Day 2, Part 5: Linear Regression & Communicating Results

Introduction to Python

Tom Paskhalis

RECSM Summer School 2023

Anscombe's quartet

- 4 artificial datasets constructed by Anscombe (1973)
- All of them have nearly identical summary statistics
- But show dramatically different relationships between variables
- Designed to illustrate the importance of data visualization

Data for Anscombe's quartet

Data for Anscombe's quartet

```
In [1]:
import pandas as pd
anscombe_quartet = pd.read_csv('../data/anscombes_quartet.csv')
```

Data for Anscombe's quartet

Summary statistics for Anscombe's quartet

Summary statistics for Anscombe's quartet

In [3]: # Here we use `groupby` method to create summary by a variable ('datase
anscombe_quartet.groupby(['dataset']).describe()

Out[3]:

	count	mean	std	min	25%	50%	75%	max	count	mean
dataset										
I	11.0	9.0	3.316625	4.0	6.5	9.0	11.5	14.0	11.0	7.500909
II	11.0	9.0	3.316625	4.0	6.5	9.0	11.5	14.0	11.0	7.500909
III	11.0	9.0	3.316625	4.0	6.5	9.0	11.5	14.0	11.0	7.500000
IV	11.0	9.0	3.316625	8.0	8.0	8.0	8.0	19.0	11.0	7.500909

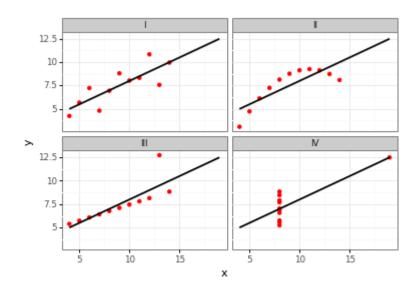
X

Plotting Anscombe's quartet

Plotting Anscombe's quartet

/home/tpaskhalis/Decrypted/Git/RECSM/venv/lib/python3.8/site-pac kages/plotnine/utils.py:371: FutureWarning: The frame.append met hod is deprecated and will be removed from pandas in a future ve rsion. Use pandas.concat instead.

/home/tpaskhalis/Decrypted/Git/RECSM/venv/lib/python3.8/site-pac kages/plotnine/utils.py:371: FutureWarning: The frame.append met hod is deprecated and will be removed from pandas in a future ve rsion. Use pandas.concat instead.



Out[4]: <ggplot: (8774988838066)>

Linear regression

- Linear regression is the classical tool of statistical analysis
- It allows to estimate the degree of association between variables
- Typically, it is the association between one or more independent variables (IV) and one dependent variable (DV)
- The main quantities of interest usually are direction, magnitude of association and its statistical significance

Linear regression in Python

- As for tabular data and visualization we need external libraries for running regression
- statsmodels library provides tools for estimating many statistical models
- Another useful library is scikit-learn
- It is more focussed on machine-learning applications

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```
In [5]: import statsmodels.api as sm
import statsmodels.formula.api as smf # Formula API provides R-style formula.api
```

```
In [6]: kaggle2021 = pd.read_csv('../data/kaggle_survey_2021_responses.csv', sk

/tmp/ipykernel_24423/2749400638.py:1: DtypeWarning: Columns (19
5,201) have mixed types. Specify dtype option on import or set l
ow_memory=False.
```

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        /tmp/ipykernel 24423/2749400638.py:1: DtypeWarning: Columns (19)
        5,201) have mixed types. Specify dtype option on import or set l
        ow memory=False.
In [7]: # Let's give more intuitive names to out variables
        kaggle2021 = kaggle2021.rename(columns = {
                         'Q1': 'age',
                         'Q2': 'gender',
                         '03': 'country',
                         '04': 'education',
                         'Q25': 'compensation'})
In [8]:
        kaggle2021['compensation'].head(n = 2)
Out[8]: 0
              25,000-29,999
              60,000-69,999
         Name: compensation, dtype: object
```

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              25,000-29,999
              60,000-69,999
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In [9]: from statistics import mean
        # Here we are replacing the compensation range by its midpoint (i.e. 1)
        # This variable requires substantial cleaning before transformation
        # Such as extraneous symbols ('$', ',', '>') have to be removed
```

```
kaggle2021['compensation'] = kaggle2021['compensation'].map(
    lambda x: mean([float(x.replace(',','').replace('$','').replace('>')))
```

```
In [10]:
         kaggle2021['compensation'] # Level of compensation (in USD) - our DV
Out[10]:
                   27499.5
                   64999.5
          1
          2
                     499.5
                   34999.5
                   34999.5
          25968
                   17499.5
          25969
                       NaN
          25970
                     499.5
          25971
                       NaN
          25972
                     499.5
          Name: compensation, Length: 25973, dtype: float64
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          Name: compensation, Length: 25973, dtype: float64
In [11]:
         kaggle2021['gender'].value counts() # Frequencies of gender categories
Out[11]:
          Man
                                      20598
                                       4890
          Woman
          Prefer not to say
                                        355
                                         88
          Nonbinary
          Prefer to self-describe
                                         42
          Name: gender, dtype: int64
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                                         42
          Name: gender, dtype: int64
```

```
In [12]: # Formula specification allows to write 'DV \sim IV_1 + IV_2 + ... + IV_N' fit1 = smf.ols('compensation \sim gender', data = kaggle2021).fit()
```

Model summary

Model summary

In [13]: fit1.summary() **OLS Regression Results** Out[13]: Dep. Variable: compensation R-squared: 0.007 Adj. R-squared: Model: OLS 0.007 Method: **Least Squares** F-statistic: 26.46 Date: Mon, 27 Jun 2022 **Prob** (F-statistic): 6.64e-22 Time: 22:08:46 Log-Likelihood: -1.9707e+05 No. Observations: 15391 AIC: 3.941e+05 **Df Residuals:** 15386 BIC: 3.942e+05 **Df Model:** 4 **Covariance Type:** nonrobust 0.9751 std err P>|t| [0.025 coef Intercept 4.593e+04 782.805 58.672 0.000 4.44e+04 4.75e+04 gender[T.Nonbinary] 7.016e+04 1.29e+04 5.455 0.000 4.49e+04 9.54e + 04gender[T.Prefer not 2.166e+04 6335.402 3.419 0.001 9242.046 3.41e+04 to say gender[T.Prefer to 2.498e+04 1.8e+04 1.389 0.165 -1.03e+04 6.02e+04 self-describe]

gender[T.Wom	nan] -1.466	6e+04 1932.351	-7.588	0.000	-1.84e+04	-1.09e+04
Omnibus:	18458.954	Durbin-Wats	on:	2.00	1	
Prob(Omnibus):	0.000	Jarque-Bera (.	JB): 234	3660.164	4	
Skew:	6.472	Prob(JB):	0.00)	
Kurtosis:	62.051	Cond.	No.	25.7	7	

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Multiple linear regression

Multiple linear regression

```
In [14]: # Let's now also control for age and education
fit2 = smf.ols('compensation ~ gender + age + education', data = kaggle
```

Multiple linear regression

```
In [14]:
          # Let's now also control for age and education
          fit2 = smf.ols('compensation ~ gender + age + education', data = kaggle
In [15]:
          fit2.summary()
                                  OLS Regression Results
Out[15]:
               Dep. Variable:
                                                                          0.068
                                  compensation
                                                       R-squared:
                      Model:
                                          OLS
                                                  Adj. R-squared:
                                                                          0.067
                    Method:
                                  Least Squares
                                                       F-statistic:
                                                                          55.98
                       Date:
                              Mon, 27 Jun 2022
                                                 Prob (F-statistic):
                                                                      1.77e-216
                       Time:
                                       22:08:46
                                                  Log-Likelihood:
                                                                   -1.9658e+05
           No. Observations:
                                         15391
                                                             AIC:
                                                                     3.932e+05
               Df Residuals:
                                         15370
                                                             BIC:
                                                                     3.934e+05
                   Df Model:
                                            20
            Covariance Type:
                                      nonrobust
                                                   std err
                                           coef
                                                                    P>|t|
                                                                              [0.025
                                                                                          0.9
                                      1.483e+04
                                                 2910.746
                                                             5.093
                                                                    0.000
                                                                            9120.353
                                                                                       2.05e-
                          Intercept
               gender[T.Nonbinary]
                                     6.443e+04
                                                 1.25e+04
                                                             5.163
                                                                    0.000
                                                                               4e+04
                                                                                       8.89e-
              gender[T.Prefer not to
                                      2.033e+04
                                                 6157.104
                                                             3.302
                                                                    0.001
                                                                            8261.253
                                                                                       3.24e-
                               say]
```

doctorate]	0007.2001	5216.498	1.698	0.090	-1367.698 	1.91e-
education[T.Professional	8857.2561	5216 /02	1 602	0 000	_1367 609	1 010-
education[T.No formal education past high school]	-1.059e+04	5801.400	-1.825	0.068	-2.2e+04	782.
education[T.Master's degree]	7168.1892	1666.521	4.301	0.000	3901.611	1.04e-
education[T.I prefer not to answer]	-1.029e+04	4857.239	-2.118	0.034	-1.98e+04	-769.1
education[T.Doctoral degree]	1.187e+04	2322.458	5.111	0.000	7318.325	1.64e-
age[T.70+]	6.918e+04	9180.635	7.535	0.000	5.12e+04	8.72e-
age[T.60-69]	5.718e+04	4971.283	11.502	0.000	4.74e+04	6.69e-
age[T.55-59]	6.666e+04	4792.714	13.910	0.000	5.73e+04	7.61e-
age[T.50-54]	5.354e+04	4211.610	12.713	0.000	4.53e+04	6.18e-
age[T.45-49]	5.368e+04	3872.345	13.862	0.000	4.61e+04	6.13e-
age[T.40-44]	4.192e+04	3656.035	11.465	0.000	3.48e+04	4.91e-
age[T.35-39]	3.405e+04	3485.133	9.770	0.000	2.72e+04	4.09e-
age[T.30-34]	2.427e+04	3347.112	7.251	0.000	1.77e+04	3.08e-
age[T.25-29]	8811.2235	3235.996	2.723	0.006	2468.289	1.52e-
age[T.22-24]	2313.5562	3387.043	0.683	0.495	-4325.450	8952.
gender[T.Woman]	-1.1e+04	1884.889	-5.838	0.000	-1.47e+04	-7309.
gender[T.Prefer to self- describe]	3.486e+04	1.74e+04	1.998	0.046	667.732	6.91e-

education college/universi without ea bachelor's	ty study arning a	-912.0023	3378.159	-0.270	0.787	-7533.593	5709.
Omnibus:	19216.780	Durbin-Watson:		2	.008		
Prob(Omnibus):	0.000	Jarque-E	Bera (JB):	2958551	.621		
Skew:	6.892	F	Prob(JB):		0.00		
Kurtosis:	69.509	C	Cond. No.		30.2		

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Markdown - a language of reports

- Markdown is a markup language for formatting text with simple syntax
- The key goal of Markdown is readability
- Only a limited set of formatting options is supported
- · Markdown is used in online documentation, blogging and instant messaging

Formatting text in Markdown

- For *italics* *one star on each side*
- For **bold** **two stars on each side**
- For strikethrough ~~two tildes on each side~~

Lists in Markdown

For bulleted or unordered list of items:

- Just add a dash first and then write a text.
- If you add another dash in the following line, you will have another item in the list.
 - If you add four spaces or use a tab key, you will create an indented list.

For numbered or ordered list of items:

- 1. Just type a number and then write a text.
- 2. If you want to add a second item, just type in another number.
- 1. If you make a mistake when typing numbers, fear not, Markdown will correct it for you.
 - 1. If you press a tab key or type four spaces, you will get an indented list and the numbering will start from scratch.

Headers in Markdown

Headers or section titles are created with hashes(#)

```
# This is a first-tier header
## This is a second-tier header
### This is a third-tier header
```

Images and links in Markdown

- To add an image you can write ![some text](image_path)
- To add a link you can write [some text](URL)
- For more complex cases HTML code can be used

Tables in Markdown

 Tables in Markdown can be created using the following syntax (there are a few variants)

```
| Header1 | Header2 |
|:----|:----|
| content | content |
```

- :--- produces left-aligned text in cells
- ---: produces right-aligned text in cells
- :--: produces centered text in cells

Markdown tables in pandas

• Pandas can generate Markdown tables from DataFrame

Markdown tables in pandas

Ш

IV

11.0

11.0

Pandas can generate Markdown tables from DataFrame

9.0 3.316625

9.0 3.316625

Markdown tables in pandas

Pandas can generate Markdown tables from DataFrame

```
In [16]: # Let's revisit the summary statistics of Anscombe's quartet
         anscombe quartet.groupby(['dataset']).describe().iloc[:,0:3]
Out[16]:
                  count mean
                                    std
          dataset
                   11.0
                          9.0 3.316625
                   11.0
                          9.0 3.316625
                   11.0
                          9.0 3.316625
              IV
                   11.0
                          9.0
                              3.316625
In [17]:
         print(anscombe_quartet.groupby(['dataset']).describe().iloc[:,0:3].to_n
             ('x', 'count') |
                                ('x', 'mean') |
                                                  ('x', 'std')
                         11 |
                                                        3.31662
                                                      3.31662
                                                        3.31662
                         11
                                                        3.31662
```

The end

