Dive into Deep Learning for NLP

4. Context-Free Representations

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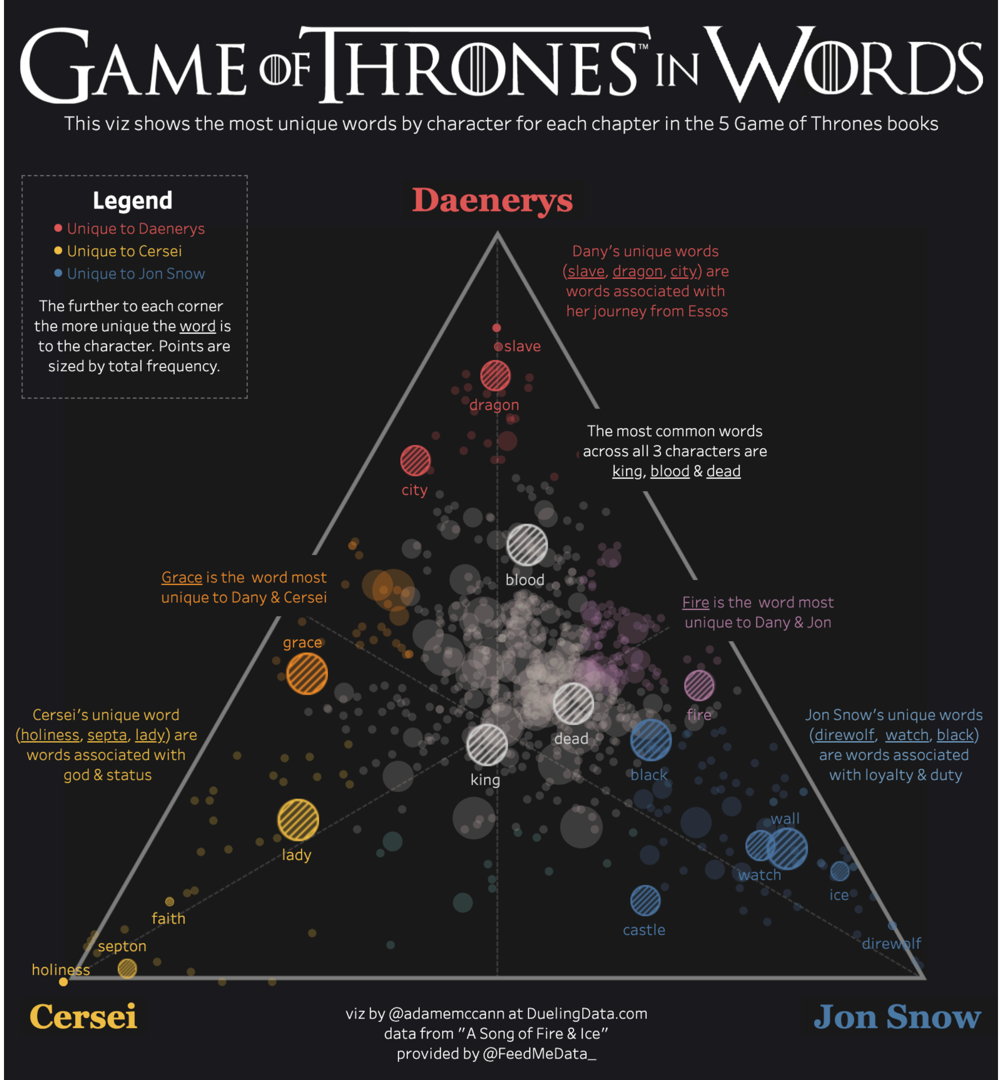
Word Embeddings



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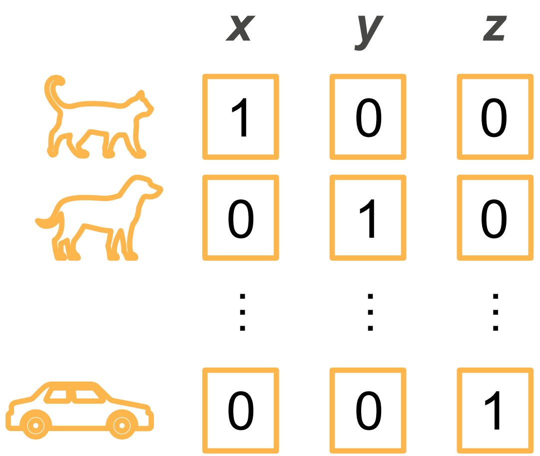
Motivation

- One-hot vectors map objects/ words into fixed-length vectors
- These vectors only contain the identity information, not semantic meaning, e.g.

$$\langle \mathbf{x}, \mathbf{y} \rangle = \langle \mathbf{z}, \mathbf{y} \rangle = 0$$

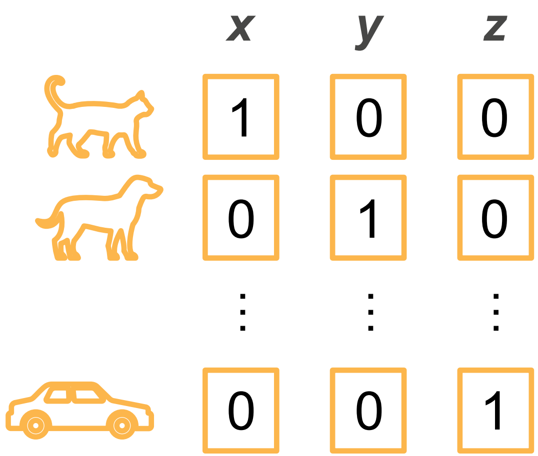


Word2vec

- Learn an embedding vector for each word
- Use $\langle \mathbf{x}, \mathbf{y} \rangle$ to measure the similarity

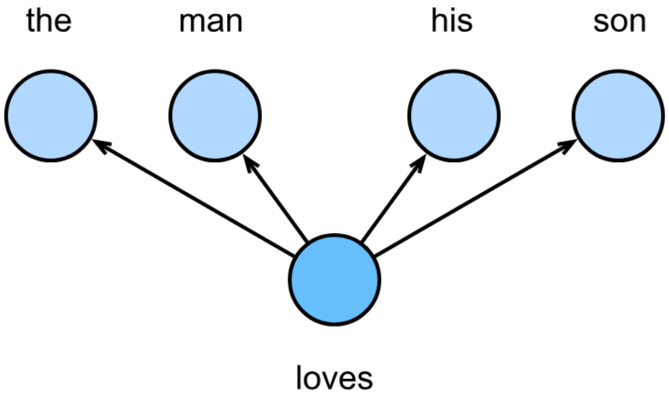
$$\langle \mathbf{x}, \mathbf{y} \rangle > \langle \mathbf{z}, \mathbf{y} \rangle$$

- Build a probability model
- Maximize the likelihood function to learn the model



The Skip-Gram Model

- A word can be used to generate the words surround it
- Given the center word, the context words are generated independently



$$\mathbb{P}(\text{"the"}, \text{"man"}, \text{"his"}, \text{"son"} \mid \text{"loves"})$$

$$= \mathbb{P}(\text{"the"} \mid \text{"loves"}) \cdot \mathbb{P}(\text{"man"} \mid \text{"loves"}) \cdot \mathbb{P}(\text{"his"} \mid \text{"loves"}) \cdot \mathbb{P}(\text{"son"} \mid \text{"loves"})$$

Likelihood Function

Summing over all words is too expensive

	Word	Embedding
Center	w_c	$\mathbf{v}_c \in \mathbb{R}^d$
Context	w_o	$\mathbf{u}_o \in \mathbb{R}^d$

$$\mathbb{P}(w_o \mid w_c) = \frac{\exp(\mathbf{u}_o^\top \mathbf{v}_c)}{\sum_{i \in \mathcal{V}} \exp(\mathbf{u}_i^\top \mathbf{v}_c)}$$

$\mathcal{V}$: all context words

- Given length T sequence, context window m, the likelihood function:

$$\prod_{t=1}^{T} \prod_{-m \leq j \leq m,\ j \neq 0} \mathbb{P}(w^{(t+j)} \mid w^{(t)})$$

Negative Sampling

- Treat a center word and a context word appear in the same context window as an event

$$\mathbb{P}\left(D = 1 \mid w_c, w_o\right) = \sigma\left(\mathbf{u}_c^T \mathbf{v}_o\right) \qquad \sigma(x) = \frac{1}{1 + \exp(-x)}$$

- Change the likelihood function from $\prod_{t=1}^{T} \prod_{-m \le j \le m,\ j \ne 0} \mathbb{P}(w^{(t+j)} \mid w^{(t)})$ to

$$\prod_{t=1}^{T} \prod_{-m \le j \le m,\ j \ne 0} \mathbb{P}(D = 1 \mid w^{(t)}, w^{(t+j)})$$

Naive solution: infinity

Negative Sampling

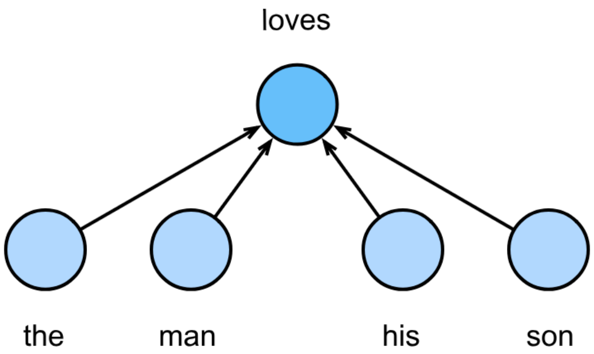
- Sample noise word w_n that doesn't appear in the window

$$\mathbb{P}\left(D=0 \,|\, w_c, w_n\right) = 1 - \sigma\left(\mathbf{u}_n^T \mathbf{v}_c\right)$$

- Add into the likelihood function as well
- Maximizing the likelihood equals to solve a binary classification problem with a binary logistic regression loss

Continuous Bag Of Words (CBOW)

- The center word is generated based on the context words



$$\mathbb{P}(\text{"loves"} \mid \text{"the"}, \text{"man"}, \text{"his"}, \text{"son"})$$

Likelihood Function

- Compute the probability

$$\mathbb{P}(w_c \mid w_{o_1}, \ldots, w_{o_{2m}}) = \frac{\exp\left(\frac{1}{2m}\mathbf{u}_c^\top(\mathbf{v}_{o_1} + \ldots + \mathbf{v}_{o_{2m}})\right)}{\sum_{i\in\mathcal{V}} \exp\left(\frac{1}{2m}\mathbf{u}_i^\top(\mathbf{v}_{o_1} + \ldots + \mathbf{v}_{o_{2m}})\right)}$$

- Likelihood

$$\prod_{t=1}^{T} \mathbb{P}(w^{(t)} \mid w^{(t-m)}, \ldots, w^{(t-1)}, w^{(t+1)}, \ldots, w^{(t+m)})$$

FastText

- English words usually have internal structures and formation methods
  - dog, dogs, dogcatcher
- Each center word is represented as a set of subwords
  - “where” -> “<where>” -> *n*-gram
  - n=3: “<wh", "whe", "her", "ere", “re>”
- Useful for long but infrequent words
  - e.g. pneumonoultramicroscopicsilicovolcanoconiosis

FastText

- For word *w*, $\mathcal{G}_w$ is the union of subwords with length from 3 to 6
- The center vector is then

$$\mathbf{u}_w = \sum_{g \in \mathcal{G}_w} \mathbf{u}_g$$

- The rest model is same as skip-gram