Master Program in *Data Science and Business Informatics*

Statistics for Data Science

Lesson 22 - Multiple, non-linear, and logistic regression (continued)

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Issues: Omitted variable bias

- Suppose we omit a variable z_i that belongs to the true model

$$Y_i = \alpha + \beta_1 x_i + \beta_2 z_i + U_i$$

  with $\beta_2 \neq 0$ (i.e., Y is determined by Z)
  - Under-specification of the model, due to lack of data
- Fitted model $Y_i = \alpha + \beta_1 x_i + U_i'$
  - Hence, $E[U_i'] = E[\beta_2 z_i + U_i] = \beta_2 z_i + E[U_i] = \beta_2 z_i \neq 0$
- Let $\hat{\alpha}$ and $\hat{\beta}_1$ be the LSE estimators of the fitted model:

$$E[\hat{\beta}_1] = \beta_1 + \beta_2 \delta \qquad Bias(\hat{\beta}_1) = \beta_2 \delta$$

  where δ is the slope of the regression of $z_i = \gamma + \delta x_i + U_i''$, i.e.:

$$\delta = r_{xz} \frac{s_z}{s_x}$$

- $Bias(\hat{\beta}_1) \neq 0$ if X and Z correlated

See R script

Issues: Multi-collinearity and variance inflation factors

- *Multicollinearity*: two or more independent variables (regressors) are strongly correlated.
- $Y_i = \alpha + \beta_1 x_i^1 + \beta_2 x_i^2 + U_i$
- It can be shown that for $j \in \{1, 2\}$:

$$Var(\hat{\beta}_j) = \frac{1}{(1 - r^2)} \cdot \frac{\sigma^2}{SXX_j}$$

  where $r = cor(x^1, x^2)$, $\sigma^2 = Var(U_i)$ and $SXX_j = \sum_1^n (x_i^j - \bar{x}_n^j)^2$
- Correlation between regressors increases the variance of the estimators
- In general, for more than 2 variables:

$$Var(\hat{\beta}_j) = \frac{1}{(1 - R_j^2)} \cdot \frac{\sigma^2}{SXX_j}$$

  where R_j^2 is the coefficient of determination (R^2) in the regression of x_j from all other x_i's.
- The term $1/(1-R_j^2)$ is called *variance inflation factor*

See R script

Variable selection

- Recall: when $U_i \sim N(0, \sigma^2)$, we have $Y_i \sim N(\boldsymbol{x}_i \cdot \boldsymbol{\beta}, \sigma^2)$, hence we can apply MLE
- Log-likelihood is $\ell(\boldsymbol{\beta}) = \sum_{i=1}^{n} \log\left(\frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{y_i - \boldsymbol{x}_i \cdot \boldsymbol{\beta}}{\sigma^2}\right)^2}\right)$
- Akaike information criterion (AIC), balances model fit against model simplicity

$$AIC(\boldsymbol{\beta}) = 2|\boldsymbol{\beta}| - 2\ell(\boldsymbol{\beta})$$

- stepAIC(model, direction="backward") algorithm
  1. $S = \{x^1, \ldots, x^k\}$
  2. $b = AIC(S)$
  3. repeat
     - 3.1 $x = \arg\min_{x \in S} AIC(S \setminus \{x\})$
     - 3.2 $v = AIC(S \setminus \{x\})$
     - 3.3 if $v < b$ then $S, b = S \setminus \{x\}, v$
  4. until no change in S
  5. return S

See R script

Regularization methods: Ridge/Tikhonov

$$\hat{\boldsymbol{\beta}} = arg\min_{\boldsymbol{\beta}} S(\boldsymbol{\beta})$$

- Ordinary Least Square Estimation (OLS):

$$S(\boldsymbol{\beta}) = \|\boldsymbol{y} - \boldsymbol{X} \cdot \boldsymbol{\beta}\|^2$$

  where $\|(v_1, \ldots, v_n)\| = \sqrt{\sum_{i=1}^{n} v_i^2}$ is the Euclidian norm
    - Performs poorly as for prediction (overfitting) and interpretability (number of variables)
- Ridge regression:

$$S(\boldsymbol{\beta}) = \|\boldsymbol{y} - \boldsymbol{X} \cdot \boldsymbol{\beta}\|^2 + \lambda_2 \|\boldsymbol{\beta}\|^2$$

  where $\|\boldsymbol{\beta}\| = \sqrt{\alpha^2 + \sum_{i=1}^{k} \beta_i^2}$.
    - Notice that λ_2 is not in the parameters of the minimization problem!
    - Variables with minor contribution have their coefficients **close** to zero
    - It improves prediction error by reducing overfitting through a bias-variance trade-off
    - It is **not** a parsimonious method, i.e., does not reduce features

Regularization methods: Lasso and Penalized

- Lasso (Least Absolute Shrinkage and Selection Operator) regression:

$$S(\boldsymbol{\beta}) = \|\boldsymbol{y} - \boldsymbol{X} \cdot \boldsymbol{\beta}\|^2 + \lambda_1 \|\boldsymbol{\beta}\|_1$$

  where $\|\boldsymbol{\beta}\|_1 = |\alpha| + \sum_{i=1}^{k} |\beta_i|$.
  - Notice that λ_1 is not in the parameters of the minimization problem!
  - Variable with minor contribution have their coefficients **equal** to zero
  - It improves prediction error by reducing overfitting through a bias-variance trade-off
  - It **is** a parsimonious method, i.e., it reduces the number of features
- Penalized linear regression:

$$S(\boldsymbol{\beta}) = \|\boldsymbol{y} - \boldsymbol{X} \cdot \boldsymbol{\beta}\|^2 + \lambda_2 \|\boldsymbol{\beta}\|^2 + \lambda_1 \|\boldsymbol{\beta}\|_1$$

  - Both Ridge and Lasso regularization parameters
- How to solve the minimization problems? **Lagrange multiplier method** or **reduction to Support Vector Machine** learning
- How to find the best λ_1 and/or λ_2? Cross-validation!

See R script

Towards logistic regression

- Consider a bivariate dataset

$$(x_1, y_1), \ldots, (x_n, y_n)$$

  where $y_i \in \{0, 1\}$, i.e., Y_i is a binary variable
- Using directly linear regression:

$$Y_i = \alpha + \beta x_i + U_i$$

  results in poor performances (R^2)

See R script

Towards logistic regression

- Consider a bivariate dataset
$$(x_1, y_1), \ldots, (x_n, y_n)$$
where $y_i \in \{0, 1\}$, i.e., Y_i i binary variable
- Group by x values:
$$(d_1, f_1), \ldots, (d_m, f_m)$$
where $d_1, \ldots, d_m$ are the distinct values of $x_1, \ldots, x_n$ and f_i is the fraction of 1's:
$$f_i = \frac{|\{j \in [1, n] \mid x_j = d_i \wedge y_j = 1\}|}{|\{j \in [1, n] \mid x_j = d_i\}|}$$
and the linear model (we continue using x_i but it should be d_i):
$$F_i = \alpha + \beta x_i + U_i$$

See R script

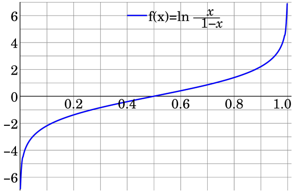
Towards logistic regression

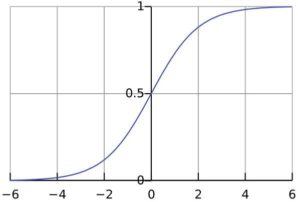
- Rather than f_i, we model the logit of f_i

$$logit(F_i) = \alpha + \beta x_i + U_i$$

where logit and its inverse (**logistic function**) are:

$$logit(p) = \log \frac{p}{1-p} \qquad inv.logit(x) = \frac{e^x}{1+e^x} = \frac{1}{1+e^{-x}}$$





- Why?
  - $F_i \in [0, 1]$ while the RHS is in $\mathbb{R}$
  - Relation between RHS and F_i is typically sigmoidal, not linear

See R script

Logistic regression and generalized linear models

- Since Y_i's are binary, $F_i = P(Y_i = 1|X = x_i) \sim Ber(f_i)$, and U_i is not necessary

$$logit(F_i) = \alpha + \beta x_i$$

  and then $F_i = P(Y_i = 1|X = x_i) = inv.logit(\alpha + \beta x_i) = \frac{e^{\alpha+\beta x_i}}{1+e^{\alpha+\beta x_i}}$

- Since $F_i/(1 - F_i) = e^{\alpha+\beta x_i}$, β can be interpreted as:
  - the expected change in log odds of having the outcome per unit change in X
  - e.g., $\beta = 0.38$ in predicting heart disease from smoking: the smoking group has $e^{\beta} = 1.46$ times the odds of the non-smoking group of having heart disease
  - e.g., $\alpha = -1.93$ means the probability a non-smoker has heart disease is $e^{\alpha}/(1 + e^{\alpha}) = 0.13$.
- Generalized linear models: family = distribution + link function
  - E.g., Binomial + logit for logistic regression
  - For $Y_i \in \{0, 1\}$, actually Bernoulli + logit *[Binary logistic regression]*
- Since distribution is known, MLE can be adopted for estimating α and β:

$$\ell(\alpha, \beta) = \sum_{i=1}^{n} \left[y_i \log\left(inv.logit(\alpha + \beta x_i)\right) + (1 - y_i) \log\left(1 - inv.logit(\alpha + \beta x_i)\right)\right]$$

See R script

Elastic net logistic regression

- Penalized linear regression minimizes:

$$\|\boldsymbol{y} - \boldsymbol{X} \cdot \boldsymbol{\beta}\|^2 + \lambda_2 \|\boldsymbol{\beta}\|^2 + \lambda_1 \|\boldsymbol{\beta}\|_1$$

  - $\lambda_1 = 0$ is the Ridge penalty
  - $\lambda_2 = 0$ is the Lasso penalty
- Elastic net regularization for logistic regression minimizes:

$$-\ell(\boldsymbol{\beta}) + \lambda \left(\frac{(1-\alpha)}{2} \|\boldsymbol{\beta}\|^2 + \alpha \|\boldsymbol{\beta}\|_1 \right)$$

  - $\alpha = 0$ is the Ridge penalty
  - $\alpha = 1$ is the Lasso penalty
  - λ is to be found, e.g., by cross-validation

See R script