Position-Wise Feed-Forward Network (FFN)

Hunter Phillips · Following

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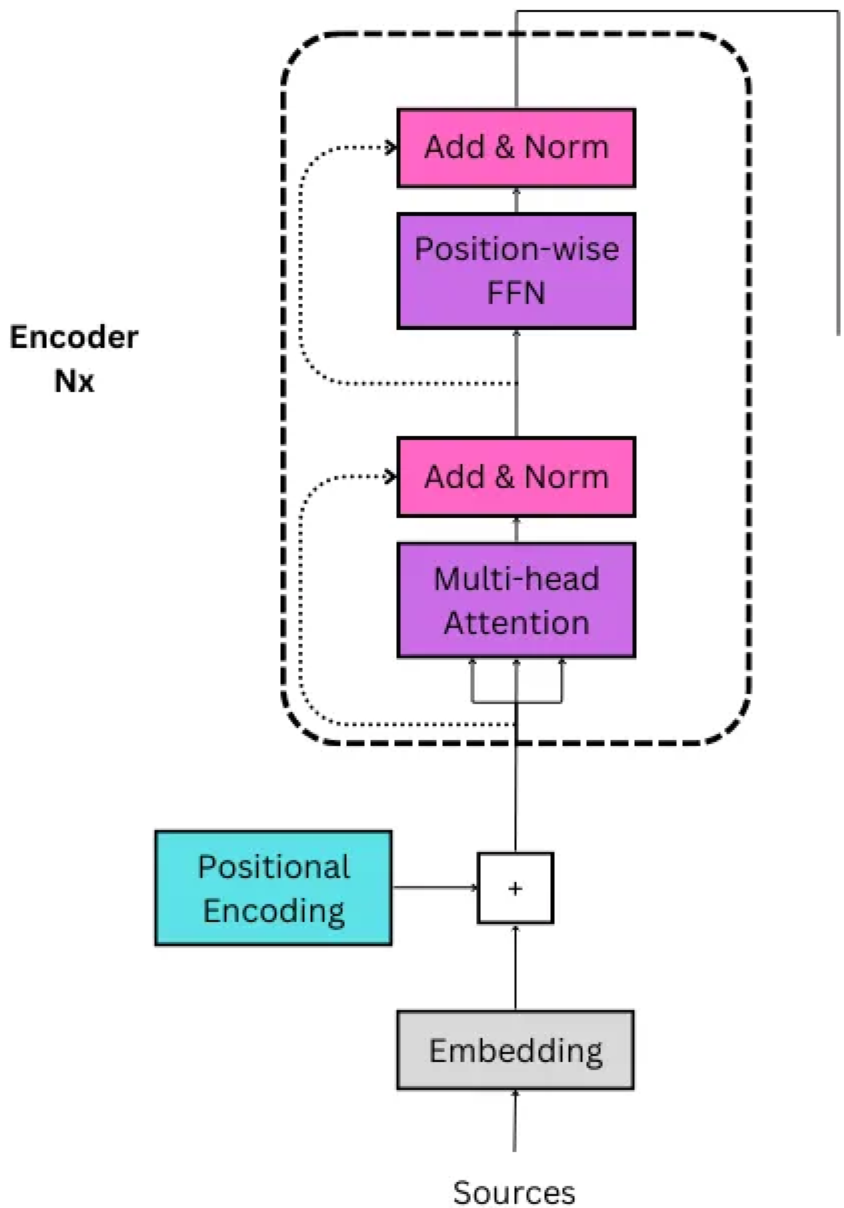
This is the fourth article in The Implemented Transformer series. The Position-wise Feed-Forward Network is an expand-and-contract network that transforms each sequence using the same dense layers.



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Background

The Position-Wise Feed-Forward Network (FFN) consists of two fully connected dense layers, or a multi-layer perceptron (MLP). The hidden layer, which is known as ***d_ffn,*** is generally set to a value about four times that of ***d_model***. This is why it is sometimes known as an expand-and-contract network.

According to d2l, it is known as a "position-wise" network because it "transforms the representation at all the sequence positions using the same MLP."

In other words, the FNN has a size of ***(d_model, d_ffn)*** in its first layer, which means it has to be broadcast across each sequence during tensor multiplication. This means each sequence is multiplied by the same weights. If identical sequences are input, the outputs will also be identical. This same logic applies to the second dense layer of size ***(d_ffn, d_model),*** which returns the tensor to its original size.

The ReLU activiation function, ***max(0, X)***, is used between the layers. Any values greater than 0 remain the same, and any values less than or equal to 0 become 0. It introduces non-linearity and helps prevent vanishing gradients.

Basic Implementation

The following code relies on the previous modules of the transformers model. The output of the layers up to this point is *(3,6,8)*. There are 3 sequences of 6 tokens with 8 dimensional embeddings.

```
torch.set_printoptions(precision=2, sci_mode=False)

# convert the sequences to integers
sequences = ["I wonder what will come next!",
```

```
             "This is a basic example paragraph.",
             "Hello, what is a basic split?"]

# tokenize the sequences
tokenized_sequences = [tokenize(seq) for seq in sequences]

# index the sequences
indexed_sequences = [[stoi[word] for word in seq] for seq in tokenized_sequences

# convert the sequences to a tensor
tensor_sequences = torch.tensor(indexed_sequences).long()

# vocab size
vocab_size = len(stoi)

# embedding dimensions
d_model = 8

# create the embeddings
lut = Embeddings(vocab_size, d_model) # look-up table (lut)

# create the positional encodings
pe = PositionalEncoding(d_model=d_model, dropout=0.1, max_length=10)

# embed the sequence
embeddings = lut(tensor_sequences)

# positionally encode the sequences
X = pe(embeddings)

# set the n_heads
n_heads = 4

# create the attention layer
attention = MultiHeadAttention(d_model, n_heads, dropout=0.1)

# pass X through the attention layer three times to create Q, K, and V
output, attn_probs = attention(X, X, X, mask=None)

output
```

```
tensor([[[-0.87, -1.03,  0.92, -0.21,  0.85,  0.80,  0.18, -0.67],
         [-1.10, -1.13,  1.03, -0.11,  0.88,  0.59, -0.03, -0.51],
         [-0.68, -1.29,  0.76, -0.47,  0.70,  0.89, -0.25, -0.42],
         [-0.21, -0.92,  0.51, -0.52,  0.43,  0.87, -0.12,  0.21],
         [-1.23, -1.60,  1.36,  0.31,  0.69, -0.22, -1.17, -1.49],
```

```
         [-1.13, -1.68,  1.35,  0.23,  0.66, -0.08, -1.23, -1.21]],

        [[-1.12, -0.46,  0.34, -0.13,  0.57, -0.23,  0.33, -0.58],
         [-1.09, -0.01,  0.31,  0.06,  0.06, -0.51,  0.68, -0.44],
         [-0.86,  0.09,  0.17, -0.27, -0.26, -0.24, -0.14,  0.32],
         [ 0.88,  1.22,  0.14,  0.32, -0.97, -0.50, -0.47, -0.56],
         [-0.49, -0.62, -0.46, -0.70, -0.10, -0.52, -0.45, -1.04],
         [-0.06,  0.09,  0.48, -0.15, -0.29,  0.28, -0.62, -0.16]],

        [[-2.44, -3.36, -0.28, -1.39,  1.83, -0.52, -1.41, -1.68],
         [ 0.00, -1.52, -0.39, -0.81, -0.15, -0.53, -1.37, -2.45],
         [ 0.52, -0.80,  0.54, -0.31, -0.46,  0.41, -1.35, -1.54],
         [-0.37, -1.55, -0.22, -1.01, -0.09, -0.19, -2.06, -1.40],
         [ 1.10,  0.80,  0.11, -0.04, -0.76,  0.22, -0.20, -1.63],
         [ 1.21,  0.05,  0.07, -0.26, -0.75,  0.20, -0.93, -2.64]]],
      grad_fn=<ViewBackward0>)
```

Now, this can be passed through the FFN. This will change the 8-dimensional embeddings to 32-dimensional embeddings. This is also passed through the ReLU activation function. The new shape will be ***(3, 6, 8) x (8, 32) → (3, 6, 32)***.

```
d_ffn = d_model * 4  # 32

w_1 = nn.Linear(d_model, d_ffn)  # (8, 32)
w_2 = nn.Linear(d_ffn, d_model)  # (32, 8)

ffn_1 = w_1(output).relu()
```

```
tensor([
        # sequence 0
        [[    0.00,     0.00,     0.58,     0.00,     0.86,     0.00,     0.00,
         [    0.00,     0.00,     0.62,     0.00,     0.90,     0.00,     0.00,
         [    0.00,     0.00,     0.28,     0.00,     0.81,     0.00,     0.00,
         [    0.06,     0.00,     0.11,     0.00,     0.60,     0.00,     0.00,
         [    0.00,     0.12,     0.40,     0.00,     0.63,     0.00,     0.00,
         [    0.00,     0.13,     0.29,     0.00,     0.67,     0.00,     0.00,

        # sequence 1
```

```
        [[    0.00,     0.00,     0.89,     0.00,     0.51,     0.00,     0.00,
         [    0.00,     0.00,     0.96,     0.00,     0.39,     0.00,     0.00,
         [    0.07,     0.00,     0.56,     0.00,     0.22,     0.00,     0.00,
         [    0.68,     0.00,     0.01,     0.31,     0.00,     0.18,     0.00,
         [    0.00,     0.00,     0.31,     0.32,     0.00,     0.00,     0.00,
         [    0.24,     0.00,     0.12,     0.00,     0.00,     0.00,     0.00,

        # sequence 2
        [[    0.00,     1.00,     0.67,     0.07,     1.18,     0.00,     0.00,
         [    0.00,     0.10,     0.00,     0.68,     0.00,     0.00,     0.42,
         [    0.00,     0.00,     0.00,     0.14,     0.00,     0.00,     0.30,
         [    0.00,     0.08,     0.00,     0.22,     0.00,     0.00,     0.45,
         [    0.35,     0.00,     0.00,     0.55,     0.00,     0.13,     0.03,
         [    0.01,     0.00,     0.00,     0.79,     0.00,     0.01,     0.42,
```

Then, the tensor can be passed through the second dense layer to return to its normal size, *(3, 6, 32) x (32, 8) = (3, 6, 8)*. The values have changed according to the weights and activation function.

```
ffn_2 = w_2(ffn_1)
ffn_2
```

```
tensor([[[ 0.09,  0.37, -0.20, -0.12,  0.30, -0.24,  0.13,  0.33],
         [ 0.13,  0.30, -0.23, -0.22,  0.25, -0.38,  0.02,  0.22],
         [ 0.05,  0.35, -0.11, -0.20,  0.32, -0.26,  0.16,  0.37],
         [ 0.08,  0.28, -0.04, -0.30,  0.34, -0.15,  0.18,  0.24],
         [ 0.08,  0.27, -0.43, -0.28,  0.43, -0.05, -0.03,  0.24],
         [ 0.14,  0.23, -0.30, -0.22,  0.19, -0.39, -0.04,  0.30]],

        [[ 0.18,  0.43, -0.23, -0.05,  0.22, -0.15,  0.13,  0.11],
         [ 0.13,  0.41, -0.20, -0.13,  0.10, -0.04,  0.10,  0.01],
         [ 0.08,  0.31, -0.08, -0.09,  0.13, -0.13,  0.16,  0.08],
         [-0.20,  0.18, -0.20,  0.21,  0.19, -0.00,  0.26,  0.25],
         [ 0.17,  0.21, -0.08, -0.07,  0.10, -0.01,  0.09,  0.08],
         [-0.02,  0.25, -0.08, -0.11,  0.23, -0.12,  0.19,  0.23]],

        [[-0.21,  0.71, -0.29, -0.08,  0.21,  0.12, -0.33,  0.49],
         [ 0.19,  0.19, -0.06,  0.19,  0.33,  0.02,  0.25,  0.29],
```

```
         [-0.04,  0.25, -0.10, -0.12,  0.21, -0.11,  0.19,  0.42],
         [ 0.05,  0.35, -0.02,  0.05,  0.27, -0.06,  0.17,  0.29],
         [-0.16,  0.22, -0.13,  0.15,  0.13,  0.00,  0.31,  0.34],
         [-0.05,  0.23, -0.18,  0.22,  0.13, -0.03,  0.26,  0.40]]],
       grad_fn=<ViewBackward0>)
```

FFN in Transformers

$$FFN(x, W_1, W_2, b_1, b_2) = \max(0, xW_1 + b_1)W_2 + b_2$$

The implementation for the FFN is straightforward. It requires two linear, or dense, layers. The first dense layer has a size of ***(d_model, d_ffn)***, and the second layer has a size of ***(d_ffn, d_model)***.

The input to the model, ***X***, will have a size of ***(batch_size, seq_length, d_model)***. The input will therefore go through the following transformations:

1. ***(batch_size, seq_length, d_model) x (d_model, d_ffn) = (batch_size, seq_length, d_ffn)***
2. ***max(0, (batch_size, seq_length, d_ffn)) = (batch_size, seq_length, d_ffn)***
3. ***(batch_size, seq_length, d_ffn) x (d_ffn, d_model) = (batch_size, seq_length, d_model)***

```
class PositionwiseFeedForward(nn.Module):
  def __init__(self, d_model: int, d_ffn: int, dropout: float = 0.1):
    """
    Args:
        d_model:      dimension of embeddings
```

```
        d_ffn:        dimension of feed-forward network
        dropout:      probability of dropout occurring
    """
    super().__init__()

    self.w_1 = nn.Linear(d_model, d_ffn)
    self.w_2 = nn.Linear(d_ffn, d_model)
    self.dropout = nn.Dropout(dropout)

  def forward(self, x):
    """
    Args:
        x:            output from attention (batch_size, seq_length, d_model)

    Returns:
        expanded-and-contracted representation (batch_size, seq_length, d_model)
    """
    # w_1(x).relu(): (batch_size, seq_length, d_model) x (d_model,d_ffn) -> (bat
    # w_2(w_1(x).relu()): (batch_size, seq_length, d_ffn) x (d_ffn, d_model) ->
    return self.w_2(self.dropout(self.w_1(x).relu()))
```

Forward Pass

This forward pass assumes the data has been passed through the embedding, positional encoding, and multi-head attention layers. It does not use layer normalization or residual addition, which will be implemented before and after this network in the Encoder in article six.

```
torch.set_printoptions(precision=2, sci_mode=False)

# convert the sequences to integers
sequences = ["I wonder what will come next!",
             "This is a basic example paragraph.",
             "Hello, what is a basic split?"]

# tokenize the sequences
tokenized_sequences = [tokenize(seq) for seq in sequences]

# index the sequences
```

```
indexed_sequences = [[stoi[word] for word in seq] for seq in tokenized_sequences

# convert the sequences to a tensor
tensor_sequences = torch.tensor(indexed_sequences).long()

# vocab size
vocab_size = len(stoi)

# embedding dimensions
d_model = 8

# create the embeddings
lut = Embeddings(vocab_size, d_model) # look-up table (lut)

# create the positional encodings
pe = PositionalEncoding(d_model=d_model, dropout=0.1, max_length=10)

# embed the sequence
embeddings = lut(tensor_sequences)

# positionally encode the sequences
X = pe(embeddings)

# set the n_heads
n_heads = 4

# create the attention layer
attention = MultiHeadAttention(d_model, n_heads, dropout=0.1)

# pass X through the attention layer three times to create Q, K, and V
output, attn_probs = attention(X, X, X, mask=None)

# calculate the d_ffn
d_ffn = d_model*4 # 32

# pass the tensor through the position-wise feed-forward network
ffn = PositionwiseFeedForward(d_model, d_ffn, dropout=0.1)

ffn(output)
```

```
tensor([[[ 0.19, -0.09,  0.05,  0.34, -0.11,  0.24,  0.03, -0.01],
         [ 0.29, -0.23, -0.19,  0.23, -0.33,  0.02, -0.08,  0.17],
         [-0.01, -0.16, -0.21,  0.23, -0.11,  0.12,  0.09, -0.02],
         [ 0.04, -0.14, -0.50,  0.12, -0.39,  0.04,  0.21,  0.12],
         [ 0.25, -0.19, -0.07,  0.47, -0.27,  0.16, -0.00,  0.39],
         [ 0.21, -0.17, -0.01,  0.46, -0.30,  0.28,  0.05,  0.23]],
```

```
          [[ 0.11, -0.16, -0.34,  0.12, -0.25, -0.01,  0.06,  0.04],
           [ 0.03, -0.16, -0.39, -0.01, -0.35, -0.07,  0.18, -0.02],
           [-0.00, -0.29, -0.44,  0.13, -0.07,  0.08, -0.01,  0.23],
           [ 0.17, -0.33, -0.49, -0.14, -0.45, -0.18,  0.22, -0.10],
           [ 0.02, -0.20, -0.53,  0.18, -0.43,  0.07,  0.32,  0.13],
           [ 0.03, -0.19, -0.50,  0.15, -0.38,  0.15,  0.20,  0.27]],

          [[ 0.07, -0.38, -0.51, -0.05, -0.48,  0.15,  0.20,  0.16],
           [ 0.03, -0.40, -0.61, -0.16, -0.59,  0.16,  0.52,  0.13],
           [-0.02, -0.18, -0.32,  0.13, -0.19,  0.08, -0.01,  0.11],
           [ 0.08, -0.52, -0.53,  0.11, -0.37,  0.31,  0.26,  0.35],
           [-0.02, -0.12, -0.50,  0.07, -0.22,  0.03,  0.26, -0.01],
           [ 0.02, -0.11, -0.29,  0.17, -0.25,  0.04, -0.00,  0.14]]],
        grad_fn=<ViewBackward0>)
```

The output is similar to the manually implemented one, but the values are different due to the dropout layer being utilized. Otherwise, the same transformations occur.

The next article briefly covers Layer Normalization before it is implemented in article six.

Please don't forget to like and follow for more! :)

References

1. The Annotated Transformer
2. d2l's Transformer Implementation

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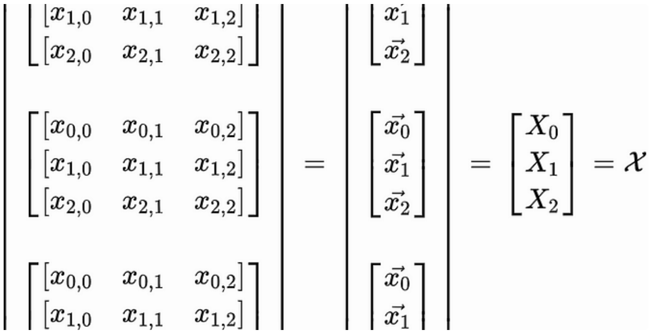

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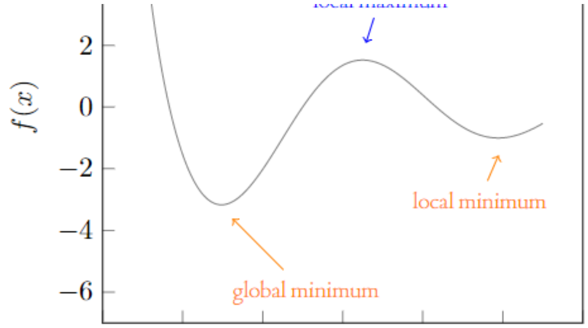

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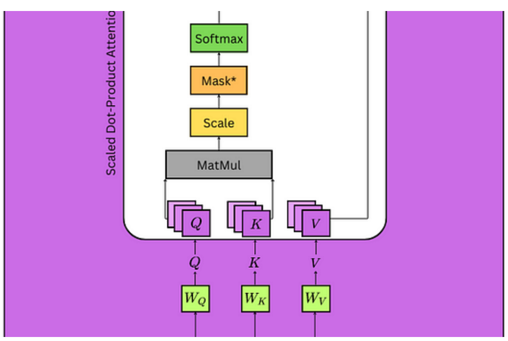

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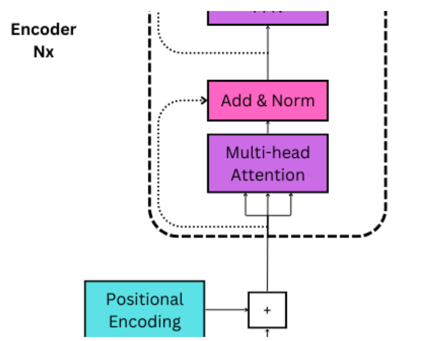

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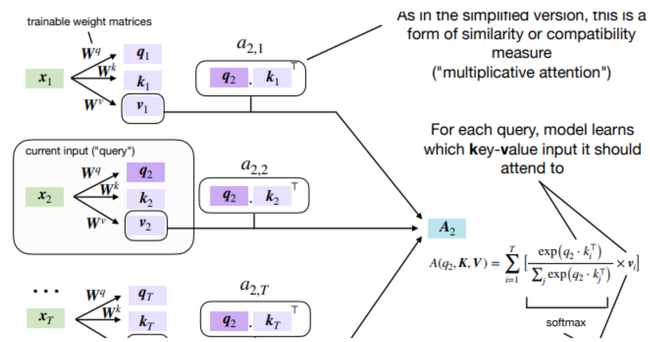

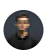

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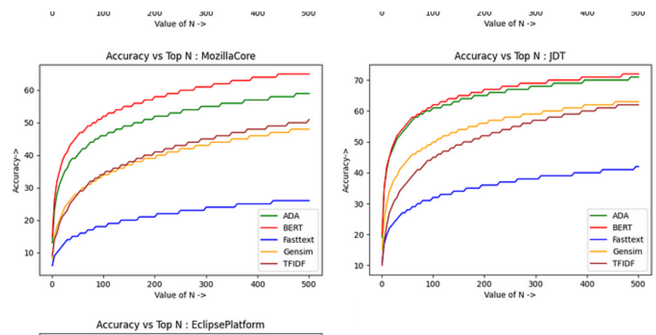

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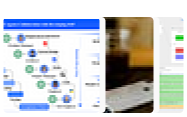

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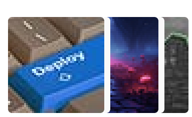

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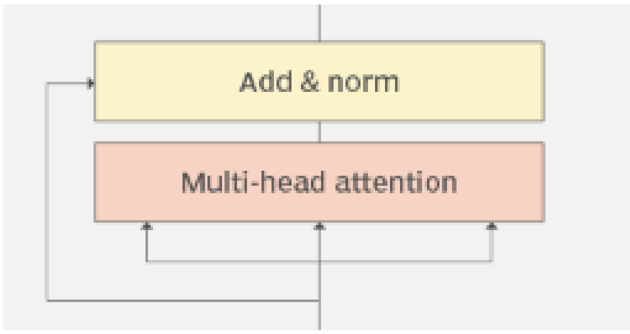

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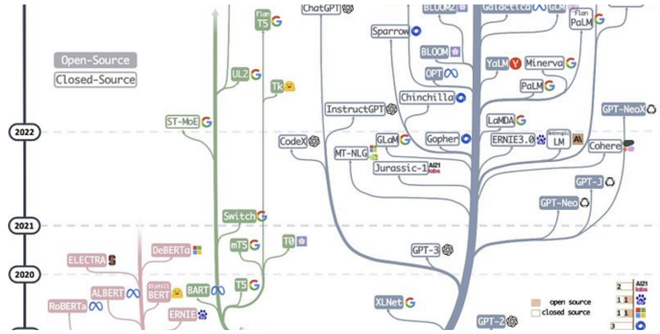

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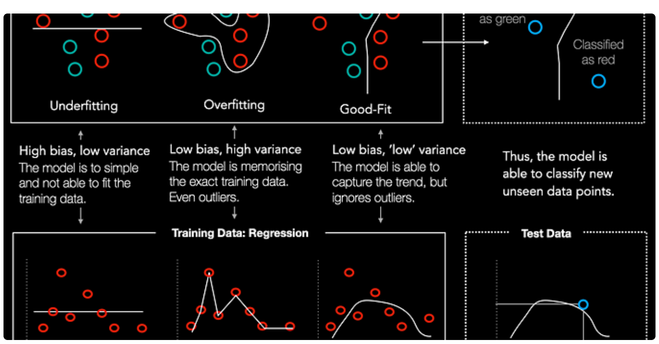

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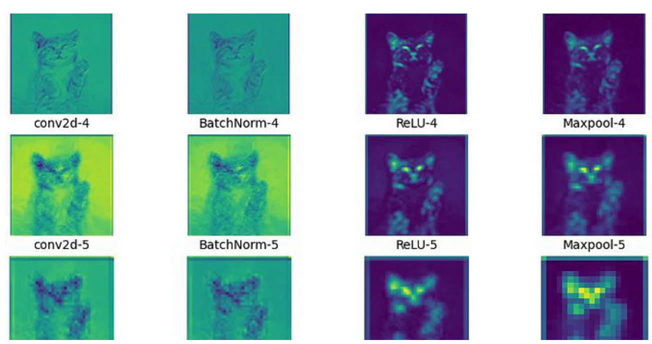

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