## Statistical Data Mining II Homework 1

Due: Friday February 16<sup>th</sup> (11:59 pm) 30 points

**Directions:** Submit all source codes with write up. You must provide thorough explanations with output. See "homework guidelines" on UB learns for detailed information.

(1) (10 points) (Adopted from <a href="http://infolab.stanford.edu/~ullman/mmds/ch9.pdf">http://infolab.stanford.edu/~ullman/mmds/ch9.pdf</a> exercise 9.3.1) Consider the following "utility matrix":

	a	b	c	d	e	f	$\boldsymbol{g}$	h
A	4	5		5	1		3	2
$A \\ B \\ C$		3	4	3	1	2	1	
C	2		1	3		4	5	3

- (a) Treat the utility matrix as Boolean and compute the Jaccard distance, and the cosine distance between users.
- (b) Use a different discretization: treat ratings 3,4,5 as 1, and ratings 1, 2, and blank as 0. Compute the Jaccard distance and cosine distance and compare to that of part A.
- (c) Normalize the matrix by subtracting from each nonblank entry the average value for its user. Using this matrix, compute the cosine distance between each pair of users.
- (2) (10 points) Consider the Boston Housing Data. This data can be accessed in the ElemStatLearn package (available through CRAN).

```
> library(ElemStatLearn)
> data(boston)
> head(boston)
     crim zn indus chas nox
                              rm age
                                        dis rad tax ptratio black lstat medv
1 0.00632 18 2.31 0 0.538 6.575 65.2 4.0900 1 296
                                                      15.3 396.90 4.98 24.0
2 0.02731 0 7.07 0 0.469 6.421 78.9 4.9671 2 242
                                                      17.8 396.90 9.14 21.6
3 0.02729 0 7.07 0 0.469 7.185 61.1 4.9671 2 242
                                                      17.8 392.83 4.03 34.7
4 0.03237 0 2.18 0 0.458 6.998 45.8 6.0622 3 222
                                                      18.7 394.63 2.94 33.4
5 0.06905 0 2.18 0 0.458 7.147 54.2 6.0622 3 222
                                                      18.7 396.90 5.33 36.2
6 0.02985 0 2.18
                    0 0.458 6.430 58.7 6.0622
                                                      18.7 394.12 5.21 28.7
                                              3 222
```

The variables are as follows:

CRIM per capita crime rate by town

ZN proportion of residential land zoned for lots over 25,000 sq.ft.

INDUS proportion of non-retail business acres per town

CHAS Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)

NOX nitric oxides concentration (parts per 10 million)

RM average number of rooms per dwelling

AGE proportion of owner-occupied units built prior to 1940

DIS weighted distances to five Boston employment centres

RAD index of accessibility to radial highways

TAX full-value property-tax rate per \$10,000

PTRATIO pupil-teacher ratio by town

B 1000(Bk - 0.63)<sup>2</sup> where Bk is the proportion of blacks by town

LSTAT % lower status of the population

MEDV Median value of owner-occupied homes in \$1000's

- a) Visualize the data using histograms of the different variables in the data set. Transform the data into a binary incidence matrix, and justify the choices you make in grouping categories.
- b) Visualize the data using the itemFrequencyPlot in the "arules" package. Apply the apriori algorithm (Do not forget to specify parameters in your write up).
- c) A student is interested is a low crime area as close to the city as possible (as measured by "dis"). What can you advise on this matter through the mining of association rules?
- d) A family is moving to the area, and has made schooling a priority. They want schools with low pupil-teacher ratios. What can you advise on this matter through the mining of association rules?
  - Extra Credit (3 points): Use a regression model to solve part d. Are you results comparable? Which provides an easier interpretation? When would regression be preferred, and when would association models be preferred?
- (3) (10 points) (Modified Exercise 14.4) Cluster the demographic data of Table 14.1 using a classification tree. Specifically, generate a reference sample the same size as the training set, by randomly permuting the values within each feature. Build a classification tree to the training sample (class 1) and the reference sample (class 0) and describe the terminal nodes having highest estimated class 1 probability.

<sup>\*</sup>Note: you may use a variety or R libraries for tree construction e.g., rpart or tree Computational lab for tree building is available upon request.