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EXPERIMENT 1

Credit Risk Assessment Description:

The business of banks is making loans. Assessing the credit worthiness of an applicant is of crucial importance. You have to develop a system to help a loan officer decide whether the credit of a customer is good, or bad. A banks business rules regarding loans must consider two opposing factors. On the one hand, a bank wants to make as many loans as possible. Interest on these loans is the banks profit source. On the other hand, a bank cannot afford to make too many bad loans. Too many bad loans could lead to the collapse of the bank. The bank's loan policy must involve a compromise not too strict, and not too lenient.

To do the assignment, you first and foremost need some knowledge about the world of credit . You can acquire such knowledge in a number of ways.

1. Knowledge Engineering. Find a loan officer who is willing to talk. Interview her and try to represent her knowledge in the form of production rules.
2. Books. Find some training manuals for loan officers or perhaps a suitable textbook on finance. Translate this knowledge from text form to production rule form.
3. Common sense. Imagine yourself as a loan officer and make up reasonable rules which can be used to judge the credit worthiness of a loan applicant.
4. Case histories. Find records of actual cases where competent loan officers correctly judged when not to, approve a loan application.

The German Credit Data :

Actual historical credit data is not always easy to come by because of confidentiality rules. Here is one such dataset (original) Excel spreadsheet version of the German credit data (download from web). In spite of the fact that the data is German, you should probably make use of it for this assignment, (Unless you really can consult a real loan officer !) A few notes on the German dataset :

- DM stands for Deutsche Mark, the unit of currency, worth about 90 cents Canadian (but looks and acts like a quarter).
- Owns_telephone. German phone rates are much higher than in Canada so fewer people own telephones.
- Foreign_worker.There are millions of these in Germany (many from Turkey). It is very hard to get German citizenship if you were not born of German parents.
- There are 20 attributes used in judging a loan applicant. The goal is the classify the applicant into one of two categories, good or bad.

SUBTASKS:

1.List all the categorical (or nominal) attributes and the real-valued attributes seperately.

AIM: To separate the nominal attributes and also the real valued attributes by using the weka tool.

PROCEDURE:
1) Open the Weka GUI Chooser.

2) Select EXPLORER present in Applications.

3) Select Preprocess Tab.

4) Go to OPEN file and browse the file that is already stored in the system “credi-g.arff”.

5) Clicking on any attribute in the left panel will show the basic statistics on that selected attribute.

Attributes:-
1. checking_status
2. duration
3. credit history
4. purpose
5. credit amount
6. savings_status
7. employment duration
8. installment rate
9. personal status
10. debitors
11. residence_since
12. property
14. installment plans
15. housing
16. existing credits
17. job
18. num_dependents
19. telephone
20. foreign worker

Categorical or Nominal attributes:-
1. checking_status
2. credit history
3. purpose
4. savings_status
5. employment
6. personal status

7. debtors
8. property
9. installment plans
10. housing
11. job
12. telephone
13. foreign worker

Real valued attributes:-
1. duration
2. credit amount
3. credit amount
4. residence
5. age
6. existing credits
7. num_dependents

2.What attributes do you think might be crucial in making the credit assessement ? Come up with some simple rules in plain English using your selected attributes.

AIM: To select interesting rules from the set of all possible rules, constraints on various measures of significance and interest can be used. The best known constraints are minimum thresholds on support and confidence. The support supp(X) of an itemset X is defined as the proportion of transactions in the data set which contain the itemset. In the example database, the
itemset {milk, bread} has a support of 2 / 5 = 0.4 since it occurs in 40% of all transactions (2 out
of 5 transactions).

ALGORITHM:
Association rule mining is to find out association rules that satisfy the predefined minimum support and confidence from a given database. The problem is usually decomposed into two sub
problems. One is to find those itemsets whose occurrences exceed a predefined threshold in the
database; those itemsets are called frequent or large itemsets. The second problem is to generate
association rules from those large itemsets with the constraints of minimal confidence.
Suppose one of the large itemsets is Lk, Lk = {I1, I2, ... , Ik}, association rules with this itemsets
are generated in the following way: the first rule is {I1, I2, ... , Ik1} and {Ik}, by checking the
confidence this rule can be determined as interesting or not.
Then other rule are generated by deleting the last items in the antecedent and inserting it to the
consequent, further the confidences of the new rules are checked to determine the interestingness

of them. Those processes iterated until the antecedent becomes empty.
Since the second subproblem is quite straight forward, most of the researches focus on the first
subproblem.
The Apriori algorithm finds the frequent sets L In Database D.
· Find frequent set Lk − 1.
· Join Step.
. Ck is generated by joining Lk − 1with itself
· Prune Step.
o Any (k − 1) itemset that is not frequent cannot be a subset of a
frequent k itemset, hence should be removed.
Where · (Ck: Candidate itemset of size k)
· (Lk: frequent itemset of size k)
Apriori Pseudocode
Apriori (T,£)
L<{ Large 1itemsets that appear in more than transactions }
while L(k1)≠ Φ
C(k)<Generate(Lk − 1)
for transactions t € T
C(t)Subset(Ck,t)
for candidates c € C(t)
count[c]<count[c]+1
L(k)<{ c € C(k)| count[c] ≥ £
K<K+ 1
return Ụ L(k) k.

PROCEDURE:

1) Given the Credit database for mining.
2) Select EXPLORER in WEKA GUI Chooser.
3) Load “Credit-g.arff” in Weka by Open file in Preprocess tab.
4) Select only Nominal values.
5) Go to Associate Tab.
6) Select Apriori algorithm from “Choose” button present in
Associator weka.associations.Apriori -N 10 -T 0 -C 0.9 -D 0.05 -
U 1.0 -M 0.1 -S -1.0 -c -1
7) Select Start button
8) Now we can see the sample rules.

According to me the following attributes may be crucial in making the credit risk assessment.
1. Credit_history
2. Employment
3. Property_magnitude
4. job
5. duration

6. credit_amount
7. installment
8. existing credit
Basing on the above attributes, we can make a decision whether to give credit or not.

3. One type of model that you can create is a Decision Tree - train a Decision Tree using the complete dataset as the training data. Report the model obtained after training.

AIM: Implementing the decision tree analysis and the training data in the data set.

Different Classification Algorithms: Oracle Data Mining provides the following algorithms for
classification:
Decision Tree - Decision trees automatically generate rules, which are conditional statements that reveal the logic used to build the tree.
Naive Bayes - Naive Bayes uses Bayes' Theorem, a formula that calculates a probability by counting the frequency of values and combinations of values in the historical data.

PROCEDURE:
1) Open Weka GUI Chooser.
2) Select EXPLORER present in Applications.
3) Select Preprocess Tab.
4) Go to OPEN file and browse the file that is already stored in the system “Credit-g.arff”.
5) Go to Classify tab.
6) j48 in Java and can be selected by clicking the button ,choose and select tree j48 .

Output:

J48 pruned tree
---
checking_status = <0
| foreign_worker = yes
| | duration <= 11
| | | existing_credits <= 1
| | | | property_magnitude = real estate: good (8.0/1.0)
| | | | property_magnitude = life insurance
| | | | | own_telephone = none: bad (2.0)
| | | | | own_telephone = yes: good (4.0)
| | | | property_magnitude = car: good (2.0/1.0)
| | | | property_magnitude = no known property: bad (3.0)
| | | existing_credits > 1: good (14.0)
| | duration > 11
| | | job = unemp/unskilled non res: bad (5.0/1.0)
| | | job = unskilled resident
| | | | purpose = new car

```
| | | | | own_telephone = none: bad (10.0/2.0)
| | | | | own_telephone = yes: good (2.0)
| | | | purpose = used car: bad (1.0)
| | | | purpose = furniture/equipment
| | employment = unemployed: good (0.0)
| | employment = <1: bad (3.0)
| | employment = 1<=X<4: good (4.0)
| | employment = 4<=X<7: good (1.0)
| | employment = >=7: good (2.0)
| purpose = radio/tv
| | existing_credits <= 1: bad (10.0/3.0)
| | existing_credits > 1: good (2.0)
| purpose = domestic appliance: bad (1.0)
| purpose = repairs: bad (1.0)
| purpose = education: bad (1.0)
| purpose = vacation: bad (0.0)
| purpose = retraining: good (1.0)
| purpose = business: good (3.0)
| purpose = other: good (1.0)
job = skilled
| other_parties = none
| | duration <= 30
| | | savings_status = <100
| | | | credit_history = no credits/all paid: bad (8.0/1.0)
| | | | credit_history = all paid: bad (6.0)
| | | | credit_history = existing paid
| | | | | own_telephone = none
| | | | | | existing_credits <= 1
| | | | | | | property_magnitude = real estate
| | | | | | | | age <= 26: bad (5.0)
| | | | | | | | age > 26: good (2.0)
| | | | | | | property_magnitude = life insurance: bad (7.0/2.0)
| | | | | | | property_magnitude = car
| | | | | | | | credit_amount <= 1386: bad (3.0)
| | | | | | | | credit_amount > 1386: good (11.0/1.0)
| | | | | | | property_magnitude = no known property: good (2.0)
| | | | | | existing_credits > 1: bad (3.0)
| | | | | own_telephone = yes: bad (5.0)
| | | | credit_history = delayed previously: bad (4.0)
| | | | credit_history = critical/other existing credit: good (14.0/4.0)
| | | savings_status = 100<=X<500
| | | | credit_history = no credits/all paid: good (0.0)
| | | | credit_history = all paid: good (1.0)
| | | | credit_history = existing paid: bad (3.0)
| | | | credit_history = delayed previously: good (0.0)
| | | | credit_history = critical/other existing credit: good (2.0)
| | | savings_status = 500<=X<1000: good (4.0/1.0)
| | | savings_status = >=1000: good (4.0)
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```
| | | savings_status = no known savings
| | | | existing_credits <= 1
| | | | | own_telephone = none: bad (9.0/1.0)
| | | | | own_telephone = yes: good (4.0/1.0)
| | | | | | | existing_credits > 1: good (2.0)
| | | | | duration > 30: bad (30.0/3.0)
| | | | other_parties = co applicant: bad (7.0/1.0)
| | | | other_parties = guarantor: good (12.0/3.0)
| | | job = high qualif/self emp/mgmt: good (30.0/8.0)
| foreign_worker = no: good (15.0/2.0)
checking_status = 0<=X<200
| credit_amount <= 9857
| | savings_status = <100
| | | other_parties = none
| | | | duration <= 42
| | | | | personal_status = male div/sep: bad (8.0/2.0)
| | | | | personal_status = female div/dep/mar
| | | | | | purpose = new car: bad (5.0/1.0)
| | | | | | purpose = used car: bad (1.0)
| | | | | | purpose = furniture/equipment
| | | | | | | duration <= 10: bad (3.0)
| | | | | | | duration > 10
| | | | | | | | duration <= 21: good (6.0/1.0)
| | | | | | | | duration > 21: bad (2.0)
| | | | | | purpose = radio/tv: good (8.0/2.0)
| | | | | | purpose = domestic appliance: good (0.0)
| | | | | | purpose = repairs: good (1.0)
| | | | | | purpose = education: good (4.0/2.0)
| | | | | | purpose = vacation: good (0.0)
| | | | | | purpose = retraining: good (0.0)
| | | | | | purpose = business
| | | | | | | residence_since <= 2: good (3.0)
| | | | | | | residence_since > 2: bad (2.0)
| | | | | | purpose = other: good (0.0)
| | | | | personal_status = male single: good (52.0/15.0)
| | | | | personal_status = male mar/wid
| | | | | | duration <= 10: good (6.0)
| | | | | | duration > 10: bad (10.0/3.0)
| | | | | personal_status = female single: good (0.0)
| | | | duration > 42: bad (7.0)
| | | other_parties = co applicant: good (2.0)
| | | other_parties = guarantor
| | | | purpose = new car: bad (2.0)
| | | | purpose = used car: good (0.0)
| | | | purpose = furniture/equipment: good (0.0)
| | | | purpose = radio/tv: good (18.0/1.0)
| | | | purpose = domestic appliance: good (0.0)
| | | | purpose = repairs: good (0.0)
```

```
| | | | purpose = education: good (0.0)
| | | | purpose = vacation: good (0.0)
| | | | purpose = retraining: good (0.0)
| | | | purpose = business: good (0.
| | | | purpose = other: good (0.0)
| | savings_status = 100<=X<500
| | | purpose = new car: bad (15.0/5.0)
| | | purpose = used car: good (3.0)
| | | purpose = furniture/equipment: bad (4.0/1.0)
| | | purpose = radio/tv: bad (8.0/2.0)
| | | purpose = domestic appliance: good (0.0)
| | | purpose = repairs: good (2.0)
| | | purpose = education: good (0.0)
| | | purpose = vacation: good (0.0)
| | | purpose = retraining: good (0.0)
| | | purpose = business
| | | | housing = rent
| | | | | existing_credits <= 1: good (2.0)
| | | | | existing_credits > 1: bad (2.0)
| | | | housing = own: good (6.0)
| | | | housing = for free: bad (1.0)
| | | purpose = other: good (1.0)
| | savings_status = 500<=X<1000: good (11.0/3.0)
| | savings_status = >=1000: good (13.0/3.0)
| | savings_status = no known savings: good (41.0/5.0)
| credit_amount > 9857: bad (20.0/3.0)
checking_status = >=200: good (63.0/14.0)
checking_status = no checking: good (394.0/46.0)
Number of Leaves : 103
Size of the tree : 140
Time taken to build model: 0.03 seconds

=== Evaluation on training set ===

=== Summary ===

Correctly Classified Instances         855          85.5 %
Incorrectly Classified Instances       145          14.5 %
Kappa statistic                        0.6251
Mean absolute error                    0.2312
Root mean squared error                0.34
Relative absolute error                55.0377 %
Root relative squared error            74.2015 %
Total Number of Instances              1000
```

4:Suppose you use your above model trained on the complete dataset, and classify credit good/bad for each of the examples in the dataset. What % of examples can you classify
correctly? (This is also called testing on the training set) Why do you think you cannot get 100 %
training accuracy?
AIM: Determining and classifying the credit good or bad in the dataset with an Accuracy.

PROCEDURE:
1) Given the credit database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system "Credit-g.arff".

6) Go to Classify tab.
7) Choose Classifier "Tree"
8) Select J48

9) Select Test options "Use training set"
10) if need select attribute.
11) Now start weka.
12) Now we can see the output details in the Classifier output.

In the above model we trained complete dataset and we classified credit good/bad for each of the examples in the dataset.

For example:

IF
purpose=vacation THEN
credit=bad

ELSE
purpose=business THEN

Credit=good
In this way we classified each of the examples in the dataset.
We classified 85.5% of examples correctly and the remaining 14.5% of examples are incorrectly classified. We can't get 100% training accuracy because out of the 20 attributes, we have some unnecessary attributes which are also been analyzed and trained.
Due to this the accuracy is affected and hence we can't get 100% training accuracy.

5)Is testing on the training set as you did above a good idea? Why or Why not?

AIM: Testing the training set is it necessary to analyze the data.
THEORY: Comparing the "Correctly Classified Instances" from this test set with the "Correctly
Classified Instances" from the training set, we see the accuracy of the model, which indicates
that the model will not break down with unknown data, or when future data is applied to it.

PROCEDURE:
i) In Test options, select the Supplied test set radio button
ii) Click Set
iii) Choose the file which contains records that were not in the training set we used to create the model.
iv) Click Start(WEKA will run this test data set through the model we already created.)
v) Compare the output results with that of the 4th experiment.

According to the rules, for the maximum accuracy, we have to take 2/3 of the dataset as training set and the remaining 1/3 as test set. But here in the above model we have taken complete
dataset as training set which results only 85.5% accuracy.
This is done for the analyzing and training of the unnecessary attributes which does not make a crucial role in credit risk assessment. And by this complexity is increasing and finally it leads to
the minimum accuracy.
If some part of the dataset is used as a training set and the remaining as test set then it leads to the accurate results and the time for computation will be less.
This is why, we prefer not to take complete dataset as training set.

6.Oneapproachforsolvingtheproblemencounteredinthepreviousquestionisusingcrossvalidation?
Describewhatiscrossvalidationbriefly.TrainaDecisionTreeagainusingcrossvalidationandreportyourresults.Doesyouraccuracyincrease/decrease?Why?

Cross validation:-
In k-fold cross-validation, the initial data are randomly portioned into ‘k’ mutually exclusive subsets or folds D1, D 2 , D 3 , ..., D k . Each of approximately equal size. Training and testing is
performed ‘k’ times. In iteration I, partition D i is reserved as the test set and the remaining partitions are
collectively used to train the model. That is in the first iteration subsets D 2 , D 3 , ..., D k collectively

serve as the training set in order to obtain as first model. Which is tested on Di . The second trained on
the subsets D 1 , D 3 , ..., D k and test on the D 2 and so on....

AIM: To test the cross validation while analyzing the data.

PROCEDURE:
1) Given the credit database for mining.
2) Use the Weka GUI Chooser.
3) Select EXPLORER present in Applications.
4) Select Preprocess Tab.
5) Go to OPEN file and browse the file that is already stored in the system “credit-g.arff”.
Go to Classify tab.
6) Choose Classifier “Tree”
7) Select J48
8) Select Test options “Cross-validation”.
9) Set “Folds” Ex:10
10) if need select attribute.
11) now Start weka.
Now we can see the output details in the Classifier output.
Compare the output results with that of the 4 th experiment
check whether the accuracy increased or decreased?

OUTPUT:

J48 pruned tree :-
---
checking_status = <0
| foreign_worker = yes
| | duration <= 11
| | | existing_credits <= 1
| | | | property_magnitude = real estate: good (8.0/1.0)
| | | | property_magnitude = life insurance
| | | | | own_telephone = none: bad (2.0)
| | | | | own_telephone = yes: good (4.0)
| | | | property_magnitude = car: good (2.0/1.0)
| | | | property_magnitude = no known property: bad (3.0)
| | | existing_credits > 1: good (14.0)
| | duration > 11
| | | job = unemp/unskilled non res: bad (5.0/1.0)
| | | job = unskilled resident
| | | | purpose = new car
| | | | | own_telephone = none: bad (10.0/2.0)
| | | | | own_telephone = yes: good (2.0)
| | | | purpose = used car: bad (1.0)
| | | | purpose = furniture/equipment
| | | | | employment = unemployed: good (0.0)

```
| | | | | employment = <1: bad (3.0)
| | | | | employment = 1<=X<4: good (4.0)
| | | | | employment = 4<=X<7: good (1.0)
| | | | | employment = >=7: good (2.0)
| | | | purpose = radio/tv
| | | | | existing_credits <= 1: bad (10.0/3.0)
| | | | | existing_credits > 1: good (2.0)
| | | | purpose = domestic appliance: bad (1.0)
| | | | purpose = repairs: bad (1.0)
| | | | purpose = education: bad (1.0)
| | | | purpose = vacation: bad (0.0)
| | | | purpose = retraining: good (1.0)
| | | | purpose = business: good (3.0)
| | | | purpose = other: good (1.0)
| | | job = skilled
| | | | other_parties = none
| | | | | duration <= 30
| | | | | | savings_status = <100
| | | | | | | credit_history = no credits/all paid: bad (8.0/1.0)
| | | | | | | credit_history = all paid: bad (6.0)
| | | | | | | credit_history = existing paid
| | | | | | | | own_telephone = none
| | | | | | | | | existing_credits <= 1
| | | | | | | | | | property_magnitude = real estate
| | | | | | | | | | | age <= 26: bad (5.0)
| | | | | | | | | | | age > 26: good (2.0)
| | | | | | | | | | property_magnitude = life insurance: bad (7.0/2.0)
| | | | | | | | | | property_magnitude = car
| | | | | | | | | | | credit_amount <= 1386: bad (3.0)
| | | | | | | | | | | credit_amount > 1386: good (11.0/1.0)
| | | | | | | | | | property_magnitude = no known property: good (2.0)
| | | | | | | | | existing_credits > 1: bad (3.0)
| | | | | | | | own_telephone = yes: bad (5.0)
| | | | | | | credit_history = delayed previously: bad (4.0)
| | | | | | | credit_history = critical/other existing credit: good (14.0/4.0)
| | | | | | savings_status = 100<=X<500
| | | | | | | credit_history = no credits/all paid: good (0.0)
| | | | | | | credit_history = all paid: good (1.0)
| | | | | | | credit_history = existing paid: bad (3.0)
| | | | | | | credit_history = delayed previously: good (0.0)
| | | | | | | credit_history = critical/other existing credit: good (2.0)
| | | | | | savings_status = 500<=X<1000: good (4.0/1.0)
| | | | | | savings_status = >=1000: good (4.0)
| | | | | | savings_status = no known savings
| | | | | | | existing_credits <= 1
| | | | | | | | own_telephone = none: bad (9.0/1.0)
| | | | | | | | own_telephone = yes: good (4.0/1.0)
| | | | | | | existing_credits > 1: good (2.0)
```

```
| | | | | duration > 30: bad (30.0/3.0)
| | | | other_parties = co applicant: bad (7.0/1.0)
| | | | other_parties = guarantor: good (12.0/3.0)
| | | job = high qualif/self emp/mgmt: good (30.0/8.0)
| foreign_worker = no: good (15.0/2.0)
checking_status = 0<=X<200
| credit_amount <= 9857
| | savings_status = <100
| | | other_parties = none
| | | | duration <= 42
| | | personal_status = male div/sep: bad (8.0/2.0)
| | | personal_status = female div/dep/mar
| | | | purpose = new car: bad (5.0/1.0)
| | | | purpose = used car: bad (1.0)
| | | | purpose = furniture/equipment
| | | | | duration <= 10: bad (3.0)
| | | | | duration > 10
| | | | | | duration <= 21: good (6.0/1.0)
| | | | | | duration > 21: bad (2.0)
| | | | purpose = radio/tv: good (8.0/2.0)
| | | | purpose = domestic appliance: good (0.0)
| | | | purpose = repairs: good (1.0)
| | | | purpose = education: good (4.0/2.0)
| | | | purpose = vacation: good (0.0)
| | | | purpose = retraining: good (0.0)
| | | | purpose = business
| | | | | residence_since <= 2: good (3.0)
| | | | | residence_since > 2: bad (2.0)
| | | | purpose = other: good (0.0)
| | | personal_status = male single: good (52.0/15.0)
| | | personal_status = male mar/wid
| | | | duration <= 10: good (6.0)
| | | | duration > 10: bad (10.0/3.0)
| | | personal_status = female single: good (0.0)
| | duration > 42: bad (7.0)
| other_parties = co applicant: good (2.0)
| other_parties = guarantor
| | purpose = new car: bad (2.0)
| | purpose = used car: good (0.0)
| | purpose = furniture/equipment: good (0.0)
| | purpose = radio/tv: good (18.0/1.0)
| | purpose = domestic appliance: good (0.0)
| | purpose = repairs: good (0.0)
| | purpose = education: good (0.0)
| | purpose = vacation: good (0.0)
| | purpose = retraining: good (0.0)
| | purpose = business: good (0.0)
| | purpose = other: good (0.0)
```

savings_status = 100<=X<500
| purpose = new car: bad (15.0/5.0)
| purpose = used car: good (3.0)
| purpose = furniture/equipment: bad (4.0/1.0)
| purpose = radio/tv: bad (8.0/2.0)
| purpose = domestic appliance: good (0.0)
| purpose = repairs: good (2.0)
| purpose = education: good (0.0)
| purpose = vacation: good (0.0)
| purpose = retraining: good (0.0)
| | | purpose = business
| | | | housing = rent
| | | | | existing_credits <= 1: good (2.0)
| | | | | existing_credits > 1: bad (2.0)
| | | | housing = own: good (6.0)
| | | | housing = for free: bad (1.0)
| | | purpose = other: good (1.0)
| | savings_status = 500<=X<1000: good (11.0/3.0)
| | savings_status = >=1000: good (13.0/3.0)
| | savings_status = no known savings: good (41.0/5.0)
| credit_amount > 9857: bad (20.0/3.0)
checking_status = >=200: good (63.0/14.0)
checking_status = no checking: good (394.0/46.0)
Number of Leaves : 103
Size of the tree : 140
Time taken to build model: 0.07 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	70570.5 %	
Incorrectly Classified Instances	295	29.5 %
Kappa statistic		0.2467
Mean absolute error	0.3467	
Root mean squared error	0.4796	
Relative absolute error		82.5233 %
Root relative squared error	104.6565 %	
Total Number of Instances	1000	

=== Detailed Accuracy By Class ===

TP Rate
0.84
0.39
Weighted Avg.
FP Rate Precision Recall F-Measure ROC Area Class
0.610.763 0.84 0.799 0.639 good
0.160.511 0.39 0.442 0.639 bad

0.705 0.475 0.687 0.705 0.692 0.639
=== Confusion Matrix ===
a b <-- classified as
588 112 | a = good
183 117 | b = bad

7. Check to see if the data shows a bias against "foreign workers" (attribute 20),or "personal-status"(attribute 9). One way to do this (perhaps rather simple minded) is to remove these attributes from the dataset and see if the decision tree created in those cases is significantly different from the full dataset case which you have already done. To remove an attribute you can use the reprocess tab in Weka's GUI Explorer. Did removing these attributes have any significant effect? Discuss.

AIM: Analyzing the removing attributes from the dataset.

PROCEDURE:

1) Given the credit database for mining.

2) Use the Weka GUI Chooser.

3) Select EXPLORER present in Applications.

4) Select Preprocess Tab.

5) Go to OPEN file and browse the file that is already stored in the system “Credit-g.arff”.

6) In the "Filter" panel, click on the "Choose" button. This will show a popup window with list available filters.

7) Select “weka.filters.unsupervised.attribute.Remove”

8) Next, click on text box immediately to the right of the "Choose" button

9) In the resulting dialog box enter the index of the attribute to be filtered out (Make sure that the "invert Selection" option is set to false)

10) Then click "OK" . Now, in the filter box you will see "Remove -R 1"

11)Click the "Apply" button to apply this filter to the data. This will remove the "id" attribute and create a new working relation

12) To save the new working relation as an ARFF file, click on save button in the top panel.

13) Go to OPEN file and browse the file that is newly saved (attribute deleted file)

14) Go to Classify tab.

15)Choose Classifier “Tree.

16) Select j48 tree

17) Select Test options “Use training set”

18) If need select attribute.

19) Now start weka.

20) Now we can see the output details in the Classifier output.

21)Right click on the result list and select ” visualize tree “option .

22)Compare the output results with that of the 4th experiment

23)Check whether the accuracy increased or decreased.

24)Check whether removing these attributes have any significant effect.

This increase in accuracy is because thus two attributes are not much important in training and analyzing by removing this, the time has been reduced to some extent and then it results in increase in the accuracy. The decision tree which is created is very large compared to the decision tree which we have trained now. This is the main difference between these two decision trees.

8. Another question might be, do you really need to input so many attributes to get good results? Maybe only a few would do. For example, you could try just having attributes 2, 3, 5, 7, 10, 17 (and 21, the class attribute (naturally)). Try out some combinations. (You had removed two attributes in problem 7. Remember to reload the arff data file to get all the attributes initially before you start selecting the ones you want.)

AIM: To removing the selected attributes and also to reload the arff data file to get all the attributes in the data set.

PROCEDURE:

1) Given the credit database for mining.

2) Use the Weka GUI Chooser.

3) Select EXPLORER present in Applications.

4) Select Preprocess Tab.

5) Go to OPEN file and browse the file that is already stored in the system “credit-g.arff”

6) Select some of the attributes from attributes list which are to be removed. With this step only the attributes necessary for classification are left in the attributes panel.

7) The go to Classify tab.

8)Choose Classifier “Tree”

9) Select j48

10) Select Test options “Use training set”

11)If need select attribute.

12) Now start Weka.

13) Now we can see the output details in the Classifier output.

14)Right click on the result list and select “visualize tree” option.

15)Compare the output results with that of the 4th experiment.

16)Check whether the accuracy increased or decreased?

17)Check whether removing these attributes have any significant effect.

=== Classifier model (full training set) ===

OUTPUT:

J48 pruned tree

---

credit_history = no credits/all paid: bad (40.0/15.0)

credit_history = all paid

| employment = unemployed

| | duration <= 36: bad (3.0)

| | duration > 36: good (2.0)

| employment = <1

| | duration <= 26: bad (7.0/1.0)

| | duration > 26: good (2.0)

| employment = 1<=X<4: good (15.0/6.0)

| employment = 4<=X<7: bad (10.0/4.0)

| employment = >=7

| | job = unemp/unskilled non res: bad (0.0)

| | job = unskilled resident: good (3.0)

| | job = skilled: bad (3.0)

| | job = high qualif/self emp/mgmt: bad (4.0)

credit_history = existing paid

| credit_amount <= 8648

| | duration <= 40: good (476.0/130.0)

| | duration > 40: bad (27.0/8.0)

| credit_amount > 8648: bad (27.0/7.0)

credit_history = delayed previously

| employment = unemployed

| | credit_amount <= 2186: bad (4.0/1.0)

| | credit_amount > 2186: good (2.0)

| employment = <1

| | duration <= 18: good (2.0)

| | duration > 18: bad (10.0/2.0)

| employment = 1<=X<4: good (33.0/6.0)

| employment = 4<=X<7

| | credit_amount <= 4530

| | | credit_amount <= 1680: good (3.0)

| | | credit_amount > 1680: bad (3.0)

| | credit_amount > 4530: good (11.0)

| employment = >=7

| | job = unemp/unskilled non res: good (0.0)

| | job = unskilled resident: good (2.0/1.0)

| | job = skilled: good (14.0/4.0)

| | job = high qualif/self emp/mgmt: bad (4.0/1.0)

credit_history = critical/other existing credit: good (293.0/50.0)

Number of Leaves : 27

Size of the tree : 40

Time taken to build model: 0.01 seconds

=== Evaluation on training set ===

=== Summary ===

Correctly Classified Instances	764	76.4 %
Incorrectly Classified Instances	236	23.6 %
Kappa statistic		0.3386
Mean absolute error		0.3488
Root mean squared error		0.4176
Relative absolute error		83.0049 %
Root relative squared error		91.1243 %
Total Number of Instances		1000

=== Classifier model (full training set) ===
J48 pruned tree
---
credit_history = no credits/all paid: bad (40.0/15.0)
credit_history = all paid
| employment = unemployed
| | duration <= 36: bad (3.0)
| | duration > 36: good (2.0)
| employment = <1
| | duration <= 26: bad (7.0/1.0)
| | duration > 26: good (2.0)
| employment = 1<=X<4: good (15.0/6.0)
| employment = 4<=X<7: bad (10.0/4.0)
| employment = >=7
| | job = unemp/unskilled non res: bad (0.0)
| | job = unskilled resident: good (3.0)

```
| | job = skilled: bad (3.0)
| | job = high qualif/self emp/mgmt: bad (4.0)
credit_history = existing paid
| credit_amount <= 8648
| | duration <= 40: good (476.0/130.0)
| | duration > 40: bad (27.0/8.0)
| credit_amount > 8648: bad (27.0/7.0)
credit_history = delayed previously
| employment = unemployed
| | credit_amount <= 2186: bad (4.0/1.0)
| | credit_amount > 2186: good (2.0)
| employment = <1
| | duration <= 18: good (2.0)
| | duration > 18: bad (10.0/2.0)
| employment = 1<=X<4: good (33.0/6.0)
| employment = 4<=X<7
| | credit_amount <= 4530
| | | credit_amount <= 1680: good (3.0)
| | | credit_amount > 1680: bad (3.0)
| | credit_amount > 4530: good (11.0)
| employment = >=7
| | job = unemp/unskilled non res: good (0.0)
| | job = unskilled resident: good (2.0/1.0)
| | job = skilled: good (14.0/4.0)
| | job = high qualif/self emp/mgmt: bad (4.0/1.0)
credit_history = critical/other existing credit: good (293.0/50.0)
Number of Leaves : 27
Size of the tree : 40


Time taken to build model: 0.01 seconds
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances         703     70.3 %
Incorrectly Classified Instances       297     29.7 %
Kappa statistic                          0.1759
Mean absolute error                      0.3862
Root mean squared error                  0.4684
Relative absolute error                 91.9029 %
Root relative squared error            102.2155 %
Total Number of Instances              1000
```

9. Sometimes, the cost of rejecting an applicant who actually has a good credit(case 1) might be higher than accepting an applicant who has bad credit (case 2). Instead of counting the misclassifications equally in both cases, give a highercost to the first case

(say cost 5) and lower cost to the second case. You can do this by using a cost matrix in Weka. Train your Decision Tree again and reportthe Decision Tree and cross-validation results. Are they significantly differentfrom results obtained in problem 6 (using equal cost)?

AIM: Determining the good credit and the bad credit in the decision tree dataset.

PROCEDURE:

1) Given the credit database for mining.

2) Use the Weka GUI Chooser.

3) Select EXPLORER present in Applications.

4) Select Preprocess Tab.

5) Go to OPEN file and browse the file that is already stored in the system “Credit-g.arff”.

6) Go to Classify tab.

7) Choose Classifier “Tree”

8) Select j48

9) Select Test options “Training set”.

10) Click on “more options”.

11) Select cost sensitive evaluation and click on set button

12) Set the matrix values and click on resize. Then close the window.

13) Click Ok and start

14) We can see the output details in the Classifier output

15) Select Test options “Cross-validation”.

16) Set “Folds” Ex: 10

17) if need select attribute.

18) Now start weka.

19) Now we can see the output details in the Classifier output.

In the Problem 6, we used equal cost and we trained the decision tree. Buthere, we consider two cases with different cost.Let us take cost 5 in case 1 and cost 2 in case 2.When we give such costs in both cases and after training the decision tree, wecan observe that almost equal to that of the decision tree obtained in problem 6.

But we find some difference in cost factor which is in summary in the difference in cost factor.

Case1 (cost 5) Case2 (cost 5)

Total Cost 3820 1705

Average cost 3.82 1.705

We don't find this cost factor in problem 6. As there we use equal cost. This is the

major difference between the results of problem 6 and problem 9.

The cost matrices we used here:

Case 1: 5 1

1 5

Case 2: 2 1

1 2

10. Do you think it is a good idea to prefer simple decision trees instead of having long complex decision trees? How does the complexity of a Decision Tree relate to the bias of the model?

AIM: Analyzing the decision tree into the shortest form by using the dataset.

PROCEDURE: This will be based on the attribute set, and the requirement of relationship among attribute we want to study. This can be viewed based on the database and user requirement.

When we consider long complex decision trees, we will have many unnecessary attributes in the tree which results in increase of the bias of the model. Because of this, the accuracy of the model can also effected. This problem can be reduced by considering simple decision tree. The attributes will be less and it decreases the bias of the model. Due to this the result will be more accurate. So it is a good idea to prefer simple decision trees instead of long complex trees.

11. You can make your Decision Trees simpler by pruning the nodes. One approach is to use Reduced Error Pruning - Explain this idea briefly. Try reduced error pruning for training your Decision Trees using cross-validation (you can do this in Weka) and

report the Decision Tree you obtain ? Also, report your accuracy using the pruned model. Does your accuracy increase ?

THEORY:

Reduced-error pruning:-

The idea of using a separate pruning set for pruning—which is applicable to decision trees as well as rule sets—is called reduced-error pruning. The variant described previously prunes a rule immediately after it has been grown and is called incremental reduced-error pruning. Another possibility is to build a full, unpruned rule set first, pruning it afterwards by discarding individual tests.However, this method is much slower. Of course, there are many different ways to assess the worth of a rule based on the pruning set. A simple measure is to consider how well the rule would do at discriminating the predicted class from other classes if it were the only rule in the theory, operating under the closed world assumption. If it gets p instances right out of the t instances that it covers, and there are P instances of this class out of a total T of instances altogether, then it gets p positive instances right. The instances that it does not cover include N - n negative ones, where n = t – p is the number of negative instances that the rule covers and N = T - P is the total number of negative instances. Thus the rule has an overall success ratio of [p +(N - n)] T , and this quantity, evaluated on the test set, has been used to evaluate the success of a rule when using reduced-error pruning.

AIM: Analyzing the decision trees is simpler by pruning the nodes in the dataset.

PROCEDURE:

1) Given the credit database for mining.

2) Use the Weka GUI Chooser.

3) Select EXPLORER present in Applications.

4) Select Preprocess Tab.

5) Go to OPEN file and browse the file that is already stored in the system “bank.csv”.6) Select some of the attributes from attributes list

7) Go to Classify tab.

8) Choose Classifier “Tree”

9) Select “NBTree” i.e., Navie Bayesian tree.

10) Select Test options “Use training set”

11) Right click on the text box besides choose button, select show properties

12) Now change unprone mode “false” to “true”.

13) Change the reduced error pruning % as needed.

14) If need select attribute.

15) Now start weka.

16) Now we can see the output details in the Classifier output.

17) Right click on the result list and select ” visualize tree “option.

OUTPUT:

J48 pruned tree

---

checking_status = <0
| foreign_worker = yes
| | credit_history = no credits/all paid: bad (11.0/3.0)
| | credit_history = all paid: bad (9.0/1.0)
| | credit_history = existing paid
| | | other_parties = none
| | | | savings_status = <100
| | | | | existing_credits <= 1
| | | | | | purpose = new car: bad (17.0/4.0)
| | | | | | purpose = used car: good (3.0/1.0)
| | | | | | purpose = furniture/equipment: good (22.0/11.0)
| | | | | | purpose = radio/tv: good (18.0/8.0)
| | | | | | purpose = domestic appliance: bad (2.0)
| | | | | | purpose = repairs: bad (1.0)
| | | | | | purpose = education: bad (5.0/1.0)
| | | | | | purpose = vacation: bad (0.0)
| | | | | | purpose = retraining: bad (0.0)
| | | | | | purpose = business: good (3.0/1.0)
| | | | | | purpose = other: bad (0.0)
| | | | | existing_credits > 1: bad (5.0)
| | | | savings_status = 100<=X<500: bad (8.0/3.0)
| | | | savings_status = 500<=X<1000: good (1.0)

```
|  |  |  |  savings_status = >=1000: good (2.0)
|  |  |  |  savings_status = no known savings
|  |  |  |  |  job = unemp/unskilled non res: bad (0.0)
|  |  |  |  |  job = unskilled resident: good (2.0)
|  |  |  |  |  job = skilled
|  |  |  |  |  |  own_telephone = none: bad (4.0)
|  |  |  |  |  |  own_telephone = yes: good (3.0/1.0)
|  |  |  |  |  job = high qualif/self emp/mgmt: bad (3.0/1.0)
|  |  |  other_parties = co applicant: good (4.0/2.0)
|  |  |  other_parties = guarantor: good (8.0/1.0)
|  |  credit_history = delayed previously: bad (7.0/2.0)
|  |  credit_history = critical/other existing credit: good (38.0/10.0)
|  foreign_worker = no: good (12.0/2.0) checking_status = 0<=X<200
|  other_parties = none
|  |  credit_history = no credits/all paid
|  |  |  other_payment_plans = bank: good (2.0/1.0)
|  |  |  other_payment_plans = stores: bad (0.0)
|  |  |  other_payment_plans = none: bad (7.0)
|  |  credit_history = all paid: bad (10.0/4.0)
|  |  credit_history = existing paid
|  |  |  credit_amount <= 8858: good (70.0/21.0)
|  |  |  credit_amount > 8858: bad (8.0)
|  |  credit_history = delayed previously: good (25.0/6.0)
|  |  credit_history = critical/other existing credit: good (26.0/7.0)
|  other_parties = co applicant: bad (7.0/1.0)
|  other_parties = guarantor: good (18.0/4.0)
 checking_status = >=200: good (44.0/9.0)
 checking_status = no checking
|  other_payment_plans = bank: good (30.0/10.0)
|  other_payment_plans = stores: good (12.0/2.0)
|  other_payment_plans = none
|  |  credit_history = no credits/all paid: good (4.0)
|  |  credit_history = all paid: good (1.0)
|  |  credit_history = existing paid
|  |  |  existing_credits <= 1: good (92.0/7.0)
|  |  |  existing_credits > 1
|  |  |  |  installment_commitment <= 2: bad (4.0/1.0)
|  |  |  |  installment_commitment > 2: good (5.0)
|  |  credit_history = delayed previously: good (22.0/6.0)
|  |  credit_history = critical/other existing credit: good (92.0/3.0)

Number of Leaves  :  47
```

Size of the tree : 64

Time taken to build model: 0.49 seconds
=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances	725	72.5 %
Incorrectly Classified Instances	275	27.5 %
Kappa statistic	0.2786	
Mean absolute error	0.3331	
Root mean squared error	0.4562	
Relative absolute error	79.2826 %	
Root relative squared error	99.5538 %	
Total Number of Instances	1000	

12. (Extra Credit): How can you convert a Decision Trees into "if-then-elserules". Make up your own small Decision Tree consisting of 2-3 levels and convert it into a set of rules. There also exist different classifiers that output the model in the form of rules - one such classifier in Weka is rules.PART, train thismodel and report the set of rules obtained. Sometimes just one attribute can be good enough in making the decision, yes, just one ! Can you predict what attribute that might be in this dataset? OneR classifier uses a single attribute to make decisions (it chooses the attribute based on minimum error). Report the rule obtained by training a one R classifier. Rank the performance of j48, PART and oneR.

AIM: Converting the decision tree to the different set of rules based on the different levels in the dataset.

PROCEDURE for J48:

1) Given the credit database for mining.

2) Use the Weka GUI Chooser.

3) Select EXPLORER present in Applications.

4) Select Preprocess Tab.

5) Go to OPEN file and browse the file that is already stored in the system “credit-g.arff”.

6) Select some of the attributes from attributes list

7) Go to Classify tab.

8) Choose Classifier “Trees Rules”

9) Select “J48”.

10) Select Test options “Use training set”

11) If need select attribute.

12) Now start weka.

13) Now we can see the output details in the Classifier output.

14) Right click on the result list and select ” visualize tree “option .

Procedure for “OneR”:

1) Given the credit database for mining.

2) Use the Weka GUI Chooser.

3) Select EXPLORER present in Applications.

4) Select Preprocess Tab.

5) Go to OPEN file and browse the file that is already stored in the system “credit-g.arff”.

6) Select some of the attributes from attributes list

7) Go to Classify tab.

8) Choose Classifier “Rules”

9) Select “OneR”.

10) Select Test options “Use training set”

11) If need select attribute.

12) Now start weka.

13) Now we can see the output details in the Classifier output.

Procedure for “PART”:

1) Given the credit database for mining.

2) Use the Weka GUI Chooser.

3) Select EXPLORER present in Applications.

4) Select Preprocess Tab.

5) Go to OPEN file and browse the file that is already stored in the system “credit-g.arff”.

6) Select some of the attributes from attributes list

7) Go to Classify tab.

8) Choose Classifier “Rules”.

9) Select “PART”.

10) Select Test options “Use training set”

11) if need select attribute.

12) Now start weka.

13) Now we can see the output details in the Classifier output.

Attribute relevance with respect to the class – relevant attribute (science) IF accounting=1 THEN class=A (Error=0, Coverage = 7 instance)

IF accounting=0 THEN class=B (Error=4/13, Coverage = 13 instances)

Converting Decision trees into “IF-THEN-ELSE” rules using rules.PART classifier:-

PART decision list

outlook = overcast: yes (4.0)

windy = TRUE: no (4.0/1.0)

outlook = sunny: no (3.0/1.0)

: yes (3.0)

Number of Rules : 4

Yes, sometimes just one attribute can be good enough in making the decision.

In this dataset (Weather), Single attribute for making the decision is “outlook”

outlook:

sunny -> no

overcast -> yes

rainy -> yes

(10/14 instances correct)

With respect to the time, the oneR classifier has higher ranking and J48 is in 2nd

place and PART gets 3

rd place.

J48 PART oneR

TIME (sec) 0.12 0.14 0.04

RANK II III I

But if you consider the accuracy, The J48 classifier has higher ranking, PART gets second place and oneR

gets lst place

J48 PART oneR

ACCURACY (%) 70.5 70.2% 66.8%

RANK I II III

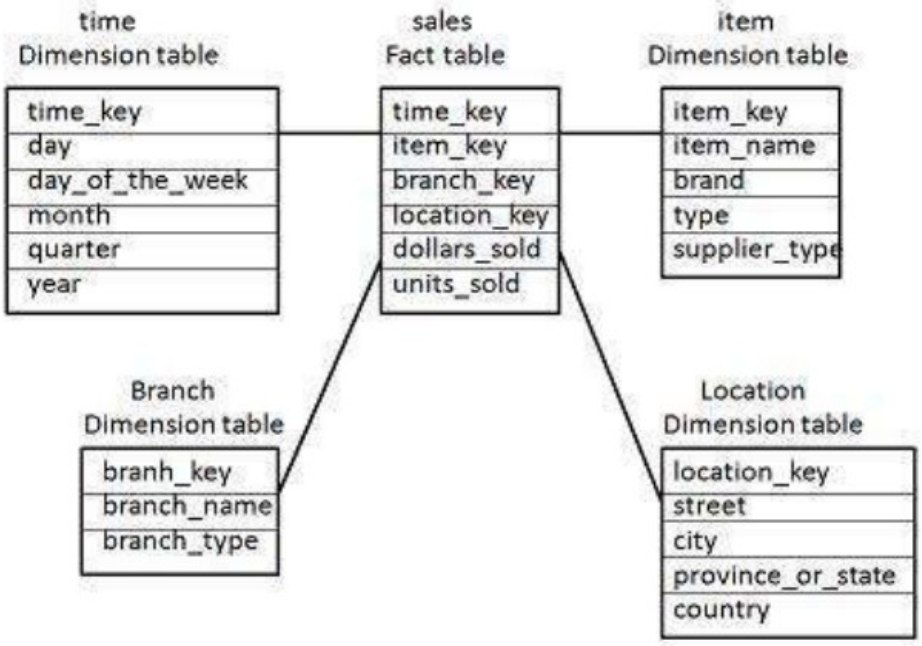
Experiment 2:

Schema Definition

Multidimensional schema is defined using Data Mining Query Language (DMQL). The two primitives, cube definition and dimension definition, can be used for defining the data warehouses and data marts.

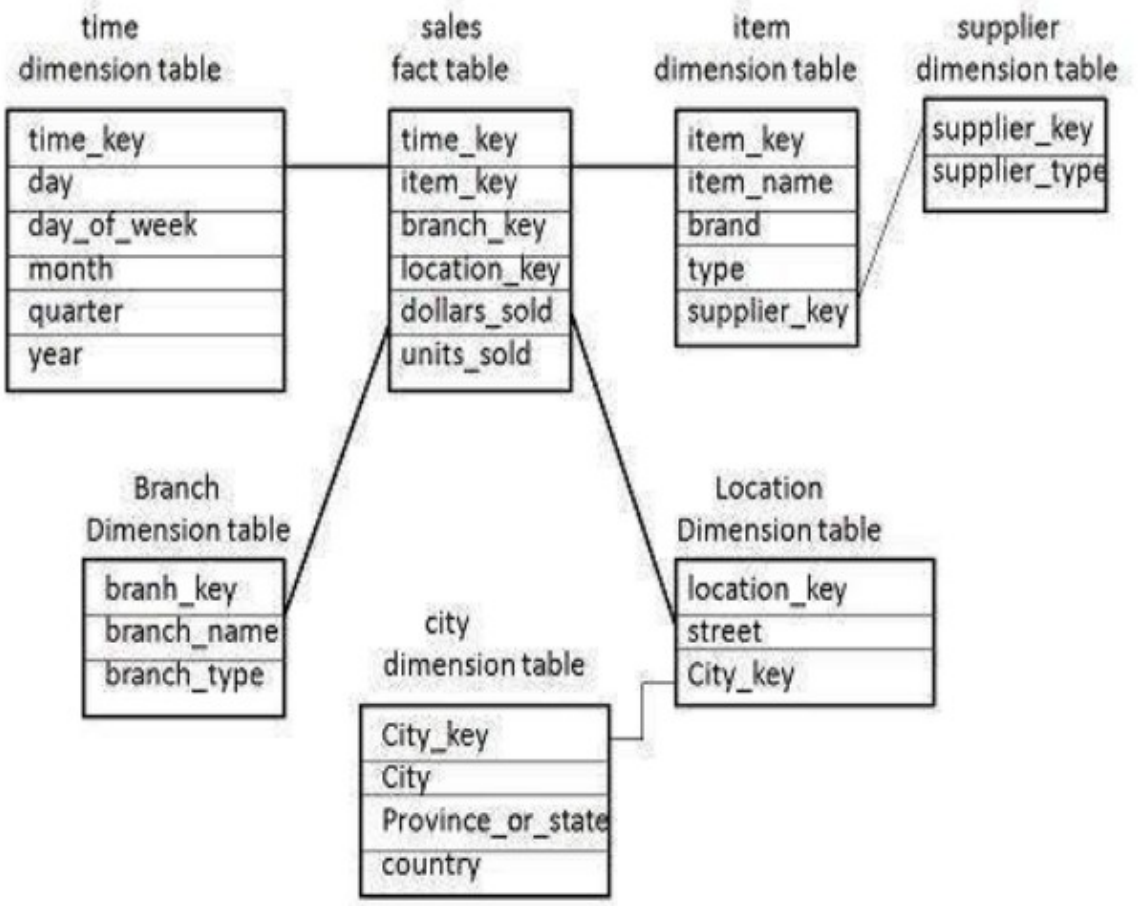
1.Star Schema:

- Each dimension in a star schema is represented with only one-dimension table.
- This dimension table contains the set of attributes.
- The following diagram shows the sales data of a company with respect to the four dimensions, namely time, item, branch, and location.
- There is a fact table at the center. It contains the keys to each of four dimensions.
- The fact table also contains the attributes, namely dollars sold and units sold.



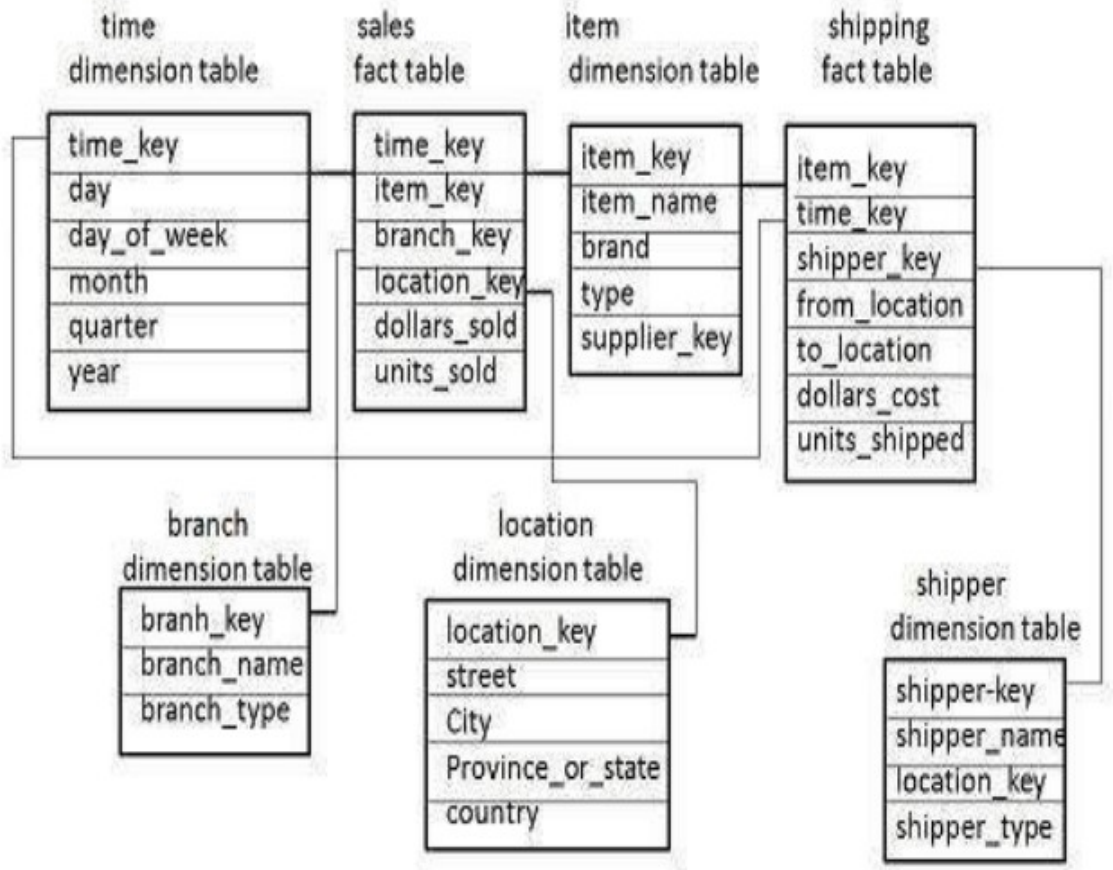
2.Snowflake Schema:

- Some dimension tables in the Snowflake schema are normalized.
- The normalization splits up the data into additional tables. Unlike Star schema, the dimensions table in a snowflake schema is normalized. For example, the item dimension table in star schema is normalized and split into two dimension tables, namely item and supplier table.
- Now the item dimension table contains the attributes item_key, item_name, type, brand, and supplier-key.
- The supplier key is linked to the supplier dimension table. The supplier dimension table contains the attributes supplier_key and supplier_type.



3.Fact Constellation Schema :

- A fact constellation has multiple fact tables. It is also known as galaxy schema.
- The following diagram shows two fact tables, namely sales and shipping.
- The sales fact table is same as that in the star schema.
- The shipping fact table has the five dimensions, namely item_key, time_key, shipper_key, from_location, to_location. The shipping fact table also contains two measures, namely dollars sold and units sold.
- It is also possible to share dimension tables between fact tables. For example, time, item, and location dimension tables are shared between the sales and shipping fact table.



Hospital Management System

DataWarehouse consists of Dimension Table and Fact Table.
Remember the following :
Dimension
The dimension objects(Dimension):
-Name
-Attributes levels,with one primary key
-Hierarchies
One time dimension is must.
About levels and hierarchies
Dimension objects(dimension) consists of set of levels and set of hierarchies defined over those levels .The levels represents level of aggregration.Hierarchies describe parent child relationships among a set of levels.
For example,a typical calender dimension could contain 5 levels.Two hierarchies can be defined on these levels:

H1: YearL>QuarterL>MonthL>WeekL>DayL
H2: YearL>WeekL>DayL

The hierarchies are described from parent to child,so that year is the parent of quater,Quater the parent of month,and so forth.
About Unique Key Constraint:

When you create a definition for a hierarchy,Warehouse builder creates an identifier key the key for each level of the hierarchy and a unique key constraint on the lowest level(base level).

Q1. Design a Hospital Management System DataWarehouse(TARGET) consits of dimensions Patient,Medicine,Suppliers,Time. Where measures are 'No Units' ,Unit Price. Assume the relation database (Source) table schema as follows:

- TIME(Day,Month,Year)
- PATIENT(Pateint_name,Age,Address,etc)
- MEDICINE(Medicine_brand_name,Drug_name,Supplier,No_units,Unit_price,etc)
- SUPPLIER(Supplier_name,Medicine_brand_name,Address,etc)

If each dimension has six levels,decide the levels and hierarchies,assume the level names suitably.

Q. Design a Hospital Management System DataWarehouse using all schemas.Given the example 4-D cube with assumptions names.

==> Dimension table for TIME:

Name: TIME

Attributes: timekey
day
day_of_week
month
quarter
year

==> Dimension table for PATIENT:

Name:PATIENT

Attributes:patient_name
patient_key
age
address
gender
health_condition

Hierarchy: problem_key
problem_name
health_condition_status

==> Dimension table for MEDICINE

Name:MEDICINE

Attributes:medicine_key
medicine_brandname
drug_name
supplies
no_units
dosage level
side effects

==> Dimension table for SUPPLIERS

Name:SUPPLIER

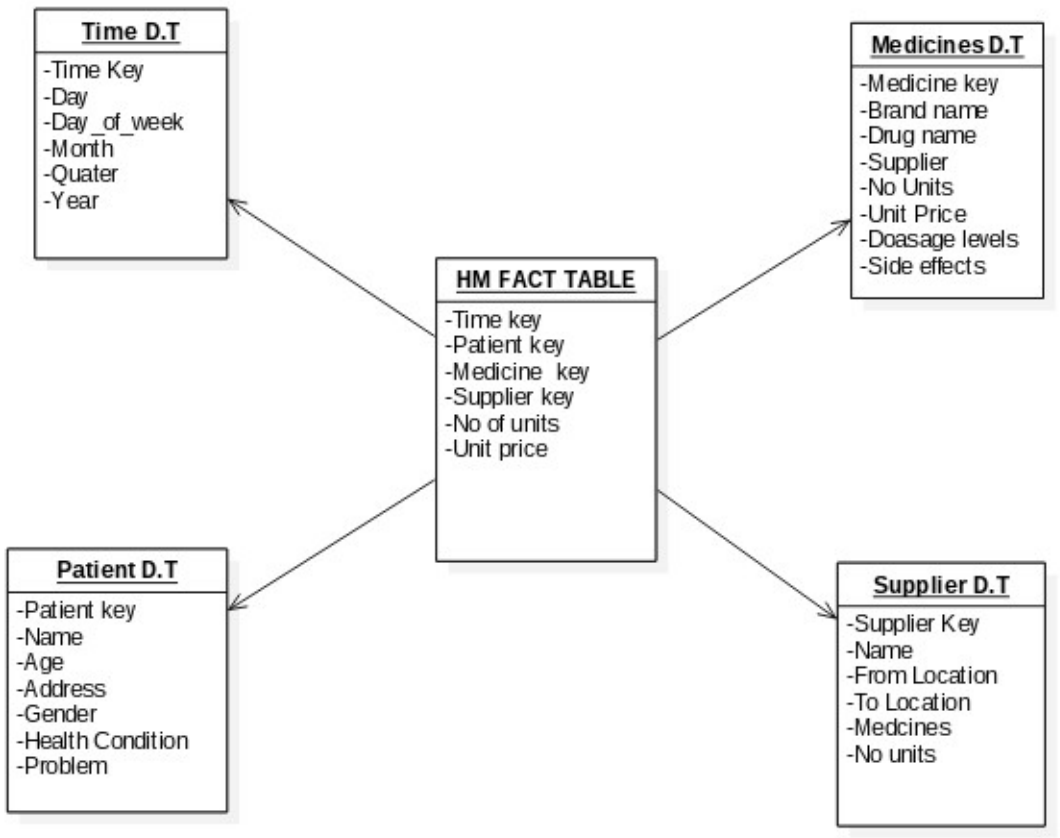
Attributes: supplier_key
supplier_name
from_location,to_location
medicine_brandname
no_units

==> FACT TABLE:

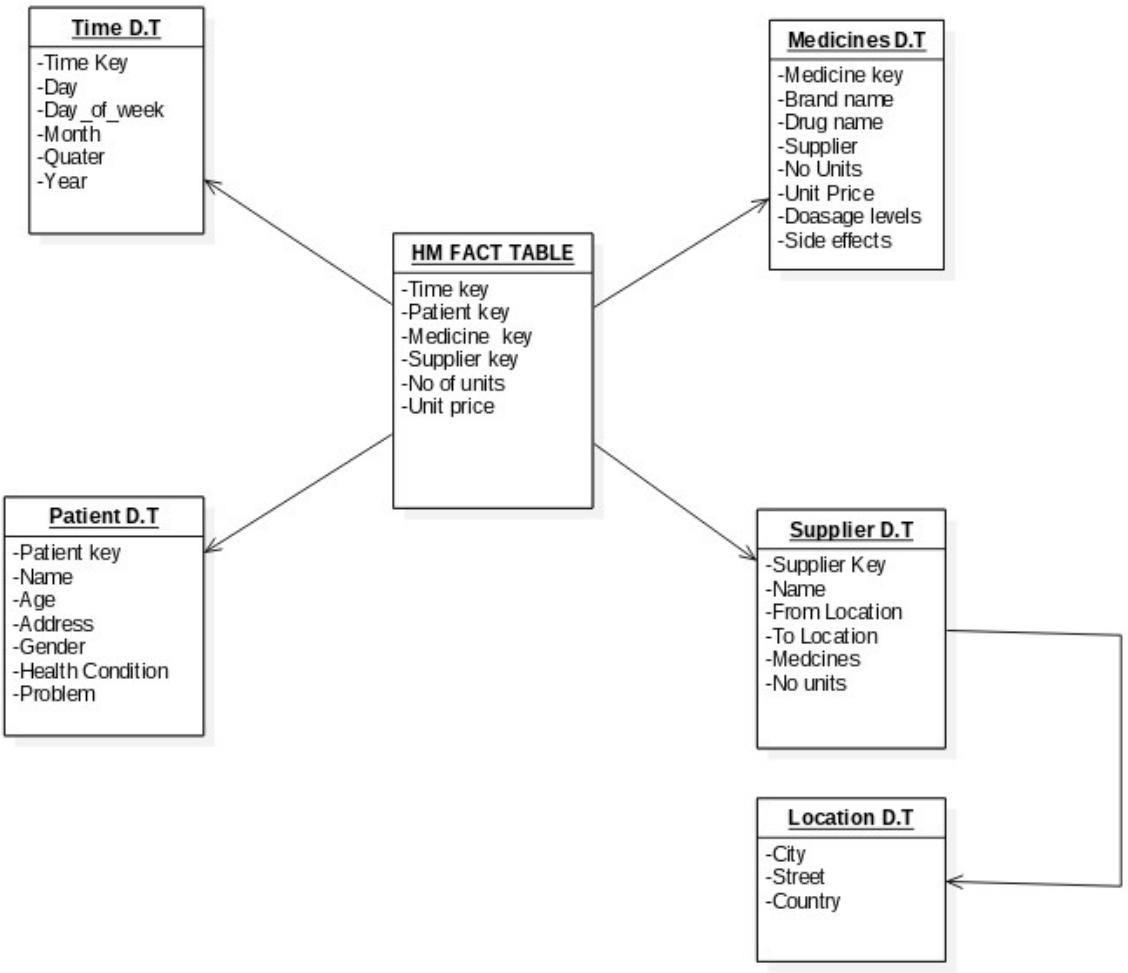
Name:Sales

Attributes: time_key
patient_key
medicine_key
supplier_key
no_units
unit_price

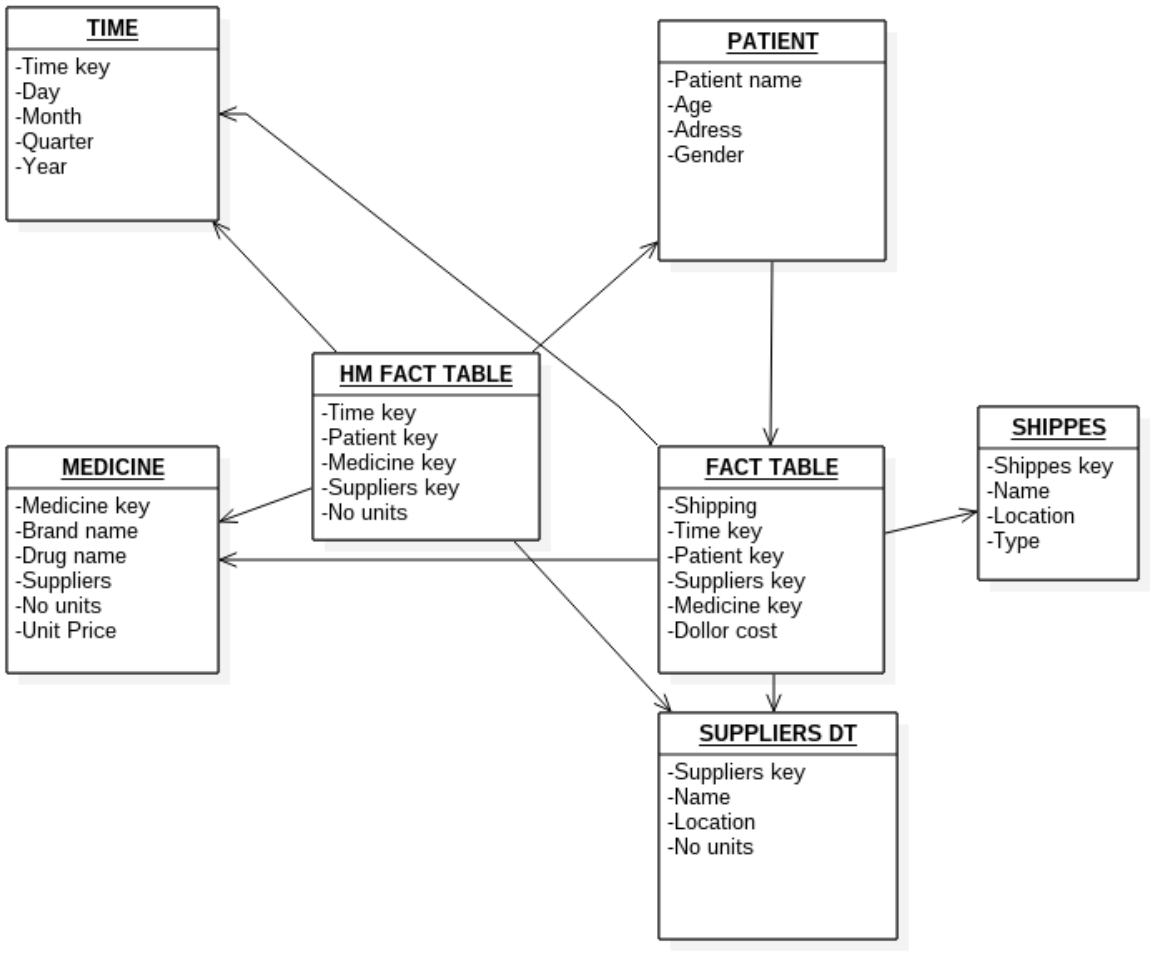
STAR SCHEMA



SNOWFLAKE SCHEMA



FACT CONSTELLATION SCHEMA



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