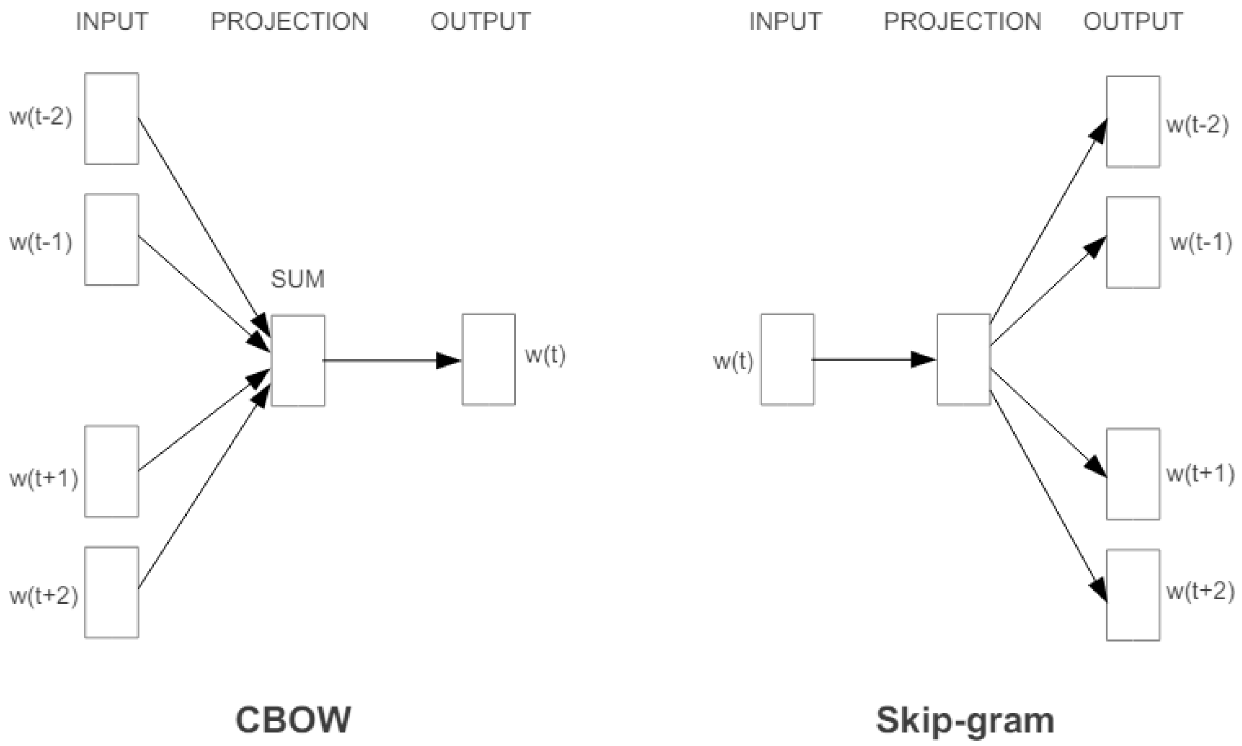
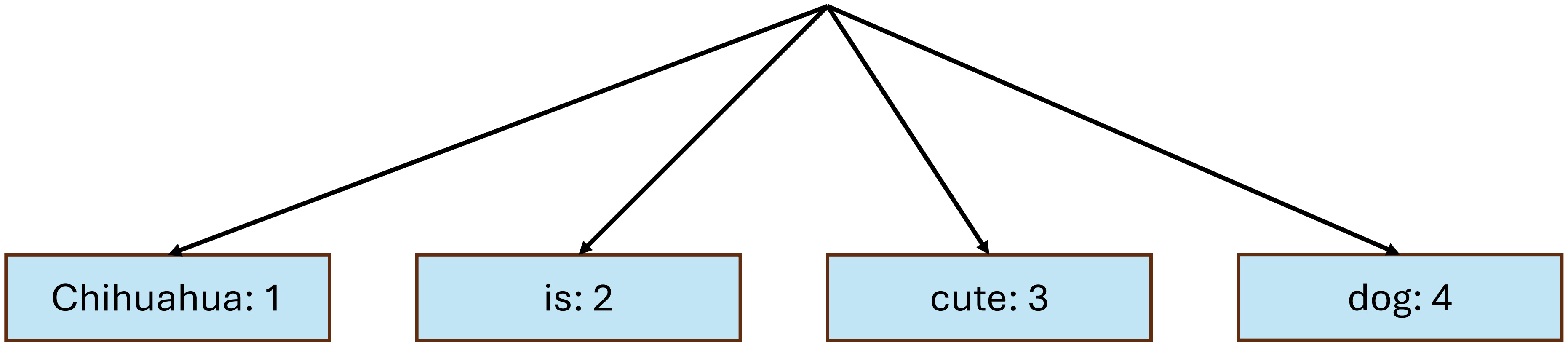
Word Embedding + Word2Vec



Chihuahua is cute dog.



This is called **tokenizer!!!**

How to change the word to vector ???

Just using word **embedding!!!**

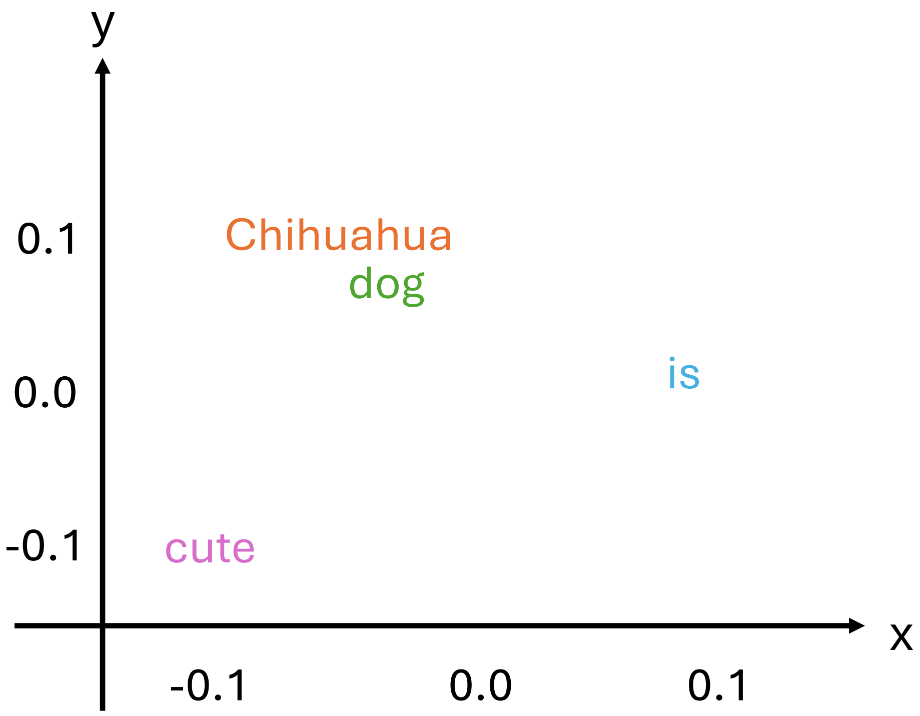
We’re going to do something called Word2Vec

Vocabulary

- Chihuahua
- is
- cute
- dog

Vectors

features	Chihuahua	is	cute	dog
x	-0.08	0.1	-0.1	-0.09
y	0.1	0.02	-0.1	0.09



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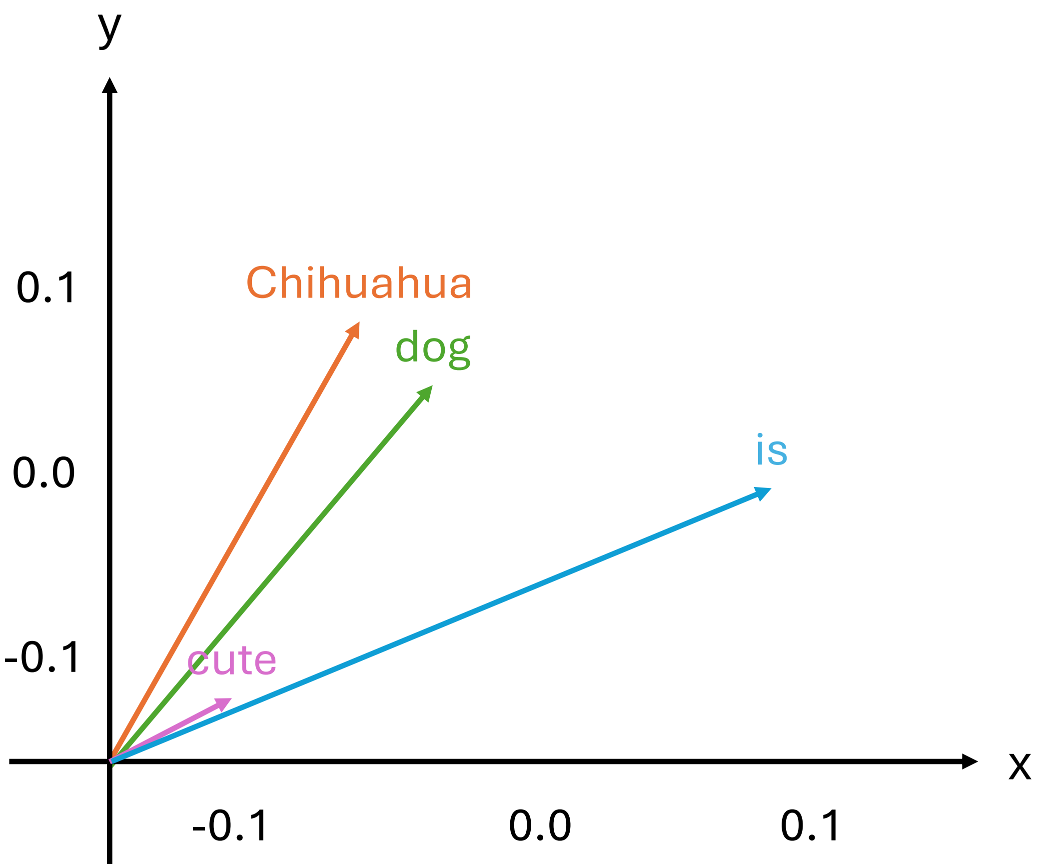

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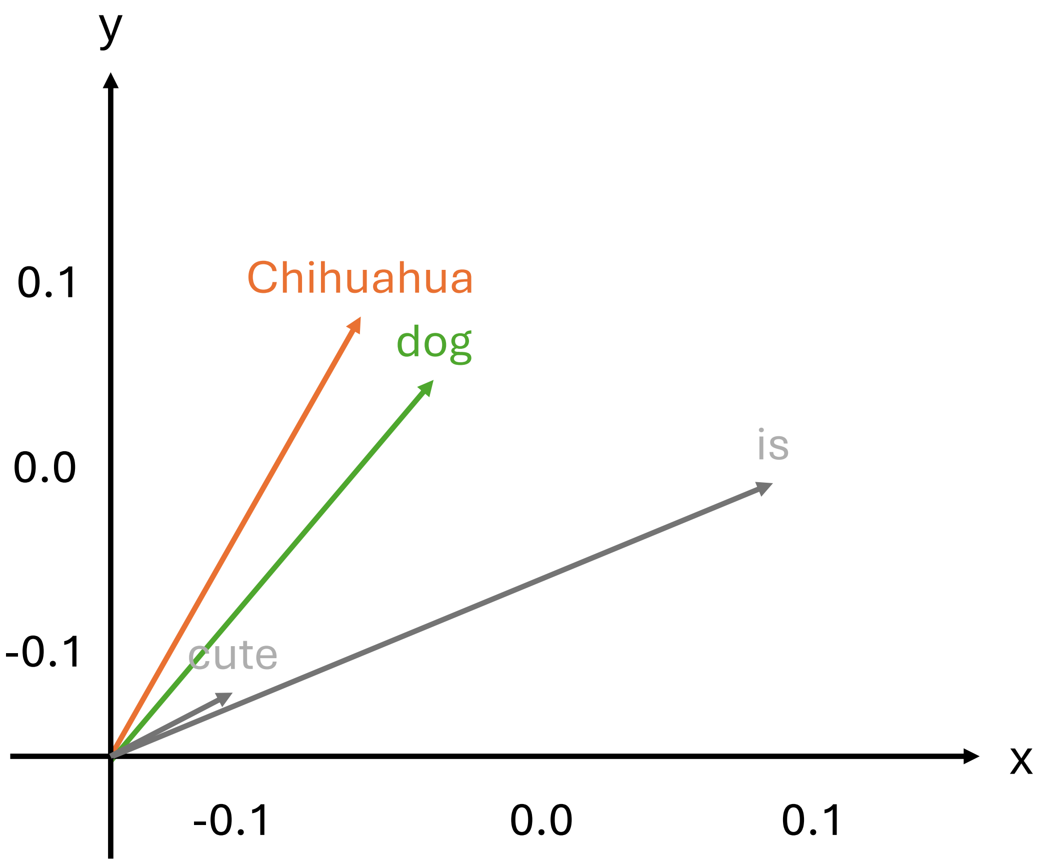
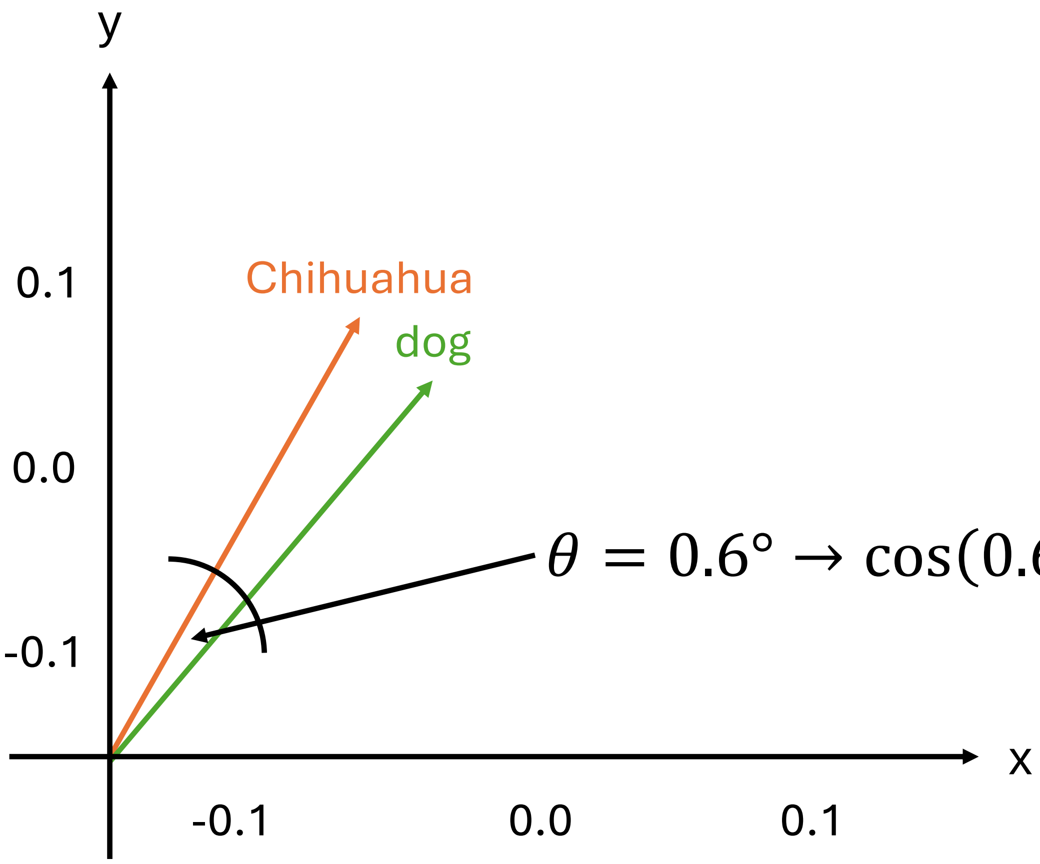


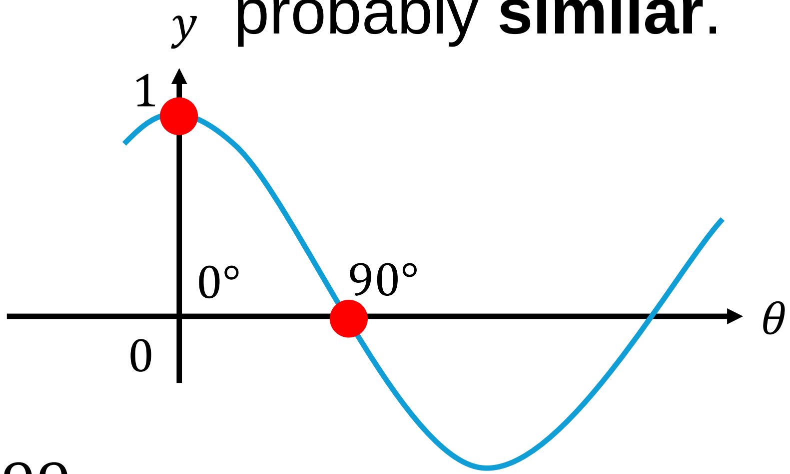
How can we determine whether words are similar or not?

Apply Cosine Similarity

If the θ is **closer to** $0°$, then it's probably **similar**.



$$\theta = 0.6° \rightarrow \cos(0.6°) = 0.99$$



What if our vocabulary is too huge and the dimension is more than 2D, How to calculate this ???

$$Cosine\ Similarity = \frac{\sum_{i=1}^{n} A_i \cdot B_i}{\sqrt{\sum_{i=1}^{n} {A_i}^2} \cdot \sqrt{\sum_{i=1}^{n} {B_i}^2}}$$

$i \longrightarrow$

features	Chihuahua	dog
x	-0.08	-0.09
y	0.1	0.09
	A	B

$$\boldsymbol{Cosine\ Similarity} = \frac{\sum_{i=1}^{n} A_i \cdot B_i}{\sqrt{\sum_{i=1}^{n} {A_i}^2} \cdot \sqrt{\sum_{i=1}^{n} {B_i}^2}}$$

$$\frac{\sum_{i=1}^{n} A_i \cdot B_i}{\sqrt{\sum_{i=1}^{n} {A_i}^2} \cdot \sqrt{\sum_{i=1}^{n} {B_i}^2}} = \frac{(-0.08 \cdot -0.09) + (0.1 \cdot 0.09)}{\sqrt{(-0.08)^2 + (0.1)^2} \cdot \sqrt{(-0.09)^2 + (0.09)^2}}$$

$$\frac{\sum_{i=1}^{n} A_i \cdot B_i}{\sqrt{\sum_{i=1}^{n} {A_i}^2} \cdot \sqrt{\sum_{i=1}^{n} {B_i}^2}} = 0.99 \rightarrow \textit{This is the same value as } \mathbf{cos(0.6°)}$$

features	Chihuahua	is	cute	dog
x	-0.08	0.1	-0.1	-0.09
y	0.1	0.02	-0.1	0.09

But, how to get all these value ???

features	Chihuahua	is	cute	dog
Chihuahua	-0.08	0.1	-0.1	-0.09
Is	0.1	0.02	-0.1	0.09
cute	...	...	...	...
dog	...	...	...	...

Just apply the DEEP LEARNING

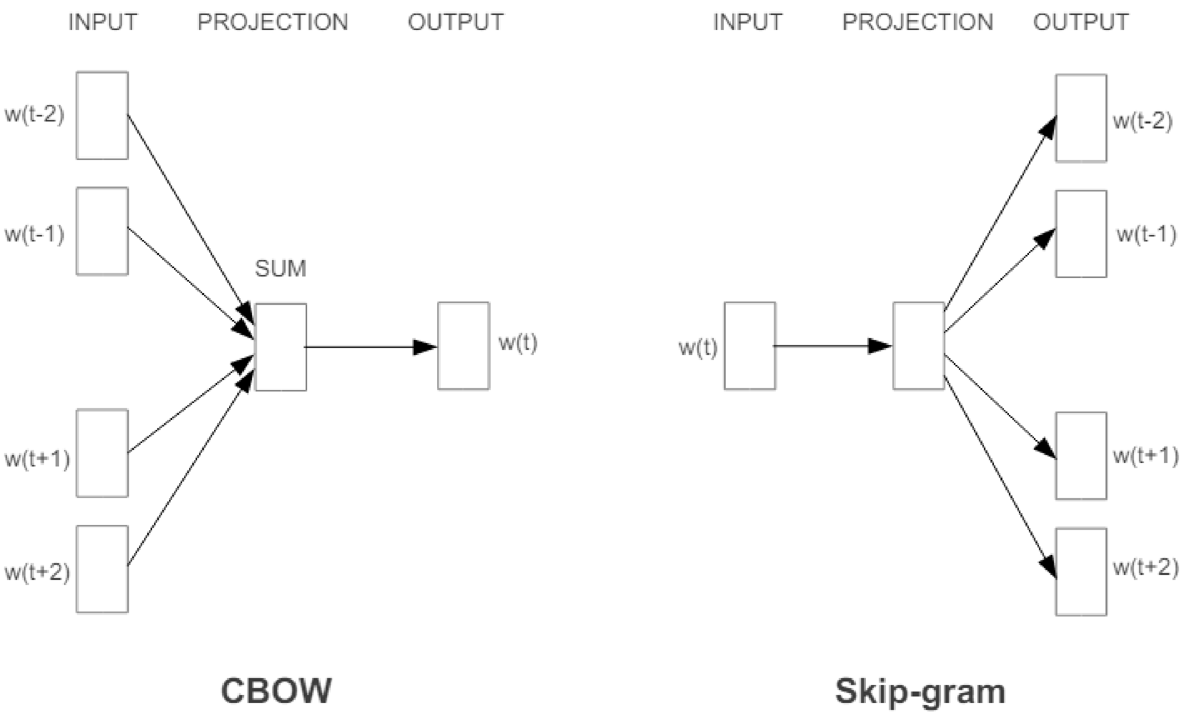
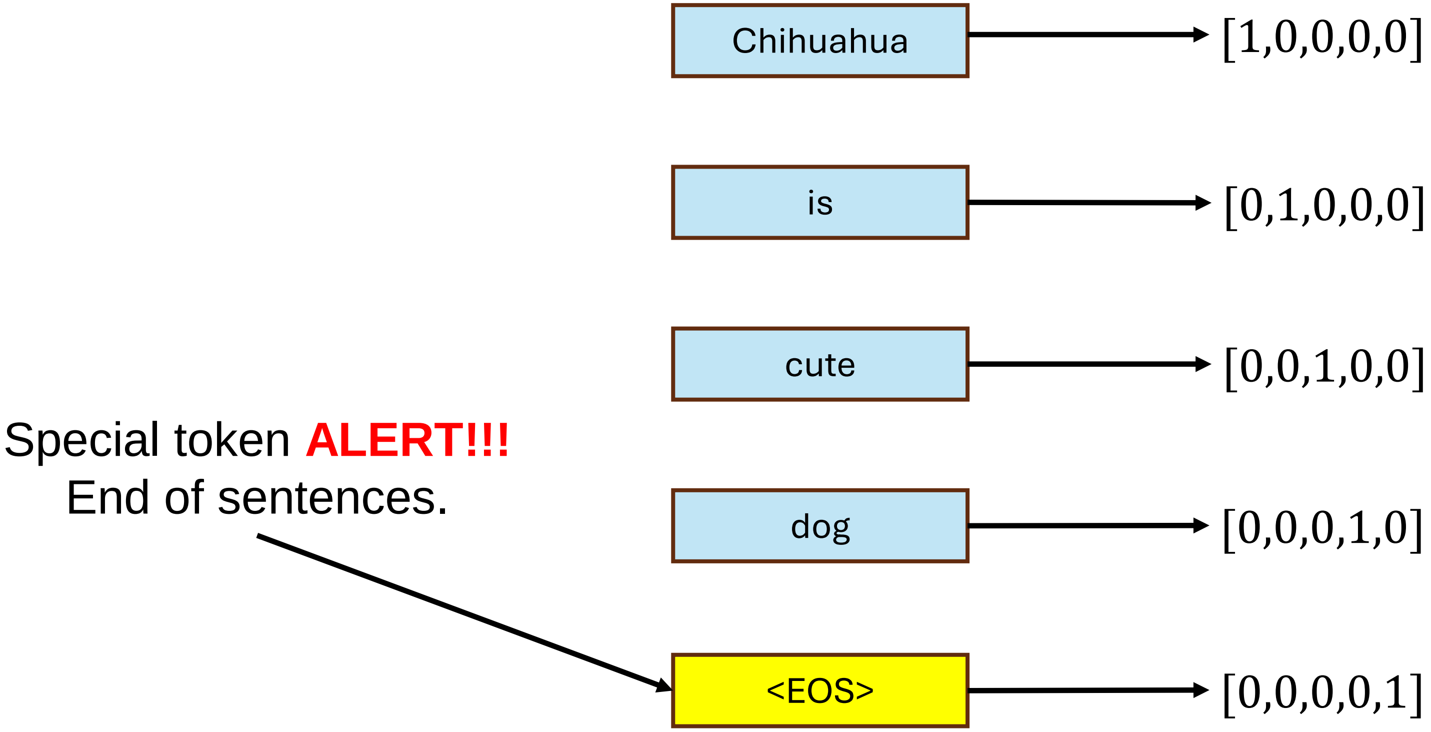
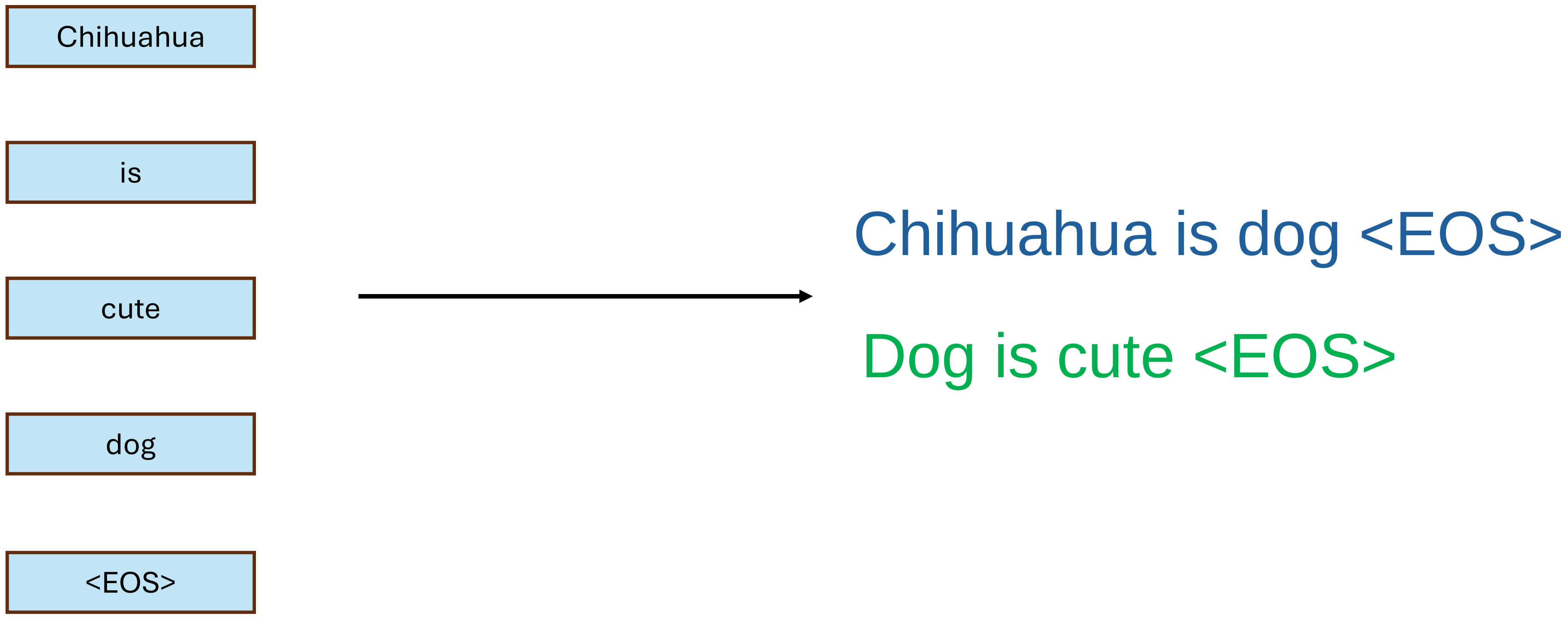


Figure 1: New model architectures. The CBOW architecture predicts the current word based on the context, and the Skip-gram predicts surrounding words given the current word.

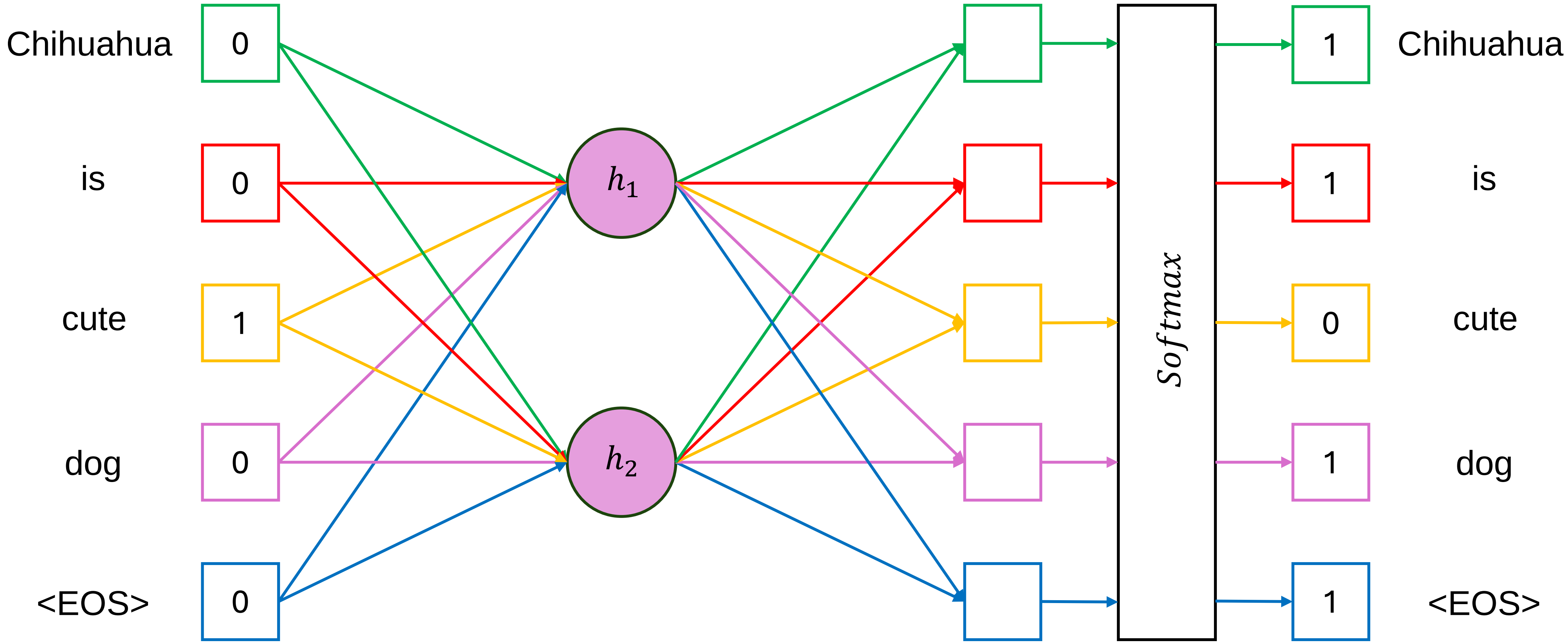
R words from the future of the current word as correct labels. This will require us to do $R \times 2$ word classifications, with the current word as input, and each of the $R + R$ words as output. In the following experiments, we use $C = 10$.

One-Hot encode!!!

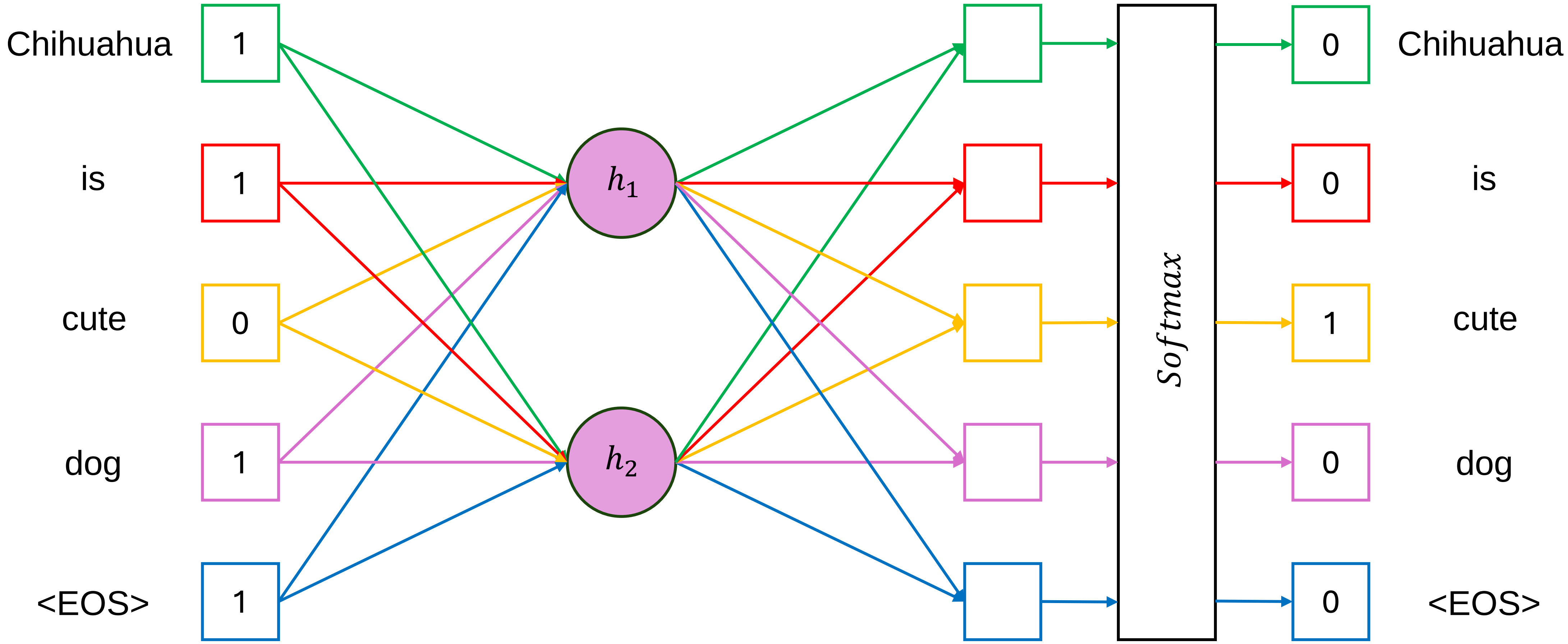



Chihuahua
is
cute
dog
<EOS>
Chihuahua is dog <EOS>
Dog is cute <EOS>

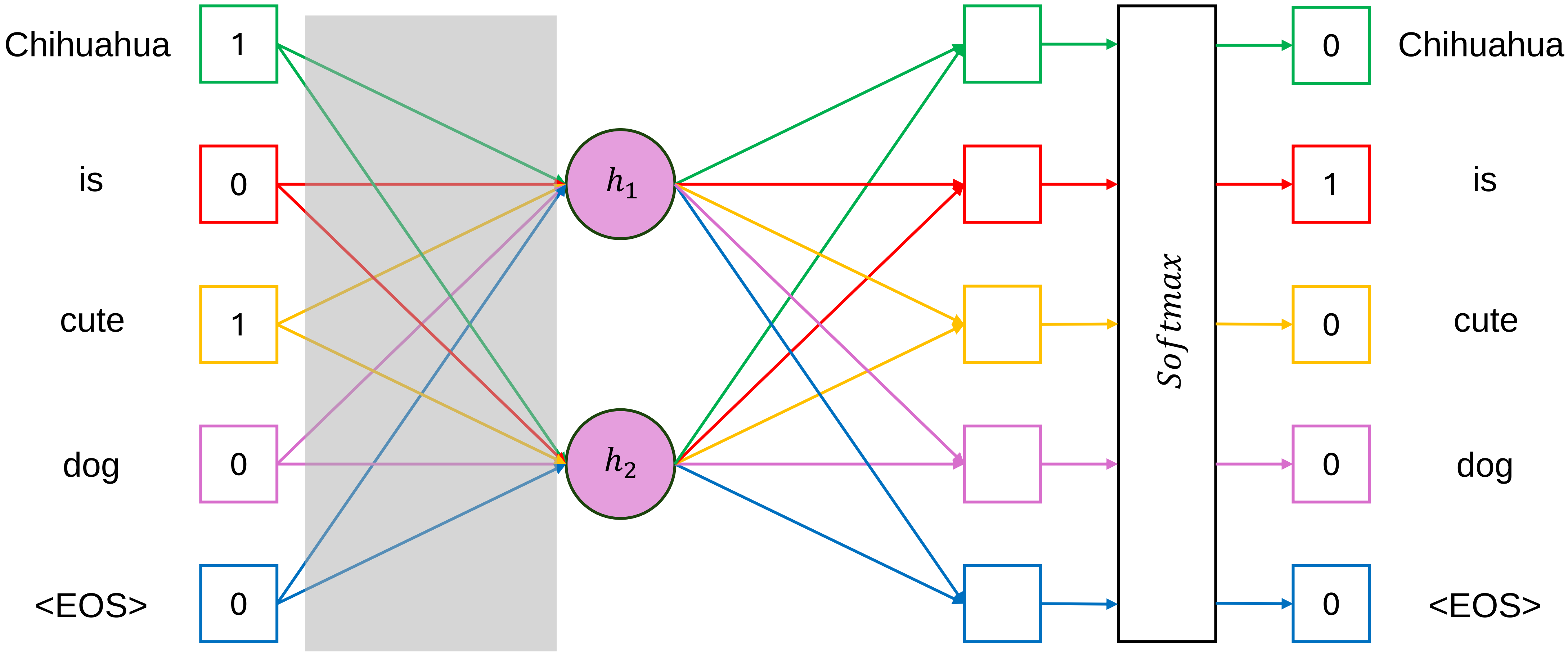
CBOW (Continuous bag of words)



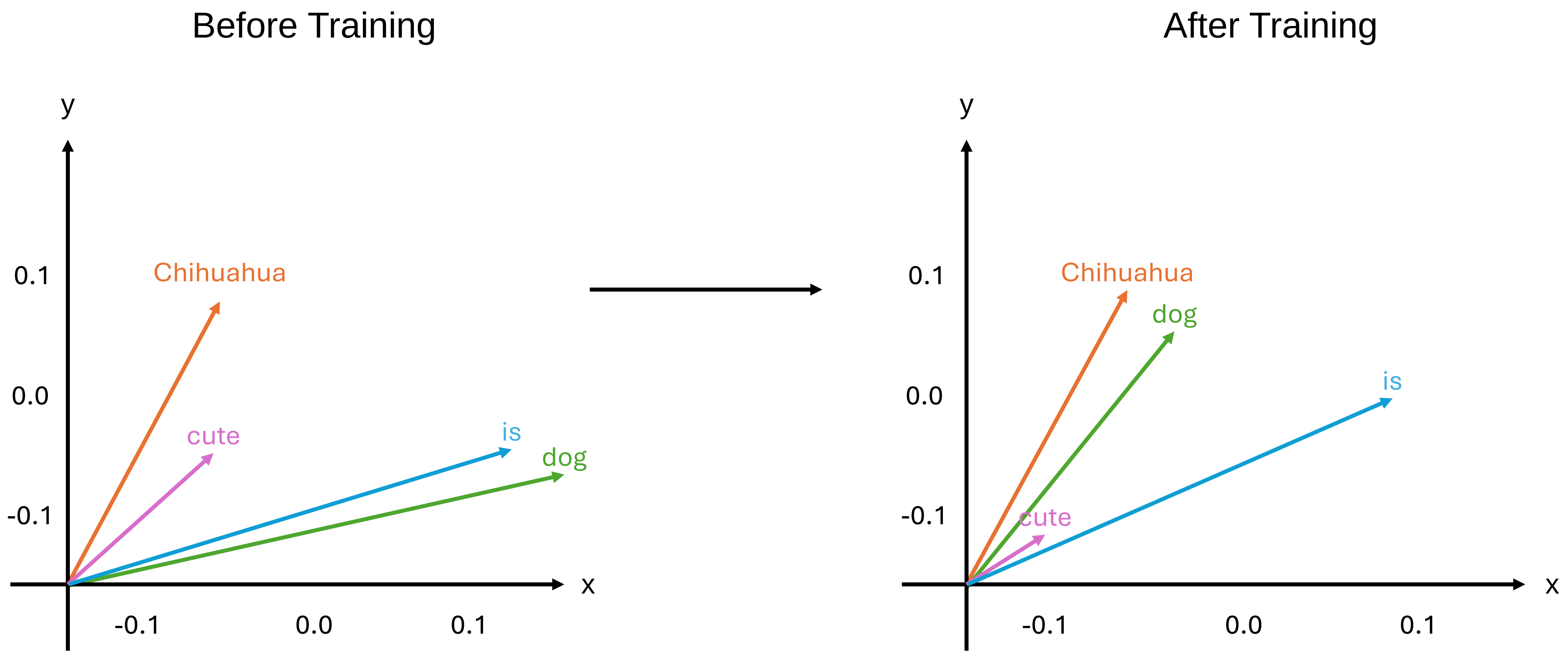
SKIP-GRAM (Continuous skip grams)

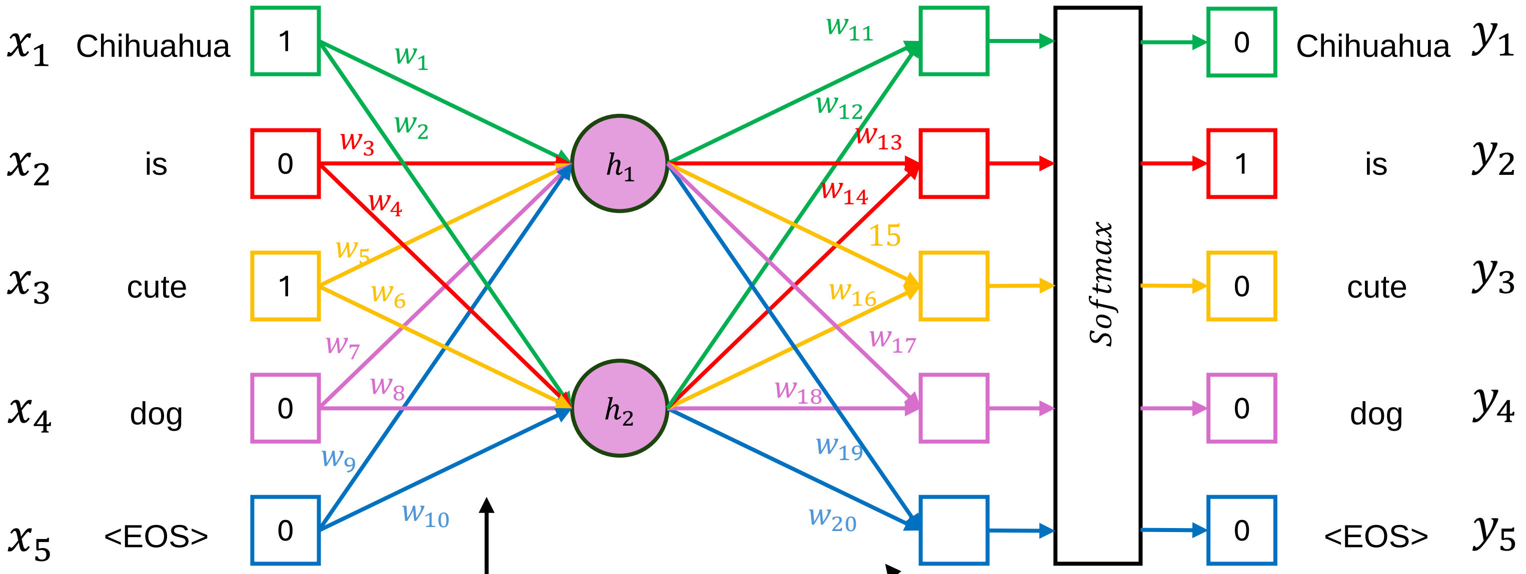


I’m going to use CBOW



Train and save the weight of this state.

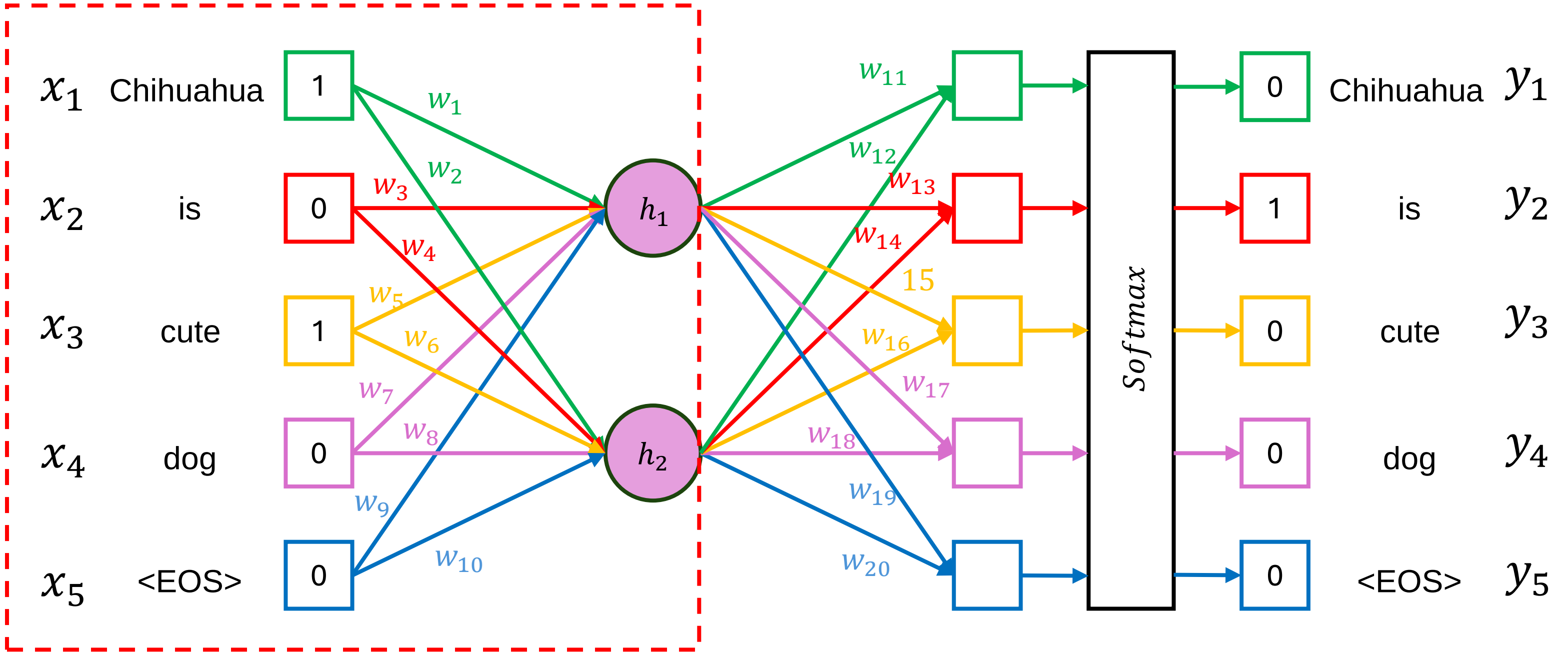

Before Training
After Training
y
x
0.1
0.0
-0.1
Chihuahua
cute
is
dog
y
x
0.1
0.0
-0.1
Chihuahua
dog
is
cute



$$
\begin{aligned}
y_1 &= Softmax(sum_1)\\
y_2 &= Softmax(sum_2)\\
y_3 &= Softmax(sum_3)\\
y_4 &= Softmax(sum_4)\\
y_5 &= Softmax(sum_5)
\end{aligned}
$$

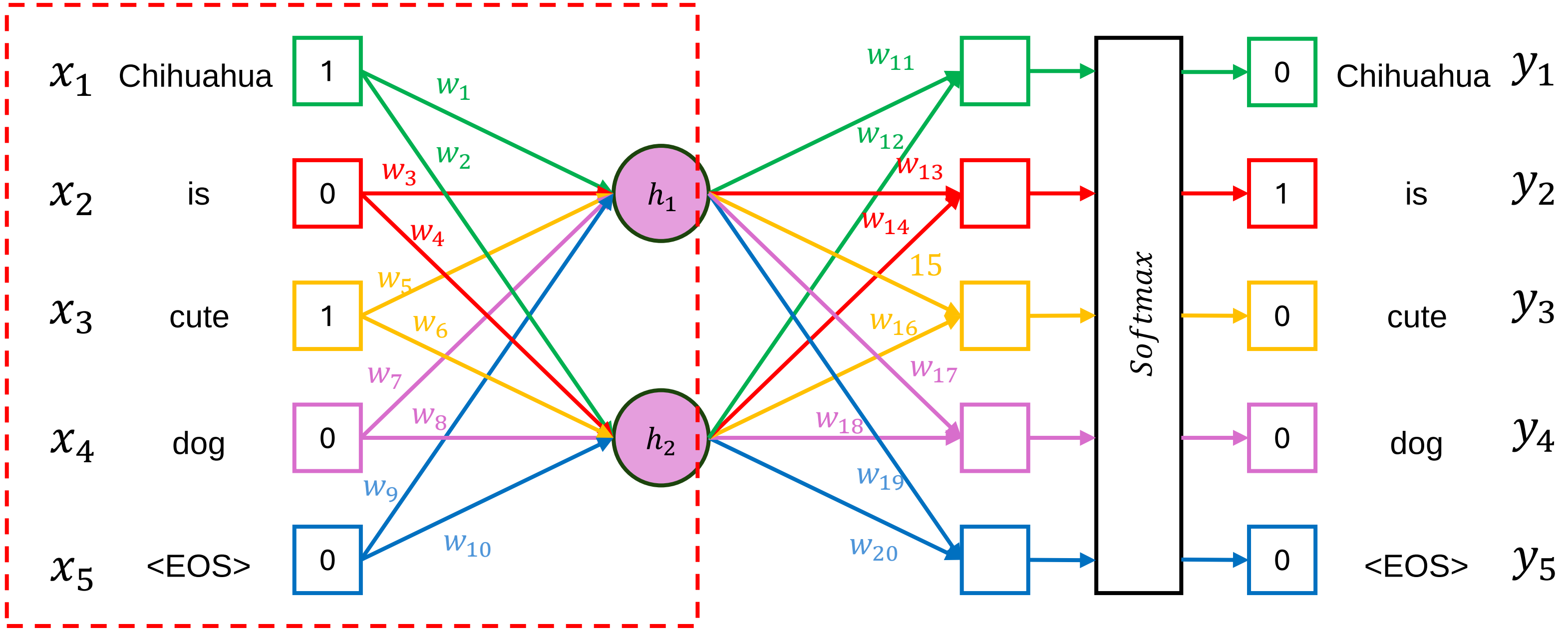
$$
\begin{aligned}
h_1 &= (x_1w_1 + x_2w_3 + x_3w_5 + x_4w_7 + x_5w_9)\\
h_2 &= (x_1w_2 + x_2w_4 + x_3w_6 + x_4w_8 + x_5w_{10})
\end{aligned}
$$

$$
\begin{aligned}
sum_1 &= (h_1w_{11} + h_2w_{12})\\
sum_2 &= (h_1w_{13} + h_2w_{14})\\
sum_3 &= (h_1w_{15} + h_2w_{16})\\
sum_4 &= (h_1w_{17} + h_2w_{18})\\
sum_5 &= (h_1w_{19} + h_2w_{20})
\end{aligned}
$$



Dot Product: *Row With Column*

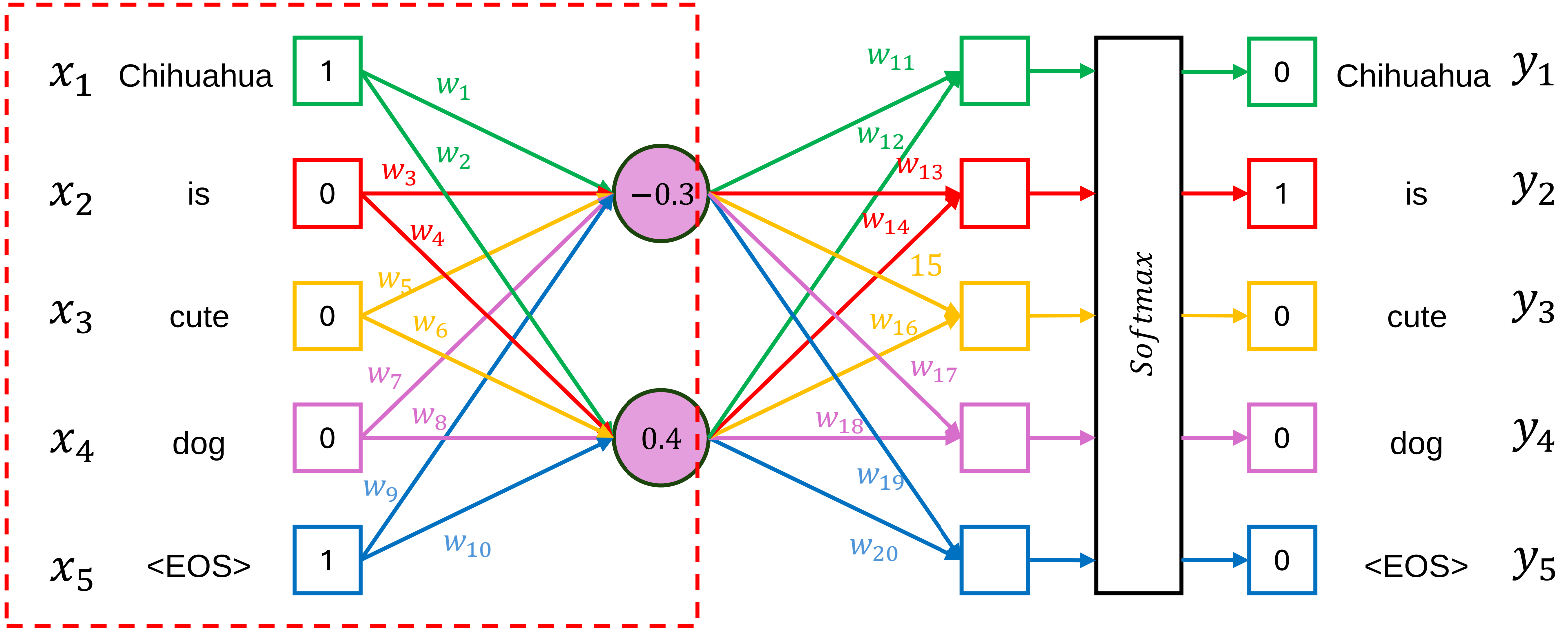
$$
\underset{(1 \times \cancel{5})}{\begin{bmatrix} x_1 & x_2 & x_3 & x_4 & x_5 \end{bmatrix}} \times \underset{(\cancel{5} \times 2)}{\begin{bmatrix} w_1 & w_2 \\ w_3 & w_4 \\ w_5 & w_6 \\ w_7 & w_8 \\ w_9 & w_{10} \end{bmatrix}} = \underset{(1 \times 2)}{\begin{bmatrix} x_1 w_1 + x_2 w_3 + x_3 w_5 + x_4 w_7 + x_5 w_9 & x_1 w_2 + x_2 w_4 + x_3 w_6 + x_4 w_8 + x_5 w_{10} \end{bmatrix}}
$$



$$[x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5] \times \begin{bmatrix} w_1 & w_2 \\ w_3 & w_4 \\ w_5 & w_6 \\ w_7 & w_8 \\ w_8 & w_{10} \end{bmatrix} = [h_1 \quad h_2]$$

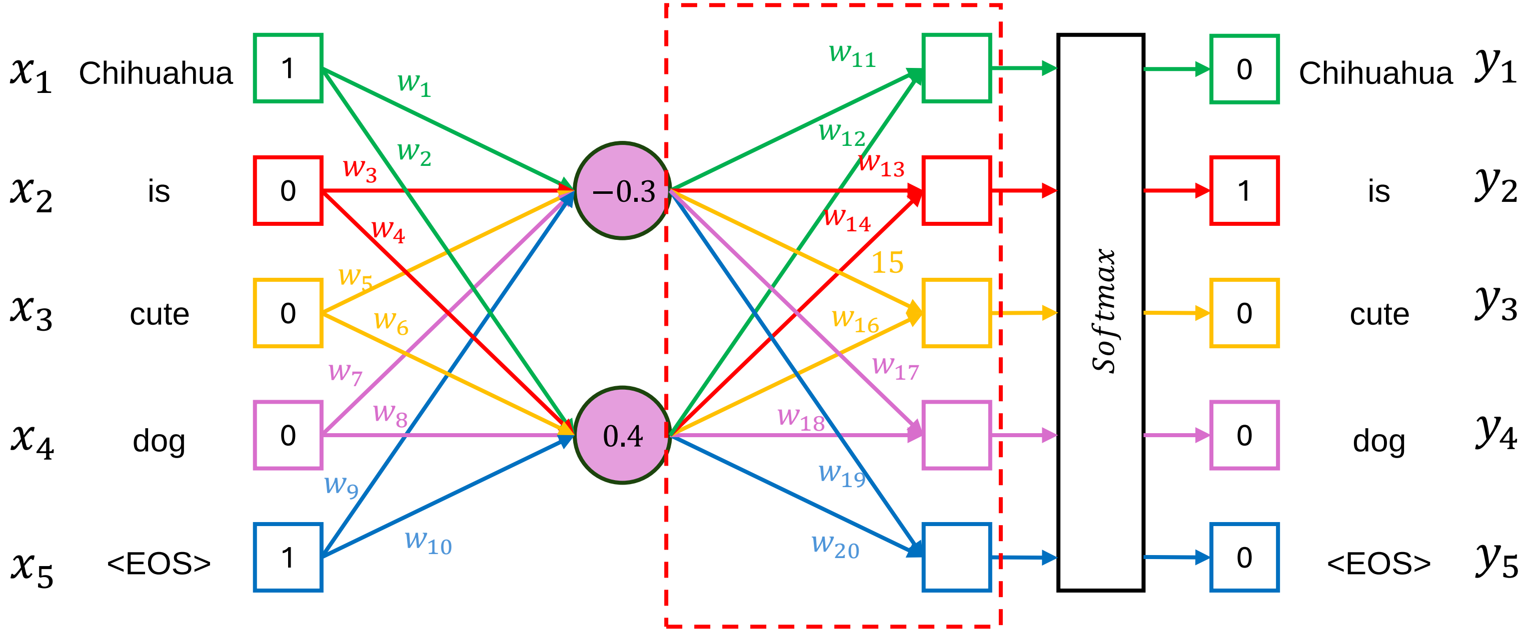
Random all weights

$$[h_1 \quad h_2] = [1 \quad 0 \quad 1 \quad 0 \quad 0] \times \begin{bmatrix} 0.1 & 0.6 \\ 0.3 & -0.2 \\ -0.4 & -0.2 \\ -0.1 & 0.5 \\ 0.7 & -0.1 \end{bmatrix} = [-0.3 \quad 0.4]$$



$$[x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5] \times \begin{bmatrix} w_1 & w_2 \\ w_3 & w_4 \\ w_5 & w_6 \\ w_7 & w_8 \\ w_8 & w_{10} \end{bmatrix} = [h_1 \quad h_2]$$

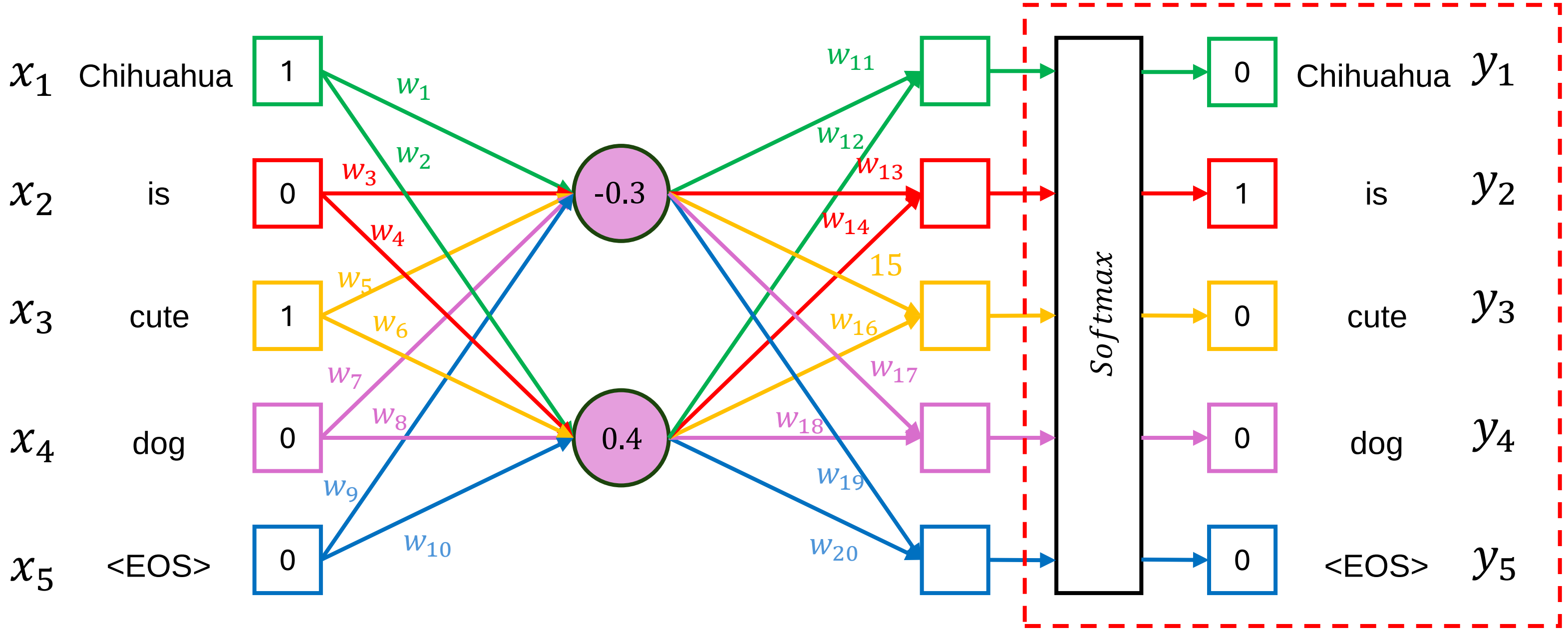
$$[h_1 \quad h_2] = [1 \quad 0 \quad 1 \quad 0 \quad 0] \times \begin{bmatrix} 0.1 & 0.6 \\ 0.3 & -0.2 \\ -0.4 & -0.2 \\ -0.1 & 0.5 \\ 0.7 & -0.1 \end{bmatrix} = [-0.3 \quad 0.4]$$



$$[sum_1 \quad sum_2 \quad sum_3 \quad sum_4 \quad sum_5] = [-0.3 \quad 0.4] \begin{bmatrix} w_{11} & w_{13} & w_{15} & w_{17} & w_{19} \\ w_{12} & w_{14} & w_{16} & w_{18} & w_{20} \end{bmatrix}$$

$$[sum_1 \quad sum_2 \quad sum_3 \quad sum_4 \quad sum_5] = [-0.3 \quad 0.4] \begin{bmatrix} 0.5 & 0.1 & 0.3 & -0.1 & 0.8 \\ 0.4 & -0.2 & -0.1 & 0.9 & 0.3 \end{bmatrix}$$

$$[sum_1 \quad sum_2 \quad sum_3 \quad sum_4 \quad sum_5] = [0.01 \quad -0.11 \quad -0.13 \quad 0.39 \quad -0.12]$$



$$[sum_1 \quad sum_2 \quad sum_3 \quad sum_4 \quad sum_5] = [0.01 \quad -0.11 \quad -0.13 \quad 0.39 \quad -0.12]$$

$$[S_1 \quad S_2 \quad S_3 \quad S_4 \quad S_5] = [0.20 \quad 0.17 \quad 0.17 \quad 0.29 \quad 0.17]$$

Argmax

Input Output

$$[S_1 \quad S_2 \quad S_3 \quad S_4 \quad S_5] = [0 \quad 0 \quad 0 \quad 1 \quad 0] \longrightarrow (Chihuahua, cute) \rightarrow dog$$

$$\boldsymbol{But\ we\ need\ this\ answer}: [S_1 \quad S_2 \quad S_3 \quad S_4 \quad S_5] = [0 \quad 1 \quad 0 \quad 0 \quad 0] \rightarrow is$$

Loss Calculation

$$CE = -\sum_{i=1}^{n} Observed \cdot \log(Softmax_i)$$

$$CE = -\log(0.17)$$

$$CE = 0.76$$

Then, Backpropagation

$$w_{new} = w_{current} - \alpha \sum_{i=1}^{n} \frac{\partial CE_i}{\partial w}$$

To minimize **“Cross Entropy”**

Time to code in

PyTorch

1. Import Library

```
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
import numpy as np
```

[1]

```
device = ("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using {device} device")
```

[2]

```
Using cuda device
```

Import library

Declare to using **GPU,** in case GPU nor found it’s going to use CPU instead.

2. Do Tokenizer

```
sentence = "Chihuahua is cute dog"
[3]  ✓ 0.0s
```

Train data

```
def tokenizer(sentence):
    vocabulary = sentence.split()
    vocabulary.append("<EOS>")

    return vocabulary
[4]  ✓ 0.0s
```

Tokenizer function

Do tokenizer

```
tokens = tokenizer(sentence)
print(tokens)
[8]  ✓ 0.0s
... ['Chihuahua', 'is', 'cute', 'dog', '<EOS>']
```

Output

3. Convert Tokens to One Hot Vector

```python
def vocabulary_one_hot_encoder(tokens):
    results = []

    for i, _ in enumerate(tokens):
        one_hot_encode_vector = [0. for i in range(len(tokens))]

        for j in range(i + 1):
            one_hot_encode_vector[j] = 1. if j == i else 0.

        results.append(one_hot_encode_vector)

    return results
```

[5] ✓ 0.0s

One hot vector encoder function

Output

```python
training_x = vocabulary_one_hot_encoder(tokens)
print(training_x)
```

[9] ✓ 0.0s

```
[[1.0, 0.0, 0.0, 0.0, 0.0], [0.0, 1.0, 0.0, 0.0, 0.0], [0.0, 0.0, 1.0, 0.0, 0.0], [0.0, 0.0, 0.0, 1.0, 0.0], [0.0, 0.0, 0.0, 0.0, 1.0]]
```

4. Make CBOW Training Data

```python
def create_cbow_pairs(sequence, window_size):
    cbow_pairs = []

    for i in range(len(sequence)):
        context = []

        for j in range(-window_size, window_size + 1):
            if i + j >= 0 and i + j < len(sequence) and j != 0:
                context.append(sequence[i + j])

        if context:
            context = np.sum(context, axis=0) / len(context)
            cbow_pairs.append(context)

    return cbow_pairs
```

[6] ✓ 0.0s

CBOW pairs maker function

```python
CONTEXT_SIZE = 2

training_y = create_cbow_pairs(training_x, CONTEXT_SIZE)
print(training_y)
```

[10] ✓ 0.0s

```
[array([0.  , 0.5, 0.5, 0.  , 0.  ]), array([0.33333333, 0.        , 0.33333333, 0.33333333, 0.
```

Context size it to define the words surrounding size.

Example: CONTEXT_SIZE=2
[0.25, 0.25, 0., 0.25, 0.25]

5. Declaring Deep Learning The Model

```
class CBOWModeler(nn.Module):
    def __init__(self, volcabulary_size, embedding_dim):
        super(CBOWModeler, self).__init__()
        self.linear1 = nn.Linear(volcabulary_size, embedding_dim, bias=False)
        self.linear2 = nn.Linear(embedding_dim, volcabulary_size, bias=False)

    def forward(self, x):
        out = self.linear1(x)
        out = self.linear2(out)
        return F.softmax(out, dim=-1)

    def save_embedding_model(self):
        params = self.linear1.state_dict()
        torch.save(params, "./embedding_model.pt")
```

[11] ✓ 0.0s

Layers

Forward propagation

Save weights for linear1 layer.

6. Training Setup

```
EMBEDDING_DIM = 2

losses = []
loss_function = nn.CrossEntropyLoss()
model = CBOWModeler(len(tokens), EMBEDDING_DIM).to(device)
optimizer = optim.Adam(model.parameters(), lr=0.001)

print(model)
```

[12] ✓ 0.7s

```
CBOWModeler(
  (linear1): Linear(in_features=5, out_features=2, bias=False)
  (linear2): Linear(in_features=2, out_features=5, bias=False)
)
```

Loss Function

Model.to(device) means to using GPU.

Optimizer

7. Training Step

```python
for epoch in range(100):
    total_loss = 0

    for x, y in zip(training_x, training_y):
        x, y = torch.tensor(x).to(device), torch.tensor(y).to(device)

        model.zero_grad()

        y_hat = model(x)

        loss = loss_function(y, y_hat)

        loss.backward()
        optimizer.step()

        total_loss += loss.item()
    losses.append(total_loss)

model.save_embedding_model()
```

[13] ✓ 0.6s

Don’t forget to change all tensors to .to(device) while training with GPU.

Stop if zero of gradient

Loss comparing

Backpropagation

Stack loss to see performance of training

Save model

7. Losses Inspection

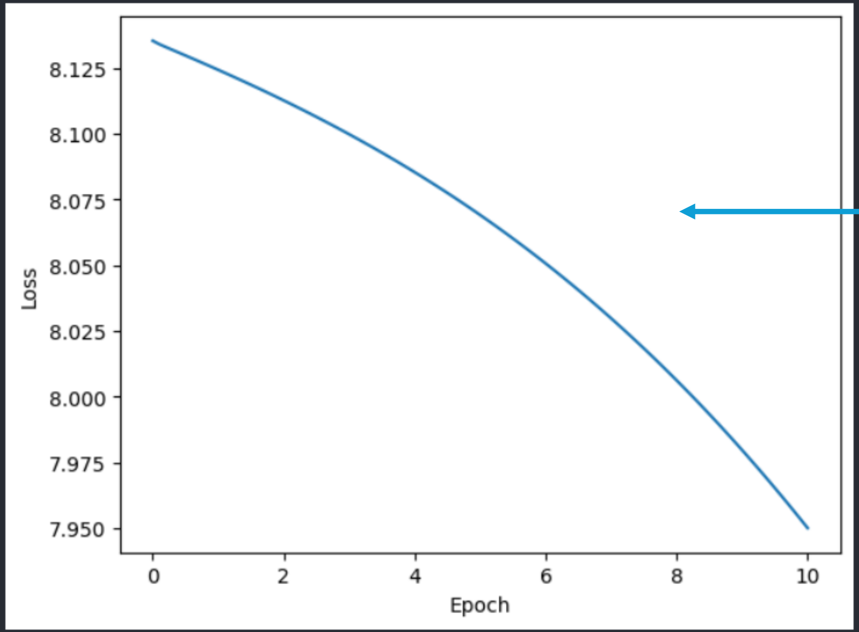
```python
def plot_losses(ax, t, losses):
    ax.plot(t, losses)
    ax.set_xlabel("Epoch")
    ax.set_ylabel("Loss")
```

[15] ✓ 0.0s

```python
fig, ax = plt.subplots()
plot_losses(ax, np.linspace(0., 10., len(losses)), losses)
```

[16] ✓ 0.1s

...



Looks Bad ☹

View Result

```
for x, y in zip(training_x, training_y):
    # Get predicted vector
    pred = model(torch.tensor(x))

    # Get the argmax index
    argmax_idx = torch.argmax(pred, keepdim=True)

    # Create a one-hot encoded tensor
    anwser_vector = F.one_hot(argmax_idx, num_classes=pred.size(-1)).int()
    anwser_list = anwser_vector.tolist()

    question = word_decoder(x, tokens)
    answer = word_decoder(anwser_list[0], tokens)
    print(question, answer)
```

[17] ✓ 0.0s

```
Chihuahua is
is cute
cute dog
dog cute
<EOS> dog
```

Argmax is only output as index of output vector

```
def word_decoder(anwser_list, vocabulary):
    idx = anwser_list.index(max(anwser_list))
    return vocabulary[idx]
```

[7] ✓ 0.0s

Convert one hot vector of result of training to human readable