

# Deep Learning and TensorFlow 2

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Machine Learning

# Introduction to Deep Learning

- Supervised Learning with Deep Neural Networks

Input( $x$ )	Output( $y$ )	Application	Model
Home features	Price	Real Estate	Fully- Connected Neural Nets
Ad, user info	Click on ad?(0/1)	Online Advertising	Fully- Connected Neural Nets
Image	Object (1,...,1000)	Photo tagging	Convolutional Neural Nets
Audio	Text transcript	Speech recognition	Recurrent Neural Nets
Korean	English	Machine translation	Recurrent Neural Nets

<https://cs230.stanford.edu/>

# Introduction to Deep Learning

- Supervised Learning with Deep Neural Networks

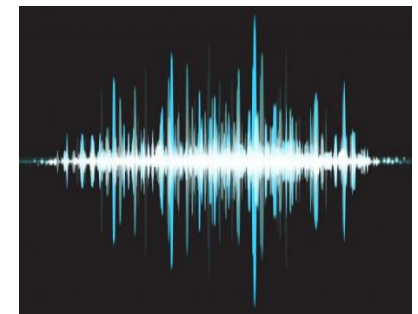
## Structured Data

Size	#bedrooms	...	Price(1000\$)
2104	3	...	400
1600	3	...	330
2400	3	...	369
...	...	...	...
3000	4	...	540

## Unstructured Data



Image



Audio

This shirt is  
very flattering  
to all due to ...

Text



Video

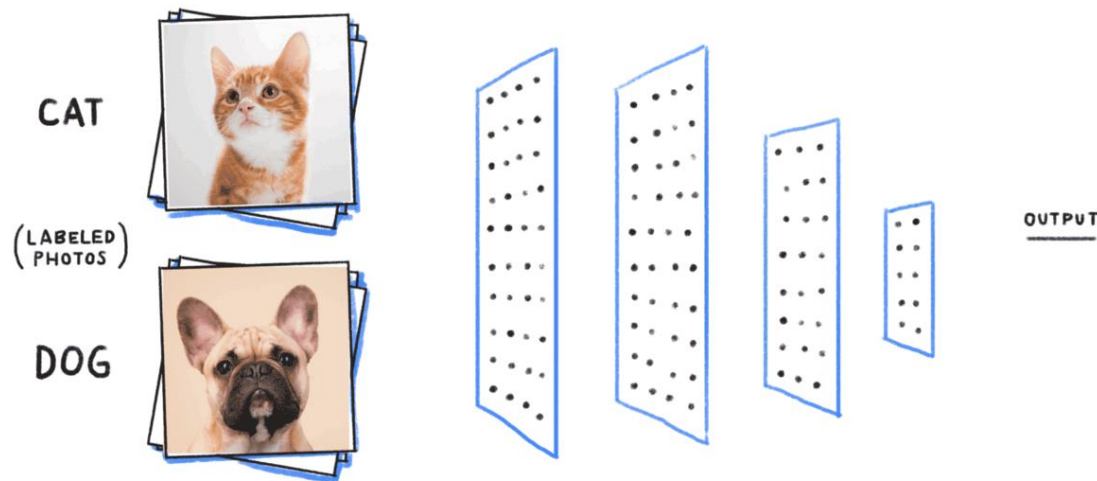
# Contents

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- Convolutional Neural Networks
- Recurrent Neural Networks

# Convolutional Neural Networks

- Convolutional Neural Networks : for Analyzing Visual Data
  - Smaller number of connection
  - Weight sharing
  - Detect features at different positions in a image



<https://becominghuman.ai/building-an-image-classifier-using-deep-learning-in-python-totally-from-a-beginners-perspective-be8dbaf22dd8>

# Convolutional Neural Networks

## ■ Image Classification with CNNs

### ■ Load Fashion-MNIST Dataset and Preprocessing

```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt

fashion_mnist = tf.keras.datasets.fashion_mnist
(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()

x_train, x_test = x_train / 255.0, x_test / 255.0
num_classes = 10

x_train = x_train.reshape(x_train.shape[0], 28, 28, 1)
x_train.shape → (60000, 28, 28, 1)
x_test = x_test.reshape(x_test.shape[0], 28, 28, 1)
x_test.shape → (10000, 28, 28, 1)
y_train = y_train.reshape(y_train.shape[0], 1)
y_train.shape → (60000, 1)
y_test = y_test.reshape(y_test.shape[0], 1)
y_test.shape → (10000, 1)
y_train → array([[9],
                  [0],
                  [0],
                  ...,
                  [3],
                  [0],
                  [5]], dtype=uint8)
```

# Convolutional Neural Networks

- Image Classification with CNNs

- Build the CNN Model

```
base_model = tf.keras.models.Sequential([
    layers.Conv2D(32, kernel_size=(3, 3), padding = "same",
                  input_shape = (28, 28, 1),
                  activation="relu"),
    layers.Conv2D(64, kernel_size=(3, 3), activation="relu"),
    layers.MaxPool2D(pool_size=2),

    layers.Flatten(),
    layers.Dense(128, activation="relu"),
    layers.Dense(10, activation="softmax")
])
```

```
base_model.compile(loss='categorical_crossentropy',
                   optimizer='adam',
                   metrics=['accuracy'])
```

# Convolutional Neural Networks

## ■ Image Classification with CNNs

### ■ Train the model

```
base_history = base_model.fit(x_train, y_train, epochs=10,  
validation_data=(X_test, y_test))
```

```
Epoch 1/10  
60000/60000 [=====] - 9s 151us/step - loss: 0.3607 - acc: 0.8718  
Epoch 2/10  
60000/60000 [=====] - 9s 142us/step - loss: 0.2224 - acc: 0.9172  
Epoch 3/10  
60000/60000 [=====] - 9s 143us/step - loss: 0.1684 - acc: 0.9377  
Epoch 4/10  
60000/60000 [=====] - 8s 138us/step - loss: 0.1264 - acc: 0.9533  
Epoch 5/10  
60000/60000 [=====] - 8s 139us/step - loss: 0.0928 - acc: 0.9657  
Epoch 6/10  
60000/60000 [=====] - 8s 140us/step - loss: 0.0667 - acc: 0.9756  
Epoch 7/10  
60000/60000 [=====] - 8s 138us/step - loss: 0.0494 - acc: 0.9822  
Epoch 8/10  
60000/60000 [=====] - 8s 139us/step - loss: 0.0361 - acc: 0.9869  
Epoch 9/10  
60000/60000 [=====] - 8s 139us/step - loss: 0.0288 - acc: 0.9896  
Epoch 10/10  
60000/60000 [=====] - 8s 138us/step - loss: 0.0255 - acc: 0.9908
```

```
<tensorflow.python.keras.callbacks.History at 0x279dbfdacf8>
```

```
base_model.evaluate(x_train, y_train) → [0.01985836104367542, 0.9931833333333333]
```

```
base_model.evaluate(x_test, y_test) → [0.42943426142530516, 0.9202]
```

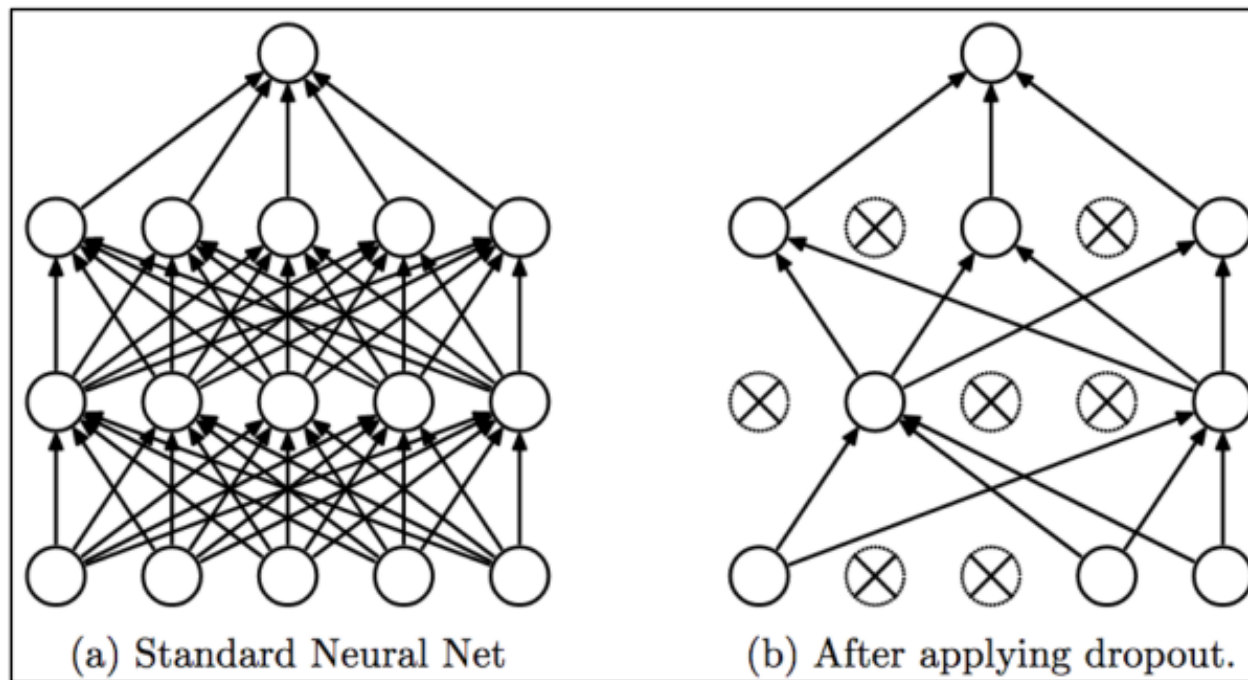
*loss*

*accuracy*



# Convolutional Neural Networks

- Avoid the Overfitting, Dropout
  - In each forward pass, randomly set some neurons to zero
  - Probability of dropping is a hyperparameter; 0.5 is common



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# Convolutional Neural Networks

- Avoid the Overfitting, Dropout

- Consider a single neuron

- Training phase

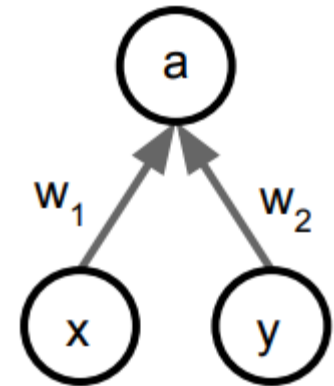
- Dropout applying probability  $p$  (ex\_ 0.5)

$$a = \frac{1}{4}(w_1x + w_2y) + \frac{1}{4}(w_1x + 0y) + \frac{1}{4}(0x + w_2y) + \frac{1}{4}(0x + 0y)$$
$$= \frac{1}{2}(w_1x + w_2y)$$

- Test phase

- No dropout

$$a = w_1x + w_2y$$



# Convolutional Neural Networks

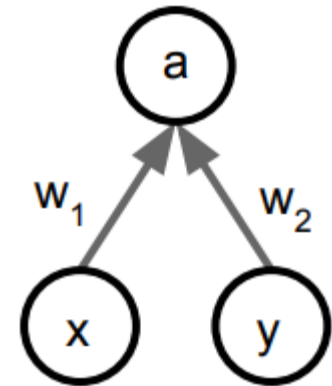
- Avoid the Overfitting, Dropout

- Consider a single neuron

- Training phase

- Dropout applying probability  $p$  (ex\_ 0.5)

$$a = \frac{1}{4}(w_1x + w_2y) + \frac{1}{4}(w_1x + 0y) + \frac{1}{4}(0x + w_2y) + \frac{1}{4}(0x + 0y)$$
$$= \frac{1}{2}(w_1x + w_2y)$$



- Test phase

- No dropout

$$a = w_1x + w_2y$$

A red arrow points from the equation above to the text below, with a red  $\times p$  next to the arrow.

- So, we need to multiply  $p$  at test time for approximation!

# Convolutional Neural Networks

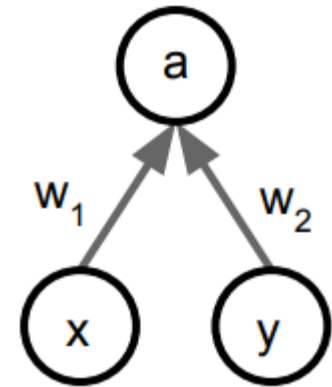
- Avoid the Overfitting, Dropout

- Consider a single neuron

- Training phase

- Dropout applying probability  $p$  (ex\_ 0.5)

$$\begin{aligned} a &= \frac{1}{4}(w_1x + w_2y) + \frac{1}{4}(w_1x + 0y) + \frac{1}{4}(0x + w_2y) + \frac{1}{4}(0x + 0y) \\ &= \frac{1}{2}(w_1x + w_2y) \end{aligned}$$



- Test phase

- No dropout

$$a = w_1x + w_2y$$

$\times 1/p$

- But commonly, we multiply  $1/p$  at training time for approximation!

- This is called “Inverted Dropout”

# Convolutional Neural Networks

- Image Classification with CNNs
  - The model with dropout regularization

```
dropout_model = tf.keras.models.Sequential([
    layers.Conv2D(32, kernel_size=(3, 3), padding = "same",
                  input_shape = (28, 28, 1),
                  activation="relu"),
    layers.Conv2D(64, kernel_size=(3, 3), activation="relu"),
    layers.MaxPool2D(pool_size=2),

    layers.Flatten(),
    layers.Dense(128, activation="relu"),
    layers.Dropout(0.5),
    layers.Dense(10, activation="softmax")
])

dropout_model.compile(loss='sparse_categorical_crossentropy',
                      optimizer='adam',
                      metrics=['accuracy'])
```

# Convolutional Neural Networks

- Image Classification with CNNs
  - The model with dropout regularization

```
drop_history = dropout_model.fit(x_train, y_train,  
epochs=10, validation_data=(X_test, y_test))
```

```
Epoch 1/10  
60000/60000 [=====] - 9s 147us/step - loss: 0.4540 - acc: 0.8393  
Epoch 2/10  
60000/60000 [=====] - 8s 139us/step - loss: 0.2944 - acc: 0.8937  
Epoch 3/10  
60000/60000 [=====] - 8s 139us/step - loss: 0.2476 - acc: 0.9098  
Epoch 4/10  
60000/60000 [=====] - 8s 139us/step - loss: 0.2151 - acc: 0.9218  
Epoch 5/10  
60000/60000 [=====] - 8s 138us/step - loss: 0.1936 - acc: 0.9286  
Epoch 6/10  
60000/60000 [=====] - 8s 139us/step - loss: 0.1668 - acc: 0.9381  
Epoch 7/10  
60000/60000 [=====] - 8s 138us/step - loss: 0.1505 - acc: 0.9434  
Epoch 8/10  
60000/60000 [=====] - 8s 139us/step - loss: 0.1363 - acc: 0.9485  
Epoch 9/10  
60000/60000 [=====] - 8s 138us/step - loss: 0.1235 - acc: 0.9527  
Epoch 10/10  
60000/60000 [=====] - 8s 140us/step - loss: 0.1123 - acc: 0.9571
```

<tensorflow.python.keras.callbacks.History at 0x2770408a7f0>

```
dropout_model.evaluate(x_train, y_train) → [0.05887163372437159, 0.9790333333333333]
```

```
dropout_model.evaluate(x_test, y_test) → [0.2695904264975339, 0.9225]
```

*loss*                      *accuracy*

# Convolutional Neural Networks

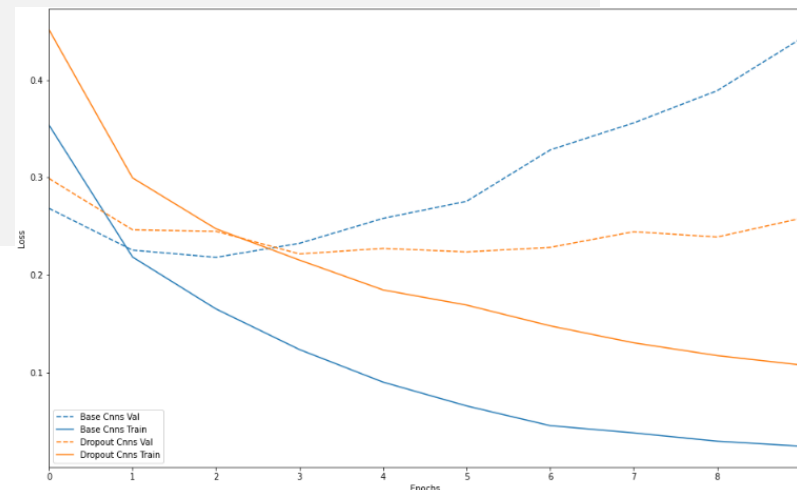
## ■ Image Classification with CNNs

### ■ Plotting the learning curve

```
def plot_history(histories, key='loss'):
    plt.figure(figsize=(16,10))
    for name, history in histories:
        val = plt.plot(history.epoch, history.history['val_'+key],
            '--', label=name.title()+' Val')
        plt.plot(history.epoch, history.history[key],
            color=val[0].get_color(),
            label=name.title()+' Train')

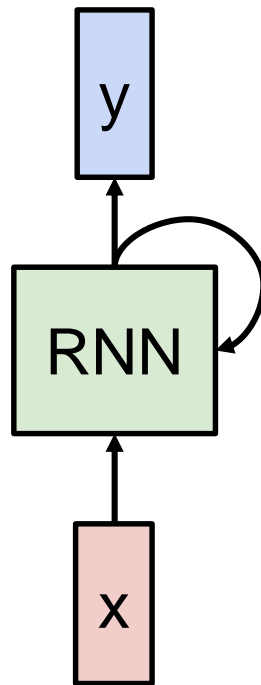
    plt.xlabel('Epochs')
    plt.ylabel(key.replace('_', ' ').title())
    plt.legend()
    plt.xlim([0,max(history.epoch)])

plot_history([('Base CNNs', base_history),
             ('Dropout CNNs', drop_history)])
```



# Recurrent Neural Networks

- Recurrent Neural Networks : for **analyzing sequential Data**
  - Sequential data : language, video, stock price, weather, ...
  - We can process a sequence of vectors **x** ( $x_1, x_2, x_3, \dots$ ) by applying a **recurrence formula** at every time step



$$y_t = W_{hy} h_t$$

$$\begin{aligned} h_t &= f_w(h_{t-1}, x_t) \\ &= \tanh(W_{hh} h_{t-1} + W_{xh} x_t) \end{aligned}$$

$$x_t$$

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# Recurrent Neural Networks

- Various types of input-output relations

"Two dogs play  
on the grass"

POS/NEG

"I love you"

Seq. of labels

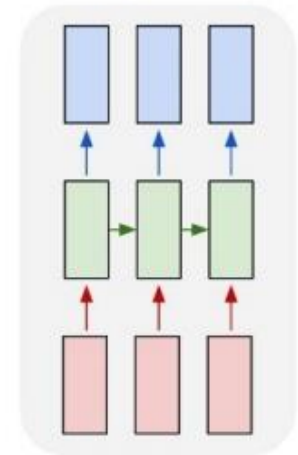
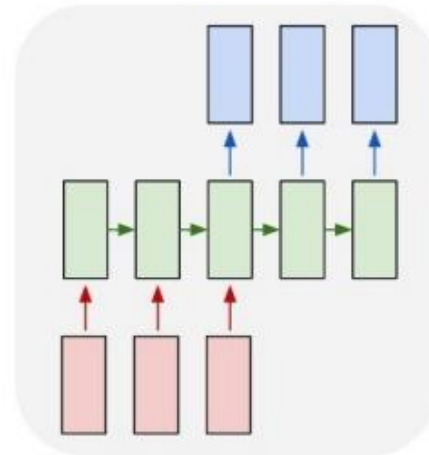
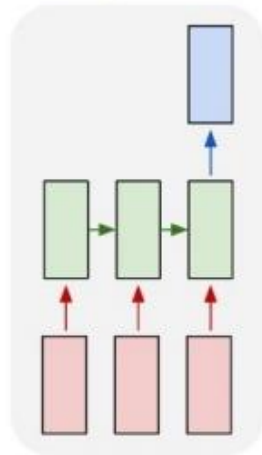
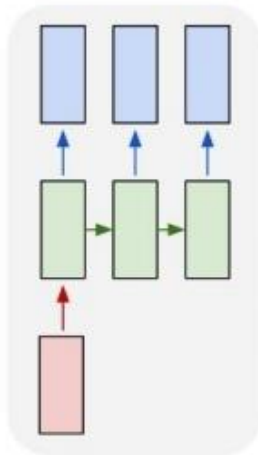
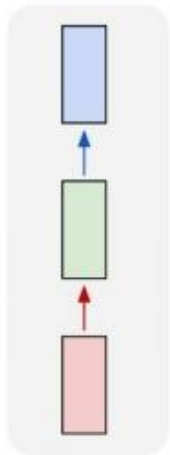
one to one

one to many

many to one

many to many

many to many



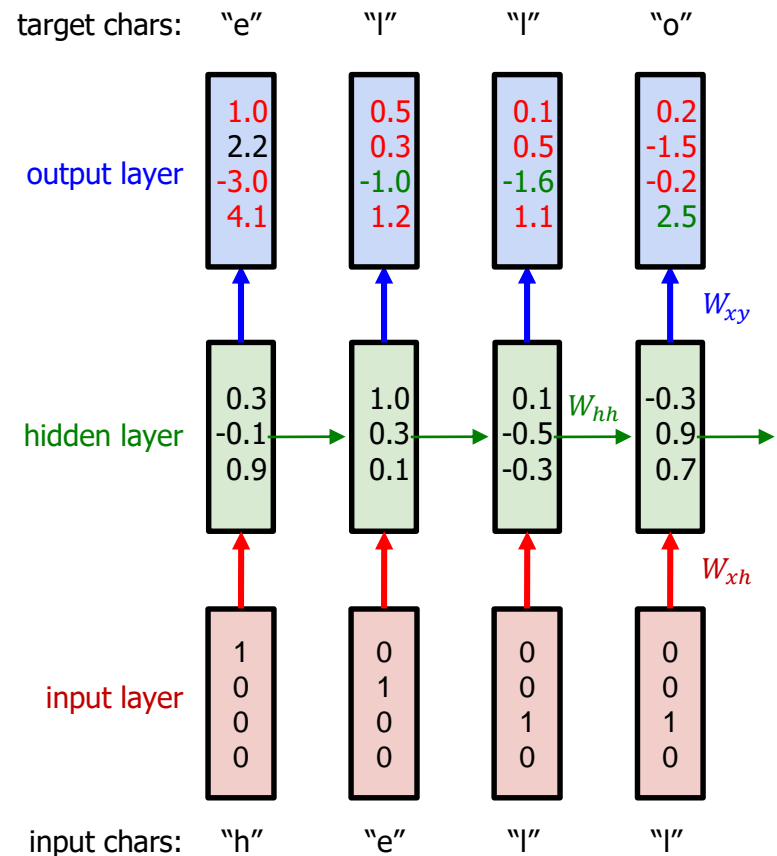
"This is a  
wonderful movie"

"Ich liebe dich"



# Text Generation using RNN

- Example :  
Learning Character-level  
Language Model
  - Vocabulary : [h, e, l, o]
  - Example training sequence : "hello"
  - $h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$
  - $\hat{y}_t = \text{Softmax}(W_{hy}h_t)$

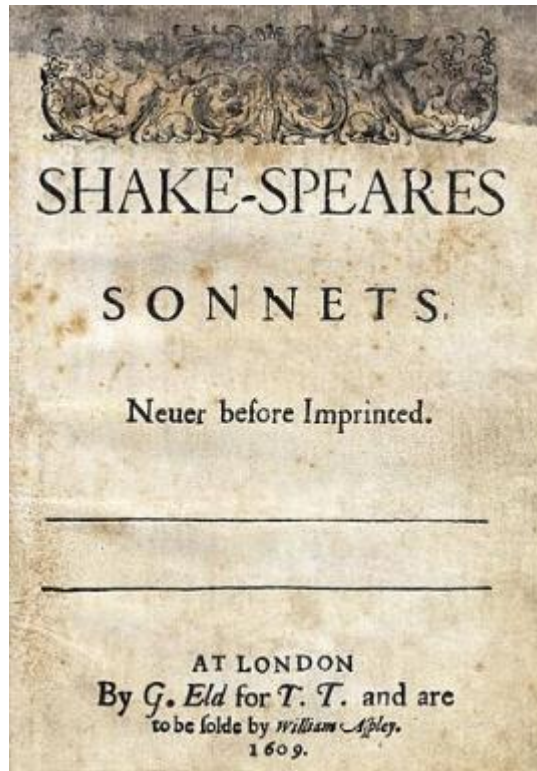


[http://cs231n.stanford.edu/slides/2017/cs231n\\_2017\\_lecture10.pdf](http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture10.pdf)

# Recurrent Neural Networks

- Implementing simple RNN with TensorFlow

- Dataset : Shakespeare's sonnets  
(Shakespeare.txt)



First Citizen:  
Before we proceed any further, hear me speak.

All:  
Speak, speak.

First Citizen:  
You are all resolved rather to die than to famish?

All:  
Resolved. resolved.

First Citizen:  
First, you know Caius Marcius is chief enemy to the people.

# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

### ■ Load and preprocess the Shakespeare dataset

```
import tensorflow as tf
import numpy as np
import os
import time

# 1. Download the Shakespeare's Sonnet dataset
path_to_file = tf.keras.utils.get_file('shakespeare.txt',
    'https://storage.googleapis.com/download.tensorflow.org/data/shakespeare.txt')

# Load whole text file as a string, then decode.
text = open(path_to_file, 'rb').read().decode(encoding='utf-8')

# length of text is the number of characters in it
print('Length of text: {} characters'.format(len(text)))

Downloading data from https://storage.googleapis.com/download.tensorflow.org/data/shakespeare.txt
1122304/1115394 [=====] - 0s 0us/step
Length of text: 1115394 characters

# We'll use the subset
text = text[:14592]
len(text)

14592
```

# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

### ■ Load and preprocess the Shakespeare dataset

```
# Take a look first 250 characters
print(text[:250])

First Citizen:
Before we proceed any further, hear me speak.

All:
Speak, speak.

First Citizen:
You are all resolved rather to die than to famish?

All:
Resolved. resolved.

First Citizen:
First, you know Caius Marcius is chief enemy to the people.

# The unique characters in the file
vocab = sorted(set(text))
print ('{} unique characters'.format(len(vocab)))

58 unique characters
```

# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

### ■ Load and preprocess the Shakespeare dataset

```
# 2. Vectorize the text
# Creating a mapping from unique characters to indices, and vice versa
char2idx = {u:i for i, u in enumerate(vocab)}
idx2char = np.array(vocab)

# Convert the characters to the indices
text_as_int = np.array([char2idx[c] for c in text])

# Show how the first 13 characters from the text are mapped to integers
print ('{} ---- characters mapped to int ---- > {}'.format(repr(text[:13]),
text_as_int[:13]))

'First Citizen' ---- characters mapped to int ---- > [18 47 56 57 58  1 15 47 58 47 64 43 52]
```

# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

### ■ Load and preprocess the Shakespeare dataset

```
# 3. Creating training task
# The maximum length sentence we want for a single input in characters
seq_length = 100

# Create training examples / targets
char_dataset = tf.data.Dataset.from_tensor_slices(text_as_int)

for i in char_dataset.take(5):
    print(idx2char[i.numpy()])

F
i
r
s
t

# Check the shape : char_dataset
np.array(list(char_dataset.as_numpy_iterator())).shape
(14592,)
```

# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

### ■ Load and preprocess the Shakespeare dataset

```
# 'batch' method convert these individual characters to sequences of the desired size
```

```
sequences = char_dataset.batch(seq_length+1, drop_remainder=True)
```

```
for item in sequences.take(5):  
    print(repr(''.join(idx2char[item.numpy()])))
```

```
'First Citizen:¶¶Before we proceed any further, hear me speak.¶¶¶All:¶¶Speak, speak.¶¶¶First Citizen  
'are all resolved rather to die than to famish?¶¶¶All:¶¶Resolved. resolved.¶¶¶First Citizen:¶¶First,  
"now Caius Marcius is chief enemy to the people.¶¶¶All:¶¶We know't, we know't.¶¶¶First Citizen:¶¶Let  
"¶¶him, and we'll have corn at our own price.¶¶¶Is't a verdict?¶¶¶All:¶¶No more talking on't; let it ¶¶  
'one: away, away!¶¶¶Second Citizen:¶¶One word, good citizens.¶¶¶First Citizen:¶¶We are accounted poo
```

```
# Check the shape : sequences
```

```
np.array(list(sequences.as_numpy_iterator())).shape
```

```
(144, 101)
```



# Recurrent Neural Networks

- Character-level Language Model with RNNs
  - Load and preprocess the Shakespeare dataset

```
# map_func
def split_input_target(chunk):
    # input text is shifted to form the target text
    input_text = chunk[:-1]
    target_text = chunk[1:]
    return input_text, target_text

# 'map' method lets us easily apply a simple function to each batch
dataset = sequences.map(split_input_target)

# Print the examples
for input_ex, target_ex in dataset.take(1):
    print ('Input : ', repr(''.join(idx2char[input_ex.numpy()])))
    print ('Target : ', repr(''.join(idx2char[target_ex.numpy()])))

Input : 'First Citizen:\nBefore we proceed any further, hear me speak.\n\nAll:\nSpeak, speak.\n\nFirst
Target : 'irst Citizen:\nBefore we proceed any further, hear me speak.\n\nAll:\nSpeak, speak.\n\nFirst

# Check the shape : dataset - (1)
np.array(list(dataset.as_numpy_iterator())).shape
```

# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

### ■ Load and preprocess the Shakespeare dataset

```
# 4. Create training batches
# Batch size
BATCH_SIZE = 16

# Buffer size to shuffle the dataset
BUFFER_SIZE = 100

dataset = dataset.shuffle(BUFFER_SIZE).batch(BATCH_SIZE, drop_remainder=True)
```

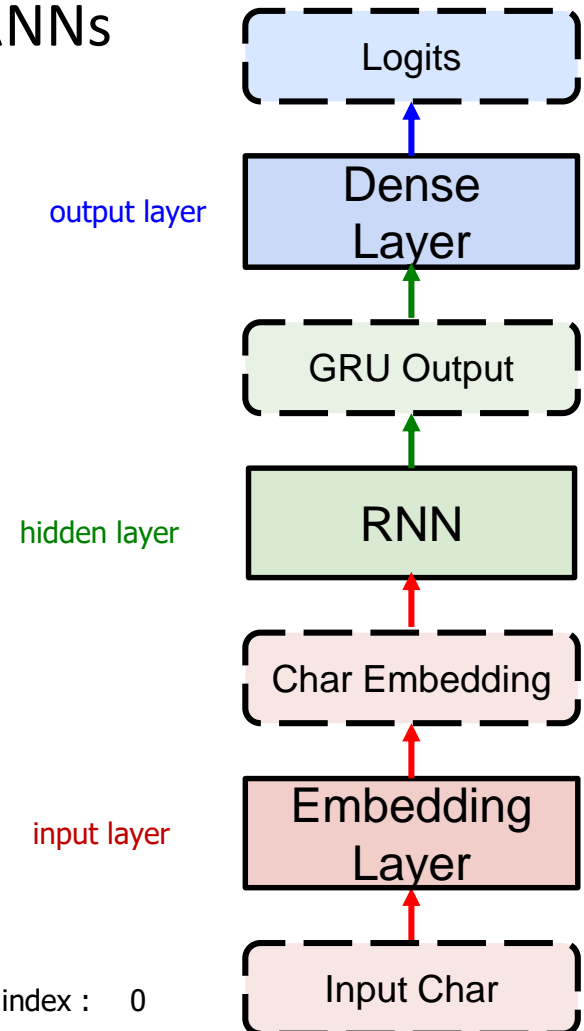
```
# Check the shape : dataset - (2)
np.array(list(dataset.as_numpy_iterator())).shape

(9, 2, 16, 100)
```

# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

- Build the model
- 3 layers are used to define this model
  1. `tf.keras.layers.Embedding`
  2. `tf.keras.layers.RNN`
  3. `tf.keras.layers.Dense`



# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

### ■ Build the model

```
# Length of the vocabulary in chars
vocab_size = len(vocab)
# The embedding dimension
embedding_dim = 128
# Number of RNN units
rnn_units = 256

def build_model(vocab_size, embedding_dim, rnn_units, batch_size):
    layers = tf.keras.layers
    model = tf.keras.Sequential([
        layers.Embedding(input_dim=vocab_size,
                        output_dim=embedding_dim,
                        batch_input_shape=[batch_size, None]
                        ),
        layers.SimpleRNN(rnn_units,
                        return_sequences=True,
                        stateful=True,
                        recurrent_initializer='glorot_uniform' # Xavier
                        Initialization
                        ),
        layers.Dense(vocab_size)
    ])
    return model
```

# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

### ■ Build the model

```
# Build the model
model = build_model(
    vocab_size=vocab_size,
    embedding_dim=embedding_dim,
    rnn_units=rnn_units,
    batch_size=BATCH_SIZE)

# Check the model architecture
# Model can be run on inputs of any length
model.summary()
```

Model: "sequential\_5"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(16, None, 128)	7424
simple_rnn (SimpleRNN)	(16, None, 256)	98560
dense_10 (Dense)	(16, None, 58)	14906
Total params: 120,890		
Trainable params: 120,890		
Non-trainable params: 0		

# Recurrent Neural Networks

- Character-level Language Model with RNNs

- Try the model

```
# Check the shape of the output
for input_example_batch, target_example_batch in dataset.take(1):
    example_batch_predictions = model(input_example_batch)
    print(example_batch_predictions.shape, "# (batch_size, sequence_length, vocab_size)")

(64, 100, 65) # (batch_size, sequence_length, vocab_size)
```

# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

### ■ Try the model

```
# We need to sample from the output distribution, not to take the argmax of the
distribution
sampled_indices = tf.random.categorical(example_batch_predictions[0],
num_samples=1)
sampled_indices = tf.squeeze(sampled_indices,axis=-1).numpy()
```

```
array([29, 25, 20, 20, 45, 46, 22, 40, 40, 36, 25, 20, 51, 57, 10, 48, 11,
       50, 22,  5, 11, 10, 16,  9, 61, 36, 36, 63, 51, 22, 54, 63, 14, 25,
       64, 16, 59, 28, 53, 47, 15, 17, 35, 32, 16, 50, 58, 51,  0,  6,  4,
       28, 23, 27, 52, 59, 12,  9, 45, 53, 63, 13, 28, 52,  3, 19, 30, 64,
       38,  2, 44, 57, 48, 58, 38, 15, 42, 40, 35, 56,  0, 40, 10, 42, 19,
       43, 27, 26,  0, 31, 39,  6, 17, 24, 27, 25, 26, 21, 52, 56])
```

```
# Decode the predictions, the model shows poor performance
print("Input: \n", repr("".join(idx2char[input_example_batch[0]])))
print()
print("Next Char Predictions: \n", repr("".join(idx2char[sampled_indices ])))
```

Input:

' :  
Now, by Saint Paul, this news is bad indeed.  
0, he hath kept an evil diet long,  
And overmuch consu'

Next Char Predictions:

"QMHHghJbbXMHms;j;IJ';:D3wXXymJpyBMzDuPoiCEWTDltm,n,&PKOnu?3goyAPn\$GRzZ!fsjtZCdbWrr#nb:dGeONnSa,ELOMNInr"

# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

### ■ Train the model

```
# 1. Attach an optimizer, and a loss function
# define the loss function
def loss(labels, logits):
    # Because the output of model is logit,
    return tf.keras.losses.sparse_categorical_crossentropy(labels, logits,
        from_logits=True)

# Test the loss function
example_batch_loss = loss(target_example_batch, example_batch_predictions)
print("Prediction shape: ", example_batch_predictions.shape, " # (batch_size,
sequence_length, vocab_size)")
print("scalar_loss: ", example_batch_loss.numpy().mean())

# Configure the training procedure
model.compile(optimizer='adam', loss=loss)
```

```
Prediction shape: (64, 100, 65) # (batch_size, sequence_length, vocab_size)
scalar_loss: 4.172501
```



# Recurrent Neural Networks

- Character-level Language Model with RNNs

- Train the model

```
# 2. Configure the checkpoints
# `tf.keras.callbacks.ModelCheckpoint` : The callback function to save the model
checkpoint

# Directory where the model weights will be saved
ckpt_dir = './training_rnn_ckpt'

# Checkpoint name
ckpt_prefix = os.path.join(ckpt_dir, "ckpt_rnn_{epoch}")

# Callback function to save the model weights
ckpt_callback=tf.keras.callbacks.ModelCheckpoint(
    filepath=ckpt_prefix,
    save_weights_only=True)
```

# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

### ■ Train the model

```
# 3. Execute the training
EPOCHS=10
rnn_history = model.fit(dataset, epochs=EPOCHS, callbacks=[ckpt_callback])
```

```
Epoch 1/10
172/172 [=====] - 20s 114ms/step - loss: 2.6591
Epoch 2/10
172/172 [=====] - 20s 114ms/step - loss: 2.0140
Epoch 3/10
172/172 [=====] - 20s 114ms/step - loss: 1.7984
Epoch 4/10
172/172 [=====] - 20s 114ms/step - loss: 1.6711
Epoch 5/10
172/172 [=====] - 20s 115ms/step - loss: 1.5867
Epoch 6/10
172/172 [=====] - 20s 114ms/step - loss: 1.5296
Epoch 7/10
172/172 [=====] - 20s 114ms/step - loss: 1.4854
Epoch 8/10
172/172 [=====] - 20s 114ms/step - loss: 1.4529
Epoch 9/10
172/172 [=====] - 20s 114ms/step - loss: 1.4287
Epoch 10/10
172/172 [=====] - 20s 114ms/step - loss: 1.4027
```

# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

### ■ Generate text

```
# Check the latest checkpoint
tf.train.latest_checkpoint(ckpt_dir)
```

```
'./training_rnn_ckpt/ckpt_rnn_10'
```

```
# To run the model with one sample(not with batch_size of samples),
# We rebuild the model, and load the weights from the saved checkpoint.
model = build_model(vocab_size, embedding_dim, rnn_units, batch_size=1)
model.load_weights(tf.train.latest_checkpoint(ckpt_dir))
```

```
# Check the model summary
model.summary()
```

```
Model: "sequential_3"
```

Layer (type)	Output Shape	Param #
embedding_1 (Embedding)	(1, None, 256)	16640
simple_rnn_1 (SimpleRNN)	(1, None, 1024)	1311744
dense_5 (Dense)	(1, None, 65)	66625

```
Total params: 1,395,009
```

```
Trainable params: 1,395,009
```

```
Non-trainable params: 0
```

# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

### ■ Generate text – (1)

```
# The prediction loop
def generate_text(model, start_string):
    # Number of characters to generate
    n_generate = 1000

    # Converting start_strings to index (vectorizing)
    input_eval = [char2idx[s] for s in start_string]
    input_eval = tf.expand_dims(input_eval, 0)

    # Making the empty list to store results
    text_generated = []

    # Low temperatures -> more predictable text.
    # Higher temperatures -> more surprising text.
    temperature = 1
```

# Recurrent Neural Networks

- Character-level Language Model with RNNs
  - Generate text – (2)

```
# Here batch size == 1
model.reset_states()
for i in range(n_generate):
    predictions = model(input_eval)
    # remove the batch dimension
    predictions = tf.squeeze(predictions, 0)

    # using a categorical distribution to predict the character
    predictions = predictions / temperature
    predicted_id = tf.random.categorical(predictions, num_samples=1)[-1,0].numpy()

    # Passing the predicted character as the next input to the model
    # along with the previous hidden state
    input_eval = tf.expand_dims([predicted_id], 0)

    text_generated.append(idx2char[predicted_id])

return (start_string + ''.join(text_generated))
```

# Recurrent Neural Networks

## ■ Character-level Language Model with RNNs

### ■ Generate text

```
# It shows poor performance  
# Sometimes it prints out a series of meaningless characters  
# -> Due to vanishing(or exploding) gradients problem  
print(generate_text(model, start_string=u"ROMEO: "))
```

ROMEO: that out of nibus of murdinge with queen of Rommant;  
And  
nother mat,  
What you do done,  
Then lathing a foul add him  
to then.

KINGS moursed  
fellow to have this of the rosprest  
Try father? For do it him, but more polighits of or thoughts are tears!

EDWARD IV:

KING RICHARD III:  
Divire,  
And so banamiced to the pleasing stands?  
Is they actions  
To free but in oherea  
Brace of our a Plorce  
Your foul offord stiful and at feer

ROMEO: QXEXEOVJUGQUXYZAQUGJUL&JUGZAUDJUKD3UK&XCKYZYXXGQUQUTZAQUFXEQVHK  
KXEZEX\$NQXYOXPZYUXXY3UX\$XX3\$ZZUF3YRUXX33ZYZULY\$\$ZYZ3RYXUKQQLJZH3QUGQL  
JUxJQULEXGZRUXEXXY&3ZAUKX3Y0XFJGHXYQYAUCKZIUUDUK\$3YZYYXY\$XK33\$KX3Z3UKE)

# Recurrent Neural Networks

- Text Classification with RNNs
  - Import TensorFlow and other libraries

```
import tensorflow_datasets as tfds #conda install -c anaconda tensorflow-datasets
import tensorflow as tf
import matplotlib.pyplot as plt
```

Downloading and preparing dataset imdb\_reviews/subwords8k/1.0.0 (download: 80.23 MiB, gen

DI Completed...: 100%  1/1 [00:01<00:00, 1.58s/ url]

DI Size...: 100%  80/80 [00:01<00:00, 51.59 MiB/s]

Shuffling and writing examples to /root/tensorflow\_datasets/imdb\_reviews/subwords8k/1.0.0.incompleteYY

83%  20794/25000 [00:00<00:00, 207937.22 examples/s]

Shuffling and writing examples to /root/tensorflow\_datasets/imdb\_reviews/subwords8k/1.0.0.incompleteYY

82%  20623/25000 [00:00<00:00, 206228.23 examples/s]

Shuffling and writing examples to /root/tensorflow\_datasets/imdb\_reviews/subwords8k/1.0.0.incompleteYY

22%  10793/50000 [00:00<00:00, 107929.59 examples/s]

Dataset imdb\_reviews downloaded and prepared to /root/tensorflow\_datasets/imdb\_reviews/su

# Recurrent Neural Networks

## ■ Text Classification with RNNs

### ■ Load and preprocess the IMDb dataset

```
# info object has the lookup table(encoder) of token and index
encoder = info.features['text'].encoder
print('Vocabulary size: {}'.format(encoder.vocab_size))
```

Vocabulary size: 8185

```
# Test the encoder
sample_string = 'Hello TensorFlow.'
encoded_string = encoder.encode(sample_string)
print('Encoded string is {}'.format(encoded_string))
original_string = encoder.decode(encoded_string)
print('The original string: "{}"'.format(original_string))
```

Encoded string is [4025, 222, 6307, 2327, 4043, 2120, 7975]  
The original string: "Hello TensorFlow."

```
# Test the encoder
for index in encoded_string:
    print('{} ----> {}'.format(index, encoder.decode([index])))
```

4025 ----> Hell  
222 ----> o  
6307 ----> Ten  
2327 ----> sor  
4043 ----> Fl  
2120 ----> ow  
7975 ----> .



# Recurrent Neural Networks

- Text Classification with RNNs
  - Load and preprocess the IMDb dataset

```
# Creating training task
BUFFER_SIZE = 10000
BATCH_SIZE = 64

train_dataset = train_dataset.shuffle(BUFFER_SIZE)
train_dataset = train_dataset.padded_batch(BATCH_SIZE)

test_dataset = test_dataset.padded_batch(BATCH_SIZE)
```

# Recurrent Neural Networks

- Text Classification with RNNs
  - Load and preprocess the IMDB dataset

```
# Check the shape of batches
for x, y in train_dataset.take(2):
    print(x)
    print(y)
    print("-"*90)

tf.Tensor(
[[[5700 1101  89 ...  0  0  0]
 [4074  370   2 ...  0  0  0]
 [ 135 7968   8 ...  0  0  0]
 ...
 [7969 2517 1104 ...  0  0  0]
 [  12  284  107 ...  0  0  0]
 [2883  798  968 ...  0  0  0]], shape=(64, 1119), dtype=int64)
tf.Tensor(
[0 0 0 1 1 0 1 1 0 0 0 0 0 1 1 1 1 0 1 1 0 0 1 0 0 0 0 0 1 1 0 1 1 0 0 0 0
 0 1 0 0 1 0 0 1 1 0 0 0 0 0 1 0 1 0 0 1 0 0 0 1 0 0 1], shape=(64,), dtype=int64)
-----

tf.Tensor(
[[[ 69  279  35 ...  0  0  0]
 [1028  330  571 ...  0  0  0]
 [  12   31   7 ...  0  0  0]
 ...
 [ 407   41 2579 ...  0  0  0]
 [  12 2768  109 ...  0  0  0]
 [ 147 5562 6904 ...  0  0  0]], shape=(64, 1335), dtype=int64)
tf.Tensor(
[0 0 0 1 1 0 1 1 1 0 1 0 0 0 1 1 1 1 0 1 1 0 1 0 1 0 0 0 1 0 1 0 1 0 1 1 1
 1 1 1 0 1 1 1 0 0 0 0 0 1 0 0 0 0 0 0 1 1 0 0 0 0 0 1], shape=(64,), dtype=int64)
-----
```

# Recurrent Neural Networks

## ■ Text Classification with RNNs

### ■ Build the model

```
layers = tf.keras.layers
model = tf.keras.Sequential([
    layers.Embedding(encoder.vocab_size, 64),
    layers.Bidirectional(layers.LSTM(64)),
    layers.Dense(64, activation='relu'),
    layers.Dense(1)
])
model.compile(loss=tf.keras.losses.BinaryCrossentropy(from_logits=True),
              optimizer=tf.keras.optimizers.Adam(1e-4),
              metrics=['accuracy'])
model.summary()
```

Model: "sequential\_2"

Layer (type)	Output Shape	Param #
embedding_2 (Embedding)	(None, None, 64)	523840
bidirectional (Bidirectional)	(None, 128)	66048
dense_2 (Dense)	(None, 64)	8256
dense_3 (Dense)	(None, 1)	65

Total params: 598,209  
Trainable params: 598,209  
Non-trainable params: 0

# Recurrent Neural Networks

## ■ Text Classification with RNNs

### ■ Train the model

```
history = model.fit(train_dataset, epochs=5,  
validation_data=test_dataset,  
validation_steps=30)
```

### ■ Evaluate the model

```
test_loss, test_acc = model.evaluate(test_dataset)  
print('Test Loss: {}'.format(test_loss))  
print('Test Accuracy: {}'.format(test_acc))
```

```
391/391 [=====] - 17s 44ms/step - loss: 0.4383 - accuracy: 0.8537  
Test Loss: 0.4383341670036316  
Test Accuracy: 0.8536800146102905
```

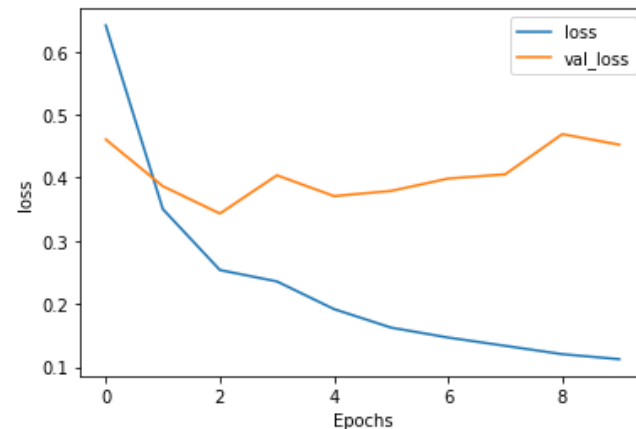
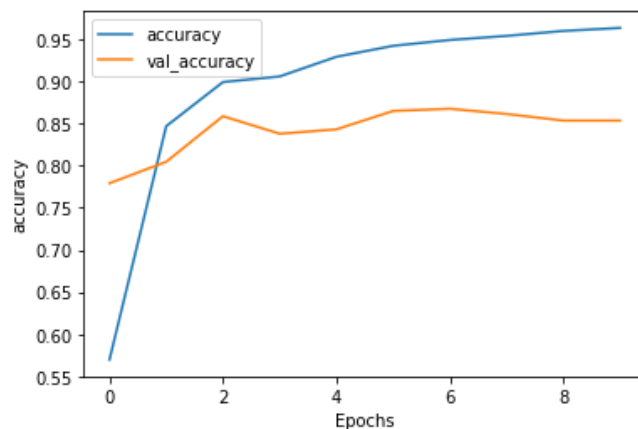
# Recurrent Neural Networks

## ■ Text Classification with RNNs

### ■ Evaluate the model

```
# helper function
def plot_graphs(history, metric):
    plt.plot(history.history[metric])
    plt.plot(history.history['val_'+metric], '')
    plt.xlabel("Epochs")
    plt.ylabel(metric)
    plt.legend([metric, 'val_'+metric])
    plt.show()

plot_graphs(history, 'accuracy')
plot_graphs(history, 'loss')
```



# Recurrent Neural Networks

## ■ Text Classification with RNNs

### ■ Evaluate the model

```
def sample_pred(text, model):  
    encoded_text = encoder.encode(text)  
    encoded_text = tf.cast(encoded_text, tf.float32)  
    predictions = model.predict(tf.expand_dims(encoded_text, 0))  
    prob = tf.sigmoid(predictions)[0][0].numpy()  
    print('Prob : ', prob)  
    if prob >= 0.5:  
        return "Positive"  
    else:  
        return "Negative"
```

```
sample_pred_text = 'You should watch this movie, this movie is excellent'  
sample_pred(sample_pred_text, model)
```

```
Prob : 0.79965454  
'Positive'
```

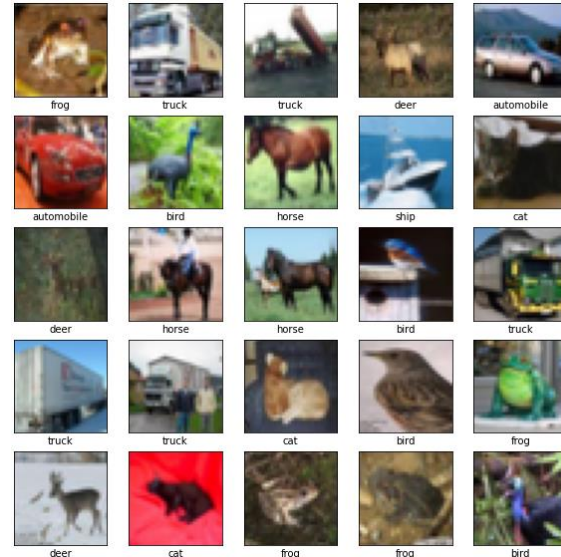
# Quiz 1 : Image Classification Model on the CIFAR-10

- Build the Convolutional Neural Networks
  - Build the model following the bellow model summary
  - Apply the dropout regularization to the model and compare the result
- Compare the performance of the model built last week

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 32, 32, 32)	896
max_pooling2d (MaxPooling2D)	(None, 16, 16, 32)	0
conv2d_1 (Conv2D)	(None, 14, 14, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 7, 7, 64)	0
flatten (Flatten)	(None, 3136)	0
dense (Dense)	(None, 128)	401536
dense_1 (Dense)	(None, 10)	1290

Total params: 422,218  
Trainable params: 422,218  
Non-trainable params: 0



## Quiz 2 : Character-level Language Model

- Build the Character-level Language Model with LSTM
- Compare the generated text to the one generated by RNNs