Python Libraries for Data Analysis and Machine Learning

Overview

- Environment Preparation for Python
- Python Libraries for Data Scientists
- Data Processing & Visualization Using Python
- Python for Basic Machine Learning Models

Environment Preparation for Python

We introduce

- **Anaconda** (https://www.anaconda.com/)
- **Jupyter Notebook** (https://jupyter.org/)

for Python environment.

Other alternatives:

- Text Editor + Command line
- IDE (Integrated Development Environment): PyCharm, Vscode, …

What is Anaconda?

- The open-source Anaconda is the easiest way to perform Python/R data science and machine learning on Linux, Windows, and Mac OS X. With over 19 million users worldwide.
- It is the industry standard for developing, testing, and training on a single machine, enabling *individual data scientists* to:
  - Quickly download 7,500+ Python/R data science packages
  - Analyze data with scalability and performance with Dask, **NumPy**, **pandas**, and Numba
  - Visualize results with **Matplotlib**, Bokeh, Datashader, and Holoviews
  - Develop and train machine learning and deep learning models with **scikit-learn**, TensorFlow, and Theano

Anaconda Installation

Please follow the instruction here to install the Anaconda (for Python 3.7)

https://www.anaconda.com/distribution/#download-section

- It provides different versions to suit different OS. Please select the one you are using.
- Just install according to the default setting, and the environment variables will be automatically configured after installation.

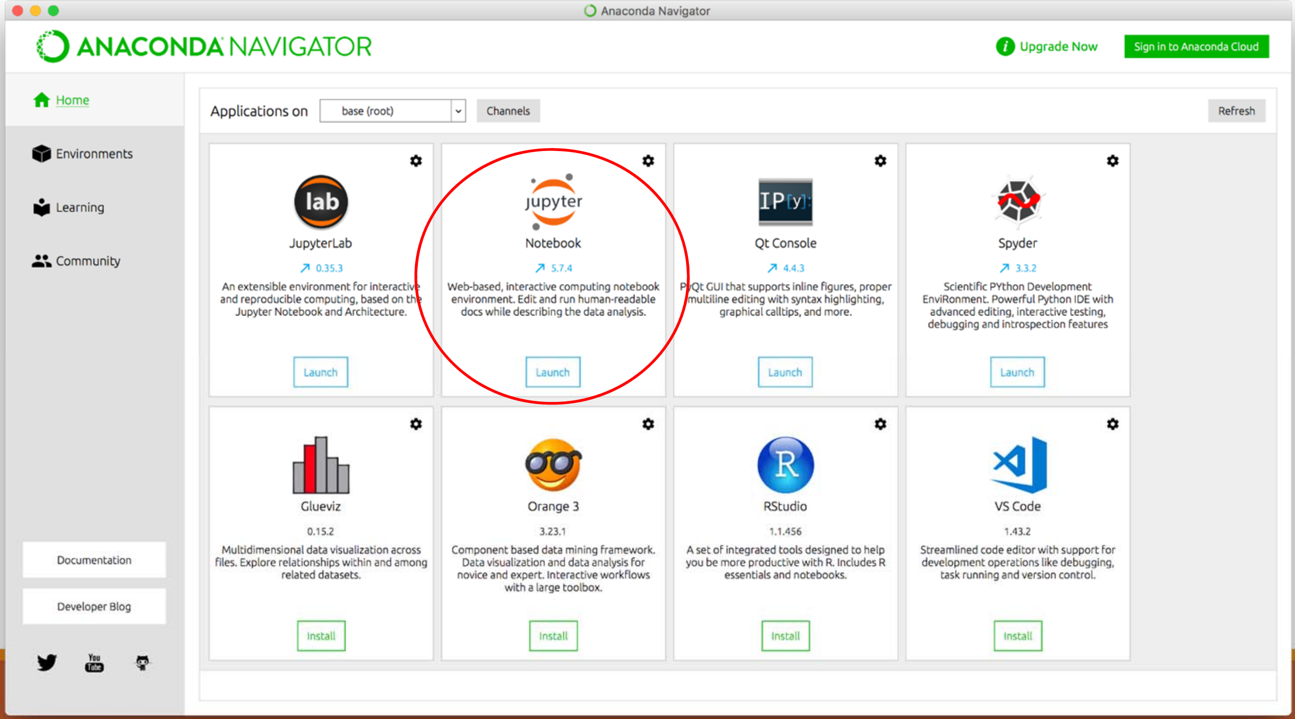
What is Jupyter Notebook?

- The Jupyter Notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations and narrative text.
- It includes: data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning, and much more.
- Jupyter Notebook is included in the Anaconda.

Basic Operation on Jupyter Notebook

After installing the Anaconda, open Anaconda-Navigator as below, and you can find the Jupyter Notebook on the Anaconda. Then click Launch.

Anaconda-Navigator



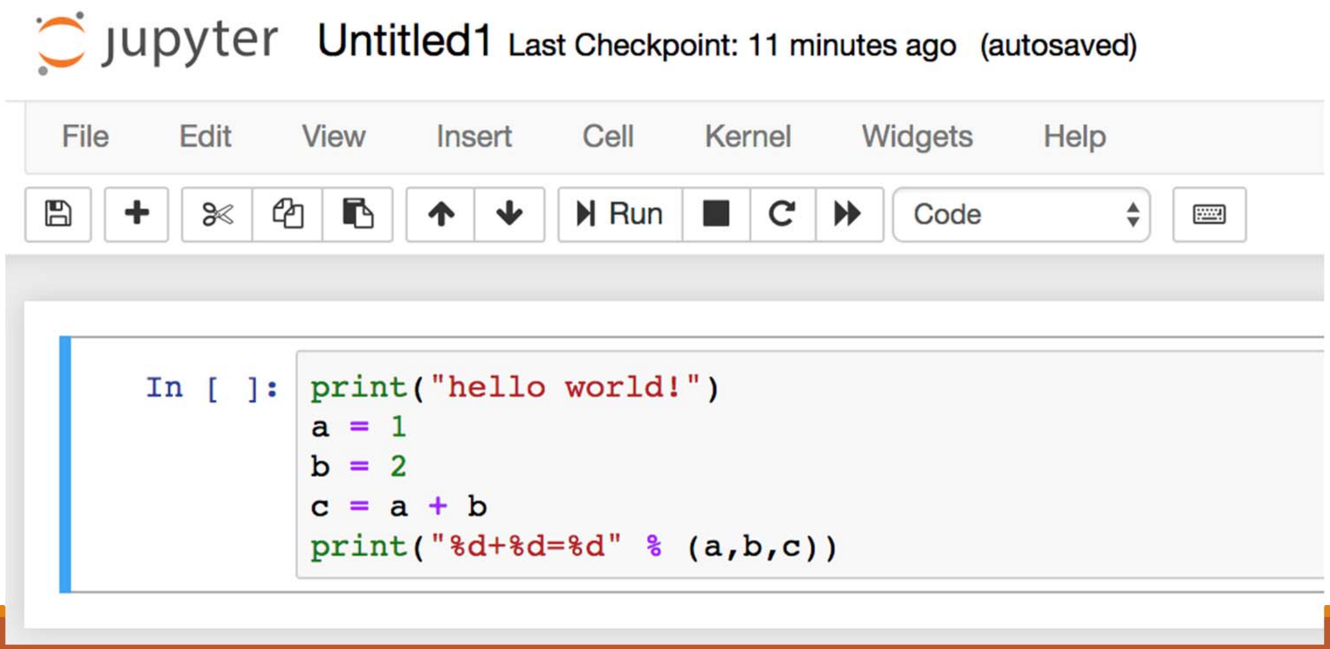
Basic Operation on Jupyter Notebook

Jupyter Notebook is presented as a website. Select the path, then under the button “New”, choose “Python 3” to open a new python file.

Basic Operation on Jupyter Notebook

Type the code into the input box on Jupyter.

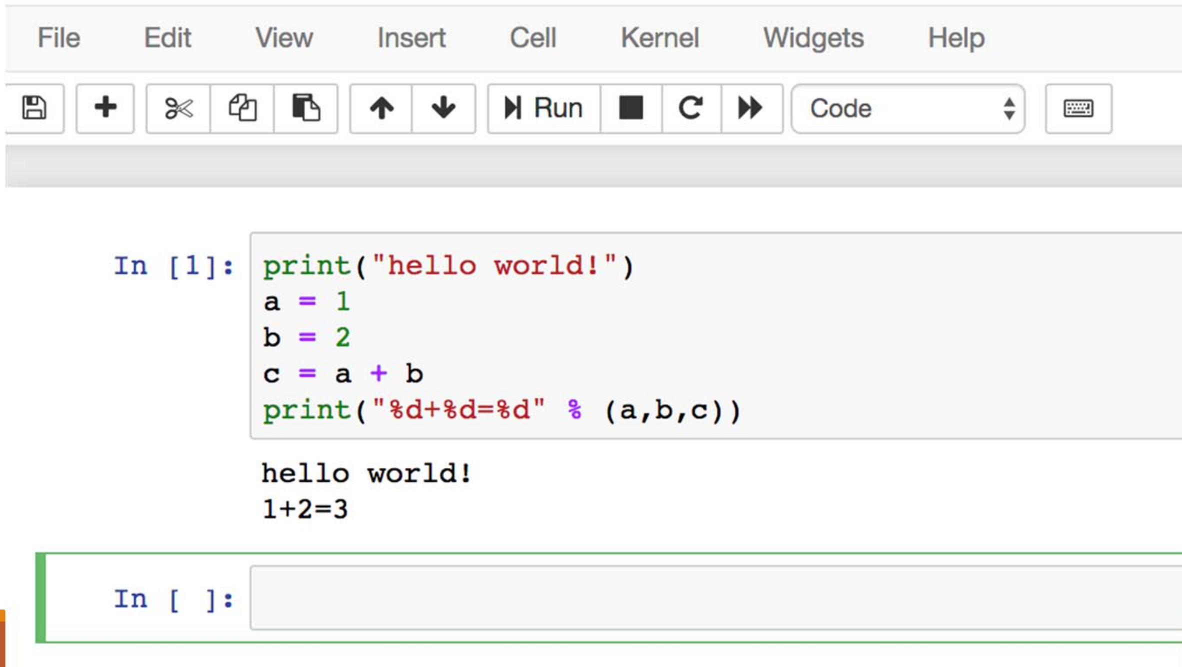
Get started learning Python: https://www.learnpython.org/



Basic Operation on Jupyter Notebook

Click “Run”.

The output will be shown in the blank area right below the input box.



Basic Operation on Jupyter Notebook

Jupyter Notebook will help you save your code automatically in ".ipynb" format.

If you want to save the code as ".py" format.

Here, we just use ".ipynb" format.

```
In [1]: print("hello world!")
        a = 1
        b = 2
        c = a + b
        print("%d+%d=%d" % (a,b,c))

        hello world!
        1+2=3

In [2]: %%writefile example.py
        print("hello world!")
        a = 1
        b = 2
        c = a + b
        print("%d+%d=%d" % (a,b,c))

        Writing example.py

In [ ]:
```

Python Libraries for Data Scientists

Python toolboxes/libraries for data processing:

- NumPy
- SciPy
- Pandas

Visualization libraries

- matplotlib
- Seaborn

Machine learning & deep learning

- Scikit-learn
- Tensorflow/Pytorch/Theano

and many more …

Python Libraries for Data Scientists

NumPy:

- introduces objects for multidimensional arrays and matrices, as well as functions that allow to easily perform advanced mathematical and statistical operations on those objects

- provides vectorization of mathematical operations on arrays and matrices which significantly improves the performance

- many other python libraries are built on NumPy

Link: http://www.numpy.org/

Python Libraries for Data Scientists

SciPy:

- collection of algorithms for linear algebra, differential equations, numerical integration, optimization, statistics and more

- part of SciPy Stack

- built on NumPy

Link: https://www.scipy.org/scipylib/

Python Libraries for Data Scientists

Pandas:

- adds data structures and tools designed to work with table-like data (similar to Series and Data Frames in R)

- provides tools for data manipulation: reshaping, merging, sorting, slicing, aggregation etc.

- allows handling missing data

Link: http://pandas.pydata.org/

Python Libraries for Data Scientists

matplotlib:

- python 2D plotting library which produces publication quality figures in a variety of hardcopy formats
- a set of functionalities similar to those of MATLAB
- line plots, scatter plots, barcharts, histograms, pie charts etc.
- relatively low-level; some effort needed to create advanced visualization

Link: https://matplotlib.org/

Python Libraries for Data Scientists

Seaborn:

- based on matplotlib
- provides high level interface for drawing attractive statistical graphics
- Similar (in style) to the popular ggplot2 library in R

Link: https://seaborn.pydata.org/

Python Libraries for Data Scientists

SciKit-Learn:

- provides machine learning algorithms: classification, regression, clustering, model validation etc.

- built on NumPy, SciPy and matplotlib

Link: http://scikit-learn.org/

Loading Python Libraries

```
In [1]: #Import Python Libraries
        import numpy as np
        import scipy as sp
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
```

Press `Shift+Enter` to execute the *jupyter* cell, or just click “Run”.

Reading data using pandas

```
In [4]: df = pd.read_csv("http://www1.se.cuhk.edu.hk/~eclt5810/lecture/weka_tutorial/bank.csv")
```

There is a number of pandas commands to read other data formats:

```
pd.read_excel('myfile.xlsx',sheet_name='Sheet1', index_col=None, na_values=['NA'])
pd.read_stata('myfile.dta')
pd.read_sas('myfile.sas7bdat')
pd.read_hdf('myfile.h5','df')
```

Exploring data frames

In [5]:
```python
#List first 5 records
df.head()
```

Out[5]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
0	30	unemployed	married	primary	no	1787	no	no	cellular	19	oct	79	1	-1	0	unknown	no
1	33	services	married	secondary	no	4789	yes	yes	cellular	11	may	220	1	339	4	failure	no
2	35	management	single	tertiary	no	1350	yes	no	cellular	16	apr	185	1	330	1	failure	no
3	30	management	married	tertiary	no	1476	yes	yes	unknown	3	jun	199	4	-1	0	unknown	no
4	59	blue-collar	married	secondary	no	0	yes	no	unknown	5	may	226	1	-1	0	unknown	no

- ✓ Try to read the first 10, 20, 50 records
- ✓ Try to view the last few records

Data Frame data types

Pandas Type	**Native Python Type**	**Description**
object	string	The most general dtype. Will be assigned to your column if column has mixed types (numbers and strings).
int64	int	Numeric characters. 64 refers to the memory allocated to hold this character.
float64	float	Numeric characters with decimals. If a column contains numbers and NaNs, pandas will default to float64, in case your missing value has a decimal.
datetime64, timedelta[ns]	N/A (but see the datetime module in Python's standard library)	Values meant to hold time data. Look into these for time series experiments.

Data Frame data types

In [7]:
```
#Check a particular column type
df['age'].dtype
```

Out[7]:
```
dtype('int64')
```

In [8]:
```
#Check types for all the columns
df.dtypes
```

Out[8]:
```
age             int64
job            object
marital        object
education      object
default        object
balance         int64
housing        object
loan           object
contact        object
day             int64
month          object
duration        int64
campaign        int64
pdays           int64
previous        int64
poutcome       object
y              object
dtype: object
```

Data Frames attributes

Python objects have *attributes* and *methods*.

df.attribute	description
dtypes	list the types of the columns
columns	list the column names
axes	list the row labels and column names
ndim	number of dimensions
size	number of elements
shape	return a tuple representing the dimensionality
values	numpy representation of the data

Data Frames attributes

```
In [11]: #Find how many records this data frame has
         df.shape

Out[11]: (4521, 17)

In [12]: #How many elements are there?
         df.size

Out[12]: 76857

In [13]: #What are the column names?
         df.columns

Out[13]: Index(['age', 'job', 'marital', 'education', 'default', 'balance', 'housing',
                'loan', 'contact', 'day', 'month', 'duration', 'campaign', 'pdays',
                'previous', 'poutcome', 'y'],
               dtype='object')
```

Data Frames methods

Unlike attributes, python methods have *parenthesis.*
All attributes and methods can be listed with a *dir()* function: `dir(df)`

df.method()	description
head([n]), tail([n])	first/last n rows
describe()	generate descriptive statistics (for numeric columns only)
max(), min()	return max/min values for all numeric columns
mean(), median()	return mean/median values for all numeric columns
std()	standard deviation
sample([n])	returns a random sample of the data frame
dropna()	drop all the records with missing values

Data Frames methods

```
In [14]: #Give the summary for the numeric columns in the dataset
         df.describe()
```

Out[14]:

	age	balance	day	duration	campaign	pdays	previous
count	4521.000000	4521.000000	4521.000000	4521.000000	4521.000000	4521.000000	4521.000000
mean	41.170095	1422.657819	15.915284	263.961292	2.793630	39.766645	0.542579
std	10.576211	3009.638142	8.247667	259.856633	3.109807	100.121124	1.693562
min	19.000000	-3313.000000	1.000000	4.000000	1.000000	-1.000000	0.000000
25%	33.000000	69.000000	9.000000	104.000000	1.000000	-1.000000	0.000000
50%	39.000000	444.000000	16.000000	185.000000	2.000000	-1.000000	0.000000
75%	49.000000	1480.000000	21.000000	329.000000	3.000000	-1.000000	0.000000
max	87.000000	71188.000000	31.000000	3025.000000	50.000000	871.000000	25.000000

Data Frames methods

In [15]:
```python
#Calculate standard deviation for all numeric columns
df.std()
```

Out[15]:
```
age            10.576211
balance      3009.638142
day             8.247667
duration      259.856633
campaign        3.109807
pdays         100.121124
previous        1.693562
dtype: float64
```

In [17]:
```python
#What are the mean values for all numeric columns?
df.mean()
```

Out[17]:
```
age            41.170095
balance      1422.657819
day            15.915284
duration      263.961292
campaign        2.793630
pdays          39.766645
previous        0.542579
dtype: float64
```

Selecting a column in a Data Frame

```
In [22]: #Subset the data frame using column name
         df['job'][:5]

Out[22]: 0      unemployed
         1        services
         2      management
         3      management
         4     blue-collar
         Name: job, dtype: object

In [23]: #Use the column name as an attribute
         df.job[:5]

Out[23]: 0      unemployed
         1        services
         2      management
         3      management
         4     blue-collar
         Name: job, dtype: object
```

Note: If we want to select a column with a name as the attribute in DataFrames we should use method 1.

E.G., Since there is an attribute – *rank* in DataFrame, if we want to select the column 'rank', we should use df['rank'], and cannot use method 2, i.e., df.rank, which will return the attribute *rank* of the data frame instead of the column "rank".

Selecting a column in a Data Frame

```
In [24]: #Calculate the basic statistics for the age column
         df.age.describe()

Out[24]: count    4521.000000
         mean       41.170095
         std        10.576211
         min        19.000000
         25%        33.000000
         50%        39.000000
         75%        49.000000
         max        87.000000
         Name: age, dtype: float64
```

```
In [26]: #Calculate the average age
         df.age.mean()

Out[26]: 41.17009511170095
```

```
In [25]: #Find how many values in the age column (use count method)
         df.age.count()

Out[25]: 4521
```

Data Frames *groupby* method

Using "group by" method we can:

- Split the data into groups based on some criteria
- Calculate statistics (or apply a function) to each group

In [27]:
```
#Group data using rank
df_job = df.groupby(['job'])
```

In [28]:
```
#Calculate mean value for each numeric column per each group
df_job.mean()
```

Out[28]:

job	age	balance	day	duration	campaign	pdays	previous
admin.	39.682008	1226.736402	16.324268	234.669456	2.631799	49.993724	0.644351
blue-collar	40.156448	1085.161734	15.482030	278.161734	2.846723	41.590909	0.493658
entrepreneur	42.011905	1645.125000	15.255952	285.476190	2.589286	32.273810	0.428571
housemaid	47.339286	2083.803571	15.294643	292.633929	2.500000	26.401786	0.357143

Data Frames *groupby* method

Once *groupby* object is create we can calculate various statistics for each group:

In [29]:
```
#Calculate mean age for each job:
df.groupby('job')[['age']].mean()
```

Out[29]:

job	age
admin.	39.682008
blue-collar	40.156448
entrepreneur	42.011905
housemaid	47.339286
management	40.540764
retired	61.869565

Note: If single brackets are used to specify the column (e.g. age), then the output is Pandas Series object. When double brackets are used the output is a Data Frame (e.g. age & balance)

Data Frames *groupby* method

groupby performance notes:

- no grouping/splitting occurs until it's needed. Creating the *groupby* object only verifies that you have passed a valid mapping
- by default the group keys are sorted during the *groupby* operation. You may want to pass sort=False for potential speedup:

```
In [30]: #Calculate mean age for each job:
         df.groupby(['job'], sort=False)[['age']].mean()
```

Data Frame: filtering

To subset the data we can apply Boolean indexing. This indexing is commonly known as a filter. For example if we want to subset the rows in which the age value is greater than 50:

```
In [31]: #Subset the rows in which the age value is greater than 50
         df_sub = df[ df['age'] > 50 ]
```

Any Boolean operator can be used to subset the data:

>   greater;   >= greater or equal;

<   less;   <= less or equal;

== equal;   != not equal;

```
In [32]: #Select only those rows whose education level is primary
         df_primary = df[ df['education'] == 'primary' ]
```

Data Frames: Slicing

There are a number of ways to subset the Data Frame:

- one or more columns
- one or more rows
- a subset of rows and columns

Rows and columns can be selected by their position or label

Data Frames: Slicing

When selecting one column, it is possible to use single set of brackets, but the resulting object will be a Series (not a DataFrame):

```
In [ ]: #Select column age:
        df['age']
```

When we need to select more than one column and/or make the output to be a DataFrame, we should use double brackets:

```
In [ ]: #Select column age and job:
        df[['age','job']]
```

Data Frames: Selecting rows

If we need to select a range of rows, we can specify the range using ":"

```
In [ ]: #Select rows by their position:
        df[10:20]
```

Notice that the first row has a position 0, and the last value in the range is omitted:
So for 0:10 range the first 10 rows are returned with the positions starting with 0 and ending with 9

Data Frames: method loc

If we need to select a range of rows, using their labels we can use method loc:

In [35]:
```
#Select rows by their labels:
df_sub.loc[10:20,['age','job','education']]
```

Out[35]:

	age	job	education
16	56	technician	secondary

Recall that In [31]:
```
#Subset the rows in which the age value is greater than 50
df_sub = df[ df['age'] > 50 ]
```

Data Frames: method iloc

If we need to select a range of rows and/or columns, using their positions we can use method iloc:

In [47]:
```
#Select rows by their labels:
df_sub.iloc[10:20,[0, 1, 3]]
```

Out[47]:

	age	job	education
46	55	blue-collar	primary
49	61	admin.	unknown
54	53	blue-collar	secondary
56	57	management	secondary
59	54	technician	secondary
61	63	retired	secondary

Data Frames: method iloc (summary)

```
df.iloc[0]  # First row of a data frame
df.iloc[i]  #(i+1)th row
df.iloc[-1] # Last row
```

```
df.iloc[:, 0]  # First column
df.iloc[:, -1] # Last column
```

```
df.iloc[0:7]       #First 7 rows
df.iloc[:, 0:2]    #First 2 columns
df.iloc[1:3, 0:2]  #Second through third rows and first 2 columns
df.iloc[[0,5], [1,3]]  #1st and 6th rows and 2nd and 4th columns
```

Data Frames: Sorting

We can sort the data by a value in the column. By default the sorting will occur in ascending order and a new data frame is return.

In [50]:
```
# Create a new data frame from the original sorted by the column Age
df_sorted = df.sort_values( by ='age')
df_sorted.head()
```

Out[50]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
503	19	student	single	primary	no	103	no	no	cellular	10	jul	104	2	-1	0	unknown	yes
1900	19	student	single	unknown	no	0	no	no	cellular	11	feb	123	3	-1	0	unknown	no
2780	19	student	single	secondary	no	302	no	no	cellular	16	jul	205	1	-1	0	unknown	yes
3233	19	student	single	unknown	no	1169	no	no	cellular	6	feb	463	18	-1	0	unknown	no
999	20	student	single	secondary	no	291	no	no	telephone	11	may	172	5	371	5	failure	no

Data Frames: Sorting

We can sort the data using 2 or more columns:

In [51]:
```
df_sorted = df.sort_values( by =['age', 'balance'], ascending = [True, False])
df_sorted.head(10)
```

Out[51]:

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration	campaign	pdays	previous	poutcome	y
3233	19	student	single	unknown	no	1169	no	no	cellular	6	feb	463	18	-1	0	unknown	no
2780	19	student	single	secondary	no	302	no	no	cellular	16	jul	205	1	-1	0	unknown	yes
503	19	student	single	primary	no	103	no	no	cellular	10	jul	104	2	-1	0	unknown	yes
1900	19	student	single	unknown	no	0	no	no	cellular	11	feb	123	3	-1	0	unknown	no
1725	20	student	single	secondary	no	1191	no	no	cellular	12	feb	274	1	-1	0	unknown	no
13	20	student	single	secondary	no	502	no	no	cellular	30	apr	261	1	-1	0	unknown	yes
999	20	student	single	secondary	no	291	no	no	telephone	11	may	172	5	371	5	failure	no
4152	21	student	single	secondary	no	6844	no	no	cellular	14	aug	126	3	127	7	other	no
110	21	student	single	secondary	no	2488	no	no	cellular	30	jun	258	6	169	3	success	yes
2046	21	services	single	secondary	no	1903	yes	no	unknown	29	may	107	2	-1	0	unknown	no

Aggregation Functions in Pandas

Aggregation - computing a summary statistic about each group, i.e.

- compute group sums or means
- compute group sizes/counts

Common aggregation functions:

min, max
count, sum, prod
mean, median, mode, mad
std, var

Aggregation Functions in Pandas

agg() method are useful when multiple statistics are computed per column:

```
In [28]: df[['age','balance']].agg(['min','mean','max'])
Out[28]:
```

	age	balance
min	19.000000	-3313.000000
mean	41.170095	1422.657819
max	87.000000	71188.000000

Basic Descriptive Statistics

df.method()	description
describe	Basic statistics (count, mean, std, min, quantiles, max)
min, max	Minimum and maximum values
mean, median, mode	Arithmetic average, median and mode
var, std	Variance and standard deviation
sem	Standard error of mean
skew	Sample skewness
kurt	kurtosis

Graphics to explore the data

Seaborn package is built on matplotlib but provides high level interface for drawing attractive statistical graphics, similar to ggplot2 library in R. It specifically targets statistical data visualization

To show graphs within Python notebook include inline directive:

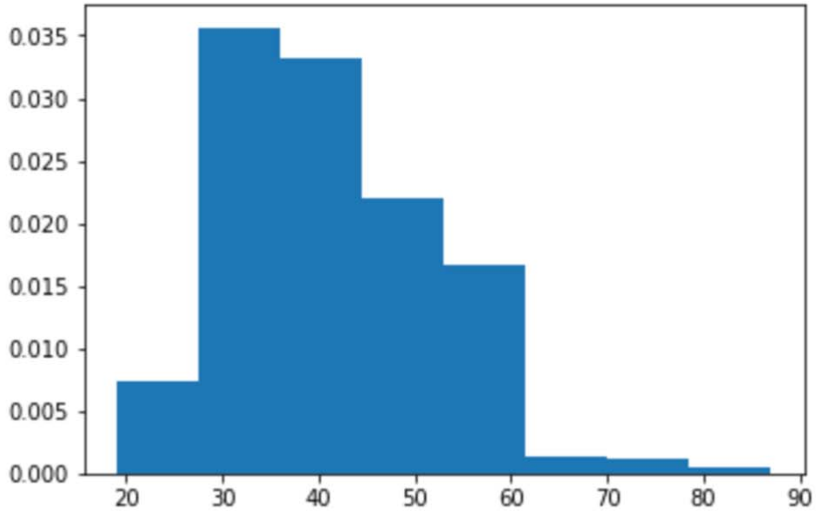
```
In [ ]: %matplotlib inline
```

Graphics

	description
histplot	histogram
barplot	estimate of central tendency for a numeric variable
violinplot	similar to boxplot, also shows the probability density of the data
jointplot	Scatterplot
regplot	Regression plot
pairplot	Pairplot
boxplot	boxplot
swarmplot	categorical scatterplot
factorplot	General categorical plot

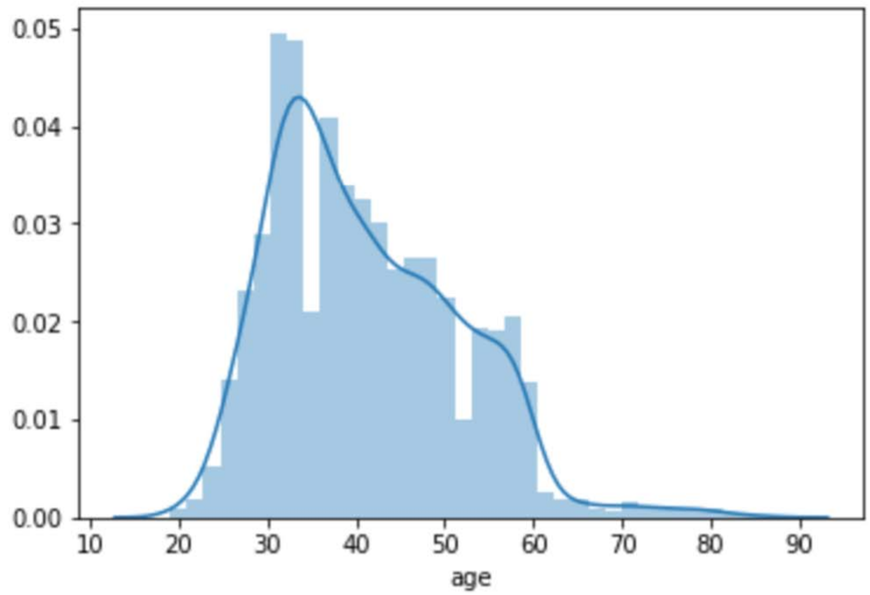
Draw Histogram Using Matplotlib

```
In [31]: #Use matplotlib to draw a histogram of a age data
         plt.hist(df['age'],bins=8, density=1)

Out[31]: (array([0.0073383 , 0.03565062, 0.03320452, 0.02193684, 0.01662828,
                 0.00130112, 0.00111896, 0.0004684 ]),
          array([19. , 27.5, 36. , 44.5, 53. , 61.5, 70. , 78.5, 87. ]),
          <a list of 8 Patch objects>)
```



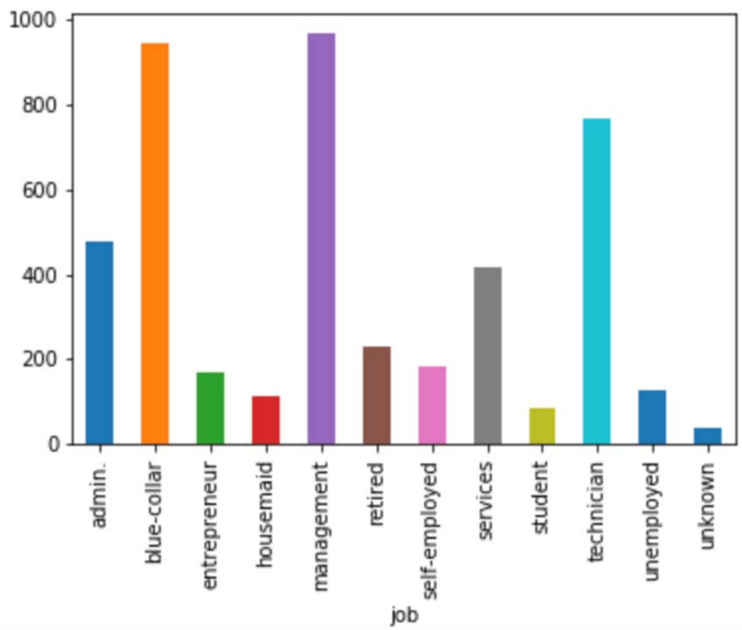
Draw Histogram Using Seaborn

```
In [33]: #Use seaborn package to draw a histogram
         sns.distplot(df[('age')])

Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x1a21b0cb00>
```



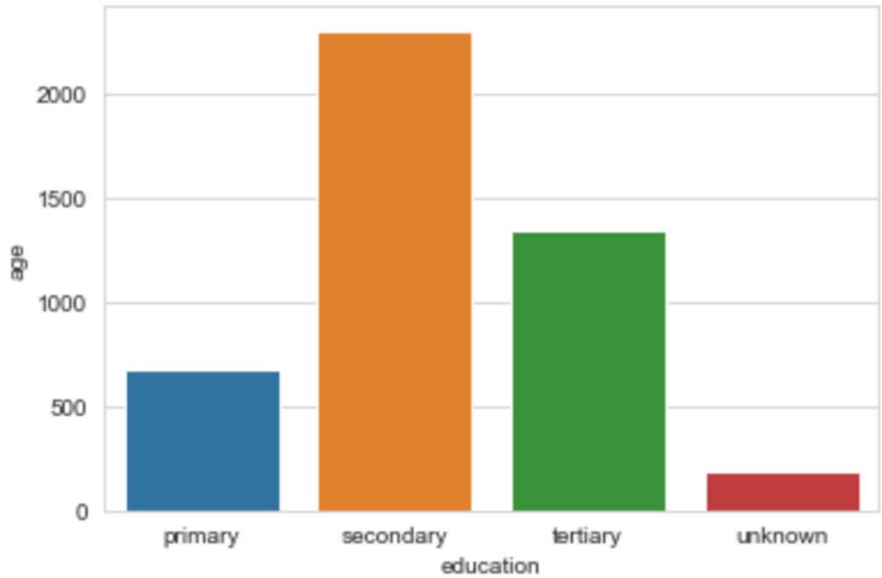
Draw Barplot Using Matplotlib

```
In [41]: # Use regular matplotlib function to display a barplot
         df.groupby(['job'])['age'].count().plot(kind='bar')

Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x1a227f29e8>
```



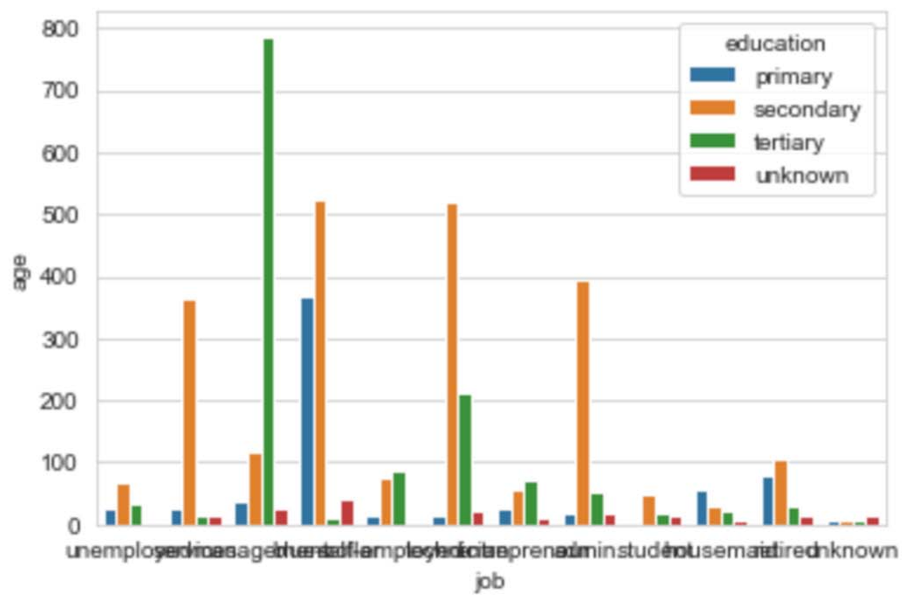
Draw Barplot Using Seaborn

```
In [43]: # Use seaborn package to display a barplot
         sns.set_style("whitegrid")

         ax = sns.barplot(x='education',y ='age', data=df, estimator=len)
```



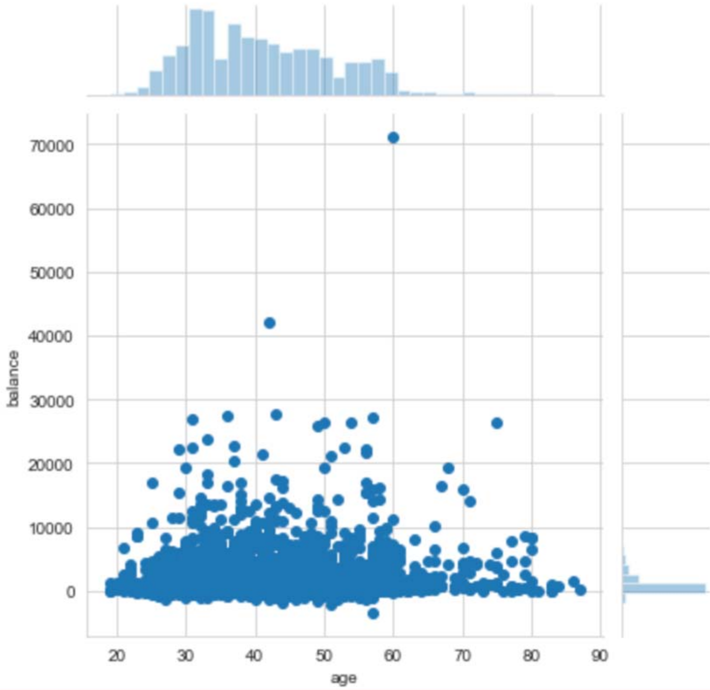
Draw Barplot Using Seaborn

In [54]:
```
# Split into groups based on education:
ax = sns.barplot(x='job',y ='age', hue='education', data=df, estimator=len)
```



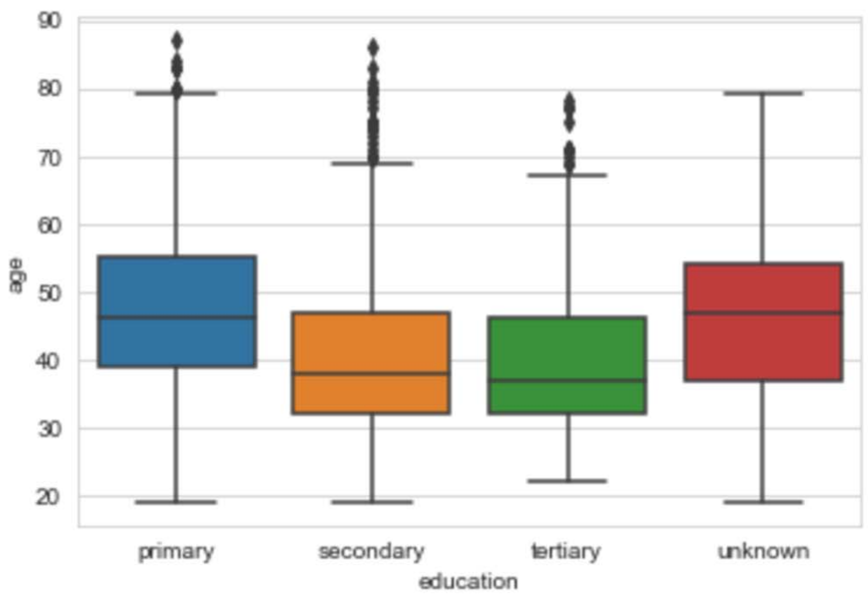
Draw Scatterplot Using Seaborn

```
In [58]: #Scatterplot in seaborn
         sns.jointplot(x='age', y='balance', data=df)

Out[58]: <seaborn.axisgrid.JointGrid at 0x1a22d9aeb8>
```



Draw Boxplot Using Seaborn

```
In [60]: # box plot
         sns.boxplot(x='education',y='age', data=df)

Out[60]: <matplotlib.axes._subplots.AxesSubplot at 0x1a22f2cac8>
```



Python for Machine Learning

Machine learning: the problem setting:

In general, a learning problem considers a set of n samples of data and then tries to predict properties of unknown data. If each sample is more than a single number and, for instance, a multi-dimensional entry (aka multivariate data), it is said to have several attributes or features.

We can separate learning problems in a few large categories:

- Supervised Learning (https://sklearn.org/supervised_learning.html#supervised-learning)
  - Classification
  - Regression
- Unsupervised Learning (https://sklearn.org/unsupervised_learning.html#unsupervised-learning)
  - Clustering

Python for Machine Learning

Training set and testing set:

Machine learning is about learning some properties of a data set and applying them to new data. This is why a common practice in machine learning to evaluate an algorithm is to split the data at hand into two sets, one that we call the **training set** on which we learn data properties and one that we call the **testing set** on which we test these properties.

scikit-learn comes with a few standard datasets, for instance the **iris** and **digits** datasets for **classification** and the **boston house prices** dataset for **regression**.

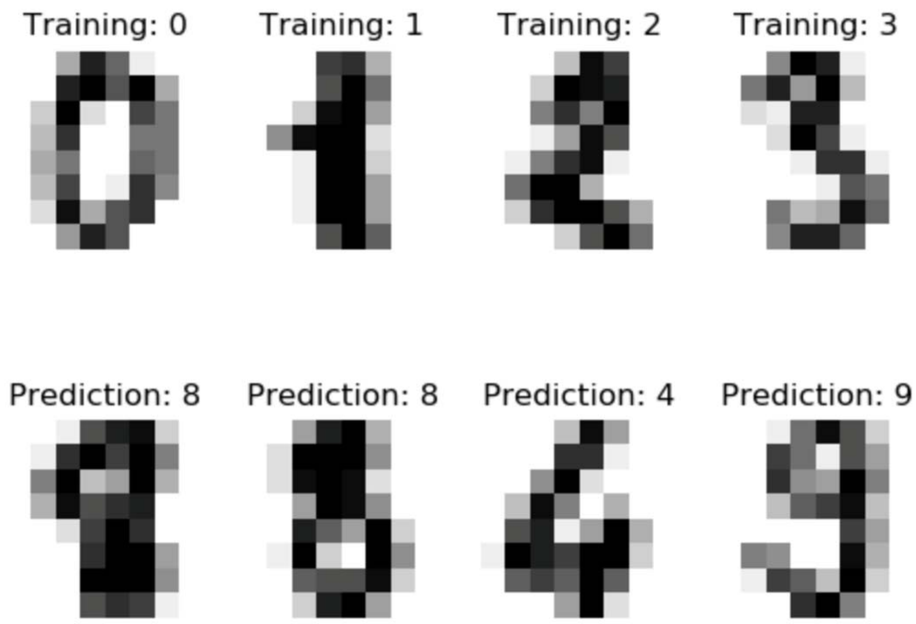
Loading an example dataset

```
In [61]: import sklearn
         from sklearn import datasets
         iris = datasets.load_iris()
         digits = datasets.load_digits()
```

A dataset is a dictionary-like object that holds all the data and some metadata about the data. This data is stored in the *.data* member, which is a *(n_samples, n_features)* array. In the case of supervised problem, one or more response variables are stored in the *.target* member.

Loading an example dataset - *digits*

An example showing how the scikit-learn can be used to recognize images of hand-written digits.



Loading an example dataset - *digits*

For instance, in the case of the digits dataset, *digits.data* gives access to the features that can be used to classify the digits samples:

```
In [62]: print(digits.data)

         [[ 0.   0.   5. ...   0.   0.   0.]
          [ 0.   0.   0. ...  10.   0.   0.]
          [ 0.   0.   0. ...  16.   9.   0.]
          ...
          [ 0.   0.   1. ...   6.   0.   0.]
          [ 0.   0.   2. ...  12.   0.   0.]
          [ 0.   0.  10. ...  12.   1.   0.]]
```

and *digits.target* gives the ground truth for the digit dataset, that is the number corresponding to each digit image that we are trying to learn:

```
In [63]: print(digits.target)

         [0 1 2 ... 8 9 8]
```

Learning and predicting

In the case of the *digits* dataset, the task is to predict, given an image, which digit it represents. We are given samples of each of the 10 possible classes (the digits *zero* through *nine*) on which we *fit* a **classifier** to be able to *predict* the classes to which unseen samples belong.

In scikit-learn, a classifier for classification is a Python object that implements the methods fit(X, y) and predict(T).

An example of a classifier is the class sklearn.svm.SVC, which implements **support vector classification**. The classifier's constructor takes as arguments the model's parameters.

Learning and predicting

For now, we will consider the classifier as a black box:

```
In [41]: from sklearn import svm
         clf = svm.SVC(gamma=0.001, C=100.)
```

Choosing the parameters of the model

In this example, we set the value of gamma manually. To find good values for these parameters, we can use tools such as grid search and cross validation.

Learning and predicting

For the training set, we'll use all the images from our dataset, except for the last image, which we'll reserve for our predicting. We select the training set with the [:-1] Python syntax, which produces a new array that contains all but the last item from digits.data:

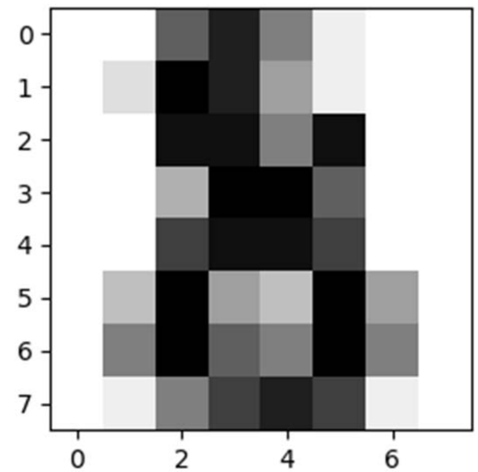
```
In [42]: clf.fit(digits.data[:-1], digits.target[:-1])

Out[42]: SVC(C=100.0, cache_size=200, class_weight=None, coef0=0.0,
           decision_function_shape='ovr', degree=3, gamma=0.001, kernel='rbf',
           max_iter=-1, probability=False, random_state=None, shrinking=True,
           tol=0.001, verbose=False)
```

Learning and predicting

Now you can *predict* new values. In this case, you'll predict using the last image from digits.data. By predicting, you'll determine the image from the training set that best matches the last image.

```
In [43]: clf.predict(digits.data[-1:])

Out[43]: array([8])
```

The corresponding image is:



Model persistence

It is possible to save a model in scikit-learn by using pickle:

```
In [45]: clf = svm.SVC(gamma='auto')
         X, y = datasets.load_iris(return_X_y=True)
         clf.fit(X, y)

Out[45]: SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
           decision_function_shape='ovr', degree=3, gamma='auto', kernel='rbf',
           max_iter=-1, probability=False, random_state=None, shrinking=True,
           tol=0.001, verbose=False)

In [46]: import pickle
         s = pickle.dumps(clf)
         clf2 = pickle.loads(s)
         clf2.predict(X[0:1])

Out[46]: array([0])

In [47]: print(y[0])

         0
```