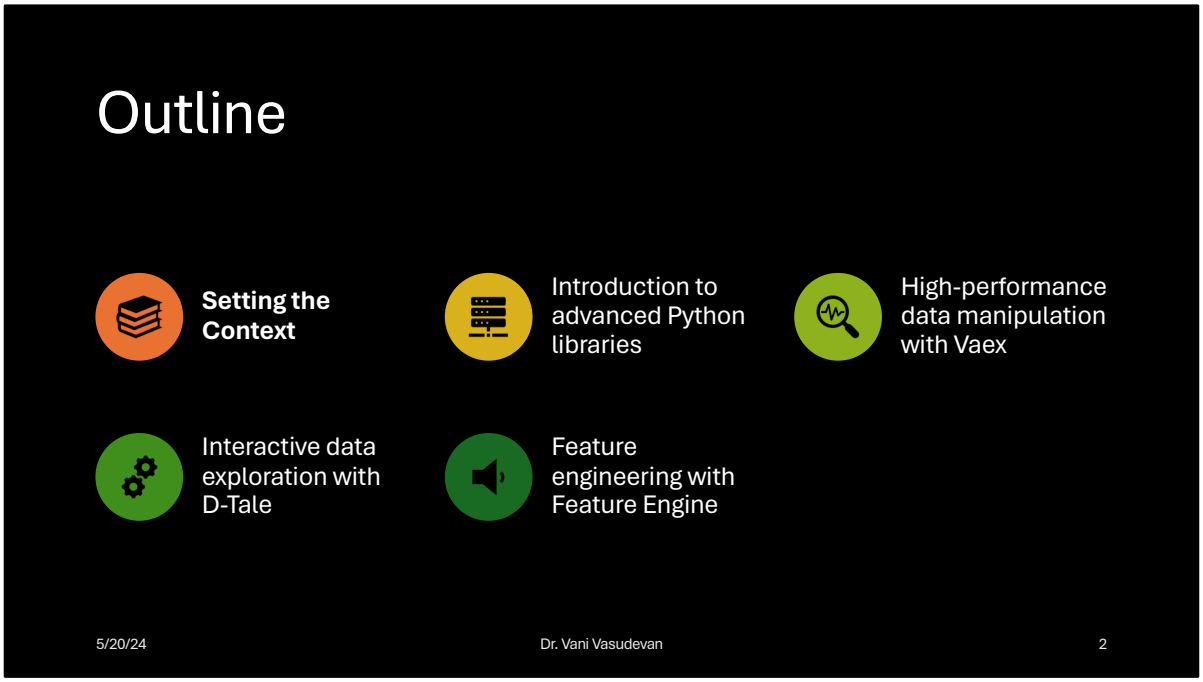
Session 14 (4: 00 PM to 6 PM)

Exploring Python's Advanced Libraries and Frameworks for Comprehensive Analysis

Dr. Vani V, Dept. of CSE,

Nitte Meenakshi Institute of Technology, Bengaluru



Importance of Advanced Python Libraries in Enhancing Data Analysis Capabilities and Improving Workflow Efficiency

1. Efficiency and Performance:

•Handling Large Datasets:

- Advanced libraries like Vaex are designed to work with large datasets that do not fit into memory, enabling efficient out-of-core data manipulation and analysis. This capability is crucial for processing large-scale data in a timely manner.

•Optimized Computations:

- These libraries leverage optimized algorithms and data structures, significantly reducing computation time. For example, Vaex uses memory-mapped files and efficient indexing to speed up data operations.

•Parallel Processing:

- Many advanced libraries support parallel processing and distributed computing, allowing for faster data processing by utilizing multiple CPU cores or even clusters of machines.

2. Ease of Use and Flexibility:

•User-Friendly APIs:

- Libraries like D-Tale provide intuitive interfaces for data exploration and

visualization, making it easier for data professionals to interact with their data without extensive coding.

•Seamless Integration:

- These libraries integrate seamlessly with other popular Python libraries such as Pandas, NumPy, and scikit-learn, allowing for a smooth transition and interoperability between different tools in the data science ecosystem.

3. Community Support and Documentation:

•Comprehensive Documentation:

- Most advanced libraries come with extensive documentation and tutorials, providing clear guidelines on how to use their features effectively. This makes it easier for users to get started and overcome any challenges they may encounter.

•Active Community:

- An active community of users and developers contributes to continuous improvement and support. Users can seek help from community forums, GitHub issues, and other online resources, ensuring they are not alone in their learning journey.

4. Improving Workflow Efficiency:

•Streamlined Data Processing:

- Feature Engine simplifies common preprocessing tasks such as handling missing data, encoding categorical variables, and scaling features, making the data preparation phase more efficient and less error-prone.

•Interactive Analysis:

- D-Tale provides an interactive environment for data exploration, enabling quick insights and facilitating a more iterative and exploratory analysis process. This leads to faster discovery of patterns and anomalies in the data.

5. Enhancing Analytical Capabilities:

•Advanced Techniques:

- By leveraging advanced libraries, data professionals can implement sophisticated techniques and models that were previously challenging or time-consuming. This includes out-of-core algorithms, automated machine learning, and complex feature engineering.

•Better Decision Making:

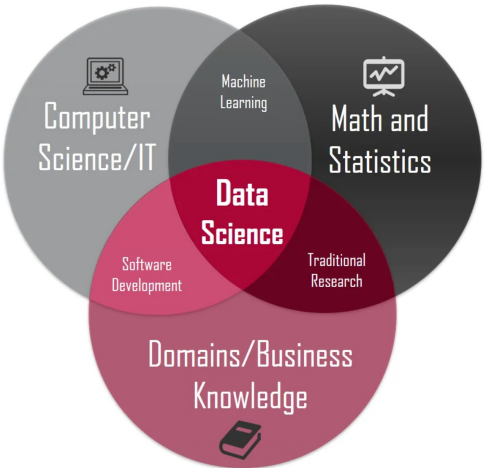
- The ability to analyze large datasets efficiently and accurately leads to more informed and data-driven decisions. This is particularly important in industries like healthcare, where timely and accurate insights can significantly impact business outcomes.

•Scalability:

- Advanced libraries are designed to scale with the data. As the volume and

complexity of data grow, these tools ensure that data analysis remains manageable and performant.

Skill Set for Data Science



Data Science vs. Data Analytics

Data science is an entire field dedicated to making data more useful.

A data scientist is a professional that uses raw data to develop new ways to model data and understand the unknown.

Often, their job responsibilities incorporate **various components of computer science, predictive analytics, statistics, and machine learning**.

The collections of information that data scientists work with can be quite large, requiring expertise to organize and navigate.

Source: Google data analytics professional certificate

Data Science vs. Data Analytics

Data analytics is a subfield of the larger data science discipline.

The aim of data analytics is to create methods to capture, process, and organize data to uncover actionable insights for current problems.

Analysts focus on processing the information stored in existing datasets and establishing the best way to present this data.

Data analysts rely on statistics and data modeling to solve problems and offer recommendations that can lead to immediate improvements.

Source: Google data analytics professional certificate

Data Science vs. Data Analytics

Data science	Data analytics
• Produces broad insights that concentrate on which questions should be asked about data	• Emphasizes discovering answers to questions being asked
• Confronts what is unknown by using advanced techniques to make predictions about the future	• Determines actionable insights that can be applied immediately based on existing queries

Source: Google data analytics professional certificate

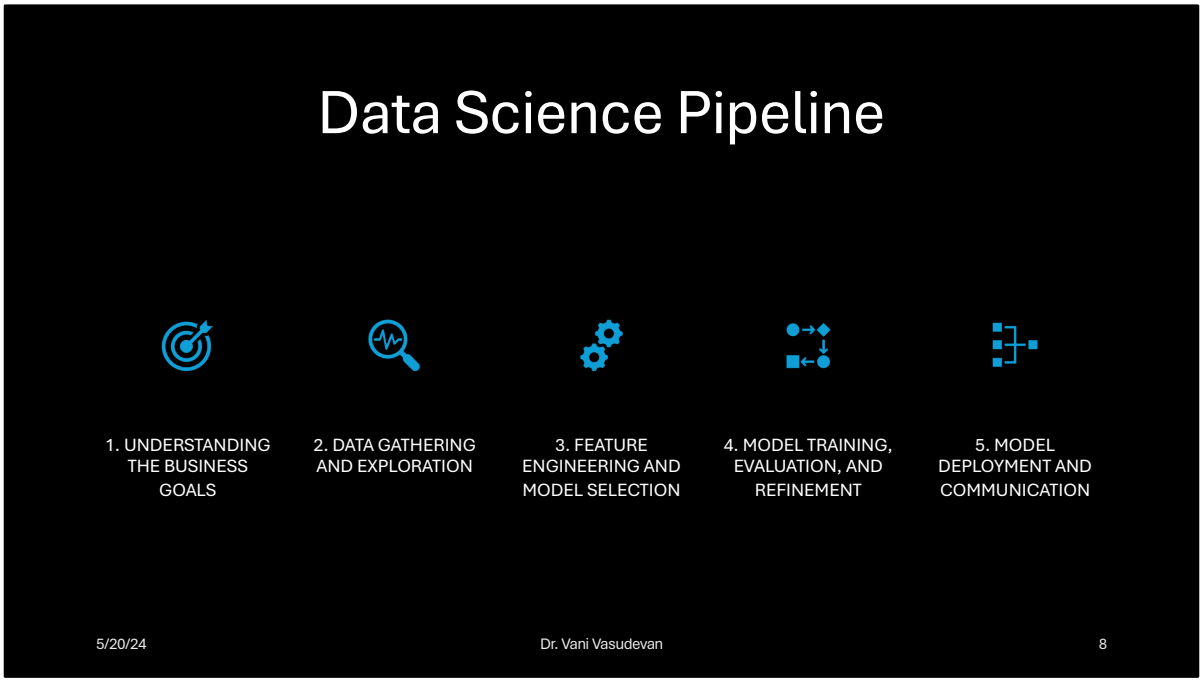
The connections between data science and data analytics

Data science and data analytics share a fundamental goal: discover insights that can be used to lead an organization to improve and grow.

They are closely connected with information gathered through interactions within the measurable world.

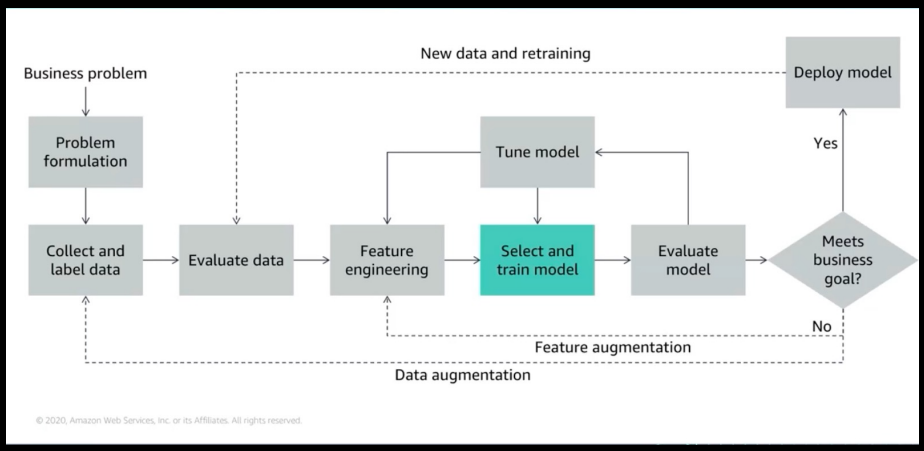
As data projects become more complicated, organizations are discovering the advantages of assembling data teams, bringing data analysts and data scientists together.

Source: Google data analytics professional certificate



Source: Google data analytics professional certificate

Machine Learning Pipeline



Source: AWS Academy – ML Foundation Course

Python For Data Science *Cheat Sheet*

Python Basics

Learn More Python for Data Science Interactively at www.datacamp.com

Variables and Data Types

Variable Assignment

```
>>> x=5
>>> x
 5
```

Calculations With Variables

```
>>> x+2
 7
>>> x-2
 3
>>> x*2
 10
>>> x**2
 25
>>> x%2
 1
>>> x/float(2)
 2.5
```

Sum of two variables
Subtraction of two variables
Multiplication of two variables
Exponentiation of a variable
Remainder of a variable
Division of a variable

Types and Type Conversion

`str()`	`'5', '3.45', 'True'`	Variables to strings
`int()`	`5, 3, 1`	Variables to integers
`float()`	`5.0, 1.0`	Variables to floats
`bool()`	`True, True, True`	Variables to booleans

Asking For Help

```
>>> help(str)
```

Strings

```
>>> my_string = 'thisStringIsAwesome'
>>> my_string
'thisStringIsAwesome'
```

String Operations

```
>>> my_string * 2
 'thisStringIsAwesomethisStringIsAwesome'
>>> my_string + 'Innit'
 'thisStringIsAwesomeInnit'
>>> 'm' in my_string
 True
```

String Operations (Index starts at 0)

```
>>> my_string[3]
>>> my_string[4:9]
```

String Methods

```
>>> my_string.upper()
>>> my_string.lower()
>>> my_string.count('w')
>>> my_string.replace('e', 'i')
>>> my_string.strip()
```

String to uppercase
String to lowercase
Count String elements
Replace String elements
Strip whitespaces

Lists (Also see NumPy Arrays)

```
>>> a = 'is'
>>> b = 'nice'
>>> my_list = ['my', 'list', a, b]
>>> my_list2 = [[4,5,6,7], [3,4,5,6]]
```

Selecting List Elements (Index starts at 0)

Subset

```
>>> my_list[1]
>>> my_list[-3]
```

Select item at index 1
Select 3rd last item

Slice

```
>>> my_list[1:3]
>>> my_list[1:]
>>> my_list[:3]
>>> my_list[:]
```

Select items at index 1 and 2
Select items after index 0
Select items before index 3
Copy my_list

Subset Lists of Lists

```
>>> my_list2[1][0]
>>> my_list2[1][:2]
```

my_list[list][itemOfList]

List Operations

```
>>> my_list + my_list
['my', 'list', 'is', 'nice', 'my', 'list', 'is', 'nice']
>>> my_list * 2
['my', 'list', 'is', 'nice', 'my', 'list', 'is', 'nice']
>>> my_list2 > 4
True
```

List Methods

```
>>> my_list.index(a)
>>> my_list.count(a)
>>> my_list.append('!')
>>> my_list.remove('!')
>>> del(my_list[0:1])
>>> my_list.reverse()
>>> my_list.extend('!')
>>> my_list.pop(-1)
>>> my_list.insert(0,'!')
>>> my_list.sort()
```

Get the index of an item
Count an item
Append an item at a time
Remove an item
Remove an item
Reverse the list
Append an item
Remove an item
Insert an item
Sort the list

Libraries

Import libraries

```
>>> import numpy
>>> import numpy as np
```

Selective import

```
>>> from math import pi
```

pandas — Data analysis
scikit-learn — Machine learning
NumPy — Scientific computing
matplotlib — 2D plotting

Install Python

ANACONDA — Leading open data science platform powered by Python
spyder — Free IDE that is included with Anaconda
jupyter — Create and share documents with live code, visualizations, text, ...

Numpy Arrays (Also see Lists)

```
>>> my_list = [1, 2, 3, 4]
>>> my_array = np.array(my_list)
>>> my_2darray = np.array([[1,2,3],[4,5,6]])
```

Selecting Numpy Array Elements (Index starts at 0)

Subset

```
>>> my_array[1]
 2
```

Select item at index 1

Slice

```
>>> my_array[0:2]
 array([1, 2])
```

Select items at index 0 and 1

Subset 2D Numpy arrays

```
>>> my_2darray[:,0]
 array([1, 4])
```

my_2darray[rows, columns]

Numpy Array Operations

```
>>> my_array > 3
 array([False, False, False,  True], dtype=bool)
>>> my_array * 2
 array([2, 4, 6, 8])
>>> my_array + np.array([5, 6, 7, 8])
 array([6, 8, 10, 12])
```

Numpy Array Functions

```
>>> my_array.shape
>>> np.append(other_array)
>>> np.insert(my_array, 1, 5)
>>> np.delete(my_array,[1])
>>> np.mean(my_array)
>>> np.median(my_array)
>>> my_array.corrcoef()
>>> np.std(my_array)
```

Get the dimensions of the array
Append items to an array
Insert items in an array
Delete items in an array
Mean of the array
Median of the array
Correlation coefficient
Standard deviation

DataCamp
Learn Python for Data Science Interactively

Dr. Vani Vasudevan

Python For Data Science *Cheat Sheet*

NumPy Basics

Learn Python for Data Science Interactively at www.DataCamp.com

NumPy

The **NumPy** library is the core library for scientific computing in Python. It provides a high-performance multidimensional array object, and tools for working with these arrays.

Use the following import convention:

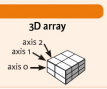
```
>>> import numpy as np
```

NumPy Arrays

1D array

2D array

3D array



Creating Arrays

```
>>> a = np.array([1,2,3])
>>> b = np.array([(1.5,2,3), (4,5,6)], dtype = float)
>>> c = np.array([[(1.5,2,3), (4,5,6)], [(3,2,1), (4,5,6)]],
                 dtype = float)
```

Initial Placeholders

```
>>> np.zeros((3,4))                  Create an array of zeros
>>> np.ones((2,3,4),dtype=np.int16)  Create an array of ones
>>> d = np.arange(10,25,5)           Create an array of evenly
                                     spaced values (step value)
>>> np.linspace(0,2,9)               Create an array of evenly
                                     spaced values (number of samples)
>>> e = np.full((2,2),7)             Create a constant array
>>> f = np.eye(2)                    Create a 2X2 identity matrix
>>> np.random.random((2,2))          Create an array with random values
>>> np.empty((3,2))                  Create an empty array
```

I/O

Saving & Loading On Disk

```
>>> np.save('my_array', a)
>>> np.savez('array.npz', a, b)
>>> np.load('my_array.npy')
```

Saving & Loading Text Files

```
>>> np.loadtxt("myfile.txt")
>>> np.genfromtxt("my_file.csv", delimiter=',')
>>> np.savetxt("myarray.txt", a, delimiter=" ")
```

Data Types

```
>>> np.int64      Signed 64-bit integer types
>>> np.float32    Standard double-precision floating point
>>> np.complex    Complex numbers represented by 128 floats
>>> np.bool       Boolean type storing TRUE and FALSE values
>>> np.object     Python object type
>>> np.string_    Fixed-length string type
>>> np.unicode_   Fixed-length unicode type
```

Inspecting Your Array

```
>>> a.shape       Array dimensions
>>> len(a)        Length of array
>>> b.ndim        Number of array dimensions
>>> e.size        Number of array elements
>>> b.dtype       Data type of array elements
>>> b.dtype.name  Name of data type
>>> b.astype(int) Convert an array to a different type
```

Asking For Help

```
>>> np.info(np.ndarray.dtype)
```

Array Mathematics

Arithmetic Operations

```
>>> g = a - b                    Subtraction
  array([[-0.5,  0. ,  0. ],
         [-3. , -3. , -3. ]])
>>> np.subtract(a,b)             Subtraction
>>> b + a                        Addition
  array([[ 2.5,  4. ,  6. ],
         [ 5. ,  7. ,  9. ]])
>>> np.add(b,a)                  Addition
>>> a / b                        Division
  array([[ 0.66666667,  1.        ,  1.        ],
         [ 0.25      ,  0.4       ,  0.5       ]])
>>> np.divide(a,b)               Division
>>> a * b                        Multiplication
  array([[  1.5,   4. ,   9. ],
         [  4. ,  10. ,  18. ]])
>>> np.multiply(a,b)             Multiplication
>>> np.exp(b)                    Exponentiation
>>> np.sqrt(b)                   Square root
>>> np.sin(a)                    Print sines of an array
>>> np.cos(b)                    Element-wise cosine
>>> np.log(a)                    Element-wise natural logarithm
>>> e.dot(f)                     Dot product
  array([[ 7.,  7.],
         [ 7.,  7.]])
```

Comparison

```
>>> a == b                       Element-wise comparison
  array([[False,  True,  True],
         [False, False, False]], dtype=bool)
>>> a < 2                        Element-wise comparison
  array([True, False, False], dtype=bool)
>>> np.array_equal(a, b)         Array-wise comparison
```

Aggregate Functions

```
>>> a.sum()                      Array-wise sum
>>> a.min()                      Array-wise minimum value
>>> b.max(axis=0)                Maximum value of an array row
>>> b.cumsum(axis=1)             Cumulative sum of the elements
>>> a.mean()                     Mean
>>> b.median()                   Median
>>> a.corrcoef()                 Correlation coefficient
>>> np.std(b)                    Standard deviation
```

Copying Arrays

```
>>> h = a.view()                 Create a view of the array with the same data
>>> np.copy(a)                   Create a copy of the array
>>> h = a.copy()                 Create a deep copy of the array
```

Sorting Arrays

```
>>> a.sort()                     Sort an array
>>> c.sort(axis=0)               Sort the elements of an array's axis
```

Subsetting, Slicing, Indexing

Also see Lists

Subsetting

```
>>> a[2]
  3
>>> b[1,2]
  6.0
```

Select the element at the 2nd index

Select the element at row 1 column 2 (equivalent to `b[1][2]`)

Slicing

```
>>> a[0:2]
  array([1, 2])
>>> b[0:2,1]
  array([ 2.,  5.])
>>> b[:1]
  array([[1.5, 2., 3.]])
>>> c[1,...]
  array([[[ 3.,  2.,  1.],
          [ 4.,  5.,  6.]]])
>>> a[ : :-1]
  array([3, 2, 1])
```

Select items at index 0 and 1

Select items at rows 0 and 1 in column 1

Select all items at row 0 (equivalent to `b[0:1, :]`)

Same as `[1,:,:]`

Reversed array `a`

Boolean Indexing

```
>>> a[a<2]
  array([1])
```

Select elements from `a` less than 2

Fancy Indexing

```
>>> b[[1, 0, 1, 0],[0, 1, 2, 0]]
  array([ 4. ,  2. ,  6. ,  1.5])
>>> b[[1, 0, 1, 0]][:,[0,1,2,0]]
  array([[ 4. ,  5. ,  6. ,  4. ],
         [ 1.5,  2. ,  3. ,  1.5],
         [ 4. ,  5. ,  6. ,  4. ],
         [ 1.5,  2. ,  3. ,  1.5]])
```

Select elements `(1,0),(0,1),(1,2)` and `(0,0)`

Select a subset of the matrix's rows and columns

Array Manipulation

Transposing Array

```
>>> i = np.transpose(b)          Permute array dimensions
>>> i.T                          Permute array dimensions
```

Changing Array Shape

```
>>> b.ravel()                    Flatten the array
>>> g.reshape(3,-2)              Reshape, but don't change data
```

Adding/Removing Elements

```
>>> h.resize((2,6))              Return a new array with shape (2,6)
>>> np.append(h,g)               Append items to an array
>>> np.insert(a, 1, 5)           Insert items in an array
>>> np.delete(a,[1])             Delete items from an array
```

Combining Arrays

```
>>> np.concatenate((a,d),axis=0) Concatenate arrays
  array([ 1,  2,  3, 10, 15, 20])
>>> np.vstack((a,b))             Stack arrays vertically (row-wise)
  array([[ 1. ,  2. ,  3. ],
         [ 1.5,  2. ,  3. ],
         [ 4. ,  5. ,  6. ]])
>>> np.r_[e,f]                   Stack arrays vertically (row-wise)
>>> np.hstack((e,f))             Stack arrays horizontally (column-wise)
  array([[ 7.,  7.,  1.,  0.],
         [ 7.,  7.,  0.,  1.]])
>>> np.column_stack((a,d))       Create stacked column-wise arrays
  array([[ 1, 10],
         [ 2, 15],
         [ 3, 20]])
>>> np.c_[a,d]                   Create stacked column-wise arrays
```

Splitting Arrays

```
>>> np.hsplit(a,3)               Split the array horizontally at the 3rd
  [array([1]),array([2]),array([3])] index
>>> np.vsplit(c,2)               Split the array vertically at the 2nd index
[array([[[ 1.5,  2. ,  1. ],
         [ 4. ,  5. ,  6. ]]]),
 array([[[ 3. ,  2. ,  3. ],
         [ 4. ,  5. ,  6. ]]])]
```

DataCamp
Learn Python for Data Science Interactively

Python For Data Science *Cheat Sheet*

Pandas Basics

Learn Python for Data Science Interactively at www.DataCamp.com

Pandas

The **Pandas** library is built on NumPy and provides easy-to-use **data structures** and **data analysis** tools for the Python programming language.

Use the following import convention:

```
>>> import pandas as pd
```

Pandas Data Structures

Series

A **one-dimensional** labeled array capable of holding any data type


```
>>> s = pd.Series([3, -5, 7, 4], index=['a', 'b', 'c', 'd'])
```

DataFrame

Columns

Index

A **two-dimensional** labeled data structure with columns of potentially different types

```
>>> data = {'Country': ['Belgium', 'India', 'Brazil'],
            'Capital': ['Brussels', 'New Delhi', 'Brasilia'],
            'Population': [11190846, 1303171035, 207847528]}

>>> df = pd.DataFrame(data,
                      columns=['Country', 'Capital', 'Population'])
```

Asking For Help

```
>>> help(pd.Series.loc)
```

Selection

Also see NumPy Arrays

Getting

```
>>> s['b']
 -5
```
Get one element

```
>>> df[1:]
   Country   Capital  Population
1   India  New Delhi  1303171035
2  Brazil  Brasilia   207847528
```
Get subset of a DataFrame

Selecting, Boolean Indexing & Setting

By Position

```
>>> df.iloc[0],[0]]
'Belgium'
>>> df.iat([0],[0])
'Belgium'
```
Select single value by row & column

By Label

```
>>> df.loc[[0], ['Country']]
'Belgium'
>>> df.at[0], ['Country'])
'Belgium'
```
Select single value by row & column labels

By Label/Position

```
>>> df.ix[2]
Country       Brazil
Capital     Brasilia
Population  207847528
```
Select single row of subset of rows

```
>>> df.ix[:,'Capital']
0    Brussels
1   New Delhi
2    Brasilia
```
Select a single column of subset of columns

```
>>> df.ix[1,'Capital']
'New Delhi'
```
Select rows and columns

Boolean Indexing

```
>>> s[~(s > 1)]
```
Series `s` where value is not >1

```
>>> s[(s < -1) | (s > 2)]
```
`s` where value is <-1 or >2

```
>>> df[df['Population']>1200000000]
```
Use filter to adjust DataFrame

Setting

```
>>> s['a'] = 6
```
Set index `a` of Series `s` to 6

Dropping

```
>>> s.drop(['a', 'c'])
```
Drop values from rows (axis=0)

```
>>> df.drop('Country', axis=1)
```
Drop values from columns(axis=1)

Sort & Rank

```
>>> df.sort_index()
```
Sort by labels along an axis

```
>>> df.sort_values(by='Country')
```
Sort by the values along an axis

```
>>> df.rank()
```
Assign ranks to entries

Retrieving Series/DataFrame Information

Basic Information

```
>>> df.shape
```
(rows,columns)

```
>>> df.index
```
Describe index

```
>>> df.columns
```
Describe DataFrame columns

```
>>> df.info()
```
Info on DataFrame

```
>>> df.count()
```
Number of non-NA values

Summary

```
>>> df.sum()
```
Sum of values

```
>>> df.cumsum()
```
Cummulative sum of values

```
>>> df.min()/df.max()
```
Minimum/maximum values

```
>>> df.idxmin()/df.idxmax()
```
Minimum/Maximum index value

```
>>> df.describe()
```
Summary statistics

```
>>> df.mean()
```
Mean of values

```
>>> df.median()
```
Median of values

Applying Functions

```
>>> f = lambda x: x*2
```

```
>>> df.apply(f)
```
Apply function

```
>>> df.applymap(f)
```
Apply function element-wise

Data Alignment

Internal Data Alignment

NA values are introduced in the indices that don't overlap:

```
>>> s3 = pd.Series([7, -2, 3], index=['a', 'c', 'd'])
>>> s + s3
a    10.0
b     NaN
c     5.0
d     7.0
```

Arithmetic Operations with Fill Methods

You can also do the internal data alignment yourself with the help of the fill methods:

```
>>> s.add(s3, fill_value=0)
a    10.0
b    -5.0
c     5.0
d     7.0
>>> s.sub(s3, fill_value=2)
>>> s.div(s3, fill_value=4)
>>> s.mul(s3, fill_value=3)
```

I/O

Read and Write to CSV

```
>>> pd.read_csv('file.csv', header=None, nrows=5)
>>> df.to_csv('myDataFrame.csv')
```

Read and Write to Excel

```
>>> pd.read_excel('file.xlsx')
>>> pd.to_excel('dir/myDataFrame.xlsx', sheet_name='Sheet1')
```

Read multiple sheets from the same file

```
>>> xlsx = pd.ExcelFile('file.xls')
>>> df = pd.read_excel(xlsx, 'Sheet1')
```

Read and Write to SQL Query or Database Table

```
>>> from sqlalchemy import create_engine
>>> engine = create_engine('sqlite:///:memory:')
>>> pd.read_sql("SELECT * FROM my_table;", engine)
>>> pd.read_sql_table('my_table', engine)
>>> pd.read_sql_query("SELECT * FROM my_table;", engine)
```

`read_sql()` is a convenience wrapper around `read_sql_table()` and `read_sql_query()`

```
>>> pd.to_sql('myDf', engine)
```

DataCamp
Learn Python for Data Science Interactively

Dr. Vani Vasudevan

Python For Data Science *Cheat Sheet*

Matplotlib

Learn Python Interactively at www.DataCamp.com

Matplotlib

Matplotlib is a Python 2D plotting library which produces publication-quality figures in a variety of hardcopy formats and interactive environments across platforms.

matplotlib

1 Prepare The Data

Also see Lists & NumPy

1D Data

```
>>> import numpy as np
>>> x = np.linspace(0, 10, 100)
>>> y = np.cos(x)
>>> z = np.sin(x)
```

2D Data or Images

```
>>> data = 2 * np.random.random((10, 10))
>>> data2 = 3 * np.random.random((10, 10))
>>> Y, X = np.mgrid[-3:3:100j, -3:3:100j]
>>> U = -1 - X**2 + Y
>>> V = 1 + X - Y**2
>>> from matplotlib.cbook import get_sample_data
>>> img = np.load(get_sample_data('axes_grid/bivariate_normal.npy'))
```

2 Create Plot

```
>>> import matplotlib.pyplot as plt
```

Figure

```
>>> fig = plt.figure()
>>> fig2 = plt.figure(figsize=plt.figaspect(2.0))
```

Axes

All plotting is done with respect to an `Axes`. In most cases, a subplot will fit your needs. A subplot is an axes on a grid system.

```
>>> fig.add_axes()
>>> ax1 = fig.add_subplot(221) # row-col-num
>>> ax3 = fig.add_subplot(212)
>>> fig3, axes = plt.subplots(nrows=2,ncols=2)
>>> fig4, axes2 = plt.subplots(ncols=3)
```

3 Plotting Routines

1D Data

```
>>> fig, ax = plt.subplots()
>>> lines = ax.plot(x,y)
>>> ax.scatter(x,y)
>>> axes[0,0].bar([1,2,3],[3,4,5])
>>> axes[1,0].barh([0.5,1,2.5],[0,1,2])
>>> axes[1,1].axhline(0.45)
>>> axes[0,1].axvline(0.65)
>>> ax.fill(x,y,color='blue')
>>> ax.fill_between(x,y,color='yellow')
```

Draw points with lines or markers connecting them
Draw unconnected points, scaled or colored
Plot vertical rectangles (constant width)
Plot horizontal rectangles (constant height)
Draw a horizontal line across axes
Draw a vertical line across axes
Draw filled polygons
Fill between y-values and 0

Vector Fields

```
>>> axes[0,1].arrow(0,0,0.5,0.5)
>>> axes[1,1].quiver(y,z)
>>> axes[0,1].streamplot(X,Y,U,V)
```

Add an arrow to the axes
Plot a 2D field of arrows
Plot a 2D field of arrows

Data Distributions

```
>>> ax1.hist(y)
>>> ax3.boxplot(y)
>>> ax3.violinplot(z)
```

Plot a histogram
Make a box and whisker plot
Make a violin plot

2D Data or Images

```
>>> fig, ax = plt.subplots()
>>> im = ax.imshow(img,
                   cmap='gist_earth',
                   interpolation='nearest',
                   vmin=-2,
                   vmax=2)
```

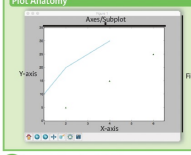
Colormapped or RGB arrays

```
>>> axes2[0].pcolor(data2)
>>> axes2[0].pcolormesh(data)
>>> CS = plt.contour(Y,X,U)
>>> axes2[2].contourf(data1)
>>> axes2[2]= ax.clabel(CS)
```

Pseudocolor plot of 2D array
Pseudocolor plot of 2D array
Plot contours
Plot filled contours
Label a contour plot

Plot Anatomy & Workflow

Plot Anatomy



Workflow

The basic steps to creating plots with matplotlib are:

1 Prepare data 2 Create plot 3 Plot 4 Customize plot 5 Save plot 6 Show plot

```
>>> import matplotlib.pyplot as plt
>>> x = [1,2,3,4]                          Step 1
>>> y = [10,20,25,30]
>>> fig = plt.figure()                     Step 2
>>> ax = fig.add_subplot(111)              Step 3
>>> ax.plot(x, y, color='lightblue', linewidth=3)  Step 3, 4
>>> ax.scatter([2,4,6],
               [5,15,25],
               color='darkgreen',
               marker='^')
>>> ax.set_xlim(1, 6.5)
>>> plt.savefig('foo.png')
>>> plt.show()                             Step 6
```

4 Customize Plot

Colors, Color Bars & Color Maps

```
>>> plt.plot(x, x, x, x**2, x, x**3)
>>> ax.plot(x, y, alpha = 0.4)
>>> ax.plot(x, y, c='k')
>>> fig.colorbar(im, orientation='horizontal')
>>> im = ax.imshow(img,
                   cmap='seismic')
```

Markers

```
>>> fig, ax = plt.subplots()
>>> ax.scatter(x,y,marker=".")
>>> ax.plot(x,y,marker="o")
```

Linestyles

```
>>> plt.plot(x,y,linewidth=4.0)
>>> plt.plot(x,y,ls='solid')
>>> plt.plot(x,y,ls='--')
>>> plt.plot(x,y,'--',x**2,y**2,'-.')
>>> plt.setp(lines,color='r',linewidth=4.0)
```

Text & Annotations

```
>>> ax.text(1,
            -2.1,
            'Example Graph',
            style='italic')
>>> ax.annotate("Sine",
                xy=(8, 0),
                xycoords='data',
                xytext=(10.5, 0),
                textcoords='data',
                arrowprops=dict(arrowstyle="->",
                                connectionstyle="arc3"),)
```

Mathtext

```
>>> plt.title(r'$sigma_i=15$', fontsize=20)
```

Limits, Legends & Layouts

Limits & Autoscaling

```
>>> ax.margins(x=0.0,y=0.1)
>>> ax.axis('equal')
>>> ax.set(xlim=[0,10.5],ylim=[-1.5,1.5])
>>> ax.set_xlim(0,10.5)
```

Add padding to a plot
Set the aspect ratio of the plot to 1
Set limits for x-and y-axis
Set limits for x-axis

Legends

```
>>> ax.set(title='An Example Axes',
           ylabel='Y-Axis',
           xlabel='X-Axis')
>>> ax.legend(loc='best')
```

Set a title and x-and y-axis labels
No overlapping plot elements

Ticks

```
>>> ax.xaxis.set(ticks=range(1,5),
                 ticklabels=[3,100,-12,"foo"])
>>> ax.tick_params(axis='y',
                   direction='inout',
                   length=10)
```

Manually set x-ticks
Make y-ticks longer and go in and out

Subplot Spacing

```
>>> fig3.subplots_adjust(wspace=0.5,
                         hspace=0.3,
                         left=0.125,
                         right=0.9,
                         top=0.9,
                         bottom=0.1)
>>> fig.tight_layout()
```

Adjust the spacing between subplots
Fit subplot(s) in to the figure area

Axis Spines

```
>>> ax1.spines['top'].set_visible(False)
>>> ax1.spines['bottom'].set_position(('outward',10))
```

Make the top axis line for a plot invisible
Move the bottom axis line outward

5 Save Plot

Save figures

```
>>> plt.savefig('foo.png')
```

Save transparent figures

```
>>> plt.savefig('foo.png', transparent=True)
```

6 Show Plot

```
>>> plt.show()
```

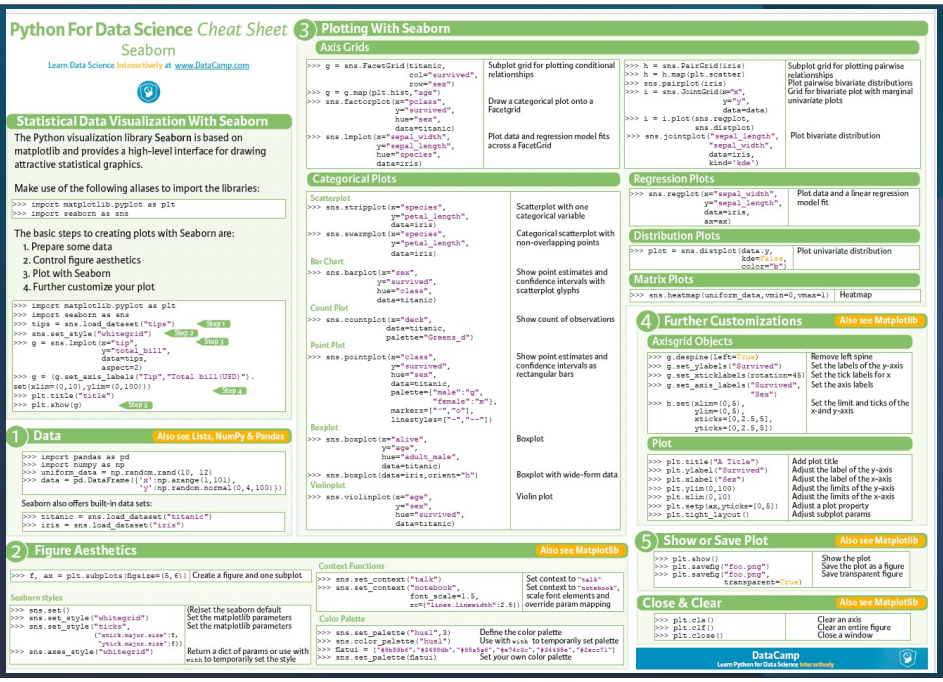
Close & Clear

```
>>> plt.cla()
>>> plt.clf()
>>> plt.close()
```

Clear an axis
Clear the entire figure
Close a window

DataCamp
Learn Python for Data Science Interactively

5/20/24 13



Python For Data Science *Cheat Sheet*

Seaborn

Learn Data Science Interactively at www.DataCamp.com

Statistical Data Visualization With Seaborn

The Python visualization library **Seaborn** is based on matplotlib and provides a high-level interface for drawing attractive statistical graphics.

Make use of the following aliases to import the libraries:

```
>>> import matplotlib.pyplot as plt
>>> import seaborn as sns
```

The basic steps to creating plots with Seaborn are:

1. Prepare some data
2. Control figure aesthetics
3. Plot with Seaborn
4. Further customize your plot

```
>>> import matplotlib.pyplot as plt
>>> import seaborn as sns
>>> tips = sns.load_dataset("tips")                    Step 1
>>> sns.set_style("whitegrid")                         Step 2
>>> g = sns.lmplot(x="tip",                            Step 3
                   y="total_bill",
                   data=tips,
                   aspect=2)
>>> g = (g.set_axis_labels("Tip","Total bill(USD)").
set(xlim=(0,10),ylim=(0,100)))
>>> plt.title("title")                                 Step 4
>>> plt.show(g)                                        Step 5
```

1 Data

Also see Lists, NumPy & Pandas

```
>>> import pandas as pd
>>> import numpy as np
>>> uniform_data = np.random.rand(10, 12)
>>> data = pd.DataFrame({'x':np.arange(1,101),
                         'y':np.random.normal(0,4,100)})
```

Seaborn also offers built-in data sets:

```
>>> titanic = sns.load_dataset("titanic")
>>> iris = sns.load_dataset("iris")
```

2 Figure Aesthetics

Also see Matplotlib

```
>>> f, ax = plt.subplots(figsize=(5,6))
```
Create a figure and one subplot

Seaborn styles

```
>>> sns.set()
>>> sns.set_style("whitegrid")
>>> sns.set_style("ticks",
                  {"xtick.major.size":8,
                   "ytick.major.size":8})
>>> sns.axes_style("whitegrid")
```
(Re)set the seaborn default
Set the matplotlib parameters
Set the matplotlib parameters

Return a dict of params or use with `with` to temporarily set the style

Context Functions

```
>>> sns.set_context("talk")
>>> sns.set_context("notebook",
                    font_scale=1.5,
                    rc={"lines.linewidth":2.5})
```
Set context to `"talk"`
Set context to `"notebook"`, scale font elements and override param mapping

Color Palette

```
>>> sns.set_palette("husl",3)
>>> sns.color_palette("husl")
>>> flatui = ["#9b59b6","#3498db","#95a5a6","#e74c3c","#34495e","#2ecc71"]
>>> sns.set_palette(flatui)
```
Define the color palette
Use with `with` to temporarily set palette
Set your own color palette

3 Plotting With Seaborn

Axis Grids

```
>>> g = sns.FacetGrid(titanic,
                      col="survived",
                      row="sex")
>>> g = g.map(plt.hist,"age")
>>> sns.factorplot(x="pclass",
                   y="survived",
                   hue="sex",
                   data=titanic)
>>> sns.lmplot(x="sepal_width",
               y="sepal_length",
               hue="species",
               data=iris)
```
Subplot grid for plotting conditional relationships

Draw a categorical plot onto a Facetgrid

Plot data and regression model fits across a FacetGrid

```
>>> h = sns.PairGrid(iris)
>>> h = h.map(plt.scatter)
>>> sns.pairplot(iris)
>>> i = sns.JointGrid(x="x",
                      y="y",
                      data=data)
>>> i = i.plot(sns.regplot,
               sns.distplot)
>>> sns.jointplot("sepal_length",
                  "sepal_width",
                  data=iris,
                  kind='kde')
```
Subplot grid for plotting pairwise relationships
Plot pairwise bivariate distributions
Grid for bivariate plot with marginal univariate plots

Plot bivariate distribution

Categorical Plots

Scatterplot

```
>>> sns.stripplot(x="species",
                  y="petal_length",
                  data=iris)
>>> sns.swarmplot(x="species",
                  y="petal_length",
                  data=iris)
```
Scatterplot with one categorical variable

Categorical scatterplot with non-overlapping points

Bar Chart

```
>>> sns.barplot(x="sex",
                y="survived",
                hue="class",
                data=titanic)
```
Show point estimates and confidence intervals with scatterplot glyphs

Count Plot

```
>>> sns.countplot(x="deck",
                  data=titanic,
                  palette="Greens_d")
```
Show count of observations

Point Plot

```
>>> sns.pointplot(x="class",
                  y="survived",
                  hue="sex",
                  data=titanic,
                  palette={"male":"g",
                           "female":"m"},
                  markers=["^","o"],
                  linestyles=["-","--"])
```
Show point estimates and confidence intervals as rectangular bars

Boxplot

```
>>> sns.boxplot(x="alive",
                y="age",
                hue="adult_male",
                data=titanic)
>>> sns.boxplot(data=iris,orient="h")
```
Boxplot

Boxplot with wide-form data

Violinplot

```
>>> sns.violinplot(x="age",
                   y="sex",
                   hue="survived",
                   data=titanic)
```
Violin plot

Regression Plots

```
>>> sns.regplot(x="sepal_width",
                y="sepal_length",
                data=iris,
                ax=ax)
```
Plot data and a linear regression model fit

Distribution Plots

```
>>> plot = sns.distplot(data.y,
                        kde=False,
                        color="b")
```
Plot univariate distribution

Matrix Plots

```
>>> sns.heatmap(uniform_data,vmin=0,vmax=1)
```
Heatmap

4 Further Customizations

Also see Matplotlib

Axisgrid Objects

```
>>> g.despine(left=True)
>>> g.set_ylabels("Survived")
>>> g.set_xticklabels(rotation=45)
>>> g.set_axis_labels("Survived",
                      "Sex")
>>> h.set(xlim=(0,5),
          ylim=(0,5),
          xticks=[0,2.5,5],
          yticks=[0,2.5,5])
```
Remove left spine
Set the labels of the y-axis
Set the tick labels for x
Set the axis labels

Set the limit and ticks of the x-and y-axis

Plot

```
>>> plt.title("A Title")
>>> plt.ylabel("Survived")
>>> plt.xlabel("Sex")
>>> plt.ylim(0,100)
>>> plt.xlim(0,10)
>>> plt.setp(ax,yticks=[0,5])
>>> plt.tight_layout()
```
Add plot title
Adjust the label of the y-axis
Adjust the label of the x-axis
Adjust the limits of the y-axis
Adjust the limits of the x-axis
Adjust a plot property
Adjust subplot params

5 Show or Save Plot

Also see Matplotlib

```
>>> plt.show()
>>> plt.savefig("foo.png")
>>> plt.savefig("foo.png",
                transparent=True)
```
Show the plot
Save the plot as a figure
Save transparent figure

Close & Clear

Also see Matplotlib

```
>>> plt.cla()
>>> plt.clf()
>>> plt.close()
```
Clear an axis
Clear an entire figure
Close a window

DataCamp
Learn Python for Data Science Interactively

Python For Data Science *Cheat Sheet*

Bokeh

Learn Bokeh Interactively at www.DataCamp.com, taught by Bryan Van de Ven, core contributor

Plotting With Bokeh

The Python interactive visualization library **Bokeh** enables high-performance visual presentation of large datasets in modern web browsers.

Bokeh's mid-level general purpose `bokeh.plotting` interface is centered around two main components: data and glyphs.

The basic steps to creating plots with the `bokeh.plotting` interface are:

1. Prepare some data:
   Python lists, NumPy arrays, Pandas DataFrames and other sequences of values
2. Create a new plot
3. Add renderers for your data, with visual customizations
4. Specify where to generate the output
5. Show or save the results

```
>>> from bokeh.plotting import figure
>>> from bokeh.io import output_file, show
>>> x = [1, 2, 3, 4, 5]                                  Step 1
>>> y = [6, 7, 2, 4, 5]
>>> p = figure(title="simple line example",               Step 2
               x_axis_label='x',
               y_axis_label='y')
>>> p.line(x, y, legend="Temp.", line_width=2)           Step 3
>>> output_file("lines.html")                            Step 4
>>> show(p)                                              Step 5
```

1 Data

Also see Lists, NumPy & Pandas

Under the hood, your data is converted to Column Data Sources. You can also do this manually:

```
>>> import numpy as np
>>> import pandas as pd
>>> df = pd.DataFrame(np.array([[33.9,4,65, 'US'],
                                [32.4,4,66, 'Asia'],
                                [21.4,4,109, 'Europe']]),
                      columns=['mpg','cyl', 'hp', 'origin'],
                      index=['Toyota', 'Fiat', 'Volvo'])
>>> from bokeh.models import ColumnDataSource
>>> cds_df = ColumnDataSource(df)
```

2 Plotting

```
>>> from bokeh.plotting import figure
>>> p1 = figure(plot_width=300, tools='pan,box_zoom')
>>> p2 = figure(plot_width=300, plot_height=300,
                x_range=(0, 8), y_range=(0, 8))
>>> p3 = figure()
```

3 Renderers & Visual Customizations

Glyphs

Scatter Markers

```
>>> p1.circle(np.array([1,2,3]), np.array([3,2,1]),
              fill_color='white')
>>> p2.square(np.array([1.5,3.5,5.5]), [1,4,3],
              color='blue', size=1)
```

Line Glyphs

```
>>> p1.line([1,2,3,4], [3,4,5,6], line_width=2)
>>> p2.multi_line(pd.DataFrame([[1,2,3],[5,6,7]]),
                  pd.DataFrame([[3,4,5],[3,2,1]]),
                  color="blue")
```

Customized Glyphs

Also see Data

Selection and Non-Selection Glyphs

```
>>> p = figure(tools='box_select')
>>> p.circle('mpg', 'cyl', source=cds_df,
             selection_color='red',
             nonselection_alpha=0.1)
```

Hover Glyphs

```
>>> from bokeh.models import HoverTool
>>> hover = HoverTool(tooltips=None, mode='vline')
>>> p3.add_tools(hover)
```

Colormapping

```
>>> from bokeh.models import CategoricalColorMapper
>>> color_mapper = CategoricalColorMapper(
                   factors=['US', 'Asia', 'Europe'],
                   palette=['blue', 'red', 'green'])
>>> p3.circle('mpg', 'cyl', source=cds_df,
              color=dict(field='origin',
                         transform=color_mapper),
              legend='Origin')
```

Legend Location

Inside Plot Area

```
>>> p.legend.location = 'bottom_left'
```

Outside Plot Area

```
>>> from bokeh.models import Legend
>>> r1 = p2.asterisk(np.array([1,2,3]), np.array([3,2,1])
>>> r2 = p2.line([1,2,3,4], [3,4,5,6])
>>> legend = Legend(items=[("One"   ,[p1, r1]),("Two",[r2])],
                    location=(0, -30))
>>> p.add_layout(legend, 'right')
```

Legend Orientation

```
>>> p.legend.orientation = "horizontal"
>>> p.legend.orientation = "vertical"
```

Legend Background & Border

```
>>> p.legend.border_line_color = "navy"
>>> p.legend.background_fill_color = "white"
```

Rows & Columns Layout

Rows

```
>>> from bokeh.layouts import row
>>> layout = row(p1,p2,p3)
```

Columns

```
>>> from bokeh.layouts import columns
>>> layout = column(p1,p2,p3)
```

Nesting Rows & Columns

```
>>>layout = row(column(p1,p2), p3)
```

Grid Layout

```
>>> from bokeh.layouts import gridplot
>>> row1 = [p1,p2]
>>> row2 = [p3]
>>> layout = gridplot([[p1,p2],[p3]])
```

Tabbed Layout

```
>>> from bokeh.models.widgets import Panel, Tabs
>>> tab1 = Panel(child=p1, title="tab1")
>>> tab2 = Panel(child=p2, title="tab2")
>>> layout = Tabs(tabs=[tab1, tab2])
```

Linked Plots

Linked Axes

```
>>> p2.x_range = p1.x_range
>>> p2.y_range = p1.y_range
```

Linked Brushing

```
>>> p4 = figure(plot_width = 100,
                tools='box_select,lasso_select')
>>> p4.circle('mpg', 'cyl', source=cds_df)
>>> p5 = figure(plot_width = 200,
                tools='box_select,lasso_select')
>>> p5.circle('mpg', 'hp', source=cds_df)
>>> layout = row(p4,p5)
```

4 Output & Export

Notebook

```
>>> from bokeh.io import output_notebook, show
>>> output_notebook()
```

HTML

Standalone HTML

```
>>> from bokeh.embed import file_html
>>> from bokeh.resources import CDN
>>> html = file_html(p, CDN, "my_plot")
```

```
>>> from bokeh.io import output_file, show
>>> output_file('my_bar_chart.html', mode='cdn')
```

Components

```
>>> from bokeh.embed import components
>>> script, div = components(p)
```

PNG

```
>>> from bokeh.io import export_png
>>> export_png(p, filename="plot.png")
```

SVG

```
>>> from bokeh.io import export_svgs
>>> p.output_backend = "svg"
>>> export_svgs(p, filename="plot.svg")
```

5 Show or Save Your Plots

```
>>> show(p1)
>>> save(p1)
```

```
>>> show(layout)
>>> save(layout)
```

DataCamp
Learn Python for Data Science Interactively

Python For Data Science *Cheat Sheet*

SciPy - Linear Algebra

Learn More Python for Data Science Interactively at www.datacamp.com

SciPy

The **SciPy** library is one of the core packages for scientific computing that provides mathematical algorithms and convenience functions built on the NumPy extension of Python.

Interacting With NumPy

Also see NumPy

```
>>> import numpy as np
>>> a = np.array([1,2,3])
>>> b = np.array([(1+5j,2j,3j), (4j,5j,6j)])
>>> c = np.array([[(1.5,2,3), (4,5,6)], [(3,2,1), (4,5,6)]])
```

Index Tricks

`>>> np.mgrid[0:5,0:5]`	Create a dense meshgrid
`>>> np.ogrid[0:2,0:2]`	Create an open meshgrid
`>>> np.r_[3,[0]*5,-1:1:10j]`	Stack arrays vertically (row-wise)
`>>> np.c_[b,c]`	Create stacked column-wise arrays

Shape Manipulation

`>>> np.transpose(b)`	Permute array dimensions
`>>> b.flatten()`	Flatten the array
`>>> np.hstack((b,c))`	Stack arrays horizontally (column-wise)
`>>> np.vstack((a,b))`	Stack arrays vertically (row-wise)
`>>> np.hsplit(c,2)`	Split the array horizontally at the 2nd index
`>>> np.vpslit(d,2)`	Split the array vertically at the 2nd index

Polynomials

`>>> from numpy import polyld`	
`>>> p = polyld([3,4,5])`	Create a polynomial object

Vectorizing Functions

`>>> def myfunc(a):`
`  if a < 0:`
`  return a*2`
`  else:`
`  return a/2`	

`>>> np.vectorize(myfunc)`	Vectorize functions

Type Handling

`>>> np.real(c)`	Return the real part of the array elements
`>>> np.imag(c)`	Return the imaginary part of the array elements
`>>> np.real_if_close(c,tol=1000)`	Return a real array if complex parts close to 0
`>>> np.cast['f'](np.pi)`	Cast object to a data type

Other Useful Functions

`>>> np.angle(b,deg=True)`	Return the angle of the complex argument
`>>> g = np.linspace(0,np.pi,num=5)`	Create an array of evenly spaced values (number of samples)
`>>> g [3:] += np.pi`	
`>>> np.unwrap(g)`	Unwrap
`>>> np.logspace(0,10,3)`	Create an array of evenly spaced values (log scale)
`>>> np.select([c<4],[c*2])`	Return values from a list of arrays depending on conditions
`>>> misc.factorial(a)`	Factorial
`>>> misc.comb(10,3,exact=True)`	Combine N things taken at k time
`>>> misc.central_diff_weights(3)`	Weights for Np-point central derivative
`>>> misc.derivative(myfunc,1.0)`	Find the n-th derivative of a function at a point

Linear Algebra

Also see NumPy

You'll use the `linalg` and `sparse` modules. Note that `scipy.linalg` contains and expands on `numpy.linalg`.

```
>>> from scipy import linalg, sparse
```

Creating Matrices

```
>>> A = np.matrix(np.random.random((2,2)))
>>> B = np.asmatrix(b)
>>> C = np.mat(np.random.random((10,5)))
>>> D = np.mat([[3,4], [5,6]])
```

Basic Matrix Routines

Inverse	
`>>> A.I`	Inverse
`>>> linalg.inv(A)`	Inverse
`>>> A.T`	Tranpose matrix
`>>> A.H`	Conjugate transposition
`>>> np.trace(A)`	Trace
Norm	
`>>> linalg.norm(A)`	Frobenius norm
`>>> linalg.norm(A,1)`	L1 norm (max column sum)
`>>> linalg.norm(A,np.inf)`	L inf norm (max row sum)
Rank	
`>>> np.linalg.matrix_rank(C)`	Matrix rank
Determinant	
`>>> linalg.det(A)`	Determinant
Solving linear problems	
`>>> linalg.solve(A,b)`	Solver for dense matrices
`>>> E = np.mat(a).T`	Solver for dense matrices
`>>> linalg.lstsq(D,E)`	Least-squares solution to linear matrix equation
Generalized inverse	
`>>> linalg.pinv(C)`	Compute the pseudo-inverse of a matrix (least-squares solver)
`>>> linalg.pinv2(C)`	Compute the pseudo-inverse of a matrix (SVD)

Creating Sparse Matrices

`>>> F = np.eye(3, k=1)`	Create a 2X2 identity matrix
`>>> G = np.mat(np.identity(2))`	Create a 2x2 identity matrix
`>>> C[C > 0.5] = 0`	
`>>> H = sparse.csr_matrix(C)`	Compressed Sparse Row matrix
`>>> I = sparse.csc_matrix(D)`	Compressed Sparse Column matrix
`>>> J = sparse.dok_matrix(A)`	Dictionary Of Keys matrix
`>>> E.todense()`	Sparse matrix to full matrix
`>>> sparse.issparse(C)`	Identify sparse matrix

Sparse Matrix Routines

Inverse	
`>>> sparse.linalg.inv(I)`	Inverse
Norm	
`>>> sparse.linalg.norm(I)`	Norm
Solving linear problems	
`>>> sparse.linalg.spsolve(H,I)`	Solver for sparse matrices

Sparse Matrix Functions

`>>> sparse.linalg.expm(I)`	Sparse matrix exponential

Matrix Functions

Addition	
`>>> np.add(A,D)`	Addition
Subtraction	
`>>> np.subtract(A,D)`	Subtraction
Division	
`>>> np.divide(A,D)`	Division
Multiplication	
`>>> np.multiply(D,A)`	Multiplication
`>>> np.dot(A,D)`	Dot product
`>>> np.vdot(A,D)`	Vector dot product
`>>> np.inner(A,D)`	Inner product
`>>> np.outer(A,D)`	Outer product
`>>> np.tensordot(A,D)`	Tensor dot product
`>>> np.kron(A,D)`	Kronecker product
Exponential Functions	
`>>> linalg.expm(A)`	Matrix exponential
`>>> linalg.expm2(A)`	Matrix exponential (Taylor Series)
`>>> linalg.expm3(D)`	Matrix exponential (eigenvalue decomposition)
Logarithm Function	
`>>> linalg.logm(A)`	Matrix logarithm
Trigonometric Functions	
`>>> linalg.sinm(D)`	Matrix sine
`>>> linalg.cosm(D)`	Matrix cosine
`>>> linalg.tanm(A)`	Matrix tangent
Hyperbolic Trigonometric Functions	
`>>> linalg.sinhm(D)`	Hyperbolic matrix sine
`>>> linalg.coshm(D)`	Hyperbolic matrix cosine
`>>> linalg.tanhm(A)`	Hyperbolic matrix tangent
Matrix Sign Function	
`>>> np.signm(A)`	Matrix sign function
Matrix Square Root	
`>>> linalg.sqrtm(A)`	Matrix square root
Arbitrary Functions	
`>>> linalg.funm(A, lambda x: x*x)`	Evaluate matrix function

Decompositions

Eigenvalues and Eigenvectors	
`>>> la, v = linalg.eig(A)`	Solve ordinary or generalized eigenvalue problem for square matrix
`>>> l1, l2 = la`	Unpack eigenvalues
`>>> v[:,0]`	First eigenvector
`>>> v[:,1]`	Second eigenvector
`>>> linalg.eigvals(A)`	Unpack eigenvalues
Singular Value Decomposition	
`>>> U,s,Vh = linalg.svd(B)`	Singular Value Decomposition (SVD)
`>>> M,N = B.shape`	
`>>> Sig = linalg.diagsvd(s,M,N)`	Construct sigma matrix in SVD
LU Decomposition	
`>>> P,L,U = linalg.lu(C)`	LU Decomposition

Sparse Matrix Decompositions

`>>> la, v = sparse.linalg.eigs(F,1)`	Eigenvalues and eigenvectors
`>>> sparse.linalg.svds(H, 2)`	SVD

Asking For Help

```
>>> help(scipy.linalg.diagsvd)
>>> np.info(np.matrix)
```

DataCamp
Learn Python for Data Science Interactively

Python For Data Science *Cheat Sheet*

Scikit-Learn

Learn Python for data science Interactively at www.DataCamp.com

Scikit-learn

Scikit-learn is an open source Python library that implements a range of machine learning, preprocessing, cross-validation and visualization algorithms using a unified interface.

A Basic Example

```
>>> from sklearn import neighbors, datasets, preprocessing
>>> from sklearn.model_selection import train_test_split
>>> from sklearn.metrics import accuracy_score
>>> iris = datasets.load_iris()
>>> X, y = iris.data[:, :2], iris.target
>>> X_train, X_test, y_train, y_test= train_test_split(X, y, random_state=33)
>>> scaler = preprocessing.StandardScaler().fit(X_train)
>>> X_train = scaler.transform(X_train)
>>> X_test = scaler.transform(X_test)
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
>>> knn.fit(X_train, y_train)
>>> y_pred = knn.predict(X_test)
>>> accuracy_score(y_test, y_pred)
```

Loading The Data

Also see NumPy & Pandas

Your data needs to be numeric and stored as NumPy arrays or SciPy sparse matrices. Other types that are convertible to numeric arrays, such as Pandas DataFrame, are also acceptable.

```
>>> import numpy as np
>>> X = np.random.random((10,5))
>>> y = np.array(['M','M','F','F','M','F','M','M','F','F','F'])
>>> X[X < 0.7] = 0
```

Training And Test Data

```
>>> from sklearn.model_selection import train_test_split
>>> X_train, X_test, y_train, y_test = train_test_split(X,
                                                        y,
                                                        random_state=0)
```

Create Your Model

Supervised Learning Estimators

Linear Regression

```
>>> from sklearn.linear_model import LinearRegression
>>> lr = LinearRegression(normalize=True)
```

Support Vector Machines (SVM)

```
>>> from sklearn.svm import SVC
>>> svc = SVC(kernel='linear')
```

Naive Bayes

```
>>> from sklearn.naive_bayes import GaussianNB
>>> gnb = GaussianNB()
```

KNN

```
>>> from sklearn import neighbors
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
```

Unsupervised Learning Estimators

Principal Component Analysis (PCA)

```
>>> from sklearn.decomposition import PCA
>>> pca = PCA(n_components=0.95)
```

K Means

```
>>> from sklearn.cluster import KMeans
>>> k_means = KMeans(n_clusters=3, random_state=0)
```

Model Fitting

Supervised learning

```
>>> lr.fit(X, y)
>>> knn.fit(X_train, y_train)
>>> svc.fit(X_train, y_train)
```

Fit the model to the data

Unsupervised Learning

```
>>> k_means.fit(X_train)
>>> pca_model = pca.fit_transform(X_train)
```

Fit the model to the data
Fit to data, then transform it

Prediction

Supervised Estimators

```
>>> y_pred = svc.predict(np.random.random((2,5)))
>>> y_pred = lr.predict(X_test)
>>> y_pred = knn.predict_proba(X_test)
```

Predict labels
Predict labels
Estimate probability of a label

Unsupervised Estimators

```
>>> y_pred = k_means.predict(X_test)
```

Predict labels in clustering algos

Preprocessing The Data

Standardization

```
>>> from sklearn.preprocessing import StandardScaler
>>> scaler = StandardScaler().fit(X_train)
>>> standardized_X = scaler.transform(X_train)
>>> standardized_X_test = scaler.transform(X_test)
```

Normalization

```
>>> from sklearn.preprocessing import Normalizer
>>> scaler = Normalizer().fit(X_train)
>>> normalized_X = scaler.transform(X_train)
>>> normalized_X_test = scaler.transform(X_test)
```

Binarization

```
>>> from sklearn.preprocessing import Binarizer
>>> binarizer = Binarizer(threshold=0.0).fit(X)
>>> binary_X = binarizer.transform(X)
```

Encoding Categorical Features

```
>>> from sklearn.preprocessing import LabelEncoder
>>> enc = LabelEncoder()
>>> y = enc.fit_transform(y)
```

Imputing Missing Values

```
>>> from sklearn.preprocessing import Imputer
>>> imp = Imputer(missing_values=0, strategy='mean', axis=0)
>>> imp.fit_transform(X_train)
```

Generating Polynomial Features

```
>>> from sklearn.preprocessing import PolynomialFeatures
>>> poly = PolynomialFeatures(5)
>>> poly.fit_transform(X)
```

Evaluate Your Model's Performance

Classification Metrics

Accuracy Score

```
>>> knn.score(X_test, y_test)
>>> from sklearn.metrics import accuracy_score
>>> accuracy_score(y_test, y_pred)
```

Estimator score method
Metric scoring functions

Classification Report

```
>>> from sklearn.metrics import classification_report
>>> print(classification_report(y_test, y_pred))
```

Precision, recall, f1-score and support

Confusion Matrix

```
>>> from sklearn.metrics import confusion_matrix
>>> print(confusion_matrix(y_test, y_pred))
```

Regression Metrics

Mean Absolute Error

```
>>> from sklearn.metrics import mean_absolute_error
>>> y_true = [3, -0.5, 2]
>>> mean_absolute_error(y_true, y_pred)
```

Mean Squared Error

```
>>> from sklearn.metrics import mean_squared_error
>>> mean_squared_error(y_test, y_pred)
```

R^2 Score

```
>>> from sklearn.metrics import r2_score
>>> r2_score(y_true, y_pred)
```

Clustering Metrics

Adjusted Rand Index

```
>>> from sklearn.metrics import adjusted_rand_score
>>> adjusted_rand_score(y_true, y_pred)
```

Homogeneity

```
>>> from sklearn.metrics import homogeneity_score
>>> homogeneity_score(y_true, y_pred)
```

V-measure

```
>>> from sklearn.metrics import v_measure_score
>>> metrics.v_measure_score(y_true, y_pred)
```

Cross-Validation

```
>>> from sklearn.cross_validation import cross_val_score
>>> print(cross_val_score(knn, X_train, y_train, cv=4))
>>> print(cross_val_score(lr, X, y, cv=2))
```

Tune Your Model

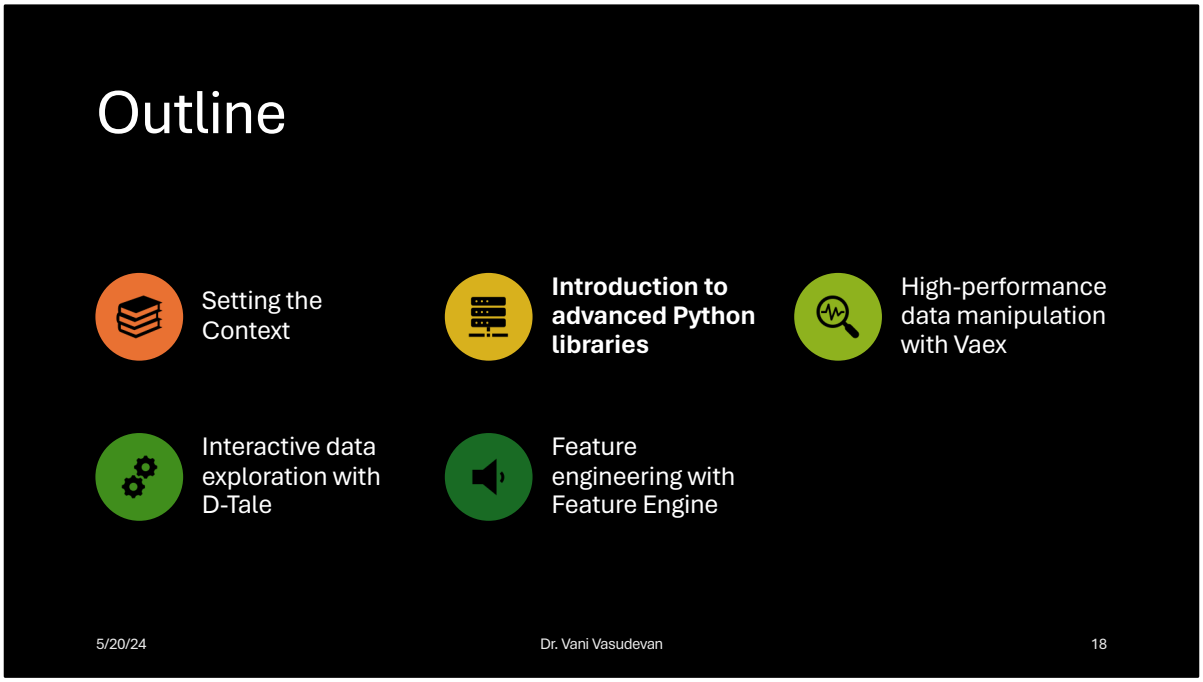
Grid Search

```
>>> from sklearn.grid_search import GridSearchCV
>>> params = {"n_neighbors": np.arange(1,3),
              "metric": ["euclidean", "cityblock"]}
>>> grid = GridSearchCV(estimator=knn,
                        param_grid=params)
>>> grid.fit(X_train, y_train)
>>> print(grid.best_score_)
>>> print(grid.best_estimator_.n_neighbors)
```

Randomized Parameter Optimization

```
>>> from sklearn.grid_search import RandomizedSearchCV
>>> params = {"n_neighbors": range(1,5),
              "weights": ["uniform", "distance"]}
>>> rsearch = RandomizedSearchCV(estimator=knn,
                                 param_distributions=params,
                                 cv=4,
                                 n_iter=8,
                                 random_state=5)
>>> rsearch.fit(X_train, y_train)
>>> print(rsearch.best_score_)
```

DataCamp
Learn Python for Data Science Interactively



Importance of Advanced Python Libraries in Enhancing Data Analysis Capabilities and Improving Workflow Efficiency

1. Efficiency and Performance:

•Handling Large Datasets:

- Advanced libraries like Vaex are designed to work with large datasets that do not fit into memory, enabling efficient out-of-core data manipulation and analysis. This capability is crucial for processing large-scale data in a timely manner.

•Optimized Computations:

- These libraries leverage optimized algorithms and data structures, significantly reducing computation time. For example, Vaex uses memory-mapped files and efficient indexing to speed up data operations.

•Parallel Processing:

- Many advanced libraries support parallel processing and distributed computing, allowing for faster data processing by utilizing multiple CPU cores or even clusters of machines.

2. Ease of Use and Flexibility:

•User-Friendly APIs:

- Libraries like D-Tale provide intuitive interfaces for data exploration and

visualization, making it easier for data professionals to interact with their data without extensive coding.

•**Seamless Integration:**

- These libraries integrate seamlessly with other popular Python libraries such as Pandas, NumPy, and scikit-learn, allowing for a smooth transition and interoperability between different tools in the data science ecosystem.

3. Community Support and Documentation:

•**Comprehensive Documentation:**

- Most advanced libraries come with extensive documentation and tutorials, providing clear guidelines on how to use their features effectively. This makes it easier for users to get started and overcome any challenges they may encounter.

•**Active Community:**

- An active community of users and developers contributes to continuous improvement and support. Users can seek help from community forums, GitHub issues, and other online resources, ensuring they are not alone in their learning journey.

4. Improving Workflow Efficiency:

•**Streamlined Data Processing:**

- Feature Engine simplifies common preprocessing tasks such as handling missing data, encoding categorical variables, and scaling features, making the data preparation phase more efficient and less error-prone.

•**Interactive Analysis:**

- D-Tale provides an interactive environment for data exploration, enabling quick insights and facilitating a more iterative and exploratory analysis process. This leads to faster discovery of patterns and anomalies in the data.

5. Enhancing Analytical Capabilities:

•**Advanced Techniques:**

- By leveraging advanced libraries, data professionals can implement sophisticated techniques and models that were previously challenging or time-consuming. This includes out-of-core algorithms, automated machine learning, and complex feature engineering.

•**Better Decision Making:**

- The ability to analyze large datasets efficiently and accurately leads to more informed and data-driven decisions. This is particularly important in industries like healthcare, where timely and accurate insights can significantly impact business outcomes.

•**Scalability:**

- Advanced libraries are designed to scale with the data. As the volume and

complexity of data grow, these tools ensure that data analysis remains manageable and performant.

Introduction to Advanced Libraries and Frameworks(1)

19

Vaex

A high-performance Data Frame library designed for out-of-core data manipulation. Vaex is optimized for working with large datasets that do not fit into memory, making it an excellent choice for big data projects.

Dr. Vani Vasudevan

repo

```
conda create -n myenv python=3.10
 conda activate myenv
```

```
pip install pydantic-settings
pip show pydantic-settings
conda install -c conda-forge vaex
vaex –version
```

https://vaex.readthedocs.io/en/latest/datasets.html

Introduction to Advanced Libraries and Frameworks(2)

D-Tale

An interactive web-based tool for visualizing and analysing Pandas Data Frames. D-Tale provides a user-friendly interface that allows you to explore data interactively, making the data exploration process more efficient and insightful.

repo

Dr. Vani Vasudevan

https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page

Introduction to Advanced Libraries and Frameworks(3)

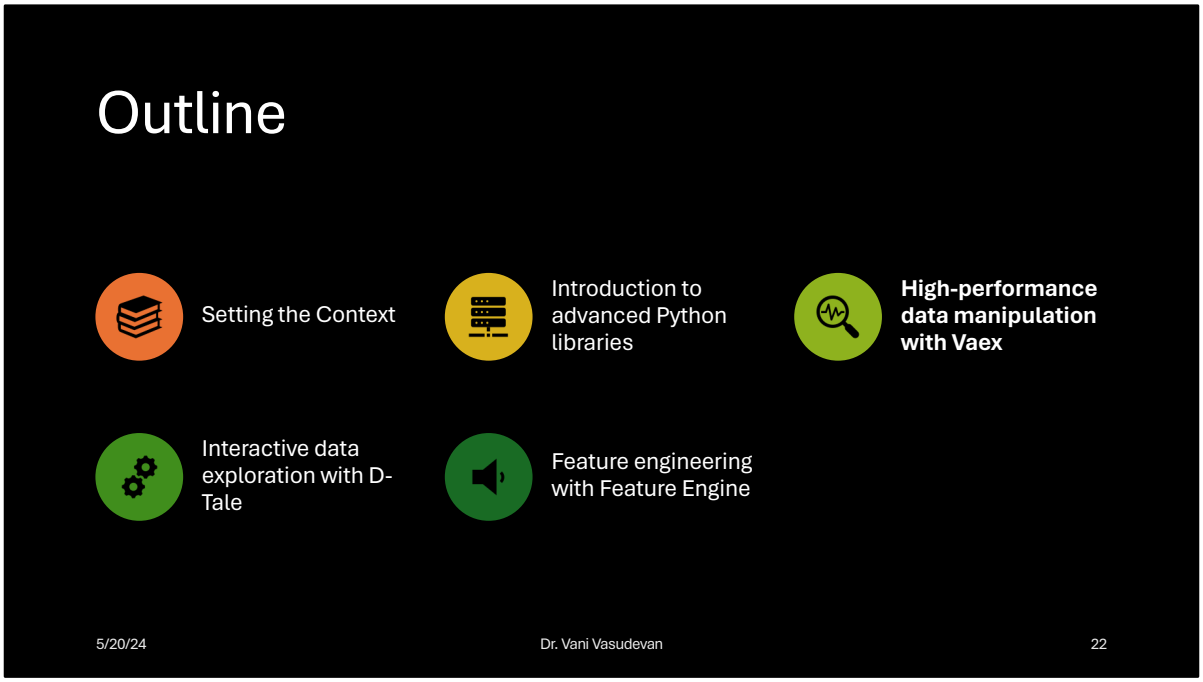
Feature Engine

A library for feature engineering that integrates seamlessly with scikit-learn. Feature Engine offers various transformers for handling missing data, encoding categorical variables, and scaling features, simplifying the data preprocessing phase.

21

Dr. Vani Vasudevan

repo



Importance of Advanced Python Libraries in Enhancing Data Analysis Capabilities and Improving Workflow Efficiency

1. Efficiency and Performance:

•Handling Large Datasets:

- Advanced libraries like Vaex are designed to work with large datasets that do not fit into memory, enabling efficient out-of-core data manipulation and analysis. This capability is crucial for processing large-scale data in a timely manner.

•Optimized Computations:

- These libraries leverage optimized algorithms and data structures, significantly reducing computation time. For example, Vaex uses memory-mapped files and efficient indexing to speed up data operations.

•Parallel Processing:

- Many advanced libraries support parallel processing and distributed computing, allowing for faster data processing by utilizing multiple CPU cores or even clusters of machines.

2. Ease of Use and Flexibility:

•User-Friendly APIs:

- Libraries like D-Tale provide intuitive interfaces for data exploration and

visualization, making it easier for data professionals to interact with their data without extensive coding.

•**Seamless Integration:**

- These libraries integrate seamlessly with other popular Python libraries such as Pandas, NumPy, and scikit-learn, allowing for a smooth transition and interoperability between different tools in the data science ecosystem.

3. Community Support and Documentation:

•**Comprehensive Documentation:**

- Most advanced libraries come with extensive documentation and tutorials, providing clear guidelines on how to use their features effectively. This makes it easier for users to get started and overcome any challenges they may encounter.

•**Active Community:**

- An active community of users and developers contributes to continuous improvement and support. Users can seek help from community forums, GitHub issues, and other online resources, ensuring they are not alone in their learning journey.

4. Improving Workflow Efficiency:

•**Streamlined Data Processing:**

- Feature Engine simplifies common preprocessing tasks such as handling missing data, encoding categorical variables, and scaling features, making the data preparation phase more efficient and less error-prone.

•**Interactive Analysis:**

- D-Tale provides an interactive environment for data exploration, enabling quick insights and facilitating a more iterative and exploratory analysis process. This leads to faster discovery of patterns and anomalies in the data.

5. Enhancing Analytical Capabilities:

•**Advanced Techniques:**

- By leveraging advanced libraries, data professionals can implement sophisticated techniques and models that were previously challenging or time-consuming. This includes out-of-core algorithms, automated machine learning, and complex feature engineering.

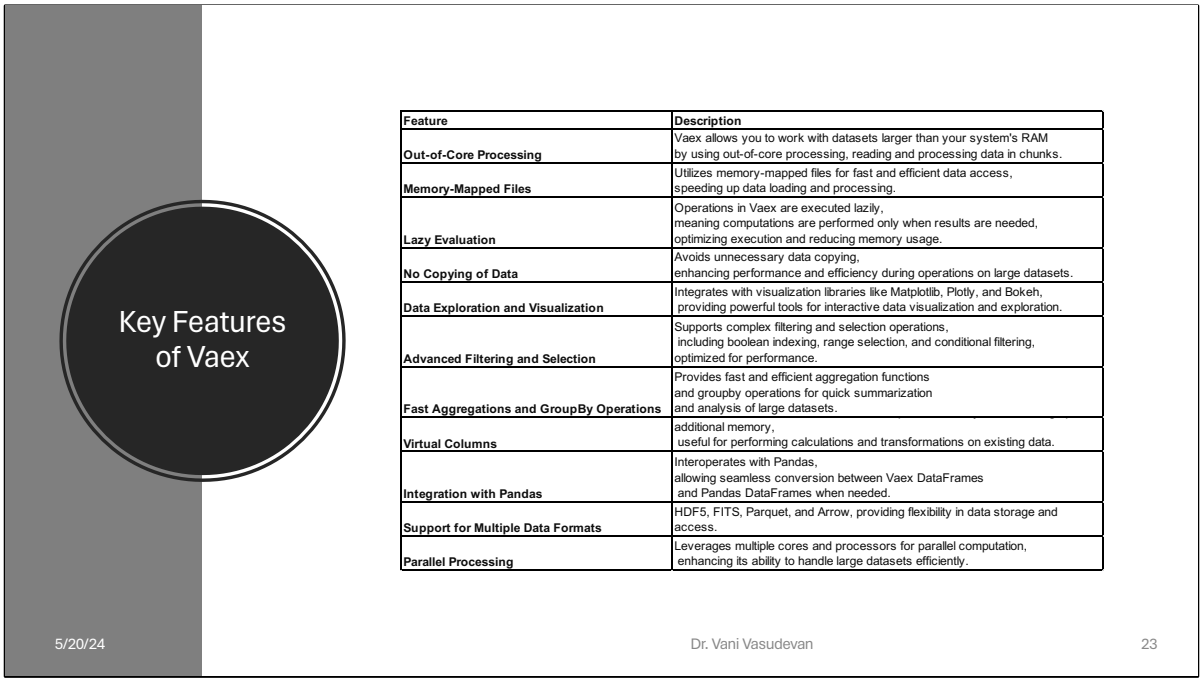
•**Better Decision Making:**

- The ability to analyze large datasets efficiently and accurately leads to more informed and data-driven decisions. This is particularly important in industries like healthcare, where timely and accurate insights can significantly impact business outcomes.

•**Scalability:**

- Advanced libraries are designed to scale with the data. As the volume and

complexity of data grow, these tools ensure that data analysis remains manageable and performant.



Sources:

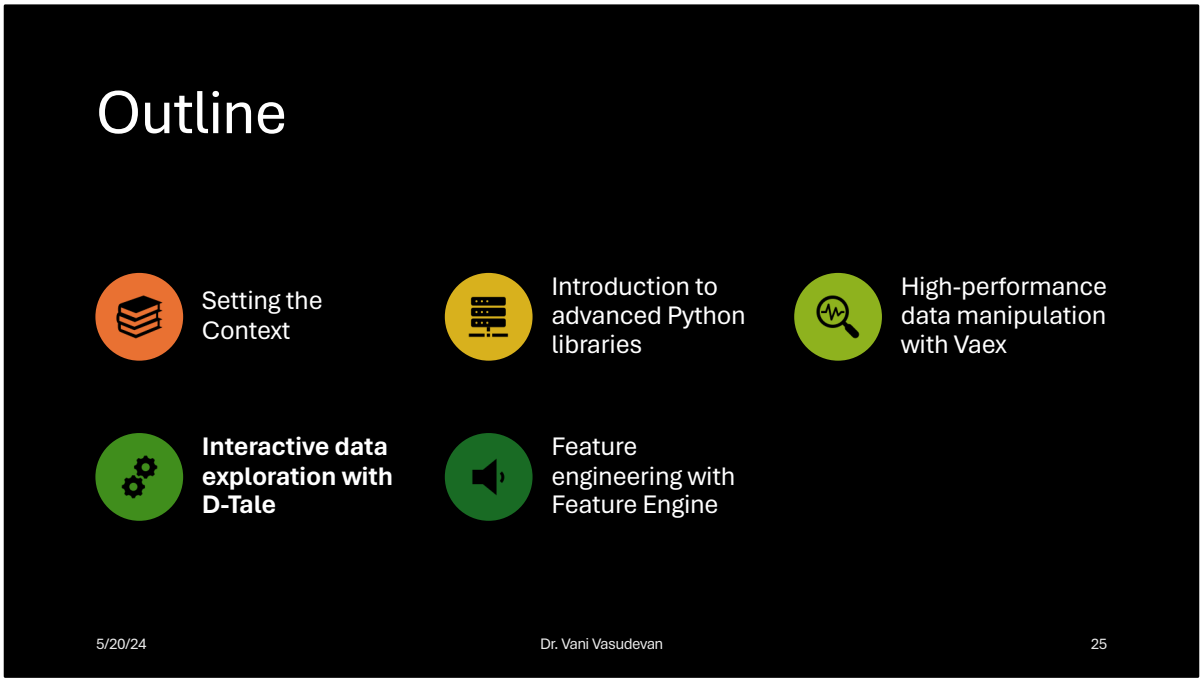
https://vaex.readthedocs.io/en/latest/

https://vaex.readthedocs.io/en/latest/guides/performance.html
https://vaex.io/blog/8-incredibly-powerful-Vaex-features-you-might-have-not-known-about

Key differences between Pandas and Vaex

Feature	Pandas	Vaex
Data Handling	In-memory	Out-of-core
Dataset Size	Limited by RAM	Handles datasets larger than RAM
Performance	Slower for very large datasets	Optimized for large datasets
Computation	Eager evaluation (immediate)	Lazy evaluation (deferred)
Parallel Processing	Limited	Supports multi-threading
Integration	Seamless with other Python libraries	Integrates well with common data science libraries
API	Intuitive and widely adopted	Similar to Pandas, easy to learn
Feature Set	Extensive (data manipulation, analysis, etc.)	Comparable for large datasets, includes virtual columns, efficient filtering, and binning
Memory Usage	High for large datasets	Low due to memory-mapped files
Installation	`pip install pandas`	`pip install vaex`
Documentation	Extensive and well-documented	Extensive and well-documented
Community Supp	Large and active community	Growing and active community

Source 1: https://www.datacamp.com/tutorial/benchmarking-high-performance-pandas-alternatives#
Source 2: https://medium.com/helpshift-engineering/vaex-pandas-on-steroids-ded8ca765f55



Importance of Advanced Python Libraries in Enhancing Data Analysis Capabilities and Improving Workflow Efficiency

1. Efficiency and Performance:

•Handling Large Datasets:

- Advanced libraries like Vaex are designed to work with large datasets that do not fit into memory, enabling efficient out-of-core data manipulation and analysis. This capability is crucial for processing large-scale data in a timely manner.

•Optimized Computations:

- These libraries leverage optimized algorithms and data structures, significantly reducing computation time. For example, Vaex uses memory-mapped files and efficient indexing to speed up data operations.

•Parallel Processing:

- Many advanced libraries support parallel processing and distributed computing, allowing for faster data processing by utilizing multiple CPU cores or even clusters of machines.

2. Ease of Use and Flexibility:

•User-Friendly APIs:

- Libraries like D-Tale provide intuitive interfaces for data exploration and

visualization, making it easier for data professionals to interact with their data without extensive coding.

•Seamless Integration:

- These libraries integrate seamlessly with other popular Python libraries such as Pandas, NumPy, and scikit-learn, allowing for a smooth transition and interoperability between different tools in the data science ecosystem.

3. Community Support and Documentation:

•Comprehensive Documentation:

- Most advanced libraries come with extensive documentation and tutorials, providing clear guidelines on how to use their features effectively. This makes it easier for users to get started and overcome any challenges they may encounter.

•Active Community:

- An active community of users and developers contributes to continuous improvement and support. Users can seek help from community forums, GitHub issues, and other online resources, ensuring they are not alone in their learning journey.

4. Improving Workflow Efficiency:

•Streamlined Data Processing:

- Feature Engine simplifies common preprocessing tasks such as handling missing data, encoding categorical variables, and scaling features, making the data preparation phase more efficient and less error-prone.

•Interactive Analysis:

- D-Tale provides an interactive environment for data exploration, enabling quick insights and facilitating a more iterative and exploratory analysis process. This leads to faster discovery of patterns and anomalies in the data.

5. Enhancing Analytical Capabilities:

•Advanced Techniques:

- By leveraging advanced libraries, data professionals can implement sophisticated techniques and models that were previously challenging or time-consuming. This includes out-of-core algorithms, automated machine learning, and complex feature engineering.

•Better Decision Making:

- The ability to analyze large datasets efficiently and accurately leads to more informed and data-driven decisions. This is particularly important in industries like healthcare, where timely and accurate insights can significantly impact business outcomes.

•Scalability:

- Advanced libraries are designed to scale with the data. As the volume and

complexity of data grow, these tools ensure that data analysis remains manageable and performant.

Dtale

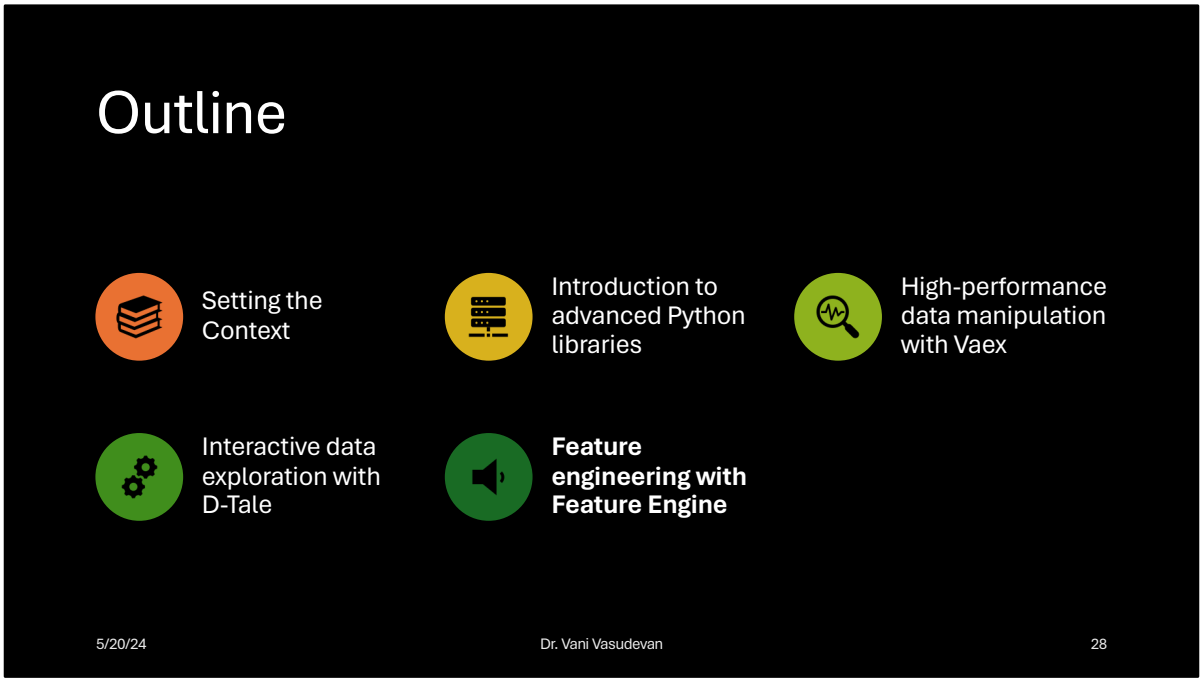
D-Tale is a Python library that provides an interactive and web-based interface for exploring and visualizing datasets.

It is the combination of a Flask back-end and a React front-end to bring you an easy way to view & analyze Panda's data structures.

Dr. Vani Vasudevan

Dtale

Feature	Description
Interactive Data Exploration	Provides an interactive web-based interface for exploring pandas DataFrames, allowing users to view, sort, filter, and visualize data in real-time.
Visualization Capabilities	Offers a wide range of built-in visualizations including histograms, bar charts, scatter plots, and more, facilitating the quick and easy analysis of data patterns and distributions.
Data Cleaning and Transformation	Provides tools for cleaning and transforming data directly within the interface, including handling missing values, creating new columns, and applying custom transformations.
Statistics and Summaries	Allows users to generate summary statistics and descriptive analyses, providing insights into data distributions, correlations, and other key metrics.
Data Filtering	Supports advanced filtering options, enabling users to subset data based on specific criteria, making it easier to focus on relevant portions of the dataset.
Real-Time Collaboration	Facilitates collaborative data analysis by allowing multiple users to interact with the same D-Tale instance, making it ideal for team projects and shared analysis efforts.
Integration with Pandas	Seamlessly integrates with pandas, allowing users to load DataFrames directly into D-Tale for exploration and analysis, and export modified DataFrames back to pandas.
Custom Python Scripts	Enables users to run custom Python scripts within the D-Tale interface, allowing for flexible and powerful data manipulation and analysis.
Performance and Scalability	Optimized for performance, D-Tale can handle large datasets efficiently, leveraging pandas' capabilities for fast data processing and manipulation.



Importance of Advanced Python Libraries in Enhancing Data Analysis Capabilities and Improving Workflow Efficiency

1. Efficiency and Performance:

•Handling Large Datasets:

- Advanced libraries like Vaex are designed to work with large datasets that do not fit into memory, enabling efficient out-of-core data manipulation and analysis. This capability is crucial for processing large-scale data in a timely manner.

•Optimized Computations:

- These libraries leverage optimized algorithms and data structures, significantly reducing computation time. For example, Vaex uses memory-mapped files and efficient indexing to speed up data operations.

•Parallel Processing:

- Many advanced libraries support parallel processing and distributed computing, allowing for faster data processing by utilizing multiple CPU cores or even clusters of machines.

2. Ease of Use and Flexibility:

•User-Friendly APIs:

- Libraries like D-Tale provide intuitive interfaces for data exploration and

visualization, making it easier for data professionals to interact with their data without extensive coding.

•Seamless Integration:

- These libraries integrate seamlessly with other popular Python libraries such as Pandas, NumPy, and scikit-learn, allowing for a smooth transition and interoperability between different tools in the data science ecosystem.

3. Community Support and Documentation:

•Comprehensive Documentation:

- Most advanced libraries come with extensive documentation and tutorials, providing clear guidelines on how to use their features effectively. This makes it easier for users to get started and overcome any challenges they may encounter.

•Active Community:

- An active community of users and developers contributes to continuous improvement and support. Users can seek help from community forums, GitHub issues, and other online resources, ensuring they are not alone in their learning journey.

4. Improving Workflow Efficiency:

•Streamlined Data Processing:

- Feature Engine simplifies common preprocessing tasks such as handling missing data, encoding categorical variables, and scaling features, making the data preparation phase more efficient and less error-prone.

•Interactive Analysis:

- D-Tale provides an interactive environment for data exploration, enabling quick insights and facilitating a more iterative and exploratory analysis process. This leads to faster discovery of patterns and anomalies in the data.

5. Enhancing Analytical Capabilities:

•Advanced Techniques:

- By leveraging advanced libraries, data professionals can implement sophisticated techniques and models that were previously challenging or time-consuming. This includes out-of-core algorithms, automated machine learning, and complex feature engineering.

•Better Decision Making:

- The ability to analyze large datasets efficiently and accurately leads to more informed and data-driven decisions. This is particularly important in industries like healthcare, where timely and accurate insights can significantly impact business outcomes.

•Scalability:

- Advanced libraries are designed to scale with the data. As the volume and

complexity of data grow, these tools ensure that data analysis remains manageable and performant.

Feature-Engine

Feature-engine is a Python library with multiple transformers to engineer and select features for machine learning models. Feature-engine adopts Scikit-learn functionality with methods fit() and transform() to learn parameters from and then transform the data.

Dr. Vani Vasudevan

Feature-engine

Feature	Description
Transformations for Feature Engineering	Provides a variety of transformers for feature engineering, including handling missing values, encoding categorical variables, and transforming numerical variables.
Pipeline Integration	Designed to integrate seamlessly with Scikit-Learn pipelines, allowing for easy incorporation of feature engineering steps in machine learning workflows.
Handling Missing Data	Includes transformers for imputing missing data using mean, median, mode, arbitrary values, or methods based on data characteristics.
Encoding Categorical Variables	Offers various encoding methods such as one-hot encoding, ordinal encoding, count or frequency encoding, target mean encoding, and more.
Variable Transformation	Allows for transformation of numerical variables through logarithmic, reciprocal, power, and box-cox transformations, among others.
Discretization	Provides methods for discretizing continuous variables into discrete intervals or bins, which can be useful for certain types of models and analyses.
Feature Scaling	Implements scaling techniques such as standardization, min-max scaling, and robust scaling to normalize data.
Feature Selection	Includes techniques for selecting relevant features based on statistical tests, model importance, or user-defined criteria.
Combining Variables	Allows for the creation of new features by combining existing variables through mathematical operations or aggregations.
Outlier Handling	Provides methods to cap, transform, or remove outliers from the data, ensuring that extreme values do not skew the model performance.

Thank you

Any Questions?

Reach me @ vani.v@nmit.ac.in

LinkedIn: www.linkedin.com/in/dr-vani-vasudevan-0b89b713

GitHub: https://github.com/vanivasudevan/AdvancedLibrariesDemo