Assignment 5

- 1. Choose a regression dataset (bikeshare is allowed), perform a test/train split, and build a regression model (just like in assingnment 3), and calculate the
 - Training Error (MSE, MAE)
 - Testing Error (MSE, MAE)
- Choose a classification dataset (not the adult.data set, The UCI repository has many datasets as well as Kaggle), perform test/train split and create a classification model (your choice but DecisionTree is fine). Calculate
 - Accuracy
 - · Confusion Matrix
 - Classifcation Report
- (Bonus) See if you can improve the classification model's performance with any tricks you can think of (modify features, remove features, polynomial features)

1) Regression model on insurance data

Data from GitHub for book Machine Learning with R by Brett Lantz.

https://github.com/stedy/Machine-Learning-with-R-datasets/blob/master/insurance.csv (https://github.com/stedy/Machine-Learning-with-R-datasets/blob/master/insurance.csv)

```
In [1]: import seaborn as sns
   import matplotlib.pyplot as plt
   %matplotlib inline
   import pandas as pd
   import numpy as np
   from sklearn.linear_model import LinearRegression
   from sklearn.model_selection import train_test_split
   from sklearn import linear_model
   from sklearn.preprocessing import PolynomialFeatures
   from sklearn.metrics import mean_squared_error
   from sklearn.metrics import mean_absolute_error
```

```
In [2]: insurance = pd.read_csv('../data/insurance.csv')
insurance.head()
```

Out[2]:

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

```
In [3]: insurance.columns
 Out[3]: Index(['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges'], dtype
         ='object')
 In [4]: |x = insurance[['bmi']]
         y = insurance[['charges']]
 In [5]: linear = linear_model.LinearRegression()
         linear.fit(x, y)
         (linear.coef_, linear.intercept_)
 Out[5]: (array([[393.8730308]]), array([1192.93720896]))
 In [6]: from sklearn.model_selection import train_test_split
         x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=.25)
 In [7]: | x.shape, x_train.shape, x_test.shape
 Out[7]: ((1338, 1), (1003, 1), (335, 1))
 In [8]: |model = LinearRegression()
         model.fit(x_train, y_train)
         model.coef_, model.intercept_
 Out[8]: (array([[371.44701056]]), array([1929.30616021]))
 In [9]: | mean_squared_error(y_test, np.dot(x_test, model.coef_) + model.intercept_)
Out[9]: 136135713.62918454
In [10]: mean_absolute_error(y_test, np.dot(x_test, model.coef_) + model.intercept_)
Out[10]: 8981.315252084027
```

2) Classification on insurance dataset

```
In [11]: # checking for unique characters
    insurance['smoker'].unique()
Out[11]: array(['yes', 'no'], dtype=object)
```

```
In [12]: non_numeric_columns = ['sex', 'region']
x = insurance.copy().drop(non_numeric_columns, axis=1)
x
```

Out[12]:

	age	bmi	children	smoker	charges
0	19	27.900	0	yes	16884.92400
1	18	33.770	1	no	1725.55230
2	28	33.000	3	no	4449.46200
3	33	22.705	0	no	21984.47061
4	32	28.880	0	no	3866.85520
1333	50	30.970	3	no	10600.54830
1334	18	31.920	0	no	2205.98080
1335	18	36.850	0	no	1629.83350
1336	21	25.800	0	no	2007.94500
1337	61	29.070	0	yes	29141.36030

1338 rows × 5 columns

```
In [13]: x['smoker'] = x.smoker.str.contains('yes').astype(int)
In [14]: | x.smoker.value_counts()
Out[14]: 0
              1064
         1
               274
         Name: smoker, dtype: int64
In [15]: from sklearn.tree import DecisionTreeClassifier
         from sklearn.ensemble import RandomForestClassifier
In [16]: model = DecisionTreeClassifier(criterion='entropy')
         model.fit(x.drop(['smoker'], axis=1), x.smoker)
Out[16]: DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                                max_depth=None, max_features=None, max_leaf_nodes=None,
                                min_impurity_decrease=0.0, min_impurity_split=None,
                                min samples leaf=1, min samples split=2,
                                min weight fraction leaf=0.0, presort='deprecated',
                                random_state=None, splitter='best')
In [17]: list(zip(x.drop(['smoker'], axis=1).columns, model.feature_importances_))
Out[17]: [('age', 0.05034195160627059),
          ('bmi', 0.13222783770450766),
          ('children', 0.011107480153152032),
          ('charges', 0.8063227305360697)]
```

Using test_train_split

```
In [18]: x_train, x_test, y_train, y_test = train_test_split(x.drop(['smoker'], axis=1),x.
In [19]: | x.shape, x_train.shape, x_test.shape
Out[19]: ((1338, 5), (669, 4), (669, 4))
In [20]: model.fit(x_train, y_train)
Out[20]: DecisionTreeClassifier(ccp alpha=0.0, class weight=None, criterion='entropy',
                                max_depth=None, max_features=None, max_leaf_nodes=None,
                                min_impurity_decrease=0.0, min_impurity_split=None,
                                min samples leaf=1, min samples split=2,
                                min weight fraction leaf=0.0, presort='deprecated',
                                random state=None, splitter='best')
In [21]: test predictions = model.predict(x test)
         Calculating accuracy.
In [22]: | from sklearn.metrics import (accuracy_score,
                                      classification report,
                                      confusion matrix, auc, roc curve
In [23]: | accuracy_score(y_test, test_predictions)
Out[23]: 0.9506726457399103
         Confusion matrix
In [24]: confusion matrix(y test, test predictions)
Out[24]: array([[507, 18],
                [ 15, 129]], dtype=int64)
```

Classification report.

```
In [25]: print(classification_report(y_test, test_predictions))
                        precision
                                     recall f1-score
                                                        support
                             0.97
                                       0.97
                                                 0.97
                                                            525
                    1
                             0.88
                                       0.90
                                                 0.89
                                                            144
             accuracy
                                                 0.95
                                                            669
                             0.92
                                       0.93
                                                 0.93
                                                            669
            macro avg
         weighted avg
                             0.95
                                       0.95
                                                 0.95
                                                            669
```

3) Removed additional feature (children) slightly improved model

```
In [26]: removed_features = ['sex', 'children', 'region']
x2 = insurance.copy().drop(removed_features, axis=1)
x2
```

Out[26]:

	age	bmi	smoker	charges
0	19	27.900	yes	16884.92400
1	18	33.770	no	1725.55230
2	28	33.000	no	4449.46200
3	33	22.705	no	21984.47061
4	32	28.880	no	3866.85520
1333	50	30.970	no	10600.54830
1334	18	31.920	no	2205.98080
1335	18	36.850	no	1629.83350
1336	21	25.800	no	2007.94500
1337	61	29.070	yes	29141.36030

1338 rows × 4 columns

```
In [27]: x2['smoker'] = x2.smoker.str.contains('yes').astype(int)
x2.smoker.value_counts()
```

Out[27]: 0 1064 1 274

Name: smoker, dtype: int64

```
In [28]: |model = DecisionTreeClassifier(criterion='entropy')
         model.fit(x2.drop(['smoker'], axis=1), x2.smoker)
Out[28]: DecisionTreeClassifier(ccp alpha=0.0, class weight=None, criterion='entropy',
                                 max depth=None, max features=None, max leaf nodes=None,
                                 min_impurity_decrease=0.0, min_impurity_split=None,
                                 min samples leaf=1, min samples split=2,
                                 min_weight_fraction_leaf=0.0, presort='deprecated',
                                 random_state=None, splitter='best')
In [29]: |list(zip(x2.drop(['smoker'], axis=1).columns, model.feature_importances_))
Out[29]: [('age', 0.05490254767566018),
          ('bmi', 0.13254866487144468),
          ('charges', 0.8125487874528952)]
In [30]: x_train, x_test, y_train, y_test = train_test_split(x2.drop(['smoker'], axis=1),x
In [31]: x.shape, x train.shape, x test.shape
Out[31]: ((1338, 5), (669, 3), (669, 3))
In [32]: |model.fit(x_train, y_train)
Out[32]: DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                                 max depth=None, max features=None, max leaf nodes=None,
                                 min_impurity_decrease=0.0, min_impurity_split=None,
                                 min samples leaf=1, min samples split=2,
                                 min weight fraction leaf=0.0, presort='deprecated',
                                 random state=None, splitter='best')
In [33]: test predictions = model.predict(x test)
In [34]: | accuracy_score(y_test, test_predictions)
Out[34]: 0.9596412556053812
In [35]: |confusion_matrix(y_test, test_predictions)
Out[35]: array([[510, 18],
                [ 9, 132]], dtype=int64)
In [36]: print(classification_report(y_test, test_predictions))
                       precision
                                     recall f1-score
                                                        support
                            0.98
                                       0.97
                    0
                                                 0.97
                                                            528
                    1
                            0.88
                                       0.94
                                                 0.91
                                                            141
                                                 0.96
                                                            669
             accuracy
                            0.93
                                                 0.94
                                                            669
            macro avg
                                       0.95
         weighted avg
                                                 0.96
                            0.96
                                       0.96
                                                            669
```