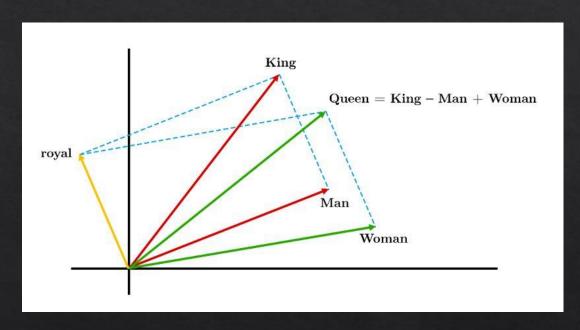
## A peek into word embeddings using word2vec

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## Word embeddings & Word2Vec

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



- ♦ The word vectors depend on the words frequently appearing near the word in the data.
- ♦ In real life applications, the vector spaces usually have much higher dimensions.

## Probability in Word2Vec models

**Softmax Function** 

- ♦ 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:

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

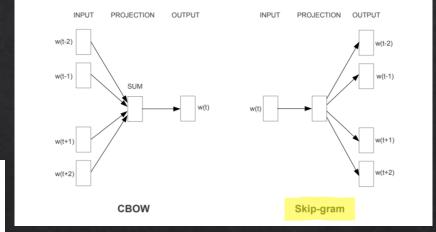
- ♦ The softmax function gives a probability distribution.
- $\diamond$  Probability of words appearing together in the data  $\rightarrow$  semantic meanings
- ♦ The word vectors are continuously adjusted to maximize the probability.

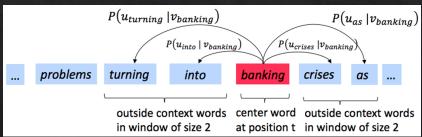


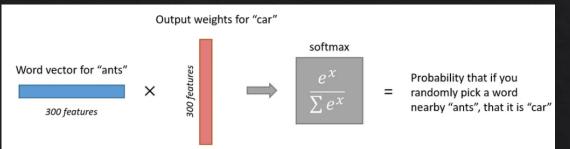
$$\Leftrightarrow$$
 Recall that  $\cos \theta = \frac{\vec{a} \cdot \vec{b}}{|\vec{a}||\vec{b}|} = \hat{a} \cdot \hat{b} \in [-1, 1]$ 

rds  $\theta$ 

- 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

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)]

<sup>2.0</sup> 1.5 1.0 0.5 0.0 -0.5

<sup>\*</sup> Link: https://github.com/yueagar/ESTR2018-project