Intro to Programming for Public Policy Week 5
Pandas Merge, Transformation, and Time series

Eric Potash

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Combining and Merging

State-year data

```
>>> state_years = pd.DataFrame({
        'state': ['Ohio', 'Ohio', 'Ohio',
                  'Nevada', 'Nevada'],
        'year': [2000, 2001, 2002, 2001, 2002],
        'pop': [1.5, 1.7, 3.6, 2.4, 2.9]
    })
>>> state_years
   pop   state  year
0  1.5    Ohio  2000
1  1.7    Ohio  2001
2  3.6    Ohio  2002
3  2.4  Nevada  2001
4  2.9  Nevada  2002
```

State data

```
>>> states = pd.DataFrame({
        'state':['Ohio', 'Utah'],
        'abbrev': ['OH', 'UT'],
        'area': [4.4, 11.0]
    })
>>> states
  abbrev  area   state
0     OH   4.4    Ohio
1     UT  11.0    Utah
```

Merge

The `merge` function allows us to combine two datasets that share a column:

```
>>> state_years.merge(states, on='state')
   pop   state  year abbrev  area
0  1.5    Ohio  2000     OH   4.4
1  1.7    Ohio  2001     OH   4.4
2  3.6    Ohio  2002     OH   4.4
```

- The `state` column is called the merge *key*
- The `state_years` table is called the *left* and `states` is called the *right*
- The rows corresponding to Nevada and Utah don't appear in the result because the `merge` function performs an *inner* merge by default.

Merge `how`

- Four ways to merge datasets: inner, outer, left, and right.
- They differ in how they treat rows that are not shared by both *left* and *right* tables.
- The default is an *inner* merge
  - Its result only includes rows that are in both left and right.
- All other merge types produce results that are supersets of the inner merge.

Merge `how` Venn diagrams

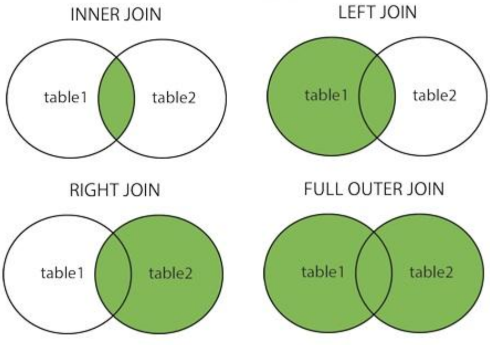

Figure 1: Merge types (source: tech.queryhome.com)

Inner

Again, an inner merge (the default) only includes rows that are present on both sides of the merge:

```
>>> state_years.merge(states, on='state', how='inner')
   pop   state  year abbrev  area
0  1.5    Ohio  2000     OH   4.4
1  1.7    Ohio  2001     OH   4.4
2  3.6    Ohio  2002     OH   4.4
```

Left

A left merge includes all rows from the left table, producing nulls when a key is missing on the right:

```
>>> state_years.merge(states, on='state', how='left')
   pop   state  year abbrev  area
0  1.5    Ohio  2000     OH   4.4
1  1.7    Ohio  2001     OH   4.4
2  3.6    Ohio  2002     OH   4.4
3  2.4  Nevada  2001    NaN   NaN
4  2.9  Nevada  2002    NaN   NaN
```

Right

A right merge includes all rows from the right table, producing nulls when a key is missing on the left:

```
>>> state_years.merge(states, on='state', how='right')
   pop state     year abbrev  area
0  1.5  Ohio   2000.0     OH   4.4
1  1.7  Ohio   2001.0     OH   4.4
2  3.6  Ohio   2002.0     OH   4.4
3  NaN  Utah      NaN     UT  11.0
```

Note that `A.merge(B, how='right')` is equivalent to `B.merge(A, how='left')`

Outer

An outer merge includes all rows, producing nulls when a ket from the left is missing on the right and vice versa:

```
>>> state_years.merge(states, on='state', how='outer')
   pop   state    year abbrev  area
0  1.5    Ohio  2000.0     OH   4.4
1  1.7    Ohio  2001.0     OH   4.4
2  3.6    Ohio  2002.0     OH   4.4
3  2.4  Nevada  2001.0    NaN   NaN
4  2.9  Nevada  2002.0    NaN   NaN
5  NaN    Utah     NaN     UT  11.0
```

Another merge

Load the salaries file again:

```
>>> salaries = pd.read_csv('salaries.csv')
>>> dept_sizes = salaries.Department.value_counts()
>>> dept_sizes
POLICE                    13414
FIRE                       4641
STREETS & SAN              2198
OEMC                       2102
WATER MGMNT                1879
AVIATION                   1629
TRANSPORTN                 1140
PUBLIC LIBRARY             1015
GENERAL SERVICES            980
FAMILY & SUPPORT            615
FINANCE                     560
HEALTH                      488
...
```

`to_frame()`

The `merge()` function only operates on DataFrames. By “resetting” the index, the series becomes a data frame:

```
>>> depts = dept_sizes.reset_index()
                   index  Department
0                 POLICE       13414
1                   FIRE        4641
2          STREETS & SAN        2198
3                   OEMC        2102
4            WATER MGMNT        1879
5               AVIATION        1629
6             TRANSPORTN        1140
7         PUBLIC LIBRARY        1015
8       GENERAL SERVICES         980
9       FAMILY & SUPPORT         615
...
```

Rename columns

But the column names are confusing. Rename them:

```
>>> depts.columns
Index(['index', 'Department'],
      dtype='object')
>>> depts.columns = ['Department', 'Department Size']
>>> depts.columns
Index(['Department', 'Department Size'],
      dtype='object')
>>> depts
                Department  Department Size
0                   POLICE            13414
1                     FIRE             4641
2           STREETS & SAN             2198
3                     OEMC             2102
4              WATER MGMNT             1879
5                 AVIATION             1629
...
```

Merge department sizes

In [78]:
```python
salaries.merge(depts, on=['Department'])
```

Out[78]:

	Name	Job Titles	Department	Full or Part-Time	Salary or Hourly	Typical Hours	Annual Salary	Hourly Rate	Department Size
0	AARON, JEFFERY M	SERGEANT	POLICE	F	Salary	NaN	$101442.00	NaN	13414
1	AARON, KARINA	POLICE OFFICER (ASSIGNED AS DETECTIVE)	POLICE	F	Salary	NaN	$94122.00	NaN	13414
2	ABBATE, TERRY M	POLICE OFFICER	POLICE	F	Salary	NaN	$93354.00	NaN	13414
3	ABDALLAH, ZAID	POLICE OFFICER	POLICE	F	Salary	NaN	$84054.00	NaN	13414
4	ABDELHADI, ABDALMAHD	POLICE OFFICER	POLICE	F	Salary	NaN	$87006.00	NaN	13414
5	ABDELMAJEID,	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Data Transformations

cut()

```
>>> salaries['salary'] = \
        salaries['Annual Salary'].str[1:].astype(float)
```

```
>>> pd.cut(salaries['salary'],
           [0, 100000, 200000, 300000])
33176          (0, 100000]
33177          (0, 100000]
33178          (0, 100000]
33179          (0, 100000]
33180          (0, 100000]
33181          (0, 100000]
33182     (100000, 200000]
Name: salary, dtype: category
Categories (3, object): [(0, 100000] <
                          (100000, 200000] <
                          (200000, 300000]]
```

cut() labels

```
>>> pd.cut(salaries['salary'],
           [0, 100000, 200000, 300000],
           labels=['low', 'medium', 'high'])
33176       low
33177       low
33178       low
33179       low
33180       low
33181       low
33182    medium
Name: salary, dtype: category
Categories (3, object): [low < medium < high]
```

Percentiles

To bin with percentiles use `qcut`. For example, to calculate quartiles:

```
>>> pd.qcut(salaries['salary'], 4)
33176      [7200, 76266]
33177      [7200, 76266]
33178      [7200, 76266]
33179      [7200, 76266]
33180     (76266, 90024]
33181     (90024, 96060]
33182    (96060, 300000]
Name: salary, dtype: category
Categories (4, object): [[7200, 76266] <
                          (76266, 90024] <
                          (90024, 96060] <
                          (96060, 300000]]
```

fillna()

To replace missing values use `fillna`:

```
>>> salaries['Typical Hours'].fillna(40)
...
33173    40.0
33174    40.0
33175    40.0
33176    40.0
33177    40.0
33178    40.0
33179    40.0
33180    40.0
33181    40.0
33182    40.0
Name: Typical Hours, dtype: float64
```

For more complicated *imputation* look at the `method` argument in the documentation.

fillna(inplace=True)

- So far we have mostly used pandas methods that return a new `Series` or `DataFrame`.
- Many methods take a boolean `inplace` argument, indicating whether to modify the existing data:

```
>>> salaries['Typical Hours'].fillna(40, inplace=True)
>>> salaries['Typical Hours']
...
33176    40.0
33177    40.0
33178    40.0
33179    40.0
33180    40.0
33181    40.0
33182    40.0
Name: Typical Hours, dtype: float64
```

Time series data

`pd.Timestamp`

Dates are notoriously complicated on a computer. There are many issues with formatting, time zones, leap years/seconds, etc. Pandas provides a `Timestamp` type:

```
>>> t1 = pd.Timestamp('2014-01-01 12:15:00 AM')
```

The constructor function automatically detects the date format.

Timestamp features

- If `t1` and `t2` are timestamps, you can compare them (>, <, etc.):

```
>>> t1 = pd.Timestamp('2004-01-01')
>>> t2 = pd.Timestamp('2002-03-12')
>>> t1 > t2
True
```

Timestamp features

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>>> t2 = pd.Timestamp('2002-03-12')
>>> t1 > t2
True
```

- You can subtract them (the result is a new type called `Timedelta`)

```
>>> t1 - t2
Timedelta('660 days 00:00:00')
```

Timestamp features

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```
>>> t1 = pd.Timestamp('2004-01-01')
>>> t2 = pd.Timestamp('2002-03-12')
>>> t1 > t2
True
```

- You can subtract them (the result is a new type called `Timedelta`)

```
>>> t1 - t2
Timedelta('660 days 00:00:00')
```

- You can get their day of the week, month, etc:

```
>>> t1.dayofweek
3
>>> t1.month
1
```

Crime data

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

In [2]: df = pd.read_csv('/home/epotash/Crimes_-_2001_to_present.csv')

In [65]: df
```

Out[65]:

	ID	Case Number	Date	Block	IUCR	Primary Type	Description	Location Description	Arrest
0	11094370	JA440032	09/21/2017 12:15:00 AM	072XX N CALIFORNIA AVE	1122	DECEPTIVE PRACTICE	COUNTERFEIT CHECK	CURRENCY EXCHANGE	True
1	11118031	JA470589	10/12/2017 07:14:00 PM	055XX W GRAND AVE	1345	CRIMINAL DAMAGE	TO CITY OF CHICAGO PROPERTY	JAIL / LOCK-UP FACILITY	True
2	11134189	JA491697	10/30/2017 11:52:00 AM	043XX S TALMAN AVE	4651	OTHER OFFENSE	SEX OFFENDER: FAIL REG NEW ADD	APARTMENT	True
3	11156462	JA521389	09/29/2017 06:45:00 PM	055XX W BELMONT AVE	1110	DECEPTIVE PRACTICE	BOGUS CHECK	CURRENCY EXCHANGE	True

Date dtype

By default, pandas reads the date column as strings:

```
>>> df.Date.dtype
dtype('O')
```

- Here `dtype('O')` means the dtype is an `object`.
- pandas uses this dtype for columns that are not all numbers or dates. The types could even vary within the column.
- To get a better sense of the dtype, you can look at the dtype of the first element:

```
>>> type(df.Date[0])
str
```

Parsing dates

There are two ways to parse the dates in this table.

- First, we could use the `parse_dates` argument to the `read_csv()` function:

```
>>> df = pd.read_csv('Crimes_-_2001_to_present.csv',
                     parse_dates=['Date'])
```

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                     parse_dates=['Date'])
```

- Instead, we could, after reading in the dates unparsed, convert them using `pd.to_datetime()`:

```
>>> df['Date'] = pd.to_datetime(df.Date)
```

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                     parse_dates=['Date'])
```

- Instead, we could, after reading in the dates unparsed, convert them using pd.to_datetime():

```
>>> df['Date'] = pd.to_datetime(df.Date)
```

- In either case, the resulting dtype is '<M8[ns]', which is a cryptic way of saying that it is a nanosecond-resolution timestamp.

```
>>> df.Date.dtype
dtype('<M8[ns]')
```

Date attribute

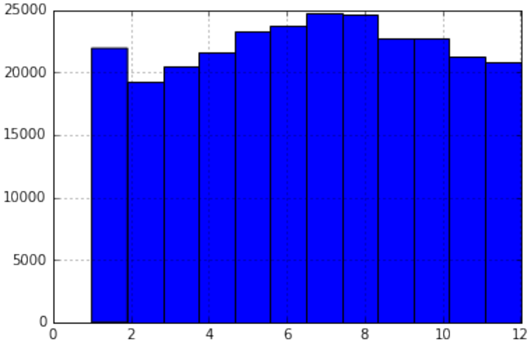
- Similar to strings, we can access the datetime functionality of a datetime column using the `.dt` attribute.
- For example, to get the month of each crime:

```
>>> df.Date.dt.month
266920    12
266921    10
266922    12
266923     8
266924    12
266925     9
266926     8
266927     1
266928    12
266929    12
Name: Date, dtype: int64
```

Month histogram

We could plot a histogram of this:

```
df.Date.dt.month.hist(bins=12)
```



Truncate

To retain only the date part of the datetimes:

```
>>> df.Date.dt.date
...
266917    2017-11-06
266918    2017-12-29
266919    2017-11-30
266920    2017-12-20
266921    2017-10-01
266922    2017-12-23
266923    2017-08-18
266924    2017-12-21
266925    2017-09-20
266926    2017-08-09
266927    2017-01-14
266928    2017-12-15
266929    2017-12-23
Name: Date, dtype: object
```

date.value_counts()

To get a series with index date and value the number of crimes on that date:

```
>>> df.Date.dt.date.value_counts()
...
2017-01-08     588
2017-02-26     574
2017-12-29     564
2017-03-12     550
2017-11-23     542
2017-12-31     540
2017-03-13     539
2017-12-26     522
2017-12-27     513
2017-12-24     500
2017-03-14     466
2017-12-25     393
Name: Date, dtype: int64
```

Time series plot

```
df.Date.dt.date.value_counts().plot(figsize=(12,8))
```