Week 7 - Pandas, SQL

Data Handling

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

- Flat Files
- Numpy arrays
- Lists of lists
- Dictionaries

None 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 want to start thinking about data in terms of vectors:

- Each variable can be considered a vector
- 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.

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 a class that accepts the following:

- data (typically as a numpy array)
- index (if you don't want this to be created for you)
- columns (so you can name your variables)
- dtype (specify the type of data)
- copy (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 then reference a single column:

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

To reference 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

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[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'])

# 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 with built-in Pandas functionality:

```
data['myDate'] = pd.to_datetime(data['stringDateColumn'],
  format = '%Y%m%d', # Need to indicate the correct
  errors = 'ignore') # 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/api.html#datetimelike-properties.

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
```

Generating Summary Statistics

Using 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 add a few arguments:

```
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
```

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

Here is a link to analogous code for many other database types:

http://docs.sqlalchemy.org/en/latest/core/engines.ht

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

```
from sqlalchemy import create_engine
engineStr = 'mysql+mysqlconnector://viewer:'
```

We are using mysql via the mysqlconnector module.

Next, we provide our username:password, which in this case is "viewer," with no password, so we do not enter text after the colon.

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

```
from sqlalchemy import create_engine
engineStr = 'mysql+mysqlconnector://viewer:'
engineStr += '@dadata.cba.edu:3306'
```

We need to direct the connection to our server, which is hosted at dadata.cba.edu, and can be reached through port 3306.

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

```
from sqlalchemy import create_engine
engineStr = 'mysql+mysqlconnector://viewer:' # Connector
engineStr += '@dadata.cba.edu:3306' # Server Address
engineStr += '/ACS' # Database Name
engine = create_engine(engineStr) # Start the Engine
```

Last, we just need to include the database that we wish to access on the server. In this case, we can use



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.

How do we write SQL Queries?

Let's take a look at some 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())
```

PandaSQL and Data Cleaning

edited_data = pysqldf(select_statement_here)

Using SQLite syntax, we can then clean any dataset using the same tools 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.

For Lab

Using SQL, collect variables covering the following information:

- Mortgage Payment
- Income from work
- Education
- Industry/Occupation

Apply the log transformation to the columns containing dollar values. Then, create a variable that takes the value 1 if an individual reports completing at least 4 years of college (BS/BA level). Finally, create a column that takes the value 1 if an individual reports working in a government industry or occupation code.