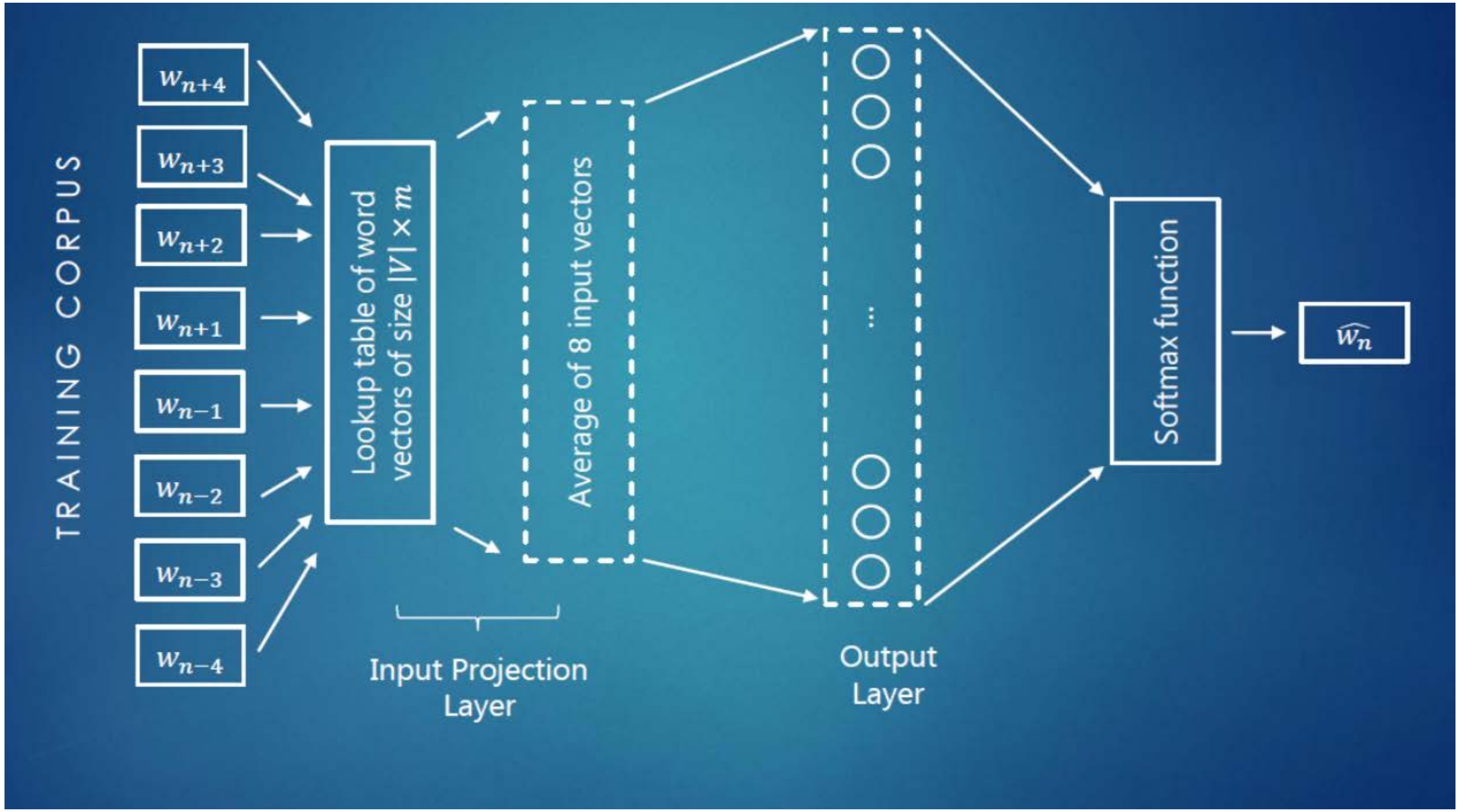
Word2Vec/Glove/FastText

Hyopil Shin(Seoul National University)
Computational Linguistics
#Semantics with Dense Vectors
Supplement Data

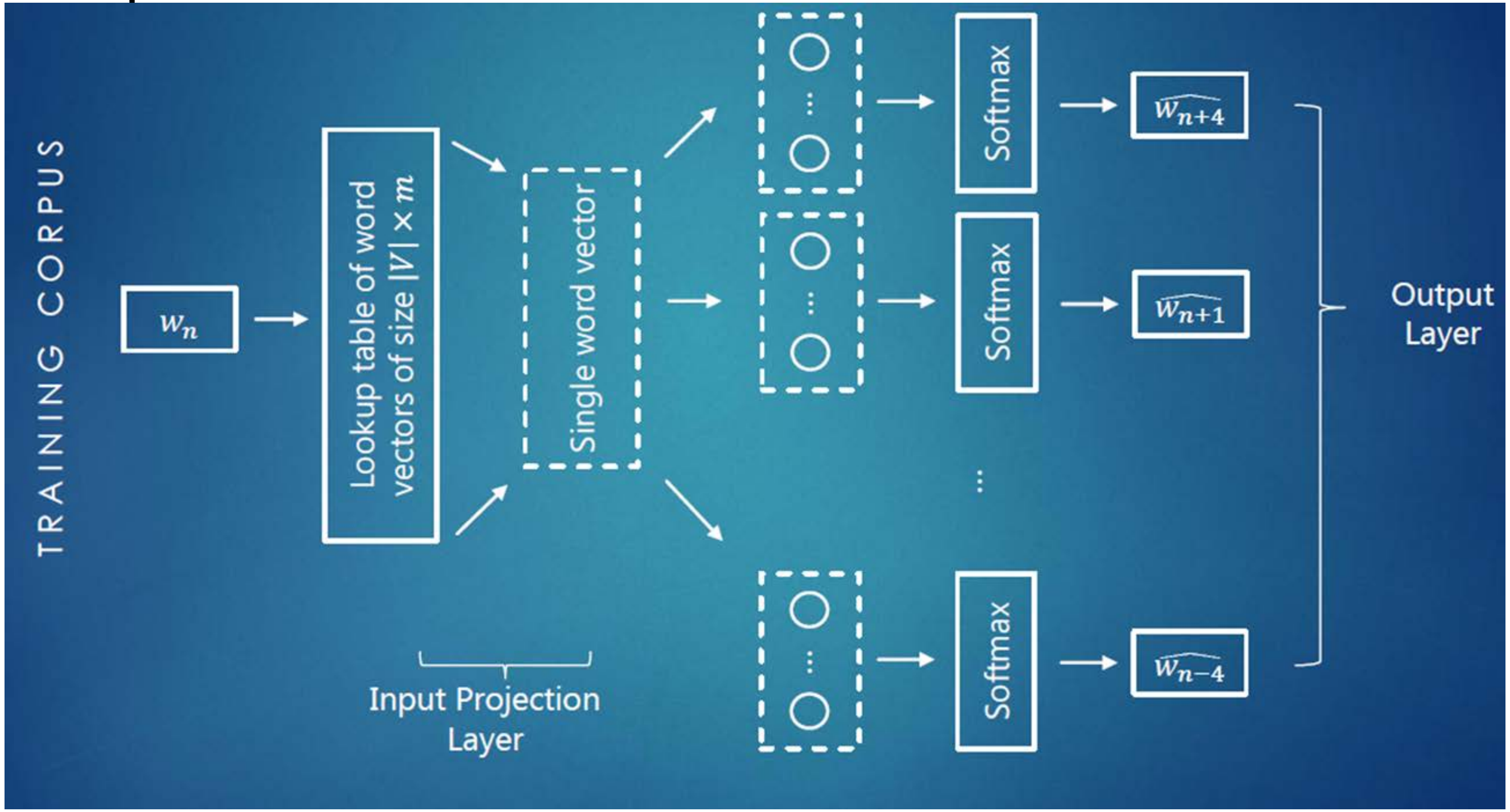
Word2Vec

- CBOW:Continuous Bag of words

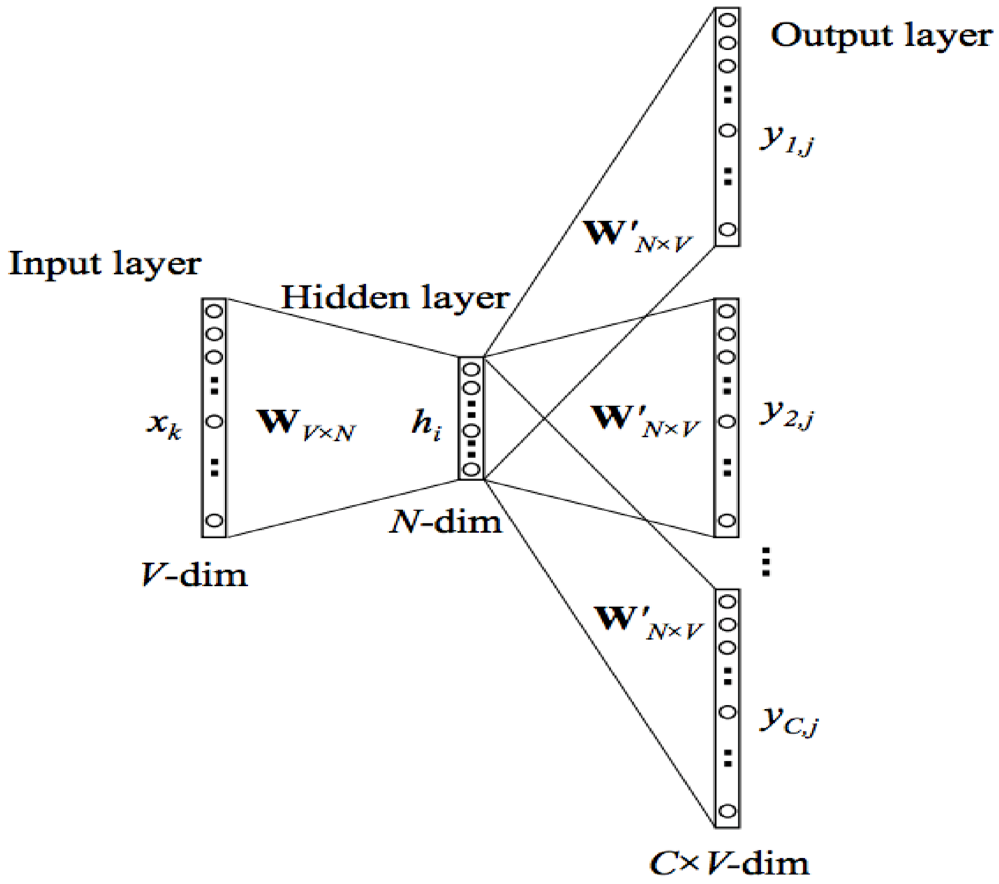


Word2Vec

- Skip-Gram



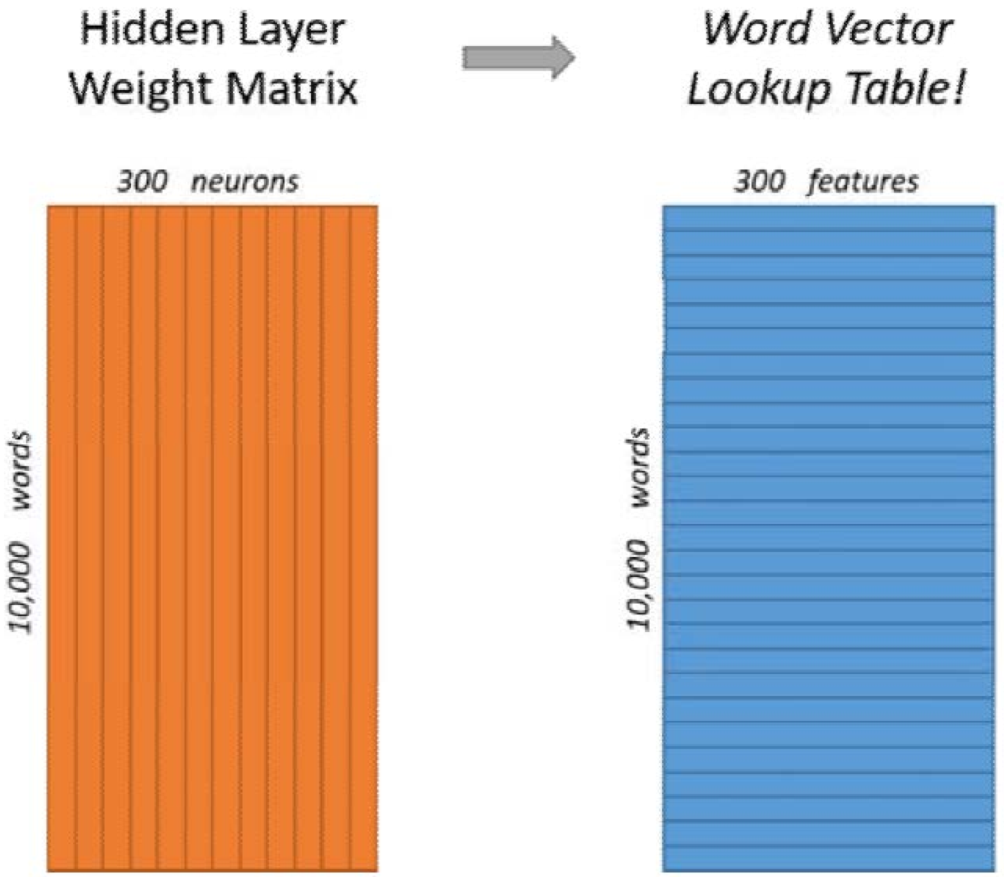
Word2Vec 학습 패러미터(skip-gram)



Word2Vec

- V-임베딩 단어수
- N-은닉층의 노드 개수

- 중심단어로 주변단어를 맞추거나, 주변단어로 중심단어를 맞추기 위해 가중치 행렬인 W, W'을 조금씩 업데이트 하면서 이루어지는 구조

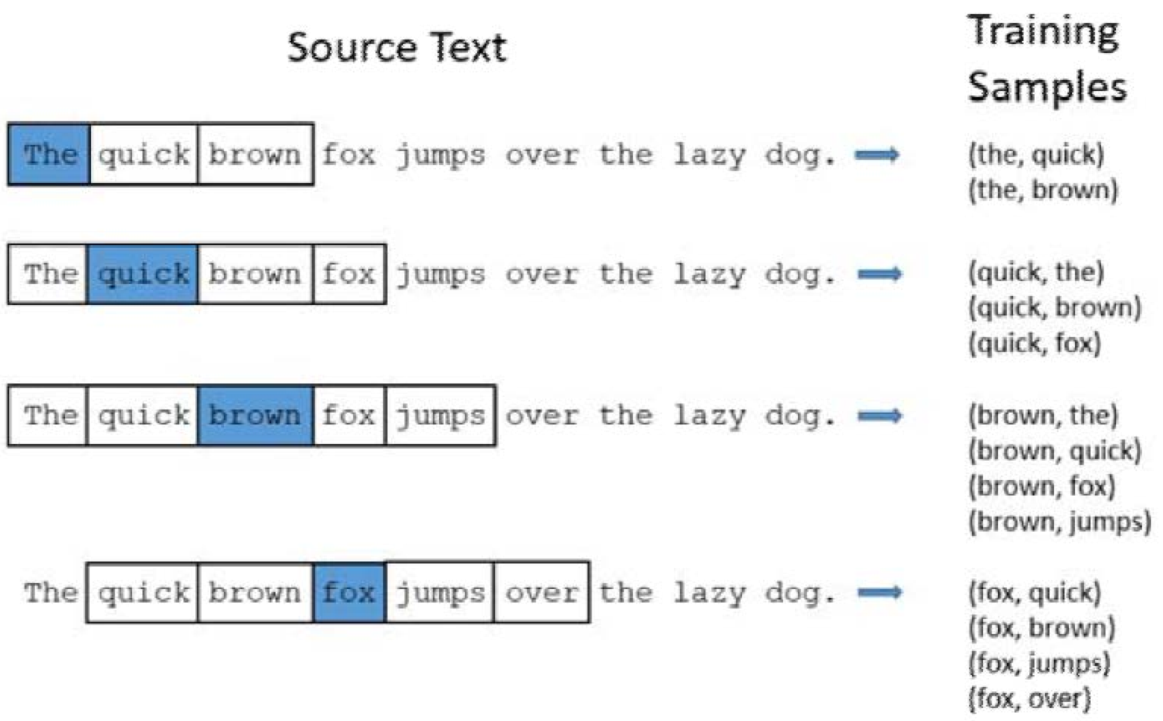


Word2Vec

- 학습이 마무리되면 W의 행벡터들이 각 단어에 해당하는 임베딩이 됨

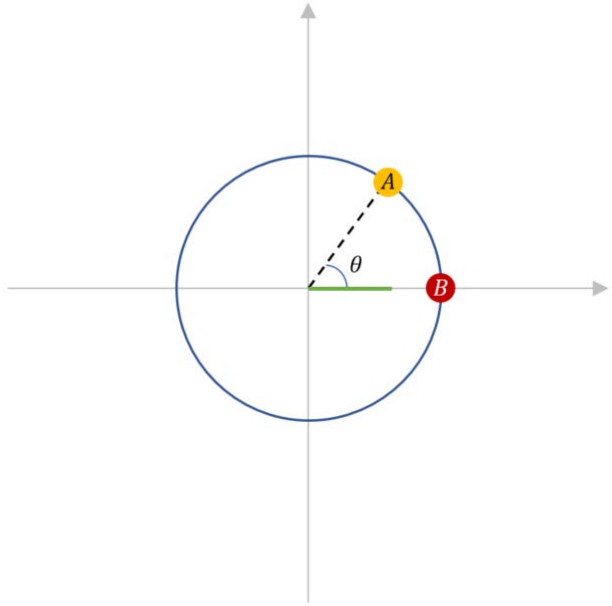
$$[0 \quad 0 \quad 0 \quad 1 \quad 0] \times \begin{bmatrix} 17 & 24 & 1 \\ 23 & 5 & 7 \\ 4 & 6 & 13 \\ 10 & 12 & 19 \\ 11 & 18 & 25 \end{bmatrix} = [10 \quad 12 \quad 19]$$

Word2Vec입력과 Skip-Gram



Word2vec학습 – 코사인 유사도

- A와 B가 겹칠때(Θ = 0), cos(Θ) = 1
- cos(Θ)는 단위원 내 벡터들끼리의 내적과 같음
- 내적이 커진다는 것은 두 벡터가 이루는 Θ가 작아지고, 유사도는 높아진다
- Cos인과 내적을 목적함수에 활용



Word2Vec 학습(skip-gram): 목적함수

- Skip-gram: 중심단어(c)가 주어졌을 때 주변단어 (o)가 나타날 확률을 최대화 하는 식으로 학습이 이루어짐

$$P(o|c) = \frac{exp(u_o^T v_c)}{\sum_{w=1}^{W} exp(u_w^T v_c)}$$

- *v*: 입력층-은닉층을 잇는 가중치 행렬 *W*의 행벡터
- *u*: 은닉층-출력층을 잇는 가중치 행렬 *W'*의 열벡터
- 최대화:
  - 분자 지수를 키움-중심단어(c)에 대한 주변단어(o) 벡터의 내적값을 높임. Θ를 줄여 유사도를 높임
  - 분모는 중심단어©와 학습말뭉치 내 모든 단어를 각각 내적한 것의 총합. 분모를 줄이기 위해서는 주변에 등장하지 않은 단어와 중심단어의 내적값을 줄여야 함. Θ를 크게함
  - 윈도우 내에 등장하지 않는 단어에 해당하는 벡터는 중심단어 벡터와 벡터 공간상에서 멀어지게(내적을 줄임), 등장하는 주변단어 벡터는 중심단어 벡터와 가까워지게(내적을 늘림) 하는 방식으로 벡터값을 업데이트 하면서 이루어짐

Word2Vec: 목적함수

$$
\begin{aligned}
\frac{\partial}{\partial v_c} \ln P(o|c) &= \frac{\partial}{\partial v_c} \ln \frac{exp(u_o^T v_c)}{\sum_{w=1}^{W} exp(u_w^T v_c)} \\
&= \frac{\partial}{\partial v_c} u_o^T v_c - \frac{\partial}{\partial v_c} \ln \sum_{w=1}^{W} exp(u_w^T v_c) \\
&= u_o^T - \frac{1}{\sum_{w=1}^{W} exp(u_w^T v_c)} \left(\sum_{w=1}^{W} exp(u_w^T v_c) \cdot u_w\right) \\
&= u_o^T - \sum_{w=1}^{W} \frac{exp(u_w^T v_c)}{\sum_{w=1}^{W} exp(u_w^T v_c)} \cdot u_w \\
&= u_o^T - \sum_{w=1}^{W} P(w|c) \cdot u_w
\end{aligned}
$$

$$
v_c^{t+1} = v_c^t + \alpha\left(u_o^T - \sum_{w=1}^{W} P(w|c) \cdot u_w\right)
$$

Word2Vec: Complexity Reduction

- 10개의 V와 N=100일 경우에, W, W′의 계산량은 2000만(2x10만x100)
- Subsampling frequent words: 자주 등장하는 단어의 학습량을 확률적인 방식으로 줄임.
  - f(w_i)는 해당 단어가 말뭉치에 등장한 비율 (해당단어빈도/전체단어수)
  - t는 사용자 지정값. 보통 0.00001
  - f(w_i)가 0.01이라면 p(w_i)는 0.9684로 100번의 학습 중 96번 정도는 학습에서 제외
  - Subsampling은 학습량을 효과적으로 줄여 계산량을 감소

$$P(w_i) = 1 - \sqrt{\frac{t}{f(w_i)}}$$

Word2Vec: Complexity Reduction

- Negative sampling:
  - 출력층의 softmax함수는 중심단어와 나머지 모든 단어들의 내적을 한 뒤 다시 exp를 취해야함. -> 계산량이 큼
  - Softmax를 구할 때 전체 단어를 대상으로 하지 않고 일부만 뽑아 계산
  - 지정한 윈도우 사이즈 내에 등장하지 않는 단어(negative sample)을 5-20개 정도 뽑은 후 이를 정답단어와 합쳐 이 것만으로 softmax를 계산.
  - 윈도우 사이즈가 5일 경우 최대 25개 단어를 대상으로만 softmax 확률을 계산하고, 패러미터 업데이트도 25개만 함
  - 윈도우 내에 등장하지 않는 어떤 단어(wi)가 negative sample로 뽑힐 확률

$$P(w_i) = \frac{f(w_i)^{3/4}}{\sum_{j=0}^{n} f(w_j)^{3/4}}$$

  - 예) is: $0.9^{(3/4)} = 0.92$ (2.2% 증가)

    Constitution: $0.09^{(3/4)} = 0.16$

    bombastic: $0.01^{(3/4)} = 0.032$ (220% 증가)

Glove(Global Vectors for Word Representation)

- GloVe is an unsupervised learning algorithm for obtaining vector representations for words. Training is performed on aggregated global word-word co-occurrence statistics from a corpus, and the resulting representations showcase interesting linear substructures of the word vector space.
  - While methods like LSA efficiently leverage statistical information, they do relatively poorly on the word analogy task, indicating a sub-optimal vector space structure. Methods like skip-gram may do better on the analogy ask, but they poorly utilize the statistics of the corpus since they train on separate local context windows instead of on global co-occurrence counts.
  - https://nlp.stanford.edu/projects/glove/

Glove(Global Vectors for Word Representation)

- GloVe is essentially a log-bilinear model with a weighted least-squares objective. The main intuition underlying the model is the simple observation that ratios of **word-word co-occurrence probabilities** have the potential for encoding some form of meaning

Probability and Ratio	$k = solid$	$k = gas$	$k = water$	$k = fashion$
$P(k\|ice)$	1.9×10^{-4}	6.6×10^{-5}	3.0×10^{-3}	1.7×10^{-5}
$P(k\|steam)$	2.2×10^{-5}	7.8×10^{-4}	2.2×10^{-3}	1.8×10^{-5}
$P(k\|ice)/P(k\|steam)$	8.9	8.5×10^{-2}	1.36	0.96

  - 특정 문맥단어가 주어졌을 때 임베딩된 두 단어벡터의 내적이 두단어의 동시등장확률간 비율에 되게끔 임베딩
  - *solid*라는 문맥단어가 주어졌을 때 *ice*와 *steam* 벡터 사이의 내적값이 8.9가 되도록
  - 단어 상호간 비율 정보를 말뭉치 전체를 놓고 한꺼번에 반영하면 좀 더 정확한 임베딩이 될 것이라고 가정

Glove(Global Vectors for Word Representation)

- Objective Function
  - $P_{ik} = P(k|i)$: i번째 단어가 등장했을 때 k라는 문맥 단어(context word)가 등장할 조건부 확률, $P(solid|ice)$
  - P_{ik}/P_{jk} : $P(solid|ice)/\ P(solid|stream) = 8.9$

$$F(w_{ice}, w_{steam}, w_{solid}) = \frac{P_{ice,solid}}{P_{steam,solid}} = \frac{P(solid|ice)}{P(solid|steam)} = \frac{1.9 \times 10^{-4}}{2.2 \times 10^{-5}} = 8.9$$

$$F(w_i, w_j, \tilde{w}_k) = \frac{P_{ik}}{P_{jk}}$$

$$F\left((w_i - w_j)^T \tilde{w}_k\right) = \frac{P_{ik}}{P_{jk}}$$

- Three conditions
  - w_i , w_k 를 서로 바꾸어도 같은 값을 가져야 함
  - 코퍼스 전체에서 구한 co-occurrence matrix X는 대칭행렬(symmetric matrix)이므로 함수는 이런 특징을 포함해야 함
  - Homomorphism조건을 만족해야 함

$$w_i \longleftrightarrow \tilde{w_k}$$

$$X \longleftrightarrow X^T$$

$$F(X - Y) = \frac{F(X)}{F(Y)}$$

Glove(Global Vectors for Word Representation)

- 이러한 조건을 만족하는 함수는 지수함수, F를 *exp*로 치환하고 정리
- w_i , w_k 를 서로 바꾸어도 식이 성립해야 하나 $\log(P_{ik})$가 $\log(P_{ki})$와 같아야 하나 $\log(X_{ik})$ - $\log(X_k)$와 $\log(X_{ki})$- $\log(X_i)$로 달라짐.
- 따라서 $\log(X_i)$ 를 상수항(b_i , b_k)로 하여 이 조건을 만족시킴
- $\log(X_{ik})$는 co-occurrence matrix에 로그값을 취한것.
- 이 차이를 최소한으로 하는 것이 목적함수

$$exp(w_i^T \tilde{w_k} - w_j^T \tilde{w_k}) = \frac{exp(w_i^T \tilde{w_k})}{exp(w_j^T \tilde{w_k})}$$

$$w_i^T \tilde{w_k} = \log P_{ik} = \log X_{ik} - \log X_i$$

$$w_i^T \tilde{w_k} = \log X_{ik} - b_i - \tilde{b_k}$$

$$w_i^T \tilde{w_k} + b_i + \tilde{b_k} = \log X_{ik}$$

$$J = \sum_{i,j=1}^{V} \left(w_i^T \tilde{w_j} + b_i + \tilde{b_j} - \log X_{ij}\right)^2$$

Glove(Global Vectors for Word Representation) : weighted least squares regression model

$$J = \sum_{i,j=1}^{V} f\left(X_{ij}\right)\left(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij}\right)^2$$

1. $f(0) = 0$. If f is viewed as a continuous function, it should vanish as $x \to 0$ fast enough that the $\lim_{x\to 0} f(x)\log^2 x$ is finite.

2. $f(x)$ should be non-decreasing so that rare co-occurrences are not overweighted.

3. $f(x)$ should be relatively small for large values of x, so that frequent co-occurrences are not overweighted.

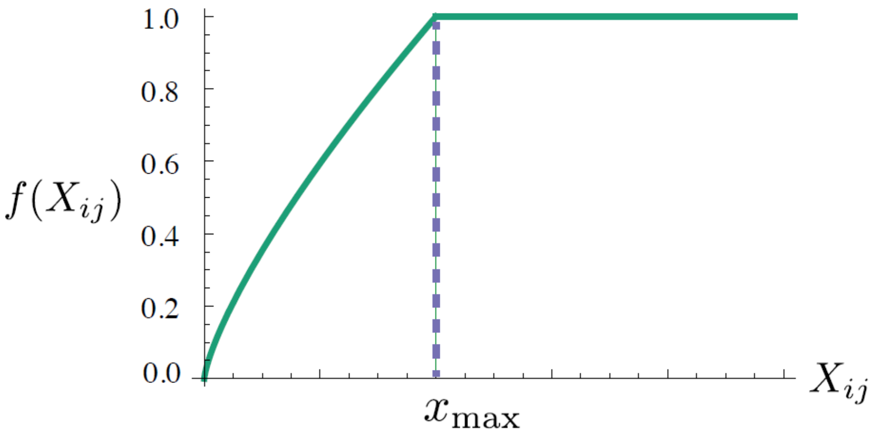


Figure 1: Weighting function f with $\alpha = 3/4$.

FastText

- Facebook AI Research lab에 의한 open source
  - https://research.fb.com/fasttext/
  - FastText combines some of the most successful concepts introduced by the natural language processing and machine learning communities in the last few decades. These include representing sentences with **bag of words** and **bag of n-grams**, as well as using **subword information**, and **sharing information across classes** through a hidden representation.
  - It also employs a hierachical softmax that takes advantage of the unbalanced distribution of the classes to speed up computation. These different concepts are being used for two different tasks: efficient text classification and learning word vector representations.

General Model

- Given a word vocabulary size W, where a word is identified by its index $w \in \{1, \ldots W\}$, the goal is to learn a vectorial representation for each word w.
- Skip-gram model is to maximize the following log-likelihood:

$$\sum_{t=1}^{T} \sum_{c \in \mathcal{C}_t} \log p(w_c \mid w_t),$$

  - where the context C_t is the set of indices of words surrounding word w_t.
  - one possible choice to define the probability of a context word is the softmax:
  - d

$$p(w_c \mid w_t) = \frac{e^{s(w_t,\, w_c)}}{\sum_{j=1}^{W} e^{s(w_t,\, j)}}.$$

General Model

- Negative Sampling
  - The problem of predicting context words can be framed as a set of independent binary classification tasks
  - For the word at position t we consider all context words as positive examples and sample negatives at random from the dictionary
  - For a chosen context position c, using the binary logistic loss, we obtain the following negative log-likelihood:

$$\log\left(1+e^{-s(w_t,\, w_c)}\right)+\sum_{n\in\mathcal{N}_{t,c}}\log\left(1+e^{s(w_t,\, n)}\right)$$

    - Where Nt,c is a set of negative examples sampled from the vocabulary
  - By denoting the logistic loss function $\ell : x \mapsto \log(1+e^{-x})$, we can rewrite the objective as:

$$\sum_{t=1}^{T}\left[\sum_{c\in\mathcal{C}_t}\ell(s(w_t,\, w_c))+\sum_{n\in\mathcal{N}_{t,c}}\ell(-s(w_t,\, n))\right]$$

Subword Model

- By using a distinct vector representation for each word, the skipgram model ignores the internal structure of words.
  - Each word *w* is represented as a bag of character n-gram. FastText adds special symbols < and > at the beginning and end of words, allowing to distinguish prefixes and suffixes from other character sequences
  - Also includes *w* itself in the set of its *n-grams*, to learn a representation for each word
  - Taking the word where and *n*=3 as an example, it will be represented by the character n-grams:
    - *<wh, whe, her, ere, re*> and the special sequence
    - *<where>*
    - Note that the sequence *<her>,* corresponding to her is different from the tri-gram *her* from the word where.
  - In practice, they extract all the *n-grams* for *n* greater or equal *2* and smaller or equal to *6*

Subword Model

- Suppose that you are given a dictionary of *n-grams* of size *G*. Given a word *w*, let us denote by $\mathcal{G}_w \subset \{1, \ldots, G\}$, the set of *n-grams* appearing in *w*.
  - Then associate a vector representation z_g to each n-gram *g*
  - The scoring function is

$$s(w, c) = \sum_{g \in \mathcal{G}_w} \mathbf{z}_g^\top \mathbf{v}_c.$$

  - This simple model allows sharing the representations across words, thus allowing to learn reliable representation for rare words