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**Semester: 6**

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In [59]:

```
# experiment 4
# Regularization
# Regularization is the change in weight. We do it to remove over fitting.
from keras.datasets import imdb
# The dataset has various attributes about the movies. Contains rating of movies.
```

In [60]:

```
(train_data, train_labels), (test_data, test_labels) = imdb.load_data(num_words=10000)
#loading the dataset and giving it to the testing and training data.
# num_word is the minimum number of occurrences of a word in the dataset.
```

```
<string>:6: VisibleDeprecationWarning: Creating an ndarray from ragged nested sequences (
which is a list-or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes)
is deprecated. If you meant to do this, you must specify 'dtype=object' when creating the
ndarray
/usr/local/lib/python3.6/dist-packages/tensorflow/python/keras/datasets/imdb.py:159: Visi
bleDeprecationWarning: Creating an ndarray from ragged nested sequences (which is a list-
or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated.
If you meant to do this, you must specify 'dtype=object' when creating the ndarray
    x_train, y_train = np.array(xs[:idx]), np.array(labels[:idx])
/usr/local/lib/python3.6/dist-packages/tensorflow/python/keras/datasets/imdb.py:160: Visi
bleDeprecationWarning: Creating an ndarray from ragged nested sequences (which is a list-
or-tuple of lists-or-tuples-or ndarrays with different lengths or shapes) is deprecated.
If you meant to do this, you must specify 'dtype=object' when creating the ndarray
    x_test, y_test = np.array(xs[idx:]), np.array(labels[idx:])
```

In [61]:

```
len(train_data[0])
# number of occurrence of zeroth sample.
# 218 words are there which are the most commonly occurring.
```

Out[61]:

218

In [62]:

```
train_data[0]
# seeing the zeroth sample, the words are represented as numbers
```

Out[62]:

```
[1,
 14,
 22,
 16,
 43,
 530,
 973,
 1622,
 1385,
 65,
 458,
 4468,
 66,
```

3941,  
4,  
173,  
36,  
256,  
5,  
25,  
100,  
43,  
838,  
112,  
50,  
670,  
2,  
9,  
35,  
480,  
284,  
5,  
150,  
4,  
172,  
112,  
167,  
2,  
336,  
385,  
39,  
4,  
172,  
4536,  
1111,  
17,  
546,  
38,  
13,  
447,  
4,  
192,  
50,  
16,  
6,  
147,  
2025,  
19,  
14,  
22,  
4,  
1920,  
4613,  
469,  
4,  
22,  
71,  
87,  
12,  
16,  
43,  
530,  
38,  
76,  
15,  
13,  
1247,  
4,  
22,  
17,  
515,  
17,  
12,  
16,  
626,

18,  
2,  
5,  
62,  
386,  
12,  
8,  
316,  
8,  
106,  
5,  
4,  
2223,  
5244,  
16,  
480,  
66,  
3785,  
33,  
4,  
130,  
12,  
16,  
38,  
619,  
5,  
25,  
124,  
51,  
36,  
135,  
48,  
25,  
1415,  
33,  
6,  
22,  
12,  
215,  
28,  
77,  
52,  
5,  
14,  
407,  
16,  
82,  
2,  
8,  
4,  
107,  
117,  
5952,  
15,  
256,  
4,  
2,  
7,  
3766,  
5,  
723,  
36,  
71,  
43,  
530,  
476,  
26,  
400,  
317,  
46,  
7,  
4,

```
2,  
1029,  
13,  
104,  
88,  
4,  
381,  
15,  
297,  
98,  
32,  
2071,  
56,  
26,  
141,  
6,  
194,  
7486,  
18,  
4,  
226,  
22,  
21,  
134,  
476,  
26,  
480,  
5,  
144,  
30,  
5535,  
18,  
51,  
36,  
28,  
224,  
92,  
25,  
104,  
4,  
226,  
65,  
16,  
38,  
1334,  
88,  
12,  
16,  
283,  
5,  
16,  
4472,  
113,  
103,  
32,  
15,  
16,  
5345,  
19,  
178,  
32]
```

In [63]:

```
len(train_data[10])
```

Out[63]:

450

In [64]:

```
print(train_data[10])
```

```
[1, 785, 189, 438, 47, 110, 142, 7, 6, 7475, 120, 4, 236, 378, 7, 153, 19, 87, 108, 141, 17, 1004, 5, 2, 883, 2, 23, 8, 4, 136, 2, 2, 4, 7475, 43, 1076, 21, 1407, 419, 5, 5202, 12, 0, 91, 682, 189, 2818, 5, 9, 1348, 31, 7, 4, 118, 785, 189, 108, 126, 93, 2, 16, 540, 324, 23, 6, 364, 352, 21, 14, 9, 93, 56, 18, 11, 230, 53, 771, 74, 31, 34, 4, 2834, 7, 4, 22, 5, 14, 11, 471, 9, 2, 34, 4, 321, 487, 5, 116, 15, 6584, 4, 22, 9, 6, 2286, 4, 114, 2679, 23, 107, 293, 1008, 1172, 5, 328, 1236, 4, 1375, 109, 9, 6, 132, 773, 2, 1412, 8, 1172, 18, 7865, 29, 9, 276, 11, 6, 2768, 19, 289, 409, 4, 5341, 2140, 2, 648, 1430, 2, 8914, 5, 27, 3000, 1432, 7130, 103, 6, 346, 137, 11, 4, 2768, 295, 36, 7740, 725, 6, 3208, 273, 11, 4, 1513, 15, 1367, 35, 154, 2, 103, 2, 173, 7, 12, 36, 515, 3547, 94, 2547, 1722, 5, 3547, 36, 203, 30, 502, 8, 361, 12, 8, 989, 143, 4, 1172, 3404, 10, 10, 328, 1236, 9, 6, 55, 221, 2989, 5, 146, 165, 179, 770, 15, 50, 713, 53, 108, 448, 23, 12, 17, 225, 38, 76, 4397, 18, 183, 8, 81, 19, 12, 45, 1257, 8, 135, 15, 2, 166, 4, 118, 7, 45, 2, 17, 466, 45, 2, 4, 22, 115, 165, 764, 6075, 5, 1030, 8, 2973, 73, 469, 167, 2127, 2, 1568, 6, 87, 841, 18, 4, 22, 4, 192, 15, 91, 7, 12, 304, 273, 1004, 4, 1375, 1172, 2768, 2, 15, 4, 22, 764, 55, 5773, 5, 14, 4233, 7444, 4, 1375, 326, 7, 4, 4760, 1786, 8, 361, 1236, 8, 989, 46, 7, 4, 2768, 45, 55, 776, 8, 79, 496, 98, 45, 400, 301, 15, 4, 1859, 9, 4, 155, 15, 66, 2, 84, 5, 14, 22, 1534, 15, 17, 4, 167, 2, 15, 75, 70, 115, 66, 30, 252, 7, 618, 51, 9, 2161, 4, 3130, 5, 14, 1525, 8, 6584, 15, 2, 165, 127, 1921, 8, 30, 179, 2532, 4, 22, 9, 906, 18, 6, 176, 7, 1007, 1005, 4, 1375, 114, 4, 105, 26, 32, 55, 221, 11, 68, 205, 96, 5, 4, 192, 15, 4, 274, 410, 220, 304, 23, 94, 205, 109, 9, 55, 73, 224, 259, 3786, 15, 4, 22, 528, 1645, 34, 4, 130, 528, 30, 685, 345, 17, 4, 277, 199, 166, 281, 5, 1030, 8, 30, 179, 4442, 444, 2, 9, 6, 371, 87, 189, 22, 5, 31, 7, 4, 118, 7, 4, 2068, 545, 1178, 829]
```

In [65]:

```
train_labels[10]
```

Out[65]:

```
1
```

In [66]:

```
# every entry in the dataset has different number of attributes in the row.  
# to solve this we need to prepare our dataset.  
# to solve this we make those attributes as 1 which are used and rest all are made zero.  
import numpy as np
```

In [67]:

```
# Preparing the dataset  
def vect_seq(sequence, dimension=10000):  
    mat = np.zeros((len(sequence), dimension)) # creating a numpy array with all zeros of shape len(sequence), 10000  
    for i, s in enumerate(sequence):  
        mat[i, s] = 1 # for every occurrence of a word we make the zero to 1  
    return mat
```

**Converting our data to the desired form using the vect\_seq function, thereafter checking thier shape.**

In [68]:

```
x_train = vect_seq(train_data)  
x_train.shape
```

Out[68]:

```
(25000, 10000)
```

In [69]:

```
x_test = vect_seq(test_data)  
x_test.shape
```

Out[69]:

```
(25000, 10000)
```

**Converting the labels to numpy array.**

In [70]:

```
y_train = np.asarray(train_labels).astype('float32')
y_test = np.asarray(test_labels).astype('float32')
```

In [71]:

```
from keras import models
from keras import layers
```

**Creating a model with 4 layers. Input layer with 10000 neurons. Followed by 2 layers with 16 neurons. And an output layer with 1 neuron and sigmoid activation function.**

In [72]:

```
model = models.Sequential()
model.add(layers.Dense(16, activation='relu', input_shape=(10000,)))
model.add(layers.Dense(16, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

In [73]:

```
from keras import losses
from keras import metrics
from keras import optimizers
```

In [74]:

```
model.compile(optimizer=optimizers.RMSprop(lr=0.01), loss = losses.binary_crossentropy,
metrics=metrics.binary_accuracy)
# compiling the model using RMSprop optimizer, binary_crossentropy as loss function, and
binary_accuracy as metrics
```

In [75]:

```
# saving first 10000 rows of trainig dataset for validation
x_val = x_train[:10000]
new_x_train = x_train[10000:]
y_val = y_train[:10000]
new_y_train = y_train[10000:]
```

In [76]:

```
# checing the shape of training and validation samples
print(x_val.shape)
print(new_x_train.shape)
```

```
(10000, 10000)
(15000, 10000)
```

In [77]:

```
# the compiled model is trained and validated using training and validation data
history = model.fit(new_x_train, new_y_train, batch_size=512, epochs=20, validation_data
=(x_val, y_val))
```

Epoch 1/20

```
30/30 [=====] - 2s 39ms/step - loss: 0.6325 - binary_accuracy: 0
.6589 - val_loss: 0.4529 - val_binary_accuracy: 0.8019
```

Epoch 2/20

```
30/30 [=====] - 1s 22ms/step - loss: 0.2850 - binary_accuracy: 0
.8863 - val_loss: 0.2862 - val_binary_accuracy: 0.8843
```

Epoch 3/20

```
30/30 [=====] - 1s 21ms/step - loss: 0.1913 - binary_accuracy: 0
.9267 - val_loss: 0.2821 - val_binary_accuracy: 0.8904
```

Epoch 4/20

```
30/30 [=====] - 1s 21ms/step - loss: 0.1661 - binary_accuracy: 0
.9399 - val_loss: 0.2957 - val_binary_accuracy: 0.8859
```

Epoch 5/20

```
30/30 [=====] - 1s 21ms/step - loss: 0.1072 - binary_accuracy: 0
```

```

30/30 [=====] - 1s 21ms/step - loss: 0.1072 - binary_accuracy: 0
.9587 - val_loss: 0.4847 - val_binary_accuracy: 0.8613
Epoch 6/20
30/30 [=====] - 1s 21ms/step - loss: 0.0895 - binary_accuracy: 0
.9665 - val_loss: 0.4235 - val_binary_accuracy: 0.8799
Epoch 7/20
30/30 [=====] - 1s 22ms/step - loss: 0.0750 - binary_accuracy: 0
.9779 - val_loss: 0.5109 - val_binary_accuracy: 0.8765
Epoch 8/20
30/30 [=====] - 1s 21ms/step - loss: 0.0338 - binary_accuracy: 0
.9894 - val_loss: 0.5046 - val_binary_accuracy: 0.8760
Epoch 9/20
30/30 [=====] - 1s 20ms/step - loss: 0.0131 - binary_accuracy: 0
.9966 - val_loss: 0.7559 - val_binary_accuracy: 0.8715
Epoch 10/20
30/30 [=====] - 1s 21ms/step - loss: 0.0808 - binary_accuracy: 0
.9867 - val_loss: 0.6861 - val_binary_accuracy: 0.8734
Epoch 11/20
30/30 [=====] - 1s 21ms/step - loss: 0.0061 - binary_accuracy: 0
.9979 - val_loss: 0.8191 - val_binary_accuracy: 0.8738
Epoch 12/20
30/30 [=====] - 1s 21ms/step - loss: 0.0039 - binary_accuracy: 0
.9981 - val_loss: 1.0008 - val_binary_accuracy: 0.8708
Epoch 13/20
30/30 [=====] - 1s 21ms/step - loss: 0.0493 - binary_accuracy: 0
.9927 - val_loss: 0.8059 - val_binary_accuracy: 0.8674
Epoch 14/20
30/30 [=====] - 1s 22ms/step - loss: 0.0047 - binary_accuracy: 0
.9984 - val_loss: 1.0309 - val_binary_accuracy: 0.8702
Epoch 15/20
30/30 [=====] - 1s 21ms/step - loss: 0.0018 - binary_accuracy: 0
.9990 - val_loss: 1.2379 - val_binary_accuracy: 0.8701
Epoch 16/20
30/30 [=====] - 1s 21ms/step - loss: 0.0261 - binary_accuracy: 0
.9978 - val_loss: 1.0025 - val_binary_accuracy: 0.8657
Epoch 17/20
30/30 [=====] - 1s 23ms/step - loss: 0.0019 - binary_accuracy: 0
.9998 - val_loss: 1.1431 - val_binary_accuracy: 0.8671
Epoch 18/20
30/30 [=====] - 1s 21ms/step - loss: 7.5881e-04 - binary_accuracy: 0
.9999 - val_loss: 1.2668 - val_binary_accuracy: 0.8684
Epoch 19/20
30/30 [=====] - 1s 21ms/step - loss: 6.0423e-04 - binary_accuracy: 1.0000
.9999 - val_loss: 1.4062 - val_binary_accuracy: 0.8686
Epoch 20/20
30/30 [=====] - 1s 21ms/step - loss: 3.3831e-04 - binary_accuracy: 1.0000
.9999 - val_loss: 1.6091 - val_binary_accuracy: 0.8669

```

In [78]:

```

# creating a dictionary of the result parameters of the trained model
history_dict = history.history
history_dict.keys()

```

Out[78]:

```
dict_keys(['loss', 'binary_accuracy', 'val_loss', 'val_binary_accuracy'])
```

In [79]:

```

import matplotlib.pyplot as plt
# calling matplotlib to visualize the results

```

In [80]:

```

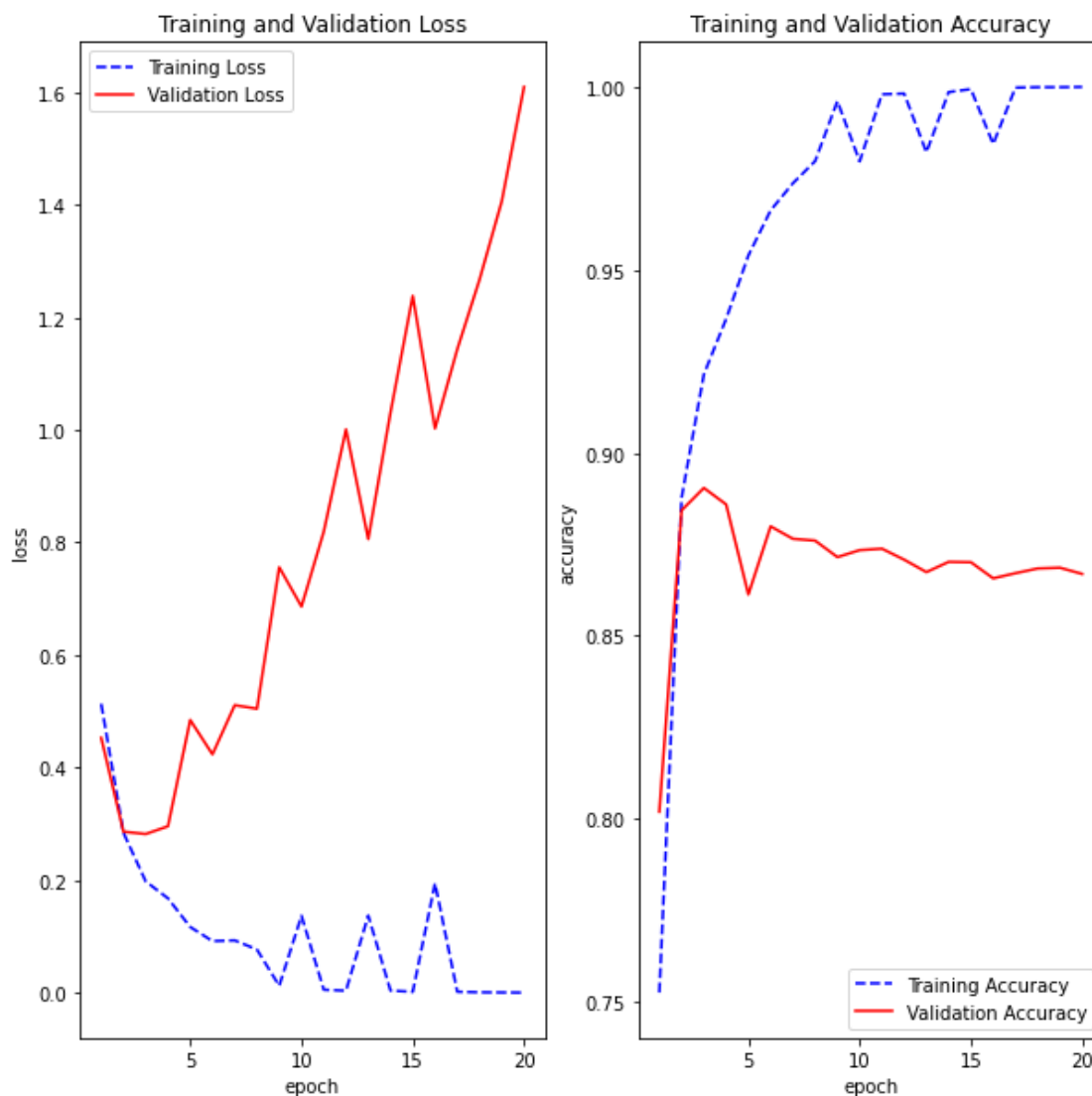
# visualising the loss and accuracy of the training and validation phase
loss = history_dict['loss']
val_loss = history_dict['val_loss']
acc = history_dict['binary_accuracy']
val_acc = history_dict['val_binary_accuracy']
epoch = range(1, len(acc)+1)
fig, ax = plt.subplots(1,2)

```

```
fig.set_size_inches(10,10)
```

```
ax[0].plot(epoch, loss, 'b--', label='Training Loss')
ax[0].plot(epoch, val_loss, 'r', label='Validation Loss')
ax[0].set_title('Training and Validation Loss')
ax[0].legend()
ax[0].set_xlabel('epoch')
ax[0].set_ylabel('loss')

ax[1].plot(epoch, acc, 'b--', label='Training Accuracy')
ax[1].plot(epoch, val_acc, 'r', label='Validation Accuracy')
ax[1].set_title('Training and Validation Accuracy')
ax[1].legend()
ax[1].set_xlabel('epoch')
ax[1].set_ylabel('accuracy')
plt.show()
```



From the above plots we can say that training process is good, but the validation gives us poor results. Thus we can say that the model has over fit.

In [81]:

```
from keras import regularizers
```

In [97]:

```
# adding regularizers to the model to prevent over fitting
model_1 = models.Sequential()
model_1.add(layers.Dense(16, activation='relu', kernel_regularizer=regularizers.l2(0.001), input_shape=(10000,)))
model_1.add(layers.Dense(16, activation='relu'))
model_1.add(layers.Dense(1, activation='sigmoid'))
```

In [98]:



In [98]:

```
model_1.compile(optimizer=optimizers.RMSprop(lr=0.01), loss = losses.binary_crossentropy,
metrics=metrics.binary_accuracy)
# compiling the updated model using RMSprop optimizer, binary_crossentropy as loss function,
and binary_accuracy as metrics
```

In [99]:

```
# the updated compiled model is trained and validated using training and validation data
history_1 = model_1.fit(new_x_train, new_y_train, batch_size=512, epochs=20, validation_data=(x_val, y_val))
```

Epoch 1/20

30/30 [=====] - 2s 32ms/step - loss: 0.7932 - binary\_accuracy: 0.6348 - val\_loss: 0.4429 - val\_binary\_accuracy: 0.8474

Epoch 2/20

30/30 [=====] - 1s 21ms/step - loss: 0.4697 - binary\_accuracy: 0.8276 - val\_loss: 0.5341 - val\_binary\_accuracy: 0.7874

Epoch 3/20

30/30 [=====] - 1s 22ms/step - loss: 0.4164 - binary\_accuracy: 0.8659 - val\_loss: 0.3968 - val\_binary\_accuracy: 0.8841

Epoch 4/20

30/30 [=====] - 1s 22ms/step - loss: 0.3777 - binary\_accuracy: 0.8912 - val\_loss: 0.4399 - val\_binary\_accuracy: 0.8573

Epoch 5/20

30/30 [=====] - 1s 23ms/step - loss: 0.3959 - binary\_accuracy: 0.8717 - val\_loss: 0.3999 - val\_binary\_accuracy: 0.8734

Epoch 6/20

30/30 [=====] - 1s 23ms/step - loss: 0.3658 - binary\_accuracy: 0.8921 - val\_loss: 0.4312 - val\_binary\_accuracy: 0.8565

Epoch 7/20

30/30 [=====] - 1s 23ms/step - loss: 0.3390 - binary\_accuracy: 0.8985 - val\_loss: 0.3806 - val\_binary\_accuracy: 0.8829

Epoch 8/20

30/30 [=====] - 1s 23ms/step - loss: 0.3300 - binary\_accuracy: 0.9048 - val\_loss: 0.3833 - val\_binary\_accuracy: 0.8809

Epoch 9/20

30/30 [=====] - 1s 21ms/step - loss: 0.3340 - binary\_accuracy: 0.9133 - val\_loss: 0.3780 - val\_binary\_accuracy: 0.8824

Epoch 10/20

30/30 [=====] - 1s 21ms/step - loss: 0.3219 - binary\_accuracy: 0.9141 - val\_loss: 0.4278 - val\_binary\_accuracy: 0.8576

Epoch 11/20

30/30 [=====] - 1s 22ms/step - loss: 0.3010 - binary\_accuracy: 0.9229 - val\_loss: 0.3885 - val\_binary\_accuracy: 0.8815

Epoch 12/20

30/30 [=====] - 1s 22ms/step - loss: 0.2966 - binary\_accuracy: 0.9279 - val\_loss: 0.4646 - val\_binary\_accuracy: 0.8613

Epoch 13/20

30/30 [=====] - 1s 32ms/step - loss: 0.3278 - binary\_accuracy: 0.9040 - val\_loss: 0.6949 - val\_binary\_accuracy: 0.8094

Epoch 14/20

30/30 [=====] - 1s 22ms/step - loss: 0.3581 - binary\_accuracy: 0.8930 - val\_loss: 0.3987 - val\_binary\_accuracy: 0.8803

Epoch 15/20

30/30 [=====] - 1s 22ms/step - loss: 0.2888 - binary\_accuracy: 0.9303 - val\_loss: 0.4904 - val\_binary\_accuracy: 0.8505

Epoch 16/20

30/30 [=====] - 1s 21ms/step - loss: 0.2991 - binary\_accuracy: 0.9230 - val\_loss: 0.4683 - val\_binary\_accuracy: 0.8713

Epoch 17/20

30/30 [=====] - 1s 23ms/step - loss: 0.3205 - binary\_accuracy: 0.9111 - val\_loss: 0.4884 - val\_binary\_accuracy: 0.8265

Epoch 18/20

30/30 [=====] - 1s 23ms/step - loss: 0.3046 - binary\_accuracy: 0.9138 - val\_loss: 0.8273 - val\_binary\_accuracy: 0.7630

Epoch 19/20

30/30 [=====] - 1s 22ms/step - loss: 0.3291 - binary\_accuracy: 0.9166 - val\_loss: 0.5096 - val\_binary\_accuracy: 0.8472

Epoch 20/20

30/30 [=====] - 1s 23ms/step - loss: 0.2911 - binary\_accuracy: 0.9265 - val\_loss: 0.4467 - val binary accuracy: 0.8689

```
In [100]:
```

```
# creating a dictionary of the result parameters of the updated trained model
history_dict_1 = history_1.history
history_dict_1.keys()
```

```
Out[100]:
```

```
dict_keys(['loss', 'binary_accuracy', 'val_loss', 'val_binary_accuracy'])
```

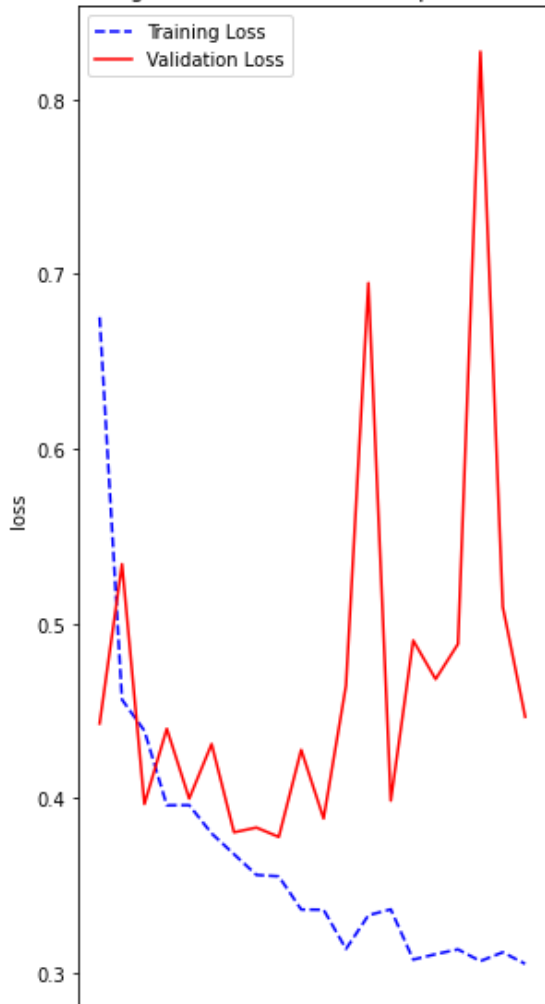
```
In [101]:
```

```
# visualising the loss and accuracy of the training and valication phase of thr updated m
odel
loss_1 = history_dict_1['loss']
val_loss_1 = history_dict_1['val_loss']
acc_1 = history_dict_1['binary_accuracy']
val_acc_1 = history_dict_1['val_binary_accuracy']
epoch_1 = range(1, len(acc)+1)
fig , ax = plt.subplots(1,2)
fig.set_size_inches(10,10)

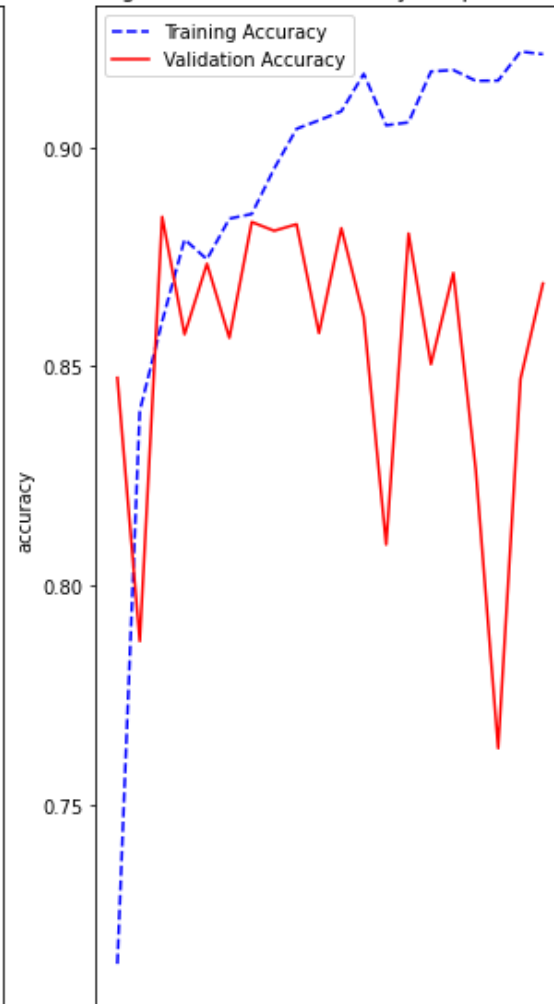
ax[0].plot(epoch_1, loss_1, 'b--', label='Training Loss')
ax[0].plot(epoch_1, val_loss_1, 'r', label='Validation Loss')
ax[0].set_title('Training and Validation Loss of Updated Model')
ax[0].legend()
ax[0].set_xlabel('epoch')
ax[0].set_ylabel('loss')

ax[1].plot(epoch_1, acc_1, 'b--', label='Training Accuracy')
ax[1].plot(epoch_1, val_acc_1, 'r', label='Validation Accuracy')
ax[1].set_title('Training and Validation Accuracy of Updated Model')
ax[1].legend()
ax[1].set_xlabel('epoch')
ax[1].set_ylabel('accuracy')
plt.show()
```

Training and Validation Loss of Updated Model



Training and Validation Accuracy of Updated Model



5 10 15 20 5 10 15 20  
epoch epoch

## Conclusion

- With each epoch training loss reduces but validation loss increases, as shown by the graph. Showing that the model has overfit.
- To avoid overfitting, the regularizer with L2 norm was used, and results show that the training loss reduces with each epoch and validation loss does not increase with each epoch, it gets stabilized, within a small range.
- For the given dataset validation loss varies from the range 0.3 to 0.5 with regularizer and 0.3 to 1.7 without regularizer.