INTERNSHIP PROGRESS REPORT

Submitted in the partial fulfilment for the award of the degree of

BACHELOR OF ENGINEERING

IN

INTERNET OF THINGS

Submitted by:

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AT
HIGHRADIUS

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

APEX INSTITUE OF TECHNOLOGY

CHANDIGARH UNIVERSITY, GHARUAN,

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Internship Organization Name	HighRadius
Organization Address	
Internship Supervisor	-
Internship Supervisor Phone	-
Internship Supervisor Email	-
Report period (start date)	28/01/2022
Report period (end date)	18/02/2022

Distribution of hours:

Orientation: 1 hours

Observing: NA

Letcures: 20 Hours

Assessment: 1.20 Hours

Planning 2Hours

Studying/Researching 19 Hours

Implementation:

a. Leadership NA

b. Counselling NA

c. Supervision 20 hours

d. Evaluation NA

e. Documentation 6 Hours

f. Discharge/Transition Plans NA

Total clock hours during this report period 48 Hours

Introduction About the Company

I am working under High Radius as an intern. High Radius is a Fintech software company based on AI Autonomous Systems.

The HighRadius platform reduces cycle times in orders-to-cash process by automating receivables and payment processes across credit, e-billing and payment processing, deductions and collections.

I have been working with this company since 28/01/2022.

HighRadius offers cloud-based Autonomous Software for the Office of the CFO. More than 700 of the world's leading companies have transformed their order to cash, treasury and record to report processes with HighRadius. Our customers include 3M, Unilever, Anheuser-Busch InBev, Sanofi, Kellogg Company, Danone, Hershey's and many more.

Autonomous Software is data-driven software that continuously morphs its behavior to the ever-changing underlying domain transactional data. It brings modern digital transformation capabilities like Artificial Intelligence, Robotic Process Automation, Natural Language Processing and Connected Workspaces as out-of-the-box features for the finance & accounting domain.

Finance business stakeholders have been led to believe that they have only two choices: pick an application software vendor that digitizes a paper or Excel-based process to an electronic system of record, or, choose a middleware platform for AI or RPA to build and maintain in-house, domain-specific capabilities. In contrast, HighRadius Autonomous Software combines the best of both worlds to deliver measurable business outcomes such as DSO reduction, working capital optimization, bad-debt reduction, reduce month close timelines and improve productivity in under six months.

Data-driven software that uses technologies like AI to continuously morph its behaviour based on the ever-changing underlying domain transactional data.

Accomplishments and Work Performed

1. During the initial stages of internship, we were given masterclasses in which we were taught the topics related to different the overall project to be made. The main topics which will be covered throughout this internship period was Machine Learning

1. Machine Learning

Week	Days	Subject	Topics	Hours	Breakup of 3 Hours in Sequence
Introduction	2022-01-28	Machine Learning	Master Class - Python Fundamentals - I	(1 + 2) Hours	1) For first 1 hour, masterclass 2) 1.5 hours - Self study time for interns. 3) Last 30 minutes - Scrum call + Attendance
Week 1	2022-01-31		Python Fundamentals - II	3 Hours	1) 1 hour - doubt clearing session 2) 1 hour 30 minutes - Self study 3) Last 30 minutes - Scrum call + Attendance
	2022-02-01		Quiz Python Fundamentals + Master Class NumPy Fundamentals	3 Hours	1) For first 1 hour, masterclass 2) 30 minutes - Quiz will be conducted 8:30pm to 9:00pm 3) 1 hour - self study 4)30 minutes - Scrum call & Attendance"
	2022-02-02		Conduct Session - Numpy	(1 + 2) Hours	1) For first 1 hour - Doubt Clearing Session 2) 1.5 hours - Self study time for interns. 3) Last 30 minutes - Scrum call & Attendance
	2022-02-03		Quiz NumPy - Master Class of Pandas	(1+ 1.5 + .5) Hours	1) For first 1 hour, Masterclass 2) 1.5 hour - self study 3) Last 30 minutes - Quiz - 8:30pm-9:00pm (Python Fundamentals & NumPy)
	2022-02-04		Conduct Doubt Clearing session - Pandas	(1 + 2) Hours	1) For first 30 minutes class. 2) 2 hours - Self study time for interns. 3) Last 30 minutes - Scrum call & Attendance
Week 2	2022-02-07		Masterclass - Data pre-process and perform EDA, Quiz - Pandas	(1 + 2) Hours	1) For first 1 hour, masterclass (6pm-7pm)/(7pm-8pm) 2) 1.5 hours - Self study time for interns. 3) Last 30 minutes - Quiz Pandas 8:30pm-9:00pm
	2022-02-08		Conduct session - Data Preprocessing and EDA	(1 + 2) Hours	1) For first 1 hour, Conduct session 2) 1.5 hours - Self study time for interns. 3) Last 30 minutes - Scrum call & Attendance
	2022-02-09		Master Class - feature engineering & feature selection	3 Hours	1) 1.5 hour - Master Class session 2) 1 hour - Self study 3) Last 30 minutes - Scrum call & Attendance
	2022-02-10		Conduct Session - Feature Engineering	(1 + 2) Hours	1) For first 1 hour, Conduct session 2) 1.5 hours - Self study time for interns. 3) Last 30 minutes - Scrum call & Attendance
	2022-02-11		Conduct Session - Feature Engineering, Quiz - data pre processing, EDA, Feature engineering and Feature Selection **Fun Friday Event** - https://forms.gle/rsvEQPaWyUXUXENW7	(1 + 1.5+.5) Hours	1) For first 1 hour Conduct Session 2) 1.5 hours - Self study time for interns. 3) Last 30 minutes - Quiz - 8:30pm-9:00pm
Week 3	2022-02-14		Master Class - Ml Models,	(1 + 2) Hours	1) 1.5 hour - Master Class session 2) 1 hour - Self study 3) Last 30 minutes - Scrum call & Attendance
	2022-02-15		Master Class - Model Evaluation, Hyperparameter Tuning, Project Discussion	(1 + 2) Hours	1) 1.5 hour - Master Class session 2) 1 hour - Self study 3) Last 30 minutes - Scrum call & Attendance
	2022-02-16		Conduct Session - ML Models	(1 + 2) Hours	1) For first 1 hour, conduct sessions 2) 1.5 hours - Self study time for interns. 3) Last 30 minutes - Scrum call & Attendance
	2022-02-17		Doubt Clearing Day, Conduct Session - ML Models	3 Hours	1) 1 hour - doubt clearing session 2) 1 hour 30 minutes - Self study 3) Last 30 minutes - Scrum call & Attendance
	2022-02-18		Conduct Session - ML Models, Machine Learning - Project Discussion	2.5 Hours	ML Project Discussion

As per the schedule shown in the above table, our internship was commenced from 28th January and for the machine learning part lasted till 18th February.

In this period, we started by learning basics of python in our masterclass which included theory and hands-on practice as well. These lectures were conducted on Zoom.

a. First Checkpoint:

For the first checkpoint, we had started with Python basic.

Checkpoint Goal	Daily Goal	Date	Technic Code	Technic	Concept videos / doc	How to video or doc?	Reference video / doc	Hours Required (Avg.)	Quiz Time	Quiz	Assignment Deadline	Assignment Submission Links	
PRS													
FIRST CHECKPOINT: Abiliy to perform basic coding required for Data Science in Python													
Python Fundamentals	Basic and Intermediate understanding of Python Understanding , should cover Python syntax, Conditional Branching, Loops, Iterators, and Basic Object Oriented Programming - Classes and Object Creation and Calling	**2022/01/28 - 2022/01/31**	**T1**	Chapter 1 : Introduction to Python	Introduction to Python	Python Implementation of all concepts	Introduction	**10 mins**	**30**	**Python Quiz**			
			T2	Chapter 2 : Python Fundamentals	Operations in Python		List, tuple, disctionary	**30 mins**					
					Variables and Data types in Python		How to do						
					Data Structure in Python								
					Itertools		How to do						
			T3	Chapter 3 : Python Programming Constructs	Conditional Statements [Selection]		How to do	**30mins**					
					Iterative Statements [Repetation]		How to do						
			T4	Chapter 4 : Functions	Pyhton functions			**30 mins**					
			T5	Chapter 5 : Classes and Objects	Python Class and Objects		How to do	**1 hr**					

Python is a Multi-Purpose programming language. It is used for developing GUI (Graphical User Interfaces), various scripting purposes, creating backend applications, web scraping and various other things. It is an Interpreted Language, that is, it is executed in a sequential manner and does not need to be compiled before it is executed. It is a strongly and dynamically typed programming language which is extendable and portable. It can be used to combine various programming languages together to work cohesively as one distinct entity. In addition to that, Python is also a free and open source programming language which means that it is free to use and everyone can contribute to its development.

Python Fundamentals

Python is a very simple coding language that uses a very familiar language to code. It uses indentation to define blocks of code and they need to be consistent throughout the block.

```
[1]  print("Hello World")
     print(1+2)

     Hello World
     3
```

```
[2]  print("Additon Example")
     a = 10
     b = 30
     print(a+b)

     Additon Example
     40
```

The above example depicts the simplicity of python as a coding language. Indentation is very important in python and not following proper indentation structure causes an error.

```
[3] print("Additon Example")
      a = 10
      b = 30
    print(a+b)

      File "<ipython-input-3-1e6fca0a7e8e>", line 2
        a = 10
        ^
    IndentationError: unexpected indent
```

Semicolons have almost no use in python but using them would not throw any error. It is not considered good practice while writing python code. It can be used to separate many commands in a single line.

Operators in Python

There are many operators in python that can be used for many purposes. They are stated below.

Operator	Description	Example
+	Addition	2 + 4 == 6
-	Subtraction	2 - 4 == -2
*	Multiplication	2 * 4 == 8
**	Power of	2 ** 4 == 16
/	Division	2 / 4.0 == 0.5
//	Floor division	2 // 4.0 == 0.0
%	String interpolate or modulus	2 % 4 == 2
<	Less than	4 < 4 == False
>	Greater than	4 > 4 == False
<=	Less than equal	4 <= 4 == True
>=	Greater than equal	4 >= 4 == True
==	Equal	4 == 5 == False
!=	Not equal	4 != 5 == True
<>	Not equal	4 <> 5 == True
( )	Parenthesis	len('hi') == 2
[ ]	List brackets	[1,3,4]
{ }	Dict curly braces	{'x': 5, 'y': 10}

Operator	Description	Example
,	Comma	range(0, 10)
:	Colon	def X():
.	Dot	self.x = 10
=	Assign equal	x = 10
;	semi-colon	Print("hi"); print("there")
+=	Add and assign	x = 1; x += 2
-=	Subtract and assign	x = 1; x -= 2
*=	Multiply and assign	x = 1; x *= 2
/=	Divide and assign	x = 1; x /= 2
//=	Floor divide and assign	x = 1; x //= 2
%=	Modulus assign	x = 1; x %= 2
**=	Power assign	x = 1; x **= 2
or, and, not	Boolean Or, Boolean And, Boolean Not	(a or b) and c

Variables and Data Types in Python

In Python, variables are considered as storage placeholders for texts and numbers.

Python is dynamically typed, such that there is no need to declare what the type of each variable is when it is declared or initialized [type() method is used to find the data type]

```
x = 123                     # integer
x = 123L                    # long integer
x = 3.14                    # double float
x = "hello"                 # string
x = [0,1,2]                 # list
x = (0,1,2)                 # tuple
x = open('hello.py', 'r')   # file
```

Although you don't need to define the type of a variable, python is strongly typed in the sense that operations can not be performed between two dissimilar data types.

```
[4]  a = [1,2]
     a+"hi"

---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-4-a238315bcc9f> in <module>()
      1 a = [1,2]
----> 2 a+"hi"

TypeError: can only concatenate list (not "str") to list
```

Python Programming Constructs

Constructs control the flow of the program. If we dive deep into the types of constructs, they are primarily of three types : Sequence, Selection and Repetition.

A Sequence is an order in which the code will get executed. Selection is the part where it is decided which block of code will get executed based on some conditions. Repetition is the construct that decides which part of the code will get executed multiple times based on specific criteria.

Conditional Statements [Selection]

Branching in Python can be achieved through the following keywords: if, elif (else-if) and else. The scope of the statement block is decided through indentation (cascading in case of nested conditions). An example of the construct can be seen in the following figure,

```
if condition:
    statement
    statement
    # ... some more indented statements if
necessary
elif <Condition>:
     statetement
else:
      statement
```

```
Ternary
max = a if (a > b) else b
```

An example of the construct in use can be found in the below code snippet,

▾ If-else

```
[ ] a = 33
    b = 200                    #be mindful of indent
    if b > a:
      print("b is greater than a")

    b is greater than a
```

```
[ ] #elif keyword
    if b > a:
      print("b is greater than a")
    elif a == b:
      print("a and b are equal")

    b is greater than a
```

```
[ ] #else keyword
    if b > a:
      print("b is greater than a")
    elif a == b:
      print("a and b are equal")
    else:
      print("a is greater than b")

    b is greater than a
```

Here the score is compared and according to specific conditions (>90,>60 and <=90) different sets of code blocks are executed.

Iterative Statements [Repetition]

Iterative constructs in python are achieved through loops. They are primarily of two types: for loop and while loop.

Iterations and Looping

```
[ ] #for loop
    fruits = ["apple", "banana", "cherry"]
    for x in fruits:
      print(x)
    #for loop does not require indexing

    apple
    banana
    cherry
```

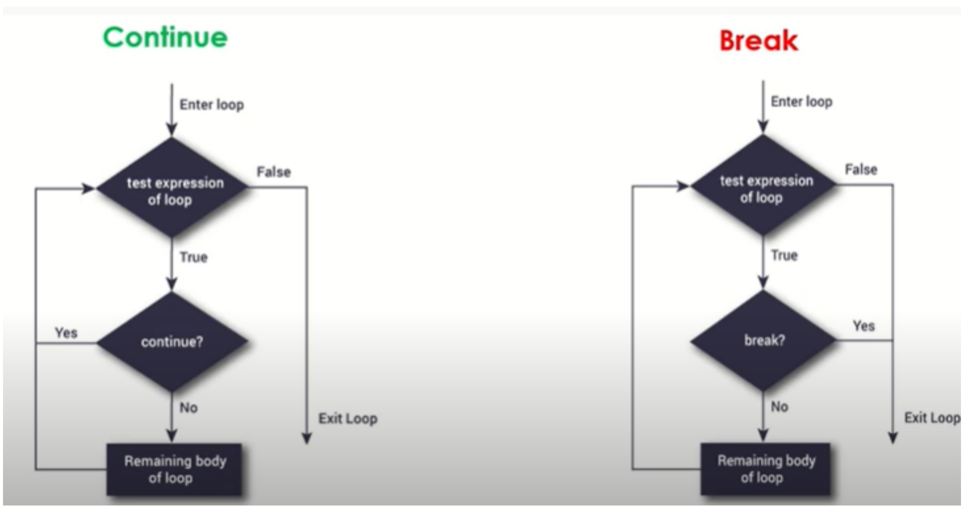
```
[50] #while loop
     i = 1
     while i < 6:
       print(i)
       i += 1

     1
     2
     3
     4
     5
```

The conditions in which the loops will continue to execute or stop after a specific number of iterations are controlled through two keywords, i.e., continue and break.

Continue statement is used to tell python to skip the rest of the statements in a current loop construct and continue with the next iteration of the code block.

Break, on the other hand, is used to completely break out of the loop.

The following figure shows the use of break and continue in separate programming constructs as they are used in python.



Use of break and continue in python:

```
[ ] #break statement
    fruits = ["apple", "banana", "cherry"]
    for x in fruits:
      print(x)
      if x == "banana":
        break

    apple
    banana
```

```
[ ] #continue statement
    fruits = ["apple", "banana", "cherry"]
    for x in fruits:
      if x == "banana":
        continue
      print(x)

    apple
    cherry
```

Data Structures in Python

There are many ways to store data in python. They are in the form of various data structures. For example, lists, tuples, dictionaries, sets, and many more.

- List

List is one of the simplest and most important data structures in python. They are defined by enclosing square brackets "[ ]" and each item is separated by a ",". Lists can be defined as a collection of items where each item has an assigned positional value (index value) starting from 0 (zero). It is mutable, i.e., its contents can be changed. It is similar to an array with some basic differences. For example, lists can store heterogeneous data types together under one name unlike matrices(arrays) that contain homogeneous data.

There are many methods that can be used to manipulate lists and do various operations. They are listed in the image below with their corresponding uses.

Append()	Add an element to the end of the list
Extend()	Add all elements of a list to the another list
Insert()	Insert an item at the defined index
Remove()	Removes an item from the list
Pop()	Removes and returns an element at the given index
Clear()	Removes all items from the list
Index()	Returns the index of the first matched item
Count()	Returns the count of number of items passed as an argument
Sort()	Sort items in a list in ascending order
Reverse()	Reverse the order of items in the list
copy()	Returns a copy of the list

There are many inbuilt functions that are applicable for a list. They are as follows:

round()	Rounds off to the given number of digits and returns the floating point number
sum()	Sums up the numbers in the list
cmp()	This function returns 1, if first list is "greater" than second list
max()	return maximum element of given list
min()	return minimum element of given list
len()	Returns length of the list or size of the list
filter()	tests if each element of a list true or not
map()	returns a list of the results after applying the given function to each item of a given itterable
lambda()	This function can have any number of arguments but only one expression, which is evaluated and returned.

- Tuple

A Tuple can be defined as an immutable list. It can not be altered. It is defined by initializing elements in between parentheses "( )". Once a tuple has been created, you can not add or alter elements in the tuple. It has only two methods: count() and index(). Count gives the frequency of a searched element while index provides the location of the searched element in the tuple (index starts with 0).

Note that, tuples are immutable,i.e., once created, its elements cannot be changed

```
[ ] #access tuple items
    thistuple = ("apple", "banana", "cherry")
    print(thistuple[1])

    banana

[8] thistuple[2] = "orange"

    ---------------------------------------------------------------------------
    TypeError                                 Traceback (most recent call last)
    <ipython-input-8-5410d42e4faf> in <module>()
    ----> 1 thistuple[2] = "orange"

    TypeError: 'tuple' object does not support item assignment
```

- Sets

A set contains an unordered collection of unique and immutable objects. All kinds of operations that are applicable to a set can be used for sets.

Set Operations

```
#access items; cannot access items by referring to an index
#example
thisset = {"apple", "banana", "cherry"}
for x in thisset:
  print(x)
```

```
banana
cherry
apple
```

Sets are immutable. Once created, we cannot change its contents.

```
[35] #adding items
     thisset.add("orange")      #adding one item at a time
     thisset.update(["orange", "mango", "grapes"])       #adding more than one item at a time.
```

```
[36] #removing items
     thisset.remove("banana")
     thisset.discard("banana")
     x = thisset.pop()    #pop will remove only the last added element
     thisset.clear()   #empties the set
     del thisset   #delete the set completely
```

```
[38] #join two sets
     set1 = {"a", "b" , "c"}
     set2 = {1, 2, 3}
     set3 = set1.union(set2)
     print(set3)
```

```
{1, 2, 3, 'c', 'a', 'b'}
```

- Dictionary

It is a python data structure that is used to store data in key-value pairs. They are a set of attributes that have corresponding values. It is an unordered, indexed, and changeable form of data that is written within curly braces.

Dictionary

```
[39] employee = {"e-id":1221,
                 "e-name":"Robert",
                 "dob":'01-01-1990'
                 }
     print(employee)
```

```
{'e-id': 1221, 'e-name': 'Robert', 'dob': '01-01-1990'}
```

- Strings

Strings can be defined as a list or an ordered chain of characters. We can perform various operations or manipulations on these strings.

Strings

```
[49] word = "Hello-World"
     print(word.split("-"))
     print(word.replace("Hello","Hi"))
     print(word[::-1])
     print(word.isalnum())

['Hello', 'World']
Hi-World
dlroW-olleH
False
```

Itertools

Python's Itertool is a module that provides various functions that work on iterators to produce complex iterators. This module works as a fast, memory-efficient tool that is used either by itself or in combination to form complex algebraic equations.

Itertools

```
[103] import itertools

      # for in loop
      for i in itertools.count(5, 5):
          if i == 35:
              break
          else:
              print(i, end =" ")

5 10 15 20 25 30
```

Slicing Function

The Python slice() function allows us to slice a sequence. It means we can retrieve a part of a string, tuple, list, etc. We can specify the start, end, and step of the slice. The step lets you skip items in the sequence.

The Syntax of slice() is:

slice(start, stop, step)

slice() Parameters:

slice() can take three parameters:

- start (optional) - Starting integer where the slicing of the object starts. Default to None if not provided.
- stop - Integer until which the slicing takes place. The slicing stops at index stop -1 (last element).
- step (optional) - Integer value which determines the increment between each index for slicing. Defaults to None if not provided.

Return Type: Returns a sliced object containing elements in the given range only.

Slicing a string:

```
# String Slicing
String = 'NewSlice'
s1 = slice(3)
s2 = slice(1, 5, 2)

print("String slicing")
print(String[s1])
print(String[s2])
```

```
String slicing
New
eS
```

Slicing a List:

```
# List Slicing
L = [1, 2, 3, 4, 5]
s1 = slice(3)
s2 = slice(1, 5, 2)
print("List slicing")
print(L[s1])
print(L[s2])
```

```
List slicing
[1, 2, 3]
[2, 4]
```

Slicing a tuple:

```
# Tuple Slicing
T = (1, 2, 3, 4, 5)
s1 = slice(3)
s2 = slice(1, 5, 2)
print("\nTuple slicing")
print(T[s1])
print(T[s2])
```

```
Tuple slicing
(1, 2, 3)
(2, 4)
```

Functions

A function is a construct that is defined by the keyword “def”. The general syntax looks like this:

def function_name(Parameter List):

#Statements, i.e, the function body

return statement (if required)

An example of a function used to add two numbers is given below,

```
[101] def add(a,b):
        c = a+b
        print(c)
      add(2,3)

5
```

```
[102] def add(a,b):
        c = a+b
        return c
      x = add(2,3)
      print(x)

5
```

Lambda Function

We use lambda functions when we require a nameless function for a short period of time. In Python, we generally use it as an argument to a higher-order function (a function that takes in other functions as arguments). Lambda functions are used along with built-in functions like filter(), map() etc.

With filter():

The filter() function in Python takes in a function and a list as arguments. The function is called with all the items in the list and a new list is returned which contains items for which the function evaluates to True.

```
# with filter()
my_list = [1, 5, 4, 6, 8, 11, 3, 12]

new_list = list(filter(lambda x: (x%2 == 0) , my_list))

print(new_list)
```

```
[4, 6, 8, 12]
```

With map():

The map() function in Python takes in a function and a list. The function is called with all the items in the list and a new list is returned which contains items returned by that function for each item.

```
# with map()
my_list = [1, 5, 4, 6, 8, 11, 3, 12]

new_list = list(map(lambda x: x * 2 , my_list))

print(new_list)
```

```
[2, 10, 8, 12, 16, 22, 6, 24]
```

Classes and Objects

A class is a user-defined blueprint or prototype from which objects are created. Classes provide a means of bundling data and functionality together. Creating a new class creates a new type of object, allowing new objects of that type to be made. Each class instance can have attributes attached to it for maintaining its state. Class instances can also have methods (defined by their class) for modifying or manipulating their state.

```
[118] # Python3 program to
      # demonstrate instantiating
      # a class
      class Car:
          # A simple class
          # attribute
          attr1 = "Petrol"
          attr2 = "750 HP"
          # A sample method
          def start(self):
              print("Engine Started : Engine Type ", self.attr1)
              print("Ready to GO : Horse Power ", self.attr2)
      # Driver code
      # Object instantiation
      BMW = Car()
      # Accessing class attributes
      # and method through objects
      print(BMW.attr1)
      BMW.start()
```

```
Petrol
Engine Started : Engine Type  Petrol
Ready to GO : Horse Power  750 HP
```

__init__ method

It is used to initialize the attributes for a class with specific values for a particular object. It is executed at the time of object creation for a particular class.

An example of the use of the __init__ function can be seen below,

```
[119] class Person:
          # init method or constructor
          def __init__(self, name):
              self.name = name
          # Sample Method
          def say_hi(self):
              print('Hello, my name is', self.name)
      p = Person('Robert')
      p.say_hi()
```

```
Hello, my name is Robert
```

b. Second Checkpoint

SECOND CHECKPOINT: Ability to perform basic python required for Data Science in Numpy and Pandas Library													
Numpy Fundamentals	Good Knowledge of Numpy library, Advantages and clear understaning of different functions of Numpy Library	2022/02/01 - 2022/02/02	T6	Chapter 1: Numpy Introduction	What is Numpy	Numpy Implementation	Numpy	30 mins	30	Numpy Quiz	Dataset	Data Dictionary	
					Numpy Features								
					Advantages over Numpy over Normal Array								
			T7	Chapter 2: Numpy ndarrays and its attributes	Ndarrays			2 hrs					
					Attributes								
					Creating Numpy ND Array Objects								
					Dimentions in array								
					Numpy array indexing and slicing								
			T8	Chapter 3: Numpy Functions	np.where()			1 hr					
					Numpy Rounding								
Pandas Fundamentals	Should have clear understanding of pandas, need to be familier with series and dataframe, clear inderstanding of dataframe creaation and manipulation, sound knowledge of data preprocessing using pandas and also different pandas functions	2022/02/03 - 2022/02/04	T9	Chpater 1 : Pandas Introduction	What is Pandas ?	Pandas Implementation	Pandas Introduction	30 mins	30	Pandas Quiz			
					What are the pandas Dataframes ?								
					Advantages of Pandas								
			T10	Chapter 2 : Data Structure in Pandas	Introductions		Series and dataframe	15 mins					
					Basic Operations								
			T11	Reading and Saving	Introductions		reading and writing dataframe	30 mins					
					Reading and Saving								
			T12	Chapter 4 : Dataframe Operations	Adding a row/column		Add, delete	15 mins					
					Deleting a row/column								
					Sorting (ascending/ descending)								
			T13	Chapter 5 : Null Handling	Finding Nulls		Null Imputation	30 mins					
					Replacing Nulls								
			T14	Chapter 6 : Aggregation of Groups	Introductions		groupby	30 mins					
					Aggregation Functions								
			T15	Chapter 7 : Lambda Functions	What are lambda functions ?		Lambda function	30 mins					
					How to use Lambda functions ?								
					Implementation of Lambda Functions								
			T16	Chapter 8 : Joining of Two Dataframes	Introductions		Pandas joining	30 mins					
					Join								
					Concat function								
			T17	Chapter 9 : Basic Pandas Functions	unique()			30 mins					
					nunique()								
					value_counts()								
					describe()								
					isin()								

Numpy is a library for the python programming language adding support to large, multi-dimensional arrays and matrices along with a large collection of high-level mathematical functions to operate on these arrays.

Numpy can deal with N-dimensional arrays.

To use Numpy in Python, we can import the numpy package as follows:

```
import numpy as np
```

Why use Numpy?

In Python we have lists that serve the purpose of arrays, but they are slow to process.

Numpy aims to provide an array object that is up to 50x faster than traditional Python lists.

The array object in Numpy is called ndarray, it provides a lot of supporting functions that make working with ndarray very easy.

Arrays are very frequently used in data science, where speed and resources are very important.

Numpy Features

Numpy is useful when it comes to array manipulation. Following table lists some features of numpy used for array creation and manipulation.

Feature	Description
Numpy 1-D Array	Making 1D array
Numpy 2-D Array	Making 2D array
Array Multiplication	Multiplying 2 or more array
numpy.ones	Matrix filled with ones
numpy.zeros	Matrix filled with zeros
numpy.random	Matrix filled with random numbers
numpy.arange	Create array with increments of a fixed step size
numpy.linspace	Create array of fixed length
numpy.full	Create a constant array of any number 'n'
numpy.tile	Create a new array by repeating an existing array for a particular number of times
numpy.eye	Create an identity matrix of any dimension
numpy.random.randint	Random integer
Numpy 3-D Array	Making 3-D array

Advantages of Numpy over Normal Array

- Numpy uses much less memory to store data
- It allows creation of N-dimensional arrays
- Mathematical operations on Numpy n-dimensional arrays
- More powerful slicing and Broadcasting functionality
- Efficient Data Representation

Numpy provides a help function, providing the documentation for its methods, functions, classes and modules, by using the .info() function.

```
print(np.info(max))
```

What is Pandas?

Pandas is a fast, powerful, flexible and easy to use open source data analysis and manipulation tool, built on top of the_python programming language.

Pandas is quite a game changer when it comes to analyzing data with Python and it is one of the most preferred and widely used tools in_data munging/wrangling. Pandas is an open source, free to use and it was originally written by Wes McKinney .

What's cool about Pandas is that it takes data (like a CSV or TSV file, or a SQL database) and creates a Python object with rows and columns called data frame that looks very similar to a table in a statistical software (like Excel).

Importing Pandas :

After the pandas have been installed into the system, you need to import the library. This module is generally imported as:

```
import pandas as pd
```

Here, pd is referred to as an alias to the Pandas. However, it is not necessary to import the library using the alias, it just helps in writing less code every time a method or property is called.

What are Pandas Data Frames?

Pandas DataFrame is a two-dimensional size-mutable, potentially heterogeneous tabular data structure with labeled axes (rows and columns).

In general, we can say that the Pandas DataFrame consists of three main components: the data, the index, and the columns. DataFrames are extremely important going forward, as we can read & store excel sheets into DataFrames and use many manipulation techniques on them, as we'll learn ahead.

Advantages of Pandas

1. Fast and efficient for manipulating and analyzing data.
2. Data from different file objects can be loaded.
3. Easy handling of missing data (represented as NaN) in floating point as well as non-floating point data
4. Size mutability: columns can be inserted and deleted from DataFrame and higher dimensional objects
5. Data set merging and joining.
6. Flexible reshaping and pivoting of data sets
7. Provides time-series functionality.
8. Powerful group by functionality for performing split-apply-combine operations on data sets.

c. Third and Fourth Checkpoint

THIRD CHECKPOINT: Statistics, Data Preprocessing pre-process, data splitting and Explaantory Data Analysis													
Ability to pre-process , split the data and perform EDA	understanding basic pre-processing and data splitting	**2022/01/08 - 2022/01/09**	**T18**	Pre-process the Data	Data Filtering , Duplicate/Constant columns removal , Identification of target column	How to do	Practical guide to preprocessing	**1 hrs**			**Masterclass Demo**		
					Date time conversion	How to do	Date-time	1 hr					
					Null Imputation	How to do	Null imputation						
			T19	Split the pre-processed data into train, test and validation sets	Train-Test-Val Set : How split , why Split	How to do	Split and it's importance	**1 hrs**					
	Understand EDA		**T20**	How to do Exploratory Data Analysis?	Continuous Variable	How to do	Further study	40 mins					
					Catagorical Variable	How to do	Further study						
					Univariate Analysis	How to do	Univariate Analysis	1 hr					
					Multivariate Analysis	How to do	Multivariate Analysis						
	Data Visualisation and Pattern Analysis				Distributions and IQR	How to do	Also read	**1 hrs**					
					Measure of Central Tendency (mean , median , mode)	How to do	Add on						
					Data Visualisation	How to do	cook book on data visualisation	**1 mins**					
					Outlier Detection and Treatment	How to do	Extended Read						
			T21	Matplotlib, Seaborn and Plotly Basic plots	Matplotlib, Seaborn and Plotly libraries	How to do	External Video	**60 mins**					
FOURTH CHECKPOINT: Ability to do feature engineering & feature selection													
Ability to do feature engineering & feature selection	Feature Engg	**2022/02/9 - 2022/02/11**	**T22**	How to do derive or make Features?	Numerical and Catagorical Columns	How to do	Extended Study	**30 mins**	**30**	**Data Preprocessing and Feature Selection Quiz**	**Master Class Demo Code and Datasets**		-
					Feature Engg Techniques	How to do	Extended Study	**2 hrs**					
					Date Columns Manupulation	How to do	Extended Study	**20 mins**					
					Normalisation , Standarization -Scaling techniques	How to do	Further Study	**1.5 hrs**					
	Feature Selection		**T23**	How to select the best features?	Filter Method	How to do	Extended Study	**1hrs**					
					Wrapper Method	How to do	Extended Study	**1 hrs**					
					Embedded Method	How to do	Extended Study	**1 hrs**					

What is a Target Variable?

The target variable of a dataset is the feature of a dataset about which you want to gain a deeper understanding. A supervised machine learning algorithm uses historical data to learn patterns and uncover relationships between other features of your dataset and the target.

The target variable will vary depending on the business goal and available data. For example, let's say you want to use sentiment analysis to classify whether tweets about your company's brand are positive or negative. Some aspects of a tweet that can be useful as features are word tokens, parts of speech, and emoticons. A model cannot learn how those features relate to sentiment without first being given examples of which tweets are positive or negative (the target).

Importance of Target Variables:

Without a labelled target, supervised machine learning algorithms would be unable to map available data to outcomes, just as a child would be incapable of figuring out that cats are called "cats" without having been told so at least a few times. It is important to have a well-defined target since the only thing an algorithm does is learn a function that maps relationships between input data and the target. The model's outcomes will be meaningless if your target doesn't make sense.

Feature engineering is the process of using domain knowledge of the data to create features that make machine learning algorithms work.

What does the term feature mean here?

Ex- How do you make decision to buy a car? You go through some of the attributes of different cars and then you make a decision to buy or not based on your understanding.

These features can be min and max speed, seating capacity etc.

What is feature engineering then?

If you are given total area of car, torque produced, in depth details of engine etc, you may not understand it well. That's why manufacturers present a more understandable entities like min-max range of speed, seating capacity, mileage etc.

This is nothing but deriving/ creating attributes which can be understood easily and can help people to make decision.

Similarly machine learning algorithms work better if we can feed attributes which cause a particular outcome to be predicted by model.

A tabular dataset contains multiple fields/attributes. These attributes are called the raw features. Majorly the data type for these fields are numerical, categorical and date time. Different kind of feature engineering techniques are applied for different kind of data types.

Objective:

This play will help you to do feature engineering on numerical columns such as amount, number of days, age, weight etc.

d. Fifth Checkpoint

FIFTH CHECKPOINT: Ability to build base model,tune hyper-parameters & decide good model evaluation metric													
Ability to build base model, tune hyper-parameters & decide good model evaluation metric	Different types of Model	**2022/02/14 - 2022/02/18**	**T24**	Different Model Building Algoritms	Supervised and Unsupervised Learning Classification and Regression	How to do	References	**2 hrs**			**Masterclass Demo code and dataset**		
					Distance Based Algorithms	How to do							
					Machine learning Models (Supervised and Unsupervised)	How to do	References	**3 hrs**					
					Ml Algo Part - 1		Extra read		-	-			
					ML Algo Part -2	How to do		**2 hrs**	-	-			
					Classification								
					Regression								
	Hyper Parameter Tuning and Evaluation of Models		**T25**	How to tune the model Hyper-Parameters?	Cross Validation , Randomied Search CV , Grid Search CV	How to do	Extra read	**3hrs**	-	-			
				How to decide the Metrics to be Used ?	Classification & Regression Based Metrices	How to do	Further Study	**2 hrs**	-	-			

e. Final project Submission for Machine learning

We will be building a web application to help the people working in the Accounts Receivable departments in their day-to-day activities. You need to build a web application where the users in the Account Receivable department can :

- View the invoice data from various buyers.
- See various fields/attributes of the invoice(s) from a particular buyer.
- Perform Data Pre-processing on the invoice data.
- Get account-level analytics to easily visualize and interpret data- EDA and Feature Engineering.
- Get a prediction of when the invoice is going to get paid.

Jupyter notebook Snippets for the backend payment date prediction

Payment Date Prediction

Importing related Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import sklearn.metrics as sm
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
```

Store the dataset into the Dataframe

In [2]:
```
data_path=(r"C:\Users\91855\Desktop\dataset(1).csv")
```

Check the shape of the dataframe

In [3]:
```
data = pd.read_csv(data_path)
print(data.shape)
```

```
(50000, 19)
```

Check the Detail information of the dataframe

```
(50000, 19)
```

Check the Detail information of the dataframe

In [4]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 19 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   business_code           50000 non-null  object
 1   cust_number             50000 non-null  object
 2   name_customer           50000 non-null  object
 3   clear_date              40000 non-null  object
 4   buisness_year           50000 non-null  float64
 5   doc_id                  50000 non-null  float64
 6   posting_date            50000 non-null  object
 7   document_create_date    50000 non-null  int64
 8   document_create_date.1  50000 non-null  int64
 9   due_in_date             50000 non-null  float64
 10  invoice_currency        50000 non-null  object
 11  document type           50000 non-null  object
 12  posting_id              50000 non-null  float64
 13  area_business           0 non-null      float64
 14  total_open_amount       50000 non-null  float64
 15  baseline_create_date    50000 non-null  float64
 16  cust_payment_terms      50000 non-null  object
 17  invoice_id              49994 non-null  float64
 18  isOpen                  50000 non-null  int64
dtypes: float64(8), int64(3), object(8)
memory usage: 7.2+ MB
```

Display All the column names

In [5]:
```
print(data.columns)
```


Display All the column names

In [5]:
```
print(data.columns)
```


```
Index(['business_code', 'cust_number', 'name_customer', 'clear_date',
       'buisness_year', 'doc_id', 'posting_date', 'document_create_date',
       'document_create_date.1', 'due_in_date', 'invoice_currency',
       'document type', 'posting_id', 'area_business', 'total_open_amount',
       'baseline_create_date', 'cust_payment_terms', 'invoice_id', 'isOpen'],
      dtype='object')
```

Describe the entire dataset

In [6]:
```
data.describe(include='all')
```

Out[6]:

	business_code	cust_number	name_customer	clear_date	buisness_year	doc_id	posting_date	document_create_date	document_create_date.1	due_in_date	invoice_currency
count	50000	50000	50000	40000	50000.000000	5.000000e+04	50000	5.000000e+04	5.000000e+04	5.000000e+04	50000
unique	6	1425	4197	403	NaN	NaN	506	NaN	NaN	NaN	2
top	U001	0200769623	WAL-MAR trust	2019-11-12 00:00:00	NaN	NaN	2020-03-24	NaN	NaN	NaN	USD
freq	45359	11483	1179	309	NaN	NaN	226	NaN	NaN	NaN	46081
mean	NaN	NaN	NaN	NaN	2019.305700	2.012238e+09	NaN	2.019351e+07	2.019354e+07	2.019368e+07	NaN
std	NaN	NaN	NaN	NaN	0.460708	2.885235e+08	NaN	4.496041e+03	4.482134e+03	4.470614e+03	NaN
min	NaN	NaN	NaN	NaN	2019.000000	1.928502e+09	NaN	2.018123e+07	2.018123e+07	2.018122e+07	NaN
25%	NaN	NaN	NaN	NaN	2019.000000	1.929342e+09	NaN	2.019050e+07	2.019051e+07	2.019052e+07	NaN
50%	NaN	NaN	NaN	NaN	2019.000000	1.929964e+09	NaN	2.019091e+07	2.019091e+07	2.019093e+07	NaN
max	NaN	NaN	NaN	NaN	2020.000000	9.500000e+09	NaN	2.020052e+07	2.020052e+07	2.020071e+07	NaN

Data Cleaning

- Show top 5 records from the dataset

In [7]:
```
data.head()
```

Out[7]:

	business_code	cust_number	name_customer	clear_date	buisness_year	doc_id	posting_date	document_create_date	document_create_date.1	due_in_date	invoice_currency	docum t
0	U001	0200769623	WAL-MAR corp	2020-02-11 00:00:00	2020.0	1.930438e+09	2020-01-26	20200125	20200126	20200210.0	USD	
1	U001	0200980828	BEN E	2019-08-08 00:00:00	2019.0	1.929646e+09	2019-07-22	20190722	20190722	20190811.0	USD	
2	U001	0200792734	MDV/ trust	2019-12-30 00:00:00	2019.0	1.929874e+09	2019-09-14	20190914	20190914	20190929.0	USD	
3	CA02	0140105686	SYSC llc	NaN	2020.0	2.960623e+09	2020-03-30	20200330	20200330	20200410.0	CAD	
4	U001	0200769623	WAL-MAR foundation	2019-11-25 00:00:00	2019.0	1.930148e+09	2019-11-13	20191113	20191113	20191128.0	USD	

00:00:00

Display the Null values percentage against every columns (compare to the total number of records)

- Output expected : area_business - 100% null, clear_data = 20% null, invoice_id = 0.12% null

In [8]:
```
percentage_missing= data.isnull().sum()*100/len(data)
missing_value_data = pd.DataFrame({'column_name':data.columns,'percentage_missing':percentage_missing})
print(missing_value_data)
```

```
                                 column_name  percentage_missing
business_code                  business_code               0.000
cust_number                      cust_number               0.000
name_customer                  name_customer               0.000
clear_date                        clear_date              20.000
buisness_year                  buisness_year               0.000
doc_id                                doc_id               0.000
posting_date                    posting_date               0.000
document_create_date    document_create_date               0.000
document_create_date.1  document_create_date.1             0.000
due_in_date                      due_in_date               0.000
invoice_currency            invoice_currency               0.000
document type                  document type               0.000
posting_id                        posting_id               0.000
area_business                  area_business             100.000
total_open_amount          total_open_amount               0.000
baseline_create_date    baseline_create_date               0.000
cust_payment_terms        cust_payment_terms               0.000
invoice_id                        invoice_id               0.012
isOpen                                isOpen               0.000
```

Display Invoice_id and Doc_Id

isOpen isOpen 0.000

Display Invoice_id and Doc_Id

In [9]:
```
data[["invoice_id","doc_id"]]
```

Out[9]:

	invoice_id	doc_id
0	1.930438e+09	1.930438e+09
1	1.929646e+09	1.929646e+09
2	1.929874e+09	1.929874e+09
3	2.960623e+09	2.960623e+09
4	1.930148e+09	1.930148e+09
...	...	...
49995	1.930797e+09	1.930797e+09
49996	1.929744e+09	1.929744e+09
49997	1.930537e+09	1.930537e+09
49998	1.930199e+09	1.930199e+09
49999	1.928576e+09	1.928576e+09

50000 rows × 2 columns

Write a code to check - 'baseline_create_date',"document_create_date",'document_create_date.1' - these columns are almost same.

- Please note, if they are same, we need to drop them later

Write a code to check - 'baseline_create_date',"document_create_date",'document_create_date.1' - these columns are almost same.

- Please note, if they are same, we need to drop them later

In [10]:
```
same_values=(data['baseline_create_date'] == data['document_create_date']) | (data['document_create_date'] == data['document_create_date.1']) | (data['documen
same_values.value_counts(normalize=True)*100 #almost same
```

Out[10]:
```
True     99.606
False     0.394
dtype: float64
```

In [11]:
```
print(data.shape)
```

```
(50000, 19)
```

Please check, Column 'posting_id' is constant columns or not

In [12]:
```
from sklearn.feature_selection import VarianceThreshold
var=VarianceThreshold(threshold=1)
data_temp=data.select_dtypes(exclude=['object'])
print(data_temp.columns)
var.fit(data_temp)
print(data_temp.columns[var.get_support()])
constant_columns = [column for column in data_temp.columns if column not in data_temp.columns[var.get_support()]]
for col in constant_columns: #constant columns
    print(col)
```

```
Index(['buisness_year', 'doc_id', 'document_create_date',
       'document_create_date.1', 'due_in_date', 'posting_id', 'area_business',
       'total_open_amount', 'baseline_create_date', 'invoice_id', 'isOpen'],
      dtype='object')
Index(['doc_id', 'document_create_date', 'document_create_date.1',
       'due_in_date', 'total_open_amount', 'baseline_create_date',
       'invoice_id'],
      dtype='object')
buisness_year
```

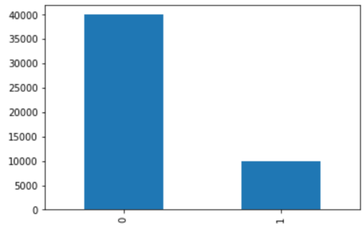
Please check 'isOpen' is a constant column and relevant column for this project or not

In [13]:
```
for col in constant_columns: #constant columns
    print(col)
#data['isOpen'].value_counts()
print(data['clear_date'][data['isOpen']==0].shape[0])
print(data['clear_date'][data['isOpen']==1].shape[0])
```

```
buisness_year
posting_id
area_business
isOpen
40000
10000
```

In [14]:
```
data['isOpen'].value_counts().plot.bar()
```

Out[14]: `<AxesSubplot:>`



Write the code to drop all the following columns from the dataframe

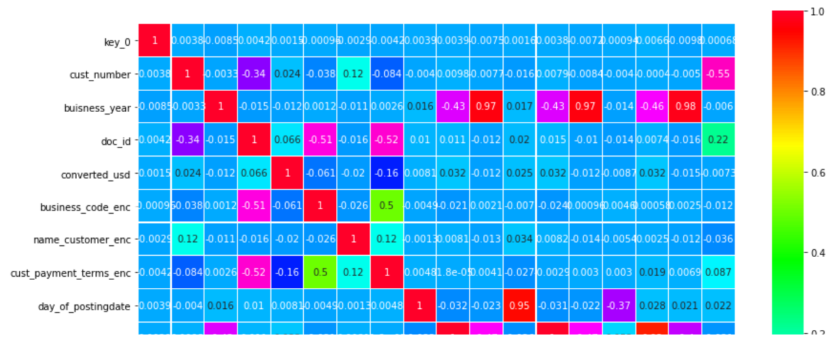
Continuing the code snippet from line 104

Heatmap for X_train

- Note - Keep the code as it is, no need to change

In [104]:
```
colormap = plt.cm.RdBu
plt.figure(figsize=(14,12))
plt.title('Pearson Correlation of Features', y=1.05, size=20)
sns.heatmap(X_train.merge(y_train , on = X_train.index ).corr(),linewidths=0.1,vmax=1.0,
            square=True, cmap='gist_rainbow_r', linecolor='white', annot=True)
```

Out[104]: `<AxesSubplot:title={'center':'Pearson Correlation of Features'}>`



Calling variance threshold for threshold value = 0.8

- Note - Fill in the blanks to call the appropriate method

In [105]:
```
from sklearn.feature_selection import VarianceThreshold
sel = VarianceThreshold(0.8)
sel.fit(X_train)
```

Out[105]: `VarianceThreshold(threshold=0.8)`

In [106]:
```
sel.variances_
```

Out[106]:
```
array([1.79496074e+15, 1.14193288e-01, 8.42021058e+16, 1.35321467e+09,
       2.87586863e-01, 1.07337851e+06, 1.39033037e+02, 7.58807379e+01,
       1.21969291e+01, 1.14669118e-01, 7.75035746e+01, 1.22004654e+01,
       1.14882442e-01, 7.65360516e+01, 1.20243278e+01, 1.17567694e-01])
```

Features columns are

- 'year_of_createdate'
- 'year_of_due'
- 'day_of_createdate'
- 'year_of_postingdate'
- 'month_of_due'
- 'month_of_createdate'

Modelling

Now you need to compare with different machine learning models, and needs to find out the best predicted model

Next we needed to compare with different machine learning models, and needs to find out the best predicted model

- Linear Regression
- Decision Tree Regression
- Random Forest Regression
- Support Vector Regression
- Extreme Gradient Boost Regression

- MSE
- R2
- Algorithm

In [107…
```
MSE_Score = []
R2_Score = []
Algorithm = []
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
```

You need to start with the baseline model Linear Regression

- Step 1 : Call the Linear Regression from sklearn library
- Step 2 : make an object of Linear Regression
- Step 3 : fit the X_train and y_train dataframe into the object
- Step 4 : Predict the output by passing the X_test Dataset into predict function

- Note - Append the Algorithm name into the algorithm list for tracking purpose

In [108…
```
from sklearn.linear_model import LinearRegression
Algorithm.append('LinearRegression')
regressor = LinearRegression()
regressor.fit(X_train, y_train)
predicted= regressor.predict(X_test)
```

Check for the

- R Square Error

for y_test and predicted dataset and store those data inside respective list for comparison

In [109…
```
MSE_Score.append(mean_squared_error(y_test, predicted))
R2_Score.append(r2_score(y_test, predicted))
```

Check the same for the Validation set also

In [110…
```
predict_test= regressor.predict(X_val)
mean_squared_error(y_val, predict_test, squared=False)
```

Out[110…
```
520276.80710837594
```

Display The Comparison Lists

In [111…
```
for i in Algorithm, MSE_Score, R2_Score:
    print(i,end=',')
```

```
['LinearRegression'],[308077330370.42926],[0.2920382097301424],
```

You need to start with the baseline model Support Vector Regression

- Step 1 : Call the Support Vector Regressor from sklearn library
- Step 2 : make an object of SVR
- Step 3 : fit the X_train and y_train dataframe into the object
- Step 4 : Predict the output by passing the X_test Dataset into predict function

- Note - Append the Algorithm name into the algorithm list for tracking purpose

In [112…
```
from sklearn.svm import SVR
```

- Note - Append the Algorithm name into the algorithm list for tracking purpose

In [112…
```python
from sklearn.svm import SVR
Algorithm.append('Support Vector Machines')
regressor = SVR()
regressor.fit(X_train, y_train)
predicted= regressor.predict(X_test)
```

Check for the

- Mean Square Error
- R Square Error

for "y_test" and "predicted" dataset and store those data inside respective list for comparison

In [113…
```python
MSE_Score.append(mean_squared_error(y_test, predicted))
R2_Score.append(r2_score(y_test, predicted))
```

Check the same for the Validation set also

In [114…
```python
predict_test= regressor.predict(X_val)
mean_squared_error(y_val, predict_test, squared=False)
```

Out[114…
```
651175.521259971
```

Display The Comparison Lists

In [115…
```python
for i in Algorithm, MSE_Score, R2_Score:
    print(i,end=',')
```

```
['LinearRegression', 'Support Vector Machines'] [308077330370.42926, 437273278029.27875] [0.2920382097301424, -0.004854113668636417]
```

The next model would be Decision Tree Regression

- Step 1 : Call the Decision Tree Regressor from sklearn library
- Step 2 : make an object of Decision Tree
- Step 3 : fit the X_train and y_train dataframe into the object
- Step 4 : Predict the output by passing the X_test Dataset into predict function

- Step 4 : Predict the output by passing the X_test Dataset into predict function
- Note - Append the Algorithm name into the algorithm list for tracking purpose

In [116…
```python
from sklearn.tree import DecisionTreeRegressor
Algorithm.append('Decision Tree Regression')
regressor = DecisionTreeRegressor()
regressor.fit(X_train, y_train)
predicted= regressor.predict(X_test)
```

Check for the

- Mean Square Error
- R Square Error

for y_test and predicted dataset and store those data inside respective list for comparison

In [117…
```python
MSE_Score.append(mean_squared_error(y_test, predicted))
R2_Score.append(r2_score(y_test, predicted))
```

Check the same for the Validation set also

In [118…
```python
predict_test= regressor.predict(X_val)
mean_squared_error(y_val, predict_test, squared=False)
```

Out[118…
```
405089.5928570871
```

Display The Comparison Lists

In [119…
```python
for i in Algorithm, MSE_Score, R2_Score:
    print(i,end=',')
```

for y_test and predicted dataset and store those data inside respective list for comparison

```
In [ ]: MSE_Score.append(mean_squared_error(y_test, predicted))
        R2_Score.append(r2_score(y_test, predicted))
```

Check the same for the Validation set also

```
In [ ]: predict_test= regressor.predict(X_val)
        mean_squared_error(y_val, predict_test, squared=False)
```

Display The Comparison Lists

```
In [ ]: for i in Algorithm, MSE_Score, R2_Score:
            print(i,end=',')
```

You need to make the comparison list into a comparison dataframe

```
In [ ]: comparison=pd.DataFrame(list(zip(Algorithm,MSE_Score,R2_Score)),columns=['Algorithm','MSE_Score','R2_Score'])
        comparison.head()
```

Now from the Comparison table, you need to choose the best fit model

- Step 1 - Fit X_train and y_train inside the model
- Step 2 - Predict the X_test dataset
- Step 3 - Predict the X_val dataset

- Note - No need to change the code

```
In [ ]: regressorfinal = xgb.XGBRegressor()
```

- Note - No need to change the code

```
In [ ]: regressorfinal = xgb.XGBRegressor()
        regressorfinal.fit(X_train, y_train)
        predictedfinal = regressorfinal.predict(X_test)
        predict_testfinal = regressorfinal.predict(X_val)
```

Calculate the Mean Square Error for test dataset

- Note - No need to change the code

```
In [ ]: mean_squared_error(y_test,predictedfinal,squared=False)
```

Calculate the mean Square Error for validation dataset

```
In [ ]: mean_squared_error(y_val,predictedfinal,squared=False)
```

Calculate the R2 score for test

```
In [ ]: r2_score(y_test,predictedfinal)
```

Calculate the R2 score for Validation

```
In [ ]: r2_score(y_val,predictedfinal)
```

Calculate the Accuracy for train Dataset

```
In [ ]: r2_score(y_test,predictedfinal)
```

Now we need to pass the Nulldata dataframe into this machine learning model

In order to pass this Nulldata dataframe into the ML model, we need to perform the following

- Step 1 : Label Encoding
- Step 2 : Day, Month and Year extraction
- Step 3 : Change all the column data type into int64 or float64
- Step 4 : Need to drop the useless columns

Display the Nulldata

```
In [ ]: test_data.head()
```

Check for the number of rows and columns in the nulldata

```
In [ ]: test_data.shape
```

Check the Description and Information of the nulldata

```
In [ ]: test_data.describe(include='all')
```

```
In [ ]: test_data.info()
```

Storing the Nulldata into a different dataset

for BACKUP

```
In [ ]: test_data1=test_data.copy()
```

Call the Label Encoder for Nulldata

- Note - you are expected to fit "business_code" as it is a categorical variable
- Note - No need to change the code

```
In [ ]: from sklearn.preprocessing import LabelEncoder
        business_codern = LabelEncoder()
```


- Note - No need to change the code


```
In [ ]: from sklearn.preprocessing import LabelEncoder
        business_codern = LabelEncoder()
        business_codern.fit(test_data['business_code'])
        test_data['business_code_enc'] = business_codern.transform(test_data['business_code'])
```

Now you need to manually replacing str values with numbers

- Note - No need to change the code

```
In [ ]: test_data['cust_number'] = test_data['cust_number'].str.replace('CCCA',"1").str.replace('CCU',"2").str.replace('CC',"3").astype(int)
```

We need to extract day, month and year from the "clear_date", "posting_date", "due_in_date", "baseline_create_date" columns

1. Extract day from "clear_date" column and store it into 'day_of_cleardate'

2. Extract month from "clear_date" column and store it into 'month_of_cleardate'

3. Extract year from "clear_date" column and store it into 'year_of_cleardate'

4. Extract day from "posting_date" column and store it into 'day_of_postingdate'

5. Extract month from "posting_date" column and store it into 'month_of_postingdate'

6. Extract year from "posting_date" column and store it into 'year_of_postingdate'

7. Extract day from "due_in_date" column and store it into 'day_of_due'

8. Extract month from "due_in_date" column and store it into 'month_of_due'

9. Extract year from "due_in_date" column and store it into 'year_of_due'

10. Extract day from "baseline_create_date" column and store it into 'day_of_createdate'

11. Extract month from "baseline_create_date" column and store it into 'month_of_createdate'

12. Extract year from "baseline_create_date" column and store it into 'year_of_createdate'

```
test_data['day_of_cleardate']=test_data['clear_date'].dt.day
test_data['month_of_cleardate']=test_data['clear_date'].dt.month
test_data['year_of_cleardate']=test_data['clear_date'].dt.year

test_data['day_of_postingdate']=test_data['posting_date'].dt.day
test_data['month_of_postingdate']=test_data['posting_date'].dt.month
test_data['year_of_postingdate']=test_data['posting_date'].dt.year

test_data['day_of_due']=test_data['due_in_date'].dt.day
test_data['month_of_due']=test_data['due_in_date'].dt.month
test_data['year_of_due']=test_data['due_in_date'].dt.year

test_data['day_of_createdate']=test_data['baseline_create_date'].dt.day
test_data['month_of_createdate']=test_data['baseline_create_date'].dt.month
test_data['year_of_createdate']=test_data['baseline_create_date'].dt.year
```

Use Label Encoder1 of all the following columns -

- 'cust_payment_terms' and store into 'cust_payment_terms_enc'
- 'business_code' and store into 'business_code_enc'
- 'name_customer' and store into 'name_customer_enc'

Note - No need to change the code

```
test_data['cust_payment_terms_enc']=label_encoder1.transform(test_data['cust_payment_terms'])
test_data['business_code_enc']=label_encoder1.transform(test_data['business_code'])
test_data['name_customer_enc']=label_encoder.transform(test_data['name_customer'])
```

Check for the datatypes of all the columns of Nulldata

```
test_data.dtypes
```

Now we need to drop all the unnecessary columns -

- 'business_code'
- "baseline_create_date"
- "due_in_date"
- "posting_date"
- "name_customer"
- "clear_date"
- "cust_payment_terms"
- 'day_of_cleardate'
- "month_of_cleardate"
- "year_of_cleardate"

```
test_data.drop(columns=['business_code','baseline_create_date','due_in_date','posting_date','name_customer','clear_date','cust_payment_terms','day_of_cleardat
```

Check the information of the "nulldata" dataframe

```
test_data.info()
```

Compare "nulldata" with the "X_test" dataframe

- use info() method

```
X_test.info()
```

You must have noticed that there is a mismatch in the column sequence while compairing the dataframes

- Note - In order to fed into the machine learning model, you need to edit the sequence of "nulldata", similar to the "X_test" dataframe

- Display all the columns of the X_test dataframe
- Display all the columns of the Nulldata dataframe
- Store the Nulldata with new sequence into a new dataframe

- Note - The code is given below, no need to change

```
X_test.columns
```

```
test_data.columns
```

```
test_data2=test_data[['cust_number', 'buisness_year', 'doc_id', 'converted_usd',
       'business_code_enc', 'name_customer_enc', 'cust_payment_terms_enc',
```

```
'day_of_due', 'month_of_due', 'year_of_due']]
```

Display the Final Dataset

```
In [ ]: test_data2.head()
```

Now you can pass this dataset into you final model and store it into "final_result"

```
In [ ]: final_result=regressorfinal.predict(test_data)
```

you need to make the final_result as dataframe, with a column name "avg_delay"

- Note - No need to change the code

```
In [ ]: final_result = pd.Series(final_result,name='avg_delay')
```

Display the "avg_delay" column

```
In [ ]: final_result
```

Now you need to merge this final_result dataframe with the BACKUP of "nulldata" Dataframe which we have created in earlier steps

```
In [ ]: test_data1.reset_index(drop=True,inplace=True)
        Final = test_data1.merge(final_result , on = test_data.index )
```

Display the "Final" dataframe

```
In [ ]: Final.head()
```


```
In [ ]: final_result=regressorfinal.predict(test_data)
```

you need to make the final_result as dataframe, with a column name "avg_delay"

- Note - No need to change the code

```
In [ ]: final_result = pd.Series(final_result,name='avg_delay')
```

Display the "avg_delay" column

```
In [ ]: final_result
```

Now you need to merge this final_result dataframe with the BACKUP of "nulldata" Dataframe which we have created in earlier steps

```
In [ ]: test_data1.reset_index(drop=True,inplace=True)
        Final = test_data1.merge(final_result , on = test_data.index )
```

Display the "Final" dataframe

```
In [ ]: Final.head()
```


Check for the Number of Rows and Columns in your "Final" dataframe

```
In [ ]: Final.shape
```

Now, you need to do convert the below fields back into date and time format

- create a list of bins i.e. bins= [0,15,30,45,60,100]
- create a list of labels i.e. labels = ['0-15','16-30','31-45','46-60','Greatar than 60']
- perform binning by using cut() function from "Final" dataframe

- Please fill up the first two rows of the code

```
In [ ]: bins= [0,15,30,45,60,100]
        labels =['0-15','16-30','31-45','46-60','>61']
        Final['Aging Bucket'] = pd.cut(Final['avg_delay'], bins=bins, labels=labels, right=False)
```

Now you need to drop "key_0" and "avg_delay" columns from the "Final" Dataframe

```
In [ ]: Final.drop(columns=['key_0','avg_delay'],inplace=True)
```

Display the count of each categoty of new "Aging Bucket" column

```
In [ ]: Final['Aging Bucket'].value_counts()
```

Display your final dataset with aging buckets

```
In [ ]: Final.loc[:,['Aging Bucket']]
```

Store this dataframe into the .csv format

```
In [ ]: Final.to_csv('HRC21153W.csv', index=False)
```

Experience During the course

In the initial stage it was easy as I had already learnt python and had a good hands-on practice regarding the same.

The difficulties started to hit me when we moved forward in the machine learning course as somethings were new to me and I needed a lot of practice to master them.

As this internship course is going simultaneously with my college classes it became a bit easy to understand as we had machine Learning as a core subject too.

During the course of working with dataset and making this prediction module, it all went smoothly as our instructors at HighRadius were always available to help.

Plans for the Rest of the Semester

The plan for the rest of the semester is as follows:

For Highradius:

Week	Days	Subject	Topics	Hours	Breakup of 3 Hours in Sequence	Content Reading Time (hours)	Self Study Time (hours)	Comments
Week 4	2022-02-21	Java	Master Class: SQL Concepts & DB Basics	(1 – 2) Hours	1) For first 1 hour masterclass is to be taken 2) 1.5 hours Self study time for interns 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-02-22		Self Study & Hands On for SQL Concepts & DB Basics	(2.5 – 0.5) Hours	1) 2.5 hours Self study time for interns 2) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-02-23		Master Class: Eclipse and Workspace setup, Java Basics & JDBC	(1 – 2) Hours	1) For first 1 hour masterclass is to be taken 2) 1.5 hours Self study time for interns 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-02-24		Java Basics & JDBC Work	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-02-25		Java Basics & JDBC Work (ML Project Submission Day)	3 Hours	1) 1 hour doubt clearing session + ML Project Submission 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
Week 5	2022-02-28		Quiz Day (SQL Concepts, Java Basics & JDBC) + Work	(1+1.5+0.5) Hours	1) 1 hour - doubt clearing session 2) last 40 minutes - Quiz (8:30PM to 9:10PM)			Breaks to be taken/given during the Self Study time
	2022-03-01		Self Study	3 Hours	1) 3 hours Self study time for interns			Breaks to be taken/given during the Self Study time
	2022-03-02		Master Class: Servlet	(1 – 2) Hours	1) For first 1 hour masterclass is to be taken 2) 1.5 hours Self study time for interns 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-03-03		Servlet Work	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-03-04		Quiz Day (core Java, J2EE, Hands on Java Coding)	(1+1.5+0.5) Hours	1) 1 hour - doubt clearing session 2) last 30 minutes - Quiz (8:30PM to 9:00PM)			Breaks to be taken/given during the Self Study time
Week 6	2022-03-07	HTML & CSS	Master Class: Introduction and Basic Fundamentals	(1 – 2) Hours	1) For first 1 hour masterclass is to be taken 2) 1.5 hours Self study time for interns 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-03-08		HTML & CSS Work	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-03-09		Doubt Clearing Day	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-03-10		Evaluation on HTML & CSS	2.5 Hours				Breaks to be taken/given during the Self Study time
	2022-03-11	Java Scripts (ReactJS)	Master Class: Introduction and Basic Fundamentals	(1 – 2) Hours	1) For first 1 hour masterclass is to be taken 2) 1.5 hours Self study time for interns 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
Week 7	2022-03-14		Creating login Screen Work	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-03-15		Quiz Day – Work	(0.5 – 2.5) Hours				Breaks to be taken/given during the Self Study time
	2022-03-16		Master Class: Creating Form, Dialog Box and Grid UI	(1 – 2) Hours	1) For first 1 hour masterclass is to be taken 2) 1.5 hours Self study time for interns 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-03-17		Form and Dialog Box Work	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
Week 8	2022-03-21		Quiz Day – Work	(0.5 – 2.5) Hours				Breaks to be taken/given during the Self Study time
	2022-03-22		Creating Grid UI Work	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-03-23		Creating Grid UI Work	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-03-24		Doubt Clearing Day	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-03-25		Evaluation on Java Scripts	2.5 Hours				Breaks to be taken/given during the Self Study time
Week 9	2022-03-28	Web App Project	Master Class: Loading Data into Grid and Search	(1 – 2) Hours	1) For first 1 hour masterclass is to be taken 2) 1.5 hours Self study time for interns 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-03-29		Loading Data into Grid Work	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-03-30		Implementation of Search Functionality	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
Week 10	2022-03-31		Implementation of Search Functionality	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-04-01		Quiz Day – Work	(0.5 – 2.5) Hours				Breaks to be taken/given during the Self Study time
	2022-04-04		Master Class: Creating ADD, EDIT & DELETE Functionality	(1 – 2) Hours	1) For first 1 hour masterclass is to be taken 2) 1.5 hours Self study time for interns 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-04-05		Creating ADD, EDIT & DELETE Functionality Work	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-04-06		Master Class: Predict Button, Sorting, Pagination & Analytics	(1 – 2) Hours	1) For first 1 hour masterclass is to be taken 2) 1.5 hours Self study time for interns 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-04-07		Predict Button Work	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-04-08		Grid Data Sorting and Pagination Work	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
Week 11	2022-04-11		Grid Data Analytics Work	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-04-12		Doubt Clearing Day	3 Hours	1) 1 hour doubt clearing session 2) 1 hour 30 minutes Self study 3) last 30 minutes Scrum call & Attendance			Breaks to be taken/given during the Self Study time
	2022-04-13		Evaluation on Web App Project	2.5 Hours				

Estimated hours to be devoted for the internship: 111 Hours

Conclusion:

As till the point the internship is going on it seems to have a good impact on my practical knowledge of Machine learning and I have good faith that as the internship progresses my hands-on practice as well as my theoretical knowledge will get better.

With this internship I have gained a good knowledge about data analysis using different tools and how to be more effective while using machine learning algorithms.