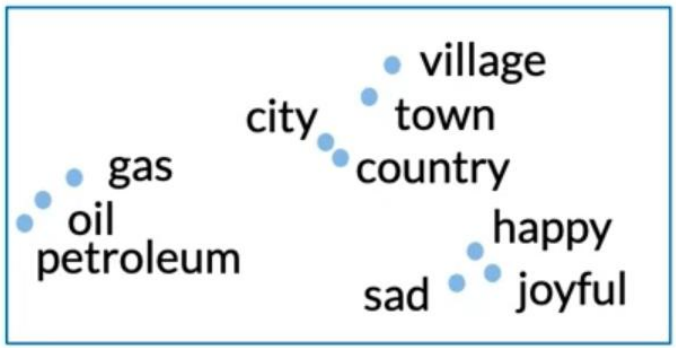
Some basic applications of word embeddings



Semantic analogies and similarity

Sentiment analysis

Classification of customer feedback

Advanced applications of word embeddings

Machine translation

Information extraction

Learning objectives

Prerequisite: neural networks

- Identify the key concepts of word representations
- Generate word embeddings
- Prepare text for machine learning
- Implement the continuous bag-of-words model

Integers

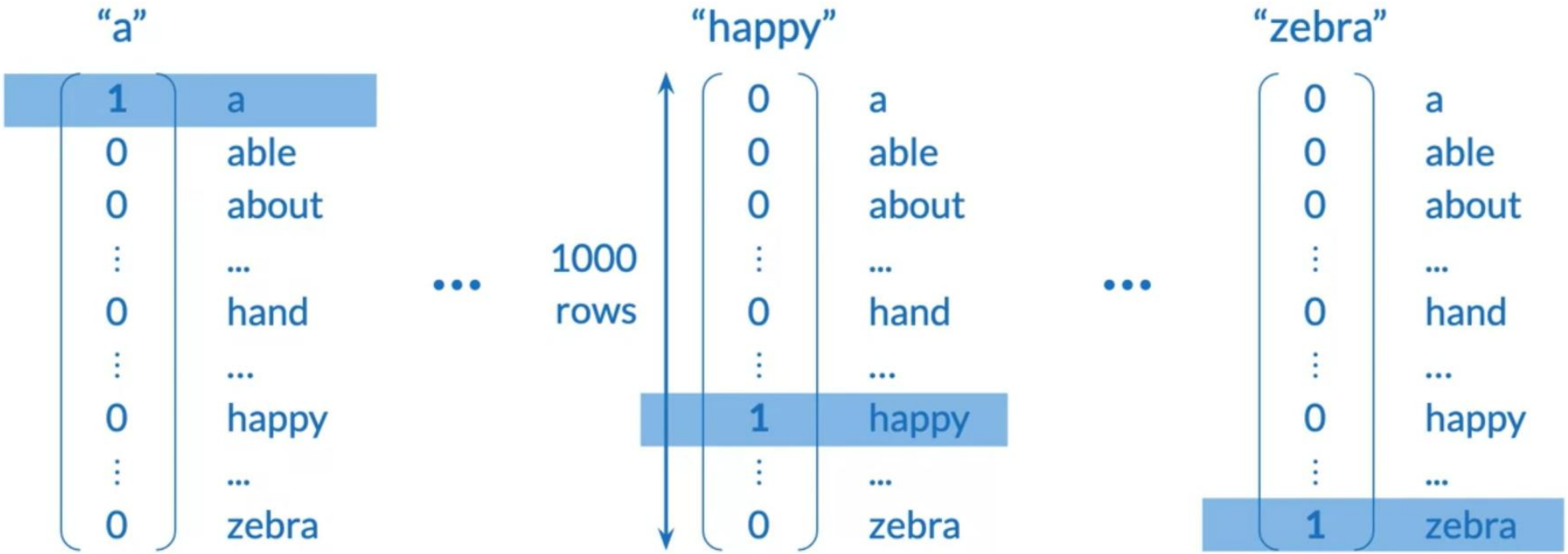
Word	Number
a	1
able	2
about	3
...	...
hand	615
...	...
happy	621
...	...
zebra	1000

Integers

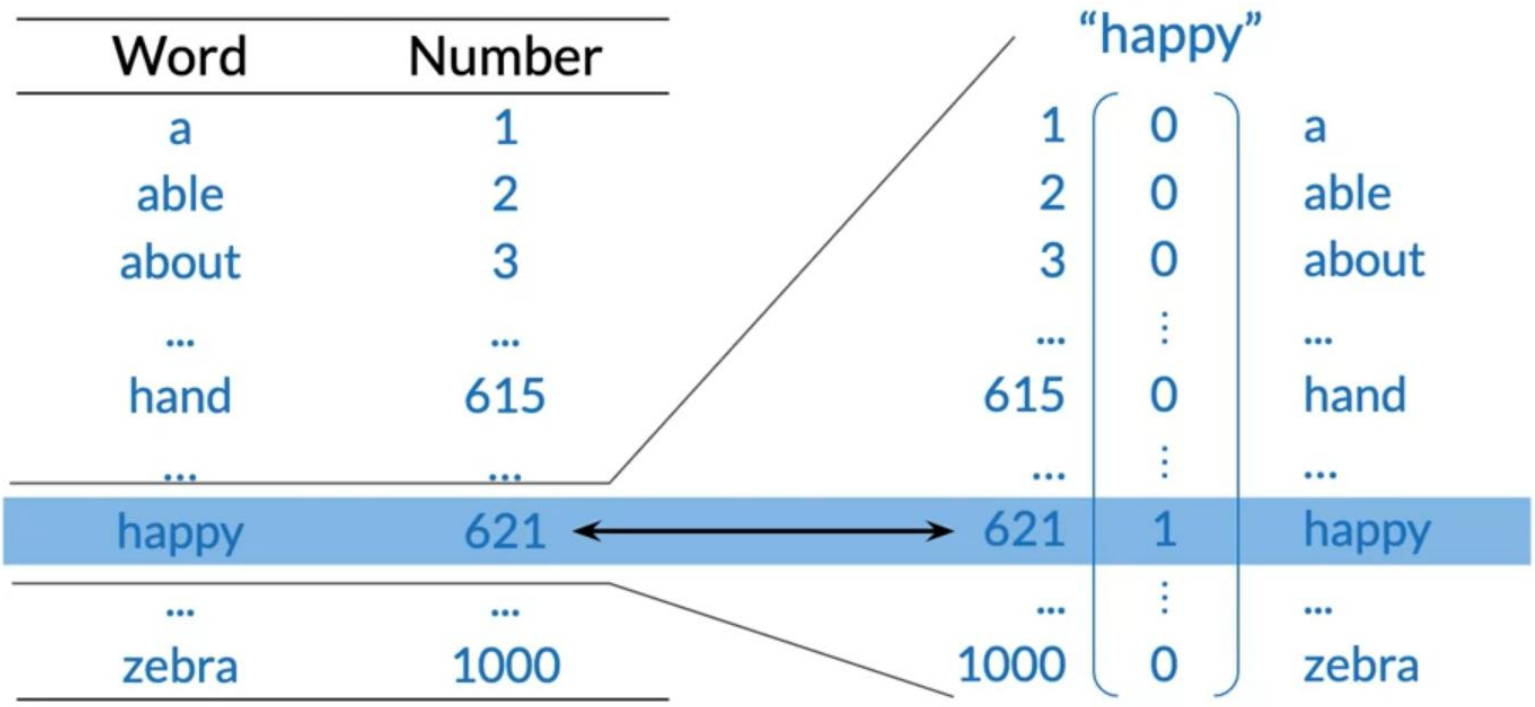
+ Simple

- Ordering: little semantic sense

One-hot vectors

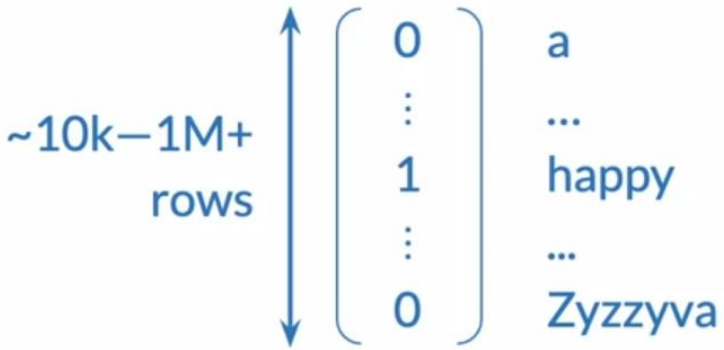


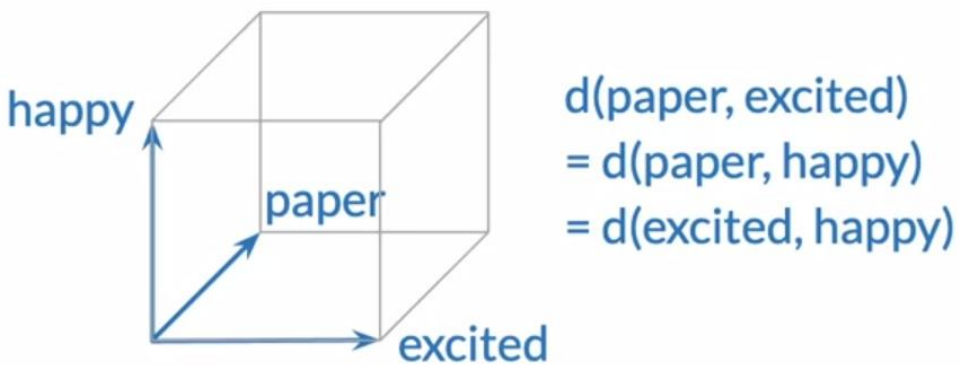
One-hot vectors



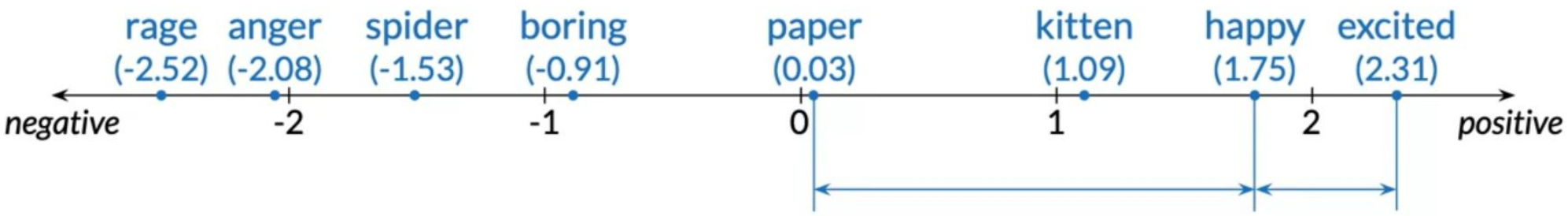
One-hot vectors

+ Simple
+ No implied ordering
- Huge vectors
- No embedded meaning

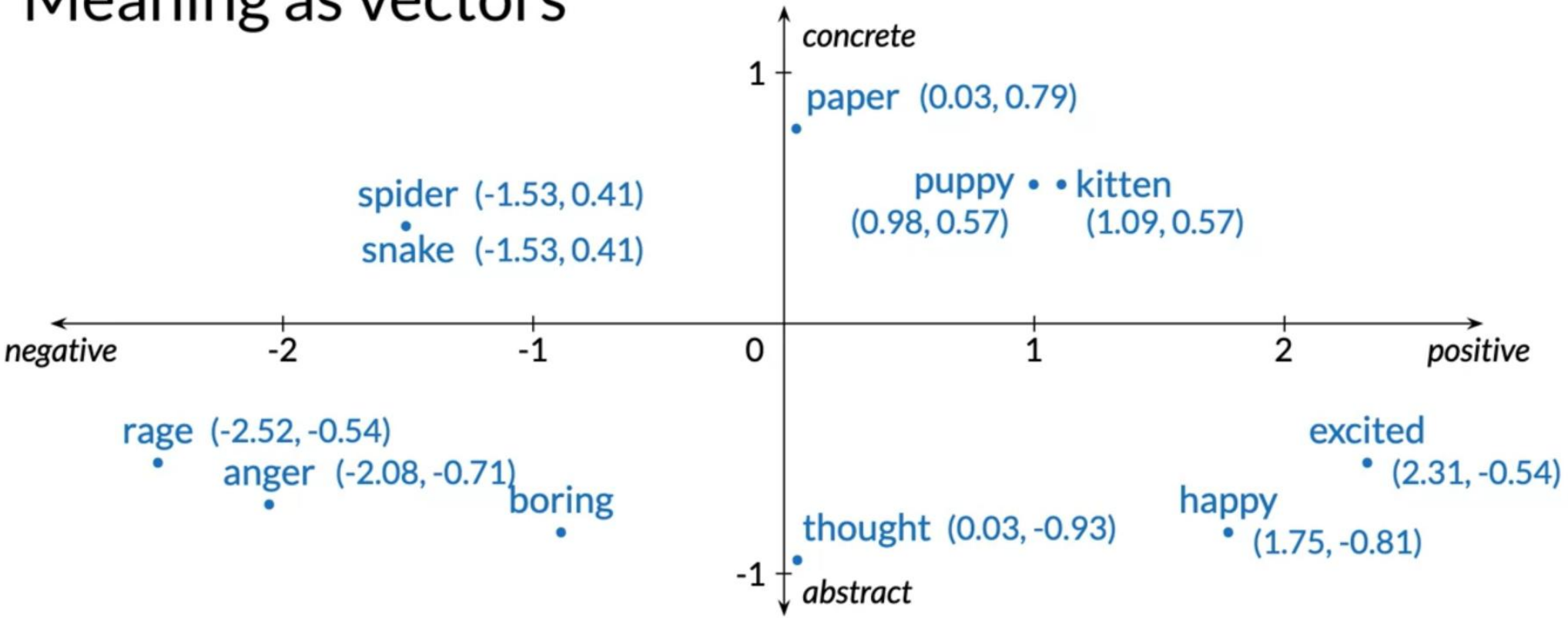




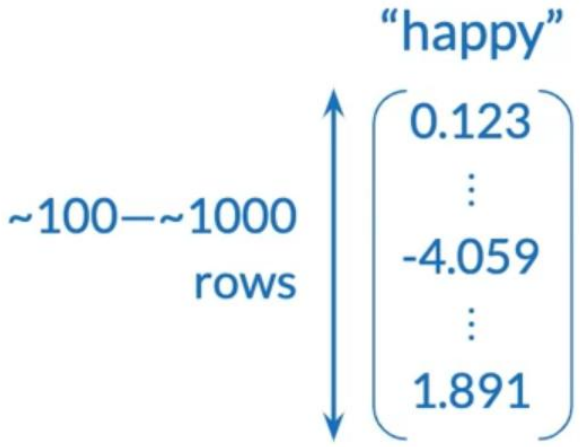
Meaning as vectors



Meaning as vectors



Word embedding vectors



+ Low dimension

+ Embed meaning
  - e.g. semantic distance

    forest ≈ tree forest ≉ ticket

  - e.g. analogies

    Paris:France :: Rome:?

Terminology

integers

word vectors

one-hot vectors

word embedding vectors

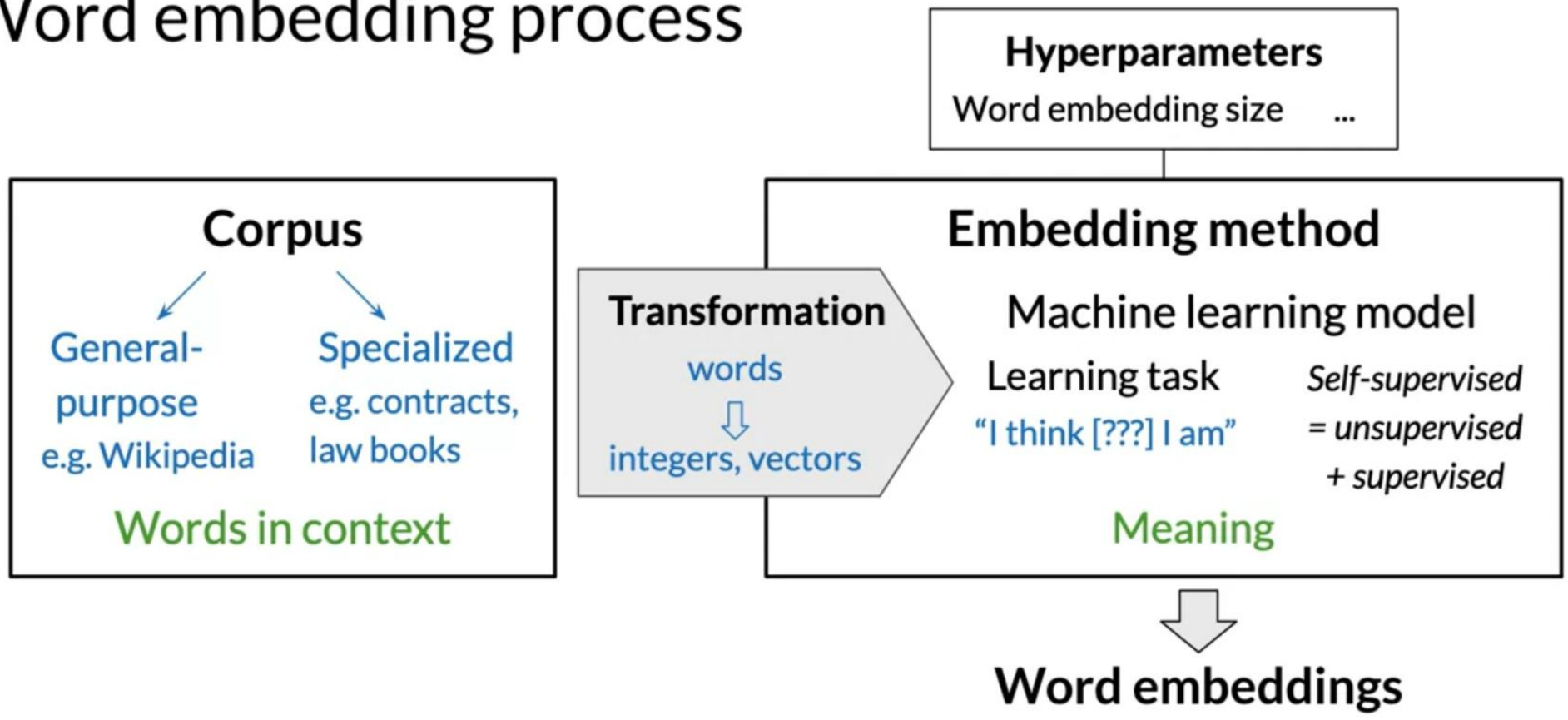
"word vectors"

word embeddings

Summary

- Words as integers
- Words as vectors
  - One-hot vectors
  - Word embedding vectors
- Benefits of word embeddings for NLP

Word embedding process



Basic word embedding methods

- word2vec (Google, 2013)
  - Continuous bag-of-words (CBOW)
  - Continuous skip-gram / Skip-gram with negative sampling (SGNS)

- Global Vectors (GloVe) (Stanford, 2014)

- fastText (Facebook, 2016)
  - Supports out-of-vocabulary (OOV) words

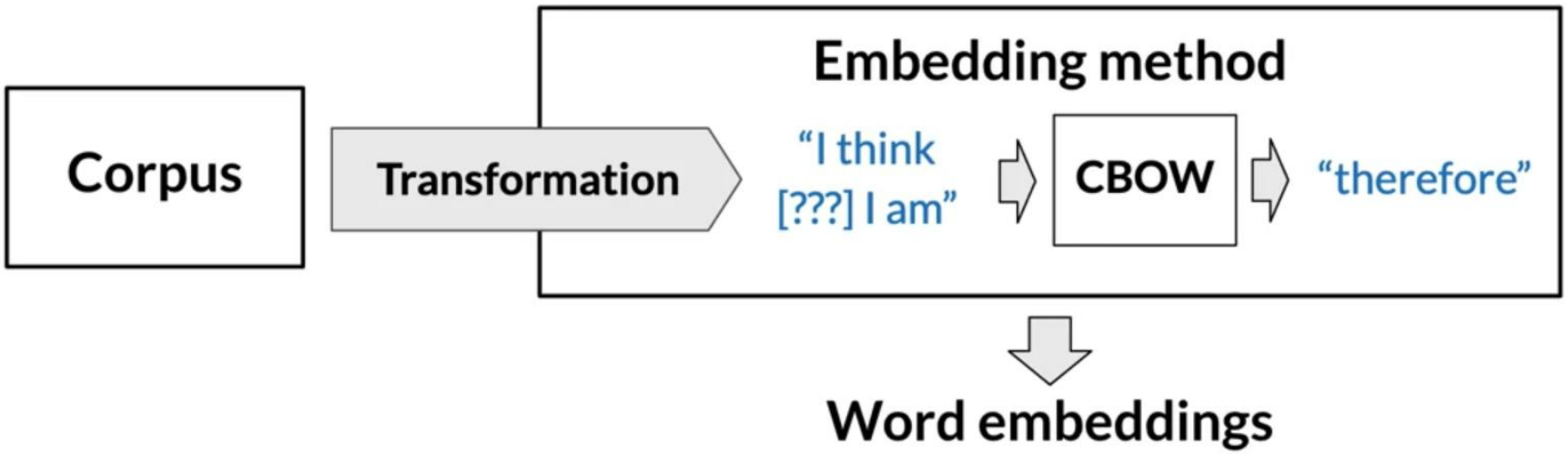
Advanced word embedding methods

Deep learning, contextual embeddings

- BERT (Google, 2018)
- ELMo (Allen Institute for AI, 2018)
- GPT-2 (OpenAI, 2018)

} Tunable pre-trained models available

Continuous bag-of-words word embedding process

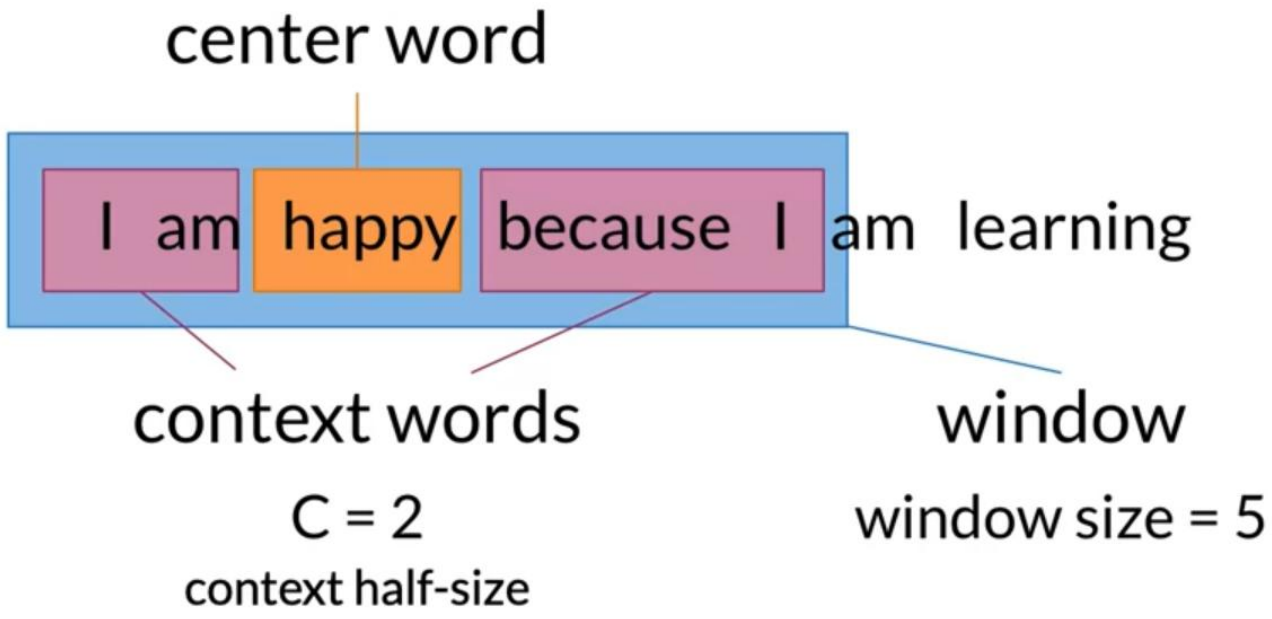


Center word prediction: rationale

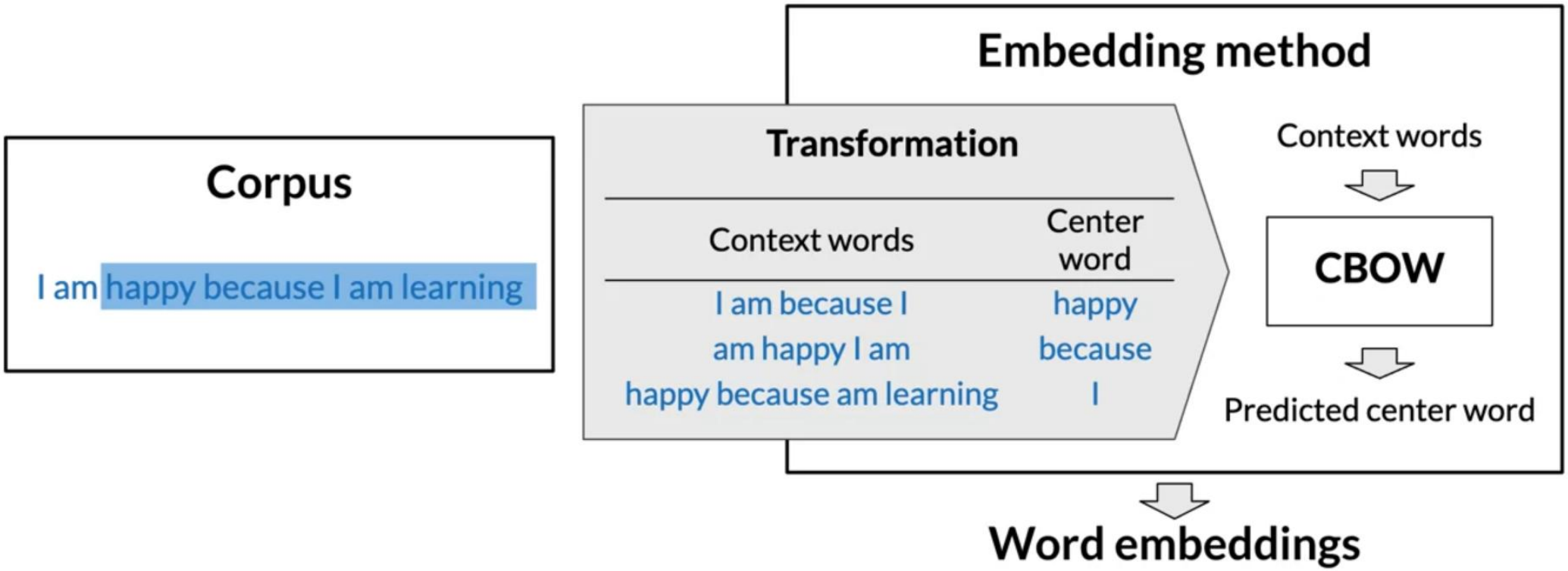
The little ? is barking

dog
puppy
hound
terrier
...

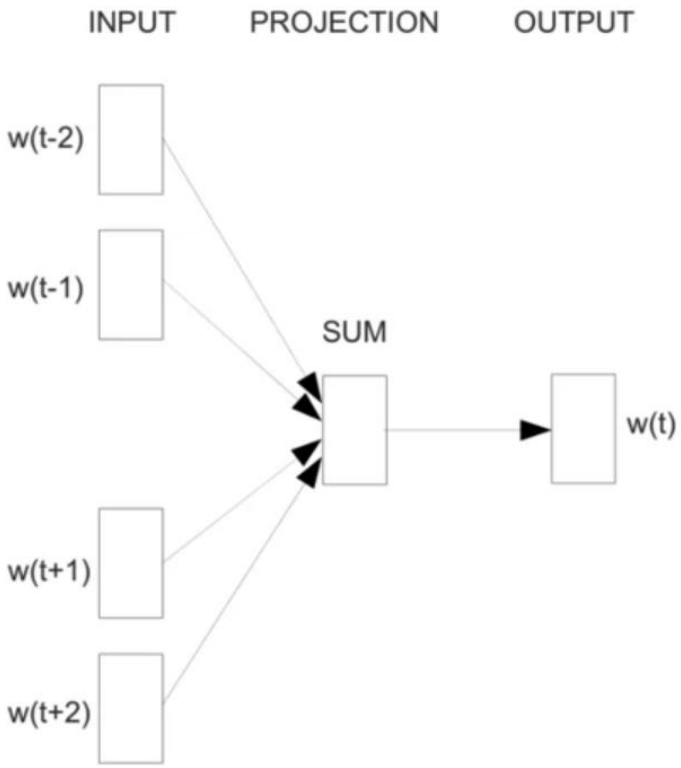
Creating a training example



From corpus to training



CBOW in a nutshell

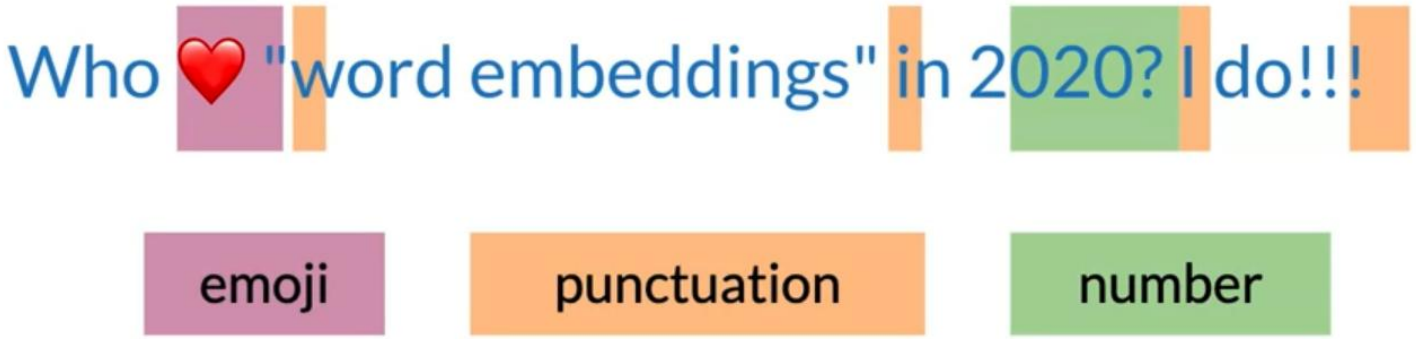


Source: Mikolov, T., Chen, K., Corrado, G.S., & Dean, J. (2013). Efficient Estimation of Word Representations in Vector Space

Cleaning and tokenization matters

- Letter case — “The” == “the” == “THE” → *lowercase / upper case*
- Punctuation — , ! . ? → . “ ‘ « » ’ ” → ∅ … !! ??? → .
- Numbers — 1 2 3 5 8 → ∅ 3.14159 90210 → *as is/<NUMBER>*
- Special characters — ∇ $ € § ¶ ** → ∅
- Special words — 😊 #nlp → :happy: #nlp

Example in Python: corpus



Example in Python: libraries

```
# pip install nltk
# pip install emoji

import nltk
from nltk.tokenize import word_tokenize
import emoji

nltk.download('punkt')  # download pre-trained Punkt tokenizer for English
```

Example in Python: code

```
corpus = 'Who ❤️ "word embeddings" in 2020? I do!!!'

data = re.sub(r'[,!?;-]+', '.', corpus)
```

→ Who ❤️ "word embeddings" in 2020. I do.

Example in Python: code

```
corpus = 'Who ❤️ "word embeddings" in 2020? I do!!!'

data = re.sub(r'[,!?;-]+', '.', corpus)
data = nltk.word_tokenize(data)  # tokenize string to words
```

```
→ ['Who', '❤️', '``', 'word', 'embeddings', "''", 'in', '2020', '.', 'I',
'do', '.']
```

Example in Python: code

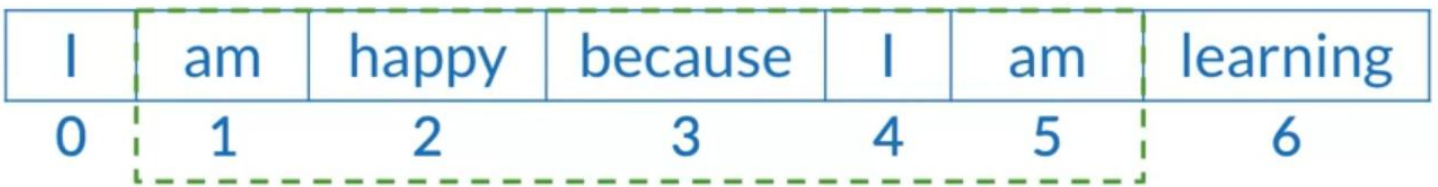
```
corpus = 'Who ❤️ "word embeddings" in 2020? I do!!!'

data = re.sub(r'[,!?;-]+', '.', corpus)
data = nltk.word_tokenize(data)  # tokenize string to words
data = [ ch.lower() for ch in data
         if ch.isalpha()
         or ch == '.'
         or emoji.get_emoji_regexp().search(ch)
       ]
```

```
→ ['who', '❤️', 'word', 'embeddings', 'in', '.', 'i', 'do', '.']
```

Sliding window of words in Python

```
def get_windows(words, C):
    i = C
    while i < len(words) - C:
        center_word = words[i]
        context_words = words[(i - C):i] + words[(i+1):(i+C+1)]
        yield context_words, center_word
        i += 1
```



Sliding window of words in Python

```
def get_windows(words, C):
    ...
        yield context_words, center_word
```

```
for x, y in get_windows(
            ['i', 'am', 'happy', 'because', 'i', 'am', 'learning'],
            2
        ):
    print(f'{x}\t{y}')
```

Sliding window of words in Python

```
for x, y in get_windows(
            ['i', 'am', 'happy', 'because', 'i', 'am', 'learning'],
            2
        ):
    print(f'{x}\t{y}')
```

```
→ ['I', 'am', 'because', 'I']    happy
  ['am', 'happy', 'I', 'am']     because
  ['happy', 'because', 'am', 'learning']  I
```

Transforming center words into vectors

Corpus: I am happy because I am learning

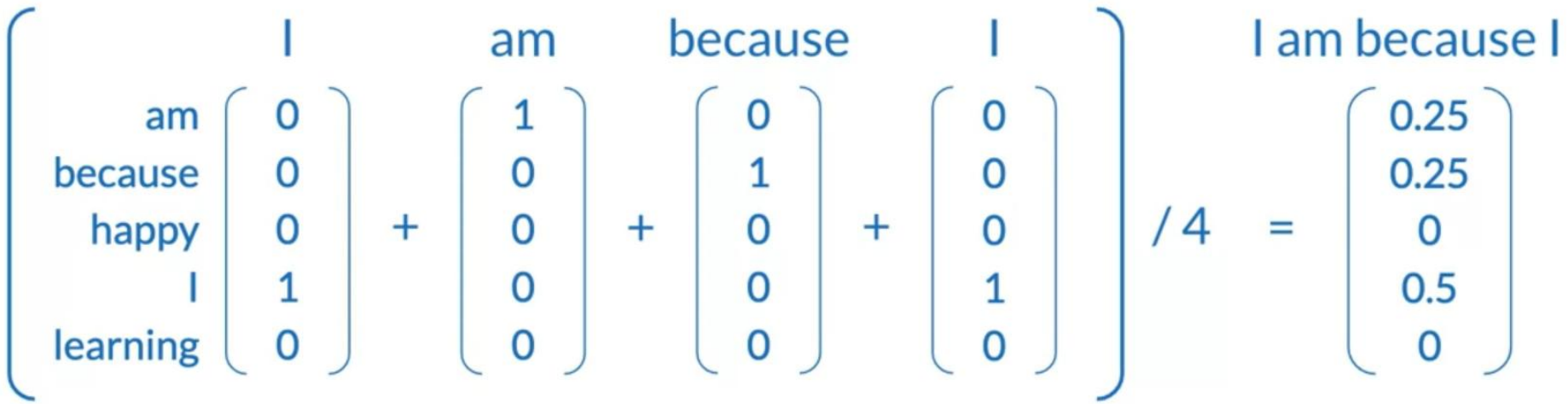
Vocabulary: am, because, happy, I, learning

One-hot vector

	am	because	happy	I	learning
am	1	0	0	0	0
because	0	1	0	0	0
happy	0	0	1	0	0
I	0	0	0	1	0
learning	0	0	0	0	1

Transforming context words into vectors

Average of individual one-hot vectors



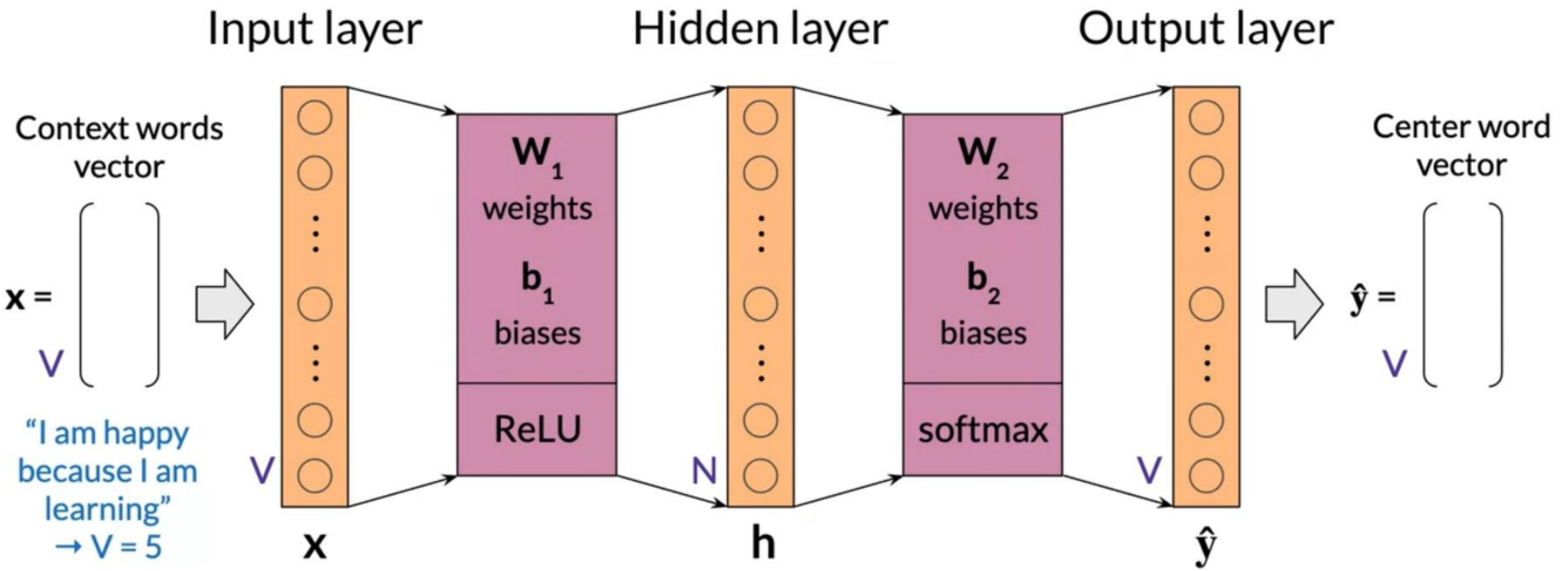
Final prepared training set

Context words	Context words vector	*Center word*	Center word vector
I am because I	[0.25; 0.25; 0; 0.5; 0]	*happy*	[0; 0; 1; 0; 0]
am happy I am	[0.5; 0; 0.25; 0.25; 0]	*because*	[0; 1; 0; 0; 0]
happy because am learning	[0.25; 0.25; 0.25; 0; 0.25]	*I*	[0; 0; 0; 1; 0]

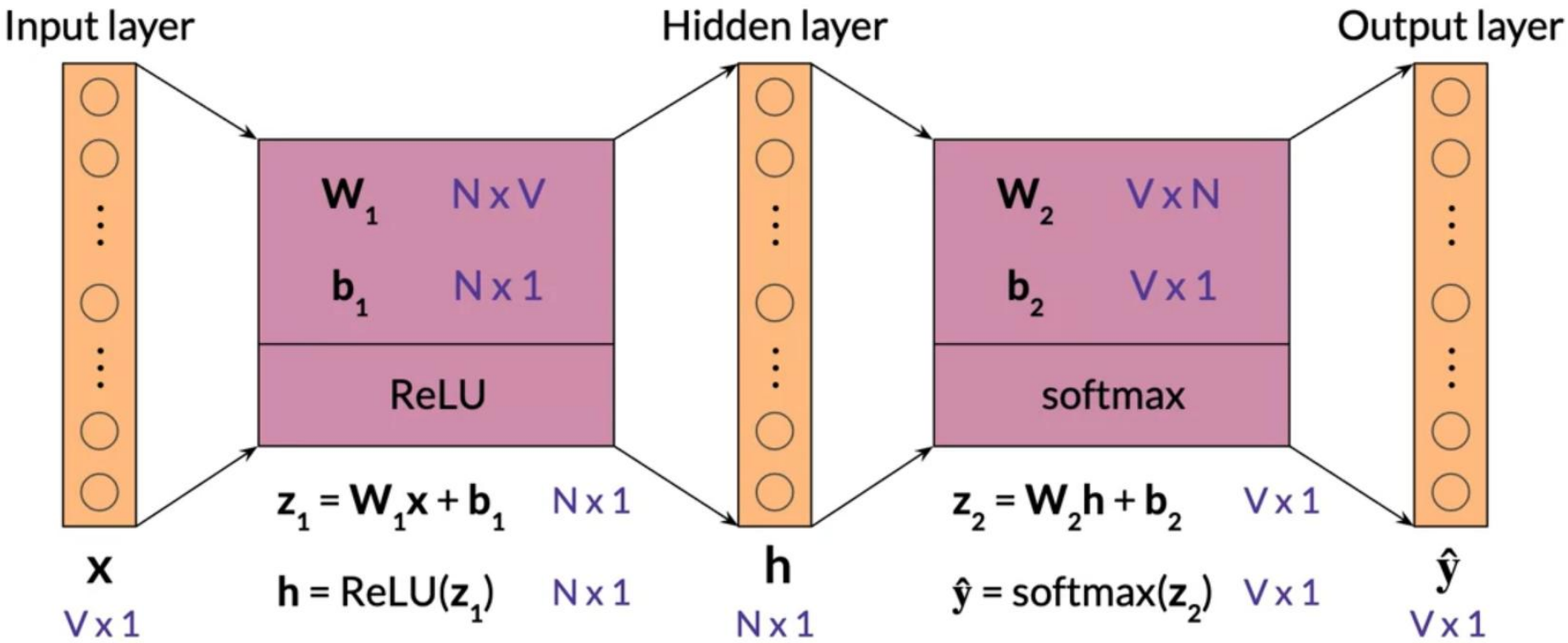
Architecture of the CBOW model

Hyperparameters

N: Word embedding size ...



Dimensions (single input)



Dimensions (single input)

Column vectors

$$z_1 = W_1 x + b_1$$

z_1 = ( ) W_1 = (N x V) x = ( ) b_1 = ( )

N x 1 V x 1 N x 1

Row vectors

$$z_1 = x W_1^{T} + b_1$$

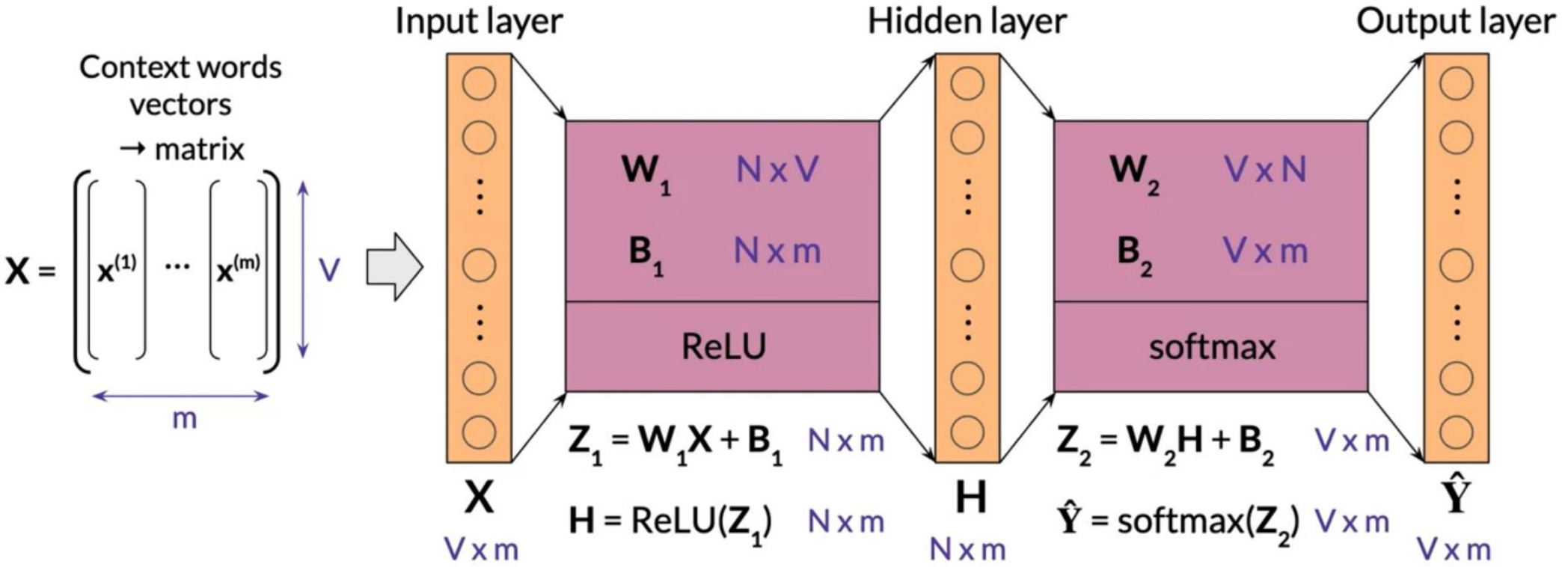
b_1 = (1 x N) W_1 = (N x V) b_1 = (1 x N)

x = (1 x V)

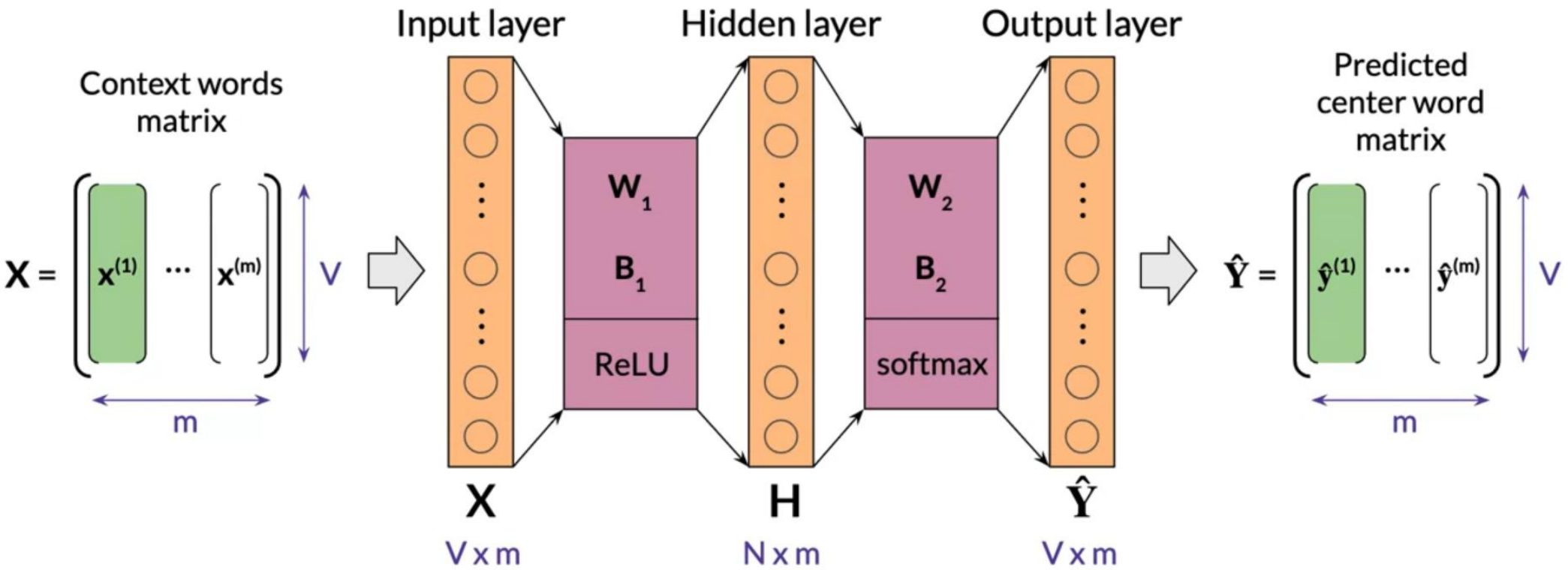
Dimensions (batch input)

$$\begin{pmatrix} b_1 \end{pmatrix} \rightarrow B_1 = \begin{pmatrix} \begin{pmatrix} b_1 \end{pmatrix} \cdots \begin{pmatrix} b_1 \end{pmatrix} \end{pmatrix} \quad N \quad \textit{broadcasting}$$

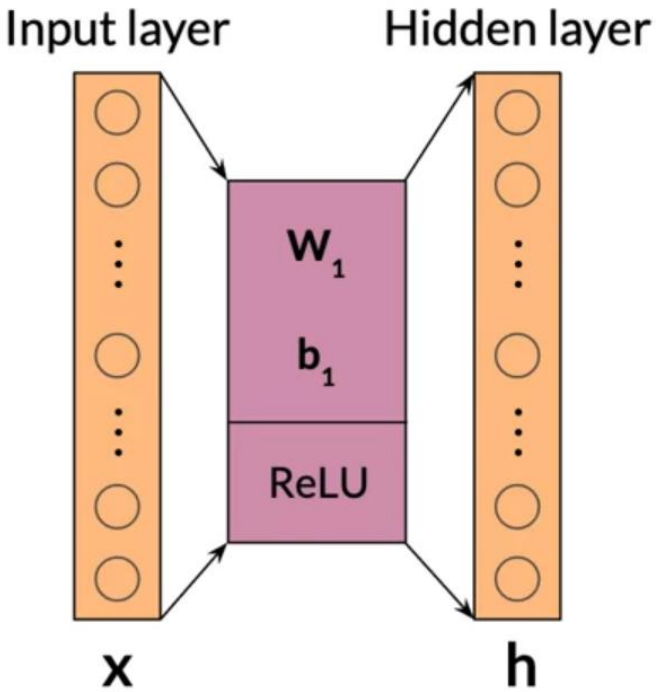
m



Dimensions (batch input)

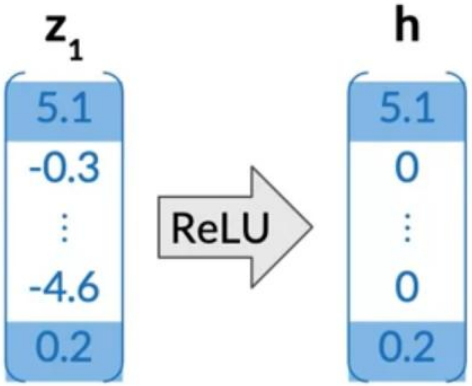


Rectified Linear Unit (ReLU)

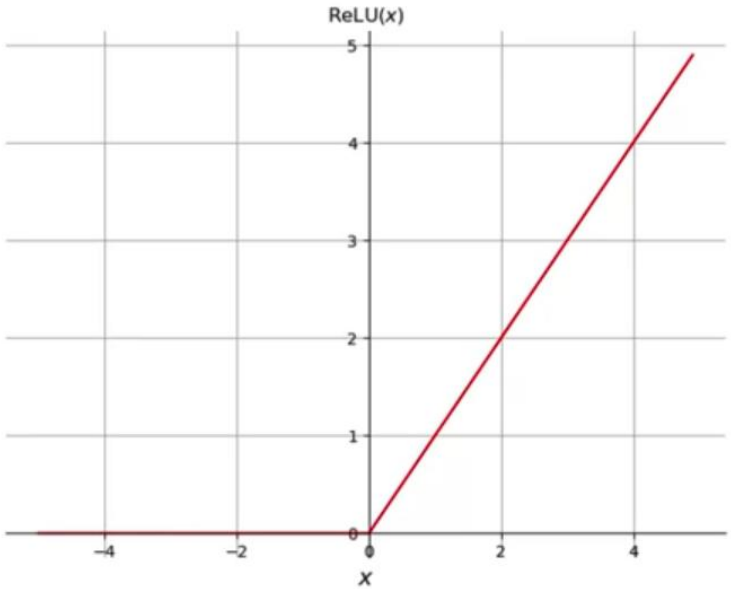


$$z_1 = W_1 x + b_1$$

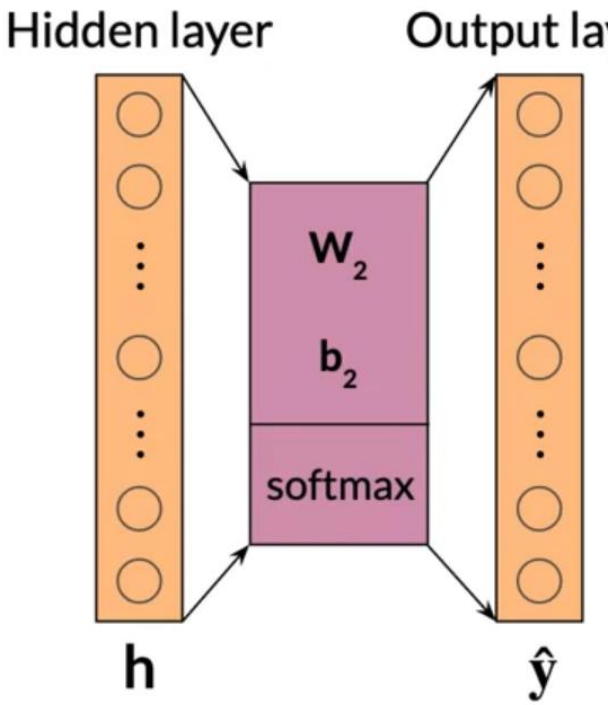
$$h = \text{ReLU}(z_1)$$



ReLU(x) = max(0, x)

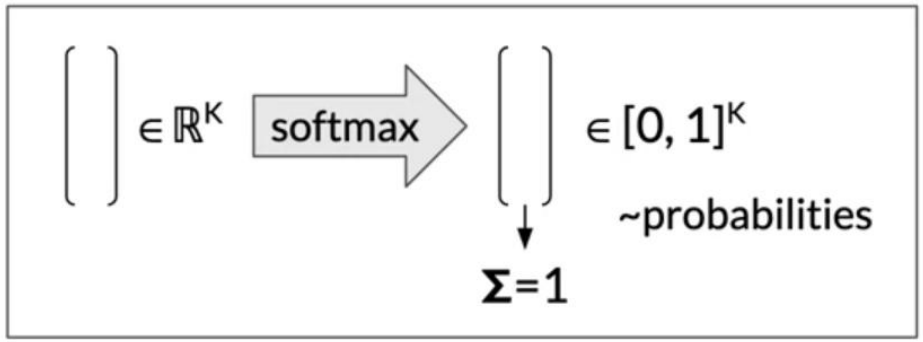


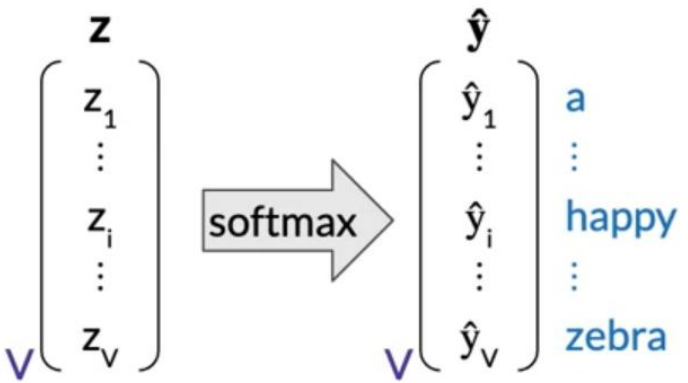
Softmax



$$z = W_2 h + b_2$$

$$\hat{y} = \text{softmax}(z)$$



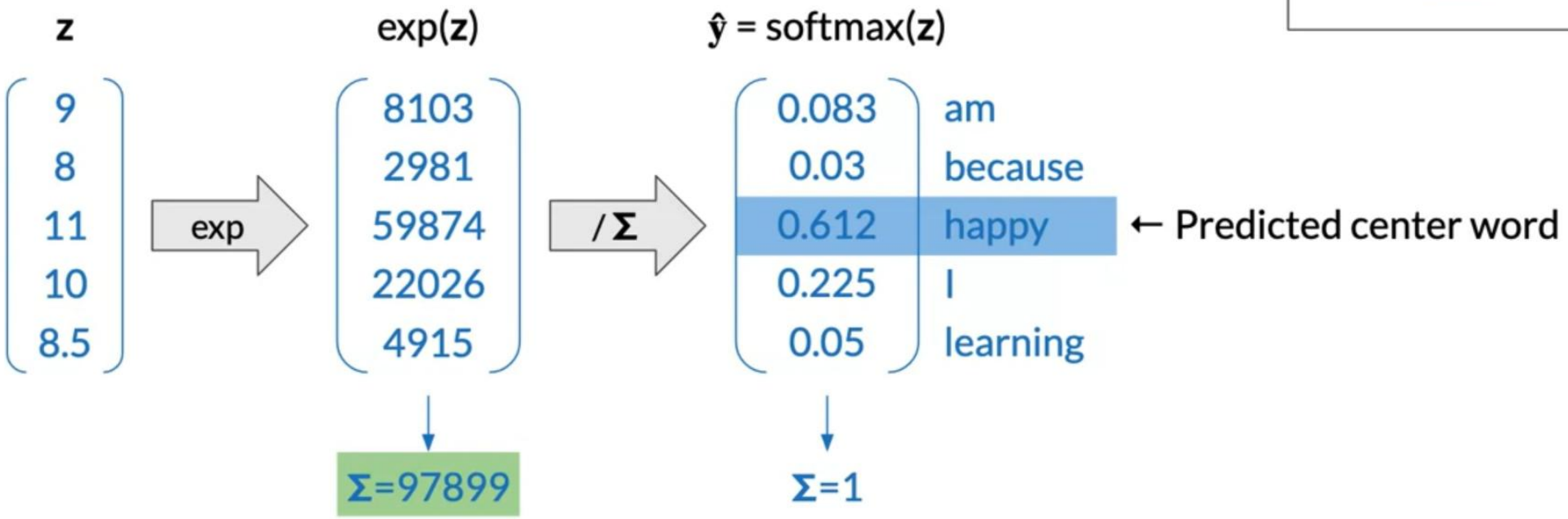


$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{V} e^{z_j}}$$

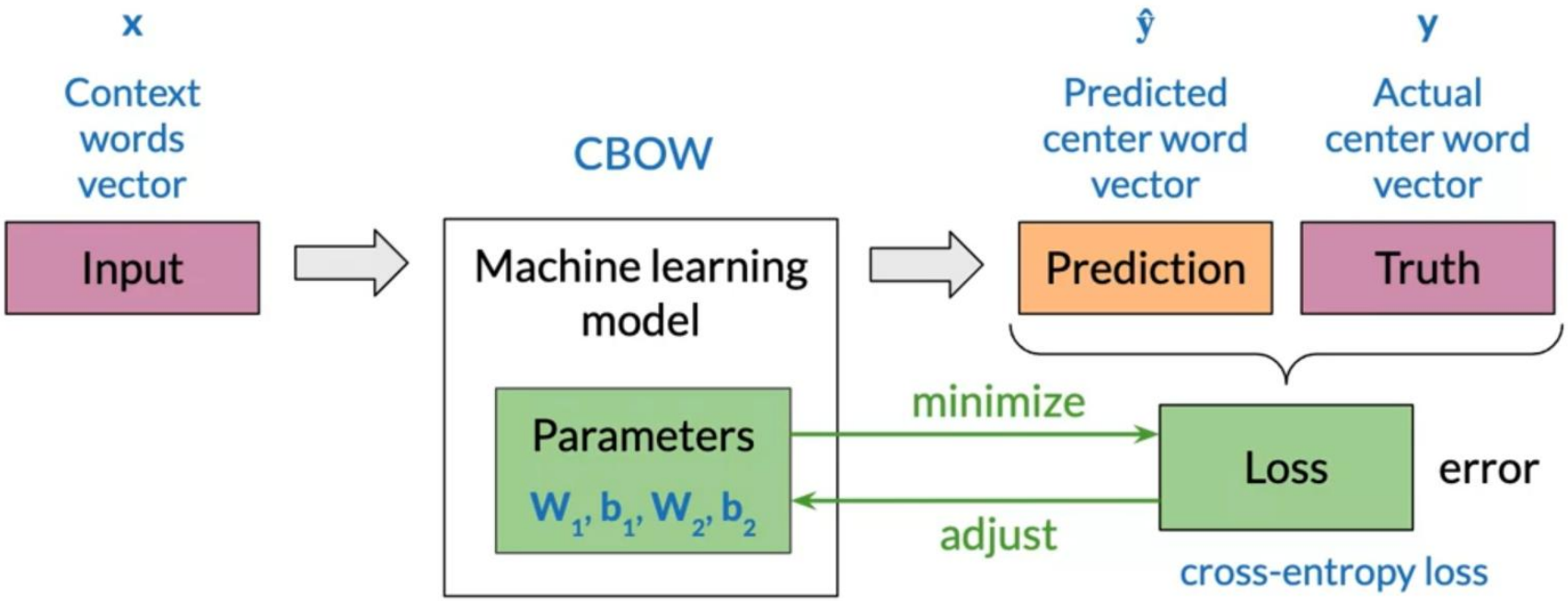
Probabilities of
being center word

Softmax: example

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{V} e^{z_j}}$$



Loss


x
Context words vector
Input
CBOW
Machine learning model
Parameters
W_1, b_1, W_2, b_2
ŷ
Predicted center word vector
Prediction
y
Actual center word vector
Truth
minimize
adjust
Loss
error
cross-entropy loss

Cross-entropy loss

$$J = -\sum_{k=1}^{V} y_k \log \hat{y}_k$$

Actual $\mathbf{y} = \begin{pmatrix} y_1 \\ \vdots \\ y_V \end{pmatrix}$ Predicted $\hat{\mathbf{y}} = \begin{pmatrix} \hat{y}_1 \\ \vdots \\ \hat{y}_V \end{pmatrix}$

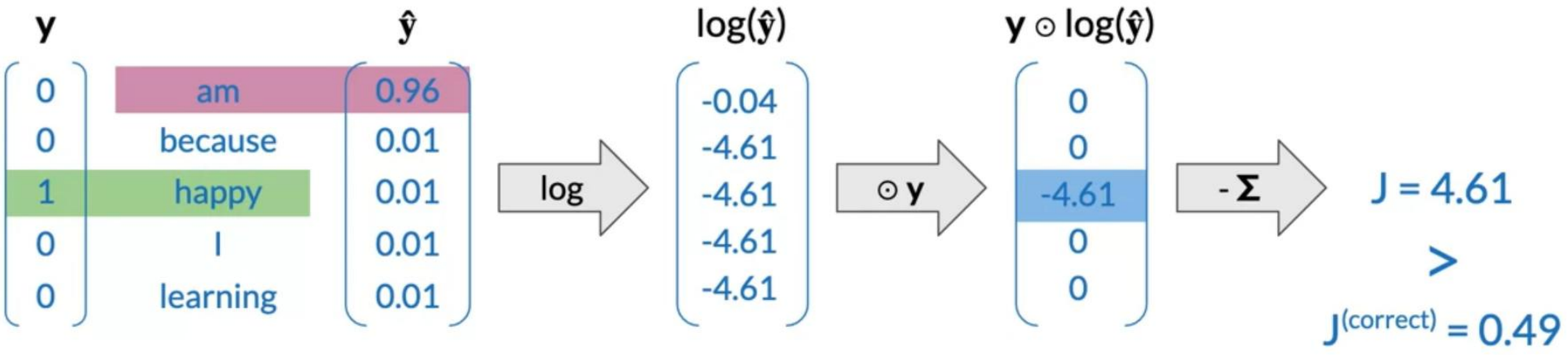
I am happy because I am learning

$\mathbf{y}$		$\hat{\mathbf{y}}$	$\log(\hat{\mathbf{y}})$	$\mathbf{y} \odot \log(\hat{\mathbf{y}})$
0	am	0.083	-2.49	0
0	because	0.03	-3.49	0
1	happy	0.611	-0.49	-0.49
0	I	0.225	-1.49	0
0	learning	0.05	-2.49	0

log → $\odot \mathbf{y}$ → $-\Sigma$ → J = 0.49

Cross-entropy loss

$$J = -\sum_{k=1}^{V} y_k \log \hat{y}_k$$



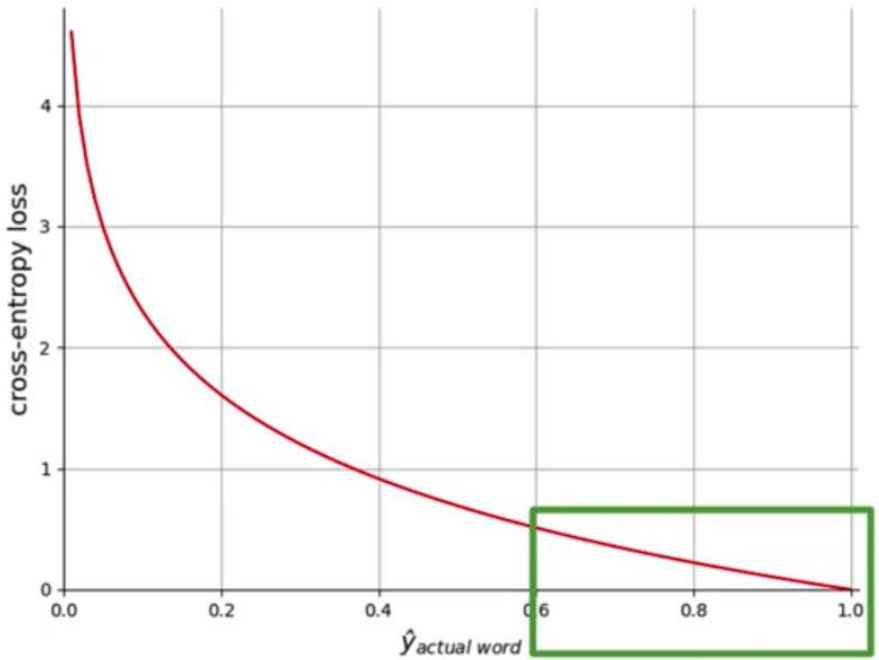
Cross-entropy loss

$$J = -\sum_{k=1}^{V} y_k \log \hat{y}_k$$

$$J = -\log \hat{y}_{\text{actual word}}$$

y		$\hat{y}$
0	am	0.96
0	because	0.01
1	happy	0.01
0	I	0.01
0	learning	0.01

→ J = 4.61



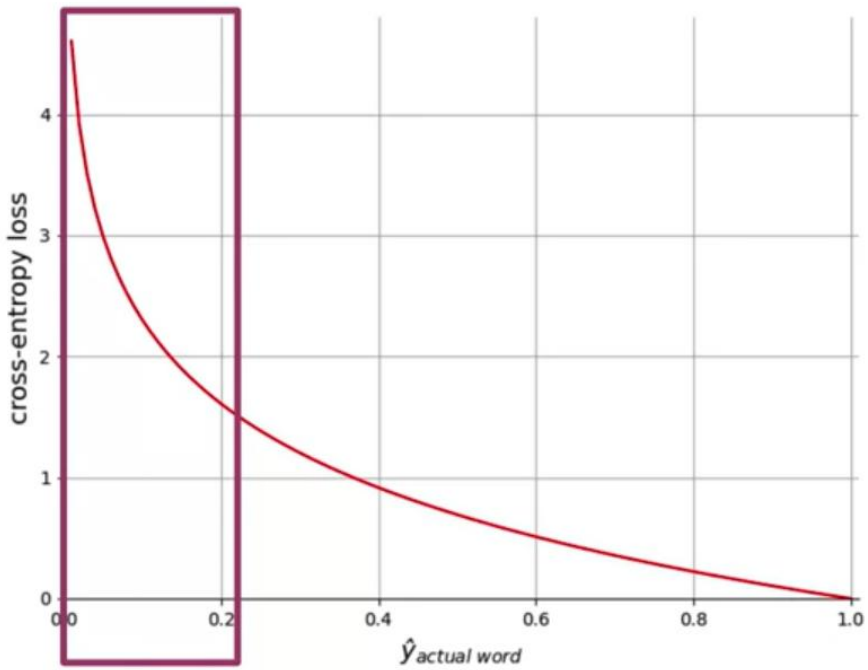
Cross-entropy loss

$$J = -\sum_{k=1}^{V} y_k \log \hat{y}_k$$

$$J = -\log \hat{y}_{\text{actual word}}$$

y		$\hat{y}$
0	am	0.96
0	because	0.01
1	happy	0.01
0	I	0.01
0	learning	0.01

→ J = 4.61



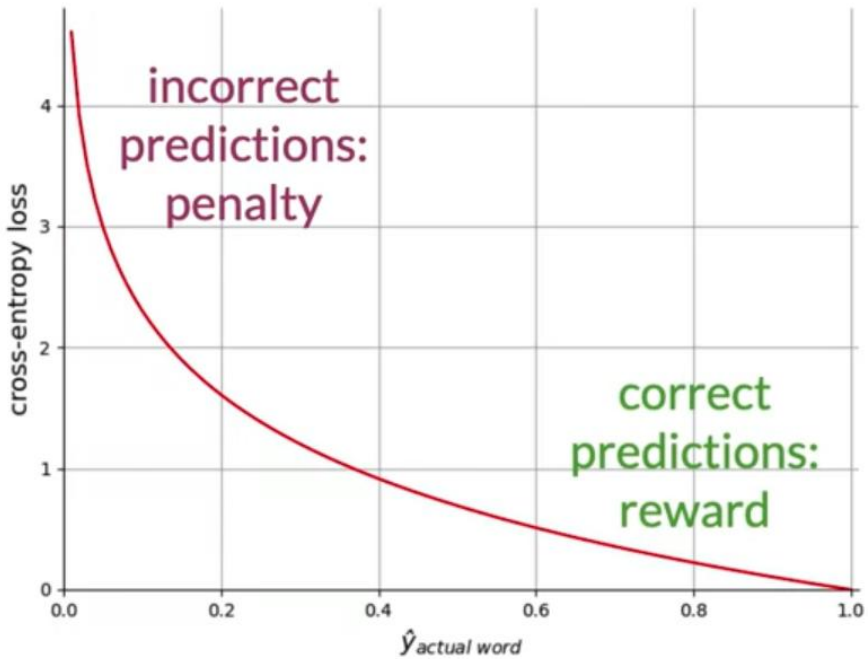
Cross-entropy loss

$$J = -\sum_{k=1}^{V} y_k \log \hat{y}_k$$

$J = -\log \hat{y}_{\text{actual word}}$

y		$\hat{y}$
0	am	0.96
0	because	0.01
1	happy	0.01
0	I	0.01
0	learning	0.01

→ J = 4.61

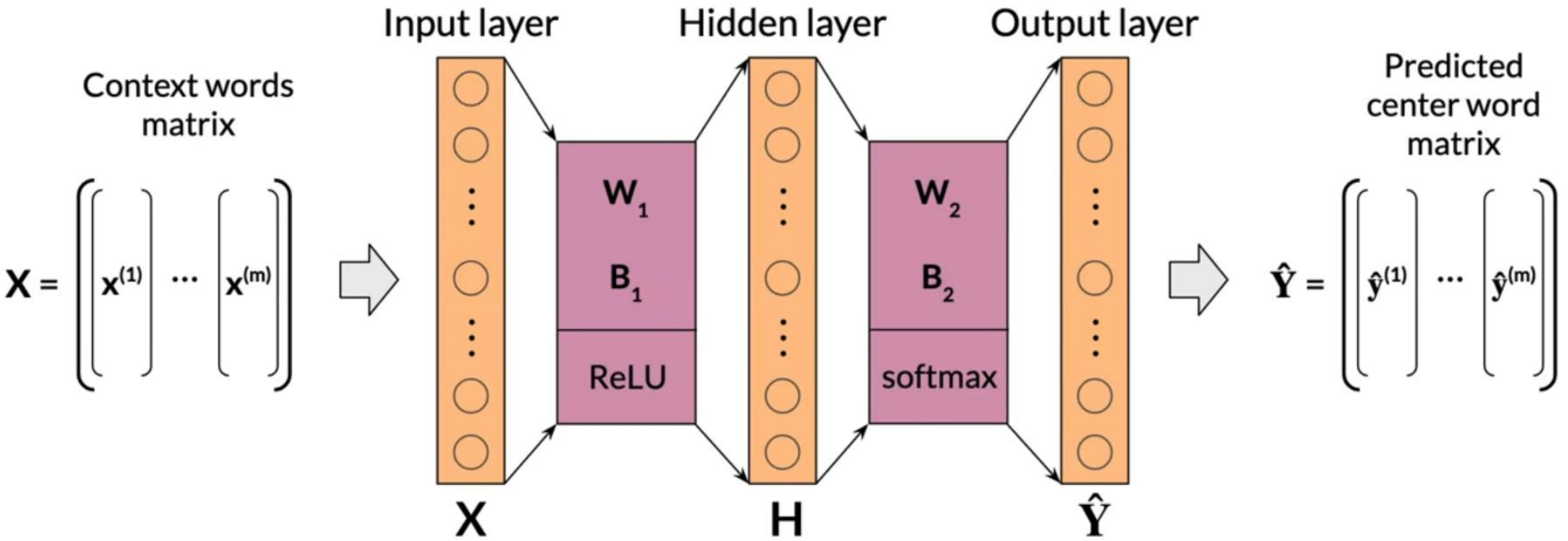


Training process

- Forward propagation
- Cost
- Backpropagation and gradient descent

Forward propagation

$$Z_1 = W_1 X + B_1 \qquad Z_2 = W_2 H + B_2$$
$$H = \text{ReLU}(Z_1) \qquad \hat{Y} = \text{softmax}(Z_2)$$



Cost

$$J = -\sum_{k=1}^{V} y_k \log \hat{y}_k$$

Cost: mean of losses

$$J_{batch} = -\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{V} y_j^{(i)} \log \hat{y}_j^{(i)}$$

$$J_{batch} = -\frac{1}{m}\sum_{i=1}^{m} J^{(i)}$$

Predicted center word matrix

$$\hat{\mathbf{Y}} = \begin{bmatrix} \hat{\mathbf{y}}^{(1)} & \cdots & \hat{\mathbf{y}}^{(m)} \end{bmatrix}$$

Actual center word matrix

$$\mathbf{Y} = \begin{bmatrix} \mathbf{y}^{(1)} & \cdots & \mathbf{y}^{(m)} \end{bmatrix}$$

Minimizing the cost

- Backpropagation: calculate partial derivatives of cost with respect to weights and biases

$$\frac{\partial J_{batch}}{\partial \mathbf{W_1}}, \frac{\partial J_{batch}}{\partial \mathbf{W_2}}, \frac{\partial J_{batch}}{\partial \mathbf{b_1}}, \frac{\partial J_{batch}}{\partial \mathbf{b_2}}$$

- Gradient descent: update weights and biases

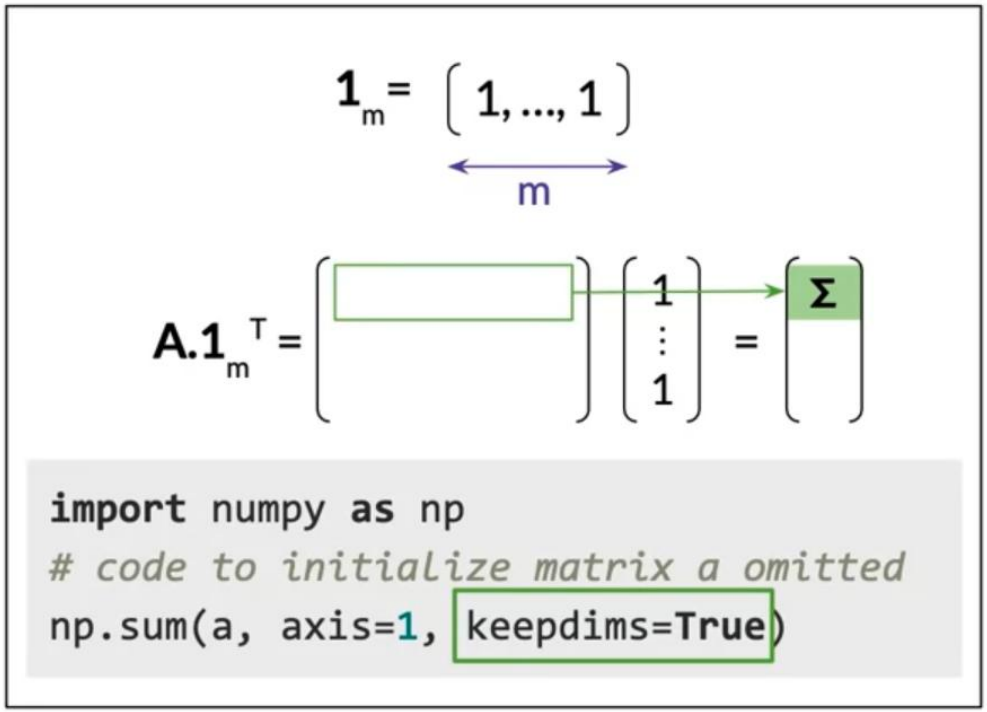
Backpropagation

$$\frac{\partial J_{batch}}{\partial \mathbf{W_1}} = \frac{1}{m}\text{ReLU}\left(\mathbf{W_2}^\top(\hat{\mathbf{Y}} - \mathbf{Y})\right)\mathbf{X}^\top$$

$$\frac{\partial J_{batch}}{\partial \mathbf{W_2}} = \frac{1}{m}(\hat{\mathbf{Y}} - \mathbf{Y})\mathbf{H}^\top$$

$$\frac{\partial J_{batch}}{\partial \mathbf{b_1}} = \frac{1}{m}\text{ReLU}\left(\mathbf{W_2}^\top(\hat{\mathbf{Y}} - \mathbf{Y})\right)\mathbf{1}_m^\top$$

$$\frac{\partial J_{batch}}{\partial \mathbf{b_2}} = \frac{1}{m}(\hat{\mathbf{Y}} - \mathbf{Y})\mathbf{1}_m^\top$$




```
import numpy as np
# code to initialize matrix a omitted
np.sum(a, axis=1, keepdims=True)
```

Gradient descent

Hyperparameter: learning rate α

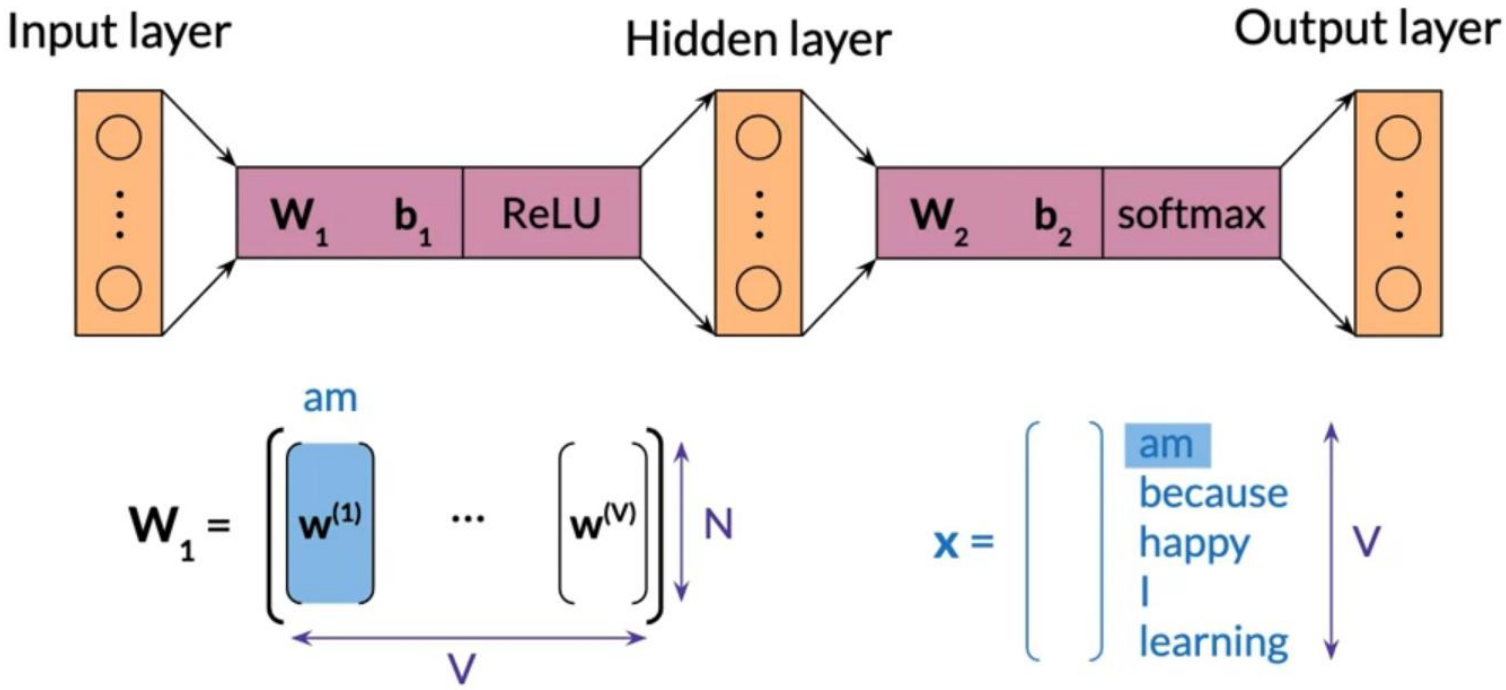
$$\mathbf{W_1} := \mathbf{W_1} - \alpha \frac{\partial J_{batch}}{\partial \mathbf{W_1}}$$

$$\mathbf{W_2} := \mathbf{W_2} - \alpha \frac{\partial J_{batch}}{\partial \mathbf{W_2}}$$

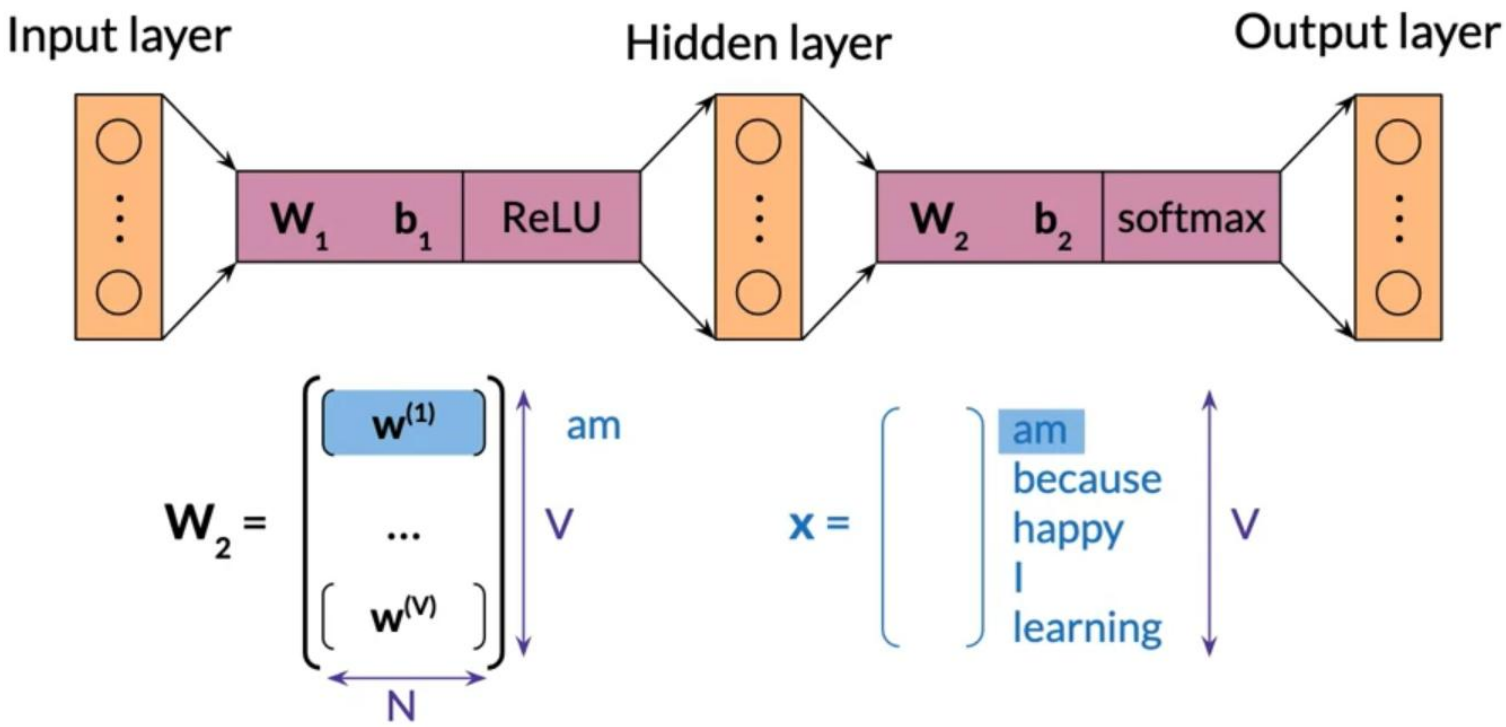
$$\mathbf{b_1} := \mathbf{b_1} - \alpha \frac{\partial J_{batch}}{\partial \mathbf{b_1}}$$

$$\mathbf{b_2} := \mathbf{b_2} - \alpha \frac{\partial J_{batch}}{\partial \mathbf{b_2}}$$

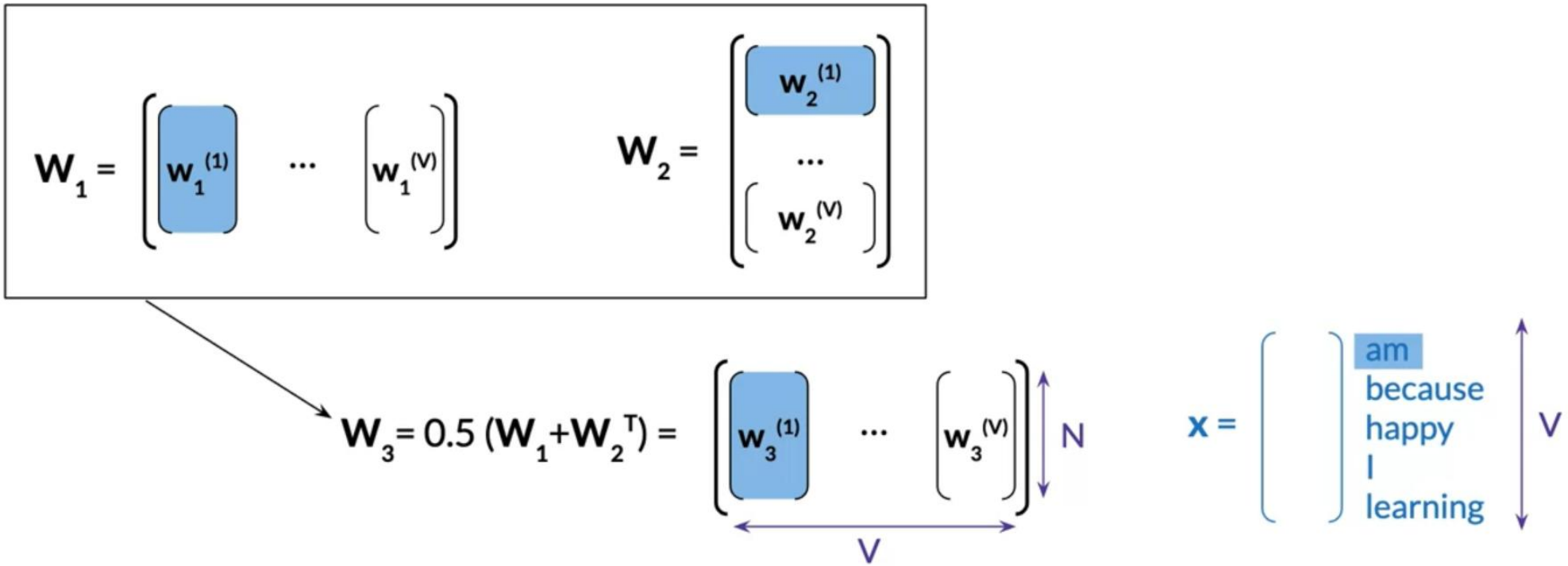
Extracting word embedding vectors: option 1



Extracting word embedding vectors: option 2



Extracting word embedding vectors: option 3



Intrinsic evaluation

Test relationships between words

- Analogies

  Semantic analogies

  “France” is to “Paris” as “Italy” is to <?>

  Syntactic analogies

  “seen” is to “saw” as “been” is to <?>

  ⚡ Ambiguity

  “wolf” is to “pack” as “bee” is to <?> → swarm? colony?

Intrinsic evaluation

Test relationships between words

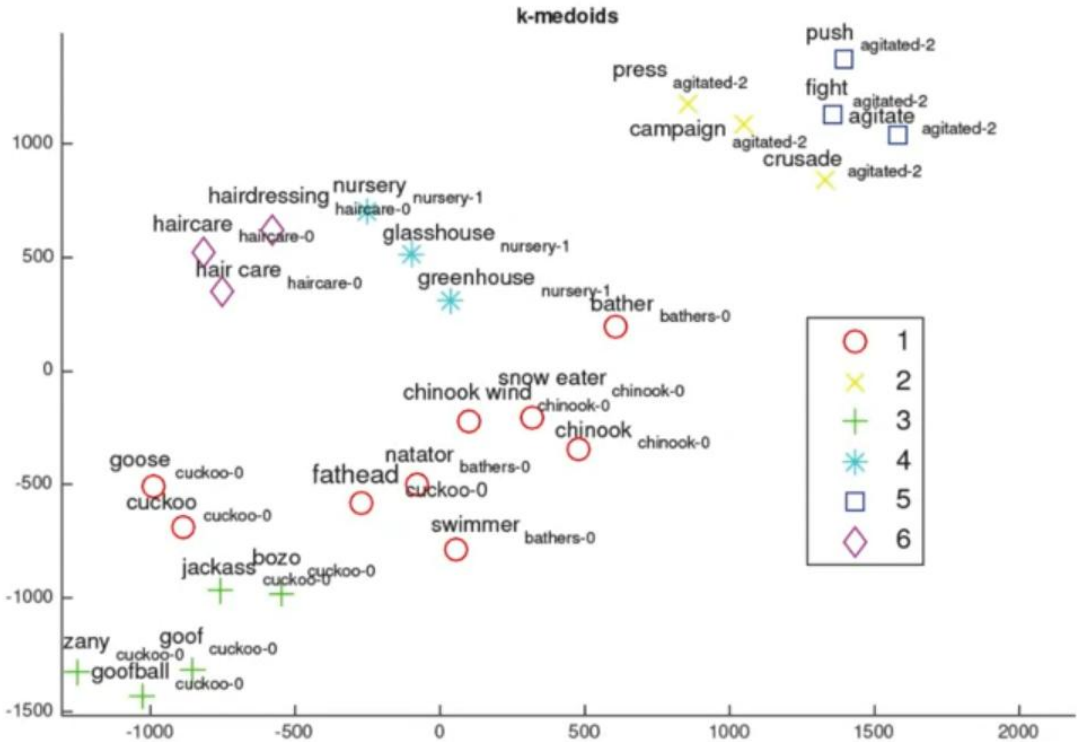
- Analogies

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

Intrinsic evaluation

Test relationships between words

- Analogies
- Clustering

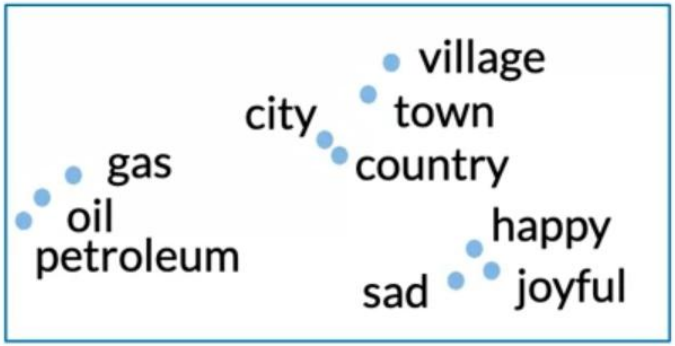


Source: Michael Zhai, Johnny Tan, and Jinho D. Choi. 2016. [Intrinsic and extrinsic evaluations of word embeddings]

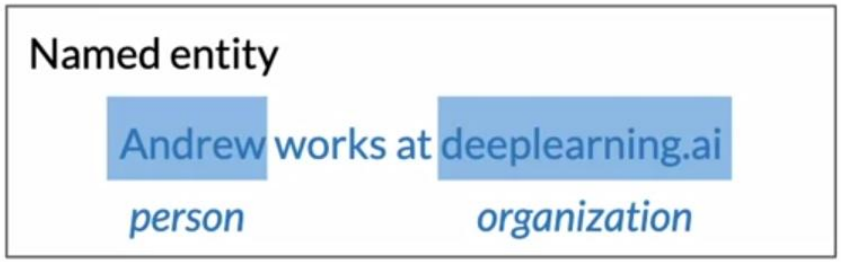
Intrinsic evaluation

Test relationships between words

- Analogies
- Clustering
- Visualization



Extrinsic evaluation



Test word embeddings on external task

e.g. named entity recognition, parts-of-speech tagging

Extrinsic evaluation

Test word embeddings on external task
e.g. named entity recognition, parts-of-speech tagging

\+ Evaluates actual usefulness of embeddings

\- Time-consuming

\- More difficult to troubleshoot

Recap and assignment

- Data preparation
- Word representations
- Continuous bag-of-words model
- Evaluation

Going further

- Advanced language modelling and word embeddings

- NLP and machine learning libraries

Keras

```
# from keras.layers.embeddings import Embedding
embed_layer = Embedding(10000, 400)
```

PyTorch

```
# import torch.nn as nn
embed_layer = nn.Embedding(10000, 400)
```