# Data Science

## Contents

# 1 Introduction to SQL

## 1.1 Relational Database Management System

A **database** is a set of data stored in a computer. This data is usually structured in a way that makes the data easily accessible. A **relational database** is a type of database. It uses a structure that allows us to identify and access data in *relation* to another piece of data in the database. Often, data in a relational database is organized into tables with records (rows) and columns.

A **relational database management system (RDBMS)** is a program that allows you to create, update, and administer a relational database. Most use SQL language to access the database. However, SQL syntax can differ based on which RDBMS you are using.

## 1.2 Data Manipulation in SQL

- A statement always ends in a semicolon **;**

Components of a statement:
1) Clause - perform specific task is SQL, written in capital letters (known as commands)
2) Table name - written in lowercase letters, name of table to apply command to
3) Parameters - list of columns, data types, or values that are passed to a clause as an argument

The **CREATE** statement allows use to create a new table in the database

```sql
CREATE TABLE table_name (
  column1 datatype,
  column2 datatype,
  column3 datatype
);
```

The **INSERT** and **VALUES** statements allows us to add new records (rows) to a table

```sql
-- Insert into columns in order:
INSERT INTO table_name
VALUES (value1, value2);

-- Insert into columns by name:
INSERT INTO table_name (column1, column2)
VALUES (value1, value2);
```

The **SELECT** statements will fetch data from a database (query data from database)

```sql
SELECT column_name FROM table_name;
SELECT * FROM tabe_name; -- all columns from table
```

The **ALTER TABLE** adds a new column(s) to the table (will be initialized to NULL (∅))

```sql
ALTER TABLE table_name
ADD column_name datatype;
```

The **UPDATE** statement allows use to edit existing records

```sql
UPDATE table_name
SET column1 = value1, column2 = value2
WHERE some_column = some_value;
```

The **DELETE FROM** statement deletes one or more rows from a table

```sql
DELETE FROM table_name
WHERE some_column = some_value;
```

**Constraints** add information about how a column can be used are invoked after specifying the data type for a column. They can be used to tell the database to reject inserted data that does not adhere to a certain restriction.

- PRIMARY KEY columns uniquely identify a row, only one per table
- UNIQUE columns have different value for every row, can be multiple per table
- NOT NULL columns must have a value
- DEFAULT columns will pass an assumed value if non specified

```
CREATE TABLE student (
  id INTEGER PRIMARY KEY, -- Can't add another row called ID or any of the values
  name TEXT UNIQUE, -- Can't add same value in name row
  grade INTEGER NOT NULL, -- Can't leave value NULL when adding new grade
  age INTEGER DEFAULT 10 -- Passes given parameter if non given
);
```

## 1.3 Writing Queries

**Queries** allow us to communicate with the database by asking questions and having the result set return data relevant to the question. One of the core purposes of the SQL language is to retrieve information stored in a database.

The **SELECT** statement is used to query data from a database, with * meaning all columns

```
SELECT column1, column2
FROM table_name;
```

The **AS** keyword lets you rename a column or table using an specified alias. However, this doesn't rename the column in the table, only the results outputted

```
SELECT column_name AS 'alias'
FROM table_name;
```

The **DISTINCT** keyword allows us to return only unique values in the output, filtering all duplicates

```
SELECT DISTINCT column_name
FROM table_name;
```

The **WHERE** clause lets us restrict our query results where a condition is true $(=, !=, <, >, <=, >=)$

```
SELECT column_name
FROM table_name
WHERE condition;
```

The **LIKE** is a special operator used with WHERE to search for a specific pattern in a column

- The _ wildcard means substitute any character
- The % wildcard means matching zero or more missing letters in the pattern (not case sensitive)

```
SELECT *
FROM movies
WHERE name LIKE 'Se_en'; -- The _ means any character (return 'Seven' and 'Se7en')
-- WHERE name LIKE 'A%' matches all movies beginning with letter A
-- WHERE name LIKE '%a' matches all movies end with letter a
-- WHERE name LIKE '%man%' matches all movies containing 'man'
```

We can test for NULL values with operates **IS NULL** and **IS NOT NULL** (can't use = or !=)

```
SELECT column_name
FROM table_name
WHERE column_name IS NULL; -- or IS NOT NULL
```

The **BETWEEN** operator is used with WHERE to filter results within a certain range
 - Number ranges include the final value (ex: 1970 AND 1979 includes 1979)
 - Text ranges do not include final value (ex: ‘A’ AND ‘D’ stops before D)

```sql
SELECT *
FROM movies
WHERE year BETWEEN 1990 AND 1999; -- includes 1999
-- WHERE name BETWEEN 'A' AND 'J'; up to, but not including, J
```

The **AND** or **OR** operators to combine multiple conditions in a WHERE clause

```sql
SELECT *
FROM movies
WHERE year BETWEEN 1990 AND 1999
  AND genre = 'romance'; -- both conditions must be true

SELECT *
FROM movies
WHERE year > 2014 OR genre = 'action'; -- either condition is true
```

The **ORDER BY** lets ys sort results (alphabetic or numeric). We can pass the given keywords:
 - DESC to sort results descending (high-low or Z-A)
 - ASC to sort results ascending (low-high or A-Z)

NOTE: If a WHERE clause is present, the ORDER BY goes after

```sql
SELECT column_name
FROM table_name
ORDER BY column_name DESC; -- can also be ASC (ASC is same as blank)
```

The **LIMIT** clause lets you specify the max number of rows the result set will have (at end of query)

```sql
SELECT column_name
FROM table_name
LIMIT num_value; -- replace num_value with an integer
```

The **CASE** statement allows us to create different outputs (SQL’s if-then logic). Each WHEN tests a condition and if true, executes the THEN parameter. ELSE parameter is executed if all WHEN tests are false. Always finish CASE statement with END.

```sql
SELECT name, -- given column name
  CASE
    WHEN genre = 'romance' THEN 'Chill' -- If romance genre then label chill
    WHEN genre = 'comedy' THEN 'Chill' -- if comedy then label chill
    ELSE 'Intense' -- if both above false, then label intense
  END AS 'Mood' -- label column with all results
FROM movies; -- table to read from
```

## 1.4 Aggregate Functions

We will know learn about **aggregates** which are calculations performed on multiple rows of a table.

The **COUNT()** function returns the total number of rows that match the specified criteria (excludes ∅)

```sql
SELECT COUNT(column_name) -- can be *
FROM table_name
WHERE condition; -- this line is optional
```

The **SUM()** function takes a column name as an argument and returns sum of all values in column.

```sql
SELECT SUM(column_name)
FROM table_name;
```

The **MAX()** and **MIN()** functions return the highest and lowest values in a column, respectively.

```sql
SELECT MAX(column_name) -- can also be MIN(column_name)
FROM table_name;
```

The **AVG()** function to quickly calculate the average value of a particular column

```sql
SELECT AVG(column_name)
FROM table_name;
```

The **ROUND()** function takes two parameter, a column name and an integer, and rounds the result

```sql
SELECT ROUND(column_name, integer)
FROM table_name;
```

The **GROUP BY** function arranges identical data into groups (NOTE: comes after FROM or WHERE, but before ORDER BY or LIMIT). We can also use GROUP BY on columns by using integers instead of strings (1 = first column select, 2 = second column selected, ...)

```sql
SELECT price, COUNT(*) -- shows price and count all rows
FROM fake_apps
WHERE downloads > 20000 -- where over 20000 downloads
GROUP BY price; -- sort results by price

SELECT category, price, AVG(downloads)
FROM fake_apps
GROUP BY 1, 2; -- groups by category and price
```

The **HAVING** function filters groups for a query built with aggregate properties (similar to WHERE) NOTE: HAVING always comes after GROUP BY but before ORDER BY and LIMIT

```sql
SELECT price, ROUND(AVG(downloads)), COUNT(*)
FROM fake_apps
GROUP BY price -- group by price
HAVING COUNT(name) > 10; -- filter groups where they must have 10+ apps
```

The **strftime()** function takes two parameters, the format a column name
  - Formats: Click this link to see all the format options

```sql
SELECT timestamp,
strftime('%H', timestamp) -- returns the hour of our timestamp column
FROM hacker_news
GROUP BY 1
LIMIT 20;
```

FROM 'THE MET' PROJECT

```sql
SELECT CASE
    WHEN medium LIKE '%gold%'   THEN 'Gold' -- any art piece with gold in name
    WHEN medium LIKE '%silver%' THEN 'Silver' -- any art piece with silver in name
    ELSE NULL -- all other art pieces are NULL
  END AS 'Bling', -- rename results column as Bling
  COUNT(*) -- part of select statement to count all rows
FROM met
WHERE Bling IS NOT NULL -- discard all non gold/silver pieces
GROUP BY 1 -- group by CASE column
ORDER BY 2 DESC; -- order by number of items (COUNT)
```

## 1.5 Multiple Tables

In order to efficiently store data, we often spread related information across multiple tables.

The **JOIN** function lets us combine tables easily. This simple JOIN is called an *inner join*, and will only include rows that have matching values, but will omit any rows not matching our ON condition.

```
SELECT * -- all columns
FROM orders -- from orders table
JOIN subscriptions -- joined with subscriptions table
  ON orders.subscription_id = subscriptions.subscription_id -- match these columns
WHERE subscriptions.description = 'Fashion Magazine'; -- only for this description
```

The **LEFT JOIN** allows us to combine two tables and keep the unmatched rows we would lose in the inner join (keeps all values from the left table in the FROM statement and fills in missing values in the right table with NULL values)

```
SELECT * -- select all columns
FROM newspaper -- keep all rows from newspaper table
LEFT JOIN online -- join with online table
  ON newspaper.id = online.id -- match these columns
WHERE online.id IS NULL; -- see who subscribes to newspaper but not online
```

A **Primary Key** is a column that uniquely identifies each row of a table. They have a few requirements:
- None of the values can be NULL
- Each value is unique (no 2 rows with same value)
- A table can only have one primary key column

Now, when a primary key for one table appears in a different table, it is a **Foreign Key**. This is important because the most common types of joins will be joining a foreign key from one table to the primary key from another table.

```
SELECT *
FROM classes -- primary key = id
JOIN students -- primary key = id, foreign_key = class id
  ON classes.id = students.class_id; -- join primary key with foreign key
```

The **CROSS JOIN** lets all combine all rows of one table with all rows of another table (think of as finding all possible combinations of the two tables).

```
SELECT month, COUNT(*) AS 'subscribers' -- columns to display
FROM newspaper -- table 1
CROSS JOIN months -- table 2
WHERE start_month <= month AND end_month >= month -- where user was subscribed
GROUP BY month; -- group together results by month
```

The **UNION** operator lets us stack data sets on top of one another, given that thy have the same number of columns and the columns have the same data types.

```
SELECT *
FROM table_name1
UNION
SELECT *
FROM table_name2; -- will put table_name2 below table_name1
```

The **WITH** clause allows us to perform a separate query and store it in a temporary table that we can reference any columns from. We can then join this temporary table with another table

```
WITH previous_query AS ( -- create a temp table
  SELECT customer_id, COUNT(subscription_id) AS 'subscriptions' -- select columns
  FROM orders -- table
  GROUP BY customer_id -- grouped by customer id
) -- end of our temp table query
SELECT customers.customer_name, previous_query.subscriptions -- new col., temp col.
from previous_query -- from temp table
JOIN customers -- inner join with cutomers table
  ON previous_query.customer_id = customers.customer_id; -- if parameters met
```

## 1.6 Usage Funnels

A **funnel** is a marketing model which illustrates the theoretical customer journey towards the purchase of a product or service. Oftentimes, we want to track how many users complete a series of steps and know which steps have the most number of users giving up.

We can **build a funnel from a single table**. Lets count the distinct users who answered each question.

```
SELECT question_text, COUNT(DISTINCT user_id)
FROM survey_responses
GROUP BY 1;
```

We can **compare funnels for A/B tests**. Half of the users view the original control version and half view the new variant version, lets count the control and variant clicks for each modal step

```
SELECT modal_text,
  COUNT(DISTINCT CASE
    WHEN ab_group = 'control' THEN user_id
    END) AS 'control_clicks', -- creat column for control clicks
  COUNT(DISTINCT CASE
    WHEN ab_group = 'variant' THEN user_id
    END) AS 'variant_clicks' -- create column for version clicks
FROM onboarding_modals
GROUP BY 1
ORDER BY 1;
```

We can also **build a funnel from multiple tables**. In the end, we want to see if the conversion rate from checkout to purchase changes as we get closer to Christmas.

```
WITH funnels AS (
  SELECT DISTINCT b.browse_date, -- distinct browse dates
    b.user_id, -- get all user id's
    c.user_id IS NOT NULL AS 'is_checkout', -- 1 if in checkout, 0 if not
    p.user_id IS NOT NULL AS 'is_purchase' -- 1 if purchased, 0 if not
  FROM browse AS 'b' -- rename table browse as b
  LEFT JOIN checkout AS 'c' -- join c with b
    ON c.user_id = b.user_id -- match c user id to b user id
  LEFT JOIN purchase AS 'p' -- join p with bc table
    ON p.user_id = c.user_id) -- match p user id to bc table user id
SELECT browse_date, COUNT(*) AS 'num_browse', -- browse dates, users in browse stage
  SUM(is_checkout) AS 'num_checkout', -- total number in checkout stage
  SUM(is_purchase) AS 'num_purchase', -- total numberin  purchased stage
  1.0 * SUM(is_checkout) / COUNT(user_id) AS 'browse_to_checkout', -- b:c ratio
  1.0 * SUM(is_purchase) / SUM(is_checkout) AS 'checkout_to_purchase' -- c:p ratio
FROM funnels -- from temp table
GROUP BY 1 -- group by browse date
ORDER BY 1; -- order by browse date (ASC)
```

```sql
WITH temp_results AS ( -- create temp table
  SELECT DISTINCT q.user_id,
    ht.user_id IS NOT NULL AS 'is_home_try_on', -- 0 if no glasses, 1 if has glasses
    ht.number_of_pairs, -- 3 pairs, 5 pairs (A/B testing)
    p.user_id IS NOT NULL as 'is_purchase' -- 0 if no purchase, 1 if purchase
  FROM quiz q -- quiz table referenced as q
  LEFT JOIN home_try_on ht
    ON q.user_id = ht.user_id -- where user id's match
  LEFT JOIN purchase p
    ON q.user_id = p.user_id -- where user id's match
  WHERE ht.number_of_pairs IS NOT NULL ) -- customer has either A/B test
SELECT number_of_pairs AS 'Try On Pairs', -- 3 or 4 pairs
  COUNT(*) AS 'Customers', -- total for customers
  SUM(is_purchase) AS 'Purchased Product', -- if customer bought product
  1.0 * SUM(is_purchase) / COUNT(*) AS 'Purchase Rate' -- rate of purchase
FROM temp_results -- from temp table above
GROUP BY 1 -- group by pair type
ORDER BY 4 DESC; -- order by purchase rate
-- We see that 5 pairs purchase rate = 79%, 3 pairs purchase rate = 53%
```

## 1.7 User Churn

**Churn rate** is the percent of subscribers that have canceled within a certain period, usually a month. For a user base to grow, the churn rate must be less than the new subscriber rate for the same period and is calculated by $\frac{cancellations}{total\ subscribers}$.

We can calculate churn for a month from a single table

```sql
SELECT 1.0 * (
  SELECT COUNT(*)
  FROM subscriptions
  WHERE subscription_start < '2017-01-01'
  AND (subscription_end BETWEEN '2017-01-01' AND '2017-01-31')
 ) / (
  SELECT COUNT(*)
  FROM subscriptions
  WHERE subscription_start < '2017-01-01'
  AND ((subscription_end >= '2017-01-01')
    OR (subscription_end IS NULL))
) AS results;
```

# 2 Introduction to Python

## 2.1 Lists

We can use **zip()** to create pairs from multiple lists. However, it returns the location in memory and must be converted back to a **list()** in order to print it.
We can add a single element to a list using **.append()**, which will place at the end of the list.
We can add multiple lists together by using + to concatenate them.

```
last_semester_gradebook = [("politics", 80), ("latin", 96), ("dance", 97),
                           ("architecture", 65)]

subjects = ["physics", "calculus", "poetry", "history"]
grades = [98, 97, 85, 88]
subjects.append("computer science")
grades.append(100)
gradebook = list(zip(subjects,grades)) # combine and cast as a list
gradebook.append(("visual arts", 93)) # append a tuple
print(gradebook)

full_gradebook = gradebook + last_semester_gradebook
print(full_gradebook)
```

We can create an array of integers for a given size by **range()**, which generates starting at a point (0 by default) to the (input value - 1). However, you must convert it to a list since it returns on object.

```
my_list = range(9) # values 0 to 8
my_list_2 = range(5, 15, 3) # start at 5, end at 14, increment by 3
print(list(my_list_2)) # [5, 8, 11, 14]
```

We can select a section of a list by using syntax array[start:stop], called **slicing**.

```
suitcase = ['shirt', 'shirt', 'pants', 'pants', 'pajamas', 'books']
start = suitcase[:3] # same as suitcase[0:3]
end = suitcase[-2:] # gets last 2 elements of suitcase
```

We can count how many times an element appears in a list with **.count()**

```
votes = ['Jake', 'Jake', 'Laurie', 'Laurie', 'Laurie', 'Jake']
jake_votes = votes.count('Jake')
print(jake_votes)
```

We can sort a list alphabetically or numerically with **.sort()** - only alters a list, doesn't return a value
We can use **sorted()** to also sort a list, but it will not affect the original list (returns sorted copy)

```
games = ['Portal', 'Minecraft', 'Pacman', 'Tetris', 'The Sims', 'Pokemon']

games_sorted = sorted(games)
print(games) # in same order as above
print(games_sorted) # new list of sorted games

games.sort()
print(games) # now the games list is also sorted
```

**Tuples** are immutable (can't change any values after creating) and are denoted with ( )
We use tuples to store data that belongs together and don't need order or size to change

```
my_info = ('Derek', 22, 'Student')
name, age, occupation = my_info # will assign each value to a varaible

one_element_tuple = (4,) # NOTE: we need the , after 4 otherwise it wont be a tuple
one_element_tuple_2 = (4) # same as one_element_tuple_2 = 4
```

## 2.2 Loops

We can use **for** loops to iterate through each item in a list, with the following general formula
- We can use range() to execute a for loop from start (0 by default) to stop (n-1)
- We can use *break* to exit a for loop when a certain value is found
- We can use *continue* to move to the next index in a list if a condition is found

If we have a list made of multiple lists, we use **nested** loops to iterate through them

```python
sales_data = [[12, 17, 22], [2, 10, 3], [5, 12, 13]]
scoops_sold = 0

for location in sales_data: # for each list in list
  for sales in location: # for each element in inner list
    scoops_sold += sales

print(scoops_sold)
```

We can use **list comprehension** to efficiently iterate through a list instead of a for loop
We can also use this to alter values in a list and create a new list

```python
heights = [161, 164, 156, 144, 158, 170, 163, 163, 157] # in cm's

can_ride_coaster = [cm for cm in heights if cm > 161]
print(can_ride_coaster) # [164, 170, 163, 163]

celsius = [0, 10, 15, 32, -5, 27, 3] # degrees in C

fahrenheit = [f_temp * (9/5) + 32 for f_temp in celsius] # convert C to F degrees
print(fahrenheit) # [32.0, 50.0, 59.0, 89.6, 23.0, 80.6, 37.4]
```

## 2.3 List Comprehension / Lambda Functions

We can iterate through lists within lists with the following syntax

```python
nested_lists = [[4, 8], [15, 16], [23, 42]]

product = [(val1 * val2) for (val1, val2) in nested_lists]
print(product) # [32, 240, 966]

greater_than = [ (val1 > val2) for (val1, val2) in nested_lists]
print(greater_than) # [False, False, False]
```

We can iterate through two lists in one list comprehension by using the zip() function.

```python
x_values_1 = [2*index for index in range(5)] # [0.0, 2.0, 4.0, 6.0, 8.0]
x_values_2 = [2*index + 0.8 for index in range(5)] # [0.8, 2.8, 4.8, 6.8, 8.8]

x_values_midpoints = [(x1 + x2)/2.0 for (x1, x2) in zip(x_values_1, x_values_2)]
# [0.4, 2.4, 4.4, 6.4, 8.4]

names = ["Jon", "Arya", "Ned"]
ages = [14, 9, 35]

users = ["Name: " + n + ", Age: " + str(a) for (n,a) in zip(names,ages)]
print(users) # ['Name: Jon, Age: 14', 'Name: Arya, Age: 9', 'Name: Ned, Age: 35']
```

A lambda function is a one-line shorthand for a simple function. It allows us to efficiently run an expression and produce an output for a specific task, such as defining a column in a table, or populating information in a dictionary. It has the following format:
*variableName* = lambda *parameters* : *return value*

We can also use an if... else... loops within a lambda function with the following format:
(RETURN IF STATEMENT IS TRUE) if (STATEMENT) else (RETURN IF STATEMENT IS FALSE)

```python
even_or_odd = lambda num : "even" if (num%2 == 0) else "odd"

print even_or_odd(10) # even
print even_or_odd(5) # odd

import random as r
add_random = lambda num : num + r.randint(1,10) # add random int from 1 to 10 to num

print add_random(5)
print add_random(100)
```

# 3 Data Analysis with Pandas

## 3.1 Introduction to Pandas

You can pass a **dictionary** into a DataFrame, where each key is a column name and each value is a list of column values (rows). Note that column lengths must all be the same length or you will get an error.

```python
import pandas as pd

df1 = pd.DataFrame({
  'Product ID': [1, 2, 3, 4],
  'Product Name' : ['t-shirt', 't-shirt', 'skirt', 'skirt'],
  'Color' : ['blue', 'green', 'red', 'black']
})
```

You can also pass a **list of lists**, where each inner list represents a row of data. You must also add the keyword 'columns=' at the end to pass a list of column names.

```python
df = pd.DataFrame([
  ['January', 100, 100, 23, 100],
  ['February', 51, 45, 145, 45],
  ['March', 81, 96, 65, 96],
  ['April', 80, 80, 54, 180],
  ['May', 51, 54, 54, 154],
  ['June', 112, 109, 79, 129]],
  columns=['month', 'clinic_east', 'clinic_north', 'clinic_south', 'clinic_west'])
```

We can access a **CSV** (comma separated values) from within pandas. We can get CSV's from online data sets, export from Excel, and export from SQL (assume we read a CSV into a variable df).
- We can load a CSV file with pd.read_csv('filename.csv')
- We can save data to a CSV with df.to_csv('newFilename.csv')
- The df.head(n) method gives the first n rows of a dataFrame (5 is no n given)
- The df.info() method gives statistics about each column (data types, etc.)

We can access **specific columns** from a DataFrame by using df[‘columnName’] or df.columnName (we use the second option of the column has no spaces or special characters). This call will return a Series.
- We can access **multiple columns** by passing a list of column names as the parameter. Note that this will return a DataFrame data type, not a Series.

```
# use df from above (list of lists example)
clinic_north = df.clinic_north # same as df['clinic_north']
print(type(clinic_north)) # pandas.core.frame.Series

clinic_north_south = df[['clinic_north', 'clinic_south']]
print(type(clinic_north_south)) # pandas.core.frame.DataFrame
```

We can access **specific rows** that are *indexed numerically* by using the df.iloc[n] function for any n in our rows. Note that this will also return a Series data type.
- We can access **multiple rows** by using splicing on our .iloc[ ] call

```
march = df.iloc[2] # gives us all column values for March row
april_may_june = df.iloc[3:7] # gives row 3 to 6 and all corresponding column values
# note that we can also splice from the end using negative numbers
```

We can create **subsets** of a DataFrame by using logical statements
- We can combine multiple logical statements with ( ) - We can use the .isin( ) function to see if a value is in a column

```
january = df[df.month == 'January'] # gives all row values if column value is January

march_april = df[(df.month == 'March') | (df.month == 'April')]
# the above call will gives all row values where month column is March or April

jan_feb_mar = df[df.month.isin(['January', 'February', 'March'])]
# the above call gives all row values if the .isin parameters are in the month column
```

When we select a subset of a DataFrame using logic, we get non-consecutive indices and is hard to use .iloc[ ] but we can **change indices** by using .reset_index( ) to change.
- This function also puts old indices in a new column, to avoid this use keyword drop=True
- This function will also return a new DataFrame, but to modify our existing use inplace=True

```
df2 = df.loc[[1, 3, 5]] # indices are 1, 3, and 5
df2.reset_index(inplace=True, drop=True) # reset to 0,1,2 and drop old indices column
```

## 3.2 Modifying DataFrames

We can **add a column** to an existing DataFrame (new information or calculations from data we already have) by giving a list the *same length* as the existing DataFrame. We can do this a few ways.

```
# Add a new column to a DataFrame (assume there are 4 rows)
df['Sold in Bulk?'] = ['Yes', 'Yes', 'No', 'No']

# We can also set an entire column to the same value for every row
df['Is taxed?'] = 'Yes' # create a new column with 'Yes' in each row

# lets calculate the difference between 2 columns and create a new column from result
df['Margin'] = df.Price - df['Cost to Manufacture']
#note the difference in calls to the columns due to spaces in column name
```

We can use the **apply()** function to apply a function to every value in a particular column

```
from string import lower

df['Lowercase Name'] = df.Name.apply(lower)
# create a new column from the Name column and apply the lowercase function to it
```

We can use the **lambda** function to perform complex operations on columns or rows.

- To operate on **multiple columns** at once we don't specify a particular column and add the argument axis=1 (making the input to our lambda an entire row and not a column).
- To access a particular value of a row, use row.column_name or row['column_name']

```
# Apply lambda to a column
df = pd.read_csv('employees.csv')
get_last_name = lambda x : x.split(' ')[-1]  # split on space & return end of string

df['last_name'] = df.name.apply(get_last_name)

# Apply plambda to a row (calculate hourly wage)
total_earned = lambda row: (row.hourly_wage * 40) + ((row.hourly_wage * 1.5) * \
(row.hours_worked - 40)) if row.hours_worked > 40 \
else row.hourly_wage * row.hours_worked

df['total_earned'] = df.apply(total_earned, axis = 1)
```

We can **rename** columns so that they are easier to access or read. We can do this a few ways.

- To change **all** column names by using df.columns = [ ] (be sure to correctly labeled).
- To change **individual** column names, use the .rename() method and pass a dictionary. Note that using the rename function with only the column keyword creates a new DataFrame, so use keyword inplace=True to edit original.

```
df = pd.read_csv('imdb.csv')

# we can rename all columns in the DataFrame at once (not the preferable method)
df.columns = ['ID', 'Title', 'Category', 'Year Released', 'Rating']

# we can rename single or multiple columns by passing a dictionary to rename
df.rename(columns={
  'name' : 'movie_title'},
  inplace=True)
# notice the key is the old column name, and the value is new column name
```

Review

```
inventory = pd.read_csv('inventory.csv') # read in csv
# select all rows where location is Staten Island
staten_island = inventory[inventory.location == 'Staten Island']
# get all product descriptions for staten island
product_request = staten_island.product_description
# get all rows where location is Brooklyn and product type is seeds
seed_request = inventory[(inventory.location == 'Brooklyn') &
                         (inventory.product_type == 'seeds')]

in_stock_lambda = lambda x : True if x > 0 else False
# use lambda function to create new column if item is in stock based on quantity
inventory['in_stock'] = inventory.quantity.apply(in_stock_lambda)
# create new column for price * quantity
inventory['total_value'] = inventory.price * inventory.quantity

combine_lam = lambda row: '{} - {}'.format(row.product_type, row.product_description)
# use lambda to create a new column for product type and description in one
inventory['full_description'] = inventory.apply(combine_lam, axis=1)
```

## 3.3 Aggregate Functions

NOTE: We will be working with the **orders = pd.read_csv('orders.csv')** DataFrame for examples

We can combine all values from a column to find a single calculation (**column statistics**)

- General syntax is df.column_name.command()
- Common commands: mean, median, max, min, std, count, unique (returns list), nunique (number)

```
most_expensive = orders.price.max() # max value in price column

num_colors = orders.shoe_color.nunique() # number of unique shoes colors
```

When we have a bunch of data, we often want to calculate **aggregate statistics** (mean, standard deviation, median, percentiles, etc.) over certain subsets of the data. Note that groupby creates a *Series*.

- General syntax is df.groupby('column1').column2.measurement()
- Since .groupby( ) returns a Series, use .reset_index( ) to convert back to DataFrame
- We also should rename columns that we perform measurements on with .rename( )

```
# calculate the most expensive shoes for each shoe type
pricey_shoes = orders.groupby('shoe_type').price.max()

# do the same as above, but convert back to DataFrame and rename column
pricey_shoes = orders.groupby('shoe_type').price.max().reset_index()
pricey_shoes = pricey_shoes.rename(columns={'price':'max_price'})
```

We can perform more **complicated aggregate functions** using the .apply( ) method with lambda

- We can calculate the percentile (point at which a given amount are below and the others are above) and we can do this by using NumPy's .percentile( ) function

```
import numpy as np

#calculate the 25th percentile for shoe color and rename the column
cheap_lambda = lambda x : np.percentile(x, 25)
cheap_shoes = orders.groupby('shoe_color').price.apply(cheap_lambda).reset_index()
cheap_shoes = cheap_shoes.rename(columns={'price':'25th percentile for shoe price'})
```

We can **group by multiple columns** by passing a list of column names to the groupby( ) method

- Note: When using .count( ) it doesn't matter which column we perform it on (same answer for all)

```
# Create a DataFrame with the total number for each shoe type / color combination
shoe_counts = orders.groupby(['shoe_type', 'shoe_color']).id.count().reset_index()
shoe_counts = shoe_counts.rename(columns={'id':'count'})
```

We can reorganize a table in a way called **pivoting** that creates a new pivot table (click for visual)

- df.pivot(columns='ColumnToPivot', index='ColumnToBeRows', values='ColumnToBeValues')

```
unpivoted = orders.groupby(['shoe_type', 'shoe_color']).id.count().reset_index()

pivoted = unpivoted.pivot(columns = 'shoe_color', index = 'shoe_type',
                          values = 'id').reset_index()
```

```python
ad_clicks = pd.read_csv('ad_clicks.csv') # read in csv

# see how many views came from each utm source (platform)
view_count = ad_clicks.groupby('utm_source').user_id.count().reset_index()

# create new column that tells us if an ad was clicked or not
ad_clicks['is_click'] = ad_clicks.ad_click_timestamp.isnull()

# see how many people click on ads for each utm source
c_srce = ad_clicks.groupby(['utm_source', 'is_click']).user_id.count().reset_index()

# pivot the data so it is more readable
clicks_pivot = c_srce.pivot(columns = 'is_click', index = 'utm_source',
                            values = 'user_id').reset_index()

# calculate the percent clicked for each group
clicks_pivot['percent_clicked'] = clicks_pivot[True] / (clicks_pivot[True] +
                                  clicks_pivot[False])

# see if more people clicked the ads from group A or group B (use pivot table)
a_or_b = ad_clicks.groupby(['experimental_group', 'is_click']).user_id.count().
         reset_index()
ab_pivot = a_or_b.pivot(columns = 'is_click', index = 'experimental_group',
                        values = 'user_id').reset_index()

print(ab_pivot) # more clicked on B

# create two data frames that contain results from only A group or B group
a_clicks = ad_clicks[ad_clicks.experimental_group == 'A']
b_clicks = ad_clicks[ad_clicks.experimental_group == 'B']

# calculate the percent of users who clicked on ads for each day
a_day = a_clicks.groupby(['day', 'is_click']).user_id.count().reset_index()
a_pivot = a_day.pivot(columns = 'is_click', index = 'day',
                      values = 'user_id').reset_index()
a_pivot['percent_clicked'] = a_pivot[True] / (a_pivot[True] + a_pivot[False])

# calculate the percent of users who clicked on ads for each day
b_day = b_clicks.groupby(['day', 'is_click']).user_id.count().reset_index()
b_pivot = b_day.pivot(columns = 'is_click', index = 'day',
                      values = 'user_id').reset_index()
b_pivot['percent_clicked'] = b_pivot[True] / (b_pivot[True] + b_pivot[False])


print(a_pivot)
print(a_pivot.percent_clicked.mean()) # 0.6246
print(b_pivot)
print(b_pivot.percent_clicked.mean()) # 0.6917
# Ad B performed bettter and maintained a higher average click percentage
```

NOTES:

- percent_clicked column was calculated by clicks_pivot[True] being the number of people who clicked (is_click was True for those users) and clicks_pivot[False] being the number of people who didn't clicked (is_click was False for those users).

- click here for a GitHub link to the 'ad_click.csv' file to run on your computer and see printed tables.

## 3.4 Multiple DataFrames

In order to efficiently store data we often spread related information across multiple tables. For this section, we will be using the following three tables with the given columns:
- orders: order_id, customer_id, product_id, quantity, and timestamp
- products: product_id, product_description and product_price
- customers: customer_id, customer_name, customer_address, and customer_phone_number

**Inner Merge:**

We often have data from one table that corresponds to another table, and we can match entire tables with the .merge( ) method. This looks for columns that are common between two DataFrames and matches value's that are equal. It combines the matching rows into a single row in a new table.
 - Note: Each DataFrame has its own merge method (use when combining multiple tables).

```
# match up all of the customer information to the orders that each customer made
new_df = pd.merge(orders, customers)
# same as new_df = orders.merge(customers)

# merge orders to customers, then merge resulting dataframe to products
big_df = orders.merge(customers).merge(products)
```

We won't always have matching column names to perform a merge on. However, one way that we can **merge on specific columns** by using the .rename method to have a common column to merge on. Option two is to pass the following keywords into the merge( ) method:
 - left_on : the column from the table that comes first in the merge
 - right_on : the column that comes from the second table in the merge
 - suffices : added onto any overlapping columns (pass in order of tables)

```
# merge orders and products on their corresponding id's
orders_products = pd.merge(orders, products, left_on='product_id', right_on='id',
                           suffixes=['_orders', '_products'])
# Note that the default suffix will be _x and _y if no parameters passed in
```

**Outer Merge:**

When we have two DataFrames whose rows don't match perfectly we can lose them with an inner merge. Instead we can do an outer join to combine the data without losing the non-matching rows (fills musing values with None or nan). We can do this by passing the keyword how="outer".

```
# merge orders and products without losing rows
outer_join = pd.merge(orders, products, how="outer)
```

**Left and Right Merge:**

A left merge includes all rows from first table but only rows from the second table that match the first. A right merge includes all rows from the second table but only rows from the first that match the second. We can do these by passing the keyword how " " (note: it fills the missing values in with None or nan).

```
store_a_b_outer = pd.merge(store_a, store_b, how = 'outer') # 11 products total
# find out which products are carried by a given store and missing from the other
store_a_b_left = pd.merge(store_a, store_b, how="left") # store b missing 3
store_a_b_right = pd.merge(store_a, store_b, how ="right") # store a missing 3
```

**Concatenate DataFrames:**

A dataset is sometimes broken into multiple tables but they have the exact same columns. If this is true, we can reconstruct a single DataFrame using the method pd.concat([df1, df2, ...]). (think of as stacking).

```
bakery = pd.read_csv('bakery.csv')
ice_cream = pd.read_csv('ice_cream.csv')
# both tables contain only the 'item' and 'price' columns (combine to one dataframe)
menu = pd.concat([bakery, ice_cream]) # put ice_cream table below bakery table
```

PAGE VISIT FUNNEL PROJECT

```python
import pandas as pd

# read in csv files
visits = pd.read_csv('visits.csv', parse_dates=[1])
cart = pd.read_csv('cart.csv', parse_dates=[1])
checkout = pd.read_csv('checkout.csv', parse_dates=[1])
purchase = pd.read_csv('purchase.csv', parse_dates=[1])

# What percent of users ended up NOT placing a shirt in their cart?
visits_cart_left = pd.merge(visits, cart, how='left')
visits_cart_len = len(visits_cart_left)
print(visits_cart_len) #2052 rows in dataframe

null_cart_time = len(visits_cart_left[visits_cart_left.cart_time.isnull()])
print(null_cart_time) #1652 null rows in cart_time column

not_in_cart = float(null_cart_time) / visits_cart_len
print(not_in_cart) # 80.5% didn't place a tshirt in cart

# What percent of users put items in their cart, but did NOT proceed to checkout?
cart_checkout_left = pd.merge(cart, checkout, how="left")
cart_checkout_len = len(cart_checkout_left)
print(cart_checkout_len) # 602 rows in dataframe

checkout_null = len(cart_checkout_left[cart_checkout_left.checkout_time.isnull()])
print(checkout_null) # 126 null rows in checkout_time column

no_checkout = float(checkout_null) / cart_checkout_len
print(no_checkout) # 20.93% didn't proceed to checkout

# Merge all four steps of the funnel in order
all_data = visits.merge(cart, how="left").merge(checkout, how="left").
           merge(purchase, how="left")
print(all_data)

# What percent of users proceeded to checkout, but did NOT purchase a shirt?
checkout_purchase_left = pd.merge(checkout, purchase, how="left")
checkout_purchase_len = len(checkout_purchase_left)
null_purchase = len(checkout_purchase_left[checkout_purchase_left.purchase_time.
                isnull()])
no_purchase = float(null_purchase) / checkout_purchase_len
# 16.89% didn't purchase from checkout

# Weakest step is placing a shirt in the cart (80.5% don't place a shirt in cart)

# What is the average time from visiting the webstire to purchase?
all_data['time_to_purchase'] = all_data.purchase_time-all_data.visit_time
print(all_data.time_to_purchase)
print(all_data.time_to_purchase.mean()) # 44:02 average purchase time
```

# 4 Data Visualization

## 4.1 Introduction to Matplotlib

We will use 'from matplotlib import pyplot as plt' for this section.

We can create **simple line graphs** by using the .plot( ) and .show( ) methods and passing x/y values
- Note: We can create multiple lines on the graph by calling plot( ) more than once before show( )
- By default, the first line is blue and the second line will be orange

```
time = [0, 1, 2, 3, 4]
revenue = [200, 400, 650, 800, 850]
costs = [150, 500, 550, 550, 560]

plt.plot(time, revenue) # revenue vs. time
plt.plot(time, costs) # costs vs. time
plt.show() # display both lines in one graph
```

We can change the **linestyles** of our graphs with different colors, markers, and line types.
- We can change the style for any of these (click for options): line color, line style, or marker.

```
# using the same lists as above

plt.plot(time, revenue, color='purple', linestyle='--') # purple dotted line
plt.plot(time, costs, color='#82edc9', marker='s') # teal line, square at each point
plt.show() # display both lines in one graph
```

We can **change the range** displayed on our graph by using the .axis( ) method and passing a list.
- We pass the parameters for min/max x value and min/max y value four our graph.

```
x = range(12)
y = [3000, 3005, 3010, 2900, 2950, 3050, 3000, 3100, 2980, 2980, 2920, 3010]

plt.plot(x, y) # plot the line
plt.axis([0,12,2900,3100]) # x-range: 0-12, y-range: 2900, 3100
plt.show() # display the graph with given range
```

We can add **labels** to our graphs by using the .xlabel( ), .ylabel( ), and .title( ) and passing a string.

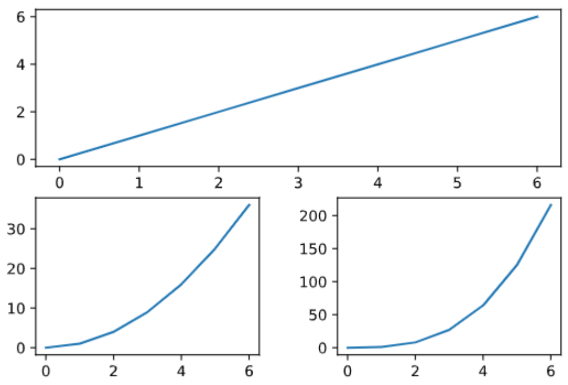
```
#using same x and y from above example

plt.plot(x, y)
plt.axis([0, 12, 2900, 3100]) # range
plt.xlabel('Time') # x-axis label
plt.ylabel('Dollars spent on coffee') # y-axis label
plt.title('My Last Twelve Years of Coffee Drinking') # title
plt.show() # display graphs with labels/title
```

We can display multiple graphs **side-by-side** in a subplot (where each picture that contains all the subplots is called a figure). Using the .subplot( ) method we pass the number of rows, columns, and the index of where to create it.

```
months = range(12)
temperature = [36, 36, 39, 52, 61, 72, 77, 75, 68, 57, 48, 48]
flights_to_hawaii = [1200, 1300, 1100, 1450, 850, 750, 400, 450, 400, 860, 990, 1000]

plt.subplot(1,2,1) # Create subplot of size 1 row, 2 column, at position 1
plt.plot(months, temperature) # plot to be placed at position 1

plt.subplot(1,2,2) # Using subplot of 1 row, 2 column, at position 2
plt.plot(temperature, flights_to_hawaii, "o") # plot scatterplot at position 2
plt.show() # display graphs side-by-side
```

For our subplots, we can **adjust spacing** between them by using .subplots_adjust( ) (click for keywords)

```python
x = range(7)
straight_line = [0, 1, 2, 3, 4, 5, 6]
parabola = [0, 1, 4, 9, 16, 25, 36]
cubic = [0, 1, 8, 27, 64, 125, 216]

plt.subplot(2,1,1) # 2 rows, 1 column, 1st pos
plt.plot(x, straight_line)

plt.subplot(2,2,3) # 2 rows, 2 columns, 3rd pos
plt.plot(x, parabola)

plt.subplot(2,2,4) # 2 rows, 2 columns, 4th pos
plt.plot(x, cubic)

plt.subplots_adjust(wspace= 0.35, bottom = 0.2)
plt.show()
```

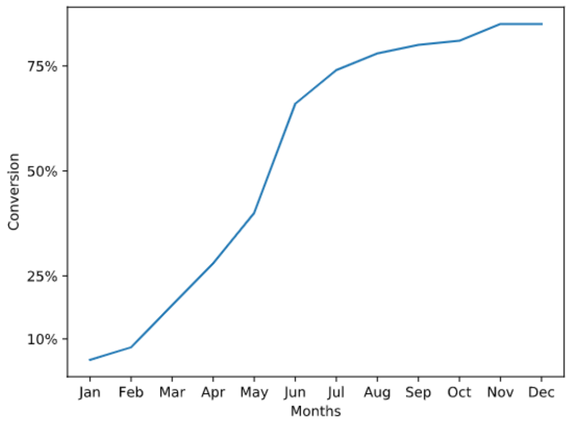


We can add a **legend** to our graph, be either passing a list of strings to the .legend( ) method or passing the keywords label=“ ” to the .plot method and then calling plt.legend( ) afterwards with no parameters.

```python
months = range(12)
hyrule = [63, 65, 68, 70, 72, 72, 73, 74, 71, 70, 68, 64]
kakariko = [52, 52, 53, 68, 73, 74, 74, 76, 71, 62, 58, 54]

plt.plot(months, hyrule) # could also pass label="Hyrule"
plt.plot(months, kakariko) # could also pass label="Kakariko"

plt.legend(["Hyrule", "Kakariko"], loc=8) # default loc is 'best position'

plt.show()
```

We can **modify tick marks** by creating an axes object and modifying the axes of that specific subplot.

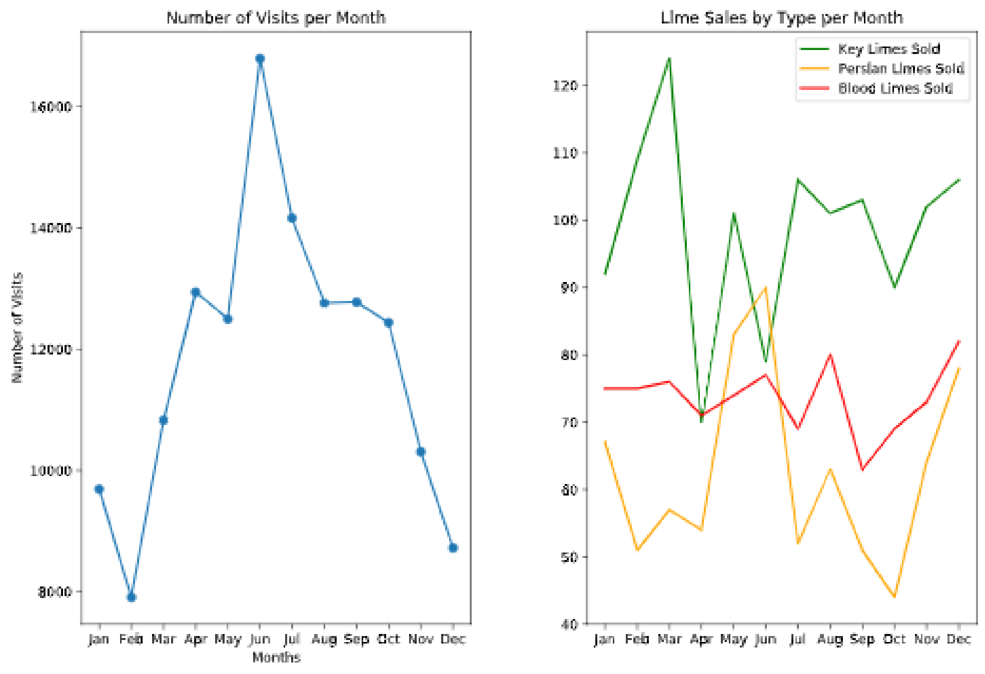
```python
month_names = ["Jan", "Feb", "Mar", "Apr",
               "May", "Jun", "Jul", "Aug",
               "Sep","Oct", "Nov", "Dec"]

months = range(12)
conversion = [0.05, 0.08, 0.18, 0.28, 0.4, 0.66,
              0.74, 0.78, 0.8, 0.81, 0.85, 0.85]

plt.xlabel("Months")
plt.ylabel("Conversion")

plt.plot(months, conversion)

ax = plt.subplot() # create axes object
ax.set_xticks(months) # set x ticks to months
ax.set_xticklabels(month_names) # string labels
ax.set_yticks([0.10, 0.25, 0.5, 0.75])
ax.set_yticklabels(["10%", "25%", "50%", "75%"])

plt.show()
```



We can create **figures** and save them to an output file on our system using the following commands.

```python
plt.close('all') # clear all existing plots before new one is plotted
plt.figure(figsize=(7,3)) # creat a figure with width = 7in, height = 3in
plt.plot(years, power_generated) # plot our data (instead of showing, save to file)
plt.savefig('power_generated.png') # can also save as .pdf or .svg
```

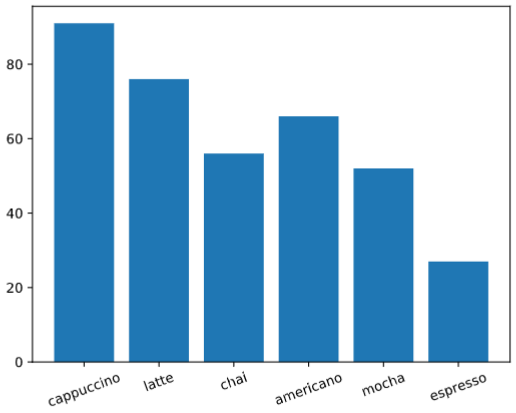
```python
months = ["Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct",
          "Nov", "Dec"]

visits_per_month = [9695, 7909, 10831, 12942, 12495, 16794, 14161, 12762,
                    12777, 12439, 10309, 8724]

# numbers of limes of different species sold each month
key_limes_per_month = [92.0, 109.0, 124.0, 70.0, 101.0, 79.0, 106.0, 101.0,
                       103.0, 90.0, 102.0, 106.0]
persian_limes_per_month = [67.0, 51.0, 57.0, 54.0, 83.0, 90.0, 52.0, 63.0,
                           51.0, 44.0, 64.0, 78.0]
blood_limes_per_month = [75.0, 75.0, 76.0, 71.0, 74.0, 77.0, 69.0, 80.0,
                         63.0, 69.0, 73.0, 82.0]

plt.figure(figsize=(12,8)) # create new figure
ax1 = plt.subplot(1,2,1) # axes object for left plot
x_values = range(len(months))
plt.plot(x_values, visits_per_month, marker='o')
plt.xlabel("Months")
plt.ylabel("Number of Visits")
ax1.set_xticks(x_values)
ax1.set_xticklabels(months)
plt.title("Number of Visits per Month")

ax2 = plt.subplot(1,2,2) # axes object for right plot
plt.plot(x_values, key_limes_per_month, color='green', label='Key Limes')
plt.plot(x_values, persian_limes_per_month, color='orange', label='Persian Limes')
plt.plot(x_values, blood_limes_per_month, color='red', label='Blood Limes')
plt.legend()
ax2.set_xticks(x_values)
ax2.set_xticklabels(months)
plt.title("Lime Sales by Type per Month")

plt.subplots_adjust(wspace=0.3)
plt.savefig("LimeGraphComparison.png")
plt.show()
```



## 4.2 Different Plot Types & Error

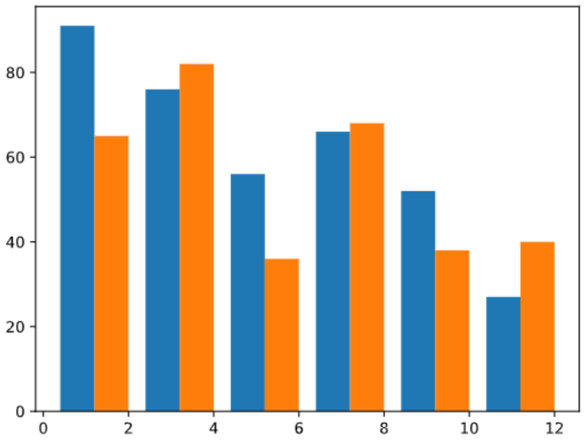
We can create **simple bar charts** to compare multiple categories of data with the plt.bar( ) function.
 - Note: We want our x to have the same number of elements as y, often we use range(len(y_value))

```python
drinks = ["cappuccino", "latte", "chai",
"americano", "mocha", "espresso"]
sales =  [91, 76, 56, 66, 52, 27]
# create bar graph
plt.bar(range(len(drinks)), sales)
# create axes object
ax = plt.subplot()
ax.set_xticks(range(len(drinks)))
# label each x to corresponding drinks
ax.set_xticklabels(drinks, rotation=20)
plt.show()
```



We can use **side-by-side bar charts** to compare two sets of data with the same types of axis values. We must generate the x-axis values using list comprehension (same formula every time).

```python
drinks = ["cappuccino", "latte", "chai",
          "americano", "mocha", "espresso"]
sales1 =  [91, 76, 56, 66, 52, 27]
sales2 = [65, 82, 36, 68, 38, 40]

n = 1  # Current dataset number
t = 2 # Number of datasets
d = 6 # Number of sets of bars
w = 0.8 # Width of each bar
store1_x = [t*element + w*n for element in
            range(d)]

n=2 # 2nd dataset number (use prev. t,d,w)
store2_x = [t*element + w*n for element in
            range(d)]

plt.bar(store1_x, sales1) #plot first bar
plt.bar(store2_x, sales2) # plot 2nd bar
plt.show() # display graph
```



We can use **stacked bar charts** to compare two data sets while preserving the total between them. We do this by plotting the first graph, then passing the keyword ‘bottom=’ for the 2nd graph to be on top. Click here for visual of graph style.

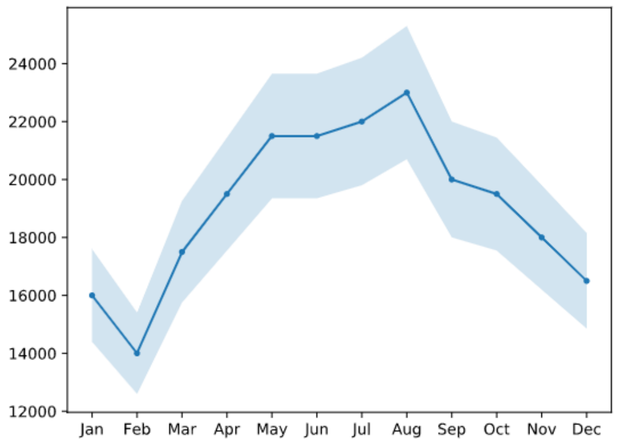
```python
# use datasets from above: drinks, sales1, sales2

plt.bar(range(len(drinks)), sales1, label='Location 1')
plt.bar(range(len(drinks)), sales2, bottom=sales1, label='Location 2')
plt.legend()
plt.show()
```

We can visually represent uncertainty in our graph through using **error bars**, by passing the keywords ‘yerr’ and ‘capsize’ to the plt.bar( ) function. Note that you can change the error for each y-value by passing a list to yerr. (Click above link in stacked bar chart section to see example of yerr).

```python
drinks = ["cappuccino", "latte", "chai", "americano", "mocha", "espresso"]
ounces_of_milk = [6, 9, 4, 0, 9, 0]
error = [0.6, 0.9, 0.4, 0, 0.9, 0]

plt.bar(range(len(drinks)), ounces_of_milk, yerr=error, capsize=5)
plt.show()
```

Just like in bar charts, we can represent **error in line graphs** by using the .fill_between( ) method and passing x-values, lower y bounds, upper y bounds, and alpha. We also must use list comprehension to calculate the upper/lower y bounds from the original y-values. (note: alpha changes error transparency).

```
months = range(12)
month_names = ["Jan", "Feb", "Mar", "Apr",
               "May", "Jun", "Jul", "Aug",
               "Sep", "Oct", "Nov", "Dec"]
revenue = [16000, 14000, 17500, 19500,
           21500, 21500, 22000, 23000,
           20000, 19500, 18000, 16500]

y_lower = [0.9*i for i in revenue]
y_upper = [1.1*i for i in revenue]

ax = plt.subplot()
plt.fill_between(months, y_lower, y_upper,
                 alpha=0.2)
plt.plot(months, revenue, marker=".")
ax.set_xticks(months)
ax.set_xticklabels(month_names)
plt.show()
```



We can use **pie charts** to display elements of a data set as proportions of a whole by using plt.pie( ). Note that it will be tilted and we don't want this, so we must past plt.axis("equal") to flatten. Labeling a pie chart can be done in two different ways:

- Use plt.legend( ) to create a color coded legend for each slice
- Pass the keyword *labels=*' ' to plt.pie( ) to add labels on each slice

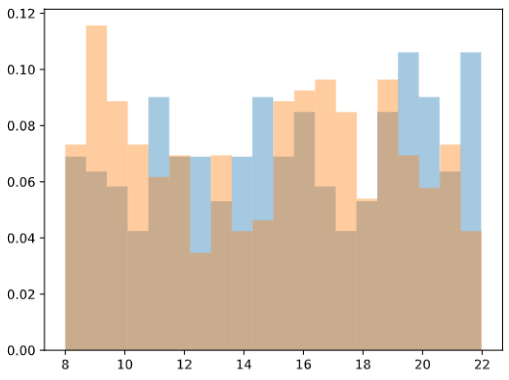
We can also add the percent to the pie chart by passing the keyword autopct=' ' to the plt.pie( ) function

```
payment_method_names = ["Card Swipe", "Cash", "Apple Pay", "Other"]
payment_method_freqs = [270, 77, 32, 11]

plt.pie(payment_method_freqs, autopct='%0.1f%%') # percent to 1 decimal place with %
  sign
plt.axis('equal') # flatten our pie chart
plt.legend(payment_method_names) # create color coded legend for graph
plt.show()
```

We can create **histograms** to find a more intuitive sense for a dataset and see how many values fall in between a certain range. We do this by calling plt.hist( ). Note that we can also compare two different distribution by plotting multiple histograms, but we need to know a few keywords for this:

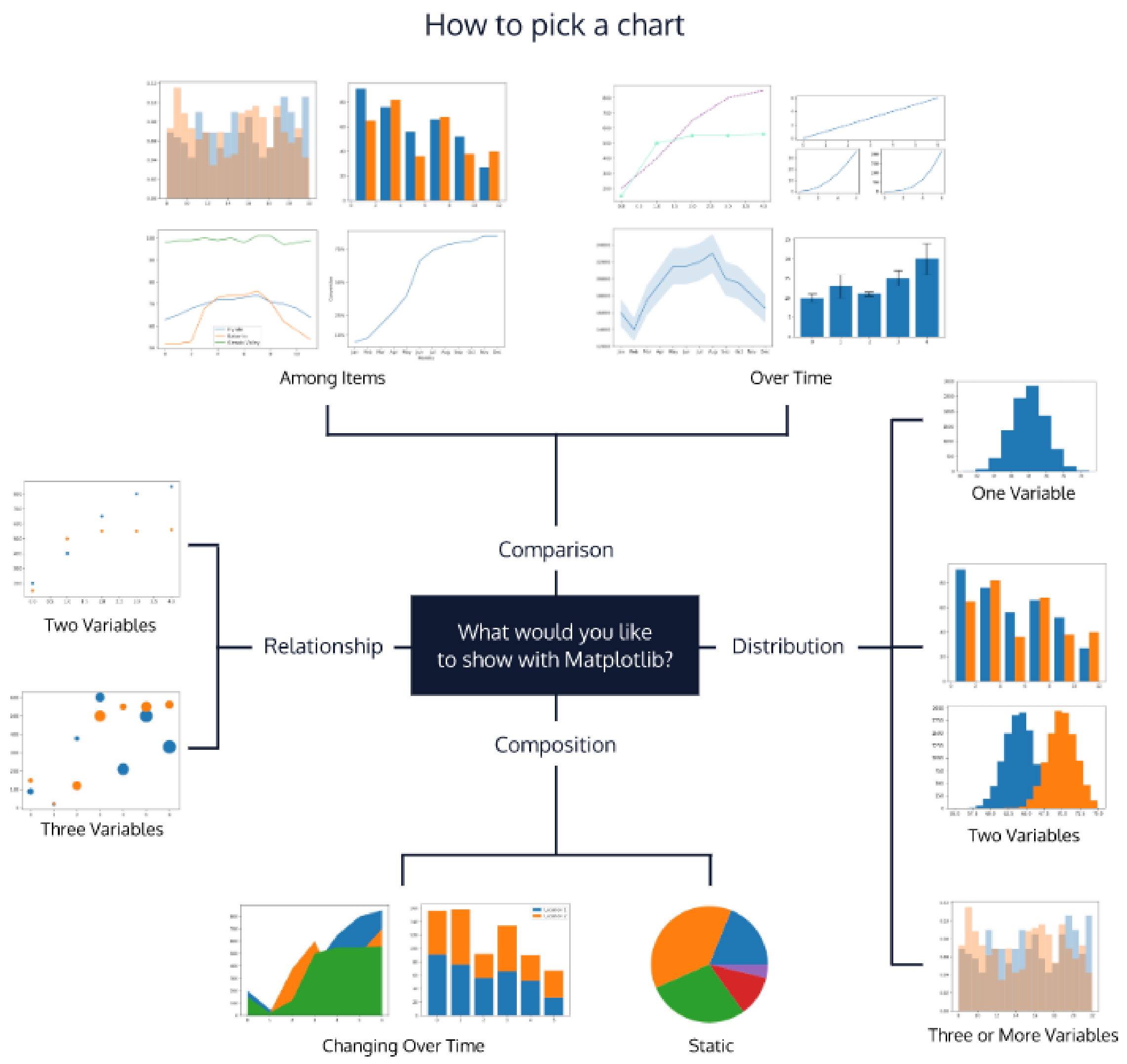
- *bins=* changes the number of bins to divide the data into (default is 10)
- *range=( )* to change the x-axis display value range
- *alpha=* to change the transparency of our graphs (lets us see overlap of 2 histograms)
- *histtype='step'* will only draw the outline of our graphs (good for viewing overlap)
- *normed=True* will normalize the data so total shaded area = 1 (good for different sized data sets)

```
# plot the first histogram (blue)
plt.hist(sales_times1, bins=20, alpha=0.4,
         normed=True)

# plot the second histogram (orange)
plt.hist(sales_times2, bins=20, alpha=0.4,
         normed=True)

plt.show() # overlap is brown
```



## 4.3 Selecting the Correct Visualization

The three steps of the data visualization process are *preparing, visualizing, and styling.* We often wonder which chart to use (the visualization stage), so we can use this diagram to help us select a chart based on the data we are using and the question we are focusing on:



**Composition Charts** - Used when asking "what are the parts of some whole" or "what is the data made of". Data pertaining to proportions or percentages as a whole are a good fit.

**Distribution Charts** - Data in large quantities work well (see patterns, re-occurrences, clustering). Data that we want to see its "distribution" of is a good fit (such as seeing a normal dist. in statistics).

**Relationship Charts** - Used when asking "how do variables relate to each other". Data with two or more variables area good fit (used to see correlation between them).

**Comparison Charts** - Used when asking "how do variables compare to each other". Data must have multiple variables and are being used to compare against one another.

**Resources**:
1) Matplotlib Cheat Sheet from Codecademy.
2) Tutorials from Matplotlib website.
3) See 'Constellation' project in Python folder for scatter plot and 3d rotations in Matplotlib.

## 4.4 Introduction to Seaborn

Seaborn is a Python data visualization library that provides simple code to create elegant visualizations for statistical exploration and insight. Seaborn is based on Matplotlib, but improves on Matplotlib in several ways:

- Seaborn provides a more visually appealing plotting style and concise syntax.
- Seaborn natively understands Pandas DataFrames, making it easier to plot data directly from CSVs.
- Seaborn can easily summarize Pandas DataFrames with many rows of data into aggregated charts.

Assume the following imports are all done in the examples:

```python
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
import numpy at np
```

Seaborn has a much simpler way to create **bar charts** compared to Matplotlib, and we can do so with the function sns.barplot( ) and the following three keywords:

- *data=* is a Pandas DataFrame that contains the data.
- *x=* is a string that tells Seaborn which column in the DataFrame contains x-labels.
- *y=* is a string that tells Seaborn which column in the DataFrame contains y-values.

Note: By default, Seaborn will aggregate and plot the mean of each category.

```python
df = pd.read_csv('results.csv') # contains columns 'Gender' and 'Mean Satisfaction'
sns.barplot(x='Gender', y='Mean Satisfaction', data= df)
plt.show()
```

Seaborn can also calculate **aggregate statistics** (a single number used to describe a set of data) for large datasets. We can use NumPy to calculate these aggregates from our DataFrames.

```python
gradebook = pd.read_csv("gradebook.csv")

assignment1 = gradebook[gradebook.assignment_name == 'Assignment 1']
asn1_median = np.median(assignment1.grade)

# Seaborn will agregate grade by assignment_name and plot average grade for both
# assignment 1 and assignment 2
sns.barplot(data=gradebook, x='assignment_name', y='grade')
plt.show()
```

By default, the barplot( ) function will place **error bars** (the range of values that might be expected for that bar) on all of our bars in the graph. By default, Seaborn uses a *bootstrapped confidence interval* at a 95% confidence level (but we can change the error types of these bars using the *ci=* keyword).

```python
gradebook = pd.read_csv("gradebook.csv")

# change error bars to one standard deviation instead of 95% confidence intervals
sns.barplot(data=gradebook, x="name", y="grade", ci='sd')
```

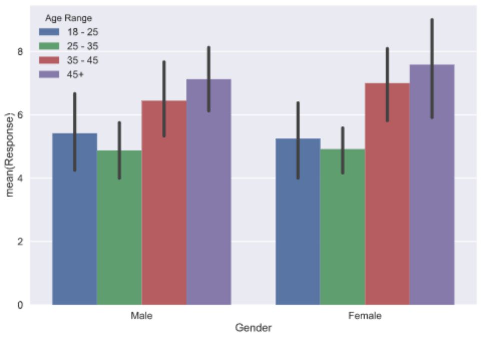
We can **calculate different aggregates** than just the mean of our data (Seaborn's default aggregate) by using the *estimator=* keyword, which accepts any function that works on a list. Some examples:

- np.median : use if our data has many outliers.
- len : how many times a value appears (categorical data).

```python
df = pd.read_csv("survey.csv")

# Show how many men and women answered the survey (grouped by gender)
sns.barplot(data=df, x='Gender', y='Response', estimator=len)
# Show the median response value aggregated by gender
sns.barplot(data=df, x='Gender', y='Response', estimator=np.median)
```

We can **aggregate by multiple columns** to visualize nested categorical variables. We can compare two columns at once by using the keyword *hue=* to add a nested categorical variable to the plot.

```
gradebook = pd.read_csv("gradebook.csv")

# Visualize mean response value by gender
# with age range nested
sns.barplot(data=df, x="Gender",
            y="Response",
            hue="Age Range")
plt.show()
```

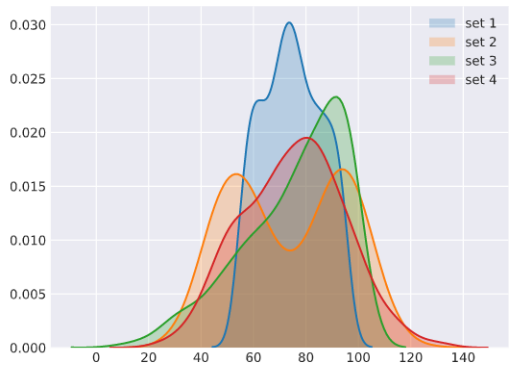


### 4.4.1 Plotting Distributions

One of the most powerful aspects of Seaborn is its ability to visualize and compare distributions. Calculating and graphing distributions is integral to analyzing massive amounts of data. We'll look at how Seaborn allows us to communicate important statistical information through plots.

We can use **KDE Plots** (Kernel Density Estimator) to give us the sense of a univariate (only on varaible, 'one-dimensional') as a curve. KDE plots are preferable to histograms because they smooth the datasets and allow us to generalize over the shape of our data (and aren't beholden to specific data points).

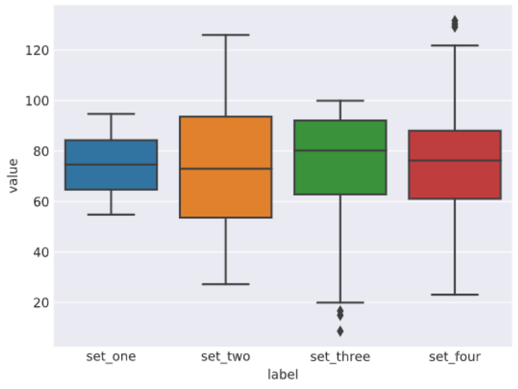
```
# Take in the data from the CSVs as NumPy arrays:
s1 = np.genfromtxt("dataset1.csv", delimiter=",")
s2 = np.genfromtxt("dataset2.csv", delimiter=",")
s3 = np.genfromtxt("dataset3.csv", delimiter=",")
s4 = np.genfromtxt("dataset4.csv", delimiter=",")

sns.set_style("darkgrid") # set style

# Plot the 4 datasets
sns.kdeplot(s1, shade=True)
sns.kdeplot(s2, shade=True) # bimodal (two peaks)
sns.kdeplot(s3, shade=True) # skewed left
sns.kdeplot(s4, shade=True) # normal-ish
plt.legend(['set 1', 'set 2', 'set 3', 'set 4'])
plt.show()
```



We can use **box plots** to show us the range of our dataset, give us an idea about where a significant portion of our data lies, and whether or not any outliers are present. We interpret a box plot as: the *box* represents interquartile range, the *line in the middle* of the box is the mean, the *end lines* are the first and third quartiles, and the *diamonds* show outliers.

- An advantage of box plots over KDE is that it's easy to plot multiples and compare range of values.
- Note that it shows the range of values and not the curve (distribution) of the datasets.

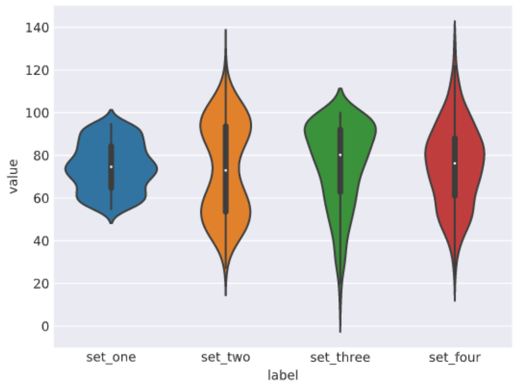
```
n=500
df = pd.DataFrame({ # using s1-s4 from above
"label": ["set_one"] * n + ["set_two"] * n +
         ["set_three"] * n + ["set_four"] * n,
"value": np.concatenate([s1, s2, s3, s4])
})

sns.set_style("darkgrid") # set style

# Plot the 4 datasets using the dataframe
sns.boxplot(data=df, x='label', y='value')
plt.show()
```



We can use **violin plots** to compare distributions by giving us an estimation of the dataset. It can show us the distribution (like the KDE plot) and information about the median/interquartile range (like the box plot). They are trickier to read and can be broken down to the following parts:

- There are two *KDE plots* that are symmetrical along the center line.
- A *white dot* represents the median.
- The *thick black line* in the center of each violin represents the interquartile range.
- The *lines extending from the center* are 95% confidence intervals for our data.

```python
# using s1, s2, s3, and s4 from above
# and using df from above

sns.set_style("darkgrid") # set style

# plot the 4 distributions using violin plot
sns.violinplot(data=df, x='label', y='value')
plt.show()
# notice we see the same distributions from KDE
# and same ranges from the boxplot
```



### 4.4.2 Styling Graphs

Styling your graphs will influence how your audience understands what you're trying to convey. When deciding the style, ask yourself: is it part of a report, is it part of a presentation, is it stand alone with no explanation? These questions will help decide which style to chose in order to best convey your data.

Seaborn has five **built in themes**: darkgrid, whitegrid, dark, white, and ticks. All of which can be passed into the sns.set_style( ) method.

It is important to consider **background color**. The higher the contrast between you plot color palette and the figure background, the more legible the data visualization will be.

Including a **grid** can be helpful when you want your audience to be able to draw their own conclusions about data. Research papers and reports are a good example of when you would want to include a grid.

We can remove **spines** from plots (the four black borders that contain the graph) by using sns.despine(), which by default will remove the top/right spines (can pass *left=True, bottom=True* to remove all spines).

We can **customize plots for presentation** by using sns.set_context( ) and passing these keywords:

- the first parameter adjusts the scale of the plot: 'paper', 'notebook', 'talk', 'poster'.
- *font_scale=* will change the size of the text.
- *rc=* will let us change any value in a dictionary (run sns.plotting_context() to see which values can be changed).

We can change **palette color** with two different functions, sns.color_palette( ) and sns.set_pallete( ).

- sns.color_palette( ) can be saved to a variable, then passed in sns.palplot( ) to see an array of colors.
- sns.set_pallete( ) is passed the name of the pallete you want to use for the plot.

Note: you can also use Color Brewer Palettes instead of the default Seaborn colors by passing the name and number of colors needed.

```python
palette = sns.color_palette("bright") # to visualize the colors in a pallete
sns.palplot(palette)

sns.set_palette("Paired") # to set the pallete for the plot

sns.set_palette("Set3", 10) # color brewer pallete with 10 different shades
```

## 4.5 Data Visualization Cumulative Projects