

ann1-3

October 14, 2023

```
[155]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
#from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
```

```
[157]: df = pd.read_csv('/content/car_purchasing.csv', encoding='ISO-8859-1')
df.head()
```

```
[157]:
```

	customer name	customer e-mail	\
0	Martina Avila	cubilia.Curae.Phasellus@quisaccumsanconvallis.edu	
1	Harlan Barnes	eu.dolor@diam.co.uk	
2	Naomi Rodriquez	vulputate.mauris.sagittis@ametconsectetueradip...	
3	Jade Cunningham	malesuada@dignissim.com	
4	Cedric Leach	felis.ullamcorper.viverra@egetmollislectus.net	

	country	gender	age	annual Salary	credit card debt	\
0	Bulgaria	0	41.851720	62812.09301	11609.380910	
1	Belize	0	40.870623	66646.89292	9572.957136	
2	Algeria	1	43.152897	53798.55112	11160.355060	
3	Cook Islands	1	58.271369	79370.03798	14426.164850	
4	Brazil	1	57.313749	59729.15130	5358.712177	

	net worth	car purchase amount
0	238961.2505	35321.45877
1	530973.9078	45115.52566
2	638467.1773	42925.70921
3	548599.0524	67422.36313
4	560304.0671	55915.46248

```
[158]: # number of rows and columns
df.shape
```

[158]: (500, 9)

```
[159]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 9 columns):
#   Column                Non-Null Count  Dtype
---  -
0   customer name         500 non-null    object
1   customer e-mail       500 non-null    object
2   country               500 non-null    object
3   gender                500 non-null    int64
4   age                   500 non-null    float64
5   annual Salary         500 non-null    float64
6   credit card debt      500 non-null    float64
7   net worth             500 non-null    float64
8   car purchase amount   500 non-null    float64
dtypes: float64(5), int64(1), object(3)
memory usage: 35.3+ KB
```

```
[160]: df.isnull().sum()
```

```
[160]: customer name         0
customer e-mail         0
country                 0
gender                  0
age                     0
annual Salary           0
credit card debt        0
net worth               0
car purchase amount     0
dtype: int64
```

```
[161]: df.isnull().sum().sum()
```

[161]: 0

```
[162]: df.head()
```

```
[162]:   customer name                customer e-mail \
0  Martina Avila  cubilia.Curae.Phasellus@quisaccumsanconvallis.edu
1   Harlan Barnes                eu.dolor@diam.co.uk
2  Naomi Rodriguez  vulputate.mauris.sagittis@ametconsectetueradip..
3   Jade Cunningham                malesuada@dignissim.com
4   Cedric Leach    felis.ullamcorper.viverra@egetmollislectus.net
```

	country	gender	age	annual Salary	credit card debt	\
0	Bulgaria	0	41.851720	62812.09301	11609.380910	
1	Belize	0	40.870623	66646.89292	9572.957136	
2	Algeria	1	43.152897	53798.55112	11160.355060	
3	Cook Islands	1	58.271369	79370.03798	14426.164850	
4	Brazil	1	57.313749	59729.15130	5358.712177	

	net worth	car purchase amount
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2	638467.1773	42925.70921
3	548599.0524	67422.36313
4	560304.0671	55915.46248

```
[205]: df.drop(columns= ['customer name' , 'customer e-mail' , 'country' , 'gender' ] ,
↳axis = 1 , inplace = True)
```

```
[206]: target = 'car purchase amount'
X = df.drop(target , axis= 1)
y= df[target]
```

```
[208]: X
```

```
[208]:
```

	age	annual Salary	credit card debt	net worth	
0	41.851720	62812.09301	11609.380910	238961.2505	0.0
1	40.870623	66646.89292	9572.957136	530973.9078	0.0
2	43.152897	53798.55112	11160.355060	638467.1773	1.0
3	58.271369	79370.03798	14426.164850	548599.0524	1.0
4	57.313749	59729.15130	5358.712177	560304.0671	1.0
..
495	41.462515	71942.40291	6995.902524	541670.1016	0.0
496	37.642000	56039.49793	12301.456790	360419.0988	1.0
497	53.943497	68888.77805	10611.606860	764531.3203	1.0
498	59.160509	49811.99062	14013.034510	337826.6382	1.0
499	46.731152	61370.67766	9391.341628	462946.4924	1.0

[500 rows x 5 columns]

```
[209]: scaler = MinMaxScaler()

X = scaler.fit_transform(X)
y = scaler.fit_transform(y.values.reshape(-1 , 1))
```

```
[210]: print(f'The shape of X is {X.shape}')
print(f'The shape of y is {y.shape}')
```

The shape of X is (500, 5)

The shape of y is (500, 1)

```
[211]: X_train , X_test , y_train , y_test = train_test_split(X, y , test_size = 0.2 ,  
↳random_state = 42)  
  
print(f'the shape of X train is {X_train.shape}')  
print(f'the shape of y train is {y_train.shape}')  
print(f'the shape of X test is {X_test.shape}')  
print(f'the shape of y test is {y_test.shape}')
```

the shape of X train is (400, 5)
the shape of y train is (400, 1)
the shape of X test is (100, 5)
the shape of y test is (100, 1)

```
[212]: y_mean = y_train.mean()  
y_pred_baseline= [y_mean] * len(y_train)  
print("Mean apt price:", y_mean)  
  
print("Baseline MAE:", mean_absolute_error(y_train,y_pred_baseline))
```

Mean apt price: 0.49219817948908456
Baseline MAE: 0.11921386215413556

```
[215]: model = Sequential()  
model.add(Dense(10, activation='relu', input_dim=5))  
model.add(Dense(10, activation='relu'))  
model.add(Dense(1, activation='linear'))  
  
model.compile(optimizer='adam', loss='mean_squared_error',  
↳metrics=['mean_absolute_error'])  
model.summary()
```

Model: "sequential_26"

Layer (type)	Output Shape	Param #
dense_79 (Dense)	(None, 10)	60
dense_80 (Dense)	(None, 10)	110
dense_81 (Dense)	(None, 1)	11

=====
Total params: 181 (724.00 Byte)
Trainable params: 181 (724.00 Byte)
Non-trainable params: 0 (0.00 Byte)
=====

```
[216]: history = model.fit(X_train , y_train , epochs = 50 , validation_split= 0.2)
```

```
Epoch 1/50
10/10 [=====] - 1s 21ms/step - loss: 0.0926 -
mean_absolute_error: 0.2678 - val_loss: 0.0411 - val_mean_absolute_error: 0.1641
Epoch 2/50
10/10 [=====] - 0s 7ms/step - loss: 0.0412 -
mean_absolute_error: 0.1697 - val_loss: 0.0238 - val_mean_absolute_error: 0.1265
Epoch 3/50
10/10 [=====] - 0s 8ms/step - loss: 0.0268 -
mean_absolute_error: 0.1352 - val_loss: 0.0274 - val_mean_absolute_error: 0.1409
Epoch 4/50
10/10 [=====] - 0s 5ms/step - loss: 0.0245 -
mean_absolute_error: 0.1256 - val_loss: 0.0247 - val_mean_absolute_error: 0.1322
Epoch 5/50
10/10 [=====] - 0s 7ms/step - loss: 0.0207 -
mean_absolute_error: 0.1155 - val_loss: 0.0185 - val_mean_absolute_error: 0.1119
Epoch 6/50
10/10 [=====] - 0s 7ms/step - loss: 0.0175 -
mean_absolute_error: 0.1055 - val_loss: 0.0155 - val_mean_absolute_error: 0.1000
Epoch 7/50
10/10 [=====] - 0s 7ms/step - loss: 0.0155 -
mean_absolute_error: 0.0983 - val_loss: 0.0139 - val_mean_absolute_error: 0.0936
Epoch 8/50
10/10 [=====] - 0s 6ms/step - loss: 0.0138 -
mean_absolute_error: 0.0923 - val_loss: 0.0130 - val_mean_absolute_error: 0.0902
Epoch 9/50
10/10 [=====] - 0s 6ms/step - loss: 0.0125 -
mean_absolute_error: 0.0873 - val_loss: 0.0119 - val_mean_absolute_error: 0.0852
Epoch 10/50
10/10 [=====] - 0s 5ms/step - loss: 0.0116 -
mean_absolute_error: 0.0838 - val_loss: 0.0110 - val_mean_absolute_error: 0.0813
Epoch 11/50
10/10 [=====] - 0s 5ms/step - loss: 0.0108 -
mean_absolute_error: 0.0809 - val_loss: 0.0101 - val_mean_absolute_error: 0.0770
Epoch 12/50
10/10 [=====] - 0s 7ms/step - loss: 0.0101 -
mean_absolute_error: 0.0785 - val_loss: 0.0098 - val_mean_absolute_error: 0.0753
Epoch 13/50
10/10 [=====] - 0s 5ms/step - loss: 0.0096 -
mean_absolute_error: 0.0760 - val_loss: 0.0089 - val_mean_absolute_error: 0.0709
Epoch 14/50
10/10 [=====] - 0s 7ms/step - loss: 0.0090 -
mean_absolute_error: 0.0739 - val_loss: 0.0083 - val_mean_absolute_error: 0.0676
Epoch 15/50
10/10 [=====] - 0s 5ms/step - loss: 0.0086 -
mean_absolute_error: 0.0719 - val_loss: 0.0078 - val_mean_absolute_error: 0.0654
```

Epoch 16/50
10/10 [=====] - 0s 7ms/step - loss: 0.0081 -
mean_absolute_error: 0.0699 - val_loss: 0.0074 - val_mean_absolute_error: 0.0631
Epoch 17/50
10/10 [=====] - 0s 5ms/step - loss: 0.0077 -
mean_absolute_error: 0.0680 - val_loss: 0.0069 - val_mean_absolute_error: 0.0609
Epoch 18/50
10/10 [=====] - 0s 9ms/step - loss: 0.0073 -
mean_absolute_error: 0.0662 - val_loss: 0.0065 - val_mean_absolute_error: 0.0585
Epoch 19/50
10/10 [=====] - 0s 5ms/step - loss: 0.0069 -
mean_absolute_error: 0.0645 - val_loss: 0.0060 - val_mean_absolute_error: 0.0560
Epoch 20/50
10/10 [=====] - 0s 5ms/step - loss: 0.0065 -
mean_absolute_error: 0.0629 - val_loss: 0.0057 - val_mean_absolute_error: 0.0541
Epoch 21/50
10/10 [=====] - 0s 5ms/step - loss: 0.0061 -
mean_absolute_error: 0.0608 - val_loss: 0.0053 - val_mean_absolute_error: 0.0521
Epoch 22/50
10/10 [=====] - 0s 9ms/step - loss: 0.0057 -
mean_absolute_error: 0.0586 - val_loss: 0.0049 - val_mean_absolute_error: 0.0499
Epoch 23/50
10/10 [=====] - 0s 9ms/step - loss: 0.0053 -
mean_absolute_error: 0.0564 - val_loss: 0.0044 - val_mean_absolute_error: 0.0473
Epoch 24/50
10/10 [=====] - 0s 8ms/step - loss: 0.0049 -
mean_absolute_error: 0.0545 - val_loss: 0.0041 - val_mean_absolute_error: 0.0455
Epoch 25/50
10/10 [=====] - 0s 9ms/step - loss: 0.0046 -
mean_absolute_error: 0.0530 - val_loss: 0.0037 - val_mean_absolute_error: 0.0432
Epoch 26/50
10/10 [=====] - 0s 8ms/step - loss: 0.0043 -
mean_absolute_error: 0.0513 - val_loss: 0.0035 - val_mean_absolute_error: 0.0414
Epoch 27/50
10/10 [=====] - 0s 10ms/step - loss: 0.0041 -
mean_absolute_error: 0.0500 - val_loss: 0.0032 - val_mean_absolute_error: 0.0403
Epoch 28/50
10/10 [=====] - 0s 9ms/step - loss: 0.0038 -
mean_absolute_error: 0.0486 - val_loss: 0.0030 - val_mean_absolute_error: 0.0384
Epoch 29/50
10/10 [=====] - 0s 8ms/step - loss: 0.0036 -
mean_absolute_error: 0.0473 - val_loss: 0.0028 - val_mean_absolute_error: 0.0371
Epoch 30/50
10/10 [=====] - 0s 7ms/step - loss: 0.0034 -
mean_absolute_error: 0.0462 - val_loss: 0.0026 - val_mean_absolute_error: 0.0361
Epoch 31/50
10/10 [=====] - 0s 8ms/step - loss: 0.0033 -
mean_absolute_error: 0.0450 - val_loss: 0.0024 - val_mean_absolute_error: 0.0347

Epoch 32/50
10/10 [=====] - 0s 7ms/step - loss: 0.0031 -
mean_absolute_error: 0.0439 - val_loss: 0.0023 - val_mean_absolute_error: 0.0336
Epoch 33/50
10/10 [=====] - 0s 8ms/step - loss: 0.0029 -
mean_absolute_error: 0.0428 - val_loss: 0.0022 - val_mean_absolute_error: 0.0331
Epoch 34/50
10/10 [=====] - 0s 9ms/step - loss: 0.0028 -
mean_absolute_error: 0.0417 - val_loss: 0.0020 - val_mean_absolute_error: 0.0317
Epoch 35/50
10/10 [=====] - 0s 8ms/step - loss: 0.0027 -
mean_absolute_error: 0.0410 - val_loss: 0.0019 - val_mean_absolute_error: 0.0306
Epoch 36/50
10/10 [=====] - 0s 8ms/step - loss: 0.0025 -
mean_absolute_error: 0.0395 - val_loss: 0.0018 - val_mean_absolute_error: 0.0306
Epoch 37/50
10/10 [=====] - 0s 9ms/step - loss: 0.0024 -
mean_absolute_error: 0.0387 - val_loss: 0.0017 - val_mean_absolute_error: 0.0290
Epoch 38/50
10/10 [=====] - 0s 9ms/step - loss: 0.0022 -
mean_absolute_error: 0.0374 - val_loss: 0.0016 - val_mean_absolute_error: 0.0284
Epoch 39/50
10/10 [=====] - 0s 7ms/step - loss: 0.0021 -
mean_absolute_error: 0.0365 - val_loss: 0.0015 - val_mean_absolute_error: 0.0276
Epoch 40/50
10/10 [=====] - 0s 9ms/step - loss: 0.0020 -
mean_absolute_error: 0.0359 - val_loss: 0.0014 - val_mean_absolute_error: 0.0267
Epoch 41/50
10/10 [=====] - 0s 7ms/step - loss: 0.0020 -
mean_absolute_error: 0.0351 - val_loss: 0.0013 - val_mean_absolute_error: 0.0267
Epoch 42/50
10/10 [=====] - 0s 7ms/step - loss: 0.0018 -
mean_absolute_error: 0.0333 - val_loss: 0.0012 - val_mean_absolute_error: 0.0253
Epoch 43/50
10/10 [=====] - 0s 9ms/step - loss: 0.0017 -
mean_absolute_error: 0.0327 - val_loss: 0.0012 - val_mean_absolute_error: 0.0249
Epoch 44/50
10/10 [=====] - 0s 8ms/step - loss: 0.0016 -
mean_absolute_error: 0.0318 - val_loss: 0.0011 - val_mean_absolute_error: 0.0243
Epoch 45/50
10/10 [=====] - 0s 7ms/step - loss: 0.0015 -
mean_absolute_error: 0.0310 - val_loss: 0.0010 - val_mean_absolute_error: 0.0234
Epoch 46/50
10/10 [=====] - 0s 10ms/step - loss: 0.0014 -
mean_absolute_error: 0.0300 - val_loss: 0.0010 - val_mean_absolute_error: 0.0235
Epoch 47/50
10/10 [=====] - 0s 8ms/step - loss: 0.0013 -
mean_absolute_error: 0.0287 - val_loss: 9.1863e-04 - val_mean_absolute_error:

```

0.0224
Epoch 48/50
10/10 [=====] - 0s 9ms/step - loss: 0.0013 -
mean_absolute_error: 0.0281 - val_loss: 8.8108e-04 - val_mean_absolute_error:
0.0220
Epoch 49/50
10/10 [=====] - 0s 9ms/step - loss: 0.0012 -
mean_absolute_error: 0.0272 - val_loss: 8.2292e-04 - val_mean_absolute_error:
0.0212
Epoch 50/50
10/10 [=====] - 0s 8ms/step - loss: 0.0011 -
mean_absolute_error: 0.0263 - val_loss: 7.7785e-04 - val_mean_absolute_error:
0.0207

```

```

[217]: tr_acc = history.history['mean_absolute_error']
tr_loss = history.history['loss']
val_acc = history.history['val_mean_absolute_error']
val_loss = history.history['val_loss']
index_loss = np.argmin(val_loss)
val_lowest = val_loss[index_loss]
index_acc = np.argmin(val_acc)
acc_highest = val_acc[index_acc]
Epochs = [i+1 for i in range(len(tr_acc))]
loss_label = f'best epoch= {str(index_loss + 1)}'
acc_label = f'best epoch= {str(index_acc + 1)}'

# Plot training history
plt.figure(figsize= (20, 8))
plt.style.use('fivethirtyeight')

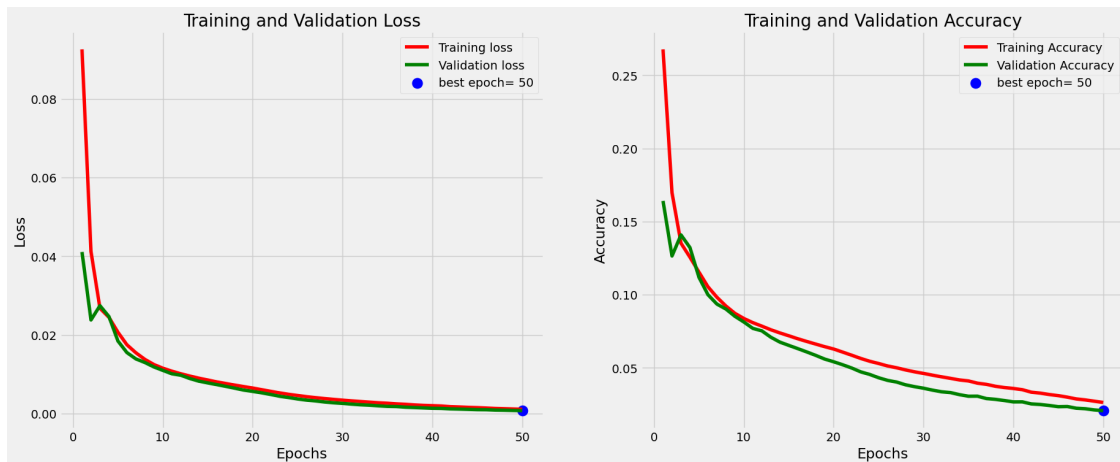
plt.subplot(1, 2, 1)
plt.plot(Epochs, tr_loss, 'r', label= 'Training loss')
plt.plot(Epochs, val_loss, 'g', label= 'Validation loss')
plt.scatter(index_loss + 1, val_lowest, s= 150, c= 'blue', label= loss_label)
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(Epochs, tr_acc, 'r', label= 'Training Accuracy')
plt.plot(Epochs, val_acc, 'g', label= 'Validation Accuracy')
plt.scatter(index_acc + 1, acc_highest, s= 150, c= 'blue', label= acc_label)
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

```



```
plt.tight_layout
plt.show()
```



```
[218]: y_pred = model.predict(X_test)
```

```
4/4 [=====] - 0s 2ms/step
```

```
[219]: from sklearn.metrics import r2_score
```

```
[220]: test_acc = r2_score(y_test , y_pred)
print(f'R2 Score = {test_acc}')
```

```
R2 Score = 0.962160778590368
```

```
[293]: import keras
from keras.models import Sequential
from keras.layers import Dense #sparse or dense
from keras.layers import LeakyReLU, PReLU, ELU # activation functions

# initialize the empty artificial neural network without inputs and outputs
classifier=Sequential()

# adding the input layer and the first hidden layer
classifier.add(Dense(units =4, kernel_initializer =_
↳ 'he_uniform',activation='relu',input_dim = 5)) #units are output_
↳ dimension(neurons),keral_intializers are weight intilalization Technqies
```

```

# adding the second input layer and the first hidden layer
classifier.add(Dense(units = 4, kernel_initializer =
↳ 'he_uniform',activation='relu')) # for relu u can use he_uniform, he_normal

# adding the output layer
classifier.
↳add(Dense(units=1,kernel_initializer='glorot_uniform',activation="relu")) #
↳for sigmoid we have to use weight intialzers as a glorot

# sigmoid actiavtion function will be used in output layers if your ouptut is
↳binary classification

#compling the ANN
classifier.
↳compile(optimizer='Adamax',loss="binary_crossentropy",metrics=["mae"])

```

```

[294]: annhistory=classifier.fit(X_train,y_train,validation_split=.
↳33,batch_size=10,epochs=100)

```

```

Epoch 1/100
27/27 [=====] - 1s 9ms/step - loss: 7.1948 - mae:
0.4916 - val_loss: 6.7039 - val_mae: 0.4755
Epoch 2/100
27/27 [=====] - 0s 4ms/step - loss: 6.9027 - mae:
0.4881 - val_loss: 6.3652 - val_mae: 0.4705
Epoch 3/100
27/27 [=====] - 0s 3ms/step - loss: 6.5648 - mae:
0.4836 - val_loss: 5.7855 - val_mae: 0.4638
Epoch 4/100
27/27 [=====] - 0s 3ms/step - loss: 6.2303 - mae:
0.4793 - val_loss: 5.4448 - val_mae: 0.4588
Epoch 5/100
27/27 [=====] - 0s 4ms/step - loss: 6.0295 - mae:
0.4753 - val_loss: 5.2280 - val_mae: 0.4529
Epoch 6/100
27/27 [=====] - 0s 3ms/step - loss: 5.7904 - mae:
0.4712 - val_loss: 5.1482 - val_mae: 0.4493
Epoch 7/100
27/27 [=====] - 0s 5ms/step - loss: 5.6736 - mae:
0.4695 - val_loss: 5.1359 - val_mae: 0.4481
Epoch 8/100
27/27 [=====] - 0s 3ms/step - loss: 5.6329 - mae:

```

0.4686 - val_loss: 5.0945 - val_mae: 0.4471
Epoch 9/100
27/27 [=====] - 0s 3ms/step - loss: 5.5689 - mae:
0.4678 - val_loss: 5.0335 - val_mae: 0.4458
Epoch 10/100
27/27 [=====] - 0s 3ms/step - loss: 5.5400 - mae:
0.4663 - val_loss: 4.9752 - val_mae: 0.4441
Epoch 11/100
27/27 [=====] - 0s 3ms/step - loss: 5.5277 - mae:
0.4654 - val_loss: 4.9676 - val_mae: 0.4434
Epoch 12/100
27/27 [=====] - 0s 3ms/step - loss: 5.5081 - mae:
0.4648 - val_loss: 4.9081 - val_mae: 0.4424
Epoch 13/100
27/27 [=====] - 0s 3ms/step - loss: 5.4982 - mae:
0.4641 - val_loss: 4.8949 - val_mae: 0.4418
Epoch 14/100
27/27 [=====] - 0s 4ms/step - loss: 5.4590 - mae:
0.4634 - val_loss: 4.8018 - val_mae: 0.4403
Epoch 15/100
27/27 [=====] - 0s 4ms/step - loss: 5.3704 - mae:
0.4617 - val_loss: 4.7498 - val_mae: 0.4384
Epoch 16/100
27/27 [=====] - 0s 3ms/step - loss: 5.3252 - mae:
0.4607 - val_loss: 4.7389 - val_mae: 0.4374
Epoch 17/100
27/27 [=====] - 0s 3ms/step - loss: 5.3061 - mae:
0.4599 - val_loss: 4.7028 - val_mae: 0.4362
Epoch 18/100
27/27 [=====] - 0s 3ms/step - loss: 5.1992 - mae:
0.4582 - val_loss: 4.6520 - val_mae: 0.4340
Epoch 19/100
27/27 [=====] - 0s 5ms/step - loss: 5.1379 - mae:
0.4568 - val_loss: 4.6396 - val_mae: 0.4326
Epoch 20/100
27/27 [=====] - 0s 4ms/step - loss: 5.1056 - mae:
0.4558 - val_loss: 4.5959 - val_mae: 0.4315
Epoch 21/100
27/27 [=====] - 0s 3ms/step - loss: 5.0653 - mae:
0.4549 - val_loss: 4.5843 - val_mae: 0.4305
Epoch 22/100
27/27 [=====] - 0s 3ms/step - loss: 5.0376 - mae:
0.4540 - val_loss: 4.5509 - val_mae: 0.4296
Epoch 23/100
27/27 [=====] - 0s 3ms/step - loss: 4.9809 - mae:
0.4531 - val_loss: 4.4504 - val_mae: 0.4280
Epoch 24/100
27/27 [=====] - 0s 4ms/step - loss: 4.9473 - mae:

0.4518 - val_loss: 4.4299 - val_mae: 0.4268
Epoch 25/100
27/27 [=====] - 0s 3ms/step - loss: 4.9379 - mae:
0.4509 - val_loss: 4.4021 - val_mae: 0.4259
Epoch 26/100
27/27 [=====] - 0s 3ms/step - loss: 4.9307 - mae:
0.4503 - val_loss: 4.3927 - val_mae: 0.4252
Epoch 27/100
27/27 [=====] - 0s 3ms/step - loss: 4.9251 - mae:
0.4496 - val_loss: 4.3850 - val_mae: 0.4244
Epoch 28/100
27/27 [=====] - 0s 3ms/step - loss: 4.8791 - mae:
0.4485 - val_loss: 4.3688 - val_mae: 0.4225
Epoch 29/100
27/27 [=====] - 0s 4ms/step - loss: 4.8325 - mae:
0.4473 - val_loss: 4.3418 - val_mae: 0.4213
Epoch 30/100
27/27 [=====] - 0s 4ms/step - loss: 4.7348 - mae:
0.4457 - val_loss: 4.1505 - val_mae: 0.4180
Epoch 31/100
27/27 [=====] - 0s 3ms/step - loss: 4.5755 - mae:
0.4427 - val_loss: 4.0677 - val_mae: 0.4156
Epoch 32/100
27/27 [=====] - 0s 3ms/step - loss: 4.4384 - mae:
0.4407 - val_loss: 3.8057 - val_mae: 0.4117
Epoch 33/100
27/27 [=====] - 0s 3ms/step - loss: 4.2707 - mae:
0.4366 - val_loss: 3.4825 - val_mae: 0.4079
Epoch 34/100
27/27 [=====] - 0s 4ms/step - loss: 4.0954 - mae:
0.4344 - val_loss: 3.4025 - val_mae: 0.4064
Epoch 35/100
27/27 [=====] - 0s 3ms/step - loss: 4.0609 - mae:
0.4334 - val_loss: 3.3834 - val_mae: 0.4054
Epoch 36/100
27/27 [=====] - 0s 3ms/step - loss: 3.9080 - mae:
0.4322 - val_loss: 3.2291 - val_mae: 0.4019
Epoch 37/100
27/27 [=====] - 0s 3ms/step - loss: 3.6413 - mae:
0.4282 - val_loss: 3.1520 - val_mae: 0.3987
Epoch 38/100
27/27 [=====] - 0s 4ms/step - loss: 3.5529 - mae:
0.4263 - val_loss: 3.0705 - val_mae: 0.3972
Epoch 39/100
27/27 [=====] - 0s 4ms/step - loss: 3.4773 - mae:
0.4248 - val_loss: 2.9852 - val_mae: 0.3954
Epoch 40/100
27/27 [=====] - 0s 4ms/step - loss: 3.3641 - mae:

0.4231 - val_loss: 2.7962 - val_mae: 0.3935
Epoch 41/100
27/27 [=====] - 0s 3ms/step - loss: 3.2708 - mae:
0.4210 - val_loss: 2.6138 - val_mae: 0.3895
Epoch 42/100
27/27 [=====] - 0s 4ms/step - loss: 3.0481 - mae:
0.4174 - val_loss: 2.5298 - val_mae: 0.3871
Epoch 43/100
27/27 [=====] - 0s 5ms/step - loss: 2.9372 - mae:
0.4155 - val_loss: 2.4040 - val_mae: 0.3849
Epoch 44/100
27/27 [=====] - 0s 4ms/step - loss: 2.8887 - mae:
0.4136 - val_loss: 2.3761 - val_mae: 0.3832
Epoch 45/100
27/27 [=====] - 0s 3ms/step - loss: 2.7945 - mae:
0.4120 - val_loss: 2.1862 - val_mae: 0.3809
Epoch 46/100
27/27 [=====] - 0s 3ms/step - loss: 2.7004 - mae:
0.4093 - val_loss: 2.0507 - val_mae: 0.3779
Epoch 47/100
27/27 [=====] - 0s 3ms/step - loss: 2.4393 - mae:
0.4058 - val_loss: 1.8047 - val_mae: 0.3719
Epoch 48/100
27/27 [=====] - 0s 3ms/step - loss: 2.1042 - mae:
0.4006 - val_loss: 1.7538 - val_mae: 0.3684
Epoch 49/100
27/27 [=====] - 0s 4ms/step - loss: 1.9854 - mae:
0.3978 - val_loss: 1.6881 - val_mae: 0.3658
Epoch 50/100
27/27 [=====] - 0s 3ms/step - loss: 1.8702 - mae:
0.3956 - val_loss: 1.6084 - val_mae: 0.3629
Epoch 51/100
27/27 [=====] - 0s 3ms/step - loss: 1.7687 - mae:
0.3923 - val_loss: 1.5394 - val_mae: 0.3600
Epoch 52/100
27/27 [=====] - 0s 3ms/step - loss: 1.7106 - mae:
0.3897 - val_loss: 1.5157 - val_mae: 0.3576
Epoch 53/100
27/27 [=====] - 0s 3ms/step - loss: 1.6604 - mae:
0.3878 - val_loss: 1.4995 - val_mae: 0.3557
Epoch 54/100
27/27 [=====] - 0s 3ms/step - loss: 1.5680 - mae:
0.3855 - val_loss: 1.3635 - val_mae: 0.3530
Epoch 55/100
27/27 [=====] - 0s 3ms/step - loss: 1.5244 - mae:
0.3822 - val_loss: 1.3158 - val_mae: 0.3497
Epoch 56/100
27/27 [=====] - 0s 3ms/step - loss: 1.5027 - mae:

0.3801 - val_loss: 1.2650 - val_mae: 0.3481
Epoch 57/100
27/27 [=====] - 0s 4ms/step - loss: 1.4636 - mae:
0.3785 - val_loss: 1.2418 - val_mae: 0.3461
Epoch 58/100
27/27 [=====] - 0s 3ms/step - loss: 1.3730 - mae:
0.3759 - val_loss: 1.2164 - val_mae: 0.3431
Epoch 59/100
27/27 [=====] - 0s 3ms/step - loss: 1.3128 - mae:
0.3734 - val_loss: 1.2006 - val_mae: 0.3409
Epoch 60/100
27/27 [=====] - 0s 3ms/step - loss: 1.2927 - mae:
0.3715 - val_loss: 1.1895 - val_mae: 0.3392
Epoch 61/100
27/27 [=====] - 0s 4ms/step - loss: 1.2782 - mae:
0.3699 - val_loss: 1.1801 - val_mae: 0.3376
Epoch 62/100
27/27 [=====] - 0s 3ms/step - loss: 1.2661 - mae:
0.3683 - val_loss: 1.1706 - val_mae: 0.3359
Epoch 63/100
27/27 [=====] - 0s 3ms/step - loss: 1.2550 - mae:
0.3667 - val_loss: 1.1621 - val_mae: 0.3344
Epoch 64/100
27/27 [=====] - 0s 4ms/step - loss: 1.2443 - mae:
0.3652 - val_loss: 1.1546 - val_mae: 0.3329
Epoch 65/100
27/27 [=====] - 0s 3ms/step - loss: 1.2351 - mae:
0.3637 - val_loss: 1.1465 - val_mae: 0.3313
Epoch 66/100
27/27 [=====] - 0s 3ms/step - loss: 1.2256 - mae:
0.3623 - val_loss: 1.1394 - val_mae: 0.3298
Epoch 67/100
27/27 [=====] - 0s 4ms/step - loss: 1.2168 - mae:
0.3608 - val_loss: 1.1323 - val_mae: 0.3283
Epoch 68/100
27/27 [=====] - 0s 3ms/step - loss: 1.2084 - mae:
0.3593 - val_loss: 1.1253 - val_mae: 0.3267
Epoch 69/100
27/27 [=====] - 0s 4ms/step - loss: 1.2000 - mae:
0.3578 - val_loss: 1.1188 - val_mae: 0.3253
Epoch 70/100
27/27 [=====] - 0s 3ms/step - loss: 1.1922 - mae:
0.3563 - val_loss: 1.1123 - val_mae: 0.3238
Epoch 71/100
27/27 [=====] - 0s 3ms/step - loss: 1.1844 - mae:
0.3549 - val_loss: 1.1061 - val_mae: 0.3223
Epoch 72/100
27/27 [=====] - 0s 3ms/step - loss: 1.1769 - mae:

0.3534 - val_loss: 1.0999 - val_mae: 0.3207
Epoch 73/100
27/27 [=====] - 0s 5ms/step - loss: 1.1697 - mae:
0.3519 - val_loss: 1.0935 - val_mae: 0.3192
Epoch 74/100
27/27 [=====] - 0s 5ms/step - loss: 1.1624 - mae:
0.3504 - val_loss: 1.0876 - val_mae: 0.3176
Epoch 75/100
27/27 [=====] - 0s 6ms/step - loss: 1.1552 - mae:
0.3490 - val_loss: 1.0820 - val_mae: 0.3161
Epoch 76/100
27/27 [=====] - 0s 5ms/step - loss: 1.1486 - mae:
0.3474 - val_loss: 1.0759 - val_mae: 0.3145
Epoch 77/100
27/27 [=====] - 0s 5ms/step - loss: 1.1416 - mae:
0.3459 - val_loss: 1.0701 - val_mae: 0.3130
Epoch 78/100
27/27 [=====] - 0s 5ms/step - loss: 1.1349 - mae:
0.3444 - val_loss: 1.0645 - val_mae: 0.3114
Epoch 79/100
27/27 [=====] - 0s 5ms/step - loss: 1.1282 - mae:
0.3430 - val_loss: 1.0590 - val_mae: 0.3098
Epoch 80/100
27/27 [=====] - 0s 7ms/step - loss: 1.1217 - mae:
0.3414 - val_loss: 1.0536 - val_mae: 0.3082
Epoch 81/100
27/27 [=====] - 0s 6ms/step - loss: 1.1154 - mae:
0.3399 - val_loss: 1.0480 - val_mae: 0.3066
Epoch 82/100
27/27 [=====] - 0s 5ms/step - loss: 1.1090 - mae:
0.3384 - val_loss: 1.0425 - val_mae: 0.3049
Epoch 83/100
27/27 [=====] - 0s 6ms/step - loss: 1.1028 - mae:
0.3368 - val_loss: 1.0370 - val_mae: 0.3033
Epoch 84/100
27/27 [=====] - 0s 5ms/step - loss: 1.0964 - mae:
0.3353 - val_loss: 1.0320 - val_mae: 0.3018
Epoch 85/100
27/27 [=====] - 0s 5ms/step - loss: 1.0904 - mae:
0.3337 - val_loss: 1.0266 - val_mae: 0.3001
Epoch 86/100
27/27 [=====] - 0s 5ms/step - loss: 1.0842 - mae:
0.3321 - val_loss: 1.0215 - val_mae: 0.2985
Epoch 87/100
27/27 [=====] - 0s 7ms/step - loss: 1.0783 - mae:
0.3306 - val_loss: 1.0162 - val_mae: 0.2968
Epoch 88/100
27/27 [=====] - 0s 5ms/step - loss: 1.0723 - mae:

```

0.3289 - val_loss: 1.0110 - val_mae: 0.2951
Epoch 89/100
27/27 [=====] - 0s 7ms/step - loss: 1.0664 - mae:
0.3272 - val_loss: 1.0058 - val_mae: 0.2934
Epoch 90/100
27/27 [=====] - 0s 5ms/step - loss: 1.0604 - mae:
0.3257 - val_loss: 1.0008 - val_mae: 0.2917
Epoch 91/100
27/27 [=====] - 0s 3ms/step - loss: 1.0546 - mae:
0.3240 - val_loss: 0.9957 - val_mae: 0.2901
Epoch 92/100
27/27 [=====] - 0s 4ms/step - loss: 1.0487 - mae:
0.3223 - val_loss: 0.9908 - val_mae: 0.2884
Epoch 93/100
27/27 [=====] - 0s 3ms/step - loss: 1.0431 - mae:
0.3206 - val_loss: 0.9856 - val_mae: 0.2866
Epoch 94/100
27/27 [=====] - 0s 3ms/step - loss: 1.0372 - mae:
0.3189 - val_loss: 0.9808 - val_mae: 0.2849
Epoch 95/100
27/27 [=====] - 0s 4ms/step - loss: 1.0317 - mae:
0.3171 - val_loss: 0.9758 - val_mae: 0.2831
Epoch 96/100
27/27 [=====] - 0s 3ms/step - loss: 1.0259 - mae:
0.3154 - val_loss: 0.9710 - val_mae: 0.2813
Epoch 97/100
27/27 [=====] - 0s 3ms/step - loss: 1.0204 - mae:
0.3136 - val_loss: 0.9660 - val_mae: 0.2794
Epoch 98/100
27/27 [=====] - 0s 4ms/step - loss: 1.0148 - mae:
0.3118 - val_loss: 0.9613 - val_mae: 0.2775
Epoch 99/100
27/27 [=====] - 0s 5ms/step - loss: 1.0093 - mae:
0.3101 - val_loss: 0.9565 - val_mae: 0.2757
Epoch 100/100
27/27 [=====] - 0s 3ms/step - loss: 1.0038 - mae:
0.3082 - val_loss: 0.9517 - val_mae: 0.2738

```

```
[295]: print(annhistory.history.keys())
```

```
dict_keys(['loss', 'mae', 'val_loss', 'val_mae'])
```

```
[297]: #summarize histiry for accuracy
plt.plot(annhistory.history['mae'])
plt.plot(annhistory.history['val_mae'])
plt.title('model accuracy')
plt.ylabel('accuracy')
```



```
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()

# summarize history for loss
plt.plot(annhistory.history['loss'])
plt.plot(annhistory.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```

