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TABLE OF CONTENTS

Modeling
Data Partition
Naive Bayes
Decision Tree

Conclusion
Conclusion & Insight Recap

Fun Facts
Group Photo

01 Introduction

Background:

- Directed marketing: focus on targets that will be keener to specific product/services
- Bank marketing: contact less but achieve higher number of clients subscribing the deposit
- Dataset: direct marketing campaigns of a Portuguese banking institution

Goals:

- Build predictive models to predict the success of a contact
- Rank the variables based upon the important level in the success of direct marketing campaigns

02 Process Overview















Understand Business and Data

Prepare Data

Build Models

Generate Insights

03 Data Pre-Processing

Part 1 — Attribute Conversion

Part 2

Complexity Reduction

Part 3

Confirmation of Significance Difference

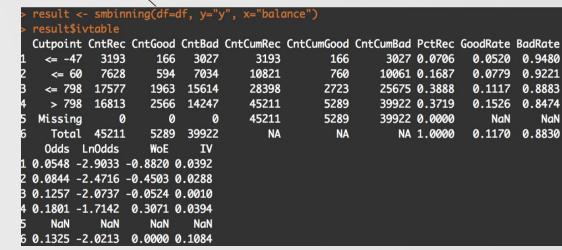


Attribute Conversion

1. Model Selection

- Naive Bayes
- Decision Tree
- 2. Binning (Numerical -> Categorical)
 - Disadvantage: Lose accuracy
 - Purpose: Reduce overfitting, Process time





Complexity Reduction

1. Level Reduction - "Job"

Clustering method with personal data attributes as the input

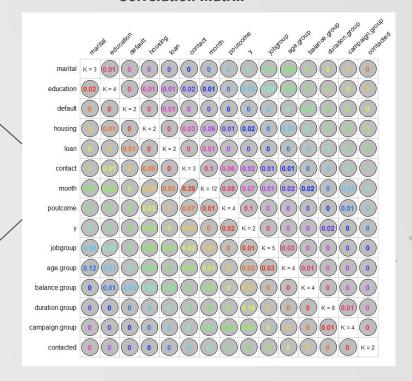
2. Drop low impact variables

- "Pday"
- "Previous"
- "Default"
- "Contacted"

Top 5 variables:

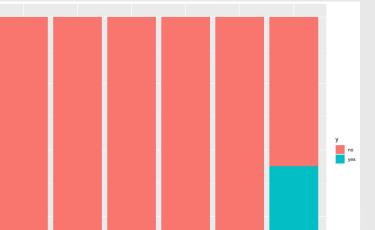
- poutcome: 0.02287
- duration.group: 0.02208
- housing: 0.01937
- contact: 0.01803
- loan: 0.00465

Correlation Matrix



Confirmation of Significance Difference



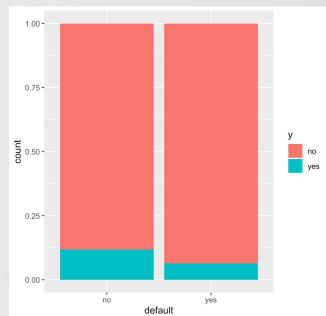


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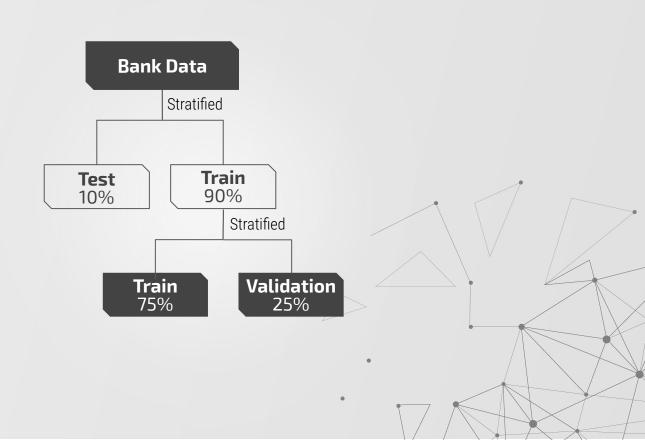
349-521

"Duration" - Keep

"Default" - Toss



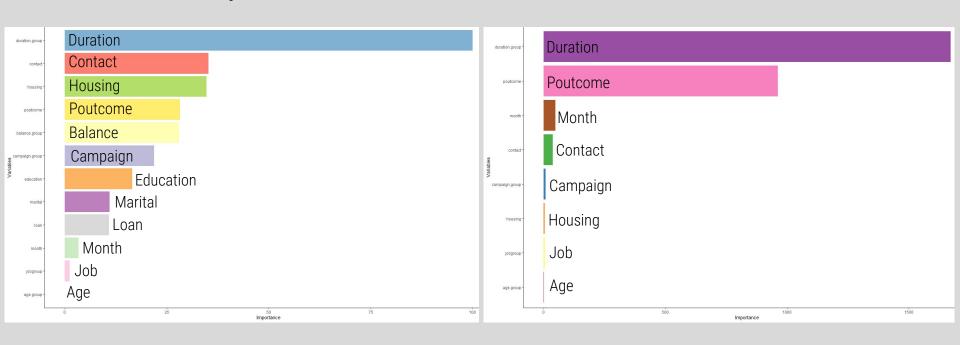
04 Modeling: Data Partition



Model Comparison: Variable Importance

Naive Bayes

Decision Tree



Model Comparison: Accuracy

Naive Bayes

> confusionMatrix(nb.pred, validate.data\$y) Confusion Matrix and Statistics Reference Prediction no yes no 8579 698 ves 403 492 Accuracy : 0.8918 95% CI: (0.8856, 0.8977) No Information Rate: 0.883 P-Value [Acc > NIR] : 0.002921 Kappa : 0.413 Mcnemar's Test P-Value : < 0.000000000000000022 Sensitivity: 0.9551 Specificity: 0.4134 Pos Pred Value: 0.9248 Nea Pred Value: 0.5497 Prevalence: 0.8830 Detection Rate: 0.8434 Detection Prevalence: 0.9120 Balanced Accuracy: 0.6843 'Positive' Class : no

Accuracy: 0.8918

Decision Tree

```
confusionMatrix(dtree.pred, validate.data$y)
Confusion Matrix and Statistics
          Reference
Prediction no yes
       no 8784 825
       ves 198 365
              Accuracy : 0.8994
                95% CI: (0.8934, 0.9052)
    No Information Rate: 0.883
    P-Value [Acc > NIR] : 0.00000007894
                 Kappa: 0.369
 Mcnemar's Test P-Value : < 0.000000000000000022
           Sensitivity: 0.9780
           Specificity: 0.3067
        Pos Pred Value: 0.9141
         Neg Pred Value: 0.6483
             Prevalence: 0.8830
         Detection Rate: 0.8635
   Detection Prevalence: 0.9447
      Balanced Accuracy: 0.6423
       'Positive' Class : no
```

Accuracy: 0.8994

VS.

Decision Tree-Test

```
confusionMatrix(dtree.test, test.data$y)
Confusion Matrix and Statistics
         Reference
Prediction no yes
      no 3902 391
      ves 90 137
             Accuracy : 0.8936
              95% CI: (0.8842, 0.9024)
   No Information Rate: 0.8832
   P-Value [Acc > NIR] : 0.01478
               Kappa: 0.3148
 Sensitivity: 0.9775
          Specificity: 0.2595
        Pos Pred Value: 0.9089
        Neg Pred Value: 0.6035
           Prevalence: 0.8832
        Detection Rate: 0.8633
   Detection Prevalence: 0.9498
     Balanced Accuracy: 0.6185
      'Positive' Class : no
```

Accuracy: 0.8936

TAKE-HOME MESSAGES

What we did:

- Attribute conversion
- Complexity reduction
- Cross-validation

What we found:

- Effective approach to data preparation for modeling
- Reliable model in predicting the bank marketing campaign outcomes
- Duration has the highest influence over whether the clients deposit or not
 - Longer duration -> higher success rate
- Systematic approach to improving model accuracy

Application:

 Such knowledge can be used by managers to increase the call time or segmenting audience with a specific goal of focusing more on clients who have previously deposited



Day 7 6



hooray!!!



Pay 2: To be a familie &







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THANK YOU!



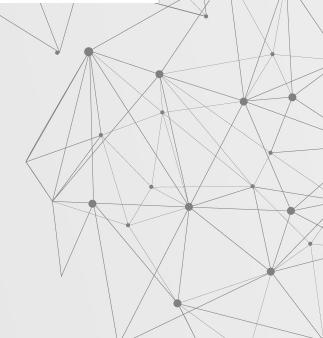
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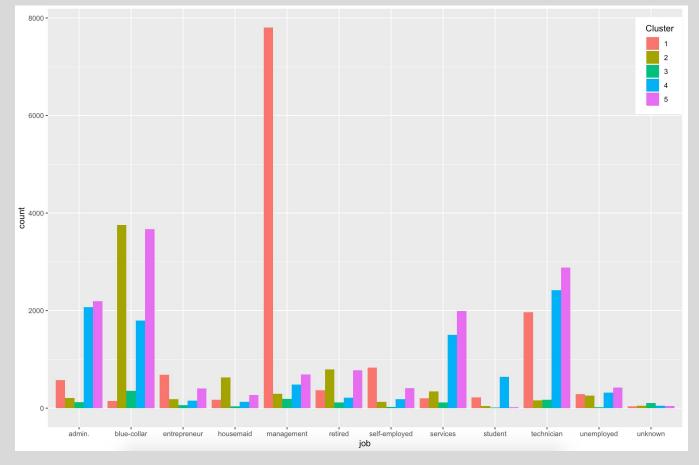
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MSBA 20' at UC, Irvine | Student Ambassador



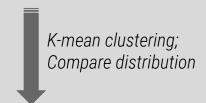


Level Reduction via Clustering



Bank client data:

Age, marital, education, default, balance, housing, loan



Job group 1:

entrepreneur, management, self-employed

Job group 2:

blue-collar, housemaid, retired

Job group 3:

unknown

Job group 4:

student

Job group 5:

admin, services, technician, unemployed