

报告

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1. 目标

练习如何构建决策树。认识归一化和离散化对构建决策树的影响。

2. Data

1) Bank-all.arff 是银行的所有数据。当我们不拆分数据的时候，我们可以用 10-crossvalidation 来测试分类器的准确性。数据的最后一个属性是类标签。

2) Bank-train.arff is used for constructing the model.

Bank-test.arff is used for testing the model.

The last attribute is the class label.

3) weather-nominal.arff

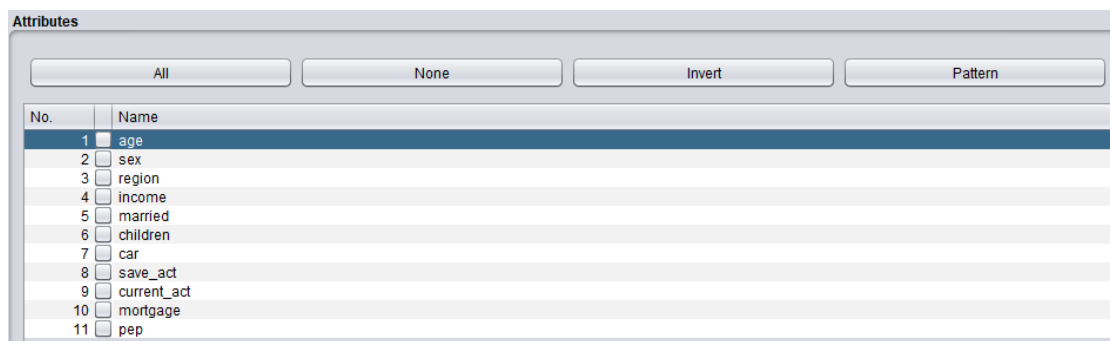
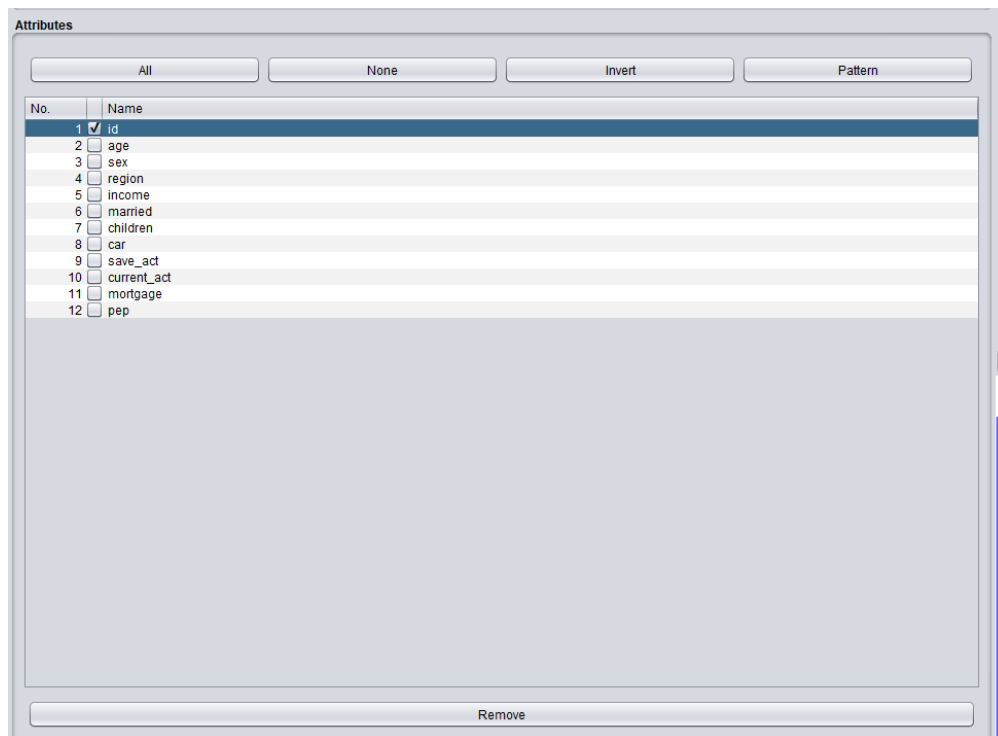
3. Contents

两个实验:

1. Bank-all.arff

1) 预处理，删除无用属性，保存到新的数据文件。

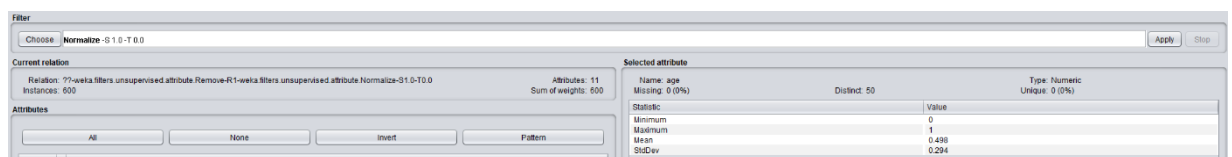
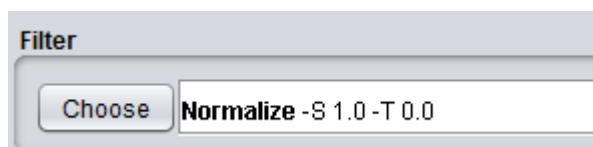
导入 weka, id 这一属性对于我们分类是无用属性，因此 remove，保存到新的文件 Bank-all-1.arff。



2) 选择两种方法对数据进行规范化，保存到新的数据文件中。并列出规范化的结果。

min-max 标准化:

点击该页中，Filter 下方的 Choose，在 unsupervised 文件夹下找到 Normalize。



Selected attribute

Name: age	Distinct: 50	Type: Numeric
Missing: 0 (0%)		Unique: 0 (0%)

Statistic	Value
Minimum	0
Maximum	1
Mean	0.498
StdDev	0.294

点击 Apply 归一，并 save 保存为新的文件 bank-all-2. 1. arff

z-score 标准化:

点击该页中，Filter 下方的 Choose，在 unsupervised 文件夹下找到 Standardize。点击 Apply 归一，并 save 保存为新的文件 bank-all-2. 2. arff。

Filter

Current relation

Relation: ??-weka.filters.unsupervised.attribute.Remove-R1-weka.filters.unsupervised.attribute.Normalize-S1.0-T0.0-weka.filters.unsupervi...

Instances: 600

Selected attribute

Name: age	Distinct: 50	Type: Numeric
Missing: 0 (0%)		Unique: 0 (0%)

Statistic	Value
Minimum	-1.691
Maximum	1.706
Mean	-0
StdDev	1

3) 选择两种方法对数据进行离散，保存到新的数据文件中。并列
出离散化的结果。

等宽离散化

点击该页中，Filter 下方的 Choose，在 unsupervised 文件夹下找到 Discretize，并修改参数。点击 Apply 离散，并 save 保存为新的文件 bank-all-3. 1. arff。

Choose

Discretize -B 5 -M -1.0 -R first-last-precision 6

current relation

Relation: ??-weka.filters.unsupervised.attribute.Remove-R1

Instances: 600

attributes

All

None

Invert

No.	Name
1	age
2	sex
3	region
4	income
5	married
6	children
7	car
8	save_act
9	current_act
10	mortgage
11	pep

weka.gui.GenericObjectEditor

weka.filters.unsupervised.attribute.Discretize

About

An instance filter that discretizes a range of numeric attributes in the dataset into nominal attributes.

More

Capabilities

attributeIndices

first-last

binRangePrecision

6

bins

5

debug

False

desiredWeightOfInstancesPerInterval

-1.0

doNotCheckCapabilities

False

findNumBins

False

ignoreClass

False

invertSelection

False

makeBinary

False

spreadAttributeWeight

False

useBinNumbers

False

useEqualFrequency

False

Open...

Save...

OK

Cancel

Apply

Stop

Selected attribute

Name: age

Missing: 0 (0%)

Distinct: 5

Type: Nominal

Unique: 0 (0%)

No.	Label	Count	Weight
1	'(-inf-27.8]'	126	126.0
2	'(27.8-37.6]'	111	111.0
3	'(37.6-47.4]'	137	137.0
4	'(47.4-57.2]'	99	99.0
5	'(57.2-inf)'	127	127.0

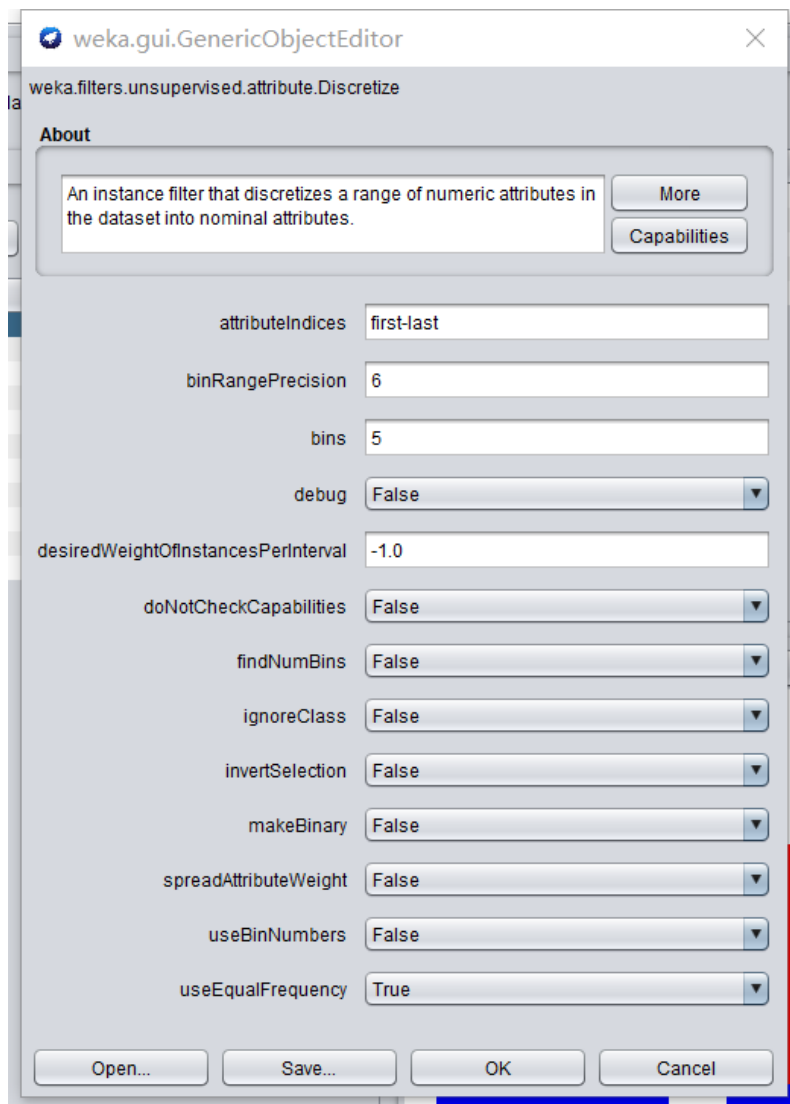
等频离散化

点击该页中，Filter 下方的 Choose，在 unsupervised 文件夹下找到 Discretize，并修改参数。点击 Apply 离散，并 save 保存为新的文件 bank-all-3.2.arff。

Filter

Choose

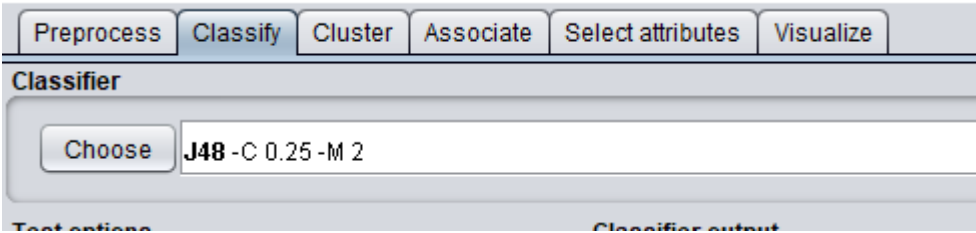
Discretize -F -B 5 -M -1.0 -R first-last-precision 6



Selected attribute			
Name: age		Type: Nominal	
Missing: 0 (0%)		Unique: 0 (0%)	
		Distinct: 5	
No.	Label	Count	Weight
1	'(-inf-27.5]'	126	126.0
2	'(27.5-38.5]'	123	123.0
3	'(38.5-47.5]'	125	125.0
4	'(47.5-58.5]'	118	118.0
5	'(58.5-inf)'	108	108.0

- 4) 利用银行原始数据，用 J48 构建决策树。选择 10-crossvalidation。比较 J48 与 binary split 或 multiple split 的结果。分析 "minNumObj" 参数的影响（选择 minNumObj=2 或 1）。

打开原始数据，在 classify 界面中，点击 choose 里的 tree 文件夹，选择 J48，并根据要求调整参数



multiple split minNumObj=2

```
| | save_act = YES: NO (119.0/12.0)
children = 1
| income <= 15538.8
| | age <= 41: NO (22.0/2.0)
| | age > 41: YES (2.0)
| income > 15538.8: YES (111.0/5.0)
children = 2
| income <= 30189.4: NO (83.0/9.0)
| income > 30189.4: YES (51.0/5.0)
children = 3
| income <= 44288.3: NO (60.0/5.0)
| income > 44288.3: YES (8.0)

Number of Leaves :    15
Size of the tree :    27

Time taken to build model: 0.02 seconds

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

Correctly Classified Instances      546           91      %
Incorrectly Classified Instances    54           9      %
Kappa statistic                    0.8178
Mean absolute error                 0.1559
Root mean squared error             0.2903
Relative absolute error             31.4168 %
Root relative squared error        58.2815 %
Total Number of Instances          600

=== Detailed Accuracy By Class ===

      TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
      0.872    0.058    0.926    0.872    0.898    0.819    0.893    0.862    YES
      0.942    0.128    0.898    0.942    0.919    0.819    0.893    0.869    NO
Weighted Avg.   0.910    0.096    0.911    0.910    0.910    0.819    0.893    0.866

=== Confusion Matrix ===

  a  b  <-- classified as
239 35 |  a = YES
 19 307 |  b = NO
```

multiple split minNumObj=1

```

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

J48 pruned tree
-----
: NO (600.0/274.0)

Number of Leaves :    1
Size of the tree :    1

Time taken to build model: 0 seconds

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

Correctly Classified Instances      326           54.3333 %
Incorrectly Classified Instances    274           45.6667 %
Kappa statistic                     0
Mean absolute error                 0.4963
Root mean squared error             0.4981
Relative absolute error             99.9972 %
Root relative squared error         100 %
Total Number of Instances          600

=== Detailed Accuracy By Class ===

                TP Rate  FP Rate  Precision  Recall  F-Measure  MCC      ROC Area  PRC Area  Class
                0.000    0.000    ?          0.000    ?          ?        0.492    0.453    YES
                1.000    1.000    0.543      1.000    0.704      ?        0.492    0.539    NO
Weighted Avg.   0.543    0.543    ?          0.543    ?          ?        0.492    0.500

=== Confusion Matrix ===

  a  b  <-- classified as
  0 274 |  a = YES
  0 326 |  b = NO

```

Binary split minNumObj=1

```

=== Summary ===

Correctly Classified Instances      525           87.5 %
Incorrectly Classified Instances     75           12.5 %
Kappa statistic                     0.747
Mean absolute error                 0.1806
Root mean squared error             0.3431
Relative absolute error             36.3861 %
Root relative squared error         68.8846 %
Total Number of Instances          600

=== Detailed Accuracy By Class ===

                TP Rate  FP Rate  Precision  Recall  F-Measure  MCC      ROC Area  PRC Area  Class
                0.836    0.092    0.884      0.836    0.859      0.748    0.848    0.779    YES
                0.908    0.164    0.868      0.908    0.888      0.748    0.848    0.832    NO
Weighted Avg.   0.875    0.131    0.875      0.875    0.875      0.748    0.848    0.808

=== Confusion Matrix ===

  a  b  <-- classified as
 229 45 |  a = YES
 30 296 |  b = NO

```

Binary split minNumObj=2

```

=== Summary ===

Correctly Classified Instances      523           87.1667 %
Incorrectly Classified Instances    77           12.8333 %
Kappa statistic                     0.7401
Mean absolute error                 0.1856
Root mean squared error            0.3451
Relative absolute error             37.3999 %
Root relative squared error        69.2717 %
Total Number of Instances          600

=== Detailed Accuracy By Class ===

      TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
      0.828    0.092    0.883    0.828    0.855      0.741    0.848    0.794    YES
      0.908    0.172    0.863    0.908    0.885      0.741    0.848    0.818    NO
Weighted Avg.   0.872    0.135    0.872    0.872    0.871      0.741    0.848    0.807

=== Confusion Matrix ===

  a  b  <-- classified as
227 47 | a = YES
 30 296 | b = NO

```

对于原始数据,Binary split 准确率比 multiple split 的偏低, minNumObj 的选择也有影响,minNumObj=2 准确率较高

5) 利用规范化数据用 J48 构建决策树。选择 10-crossvalidation。比较 J48 与 binary split 或 multiple split 的结果。分析 "minNumObj" 参数的影响 (选择 minNumObj=2 或 1)。

选择归一化数据,并重复以上步骤
multiple split minNumObj=2

Weka Explorer

Preprocess Classify Cluster Associate Select attributes Visualize

Classifier

Choose J48 - C 0.25 - M 2

Test options

Use training set
Supplied test set
Cross-validation Folds 10
Percentage split % 66
More options...

(Nom) pep

Start Stop

Result list (right-click for options)

14.15.44 - trees.J48

Classifier output

```

| | save_act = YES: NO (119.0/12.0)
| | children = 1
| | | income <= 15538.8
| | | | age <= 41: NO (22.0/2.0)
| | | | | age > 41: YES (2.0)
| | | | income > 15538.8: YES (111.0/5.0)
| | | children = 2
| | | | income <= 30189.4: NO (83.0/9.0)
| | | | | income > 30189.4: YES (51.0/5.0)
| | | children = 3
| | | | income <= 44288.3: NO (60.0/5.0)
| | | | | income > 44288.3: YES (8.0)
Number of Leaves : 15
Size of the tree : 27

Time taken to build model: 0 seconds

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

Correctly Classified Instances      546           91 %
Incorrectly Classified Instances    54           9 %
Kappa statistic                     0.8178
Mean absolute error                 0.1559
Root mean squared error            0.2903
Relative absolute error             31.4168 %
Root relative squared error        58.2815 %
Total Number of Instances          600

=== Detailed Accuracy By Class ===

      TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
      0.872    0.058    0.926    0.872    0.898      0.819    0.893    0.862    YES
      0.942    0.128    0.899    0.942    0.919      0.819    0.893    0.869    NO
Weighted Avg.   0.910    0.096    0.911    0.910    0.910      0.819    0.893    0.866

=== Confusion Matrix ===

  a  b  <-- classified as
239 35 | a = YES
 19 307 | b = NO

```

Status

OK

multiple split minNumObj=1

Time taken to build model: 0 seconds

=== Stratified cross-validation ===

=== Summary ===

Correctly Classified Instances	546	91	%
Incorrectly Classified Instances	54	9	%
Kappa statistic	0.8178		
Mean absolute error	0.1559		
Root mean squared error	0.2903		
Relative absolute error	31.4168 %		
Root relative squared error	58.2815 %		
Total Number of Instances	600		

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.872	0.058	0.926	0.872	0.898	0.819	0.893	0.862	YES
	0.942	0.128	0.898	0.942	0.919	0.819	0.893	0.869	NO
Weighted Avg.	0.910	0.096	0.911	0.910	0.910	0.819	0.893	0.866	

=== Confusion Matrix ===

```
a  b  <-- classified as
239 35 | a = YES
19 307 | b = NO
```

Binary split minNumObj=1

=== Summary ===

Correctly Classified Instances	526	87.6667 %
Incorrectly Classified Instances	74	12.3333 %
Kappa statistic	0.7504	
Mean absolute error	0.1787	
Root mean squared error	0.3396	
Relative absolute error	36.0083 %	
Root relative squared error	68.1725 %	
Total Number of Instances	600	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.839	0.092	0.885	0.839	0.861	0.751	0.856	0.792	YES
	0.908	0.161	0.871	0.908	0.889	0.751	0.856	0.839	NO
Weighted Avg.	0.877	0.129	0.877	0.877	0.876	0.751	0.856	0.818	

=== Confusion Matrix ===

```
a  b  <-- classified as
230 44 | a = YES
30 296 | b = NO
```

Binary split minNumObj=2

=== Summary ===

Correctly Classified Instances	523	87.1667 %
Incorrectly Classified Instances	77	12.8333 %
Kappa statistic	0.7401	
Mean absolute error	0.1856	
Root mean squared error	0.3451	
Relative absolute error	37.3999 %	
Root relative squared error	69.2717 %	
Total Number of Instances	600	

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.828	0.092	0.883	0.828	0.855	0.741	0.848	0.794	YES
	0.908	0.172	0.863	0.908	0.885	0.741	0.848	0.818	NO
Weighted Avg.	0.872	0.135	0.872	0.872	0.871	0.741	0.848	0.807	

=== Confusion Matrix ===

```
a  b  <-- classified as
227 47 | a = YES
30 296 | b = NO
```

对于归一化数据，Binary split 准确率比 multiple split 的偏低，但 minNumObj 的选择几乎无影响

6) 利用离散化数据，用 ID3 构建决策树，展示结果。

首先，在 weka 的 Tools->package manager 里找到下述包进行安装
simpleEducationalLearningSchemes

```
=== SUMMARY ===

Correctly Classified Instances      459           76.5 %
Incorrectly Classified Instances    116           19.3333 %
Kappa statistic                     0.5931
Mean absolute error                 0.1974
Root mean squared error             0.4418
Relative absolute error             41.5496 %
Root relative squared error         90.705 %
Unclassified Instances              25           4.1667 %
Total Number of Instances          600

=== Detailed Accuracy By Class ===

      TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
0.784    0.190    0.772    0.784    0.778    0.593    0.784    0.701    YES
0.810    0.216    0.821    0.810    0.815    0.593    0.797    0.765    NO
Weighted Avg.  0.798    0.204    0.799    0.798    0.798    0.593    0.791    0.736

=== Confusion Matrix ===

  a  b  <-- classified as
203 56 | a = YES
60 256 | b = NO
```

7) 对比 J48 和 ID3 的结果。

本实验 J48 的分类效果要好于 ID3，应采用 J48 来进行，可能由于 J48 的属性可以是连续值，ID3 的属性必须是离散值，而该实验的数据并不均是离散的。

2. 用规范化数据和离散化数据生成训练（400 个对象）和测试（200 个对象）文件。使用训练数据来训练模型，使用测试数据来测试模型。

1) 对于规范化数据，比较 J48 中 binary split 或 multiple split 的结果。分析 "minNumObj" 参数的影响（选择 minNumObj=2 或 1）。

multiple split minNumObj=2

=== Summary ===

Correctly Classified Instances	177	88.5	%
Incorrectly Classified Instances	23	11.5	%
Kappa statistic	0.7681		
Mean absolute error	0.1685		
Root mean squared error	0.3248		
Total Number of Instances	200		

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.821	0.057	0.929	0.821	0.872	0.773	0.886	0.878	YES
	0.943	0.179	0.853	0.943	0.896	0.773	0.886	0.856	NO
Weighted Avg.	0.885	0.121	0.889	0.885	0.884	0.773	0.886	0.866	

=== Confusion Matrix ===

```

a b  <-- classified as
78 17 | a = YES
 6 99 | b = NO

```

multiple split minNumObj=1

=== Summary ===

Correctly Classified Instances	175	87.5	%
Incorrectly Classified Instances	25	12.5	%
Kappa statistic	0.7482		
Mean absolute error	0.1688		
Root mean squared error	0.3368		
Total Number of Instances	200		

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.821	0.076	0.907	0.821	0.862	0.751	0.883	0.846	YES
	0.924	0.179	0.851	0.924	0.886	0.751	0.883	0.871	NO
Weighted Avg.	0.875	0.130	0.878	0.875	0.874	0.751	0.883	0.859	

=== Confusion Matrix ===

```

a b  <-- classified as
78 17 | a = YES
 8 97 | b = NO

```

Binary split minNumObj=1

=== Summary ===

Correctly Classified Instances	173	86.5	%
Incorrectly Classified Instances	27	13.5	%
Kappa statistic	0.7281		
Mean absolute error	0.1736		
Root mean squared error	0.3527		
Relative absolute error	34.9003 %		
Root relative squared error	70.5275 %		
Total Number of Instances	200		

=== Detailed Accuracy By Class ===

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.811	0.086	0.895	0.811	0.851	0.731	0.869	0.814	YES
	0.914	0.189	0.842	0.914	0.877	0.731	0.869	0.857	NO
Weighted Avg.	0.865	0.140	0.867	0.865	0.864	0.731	0.869	0.837	

=== Confusion Matrix ===

```

a b  <-- classified as
77 18 | a = YES
 9 96 | b = NO

```

```

Binary split minNumObj=2

=== Summary ===

Correctly Classified Instances      177          88.5  %
Incorrectly Classified Instances    23          11.5  %
Kappa statistic                    0.7681
Mean absolute error                 0.1693
Root mean squared error             0.3246
Relative absolute error             34.0386 %
Root relative squared error        64.9126 %
Total Number of Instances          200

=== Detailed Accuracy By Class ===

                TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Clas
                0.821   0.057   0.929     0.821   0.872     0.773   0.887    0.874    YES
                0.943   0.179   0.853     0.943   0.896     0.773   0.887    0.861    NO
Weighted Avg.   0.885   0.121   0.889     0.885   0.884     0.773   0.887    0.867

=== Confusion Matrix ===

  a  b  <-- classified as
78 17 | a = YES
 6 99 | b = NO

```

该实验，binary split 和 mutiple split 的结果相近，minNumObj=2 时的结果略好于 minNumObj=1 时的结果。

2) 对于离散数据，给出 1) 中的结果，并分析规范化数据与离散数据效果上的差别。

选择相同的离散化标准，对测试集和训练集，而后用测试集对模型进行训练。

```

=== Summary ===

Correctly Classified Instances      157          78.5  %
Incorrectly Classified Instances    39          19.5  %
Kappa statistic                    0.5995
Mean absolute error                 0.199
Root mean squared error             0.4432
UnClassified Instances              4           2      %
Total Number of Instances          200

=== Detailed Accuracy By Class ===

                TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                0.753   0.155   0.814     0.753   0.782     0.601   0.795    0.730    YES
                0.845   0.247   0.791     0.845   0.817     0.601   0.796    0.748    NO
Weighted Avg.   0.801   0.204   0.802     0.801   0.800     0.601   0.795    0.739

=== Confusion Matrix ===

  a  b  <-- classified as
70 23 | a = YES
16 87 | b = NO

```

离散数据的准确率比规范化数据的较低，minNumObj 选择影响不大

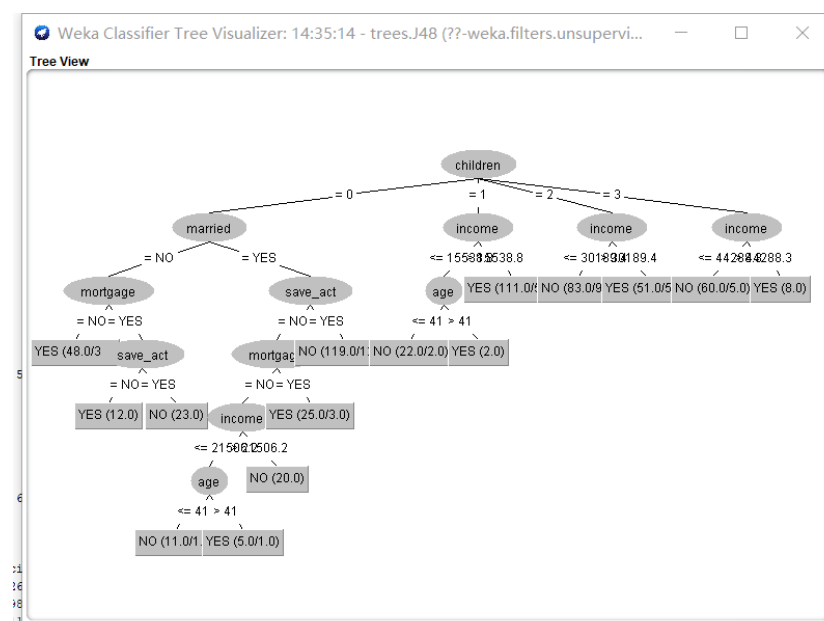
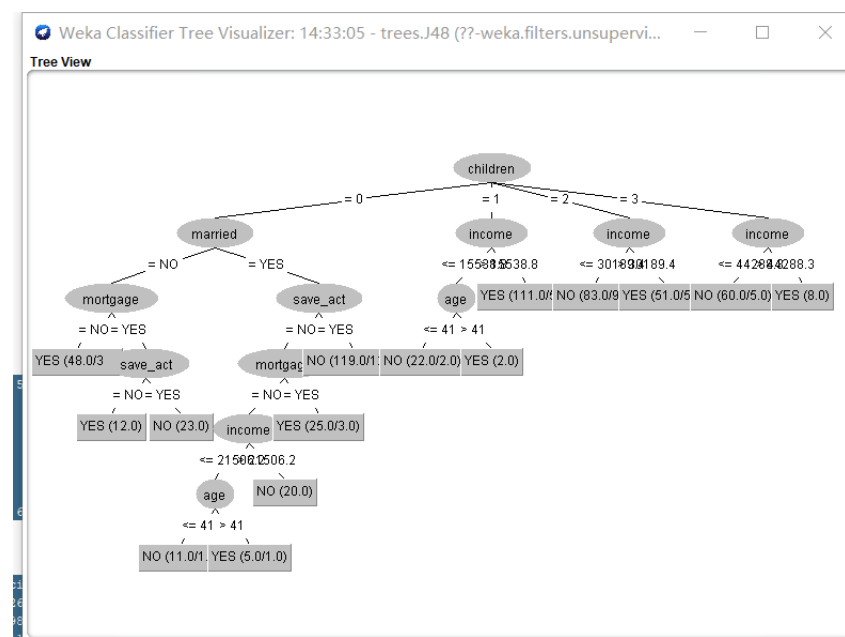
给出算法中得到的混淆矩阵及计算的准确率、错误率、精确率和召回率。对计算结果进行截图，并用一些可视化的结果来展示你的结果。

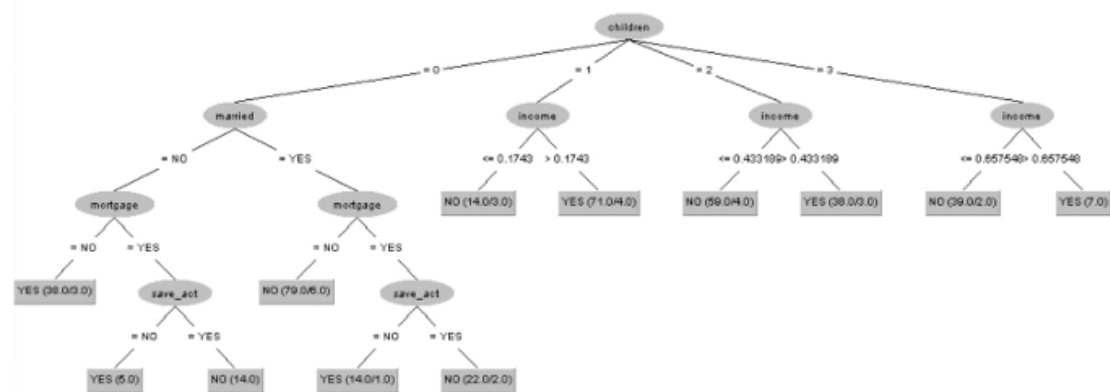
混淆矩阵:

=== Confusion Matrix ===

```
a b <-- classified as
78 17 | a = YES
6 99 | b = NO
```

（面板中，右键单击相应的输出，然后选择 Visualize tree）
可视化：





准确率=(78+99)/200=88.5%

错误率=1-88.5%=11.5%

精确率=78/(78+6)=92.9%

召回率=78/(78+17)=82.1%

ID3:

混淆矩阵:

=== Confusion Matrix ===

```

a  b  <-- classified as
70 23 |  a = YES
16 87 |  b = NO
  
```

上网查阅了 ID3 可视化是要修改代码，由 dot 语言进行 Graphviz 绘图的，但多次修改后仍未成功，进行如下展示：

```

| children = 1
| income = a
| age = '[inf-27.8]':
| | sex = FEMALE: NO
| | sex = MALE
| | | married = NO: NO
| | | married = YES
| | | | save_act = NO: NO
| | | | save_act = YES: YES
| age = '[27.8-37.6]':
| | region = INNER_CITY
| | sex = FEMALE: NO
| | sex = MALE
| | | save_act = NO: NO
| | | save_act = YES
| | | | current_act = NO: NO
| | | | current_act = YES: YES
| region = TOWN: YES
| region = RURAL: null
| region = SUBURBAN: null
| age = '[37.6-47.4]':
| | region = INNER_CITY: NO
| | region = TOWN: YES
| | region = RURAL: null
| | region = SUBURBAN: null
| age = '[47.4-57.2]': YES
| age = '[57.2-inf]': null
income = b
| sex = FEMALE
| | region = INNER_CITY: YES
| | region = TOWN
| | | car = NO: YES
| | | car = YES: NO
| region = RURAL: NO
| region = SUBURBAN: YES

```

```
| | | | current_act = YES: YES
| | | | region = TOWN: YES
| | | | region = RURAL: null
| | | | region = SUBURBAN: null
| | | | age = '(37.6-47.4)':
| | | | region = INNER_CITY: NO
| | | | region = TOWN: YES
| | | | region = RURAL: null
| | | | region = SUBURBAN: null
| | | | age = '(47.4-57.2)': YES
| | | | age = '(57.2-inf)': null
| | income = b
| | sex = FEMALE
| | | | region = INNER_CITY: YES
| | | | region = TOWN
| | | | | car = NO: YES
| | | | | car = YES: NO
| | | | region = RURAL: NO
| | | | region = SUBURBAN: YES
| | | sex = MALE: YES
| | income = c
| | mortgage = NO: YES
| | mortgage = YES
| | | | age = '(-inf-27.8)': null
| | | | age = '(27.8-37.6)': NO
| | | | age = '(37.6-47.4)': YES
| | | | age = '(47.4-57.2)': YES
| | | | age = '(57.2-inf)':
| | | | | sex = FEMALE: YES
| | | | | sex = MALE: NO
| | income = d: YES
| | income = e: YES
children = 2
| | income = a
| | | | region = INNER_CITY
| | | | age = '(-inf-27.8)': NO
| | | | age = '(27.8-37.6)'
```

			SEX = FEMALE: YES			age = {'(inf-27.8)'}: null
			age = {'(37.6-47.4)': null			age = {'(27.8-37.6)': null
			age = {'(47.4-57.2)': null			age = {'(37.6-47.4)': YES
			age = {'(57.2-inf)': null			age = {'(47.4-57.2)': YES
			region = TOWN: NO			age = {'(57.2-inf)'
			region = RURAL			sex = FEMALE: YES
			age = {'(-inf-27.8)': NO			sex = MALE: YES
			age = {'(27.8-37.6)': YES			income = e: YES
			age = {'(37.6-47.4)': null		children = 3	
			age = {'(47.4-57.2)': null		income = a: NO	
			age = {'(57.2-inf)': null		income = b	
			region = SUBURBAN: YES		age = {'(-inf-27.8)': NO	
	income = b				age = {'(27.8-37.6)': NO	
	age = {'(-inf-27.8)'				age = {'(37.6-47.4)': NO	
	current_act = NO				age = {'(47.4-57.2)': NO	
	sex = FEMALE: NO				age = {'(57.2-inf)': NO	
	sex = MALE: YES				income = c	
	current_act = YES: NO				age = {'(-inf-27.8)': null	
	age = {'(27.8-37.6)': NO				age = {'(27.8-37.6)'	
	age = {'(37.6-47.4)': NO				sex = FEMALE: NO	
	age = {'(47.4-57.2)': NO				sex = MALE: YES	
	age = {'(57.2-inf)': NO				age = {'(37.6-47.4)': NO	
	income = c				age = {'(47.4-57.2)': NO	
	age = {'(-inf-27.8)': null				age = {'(57.2-inf)': NO	
	age = {'(27.8-37.6)': YES				income = d	
	age = {'(37.6-47.4)'				mortgage = NO	
	mortgage = NO				age = {'(-inf-27.8)': null	
	sex = FEMALE				age = {'(27.8-37.6)': null	
	married = NO: YES				age = {'(37.6-47.4)': YES	
	married = YES: NO				age = {'(47.4-57.2)'	
	sex = MALE: YES				sex = FEMALE: YES	
	mortgage = YES: NO				sex = MALE: YES	
	age = {'(47.4-57.2)'				age = {'(57.2-inf)': YES	
	region = INNER_CITY: YES				mortgage = YES: NO	
	region = TOWN				income = e: YES	
	sex = FEMALE: YES					
	sex = MALE: NO					
	region = RURAL: null					
	region = SUBURBAN: YES					

准确率=(70+87)/200=78.5%

错误率=1-78.5%=11.5%

精确率=70/(70+6)=92.1%

召回率=70/(70+23)=75.3%

3. Data: weather-nominal.arff, which is included in the path of weka.

1) use weka with ID3 to construct a tree.

决策树:

outlook = sunny

| humidity = high: no

| humidity = normal: yes

outlook = overcast: yes

outlook = rainy

| windy = TRUE: no

| windy = FALSE: yes

混淆矩阵:

=== Confusion Matrix ===

a b <-- classified as

8 1 | a = yes

1 4 | b = no

2) construct a tree manually

No.	1: outlook	2: temperature	3: humidity	4: windy	5: play
	Nominal	Nominal	Nominal	Nominal	Nominal
1	sunny	hot	high	FALSE	no
2	sunny	hot	high	TRUE	no
3	overcast	hot	high	FALSE	yes
4	rainy	mild	high	FALSE	yes
5	rainy	cool	normal	FALSE	yes
6	rainy	cool	normal	TRUE	no
7	overcast	cool	normal	TRUE	yes
8	sunny	mild	high	FALSE	no
9	sunny	cool	normal	FALSE	yes
10	rainy	mild	normal	FALSE	yes
11	sunny	mild	normal	TRUE	yes
12	overcast	mild	high	TRUE	yes
13	overcast	hot	normal	FALSE	yes
14	rainy	mild	high	TRUE	no

信息熵 $H(S) = -\frac{9}{14} \log_2 \frac{9}{14} - \frac{5}{14} \log_2 \frac{5}{14} = 0.9403$

$Gain_0(outlook) = H(S) - H_{outlook}$
 $= 0.9403 - \frac{9}{14} \times (-\frac{2}{9} \log_2 \frac{2}{9}) - \frac{5}{14} \times (-\frac{1}{5} \log_2 \frac{1}{5})$
 $= 0.2467$

问题: $Gain_0(temperature) = 0.0292$
 $Gain_0(humidity) = 0.1318$
 $Gain_0(windy) = 0.0481$

划分 Sunny: 问题 $Gain_1(temperature) = 0.4000$
 $Gain_1(humidity) = 0.9710$
 $Gain_1(windy) = 0.0200$

决策树结构:

```

graph TD
    outlook((outlook)) -- "= sunny" --> humidity((humidity))
    outlook -- "= overcast" --> leaf1["4 yes  
0 no"]
    outlook -- "= rainy" --> windy((windy))
    humidity -- "= high" --> leaf2["0 yes  
3 no"]
    humidity -- "= normal" --> leaf3["2 yes  
0 no"]
    windy -- "= FALSE" --> leaf4["3 yes  
0 no"]
    windy -- "= TRUE" --> leaf5["0 yes  
2 no"]
  
```

3) compare the upper two methods.

两种方法，所得实验结果相同