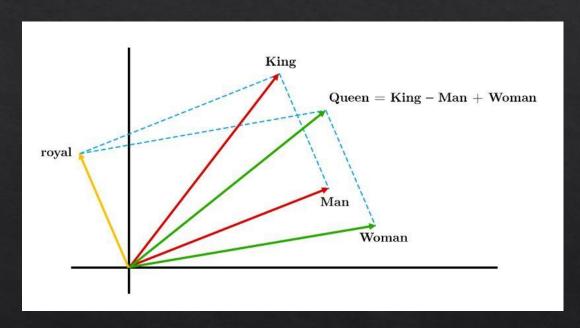
A peek into word embeddings using word2vec

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Word embeddings & Word2Vec

- ♦ Represent words as vectors. (String → double[])
 - ♦ Here we have an example.
 - \diamond Basis: < w, $\not < >$ (instead of the standard < 1, 1 >)
 - $\Rightarrow Man = <1, 1>$
 - \Leftrightarrow Woman = <1, 2>
 - \Leftrightarrow King = <2, 1>
 - \Rightarrow Queen = King Man + Woman = <2, 1> - <1, 1> + <1, 2>= <2, 2>



- ♦ The word vectors capture the semantic meanings* of words.
- ♦ In real life applications, the vector spaces usually have much higher dimensions.

^{*} Semantic meaning: the interpretation or the inherent meaning of a word, phrase, sentence or text within a particular context.

Probability in Word2Vec models

- ♦ CBOW: input Outside context words → output Center word
- ♦ Skip-gram: input Center word → output Outside context words
- Let's focus on Skip-gram.
- ♦ We calculate the **probability** in the training of models:

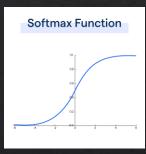
$$\Rightarrow P(O = o | C = c) = \frac{e^{\overrightarrow{u_O^T} \cdot \overrightarrow{v_C}}}{\sum_{w \in Vocab} e^{\overrightarrow{u_W^T} \cdot \overrightarrow{v_C}}} \in [0, 1]$$

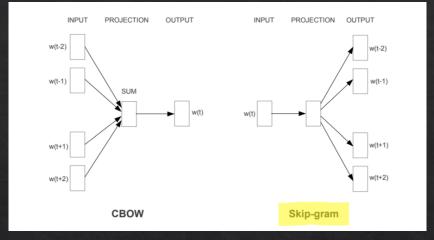
- ♦ The softmax function gives a probability distribution.
- \diamond Probability of words appearing together in the data \rightarrow semantic meanings
- ♦ The word vectors are continuously adjusted to maximize the probability.

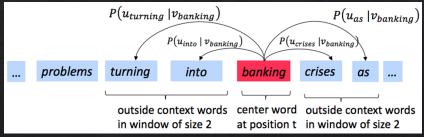


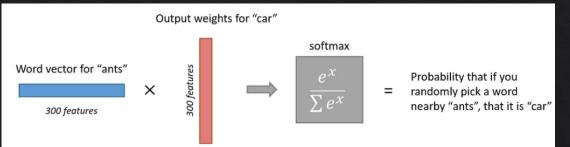
$$\Leftrightarrow$$
 Recall that $\cos \theta = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|} = \hat{a} \cdot \hat{b} \in [-1, 1]$

- ♦ Similarity of the semantic meanings of the words
- \diamond Note that dot products are involved in both the calculations of $\cos \theta$ and P...









Code implementation

Implementing a basic Skip-Gram model: epoch 999 loss = 15919.783211167764 Top 3 words most similar to 'food' in the essay: ['i', 'nourish', 'plant-based']

Using a pre-trained model (word2vec-google-news-300):

```
# Get the analogy
print("Man is to king as woman is to", analogy("man", "king", "woman")) # queen
Man is to king as woman is to queen
```

Factors affecting prediction: size of corpus, preprocessing techniques (stop word removal, tokenization), epochs, sampling etc.

Please visit the GitHub Repository* to read the more detailed explanation and download the full source code. Thank you.

Most similar words to the word "food" foods 0.6804922819137573 Food 0.6538903713226318 foodstuffs 0.642582893371582 meals 0.616668701171875 food stuffs 0.5928642153739929 nourishing meals 0.5847609043121338 foodstuff 0.5835224986076355 staple_foods 0.5535788536071777 nutritious 0.5466451644897461 meal 0.5433712601661682

2.5

wv.most similar("good") [('great', 0.7291510105133057), ('bad', 0.7190051078796387), ('terrific', 0.6889115571975708), ('decent', 0.6837348341941833), ('nice', 0.6836092472076416), ('excellent', 0.644292950630188), ('fantastic', 0.6407778263092041), ('better', 0.6120728850364685), ('solid', 0.5806034803390503), ('lousy', 0.576420247554779)]

^{2.0} 1.5 1.0 0.5 0.0 -0.5 -1.0 1.0

^{*} Link: https://github.com/yueagar/ESTR2018-project