Exploratory Data Analysis in Python

Wednesday, 18 November 2020 7:11 PM

Read, clean, and validate

Using data to answer questions

What is the average birth weight of babies in the United States?

- Find appropriate data, or collect it
- Read data in your development environment
- Clean and validate

National Survey of Family Growth (NSFG)

NSFG data, from the National Center for Health Statistics

"nationally representative of women 15-44 years of age in the ... United States

"information on family life, marriage and divorce, pregnancy, infertility, use of contraception, and general and reproductive health."

Reading data

```
import pandas as pd
nsfg = pd.read_hdf('nsfg.hdf5', 'nsfg')
type(nsfg)
```

```
pandas.core.frame.DataFrame
```

Reading data

```
nsfg.head()
```

```
   caseid  outcome  birthwgt_lb1  birthwgt_oz1  prglngth  nbrnaliv  agecon  \
0   60418        1           5.0           4.0        40       1.0    2000
1   60418        1           4.0          12.0        36       1.0    2291
2   60418        1           5.0           4.0        36       1.0    3241
3   60419        6           NaN           NaN        33       NaN    3650
4   60420        1           8.0          13.0        41       1.0    2191

   agepreg  hpagelb  wgt2013_2015
0   2075.0     22.0   3554.964843
1   2358.0     25.0   3554.964843
2   3308.0     52.0   3554.964843
3      NaN      NaN   2484.535358
4   2266.0     24.0   2903.782914
```

Columns and rows

```
nsfg.shape
```

```
(9358, 10)
```

```
nsfg.columns
```

```
Index(['caseid', 'outcome', 'birthwgt_lb1', 'birthwgt_oz1', 'prglngth',
       'nbrnaliv', 'agecon', 'agepreg', 'hpagelb', 'wgt2013_2015'],
      dtype='object')
```

Columns and rows

BIRTHWGT_LB1 (46-47)

Variable Type : raw

BD-3 : How much did (BABY'S NAME/this 1st baby) weigh at birth? (POUNDS)

value	label	Total
.	INAPPLICABLE	2873
0-5	UNDER 6 POUNDS	936
6	6 POUNDS	1666
7	7 POUNDS	2146
8	8 POUNDS	1168
9-95	9 POUNDS OR MORE	474
98	Refused	1
99	Don't know	94
	Total	**9358**

Each column is a Series

```
pounds = nsfg['birthwgt_lb1']
type(pounds)
```

```
pandas.core.series.Series
```

Each column is a series

```
pounds.head()
```

```
0    5.0
1    4.0
2    5.0
3    NaN
4    8.0
Name: birthwgt_lb1, dtype: float64
```

Selecting columns

```
pounds = nsfg['birthwgt_lb1']
```

```
ounces = nsfg['birthwgt_oz1']
```

```
pounds.value_counts().sort_index()
```

```
0.0        6
1.0       34
2.0       47
3.0       67
4.0      196
5.0      586
6.0     1666
7.0     2146
8.0     1168
9.0      363
10.0      82
11.0      17
12.0       7
13.0       2
14.0       2
17.0       1
98.0       1
99.0      94
Name: birthwgt_lb1, dtype: int64
```

BIRTHWGT_LB1 (46-47)

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99	Don't know	94
	Total	**9358**

Describe

```
pounds.describe()
```

```
count    6485.000000
mean        8.055204
std        11.178893
min         0.000000
25%         6.000000
50%         7.000000
75%         8.000000
max        99.000000
Name: birthwgt_lb1, dtype: float64
```

Replace

```
pounds = pounds.replace([98, 99], np.nan)
pounds.mean()
```

```
6.703286384976526
```

```
ounces.replace([98, 99], np.nan, inplace=True)
```

Arithmetic with Series

```
birth_weight = pounds + ounces / 16.0
birth_weight.describe()
```

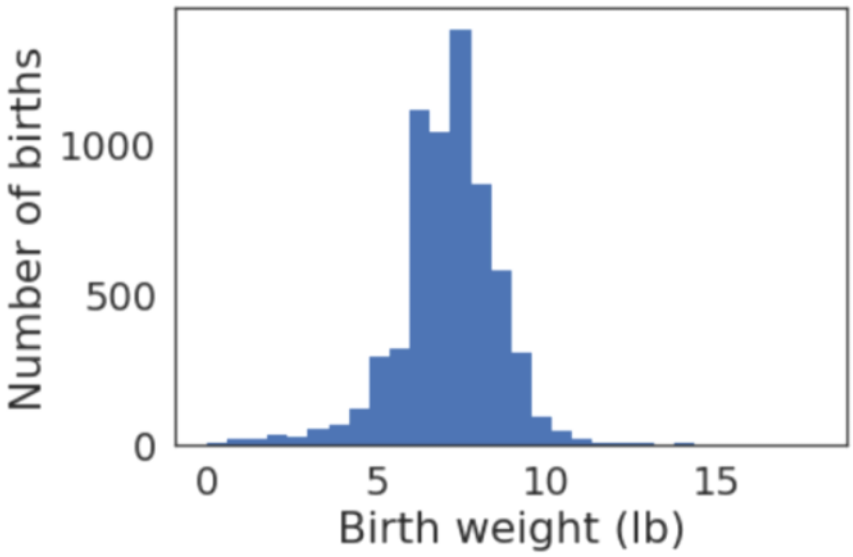
```
count    6355.000000
mean        7.120978
std         1.422236
min         0.000000
25%         6.375000
50%         7.187500
75%         8.000000
max        17.937500
dtype: float64
```

Histogram

```
import matplotlib.pyplot as plt
```

```
plt.hist(birth_weight.dropna(), bins=30)
```

```
plt.xlabel('Birth weight (lb)')
plt.ylabel('Fraction of births')
plt.show()
```



Boolean Series

```
preterm = nsfg['prglngth'] < 37
preterm.head()
```

```
0    False
1     True
2     True
3     True
4    False
Name: prglngth, dtype: bool
```

Boolean Series

```
preterm.sum()
```

```
3742
```

```
preterm.mean()
```

```
0.39987176747168196
```

Filtering

```
preterm_weight = birth_weight[preterm]
preterm_weight.mean()
```

```
5.577598314606742
```

```
full_term_weight = birth_weight[~preterm]
full_term_weight.mean()
```

```
7.372323879231473
```

Filtering

Other logical operators:

- `&` for AND (both must be true)
- `|` for OR (either or both can be true)

Example:

```
birth_weight[A & B]    # both true
birth_weight[A | B]    # either or both true
```

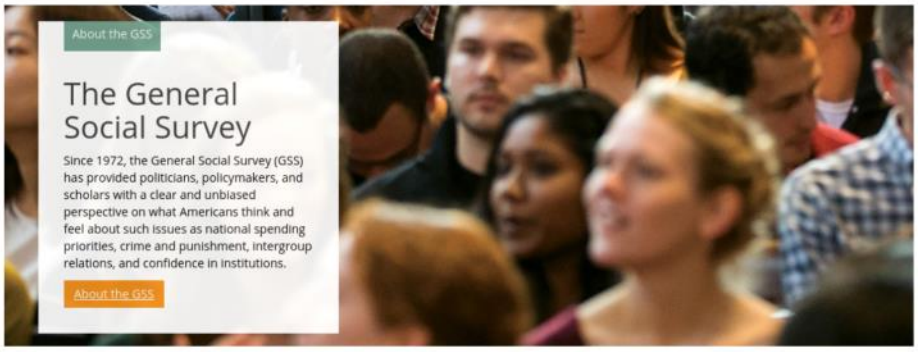
Resampling

- NSFG is not representative
- Some groups are "oversampled"
- We can correct using `resample_rows_weighted()`

Distributions

GSS

- Annual sample of U.S. population.
- Asks about demographics, social and political beliefs.
- Widely used by policy makers and researchers.

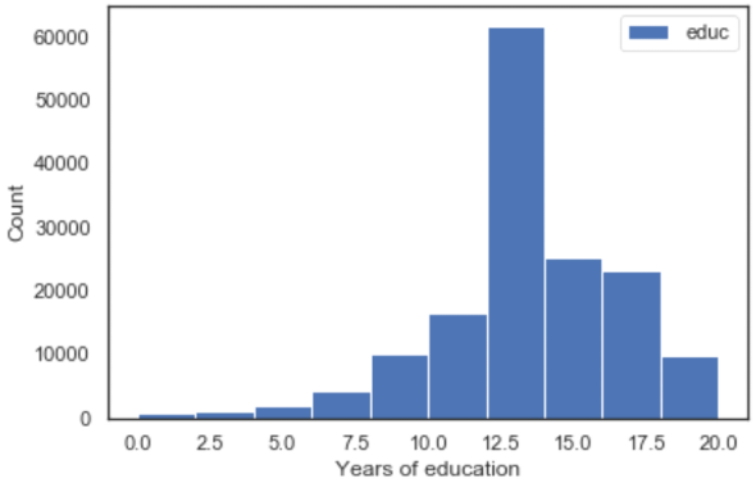


Read the data

```
gss = pd.read_hdf('gss.hdf5', 'gss')

gss.head()
```

	year	sex	age	cohort	race	educ	realinc	wtssall
0	1972	1	26.0	1946.0	1	18.0	13537.0	0.8893
1	1972	2	38.0	1934.0	1	12.0	18951.0	0.4446
2	1972	1	57.0	1915.0	1	12.0	30458.0	1.3339
3	1972	2	61.0	1911.0	1	14.0	37226.0	0.8893
4	1972	1	59.0	1913.0	1	12.0	30458.0	0.8893

```
educ = gss['educ']
plt.hist(educ.dropna(), label='educ')
plt.show()
```



PMF

```
pmf_educ = Pmf(educ, normalize=False)
pmf_educ.head()
```

```
0.0    566
1.0    118
2.0    292
3.0    686
4.0    746
Name: educ, dtype: int64
```

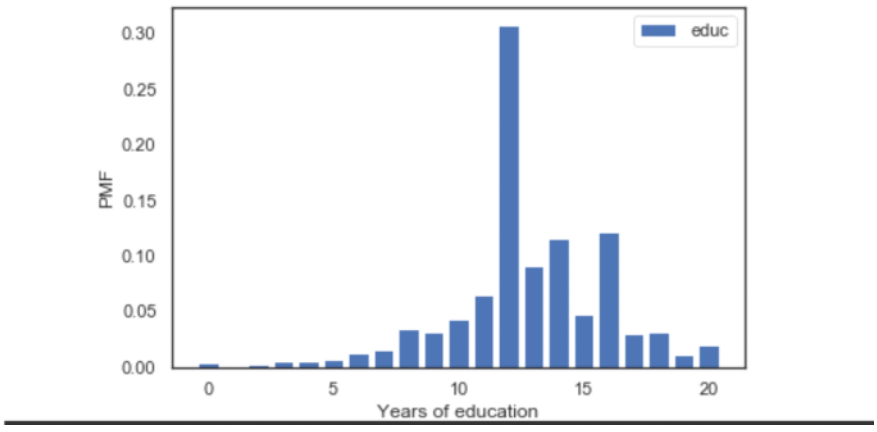
```
pmf_educ = Pmf(educ, normalize=True)

pmf_educ.head()
```

```
0.0    0.003663
1.0    0.000764
2.0    0.001890
3.0    0.004440
4.0    0.004828
Name: educ, dtype: int64
```

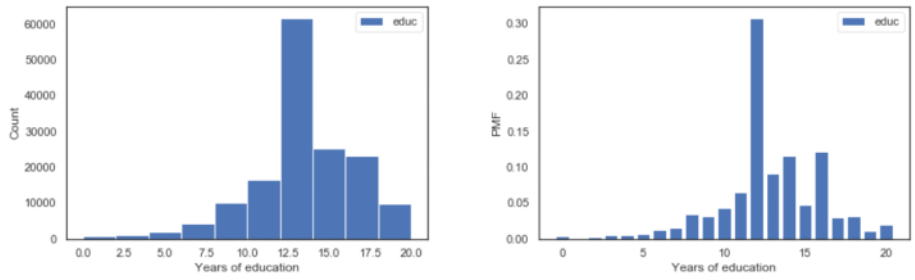
```
pmf_educ[12]
```

```
0.30863869940587907
```

```
pmf_educ.bar(label='educ')
plt.xlabel('Years of education')
plt.ylabel('PMF')
plt.show()
```



Histogram vs. PMF



The PMF shows all unique values, so we can see exactly where the peaks are.

Because the histogram puts values into bins, it obscures some details.

In this example, we can't see the peaks at 14 and 16 years.

From PMF to CDF

If you draw a random element from a distribution:

- PMF (Probability Mass Function) is the probability that you get exactly x
- CDF (Cumulative Distribution Function) is the probability that you get a value <= x

for a given value of x.

Example

PMF of {1, 2, 2, 3, 5}

PMF(1) = 1/5

PMF(2) = 2/5

PMF(3) = 1/5

PMF(5) = 1/5

CDF is the cumulative sum of the PMF.

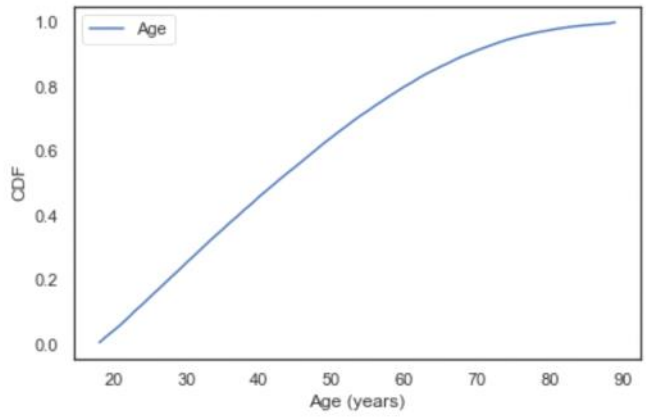
CDF(1) = 1/5

CDF(2) = 3/5

CDF(3) = 4/5

CDF(5) = 1

```
cdf = Cdf(gss['age'])
cdf.plot()
plt.xlabel('Age')
plt.ylabel('CDF')
plt.show()
```



That means that about 66% of the respondents are 51 years old or younger.

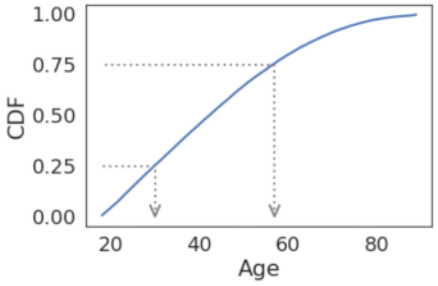
Evaluating the inverse CDF

```
p = 0.25
q = cdf.inverse(p)
print(q)
```

```
30
```

```
p = 0.75
q = cdf.inverse(p)
print(q)
```

```
57
```



The CDF is an invertible function, which means that if you have a probability, p, you can look up the corresponding quantity, q.

By the way, the distance from the 25th to the 75th percentile is called the interquartile range, or IQR.

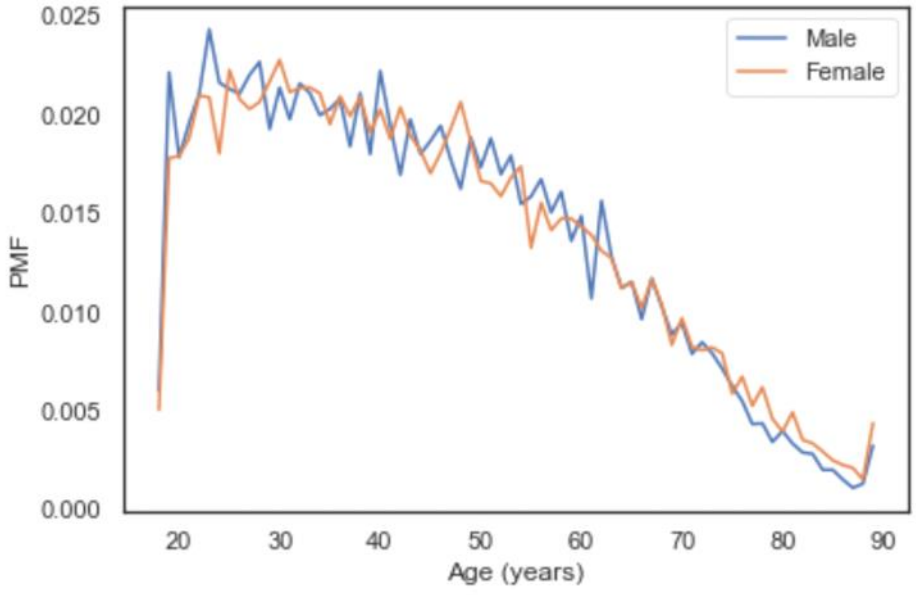
It measures the spread of the distribution, so it is similar to standard deviation or variance.

Because it is based on percentiles, it doesn't get thrown off by extreme values or outliers, the way variance does.

So IQR can be more "robust" than variance, which means it works well even if there are errors in the data or extreme values.

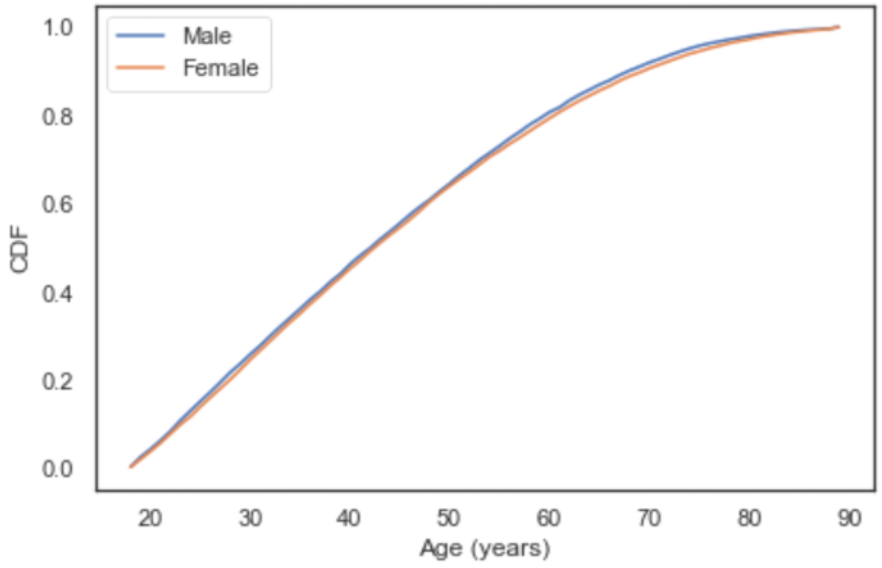
Multiple PMFs

```
male = gss['sex'] == 1
age = gss['age']
male_age = age[male]
female_age = age[~male]
Pmf(male_age).plot(label='Male')
Pmf(female_age).plot(label='Female')
plt.xlabel('Age (years)')
plt.ylabel('Count')
plt.show()
```



Multiple CDFs

```
Cdf(male_age).plot(label='Male')
Cdf(female_age).plot(label='Female')

plt.xlabel('Age (years)')
plt.ylabel('Count')
plt.show()
```



In general, CDFs are smoother than PMFs.

Because they smooth out randomness, we can often get a better view of real differences between distributions.

In this case, the lines overlap over the whole range; that is, the distributions are nearly identical.

Income distribution

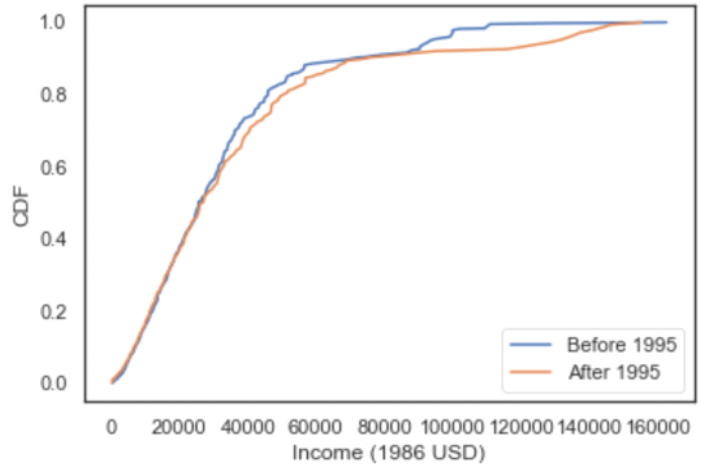
```
income = gss['realinc']
pre95 = gss['year'] < 1995
Pmf(income[pre95]).plot(label='Before 1995')
Pmf(income[~pre95]).plot(label='After 1995')
plt.xlabel('Income (1986 USD)')
plt.ylabel('PMF')
plt.show()
```

There are a lot of unique values in this distribution, and none of them appear very often.

The PMF is so noisy, we can't really see the shape of the distribution.

It looks like there are more people with high incomes after 1995, but it's hard to tell.

We can get a clearer picture with a CDF.

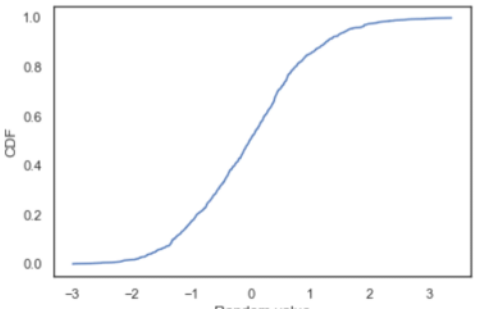


Below $30,000 the CDFs are almost identical; above that

In general, I recommend CDFs for exploratory analysis.

The normal distribution

```
sample = np.random.normal(size=1000)
Cdf(sample).plot()
```



This sigmoid shape is what we expect to see with values from a normal distribution

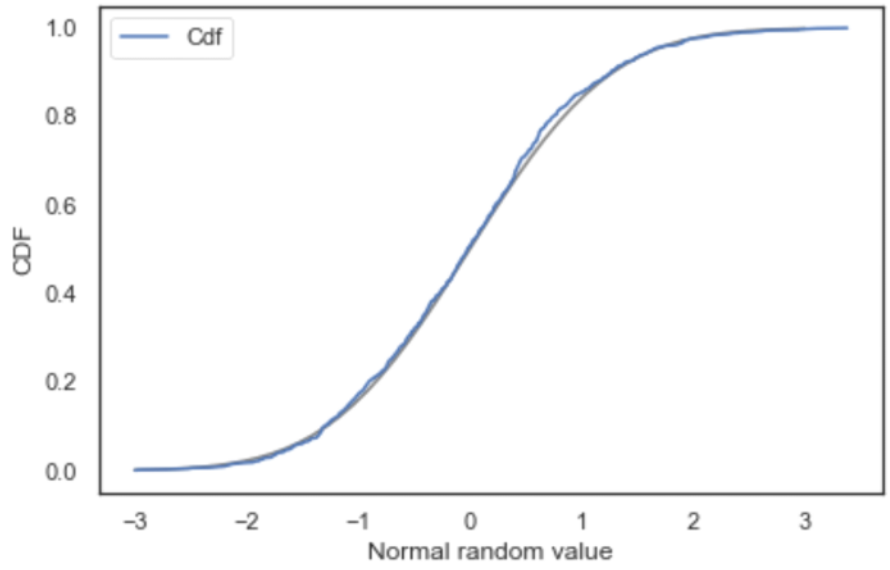
The normal CDF

```
from scipy.stats import norm
```

```
xs = np.linspace(-3, 3)
ys = norm(0, 1).cdf(xs)
```

```
plt.plot(xs, ys, color='gray')
```

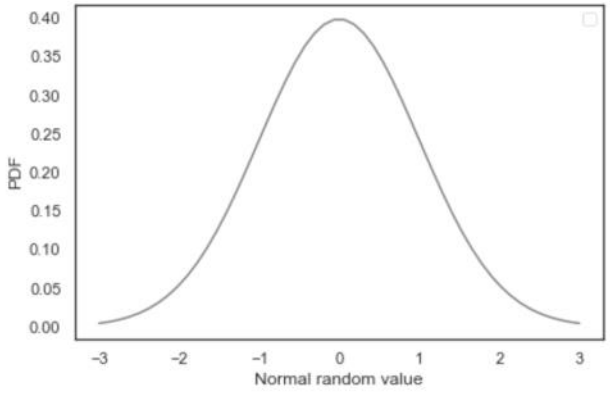
```
Cdf(sample).plot()
```

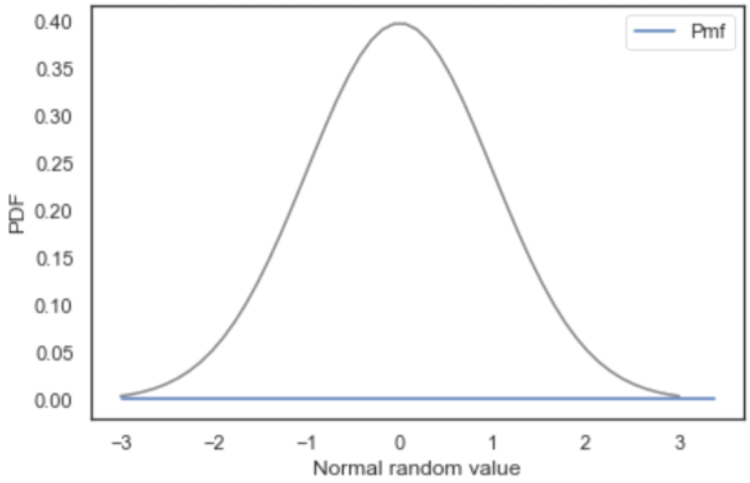


If this were real data, we would conclude that the normal distribution is a good model for the data.

The bell curve

```
xs = np.linspace(-3, 3)
ys = norm(0,1).pdf(xs)
plt.plot(xs, ys, color='gray')
```

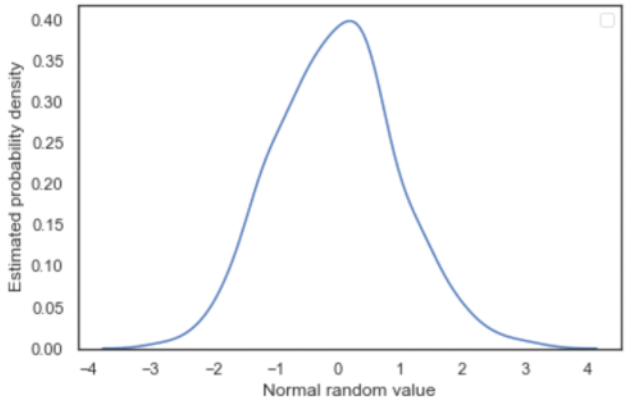




The PMF of the sample is a flat line across the bottom.

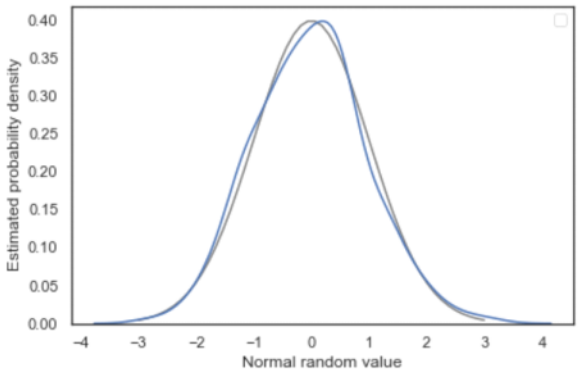
KDE plot

```
import seaborn as sns
sns.kdeplot(sample)
```



KDE and PDF

```
xs = np.linspace(-3, 3)
ys = norm.pdf(xs)
plt.plot(xs, ys, color='gray')
sns.kdeplot(sample)
```

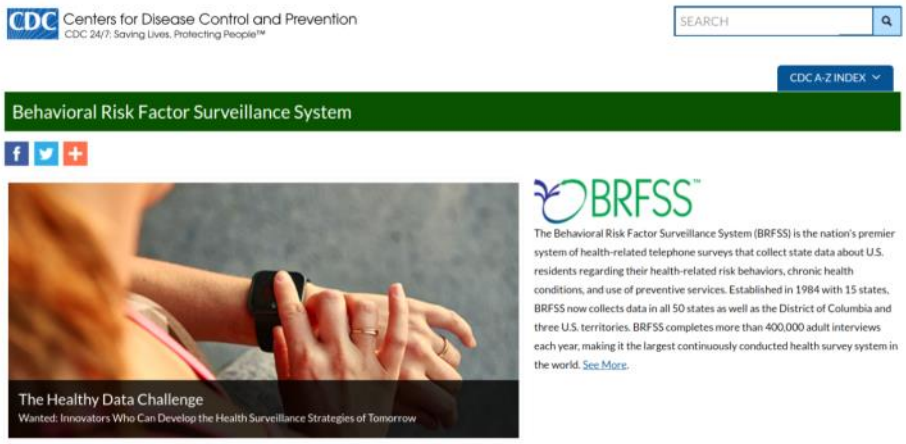


PMF, CDF, KDE

- Use CDFs for exploration.
- Use PMFs if there are a small number of unique values.
- Use KDE if there are a lot of values.

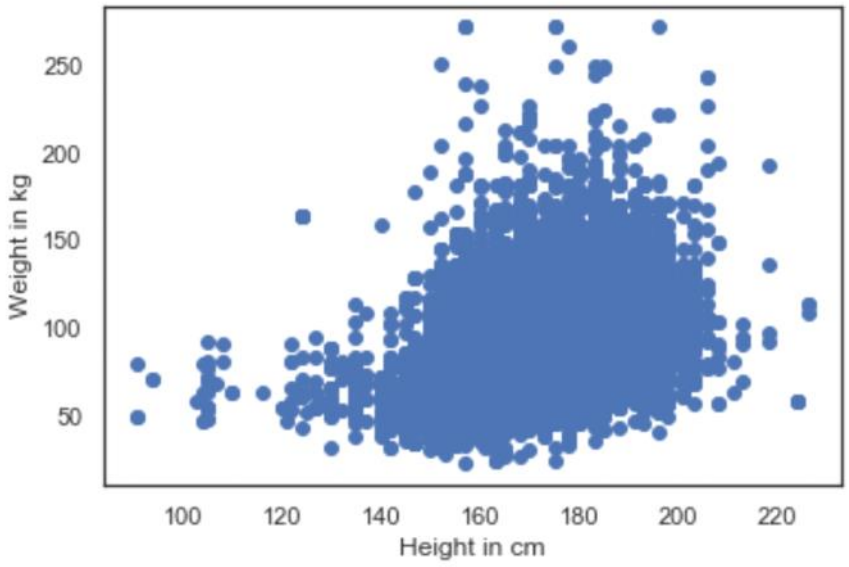
Relationships

Height and weight



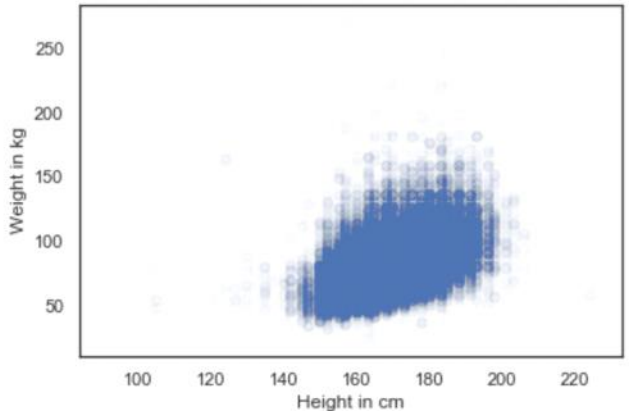
Scatter plot

```
brfss = pd.read_hdf('brfss.hdf5', 'brfss')
height = brfss['HTM4']
weight = brfss['WTKG3']
plt.plot(height, weight, 'o')
plt.xlabel('Height in cm')
plt.ylabel('Weight in kg')
plt.show()
```



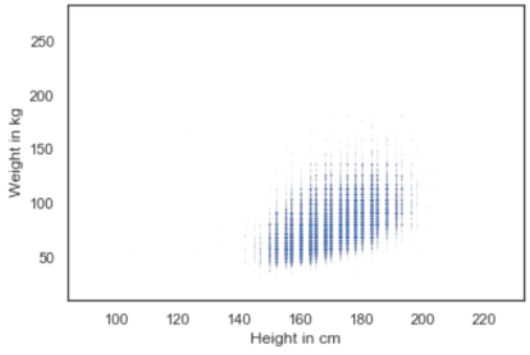
Transparency

```
plt.plot(height, weight, 'o', alpha=0.02)
plt.show()
```



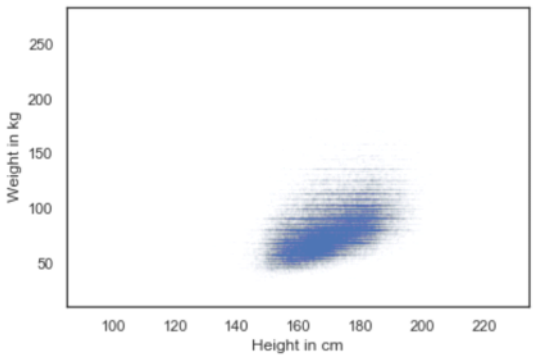
Marker size

```
plt.plot(height, weight, 'o', markersize=1, alpha=0.02)
plt.show()
```



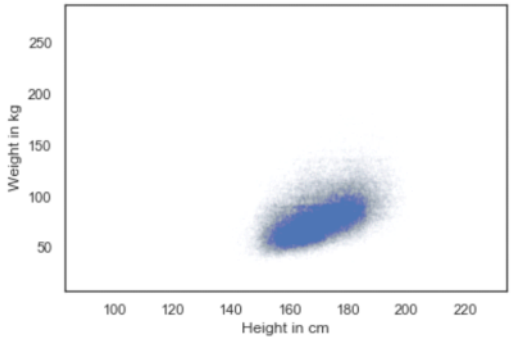
Jittering

```
height_jitter = height + np.random.normal(0, 2, size=len(brfss))
plt.plot(height_jitter, weight, 'o', markersize=1, alpha=0.02)
plt.show()
```



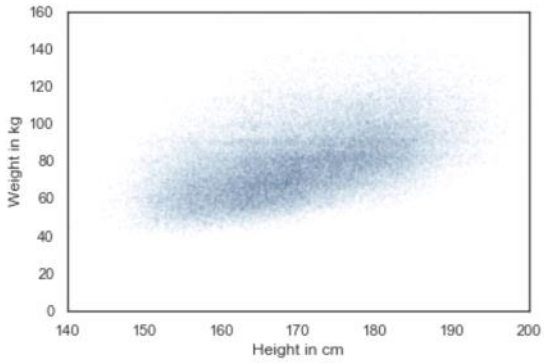
More jittering

```
height_jitter = height + np.random.normal(0, 2, size=len(brfss))
weight_jitter = weight + np.random.normal(0, 2, size=len(brfss))
plt.plot(height_jitter, weight_jitter, 'o', markersize=1, alpha=0.01)
plt.show()
```

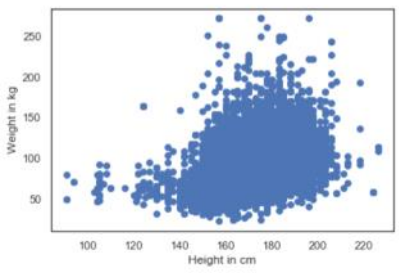


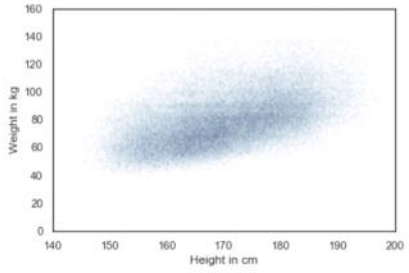
Zoom

```
plt.plot(height_jitter, weight_jitter, 'o', markersize=1, alpha=0.02)
plt.axis([140, 200, 0, 160])
plt.show()
```



Before and after

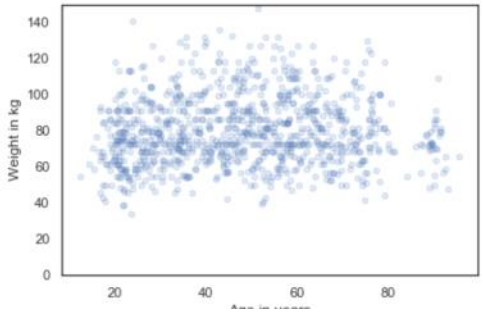




The point of this example is that it takes some effort to make an effective scatter plot.

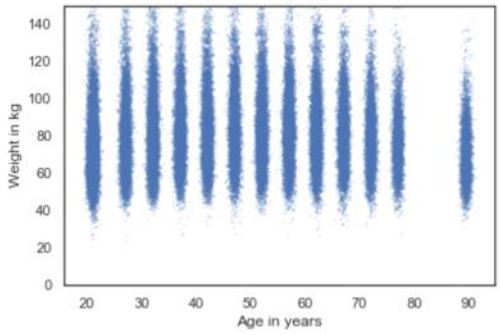
Weight and age

```
age = brfss['AGE'] + np.random.normal(0, 2.5, size=len(brfss))
weight = brfss['WTKG3']
plt.plot(age, weight, 'o', markersize=5, alpha=0.2)
plt.show()
```



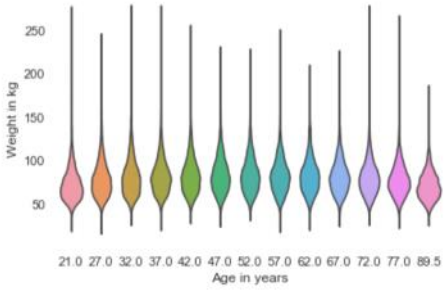
More data

```
age = brfss['AGE'] + np.random.normal(0, 0.5, size=len(brfss))
weight = brfss['WTKG3'] + np.random.normal(0, 2, size=len(brfss))
plt.plot(age, weight, 'o', markersize=1, alpha=0.2)
plt.show()
```



Violin plot

```
data = brfss.dropna(subset=['AGE', 'WTKG3'])
sns.violinplot(x='AGE', y='WTKG3', data=data, inner=None)
plt.show()
```



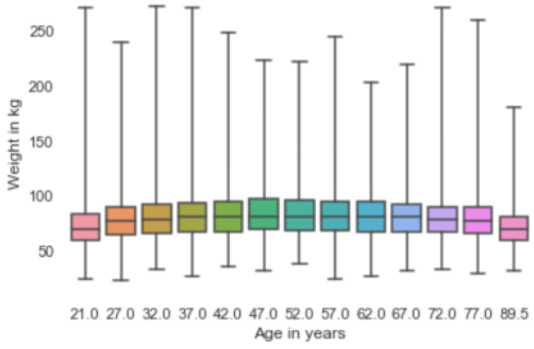
Each column is a graphical representation of the distribution of weight in one age group.

The width of these shapes is proportional to the

estimated density, so it's like two vertical PDFs plotted back to back, and filled in with nice colors.

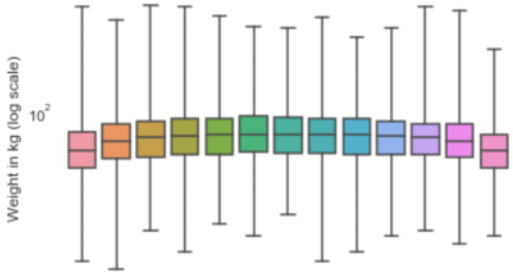
Box plot

```
sns.boxplot(x='AGE', y='WTKG3', data=data, whis=10)
plt.show()
```



Log scale

```
sns.boxplot(x='AGE', y='WTKG3', data=data, whis=10)
plt.yscale('log')
plt.show()
```



Correlation coefficient

In statistics, it usually means Pearson's correlation coefficient, which is a number between -1 and 1 that quantifies the strength of a linear relationship between variables.

Correlation coefficient

```
columns = ['HTM4', 'WTKG3', 'AGE']
subset = brfss[columns]
```

```
subset.corr()
```

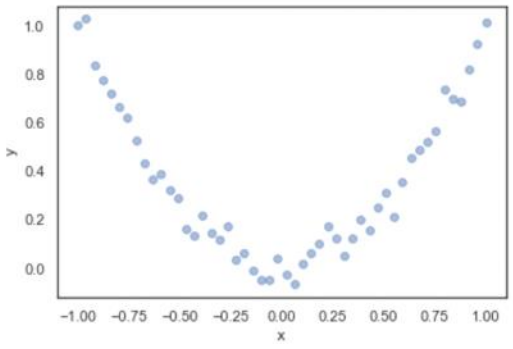
Correlation matrix

	HTM4	WTKG3	AGE
HTM4	1.000000	0.474203	-0.093684
WTKG3	0.474203	1.000000	0.021641
AGE	-0.093684	0.021641	1.000000

- Height with itself: 1
- Height and weight: 0.47
- Height and age: -0.09
- Weight and age: 0.02

```
xs = np.linspace(-1, 1)
ys = xs**2
ys += normal(0, 0.05, len(xs))
np.corrcoef(xs, ys)
```

```
array([[ 1.        , -0.01111647],
       [-0.01111647,  1.        ]])
```

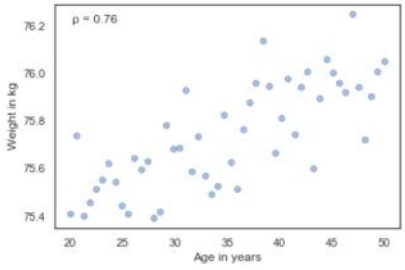


In general, if correlation is high -- that is, close to 1 or -1, you can conclude that there is a strong linear relationship

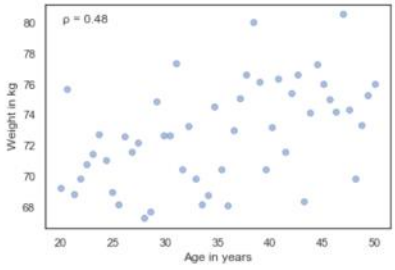
But if correlation is close to 0, that doesn't mean there is no relationship; there might be a strong, non-linear relationship.

Strength of relationship

Hypothetical #1



Hypothetical #2



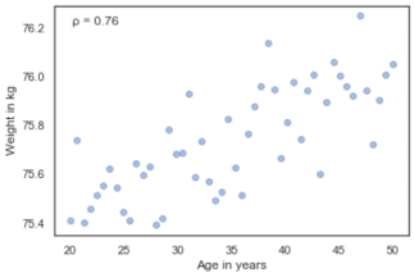
But on the left, the average weight gain over 30 years is less than 1 kg; on the right, it is almost 10 kilograms!

In this scenario, the relationship on the right is probably more important, even though the correlation is lower.

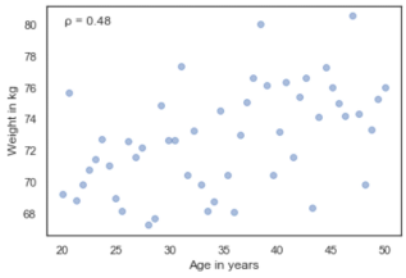
The statistic we really care about is the slope of the line.

Strength of relationship

Hypothetical #1



Hypothetical #2



In this context, the statistic we probably care about is the slope of the line, not the correlation coefficient.

Strength of effect

```
from scipy.stats import linregress

# Hypothetical 1
res = linregress(xs, ys)
```

```
LinregressResult(slope=0.018821034903244386,
           intercept=75.08049023710964,
               rvalue=0.7579660563439402,
               pvalue=1.8470158725246148e-10,
               stderr=0.002337849260560818)
```

Strength of effect

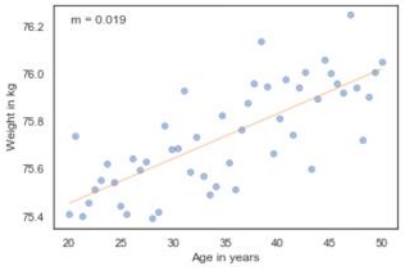
```
# Hypothetical 2
res = linregress(xs, ys)
```

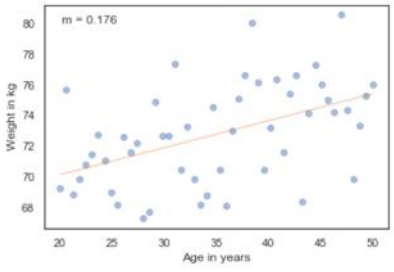
```
LinregressResult(slope=0.17642069806488855,
            intercept=66.60980474219305,
                rvalue=0.47827769765763173,
                pvalue=0.0004430600283776241,
                stderr=0.04675698521121631)
```

Regression lines

```
fx = np.array([xs.min(), xs.max()])
fy = res.intercept + res.slope * fx
plt.plot(fx, fy, '-')
```

```
fx = ...
fy = ...
plt.plot(fx, fy, '-')
```





The visualization here might be misleading unless you look closely at the vertical scales; the slope on the right is almost 10 times higher.

Regression line

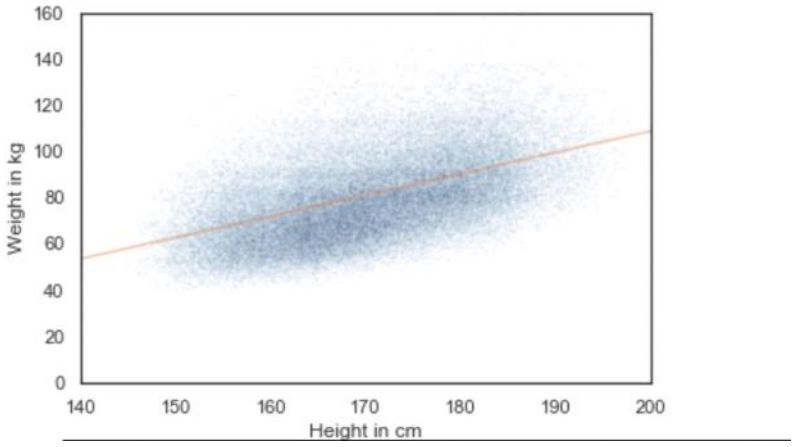
```
subset = brfss.dropna(subset=['WTKG3', 'HTM4'])
```

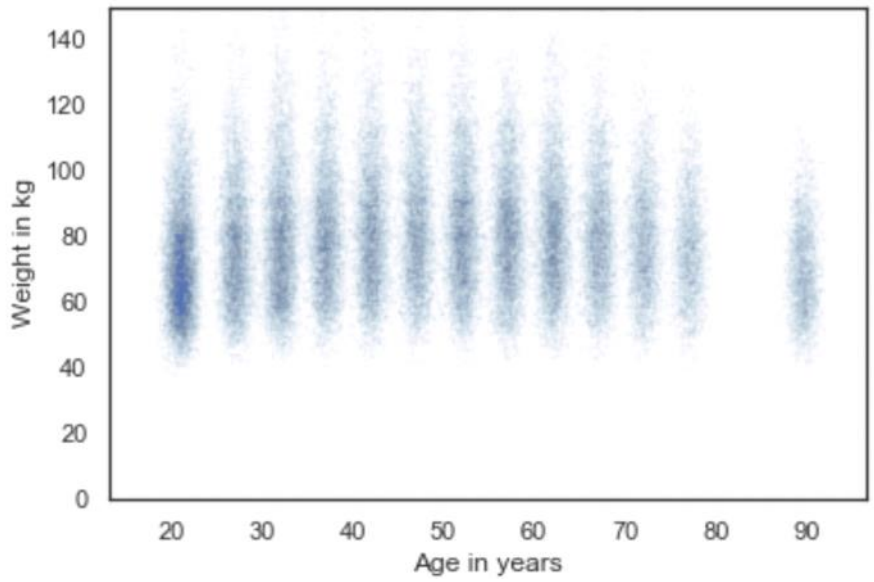
```
xs = subset['HTM4']
ys = subset['WTKG3']
res = linregress(xs, ys)
```

```
LinregressResult(slope=0.9192115381848297,
           intercept=-75.12704250330233,
                rvalue=0.47420308979024584,
                pvalue=0.0,
                stderr=0.005632863769802998)
```

The slope is about 0 point 9 kilograms per centimeter, which means that we expect a person one centimeter taller to be almost a kilogram heavier.

```
fx = np.array([xs.min(), xs.max()])
fy = res.intercept + res.slope * fx
plt.plot(fx, fy, '-')
```





People in their 40s are the heaviest; younger and older people are lighter.

So the relationship is nonlinear.

Nonlinear relationships

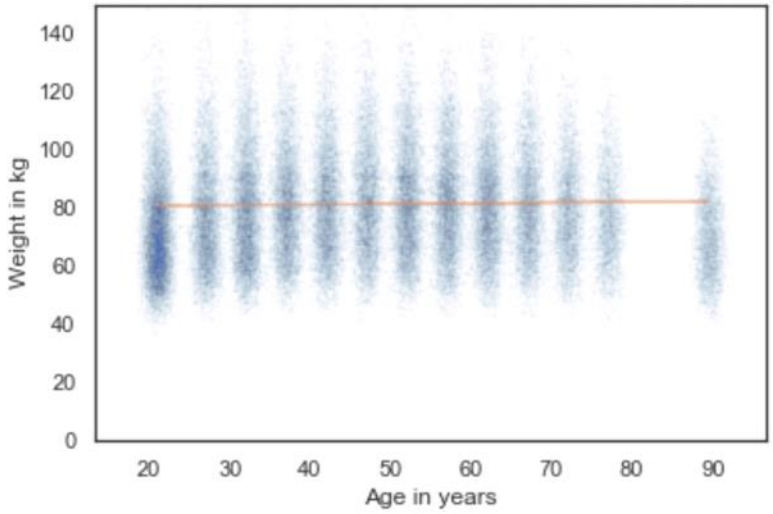
```
subset = brfss.dropna(subset=['WTKG3', 'AGE'])
xs = subset['AGE']
ys = subset['WTKG3']

res = linregress(xs, ys)
```

```
LinregressResult(slope=0.023981159566968724,
           intercept=80.07977583683224,
               rvalue=0.021641432889064068,
               pvalue=4.374327493007566e-11,
               stderr=0.003638139410742186)
```

If we don't look at the scatter plot and blindly compute the regression line, here's what we get.

The estimated slope is only 0 point 02 kilograms per year, or 0 point 6 kilograms in 30 years.

Not a good fit

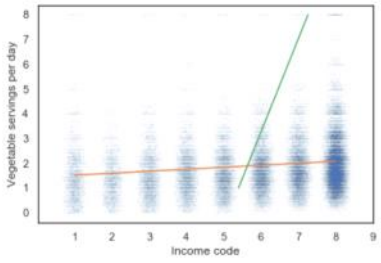


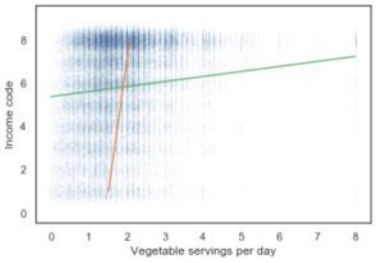
A straight line does not capture the relationship between these variables well.

In the next lesson, we'll learn how to use multiple regression to estimate non-linear relationships.

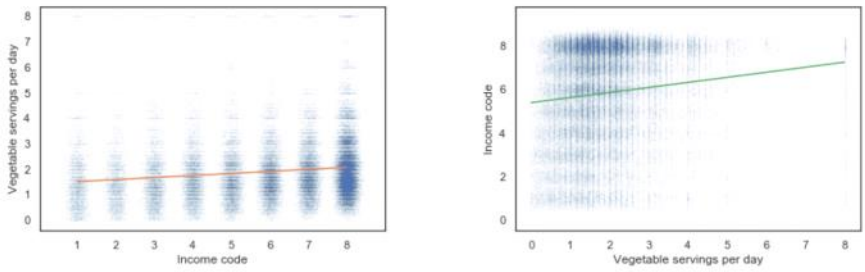
Multivariate Thinking

Regression is not symmetric





Regression is not causation



In this example, A might cause B, or B might cause A, or there might be other factors that cause both A and B.

Multiple regression

```
import statsmodels.formula.api as smf
```

```
results = smf.ols('INCOME2 ~ _VEGESU1', data=brfss).fit()
results.params
```

```
Intercept    5.399903
_VEGESU1     0.232515
dtype: float64
```

Income and education

```
gss = pd.read_hdf('gss.hdf5', 'gss')
```

```
results = smf.ols('realinc ~ educ', data=gss).fit()
results.params
```

```
Intercept   -11539.147837
educ          3586.523659
dtype: float64
```

The estimated slope is 3586, which means that each additional year of education is associated with an increase of almost $3600 of income.

But income also depends on age, so it would be good to include that in the model, too.

Adding age

```
results = smf.ols('realinc ~ educ + age', data=gss).fit()
results.params
```

```
Intercept   -16117.275684
educ          3655.166921
age             83.731804
dtype: float64
```

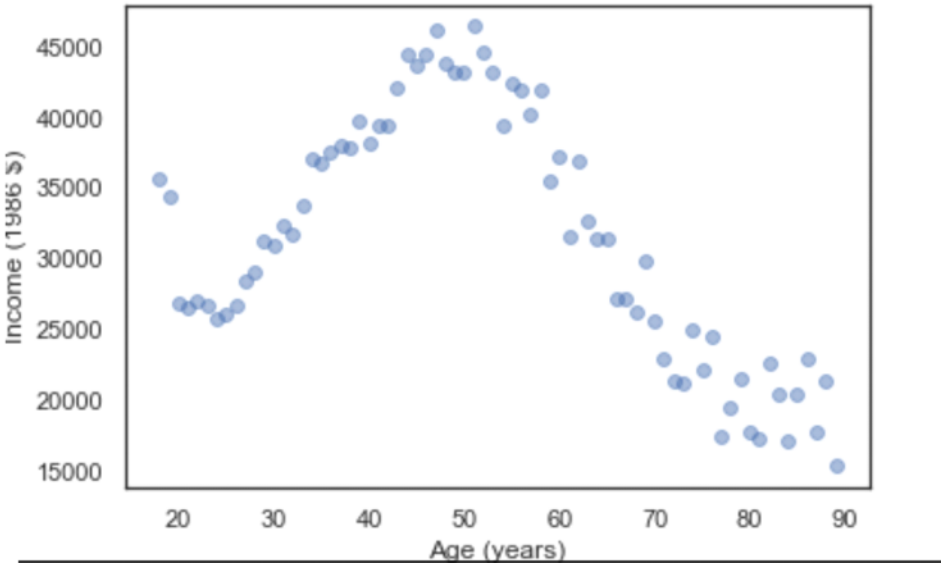
Income and age

```
grouped = gss.groupby('age')
```

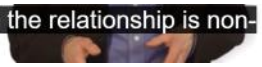
```
<pandas.core.groupby.groupby.DataFrameGroupBy object
at 0x7f1264b8ce80>
```

```
mean_income_by_age = grouped['realinc'].mean()
```

```
plt.plot(mean_income_by_age, 'o', alpha=0.5)
plt.xlabel('Age (years)')
plt.ylabel('Income (1986 $)')
```



And that explains why the estimated slope is so small, because the relationship is non-linear.



Remember that correlation and simple regression can't measure non-linear relationships.

But multiple regression can!

To describe a non-linear relationship,

one option is to add a new variable that is a non-linear combination of other variables.

Adding a quadratic term

```
gss['age2'] = gss['age']**2
```

```
model = smf.ols('realinc ~ educ + age + age2', data=gss)
results = model.fit()
results.params
```

```
Intercept   -48058.679679
educ          3442.447178
age           1748.232631
age2           -17.437552
dtype: float64
```

Modeling income and age

```
gss['age2'] = gss['age']**2
gss['educ2'] = gss['educ']**2
```

```
model = smf.ols('realinc ~ educ + educ2 + age + age2',
                data=gss)
results = model.fit()
results.params
```

```
Intercept   -23241.884034
educ          -528.309369
educ2          159.966740
age           1696.717149
age2           -17.196984
```

The parameters are hard to interpret.

Fortunately, we don't have to -- sometimes the best way to understand a model is by looking at its predictions rather than its parameters.

Generating predictions

```
df = pd.DataFrame()
df['age'] = np.linspace(18, 85)
df['age2'] = df['age']**2
```

```
df['educ'] = 12
df['educ2'] = df['educ']**2
```

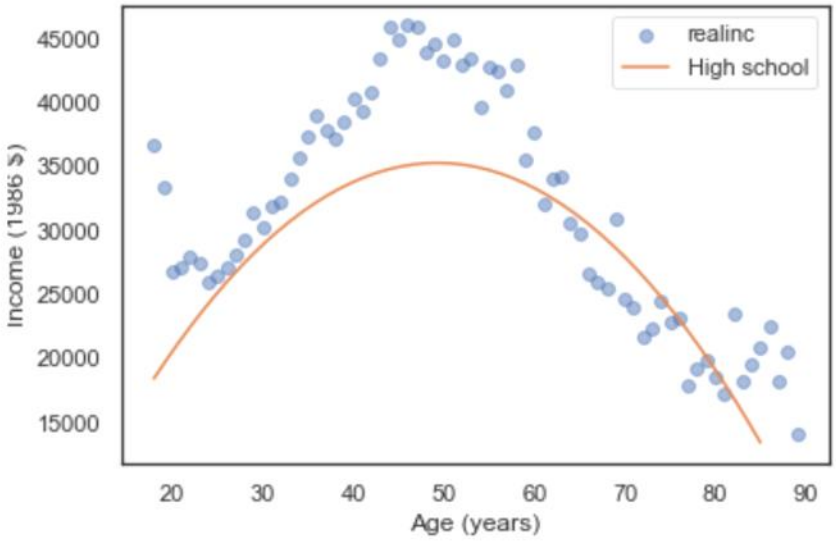
```
pred12 = results.predict(df)
```

Plotting predictions

```
plt.plot(df['age'], pred12, label='High school')
```

```
plt.plot(mean_income_by_age, 'o', alpha=0.5)
```

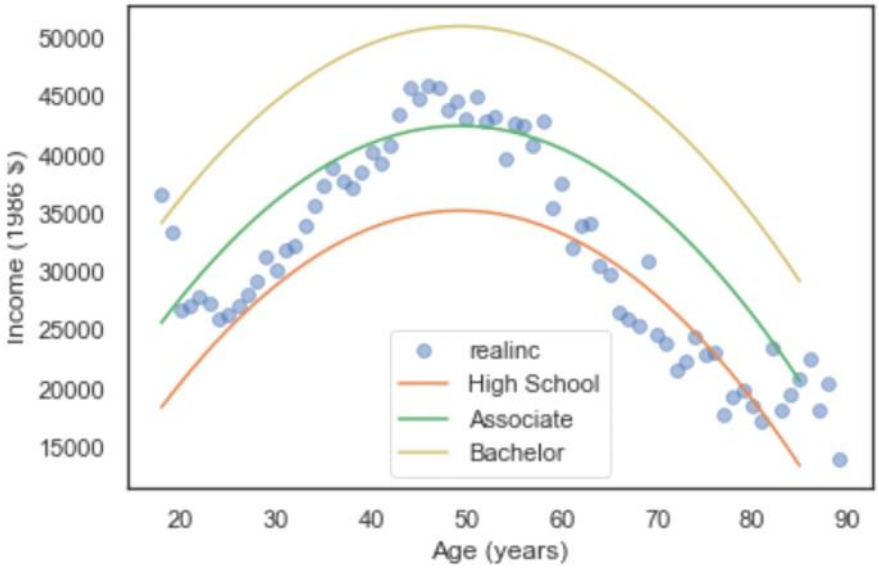
```
plt.xlabel('Age (years)')
plt.ylabel('Income (1986 $)')
plt.legend()
```



Levels of education

```
df['educ'] = 14
df['educ2'] = df['educ']**2
pred14 = results.predict(df)
plt.plot(df['age'], pred14, label='Associate')
```

```
df['educ'] = 16
df['educ2'] = df['educ']**2
pred16 = results.predict(df)
plt.plot(df['age'], pred16, label='Bachelor'
```



Categorical variables

- Numerical variables: income, age, years of education.
- Categorical variables: sex, race.

Sex and income

```
formula = 'realinc ~ educ + educ2 + age + age2 + C(sex)'
results = smf.ols(formula, data=gss).fit()
results.params
```

```
Intercept     -22369.453641
C(sex)[T.2]    -4156.113865
educ             -310.247419
educ2             150.514091
age              1703.047502
age2              -17.238711
```

The regression treats the value sex=1, which is male, as the default,

and reports the difference associated with the value sex=2, which is female.

$4100 less than for men, after controlling for age and education.

Boolean variable

```
gss['gunlaw'].value_counts()
```

```
1.0    30918
2.0     9632
```

1 means yes and 2 means no, so most respondents are in favor.

Boolean variable

```
gss['gunlaw'].value_counts()
```

```
1.0    30918
2.0     9632
```

```
gss['gunlaw'].replace([2], [0], inplace=True)
```

```
gss['gunlaw'].value_counts()
```

```
1.0    30918
0.0     9632
```

Logistic regression

```
formula = 'gunlaw ~ age + age2 + educ + educ2 + C(sex)'
results = smf.logit(formula, data=gss).fit()
```

```
results.params
```

```
Intercept      1.653862
C(sex)[T.2]    0.757249
age           -0.018849
age2           0.000189
educ          -0.124373
educ2          0.006653
```

Generating predictions

```
df = pd.DataFrame()
df['age'] = np.linspace(18, 89)
df['educ'] = 12
```

```
df['age2'] = df['age']**2
df['educ2'] = df['educ']**2
```

```
df['sex'] = 1
pred1 = results.predict(df)
```

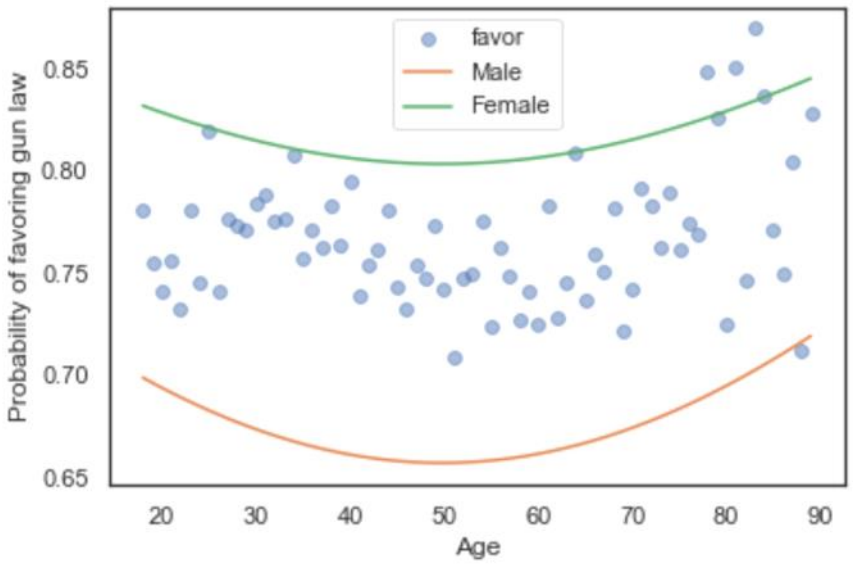
```
df['sex'] = 2
pred2 = results.predict(df)
```

Visualizing results

```
grouped = gss.groupby('age')
favor_by_age = grouped['gunlaw'].mean()
plt.plot(favor_by_age, 'o', alpha=0.5)
```

```
plt.plot(df['age'], pred1, label='Male')
plt.plot(df['age'], pred2, label='Female')
```

```
plt.xlabel('Age')
plt.ylabel('Probability of favoring gun law')
plt.legend()
```


favor
Male
Female
Probability of favoring gun law
0.85
0.80
0.75
0.70
0.65
20
30
40
50
60
70
80
90
Age