## 10. Regression

## Outline

- Definition
- Example applications
- Least squares
- Solving linear problems
- Diagnostics ( $R^{2}$, adjusted $R^{2}$, AIC)


## Definition

- Fit a function of (some) given type, say $f$, approximately through given points $\left(x_{i}, y_{i}\right)$ so that for the given points, $f\left(x_{i}\right) \approx y_{i}, i=1,2, \ldots n$
- This function is usually intended to predict $y$ given a predictor value $x$ (this $x$ can actually be a vector that contains several different relevant predictors)


## Example applications

- Forecasting travel time for a route based on predictors such as time of day, day of week, closeness to holiday, amount of construction...
- Forecasting transit ridership based on similar factors, and perhaps ones that change more slowly such as population density, amount of commercial space, and economic activity
- Estimating house prices from predictors such as size, age, location, ...


## Example problem

Given the following data on $u, v, z$ values, develop a function $f(u, v)$ that we can use to predict $z$ where it's not known.

| $u$ | 2 | 1 | 6 | 0 | 2 | 1 |
| ---: | ---: | ---: | ---: | ---: | ---: | ---: |
| $v$ | 4 | 1 | 3 | 1 | 0 | 14 |
| $z$ | 11 | 3 | 26 | 3 | 10 | 8 |

## Least squares

- If the points are grouped as vectors $\boldsymbol{x}, \boldsymbol{y}$, the residual vector of the fitted function is $\boldsymbol{r}=\boldsymbol{y}-f(\boldsymbol{x})$ (i.e. $r_{i}=y_{i}-f\left(x_{i}\right)$ )
- We'd like $\boldsymbol{r}$ to be close to all zeros (which would be the case for interpolation, where $\left.y_{i}=f\left(x_{i}\right)\right)$
- Problem: Out of all the functions $f$ in the given type, find the one that has the smallest the residual sum of squares, RSS $=\boldsymbol{r}^{T} \boldsymbol{r}=\sum_{i=1}^{n} r_{i}^{2}$


## Linear least squares

- Suppose the function type is such that we can write $f(\boldsymbol{x})=\boldsymbol{A} \boldsymbol{\beta}$ (linear regression)
- $\boldsymbol{A}$ is a known $n \times m$ design matrix for the given $\boldsymbol{x}$
- $\boldsymbol{\beta}$ is an unknown $m \times 1$ vector of 'parameters'
- So $f\left(x_{i}\right)=A_{i, 1} \beta_{1}+A_{i, 2} \beta_{2}+\ldots A_{i, m} \beta_{m}$
- Then we can find using linear algebra methods the value of $\boldsymbol{\beta}$ that minimizes the RSS for the given $\boldsymbol{x}$ and $\boldsymbol{y}$


## The normal equations

$\boldsymbol{A}^{T} \boldsymbol{A} \boldsymbol{\beta}=\boldsymbol{A}^{T} \boldsymbol{y}$ is the system of normal equations for a linear regression problem. Solving it for $\boldsymbol{\beta}$ gives us the least squares (lowest RSS) set of parameter values.

## Example problem

Suppose our function type is $f(u, v)=\beta_{1} u+\beta_{2} \sqrt{v}$. This is linear in the unknown $\beta_{i}$, so we can write $f(\boldsymbol{u}, \boldsymbol{v})=\boldsymbol{A} \boldsymbol{\beta}$, where the
design matrix $\boldsymbol{A}$ is

$$
\left(\begin{array}{cc}
u_{1} & \sqrt{v_{1}} \\
u_{2} & \sqrt{v_{2}} \\
u_{3} & \sqrt{v_{3}} \\
u_{4} & \sqrt{v_{4}} \\
u_{5} & \sqrt{v_{5}} \\
u_{6} & \sqrt{v_{6}}
\end{array}\right)=\left(\begin{array}{rr}
2 & 2 \\
1 & 1 \\
6 & \sqrt{3} \\
0 & 1 \\
2 & 0 \\
1 & \sqrt{14}
\end{array}\right)
$$

The normal equations are then
$\left(\begin{array}{ll}46 & 19.134 \\ 19.134 & 23\end{array}\right)\binom{\beta_{1}}{\beta_{2}}=\binom{209}{102.97}$
Resulting in $\boldsymbol{\beta}=\binom{4.100}{1.066}$

## Diagnostics

- These are measures of how well a function fits given $y$ values, meant to give an indication of how good it might be as a predictor
- $R^{2}=1-\frac{\text { RSS }}{\text { TSS }}$, where the total sum of squares TSS is $(\boldsymbol{y}-\bar{y})^{T}(\boldsymbol{y}-\bar{y})$, with $\bar{y}$ the average value of $\boldsymbol{y}$
- Adjusted $R^{2}: R_{a}^{2}=1-\frac{n-1}{n-m} \frac{\text { RSS }}{\text { TSS }}$, where $n$ is the number of data points and $m$ is the number of unknown parameters in $\boldsymbol{\beta}$
- Akaike information criterion (AIC): $n \log (\mathrm{RSS} / n)+2 m n /(n-m-1)$ (lower value denotes better fit)
- $R_{a}^{2}$ and AIC include $m$ as well as RSS in their formulas to reflect that all else being equal, a more complicated function type (with more parameters that need to be determined) will not be as good at predicting unknown values


## Example

- For the function type $f(u, v)=\beta_{1} u+\beta_{2} \sqrt{v}$, the least-squares $\beta$ give RSS $=12.3, R^{2}=0.966, R_{a}^{2}=0.957$, AIC $=12.3$
- Changing the function type to one with another parameter with $g(u, v)=\beta_{1} u+\beta_{2} \sqrt{v}+\beta_{3}$, gives RSS
$=10.4, R^{2}=0.971, R_{a}^{2}=0.952, \mathrm{AIC}=21.3$
- Although $R^{2}$ improves with the additional parameter, $R_{a}^{2}$ and AIC both worsen, implying that this function type may not be better at predicting $y$ given the points available for fitting


## Nonlinear least squares

- The regression model or function type, $f(\boldsymbol{\beta} ; x)$, may also be nonlinear in $\boldsymbol{\beta}$ - for example, it might look like $x^{\beta}$ or $\cos (\beta x)$.
- In that case, we can still look for the least-squares values of $\beta$, but we typically need to use iterative numerical methods to approximate it, instead of just solving a linear system.
- Once the least-squares value of $\beta$ is found, $R^{2}$ and other diagnostics can be calculated following the same formulas as before.

