



# 3TS: ML Engineering

TÉCNICAS BÁSICAS DE MODELADO PREDICTIVO

# Objetivos

- ▶ Estructurar el proceso de desarrollo de un modelo
- ▶ Sistematizar las operaciones de exploración-preparación
- ▶ Entrenar modelos básicos
- ▶ Evaluar modelos

# Objetivos

- ▶ Debatir, discutir y compartir experiencias y prácticas.
- ▶ Preguntarnos por qué



REPO: [https://github.com/manualrg/DSLAB\\_Python](https://github.com/manualrg/DSLAB_Python)



# Índice de la sesión

- ▶ Vocabulario
- ▶ Visión holística del proceso de exploración-preparación
- ▶ Modelos básicos
- ▶ Evaluación de modelos (más allá de ROC)

# Glossary

Features  
or  
predictors

Label,  
target  
or  
response

Prediction  
or  
scoring

id	x1	x2	...	y	$\hat{y}_{\text{prob}}$	$\hat{y}_{\text{pred}}$
cli101	1	1001		1 <b>event</b>	0.87	1
cli102				0	0.12	0

Example,  
instance or  
observation

Prior=  
 $\text{AVG}(y)$

Posterior=  
 $\text{AVG}(\hat{y}_{\text{prob}})$

# Exploration-Feature Engineering

Numeric  
features

Categorical  
features

Metadata  
Analysis

Low skewness

High skewness

Low  
cardinality

High  
cardinality

Descriptive Stats  
checkMissing()  
checkSkewness()  
checkCatFreq()

OI\_: Outlier idx  
MI\_: NaN idx  
Missing imp.

Missing imp.  
Rare levels  
Min cell freq

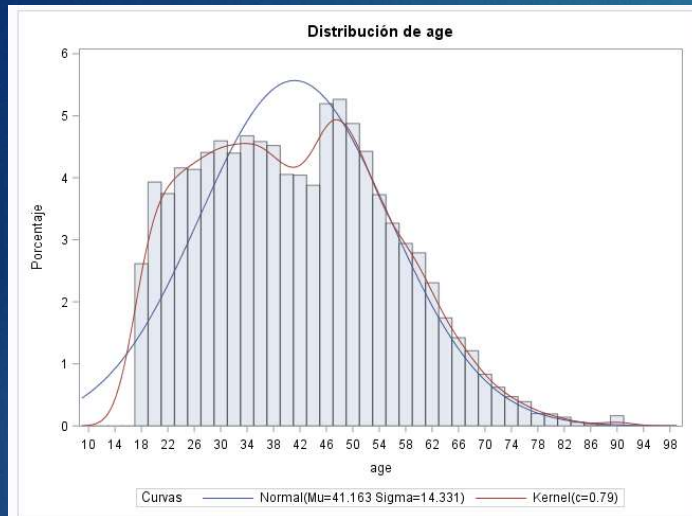
Variable  
Screening  
screenMissing()  
screenOutliers()  
screenLowFreq()

Binning  
Bucketing  
Transformation  
Normalization [0,1]  
Standartization  $\{\mu = 0, \sigma = 1\}$

Low freq grouping  
Numeric mapping  
OHE  
Dense representation  
Embeddings

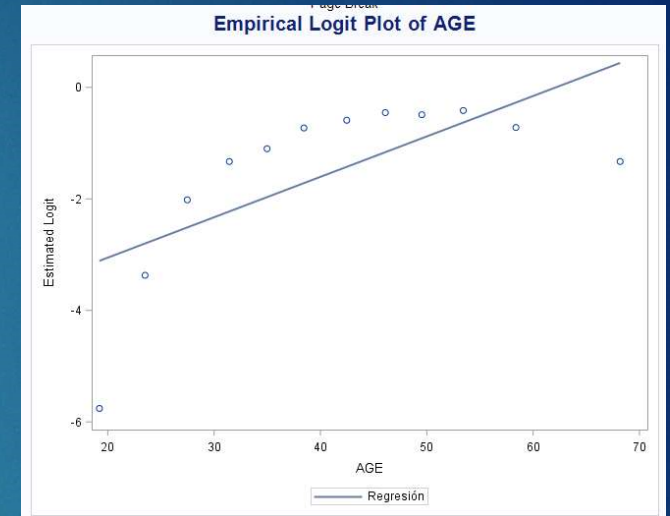
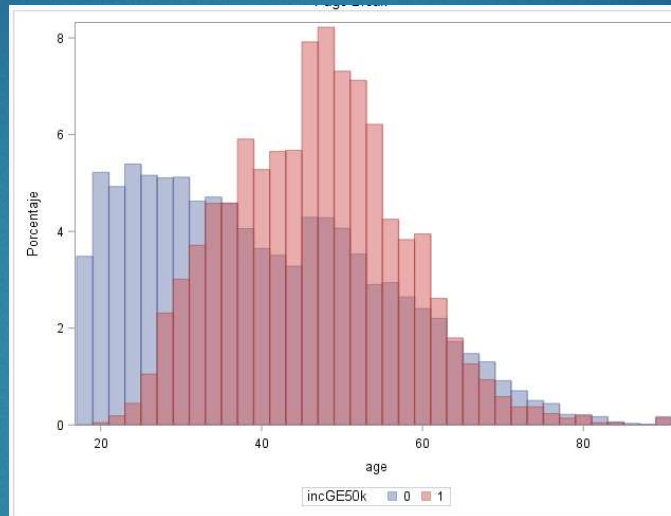
Feature  
Engineering

# Numeric Features: Low Skewness



raw numeric feature

Procedimiento HPLOGISTIC



Estadísticas de ajuste de partición		
Estadístico	Entrenamiento	Validación
Area bajo ROCC	0.6522	0.6499

transformed numeric feature

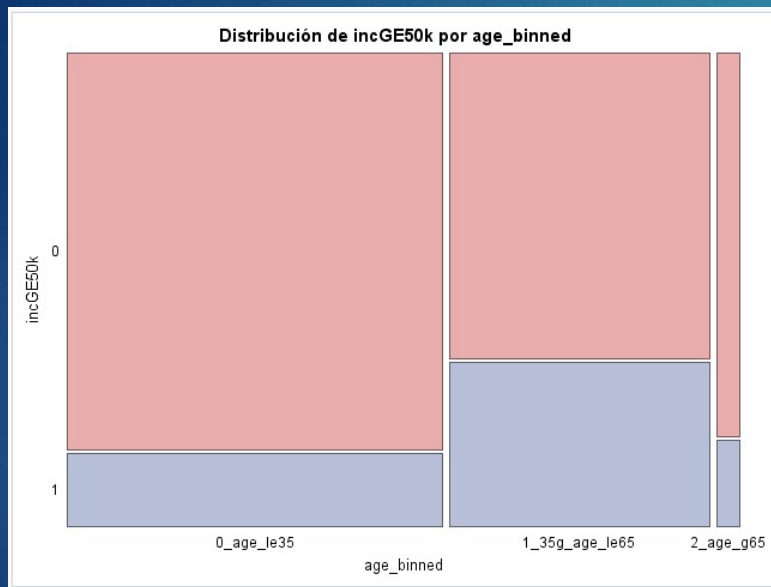
Procedimiento HPLOGISTIC

Estadísticas de ajuste de partición		
Estadístico	Entrenamiento	Validación
Area bajo ROCC	0.6945	0.6934

$$\text{logit}(p) = \log \left( \frac{p}{1-p} \right)$$



# Numeric Features: Low Skewness



Variable de análisis : age						
age_binned	Número de observaciones	N	Media	Dev std	Mínimo	Máximo
0_age_le35	13927	6679	26.6548885	5.2977745	17.0000000	35.0000000
1_35g_age_le65	9640	9640	48.5193983	7.8466232	36.0000000	65.0000000
2_age_g65	853	853	71.6213365	5.6303057	66.0000000	90.0000000

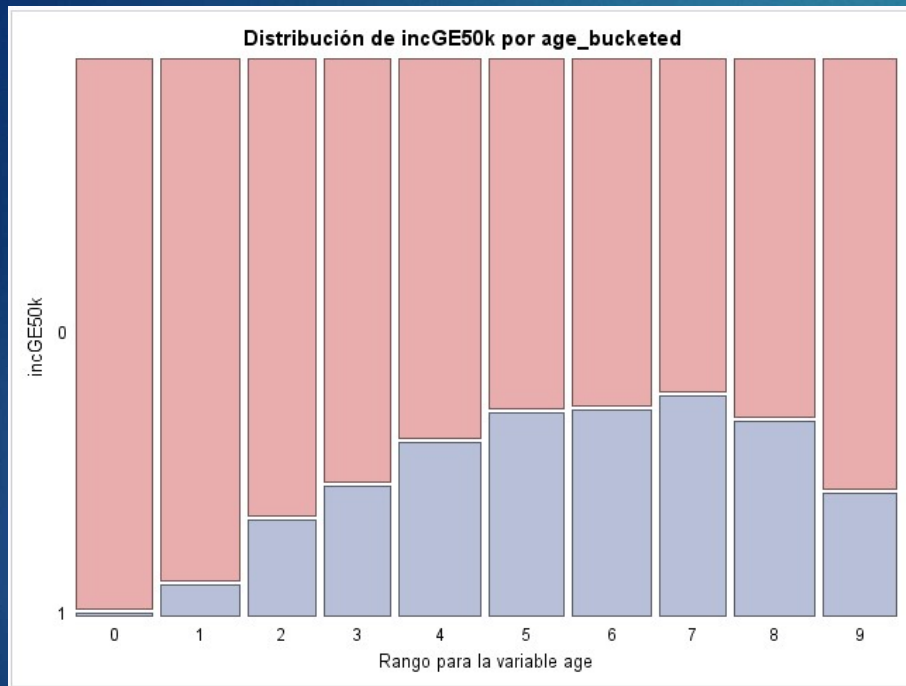
## binned numeric feature

### Procedimiento HPLOGISTIC

Estadísticas de ajuste de partición		
Estadístico	Entrenamiento	Validación
Área bajo ROCC	0.6304	0.6297



# Numeric Features: Low Skewness



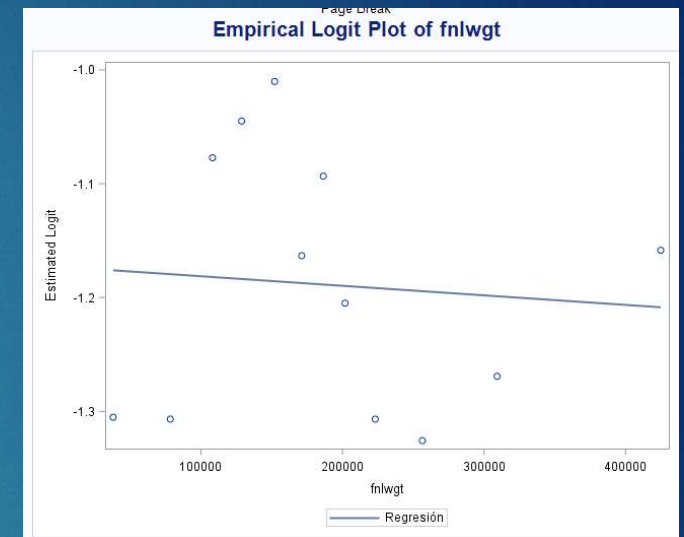
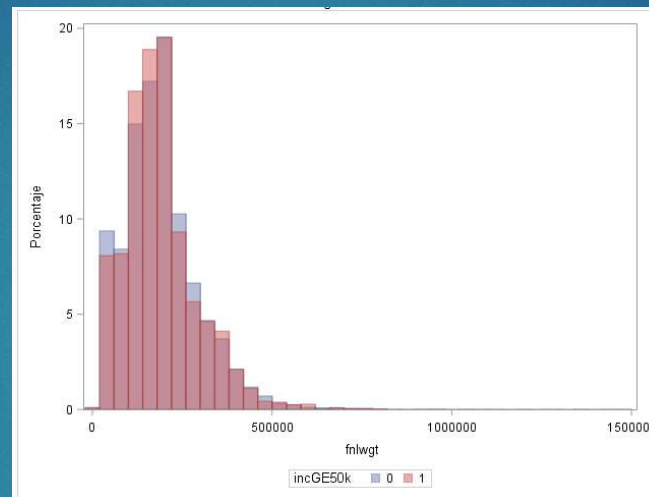
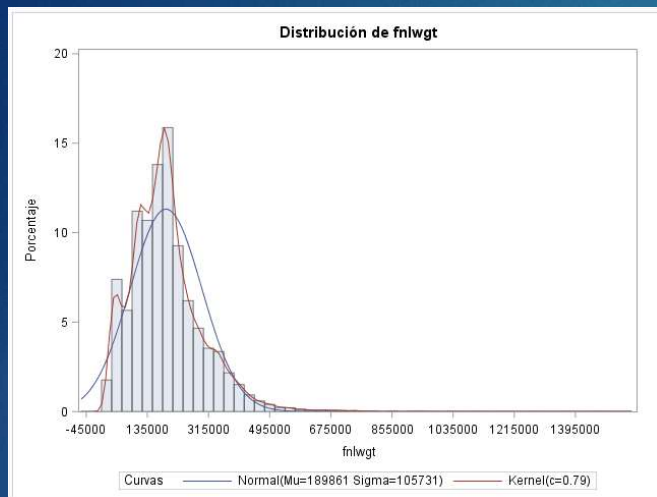
Variable de análisis : age						
Rango para la variable age	Número de observaciones	N	Media	Dev std	Mínimo	Máximo
0	1767	1767	19.7475948	1.6127724	17.0000000	22.0000000
1	1812	1812	25.0336645	1.4314729	23.0000000	27.0000000
2	1558	1558	29.5577664	1.1111339	28.0000000	31.0000000
3	1542	1542	33.5421530	1.0988638	32.0000000	35.0000000
4	1875	1875	37.9189333	1.4182975	36.0000000	40.0000000
5	1728	1728	43.0104167	1.4247812	41.0000000	45.0000000
6	1830	1830	47.3726776	1.1164641	46.0000000	49.0000000
7	1531	1531	51.3742652	1.1145344	50.0000000	53.0000000
8	1849	1849	56.8253110	2.0000778	54.0000000	60.0000000
9	1680	1680	67.2523810	6.0640315	61.0000000	90.0000000

## bucketed numeric feature

### Procedimiento HPLOGISTIC

Estadísticas de ajuste de partición		
Estadístico	Entrenamiento	Validación
Área bajo ROCC	0.6930	0.6915

# Numeric Features: High Skewness



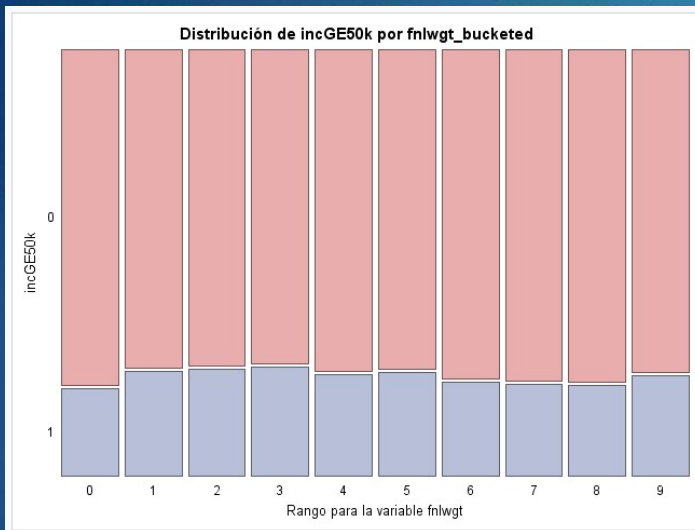
Page Break

raw numeric feature

Procedimiento HPLOGISTIC

Estadísticas de ajuste de partición		
Estadístico	Entrenamiento	Validación
Area bajo ROCC	0.5055	0.5067

# Numeric Features: High Skewness



Variable de análisis : fnlwgt						
Rango para la variable fnlwgt	Número de observaciones	N	Media	Dev std	Mínimo	Máximo
0	2441	2441	41663.27	11901.64	12285.00	65368.00
1	2443	2443	89261.97	12006.26	65372.00	106437.00
2	2442	2442	118040.10	6782.76	106491.00	130557.00
3	2442	2442	145338.68	7854.66	130571.00	158712.00
4	2441	2441	169418.24	5866.00	158734.00	178778.00
5	2443	2443	187964.40	4987.43	178780.00	196791.00
6	2443	2443	207311.38	6555.10	196797.00	219838.00
7	2442	2442	238208.39	11349.59	219841.00	259496.00
8	2441	2441	291215.68	19980.83	259505.00	329759.00
9	2442	2442	410198.32	98322.91	329783.00	1484705.00

## bucketed numeric feature

### Procedimiento HPLOGISTIC

#### Estadísticas de ajuste de partición

Estadístico	Entrenamiento	Validación
Área bajo ROCC	0.5269	0.5254



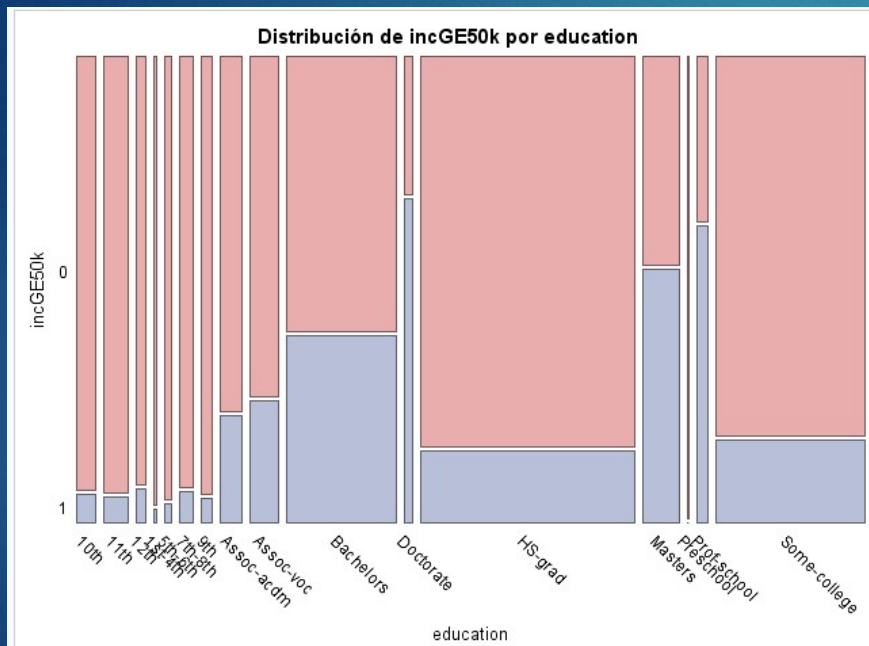
# Categorical Features

- ▶ Nominal levels (as strings): OHE
- ▶ Ordinal levels (as numeric)
- ▶ Numeric mapping:
  - ▶ Freq count
  - ▶ Freq idx
  - ▶ Event proportion
- ▶ ...

## Design matrix (Sparse representation)

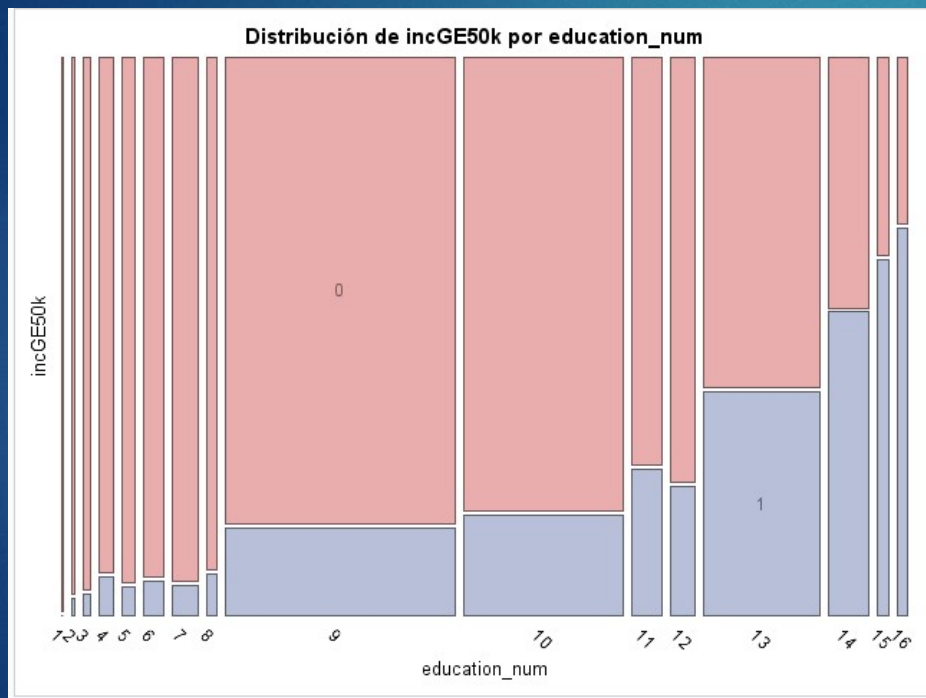
[illegible]

# Categorical Features: Nominal



Estadísticas de ajuste de partición		
Estadístico	Entrenamiento	Validación
Area bajo ROCC	0.7162	0.7025
F1	0.4588	0.4588

# Categorical Features: Ordinal



Page Break

## Ordinal: education\_NUM

Procedimiento HPLOGISTIC

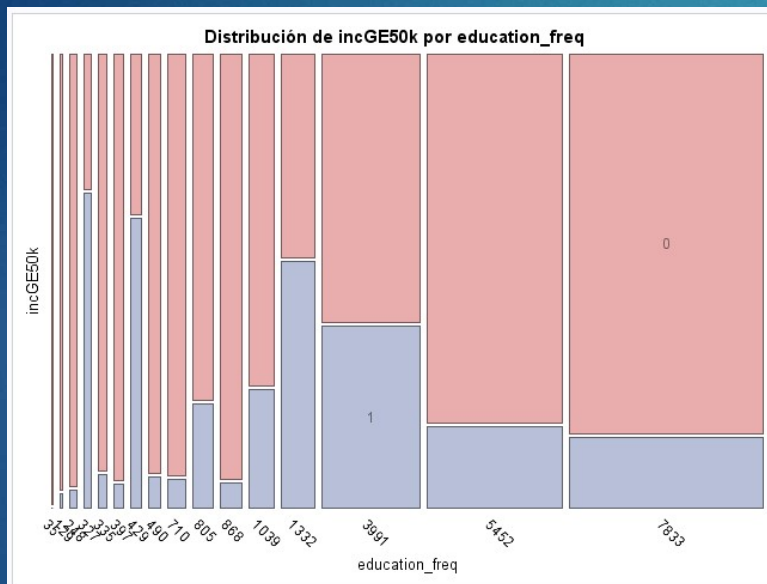
### Estadísticas de ajuste de partición

Estadístico	Entrenamiento	Validación
Área bajo ROCC	0.7162	0.7025

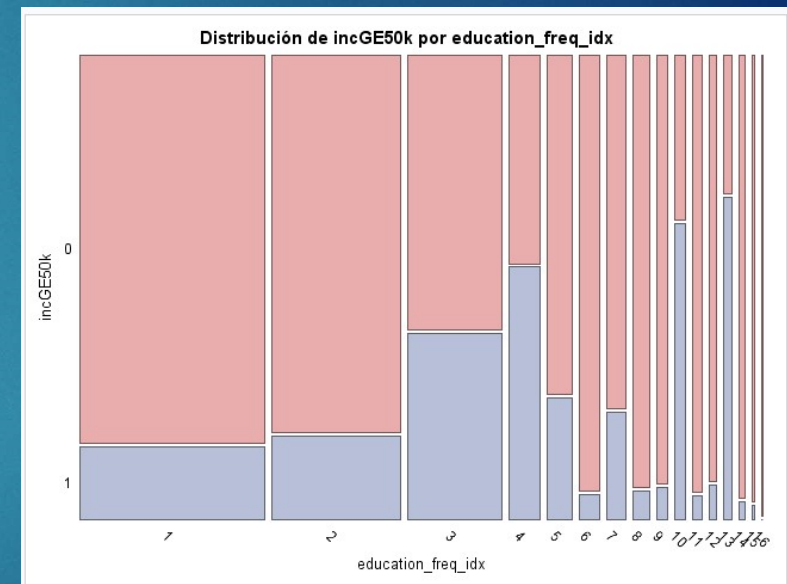
Magical numbers?  
Distances?



# Categorical Features: Freq mappings



Estadísticas de ajuste de partición		
Estadístico	Entrenamiento	Validación
Área bajo ROCC	0.5791	0.5709



Estadísticas de ajuste de partición		
Estadístico	Entrenamiento	Validación
Área bajo ROCC	0.5795	0.5712

# Basic Modelling: Logistic Regression

## 4.3.4 Multiple Logistic Regression

We now consider the problem of predicting a binary response using multiple predictors. By analogy with the extension from simple to multiple linear regression in Chapter 3, we can generalize (4.4) as follows:

$$\log \left( \frac{p(X)}{1 - p(X)} \right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p, \quad (4.6)$$

where  $X = (X_1, \dots, X_p)$  are  $p$  predictors. Equation 4.6 can be rewritten as

$$p(X) = \frac{e^{\beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p}}. \quad (4.7)$$

Just as in Section 4.3.2, we use the maximum likelihood method to estimate  $\beta_0, \beta_1, \dots, \beta_p$ .

### Logistic Regression Model

Want  $0 \leq h_\theta(x) \leq 1$

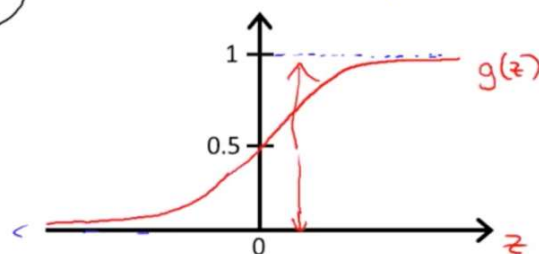
$$h_\theta(x) = g(\theta^T x)$$

$$\rightarrow g(z) = \frac{1}{1 + e^{-z}}$$

$\theta^T x$

Sigmoid function  
Logistic function

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$



Parameters  $\theta$ .

### Gradient Descent

$$\rightarrow J(\theta) = -\frac{1}{m} \left[ \sum_{i=1}^m y^{(i)} \log h_\theta(x^{(i)}) + (1 - y^{(i)}) \log (1 - h_\theta(x^{(i)})) \right]$$

Want  $\min_\theta J(\theta)$ :

Repeat {

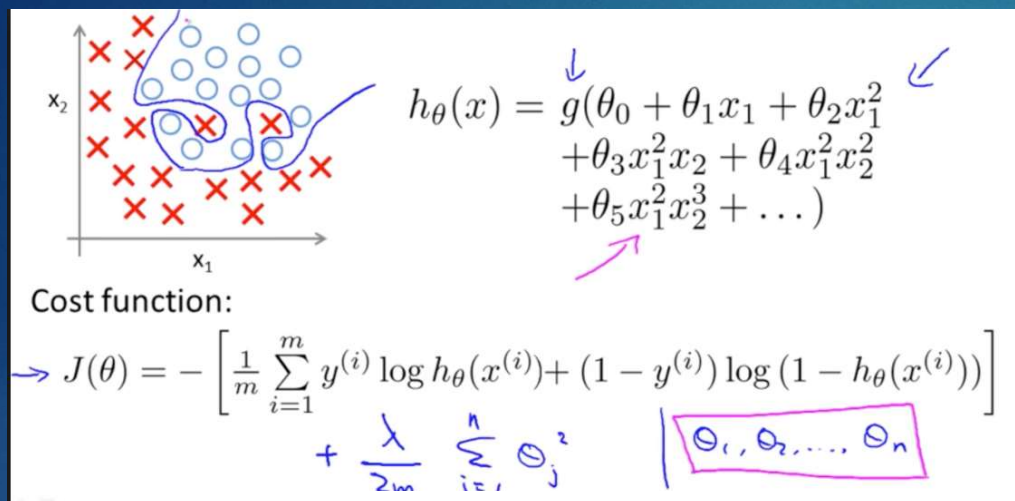
$$\theta_j := \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$

}

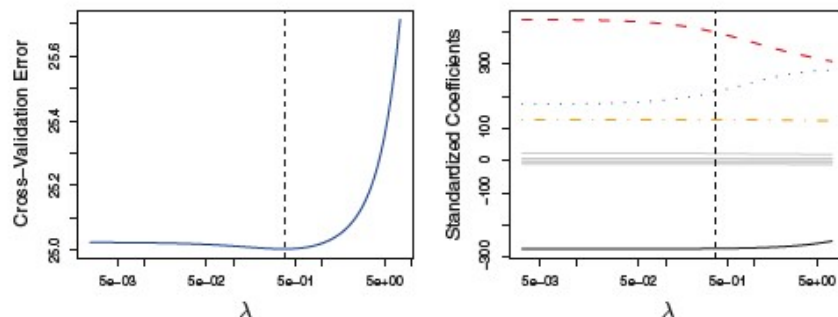
(simultaneously update all  $\theta_j$ )

$$\frac{\partial}{\partial \theta_j} J(\theta) = \frac{1}{m} \sum_{i=1}^m (h_\theta(x^{(i)}) - y^{(i)}) x_j^{(i)}$$

# Basic Modelling: Regularization

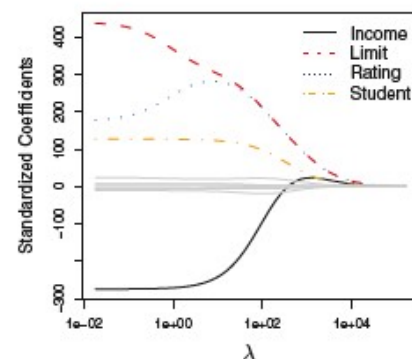


228 6. Linear Model Selection and Regularization

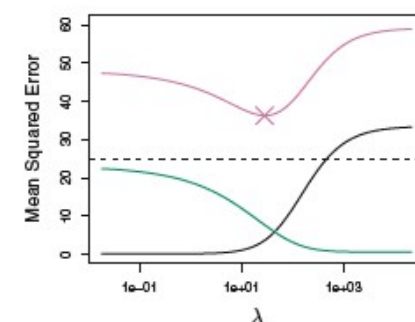


**FIGURE 6.12.** Left: Cross-validation errors that result from applying ridge regression to the **Credit** data set with various value of  $\lambda$ . Right: The coefficient estimates as a function of  $\lambda$ . The vertical dashed lines indicate the value of  $\lambda$  selected by cross-validation.

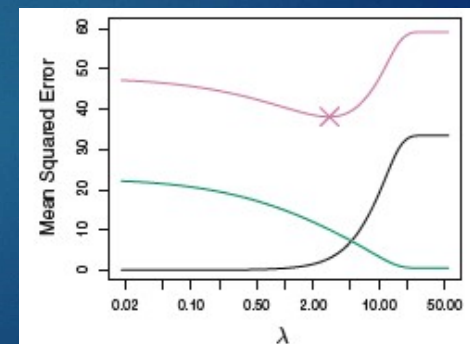
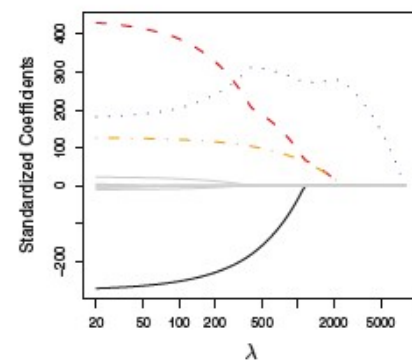
216 6. Linear Model Selection and Regularization



218 6. Linear Model Selection and Regularization



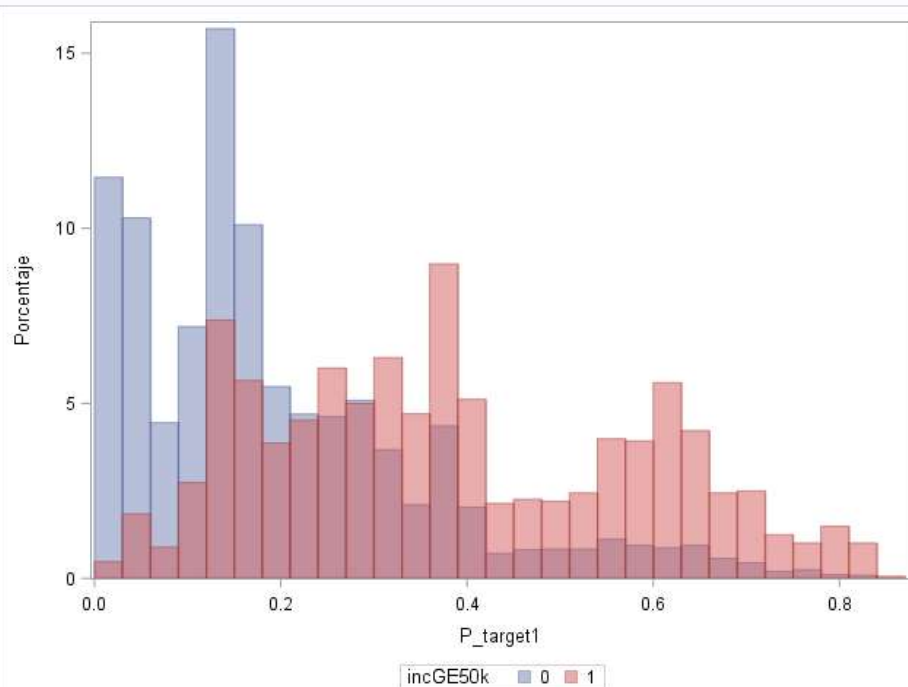
220 6. Linear Model Selection and Regularization





# Model Assessment: Beyond ROC

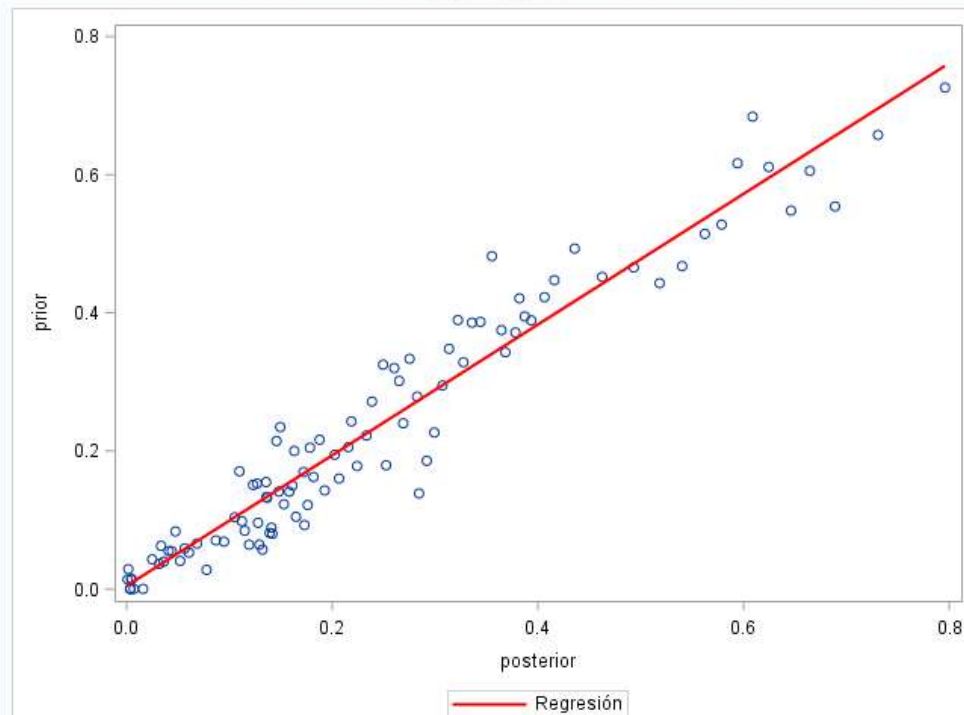
Page Break  
label plot  
\_partId\_=2



- ▶ Models that classify low probability examples correctly as non-event can yield a high AUC ( $>0.99$ ) and not perform properly
- ▶ RARE EVENT BINARY CLASSIFICATION
- ▶ What is AUROC?

# Model Assessment: Beyond ROC

Page Break  
calibration plot  
\_partId\_=2



- ▶ Class separation (KS metric)
- ▶ PR Curves
- ▶ Analyze scoring by predicted probability bucket!!! (e.g. calibration plot, Lift, Gain.)

# GRACIAS !!!

- ▶ BIBLIOGRAFÍA:
- ▶ Introduction to Statistical Learning (R)
  - ▶ <https://www-bcf.usc.edu/~gareth/ISL/ISLR%20First%20Printing.pdf>
- ▶ Elements of Statistical Learning (R)
  - ▶ <https://web.stanford.edu/~hastie/Papers/ESLII.pdf>
- ▶ Machine Learning Andrew NG (Matlab-Octave)
  - ▶ <https://www.coursera.org/learn/machine-learning>
- ▶ Categorical Data Analysis Using Logistic Regression (SAS)
  - ▶ <https://support.sas.com/edu/schedules.html?ctry=us&crs=CDALR>
- ▶ Predictive Modeling Using Logistic Regression (SAS)
  - ▶ <https://support.sas.com/edu/schedules.html?ctry=us&crs=PMLR>