CLydonAssignment2

March 1, 2022

1 Assignment 1

1) Read chapters 2-4 in your textbook and review the coding examples we went over in class
2) Review the Keras documentation for things like the Layer types and Optimizer types to better familiarize yourself
3) Redo the coding examples and do the "Further experiments" in chapter 3 of your book with datasets you find interesting and may want to use for further assignments and projects
4) Provide a brief write up of the experiment and analysis.

2 table of contents

2.1 1 import libraries

[250]:
```python
# data prep
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

import numpy as np
import pandas as pd

# keras imports
from keras import models
from keras import layers
from keras import optimizers

# random seed for pseudo-random operations
random_seed = 100
```

2.2 2 data prep

2.1 reading dataset

[251]:
```python
math_data = pd.read_csv("https://raw.githubusercontent.com/connoralydon/
↪datasets/main/student-math.csv", sep=";")
```

2.2 summary info about data

[252]:
```python
math_data.head
```

[252]:
```
<bound method NDFrame.head of     school sex  age address famsize Pstatus  Medu
Fedu      Mjob      Fjob  \
0       GP   F   18       U     GT3       A     4     4   at_home   teacher
1       GP   F   17       U     GT3       T     1     1   at_home     other
2       GP   F   15       U     LE3       T     1     1   at_home     other
3       GP   F   15       U     GT3       T     4     2    health  services
4       GP   F   16       U     GT3       T     3     3     other     other
..     … ..  …      …     …     …   …    …       …        …
390     MS   M   20       U     LE3       A     2     2  services  services
391     MS   M   17       U     LE3       T     3     1  services  services
392     MS   M   21       R     GT3       T     1     1     other     other
393     MS   M   18       R     LE3       T     3     2  services     other
394     MS   M   19       U     LE3       T     1     1     other   at_home

     … famrel freetime  goout  Dalc  Walc health absences  G1  G2  G3
0    …      4        3      4     1     1      3        6   5   6   6
1    …      5        3      3     1     1      3        4   5   5   6
2    …      4        3      2     2     3      3       10   7   8  10
3    …      3        2      2     1     1      5        2  15  14  15
4    …      4        3      2     1     2      5        4   6  10  10
..   …    …        …     …    …    …      …        …  ..  ..  ..
```

```
390  ...     5         5      4     4     5      4         11   9   9   9
391  ...     2         4      5     3     4      2          3  14  16  16
392  ...     5         5      3     3     3      3          3  10   8   7
393  ...     4         4      1     3     4      5          0  11  12  10
394  ...     3         2      3     3     3      5          5   8   9   9

[395 rows x 33 columns]>
```

[253]:

```
math_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 395 entries, 0 to 394
Data columns (total 33 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   school      395 non-null    object
 1   sex         395 non-null    object
 2   age         395 non-null    int64
 3   address     395 non-null    object
 4   famsize     395 non-null    object
 5   Pstatus     395 non-null    object
 6   Medu        395 non-null    int64
 7   Fedu        395 non-null    int64
 8   Mjob        395 non-null    object
 9   Fjob        395 non-null    object
 10  reason      395 non-null    object
 11  guardian    395 non-null    object
 12  traveltime  395 non-null    int64
 13  studytime   395 non-null    int64
 14  failures    395 non-null    int64
 15  schoolsup   395 non-null    object
 16  famsup      395 non-null    object
 17  paid        395 non-null    object
 18  activities  395 non-null    object
 19  nursery     395 non-null    object
 20  higher      395 non-null    object
 21  internet    395 non-null    object
 22  romantic    395 non-null    object
 23  famrel      395 non-null    int64
 24  freetime    395 non-null    int64
 25  goout       395 non-null    int64
 26  Dalc        395 non-null    int64
 27  Walc        395 non-null    int64
 28  health      395 non-null    int64
 29  absences    395 non-null    int64
 30  G1          395 non-null    int64
 31  G2          395 non-null    int64
 32  G3          395 non-null    int64
```

```
dtypes: int64(16), object(17)
memory usage: 102.0+ KB
```

[254]:
```
math_data.dtypes
```

[254]:
```
school        object
sex           object
age            int64
address       object
famsize       object
Pstatus       object
Medu           int64
Fedu           int64
Mjob          object
Fjob          object
reason        object
guardian      object
traveltime     int64
studytime      int64
failures       int64
schoolsup     object
famsup        object
paid          object
activities    object
nursery       object
higher        object
internet      object
romantic      object
famrel         int64
freetime       int64
goout          int64
Dalc           int64
Walc           int64
health         int64
absences       int64
G1             int64
G2             int64
G3             int64
dtype: object
```

[255]:
```
math_data.columns
```

[255]:
```
Index(['school', 'sex', 'age', 'address', 'famsize', 'Pstatus', 'Medu', 'Fedu',
       'Mjob', 'Fjob', 'reason', 'guardian', 'traveltime', 'studytime',
       'failures', 'schoolsup', 'famsup', 'paid', 'activities', 'nursery',
       'higher', 'internet', 'romantic', 'famrel', 'freetime', 'goout', 'Dalc',
       'Walc', 'health', 'absences', 'G1', 'G2', 'G3'],
      dtype='object')
```

[256]:
```python
math_data.shape
```

[256]: (395, 33)

[257]:
```python
# observe the different values used for species - 2 different values: 0, 1
def print_range(data):
    print(f"range of {data.min()} to {data.max()}\n")

print("First test")
print_range(math_data["G2"])

print("Second test")
print_range(math_data["G1"])

print("Final test")
print_range(math_data["G3"])
```

```
First test
range of 0 to 19

Second test
range of 3 to 19

Final test
range of 0 to 20
```

[258]:
```python
print("total null values")
math_data.isnull().sum(axis=0).sum()
```

```
total null values
```

[258]: 0

[259]:
```python
print("num duplicates")
math_data.duplicated().sum(axis=0)
```

```
num duplicates
```

[259]: 0

2.3 dummyizing data

[260]:
```python
categorical_cols = {}

for col in math_data.columns:
    if(math_data[col].dtype == "object"):
        categorical_cols[col] = list(math_data[col].unique())
```

```
numerical_cols = list(set(math_data.columns) - set(categorical_cols.keys())) #␣
↪set difference

math_data_dummy = pd.get_dummies(math_data, columns = categorical_cols.keys())
```

2.4 model variables removing g1, g2, g3 because they would be highly autocorrelary. someone who does good on one test is likely t odo good on another.

[261]:
```
predictors = list(math_data_dummy.columns)
predictors.remove("G1") # first exam
predictors.remove("G2") # second exam
predictors.remove("G3") # third exam

outcome = "G3"
```

2.5 transforming data into numpy arrays this is because keras won't take pandas dataframes

[262]:
```
X = np.array(math_data_dummy[predictors])
y = np.array(math_data_dummy[outcome])
```

2.6 creating training and testing data

[263]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,␣
↪shuffle=True, random_state=random_seed)
```

2.7 standardizing the data (z-scoring) to avoid wildy wifferent values in the model

[264]:
```
z = StandardScaler() # standard scaling object

# fitting scaler object to training data then outputting it
X_train = z.fit_transform(X_train)
# fit the testing data on the distributions found in the training data
X_test = z.transform(X_test)
```

2.3 3 modeling

3.1 building initial model

[265]:
```
model = models.Sequential()
model.add(layers.Dense(32, activation='relu', input_shape=(X_train.shape[1],)))
model.add(layers.Dropout(0.3, seed=random_seed)) # adding dropout layers to␣
↪help with overfitting
model.add(layers.Dense(16, activation='relu'))
model.add(layers.Dense(1)) # adding this layer because it is a regression␣
↪problem
```

3.1.1 compiling model loss

[266]:
```
model.compile(optimizer='rmsprop',
              loss='mse',
              metrics=['mae'])
```

3.1.2 fitting model on training data

[267]:
```
model_output = model.fit(X_train, y_train, batch_size=20, epochs=20)
```

```
Epoch 1/20
316/316 [==============================] - 0s 1ms/step - loss: 119.6751 - mae:
9.9906
Epoch 2/20
316/316 [==============================] - 0s 72us/step - loss: 101.0312 - mae:
9.1572
Epoch 3/20
316/316 [==============================] - 0s 64us/step - loss: 86.5112 - mae:
8.4750
Epoch 4/20
316/316 [==============================] - 0s 68us/step - loss: 72.8146 - mae:
7.6959
Epoch 5/20
316/316 [==============================] - 0s 69us/step - loss: 58.0657 - mae:
6.8205
Epoch 6/20
316/316 [==============================] - 0s 64us/step - loss: 47.2777 - mae:
6.0455
Epoch 7/20
316/316 [==============================] - 0s 64us/step - loss: 35.8962 - mae:
5.1757
Epoch 8/20
316/316 [==============================] - 0s 65us/step - loss: 28.4997 - mae:
4.3849
Epoch 9/20
316/316 [==============================] - 0s 60us/step - loss: 25.6380 - mae:
4.1440
Epoch 10/20
316/316 [==============================] - 0s 63us/step - loss: 25.0365 - mae:
3.9596
Epoch 11/20
316/316 [==============================] - 0s 62us/step - loss: 23.5457 - mae:
3.8782
Epoch 12/20
316/316 [==============================] - 0s 69us/step - loss: 21.7583 - mae:
3.7079
Epoch 13/20
316/316 [==============================] - 0s 63us/step - loss: 21.3804 - mae:
3.5563
Epoch 14/20
```

```
316/316 [==============================] - 0s 63us/step - loss: 20.8165 - mae:
3.6028
Epoch 15/20
316/316 [==============================] - 0s 64us/step - loss: 20.0247 - mae:
3.5211
Epoch 16/20
316/316 [==============================] - 0s 66us/step - loss: 19.4162 - mae:
3.5992
Epoch 17/20
316/316 [==============================] - 0s 62us/step - loss: 19.7602 - mae:
3.4783
Epoch 18/20
316/316 [==============================] - 0s 61us/step - loss: 18.5260 - mae:
3.4555
Epoch 19/20
316/316 [==============================] - 0s 65us/step - loss: 19.4620 - mae:
3.4493
Epoch 20/20
316/316 [==============================] - 0s 65us/step - loss: 18.6162 - mae:
3.3783
```

3.1.3 predicting with test data

[268]:
```
predicted = model.evaluate(X_test, y_test)
print(f"test: mean squared error loss {predicted[0]}")
print(f"test: mean absolute error loss {predicted[1]}")
```

```
79/79 [==============================] - 0s 934us/step
test: mean squared error loss 15.240999076939836
test: mean absolute error loss 3.09421443939209
```

3.2 further experiments The following experiments will help convince you that the architecture choices you've made are all fairly reasonable, although there's still room for improvement: 1. You used two hidden layers. Try using one or three hidden layers, and see how doing so affects validation and test accuracy. 2. Try using layers with more hidden units or fewer hidden units: 32 units, 64 units, and so on. 3. Try using the mae loss function instead of mse. 4. Try using the tanh activation (an activation that was popular in the early days of neural networks) instead of relu.

3.2.1 model using one hiddden layer

[269]:
```
model_slim = models.Sequential()
model_slim.add(layers.Dense(32, activation='relu', input_shape=(X_train.
 ↪shape[1],)))
model_slim.add(layers.Dropout(0.3, seed=random_seed)) # adding dropout layers␣
 ↪to help with overfitting
model_slim.add(layers.Dense(1)) # adding this layer because it is a regression␣
 ↪problem
```

```
model_slim.compile(optimizer='rmsprop',
              loss='mse',
              metrics=['mae'])

model_slim_output = model_slim.fit(X_train, y_train, batch_size=20, epochs=20)
```

```
Epoch 1/20
316/316 [==============================] - 0s 876us/step - loss: 114.9323 - mae:
9.7166
Epoch 2/20
316/316 [==============================] - 0s 60us/step - loss: 106.8649 - mae:
9.4300
Epoch 3/20
316/316 [==============================] - 0s 59us/step - loss: 96.7718 - mae:
8.9687
Epoch 4/20
316/316 [==============================] - 0s 55us/step - loss: 87.5347 - mae:
8.4870
Epoch 5/20
316/316 [==============================] - 0s 86us/step - loss: 81.4040 - mae:
8.1444
Epoch 6/20
316/316 [==============================] - 0s 77us/step - loss: 74.4145 - mae:
7.7717
Epoch 7/20
316/316 [==============================] - 0s 59us/step - loss: 67.0496 - mae:
7.3437
Epoch 8/20
316/316 [==============================] - 0s 60us/step - loss: 60.9565 - mae:
6.9774
Epoch 9/20
316/316 [==============================] - 0s 54us/step - loss: 54.7326 - mae:
6.5678
Epoch 10/20
316/316 [==============================] - 0s 58us/step - loss: 47.6141 - mae:
6.0871
Epoch 11/20
316/316 [==============================] - 0s 55us/step - loss: 45.6499 - mae:
5.8310
Epoch 12/20
316/316 [==============================] - 0s 56us/step - loss: 42.7735 - mae:
5.6728
Epoch 13/20
316/316 [==============================] - 0s 57us/step - loss: 35.2782 - mae:
5.0216
Epoch 14/20
316/316 [==============================] - 0s 58us/step - loss: 33.4923 - mae:
4.8642
```

```
Epoch 15/20
316/316 [==============================] - 0s 57us/step - loss: 28.8793 - mae:
4.4988
Epoch 16/20
316/316 [==============================] - 0s 56us/step - loss: 28.3410 - mae:
4.4444
Epoch 17/20
316/316 [==============================] - 0s 60us/step - loss: 26.5100 - mae:
4.3034
Epoch 18/20
316/316 [==============================] - 0s 57us/step - loss: 24.3877 - mae:
4.0470
Epoch 19/20
316/316 [==============================] - 0s 56us/step - loss: 23.3842 - mae:
3.9314
Epoch 20/20
316/316 [==============================] - 0s 56us/step - loss: 23.1853 - mae:
3.9243
```

[270]:
```
predicted_slim = model_slim.evaluate(X_test, y_test)
print(f"test: mean squared error loss {predicted_slim[0]}")
print(f"test: mean absolute error loss {predicted_slim[1]}")
```

```
79/79 [==============================] - 0s 851us/step
test: mean squared error loss 22.277899392043487
test: mean absolute error loss 3.940617799758911
```

underfitting here, and not capturing the real values in the data.

3.2.2 model using more hidden units

[271]:
```
model_fat = models.Sequential()
model_fat.add(layers.Dense(256, activation='relu', input_shape=(X_train.
 ↪shape[1],)))
model_fat.add(layers.Dropout(0.3, seed=random_seed)) # adding dropout layers to␣
 ↪help with overfitting
model_fat.add(layers.Dense(128, activation='relu'))
model_fat.add(layers.Dropout(0.3, seed=random_seed))
model_fat.add(layers.Dense(1)) # adding this layer because it is a regression␣
 ↪problem


model_fat.compile(optimizer='rmsprop',
              loss='mse',
              metrics=['mae'])

model_fat_output = model_fat.fit(X_train, y_train, batch_size=20, epochs=20)
```

```
Epoch 1/20
316/316 [==============================] - 0s 1ms/step - loss: 57.5891 - mae:
```

```
6.4724
Epoch 2/20
316/316 [==============================] - 0s 244us/step - loss: 22.2892 - mae:
3.7171
Epoch 3/20
316/316 [==============================] - 0s 251us/step - loss: 17.6542 - mae:
3.2800
Epoch 4/20
316/316 [==============================] - 0s 260us/step - loss: 17.3445 - mae:
3.3105
Epoch 5/20
316/316 [==============================] - 0s 264us/step - loss: 16.1278 - mae:
3.1216
Epoch 6/20
316/316 [==============================] - 0s 261us/step - loss: 15.1920 - mae:
3.0420
Epoch 7/20
316/316 [==============================] - 0s 245us/step - loss: 14.4454 - mae:
3.0478
Epoch 8/20
316/316 [==============================] - 0s 234us/step - loss: 12.9277 - mae:
2.7721
Epoch 9/20
316/316 [==============================] - 0s 246us/step - loss: 12.9546 - mae:
2.7830
Epoch 10/20
316/316 [==============================] - 0s 241us/step - loss: 11.2297 - mae:
2.6013
Epoch 11/20
316/316 [==============================] - 0s 239us/step - loss: 12.4494 - mae:
2.7967
Epoch 12/20
316/316 [==============================] - 0s 239us/step - loss: 11.2532 - mae:
2.5223
Epoch 13/20
316/316 [==============================] - 0s 234us/step - loss: 9.3080 - mae:
2.4208
Epoch 14/20
316/316 [==============================] - 0s 236us/step - loss: 10.1783 - mae:
2.4969
Epoch 15/20
316/316 [==============================] - 0s 245us/step - loss: 10.4879 - mae:
2.5408
Epoch 16/20
316/316 [==============================] - 0s 235us/step - loss: 9.5909 - mae:
2.3872
Epoch 17/20
316/316 [==============================] - 0s 274us/step - loss: 9.8122 - mae:
```

```
2.3864
Epoch 18/20
316/316 [==============================] - 0s 247us/step - loss: 9.6088 - mae:
2.4541
Epoch 19/20
316/316 [==============================] - 0s 257us/step - loss: 8.8385 - mae:
2.3844
Epoch 20/20
316/316 [==============================] - 0s 259us/step - loss: 7.9328 - mae:
2.2292
```

[272]:
```
predicted_fat = model_fat.evaluate(X_test, y_test)
print(f"test: mean squared error loss {predicted_fat[0]}")
print(f"test: mean absolute error loss {predicted_fat[1]}")
```

```
79/79 [==============================] - 0s 1ms/step
test: mean squared error loss 15.176022903828681
test: mean absolute error loss 2.9776809215545654
```

model performs good here, better than the original geometry

3.2.3 model using mae loss

[273]:
```
model_mae = models.Sequential()
model_mae.add(layers.Dense(32, activation='relu', input_shape=(X_train.
 ↪shape[1],)))
model_mae.add(layers.Dropout(0.3, seed=random_seed)) # adding dropout layers to␣
 ↪help with overfitting
model_mae.add(layers.Dense(16, activation='relu'))
model_mae.add(layers.Dense(1)) # adding this layer because it is a regression␣
 ↪problem


model_mae.compile(optimizer='rmsprop',
              loss='mae',
              metrics=['mse'])

model_mae_output = model_mae.fit(X_train, y_train, batch_size=20, epochs=20)
```

```
Epoch 1/20
316/316 [==============================] - 0s 1ms/step - loss: 10.0771 - mse:
122.1471
Epoch 2/20
316/316 [==============================] - 0s 72us/step - loss: 9.1377 - mse:
101.8730
Epoch 3/20
316/316 [==============================] - 0s 64us/step - loss: 8.2996 - mse:
85.0169
Epoch 4/20
316/316 [==============================] - 0s 72us/step - loss: 7.4872 - mse:
```

```
69.8086
Epoch 5/20
316/316 [==============================] - 0s 66us/step - loss: 6.3562 - mse:
53.3596
Epoch 6/20
316/316 [==============================] - 0s 67us/step - loss: 5.5196 - mse:
41.4658
Epoch 7/20
316/316 [==============================] - 0s 67us/step - loss: 5.0455 - mse:
34.3769
Epoch 8/20
316/316 [==============================] - 0s 61us/step - loss: 4.5097 - mse:
29.7655
Epoch 9/20
316/316 [==============================] - 0s 64us/step - loss: 4.2765 - mse:
27.2567
Epoch 10/20
316/316 [==============================] - 0s 61us/step - loss: 3.9621 - mse:
24.7270
Epoch 11/20
316/316 [==============================] - 0s 66us/step - loss: 3.8453 - mse:
24.1783
Epoch 12/20
316/316 [==============================] - 0s 62us/step - loss: 3.9050 - mse:
23.8684
Epoch 13/20
316/316 [==============================] - 0s 64us/step - loss: 3.6350 - mse:
21.7358
Epoch 14/20
316/316 [==============================] - 0s 63us/step - loss: 3.8395 - mse:
22.9980
Epoch 15/20
316/316 [==============================] - 0s 67us/step - loss: 3.5856 - mse:
21.3374
Epoch 16/20
316/316 [==============================] - 0s 62us/step - loss: 3.6338 - mse:
20.5292
Epoch 17/20
316/316 [==============================] - 0s 63us/step - loss: 3.5319 - mse:
20.0993
Epoch 18/20
316/316 [==============================] - 0s 66us/step - loss: 3.4101 - mse:
18.6605
Epoch 19/20
316/316 [==============================] - 0s 64us/step - loss: 3.4450 - mse:
20.0430
Epoch 20/20
316/316 [==============================] - 0s 62us/step - loss: 3.4815 - mse:
```

```
20.1830
```

[274]:
```
predicted_mae_model = model_mae.evaluate(X_test, y_test)
print(f"test: mean squared error loss {predicted_mae_model[1]}")
print(f"test: mean absolute error loss {predicted_mae_model[0]}")
```

```
79/79 [==============================] - 0s 933us/step
test: mean squared error loss 16.141311645507812
test: mean absolute error loss 3.067770185349863
```

the model performs about the same in this case with a little bit better scores overall

3.2.4 model using tanh activation

[275]:
```
model_tanh = models.Sequential()
model_tanh.add(layers.Dense(32, activation='tanh', input_shape=(X_train.
 ↪shape[1],)))
model_tanh.add(layers.Dropout(0.3, seed=random_seed)) # adding dropout layers␣
 ↪to help with overfitting
model_tanh.add(layers.Dense(16, activation='tanh'))
model_tanh.add(layers.Dense(1)) # adding this layer because it is a regression␣
 ↪problem


model_tanh.compile(optimizer='rmsprop',
              loss='mse',
              metrics=['mae'])

model_tanh_output = model_tanh.fit(X_train, y_train, batch_size=20, epochs=20)
```

```
Epoch 1/20
316/316 [==============================] - 0s 1ms/step - loss: 126.9281 - mae:
10.2410
Epoch 2/20
316/316 [==============================] - 0s 70us/step - loss: 122.7916 - mae:
10.0862
Epoch 3/20
316/316 [==============================] - 0s 66us/step - loss: 120.1034 - mae:
9.9677
Epoch 4/20
316/316 [==============================] - 0s 64us/step - loss: 115.7618 - mae:
9.7880
Epoch 5/20
316/316 [==============================] - 0s 70us/step - loss: 112.6738 - mae:
9.6679
Epoch 6/20
316/316 [==============================] - 0s 64us/step - loss: 107.7759 - mae:
9.4378
Epoch 7/20
316/316 [==============================] - 0s 65us/step - loss: 103.9476 - mae:
```

```
9.2530
Epoch 8/20
316/316 [==============================] - 0s 64us/step - loss: 97.5534 - mae:
8.9889
Epoch 9/20
316/316 [==============================] - 0s 65us/step - loss: 93.6230 - mae:
8.7832
Epoch 10/20
316/316 [==============================] - 0s 63us/step - loss: 88.3186 - mae:
8.4938
Epoch 11/20
316/316 [==============================] - 0s 63us/step - loss: 82.2173 - mae:
8.1885
Epoch 12/20
316/316 [==============================] - 0s 63us/step - loss: 77.5650 - mae:
7.9221
Epoch 13/20
316/316 [==============================] - 0s 67us/step - loss: 71.0205 - mae:
7.5801
Epoch 14/20
316/316 [==============================] - 0s 62us/step - loss: 67.1885 - mae:
7.2732
Epoch 15/20
316/316 [==============================] - 0s 64us/step - loss: 59.8460 - mae:
6.8081
Epoch 16/20
316/316 [==============================] - 0s 67us/step - loss: 54.1449 - mae:
6.4695
Epoch 17/20
316/316 [==============================] - 0s 64us/step - loss: 49.7382 - mae:
6.1439
Epoch 18/20
316/316 [==============================] - 0s 65us/step - loss: 44.5213 - mae:
5.7813
Epoch 19/20
316/316 [==============================] - 0s 64us/step - loss: 41.7015 - mae:
5.5089
Epoch 20/20
316/316 [==============================] - 0s 65us/step - loss: 36.0837 - mae:
5.1028
```

[276]:
```
predicted_tanh = model_tanh.evaluate(X_test, y_test)
print(f"test: mean squared error loss {predicted_tanh[0]}")
print(f"test: mean absolute error loss {predicted_tanh[1]}")
```

```
79/79 [==============================] - 0s 923us/step
test: mean squared error loss 44.83786131460455
test: mean absolute error loss 5.621185779571533
```

lots more loss in a model that uses a tanh actuvation vs relu activation for this neural network geometry

3.3 k fold validation the code here is taken out of the textbook for the regression examples

3.3.1 build model function definition

[277]:
```
def build_model():
    model = models.Sequential()
    model.add(layers.Dense(32, activation='relu',
                           input_shape=(X_train.shape[1],)))
    model.add(layers.Dense(16, activation='relu'))
    model.add(layers.Dense(1))
    model.compile(optimizer='rmsprop', loss='mse', metrics=['mae'])
    return model
```

3.3.2 defining k-fold variables

[278]:
```
n_folds = 10
num_epochs = 20
num_val_samples = len(X_train) // n_folds
all_mae_histories = []
```

3.3.3 k-fold loop

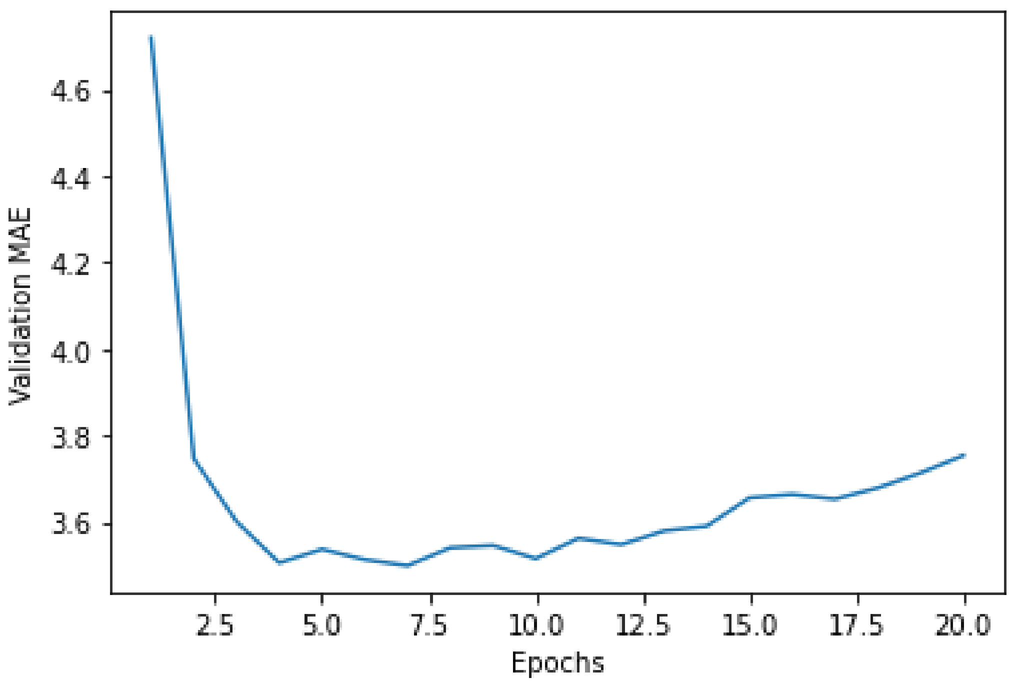
[279]:
```
for i in range(n_folds):
    print("processing fold #", i)
    val_data = X_train[i * num_val_samples : (i + 1) * num_val_samples]
    val_targets = y_train[i * num_val_samples : (i + 1) * num_val_samples]

    partial_train_data = np.concatenate(
        [X_train[:i * num_val_samples],
         X_train[(i + 1) * num_val_samples:]],
        axis = 0)

    partial_train_targets = np.concatenate(
        [y_train[:i * num_val_samples],
         y_train[(i + 1) * num_val_samples:]],
        axis = 0)

    model = build_model()
    history = model.fit(partial_train_data, partial_train_targets,
        validation_data=(val_data, val_targets),
        epochs=num_epochs, batch_size=1, verbose=0)

    mae_history = history.history['val_mae']
    all_mae_histories.append(mae_history)
```

```
processing fold # 0
processing fold # 1
processing fold # 2
processing fold # 3
processing fold # 4
processing fold # 5
processing fold # 6
processing fold # 7
processing fold # 8
processing fold # 9
```

3.3.4 plotting k-fold results

[280]:
```python
average_mae_history = [
    np.mean([x[i] for x in all_mae_histories]) for i in range(num_epochs)]
```

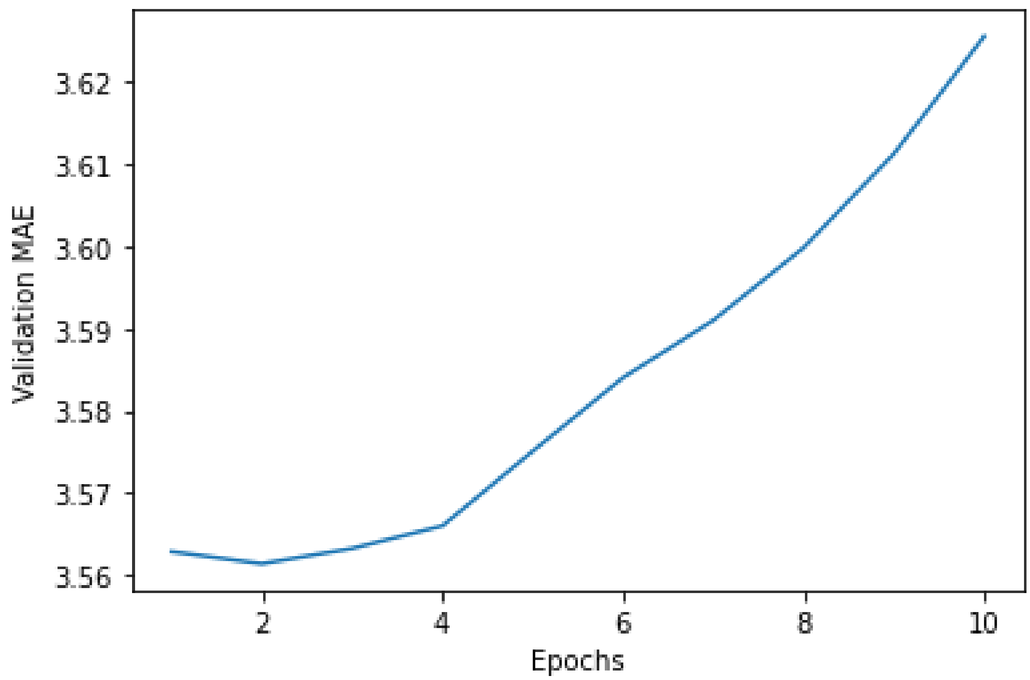
[281]:
```python
import matplotlib.pyplot as plt
plt.plot(range(1, len(average_mae_history) + 1), average_mae_history)
plt.xlabel('Epochs')
plt.ylabel('Validation MAE')
plt.show()
```



looks like validation mean absolute error is minimized at around 10 epochs or so

[282]:
```python
def smooth_curve(points, factor=0.9):
  smoothed_points = []
```

```
  for point in points:
    if smoothed_points:
      previous = smoothed_points[-1]
      smoothed_points.append(previous * factor + point * (1 - factor))
    else:
      smoothed_points.append(point)
  return smoothed_points
smooth_mae_history = smooth_curve(average_mae_history[10:])
plt.plot(range(1, len(smooth_mae_history) + 1), smooth_mae_history)
plt.xlabel('Epochs')
plt.ylabel('Validation MAE')
plt.show()
```



this shows the average validation score vs number of epochs. it goes up over the epochs, but is not that different in absolute terms.

3.3.5 building model from validation

[283]:
```
model = build_model()
model.fit(X_train, y_train,
          epochs = 10, batch_size = 20)

test_mse_score, test_mae_score = model.evaluate(X_test, y_test)
print(f"testing mean absolute error {test_mae_score}")
```

```
Epoch 1/10
```

```
316/316 [==============================] - 0s 852us/step - loss: 123.0432 - mae:
10.0735
Epoch 2/10
316/316 [==============================] - 0s 62us/step - loss: 109.4362 - mae:
9.5152
Epoch 3/10
316/316 [==============================] - 0s 53us/step - loss: 96.4149 - mae:
8.9209
Epoch 4/10
316/316 [==============================] - 0s 58us/step - loss: 82.2523 - mae:
8.2291
Epoch 5/10
316/316 [==============================] - 0s 59us/step - loss: 67.8744 - mae:
7.4199
Epoch 6/10
316/316 [==============================] - 0s 57us/step - loss: 53.8478 - mae:
6.5491
Epoch 7/10
316/316 [==============================] - 0s 54us/step - loss: 41.5124 - mae:
5.6553
Epoch 8/10
316/316 [==============================] - 0s 55us/step - loss: 31.3870 - mae:
4.8664
Epoch 9/10
316/316 [==============================] - 0s 54us/step - loss: 24.1829 - mae:
4.1737
Epoch 10/10
316/316 [==============================] - 0s 52us/step - loss: 20.1880 - mae:
3.7080
79/79 [==============================] - 0s 666us/step
testing mean absolute error 3.905726909637451
```

the mean absolute error for the testing error is 3.3 grade units out of 20. this model does pretty well and is not far off from the training data. 3.26 mae in training and 3.3 in testing. epochs of 10 are a good way to normalize it for this network geometry.