

Text Classification with CNN

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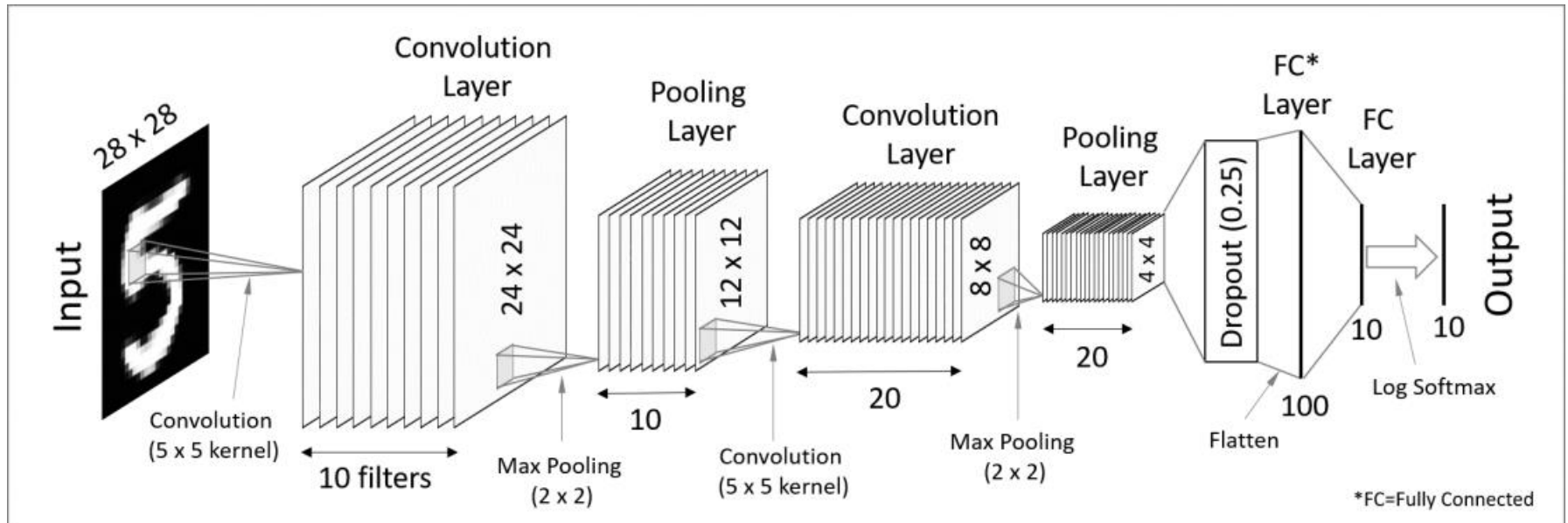
- Brief Introduction to Convolutional Neural Network(CNN)
- Implementing Text Classification with CNN using Tensorflow

Tensorflow Tutorial

- <https://github.com/hunkim/DeepLearningZeroToAll>

Introduction

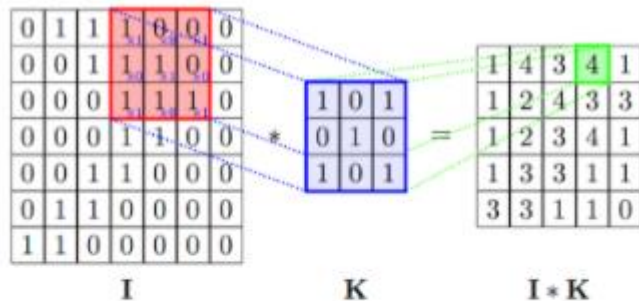
Convolutional Neural Networks



A Convolutional Neural Network (CNN) is comprised of one or more convolutional layers (often with a pooling step) and then followed by one or more fully connected layers as in a standard multilayer neural network.

The architecture of a CNN is designed to **take advantage of the 2D structure of an input such as image**

Convolution Layer



Overlaying the kernel(filter) on top of the input in all possible ways, and recording the **sum of elementwise products** between the input and the kernel(filter):

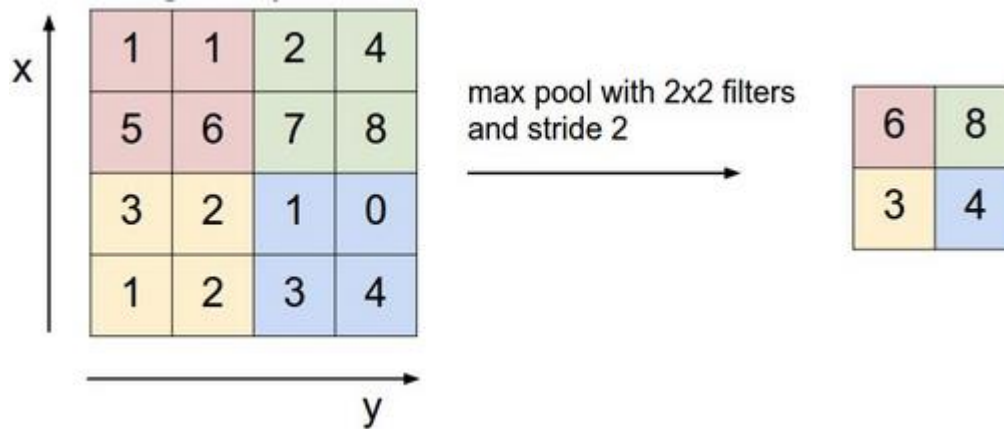
Convolution Filter act as retrieving specific features form local area of input. (such as contour for image)

Many Filters are used so that various type of feature can be extracted

Convolution Filters are learned automatically in network architecture of CNN, not defined by human.



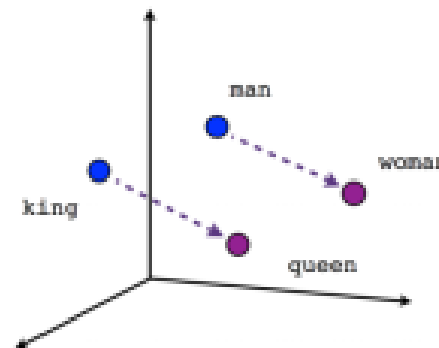
Pooling Layer



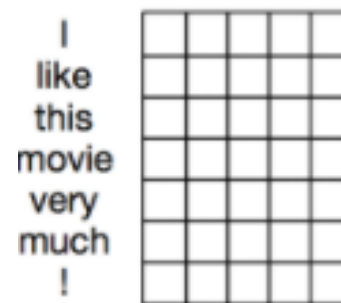
- Down Sampling
 - Reducing Operation time and memory
 - Could prevent overfitting
 - Types of Pooling
 - Max Pooling
 - Select only maximum Value
 - Average Pooling
 - ...

Natural Language Text → 2D Matrix

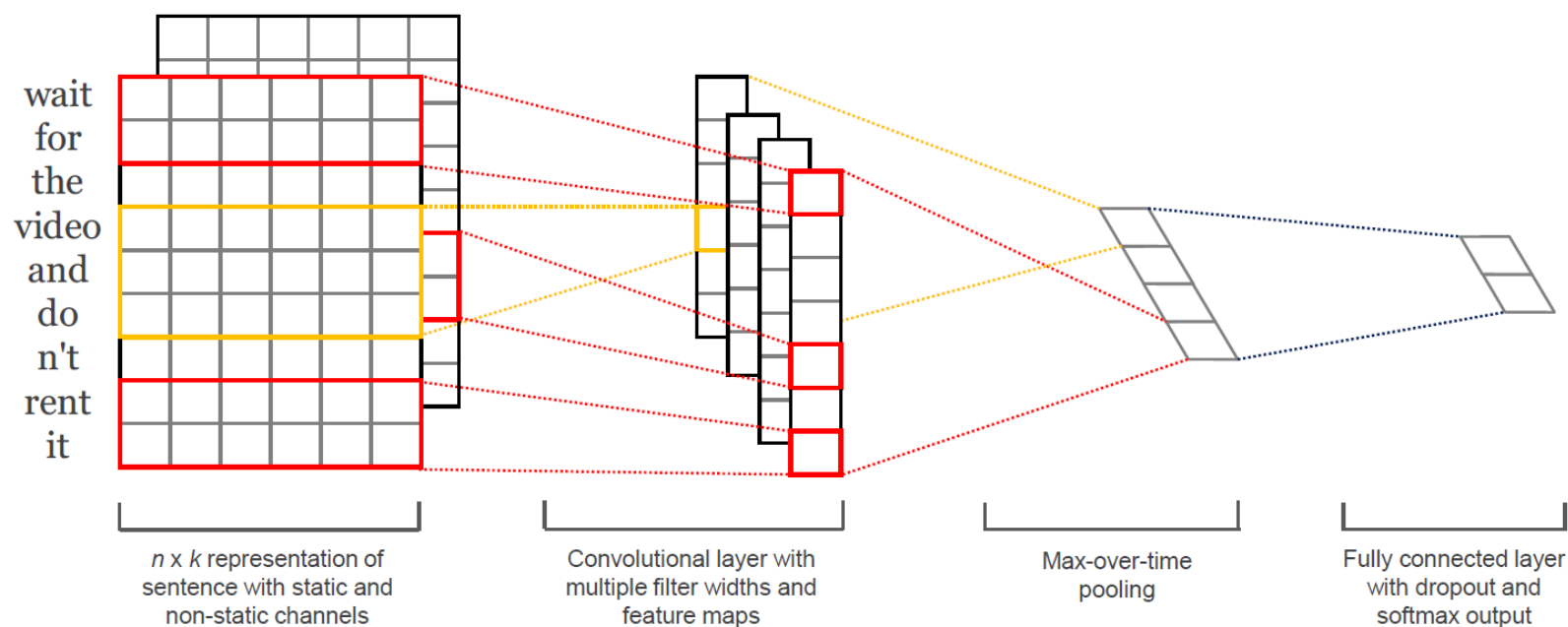
- Word can be represented as semantically-meaningful dense vectors.
(word2vec, Glove, fasttext)



- Sentence or Document can be represented as matrix by concatenating word vectors.



Architecture



Convolution Filters retrieve features from phrase (N consecutive words, N-gram)

Use various size of filters(various N consecutive words)

Not linguistically or cognitively plausible but very fast and robust.

Goal

- Implement Movie Review Text Classification with CNN using Tensorflow.
- Dataset
 - MR movie review dataset.
 - 10,662 review text, 2classes(positive,negative)

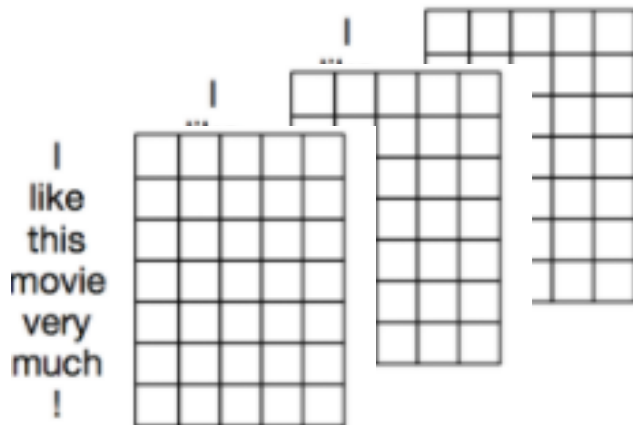
Implementation

Part1. Prepare Data

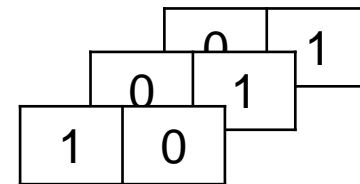
```
rt-pol.pos x rt-pol.neg x
1 the rock is destined to be the 21st
  greater than arnold schwarzenegger
2 the gorgeously elaborate continuati
  words cannot adequately describe co
  tolkien's middle-earth .
3 effective but too-tepid biopic
4 if you sometimes like to go to the
5 emerges as something rare , an issu
```



X



Y



Load libraries

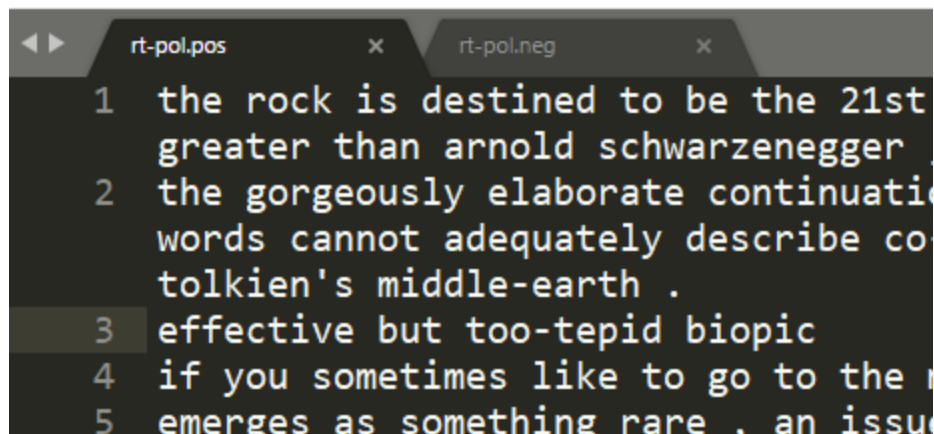
```
1 | import tensorflow as tf
2 | import numpy as np
3 | from gensim.models.word2vec import Word2Vec
.
```

Load data from files

```
5 print("Loading data...")
6 # Load data from files
7 positive_examples = list(open("../data/rt-pol.pos", "r", encoding='utf-8').readlines())
8 positive_examples = [s.strip() for s in positive_examples]
9 negative_examples = list(open("../data/rt-pol.neg", "r", encoding='utf-8').readlines())
10 negative_examples = [s.strip() for s in negative_examples]
11 x_text = positive_examples + negative_examples
```

x_text = ["the rock is destined to be the ...", "the gorgeously ...", ".."]

Movie review data file (rt-pol.pos, rt-pol.neg)
- One review sentence per one line.



The screenshot shows a text editor with two tabs: 'rt-pol.pos' and 'rt-pol.neg'. The 'rt-pol.pos' tab is active, displaying five lines of positive movie reviews. The text is as follows:

```
1 the rock is destined to be the 21st
  greater than arnold schwarzenegger
2 the gorgeously elaborate continuati
  words cannot adequately describe co
  tolkien's middle-earth .
3 effective but too-tepid biopic
4 if you sometimes like to go to the
5 emerges as something rare , an issu
```

Generate Labels

```
13 # Generate labels
14 positive_labels = [[0, 1] for _ in positive_examples]
15 negative_labels = [[1, 0] for _ in negative_examples]
16 y = np.concatenate([positive_labels, negative_labels], 0)
```


y = [[0,1],[0,1], [1,0], [1,0]]

list of 2-dimensional vector represent class(pos,neg) of each data.

Load pre-trained word embedding

```
18 | # Load pre-trained word embedding  
19 | w2vec_model = Word2Vec.load('./data/model-brown-vectors.bin')  
20 | embedding_size = w2vec_model.vector_size
```

embedding_size


w2vec_model['apple'] = [-0.502, 0.236, ... , -0.268, 0.463]

Text → matrix

```
22 # Convert text to matrix consist of word embedding
23 sequence_length = max([len(x.split(" ")) for x in x_text])
24 x = np.zeros((len(x_text), sequence_length, embedding_size), dtype=float)
25 for i, xi in enumerate(x_text):
26     tokens = xi.split(' ')
27     for j, token in enumerate(tokens):
28         if token in w2vec_model:
29             x[i, j] = w2vec_model[token]
```

x[0] =

I				
like				
this				
movie				
very				
much				
!				

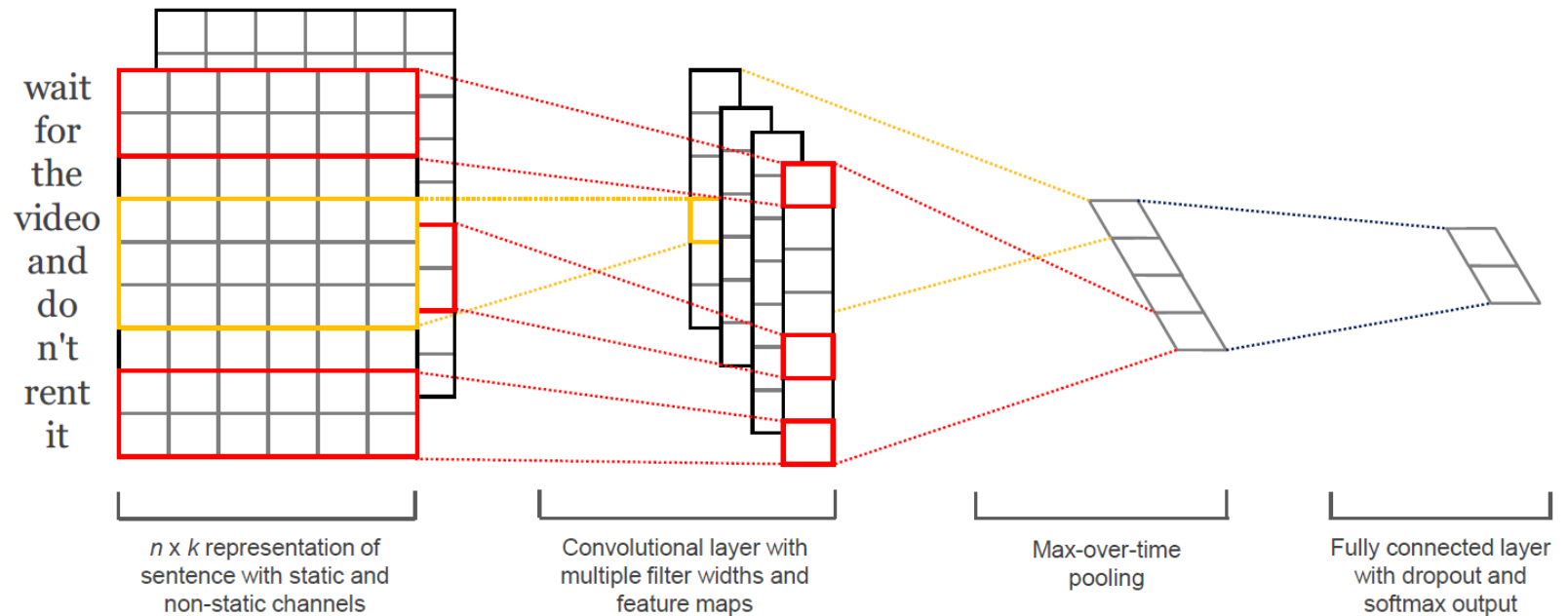
- Set unknown word as zero vectors
- x.shape = (data_size, sequence_length, embedding_size)
 - ↑
Number of data.
 - ↑
Max length(# of words) of sentence
 - ↑
Length of word vectors

Shuffle and Split Data

```
31 # Randomly shuffle data
32 np.random.seed(10)
33 shuffle_indices = np.random.permutation(np.arange(len(y)))
34 x_shuffled = x[shuffle_indices]
35 y_shuffled = y[shuffle_indices]
36
37 # Split train/test set
38 test_sample_index = -1 * int(0.1 * float(len(y)))
39 x_train, x_test = x_shuffled[:test_sample_index], x_shuffled[test_sample_index:]
40 y_train, y_test = y_shuffled[:test_sample_index], y_shuffled[test_sample_index:]
```

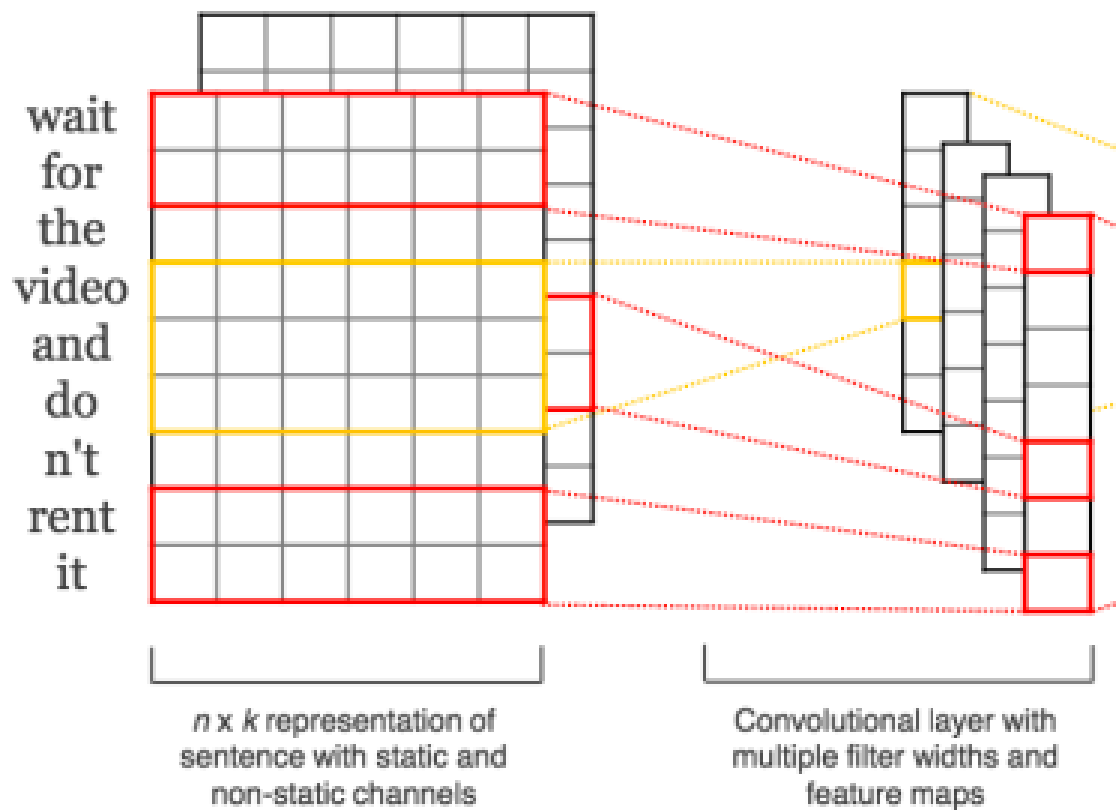
- Randomly shuffle data
- Split data into Train:Test = 90% : 10%

Part2. Build Network



Yoon Kim. Convolutional Neural Networks for Sentence Classification. EMNLP(2014)

Convolution Layer

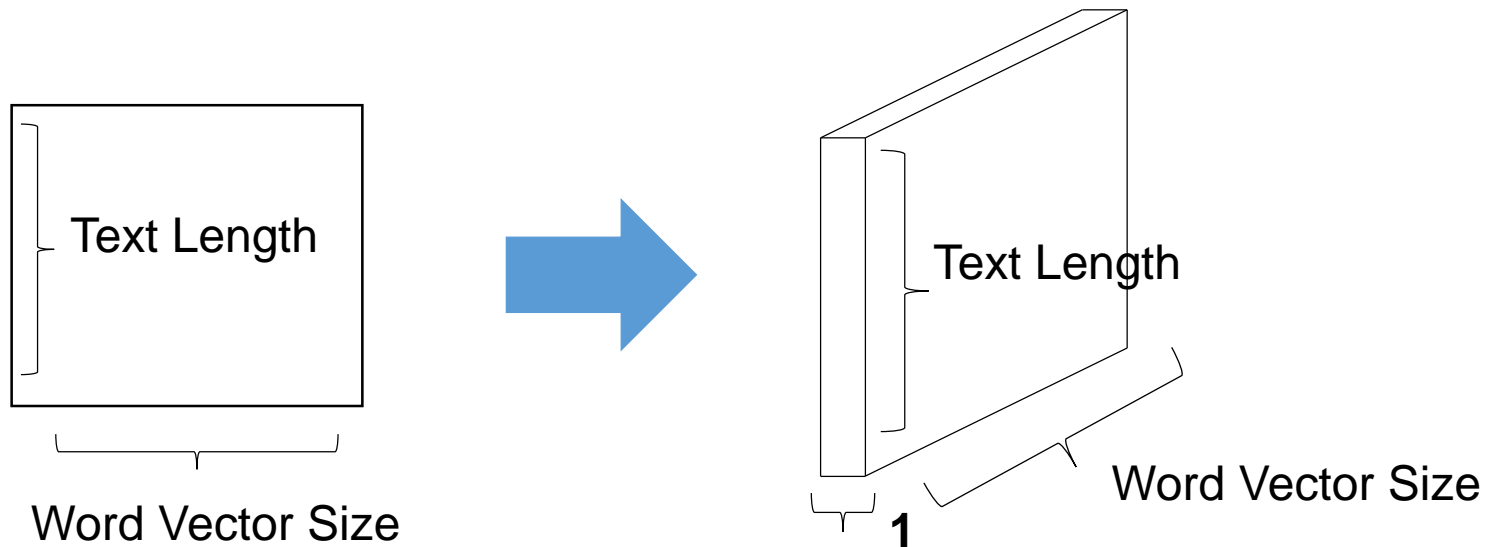


*2D Data -> 3D Data

- 1 Text : [Text Length * Word Vector Size] \rightarrow 2D
- 1 Image : [Height * Width * Channel] \rightarrow 3D (Channel : RGB, etc..)

How to change text data into 3D?

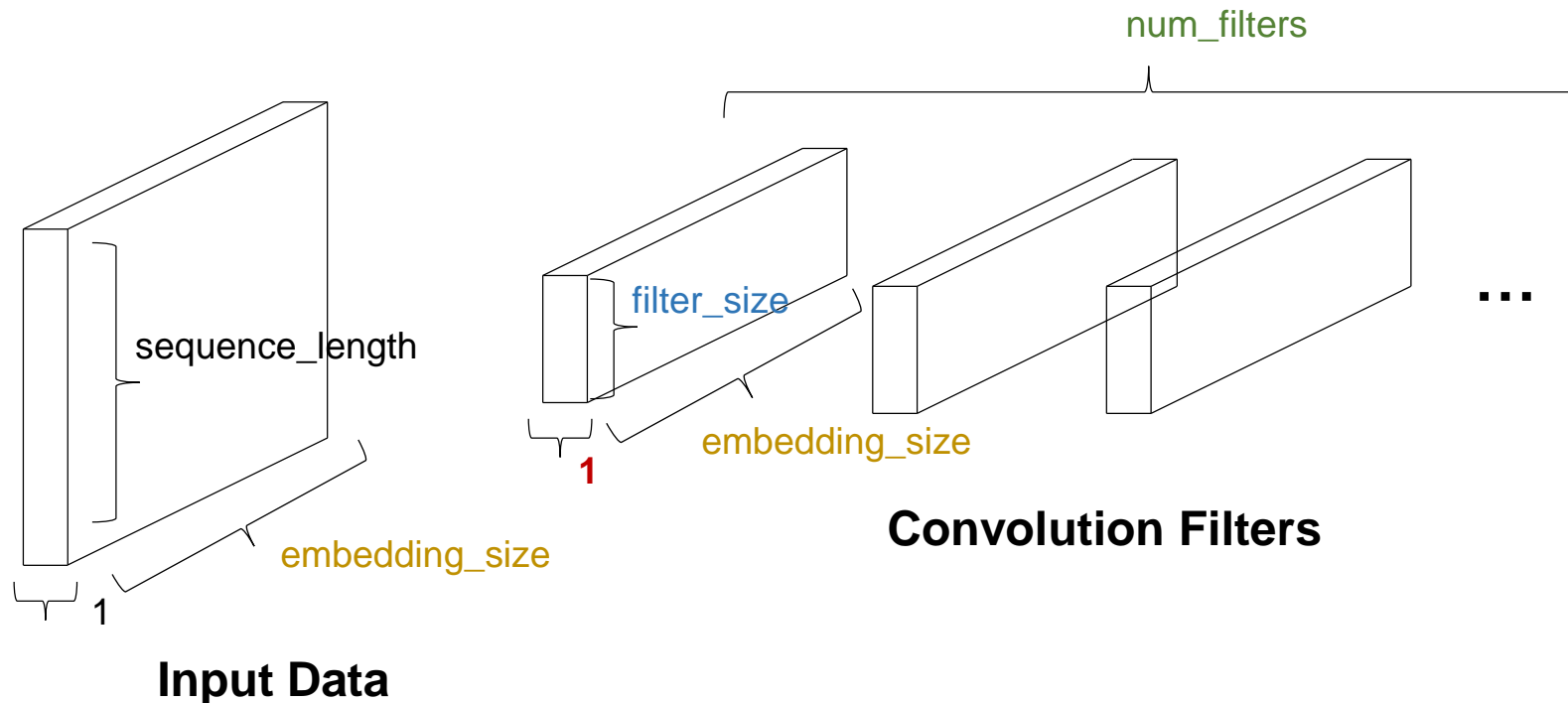
\rightarrow Just expand dimension of data to have 1 channel like black and white image



59 | `extended_input_x = tf.expand_dims(input_x, -1)`

Convolution Layer

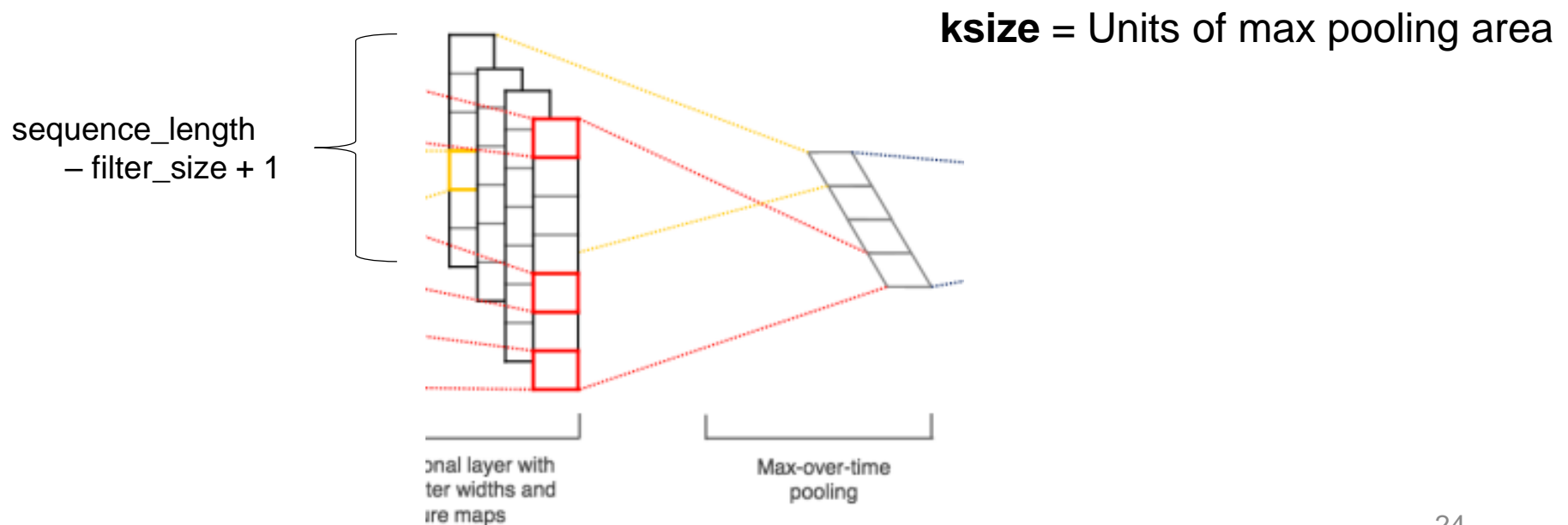
```
filter_shape = [filter_size, embedding_size, 1, num_filters]  
W_c = tf.Variable(tf.truncated_normal(filter_shape, stddev=0.1), name="W_c")  
conv = tf.nn.conv2d(  
    extended_input_x, W_c, strides=[1, 1, 1, 1], padding="VALID", name="conv")
```



Max Pooling Layer

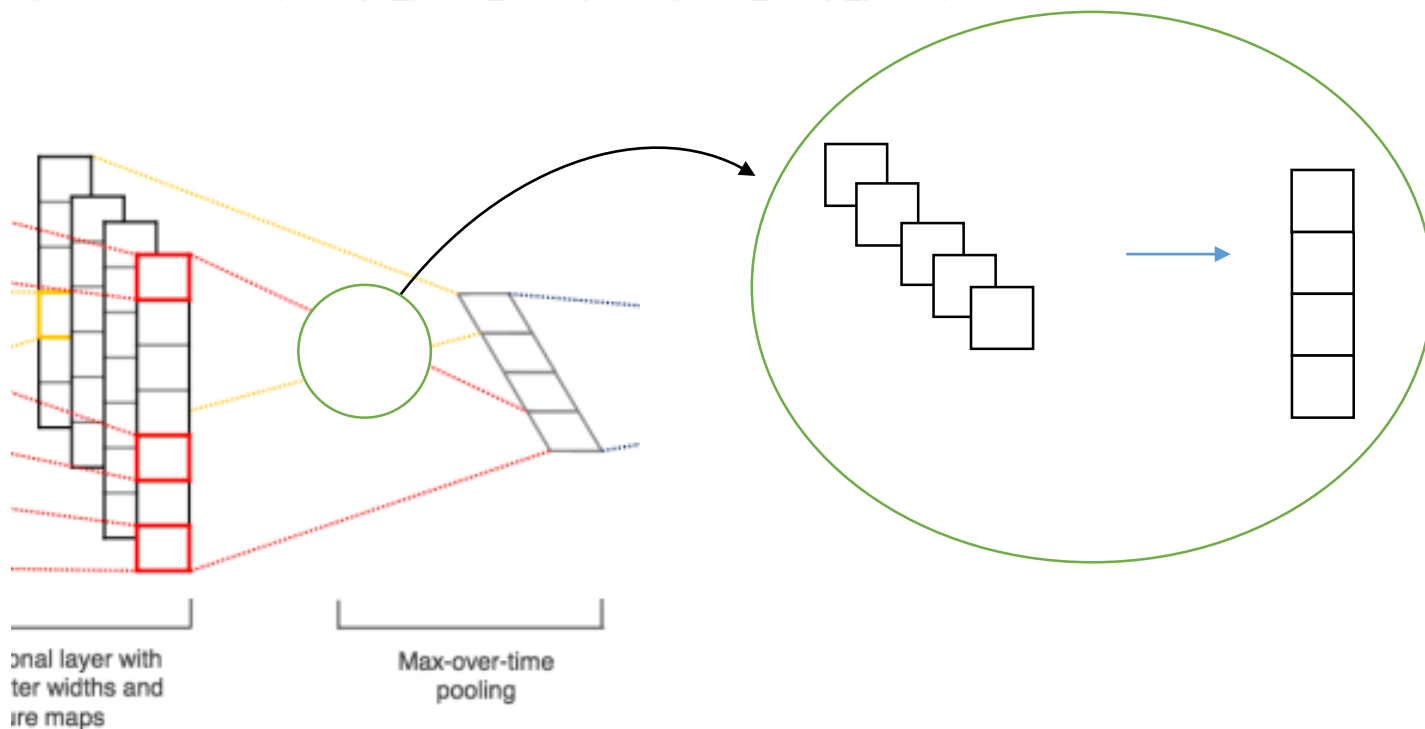
```
66 pooled = tf.nn.max_pool(  
67     h, ksize=[1, sequence_length - filter_size + 1, 1, 1],  
68     strides=[1, 1, 1, 1],  
69     padding='VALID',  
70     name="pool")
```

data, height, width, channel



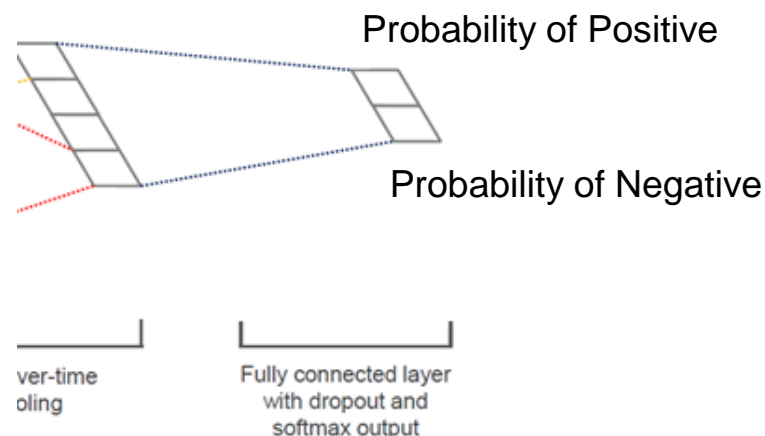
Flatten and Dropout

```
73 # Flatten and Dropout
74 num_filters_total = num_filters * len(filter_sizes)
75 h_pool = tf.concat(pooled_outputs, 3)
76 h_pool_flat = tf.reshape(h_pool, [-1, num_filters_total])
77 h_drop = tf.nn.dropout(h_pool_flat, dropout_keep_prob)
```



Fully Connected Layer with Softmax Output

```
79 # Final Fully Connected Layer
80 W_f = tf.get_variable(
81     "W_f",
82     shape=[num_filters_total, num_classes],
83     initializer=tf.contrib.layers.xavier_initializer())
84 b_f = tf.Variable(tf.constant(0.1, shape=[num_classes]), name="b_f")
85 scores = tf.nn.xw_plus_b(h_drop, W_f, b_f, name="scores")
86 predictions = tf.argmax(scores, 1, name="predictions")
```



Loss, Accuracy, Optimizer

```
88 #loss
89 loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=scores, labels=input_y))
90
91 #accuracy
92 correct_predictions = tf.equal(predictions, tf.argmax(input_y, 1))
93 accuracy = tf.reduce_mean(tf.cast(correct_predictions, "float"))
94
95 #optimizer
96 optimizer = tf.train.AdamOptimizer(1e-3).minimize(loss)
```

Output of 'correct_predictions' node

[True, True, False, ..., False, True]

True for right prediction, False for wrong prediction.