a) Using null model report avg MSE of the abalone dataset.

Import modules and locate dataset

```
import pandas as pd
import numpy as np
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
import os
os.chdir("C:/Users/rique/Downloads")
```

per the homework; first 7 variables are predictors X, and the 8th variable is our response y.

use test_size of 0.15 to divide each random split into 85% training and 15% testing

null model really just means to use the numpy mean to "fit" our model. and full_like to make our predictions.

```
abalone_data = pd.read_csv("abalone.csv")

X = abalone_data.iloc[:, :7]
y = abalone_data.iloc[:, 7]

splits = np.arange(20)+1

train_mse_list = []

test_mse_list = []

for i in range(splits.shape[0]):
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.15)

null_model = np.mean(y_train)

y_pred = np.full_like(y_train, null_model)
    yTest_pred = np.full_like(y_test, null_model)

train_mse = mean_squared_error(y_train, y_pred)
```

```
train_mse_list.append(train_mse)
  test_mse = mean_squared_error(y_test, yTest_pred)
  test_mse_list.append(test_mse)

null_train_avg = np.mean(train_mse_list)
null_test_avg = np.mean(test_mse_list)
```

We have our results. Simply output them.

```
print(f"Train Average MSE: {null_train_avg}")
print(f"Test Average MSE: {null_test_avg}")

Train Average MSE: 11.162862778247392
Test Average MSE: 11.800637958532695
```

b) Using OLS regression, analytically (gross) report avg MSE and R-squared.

the formula is $Y = \alpha + \beta X + \epsilon$

where Y is our response

where α is our intercept/constant

where β are the coefficients of our predictors represented by X

and where ε is the error

Treat β as our "fit" method, and can be found with $(X^TX)^-1*X^Ty$ as shown in slide 14 of the Regression lecture

```
from sklearn.metrics import r2_score

OLS_train_mse_list = []
OLS_test_mse_list = []
OLS_train_r2_list = []
OLS_test_r2_list = []

lambda_value = 0.0001
```

```
for i in range(splits.shape[0]):
   X train, X test, y train, y test = train test split(X,
y, test size=0.15)
   #all of this is our "fit" method for OLS or \beta as described above.
   X_{transpose} = X_{train.T}
   \overline{XTX} = \text{np.dot}(X \text{ transpose}, X \text{ train})
   matrix = lambda value * np.identity(XTX.shape[0])
   XTX lambda = XTX + matrix
   XTy = np.dot(X transpose, y train)
   coefficients = np.linalg.solve(XTX lambda, XTy)
   #from here, simply use dot for our predictions, and find our
results as per usual
   OLS y pred = np.dot(X train, coefficients)
   OLS yTest pred = np.dot(X test, coefficients)
   train mse = mean squared error(y train, OLS y pred)
   OLS train mse list.append(train mse)
   test_mse = mean_squared_error(y_test, OLS_yTest_pred)
   OLS test mse list.append(test mse)
   r2 train = r2 score(y train, OLS y pred)
   OLS train r2 list.append(r2 train)
   r2_test = r2_score(y_test, OLS_yTest_pred)
   OLS test r2 list.append(r2 test)
OLS train avg = np.mean(OLS train mse list)
OLS test avg = np.mean(OLS test mse list)
OLS r2 train avg = np.mean(OLS test r2 list)
OLS r2 test avg = np.mean(OLS test r2 list)
```

We have our results for the OLS regression. Simply output them.

```
print(f"Train Average MSE: {OLS_train_avg}")
print(f"Test Average MSE: {OLS_test_avg}")
print(f"Train Average r-squared: {OLS_r2_train_avg}")
print(f"Test Average r-squared: {OLS_r2_test_avg}")

Train Average MSE: 5.051139932259096
Test Average MSE: 5.083171029726857
Train Average r-squared: 0.49890446080239714
Test Average r-squared: 0.49890446080239714
```

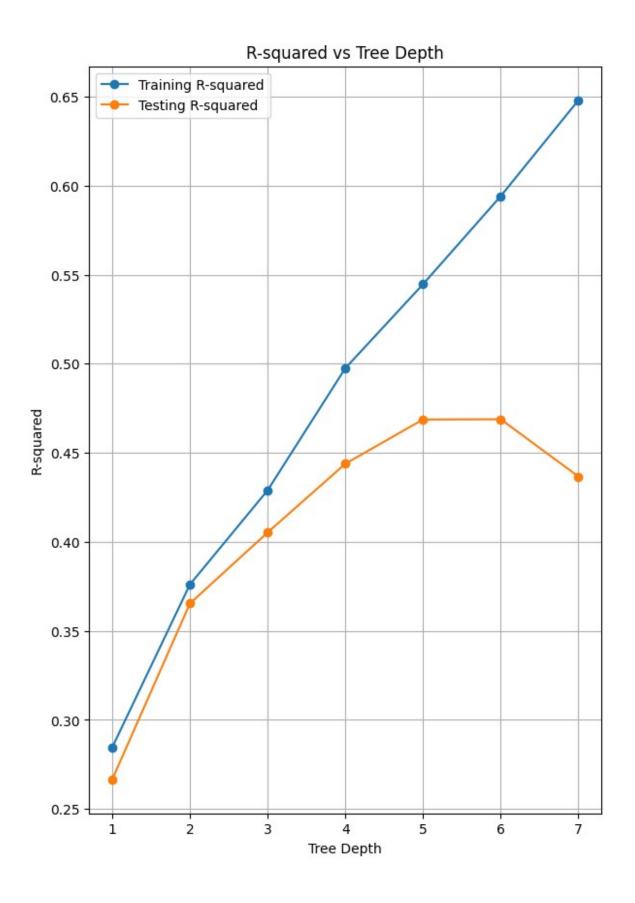
c) Use a regression tree, of max depth 7. Find the avg MSE and R-squared. Plot on separate graphs. For the MSE one, also plot the null MSE as horizontal line.

```
from sklearn.tree import DecisionTreeRegressor
\max depth = np.arange(7)+1
regTree train mse avg = []
regTree test mse avg = []
regTree_train_r2_avg = []
regTree test_r2_avg = []
#we should only care for the test results from the null model
null mse = null test avg
for depth in max depth:
#since we have to do this per depth, i need another set of my lists
 regTree_train_mse_list = []
 regTree test mse list = []
 regTree_train_r2_list = []
 regTree test r2 list = []
 for i in range(splits.shape[0]):
    X_train, X_test, y_train, y_test = train_test_split(X, y,
test size=0.15)
    dt = DecisionTreeRegressor(max_depth = depth)
    dt.fit(X train, y train)
    dt y pred = dt.predict(X train)
    dt yTest pred = dt.predict(X test)
    train mse = mean squared error(y train, dt y pred)
    regTree train mse list.append(train mse)
    test_mse = mean_squared_error(y_test, dt_yTest_pred)
    regTree test mse list.append(test mse)
    r2_train = r2_score(y_train, dt_y_pred)
    regTree train r2 list.append(r2 train)
    r2_test = r2_score(y_test, dt_yTest_pred)
    regTree_test_r2_list.append(r2_test)
 #find the average for this specific depth. Annoying thing about
python, i miss my brackets for clearer end of for-loops.
 regTree train mse avg.append(np.mean(regTree train mse list))
 regTree test mse avg.append(np.mean(regTree test mse list))
 regTree_train_r2_avg.append(np.mean(regTree_train_r2_list))
 regTree test r2 avg.append(np.mean(regTree test r2 list))
```

We have our results. Now plot. Here is R-squared vs Tree Depth

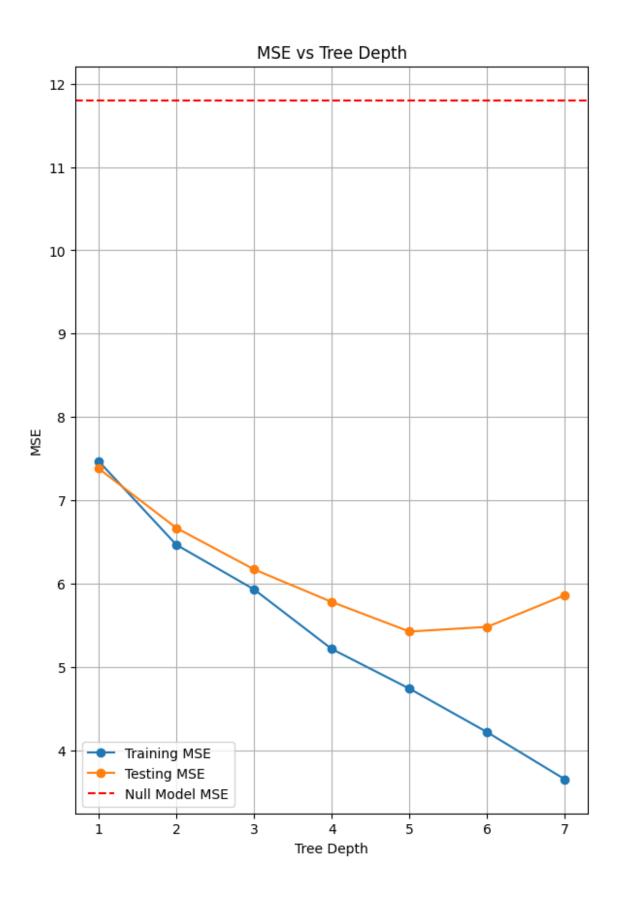
```
import matplotlib.pyplot as plt

plt.figure(figsize=(15, 10))
plt.subplot(1, 2, 1)
plt.plot(max_depth, regTree_train_r2_avg, label='Training R-squared',
marker='o')
plt.plot(max_depth, regTree_test_r2_avg, label='Testing R-squared',
marker='o')
plt.xlabel('Tree Depth')
plt.ylabel('R-squared')
plt.title('R-squared vs Tree Depth')
plt.legend()
plt.grid(True)
plt.show()
```



Here is MSE vs Tree Depth & Null MSE as the horizontal line.

```
plt.figure(figsize=(15, 10))
plt.subplot(1, 2, 2)
plt.plot(max_depth, regTree_train_mse_avg, label='Training MSE',
marker='o')
plt.plot(max_depth, regTree_test_mse_avg, label='Testing MSE',
marker='o')
plt.axhline(y=null_mse, color='r', linestyle='--', label='Null Model
MSE')
plt.xlabel('Tree Depth')
plt.ylabel('MSE')
plt.title('MSE vs Tree Depth')
plt.legend()
plt.grid(True)
plt.show()
```



e) Using random forest regression, and k tree values of [10,30,100,300] report avg R-squared and MSE.

```
from sklearn.ensemble import RandomForestRegressor
k values = np.array([10,30,100,300])
rForest train mse avg = []
rForest test mse avg = []
rForest_train_r2_avg = []
rForest test r2 avg = []
for k in k values:
#since we have to do this per k value tree, i need another set of my
lists
 rForest train mse list = []
 rForest_test_mse_list = []
 rForest_train_r2_list = []
 rForest_test_r2_list = []
 for i in range(splits.shape[0]):
    X train, X test, y train, y test = train test split(X, y,
test size=0.15)
    rf = RandomForestRegressor(n estimators=k, random state=1000)
    rf.fit(X train, y train)
    rf y pred = rf.predict(X train)
    rf vTest pred = rf.predict(X test)
    train mse = mean squared error(y train, rf y pred)
    rForest_train_mse_list.append(train_mse)
    test mse = mean squared error(y test, rf yTest pred)
    rForest test mse list.append(test mse)
    r2 train = r2 score(y train, rf y pred)
    rForest train r2 list.append(r2 train)
    r2 test = r2 score(y test, rf yTest pred)
    rForest test r2 list.append(r2 test)
#find the average for this specific k value tree. Annoying thing
about python, i miss my brackets for clearer end of for-loops.
 rForest train mse avg.append(np.mean(rForest train mse list))
 print(f"K tree: {k}'s Train Average MSE:
{np.mean(rForest train mse list)}")
 rForest_test_mse_avg.append(np.mean(rForest_test_mse_list))
```

```
print(f"K tree: {k}'s Test Average MSE:
{np.mean(rForest test mse list)}")
 rForest train r2 avg.append(np.mean(rForest train r2 list))
 print(f"K tree: {k}'s Train Average R-squared:
{np.mean(rForest train r2 list)}")
 rForest test r2 avg.append(np.mean(rForest test r2 list))
 print(f"K tree: {k}'s Test Average R-squared:
{np.mean(rForest test r2 list)}\n")
K tree: 10's Train Average MSE: 0.9277744435052127
K tree: 10's Test Average MSE: 5.219666666666666
K tree: 10's Train Average R-squared: 0.9104926141696714
K tree: 10's Test Average R-squared: 0.5014526683460753
K tree: 30's Train Average MSE: 0.7340138380138379
K tree: 30's Test Average MSE: 4.969228070175438
K tree: 30's Train Average R-squared: 0.929293037146639
K tree: 30's Test Average R-squared: 0.5223710650338125
K tree: 100's Train Average MSE: 0.6681857748661595
K tree: 100's Test Average MSE: 4.864031323763955
K tree: 100's Train Average R-squared: 0.9356508478934134
K tree: 100's Test Average R-squared: 0.5313308848994536
K tree: 300's Train Average MSE: 0.652961310384772
K tree: 300's Test Average MSE: 4.692826666666666
K tree: 300's Train Average R-squared: 0.9371328316773815
K tree: 300's Test Average R-squared: 0.5476798914854717
```