Lab 7 - CCPS 844 Data Mining

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Answer the following questions and submit a PDF file on the D2L.

Select a dataset or datasets of your choice.

- Apply Cross-validation for parameter tuning, model selection, & feature selection like "cross_validation.ipynb".
- Apply a classification algorithm and then evaluate the classification model as it is done in "classification_model_evaluation.ipynb".
- Apply simple linear or multivariate linear regression and then evaluate it as it is done in "regression_model_Evaluation.ipynb".

1A - Cross-validation: parameter tuning

```
import pandas as pd
from sklearn.datasets import load_iris
#from sklearn.cross_validation import train_test_split
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
In []: df=pd.read_csv('pima-indians-diabetes.csv',index_col=0)
df

Out[]: pregnant glucose bp skin insulin bmi pedigree age label
```

ut[]:		pregnant	glucose	bp	skin	insulin	bmi	pedigree	age	label
	1	6	148	72	35	0	33.6	0.627	50	1
	2	1	85	66	29	0	26.6	0.351	31	0
	3	8	183	64	0	0	23.3	0.672	32	1
	4	1	89	66	23	94	28.1	0.167	21	0
	5	0	137	40	35	168	43.1	2.288	33	1
	•••									
70	64	10	101	76	48	180	32.9	0.171	63	0
70	65	2	122	70	27	0	36.8	0.340	27	0
70	66	5	121	72	23	112	26.2	0.245	30	0
70	67	1	126	60	0	0	30.1	0.349	47	1
70	68	1	93	70	31	0	30.4	0.315	23	0

768 rows × 9 columns

```
features = ['pregnant','glucose','bp','skin','insulin','bmi','pedigree','age']
    X=df[features]
    y=df.label
    X
```

Out[]:		pregnant	glucose	bp	skin	insulin	bmi	pedigree	age
	1	6	148	72	35	0	33.6	0.627	50
	2	1	85	66	29	0	26.6	0.351	31
	3	8	183	64	0	0	23.3	0.672	32
	4	1	89	66	23	94	28.1	0.167	21
	5	0	137	40	35	168	43.1	2.288	33
	•••		•••						
	764	10	101	76	48	180	32.9	0.171	63
	765	2	122	70	27	0	36.8	0.340	27
	766	5	121	72	23	112	26.2	0.245	30
	767	1	126	60	0	0	30.1	0.349	47
	768	1	93	70	31	0	30.4	0.315	23

768 rows × 8 columns

```
In [ ]:
    X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=4)
    knn = KNeighborsClassifier(n_neighbors=6)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)
    print(metrics.accuracy_score(y_test, y_pred))
```

0.760416666666666

```
from sklearn.model_selection import KFold

example3 = [10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31,32,33,34]
kf = KFold(n_splits=5,shuffle=True)
print('{} {:^61} {}'.format('Iteration', 'Train observations indices', 'Test observation')
i = 1
for train_index, test_index in kf.split(example3):
    print(f'{i:^9}', train_index, test_index);i+=1
```

```
In [ ]: from sklearn.model_selection import cross_val_score
    knn = KNeighborsClassifier(n_neighbors=6)
    scores = cross_val_score(knn, X, y, cv=10, scoring='accuracy')
    print(scores)

[0.68831169 0.77922078 0.74025974 0.66233766 0.71428571 0.75324675
    0.71428571 0.80519481 0.73684211 0.76315789]
```

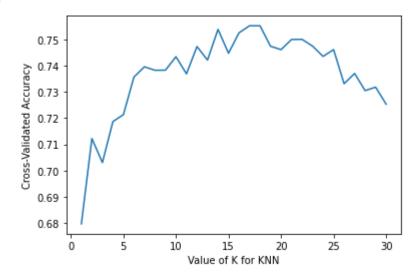
```
In []:
    k_range = list(range(1, 31))
    k_scores = []
    for k in k_range:
        knn = KNeighborsClassifier(n_neighbors=k)
        scores = cross_val_score(knn, X, y, cv=10, scoring='accuracy')
        k_scores.append(scores.mean())
    print(k_scores)
```

[0.6796650717703349, 0.7122351332877648, 0.7030587833219413, 0.7187115516062884, 0.72137 73069036227, 0.7357142857142858, 0.7396274777853726, 0.7383116883116883, 0.7383458646616 542, 0.7434723171565277, 0.7369446343130555, 0.7473684210526316, 0.7422077922077922, 0.7 539131920710869, 0.7448051948051948, 0.7526144907723855, 0.7552973342447027, 0.755280246 0697198, 0.7474709501025291, 0.7461893369788107, 0.7500683526999316, 0.7501196172248804, 0.7475222146274778, 0.7435919343814081, 0.7462064251537937, 0.7331681476418319, 0.737081 3397129188, 0.7305365686944635, 0.7318523581681476, 0.7253588516746412]

```
import matplotlib.pyplot as plt
%matplotlib inline

# plot the value of K for KNN (x-axis) versus the cross-validated accuracy (y-axis)
plt.plot(k_range, k_scores)
plt.xlabel('Value of K for KNN')
plt.ylabel('Cross-Validated Accuracy')
```

Out[]: Text(0, 0.5, 'Cross-Validated Accuracy')



1B - Cross-validation: Model Selection

```
In [ ]: # 10-fold cross-validation with the best KNN model
knn = KNeighborsClassifier(n_neighbors=20)
```

```
print(cross_val_score(knn, X, y, cv=10, scoring='accuracy').mean())

0.7461893369788107
```

```
# 10-fold cross-validation with Logistic regression
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression( solver='liblinear', multi_class='auto')
print(cross_val_score(logreg, X, y, cv=10, scoring='accuracy').mean())
```

0.7669685577580314

1C - Cross-validation: Feature Selection

```
In [ ]:
         from sklearn.linear_model import LinearRegression
         import numpy as np
         lm = LinearRegression()
         mse_scores = cross_val_score(lm, X, y, cv=10, scoring= 'neg_mean_squared_error')
         mse_scores = -mse_scores
         print("MSE Scores all features:",mse scores)
         #RMSE
         rmse scores = np.sqrt(mse scores)
         print("RMSE Scores all features:",rmse_scores)
         print("RMSE Mean all features:",rmse_scores.mean())
         #new feature column (remmove 'glucose', 'bp', 'skin', 'pedigree')
         new_feature=['pregnant','insulin','bmi','age']
         print("RMSE (remove 'glucose', 'bp', 'skin', 'pedigree'):",np.sqrt(-cross_val_score(lm,
        MSE Scores all features: [0.20449319 0.13855495 0.17842096 0.1797556 0.17059818 0.16068
        093
         0.15263222 0.11996205 0.15652963 0.16649737]
        RMSE Scores all features: [0.45220923 0.37222969 0.42239905 0.42397594 0.41303532 0.4008
        5026
         0.39068174 0.34635538 0.39563826 0.40804089]
        RMSE Mean all features: 0.4025415762556528
        RMSE (remove 'glucose', 'bp', 'skin', 'pedigree'): 0.44016290843995665
```

2- Classification algorithm

```
In [ ]:
         # save confusion matrix and slice into four pieces
         confusion_matrix = metrics.confusion_matrix(y_test, y_pred)
         print(confusion matrix)
         TP = confusion matrix[1, 1]
         TN = confusion matrix[0, 0]
         FP = confusion_matrix[0, 1]
         FN = confusion matrix[1, 0]
         print("True Positive: ",TP)
         print("True Negative: ",TN)
         print("False Positive: ",FP)
         print("False Negative: ",FN)
        [[110 16]
         [ 30 36]]
        True Positive: 36
        True Negative: 110
        False Positive: 16
        False Negative: 30
In [ ]:
         print("Accuracy: ",(TP + TN) / float(TP + TN + FP + FN))
         print("Misclassification Rate: ",(FP + FN) / float(TP + TN + FP + FN))
         print("Recall: ",TP / float(TP + FN))
         print("Specificity: ",TN / float(TN + FP))
         print("False Positive Rate: ",FP / float(TN + FP))
         print("Percision", TP / float(TP + FP))
        Accuracy: 0.760416666666666
        Misclassification Rate: 0.23958333333333334
        Recall: 0.5454545454545454
        Specificity: 0.873015873015873
        False Positive Rate: 0.12698412698412698
        Percision 0.6923076923076923
In [ ]:
         %matplotlib inline
         import matplotlib.pyplot as plt
         y pred prob = logreg.predict proba(X test)[:, 1]
         plt.rcParams['font.size'] = 14
                                                  Traceback (most recent call last)
        NotFittedError
        ~\AppData\Local\Temp/ipykernel_31272/3098311571.py in <module>
              2 import matplotlib.pyplot as plt
        ----> 4 y pred prob = logreg.predict proba(X test)[:, 1]
              5 plt.rcParams['font.size'] = 14
        c:\Users\almas\anaconda3\lib\site-packages\sklearn\linear model\ logistic.py in predict
        proba(self, X)
           1461
                            where classes are ordered as they are in ``self.classes ``.
           1462
        -> 1463
                        check_is_fitted(self)
           1464
                        ovr = (self.multi class in ["ovr", "warn"] or
           1465
        c:\Users\almas\anaconda3\lib\site-packages\sklearn\utils\validation.py in inner f(*args,
        **kwargs)
```

```
61 extra_args = len(args) - len(all_args)
62 if extra_args <= 0:
---> 63 return f(*args, **kwargs)
64
65 # extra_args > 0
```

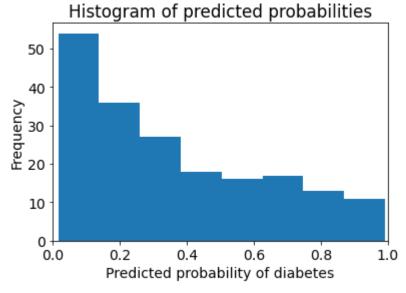
c:\Users\almas\anaconda3\lib\site-packages\sklearn\utils\validation.py in check_is_fitte
d(estimator, attributes, msg, all_or_any)

```
1096
1097    if not attrs:
-> 1098        raise NotFittedError(msg % {'name': type(estimator).__name__})
1099
1100
```

NotFittedError: This LogisticRegression instance is not fitted yet. Call 'fit' with appr opriate arguments before using this estimator.

```
# histogram of predicted probabilities
plt.hist(y_pred_prob, bins=8)
plt.xlim(0, 1)
plt.title('Histogram of predicted probabilities')
plt.xlabel('Predicted probability of diabetes')
plt.ylabel('Frequency')
```

Out[]: Text(0, 0.5, 'Frequency')

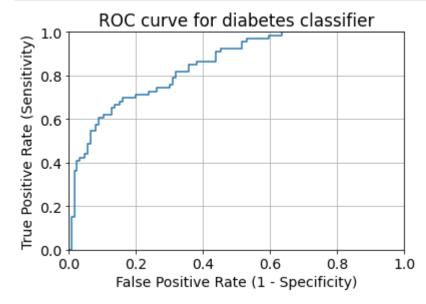


```
In [ ]: from sklearn.preprocessing import binarize
    y_pred_class = binarize([y_pred_prob], threshold=0.3)[0]

In [ ]: print("Threshold 0.5:\n ",confusion_matrix)
    print("Threshold 0.3:\n ",metrics.confusion_matrix(y_test, y_pred_class))

Threshold 0.5:
    [[110    16]
    [ 30    36]]
    Threshold 0.3:
    [[82    44]
    [12    54]]
```

```
In [ ]:
         print("Recall Threshold 0.5: ",TP / float(TP + FN))
         print("Recall Threshold 0.3: ", 82 / float(82+12) )
         print("Recall increased" )
         print("\n")
         print("Specificity Threshold 0.5: ",TN / float(TN + FP))
         print("Specificity Threshold 0.3: ", 54/ float(54 + 44))
         print("Specificity decreased")
        Recall Threshold 0.5: 0.5454545454545454
        Recall Threshold 0.3: 0.8723404255319149
        Recall increased
        Specificity Threshold 0.5: 0.873015873015873
        Specificity Threshold 0.3:
                                    0.5510204081632653
        Specificity decreased
In [ ]:
         # IMPORTANT: first argument is true values, second argument is predicted probabilities
         fpr, tpr, thresholds = metrics.roc curve(y test, y pred prob)
         plt.plot(fpr, tpr)
         plt.xlim([0.0, 1.0])
         plt.ylim([0.0, 1.0])
         plt.title('ROC curve for diabetes classifier')
         plt.xlabel('False Positive Rate (1 - Specificity)')
         plt.ylabel('True Positive Rate (Sensitivity)')
         plt.grid(True)
```



```
def evaluate_threshold(threshold):
    print('Sensitivity:', tpr[thresholds > threshold][-1])
    print('Specificity:', 1 - fpr[thresholds > threshold][-1])
In []: evaluate_threshold(0.5)
```

Sensitivity: 0.6515151515151515 Specificity: 0.873015873015873

```
In [ ]: evaluate_threshold(0.3)
```

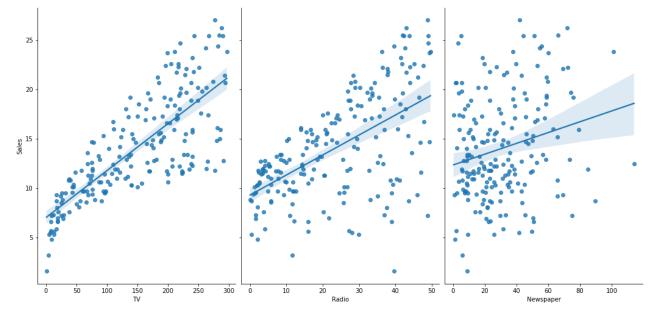
Sensitivity: 0.8181818181818182 Specificity: 0.6825396825396826

3- Regression Model

```
Out[]:
                  TV Radio Newspaper Sales
             1 230.1
                                            22.1
                        37.8
                                     69.2
             2
                 44.5
                        39.3
                                     45.1
                                            10.4
             3
                 17.2
                        45.9
                                     69.3
                                             9.3
               151.5
                        41.3
                                     58.5
                                            18.5
               180.8
                        10.8
                                     58.4
                                            12.9
          196
                 38.2
                          3.7
                                     13.8
                                             7.6
          197
                 94.2
                                      8.1
                                             9.7
                          4.9
          198 177.0
                          9.3
                                            12.8
                                      6.4
          199 283.6
                        42.0
                                     66.2
                                            25.5
          200 232.1
                                      8.7
                          8.6
                                            13.4
```

200 rows × 4 columns

```
In [ ]: sns.pairplot(df, x_vars=['TV','Radio','Newspaper'], y_vars='Sales', height=7, aspect=0.
Out[ ]: <seaborn.axisgrid.PairGrid at 0x19a27532460>
```



```
In [ ]: X=df[['TV','Radio','Newspaper']]
    y=df['Sales']
    X
```

Out[]:		TV	Radio	Newspaper
	1	230.1	37.8	69.2
	2	44.5	39.3	45.1
	3	17.2	45.9	69.3
	4	151.5	41.3	58.5
	5	180.8	10.8	58.4
	•••	•••		
	196	38.2	3.7	13.8
	197	94.2	4.9	8.1
	198	177.0	9.3	6.4
	199	283.6	42.0	66.2
	200	232.1	8.6	8.7

200 rows × 3 columns

```
In [ ]:
         list(zip(df[['TV','Radio','Newspaper']], linreg.coef_))
        [('TV', 0.04656456787415029),
Out[]:
         ('Radio', 0.17915812245088839),
         ('Newspaper', 0.003450464711180378)]
In [ ]:
         y_pred = linreg.predict(X_test)
In [ ]:
         print('Mean Absoulute Error', metrics.mean_absolute_error(y_test, y_pred))
         print('Mean Squared Error:',metrics.mean_squared_error(y_test, y_pred))
         print('Root Mean Squared Error: ',np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
        Mean Absoulute Error 1.0668917082595206
        Mean Squared Error: 1.9730456202283368
        Root Mean Squared Error: 1.404651423032895
In [ ]:
```