

PROBLEM SET 4, MRIDUL HARISH, CED18I034

```
In [ ]: import pandas as pd
        from sklearn.preprocessing import Binarizer, OneHotEncoder
```

```
In [ ]: df = pd.read_csv('Avocado Dataset.csv')
df1 = pd.read_csv('Trail.csv')
```

Question 1 - Select a subset of relevant attributes from the given dataset that are necessary to know about the total volume of avocados with product lookup codes (PLU) 4046, 4225, 4770 which are of organic type. (Use AVOCADO dataset)

```
In [ ]: v4046 = df.groupby('type')['4046'].sum()
v4225 = df.groupby('type')['4225'].sum()
v4770 = df.groupby('type')['4770'].sum()
```

```
In [ ]: print("Volume of organic avocado sold with PLU of 4046: {}".format(v4046['organic_avocado']))
print("Volume of organic avocado sold with PLU of 4225: {}".format(v4225['organic_avocado']))
print("Volume of organic avocado sold with PLU of 4770: {}".format(v4770['organic_avocado']))
```

Volume of organic avocado sold with PLU of 4046:	66702877.38999989
Volume of organic avocado sold with PLU of 4225:	140603877.57000032
Volume of organic avocado sold with PLU of 4770:	2429040.549999998

Question 2 - Discard all duplicate entries in the dataset given and fill all the missing values in the attribute "AveragePrice" as 1.25. Also print the size of the dataset before and after removing duplicates. (Use Trail dataset)

```
In [ ]: before = df1.shape[0]
df1.drop_duplicates(inplace=True)
after = df1.shape[0]
print("Number of duplicate rows removed: {}".format(before - after))
```

Number of duplicate rows removed: 7

```
In [ ]: before = df1.AveragePrice.isna().sum()
df1.AveragePrice.fillna(1.25, inplace=True)
after = df1.AveragePrice.isna().sum()
print("Number of missing values filled: {}".format(before - after))
```

Number of missing values filled: 24

Question 3 - Binarize the attribute "Year". Set the threshold above 2016 and print it without truncation. (Use AVOCADO dataset)

```
In [ ]: years = df.year.values.reshape(1, -1)

print("Binarized data: {}".format(Binarizer(threshold=2016).fit_transform(years)))
```

Binarized data: [0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

Question 4 - Transform all categorical attributes in the dataset AVOCADO using Integer Encoding.

```
Out[ ]: Date      object
AveragePrice     object
Total Volume     float64
4046             float64
4225             float64
4770             float64
```

```
Total Bags      float64
Small Bags      float64
Large Bags      float64
XLarge Bags     float64
type            category
year            int64
region          category
dtype: object
```

```
In [ ]: print("The categorical attributes in the dataset are as follows: {}".format(d
```

```
The categorical attributes in the dataset are as follows: ['type', 'region']
```

```
In [ ]: intEncoding = {}
regions = list(df.region.unique())
intEncoding["region"] = {i: regions.index(i) for i in regions}
types = list(df.type.unique())
intEncoding["type"] = {i: types.index(i) for i in types}

print("The integer encoding for the categorical attributes is as follows: {}"
```

```
The integer encoding for the categorical attributes is as follows: {'region':
{'Albany': 0, 'Atlanta': 1, 'BaltimoreWashington': 2, 'Boise': 3, 'Boston': 4,
'BuffaloRochester': 5, 'California': 6, 'Charlotte': 7, 'Chicago': 8, 'CincinnatiDayton': 9, 'Columbus': 10, 'DallasFtWorth': 11, 'Denver': 12, 'Detroit': 13, 'GrandRapids': 14, 'GreatLakes': 15, 'HarrisburgScranton': 16, 'HartfordSpringfield': 17, 'Houston': 18, 'Indianapolis': 19, 'Jacksonville': 20, 'LasVegas': 21, 'LosAngeles': 22, 'Louisville': 23, 'MiamiFtLauderdale': 24, 'Midsouth': 25, 'Nashville': 26, 'NewOrleansMobile': 27, 'NewYork': 28, 'Northeast': 29, 'NorthernNewEngland': 30, 'Orlando': 31, 'Philadelphia': 32, 'PhoenixTucson': 33, 'Pittsburgh': 34, 'Plains': 35, 'Portland': 36, 'RaleighGreensboro': 37, 'RichmondNorfolk': 38, 'Roanoke': 39, 'Sacramento': 40, 'SanDiego': 41, 'SanFrancisco': 42, 'Seattle': 43, 'SouthCarolina': 44, 'SouthCentral': 45, 'Southeast': 46, 'Spokane': 47, 'StLouis': 48, 'Syracuse': 49, 'Tampa': 50, 'TotalUS': 51, 'West': 52, 'WestTexNewMexico': 53}, 'type': {'conventional': 0, 'organic': 1}}
```

```
In [ ]: df = df.replace(intEncoding)
df
```

```
Out[ ]:
```

	Date	AveragePrice	Total Volume	4046	4225	4770	Total Bags	Small Bags	Large Bags
0	27-12-2015	1.33	64236.62	1036.74	54454.85	48.16	8696.87	8603.62	93.25
1	20-12-2015	1.35	54876.98	674.28	44638.81	58.33	9505.56	9408.07	97.49
2	13-12-2015	0.93	118220.22	794.70	109149.67	130.50	8145.35	8042.21	103.14
3	06-12-2015	1.08	78992.15	1132.00	71976.41	72.58	5811.16	5677.40	133.76
4	29-11-2015	1.29	51039.60	941.48	43838.39	75.78	6183.95	5986.26	197.69
...
18245	28-01-2018	1.71	13888.04	1191.70	3431.50	0.00	9264.84	8940.04	324.80
18246	21-01-2018	1.87	13766.76	1191.92	2452.79	727.94	9394.11	9351.80	42.31
18247	14-01-2018	1.93	16205.22	1527.63	2981.04	727.01	10969.54	10919.54	50.00

	Date	AveragePrice	Total Volume	4046	4225	4770	Total Bags	Small Bags	Large Bags
18248	07-01-2018	1.62	17489.58	2894.77	2356.13	224.53	12014.15	11988.14	26.01

Question 5 - Transform the attribute = "Region" in the given dataset AVOCADO using One-Hot Encoding.

```
In [ ]: enc = OneHotEncoder(handle_unknown='ignore')

dfEnc = pd.DataFrame(enc.fit_transform(df[['region']]).toarray())
dfMerge = df.join(dfEnc)

dfMerge.columns
```

```
Out[ ]: Index([
      'Date', 'AveragePrice', 'Total Volume',      '4046',
      '4225',      '4770', 'Total Bags', 'Small Bags',
      'Large Bags', 'XLarge Bags',      'type',      'year',
      'region',      0,      1,      2,
      3,      4,      5,      6,
      7,      8,      9,      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,
      35,      36,      37,      38,
      39,      40,      41,      42,
      43,      44,      45,      46,
      47,      48,      49,      50,
      51,      52,      53],
      dtype='object')
```

Question 6 - Ignore the tuples that hold missing values and print the subset of data from AVOCADO dataset excluding "NaN" values.

```
In [ ]: dfCleaned = df.dropna()
dfCleaned
```

```
Out[ ]:
```

	Date	AveragePrice	Total Volume	4046	4225	4770	Total Bags	Small Bags	Large Bags
0	27-12-2015	1.33	64236.62	1036.74	54454.85	48.16	8696.87	8603.62	93.25
1	20-12-2015	1.35	54876.98	674.28	44638.81	58.33	9505.56	9408.07	97.49
2	13-12-2015	0.93	118220.22	794.70	109149.67	130.50	8145.35	8042.21	103.14
3	06-12-2015	1.08	78992.15	1132.00	71976.41	72.58	5811.16	5677.40	133.76
4	29-11-2015	1.29	51039.60	941.48	43838.39	75.78	6183.95	5986.26	197.69
...
18245	28-01-2018	1.71	13888.04	1191.70	3431.50	0.00	9264.84	8940.04	324.80
18246	21-01-2018	1.87	13766.76	1191.92	2452.79	727.94	9394.11	9351.80	42.31

	Date	AveragePrice	Total Volume	4046	4225	4770	Total Bags	Small Bags	Large Bags
18247	14-01-2018	1.93	16205.22	1527.63	2981.04	727.01	10969.54	10919.54	50.00
18248	07-01-2018	1.62	17489.58	2894.77	2356.13	224.53	12014.15	11988.14	26.01

Question 7 - Drop the attribute that has high nullity as it facilitates efficient prediction. (Use AVOCADO dataset)

```
In [ ]: df.isnull().sum()
```

```
Out[ ]: Date          0
AveragePrice      28
Total Volume      0
4046              0
4225              0
4770              0
Total Bags        0
Small Bags        0
Large Bags        0
XLarge Bags       0
type              0
year              0
region            0
dtype: int64
```

```
In [ ]: df_drop = df.dropna(axis=1, how='any', inplace=False)
df_drop.isnull().sum()
```

```
Out[ ]: Date          0
Total Volume      0
4046              0
4225              0
4770              0
Total Bags        0
Small Bags        0
Large Bags        0
XLarge Bags       0
type              0
year              0
region            0
dtype: int64
```

Question 8 - Study the entire dataset and report the complete statistical summary about the data (Use AVOCADO dataset) • Dimension of the dataset

- Most frequently occurring value under every attribute.
- Datatype of every attribute
- Count
- Mean
- Standard Deviation

- Minimum Value
- Maximum value
- 25% o
- Median i.e. 50%
- 75%
- Find whether the class distribution of dataset is imbalanced. (Note: Fix the class label as "Type" in the given dataset)
- Correlation matrix
- Skewness of every attribute.

(For the below exercises, you are free to choose an appropriate data set as merited by the problem statements)

```
In [ ]: df.shape
```

```
Out[ ]: (18250, 13)
```

```
In [ ]: dict(zip(df.columns, df.value_counts().idxmax()))
```

```
Out[ ]: {'Date': '18-03-2018',  
        'AveragePrice': '1.56',  
        'Total Volume': 15896.38,  
        '4046': 2055.35,  
        '4225': 1499.55,  
        '4770': 0.0,  
        'Total Bags': 12341.48,  
        'Small Bags': 12114.81,  
        'Large Bags': 226.67,  
        'XLarge Bags': 0.0,  
        'type': 1,  
        'year': 2018,  
        'region': 53}
```

```
In [ ]: df.dtypes
```

```
Out[ ]: Date          object  
        AveragePrice  object  
        Total Volume  float64  
        4046          float64  
        4225          float64  
        4770          float64  
        Total Bags    float64  
        Small Bags    float64  
        Large Bags    float64  
        XLarge Bags   float64  
        type          int64  
        year          int64  
        region        int64  
        dtype: object
```



```
In [ ]: df.count()
```

```
Out[ ]: Date          18250
AveragePrice        18222
Total Volume        18250
4046                18250
4225                18250
4770                18250
Total Bags          18250
Small Bags          18250
Large Bags          18250
XLarge Bags         18250
type                18250
year                18250
region              18250
dtype: int64
```

```
In [ ]: df.select_dtypes(include=['float64']).mean()
```

```
Out[ ]: Total Volume    850598.273413
4046                292992.481896
4225                295138.477670
4770                22838.484500
Total Bags          239626.747390
Small Bags          182185.367250
Large Bags          54335.123135
XLarge Bags         3106.256292
dtype: float64
```

```
In [ ]: df.select_dtypes(include=['float64']).std()
```

```
Out[ ]: Total Volume    3.453456e+06
4046                1.264956e+06
4225                1.204089e+06
4770                1.074613e+05
Total Bags          9.862168e+05
Small Bags          7.461591e+05
Large Bags          2.439596e+05
XLarge Bags         1.769242e+04
dtype: float64
```

```
In [ ]: df.select_dtypes(include=['float64']).min()
```

```
Out[ ]: Total Volume    84.56
4046                0.00
4225                0.00
4770                0.00
Total Bags          0.00
Small Bags          0.00
Large Bags          0.00
XLarge Bags         0.00
dtype: float64
```

```
In [ ]: df.select_dtypes(include=['float64']).max()
```

```
Out[ ]: Total Volume    62505646.52
4046                22743616.17
4225                20470572.61
```

```
4770          2546439.11
Total Bags    19373134.37
Small Bags    13384586.80
Large Bags    5719096.61
XLarge Bags   551693.65
dtype: float64
```

```
In [ ]: df.select_dtypes(include=['float64']).quantile([0.25, 0.5, 0.75])
```

```
Out [ ]:
```

	Total Volume	4046	4225	4770	Total Bags	Small Bags	Large Bags	XLarge Bags
0.25	10839.6275	854.2100	3008.0975	0.000	5089.0825	2850.3225	127.580	0.0000
0.50	107365.5050	8643.2000	29058.8750	184.975	39741.1800	26351.6150	2647.270	0.0000
0.75	432952.6650	111008.7125	150166.3350	6242.055	110781.1150	83336.2100	22018.275	132.4325

```
In [ ]: counts = df['type'].value_counts()

print("The distribution of the types of avocado sold is as follows: {}".format
```

```
The distribution of the types of avocado sold is as follows: 0    9126
1    9124
Name: type, dtype: int64
```

Question 9 - Test drive the use of Gini Index, Information Gain, Entropy and other measures that are supported in your platform, performing the role of data selection.

In []:

```

import matplotlib.pyplot as plt
import numpy as np

def gini(p):
    return (p)*(1 - (p)) + (1 - p)*(1 - (1-p))

def entropy(p):
    return - p*np.log2(p) - (1 - p)*np.log2((1 - p))

def classification_error(p):
    return 1 - np.max([p, 1 - p])

x = np.arange(0.0, 1.0, 0.01)
ent = [entropy(p) if p != 0 else None for p in x]
scaled_ent = [e*0.5 if e else None for e in ent]
c_err = [classification_error(i) for i in x]

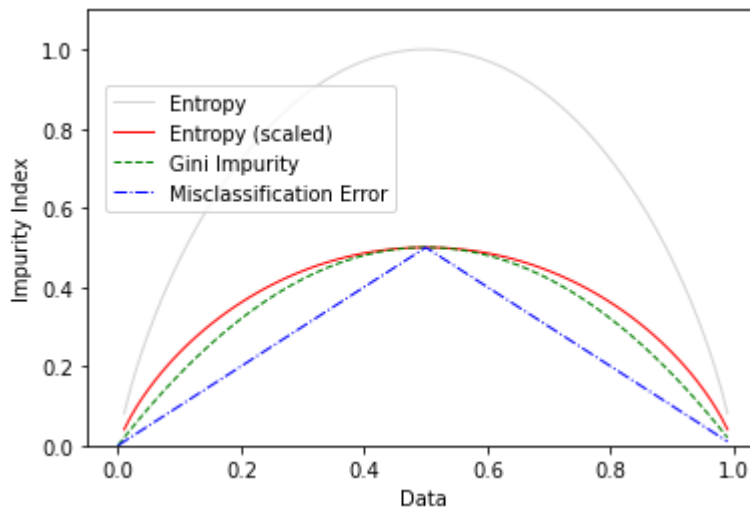
fig = plt.figure()
ax = plt.subplot(111)

for j, lab, ls, c, in zip(
    [ent, scaled_ent, gini(x), c_err],
    ['Entropy', 'Entropy (scaled)', 'Gini Impurity', 'Misclassification Error'],
    ['-', '-', '--', '-.'],
    ['lightgray', 'red', 'green', 'blue']):
    line = ax.plot(x, j, label=lab, linestyle=ls, lw=1, color=c)

ax.legend(loc='upper left', bbox_to_anchor=(0.01, 0.85), ncol=1, fancybox=True)

plt.ylim([0, 1.1])
plt.xlabel('Data')
plt.ylabel('Impurity Index')
plt.show()

```



Question 10 - Test drive the implementation support in your platform of choice for data preprocessing phases such as cleaning, selection, transformation, integration in addition to the earlier exercises.

```
In [ ]: from sklearn.impute import SimpleImputer
from sklearn.preprocessing import Normalizer
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import KBinsDiscretizer
```

```
In [ ]: df3 = pd.read_csv('auto.csv')
df3
```

```
Out[ ]:
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	modelyear	origin	car name
0	18.0	8	307.0	130.0	3504.0	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165.0	3693.0	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150.0	3436.0	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150.0	3433.0	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140.0	3449.0	10.5	70	1	ford torino
...
393	27.0	4	140.0	86.0	2790.0	15.6	82	1	ford mustang gl
394	44.0	4	97.0	52.0	2130.0	24.6	82	2	vw pickup
395	32.0	4	135.0	84.0	2295.0	11.6	82	1	dodge rampage
396	28.0	4	120.0	79.0	2625.0	18.6	82	1	ford ranger
397	31.0	4	119.0	82.0	2720.0	19.4	82	1	chevy

398 rows × 9 columns

```
In [ ]: df3.isnull().sum()
```

```
Out[ ]: mpg          0
cylinders        0
displacement     0
horsepower       6
weight           0
acceleration     0
modelyear        0
origin           0
```

car name 0

```
In [ ]: imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
imputer = imputer.fit(df3.iloc[:, 1:7])
df3.iloc[:, 1:7] = imputer.transform(df3.iloc[:, 1:7])
df3.iloc[330]
```

```
Out[ ]: mpg                40.9
cylinders                4.0
displacement             85.0
horsepower              104.469388
weight                 1835.0
acceleration            17.3
modelyear               80.0
origin                  2
car name                renault lecar deluxe
Name: 330, dtype: object
```

```
In [ ]: sc = StandardScaler(with_mean=False)
df3_stand = sc.fit_transform(df3.drop(['car name'], axis=1))
df3_stand = pd.DataFrame(df3_stand, columns=df3.columns.tolist()[:-1])
df3_stand
```

```
Out[ ]:
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	modelyear	origin
0	2.305872	4.709024	2.947990	3.407497	4.142935	4.356947	18.95489	1.248367
1	1.921560	4.709024	3.360900	4.324900	4.366398	4.175407	18.95489	1.248367
2	2.305872	4.709024	3.053618	3.931728	4.062535	3.993868	18.95489	1.248367
3	2.049664	4.709024	2.919182	3.931728	4.058988	4.356947	18.95489	1.248367
4	2.177768	4.709024	2.899977	3.669612	4.077906	3.812328	18.95489	1.248367
...
393	3.458807	2.354512	1.344360	2.254190	3.298741	5.664031	22.20430	1.248367
394	5.636575	2.354512	0.931450	1.362999	2.518394	8.931741	22.20430	2.496734
395	4.099327	2.354512	1.296347	2.201767	2.713480	4.211715	22.20430	1.248367
396	3.586911	2.354512	1.152309	2.070710	3.103654	6.753267	22.20430	1.248367
397	3.971223	2.354512	1.142706	2.149344	3.215977	7.043731	22.20430	1.248367

398 rows × 8 columns

```
In [ ]: nm = Normalizer()
df3_norm = nm.fit_transform(df3_stand)
df3_norm = pd.DataFrame(df3_norm)
df3_norm
```

```
Out[ ]:
```

	0	1	2	3	4	5	6	7
0	0.109335	0.223283	0.139782	0.161570	0.196441	0.206589	0.898763	0.059192
1	0.090261	0.221197	0.157872	0.203154	0.205103	0.196132	0.890369	0.058640

	0	1	2	3	4	5	6	7
2	0.109238	0.223085	0.144662	0.186261	0.192458	0.189205	0.897967	0.059140
3	0.096983	0.222814	0.138125	0.186035	0.192056	0.206155	0.896876	0.059068
4	0.103726	0.224289	0.138125	0.174783	0.194229	0.181580	0.902816	0.059459
...
393	0.145908	0.099324	0.056711	0.095092	0.139155	0.238934	0.936675	0.052662
394	0.225387	0.094149	0.037245	0.054502	0.100702	0.357149	0.887872	0.099836
395	0.175024	0.100528	0.055349	0.094006	0.115854	0.179822	0.948030	0.053300
396	0.149734	0.098288	0.048103	0.086441	0.129561	0.281912	0.926907	0.052112
397	0.164643	0.097616	0.047375	0.089110	0.133331	0.292026	0.920567	0.051756

```
In [ ]: disc = KBinsDiscretizer(n_bins=6, encode='ordinal', strategy='uniform')
df3_disc = pd.DataFrame(disc.fit_transform(df3_norm), columns=df3.columns.tolist())
df3_disc
```

```
Out[ ]:
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	modelyear	origin
0	1.0	5.0	3.0	2.0	3.0	1.0	2.0	0.0
1	1.0	5.0	4.0	4.0	3.0	1.0	2.0	0.0
2	1.0	5.0	4.0	3.0	3.0	1.0	2.0	0.0
3	1.0	5.0	3.0	3.0	3.0	1.0	2.0	0.0
4	1.0	5.0	3.0	3.0	3.0	1.0	3.0	0.0
...
393	2.0	0.0	0.0	1.0	1.0	2.0	5.0	0.0
394	5.0	0.0	0.0	0.0	0.0	5.0	2.0	2.0
395	3.0	0.0	0.0	1.0	0.0	0.0	5.0	0.0
396	2.0	0.0	0.0	0.0	1.0	3.0	4.0	0.0
397	3.0	0.0	0.0	1.0	1.0	3.0	4.0	0.0

398 rows × 8 columns

In []:

```
pip install mlxtend
```

```
Requirement already satisfied: mlxtend in c:\users\hp\anaconda3\lib\site-packages (0.19.0)
Requirement already satisfied: setuptools in c:\users\hp\anaconda3\lib\site-packages (from mlxtend) (52.0.0.post20210125)
Requirement already satisfied: pandas>=0.24.2 in c:\users\hp\anaconda3\lib\site-packages (from mlxtend) (1.2.4)
Requirement already satisfied: scikit-learn>=0.20.3 in c:\users\hp\anaconda3\lib\site-packages (from mlxtend) (0.24.1)
Requirement already satisfied: scipy>=1.2.1 in c:\users\hp\anaconda3\lib\site-packages (from mlxtend) (1.6.2)
Requirement already satisfied: matplotlib>=3.0.0 in c:\users\hp\anaconda3\lib\site-packages (from mlxtend) (3.3.4)
Requirement already satisfied: joblib>=0.13.2 in c:\users\hp\anaconda3\lib\site-packages (from mlxtend) (1.0.1)
Requirement already satisfied: numpy>=1.16.2 in c:\users\hp\anaconda3\lib\site-packages (from mlxtend) (1.20.1)
Requirement already satisfied: python-dateutil>=2.1 in c:\users\hp\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (2.8.1)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\hp\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (1.3.1)
Requirement already satisfied: cyclor>=0.10 in c:\users\hp\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (0.10.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 in c:\users\hp\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (2.4.7)
Requirement already satisfied: pillow>=6.2.0 in c:\users\hp\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (8.2.0)
Requirement already satisfied: six in c:\users\hp\anaconda3\lib\site-packages (from cyclor>=0.10->matplotlib>=3.0.0->mlxtend) (1.15.0)
Requirement already satisfied: pytz>=2017.3 in c:\users\hp\anaconda3\lib\site-packages (from pandas>=0.24.2->mlxtend) (2021.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\hp\anaconda3\lib\site-packages (from scikit-learn>=0.20.3->mlxtend) (2.1.0)
Note: you may need to restart the kernel to use updated packages.
```

In []:

```
from mlxtend.frequent_patterns import apriori, association_rules, fpgrowth
from mlxtend.preprocessing import TransactionEncoder
import matplotlib.pyplot as plt
from time import time
```

In []:

```
import pandas as pd
from sklearn.preprocessing import Binarizer, OneHotEncoder
```

In []:

```
df = pd.read_csv('Avocado Dataset.csv')
df1 = pd.read_csv('Trail.csv')
```

Question 11 - Test drive the basic version of Apriori algorithms for Frequent Itemset Mining using the package / library support in the platform of your choice. Test it with various support and confidence measures and generate a time comparison for varied data set sizes. To do the performance comparison you may use benchmark datasets provided for FIM such as the FIMI workshop or other sources.

```
In [ ]: def apriori_function(df):
df_out = df.apply(lambda x: list(x.dropna().values), axis=1).tolist()
te = TransactionEncoder()
out = te.fit(df_out).transform(df_out)
final = pd.DataFrame(out, columns=te.columns_)
frequent_itemsets = apriori(final, min_support=0.1, max_len=3, use_colnames=True)
rules = association_rules(frequent_itemsets, metric="confidence", min_threshold=0.5)
return frequent_itemsets, rules
```

Question 12 - Test drive the basic version of FP Growth algorithms for Frequent Itemset Mining using the package / library support in the platform of your choice. Test it with various support and confidence measures and generate a time comparison for varied data set sizes. To do the performance comparison you may use benchmark datasets provided for FIM such as the FIMI workshop or other sources.

```
In [ ]: def fp_growth_function(df):
df_out = df.apply(lambda x: list(x.dropna().values), axis=1).tolist()
te = TransactionEncoder()
out = te.fit(df_out).transform(df_out)
chess = pd.DataFrame(out, columns=te.columns_)
frequent_itemsets = fpgrowth(chess, min_support=0.1, max_len=3, use_colnames=True)
rules = association_rules(frequent_itemsets, metric="confidence", min_threshold=0.5)
return frequent_itemsets, rules
```

Question 14 - Mine frequent itemsets using FP-Growth* algorithm.

```
In [ ]: df = pd.read_csv('connect.dat', header=None, sep='\n')
df = df[0].str.split(' ', expand=True)
freq, rules = fp_growth_function(df)

print(freq)
print(rules)
```

	support	itemsets		
0	1.000000	(109)		
1	1.000000	(67)		
2	1.000000	(16)		
3	1.000000	(34)		
4	1.000000	(37)		
...		
25905	0.319783	(44, 97, 72)		
25906	0.319783	(7, 44, 72)		
25907	0.308943	(44, 72, 115)		
25908	0.360434	(44, 82, 72)		
25909	0.325203	(44, 79, 72)		
[25910 rows x 2 columns]				
	antecedents	consequents	antecedent support	consequent support \
0	(109)	(67)	1.000000	1.000000
1	(67)	(109)	1.000000	1.000000
2	(16)	(67)	1.000000	1.000000
3	(67)	(16)	1.000000	1.000000
4	(16)	(109)	1.000000	1.000000
...
104276	(82, 72)	(44)	0.493225	0.791328
104277	(72)	(44, 82)	0.498645	0.785908

104278	(44, 72)	(79)	0.365854	0.940379
104279	(79, 72)	(44)	0.452575	0.791328
104280	(72)	(44, 79)	0.498645	0.737127

	support	confidence	lift	leverage	conviction
0	1.000000	1.000000	1.000000	0.000000	inf
1	1.000000	1.000000	1.000000	0.000000	inf
2	1.000000	1.000000	1.000000	0.000000	inf
3	1.000000	1.000000	1.000000	0.000000	inf
4	1.000000	1.000000	1.000000	0.000000	inf
...
104276	0.360434	0.730769	0.923472	-0.029869	0.775068
104277	0.360434	0.722826	0.919734	-0.031455	0.772411
104278	0.325203	0.888889	0.945245	-0.018838	0.536585
104279	0.325203	0.718563	0.908047	-0.032932	0.741452
104280	0.325203	0.652174	0.884751	-0.042362	0.755759

```
[104281 rows x 9 columns]
```