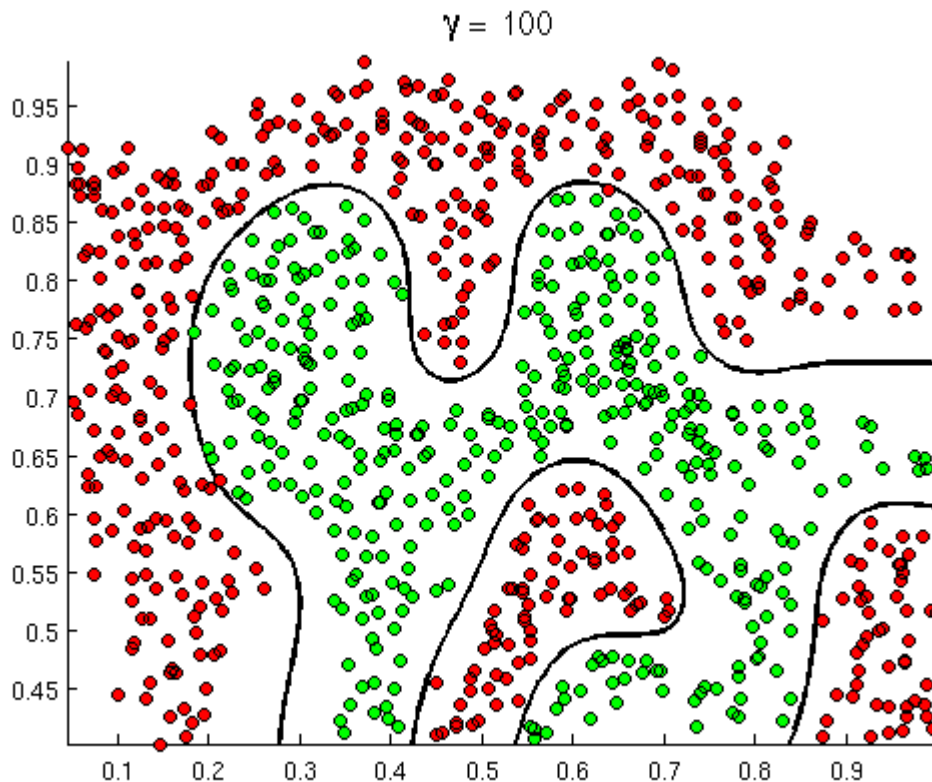


# Model Building and Goodness of Fit: (Case Study: Logistic Regression)



# Reminder: Logistic Regression

- Logistic Regression:

- $\log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 x_1^{(i)} + \dots + \beta_k x_k^{(i)}$

- $\pi_i$ : the likelihood that  $y^{(i)} = 1$

- (Log-)Likelihood:

- Compute  $\pi_i$  for every datapoint for which  $y^{(i)} = 1$ , and  $(1 - \pi_i)$  for every datapoint for which  $y^{(i)} = 0$ .

- If the fit is very good, the product

- $P(y|\beta) = \prod_{i=1}^n \pi_i^{y_i} (1 - \pi_i)^{1-y_i}$  is close to 1

- $\log P(y|\beta) = \sum_{i=1}^n (y_i \log \pi_i + (1 - y_i) \log(1 - \pi_i))$  is close to 0

# Deviance

$$\text{deviance} = \text{const} - 2 \log P(y|\beta)$$

- (where  $\beta$  is the fitted parameter – the one that maximizes  $\log P(y|\beta)$ ). In other words,  $\log P(y|\beta) = LMAX$ )
- Smaller deviance => better fit
  - “Better fit” means  $\pi_i$  is close to 1 if  $y_i$  is close to 1, and  $\pi_i$  is close to 0 if  $y_i$  is close to 0

# Last Time

- Null Hypothesis: the extra coefficients in the full model are 0
- Test Statistic:
  - $LRT = 2 \log(LMAX_{full}) - 2 \log(LMAX_{reduced})$
  - Has a  $\chi^2$  distribution with  $df=(\# \text{ of extra parameters in the full model})$
- Test?

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  - $(1-pchisq(L, df=df))$

# Which Covariates to Include?

- $AIC = Deviance + 2 \times p$ 
  - $p$  – number of parameters
  - Popularly called “Akaike Information Criterion”
    - Hirutogu Akaike calls it “An Information Criterion”
- Smaller AIC => Better Model
  - Note: larger model always implies smaller deviance
    - Problem: Why?
  - AIC compensates for that
    - The full model has to be reduce the deviance by enough to be considered better than the reduced model



# Classification (Iris Example)



# Visualization

- (in R)



# Classification

- Classification:
  - Given data, we want to predict the class of the datapoint
- Fit a logistic model and pick a cut point
  - Default: 0.5
- If  $\hat{\pi}^* > 0.5$ , predict  $y^* = 1$
- If  $\hat{\pi}^* < 0.5$ , predict  $y^* = 0$

# Confusion Matrix

	+	-	
D	TP	FN	Sensitivity = $TP / (TP + FN)$
D <sup>c</sup>	FP	TN	Specificity = $TN / (TN + FP)$
	PPV = $TP / (TP + FP)$	NPV = $TN / (TN + FN)$	

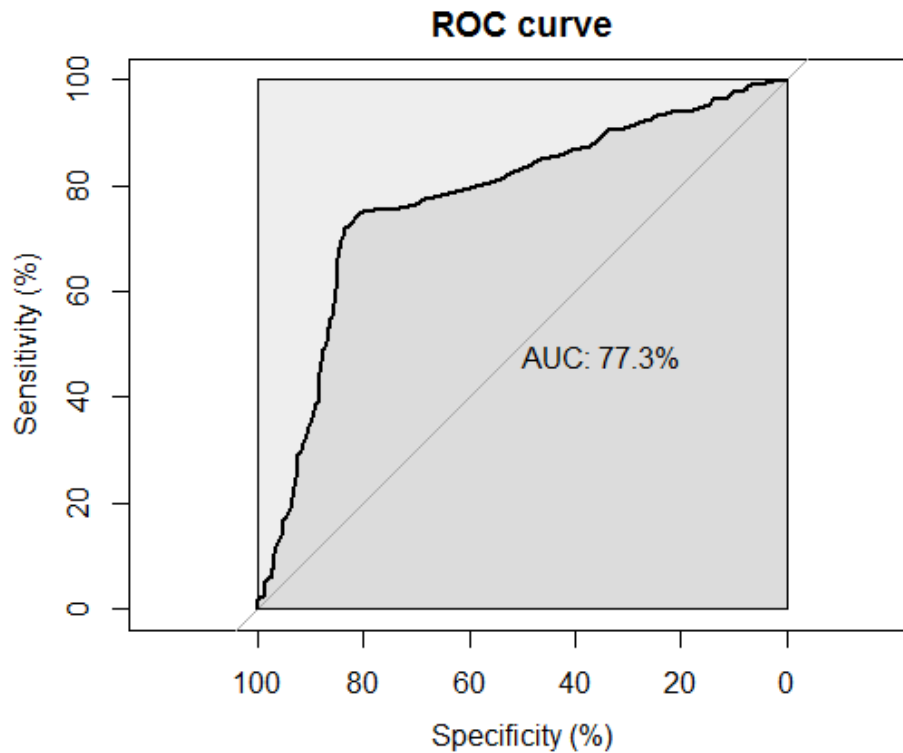
# ROC Curves

- Receiver Operating Characteristic
- A plot of sensitivity vs. specificity (complement)
- Originally designed to grade radar detection methods for German planes
- Decades later, their usefulness in classification problems was realized
  - But the name stuck

# ROC Curve

```
require (pROC)
```

```
> titan.roc <- with(titanR, roc(Isurvived, p, percent=T, auc=T, plot=T,  
auc.polygon=T, max.auc.polygon=T, print.auc=T, main= "ROC curve"))
```



# AUC

- Area Under the Curve
  - Larger is better
  - Ideally: 100% sensitivity for any specificity