







In the previous lecture, we have seen about

- Introduction to pandas
- Importing data into Spyder
- Creating copy of original data
- Attributes of data
- Indexing and selecting data

In this lecture



- Data types
 - Numeric
 - Character
- Checking data types of each column
- Count of unique data types
- Selecting data based on data types
- Concise summary of dataframe
- Checking format of each column
- Getting unique elements of each column

Data types



- The way information gets stored in a dataframe or a python object affects the analysis and outputs of calculations
- There are two main types of data
 - numeric and character types
- Numeric data types includes integers and floats
 - For example: integer − 10, float − 10.53
- Strings are known as objects in pandas which can store values that contain numbers and / or characters
 - For example: 'category 1'

Numeric types



Pandas and base Python uses different names for data types

Python data type	Pandas data type Description	
int	int64	Numeric characters
float	float64	Numeric characters with decimals

- '64' simply refers to the memory allocated to store data in each cell which effectively relates to how many digits it can store in each "cell"
- 64 bits is equivalent to 8 bytes
- Allocating space ahead of time allows computers to optimize storage and processing efficiency

Character types



Difference between category & object

category

- A string variable
 consisting of only a few
 different values.
 Converting such a
 string variable to a
 categorical variable will
 save some memory
- A categorical variable takes on a limited, fixed number of possible values

object

- The column will be assigned as object data type when it has mixed types (numbers and strings). If a column contains 'nan' (blank cells), pandas will default to object datatype.
- For strings, the length is not fixed



Checking data types of each column

dtypes returns a series with the data type of each column

Syntax: DataFrame.dtypes

cars_data1.dtypes

Out[**37**]: Price int64 Age float64 object KΜ FuelType object object HP MetColor float64 Automatic int64 int64 CC object Doors Weight int64 dtype: object



Count of unique data types

get_dtype_counts() returns counts of
unique data types in the dataframe

```
Syntax: DataFrame.get_dtype_counts()
```

```
cars_data1.get_dtype_counts()
```

```
Out[38]:
float64 2
int64 4
object 4
dtype: int64
```



Selecting data based on data types

pandas.DataFrame.select_dtypes() returns a
subset of the columns from dataframe based on the column
dtypes

```
Syntax: DataFrame.select_dtypes(include=None,
exclude=None)
```

cars_data1.select_dtypes(exclude=[object])

Out[39]:							
	Price	Age	MetColor	Automatic	CC	Weight	
0	13500	23.0	1.0	0	2000	1165	
1	13750	23.0	1.0	0	2000	1165	
2	13950	24.0	NaN	0	2000	1165	
3	14950	26.0	0.0	0	2000	1165	
4	13750	30.0	0.0	0	2000	1170	



Concise summary of dataframe

info() returns a concise summary of a

dataframe

- data type of index
- data type of columns
- count of non-null values
- memory usage

```
Syntax: DataFrame.info()
```

```
cars_data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1436 entries, 0 to 1435
Data columns (total 10 columns):
Price
            1436 non-null int64
Age
            1336 non-null float64
            1436 non-null object
KM
FuelType
            1336 non-null object
           1436 non-null object
MetColor
           1286 non-null float64
Automatic
           1436 non-null int64
            1436 non-null int64
CC
            1436 non-null object
Doors
Weight
            1436 non-null int64
dtypes: float64(2), int64(4), object(4)
memory usage: 163.4+ KB
```

Checking format of each column



By using info(), we can see

- 'KM' has been read as object instead of integer
- 'HP' has been read as object instead of integer
- 'MetColor' and 'Automatic' have been read as float64 and int64 respectively since it has values 0/1
- Ideally, 'Doors' should've been read as int64 since it has values 2, 3, 4, 5. But it has been read as object
- Missing values present in few variables

Let's encounter the reason!



Unique elements of columns

unique() is used to find the unique
elements of a column

```
Syntax: numpy.unique(array)
print(np.unique(cars_data1['KM']))
['1' '10000' '100123' ... '99865' '99971' '??']
```

- 'KM' has special character to it '??'
- Hence, it has been read as object instead of int64

Unique elements of columns



```
Variable 'HP':
print(np.unique(cars_data1['HP']))

['107' '110' '116' '192' '69' '71' '72'
'73' '86' '90' '97' '98' '????']
```

- 'HP' has special character to it '????'
- Hence, it has been read as object instead of int64

```
Variable 'MetColor':
print(np.unique(cars_data1['MetColor']))
```

- 'MetColor' have been read as float64 since it has values 0. & 1.

Unique elements of columns



```
Variable 'Automatic':

print(np.unique(cars_data1['Automatic']))
[0 1]
```

'Automatic' has been read as int64 since it has values 0 & 1

```
Variable 'Doors':
```

```
print(np.unique(cars_data1['Doors']))
['2' '3' '4' '5' 'five' 'four' 'three']
```

• 'Doors' has been read as object instead of int64 because of values 'five' 'four' 'three' which are strings

Summary



- Data types
 - Numeric
 - Character
- Checked data types of each column
- Count of unique data types
- Selected data based on data types
- Concise summary of dataframe
- Checked format of each column
- Got unique elements of each column

```
peration == "MIRROR_X":
              . r or _object
mirror_mod.use_x = True
mirror_mod.use_y = False
mirror_mod.use_z = False
 _operation == "MIRROR_Y"|
irror_mod.use_x = False
lrror_mod.use_y = True
 mirror_mod.use_z = False
  operation == "MIRROR_Z":
  rror_mod.use_x = False
  rror mod.use y = False
  Irror mod.use z = True
   ob.select= 1
   er ob.select=1
   ntext.scene.objects.active
  "Selected" + str(modifier
   ata.objects[one.name].sel
  Int("please select exaction
```

THANK YOU