Data Mining for Bank Telemarketing

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Motivation

- Positive response rate to mass campaigns are typically very low. In order to save costs and time, it is important to filter the contacts but keep a certain success rate.
- GOAL: To build a classifier to predict whether or not a client will subscribe a term deposit. Besides, we plan to find out which factors are influential to customers decision, so that a more efficient and precise campaign strategy can be designed to help to reduce the costs and improve the profits.

Data Source

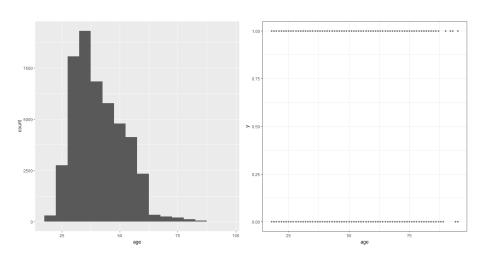
Our data were collected from a Portuguese marketing campaign related with bank deposit subscription for 45211 clients and 16 features, and the response is whether the client has subscribed a term deposit. Our data set is downloaded from

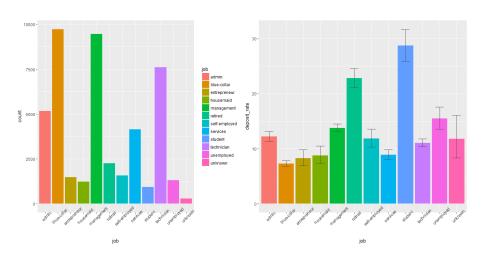
http://archive.ics.uci.edu/ml/datasets/Bank+Marketing.

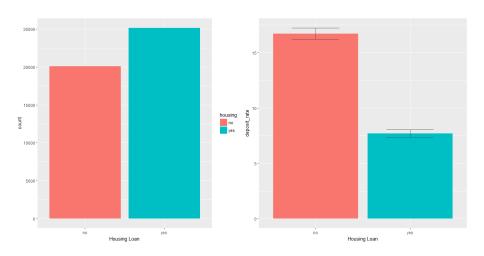
Two kinds of features:

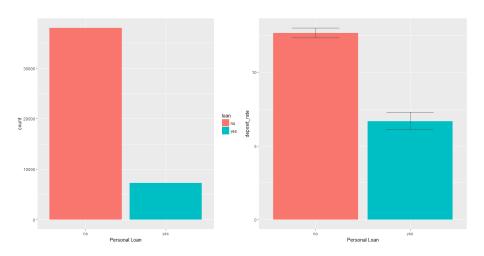
- customer feature:
 - age, yearly balance (continuous var.)
 - education, default, job, marital status, housing loan, personal loan (categorical var.)
- Phone call feature:
 - duration (continuous var.)
 - contact communication type, day, month, campaign, pdays, previous, poutcome(categorical var.)

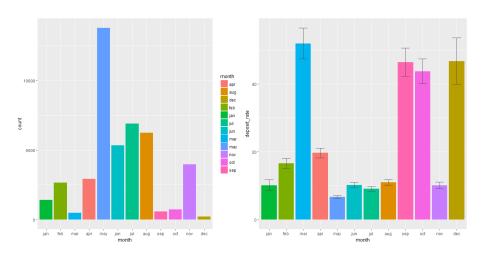
Data Visualization

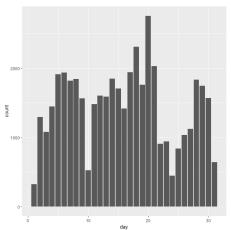


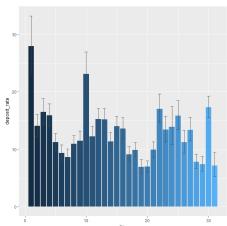


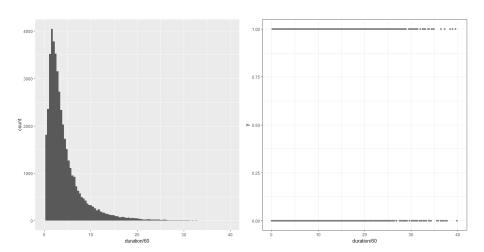


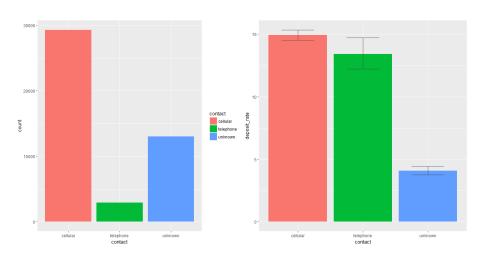












Feature Selection

select the most influential features from the original feature set and remove redundant features from your dataset, two ways:

- rank features by some criteria and select the ones that are above a defined threshold: chi-squared, information gain, linear correlation...
- Search for optimum feature subsets from a space of feature subsets: best-first search, back-ward search, forward search, hill climbing search...

R package "Fselector"

- install and load the package, FSelector: install.packages("FSelector") library(FSelector)
- calculate weights for each attribute using some function SOMEFUNCTION(class~., train), chi.squared, information.gain, random.forest.importance...

```
attr_importance
             0.0119225202
age
job
             0.0080246244
marital
             0.0016934420
education
             0.0031712869
default
             0.0002202107
balance
             0.0054601413
housing
             0.0092010547
             0.0027664915
loan
contact
             0.0145914521
day
             0.0032258538
month
             0.0253083723
duration
             0.0703595860
             0.0039872287
campaign
pdays
             0.0245426595
previous
             0.0120962089
             0.0293272594
poutcome
```

- use the cutoff function to obtain the attributes of the top five weights:
 subset = cutoff.k(weights, 5)
- print the results:

```
f=as.simple.formula(subset, "y")
print(f)
y ~ duration + poutcome + month + pdays + contact
```

Logistic Regression

Linearity

•

$$\log \frac{p}{1-p} = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k$$
$$p = \frac{e^{\beta X}}{1 + e^{\beta X}}$$

Logistic Regression

Linearity

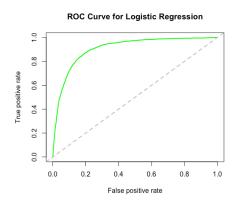
•

$$\log \frac{p}{1-p} = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k$$
$$p = \frac{e^{\beta X}}{1 + e^{\beta X}}$$

$$\begin{split} & \mathsf{glm}(\mathsf{f},\,\mathsf{family=binomial}(\mathsf{link='logit'}),\,\mathsf{data=train}) \\ & \mathsf{f:}\,\,\mathsf{y} \sim \mathsf{duration} + \mathsf{poutcome} + \mathsf{month} + \mathsf{pday} + \!\!\mathsf{contact} \end{split}$$

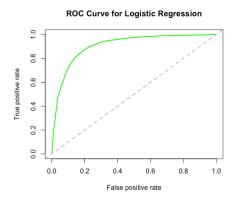
predict(model, newdata=test, type="response")

predict(model, newdata=test, type="response")



AUC=0.8976556

predict(model, newdata=test, type="response")



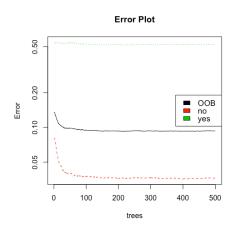
AUC=0.8976556 versus AUC(full)=0.9086456

Random Forest

- machine learning technique, nonlinear
- number of decision trees are built during the process
- reduce chances of over-fitting

R package "randomForest"

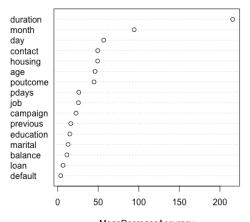
model=randomForest(y ., data=train, importance=TRUE, ntree=500) plot(model)



Variable Importance

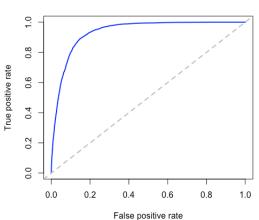
varImpPlot(model, main="Variable Importance", type=1)

Variable Importance



21 / 23

ROC Curve for Random Forest



Conclusion

- Used ggplot2 to visualize and analyze the dataset
- Introduced a R package "Fselector" for feature selection and select the most influential factors for customers decision
- Applied the classification methods logistic regression and randome forest to predict the success of bank telemarketing