Income_Prediction_Report

April 16, 2020

1 Income prediction based on census data

1.1 Introduction

The prediction task is to determine whether a person makes over 50K a year.

In this report, I will use logistic regression and deep neural network (DNN model).

1.2 Dataset

This dataset is downloaded from Kaggle.

Data recource: UCI machine learning repository

1.3 import some libraries and our dataset.

[1]:
```
# Import some libraries
import pandas as pd
import numpy as np
import matplotlib as mlt
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
```

[2]:
```
# Import datasets
train_data=pd.read_csv('/Users/Stylewsxcde991/Desktop/     /qbs-competition-1/
 ↪data/train.csv',index_col=0)
X_test=pd.read_csv('/Users/Stylewsxcde991/Desktop/     /qbs-competition-1/data/
 ↪test.csv',index_col=0)
```

1.4 Look some basic information of our dataset.

[3]:
```
# Some basic information of training data
print('The shape of training data: ' + str(train_data.shape))
print('')
```

```python
print('The shape of training data: ' + str(X_test.shape))
print('')
print('Basic information of our training data: ')
print(train_data.info())
print('')
print('Basic information of our testing data: ')
print(X_test.info())
```

```
The shape of training data: (29514, 15)

The shape of training data: (19328, 14)

Basic information of our training data:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 29514 entries, 2 to 48841
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Age             29514 non-null  int64
 1   Workclass       27665 non-null  object
 2   fnlwgt          29514 non-null  int64
 3   Education       29514 non-null  object
 4   Education_Num   29514 non-null  int64
 5   Martial_Status  29514 non-null  object
 6   Occupation      27657 non-null  object
 7   Relationship    29514 non-null  object
 8   Race            29514 non-null  object
 9   Sex             29514 non-null  object
 10  Capital_Gain    29514 non-null  int64
 11  Capital_Loss    29514 non-null  int64
 12  Hours_per_week  29514 non-null  int64
 13  Country         28988 non-null  object
 14  Target          29514 non-null  int64
dtypes: int64(7), object(8)
memory usage: 3.6+ MB
None

Basic information of our testing data:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19328 entries, 1 to 48842
Data columns (total 14 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Age             19328 non-null  int64
 1   Workclass       18378 non-null  object
 2   fnlwgt          19328 non-null  int64
 3   Education       19328 non-null  object
```

```
 4   Education_Num   19328 non-null  int64
 5   Martial_Status  19328 non-null  object
 6   Occupation      18376 non-null  object
 7   Relationship    19328 non-null  object
 8   Race            19328 non-null  object
 9   Sex             19328 non-null  object
 10  Capital_Gain    19328 non-null  int64
 11  Capital_Loss    19328 non-null  int64
 12  Hours_per_week  19328 non-null  int64
 13  Country         18997 non-null  object
dtypes: int64(6), object(8)
memory usage: 2.2+ MB
None
```

According to above information, the shape of training data is (29514, 15) and the shape of test data is (19328, 14).

Furthermore, notice that we have missing data problem in our training dataset and test dataset (there are Null value in some features).

In particular, we have to deal with the missing data problem of 'Workclass', 'Occupation', 'Country' in our training dataset and testing dataset. We can deal with this problem by replacing all Null value with 'unknown'.

1.5 Deal with missing data

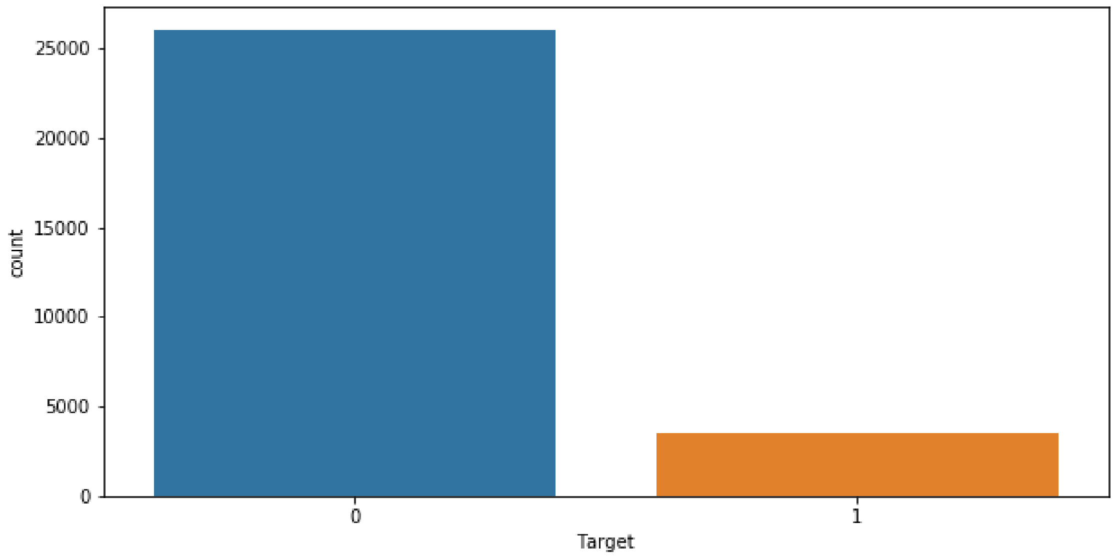
[4]:
```
# Deal with missing data
train_data.Workclass=train_data.Workclass.fillna('unknown')
train_data.Occupation=train_data.Occupation.fillna('unknown')
train_data.Country=train_data.Country.fillna('unknown')
X_test.Workclass=X_test.Workclass.fillna('unknown')
X_test.Occupation=X_test.Occupation.fillna('unknown')
X_test.Country=X_test.Country.fillna('unknown')
```

1.6 Proportion of each target class (make over 50k a year or not).

[5]:
```
# The proportion of each target class
NotOver50k,Over50k = train_data.Target.value_counts()
print(f'NotOver50k {NotOver50k}')
print(f'Over50k {Over50k}')
print(f'Over50k proportion {round((100*Over50k/(Over50k+NotOver50k)),2)}%')
plt.figure(figsize=(10,5))
sns.countplot(train_data['Target'])
```

```
NotOver50k 26008
Over50k 3506
Over50k proportion 11.88%
```

[5]: <matplotlib.axes._subplots.AxesSubplot at 0x1088f3f10>



According to above calculation and plot, there are only 11.88% samples makes over 50K a year. Therefore, our training dataset is quiet imbalanced.

1.7 Explorative data analysis for numerical features

As following, we analyze the correlation coefficients between our numerical features.

[6]:
```
# EDA for numerical features
# data.corr()
plt.figure(figsize=(10,8))
sns.heatmap(train_data.corr(),cmap='Accent',annot=True)
plt.title('Heatmap showing correlations between numerical data')
```

[6]: Text(0.5, 1, 'Heatmap showing correlations between numerical data')

One thing to note is that the correlation coefficient between 'fnlwgt' and our target is quiet small (which is -0.01).

Therefore, I don't consider 'fnlwgt' in my NN models.

(In fact, I have tried to incorporate 'fnlwgt' in my NN models and got really bad results.)

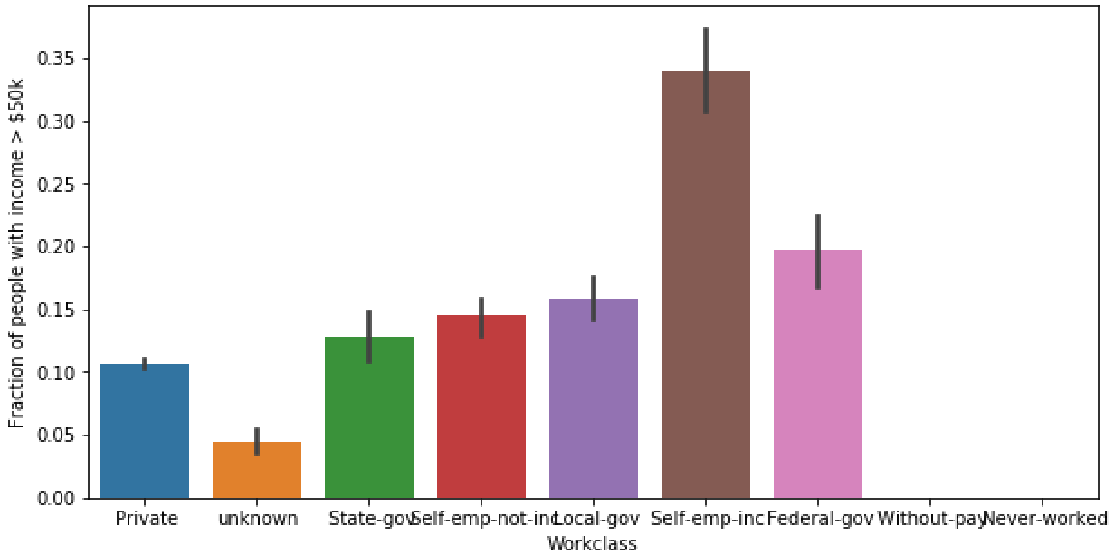
In addition, because I think 'Education' and 'Education_Num' contain the same information, I only use 'Education_Num' in my NN models.

1.8 Explorative data analysis for categorical features.

[7]:
```
# Drop 'fnlwgt' & 'Education'
train_data = train_data.drop(columns=['fnlwgt','Education'])
X_test = X_test.drop(columns=['fnlwgt','Education'])
```

[8]:
```
# EDA for categorical features
plt.figure(figsize=(10,5))
ax = sns.barplot(x='Workclass',y='Target',data=train_data)
ax.set(ylabel='Fraction of people with income > $50k')
```

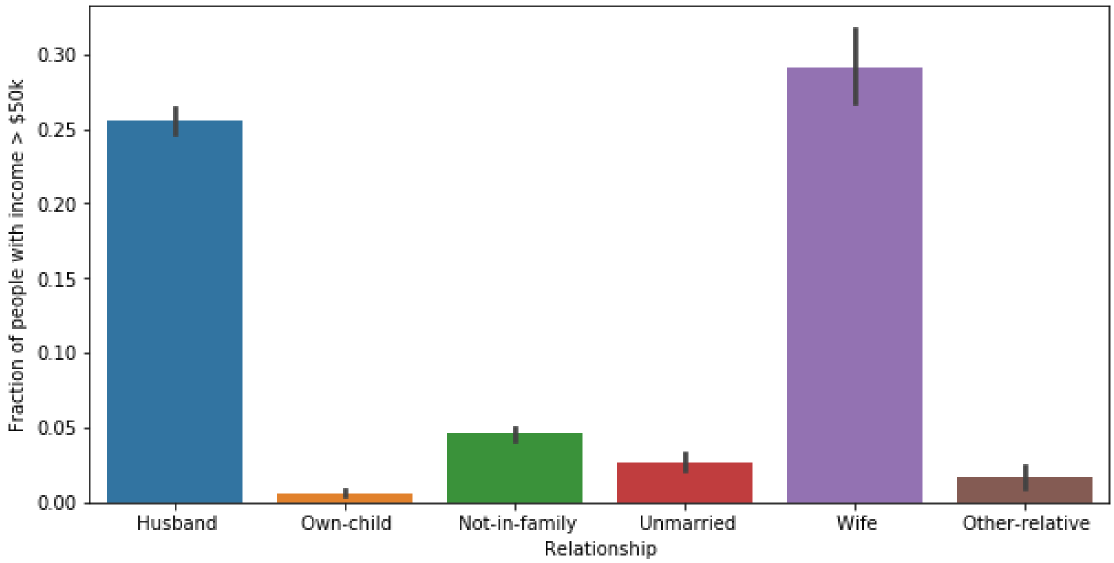
[8]: [Text(0, 0.5, 'Fraction of people with income > $50k')]



As above, people who are 'Self-emp-inc' are more likely makes over 50K a year.

[9]:
```
plt.figure(figsize=(10,5))
ax = sns.barplot(x='Relationship',y='Target',data=train_data)
ax.set(ylabel='Fraction of people with income > $50k')
```

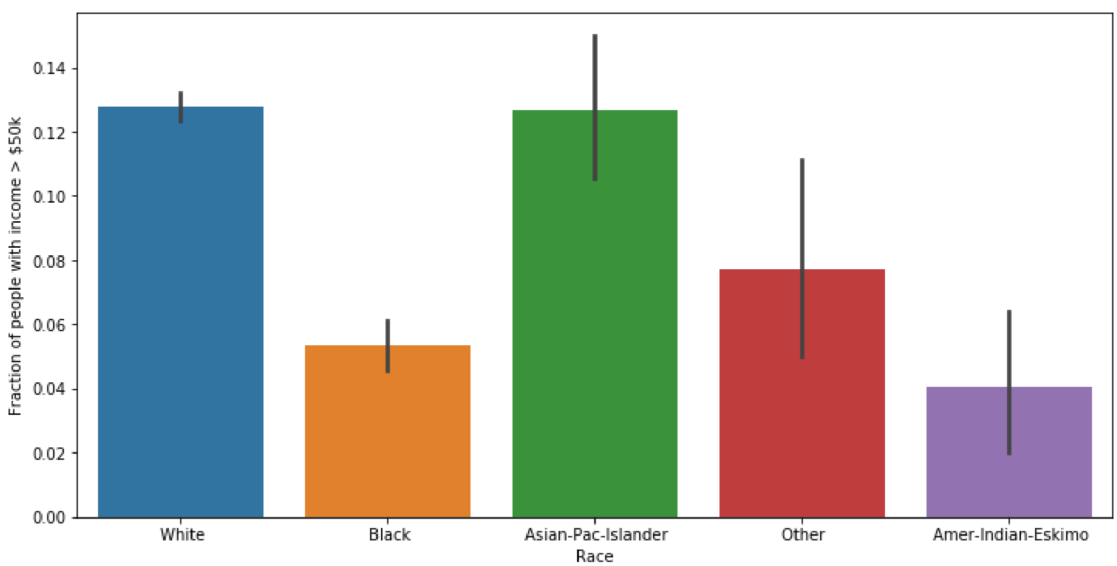
[9]: [Text(0, 0.5, 'Fraction of people with income > $50k')]



As above, 'Husband' and 'Wife' are more likely makes over 50K a year.

[10]:
```
plt.figure(figsize=(12,6))
ax=sns.barplot(x='Race',y='Target',data=train_data)
ax.set(ylabel='Fraction of people with income > $50k')
```

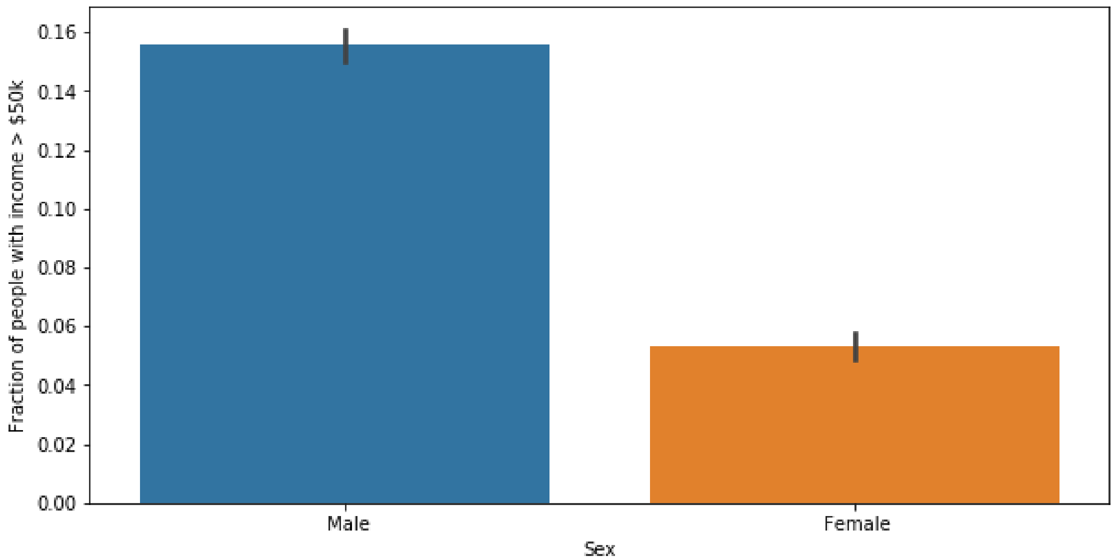
[10]: `[Text(0, 0.5, 'Fraction of people with income > $50k')]`



As above, 'White' and 'Asian-Pac-Islander Race' have higher proportion of people who make over 50K a year.

[11]:
```
plt.figure(figsize=(10,5))
ax = sns.barplot(x='Sex',y='Target',data=train_data)
ax.set(ylabel='Fraction of people with income > $50k')
```

[11]: [Text(0, 0.5, 'Fraction of people with income > $50k')]



As above, ‘Male’ group has higher proportion of people who make over 50K a year.

1.9 Split the training data into features (X) and label (y).

[12]:
```
# Split our train_data
X_train=train_data.iloc[:,:-1]
y_train=train_data.iloc[:,-1]
```

Now, we have to deal with the issue of categorical features.

In our training data and testing data, we have many categorical features (‘Workclass’,‘Martial_Status’, ‘Education’, ‘Occupation’,‘Relationship’,‘Race’,‘Sex’,‘Country’). Because our NN models can only deal with numbers, we have to encode these categorical features into numbers.

In fact, there are many different ways to encode categorical features. The method I used is so-called ‘One-hot encoding’ (as following).

1.10 One-hot encoding

[13]:
```
# Use 'One-hot encoding' to encode categorical features.
X = X_train.append(X_test)
X = pd.get_dummies(X)
X_train = X[:29514]
X_test = X[29514:]
```

2 Standardize the data

[14]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler().fit(X_train)
X_train=sc.transform(X_train)
X_test=sc.transform(X_test)
```

Now, we transform our datasets from dataframes to arrays, so we can feed them into NN models.

In addition, we use 7500 samples in our training dataset to be our validation set and use other samples to train our NN models.

[15]:
```
# Change dataframes to arrays
X_train = np.asarray(X_train)
X_test = np.asarray(X_test)
y_train = np.asarray(y_train).astype('float32')

# validation set
X_valid = X_train[:7500]
partial_X_train = X_train[7500:]
y_valid = y_train[:7500]
partial_y_train = y_train[7500:]
```

2.1 Logistic Regression

So far, we have dealed with all issues of data pre-processing.

Now, we can start to build our logistic regression model.

[20]:
```
# logistic model
from sklearn.linear_model import LogisticRegression
logistic_model = LogisticRegression(random_state=0).fit(X_train, y_train)
```

[21]:
```
# Compute the confusion matrix
y_preds = logistic_model.predict(X_valid)
y_preds = (y_preds>0.5).astype(int)
print('confusion matrix')
```

```
print(sklearn.metrics.confusion_matrix(y_valid,y_preds))

# Compute accuracy
print('accuracy = '+ str(sklearn.metrics.accuracy_score(y_valid,y_preds)))


# Compute Precision
print('precision = '+str(sklearn.metrics.precision_score(y_valid,y_preds)))

# Compute Recall
print('recall = '+ str(sklearn.metrics.recall_score(y_valid,y_preds)))

# Compute F1 score
print('F1 score = '+ str(sklearn.metrics.f1_score(y_valid,y_preds)))
```

```
confusion matrix
[[6496  118]
 [ 528  358]]
accuracy = 0.9138666666666667
precision = 0.7521008403361344
recall = 0.4040632054176072
F1 score = 0.5256975036710719
```

2.2 Deep neural network (DNN model)

Now, we can start to build our NN models.

DL model draft:

3 hidden layers in this model.

The first hidden layer: 16 units with 'relu' activation function.

The second hidden layer: 16 units with 'relu' activation function.

The third hidden layer: 1 unit with 'sigmoid' activation function.

I choose the 'rmsprop' optimizer, 'binary_crossentropy' loss function, and the 'accuracy' metrics.

parameter initialization:

I use 200 epochs to train my model. The batch_size of my model is 512.

parameter tuning:

Because I think this model did well in my training dataset, I didn't tune it's parameters.

To begin with, we build our NN model with very simple structure as following.

[22]:
```
# Construct our model
from keras import models
from keras import layers
```

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

model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['accuracy'])
```

```
Using TensorFlow backend.
```

Now we can start to fit our NN model and record all information in 'history'.

[23]:
```python
# Iterate on your training data by calling the fit() method of your model
history = model.fit(partial_X_train,
                    partial_y_train,
                    epochs=200,
                    batch_size=512,
                    validation_data=(X_valid, y_valid))
```

```
Train on 22014 samples, validate on 7500 samples
Epoch 1/200
22014/22014 [==============================] - 1s 25us/step - loss: 0.5131 -
accuracy: 0.8166 - val_loss: 0.3800 - val_accuracy: 0.8819
Epoch 2/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3256 -
accuracy: 0.8810 - val_loss: 0.2898 - val_accuracy: 0.8824
Epoch 3/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2752 -
accuracy: 0.8828 - val_loss: 0.2643 - val_accuracy: 0.8857
Epoch 4/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.2577 -
accuracy: 0.8902 - val_loss: 0.2540 - val_accuracy: 0.8937
Epoch 5/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2487 -
accuracy: 0.8937 - val_loss: 0.2478 - val_accuracy: 0.9004
Epoch 6/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2429 -
accuracy: 0.8990 - val_loss: 0.2441 - val_accuracy: 0.9035
Epoch 7/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.2385 -
accuracy: 0.9003 - val_loss: 0.2405 - val_accuracy: 0.9048
Epoch 8/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2348 -
accuracy: 0.9020 - val_loss: 0.2381 - val_accuracy: 0.9052
Epoch 9/200
22014/22014 [==============================] - 0s 14us/step - loss: 0.2320 -
```

```
accuracy: 0.9027 - val_loss: 0.2362 - val_accuracy: 0.9047
Epoch 10/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.2294 -
accuracy: 0.9036 - val_loss: 0.2341 - val_accuracy: 0.9075
Epoch 11/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2272 -
accuracy: 0.9047 - val_loss: 0.2324 - val_accuracy: 0.9067
Epoch 12/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.2253 -
accuracy: 0.9056 - val_loss: 0.2310 - val_accuracy: 0.9075
Epoch 13/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.2236 -
accuracy: 0.9052 - val_loss: 0.2299 - val_accuracy: 0.9096
Epoch 14/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2222 -
accuracy: 0.9067 - val_loss: 0.2288 - val_accuracy: 0.9101
Epoch 15/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2210 -
accuracy: 0.9081 - val_loss: 0.2279 - val_accuracy: 0.9101
Epoch 16/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2199 -
accuracy: 0.9081 - val_loss: 0.2285 - val_accuracy: 0.9092
Epoch 17/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2189 -
accuracy: 0.9090 - val_loss: 0.2272 - val_accuracy: 0.9096
Epoch 18/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2181 -
accuracy: 0.9088 - val_loss: 0.2268 - val_accuracy: 0.9103
Epoch 19/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2174 -
accuracy: 0.9096 - val_loss: 0.2269 - val_accuracy: 0.9092
Epoch 20/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2168 -
accuracy: 0.9092 - val_loss: 0.2263 - val_accuracy: 0.9092
Epoch 21/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2162 -
accuracy: 0.9098 - val_loss: 0.2256 - val_accuracy: 0.9109
Epoch 22/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2156 -
accuracy: 0.9098 - val_loss: 0.2253 - val_accuracy: 0.9113
Epoch 23/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2151 -
accuracy: 0.9111 - val_loss: 0.2256 - val_accuracy: 0.9111
Epoch 24/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2147 -
accuracy: 0.9098 - val_loss: 0.2252 - val_accuracy: 0.9111
Epoch 25/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2141 -
```

```
accuracy: 0.9116 - val_loss: 0.2255 - val_accuracy: 0.9107
Epoch 26/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2136 -
accuracy: 0.9103 - val_loss: 0.2247 - val_accuracy: 0.9120
Epoch 27/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2132 -
accuracy: 0.9105 - val_loss: 0.2250 - val_accuracy: 0.9123
Epoch 28/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2132 -
accuracy: 0.9111 - val_loss: 0.2247 - val_accuracy: 0.9115
Epoch 29/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2125 -
accuracy: 0.9116 - val_loss: 0.2250 - val_accuracy: 0.9115
Epoch 30/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2121 -
accuracy: 0.9115 - val_loss: 0.2251 - val_accuracy: 0.9112
Epoch 31/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2118 -
accuracy: 0.9119 - val_loss: 0.2254 - val_accuracy: 0.9104
Epoch 32/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2114 -
accuracy: 0.9116 - val_loss: 0.2251 - val_accuracy: 0.9113
Epoch 33/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2110 -
accuracy: 0.9119 - val_loss: 0.2254 - val_accuracy: 0.9096
Epoch 34/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2107 -
accuracy: 0.9121 - val_loss: 0.2254 - val_accuracy: 0.9107
Epoch 35/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2104 -
accuracy: 0.9121 - val_loss: 0.2254 - val_accuracy: 0.9112
Epoch 36/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2100 -
accuracy: 0.9124 - val_loss: 0.2253 - val_accuracy: 0.9107
Epoch 37/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2097 -
accuracy: 0.9124 - val_loss: 0.2256 - val_accuracy: 0.9120
Epoch 38/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2092 -
accuracy: 0.9127 - val_loss: 0.2262 - val_accuracy: 0.9111
Epoch 39/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.2092 -
accuracy: 0.9126 - val_loss: 0.2259 - val_accuracy: 0.9116
Epoch 40/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2087 -
accuracy: 0.9133 - val_loss: 0.2263 - val_accuracy: 0.9109
Epoch 41/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.2085 -
```

```
accuracy: 0.9136 - val_loss: 0.2260 - val_accuracy: 0.9117
Epoch 42/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.2081 -
accuracy: 0.9136 - val_loss: 0.2262 - val_accuracy: 0.9129
Epoch 43/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.2079 -
accuracy: 0.9126 - val_loss: 0.2267 - val_accuracy: 0.9115
Epoch 44/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.2076 -
accuracy: 0.9135 - val_loss: 0.2266 - val_accuracy: 0.9108
Epoch 45/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.2071 -
accuracy: 0.9136 - val_loss: 0.2273 - val_accuracy: 0.9097
Epoch 46/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.2070 -
accuracy: 0.9134 - val_loss: 0.2277 - val_accuracy: 0.9105
Epoch 47/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.2068 -
accuracy: 0.9134 - val_loss: 0.2271 - val_accuracy: 0.9116
Epoch 48/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.2065 -
accuracy: 0.9138 - val_loss: 0.2273 - val_accuracy: 0.9104
Epoch 49/200
22014/22014 [==============================] - 0s 17us/step - loss: 0.2064 -
accuracy: 0.9132 - val_loss: 0.2279 - val_accuracy: 0.9104
Epoch 50/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.2061 -
accuracy: 0.9133 - val_loss: 0.2280 - val_accuracy: 0.9113
Epoch 51/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.2058 -
accuracy: 0.9137 - val_loss: 0.2276 - val_accuracy: 0.9109
Epoch 52/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.2056 -
accuracy: 0.9138 - val_loss: 0.2283 - val_accuracy: 0.9112
Epoch 53/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.2052 -
accuracy: 0.9137 - val_loss: 0.2293 - val_accuracy: 0.9109
Epoch 54/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.2052 -
accuracy: 0.9142 - val_loss: 0.2290 - val_accuracy: 0.9107
Epoch 55/200
22014/22014 [==============================] - 0s 17us/step - loss: 0.2051 -
accuracy: 0.9140 - val_loss: 0.2289 - val_accuracy: 0.9113
Epoch 56/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.2047 -
accuracy: 0.9141 - val_loss: 0.2288 - val_accuracy: 0.9109
Epoch 57/200
22014/22014 [==============================] - 0s 17us/step - loss: 0.2044 -
```

```
accuracy: 0.9135 - val_loss: 0.2291 - val_accuracy: 0.9112
Epoch 58/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.2043 -
accuracy: 0.9142 - val_loss: 0.2293 - val_accuracy: 0.9105
Epoch 59/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.2040 -
accuracy: 0.9141 - val_loss: 0.2292 - val_accuracy: 0.9107
Epoch 60/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.2040 -
accuracy: 0.9140 - val_loss: 0.2289 - val_accuracy: 0.9115
Epoch 61/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.2038 -
accuracy: 0.9145 - val_loss: 0.2290 - val_accuracy: 0.9109
Epoch 62/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.2035 -
accuracy: 0.9141 - val_loss: 0.2301 - val_accuracy: 0.9092
Epoch 63/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.2035 -
accuracy: 0.9136 - val_loss: 0.2298 - val_accuracy: 0.9113
Epoch 64/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.2032 -
accuracy: 0.9148 - val_loss: 0.2303 - val_accuracy: 0.9108
Epoch 65/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.2029 -
accuracy: 0.9141 - val_loss: 0.2298 - val_accuracy: 0.9096
Epoch 66/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.2028 -
accuracy: 0.9146 - val_loss: 0.2303 - val_accuracy: 0.9103
Epoch 67/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.2028 -
accuracy: 0.9138 - val_loss: 0.2298 - val_accuracy: 0.9117
Epoch 68/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.2026 -
accuracy: 0.9137 - val_loss: 0.2303 - val_accuracy: 0.9111
Epoch 69/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2023 -
accuracy: 0.9143 - val_loss: 0.2303 - val_accuracy: 0.9109
Epoch 70/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2022 -
accuracy: 0.9140 - val_loss: 0.2307 - val_accuracy: 0.9103
Epoch 71/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2021 -
accuracy: 0.9142 - val_loss: 0.2303 - val_accuracy: 0.9109
Epoch 72/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.2021 -
accuracy: 0.9150 - val_loss: 0.2306 - val_accuracy: 0.9107
Epoch 73/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2016 -
```

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accuracy: 0.9151 - val_loss: 0.2310 - val_accuracy: 0.9107
Epoch 74/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2017 -
accuracy: 0.9149 - val_loss: 0.2309 - val_accuracy: 0.9121
Epoch 75/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2015 -
accuracy: 0.9147 - val_loss: 0.2313 - val_accuracy: 0.9108
Epoch 76/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2015 -
accuracy: 0.9149 - val_loss: 0.2319 - val_accuracy: 0.9108
Epoch 77/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2012 -
accuracy: 0.9149 - val_loss: 0.2319 - val_accuracy: 0.9112
Epoch 78/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2012 -
accuracy: 0.9148 - val_loss: 0.2322 - val_accuracy: 0.9101
Epoch 79/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2011 -
accuracy: 0.9146 - val_loss: 0.2326 - val_accuracy: 0.9092
Epoch 80/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.2007 -
accuracy: 0.9158 - val_loss: 0.2322 - val_accuracy: 0.9107
Epoch 81/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2008 -
accuracy: 0.9146 - val_loss: 0.2327 - val_accuracy: 0.9099
Epoch 82/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.2005 -
accuracy: 0.9146 - val_loss: 0.2335 - val_accuracy: 0.9107
Epoch 83/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2006 -
accuracy: 0.9151 - val_loss: 0.2330 - val_accuracy: 0.9097
Epoch 84/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2002 -
accuracy: 0.9152 - val_loss: 0.2336 - val_accuracy: 0.9116
Epoch 85/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2001 -
accuracy: 0.9153 - val_loss: 0.2337 - val_accuracy: 0.9095
Epoch 86/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.2001 -
accuracy: 0.9154 - val_loss: 0.2347 - val_accuracy: 0.9084
Epoch 87/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1999 -
accuracy: 0.9151 - val_loss: 0.2337 - val_accuracy: 0.9101
Epoch 88/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1999 -
accuracy: 0.9160 - val_loss: 0.2349 - val_accuracy: 0.9081
Epoch 89/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1997 -
```

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accuracy: 0.9151 - val_loss: 0.2341 - val_accuracy: 0.9099
Epoch 90/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1996 -
accuracy: 0.9146 - val_loss: 0.2341 - val_accuracy: 0.9101
Epoch 91/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1994 -
accuracy: 0.9156 - val_loss: 0.2341 - val_accuracy: 0.9103
Epoch 92/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1995 -
accuracy: 0.9157 - val_loss: 0.2342 - val_accuracy: 0.9104
Epoch 93/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1991 -
accuracy: 0.9159 - val_loss: 0.2344 - val_accuracy: 0.9103
Epoch 94/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1990 -
accuracy: 0.9151 - val_loss: 0.2346 - val_accuracy: 0.9091
Epoch 95/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1991 -
accuracy: 0.9151 - val_loss: 0.2347 - val_accuracy: 0.9104
Epoch 96/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1989 -
accuracy: 0.9157 - val_loss: 0.2348 - val_accuracy: 0.9085
Epoch 97/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1986 -
accuracy: 0.9163 - val_loss: 0.2363 - val_accuracy: 0.9073
Epoch 98/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1986 -
accuracy: 0.9161 - val_loss: 0.2357 - val_accuracy: 0.9087
Epoch 99/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1983 -
accuracy: 0.9156 - val_loss: 0.2356 - val_accuracy: 0.9079
Epoch 100/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1983 -
accuracy: 0.9155 - val_loss: 0.2356 - val_accuracy: 0.9081
Epoch 101/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1983 -
accuracy: 0.9165 - val_loss: 0.2352 - val_accuracy: 0.9099
Epoch 102/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1982 -
accuracy: 0.9161 - val_loss: 0.2357 - val_accuracy: 0.9095
Epoch 103/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1979 -
accuracy: 0.9167 - val_loss: 0.2362 - val_accuracy: 0.9083
Epoch 104/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1979 -
accuracy: 0.9161 - val_loss: 0.2356 - val_accuracy: 0.9091
Epoch 105/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1977 -
```

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accuracy: 0.9163 - val_loss: 0.2360 - val_accuracy: 0.9076
Epoch 106/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1978 -
accuracy: 0.9164 - val_loss: 0.2357 - val_accuracy: 0.9097
Epoch 107/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1976 -
accuracy: 0.9166 - val_loss: 0.2358 - val_accuracy: 0.9092
Epoch 108/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1973 -
accuracy: 0.9166 - val_loss: 0.2362 - val_accuracy: 0.9069
Epoch 109/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1974 -
accuracy: 0.9161 - val_loss: 0.2360 - val_accuracy: 0.9093
Epoch 110/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1973 -
accuracy: 0.9171 - val_loss: 0.2360 - val_accuracy: 0.9085
Epoch 111/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1971 -
accuracy: 0.9171 - val_loss: 0.2370 - val_accuracy: 0.9084
Epoch 112/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1971 -
accuracy: 0.9168 - val_loss: 0.2369 - val_accuracy: 0.9088
Epoch 113/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1969 -
accuracy: 0.9169 - val_loss: 0.2370 - val_accuracy: 0.9080
Epoch 114/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1969 -
accuracy: 0.9168 - val_loss: 0.2368 - val_accuracy: 0.9087
Epoch 115/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1968 -
accuracy: 0.9158 - val_loss: 0.2373 - val_accuracy: 0.9079
Epoch 116/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1968 -
accuracy: 0.9169 - val_loss: 0.2366 - val_accuracy: 0.9093
Epoch 117/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1966 -
accuracy: 0.9166 - val_loss: 0.2379 - val_accuracy: 0.9079
Epoch 118/200
22014/22014 [==============================] - ETA: 0s - loss: 0.1974 -
accuracy: 0.91 - 0s 7us/step - loss: 0.1965 - accuracy: 0.9168 - val_loss:
0.2374 - val_accuracy: 0.9092
Epoch 119/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.1963 -
accuracy: 0.9167 - val_loss: 0.2381 - val_accuracy: 0.9083
Epoch 120/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1963 -
accuracy: 0.9168 - val_loss: 0.2380 - val_accuracy: 0.9081
Epoch 121/200
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22014/22014 [==============================] - 0s 8us/step - loss: 0.1962 -
accuracy: 0.9167 - val_loss: 0.2379 - val_accuracy: 0.9087
Epoch 122/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1960 -
accuracy: 0.9167 - val_loss: 0.2390 - val_accuracy: 0.9072
Epoch 123/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1960 -
accuracy: 0.9168 - val_loss: 0.2383 - val_accuracy: 0.9073
Epoch 124/200
22014/22014 [==============================] - 0s 14us/step - loss: 0.1960 -
accuracy: 0.9171 - val_loss: 0.2389 - val_accuracy: 0.9056
Epoch 125/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1957 -
accuracy: 0.9174 - val_loss: 0.2379 - val_accuracy: 0.9075
Epoch 126/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1956 -
accuracy: 0.9172 - val_loss: 0.2381 - val_accuracy: 0.9059
Epoch 127/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1957 -
accuracy: 0.9171 - val_loss: 0.2383 - val_accuracy: 0.9067
Epoch 128/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1957 -
accuracy: 0.9165 - val_loss: 0.2383 - val_accuracy: 0.9079
Epoch 129/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1953 -
accuracy: 0.9171 - val_loss: 0.2395 - val_accuracy: 0.9076
Epoch 130/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1953 -
accuracy: 0.9171 - val_loss: 0.2396 - val_accuracy: 0.9044
Epoch 131/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1954 -
accuracy: 0.9176 - val_loss: 0.2384 - val_accuracy: 0.9081
Epoch 132/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1953 -
accuracy: 0.9174 - val_loss: 0.2388 - val_accuracy: 0.9083
Epoch 133/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1952 -
accuracy: 0.9168 - val_loss: 0.2390 - val_accuracy: 0.9073
Epoch 134/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1950 -
accuracy: 0.9170 - val_loss: 0.2390 - val_accuracy: 0.9067
Epoch 135/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1950 -
accuracy: 0.9177 - val_loss: 0.2390 - val_accuracy: 0.9061
Epoch 136/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1949 -
accuracy: 0.9175 - val_loss: 0.2391 - val_accuracy: 0.9076
Epoch 137/200
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22014/22014 [==============================] - 0s 7us/step - loss: 0.1948 -
accuracy: 0.9170 - val_loss: 0.2394 - val_accuracy: 0.9077
Epoch 138/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1947 -
accuracy: 0.9169 - val_loss: 0.2396 - val_accuracy: 0.9063
Epoch 139/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1946 -
accuracy: 0.9171 - val_loss: 0.2396 - val_accuracy: 0.9076
Epoch 140/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1946 -
accuracy: 0.9179 - val_loss: 0.2394 - val_accuracy: 0.9084
Epoch 141/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1945 -
accuracy: 0.9173 - val_loss: 0.2395 - val_accuracy: 0.9079
Epoch 142/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1945 -
accuracy: 0.9177 - val_loss: 0.2400 - val_accuracy: 0.9061
Epoch 143/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1943 -
accuracy: 0.9179 - val_loss: 0.2395 - val_accuracy: 0.9068
Epoch 144/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1942 -
accuracy: 0.9171 - val_loss: 0.2397 - val_accuracy: 0.9069
Epoch 145/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1941 -
accuracy: 0.9179 - val_loss: 0.2408 - val_accuracy: 0.9061
Epoch 146/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1941 -
accuracy: 0.9182 - val_loss: 0.2404 - val_accuracy: 0.9056
Epoch 147/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1940 -
accuracy: 0.9180 - val_loss: 0.2407 - val_accuracy: 0.9069
Epoch 148/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1940 -
accuracy: 0.9182 - val_loss: 0.2414 - val_accuracy: 0.9049
Epoch 149/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1939 -
accuracy: 0.9186 - val_loss: 0.2409 - val_accuracy: 0.9072
Epoch 150/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1939 -
accuracy: 0.9181 - val_loss: 0.2402 - val_accuracy: 0.9073
Epoch 151/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1938 -
accuracy: 0.9180 - val_loss: 0.2412 - val_accuracy: 0.9059
Epoch 152/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1938 -
accuracy: 0.9182 - val_loss: 0.2410 - val_accuracy: 0.9063
Epoch 153/200
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22014/22014 [==============================] - 0s 8us/step - loss: 0.1937 -
accuracy: 0.9177 - val_loss: 0.2410 - val_accuracy: 0.9057
Epoch 154/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1936 -
accuracy: 0.9176 - val_loss: 0.2419 - val_accuracy: 0.9047
Epoch 155/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1935 -
accuracy: 0.9180 - val_loss: 0.2413 - val_accuracy: 0.9067
Epoch 156/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1933 -
accuracy: 0.9181 - val_loss: 0.2415 - val_accuracy: 0.9060
Epoch 157/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1932 -
accuracy: 0.9177 - val_loss: 0.2412 - val_accuracy: 0.9072
Epoch 158/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1934 -
accuracy: 0.9177 - val_loss: 0.2422 - val_accuracy: 0.9056
Epoch 159/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1932 -
accuracy: 0.9186 - val_loss: 0.2416 - val_accuracy: 0.9077
Epoch 160/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1932 -
accuracy: 0.9182 - val_loss: 0.2421 - val_accuracy: 0.9057
Epoch 161/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1931 -
accuracy: 0.9185 - val_loss: 0.2423 - val_accuracy: 0.9060
Epoch 162/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1930 -
accuracy: 0.9184 - val_loss: 0.2433 - val_accuracy: 0.9047
Epoch 163/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1930 -
accuracy: 0.9183 - val_loss: 0.2430 - val_accuracy: 0.9057
Epoch 164/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1927 -
accuracy: 0.9187 - val_loss: 0.2443 - val_accuracy: 0.9040
Epoch 165/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1928 -
accuracy: 0.9181 - val_loss: 0.2431 - val_accuracy: 0.9052
Epoch 166/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1924 -
accuracy: 0.9189 - val_loss: 0.2431 - val_accuracy: 0.9076
Epoch 167/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1930 -
accuracy: 0.9178 - val_loss: 0.2435 - val_accuracy: 0.9053
Epoch 168/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1927 -
accuracy: 0.9186 - val_loss: 0.2430 - val_accuracy: 0.9060
Epoch 169/200
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22014/22014 [==============================] - 0s 9us/step - loss: 0.1925 -
accuracy: 0.9187 - val_loss: 0.2435 - val_accuracy: 0.9057
Epoch 170/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1927 -
accuracy: 0.9181 - val_loss: 0.2436 - val_accuracy: 0.9045
Epoch 171/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1922 -
accuracy: 0.9193 - val_loss: 0.2438 - val_accuracy: 0.9069
Epoch 172/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1924 -
accuracy: 0.9184 - val_loss: 0.2433 - val_accuracy: 0.9060
Epoch 173/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1924 -
accuracy: 0.9186 - val_loss: 0.2439 - val_accuracy: 0.9080
Epoch 174/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1924 -
accuracy: 0.9180 - val_loss: 0.2451 - val_accuracy: 0.9047
Epoch 175/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1921 -
accuracy: 0.9187 - val_loss: 0.2451 - val_accuracy: 0.9033
Epoch 176/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1922 -
accuracy: 0.9191 - val_loss: 0.2437 - val_accuracy: 0.9076
Epoch 177/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1921 -
accuracy: 0.9179 - val_loss: 0.2441 - val_accuracy: 0.9059
Epoch 178/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1921 -
accuracy: 0.9185 - val_loss: 0.2443 - val_accuracy: 0.9057
Epoch 179/200
22014/22014 [==============================] - 0s 14us/step - loss: 0.1921 -
accuracy: 0.9180 - val_loss: 0.2440 - val_accuracy: 0.9065
Epoch 180/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1919 -
accuracy: 0.9184 - val_loss: 0.2443 - val_accuracy: 0.9056
Epoch 181/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1918 -
accuracy: 0.9188 - val_loss: 0.2455 - val_accuracy: 0.9049
Epoch 182/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1919 -
accuracy: 0.9186 - val_loss: 0.2450 - val_accuracy: 0.9065
Epoch 183/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1919 -
accuracy: 0.9183 - val_loss: 0.2458 - val_accuracy: 0.9048
Epoch 184/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.1916 -
accuracy: 0.9183 - val_loss: 0.2458 - val_accuracy: 0.9051
Epoch 185/200
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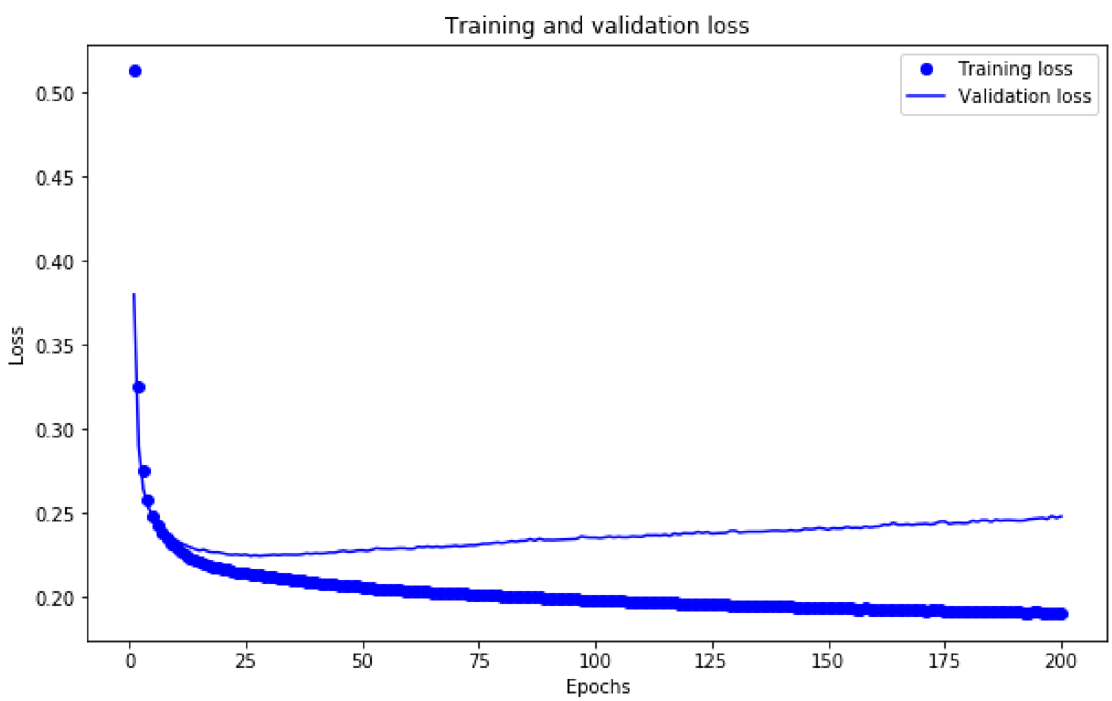
22014/22014 [==============================] - 0s 12us/step - loss: 0.1915 -
accuracy: 0.9199 - val_loss: 0.2449 - val_accuracy: 0.9081
Epoch 186/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1916 -
accuracy: 0.9186 - val_loss: 0.2461 - val_accuracy: 0.9040
Epoch 187/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1914 -
accuracy: 0.9185 - val_loss: 0.2455 - val_accuracy: 0.9063
Epoch 188/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1915 -
accuracy: 0.9186 - val_loss: 0.2459 - val_accuracy: 0.9053
Epoch 189/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1915 -
accuracy: 0.9195 - val_loss: 0.2459 - val_accuracy: 0.9075
Epoch 190/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1915 -
accuracy: 0.9187 - val_loss: 0.2457 - val_accuracy: 0.9055
Epoch 191/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1912 -
accuracy: 0.9188 - val_loss: 0.2455 - val_accuracy: 0.9069
Epoch 192/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1911 -
accuracy: 0.9184 - val_loss: 0.2456 - val_accuracy: 0.9064
Epoch 193/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1911 -
accuracy: 0.9189 - val_loss: 0.2463 - val_accuracy: 0.9063
Epoch 194/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1912 -
accuracy: 0.9191 - val_loss: 0.2466 - val_accuracy: 0.9061
Epoch 195/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1913 -
accuracy: 0.9187 - val_loss: 0.2471 - val_accuracy: 0.9051
Epoch 196/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1910 -
accuracy: 0.9191 - val_loss: 0.2472 - val_accuracy: 0.9044
Epoch 197/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1909 -
accuracy: 0.9194 - val_loss: 0.2464 - val_accuracy: 0.9063
Epoch 198/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1907 -
accuracy: 0.9186 - val_loss: 0.2484 - val_accuracy: 0.9031
Epoch 199/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1909 -
accuracy: 0.9192 - val_loss: 0.2471 - val_accuracy: 0.9048
Epoch 200/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1906 -
accuracy: 0.9186 - val_loss: 0.2481 - val_accuracy: 0.9036
```

Now, we can plot the results of loss values from the training and validation set.

[27]:
```
# plot the results of loss values from the training set and validtion set
history_dict = history.history
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']

epochs = range(1, len(history_dict['accuracy']) + 1)

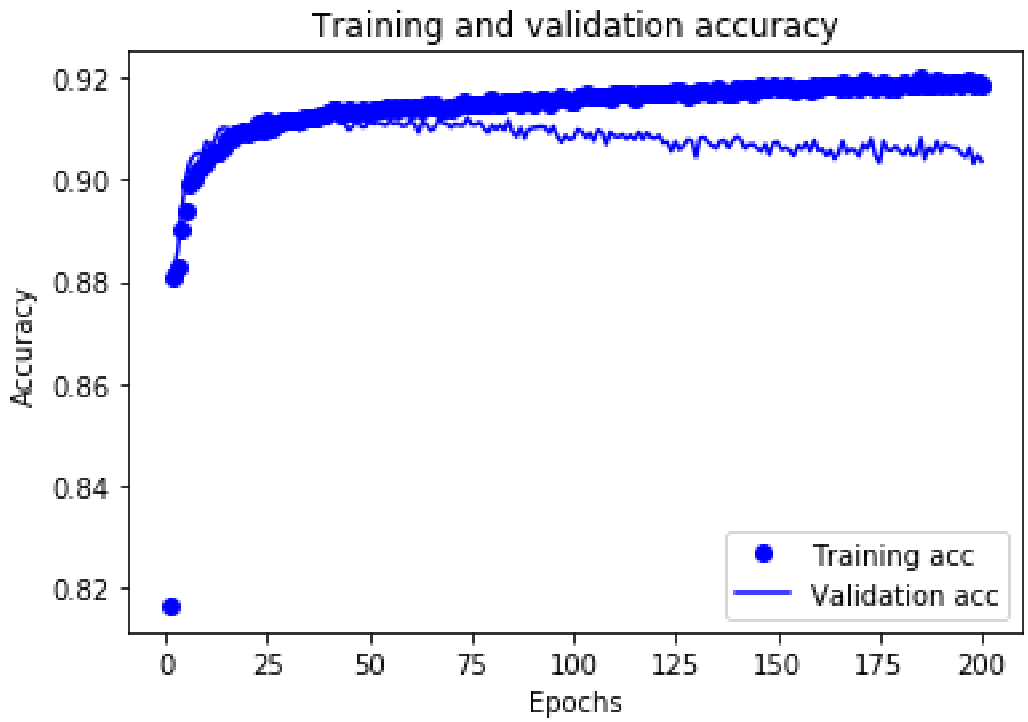
plt.figure(figsize=(10,6))
plt.plot(epochs, loss_values, 'bo', label='Training loss')
plt.plot(epochs, val_loss_values, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



Now, we can plot the results of accuracy from the training and validation set.

[28]:
```
# plot the results of accuracy from the training set and validtion set
acc = history_dict['accuracy']
val_acc = history_dict['val_accuracy']
plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
```

```
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



[29]:
```
# Compute the confusion matrix
y_preds = model.predict(X_valid)
y_preds = (y_preds>0.5).astype(int)
print('confusion matrix')
print(sklearn.metrics.confusion_matrix(y_valid,y_preds))

# Compute accuracy
print('accuracy = '+ str(sklearn.metrics.accuracy_score(y_valid,y_preds)))


# Compute Precision
print('precision = '+str(sklearn.metrics.precision_score(y_valid,y_preds)))

# Compute Recall
print('recall = '+ str(sklearn.metrics.recall_score(y_valid,y_preds)))

# Compute F1 score
```

```
print('F1 score = '+ str(sklearn.metrics.f1_score(y_valid,y_preds)))
```

```
confusion matrix
[[6387  227]
 [ 496  390]]
accuracy = 0.9036
precision = 0.6320907617504052
recall = 0.4401805869074492
F1 score = 0.5189620758483035
```

This simple works well in our training set and validation set(with accuracy about 0.9).

However, this model didn't perform well on our test set. When I used all the training data to train this model, the public score of this model is about 0.62. Why this happened? Well, I think the reason is about our imbalanced data, there are too many 0s in 'Target'. As a result, our model prefer to give us many 0s, which leads to our fail on testing dataset.

Now, in order to deal with the issue of imbalanced dataset, I use a weighted model.

2.3 Calculate class_weights.

[30]:
```
# Calculate class weight
NotOver50k, Over50k = np.bincount(train_data.Target)
total_count = len(train_data.Target)

weight_no_over50k = (1/NotOver50k)*(total_count)/2.0
weight_over50k = (1/Over50k)*(total_count)/2.0

class_weights = {0:weight_no_over50k, 1:weight_over50k}
```

Now, we can use class_weights as an argument when we construct our second NN model.

DL model draft:

3 hidden layers in this model.

The first hidden layer: 16 units with 'relu' activation function.

The second hidden layer: 16 units with 'relu' activation function.

The third hidden layer: 1 unit with 'sigmoid' activation function.

I choose the 'rmsprop' optimizer, 'binary_crossentropy' loss function, and the 'accuracy' metrics.

parameter initialization:

I use 200 epochs to train my model. The batch_size of my model is 512.

parameter tuning:

Because I think this model did well in my training dataset, I didn't tune it's parameters.

Now, let's construct our second NN model.

[31]:

```python
# Use weighted model!
model = models.Sequential()
model.add(layers.Dense(16, activation='relu'))
model.add(layers.Dense(16, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))

model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['accuracy'])

history = model.fit(partial_X_train,
                    partial_y_train,
                    epochs=200,
                    batch_size=512,
                    validation_data=(X_valid, y_valid),
                    class_weight=class_weights)
```

```
Train on 22014 samples, validate on 7500 samples
Epoch 1/200
22014/22014 [==============================] - 0s 16us/step - loss: 0.6550 -
accuracy: 0.8089 - val_loss: 0.4914 - val_accuracy: 0.7552
Epoch 2/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.5194 -
accuracy: 0.7345 - val_loss: 0.4661 - val_accuracy: 0.7255
Epoch 3/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.4516 -
accuracy: 0.7318 - val_loss: 0.4607 - val_accuracy: 0.7333
Epoch 4/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.4220 -
accuracy: 0.7471 - val_loss: 0.4470 - val_accuracy: 0.7511
Epoch 5/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.4066 -
accuracy: 0.7619 - val_loss: 0.4354 - val_accuracy: 0.7620
Epoch 6/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3976 -
accuracy: 0.7724 - val_loss: 0.4339 - val_accuracy: 0.7659
Epoch 7/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3907 -
accuracy: 0.7757 - val_loss: 0.4171 - val_accuracy: 0.7769
Epoch 8/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3855 -
accuracy: 0.7799 - val_loss: 0.4110 - val_accuracy: 0.7816
Epoch 9/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3819 -
accuracy: 0.7835 - val_loss: 0.4212 - val_accuracy: 0.7739
Epoch 10/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3786 -
```

```
accuracy: 0.7831 - val_loss: 0.4191 - val_accuracy: 0.7753
Epoch 11/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3756 -
accuracy: 0.7864 - val_loss: 0.4191 - val_accuracy: 0.7756
Epoch 12/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3731 -
accuracy: 0.7875 - val_loss: 0.4078 - val_accuracy: 0.7807
Epoch 13/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3713 -
accuracy: 0.7871 - val_loss: 0.3982 - val_accuracy: 0.7869
Epoch 14/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3694 -
accuracy: 0.7893 - val_loss: 0.4198 - val_accuracy: 0.7743
Epoch 15/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3681 -
accuracy: 0.7882 - val_loss: 0.4114 - val_accuracy: 0.7789
Epoch 16/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3663 -
accuracy: 0.7906 - val_loss: 0.4115 - val_accuracy: 0.7780
Epoch 17/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3651 -
accuracy: 0.7897 - val_loss: 0.3990 - val_accuracy: 0.7843
Epoch 18/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.3638 -
accuracy: 0.7922 - val_loss: 0.4100 - val_accuracy: 0.7785
Epoch 19/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3628 -
accuracy: 0.7916 - val_loss: 0.4039 - val_accuracy: 0.7816
Epoch 20/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3615 -
accuracy: 0.7936 - val_loss: 0.4109 - val_accuracy: 0.7772
Epoch 21/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3609 -
accuracy: 0.7896 - val_loss: 0.4091 - val_accuracy: 0.7797
Epoch 22/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3596 -
accuracy: 0.7922 - val_loss: 0.4000 - val_accuracy: 0.7841
Epoch 23/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3590 -
accuracy: 0.7944 - val_loss: 0.4100 - val_accuracy: 0.7792
Epoch 24/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.3576 -
accuracy: 0.7953 - val_loss: 0.4030 - val_accuracy: 0.7833
Epoch 25/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3576 -
accuracy: 0.7947 - val_loss: 0.4005 - val_accuracy: 0.7831
Epoch 26/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.3563 -
```

```
accuracy: 0.7952 - val_loss: 0.3999 - val_accuracy: 0.7856
Epoch 27/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3559 -
accuracy: 0.7993 - val_loss: 0.4185 - val_accuracy: 0.7755
Epoch 28/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3553 -
accuracy: 0.7966 - val_loss: 0.4142 - val_accuracy: 0.7775
Epoch 29/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3543 -
accuracy: 0.7958 - val_loss: 0.4016 - val_accuracy: 0.7839
Epoch 30/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3537 -
accuracy: 0.7970 - val_loss: 0.3986 - val_accuracy: 0.7864
Epoch 31/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3533 -
accuracy: 0.7991 - val_loss: 0.4134 - val_accuracy: 0.7781
Epoch 32/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3526 -
accuracy: 0.7962 - val_loss: 0.3999 - val_accuracy: 0.7865
Epoch 33/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3519 -
accuracy: 0.7984 - val_loss: 0.3960 - val_accuracy: 0.7885
Epoch 34/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3516 -
accuracy: 0.7980 - val_loss: 0.3900 - val_accuracy: 0.7936
Epoch 35/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3506 -
accuracy: 0.8002 - val_loss: 0.4058 - val_accuracy: 0.7836
Epoch 36/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3504 -
accuracy: 0.8009 - val_loss: 0.4082 - val_accuracy: 0.7817
Epoch 37/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3498 -
accuracy: 0.7986 - val_loss: 0.3945 - val_accuracy: 0.7880
Epoch 38/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3493 -
accuracy: 0.7999 - val_loss: 0.3952 - val_accuracy: 0.7899
Epoch 39/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3488 -
accuracy: 0.8007 - val_loss: 0.3980 - val_accuracy: 0.7887
Epoch 40/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3482 -
accuracy: 0.7989 - val_loss: 0.3957 - val_accuracy: 0.7896
Epoch 41/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3474 -
accuracy: 0.8039 - val_loss: 0.4071 - val_accuracy: 0.7832
Epoch 42/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3473 -
```

```
accuracy: 0.8014 - val_loss: 0.3987 - val_accuracy: 0.7872
Epoch 43/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3467 -
accuracy: 0.8018 - val_loss: 0.3944 - val_accuracy: 0.7900
Epoch 44/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3465 -
accuracy: 0.8012 - val_loss: 0.3842 - val_accuracy: 0.7983
Epoch 45/200
22014/22014 [==============================] - 0s 18us/step - loss: 0.3460 -
accuracy: 0.8046 - val_loss: 0.4052 - val_accuracy: 0.7829
Epoch 46/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3455 -
accuracy: 0.8042 - val_loss: 0.4120 - val_accuracy: 0.7801
Epoch 47/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3449 -
accuracy: 0.8023 - val_loss: 0.4007 - val_accuracy: 0.7856
Epoch 48/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3444 -
accuracy: 0.8019 - val_loss: 0.3967 - val_accuracy: 0.7897
Epoch 49/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.3442 -
accuracy: 0.8017 - val_loss: 0.3938 - val_accuracy: 0.7913
Epoch 50/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3439 -
accuracy: 0.8049 - val_loss: 0.4079 - val_accuracy: 0.7831
Epoch 51/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3432 -
accuracy: 0.8039 - val_loss: 0.3904 - val_accuracy: 0.7936
Epoch 52/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3430 -
accuracy: 0.8048 - val_loss: 0.4065 - val_accuracy: 0.7857
Epoch 53/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3421 -
accuracy: 0.8026 - val_loss: 0.3872 - val_accuracy: 0.7956
Epoch 54/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3420 -
accuracy: 0.8063 - val_loss: 0.4032 - val_accuracy: 0.7879
Epoch 55/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3415 -
accuracy: 0.8054 - val_loss: 0.3986 - val_accuracy: 0.7907
Epoch 56/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3413 -
accuracy: 0.8057 - val_loss: 0.4005 - val_accuracy: 0.7889
Epoch 57/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3407 -
accuracy: 0.8062 - val_loss: 0.4029 - val_accuracy: 0.7867
Epoch 58/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3408 -
```

```
accuracy: 0.8051 - val_loss: 0.4051 - val_accuracy: 0.7839
Epoch 59/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3401 -
accuracy: 0.8052 - val_loss: 0.3944 - val_accuracy: 0.7931
Epoch 60/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3396 -
accuracy: 0.8077 - val_loss: 0.4052 - val_accuracy: 0.7840
Epoch 61/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3395 -
accuracy: 0.8052 - val_loss: 0.4119 - val_accuracy: 0.7820
Epoch 62/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.3388 -
accuracy: 0.8052 - val_loss: 0.4006 - val_accuracy: 0.7884
Epoch 63/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3384 -
accuracy: 0.8061 - val_loss: 0.3915 - val_accuracy: 0.7931
Epoch 64/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3380 -
accuracy: 0.8083 - val_loss: 0.4047 - val_accuracy: 0.7857
Epoch 65/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3377 -
accuracy: 0.8053 - val_loss: 0.3823 - val_accuracy: 0.8013
Epoch 66/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3376 -
accuracy: 0.8088 - val_loss: 0.4070 - val_accuracy: 0.7860
Epoch 67/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3368 -
accuracy: 0.8075 - val_loss: 0.4043 - val_accuracy: 0.7876
Epoch 68/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3365 -
accuracy: 0.8078 - val_loss: 0.4039 - val_accuracy: 0.7879
Epoch 69/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3364 -
accuracy: 0.8072 - val_loss: 0.3977 - val_accuracy: 0.7931
Epoch 70/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3358 -
accuracy: 0.8084 - val_loss: 0.4024 - val_accuracy: 0.7897
Epoch 71/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3360 -
accuracy: 0.8081 - val_loss: 0.4054 - val_accuracy: 0.7868
Epoch 72/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3352 -
accuracy: 0.8069 - val_loss: 0.3952 - val_accuracy: 0.7937
Epoch 73/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3347 -
accuracy: 0.8081 - val_loss: 0.3858 - val_accuracy: 0.7981
Epoch 74/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3343 -
```

```
accuracy: 0.8096 - val_loss: 0.4037 - val_accuracy: 0.7861
Epoch 75/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3343 -
accuracy: 0.8068 - val_loss: 0.3986 - val_accuracy: 0.7915
Epoch 76/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3335 -
accuracy: 0.8094 - val_loss: 0.4111 - val_accuracy: 0.7845
Epoch 77/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3334 -
accuracy: 0.8068 - val_loss: 0.3916 - val_accuracy: 0.7952
Epoch 78/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3326 -
accuracy: 0.8110 - val_loss: 0.4088 - val_accuracy: 0.7863
Epoch 79/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3326 -
accuracy: 0.8060 - val_loss: 0.3920 - val_accuracy: 0.7969
Epoch 80/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3324 -
accuracy: 0.8086 - val_loss: 0.3993 - val_accuracy: 0.7935
Epoch 81/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.3324 -
accuracy: 0.8088 - val_loss: 0.4025 - val_accuracy: 0.7879
Epoch 82/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3315 -
accuracy: 0.8083 - val_loss: 0.3968 - val_accuracy: 0.7944
Epoch 83/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3316 -
accuracy: 0.8095 - val_loss: 0.4062 - val_accuracy: 0.7893
Epoch 84/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3310 -
accuracy: 0.8078 - val_loss: 0.3961 - val_accuracy: 0.7956
Epoch 85/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3310 -
accuracy: 0.8098 - val_loss: 0.3987 - val_accuracy: 0.7923
Epoch 86/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3304 -
accuracy: 0.8072 - val_loss: 0.3921 - val_accuracy: 0.7979
Epoch 87/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3303 -
accuracy: 0.8110 - val_loss: 0.4142 - val_accuracy: 0.7848
Epoch 88/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3300 -
accuracy: 0.8099 - val_loss: 0.4058 - val_accuracy: 0.7903
Epoch 89/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.3295 -
accuracy: 0.8091 - val_loss: 0.3999 - val_accuracy: 0.7931
Epoch 90/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3292 -
```

```
accuracy: 0.8110 - val_loss: 0.4013 - val_accuracy: 0.7927
Epoch 91/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.3289 -
accuracy: 0.8111 - val_loss: 0.4161 - val_accuracy: 0.7849
Epoch 92/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3282 -
accuracy: 0.8104 - val_loss: 0.4028 - val_accuracy: 0.7937
Epoch 93/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3284 -
accuracy: 0.8112 - val_loss: 0.4068 - val_accuracy: 0.7896
Epoch 94/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3282 -
accuracy: 0.8094 - val_loss: 0.3902 - val_accuracy: 0.7984
Epoch 95/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3277 -
accuracy: 0.8121 - val_loss: 0.4110 - val_accuracy: 0.7876
Epoch 96/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3277 -
accuracy: 0.8108 - val_loss: 0.4133 - val_accuracy: 0.7859
Epoch 97/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.3275 -
accuracy: 0.8113 - val_loss: 0.4113 - val_accuracy: 0.7888
Epoch 98/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3270 -
accuracy: 0.8103 - val_loss: 0.4127 - val_accuracy: 0.7871
Epoch 99/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3264 -
accuracy: 0.8124 - val_loss: 0.4098 - val_accuracy: 0.7901
Epoch 100/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3260 -
accuracy: 0.8136 - val_loss: 0.4023 - val_accuracy: 0.7944
Epoch 101/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3264 -
accuracy: 0.8113 - val_loss: 0.3934 - val_accuracy: 0.8000
Epoch 102/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3256 -
accuracy: 0.8132 - val_loss: 0.3868 - val_accuracy: 0.8056
Epoch 103/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3257 -
accuracy: 0.8141 - val_loss: 0.3949 - val_accuracy: 0.7993
Epoch 104/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3255 -
accuracy: 0.8148 - val_loss: 0.4102 - val_accuracy: 0.7907
Epoch 105/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3252 -
accuracy: 0.8131 - val_loss: 0.3996 - val_accuracy: 0.7995
Epoch 106/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3248 -
```

```
accuracy: 0.8136 - val_loss: 0.3993 - val_accuracy: 0.7995
Epoch 107/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3246 -
accuracy: 0.8157 - val_loss: 0.4027 - val_accuracy: 0.7956
Epoch 108/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3242 -
accuracy: 0.8143 - val_loss: 0.3954 - val_accuracy: 0.7996
Epoch 109/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3240 -
accuracy: 0.8147 - val_loss: 0.3947 - val_accuracy: 0.8024
Epoch 110/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3240 -
accuracy: 0.8160 - val_loss: 0.4106 - val_accuracy: 0.7893
Epoch 111/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3232 -
accuracy: 0.8162 - val_loss: 0.4055 - val_accuracy: 0.7932
Epoch 112/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3233 -
accuracy: 0.8155 - val_loss: 0.4158 - val_accuracy: 0.7885
Epoch 113/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3229 -
accuracy: 0.8154 - val_loss: 0.3977 - val_accuracy: 0.8007
Epoch 114/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3230 -
accuracy: 0.8175 - val_loss: 0.4037 - val_accuracy: 0.7948
Epoch 115/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3225 -
accuracy: 0.8161 - val_loss: 0.4099 - val_accuracy: 0.7907
Epoch 116/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3221 -
accuracy: 0.8156 - val_loss: 0.4105 - val_accuracy: 0.7921
Epoch 117/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3218 -
accuracy: 0.8172 - val_loss: 0.4048 - val_accuracy: 0.7935
Epoch 118/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3216 -
accuracy: 0.8176 - val_loss: 0.4055 - val_accuracy: 0.7940
Epoch 119/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3212 -
accuracy: 0.8154 - val_loss: 0.3920 - val_accuracy: 0.8040
Epoch 120/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.3211 -
accuracy: 0.8183 - val_loss: 0.4219 - val_accuracy: 0.7848
Epoch 121/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.3211 -
accuracy: 0.8171 - val_loss: 0.4169 - val_accuracy: 0.7884
Epoch 122/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3205 -
```

```
accuracy: 0.8157 - val_loss: 0.3883 - val_accuracy: 0.8056
Epoch 123/200
22014/22014 [==============================] - 0s 14us/step - loss: 0.3208 -
accuracy: 0.8174 - val_loss: 0.3952 - val_accuracy: 0.8025
Epoch 124/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.3203 -
accuracy: 0.8177 - val_loss: 0.4039 - val_accuracy: 0.7971
Epoch 125/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3202 -
accuracy: 0.8184 - val_loss: 0.4002 - val_accuracy: 0.7977
Epoch 126/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3202 -
accuracy: 0.8164 - val_loss: 0.4065 - val_accuracy: 0.7937
Epoch 127/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3194 -
accuracy: 0.8186 - val_loss: 0.4108 - val_accuracy: 0.7916
Epoch 128/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3195 -
accuracy: 0.8182 - val_loss: 0.4213 - val_accuracy: 0.7863
Epoch 129/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3193 -
accuracy: 0.8173 - val_loss: 0.4055 - val_accuracy: 0.7956
Epoch 130/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3192 -
accuracy: 0.8186 - val_loss: 0.4212 - val_accuracy: 0.7857
Epoch 131/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3188 -
accuracy: 0.8163 - val_loss: 0.3932 - val_accuracy: 0.8033
Epoch 132/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3185 -
accuracy: 0.8207 - val_loss: 0.4178 - val_accuracy: 0.7884
Epoch 133/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3186 -
accuracy: 0.8181 - val_loss: 0.4054 - val_accuracy: 0.7977
Epoch 134/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3184 -
accuracy: 0.8187 - val_loss: 0.4079 - val_accuracy: 0.7928
Epoch 135/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3180 -
accuracy: 0.8180 - val_loss: 0.4087 - val_accuracy: 0.7955
Epoch 136/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3179 -
accuracy: 0.8198 - val_loss: 0.4175 - val_accuracy: 0.7884
Epoch 137/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3175 -
accuracy: 0.8187 - val_loss: 0.4094 - val_accuracy: 0.7916
Epoch 138/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3171 -
```

```
accuracy: 0.8192 - val_loss: 0.4013 - val_accuracy: 0.8001
Epoch 139/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3172 -
accuracy: 0.8190 - val_loss: 0.4034 - val_accuracy: 0.7977
Epoch 140/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3167 -
accuracy: 0.8180 - val_loss: 0.3886 - val_accuracy: 0.8056
Epoch 141/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3167 -
accuracy: 0.8199 - val_loss: 0.4022 - val_accuracy: 0.7983
Epoch 142/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3164 -
accuracy: 0.8194 - val_loss: 0.4010 - val_accuracy: 0.8008
Epoch 143/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3166 -
accuracy: 0.8209 - val_loss: 0.4115 - val_accuracy: 0.7943
Epoch 144/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3158 -
accuracy: 0.8199 - val_loss: 0.4164 - val_accuracy: 0.7905
Epoch 145/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.3158 -
accuracy: 0.8169 - val_loss: 0.4018 - val_accuracy: 0.8025
Epoch 146/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3159 -
accuracy: 0.8201 - val_loss: 0.4056 - val_accuracy: 0.7960
Epoch 147/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3154 -
accuracy: 0.8211 - val_loss: 0.4081 - val_accuracy: 0.7951
Epoch 148/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3155 -
accuracy: 0.8191 - val_loss: 0.4019 - val_accuracy: 0.7991
Epoch 149/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3149 -
accuracy: 0.8203 - val_loss: 0.4086 - val_accuracy: 0.7923
Epoch 150/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3151 -
accuracy: 0.8211 - val_loss: 0.4127 - val_accuracy: 0.7909
Epoch 151/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3144 -
accuracy: 0.8202 - val_loss: 0.3916 - val_accuracy: 0.8072
Epoch 152/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3149 -
accuracy: 0.8222 - val_loss: 0.4100 - val_accuracy: 0.7949
Epoch 153/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3142 -
accuracy: 0.8214 - val_loss: 0.4152 - val_accuracy: 0.7937
Epoch 154/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.3143 -
```

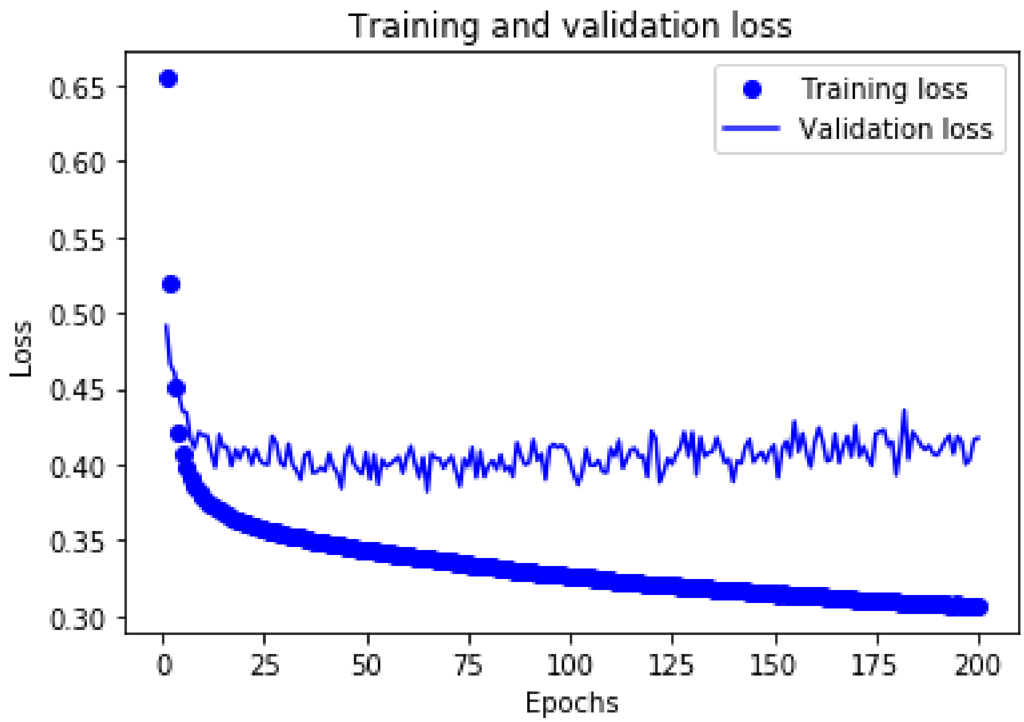
```
accuracy: 0.8218 - val_loss: 0.4051 - val_accuracy: 0.7977
Epoch 155/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3137 -
accuracy: 0.8222 - val_loss: 0.4283 - val_accuracy: 0.7869
Epoch 156/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3140 -
accuracy: 0.8202 - val_loss: 0.4084 - val_accuracy: 0.7961
Epoch 157/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3136 -
accuracy: 0.8217 - val_loss: 0.4204 - val_accuracy: 0.7911
Epoch 158/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3136 -
accuracy: 0.8213 - val_loss: 0.4075 - val_accuracy: 0.7959
Epoch 159/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3129 -
accuracy: 0.8215 - val_loss: 0.3985 - val_accuracy: 0.8001
Epoch 160/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3134 -
accuracy: 0.8210 - val_loss: 0.4149 - val_accuracy: 0.7935
Epoch 161/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3128 -
accuracy: 0.8226 - val_loss: 0.4242 - val_accuracy: 0.7879
Epoch 162/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3129 -
accuracy: 0.8213 - val_loss: 0.4148 - val_accuracy: 0.7932
Epoch 163/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3122 -
accuracy: 0.8222 - val_loss: 0.4024 - val_accuracy: 0.7993
Epoch 164/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3119 -
accuracy: 0.8226 - val_loss: 0.4034 - val_accuracy: 0.7993
Epoch 165/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3119 -
accuracy: 0.8245 - val_loss: 0.4202 - val_accuracy: 0.7903
Epoch 166/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3117 -
accuracy: 0.8218 - val_loss: 0.4012 - val_accuracy: 0.8016
Epoch 167/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3114 -
accuracy: 0.8232 - val_loss: 0.4113 - val_accuracy: 0.7980
Epoch 168/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3116 -
accuracy: 0.8229 - val_loss: 0.4187 - val_accuracy: 0.7916
Epoch 169/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3112 -
accuracy: 0.8234 - val_loss: 0.4053 - val_accuracy: 0.7985
Epoch 170/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3109 -
```

```
accuracy: 0.8240 - val_loss: 0.4260 - val_accuracy: 0.7877
Epoch 171/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3109 -
accuracy: 0.8221 - val_loss: 0.4055 - val_accuracy: 0.7969
Epoch 172/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3106 -
accuracy: 0.8235 - val_loss: 0.4119 - val_accuracy: 0.7947
Epoch 173/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3106 -
accuracy: 0.8239 - val_loss: 0.4048 - val_accuracy: 0.7983
Epoch 174/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3103 -
accuracy: 0.8234 - val_loss: 0.3993 - val_accuracy: 0.8028
Epoch 175/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3106 -
accuracy: 0.8242 - val_loss: 0.4204 - val_accuracy: 0.7933
Epoch 176/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3101 -
accuracy: 0.8234 - val_loss: 0.4214 - val_accuracy: 0.7941
Epoch 177/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3098 -
accuracy: 0.8248 - val_loss: 0.4227 - val_accuracy: 0.7936
Epoch 178/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3099 -
accuracy: 0.8237 - val_loss: 0.4124 - val_accuracy: 0.7968
Epoch 179/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3096 -
accuracy: 0.8239 - val_loss: 0.4151 - val_accuracy: 0.7941
Epoch 180/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3093 -
accuracy: 0.8226 - val_loss: 0.3931 - val_accuracy: 0.8084
Epoch 181/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3091 -
accuracy: 0.8246 - val_loss: 0.4111 - val_accuracy: 0.7981
Epoch 182/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3091 -
accuracy: 0.8248 - val_loss: 0.4359 - val_accuracy: 0.7848
Epoch 183/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3092 -
accuracy: 0.8227 - val_loss: 0.4036 - val_accuracy: 0.8012
Epoch 184/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3088 -
accuracy: 0.8244 - val_loss: 0.4213 - val_accuracy: 0.7939
Epoch 185/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3087 -
accuracy: 0.8238 - val_loss: 0.4176 - val_accuracy: 0.7927
Epoch 186/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3090 -
```

```
accuracy: 0.8242 - val_loss: 0.4126 - val_accuracy: 0.7952
Epoch 187/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3085 -
accuracy: 0.8244 - val_loss: 0.4098 - val_accuracy: 0.8005
Epoch 188/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.3087 -
accuracy: 0.8254 - val_loss: 0.4123 - val_accuracy: 0.7983
Epoch 189/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3083 -
accuracy: 0.8241 - val_loss: 0.4071 - val_accuracy: 0.8003
Epoch 190/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3081 -
accuracy: 0.8254 - val_loss: 0.4062 - val_accuracy: 0.8011
Epoch 191/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3083 -
accuracy: 0.8248 - val_loss: 0.4105 - val_accuracy: 0.7993
Epoch 192/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3077 -
accuracy: 0.8253 - val_loss: 0.4156 - val_accuracy: 0.7971
Epoch 193/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3075 -
accuracy: 0.8247 - val_loss: 0.4192 - val_accuracy: 0.7967
Epoch 194/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3074 -
accuracy: 0.8243 - val_loss: 0.4072 - val_accuracy: 0.8013
Epoch 195/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3079 -
accuracy: 0.8257 - val_loss: 0.4186 - val_accuracy: 0.7956
Epoch 196/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3072 -
accuracy: 0.8255 - val_loss: 0.4150 - val_accuracy: 0.7976
Epoch 197/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3070 -
accuracy: 0.8256 - val_loss: 0.4002 - val_accuracy: 0.8051
Epoch 198/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3068 -
accuracy: 0.8246 - val_loss: 0.4035 - val_accuracy: 0.8065
Epoch 199/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3075 -
accuracy: 0.8261 - val_loss: 0.4159 - val_accuracy: 0.7979
Epoch 200/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3070 -
accuracy: 0.8244 - val_loss: 0.4174 - val_accuracy: 0.7977
```

After constructing our weighted model, we can plot the results of loss values from the training and validation set.

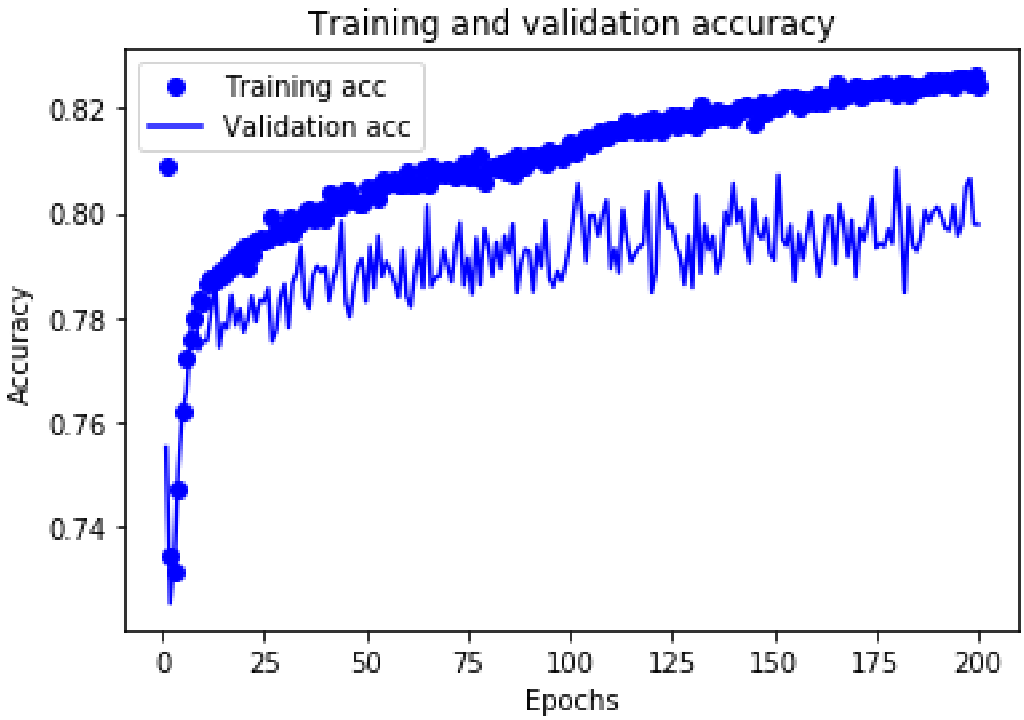
[32]:
```
# plot the results of loss values from the training set and validtion set
history_dict = history.history
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']

epochs = range(1, len(history_dict['accuracy']) + 1)

plt.plot(epochs, loss_values, 'bo', label='Training loss')
plt.plot(epochs, val_loss_values, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



Also, we can plot the results of accuracy from the training and validation set.

[33]:
```
#plt.clf()
acc = history_dict['accuracy']
val_acc = history_dict['val_accuracy']
plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
```

```
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



[34]:
```
# Compute the confusion matrix
y_preds = model.predict(X_valid)
y_preds = (y_preds>0.5).astype(int)
print('confusion matrix')
print(sklearn.metrics.confusion_matrix(y_valid,y_preds))

# Compute accuracy
print('accuracy = '+ str(sklearn.metrics.accuracy_score(y_valid,y_preds)))


# Compute Precision
print('precision = '+str(sklearn.metrics.precision_score(y_valid,y_preds)))

# Compute Recall
print('recall = '+ str(sklearn.metrics.recall_score(y_valid,y_preds)))

# Compute F1 score
print('F1 score = '+ str(sklearn.metrics.f1_score(y_valid,y_preds)))
```

```
confusion matrix
```

```
[[5254 1360]
 [ 157  729]]
accuracy = 0.7977333333333333
precision = 0.3489707994255625
recall = 0.8227990970654627
F1 score = 0.4900840336134454
```

When I used all the training data to train this model, the public score of this model is about 0.83 (the private score is also about 0.82). By using weighted model, we successfully overcome the problem of imbalanced training dataset.

Now, we should try to improve our performance in training data.

Let's add two layers and units.

(After we get great performance in training data, we should deal with the overfitting problem.)

[41]:
```
model = models.Sequential()
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))

model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['accuracy'])

history = model.fit(partial_X_train,
                    partial_y_train,
                    epochs=200,
                    batch_size=512,
                    validation_data=(X_valid, y_valid),
                    class_weight=class_weights)

# plot the results of loss values from the training set and validtion set
history_dict = history.history
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']

epochs = range(1, len(history_dict['accuracy']) + 1)

plt.plot(epochs, loss_values, 'bo', label='Training loss')
plt.plot(epochs, val_loss_values, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
```

```python
plt.legend()
plt.show()

#plt.clf()
acc = history_dict['accuracy']
val_acc = history_dict['val_accuracy']
plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Compute the confusion matrix
y_preds = model.predict(X_valid)
y_preds = (y_preds>0.5).astype(int)
print('confusion matrix')
print(sklearn.metrics.confusion_matrix(y_valid,y_preds))

# Compute accuracy
print('accuracy = '+ str(sklearn.metrics.accuracy_score(y_valid,y_preds)))


# Compute Precision
print('precision = '+str(sklearn.metrics.precision_score(y_valid,y_preds)))

# Compute Recall
print('recall = '+ str(sklearn.metrics.recall_score(y_valid,y_preds)))

# Compute F1 score
print('F1 score = '+ str(sklearn.metrics.f1_score(y_valid,y_preds)))
```

```
Train on 22014 samples, validate on 7500 samples
Epoch 1/200
22014/22014 [==============================] - 1s 31us/step - loss: 0.4784 -
accuracy: 0.7330 - val_loss: 0.4848 - val_accuracy: 0.7391
Epoch 2/200
22014/22014 [==============================] - 1s 26us/step - loss: 0.4038 -
accuracy: 0.7715 - val_loss: 0.3936 - val_accuracy: 0.7897
Epoch 3/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.3876 -
accuracy: 0.7810 - val_loss: 0.3727 - val_accuracy: 0.7991
Epoch 4/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.3715 -
accuracy: 0.7885 - val_loss: 0.3757 - val_accuracy: 0.7913
Epoch 5/200
```

```
22014/22014 [==============================] - 0s 18us/step - loss: 0.3641 -
accuracy: 0.7884 - val_loss: 0.4322 - val_accuracy: 0.7645
Epoch 6/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.3581 -
accuracy: 0.7913 - val_loss: 0.3333 - val_accuracy: 0.8220
Epoch 7/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.3519 -
accuracy: 0.7928 - val_loss: 0.4256 - val_accuracy: 0.7648
Epoch 8/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.3440 -
accuracy: 0.7949 - val_loss: 0.3811 - val_accuracy: 0.7937
Epoch 9/200
22014/22014 [==============================] - 1s 24us/step - loss: 0.3395 -
accuracy: 0.8036 - val_loss: 0.4546 - val_accuracy: 0.7427
Epoch 10/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.3365 -
accuracy: 0.7998 - val_loss: 0.3892 - val_accuracy: 0.7851
Epoch 11/200
22014/22014 [==============================] - 1s 26us/step - loss: 0.3296 -
accuracy: 0.8037 - val_loss: 0.3675 - val_accuracy: 0.8017
Epoch 12/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.3257 -
accuracy: 0.8037 - val_loss: 0.3606 - val_accuracy: 0.8241
Epoch 13/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.3207 -
accuracy: 0.8123 - val_loss: 0.4424 - val_accuracy: 0.7829
Epoch 14/200
22014/22014 [==============================] - 0s 18us/step - loss: 0.3180 -
accuracy: 0.8108 - val_loss: 0.3670 - val_accuracy: 0.8133
Epoch 15/200
22014/22014 [==============================] - 1s 27us/step - loss: 0.3115 -
accuracy: 0.8142 - val_loss: 0.3409 - val_accuracy: 0.8384
Epoch 16/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.3076 -
accuracy: 0.8145 - val_loss: 0.5024 - val_accuracy: 0.7363
Epoch 17/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.3045 -
accuracy: 0.8230 - val_loss: 0.4379 - val_accuracy: 0.7637
Epoch 18/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.3011 -
accuracy: 0.8187 - val_loss: 0.4581 - val_accuracy: 0.7823
Epoch 19/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.2957 -
accuracy: 0.8220 - val_loss: 0.4728 - val_accuracy: 0.7664
Epoch 20/200
22014/22014 [==============================] - 1s 31us/step - loss: 0.2962 -
accuracy: 0.8203 - val_loss: 0.4315 - val_accuracy: 0.8041
Epoch 21/200
```

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22014/22014 [==============================] - 1s 25us/step - loss: 0.2912 -
accuracy: 0.8262 - val_loss: 0.4079 - val_accuracy: 0.8025
Epoch 22/200
22014/22014 [==============================] - 1s 27us/step - loss: 0.2871 -
accuracy: 0.8289 - val_loss: 0.4407 - val_accuracy: 0.7860
Epoch 23/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2864 -
accuracy: 0.8289 - val_loss: 0.4557 - val_accuracy: 0.7925
Epoch 24/200
22014/22014 [==============================] - 1s 25us/step - loss: 0.2802 -
accuracy: 0.8337 - val_loss: 0.4789 - val_accuracy: 0.7832
Epoch 25/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.2800 -
accuracy: 0.8337 - val_loss: 0.4538 - val_accuracy: 0.7949
Epoch 26/200
22014/22014 [==============================] - 1s 25us/step - loss: 0.2801 -
accuracy: 0.8272 - val_loss: 0.4999 - val_accuracy: 0.7708
Epoch 27/200
22014/22014 [==============================] - 0s 18us/step - loss: 0.2751 -
accuracy: 0.8317 - val_loss: 0.4437 - val_accuracy: 0.8085
Epoch 28/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2727 -
accuracy: 0.8372 - val_loss: 0.3851 - val_accuracy: 0.8060
Epoch 29/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2691 -
accuracy: 0.8370 - val_loss: 0.4437 - val_accuracy: 0.8103
Epoch 30/200
22014/22014 [==============================] - 0s 23us/step - loss: 0.2691 -
accuracy: 0.8382 - val_loss: 0.4539 - val_accuracy: 0.8259
Epoch 31/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.2701 -
accuracy: 0.8358 - val_loss: 0.4987 - val_accuracy: 0.7907
Epoch 32/200
22014/22014 [==============================] - 0s 18us/step - loss: 0.2643 -
accuracy: 0.8401 - val_loss: 0.5038 - val_accuracy: 0.7956
Epoch 33/200
22014/22014 [==============================] - 1s 27us/step - loss: 0.2604 -
accuracy: 0.8417 - val_loss: 0.5550 - val_accuracy: 0.7684
Epoch 34/200
22014/22014 [==============================] - 0s 18us/step - loss: 0.2609 -
accuracy: 0.8373 - val_loss: 0.4585 - val_accuracy: 0.7945
Epoch 35/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.2572 -
accuracy: 0.8396 - val_loss: 0.4660 - val_accuracy: 0.8284
Epoch 36/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.2561 -
accuracy: 0.8422 - val_loss: 0.5567 - val_accuracy: 0.7745
Epoch 37/200
```

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22014/22014 [==============================] - 0s 22us/step - loss: 0.2610 -
accuracy: 0.8407 - val_loss: 0.4992 - val_accuracy: 0.8092
Epoch 38/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.2540 -
accuracy: 0.8412 - val_loss: 0.5585 - val_accuracy: 0.7457
Epoch 39/200
22014/22014 [==============================] - 1s 28us/step - loss: 0.2557 -
accuracy: 0.8377 - val_loss: 0.5159 - val_accuracy: 0.8053
Epoch 40/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.2466 -
accuracy: 0.8441 - val_loss: 0.5017 - val_accuracy: 0.8120
Epoch 41/200
22014/22014 [==============================] - 1s 28us/step - loss: 0.2543 -
accuracy: 0.8434 - val_loss: 0.5718 - val_accuracy: 0.7164
Epoch 42/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.2439 -
accuracy: 0.8463 - val_loss: 0.5459 - val_accuracy: 0.8123
Epoch 43/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.2458 -
accuracy: 0.8433 - val_loss: 0.5167 - val_accuracy: 0.7988
Epoch 44/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.2512 -
accuracy: 0.8440 - val_loss: 0.5358 - val_accuracy: 0.7977
Epoch 45/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.2386 -
accuracy: 0.8444 - val_loss: 0.5027 - val_accuracy: 0.8273
Epoch 46/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2386 -
accuracy: 0.8482 - val_loss: 0.6107 - val_accuracy: 0.8060
Epoch 47/200
22014/22014 [==============================] - 0s 18us/step - loss: 0.2428 -
accuracy: 0.8425 - val_loss: 0.5180 - val_accuracy: 0.8385
Epoch 48/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.2438 -
accuracy: 0.8463 - val_loss: 0.5627 - val_accuracy: 0.8253
Epoch 49/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.2403 -
accuracy: 0.8505 - val_loss: 0.5544 - val_accuracy: 0.7911
Epoch 50/200
22014/22014 [==============================] - 1s 24us/step - loss: 0.2322 -
accuracy: 0.8517 - val_loss: 0.6342 - val_accuracy: 0.7479
Epoch 51/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.2353 -
accuracy: 0.8520 - val_loss: 0.5482 - val_accuracy: 0.8179
Epoch 52/200
22014/22014 [==============================] - 1s 24us/step - loss: 0.2387 -
accuracy: 0.8496 - val_loss: 0.5543 - val_accuracy: 0.8064
Epoch 53/200
```

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22014/22014 [==============================] - 0s 19us/step - loss: 0.2352 -
accuracy: 0.8529 - val_loss: 0.5451 - val_accuracy: 0.8051
Epoch 54/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2391 -
accuracy: 0.8491 - val_loss: 0.4896 - val_accuracy: 0.7828
Epoch 55/200
22014/22014 [==============================] - 0s 18us/step - loss: 0.2328 -
accuracy: 0.8506 - val_loss: 0.5507 - val_accuracy: 0.8023
Epoch 56/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.2304 -
accuracy: 0.8495 - val_loss: 0.6483 - val_accuracy: 0.8071
Epoch 57/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.2286 -
accuracy: 0.8519 - val_loss: 0.5910 - val_accuracy: 0.8007
Epoch 58/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.2267 -
accuracy: 0.8515 - val_loss: 0.5778 - val_accuracy: 0.8279
Epoch 59/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2276 -
accuracy: 0.8567 - val_loss: 0.5555 - val_accuracy: 0.8185
Epoch 60/200
22014/22014 [==============================] - 1s 25us/step - loss: 0.2304 -
accuracy: 0.8525 - val_loss: 0.5807 - val_accuracy: 0.7692
Epoch 61/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.2193 -
accuracy: 0.8619 - val_loss: 0.6509 - val_accuracy: 0.8292
Epoch 62/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2357 -
accuracy: 0.8563 - val_loss: 0.6189 - val_accuracy: 0.7835
Epoch 63/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.2267 -
accuracy: 0.8579 - val_loss: 0.6743 - val_accuracy: 0.7991
Epoch 64/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.2245 -
accuracy: 0.8557 - val_loss: 0.6307 - val_accuracy: 0.8015
Epoch 65/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2270 -
accuracy: 0.8511 - val_loss: 0.6844 - val_accuracy: 0.8065
Epoch 66/200
22014/22014 [==============================] - 1s 24us/step - loss: 0.2176 -
accuracy: 0.8593 - val_loss: 0.6401 - val_accuracy: 0.8216
Epoch 67/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.2214 -
accuracy: 0.8601 - val_loss: 0.7039 - val_accuracy: 0.7751
Epoch 68/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.2210 -
accuracy: 0.8613 - val_loss: 0.6935 - val_accuracy: 0.7779
Epoch 69/200
```

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22014/22014 [==============================] - 0s 21us/step - loss: 0.2178 -
accuracy: 0.8609 - val_loss: 0.7528 - val_accuracy: 0.7229
Epoch 70/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.2215 -
accuracy: 0.8595 - val_loss: 0.5657 - val_accuracy: 0.7969
Epoch 71/200
22014/22014 [==============================] - 1s 27us/step - loss: 0.2206 -
accuracy: 0.8594 - val_loss: 0.5951 - val_accuracy: 0.7997
Epoch 72/200
22014/22014 [==============================] - 1s 25us/step - loss: 0.2216 -
accuracy: 0.8623 - val_loss: 0.6047 - val_accuracy: 0.7903
Epoch 73/200
22014/22014 [==============================] - 1s 25us/step - loss: 0.2146 -
accuracy: 0.8616 - val_loss: 0.6306 - val_accuracy: 0.8017
Epoch 74/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.2195 -
accuracy: 0.8601 - val_loss: 0.5957 - val_accuracy: 0.8221
Epoch 75/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2167 -
accuracy: 0.8642 - val_loss: 0.7052 - val_accuracy: 0.8208
Epoch 76/200
22014/22014 [==============================] - 0s 23us/step - loss: 0.2168 -
accuracy: 0.8600 - val_loss: 0.6169 - val_accuracy: 0.8087
Epoch 77/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2114 -
accuracy: 0.8638 - val_loss: 0.5551 - val_accuracy: 0.7921
Epoch 78/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.2152 -
accuracy: 0.8636 - val_loss: 0.7109 - val_accuracy: 0.8297
Epoch 79/200
22014/22014 [==============================] - 1s 27us/step - loss: 0.2141 -
accuracy: 0.8679 - val_loss: 0.7735 - val_accuracy: 0.8276
Epoch 80/200
22014/22014 [==============================] - 1s 27us/step - loss: 0.2160 -
accuracy: 0.8630 - val_loss: 0.6073 - val_accuracy: 0.7808
Epoch 81/200
22014/22014 [==============================] - 1s 25us/step - loss: 0.2120 -
accuracy: 0.8649 - val_loss: 0.6369 - val_accuracy: 0.8161
Epoch 82/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.2099 -
accuracy: 0.8645 - val_loss: 0.6713 - val_accuracy: 0.7936
Epoch 83/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2134 -
accuracy: 0.8696 - val_loss: 0.6212 - val_accuracy: 0.8279
Epoch 84/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.2077 -
accuracy: 0.8704 - val_loss: 0.7087 - val_accuracy: 0.7571
Epoch 85/200
```

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22014/22014 [==============================] - 0s 19us/step - loss: 0.2115 -
accuracy: 0.8678 - val_loss: 0.6853 - val_accuracy: 0.8177
Epoch 86/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.2073 -
accuracy: 0.8709 - val_loss: 0.7718 - val_accuracy: 0.8261
Epoch 87/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.2104 -
accuracy: 0.8706 - val_loss: 0.7053 - val_accuracy: 0.8185
Epoch 88/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.2035 -
accuracy: 0.8686 - val_loss: 0.7563 - val_accuracy: 0.8111
Epoch 89/200
22014/22014 [==============================] - 0s 18us/step - loss: 0.2088 -
accuracy: 0.8665 - val_loss: 0.7043 - val_accuracy: 0.8352
Epoch 90/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2019 -
accuracy: 0.8699 - val_loss: 0.7195 - val_accuracy: 0.8133
Epoch 91/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.2143 -
accuracy: 0.8728 - val_loss: 0.7261 - val_accuracy: 0.7545
Epoch 92/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1995 -
accuracy: 0.8731 - val_loss: 0.7529 - val_accuracy: 0.7733
Epoch 93/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2056 -
accuracy: 0.8699 - val_loss: 0.6976 - val_accuracy: 0.8057
Epoch 94/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.2034 -
accuracy: 0.8714 - val_loss: 0.6837 - val_accuracy: 0.8332
Epoch 95/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.2009 -
accuracy: 0.8744 - val_loss: 0.8735 - val_accuracy: 0.8055
Epoch 96/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2066 -
accuracy: 0.8690 - val_loss: 0.7801 - val_accuracy: 0.8356
Epoch 97/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1940 -
accuracy: 0.8769 - val_loss: 0.9140 - val_accuracy: 0.7484
Epoch 98/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.2116 -
accuracy: 0.8713 - val_loss: 0.8395 - val_accuracy: 0.8193
Epoch 99/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.1971 -
accuracy: 0.8753 - val_loss: 0.8201 - val_accuracy: 0.8175
Epoch 100/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.1987 -
accuracy: 0.8733 - val_loss: 0.7796 - val_accuracy: 0.8195
Epoch 101/200
```

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22014/22014 [==============================] - 0s 21us/step - loss: 0.2019 -
accuracy: 0.8755 - val_loss: 0.7396 - val_accuracy: 0.7957
Epoch 102/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.1969 -
accuracy: 0.8714 - val_loss: 0.6214 - val_accuracy: 0.8128
Epoch 103/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1928 -
accuracy: 0.8761 - val_loss: 0.8249 - val_accuracy: 0.8052
Epoch 104/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1915 -
accuracy: 0.8772 - val_loss: 0.7459 - val_accuracy: 0.7755
Epoch 105/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.2020 -
accuracy: 0.8710 - val_loss: 0.9243 - val_accuracy: 0.8268
Epoch 106/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.1946 -
accuracy: 0.8751 - val_loss: 0.9196 - val_accuracy: 0.8063
Epoch 107/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.1957 -
accuracy: 0.8737 - val_loss: 0.9394 - val_accuracy: 0.8217
Epoch 108/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.1983 -
accuracy: 0.8740 - val_loss: 0.7852 - val_accuracy: 0.8044
Epoch 109/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.1896 -
accuracy: 0.8784 - val_loss: 0.8840 - val_accuracy: 0.7992
Epoch 110/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2044 -
accuracy: 0.8760 - val_loss: 0.8405 - val_accuracy: 0.8147
Epoch 111/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1922 -
accuracy: 0.8798 - val_loss: 0.9854 - val_accuracy: 0.8089
Epoch 112/200
22014/22014 [==============================] - 1s 26us/step - loss: 0.1927 -
accuracy: 0.8786 - val_loss: 0.8998 - val_accuracy: 0.8213
Epoch 113/200
22014/22014 [==============================] - 1s 30us/step - loss: 0.1885 -
accuracy: 0.8800 - val_loss: 0.8995 - val_accuracy: 0.8147
Epoch 114/200
22014/22014 [==============================] - 1s 28us/step - loss: 0.1980 -
accuracy: 0.8755 - val_loss: 0.8866 - val_accuracy: 0.8155
Epoch 115/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1962 -
accuracy: 0.8801 - val_loss: 0.9217 - val_accuracy: 0.7601
Epoch 116/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1903 -
accuracy: 0.8842 - val_loss: 0.8528 - val_accuracy: 0.8108
Epoch 117/200
```

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22014/22014 [==============================] - 1s 26us/step - loss: 0.1909 -
accuracy: 0.8798 - val_loss: 0.8652 - val_accuracy: 0.8376
Epoch 118/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.1976 -
accuracy: 0.8811 - val_loss: 0.7272 - val_accuracy: 0.7989
Epoch 119/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1838 -
accuracy: 0.8843 - val_loss: 1.0096 - val_accuracy: 0.8259
Epoch 120/200
22014/22014 [==============================] - 1s 24us/step - loss: 0.1986 -
accuracy: 0.8793 - val_loss: 0.9809 - val_accuracy: 0.8049
Epoch 121/200
22014/22014 [==============================] - 1s 24us/step - loss: 0.1845 -
accuracy: 0.8825 - val_loss: 0.9231 - val_accuracy: 0.8037
Epoch 122/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1879 -
accuracy: 0.8849 - val_loss: 0.8919 - val_accuracy: 0.8184
Epoch 123/200
22014/22014 [==============================] - 1s 24us/step - loss: 0.1870 -
accuracy: 0.8830 - val_loss: 0.9810 - val_accuracy: 0.8232
Epoch 124/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.1840 -
accuracy: 0.8858 - val_loss: 0.9030 - val_accuracy: 0.7996
Epoch 125/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2079 -
accuracy: 0.8774 - val_loss: 0.7612 - val_accuracy: 0.8299
Epoch 126/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1823 -
accuracy: 0.8862 - val_loss: 0.8475 - val_accuracy: 0.8197
Epoch 127/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.1936 -
accuracy: 0.8816 - val_loss: 0.8624 - val_accuracy: 0.7812
Epoch 128/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1908 -
accuracy: 0.8849 - val_loss: 0.7172 - val_accuracy: 0.8064
Epoch 129/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.1858 -
accuracy: 0.8831 - val_loss: 0.7372 - val_accuracy: 0.8227
Epoch 130/200
22014/22014 [==============================] - 0s 18us/step - loss: 0.1916 -
accuracy: 0.8816 - val_loss: 0.8725 - val_accuracy: 0.8023
Epoch 131/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.2116 -
accuracy: 0.8872 - val_loss: 0.9028 - val_accuracy: 0.8272
Epoch 132/200
22014/22014 [==============================] - 1s 24us/step - loss: 0.1779 -
accuracy: 0.8865 - val_loss: 0.8736 - val_accuracy: 0.8312
Epoch 133/200
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22014/22014 [==============================] - 1s 23us/step - loss: 0.1888 -
accuracy: 0.8859 - val_loss: 0.6364 - val_accuracy: 0.8437
Epoch 134/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.1821 -
accuracy: 0.8896 - val_loss: 0.8263 - val_accuracy: 0.8241
Epoch 135/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1830 -
accuracy: 0.8885 - val_loss: 0.8715 - val_accuracy: 0.8251
Epoch 136/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1772 -
accuracy: 0.8895 - val_loss: 1.0257 - val_accuracy: 0.8317
Epoch 137/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.1850 -
accuracy: 0.8869 - val_loss: 0.8483 - val_accuracy: 0.8131
Epoch 138/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.1839 -
accuracy: 0.8878 - val_loss: 0.9348 - val_accuracy: 0.8200
Epoch 139/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1831 -
accuracy: 0.8870 - val_loss: 0.9079 - val_accuracy: 0.8388
Epoch 140/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1762 -
accuracy: 0.8887 - val_loss: 0.9835 - val_accuracy: 0.8175
Epoch 141/200
22014/22014 [==============================] - 1s 24us/step - loss: 0.1926 -
accuracy: 0.8868 - val_loss: 0.8806 - val_accuracy: 0.8227
Epoch 142/200
22014/22014 [==============================] - 0s 23us/step - loss: 0.1961 -
accuracy: 0.8903 - val_loss: 0.8878 - val_accuracy: 0.8000
Epoch 143/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1736 -
accuracy: 0.8928 - val_loss: 0.8197 - val_accuracy: 0.7947
Epoch 144/200
22014/22014 [==============================] - 1s 24us/step - loss: 0.1823 -
accuracy: 0.8903 - val_loss: 0.7459 - val_accuracy: 0.7680
Epoch 145/200
22014/22014 [==============================] - 1s 29us/step - loss: 0.1799 -
accuracy: 0.8923 - val_loss: 0.9606 - val_accuracy: 0.8044
Epoch 146/200
22014/22014 [==============================] - 1s 25us/step - loss: 0.1803 -
accuracy: 0.8879 - val_loss: 0.8550 - val_accuracy: 0.8233
Epoch 147/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.1784 -
accuracy: 0.8903 - val_loss: 0.8576 - val_accuracy: 0.8315
Epoch 148/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.1809 -
accuracy: 0.8929 - val_loss: 0.8744 - val_accuracy: 0.8276
Epoch 149/200
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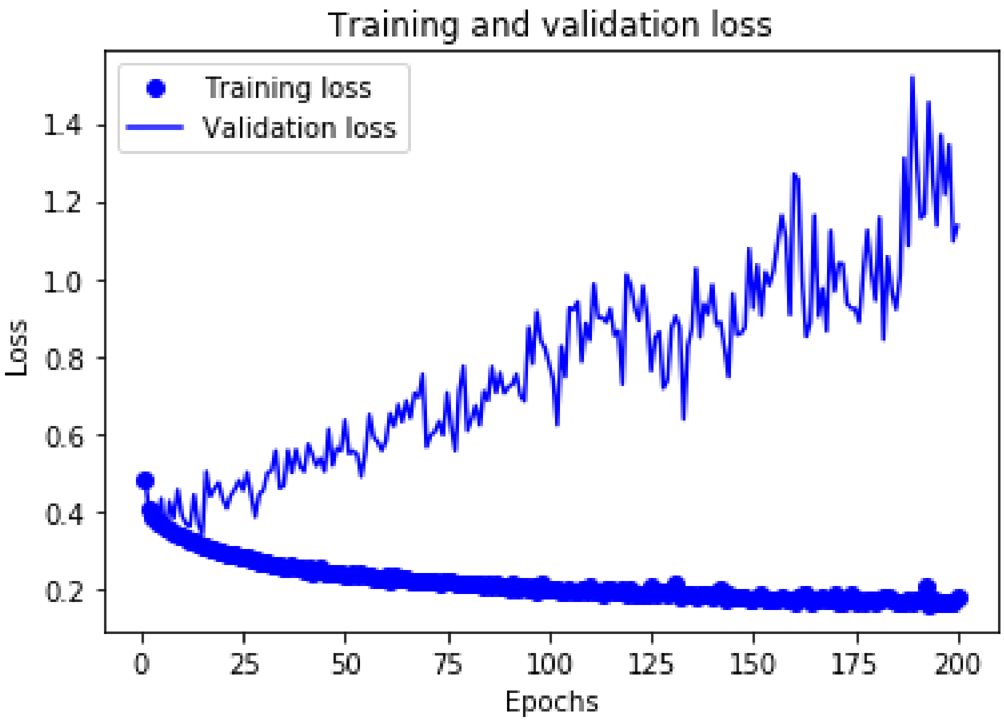
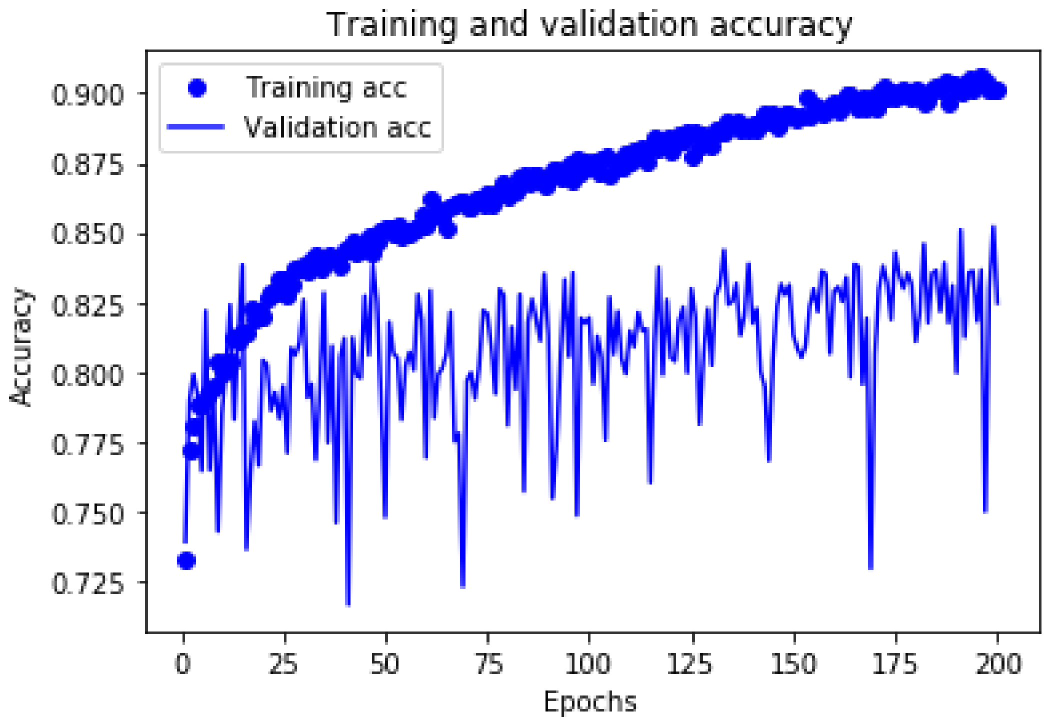
22014/22014 [==============================] - 0s 23us/step - loss: 0.1747 -
accuracy: 0.8927 - val_loss: 1.0759 - val_accuracy: 0.8312
Epoch 150/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.1747 -
accuracy: 0.8916 - val_loss: 0.9231 - val_accuracy: 0.8131
Epoch 151/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1774 -
accuracy: 0.8912 - val_loss: 1.0339 - val_accuracy: 0.8084
Epoch 152/200
22014/22014 [==============================] - 0s 19us/step - loss: 0.1836 -
accuracy: 0.8922 - val_loss: 0.9041 - val_accuracy: 0.8051
Epoch 153/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.1718 -
accuracy: 0.8987 - val_loss: 1.0167 - val_accuracy: 0.8092
Epoch 154/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.1745 -
accuracy: 0.8918 - val_loss: 0.9828 - val_accuracy: 0.8233
Epoch 155/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1713 -
accuracy: 0.8956 - val_loss: 1.0213 - val_accuracy: 0.8297
Epoch 156/200
22014/22014 [==============================] - 0s 18us/step - loss: 0.1730 -
accuracy: 0.8952 - val_loss: 1.0914 - val_accuracy: 0.8215
Epoch 157/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.1772 -
accuracy: 0.8927 - val_loss: 1.1620 - val_accuracy: 0.8361
Epoch 158/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1743 -
accuracy: 0.8940 - val_loss: 1.1050 - val_accuracy: 0.8351
Epoch 159/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.1738 -
accuracy: 0.8956 - val_loss: 0.9062 - val_accuracy: 0.8065
Epoch 160/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.1680 -
accuracy: 0.8963 - val_loss: 1.2690 - val_accuracy: 0.8289
Epoch 161/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.1813 -
accuracy: 0.8935 - val_loss: 1.2557 - val_accuracy: 0.8305
Epoch 162/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1876 -
accuracy: 0.8970 - val_loss: 0.9954 - val_accuracy: 0.8252
Epoch 163/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1858 -
accuracy: 0.8993 - val_loss: 0.8500 - val_accuracy: 0.8340
Epoch 164/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1660 -
accuracy: 0.8997 - val_loss: 0.8859 - val_accuracy: 0.7981
Epoch 165/200
```

```
22014/22014 [==============================] - 1s 24us/step - loss: 0.1695 -
accuracy: 0.8974 - val_loss: 1.1621 - val_accuracy: 0.8387
Epoch 166/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.1733 -
accuracy: 0.8946 - val_loss: 0.9025 - val_accuracy: 0.8377
Epoch 167/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.1763 -
accuracy: 0.8989 - val_loss: 0.9745 - val_accuracy: 0.7956
Epoch 168/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1708 -
accuracy: 0.8950 - val_loss: 0.8637 - val_accuracy: 0.8193
Epoch 169/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1732 -
accuracy: 0.8981 - val_loss: 1.1227 - val_accuracy: 0.7293
Epoch 170/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1874 -
accuracy: 0.8944 - val_loss: 0.9670 - val_accuracy: 0.8061
Epoch 171/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1675 -
accuracy: 0.9002 - val_loss: 1.0383 - val_accuracy: 0.8296
Epoch 172/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.1648 -
accuracy: 0.9027 - val_loss: 1.0367 - val_accuracy: 0.8380
Epoch 173/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1701 -
accuracy: 0.8989 - val_loss: 0.9359 - val_accuracy: 0.8319
Epoch 174/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.1865 -
accuracy: 0.9003 - val_loss: 0.9227 - val_accuracy: 0.8187
Epoch 175/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1668 -
accuracy: 0.8986 - val_loss: 0.9218 - val_accuracy: 0.8428
Epoch 176/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1743 -
accuracy: 0.8990 - val_loss: 0.8874 - val_accuracy: 0.8347
Epoch 177/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1652 -
accuracy: 0.9011 - val_loss: 1.0134 - val_accuracy: 0.8299
Epoch 178/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1691 -
accuracy: 0.9003 - val_loss: 1.1242 - val_accuracy: 0.8355
Epoch 179/200
22014/22014 [==============================] - 1s 25us/step - loss: 0.1733 -
accuracy: 0.8986 - val_loss: 1.0155 - val_accuracy: 0.8313
Epoch 180/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.1655 -
accuracy: 0.9011 - val_loss: 0.9432 - val_accuracy: 0.8108
Epoch 181/200
```

```
22014/22014 [==============================] - 1s 24us/step - loss: 0.1704 -
accuracy: 0.9000 - val_loss: 1.1567 - val_accuracy: 0.8212
Epoch 182/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1764 -
accuracy: 0.8969 - val_loss: 0.8420 - val_accuracy: 0.8459
Epoch 183/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1770 -
accuracy: 0.8977 - val_loss: 1.0550 - val_accuracy: 0.8176
Epoch 184/200
22014/22014 [==============================] - 1s 28us/step - loss: 0.1689 -
accuracy: 0.9010 - val_loss: 0.9633 - val_accuracy: 0.8353
Epoch 185/200
22014/22014 [==============================] - 1s 26us/step - loss: 0.1642 -
accuracy: 0.9028 - val_loss: 0.9206 - val_accuracy: 0.8365
Epoch 186/200
22014/22014 [==============================] - 1s 26us/step - loss: 0.1672 -
accuracy: 0.9015 - val_loss: 1.0095 - val_accuracy: 0.8216
Epoch 187/200
22014/22014 [==============================] - 1s 24us/step - loss: 0.1631 -
accuracy: 0.9038 - val_loss: 1.3106 - val_accuracy: 0.8392
Epoch 188/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1738 -
accuracy: 0.8968 - val_loss: 1.0838 - val_accuracy: 0.8176
Epoch 189/200
22014/22014 [==============================] - 0s 20us/step - loss: 0.1626 -
accuracy: 0.9030 - val_loss: 1.5192 - val_accuracy: 0.8311
Epoch 190/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1686 -
accuracy: 0.9015 - val_loss: 1.3179 - val_accuracy: 0.7996
Epoch 191/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.1697 -
accuracy: 0.9009 - val_loss: 1.1561 - val_accuracy: 0.8509
Epoch 192/200
22014/22014 [==============================] - 0s 21us/step - loss: 0.2058 -
accuracy: 0.9029 - val_loss: 1.1658 - val_accuracy: 0.8124
Epoch 193/200
22014/22014 [==============================] - 1s 24us/step - loss: 0.1584 -
accuracy: 0.9050 - val_loss: 1.4541 - val_accuracy: 0.8356
Epoch 194/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.1744 -
accuracy: 0.9013 - val_loss: 1.2607 - val_accuracy: 0.8363
Epoch 195/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1653 -
accuracy: 0.9030 - val_loss: 1.1369 - val_accuracy: 0.8181
Epoch 196/200
22014/22014 [==============================] - 1s 23us/step - loss: 0.1626 -
accuracy: 0.9060 - val_loss: 1.3697 - val_accuracy: 0.8367
Epoch 197/200
```

```
22014/22014 [==============================] - 0s 21us/step - loss: 0.1680 -
accuracy: 0.9042 - val_loss: 1.2173 - val_accuracy: 0.7499
Epoch 198/200
22014/22014 [==============================] - 1s 24us/step - loss: 0.1620 -
accuracy: 0.9015 - val_loss: 1.3438 - val_accuracy: 0.8296
Epoch 199/200
22014/22014 [==============================] - 0s 22us/step - loss: 0.1645 -
accuracy: 0.9016 - val_loss: 1.0962 - val_accuracy: 0.8521
Epoch 200/200
22014/22014 [==============================] - 1s 24us/step - loss: 0.1753 -
accuracy: 0.9016 - val_loss: 1.1354 - val_accuracy: 0.8247
```






```
confusion matrix
[[5568 1046]
 [ 269  617]]
accuracy = 0.8246666666666667
precision = 0.3710162357185809
recall = 0.6963882618510158
F1 score = 0.4841114162416634
```

2.4 Deal with overfitting

Our model has already performed well on our training data.

Now, let's use 'dropout' method to deal with the overfitting problem.

[45]:
```
model = models.Sequential()
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dropout(0.1))
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dropout(0.3))
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dropout(0.3))
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dropout(0.3))
model.add(layers.Dense(100, activation='relu'))
```

```
model.add(layers.Dropout(0.3))
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dropout(0.1))
model.add(layers.Dense(1, activation='sigmoid'))

model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['accuracy'])

history = model.fit(partial_X_train,
                    partial_y_train,
                    epochs=50,
                    batch_size=512,
                    validation_data=(X_valid, y_valid),
                    class_weight=class_weights)

# plot the results of loss values from the training set and validtion set
history_dict = history.history
loss_values = history_dict['loss']
val_loss_values = history_dict['val_loss']

epochs = range(1, len(history_dict['accuracy']) + 1)

plt.plot(epochs, loss_values, 'bo', label='Training loss')
plt.plot(epochs, val_loss_values, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

#plt.clf()
acc = history_dict['accuracy']
val_acc = history_dict['val_accuracy']
plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Compute the confusion matrix
y_preds = model.predict(X_valid)
y_preds = (y_preds>0.5).astype(int)
print('confusion matrix')
print(sklearn.metrics.confusion_matrix(y_valid,y_preds))
```

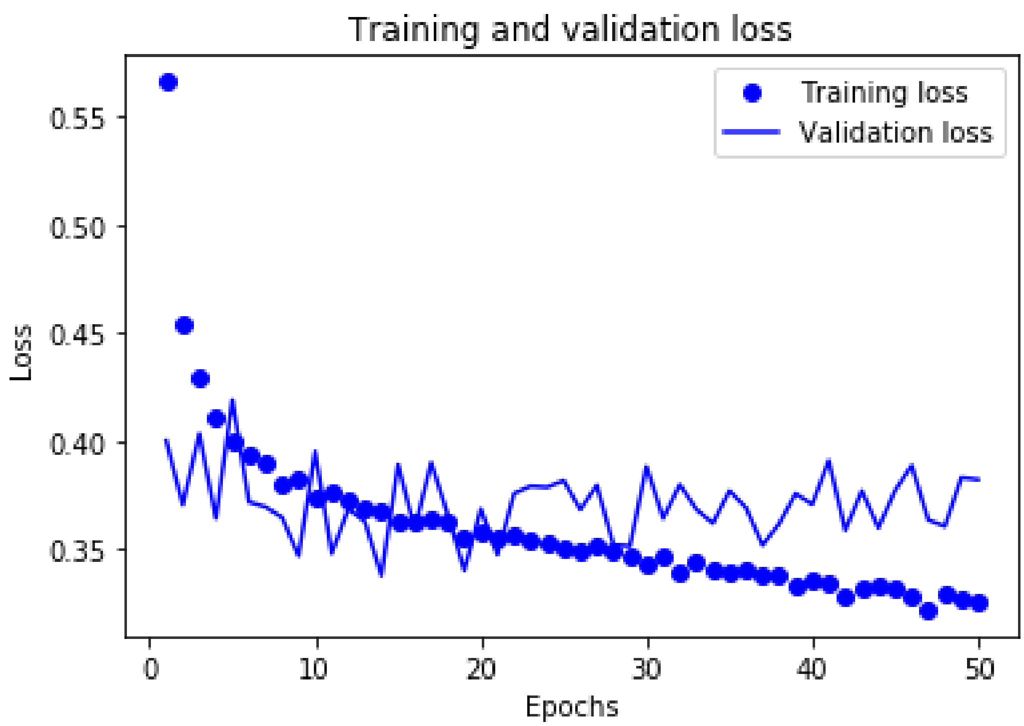
```python
# Compute accuracy
print('accuracy = '+ str(sklearn.metrics.accuracy_score(y_valid,y_preds)))


# Compute Precision
print('precision = '+str(sklearn.metrics.precision_score(y_valid,y_preds)))

# Compute Recall
print('recall = '+ str(sklearn.metrics.recall_score(y_valid,y_preds)))

# Compute F1 score
print('F1 score = '+ str(sklearn.metrics.f1_score(y_valid,y_preds)))
```

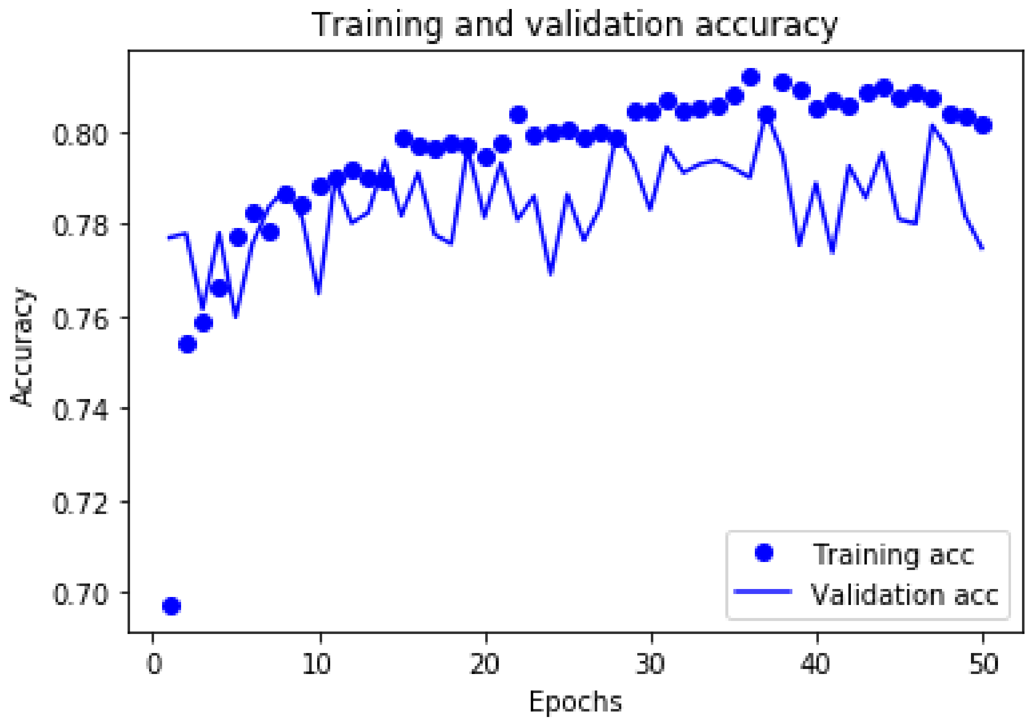
```
Train on 22014 samples, validate on 7500 samples
Epoch 1/50
22014/22014 [==============================] - 2s 80us/step - loss: 0.5662 -
accuracy: 0.6973 - val_loss: 0.4001 - val_accuracy: 0.7769
Epoch 2/50
22014/22014 [==============================] - 1s 32us/step - loss: 0.4537 -
accuracy: 0.7542 - val_loss: 0.3703 - val_accuracy: 0.7779
Epoch 3/50
22014/22014 [==============================] - 1s 27us/step - loss: 0.4294 -
accuracy: 0.7587 - val_loss: 0.4032 - val_accuracy: 0.7615
Epoch 4/50
22014/22014 [==============================] - 1s 24us/step - loss: 0.4108 -
accuracy: 0.7661 - val_loss: 0.3641 - val_accuracy: 0.7780
Epoch 5/50
22014/22014 [==============================] - 1s 25us/step - loss: 0.4001 -
accuracy: 0.7774 - val_loss: 0.4188 - val_accuracy: 0.7597
Epoch 6/50
22014/22014 [==============================] - 1s 41us/step - loss: 0.3936 -
accuracy: 0.7825 - val_loss: 0.3717 - val_accuracy: 0.7755
Epoch 7/50
22014/22014 [==============================] - 1s 41us/step - loss: 0.3903 -
accuracy: 0.7784 - val_loss: 0.3694 - val_accuracy: 0.7836
Epoch 8/50
22014/22014 [==============================] - 1s 37us/step - loss: 0.3804 -
accuracy: 0.7867 - val_loss: 0.3645 - val_accuracy: 0.7876
Epoch 9/50
22014/22014 [==============================] - 1s 28us/step - loss: 0.3827 -
accuracy: 0.7840 - val_loss: 0.3466 - val_accuracy: 0.7813
Epoch 10/50
22014/22014 [==============================] - 1s 29us/step - loss: 0.3733 -
accuracy: 0.7883 - val_loss: 0.3950 - val_accuracy: 0.7648
Epoch 11/50
22014/22014 [==============================] - 1s 28us/step - loss: 0.3756 -
```

```
accuracy: 0.7897 - val_loss: 0.3478 - val_accuracy: 0.7896
Epoch 12/50
22014/22014 [==============================] - 1s 33us/step - loss: 0.3726 -
accuracy: 0.7920 - val_loss: 0.3684 - val_accuracy: 0.7801
Epoch 13/50
22014/22014 [==============================] - 1s 32us/step - loss: 0.3686 -
accuracy: 0.7898 - val_loss: 0.3626 - val_accuracy: 0.7824
Epoch 14/50
22014/22014 [==============================] - 1s 36us/step - loss: 0.3676 -
accuracy: 0.7895 - val_loss: 0.3376 - val_accuracy: 0.7939
Epoch 15/50
22014/22014 [==============================] - 1s 33us/step - loss: 0.3619 -
accuracy: 0.7985 - val_loss: 0.3890 - val_accuracy: 0.7817
Epoch 16/50
22014/22014 [==============================] - 1s 33us/step - loss: 0.3623 -
accuracy: 0.7969 - val_loss: 0.3591 - val_accuracy: 0.7911
Epoch 17/50
22014/22014 [==============================] - 1s 37us/step - loss: 0.3643 -
accuracy: 0.7962 - val_loss: 0.3899 - val_accuracy: 0.7776
Epoch 18/50
22014/22014 [==============================] - 1s 32us/step - loss: 0.3621 -
accuracy: 0.7975 - val_loss: 0.3657 - val_accuracy: 0.7756
Epoch 19/50
22014/22014 [==============================] - 1s 32us/step - loss: 0.3548 -
accuracy: 0.7968 - val_loss: 0.3399 - val_accuracy: 0.7964
Epoch 20/50
22014/22014 [==============================] - 1s 32us/step - loss: 0.3577 -
accuracy: 0.7947 - val_loss: 0.3685 - val_accuracy: 0.7813
Epoch 21/50
22014/22014 [==============================] - 1s 34us/step - loss: 0.3547 -
accuracy: 0.7975 - val_loss: 0.3471 - val_accuracy: 0.7932
Epoch 22/50
22014/22014 [==============================] - 1s 32us/step - loss: 0.3560 -
accuracy: 0.8039 - val_loss: 0.3756 - val_accuracy: 0.7808
Epoch 23/50
22014/22014 [==============================] - 1s 31us/step - loss: 0.3535 -
accuracy: 0.7995 - val_loss: 0.3790 - val_accuracy: 0.7860
Epoch 24/50
22014/22014 [==============================] - 1s 45us/step - loss: 0.3532 -
accuracy: 0.8001 - val_loss: 0.3785 - val_accuracy: 0.7691
Epoch 25/50
22014/22014 [==============================] - 1s 36us/step - loss: 0.3497 -
accuracy: 0.8005 - val_loss: 0.3816 - val_accuracy: 0.7864
Epoch 26/50
22014/22014 [==============================] - 1s 39us/step - loss: 0.3490 -
accuracy: 0.7986 - val_loss: 0.3681 - val_accuracy: 0.7764
Epoch 27/50
22014/22014 [==============================] - 1s 32us/step - loss: 0.3520 -
```

```
accuracy: 0.7997 - val_loss: 0.3794 - val_accuracy: 0.7836
Epoch 28/50
22014/22014 [==============================] - 1s 29us/step - loss: 0.3485 -
accuracy: 0.7987 - val_loss: 0.3518 - val_accuracy: 0.7997
Epoch 29/50
22014/22014 [==============================] - 1s 32us/step - loss: 0.3460 -
accuracy: 0.8046 - val_loss: 0.3513 - val_accuracy: 0.7933
Epoch 30/50
22014/22014 [==============================] - 1s 31us/step - loss: 0.3425 -
accuracy: 0.8047 - val_loss: 0.3881 - val_accuracy: 0.7831
Epoch 31/50
22014/22014 [==============================] - 1s 28us/step - loss: 0.3469 -
accuracy: 0.8065 - val_loss: 0.3640 - val_accuracy: 0.7967
Epoch 32/50
22014/22014 [==============================] - 1s 32us/step - loss: 0.3391 -
accuracy: 0.8045 - val_loss: 0.3798 - val_accuracy: 0.7911
Epoch 33/50
22014/22014 [==============================] - 1s 32us/step - loss: 0.3441 -
accuracy: 0.8053 - val_loss: 0.3683 - val_accuracy: 0.7929
Epoch 34/50
22014/22014 [==============================] - 1s 34us/step - loss: 0.3404 -
accuracy: 0.8057 - val_loss: 0.3618 - val_accuracy: 0.7937
Epoch 35/50
22014/22014 [==============================] - 1s 36us/step - loss: 0.3396 -
accuracy: 0.8079 - val_loss: 0.3769 - val_accuracy: 0.7921
Epoch 36/50
22014/22014 [==============================] - 1s 29us/step - loss: 0.3408 -
accuracy: 0.8119 - val_loss: 0.3690 - val_accuracy: 0.7900
Epoch 37/50
22014/22014 [==============================] - 1s 26us/step - loss: 0.3381 -
accuracy: 0.8040 - val_loss: 0.3517 - val_accuracy: 0.8041
Epoch 38/50
22014/22014 [==============================] - 1s 27us/step - loss: 0.3382 -
accuracy: 0.8108 - val_loss: 0.3615 - val_accuracy: 0.7949
Epoch 39/50
22014/22014 [==============================] - 1s 27us/step - loss: 0.3326 -
accuracy: 0.8093 - val_loss: 0.3755 - val_accuracy: 0.7753
Epoch 40/50
22014/22014 [==============================] - 1s 28us/step - loss: 0.3359 -
accuracy: 0.8050 - val_loss: 0.3706 - val_accuracy: 0.7888
Epoch 41/50
22014/22014 [==============================] - 1s 26us/step - loss: 0.3342 -
accuracy: 0.8069 - val_loss: 0.3908 - val_accuracy: 0.7737
Epoch 42/50
22014/22014 [==============================] - 1s 25us/step - loss: 0.3285 -
accuracy: 0.8055 - val_loss: 0.3585 - val_accuracy: 0.7925
Epoch 43/50
22014/22014 [==============================] - 1s 28us/step - loss: 0.3318 -
```

```
accuracy: 0.8088 - val_loss: 0.3769 - val_accuracy: 0.7856
Epoch 44/50
22014/22014 [==============================] - 1s 27us/step - loss: 0.3331 -
accuracy: 0.8098 - val_loss: 0.3596 - val_accuracy: 0.7955
Epoch 45/50
22014/22014 [==============================] - 1s 29us/step - loss: 0.3317 -
accuracy: 0.8071 - val_loss: 0.3769 - val_accuracy: 0.7809
Epoch 46/50
22014/22014 [==============================] - 1s 28us/step - loss: 0.3284 -
accuracy: 0.8088 - val_loss: 0.3885 - val_accuracy: 0.7800
Epoch 47/50
22014/22014 [==============================] - 1s 28us/step - loss: 0.3218 -
accuracy: 0.8071 - val_loss: 0.3633 - val_accuracy: 0.8013
Epoch 48/50
22014/22014 [==============================] - 1s 40us/step - loss: 0.3287 -
accuracy: 0.8039 - val_loss: 0.3604 - val_accuracy: 0.7960
Epoch 49/50
22014/22014 [==============================] - 1s 32us/step - loss: 0.3272 -
accuracy: 0.8031 - val_loss: 0.3830 - val_accuracy: 0.7816
Epoch 50/50
22014/22014 [==============================] - 1s 26us/step - loss: 0.3254 -
accuracy: 0.8016 - val_loss: 0.3821 - val_accuracy: 0.7747
```






```
confusion matrix
[[5049 1565]
 [ 125  761]]
accuracy = 0.7746666666666666
precision = 0.3271711092003439
recall = 0.8589164785553047
F1 score = 0.4738480697384807
```

2.5 Final DNN model

Now, I can use all the training data to train this model.

[47]:
```
# Use whole training data to train our final model

model = models.Sequential()
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dropout(0.1))
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dropout(0.3))
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dropout(0.3))
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dropout(0.3))
```

```python
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dropout(0.3))
model.add(layers.Dense(100, activation='relu'))
model.add(layers.Dropout(0.1))
model.add(layers.Dense(1, activation='sigmoid'))

model.compile(optimizer='rmsprop',
              loss='binary_crossentropy',
              metrics=['accuracy'])

history = model.fit(X_train,
                    y_train,
                    epochs=50,
                    batch_size=512,
                    class_weight=class_weights)
```

```
Epoch 1/50
29514/29514 [==============================] - 1s 48us/step - loss: 0.5404 -
accuracy: 0.7186
Epoch 2/50
29514/29514 [==============================] - 1s 25us/step - loss: 0.4468 -
accuracy: 0.7585
Epoch 3/50
29514/29514 [==============================] - 1s 24us/step - loss: 0.4242 -
accuracy: 0.7700
Epoch 4/50
29514/29514 [==============================] - 1s 25us/step - loss: 0.4082 -
accuracy: 0.7787
Epoch 5/50
29514/29514 [==============================] - 1s 25us/step - loss: 0.4013 -
accuracy: 0.7742
Epoch 6/50
29514/29514 [==============================] - 1s 24us/step - loss: 0.3923 -
accuracy: 0.7889
Epoch 7/50
29514/29514 [==============================] - 1s 27us/step - loss: 0.3889 -
accuracy: 0.7794
Epoch 8/50
29514/29514 [==============================] - 1s 24us/step - loss: 0.3877 -
accuracy: 0.7906
Epoch 9/50
29514/29514 [==============================] - 1s 22us/step - loss: 0.3823 -
accuracy: 0.7877
Epoch 10/50
29514/29514 [==============================] - 1s 22us/step - loss: 0.3806 -
accuracy: 0.7870
Epoch 11/50
```

```
29514/29514 [==============================] - 1s 23us/step - loss: 0.3799 -
accuracy: 0.7954
Epoch 12/50
29514/29514 [==============================] - 1s 23us/step - loss: 0.3765 -
accuracy: 0.7884
Epoch 13/50
29514/29514 [==============================] - 1s 24us/step - loss: 0.3738 -
accuracy: 0.7949
Epoch 14/50
29514/29514 [==============================] - 1s 22us/step - loss: 0.3721 -
accuracy: 0.7986
Epoch 15/50
29514/29514 [==============================] - 1s 22us/step - loss: 0.3686 -
accuracy: 0.7959
Epoch 16/50
29514/29514 [==============================] - 1s 23us/step - loss: 0.3667 -
accuracy: 0.7979
Epoch 17/50
29514/29514 [==============================] - 1s 25us/step - loss: 0.3663 -
accuracy: 0.7995
Epoch 18/50
29514/29514 [==============================] - 1s 34us/step - loss: 0.3643 -
accuracy: 0.8021
Epoch 19/50
29514/29514 [==============================] - 1s 28us/step - loss: 0.3603 -
accuracy: 0.8020
Epoch 20/50
29514/29514 [==============================] - 1s 24us/step - loss: 0.3612 -
accuracy: 0.8091
Epoch 21/50
29514/29514 [==============================] - 1s 23us/step - loss: 0.3589 -
accuracy: 0.8082
Epoch 22/50
29514/29514 [==============================] - 1s 22us/step - loss: 0.3568 -
accuracy: 0.8107
Epoch 23/50
29514/29514 [==============================] - 1s 25us/step - loss: 0.3570 -
accuracy: 0.8043
Epoch 24/50
29514/29514 [==============================] - 1s 24us/step - loss: 0.3558 -
accuracy: 0.8106
Epoch 25/50
29514/29514 [==============================] - 1s 35us/step - loss: 0.3533 -
accuracy: 0.8116 0s
Epoch 26/50
29514/29514 [==============================] - 1s 34us/step - loss: 0.3523 -
accuracy: 0.8077
Epoch 27/50
```

```
29514/29514 [==============================] - 1s 27us/step - loss: 0.3542 -
accuracy: 0.8105
Epoch 28/50
29514/29514 [==============================] - 1s 28us/step - loss: 0.3474 -
accuracy: 0.8093
Epoch 29/50
29514/29514 [==============================] - 1s 32us/step - loss: 0.3486 -
accuracy: 0.8096
Epoch 30/50
29514/29514 [==============================] - 1s 34us/step - loss: 0.3499 -
accuracy: 0.8154
Epoch 31/50
29514/29514 [==============================] - 1s 25us/step - loss: 0.3469 -
accuracy: 0.8150
Epoch 32/50
29514/29514 [==============================] - 1s 25us/step - loss: 0.3438 -
accuracy: 0.8095
Epoch 33/50
29514/29514 [==============================] - 1s 28us/step - loss: 0.3422 -
accuracy: 0.8105
Epoch 34/50
29514/29514 [==============================] - 1s 27us/step - loss: 0.3409 -
accuracy: 0.8079
Epoch 35/50
29514/29514 [==============================] - 1s 30us/step - loss: 0.3461 -
accuracy: 0.8105
Epoch 36/50
29514/29514 [==============================] - 1s 27us/step - loss: 0.3433 -
accuracy: 0.8145
Epoch 37/50
29514/29514 [==============================] - 1s 24us/step - loss: 0.3397 -
accuracy: 0.8145
Epoch 38/50
29514/29514 [==============================] - 1s 24us/step - loss: 0.3390 -
accuracy: 0.8123
Epoch 39/50
29514/29514 [==============================] - 1s 39us/step - loss: 0.3391 -
accuracy: 0.8105
Epoch 40/50
29514/29514 [==============================] - 1s 29us/step - loss: 0.3384 -
accuracy: 0.8097
Epoch 41/50
29514/29514 [==============================] - 1s 26us/step - loss: 0.3372 -
accuracy: 0.8140
Epoch 42/50
29514/29514 [==============================] - 1s 26us/step - loss: 0.3388 -
accuracy: 0.8099
Epoch 43/50
```

```
29514/29514 [==============================] - 1s 26us/step - loss: 0.3367 -
accuracy: 0.8122
Epoch 44/50
29514/29514 [==============================] - 1s 25us/step - loss: 0.3417 -
accuracy: 0.8095
Epoch 45/50
29514/29514 [==============================] - 1s 23us/step - loss: 0.3355 -
accuracy: 0.8067
Epoch 46/50
29514/29514 [==============================] - 1s 25us/step - loss: 0.3377 -
accuracy: 0.8112
Epoch 47/50
29514/29514 [==============================] - 1s 23us/step - loss: 0.3339 -
accuracy: 0.8088
Epoch 48/50
29514/29514 [==============================] - 1s 25us/step - loss: 0.3359 -
accuracy: 0.8056
Epoch 49/50
29514/29514 [==============================] - 1s 30us/step - loss: 0.3333 -
accuracy: 0.8092
Epoch 50/50
29514/29514 [==============================] - 1s 30us/step - loss: 0.3363 -
accuracy: 0.8029
```

After training our final model, we can then use this model to predict our final answer (use our test dataset).

2.6 Using a trained network to generate predictions on testing data

[49]:

```
#Using a trained network to generate predictions on new data
y_preds=model.predict(X_test)
y_preds=(y_preds>0.5).astype(int)
answer=pd.DataFrame(y_preds)

X_test=pd.read_csv('/Users/Stylewsxcde991/Desktop/     /qbs-competition-1/data/
↪test.csv',index_col=0)
answer.index=X_test.index
result = pd.read_csv('/Users/Stylewsxcde991/Desktop/     /qbs-competition-1/
↪data/sub_try.csv',index_col=0)
result['Target'] = answer
result.to_csv('/Users/Stylewsxcde991/Desktop/     /qbs-competition-1/data/
↪Result_1.csv')
```

After some dataframe operations, we can then export our answer.

Now, let’s see the prediction result of our final model.

2.7 The prediction result:

As we talked before, by using our final weighted model, in Kaggle competition, the public score of this model is about 0.83 (the private score is also about 0.82).

In my opinion, this model's great performance in Kaggle competition means this model can effectively predict whether a person makes over 50K a year. That is to say, if we want to predict if a person makes over 50K a year, our final model is trustable and reasonable.

2.8 Learning progress and reflection

To be honest, when I first built a NN model for this assignment, the result was very bad. Even if I used the weighted model technique, I still got bad results (accuracy scores are very unstable).

In order to overcome this situation, I started to do explorative data analysis and I found that 'fnlwgt' is almost unrelated with 'Target'.

Therefore, I decided to drop 'fnlwgt'. Fortunately, my models started to improve and got trustable predictions.

In short, never forget to do EDA before modeling.