CIND 110 Data Organization for Data Analysts
Assignment 3 – Three Data Mining Algorithms
Ilhak Park
April 13, 2021

1. Association rules: Marks: 30

One of the major techniques in data mining involves the discovery of association rules. These rules correlate the presence of a set of items with another range of values for another set of variables. The database in this context is regarded as a collection of transactions, each involving a set of items, as shown below.

Trans ID	Items Purchased
2001	Meat, Potato, Onion
2002	Meat, Noodle
2003	Noodle, Spinach
2004	Meat, Potato, Onion
2005	Onion, Potato, Noodle
2006	Eggs, Spinach
2007	Eggs, Noodle
2008	Meat, Potato, Salt, Onion
2009	Salt, Spinach
2010	Meat, Potato

1.1 Apply the **Apriori** algorithm on this dataset.

Note that, the set of items is {Meat, Potato, Onion, Noodle, Spinach, Eggs, Salt}.
You may use **0.3 for the minimum support** value.

Candidate 1-itemlist, C_1

Itemset	Count	Support
Meat	5	0.5
Potato	5	0.5
Onion	4	0.4
Noodle	4	0.4
Spinach	3	0.3
Eggs	2	0.2
Salt	2	0.2

1-itemset, L_1

Itemset	Count	Support
Meat	5	0.5
Potato	5	0.5
Onion	4	0.4
Noodle	4	0.4
Spinach	3	0.3

Candidate 2-itemlist, C_2

Itemset	Count	Support
Meat, Potato	4	0.4
Meat, Onion	3	0.3
Meat, Noodle	1	0.1
Meat, Spinach	0	0.0
Potato, Onion	3	0.3
Potato, Noodle	1	0.1
Potato, Spinach	0	0.0
Onion, Noodle	1	0.1
Onion, Spinach	0	0.0
Noodle, Spinach	1	0.1

2-itemset, L_2

Itemset	Count	Support
Meat, Potato	4	0.4
Meat, Onion	3	0.3
Potato, Onion	4	0.4

Candidate 3-itemlist, C_3 and 3-itemset, L_3

Itemset	Count	Support
Meat, Potato, Onion	3	0.3

1.2. Show the rules that have a confidence of 0.8 or greater for an itemset containing three items.

$$Confidence = \frac{support(LHS \cup RHS)}{support(LHS)}$$

1) Confidence {Meat, Onion} → {Potato}:
support (LHS U RHS) = 0.3
support (LHS) = 0.3
confidence = 1

2) Confidence {Potato, Onion} → {Meat}:
support (LHS U RHS) = 0.3
support (LHS) = 0.4
confidence = 0.75

3) Confidence {Meat, Potato} → {Onion}:
support (LHS U RHS) = 0.3
support (LHS) = 0.4
confidence = 0.75

Therefore, the rules that have a confidence of 0.8 or greater for an itemset containing three items are:

1) Confidence {Meat, Onion} → {Potato}

2. Classification: **Marks: 40**

Classification is the process of learning a model that describes different classes of data and the classes should be pre-determined. Consider the following set of data records:

ID	Age	City	Gender	Education	Profile
101	20-30	NY	F	College	Employed
102	31-40	NY	F	College	Employed
103	51-60	NY	F	College	Unemployed
104	20-30	LA	M	High School	Unemployed
105	41-50	NY	F	College	Employed
106	41-50	NY	F	Graduate	Employed
107	20-30	LA	M	College	Employed
108	20-30	NY	F	High School	Unemployed
109	20-30	NY	F	College	Employed
110	51-60	SF	M	College	Unemployed

Assuming, that the class attribute is Profile, apply a classification algorithm to this dataset.

Step 1: Determine the Decision Column

Frequency Table for the class attribute:

Profile (10)	
Employed	Unemployed
6	4

Step 2: Calculating Entropy for the classes (Profile)

Entropy(Profile) = Entropy(6,4)

$$= -\left(\frac{6}{10} log_2 \frac{6}{10}\right) - \left(\frac{4}{10} log_2 \frac{4}{10}\right)$$

= 0.97095

Step 3: Calculate Entropy for Other Attributes After Split

Entropy(S,T) = E(S,T)

- E(Profile, Age)
- E(Profile, City)
- E(Profile, Gender)
- E(Profile, Education)

		Profile (10)		
		Employed	Unemployed	Total
Age	20-30	3	2	5
	31-40	1	0	1
	41-50	2	0	2
	51-60	0	2	2

E(Profile, Age) = P(20-30)E(20-30) + P(31-40)E(31-40) + P(41-50)E(41-50) +P(51-60)E(51-60)
= 0.5E(3,2) + 0.1E(1,0) + 0.2E(2,0) + 0.2(0,2)
= 0.5(0.97095) + 0 + 0 + 0
= 0.485475

		Profile (10)		
		Employed	Unemployed	Total
City	NY	5	2	7
	LA	1	1	2
	SF	0	1	1

E(Profile, City) = P(NY)E(NY) + P(LA)E(LA) + P(SF)E(SF)
= 0.7E(5,2) + 0.2E(1,1) + 0.1E(0,1)
= 0.7(0.86312) + 0.2 + 0
= 0.804184

		Profile (10)		
		Employed	Unemployed	Total
Gender	M	1	2	3
	F	5	2	7

E(Profile, Gender) = P(M)E(M) + P(F)E(F)
= 0.3E(1,2) + 0.7E(5,2)
= 0.3(0.91829) + 0.7(0.86312)
= 0.879671

		Profile (10)		
		Employed	Unemployed	Total
Education	College	5	2	7
	High School	0	2	2
	Graduate	1	0	1

E(Profile, Education) = P(College)E(College) + P(HS)E(HS) + P(Graduate)E(Graduate)
= 0.7E(5,2) + 0.2E(0,2) + 0.1E(0,1)
= 0.7(0.86312) + 0 + 0
= 0.804184
= 0.604184

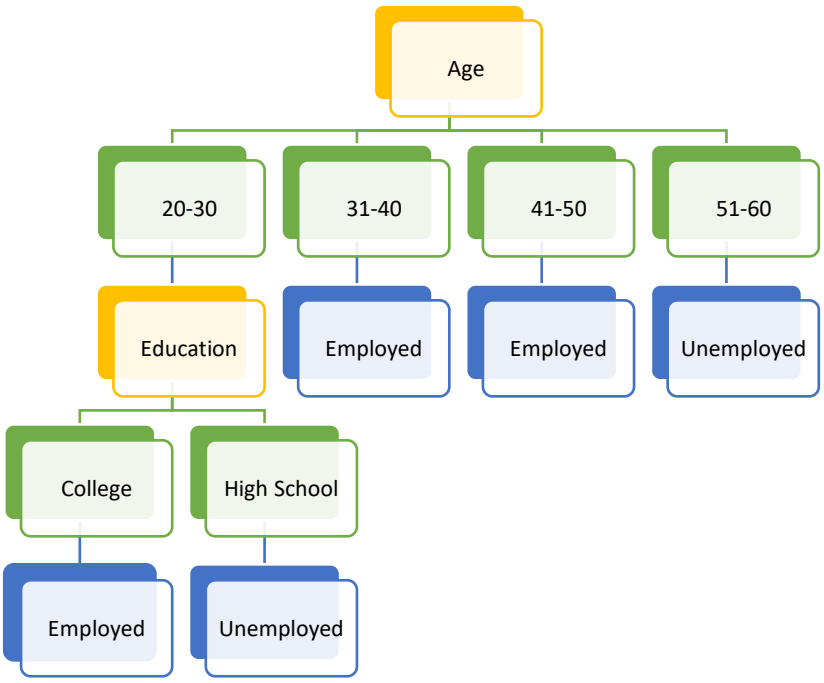
Step 4: Calculating Information Gain for Each Split
Gain(S,T) = Entropy(S) – Entropy(S,T)

Gain(Profile, Age) = E(Profile) – E(Profile, Age)
= 0.97095 - 0.485475 = 0.485475
Gain(Profile, City) = E(Profile) – E(Profile, City)
= 0.97095-0.804184 =0.166766
Gain(Profile, Gender) = E(Profile) – E(Profile, Gender)
= 0.97095-0.879671 = 0.091279
Gain(Profile, Education) = E(Profile) – E(Profile, Education)
= 0.97095-0.604184 = 0.366766
The attribute "Age" gives the highest information gain after the split, therefore; it will be the decision node of the decision tree.

Step 5: Find the Second Node:
Entropy(Age = 20-30) = $-\left(\frac{3}{5}log_2\frac{3}{5}\right)-\left(\frac{2}{5}log_2\frac{2}{5}\right)$
= 0.97095
Gain(Age = 20-30, Education) = E(Age = 20-30) – E(Age = 20-30, Education)
= 0.97095 – 0 – 0 – 0
= 0.97095
Since 0.97095 is the highest possible value for the second information gain, Education is the second decision node of the decision tree.

Step 6: Decision Tree

Yellow – Decision node
Blue – Leaf nodes



3. Clustering: Consider the following set of two-dimensional records:

RID	Age	Years of Service
101	30	5
102	50	25
103	50	15
104	25	5
105	30	10
106	55	25

3.1 **Marks: 20**

Use the K-means algorithm to cluster this dataset. You can use a value of 2 for K and can assume that the records with RIDs 103, and 104 are used for the initial cluster centroids.

Using Euclidean Distance:

Distance [(x,y), (a,b)] = $\sqrt{(x-a)^2+(y-b)^2}$

Initial cluster centroids: (50,15) and (25,5)

RID 101:

$\sqrt{(30-50)^2+(5-15)^2}$ = 17.32050

$\sqrt{(30-25)^2+(5-5)^2}$ = 5

RID 102:

$\sqrt{(50-50)^2+(25-15)^2}$ = 10

$\sqrt{(50-25)^2+(25-5)^2}$ = 32.01562

RID 103:

$\sqrt{(50-50)^2+(15-15)^2}$ = 0

$\sqrt{(50-25)^2+(15-5)^2}$ = 26.92582

RID 104:

$\sqrt{(25-50)^2+(5-15)^2}$ = 26.92582

$\sqrt{(25-25)^2+(5-5)^2}$ = 0

RID 105:

$\sqrt{(30-50)^2+(10-15)^2}$ = 20.61552

$\sqrt{(30-25)^2+(10-5)^2}$ = 7.07106

RID 106:

$\sqrt{(55-50)^2+(25-15)^2}$ = 11.18033

$\sqrt{(55-25)^2+(25-5)^2}$ = 36.551

Cluster 1: RID 101, 104, 105
Cluster 2: RID 102, 103, 106

Location:
Cluster 1: (28.33, 6.67)
Cluster 2: (51.67, 21.67)

Iteration 2

RID 1011:
$\sqrt{(30 - 28.33)^2 + (5 - 6.67)^2}$ = 2.36173
$\sqrt{(30 - 51.67)^2 + (5 - 21.67)^2}$ = 27.34004

RID 102:
$\sqrt{(50 - 28.33)^2 + (25 - 6.67)^2}$ = 28.38270
$\sqrt{(50 - 51.67)^2 + (25 - 21.67)^2}$ = 3.72529

RID 103:
$\sqrt{(50 - 28.33)^2 + (15 - 6.67)^2}$ = 23.21589
$\sqrt{(50 - 51.67)^2 + (15 - 21.67)^2}$ = 6.87588

RID 104:
$\sqrt{(25 - 28.33)^2 + (5 - 6.67)^2}$ = 3.72529
$\sqrt{(25 - 51.67)^2 + (5 - 21.67)^2}$ = 31.45119

RID 105:
$\sqrt{(30 - 28.33)^2 + (10 - 6.67)^2}$ = 3.72529
$\sqrt{(30 - 51.67)^2 + (10 - 21.67)^2}$ = 24.61255

RID 106:
$\sqrt{(55 - 28.33)^2 + (25 - 6.67)^2}$ = 32.36167
$\sqrt{(55 - 51.67)^2 + (25 - 21.67)^2}$ = 4.70933

Cluster 1: RID 101, 104, 105
Cluster 2: RID 102, 103, 106

Location:
Cluster 1: (28.33, 6.67)
Cluster 2: (51.67, 21.67)

Since locations of two clusters do not change, K-means algorithm ends.

3.2 **Marks: 10**

What is the difference between describing discovered knowledge using clustering and describing it using classification?

The purpose of clustering is to understand data and patterns in data set (descriptive method), whereas the goal of classification is to predict a value for categorical variable (predictive method).

Clustering is an unsupervised learning method that groups a set of objects in such a way that objects in the same group are more similar to each other than to those in other groups. Discovered knowledge of clustering is the descriptions of the dataset.

On the other hand, classification is a supervised learning method that identifies which of a set of categories a new observation belongs to, on the basis of a training set. Discovered knowledge of classification is the prediction of the class variable for the test set.