Layers — ML Glossary documentation

13-17 minutes

ML Glossary

- BatchNorm
- Convolution
- Dropout
- Linear
- Pooling
- RNN
- GRU
- LSTM

Convolution¶

In CNN, a convolution is a linear operation that involves multiplication of weight (kernel/filter) with the input and it does most of the heavy lifting job.

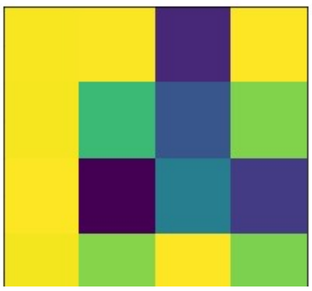
Convolution layer consists of 2 major component 1. Kernel(Filter) 2. Stride

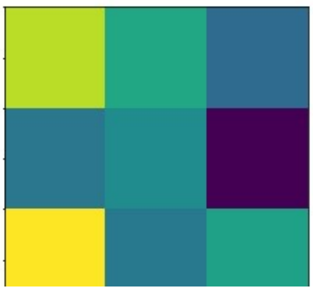
1. Kernel (Filter): A convolution layer can have more than one filter. The size of the filter should be smaller than the size of input dimension. It is intentional as it allows filter to be applied multiple times at difference point (position) on the input.Filters are helpful in understanding and identifying important features from given input. By applying different filters (more than one filter) on the same input helps in extracting different features from given input. Output from multiplying filter with the input gives Two dimensional array. As such, the output array from this operation is called “Feature Map”.
2. Stride: This property controls the movement of filter over input. when the value is set to 1, then filter moves 1 column at a time over input. When the value is set to 2 then the filer jump 2 columns at a

time as filter moves over the input.

Code

```
# this code demonstate on how Convolution works
# Assume we have a image of 4 X 4 and a filter fo
2 X 2 and Stride = 1

def
conv_filter_ouput(input_img_section,filter_value):
      # this method perfromas the multiplication
of input and filter
      # returns singular value

      value = 0
      for i in range(len(filter_value)):
            for j in range(len(filter_value[0])):
                  value = value +
(input_img_section[i][j]*filter_value[i][j])
      return value

img_input = [[260.745, 261.332, 112.27 , 262.351],
 [260.302, 208.802, 139.05 , 230.709],
 [261.775,  93.73 , 166.118, 122.847],
 [259.56 , 232.038, 262.351, 228.937]]

filter = [[1,0],
   [0,1]]

filterX,filterY = len(filter),len(filter[0])
filtered_result = []
for i in range(0,len(img_mx)-filterX+1):
clm = []
for j in range(0,len(img_mx[0])-filterY+1):

clm.append(conv_filter_ouput(img_mx[i:i+filterX,j:j+filterY],filte
filtered_result.append(clm)

print(filtered_result)
```





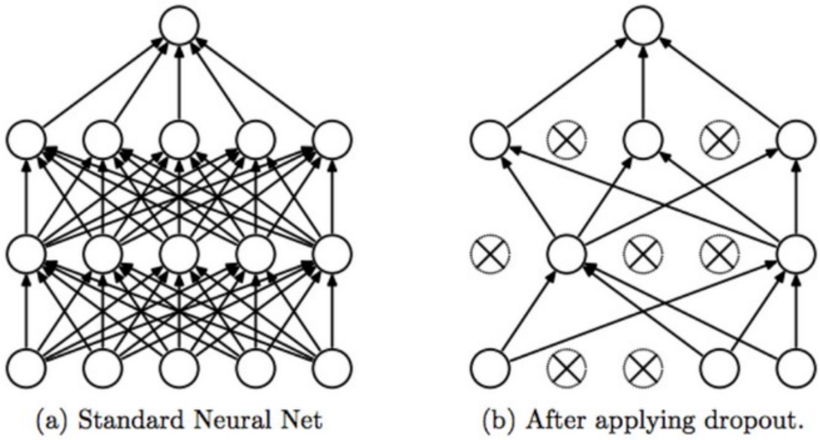
Further reading

- [cs231n reference]

Dropout¶

A dropout layer takes the output of the previous layer's activations and randomly sets a certain fraction (dropout rate) of the activatons to 0, cancelling or 'dropping' them out.

It is a common regularization technique used to prevent overfitting in Neural Networks.



Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting", JMLR 2014

The dropout rate is the tunable hyperparameter that is adjusted to measure performance with different values. It is typically set between 0.2 and 0.5 (but may be arbitrarily set).

Dropout is only used during training; At test time, no activations are dropped, but scaled down by a factor of dropout rate. This is to account for more units being active during test time than training time.

For example:

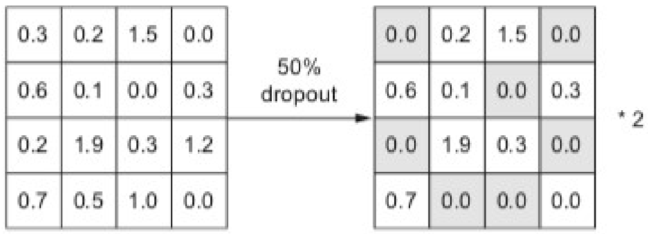
- A layer in a neural net outputs a tensor (matrix) A of shape (batch_size, num_features).
- The dropout rate of the layer is set to 0.5 (50%).
- A random 50% of the values in A will be set to 0.
- These will then be multiplied with the weight matrix to form the inputs to the next layer.

The premise behind dropout is to introduce noise into a layer in order to disrupt any interdependent learning or coincidental patterns that may occur between units in the layer, that aren't significant.

Code

```
# layer_output is a 2D numpy matrix of activations

layer_output *= np.random.randint(0, high=2,
size=layer_output.shape) # dropping out values

# scaling up by dropout rate during TRAINING time,
so no scaling needs to be done at test time
layer_output /= 0.5
# OR
layer_output *= 0.5 # Scaling down during TEST
time.
```

This results in the following operation.



All reference, images and code examples, unless mentioned otherwise, are from section 4.4.3 of Deep Learning for Python by François Chollet.

Pooling¶

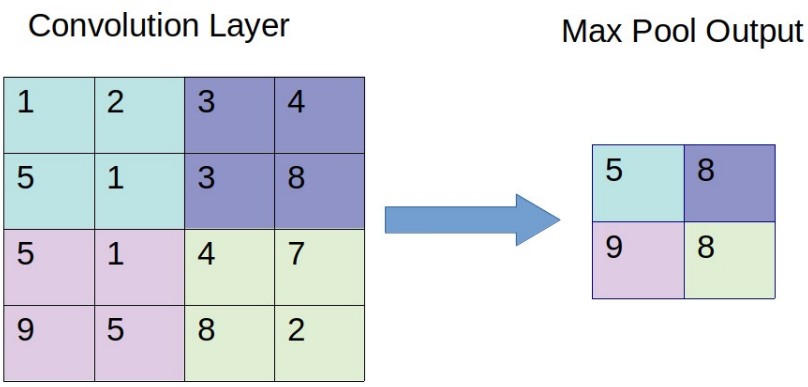
Pooling layers often take convolution layers as input. A complicated dataset with many object will require a large number of filters, each responsible finding pattern in an image so the dimensionally of convolutional layer can get large. It will cause an increase of parameters, which can lead to over-fitting. Pooling layers are methods for reducing this high dimensionally. Just like the convolution layer, there is kernel size and stride. The size of the kernel is smaller than the feature map. For most of the cases the size of the kernel will be 2X2 and the stride of 2. There are mainly two types of pooling layers.

The first type is max pooling layer. Max pooling layer will take a stack of feature maps (convolution layer) as input. The value of the node in the max pooling layer is calculated by just the maximum of the pixels contained in the window.

The other type of pooling layer is the Average Pooling layer. Average pooling layer calculates the average of pixels contained in the window. Its not used often but you may see this used in applications for which smoothing an image is preferable.

Code

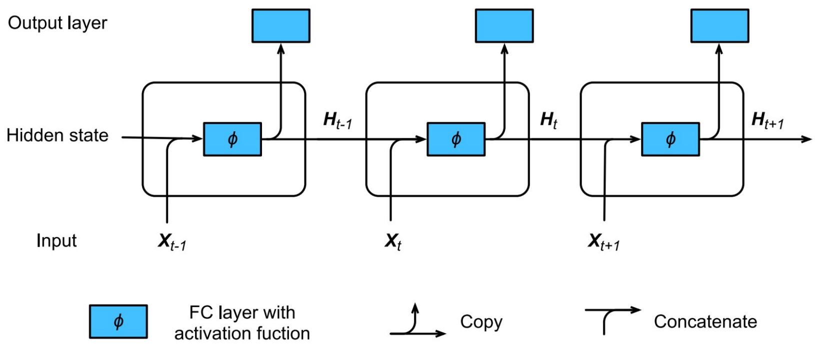
```
def max_pooling(feature_map, size=2, stride=2):
    """
    :param feature_map: Feature matrix of shape
(height, width, layers)
    :param size: size of kernal
    :param stride: movement speed of kernal
    :return: max-pooled feature vector
    """
    pool_shape = (feature_map.shape[0]//stride,
feature_map.shape[1]//stride,
feature_map.shape[-1]) #shape of output
    pool_out = numpy.zeros(pool_shape)
    for layer in range(feature_map.shape[-1]):
            #for each layer
            row = 0
            for r in
numpy.arange(0,feature_map.shape[0], stride):
                col = 0
                for c in numpy.arange(0,
feature_map.shape[1], stride):
                    pool_out[row, col, layer] =
numpy.max([feature_map[c:c+size,  r:r+size,
layer]])
                    col = col + 1
                row = row +1
    return pool_out
```



RNN¶

RNN (Recurrent Neural Network) is the neural network with hidden state, which captures the historical information up to current timestep. Because the hidden state of current state uses the same definition as that in previous timestep, which means the computation is recurrent, hence it is called recurrent neural network.(Ref 2)

The structure is as follows:



Code

For detail code, refer to [layers.py]()

```
class RNN:
    def __init__(self, input_dim: int, hidden_dim:
int, output_dim: int, batch_size=1) -> None:
        self.input_dim = input_dim
        self.hidden_dim = hidden_dim
        self.out_dim = output_dim
        self.batch_size = batch_size
        # initialization
        self.params = self._init_params()
        self.hidden_state =
self._init_hidden_state()

    def _init_params(self) -> List[np.array]:
        scale = 0.01
        Waa = np.random.normal(scale=scale,
size=[self.hidden_dim, self.hidden_dim])
        Wax = np.random.normal(scale=scale,
size=[self.hidden_dim, self.input_dim])
        Wy = np.random.normal(scale=scale,
size=[self.out_dim, self.hidden_dim])
        ba = np.zeros(shape=[self.hidden_dim, 1])
        by = np.zeros(shape=[self.out_dim, 1])
        return [Waa, Wax, Wy, ba, by]

    def _init_hidden_state(self) -> np.array:
        return np.zeros(shape=[self.hidden_dim,
self.batch_size])
```

```
    def forward(self, input_vector: np.array) ->
np.array:
        """
        input_vector:
            dimension: [num_steps, self.input_dim,
self.batch_size]
        out_vector:
            dimension: [num_steps,
self.output_dim, self.batch_size]
        """
        Waa, Wax, Wy, ba, by = self.params
        output_vector = []
        for vector in input_vector:
            self.hidden_state = np.tanh(
                np.dot(Waa, self.hidden_state) +
np.dot(Wax, vector) + ba
            )
            y = softmax(
                np.dot(Wy, self.hidden_state) + by
            )
            output_vector.append(y)
        return np.array(output_vector)

if __name__ == "__main__":
    input_data = np.array([
        [
            [1, 3]
            , [2, 4]
            , [3, 6]
        ]
        , [
            [4, 3]
            , [3, 4]
            , [1, 5]
        ]
    ])
    batch_size = 2
    input_dim = 3
    output_dim = 4
    hidden_dim = 5
    time_step = 2
    rnn = RNN(input_dim=input_dim,
batch_size=batch_size, output_dim=output_dim,
```

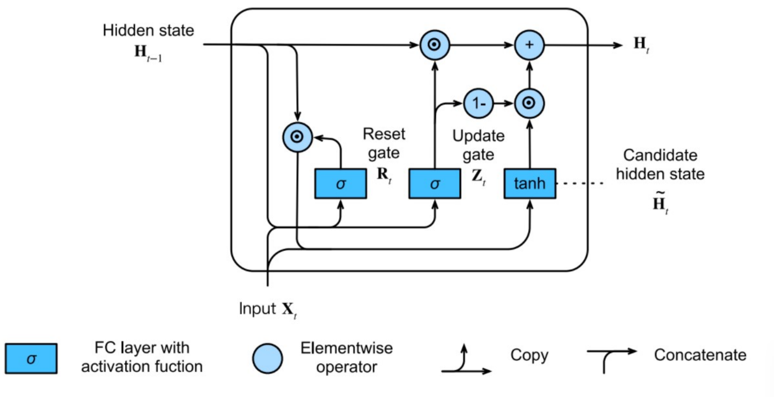
```
hidden_dim=hidden_dim)
    output_vector =
rnn.forward(input_vector=input_data)
    print("RNN:")
    print(f"Input data dimensions:
{input_data.shape}")
    print(f"Output data dimensions
{output_vector.shape}")
    ## We will get the following output:
    ##  RNN:
    ## Input data dimensions: (2, 3, 2)
    ## Output data dimensions (2, 4, 2)
```

GRU¶

GRU (Gated Recurrent Unit) supports the gating of hidden state:

1. Reset gate controls how much of previous hidden state we might still want to remember
2. Update gate controls how much of current hidden state is just a copy of previous state

The structure and math are as follow:



1. Reset gate: $R_t = sigmoid(W_r[\frac{h^{<t-1>}}{x_t}] + b_r)$
2. Update gate: $Z_t = sigmoid(W_z[\frac{h^{<t-1>}}{x_t}] + b_u)$
3. Candidate hidden state: $h^{\tilde{<t>}} = tanh(R_t * h^{<t-1>})$
4. Hidden state: $h^{<t>} = Z_t * h^{<t>} + (1 - Z_t) * h^{\tilde{<t>}}$
5. Output layer: $\hat{y}_t = softmax(W_y a^{<t>} + b_y)$

Code

For detail code, refer to layers.py

```
class GRU:
    def __init__(self, input_dim: int, hidden_dim:
int, output_dim: int, batch_size=1) -> None:
        self.input_dim = input_dim
        self.hidden_dim = hidden_dim
```

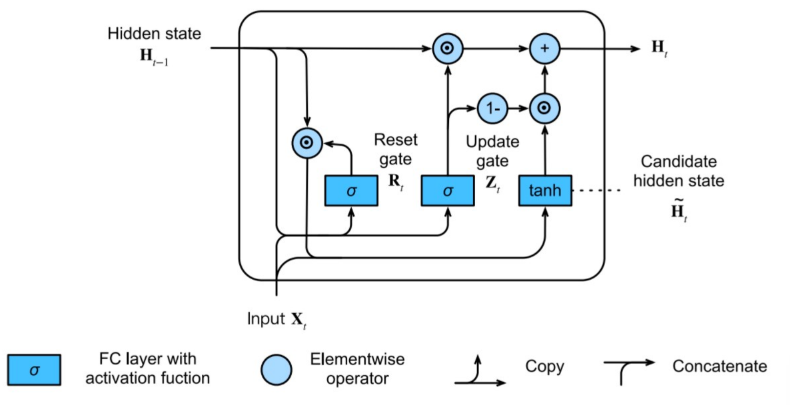
```
        self.out_dim = output_dim
        self.batch_size = batch_size
        # initialization
        self.params = self._init_params()
        self.hidden_state =
self._init_hidden_state()

    def _init_params(self) -> List[np.array]:
        scale = 0.01
        def param_single_layer():
            w = np.random.normal(scale=scale,
size=(self.hidden_dim, self.hidden_dim+input_dim))
            b = np.zeros(shape=[self.hidden_dim,
1])
            return w, b

        # reset, update gate
        Wr, br = param_single_layer()
        Wu, bu = param_single_layer()
        # output layer
        Wy = np.random.normal(scale=scale,
size=[self.out_dim, self.hidden_dim])
        by = np.zeros(shape=[self.out_dim, 1])
        return [Wr, br, Wu, bu, Wy, by]

    def _init_hidden_state(self) -> np.array:
        return np.zeros(shape=[self.hidden_dim,
self.batch_size])

    def forward(self, input_vector: np.array) ->
np.array:
        """
        input_vector:
            dimension: [num_steps, self.input_dim,
self.batch_size]
        out_vector:
            dimension: [num_steps,
self.output_dim, self.batch_size]
        """
        Wr, br, Wu, bu, Wy, by = self.params
        output_vector = []
        for vector in input_vector:
            # expit in scipy is sigmoid function
            reset_gate = expit(
```

```
                    np.dot(Wr,
np.concatenate([self.hidden_state, vector],
axis=0)) + br
                )
                update_gate = expit(
                    np.dot(Wu,
np.concatenate([self.hidden_state, vector],
axis=0)) + bu
                )
                candidate_hidden = np.tanh(
                    reset_gate * self.hidden_state
                )
                self.hidden_state = update_gate *
self.hidden_state + (1-update_gate) *
candidate_hidden
                y = softmax(
                    np.dot(Wy, self.hidden_state) + by
                )
                output_vector.append(y)
        return np.array(output_vector)
```

LSTM¶

In order to address the **long-term information preservation** and **shor-term skipping** in latent variable model, we introduced LSTM. In LSTM, we introduce the memory cell that has the same shape as the hidden state, which is actually a fancy version of a hidden state, engineered to record additional information.

The structure and math are as follow:



1. Forget gate: $F_t = sigmoid(W_f[\frac{h^{<t-1>}}{x_t}] + b_f)$
2. Input gate: $I_i = sigmoid(W_i[\frac{h^{<t-1>}}{x_t}] + b_i)$
3. Output gate: $O_i = sigmoid(W_o[\frac{h^{<t-1>}}{x_t}] + b_o)$
4. Candidate memory: $\tilde{c} = tanh(W_c[\frac{h^{<t-1>}}{x_t}] + b_c)$
5. Memory: $c^{<t>} = U_i * \tilde{c} + F_i * c^{<t-1>}$
6. Hidden state: $h^{<t>} = O_i * tanh(c^{<t>})$
7. Output layer: $\hat{y} = softmax(W_y h^{<t>} + b_y)$

7. Output layer: $y_t = softmax(W_y h^{<t>} + b_y)$

Code

For detail code, refer to [layers.py]

```
class LSTM:
    def __init__(self, input_dim: int, hidden_dim:
int, output_dim: int, batch_size=1) -> None:
        self.input_dim = input_dim
        self.hidden_dim = hidden_dim
        self.out_dim = output_dim
        self.batch_size = batch_size
        # initialization
        self.params = self._init_params()
        self.hidden_state =
self._init_hidden_state()
        self.memory_state =
self._init_hidden_state()

    def _init_params(self) -> List[np.array]:
        scale = 0.01
        def param_single_layer():
            w = np.random.normal(scale=scale,
size=(self.hidden_dim, self.hidden_dim+input_dim))
            b = np.zeros(shape=[self.hidden_dim,
1])
            return w, b

        # forget, input, output gate + candidate
memory state
        Wf, bf = param_single_layer()
        Wi, bi = param_single_layer()
        Wo, bo = param_single_layer()
        Wc, bc = param_single_layer()
        # output layer
        Wy = np.random.normal(scale=scale,
size=[self.out_dim, self.hidden_dim])
        by = np.zeros(shape=[self.out_dim, 1])
        return [Wf, bf, Wi, bi, Wo, bo, Wc, bc,
Wy, by]

    def _init_hidden_state(self) -> np.array:
        return np.zeros(shape=[self.hidden_dim,
self.batch_size])
```

```
    def forward(self, input_vector: np.array) ->
np.array:
        """
        input_vector:
            dimension: [num_steps, self.input_dim,
self.batch_size]
        out_vector:
            dimension: [num_steps,
self.output_dim, self.batch_size]
        """
        Wf, bf, Wi, bi, Wo, bo, Wc, bc, Wy, by =
self.params
        output_vector = []
        for vector in input_vector:
            # expit in scipy is sigmoid function
            foget_gate = expit(
                np.dot(Wf,
np.concatenate([self.hidden_state, vector],
axis=0)) + bf
            )
            input_gate = expit(
                np.dot(Wi,
np.concatenate([self.hidden_state, vector],
axis=0)) + bi
            )
            output_gate = expit(
                np.dot(Wo,
np.concatenate([self.hidden_state, vector],
axis=0)) + bo
            )
            candidate_memory = np.tanh(
                np.dot(Wc,
np.concatenate([self.hidden_state, vector],
axis=0)) + bc
            )
            self.memory_state = foget_gate *
self.memory_state + input_gate * candidate_memory
            self.hidden_state = output_gate *
np.tanh(self.memory_state)
            y = softmax(
                np.dot(Wy, self.hidden_state) + by
            )
            output_vector.append(y)
        return np.array(output_vector)
```

References