

# Leaflets three, let it be?

-- Mushroom edibility classification

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# Introduction

- **Task:**

Classify mushrooms as poisonous or edible based on their physical attributes

- **Method**

- Binary classification problem
- Naive Bayes

# Introduction

- **Data set:**

- Response: Binary (poisonous/edible)
- Attribute: Categorical
- Instances: 8124
- Attributes: 22
  - Missing value in one attribute (2480)
  - Not missing completely at random
  - Treat missing values as another category

# Methodology

## Naïve Bayes classifier

Bayesian classifiers assign the most likely class to a given instance described by its feature vector.

Aim to computing the probability:

$$p(C|F_1, \dots F_n)$$

Where  $C$  denotes a class variable with some number of classes.

# Methodology

Based on the Naïve Bayes assumption

$$p(C|F_1, \dots F_n) = \frac{1}{Z} p(C) \prod_{i=1}^n p(F_i|C)$$

Where

$$Z = p(F_1, \dots F_n)$$

$p(C)$ : Calculated or estimated by relative frequencies.

$p(F_i|C)$ : Bernoulli and Multinomial distribution are adopted for feature probability distribution.

# Methodology

## Classification Rule

In Binary classification, a threshold is utilized:

- If the prediction probability falls above the threshold, the instance is labeled positive (poisonous, in our case)
- If not, negative (edible).

Multi-class:

- Assign instance to most probable class

# Methodology

## Validation

### K-fold cross validation

- Data set is split into six equally-sized folds
- Apply Naïve Bayes once for each run
- Each time:
  - Five folds as training set
  - Remaining one as test set

# Methodology

## ➤ Receiver Operating Characteristics (ROC)

Select an optimal threshold to map instances to predicted classes

## ➤ Apparent Error Rate (APER)

Fraction of misclassified sample observations

## ➤ False Negative (FN) Rate

The probability of classifying a poisonous (positive) mushroom as being edible (negative)



# Methodology

## R packages

- **Naïve Bayes:**

```
library(e1071 )
```

```
Function: naiveBayes()
```

```
predict()
```

- **ROC plot:**

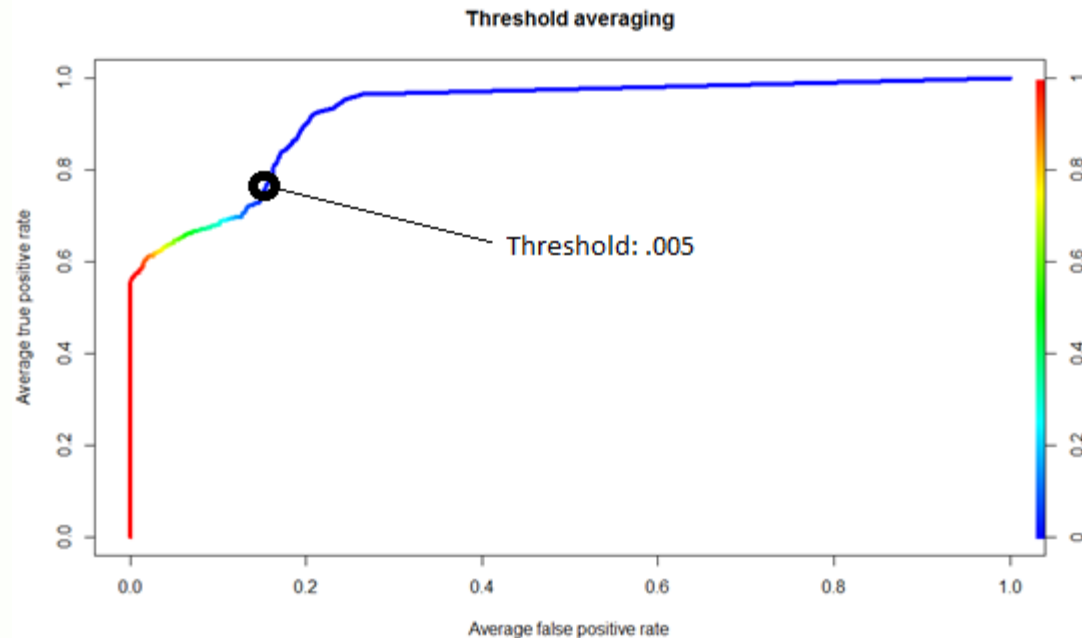
```
library(ROCR )
```

```
Function: pred()
```

```
performance()
```

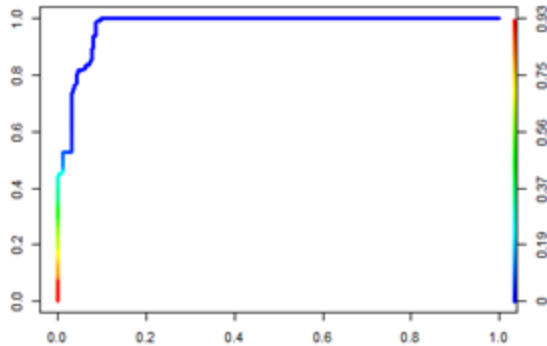
# Findings

ROC graph depicts relative tradeoffs between benefits (TP) and costs (FP). The more top-left a point lies, the better the corresponding classifier performance.

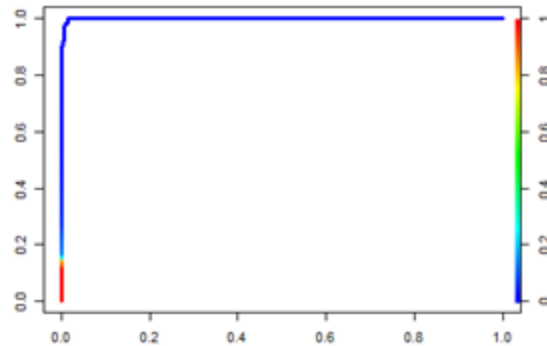


# Findings

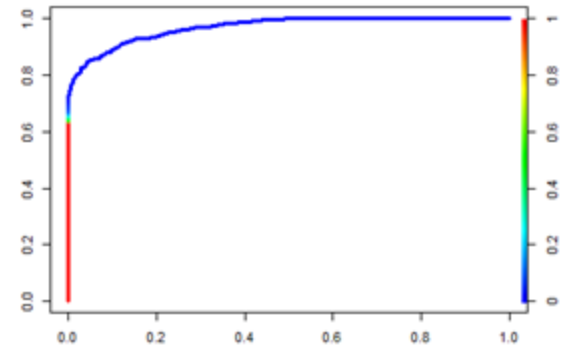
Run 1: First 1/6 Test Set



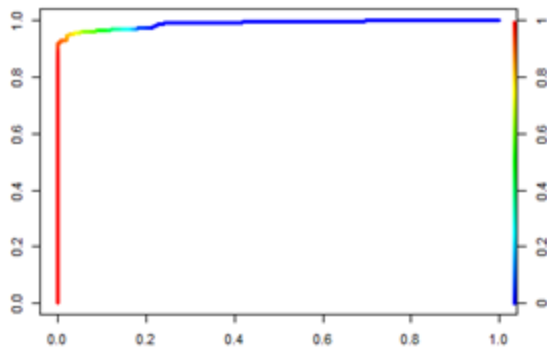
Run 2: Second 1/6 Test Set



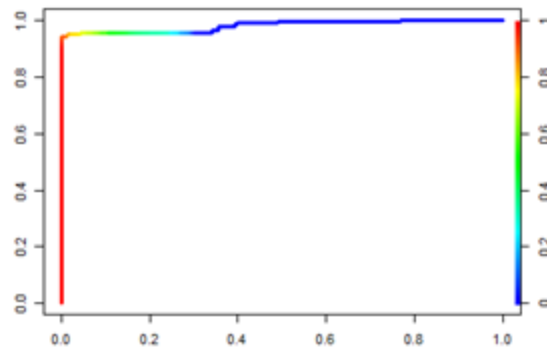
Run 3: Third 1/6 Test Set



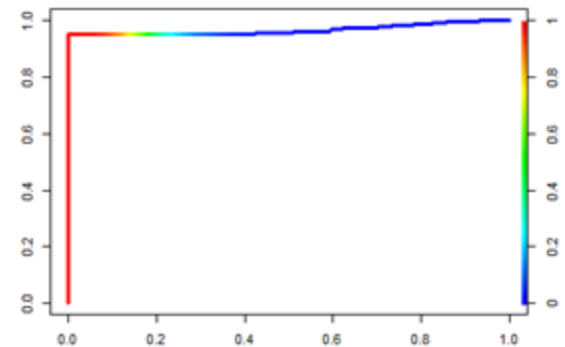
Run 4: Fourth 1/6 Test Set



Run 5: Fifth 1/6 Test Set

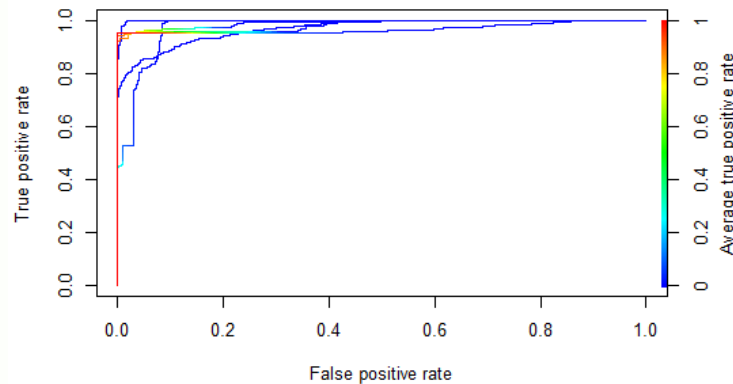


Run 6: Last 1/6 Test Set

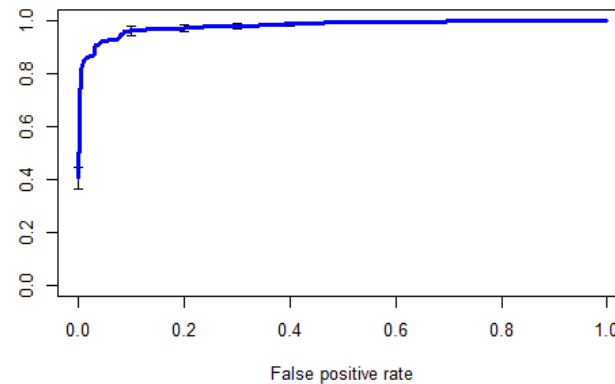


# Findings

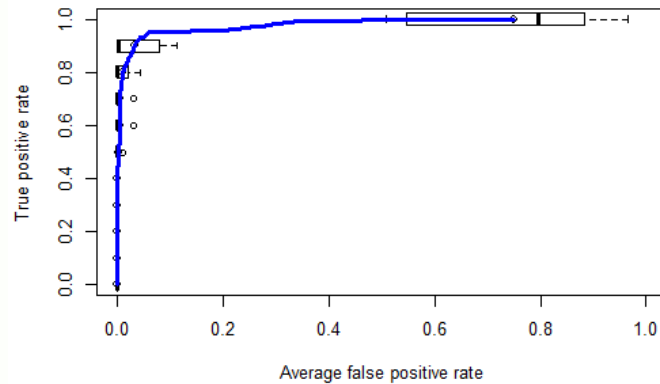
ROC curves from 6-fold cross-validation



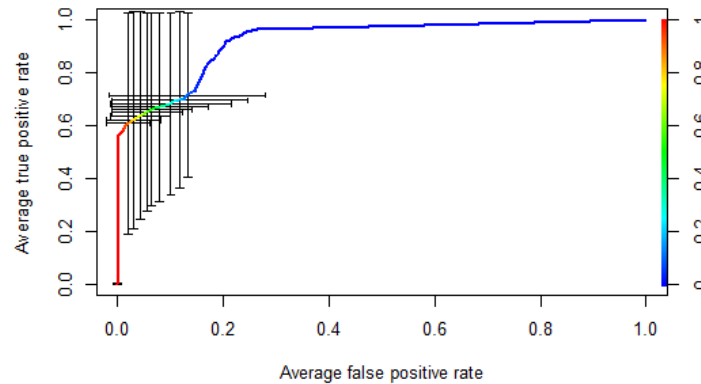
Vertical averaging + 1 standard error



Horizontal averaging + boxplots



Threshold averaging + 1 standard deviation



# Findings

Finding optimal threshold by averaging over all runs:

Threshold	False Negative Rate	Apparent Error Rate
0.5	0.70588235	0.07976366
0.1	0.48366013	0.06351551
0.05	0.45751634	0.07828656
0.01	0.1633987	0.0760709
0.005	0.03921569	0.07976366
0.001	0.0000000	0.1329394

# Findings

APER & FNR for each run:

Run	APER	FNR
1	0.0798	0.0392
2	0.0214	0.2302
3	0.0805	0.2013
4	0.0517	0.0234
5	0.0805	0.0428
6	0.2349	0.0385
Avg	0.0798	0.0392

Threshold = 0.005

# Findings

With our choice of threshold (0.005):

- Naïve Bayes misclassifies 7.98% of mushrooms
- Poisonous mushrooms identified as being edible 3.92% of time

# Discussion

## Assumption

- Independence between features given class labels
- Unrealistic in practice
- Naïve Bayes gives good results even if assumption is not met
- Reason behind robustness is an open question



# Discussion

## Scaling to Big data

- Run time of 6-fold CV: **6.13s**
- Expect run time to increase with size of test set
- 1/6 training and 5/6 testing : **42.14s**
- Expect run time to increase with # of features
  - Assume multinomial distribution
  - Each new feature with  $k$  levels means an extra  $k-1$  parameters to estimate

# Discussion

## Obstacles

Which classification method should we use?

- Logistic regression: did not work, because iterative algorithm didn't converge
- K-nearest neighbors: did not work, because *knn* does not take distance matrix as input, instead, it calculates a Euclidean distance matrix automatically
  - Side: R doesn't like a distance matrix of dim 8124 X 8124

ANY  
QUESTIONS  
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