Homework 2

[Name] - [vhh2105]

Due: Fri Nov 5th @ 11:59pm ET

In this homework we will be performing model evaluation, model selection and hyperparameter tuning in both a regression and classification setting.

We will be working with a small set of home sales data as we might see on a real-estate website.

Instructions

- Follow the comments below and fill in the blanks (____) to complete.
- Please **'Restart and Run All'** prior to submission.
- **Save pdf in Landscape** and **check that all of your code is shown** in the submission.
- When submitting in Gradescope, be sure to **select which page corresponds to which question.**

Out of 50 points total.

Part 0: Environment Setup

In [1]:
```
# 1. (2pts) Set up our environment with common libraries and plot settings.
#    Note: generally we would do all of our imports here but some imports
#    have been left till later where they are used.

# Import numpy as np, pandas as pd, matplotlib.pyplot as plt and seaborn as sns
# Note: use as many lines of code as necessary
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
# Set the seaborn style to 'darkgrid'
sns.set_style('darkgrid')

# Execute the matplotlib magic function to ensure plots are displayed inline
%matplotlib inline
```

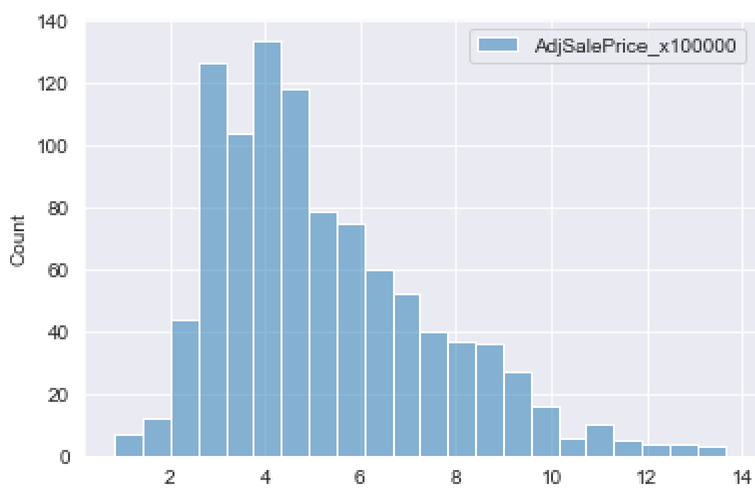
Part 1: Regression

In Part 1 we will try to predict a real value home sale price using several models.

In [2]:
```
# 2. (4pts) Load and prepare our data.

# Read in the csv file ../data/house_sales_subset.csv using pandas read_csv() wi
df = pd.read_csv('../data/house_sales_subset.csv')
# Create a dataframe X which contains these 3 columns from df:
```

```
#   'SqFtTotLiving_x1000','SqFtLot_x1000','Bedrooms'
X = df[['SqFtTotLiving_x1000','SqFtLot_x1000','Bedrooms']]

# Create a series y_r which contains only the column AdjSalePrice_x100000
#    Note: the '_r' is for our regression target
y_r = df[['AdjSalePrice_x100000']]

# Check that X and y_r is the correct shape
assert X.shape == (1000,3)
assert y_r.shape == (1000,1)

# To confirm that all features of X are similar in scale display the .describe()
X.describe()

# To get a sense of the distribution of the target, plot a histogram of y_r usin
sns.histplot(y_r)
```

Out[2]: <AxesSubplot:ylabel='Count'>



In [3]:

```
# 3. (3pts) Create a held-aside set

# Import train_test_split from sklearn
from sklearn.model_selection import train_test_split

# Split X and y_r into 80% train and 20% test using train_test_split
#   Use random_state=123 for grading consistency.
X_train_r, X_test_r, y_train_r, y_test_r = train_test_split(X,y_r,test_size=0.2,
y_test_r

# Print out the the length of y_test_r divided by the length y_r  to confirm our
print(f'proportion of data in test set: {len(y_test_r)/len(y_r):0.2f}')
```

```
proportion of data in test set: 0.20
```

Part 1.1 Baseline Regressor

In [18]:

```
# 4. (3pts) Create a DummyRegressor and fit on the training set.

# Import the DummyRegressor model from sklearn
from sklearn.dummy import DummyRegressor

'''
```

```
dummyr = DummyRegressor(strategy='mean') # default strategy
dummyr.fit(X[['proline']],y_r)
dummy_rmse = root_mean_squared_error(y_r,dummyr.predict(X[['proline']])) print(f
'''
# Instantiate a DummyRegessor model with strategy="mean"
dummyr = DummyRegressor(strategy='mean')
# Train the DummyRegressor on the regression training set
dummyr.fit(X_train_r,y_train_r)

y_pred = dummyr.predict(X_test_r)
# Calculate and print the training set R^2 score of the DummyRegressor
dummy_r_training_r2 = dummyr.score(X_train_r,y_train_r)

print(f'dummy training set R^2: {dummy_r_training_r2:.2f}')
```

```
dummy training set R^2: 0.00
```

Part 1.2 Linear Regression and Cross-Validation

In [19]:

```
# 5. (4pts) Train a Linear Regression model and calculate training set R^2.

# Import the LinearRegression model from sklearn
from sklearn.linear_model import LinearRegression

# Instantiate a LinearRegression model with default arguments and fit on the tra
lr = LinearRegression(fit_intercept=True, # by default
                      normalize=False) # by default
lr.fit(X=X_train_r, y=y_train_r);
# Calculate and print the training set R^2 of the LinearRegression model
lr_training_r2 =lr.score(X_train_r,y_train_r)

print(f'lr training set R^2: {lr_training_r2:.2f}')
```

```
lr training set R^2: 0.53
```

In [14]:

```
# 6. (2pts) Use 5-fold Cross Validation to get a sense of variation
#    of Liner Regression R^2 performance on the training set.

# Import cross_val_score from sklearn.
from sklearn.model_selection import cross_val_score

# Generate 5-fold cross-validation R^2 scores
#    for a LinearRegression model with default arguments
#    on the training set
lr_cv_scores = cross_val_score(lr, X_train_r,y_train_r,cv=5)


# Print out the R^2 scores found by cross_val_score
np.round(lr_cv_scores,2)
```

Out[14]:

```
array([0.48, 0.58, 0.5 , 0.44, 0.58])
```

In [16]:

```
# 7. (1pts) Calculate mean cv R^2 score +- 2 std. deviations

# Calculate the mean cross validation score using the scores created above
lr_cv_mean = np.mean(lr_cv_scores)

# Calculate 2 standard deviations of the cross validation scores
```

```
lr_cv_2std = 2*np.std(lr_cv_scores)

# Print out the mean R^2 +- 2 standard variations for the LinearRegression model
print(f'lr mean cv r2: {lr_cv_mean:.2f} +- {lr_cv_2std:.2f}')
```

```
lr mean cv r2: 0.52 +- 0.11
```

Part 1.3 Evaluate on Test Set

In [21]:

```
# 8. (2pts) Evaluate performance of our trained DummyRegressor and LinearRegress

# Calculate R^2 on the test set using the previously trained models
dummy_r_test_r2 = dummyr.score(X_test_r, y_test_r)

lr_test_r2 = lr.score(X_test_r,y_test_r)

print(f'dummy test R2 : {dummy_r_test_r2: .2f}')
print(f'   lr test R2 : {lr_test_r2: .2f}')
```

```
dummy test R2 : -0.01
   lr test R2 :  0.47
```

Part 2: Classification

Here we build several models to classify low vs. high adjusted sales price, creating a validation curve and performing grid search.

Create Classification Target

In [22]:

```
# To reuse the same dataset, we'll first create a binary target for
#    classification by thresholding at the mean of our AdjSalePrice

# The classes are:
#    Low AdjSalePrice  = 0
#    High AdjSalePrice = 1

y_c = (df.AdjSalePrice_x100000 > df.AdjSalePrice_x100000.mean()).astype(int)

# Print out the unique labels and note it's 0,1 or binary classification
y_c.unique()
```

Out[22]:

```
array([0, 1])
```

Part 2.1 Create a Held-Aside Aet

In [56]:

```
# 9. (3pts) Create a training and test/held-aside set

# Split into 80% train and 20% test using train_test_split
#    Use the new y_c target and the same X we used for regression
#    Stratify according to y_c so class proportions are the same in train and te
#    Use random_state=123 for reproducibility
#    Save the result into the variables X_train_c,X_test_c,y_train_c,y_test_c
X_train_c,X_test_c,y_train_c,y_test_c=train_test_split(X,y_c,test_size=0.2,train
```

```
count=0
for x in y_test_c:
    if (x == 0):
        count=count+1

low_label_proportion_test=count/len(y_test_c)
low_label_proportion_train=count/len(y_train_c)

#Print out the proportion of Low values (label of 0) in y_c
print(f'proportion of low values: {low_label_proportion:0.2f}')

print(low_label_proportion_test-low_label_proportion_train)
# Assert that train and test have similar class proportions.
# Find the proportion of Low (0) values in both y_train_c and y_test_c and
#    assert that the absolute difference of these proportions is less than .01
assert abs(low_label_proportion_test-low_label_proportion_train)<0.01
```

```
proportion of low values: 0.60
0.45375

---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
/var/folders/8d/5cjl8nt16vn33pwb3mh4mphm0000gn/T/ipykernel_9825/3746563807.py in
<module>
     23 # Find the proportion of Low (0) values in both y_train_c and y_test_c a
nd
     24 #    assert that the absolute difference of these proportions is less th
an .01
---> 25 assert abs(low_label_proportion_test-low_label_proportion_train)<0.01

AssertionError:
```

Part 2.2 Measure baseline performance

In [61]:

```
# 10. (2pts)  Create a Dummy Classifier and confirm the expected performance on
'''
from sklearn.dummy import DummyClassifier
from sklearn.tree import DecisionTreeClassifier
dummyc = DummyClassifier(strategy='prior').fit(X_train_bc,y_train_bc) # works li
print(f'{dummyc.score(X_test_bc,y_test_bc) = :0.2f}') # default classification s


'''
# Import DummyClassifier from sklearn
from sklearn.dummy import DummyClassifier


# Instantiate and a DummyClassifier with strategy="most_frequent" and fit on the
dummy_c = DummyClassifier(strategy='prior').fit(X_train_c,y_train_c) # works lik

# Print the trained DummyClassifier accuracy on the training set.
# It should match the proportion of low values we saw above.
print(f'dummy training set accuracy: {dummy_c.score(X_train_c,y_train_c):.2f}')
```

```
dummy training set accuracy: 0.58
```

Part 2.3 Logistic Regression model

In [65]:

```
# 11. (3pts) It's good practice to start with a "simple" model.
#     Train and calculate 5-fold cv training set accuracy for a Logistic Regress
```

```
'''
from sklearn.linear_model import LogisticRegression
logr = LogisticRegression(penalty='l2', # default
C=1.0, # weight on regularization, 1/lambda above
l1_ratio=None # only used when penalty is 'elasticnet' )

'''
# Import LogisticRegression from sklearn
from sklearn.linear_model import LogisticRegression

# Generate 5-fold cross validation accuracy on the training set
#    using LogisticRegression with default hyperparameters
#    store as logr_cvscores
logr_cv_scores = cross_val_score(LogisticRegression(),X_train_c,y_train_c,cv=5)

# Print out the mean cv accuracy for the LogisticRegression model
print(f'logr mean cv accuracy: {np.mean(logr_cv_scores):0.2f}')
```

```
logr mean cv accuracy: 0.83
```

Part 2.4 GradientBoosting model

In [79]:

```
# 12. (4pts) Now let's try a more complex model.
#     Train and calculate 5-fold cv accuracy
#     for a GradientBoosting model using the training set.

# Import the GradientBoostingClassifier model from sklearn
from sklearn.ensemble import GradientBoostingClassifier


# Calculate 5-fold cv training set accuracy scores for a GradientBoostingClassif
#   with 50 trees and max_depth=2
#   To speed up training also set n_jobs=-1 in the cross_val_score (use one core
gbc = GradientBoostingClassifier(n_estimators=50)


gbc_cv_scores = cross_val_score(GradientBoostingClassifier(n_estimators=50),X_tr


# Calculate mean cv accuracy
gbc_cv_mean = np.mean(gbc_cv_scores)

# Calculate 2 standard deviations for the cv scores
gbc_cv_2std = np.std(gbc_cv_scores)

print(f'gbc mean cv accuracy: {gbc_cv_mean:.2f} +- {gbc_cv_2std:.2f}')
```

```
gbc mean cv accuracy: 0.81 +- 0.03
```

Part 2.5 GradientBoosting and Validation Curve

In [77]:

```
# 13. (5pts) Let's investigate how the depth of trees (max_depth) affects perfor
#     Generate a validation curve for tree depths in the GradientBoosting model.

# Import the validation_curve function from sklearn
from sklearn.model_selection import validation_curve

# In the GradientBoostingClassifier model, the depth of trees is set via max_dep
```

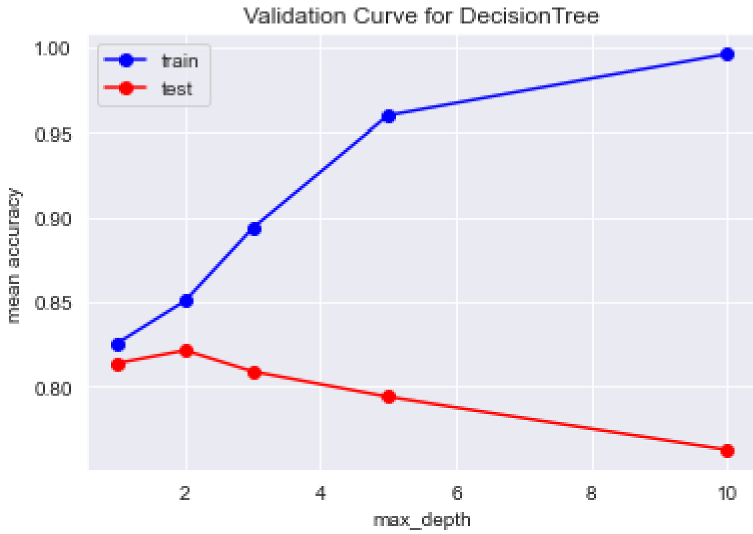
```
# Here we'll try the depths 1,2,3,5,10
depths = [1,2,3,5,10]

# Generate the train_scores and test_scores for max_depth at different max_depth
#   Use the validation_curve function
#   Use a GradientBoostingClassiier with 50 trees
#   Use our training set X_train_c, y_train_c
#   Use the 'max_depth' parameter
#   Use the depths list created above as the parameter range
#   Use 3-fold cross validation (reducing to 3 to speed things up)
#   Use accuracy as the scoring metric
#   Store the results in train_scores,test_scores
train_scores,test_scores = validation_curve(GradientBoostingClassifier(n_estimat
                                          X_train_c, y_train_c,
                                          param_name='max_depth',
                                          param_range=depths,
                                          cv=3)



# train_scores and test_scores each contain a 2-D array of values
#   For each depth (rows) there are 3 scores (columns), one for each fold
#   Take the mean for each depth across folds (columns, axis=1)
#      and store in mean_train_scores and mean_test_scores
mean_train_scores = np.mean(train_scores,axis=1)
mean_test_scores = np.mean(test_scores,axis=1)

# We should get 10 values between 0 and 1
# Note that as depth increases, both train and test accuracy go up and then begi
pd.DataFrame([mean_train_scores.round(2),mean_test_scores.round(2)],
             columns=pd.Series(depths,name='max_depth'),
             index=['mean_train_scores','mean_test_scores'])
```

Out[77]:

max_depth	1	2	3	5	10
mean_train_scores	0.83	0.85	0.89	0.96	1.00
mean_test_scores	0.81	0.82	0.81	0.79	0.76

In [87]:

```
# 14. (4pts) Plot the validation curve

# Plot mean_train_scores and mean_test_scores on the same plot
#    create an axis to plot on using subplots, with figsize=(6,4)
#    plot two lines using ax.plot()
#      each with "depths" on the x-axis
#      one for mean_train_scores on the y-axis with label "train"
#      one for mean_test_scores on the y-axis with label "test"
#    add a legend using ax.legend()
#    label the x-axis as "max_depth" and the y-axis as "mean accuracy"
# Note: use as many lines of code as necessary
fig,ax = plt.subplots(1,1,figsize=(6,4))
ax.plot(depths, mean_train_scores, 'o-', color='b',label='train');
ax.plot(depths, mean_test_scores, 'o-', color='r', label='test');
ax.set_xlabel('max_depth'), ax.set_ylabel('mean accuracy');
ax.set_title('Validation Curve for DecisionTree');
ax.legend();
```



Part 2.6 GradientBoosting and Grid Search

In [96]:

```
# 15. (4pts) Above we're looking at tuning a single hyperparameter (max_depth).
#     Now let's tune two hyperparameters at the same time.
#     Perform 3-fold cross validated grid search over number of trees and tree d
'''
from sklearn.neighbors import KNeighborsRegressor
params = {'n_neighbors':[1,2,3,5,10], 'metric':['euclidean','manhattan']}
gscv = GridSearchCV(KNeighborsRegressor(), param_grid=params, # grid of size 10
cv=3, # do 3-fold CV at every grid point
refit=True) # refit True trains one more time on the entire training set
gscv.fit(X_train_r,y_train_r) # How many times are we training a model here? (2*

'''
# Import GridSearchCV from sklearn
from sklearn.model_selection import GridSearchCV

# Create the grid of parameters to test
#   The parameter settings to try are
#   'n_estimators':[10,50,100,200],'max_depth':[1,2,3,5,10]
params = {
    'n_estimators':[10,50,100,200],
    'max_depth':[1,2,3,5,10]
}

# Instantiate and fit GridSearchCV on the classification training set
#   Use GradientBoostingClassifier with default arguments
#   Use 3-folds
#   Use default scoring (accuracy)
#   Use refit=True (default) so the model is retrained on the entire training se
#   Set n_jobs=-1 to use all cores
gbc_gscv = GridSearchCV(GradientBoostingClassifier(),param_grid=params,cv=3,refi
gbc_gscv.fit(X_train_c,y_train_c)
# Print out the best the best hyperparameter setting found (best_params_)
#    and the mean accuracy they produced (best_score_)
print(f'gbc best hyperparams      : {gbc_gscv.best_params_}')
gbc_scores = cross_val_score(gbc_gscv.best_estimator_,X_train_c,y_train_c,cv=5)
print(f'gbc best mean cv accuracy : {np.mean(gbc_scores):.2f}')

# Note that you may get different answers on different runs due to
#   the random cv splits used at each grid point
```

```
gbc best hyperparams      : {'max_depth': 1, 'n_estimators': 200}
gbc best mean cv accuracy : 0.82
```

Part 2.7 Evaluate on Test

In [117…

```
# 16. (4pts) Evaluate the best model on the test set

# Which of our models has the highest training set cv accuracy?
#   (GradientBoostingClassifier or LogisticRegression?)

print(f'best model found: {"GradientBoostingClassifier"  if np.mean(gbc_scores)

# To see how each of our models would generalize to new data,
#     calculate the **test set** accuracy for each of our trained models

'''

from sklearn.linear_model import LogisticRegression
logr = LogisticRegression(penalty='l2', # default
C=1.0, # weight on regularization, 1/lambda above
l1_ratio=None # only used when penalty is 'elasticnet' )

'''


# First, instantiate and train a new LogisticRegression model with default setti
# Note that, while we did train a LogisticRegression model several times when
#  calculating the cross-validation accuracy, we never trained it on the full tr
logr = LogisticRegression(penalty='l2',
                          C=1.0,
                          l1_ratio=None
                         ).fit(X_train_c,y_train_c)

# Find the test set accuracy of both of our trained models
# Recall that since we used refit=True when doing grid search
#  on the GradientBoostingClassifier, we can use gscv_rf.score() without retrain
logr_test_acc = cross_val_score(logr,X_train_c,y_train_c,cv=5).mean()

gscv_rf = GridSearchCV(GradientBoostingClassifier(),param_grid=params,cv=5,refit
gscv_rf.fit(X_train_c,y_train_c)

gbc_test_acc = gscv_rf.score(X_test_c, y_test_c)

print(f'logr test acc : {logr_test_acc:.2f}')
print(f'gbc  test acc : {gbc_test_acc:.2f}')

# TO THINK ABOUT, BUT DON'T NEED TO ANSWER:
# Did the model we chose have the best test set performance?
# Is it guaranteed that the model with the best cv scores on the training set ha
```

```
best model found: LogisticRegression
logr test acc : 0.83
gbc  test acc : 0.76
```

In [ ]: