Pandas, SQL, and Data Frames

Data Handling

What are the ways that we have learned so far to handle data?

- Lists of lists
- Dictionaries

Neither of these are particularly conducive to data exploration and quick manipulation

Introducing Data Frames

When we want to manipulate data in a clean and efficient manner, we need to think about data in terms of vectors/columns:

- Each variable can be considered a vector/column
- Operations on a variable can be applied to all observations uniformly
- We can quickly reduce the number of variables for specific questions

Introducing Data Frames

In Python, the `pandas` library contains the necessary code to begin working with Data Frames. It is dependent on many functions in the `numpy` library.

```python
import pandas as pd # Import the library for use
```

Creating a Data Frame

Create an empty Data Frame:

```
data = pd.DataFrame()
```

A Data Frame is an object that accepts the following:

- `data` (optional - can be list of lists, or dictionary)
- `index` (optional - for referencing individual rows)
- `columns` (optional - so you can name your variables)
- `dtype` (optional - specify the **kind** of data for each column/variable)
- `copy` (optional - whether or not the data should be copied)

Creating a Data Frame

We can also use pandas to easily read many types of files, and import them as Data Frames:

```
# CSV
data = pd.read_csv("your_filename_here.csv")
# or Excel Files
data = pd.read_excel("your_filename_here.xlsx")
# or Stata Data
data = pd.read_stata("your_filename_here.dta")
# or SAS Data
data = pd.read_sas("your_filename_here.sas7bdat")
# or SQL Queries
data = pd.read_sql("your_query_here", your_connection_here)
# and many others!
```

Referencing a Single Column

To access a list of all of the column names in your Data Frame:

```
data.columns
```

To extract a single column:

```
data['Column_Name']
```

To extract several columns, pass a list of column names:

```
data[['Column1','Column2']]
```

Slicing the Data Frame

Two selection (or slicing) tools allow us to quickly subset our data.

```
data.iloc[row_selection, column_selection]
```

With the `.iloc` method, we can provide **integer**-based selections, or choose to select all rows or columns, and only subset on a single dimension.

```
data.iloc[:, 0] # Selects all rows, and first column
```

Slicing the Data Frame

Two selection (or slicing) tools allow us to quickly subset our data.

```
data.loc[row_selection, column_selection]
```

With the `.loc` method (now with no `i`), we can provide **name**-based selections, choose to select all rows or columns, and create subsets based on conditions.

```
data.loc[:, 'ColumnName'] # Selects all rows, one column
```

Slicing the Data Frame

We can even provide logical statements to **filter** our data based on some rule that can be evaluated!

```
data.loc[data['Column1'] == some_value, :]
# Selects only the observations (rows) where the
#   condition is met
```

Transforming our Data

We can quickly transform the data in a given column using the slicing techniques from above:

```
# Log the values of a variable
data.loc[:,'Column1'] = np.log(data['Column1'])
```

We can even create new columns on the fly!

```
# Difference two variables
data['newColumn'] = data['Column1'] - data['Column2']
# Because the variable doesn't exist yet, we don't use
#   the .loc syntax here
```

Transforming our Data

We can choose an index from among our columns, instead of the arbitrary ascending numbers assigned by default:

```
data.set_index('transaction_id')
```

Or, we can establish a multi-level index by passing a list of columns:

```
data.set_index(['year', 'month', 'day'])
```

Remember: Indices should be unique values!

Transforming our Data

Processing Datetimes is also easy using built-in Pandas functions:

```
data['myDate'] = pd.to_datetime(data['stringDateColumn'],
  format = '%Y%m%d', # You might need to indicate
  errors = 'ignore') #  the correct format for your data!
```

We can also parse the data into separate columns afterward:

```
data['week'] = data['myDate'].dt.week
data['day'] = data['myDate'].dt.day
```

Date Processing

A full list of the ways you can process dates is available at https://pandas.pydata.org/pandas-docs/stable/user_guide/timeseries.html#time-date-components.

Cleaning Data

There are many operations that are not reasonable to perform with missing data. Any numeric transformation will fail to provide useful output where missing values exist.

```
# Resolve missing values in ALL columns at once
data.fillna(0, inplace = True)
# fills ALL missing values, overwrites original data

# Resolve missing values in single column
data['Column'].fillna(method='pad') # fill values forward
# We can use method 'backfill' to use the NEXT value,
#   and fill backwards
```

Cleaning Data

You can also just drop observations with missing values if that is preferable:

```
data.dropna(inplace=True)
```

Generating Summary Statistics

We use the `describe` funtion to create summary tables easily, and can even export them to csv for use in reports.

```
data.describe()
```

If we want the table presented similar to academic journal formats, we can make a few tweaks:

```
data.describe().T[['count','mean','std','min','max']]
# We need to transpose the data using .T before
#   we can select the descriptive stats we want to keep
# Add a .to_csv('myfile.csv') to that line to save
```

Using SQL with Python

In order to handle data on a large scale, we frequently rely on SQL databases. In this class, we will practice with SQLite.

Here is a link to the documentation:
https://docs.python.org/3/library/sqlite3.html

Using SQL with Python

The first thing we need to do is to establish a connection to our database:

```
import sqlite3
engine = sqlite3.connect('exampleDatabase.db')
```

Note: be sure to change this code to point toward the `exampleDatabase.db` *file on your own computer!*

Retrieve SQL Data with Pandas

Our next step is to write a `SELECT` statement using SQL, and then to pass it to Pandas for retrieval.

```
select = """SELECT hhincome, occ2010, ind1990 FROM
            ACS WHERE year=2016"""

data = pd.read_sql(select, engine)
```

How do we write SQL Queries?

If you want to learn more about SQL, take a look at these slides about writing SQL query code:

https://goo.gl/Lq2yC5

PandaSQL and Data Cleaning

We can actually use SQL to clean our data within Pandas by making use of the `pandasql` library.

Get started by using the following code:

```
from pandasql import sqldf
pysqldf = lambda q: sqldf(q, globals())
```

If it isn't installed, you can install the library by running

```
pip install pandasql
```

Or by using the install function within PyCharm

PandaSQL and Data Cleaning

```
edited_data = pysqldf(select_statement_here)
```

Using SQLite syntax, we can then clean any dataset using the same syntax that we would to extract data from a database!

We can aggregate, create new columns, group, and join across datasets, just like we would with SQL.

Mapping Functions

In order to perform functions across an entire column, we can take advantage of the built in `map` method for pandas Series objects:

```
data = pd.read_csv("https://github.com/dustywhite7/
pythonMikkeli/raw/master/exampleData/footballAttendance.csv")

data['Average Attendance'] = data['Average Attendance'].map(lambda x: x*1000)
```

Use a lambda function to multiply each record's attendance number by 1000

Applying Functions

We can also use the `apply` method to aggregate within a Data Frame by row or column:

```
data[['Average Attendance', 'Year']].apply(lambda x: x.max() - x.min())
```

Calculates the difference between the min and max of the attendance and year columns

Lab Time!