UNIVERSITY OF MALAYA

EXAMINATION FOR THE DEGREE OF MASTER OF DATA SCIENCE

ACADEMIC SESSION 2019/2020 : SEMESTER II

WQD7005 : Data Mining

June 2020

INSTRUCTIONS TO CANDIDATES :

Answer **ALL** questions (50 marks).

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Link to codes and data:
https://github.com/Nurullainy/Data-Mining-Final-Exam

Link to video :
https://drive.google.com/drive/folders/1hMqLYw5ubSpMRsPvyJwjDG8MuV3GO_Qt?usp=sharing

(This question paper consists of 5 questions on 3 printed pages)

Mini-assignment (50 marks)

Instructions: Work individually, submission via Spectrum.

1. You are required to make a user-agent that will crawl the WWW (your familiar domain) to produce dataset of a particular website.
   - the web site can be as simple as a list of webpages and what other pages they link to
   - the output does not need to be in XHTML (or HTML) form a multi-stage approach (e.g. produce the xhtml or html in csv format)

(10 marks)

2. Draw snowflake schema diagram for the above dataset. Justify your attributes to be selected in the respective dimensions.

(10 marks)

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

In [2]:
```
import pandas as pd
import numpy as np

import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px

from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor

from sklearn.tree import export_graphviz
from sklearn.model_selection import GridSearchCV
import pydot
from io import StringIO
from sklearn.tree import export_graphviz
```

   - Loading Data

```
In [3]: # Load dataset

df = pd.read_csv('movies_imdb_preprocessed.csv')
df.head()
```

Out[3]:

	movie_name	year_released	runtime_in_min	genre	revenues	imdb_rating	user_votes	director	actor
0	Gladiator	2000	155	Action, Adventure, Drama	187705427.0	8.5	1295546	Ridley Scott	Russell Crowe, Joaquin Phoenix, Connie Nielsen...
1	Memento	2000	113	Mystery, Thriller	25544867.0	8.4	1088700	Christopher Nolan	Guy Pearce, Carrie-Anne Moss, Joe Pantoliano, ...
2	Snatch	2000	104	Comedy, Crime	30328156.0	8.3	760646	Guy Ritchie	Jason Statham, Brad Pitt, Benicio Del Toro, De...
3	Requiem for a Dream	2000	102	Drama	3635482.0	8.3	742193	Darren Aronofsky	Ellen Burstyn, Jared Leto, Jennifer Connelly, ...
4	X-Men	2000	104	Action, Adventure, Sci-Fi	157299717.0	7.4	558716	Bryan Singer	Patrick Stewart, Hugh Jackman, Ian McKellen, F...

```
In [4]: # Remove NAs and unused attribute

df.dropna(how='any', inplace=True)
df = df.drop(['movie_name'], axis=1)
```

```
In [7]: # Preprocessing revenues column

df_revenue = df['revenues'].div(1000000).to_frame('col') # Change to Million notation
df_revenue.shape

df['revenues'] = df_revenue['col']

df['revenues'] = df['revenues'].round(0).astype(int)
#df.columns = ['revenues in mil']  # Rename the columns name
```

```
In [8]: # Change data to categorical variables

df['year_released'] = df['year_released'].astype('str')
df['genre'] = df['genre'].astype('str')
df['director'] = df['director'].astype('str')
df['actor'] = df['actor'].astype('str')
```

```
In [9]: # one hot encoding all categorical variables
# all numerical variables are automatically excluded
# number of columns after the conversion should explode
print("Before:", len(df.columns))

# one hot encoding
df = pd.get_dummies(df)

print("After:", len(df.columns))

Before: 8
After: 1351
```

- Feature Selection

```
In [11]: # Find average revenue number to estimate a threshold

df['revenues'].mean()

Out[11]: 122.46446078431373
```

Based on average revenue, I set USD 100 million as threshold to binarize the target variable

```
In [12]: # Change revenues column to binary variables

         threshold, upper, lower = 100, 1, 0

         df['revenues'] = np.where(df['revenues']>threshold, upper, lower)
```

```
In [13]: df['revenues'].unique()
Out[13]: array([1, 0])
```

```
In [31]: df.head()
Out[31]:
```

	runtime_in_min	revenues	imdb_rating	user_votes	year_released_2000	year_released_2001	year_released_2002	year_released_2003	year_released_2004	ye
0	155	1	8.5	1295546	1	0	0	0	0	
1	113	0	8.4	1088700	1	0	0	0	0	
2	104	0	8.3	760646	1	0	0	0	0	
3	102	0	8.3	742193	1	0	0	0	0	
4	104	1	7.4	558716	1	0	0	0	0	

5 rows × 1351 columns

```
In [14]: # Assigning X and y variables. y variable is revenues in mil while the rest of the variables are X variables

         X = df.drop(['revenues'], axis=1)
         y = df['revenues']
```

- Splitting Data

```
In [15]: # Setting random state = 0
         rs = 0

         # Training set = 70%
         # Test Set = 30%
         # Stratify = Yes
         X_mat = np.asmatrix(X)
         X_train, X_test, y_train, y_test = train_test_split(X_mat, y, test_size=0.3, stratify=y, random_state=rs)
```

As train_test_split shuffles the dataset before splitting it, it is important to set a consistent random state, which is the seed number used to generate the shuffle. I am using 0 for random state number

Convert X (DataFrame object) into a numpy matrix that can be consumed by sklearn. Next, use the train_test_split function to split dataset into 70% training and 30% test data. This is to ensure there is enough representation of the minority class in the training set. In this case, I need larger training set, which is 70/30.

Stratification method ensures the same ratio of positive and negative targets in both train and test data set.

- Building Decision Tree Model

Initialise a model and training it using .fit function.

```
In [16]: # Decision tree training

         model = DecisionTreeClassifier()
         model.fit(X_train, y_train)

Out[16]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                                max_features=None, max_leaf_nodes=None,
                                min_impurity_decrease=0.0, min_impurity_split=None,
                                min_samples_leaf=1, min_samples_split=2,
                                min_weight_fraction_leaf=0.0, presort=False,
                                random_state=None, splitter='best')
```

- Evaluating Model

```
In [17]: print("Train accuracy:", model.score(X_train, y_train))

         Train accuracy: 1.0
```

It seems that the model has managed to learn all of the patterns in training data and is able to predict with 100% accuracy. However, need to check whether it can replicate the performance on similar data that it is not trained on (test data).

```
In [18]: print("Test accuracy:", model.score(X_test, y_test))

         Test accuracy: 0.7224489795918367
```

This is a clear indication of overfitting of the model. This model will fail to make accurate predictions with new data because it learned the training data too well. Need to make the model generalize better on training dataset.

I'm using classification_report() function to assess the model's prediction on test data. classification_report() outputs a number of statistics for each target class:

1. Precision: Proportion of all positive predictions that are correct. Precision is a measure of how many positive predictions were actual positive observations.
2. Recall: Proportion of all real positive observations that are correct. Precision is a measure of how many actual positive observations were predicted correctly.
3. F1: The harmonic mean of precision and recall. F1 score is an 'average' of both precision and recall.
4. Support: Number of instances in each class.

```
In [19]: y_pred = model.predict(X_test)

         print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.74      0.75      0.74       132
           1       0.70      0.69      0.70       113

    accuracy                           0.72       245
   macro avg       0.72      0.72      0.72       245
weighted avg       0.72      0.72      0.72       245
```

To understand the Decision Tree model built, lets view the feature importance and visualize the tree using sklearn module.

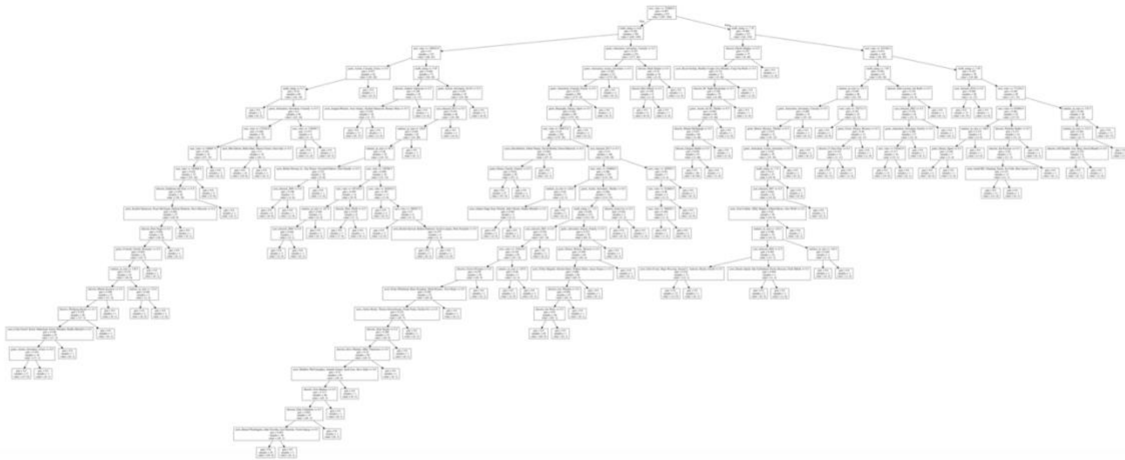
- Visualizing Decision Trees

```
In [20]: # grab feature importances from the model and feature name from the original X
         importances = model.feature_importances_
         feature_names = X.columns

         # sort them out in descending order
         indices = np.argsort(importances)
         indices = np.flip(indices, axis=0)

         # Print 10 most important features
         indices = indices[:10]

         for i in indices:
             print(feature_names[i], ':', importances[i])
```

```
user_votes : 0.33192163958645887
imdb_rating : 0.14176438634151728
runtime_in_min : 0.08031531119929572
genre_Animation, Adventure, Comedy : 0.03344948847789565
year_released_2013 : 0.017474449105946074
genre_Animation, Action, Adventure : 0.01494659694261953
genre_Action, Adventure, Sci-Fi : 0.013854789878016046
genre_Animation, Comedy, Family : 0.01016894017695399
genre_Biography, Drama, Sport : 0.009785232690288675
year_released_2001 : 0.008648437889323644
```

We can't really gain insights of the decision tree with feature importance only. Need to perform feature importance and visualization to understand the decision tree model. Use export_graphviz function and pydot module and save .png file to view the decision tree.

In [21]:
```
# Visualize the 1st Decision Tree

dotfile = StringIO()
export_graphviz(model, out_file=dotfile, feature_names=X.columns)

graph = pydot.graph_from_dot_data(dotfile.getvalue())
graph[0].write_png("dt1.png")
```



The above tree shows that the model is very complex, incomprehensible, and deep, which is a typical characteristic of an overfitting model. I want to limit the complexity of the model by setting the max_depth that the model can go. max_depth in a decision tree is a hyperparameter for structuring the depth of the tree (model).

In [22]:
```
# Retrain model with a smaller max_depth limit = 9

model = DecisionTreeClassifier(max_depth=9, random_state=rs)
model.fit(X_train, y_train)

print("Train accuracy:", model.score(X_train, y_train),"\nTest accuracy:", model.score(X_test, y_test))
print()

y_pred = model.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
Train accuracy: 0.9124343257443083
Test accuracy: 0.7020408163265306

              precision    recall  f1-score   support

           0       0.70      0.78      0.74       132
           1       0.70      0.61      0.65       113

    accuracy                           0.70       245
   macro avg       0.70      0.70      0.70       245
weighted avg       0.70      0.70      0.70       245
```

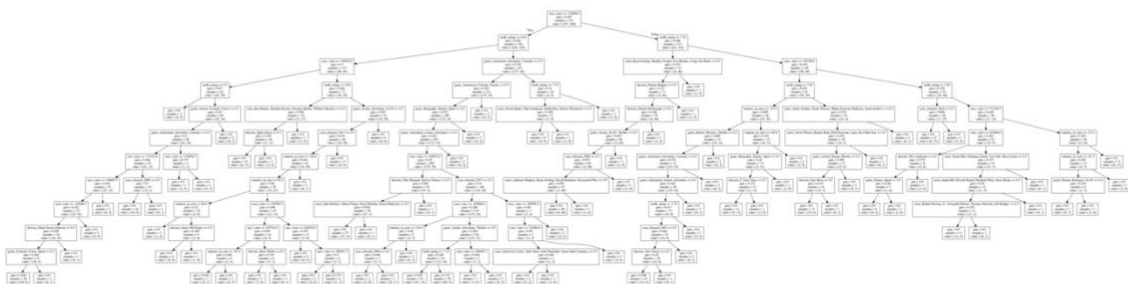
The simpler model (smaller max_depth) resulting the accuracy of the model on training data reduce to 91.2%. This means that model notes there is a trend in the data but not learning the training data too well.

View new feature importance and visualize this new decision tree.

```
In [41]: importances = model.feature_importances_
         feature_names = X.columns

         # sort them out in descending order
         indices = np.argsort(importances)
         indices = np.flip(indices, axis=0)

         # Print 10 variable X
         indices = indices[:10]

         for i in indices:
             print(feature_names[i], ':', importances[i])
```

```
user_votes : 0.3768873337944813
imdb_rating : 0.16509594141580766
runtime_in_min : 0.07063236145916083
genre_Animation, Adventure, Comedy : 0.04790613932512415
genre_Animation, Action, Adventure : 0.020414692785475655
genre_Biography, Drama, Sport : 0.018912354024285566
genre_Action, Adventure, Sci-Fi : 0.016971881080745224
year_released_2000 : 0.01642744187308721
year_released_2013 : 0.014008536765059568
genre_Animation, Comedy, Family : 0.01198674299857236
```

```
In [42]: # Visualize the new tree

         dotfile = StringIO()
         export_graphviz(model, out_file=dotfile, feature_names=X.columns)
         graph = pydot.graph_from_dot_data(dotfile.getvalue())
         graph[0].write_png("dt2.png") # saved in the following file
```



This looks better from the first model. However, the tree has more 20 leaf nodes here. Furthermore, there are a number of samples and value splits in each node.

Next is to find the optimal combination of parameters for the model.

Finding optimal Hyperparameters with GridSearchCV

A common method to find the optimal set of parameters for a model is to run an exhaustive search over all possible values of each parameter. Cross validation typically used to prevent overfitting.

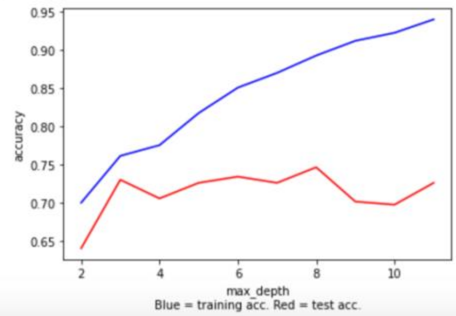
Grid-search builds a model for every combination of hyperparameters specified and evaluates each model.

In sklearn, the grid-search and k-fold validation is implemented in *GridSearchCV*.

Begin with plotting max_depth values vs training and test accuracy score to a give an idea of the optimal max_depth.

```
In [43]: test_score = []
         train_score = []

         # check the model performance for max depth from 2-12
         for max_depth in range(2, 12):
             model = DecisionTreeClassifier(max_depth=max_depth, random_state=rs)
             model.fit(X_train, y_train)

             test_score.append(model.score(X_test, y_test))
             train_score.append(model.score(X_train, y_train))
```

```
In [44]: # plot max depth hyperparameter values vs training and test accuracy score

         plt.plot(range(2, 12), train_score, 'b', range(2,12), test_score, 'r')
         plt.xlabel('max_depth\nBlue = training acc. Red = test acc.')
         plt.ylabel('accuracy')
         plt.show()
```



To perform a GridSearchCV, we first have to determine the hyperparameters and possible values of parameters that we want to use. A model hyperparameter is a characteristic of a model that is external to the model and whose value cannot be estimated from data.

For decision tree model, I will search on 3 hyperparameters:

- Criterion: The function to measure the quality of a split. There are two criterias we will use, “gini” for the Gini impurity and “entropy” for the information gain.
- Max depth: The maximum depth of the tree. Let's start with range of 2-11.
- Min samples leaf: The minimum number of samples required to be at a leaf node, allowing us to limit the minimum size of a leaf node. Let's start with range of 20-60 with step of 10.

In [27]:
```
# GridsearchCV #1

params = {'criterion': ['gini', 'entropy'],
          'max_depth': range(1, 10),
          'min_samples_leaf': range(20, 60, 10)}

cv = GridSearchCV(param_grid=params, estimator=DecisionTreeClassifier(random_state=rs), cv=10)
cv.fit(X_train, y_train)

print("Train accuracy:", cv.score(X_train, y_train))
print("Test accuracy:", cv.score(X_test, y_test))

# test the best model
y_pred = cv.predict(X_test)
print(classification_report(y_test, y_pred))

# print parameters of the best model
print(cv.best_params_)
```

```
Train accuracy: 0.7495621716287215
Test accuracy: 0.7183673469387755
              precision    recall  f1-score   support

           0       0.71      0.81      0.76       132
           1       0.73      0.61      0.67       113

    accuracy                           0.72       245
   macro avg       0.72      0.71      0.71       245
weighted avg       0.72      0.72      0.71       245

{'criterion': 'gini', 'max_depth': 4, 'min_samples_leaf': 40}
```

The accuracy score for the 3rd model is 72% which improved from the 2nd model, 70%. At the same time, the Precision is increased by 2% from the previous model. I want to fine tune and further optimise on the parameters if possible.

At this moment, the metric Recall (sensitivity) is acceptable at 81% and 61%.

Let's do another grid search, now being more specific based on the 1st grid search result.

In [28]:
```
# GridsearchCV #2

params = {'criterion': ['gini'],
          'max_depth': range(1, 6),
          'min_samples_leaf': range(40, 60, 5)}

cv = GridSearchCV(param_grid=params, estimator=DecisionTreeClassifier(random_state=rs), cv=10)
cv.fit(X_train, y_train)

print("Train accuracy:", cv.score(X_train, y_train))
print("Test accuracy:", cv.score(X_test, y_test))

# test the best model
y_pred = cv.predict(X_test)
print(classification_report(y_test, y_pred))

# print parameters of the best model
print(cv.best_params_)
```

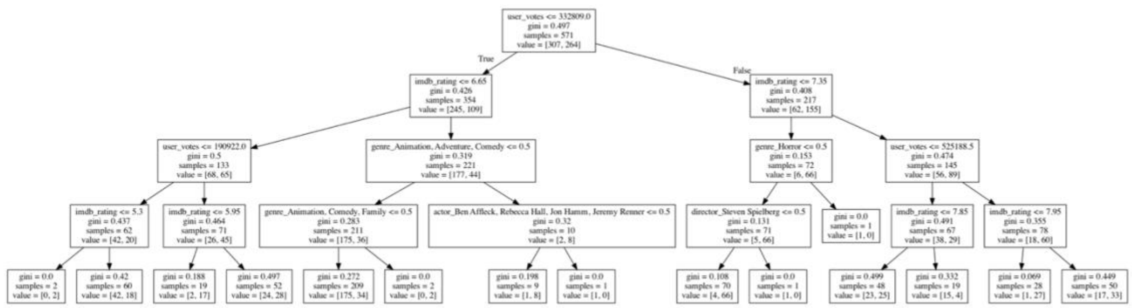
```
Train accuracy: 0.7495621716287215
Test accuracy: 0.7183673469387755
              precision    recall  f1-score   support

           0       0.71      0.81      0.76       132
           1       0.73      0.61      0.67       113

    accuracy                           0.72       245
   macro avg       0.72      0.71      0.71       245
weighted avg       0.72      0.72      0.71       245

{'criterion': 'gini', 'max_depth': 4, 'min_samples_leaf': 45}
```

The classification report of 4th model return not much different from the 3rd model. Both models have same weighted average score for Accuracy, Precision and Recall. In this case, I will retrain a new model based simpler hyperparameter, *being only 4 levels deep.*

In [69]:
```python
# Retrain final model with optimal parameter, max_depth limit = 4

model = DecisionTreeClassifier(max_depth=4, random_state=rs)
model.fit(X_train, y_train)

print("Train accuracy:", model.score(X_train, y_train),"\nTest accuracy:", model.score(X_test, y_test))
print()
```

```
Train accuracy: 0.7758318739054291
Test accuracy: 0.7061224489795919
```

In [70]:
```python
# Visualize the optimal tree

dotfile = StringIO()
export_graphviz(model, out_file=dotfile, feature_names=X.columns)

graph = pydot.graph_from_dot_data(dotfile.getvalue())
graph[0].write_png("optimal_tree.png") # saved in the following file
```



Note for Leaf node:

1. **True**: The movie will generate USD 100 million and above
2. **False**: The movie will generate less than USD 100 million

(10 marks)

4. 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

In [182]:
```python
import pandas as pd
import numpy as np

from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import fpgrowth
from mlxtend.frequent_patterns import association_rules

import csv
```

In [183]:
```python
# Load dataset

df = pd.read_csv('movies_imdb_preprocessed.csv')
df.head()
```

Out[183]:

	movie_name	year_released	runtime_in_min	genre	revenues	imdb_rating	user_votes	director	actor
0	Gladiator	2000	155	Action, Adventure, Drama	187705427	8.5	1295546	Ridley Scott	Russell Crowe, Joaquin Phoenix, Connie Nielsen...
1	Memento	2000	113	Mystery, Thriller	25544867	8.4	1088700	Christopher Nolan	Guy Pearce, Carrie-Anne Moss, Joe Pantoliano, ...
2	Snatch	2000	104	Comedy, Crime	30328156	8.3	760646	Guy Ritchie	Jason Statham, Brad Pitt, Benicio Del Toro, De...
3	Requiem for a Dream	2000	102	Drama	3635482	8.3	742193	Darren Aronofsky	Ellen Burstyn, Jared Leto, Jennifer Connelly, ...
4	X-Men	2000	104	Action, Adventure, Sci-Fi	157299717	7.4	558716	Bryan Singer	Patrick Stewart, Hugh Jackman, Ian McKellen, F...

- Creating a list from dataset (Question 1)

In [9]:
```python
# Create new subset of dataset

revenue_actor = df[['revenues', 'genre']]

revenue_actor.head(10)
```

Out[9]:

	revenues	genre
0	187705427	Action, Adventure, Drama
1	25544867	Mystery, Thriller
2	30328156	Comedy, Crime
3	3635482	Drama
4	157299717	Action, Adventure, Sci-Fi
5	233632142	Adventure, Drama, Romance
6	15070285	Comedy, Crime, Drama
7	95011339	Drama, Mystery, Sci-Fi
8	215409889	Action, Adventure, Thriller
9	166244045	Comedy, Romance

Consolidate the items into each revenue number, in this case revenues in million

```
In [50]: # Group actor by revenue generated (298 unique revenue number)

         basket = revenue_actor.groupby(['revenues in mil'])['genre'].apply(list)

         print("\n", basket[:6])
```

```
 revenues in mil
0    [Action, Crime, Thriller, Crime, Drama, Myster...
1    [Drama, Mystery, Sci-Fi, Action, Drama, Sci-Fi...
2    [Crime, Drama, Crime, Drama, Comedy, Romance, ...
3                                     [Drama, Romance]
4    [Drama, Crime, Drama, Musical, Comedy, Drama, ...
5    [Drama, Thriller, Animation, Adventure, Family...
Name: genre, dtype: object
```

```
In [51]: # List all the actor in list format (for model preparation)

         basket_list = list(basket)

         print("\n", basket_list[:10])
```

```
 [['Action, Crime, Thriller', 'Crime, Drama, Mystery', 'Action, Crime, Drama', 'Crime, Drama, Sport', 'Adventure, C
omedy, Sci-Fi', 'Drama', 'Drama, Fantasy, Romance', 'Comedy, Horror', 'Action, Adventure, Drama'], ['Drama, Mystery
, Sci-Fi', 'Action, Drama, Sci-Fi', 'Action, Drama, Mystery', 'Drama, Thriller', 'Drama, Thriller', 'Drama'], ['Cri
me, Drama', 'Crime, Drama', 'Comedy, Romance, Sport', 'Drama, Horror, Romance', 'Biography, Crime, Drama'], ['Drama
, Romance'], ['Drama', 'Crime, Drama, Musical', 'Comedy, Drama, Romance', 'Action, Comedy, Crime', 'Sci-Fi, Thrille
r'], ['Drama, Thriller', 'Animation, Adventure, Family', 'Drama, Mystery, Sci-Fi', 'Action, Drama, Sci-Fi', 'Animat
ion, Drama, Fantasy'], ['Comedy, Drama', 'Biography, Drama, History', 'Drama, Romance', 'Action, Crime, Thriller',
'Drama, Mystery, Romance', 'Action, Adventure, Comedy', 'Comedy, Drama'], ['Drama, Mystery, Thriller', 'Comedy, Dra
ma', 'Drama'], ['Crime, Drama', 'Comedy, Crime, Drama'], ['Comedy, Drama, Romance']]
```

- Convert list to dataframe with Boolean values

```
In [52]: # Convert list to dataframe with Boolean values

         te = TransactionEncoder()
         te_ary = te.fit(basket_list).transform(basket_list)

         df2 = pd.DataFrame(te_ary, columns=te.columns_)
         df2.head(10)
```

Out[52]:

	Action, Adventure	Action, Adventure, Biography	Action, Adventure, Comedy	Action, Adventure, Crime	Action, Adventure, Drama	Action, Adventure, Family	Action, Adventure, Fantasy	Action, Adventure, History	Action, Adventure, Horror	Action, Adventure, Mystery	...	Horror	Horror, Mystery	Horror, Mystery, Thriller	Hor Sc
0	False	False	False	False	True	False	False	False	False	False	...	False	False	False	Fa
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fa
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fa
3	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fa
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fa
5	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fa
6	False	False	True	False	False	False	False	False	False	False	...	False	False	False	Fa
7	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fa
8	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fa
9	False	False	False	False	False	False	False	False	False	False	...	False	False	False	Fa

10 rows × 157 columns

The above table shows the distribution of each movie genre(s) in one revenue number. *False* indicates no genre(s) by the specific revenue number whereas *True* indicates that the movie genre(s) falls under that specific revenue number.

- Find frequently occurring itemsets using Apriori Algorithm

1) Pros: Easy to code up
2) Cons: May be slow on large datasets
3) Works with: Numeric values, nominal values

General approach to the Apriori algorithm:

1) Preparation: Any data type will work because we storing sets.
2) Train: Use the Apriori algorithm to find frequent itemsets.
3) Test: Doesn't apply.
4) Application: This will be used to find frequent itemsets and association rules between items.

`Apriori` is an algorithm for frequent itemset mining and Association Rule learning over relational databases. The algorithm identify the frequent individual items in the database and extending them to larger and larger itemsets as long as those itemsets appear sufficiently often in the database.

The frequent itemsets determined by `Apriori` can be used to generate `Association Rules` which highlight general trends in the database. This application is widely used in market basket analysis.

The Support and Confidence are measures to measure how interesting a rule is. These parameters are used to exclude rules in the result that have a Support or a Confidence lower than the minimum support and minimum confidence respectively. *I have experimented a number trial of minimum support number and 0.01 is the best for this dataset.*

In [59]:
```
# Frequently occurring itemsets using Apriori Algorithm

frequent_itemsets_apriori = apriori(df2, min_support=0.01,
                                    use_colnames=True).sort_values(by='support', ascending=0)
frequent_itemsets_apriori.head(10)
```

Out[59]:

	support	itemsets
7	0.204698	(Action, Adventure, Sci-Fi)
31	0.117450	(Animation, Adventure, Comedy)
5	0.097315	(Action, Adventure, Fantasy)
39	0.083893	(Comedy)
45	0.080537	(Comedy, Drama, Romance)
3	0.070470	(Action, Adventure, Drama)
1	0.070470	(Action, Adventure, Comedy)
51	0.057047	(Crime, Drama, Thriller)
10	0.057047	(Action, Comedy, Crime)
48	0.057047	(Comedy, Romance)

The 1st row shows that (Action, Adventure, Sci-Fi) has support value of 0.204698 which means it occurred 167 times in the dataset. Let's view all itemset frequency in dataframe

```
In [60]: # Frequently occurring itemsets using Apriori Algorithm
         # Adding new column frequency (number of occurence) of each itemset

         frequent_itemsets_apriori['frequency'] = frequent_itemsets_apriori['support'].mul(816)  # 816 is total of transactio
         frequent_itemsets_apriori['frequency'] = frequent_itemsets_apriori['frequency'].round(0).astype(int)
         frequent_itemsets_apriori = frequent_itemsets_apriori[frequent_itemsets_apriori.columns[[1,2,0]]]

         frequent_itemsets_apriori
```

Out[60]:

	itemsets	frequency	support
7	(Action, Adventure, Sci-Fi)	167	0.204698
31	(Animation, Adventure, Comedy)	96	0.117450
5	(Action, Adventure, Fantasy)	79	0.097315
39	(Comedy)	68	0.083893
45	(Comedy, Drama, Romance)	66	0.080537
3	(Action, Adventure, Drama)	58	0.070470
1	(Action, Adventure, Comedy)	58	0.070470
51	(Crime, Drama, Thriller)	47	0.057047
10	(Action, Comedy, Crime)	47	0.057047
48	(Comedy, Romance)	47	0.057047
13	(Action, Crime, Thriller)	47	0.057047
42	(Comedy, Drama)	44	0.053691
61	(Drama, Romance)	44	0.053691
8	(Action, Adventure, Thriller)	44	0.053691
12	(Action, Crime, Sci-Fi)	8	0.010067
18	(Action, Fantasy, Horror)	8	0.010067
19	(Action, Fantasy, Thriller)	8	0.010067
25	(Adventure, Comedy, Drama)	8	0.010067
27	(Adventure, Comedy, Sci-Fi)	8	0.010067
34	(Biography, Comedy, Drama)	8	0.010067
44	(Comedy, Drama, Music)	8	0.010067
46	(Comedy, Family, Fantasy)	8	0.010067
58	(Drama, Mystery, Romance)	8	0.010067
86	(Action, Adventure, Sci-Fi, Comedy, Romance)	8	0.010067
62	(Drama, Romance, Sci-Fi)	8	0.010067
72	(Action, Adventure, Comedy, Action, Crime, Thr...	8	0.010067
75	(Action, Adventure, Sci-Fi, Action, Adventure,...	8	0.010067
76	(Action, Adventure, Drama, Action, Crime, Drama)	8	0.010067
77	(Comedy, Drama, Romance, Action, Adventure, Fa...	8	0.010067
79	(Action, Adventure, Sci-Fi, Action, Crime, Thr...	8	0.010067
83	(Action, Adventure, Sci-Fi, Biography, Drama)	8	0.010067
84	(Comedy, Action, Adventure, Sci-Fi)	8	0.010067
85	(Comedy, Drama, Action, Adventure, Sci-Fi)	8	0.010067
112	(Action, Adventure, Comedy, Comedy, Comedy, Dr...	8	0.010067

113 rows × 3 columns

- Find frequently occurring itemsets using F-P Growth

  The FP-Growth Algorithm is an alternative way to find frequent itemsets. It uses a divide-and-conquer strategy where the core of this method is the usage of pattern fragment growth named frequent-pattern tree (FP-tree). This method retains the itemset association information using an extended prefix-tree structure for storing information about frequent patterns.

This method is proven to be more efficient and scalable for mining the complete set of frequent patterns over other algorithm such as Apriori Algorithm.

1) Pros: Usually faster than Apriori.
2) Cons: Not possible to hold the FP-tree in the main memory. Partition the database into a set of smaller databases and then construct an FP-tree from each of these smaller databases.
3) Works with Nominal values.

General approach to FP-growth algorithm:

1) Preparation: Discrete data is needed because we're storing sets. For continuous data, it will need to be quantized into discrete values.
2) Train: Build an FP-tree and mine the tree.
3) Test: Doesn't apply.
4) Application: This can be used to identify commonly occurring items that can be used to make decisions, suggest items, make forecasts, and so on.

I have experimented a number trial of minimum support number and 0.01 is the best for this dataset.

In [62]:
```
# Frequently occurring itemsets using F-P Growth (Frequent Pattern Growth)

frequent_itemsets_fpgrowth = fpgrowth(df2, min_support=0.01,
                                      use_colnames=True).sort_values(by='support', ascending=0)
frequent_itemsets_fpgrowth.head(10)
```

Out[62]:

	support	itemsets
39	0.204698	(Action, Adventure, Sci-Fi)
37	0.117450	(Animation, Adventure, Comedy)
45	0.097315	(Action, Adventure, Fantasy)
33	0.083893	(Comedy)
15	0.080537	(Comedy, Drama, Romance)
0	0.070470	(Action, Adventure, Drama)
18	0.070470	(Action, Adventure, Comedy)
1	0.057047	(Action, Crime, Thriller)
32	0.057047	(Crime, Drama, Thriller)
16	0.057047	(Action, Comedy, Crime)

There are 113 number of itemsets found by F-P Growth algorithm in this dataset.

The 1st row shows that (Action, Adventure, Sci-Fi) has support value of 0.204698 which means it occurred 167 times in the dataset. Let's view all itemsets frequency in dataframe

In [65]:
```python
# Frequently occurring itemsets using F-P Growth (Frequent Pattern Growth)
# Adding new column number of occurence (frequency) of each itemset

frequent_itemsets_fpgrowth['frequency'] = frequent_itemsets_fpgrowth['support'].mul(816)  # 816 is total of transact
frequent_itemsets_fpgrowth['frequency'] = frequent_itemsets_fpgrowth['frequency'].round(0).astype(int)
frequent_itemsets_fpgrowth = frequent_itemsets_fpgrowth[frequent_itemsets_fpgrowth.columns[[1,2,0]]]

frequent_itemsets_fpgrowth
```

Out[65]:

	itemsets	frequency	support
39	(Action, Adventure, Sci-Fi)	167	0.204698
37	(Animation, Adventure, Comedy)	96	0.117450
45	(Action, Adventure, Fantasy)	79	0.097315
33	(Comedy)	68	0.083893
15	(Comedy, Drama, Romance)	66	0.080537
0	(Action, Adventure, Drama)	58	0.070470
18	(Action, Adventure, Comedy)	58	0.070470
1	(Action, Crime, Thriller)	47	0.057047
32	(Crime, Drama, Thriller)	47	0.057047
16	(Action, Comedy, Crime)	47	0.057047
44	(Comedy, Romance)	47	0.057047
14	(Drama, Romance)	44	0.053691
63	(Action, Adventure, Thriller)	44	0.053691
19	(Comedy, Drama)	44	0.053691
7	(Adventure, Comedy, Sci-Fi)	8	0.010067
21	(Drama, Mystery, Romance)	8	0.010067
24	(Adventure, Comedy, Drama)	8	0.010067
25	(Drama, Music)	8	0.010067
26	(Action, Crime, Sci-Fi)	8	0.010067
27	(Biography, Comedy, Drama)	8	0.010067
35	(Drama, Horror, Mystery)	8	0.010067
41	(Drama, Romance, Sci-Fi)	8	0.010067
43	(Comedy, Drama, Music)	8	0.010067
59	(Action, Biography, Drama)	8	0.010067
82	(Drama, Romance, Action, Crime, Thriller)	8	0.010067
64	(Comedy, Family, Fantasy)	8	0.010067
70	(Action, Adventure)	8	0.010067
71	(Action, Adventure, Sci-Fi, Action, Adventure,...	8	0.010067
72	(Action, Adventure, Comedy, Action, Crime, Thr...	8	0.010067
73	(Comedy, Romance, Action, Crime, Thriller)	8	0.010067
74	(Action, Adventure, Sci-Fi, Action, Crime, Thr...	8	0.010067
75	(Action, Adventure, Drama, Action, Crime, Drama)	8	0.010067
78	(Comedy, Romance, Crime, Drama, Mystery)	8	0.010067
80	(Comedy, Drama, Drama, Mystery, Sci-Fi)	8	0.010067
112	(Comedy, Drama, Romance, Action, Adventure, Fa...	8	0.010067

113 rows × 3 columns

- Mine the Association Rules

  Association rules analysis is a technique to uncover how items are associated to each other. There are 3 common ways to measure association:

  1) Measure 1: **Support** - This says how popular an itemset is, as measured by the proportion of transactions in which an itemset appears. If we

discover that genre of certain movie beyond a certain proportion, we might consider using that proportion as our support threshold. Thus, we identify itemsets with support values above this threshold as significant itemsets.

2) Measure 2: **Confidence** - This says how likely genre B is chosen when genre A is chosen, expressed as {A -> B}. This is measured by the proportion of transactions with genre A, in which genre B also appears. One drawback of the confidence measure is that it might misrepresent the importance of an association. This is because it only accounts for how popular A are, but not B. If B are also very popular in general, there will be a higher chance that a transaction containing A will also contain B, thus inflating the confidence measure. To account for the base popularity of both items, we use a third measure called Lift.
3) Measure 3: `Lift`. This says how likely item B is purchased when item A is purchased, while controlling for how popular item B is. This measurement take the account of probability of having B in the basket with knowledge of A being present over the probability of having B in the basket without any knowledge about present of A.
   i. Lift of {A -> B} = 1, means no association between items.
   ii. Lift of {A -> B} > 1, means that item B is likely to be bought if item A is bought,
   iii. Lift of {A -> B} < 1, means that item B is unlikely to be bought if item A is bought

a) Mine the Association Rules using Apriori Algorithm

In [41]:
```
# Generate the Association Rules using Apriori Algorithm with their corresponding support, confidence and lift.

rules_apriori = association_rules(frequent_itemsets_apriori, metric="lift", min_threshold=1)  # min_threshold = mini
rules_apriori = rules_apriori.sort_values(by='lift', ascending=0)
```

In [42]:
```
# View top 5 rules

rules_apriori.head()
```

Out[42]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
71	(Comedy, Drama)	(Comedy, Action, Adventure, Comedy)	0.053691	0.016779	0.010067	0.187500	11.175000	0.009166	1.210119
70	(Comedy, Action, Adventure, Comedy)	(Comedy, Drama)	0.016779	0.053691	0.010067	0.600000	11.175000	0.009166	2.365772
68	(Comedy, Drama, Comedy)	(Action, Adventure, Comedy)	0.013423	0.070470	0.010067	0.750000	10.642857	0.009121	3.718121
73	(Action, Adventure, Comedy)	(Comedy, Drama, Comedy)	0.070470	0.013423	0.010067	0.142857	10.642857	0.009121	1.151007
47	(Comedy, Crime, Drama)	(Comedy, Drama, Romance)	0.020134	0.080537	0.010067	0.500000	6.208333	0.008446	1.838926

Antecedent and a Consequent, both of which are a list of genres. Note that implication here is co-occurrence and not causality.

The maximum value of Lift is 11.1 and maximum value for Confidence is 0.75 found in Association Rules using Apriori Algorithm. I want to view for a large value of Lift and Confidence with range value of more than 1 and more than 0.4 respectively. This means that genre B is likely to be chosen if genre A is chosen

In [64]:
```
# Filter the dataframe for Lift > 1 and high confidence >= 0.5

rules_apriori[(rules_apriori['lift'] > 1) &
              (rules_apriori['confidence'] >= 0.5)].sort_values(by='lift', ascending=0)
```

Out[64]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
69	(Comedy, Action, Adventure, Comedy)	(Comedy, Drama)	0.016779	0.053691	0.010067	0.60	11.175000	0.009166	2.365772
68	(Comedy, Comedy, Drama)	(Action, Adventure, Comedy)	0.013423	0.070470	0.010067	0.75	10.642857	0.009121	3.718121
47	(Comedy, Crime, Drama)	(Comedy, Drama, Romance)	0.020134	0.080537	0.010067	0.50	6.208333	0.008446	1.838926
70	(Comedy, Drama, Action, Adventure, Comedy)	(Comedy)	0.020134	0.083893	0.010067	0.50	5.960000	0.008378	1.832215
44	(Comedy, Crime)	(Comedy)	0.020134	0.083893	0.010067	0.50	5.960000	0.008378	1.832215
59	(Drama, Sport)	(Action, Adventure, Sci-Fi)	0.013423	0.204698	0.010067	0.75	3.663934	0.007319	3.181208

Now I want to view small value of Lift and Confidence with range value of less than 1, equal and more than 0 respectively. This means that genre B is unlikely to be chosen if genre A is chosen

In [68]:
```
# Filter the dataframe for Lift < 1 and high confidence >= 0

rules_apriori[(rules_apriori['lift'] < 1) &
              (rules_apriori['confidence'] >= 0)].sort_values(by='lift', ascending=1)
```

Out[68]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
79	(Action, Adventure, Sci-Fi)	(Comedy)	0.204698	0.083893	0.010067	0.049180	0.586230	-0.007106	0.963492
78	(Comedy)	(Action, Adventure, Sci-Fi)	0.083893	0.204698	0.010067	0.120000	0.586230	-0.007106	0.903752
16	(Action, Adventure, Sci-Fi)	(Action, Adventure, Fantasy)	0.204698	0.097315	0.013423	0.065574	0.673827	-0.006497	0.966031
17	(Action, Adventure, Fantasy)	(Action, Adventure, Sci-Fi)	0.097315	0.204698	0.013423	0.137931	0.673827	-0.006497	0.922550
68	(Action, Adventure, Drama)	(Action, Adventure, Sci-Fi)	0.070470	0.204698	0.010067	0.142857	0.697892	-0.004358	0.927852
69	(Action, Adventure, Sci-Fi)	(Action, Adventure, Drama)	0.204698	0.070470	0.010067	0.049180	0.697892	-0.004358	0.977609
75	(Action, Adventure, Sci-Fi)	(Action, Crime, Thriller)	0.204698	0.057047	0.010067	0.049180	0.862102	-0.001610	0.991726
65	(Action, Adventure, Sci-Fi)	(Comedy, Romance)	0.204698	0.057047	0.010067	0.049180	0.862102	-0.001610	0.991726
64	(Comedy, Romance)	(Action, Adventure, Sci-Fi)	0.057047	0.204698	0.010067	0.176471	0.862102	-0.001610	0.965724
74	(Action, Crime, Thriller)	(Action, Adventure, Sci-Fi)	0.057047	0.204698	0.010067	0.176471	0.862102	-0.001610	0.965724
81	(Action, Adventure, Sci-Fi)	(Comedy, Drama)	0.204698	0.053691	0.010067	0.049180	0.915984	-0.000923	0.995256
80	(Comedy, Drama)	(Action, Adventure, Sci-Fi)	0.053691	0.204698	0.010067	0.187500	0.915984	-0.000923	0.978833
2	(Animation, Adventure, Comedy)	(Action, Adventure, Sci-Fi)	0.117450	0.204698	0.023490	0.200000	0.977049	-0.000552	0.994128
3	(Action, Adventure, Sci-Fi)	(Animation, Adventure, Comedy)	0.204698	0.117450	0.023490	0.114754	0.977049	-0.000552	0.996955

Rules with Lift value equal to 1

In [89]:
```
# Filter the dataframe for Lift == 1 and high confidence >= 0

rules_apriori[(rules_apriori['lift'] == 1) &
              (rules_apriori['confidence'] >= 0)].sort_values(by='lift', ascending=1)
```

Out[89]:

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction

Findings 1:

- About 74 rules have a high Lift value (more than 1), which means that it increase the chances of occurence of movie genre in Consequents in spite high Confidence value.
- A value of Lift which greater than 1 indicate for high association between Antecedents and Consequents. The greater the value of Lift, the greater are the chances of preference to choose genre in Consequents. Here, if the viewer has already watched movie with genre of (Comedy, Action, Adventure, Comedy), viewer will likely watch (Comedy, Drama) movie genre.
- Comedy genre has high Lift value
- Lift is the measure that will help movie producer to decide what kind of movie genre to produce next based on revenue generated from an individual movie.
- These 74 rules also have wide range of Confidence number, range between 0.04 to 0.75.
- 14 rules showed that genre fall in antecedent does not increase the chances of viewer to watch genre in consequent. Eg: Viewer who likes to watch (Action, Adventure, Sci-Fi) movie most likely does not watch (Comedy) movie genre.
- There is no Association Rule for Lift value equal to 1

b) Mine the Association Rules using F-P Growth

6b) Mine the Association Rules using F-P Growth

In [74]:
```
rules_fpgrowth = association_rules(frequent_itemsets_fpgrowth, metric="lift", min_threshold=1)
rules_fpgrowth = rules_fpgrowth.sort_values(by='lift', ascending=0)
```

In [75]:
```
rules_fpgrowth
```

Out[75]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
31	(Comedy, Action, Adventure, Comedy)	(Comedy, Drama)	0.016779	0.053691	0.010067	0.600000	11.175000	0.009166	2.365772
34	(Comedy, Drama)	(Comedy, Action, Adventure, Comedy)	0.053691	0.016779	0.010067	0.187500	11.175000	0.009166	1.210119
30	(Comedy, Comedy, Drama)	(Action, Adventure, Comedy)	0.013423	0.070470	0.010067	0.750000	10.642857	0.009121	3.718121
35	(Action, Adventure, Comedy)	(Comedy, Comedy, Drama)	0.070470	0.013423	0.010067	0.142857	10.642857	0.009121	1.151007
57	(Comedy, Crime, Drama)	(Comedy, Drama, Romance)	0.020134	0.080537	0.010067	0.500000	6.208333	0.008446	1.838926
56	(Comedy, Drama, Romance)	(Comedy, Crime, Drama)	0.080537	0.020134	0.010067	0.125000	6.208333	0.008446	1.119847
71	(Drama, Mystery, Sci-Fi)	(Comedy, Drama)	0.030201	0.053691	0.010067	0.333333	6.208333	0.008446	1.419463
70	(Comedy, Drama)	(Drama, Mystery, Sci-Fi)	0.053691	0.030201	0.010067	0.187500	6.208333	0.008446	1.193598
48	(Comedy, Crime)	(Comedy)	0.020134	0.083893	0.010067	0.500000	5.960000	0.008378	1.832215
32	(Comedy, Drama, Action, Adventure, Comedy)	(Comedy)	0.020134	0.083893	0.010067	0.500000	5.960000	0.008378	1.832215

The maximum value of Lift is 11.1 and maximum value for Confidence is 1.0 found in Association Rules using F-P Growth Algorithm same like the Apriori Algorithm.

I want to view for a large value of Lift and Confidence with range value of more than 1 and more than 0.8 respectively. This means that genre B is likely to be chosen if genre A is chosen

In [151]:
```
# Filter the dataframe for Lift > 1 and high confidence >= 0.5

rules_fpgrowth[(rules_fpgrowth['lift'] > 1) &
               (rules_fpgrowth['confidence'] >= 0.5)].sort_values(by='lift', ascending=0)
```

Out[151]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
37	(Comedy, Action, Adventure, Comedy)	(Comedy, Drama)	0.016779	0.053691	0.010067	0.60	11.175000	0.009166	2.365772
36	(Comedy, Comedy, Drama)	(Action, Adventure, Comedy)	0.013423	0.070470	0.010067	0.75	10.642857	0.009121	3.718121
66	(Comedy, Crime, Drama)	(Comedy, Drama, Romance)	0.020134	0.080537	0.010067	0.50	6.208333	0.008446	1.838926
38	(Comedy, Drama, Action, Adventure, Comedy)	(Comedy)	0.020134	0.083893	0.010067	0.50	5.960000	0.008378	1.832215
57	(Comedy, Crime)	(Comedy)	0.020134	0.083893	0.010067	0.50	5.960000	0.008378	1.832215
50	(Drama, Sport)	(Action, Adventure, Sci-Fi)	0.013423	0.204698	0.010067	0.75	3.663934	0.007319	3.181208

For rules with Lift value less than 1 and Confidence is equal and more than 0

In [36]:
```
# Filter the dataframe for Lift < 1 and high confidence >= 0

rules_fpgrowth[(rules_fpgrowth['lift'] < 1) &
              (rules_fpgrowth['confidence'] >= 0)].sort_values(by='lift', ascending=1)
```

Out[36]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
63	(Comedy)	(Action, Adventure, Sci-Fi)	0.083893	0.204698	0.010067	0.120000	0.586230	-0.007106	0.903752
62	(Action, Adventure, Sci-Fi)	(Comedy)	0.204698	0.083893	0.010067	0.049180	0.586230	-0.007106	0.963492
16	(Action, Adventure, Sci-Fi)	(Action, Adventure, Fantasy)	0.204698	0.097315	0.013423	0.065574	0.673827	-0.006497	0.966031
17	(Action, Adventure, Fantasy)	(Action, Adventure, Sci-Fi)	0.097315	0.204698	0.013423	0.137931	0.673827	-0.006497	0.922550
72	(Action, Adventure, Sci-Fi)	(Action, Adventure, Drama)	0.204698	0.070470	0.010067	0.049180	0.697892	-0.004358	0.977609
73	(Action, Adventure, Drama)	(Action, Adventure, Sci-Fi)	0.070470	0.204698	0.010067	0.142857	0.697892	-0.004358	0.927852
46	(Action, Adventure, Sci-Fi)	(Comedy, Romance)	0.204698	0.057047	0.010067	0.049180	0.862102	-0.001610	0.991726
78	(Action, Adventure, Sci-Fi)	(Action, Crime, Thriller)	0.204698	0.057047	0.010067	0.049180	0.862102	-0.001610	0.991726
47	(Comedy, Romance)	(Action, Adventure, Sci-Fi)	0.057047	0.204698	0.010067	0.176471	0.862102	-0.001610	0.965724
79	(Action, Crime, Thriller)	(Action, Adventure, Sci-Fi)	0.057047	0.204698	0.010067	0.176471	0.862102	-0.001610	0.965724
32	(Action, Adventure, Sci-Fi)	(Comedy, Drama)	0.204698	0.053691	0.010067	0.049180	0.915984	-0.000923	0.995256
33	(Comedy, Drama)	(Action, Adventure, Sci-Fi)	0.053691	0.204698	0.010067	0.187500	0.915984	-0.000923	0.978833
1	(Animation, Adventure, Comedy)	(Action, Adventure, Sci-Fi)	0.117450	0.204698	0.023490	0.200000	0.977049	-0.000552	0.994128
0	(Action, Adventure, Sci-Fi)	(Animation, Adventure, Comedy)	0.204698	0.117450	0.023490	0.114754	0.977049	-0.000552	0.996955

For rules with Lift value equal to 1

```
In [37]: # Filter the dataframe for Lift == 1 and high confidence >= 0

rules_fpgrowth[(rules_fpgrowth['lift'] == 1) &
               (rules_fpgrowth['confidence'] >= 0)].sort_values(by='lift', ascending=1)
```

Out[37]:

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction

Findings 2:

- The output from F-P Growth algorithm is same like Apriori algorithm for this case study. About 74 rule have a high Lift value (more than 1), which means that it increase the chances of occurrence of movie genre in `Consequents` in spite high `Confidence` value.
- These 74 rules of high Lift value also have wide range of Confidence number, range between 0.04 to 0.75.
- F-P Growth algorithm showed faster in processing the data than Apriori algorithm because it scan the database twice to generate the itemsets unlike Apriori scans multiple times over database to generate itemsets.
- There are about 4 rules with Lift value less than 1
- There is no Association Rule for Lift value equal to 1

(10 marks)

5. It will be appeared in week 14.

(10 marks)

Submissions:

The student is expected to submit answers to each question individually, and submit the document in PDF format. The student can include online materials, screenshots, videos and/or codes (ipynb format) to support your answer