Agenda

Day1	**1. Fundamentals of Machine Learning: Introduction to Machine Learning and its Applications, Machine Learning Python Tools. Simple machine learning application.** **2. Data Preprocessing: Data Sets, Classic Data Sets, What is Data Preprocessing ?, Need of Data Preprocessing , Major Tasks in Data Preprocessing , Preprocessing the Data in Python : Importing Libraries , Splitting Data into Training and Testing Data, Data Preprocessing Steps: Importing the useful packages , Defining Sample Data , Applying Preprocessing Techniques like Scaling , Standardization , Normalization , Mean Removal and Labelling the Data**
Day2	**1. Types of Machine Learning Algorithms** **2. Bayesian Learning: Bayes Theorem and Concept Learning, ML and LS error Hypothesis, Naïve Bayes Classifier, Bayesian belief networks, EM Algorithm**
Day 3	**1. Instance Based Learning: Introduction, K-nearest neighbor learning, locally weighted regression, radial basis function, cased based reasoning.** **2. Reinforced Learning: Introduction, Learning Task, Q Learning**

Day 1

1. Fundamentals of Machine Learning
2. Data Preprocessing

1.Fundamentals of Machine Learning

a) **Why Machine Learning**
b) **What is Machine Learning ?**
c) **How Does ML Works**
d) **ML Applications**
e) **ML Use Cases**
f) **Understanding ML using Analogy**
g) **AI , ML and DL**
h) **Machine Learning Python Tools.**
i) **Simple machine learning application.**

Why Machine Learning ?

a. Why Machine Learning ?

Navigation on Mars or Deep ocean
Where no humans are present

a. Why Machine Learning ?

Analyzing huge sensor data and predicting the outcome eg: in Forecasting Systems is not possible by manual calculations

Recommending a product to buyers e.g. used by amazon , flipkart , Snapdeal etc., is not possible by manual calculations

Purchase History of a Customer

Search list of a Customer

a. Why Machine Learning ?

b. What is Machine Learning ?

b. What is Machine Learning ?

- **Is a type of Artificial Intelligence that provides computers with the ability to learn without being explicitly programmed.**
- Machine Learning is a concept which allows the ***machine to learn from examples and experience***, and that too without being explicitly programmed.
  - So instead of you writing the code, ***what you do is you feed data to the generic algorithm***, and the algorithm/ machine builds the logic based on the given data.
- ML enables ***the computers or the machines to make data-driven decisions rather than being explicitly programmed for carrying out a certain task***. These programs or algorithms are designed in a way that they learn and improve over time when are exposed to new data.

b. What is Machine Learning?

- Have you ever shopped online? So while checking for a product, did you noticed ***when it recommends for a product similar to what you are looking for***? or did you noticed "***the person bought this product also bought this***" combination of products. How are they doing this recommendation? **This is machine learning**.
- Did you ever get a call from any bank or finance company ***asking you to take a loan or an insurance policy***? What do you think, do they call everyone? ***No, they call only a few selected customers who they think will purchase their product. How do they select***? This is target marketing and can be applied using Clustering. **This is machine learning.**


Frequently bought together
Total price: ₹792.00
Add both to Cart
Customers who bought this item also bought
Sponsored products related to this item (What's this?)
NTSE (National Talent Search Examination) Study Guide
TCY Online
1
Paperback
₹ 565.00
Mental Ability for NTSE & Olympiad Exams for Class 10 (Quick Start for Class 6, 7, ...
Disha Experts
Paperback
₹ 276.00 prime
NTSE – National Talent Search Examination with CD: Top Guide , with Fully Solved P...
Jaya Ghosh
2
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₹ 467.00 prime
Pearson IIT Foundation Physics Class 10
Trishna
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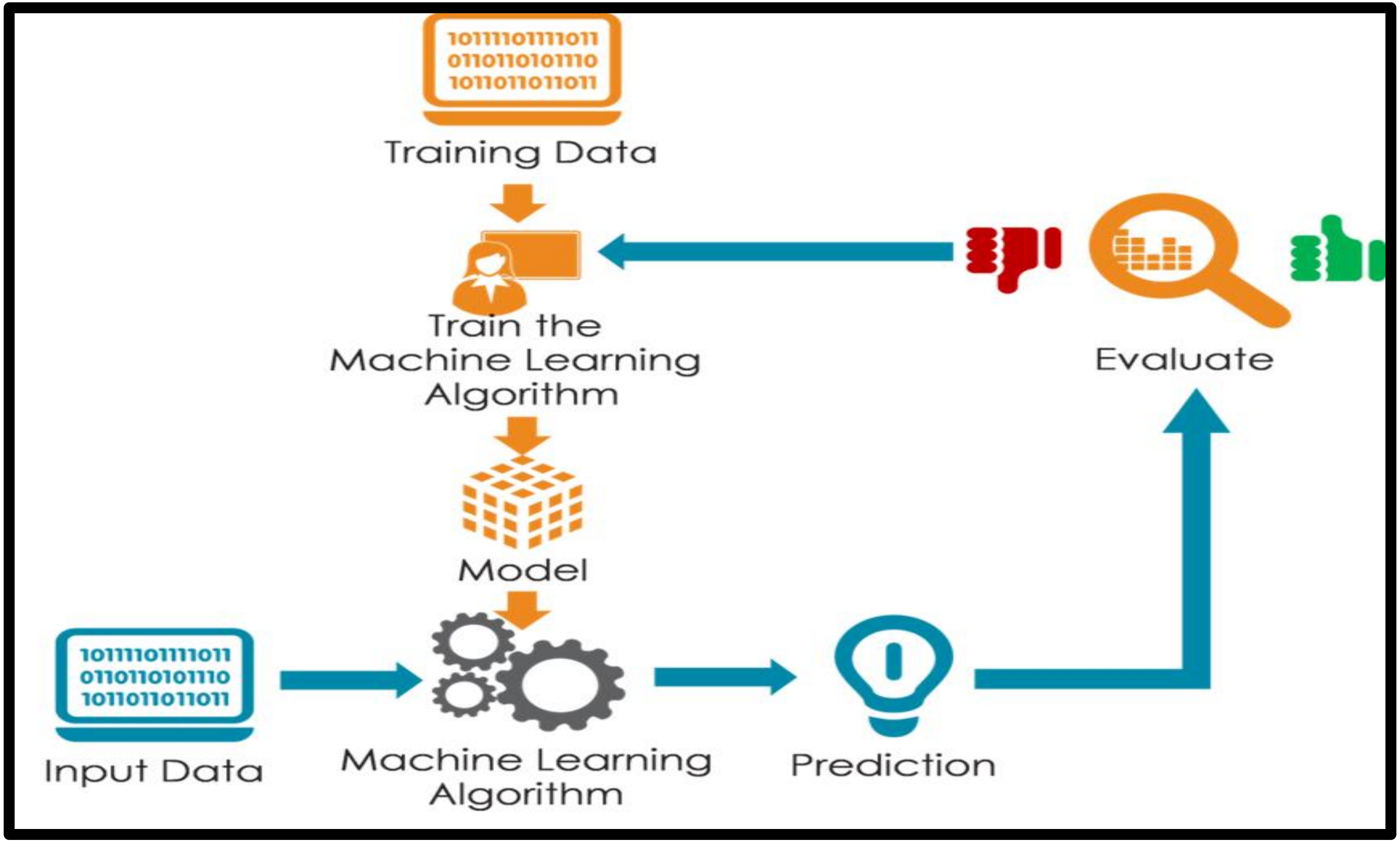
Paperback
₹ 329.00 prime
Customers who viewed this item also viewed
Study Package For NTSE Class X
Mc graw hill
197
Paperback
₹ 770.00 prime
MEGA Study Guide for NTSE (SAT, MAT & LCT) Class 10 Stage 1 & 2
› Disha Experts
6
Paperback
₹ 535.00 prime
NTSE Explorer
Sonia Lal
30
Paperback
₹ 618.00 prime

c. How does Machine Learning Works ?

c. How does Machine Learning Work?

- Machine Learning algorithm is trained using a training data set to create a model. ***When new input data is introduced to the ML algorithm, it makes a prediction on the basis of the mode***l.
- The prediction is evaluated for accuracy and if the accuracy is acceptable, the Machine Learning algorithm is deployed. ***If the accuracy is not acceptable, the Machine Learning algorithm is trained again and again with an augmented training data set.***
- This is just a very high-level example as there are many factors and other steps involved.

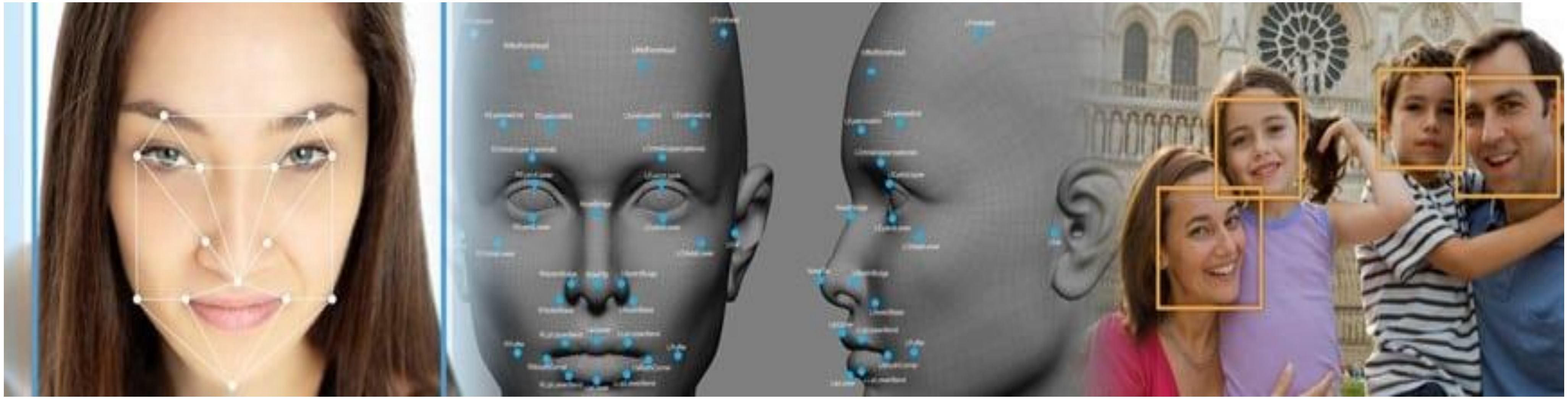

101111011111011
011011010101110
101101101011011
Training Data
Train the
Machine Learning
Algorithm
Evaluate
Model
101111011111011
011011010101110
101101101011011
Input Data
Machine Learning
Algorithm
Prediction

d. Machine Learning Applications

- **Virtual Personal Assistants**
- **Videos Surveillance**
- **Social Media Services**
- **Email Spam and Malware Filtering**
- **Online Customer Support**
- **Search Engine Result Refining**
- **Product Recommendations**
- **Online Fraud Detection**

d. Machine Learning Use Cases

Face Detection.



Hi. I'm Cortana.

Ask me a question!

Cortana or any speech automated system in your mobile phone trains your voice and then starts working based on this training.


Dynamic pricing
Predicting flight delay
01
TRAVEL
Upselling
Cross selling
Predicting lifetime valueof customer
02
MARKETING
Churn
Sentiment analysis
Digital marketing
04
SOCIAL MEDIA
Disease prediction
Medication effectiveness
03
HEALTHCARE
Discount offering
Demand forecasting
05
SALES
Self driving cars
06
AUTOMATION
Pilotless aircrafts, drones
Claims prediction
07
CREDIT & INSURANCE
Fraud & risk detection

e. Understanding Machine Learning with an Analogy

- **As a Human:** Let's suppose one day you went for shopping mangoes. The vendor had a cart full of mangoes from where you could handpick the mangoes, get them weighed and pay according to the rate fixed per Kg.
- **Task: How will you choose the best mangoes?**

Set of learning,

- Given below is set of learning, human gains from his experience of shopping mangoes, you can drill it down to have a further look at it in detail. Go through it once, you will relate it to machine learning very easily.

  - Learning 1: Bright yellow mangoes are sweeter than pale yellow ones
  - Learning 2: The smaller and bright yellow mangoes are sweet only half the time
  - Learning 3: Small, pale yellow ones are the sweetest of all
  - Learning 4: Soft mangoes are jucier
  - Learning 5: Green mangoes are tastier than yellow ones
  - Learning 6: You don't need mangoes anymore

Learning 1

- **Experience 1:**
- You were informed that bright and yellow mangoes are sweeter than pale and yellow ones.
- So you make a simple **rule: pick only from the bright yellow mangoes.** You check the colour of the mangoes, pick the bright yellow ones, pay up, and return home. Right?

Learning2

- **Experience 2:**
- Now when you went home and tasted the mangoes, some of them were not sweet as you thought. You are worried as your wisdom was insufficient. You concluded that when it comes shopping mangoes, you have to look for more than just the colours.
- After a lot of pondering and tasting different types of mangoes,**you concluded that** the *bigger and bright yellow mangoes are guaranteed to be sweet,* while the *smaller, bright yellow mangoes* are sweet only half the time (i.e. if you bought 100 bright yellow mangoes (50 will be big in size and rest 50 will be small), then the 50 big mangoes will all be sweet, while out of the 50 small ones, only 25 mangoes will turn out to be sweet). You will then update your rule about the mango shopping and from next time you will keep this in mind.

Learning 3

- **Experience 3:** ***Tragedy:*** *Next time at the market, you see that your favorite vendor has gone out of town. You decide to buy from a different vendor, who supplies mangoes grown from a different part of the country. Now, you realize that the rule which you had learnt (that big, bright yellow mangoes are the sweetest) is no longer applicable. You have to learn from scratch. You taste a mango of each kind from this vendor and realize that the small, pale yellow ones are in fact the sweetest of all.*

Learning 4

- **Experience 4:** *One day your cousin visits you from another city. You decide to treat her with mangoes. But she is like "I don't care about the sweetness of a mango, I only want the juiciest ones". Now once again, you run your experiments, tasting all kinds of mangoes, and realizing that the softer ones are juicier.*

Learning 5

- **Experience 5:** *Later on, you move to a different part of the world and you found that the mangoes here taste surprisingly different from your home country. You realized that for this country the* ***green mangoes*** *are tastier than the yellow ones.*

Learning 6

- **Experience 6:** *You marry someone who hates mangoes but loves apples instead. Now you go for shopping oranges instead of mangoes. Now, all your accumulated knowledge about mangoes is worthless. Now you have to learn everything about the correlation between the physical characteristics and the taste of apples, by the same method of experimentation.*

Training and Testing Phase

- Machine Learning algorithms are an evolution of normal algorithms. They make your programs **“smarter”,** by allowing them to automatically learn from the data you provide. The algorithm is mainly divided into:
  - **Training Phase**
  - **Testing phase**

Training Phase

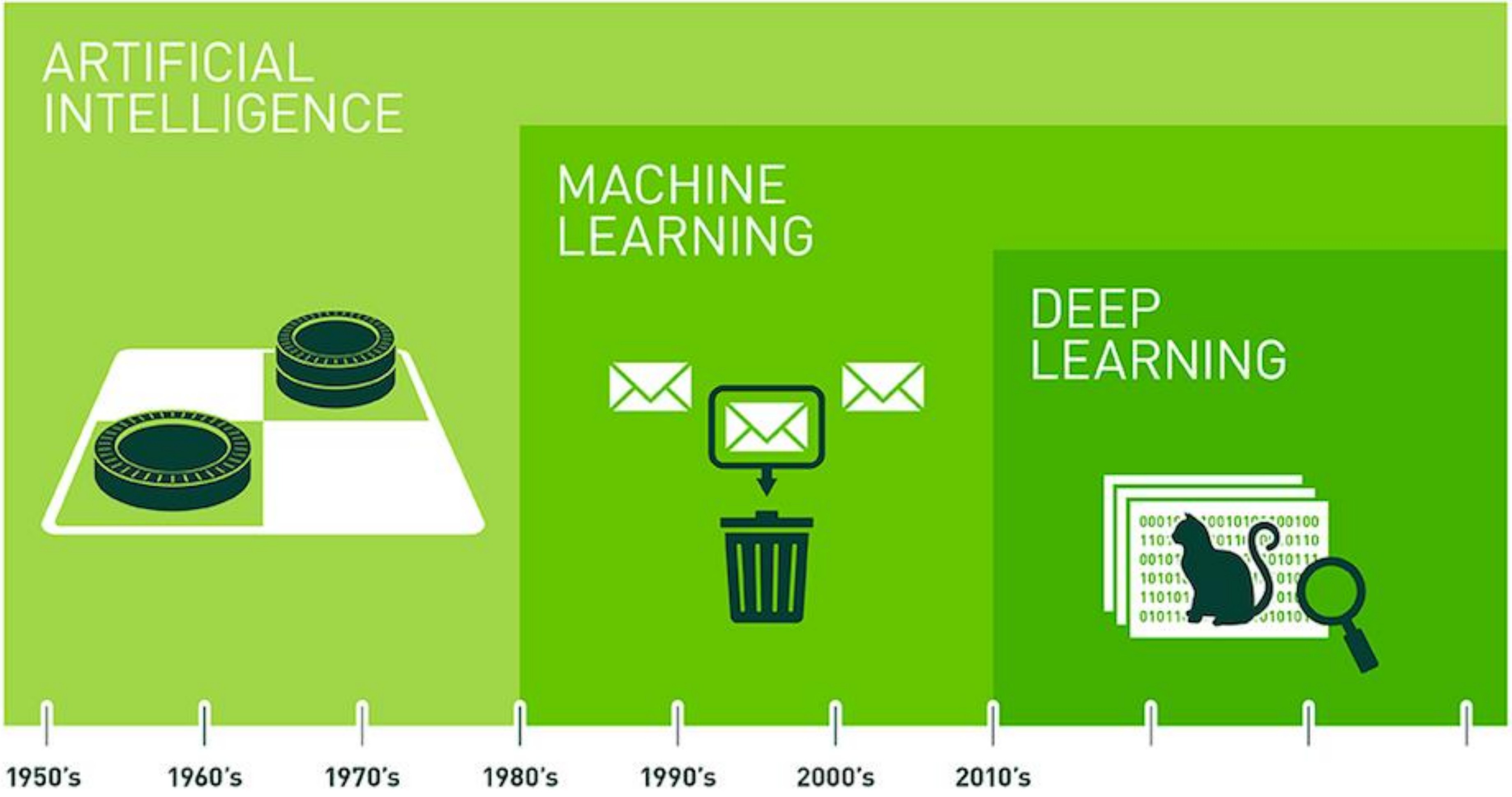
- You take a randomly selected specimen of mangoes from the market (**training data**), make a table of all the physical characteristics of each *mango, like color, size, shape, grown in which part of the country, sold by which vendor, etc (**features**), along with the sweetness, juiciness, ripeness of that mango (**output variables**)*.
- You feed this data to the machine learning algorithm (**classification/regression**), and it learns a model of the correlation between an average mango's physical characteristics, and its quality.

	**Color**	**Size**	**Location**	**Vendor**	**Sweetness**	**Juiciness**
Exp1	Bright Yellow	Any	local	known	Few	
Exp2	Bright Yellow	Bigger	local	Known	100 % Sweet	
	Bright Yellow	Smaller	local	known	50% Sweet	
Exp3	Pale Yellow	Smaller	local	unknown	Sweetest	
Exp4	Soft					Jucy
Exp5	Green	Any	Foreign	unknown	Sweetest	
Exp6	Repeat the learning process for Apple					

Testing Phase

- Next time when you go shopping, you will measure the characteristics of the mangoes which you are purchasing(**test data**)and feed it to the Machine Learning algorithm.
- It will use the model which was computed earlier ***to predict if the mangoes are sweet, ripe and/or juicy***.
- Finally, you can now shop for mangoes with great confidence, without worrying about the details of how to choose the best mangoes.

f. AI , ML and DL



ARTIFICIAL
INTELLIGENCE
MACHINE
LEARNING
DEEP
LEARNING
1950's
1960's
1970's
1980's
1990's
2000's
2010's

g. Open Source Machine Learning Tools

Open Source Tools

1. Scikit Learn
2. Shogun
3. Accord.NET Framework
4. Spark MLlib
5. H20
6. Coudera Oryx
7. GoLearn
8. Weka
9. Deep Learn.js
10. ConvNet.Js
11. OpenAI
12. TensorFlow
13. Keras
14. Charnn
15. Paddle
16. CNTK
17. R
18. Monte Carlo ML Library
19. Octave Forge

Commercial Tools

1. Microsoft Azure Machine Learning
2. SAS Enterprise Miner
3. IBM SPSS Modeler
4. RapidMiner
5. Apache Mahout
6. MATLAB
7. Oracle Data Mining

Steps involved in machine learning

1. Collecting Data
2. Cleaning Data
3. Analyze Data
4. Build Model
5. Train the Algorithm
6. Test the Algorithm
7. Use it

i. Simple Machine Learning Application

Training data

Features

Weight	Texture	Label
150g	Bumpy	Orange
170g	Bumpy	Orange
140g	Smooth	Apple
130g	Smooth	Apple
...	...	...

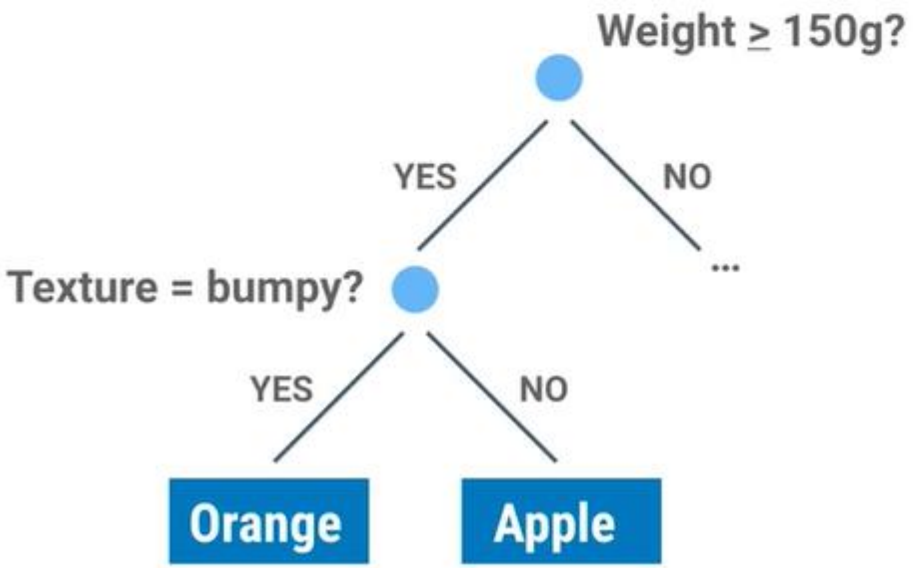
Supervised Learning Recipe

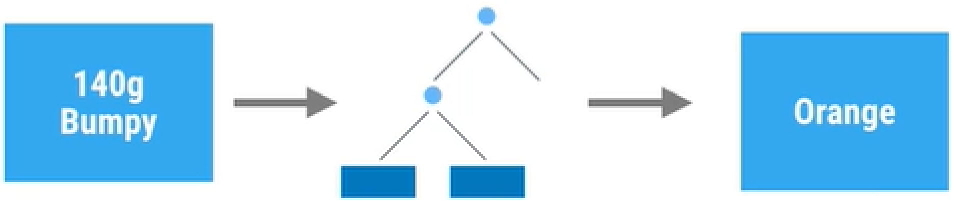
Training data

Features

Weight	Texture	Label
150g	Bumpy	Orange
170g	Bumpy	Orange
140g	Smooth	Apple
130g	Smooth	Apple
...	...	...

Decision Tree





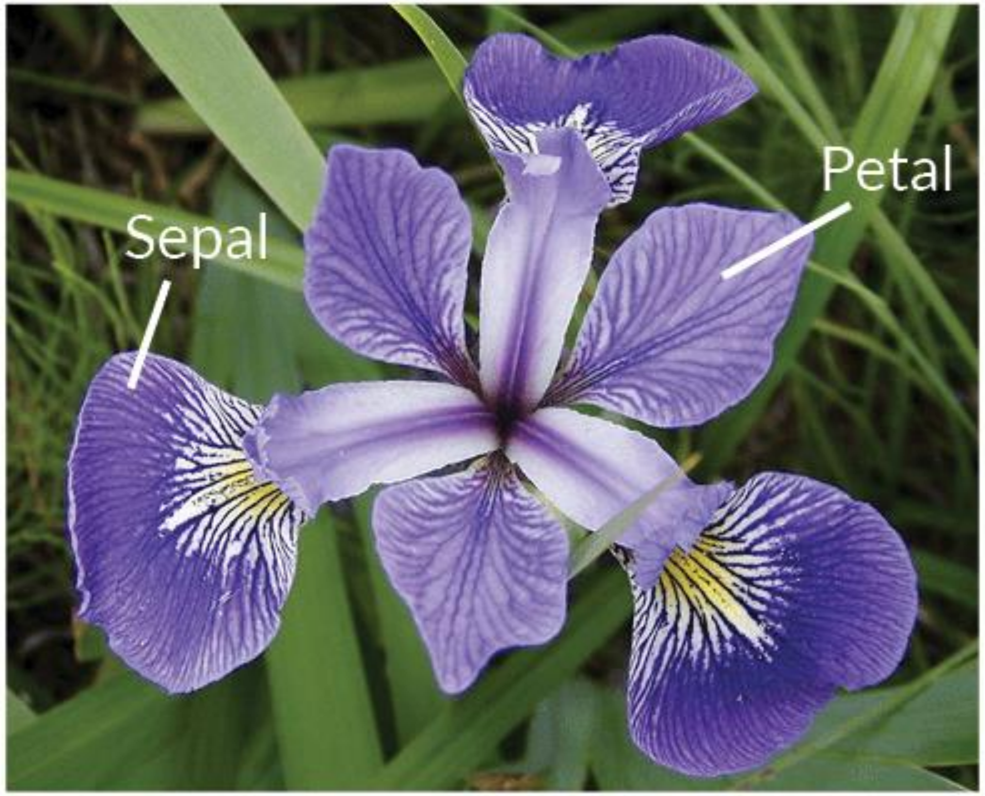
Hands On

End of Day1 Part1

2 .Data Preprocessing

Data Sets

- A **data set** (or **dataset**) is a collection of data/examples/experiences in the from of database table or data matrix.
- Column represents attributes/ target attributes .
- Row corresponds to a given member of the data set in question (each experience or examples)
- Each value is known as a **datum**.



Iris Versicolor

Iris Setosa

Iris Virginica

Target Attribute

Attributes

sepal_length	sepal_width	petal_length	petal_width	Iris_class
5	2	3.5	1	versicolor
6	2.2	4	1	versicolor
6.2	2.2	4.5	1.5	versicolor
6	2.2	5	1.5	virginica
4.5	2.3	1.3	0.3	setosa
5.5	2.3	4	1.3	versicolor
6.3	2.3	4.4	1.3	versicolor
5	2.3	3.3	1	versicolor
4.9	2.4	3.3	1	versicolor
5.5	2.4	3.8	1.1	versicolor
5.5	2.4	3.7	1	versicolor
5.6	2.5	3.9	1.1	versicolor
6.3	2.5	4.9	1.5	versicolor
5.5	2.5	4	1.3	versicolor
5.1	2.5	3	1.1	versicolor
4.9	2.5	4.5	1.7	virginica
6.7	2.5	5.8	1.8	virginica
5.7	2.5	5	2	virginica
6.3	2.5	5	1.9	virginica
5.7	2.6	3.5	1	versicolor
5.5	2.6	4.4	1.2	versicolor
5.8	2.6	4	1.2	versicolor

Data point /example

Numerical value

Categorical value

Predictors/Attributes

Target

Outlook	Temperature	Humidity	Windy	Play Tennis
Overcast	Hot	High	FALSE	Yes
Overcast	Cool	Normal	TRUE	Yes
Overcast	Mild	High	TRUE	Yes
Overcast	Hot	Normal	FALSE	Yes
Rainy	Cool	Normal	FALSE	Yes
Rainy	Mild	Normal	TRUE	Yes
Rainy	Hot	High	FALSE	No
Rainy	Hot	High	TRUE	No
Rainy	Mild	High	FALSE	No
Sunny	Mild	High	FALSE	Yes
Sunny	Cool	Normal	FALSE	Yes
Sunny	Mild	Normal	FALSE	Yes
Sunny	Cool	Normal	TRUE	No
Sunny	Mild	High	TRUE	No

Weekend (Example)	Weather	Parents	Money	Decision (Category)
W1	Sunny	Yes	Rich	Cinema
W2	Sunny	No	Rich	Tennis
W3	Windy	Yes	Rich	Cinema
W4	Rainy	Yes	Poor	Cinema
W5	Rainy	No	Rich	Stay in
W6	Rainy	Yes	Poor	Cinema
W7	Windy	No	Poor	Cinema
W8	Windy	No	Rich	Shopping
W9	Windy	Yes	Rich	Cinema
W10	Sunny	No	Rich	Tennis

Features					Label
Position	Experience	Skill	Country	City	Salary ($)
Developer	0	1	USA	New York	103100
Developer	1	1	USA	New York	104900
Developer	2	1	USA	New York	106800
Developer	3	1	USA	New York	108700
Developer	4	1	USA	New York	110400
Developer	5	1	USA	New York	112300
Developer	6	1	USA	New York	114200
Developer	7	1	USA	New York	116100
Developer	8	1	USA	New York	117800
Developer	9	1	USA	New York	119700
Developer	10	1	USA	New York	121600

Classic Data Sets Examples

Example1 : IRIS Data Set

- The ***Iris* flower data set** or **Fisher's *Iris* data set** is a multivariate data set introduced by the British statistician and biologist Ronald Fisher in his 1936 paper .
- The data set consists of 50 samples from each of three species (150) of *Iris* (*Iris setosa*, *Iris virginica* and *Iris versicolor*). Four features were measured from each sample: the length and the width of the sepals and petals, in centimeters.

Iris Versicolor

Iris Setosa

Iris Virginica

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3.0	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
4	4.6	3.1	1.5	0.2	setosa
5	5.0	3.6	1.4	0.2	setosa
6	5.4	3.9	1.7	0.4	setosa
7	4.6	3.4	1.4	0.3	setosa
8	5.0	3.4	1.5	0.2	setosa
9	4.4	2.9	1.4	0.2	setosa
10	4.9	3.1	1.5	0.1	setosa
11	5.4	3.7	1.5	0.2	setosa

Example2 : MNSIT DATABASE

- The **MNIST database** (Modified National Institute of Standards and Technology database) is a large database of handwritten digits that is commonly used for training various image processing systems.
- The MNIST database contains 60,000 training images and 10,000 testing images.

Example 3: HOUSE PRICE DATA SET

- Variables in order:
- **CRIM** per capita crime rate by town
- **ZN** proportion of residential land zoned for lots over 25,000 sq.ft.
- INDUS proportion of non-retail business acres per town
- CHAS Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
- NOX nitric oxides concentration (parts per 10 million)
- RM average number of rooms per dwelling
- AGE proportion of owner-occupied units built prior to 1940
- DIS weighted distances to five Boston employment centres
- RAD index of accessibility to radial highways
- TAX full-value property-tax rate per $10,000
- PTRATIO pupil-teacher ratio by town B 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
- LSTAT % lower status of the population
- MEDV Median value of owner-occupied homes in $1000's

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98
1	0.02731	0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14
2	0.02729	0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03
3	0.03237	0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94
4	0.06905	0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.33

Example 4: Diabetes Data Set

- This dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases. The objective of the dataset is to diagnostically predict whether or not a patient has diabetes, based on certain diagnostic measurements included in the dataset. Several constraints were placed on the selection of these instances from a larger database. In particular, all patients here are females at least 21 years old of Pima Indian heritage.
- The datasets consists of several medical predictor variables and one target variable, Outcome. Predictor variables includes the number of pregnancies the patient has had, their BMI, insulin level, age, and so on

Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
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	0.248	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	0.232	54	1
4	110	92	0	0	37.6	0.191	30	0
10	168	74	0	0	38	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	0.484	32	1

Example5: Wine Data Set

This data set is the result of a chemical analysis of wines grown in the same region in Italy but derived from three different cultivars. The analysis determined the quantities of 13 constituents found in each of the three types of wines"

- **Labels**: "name" - Number denoting a specific wine class
- **Number of instances of each wine class** : Class 1 – 59 , Class 2 – 71 , Class 3 – 48 ,
- **Features:** *Alcohol , Malic acid , Ash , Alcalinity of ash , Magnesium, Total phenols , Flavanoids , Nonflavanoid phenols , Proanthocyanins , Color intensity , Hue , OD280/OD315 of diluted wines, Proline*

Example 6: Breast Cancer (Diagnostic) Data Set

- Features are computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. They describe characteristics of the cell nuclei present in the image.
- Attribute Information:
- 1) ID number 2) Diagnosis (M = malignant, B = benign)
- Ten real-valued features are computed for each cell nucleus:

  a) radius (mean of distances from center to points on the perimeter)

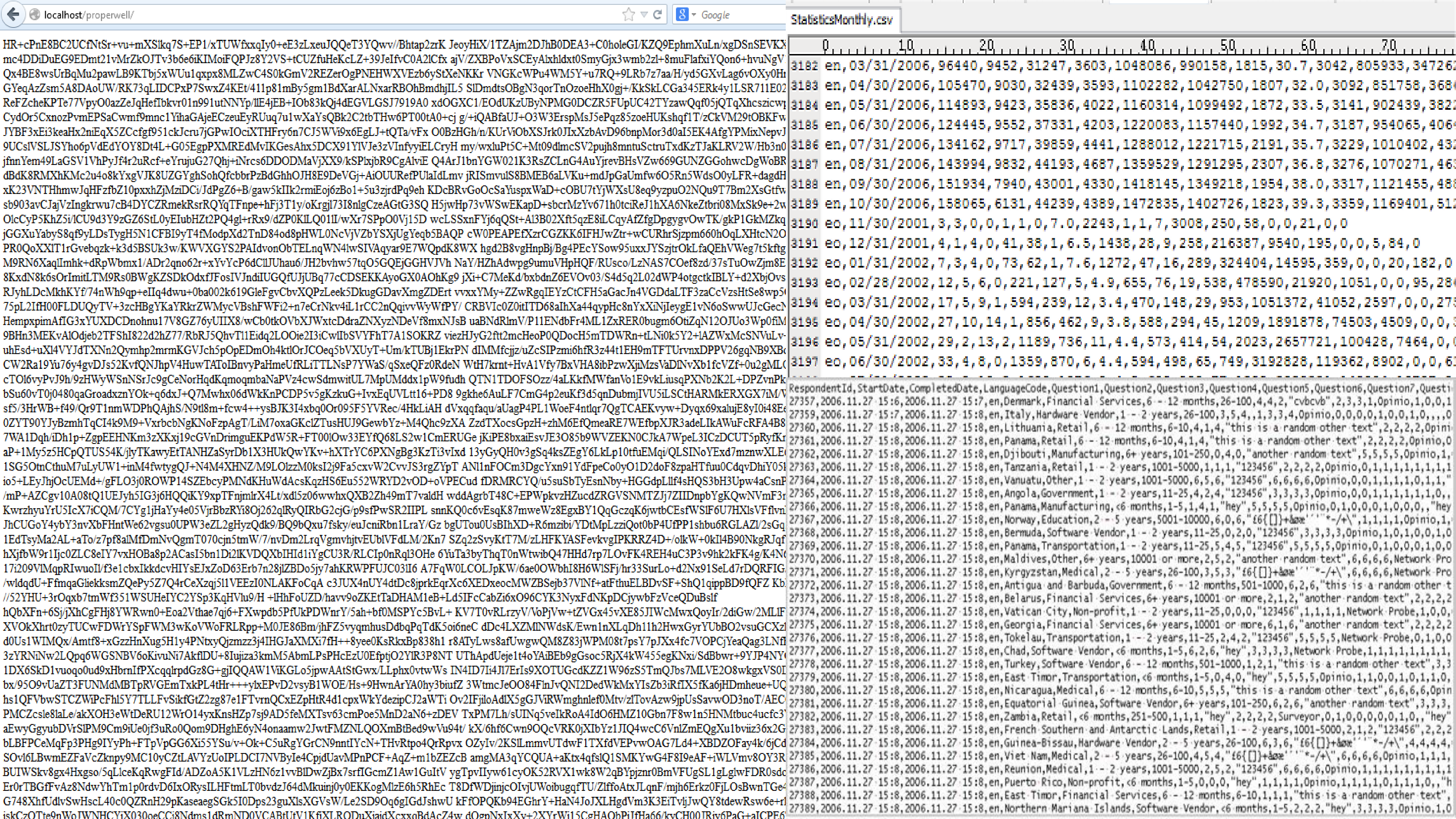
  b) texture (standard deviation of gray-scale values)

  c) perimeter **d)** area **e)** smoothness (local variation in radius lengths) **f)** compactness (perimeter^2 / area - 1.0) **g)** concavity (severity of concave portions of the contour) **h)** concave points (number of concave portions of the contour) **i)** symmetry **j)** fractal dimension ("coastline approximation" - 1)

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst radius	worst texture	worst perimeter	worst area	w s
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871	...	25.38	17.33	184.60	2019.0	0
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667	...	24.99	23.41	158.80	1956.0	0
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999	...	23.57	25.53	152.50	1709.0	0
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	0.09744	...	14.91	26.50	98.87	567.7	0
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	0.05883	...	22.54	16.67	152.20	1575.0	0

Types of Data

- Raw Data
- Structured Data
- Unstructured Data


localhost/properwell/
Google
StatisticsMonthly.csv
0 10 20 30 40 50 60 70
3182 en,03/31/2006,96440,9452,31247,3603,1048086,990158,1815,30.7,3042,805933,34726
3183 en,04/30/2006,105470,9030,32439,3593,1102282,1042750,1807,32.0,3092,851758,368
3184 en,05/31/2006,114893,9423,35836,4022,1160314,1099492,1872,33.5,3141,902439,382
3185 en,06/30/2006,124445,9552,37331,4203,1220083,1157440,1992,34.7,3187,954065,406
3186 en,07/31/2006,134162,9717,39859,4441,1288012,1221715,2191,35.7,3229,1010402,43
3187 en,08/31/2006,143994,9832,44193,4687,1359529,1291295,2307,36.8,3276,1070271,46
3188 en,09/30/2006,151934,7940,43001,4330,1418145,1349218,1954,38.0,3317,1121455,48
3189 en,10/30/2006,158065,6131,44239,4389,1472835,1402726,1823,39.3,3359,1169401,51
3190 eo,11/30/2001,3,3,0,0,1,1,0,7.0,2243,1,1,7,3008,250,58,0,0,21,0,0
3191 eo,12/31/2001,4,1,4,0,41,38,1,6.5,1438,28,9,258,216387,9540,195,0,0,5,84,0
3192 eo,01/31/2002,7,3,4,0,73,62,1,7.6,1272,47,16,289,324404,14595,359,0,0,20,182,0
3193 eo,02/28/2002,12,5,6,0,221,127,5,4.9,655,76,19,538,478590,21920,1051,0,0,95,28
3194 eo,03/31/2002,17,5,9,1,594,239,12,3.4,470,148,29,953,1051372,41052,2597,0,0,27
3195 eo,04/30/2002,27,10,14,1,856,462,9,3.8,588,294,45,1209,1891878,74503,4509,0,0,
3196 eo,05/31/2002,29,2,13,2,1189,736,11,4.4,573,414,54,2023,2657721,100428,7464,0,0
3197 eo,06/30/2002,33,4,8,0,1359,870,6,4.4,594,498,65,749,3192828,119362,8902,0,0,6
RespondentId,StartDate,CompletedDate,LanguageCode,Question1,Question2,Question3,Question4,Question5,Question6,Question7,Questi
27357,2006.11.27 15:6,2006.11.27 15:7,en,Denmark,Financial Services,6 - 12 months,26-100,4,4,2,"cvbcvb",2,3,3,1,Opinio,1,0,0,1
27359,2006.11.27 15:7,2006.11.27 15:8,en,Italy,Hardware Vendor,1 - 2 years,26-100,3,5,4,,1,3,3,4,Opinio,0,0,0,0,1,0,0,1,0,,,,0
27360,2006.11.27 15:8,2006.11.27 15:8,en,Lithuania,Retail,6 - 12 months,6-10,4,1,4,"this is a random other text",2,2,2,2,Opini
27361,2006.11.27 15:8,2006.11.27 15:8,en,Panama,Retail,6 - 12 months,6-10,4,1,4,"this is a random other text",2,2,2,2,Opinio,0
27362,2006.11.27 15:8,2006.11.27 15:8,en,Djibouti,Manufacturing,6+ years,101-250,0,4,0,"another random text",5,5,5,5,Opinio,1,
27363,2006.11.27 15:8,2006.11.27 15:8,en,Tanzania,Retail,1 - 2 years,1001-5000,1,1,1,"123456",2,2,2,2,Opinio,0,1,1,1,1,1,1,1
27364,2006.11.27 15:8,2006.11.27 15:8,en,Vanuatu,Other,1 - 2 years,1001-5000,6,5,6,"123456",6,6,6,6,Opinio,0,0,1,1,1,1,0,1,1,"
27365,2006.11.27 15:8,2006.11.27 15:8,en,Angola,Government,1 - 2 years,11-25,4,2,4,"123456",3,3,3,3,Opinio,0,0,1,1,1,1,1,0,,
27366,2006.11.27 15:8,2006.11.27 15:8,en,Panama,Manufacturing,<6 months,1-5,1,4,1,"hey",5,5,5,5,Opinio,0,1,0,0,0,1,0,0,0,,"hey
27367,2006.11.27 15:8,2006.11.27 15:8,en,Norway,Education,2 - 5 years,5001-10000,6,0,6,"£6{[]}+åøæ'´'¨*-/+\",1,1,1,1,Opinio,1,
27368,2006.11.27 15:8,2006.11.27 15:8,en,Bermuda,Software Vendor,1 - 2 years,11-25,0,2,0,"123456",3,3,3,3,Opinio,1,0,1,0,0,1,0
27369,2006.11.27 15:8,2006.11.27 15:8,en,Panama,Transportation,1 - 2 years,11-25,5,4,5,"123456",5,5,5,5,Opinio,0,1,0,0,0,1,0,0
27370,2006.11.27 15:8,2006.11.27 15:8,en,Maldives,Other,6+ years,10001 or more,2,5,2,"another random text",6,6,6,6,Network Pro
27371,2006.11.27 15:8,2006.11.27 15:8,en,Kyrgyzstan,Medical,2 - 5 years,26-100,3,5,3,"£6{[]}+åøæ'´'¨*-/+\",6,6,6,6,Network Pro
27372,2006.11.27 15:8,2006.11.27 15:8,en,Antigua and Barbuda,Government,6 - 12 months,501-1000,6,2,6,"this is a random other t
27373,2006.11.27 15:8,2006.11.27 15:8,en,Belarus,Financial Services,6+ years,10001 or more,2,1,2,"another random text",2,2,2,2
27374,2006.11.27 15:8,2006.11.27 15:8,en,Vatican City,Non-profit,1 - 2 years,11-25,0,0,0,"123456",1,1,1,1,Network Probe,1,0,0,
27375,2006.11.27 15:8,2006.11.27 15:8,en,Georgia,Financial Services,6+ years,10001 or more,6,1,6,"another random text",2,2,2,2
27376,2006.11.27 15:8,2006.11.27 15:8,en,Tokelau,Transportation,1 - 2 years,11-25,2,4,2,"123456",5,5,5,5,Network Probe,0,1,0,0
27377,2006.11.27 15:8,2006.11.27 15:8,en,Chad,Software Vendor,<6 months,1-5,6,2,6,"hey",3,3,3,3,Network Probe,1,1,1,1,1,1,1,1,
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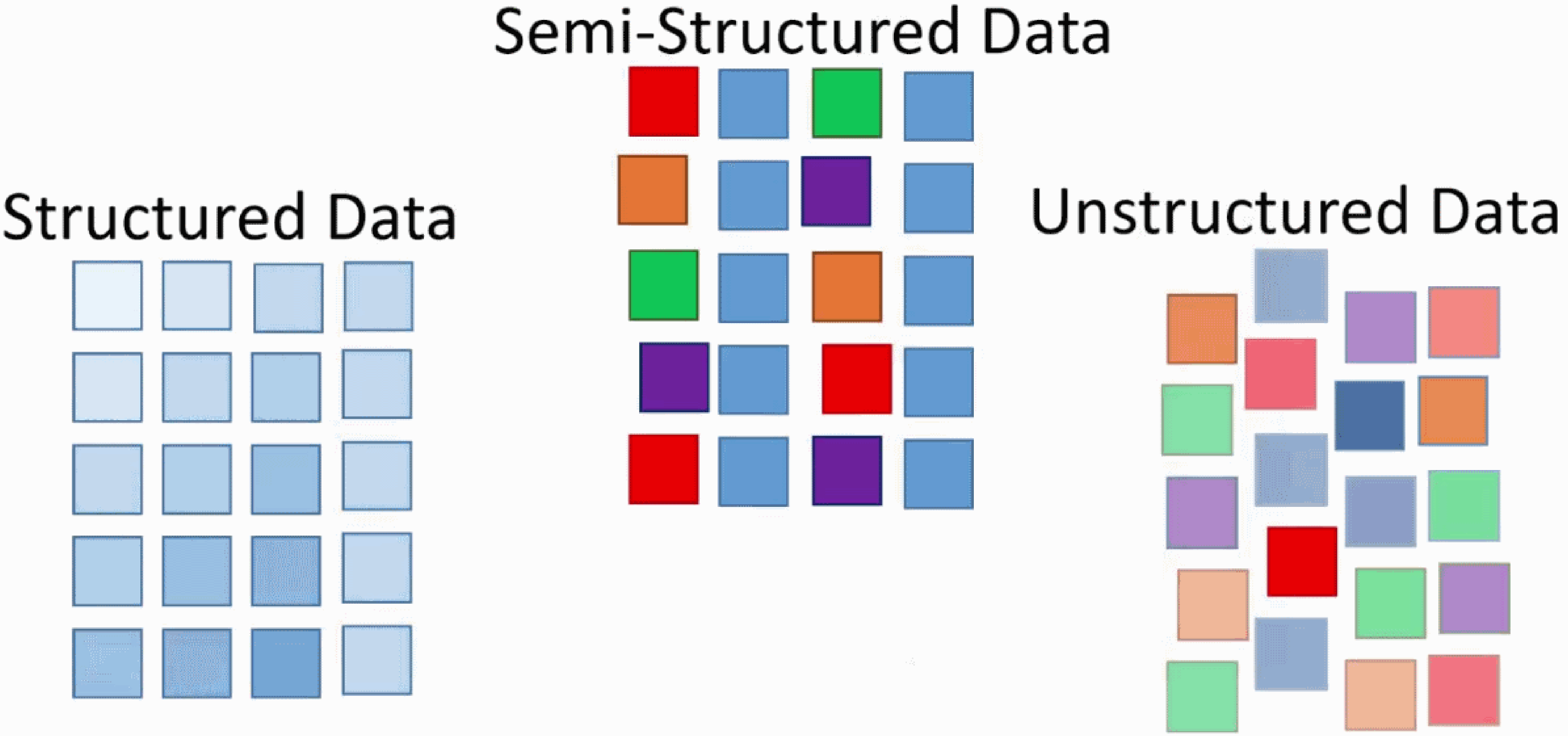
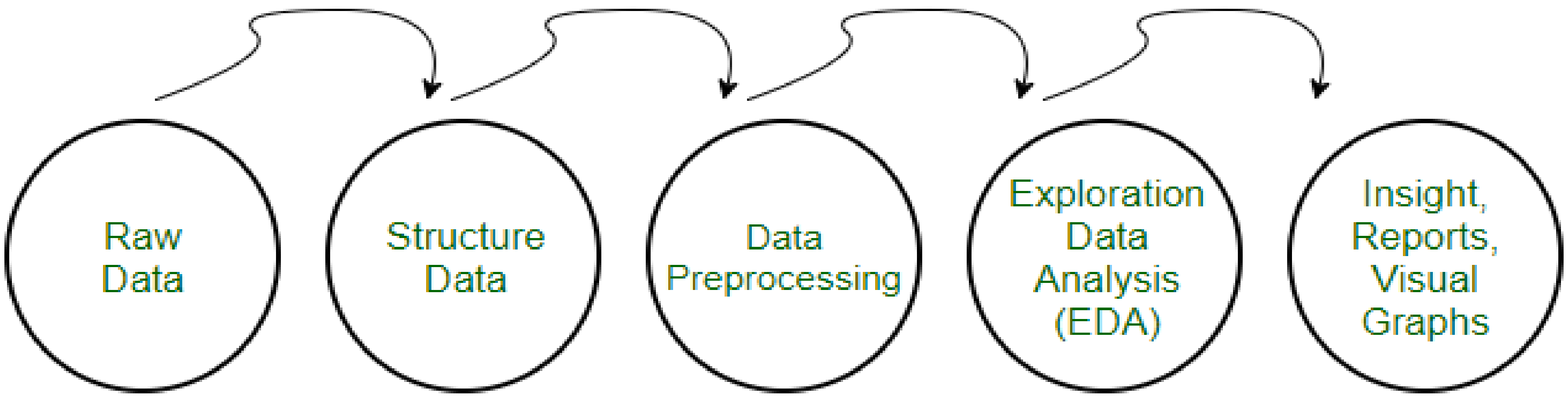
27379,2006.11.27 15:8,2006.11.27 15:8,en,East Timor,Transportation,<6 months,1-5,0,4,0,"hey",5,5,5,5,Opinio,1,1,0,0,1,0,1,1,0,
27380,2006.11.27 15:8,2006.11.27 15:8,en,Nicaragua,Medical,6 - 12 months,6-10,5,5,5,"this is a random other text",6,6,6,6,Opin
27381,2006.11.27 15:8,2006.11.27 15:8,en,Equatorial Guinea,Software Vendor,6+ years,101-250,6,2,6,"another random text",3,3,3,
27382,2006.11.27 15:8,2006.11.27 15:8,en,Zambia,Retail,<6 months,251-500,1,1,1,"hey",2,2,2,2,Surveyor,0,1,0,0,0,0,0,1,0,,"hey"
27383,2006.11.27 15:8,2006.11.27 15:8,en,French Southern and Antarctic Lands,Retail,1 - 2 years,1001-5000,2,1,2,"123456",2,2,2
27384,2006.11.27 15:8,2006.11.27 15:8,en,Guinea-Bissau,Hardware Vendor,2 - 5 years,26-100,6,3,6,"£6{[]}+åøæ'´'¨*-/+\",4,4,4,4,
27385,2006.11.27 15:8,2006.11.27 15:8,en,Viet Nam,Medical,2 - 5 years,26-100,4,5,4,"£6{[]}+åøæ'´'¨*-/+\",6,6,6,6,Opinio,1,1,1,
27386,2006.11.27 15:8,2006.11.27 15:8,en,Reunion,Medical,1 - 2 years,1001-5000,2,5,2,"123456",6,6,6,6,Opinio,1,1,1,1,1,1,1,1,1
27387,2006.11.27 15:8,2006.11.27 15:8,en,Puerto Rico,Non-profit,<6 months,1-5,0,0,0,"hey",1,1,1,1,Opinio,1,1,1,1,0,1,1,1,0,,"h
27388,2006.11.27 15:8,2006.11.27 15:8,en,East Timor,Financial Services,6 - 12 months,6-10,1,1,1,"this is a random other text",
27389,2006.11.27 15:8,2006.11.27 15:8,en,Northern Mariana Islands,Software Vendor,<6 months,1-5,2,2,2,"hey",3,3,3,3,Opinio,1,0

Structured, Unstructured and Semi-Structured



Data Preprocessing for Machine learning in Python

- Pre-processing refers to the transformations applied to our data before feeding it to the algorithm.
- Data Preprocessing is a technique that is used to convert the raw data into a clean data set. In other words, whenever the data is gathered from different sources it is collected in raw format which is not feasible for the analysis.



Need of Data Preprocessing

- For achieving better results from the applied model in Machine Learning projects the format of the data has to be in a proper manner.
- Some specified Machine Learning model needs information in a specified format, for example, *Random Forest algorithm does not support null values, therefore to execute random forest algorithm null values have to be managed from the original raw data set*.
- Another aspect is that data set should be formatted in such a way *that more than one Machine Learning and Deep Learning algorithms* are executed in one data set, and best out of them is chosen.

Major Tasks in Data Preprocessing

- **Data cleaning**
    - Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- **Data integration**
    - Integration of multiple databases, data cubes, or files
- **Data reduction**
    - Dimensionality reduction
    - Numerosity reduction
    - Data compression
- **Data transformation and data discretization**
    - Normalization
    - Concept hierarchy generation

Data Cleaning

- **Data in the Real World Is Dirty:** Lots of potentially incorrect data, e.g., instrument faulty, human or computer error, transmission error
  - **Incomplete(missing):** lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
    - e.g., *Occupation*=" " (missing data)
  - **noisy:** containing noise, errors, or outliers
    - e.g., *Salary*="−10" (an error)
  - **inconsistent:** containing discrepancies in codes or names, e.g.,
    - *Age*="42", *Birthday*="03/07/2010"
    - Was rating "1, 2, 3", now rating "A, B, C"
    - discrepancy between duplicate records
  - **Intentional (e.g., *disguised missing* data)**
    - Jan. 1 as everyone's birthday?

Incomplete (Missing) Data

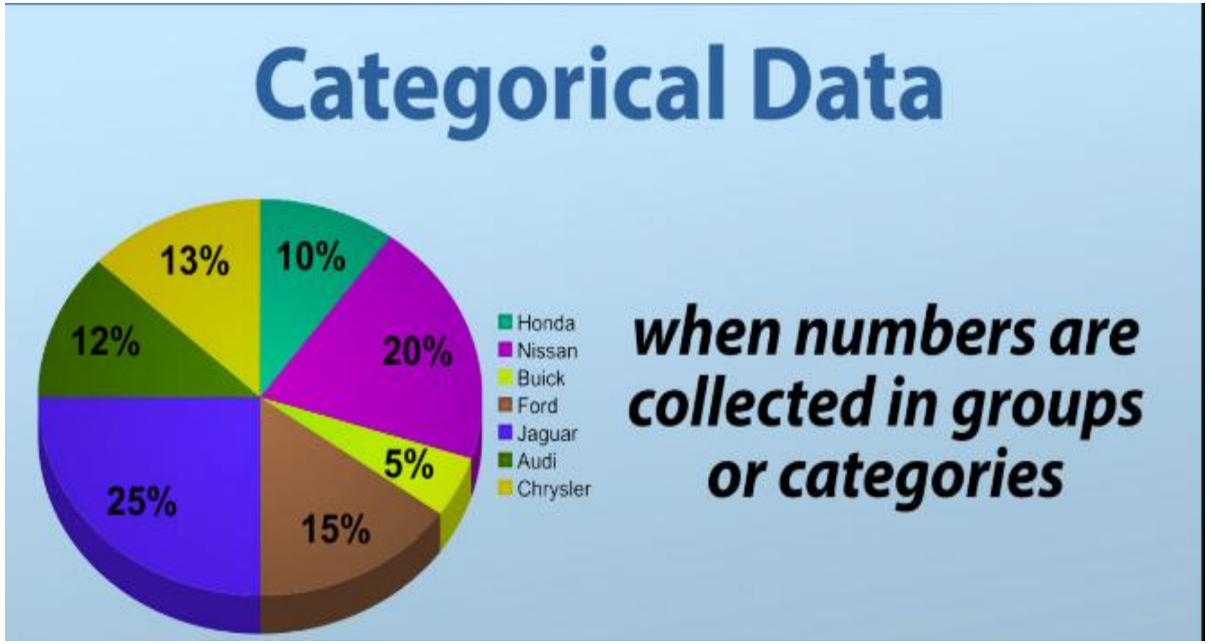
- **Data is not always available**
  - E.g., many tuples have no recorded value for several attributes, such as customer income in sales data
- **Missing data may be due to**
  - equipment malfunction
  - inconsistent with other recorded data and thus deleted
  - data not entered due to misunderstanding
  - certain data may not be considered important at the time of entry
  - not register history or changes of the data
- **Missing data may need to be inferred**

How to Handle Missing Data?

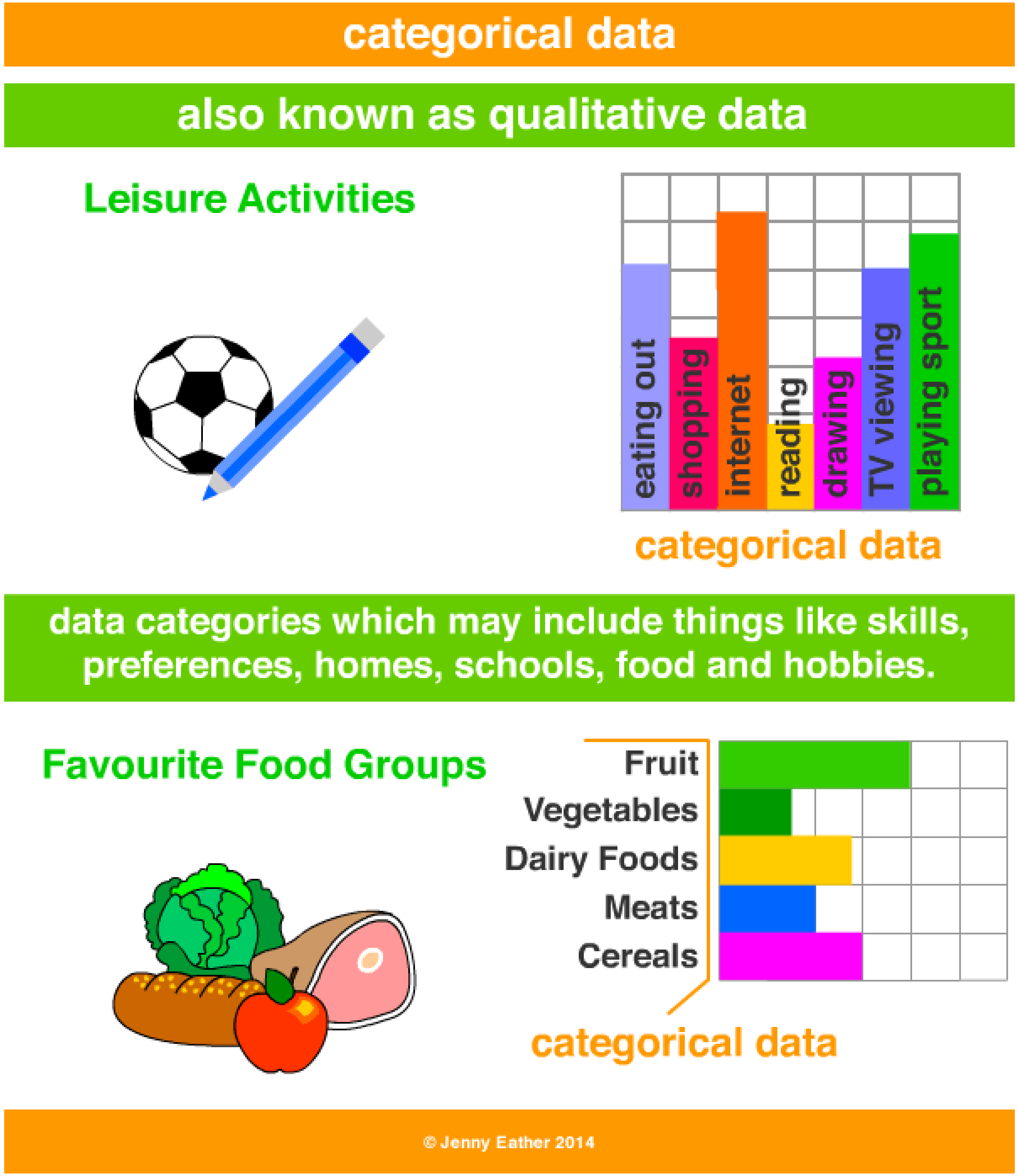
- **Ignore the tuple:** usually done when class label is missing (when doing classification)—not effective when the % of missing values per attribute varies considerably
- **Fill in the missing value manually**: tedious + infeasible?
- **Fill in it automatically with**
  - a global constant : e.g., “unknown”, a new class?!
  - the attribute mean
  - the attribute mean for all samples belonging to the same class: smarter
  - the most probable value: inference-based such as Bayesian formula or decision tree

	name	gender	height	weight	age
0	Michael	None	123.0	10.0	14.0
1	Jessica	F	145.0	NaN	NaN
2	Sue	NaN	100.0	30.0	29.0
3	Jake	F	NaN	NaN	NaN
4	Amy	NaN	NaN	NaN	52.0
5	Tye	M	150.0	20.0	45.0

	A	B	C	D	E	F	G
3	No missing data				Missing data		
4							
5	Id	math	science		Id	math	science
6	1	14	27		1	14	27
7	2	13	29		2	13	29
8	3	23	49		3	23	49
9	4	19	37		4	19	37
10	5	21	31		5	21	31
11	6	25	40		6	25	40
12	7	18	35		7	18	35
13	8	22	44		8	22	x
14	9	18	32		9	18	x
15	10	28	48		10	28	x
16	11	25	43		11	25	x
17	12	17	35		12	17	x
18	mean	20.25	37.5		mean	20.25	35.42857
19	stdev	4.57513	7.317476		stdev	4.57513	7.524563
20	correl	0.845864			correl	0.769171	



Degree	Frequency
High School	2
Bachelor's	7
MBA	20
Master's	3
Law	4
PhD	4
	40



Noisy Data

- **Noise**: random error or variance in a measured variable
- **Incorrect attribute values** may be due to
  - faulty data collection instruments
  - data entry problems
  - data transmission problems
  - technology limitation
  - inconsistency in naming convention
- **Other data problems** which require data cleaning
  - duplicate records
  - incomplete data
  - inconsistent data

Preprocessing the Data in Python

- In our daily life, we deal with lots of data but this data is in raw form. To provide the data as the input of machine learning algorithms, we need to convert it into a meaningful data.
- That is where data preprocessing comes into picture. In other simple words, we can say that before providing the data to the machine learning algorithms we need to preprocess the data.

Hands On

Training , Testing and Validation Data set

- **Training Dataset**: *A set of examples used for learning, that is to fit the parameters [i.e., weights] of the classifier or model.*
- **Validation Dataset**: *The sample of data used to provide an unbiased evaluation of a model fit on the training dataset while tuning model hyperparameters. A set of examples used to tune the parameters [i.e., architecture, not weights] of a classifier, for example to choose the number of hidden units in a neural network.*
- **Test Dataset**: *The sample of data used to provide an unbiased evaluation of a final model fit on the training dataset*. *A set of examples used only to assess the performance [generalization] of a fully specified classifier.*

A sample dataset to be used is divided like this:

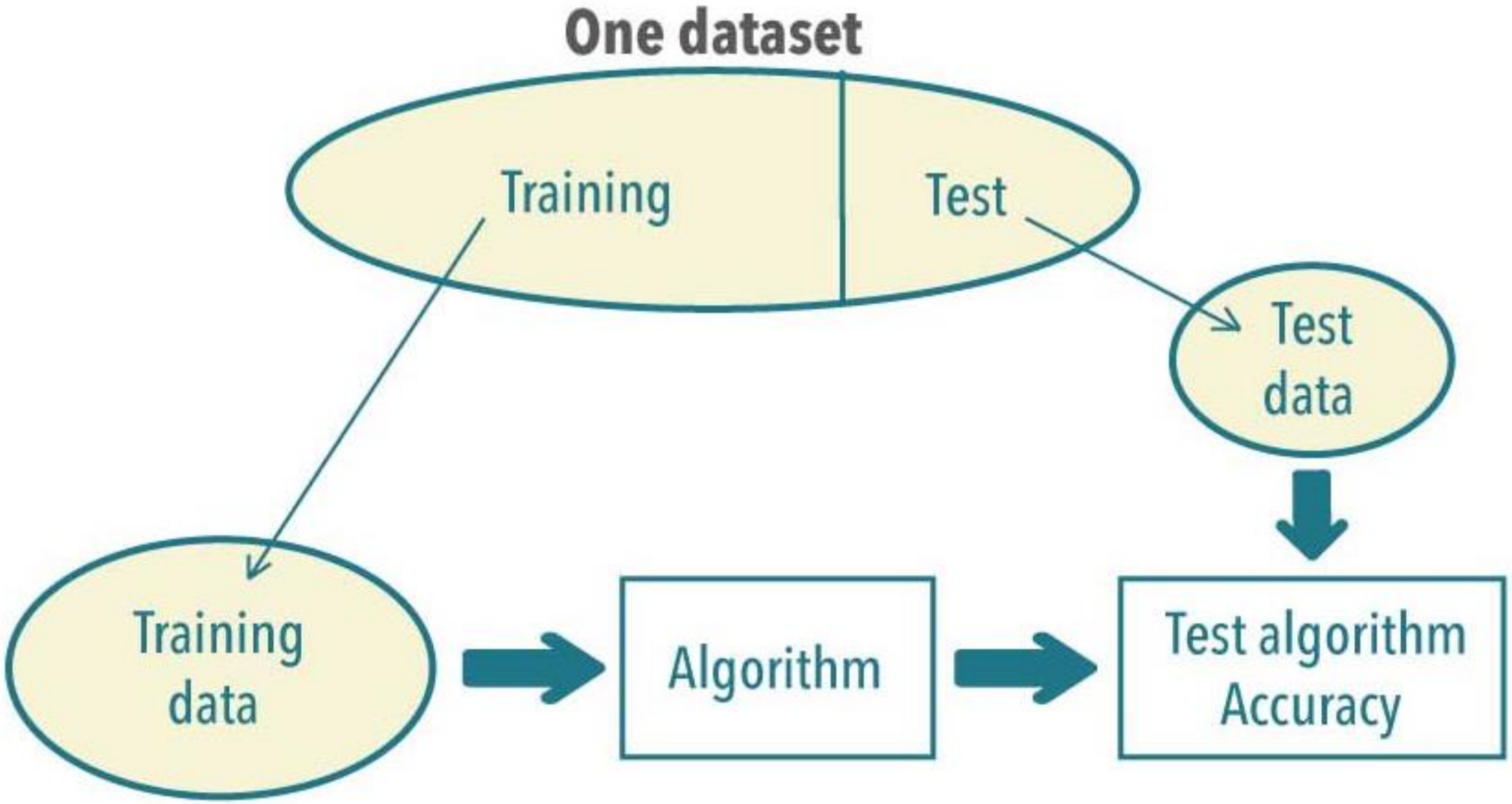
Training Dataset

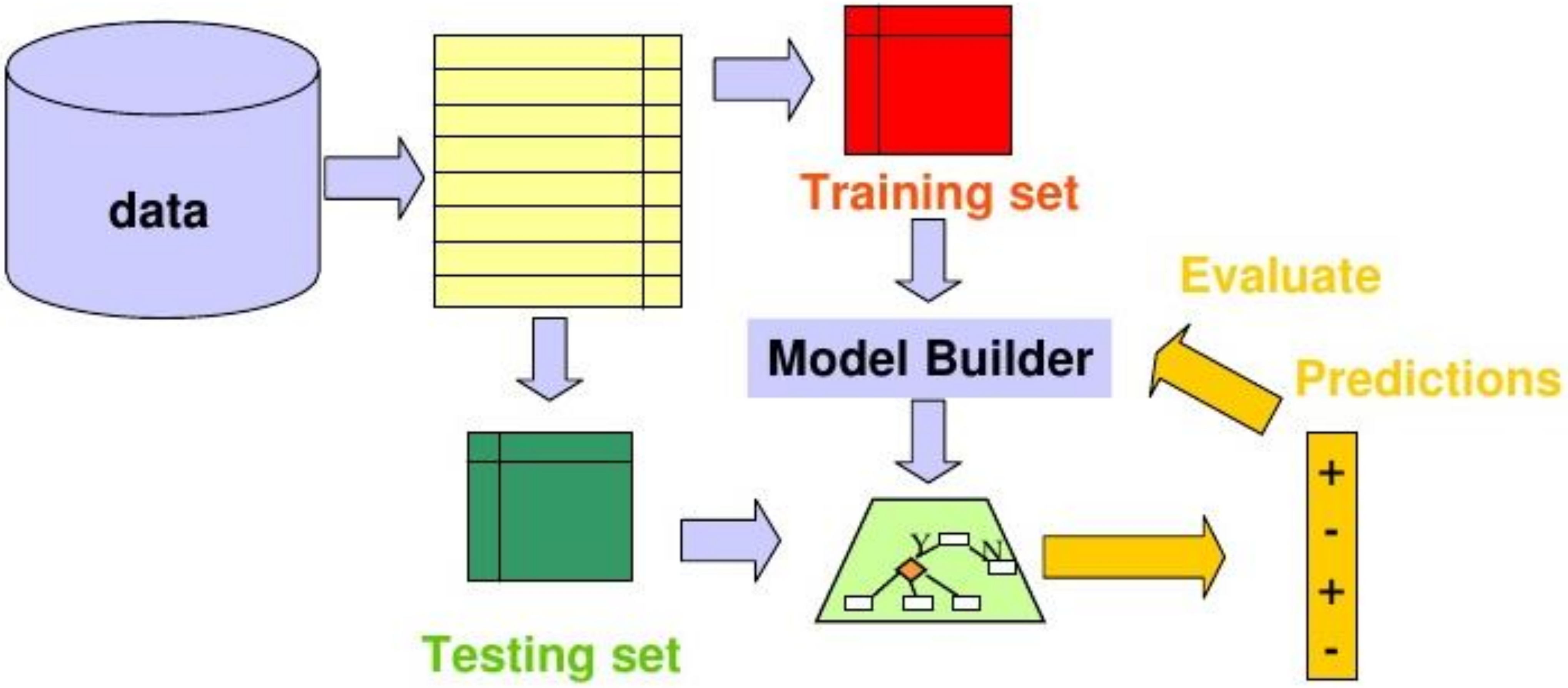
	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2
Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0	3	1
Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0	3	4
Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2
Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4	2
Merc 280	19.2	6	167.6	123	3.92	3.440	18.30	1	0	4	4
Merc 280C	17.8	6	167.6	123	3.92	3.440	18.90	1	0	4	4
Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0	3	3
Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0	3	3
Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0	3	3
Cadillac Fleetwood	10.4	8	472.0	205	2.93	5.250	17.98	0	0	3	4
Lincoln Continental	10.4	8	460.0	215	3.00	5.424	17.82	0	0	3	4
Chrysler Imperial	14.7	8	440.0	230	3.23	5.345	17.42	0	0	3	4
Fiat 128	32.4	4	78.7	66	4.08	2.200	19.47	1	1	4	1
Honda Civic	30.4	4	75.7	52	4.93	1.615	18.52	1	1	4	2
Toyota Corolla	33.9	4	71.1	65	4.22	1.835	19.90	1	1	4	1
Toyota Corona	21.5	4	120.1	97	3.70	2.465	20.01	1	0	3	1
Dodge Challenger	15.5	8	318.0	150	2.76	3.520	16.87	0	0	3	2

Testing Dataset

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
AMC Javelin	15.2	8	304.0	150	3.15	3.435	17.30	0	0	3	2
Camaro Z28	13.3	8	350.0	245	3.73	3.840	15.41	0	0	3	4
Pontiac Firebird	19.2	8	400.0	175	3.08	3.845	17.05	0	0	3	2
Fiat X1-9	27.3	4	79.0	66	4.08	1.935	18.90	1	1	4	1
Porsche 914-2	26.0	4	120.3	91	4.43	2.140	16.70	0	1	5	2
Lotus Europa	30.4	4	95.1	113	3.77	1.513	16.90	1	1	5	2
Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.50	0	1	5	4
Ferrari Dino	19.7	6	145.0	175	3.62	2.770	15.50	0	1	5	6
Maserati Bora	15.0	8	301.0	335	3.54	3.570	14.60	0	1	5	8
Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4	2

Training data vs. test data




data
Training set
Model Builder
Evaluate
Predictions
Testing set
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N
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Hands on

Data preprocessing steps

- **Step 1 – Importing the useful packages**
- **Step 2 – Defining sample data**
- **Step3 – Applying preprocessing technique**

Hands on

Step 1 – Importing the useful packages

- If we are using Python then this would be the first step for converting the data into a certain format, i.e., preprocessing. It can be done as follows −
  - **import numpy as np**
  - **from sklearn import preprocessing**
- Here we have used the following two packages −
  - **NumPy** − Basically NumPy is a general purpose array-processing package designed to efficiently manipulate large multi-dimensional arrays of arbitrary records without sacrificing too much speed for small multi-dimensional arrays.
  - **sklearn.preprocessing** − This package provides many common utility functions and transformer classes to change raw feature vectors into a representation that is more suitable for machine learning algorithms.

Step 2 – Defining sample data

- After importing the packages, we need to define some sample data so that we can apply preprocessing techniques on that data.
- We will now define the following sample data –

```
input_data = np.array([2.1, -1.9, 5.5],
                      [-1.5, 2.4, 3.5],
                      [0.5, -7.9, 5.6],
                      [5.9, 2.3, -5.8 ]])
```

Step3 – Applying preprocessing technique

- In this step, we need to apply any of the preprocessing techniques.

Techniques for Data Preprocessing

1. Scaling /Rescaling : **# Min max scaling**
2. **Standardization**
3. Normalization
    1. **L1 Normalization**
    2. **L2 Normalization**
4. Binarization
5. Mean Removal
6. Labeling the Data

1. Scaling or Rescaling Data

- When your data is comprised of attributes with varying scales, many machine learning algorithms can benefit from rescaling the attributes to all have the same scale.
- The attributes are often rescaled into the ***range between 0 and 1***.
- You can rescale data using ***scikit-learn*** using the ***MinMaxScaler*** class.

Example : Min max scaled data

Min max scaled data

```
data_scaler_minmax = preprocessing.MinMaxScaler(feature_range=(0,1))
data_scaled_minmax = data_scaler_minmax.fit_transform(input_data)
print ("\nMin max scaled data:\n", data_scaled_minmax)
```

```
Min max scaled data:
 [[1.         0.         1.         0.        ]
 [0.         1.         0.27118644 1.        ]
 [0.33333333 0.84444444 0.         0.2       ]]
```

2 . Standardize Data

- Standardization is a useful technique to transform attributes with a Gaussian distribution and differing means and standard deviations to a standard Gaussian distribution with a *mean of 0 and a standard deviation of 1.*
- You can standardize data using scikit-learn with the **StandardScaler class.**

```python
# Python code to Standardize data (0 mean, 1 stdev)
from sklearn.preprocessing import StandardScaler
import pandas
import numpy
#url = "https://archive.ics.uci.edu/ml/machine-learning-databases/pima-indians-diabetes/pima-indians-diabetes.data"
url = "C:\\Users\\Administrator\\Desktop\\Data\\pima-indians-diabetes.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = pandas.read_csv(url, names=names)
array = dataframe.values

# separate array into input and output components
X = array[:,0:8]
Y = array[:,8]
scaler = StandardScaler().fit(X)
rescaledX = scaler.transform(X)

# summarize transformed data
numpy.set_printoptions(precision=3)
print(rescaledX[0:5,:])
```

```
[[ 0.64   0.848  0.15   0.907 -0.693  0.204  0.468  1.426]
 [-0.845 -1.123 -0.161  0.531 -0.693 -0.684 -0.365 -0.191]
 [ 1.234  1.944 -0.264 -1.288 -0.693 -1.103  0.604 -0.106]
 [-0.845 -0.998 -0.161  0.155  0.123 -0.494 -0.921 -1.042]
 [-1.142  0.504 -1.505  0.907  0.766  1.41   5.485 -0.02 ]]
```

3. Normalization

- Normalizing in *scikit-learn refers to rescaling each observation (row) to have a length of 1 (called a unit norm in linear algebra).*
- You can normalize data in Python with scikit-learn using the Normalizer class.
- It is another data preprocessing technique that is used to modify the feature vectors. Such kind of modification is necessary to measure the feature vectors on a common scale.
- Followings are two types of normalization which can be used in machine learning −

L1 Normalization

- It is also referred to as ***Least Absolute Deviations***. This kind of normalization modifies the values so that the ***sum of the absolute values is always up to 1 in each row***. It can be implemented on the input data with the help of the following Python code –

```python
# Normalize data
data_normalized_l1 = preprocessing.normalize(input_data, norm = 'l1')
print("\nL1 normalized data:\n", data_normalized_l1)
```

```
L1 normalized data:
 [[ 0.21582734 -0.10791367  0.21582734 -0.46043165]
 [ 0.          0.35714286 -0.1547619   0.48809524]
 [ 0.0952381   0.21904762 -0.27619048 -0.40952381]]
```

L2 Normalization

- It is also referred to as **least squares**. This kind of normalization modifies the values so that the sum of the squares is always up to 1 in each row.
- It can be implemented on the input data with the help of the following Python code –

```
# Normalize data
data_normalized_l2 = preprocessing.normalize(input_data, norm = 'l2')
print("\nL2 normalized data:\n", data_normalized_l2)
```

```
L2 normalized data:
 [[ 0.38345117 -0.19172558  0.38345117 -0.81802916]
 [ 0.          0.57207755 -0.24790027  0.78183932]
 [ 0.17357868  0.39923096 -0.50337816 -0.74638831]]
```

```python
# Normalize data (length of 1)
from sklearn.preprocessing import Normalizer
import pandas
import numpy
#url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.data.csv"
url = "C:\\Users\\Administrator\\Desktop\\Data\\pima-indians-diabetes.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = pandas.read_csv(url, names=names)
array = dataframe.values
# separate array into input and output components
X = array[:,0:8]
Y = array[:,8]
scaler = Normalizer().fit(X)
normalizedX = scaler.transform(X)
# summarize transformed data
numpy.set_printoptions(precision=3)
print(normalizedX[0:5,:])
```

```
[[0.034 0.828 0.403 0.196 0.    0.188 0.004 0.28 ]
 [0.008 0.716 0.556 0.244 0.    0.224 0.003 0.261]
 [0.04  0.924 0.323 0.    0.    0.118 0.003 0.162]
 [0.007 0.588 0.436 0.152 0.622 0.186 0.001 0.139]
 [0.    0.596 0.174 0.152 0.731 0.188 0.01  0.144]]
```

4.Binarization

- You can transform your data using a binary threshold. All values above the threshold are marked 1 and all equal to or below are marked as 0.
- This is called binarizing your data or threshold your data
- You can create new binary attributes in Python using ***scikit-learn*** with the ***Binarizer*** class.

```
data_binarized = preprocessing.Binarizer(threshold = 0.5).transform(Input_data)
print("\nBinarized data:\n", data_binarized)
```

```
Binarized data:
 [[1. 0. 1.]
 [0. 1. 1.]
 [0. 0. 1.]
 [1. 1. 0.]]
```

5. Mean Removal

- It is another very common preprocessing technique that is used in machine learning. Basically it is used to ***eliminate the mean from feature vector*** so that every feature is centered on zero.
- We can also remove the bias from the features in the feature vector. For applying mean removal preprocessing technique on the sample data, we can write the Python code shown below.

```python
input_data = np.array([[3, -1.5, 3, -6.4], [0, 3, -1.3, 4.1], [1, 2.3, -2.9, -4.3]])
print("Mean = ", input_data.mean(axis = 0))
print("Std deviation = ", input_data.std(axis = 0))
data_standardized = preprocessing.scale(input_data)
print("\nMean = ", data_standardized.mean(axis = 0))
print("Std deviation = ", data_standardized.std(axis = 0))
```

```
Mean =  [ 1.333  1.267 -0.4   -2.2  ]
Std deviation =  [1.247 1.977 2.491 4.537]

Mean =  [ 5.551e-17 -3.701e-17  0.000e+00 -1.850e-17]
Std deviation =  [1. 1. 1. 1.]
```

6. Labelling the Data

- We already know that data in a certain format is necessary for machine learning algorithms.
- Another important requirement is that the data must be labelled properly before sending it as the input of machine learning algorithms.
- The process of transforming the word labels into numerical form is called label encoding.

Label encoding steps

- **Step 1 – Importing the useful packages**
- **Step 2 – Defining sample labels**
- **Step 3 – Creating & training of label encoder object**
- **Step 4 – Checking the performance by encoding random ordered list**
- **Step 5 – Checking the performance by decoding a random set of numbers –**

Step 1 – Importing the useful packages¶

If we are using Python then this would be first step for converting the data into certain format, i.e., preprocessing. It can

```
import numpy as np
from sklearn import preprocessing
```

Step 2 – Defining sample labels

After importing the packages, we need to define some sample labels so that we can create and train the label encoder. labels –

```
# Sample input labels
input_labels = ['red','black','red','green','black','yellow','white']
```

Step 3 – Creating & training of label encoder object

In this step, we need to create the label encoder and train it. The following Python code will help in doing this –

```
# Creating the label encoder
encoder = preprocessing.LabelEncoder()
encoder.fit(input_labels)
```

```
LabelEncoder()
```

Step 4 – Checking the performance by encoding random ordered list

This step can be used to check the performance by encoding the random ordered list. Following Python code can be written to do the same
get printed as follows –

```
# encoding a set of labels
test_labels = ['green','red','black']
encoded_values = encoder.transform(test_labels)
print("\nLabels =", test_labels)
```

Step 4 – Checking the performance by encoding random ordered list

This step can be used to check the performance by encoding the random ordered list. Following Python code can be written to do the same – The labels would get printed as follows –

```python
# encoding a set of labels
test_labels = ['green','red','black']
encoded_values = encoder.transform(test_labels)
print("\nLabels =", test_labels)
```

```
Labels = ['green', 'red', 'black']
```

```python
print("Encoded values =", list(encoded_values))
```

```
Encoded values = [1, 2, 0]
```

Step 5 – Checking the performance by decoding a random set of numbers –

This step can be used to check the performance by decoding the random set of numbers. Following Python code can be written to do the same –

```
# decoding a set of values
encoded_values = [3,0,4,1]
decoded_list = encoder.inverse_transform(encoded_values)
print("\nEncoded values =", encoded_values)
```

```
Encoded values = [3, 0, 4, 1]
```

```
C:\Users\Administrator\Anaconda3\lib\site-packages\sklearn\preprocessing\label.py:151: DeprecationWarning: The truth value of an empty array is ambiguous. Returning False, but in future this will result in an error. Use `array.size > 0` to check that an array is not empty.
  if diff:
```

```
print("\nDecoded labels =", list(decoded_list))
```

```
Decoded labels = ['white', 'black', 'yellow', 'green']
```

Hands on