# Content

# Introduction to DAV (Data Analysis and Visualization) Module

It will contain 3 sections -

1. DAV-1: Python Libraries

- Numpy
- Pandas
- Matplotlib & Seaborn

2. DAV-2: Probability Statistics
3. DAV-3: Hypothesis Testing

# Python Lists vs Numpy Arrays

## Homogeneity of data

So far, we've been working with Python lists, that can have **heterogenous data**.

In [1]:
```
a = [1, 2, 3, "Michael", True]
a
```

Out[1]:
```
[1, 2, 3, 'Michael', True]
```

Because of this hetergenity, in Python lists, the data elements are not stored together in the memory (RAM).

- Each element is stored in a different location.
- Only the address of each of the element will be stored together.
- So, a list is actually just referencing to these different locations, in order to access the actual element.

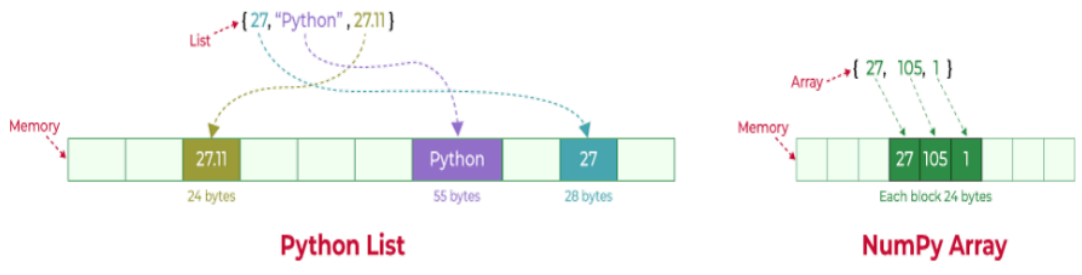
On the other hand, Numpy only stores **homogenous data**, i.e. a numpy array cannot contain mixed data types.

It will either

- ONLY contain integers
- ONLY contain floats
- ONLY contain characters

... and so on.

Because of this, we can now store these different data items together, as they are of the same type.



## Speed

Programming languages can also be slow or fast.

In fact,

- Java is a decently fast language.
- Python is a slow language.
- C, one of the earliest available languages, is super fast.

This is because C has concepts like memory allocation, pointers, etc.

#### How is this possible?

With Numpy, though we will be writing our code using Python, but behind the scene, all the code is written in the **C programming language**, to make it faster.

Because of this, a Numpy Array will be significantly faster than a Python List in performing the same operation.

This is very important to us, because in data science, we deal with huge amount of data.

## Properties

- **In-built Functions**
- For a Python list `a`, we had in-built functions like `.sum(a)`, etc.
- For NumPy arrays also, we will have such in-built functions.
- **Slicing**
- Recall that we were able to perform list slicing.
- All of that is still applicable here.

Recall how we used to import a module/library in Python.

- In order to use Python Lists, we do not need to import anything extra.
- However to use Numpy Arrays, we need to import it into our environment, as it is a Library.

Generally, we do so while using the alias **np** .

In [2]:
```
import numpy as np
```

**Note:**

- In this terminal, we will already have numpy installed as we are working on Google Colab
- However, when working on an evironment that does not have it installed, you'll have to install it the first time working.
- This can be done with the command: `!pip install numpy`

## Why use Numpy? - Time Comparison

Suppose you are given a list of numbers. You have to find the square of each number and store it in the original list.

In [3]:
```
a = [1,2,3,4,5]
```

In [4]:
```
type(a)
```

Out[4]:
```
list
```

The basic approach here would be to iterate over the list and square each element.

In [5]:
```
res = [i**2 for i in a]
print(res)
```

```
[1, 4, 9, 16, 25]
```

Let's try the same operation with Numpy.

To do so, first of all we need to define the Numpy array.

We can convert any list `a` into a Numpy array using the `array()` function.

In [6]:
```
b = np.array(a)
b
```

Out[6]:
```
array([1, 2, 3, 4, 5])
```

In [7]:
```
type(b)
```

Out[7]:
```
numpy.ndarray
```

- `nd` in `numpy.ndarray` stands for **n-dimensional**

Now, how can we get the square of each element in the same Numpy array?

In [8]:
```
b**2
```

Out[8]:
```
array([ 1,  4,  9, 16, 25])
```

**The biggest benefit of Numpy is that it supports element-wise operation.**

Notice how easy and clean is the syntax.

But is the clean syntax and ease in writing the only benefit we are getting here?

- To understand this, let's measure the time for these operations.
- We will use `%timeit`.

In [9]:
```
l = range(1000000)
```

In [10]:
```
%timeit [i**2 for i in l]
```

```
31.3 ms ± 2.68 ms per loop (mean ± std. dev. of 7 runs, 10 loops
each)
```

**It took approx 300 ms per loop to iterate and square all elements from 0 to 999,999**

Let's peform the same operation using Numpy arrays -

- We will use `np.array()` method for this.
- We can peform element wise operation using numpy.

In [11]:
```
l = np.array(range(1000000))
```

In [12]:
```
%timeit l**2
```

```
567 µs ± 29.3 µs per loop (mean ± std. dev. of 7 runs, 1,000 loop
s each)
```

Notice that it only took 900 $\mu$s per loop time for the numpy operation.

**What is the major reason behind numpy's faster computation?**

- Numpy array is densely packed in memory due to it's **homogenous** type.
- Numpy functions are implemented in **C programming laununage**.
- Numpy is able to divide a task into multiple subtasks and process them **parallelly.**

## Dimensions and Shape

**We can get the dimension of an array using the `ndim` property.**

In [13]:
```
arr1 = np.array(range(1000000))
arr1.ndim
```

Out[13]:
```
1
```

**Numpy arrays have another property called `shape` that tells us number of elements across every dimension.**

In [14]:
```
arr1.shape
```

Out[14]:
```
(1000000,)
```

This means that the array `arr1` has 1000000 elements in a single dimension.

Let's take another example to understand `shape` and `ndim` better.

In [15]:
```
arr2 = np.array([[1, 2, 3], [4, 5, 6], [10, 11, 12]])
print(arr2)
```

```
[[ 1  2  3]
 [ 4  5  6]
 [10 11 12]]
```

In [16]:
```
arr2.ndim
```

Out[16]:
```
2
```

In [17]:
```
arr2.shape
```

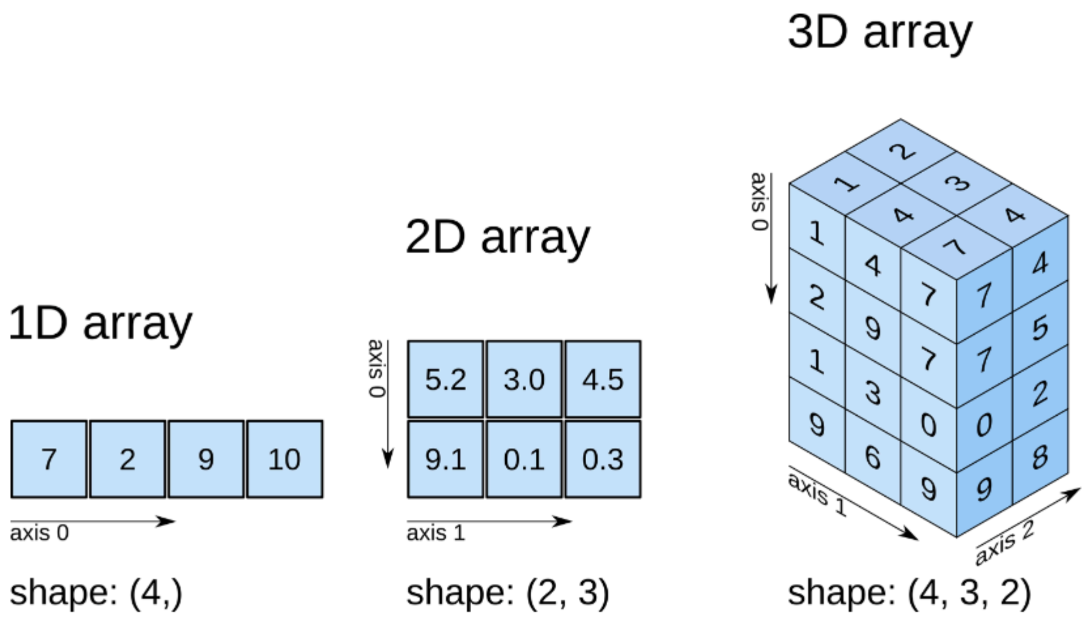
Out[17]:
```
(3, 3)
```

`ndim` specifies the number of dimensions of the array i.e. 1D (1), 2D (2), 3D (3) and so on.

`shape` returns the exact shape in all dimensions, that is (3,3) which implies 3 in axis 0 and 3 in axis 1.

In [18]:
```python
from IPython.display import Image
Image(filename='download.png')
```

Out[18]:



## `np.arange()`

Let's create some sequences in Numpy.

We can pass **starting** point, **ending** point (not included in the array) and **step-size**.

**Syntax:**

- `arange(start, end, step)`

In [19]:
```python
arr2 = np.arange(1, 5)
arr2
```

Out[19]:
```
array([1, 2, 3, 4])
```

In [20]:
```python
arr2_step = np.arange(1, 5, 2)
arr2_step
```

Out[20]:
```
array([1, 3])
```

`np.arange()` behaves in the same way as `range()` function.

**But then why not call it np.range?**

- In `np.arange()`, we can pass a **floating point number** as **step-size**.

In [21]:
```
arr3 = np.arange(1, 5, 0.5)
arr3
```

Out[21]:
```
array([1. , 1.5, 2. , 2.5, 3. , 3.5, 4. , 4.5])
```

## Type Conversion in Numpy Arrays

For this, let's pass a **float** as one of the values in a **numpy array**.

In [22]:
```
arr4 = np.array([1, 2, 3, 4])
arr4
```

Out[22]:
```
array([1, 2, 3, 4])
```

In [23]:
```
arr4 = np.array([1, 2, 3, 4.0])
arr4
```

Out[23]:
```
array([1., 2., 3., 4.])
```

- Notice that **`int` is raised to `float`**
- Because a numpy array can only store **homogenous data** i.e. values of one data type.

Similarly, what will happen when we run the following code? Will it give an error?

In [24]:
```
np.array(["Harry Potter", 1, 2, 3])
```

Out[24]:
```
array(['Harry Potter', '1', '2', '3'], dtype='<U21')
```

No. It will convert all elements of the array to `char` type.

There's a `dtype` parameter in the `np.array()` function.

**What if we set the `dtype` of array containing `integer` values to `float` ?**

In [25]:
```
arr5 = np.array([1, 2, 3, 4])
arr5
```

Out[25]:
```
array([1, 2, 3, 4])
```

In [26]:
```
arr5 = np.array([1, 2, 3, 4], dtype="float")
arr5
```

Out[26]:
```
array([1., 2., 3., 4.])
```

**Question:** What will happen in the following code?

In [27]:
```
np.array(["Shivank", "Bipin", "Ritwik"], dtype=float)
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent
call last)
Cell In[27], line 1
----> 1 np.array(["Shivank", "Bipin", "Ritwik"], dtype=float)

ValueError: could not convert string to float: 'Shivank'
```

Since it is not possible to convert strings of alphabets to floats, it will naturally return an Error.

We can also convert the data type with the `astype()` method.

In [28]:
```
arr = np.array([10, 20, 30, 40, 50])
arr
```

Out[28]:
```
array([10, 20, 30, 40, 50])
```

In [29]:
```
arr = arr.astype('float64')
print(arr)
```

```
[10. 20. 30. 40. 50.]
```

## Indexing

- Similar to Python lists

In [30]:
```
m1 = np.arange(12)
m1
```

Out[30]:
```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])
```

In [31]:
```
m1[0] # gives first element of array
```

Out[31]:
```
0
```

In [32]:
```
m1[-1] # negative indexing in numpy array
```

Out[32]:
```
11
```

You can also use list of indexes in numpy.

```
In [33]: m1 = np.array([100,200,300,400,500,600])
```

```
In [34]: m1[[2,3,4,1,2,2]]
```

```
Out[34]: array([300, 400, 500, 200, 300, 300])
```

Did you notice how single index can be repeated multiple times when giving list of indexes?

**Note:**

- If you want to extract multiple indices, you need to use two sets of square brackets `[[ ]]`
    - Otherwise, you will get an error.
- Because it is only expecting a single index.
- For multiple indices, you need to pass them as a list.

```
In [35]: m1[2,3,4,1,2,2]
```

```
---------------------------------------------------------------------------
IndexError                                Traceback (most recent call last)
Cell In[35], line 1
----> 1 m1[2,3,4,1,2,2]

IndexError: too many indices for array: array is 1-dimensional, but 6 were indexed
```

## Slicing

- Similar to Python lists

```
In [36]: m1 = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9, 10])
         m1
```

```
Out[36]: array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10])
```

```
In [37]: m1[:5]
```

```
Out[37]: array([1, 2, 3, 4, 5])
```

**Question:** What'll be output of `arr[-5:-1]` ?

In [38]:
```
m1[-5:-1]
```
Out[38]:
```
array([6, 7, 8, 9])
```

**Question:** What'll be the output for `arr[-5:-1: -1]` ?

In [39]:
```
m1[-5: -1: -1]
```
Out[39]:
```
array([], dtype=int64)
```

## Fancy Indexing (Masking)

- Numpy arrays can be indexed with boolean arrays (masks).
- This method is called **fancy indexing** or **masking**.

What would happen if we do this?

In [40]:
```
m1 = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9, 10])
m1 < 6
```
Out[40]:
```
array([ True,  True,  True,  True,  True, False, False, False, Fa
lse,
       False])
```

**Comparison operation also happens on each element.**

- All the values before 6 return `True`
- All the values after 6 return `False`

**Question:** What will be the output of the following?

In [41]:
```
m1[[True,  True,  True,  True,  True, False, False, False, False,
```
Out[41]:
```
array([1, 2, 3, 4, 5])
```

Notice that we are passing a list of indices.

- For every instance of `True` , it will print the corresponding index.
- Conversely, for every `False` , it will skip the corresponding index, and not print it.

So, this becomes a **filter** of sorts.

Now, let's use this to filter or mask values from our array.

**Condition will be passed instead of indices and slice ranges.**

In [42]:
```
m1[m1 < 6]
```

Out[42]:
```
array([1, 2, 3, 4, 5])
```

This is known as **Fancy Indexing** in Numpy.

**Question:** How can we filter/mask even values from our array?

In [43]:
```
m1[m1%2 == 0]
```

Out[43]:
```
array([ 2,  4,  6,  8, 10])
```

**Imagine you are a Data Analyst @ Airbnb**

You've been asked to analyze user survey data and report NPS to the management.

**But, what exactly is NPS?**

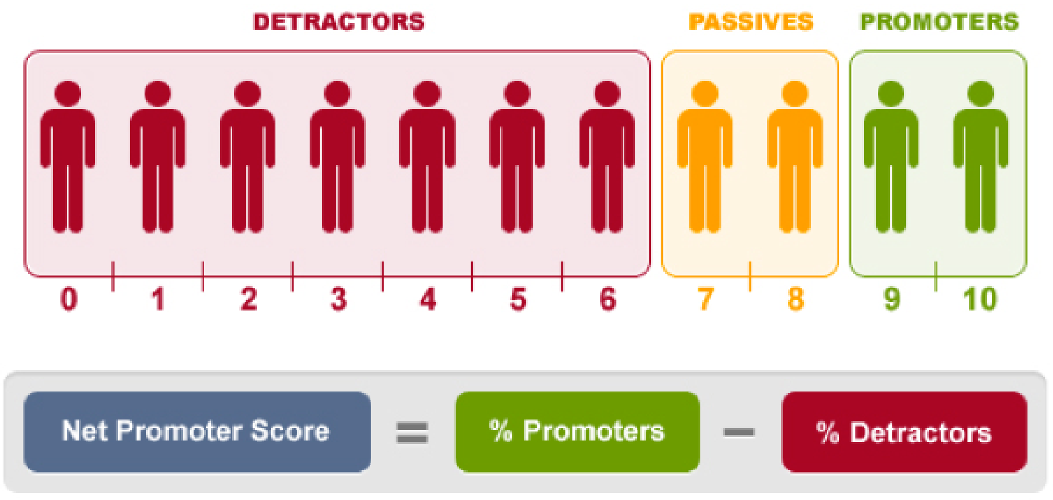
Have you all seen that every month, you get a survey form from airbnb?

- This form asks you to fill in feedback regarding how you are liking the services of airbnb in terms of a numerical score.
- This is known as the **Likelihood to Recommend Survey**.
- It is widely used by different companies and service providers to evaluate their performance and customer satisfaction.
- Responses are given a scale ranging from 0–10,
  - with 0 labeled with “Not at all likely,” and
  - 10 labeled with “Extremely likely.”

Based on this, we calculate the **Net Promoter Score**.

In [44]:
```
from IPython.display import Image
Image(filename='nps.png')
```

Out[44]:



We label our responses into 3 categories:

- **Detractors**: Respondents with a score of 0-6
- **Passive**: Respondents with a score of 7-8
- **Promoters**: Respondents with a score of 9-10.

``` Net Promoter score = % Promoters - % Detractors.

### Range of NPS

- If all people are promoters (rated 9-10), we get $100$ NPS
- Conversely, if all people are detractors (rated 0-6), we get $-100$ NPS
- Also, if all people are neutral (rated 7-8), we get a $0$ NPS

Therefore, the range of NPS lies between $[-100, 100]$

Generally, each company targets to get at least a threshold NPS.

- this is a score of 70.
- This means that if $NPS > 70$, it is great performance of the company.

Naturally, this varies from business to business.

### How is NPS helpful?

#### Why would we want to analyse the survey data for NPS?

NPS helps a brand in gauging its brand value and sentiment in the market.

- Promoters are highly likely to recommend your product or sevice. Hence, bringing in more business.
- whereas, Detractors are likely to recommend against your product or service’s usage. Hence, bringing the business down.

These insights can help business make customer oriented decision along with product improvisation.

#### 2/3 of Fortune 500 companies use NPS

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Let's first look at the data we have gathered.

Loading the data -

- For this we will use the `.loadtxt() function`
- We provide file name along with the dtype of data that we want to load.
- Documentation: https://numpy.org/doc/stable/reference/generated/numpy.loadtxt.html (https://numpy.org/doc/stable/reference/generated/numpy.loadtxt.html)
```

```
In [45]: score = np.loadtxt('survey.txt', dtype ='int')
```

Let's check the type of this data variable `score` -

```
In [46]: type(score)

Out[46]: numpy.ndarray
```

Let's see what the data looks like -

```
In [47]: score[:5]

Out[47]: array([ 7, 10,  5,  9,  9])
```

Let's check the number of responses -

```
In [48]: score.shape

Out[48]: (1167,)
```

There are a total of 1167 responses for the LTR survey.

Now, let's calculate NPS using these response.

**NPS = % Promoters - % Detractors**

In order to calculate NPS, we need to calculate two things:

- % Promoters
- % Detractors

In order to calculate `% Promoters` and `% Detractors` , we need to get the count of promoter as well as detractor.

**Question:** How can we get the count of Promoter/Detractor ?

- We can do so by using fancy indexing (masking).

Let's get the count of promoter and detractors -

Detractors have a score <= 6

```
In [49]: detractors = score[score <= 6]
```

In [50]:
```
# Number of detractors -

num_detractors = len(detractors)
num_detractors
```

Out[50]:
```
332
```

Promoters have a score >= 9

In [51]:
```
promoters = score[score >= 9]
```

In [52]:
```
# Number of promoters -

num_promoters = len(promoters)
num_promoters
```

Out[52]:
```
609
```

In [53]:
```
total = len(score)
total
```

Out[53]:
```
1167
```

In [54]:
```
# % of detractors -

percentage_detractors = (num_detractors/total) * 100
percentage_detractors
```

Out[54]:
```
28.449014567266495
```

In [55]:
```
# % of promoters -

percentage_promoters = (num_promoters/total) * 100
percentage_promoters
```

Out[55]:
```
52.185089974293064
```

In [56]:
```
nps = percentage_promoters - percentage_detractors
nps
```

Out[56]:
```
23.73607540702657
```

In [57]:
```
# Rounding off upto 2 decimal places -

np.round(nps, 2)
```

Out[57]:
```
23.74
```