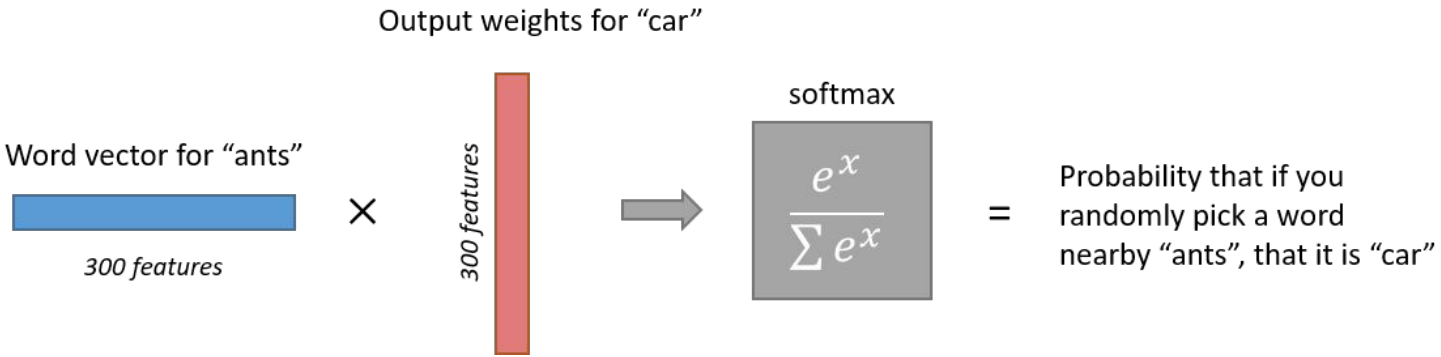

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