8.3

Introduction to Recurrent Neural Networks

Part 4: Embedding Layers in PyTorch

Sebastian Raschka and the Lightning Al Team

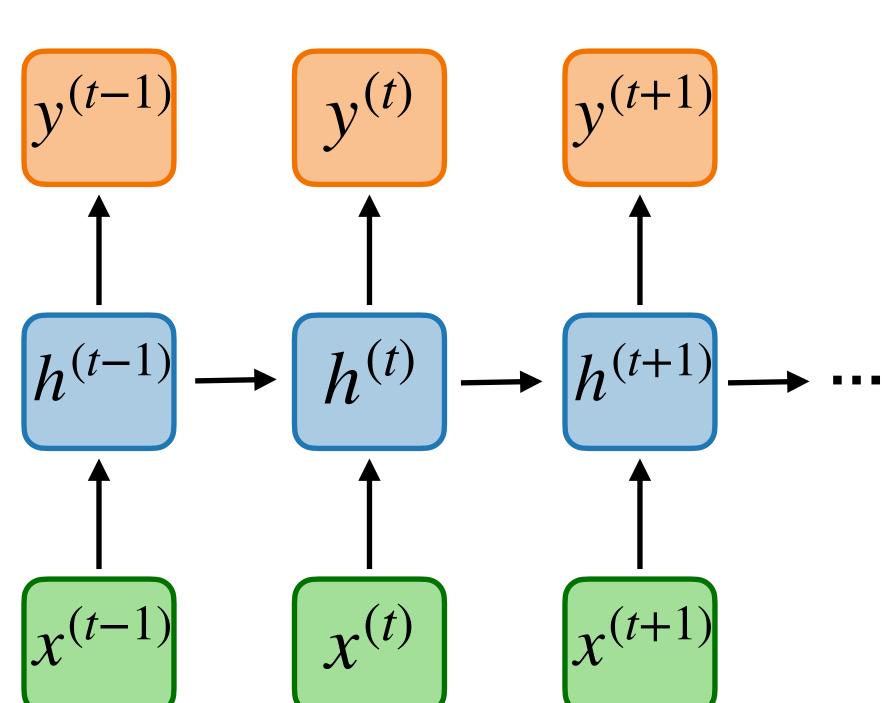
A simple RNN that predicts the next character

Desired outputs:



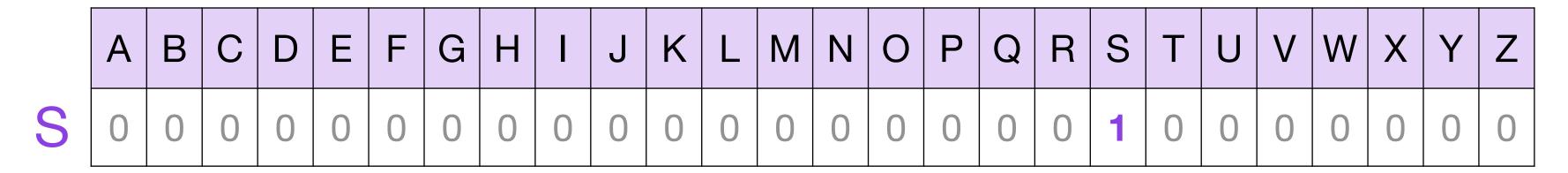
Sentence:

"Sunny days are the best days to go for a walk or have a picnic."



Character inputs: S Unit 8

One-hot encoded input letter





One-hot encoded ("sparse") representation of "S U N N Y"

| | Α | В | С | D | Ε | F | G | Н | I | J | K | L | М | N | 0 | Р | Q | R | S | Т | U | V | W | X | Y | Z |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| S | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| U | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| N | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| N | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Y | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |



```
Embedded ("dense")
representation of
"S U N N Y"
```

```
[[0.9816, 0.7363, 0.5899], [0.2605, 0.3766, 0.3502], [0.7382, 0.9807, 0.4762], [0.6231, 0.8825, 0.8836]]
```

Embedding layer

```
[[0.6912, 0.8765, 0.4939],
 [0.6342, 0.7481, 0.7717],
 [0.8395, 0.2128, 0.3696],
 [0.4900, 0.1509, 0.0689],
 [0.2587, 0.9171, 0.8670],
 [0.7213, 0.9922, 0.5701],
 [0.7598, 0.5231, 0.3666],
 [0.5150, 0.5216, 0.9682],
 [0.2248, 0.0261, 0.4427],
 [0.1818, 0.6863, 0.8713],
 [0.4192, 0.1566, 0.9004],
 [0.8102, 0.5741, 0.4241],
 [0.1116. 0.0466. 0.2786]
[0.9816, 0.7363, 0.5899],
 [0.9224, 0.3672, 0.6972],
 [0.1207, 0.3372, 0.2128],
 [0.0660, 0.1524, 0.8440],
 [0.2162. 0.5640. 0.0988]
[0.2605, 0.3766, 0.3502],
 10_2334 0 4757 0 75211
[0.7382, 0.9807, 0.4762],
 [0.2369, 0.8102, 0.8798],
 [0.6932, 0.2671, 0.8018],
 [0.9593. 0.5302. 0.4290]
[0.6231, 0.8825, 0.8836],
[0.4623, 0.8503, 0.7279]]
         Lightning Al
```

We learned that embeddings layers are efficient forms of matrix multiplications when working with one-hot encoded vectors

1) Using torch.nn.Embedding

```
import torch
torch.manual_seed(123);
```

```
idx = torch.tensor([2, 3, 1]) # 3 training examples
```

```
import torch
     torch.manual_seed(123);
     idx = torch.tensor([2, 3, 1]) # 3 training examples
     num_idx = max(idx)+1
    out_dim = 5
                                                  Input dimension of a one-hot encoded
                                                     vector is the number of indices
                                                         (the highest index + 1)
Suppose we want embeddings of size 5
```

```
import torch
torch.manual_seed(123);
idx = torch.tensor([2, 3, 1]) # 3 training examples
num_idx = max(idx)+1
out_dim = 5
embedding = torch.nn.Embedding(num_idx, out_dim)
embedding(idx)
tensor([[ 0.6957, -1.8061, -1.1589, 0.3255, -0.6315], Each row is a training
        [-2.8400, -0.7849, -1.4096, -0.4076, 0.7953],
                                                                  example
        [1.3010, 1.2753, -0.2010, -0.1606, -0.4015]],
       grad_fn=<EmbeddingBackward0>)
```

```
import torch
torch.manual_seed(123);
idx = torch.tensor([2, 3, 1]) # 3 training examples
num_idx = max(idx)+1
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embedding = torch.nn.Embedding(num_idx, out_dim)
embedding(idx)
tensor([[ 0.6957, -1.8061, -1.1589, 0.3255, -0.6315],
                                                              Each training example has
        [-2.8400, -0.7849, -1.4096, -0.4076, 0.7953],
                                                                   5 feature values
        [1.3010, 1.2753, -0.2010, -0.1606, -0.4015]],
       grad_fn=<EmbeddingBackward0>)
```

Let's summarize this step by step

```
import torch
torch.manual_seed(123);

idx = torch.tensor([2, 3, 1]) # 3 training examples
```

```
1) Indices of 3 training examples 3 1
```

```
import torch
torch.manual_seed(123);
```

```
idx = torch.tensor([2, 3, 1]) # 3 training examples

num_idx = max(idx)+1
out_dim = 5

embedding = torch.nn.Embedding(num_idx, out_dim)
```

```
1) Indices of 3 training examples 3 1
```

2) Embedding matrix

$$\begin{bmatrix} 0.3374 & -0.1778 & -0.3035 & -0.5880 & 1.5810 \\ 1.3010 & 1.2753 & -0.2010 & -0.1606 & -0.4015 \\ 0.6957 & -1.8061 & -1.1589 & 0.3255 & -0.6315 \\ -2.8400 & -0.7849 & -1.4096 & -0.4076 & 0.7953 \end{bmatrix}$$

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import torch

torch.manual_seed(123);

idx = torch.tensor([2, 3, 1]) # 3 training examples

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3) Look up entries by index

| + | 0.6957 | -1.8061 | -1.1589 | 0.3255 | -0.6315 |
|---|--------|---------|---------|---------|---------|
| ı | | -0.7849 | | | |
| | 1.3010 | 1.2753 | -0.2010 | -0.1606 | -0.4015 |

2) Using torch.nn.Linear

```
idx = torch.tensor([2, 3, 1]) # 3 training examples
num_idx = max(idx)+1
out dim = 5
embedding = torch.nn.Embedding(num_idx, out_dim)
embedding(idx)
tensor([[ 0.6957, -1.8061, -1.1589, 0.3255, -0.6315],
        [-2.8400, -0.7849, -1.4096, -0.4076, 0.7953],
        [1.3010, 1.2753, -0.2010, -0.1606, -0.4015]],
       grad_fn=<EmbeddingBackward0>)
onehot = torch.nn.functional.one_hot(idx)
linear = torch.nn.Linear(num_idx, 5, bias=False)
linear.weight = torch.nn.Parameter(embedding.weight.T.detach())
```

Transpose required, because nn.Linear multiplies xW^{T} instead of xW

```
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onehot = torch.nn.functional.one_hot(idx)
linear = torch.nn.Linear(num_idx, 5, bias=False)
linear.weight = torch.nn.Parameter(embedding.weight.T.detach())
linear(onehot.float())
tensor([[ 0.6957, -1.8061, -1.1589, 0.3255, -0.6315],
        [-2.8400, -0.7849, -1.4096, -0.4076, 0.7953],
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Deep Learning Fundamentals, Unit 8

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         [ 1.3010, 1.2753, -0.2010, -0.1606, -0.4015]], grad_fn=<MmBackward0>)
```

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Let's summarize this step by step

1) Convert indices of 3 training examples to one-hot encoding

$$\begin{bmatrix} 2 \\ 3 \\ 1 \end{bmatrix} \longrightarrow \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

1) Convert indices of 3 training examples to one-hot encoding

$$\begin{bmatrix} 2 \\ 3 \\ 1 \end{bmatrix} \longrightarrow \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

2) Weight (embedding) matrix

$$\begin{bmatrix} 0.3374 & -0.1778 & -0.3035 & -0.5880 & 1.5810 \\ 1.3010 & 1.2753 & -0.2010 & -0.1606 & -0.4015 \\ 0.6957 & -1.8061 & -1.1589 & 0.3255 & -0.6315 \\ -2.8400 & -0.7849 & -1.4096 & -0.4076 & 0.7953 \end{bmatrix}$$

tensor([[0.6957, -1.8061, -1.1589, 0.3255, -0.6315],

[-2.8400. -0.7849. -1.4096. -0.4076. 0.7953].

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3) Multiply one-hot encoded inputs with weight matrix

```
1.5810
                                            -0.1778 \quad -0.3035 \quad -0.5880
                                    0.3374
                       0
                                                    -0.2010 \quad -0.1606 \quad -0.4015
                                    1.3010
                                             1.2753
                                            -1.8061 -1.1589
                                    0.6957
                                                               0.3255
                                                                       -0.6315
  0 \times 0.3374
                                            -0.7849 -1.4096 -0.4076
                                   -2.8400
+0 \times 1.3010
+1 \times 0.6957
                      0.6957 -1.8061 -1.1589 0.3255 -0.6315
+0 \times -2.8400
                     = | -2.8400 -0.7849 -1.4096 -0.4076 0.7953
Deep Learning Fun 3010 nen 2753, Uni 2010 -0.1606 -0.4015 Ining Al
```

Next: RNNs with Attentions and Transformers