COS 484

Natural Language Processing

L5: Word Embeddings II

Spring 2025

(Some slides adapted from Chris Manning, Dan Jurafsky)

Word embeddings

Goal: represent words as **short** (50-300 dimensional) & **dense** (real-valued) vectors

Count-based approaches

- Used since the 90s
- Sparse word-word co-occurrence PPMI matrix
- Decomposed with SVD

Prediction-based approaches

- Formulated as a machine learning problem
- Word2vec (Mikolov et al., 2013)
- GloVe (Pennington et al., 2014)

Underlying theory: Distributional Hypothesis *(Firth, '57)*
"Similar words occur in similar contexts"

Word embeddings: the learning problem

Learning vectors from text for representing words

- **Input**:
  - a large text corpus,
  - vocabulary V
  - vector dimension d (e.g., 300)
- **Output**: $f \colon V \rightarrow \mathbb{R}^d$

$$v_{\text{cat}} = \begin{pmatrix} -0.224 \\ 0.130 \\ -0.290 \\ 0.276 \end{pmatrix} \quad v_{\text{dog}} = \begin{pmatrix} -0.124 \\ 0.430 \\ -0.200 \\ 0.329 \end{pmatrix}$$

$$v_{\text{the}} = \begin{pmatrix} 0.234 \\ 0.266 \\ 0.239 \\ -0.199 \end{pmatrix} \quad v_{\text{language}} = \begin{pmatrix} 0.290 \\ -0.441 \\ 0.762 \\ 0.982 \end{pmatrix}$$

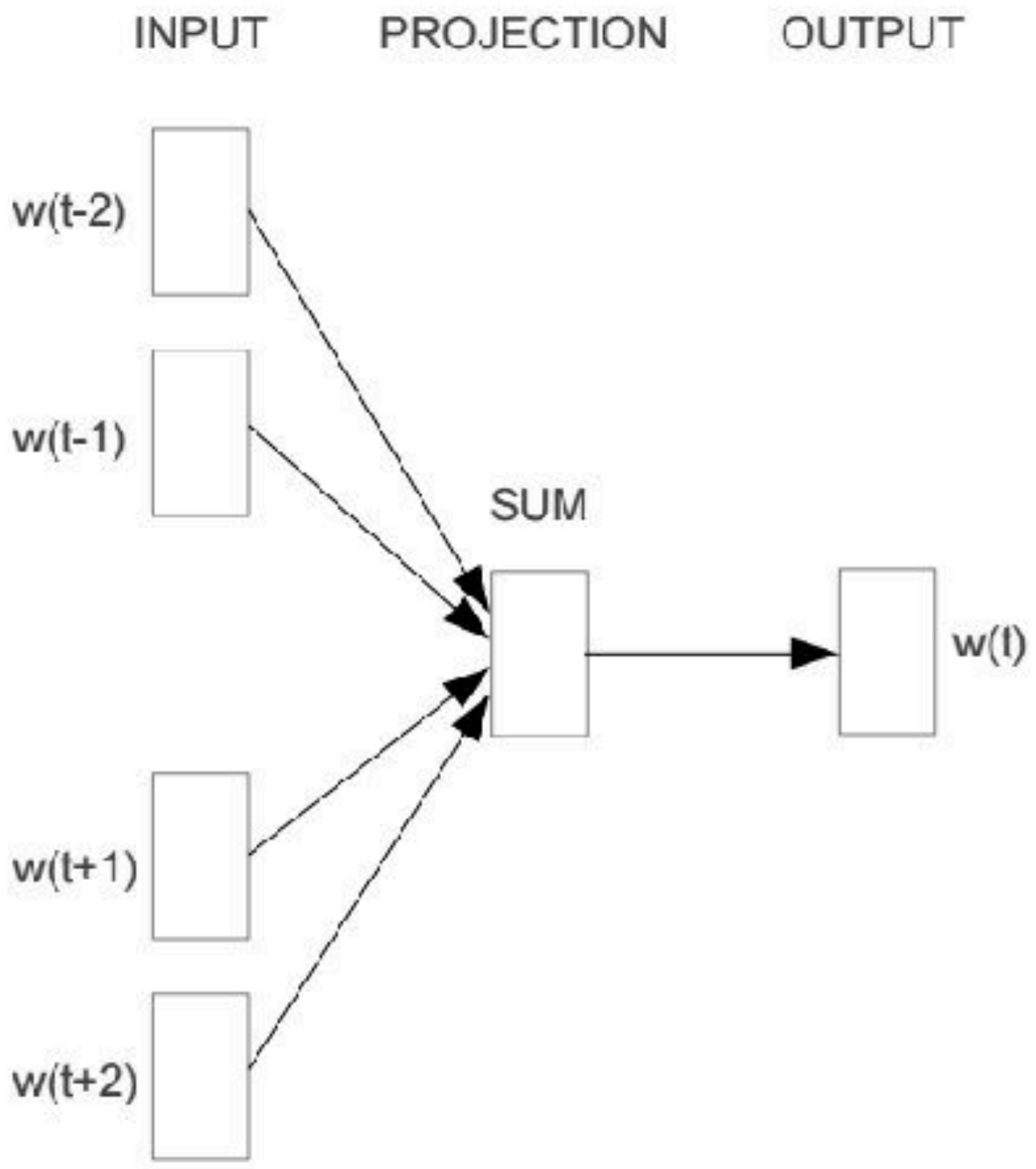
Note: Each coordinate/dimension of the vector doesn't have a particular interpretation

Word2vec: How does it work?

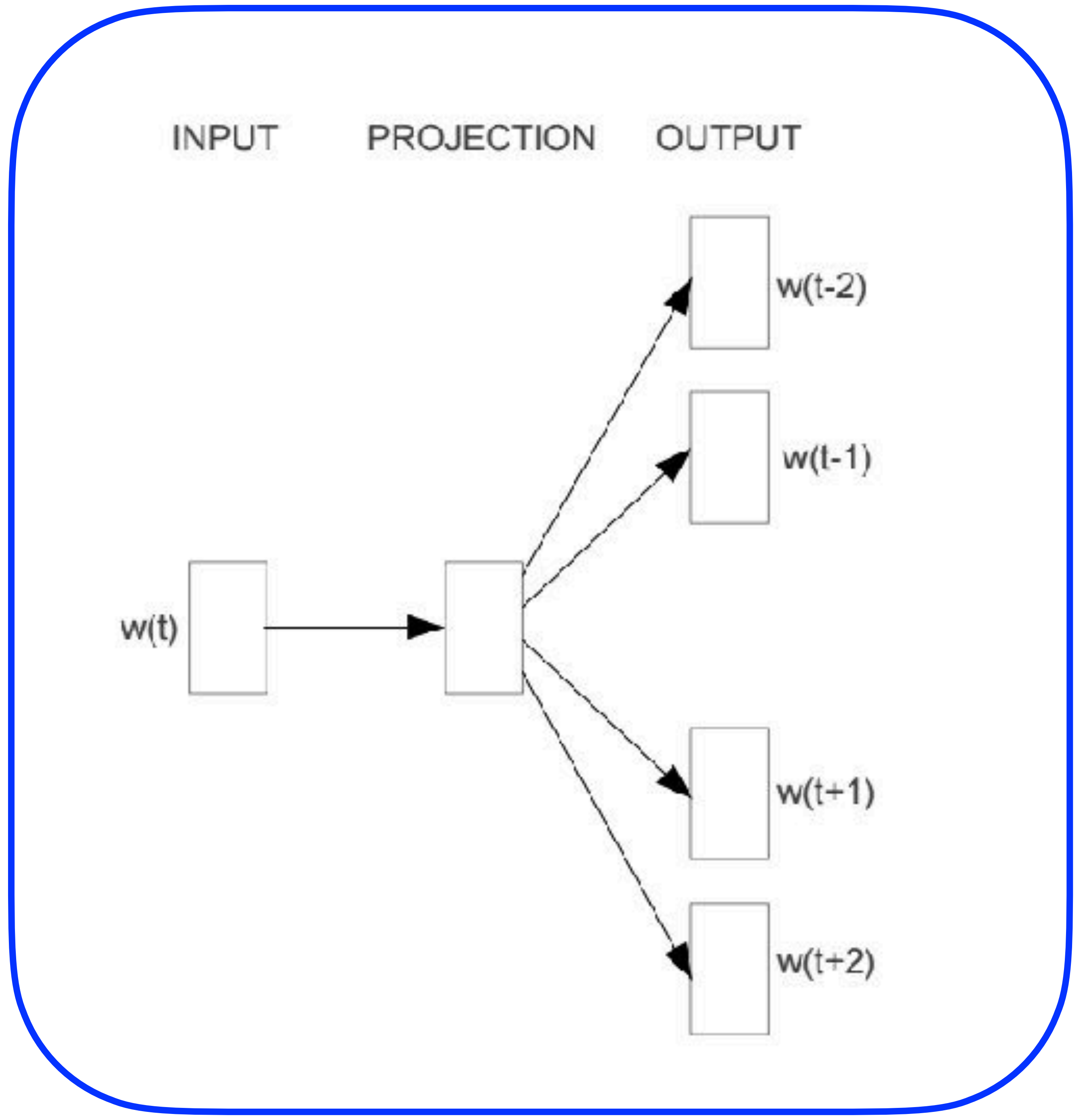
word2vec

- (Mikolov et al 2013a): Efficient Estimation of Word Representations in Vector Space
- (Mikolov et al 2013b): Distributed Representations of Words and Phrases and their Compositionality

Tomáš Mikolov



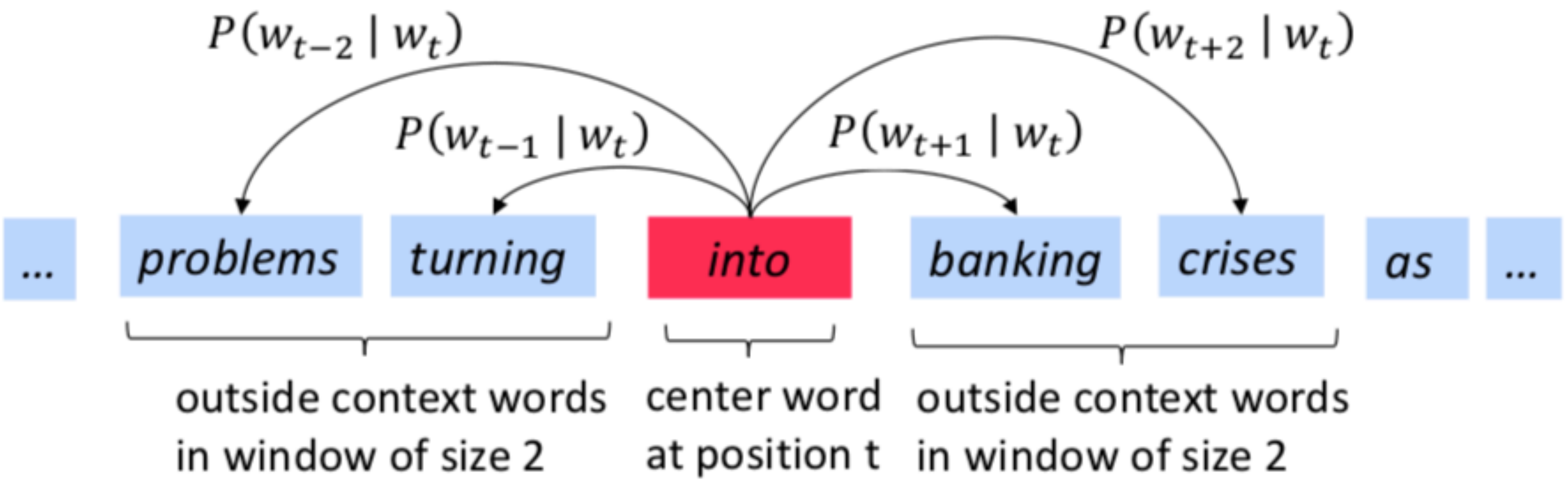
Continuous Bag of Words (CBOW)



Skip-gram

Skip-gram

- Assume that we have a large corpus $w_1, w_2, \ldots, w_T \in V$
- Key idea: Use each word to predict other words in its context
- Context: a fixed window of size 2m (m = 2 in the example)



A classification problem!

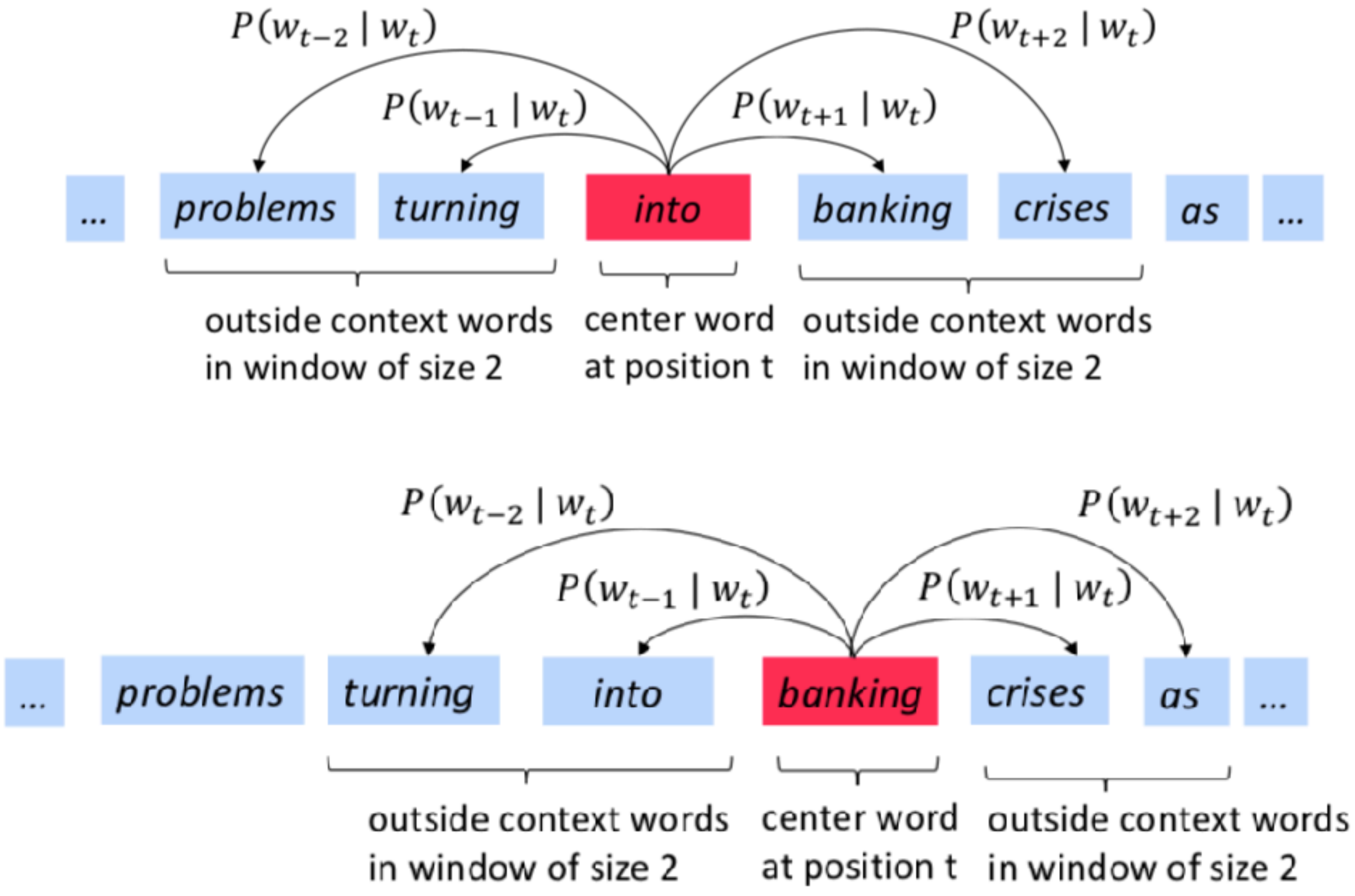
$P(b \mid a)$ = given the center word is a, what is the probability that b is a context word?

$P(\cdot \mid a)$ is a probability distribution defined over V:

$$\sum_{w \in V} P(w \mid a) = 1$$

We are going to define this distribution soon!

Skip-gram



Convert into training data:

(into, problems)
(into, turning)
(into, banking)
(into, crises)
(banking, turning)
(banking, into)
(banking, crises)
(banking, as)
...

Our goal is to find parameters that can maximize

$P(\text{problems} \mid \text{into}) \times P(\text{turning} \mid \text{into}) \times P(\text{banking} \mid \text{into}) \times P(\text{crises} \mid \text{into}) \times$

$P(\text{turning} \mid \text{banking}) \times P(\text{into} \mid \text{banking}) \times P(\text{crises} \mid \text{banking}) \times P(\text{as} \mid \text{banking}) \ldots$

Skip-gram: objective function

- For each position $t = 1,2,\ldots T$, predict context words within context size m, given center word w_t:

all the parameters to be optimized

$$\mathcal{L}(\theta) = \prod_{t=1}^{T} \prod_{-m \le j \le m, j \ne 0} P(w_{t+j} \mid w_t; \theta)$$

- It is equivalent to minimizing the (average) negative log likelihood:

$$J(\theta) = -\frac{1}{T} \log \mathcal{L}(\theta) = -\frac{1}{T} \sum_{t=1}^{T} \sum_{-m \le j \le m, j \ne 0} \log P(w_{t+j} \mid w_t; \theta)$$

How to define $P(w_{t+j} \mid w_t; \theta)$?

- Use two sets of vectors for each word in the vocabulary

$$\mathbf{u}_a \in \mathbb{R}^d \quad \text{: vector for center word } a, \forall a \in V$$

$$\mathbf{v}_b \in \mathbb{R}^d \quad \text{: vector for context word } b, \forall b \in V$$

- Use inner product $\mathbf{u}_a \cdot \mathbf{v}_b$ to measure how likely word a appears with context word b

$$P(w_{t+j} \mid w_t) = \frac{\exp\left(\mathbf{u}_{w_t} \cdot \mathbf{v}_{w_{t+j}}\right)}{\sum_{k \in V} \exp\left(\mathbf{u}_{w_t} \cdot \mathbf{v}_k\right)}$$

Does this term seem familiar?

… vs multinominal logistic regression

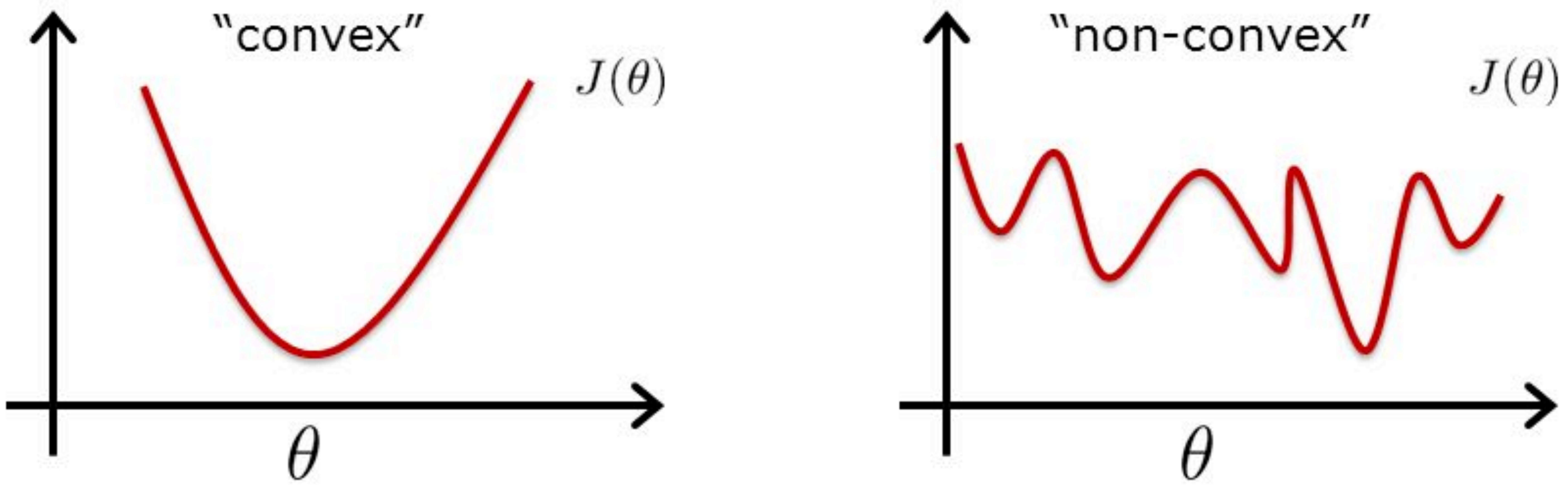
- Essentially a |V|-way classification problem
- Recall: multinomial logistic regression:

$$P(y = c \mid x) = \frac{\exp(\mathbf{w}_c \cdot \mathbf{x} + b_c)}{\sum_{j=1}^{m} \exp(\mathbf{w}_j \cdot \mathbf{x} + b_j)}$$

$$P(w_{t+j} \mid w_t) = \frac{\exp(\mathbf{u}_{w_t} \cdot \mathbf{v}_{w_{t+j}})}{\sum_{k \in V} \exp(\mathbf{u}_{w_t} \cdot \mathbf{v}_k)}$$

- If we fix $\mathbf{u}_{w_t}$, it is reduced to a multinomial logistic regression problem.
- However, since we have to learn both $\mathbf{u}$ and $\mathbf{v}$ together, the training objective is non-convex.

… vs multinominal logistic regression



- It is hard to find a global minimum
- But can still use stochastic gradient descent to optimize θ:

$$\theta^{(t+1)} = \theta^{(t)} - \eta \nabla_\theta J(\theta)$$

Important note

$$J(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{-m\leq j\leq m, j\neq 0}\log\frac{\exp(\mathbf{u}_{w_t}\cdot\mathbf{v}_{w_{t+j}})}{\sum_{k\in V}\exp(\mathbf{u}_{w_t}\cdot\mathbf{v}_k)}$$

- In this formulation, we don't care about the classification task itself like we do for the logistic regression model we saw previously.
- The key point is that the parameters used to optimize this training objective—when the training corpus is large enough—can give us very good representations of words (following the principle of distributional hypothesis)!

How many parameters in this model?

How many parameters does this model have (i.e. what is size of θ)?

$$J(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{-m\leq j\leq m, j\neq 0}\log\frac{\exp(\mathbf{u}_{w_t}\cdot\mathbf{v}_{w_{t+j}})}{\sum_{k\in V}\exp(\mathbf{u}_{w_t}\cdot\mathbf{v}_k)}$$

(a) $d|V|$

(b) $2d|V|$

(c) $2m|V|$

(d) $2md|V|$

V := Vocabulary

d := dimension of embedding

m := size of context window

The answer is (b).

Each word has two d-dimensional vectors, so it is $2 \times |V| \times d$.

word2vec formulation

$$J(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{-m\leq j\leq m, j\neq 0}\log\frac{\exp(\mathbf{u}_{w_t}\cdot\mathbf{v}_{w_{t+j}})}{\sum_{k\in V}\exp(\mathbf{u}_{w_t}\cdot\mathbf{v}_k)}$$

Q: Why do we need two vectors for each word?

- Because one word is not likely to appear in its own context window, e.g., $P(\text{dog} \mid \text{dog})$ should be low. If we use one set of vectors only, it essentially needs to minimize $\mathbf{u}_{\text{dog}} \cdot \mathbf{u}_{\text{dog}}$

Q: Which set of vectors are used as word embeddings?

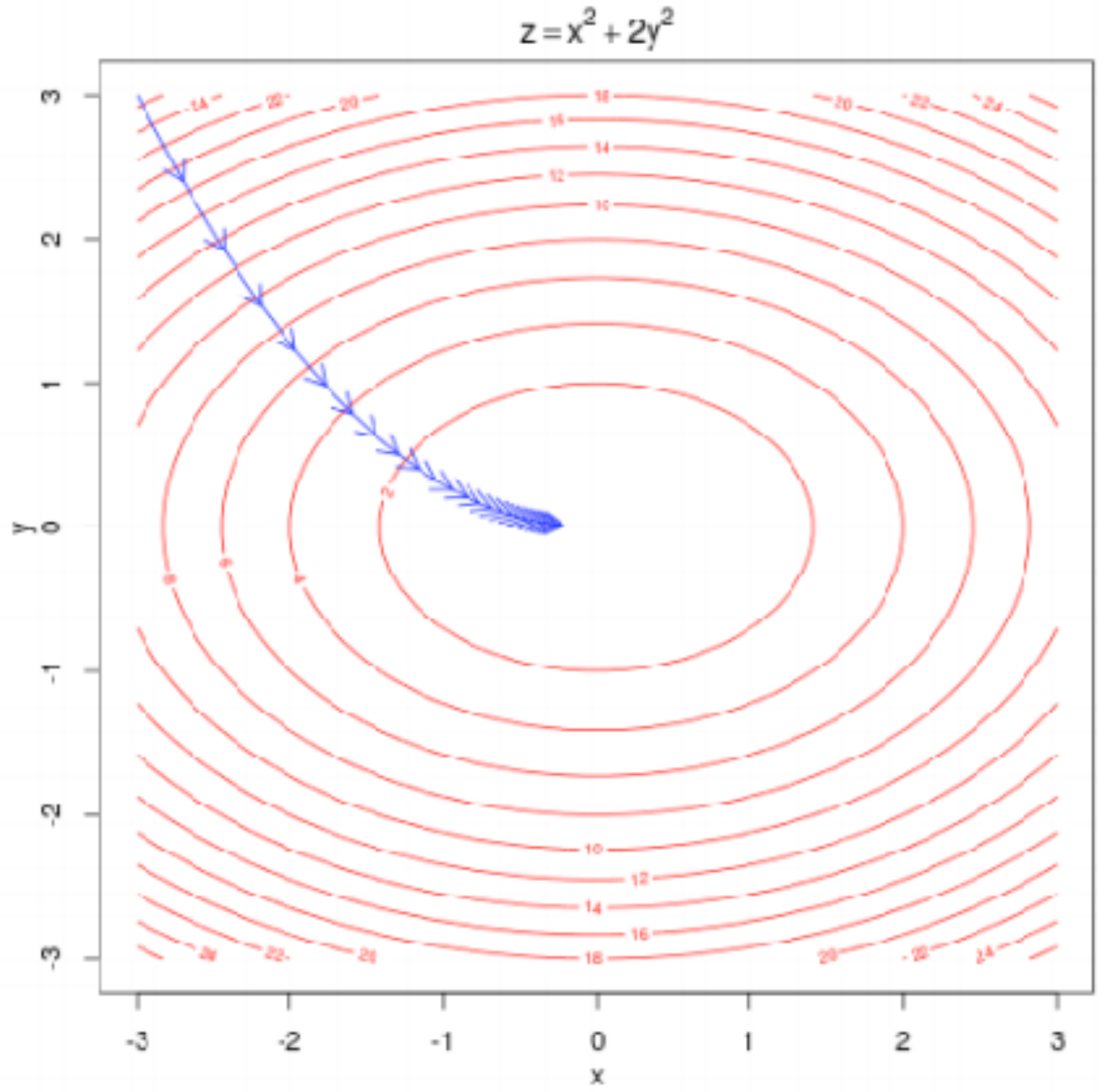
- This is an empirical question. Typically just $\mathbf{u}_w$ but you can also concatenate the two vectors..

How to train this model?

$$J(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{-m\leq j\leq m, j\neq 0}\log\frac{\exp(\mathbf{u}_{w_t}\cdot\mathbf{v}_{w_{t+j}})}{\sum_{k\in V}\exp(\mathbf{u}_{w_t}\cdot\mathbf{v}_k)}$$

- To train such a model, we need to compute the vector gradient $\nabla_\theta J(\theta) = ?$
- Remember that θ represents all $2d|V|$ model parameters, in one vector.

$$\theta = \begin{bmatrix} v_{aardvark} \\ v_a \\ \vdots \\ v_{zebra} \\ u_{aardvark} \\ u_a \\ \vdots \\ u_{zebra} \end{bmatrix}$$



Vectorized gradients

$$f(\mathbf{x}) = \mathbf{x} \cdot \mathbf{a}$$

$$\mathbf{x}, \mathbf{a} \in \mathbb{R}^n$$

$$\frac{\partial f}{\partial \mathbf{x}} = \mathbf{a}$$

$$f = x_1 a_1 + x_2 a_2 + \ldots + x_n a_n$$

$$\frac{\partial f}{\partial \mathbf{x}} = [\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2}, \ldots, \frac{\partial f}{\partial x_n}]$$

Vectorized gradients: exercises

Let $f = \exp(\mathbf{w} \cdot \mathbf{x})$, what is the value of $\dfrac{\partial f}{\partial \mathbf{x}}$? (Assume $\mathbf{w}, \mathbf{x} \in \mathbb{R}^n$)

(a) $\mathbf{w}$

(b) $\exp(\mathbf{w} \cdot \mathbf{x})$

(c) $\exp(\mathbf{w} \cdot \mathbf{x})\mathbf{w}$

(d) $\mathbf{x}$

The answer is (c).

$$\frac{\partial}{\partial x_i} = \frac{\exp(\sum_{k=1}^{n} w_i x_i)}{\partial x_i} = \exp(\sum_{k=1}^{n} w_i x_i) w_i$$

Let's compute gradients for word2vec

$$J(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{-m\leq j\leq m, j\neq 0}\log\frac{\exp(\mathbf{u}_{w_t}\cdot\mathbf{v}_{w_{t+j}})}{\sum_{k\in V}\exp(\mathbf{u}_{w_t}\cdot\mathbf{v}_k)}$$

Consider one pair of center/context words (t, c):

$$y = -\log\left(\frac{\exp(\mathbf{u}_t\cdot\mathbf{v}_c)}{\sum_{k\in V}\exp(\mathbf{u}_t\cdot\mathbf{v}_k)}\right)$$

We need to compute the gradient of y with respect to

$$\mathbf{u}_t \text{ and } \mathbf{v}_k, \forall k \in V$$

Let's compute gradients for word2vec

$$y = -\log\left(\frac{\exp(\mathbf{u}_t \cdot \mathbf{v}_c)}{\sum_{k \in V} \exp(\mathbf{u}_t \cdot \mathbf{v}_k)}\right)$$

$$y = -\log(\exp(\mathbf{u}_t \cdot \mathbf{v}_c)) + \log(\sum_{k \in V} \exp(\mathbf{u}_t \cdot \mathbf{v}_k))$$

$$= -\mathbf{u}_t \cdot \mathbf{v}_c + \log(\sum_{k \in V} \exp(\mathbf{u}_t \cdot \mathbf{v}_k))$$

Recall that

$$P(w_{t+j} \mid w_t) = \frac{\exp(\mathbf{u}_{w_t} \cdot \mathbf{v}_{w_{t+j}})}{\sum_{k \in V} \exp(\mathbf{u}_{w_t} \cdot \mathbf{v}_k)}$$

$$\frac{\partial y}{\partial \mathbf{u}_t} = \frac{\partial(-\mathbf{u}_t \cdot \mathbf{v}_c)}{\partial \mathbf{u}_t} + \frac{\partial(\log \sum_{k \in V} \exp(\mathbf{u}_t \cdot \mathbf{v}_k))}{\partial \mathbf{u}_t}$$

$$= -\mathbf{v}_c + \frac{\frac{\partial \sum_{k \in V} \exp(\mathbf{u}_t \cdot \mathbf{v}_k)}{\partial \mathbf{u}_t}}{\sum_{k \in V} \exp(\mathbf{u}_t \cdot \mathbf{v}_k)}$$

$$= -\mathbf{v}_c + \frac{\sum_{k \in V} \exp(\mathbf{u}_t \cdot \mathbf{v}_k) \cdot \mathbf{v}_k}{\sum_{k \in V} \exp(\mathbf{u}_t \cdot \mathbf{v}_k)}$$

$$= -\mathbf{v}_c + \sum_{k \in V} \frac{\exp(\mathbf{u}_t \cdot \mathbf{v}_k)}{\sum_{k' \in V} \exp(\mathbf{u}_t \cdot \mathbf{v}_{k'})} \mathbf{v}_k$$

$$= -\mathbf{v}_c + \sum_{k \in V} P(k \mid t) \mathbf{v}_k$$

Gradients for word2vec

What about context vectors?

$$\frac{\partial y}{\partial \mathbf{v}_k} = \begin{cases} (P(k \mid t) - 1)\,\mathbf{u}_t & k = c \\ P(k \mid t)\mathbf{u}_t & k \neq c \end{cases}$$

$$y = -\log\left(\frac{\exp(\mathbf{u}_t \cdot \mathbf{v}_c)}{\sum_{k \in V} \exp(\mathbf{u}_t \cdot \mathbf{v}_k)}\right)$$

See assignment 2 :)

Overall algorithm

- Input: text corpus, embedding size d, vocabulary V, context size m
- Initialize $\mathbf{u}_i, \mathbf{v}_i$ randomly $\forall i \in V$
- Run through the training corpus and for each training instance (*t*, *c*):
  - Update $\mathbf{u}_t \leftarrow \mathbf{u}_t - \eta \frac{\partial y}{\partial \mathbf{u}_t}$; $\quad \frac{\partial y}{\partial \mathbf{u}_t} = -\mathbf{v}_c + \sum_{k \in V} P(k \mid t)\mathbf{v}_k$
  - Update $\mathbf{v}_k \leftarrow \mathbf{v}_k - \eta \frac{\partial y}{\partial \mathbf{v}_k}, \forall k \in V$; $\quad \frac{\partial y}{\partial \mathbf{v}_k} = \begin{cases} (P(k \mid t) - 1)\mathbf{u}_t & k = c \\ P(k \mid t)\mathbf{u}_t & k \neq c \end{cases}$

2 min stretch-break

Overall algorithm

- Input: text corpus, embedding size d, vocabulary V, context size m
- Initialize $\mathbf{u}_i, \mathbf{v}_i$ randomly $\forall i \in V$
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  - Update $\mathbf{v}_k \leftarrow \mathbf{v}_k - \eta \frac{\partial y}{\partial \mathbf{v}_k}, \forall k \in V$; $\quad \frac{\partial y}{\partial \mathbf{v}_k} = \begin{cases} (P(k \mid t) - 1)\mathbf{u}_t & k = c \\ P(k \mid t)\mathbf{u}_t & k \neq c \end{cases}$

Q: Can you think of any issues with this algorithm?

Skip-gram with negative sampling (SGNS)

Problem: every time you get one pair of (t, c), you need to update $\mathbf{v}_k$ with all the words in the vocabulary! This is very expensive computationally.

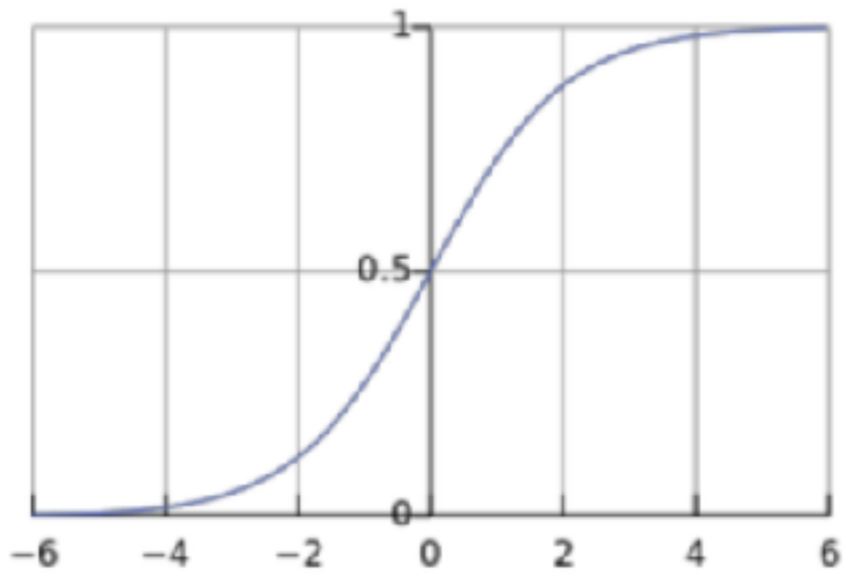
$$\frac{\partial y}{\partial \mathbf{u}_t} = -\mathbf{v}_c + \sum_{k \in V} P(k \mid t)\mathbf{v}_k \quad ; \quad \frac{\partial y}{\partial \mathbf{v}_k} = \begin{cases} (P(k \mid t) - 1)\ \mathbf{u}_t & k = c \\ P(k \mid t)\ \mathbf{u}_t & k \neq c \end{cases}$$

Negative sampling: instead of considering all the words in V, let's randomly sample K (5-20) negative examples.

$$\sigma(x) = \frac{1}{1 + \exp(-x)}$$

Softmax: $$y = -\log\left(\frac{\exp\left(\mathbf{u}_t \cdot \mathbf{v}_c\right)}{\sum_{k \in V} \exp\left(\mathbf{u}_t \cdot \mathbf{v}_k\right)}\right)$$

Negative sampling: $$y = -\log\left(\sigma(\mathbf{u}_t \cdot \mathbf{v}_c)\right) - \sum_{i=1}^{K} \mathbb{E}_{j \sim P(w)} \log\left(\sigma(-\mathbf{u}_t \cdot \mathbf{v}_j)\right)$$



Skip-gram with negative sampling (SGNS)

Key idea: Convert the $|V|$-way classification into a set of binary classification tasks.

Every time we get a pair of words (*t*, *c*), we don't predict *c* among all the words in the vocabulary. Instead, we predict (*t*, *c*) is a positive pair, and (*t*, *c'*) is a negative pair for a small number of sampled *c'*.

positive examples +

t	c
apricot	tablespoon
apricot	of
apricot	jam
apricot	a

negative examples -

t	c	t	c
apricot	aardvark	apricot	seven
apricot	my	apricot	forever
apricot	where	apricot	dear
apricot	coaxial	apricot	if

$$y = -\log(\sigma(\mathbf{u}_t \cdot \mathbf{v}_c)) - \sum_{i=1}^{K} \mathbb{E}_{j \sim P(w)} \log(\sigma(-\mathbf{u}_t \cdot \mathbf{v}_j))$$

P(w): sampling according to the frequency of words

Similar to **binary logistic regression**, but we need to optimize $\mathbf{u}$ and $\mathbf{v}$ together.

$$P(y = 1 \mid t, c) = \sigma(\mathbf{u}_t \cdot \mathbf{v}_c) \qquad p(y = 0 \mid t, c') = 1 - \sigma(\mathbf{u}_t \cdot \mathbf{v}_{c'}) = \sigma(-\mathbf{u}_t \cdot \mathbf{v}_{c'})$$

Understanding SGNS

In skip-gram with negative sampling (SGNS), how many parameters need to be updated in θ for every (t, c) pair?

$$y = -\log(\sigma(\mathbf{u}_t \cdot \mathbf{v}_c)) - \sum_{i=1}^{K} \mathbb{E}_{j \sim P(w)} \log(\sigma(-\mathbf{u}_t \cdot \mathbf{v}_j))$$

(a) Kd

(b) $2Kd$

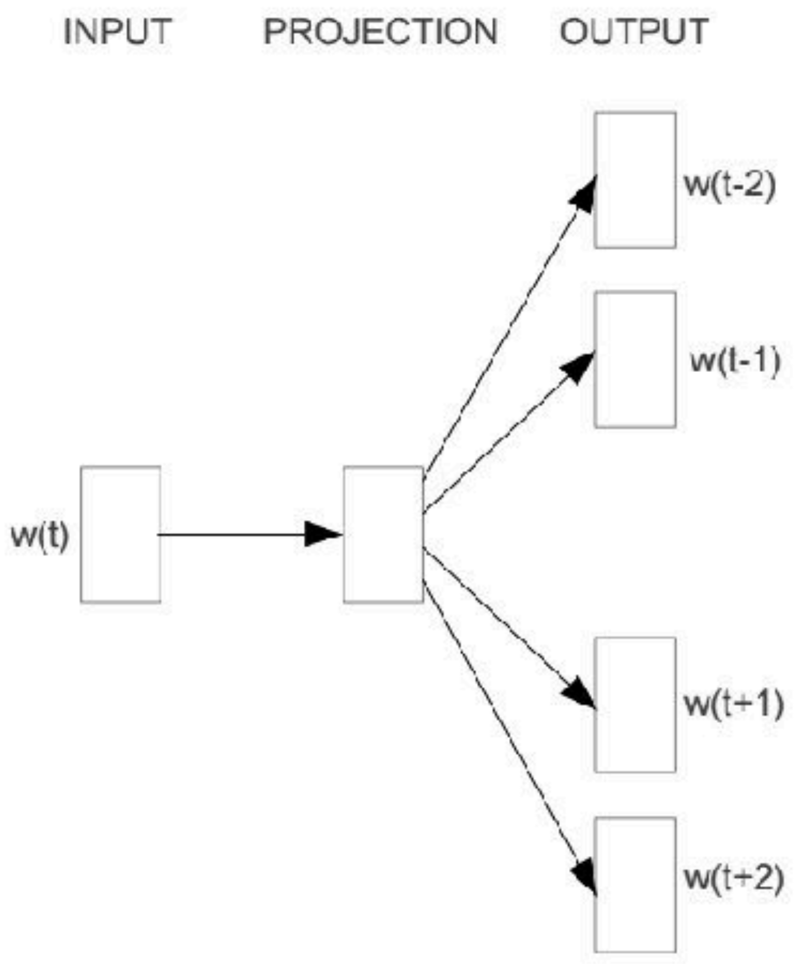
(c) $(K + 1)d$

(d) $(K + 2)d$

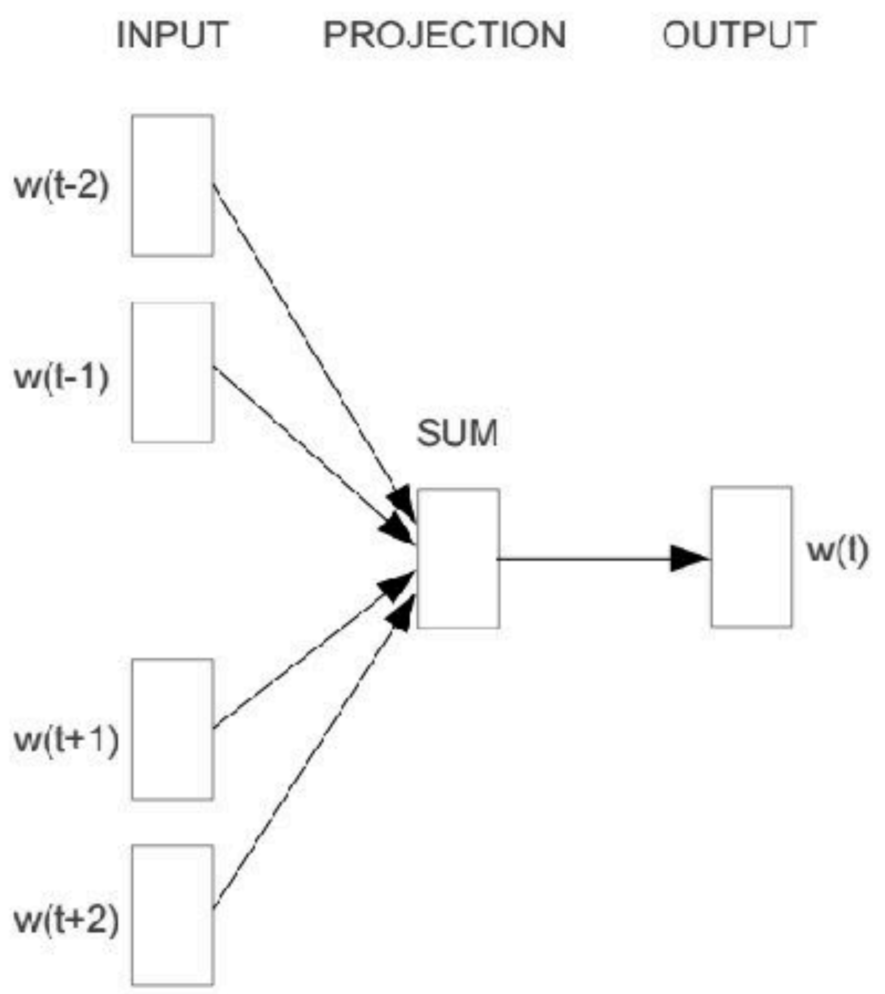
The answer is (d).

We need to calculate gradients with respect to $\mathbf{u}_t$ and (K + 1) $\mathbf{v}_i$ (one positive and K negatives).

Continuous Bag of Words (CBOW)



Skip-gram



Continuous Bag of Words (CBOW)

$$L(\theta) = \prod_{t=1}^{T} P\left(w_t \mid \{w_{t+j}\}, -m \leq j \leq m, j \neq 0\right)$$

$$\bar{\mathbf{v}}_t = \frac{1}{2m} \sum_{-m \leq j \leq m, j \neq 0} \mathbf{v}_{t+j}$$

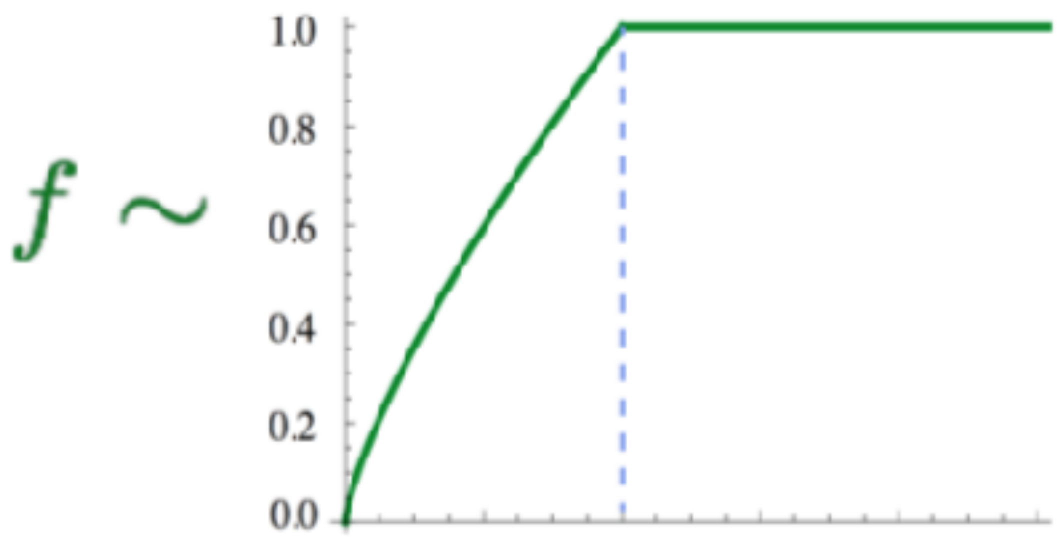
$$P(w_t \mid \{w_{t+j}\}) = \frac{\exp(\mathbf{u}_{w_t} \cdot \bar{\mathbf{v}}_t)}{\sum_{k \in V} \exp(\mathbf{u}_k \cdot \bar{\mathbf{v}}_t)}$$

GloVe: **Glo**bal **Ve**ctors

- Take the global co-occurrence statistics: $X_{i,j}$
- Key idea: let's approximate $\mathbf{u}_i \cdot \mathbf{v}_j$ using their co-occurrence counts directly

$$J(\theta) = \sum_{i,j \in V} f(X_{i,j}) \left(\mathbf{u}_i \cdot \mathbf{v}_j + b_i + \tilde{b}_j - \log X_{i,j} \right)$$

- f: Weighting function, want to give more importance to more common pairs, but capped at a certain point



Advantages:

- Training faster
- Scalable to very large corpora

(Pennington et al, 2014): GloVe: Global Vectors for Word Representation

FastText: Subword Embeddings

- Similar to Skip-gram, but break words into n-grams with n = 3 to 6

where:

3-grams: <wh, whe, her, ere, re>

4-grams: <whe, wher, here, ere>

5-grams: <wher, where, here>

6-grams: <where, where>

- Replace $\mathbf{u}_i \cdot \mathbf{v}_j$ by $\sum_{g \in n\text{-grams}(w_i)} \mathbf{u}_g \cdot \mathbf{v}_j$

(Bojanowski et al, 2017): Enriching Word Vectors with Subword Information

Trained word embeddings available

- word2vec: https://code.google.com/archive/p/word2vec/
- GloVe: https://nlp.stanford.edu/projects/glove/
- FastText: https://fasttext.cc/

Download pre-trained word vectors

- Pre-trained word vectors. This data is made available under the Public Domain Dedication and License v1.0 whose full text can be found at: http://www.opendatacommons.org/licenses/pddl/1.0/.
  - Wikipedia 2014 + Gigaword 5 (6B tokens, 400K vocab, uncased, 50d, 100d, 200d, & 300d vectors, 822 MB download): glove.6B.zip
  - Common Crawl (42B tokens, 1.9M vocab, uncased, 300d vectors, 1.75 GB download): glove.42B.300d.zip
  - Common Crawl (840B tokens, 2.2M vocab, cased, 300d vectors, 2.03 GB download): glove.840B.300d.zip
  - Twitter (2B tweets, 27B tokens, 1.2M vocab, uncased, 25d, 50d, 100d, & 200d vectors, 1.42 GB download): glove.twitter.27B.zip
- Ruby script for preprocessing Twitter data

Differ in algorithms, text corpora, dimensions, cased/uncased…

Applied to many other languages

Easy to use!

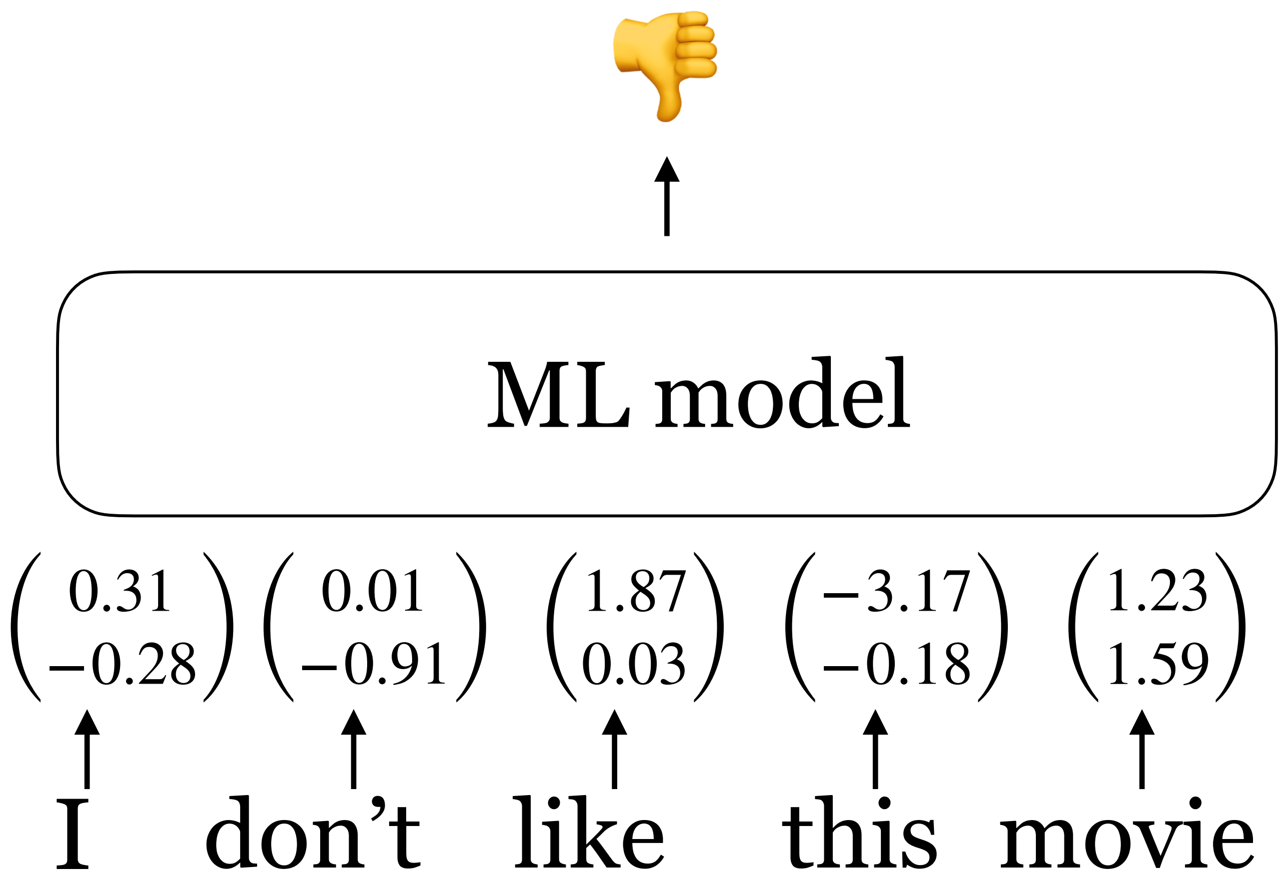
```python
from gensim.models import KeyedVectors
# Load vectors directly from the file
model = KeyedVectors.load_word2vec_format('data/GoogleGoogleNews-vectors-negative300.bin', binary=True)
# Access vectors for specific words with a keyed lookup:
vector = model['easy']
```

```
In [17]: model.similarity('straightforward', 'easy')
Out[17]: 0.5717043285477517

In [18]: model.similarity('simple', 'impossible')
Out[18]: 0.29156160264633707

In [19]: model.most_similar('simple')
Out[19]: [('straightforward', 0.7460169196128845),
          ('Simple', 0.7108174562454224),
          ('uncomplicated', 0.6297484636306763),
          ('simplest', 0.6171397566795349),
          ('easy', 0.5990299582481384),
          ('fairly_straightforward', 0.5893306732177734),
          ('deceptively_simple', 0.5743066072463989),
          ('simpler', 0.5537199378013611),
          ('simplistic', 0.5516539216041565),
          ('disarmingly_simple', 0.5365327000617981)]
```

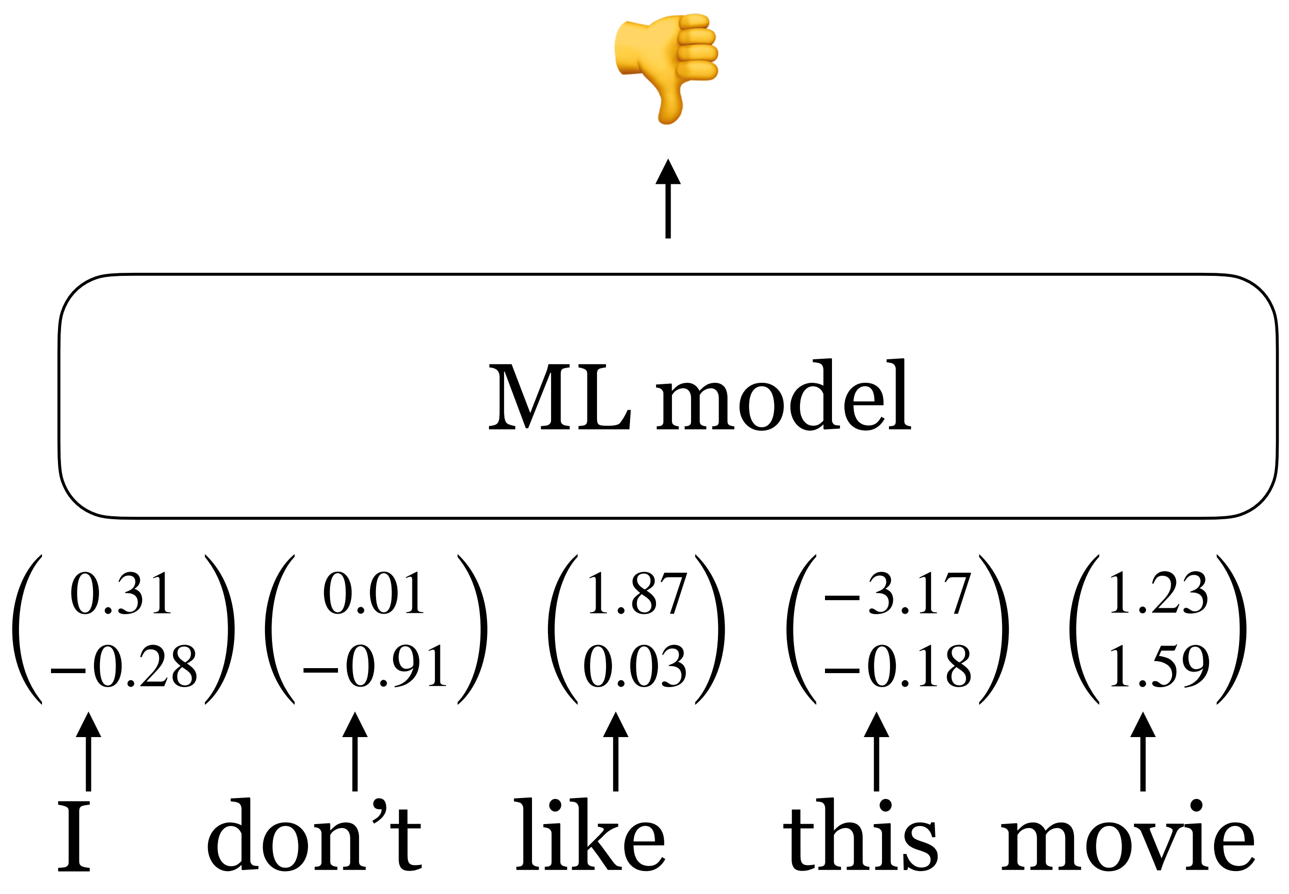
Evaluating word embeddings

Extrinsic vs intrinsic evaluation

- **Extrinsic evaluation**
  - Let's plug these word embeddings into a real NLP system and see whether this improves performance
  - Could take a long time but still the most important evaluation metric



Extrinsic evaluation



A straightforward solution: given an input sentence $x_1, x_2, \ldots, x_n$

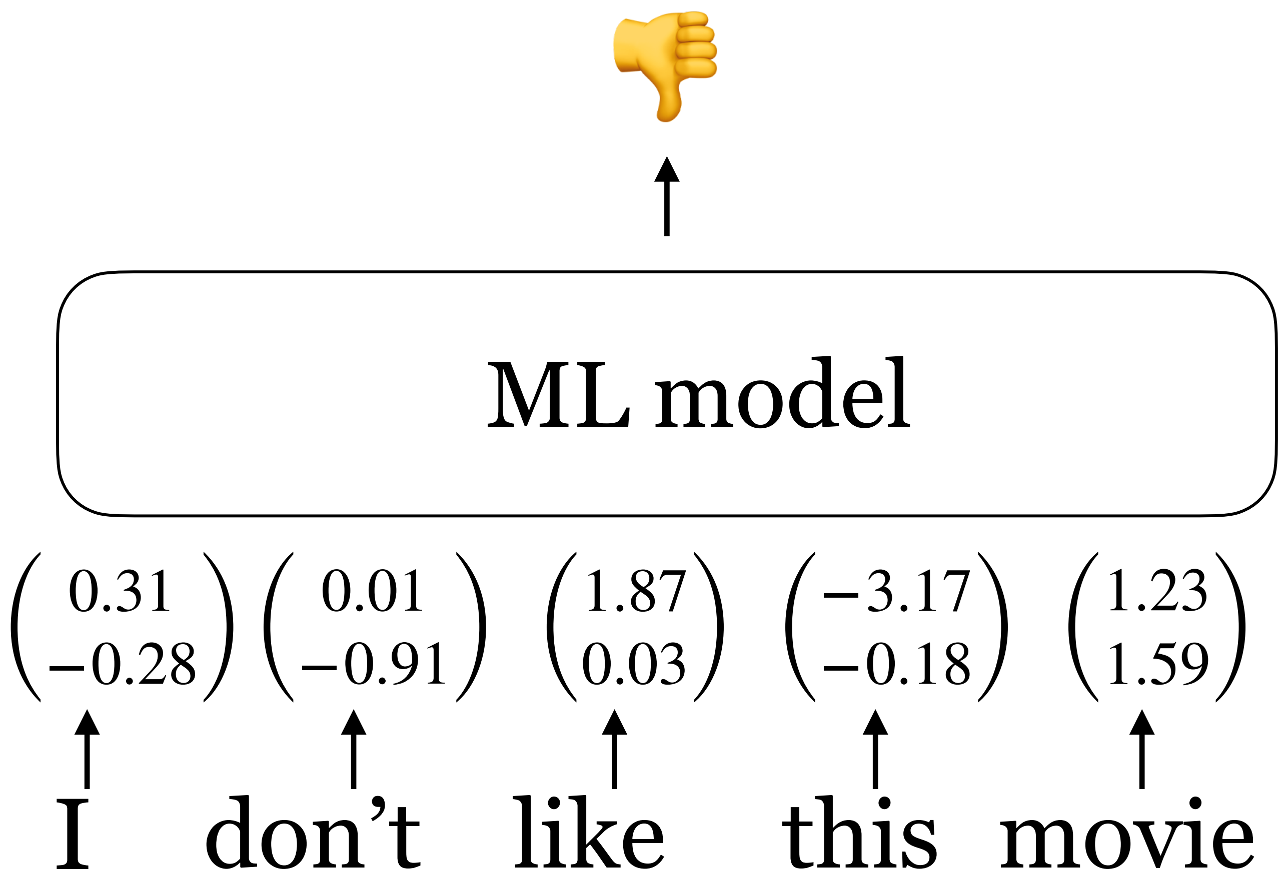
Instead of using a bag-of-words model, we can compute $\text{vec}(x) = \mathbf{e}(x_1) + \mathbf{e}(x_2) + \ldots \mathbf{e}(x_n)$

And then train a logistic regression classifier on vec(x) as we did before!

Note: There are much better ways to do this e.g., take word embeddings as input of neural networks

Extrinsic vs intrinsic evaluation

- **Extrinsic evaluation**
  - Let's plug these word embeddings into a real NLP system and see whether this improves performance
  - Could take a long time but still the most important evaluation metric
- **Intrinsic evaluation**
  - Evaluate on a specific/intermediate subtask
  - Fast to compute
  - Not clear if it really helps downstream tasks



Intrinsic evaluation: word similarity

Word similarity

Example dataset: wordsim-353: 353 pairs of words with human judgement

http://www.cs.technion.ac.il/~gabr/resources/data/wordsim353/

Word 1	Word 2	Human (mean)
tiger	cat	7.35
tiger	tiger	10
book	paper	7.46
computer	internet	7.58
plane	car	5.77
professor	doctor	6.62
stock	phone	1.62
stock	CD	1.31
stock	jaguar	0.92

$$\cos(\boldsymbol{u}_i, \boldsymbol{u}_j) = \frac{\boldsymbol{u}_i \cdot \boldsymbol{u}_j}{||\boldsymbol{u}_i||_2 \times ||\boldsymbol{u}_j||_2}.$$

Metric: Spearman rank correlation

Intrinsic evaluation: word similarity

Model	Size	WS353	MC	RG	SCWS	RW
SVD	6B	35.3	35.1	42.5	38.3	25.6
SVD-S	6B	56.5	71.5	71.0	53.6	34.7
SVD-L	6B	65.7	<u>72.7</u>	75.1	56.5	37.0
CBOW†	6B	57.2	65.6	68.2	57.0	32.5
SG†	6B	62.8	65.2	69.7	<u>58.1</u>	37.2
GloVe	6B	<u>65.8</u>	<u>72.7</u>	<u>77.8</u>	53.9	<u>38.1</u>
SVD-L	42B	74.0	76.4	74.1	58.3	39.9
GloVe	42B	<u>**75.9**</u>	<u>**83.6**</u>	<u>**82.9**</u>	<u>**59.6**</u>	<u>**47.8**</u>
CBOW*	100B	68.4	79.6	75.4	59.4	45.5

SG: Skip-gram

Intrinsic evaluation: word analogy

Word analogy test: $a : a* :: b : b*$

$$b^* = \arg\max_{w \in V} \cos(e(w), e(a^*) - e(a) + e(b))$$

semantic	syntactic
Chicago:Illinois≈Philadelphia: ?	bad:worst ≈ cool: ?

More examples at

http://download.tensorflow.org/data/questions-words.txt

Metric: accuracy

Model	Dim.	Size	Sem.	Syn.	Tot.
ivLBL	100	1.5B	55.9	50.1	53.2
HPCA	100	1.6B	4.2	16.4	10.8
GloVe	100	1.6B	67.5	54.3	60.3
SG	300	1B	61	61	61
CBOW	300	1.6B	16.1	52.6	36.1
vLBL	300	1.5B	54.2	64.8	60.0
ivLBL	300	1.5B	65.2	63.0	64.0
GloVe	300	1.6B	80.8	61.5	70.3
SVD	300	6B	6.3	8.1	7.3
SVD-S	300	6B	36.7	46.6	42.1
SVD-L	300	6B	56.6	63.0	60.1
CBOW†	300	6B	63.6	67.4	65.7
SG†	300	6B	73.0	66.0	69.1
GloVe	300	6B	77.4	67.0	71.7
CBOW	1000	6B	57.3	68.9	63.7
SG	1000	6B	66.1	65.1	65.6
SVD-L	300	42B	38.4	58.2	49.2
GloVe	300	42B	**81.9**	**69.3**	**75.0**

Word embeddings recap

Goal: represent words as **short** (50-300 dimensional) & **dense** (real-valued) vectors

Count-based approaches

- Used since the 90s
- Sparse word-word co-occurrence PPMI matrix
- Decomposed with SVD

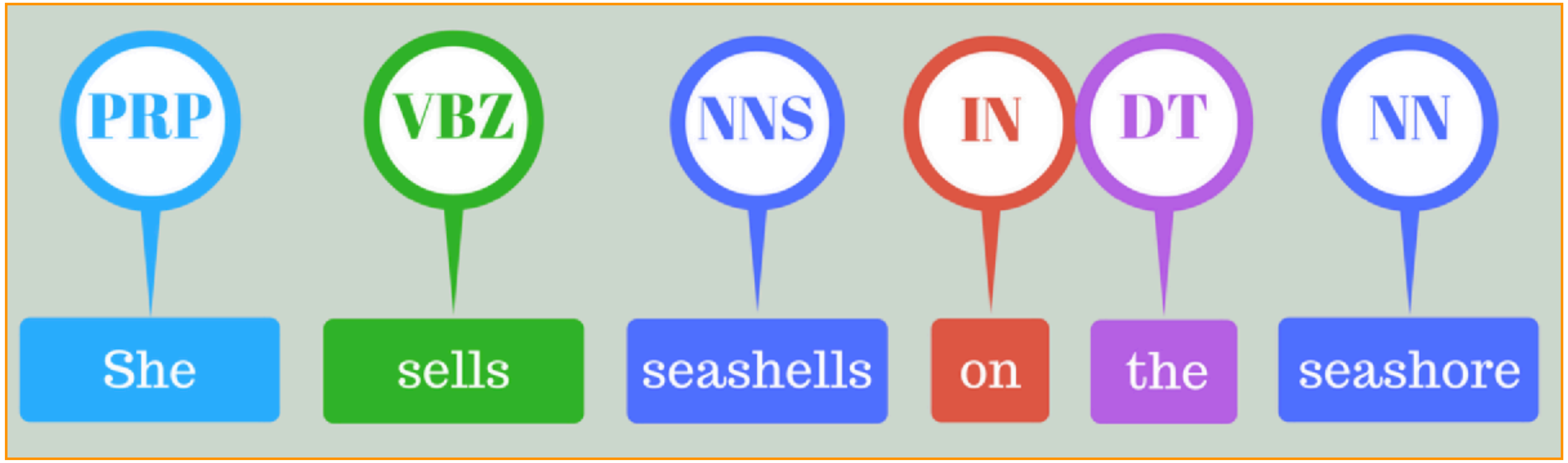
Prediction-based approaches

- Formulated as a machine learning problem
- Using center word to predict context words (or vice-versa)
- Word2vec (Mikolov et al., 2013), GloVe (Pennington et al., 2014), Fasttext (Bojanowski et al., 2017)

Evaluations:

- Extrinsic (performance on downstream task)
- Intrinsic (word similarity, analogy prediction)

Up next: Sequence models



Part-of-speech (POS) tagging

PRP: Personal pronoun

VBZ: Verb, 3rd person singular present

NN: singular noun
NNS: plural noun

IN: preposition or subordinating conjunction
DT: determiner