## **Data Preprocessing**

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Overview ML Basics Load Dataset Data Preprocessing Data Preprocessing Steps Feature Scaling Summary

#### Overview

- Basics of Machine Learning
- Load Dataset
- Need for Data Preprocessing
- Objectives of Data Preprocessing
- Data Preprocessing Steps
- Need for Feature Scaling
- Summary

# **Basics of Machine Learning**

Overview ML Basics Load Dataset Data Preprocessing Data Preprocessing Steps Feature Scaling Summary

## Sample Bike Dataset

#### Features / Attributes

### **Dataset**

/												
Sampl	Bike e	Length (in mm)	Width (in mm)	Height (in mm)	Wheel Base (in mm)	Ground Clearance (in mm)	Fuel Tank Capacity (in L)	Price (in Rs)	Value for Price			
	Honda <mark>c</mark> Activa	1814	704	1151	1260	155	5.3	78,000	Yes			
	Yamahas Fascino	1820	675	1120	1270	130	5.2	85,000	Yes			
	Hero <mark>s</mark> Maestro	1841	695	1190	1261	155	5.2	70,000	No			
	Suzuki <mark>s</mark> Access	1870	655	1160	1265	160	5.6	65,000	Yes			
	TVS <mark>K</mark> Jupiter	1834	650	1115	1275	150	5.6	78,000	No			
	TVS <mark>K</mark> Scooty	1834	650	1115	1230	135	5	55,000	No			

Target

## **Load Dataset**

Overview

#### Numpy

- ✓ Arrays & Matrices
- ✓ Used for scientific computing

$$A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}$$

#### Pandas

✓ Used for data manipulation and analysis

Х	Y	Z
1	1	1.2
2	4	2.2
4	16	3.1

 Best for handling tabular datasets comprising different variable types

## Numpy vs Pandas Dataframe





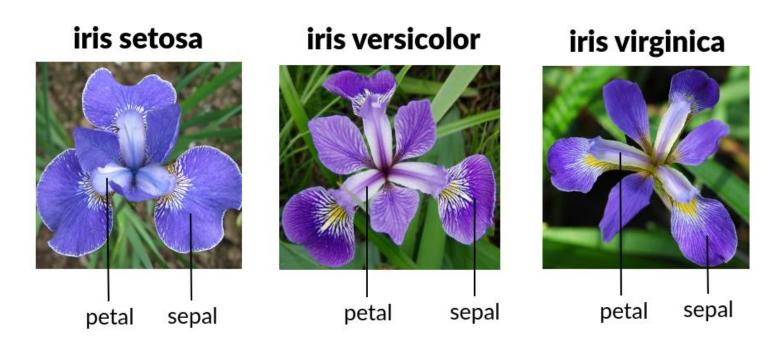
### **Built-In Datasets**

Dataset	Usage
Boston	Regression
Iris	Classification
Diabetes	Regression
Digits	Classification
Linnerud	Multivariate Regression
Wine	Classification
Breast Cancer	Classification

#### **Iris Dataset**

Overview

- Is a multivariate data set
- Consists of 50 samples from each Setosa, Virginica and Versicolor
- Length and Width of Sepals and Petals



Summary

```
'target names': array(['setosa', 'versicolor', 'virginica'], dtype='|S10'), 'feature names':
['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)'], 'data':
array([[5.1, 3.5, 1.4, 0.2],
    [4.9, 3., 1.4, 0.2],
     [4.7, 3.2, 1.3, 0.2],
    [4.6, 3.1, 1.5, 0.2],
    [5., 3.6, 1.4, 0.2],
    [5.4, 3.9, 1.7, 0.4],
    [4.6, 3.4, 1.4, 0.3],
    [5., 3.4, 1.5, 0.2],
    [4.4, 2.9, 1.4, 0.2],
    [4.9, 3.1, 1.5, 0.1],
     [5.4, 3.7, 1.5, 0.2],
     [4.8, 3.4, 1.6, 0.2],
                    [4.8, 3., 1.4, 0.1],
                        [4.3, 3., 1.1, 0.1],
                        [5.8, 4., 1.2, 0.2],
                        [5.7, 4.4, 1.5, 0.4],
                        1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
                        [5.4, 3.9, 1.3, 0.4],
                        [5.1, 3.5, 1.4, 0.3],
     [5.7, 3.8, 1.7, 0.3],
     [5.1, 3.8, 1.5, 0.3],
```

#### **Load Iris Dataset**

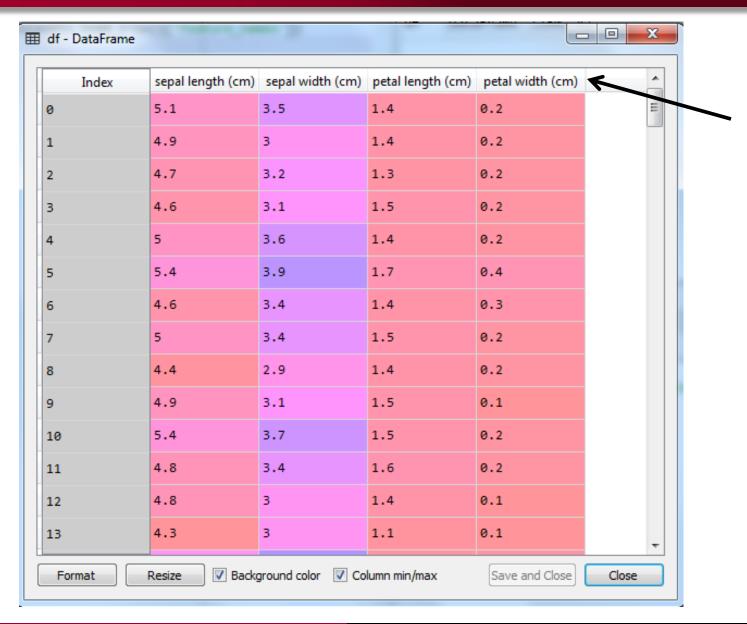
## <u>Normal</u>

from sklearn import datasets iris = datasets.load\_iris()

## **Using Pandas**

```
from sklearn import datasets
import pandas as pd
df=pd.DataFrame(datasets.load_iris()['data'],
        columns=datasets.load_iris()['feature_names'])
```

### Pandas Dataframe



**Data Preprocessing** 

#### Load Dataset from URL

Overview

```
6,148,72,35,0,33.6,0.627,50,1
1,85,66,29,0,26.6,0.351,31,0
8,183,64,0,0,23.3,0.672,32,1
1,89,66,23,94,28.1,0.167,21,0
0,137,40,35,168,43.1,2.288,33,1
5,116,74,0,0,25.6,0.201,30,0
3,78,50,32,88,31.0,0.248,26,1
10,115,0,0,0,35.3,0.134,29,0
2,197,70,45,543,30.5,0.158,53,1
8,125,96,0,0,0.0,0.232,54,1
4,110,92,0,0,37.6,0.191,30,0
10,168,74,0,0,38.0,0.537,34,1
10,139,80,0,0,27.1,1.441,57,0
1,189,60,23,846,30.1,0.398,59,1
5,166,72,19,175,25.8,0.587,51,1
7,100,0,0,0,30.0,0.484,32,1
0,118,84,47,230,45.8,0.551,31,1
7,107,74,0,0,29.6,0.254,31,1
1,103,30,38,83,43.3,0.183,33,0
1,115,70,30,96,34.6,0.529,32,1
3,126,88,41,235,39.3,0.704,27,0
8,99,84,0,0,35.4,0.388,50,0
7,196,90,0,0,39.8,0.451,41,1
9,119,80,35,0,29.0,0.263,29,1
11,143,94,33,146,36.6,0.254,51,1
10,125,70,26,115,31.1,0.205,41,1
7,147,76,0,0,39.4,0.257,43,1
1,97,66,15,140,23.2,0.487,22,0
```

```
import numpy as np
import urllib
url =
https://raw.githubusercontent.com/j
brownlee/Datasets/master/pima-
indians-diabetes.data.csv
raw_data = urllib.urlopen(url)
dataset = np.loadtxt(raw_data,
delimiter=",")
X = dataset[:,0:7]
y = dataset[:,8]
```

#### Load Dataset from File

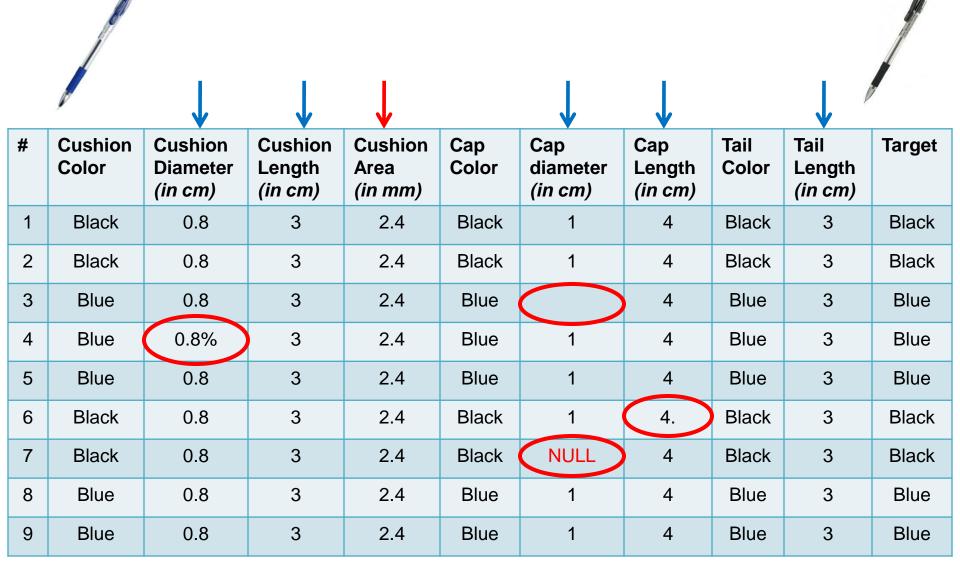
4	Α	В	С	D	Е	F	G	Н
1	Car;MPG;0	Cylinders;(	Displaceme	nt;Horsep	ower;Weig	tht;Acceler	ation;Mod	el;Origin
2	STRING;D	OUBLE;INT	;DOUBLE;D	OUBLE;DO	UBLE;DOU	BLE;INT;CA	Т	
3	Chevrolet	Chevelle	Malibu;18.0	0;8;307.0;1	30.0;3504.;	12.0;70;US		
4	Buick Skyl	ark 320;15	.0;8;350.0;1	.65.0;3693.;	;11.5;70;US	,		
5	Plymouth	Satellite;	18.0;8;318.0	;150.0;343	6.;11.0;70;	JS		
6	AMC Rebe	el SST;16.0	;8;304.0;150	0.0;3433.;12	2.0;70;US			
7	Ford Torin	0;17.0;8;3	02.0;140.0;	3449.;10.5;	70;US			
8	Ford Galax	kie 500;15.	0;8;429.0;1	98.0;4341.;	10.0;70;US			
9	Chevrolet	Impala;14	.0;8;454.0;2	220.0;4354.	;9.0;70;US			
10	Plymouth	Fury iii;14	.0;8;440.0;2	215.0;4312.	;8.5;70;US			
11	Pontiac Ca	atalina;14.	0;8;455.0;22	25.0;4425.;	10.0;70;US			
12	AMC Amb	assador Di	PL;15.0;8;39	0.0;190.0;3	3850.;8.5;70	O;US		
13	Citroen DS	S-21 Pallas	;0;4;133.0;1	15.0;3090.	;17.5;70;Eu	rope		
14	Chevrolet	Chevelle	Concours (	sw);0;8;350	0.0;165.0;41	142.;11.5;70	);US	
15	Ford Torin	o (sw);0;8	;351.0;153.	0;4034.;11.	0;70;US			
16	Plymouth	Satellite (	sw);0;8;383	3.0;175.0;41	166.;10.5;70	O;US		
17	AMC Rebe	el SST (sw)	;0;8;360.0;1	75.0;3850.;	;11.0;70;US			
18	Dodge Cha	allenger SI	E;15.0;8;383	3.0;170.0;35	63.;10.0;70	O;US		
19	Plymouth	'Cuda 340	14.0;8;340.	0;160.0;360	09.;8.0;70;l	JS		
20	Ford Must	ang Boss 3	02;0;8;302.	0;140.0;33	53.;8.0;70;l	JS		
21	Chevrolet	Monte Ca	rlo;15.0;8;4	00.0;150.0	3761.;9.5;7	70;US		
22	Buick Esta	te Wagon	(sw);14.0;8	;455.0;225.	0;3086.;10	.0;70;US		
23	Toyota Co	rolla Mark	ii;24.0;4;11	13.0;95.00;2	2372.;15.0;	70;Japan		
24	Plymouth	Duster;22	.0;6;198.0;9	5.00;2833.;	:15.5;70;US			
25	AMC Horn	et;18.0;6;1	199.0;97.00;	2774.;15.5	;70;US			
26	Ford Mave	erick;21.0;	5;200.0;85.0	0;2587.;16	.0;70;US			
27	Datsun PL	510;27.0;4	97.00;88.00	);2130.;14.5	5;70;Japan			
28	Volkswage	en 1131 De	luxe Sedar	1;26.0;4;97	.00;46.00;1	835.;20.5;7	0;Europe	

import pandas as pd
dataset =
pd.read\_csv('C:\Users\bala\
Desktop\cars.csv',
delimiter=";")

# Data Preprocessing

## Need for Data Preprocessing

Overview



## Objectives of Data Preprocessing

Format the data to make it suitable for running ML algorithms

Clean the data to remove incomplete variables

 Sample the data further to reduce running times for algorithms and memory requirements

## Data Preprocessing Steps

Preliminary Steps

Overview

- ✓ Drop duplicate rows
- ✓ Drop columns with only-one/less unique values
- Intermediate Steps
  - ✓ Drop columns with NULL values
  - ✓ Drop rows with NULL values
  - ✓ Drop redundant columns
  - ✓ Find target column
- Advanced Steps
  - ✓ Handle missing values
  - ✓ Investigate categorical columns
- More Advanced Step
  - √ Feature scaling

Summary

Overview

## Commands for Data Preprocessing

#### Step 1: Find & Drop Duplicate Rows

```
print(any(loans_2007_repeated['id'].duplicated()))
loans_2007_repeated.drop_duplicates(subset=['id'], keep='first')
```

#### Step 2: No. of NULL

```
row_NULL = loans_2007.isnull().sum(axis = 1)
column_NULL = loans_2007.isnull().sum(axis = 0)
```

#### Step 3: Drop Columns

```
half_count = len(loans_2007) / 2
loans_2007 = loans_2007.dropna(thresh=half_count, axis=1)
loans_2007 = loans_2007.drop(['url', 'desc'], axis=1)
```

## Commands for Data Preprocessing

#### Step 4: Drop Columns with Only One Value

loans\_2007.apply(pd.Series.nunique)

loans\_2007 = loans\_2007.loc[:,loans\_2007.apply(pd.Series.nunique) != 1]

#### Step 5: Drop Columns with Less Unique Values

for col in loans\_2007.columns:

if (len(loans\_2007[col].unique()) < 4):

 $loans_2007 = loans_2007.drop(col,axis=1)$ 

Sl. No.	Length	Width
1	55	50
2	55	45
3	55	25
4	55	11
5	55	25
6	55	11

## Handle Missing Values

Drop rows

Overview

Replace with default value

```
loans_2007['loan_amnt'].fillna(0, inplace=True)
```

Mean

Missing values will be displayed as NaN

"inplace = True" ->
Updates the dataframe in which you are working on

```
loans_2007['loan_amnt'].fillna(loans_2007['loan_amnt'].mean(), inplace=True)
```

Median

```
loans_2007['loan_amnt'].fillna(loans_2007['loan_amnt'].median(),
  inplace=True)
```

Mode

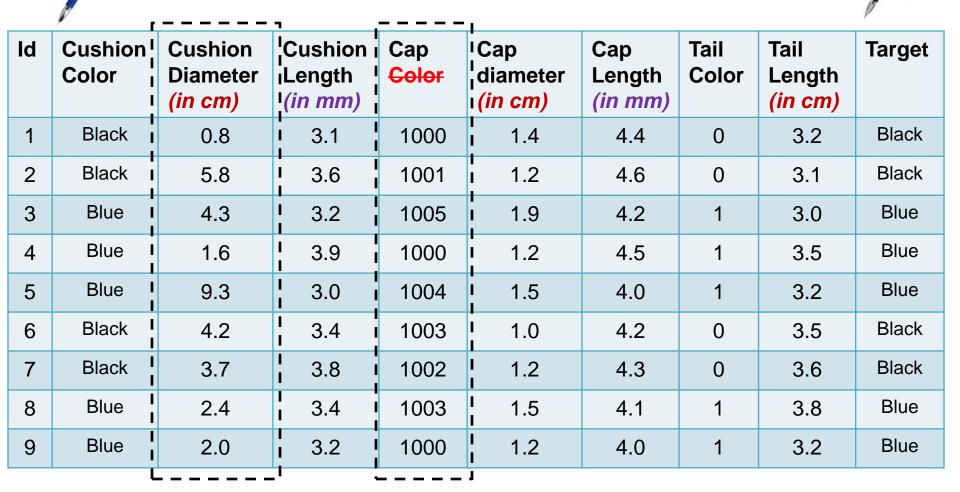
```
loans_2007['loan_amnt'].fillna(loans_2007['loan_amnt'].mode()[0], inplace=True)
```

## Handle Categorical Values

- A < B < C < D < E < F < G</li>
- mapping\_dict = {"grade":{ "A": 1, "B": 2, "C": 3, "D": 4, "E": 5, "F": 6, "G": 7 } }
- filtered\_loans = filtered\_loans.replace(mapping\_dict)

# Feature Scaling

## Need for Feature Scaling / Normalization / Standardization



Overview ML Basics Load Dataset Data Preprocessing Data Preprocessing Steps Feature Scaling Summary

## Summary

- Dataset
- Load dataset In-built, URL, File
- Need & Objectives of Preprocessing
- Preprocessing Steps
  - ✓ Drop duplicate rows
  - ✓ Drop columns with only-one/less unique values
  - ✓ Drop columns with NULL values
  - ✓ Drop rows with NULL values
  - ✓ Drop redundant columns
  - ✓ Handle missing values
  - ✓ Investigate categorical columns
  - ✓ Feature scaling

## Feature Engineering

 Process of transforming raw data into features that better represent the underlying problem to the machine learning algorithm

CITY 1 LAT.	CITY 1 LNG.	CITY 2 LAT.	CITY 2 LNG.	Driveable?		DISTANCE (MI.)	
123.24	46.71	121.33	47.34	Yes		14	
123.24	56.91	121.33	55.23	Yes	=>	28	
123.24	46.71	121.33	55.34	No		705	
123.24	46.71	130.99	47.34	No		2432	N

- Exceptionally difficult for a machine learning algorithm to learn the relationships between these four attributes and the class label
- Compute the distance between the source and destination and use it as a feature
- Results in improved model accuracy on unseen data



## Feature Engineering

- Feature engineering is when you use your knowledge about the data to create fields that make a machine learning algorithm work better
- Engineered features that enhance the training provide information that better differentiate the patterns in the data
- Should strive to add a feature that provides additional information that is not clearly captured or easily apparent in the original or existing feature set

# Feature Engineering



- Decompose Categorical Attributes
  - Item\_Color -> Red, Blue, Unknown
  - Binary Feature -> Has\_Color
  - Binary Features -> Is\_red, Is\_Blue, Is\_Unknown
- Decompose Date and Time
  - 2014-09-20T20:45:40Z
  - Numerical Feature -> Hour\_of\_Day
- Reframe Numerical Quantities
  - Transform into a new unit or the decomposition into multiple components
  - Quantity like weight, distance, timing
  - A linear transform may be useful to regression and other scale dependent

# Thank You