# 6242 Data Analysis Project:

Default Payments of Credit Card Clients in Taiwan from 2005

Michael Chiang

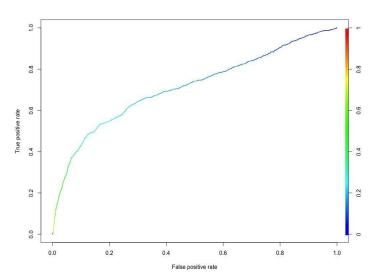
Jian Sun

# Logistic Regression

```
Call:
glm(formula = UCC$default.payment.next.month ~ MARRIAGE + AGE +
   PAY_0 + PAY_2 + PAY_3 + BILL_AMT1 + BILL_AMT4 + PAY_AMT1 +
   PAY_AMT2 + PAY_AMT5, family = binomial("logit"), data = UCC)
Deviance Residuals:
   Min
                  Median
-2.5895 -0.6789 -0.5481 -0.3035
                                   3.1742
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.275e+00 2.318e-01 -5.501 3.77e-08 ***
MARRIAGE
           -1.896e-01 7.728e-02 -2.453 0.014162 *
            1.206e-02 4.257e-03 2.832 0.004629 **
AGE
PAY_0
            5.649e-01 4.363e-02 12.948 < 2e-16 ***
PAY_2
            1.111e-01 4.901e-02 2.267 0.023386 *
PAY_3
            1.445e-01 4.445e-02 3.251 0.001152 **
BILL_AMT1
          -4.858e-06 1.317e-06 -3.688 0.000226 ***
BILL_AMT4
           3.113e-06 1.490e-06 2.089 0.036728 *
           -8.345e-06 4.368e-06 -1.910 0.056070 .
PAY_AMT1
PAY_AMT2
           -1.650e-05 5.616e-06 -2.939 0.003293 **
PAY_AMT5
           -1.066e-05 4.908e-06 -2.171 0.029895 *
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
(Dispersion parameter for binomial family taken to be 1)
   Null deviance: 5207.7 on 4999 degrees of freedom
Residual deviance: 4578.6 on 4989 degrees of freedom
```

AIC: 4600.6

Number of Fisher Scoring iterations: 6



Area Under Curve = 0.7123

**Result** - Classification Rate = 71.23%

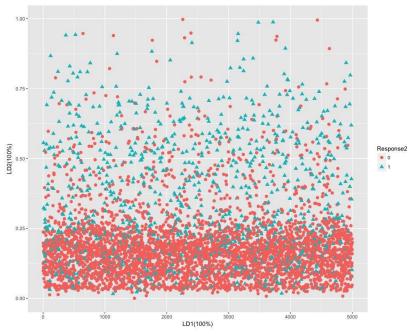
# Linear Discriminant Analysis

#### Coefficients of linear discriminants: LD1

LIMIT\_BAL -4.928587e-07 SEX -6.585150e-02 EDUCATION -8.032433e-02 MARRIAGE -2.488607e-01 AGE 1.581510e-02 PAY\_0 6.701662e-01 1.601329e-01 PAY\_2 PAY\_3 1.733721e-01 PAY\_4 -5.809809e-02 1.246299e-01 PAY\_5 PAY\_6 -8.132672e-02 BILL\_AMT1 -3.876569e-06 BILL\_AMT2 -6.001636e-07 BILL\_AMT3 -3.147193e-06 BILL\_AMT4 5.126440e-06 BILL AMT5 -2.748228e-06 BILL\_AMT6 2.587035e-06 PAY\_AMT1 -4.613871e-06 PAY\_AMT2 -3.912667e-06 PAY\_AMT3 -5.001320e-06 PAY\_AMT4 1.251129e-06 PAY\_AMT5 -6.097643e-06

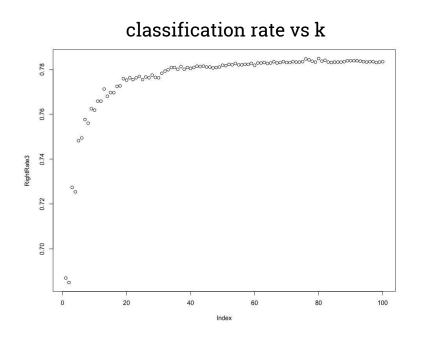
PAY\_AMT6 -4.704967e-07

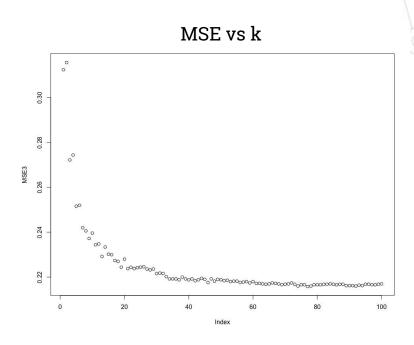
#### fitted response values from our LDA model



**Result** - Classification Rate = 80.9%

# k-Nearest Neighbors Classification





we select k = 7



# **Support Vector Classifier**

#### optimization problem

Figure 1 to elaborate Figure 2 to elaborate

$$\begin{array}{cc}
\text{maximize} & M \\
\beta_0, \beta_1, \dots, \beta_p, \epsilon_1, \dots, \epsilon_n
\end{array}$$

subject to 
$$\sum_{j=1}^{p} \beta_j^2 = 1$$
,

$$y_i(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_p x_{ip}) \ge M(1 - \epsilon_i),$$

$$\epsilon_i \ge 0, \ \sum_{i=1}^n \epsilon_i \le C,$$

#### tuning parameter: we select cost = 4

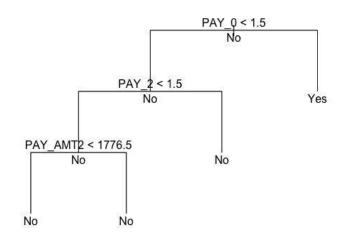
Parameter tuning of 'svm':

- sampling method: 10-fold cross validation
- best parameters: cost
- best performance: 0.188
- Detailed performance results: cost error dispersion
- 1 0.1 0.1896 0.02669665
- 2 1.0 0.1882 0.02652378
- 3 4.0 0.1880 0.02602563
- 4 5.0 0.1880 0.02602563
- 5 5.5 0.1882 0.02593068
- 6 6.0 0.1880 0.02602563

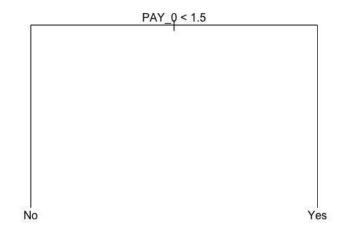
**Result** - Classification Rate = 80.82%

## Classification Tree

#### classification tree prior to pruning



#### classification tree after pruning





### Conclusion

- 1. How does the probability of default payment (default.payment.next.month) vary by categories of different demographic variables?
  - Logistic
    - Marriage
      - Age
  - LDA
- Sex
- Education
- Marriage
  - Age
- Classification Tree
  - None
- 2. Which variables are the best predictors of default payment?
  - Logistic, LDA & Classification Tree
    - PAY\_0
  - Logistic & LDA
    - MARRIAGE
    - AGE
    - PAY\_2
    - PAY\_3
- 3. What is the best model for predicting default payment?
  - Classification Tree
    - Classification Rate = 81.54%