Income_Prediction_Report

April 15, 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.

[35]:
```
# 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
```

[36]:
```
# 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.

[37]:
```
# 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

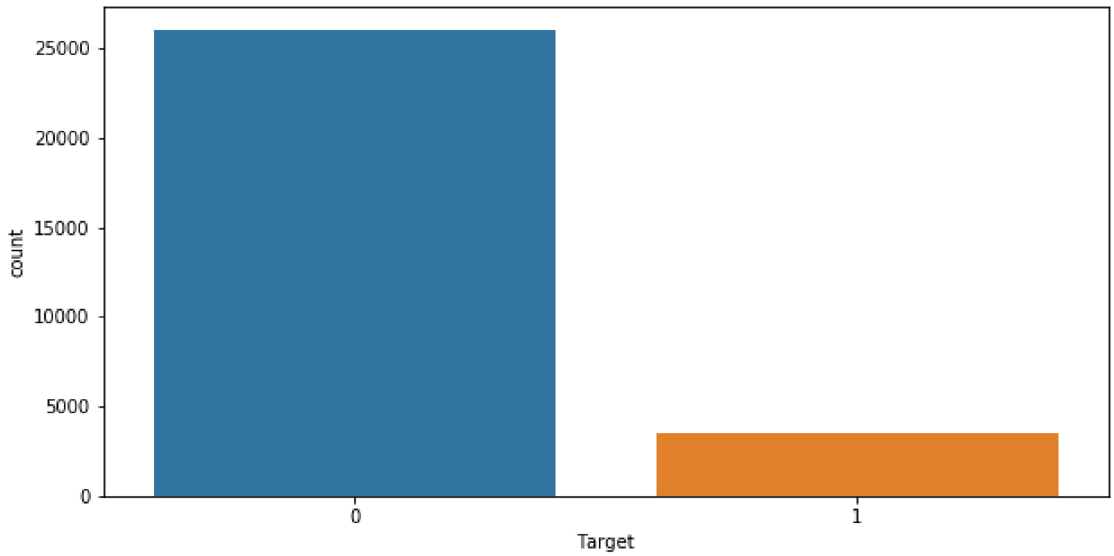
[38]:
```
# Deal with missing data
train_data.Workclass=train_data.Workclass.fillna('unknown')
train_data.Occupation=train_data.Occupation.fillna('unknown')
train_data.Country=train_data.Country.fillna('unknown')
X_test.Workclass=X_test.Workclass.fillna('unknown')
X_test.Occupation=X_test.Occupation.fillna('unknown')
X_test.Country=X_test.Country.fillna('unknown')
```

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

[39]:
```
# 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%
```

[39]: <matplotlib.axes._subplots.AxesSubplot at 0x14cbe90d0>



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.

[40]:
```
# 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')
```

[40]: 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.)

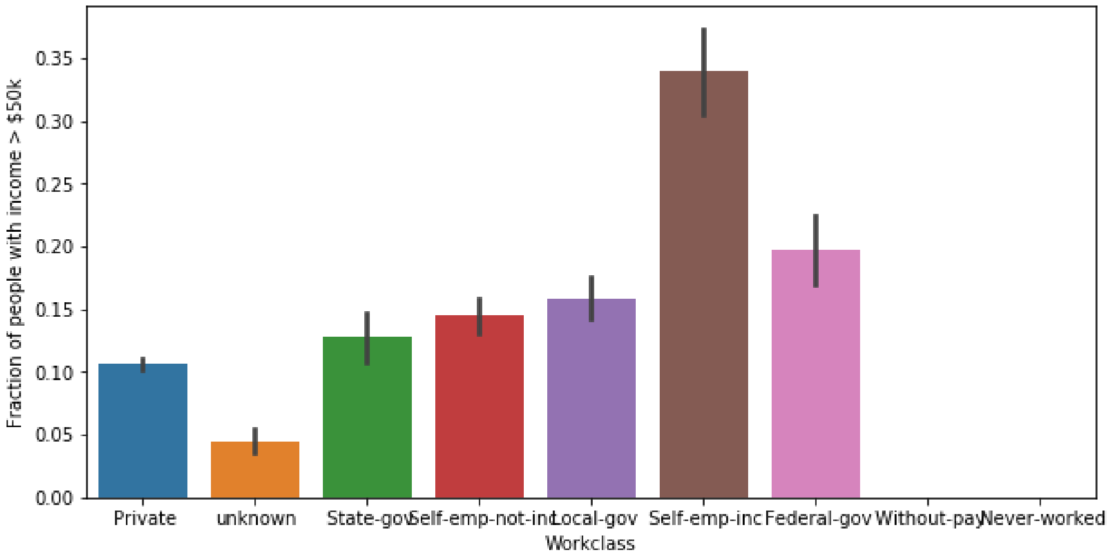
In addition, because I think 'Education' and 'Education_Num' contain the same information, I only use 'Education_Num' in my NN models.

1.8 Explorative data analysis for categorical features.

[41]:
```
# Drop 'fnlwgt' & 'Education'
train_data = train_data.drop(columns=['fnlwgt','Education'])
X_test = X_test.drop(columns=['fnlwgt','Education'])
```

```
[42]: # 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')
```

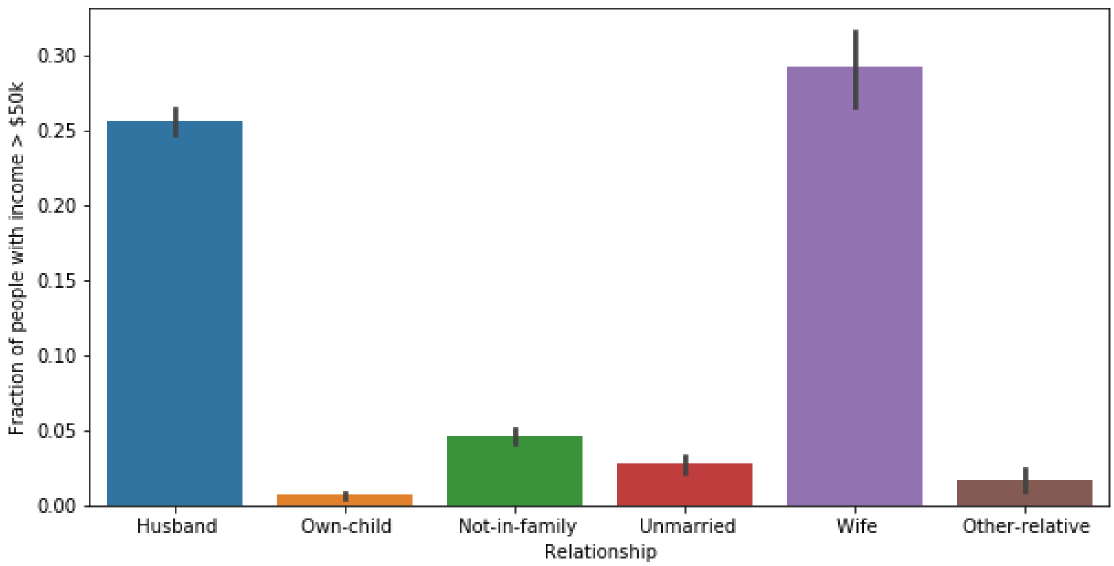
```
[42]: [Text(0, 0.5, 'Fraction of people with income > $50k')]
```



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

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

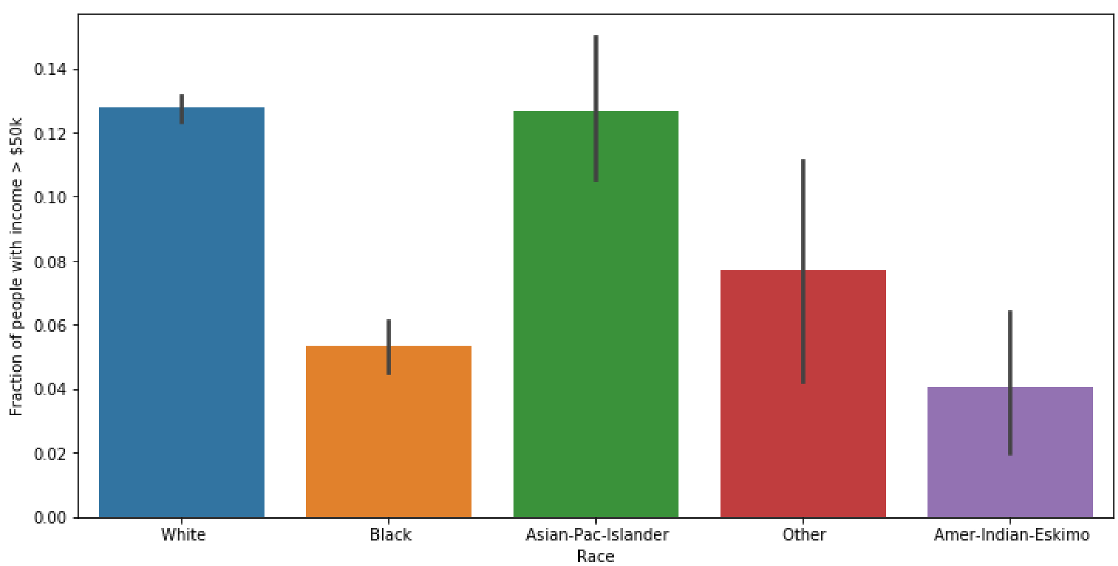
```
[43]: [Text(0, 0.5, 'Fraction of people with income > $50k')]
```



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

[44]:
```
plt.figure(figsize=(12,6))
ax=sns.barplot(x='Race',y='Target',data=train_data)
ax.set(ylabel='Fraction of people with income > $50k')
```

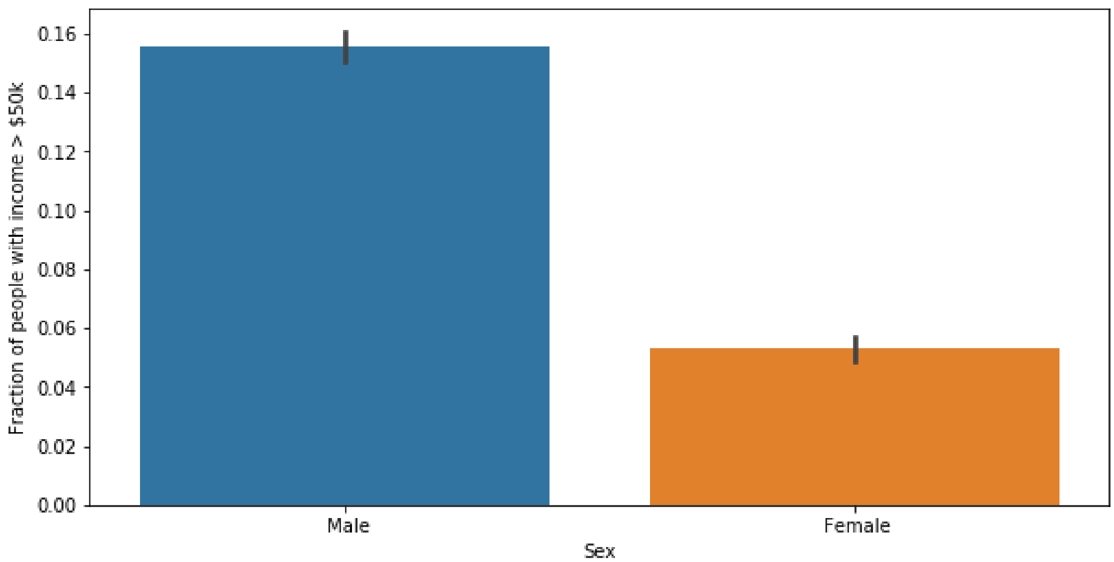
[44]: `[Text(0, 0.5, 'Fraction of people with income > $50k')]`



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

[45]:
```
plt.figure(figsize=(10,5))
ax = sns.barplot(x='Sex',y='Target',data=train_data)
ax.set(ylabel='Fraction of people with income > $50k')
```

[45]: [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).

[46]:
```
# 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

[47]:
```
# 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

[48]:
```
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.

[49]:
```
# 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.

[50]:
```
# logistic model
from sklearn.linear_model import LogisticRegression
logistic_model = LogisticRegression(random_state=0).fit(X_train, y_train)
logistic_model.score(X_valid,y_valid)
```

[50]:
```
0.9138666666666667
```

As above, it's mean accuracy on validation data set is about 0.91

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.

[51]:
```
# Construct our model
from keras import models
from keras import layers

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'])
```

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

[52]:
```
# 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 [==============================] - 0s 15us/step - loss: 0.4612 -
accuracy: 0.8333 - val_loss: 0.3303 - val_accuracy: 0.8879
Epoch 2/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2903 -
```

```
accuracy: 0.8904 - val_loss: 0.2616 - val_accuracy: 0.9004
Epoch 3/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2518 -
accuracy: 0.8997 - val_loss: 0.2428 - val_accuracy: 0.9036
Epoch 4/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.2399 -
accuracy: 0.9017 - val_loss: 0.2372 - val_accuracy: 0.9048
Epoch 5/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.2339 -
accuracy: 0.9039 - val_loss: 0.2340 - val_accuracy: 0.9060
Epoch 6/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2299 -
accuracy: 0.9054 - val_loss: 0.2309 - val_accuracy: 0.9079
Epoch 7/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.2270 -
accuracy: 0.9063 - val_loss: 0.2292 - val_accuracy: 0.9088
Epoch 8/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.2246 -
accuracy: 0.9077 - val_loss: 0.2278 - val_accuracy: 0.9096
Epoch 9/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2227 -
accuracy: 0.9082 - val_loss: 0.2271 - val_accuracy: 0.9087
Epoch 10/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2211 -
accuracy: 0.9088 - val_loss: 0.2264 - val_accuracy: 0.9100
Epoch 11/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2197 -
accuracy: 0.9095 - val_loss: 0.2252 - val_accuracy: 0.9100
Epoch 12/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2186 -
accuracy: 0.9101 - val_loss: 0.2254 - val_accuracy: 0.9096
Epoch 13/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.2173 -
accuracy: 0.9101 - val_loss: 0.2263 - val_accuracy: 0.9085
Epoch 14/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2168 -
accuracy: 0.9113 - val_loss: 0.2249 - val_accuracy: 0.9097
Epoch 15/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2160 -
accuracy: 0.9111 - val_loss: 0.2246 - val_accuracy: 0.9097
Epoch 16/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2153 -
accuracy: 0.9111 - val_loss: 0.2246 - val_accuracy: 0.9100
Epoch 17/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2147 -
accuracy: 0.9114 - val_loss: 0.2248 - val_accuracy: 0.9101
Epoch 18/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.2141 -
```

```
accuracy: 0.9115 - val_loss: 0.2251 - val_accuracy: 0.9099
Epoch 19/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2136 -
accuracy: 0.9114 - val_loss: 0.2255 - val_accuracy: 0.9099
Epoch 20/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2131 -
accuracy: 0.9112 - val_loss: 0.2248 - val_accuracy: 0.9100
Epoch 21/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2127 -
accuracy: 0.9118 - val_loss: 0.2248 - val_accuracy: 0.9105
Epoch 22/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2122 -
accuracy: 0.9114 - val_loss: 0.2253 - val_accuracy: 0.9109
Epoch 23/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.2117 -
accuracy: 0.9123 - val_loss: 0.2251 - val_accuracy: 0.9100
Epoch 24/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2115 -
accuracy: 0.9124 - val_loss: 0.2248 - val_accuracy: 0.9109
Epoch 25/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2109 -
accuracy: 0.9115 - val_loss: 0.2259 - val_accuracy: 0.9092
Epoch 26/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2107 -
accuracy: 0.9126 - val_loss: 0.2255 - val_accuracy: 0.9099
Epoch 27/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2103 -
accuracy: 0.9127 - val_loss: 0.2253 - val_accuracy: 0.9113
Epoch 28/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2099 -
accuracy: 0.9127 - val_loss: 0.2254 - val_accuracy: 0.9099
Epoch 29/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2097 -
accuracy: 0.9128 - val_loss: 0.2252 - val_accuracy: 0.9117
Epoch 30/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2092 -
accuracy: 0.9126 - val_loss: 0.2248 - val_accuracy: 0.9117
Epoch 31/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2089 -
accuracy: 0.9135 - val_loss: 0.2257 - val_accuracy: 0.9109
Epoch 32/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2087 -
accuracy: 0.9127 - val_loss: 0.2255 - val_accuracy: 0.9103
Epoch 33/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2082 -
accuracy: 0.9136 - val_loss: 0.2253 - val_accuracy: 0.9104
Epoch 34/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2080 -
```

```
accuracy: 0.9137 - val_loss: 0.2261 - val_accuracy: 0.9116
Epoch 35/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2078 -
accuracy: 0.9139 - val_loss: 0.2261 - val_accuracy: 0.9112
Epoch 36/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.2075 -
accuracy: 0.9131 - val_loss: 0.2263 - val_accuracy: 0.9097
Epoch 37/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2074 -
accuracy: 0.9134 - val_loss: 0.2262 - val_accuracy: 0.9096
Epoch 38/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2071 -
accuracy: 0.9139 - val_loss: 0.2259 - val_accuracy: 0.9100
Epoch 39/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2068 -
accuracy: 0.9141 - val_loss: 0.2262 - val_accuracy: 0.9111
Epoch 40/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2067 -
accuracy: 0.9140 - val_loss: 0.2264 - val_accuracy: 0.9115
Epoch 41/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2061 -
accuracy: 0.9144 - val_loss: 0.2268 - val_accuracy: 0.9109
Epoch 42/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2061 -
accuracy: 0.9136 - val_loss: 0.2270 - val_accuracy: 0.9096
Epoch 43/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2058 -
accuracy: 0.9141 - val_loss: 0.2268 - val_accuracy: 0.9101
Epoch 44/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2057 -
accuracy: 0.9140 - val_loss: 0.2268 - val_accuracy: 0.9088
Epoch 45/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2053 -
accuracy: 0.9142 - val_loss: 0.2270 - val_accuracy: 0.9097
Epoch 46/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2052 -
accuracy: 0.9141 - val_loss: 0.2273 - val_accuracy: 0.9097
Epoch 47/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.2048 -
accuracy: 0.9143 - val_loss: 0.2271 - val_accuracy: 0.9089
Epoch 48/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2048 -
accuracy: 0.9145 - val_loss: 0.2273 - val_accuracy: 0.9101
Epoch 49/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2045 -
accuracy: 0.9153 - val_loss: 0.2271 - val_accuracy: 0.9096
Epoch 50/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2043 -
```

```
accuracy: 0.9145 - val_loss: 0.2279 - val_accuracy: 0.9089
Epoch 51/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2041 -
accuracy: 0.9146 - val_loss: 0.2274 - val_accuracy: 0.9087
Epoch 52/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2037 -
accuracy: 0.9149 - val_loss: 0.2284 - val_accuracy: 0.9091
Epoch 53/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2039 -
accuracy: 0.9151 - val_loss: 0.2282 - val_accuracy: 0.9093
Epoch 54/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2035 -
accuracy: 0.9144 - val_loss: 0.2283 - val_accuracy: 0.9093
Epoch 55/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2033 -
accuracy: 0.9150 - val_loss: 0.2282 - val_accuracy: 0.9100
Epoch 56/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2033 -
accuracy: 0.9143 - val_loss: 0.2279 - val_accuracy: 0.9095
Epoch 57/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2031 -
accuracy: 0.9140 - val_loss: 0.2284 - val_accuracy: 0.9097
Epoch 58/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.2028 -
accuracy: 0.9150 - val_loss: 0.2287 - val_accuracy: 0.9091
Epoch 59/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2029 -
accuracy: 0.9143 - val_loss: 0.2286 - val_accuracy: 0.9088
Epoch 60/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2025 -
accuracy: 0.9150 - val_loss: 0.2285 - val_accuracy: 0.9097
Epoch 61/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2024 -
accuracy: 0.9152 - val_loss: 0.2290 - val_accuracy: 0.9091
Epoch 62/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2023 -
accuracy: 0.9149 - val_loss: 0.2293 - val_accuracy: 0.9091
Epoch 63/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.2021 -
accuracy: 0.9150 - val_loss: 0.2293 - val_accuracy: 0.9095
Epoch 64/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2018 -
accuracy: 0.9154 - val_loss: 0.2302 - val_accuracy: 0.9076
Epoch 65/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2019 -
accuracy: 0.9149 - val_loss: 0.2293 - val_accuracy: 0.9097
Epoch 66/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2016 -
```

```
accuracy: 0.9156 - val_loss: 0.2298 - val_accuracy: 0.9091
Epoch 67/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2015 -
accuracy: 0.9157 - val_loss: 0.2302 - val_accuracy: 0.9088
Epoch 68/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2014 -
accuracy: 0.9152 - val_loss: 0.2298 - val_accuracy: 0.9092
Epoch 69/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2012 -
accuracy: 0.9161 - val_loss: 0.2303 - val_accuracy: 0.9085
Epoch 70/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2012 -
accuracy: 0.9156 - val_loss: 0.2305 - val_accuracy: 0.9103
Epoch 71/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2010 -
accuracy: 0.9158 - val_loss: 0.2304 - val_accuracy: 0.9092
Epoch 72/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2009 -
accuracy: 0.9151 - val_loss: 0.2308 - val_accuracy: 0.9081
Epoch 73/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2009 -
accuracy: 0.9156 - val_loss: 0.2308 - val_accuracy: 0.9096
Epoch 74/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2006 -
accuracy: 0.9160 - val_loss: 0.2303 - val_accuracy: 0.9088
Epoch 75/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2006 -
accuracy: 0.9157 - val_loss: 0.2299 - val_accuracy: 0.9096
Epoch 76/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2003 -
accuracy: 0.9156 - val_loss: 0.2305 - val_accuracy: 0.9091
Epoch 77/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2003 -
accuracy: 0.9164 - val_loss: 0.2307 - val_accuracy: 0.9101
Epoch 78/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2001 -
accuracy: 0.9153 - val_loss: 0.2309 - val_accuracy: 0.9099
Epoch 79/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.2001 -
accuracy: 0.9157 - val_loss: 0.2316 - val_accuracy: 0.9089
Epoch 80/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.2001 -
accuracy: 0.9156 - val_loss: 0.2309 - val_accuracy: 0.9095
Epoch 81/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1999 -
accuracy: 0.9156 - val_loss: 0.2314 - val_accuracy: 0.9093
Epoch 82/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1997 -
```

```
accuracy: 0.9155 - val_loss: 0.2312 - val_accuracy: 0.9089
Epoch 83/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1996 -
accuracy: 0.9156 - val_loss: 0.2311 - val_accuracy: 0.9096
Epoch 84/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1995 -
accuracy: 0.9156 - val_loss: 0.2314 - val_accuracy: 0.9093
Epoch 85/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1994 -
accuracy: 0.9156 - val_loss: 0.2319 - val_accuracy: 0.9097
Epoch 86/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1991 -
accuracy: 0.9161 - val_loss: 0.2315 - val_accuracy: 0.9089
Epoch 87/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1992 -
accuracy: 0.9162 - val_loss: 0.2320 - val_accuracy: 0.9095
Epoch 88/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1992 -
accuracy: 0.9165 - val_loss: 0.2323 - val_accuracy: 0.9100
Epoch 89/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1990 -
accuracy: 0.9153 - val_loss: 0.2323 - val_accuracy: 0.9081
Epoch 90/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1991 -
accuracy: 0.9162 - val_loss: 0.2322 - val_accuracy: 0.9093
Epoch 91/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1989 -
accuracy: 0.9162 - val_loss: 0.2327 - val_accuracy: 0.9080
Epoch 92/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1987 -
accuracy: 0.9161 - val_loss: 0.2326 - val_accuracy: 0.9084
Epoch 93/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1987 -
accuracy: 0.9161 - val_loss: 0.2325 - val_accuracy: 0.9087
Epoch 94/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1984 -
accuracy: 0.9161 - val_loss: 0.2327 - val_accuracy: 0.9095
Epoch 95/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1986 -
accuracy: 0.9164 - val_loss: 0.2330 - val_accuracy: 0.9080
Epoch 96/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1983 -
accuracy: 0.9162 - val_loss: 0.2327 - val_accuracy: 0.9093
Epoch 97/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1982 -
accuracy: 0.9167 - val_loss: 0.2338 - val_accuracy: 0.9091
Epoch 98/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1983 -
```

```
accuracy: 0.9162 - val_loss: 0.2332 - val_accuracy: 0.9084
Epoch 99/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1981 -
accuracy: 0.9159 - val_loss: 0.2335 - val_accuracy: 0.9073
Epoch 100/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1979 -
accuracy: 0.9165 - val_loss: 0.2336 - val_accuracy: 0.9083
Epoch 101/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1979 -
accuracy: 0.9169 - val_loss: 0.2342 - val_accuracy: 0.9075
Epoch 102/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1977 -
accuracy: 0.9157 - val_loss: 0.2330 - val_accuracy: 0.9093
Epoch 103/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1976 -
accuracy: 0.9161 - val_loss: 0.2337 - val_accuracy: 0.9079
Epoch 104/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1978 -
accuracy: 0.9159 - val_loss: 0.2338 - val_accuracy: 0.9067
Epoch 105/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1975 -
accuracy: 0.9168 - val_loss: 0.2337 - val_accuracy: 0.9087
Epoch 106/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1975 -
accuracy: 0.9166 - val_loss: 0.2343 - val_accuracy: 0.9080
Epoch 107/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1973 -
accuracy: 0.9168 - val_loss: 0.2346 - val_accuracy: 0.9087
Epoch 108/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1971 -
accuracy: 0.9164 - val_loss: 0.2338 - val_accuracy: 0.9093
Epoch 109/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1972 -
accuracy: 0.9160 - val_loss: 0.2352 - val_accuracy: 0.9071
Epoch 110/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1973 -
accuracy: 0.9161 - val_loss: 0.2346 - val_accuracy: 0.9088
Epoch 111/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1970 -
accuracy: 0.9171 - val_loss: 0.2344 - val_accuracy: 0.9087
Epoch 112/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1970 -
accuracy: 0.9176 - val_loss: 0.2353 - val_accuracy: 0.9075
Epoch 113/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1969 -
accuracy: 0.9172 - val_loss: 0.2346 - val_accuracy: 0.9089
Epoch 114/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1969 -
```

```
accuracy: 0.9166 - val_loss: 0.2354 - val_accuracy: 0.9073
Epoch 115/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1966 -
accuracy: 0.9163 - val_loss: 0.2353 - val_accuracy: 0.9091
Epoch 116/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1966 -
accuracy: 0.9171 - val_loss: 0.2353 - val_accuracy: 0.9084
Epoch 117/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1965 -
accuracy: 0.9170 - val_loss: 0.2358 - val_accuracy: 0.9089
Epoch 118/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1964 -
accuracy: 0.9175 - val_loss: 0.2357 - val_accuracy: 0.9081
Epoch 119/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1964 -
accuracy: 0.9163 - val_loss: 0.2361 - val_accuracy: 0.9080
Epoch 120/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1963 -
accuracy: 0.9168 - val_loss: 0.2357 - val_accuracy: 0.9089
Epoch 121/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1962 -
accuracy: 0.9170 - val_loss: 0.2367 - val_accuracy: 0.9087
Epoch 122/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1960 -
accuracy: 0.9169 - val_loss: 0.2360 - val_accuracy: 0.9088
Epoch 123/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1962 -
accuracy: 0.9166 - val_loss: 0.2362 - val_accuracy: 0.9097
Epoch 124/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1957 -
accuracy: 0.9168 - val_loss: 0.2364 - val_accuracy: 0.9067
Epoch 125/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1958 -
accuracy: 0.9173 - val_loss: 0.2361 - val_accuracy: 0.9091
Epoch 126/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1957 -
accuracy: 0.9170 - val_loss: 0.2387 - val_accuracy: 0.9040
Epoch 127/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1958 -
accuracy: 0.9181 - val_loss: 0.2367 - val_accuracy: 0.9079
Epoch 128/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1956 -
accuracy: 0.9176 - val_loss: 0.2368 - val_accuracy: 0.9088
Epoch 129/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1956 -
accuracy: 0.9166 - val_loss: 0.2369 - val_accuracy: 0.9095
Epoch 130/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1955 -
```

```
accuracy: 0.9164 - val_loss: 0.2369 - val_accuracy: 0.9091
Epoch 131/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1954 -
accuracy: 0.9165 - val_loss: 0.2371 - val_accuracy: 0.9088
Epoch 132/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1954 -
accuracy: 0.9168 - val_loss: 0.2373 - val_accuracy: 0.9085
Epoch 133/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1952 -
accuracy: 0.9163 - val_loss: 0.2384 - val_accuracy: 0.9079
Epoch 134/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1951 -
accuracy: 0.9171 - val_loss: 0.2380 - val_accuracy: 0.9095
Epoch 135/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1951 -
accuracy: 0.9174 - val_loss: 0.2379 - val_accuracy: 0.9064
Epoch 136/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1951 -
accuracy: 0.9169 - val_loss: 0.2378 - val_accuracy: 0.9080
Epoch 137/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1949 -
accuracy: 0.9173 - val_loss: 0.2385 - val_accuracy: 0.9076
Epoch 138/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1947 -
accuracy: 0.9181 - val_loss: 0.2387 - val_accuracy: 0.9079
Epoch 139/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1947 -
accuracy: 0.9180 - val_loss: 0.2385 - val_accuracy: 0.9072
Epoch 140/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1946 -
accuracy: 0.9172 - val_loss: 0.2397 - val_accuracy: 0.9059
Epoch 141/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1946 -
accuracy: 0.9180 - val_loss: 0.2384 - val_accuracy: 0.9083
Epoch 142/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.1948 -
accuracy: 0.9182 - val_loss: 0.2384 - val_accuracy: 0.9079
Epoch 143/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1944 -
accuracy: 0.9185 - val_loss: 0.2387 - val_accuracy: 0.9095
Epoch 144/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1945 -
accuracy: 0.9171 - val_loss: 0.2386 - val_accuracy: 0.9088
Epoch 145/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1943 -
accuracy: 0.9183 - val_loss: 0.2389 - val_accuracy: 0.9068
Epoch 146/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1942 -
```

```
accuracy: 0.9182 - val_loss: 0.2390 - val_accuracy: 0.9080
Epoch 147/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1941 -
accuracy: 0.9181 - val_loss: 0.2392 - val_accuracy: 0.9083
Epoch 148/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1941 -
accuracy: 0.9184 - val_loss: 0.2389 - val_accuracy: 0.9091
Epoch 149/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1939 -
accuracy: 0.9186 - val_loss: 0.2400 - val_accuracy: 0.9055
Epoch 150/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1940 -
accuracy: 0.9187 - val_loss: 0.2394 - val_accuracy: 0.9064
Epoch 151/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1938 -
accuracy: 0.9176 - val_loss: 0.2396 - val_accuracy: 0.9055
Epoch 152/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1935 -
accuracy: 0.9186 - val_loss: 0.2396 - val_accuracy: 0.9088
Epoch 153/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1937 -
accuracy: 0.9186 - val_loss: 0.2398 - val_accuracy: 0.9071
Epoch 154/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1938 -
accuracy: 0.9188 - val_loss: 0.2397 - val_accuracy: 0.9080
Epoch 155/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.1936 -
accuracy: 0.9187 - val_loss: 0.2400 - val_accuracy: 0.9081
Epoch 156/200
22014/22014 [==============================] - 0s 12us/step - loss: 0.1937 -
accuracy: 0.9183 - val_loss: 0.2400 - val_accuracy: 0.9076
Epoch 157/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1936 -
accuracy: 0.9184 - val_loss: 0.2398 - val_accuracy: 0.9069
Epoch 158/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1933 -
accuracy: 0.9188 - val_loss: 0.2401 - val_accuracy: 0.9067
Epoch 159/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1931 -
accuracy: 0.9188 - val_loss: 0.2414 - val_accuracy: 0.9056
Epoch 160/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1930 -
accuracy: 0.9189 - val_loss: 0.2408 - val_accuracy: 0.9073
Epoch 161/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1932 -
accuracy: 0.9185 - val_loss: 0.2411 - val_accuracy: 0.9071
Epoch 162/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1929 -
```

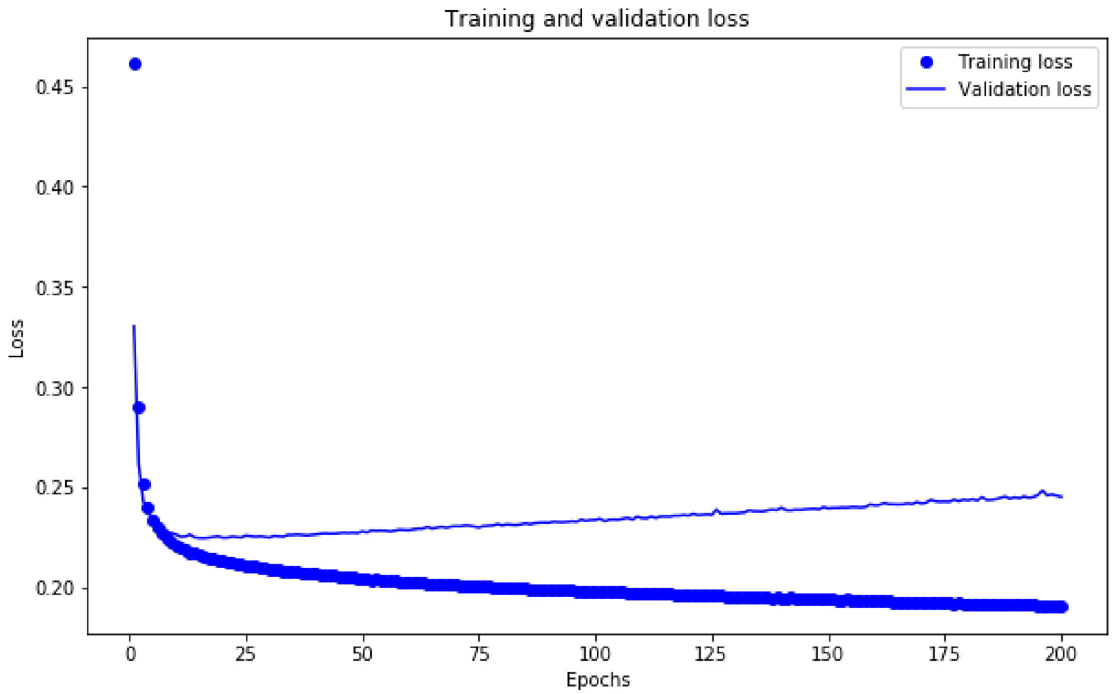
```
accuracy: 0.9186 - val_loss: 0.2420 - val_accuracy: 0.9075
Epoch 163/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1930 -
accuracy: 0.9194 - val_loss: 0.2415 - val_accuracy: 0.9060
Epoch 164/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1928 -
accuracy: 0.9191 - val_loss: 0.2413 - val_accuracy: 0.9065
Epoch 165/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1928 -
accuracy: 0.9199 - val_loss: 0.2413 - val_accuracy: 0.9081
Epoch 166/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1928 -
accuracy: 0.9194 - val_loss: 0.2414 - val_accuracy: 0.9072
Epoch 167/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1927 -
accuracy: 0.9193 - val_loss: 0.2418 - val_accuracy: 0.9069
Epoch 168/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1925 -
accuracy: 0.9186 - val_loss: 0.2415 - val_accuracy: 0.9079
Epoch 169/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1926 -
accuracy: 0.9193 - val_loss: 0.2425 - val_accuracy: 0.9072
Epoch 170/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1926 -
accuracy: 0.9190 - val_loss: 0.2417 - val_accuracy: 0.9065
Epoch 171/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1922 -
accuracy: 0.9185 - val_loss: 0.2422 - val_accuracy: 0.9085
Epoch 172/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1923 -
accuracy: 0.9192 - val_loss: 0.2436 - val_accuracy: 0.9047
Epoch 173/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1922 -
accuracy: 0.9186 - val_loss: 0.2429 - val_accuracy: 0.9083
Epoch 174/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1923 -
accuracy: 0.9196 - val_loss: 0.2427 - val_accuracy: 0.9073
Epoch 175/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1920 -
accuracy: 0.9189 - val_loss: 0.2428 - val_accuracy: 0.9057
Epoch 176/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1922 -
accuracy: 0.9195 - val_loss: 0.2427 - val_accuracy: 0.9080
Epoch 177/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1919 -
accuracy: 0.9198 - val_loss: 0.2437 - val_accuracy: 0.9053
Epoch 178/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1920 -
```

```
accuracy: 0.9196 - val_loss: 0.2430 - val_accuracy: 0.9080
Epoch 179/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1919 -
accuracy: 0.9196 - val_loss: 0.2438 - val_accuracy: 0.9051
Epoch 180/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1917 -
accuracy: 0.9200 - val_loss: 0.2434 - val_accuracy: 0.9079
Epoch 181/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1918 -
accuracy: 0.9187 - val_loss: 0.2439 - val_accuracy: 0.9057
Epoch 182/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1915 -
accuracy: 0.9199 - val_loss: 0.2433 - val_accuracy: 0.9084
Epoch 183/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1915 -
accuracy: 0.9193 - val_loss: 0.2450 - val_accuracy: 0.9055
Epoch 184/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.1914 -
accuracy: 0.9199 - val_loss: 0.2436 - val_accuracy: 0.9075
Epoch 185/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1915 -
accuracy: 0.9193 - val_loss: 0.2436 - val_accuracy: 0.9060
Epoch 186/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1915 -
accuracy: 0.9196 - val_loss: 0.2440 - val_accuracy: 0.9079
Epoch 187/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1914 -
accuracy: 0.9194 - val_loss: 0.2446 - val_accuracy: 0.9056
Epoch 188/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1915 -
accuracy: 0.9200 - val_loss: 0.2452 - val_accuracy: 0.9051
Epoch 189/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.1912 -
accuracy: 0.9199 - val_loss: 0.2442 - val_accuracy: 0.9071
Epoch 190/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1912 -
accuracy: 0.9192 - val_loss: 0.2448 - val_accuracy: 0.9064
Epoch 191/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1913 -
accuracy: 0.9201 - val_loss: 0.2444 - val_accuracy: 0.9073
Epoch 192/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.1911 -
accuracy: 0.9196 - val_loss: 0.2453 - val_accuracy: 0.9051
Epoch 193/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1911 -
accuracy: 0.9196 - val_loss: 0.2447 - val_accuracy: 0.9068
Epoch 194/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1911 -
```

```
accuracy: 0.9201 - val_loss: 0.2450 - val_accuracy: 0.9072
Epoch 195/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1910 -
accuracy: 0.9198 - val_loss: 0.2460 - val_accuracy: 0.9047
Epoch 196/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1906 -
accuracy: 0.9207 - val_loss: 0.2483 - val_accuracy: 0.9028
Epoch 197/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1908 -
accuracy: 0.9193 - val_loss: 0.2458 - val_accuracy: 0.9049
Epoch 198/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1908 -
accuracy: 0.9198 - val_loss: 0.2464 - val_accuracy: 0.9053
Epoch 199/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1908 -
accuracy: 0.9191 - val_loss: 0.2457 - val_accuracy: 0.9071
Epoch 200/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.1907 -
accuracy: 0.9198 - val_loss: 0.2452 - val_accuracy: 0.9071
```

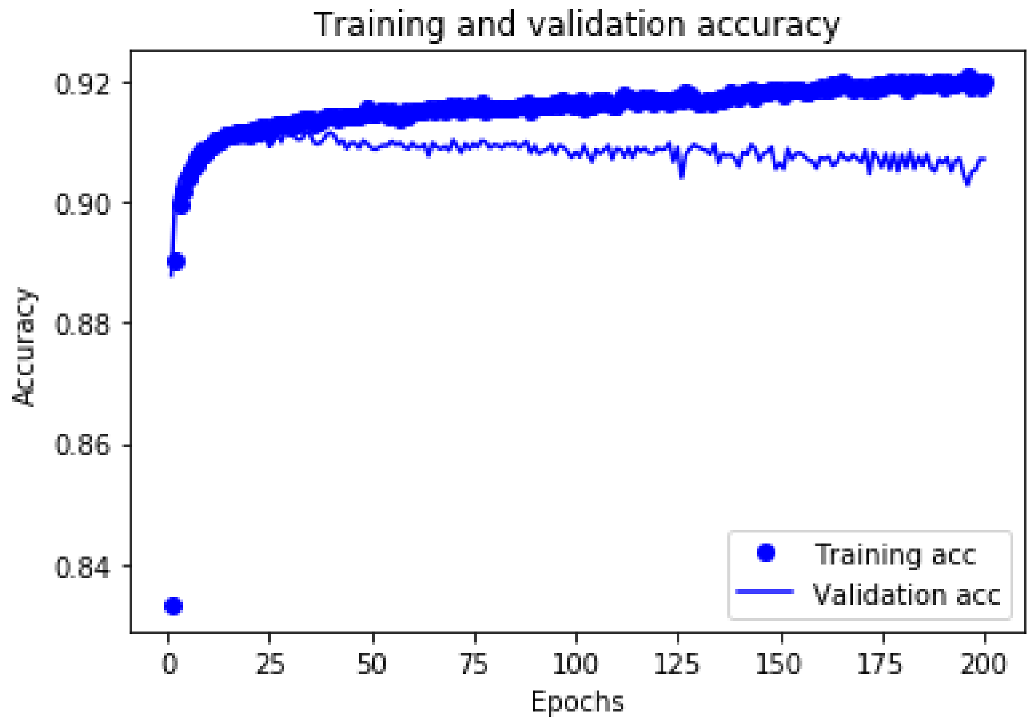
Now, we can plot the results of loss values from the training and validation set.

[53]:
```
# 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.

[54]:
```
# 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()
```



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.

[55]:
```
# 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.

[56]:
```
# 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 15us/step - loss: 0.6409 -
accuracy: 0.5171 - val_loss: 0.5960 - val_accuracy: 0.6753
Epoch 2/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.5049 -
accuracy: 0.7114 - val_loss: 0.5042 - val_accuracy: 0.7364
Epoch 3/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.4457 -
accuracy: 0.7482 - val_loss: 0.4606 - val_accuracy: 0.7547
Epoch 4/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.4180 -
accuracy: 0.7671 - val_loss: 0.4346 - val_accuracy: 0.7747
Epoch 5/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.4036 -
accuracy: 0.7815 - val_loss: 0.4226 - val_accuracy: 0.7791
Epoch 6/200
```

```
22014/22014 [==============================] - 0s 8us/step - loss: 0.3948 -
accuracy: 0.7862 - val_loss: 0.4197 - val_accuracy: 0.7801
Epoch 7/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3886 -
accuracy: 0.7882 - val_loss: 0.4132 - val_accuracy: 0.7829
Epoch 8/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3838 -
accuracy: 0.7918 - val_loss: 0.4208 - val_accuracy: 0.7797
Epoch 9/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3801 -
accuracy: 0.7924 - val_loss: 0.4123 - val_accuracy: 0.7825
Epoch 10/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3776 -
accuracy: 0.7938 - val_loss: 0.4048 - val_accuracy: 0.7863
Epoch 11/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3754 -
accuracy: 0.7928 - val_loss: 0.4042 - val_accuracy: 0.7857
Epoch 12/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3733 -
accuracy: 0.7959 - val_loss: 0.4113 - val_accuracy: 0.7831
Epoch 13/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3710 -
accuracy: 0.7944 - val_loss: 0.3816 - val_accuracy: 0.7996
Epoch 14/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3696 -
accuracy: 0.7977 - val_loss: 0.3832 - val_accuracy: 0.7983
Epoch 15/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3683 -
accuracy: 0.7983 - val_loss: 0.3919 - val_accuracy: 0.7951
Epoch 16/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3669 -
accuracy: 0.7992 - val_loss: 0.3877 - val_accuracy: 0.7960
Epoch 17/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3662 -
accuracy: 0.7998 - val_loss: 0.4050 - val_accuracy: 0.7849
Epoch 18/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3648 -
accuracy: 0.7985 - val_loss: 0.4070 - val_accuracy: 0.7835
Epoch 19/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3639 -
accuracy: 0.7984 - val_loss: 0.4076 - val_accuracy: 0.7836
Epoch 20/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3631 -
accuracy: 0.7979 - val_loss: 0.3962 - val_accuracy: 0.7903
Epoch 21/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3622 -
accuracy: 0.8003 - val_loss: 0.4008 - val_accuracy: 0.7848
Epoch 22/200
```

```
22014/22014 [==============================] - 0s 8us/step - loss: 0.3615 -
accuracy: 0.7979 - val_loss: 0.3986 - val_accuracy: 0.7879
Epoch 23/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3607 -
accuracy: 0.7984 - val_loss: 0.3835 - val_accuracy: 0.7964
Epoch 24/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3603 -
accuracy: 0.7996 - val_loss: 0.3928 - val_accuracy: 0.7904
Epoch 25/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3592 -
accuracy: 0.7987 - val_loss: 0.3873 - val_accuracy: 0.7957
Epoch 26/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3586 -
accuracy: 0.8017 - val_loss: 0.3972 - val_accuracy: 0.7883
Epoch 27/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3580 -
accuracy: 0.7996 - val_loss: 0.3968 - val_accuracy: 0.7884
Epoch 28/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3572 -
accuracy: 0.8002 - val_loss: 0.3941 - val_accuracy: 0.7880
Epoch 29/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3569 -
accuracy: 0.7991 - val_loss: 0.3858 - val_accuracy: 0.7932
Epoch 30/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3559 -
accuracy: 0.8022 - val_loss: 0.4075 - val_accuracy: 0.7819
Epoch 31/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3554 -
accuracy: 0.7999 - val_loss: 0.3904 - val_accuracy: 0.7899
Epoch 32/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3551 -
accuracy: 0.7999 - val_loss: 0.3907 - val_accuracy: 0.7884
Epoch 33/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3540 -
accuracy: 0.8023 - val_loss: 0.4006 - val_accuracy: 0.7824
Epoch 34/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3538 -
accuracy: 0.7984 - val_loss: 0.3822 - val_accuracy: 0.7908
Epoch 35/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3530 -
accuracy: 0.8019 - val_loss: 0.3939 - val_accuracy: 0.7859
Epoch 36/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3527 -
accuracy: 0.7993 - val_loss: 0.3774 - val_accuracy: 0.7952
Epoch 37/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3526 -
accuracy: 0.8009 - val_loss: 0.3832 - val_accuracy: 0.7924
Epoch 38/200
```

```
22014/22014 [==============================] - 0s 7us/step - loss: 0.3517 -
accuracy: 0.7982 - val_loss: 0.3772 - val_accuracy: 0.7969
Epoch 39/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3513 -
accuracy: 0.8020 - val_loss: 0.3859 - val_accuracy: 0.7907
Epoch 40/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3509 -
accuracy: 0.8024 - val_loss: 0.3971 - val_accuracy: 0.7845
Epoch 41/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3504 -
accuracy: 0.8007 - val_loss: 0.4022 - val_accuracy: 0.7792
Epoch 42/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3498 -
accuracy: 0.7996 - val_loss: 0.3834 - val_accuracy: 0.7921
Epoch 43/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3494 -
accuracy: 0.8014 - val_loss: 0.3788 - val_accuracy: 0.7941
Epoch 44/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3489 -
accuracy: 0.8025 - val_loss: 0.3994 - val_accuracy: 0.7841
Epoch 45/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3488 -
accuracy: 0.8021 - val_loss: 0.3942 - val_accuracy: 0.7861
Epoch 46/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3484 -
accuracy: 0.8038 - val_loss: 0.3943 - val_accuracy: 0.7848
Epoch 47/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3479 -
accuracy: 0.8023 - val_loss: 0.3966 - val_accuracy: 0.7851
Epoch 48/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3478 -
accuracy: 0.8021 - val_loss: 0.3929 - val_accuracy: 0.7861
Epoch 49/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3473 -
accuracy: 0.8017 - val_loss: 0.3980 - val_accuracy: 0.7825
Epoch 50/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3464 -
accuracy: 0.8025 - val_loss: 0.4008 - val_accuracy: 0.7827
Epoch 51/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3468 -
accuracy: 0.8032 - val_loss: 0.3921 - val_accuracy: 0.7871
Epoch 52/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3461 -
accuracy: 0.8024 - val_loss: 0.3818 - val_accuracy: 0.7927
Epoch 53/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3461 -
accuracy: 0.8032 - val_loss: 0.3952 - val_accuracy: 0.7841
Epoch 54/200
```

```
22014/22014 [==============================] - 0s 7us/step - loss: 0.3452 -
accuracy: 0.8039 - val_loss: 0.3884 - val_accuracy: 0.7896
Epoch 55/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3448 -
accuracy: 0.8049 - val_loss: 0.4001 - val_accuracy: 0.7823
Epoch 56/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3444 -
accuracy: 0.8049 - val_loss: 0.3915 - val_accuracy: 0.7896
Epoch 57/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3441 -
accuracy: 0.8052 - val_loss: 0.3950 - val_accuracy: 0.7877
Epoch 58/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3435 -
accuracy: 0.8039 - val_loss: 0.3826 - val_accuracy: 0.7939
Epoch 59/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3430 -
accuracy: 0.8044 - val_loss: 0.3835 - val_accuracy: 0.7945
Epoch 60/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3427 -
accuracy: 0.8036 - val_loss: 0.3764 - val_accuracy: 0.7993
Epoch 61/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3428 -
accuracy: 0.8060 - val_loss: 0.3936 - val_accuracy: 0.7895
Epoch 62/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3421 -
accuracy: 0.8050 - val_loss: 0.3894 - val_accuracy: 0.7931
Epoch 63/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3418 -
accuracy: 0.8042 - val_loss: 0.3901 - val_accuracy: 0.7933
Epoch 64/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3410 -
accuracy: 0.8051 - val_loss: 0.3865 - val_accuracy: 0.7947
Epoch 65/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3408 -
accuracy: 0.8057 - val_loss: 0.3915 - val_accuracy: 0.7920
Epoch 66/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3406 -
accuracy: 0.8058 - val_loss: 0.4043 - val_accuracy: 0.7849
Epoch 67/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3403 -
accuracy: 0.8049 - val_loss: 0.3905 - val_accuracy: 0.7928
Epoch 68/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3399 -
accuracy: 0.8047 - val_loss: 0.3803 - val_accuracy: 0.7979
Epoch 69/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3393 -
accuracy: 0.8053 - val_loss: 0.3768 - val_accuracy: 0.8009
Epoch 70/200
```

```
22014/22014 [==============================] - 0s 7us/step - loss: 0.3394 -
accuracy: 0.8069 - val_loss: 0.3861 - val_accuracy: 0.7948
Epoch 71/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3389 -
accuracy: 0.8047 - val_loss: 0.3882 - val_accuracy: 0.7948
Epoch 72/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3385 -
accuracy: 0.8058 - val_loss: 0.3814 - val_accuracy: 0.7993
Epoch 73/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3380 -
accuracy: 0.8070 - val_loss: 0.3935 - val_accuracy: 0.7896
Epoch 74/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3378 -
accuracy: 0.8069 - val_loss: 0.3907 - val_accuracy: 0.7944
Epoch 75/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3377 -
accuracy: 0.8081 - val_loss: 0.3916 - val_accuracy: 0.7904
Epoch 76/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3373 -
accuracy: 0.8059 - val_loss: 0.3839 - val_accuracy: 0.7976
Epoch 77/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3369 -
accuracy: 0.8073 - val_loss: 0.3927 - val_accuracy: 0.7933
Epoch 78/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3367 -
accuracy: 0.8065 - val_loss: 0.3879 - val_accuracy: 0.7945
Epoch 79/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3361 -
accuracy: 0.8074 - val_loss: 0.3748 - val_accuracy: 0.8021
Epoch 80/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3357 -
accuracy: 0.8073 - val_loss: 0.3649 - val_accuracy: 0.8052
Epoch 81/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3357 -
accuracy: 0.8087 - val_loss: 0.3914 - val_accuracy: 0.7923
Epoch 82/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3351 -
accuracy: 0.8095 - val_loss: 0.3894 - val_accuracy: 0.7928
Epoch 83/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3352 -
accuracy: 0.8076 - val_loss: 0.3956 - val_accuracy: 0.7893
Epoch 84/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.3346 -
accuracy: 0.8077 - val_loss: 0.3935 - val_accuracy: 0.7905
Epoch 85/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3343 -
accuracy: 0.8084 - val_loss: 0.3872 - val_accuracy: 0.7940
Epoch 86/200
```

```
22014/22014 [==============================] - 0s 12us/step - loss: 0.3337 -
accuracy: 0.8098 - val_loss: 0.4031 - val_accuracy: 0.7847
Epoch 87/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3335 -
accuracy: 0.8081 - val_loss: 0.3731 - val_accuracy: 0.8045
Epoch 88/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3333 -
accuracy: 0.8110 - val_loss: 0.3906 - val_accuracy: 0.7925
Epoch 89/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3327 -
accuracy: 0.8107 - val_loss: 0.3908 - val_accuracy: 0.7932
Epoch 90/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3326 -
accuracy: 0.8108 - val_loss: 0.4049 - val_accuracy: 0.7837
Epoch 91/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3323 -
accuracy: 0.8104 - val_loss: 0.3949 - val_accuracy: 0.7887
Epoch 92/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3323 -
accuracy: 0.8091 - val_loss: 0.3889 - val_accuracy: 0.7923
Epoch 93/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3319 -
accuracy: 0.8082 - val_loss: 0.3832 - val_accuracy: 0.7987
Epoch 94/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3314 -
accuracy: 0.8102 - val_loss: 0.3798 - val_accuracy: 0.8004
Epoch 95/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3311 -
accuracy: 0.8105 - val_loss: 0.3868 - val_accuracy: 0.7975
Epoch 96/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3308 -
accuracy: 0.8127 - val_loss: 0.4011 - val_accuracy: 0.7876
Epoch 97/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3306 -
accuracy: 0.8117 - val_loss: 0.3964 - val_accuracy: 0.7888
Epoch 98/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3302 -
accuracy: 0.8100 - val_loss: 0.4026 - val_accuracy: 0.7864
Epoch 99/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3302 -
accuracy: 0.8116 - val_loss: 0.4051 - val_accuracy: 0.7824
Epoch 100/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3297 -
accuracy: 0.8100 - val_loss: 0.3863 - val_accuracy: 0.7967
Epoch 101/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3293 -
accuracy: 0.8098 - val_loss: 0.3698 - val_accuracy: 0.8084
Epoch 102/200
```

```
22014/22014 [==============================] - 0s 6us/step - loss: 0.3291 -
accuracy: 0.8123 - val_loss: 0.3718 - val_accuracy: 0.8059
Epoch 103/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3290 -
accuracy: 0.8136 - val_loss: 0.3821 - val_accuracy: 0.8016
Epoch 104/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3284 -
accuracy: 0.8131 - val_loss: 0.3834 - val_accuracy: 0.7981
Epoch 105/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3281 -
accuracy: 0.8133 - val_loss: 0.3817 - val_accuracy: 0.8009
Epoch 106/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3280 -
accuracy: 0.8138 - val_loss: 0.3877 - val_accuracy: 0.7956
Epoch 107/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3276 -
accuracy: 0.8119 - val_loss: 0.3863 - val_accuracy: 0.7967
Epoch 108/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3275 -
accuracy: 0.8139 - val_loss: 0.3932 - val_accuracy: 0.7940
Epoch 109/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3273 -
accuracy: 0.8126 - val_loss: 0.3832 - val_accuracy: 0.7975
Epoch 110/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3267 -
accuracy: 0.8115 - val_loss: 0.3833 - val_accuracy: 0.8003
Epoch 111/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3269 -
accuracy: 0.8144 - val_loss: 0.3902 - val_accuracy: 0.7947
Epoch 112/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3264 -
accuracy: 0.8133 - val_loss: 0.3876 - val_accuracy: 0.7967
Epoch 113/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3263 -
accuracy: 0.8130 - val_loss: 0.3729 - val_accuracy: 0.8051
Epoch 114/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3258 -
accuracy: 0.8153 - val_loss: 0.3829 - val_accuracy: 0.7971
Epoch 115/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3258 -
accuracy: 0.8144 - val_loss: 0.3930 - val_accuracy: 0.7931
Epoch 116/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3258 -
accuracy: 0.8150 - val_loss: 0.3951 - val_accuracy: 0.7911
Epoch 117/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3256 -
accuracy: 0.8133 - val_loss: 0.3826 - val_accuracy: 0.8009
Epoch 118/200
```

```
22014/22014 [==============================] - 0s 9us/step - loss: 0.3252 -
accuracy: 0.8133 - val_loss: 0.3807 - val_accuracy: 0.8003
Epoch 119/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3246 -
accuracy: 0.8148 - val_loss: 0.3921 - val_accuracy: 0.7927
Epoch 120/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3248 -
accuracy: 0.8131 - val_loss: 0.3827 - val_accuracy: 0.7996
Epoch 121/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3242 -
accuracy: 0.8166 - val_loss: 0.4027 - val_accuracy: 0.7856
Epoch 122/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3237 -
accuracy: 0.8134 - val_loss: 0.3854 - val_accuracy: 0.7951
Epoch 123/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3239 -
accuracy: 0.8140 - val_loss: 0.3971 - val_accuracy: 0.7889
Epoch 124/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3235 -
accuracy: 0.8132 - val_loss: 0.3811 - val_accuracy: 0.7995
Epoch 125/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3234 -
accuracy: 0.8155 - val_loss: 0.3998 - val_accuracy: 0.7885
Epoch 126/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3233 -
accuracy: 0.8141 - val_loss: 0.3987 - val_accuracy: 0.7885
Epoch 127/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3226 -
accuracy: 0.8138 - val_loss: 0.3961 - val_accuracy: 0.7932
Epoch 128/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3227 -
accuracy: 0.8142 - val_loss: 0.3777 - val_accuracy: 0.8007
Epoch 129/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3221 -
accuracy: 0.8151 - val_loss: 0.3854 - val_accuracy: 0.7979
Epoch 130/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3223 -
accuracy: 0.8156 - val_loss: 0.3917 - val_accuracy: 0.7952
Epoch 131/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3219 -
accuracy: 0.8145 - val_loss: 0.3959 - val_accuracy: 0.7925
Epoch 132/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3219 -
accuracy: 0.8151 - val_loss: 0.3916 - val_accuracy: 0.7945
Epoch 133/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3213 -
accuracy: 0.8156 - val_loss: 0.3840 - val_accuracy: 0.8000
Epoch 134/200
```

```
22014/22014 [==============================] - 0s 6us/step - loss: 0.3215 -
accuracy: 0.8175 - val_loss: 0.3957 - val_accuracy: 0.7925
Epoch 135/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3212 -
accuracy: 0.8156 - val_loss: 0.3881 - val_accuracy: 0.7984
Epoch 136/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3209 -
accuracy: 0.8145 - val_loss: 0.3854 - val_accuracy: 0.8008
Epoch 137/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3209 -
accuracy: 0.8157 - val_loss: 0.3868 - val_accuracy: 0.7999
Epoch 138/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3203 -
accuracy: 0.8163 - val_loss: 0.3838 - val_accuracy: 0.8017
Epoch 139/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3206 -
accuracy: 0.8161 - val_loss: 0.3800 - val_accuracy: 0.8016
Epoch 140/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3200 -
accuracy: 0.8162 - val_loss: 0.4030 - val_accuracy: 0.7875
Epoch 141/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3196 -
accuracy: 0.8165 - val_loss: 0.3911 - val_accuracy: 0.7951
Epoch 142/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3194 -
accuracy: 0.8160 - val_loss: 0.3913 - val_accuracy: 0.7956
Epoch 143/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3193 -
accuracy: 0.8161 - val_loss: 0.3911 - val_accuracy: 0.7979
Epoch 144/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3190 -
accuracy: 0.8187 - val_loss: 0.4057 - val_accuracy: 0.7847
Epoch 145/200
22014/22014 [==============================] - 0s 13us/step - loss: 0.3189 -
accuracy: 0.8165 - val_loss: 0.3873 - val_accuracy: 0.7988
Epoch 146/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3189 -
accuracy: 0.8175 - val_loss: 0.3969 - val_accuracy: 0.7941
Epoch 147/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3182 -
accuracy: 0.8178 - val_loss: 0.4091 - val_accuracy: 0.7829
Epoch 148/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3185 -
accuracy: 0.8167 - val_loss: 0.3942 - val_accuracy: 0.7952
Epoch 149/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3181 -
accuracy: 0.8184 - val_loss: 0.3806 - val_accuracy: 0.8024
Epoch 150/200
```

```
22014/22014 [==============================] - 0s 8us/step - loss: 0.3179 -
accuracy: 0.8175 - val_loss: 0.3844 - val_accuracy: 0.8021
Epoch 151/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3178 -
accuracy: 0.8168 - val_loss: 0.3839 - val_accuracy: 0.8037
Epoch 152/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3173 -
accuracy: 0.8192 - val_loss: 0.3849 - val_accuracy: 0.8049
Epoch 153/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3174 -
accuracy: 0.8162 - val_loss: 0.3752 - val_accuracy: 0.8079
Epoch 154/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3174 -
accuracy: 0.8203 - val_loss: 0.3904 - val_accuracy: 0.7992
Epoch 155/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3172 -
accuracy: 0.8187 - val_loss: 0.3948 - val_accuracy: 0.7945
Epoch 156/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3166 -
accuracy: 0.8185 - val_loss: 0.3866 - val_accuracy: 0.8011
Epoch 157/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3168 -
accuracy: 0.8179 - val_loss: 0.3889 - val_accuracy: 0.8007
Epoch 158/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3164 -
accuracy: 0.8198 - val_loss: 0.3941 - val_accuracy: 0.7939
Epoch 159/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3166 -
accuracy: 0.8175 - val_loss: 0.3835 - val_accuracy: 0.8032
Epoch 160/200
22014/22014 [==============================] - 0s 10us/step - loss: 0.3158 -
accuracy: 0.8205 - val_loss: 0.4037 - val_accuracy: 0.7945
Epoch 161/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3159 -
accuracy: 0.8219 - val_loss: 0.4078 - val_accuracy: 0.7901
Epoch 162/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3157 -
accuracy: 0.8215 - val_loss: 0.4069 - val_accuracy: 0.7883
Epoch 163/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3156 -
accuracy: 0.8203 - val_loss: 0.3952 - val_accuracy: 0.7957
Epoch 164/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3151 -
accuracy: 0.8212 - val_loss: 0.4048 - val_accuracy: 0.7933
Epoch 165/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3151 -
accuracy: 0.8192 - val_loss: 0.4021 - val_accuracy: 0.7947
Epoch 166/200
```

```
22014/22014 [==============================] - 0s 7us/step - loss: 0.3150 -
accuracy: 0.8190 - val_loss: 0.3938 - val_accuracy: 0.8008
Epoch 167/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3150 -
accuracy: 0.8198 - val_loss: 0.3832 - val_accuracy: 0.8048
Epoch 168/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3148 -
accuracy: 0.8199 - val_loss: 0.3891 - val_accuracy: 0.8039
Epoch 169/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3145 -
accuracy: 0.8219 - val_loss: 0.3951 - val_accuracy: 0.7984
Epoch 170/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3142 -
accuracy: 0.8227 - val_loss: 0.3849 - val_accuracy: 0.8055
Epoch 171/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3144 -
accuracy: 0.8209 - val_loss: 0.3902 - val_accuracy: 0.8000
Epoch 172/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3139 -
accuracy: 0.8219 - val_loss: 0.3902 - val_accuracy: 0.8021
Epoch 173/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3137 -
accuracy: 0.8227 - val_loss: 0.3920 - val_accuracy: 0.8012
Epoch 174/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3137 -
accuracy: 0.8216 - val_loss: 0.3795 - val_accuracy: 0.8085
Epoch 175/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3136 -
accuracy: 0.8220 - val_loss: 0.4107 - val_accuracy: 0.7896
Epoch 176/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3134 -
accuracy: 0.8202 - val_loss: 0.3857 - val_accuracy: 0.8060
Epoch 177/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3134 -
accuracy: 0.8228 - val_loss: 0.3951 - val_accuracy: 0.7979
Epoch 178/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3132 -
accuracy: 0.8226 - val_loss: 0.4119 - val_accuracy: 0.7897
Epoch 179/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3126 -
accuracy: 0.8197 - val_loss: 0.3791 - val_accuracy: 0.8087
Epoch 180/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3124 -
accuracy: 0.8213 - val_loss: 0.3790 - val_accuracy: 0.8104
Epoch 181/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3126 -
accuracy: 0.8218 - val_loss: 0.3839 - val_accuracy: 0.8073
Epoch 182/200
```

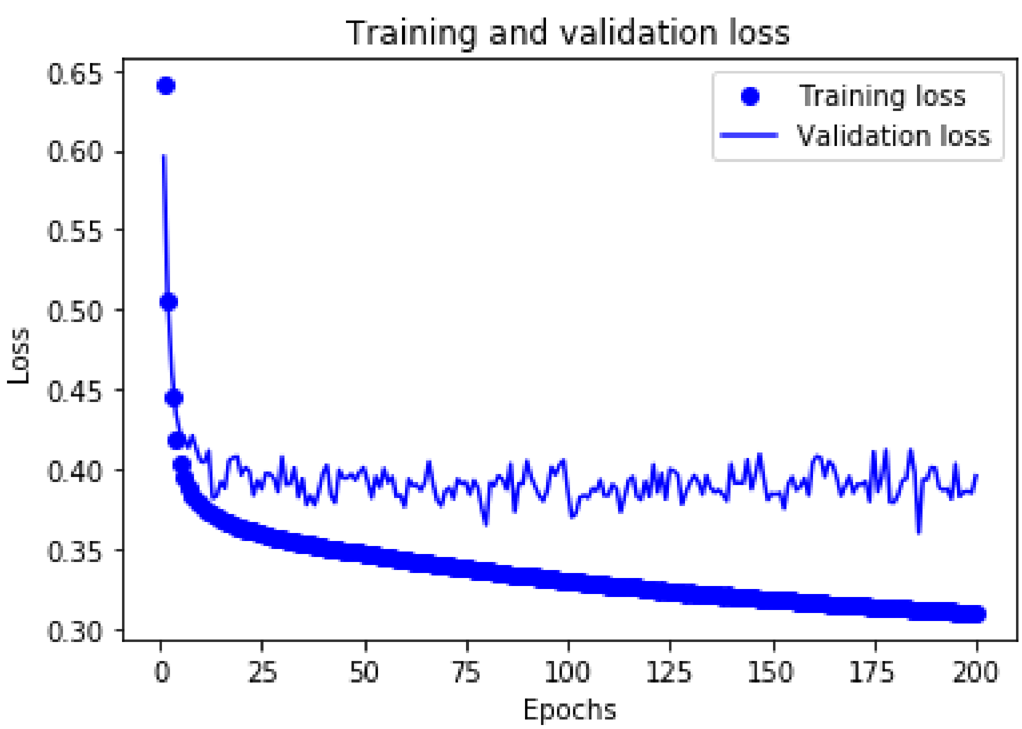
```
22014/22014 [==============================] - 0s 7us/step - loss: 0.3123 -
accuracy: 0.8226 - val_loss: 0.3927 - val_accuracy: 0.8037
Epoch 183/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3122 -
accuracy: 0.8214 - val_loss: 0.3937 - val_accuracy: 0.8021
Epoch 184/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3120 -
accuracy: 0.8230 - val_loss: 0.4118 - val_accuracy: 0.7873
Epoch 185/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3118 -
accuracy: 0.8211 - val_loss: 0.3981 - val_accuracy: 0.7988
Epoch 186/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3116 -
accuracy: 0.8200 - val_loss: 0.3600 - val_accuracy: 0.8200
Epoch 187/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3115 -
accuracy: 0.8241 - val_loss: 0.3934 - val_accuracy: 0.8044
Epoch 188/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3112 -
accuracy: 0.8228 - val_loss: 0.3932 - val_accuracy: 0.8036
Epoch 189/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3110 -
accuracy: 0.8234 - val_loss: 0.4008 - val_accuracy: 0.7952
Epoch 190/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3110 -
accuracy: 0.8226 - val_loss: 0.4004 - val_accuracy: 0.7981
Epoch 191/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3108 -
accuracy: 0.8214 - val_loss: 0.3884 - val_accuracy: 0.8048
Epoch 192/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3107 -
accuracy: 0.8234 - val_loss: 0.3867 - val_accuracy: 0.8059
Epoch 193/200
22014/22014 [==============================] - 0s 7us/step - loss: 0.3108 -
accuracy: 0.8223 - val_loss: 0.3875 - val_accuracy: 0.8073
Epoch 194/200
22014/22014 [==============================] - 0s 6us/step - loss: 0.3104 -
accuracy: 0.8229 - val_loss: 0.3812 - val_accuracy: 0.8101
Epoch 195/200
22014/22014 [==============================] - 0s 14us/step - loss: 0.3101 -
accuracy: 0.8241 - val_loss: 0.4031 - val_accuracy: 0.7985
Epoch 196/200
22014/22014 [==============================] - 0s 8us/step - loss: 0.3101 -
accuracy: 0.8228 - val_loss: 0.3827 - val_accuracy: 0.8092
Epoch 197/200
22014/22014 [==============================] - 0s 11us/step - loss: 0.3099 -
accuracy: 0.8227 - val_loss: 0.3853 - val_accuracy: 0.8061
Epoch 198/200
```

```
22014/22014 [==============================] - 0s 13us/step - loss: 0.3100 -
accuracy: 0.8247 - val_loss: 0.3859 - val_accuracy: 0.8055
Epoch 199/200
22014/22014 [==============================] - 0s 9us/step - loss: 0.3097 -
accuracy: 0.8229 - val_loss: 0.3849 - val_accuracy: 0.8072
Epoch 200/200
22014/22014 [==============================] - 0s 16us/step - loss: 0.3097 -
accuracy: 0.8239 - val_loss: 0.3956 - val_accuracy: 0.8007
```

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

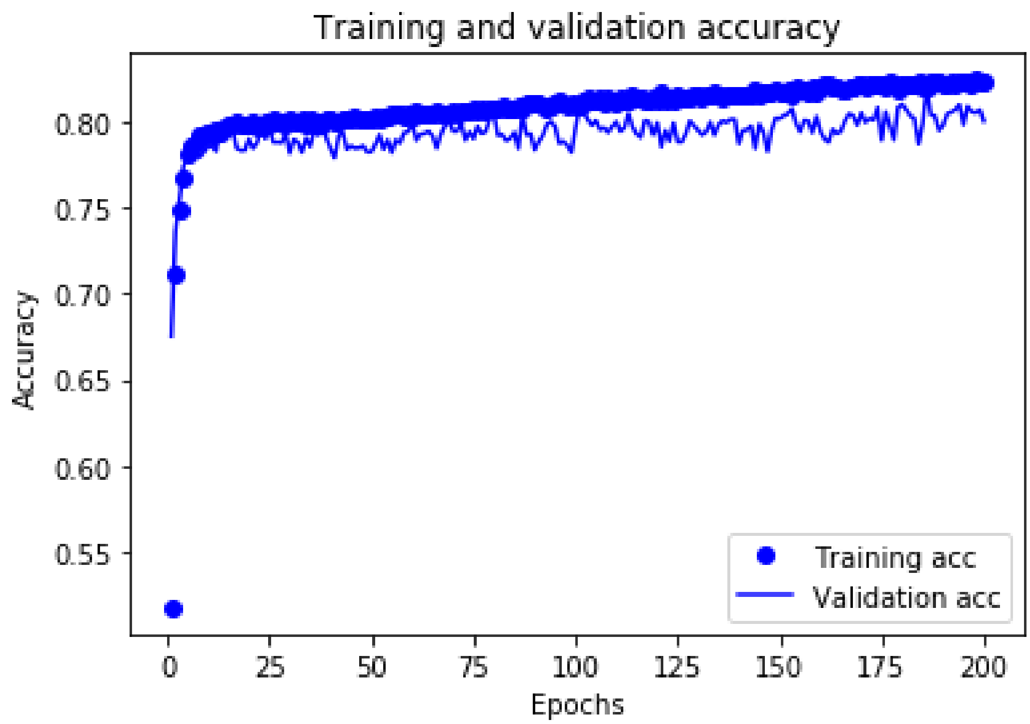
[57]:

```python
# 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.

[58]:
```
#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()
```



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

[59]:
```
# Training the final 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'])

model.fit(X_train,y_train,
                    epochs=200,
                    batch_size=512,
                    class_weight=class_weights)
```

```
Epoch 1/200
29514/29514 [==============================] - 0s 10us/step - loss: 0.5889 -
accuracy: 0.6675
Epoch 2/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.4631 -
accuracy: 0.7317
Epoch 3/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.4209 -
accuracy: 0.7627
Epoch 4/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.4042 -
accuracy: 0.7757
Epoch 5/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3952 -
accuracy: 0.7804
Epoch 6/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3884 -
accuracy: 0.7833
Epoch 7/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3842 -
accuracy: 0.7871
Epoch 8/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3806 -
accuracy: 0.7866
Epoch 9/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3776 -
accuracy: 0.7869
Epoch 10/200
29514/29514 [==============================] - 0s 8us/step - loss: 0.3754 -
accuracy: 0.7924
Epoch 11/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3733 -
accuracy: 0.7907
Epoch 12/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3720 -
```

```
accuracy: 0.7913
Epoch 13/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3707 -
accuracy: 0.7940
Epoch 14/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3695 -
accuracy: 0.7941
Epoch 15/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3683 -
accuracy: 0.7941
Epoch 16/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3677 -
accuracy: 0.7966
Epoch 17/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3670 -
accuracy: 0.7956
Epoch 18/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3660 -
accuracy: 0.7971
Epoch 19/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3654 -
accuracy: 0.7978
Epoch 20/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3648 -
accuracy: 0.7948
Epoch 21/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3643 -
accuracy: 0.7967
Epoch 22/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3636 -
accuracy: 0.7959
Epoch 23/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3631 -
accuracy: 0.7968
Epoch 24/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3626 -
accuracy: 0.7961
Epoch 25/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3623 -
accuracy: 0.7964
Epoch 26/200
29514/29514 [==============================] - 0s 10us/step - loss: 0.3616 -
accuracy: 0.7974
Epoch 27/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3612 -
accuracy: 0.7996
Epoch 28/200
29514/29514 [==============================] - 0s 9us/step - loss: 0.3611 -
```

```
accuracy: 0.7955
Epoch 29/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3603 -
accuracy: 0.7982
Epoch 30/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3600 -
accuracy: 0.7971
Epoch 31/200
29514/29514 [==============================] - 0s 8us/step - loss: 0.3596 -
accuracy: 0.7977
Epoch 32/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3594 -
accuracy: 0.7982
Epoch 33/200
29514/29514 [==============================] - 0s 11us/step - loss: 0.3586 -
accuracy: 0.7998
Epoch 34/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3584 -
accuracy: 0.7991
Epoch 35/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3576 -
accuracy: 0.7978
Epoch 36/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3577 -
accuracy: 0.7984
Epoch 37/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3574 -
accuracy: 0.7978
Epoch 38/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3567 -
accuracy: 0.7993
Epoch 39/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3563 -
accuracy: 0.7985
Epoch 40/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3563 -
accuracy: 0.7969
Epoch 41/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3559 -
accuracy: 0.7990
Epoch 42/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3557 -
accuracy: 0.7989
Epoch 43/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3552 -
accuracy: 0.7986
Epoch 44/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3551 -
```

```
accuracy: 0.7987
Epoch 45/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3546 -
accuracy: 0.7983
Epoch 46/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3544 -
accuracy: 0.7990
Epoch 47/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3539 -
accuracy: 0.7993
Epoch 48/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3537 -
accuracy: 0.8000
Epoch 49/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3530 -
accuracy: 0.7997
Epoch 50/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3531 -
accuracy: 0.8022
Epoch 51/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3523 -
accuracy: 0.8007
Epoch 52/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3522 -
accuracy: 0.8002
Epoch 53/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3522 -
accuracy: 0.7992
Epoch 54/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3519 -
accuracy: 0.8003
Epoch 55/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3514 -
accuracy: 0.8007
Epoch 56/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3512 -
accuracy: 0.8018
Epoch 57/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3511 -
accuracy: 0.7989
Epoch 58/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3508 -
accuracy: 0.8017
Epoch 59/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3504 -
accuracy: 0.8013
Epoch 60/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3499 -
```

```
accuracy: 0.8020
Epoch 61/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3499 -
accuracy: 0.8002
Epoch 62/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3495 -
accuracy: 0.8004
Epoch 63/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3490 -
accuracy: 0.8020
Epoch 64/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3489 -
accuracy: 0.7998
Epoch 65/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3484 -
accuracy: 0.8026
Epoch 66/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3481 -
accuracy: 0.8011
Epoch 67/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3479 -
accuracy: 0.8002
Epoch 68/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3477 -
accuracy: 0.8038
Epoch 69/200
29514/29514 [==============================] - 0s 5us/step - loss: 0.3471 -
accuracy: 0.8015
Epoch 70/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3468 -
accuracy: 0.8029
Epoch 71/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3466 -
accuracy: 0.8015
Epoch 72/200
29514/29514 [==============================] - 0s 5us/step - loss: 0.3464 -
accuracy: 0.8015
Epoch 73/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3458 -
accuracy: 0.8016
Epoch 74/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3456 -
accuracy: 0.8033
Epoch 75/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3458 -
accuracy: 0.8054
Epoch 76/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3453 -
```

```
accuracy: 0.8031
Epoch 77/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3454 -
accuracy: 0.7999
Epoch 78/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3448 -
accuracy: 0.8032
Epoch 79/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3446 -
accuracy: 0.8059
Epoch 80/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3444 -
accuracy: 0.8036
Epoch 81/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3443 -
accuracy: 0.8021
Epoch 82/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3441 -
accuracy: 0.8038
Epoch 83/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3437 -
accuracy: 0.8036
Epoch 84/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3435 -
accuracy: 0.8057
Epoch 85/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3433 -
accuracy: 0.8036
Epoch 86/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3429 -
accuracy: 0.8055
Epoch 87/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3429 -
accuracy: 0.8040
Epoch 88/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3427 -
accuracy: 0.8032
Epoch 89/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3425 -
accuracy: 0.8048
Epoch 90/200
29514/29514 [==============================] - 0s 8us/step - loss: 0.3424 -
accuracy: 0.8047
Epoch 91/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3420 -
accuracy: 0.8042
Epoch 92/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3417 -
```

```
accuracy: 0.8051
Epoch 93/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3415 -
accuracy: 0.8045
Epoch 94/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3414 -
accuracy: 0.8037
Epoch 95/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3410 -
accuracy: 0.8041
Epoch 96/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3410 -
accuracy: 0.8049
Epoch 97/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3407 -
accuracy: 0.8037
Epoch 98/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3404 -
accuracy: 0.8032
Epoch 99/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3400 -
accuracy: 0.8044
Epoch 100/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3398 -
accuracy: 0.8068
Epoch 101/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3396 -
accuracy: 0.8031
Epoch 102/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3395 -
accuracy: 0.8059
Epoch 103/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3392 -
accuracy: 0.8042
Epoch 104/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3390 -
accuracy: 0.8072
Epoch 105/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3389 -
accuracy: 0.8032
Epoch 106/200
29514/29514 [==============================] - 0s 8us/step - loss: 0.3384 -
accuracy: 0.8049
Epoch 107/200
29514/29514 [==============================] - 0s 11us/step - loss: 0.3387 -
accuracy: 0.8073
Epoch 108/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3382 -
```

```
accuracy: 0.8072
Epoch 109/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3378 -
accuracy: 0.8063
Epoch 110/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3378 -
accuracy: 0.8062
Epoch 111/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3377 -
accuracy: 0.8055
Epoch 112/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3374 -
accuracy: 0.8083
Epoch 113/200
29514/29514 [==============================] - 0s 9us/step - loss: 0.3372 -
accuracy: 0.8062
Epoch 114/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3369 -
accuracy: 0.8069
Epoch 115/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3369 -
accuracy: 0.8086
Epoch 116/200
29514/29514 [==============================] - 0s 8us/step - loss: 0.3370 -
accuracy: 0.8071
Epoch 117/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3366 -
accuracy: 0.8092
Epoch 118/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3365 -
accuracy: 0.8062
Epoch 119/200
29514/29514 [==============================] - 0s 8us/step - loss: 0.3362 -
accuracy: 0.8066
Epoch 120/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3360 -
accuracy: 0.8081
Epoch 121/200
29514/29514 [==============================] - 0s 5us/step - loss: 0.3357 -
accuracy: 0.8069
Epoch 122/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3359 -
accuracy: 0.8081
Epoch 123/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3354 -
accuracy: 0.8082
Epoch 124/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3354 -
```

```
accuracy: 0.8071
Epoch 125/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3351 -
accuracy: 0.8081
Epoch 126/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3350 -
accuracy: 0.8079
Epoch 127/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3350 -
accuracy: 0.8068
Epoch 128/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3346 -
accuracy: 0.8078
Epoch 129/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3345 -
accuracy: 0.8066
Epoch 130/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3342 -
accuracy: 0.8082
Epoch 131/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3342 -
accuracy: 0.8093
Epoch 132/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3342 -
accuracy: 0.8118
Epoch 133/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3337 -
accuracy: 0.8086
Epoch 134/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3339 -
accuracy: 0.8080
Epoch 135/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3334 -
accuracy: 0.8096
Epoch 136/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3336 -
accuracy: 0.8083
Epoch 137/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3335 -
accuracy: 0.8100
Epoch 138/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3335 -
accuracy: 0.8092
Epoch 139/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3331 -
accuracy: 0.8103
Epoch 140/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3331 -
```

```
accuracy: 0.8089
Epoch 141/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3328 -
accuracy: 0.8092
Epoch 142/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3326 -
accuracy: 0.8093
Epoch 143/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3322 -
accuracy: 0.8106
Epoch 144/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3324 -
accuracy: 0.8112
Epoch 145/200
29514/29514 [==============================] - 0s 9us/step - loss: 0.3319 -
accuracy: 0.8090
Epoch 146/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3319 -
accuracy: 0.8110
Epoch 147/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3321 -
accuracy: 0.8095
Epoch 148/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3316 -
accuracy: 0.8110
Epoch 149/200
29514/29514 [==============================] - 0s 5us/step - loss: 0.3318 -
accuracy: 0.8102
Epoch 150/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3317 -
accuracy: 0.8081
Epoch 151/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3313 -
accuracy: 0.8117
Epoch 152/200
29514/29514 [==============================] - 0s 5us/step - loss: 0.3312 -
accuracy: 0.8104
Epoch 153/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3310 -
accuracy: 0.8095
Epoch 154/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3310 -
accuracy: 0.8107
Epoch 155/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3307 -
accuracy: 0.8107
Epoch 156/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3303 -
```

```
accuracy: 0.8114
Epoch 157/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3304 -
accuracy: 0.8088
Epoch 158/200
29514/29514 [==============================] - 0s 5us/step - loss: 0.3302 -
accuracy: 0.8102
Epoch 159/200
29514/29514 [==============================] - 0s 5us/step - loss: 0.3305 -
accuracy: 0.8095
Epoch 160/200
29514/29514 [==============================] - 0s 5us/step - loss: 0.3304 -
accuracy: 0.8103
Epoch 161/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3302 -
accuracy: 0.8111
Epoch 162/200
29514/29514 [==============================] - 0s 9us/step - loss: 0.3300 -
accuracy: 0.8102
Epoch 163/200
29514/29514 [==============================] - 0s 9us/step - loss: 0.3295 -
accuracy: 0.8098
Epoch 164/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3296 -
accuracy: 0.8112
Epoch 165/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3296 -
accuracy: 0.8101
Epoch 166/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3293 -
accuracy: 0.8089
Epoch 167/200
29514/29514 [==============================] - 0s 9us/step - loss: 0.3288 -
accuracy: 0.8103
Epoch 168/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3288 -
accuracy: 0.8104
Epoch 169/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3293 -
accuracy: 0.8115
Epoch 170/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3290 -
accuracy: 0.8099
Epoch 171/200
29514/29514 [==============================] - 0s 8us/step - loss: 0.3283 -
accuracy: 0.8094
Epoch 172/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3278 -
```

```
accuracy: 0.8103
Epoch 173/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3285 -
accuracy: 0.8097
Epoch 174/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3277 -
accuracy: 0.8117
Epoch 175/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3276 -
accuracy: 0.8091
Epoch 176/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3279 -
accuracy: 0.8099
Epoch 177/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3271 -
accuracy: 0.8111
Epoch 178/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3275 -
accuracy: 0.8115
Epoch 179/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3271 -
accuracy: 0.8103
Epoch 180/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3272 -
accuracy: 0.8109
Epoch 181/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3270 -
accuracy: 0.8106
Epoch 182/200
29514/29514 [==============================] - 0s 5us/step - loss: 0.3267 -
accuracy: 0.8107
Epoch 183/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3260 -
accuracy: 0.8095
Epoch 184/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3265 -
accuracy: 0.8110
Epoch 185/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3261 -
accuracy: 0.8108
Epoch 186/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3263 -
accuracy: 0.8121
Epoch 187/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3262 -
accuracy: 0.8079
Epoch 188/200
29514/29514 [==============================] - 0s 5us/step - loss: 0.3263 -
```

```
accuracy: 0.8120
Epoch 189/200
29514/29514 [==============================] - 0s 5us/step - loss: 0.3258 -
accuracy: 0.8092
Epoch 190/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3260 -
accuracy: 0.8104
Epoch 191/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3258 -
accuracy: 0.8098
Epoch 192/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3253 -
accuracy: 0.8105
Epoch 193/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3256 -
accuracy: 0.8093
Epoch 194/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3252 -
accuracy: 0.8102
Epoch 195/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3254 -
accuracy: 0.8108
Epoch 196/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3250 -
accuracy: 0.8103
Epoch 197/200
29514/29514 [==============================] - 0s 7us/step - loss: 0.3248 -
accuracy: 0.8104
Epoch 198/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3251 -
accuracy: 0.8094
Epoch 199/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3246 -
accuracy: 0.8125
Epoch 200/200
29514/29514 [==============================] - 0s 6us/step - loss: 0.3245 -
accuracy: 0.8109
```

```
[59]: <keras.callbacks.callbacks.History at 0x130c16e90>
```

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

2.4 Using a trained network to generate predictions on testing data

[60]:
```
#Using a trained network to generate predictions on new data
y_pred_probability=model.predict(X_test)
y_pred=(y_pred_probability>0.5).astype(int)
answer=pd.DataFrame(y_pred)
```

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

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

2.5 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.

2.6 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.