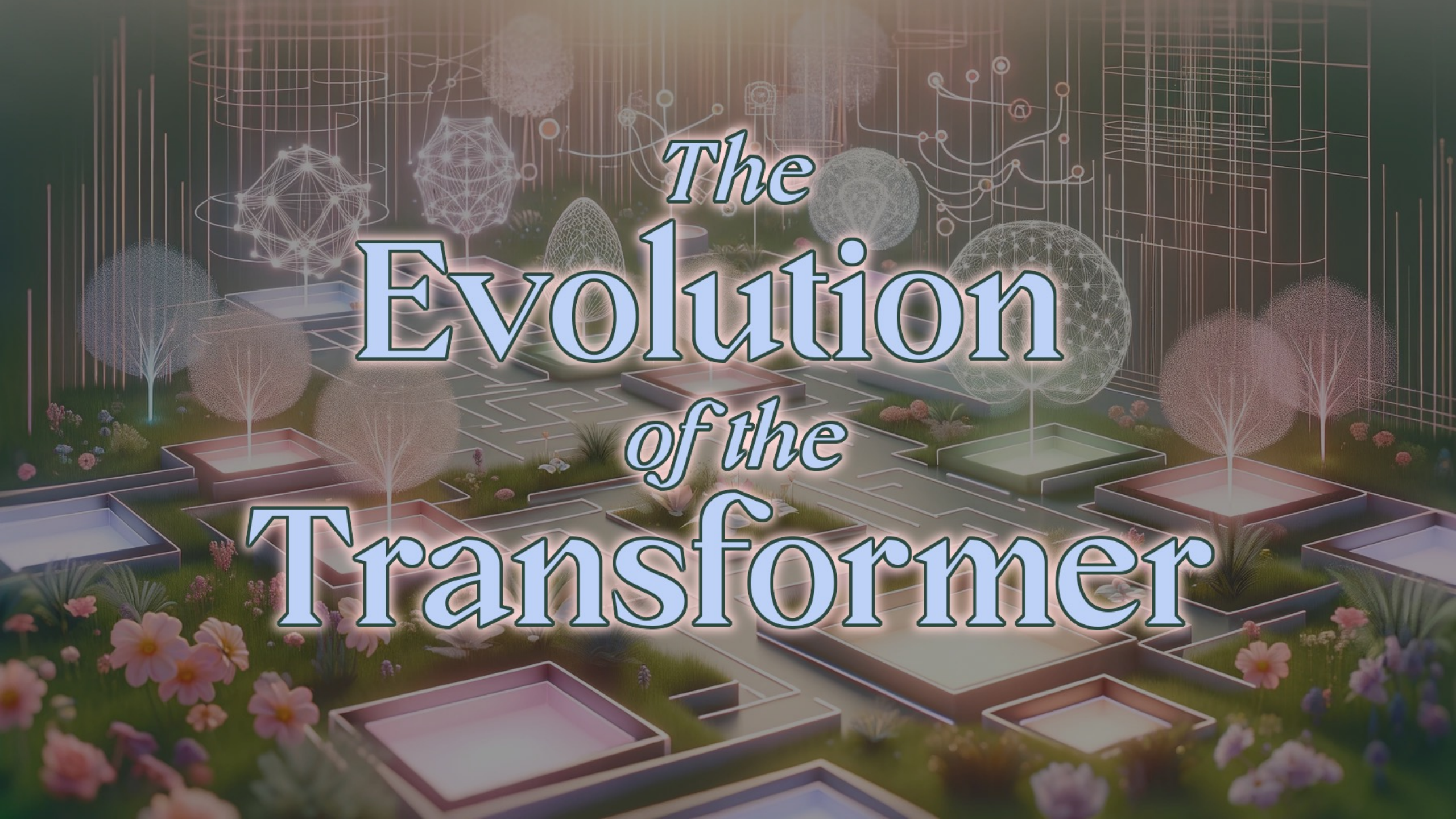
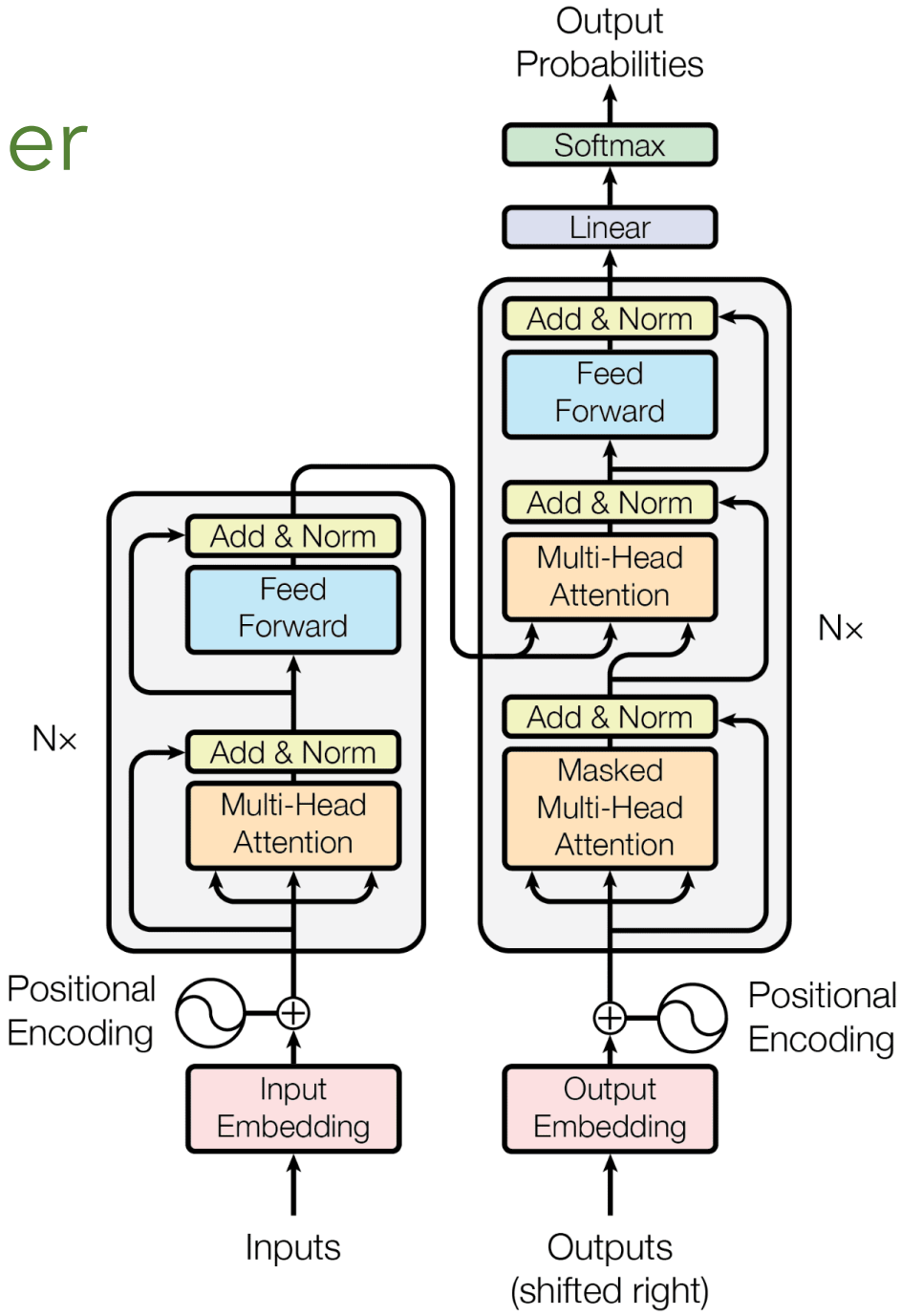
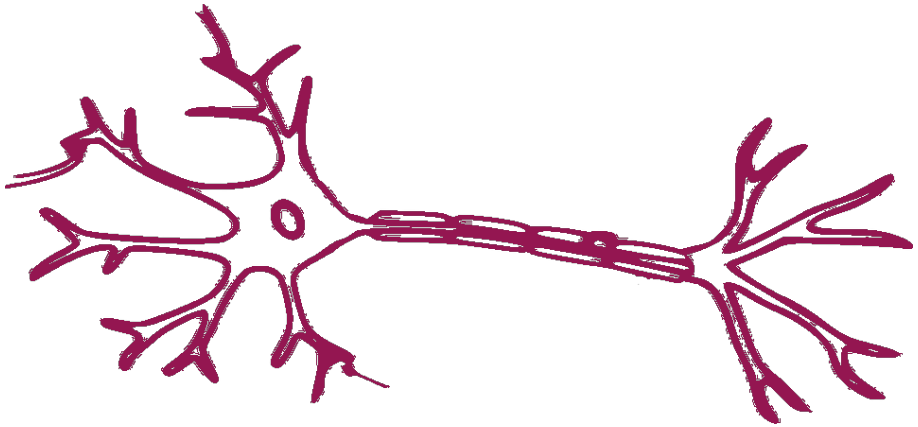

The
Evolution
of the
Transformer

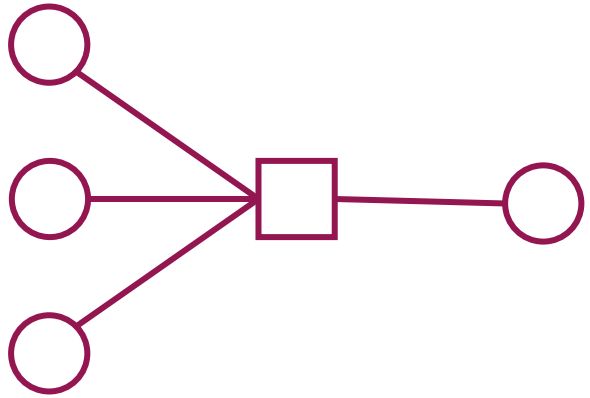
The Transformer



1943: The "Artificial Neuron"

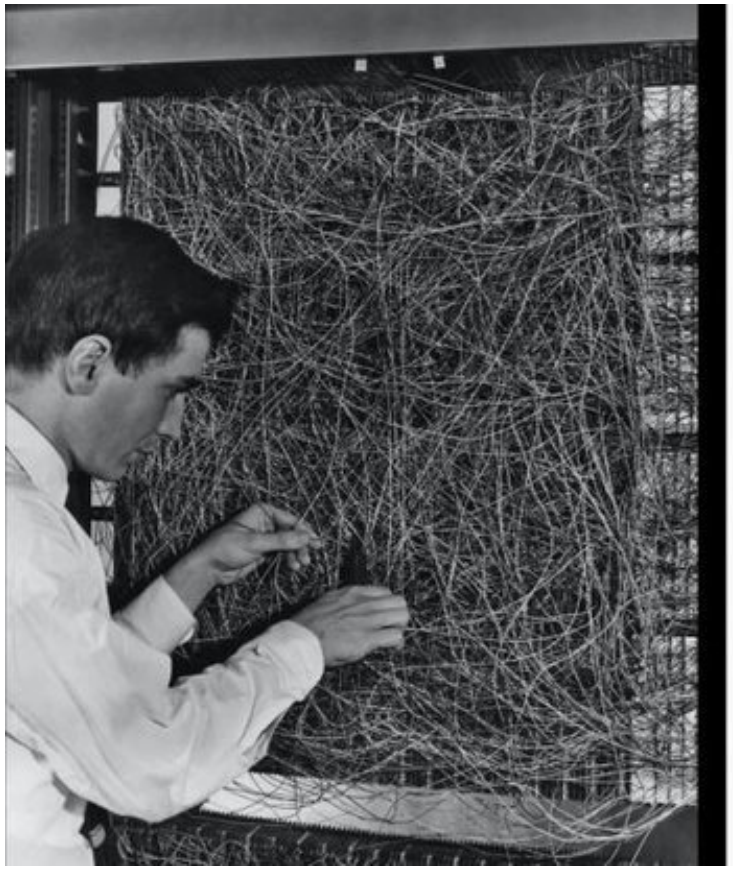
Warren McCulloch and Walter Pitts





1957: The Perceptron

Frank Rosenblatt



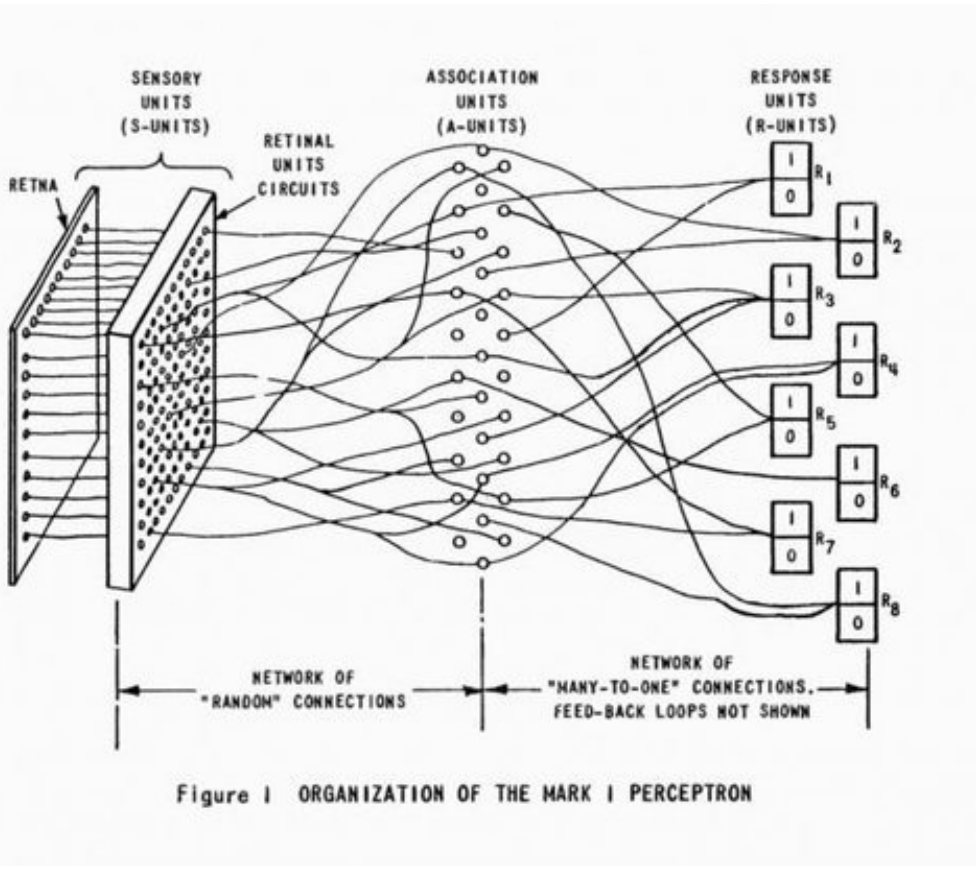
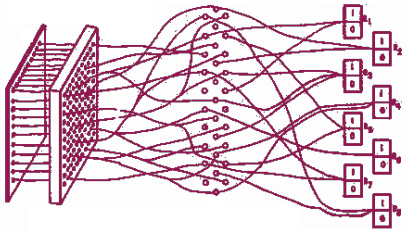


Figure 1 ORGANIZATION OF THE MARK I PERCEPTRON

1943:
The “Artificial Neuron”

1957: The ”Perceptron”



1943:
The “Artificial Neuron”

1969: Perceptrons

Marvin Minsky and Seymour Papert

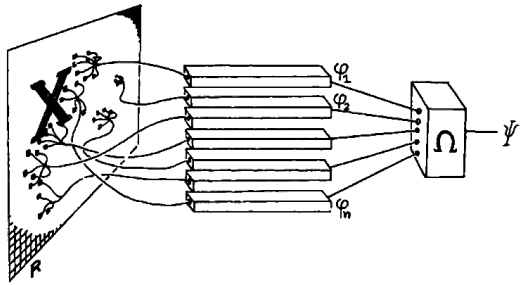


Figure 0.1

1970: Backpropagation

Seppo Linnainmaa

TAYLOR EXPANSION OF THE ACCUMULATED ROUNDING ERROR

*T*1. [Initialize.] $p \leftarrow n$, $C[i] \leftarrow 0$ for $i = 1, \ldots, m$, $i \neq N$, $C[N] \leftarrow 1$.
*T*2. [Read.] $i \leftarrow I[p]$, $j \leftarrow J[p]$, $k \leftarrow K[p]$, $dj \leftarrow Dj[p]$, $dk \leftarrow Dk[p]$.
*T*3. [Coefficient $c_{n,p}$ completed.] coef $\leftarrow C[i]$, $C[i] \leftarrow 0$. The contents of coef is now equal to the value of $c_{n,p}$ and can be utilized.
*T*4. [Coefficient zero?] If coef $= 0$, go to step *T*6.
*T*5. [Update table *C*.] If $dj \neq 0$ then $C[j] \leftarrow C[j] + \text{coef} \times dj$. If $dk \neq 0$ then $C[k] \leftarrow C[k] + \text{coef} \times dk$.
*T*6. [Decrease *p*.] Decrease p by 1. If $p > 0$, return to step *T*2, otherwise the algorithm terminates.

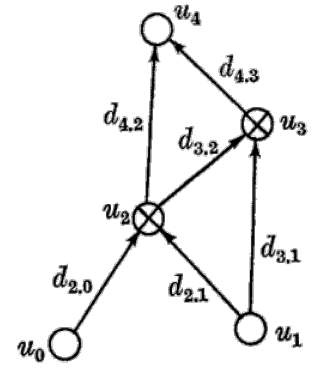
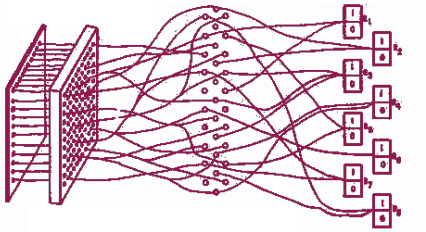
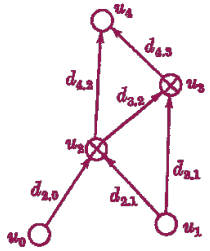


Figure 1. A computing process as a graph.

1957: The ”Perceptron”

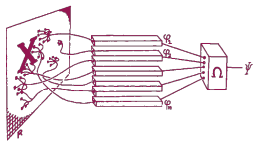


1970:
Backprop
proposed



1943:
The “Artificial Neuron”

1969:
Perceptrons

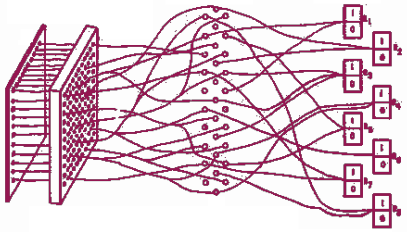


1970s & 1980s:
“AI Winter”

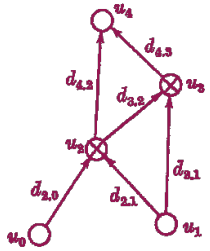
1986: Applied backprop

D Rumelhart, G Hinton, R Williams

1957: The ”Perceptron”

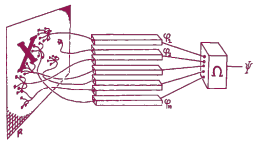


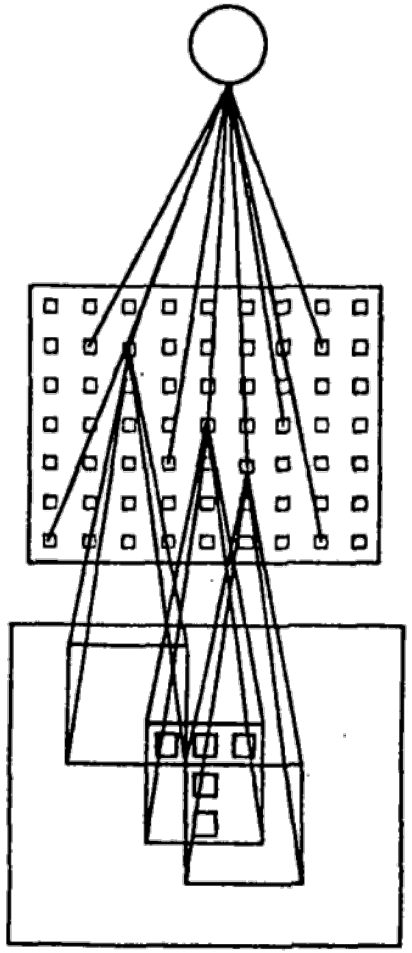
1970: Backprop proposed



1943: The “Artificial Neuron”

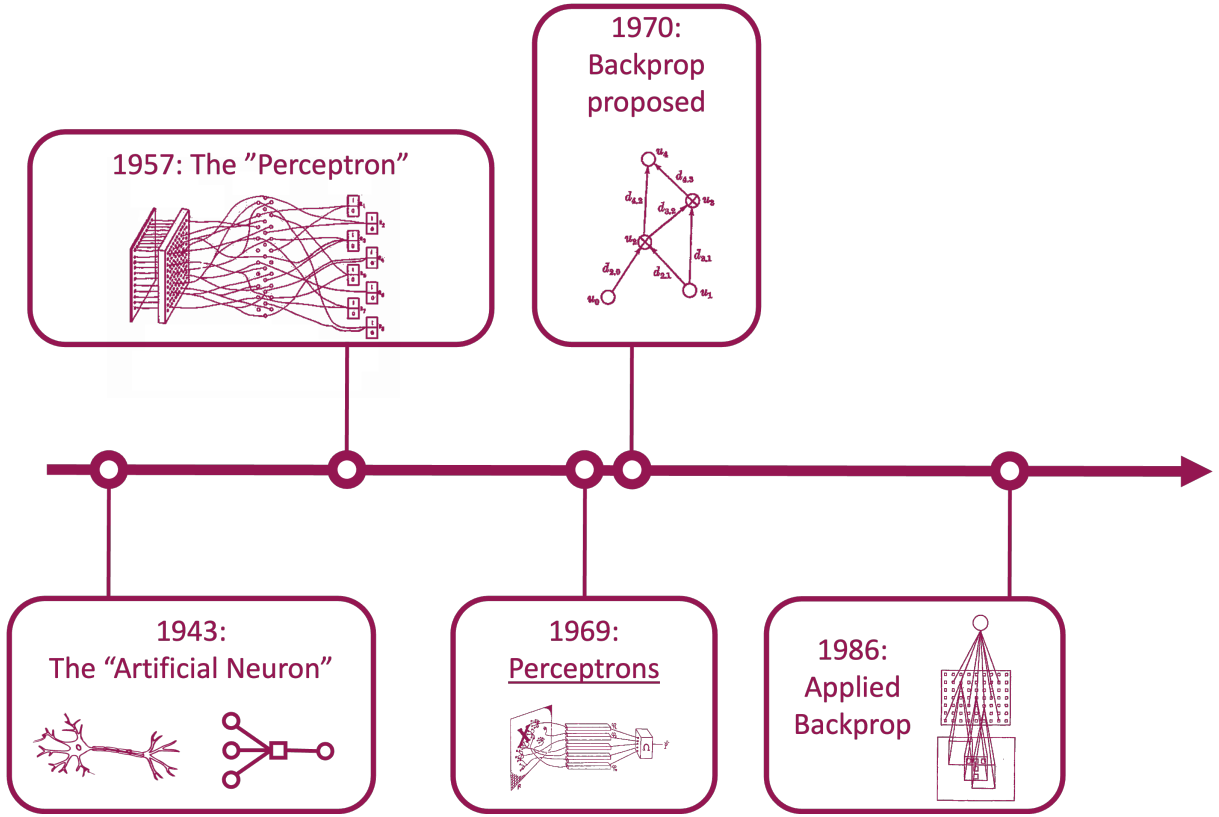
1969: Perceptrons





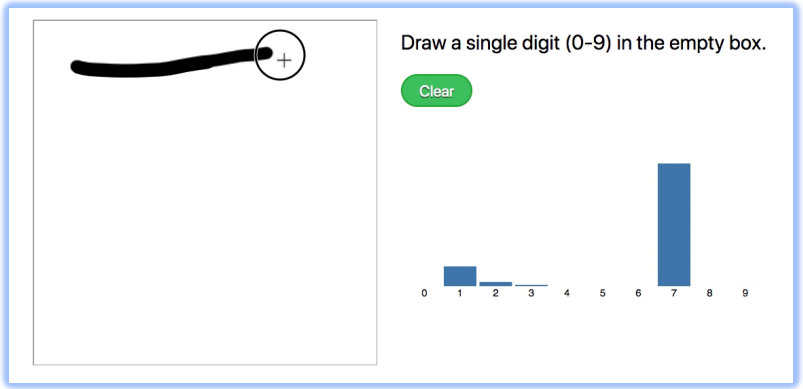
Neural Networking in the 20th Century

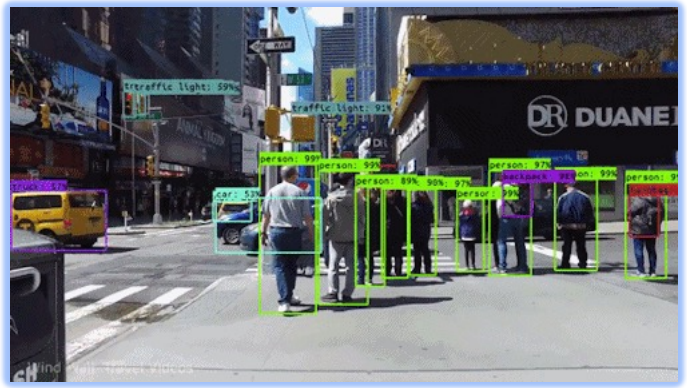
- **Linear & Nonlinear**: Composition of layers for computation
- **Trainable**: backpropagation

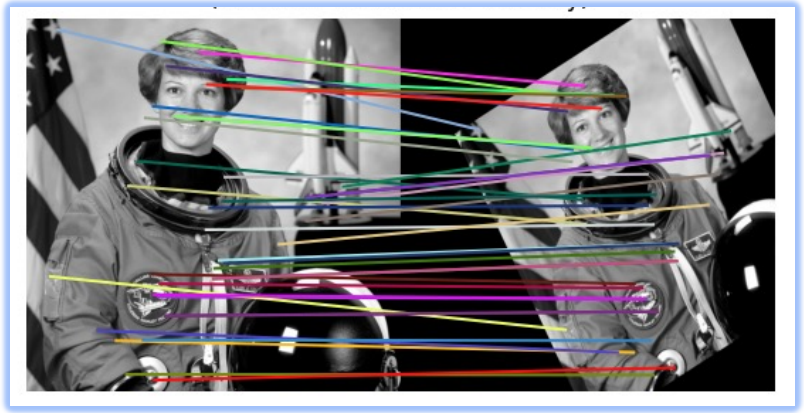


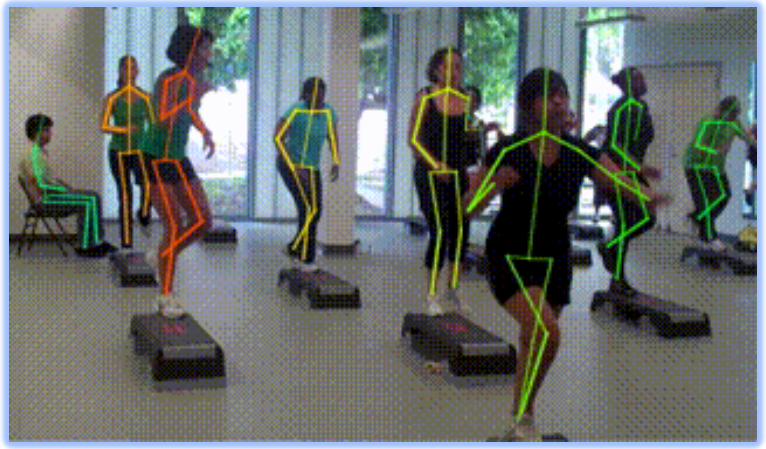
Computer Vision

A multitude of interesting challenges







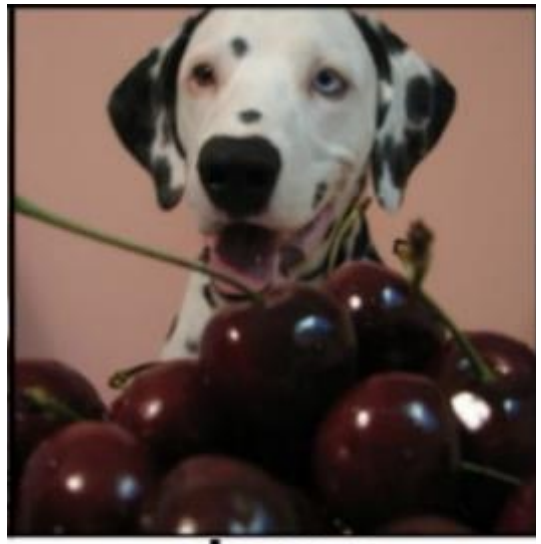


ImageNet & ILSVRC (2009)

1,000 image categories

1.2 million images for training

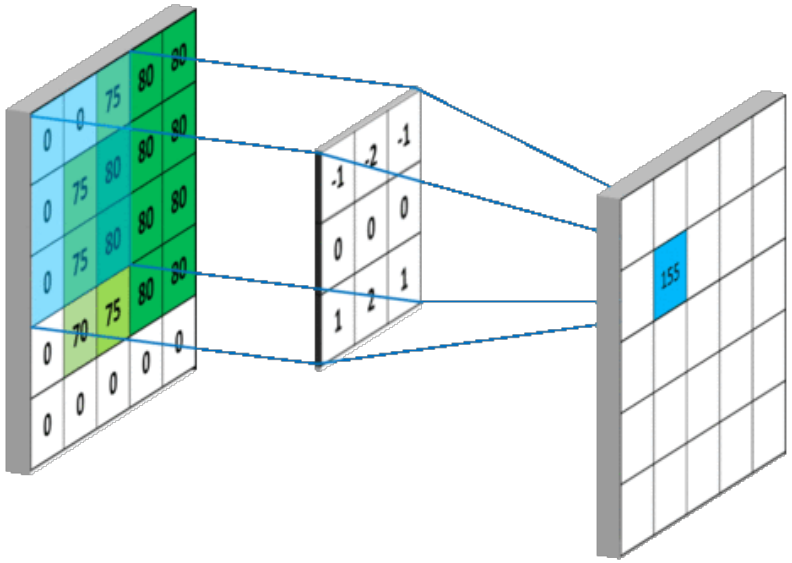
100k images for evaluation

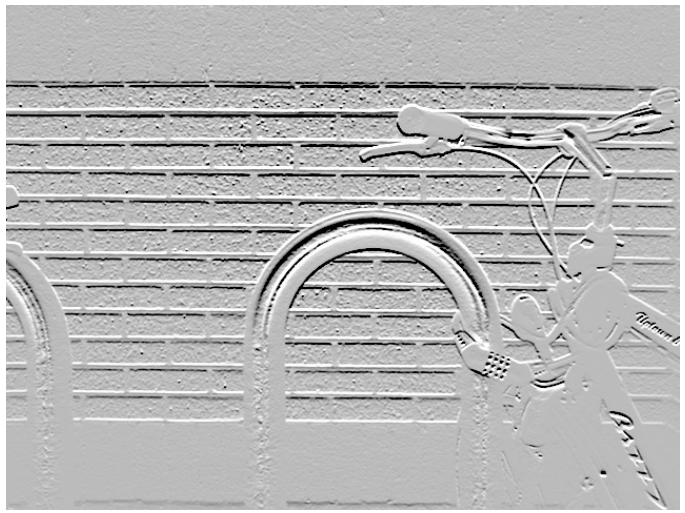


Filters

1	2	1
0	0	0
-1	-2	-1

Horizontal
Edge Detector

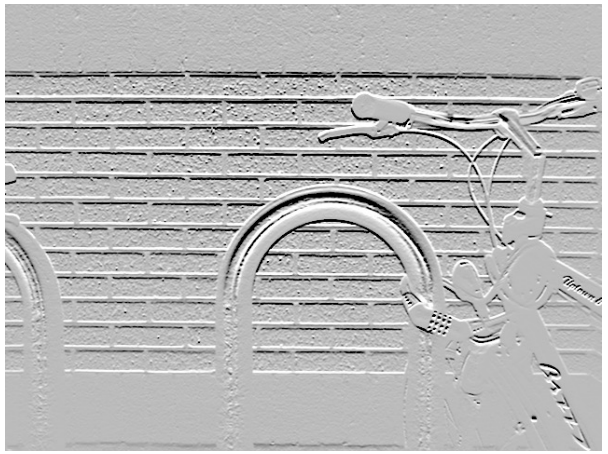




Filters

1	2	1
0	0	0
-1	-2	-1

Horizontal
Edge Detector



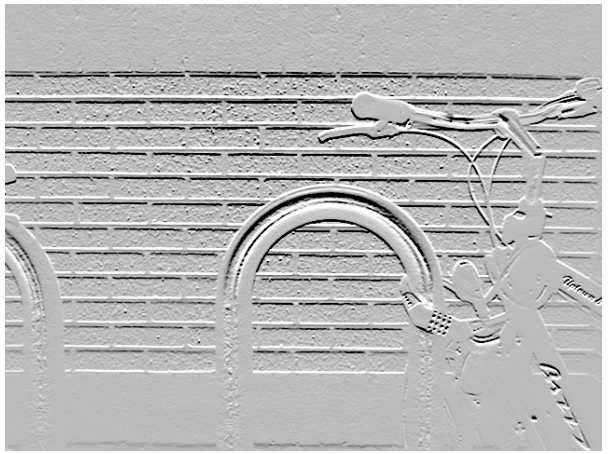
```
Gy = np.array([[1, 2, 1],
               [0, 0, 0],
               [-1, -2, -1]])
rows, columns = np.shape(grayscale_image)
sobel_filtered_image = np.zeros(shape=(rows, columns))

for i in range(rows - 2):
    for j in range(columns - 2):
        gy = np.sum(np.multiply(Gy, grayscale_image[i:i+3, j:j+3]))
        sobel_filtered_image[i + 1, j + 1] = gy
```

Filters

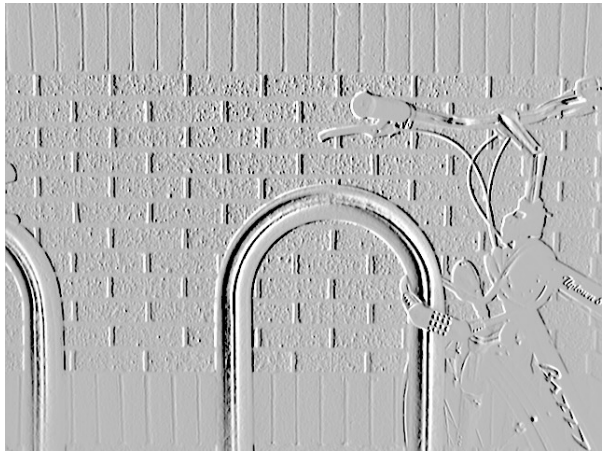
1	2	1
0	0	0
-1	-2	-1

Horizontal
Edge Detector

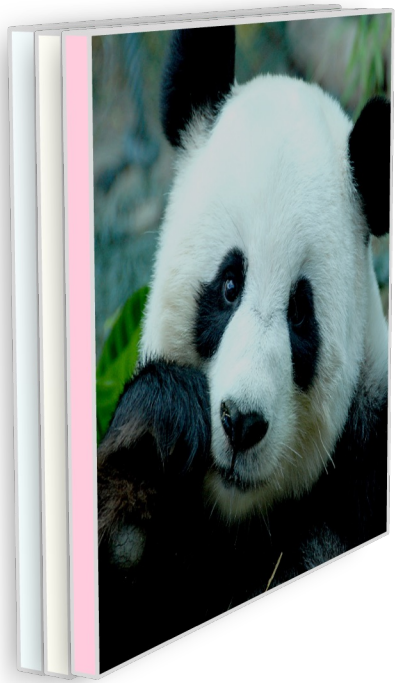


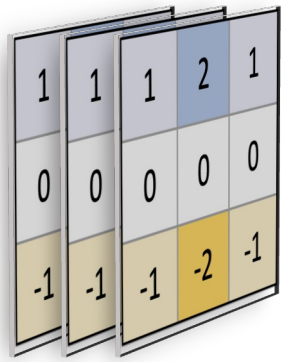
1	0	-1
2	0	-2
1	0	-1

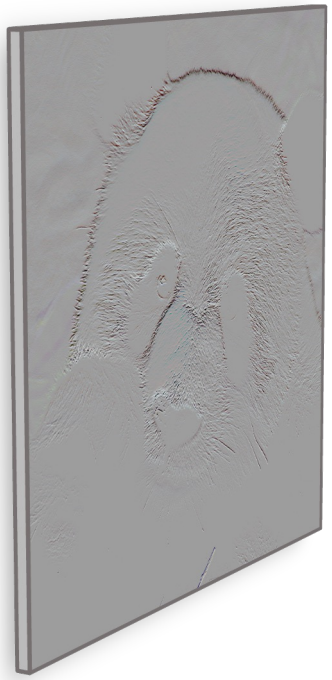
Vertical
Edge Detector



Filters

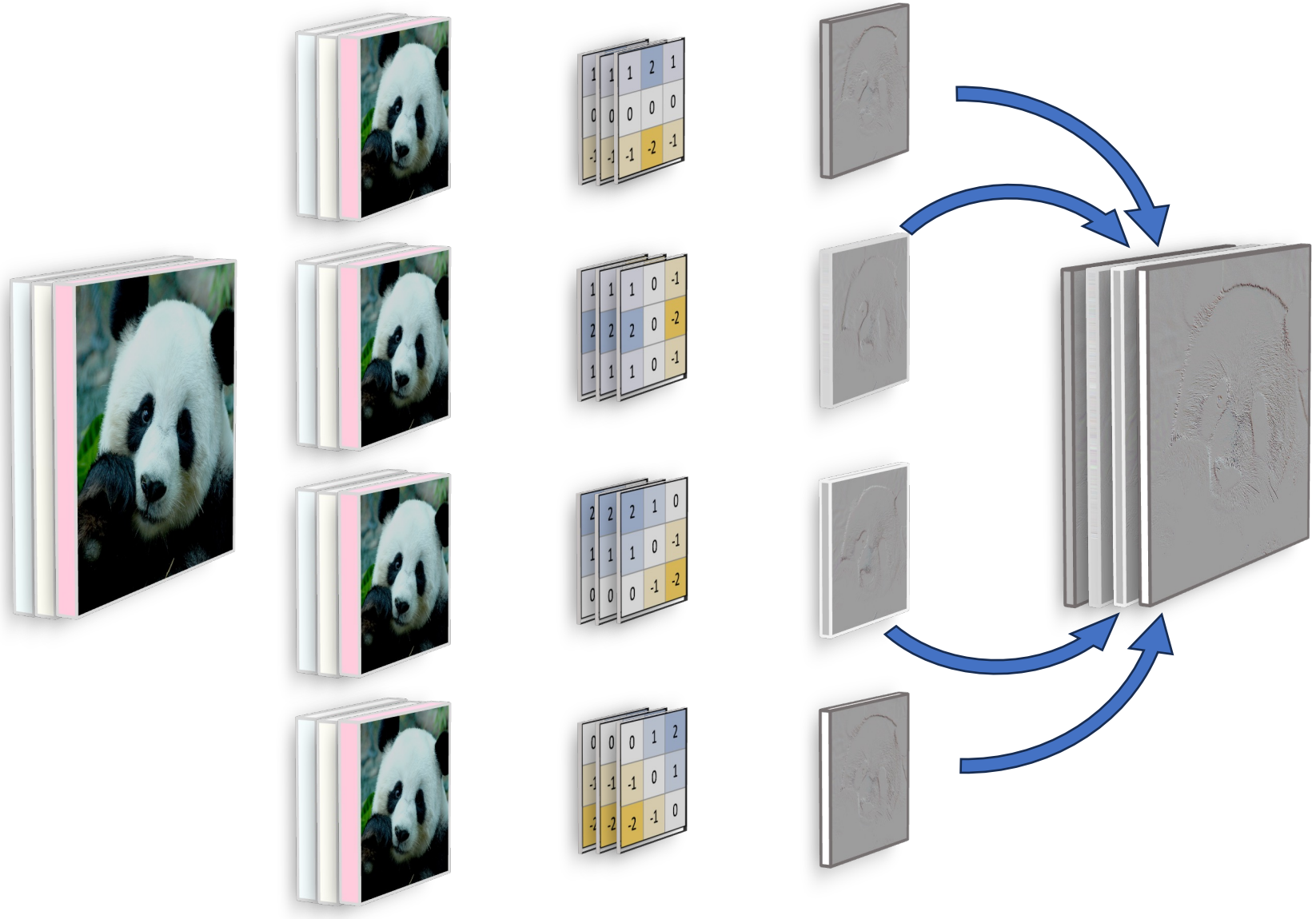






Filters

Filters



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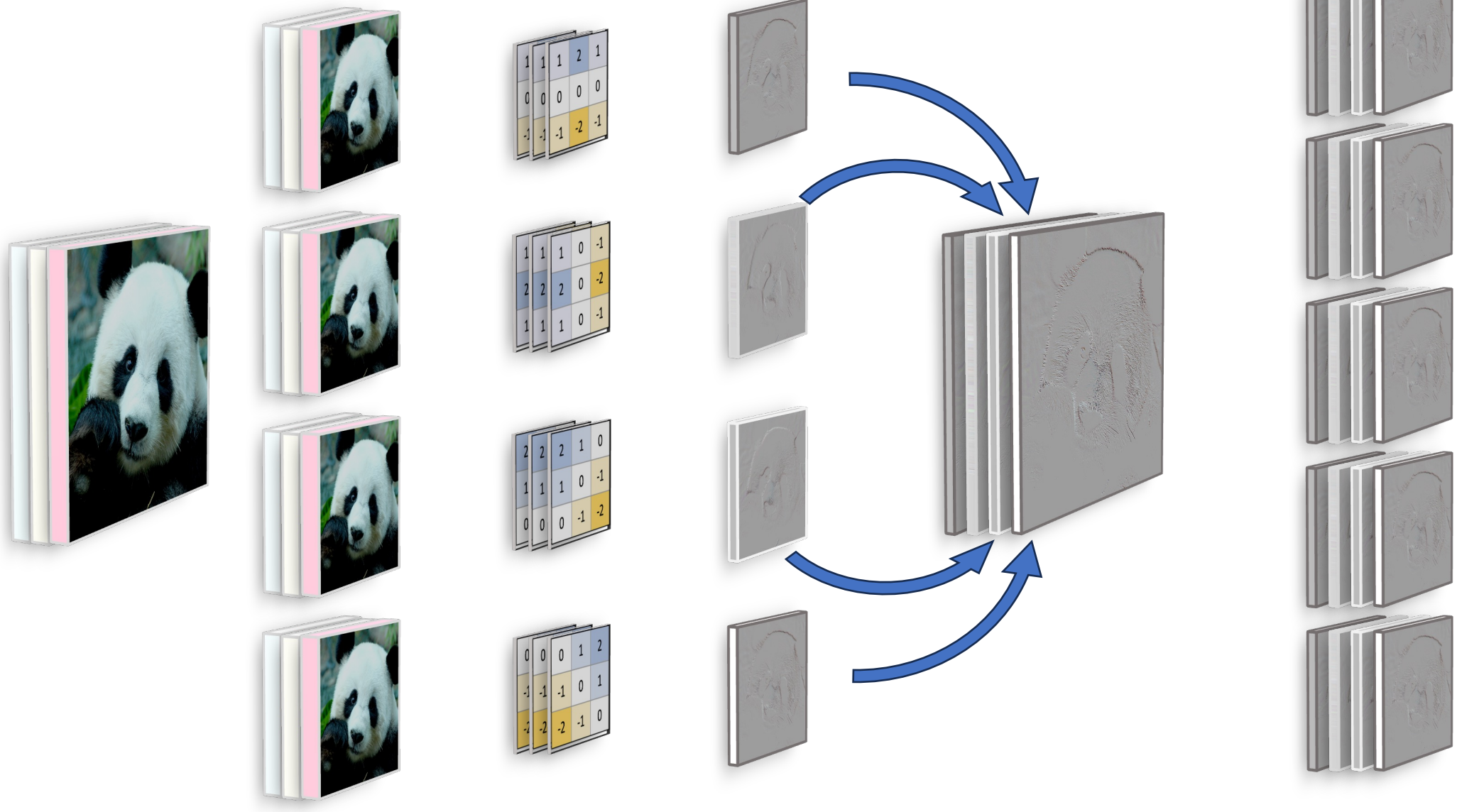

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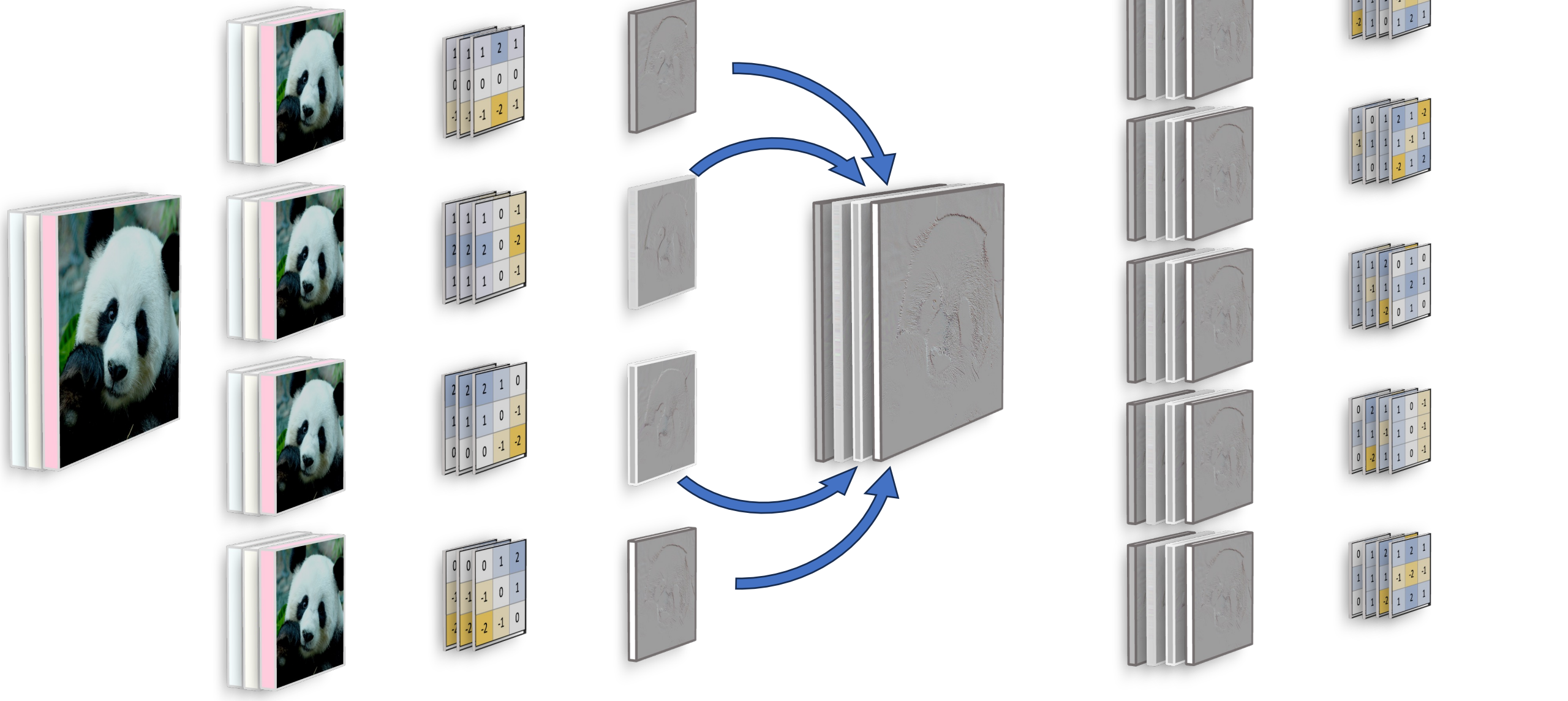
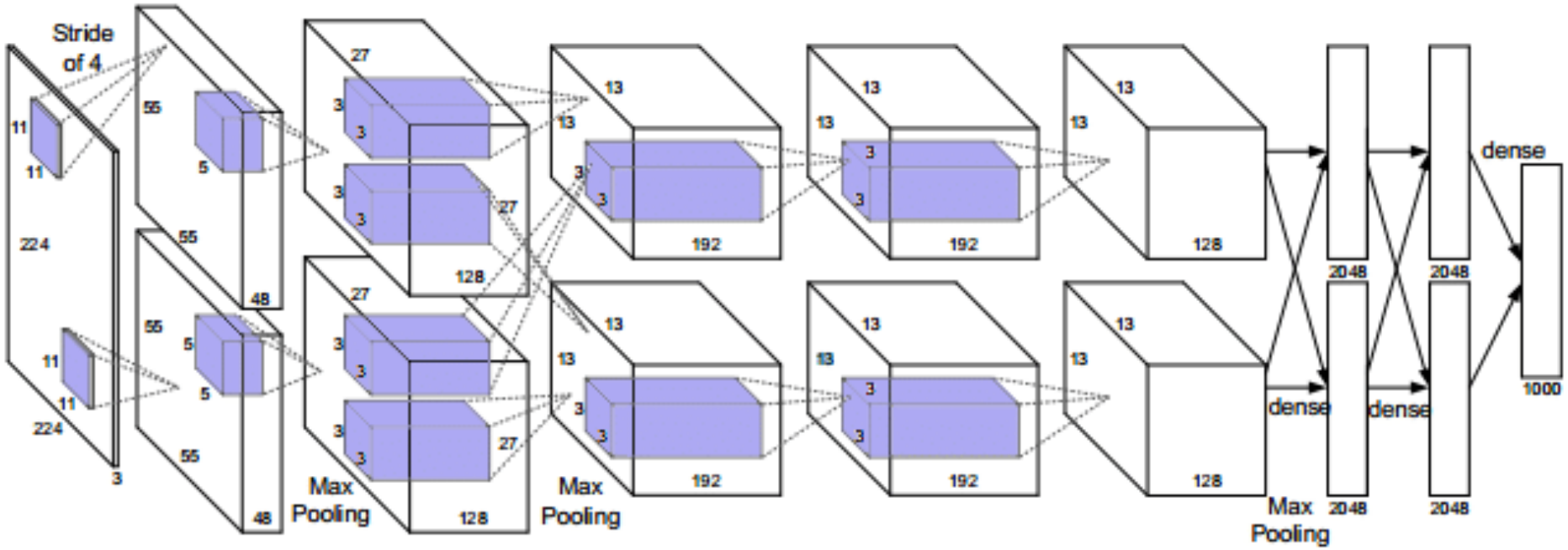
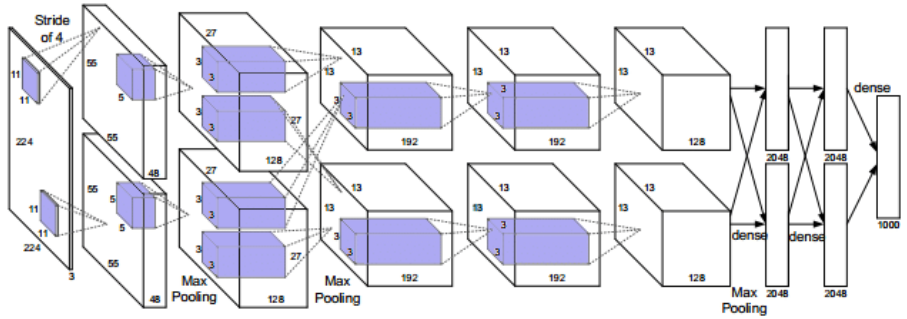


AlexNet (2012)

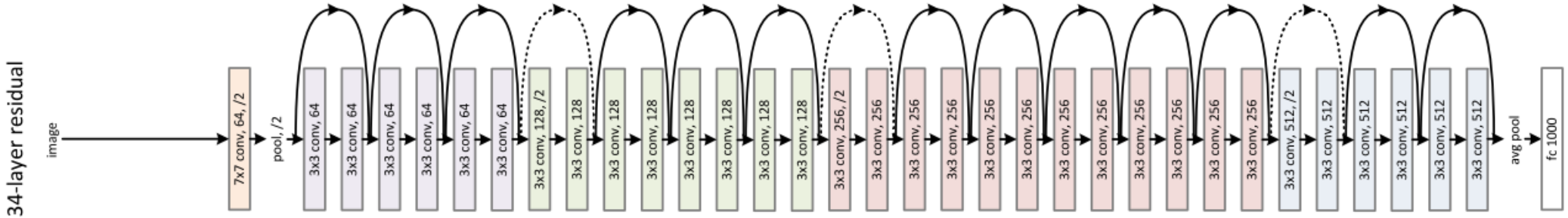


AlexNet (2012)

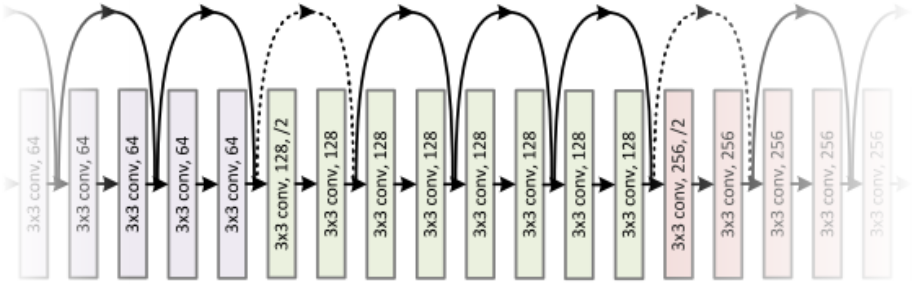



```python
import torch.nn as nn

class AlexNet(nn.Module):
    def __init__(self, num_classes: int = 1000, dropout: float = 0.5) -> None:
        super().__init__()
        _log_api_usage_once(self)
        self.features = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=11, stride=4, padding=2),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),
            nn.Conv2d(64, 192, kernel_size=5, padding=2),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),
            nn.Conv2d(192, 384, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(384, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),
        )
        self.avgpool = nn.AdaptiveAvgPool2d((6, 6))
        self.classifier = nn.Sequential(
            nn.Dropout(p=dropout),
            nn.Linear(256 * 6 * 6, 4096),
            nn.ReLU(inplace=True),
            nn.Dropout(p=dropout),
            nn.Linear(4096, 4096),
            nn.ReLU(inplace=True),
            nn.Linear(4096, num_classes),
        )

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        x = self.features(x)
        x = self.avgpool(x)
        x = torch.flatten(x, 1)
        x = self.classifier(x)
        return x
```

ResNet (2015)

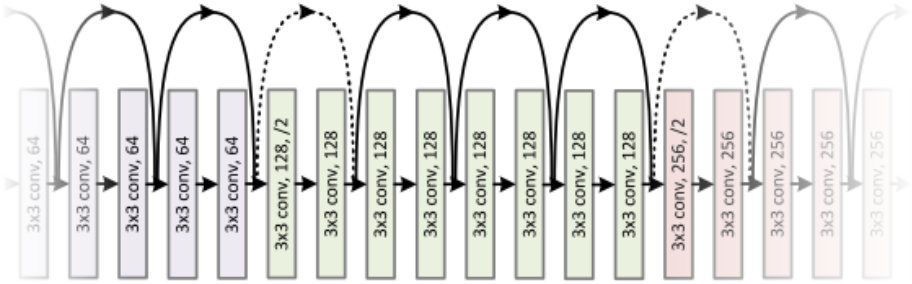

34-layer residual
image
7x7 conv, 64, /2
pool, /2
3x3 conv, 64
3x3 conv, 128, /2
3x3 conv, 256, /2
3x3 conv, 512, /2
avg pool
fc 1000

ResNet (2015)




```python
class Bottleneck(nn.Module):
    def __init__(self, *args, **kwargs) -> None:
        self.conv1 = conv1x1(inplanes, width)
        self.bn1 = norm_layer(width)
        self.conv2 = conv3x3(width, width, stride, groups, dilation)
        self.bn2 = norm_layer(width)
        self.conv3 = conv1x1(width, planes * self.expansion)
        self.bn3 = norm_layer(planes * self.expansion)
        self.relu = nn.ReLU(inplace=True)
        self.downsample = downsample
        self.stride = stride

    def forward(self, x: Tensor) -> Tensor:
        identity = x

        out = self.conv1(x)
        out = self.bn1(out)
        out = self.relu(out)

        out = self.conv2(out)
        out = self.bn2(out)
        out = self.relu(out)

        out = self.conv3(out)
        out = self.bn3(out)

        out += identity
        out = self.relu(out)

        return out
```

ResNet (2015)



Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

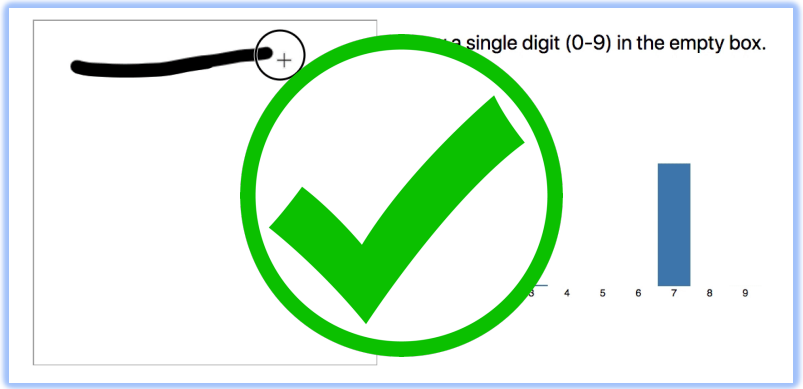
$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

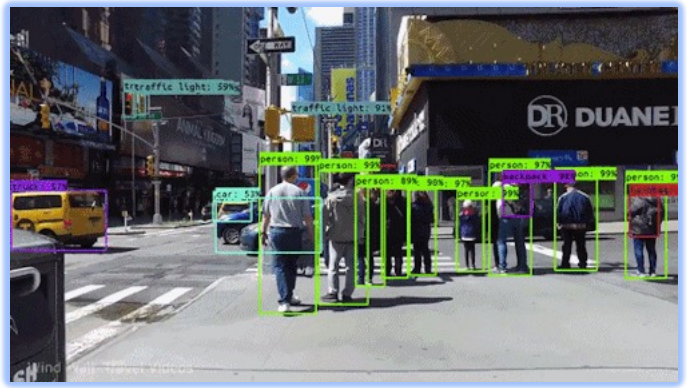
$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

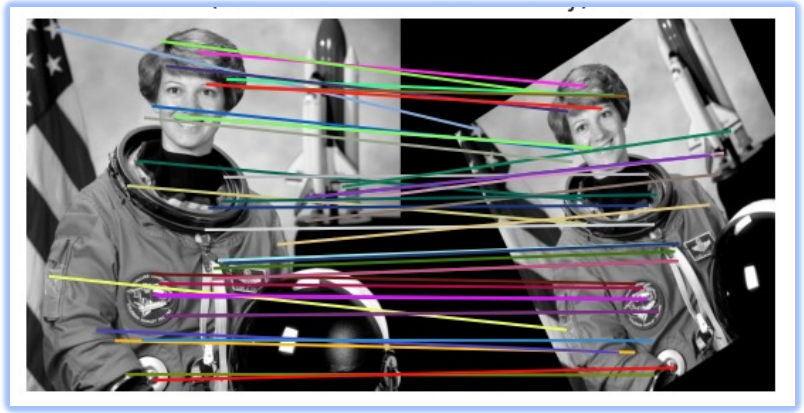
```python
class Bottleneck(nn.Module):
    def __init__(self, *args, **kwargs) -> None:
        self.conv1 = conv1x1(inplanes, width)
        self.bn1 = norm_layer(width)
        self.conv2 = conv3x3(width, width, stride, groups, dilation)
        self.bn2 = norm_layer(width)
        self.conv3 = conv1x1(width, planes * self.expansion)
        self.bn3 = norm_layer(planes * self.expansion)
        self.relu = nn.ReLU(inplace=True)
        self.downsample = downsample
        self.stride = stride

    def forward(self, x: Tensor) -> Tensor:
        identity = x

        out = self.conv1(x)
        out = self.bn1(out)
        out = self.relu(out)

        out = self.conv2(out)
        out = self.bn2(out)
        out = self.relu(out)

        out = self.conv3(out)
        out = self.bn3(out)

        out += identity
        out = self.relu(out)

        return out
```

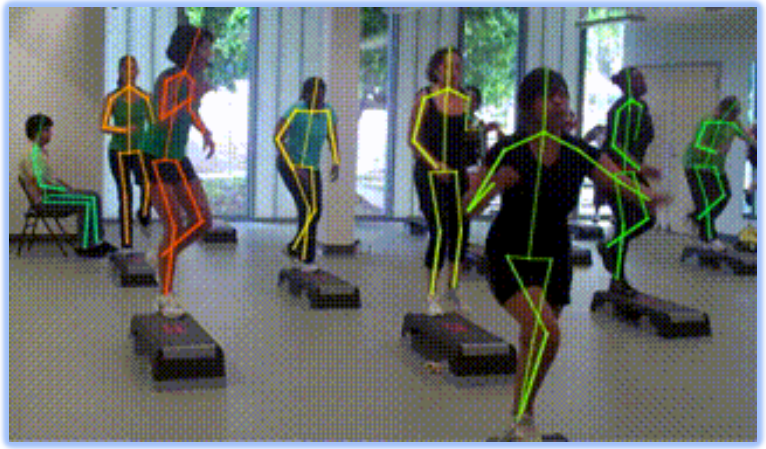
Computer Vision

A multitude of interesting challenges



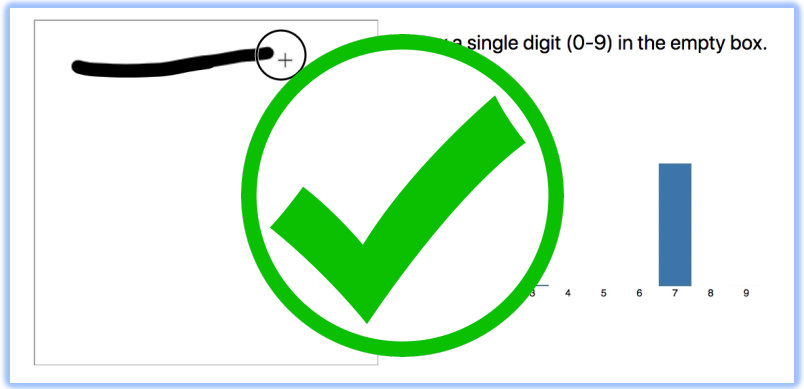


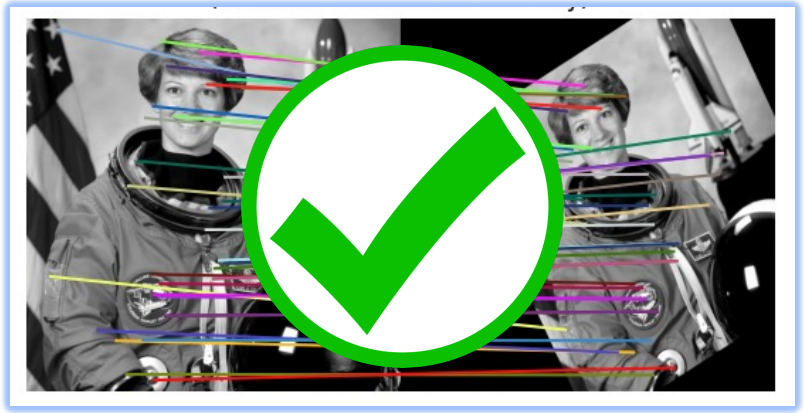




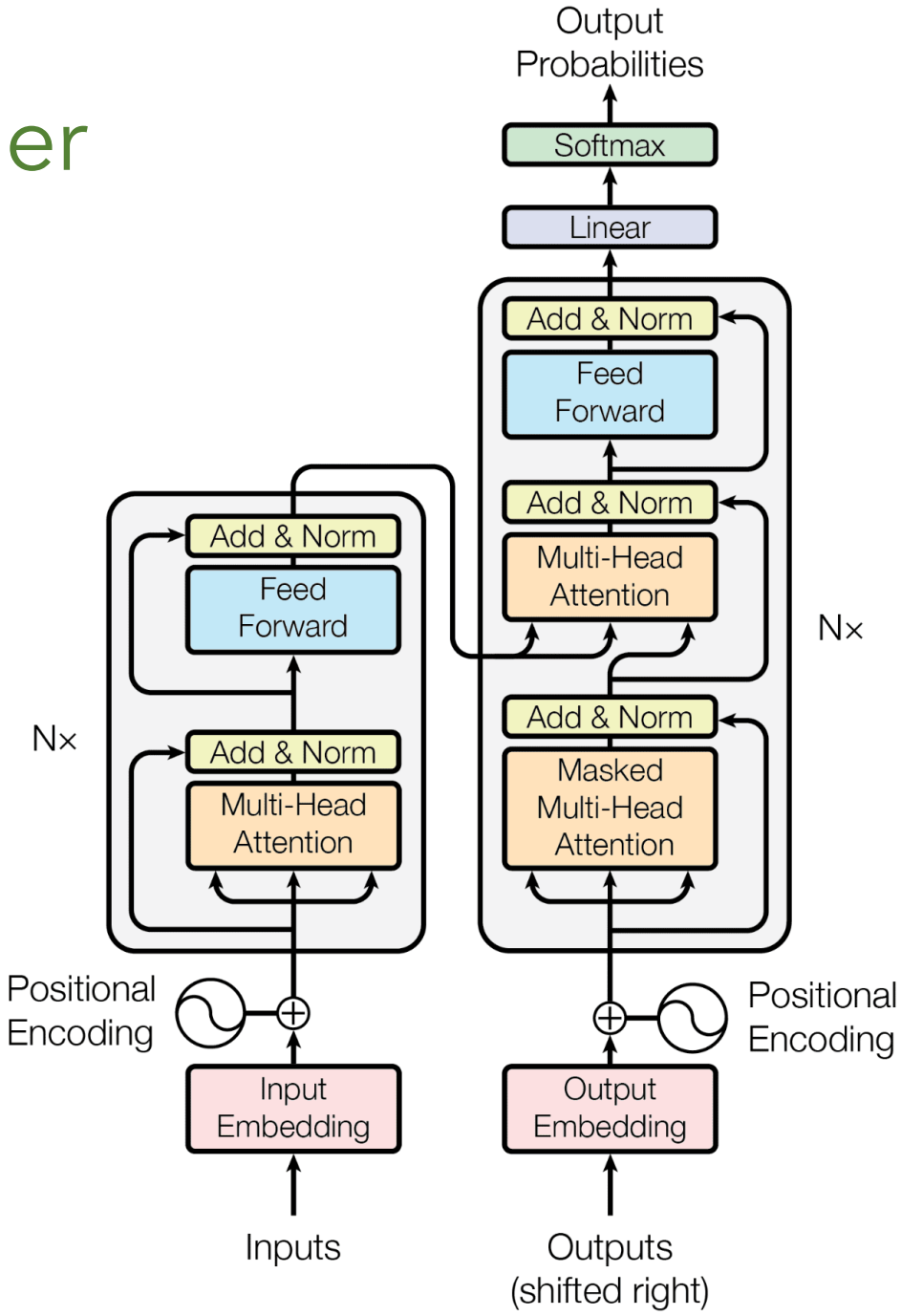
Computer Vision

A multitude of interesting challenges





The Transformer



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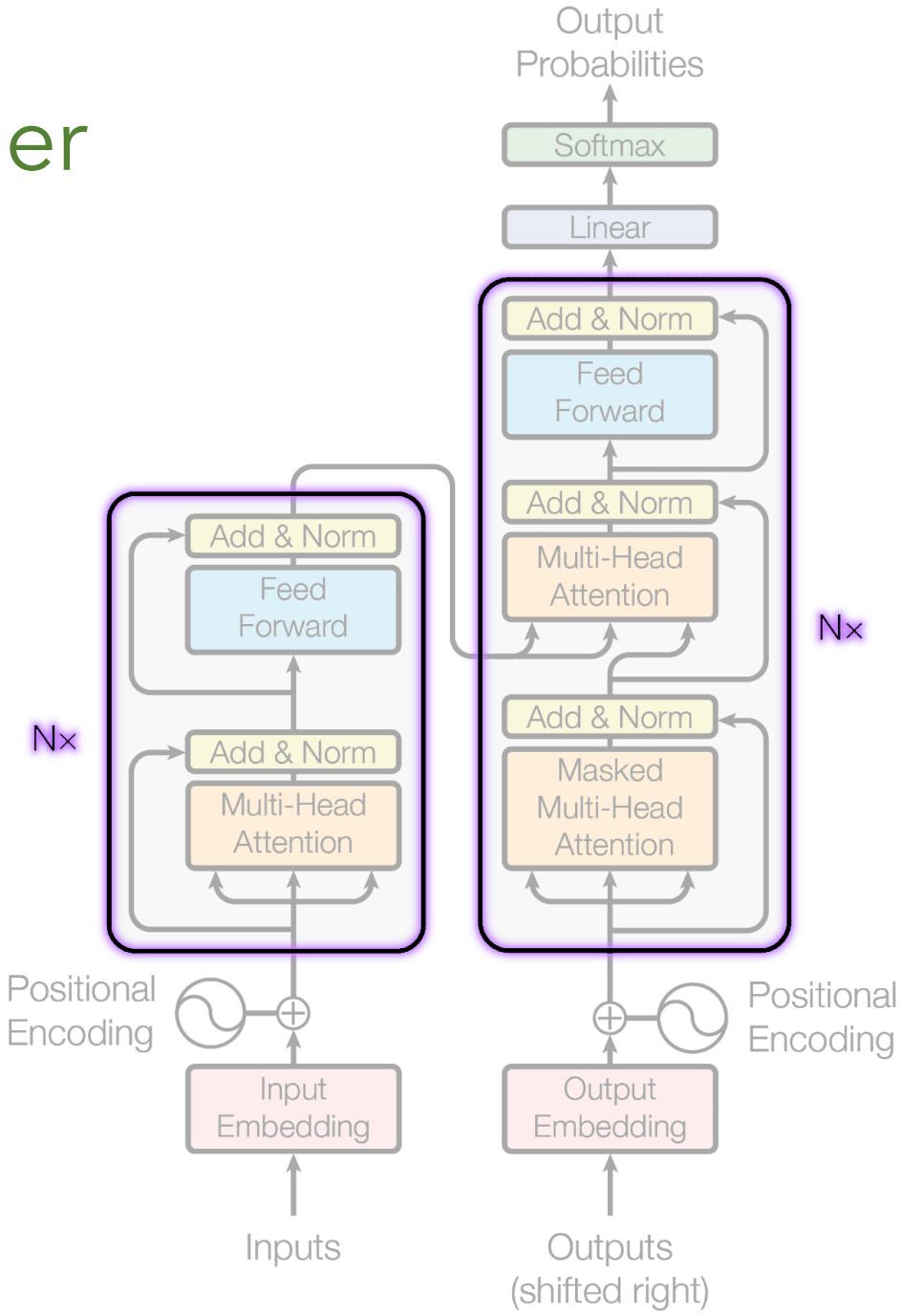

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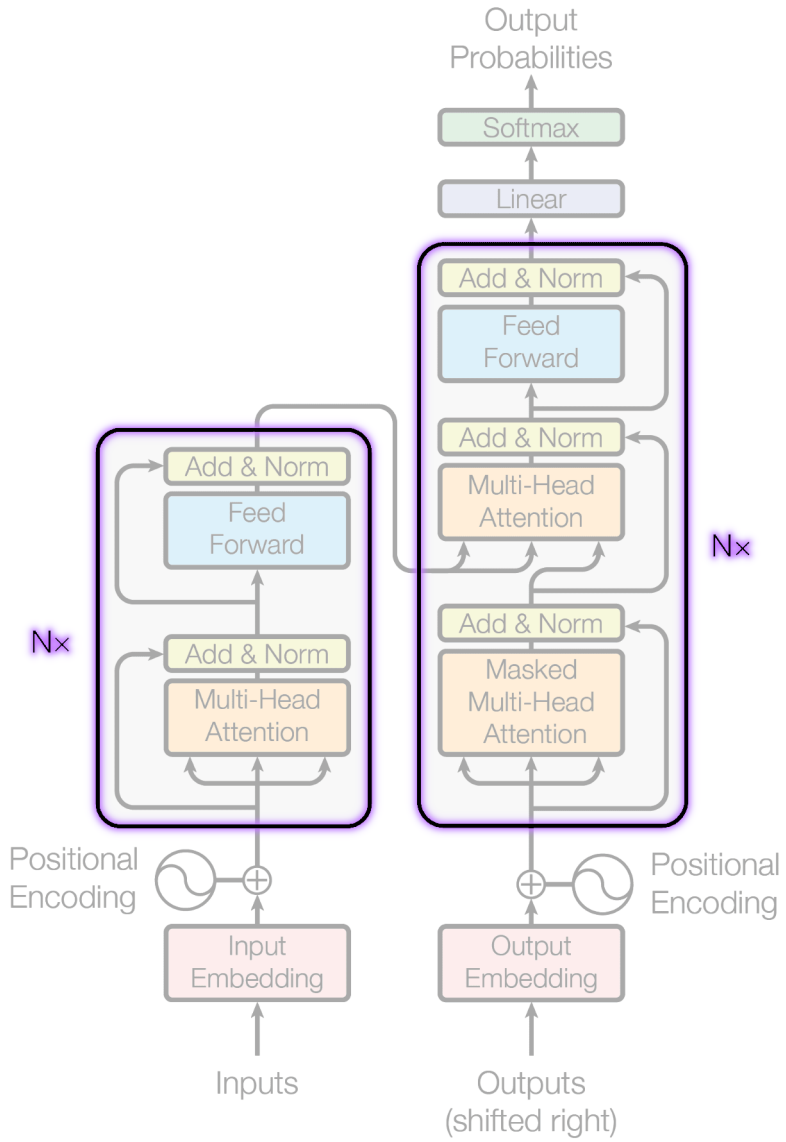

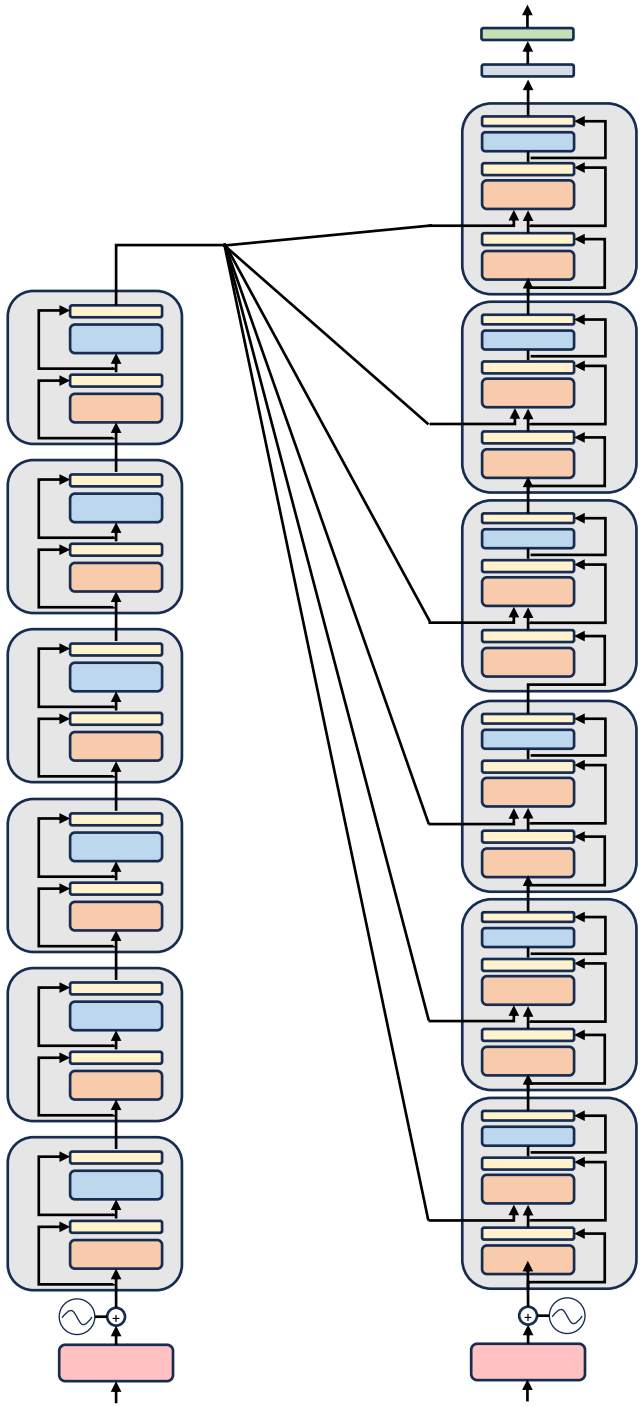

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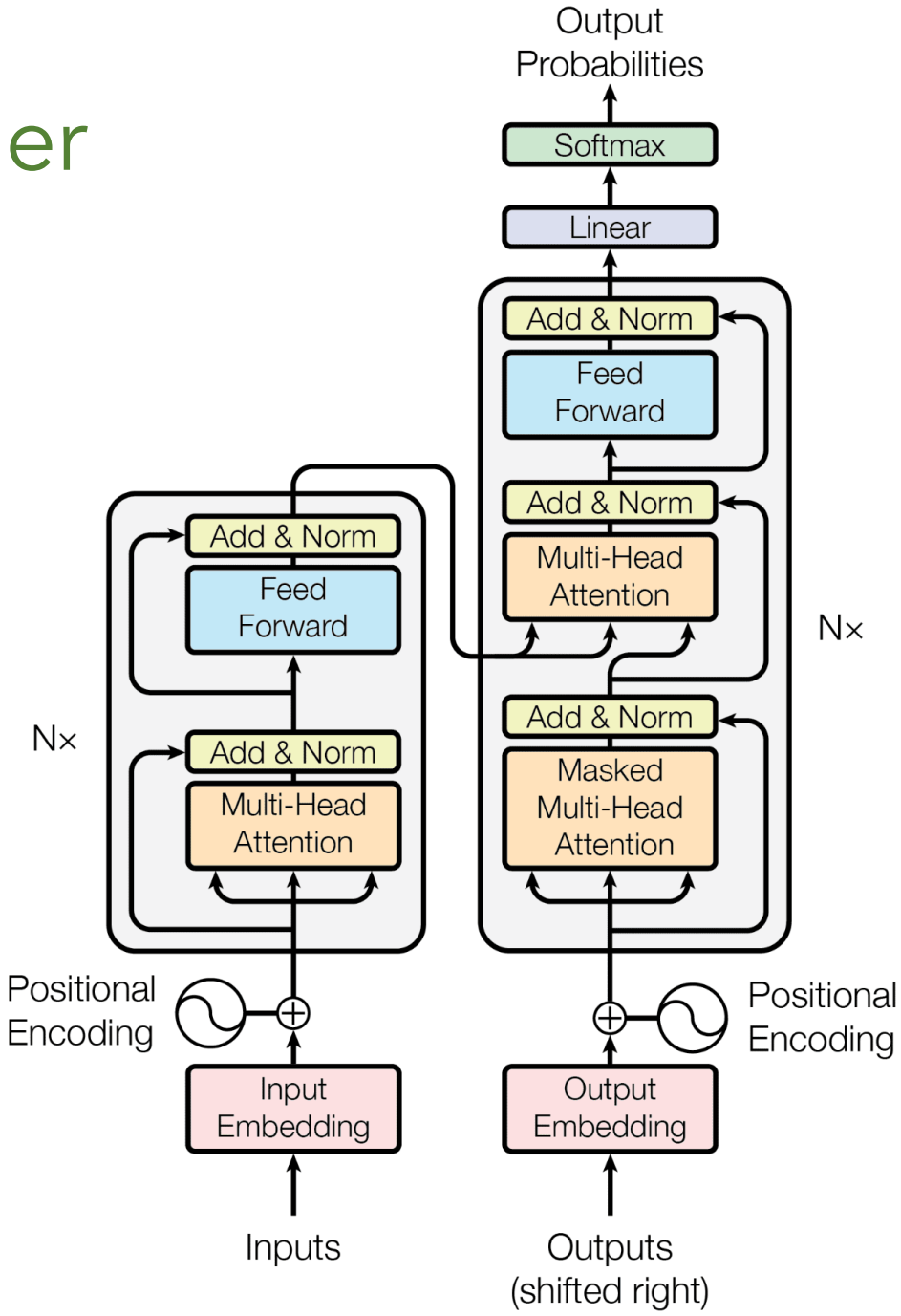

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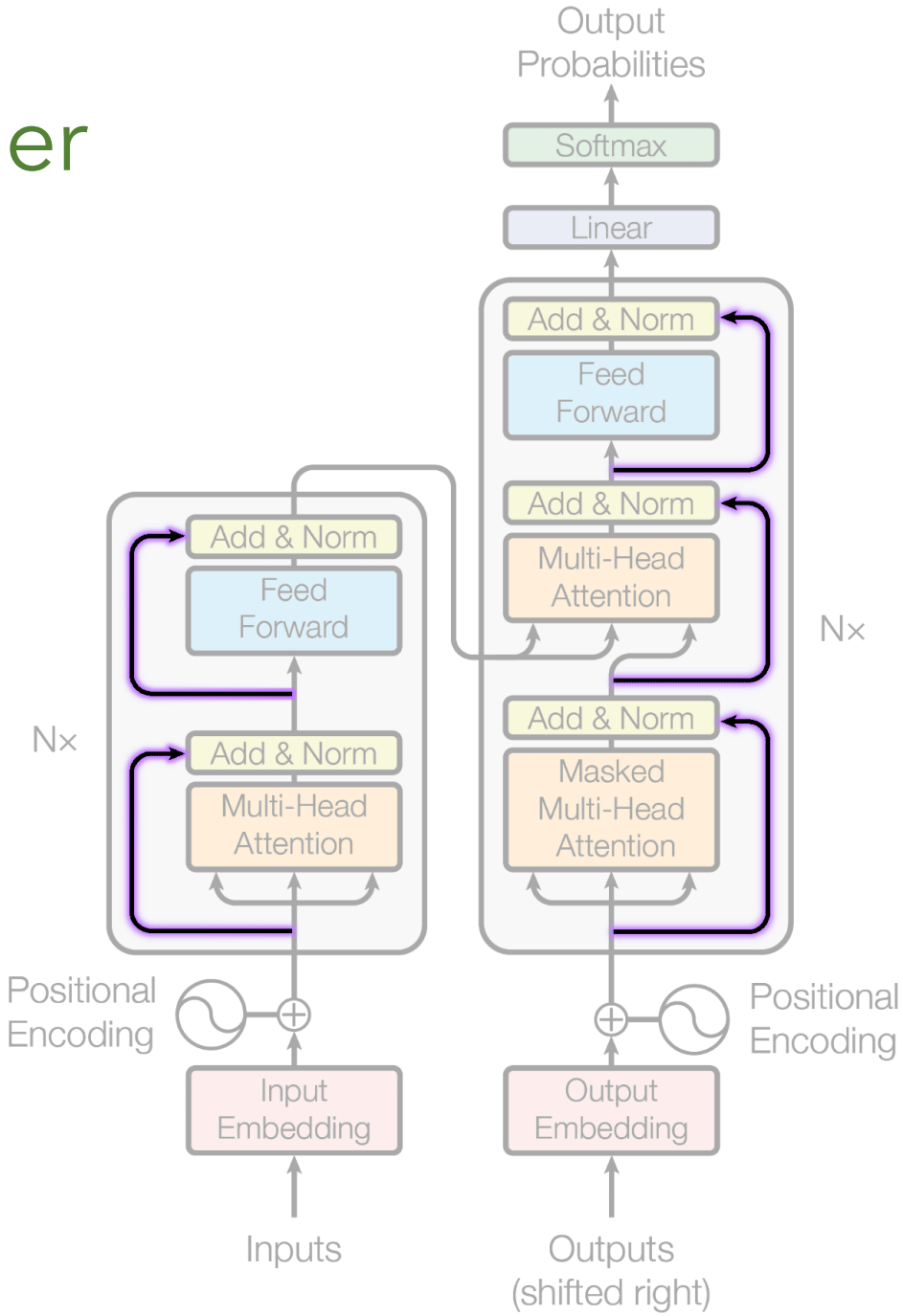

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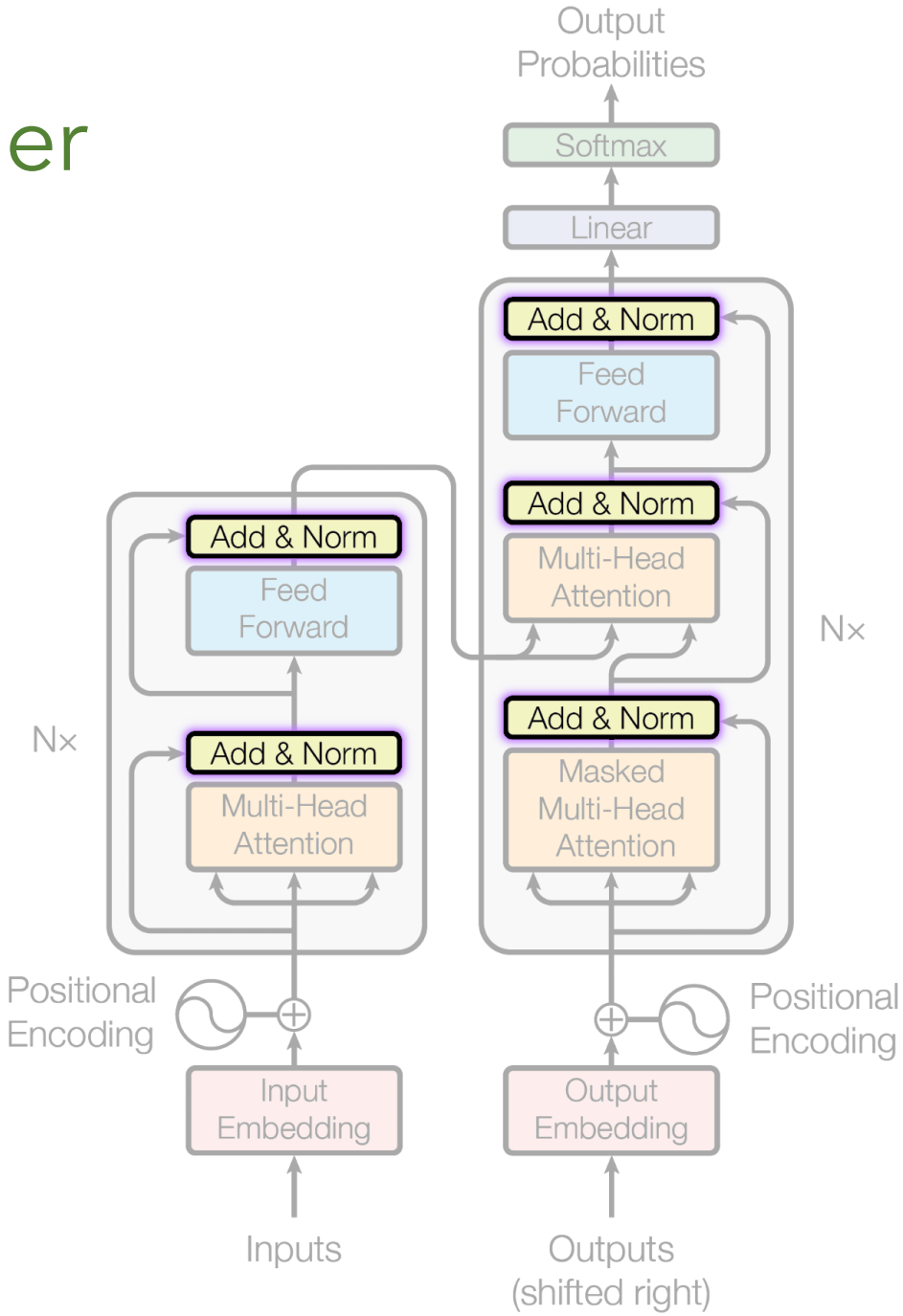

Natural Language Processing

Manipulating Human Language with Computers

Are there many interesting problems in this space?

Sequence to Sequence Modeling

E.g., Translation

Como un cordero al matadero	→	Like a lamb to the slaughter
Donde hay humo, hay fuego	→	Where there's smoke, there's fire
Nunca es tarde para aprender	→	It's never too late to learn
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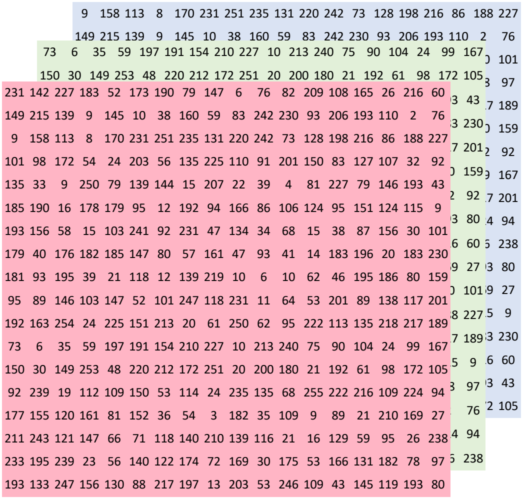
Representation: CV vs NLP

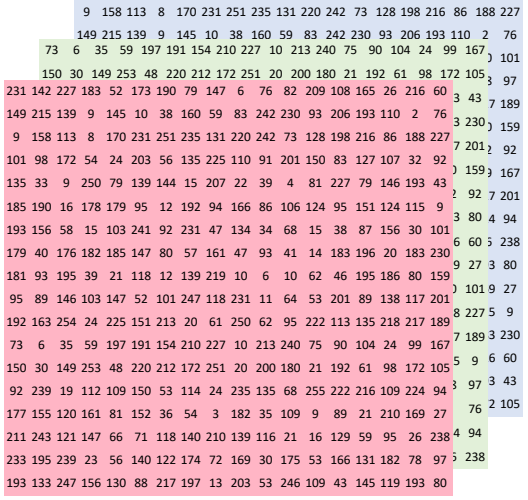


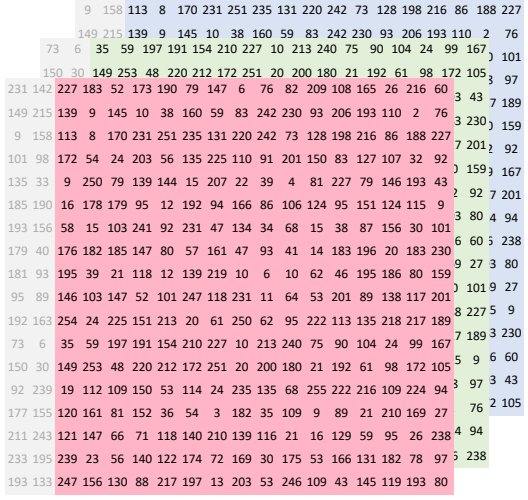
Representation: CV vs NLP

Representation: CV vs NLP

slaughter

73	6C	61	75	67	68	74	65	72





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Embedding

Encoding Words into Vectors

king → `np.array([ 0.603  0.198 -0.585 … -0.074])`

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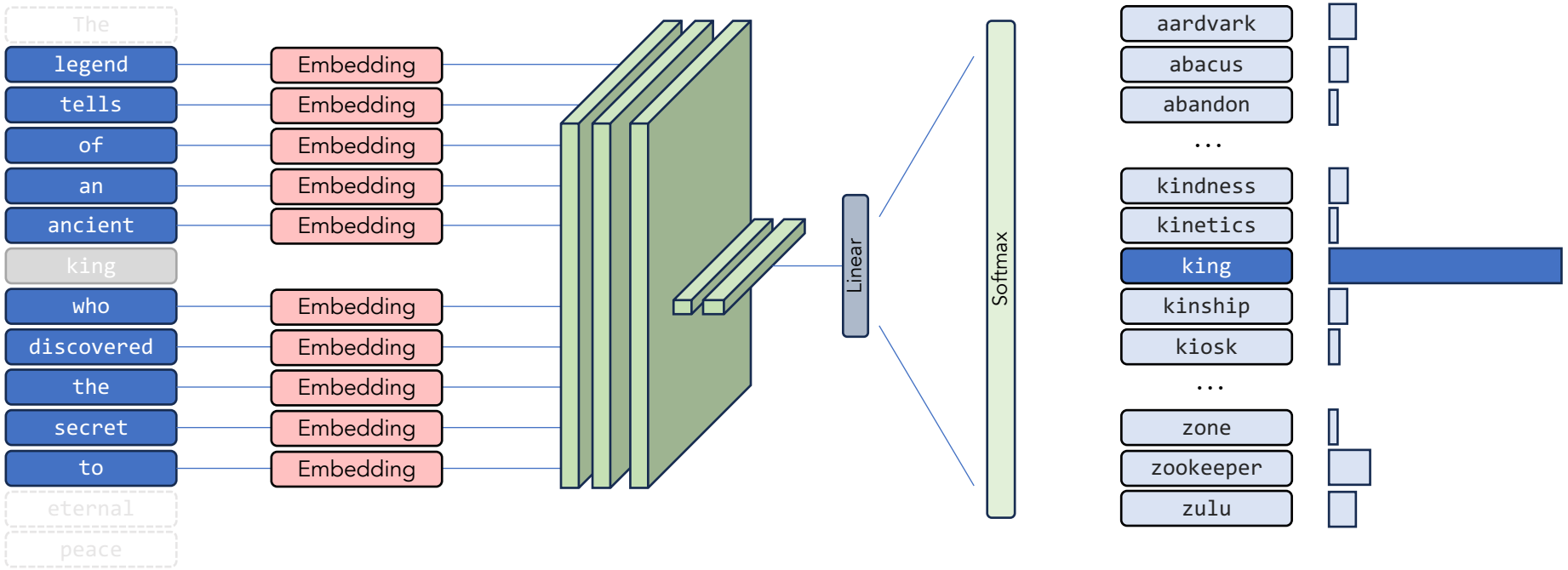

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queen → `np.array([ 1.298  1.422 -1.122 …  0.244])`

man → `np.array([ 0.252 -0.836 -0.294 …  0.455])`

woman → `np.array([ 0.947  0.388 -0.831 …  0.773])`

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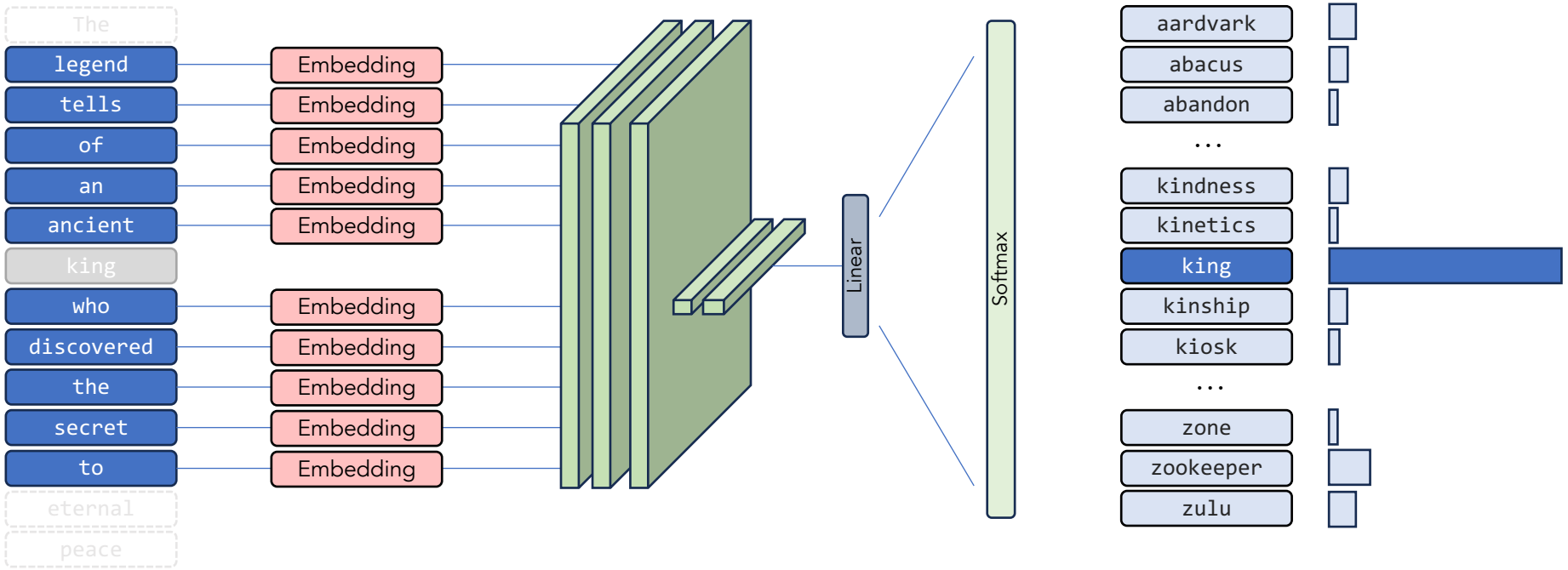

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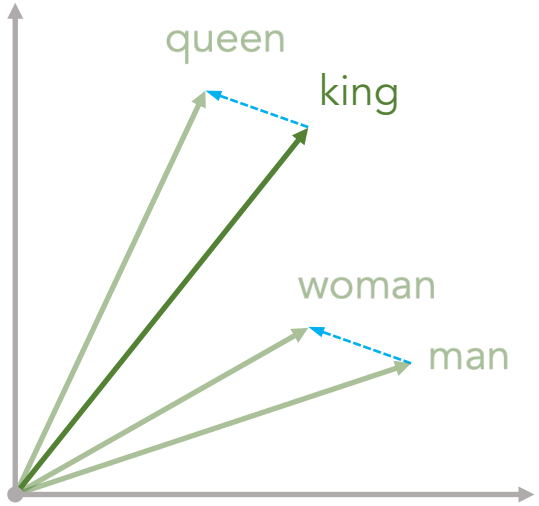

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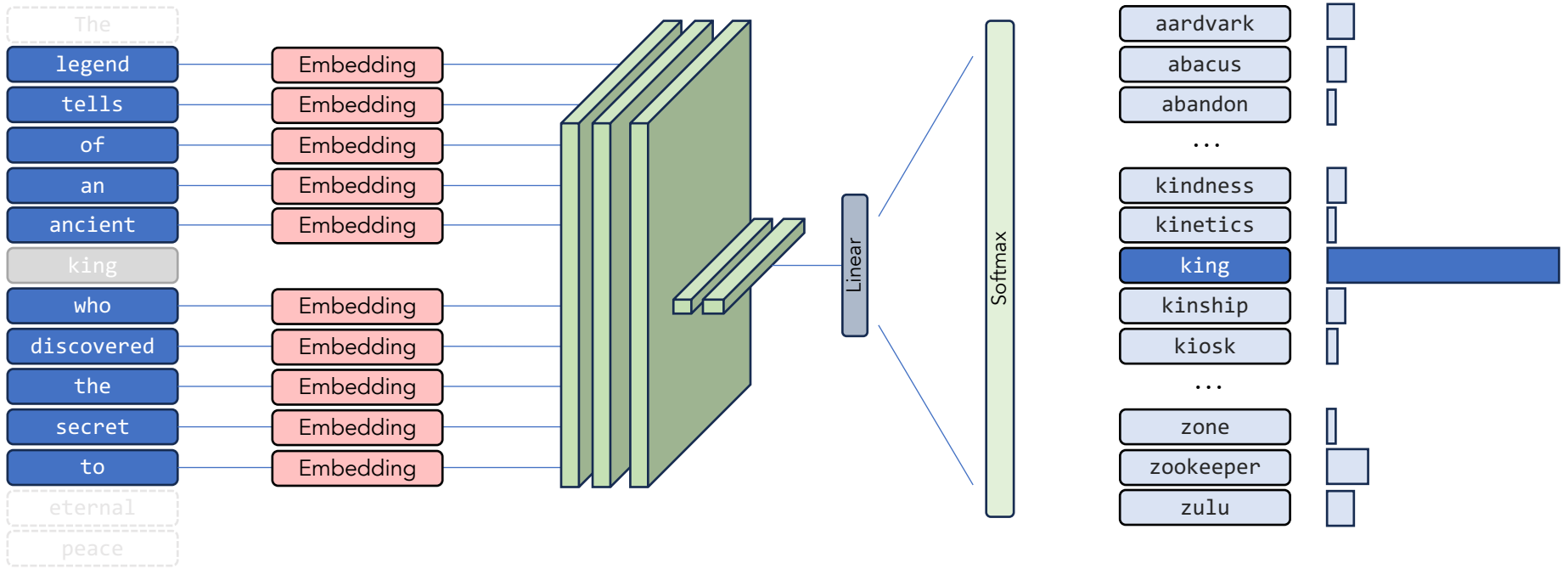

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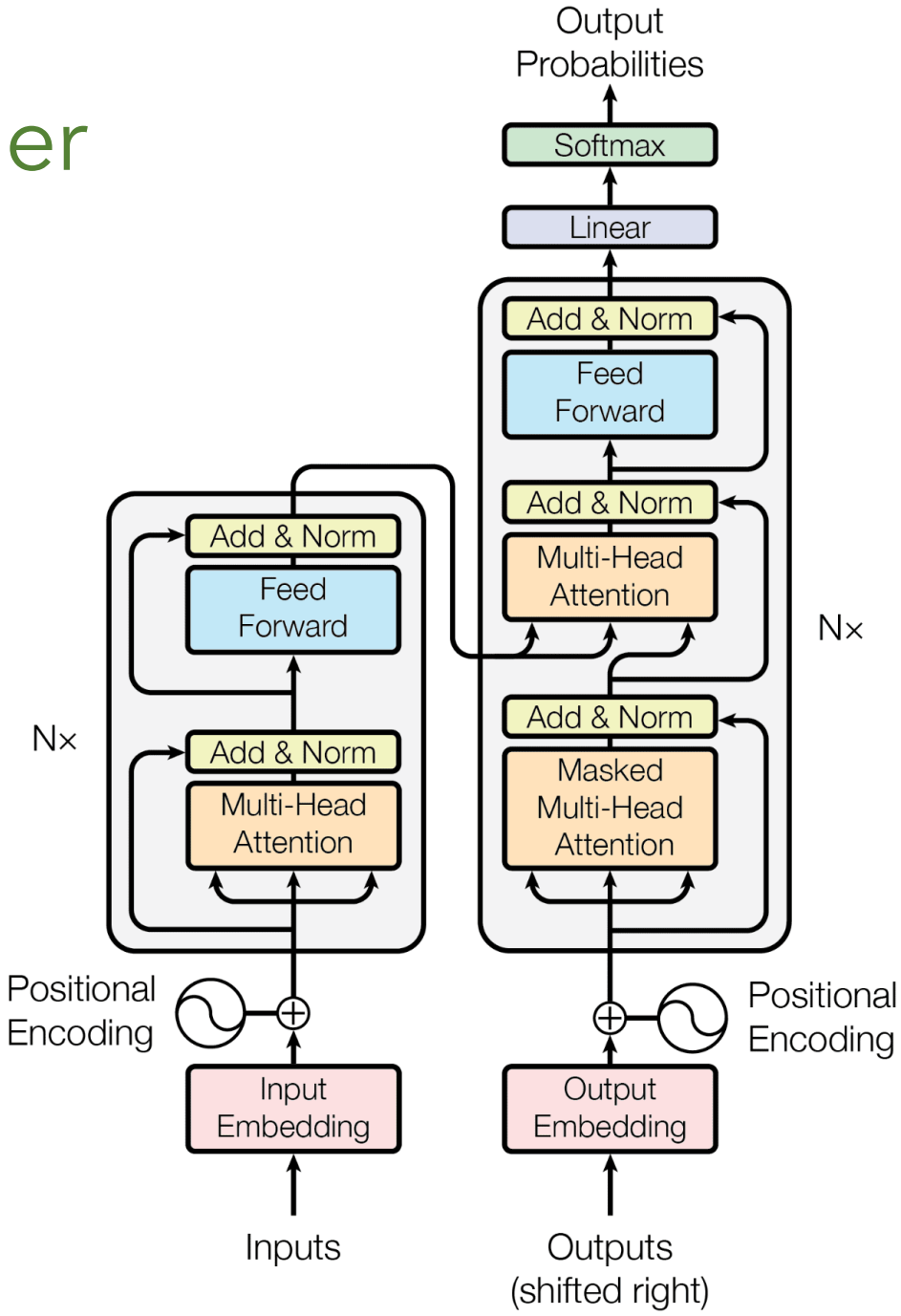

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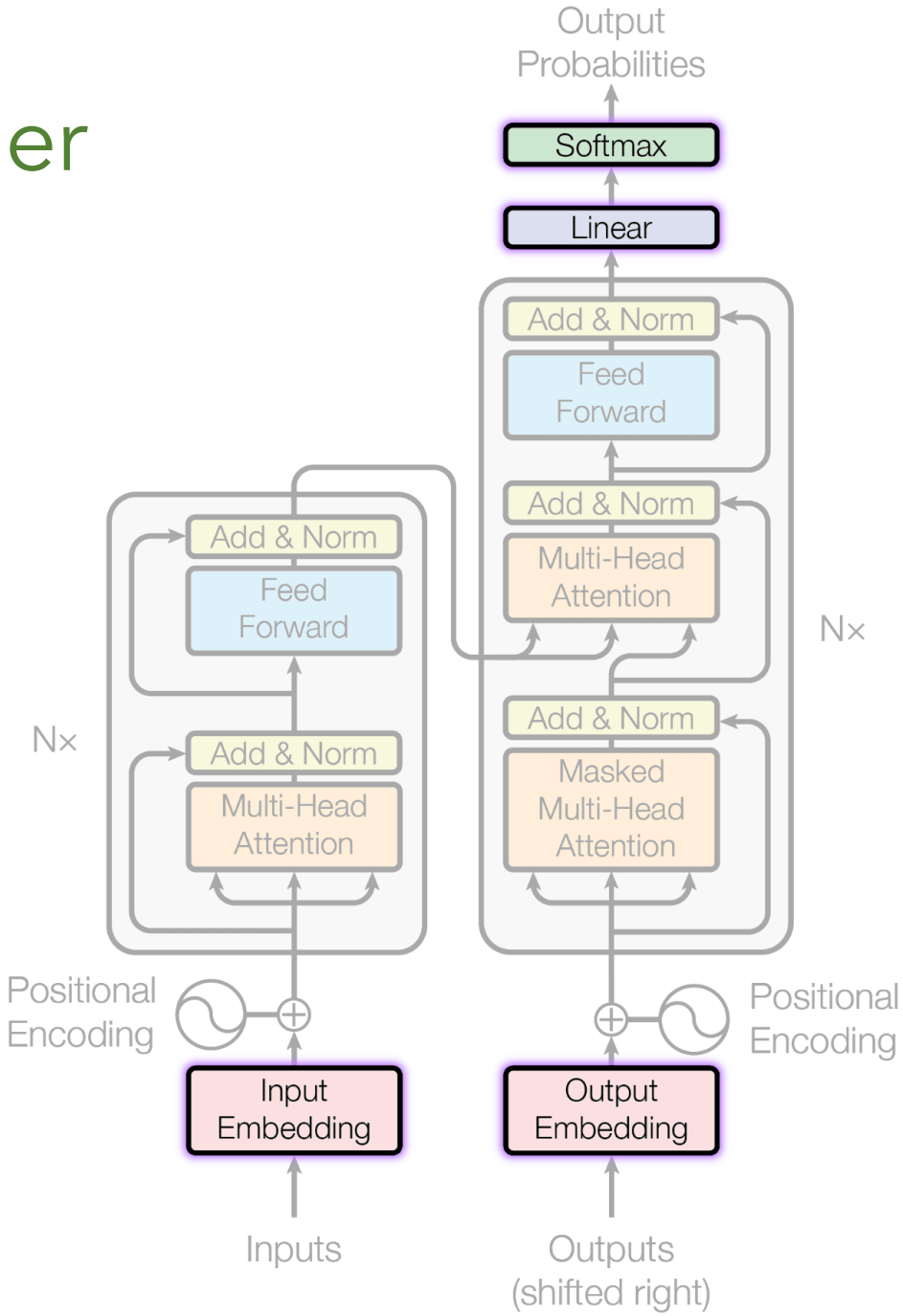

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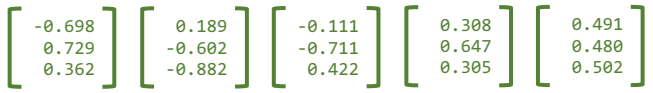
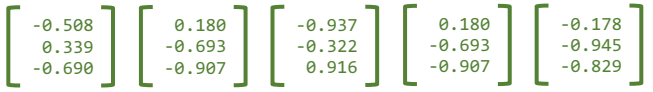


Donde hay humo, hay fuego → Where there's smoke, there's fire



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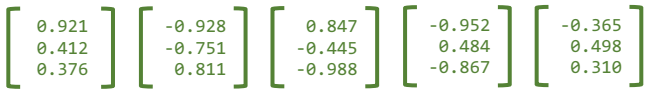

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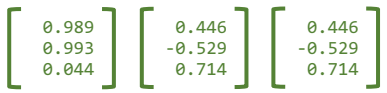
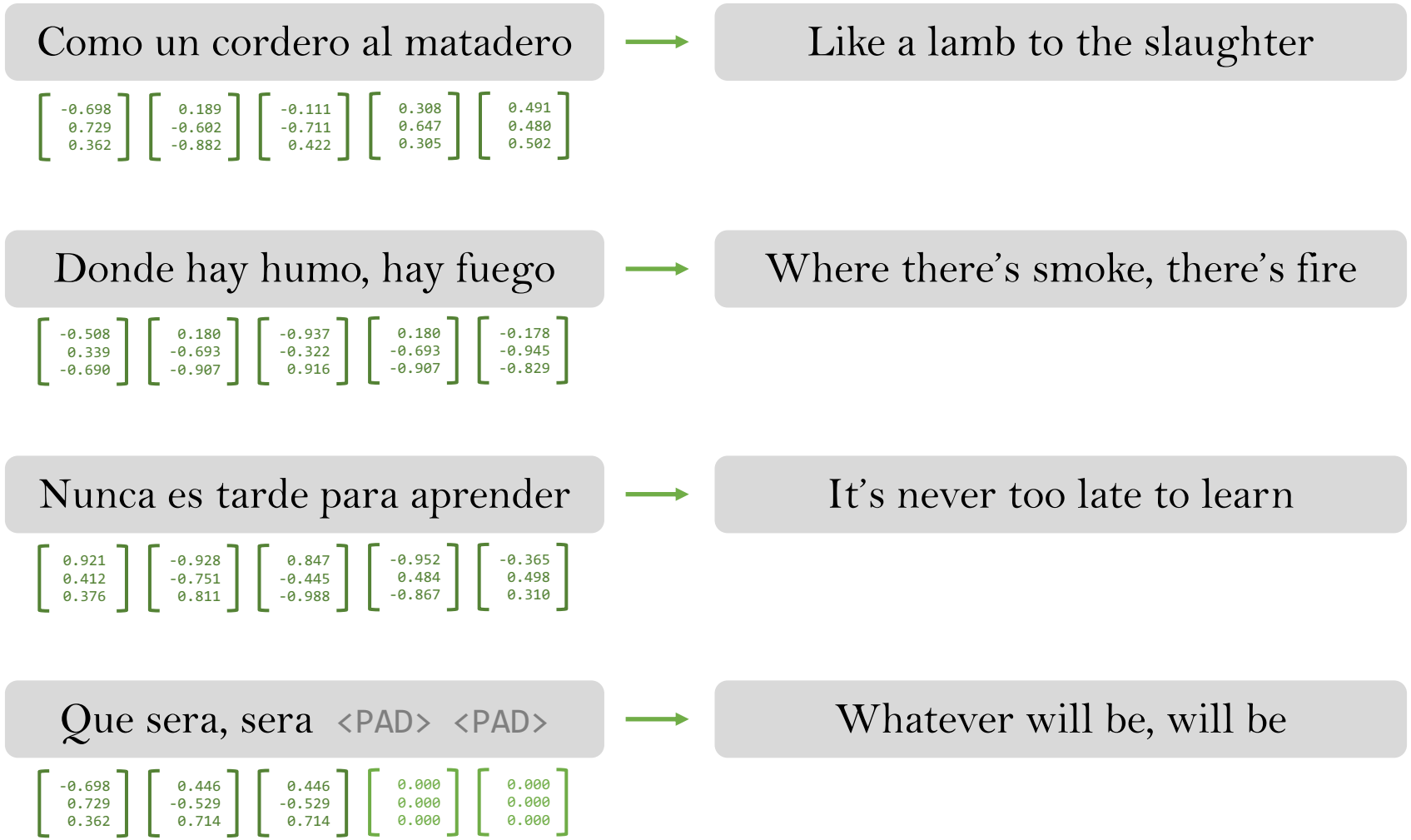


Sequence to Sequence Modeling

E.g., Translation



Sequence to Sequence Modeling

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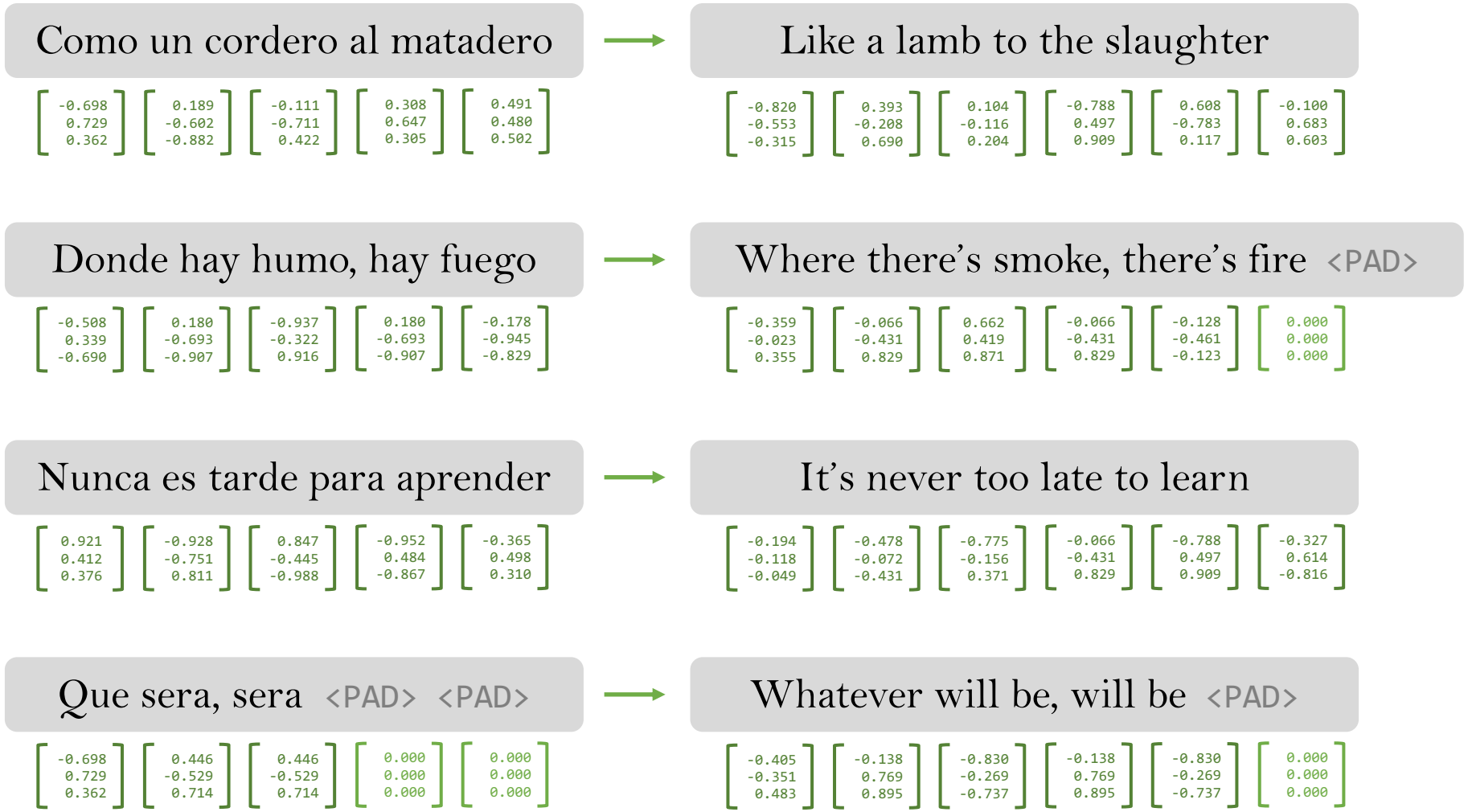
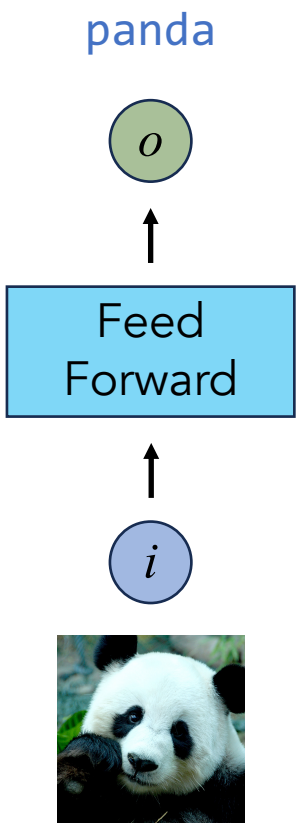


An Alternative Neural Network



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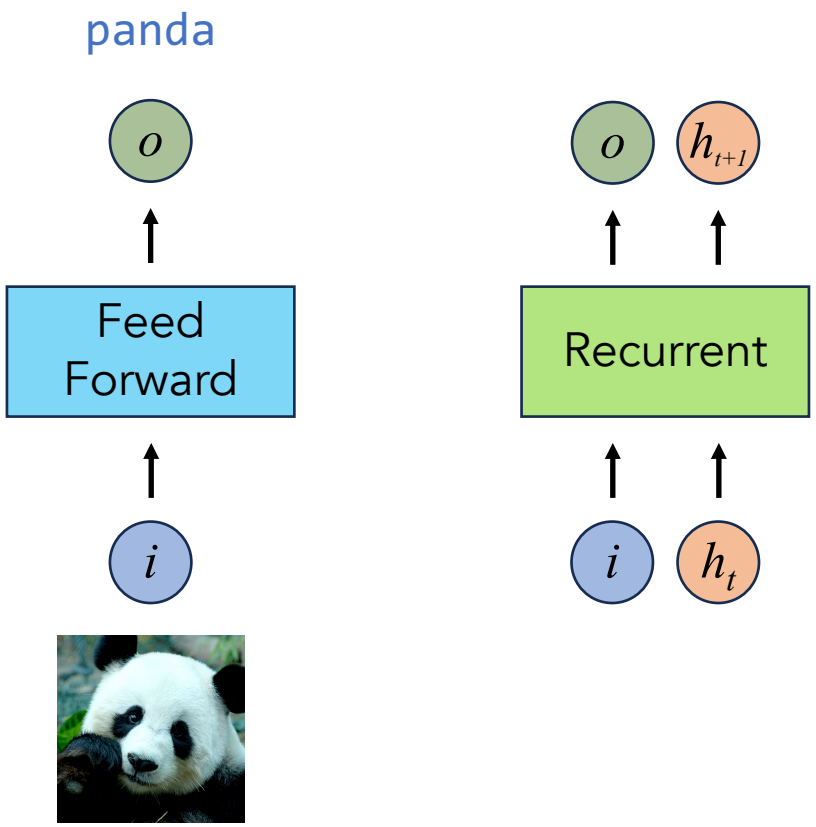

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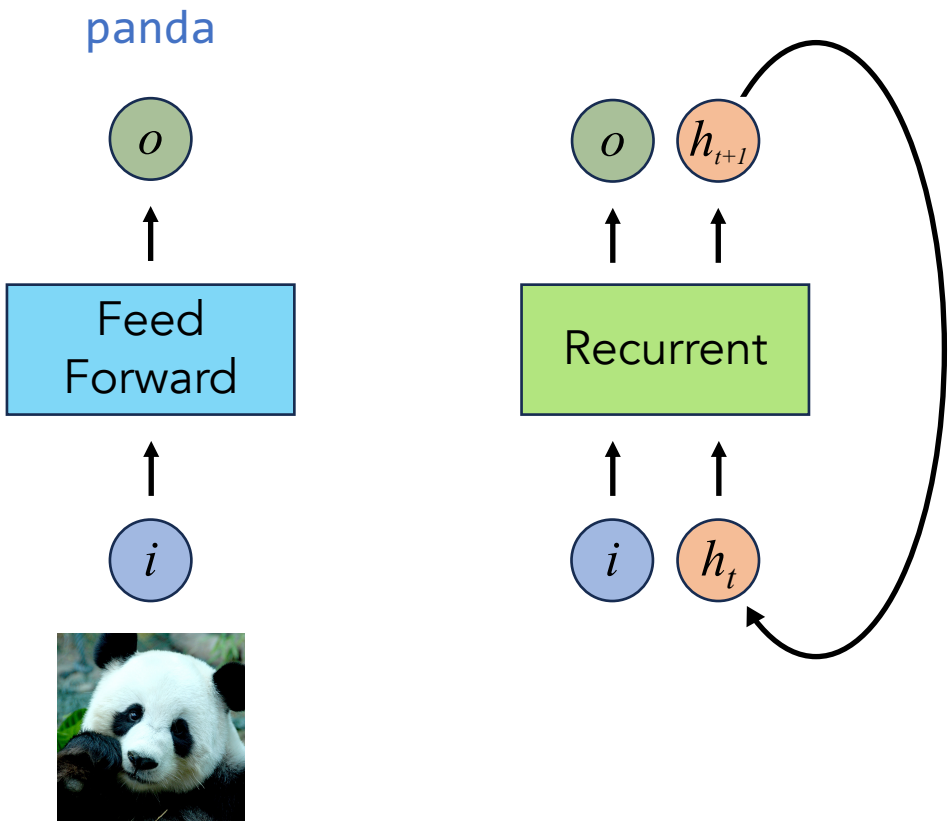

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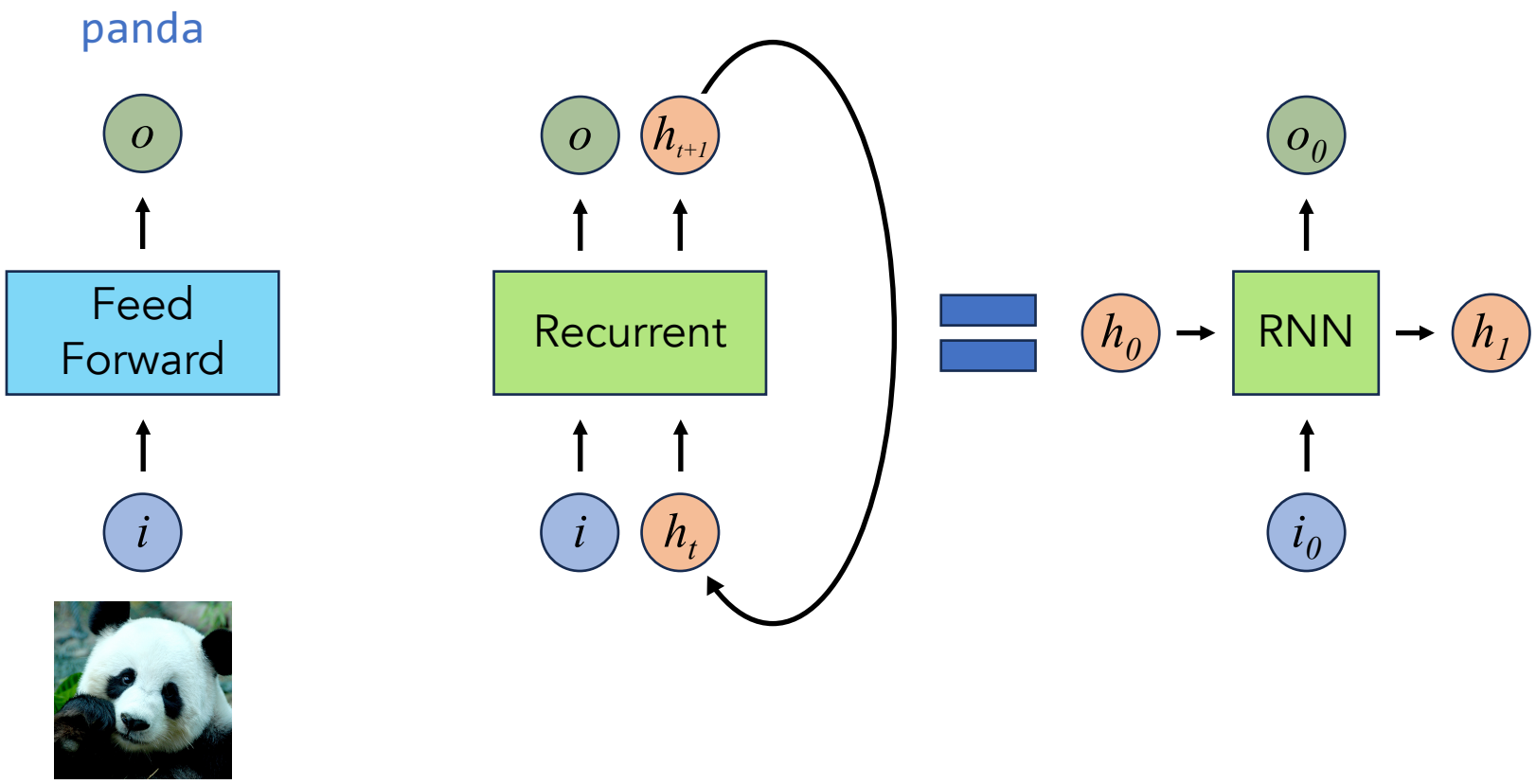

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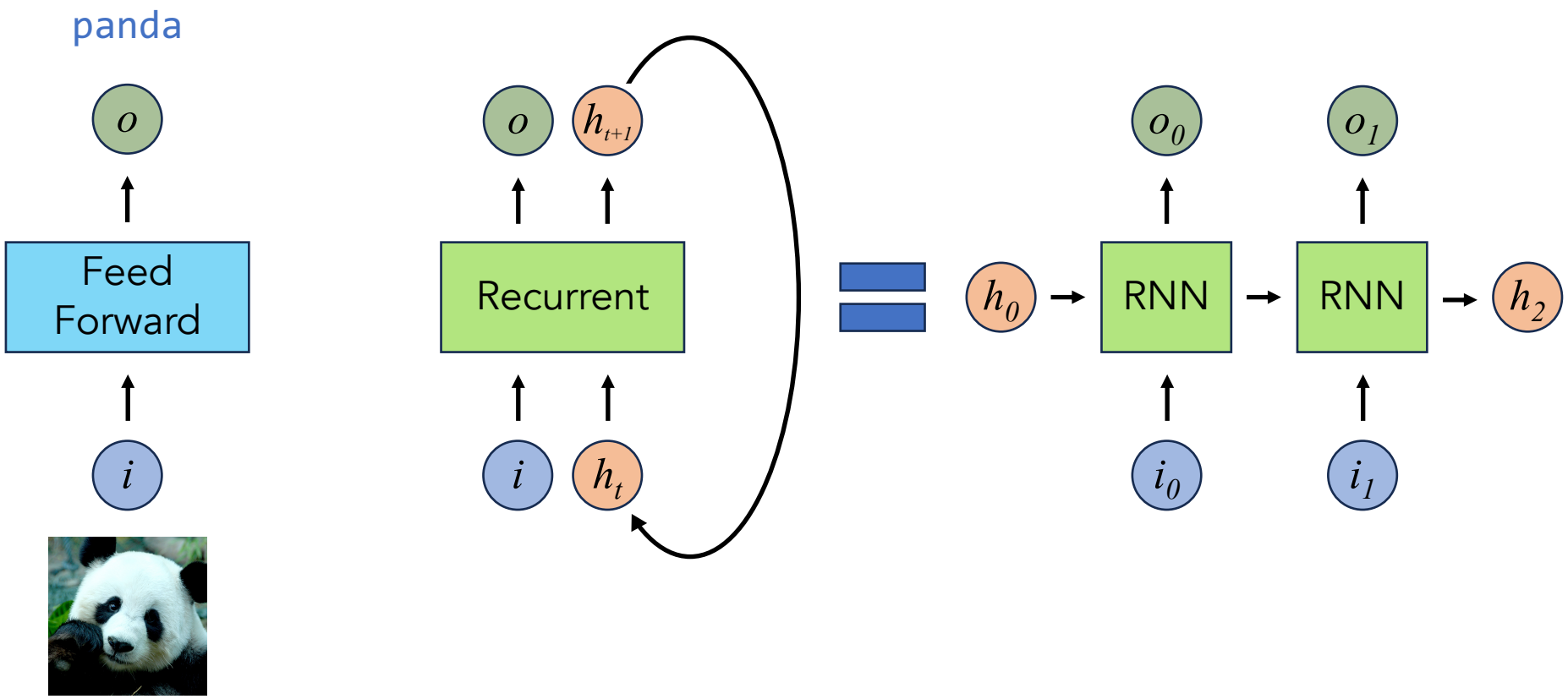

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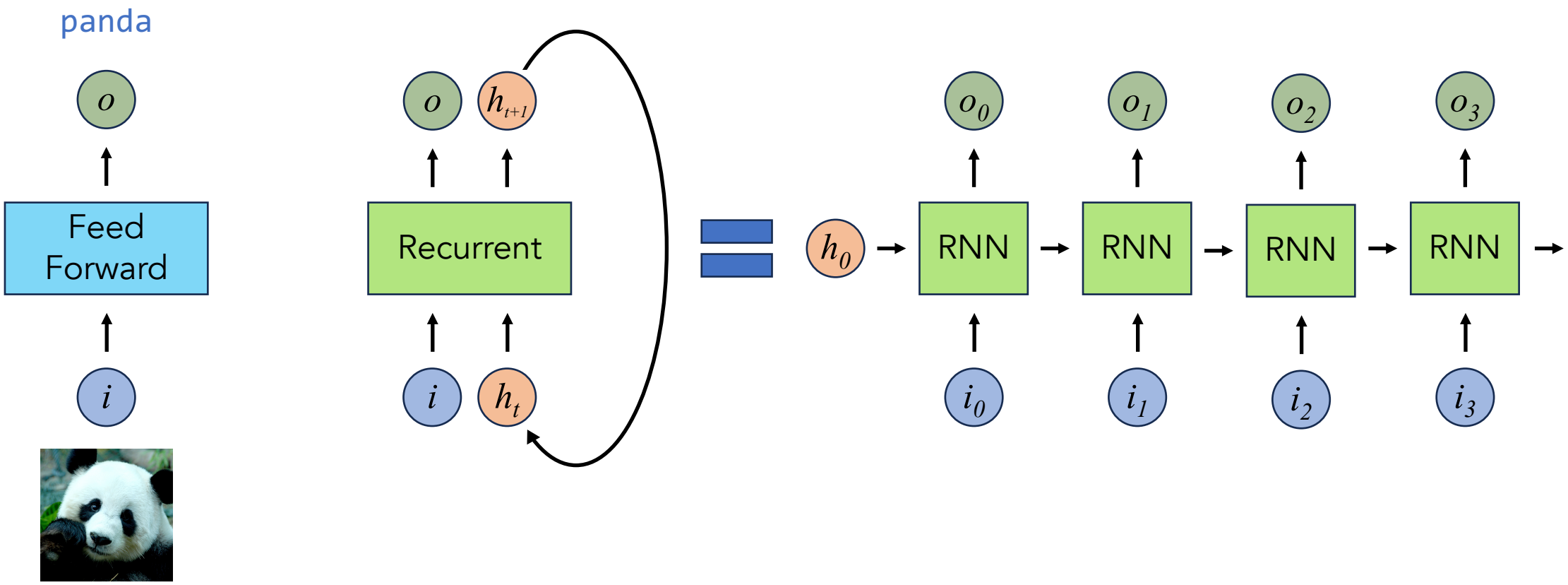
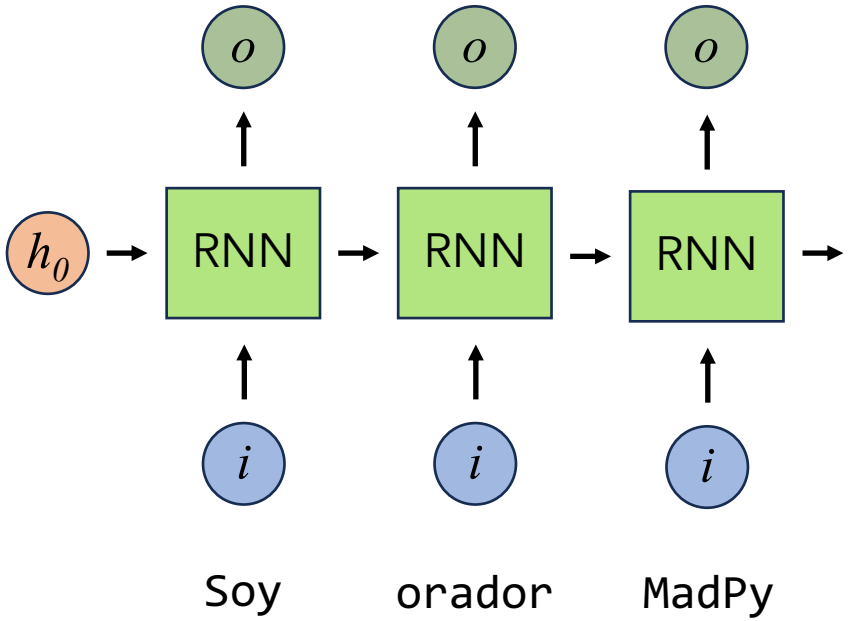


RNNs for NLP

Soy orador MadPy

I am a MadPy speaker



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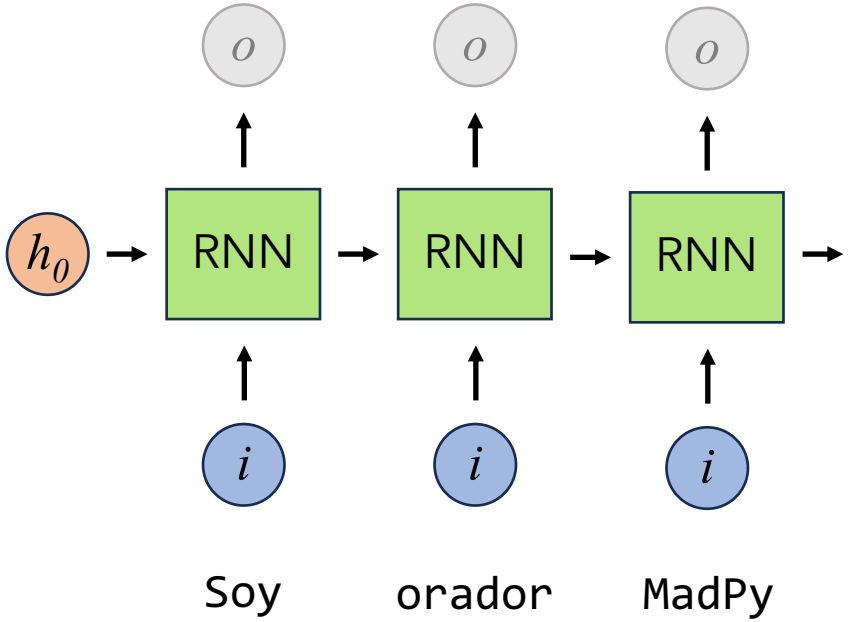

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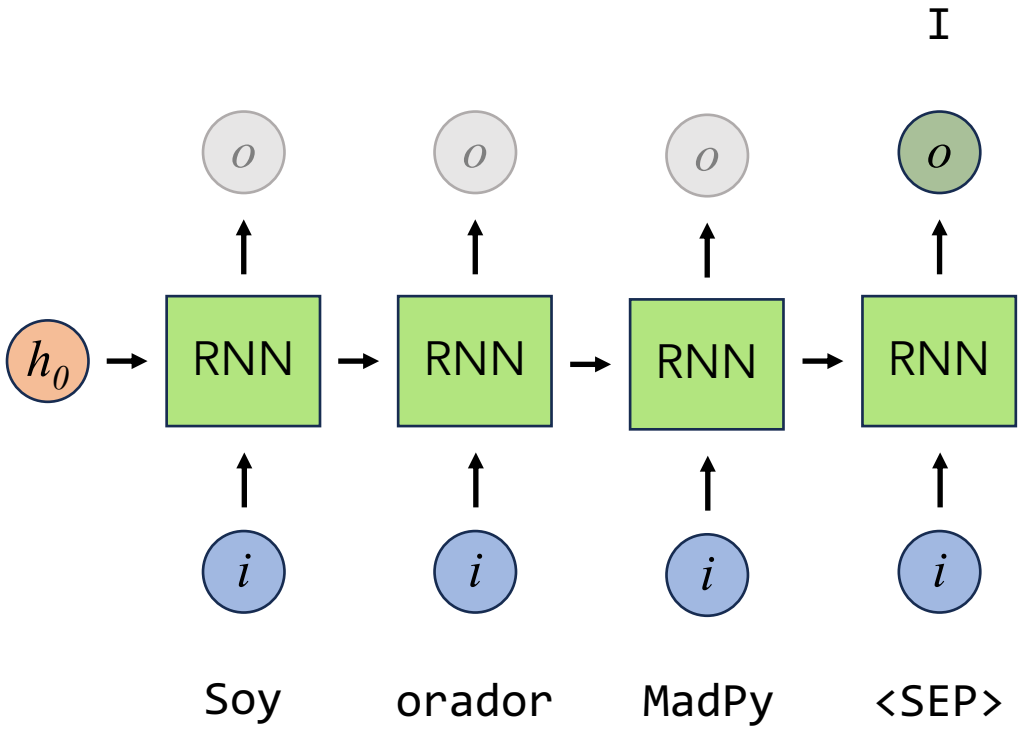

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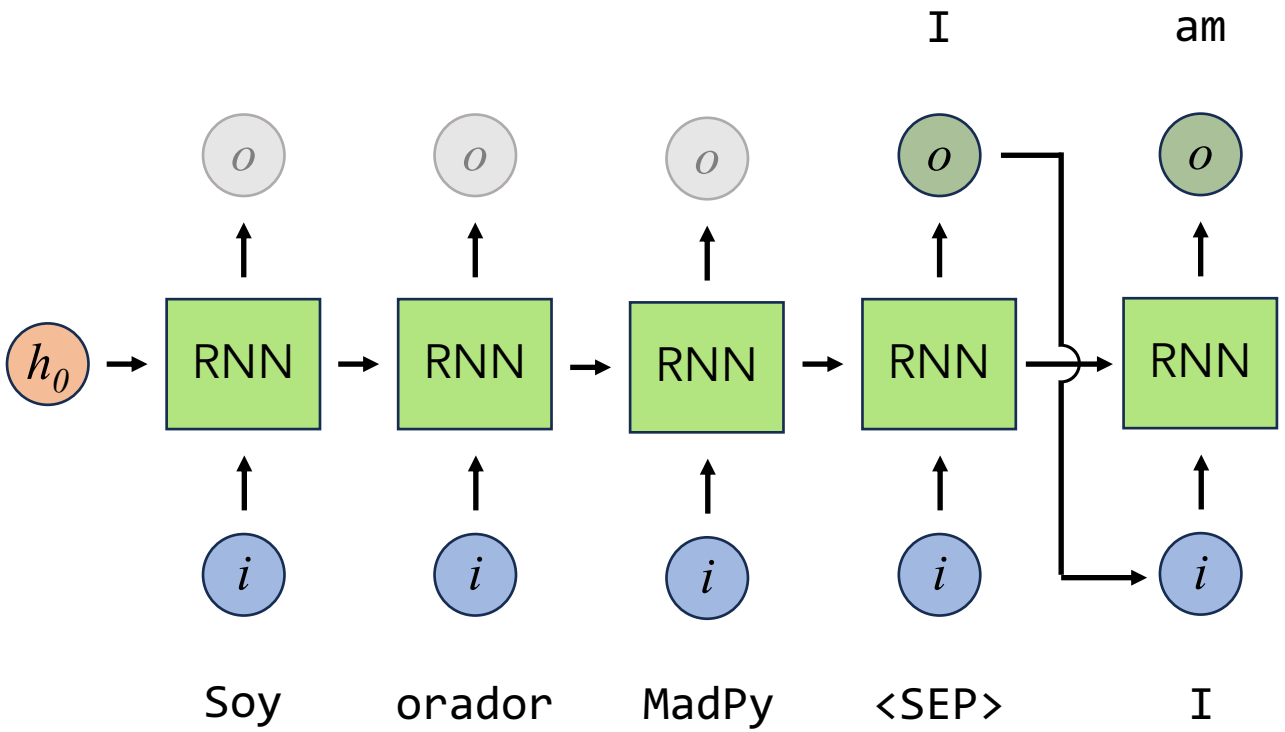

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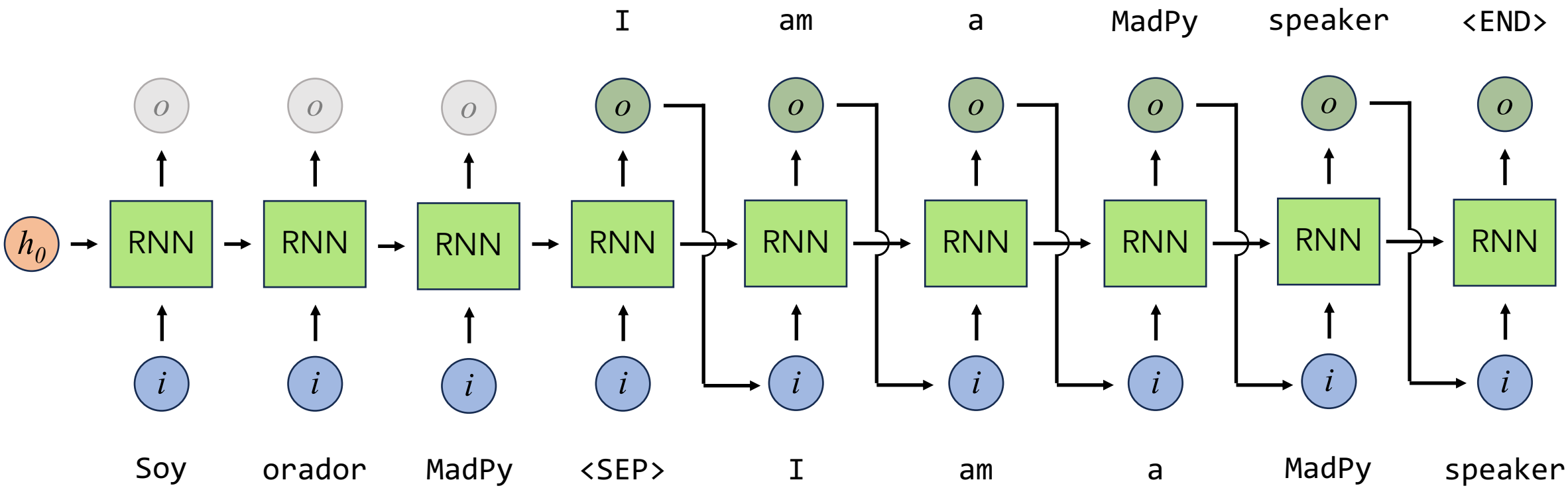

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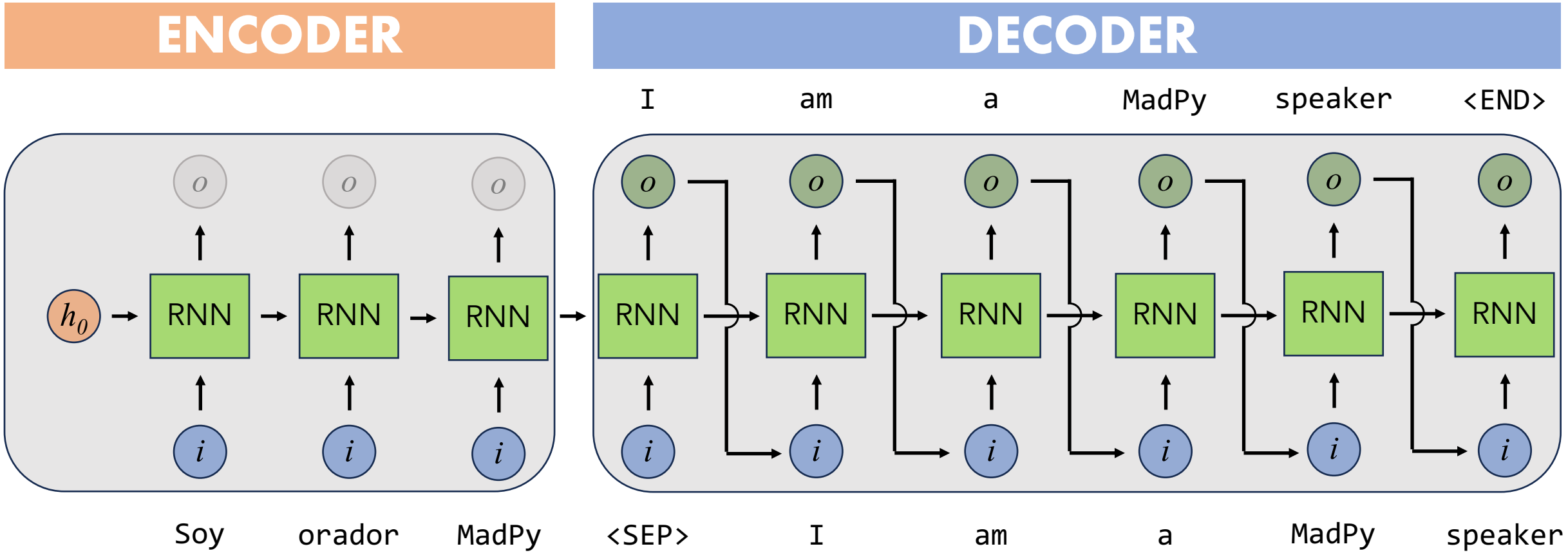

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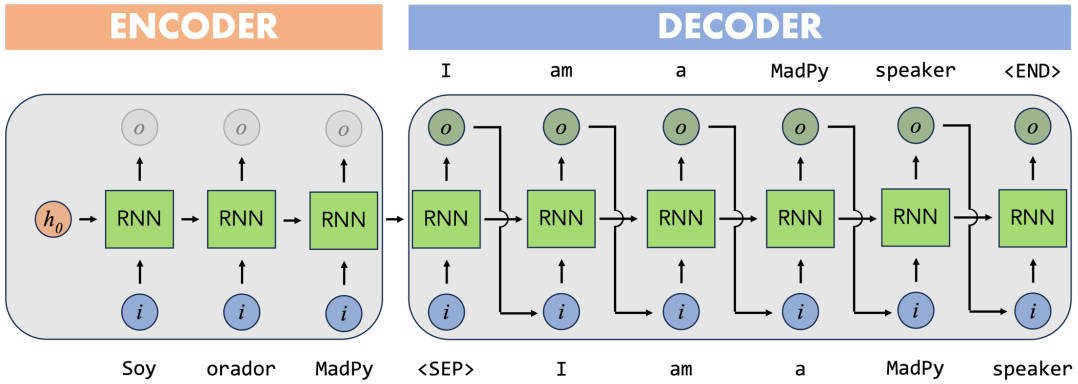
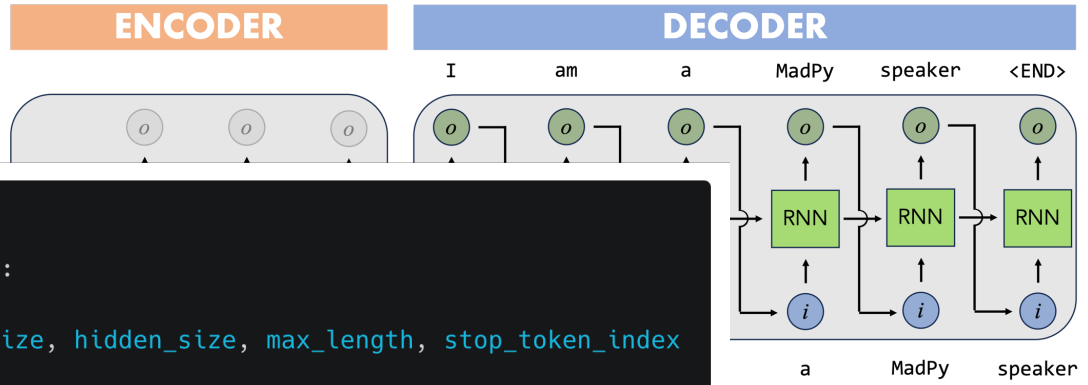


ENCODER

```python
class EncoderRNN(nn.Module):
    def __init__(self, input_size, embedding_size, hidden_size):
        super(EncoderRNN, self).__init__()
        self.hidden_size = hidden_size
        self.embedding = nn.Embedding(input_size, embedding_size)
        self.rnn = nn.RNN(embedding_size, hidden_size)

    def forward(self, input, hidden=None):
        embedded = self.embedding(input)
        output, hidden = self.rnn(embedded, hidden)
        return output, hidden
```

RNNs for NLP

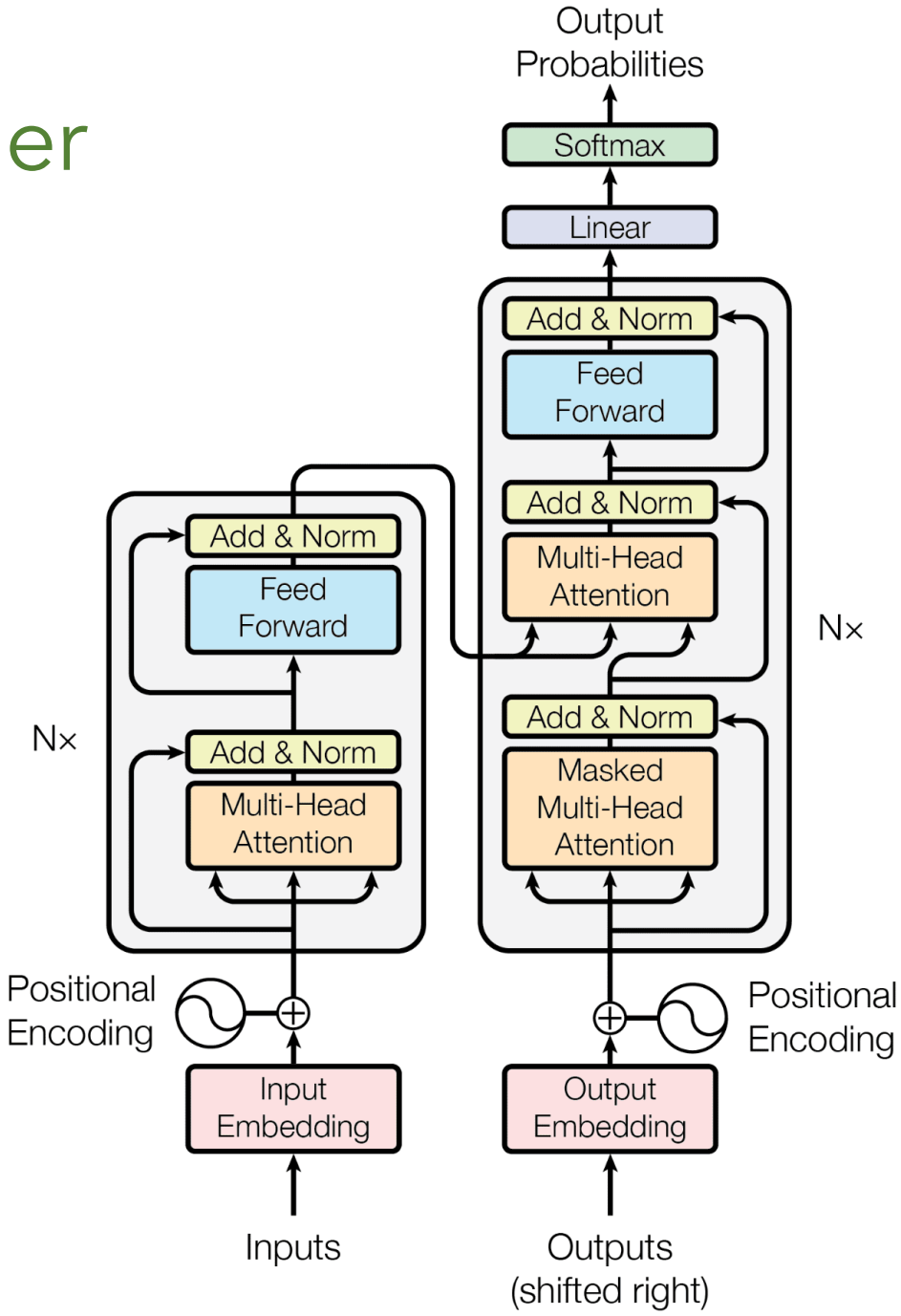


DECODER

```python
class AutoRegressiveDecoder(nn.Module):
    def __init__(
        self, output_size, embedding_size, hidden_size, max_length, stop_token_index
    ):
        super(AutoRegressiveDecoder, self).__init__()
        self.hidden_size = hidden_size
        self.embedding = nn.Embedding(output_size, embedding_size)
        self.rnn = nn.RNN(embedding_size, hidden_size)
        self.out = nn.Linear(hidden_size, output_size)
        self.max_length = max_length
        self.stop_token_index = stop_token_index

    def forward(self, hidden, start_token_index):
        device = hidden.device
        input = torch.tensor([[start_token_index]], device=device)
        outputs = []
        logits_list = []
        for _ in range(self.max_length):
            embedded = self.embedding(input)
            rnn_output, hidden = self.rnn(embedded, hidden)
            logits = self.out(rnn_output[0])
            logits_list.append(logits)
            top1 = logits.argmax(1)
            outputs.append(top1.item())
            if top1.item() == self.stop_token_index:
                break
            input = top1.unsqueeze(0)
        return outputs, torch.stack(logits_list, dim=0)
```

The Transformer



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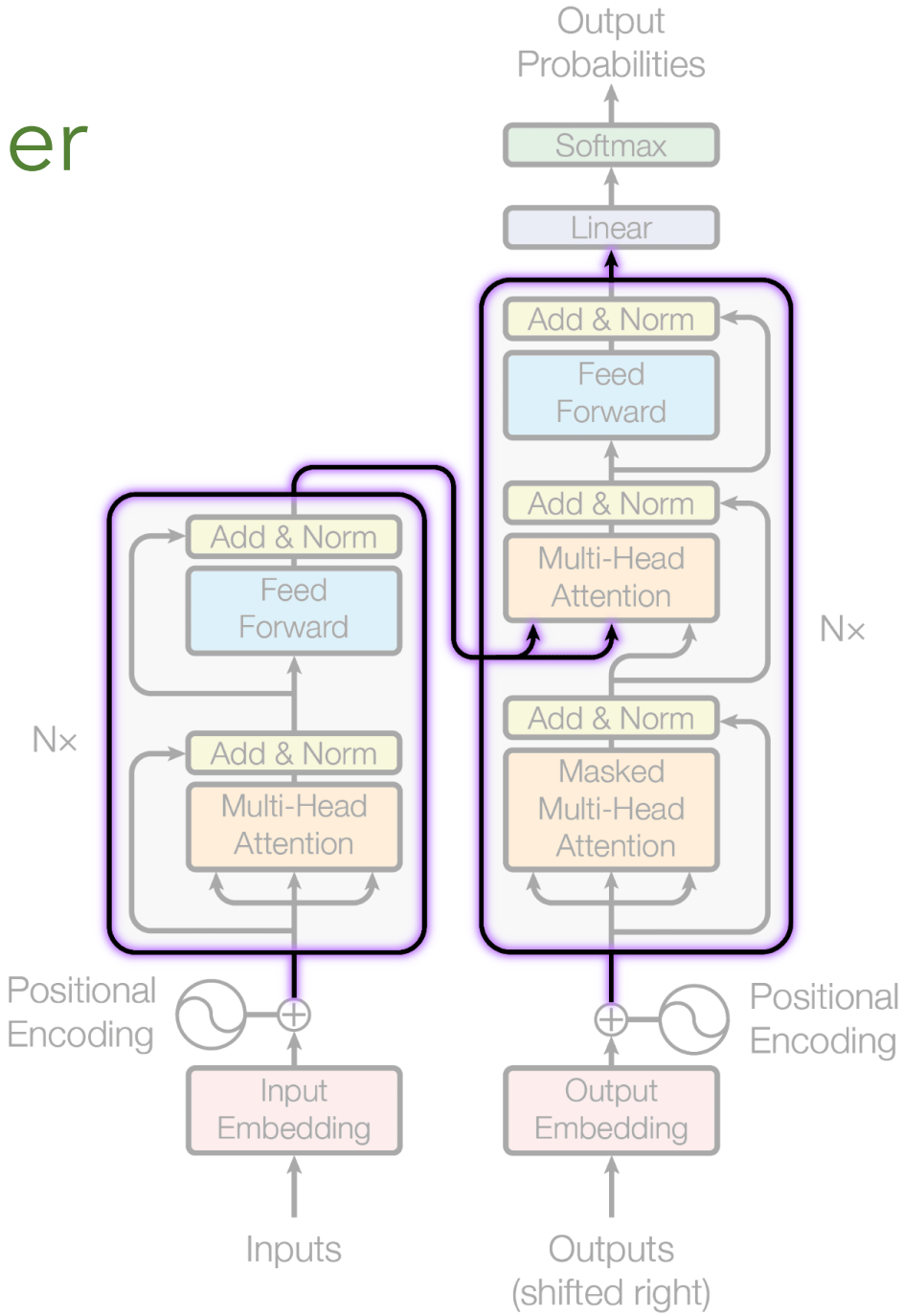

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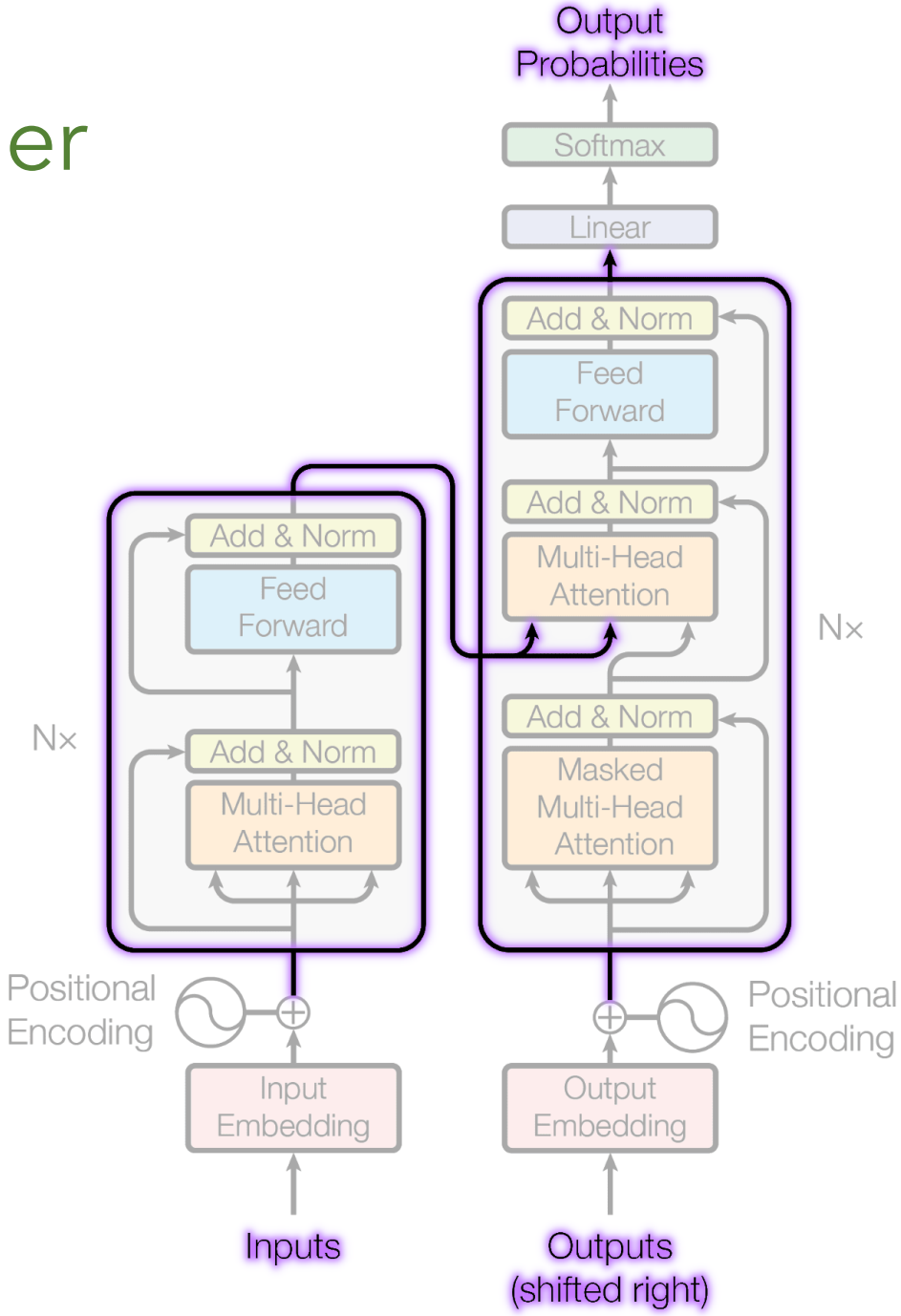
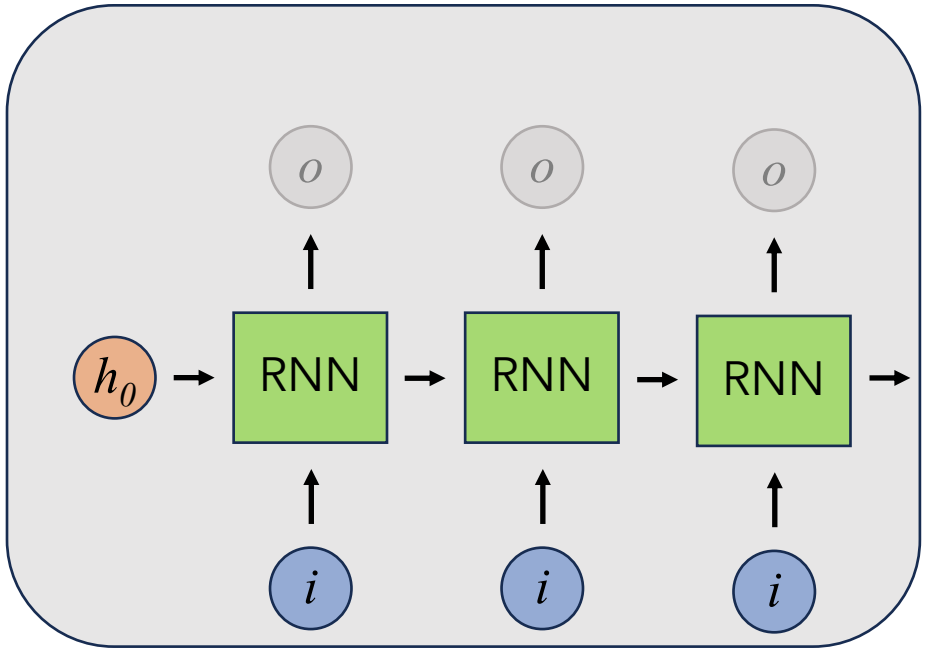


RNNsearch



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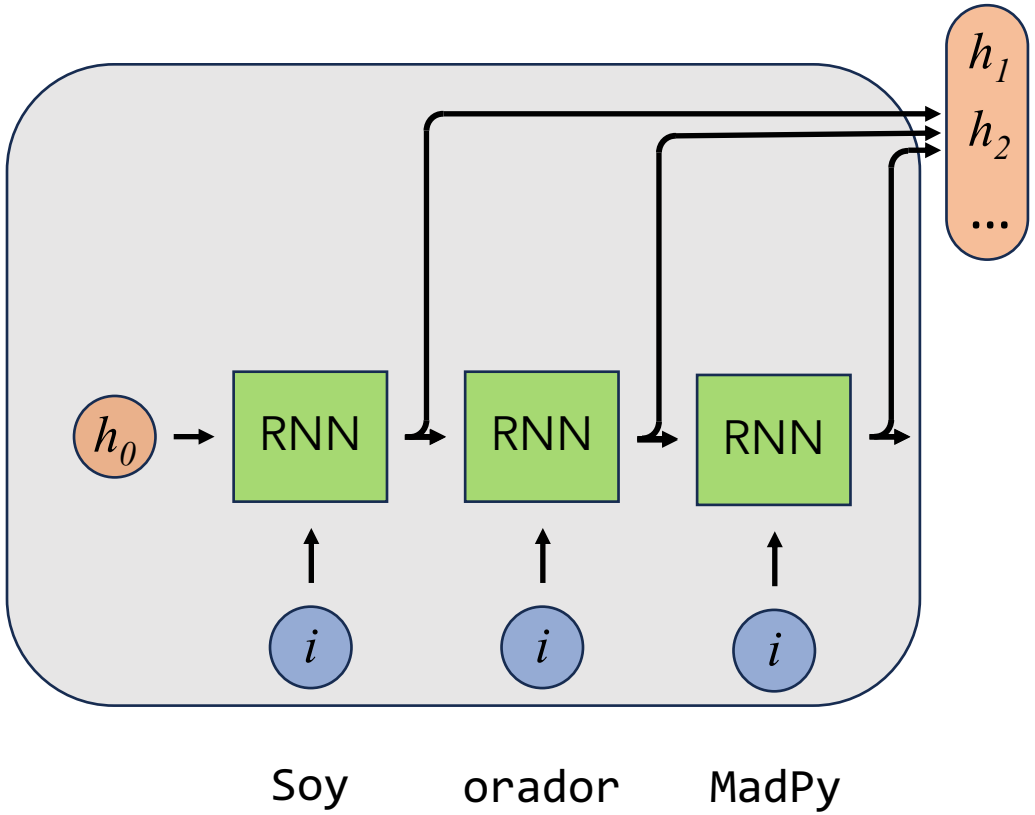

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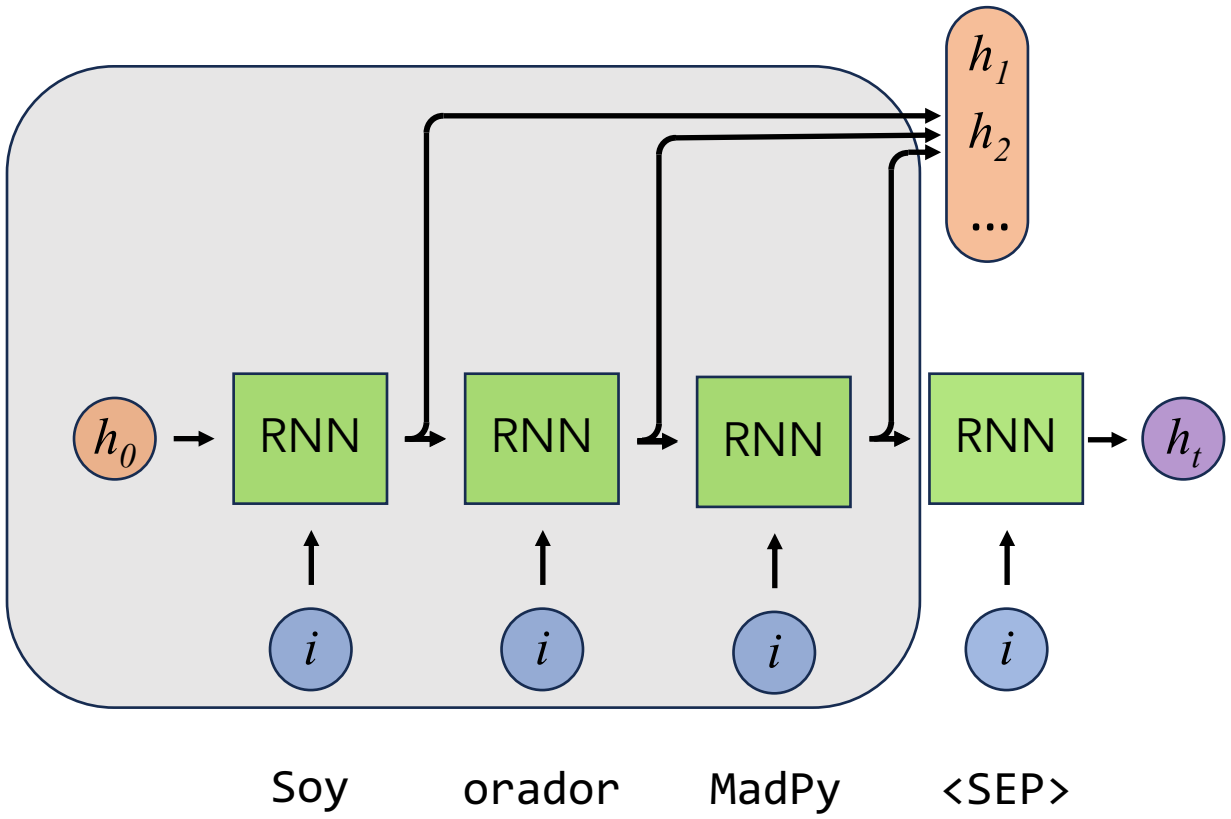
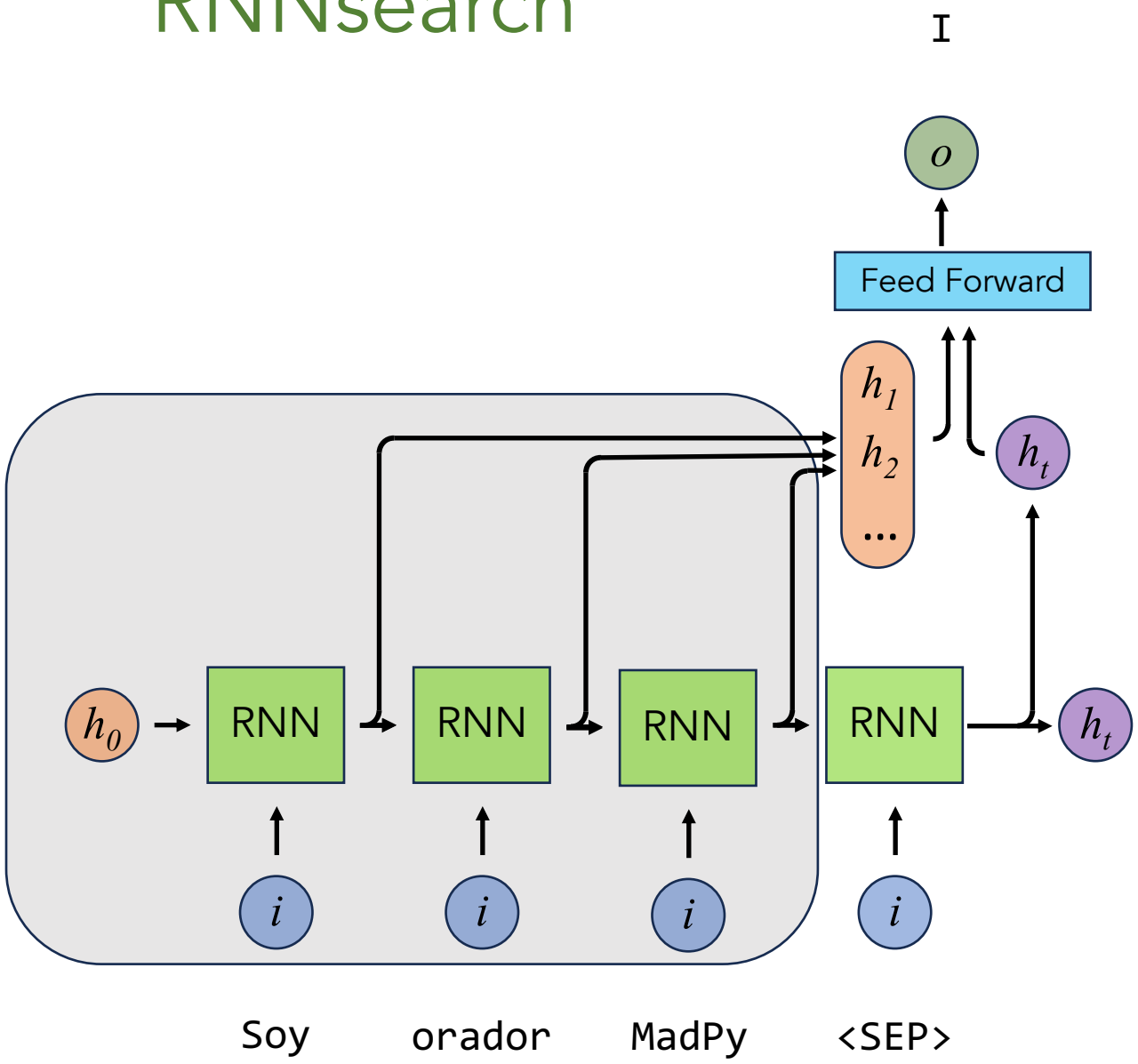


RNNsearch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RNNsearch

The “Attention” Mechanism

RNNsearch

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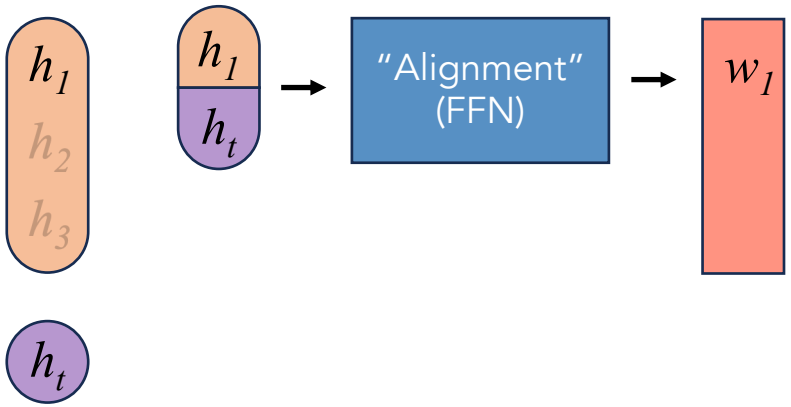

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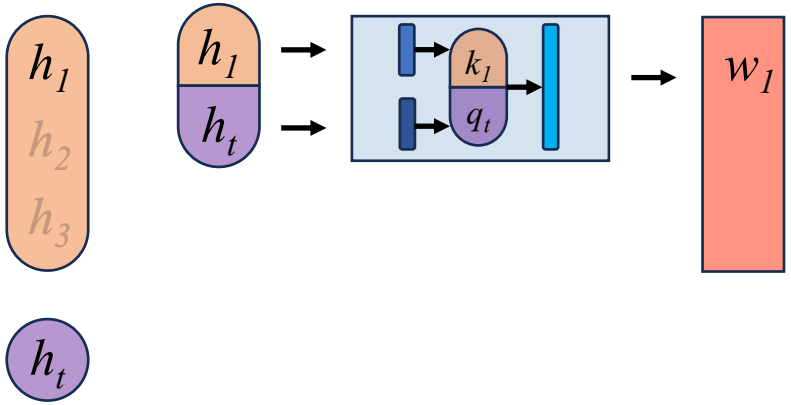

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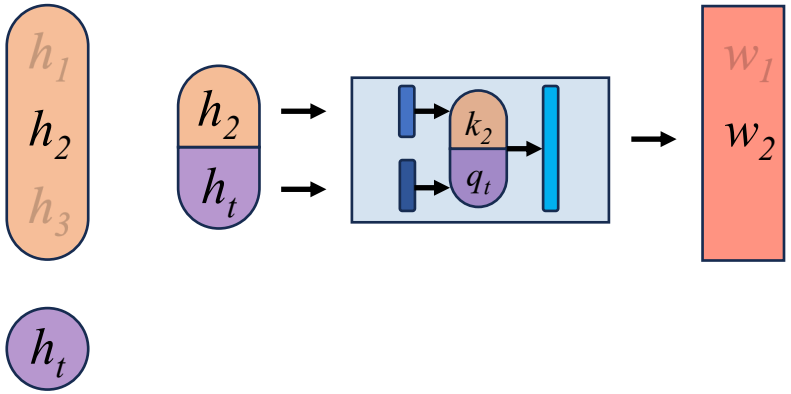

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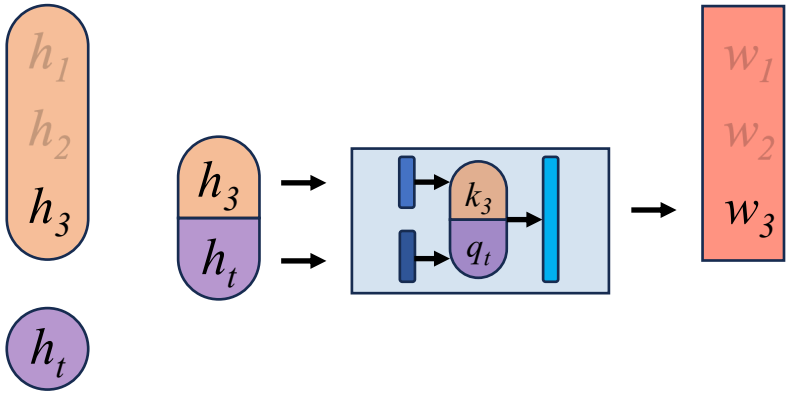
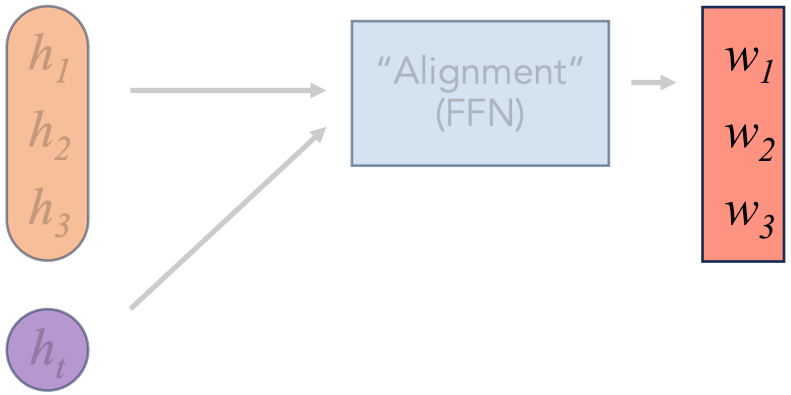


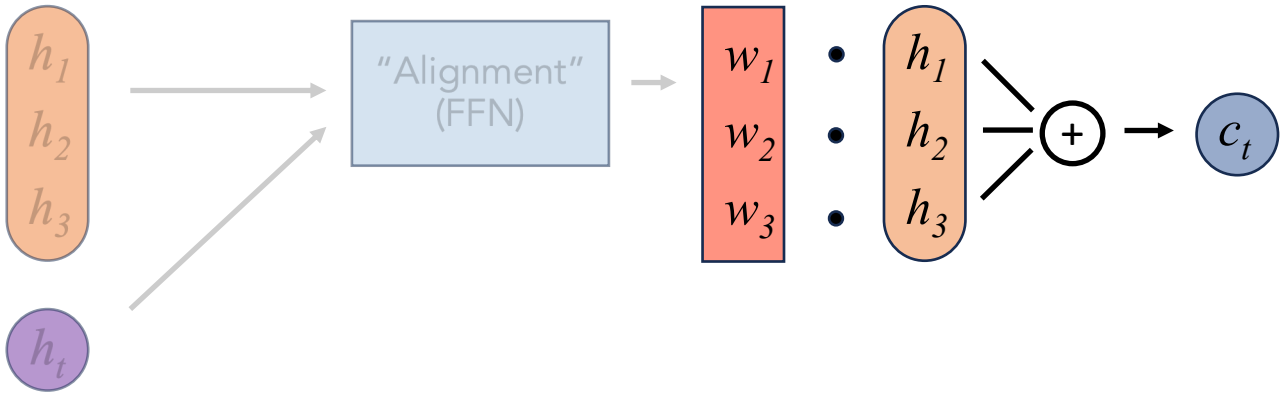
RNNsearch

The “Attention” Mechanism



RNNsearch

The "Attention" Mechanism



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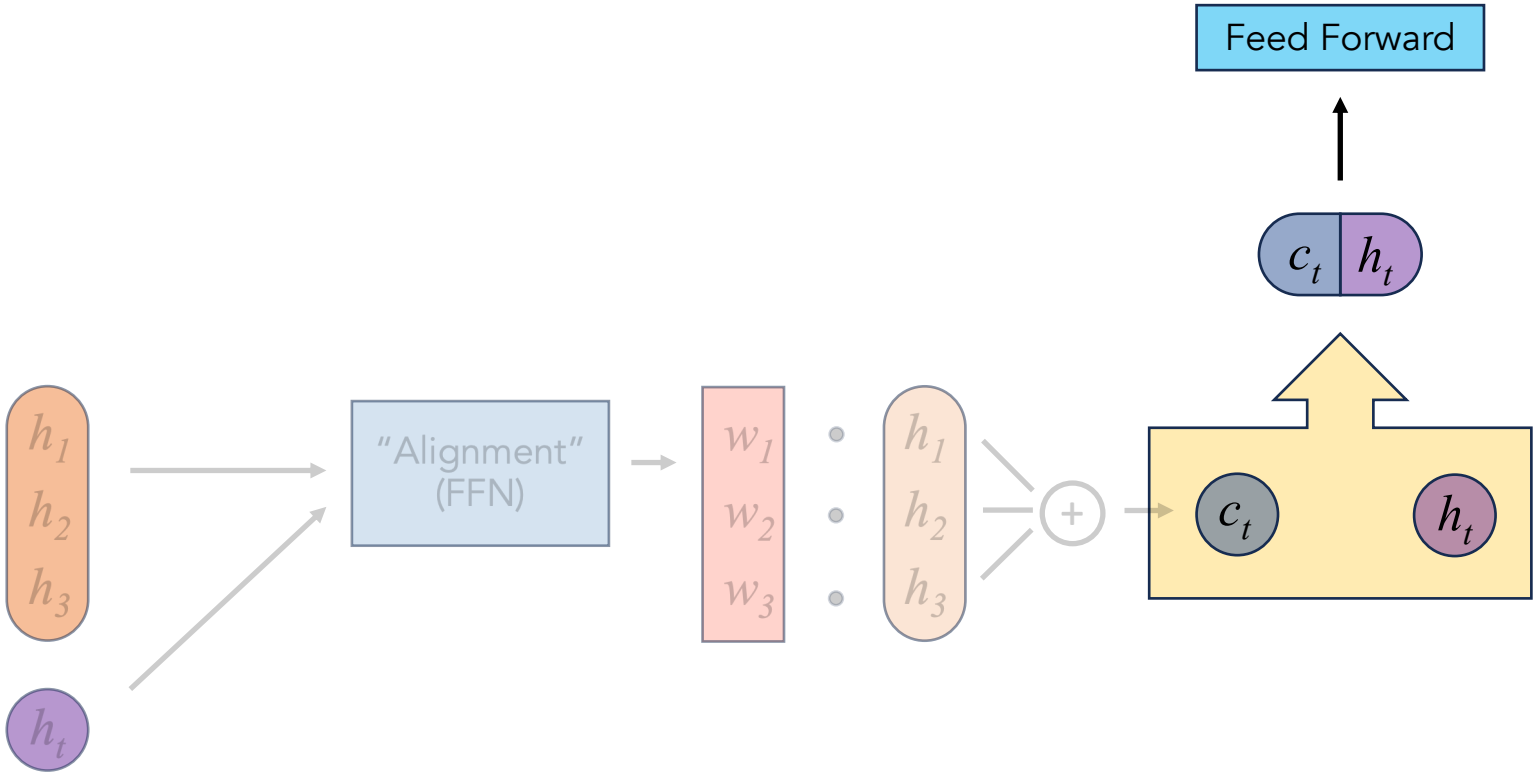
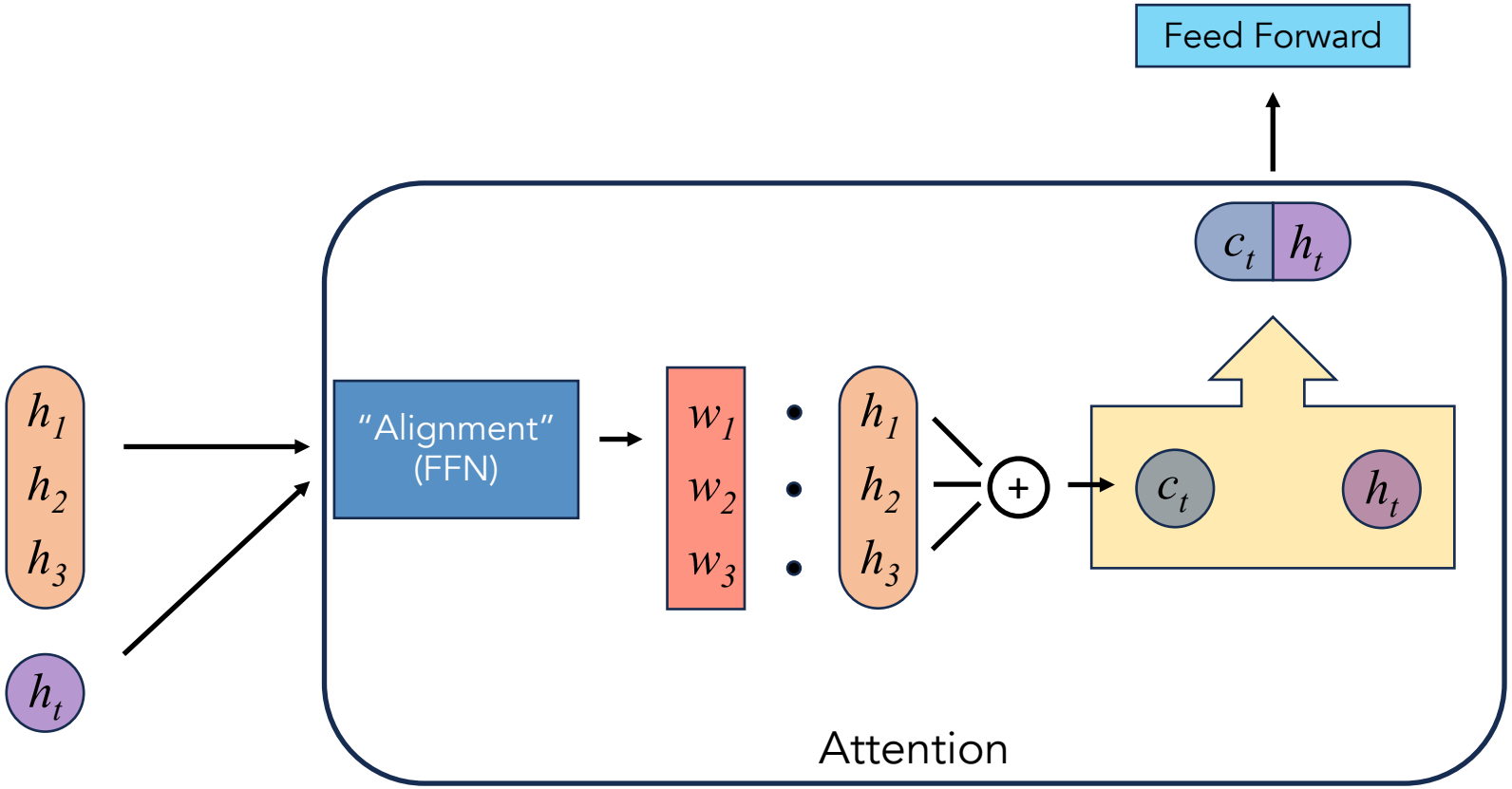
The "Attention" Mechanism



RNNsearch

The "Attention" Mechanism



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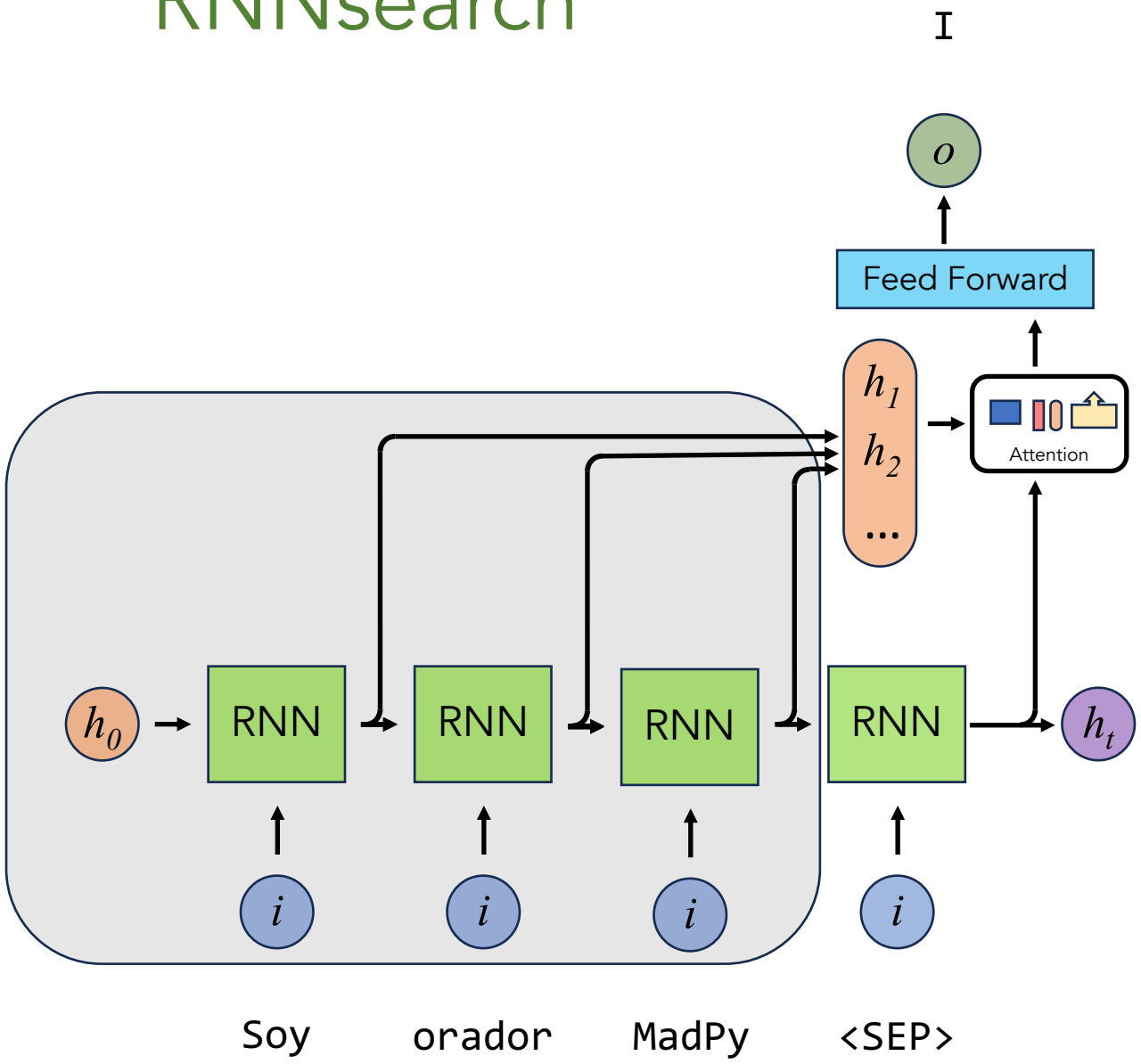
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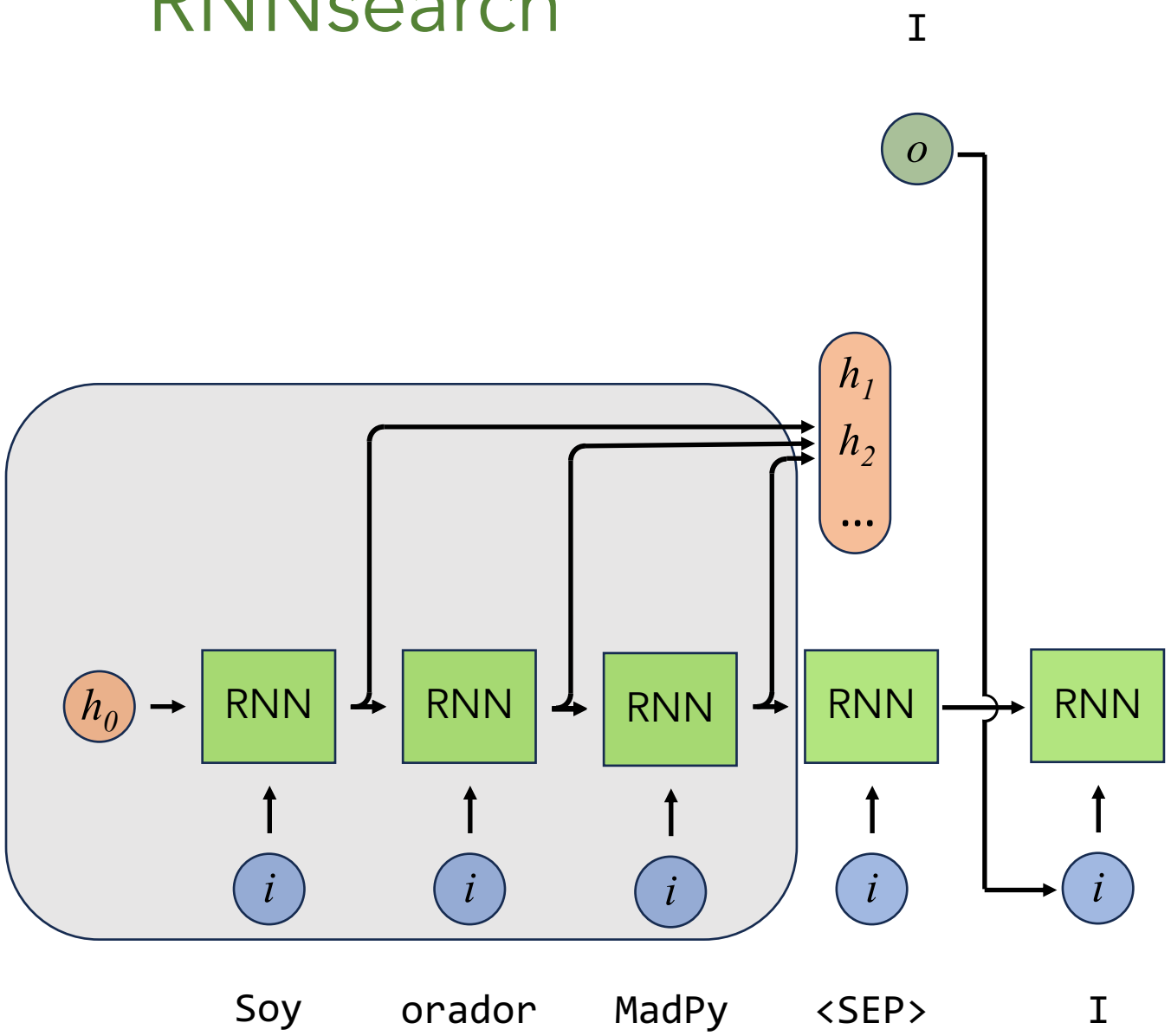

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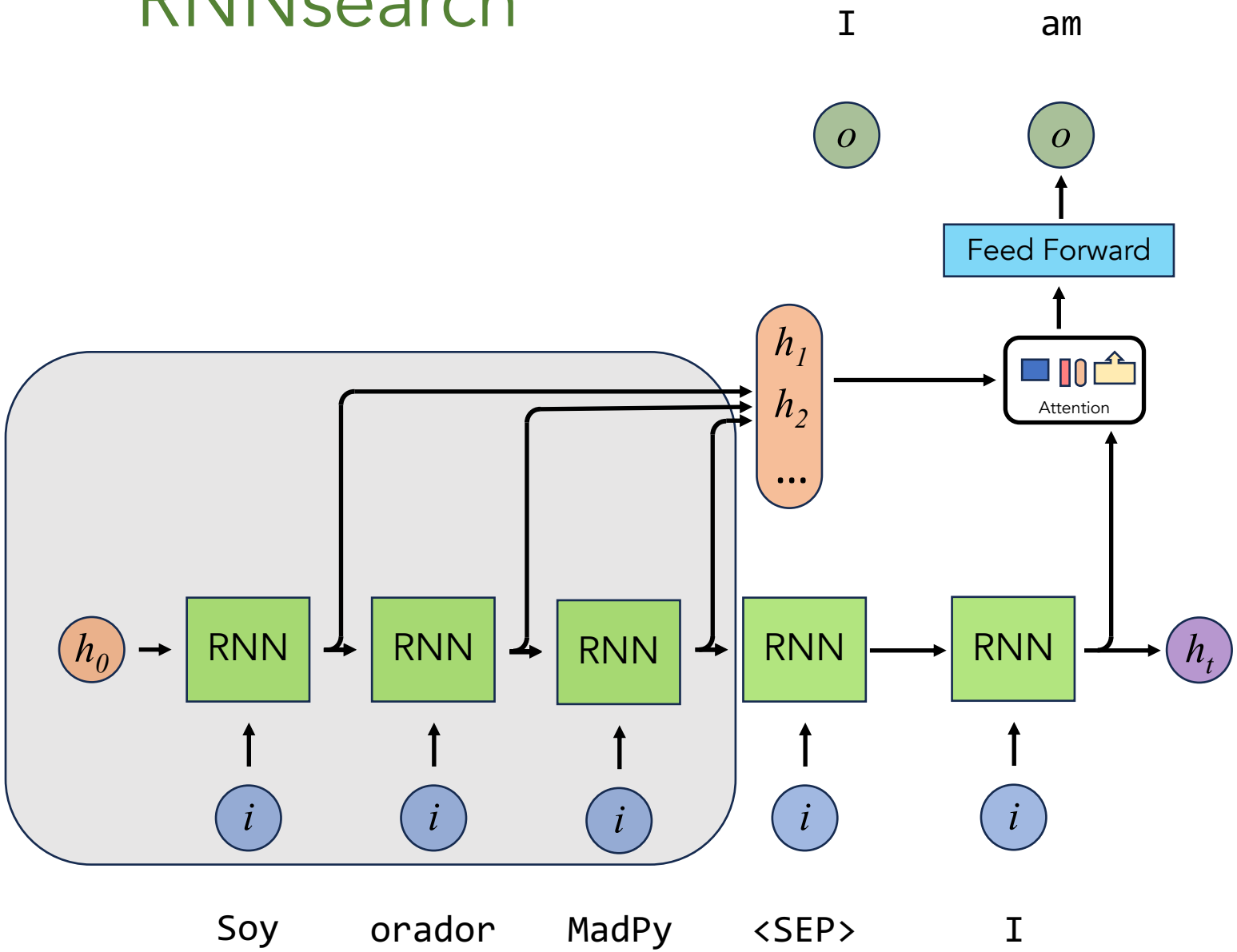
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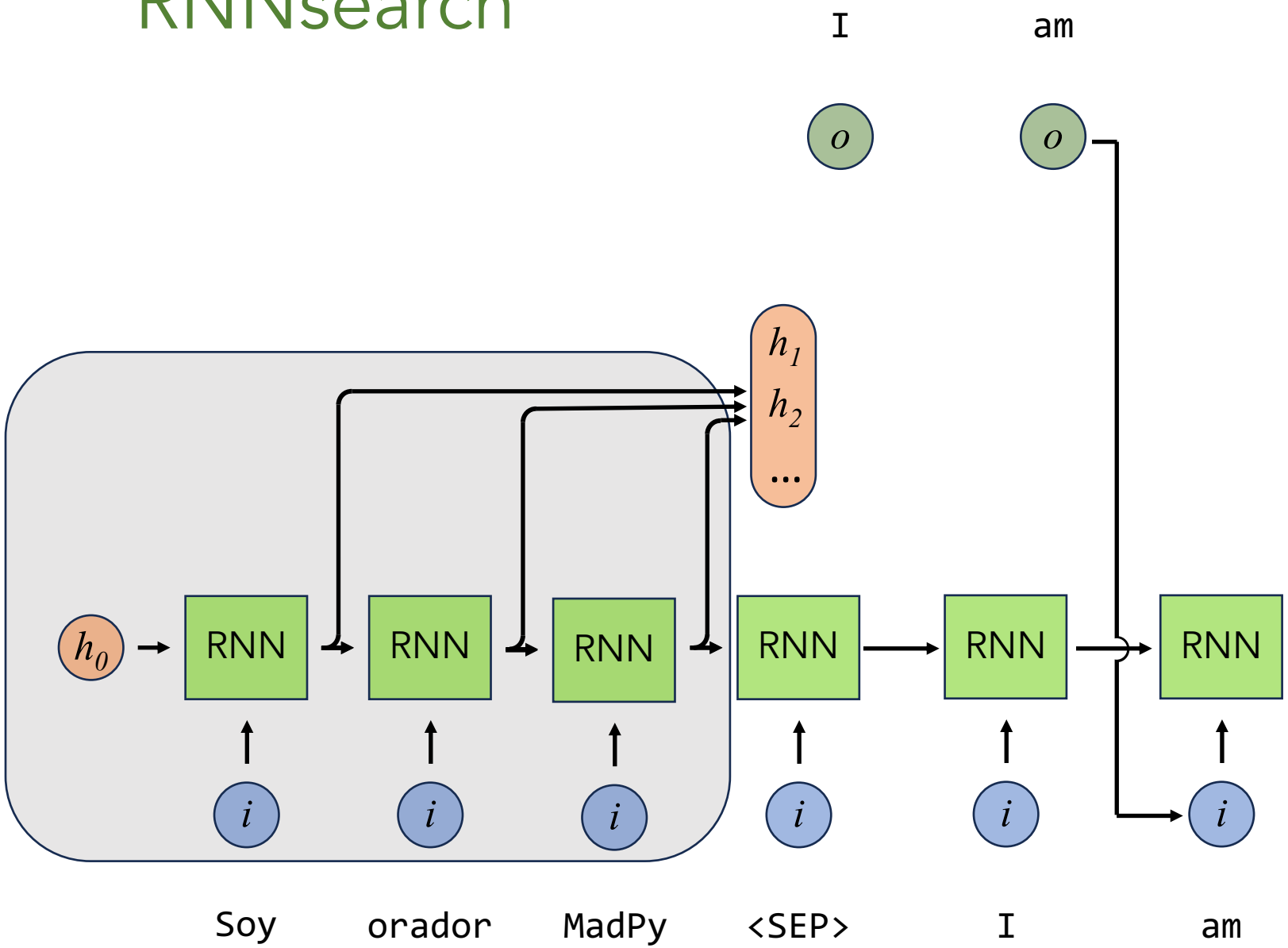
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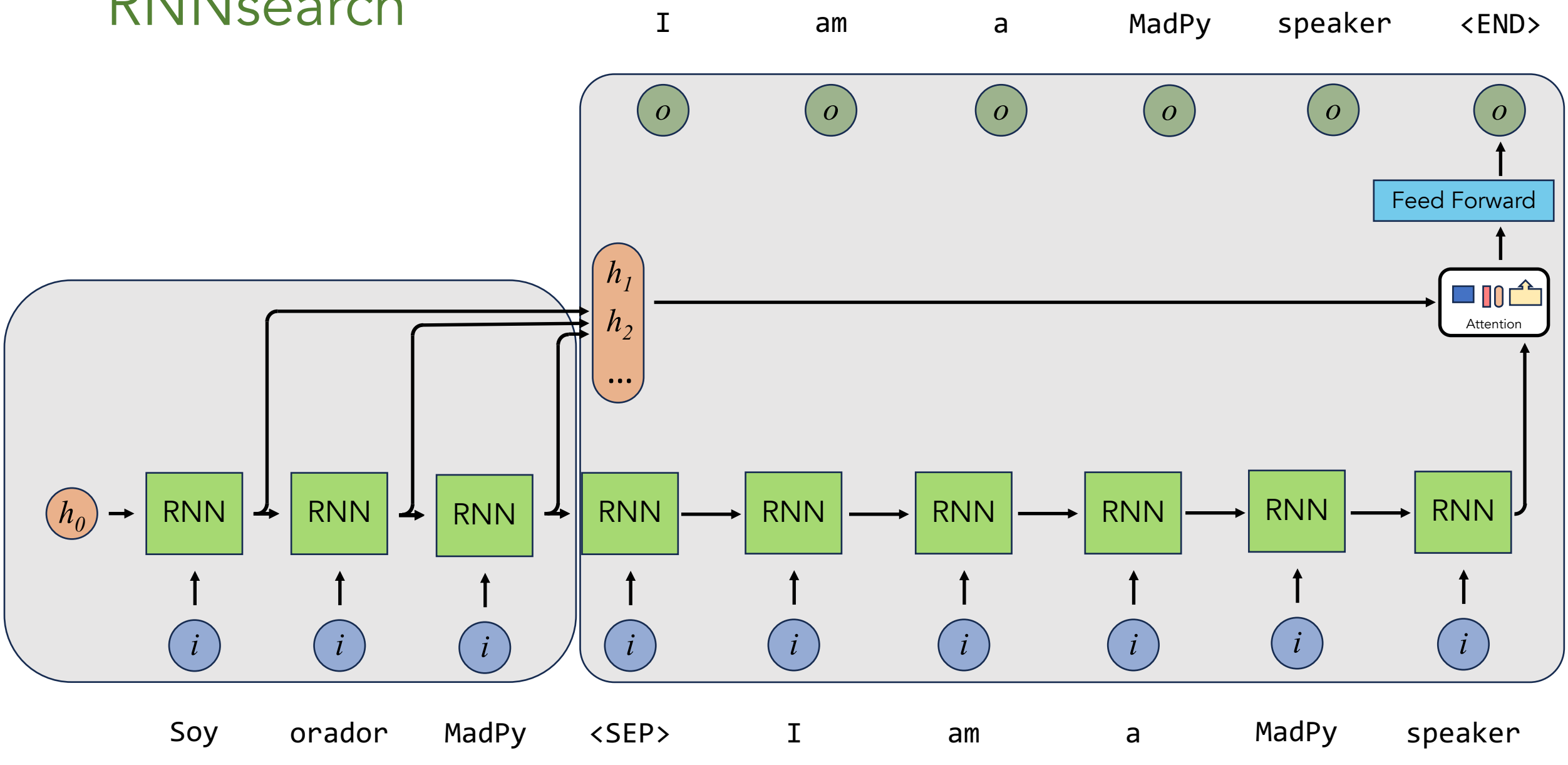
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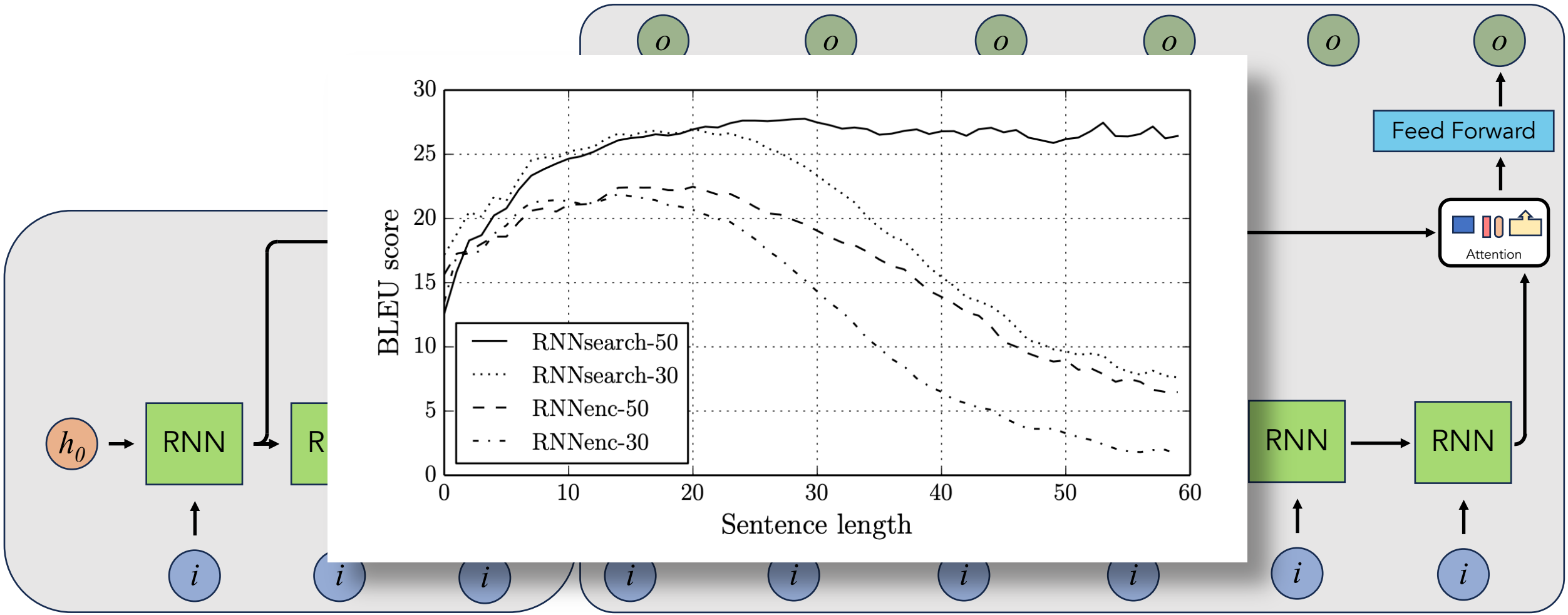
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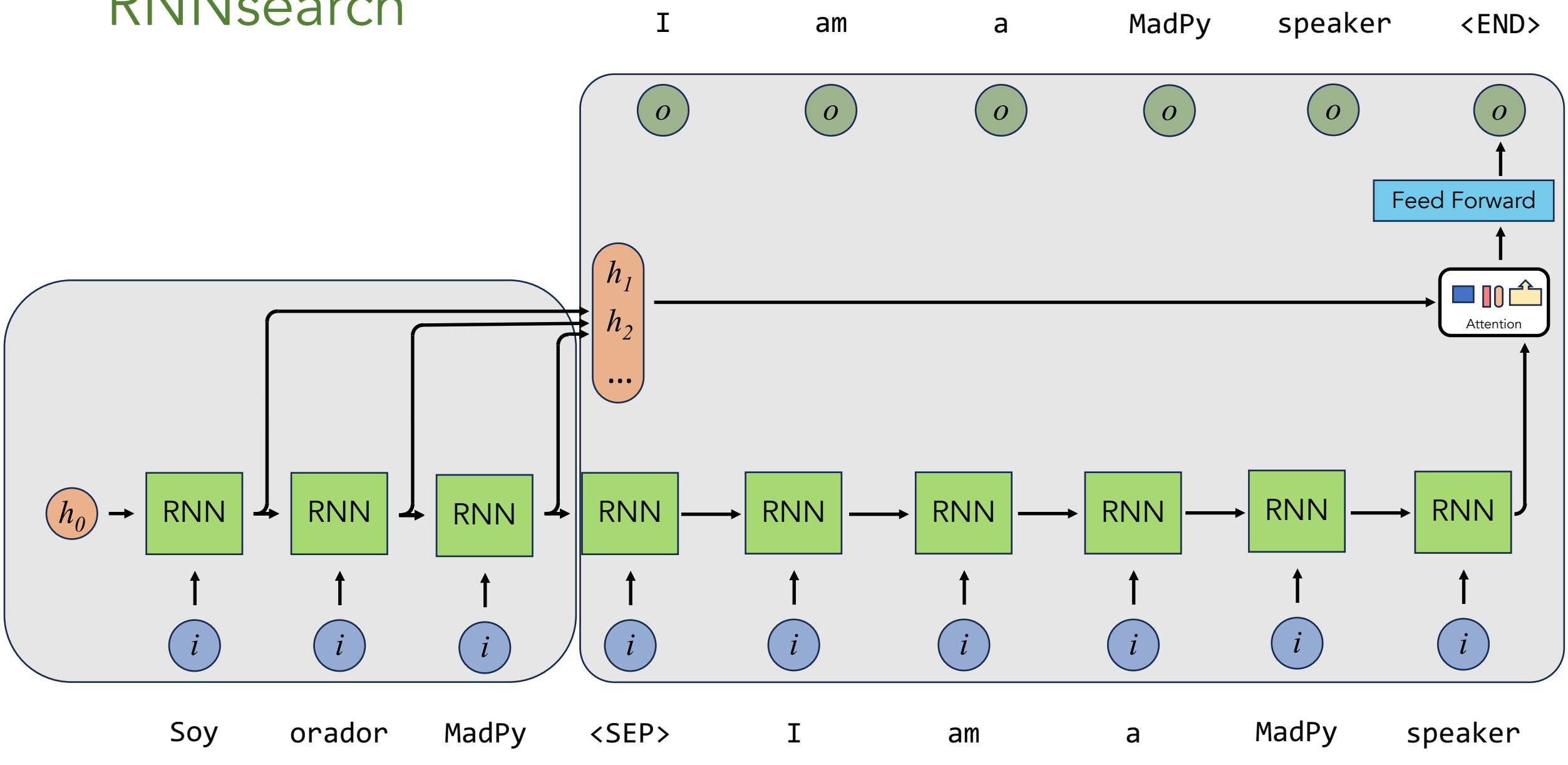
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Attention Is All You Need

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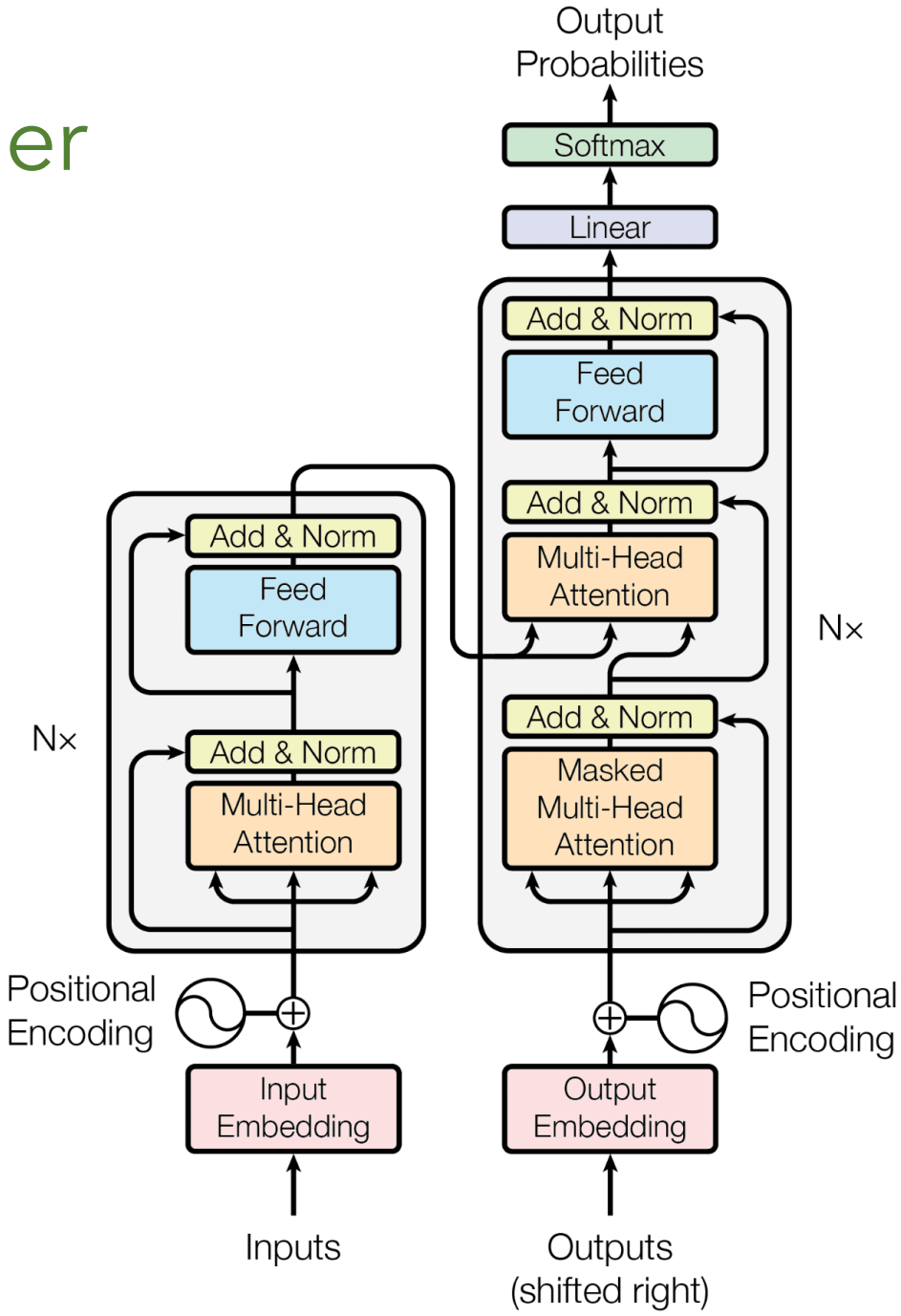
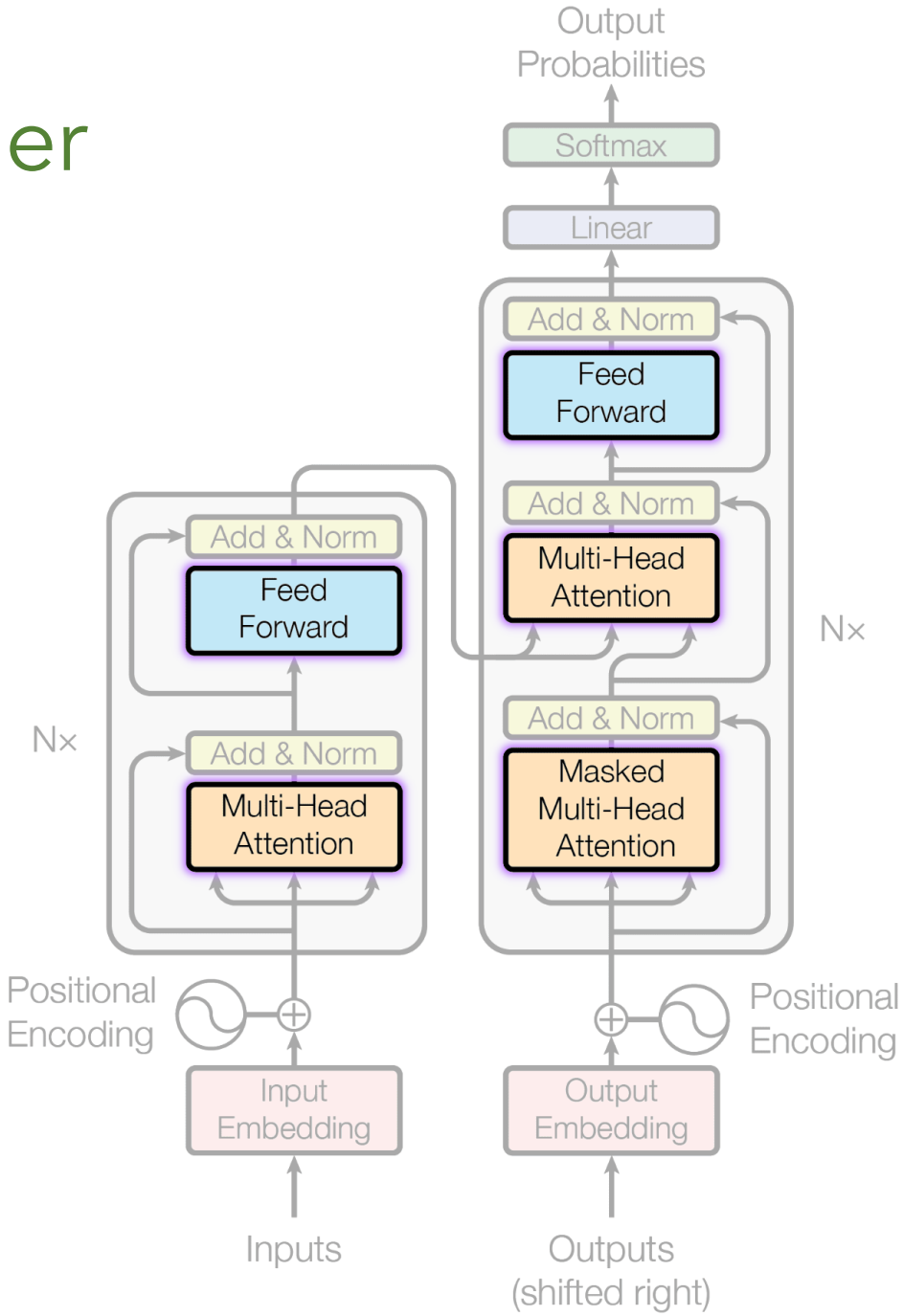
Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks in an encoder-decoder configuration. The best performing models also connect the encoder and decoder through an attention

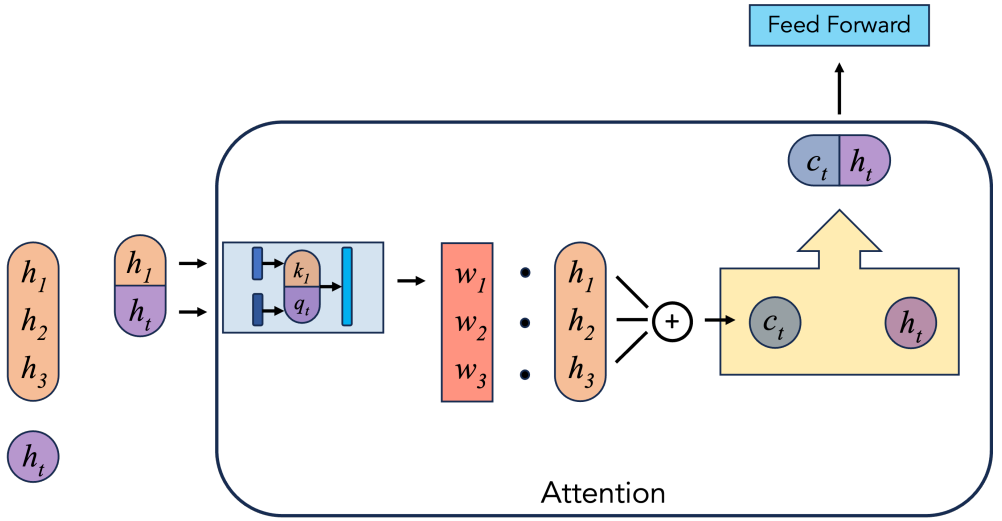
The Transformer



The Transformer



The Evolution of Attention



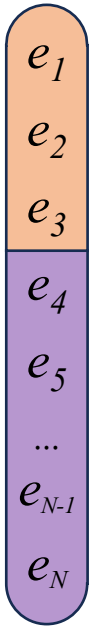
Hidden states generated by RNNs

Alignment NN layers convert:

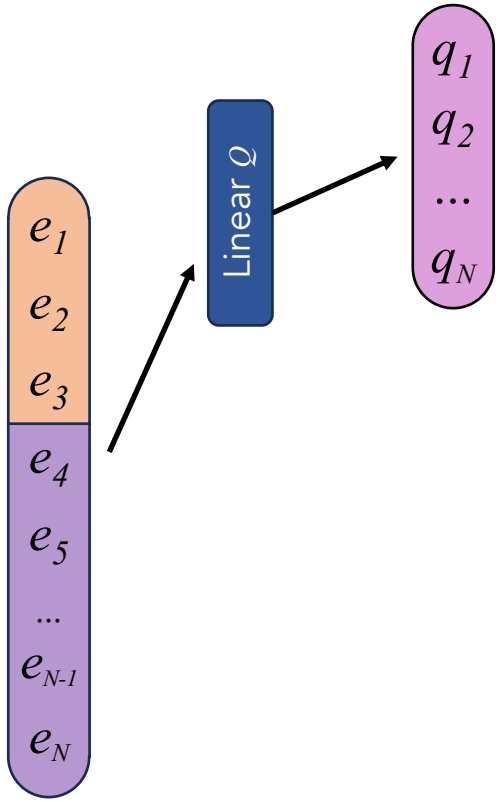
- encoder hidden states to *keys*
- decoder hidden states to *queries*
- *keys* & *queries* to *weights*

weights used to average unmodified encoder hidden states

The Evolution of Attention



The Evolution of Attention



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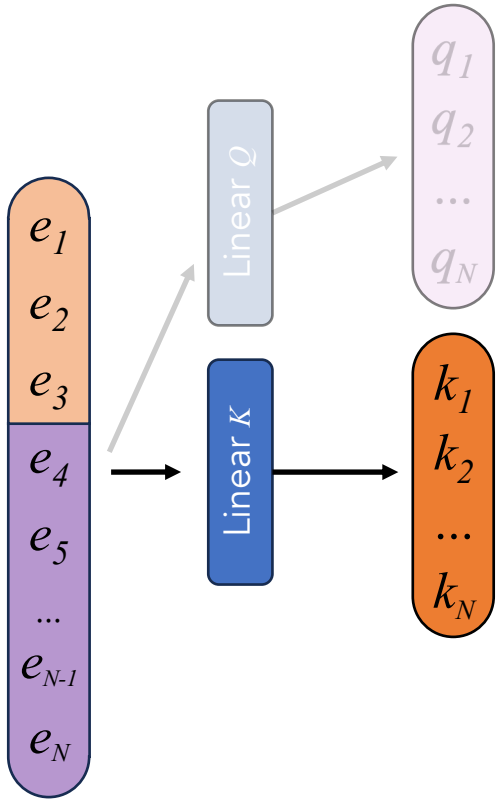

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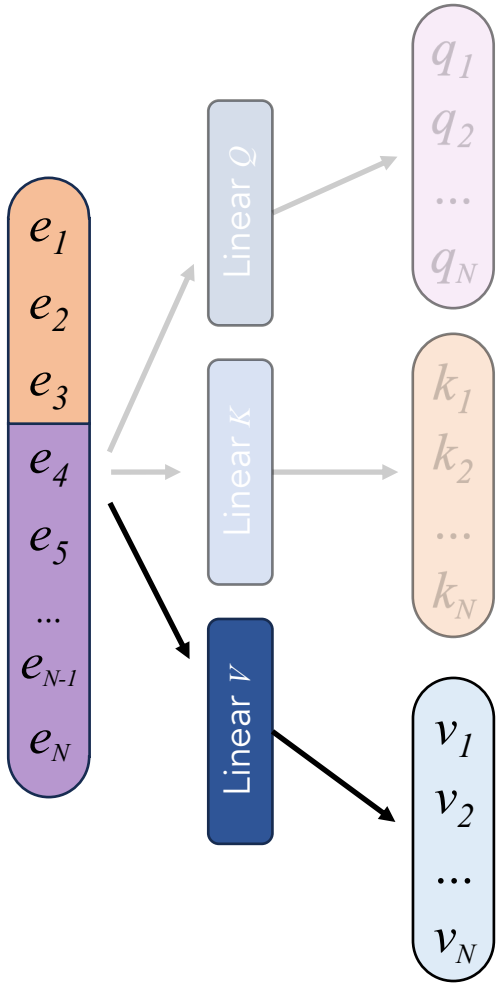

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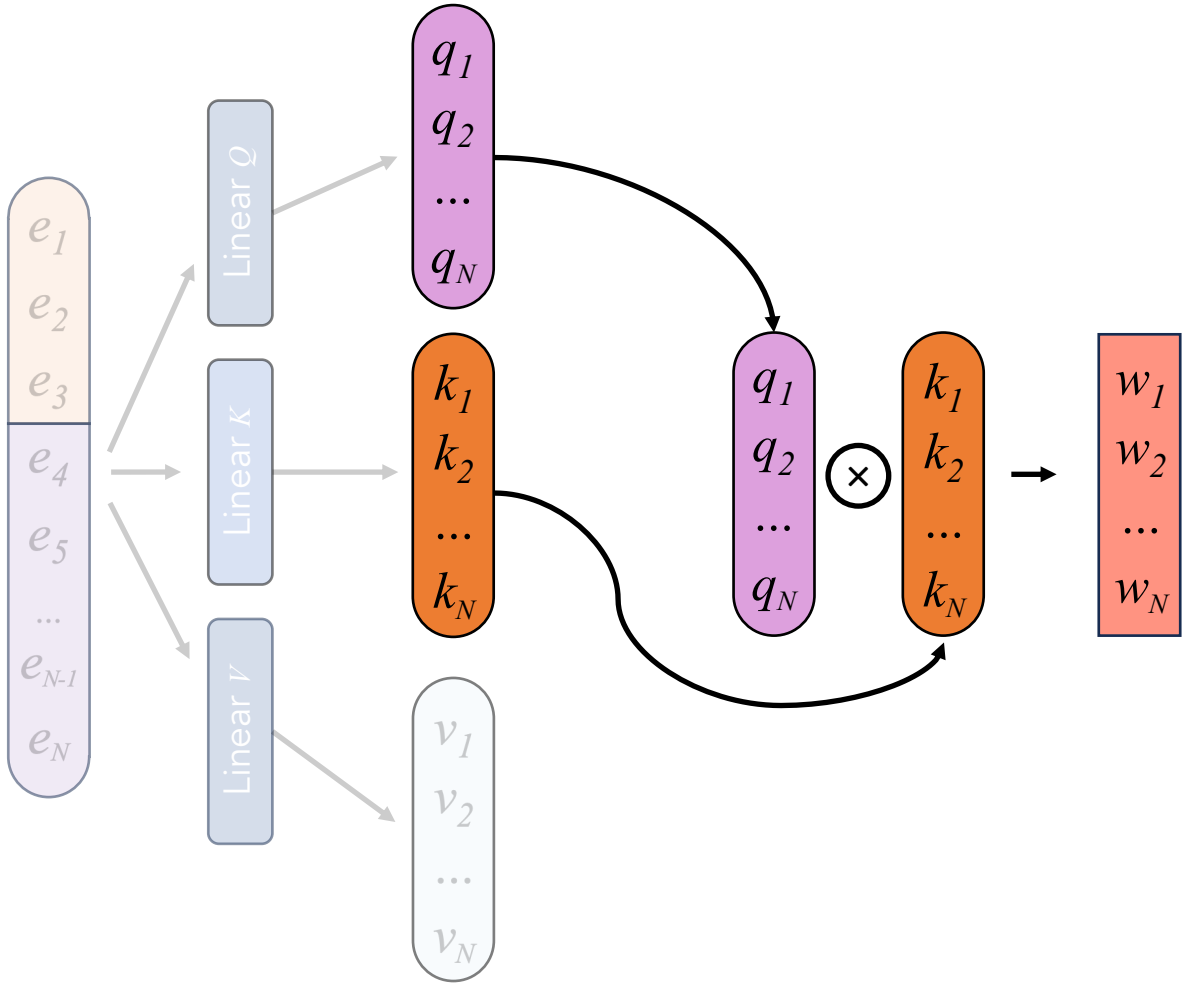

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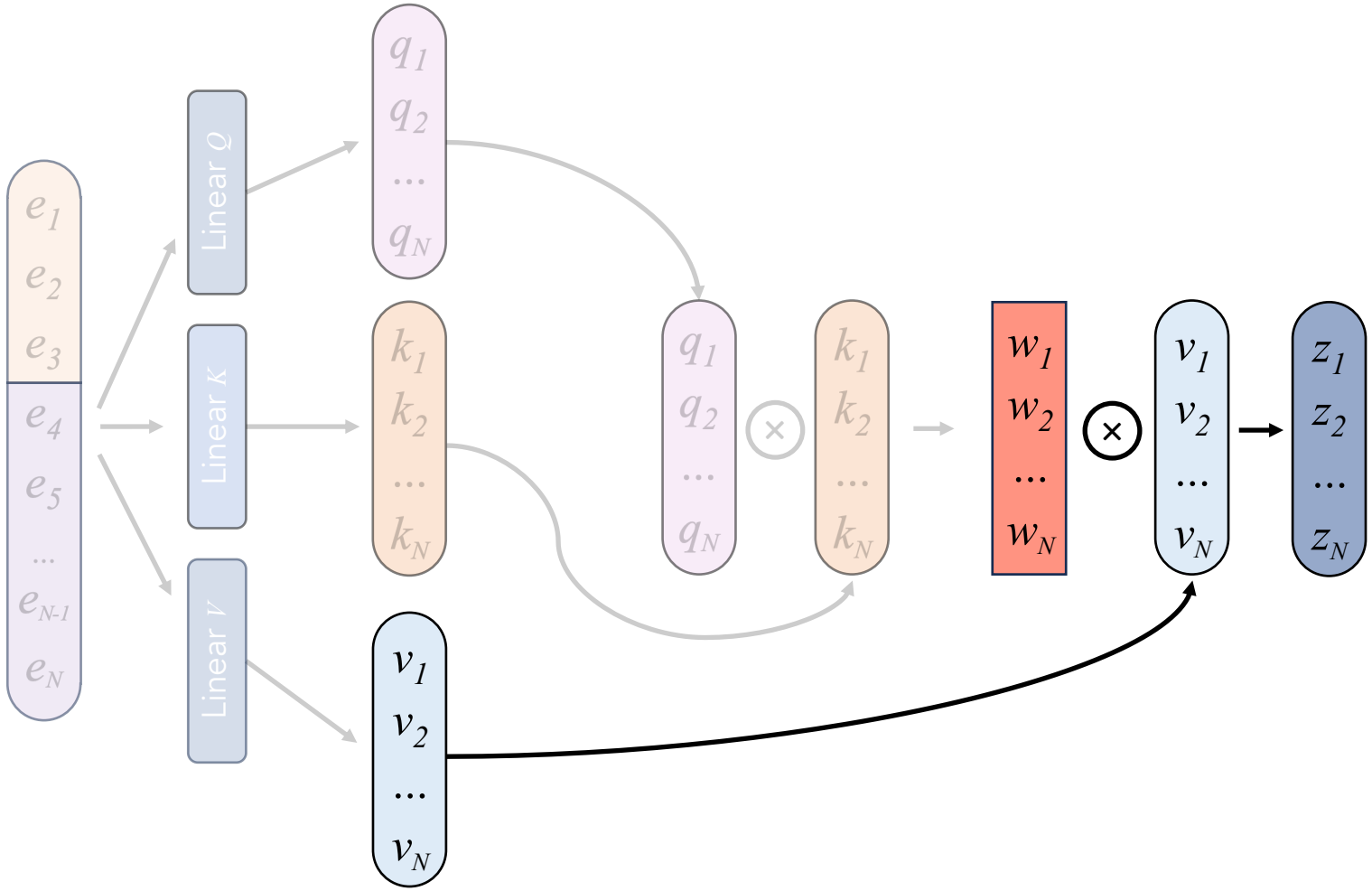

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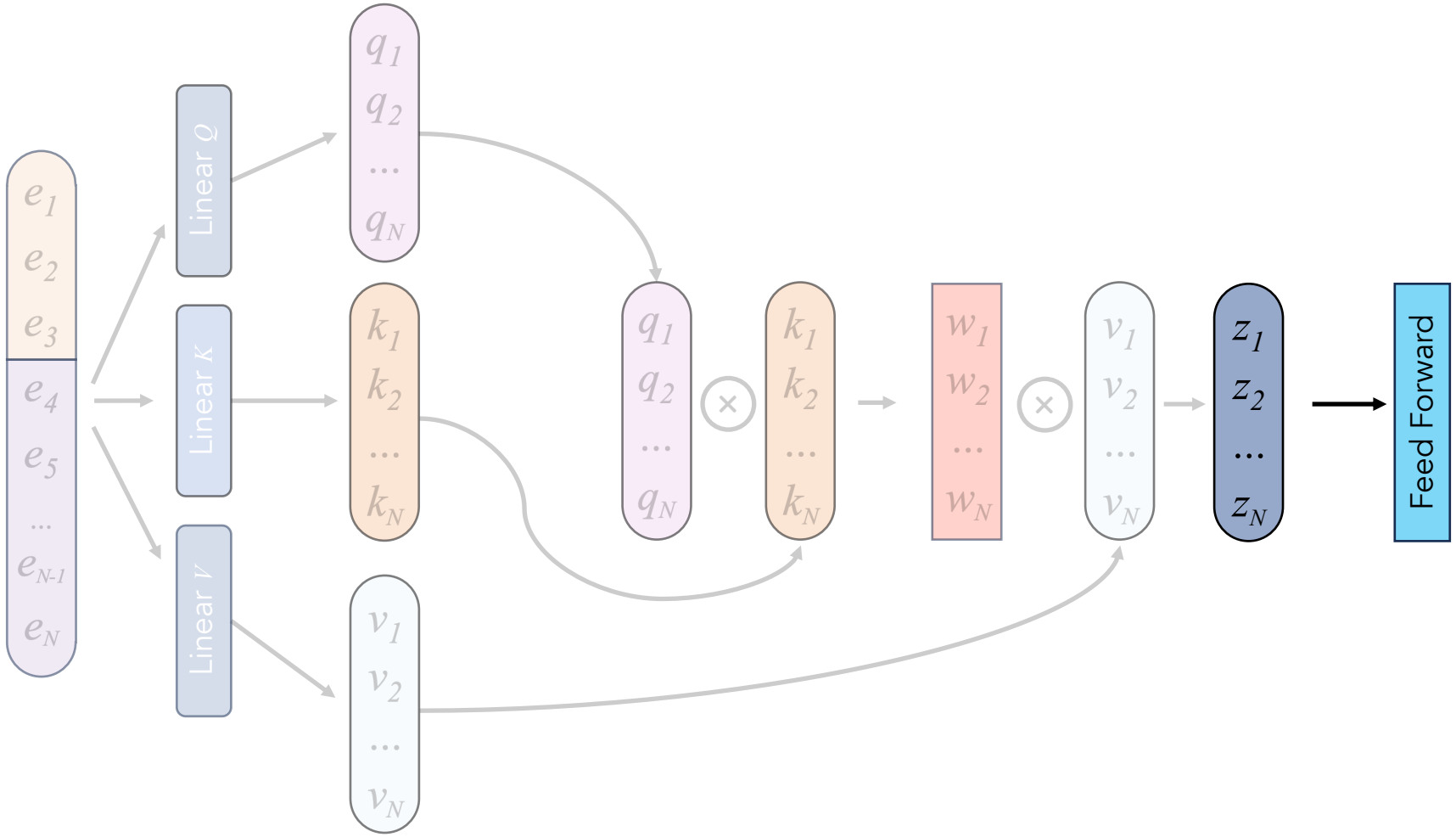
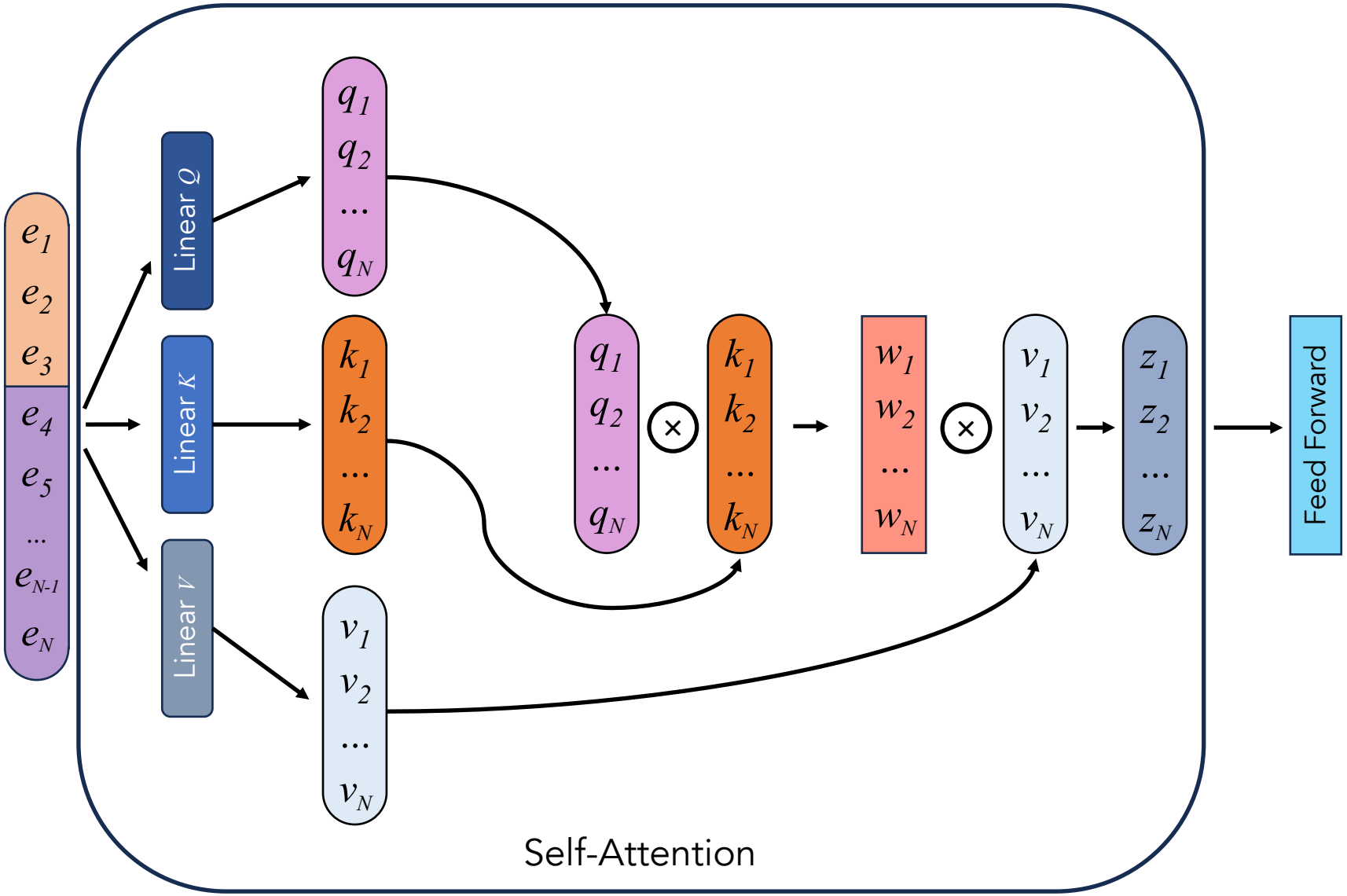
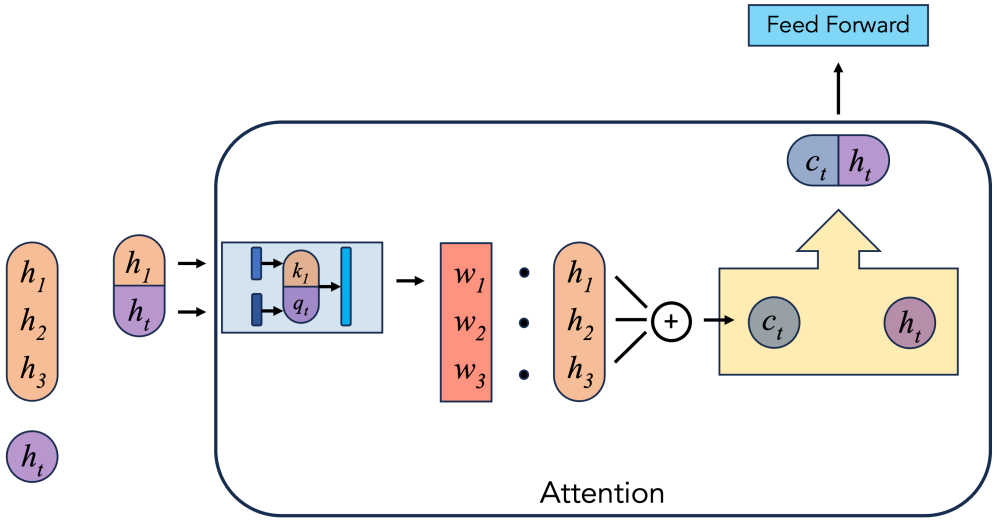


The Evolution of Attention



The Evolution of Attention



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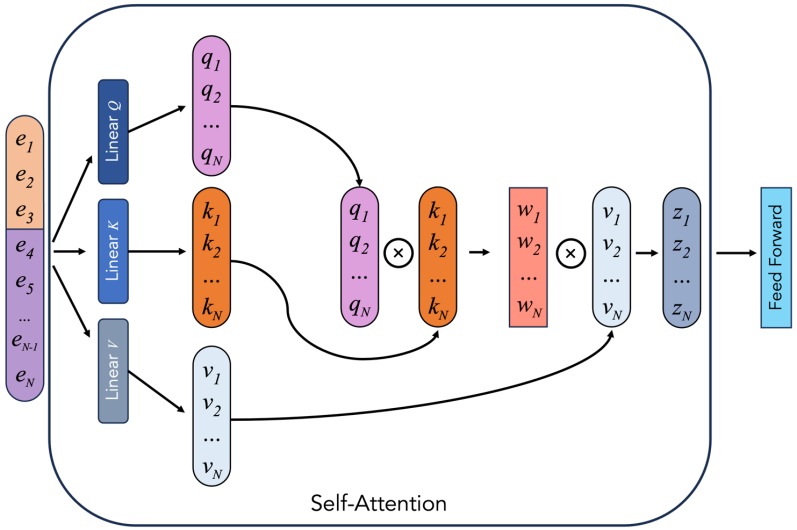
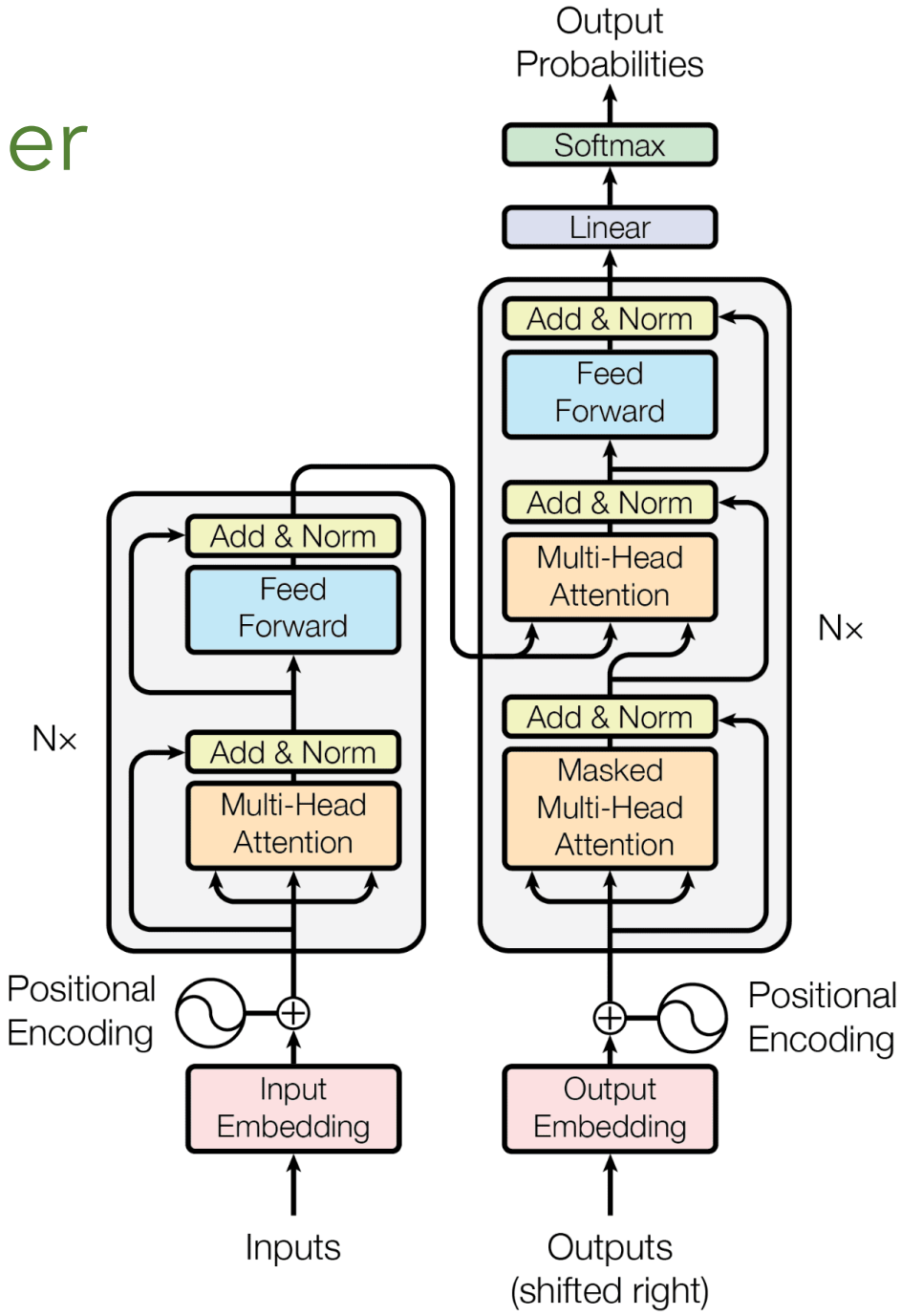


Linear NNs directly create *keys*, *queries*, and *values*

Matrix mult converts *keys* & *queries* to *weights*

weights used to average *values*

The Transformer



Multi-Head Attention