

Data - Questions

Thursday 24th November, 2016

- 1 Introduction
- 2 Questions About the Data
- 3 Linear Regression
- 4 Conclusion

Order of the Day

- ▶ what type of questions can be asked (and answered) regarding the data
 - a primer for next topics in statistical inference
- ▶ introduction to two important and basic machine learning tasks

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Questions About the Data

	name	filming time (<i>years</i>)	budget (10^6 \$)	profit (10^6 \$)	genre
	Avatar	1.5	350	650	action
	Titanic	0.8	300	500	drama
V	Die Hard	0.5	-	350	-
	Looper	0.6	-	400	-
	Fight Club	0.4	-	700	-
	Inception	0.7	250	400	action
	⋮	⋮	⋮	⋮	⋮

what can we ask about it?

discussion

Questions About the Data

- ▶ how was it generated?
- ▶ was it generated the same way as another data set D' ?
- ▶ is it surprising?
- ▶ are data elements A and B dependent on each other?
- ▶ which category do the points in V belong to?
- ▶ what are the missing values for data element A ?

Categories and Missing Values

The last two questions:

- ▶ which category do the points in V belong to?
 - ▶ what are the missing values for data element A ?
- are closely related

Categories and Missing Values

The last two questions:

▶ which category do the points in V belong to?

- estimate a missing *categorical* value
 - example: *genre*
 - task: **classification**
-

▶ what are the missing values for data element A ?

- estimate a missing *numerical* value
- example: *budget*
- task: **regression**

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Linear Regression

Data

X^1	X^2	\dots	X^p	Y
1	200	\dots	-0.05	5
1.01	400	\dots	-0.06	7
\vdots				\vdots
1.1	460	\dots	-0.1	-
1.5	430	\dots	-0.08	-

Task

- ▶ assume $\forall i = 1, \dots, n : Y_i \approx \sum_{j=1}^p \beta^j X_i^j$
- ▶ estimate β^1, \dots, β^p

Linear Regression

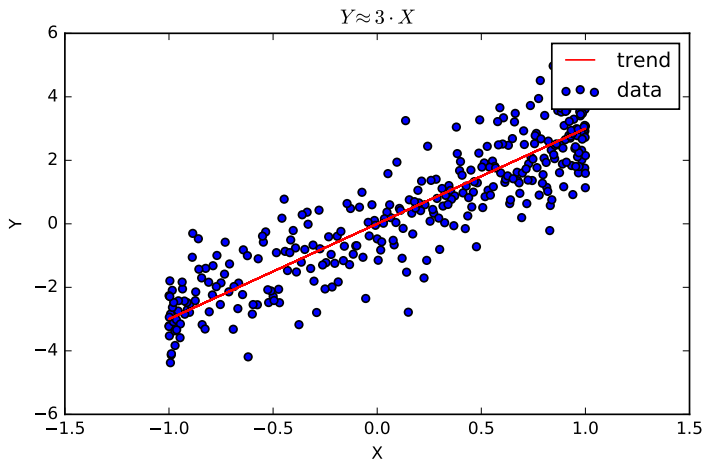
Task

- ▶ assume $\forall i = 1, \dots, n : Y_i \approx \sum_{j=1}^p \beta^j X_i^j$
- ▶ estimate β^1, \dots, β^p

Naming

notation	name
X^1, \dots, X^p	independent/explanatory variables
Y	target/dependent/explained
$\epsilon_i = Y_i - \sum_{j=1}^p \beta^j X_i^j$	residuals
β^1, \dots, β^p	coefficients

Example: Trend Line



Estimating the Coefficients

First we transform our equations to matrix notation

$$\forall i = 1, \dots, n : Y_i \approx \sum_{j=1}^p \beta^j X_i^j$$

system of linear equations

Estimating the Coefficients

First we transform our equations to matrix notation

$$\begin{pmatrix} \beta^1 \cdot X_1^1 + \beta^2 \cdot X_1^2 + \dots + \beta^p \cdot X_1^p \\ \vdots \\ \beta^1 \cdot X_n^1 + \beta^2 \cdot X_n^2 + \dots + \beta^p \cdot X_n^p \end{pmatrix} \approx \begin{pmatrix} Y_1 \\ \vdots \\ Y_n \end{pmatrix}$$

Estimating the Coefficients

First we transform our equations to matrix notation

$$\begin{pmatrix} \beta^1 \cdot X_1^1 & \beta^2 \cdot X_1^2 & \dots & \beta^p \cdot X_1^p \\ & \vdots & & \\ \beta^1 \cdot X_n^1 & \beta^2 \cdot X_n^2 & \dots & \beta^p \cdot X_n^p \end{pmatrix} \cdot \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} \approx \begin{pmatrix} Y_1 \\ \vdots \\ Y_n \end{pmatrix}$$

Estimating the Coefficients

First we transform our equations to matrix notation

$$\begin{pmatrix} X_1^1 & X_1^2 & \dots & X_1^p \\ & \vdots & & \\ X_n^1 & X_n^2 & \dots & X_n^p \end{pmatrix} \cdot \begin{pmatrix} \beta^1 \\ \vdots \\ \beta^p \end{pmatrix} \approx \begin{pmatrix} Y_1 \\ \vdots \\ Y_n \end{pmatrix}$$

in short:

$$X \cdot \beta \approx Y$$

Estimating the Coefficients

Let's solve:

$$X \cdot \beta = Y$$

problem:

X	Y
2	6
3	9
10	30
1	3.001

Estimating the Coefficients

Idea

solving

$$X \cdot \beta = Y$$

is equivalent to demanding

$$X \cdot \beta - Y = 0$$

instead we can minimize

$$\arg \min_{\beta} |X \cdot \beta - Y|$$

problem - non differentiable

Least Squares

Let's solve:

$$\arg \min_{\beta} \|X \cdot \beta - Y\|^2$$

- ▶ differentiable
- ▶ convex (unique minimizer)

solution:

$$\beta = (X^T \cdot X)^{-1} \cdot X^T \cdot Y$$

Linearity

So we can solve:

- ▶ $Y \approx \beta^1 \cdot 3X^1$
- ▶ $Y \approx \beta^1 \cdot 3X^1 + \beta^2 \cdot 5X^2$

But what about?

- ▶ $Y \approx \beta^1 \cdot 3X^1 - \beta^2 \cdot 2(X^1)^2$
- ▶ $Y \approx \beta^1 \cdot 3X^1 + \beta^0 \cdot 1$
- ▶ $Y \approx \beta^1 \cdot 3 \sin(X^1) + \beta^2 \cdot 5 \cos(X^2)$

Linearity

We can simply transform:

X^1	X^2
2	6
3	9
\vdots	\vdots

 \longrightarrow

$3X^1$	$-2(X^1)^2$
2	-8
3	-18
\vdots	\vdots

Linearity

We can simply transform:

X^1	X^2
2	6
3	9
\vdots	\vdots

 \longrightarrow

$3X^1$	1
2	1
3	1
\vdots	\vdots

Linearity

We can simply transform:

X^1	X^2		$3 \sin(X^1)$	$5 \cos(X^1)^2$
2	6	\longrightarrow	2.73	0.42
3	9		-4.80	4.56
\vdots	\vdots		\vdots	\vdots

Linearity

- ▶ the linearity is in the regression coefficients
- ▶ strictly speaking
 - polynomial regression
 - ...
- ▶ in practice - same solution

Linearity

what can't we solve?

- ▶ $Y \approx \sin(\beta^1 \cdot X^1)$
- ▶ $Y \approx \beta(X^1) \cdot X^1$
- ▶ ...

Intercept

X^1	X^2		$3X^1$	1
2	6	\longrightarrow	2	1
3	9		3	1
\vdots	\vdots		\vdots	\vdots

in this case the result of our regression would be coefficients β^0, β^1 that satisfy

$$\beta^1 \cdot 3X^1 + \beta^0 \cdot 1 \approx Y$$

β^0 the coefficient for the constant term is named the intercept

Assumptions

- ▶ X^1, \dots, X^p - linearly independent
- ▶ more samples than variables (overdetermined)
- ▶ low measurement error X^1, \dots, X^p
- ▶ fixed variance - homoscedasticity
- ▶ $\epsilon_1, \dots, \epsilon_n$ - statistically independent

Another Direction

- ▶ least squares - cool trick
- ▶ what about some statistics?

Another Direction

Residuals (1D)

$$\forall i = 1, \dots, n : \epsilon_i = Y_i - X_i \cdot \beta$$

- ▶ $\epsilon_1, \dots, \epsilon_n$ are independent
 - ▶ we assume $E[\epsilon_i] = 0$ (always) explain
 - ▶ let's assume that $\forall i = 1, \dots, n : \epsilon_i \sim \mathcal{N}(0, \sigma_\epsilon^2)$
-
- ▶ $Y_i = X_i \cdot \beta + \epsilon_i$

Another Direction

Residuals (1D)

$$\forall i = 1, \dots, n : \epsilon_i = Y_i - X_i \cdot \beta$$

- ▶ $\epsilon_1, \dots, \epsilon_n$ are independent
 - ▶ we assume $E[\epsilon_i] = 0$ (always) explain
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-
- ▶ $(Y_i \mid X_i, \beta) \sim \mathcal{N}(X_i \cdot \beta, \sigma_\epsilon^2)$ independently notation, what now?

Maximum Likelihood Estimation

$$\begin{aligned} P(Y \mid X, \beta) &= \prod_{i=1}^n P(Y_i \mid X_i, \beta) \\ &= \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma_\epsilon^2}} e^{-\frac{(Y_i - X_i \cdot \beta)^2}{2\sigma_\epsilon^2}} \\ &= \frac{1}{\sqrt{2\pi\sigma_\epsilon^2}} e^{-\frac{1}{2\sigma_\epsilon^2} \sum_{i=1}^n (Y_i - X_i \cdot \beta)^2} \end{aligned}$$

Maximum Likelihood Estimation

$$\beta_{mle} = \arg \max_{\beta} P(Y | X, \beta)$$

$$= \arg \max_{\beta} \frac{1}{\sqrt{2\pi\sigma_{\epsilon}^2}} e^{-\frac{1}{2\sigma_{\epsilon}^2} \sum_{i=1}^n (Y_i - X_i \cdot \beta)^2}$$

$$= \arg \max_{\beta} -\frac{1}{2\sigma_{\epsilon}^2} \sum_{i=1}^n (Y_i - X_i \cdot \beta)^2$$

$$= \arg \min_{\beta} \sum_{i=1}^n (Y_i - X_i \cdot \beta)^2$$

Maximum Likelihood Estimation

$$\beta_{mle} = \arg \min_{\beta} \|Y - X \cdot \beta\|^2$$

how do we measure success?

- ▶ Mean Squared Error (MSE)

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i^{true} - Y_i)^2$$

- ▶ Coefficient of Determination r^2

$$r^2 = 1 - \frac{\sum_{i=1}^n (Y_i - X_i \cdot \beta)^2}{\sum_{i=1}^n (Y_i - \mathbb{E}[Y_i])^2}$$

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Questions About the Data

- ▶ how was it generated?
- ▶ was it generated the same way as another data set D' ? - Statistical tests
- ▶ is it surprising? - hypothesis testing
- ▶ are data elements A and B dependent on each other? - Statistical tests
- ▶ which category do the points in V belong to? - Data Science
- ▶ what are the missing values for data element A ? - Linear Regression