

Lecture 8: Classification

Reading: Chapter 4

STATS 202: Data mining and analysis

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Classification problems

Supervised learning with a **qualitative or categorical** response.

Just as common, if not more common than regression:

- ▶ *Medical diagnosis*: Given the symptoms a patient shows, predict which of 3 conditions they are attributed to.
- ▶ *Online banking*: Determine whether a transaction is fraudulent or not, on the basis of the IP address, client's history, etc.
- ▶ *Web searching*: Based on a user's history, location, and the string of a web search, predict which link a person is likely to click.
- ▶ *Online advertising*: Predict whether a user will click on an ad or not.

Review: Bayes classifier

Suppose $P(Y | X)$ is known. Then, given an input x_0 , we predict the response

$$\hat{y}_0 = \operatorname{argmax}_y P(Y = y | X = x_0).$$

The Bayes classifier minimizes the 0-1 loss:

$$E \left[\frac{1}{m} \sum_{i=1}^m \mathbf{1}(\hat{y}_i \neq y_i) \right]$$

This minimum 0-1 loss (the best we can hope for) is the **Bayes error rate**.

Strategy: estimate $P(Y | X)$

If we have a good estimate for the conditional probability $\hat{P}(Y | X)$, we can use the classifier:

$$\hat{y}_0 = \operatorname{argmax}_y \hat{P}(Y = y | X = x_0).$$

Suppose Y is a binary variable. Could we use a linear model?

$$P(Y = 1|X) = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p$$

Problems:

- ▶ This would allow probabilities <0 and >1 .
- ▶ Difficult to extend to more than 2 categories.

Logistic regression

We model the joint probability as:

$$P(Y = 1 \mid X) = \frac{e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}}{1 + e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}},$$

$$P(Y = 0 \mid X) = \frac{1}{1 + e^{\beta_0 + \beta_1 X_1 + \dots + \beta_p X_p}}.$$

This is the same as using a linear model for the log odds:

$$\log \left[\frac{P(Y = 1 \mid X)}{P(Y = 0 \mid X)} \right] = \beta_0 + \beta_1 X_1 + \dots + \beta_p X_p.$$

Fitting logistic regression

The training data is a list of pairs $(y_1, x_1), (y_2, x_2), \dots, (y_n, x_n)$. In the linear model

$$\log \left[\frac{P(Y = 1 \mid X)}{P(Y = 0 \mid X)} \right] = \beta_0 + \beta_1 X_1 + \dots + \beta_p X_p,$$

we don't observe the left hand side.

We cannot use a least squares fit.

Fitting logistic regression

Solution:

The likelihood is the probability of the training data, for a fixed set of coefficients β_0, \dots, β_p :

$$\begin{aligned} & \prod_{i=1}^n P(Y = y_i \mid X = x_i) \\ &= \underbrace{\prod_{i; y_i=1} \frac{e^{\beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip}}}{1 + e^{\beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip}}}}_{\text{Probability of responses} = 1} \underbrace{\prod_{j; y_j=0} \frac{1}{1 + e^{\beta_0 + \beta_1 x_{j1} + \dots + \beta_p x_{jp}}}}_{\text{Probability of responses} = 0} \end{aligned}$$

- ▶ Choose estimates $\hat{\beta}_0, \dots, \hat{\beta}_p$ which maximize the likelihood.
- ▶ Solved with numerical methods (e.g. Newton's algorithm).

Logistic regression in R

```
> glm.fit=glm(Direction~Lag1+Lag2+Lag3+Lag4+Lag5+Volume ,  
  data=Smarket ,family=binomial)  
> summary(glm.fit)
```

Call:

```
glm(formula = Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5  
  + Volume, family = binomial, data = Smarket)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.45	-1.20	1.07	1.15	1.33

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.12600	0.24074	-0.52	0.60
Lag1	-0.07307	0.05017	-1.46	0.15
Lag2	-0.04230	0.05009	-0.84	0.40
Lag3	0.01109	0.04994	0.22	0.82
Lag4	0.00936	0.04997	0.19	0.85
Lag5	0.01031	0.04951	0.21	0.83
Volume	0.13544	0.15836	0.86	0.39

Logistic regression in R

- ▶ We can estimate the Standard Error of each coefficient.
- ▶ The z -statistic is the equivalent of the t -statistic in linear regression:

$$z = \frac{\hat{\beta}_j}{\text{SE}(\hat{\beta}_j)}.$$

- ▶ The p -values are test of the null hypothesis $\beta_j = 0$ (Wald's test).
- ▶ Other possible hypothesis tests: likelihood ratio test (chi-square distribution).

Example: Predicting credit card default

Predictors:

- ▶ student: 1 if student, 0 otherwise.
- ▶ balance: credit card balance.
- ▶ income: person's income.

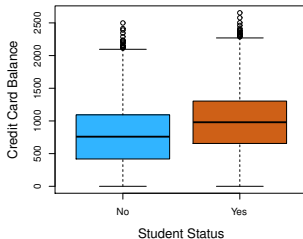
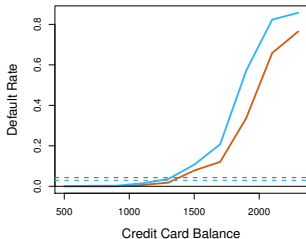
In this dataset, there is *confounding*, but little collinearity.

- ▶ Students tend to have higher balances. So, balance is explained by student, but not very well.
- ▶ People with a high balance are more likely to default.
- ▶ Among people with a given balance, students are less likely to default.

Example: Predicting credit card default

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Example: Predicting credit card default

Logistic regression using only balance:

	Coefficient	Std. error	Z-statistic	P-value
Intercept	-10.6513	0.3612	-29.5	<0.0001
balance	0.0055	0.0002	24.9	<0.0001

Logistic regression using only student:

	Coefficient	Std. error	Z-statistic	P-value
Intercept	-3.5041	0.0707	-49.55	<0.0001
student[Yes]	0.4049	0.1150	3.52	0.0004

Logistic regression using all 3 predictors:

	Coefficient	Std. error	Z-statistic	P-value
Intercept	-10.8690	0.4923	-22.08	<0.0001
balance	0.0057	0.0002	24.74	<0.0001
income	0.0030	0.0082	0.37	0.7115
student[Yes]	-0.6468	0.2362	-2.74	0.0062

Extending logistic regression to more than 2 categories

Multinomial logistic regression:

Suppose Y takes values in $\{1, 2, \dots, K\}$, then we use a linear model for the log odds against a baseline category (e.g. 1):

$$\log \left[\frac{P(Y = 2 \mid X)}{P(Y = 1 \mid X)} \right] = \beta_{0,2} + \beta_{1,2}X_1 + \dots + \beta_{p,2}X_p,$$

...

$$\log \left[\frac{P(Y = K \mid X)}{P(Y = 1 \mid X)} \right] = \beta_{0,K} + \beta_{1,K}X_1 + \dots + \beta_{p,K}X_p.$$

Some issues with logistic regression

- ▶ The coefficients become unstable when there is collinearity. Furthermore, this affects the convergence of the fitting algorithm.
- ▶ When the classes are well separated, the coefficients become unstable.

Linear Discriminant Analysis (LDA)

Strategy: Instead of estimating $P(Y | X)$, we will estimate:

1. $\hat{P}(X | Y)$: Given the response, what is the distribution of the inputs.
2. $\hat{P}(Y)$: How likely are each of the categories.

Then, we use *Bayes rule* to obtain the estimate:

$$\hat{P}(Y = k | X = x) = \frac{\hat{P}(X = x | Y = k)\hat{P}(Y = k)}{\hat{P}(X = x)}$$

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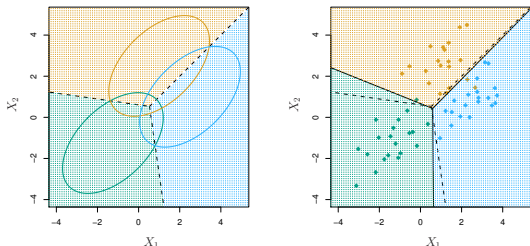
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$$\hat{P}(Y = k | X = x) = \frac{\hat{P}(X = x | Y = k)\hat{P}(Y = k)}{\sum_j \hat{P}(X = x | Y = j)\hat{P}(Y = j)}$$

Linear Discriminant Analysis (LDA)

Strategy: Instead of estimating $P(Y | X)$, we will estimate:

1. We model $\hat{P}(X = x | Y = k) = \hat{f}_k(x)$ as a *Multivariate Normal Distribution*:



2. $\hat{P}(Y = k) = \hat{\pi}_k$ is estimated by the fraction of training samples of class k .

Next time

- ▶ Linear Discriminant Analysis (LDA):
 - ▶ How do we estimate the parameters of the MVN distribution \hat{f}_k for each class k ?
 - ▶ What do LDA predictions look like.
- ▶ How to evaluate a classification method?
- ▶ Examples: comparing KNN, logistic regression and LDA.