

Import needed modules

```
In [1]: #general Libraries needed
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

#TensorFlow requirements
import tensorflow as tf
from tensorflow import keras

#scikit Learn imports
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder, StandardScaler, MinMaxScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import mean_squared_error, mean_absolute_error
from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearchCV,
from pandas.plotting import scatter_matrix
from sklearn.linear_model import SGDRegressor, LinearRegression, Ridge, Lasso, ElasticN
```

Function Definitions

```
In [2]: #function to verify the existence of a file in the current working directory and downlo
import os,urllib, urllib.request, sys, tarfile
def downloadDataResource(file, sourcePath, compressed=None):
    if not os.path.isfile(file):
        try:
            urllib.request.urlretrieve(sourcePath+(compressed if compressed else file),
            print("Downloaded", (compressed if compressed else file) )
            if compressed:
                ucomp = tarfile.open(compressed)
                ucomp.extractall()
                ucomp.close()
                print("File uncompressed.")
        except:
            print("ERROR: File", (compressed if compressed else file), "not found. Data
    else:
        print("Data resource", file, "already downloaded.")
```

```
In [3]: #function that shows a Learning curve for any model that has predict or fit methods
from sklearn.model_selection import learning_curve

def non_nn_plot_learning_curve(estimator,X,y,ylim=None,cv=None,n_jobs=None,train_sizes=

    _, axes = plt.subplots(1, 1, figsize=(10, 5))
    axes.set_title('Learning Curve')
    if ylim is not None:
        axes.set_ylim(*ylim)
    axes.set_xlabel("Training examples")
    axes.set_ylabel(scoring)

    train_sizes, train_scores, test_scores= learning_curve(estimator,X,y,cv=cv,n_jobs=n
```

```

train_scores_mean = np.mean(train_scores, axis=1)
train_scores_std = np.std(train_scores, axis=1)
test_scores_mean = np.mean(test_scores, axis=1)
test_scores_std = np.std(test_scores, axis=1)

# Plot Learning curve
axes.grid()
axes.fill_between(train_sizes, train_scores_mean - train_scores_std, train_scores_mean + train_scores_std, color="r", label="Training score")
axes.fill_between(train_sizes, test_scores_mean - test_scores_std, test_scores_mean + test_scores_std, color="g", label="Cross-validation score")
axes.plot(train_sizes, train_scores_mean, "o-", color="r", label="Training score")
axes.plot(train_sizes, test_scores_mean, "o-", color="g", label="Cross-validation score")
axes.legend(loc="best")
plt.show()

return

#code to prevent warnings that can occur as a result of this function
from warnings import simplefilter
from sklearn.exceptions import ConvergenceWarning
simplefilter("ignore", category=ConvergenceWarning)

```

```

In [4]: #function provided that plots the learning curve for neural networks
def plot_learning_curve( history ):
    pd.DataFrame(history.history).plot(figsize=(8, 5))
    plt.grid(True)
    ymin, ymax = [], []
    for x in history.history.keys():
        ymax.append( max(history.history[x]))
        ymin.append( min(history.history[x]))
    plt.gca().set_ylim(min(ymin)*.95, max(ymax)*1.05)
    plt.xlabel("EPOCHS")
    plt.show()

```

```

In [5]: #define a function that will create AND compile a Sequential model with n_hidden layers
#and n_neurons and a learning_rate
#the model default to using ReLU activation and is currently designed for 1 output (R)
def build_RegMLP_model(n_hidden=1, n_neurons=30, learning_rate=1e-3, input_shape=[8]):
    model = keras.models.Sequential()
    model.add(keras.layers.Flatten())
    for layer in range(n_hidden):
        model.add(keras.layers.Dense(n_neurons, activation="relu"))
    model.add(keras.layers.Dense(1))
    model.compile(loss="mean_squared_error", optimizer=keras.optimizers.SGD(learning_rate))
    return model

```

Source Data

```

In [6]: #source data and create dataframe

path = 'https://raw.githubusercontent.com/SueMcMetzger/MachineLearning/main/chpt4/'

covid_data = 'COVID_31Dec2021.csv'
election_data = 'ElectionEconomicSocialDataByFIPS.csv'

```

```
#download data files if not currently downloaded into the current working directory
downloadDataResource(covid_data, path)
downloadDataResource(election_data, path)

#create the dataframe
COVID = pd.read_csv(covid_data)
election = pd.read_csv(election_data)
```

Data resource COVID_31Dec2021.csv already downloaded.
Data resource ElectionEconomicSocialDataByFIPS.csv already downloaded.

```
In [7]: #merge COVID and election datasets into one

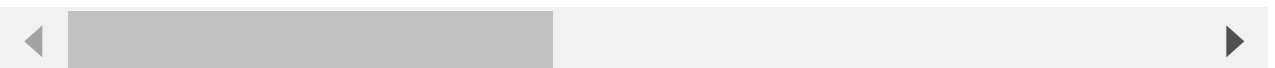
data = pd.merge(COVID, election, left_on = 'fips', right_on = 'fips', how = 'inner')
```

Prepare the data set

```
In [8]: data.describe()
```

```
Out[8]:
```

	fips	population	vaccinationRate	cases	deaths	MedianIncome	Pov
count	3140.000000	3.140000e+03	3007.000000	3.140000e+03	3140.000000	3140.000000	3.1400
mean	30397.503185	1.045319e+05	0.483812	1.719046e+04	260.546815	57455.856688	1.2219
std	15156.538249	3.335534e+05	0.115351	5.568672e+04	870.099723	14582.812140	4.1956
min	1001.000000	1.690000e+02	0.030000	0.000000e+00	0.000000	22901.000000	7.0000
25%	18180.500000	1.091375e+04	0.405000	1.879000e+03	34.000000	47821.500000	1.4425
50%	29178.000000	2.576350e+04	0.474000	4.534500e+03	80.000000	55143.500000	3.4790
75%	45081.500000	6.810400e+04	0.551000	1.183500e+04	191.250000	64051.000000	8.4685
max	56045.000000	1.003911e+07	1.304000	1.697286e+06	27637.000000	160305.000000	1.2893



```
In [9]: # Clean up >100% values

data.loc[data.vaccinationRate > 1, 'vaccinationRate'] = np.nan

data.loc[data.AdherentPercent > 100, 'AdherentPercent'] = np.nan
```

```
In [10]: #remove 133 instances w/o vaccinationRate data and check

data = data.dropna( subset = ['vaccinationRate'])

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3006 entries, 0 to 3139
Data columns (total 19 columns):
#   Column                Non-Null Count  Dtype
#   ...
```

```

-----
0  fips                3006 non-null  int64
1  state               3006 non-null  object
2  county              3006 non-null  object
3  population          3006 non-null  int64
4  vaccinationRate     3006 non-null  float64
5  cases               3006 non-null  int64
6  deaths              3006 non-null  int64
7  Region              3006 non-null  object
8  MedianIncome        3006 non-null  int64
9  PovertyEst          3006 non-null  int64
10 LaborForce          3006 non-null  int64
11 UnemploymentRate    3006 non-null  float64
12 Older               2872 non-null  float64
13 Urban               2872 non-null  float64
14 Trump2016           2872 non-null  float64
15 Trump2020           2872 non-null  float64
16 RepGov              2872 non-null  float64
17 Female              2872 non-null  float64
18 AdherentPercent     2951 non-null  float64
dtypes: float64(9), int64(7), object(3)
memory usage: 469.7+ KB

```

```

In [11]: pop = data["population"]
data["DeathsPerCapita"] = data["deaths"]/pop
data["CasesPerCapita"] = data["cases"]/pop
data["LaborForcePerCapita"] = data["LaborForce"]/pop
data["PovertyRate"] = data["PovertyEst"]/pop
data["FatalityRate"] = data["deaths"]/data["cases"]

```

```

In [12]: data = data.drop(columns = ['deaths', 'cases', 'LaborForce', 'PovertyEst', 'population'])

```

```

In [13]: #Remove Delaware County, PA
#Remove Delaware County, PA
X_instance = data[data.fips == 42045] #copies Delaware County to new dataset
data = data[data.fips !=42045].copy()

```

```

In [14]: #Drop unneeded features
data = data.drop(columns = ['fips', 'county', 'state'])

#Separate DelCounty actual and X_instance, drop unique columns and Y column
DelCounty_vaccinationRate = X_instance.vaccinationRate
X_instance = X_instance.drop(columns = ['fips', 'county', 'state', 'vaccinationRate'])

```

```

In [15]: #create training and test data sets based on the data dataframe.
X_train_pre, X_test_pre, y_train, y_test = train_test_split(
    data.drop(columns=['vaccinationRate']),
    data.vaccinationRate,
    test_size=.2,
    random_state=36,
    stratify = data.Region
)

```

```
In [16]: #set the categorical attributes
cat_attrbs = ['Region']

#set the numerical attributes
num_attrbs = list( X_train_pre.drop(columns=cat_attrbs) )

#define pipeline for numeric attributes (this code is just a definition)
#each numeric attribute will be imputed using the Median strategy
#each numeric attribute will be scaled
num_pipeline = Pipeline( [
    ('imputer', SimpleImputer(strategy="median")),
    ('std_scaler', MinMaxScaler()),
] )

#define the pipeline process for the data set
full_pipeline = ColumnTransformer( [
    ('num', num_pipeline, num_attrbs),
    ('cat', OneHotEncoder(sparse=False), cat_attrbs)
])
```

Regression Neural Network

```
In [17]: #display sets

X_train_pre.shape, X_test_pre.shape, y_train.shape, y_test.shape
```

```
Out[17]: ((2404, 15), (601, 15), (2404,), (601,))
```

```
In [18]: #vaccination rate for Delaware County
DelCounty_vaccinationRate
```

```
Out[18]: 2264    0.591
Name: vaccinationRate, dtype: float64
```

Prepare the data

```
In [19]: #create an array of prepared data based on the training & test data set
X_train = full_pipeline.fit_transform( X_train_pre)
X_test = full_pipeline.transform( X_test_pre)
X_train.shape, X_test.shape
```

```
Out[19]: ((2404, 22), (601, 22))
```

```
In [20]: #create an array of prepared data based on Delaware County
X_example = full_pipeline.transform( X_instance )
```

```
In [21]: #create an array of prepared data based on the training data set and the Pipeline proce
X_train = full_pipeline.fit_transform( X_train_pre)
```

```
X_test = full_pipeline.transform(X_test_pre)

X_train.shape, X_test.shape
```

Out[21]: ((2404, 22), (601, 22))

```
In [22]: #scale all data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
X_example = scaler.transform(X_example)
```

Best Non-Neural Model - Linear Regression Model

```
In [23]: #create the model object
lin_reg = LinearRegression()

#fit the model to the prepared test data
lin_reg.fit(X_train, y_train)

#calculated the predicted values for the training data set
predictions = lin_reg.predict(X_train)

#compare the predicted to the actuals
rmse = mean_squared_error(y_train, predictions, squared=True)
print("Prediction Error (MSE): {:.4%}".format(rmse))
```

Prediction Error (MSE): 0.5060%

```
In [24]: #run cross validation
scores = cross_val_score(lin_reg, X_train, y_train, scoring='neg_mean_squared_error', c

#report the results
print("MSE: {:.4%}".format( -scores.mean() ) )
```

MSE: 0.5208%

```
In [25]: predictions = lin_reg.predict(X_test)

#compare the predicted to the actuals
mse = mean_squared_error(y_test, predictions, squared=True)
print("Prediction Error (MSE): {:.4%}".format(mse))
```

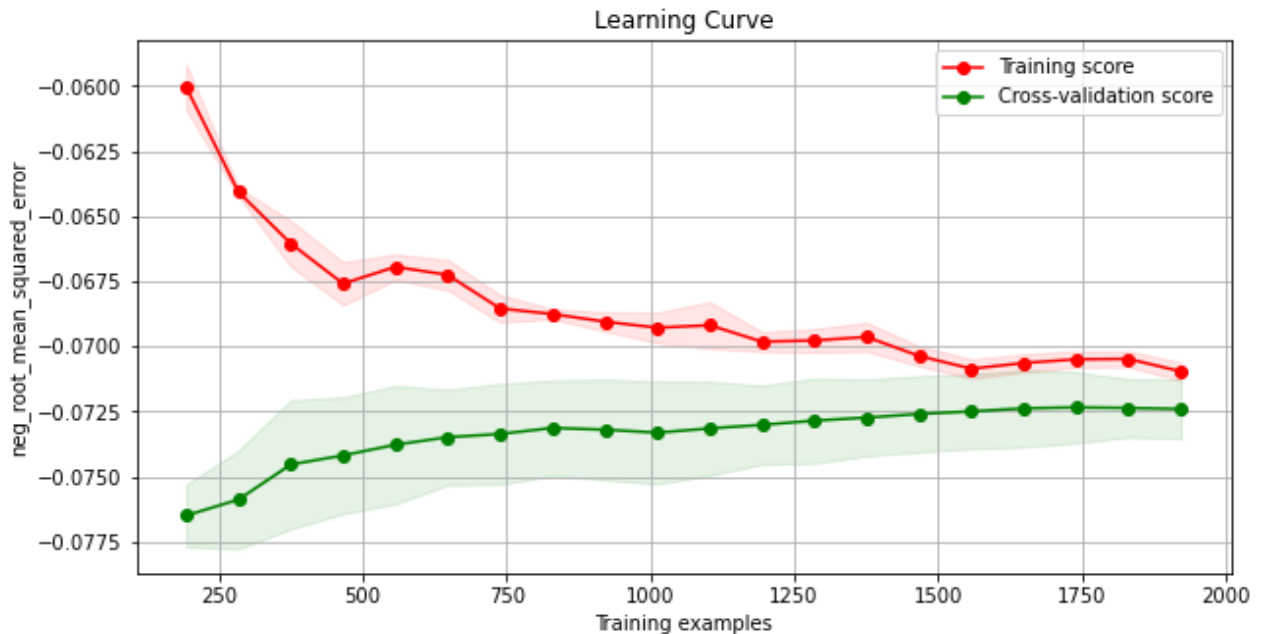
Prediction Error (MSE): 0.6670%

```
In [27]: predictions = lin_reg.predict(X_test)

#compare the predicted to the actuals
rmse = mean_squared_error(y_test, predictions, squared=False)
print("Prediction Error (RMSE): {:.4%}".format(rmse))
```

Prediction Error (RMSE): 8.1668%

```
In [28]: non_nn_plot_learning_curve(lin_reg, X_train, y_train, )
```



```
In [29]: #Predicted value  
lin_reg.predict( X_example )
```

```
Out[29]: array([0.68484669])
```

```
In [30]: #Actual value  
DelCounty_vaccinationRate
```

```
Out[30]: 2264    0.591  
Name: vaccinationRate, dtype: float64
```

Build the Neural Network, Compile & Train

```
In [31]: #starting by setting random seeds and restarting keras backend session  
np.random.seed(42)  
tf.random.set_seed(42)  
  
#resets the Keras global state - helps avoid clutter from old models and layers, espec  
keras.backend.clear_session()
```

```
In [32]: #the same steps above can be built and saved in a single command with the same results  
model = keras.models.Sequential([  
    keras.layers.Flatten(input_shape=X_train.shape[1:]),  
    keras.layers.Dense(15, activation="relu"),  
    keras.layers.Dense(15, activation="relu"),  
    keras.layers.Dense(15, activation="relu"),  
    keras.layers.Dense(15, activation="relu"),  
    keras.layers.Dense(1)  
)
```

```
In [33]: #After model is created, it needs to be compiled - this requires setting
#the loss function to mean_squared_error
model.compile(loss="mean_squared_error",
              optimizer=keras.optimizers.SGD(learning_rate=.001),
              )
```

```
In [34]: #fit the model and capture the details of the fit to a variable called history
#note that validation data is dynamically allocated at 20% of the training data

early_stopping = keras.callbacks.EarlyStopping( monitor='val_loss', mode='min', patience=10)

history = model.fit(X_train,
                    y_train,
                    epochs=500,
                    validation_split=.2,
                    callbacks=[early_stopping]
                    )
```

```
Epoch 1/500
61/61 [=====] - 1s 8ms/step - loss: 0.0892 - val_loss: 0.0826
Epoch 2/500
61/61 [=====] - 0s 4ms/step - loss: 0.0701 - val_loss: 0.0693
Epoch 3/500
61/61 [=====] - 0s 3ms/step - loss: 0.0592 - val_loss: 0.0602
Epoch 4/500
61/61 [=====] - 0s 4ms/step - loss: 0.0515 - val_loss: 0.0532
Epoch 5/500
61/61 [=====] - 0s 4ms/step - loss: 0.0456 - val_loss: 0.0477
Epoch 6/500
61/61 [=====] - 0s 4ms/step - loss: 0.0409 - val_loss: 0.0431
Epoch 7/500
61/61 [=====] - 0s 4ms/step - loss: 0.0370 - val_loss: 0.0395
Epoch 8/500
61/61 [=====] - 0s 4ms/step - loss: 0.0339 - val_loss: 0.0365
Epoch 9/500
61/61 [=====] - 0s 4ms/step - loss: 0.0313 - val_loss: 0.0340
Epoch 10/500
61/61 [=====] - 0s 4ms/step - loss: 0.0292 - val_loss: 0.0319
Epoch 11/500
61/61 [=====] - 0s 7ms/step - loss: 0.0274 - val_loss: 0.0301
Epoch 12/500
61/61 [=====] - 0s 4ms/step - loss: 0.0259 - val_loss: 0.0284
Epoch 13/500
61/61 [=====] - 0s 7ms/step - loss: 0.0245 - val_loss: 0.0270
Epoch 14/500
61/61 [=====] - 0s 7ms/step - loss: 0.0233 - val_loss: 0.0258
Epoch 15/500
61/61 [=====] - 0s 5ms/step - loss: 0.0224 - val_loss: 0.0248
Epoch 16/500
61/61 [=====] - 0s 5ms/step - loss: 0.0215 - val_loss: 0.0239
Epoch 17/500
61/61 [=====] - 0s 4ms/step - loss: 0.0207 - val_loss: 0.0231
Epoch 18/500
61/61 [=====] - 0s 5ms/step - loss: 0.0200 - val_loss: 0.0224
Epoch 19/500
61/61 [=====] - 0s 5ms/step - loss: 0.0194 - val_loss: 0.0217
Epoch 20/500
61/61 [=====] - 0s 4ms/step - loss: 0.0188 - val_loss: 0.0211
```



```
Epoch 21/500
61/61 [=====] - 0s 5ms/step - loss: 0.0183 - val_loss: 0.0206
Epoch 22/500
61/61 [=====] - 0s 5ms/step - loss: 0.0178 - val_loss: 0.0201
Epoch 23/500
61/61 [=====] - 0s 5ms/step - loss: 0.0173 - val_loss: 0.0196
Epoch 24/500
61/61 [=====] - 0s 5ms/step - loss: 0.0169 - val_loss: 0.0192
Epoch 25/500
61/61 [=====] - 0s 5ms/step - loss: 0.0166 - val_loss: 0.0188
Epoch 26/500
61/61 [=====] - 0s 5ms/step - loss: 0.0162 - val_loss: 0.0184
Epoch 27/500
61/61 [=====] - 0s 5ms/step - loss: 0.0159 - val_loss: 0.0181
Epoch 28/500
61/61 [=====] - 0s 5ms/step - loss: 0.0156 - val_loss: 0.0177
Epoch 29/500
61/61 [=====] - 0s 4ms/step - loss: 0.0153 - val_loss: 0.0175
Epoch 30/500
61/61 [=====] - 0s 5ms/step - loss: 0.0151 - val_loss: 0.0172
Epoch 31/500
61/61 [=====] - 0s 4ms/step - loss: 0.0148 - val_loss: 0.0169
Epoch 32/500
61/61 [=====] - 0s 4ms/step - loss: 0.0146 - val_loss: 0.0167
Epoch 33/500
61/61 [=====] - 0s 5ms/step - loss: 0.0144 - val_loss: 0.0165
Epoch 34/500
61/61 [=====] - 0s 5ms/step - loss: 0.0142 - val_loss: 0.0163
Epoch 35/500
61/61 [=====] - 0s 4ms/step - loss: 0.0140 - val_loss: 0.0161
Epoch 36/500
61/61 [=====] - 0s 4ms/step - loss: 0.0139 - val_loss: 0.0159
Epoch 37/500
61/61 [=====] - 0s 4ms/step - loss: 0.0137 - val_loss: 0.0157
Epoch 38/500
61/61 [=====] - 0s 4ms/step - loss: 0.0136 - val_loss: 0.0155
Epoch 39/500
61/61 [=====] - 0s 5ms/step - loss: 0.0134 - val_loss: 0.0154
Epoch 40/500
61/61 [=====] - 0s 4ms/step - loss: 0.0133 - val_loss: 0.0152
Epoch 41/500
61/61 [=====] - 0s 4ms/step - loss: 0.0132 - val_loss: 0.0151
Epoch 42/500
61/61 [=====] - 0s 4ms/step - loss: 0.0130 - val_loss: 0.0150
Epoch 43/500
61/61 [=====] - 0s 4ms/step - loss: 0.0129 - val_loss: 0.0148
Epoch 44/500
61/61 [=====] - 0s 4ms/step - loss: 0.0128 - val_loss: 0.0147
Epoch 45/500
61/61 [=====] - 0s 4ms/step - loss: 0.0127 - val_loss: 0.0146
Epoch 46/500
61/61 [=====] - 0s 4ms/step - loss: 0.0126 - val_loss: 0.0145
Epoch 47/500
61/61 [=====] - 0s 4ms/step - loss: 0.0125 - val_loss: 0.0144
Epoch 48/500
61/61 [=====] - 0s 4ms/step - loss: 0.0124 - val_loss: 0.0143
Epoch 49/500
61/61 [=====] - 0s 4ms/step - loss: 0.0123 - val_loss: 0.0142
Epoch 50/500
61/61 [=====] - 0s 4ms/step - loss: 0.0122 - val_loss: 0.0141
```

Epoch 51/500
61/61 [=====] - 0s 4ms/step - loss: 0.0122 - val_loss: 0.0140
Epoch 52/500
61/61 [=====] - 0s 4ms/step - loss: 0.0121 - val_loss: 0.0139
Epoch 53/500
61/61 [=====] - 0s 5ms/step - loss: 0.0120 - val_loss: 0.0138
Epoch 54/500
61/61 [=====] - 0s 4ms/step - loss: 0.0120 - val_loss: 0.0137
Epoch 55/500
61/61 [=====] - 0s 4ms/step - loss: 0.0119 - val_loss: 0.0136
Epoch 56/500
61/61 [=====] - 0s 4ms/step - loss: 0.0118 - val_loss: 0.0136
Epoch 57/500
61/61 [=====] - 0s 4ms/step - loss: 0.0118 - val_loss: 0.0135
Epoch 58/500
61/61 [=====] - 0s 4ms/step - loss: 0.0117 - val_loss: 0.0134
Epoch 59/500
61/61 [=====] - 0s 4ms/step - loss: 0.0116 - val_loss: 0.0133
Epoch 60/500
61/61 [=====] - 0s 4ms/step - loss: 0.0116 - val_loss: 0.0133
Epoch 61/500
61/61 [=====] - 0s 4ms/step - loss: 0.0115 - val_loss: 0.0132
Epoch 62/500
61/61 [=====] - 0s 4ms/step - loss: 0.0115 - val_loss: 0.0131
Epoch 63/500
61/61 [=====] - 0s 4ms/step - loss: 0.0114 - val_loss: 0.0131
Epoch 64/500
61/61 [=====] - 0s 4ms/step - loss: 0.0114 - val_loss: 0.0130
Epoch 65/500
61/61 [=====] - 0s 4ms/step - loss: 0.0113 - val_loss: 0.0130
Epoch 66/500
61/61 [=====] - 0s 4ms/step - loss: 0.0113 - val_loss: 0.0129
Epoch 67/500
61/61 [=====] - 0s 4ms/step - loss: 0.0112 - val_loss: 0.0129
Epoch 68/500
61/61 [=====] - 0s 4ms/step - loss: 0.0112 - val_loss: 0.0128
Epoch 69/500
61/61 [=====] - 0s 4ms/step - loss: 0.0111 - val_loss: 0.0128
Epoch 70/500
61/61 [=====] - 0s 4ms/step - loss: 0.0111 - val_loss: 0.0127
Epoch 71/500
61/61 [=====] - 0s 4ms/step - loss: 0.0111 - val_loss: 0.0126
Epoch 72/500
61/61 [=====] - 0s 4ms/step - loss: 0.0110 - val_loss: 0.0126
Epoch 73/500
61/61 [=====] - 0s 4ms/step - loss: 0.0110 - val_loss: 0.0125
Epoch 74/500
61/61 [=====] - 0s 4ms/step - loss: 0.0109 - val_loss: 0.0125
Epoch 75/500
61/61 [=====] - 0s 4ms/step - loss: 0.0109 - val_loss: 0.0125
Epoch 76/500
61/61 [=====] - 0s 4ms/step - loss: 0.0109 - val_loss: 0.0124
Epoch 77/500
61/61 [=====] - 0s 4ms/step - loss: 0.0108 - val_loss: 0.0124
Epoch 78/500
61/61 [=====] - 0s 4ms/step - loss: 0.0108 - val_loss: 0.0123
Epoch 79/500
61/61 [=====] - 0s 4ms/step - loss: 0.0108 - val_loss: 0.0123
Epoch 80/500
61/61 [=====] - 0s 4ms/step - loss: 0.0107 - val_loss: 0.0123

Epoch 81/500
61/61 [=====] - 0s 4ms/step - loss: 0.0107 - val_loss: 0.0122
Epoch 82/500
61/61 [=====] - 0s 4ms/step - loss: 0.0107 - val_loss: 0.0122
Epoch 83/500
61/61 [=====] - 0s 4ms/step - loss: 0.0106 - val_loss: 0.0121
Epoch 84/500
61/61 [=====] - 0s 4ms/step - loss: 0.0106 - val_loss: 0.0121
Epoch 85/500
61/61 [=====] - 0s 4ms/step - loss: 0.0106 - val_loss: 0.0121
Epoch 86/500
61/61 [=====] - 0s 4ms/step - loss: 0.0105 - val_loss: 0.0120
Epoch 87/500
61/61 [=====] - 0s 4ms/step - loss: 0.0105 - val_loss: 0.0120
Epoch 88/500
61/61 [=====] - 0s 4ms/step - loss: 0.0105 - val_loss: 0.0120
Epoch 89/500
61/61 [=====] - 0s 4ms/step - loss: 0.0104 - val_loss: 0.0119
Epoch 90/500
61/61 [=====] - 0s 4ms/step - loss: 0.0104 - val_loss: 0.0119
Epoch 91/500
61/61 [=====] - 0s 5ms/step - loss: 0.0104 - val_loss: 0.0119
Epoch 92/500
61/61 [=====] - 0s 4ms/step - loss: 0.0104 - val_loss: 0.0119
Epoch 93/500
61/61 [=====] - 0s 4ms/step - loss: 0.0103 - val_loss: 0.0118
Epoch 94/500
61/61 [=====] - 0s 4ms/step - loss: 0.0103 - val_loss: 0.0118
Epoch 95/500
61/61 [=====] - 0s 4ms/step - loss: 0.0103 - val_loss: 0.0118
Epoch 96/500
61/61 [=====] - 0s 4ms/step - loss: 0.0103 - val_loss: 0.0118
Epoch 97/500
61/61 [=====] - 0s 4ms/step - loss: 0.0102 - val_loss: 0.0117
Epoch 98/500
61/61 [=====] - 0s 4ms/step - loss: 0.0102 - val_loss: 0.0117
Epoch 99/500
61/61 [=====] - 0s 4ms/step - loss: 0.0102 - val_loss: 0.0117
Epoch 100/500
61/61 [=====] - 0s 4ms/step - loss: 0.0102 - val_loss: 0.0117
Epoch 101/500
61/61 [=====] - 0s 4ms/step - loss: 0.0102 - val_loss: 0.0116
Epoch 102/500
61/61 [=====] - 0s 4ms/step - loss: 0.0101 - val_loss: 0.0116
Epoch 103/500
61/61 [=====] - 0s 4ms/step - loss: 0.0101 - val_loss: 0.0116
Epoch 104/500
61/61 [=====] - 0s 4ms/step - loss: 0.0101 - val_loss: 0.0116
Epoch 105/500
61/61 [=====] - 0s 4ms/step - loss: 0.0101 - val_loss: 0.0115
Epoch 106/500
61/61 [=====] - 0s 4ms/step - loss: 0.0100 - val_loss: 0.0115
Epoch 107/500
61/61 [=====] - 0s 4ms/step - loss: 0.0100 - val_loss: 0.0115
Epoch 108/500
61/61 [=====] - 0s 4ms/step - loss: 0.0100 - val_loss: 0.0115
Epoch 109/500
61/61 [=====] - 0s 4ms/step - loss: 0.0100 - val_loss: 0.0115
Epoch 110/500
61/61 [=====] - 0s 4ms/step - loss: 0.0100 - val_loss: 0.0114

Epoch 111/500
61/61 [=====] - 0s 4ms/step - loss: 0.0099 - val_loss: 0.0114
Epoch 112/500
61/61 [=====] - 0s 4ms/step - loss: 0.0099 - val_loss: 0.0114
Epoch 113/500
61/61 [=====] - 0s 4ms/step - loss: 0.0099 - val_loss: 0.0114
Epoch 114/500
61/61 [=====] - 0s 4ms/step - loss: 0.0099 - val_loss: 0.0114
Epoch 115/500
61/61 [=====] - 0s 4ms/step - loss: 0.0099 - val_loss: 0.0113
Epoch 116/500
61/61 [=====] - 0s 4ms/step - loss: 0.0099 - val_loss: 0.0113
Epoch 117/500
61/61 [=====] - 0s 4ms/step - loss: 0.0098 - val_loss: 0.0113
Epoch 118/500
61/61 [=====] - 0s 4ms/step - loss: 0.0098 - val_loss: 0.0113
Epoch 119/500
61/61 [=====] - 0s 4ms/step - loss: 0.0098 - val_loss: 0.0113
Epoch 120/500
61/61 [=====] - 0s 5ms/step - loss: 0.0098 - val_loss: 0.0113
Epoch 121/500
61/61 [=====] - 0s 3ms/step - loss: 0.0098 - val_loss: 0.0112
Epoch 122/500
61/61 [=====] - 0s 4ms/step - loss: 0.0098 - val_loss: 0.0112
Epoch 123/500
61/61 [=====] - 0s 4ms/step - loss: 0.0097 - val_loss: 0.0112
Epoch 124/500
61/61 [=====] - 0s 4ms/step - loss: 0.0097 - val_loss: 0.0112
Epoch 125/500
61/61 [=====] - 0s 4ms/step - loss: 0.0097 - val_loss: 0.0111
Epoch 126/500
61/61 [=====] - 0s 4ms/step - loss: 0.0097 - val_loss: 0.0111
Epoch 127/500
61/61 [=====] - 0s 4ms/step - loss: 0.0097 - val_loss: 0.0111
Epoch 128/500
61/61 [=====] - 0s 5ms/step - loss: 0.0097 - val_loss: 0.0111
Epoch 129/500
61/61 [=====] - 0s 4ms/step - loss: 0.0096 - val_loss: 0.0111
Epoch 130/500
61/61 [=====] - 0s 5ms/step - loss: 0.0096 - val_loss: 0.0111
Epoch 131/500
61/61 [=====] - 0s 5ms/step - loss: 0.0096 - val_loss: 0.0111
Epoch 132/500
61/61 [=====] - 0s 5ms/step - loss: 0.0096 - val_loss: 0.0110
Epoch 133/500
61/61 [=====] - 0s 5ms/step - loss: 0.0096 - val_loss: 0.0110
Epoch 134/500
61/61 [=====] - 0s 5ms/step - loss: 0.0096 - val_loss: 0.0110
Epoch 135/500
61/61 [=====] - 0s 5ms/step - loss: 0.0096 - val_loss: 0.0110
Epoch 136/500
61/61 [=====] - 0s 4ms/step - loss: 0.0095 - val_loss: 0.0110
Epoch 137/500
61/61 [=====] - 0s 4ms/step - loss: 0.0095 - val_loss: 0.0110
Epoch 138/500
61/61 [=====] - 0s 4ms/step - loss: 0.0095 - val_loss: 0.0109
Epoch 139/500
61/61 [=====] - 0s 4ms/step - loss: 0.0095 - val_loss: 0.0109
Epoch 140/500
61/61 [=====] - 0s 4ms/step - loss: 0.0095 - val_loss: 0.0109

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

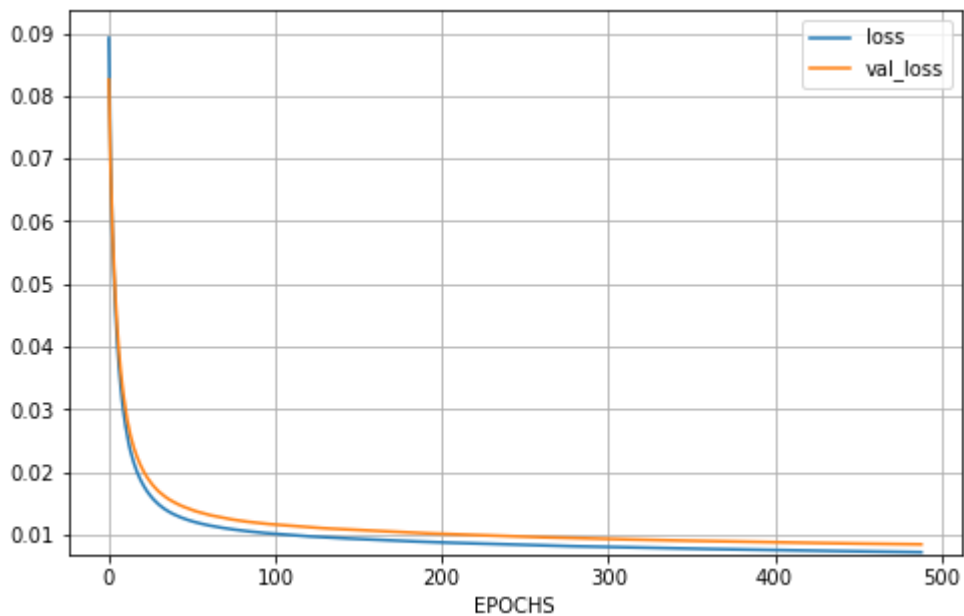
[illegible]

[illegible]

```
Epoch 471/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 472/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 473/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 474/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 475/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 476/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 477/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 478/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 479/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 480/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 481/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 482/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 483/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 484/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 485/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 486/500
61/61 [=====] - 0s 4ms/step - loss: 0.0073 - val_loss: 0.0085
Epoch 487/500
61/61 [=====] - 0s 4ms/step - loss: 0.0072 - val_loss: 0.0085
Epoch 488/500
61/61 [=====] - 0s 4ms/step - loss: 0.0072 - val_loss: 0.0085
Epoch 489/500
61/61 [=====] - 0s 4ms/step - loss: 0.0072 - val_loss: 0.0085
```

Evaluate Performance

```
In [35]: #plot the loss learning curve
plot_learning_curve(history)
```

Model is slightly underfitting the training data, but both have reached a nice plateau

```
In [36]: #evaluate model's loss metric on the training set
model.evaluate(X_train, y_train)
```

```
76/76 [=====] - 0s 2ms/step - loss: 0.0075
Out[36]: 0.007490815594792366
```

```
In [37]: #evaluate Test set
mse_test = model.evaluate(X_test, y_test)
```

```
19/19 [=====] - 0s 2ms/step - loss: 0.0095
```

```
In [38]: #predict the test data set based on SCALED values
pred = model.predict(X_test)

#calculate the Root Mean Squared Error using the scaled values
rmse = np.sqrt(np.mean(keras.losses.mean_squared_error(pred,y_test)))
print('RMSE: {:.4%}'.format( rmse ) )

#calculate the Mean Absolute Error using the scaled values
mae = np.mean(keras.losses.mean_absolute_error(pred,y_test))
print(' MAE: {:.4%}'.format( mae ) )
```

```
RMSE: 13.9909%
MAE: 10.7312%
```

```
In [39]: pred = model.predict(X_test)
```

Model commonly underestimates Delaware County vaccination rate, typically under by at least 10%

```
In [40]: np.mean(pred)
```

```
Out[40]: 0.4827456
```

