Diagnose data for cleaning

Cleaning data

- Prepare data for analysis
- Data almost never comes in clean
- Diagnose your data for problems

Common data problems

- Inconsistent column names
- Missing data
- Outliers
- Duplicate rows
- Untidy
- Need to process columns
- Column types can signal unexpected data values

Unclean data

	Continent	Country	female literacy	fertility	population
0	ASI	Chine	90.5	1.769	1.324655e+09
1	ASI	Inde	50.8	2.682	1.139965e+09
2	NAM	USA	99.0	2.077	3.040600e+08
3	ASI	Indonésie	88.8	2.132	2.273451e+08
4	LAT	Brésil	90.2	1.827	NaN

- Column name inconsistencies
- Missing data
- Country names are in French

Source: http://www.eea.europa.eu/data-and-maps/figures/correlation-between-fertility-and-female-education

Load your data

```
In [1]: import pandas as pd

In [2]: df = pd.read_csv('literary_birth_rate.csv')
```

Visually inspect

```
In [3]: df.head()
Out[3]:
 Continent     Country   female literacy  fertility    population
0       ASI       Chine             90.5      1.769  1.324655e+09
1       ASI        Inde             50.8      2.682  1.139965e+09
2       NAM         USA             99.0      2.077  3.040600e+08
3       ASI   Indonésie             88.8      2.132  2.273451e+08
4       LAT      Brésil             90.2      1.827           NaN

In [4]: df.tail()
Out[4]:
 Continent                Country   female literacy  fertility    population
0        AF  Sao Tomé-et-Principe              90.5      1.769  1.324655e+09
1       LAT                 Aruba              50.8      2.682  1.139965e+09
2       ASI                 Tonga              99.0      2.077  3.040600e+08
3       OCE             Australia              88.8      2.132  2.273451e+08
4       OCE                Sweden              90.2      1.827           NaN
```

Visually inspect

```
In [5]: df.columns
Out[5]: Index(['Continent', 'Country ', 'female literacy',
'fertility', 'population'], dtype='object')

In [6]: df.shape
Out[6]: (164, 5)

In [7]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 164 entries, 0 to 163
Data columns (total 5 columns):
Continent              164 non-null object
Country                164 non-null object
female literacy        164 non-null float64
fertility              164 non-null object
population             122 non-null float64
dtypes float64(2), object(3)
memory usage: 6.5+ KB
```

Let's practice!

Exploratory data analysis

Frequency counts

- Count the number of unique values in our data

Data type of each column

```
In [1]: df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 164 entries, 0 to 163
Data columns (total 5 columns):
continent          164 non-null object
country            164 non-null object
female literacy    164 non-null float64
fertility          164 non-null object
population         122 non-null float64
dtypes float64(2), object(3)
memory usage: 6.5+ KB
```

Frequency counts: continent

```
In [2]: df.continent.value_counts(dropna=False)
Out[2]:
AF      49
ASI     47
EUR     36
LAT     24
OCE      6
NAM      2
Name:   continent, dtype: int64
```

Frequency counts: continent

```
In [3]: df['continent'].value_counts(dropna=False)
Out[3]:
AF     49
ASI    47
EUR    36
LAT    24
OCE     6
NAM     2
Name: continent, dtype: int64
```

Frequency counts: country

```
In [4]: df.country.value_counts(dropna=False).head()
Out[4]:
Sweden       2
Algerie      1
Germany      1
Angola       1
Indonésie    1
Name: country, dtype: int64
```

Frequency counts: fertility

```
In [5]: df.fertility.value_counts(dropna=False).head()
Out[5]:
missing   5
1.854     2
1.93      2
1.841     2
1.393     2
Name: fertility, dtype: int64
```

Frequency counts: population

```
In [6]: df.population.value_counts(dropna=False).head()
Out[6]:
NaN              42
5.667325e+06      1
3.773100e+06      1
1.333388e+06      1
1.661115e+08      1
Name: population, dtype: int64
```

Summary statistics

- Numeric columns
- Outliers
  - Considerably higher or lower
  - Require further investigation

Summary statistics: Numeric data

```
In [7]: df.describe()
Out[7]:
       female_literacy    population
count       164.000000  1.220000e+02
mean         80.301220  6.345768e+07
std          22.977265  2.605977e+08
min          12.600000  1.035660e+05
25%          66.675000  3.778175e+06
50%          90.200000  9.995450e+06
75%          98.500000  2.642217e+07
max         100.000000  2.313000e+09
```

Let's practice!

Visual exploratory data analysis

Data visualization

- Great way to spot outliers and obvious errors
- More than just looking for patterns
- Plan data cleaning steps

Summary statistics

```
In [1]: df.describe()
Out[1]:
       female_literacy   fertility    population
count        164.000000  163.000000  1.220000e+02
mean          80.301220    2.872853  6.345768e+07
std           22.977265    1.425122  2.605977e+08
min           12.600000    0.966000  1.035660e+05
25%           66.675000    1.824500  3.778175e+06
50%           90.200000    2.362000  9.995450e+06
75%           98.500000    3.877500  2.642217e+07
max          100.000000    7.069000  2.313000e+09
```

Bar plots and histograms

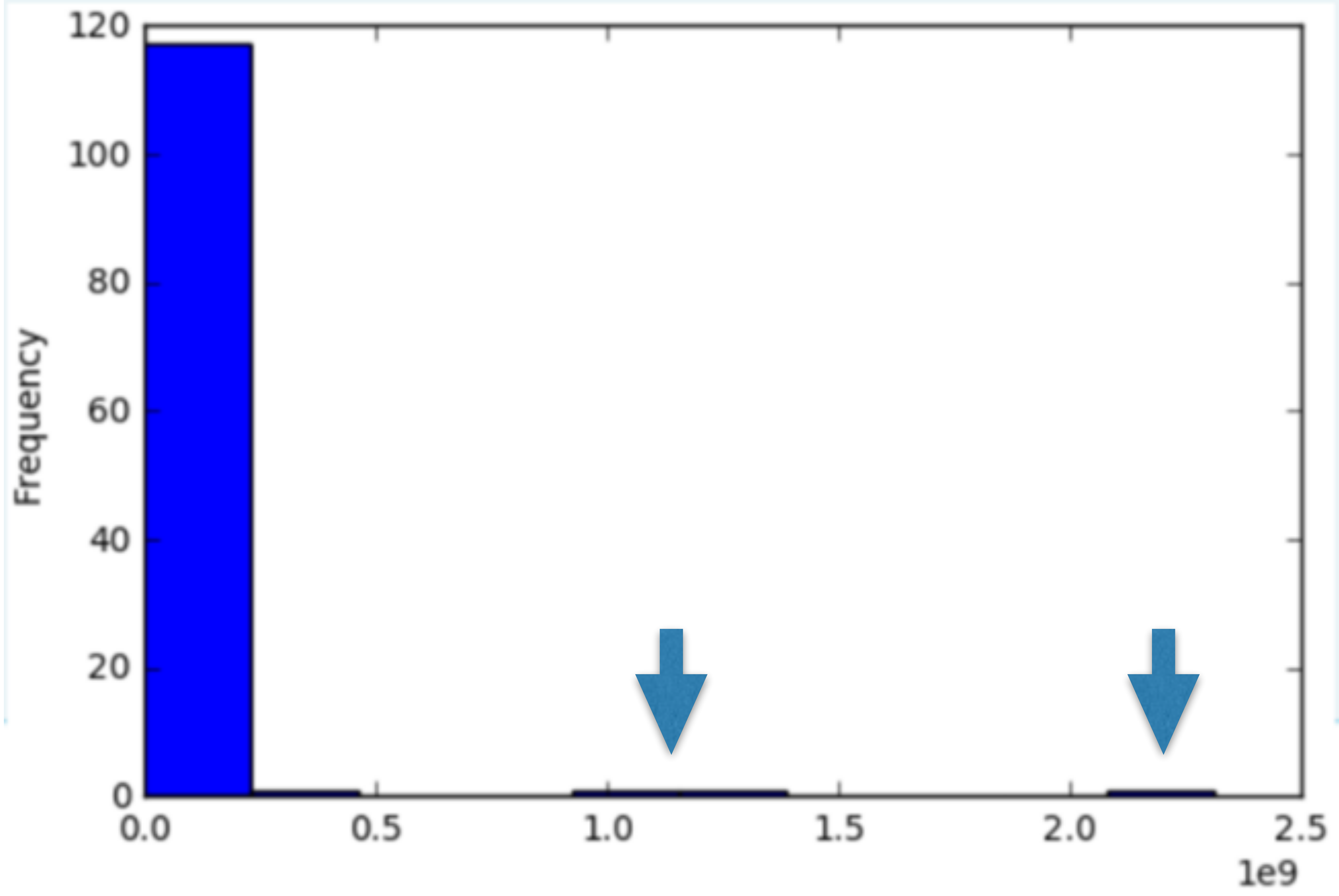
- Bar plots for discrete data counts
- Histograms for continuous data counts
- Look at frequencies

Histogram

```
In [2]: df.population.plot('hist')
Out[2]: <matplotlib.axes._subplots.AxesSubplot at 0x7f78e4abafd0>

In [3]: import matplotlib.pyplot as plt

In [4]: plt.show()
```



Identifying the error

```
In [5]: df[df.population > 1000000000]
Out[5]:
   continent    country  female literacy  fertility    population
0        ASI      Chine             90.5      1.769  1.324655e+09
1        ASI       Inde             50.8      2.682  1.139965e+09
162      OCE  Australia             96.0      1.930  2.313000e+09
```

- Not all outliers are bad data points
- Some can be an error, but others are valid values

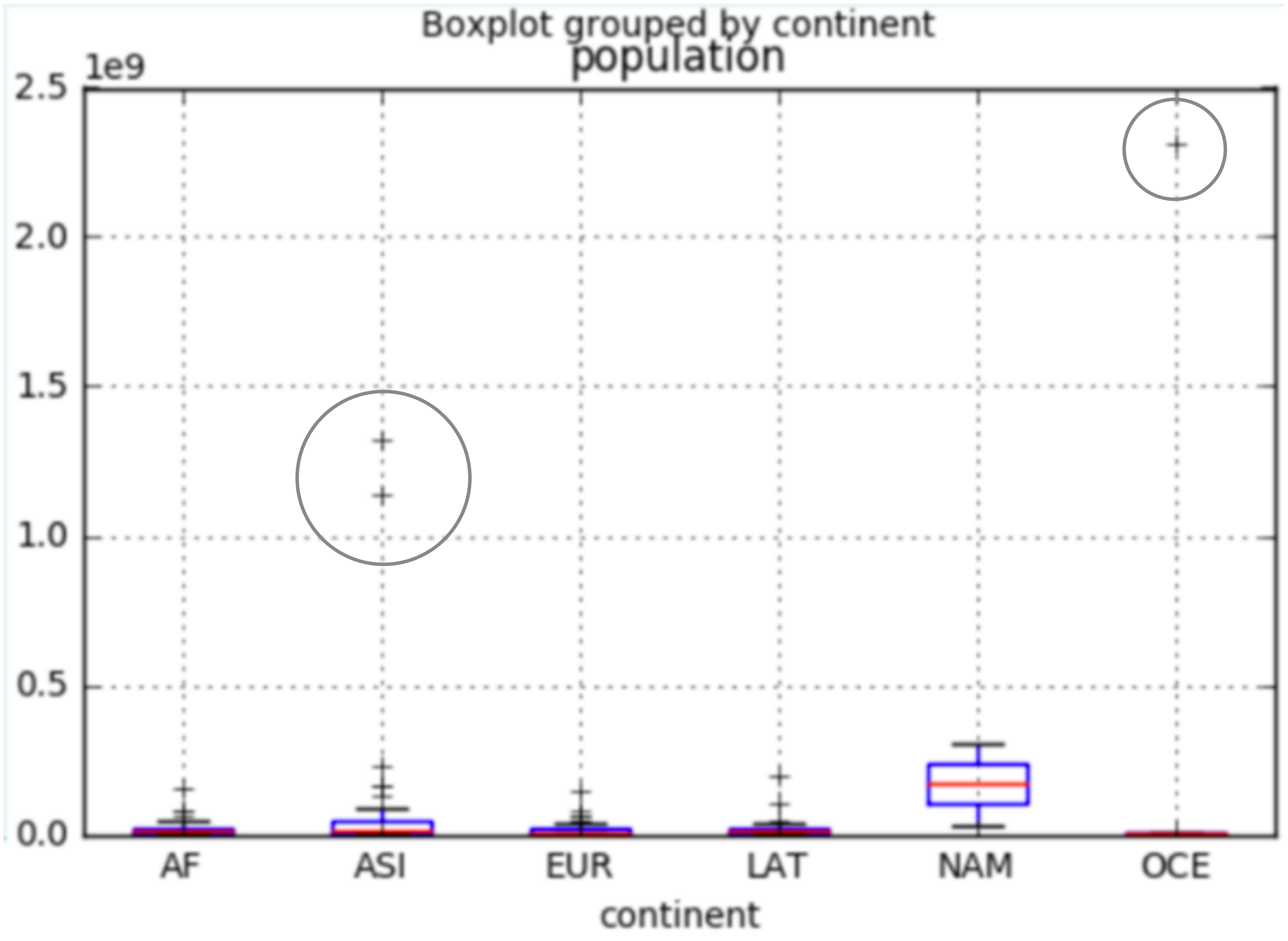
Box plots

- Visualize basic summary statistics
  - Outliers
  - Min/max
  - 25th, 50th, 75th percentiles

Box plot

```
In [6]: df.boxplot(column='population', by='continent')
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff5581bb630>

In [7]: plt.show()
```



Scatter plots

- Relationship between 2 numeric variables
- Flag potentially bad data
  - Errors not found by looking at 1 variable

Let's practice!

Tidy data

Tidy data

- “Tidy Data” paper by Hadley Wickham, PhD
- Formalize the way we describe the shape of data
- Gives us a goal when formatting our data
- “Standard way to organize data values within a dataset”

Motivation for tidy data

	name	treatment a	treatment b
0	Daniel	-	42
1	John	12	31
2	Jane	24	27

	0	1	2
name	Daniel	John	Jane
treatment a	-	12	24
treatment b	42	31	27

Principles of tidy data

- Columns represent separate variables
- Rows represent individual observations
- Observational units form tables

	name	treatment a	treatment b
0	Daniel	-	42
1	John	12	31
2	Jane	24	27

Converting to tidy data

	name	treatment a	treatment b
0	Daniel	-	42
1	John	12	31
2	Jane	24	27

	name	treatment	value
0	Daniel	treatment a	-
1	John	treatment a	12
2	Jane	treatment a	24
3	Daniel	treatment b	42
4	John	treatment b	31
5	Jane	treatment b	27

- Better for reporting vs. better for analysis
- Tidy data makes it easier to fix common data problems

Converting to tidy data

- The data problem we are trying to fix:
  - Columns containing values, instead of variables
- Solution: pd.melt()

Melting

```
In [1]: pd.melt(frame=df, id_vars='name',
   ...:         value_vars=['treatment a', 'treatment b'])
Out[1]:
     name     variable  value
0  Daniel  treatment a      _
1    John  treatment a     12
2    Jane  treatment a     24
3  Daniel  treatment b     42
4    John  treatment b     31
5    Jane  treatment b     27
```

Melting

```
In [2]: pd.melt(frame=df, id_vars='name',
   ...:         value_vars=['treatment a', 'treatment b’],
   ...:         var_name='treatment', value_name='result')
Out[2]:
     name    treatment  result
0  Daniel  treatment a       _
1    John  treatment a      12
2    Jane  treatment a      24
3  Daniel  treatment b      42
4    John  treatment b      31
5    Jane  treatment b      27
```

Let's practice!

Pivoting data

Pivot: un-melting data

- Opposite of melting
- In melting, we turned columns into rows
- Pivoting: turn unique values into separate columns
- Analysis friendly shape to reporting friendly shape
- Violates tidy data principle: rows contain observations
    - Multiple variables stored in the same column

Pivot: un-melting data

	date	element	value
0	2010-01-30	tmax	27.8
1	2010-01-30	tmin	14.5
2	2010-02-02	tmax	27.3
3	2010-02-02	tmin	14.4

element	tmax	tmin
date		
2010-01-30	27.8	14.5
2010-02-02	27.3	14.4

Pivot

```
In [1]: weather_tidy = weather.pivot(index='date',
   ...:                              columns='element',
   ...:                              values='value')

In [2]: print(weather_tidy)
element     tmax tmin
date
2010-01-30  27.8 14.5
2010-02-02  27.3 14.4
```

Pivot

	date	element	value
0	2010-01-30	tmax	27.8
1	2010-01-30	tmin	14.5
2	2010-02-02	tmax	27.3
3	2010-02-02	tmin	14.4

	date	element	value
0	2010-01-30	tmax	27.8
1	2010-01-30	tmin	14.5
2	2010-02-02	tmax	27.3
3	2010-02-02	tmin	14.4
4	2010-02-02	tmin	16.4

Using pivot when you have duplicate entries

```
In [3]: import numpy as np

In [4]: weather2_tidy = weather.pivot(values='value',
   ...:                               index='date',
   ...:                               columns='element')
Out[4]:
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-9-2962bb23f5a3> in <module>()
      1 weather2_tidy = weather2.pivot(values='value',
      2                                index='date',
----> 3                                columns='element')
ValueError: Index contains duplicate entries, cannot reshape
```

Pivot table

- Has a parameter that specifies how to deal with duplicate values
- Example: Can aggregate the duplicate values by taking their average

Pivot table

```
In [5]: weather2_tidy = weather.pivot_table(values='value',
   ...:                                     index='date',
   ...:                                     columns='element',
   ...:                                     aggfunc=np.mean)
Out[5]:
element     tmax  tmin
date
2010-01-30  27.8  14.5
2010-02-02  27.3  15.4
```

Let's practice!

Beyond melt and pivot

Beyond melt and pivot

- Melting and pivoting are basic tools
- Another common problem:
    - Columns contain multiple bits of information

Beyond melt and pivot

	country	year	m014	m1524
0	AD	2000	0	0
1	AE	2000	2	4
2	AF	2000	52	228

Melting and parsing

```
In [1]: pd.melt(frame=tb, id_vars=['country', 'year'])
Out[1]:
   country   year  variable  value
0       AD   2000      m014      0
1       AE   2000      m014      2
2       AF   2000      m014     52
3       AD   2000     m1524      0
4       AE   2000     m1524      4
5       AF   2000     m1524    228
```

- Nothing inherently wrong about original data shape
- Not conducive for analysis

Melting and parsing

```
In [2]: tb_melt['sex'] = tb_melt.variable.str[0]

In [3]: tb_melt
Out[3]:
   country  year variable value  sex
0       AD  2000     m014     0    m
1       AE  2000     m014     2    m
2       AF  2000     m014    52    m
3       AD  2000    m1524     0    m
4       AE  2000    m1524     4    m
5       AF  2000    m1524   228    m
```

Let’s practice!

Concatenating data

Combining data

- Data may not always come in 1 huge file
  - 5 million row dataset may be broken into 5 separate datasets
  - Easier to store and share
  - May have new data for each day
- Important to be able to combine then clean, or vice versa

Concatenation

	date	element	value
0	2010-01-30	tmax	27.8
1	2010-01-30	tmin	14.5

	date	element	value
0	2010-02-02	tmax	27.3
1	2010-02-02	tmin	14.4

	date	element	value
0	2010-01-30	tmax	27.8
1	2010-01-30	tmin	14.5
0	2010-02-02	tmax	27.3
1	2010-02-02	tmin	14.4

pandas concat

```
In [1]: concatenated = pd.concat([weather_p1, weather_p2])

In [2]: print(concatenated)
        date       element   value
0  2010-01-30   tmax       27.8
1  2010-01-30   tmin       14.5
0  2010-02-02   tmax       27.3
1  2010-02-02   tmin       14.4
```

pandas concat

```
In [3]: concatenated = concatenated.loc[0, :]
Out[3]:
      date      element   value
0   2010-01-30   tmax      27.8
0   2010-02-02   tmax      27.3
```

pandas concat

```
In [4]: pd.concat([weather_p1, weather_p2], ignore_index=True)
Out[4]:
      date      element  value
0  2010-01-30  tmax       27.8
1  2010-01-30  tmin       14.5
2  2010-02-02  tmax       27.3
3  2010-02-02  tmin       14.4
```

Concatenating DataFrames

	country	year	variable	value
0	AD	2000	m014	0
1	AE	2000	m014	2
2	AF	2000	m014	52
3	AD	2000	m1524	0
4	AE	2000	m1524	4
5	AF	2000	m1524	228

	age_group	sex
0	014	m
1	014	m
2	014	m
3	1524	m
4	1524	m
5	1524	m

Let's practice!

Finding and concatenating data

Concatenating many files

- Leverage Python's features with data cleaning in pandas
- In order to concatenate DataFrames:
  - They must be in a list
  - Can individually load if there are a few datasets
  - But what if there are thousands?
- Solution: glob function to find files based on a pattern

Globbing

- Pattern matching for file names
- Wildcards: * ?
    - Any csv file: *.csv
    - Any single character: file_?.csv
- Returns a list of file names
- Can use this list to load into separate DataFrames

The plan

- Load files from globbing into pandas
- Add the DataFrames into a list
- Concatenate multiple datasets at once

Find and concatenate

```
In [1]: import glob

In [2]: csv_files = glob.glob('*.csv')

In [3]: print(csv_files)
['file5.csv', 'file2.csv', 'file3.csv', 'file1.csv', 'file4.csv']
```

Using loops

```
In [4]: list_data = []

In [5]: for filename in csv_files:
   ...:     data = pd.read_csv(filename)
   ...:     list_data.append(data)

In [6]: pd.concat(list_data)
```

Let's practice!

Merge data

Combining data

- Concatenation is not the only way data can be combined

	state	population_2016
0	California	39250017
1	Texas	27862596
2	Florida	20612439
3	New York	19745289

	name	ANSI
0	California	CA
1	Florida	FL
2	New York	NY
3	Texas	TX

Merging data

- Similar to joining tables in SQL
- Combine disparate datasets based on common columns

	state	population_2016
0	California	39250017
1	Texas	27862596
2	Florida	20612439
3	New York	19745289

	name	ANSI
0	California	CA
1	Florida	FL
2	New York	NY
3	Texas	TX

Merging data

```
In [1]: pd.merge(left=state_populations, right=state_codes,
   ...:          on=None, left_on='state', right_on='name')
Out[1]:
        state  population_2016        name  ANSI
0  California         39250017  California    CA
1       Texas         27862596       Texas    TX
2     Florida         20612439     Florida    FL
3    New York         19745289    New York    NY
```

Types of merges

- One-to-one
- Many-to-one / one-to-many
- Many-to-many

One-to-one

	state	population_2016
0	California	39250017
1	Texas	27862596
2	Florida	20612439
3	New York	19745289

	name	ANSI
0	California	CA
1	Florida	FL
2	New York	NY
3	Texas	TX

One-to-one

	state	population_2016	name	ANSI
0	California	39250017	California	CA
1	Texas	27862596	Texas	TX
2	Florida	20612439	Florida	FL
3	New York	19745289	New York	NY

Many-to-one / one-to-many

	state	City
0	California	San Diego
1	California	Sacramento
2	New York	New York City
3	New York	Albany

	name	ANSI
0	California	CA
1	Florida	FL
2	New York	NY
3	Texas	TX

Many-to-one / one-to-many

	name	ANSI	state	City
0	California	CA	California	San Diego
1	California	CA	California	Sacramento
2	New York	NY	New York	New York City
3	New York	NY	New York	Albany

Different types of merges

- One-to-one
- Many-to-one
- Many-to-many
- All use the same function
- Only difference is the DataFrames you are merging

Let's practice!

Data types

Prepare and clean data

	name	sex	treatment a	treatment b
0	Daniel	male	-	42
1	John	male	12	31
2	Jane	female	24	27

Data types

```
In [1]: print(df.dtypes)
name            object
sex             object
treatment a     object
treatment b      int64
dtype: object
```

- There may be times we want to convert from one type to another
    - Numeric columns can be strings, or vice versa

Converting data types

```
In [2]: df['treatment b'] = df['treatment b'].astype(str)

In [3]: df['sex'] = df['sex'].astype('category')

In [4]: df.dtypes
Out[4]:
name               object
sex              category
treatment a        object
treatment b        object
dtype: object
```

Categorical data

- Converting categorical data to 'category' dtype:
    - Can make the DataFrame smaller in memory
    - Can make them be utilized by other Python libraries for analysis

Cleaning data

- Numeric data loaded as a string

	name	sex	treatment a	treatment b
0	Daniel	male	-	42
1	John	male	12	31
2	Jane	female	24	27

Cleaning bad data

```
In [5]: df['treatment a'] = pd.to_numeric(df['treatment a'],
   ...:                                   errors='coerce')

In [6]: df.dtypes
Out[6]:
name                object
sex               category
treatment a        float64
treatment b         object
dtype: object
```

Let's practice!

Using regular expressions to clean strings

String manipulation

- Much of data cleaning involves string manipulation
    - Most of the world's data is unstructured text
- Also have to do string manipulation to make datasets consistent with one another

Validate values

- 17
- $17
- $17.89
- $17.895

String manipulation

- Many built-in and external libraries
- ‘re’ library for regular expressions
  - A formal way of specifying a pattern
  - Sequence of characters
- Pattern matching
  - Similar to globbing

Example match

17	12345678901	\d*
$17	$12345678901	\$\d*
$17.00	$12345678901.42	\$\d* \.\d*
$17.89	$12345678901.24	\$\d*\.\d{2}
~~$17.895~~	~~$12345678901.999~~	^\$\d*\.\d{2}$

"I have 17.89 USD"

Using regular expressions

- Compile the pattern
- Use the compiled pattern to match values
- This lets us use the pattern over and over again
- Useful since we want to match values down a column of values

Using regular expressions

```
In [1]: import re

In [2]: pattern = re.compile('\$\d*\.\d{2}')

In [3]: result = pattern.match('$17.89')

In [4]: bool(result)
True
```

Let's practice!

Using functions to clean data

Complex cleaning

- Cleaning step requires multiple steps
    - Extract number from string
    - Perform transformation on extracted number
- Python function

Apply

```
In [1]: print(df)
        treatment a  treatment b
Daniel           18           42
John             12           31
Jane             24           27

In [2]: df.apply(np.mean, axis=0)
Out[2]:
treatment a    18.000000
treatment b    33.333333
dtype: float64
```

Apply

```
In [3]: print(df)
        treatment a  treatment b
Daniel           18           42
John             12           31
Jane             24           27

In [4]: df.apply(np.mean, axis=1)
Out[4]:
Daniel    30.0
John      21.5
Jane      25.5
dtype: float64
```

Applying functions

	Job #	Doc #	Borough	Initial Cost	Total Est. Fee
0	121577873	2	MANHATTAN	$75000.00	$986.00
1	520129502	1	STATEN ISLAND	$0.00	$1144.00
2	121601560	1	MANHATTAN	$30000.00	$522.50
3	121601203	1	MANHATTAN	$1500.00	$225.00
4	121601338	1	MANHATTAN	$19500.00	$389.50

Write the regular expression

```
In [5]: import re

In [6]: from numpy import NaN

In [7]: pattern = re.compile('^\$\d*\.\d{2}$')
```

Writing a function

example.py

```
def my_function(input1, input2):

    # Function Body

    return value
```

Write the function

diff_money.py

```
def diff_money(row, pattern):

    icost = row['Initial Cost']
    tef = row['Total Est. Fee']

    if bool(pattern.match(icost)) and bool(pattern.match(tef)):

        icost = icost.replace("$", "")
        tef = tef.replace("$", "")

        icost = float(icost)
        tef = float(tef)

        return icost - tef
    else:

        return(NaN)
```

Write the function

```
In [8]: df_subset['diff'] = df_subset.apply(diff_money,
   ...:                                     axis=1,
   ...:                                     pattern=pattern)

In [9]: print(df_subset.head())
        Job #  Doc #        Borough Initial Cost Total Est. Fee     diff
0   121577873      2      MANHATTAN    $75000.00        $986.00  74014.0
1   520129502      1  STATEN ISLAND        $0.00       $1144.00  -1144.0
2   121601560      1      MANHATTAN    $30000.00        $522.50  29477.5
3   121601203      1      MANHATTAN     $1500.00        $225.00   1275.0
4   121601338      1      MANHATTAN    $19500.00        $389.50  19110.5
```

Let's practice!

Duplicate and missing data

Duplicate data

- Can skew results
- ‘.drop_duplicates()’ method

	name	sex	treatment a	treatment b
0	Daniel	male	-	42
1	John	male	12	31
2	Jane	female	24	27
3	Daniel	male	-	42

Drop duplicates

```
In [1]: df = df.drop_duplicates()

In [2]: print(df)
     name     sex  treatment a  treatment b
0  Daniel    male            -           42
1    John    male           12           31
2    Jane  female           24           27
```

Missing data

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2.0
1	NaN	1.66	Male	No	Sun	Dinner	3.0
2	21.01	3.50	Male	No	Sun	Dinner	3.0
3	23.68	NaN	Male	No	Sun	Dinner	2.0
4	24.59	3.61	NaN	NaN	Sun	NaN	4.0

- Leave as-is
- Drop them
- Fill missing value

Count missing values

```
In [3]: tips_nan.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 7 columns):
total_bill    202 non-null float64
tip           220 non-null float64
sex           234 non-null object
smoker        229 non-null object
day           243 non-null object
time          227 non-null object
size          231 non-null float64
dtypes: float64(3), object(4)
memory usage: 13.4+ KB
None
```

Drop missing values

```
In [4]: tips_dropped = tips_nan.dropna()

In [5]: tips_dropped.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 147 entries, 0 to 243
Data columns (total 7 columns):
total_bill     147 non-null float64
tip            147 non-null float64
sex            147 non-null object
smoker         147 non-null object
day            147 non-null object
time           147 non-null object
size           147 non-null float64
dtypes: float64(3), object(4)
memory usage: 9.2+ KB
```

Fill missing values with .fillna()

- Fill with provided value
- Use a summary statistic

Fill missing values

```
In [6]: tips_nan['sex'] = tips_nan['sex'].fillna('missing')

In [7]: tips_nan[['total_bill', 'size']] = tips_nan[['total_bill',
   ...:                                             'size']].fillna(0)

In [8]: tips_nan.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 7 columns):
total_bill    244 non-null float64
tip           220 non-null float64
sex           244 non-null object
smoker        229 non-null object
day           243 non-null object
time          227 non-null object
size          244 non-null float64
dtypes: float64(3), object(4)
memory usage: 13.4+ KB
```

Fill missing values with a test statistic

- Careful when using test statistics to fill
- Have to make sure the value you are filling in makes sense
- Median is a better statistic in the presence of outliers

Fill missing values with a test statistic

```
In [9]: mean_value = tips_nan['tip'].mean()

In [10]: print(mean_value)
2.964681818181819

In [11]: tips_nan['tip'] = tips_nan['tip'].fillna(mean_value)

In [12]: tips_nan.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 244 entries, 0 to 243
Data columns (total 7 columns):
total_bill    244 non-null float64
tip           244 non-null float64
sex           244 non-null object
smoker        229 non-null object
day           243 non-null object
time          227 non-null object
size          244 non-null float64
dtypes: float64(3), object(4)
memory usage: 13.4+ KB
```

Let’s practice!

Testing with asserts

Assert statements

- Programmatically vs visually checking
- If we drop or fill NaNs, we expect 0 missing values
- We can write an assert statement to verify this
- We can detect early warnings and errors
- This gives us confidence that our code is running correctly

Asserts

```
In [1]: assert 1 == 1

In [2]: assert 1 == 2
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
<ipython-input-65-a810b3a4aded> in <module>()
----> 1 assert 1 == 2

AssertionError:
```

Google stock data

	Date	Open	High	Low	Close	Volume	Adj Close
0	2017-02-09	831.729980	NaN	826.500000	830.059998	1192000.0	NaN
1	2017-02-08	830.530029	834.250000	825.109985	829.880005	1300600.0	829.880005
2	2017-02-07	NaN	NaN	823.289978	NaN	1664800.0	NaN
3	2017-02-06	820.919983	822.390015	NaN	821.619995	NaN	821.619995
4	2017-02-03	NaN	826.130005	819.349976	820.130005	1524400.0	820.130005

Test column

```
In [1]: assert google.Close.notnull().all()
---------------------------------------------------------------------------
AssertionError                            Traceback (most recent call last)
<ipython-input-49-eec77130a77f> in <module>()
----> 1 assert google.Close.notnull().all()

AssertionError:
```

Test column

```
In [1]: google_0 = google.fillna(value=0)

In [2]: assert google_0.Close.notnull().all()
```

Let's practice!

Putting it all together

Putting it all together

- Use the techniques you've learned on Gapminder data
- Clean and tidy data saved to a file
    - Ready to be loaded for analysis!
- Dataset consists of life expectancy by country and year
- Data will come in multiple parts
    - Load
    - Preliminary quality diagnosis
    - Combine into single dataset

Useful methods

```
In [1]: import pandas as pd

In [2]: df = pd.read_csv('my_data.csv')

In [3]: df.head()

In [4]: df.info()

In [5]: df.columns

In [6]: df.describe()

In [7]: df.column.value_counts()

In [8]: df.column.plot('hist')
```

Data quality

```
In [9]: def cleaning_function(row_data):
   ...:     # data cleaning steps
   ...:     return ...

In [10]: df.apply(cleaning_function, axis=1)

In [11]: assert (df.column_data > 0).all()
```

Combining data

- pd.merge(df1, df2, ...)
- pd.concat([df1, df2, df3, ...])

Let's practice!

Initial impressions of the data

Principles of tidy data

- Rows form observations
- Columns form variables
- Tidying data will make data cleaning easier
- Melting turns columns into rows
- Pivot will take unique values from a column and create new columns

Checking data types

```
In [1]: df.dtypes

In [2]: df['column'] = df['column'].to_numeric()

In [3]: df['column'] = df['column'].astype(str)
```

Additional calculations and saving your data

```
In [4]: df['new_column'] = df['column_1'] + df['column_2']

In [5]: df['new_column'] = df.apply(my_function, axis=1)

In [6]: df.to_csv['my_data.csv']
```

Let's practice!

Final thoughts

You’ve learned how to...

- Load and view data in pandas
- Visually inspect data for errors and potential problems
- Tidy data for analysis and reshape it
- Combine datasets
- Clean data by using regular expressions and functions
- Test your data and be proactive in finding potential errors

Congratulations!