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Regression

Problem: Determine the best algorithm that accurately predict the percetage of hospitalized patient with COVID given data (features such as previous day COVID admission, hospital beds used, etc).

Check data type and visualize data

```
import pandas as pd
from sklearn.model_selection import train_test_split
import numpy as np
from sklearn import metrics, datasets
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.feature_selection import RFECV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import KFold
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from scipy.cluster.hierarchy import linkage, dendrogram
from sklearn import preprocessing
from sklearn.decomposition import PCA
from sklearn import decomposition

pd.set_option('display.max_columns', 10)
pd.set_option('display.max_rows', 30)
pd.set_option('display.width', 10000)

data = pd.read_csv('/COVID-
19_Reported_Patient_Impact_and_Hospital_Capacity_by_State.csv')

print(data.info())
print(data.describe())
print(data)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 54 entries, 0 to 53
Columns: 134 entries, state to
total_staffed_pediatric_icu_beds_coverage
dtypes: float64(41), int64(92), object(1)
memory usage: 56.7+ KB
None
       critical_staffing_shortage_today_yes
critical_staffing_shortage_today_no
critical_staffing_shortage_today_not_reported
critical_staffing_shortage_anticipated_within_week_yes
critical_staffing_shortage_anticipated_within_week_no  ...
staffed_icu_pediatric_patients_confirmed_covid_coverage
staffed_pediatric_icu_bed_occupancy
staffed_pediatric_icu_bed_occupancy_coverage
total_staffed_pediatric_icu_beds
total_staffed_pediatric_icu_beds_coverage
count                             54.000000
```

```
54.000000                                               54.000000
54.000000                                                        54.000000
...                                                   54.000000
54.000000                                              54.000000
54.000000                                           54.000000
mean                                        2.388889
17.648148                                               75.407407
6.148148
58.777778      ...                                                   93.166667
111.740741                                              93.166667
168.222222                                           93.148148
std                                         4.759961
26.142684                                               70.871800
7.953657
50.346223      ...                                                   80.642175
170.736605                                              80.642175
248.683148                                           80.642329
min                                         0.000000
0.000000                                                1.000000
0.000000
0.000000      ...                                                    1.000000
0.000000                                               1.000000
0.000000                                            1.000000
25%                                         0.000000
2.000000                                               31.250000
1.000000
18.000000      ...                                                   44.250000
14.250000                                              44.250000
30.250000                                           44.250000
50%                                         1.000000
6.500000                                               53.500000
2.500000
50.500000      ...                                                   86.000000
53.500000                                              86.000000
89.000000                                           86.000000
75%                                         2.000000
22.500000                                               96.500000
8.000000
84.000000      ...                                                  122.750000
115.000000                                             122.750000
178.000000                                          122.750000
max                                        26.000000
110.000000                                              432.000000
37.000000                                                       248.000000
...                                                  459.000000
837.000000                                             459.000000
1294.000000                                          459.000000

[8 rows x 133 columns]
```

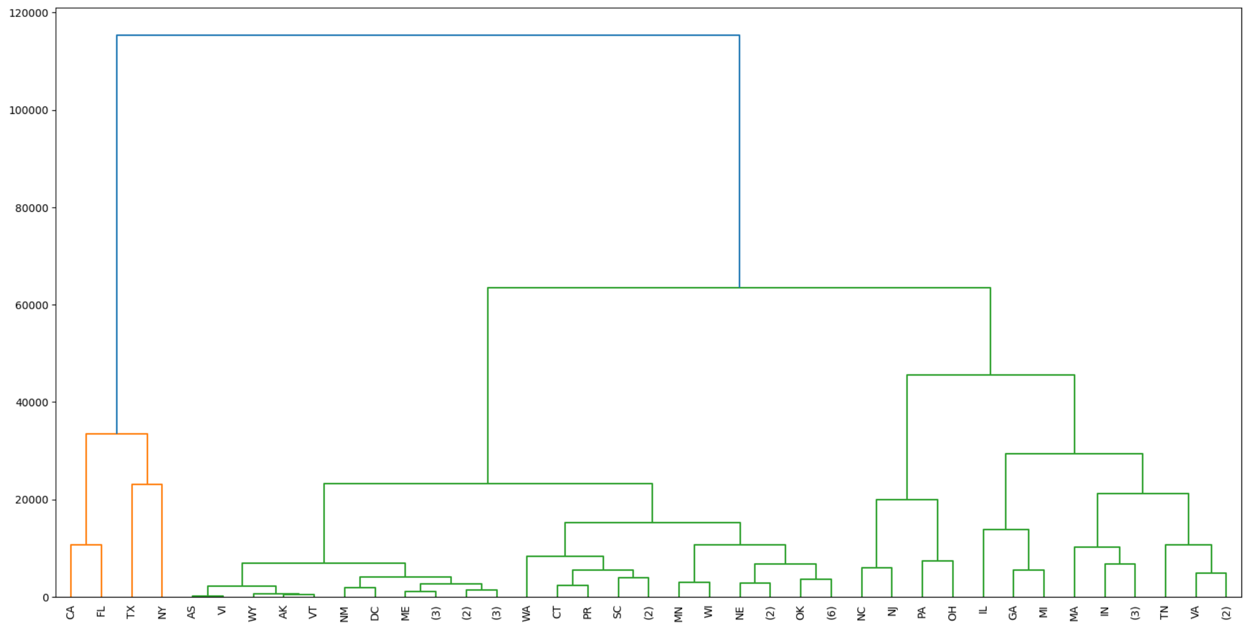
```
   state  critical_staffing_shortage_today_yes
critical_staffing_shortage_today_no
critical_staffing_shortage_today_not_reported
critical_staffing_shortage_anticipated_within_week_yes  ...
staffed_icu_pediatric_patients_confirmed_covid_coverage
staffed_pediatric_icu_bed_occupancy
staffed_pediatric_icu_bed_occupancy_coverage
total_staffed_pediatric_icu_beds
total_staffed_pediatric_icu_beds_coverage
0     AK                                     1
6                                             11
1       ...                                                 18
5                                            18
6                                         18
1     CA                                    10
102                                            241
37       ...                                                345
837                                          345
1294                                        345
2     FL                                     3
41                                            171
8       ...                                                209
695                                          209
980                                         209
3     SC                                    17
6                                             39
20       ...                                                61
54                                            61
95                                         61
4     MN                                     0
0                                            128
6       ...                                                127
89                                           127
118                                         127
..   ...                                    ...
...                                             ...
...       ...                                                ...
...                                           ...
...                                         ...
49    WI                                     9
73                                             52
8       ...                                                131
69                                           131
93                                        131
50    LA                                     3
21                                            121
2       ...                                                142
142                                          142
215                                         142
```

```
51     AZ                                              0
11                                                       78
0        ...                                                          86
181                                                      86
297                                                    86
52     VA                                              9
31                                                       53
11         ...                                                         90
120                                                      90
184                                                    90
53     IL                                              2
50                                                      121
2        ...                                                         168
354                                                     168
525                                                   168

[54 rows x 134 columns]
```

Data Exploratory using Clustering:

After data visualization, do some data exloration using Hierarchical Clustering using states as labels and see if we can spot any patterns

```
state = list(data['state'])

data = data.iloc[: , 1:]
data = data.fillna(0)

mergings = linkage(data, method='complete')

plt.figure(figsize=(20, 10))

dendrogram(mergings,
           p = 6,
           truncate_mode = 'level',
           labels = state,
leaf_rotation=90,
leaf_font_size=10,
)

plt.show()
```



Conclusion from clustering: States like CA and FL, and TX and NY appears to be similar to each other in terms of Covid hospitalization.

Others states that are similar includes AS and VI, AK and VT

Select Optimal Features

Given we have 49 features, and given the target variable is percentage of hospitalized patient with COVID in each state, we want to find number of optimal features out of all 49 features

Since feature selection for LogReg only work with discrete dataset, we want to apply discretization to our target variable first

```
# discretization of the target variable
y = data['percent_of_inpatients_with_covid'] * 100
y_discrete = np.digitize(y,[0,1,2,3,4,5,6,7,8,9,10])

# drop the target feature and select the first 49 columns
data = data.drop(columns=['percent_of_inpatients_with_covid'])
X = data.iloc[: , 0:49]

logit=LogisticRegression(multi_class='ovr',solver='liblinear',
max_iter=1000)

rfecv = RFECV(estimator=logit, step=1, cv=StratifiedKFold(10),
scoring='accuracy')
rfecv.fit(X, y_discrete)

print(f"Optimal number of features : {rfecv.n_features_}")
print("Features rankings:", rfecv.ranking_)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/
_split.py:700: UserWarning: The least populated class in y has only 1
members, which is less than n_splits=10.
  warnings.warn(

Optimal number of features : 40
Features rankings: [ 1  1  1  1  1  1  1  1  2  6  1  7  1  1  1  1  1
1  1  1  1  1  1  1
  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  5  3  4  1  1  9 10  1
1
  8]
```

Optimal feature selection conclusion: According to the print statements above, 40 out of 49 features are optimal.

Reduce Data Dimension:

Now that we know the optimal number of features is 40 out of 49 features, reduce dimension to n = 40

```
print("Shape of the original data set",X.shape)

pca = decomposition.PCA(n_components=40)
pca.fit(X)
X_reduced = pca.transform(X)
print("Shape of the new data set",X_reduced.shape)

print(X)

Shape of the original data set (54, 49)
Shape of the new data set (54, 40)
    critical_staffing_shortage_today_yes
critical_staffing_shortage_today_no
critical_staffing_shortage_today_not_reported
critical_staffing_shortage_anticipated_within_week_yes
critical_staffing_shortage_anticipated_within_week_no  ...
percent_of_inpatients_with_covid_denominator
inpatient_bed_covid_utilization
inpatient_bed_covid_utilization_coverage
inpatient_bed_covid_utilization_numerator
inpatient_bed_covid_utilization_denominator
0                                       1
6                                              11
1                                                       15       ...
592.0                         0.016993
10.0                                      13.0
765.0
1                                      10
```

```
102                                            241
37                                                      248      ...
24933.0                         0.024654
166.0                                      797.0
32327.0
2                                       3
41                                         171
8                                                      129      ...
21489.0                         0.018129
96.0                                      553.0
30503.0
3                                      17
6                                          39
20                                                       33      ...
5702.0                         0.019324
44.0                                      148.0
7659.0
4                                       0
0                                        128
6                                                       81      ...
107.0                         0.003546
11.0                                        1.0
282.0
..                                     ...
...                                            ...
...                                                      ...      ...
...                                 ...
...                                         ...
...
49                                      9
73                                             52
8                                                       88      ...
1073.0                         0.012000
20.0                                       21.0
1750.0
50                                      3
21                                         121
2                                                      128      ...
2297.0                         0.016740
22.0                                       57.0
3405.0
51                                      0
11                                             78
0                                                       60      ...
7298.0                         0.018110
49.0                                      174.0
9608.0
52                                      9
31                                             53
```

```
11                                                                    49       ...
8036.0                        0.010462
57.0                                     125.0
11948.0
53                                     2
50                                              121
2                                                         137       ...
7954.0                        0.009653
71.0                                     115.0
11913.0

[54 rows x 49 columns]
```

Apply all regression methods for both original features and reduced features, and compare the result

Decision Tree (regression)

Apply decision tree (regerssion) on both the original X and reduced X and compare error rates

```
from sklearn import tree

X_train, X_test, y_train, y_test = train_test_split(X, y,
random_state=0)
X_train2, X_test2, y_train2, y_test2 = train_test_split(X_reduced, y,
random_state=5)

clf = tree.DecisionTreeRegressor()

print("X original")
print("--------------------")
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
print("y prediction: ", y_pred)
print("y actual: ", list(y_test))
print("MAE: ", metrics.mean_absolute_error(y_test, y_pred))
print("MSE: ", metrics.mean_squared_error(y_test, y_pred))
print("RMSE: ", np.sqrt(metrics.mean_squared_error(y_test, y_pred)))

print("\nX reduced")
print("--------------------")
clf.fit(X_train2, y_train2)
y_pred2 = clf.predict(X_test2)
print("y prediction: ", y_pred2)
print("y actual: ", list(y_test2))
print("X_reduced MAE: ", metrics.mean_absolute_error(y_test2,
y_pred2))
print("X_reduced MSE: ", metrics.mean_squared_error(y_test2, y_pred2))
```

```
print("X_reduced RMSE: ", np.sqrt(metrics.mean_squared_error(y_test2, y_pred2)))
```

```
X original
--------------------
y prediction:  [1.4046823 1.8046358 0.6547836 0.        0.8207934
3.1965668 1.2970169
 0.        0.6036217 3.1350196 0.8207934 0.6036217 0.5802708
2.1661932]
y actual:  [1.4458134, 1.7132505, 0.9060023, 0.4056795, 0.8974359,
2.5734097, 1.0485197, 0.27777779999999996, 0.650524, 4.0931546,
0.9345794, 0.9225092, 0.7972857999999999, 2.1671827]
MAE:  0.2622288928571429
MSE:  0.13234253041559793
RMSE:  0.3637891290508801

X_reduced
--------------------
y prediction:  [0.78125   3.1350196 2.1959459 2.1959459 0.280112
1.2263158 4.1076115
 1.2263158 3.1845799 0.78125   9.9337748 1.3842746 1.7132505
1.2263158]
y actual:  [0.0, 0.8207934, 1.0282776, 0.8849558000000001, 0.4056795,
2.3842149, 1.4458134, 1.1491301, 2.6527649, 1.5594542, 2.5734097,
2.5955804999999996, 1.2970169, 0.650524]
X_reduced MAE:  1.4621643285714285
X_reduced MSE:  5.323658215370439
X_reduced RMSE:  2.3073054014088465
```

Decision Tree Conclusion: X original (MSE: 0.1323) performs better than X reduced (MSE: 5.3237) for decision tree

---

Linear Regression

Apply linear regerssion on both the original X and reduced X and compare error rates

```
from sklearn.linear_model import LinearRegression

regr = LinearRegression()

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=54)
X_train2, X_test2, y_train2, y_test2 = train_test_split(X_reduced, y, random_state=29)

#print(X_train)
#X_train = X_train.values.reshape(-1, 1)
```

```
print("X original")
print("-------------------")
regr.fit(X_train, y_train)
#print('Coefficients: \n', regr.coef_)
#print('Intercept: \n', regr.intercept_)
y_pred = regr.predict(X_test)
print("y prediction: ", y_pred)
print("y actual:", list(y_test))
print("MAE: ", metrics.mean_absolute_error(y_test, y_pred))
print("MSE: ", metrics.mean_squared_error(y_test, y_pred))
print("RMSE: ", np.sqrt(metrics.mean_squared_error(y_test, y_pred)))

print("\nX reduced")
print("-------------------")
regr.fit(X_train2, y_train2)
#print('Coefficients: \n', regr.coef_)
#print('Intercept: \n', regr.intercept_)
y_pred2 = regr.predict(X_test2)
print("y prediction: ", y_pred2)
print("y actual:", list(y_test2))
print("X_reduced MAE: ", metrics.mean_absolute_error(y_test2,
y_pred2))
print("X_reduced MSE: ", metrics.mean_squared_error(y_test2, y_pred2))
print("X_reduced RMSE: ", np.sqrt(metrics.mean_squared_error(y_test2,
y_pred2)))
```

```
X original
-------------------
y prediction:  [ 1.47977677 -5.11671021  0.58461891  1.69356697
3.79253299  0.88606438
  0.82722214  1.57186861  1.13886408  0.48451727 -0.09902136
3.40747696
  0.70959366 -0.82098398]
y actual [1.4046823, 2.3842149, 1.4458134, 3.1845799, 0.8207934,
0.27777779999999996, 0.9225092, 1.5238095, 1.0485197,
0.8849558000000001, 0.0, 2.4814976, 0.6036217, 0.78125]
MAE:  1.2053992078463491
MSE:  5.147219292808846
RMSE:  2.268748397863643

X reduced
-------------------
y prediction:  [2.53608512e+00 2.22671295e+00 9.25461383e+07
2.00594940e+00
 1.03273241e+00 1.28518780e+00 3.66085730e+00 8.35181165e-01
 9.64648742e-01 5.25546729e-01 1.36883373e+00 4.88298025e+00
 2.25242901e+00 2.14032262e+00]
y actual [2.3424879, 1.2263158, 0.0, 0.650524, 1.4764008, 0.0,
2.4671735, 0.9060023, 1.0282776, 0.78125, 1.3096098,
```

```
3.1965668000000003, 1.0638298, 3.1845799]
X_reduced MAE:  6610439.149971054
X_reduced MSE:  611770550475122.1
X_reduced RMSE:  24733995.845296048
```

Linear Regression Conclusion: X original (MSE: 5.14) performs much better than X reduced (MSE: very large) for linear regression as X original MSE error rate is much lower. Linear regression in general perform worst than decision tree

---

KNN (regression)

Apply KNN on both the original X and reduced X and compare error rates. Find error rate for K between 1 to 20 to see which one performs the best

```
from sklearn import neighbors

X_train, X_test, y_train, y_test = train_test_split(X, y,
random_state=8)
X_train2, X_test2, y_train2, y_test2 = train_test_split(X_reduced, y,
random_state=9)

#rmse_val = [] #to store rmse values for different k
print("X original")
print("-------------------")
for K in range(20):
    K = K+1
    model = neighbors.KNeighborsRegressor(n_neighbors = K)

    model.fit(X_train, y_train)  #fit the model
    y_pred=model.predict(X_test) #make prediction on test set
    error = metrics.mean_squared_error(y_test, y_pred) #calculate rmse
    #rmse_val.append(error) #store rmse values
    print('MSE value for k= ' , K , 'is:', error)

print("\nX reduced")
print("-------------------")
for K in range(20):
    K = K+1
    model = neighbors.KNeighborsRegressor(n_neighbors = K)
    model.fit(X_train2, y_train2)  #fit the model
    y_pred2=model.predict(X_test2) #make prediction on test set
    error = metrics.mean_squared_error(y_test2, y_pred2) #calculate
rmse
    #rmse_val.append(error) #store rmse values
    print('X_reduced MSE value for k= ' , K , 'is:', error)

X original
-------------------
```

```
MSE value for k=  1 is: 7.887403794204283
MSE value for k=  2 is: 6.142704717334602
MSE value for k=  3 is: 5.726131413014052
MSE value for k=  4 is: 5.729782561528443
MSE value for k=  5 is: 5.686724674366024
MSE value for k=  6 is: 5.545855019724544
MSE value for k=  7 is: 5.637963710662381
MSE value for k=  8 is: 5.604338330176371
MSE value for k=  9 is: 5.701514773253135
MSE value for k=  10 is: 5.602002482738833
MSE value for k=  11 is: 5.753047724203708
MSE value for k=  12 is: 5.823654003833712
MSE value for k=  13 is: 5.965731335588771
MSE value for k=  14 is: 6.11642768424984
MSE value for k=  15 is: 6.187884605127481
MSE value for k=  16 is: 6.12242320302563 4
MSE value for k=  17 is: 6.0708579478704925
MSE value for k=  18 is: 6.058121843537757
MSE value for k=  19 is: 6.117670317831227
MSE value for k=  20 is: 6.20081954153935

X reduced
--------------------
X_reduced MSE value for k=  1 is: 1.8856960446440336
X_reduced MSE value for k=  2 is: 1.4665693445178156
X_reduced MSE value for k=  3 is: 1.2699453677190884
X_reduced MSE value for k=  4 is: 1.1442822397865413
X_reduced MSE value for k=  5 is: 1.0970414108458357
X_reduced MSE value for k=  6 is: 1.1312609200680268
X_reduced MSE value for k=  7 is: 1.4118408323757197
X_reduced MSE value for k=  8 is: 1.394379793281777
X_reduced MSE value for k=  9 is: 1.449337889800653
X_reduced MSE value for k=  10 is: 1.3287677483902958
X_reduced MSE value for k=  11 is: 1.3519340159944566
X_reduced MSE value for k=  12 is: 1.1800182971793556
X_reduced MSE value for k=  13 is: 0.9296640235711304
X_reduced MSE value for k=  14 is: 0.9080549131317665
X_reduced MSE value for k=  15 is: 1.0093089720379125
X_reduced MSE value for k=  16 is: 1.0224256074713078
X_reduced MSE value for k=  17 is: 0.9187521310084316
X_reduced MSE value for k=  18 is: 0.9063203734501801
X_reduced MSE value for k=  19 is: 0.9294522107206559
X_reduced MSE value for k=  20 is: 0.9768232692721852
```

KNN Conclusion: X reduced performs better than X original in general for KNN as the error rate for X reduced is lower.

For X original: K = 6 is the best option (MSE: 5.55)

For X rediced: K = 18 is the best option (MSE: 0.91)

KNN performed better than linear regression but worst than decision tree

---

Random Forest (regression)

Apply Random Forest on both the original X and reduced X and compare error rates.

```
from sklearn.ensemble import RandomForestRegressor

X_train, X_test, y_train, y_test = train_test_split(X, y,
random_state=11)
X_train2, X_test2, y_train2, y_test2 = train_test_split(X_reduced, y,
random_state=12)

print("X original")
print("-------------------")
rfc = RandomForestRegressor(n_estimators=600)
rfc.fit(X_train,y_train)
y_pred = rfc.predict(X_test)
# print MAE. MSE, and RMSE
print("y prediction: ", y_pred)
print("y actual: ", list(y_test))
print("MAE: ", metrics.mean_absolute_error(y_test, y_pred))
print("MSE: ", metrics.mean_squared_error(y_test, y_pred))
print("RMSE: ", np.sqrt(metrics.mean_squared_error(y_test, y_pred)))

print("\nX reduced")
print("-------------------")
rfc = RandomForestRegressor(n_estimators=600)
rfc.fit(X_train2,y_train2)
y_pred2 = rfc.predict(X_test2)
# print MAE. MSE, and RMSE for X_reduced
print("y prediction: ", y_pred)
print("y actual: ", list(y_test))
print("X_reduced MAE: ", metrics.mean_absolute_error(y_test2,
y_pred2))
print("X_reduced MSE: ", metrics.mean_squared_error(y_test2, y_pred2))
print("X_reduced RMSE: ", np.sqrt(metrics.mean_squared_error(y_test2,
y_pred2)))
```

```
X original
-------------------
y prediction:  [0.37976312 1.52120928 1.30881701 1.52940619 2.30780549
2.56373217
 1.10690158 3.2641008  0.5337374  0.08533147 2.55634727 0.92396997
 1.50797343 1.42403152]
y actual:  [0.28011199999999997, 1.8046357999999998, 0.0, 1.9571295,
1.4764008, 2.1671827, 1.0282776, 2.5734097, 0.27777779999999996, 0.0,
2.1661932, 0.8207934, 0.8849558000000001, 1.5555002]
MAE:  0.40757108673809495
```

```
MSE:  0.2827877604933337
RMSE:  0.5317779240372185

X reduced
-------------------
y prediction:  [0.37976312 1.52120928 1.30881701 1.52940619 2.30780549
2.56373217
 1.10690158 3.2641008  0.5337374  0.08533147 2.55634727 0.92396997
 1.50797343 1.42403152]
y actual:  [0.28011199999999997, 1.8046357999999998, 0.0, 1.9571295,
1.4764008, 2.1671827, 1.0282776, 2.5734097, 0.27777779999999996, 0.0,
2.1661932, 0.8207934, 0.8849558000000001, 1.5555002]
X_reduced MAE:  1.22535963313095
X_reduced MSE:  2.683669514450389
X_reduced RMSE:  1.6381909273495532
```

Random forest Conclusion: X original (MSE: 0.2828) performs better than X reduced (MSE: 2.6837) for random forest.

All regression methods conclusion:

Regression algorithms for the selected data ranked from best to worst according to the conclusions above:

- **X original:** Decision Tree (MSE: 0.1323) > Random Forest (MSE: 0.2828) > Linear Regression (MSE: 5.14) > KNN (MSE: 5.55)
- **X reduced:** KNN (MSE: 0.91) > Random Forest (MSE: 2.6837) > Decision Tree (MSE: 5.3237) > Linear Regression (MSE: very large)

Findings: For X original, Decision Tree and Random Forest seems to perform very well while Linear Regression and KNN performed poorly. This makes sense as there are some outliers in the data (ex: some state has abnormally high staff shortage in hospital) and Decision Tree and Random Forest are not sensetive to outliers.

Classification

Problem: Determine the best algorithm that accurately predict if an insurance claim for an individual is santioned or not (based on features such as insurance agency name, agency net sales, insurance plan of the individual etc).

Check data type and visualize data

```
data2 = pd.read_csv('/insurance_dataset.csv')

agency = list(data2["Agency"].iloc[:100])
```

```python
# fill NaN fields with 0
data2 = data2.fillna(0)
data2 = data2.drop(columns=['Gender'])


print(data2.info())
print(data2.describe())
print(data2)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10537 entries, 0 to 10536
Data columns (total 11 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   ID                    10537 non-null  int64
 1   Age                   10537 non-null  int64
 2   Agency                10537 non-null  object
 3   Agency Type           10537 non-null  object
 4   Commision (in value)  10537 non-null  float64
 5   Destination           10537 non-null  object
 6   Distribution Channel  10537 non-null  object
 7   Duration              10537 non-null  int64
 8   Net Sales             10537 non-null  float64
 9   Product Name          10537 non-null  object
 10  Claim                 10537 non-null  int64
dtypes: float64(2), int64(4), object(5)
memory usage: 905.6+ KB
None
                 ID           Age  Commision (in value)      Duration
Net Sales         Claim
count  10537.000000  10537.000000          10537.000000  10537.000000
10537.000000  10537.000000
mean   32819.611654     39.589447             12.793249     61.090158
51.391107      0.199013
std    18158.084102     13.962649             23.777388    105.559453
64.475120      0.399277
min        7.000000      0.000000              0.000000     -1.000000
-389.000000      0.000000
25%    17367.000000     33.000000              0.000000     10.000000
20.000000      0.000000
50%    33395.000000     36.000000              0.270000     24.000000
29.700000      0.000000
75%    48784.000000     43.000000             13.630000     60.000000
59.400000      0.000000
max    63317.000000    118.000000            210.210000   4844.000000
599.000000      1.000000
          ID  Age Agency    Agency Type  Commision (in value)  ...
Distribution Channel Duration  Net Sales                    Product
Name Claim
0      45341   28    C2B       Airlines                 28.13  ...
```

```
Online       34      112.5                      Silver Plan     1
1      12958   37     JZI       Airlines                  12.95  ...
Online       53       37.0                       Basic Plan     0
2      18233   27     EPX  Travel Agency                   0.00  ...
Online       28       13.0                Cancellation Plan     0
3      31742   36     EPX  Travel Agency                   0.00  ...
Online        1       34.0                Cancellation Plan     0
4      14381   26     CWT  Travel Agency                  23.76  ...
Online       33       39.6  Rental Vehicle Excess Insurance     0
...      ...  ...     ...            ...                    ...  ...
...      ...         ...                               ...   ...
10532   9441   36     EPX  Travel Agency                   0.00  ...
Online       22       25.0         1 way Comprehensive Plan     0
10533  46089   58     C2B       Airlines                  54.00  ...
Online      368      216.0               Annual Silver Plan     1
10534  30389   36     EPX  Travel Agency                   0.00  ...
Online       15       15.0                Cancellation Plan     0
10535   1932   34     JZI       Airlines                   7.70  ...
Online       25       22.0                       Basic Plan     0
10536    691   28     EPX  Travel Agency                   0.00  ...
Online       90       10.0                Cancellation Plan     0

[10537 rows x 11 columns]
```

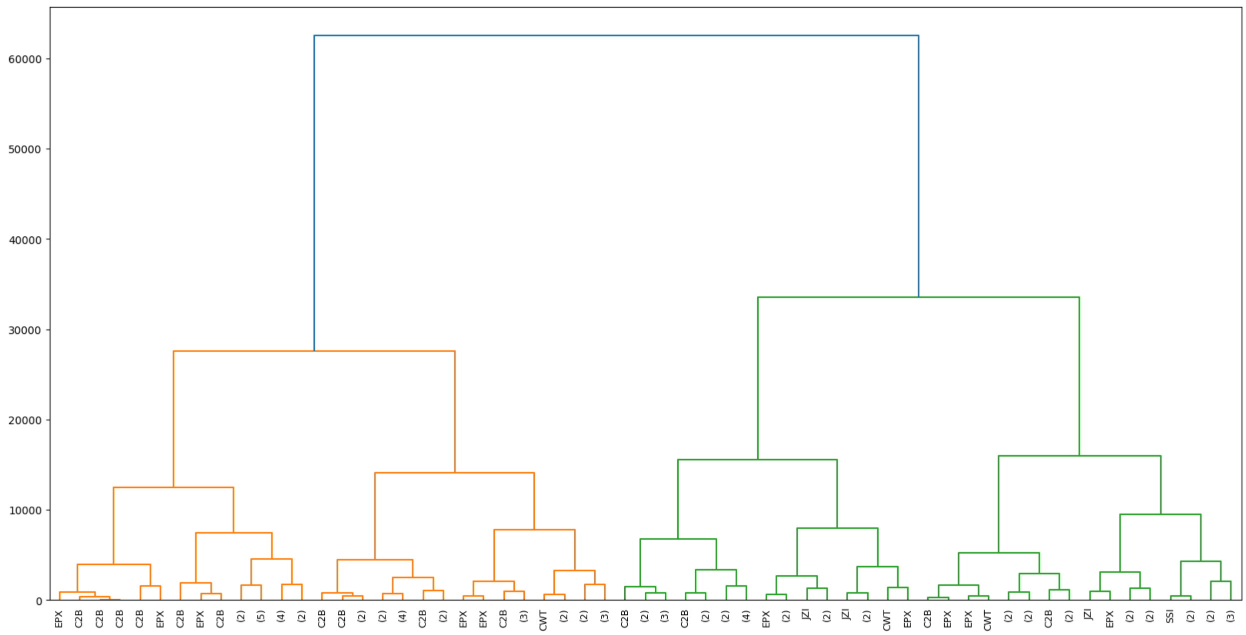
Data Exploratory using Clustering:

After data visualization, do some data exloration using Hierarchical Clustering and agency name as labels and see if we can spot any patterns.

Hierarchical Clustering only work with numeric data, so apply LabelEncoder() to transform categorical data to numeric.

```
from sklearn import preprocessing

label_encoder = preprocessing.LabelEncoder()

data2['Agency'] = label_encoder.fit_transform(data2['Agency'])
data2['Agency Type'] = label_encoder.fit_transform(data2['Agency
Type'])
data2['Destination'] =
label_encoder.fit_transform(data2['Destination'])
data2['Distribution Channel'] =
label_encoder.fit_transform(data2['Distribution Channel'])
data2['Product Name'] = label_encoder.fit_transform(data2['Product
Name'])
```

```
print(data2)
mergings = linkage(data2.head(100), method='complete')
plt.figure(figsize=(20, 10))

dendrogram(mergings,
           p = 5,
           truncate_mode = 'level',
           labels = agency,
leaf_rotation=90,
leaf_font_size=9,
)

plt.show()


          ID  Age  Agency  Agency Type  Commision (in value)  ...
Distribution Channel  Duration  Net Sales  Product Name  Claim
0      45341   28       2            0                 28.13  ...
1        34      112.5            17      1
1      12958   37       9            0                 12.95  ...
1        53       37.0             8      0
2      18233   27       7            1                  0.00  ...
1        28       13.0            10      0
3      31742   36       7            1                  0.00  ...
1         1       34.0            10      0
4      14381   26       6            1                 23.76  ...
1        33       39.6            16      0
...      ...  ...     ...          ...                   ...  ...
...       ...       ...            ...      ...
10532   9441   36       7            1                  0.00  ...
1        22       25.0             0      0
10533  46089   58       2            0                 54.00  ...
1       368      216.0             4      1
10534  30389   36       7            1                  0.00  ...
1        15       15.0            10      0
10535   1932   34       9            0                  7.70  ...
1        25       22.0             8      0
10536    691   28       7            1                  0.00  ...
1        90       10.0            10      0

[10537 rows x 11 columns]
```



Conclusion from clustering: claim submission for agency C2B is similar to other C2B submissions(which make sense). On top of that, it seems data for C2B claim submission is also similar to EPX submission as they are grouped closely in several instance (small distance between them compare to other agencies)

Select Optimal Features

Given we have 10 features, and given the target variable is whether the claim submissions are sanctioned or not (1 = sanctioned, 0 = not sanctioned), we want to find number of optimal features out of all 10 features.

```
X = data2.drop(columns=['Claim'])
y = data2['Claim']

logit=LogisticRegression(multi_class='ovr',solver='liblinear',
max_iter=1000)

rfecv = RFECV(estimator=logit, step=1, cv=StratifiedKFold(10),
scoring='accuracy')
rfecv.fit(X, y)

print(f"Optimal number of features : {rfecv.n_features_}")
print("listing column names and their ranking")
print(list(X.columns.values))
print(rfecv.ranking_)
#print(X.columns[0], X.columns[1],X.columns[30],X.columns[33],
X.columns[37])
```

```
Optimal number of features : 9
listing column names and their ranking
['ID', 'Age', 'Agency', 'Agency Type', 'Commision (in value)',
'Destination', 'Distribution Channel', 'Duration', 'Net Sales',
'Product Name']
[2 1 1 1 1 1 1 1 1 1]
```

Optimal feature selection conclusion: According to the print statements above, besides feature "ID", every other feature is optimal

---

Reduce Data Dimension:

Now that we know the optimal number of features is 9 out of 10 features, reduce dimension to n = 9

```
print("Shape of the original data set",X.shape)

pca = decomposition.PCA(n_components=9)
pca.fit(X)
X_reduced = pca.transform(X)
print("Shape of the new data set",X_reduced.shape)

print(X_reduced)
```

```
Shape of the original data set (10537, 10)
Shape of the new data set (10537, 9)
[[-1.25214041e+04  6.94903888e-01 -6.62689603e+01 ...  8.65136249e+00
  -2.66931134e+00 -1.58979702e-01]
 [ 1.98616154e+04 -5.80722375e+00  4.31938512e+00 ... -1.47772662e+00
   2.60146863e+00 -9.16397072e-01]
 [ 1.45866296e+04 -4.14461552e+01  1.69472912e+01 ...  2.11669228e+00
   1.23763606e+00  2.60567442e-01]
 ...
 [ 2.43063432e+03 -5.71109810e+01  1.20448400e+01 ...  1.04409617e+00
   8.91024028e-01  2.87956733e-01]
 [ 3.08876277e+04 -3.43787486e+01  3.85013609e+00 ... -1.07036743e+00
   1.96276368e+00 -1.00272027e+00]
 [ 3.21286183e+04  1.70789795e+01  4.60131416e+01 ...  2.91315944e+00
  -4.55087652e-01  1.51465425e-01]]
```

Apply all classification methods for both original features and reduced features, and compare the result

Decision Tree (classification)

Apply decision tree (classification) on both the original X and reduced X and compare error rates

```
from sklearn import tree

X_train, X_test, y_train, y_test = train_test_split(X, y,
random_state=0)
X_train2, X_test2, y_train2, y_test2 = train_test_split(X_reduced, y,
random_state=5)

clf = tree.DecisionTreeClassifier()
print("X original")
print("-------------------")
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
print("Accuracy score: ", metrics.accuracy_score(y_test, y_pred))
print("Recall/Sensitivity: ", metrics.recall_score(y_test, y_pred))
print("Precision: ", metrics.precision_score(y_test, y_pred))

print("\nX reduced")
print("-------------------")
clf.fit(X_train2, y_train2)
y_pred2 = clf.predict(X_test2)
print("X_reduced Accuracy score: ", metrics.accuracy_score(y_test2,
y_pred2))
print("X_reduced Recall/Sensitivity: ", metrics.recall_score(y_test2,
y_pred2))
print("X_reduced Precision: ", metrics.precision_score(y_test2,
y_pred2))
```

```
X original
-------------------
Accuracy score:  0.9009487666034156
Recall/Sensitivity:  0.8693181818181818
Precision:  0.7050691244239631

X reduced
-------------------
X_reduced Accuracy score:  0.8941176470588236
X_reduced Recall/Sensitivity:  0.8662900188323918
X_reduced Precision:  0.688622754491018
```

Decision Tree Conclusion: X original (Accuracy: 0.9039) performs sightly better than X reduced (Accuracy: 0.8934) for decision tree but the difference is not significant.

KNN (classification)

Apply KNN on both the original X and reduced X and compare error rates. Find error rate for K between 1 to 20 to see which one performs the best

```python
from sklearn import neighbors

X_train, X_test, y_train, y_test = train_test_split(X, y,
random_state=12)
X_train2, X_test2, y_train2, y_test2 = train_test_split(X_reduced, y,
random_state=18)

print("X original")
print("-------------------")
for K in range(20):
    K = K+1
    model = neighbors.KNeighborsClassifier(n_neighbors = K)
    model.fit(X_train, y_train)  #fit the model
    y_pred=model.predict(X_test) #make prediction on test set
    # find accuracy score
    print("Accuracy score: ", metrics.accuracy_score(y_test, y_pred),
"for k = ", K)
print("\nX reduced")
print("-------------------")
for K in range(20):
    K = K+1
    model = neighbors.KNeighborsClassifier(n_neighbors = K)
    model.fit(X_train2, y_train2)  #fit the model
    y_pred2=model.predict(X_test2) #make prediction on test set
    # find accuracy score
    print("X reduced Accuracy score: ",
metrics.accuracy_score(y_test2, y_pred2), "for k = ", K)
```

```
X original
-------------------
Accuracy score:  0.8971537001897533 for k =  1
Accuracy score:  0.8755218216318785 for k =  2
Accuracy score:  0.845161290322580 7 for k =  3
Accuracy score:  0.8368121442125237 for k =  4
Accuracy score:  0.8242884250474384 for k =  5
Accuracy score:  0.8178368121442126 for k =  6
Accuracy score:  0.8144212523719165 for k =  7
Accuracy score:  0.8174573055028463 for k =  8
Accuracy score:  0.8178368121442126 for k =  9
Accuracy score:  0.8159392789373814 for k =  10
Accuracy score:  0.8144212523719165 for k =  11
Accuracy score:  0.8140417457305503 for k =  12
Accuracy score:  0.8106261859582543 for k =  13
Accuracy score:  0.8098671726755218 for k =  14
Accuracy score:  0.8064516129032258 for k =  15
Accuracy score:  0.8068311195445921 for k =  16
Accuracy score:  0.8 for k =  17
Accuracy score:  0.8022770398481973 for k =  18
Accuracy score:  0.8037950664136623 for k =  19
Accuracy score:  0.7992409867172675 for k =  20
```

```
X reduced
-------------------
X reduced Accuracy score:  0.8990512333965844 for k =  1
X reduced Accuracy score:  0.8785578747628083 for k =  2
X reduced Accuracy score:  0.8489563567362429 for k =  3
X reduced Accuracy score:  0.8432637571157495 for k =  4
X reduced Accuracy score:  0.8330170777988615 for k =  5
X reduced Accuracy score:  0.8299810246679317 for k =  6
X reduced Accuracy score:  0.8178368121442126 for k =  7
X reduced Accuracy score:  0.8269449715370019 for k =  8
X reduced Accuracy score:  0.8166982922201138 for k =  9
X reduced Accuracy score:  0.8216318785578748 for k =  10
X reduced Accuracy score:  0.8178368121442126 for k =  11
X reduced Accuracy score:  0.822011385199241 for k =  12
X reduced Accuracy score:  0.8155597722960152 for k =  13
X reduced Accuracy score:  0.8148007590132827 for k =  14
X reduced Accuracy score:  0.8163187855787476 for k =  15
X reduced Accuracy score:  0.8189753320683112 for k =  16
X reduced Accuracy score:  0.818595825426945 for k =  17
X reduced Accuracy score:  0.8140417457305503 for k =  18
X reduced Accuracy score:  0.8129032258064516 for k =  19
X reduced Accuracy score:  0.8113851992409867 for k =  20
```

KNN conclusion: We found that k = 1 is the optimal for both X and X_reduced and X original's accuracy. Also accuracy for both dataset is very similar (~0.9 or 90%)

Logistic Regression

Apply Logistic Regression with stratified cross validation and compare error rates

```
from sklearn.linear_model import LogisticRegression

logit=LogisticRegression(multi_class='ovr',solver='liblinear',
max_iter=1000)

X_train, X_test, y_train, y_test = train_test_split(X, y,
random_state=17)
X_train2, X_test2, y_train2, y_test2 = train_test_split(X_reduced, y,
random_state=13)

rfecv = RFECV(estimator=logit, step=1, cv=StratifiedKFold(10),
scoring='accuracy')
print("X original")
print("-------------------")
rfecv.fit(X_train, y_train)
y_pred=rfecv.predict(X_test)
print("Accuracy score: ", metrics.accuracy_score(y_test, y_pred))
```

```
print("Recall/Sensitivity: ", metrics.recall_score(y_test, y_pred))
print("Precision: ", metrics.precision_score(y_test, y_pred))

print("\nX reduced")
print("-------------------")
rfecv.fit(X_train2, y_train2)
y_pred2=rfecv.predict(X_test2)
print("X_reduced Accuracy score: ", metrics.accuracy_score(y_test2, 
y_pred2))
print("X_reduced Recall/Sensitivity: ", metrics.recall_score(y_test2, 
y_pred2))
print("X_reduced Precision: ", metrics.precision_score(y_test2, 
y_pred2))
```

```
X original
-------------------
Accuracy score:  0.8250474383301708
Recall/Sensitivity:  0.22285714285714286
Precision:  0.6882352941176471

X reduced
-------------------
X_reduced Accuracy score:  0.8333965844402277
X_reduced Recall/Sensitivity:  0.30038022813688214
X_reduced Precision:  0.6899563318777293
```

Logistic Regression Conclusion: X reduced (Accuracy: 0.8334) performs sightly better than X original (Accuracy: 0.8250) for logistic regression but the difference is not significant.

Random Forest (classification)

Apply Random Forest on both the original X and reduced X and compare error rates.

```
from sklearn.ensemble import RandomForestClassifier

X_train, X_test, y_train, y_test = train_test_split(X, y, 
random_state=11)
X_train2, X_test2, y_train2, y_test2 = train_test_split(X_reduced, y, 
random_state=12)

rfc = RandomForestClassifier(n_estimators=300, criterion='entropy')
rfc.fit(X_train,y_train)


print("X original")
print("-------------------")
y_pred = rfc.predict(X_test)
# print Accuracy. Sensitivity, and Precision
```

```
print("Accuracy score: ", metrics.accuracy_score(y_test, y_pred))
print("Recall/Sensitivity: ", metrics.recall_score(y_test, y_pred))
print("Precision: ", metrics.precision_score(y_test, y_pred))

rfc = RandomForestClassifier(n_estimators=300, criterion='entropy')
rfc.fit(X_train2,y_train2)

print("\nX reduced")
print("-------------------")
y_pred2 = rfc.predict(X_test2)
# print Accuracy. Sensitivity, and Precision
print("X_reduced Accuracy score: ", metrics.accuracy_score(y_test2,
y_pred2))
print("X_reduced Recall/Sensitivity: ", metrics.recall_score(y_test2,
y_pred2))
print("X_reduced Precision: ", metrics.precision_score(y_test2,
y_pred2))
```

```
X original
-------------------
Accuracy score:  0.9499051233396585
Recall/Sensitivity:  0.8986866791744841
Precision:  0.8599640933572711

X reduced
-------------------
X_reduced Accuracy score:  0.932068311195446
X_reduced Recall/Sensitivity:  0.8505535055350554
X_reduced Precision:  0.8246869409660107
```

Random Forest Conclusion: X original (Accuracy: 0.95) performs sightly better than X reduced (Accuracy: 0.932) for random forest.

All classification methods conclusion:

Classification algorithms for the selected data ranked from best to worst according to the conclusions above:

- **X original:** Random Forest (Accuracy: 0.95) > Decision Tree (Accuracy: 0.9039) > KNN (Accuracy: 0.8971) > Logistic Regression (Accuracy: 0.825)
- **X reduced:** Random Forest (Accuracy: 0.932) > KNN (Accuracy: 0.899) > Decision Tree (Accuracy: 0.893) > Logistic Regression (Accuracy: 0.8334)

Findings: For both X original and X reduced, Logistic Regression does not do as well as the other 3 algorithms. It's the only algorithm that rely the linearity of the data for accurate prediction. But since the claim approval (our target variable) are judge on a case by case basis by the agency, the outcome is sometimes unpredictable regardless of the features provided. Therefore the chance of non-linear data is high and it makes sense Logistic regression didn't do as well.