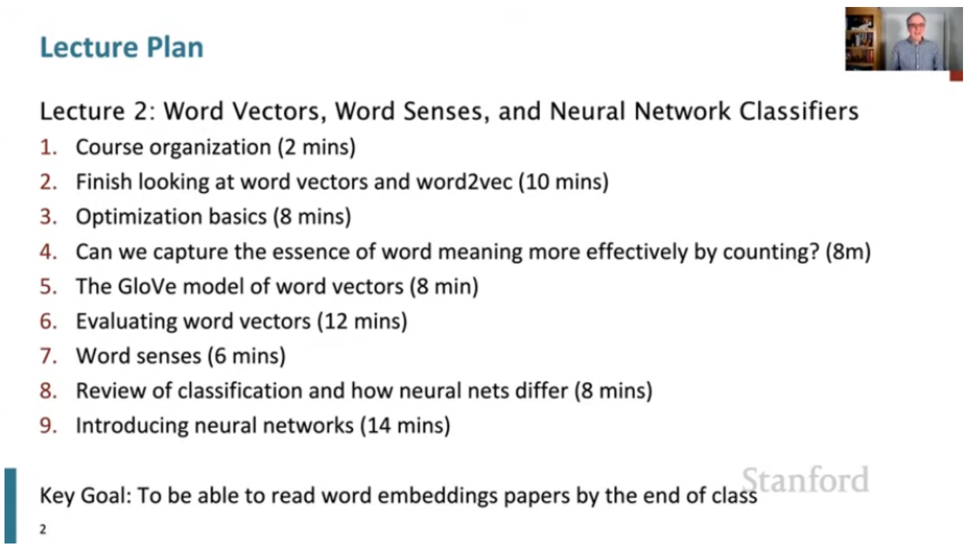
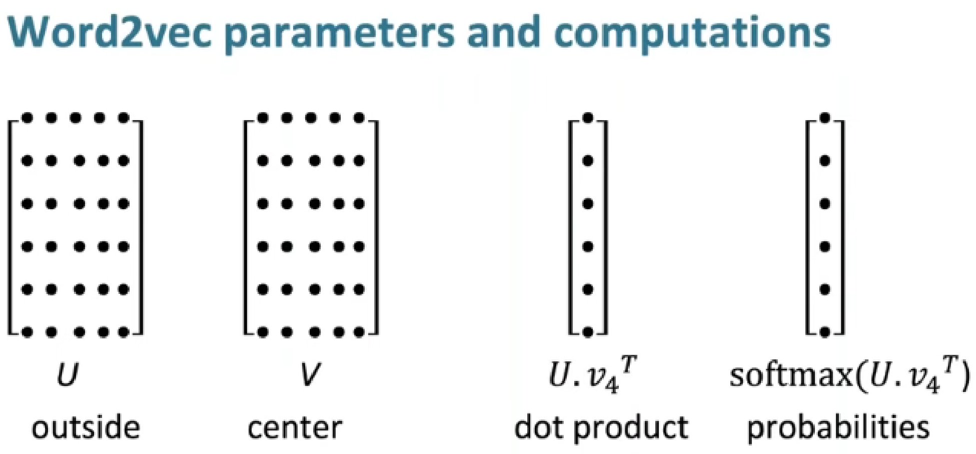
# NLP Week 2




word2vec - softmax

**Word2vec maximizes objective function(J) by putting similar words nearby in space**

## Gradient Descent

- Update equation (in matrix notation):

$$\theta^{new} = \theta^{old} - \alpha \nabla_\theta J(\theta)$$

$\alpha$ = *step size* or *learning rate*

- Update equation (for a single parameter):

$$\theta_j^{new} = \theta_j^{old} - \alpha \frac{\partial}{\partial \theta_j^{old}} J(\theta)$$

## Stochastic Gradient Descent

Problem : J is a function of all windows in the corpus

Solution : SGD

repeatedly sample windows and update after each one or each small batch

- But in each window, we only have at most $2m + 1$ words, so $\nabla_\theta J_t(\theta)$ is very sparse!

## 2b. Word2vec algorithm family : More details

Two model variants

1. Skip-grams
2. CBOW

additional efficiency

1. Negative sampling

## The skip-gram model with negative Sampling

- The normalization term is computationally expensive

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

Main : train binary logistic regression for a true pair (center-context) VS several noise pairs(the center word-random words)

- objective function

$$J(\theta) = \frac{1}{T} \sum_{t=1}^{T} J_t(\theta)$$

$$J_t(\theta) = \log \sigma\left(u_o^T v_c\right) + \sum_{i=1}^{k} \mathbb{E}_{j \sim P(w)} \left[\log \sigma\left(-u_j^T v_c\right)\right]$$

- logistic/sigmoid function y: 0~1
- Maximize the prob of two words co-occurring in first log

and minimize the prob of noise words

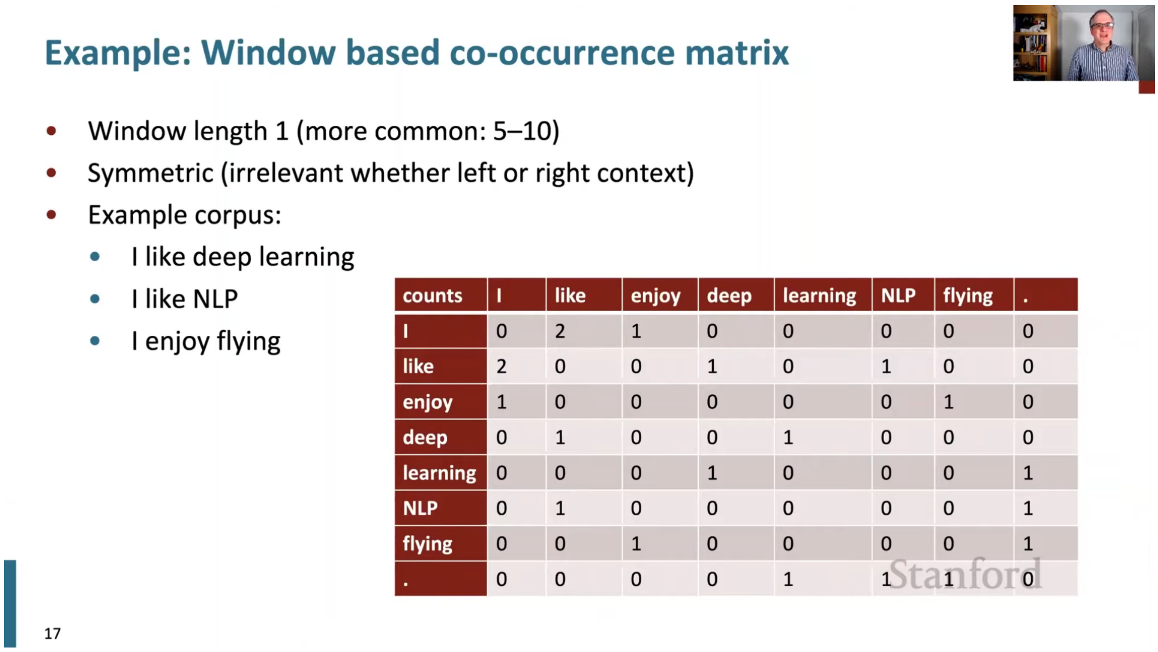
$$J_{neg-sample}(\boldsymbol{u}_o, \boldsymbol{v}_c, U) = -\log \sigma(\boldsymbol{u}_o^T \boldsymbol{v}_c) - \sum_{k \in \{K \text{ sampled indices}\}} \log \sigma(-\boldsymbol{u}_k^T \boldsymbol{v}_c)$$

- take k negative samples
- Max-prob that real outside word appears, Min-prob that random words appear around center words
- Sample with P(w) = U(w)^(3/4) / Z (less frequent→ sampled more)

## 4. Why not capture co-occurrence counts directly?

Building a co-occurrence matrix X

- windows vs full document
- window : captures syntactic(구문) and semantic info
- Word-docu co-occurrence matrix will give general topics leading to ‘LSA’(잠재의미분석)



Example: Window based co-occurrence matrix

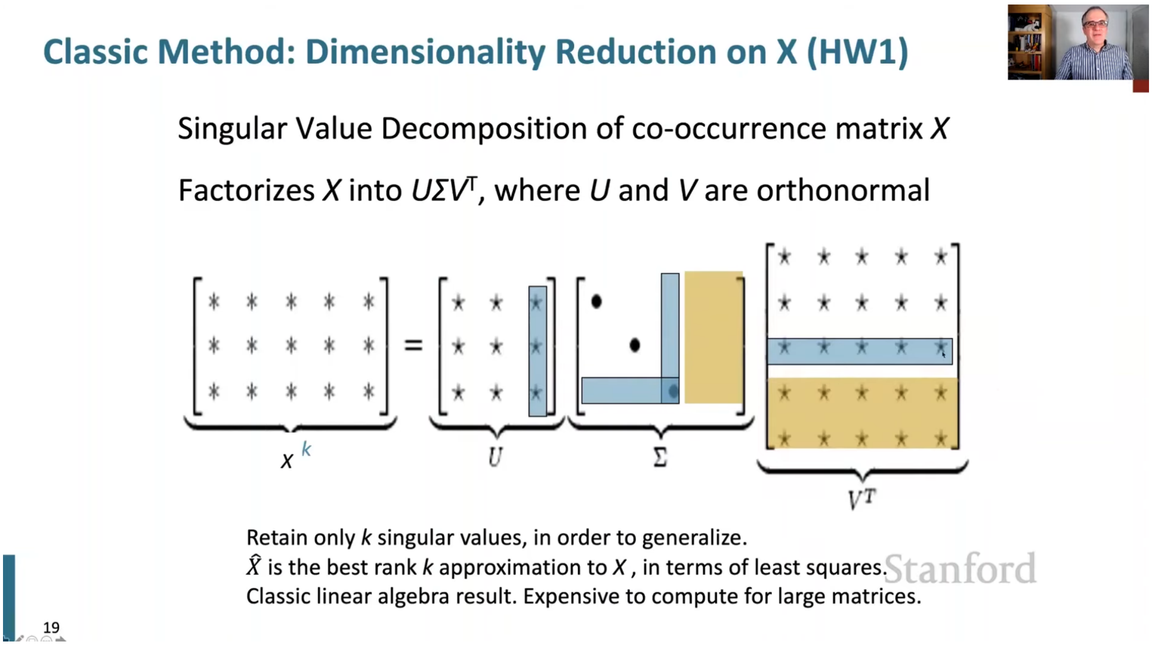
- Window length 1 (more common: 5–10)
- Symmetric (irrelevant whether left or right context)
- Example corpus:
  - I like deep learning
  - I like NLP
  - I enjoy flying

| counts | I | like | enjoy | deep | learning | NLP | flying | . |
|---|---|---|---|---|---|---|---|---|
| I | 0 | 2 | 1 | 0 | 0 | 0 | 0 | 0 |
| like | 2 | 0 | 0 | 1 | 0 | 1 | 0 | 0 |
| enjoy | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| deep | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 |
| learning | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 |
| NLP | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| flying | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 |
| . | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 |

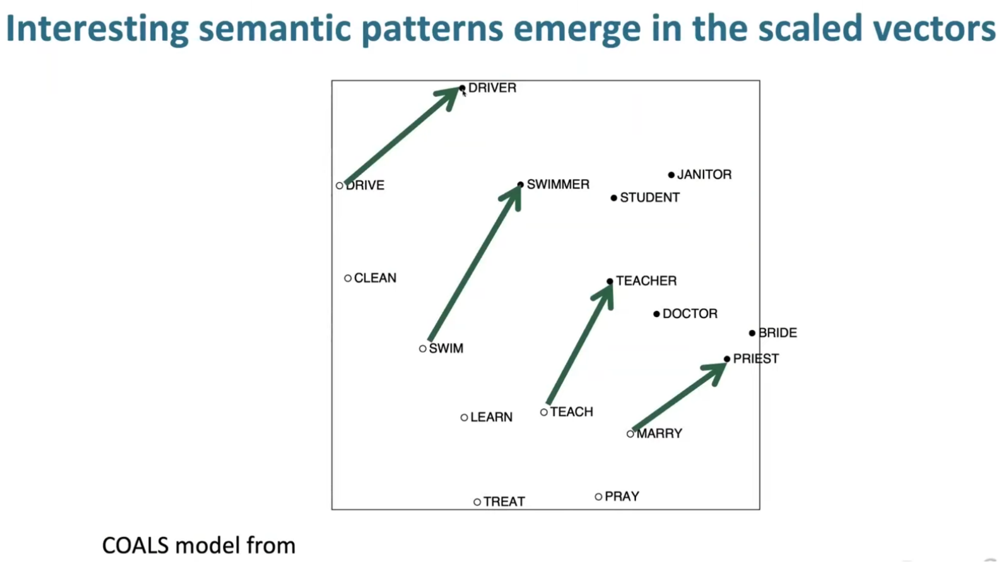


## Co-occurrence vectors

- simple count co-occur vec
  - very high dimensional
  - sparsity issues
- Low-dimensional vec
  - idea: store ‘most’ of the important info in a fixed small # of dimension : a **dense vector**




delete more of the matrix




## 5. Towards GloVe: Count based vs. direct prediction

- LSA, HAL, COALS, PCA

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- Fast training
- efficient usage of statistics
- used to capture word similarity

- Skip-Gram/CBOW, NNLM,HLBL, RNN

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- Scales with corpus size
- Inefficient usage of statistics

- Disproportionate importance given to large corpus

- generate improved performance
- Can capture complex patterns (ex.analogy)

## Encoding meaning in vector differences

Crucial insight : Ratio of co-occurrence probs can encode meaning components

| | $x$ = solid | $x$ = gas | $x$ = water | $x$ = random |
|---|---|---|---|---|
| $P(x \vert \text{ice})$ | large | small | large | small |
| $P(x \vert \text{steam})$ | small | large | large | small |
| $\frac{P(x \vert \text{ice})}{P(x \vert \text{steam})}$ | large | small | ~1 | ~1 |

Q : How can we capture ratios of co-occurrence probs as linear meaning components in a word vector space?

A: Log-bilinear model: $$w_i \cdot w_j = \log P(i|j)$$

with vector differences $$w_x \cdot (w_a - w_b) = \log \frac{P(x|a)}{P(x|b)}$$

## Combining the best of both worlds GloVe

objective funtion J

wi,wj - log Xij : as small as possible

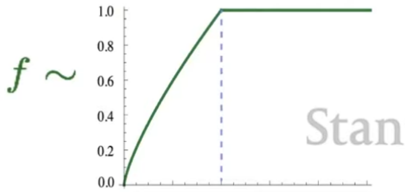
f(Xij) : depending on the frequency of a word

: pay more attention to more common words.

But  having extremely common words like function words (he, the..) leads you astray. so paid more attention to words that co-occur until a certain point. Then the curve went flat.

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

- Fast training
- scalable to huge corpora
- Good performance even with small corpus and small vectors



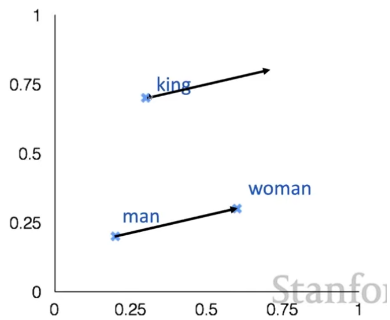

## Intrinsic word vector evaluation

- Word Vector Analogies

a:b :: c:?

man:woman :: king:?

$$d = \arg\max_i \frac{(x_b - x_a + x_c)^T x_i}{||x_b - x_a + x_c||}$$




cosine distance

problem : what is the information is there but not linear?

## Extrinsic word vector evaluation

- Extrinsic evaluation of word vectors: All subsequent NLP tasks in this class. More examples soon.
- One example where good word vectors should help directly: **named entity recognition**: identifying references to a person, organization or location

## Linear Algebraic Structure of Word Senses, with Applications to Polysemy **(Arora, …, Ma, …, TACL 2018)**

- Different senses of a word reside in a linear superposition (weighted sum) in standard word embeddings like word2vec
- $v_{\text{pike}} = \alpha_1 v_{\text{pike}_1} + \alpha_2 v_{\text{pike}_2} + \alpha_3 v_{\text{pike}_3}$
- Where $\alpha_1 = \frac{f_1}{f_1+f_2+f_3}$, etc., for frequency $f$
- Surprising result:
  - Because of ideas from *sparse coding* you can actually separate out the senses (providing they are relatively common)!

| tie | | | | |
|---|---|---|---|---|
| trousers | season | scoreline | wires | operatic |
| blouse | teams | goalless | cables | soprano |
| waistcoat | winning | equaliser | wiring | mezzo |
| skirt | league | clinching | electrical | contralto |
| sleeved | finished | scoreless | wire | baritone |
| pants | championship | replay | cable | coloratura |



> 단어의 다른 의미들은 선형 중첩에 있다. (가중합)

superposition : 중첩 원리는 선형 미분 방정식의 해의 선형 결합이 선형 미분 방정식의 또다른 해가 된다는 원리다