deep_learning_flights

November 18, 2020

[1]:
```python
from numpy import loadtxt
import tensorflow as tf
from tensorflow import keras
import pandas as pd
from matplotlib import pyplot as plt
import numpy as np

from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error
```

[2]:
```python
# Read in and shuffle dataset
dataset = pd.read_csv("../data_raw/full_data_one_hot.csv").sample(frac=1)

print(dataset.shape)

dataset
```

```
(581328, 203)
```

[2]:
```
        departure_delay  time_taxi_out  elapsed_time_scheduled  delay_carrier  \
50738                -4             16                      61              0
195908               13             21                     145              0
462546               43             14                     102              0
49188                92             12                     126             92
318575              -10             13                     213              0
…                     …              …                       …              …
364474                1             12                     283              0
88432                -4             19                     151              0
483395               43             16                     100              0
207499               -6             22                     235              0
306795               -3             10                      70              0

        delay_weather  delay_nas  delay_security  delay_late_aircraft  \
50738               0          0               0                    0
195908             13          6               0                    0
462546              0          0               0                   22
49188               0          7               0                    0
318575              0          0               0                    0
```

```
…               …        …            …                  …
364474          0        0            0                      0
88432           0        0            0                      0
483395          0       10            0                     20
207499          0        0            0                      0
306795          0        0            0                      0

        humidity  dew_point  …  wind_direction_NW  wind_direction_S  \
50738         79         69  …                  0                 0
195908        85         25  …                  0                 0
462546        57         57  …                  0                 0
49188         85         75  …                  0                 0
318575        14         27  …                  0                 0
…            …         …  …                …                 …
364474        39         27  …                  0                 0
88432         73         63  …                  0                 0
483395        70         51  …                  1                 0
207499        46         54  …                  1                 0
306795        51         48  …                  0                 0

        wind_direction_SE  wind_direction_SSE  wind_direction_SSW  \
50738                   0                   1                   0
195908                  0                   0                   0
462546                  0                   0                   0
49188                   0                   0                   0
318575                  0                   0                   0
…                     …                  …                  …
364474                  0                   0                   0
88432                   0                   0                   0
483395                  0                   0                   0
207499                  0                   0                   0
306795                  0                   1                   0

        wind_direction_SW  wind_direction_VAR  wind_direction_W  \
50738                   0                   0                 0
195908                  0                   0                 0
462546                  0                   0                 0
49188                   1                   0                 0
318575                  0                   0                 0
…                     …                  …                …
364474                  0                   0                 1
88432                   0                   0                 0
483395                  0                   0                 0
207499                  0                   0                 0
306795                  0                   0                 0

        wind_direction_WNW  wind_direction_WSW
```

```
50738                     0                   0
195908                    0                   0
462546                    1                   0
49188                     0                   0
318575                    0                   0
…                     …                   …
364474                    0                   0
88432                     0                   0
483395                    0                   0
207499                    0                   0
306795                    0                   0

[581328 rows x 203 columns]
```

[3]:
```
# Get training labels
Y = dataset.head(400000)['time_taxi_out'].values
Y
```

[3]:
```
array([16, 21, 14, …, 15, 15, 13])
```

[4]:
```
# Get training features
X = dataset.head(400000).drop('time_taxi_out', axis=1).values
X.shape
```

[4]:
```
(400000, 202)
```

1 Deep Learning

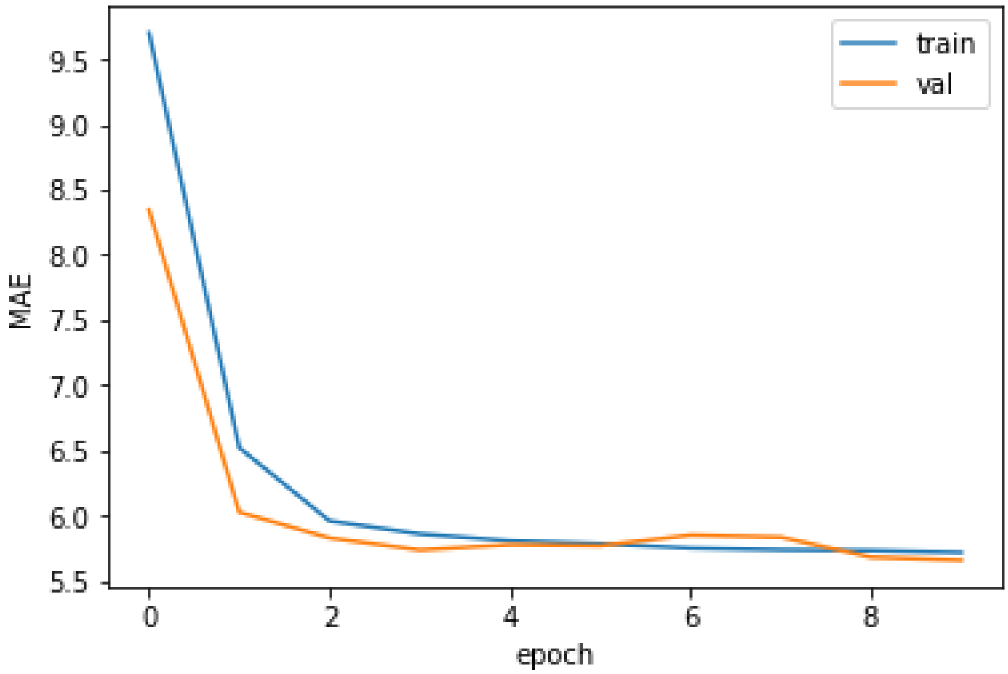
[5]:
```
# Create and fit model
model = keras.Sequential()

model.add(keras.layers.Dense(100, input_dim = X.shape[1], activation =␣
↪'sigmoid'))
model.add(keras.layers.Dense(30, activation = 'sigmoid'))
model.add(keras.layers.Dense(10, activation = 'relu'))
model.add(keras.layers.Dense(1, activation = 'relu'))

model.compile(loss = 'mse', optimizer = 'adam', metrics = [keras.metrics.
↪MeanAbsoluteError()])

history = model.fit(X, Y, validation_split = 0.2, epochs = 10, batch_size = 200)
```

```
Epoch 1/10
1600/1600 [==============================] - 2s 1ms/step - loss: 211.6716 -
mean_absolute_error: 9.7036 - val_loss: 158.6571 - val_mean_absolute_error:
8.3450
```

```
Epoch 2/10
1600/1600 [==============================] - 2s 2ms/step - loss: 103.7929 -
mean_absolute_error: 6.5229 - val_loss: 81.7991 - val_mean_absolute_error:
6.0273
Epoch 3/10
1600/1600 [==============================] - 2s 2ms/step - loss: 76.1877 -
mean_absolute_error: 5.9604 - val_loss: 73.2011 - val_mean_absolute_error:
5.8295
Epoch 4/10
1600/1600 [==============================] - 2s 1ms/step - loss: 71.2044 -
mean_absolute_error: 5.8603 - val_loss: 70.4624 - val_mean_absolute_error:
5.7370
Epoch 5/10
1600/1600 [==============================] - 2s 1ms/step - loss: 69.2120 -
mean_absolute_error: 5.8076 - val_loss: 68.1306 - val_mean_absolute_error:
5.7780
Epoch 6/10
1600/1600 [==============================] - 2s 1ms/step - loss: 68.3088 -
mean_absolute_error: 5.7848 - val_loss: 68.6899 - val_mean_absolute_error:
5.7697
Epoch 7/10
1600/1600 [==============================] - 2s 1ms/step - loss: 67.2939 -
mean_absolute_error: 5.7516 - val_loss: 67.6030 - val_mean_absolute_error:
5.8512
Epoch 8/10
1600/1600 [==============================] - 2s 1ms/step - loss: 66.8326 -
mean_absolute_error: 5.7382 - val_loss: 67.4560 - val_mean_absolute_error:
5.8358
Epoch 9/10
1600/1600 [==============================] - 2s 1ms/step - loss: 66.4438 -
mean_absolute_error: 5.7329 - val_loss: 66.8489 - val_mean_absolute_error:
5.6814
Epoch 10/10
1600/1600 [==============================] - 2s 1ms/step - loss: 66.1275 -
mean_absolute_error: 5.7182 - val_loss: 67.4736 - val_mean_absolute_error:
5.6583
```

[6]:

```
# Plot training/validation loss
plt.plot(history.history['mean_absolute_error'])
plt.plot(history.history['val_mean_absolute_error'])
plt.legend(['train', 'val'], loc = 'upper right')
plt.xlabel("epoch")
plt.ylabel("MAE")
plt.show()
```

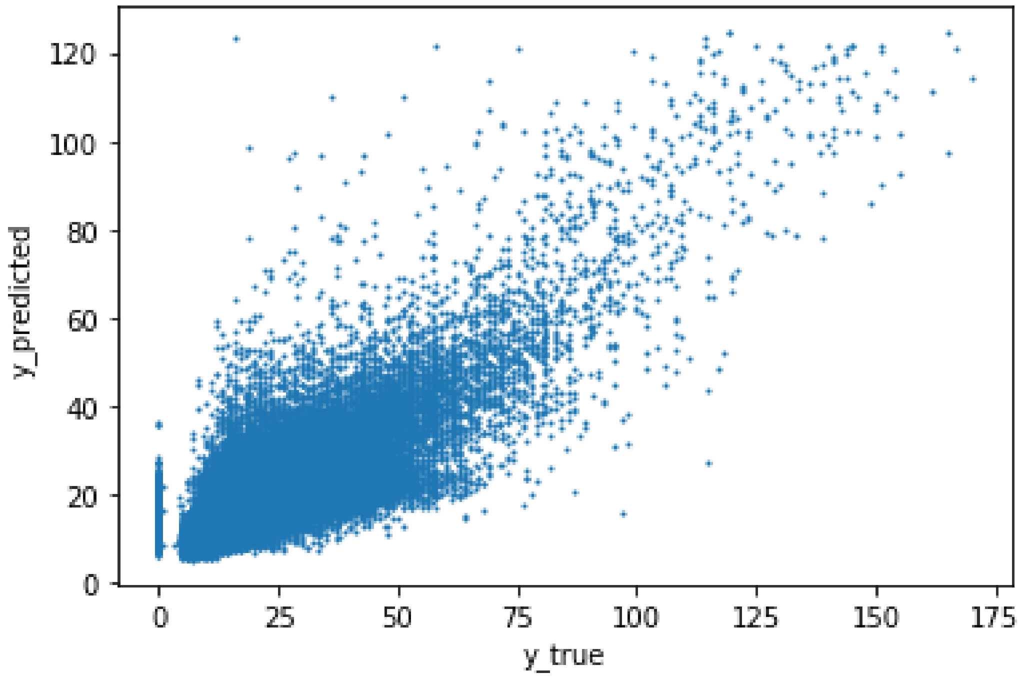


[5]:
```
# Predict values for unseen data

x_predict = dataset[400000:500000].drop('time_taxi_out', axis=1).values
y_true = dataset[400000:500000]['time_taxi_out'].values
```

[8]:
```
y_predicted = model.predict(x_predict)
print("MAE training: ", mean_absolute_error(Y, model.predict(X)))
print("MAE test: ", mean_absolute_error(y_true, y_predicted))
```

```
MAE training:  5.6347700267148015
MAE test:  5.645663092269897
```

[9]:
```
plt.scatter(y_true, y_predicted, s = 1)
plt.xlabel("y_true")
plt.ylabel("y_predicted")
plt.show()
```



2 Linear Regression

[6]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error
```

[7]:
```
model = LinearRegression().fit(X, Y)
```

[8]:
```
print("r_sq training: ", model.score(X, Y))
print("r_sq test: ", model.score(x_predict, y_true))
```

```
r_sq training:  0.4238081919600284
r_sq test:  0.4140695987558387
```

[9]:
```
y_predicted = model.predict(x_predict)
test_mae = mean_absolute_error(y_true, y_predicted)
print("MAE training: ", mean_absolute_error(Y, model.predict(X)))
print("MAE test: ", test_mae)
```

```
MAE training:  6.6418192713803546
MAE test:  6.653655706379016
```

3 Polynomial Regression

[6]:
```
from sklearn.preprocessing import PolynomialFeatures
```

[7]:
```
x_numeric = X[:, 0:13]
x_one_hot = X[:, 13:]
transformer = PolynomialFeatures(degree = 2, include_bias = True)
transformer.fit(x_numeric)
x_numeric_ = transformer.transform(x_numeric)
X_ = np.concatenate((x_numeric_, x_one_hot), axis = 1)
```

[8]:
```
model = LinearRegression().fit(X_, Y)
```

[9]:
```
x_predict_numeric_ = transformer.transform(x_predict[:, 0:13])
x_predict_ = np.concatenate((x_predict_numeric_, x_predict[:, 13:]), axis = 1)
print("r_sq training: ", model.score(X_, Y))
print("r_sq test: ", model.score(x_predict_, y_true))
```

```
r_sq training:  0.4962595935412766
r_sq test:  0.4982515373554338
```

[10]:
```
y_predicted = model.predict(x_predict_)
test_mae = mean_absolute_error(y_true, y_predicted)
print("MAE training: ", mean_absolute_error(Y, model.predict(X_)))
print("MAE test: ", test_mae)
```

```
MAE training:  6.276235768111072
MAE test:  6.2347969036412145
```

[ ]:
```
```