Python Tutorial – Part II: Data

Mark A. Austin

University of Maryland

austin@umd.edu
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Overview

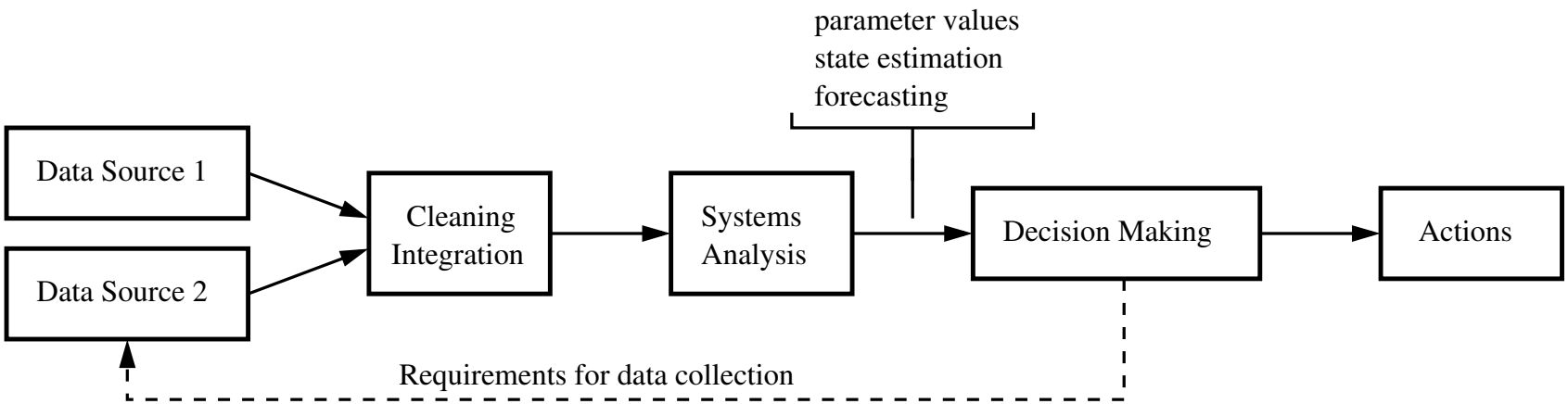
Data-Driven Decision Making

Data-Driven Decision Making

Data-Driven Decision Making

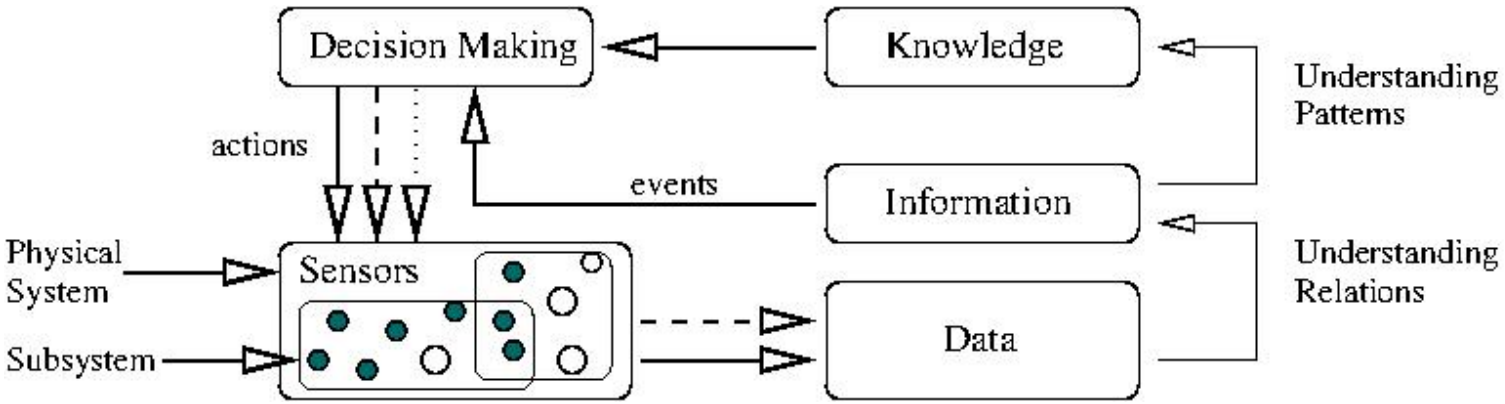
Data-driven decision making is the process of collecting data and using analysis to gain insights and inform engineering decisions, rather than rely solely on intuition and/or experience.

Simplified Procedure:



Data-Driven Decision Making

Framework for Sensor-Enabled Decision Making:

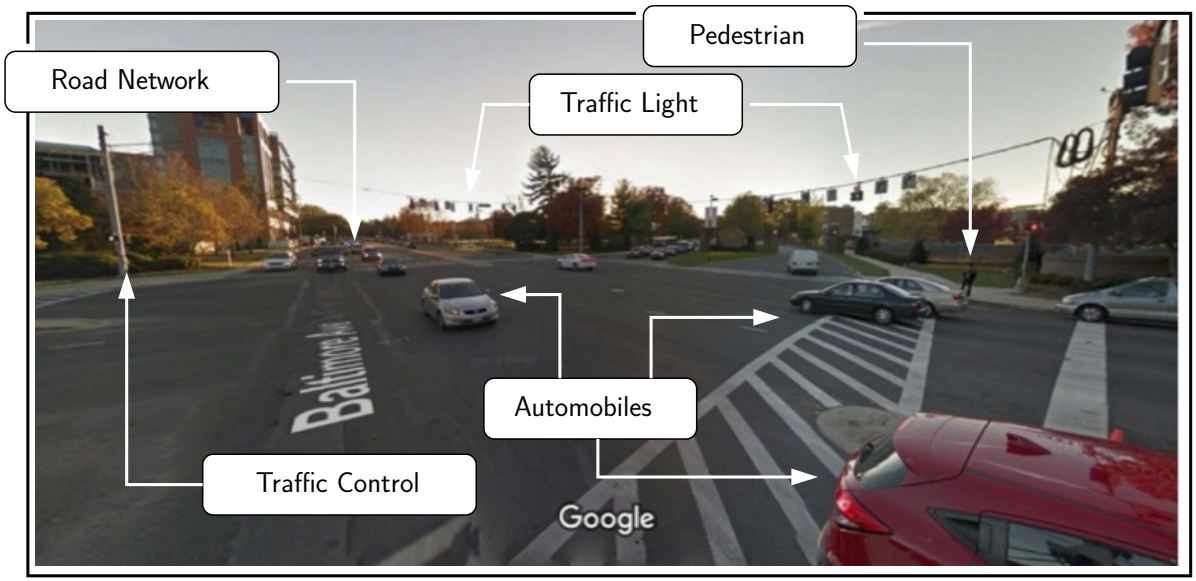


Chain of dependency relationships:

1. improved performance <-- actions
2. actions <-- ability to identify events.
3. identify events <-- data processing
4. data processing <-- types and quality of data
5. types and quality of data <-- sensor design and placement.

Data-Driven Decision Making

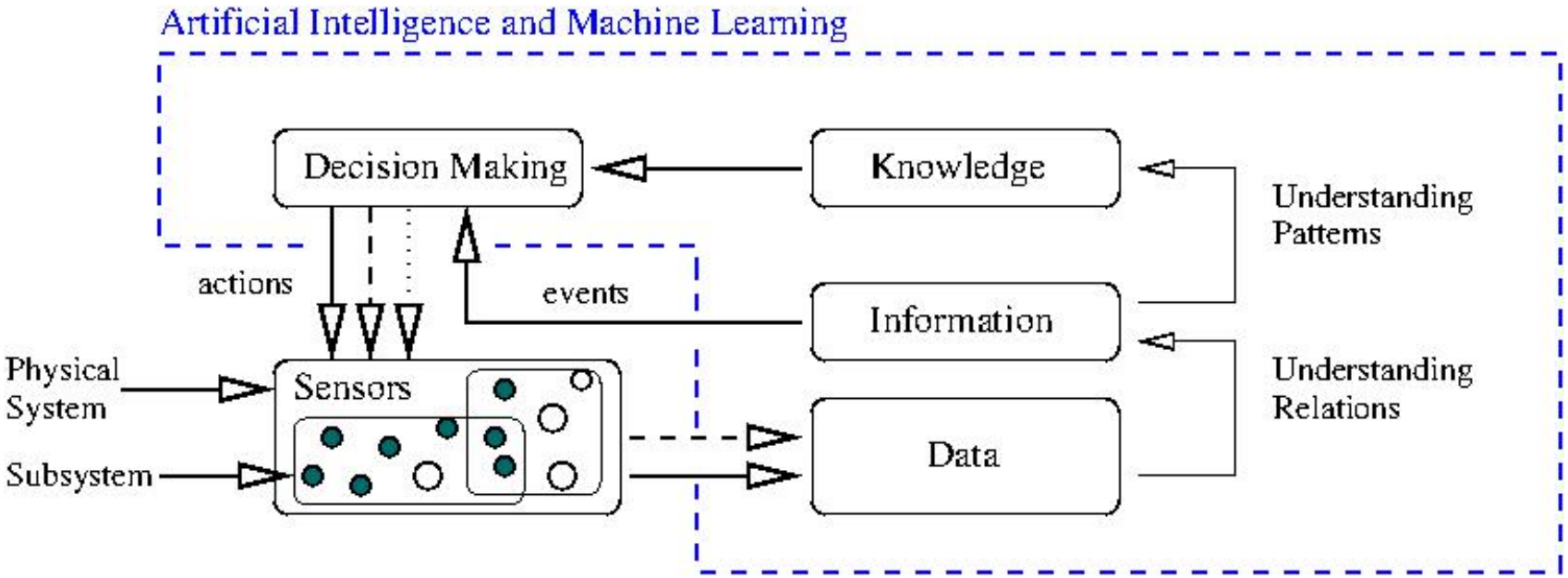
Example A: Traversal of a traffic intersection ...



Required Capability. Observe, evaluate, reason, take actions.
Challenges. Multiple domains, multiple streams of heterogeneous data, event-driven behavior, dynamic, time critical.

Data-Driven Decision Making

Solution Procedure: Pathway from sensing and data collection to AI/ML-enabled decision making ...



Challenges: Stringent requirements for real-time processing $\longrightarrow$ drive custom approaches to collection and fusion of data.

Data-Driven Decision Making

No sensor type works well for all tasks and in all conditions, so sensor fusion will be necessary to provide redundancy for autonomous functions

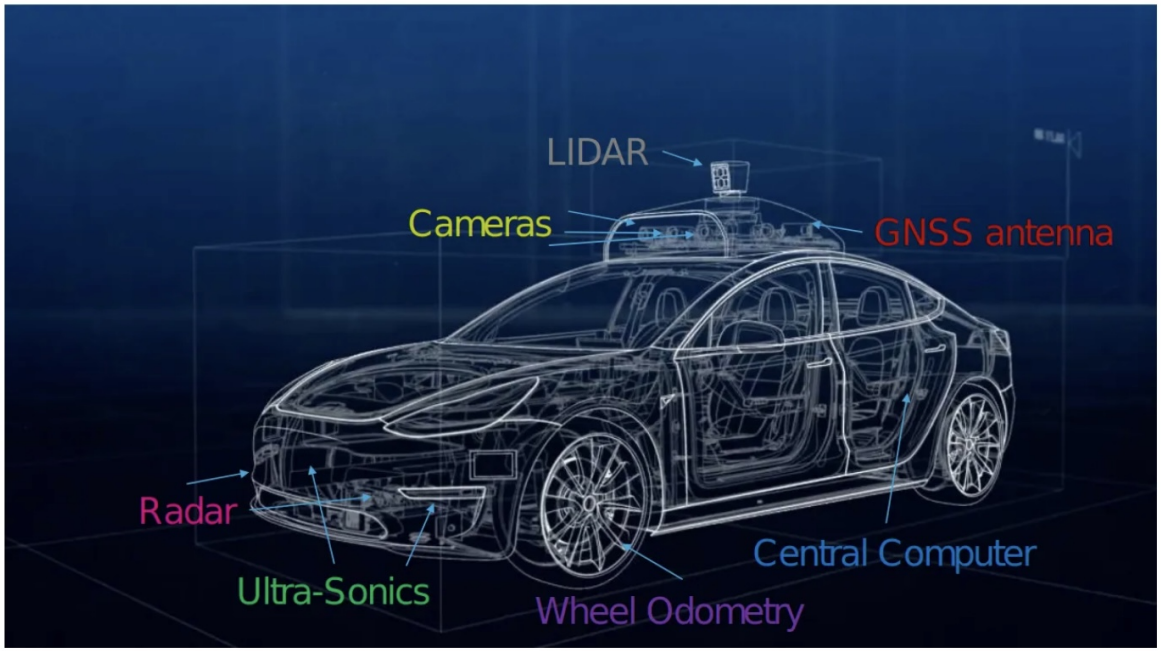
Most likely used fusion solution in future — Good — Fair — Poor

	Camera	Radar	LiDAR	Ultrasonic	LiDAR+Radar+ Camera
Object detection	Fair	Good	Good	Good	Good
Object classification	Good	Poor	Fair	Poor	Good
Distance estimation	Fair	Good	Good	Good	Good
Object edge precision	Good	Poor	Good	Good	Good
Lane tracking	Good	Poor	Poor	Poor	Good
Range of visibility	Fair	Good	Fair	Poor	Good
Functionality in bad weather	Poor	Good	Fair	Good	Good
Functionality in poor lighting	Fair	Good	Good	Good	Good

Source: ...

Data-Driven Decision Making

Solution Procedure: Self-driving car sensors ...



Diversity of Sensors: GPS/position, radar, orientation, video, microphones.

Source: ...

Data-Driven Decision Making

Video Cameras: (corners of car and roof) ...

- Help to recognize objects around the vehicle.

Position Sensors: (located in wheels) ...

- Helps to determine car's location from wheel rotations.

LIDAR/Radar: (located on car corners + roof) ...

- Measures speed of cars ahead.

Ultrasonic: (located on car bumpers) ...

- Near-range sensing to support operations such as parking.

Orientation Sensor: (located in car interior) ...

- Acts like the car's inner ear, sensing motion and balance.

Microphone: (located on roof) ...

- Detect sirens of approaching emergency vehicles.

Data-Driven Decision Making

Example B: Buildings and Cities.

Use sensing and software to:

- Improve situational awareness – to understand what is actually happening in a building or city?
- Connect sensor measurements to short- and long-term urban needs (e.g., decisions on a bus stop; longer term urban planning).
- Capture the spatial, temporal, and intensity aspects of environmental phenomena (e.g., fires, flooding) and their impact on natural (e.g., air quality) and man-made systems (e.g., transportation networks, food chains).
- Look ahead and forecast future states of the system?

Data-Driven Decision Making

Historical Problems:

- Manual (ad-hoc) data acquisition procedures are slow and error prone:
  - Missing data,
  - Inconsistent formatting (e.g., of dates),
  - Poorly written (ambiguous) textual descriptions,
  - Spelling mistakes,
  - Duplicate data, etc ...
- Data is poorly organized.
- Analysis procedures are computationally inefficient.

Too often:

- Data is collected without any real thought for end usage.
- Open source data is outdated.

Present-Day Challenges

Large Data Volume:

- Large volume (size) of data collected and analyzed.
- Steadily increases with time: gigabytes, ... petabytes, ...

Diverse Data Type and Format:

- Diverse range of data types (numeric, textual, spatial, temporal, audio, visual) and formats (structured, non-structured, semi-structured).
- Data can be noisy ...

High Data Velocity:

- Refers to the speed (static vs highly dynamic) at which data is generated, collected, processed, and analyzed.
- Provides systems/organizations with insight in real time.

Tabular and Non-Tabular Data Models

Tabular and Non-Tabular Data Models

Tabular Data (Structured Data)

Tabular data refers to data presented in rows and columns. Rows represent separate observations; columns represent measured (observation) variables.

Spreadsheet formalisms allow large amounts of raw data to be sorted and reorganized in an aggregated format.

Sources: forms, online transaction processing systems.

Formats: CSV, Excel, Google Sheets.

Tabular and Non-Tabular Data Models

Non-Tabular Data (Unstructured Data)

Non-tabular data refers to any data that does not fit into a traditional tabular structure (rows and columns).

Applications: Text, images, audio, video, and graph data.

Sources: E-mails, multimedia files, observational data.

Formats: Audio files (mp3); documents (pdf); images (jpeg, png), web pages (xml,html), geospatial/openstreetmap (osm).

Tabular and Non-Tabular Data Models

Examples:

Tabular Data

homogeneous
(contains a single type of data)

columns

rows	0	1	2
0	1.5	21.0	76.4
1	4.0	35.0	99.7
2	3.0	17.0	85.3
3	4.0	53.0	90.7

All numerical data

	0	1	2
0	'a'	'Mia'	'1'
1	'c'	'Lucas'	'x-1'
2	'e'	'Ang'	'zz'
3	'b'	'Jia'	'0.3'

All string data

heterogeneous
(contains multiple types of data)

	0	1	2
0	1.5	21.0	'Mia'
1	4.0	35.0	'Lucas'
2	3.0	17.0	'Ang'
3	4.0	53.0	'Jia'

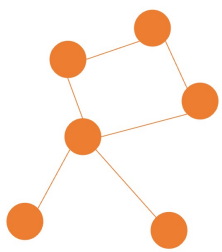
Numerical and string datatypes

Non-tabular Data Examples

Unstructured Text

```
'Twas brillig, and
the slithy toves
Did gyre and gimble
in the wabe:
All mimsy were the
borogoves,
And the mome raths
outgrabe.
```

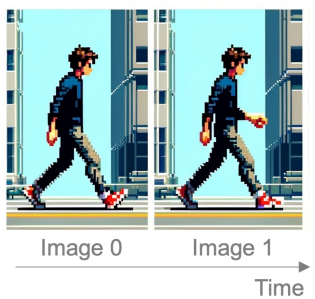
Network Data



Geospatial Data

Image Data

Video Data



Homogeneous and Heterogeneous Data

Homogeneous Data

Data that is uniform (or consistent) within a set. Data elements share a common format and kind (e.g., an array of integers).

Heterogeneous Data

Data that is not uniform (or consistent) in its structure, format or type (e.g., data from text files, image files, audio data streams).

Integration of Data Sources

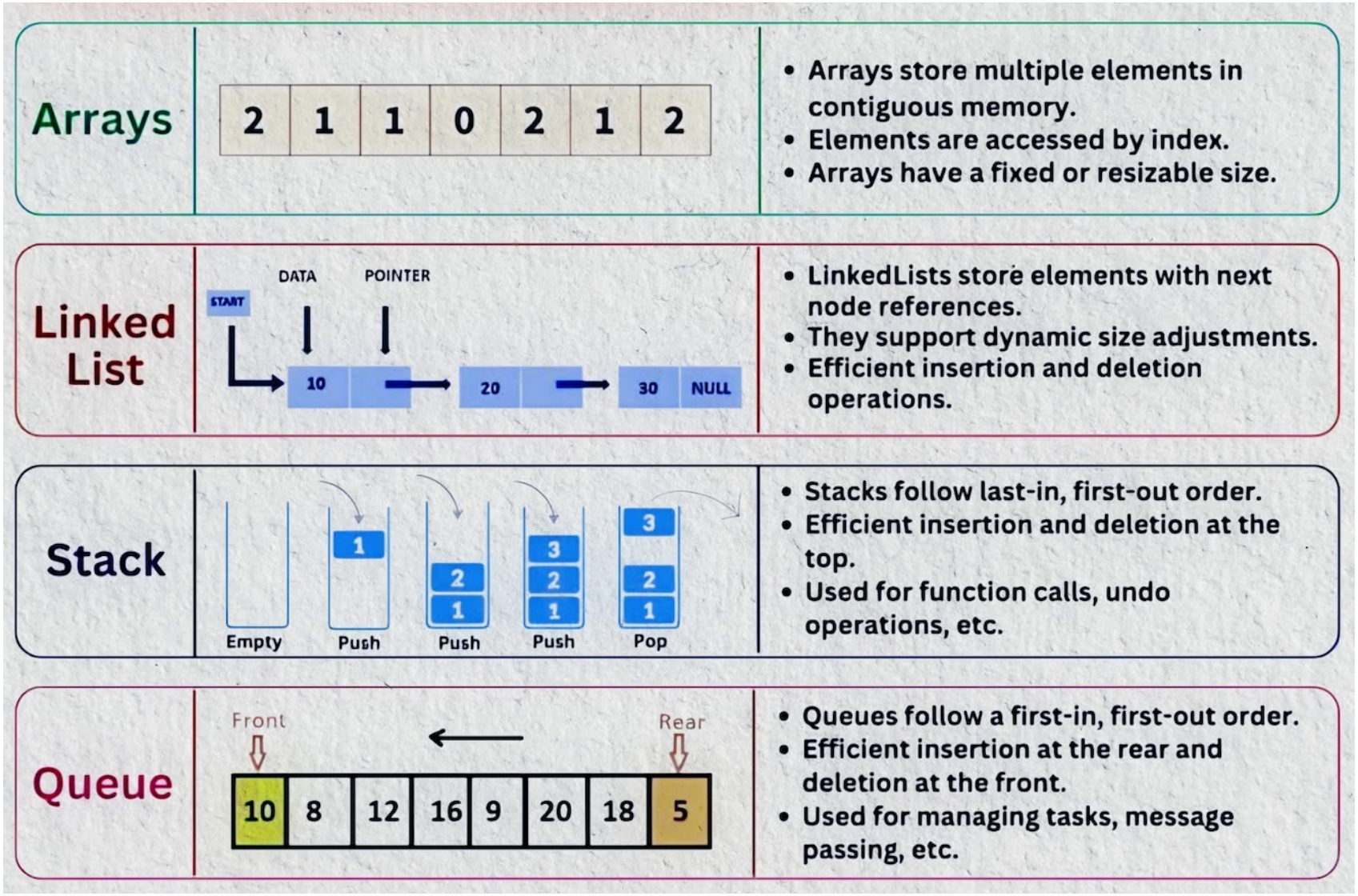
Combinations of homogeneous/heterogeneous data sources and their integration arise from a growing need to analyze diverse data from multiple perspectives (e.g., think eyes and ears).

Homogeneous and Heterogeneous Data

Example 1: Homogeneous/Heterogeneous Data in Python ...

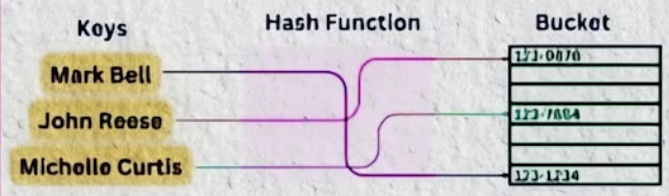
```
# Part 1: Array of Integers (homogeneous data) ...

  array01 = np.array( [ 0, 2, 4, 6, 8 ] )

# Part 2: Matrix of Integers (homogeneous data) ...

  array02 = np.array( ( [ 0, 1, 2, 3,  4 ],
                        [ 2, 4, 6, 8, 10 ] ) );

# Part 3: List of floating-point numbers (homogeneous data) ...

  list01 = [ 0.0, 1.0, 2.0, 4.0, 6.0 ];

# Part 4: List of ints, floats, booleans, and
#         character strings (heterogeneous data) ...

  list02 = [ 0, 'date', True, 4.0, 6.0 ];
```

Aside: From Data Models to Data Structures



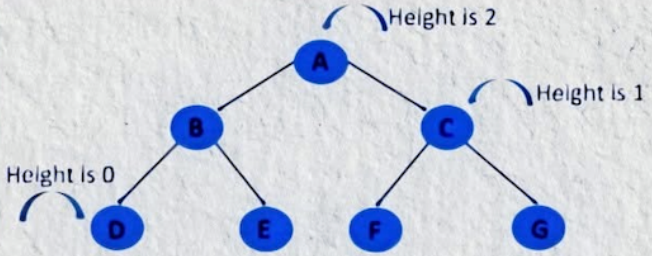
Aside: From Data Models to Data Structures

Hash Table



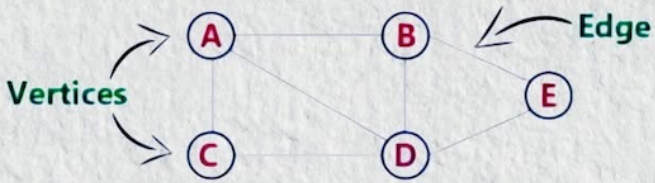
- Hash tables store key-value pairs for quick lookup.
- They use a hash function for indexing.
- Efficient retrieval, insertion, and deletion operations.

Tree



- Trees organize elements in a hierarchical structure.
- Elements have parent and child relationships.
- Used for hierarchy, searching, sorting, etc.

Graph



- Graphs represent relationships between entities.
- They consist of vertices and edges.
- Used for modeling networks, social connections, etc.

Tabular Data and Dataset Transformation

(Working with Pandas)

Working with Pandas

Introduction to Pandas

Pandas (derived from "panel data") is an open source Python Library that supports working and analysis of tabular data sets.

Benefits:

- Pandas can clean messy data sets, and make them readable and relevant.
- Pandas allows us to analyze large data sets and make conclusions based on statistical theories.
- Three data structures: Series, DataFrame and Panel.

Installation:

```
prompt >> pip3 install pandas
```

What can Pandas do?

Basic Operations:

- Create series and dataframes.
- Read CSV and JSON files.
- Plot data.

Clean Data:

- Clean empty cells.
- Fix wrong format.
- Remove duplicates.

Advanced Operations:

- Combine (concatenate, join, merge) Panda objects.
- Compute correlations.

Basic Operations

(Introduction to DataSeries and DataFrames)

Panda Series and DataFrames

Panda Series

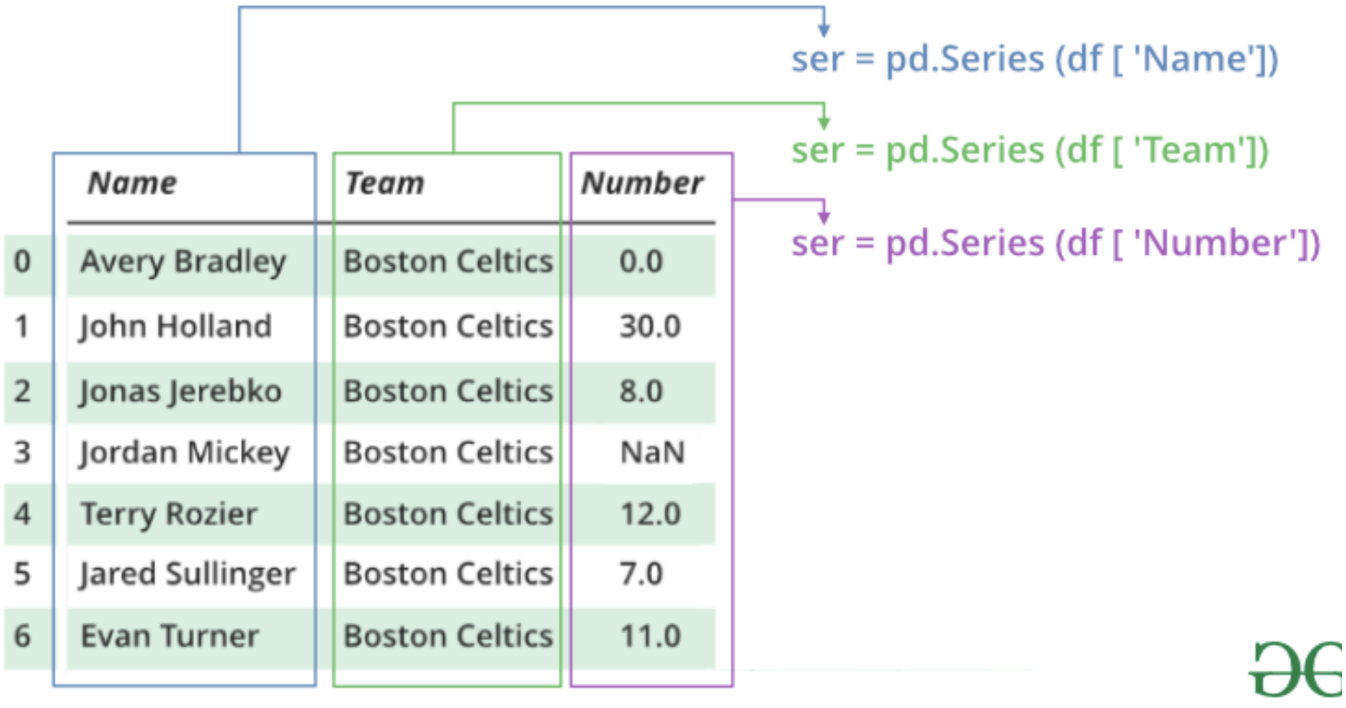
A Panda Series is a one-dimensional ... labeled array capable of holding data of any type (integer, string, float, python objects, etc.).

Panda DataFrame

A Panda DataFrame is a two-dimensional (potentially heterogeneous) tabular data structure with labeled axes for the rows and columns.

Panda Series

Panda Series Elements: columns, data ...



	Name	Team	Number
0	Avery Bradley	Boston Celtics	0.0
1	John Holland	Boston Celtics	30.0
2	Jonas Jerebko	Boston Celtics	8.0
3	Jordan Mickey	Boston Celtics	NaN
4	Terry Rozier	Boston Celtics	12.0
5	Jared Sullinger	Boston Celtics	7.0
6	Evan Turner	Boston Celtics	11.0

Basic Operations:

- Create a series; access elements; index and select data; binary operations; conversion operations.

Panda Series

Example 1: Manually create series from list:

```
# Part 1: Manually create series ...

a = [1, 2, 3, 4, 3, 2, 1 ]
myvar = pd.Series(a)
print(myvar)

# Part 2: Create series from a list with labels ...

myvar = pd.Series(a, index = ["a", "b", "c", "d", "c", "b", "a" ])
print(myvar)
```

Abbreviated Output: Parts 1 and 2 ...

```
Part 01
0    1
1    2
.....
5    2
6    1
dtype: int64
```

```
Part 02
a    1
b    2
.....
b    2
a    1
dtype: int64
```

Panda Series

Example 2: Manually create series from dictionary:

```
calories = {"day1": 420, "day2": 380, "day3": 390}
myvar = pd.Series(calories)
print(myvar)
```

Output:

```
day1    420
day2    380
day3    390
dtype: int64
```

Panda Series

Example 3: Create series from NumPy functions

```
# series01 = pd.Series(np.arange(2,8)) ... ");

series01 = pd.Series(np.arange(2,8))
print(series01)
```

Output:

```
0    2
1    3
2    4
3    5
4    6
5    7
dtype: int64
```

Panda Series

Example 4: Create series from NumPy functions

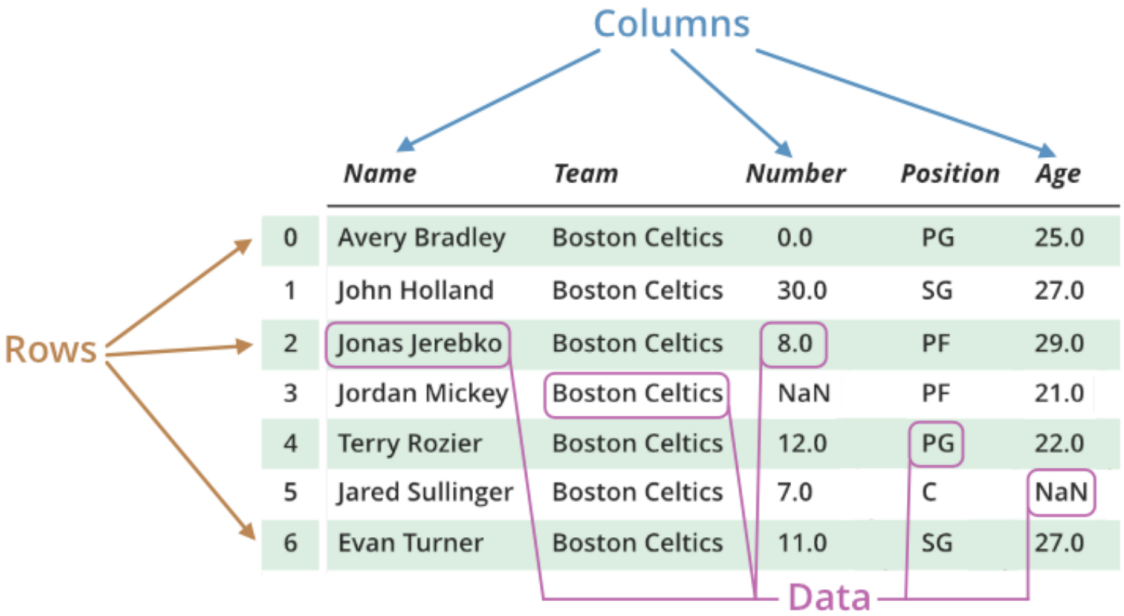
```
series02 = pd.Series( np.linspace(0,10,5) )
print(series02)

print( series02.size)
print( len(series02) )
print( series02.values )
```

Output:

```
0     0.0
1     2.5
2     5.0
3     7.5
4    10.0
dtype: float64

5                           # <-- series02.size ...
5                           # <-- series02 length ...
[ 0.   2.5  5.   7.5 10. ] # <-- series02 values ...
```

Panda DataFrames

Panda DataFrame Elements: rows, columns, data ...



	Name	Team	Number	Position	Age
0	Avery Bradley	Boston Celtics	0.0	PG	25.0
1	John Holland	Boston Celtics	30.0	SG	27.0
2	Jonas Jerebko	Boston Celtics	8.0	PF	29.0
3	Jordan Mickey	Boston Celtics	NaN	PF	21.0
4	Terry Rozier	Boston Celtics	12.0	PG	22.0
5	Jared Sullinger	Boston Celtics	7.0	C	NaN
6	Evan Turner	Boston Celtics	11.0	SG	27.0

Basic Operations:

- Create dataframe; deal with rows and columns; index and select data; iterate over rows and columns.

Working with Panda DataFrames

Data Loading:

```
import pandas as pd
df = pd.read_csv("datafile.csv")
```

Data Exploration and Inspection:

- `df.head()`: — inspect the first few rows of the dataframe.
- `df.describe()`: — generate descriptive statistics.
- `df.isnull().sum()`: — identify missing values.

Working with Panda DataFrames

Example 1: Manually create small dataset ...

```
mydataset = {
   'cars': [ "BMW", "Honda", "Acura"],
   'year': [ 2013,     2017,    2022]
}

myvar = pd.DataFrame(mydataset)
print(myvar)
```

Output:

```
     cars  year
0     BMW  2013
1   Honda  2017
2   Acura  2022
```

Working with Panda DataFrames

Example 2: Create dataframes from 1-d and 2-d arrays ...

```
myvar = pd.DataFrame( np.arange(1,8) )       # <-- dataframe from 1-d array
print(myvar)

df = pd.DataFrame( [ [1,2], [3,4], [5,6] ] ) # <-- dataframe from 2-d array
print(df)
```

Abbreviated Output:

```
Dataframe from 1-d np array
---------------------------
   0
0  1
1  2
2  3
....
5  6
6  7
```

```
Dataframe from 2-d np array
---------------------------
      0  1
   0  1  2
   1  3  4
   2  5  6
```

Working with Panda DataFrames

Example 3: Create simple dataframe from multiple series ...

```
data = {                                # <-- Create dataframe from
   "calories": [520, 480, 400],         #     multiple series.
   "duration": [ 50,  48,  40]
}

myvar = pd.DataFrame(data)
print(myvar)

index = ["day1", "day2", "day3"]  # <-- give each ros a new name.
myvar = pd.DataFrame(data, index)
print(myvar)
```

Output:

```
Part 1: dataframe from series
   calories  duration
0       520        50
1       480        48
2       400        40
```

```
Part 2: rename rows
      calories  duration
day1       520        50
day2       480        48
day3       400        40
```

Working with Panda DataFrames

Example 4: Create dataframe from JSON object ...

```
# Create JSON object (same format as Python dictionary) ...

data = {
  "Duration":{ "0":60,  "1":60, "2":60,   "3":45,  "4":45,  "5":60 },
  "Pulse":{    "0":110, "1":117, "2":103, "3":109, "4":117, "5":102 },
  "Maxpulse":{ "0":130, "1":145, "2":135, "3":175, "4":148, "5":127 },
  "Calories":{ "0":409, "1":479, "2":340, "3":282, "4":406, "5":300 }
}

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

Output:

```
   Duration  Pulse  Maxpulse  Calories
0        60    110       130       409
1        60    117       145       479
2        60    103       135       340
3        45    109       175       282
4        45    117       148       406
5        60    102       127       300
```

Working with Panda DataFrames

Example 5: Select rows and columns from dataframe ...

```
# Select columns of a dataframe ...

print( df[ [ 'Duration','Calories'] ].head() )

# Selecting rows of a dataframe ...

print( df.loc['1'].head() )     # <-- extract and print row 1
print( df.loc['2'].head() )     # <-- extract and print row 2
```

Output:

```
Columns of dataframe
--------------------

   Duration  Calories
0        60       409
1        60       479
2        60       340
3        45       282
4        45       406

Row 1
-----------------

Duration     60
Pulse       117
Maxpulse    145
Calories    479
Name: 1, dtype: int64

Row 2
-----------------

Duration     60
Pulse       103
Maxpulse    135
Calories    340
Name: 2, dtype: int64
```

Working with Pandas

Example 6: Read and plot CSV data file.

```
df = pd.read_csv('../data/AirPassengers.csv')
print(df.head())

print(df.info())  # <-- print dataframe info and shape ...
print(df.shape)
```

Output:

```
     Month  #Passengers
0  1949-01          112
1  1949-02          118
2  1949-03          132
3  1949-04          129
4  1949-05          121
```

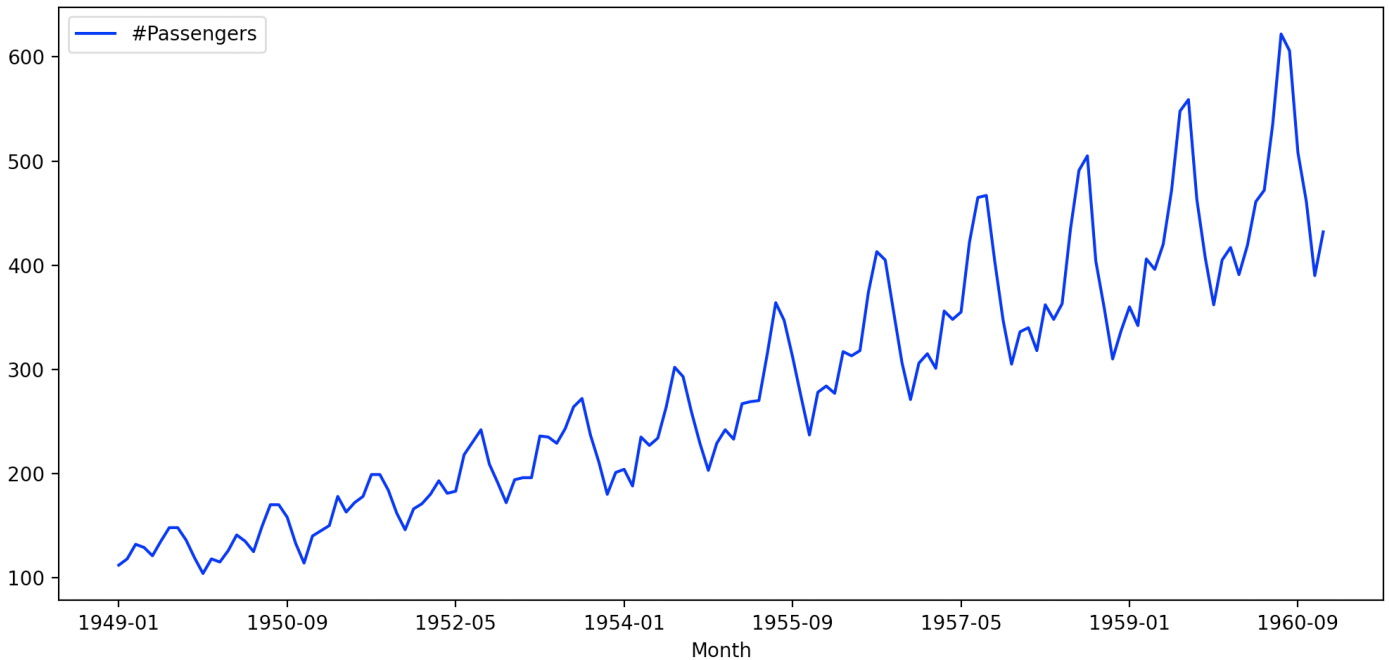
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 144 entries, 0 to 143
Data columns (total 2 columns):
#   Column       Non-Null Count  Dtype
---  ------       --------------  -----
0   Month        144 non-null    object
1   #Passengers  144 non-null    int64
dtypes: int64(1), object(1)
memory usage: 2.4+ KB
None
(144, 2)
```

Working with Pandas

Example 6: (continued)

```
import matplotlib.pyplot as plt

ax = plt.gca()
df.plot(kind='line',x='Month',y='#Passengers',color='blue',ax=ax)
plt.show()
```

Output:



Intermediate

Operations

(Data Cleaning, Data Transformation, etc ...)

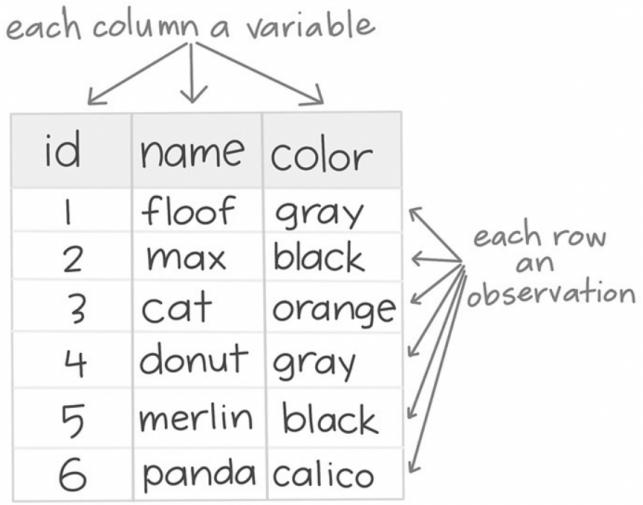
Tidy and Messy Data

Data Cleaning

Data cleaning involves identification and correction of errors, inconsistencies, and missing values in a dataset.

Tidy Data

- Each variable forms a column.
- Each observation forms a row.
- Each cell is a single measurement.



Source: Wickham H. (2014), Tidy Data, Journal Statistical Software, Vol. 59. No 10.

Tidy and Messy Data

Messy Tabular Data

- Incomplete/missing data.
- Data with spelling mistakes.
- Data with ambiguous wording.
- Data misclassified (wrong column).
- Inconsistent formatting.
- Data with anomalies.
- Data is too noisy.
- Data duplication.
- Data is completely outdated.

Data Cleaning Functions

Handling Missing Values:

- `dropna()`: Remove rows or columns with missing values.
- `fillna()`: Fill missing values with a specified value or moethod (e.g., median, mean).
- `isna()` or `isnull()`: Detect missing values and return a boolean mask.
- `replace()`: Replace missing values with a specific value.

Removing Duplicates:

- `duplicated()`: Detects duplicate rows, returning a boolean mask.
- `drop_duplicates()`: Removes duplicate rows.

Data Cleaning Tasks

Data Type Conversions:

- `astype()`: Converts columns to a different datatype.
- `to_numeric()`: Converts columns to numeric types.
- `to_datetime()`: Converts columns to datetime objects.

Removing Irrelevant Columns:

- `drop()`: Remove specified columns.

Renaming Columns:

- `rename()`: Renames columns to meaningful names.

Data Reformatting:

- `apply()`: Ensure consistent formatting for dates, numbers and strings, and standardized categorical variables.

Example 1: Basic Data Cleaning

Create dictionary of data:

```
Python: d01 = { 'ID': [123, 251, 301, 444, 649, 256, 649],
-------       'Name': ['Andrea','Mark','Angela','Nina','Eve','Joe','Eve'],
               'Age': [ 45, 45, None, 29, 52, 60, 52 ],
              'City': ['Vancouver','DC','Sydney','NYC', None,'Denver', None],
           'Country': ['Canada','USA','Australia','USA', None,'USA', None],
            'Salary': [ 60000, 80000, None, 45000, np.nan, 180000, np.nan] }

        df01 = pd.DataFrame(d01)
```

Output:

	ID	Name	Age	City	Country	Salary
0	123	Andrea	45.0	Vancouver	Canada	60000.0
1	251	Mark	45.0	DC	USA	80000.0
2	301	Angela	NaN	Sydney	Australia	NaN
3	444	Nina	29.0	NYC	USA	45000.0
4	649	Eve	52.0	None	None	NaN
5	256	Joe	60.0	Denver	USA	180000.0
6	649	Eve	52.0	None	None	NaN

Example 1: Basic Data Cleaning

Fill missing cities with 'Unknown':

```
Python:     df01['City'].fillna('Unknown', inplace=True)
-------     print(df01)
```

Output:

	ID	Name	Age	City	Country	Salary
0	123	Andrea	45.0	Vancouver	Canada	60000.0
1	251	Mark	45.0	DC	USA	80000.0
2	301	Angela	NaN	Sydney	Australia	NaN
3	444	Nina	29.0	NYC	USA	45000.0
4	649	Eve	52.0	Unknown	None	NaN
5	256	Joe	60.0	Denver	USA	180000.0
6	649	Eve	52.0	Unknown	None	NaN

Example 1: Data Cleaning

Fill missing ages with mean value:

```
Python:    df01['Age'].fillna( df01['Age'].mean(), inplace=True)
-------
```

```
Output:
-------
```

	ID	Name	Age	City	Country	Salary
0	123	Andrea	45.000000	Vancouver	Canada	60000.0
1	251	Mark	45.000000	DC	USA	80000.0
2	301	Angela	47.166667	Sydney	Australia	NaN
3	444	Nina	29.000000	NYC	USA	45000.0
4	649	Eve	52.000000	Unknown	None	NaN
5	256	Joe	60.000000	Denver	USA	180000.0
6	649	Eve	52.000000	Unknown	None	NaN

Example 1: Basic Data Cleaning

Convert age data type to int:

```
Python:    df01['Age'] = df01['Age'].astype(int)
-------
```

```
Output:
-------
```

	ID	Name	Age	City	Country	Salary
0	123	Andrea	45	Vancouver	Canada	60000.0
1	251	Mark	45	DC	USA	80000.0
2	301	Angela	47	Sydney	Australia	NaN
3	444	Nina	29	NYC	USA	45000.0
4	649	Eve	52	Unknown	None	NaN
5	256	Joe	60	Denver	USA	180000.0
6	649	Eve	52	Unknown	None	NaN

Example 1: Basic Data Cleaning

Remove duplicate rows:

```
Python:    df01.drop_duplicates(inplace=True)
-------
```

Output:

	ID	Name	Age	City	Country	Salary
0	123	Andrea	45	Vancouver	Canada	60000.0
1	251	Mark	45	DC	USA	80000.0
2	301	Angela	47	Sydney	Australia	NaN
3	444	Nina	29	NYC	USA	45000.0
4	649	Eve	52	Unknown	None	NaN
5	256	Joe	60	Denver	USA	180000.0

Remove rows with missing salaries:

```
Python:    df01.dropna(subset=['Salary'], inplace=True)
-------
```

Output:

	ID	Name	Age	City	Country	Salary
0	123	Andrea	45	Vancouver	Canada	60000.0
1	251	Mark	45	DC	USA	80000.0
3	444	Nina	29	NYC	USA	45000.0
5	256	Joe	60	Denver	USA	180000.0

Example 2: Data Transformation with apply()

Reformat: Sample dataset and dataframe ...

```
# Sample dataframe ...

data = { 'A': [  0,  1,  2,  3 ],
         'B': [  4,  5,  6,  7 ],
         'C': [  8,  9, 10, 11 ],
         'D': [ 12, 13, 14, 15 ] }
df = pd.DataFrame(data)
print(df)
```

```
# Output ...

    A   B   C   D
0   0   4   8  12
1   1   5   9  13
2   2   6  10  14
3   3   7  11  15
```

Apply square function:

```
# Square function ...

def square(x):
    return x * x

# Apply square function ...

  df_squared = df.apply(square)
  print(df_squared)
```

```
# Output ...

    A   B   C   D
0   0  16  64  144
1   1  25  81  169
2   4  36 100  196
3   9  49 121  225
```

Example 2: Data Transformation with apply()

Reformat: Sum row and column elements ...

```
df1 = df.apply(np.sum, axis=0)  # <--- sum column elements ...
print(df1)

df1 = df.apply(np.sum, axis=1)  # <--- sum row elements ...
print(df1)
```

Output:

```
A     6
B    22
C    38
D    54

dtype: int64
0    24
1    28
2    32
3    36
dtype: int64
```

Example 2: Data Transformation with apply()

Define custom function:

```
def custom_function( x, low, high ):
    return low <= x <= high;
```

Apply custom function:

```
    data   = pd.Series( [ 1, 3, 5, 7, 9, 11, 13 ] )
    result = data.apply( custom_function, low=5, high=9 )
    print( result )
```

Output:

```
0    False
1    False
2     True
3     True
4     True
5    False
6    False
dtype: bool
```

Advanced Operations

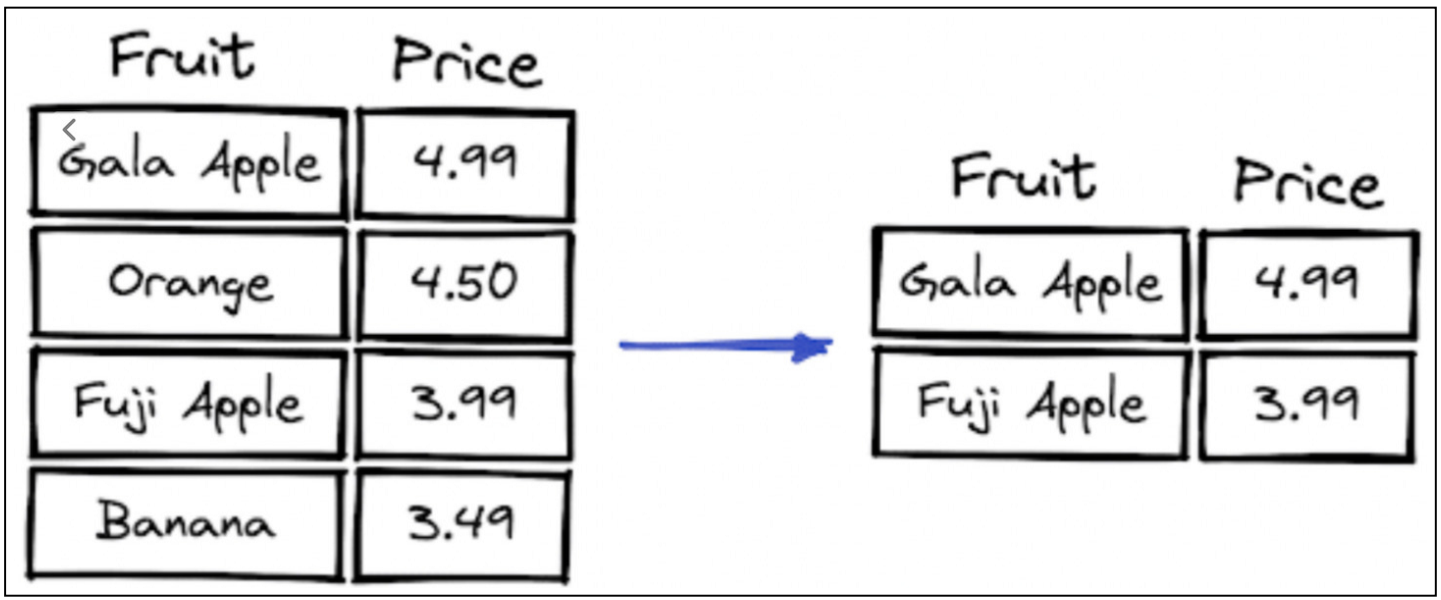
(Data Filtering, Data Merge)

Data Filtering

Data Filtering Data

Data filtering in Python involves selection of subsets (i.e., rows and columns) of data based upon certain conditions.

Example: Just get me the apples ...



Four Strategies for Basic Filtering

Filter on a Single Column:

- Use operators – equality operator, range of values in a column – to filter contents of a single column.

Filtering with Multiple Columns:

- Use multiple values – for example a range – to filter contents of a single column.

Filtering based on a List of Values:

- Use list of values to filter on a single column.

String Filtering:

- Filter rows based on contents of string functions, e.g., `.str.startswith()` and `.str.contains()`.

Example 1: Basic Data Filtering

Sample Dataset: Cities, states, politics, population

Dataset:

```
data = {'City': ['Washington DC', 'Los Angeles', ... 'Austin', 'Baltimore'],
        'State': [ 'Null', 'CA', 'CO', 'WA', 'CA', 'TX', 'TX', 'MD'],
        'Politics': [ 'Blue', 'Blue', 'Red', 'Blue', ... 'Blue', 'Blue'],
        'Population': [ 10, 30, 20, 15, 20, 15, 10, 10 ] }

df = pd.DataFrame(data)
```

Output:

	City	State	Politics	Population
0	Washington DC	Null	Blue	10
1	Los Angeles	CA	Blue	30
2	Denver	CO	Red	20
3	Seattle	WA	Blue	15
4	San Francisco	CA	Blue	20
5	Dallas	TX	Red	15
6	Austin	TX	Blue	10
7	Baltimore	MD	Blue	10

Example 1: Basic Data Filtering

Filter rows based on numeric value (pop $\geq$ 20)

```
Filter:     filtered_pop = df[df['Population'] >= 20]
-------
```

```
Output:                City State Politics  Population
-------     1    Los Angeles    CA     Blue          30
            2         Denver    CO      Red          20
            4  San Francisco    CA     Blue          20
```

Filter rows multiple conditions (pop $>$ 25) and (state $==$ 'CA')

```
Filter:     filter_multi = df[(df['Population'] > 25) & (df['State'] == 'CA')]
-------
```

```
Output:              City State Politics  Population
-------     1  Los Angeles    CA     Blue          30
```

Example 1: Basic Data Filtering

Filter rows based on list of states (states = ['CA', 'TX'])

```
Filter:     states_to_include  = ['CA', 'TX']
-------     filtered_states = df[df['State'].isin( states_to_include)]

Output:                 City State Politics  Population
-------     1    Los Angeles    CA     Blue          30
            4  San Francisco    CA     Blue          20
            5         Dallas    TX      Red          15
            6         Austin    TX     Blue          10
```

Filter state names starts with a 'C' ...

```
Filter:     filter_by_name01 = df[ df['State'].str.startswith('C') ]
-------     print( filter_by_name01 )

Output:                 City State Politics  Population
-------     1    Los Angeles    CA     Blue          30
            2         Denver    CO      Red          20
            4  San Francisco    CA     Blue          20
```

Example 1: Basic Data Filtering

Filter booleans matching (politics == 'Red')

```
Filter:         filtered_politics = df['Politics'].eq('Red')
-------

Output:         0    False
-------         1    False
                2     True
                3    False
                4    False
                5     True
                6    False
                7    False
                Name: Politics, dtype: bool
```

Source Code: See: python-code.d/pandas/

Customized Filtering with filter()

Function filter():

- `filter()`: Filters subset of a dataframe based upon specified index labels.
- Filter rows and columns based upon the `axis` argument.

Parameters:

- **items:** list-like. Keep labels from axis which are in items.
- **like:** str. Keep labels from axis for which `"like in label == True"`.
- **regex:** Keep labels from axis for which `re.search(regex,label) == True`.
- **axis:** Indicates the axis to filter on – select rows with `axis=0`, select columns with `axis=1`.

Example 2: Customized Filtering with filter()

Create dictionary of data:

Python:

```
data01 = {'ID': [123, 251, 301, 444, 649, 256, 649],
          'Name': ['Andrea', 'Nicol', 'Angela', 'Nina', ... , 'Eve'],
          'Age': [45, 45, None, 29, 18, 32, 18],
          'City': [ 'Toronto', 'Auckland', 'Sydney', ... ,None],
          'Country': [ 'Canada', 'NZ', 'Australia', .... 'Australia'
          'Salary': [ 60000, ... 45000, np.nan, 180000, np.nan]}

index = [ "friend", "family", "family", "friend", "student", "work",
df01  = pd.DataFrame(data01, index )
print(df01)
```

Output:

	ID	Name	Age	City	Country	Salary
friend	123	Andrea	45.0	Toronto	Canada	60000.0
family	251	Nicol	45.0	Auckland	NZ	80000.0
family	301	Angela	NaN	Sydney	Australia	NaN
friend	444	Nina	29.0	NYC	USA	45000.0
student	649	Eve	18.0	None	Australia	NaN
work	256	Joe	32.0	Berkeley	USA	180000.0
student	649	Eve	18.0	None	Australia	NaN

Example 2: Customized Filtering with filter()

Select columns by Name and City:

```
Python:     filtered_columns = df01.filter( [ "Name", "City" ] );
-------     print( filtered_columns )
```

```
Output:                Name      City
-------     friend    Andrea   Toronto
            family     Nicol  Auckland
            family    Angela    Sydney
            friend      Nina       NYC
            student      Eve       None
            work         Joe  Berkeley
            student      Eve       None
```

Filter data by row (index equal to family):

```
Python:       filter_family = df01.filter( like='fam', axis = 0 )
```

```
Output:                 ID    Name   Age      City    Country   Salary
-------     family  251   Nicol  45.0  Auckland         NZ  80000.0
            family  301  Angela   NaN    Sydney  Australia      NaN
```

Data Merge and Concatenation

Data Merge

Data merge operations combine data frames based on columns or indices. Similar to structured query language (SQL) operations.

Function: `merge()`

- Combines dataframes based on common columns or indices – by default, `merge()` keeps only rows with matching keys in both dataframes.

Four types of join:

- `inner` returns only matching rows.
- `left` returns all rows from the left dataframe and matching rows from the right dataframe.

Data Merge and Concatenation

- `right` returns all rows from the right dataframe and matching rows from the left dataframe.
- `outer` returns all rows from both dataframes.

Modifications:

- `on` parameter specifies the columns to join on.
- `left_on` and `right_on` can be used when column names are different in dataframes.

Function: concat()

- Concatenates dataframes either vertically (axis = 0) or horizontally (axis = 1).

Function: join()

- By default, joins dataframes based on their index.

Merging and Concatenating Data

Functions: concat(), append() and merge() ...

concat, append

Table A

User ID	Balance
100	3000
101	200

Table B

User ID	Balance
200	100
201	500

```
t1 = pandas.DataFrame([[100, 3000], [101, 200]])
t2 = pandas.DataFrame([[200, 100], [201, 500]])

pandas.concat([t1, t2])

t1.append(t2)
```

result

User ID	Balance
100	3000
101	200
200	100
201	500

merge

Table C

User ID	User Name
100	John
101	Annie

Table D

User ID	Balance
100	100
101	500

```
t3 = pandas.DataFrame({'key': [100, 101],
                       'name': ['John', 'Annie']})
t4 = pandas.DataFrame({'key': [100, 101],
                       'balance': [100, 500]})

t3.merge(t4)
```

result

User ID	User Name	Balance
100	John	100
101	Annie	500

Merging and Concatenating Data

Functions: join() and combine() ...

join

Table E

User ID	User Name
100	John
101	Annie
102	Joe

Table F

User ID	Balance
100	100
101	500

```
t5 = pandas.DataFrame({'key': [100, 101, 102],
                       'name': ['John', 'Annie', 'Joe']})
t6 = pandas.DataFrame({'key': [100, 101],
                       'balance': [100, 500]})

t5.set_index('key').join(t6.set_index('key'))
```

result

User ID	User Name	Balance
100	John	100
101	Annie	500
102	Joe	NaN

combine

Table G

User ID	Balance
100	3000
101	200

Table H

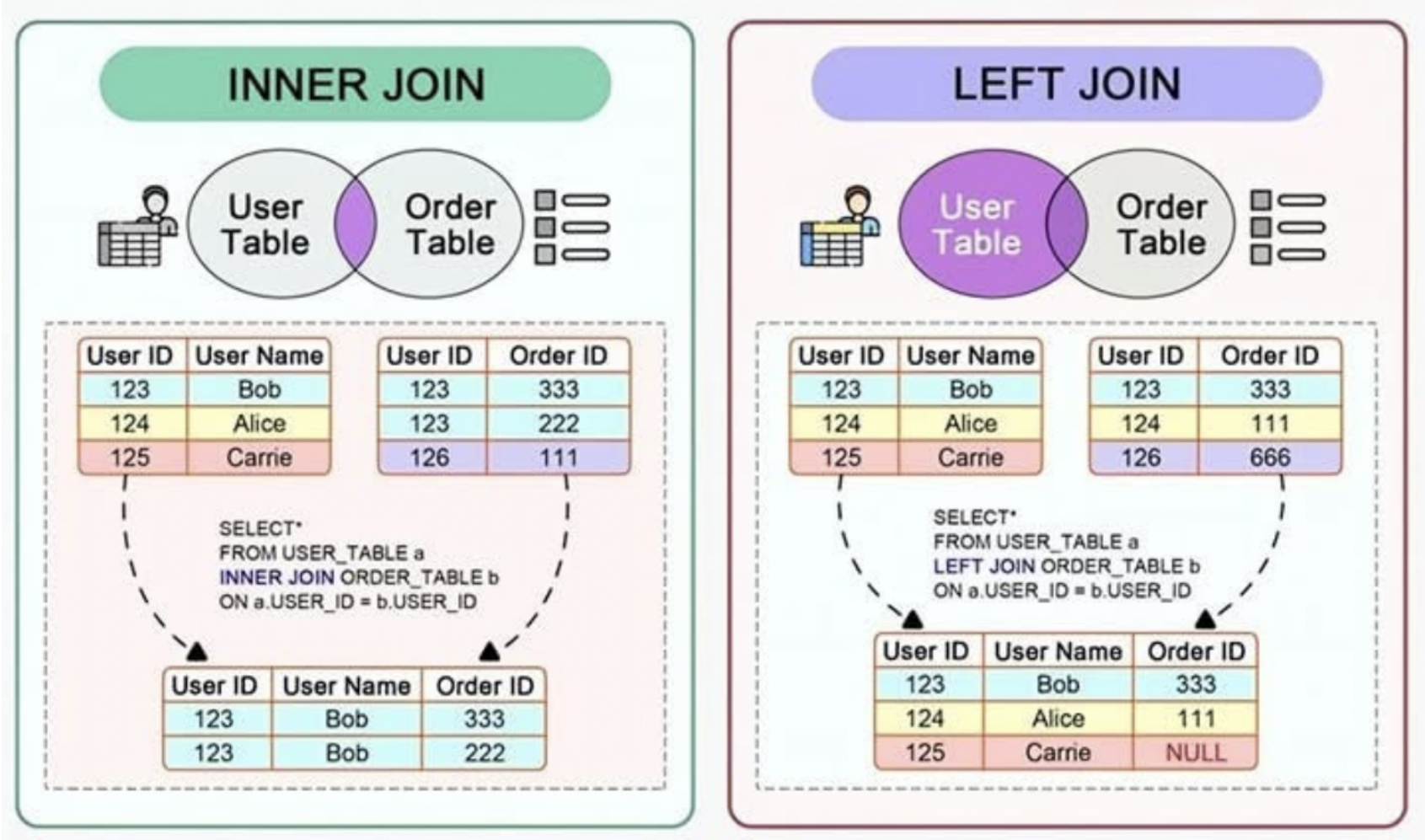
User ID	Balance
100	100
101	500

```
t7 = pandas.DataFrame({'key': [100, 101],
                       'balance': [3000, 200]})
t8 = pandas.DataFrame({'key': [100, 101],
                       'balance': [100, 500]})

choose_smaller = lambda x,y: x if x.sum() < y.sum() else y

t7.combine(t8, choose_smaller)
```

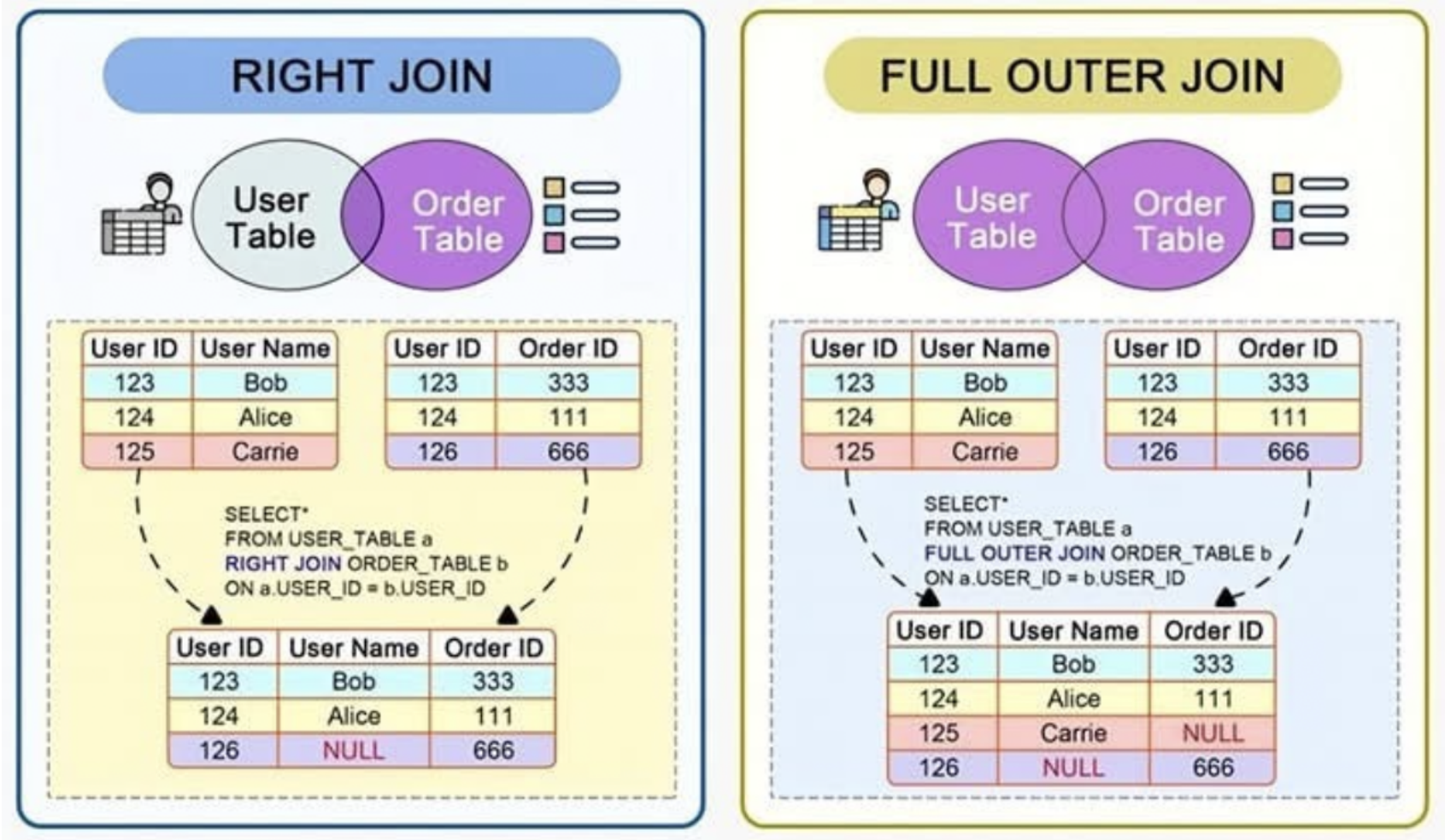
result

User ID	Balance
100	100
101	200

Structured Query Language (SQL) Joins



Structured Query Language (SQL) Joins



Example 1: Merging Dataframes

Sample Dataset: Students and Courses

Dataset 1: Students

	Student ID	Name	Gender	GPA	Institution
0	A1	Angela	F	4.0	MBHS
1	A2	Anne	F	3.6	RHHS
2	A3	Alex	M	3.0	UMCP
3	A4	Nina	F	3.2	CNHS
4	A5	Shirley	F	2.7	UMCP
5	A6	David	M	4.0	UMCP
6	A7	Alex	M	3.5	UMBC

Dataset 2: Courses

	Student ID	Name	School	Class	Grade
0	A1	Angela	UMCP	Math 201	A+
1	A3	Alex	UMCP	ENCE 201	B-
2	A7	Alex	UMCP	ENCE 353	B+
3	A2	Anne	UMCP	Math 201	A-
4	A2	Anne	UMCP	Math 215	B+

Example 1: Merging Dataframes

Merge Tables (inner merge, default)

```
Python:   inner_merge = pd.merge( students01, classes01,
-------                           on='Student ID')
          print( inner_merge)

Output:
-------
```

	Student ID	Name_x	Gender	GPA	Institution	Name_y	School	Class	Grade
0	A1	Angela	F	4.0	MBHS	Angela	UMCP	Math 201	A+
1	A2	Anne	F	3.6	RHHS	Anne	UMCP	Math 201	A-
2	A2	Anne	F	3.6	RHHS	Anne	UMCP	Math 215	B+
3	A3	Alex	M	3.0	UMCP	Alex	UMCP	ENCE 201	B-
4	A7	Alex	M	3.5	UMBC	Alex	UMCP	ENCE 353	B+

Example 1: Merging Dataframes

Merge Tables (left merge)

```
Python:  left_merge = pd.merge( students01, classes01,
-------                         on='Student ID', how='left' )
         print(left_merge)

Output:
-------
```

	Student ID	Name_x	Gender	GPA	Institution	Name_y	School	Class	Grade
0	A1	Angela	F	4.0	MBHS	Angela	UMCP	Math 201	A+
1	A2	Anne	F	3.6	RHHS	Anne	UMCP	Math 201	A-
2	A2	Anne	F	3.6	RHHS	Anne	UMCP	Math 215	B+
3	A3	Alex	M	3.0	UMCP	Alex	UMCP	ENCE 201	B-
4	A4	Nina	F	3.2	CNHS	NaN	NaN	NaN	NaN
5	A5	Shirley	F	2.7	UMCP	NaN	NaN	NaN	NaN
6	A6	David	M	4.0	UMCP	NaN	NaN	NaN	NaN
7	A7	Alex	M	3.5	UMBC	Alex	UMCP	ENCE 353	B+

Example 1: Merging Dataframes

Merge Tables (right merge)

```
Python:     right_merge = pd.merge( students01, classes01,
-------                             on='Student ID', how='right' )
            print( right_merge )

Output:
-------
```

	Student ID	Name_x	Gender	GPA	Institution	Name_y	School	Class	Grade
0	A1	Angela	F	4.0	MBHS	Angela	UMCP	Math 201	A+
1	A3	Alex	M	3.0	UMCP	Alex	UMCP	ENCE 201	B-
2	A7	Alex	M	3.5	UMBC	Alex	UMCP	ENCE 353	B+
3	A2	Anne	F	3.6	RHHS	Anne	UMCP	Math 201	A-
4	A2	Anne	F	3.6	RHHS	Anne	UMCP	Math 215	B+

Example 1: Merging Dataframes

Merge Tables (outer merge)

```
Python:     outer_merge = pd.merge( students01, classes01,
-------                             on='Student ID', how='outer' )
            print( outer_merge )

Output:
-------
```

	Student ID	Name_x	Gender	GPA	Institution	Name_y	School	Class	Grade
0	A1	Angela	F	4.0	MBHS	Angela	UMCP	Math 201	A+
1	A2	Anne	F	3.6	RHHS	Anne	UMCP	Math 201	A-
2	A2	Anne	F	3.6	RHHS	Anne	UMCP	Math 215	B+
3	A3	Alex	M	3.0	UMCP	Alex	UMCP	ENCE 201	B-
4	A4	Nina	F	3.2	CNHS	NaN	NaN	NaN	NaN
5	A5	Shirley	F	2.7	UMCP	NaN	NaN	NaN	NaN
6	A6	David	M	4.0	UMCP	NaN	NaN	NaN	NaN
7	A7	Alex	M	3.5	UMBC	Alex	UMCP	ENCE 353	B+

Spatial Data and Dataset Transformation

(Working with GeoPandas)

GeoPandas

GeoPandas

GeoPandas is an open source project to make working with geospatial data in Python easier.

Approach:

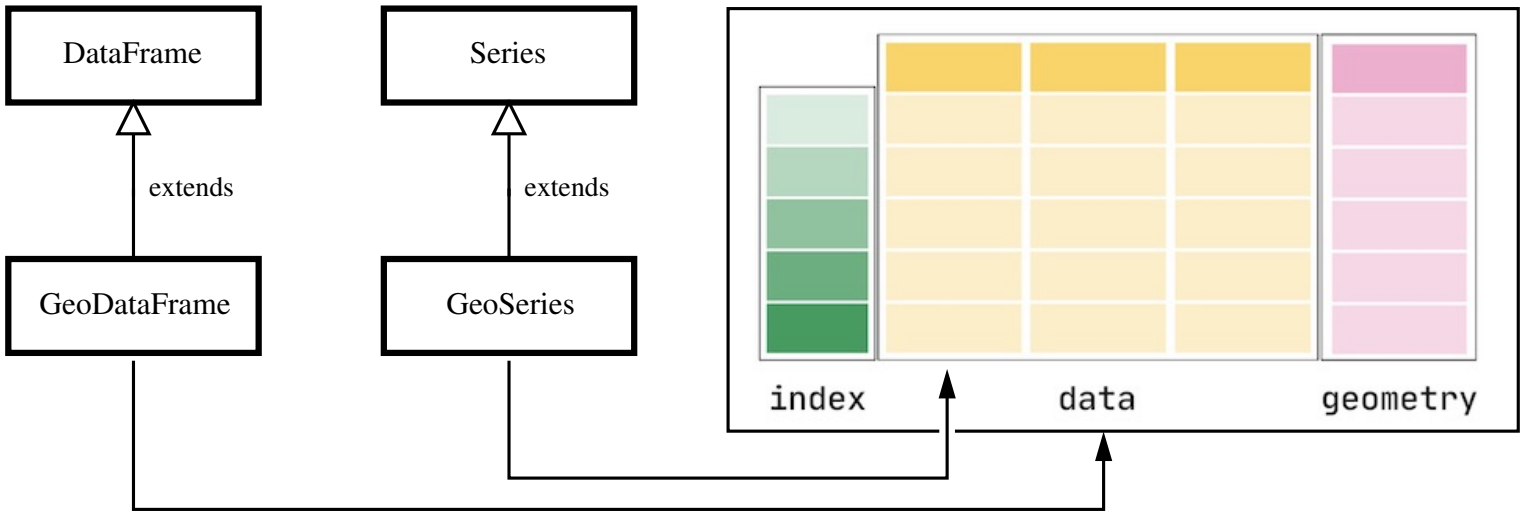
- Extend the datatypes used by Pandas to allow spatial operations on geometric types.
- Geometric operations are performed by shapely.
- Geopandas further depends on fiona for file access and matplotlib for plotting.

Installation

```
prompt >> pip3 install geopandas
```

Working with GeoPandas Dataframes

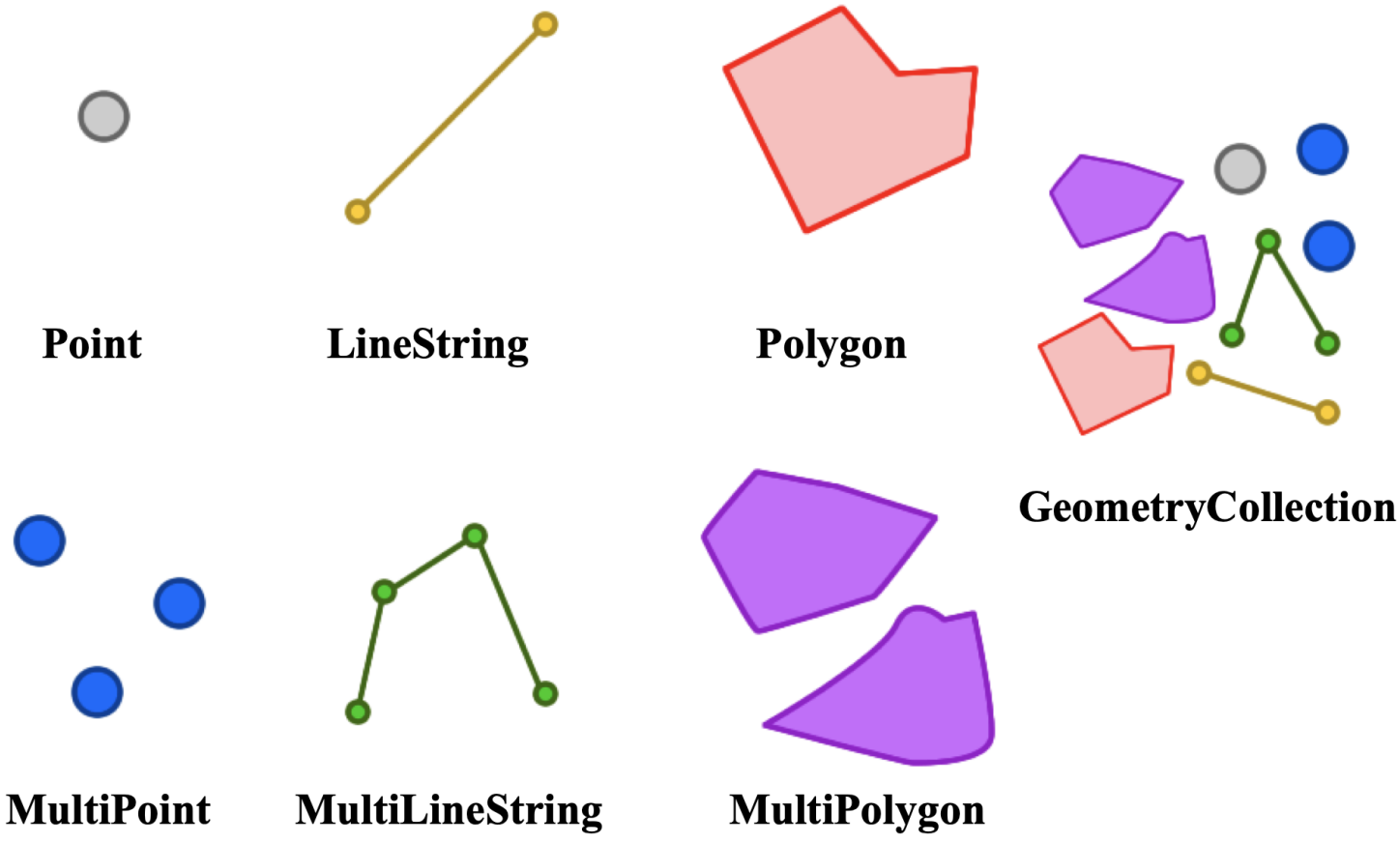
Core Modeling Concepts and Data Structure:



- GeoSeries handle geometries (points, polygons, etc).
- GeoDataFrames store geometry columns and perform spatial operations. They can be assembled from geopandas.GeoSeries.

Working with GeoPandas Dataframes

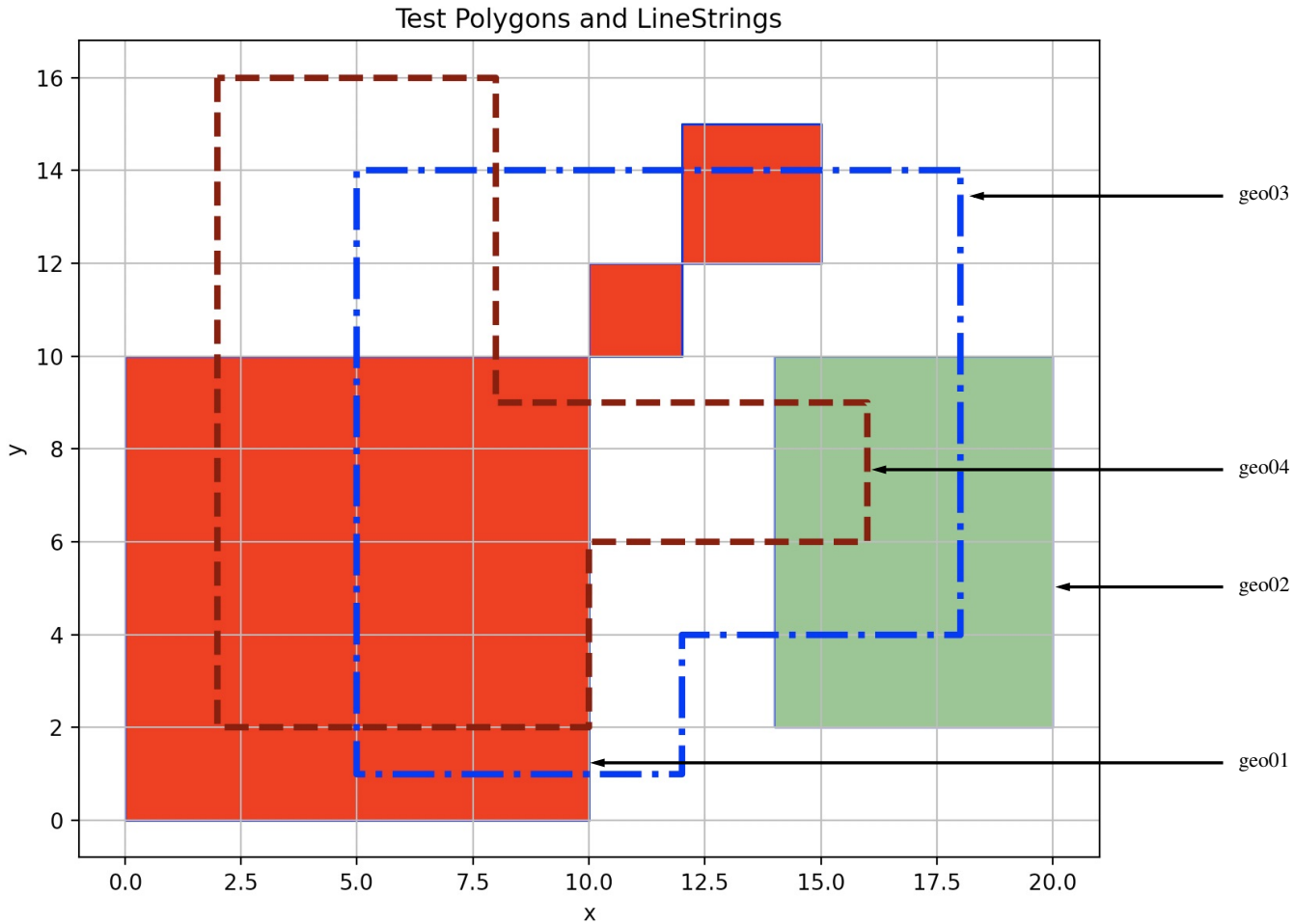
Geometric Objects: points, multi-points, lines, multi-lines, polygons, multi-polygons.



Example 1: Manual Specification of Geometric Shapes

Example 1: Manual specification of polygon and linestring shapes

...



Example 1: Manual Specification of Geometric Shapes

Part I: Problem Setup

```
1   # ========================================================================
2   # TestGeoSeries01.py. Manual assembly of simple geometries.
3   #
4   # Written by: Mark Austin                                        February 2023
5   # ========================================================================
6
7   import geopandas
8   from geopandas import GeoSeries
9   from shapely.geometry import Polygon
10  from shapely.geometry import LineString
11
12  import matplotlib.pyplot as plt
13
14  # ==============================
15  # main method ...
16  # ==============================
17
18  def main():
19      print("--- Enter TestGeoSeries01.main()                ... ");
20      print("--- ======================================== ... ");
21
22      print("--- Part 01: Create individual polygons ... ");
23
24      polygon01 = Polygon([   (0,0),  (10,0), (10,10),  (0,10) ] )
25      polygon02 = Polygon([ (10,10), (12,10), (12,12), (10,12) ] )
26      polygon03 = Polygon([ (12,12), (15,12), (15,15), (12,15) ] )
```

Example 1: Manual Specification of Geometric Shapes

Part I: Problem Setup (Continued) ....

```
27      polygon04 = Polygon([ (14,2), (20,2), (20,10), (14,10) ] )
28
29      print("--- Part 02: Add polygons to GeoSeries ... ");
30
31      geo01 = GeoSeries( [ polygon01, polygon02, polygon03 ]);
32      geo02 = GeoSeries( [ polygon04 ]);
33
34      print("--- Part 03: Create simple linestring GeoSeries ... ");
35
36      line01 = LineString([ (18,14), (5,14), (5,1), (12,1), (12,4), (18,4), (18,14) ] )
37      geo03  = GeoSeries( [ line01 ]);
38      line02 = LineString([ (2,16), (2,2), (10,2), (10,6), (16,6), (16,9), (8,9), (8,16),
39      geo04  = GeoSeries( [ line02 ]);
40
41      print("--- Part 04: Print GeoSeries info and contents ... ");
42
43      print(geo01)
44      print(geo02)
45
46      print("--- Part 05: Area and boundary of geo01 ... ");
47
48      print(geo01.area)
49      print(geo01.boundary)
50
51      print("--- Part 06: Area and boundary of geo02 ... ");
52
53      print(geo02.area)
54      print(geo02.boundary)
```

Example 1: Manual Specification of Geometric Shapes

Part I: Problem Setup (Continued) ....

```
55
56      print("--- Part 07: Spatial relationship of geo01 through geo04 ... ");
57
58      print("--- Compute intersection of (lines) geo03 and geo04 ...")
59      geo02a = geo03.intersects(geo04)
60      print("---   geo03.intersects(geo04) --> {:s} ...".format( str( geo02a[0] ) ))
61      geo02b = geo03.intersection(geo04)
62      print("---   geo03.intersection(geo04) --> {:s} ...".format( str( geo02b[0] ) ))
63
64      print("--- Compute intersection of (region) geo01 and (lines) geo03 and geo04 ...")
65      geo02c = geo01.intersection(geo03)
66      print("---   geo01.intersection(geo03) --> {:s} ...".format( str( geo02c[0] ) ))
67      geo02d = geo01.intersection(geo04)
68      print("---   geo01.intersection(geo04) --> {:s} ...".format( str( geo02d[0] ) ))
69
70      print("--- Compute intersection of (region) geo02 and (lines) geo03 and geo04 ...")
71      geo02e = geo02.intersection(geo03)
72      print("---   geo02.intersection(geo03) --> {:s} ...".format( str( geo02e[0] ) ))
73      geo02f = geo02.intersection(geo04)
74      print("---   geo02.intersection(geo04) --> {:s} ...".format( str( geo02f[0] ) ))
75
76      print("--- Part 08: Plot polygons ... ");
77
78      ax = geo01.plot( color='blue', edgecolor='black')
79      ax.set_aspect('equal')
80      ax.set_title("Test Polygons and LineStrings")
```

Example 1: Manual Specification of Geometric Shapes

Part I: Problem Setup (Continued) ....

```
81
82          # Plot polygons ...
83
84          geo01.plot(ax=ax, edgecolor='blue', color='red',   alpha= 1.0 )
85          geo02.plot(ax=ax, edgecolor='blue', color='green', alpha= 0.5 )
86
87          # Plot linestring ...
88
89          geo03.plot(ax=ax, color='blue',   alpha= 1.0, linewidth=3.0, linestyle='dashdot' )
90          geo04.plot(ax=ax, color='maroon', alpha= 1.0, linewidth=3.0, linestyle='dashed' )
91
92          plt.xlabel('x')
93          plt.ylabel('y')
94          plt.grid(True)
95          plt.show()
96
97          print("--- ======================================== ... ");
98          print("--- Leave TestGeoSeries01.main()             ... ");
99
100 # ================================================
101 # call the main method ...
102 # ================================================
103
104 main()
```

Source Code: See: python-code.d/geopandas/

Example 1: Manual Specification of Geometric Shapes

Part II: Abbreviated Output:

```
--- Enter TestGeoSeries01.main()              ...
--- Part 01: Create individual polygons ...
--- Part 02: Add polygons to GeoSeries ...
--- Part 03: Create simple linestring GeoSeries ...

--- Part 04: Print GeoSeries info and contents ...

0    POLYGON ((0.00000 0.00000, 10.00000 0.00000, 1...
1    POLYGON ((10.00000 10.00000, 12.00000 10.00000...
2    POLYGON ((12.00000 12.00000, 15.00000 12.00000...
dtype: geometry
0    POLYGON ((14.00000 2.00000, 20.00000 2.00000, ...
dtype: geometry

--- Part 05: Area and boundary of geo01 ...

0    100.0
1      4.0
2      9.0
dtype: float64
0    LINESTRING (0.00000 0.00000, 10.00000 0.00000,...
1    LINESTRING (10.00000 10.00000, 12.00000 10.000...
2    LINESTRING (12.00000 12.00000, 15.00000 12.000...
dtype: geometry
```

Example 1: Manual Specification of Geometric Shapes

Part II: Abbreviated Output:

```
--- Part 06: Area and boundary of geo02 ...

0    48.0
dtype: float64
0    LINESTRING (14.00000 2.00000, 20.00000 2.00000...
dtype: geometry

--- Part 07: Spatial relationship of geo01 through geo04 ...

--- Compute intersection of (lines) geo03 and geo04 ...

---   geo03.intersects(geo04) --> True ...
---   geo03.intersection(geo04) --> MULTIPOINT (5 2, 8 14) ...

--- Compute intersection of (region) geo01 and (lines) geo03 and geo04 ...

---   geo01.intersection(geo03) --> LINESTRING (5 10, 5 1, 10 1) ...
---   geo01.intersection(geo04) --> MULTILINESTRING ((10 2, 10 6), (2 10, 2 2, 10 2), (10 9, 8 9, 8 10))

--- Compute intersection of (region) geo02 and (lines) geo03 and geo04 ...

---   geo02.intersection(geo03) --> LINESTRING (14 4, 18 4, 18 10) ...
---   geo02.intersection(geo04) --> LINESTRING (14 6, 16 6, 16 9, 14 9) ...

--- Part 08: Plot polygons ...
--- Leave TestGeoSeries01.main()              ...
```

Applications

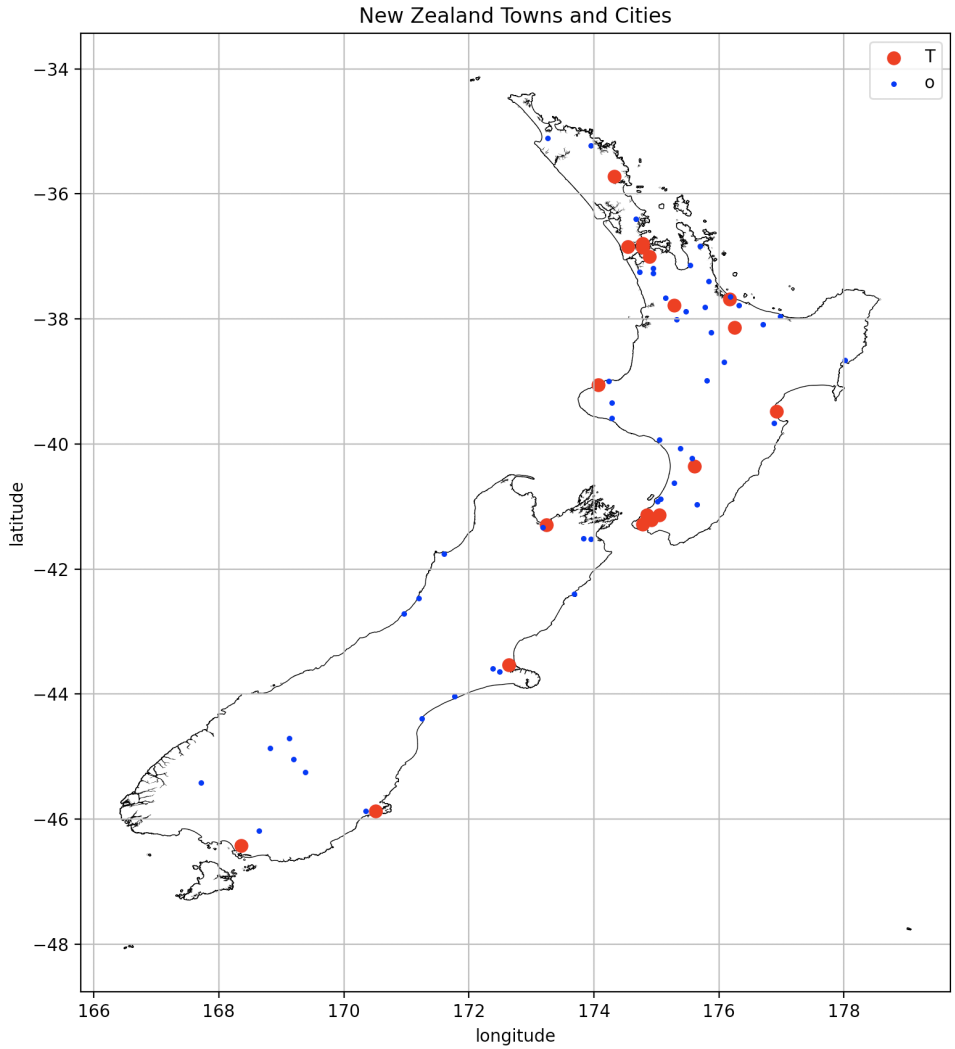
(Towns and Cities in New Zealand)

(The Worlds Megacities, Streets in Manhattan)

(Traffic Accidents in NYC, Flights to/from BWI)

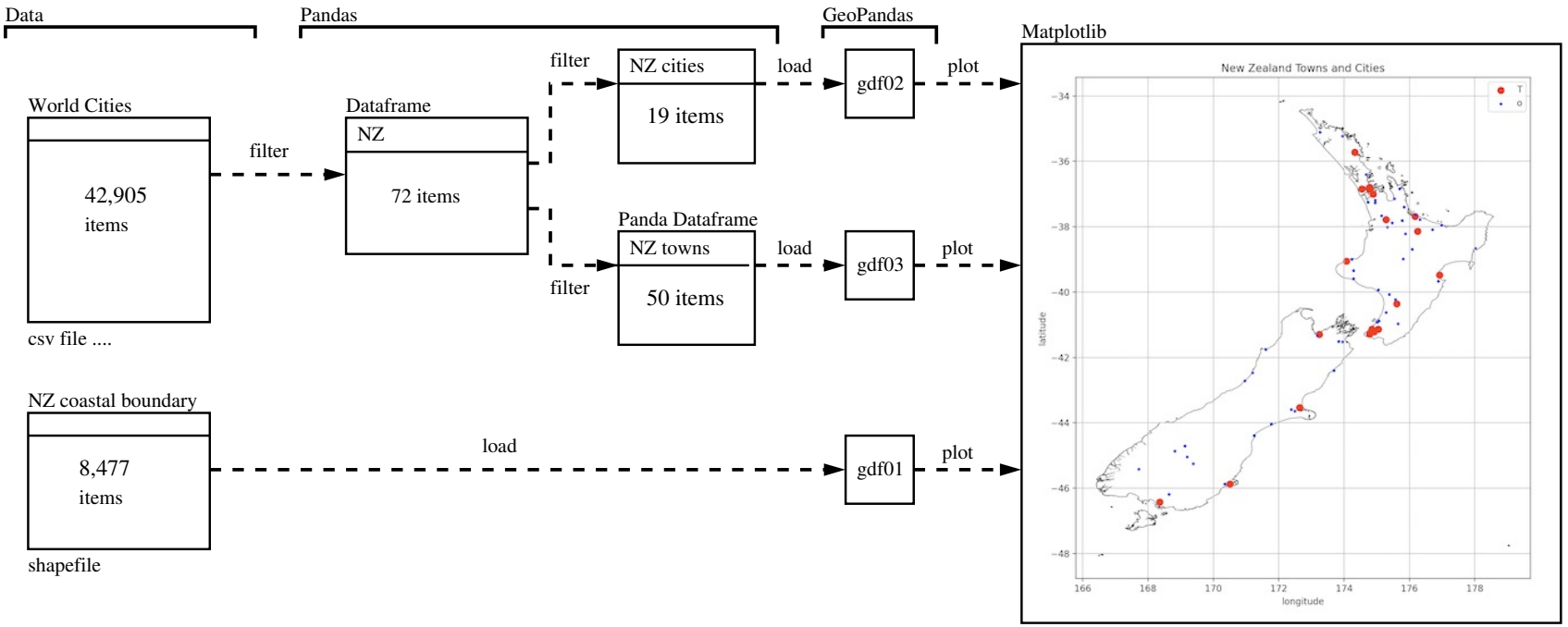
Example 2: Towns and Cities in New Zealand

Example 2: Towns and Cities in New Zealand.



Example 2: Towns and Cities in New Zealand

Part I: Data Processsing Pipeline: Use sequence of filters to specialize views of data ...



Example 2: Towns and Cities in New Zealand

Part II: Program Source Code:

```
1   # ================================================================================
2   # TestNewZealandDataModel.py. Assemble data model for towns and cities in
3   # New Zealand.
4   #
5   # Written by: Mark Austin                                          February 2023
6   # ================================================================================
7
8   from pandas import DataFrame
9   from pandas import Series
10  from pandas import read_csv
11
12  import numpy as np
13  import pandas as pd
14  import geopandas
15
16  import matplotlib.pyplot as plt
17
18  # ==============================
19  # main method ...
20  # ==============================
21
22  def main():
23      print("--- Enter TestNewZealandDataModel.main()     ... ");
24      print("--- ======================================== ... ");
25
26      print("--- Part 01: Load world city dataset ... ");
```

Example 2: Towns and Cities in New Zealand

Part II: Program Source Code: (Continued) ...

```
27
28      df = pd.read_csv("../data/cities/world-cities.csv")
29
30      print("--- Part 02: Print dataframe info and contents ... ");
31
32      print(df)
33      print(df.info() )
34
35      print("--- Part 03: Filter dataframe to keep only cities from New Zealand ... ")
36
37      options = ['New Zealand']
38      dfNZ       = df [ df['country'].isin(options) ].copy()
39
40      print("--- Part 04: Filter data to find NZ cities and towns ... ")
41
42      dfNZcities = dfNZ [ (dfNZ['population'] > 40000) ].sort_values( by=['population'] )
43
44      dfNZtowns  = dfNZ [ (dfNZ['population'] > 1000) & (dfNZ['population'] < 40000) ]
45      dfNZtowns  = dfNZtowns.sort_values( by=['population'] )
46
47      print('--- New Zealand Cities:\n', dfNZcities )
48      print('--- New Zealand Towns:\n', dfNZtowns )
49
50      print("--- Part 05: Read NZ coastline shp file into geopandas ... ")
51
52      nzboundarydata = geopandas.read_file("../data/geography/nz/Coastline02.shp")
53      print(nzboundarydata)
```

Example 2: Towns and Cities in New Zealand

Part II: Program Source Code: (Continued) ...

```
55      print("--- Part 06: Define geopandas dataframes ... ")
56
57      gdf01 = geopandas.GeoDataFrame(nzboundarydata)
58      gdf02 = geopandas.GeoDataFrame( dfNZcities,
59                  geometry=geopandas.points_from_xy(dfNZcities.lng, dfNZcities.lat))
60      gdf03 = geopandas.GeoDataFrame(  dfNZtowns,
61                  geometry=geopandas.points_from_xy( dfNZtowns.lng, dfNZtowns.lat))
62
63      print(gdf01.head())
64
65      print("--- Part 07: Create boundary map for New Zealand ... ")
66
67      # We can now plot our ``GeoDataFrame``.
68
69      ax = gdf01.plot( color='white', edgecolor='black')
70      ax.set_aspect('equal')
71      ax.set_title("New Zealand Towns and Cities")
72
73      gdf01.plot(ax=ax, color='white')
74
75      gdf02.plot(ax=ax, color =  'red', markersize = 50, label= 'Cities')
76      gdf03.plot(ax=ax, color = 'blue', markersize =  5, label= 'Towns' )
77
78      plt.legend('Towns/Cities:')
79      plt.xlabel('longitude')
80      plt.ylabel('latitude')
```

Example 2: Towns and Cities in New Zealand

Part II: Program Source Code: (Continued) ...

```
81          plt.grid(True)
82          plt.show()
83
84          print("--- ======================================== ... ");
85          print("--- Leave TestNewZealandDataModel.main()     ... ");
86
87      # ================================================
88      # call the main method ...
89      # ================================================
90
91      main()
```

Source Code: See: python-code.d/geopandas/

Example 2: Towns and Cities in New Zealand

Part III: Abbreviated Output:

```
--- Enter TestNewZealandDataModel.main()     ...
--- ======================================== ...
--- Part 01: Load world city dataset ...
--- Part 02: Print dataframe info and contents ...
             city  city_ascii      lat  ... capital population         id
0           Tokyo       Tokyo  35.6839  ... primary 39105000.0 1392685764
1         Jakarta     Jakarta  -6.2146  ... primary 35362000.0 1360771077
...           ...         ...      ...  ...     ...        ...        ...
42903 Timmiarmiut Timmiarmiut  62.5333  ...     NaN       10.0 1304206491
42904     Nordvik     Nordvik  74.0165  ...     NaN        0.0 1643587468
[42905 rows x 11 columns]

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 42905 entries, 0 to 42904
Data columns (total 11 columns):
 #   Column      Dtype              #   Column      Dtype
---  ------      -----             ---  ------      -----
 0   city        object             6   iso3        object
 1   city_ascii  object             7   admin_name  object
 2   lat         float64            8   capital     object
 3   lng         float64            9   population  float64
 4   country     object            10   id          int64
 5   iso2        object
dtypes: float64(3), int64(1), object(7)
memory usage: 3.6+ MB
```

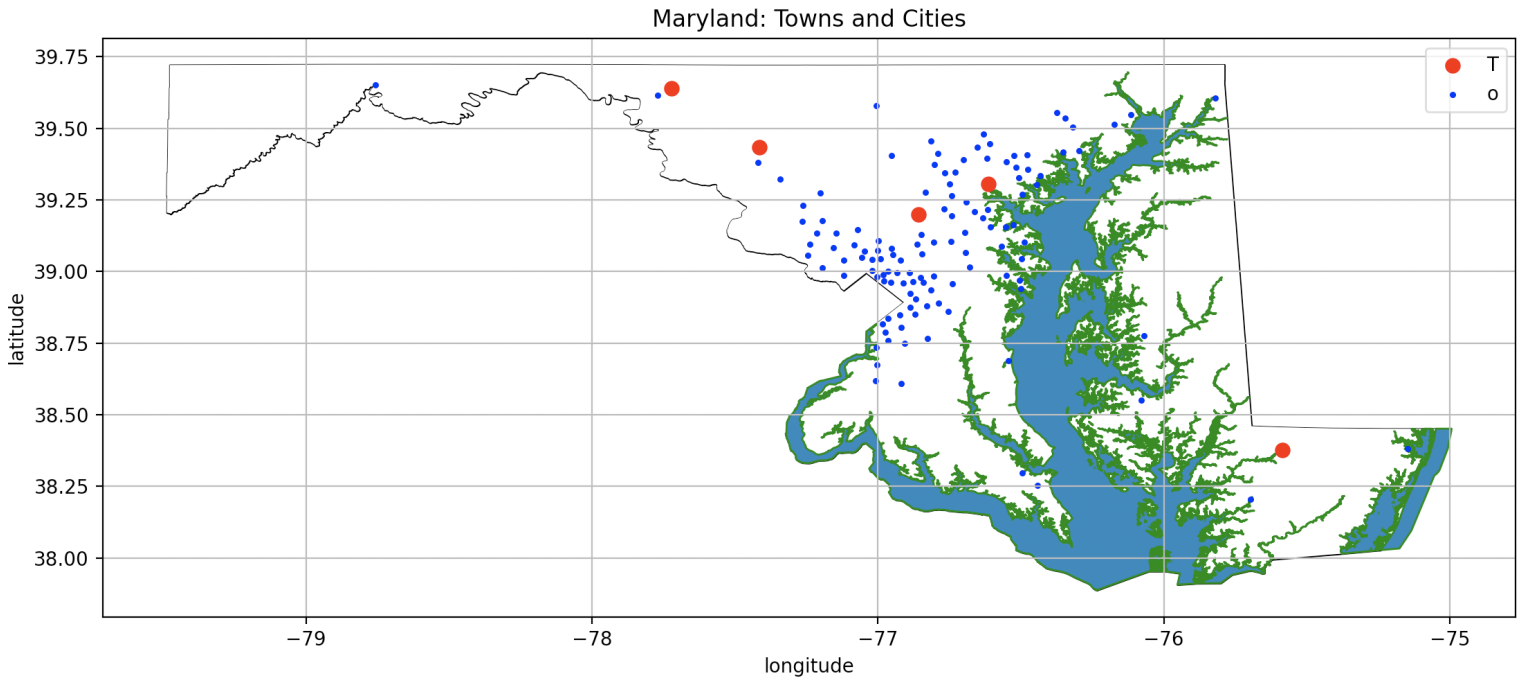
Example 2: Towns and Cities in New Zealand

Part III: Abbreviated Output (Continued) ...

```
--- Part 03: Filter dataframe to keep only cities from New Zealand ...
--- Part 04: Filter data to find NZ cities and towns ...

--- New Zealand Cities:
                  city        city_ascii  ...  population          id
14169        Upper Hutt        Upper Hutt  ...     41000.0  1554000042
6159       Invercargill      Invercargill  ...     47625.0  1554148942
.....
741          Wellington        Wellington  ...    418500.0  1554772152
516            Auckland          Auckland  ...   1346091.0  1554435911
[19 rows x 11 columns]

--- New Zealand Towns:
                  city       city_ascii  ...  population          id
42142         Kaikoura         Kaikoura  ...      2210.0  1554578431
.....
14309        Whanganui        Whanganui  ...     39400.0  1554827998
[50 rows x 11 columns]

--- Part 05: Read NZ coastline shp file into geopandas ...
0     POLYGON ((174.00369 -40.66489, 174.00372 -40.6...
.....
8476  POLYGON ((173.01384 -34.39348, 173.01395 -34.3...
[8477 rows x 1 columns]
--- Part 07: Create boundary map for New Zealand ...
--- ======================================== ...
--- Leave TestNewZealandDataModel.main()     ...
```

Example 3: Towns and Cities in Maryland

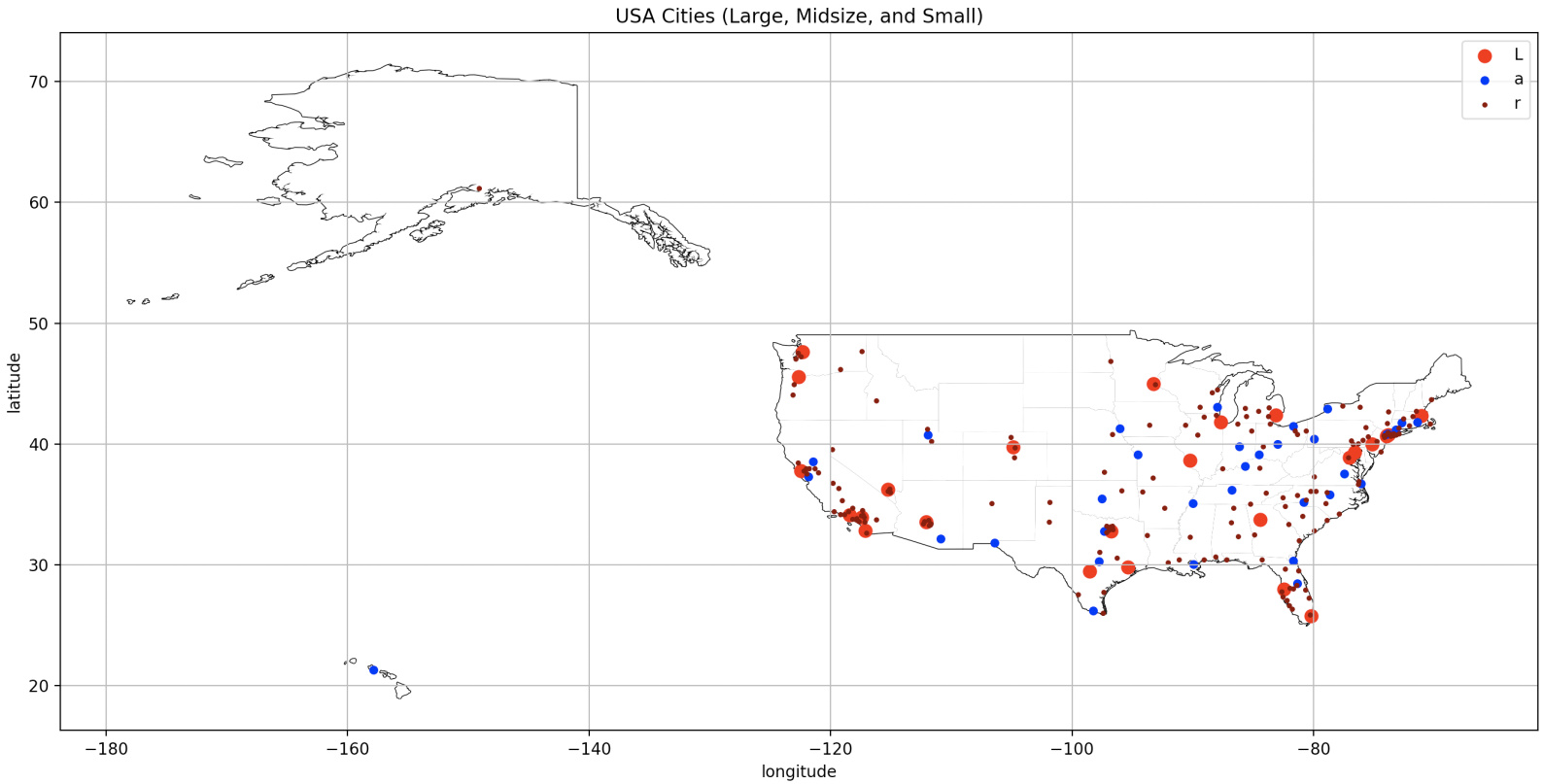
Example 3: Towns and Cities in Maryland.



Cities: Columbia (pop. 103991), Salisbury (pop. 106447), Frederick (pop. 156787), Hagerstown (pop. 184755), Baltimore (pop. 2106068).

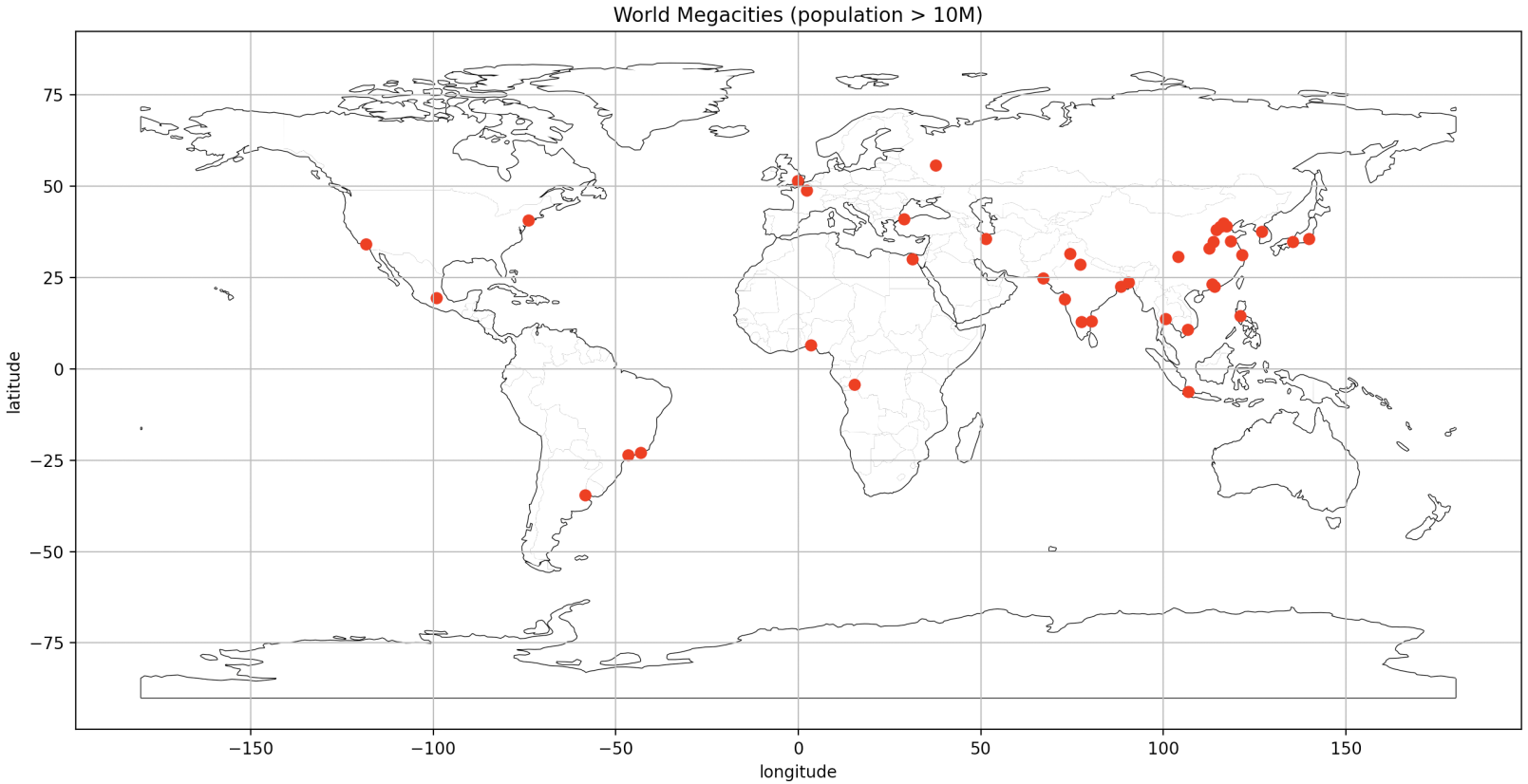
Example 4: Large, Midsize, and Small US Cities

Example 4: Large, Midsize, and Small US Cities



Cities: 26 large (pop. $>$ 2M), 34 midsize (800k $<$ pop. $<$ 2M), 172 small (200k $<$ pop. $<$ 800k).

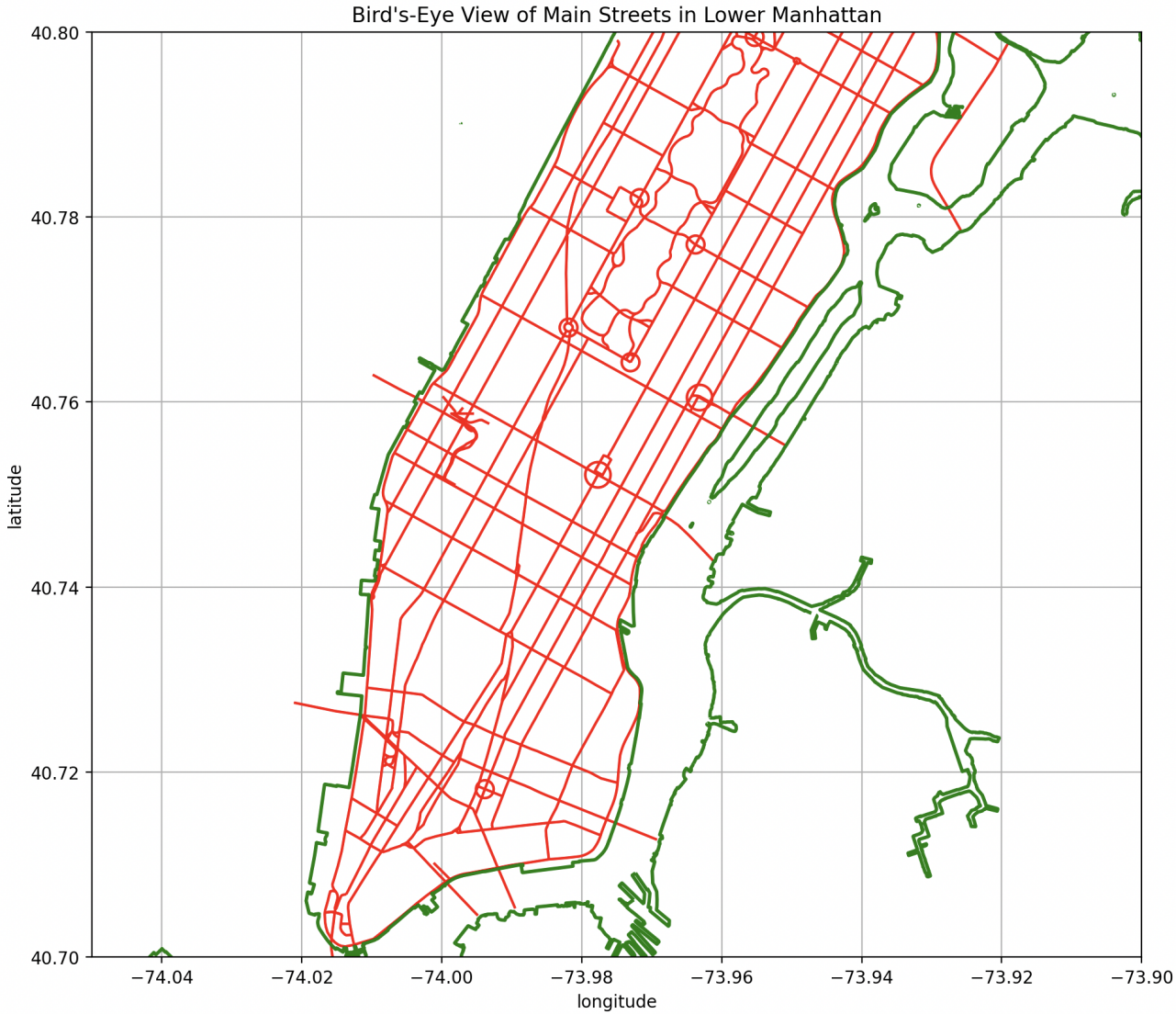
Example 5: The World's Megacities



Example 5: The World's Megacities

```
--- Part 02: Filter to keep only large cities (pop. > 10M) ...

                city        city_ascii  ...  population          id
0              Tokyo             Tokyo  ...  39105000.0  1392685764
1            Jakarta           Jakarta  ...  35362000.0  1360771077
2              Delhi             Delhi  ...  31870000.0  1356872604
3             Manila            Manila  ...  23971000.0  1608618140
4          São Paulo         Sao Paulo  ...  22495000.0  1076532519
5              Seoul             Seoul  ...  22394000.0  1410836482
6             Mumbai            Mumbai  ...  22186000.0  1356226629
7           Shanghai          Shanghai  ...  22118000.0  1156073548
8        Mexico City       Mexico City  ...  21505000.0  1484247881
9          Guangzhou         Guangzhou  ...  21489000.0  1156237133
10             Cairo             Cairo  ...  19787000.0  1818253931
11           Beijing           Beijing  ...  19437000.0  1156228865
12          New York          New York  ...  18713220.0  1840034016
13           Kolkāta           Kolkata  ...  18698000.0  1356060520
14            Moscow            Moscow  ...  17693000.0  1643318494
15           Bangkok           Bangkok  ...  17573000.0  1764068610

... details removed ...

33            London            London  ...  11120000.0  1826645935
34             Paris             Paris  ...  11027000.0  1250015082
35           Tianjin           Tianjin  ...  10932000.0  1156174046
36             Linyi             Linyi  ...  10820000.0  1156086320
37      Shijiazhuang      Shijiazhuang  ...  10784600.0  1156217541
38         Zhengzhou         Zhengzhou  ...  10136000.0  1156183137
39           Nanyang           Nanyang  ...  10013600.0  1156192287
```

Example 6: Main Streets in Lower Manhattan

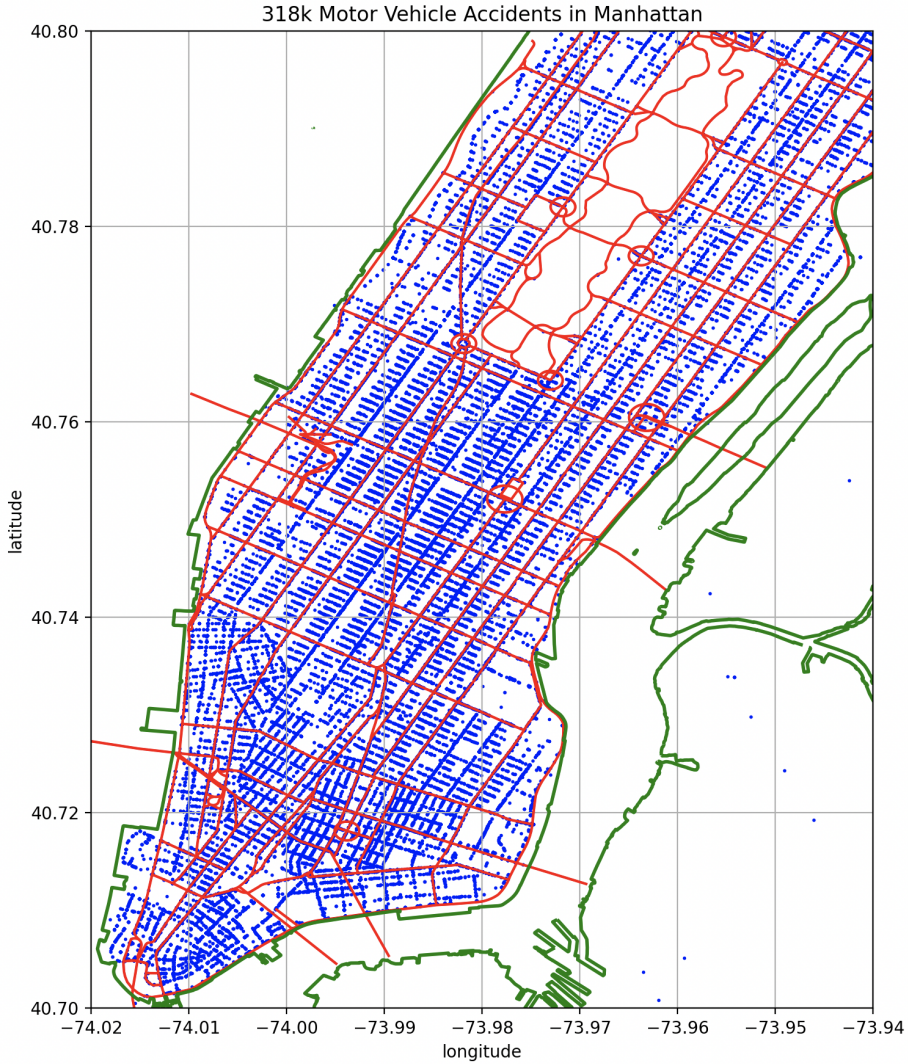


Example 6: Main Streets in Lower Manhattan

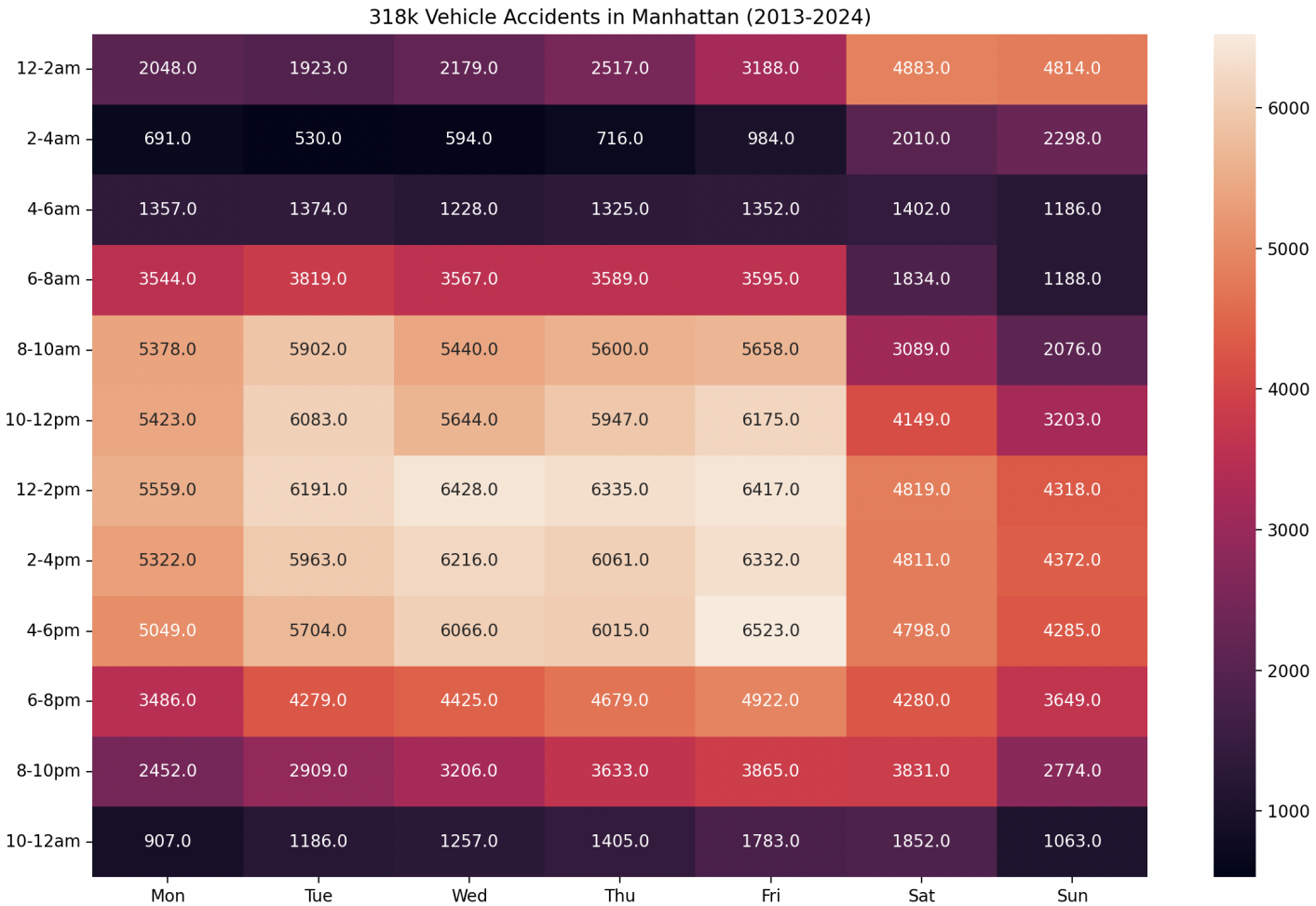
Abbreviated Datafile: 720 lines of data ...

```
the_geom,Borough,Boro_Code,Route_Name,Route_Type,Route_Sub,Route_Stat

"MULTILINESTRING ( (-73.9910241043406 40.72364943251929,
                    -73.99102457806407 40.72373532313096,
                    -73.99099489093685 40.72400907472583,
                    -73.99081902422084 40.72427429772359, ... ))",
                    Manhattan,1,2 Avenue,Major Streets,
                    Major street to be improved,Existing

....

"MULTILINESTRING ((-74.01166334821232 40.71279805585768,
                   -74.0109993711713  40.71332952150041,
                   -74.01056054567228 40.71384627551561,
                   -74.01027954718754 40.71419488854311,
                   -74.01012810711585 40.71438276644835,
                   -74.00968038665206 40.71494543483944,
                   ...
                   -74.00923907482891 40.71552016776998, ... ))",
                   Manhattan,1,West Broadway,Major Streets,
                   Major Street,Existing
```

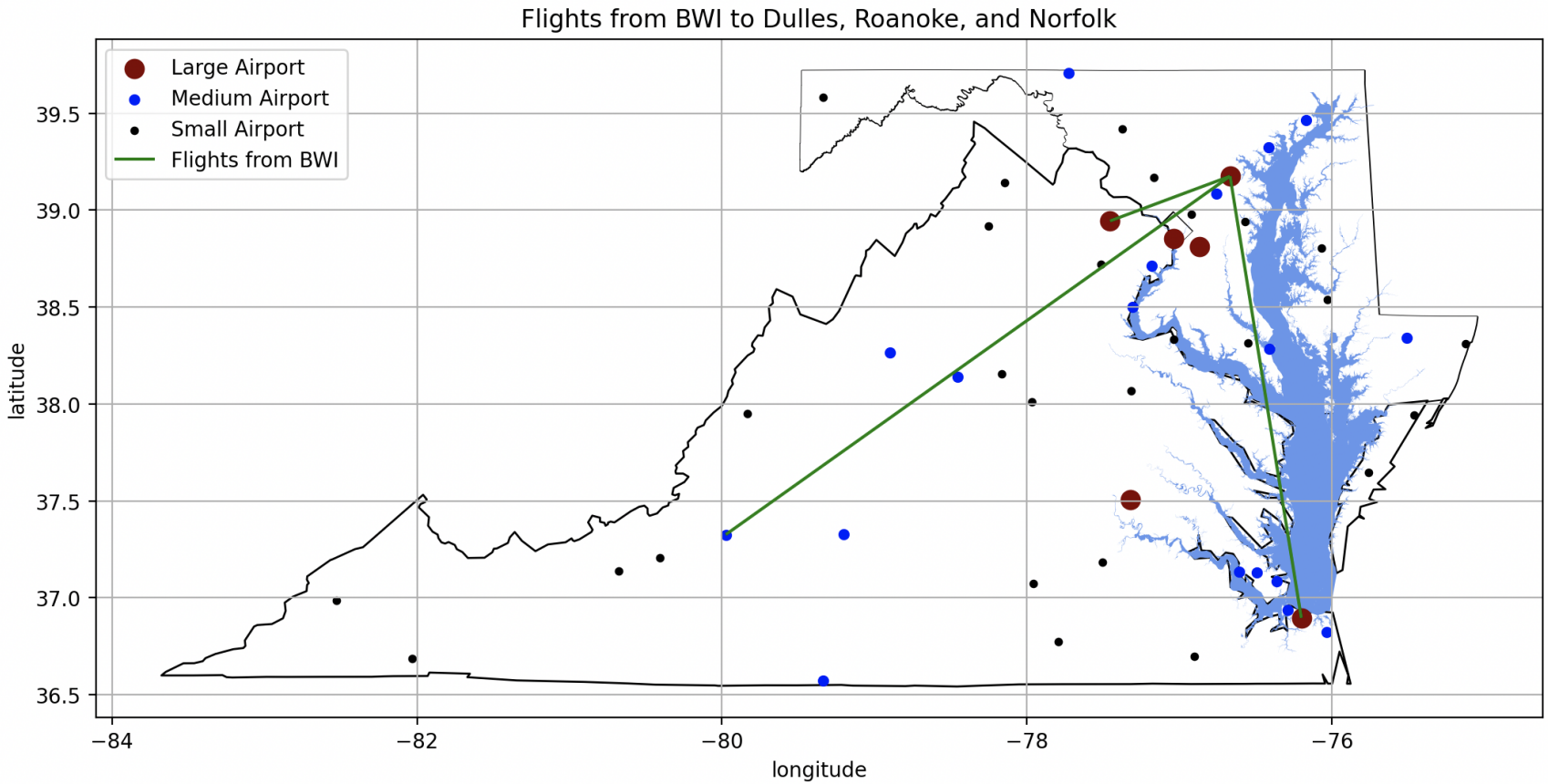
Example 7: Traffic Accidents in Lower Manhattan



Example 7: Traffic Accidents in Lower Manhattan

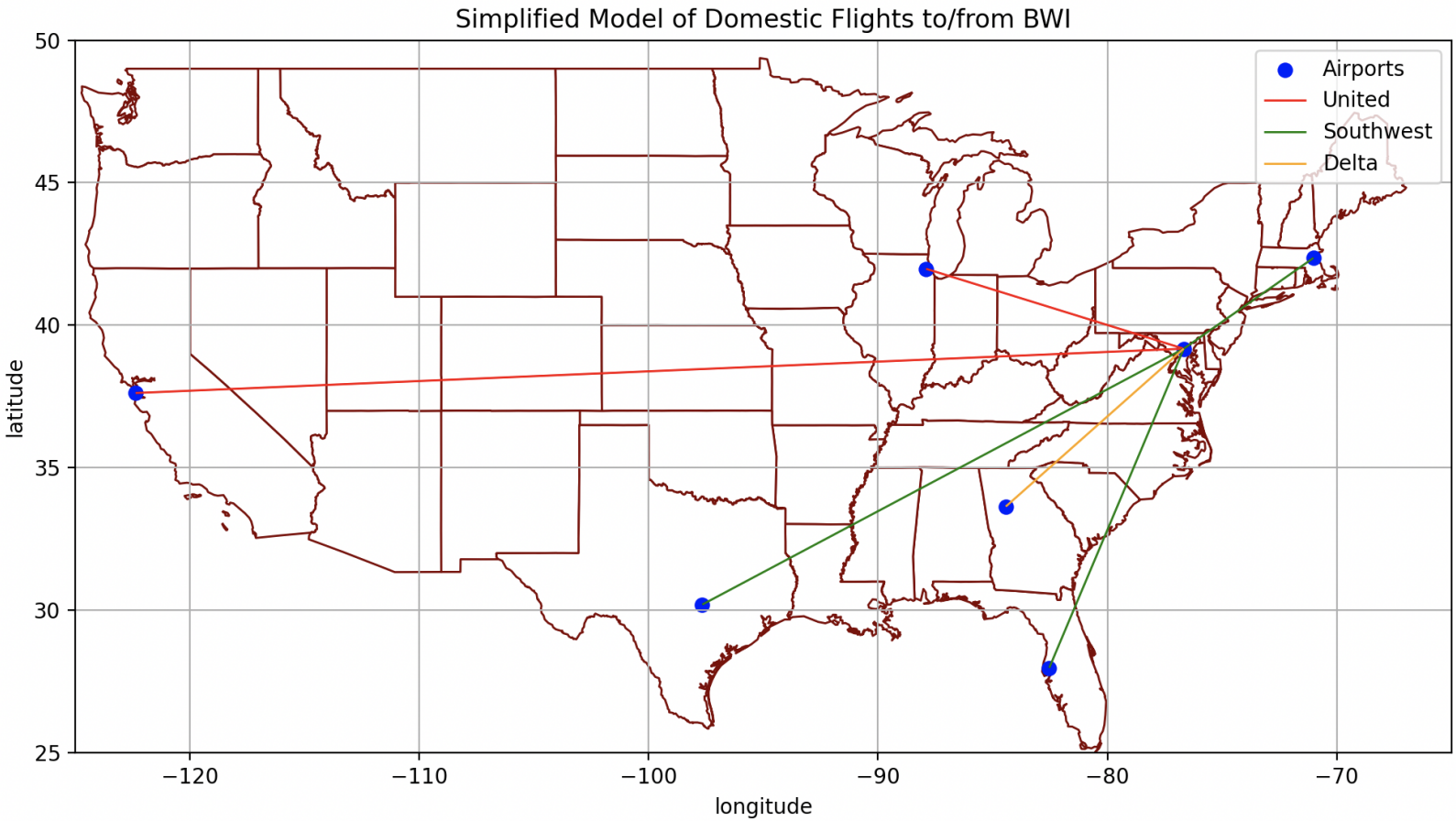


Example 8: Flights from BWI



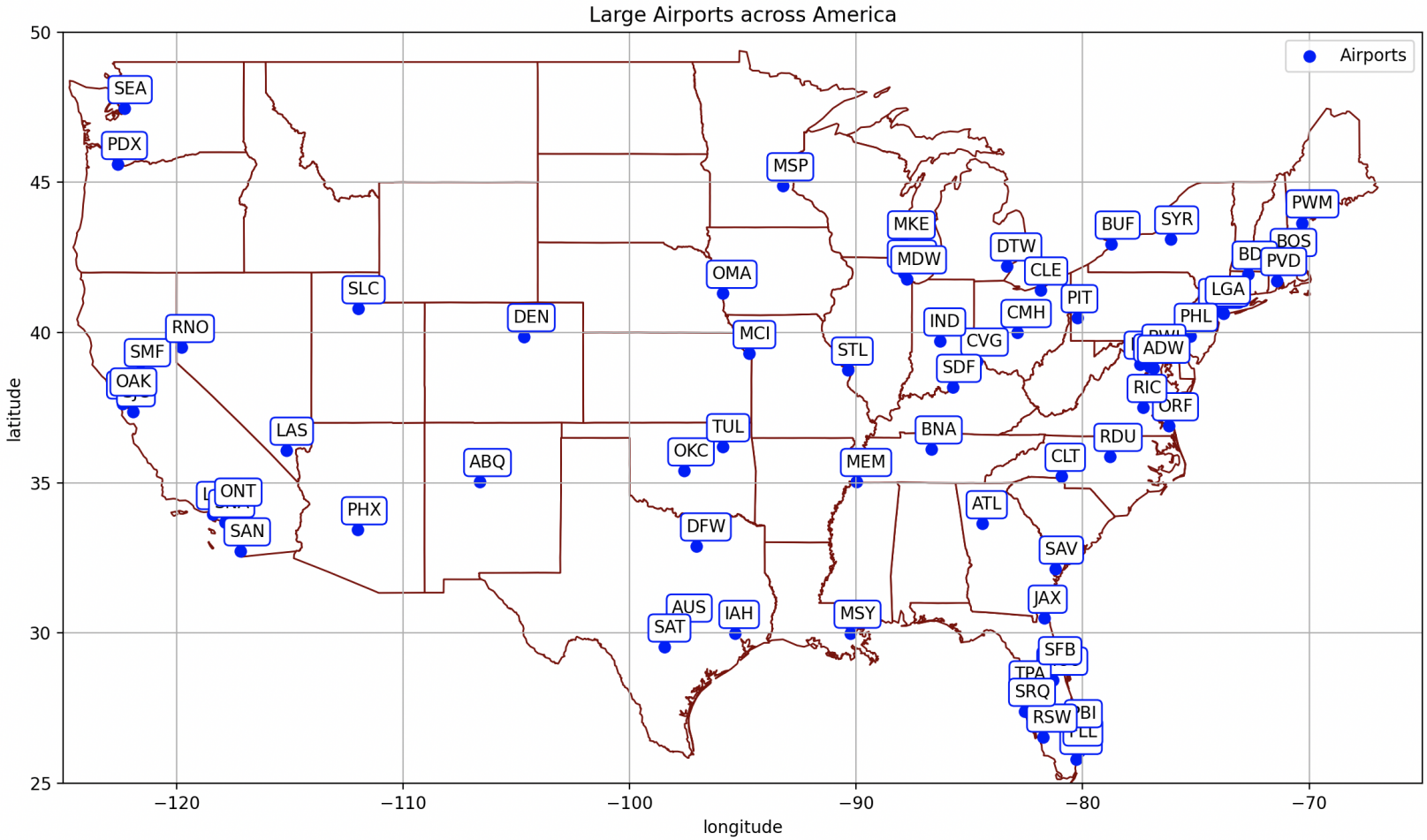
BWI Airport: GeoLocation (long, lat) = (-76.668297, 39.175400) ...

Example 8: Flights from BWI

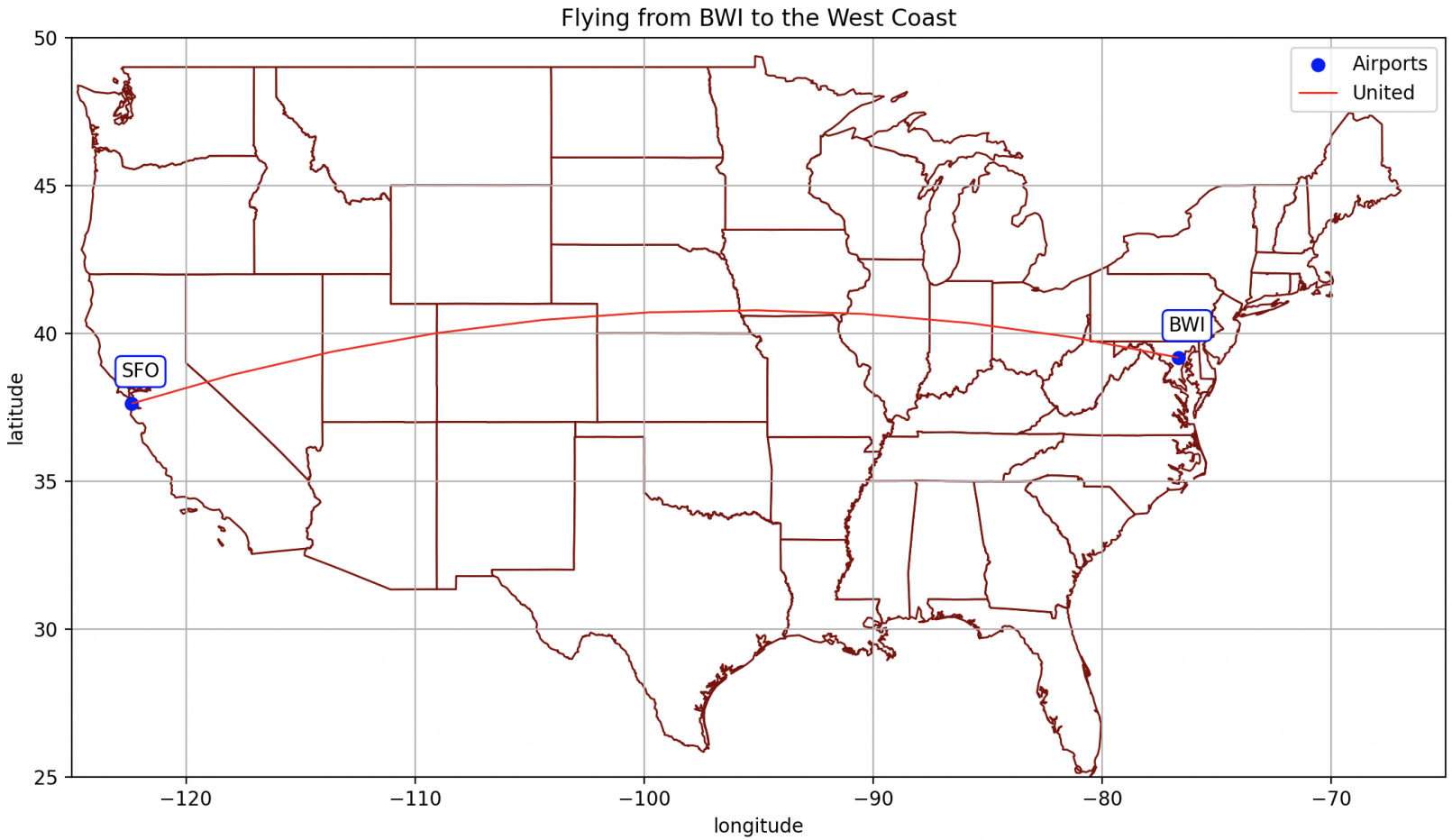


Source Code: See python-code.d/applications/transportation/air/TestAirTransportationUSA01.py

Example 8: Flights from BWI

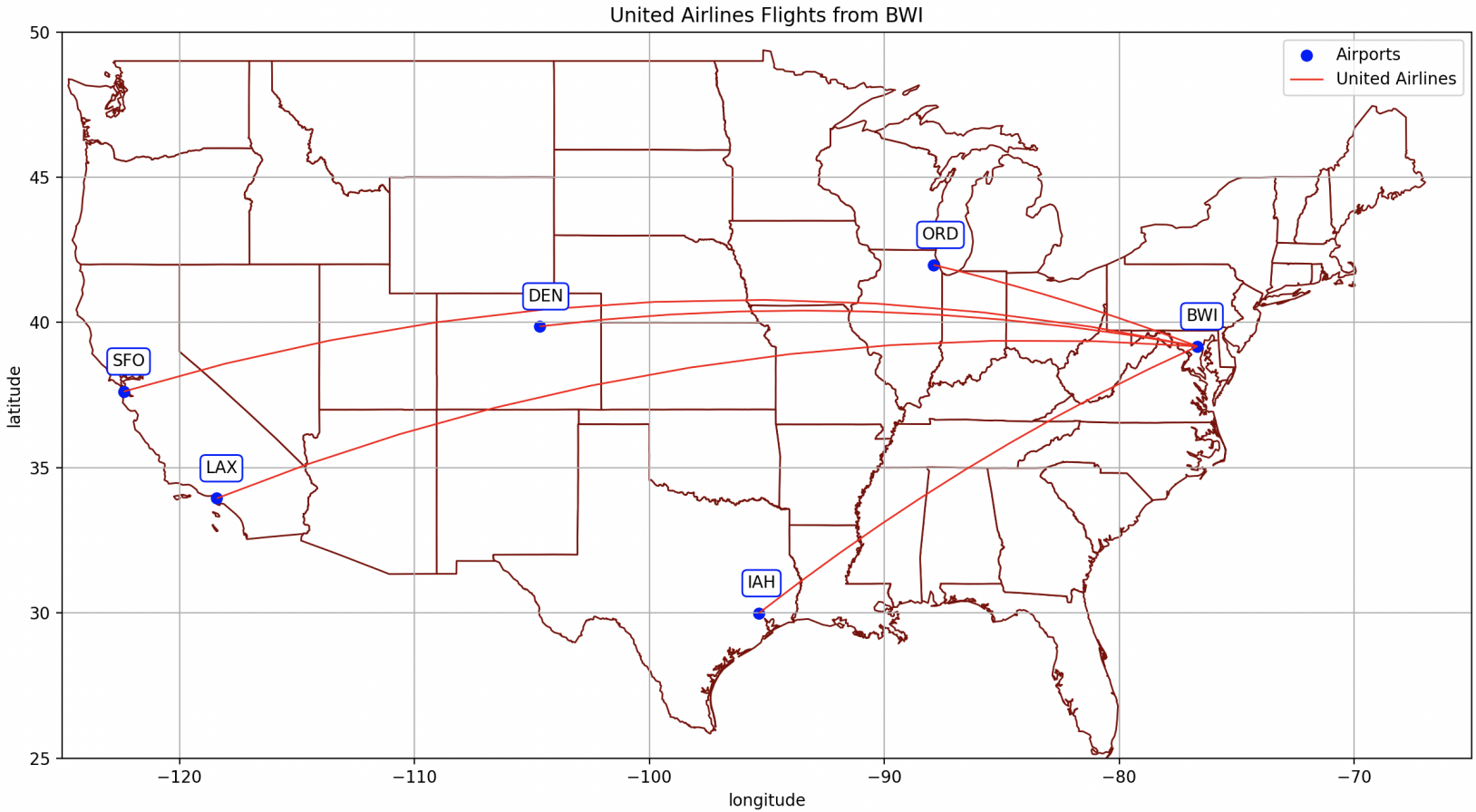


Example 8: Flights from BWI

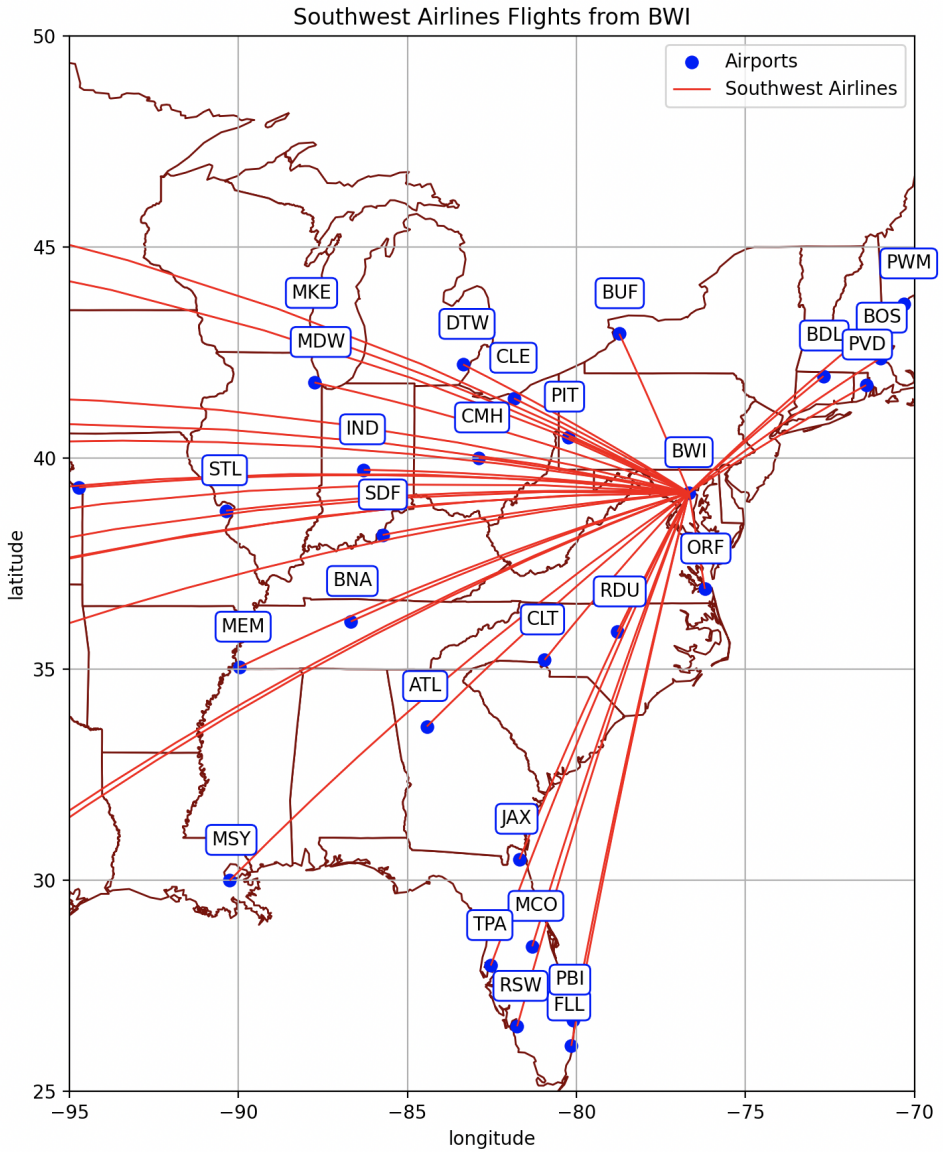


Source Code: See python-code.d/applications/transportation/air/TestAirTransportationUSA02.py

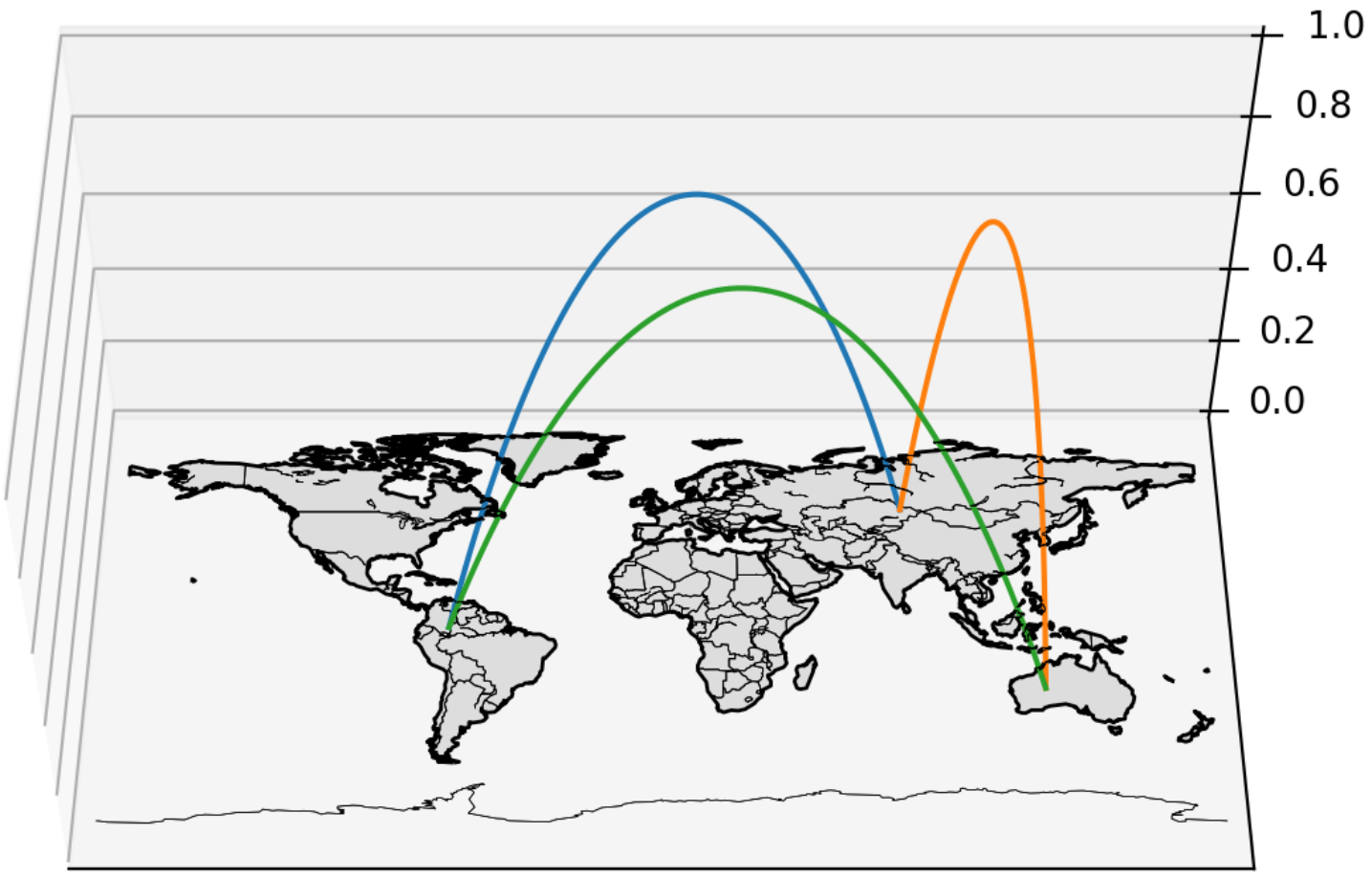
Example 8: United Flights from BWI



Example 8: Southwest Flights from BWI



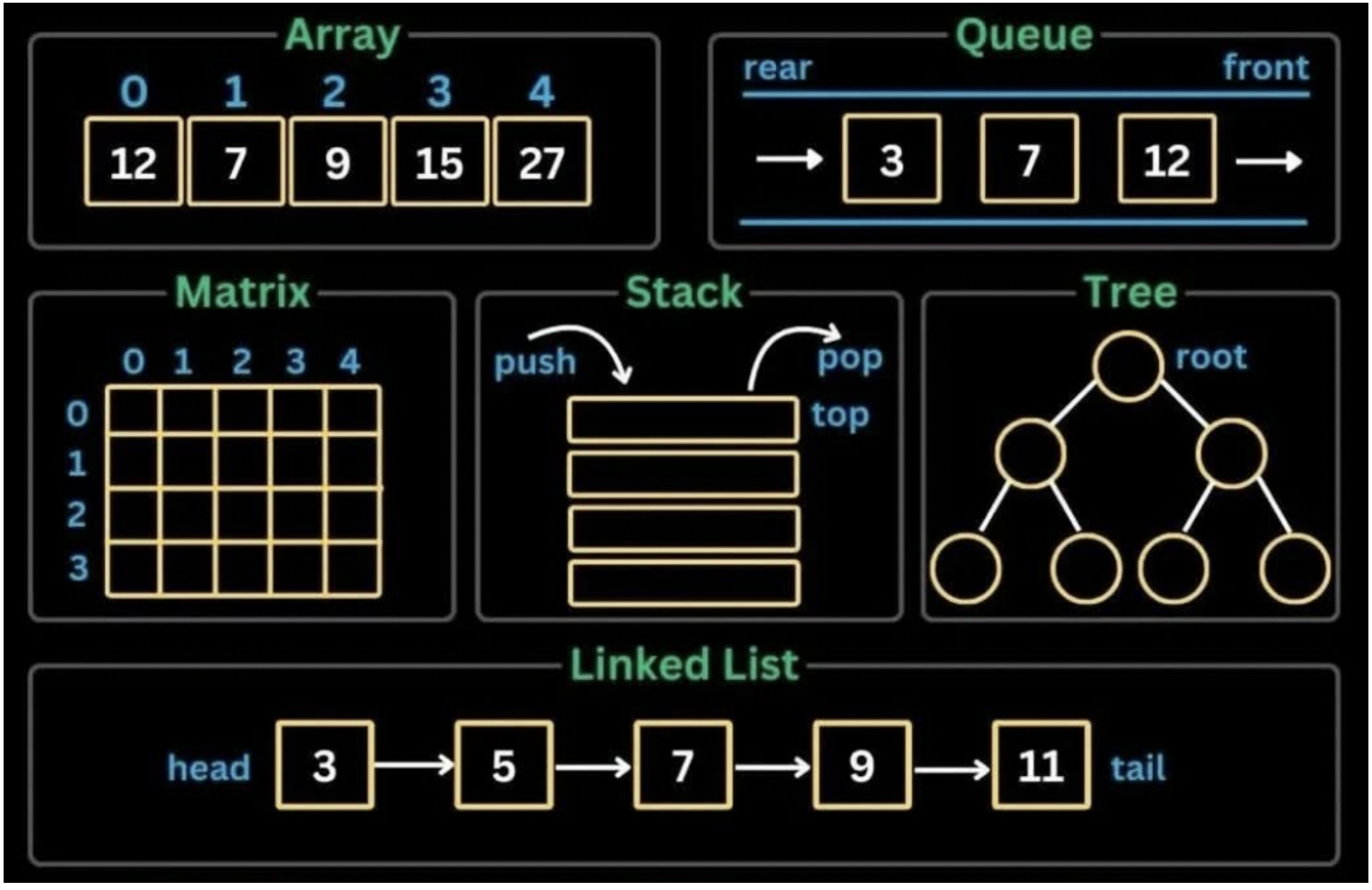
New for Fall Semester 2025



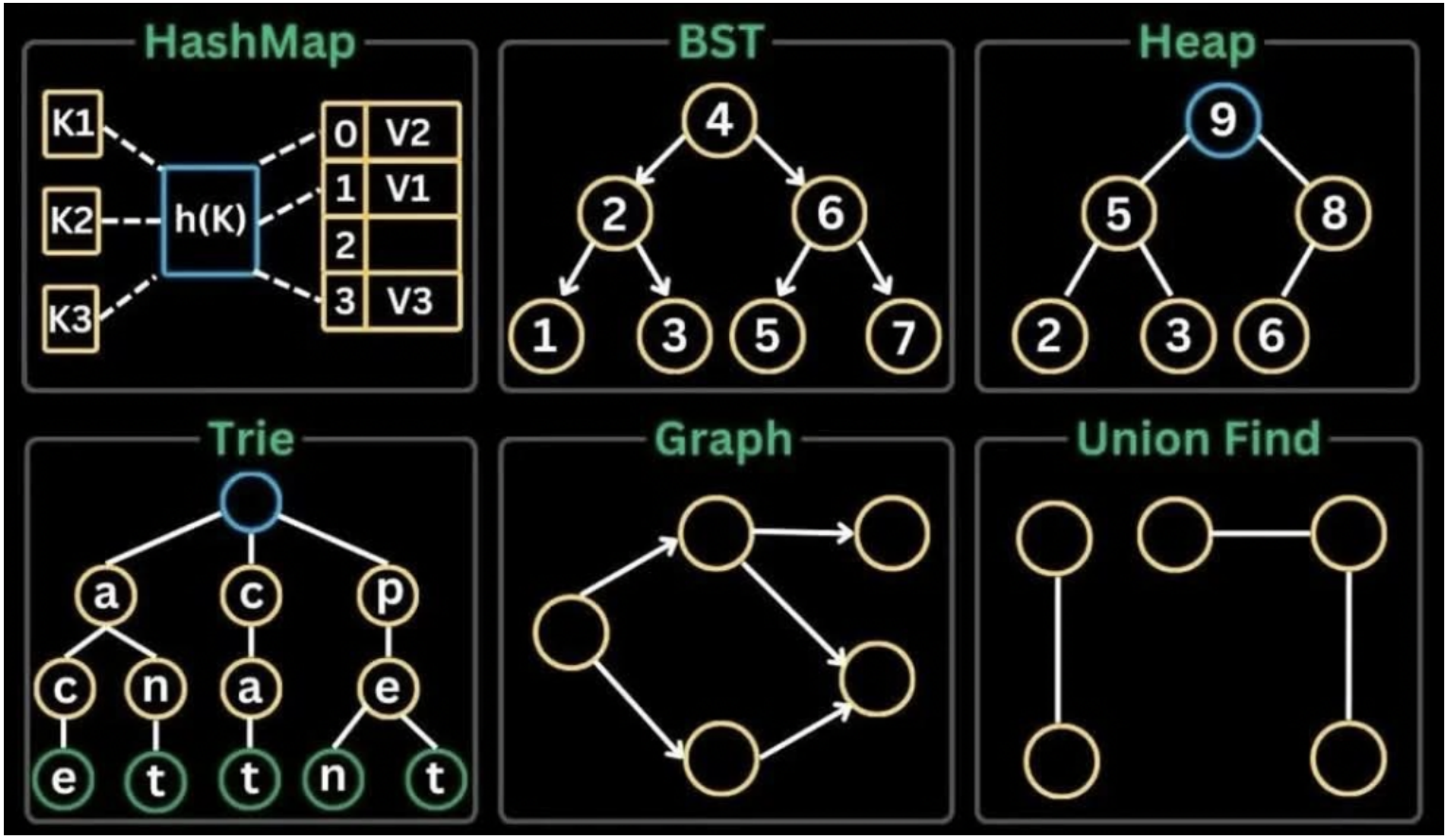
Appendix A

(From Data Models to Data Structures)

From Data Models to Data Structures



From Data Models to Data Structures



From Data Models to Data Structures

Arrays:

- Store multiple elements (of the same type) in a block of contiguous memory.
- Elements are accessed by index.
- Arrays have a fixed or resizeable size.

Matrices:

- Two-dimensional array of elements, organized into rows and columns.
- Elements are accessed using a combination of row index and column index.

From Data Models to Data Structures

Queue:

- Queues follow the rule: first-in first-out order.
- Efficient insertion at the rear. Efficient removal (deletion) at the front.

Stack:

- Stacks follow the rule: last-in first-out order.
- Efficient insertion and deletion of items at the top.

From Data Models to Data Structures

Linked List:

- Stores elements with next (and sometimes previous) node references.
- Supports dynamic size adjustments.
- Very efficient operations for node insertion and deletion.

HashMap:

- Employ (key, value) pairs for quick lookup.
- Uses a hash function for indexing.
- Efficient retrieval, insertion, and deletion operations.

From Data Models to Data Structures

Tree:

- Organizes data into a hierarchical structure.
- Elements have parent and child relationships.
- Used for hierarchy, search and sort.

Binary Search Tree (BST):

- Each node in the tree structure has a most two children, a left child and a right child.
- Left child's value is always less than the parent's node value.
- Right child's value is always greater than parent's node value.
- Hierarchy structure makes searching

From Data Models to Data Structures

Heap:

- A binary tree-based data structure that satisfies the max-heap (min-heap) property:
- Max-heap property: for every node, its value is greater than or equal (less than or equal) to the values of its children.
- The root stores the max value (max-heap) within the heap.

Trie:

- Tree-like structure for efficient storage/retrieval of strings.
- Strings are organized based on their prefixes, allowing for fast searches and auto-completion.
- Each node represents a character of a string.
- Pathway from root –> node: prefix of a stored string.

From Data Models to Data Structures

Graph:

- Represent relationships between vertex and edge entities.
- Used for modeling (physical, transportation, social) networks.

Key Takeaway:

When you have a chance (not right now) take a course on data structures and algorithms – they are the foundation of models and processes for good software development.