CS11-711 Advanced NLP

# Neural Text Representation and Classification

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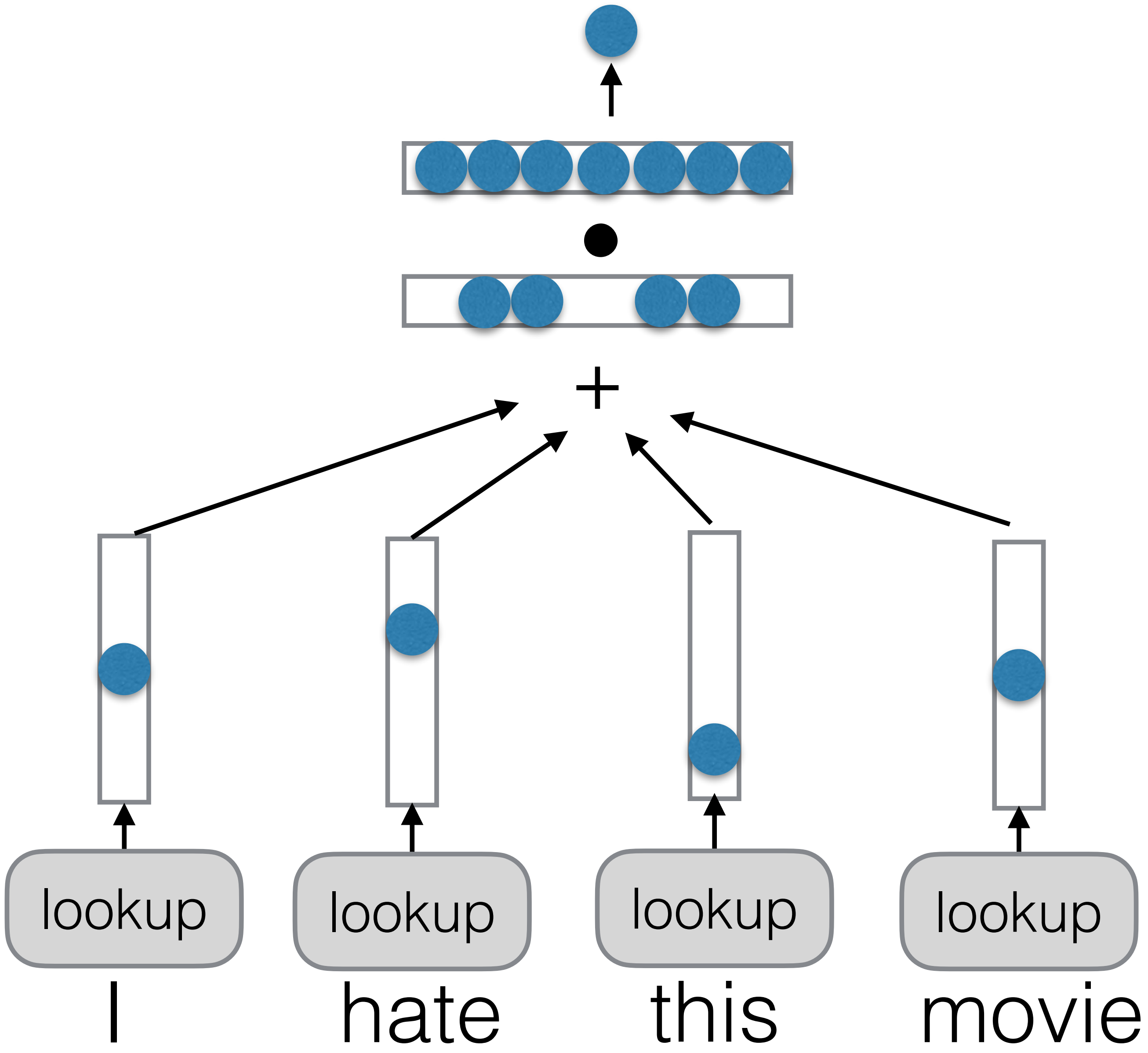
https://cmu-l3.github.io/anlp-spring2025/

Many slides adapted from Graham Neubig's from Fall 2024

# Recap: Bag of Words (BoW)



Features: sum of 1-hot vectors
Weights: learned

# Bag of Words: Symptoms

- Handling of *conjugated or compound words*
  - I **love** this move -> I **loved** this movie

Subword Models

- Handling of *word similarity*
  - I **love** this move -> I **adore** this movie

Word Embeddings

- Handling of *combination features*
  - I **love** this movie -> I **don’t love** this movie
  - I **hate** this movie -> I **don’t hate** this movie

Neural Networks

- Handling of *sentence structure*
  - It has an interesting story, **but** is boring overall

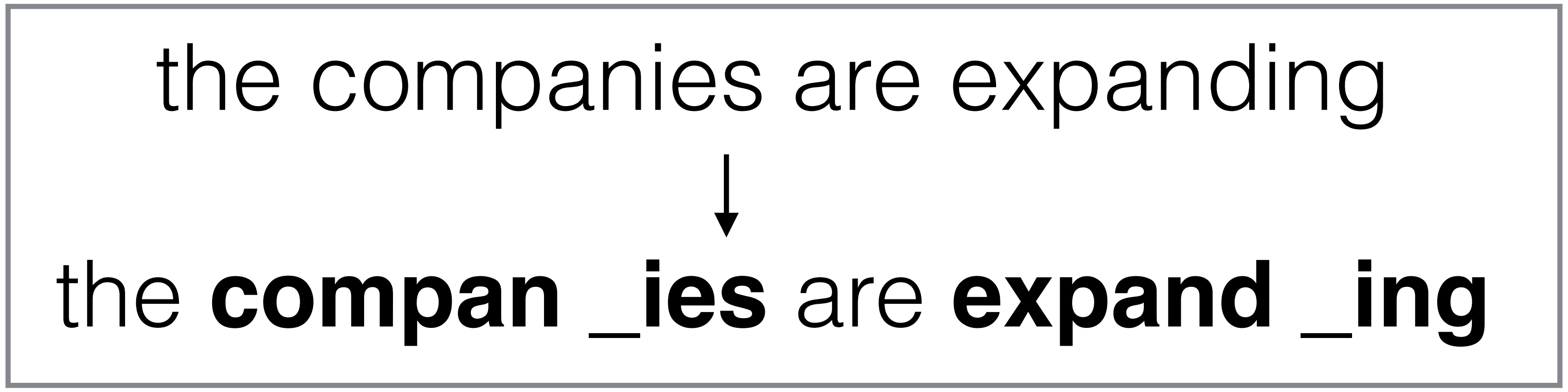
Sequence Models

# Subword Models

Example code and walkthrough:
https://github.com/cmu-l3/anlp-spring2025-code/blob/main/02_wordrep_classification/tokenization.ipynb

# Basic Idea

- Split less common words into multiple **subword tokens**



the companies are expanding

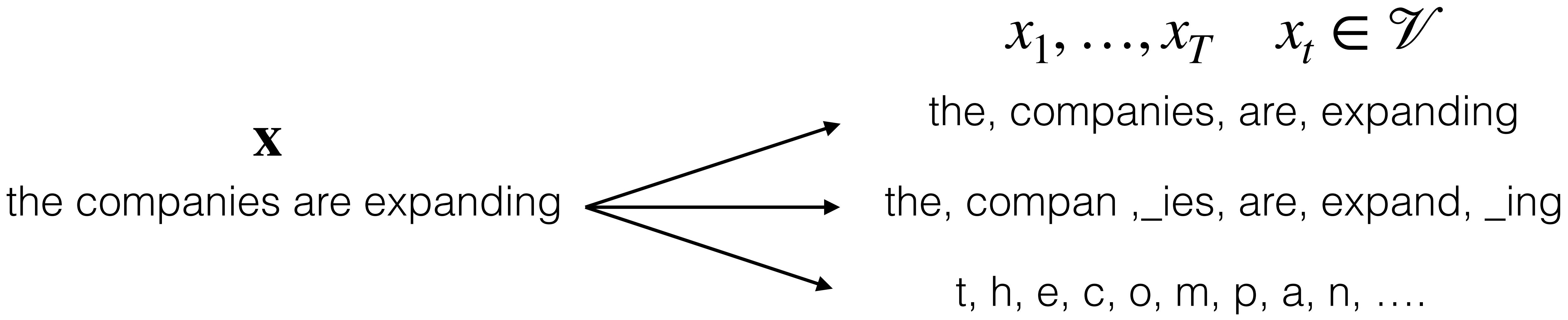
↓

the **compan _ies** are **expand _ing**

- Benefits:
    - **Share parameters** between subwords
    - Reduce parameter size, **save compute+memory**

# Core problem: tokenization

- Map text into a sequence of discrete **tokens** from a **vocabulary**



$x_1, \ldots, x_T \quad x_t \in \mathscr{V}$

$\mathbf{x}$

the companies are expanding

the, companies, are, expanding

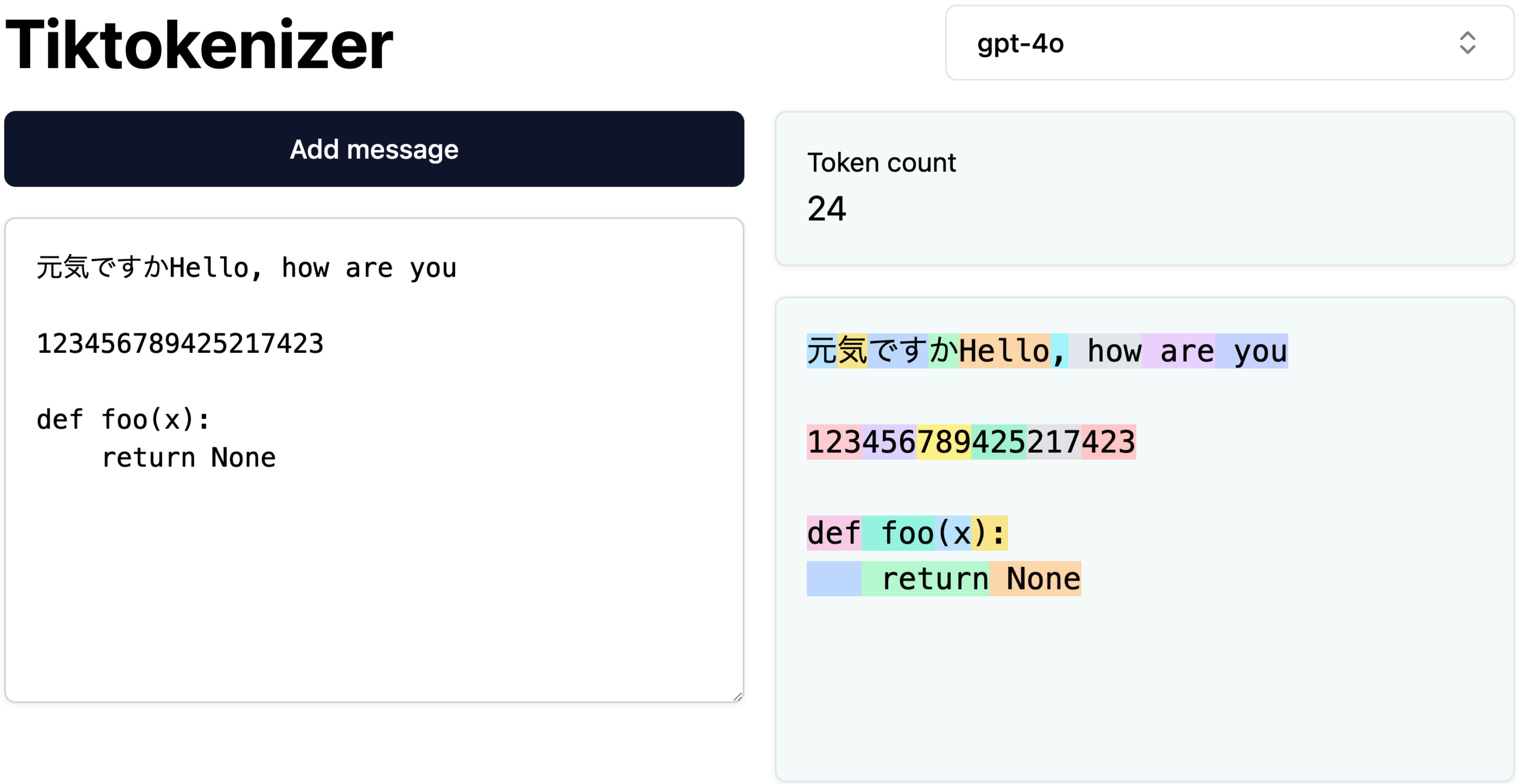
the, compan ,_ies, are, expand, _ing

t, h, e, c, o, m, p, a, n, ….

- We want a vocabulary $\mathscr{V}$ that is:
  - **Expressive**: represent any text (English, Japanese, code, …)
  - **Efficient**
    - **Not too large:** larger vocabulary means more parameters to learn/store
    - **Not too small:** smaller vocabulary means longer inputs

# Core problem: tokenization

- Demo: https://tiktokenizer.vercel.app/



## Tiktokenizer

gpt-4o

```
元気ですかHello, how are you

123456789425217423

def foo(x):
    return None
```

Token count

24

```
元気ですかHello, how are you

123456789425217423

def foo(x):
    return None
```

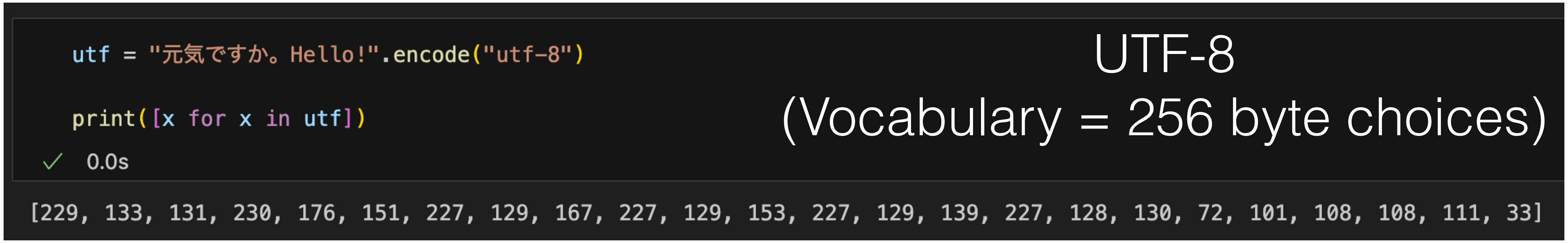
# Idea 1: UTF-8

- Tokenize text as UTF-8 bytes

元気ですか。Hello!

Unicode string

↓



```
utf = "元気ですか。Hello!".encode("utf-8")

print([x for x in utf])
```

✓ 0.0s

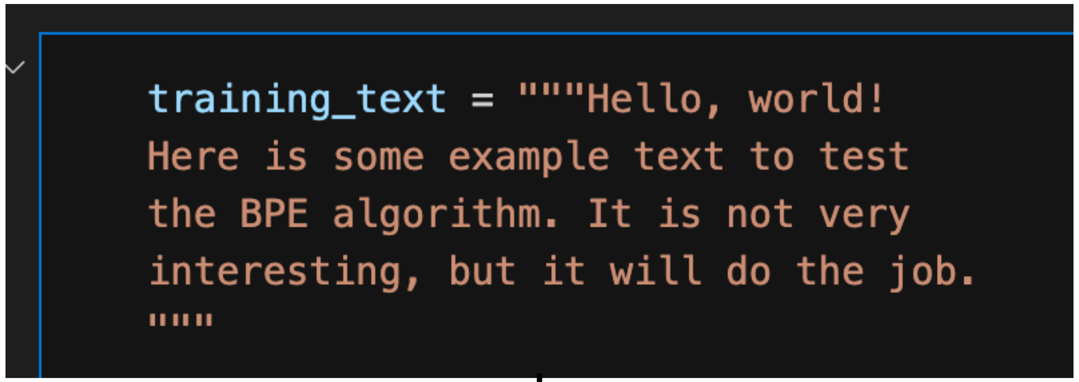
```
[229, 133, 131, 230, 176, 151, 227, 129, 167, 227, 129, 153, 227, 129, 139, 227, 128, 130, 72, 101, 108, 108, 111, 33]
```

UTF-8
(Vocabulary = 256 byte choices)

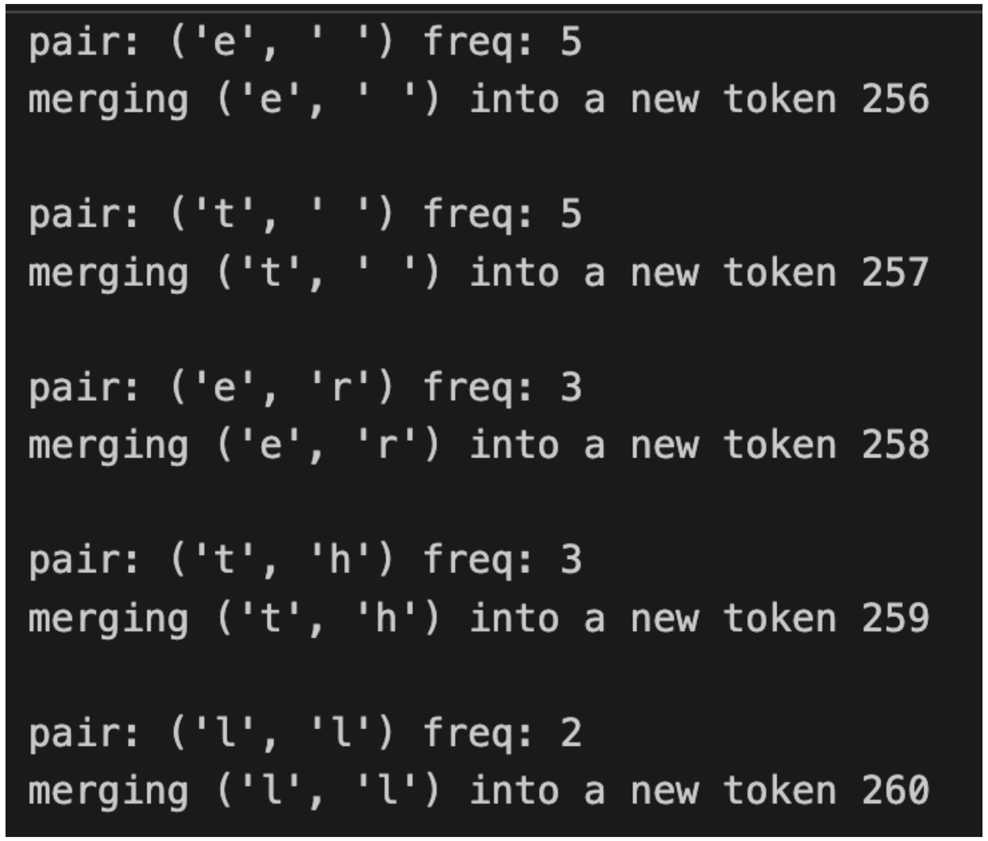
- **Expressive:** any Unicode string (Japanese, English, Latex, …)
- **Vocabulary is too small**: sequences are very long (inefficient)

# Idea 2: Byte Pair Encoding

- **Key idea**: merge the most common token pairs into new tokens
    - Start with a base vocabulary (e.g., UTF-8) and a training set
    - Repeat:
        - Find the token pair that occurs most often
        - Introduce a new token and replace the token pair



```
training_text = """Hello, world!
Here is some example text to test
the BPE algorithm. It is not very
interesting, but it will do the job.
"""
```

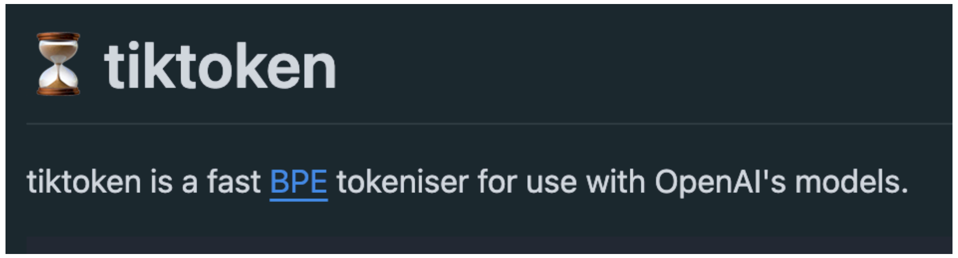


```
pair: ('e', ' ') freq: 5
merging ('e', ' ') into a new token 256

pair: ('t', ' ') freq: 5
merging ('t', ' ') into a new token 257

pair: ('e', 'r') freq: 3
merging ('e', 'r') into a new token 258

pair: ('t', 'h') freq: 3
merging ('t', 'h') into a new token 259

pair: ('l', 'l') freq: 2
merging ('l', 'l') into a new token 260
```

# Practical tools: tiktoken

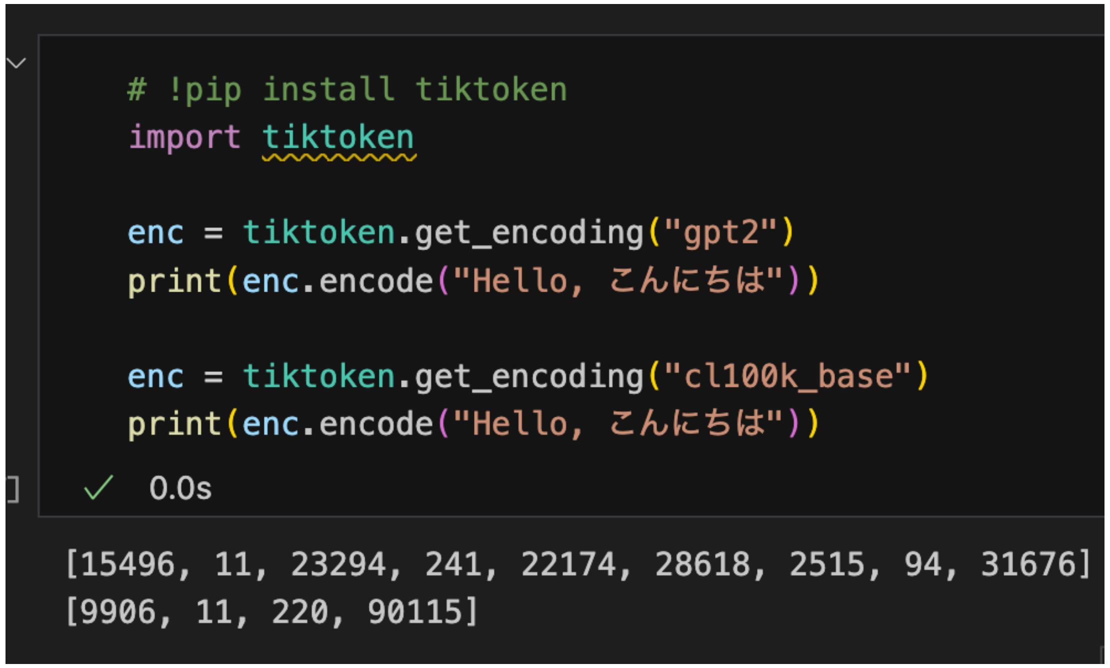
- Load pre-existing OpenAI vocabularies (e.g., GPT-2, GPT-4)

- Tokenize and decode text



## ⏳ tiktoken

tiktoken is a fast BPE tokeniser for use with OpenAI's models.



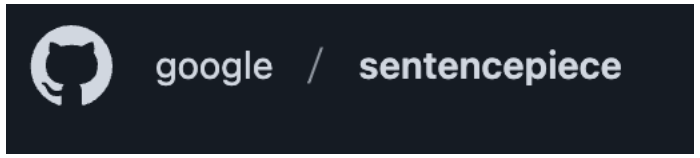
```
# !pip install tiktoken
import tiktoken

enc = tiktoken.get_encoding("gpt2")
print(enc.encode("Hello, こんにちは"))

enc = tiktoken.get_encoding("cl100k_base")
print(enc.encode("Hello, こんにちは"))
```

✓ 0.0s

```
[15496, 11, 23294, 241, 22174, 28618, 2515, 94, 31676]
[9906, 11, 220, 90115]
```

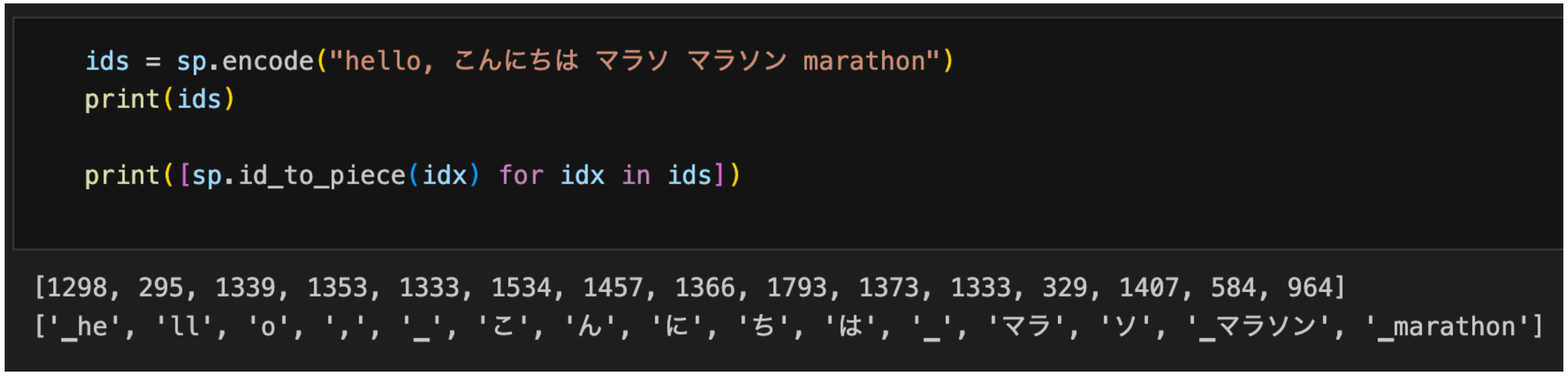
# Practical tools: SentencePiece

- Also supports *training* a tokenizer



google / sentencepiece

- Uses *Unicode* as the base vocabulary
  - *byte_fallback=True*: tokenize as UTF-8 bytes when a Unicode character is out-of-vocabulary



```
ids = sp.encode("hello, こんにちは マラソ マラソン marathon")
print(ids)

print([sp.id_to_piece(idx) for idx in ids])
```

```
[1298, 295, 1339, 1353, 1333, 1534, 1457, 1366, 1793, 1373, 1333, 329, 1407, 584, 964]
['_he', 'll', 'o', ',', '_', 'こ', 'ん', 'に', 'ち', 'は', '_', 'マラ', 'ソ', '_マラソン', '_marathon']
```

# Subword Considerations

- **Vocabulary depends on the BPE training data**:
    - Under-represented languages: merged less, hence longer sequences
    - *Work-around*: upsample under-represented languages

- **Multiple segmentations**:“es t” or “e st”? “123” or “1” “2” “3”?
    - *Work-around:* “Subword regularization" samples different segmentations at training time to make models robust (Kudo 2018)
    - *Work-around*: Hand-defined rules, e.g. never group digits together

# Recap

- Tokenization and subword models
  - Represent sequences as tokens determined based on frequency
- **Next**: Token embeddings

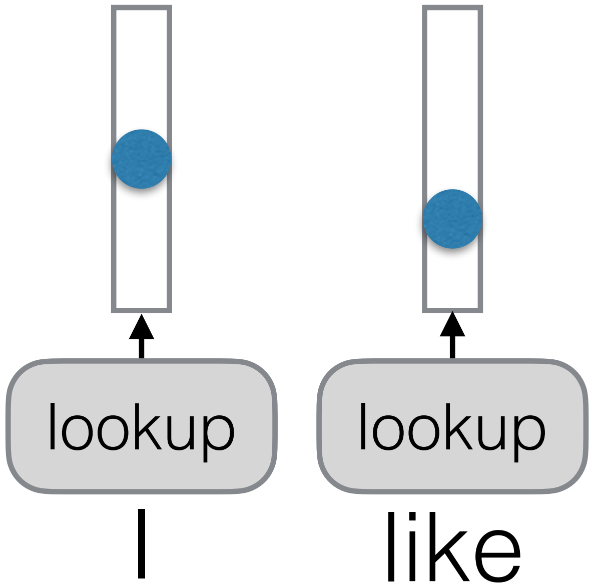
# Continuous Word Embeddings

Code:
https://github.com/cmu-l3/anlp-spring2025-code/blob/main/02_wordrep_classification/bow.ipynb

# Basic Idea

- Previously: **one-hot** vectors (*sparse*)
- Continuous embeddings: *dense* vectors in $\mathbb{R}^{d_{emb}}$

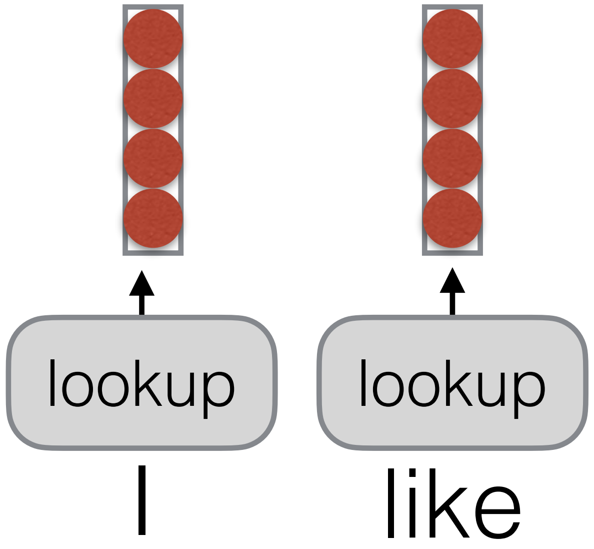
One-hot



$$x_t : [0,\ldots 1,\ldots,0] \in \{0,1\}^V$$

*V*: vocabulary size

Dense

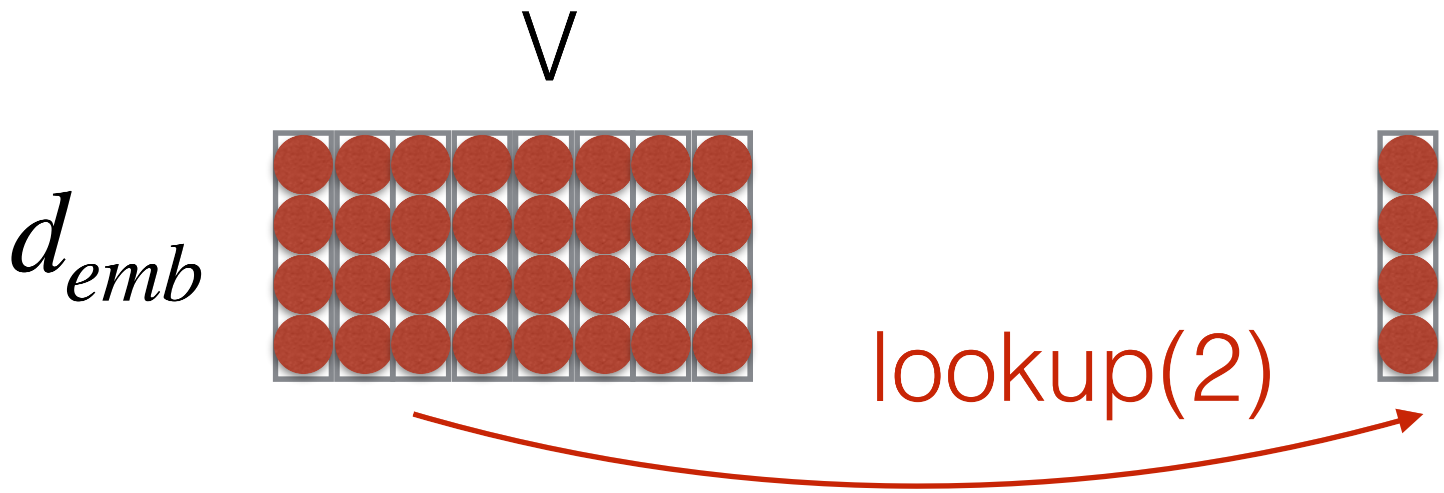


$$x_t : [0.2, -1.3,\ldots,0.6] \in \mathbb{R}^{d_{emb}}$$

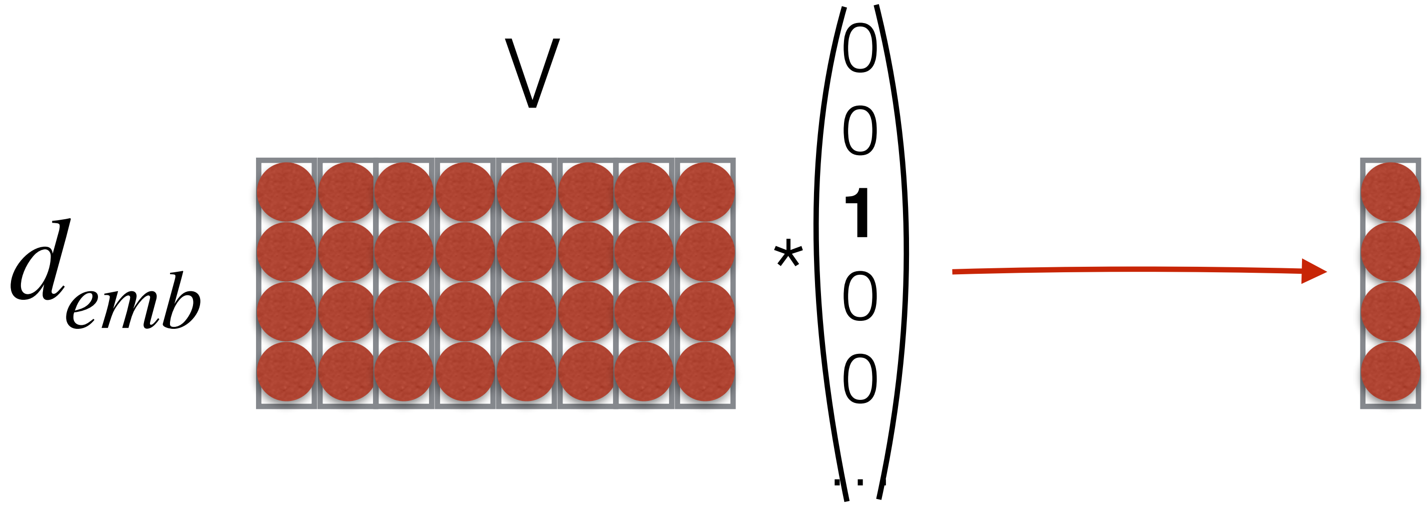
$d_{emb}$: “embedding dimension”

# Embedding Layer

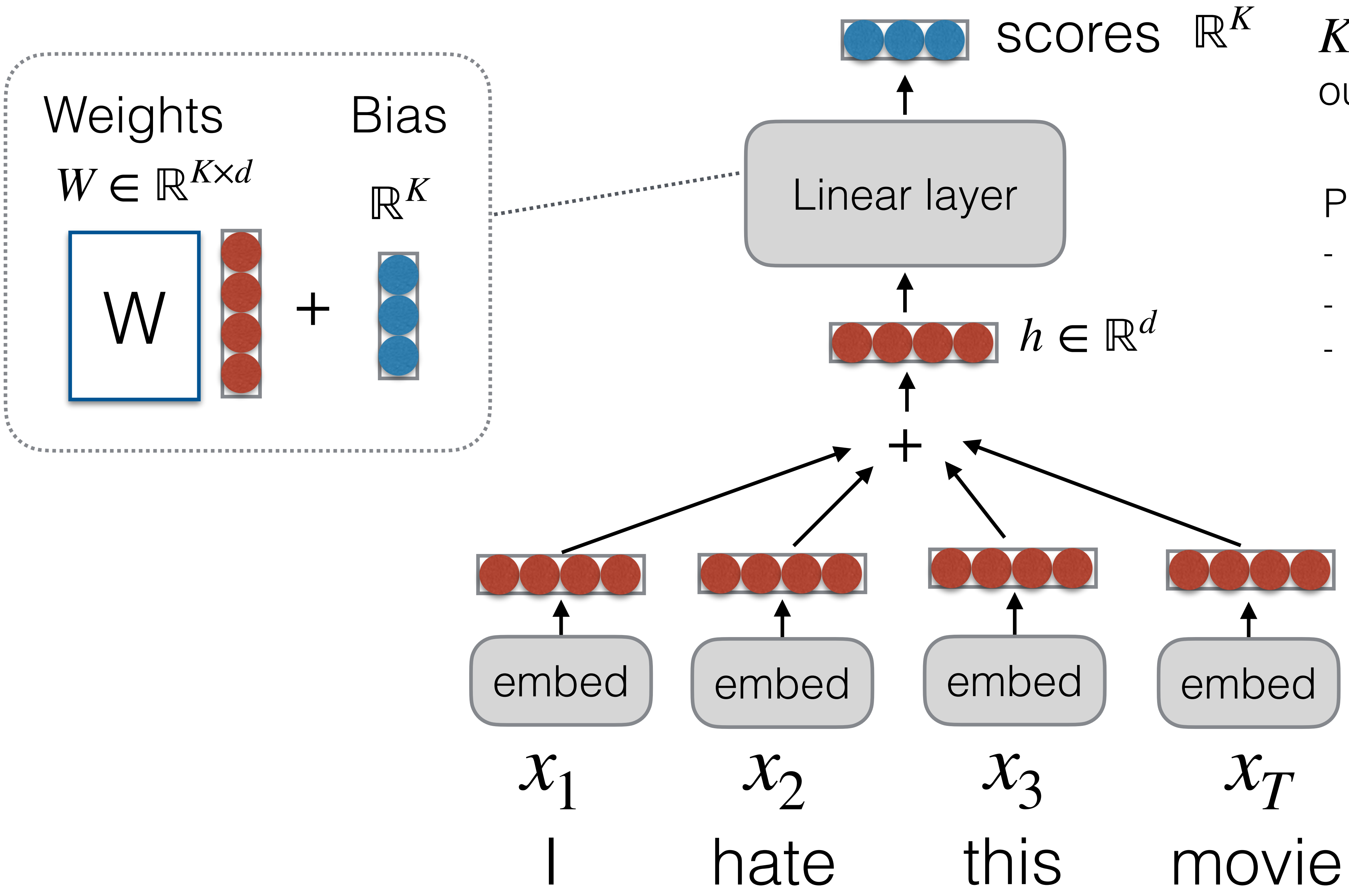
- Embedding layer: matrix with a row/column for each vocabulary token. “Lookup”: select a row/column.



- Equivalent to multiplying by a one-hot vector



# Continuous Bag of Words (CBoW)

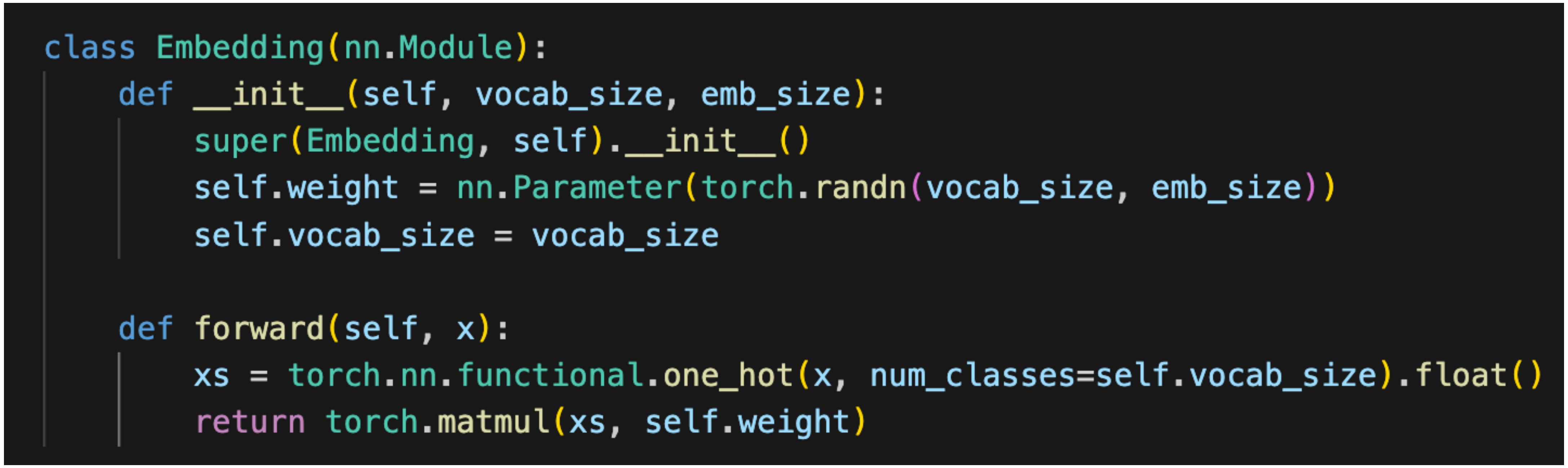


$K$: number of output classes

Parameters $\theta$

- Embedding layer
- Weights $W$
- Bias

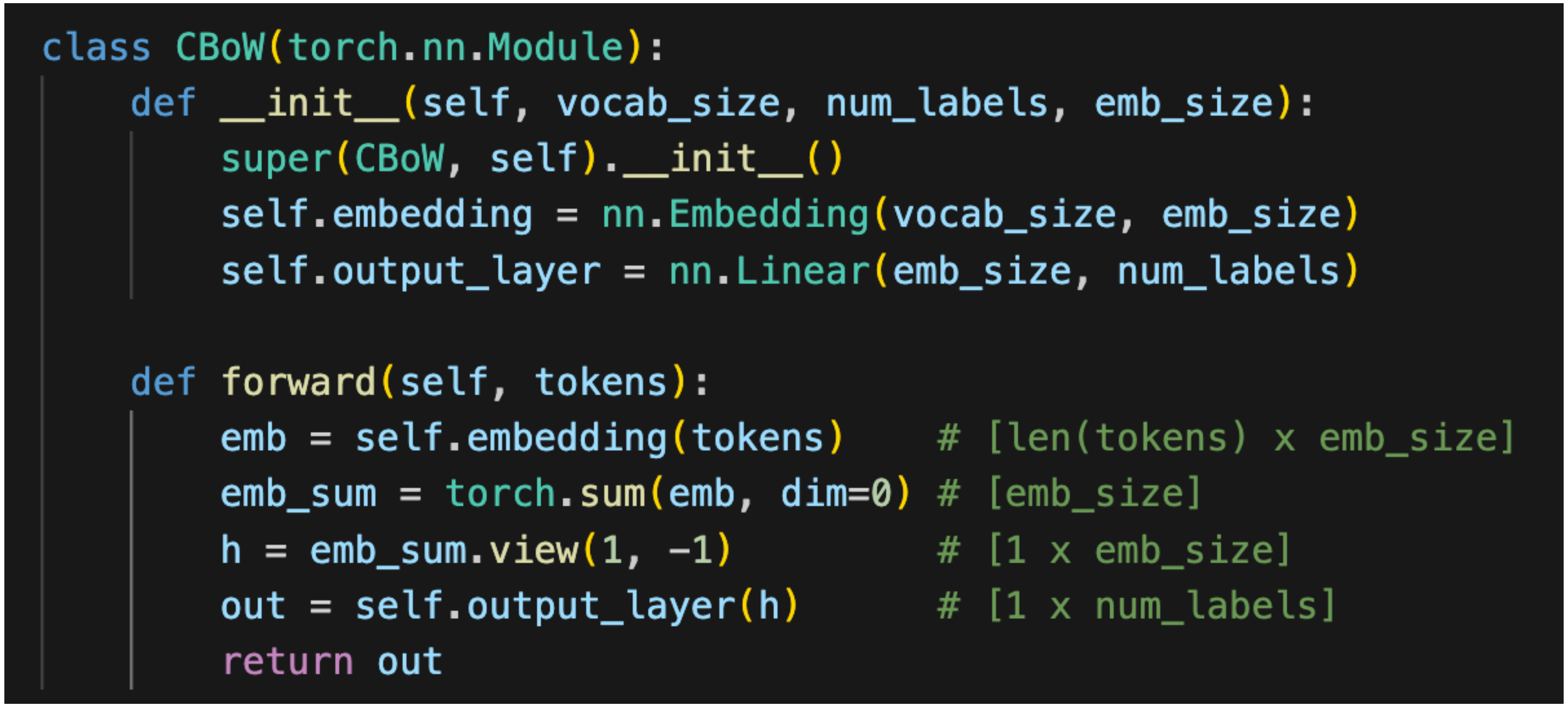
# In Code



```python
class Embedding(nn.Module):
    def __init__(self, vocab_size, emb_size):
        super(Embedding, self).__init__()
        self.weight = nn.Parameter(torch.randn(vocab_size, emb_size))
        self.vocab_size = vocab_size

    def forward(self, x):
        xs = torch.nn.functional.one_hot(x, num_classes=self.vocab_size).float()
        return torch.matmul(xs, self.weight)
```

In practice, implemented in libraries (e.g., nn.Embedding)

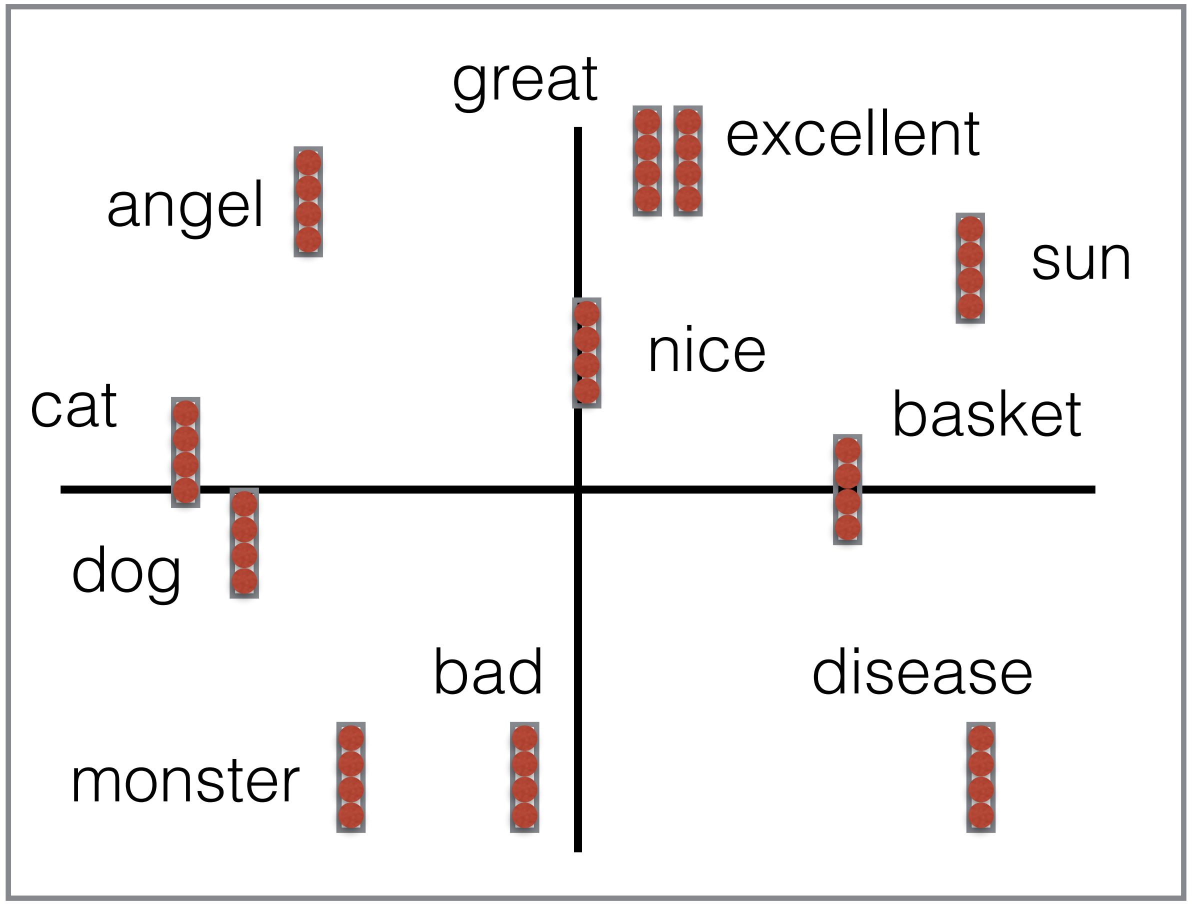
# In Code



```
class CBoW(torch.nn.Module):
    def __init__(self, vocab_size, num_labels, emb_size):
        super(CBoW, self).__init__()
        self.embedding = nn.Embedding(vocab_size, emb_size)
        self.output_layer = nn.Linear(emb_size, num_labels)

    def forward(self, tokens):
        emb = self.embedding(tokens)    # [len(tokens) x emb_size]
        emb_sum = torch.sum(emb, dim=0) # [emb_size]
        h = emb_sum.view(1, -1)         # [1 x emb_size]
        out = self.output_layer(h)      # [1 x num_labels]
        return out
```

# What do Our Vectors Represent?

- No guarantees, but we hope that:
  - Words that are **similar** are **close** in vector space
  - Each vector element is a **feature**



Shown in 2D, but in reality we use 512, 1024, etc.

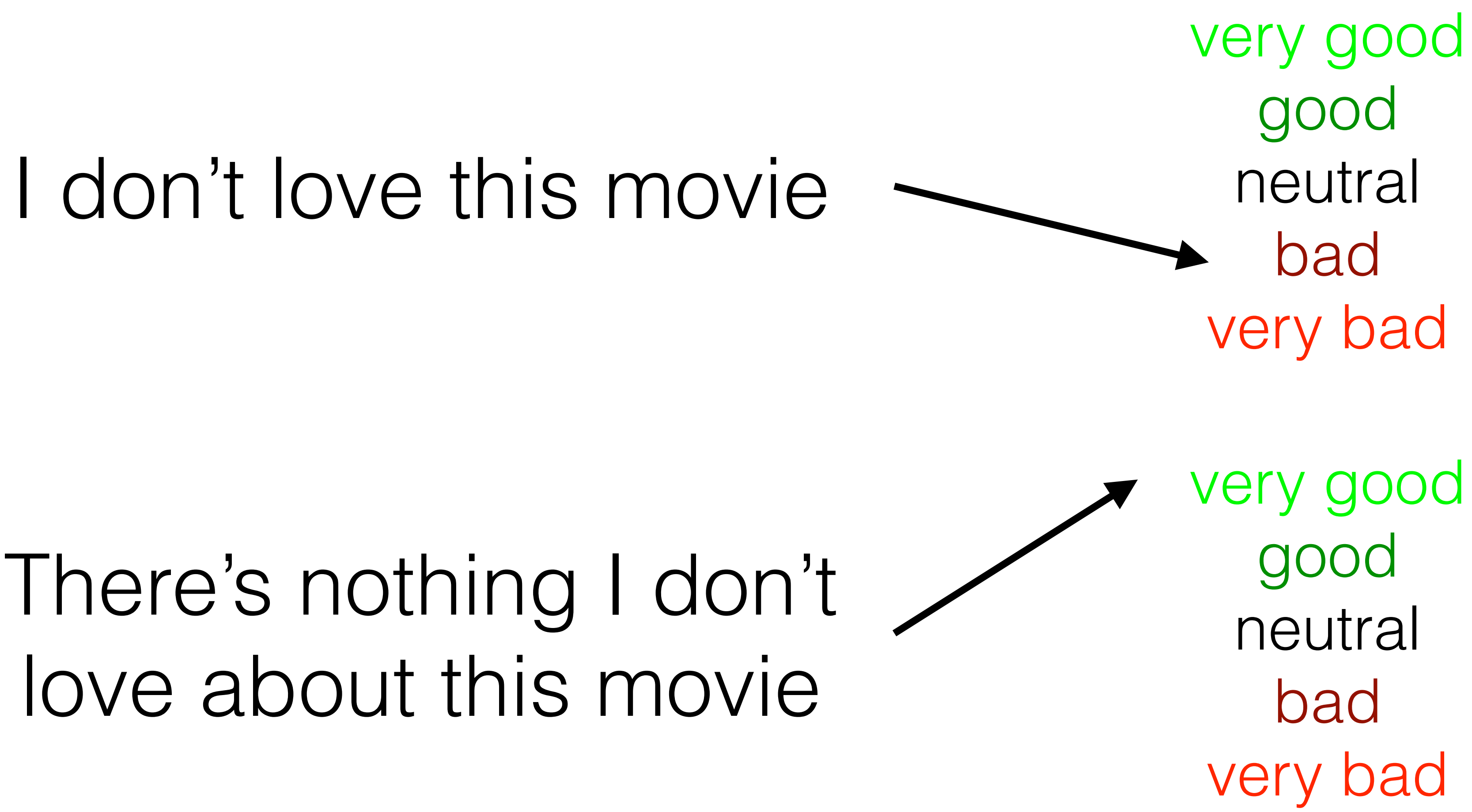
# Recap

- Tokenization and subword models
    - Represent sequences as tokens determined based on frequency
- Token embeddings
    - Represent tokens as learned continuous vectors
- **Next**: Neural networks

# Neural Network Features

Code:
https://github.com/cmu-l3/anlp-spring2025-code/blob/main/02_wordrep_classification/bow.ipynb

# Motivation: combination features



I don’t love this movie

very good

good

neutral

bad

very bad

There’s nothing I don’t love about this movie

very good

good

neutral

bad

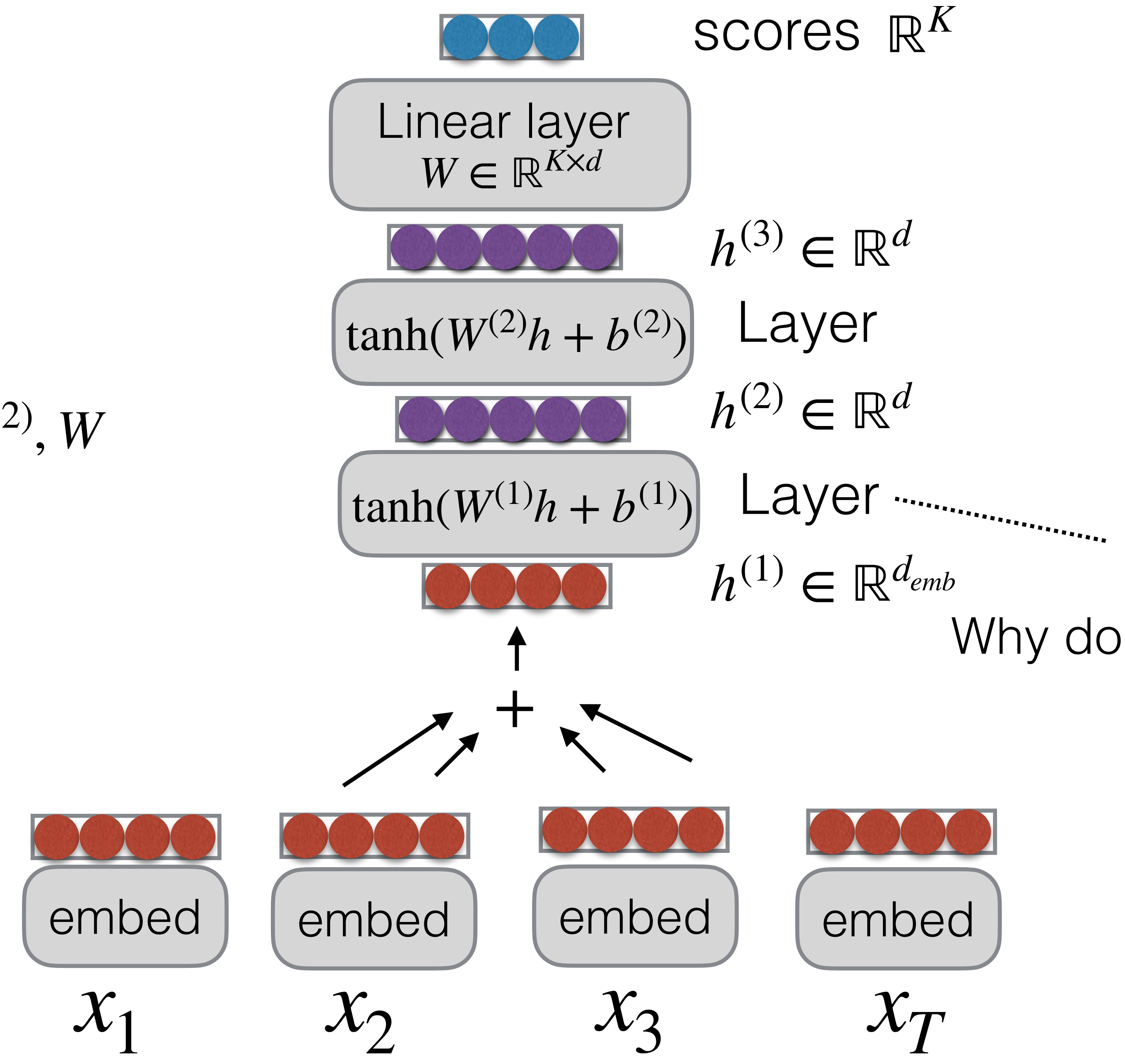
very bad

# *Deep* CBoW

$K$: number of output classes

Parameters $\theta$

- Embedding layer
- Weights $W^{(1)}, W^{(2)}, W$
- Biases



scores $\mathbb{R}^K$
Linear layer $W \in \mathbb{R}^{K\times d}$
$h^{(3)} \in \mathbb{R}^d$
$\tanh(W^{(2)}h + b^{(2)})$
Layer
$h^{(2)} \in \mathbb{R}^d$
$\tanh(W^{(1)}h + b^{(1)})$
Layer
$h^{(1)} \in \mathbb{R}^{d_{emb}}$
+
embed
embed
embed
embed
$x_1$
$x_2$
$x_3$
$x_T$

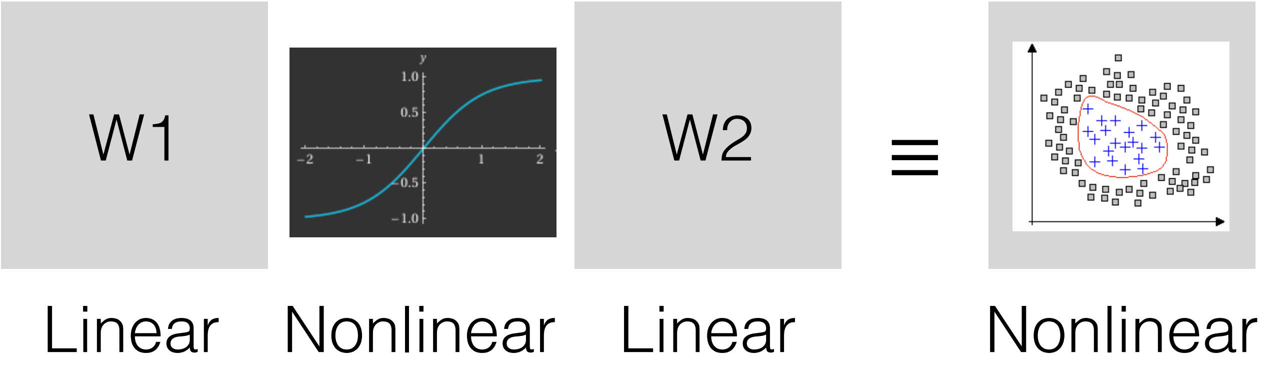
Why tanh?

Why do these layers help?

# Nonlinearities

tanh(W*h + b)

- *Activation functions* such as tanh introduce *nonlinearity*
  - Non-linearities allow the neural network to model more complex patterns
- Without activation functions, stacking matrices collapses to a linear transformation



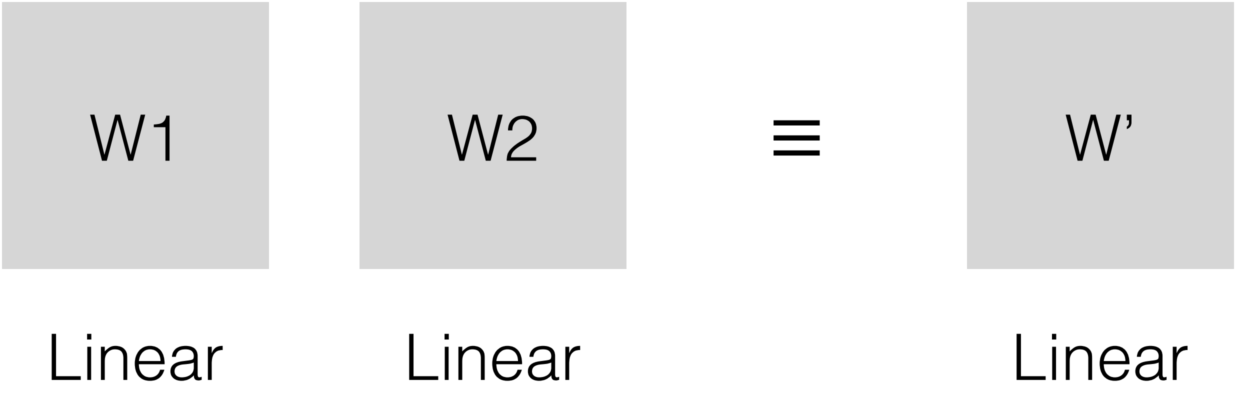
W1 Linear

Nonlinear

W2 Linear

≡

Nonlinear



W1 Linear

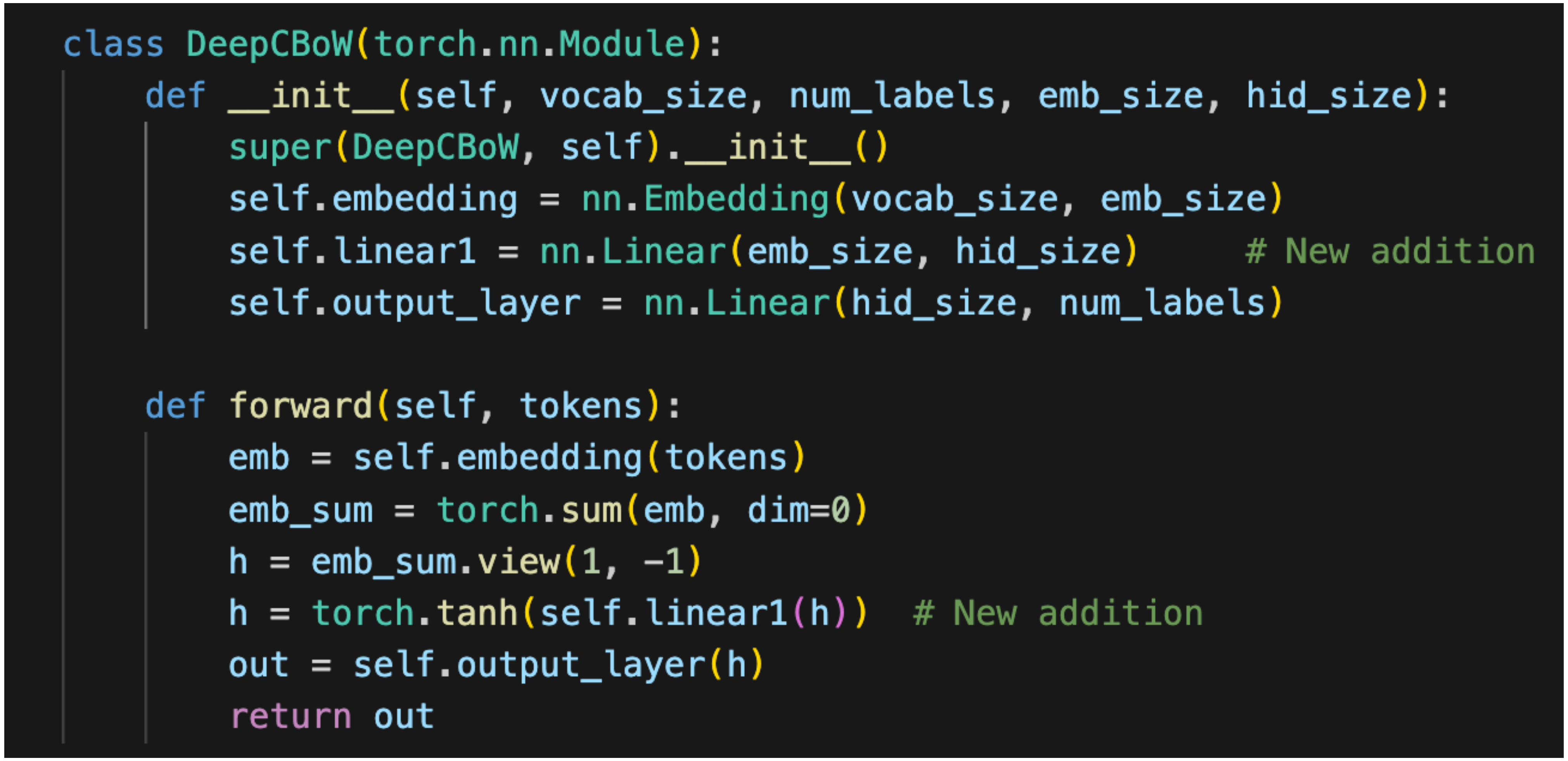
W2 Linear

≡

W’ Linear

Other activation functions: sigmoid, ReLU, GELU, see PyTorch list

# Deep CBoW In Code



```python
class DeepCBoW(torch.nn.Module):
    def __init__(self, vocab_size, num_labels, emb_size, hid_size):
        super(DeepCBoW, self).__init__()
        self.embedding = nn.Embedding(vocab_size, emb_size)
        self.linear1 = nn.Linear(emb_size, hid_size)     # New addition
        self.output_layer = nn.Linear(hid_size, num_labels)

    def forward(self, tokens):
        emb = self.embedding(tokens)
        emb_sum = torch.sum(emb, dim=0)
        h = emb_sum.view(1, -1)
        h = torch.tanh(self.linear1(h))  # New addition
        out = self.output_layer(h)
        return out
```

(One hidden-layer version)

# What do Our Vectors Represent?

- We can learn feature combinations
  - E.g., a node in the second layer might be “feature 1 AND feature 5 are active”
  - E.g. capture things such as “not” AND “hate”
- We can learn nonlinear transformations of the previous layer’s features

# Recap

- Tokenization and subword models
  - Represent sequences as tokens determined based on frequency
- Token embeddings
  - Represent tokens as learned continuous vectors
- Neural networks
  - Learn complex, non-linear feature functions
- **Next**: Training neural network models

# Training neural network models

# Training neural network models

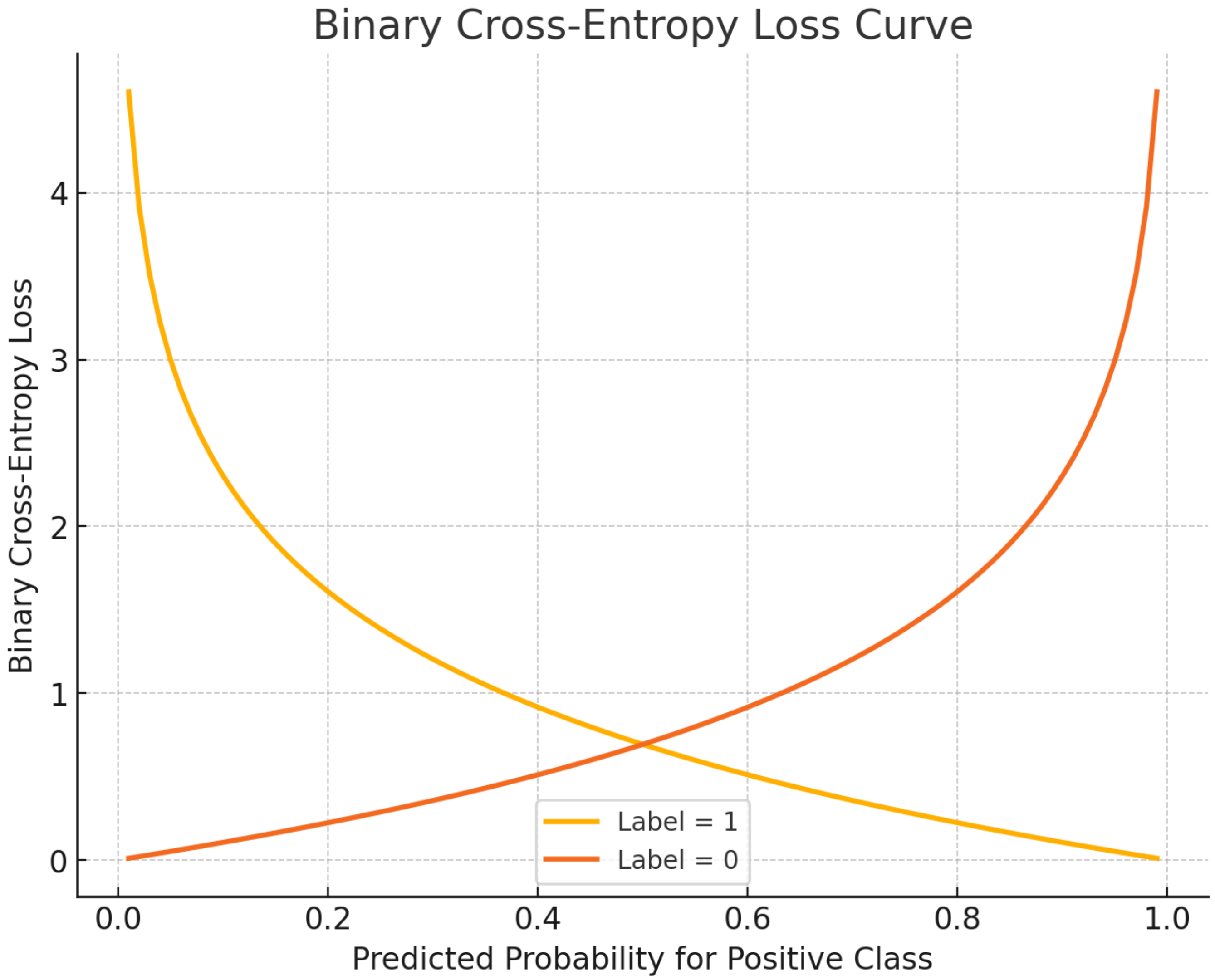
- We use *gradient descent*
  - Write down a *loss function*
  - *Calculate gradients* of the loss function with respect to the parameters
  - Move the parameters in the direction that *reduces the loss function*

# Example Loss: Binary Cross entropy

- Example task: classify tweets as positive (1) or negative (0)
  - Model outputs a probability $p \in [0,1]$ for the positive class
    - Use a *sigmoid*:

$$\text{Sigmoid}(s) = \sigma(s) = \frac{1}{1 + \exp(-s)}$$

  - Ground truth label $y \in \{0,1\}$

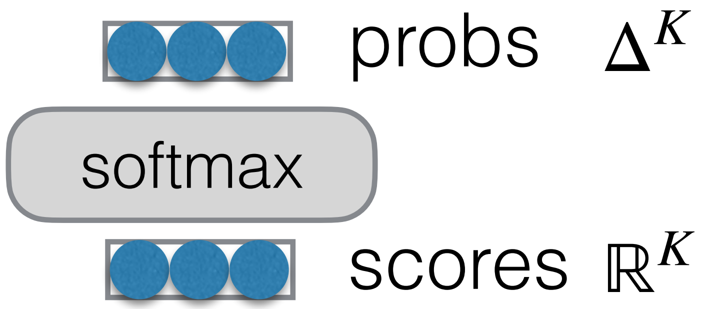


$$L_{\text{BCE}} = -y\log(p) - (1-y)\log(1-p)$$

# Cross entropy loss (multi-class)

- Example task: classify tweets as positive (2), neutral (1), or negative (0)
  - Given a training example $(x, y)$
  - Model outputs a probability vector
    - E.g. $p = [0.2,0.5,0.3]$
  - Ground truth label: one-hot vector
    - E.g. $y = [0,0,1]$

$$L_{CE} = -\sum_{i=1}^{3} y_i \log(p_i)$$



$$p_i = \frac{\exp(z_i)}{\sum_{j=1}^{3} \exp(z_j)}$$

# Cross entropy loss (multi-class)

$$L_{CE} = -\sum_{i=1}^{K} y_i \log(p_i)$$

- Model assigns high probability to correct class:
  - $p_i \approx 1 \implies \log p_i \approx 0 \implies$ **small** loss
- Model assigns low probability to correct class:
  - $p_i \approx 0 \implies \log p_i \approx -\infty \implies$ **large** loss

# Where does cross entropy loss come from?

- Minimize the KL Divergence between two distributions:

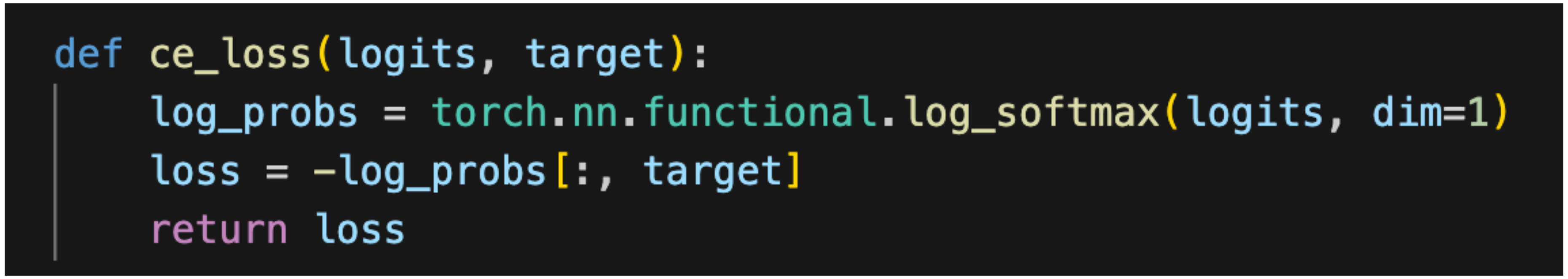
- $$\min_{p_2} \mathrm{KL}\left(p_1, p_2\right) = \min_{p_2} -\sum_x p_1(x) \log\left(\frac{p_2(x)}{p_1(x)}\right)$$

$$\equiv \min_{p_2} \sum_x -p_1(x) \log p_2(x) + p_1(x) \log p_1(x)$$

$$\equiv \min_{p_2} -\sum_x p_1(x) \log p_2(x)$$

- In our example:
  - $p_1 = [0,0,1]$, and $p_2 = [0.2,0.5,0.3]$

# Cross entropy loss (in code)



```python
def ce_loss(logits, target):
    log_probs = torch.nn.functional.log_softmax(logits, dim=1)
    loss = -log_probs[:, target]
    return loss
```

Implemented in standard libraries, e.g. nn.CrossEntropyLoss

# Training neural network models

- We use *gradient descent*
  - Write down a *loss function*
  - ***Calculate gradients* of the loss function with respect to the parameters**
  - Move the parameters in the direction that *reduces the loss function*

# Calculating gradients

- $p = \sigma(\underbrace{wx + b}_{z})$, where $\sigma(x) = \dfrac{1}{1 + \exp(-x)}$
- $L = -y \log p - (1 - y)\log(1 - p)$
- $\dfrac{\partial L}{\partial w} = \dfrac{\partial L}{\partial p}\dfrac{\partial p}{\partial z}\dfrac{\partial z}{\partial w}$
- $\dfrac{\partial L}{\partial p} = -\dfrac{y}{p} + \dfrac{1 - y}{1 - p}$

  $= \dfrac{p - y}{p(1 - p)}$
- $\dfrac{\partial p}{\partial z} = p(1 - p)$
- $\dfrac{\partial z}{\partial w} = x$
- Multiplying the three terms, we get $\dfrac{\partial L}{\partial w} = (p - y)x$

Coming up soon: gradient computation handled automatically

# Training neural network models

- We use *gradient descent*
  - Write down a *loss function*
  - *Calculate gradients* of the loss function with respect to the parameters
  - **Move the parameters in the direction that *reduces the loss function***

# Optimizing Parameters

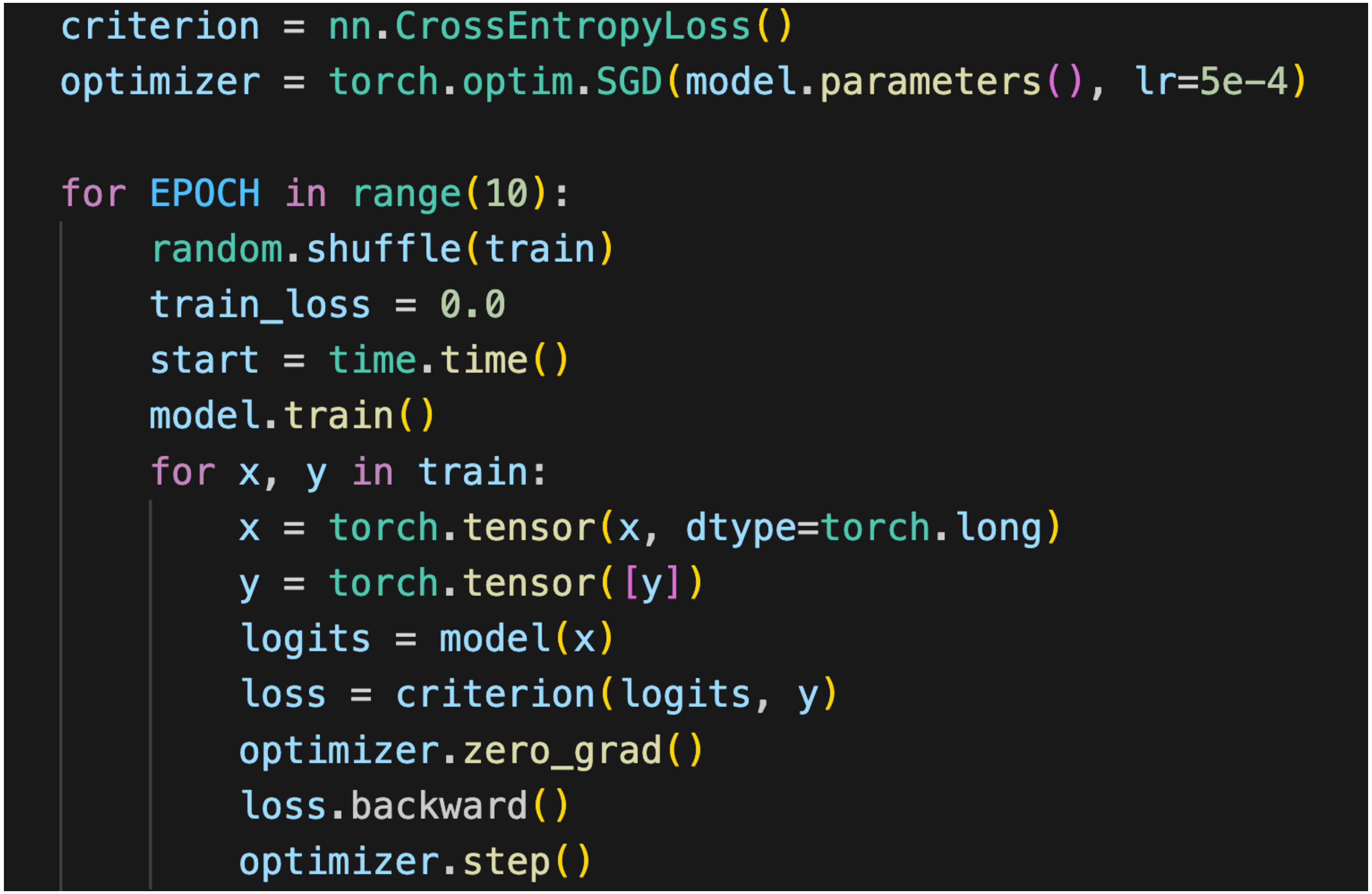
- Standard stochastic gradient descent does

$$g_t = \underbrace{\nabla_{\theta_{t-1}} \ell(\theta_{t-1})}_{\text{Gradient of Loss}}$$

$$\theta_t = \theta_{t-1} - \underbrace{\eta}_{\text{Learning Rate}} g_t$$

- There are many other optimization options! (e.g., see Ruder 2016 in the references.)

# In Code



```python
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=5e-4)

for EPOCH in range(10):
    random.shuffle(train)
    train_loss = 0.0
    start = time.time()
    model.train()
    for x, y in train:
        x = torch.tensor(x, dtype=torch.long)
        y = torch.tensor([y])
        logits = model(x)
        loss = criterion(logits, y)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```

Loss

Optimizer

Compute loss

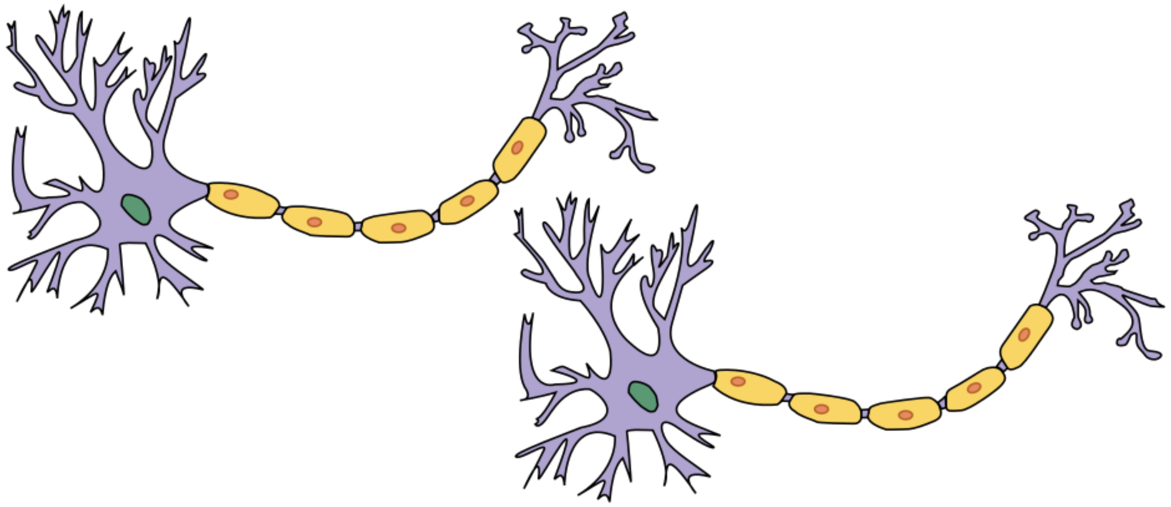
Compute gradients

Update parameters

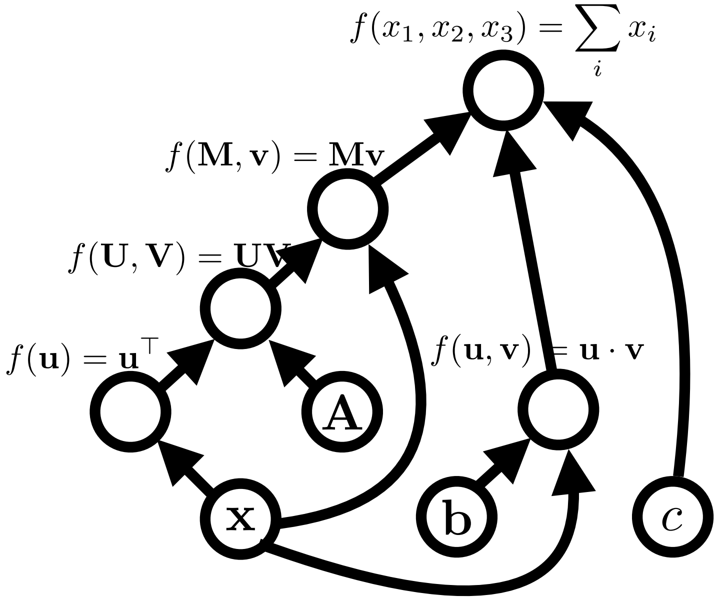
# What is a Neural Net?: Computation Graphs

# “Neural” Nets

## Original Motivation: Neurons in the Brain



## Current Conception: Computation Graphs



$f(x_1, x_2, x_3) = \sum_i x_i$
$f(\mathbf{M}, \mathbf{v}) = \mathbf{M}\mathbf{v}$
$f(\mathbf{U}, \mathbf{V}) = \mathbf{U}\mathbf{V}$
$f(\mathbf{u}) = \mathbf{u}^\top$
$f(\mathbf{u}, \mathbf{v}) = \mathbf{u} \cdot \mathbf{v}$
$\mathbf{A}$
$\mathbf{x}$
$\mathbf{b}$
$c$

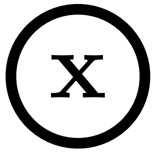
Image credit: Wikipedia

expression:

$\mathbf{x}$

graph:

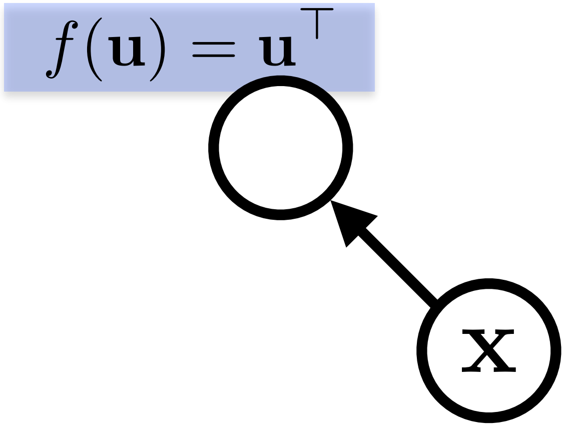
A **node** is a {tensor, matrix, vector, scalar} value



An **edge** represents a function argument. They are just pointers to nodes.

A **node** with an incoming **edge** is a **function** of that edge's tail node.

A **node** knows how to compute its value and the *gradient with respect to each input, here* $\frac{\partial f(\mathbf{u})}{\partial \mathbf{u}}$



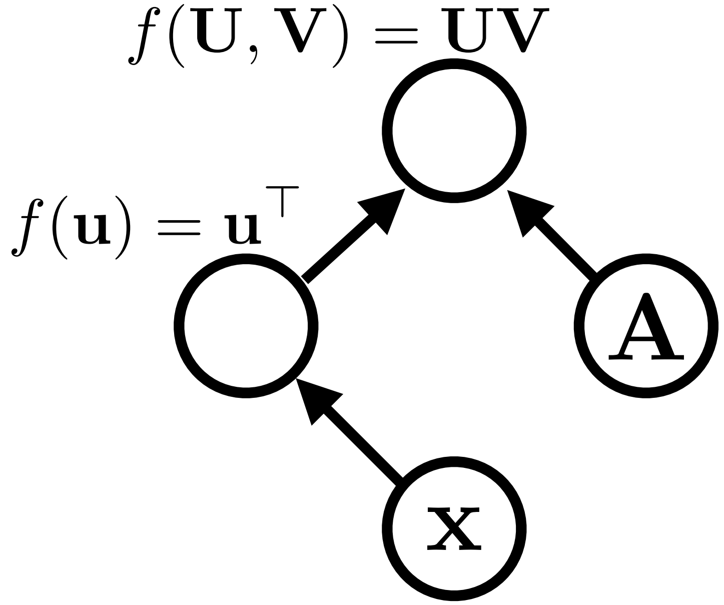
$$\frac{\partial F}{\partial \mathbf{u}} = \underbrace{\frac{\partial F}{\partial f(\mathbf{u})}}_{\text{Incoming gradient}} \underbrace{\frac{\partial f(\mathbf{u})}{\partial \mathbf{u}}}_{\text{Local Gradient}}$$

expression:

$$\mathbf{x}^\top \mathbf{A}$$

graph:

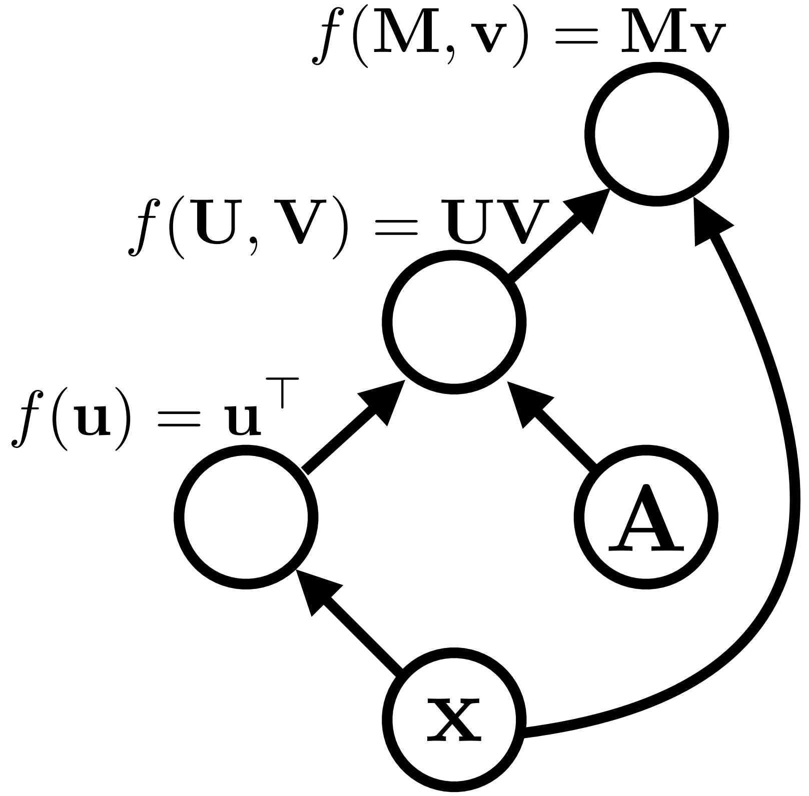
Functions can be nullary, unary, binary, … *n*-ary. Often they are unary or binary.


$f(\mathbf{U}, \mathbf{V}) = \mathbf{U}\mathbf{V}$
$f(\mathbf{u}) = \mathbf{u}^\top$
$\mathbf{A}$
$\mathbf{x}$

expression:

$$\mathbf{x}^\top \mathbf{A} \mathbf{x}$$

graph: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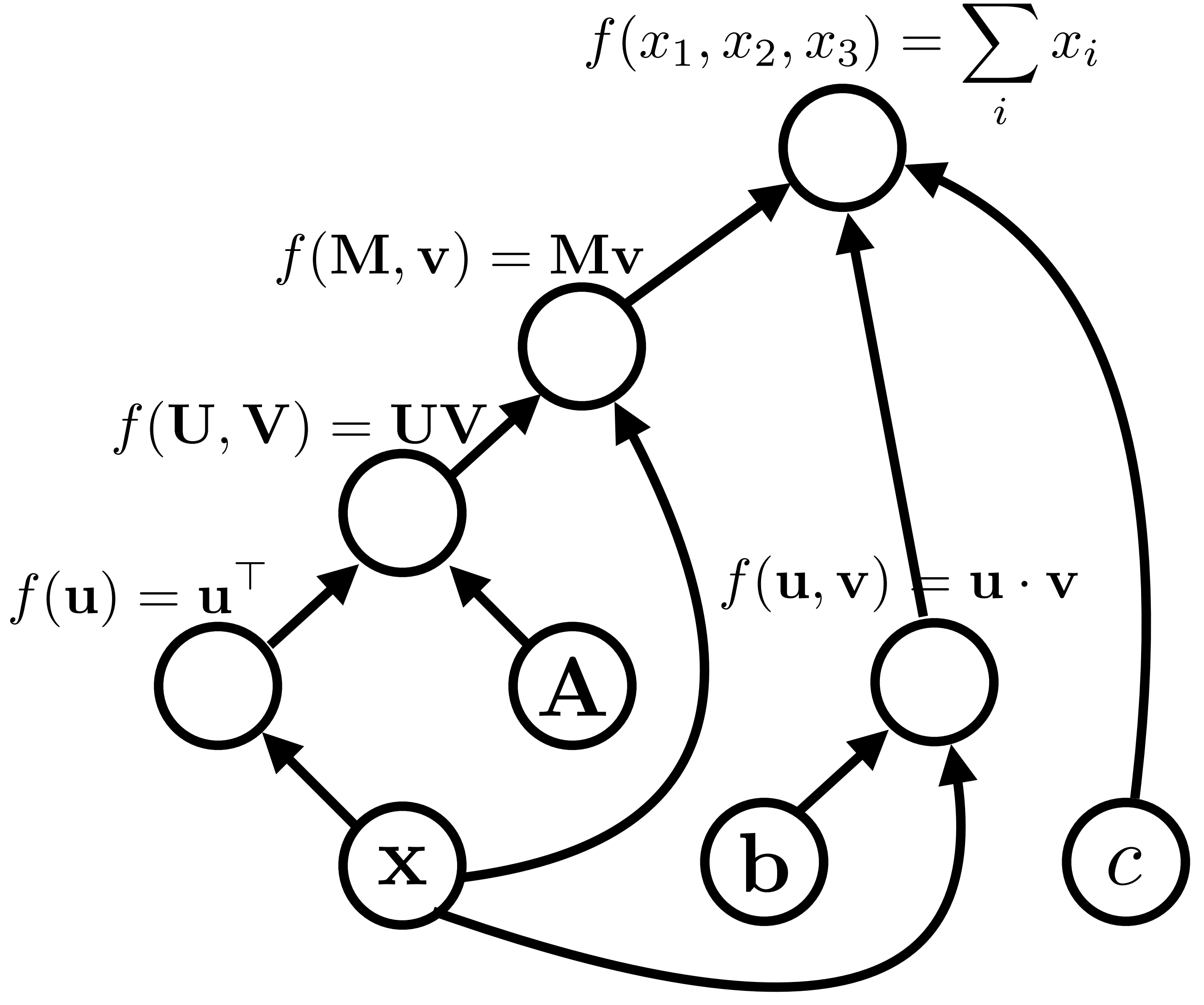
$f(\mathbf{u}) = \mathbf{u}^\top$
$\mathbf{A}$
$\mathbf{x}$

Computation graphs are directed and acyclic (in DyNet)

expression:

$$\mathbf{x}^\top \mathbf{A}\mathbf{x} + \mathbf{b}\cdot\mathbf{x} + c$$

graph: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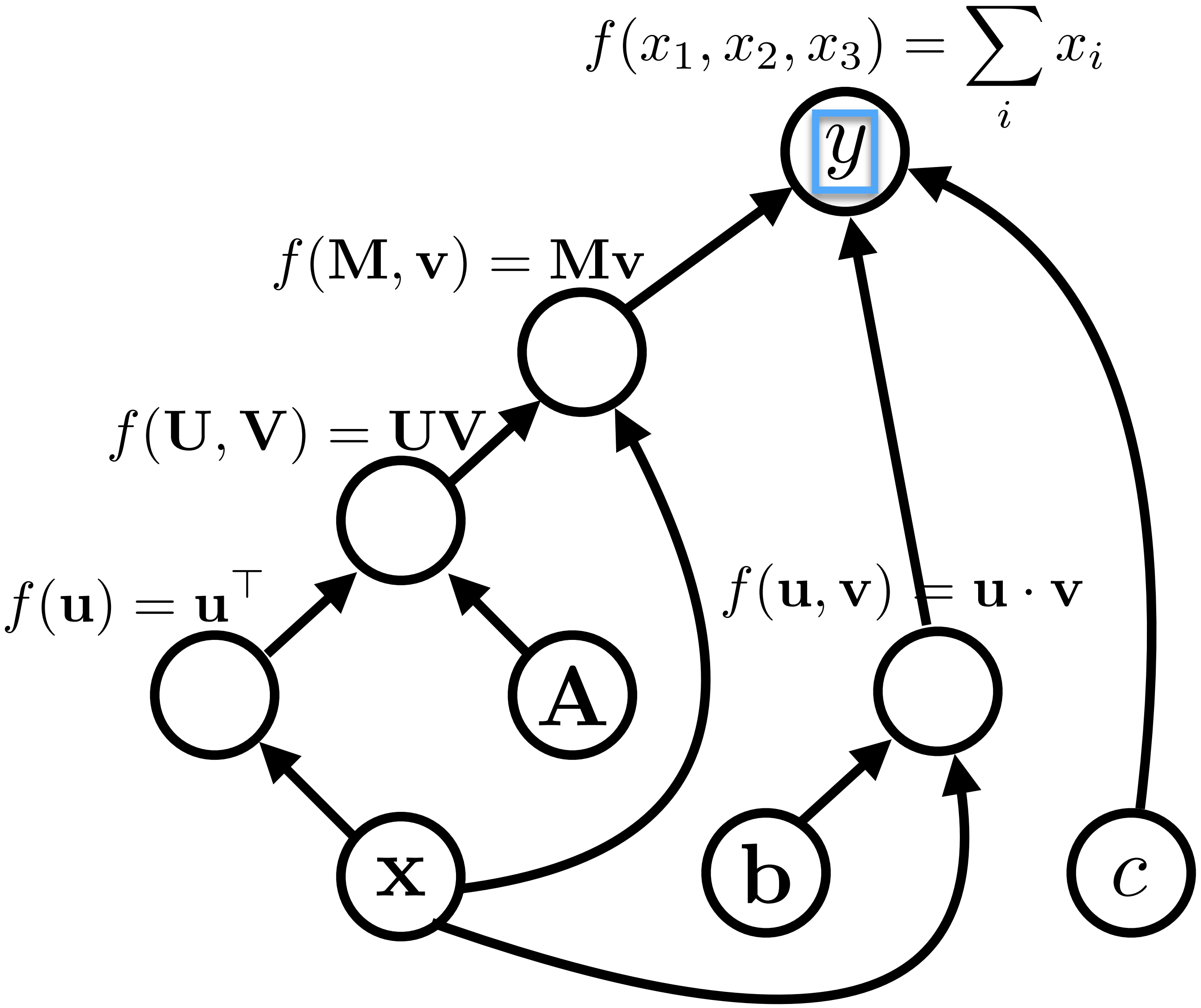
$f(\mathbf{u}, \mathbf{v}) = \mathbf{u}\cdot\mathbf{v}$
$\mathbf{A}$
$\mathbf{x}$
$\mathbf{b}$
$c$

expression:

$$\boxed{y =} \mathbf{x}^\top \mathbf{A}\mathbf{x} + \mathbf{b} \cdot \mathbf{x} + c$$

graph: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$\boxed{y}$
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$f(\mathbf{u}) = \mathbf{u}^\top$
$\mathbf{A}$
$f(\mathbf{u}, \mathbf{v}) = \mathbf{u} \cdot \mathbf{v}$
$\mathbf{x}$
$\mathbf{b}$
$c$

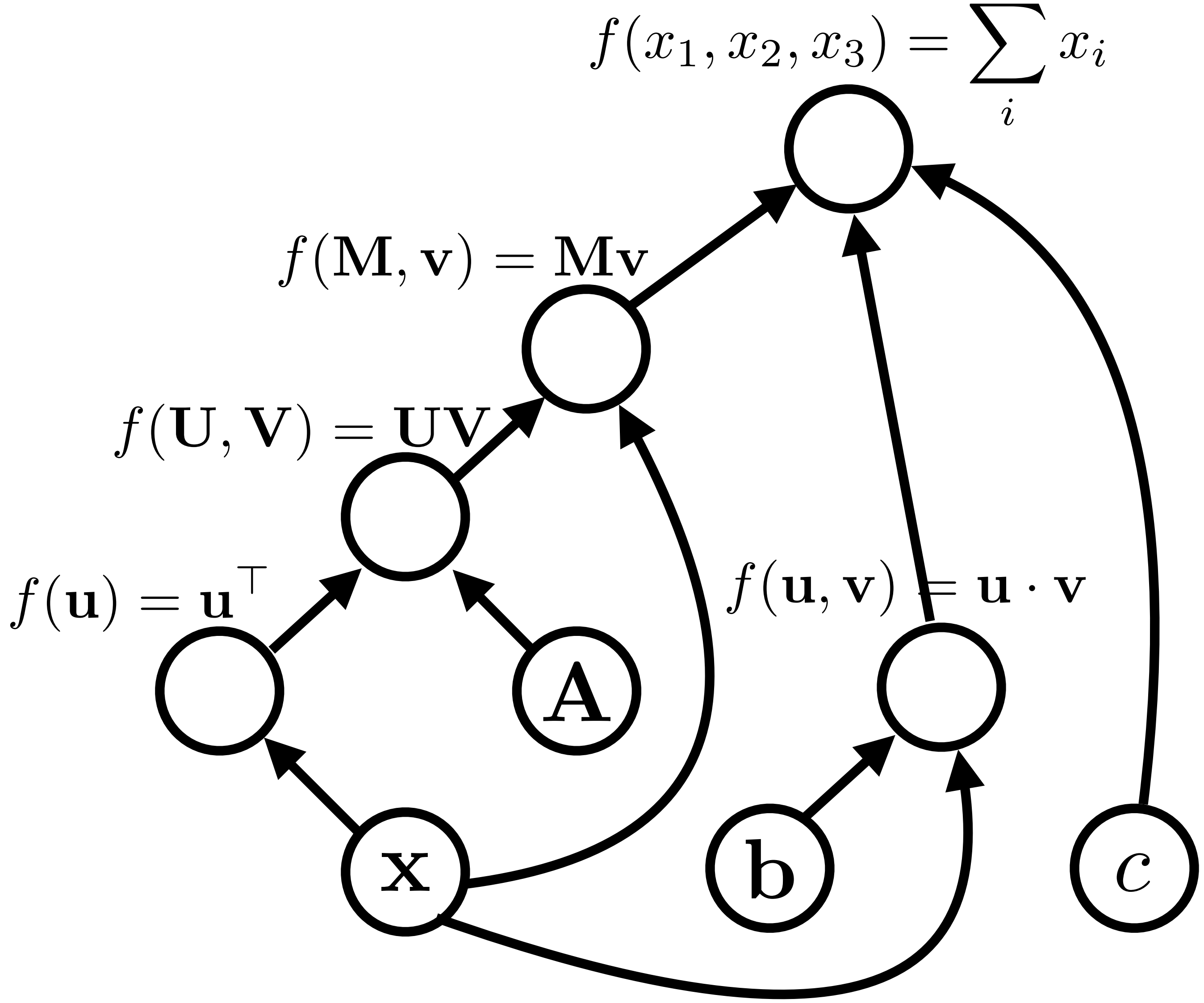
variable names are just labelings of nodes.

# Algorithms (1)

- **Graph construction**
- **Forward propagation**
  - In topological order, compute the **value** of the node given its inputs

# Forward Propagation

graph:



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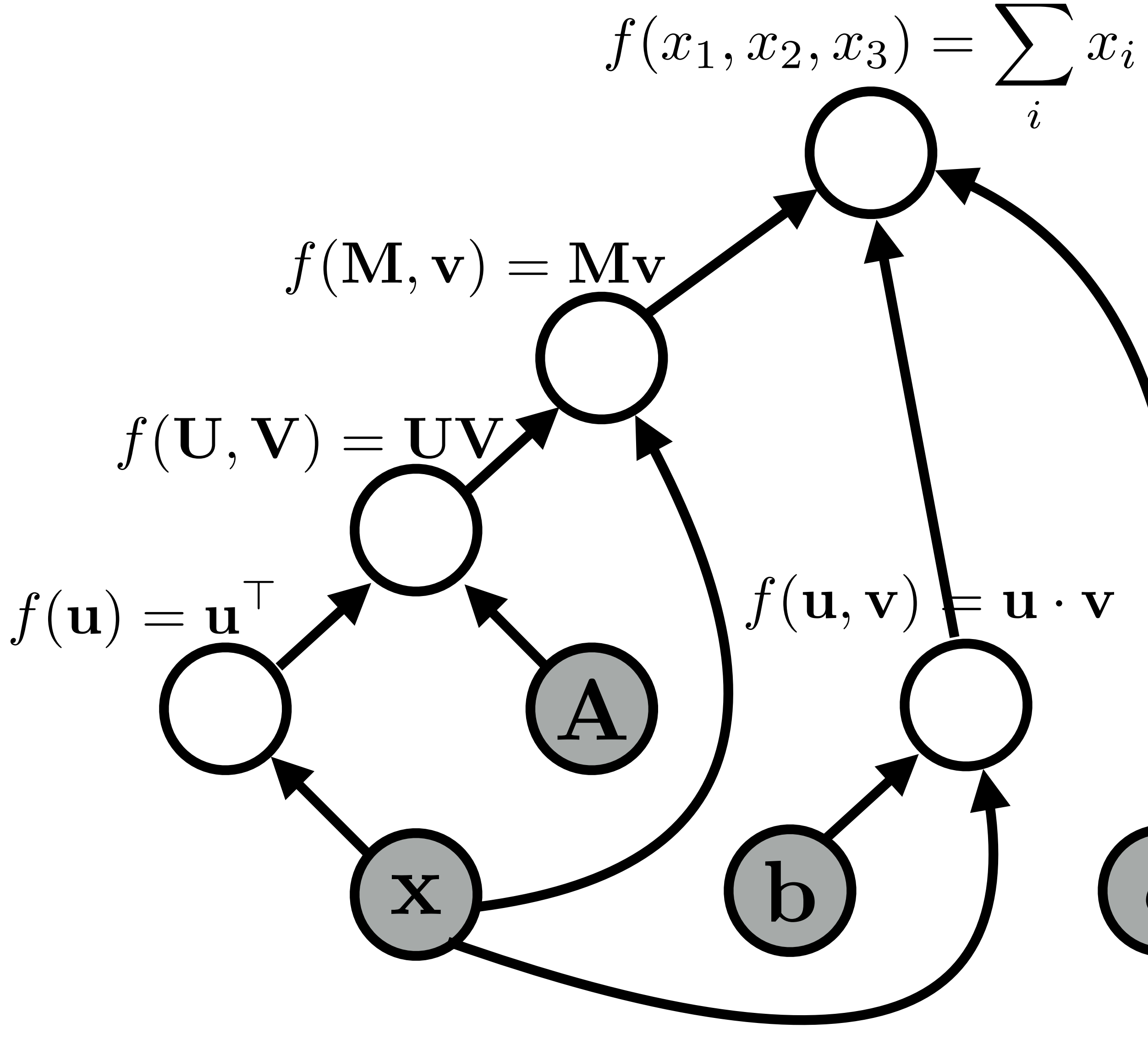
$\mathbf{x}$
$\mathbf{b}$
$c$

# Forward Propagation

graph: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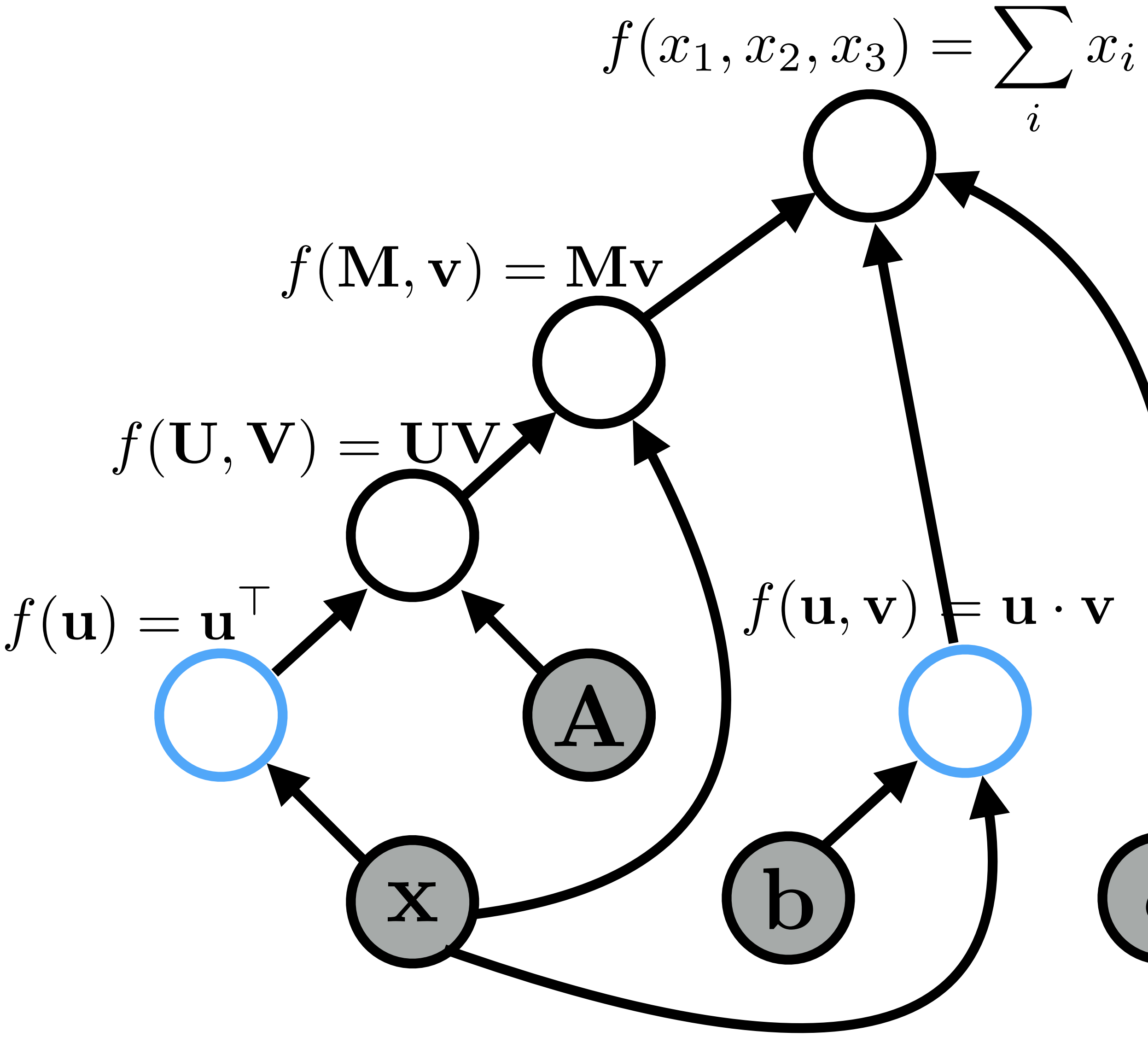
$\mathbf{A}$
$\mathbf{x}$
$\mathbf{b}$
$c$

# Forward Propagation

graph: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$\mathbf{x}$
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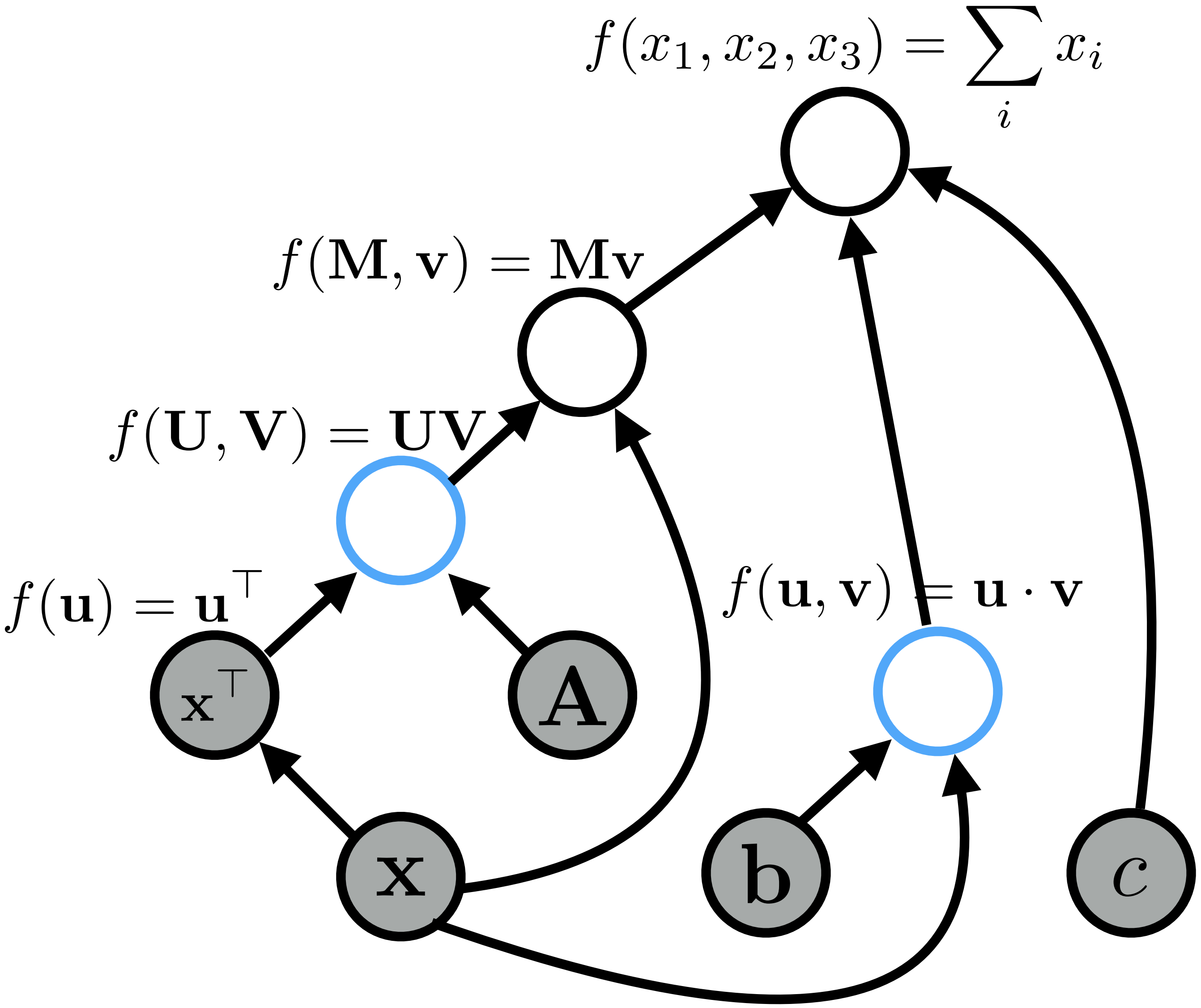
# Forward Propagation

graph: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$\mathbf{A}$
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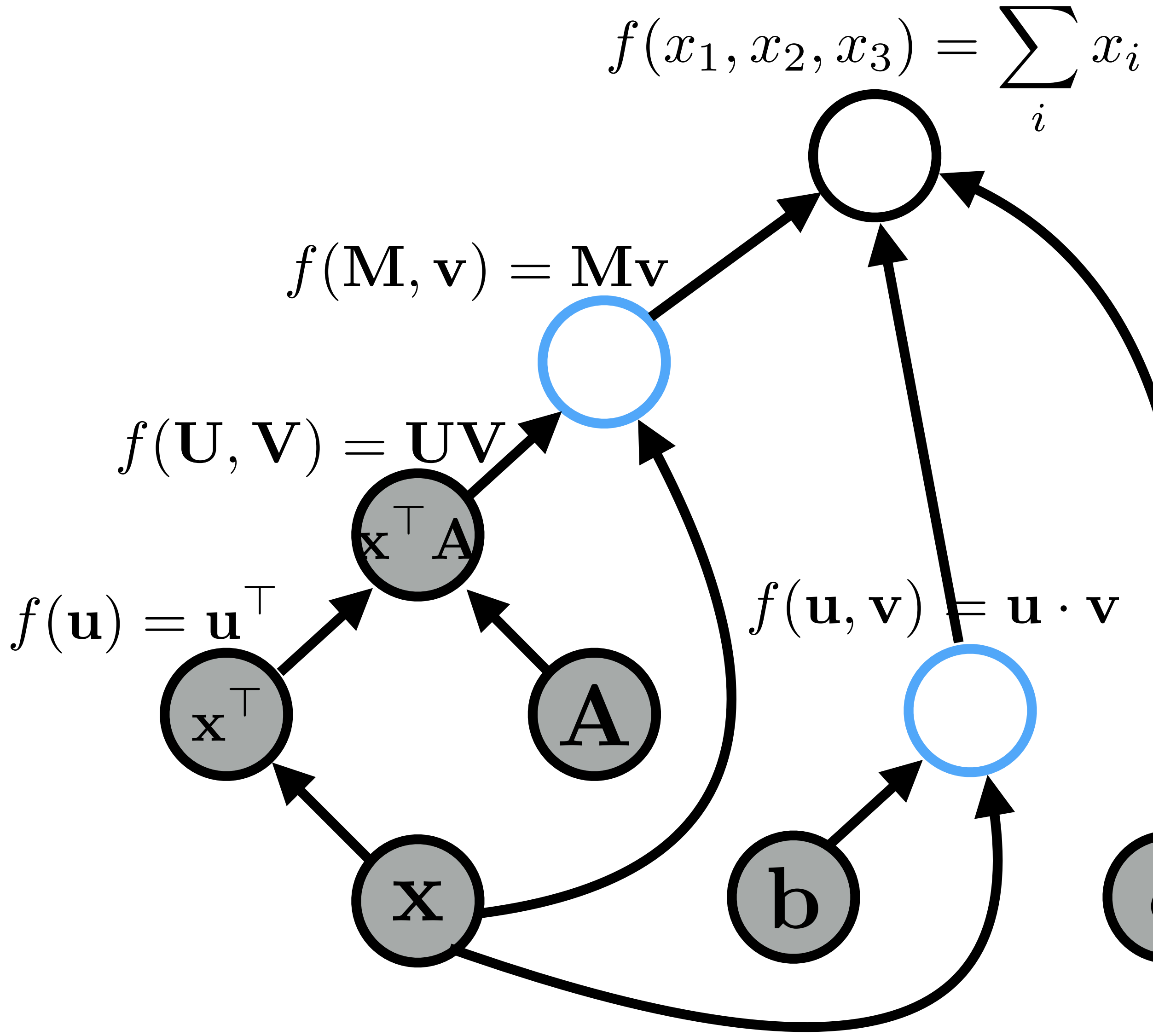
$\mathbf{b}$
$c$

# Forward Propagation

graph: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$\mathbf{x}^\top$
$\mathbf{A}$
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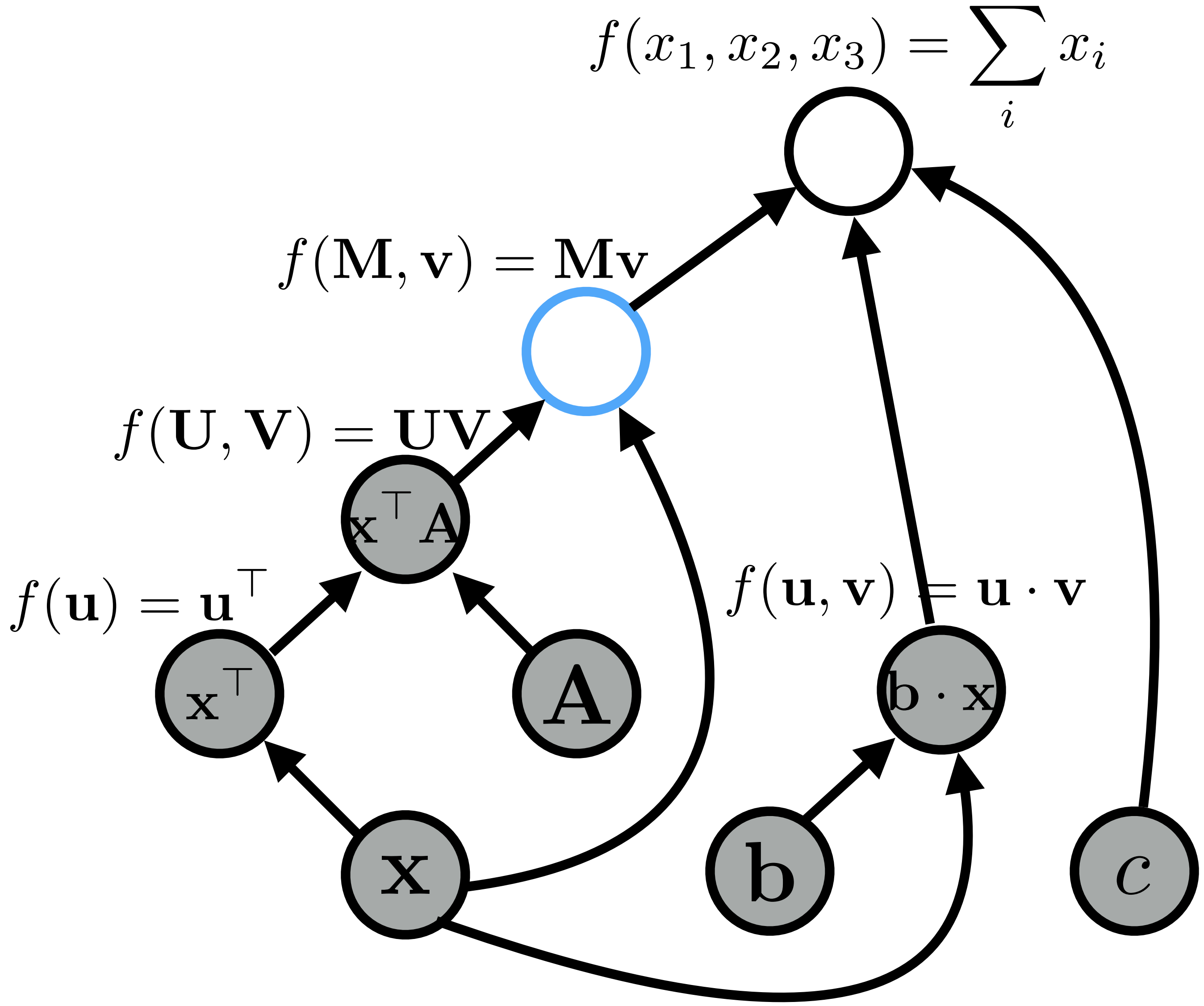
$\mathbf{x}$
$\mathbf{b}$
$c$

# Forward Propagation

graph: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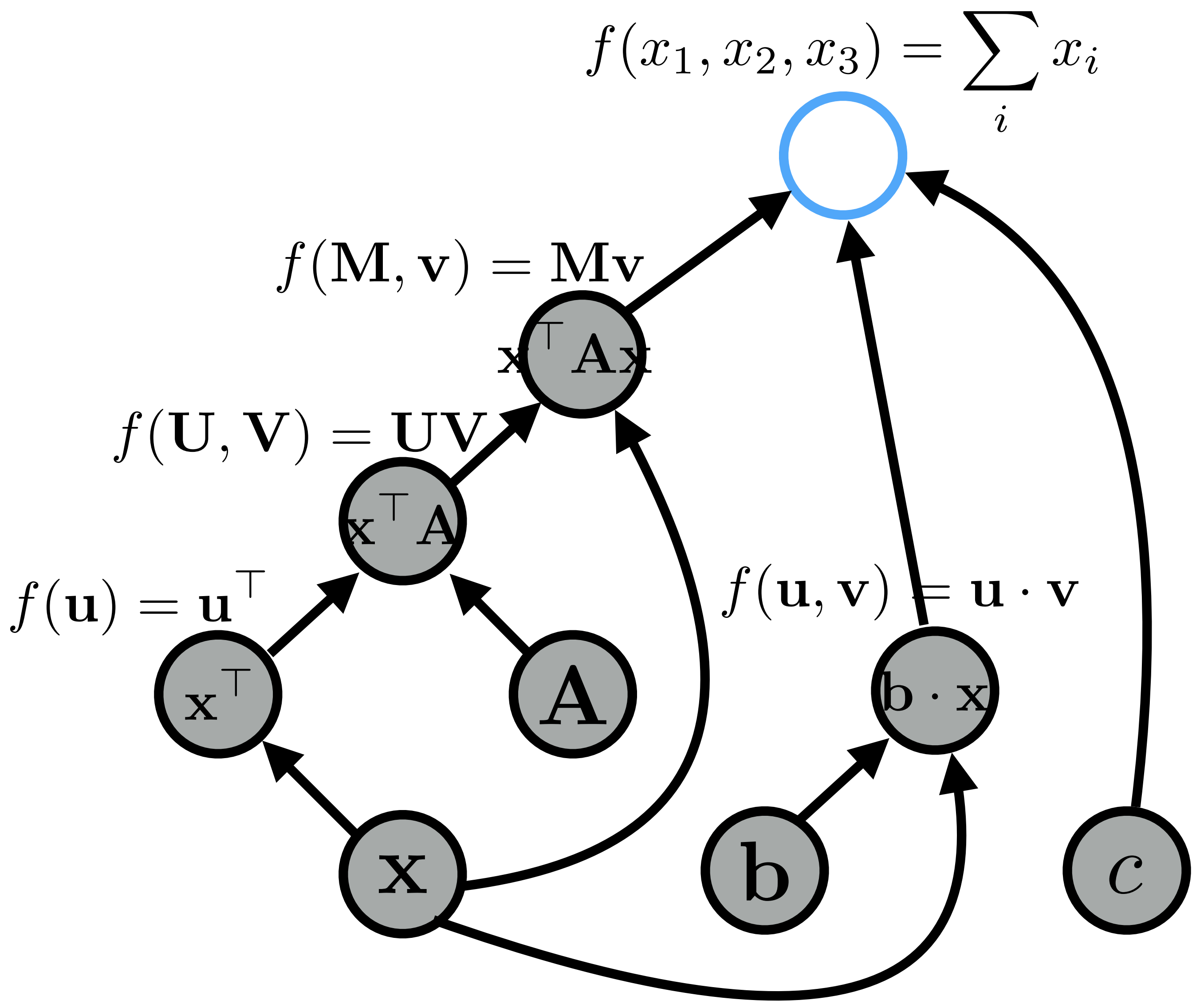
$\mathbf{x}^\top$
$\mathbf{A}$
$\mathbf{b} \cdot \mathbf{x}$
$\mathbf{x}$
$\mathbf{b}$
$c$

# Forward Propagation

graph: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$\mathbf{A}$
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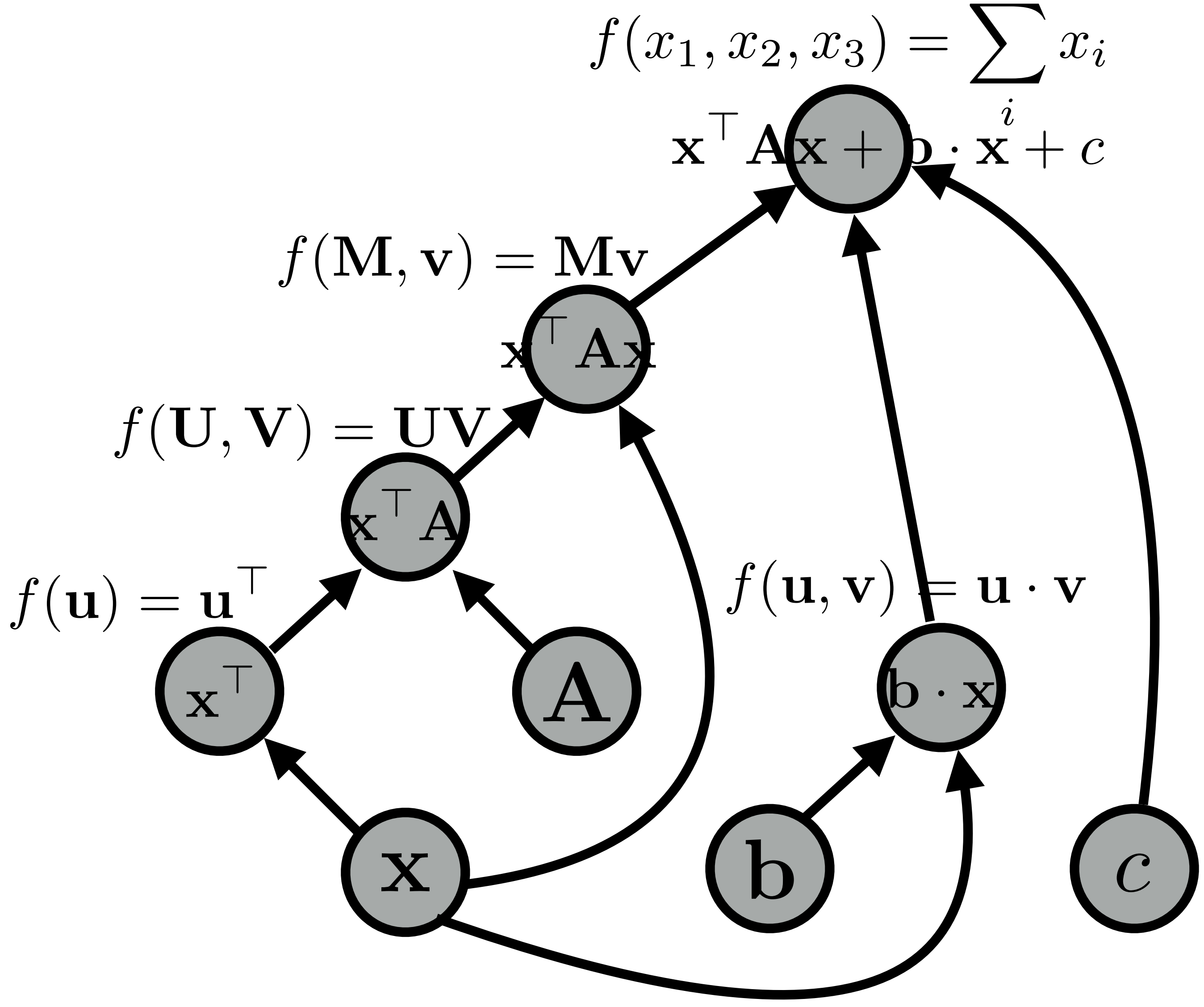
$\mathbf{b} \cdot \mathbf{x}$
$\mathbf{x}$
$\mathbf{b}$
$c$

# Forward Propagation

graph: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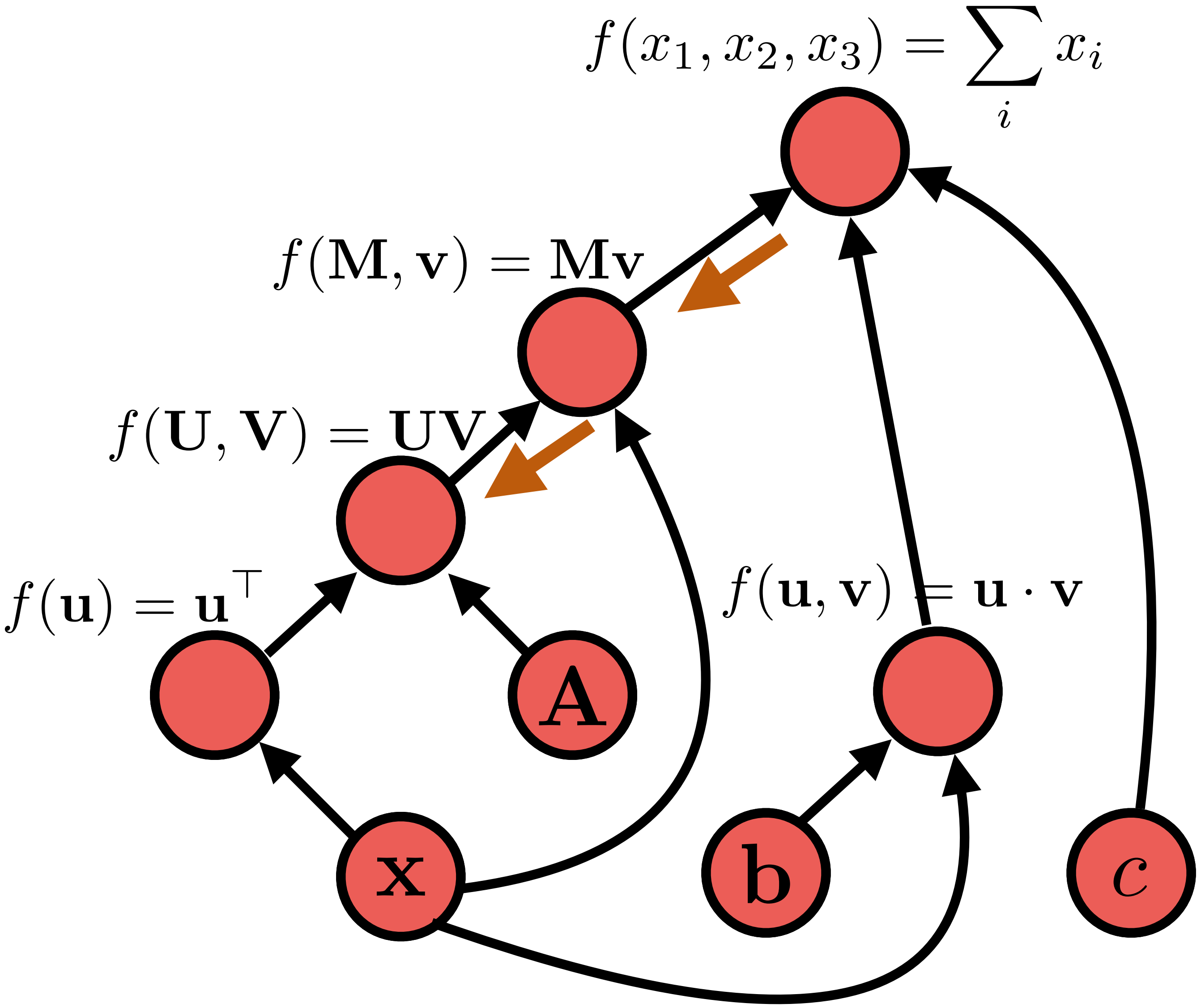
$\mathbf{x}^\top$
$\mathbf{A}$
$\mathbf{b}\cdot\mathbf{x}$
$\mathbf{x}$
$\mathbf{b}$
$c$

# Algorithms (2)

- **Back-propagation:**
  - Process examples in reverse topological order
  - Calculate the gradients of the parameters with respect to the final value (usually a loss function)
- **Parameter update:**
  - Move the parameters in the direction of this gradient
    W -= α * dl/dW

# Back Propagation

graph: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$f(\mathbf{u}, \mathbf{v}) = \mathbf{u} \cdot \mathbf{v}$
$\mathbf{A}$
$\mathbf{x}$
$\mathbf{b}$
$c$

$$\frac{\partial L}{\partial \text{output}} \frac{\partial \text{output}}{\partial \text{input}}$$

# Basic Process in Neural Network Frameworks

- Create a model
- For each example
  - **create a graph** that represents the computation you want
  - **calculate the result** of that computation
  - if training, perform **back propagation and update**

# Concrete Implementation

# Neural Network Frameworks

PYTORCH

Developed by FAIR/Meta

Most widely used in NLP

Favors dynamic execution

More flexibility

Most vibrant ecosystem

TensorFlow

JAX

Developed by Google

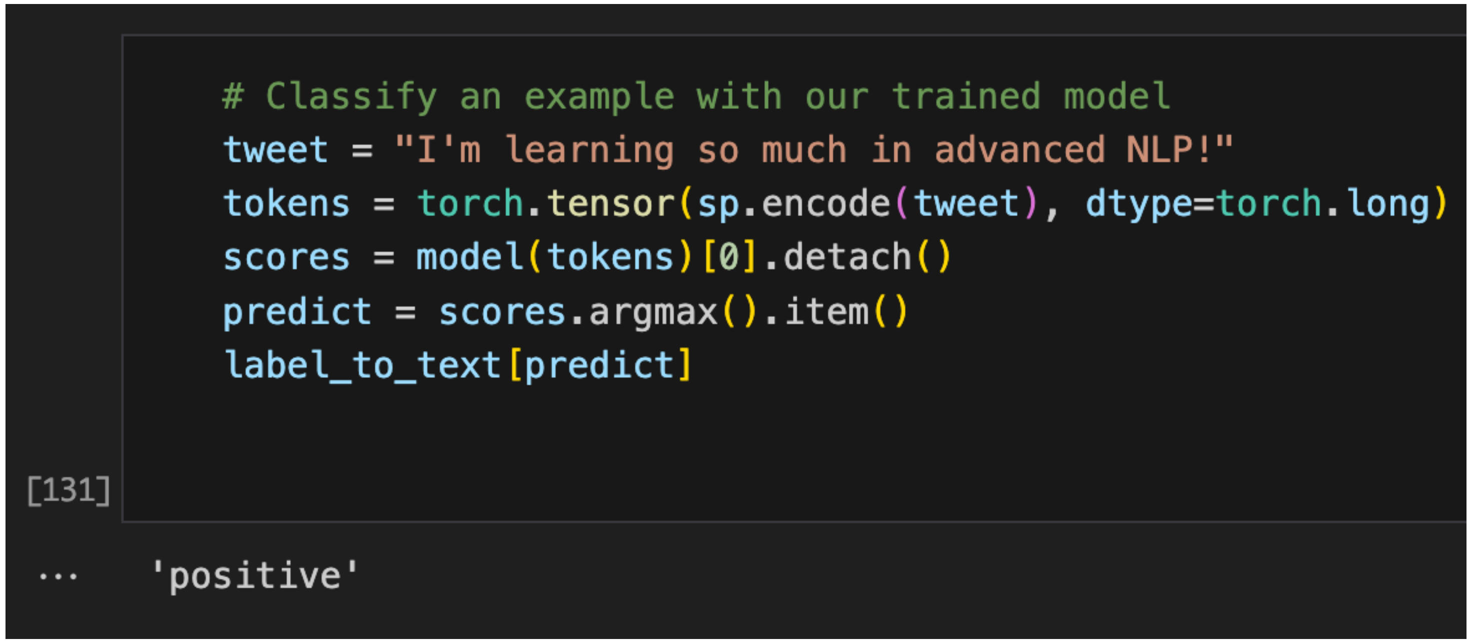
Used in some NLP projects

Favors definition+compilation

Conceptually simple parallelization

# Code Example

- Classify tweets as positive, negative, or neutral
- BoW, CBoW, DeepCBoW



```
# Classify an example with our trained model
tweet = "I'm learning so much in advanced NLP!"
tokens = torch.tensor(sp.encode(tweet), dtype=torch.long)
scores = model(tokens)[0].detach()
predict = scores.argmax().item()
label_to_text[predict]
```

```
[131]
```

```
...   'positive'
```

https://github.com/cmu-l3/anlp-spring2025-code/blob/main/02_wordrep_classification/bow.ipynb

# Recap

- Tokenization and subword models
  - Represent sequences as tokens determined based on frequency
- Token embeddings
  - Represent tokens as learned continuous vectors in $\mathbb{R}^d$
- Neural networks
  - Learn complex, non-linear feature functions
- Training a neural network
  - Choose a loss, construct a differentiable graph, take gradients

# Any Questions?

(sequence models in next class)