Final Exam: Question 3

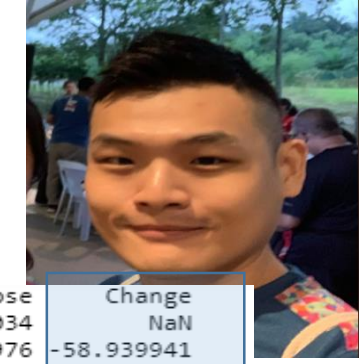
You are required to write code to create a decision tree (DT) model using the above dataset (Question 1). In order to achieve the task, you are going to cover the following steps:

- Importing required libraries
- Loading Data
- Feature Selection
- Splitting Data
- Building Decision Tree Model
- Evaluating Model
- Visualizing Decision Trees

Step 1 : Importing required libraries

```
# Load libraries
import pandas as pd
from sklearn.tree import DecisionTreeClassifier # Import Decision Tree Classifier
from sklearn import tree
from sklearn.model_selection import train_test_split # Import train_test_split function
from sklearn import metrics
```

Step 2 : Loading the dataset



i. Perform the code below to create a feature for the Change of price/ index for the stocks and index as follows:

a. Maybank –MBB
b. RHB
c. KLCI – Kuala Lumpur Composite Index
d. DJI – Dow Jone Index
e. SNP - S&P 500 Index

```
MBB1 = MBB.iloc[:, 0:2]
CIMB1= CIMB.iloc[:, 0:2]
RHB1 = RHB.iloc[:, 0:2]
KLCI1 = KLCI.iloc[:, 0:2]
DJI1 = DJI.iloc[:, 0:2]
SNP1 = SNP.iloc[:, 0:2]

for i in range(1, len(MBB1)):
    MBB1.loc[i, 'Change'] = MBB1.loc[i-1, 'close'] - MBB1.loc[i, 'close']
print(MBB1)

for i in range(1, len(CIMB1)):
    CIMB1.loc[i, 'Change'] = CIMB1.loc[i-1, 'close'] - CIMB1.loc[i, 'close']
print(CIMB1)

for i in range(1, len(RHB1)):
    RHB1.loc[i, 'Change'] = RHB1.loc[i-1, 'close'] - RHB1.loc[i, 'close']
print(CIMB1)

for i in range(1, len(KLCI1)):
    KLCI1.loc[i, 'Change'] = KLCI1.loc[i-1, 'close'] - KLCI1.loc[i, 'close']
print(KLCI1)

for i in range(1, len(DJI1)):
    DJI1.loc[i, 'Change'] = DJI1.loc[i-1, 'close'] - DJI1.loc[i, 'close']
print(DJI1)

for i in range(1, len(SNP1)):
    SNP1.loc[i, 'Change'] = SNP1.loc[i-1, 'close'] - SNP1.loc[i, 'close']
print(SNP1)
```

MBB

	date	close	Change
0	2020-03-09	8.24	NaN
1	2020-03-06	8.50	-0.260000
2	2020-03-05	8.53	-0.030000
3	2020-03-04	8.47	0.059999
4	2020-03-03	8.41	0.060000
...	...	...	...
1237	2015-03-16	9.09	0.070000
1238	2015-03-13	9.10	-0.010000
1239	2015-03-12	9.12	-0.020000
1240	2015-03-11	9.09	0.030000
1241	2015-03-10	9.23	-0.139999

[1242 rows x 3 columns]

CIMB

	date	close	Change
0	2020-03-09	4.20	NaN
1	2020-03-06	4.44	-0.24
2	2020-03-05	4.50	-0.06
3	2020-03-04	4.54	-0.04
4	2020-03-03	4.50	0.04
...	...	...	...
1238	2015-03-16	5.91	0.05
1239	2015-03-13	5.92	-0.01
1240	2015-03-12	5.85	0.07
1241	2015-03-11	5.80	0.05
1242	2015-03-10	5.95	-0.15

[1243 rows x 3 columns]

RHB

	date	close	Change
0	2020-03-09	4.20	NaN
1	2020-03-06	4.44	-0.24
2	2020-03-05	4.50	-0.06
3	2020-03-04	4.54	-0.04
4	2020-03-03	4.50	0.04
...	...	...	...
1238	2015-03-16	5.91	0.05
1239	2015-03-13	5.92	-0.01
1240	2015-03-12	5.85	0.07
1241	2015-03-11	5.80	0.05
1242	2015-03-10	5.95	-0.15

[1243 rows x 3 columns]

KLCI

	date	close	Change
0	2020-03-09	1424.160034	NaN
1	2020-03-06	1483.099976	-58.939941
2	2020-03-05	1491.030029	-7.930054
3	2020-03-04	1489.949951	1.080078
4	2020-03-03	1478.640015	11.309937
...	...	...	...
1221	2015-03-16	1780.540039	7.329956
1222	2015-03-13	1781.750000	-1.209961
1223	2015-03-12	1786.869995	-5.119995
1224	2015-03-11	1778.160034	8.709961
1225	2015-03-10	1789.729980	-11.569946

[1226 rows x 3 columns]

DJI

	date	close	Change
0	2020-03-09	23851.019531	NaN
1	2020-03-06	25864.779297	-2013.759766
2	2020-03-05	26121.279297	-256.500000
3	2020-03-04	27090.859375	-969.580078
4	2020-03-03	25917.410156	1173.449219
...	...	...	...
1254	2015-03-16	17977.419922	-128.339844
1255	2015-03-13	17749.310547	228.109375
1256	2015-03-12	17895.220703	-145.910156
1257	2015-03-11	17635.390625	259.830078
1258	2015-03-10	17662.939453	-27.548828

[1259 rows x 3 columns]

SNP

	date	close	Change
0	2020-03-09	2746.560059	NaN
1	2020-03-06	2972.370117	-225.810059
2	2020-03-05	3023.939941	-51.569824
3	2020-03-04	3130.120117	-106.180176
4	2020-03-03	3003.370117	126.750000
...	...	...	...
1254	2015-03-16	2081.189941	-6.909912
1255	2015-03-13	2053.399902	27.790039
1256	2015-03-12	2065.949951	-12.550049
1257	2015-03-11	2040.239990	25.709961
1258	2015-03-10	2044.160034	-3.920044

[1259 rows x 3 columns]

Step 2 : Loading the dataset (Continued from previous slide)

ii. Perform the following code to create a " movement" column. The value of the features as follows:

a. No Change
b. Rise
c. Drop

```
def f(row):
    if row['Change'] > 0:
        val = 'Rise'
    elif row['Change'] < 0:
        val = 'Drop'
    else:
        val = 'No Change'
    return val

MBB1['MBB_Movement'] = MBB1.apply(f, axis=1)
CIMB1['CIMB1_Movement'] = CIMB1.apply(f, axis=1)
RHB1['RHB1_Movement'] = RHB1.apply(f, axis=1)
KLCI1['KLCI1_Movement'] = KLCI1.apply(f, axis=1)
DJI1['DJI1_Movement'] = DJI1.apply(f, axis=1)
SNP1['SNP1_Movement'] = SNP1.apply(f, axis=1
```

MBB

	date	close	Change	MBB_Movement
0	2020-03-09	8.24	NaN	No Change
1	2020-03-06	8.50	-0.260000	Drop
2	2020-03-05	8.53	-0.030000	Drop
3	2020-03-04	8.47	0.059999	Rise
4	2020-03-03	8.41	0.060000	Rise
...	...	...	...	...
1237	2015-03-16	9.09	0.070000	Rise
1238	2015-03-13	9.10	-0.010000	Drop
1239	2015-03-12	9.12	-0.020000	Drop
1240	2015-03-11	9.09	0.030000	Rise
1241	2015-03-10	9.23	-0.139999	Drop

[1242 rows x 4 columns]

CIMB

	date	close	Change	CIMB1_Movement
0	2020-03-09	4.20	NaN	No Change
1	2020-03-06	4.44	-0.24	Drop
2	2020-03-05	4.50	-0.06	Drop
3	2020-03-04	4.54	-0.04	Drop
4	2020-03-03	4.50	0.04	Rise
...	...	...	...	...
1238	2015-03-16	5.91	0.05	Rise
1239	2015-03-13	5.92	-0.01	Drop
1240	2015-03-12	5.85	0.07	Rise
1241	2015-03-11	5.80	0.05	Rise
1242	2015-03-10	5.95	-0.15	Drop

[1243 rows x 4 columns]

RHB

	date	close	Change	RHB1_Movement
0	2020-03-09	5.47000	NaN	No Change
1	2020-03-06	5.70000	-0.23000	Drop
2	2020-03-05	5.71000	-0.01000	Drop
3	2020-03-04	5.71000	0.00000	No Change
4	2020-03-03	5.64000	0.07000	Rise
...	...	...	...	...
1238	2015-03-16	7.26511	0.03740	Rise
1239	2015-03-13	7.19966	0.06545	Rise
1240	2015-03-12	7.23706	-0.03740	Drop
1241	2015-03-11	7.34926	-0.11220	Drop
1242	2015-03-10	7.38666	-0.03740	Drop

[1243 rows x 4 columns]

KLCI

	date	close	Change	KLCI1_Movement
0	2020-03-09	1424.160034	NaN	No Change
1	2020-03-06	1483.099976	-58.939941	Drop
2	2020-03-05	1491.030029	-7.930054	Drop
3	2020-03-04	1489.949951	1.080078	Rise
4	2020-03-03	1478.640015	11.309937	Rise
...	...	...	...	...
1221	2015-03-16	1780.540039	7.329956	Rise
1222	2015-03-13	1781.750000	-1.209961	Drop
1223	2015-03-12	1786.869995	-5.119995	Drop
1224	2015-03-11	1778.160034	8.709961	Rise
1225	2015-03-10	1789.729980	-11.569946	Drop

[1226 rows x 4 columns]

DJI

	date	close	Change	DJI1_Movement
0	2020-03-09	23851.019531	NaN	No Change
1	2020-03-06	25864.779297	-2013.759766	Drop
2	2020-03-05	26121.279297	-256.500000	Drop
3	2020-03-04	27090.859375	-969.580078	Drop
4	2020-03-03	25917.410156	1173.449219	Rise
...	...	...	...	...
1254	2015-03-16	17977.419922	-128.339844	Drop
1255	2015-03-13	17749.310547	228.109375	Rise
1256	2015-03-12	17895.220703	-145.910156	Drop
1257	2015-03-11	17635.390625	259.830078	Rise
1258	2015-03-10	17662.939453	-27.548828	Drop

[1259 rows x 4 columns]

SNP

	date	close	Change	SNP1_Movement
0	2020-03-09	2746.560059	NaN	No Change
1	2020-03-06	2972.370117	-225.810059	Drop
2	2020-03-05	3023.939941	-51.569824	Drop
3	2020-03-04	3130.120117	-106.180176	Drop
4	2020-03-03	3003.370117	126.750000	Rise
...	...	...	...	...
1254	2015-03-16	2081.189941	-6.909912	Drop
1255	2015-03-13	2053.399902	27.790039	Rise
1256	2015-03-12	2065.949951	-12.550049	Drop
1257	2015-03-11	2040.239990	25.709961	Rise
1258	2015-03-10	2044.160034	-3.920044	Drop

[1259 rows x 4 columns]

Step 2 : Loading the dataset (Continued from previous slide)

iv. Perform the following code to drop the unnecessary features:

```
MBB2 = MBB1.drop(['close', 'Change'], axis=1)
CIMB2 = CIMB1.drop(['close', 'Change'], axis=1)
RHB2 = RHB1.drop(['close', 'Change'], axis=1)
KLCI2 = KLCI1.drop(['close', 'Change'], axis=1)
DJI2 = DJI1.drop(['close', 'Change'], axis=1)
SNP2 = SNP1.drop(['close', 'Change'], axis=1)
```

MBB2

	date	MBB_Movement
0	2020-03-09	No Change
1	2020-03-06	Drop
2	2020-03-05	Drop
3	2020-03-04	Rise
4	2020-03-03	Rise
...	...	...
1237	2015-03-16	Rise
1238	2015-03-13	Drop
1239	2015-03-12	Drop
1240	2015-03-11	Rise
1241	2015-03-10	Drop

[1242 rows x 2 columns]

CIMB2

	date	CIMB1_Movement
0	2020-03-09	No Change
1	2020-03-06	Drop
2	2020-03-05	Drop
3	2020-03-04	Drop
4	2020-03-03	Rise
...	...	...
1238	2015-03-16	Rise
1239	2015-03-13	Drop
1240	2015-03-12	Rise
1241	2015-03-11	Rise
1242	2015-03-10	Drop

[1243 rows x 2 columns]

RHB2

	date	RHB1_Movement
0	2020-03-09	No Change
1	2020-03-06	Drop
2	2020-03-05	Drop
3	2020-03-04	No Change
4	2020-03-03	Rise
...	...	...
1238	2015-03-16	Rise
1239	2015-03-13	Rise
1240	2015-03-12	Drop
1241	2015-03-11	Drop
1242	2015-03-10	Drop

[1243 rows x 2 columns]

KLCI2

	date	KLCI1_Movement
0	2020-03-09	No Change
1	2020-03-06	Drop
2	2020-03-05	Drop
3	2020-03-04	Rise
4	2020-03-03	Rise
...	...	...
1221	2015-03-16	Rise
1222	2015-03-13	Drop
1223	2015-03-12	Drop
1224	2015-03-11	Rise
1225	2015-03-10	Drop

[1226 rows x 2 columns]

DJI2

	date	DJI1_Movement
0	2020-03-09	No Change
1	2020-03-06	Drop
2	2020-03-05	Drop
3	2020-03-04	Drop
4	2020-03-03	Rise
...	...	...
1254	2015-03-16	Drop
1255	2015-03-13	Rise
1256	2015-03-12	Drop
1257	2015-03-11	Rise
1258	2015-03-10	Drop

[1259 rows x 2 columns]

SNP2

	date	SNP1_Movement
0	2020-03-09	No Change
1	2020-03-06	Drop
2	2020-03-05	Drop
3	2020-03-04	Drop
4	2020-03-03	Rise
...	...	...
1254	2015-03-16	Drop
1255	2015-03-13	Rise
1256	2015-03-12	Drop
1257	2015-03-11	Rise
1258	2015-03-10	Drop

[1259 rows x 2 columns]

Step 2 : Loading the dataset (Continued from previous slide)

v. Perform the following code to combine the required data then clean them

```
MergeD = pd.merge(KLCI1, DJI1,
                  how="left", on=["date"])

MergeD1 = pd.merge(MergeD,SNP1,
                  how="left", on=["date"])

MergeD2 = pd.merge(MergeD1,MBB2,
                  how="left", on=["date"])

MergeD3 = pd.merge(MergeD2, RHB2,
                  how="left", on=["date"])

Tree_Decision_Dataset = pd.merge(MergeD3, CIMB2,
                  how="left", on=["date"])
```

```
Tree_Decision_Dataset1 = Tree_Decision_Dataset.dropna(how='any',axis=0)
print(Tree_Decision_Dataset1.isnull().sum())
print(Tree_Decision_Dataset1)
```

```
date              0
close_x           0
Change_x          0
KLCI1_Movement    0
close_y           0
Change_y          0
DJI1_Movement     0
close             0
Change            0
SNP1_Movement     0
MBB_Movement      0
RHB1_Movement     0
CIMB1_Movement    0
dtype: int64
```

```
           date       close_x   Change_x KLCI1_Movement        close_y  \
1    2020-03-06  1483.099976 -58.939941            Drop   25864.779297
2    2020-03-05  1491.030029  -7.930054            Drop   26121.279297
3    2020-03-04  1489.949951   1.080078            Rise   27090.859375
4    2020-03-03  1478.640015  11.309937            Rise   25917.410156
5    2020-03-02  1466.939941  11.700073            Rise   26703.320312
...         ...          ...        ...             ...            ...
1221 2015-03-16  1780.540039   7.329956            Rise   17977.419922
1222 2015-03-13  1781.750000  -1.209961            Drop   17749.310547
1223 2015-03-12  1786.869995  -5.119995            Drop   17895.220703
1224 2015-03-11  1778.160034   8.709961            Rise   17635.390625
1225 2015-03-10  1789.729980 -11.569946            Drop   17662.939453

         Change_y DJI1_Movement         close       Change SNP1_Movement
1     -2013.759766          Drop   2972.370117 -225.810059          Drop
2      -256.500000          Drop   3023.939941  -51.569824          Drop
3      -969.580078          Drop   3130.120117 -106.180176          Drop
4      1173.449219          Rise   3003.370117  126.750000          Rise
5      -785.910156          Drop   3090.229980  -86.859863          Drop
...            ...           ...           ...         ...           ...
1221   -128.339844          Drop   2081.189941   -6.909912          Drop
1222    228.109375          Rise   2053.399902   27.790039          Rise
1223   -145.910156          Drop   2065.949951  -12.550049          Drop
1224    259.830078          Rise   2040.239990   25.709961          Rise
1225    -27.548828          Drop   2044.160034   -3.920044          Drop

     MBB_Movement RHB1_Movement CIMB1_Movement
1            Drop          Drop           Drop
2            Drop          Drop           Drop
3            Rise     No Change           Drop
4            Rise          Rise           Rise
5            Rise          Rise           Drop
...           ...           ...            ...
1221         Rise          Rise           Rise
1222         Drop          Rise           Drop
1223         Drop          Drop           Rise
1224         Rise          Drop           Rise
1225         Drop          Drop           Drop

[1192 rows x 13 columns]
```

Step 3 to step 6 of Question 3

MayBank Stock price movement vs daily change of KLCI, DJI & SNP

Step 3. Feature

KLCI1_Movement

```
feature_cols = ['Change_x']
X = Tree_Decision_Dataset1[feature_cols] # Features
y = Tree_Decision_Dataset1.MBB_Movement # Target variable
```

DJI1_Movement

```
feature_cols = ['Change_y']
X = Tree_Decision_Dataset1[feature_cols] # Features
y = Tree_Decision_Dataset1.MBB_Movement # Target variable
```

SNP1_Movement

```
feature_cols = ['Change']
X = Tree_Decision_Dataset1[feature_cols] # Features
y = Tree_Decision_Dataset1.MBB_Movement # Target variable
```

Step 4. Split the data

```
# Split dataset into training set and test set
# 70% training and 30% test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)
```

Step 5. Building the decision tree model

```
# Create Decision Tree classifer object
clf = DecisionTreeClassifier()

# Train Decision Tree Classifer
clf = clf.fit(X_train,y_train)

#Predict the response for test dataset
y_pred = clf.predict(X_test)
```

Step 6. Evaluating Model

```
accuracy = metrics.accuracy_score(y_test,y_pred)
accuracy
```

```
0.5446927374301676
```
KLCI1_Movement

```
0.4329608938547486
```
DJI1_Movement

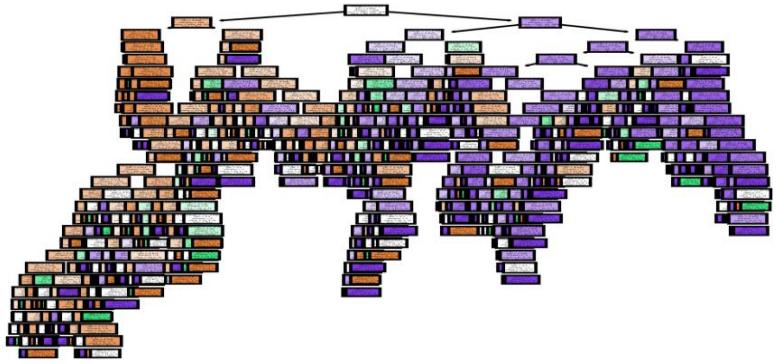
```
0.3659217877094972
```
SNP1_Movement

Step 7 : Visualizing Decision Trees by performing the code below:

MayBank Stock price movement vs daily change of KLCI, DJI & SNP

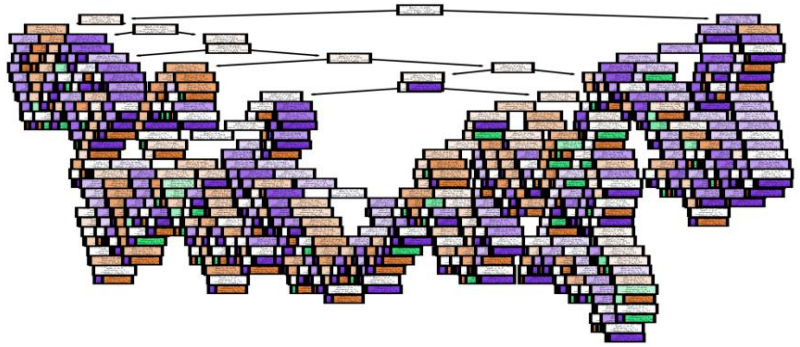
KLCI1_Movement

```
from matplotlib import pyplot as plt
fn=['Change_x']
cn=['Rise', 'Drop', 'No Change']
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=300)
tree.plot_tree(clf,
               feature_names = fn,
               class_names=cn,
               filled = True);
fig.savefig('imagename.png')
```



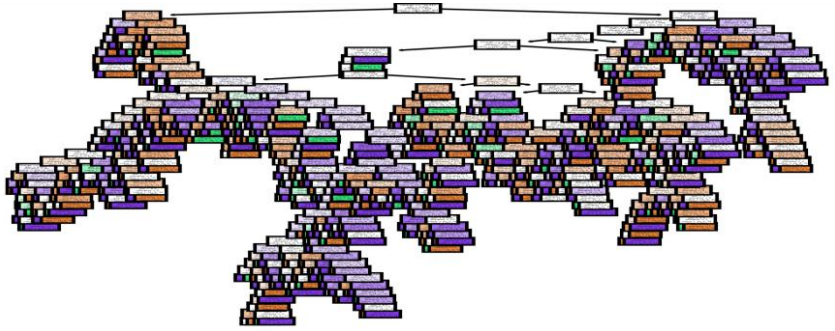
DJI1_Movement

```
from matplotlib import pyplot as plt
fn=['Change_y']
cn=['Rise', 'Drop', 'No Change']
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=300)
tree.plot_tree(clf,
               feature_names = fn,
               class_names=cn,
               filled = True);
fig.savefig('imagename.png')
```



SNP1_Movement

```
from matplotlib import pyplot as plt
fn=['Change']
cn=['Rise', 'Drop', 'No Change']
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=300)
tree.plot_tree(clf,
               feature_names = fn,
               class_names=cn,
               filled = True);
fig.savefig('imagename.png')
```



Step 3 to step 6 of Question 3

CIMB Stock price movement vs daily change of KLCI, DJI & SNP

Step 3. Feature

KLCI1_Movement

```
feature_cols = ['Change_x']
X = Tree_Decision_Dataset1[feature_cols] # Features
y = Tree_Decision_Dataset1.CIMB1_Movement # Target variable
```

DJI1_Movement

```
feature_cols = ['Change_y']
X = Tree_Decision_Dataset1[feature_cols] # Features
y = Tree_Decision_Dataset1.CIMB1_Movement # Target variable
```

SNP1_Movement

```
feature_cols = ['Change']
X = Tree_Decision_Dataset1[feature_cols] # Features
y = Tree_Decision_Dataset1.CIMB1_Movement # Target variable
```

Step 4. Split the data

```
# Split dataset into training set and test set
# 70% training and 30% test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)
```

Step 5. Building the decision tree model

```
# Create Decision Tree classifer object
clf = DecisionTreeClassifier()

# Train Decision Tree Classifer
clf = clf.fit(X_train,y_train)

#Predict the response for test dataset
y_pred = clf.predict(X_test)
```

Step 6. Evaluating Model

```
accuracy = metrics.accuracy_score(y_test,y_pred)
accuracy
```

```
0.5195530726256983
```
KLCI1_Movement

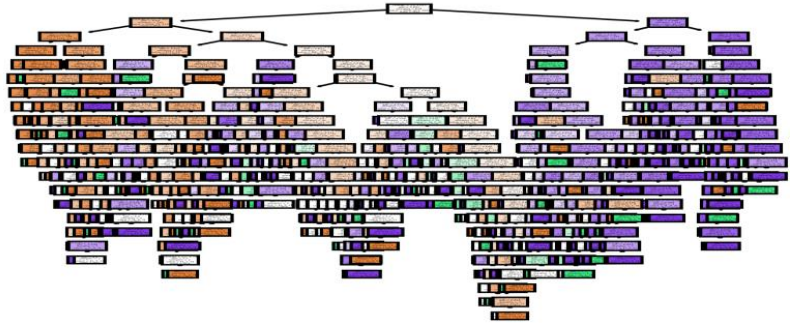
```
0.4329608938547486
```
DJI1_Movement

```
0.40502793296089384
```
SNP1_Movement

Step 7 : Visualizing Decision Trees by performing the code below:
CIMB Stock price movement vs daily change of KLCI, DJI & SNP

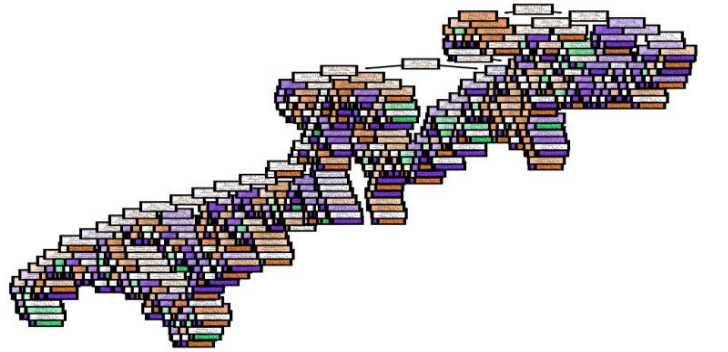
KLCI1_Movement

```
from matplotlib import pyplot as plt
fn=['Change_x']
cn=['Rise', 'Drop', 'No Change']
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=300)
tree.plot_tree(clf,
               feature_names = fn,
               class_names=cn,
               filled = True);
fig.savefig('imagename4.png')

tree.plot_tree(clf) # alternative
```



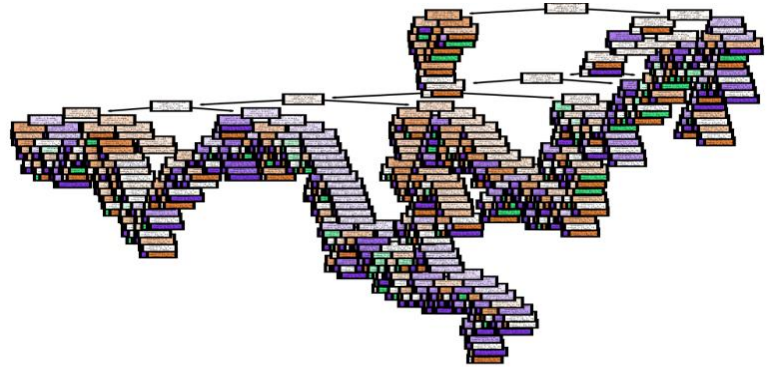
DJI1_Movement

```
from matplotlib import pyplot as plt
fn=['Change_y']
cn=['Rise', 'Drop', 'No Change']
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=300)
tree.plot_tree(clf,
               feature_names = fn,
               class_names=cn,
               filled = True);
fig.savefig('imagename5.png')

tree.plot_tree(clf) # alternative
```



SNP1_Movement

```
from matplotlib import pyplot as plt
fn=['Change']
cn=['Rise', 'Drop', 'No Change']
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=300)
tree.plot_tree(clf,
               feature_names = fn,
               class_names=cn,
               filled = True);
fig.savefig('imagename6.png')

tree.plot_tree(clf) # alternative
```



Step 3 to step 6 of Question 3

RHB Stock price movement vs daily change of KLCI, DJI & SNP

Step 3. Feature

KLCI1_Movement

```
feature_cols = ['Change_x']
X = Tree_Decision_Dataset1[feature_cols] # Features
y = Tree_Decision_Dataset1.RHB1_Movement # Target variable
```

DJI1_Movement

```
feature_cols = ['Change_y']
X = Tree_Decision_Dataset1[feature_cols] # Features
y = Tree_Decision_Dataset1.RHB1_Movement # Target variable
```

SNP1_Movement

```
feature_cols = ['Change']
X = Tree_Decision_Dataset1[feature_cols] # Features
y = Tree_Decision_Dataset1.RHB1_Movement # Target variable
```

Step 4. Split the data

```
# Split dataset into training set and test set
# 70% training and 30% test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)
```

Step 5. Building the decision tree model

```
# Create Decision Tree classifer object
clf = DecisionTreeClassifier()

# Train Decision Tree Classifer
clf = clf.fit(X_train,y_train)

#Predict the response for test dataset
y_pred = clf.predict(X_test)
```

Step 6. Evaluating Model

```
accuracy = metrics.accuracy_score(y_test,y_pred)
accuracy
```

0.4581005586592179 **KLCI1_Movement**

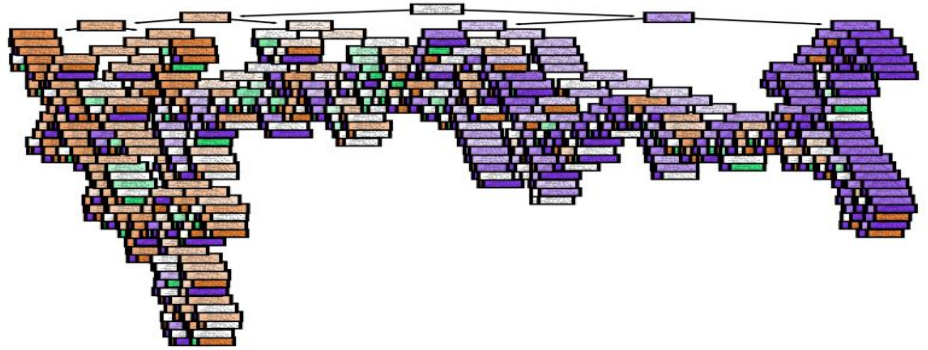
0.3575418994413408 **DJI1_Movement**

0.4022346368715084 **SNP1_Movement**

Step 7 : Visualizing Decision Trees by performing the code below:
RHB Stock price movement vs daily change of KLCI, DJI & SNP

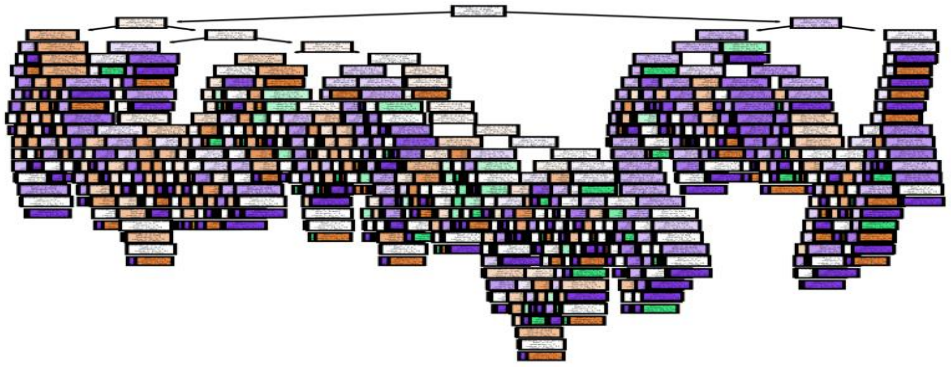
KLCI1_Movement

```
from matplotlib import pyplot as plt
fn=['Change_x']
cn=['Rise', 'Drop', 'No Change']
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=300)
tree.plot_tree(clf,
               feature_names = fn,
               class_names=cn,
               filled = True);
fig.savefig('imagename7.png')
tree.plot_tree(clf) # alternative
```



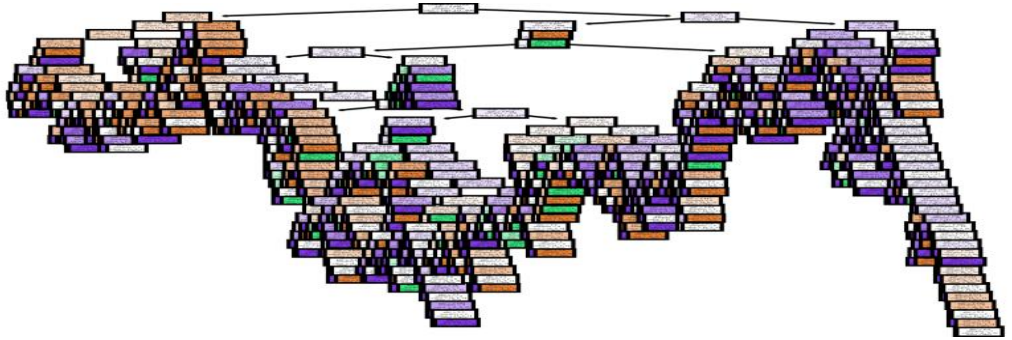
DJI1_Movement

```
from matplotlib import pyplot as plt
fn=['Change_y']
cn=['Rise', 'Drop', 'No Change']
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=300)
tree.plot_tree(clf,
               feature_names = fn,
               class_names=cn,
               filled = True);
fig.savefig('imagename8.png')
tree.plot_tree(clf) # alternative
```



SNP1_Movement

```
from matplotlib import pyplot as plt
fn=['Change']
cn=['Rise', 'Drop', 'No Change']
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (4,4), dpi=300)
tree.plot_tree(clf,
               feature_names = fn,
               class_names=cn,
               filled = True);
fig.savefig('imagename9.png')
tree.plot_tree(clf) # alternative
```



Conclusion for final exam question 3

- The accuracy of tree decision for all Maybank, CIMB and RHB share in term of their respective movement against KLCI, DJI and SNP are not more than 50%
- Thus, the level of purity is very low, presenting a messy tree decision chart

Final Exam: Question4

You are required to write code to find frequent itemsets using the above dataset (Question 1). In order to achieve the task, you are going to cover the following steps:

- Importing required libraries
- Creating a list from dataset (Question 1)
- Convert list to dataframe with boolean values
- Find frequently occurring itemsets using Apriori Algorithm
- Find frequently occurring itemsets using F-P Growth
- Mine the Association Rules

Step 1 : Importing required libraries

```
import pyfpgrowth
import pandas as pd
import matplotlib.pyplot as plt
import networkx as nx
import pandas as pd
import numpy as np
```

```
# Training the Model
## Generating Frequent Itemsets
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules
```

Step 2 : Creating a list from dataset (Question 1)

i. Perform the code below to transform the data (on the left) into the required dataset as follows:

MBB2

	date	MBB_Movement
0	2020-03-09	No Change
1	2020-03-06	Drop
2	2020-03-05	Drop
3	2020-03-04	Rise
4	2020-03-03	Rise
...	...	...
1237	2015-03-16	Rise
1238	2015-03-13	Drop
1239	2015-03-12	Drop
1240	2015-03-11	Rise
1241	2015-03-10	Drop

[1242 rows x 2 columns]

KLCI2

	date	KLCI1_Movement
0	2020-03-09	No Change
1	2020-03-06	Drop
2	2020-03-05	Drop
3	2020-03-04	Rise
4	2020-03-03	Rise
...	...	...
1221	2015-03-16	Rise
1222	2015-03-13	Drop
1223	2015-03-12	Drop
1224	2015-03-11	Rise
1225	2015-03-10	Drop

[1226 rows x 2 columns]

CIMB2

	date	CIMB1_Movement
0	2020-03-09	No Change
1	2020-03-06	Drop
2	2020-03-05	Drop
3	2020-03-04	Drop
4	2020-03-03	Rise
...	...	...
1238	2015-03-16	Rise
1239	2015-03-13	Drop
1240	2015-03-12	Rise
1241	2015-03-11	Rise
1242	2015-03-10	Drop

[1243 rows x 2 columns]

DJI2

	date	DJI1_Movement
0	2020-03-09	No Change
1	2020-03-06	Drop
2	2020-03-05	Drop
3	2020-03-04	Drop
4	2020-03-03	Rise
...	...	...
1254	2015-03-16	Drop
1255	2015-03-13	Rise
1256	2015-03-12	Drop
1257	2015-03-11	Rise
1258	2015-03-10	Drop

[1259 rows x 2 columns]

RHB2

	date	RHB1_Movement
0	2020-03-09	No Change
1	2020-03-06	Drop
2	2020-03-05	Drop
3	2020-03-04	No Change
4	2020-03-03	Rise
...	...	...
1238	2015-03-16	Rise
1239	2015-03-13	Rise
1240	2015-03-12	Drop
1241	2015-03-11	Drop
1242	2015-03-10	Drop

[1243 rows x 2 columns]

SNP2

	date	SNP1_Movement
0	2020-03-09	No Change
1	2020-03-06	Drop
2	2020-03-05	Drop
3	2020-03-04	Drop
4	2020-03-03	Rise
...	...	...
1254	2015-03-16	Drop
1255	2015-03-13	Rise
1256	2015-03-12	Drop
1257	2015-03-11	Rise
1258	2015-03-10	Drop

[1259 rows x 2 columns]

```
TD_Dataset = pd.merge(MBB2, CIMB2,
                      how="left", on=["date"])
```

```
TD_Dataset1 = pd.merge(KLCI2, TD_Dataset,
                      how="left", on=["date"])
```

```
TD_Dataset2 = pd.merge(TD_Dataset1, RHB2,
                      how="left", on=["date"])
```

```
TD_Dataset3 = pd.merge(TD_Dataset2, DJI2,
                      how="left", on=["date"])
```

```
TD_Dataset4 = pd.merge(TD_Dataset3, SNP2,
                      how="left", on=["date"])
TD_Dataset4
```

	date	KLCI1_Movement	MBB_Movement	CIMB1_Movement	RHB1_Movement	DJI1_Movement	SNP1_Movement
0	2020-03-09	No Change	No Change	No Change	No Change	No Change	No Change
1	2020-03-06	Drop	Drop	Drop	Drop	Drop	Drop
2	2020-03-05	Drop	Drop	Drop	Drop	Drop	Drop
3	2020-03-04	Rise	Rise	Drop	No Change	Drop	Drop
4	2020-03-03	Rise	Rise	Rise	Rise	Rise	Rise
...	...	...	...	...	...	...	...
1221	2015-03-16	Rise	Rise	Rise	Rise	Drop	Drop
1222	2015-03-13	Drop	Drop	Drop	Rise	Rise	Rise
1223	2015-03-12	Drop	Drop	Rise	Drop	Drop	Drop
1224	2015-03-11	Rise	Rise	Rise	Drop	Rise	Rise
1225	2015-03-10	Drop	Drop	Drop	Drop	Drop	Drop

1226 rows × 7 columns

Step 2 : Creating a list from dataset (Question 1) (continued from previous slide)

ii. Perform the code below to change the value of every index/price movement into the required dataset as follows:

```
TD_Dataset = pd.merge(MBB2, CIMB2,
                      how="left", on=["date"])
```

```
TD_Dataset1 = pd.merge(KLCI2, TD_Dataset,
                      how="left", on=["date"])
```

```
TD_Dataset2 = pd.merge(TD_Dataset1, RHB2,
                      how="left", on=["date"])
```

```
TD_Dataset3 = pd.merge(TD_Dataset2, DJI2,
                      how="left", on=["date"])
```

```
TD_Dataset4 = pd.merge(TD_Dataset3, SNP2,
                      how="left", on=["date"])
TD_Dataset4
```

	date	KLCI1_Movement	MBB_Movement	CIMB1_Movement	RHB1_Movement	DJI1_Movement	SNP1_Movement
0	2020-03-09	No Change	No Change	No Change	No Change	No Change	No Change
1	2020-03-06	Drop	Drop	Drop	Drop	Drop	Drop
2	2020-03-05	Drop	Drop	Drop	Drop	Drop	Drop
3	2020-03-04	Rise	Rise	Drop	No Change	Drop	Drop
4	2020-03-03	Rise	Rise	Rise	Rise	Rise	Rise
...	...	...	...	...	...	...	...
1221	2015-03-16	Rise	Rise	Rise	Rise	Drop	Drop
1222	2015-03-13	Drop	Drop	Drop	Rise	Rise	Rise
1223	2015-03-12	Drop	Drop	Rise	Drop	Drop	Drop
1224	2015-03-11	Rise	Rise	Rise	Drop	Rise	Rise
1225	2015-03-10	Drop	Drop	Drop	Drop	Drop	Drop

1226 rows × 7 columns

```
TD_Dataset5 = TD_Dataset4.replace(to_replace={"KLCI1_Movement": {"No Change": "KLCI:No_Change", "Drop": "KLCI:Drop","Rise": "
                                  "MBB_Movement": {"No Change": "MBB:No_Change", "Drop": "MBB:Drop","Rise": "MBB:Rise"},
                                  "CIMB1_Movement": {"No Change": "CIMB:No_Change", "Drop": "CIMB:Drop","Rise": "CIMB:Rise"},
                                  "RHB1_Movement": {"No Change": "RHB:No_Change", "Drop": "RHB:Drop","Rise": "RHB:Rise"},
                                  "DJI1_Movement": {"No Change": "DJI:No_Change", "Drop": "DJI:Drop","Rise": "DJI:Rise"},
                                  "SNP1_Movement": {"No Change": "SNP:No_Change", "Drop": "SNP:Drop","Rise": "SNP:Rise"}})
```

```
print(TD_Dataset5)
```

```
           date  KLCI1_Movement   MBB_Movement  CIMB1_Movement  RHB1_Movement  \
0    2020-03-09  KLCI:No_Change  MBB:No_Change  CIMB:No_Change  RHB:No_Change
1    2020-03-06       KLCI:Drop       MBB:Drop       CIMB:Drop       RHB:Drop
2    2020-03-05       KLCI:Drop       MBB:Drop       CIMB:Drop       RHB:Drop
3    2020-03-04       KLCI:Rise       MBB:Rise       CIMB:Drop  RHB:No_Change
4    2020-03-03       KLCI:Rise       MBB:Rise       CIMB:Rise       RHB:Rise
...         ...            ...            ...            ...            ...
1221 2015-03-16       KLCI:Rise       MBB:Rise       CIMB:Rise       RHB:Rise
1222 2015-03-13       KLCI:Drop       MBB:Drop       CIMB:Drop       RHB:Rise
1223 2015-03-12       KLCI:Drop       MBB:Drop       CIMB:Rise       RHB:Drop
1224 2015-03-11       KLCI:Rise       MBB:Rise       CIMB:Rise       RHB:Drop
1225 2015-03-10       KLCI:Drop       MBB:Drop       CIMB:Drop       RHB:Drop

      DJI1_Movement  SNP1_Movement
0     DJI:No_Change  SNP:No_Change
1          DJI:Drop       SNP:Drop
2          DJI:Drop       SNP:Drop
3          DJI:Drop       SNP:Drop
4          DJI:Rise       SNP:Rise
...             ...            ...
1221       DJI:Drop       SNP:Drop
1222       DJI:Rise       SNP:Rise
1223       DJI:Drop       SNP:Drop
1224       DJI:Rise       SNP:Rise
1225       DJI:Drop       SNP:Drop

[1226 rows x 7 columns]
```

```
TD_Dataset5.isnull().sum()
TD_Dataset6 = TD_Dataset5.dropna(how='any',axis=0)
TD_Dataset6.isnull().sum()
```

```
date              0
KLCI1_Movement    0
MBB_Movement      0
CIMB1_Movement    0
RHB1_Movement     0
DJI1_Movement     0
SNP1_Movement     0
dtype: int64
```

Ensure no empty value

Step 2 : Creating a list from dataset (Question 1) *(continued from previous slide)*

iii. Perform the code to preprocess the dataset as follows:

a. Change the trading date to “string” type of data

```
TD_Dataset6['date'] = TD_Dataset6['date'].astype('str')
TD_Dataset6
```

b. Feature selection

```
KLCI = TD_Dataset6.loc[:,['date','KLCI1_Movement']]
MBB = TD_Dataset6.loc[:,['date','MBB_Movement']]
CIMB = TD_Dataset6.loc[:,['date','CIMB1_Movement']]
RHB = TD_Dataset6.loc[:,['date','RHB1_Movement']]
DJI = TD_Dataset6.loc[:,['date','DJI1_Movement']]
SNP = TD_Dataset6.loc[:,['date','SNP1_Movement']]
```

c. Rename the column name

```
KLCI.rename(columns={'date':'Trading_Date',
                     'KLCI1_Movement':'Movement'},inplace=True)
MBB.rename(columns={'date':'Trading_Date',
                    'MBB_Movement':'Movement'},inplace=True)
CIMB.rename(columns={'date':'Trading_Date',
                     'CIMB1_Movement':'Movement'},inplace=True)
RHB.rename(columns={'date':'Trading_Date',
                    'RHB1_Movement':'Movement'},inplace=True)
DJI.rename(columns={'date':'Trading_Date',
                    'DJI1_Movement':'Movement'},inplace=True)
SNP.rename(columns={'date':'Trading_Date',
                    'SNP1_Movement':'Movement'},inplace=True)
```

d. Combine the dataset and create a frequency column

```
DATASET_AM = pd.concat([MBB, CIMB, RHB, KLCI, DJI, SNP], ignore_index=True)
DATASET_AM.sort_values(by=['Trading_Date'], inplace=True)
DATASET_AM["Frequency"] = 1
DATASET_AM
```

	Trading_Date	Movement	Frequency
3578	2015-03-10	RHB:Drop	1
5964	2015-03-10	DJI:Drop	1
4771	2015-03-10	KLCI:Drop	1
2385	2015-03-10	CIMB:Drop	1
1192	2015-03-10	MBB:Drop	1
...	...	...	...
3579	2020-03-09	KLCI:No_Change	1
4772	2020-03-09	DJI:No_Change	1
5965	2020-03-09	SNP:No_Change	1
2386	2020-03-09	RHB:No_Change	1
0	2020-03-09	MBB:No_Change	1

7158 rows × 3 columns

Step 3 :Convert list to data frame with boolean values

i. Perform code below to create the “Basket” of dataset with Boolean values :

```
MyBasket= (DATASET_AM.groupby(['Trading_Date','Movement'])['Frequency'].sum()
           .unstack().reset_index().fillna(0).set_index('Trading_Date'))

def my_encode_units(x):
    if x <=0:
        return 0
    if x >=1:
        return 1

my_basket_sets = MyBasket.applymap(my_encode_units)
my_basket_sets
```

Movement	CIMB:Drop	CIMB:No_Change	CIMB:Rise	DJI:Drop	DJI:No_Change	DJI:Rise	KLCI:Drop	KLCI:No_Change	KLCI:Rise	MBB:Drop	MBB:No_
Trading_Date											
2015-03-10	1	0	0	1	0	0	1	0	0	1	
2015-03-11	0	0	1	0	0	1	0	0	1	0	
2015-03-12	0	0	1	1	0	0	1	0	0	1	
2015-03-13	1	0	0	0	0	1	1	0	0	1	
2015-03-16	0	0	1	1	0	0	0	0	1	0	
...	...	...	...	...	...	...	...	...	...	...	...
2020-03-03	0	0	1	0	0	1	0	0	1	0	
2020-03-04	1	0	0	1	0	0	0	0	1	0	
2020-03-05	1	0	0	1	0	0	1	0	0	1	
2020-03-06	1	0	0	1	0	0	1	0	0	1	
2020-03-09	0	1	0	0	1	0	0	1	0	0	

1193 rows × 18 columns

Step 4 : Find frequently occurring itemsets using Apriori Algorithm

i. Perform code below to create the “Basket” of dataset :

```
my_frequent_itemsets = apriori(my_basket_sets, min_support = 0.07, use_colnames = True)
my_frequent_itemsets
```

	support	itemsets
0	0.433361	(CIMB:Drop)
1	0.131601	(CIMB:No_Change)
2	0.435038	(CIMB:Rise)
3	0.455993	(DJI:Drop)
4	0.541492	(DJI:Rise)
...	...	...
240	0.087175	(DJI:Drop, KLCI:Drop, RHB:Drop, MBB:Drop, SNP:...
241	0.072087	(DJI:Drop, MBB:Rise, RHB:Rise, SNP:Drop, KLCI:...
242	0.087175	(DJI:Rise, KLCI:Drop, RHB:Drop, MBB:Drop, SNP:...
243	0.116513	(DJI:Rise, MBB:Rise, RHB:Rise, SNP:Rise, KLCI:...
244	0.090528	(DJI:Rise, MBB:Rise, RHB:Rise, CIMB:Rise, SNP:...

245 rows × 2 columns

Step 5 : Find frequently occurring itemsets using F-P Growth

i. Perform code below to create the listing of “Basket” for the dataset and the patterns frequency :

```
grouped_df = DATASET_AM.groupby(by = ['Trading_Date'])

transactions = []
for group, pdf in grouped_df:
    transactions.append(pdf['Movement'].values.tolist())

transactions
```

```
[['RHB:Drop', 'DJI:Drop', 'KLCI:Drop', 'CIMB:Drop', 'MBB:Drop', 'SNP:Drop'],
 ['SNP:Rise', 'CIMB:Rise', 'RHB:Drop', 'MBB:Rise', 'DJI:Rise', 'KLCI:Rise'],
 ['DJI:Drop', 'RHB:Drop', 'CIMB:Rise', 'SNP:Drop', 'KLCI:Drop', 'MBB:Drop'],
 ['KLCI:Drop', 'RHB:Rise', 'CIMB:Drop', 'DJI:Rise', 'MBB:Drop', 'SNP:Rise'],
 ['RHB:Rise', 'MBB:Rise', 'SNP:Drop', 'KLCI:Rise', 'CIMB:Rise', 'DJI:Drop'],
 ['KLCI:Rise',
  'RHB:Drop',
  'CIMB:Drop',
  'SNP:Rise',
  'DJI:Rise',
  'MBB:No_Change'],
 ['SNP:Drop', 'CIMB:Rise', 'DJI:Drop', 'KLCI:Rise', 'MBB:Rise', 'RHB:Rise'],
 ['CIMB:No_Change',
  'MBB:Drop',
  'SNP:Rise',
  'RHB:Drop',
  'DJI:Rise',
  'KLCI:Drop'],
 ['DJI:Drop', 'SNP:Drop', 'CIMB:Drop', 'MBB:Drop', 'KLCI:Drop', 'RHB:Rise'],
```

```
patterns = pyfpgrowth.find_frequent_patterns(transactions, 300)
patterns
```

```
{('RHB:Drop',): 507,
 ('KLCI:Drop', 'RHB:Drop'): 345,
 ('CIMB:Drop', 'MBB:Drop'): 300,
 ('KLCI:Drop', 'MBB:Drop'): 387,
 ('CIMB:Drop',): 517,
 ('CIMB:Drop', 'KLCI:Drop'): 389,
 ('CIMB:Rise', 'MBB:Rise'): 313,
 ('CIMB:Rise', 'KLCI:Rise'): 377,
 ('RHB:Rise', 'SNP:Rise'): 301,
 ('DJI:Rise', 'RHB:Rise'): 307,
 ('KLCI:Rise', 'RHB:Rise'): 360,
 ('DJI:Rise', 'MBB:Rise'): 300,
 ('MBB:Rise', 'SNP:Rise'): 305,
 ('KLCI:Rise', 'MBB:Rise'): 391,
 ('DJI:Drop',): 544,
 ('DJI:Drop', 'SNP:Drop'): 474,
 ('SNP:Drop',): 545,
 ('KLCI:Rise', 'SNP:Rise'): 337,
 ('DJI:Rise', 'KLCI:Rise', 'SNP:Rise'): 307,
 ('DJI:Rise', 'KLCI:Rise'): 341,
 ('DJI:Rise', 'KLCI:Drop'): 305,
 ('KLCI:Drop', 'SNP:Rise'): 309,
 ('SNP:Rise',): 646,
 ('DJI:Rise',): 646}
```

Step 6 : Mine the Association Rules using Apriori Algorithm & F-P Growth

i. Perform code below to calculate support, confidence and lift value for the respective combination of items (mining the association rule) :

```
my_rules = association_rules(my_frequent_itemsets, metric = 'lift', min_threshold=1)
```

```
my_rules.head()
```

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(DJI:Drop)	(CIMB:Drop)	0.455993	0.433361	0.199497	0.437500	1.009550	0.001887	1.007358
1	(CIMB:Drop)	(DJI:Drop)	0.433361	0.455993	0.199497	0.460348	1.009550	0.001887	1.008070
2	(KLCI:Drop)	(CIMB:Drop)	0.504610	0.433361	0.326069	0.646179	1.491087	0.107390	1.601486
3	(CIMB:Drop)	(KLCI:Drop)	0.433361	0.504610	0.326069	0.752418	1.491087	0.107390	2.000910
4	(MBB:Drop)	(CIMB:Drop)	0.431685	0.433361	0.251467	0.582524	1.344200	0.064391	1.357297

```
my_rules[(my_rules['lift']>=3.5)&
         (my_rules['confidence']>=0.7)]
```

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
1403	(MBB:Rise, CIMB:Rise, SNP:Drop)	(DJI:Drop, KLCI:Rise)	0.108131	0.207041	0.080469	0.744186	3.594388	0.058082	3.099749
1605	(DJI:Drop, MBB:Rise, RHB:Rise)	(KLCI:Rise, SNP:Drop)	0.096396	0.210394	0.072087	0.747826	3.554408	0.051806	3.131196
1611	(MBB:Rise, RHB:Rise, SNP:Drop)	(DJI:Drop, KLCI:Rise)	0.094719	0.207041	0.072087	0.761062	3.675898	0.052476	3.318680

ii. Perform code below to mine the combination of items that have 0.8 threshold set for confidence (mining the association rule) :

```
rules = pyfpgrowth.generate_association_rules(patterns, 0.80)
rules
```

```
{('DJI:Drop',): (('SNP:Drop',), 0.8713235294117647),
 ('SNP:Drop',): (('DJI:Drop',), 0.8697247706422019),
 ('DJI:Rise', 'KLCI:Rise'): (('SNP:Rise',), 0.900293255131964 8),
 ('KLCI:Rise', 'SNP:Rise'): (('DJI:Rise',), 0.9109792284866469)}
```

Conclusion for final exam question 4

- Using Apriori required multiple scans of the database to check the support count of each item and itemsets. When the database is huge, this will cost a significant amount of disk I/O and computing power. Therefore the FP-Growth algorithm is created