04.08.2023

Statistical Methods in AI (CS7.403)

Lecture-2: ML Workflow, Data Representations,
Basic Data Transformations, Data Visualization

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https://ravika.github.io

@vikataravi

Center for Visual Information Technology (CVIT)
IIIT Hyderabad

Announcements

- Tutorial (11.40a – 12.40p Saturday, H-205)
  - Python, Pandas, Jupyter notebook, Plotting tools.
  - **Bring your laptops**.
- Ask questions.

Announcements

- IMPORTANT: All assignments/projects will need to submitted via Github Classroom
- Tutorial
  - Git
  - Github
- Ask questions.

Announcements

- TAs will share SMAI Course Calendar on Moodle
- You can add it to your Teams Calendar
- Will contain assignment release/due/eval dates
- Will contain exam paper showing dates
- Will contain project-related dates

Queries

- Post queries on Moodle
- Helps all (many may have same question)
- Do not DM TAs !

Announcements

- Do not use Python libraries for assignments unless explicitly allowed/specified.

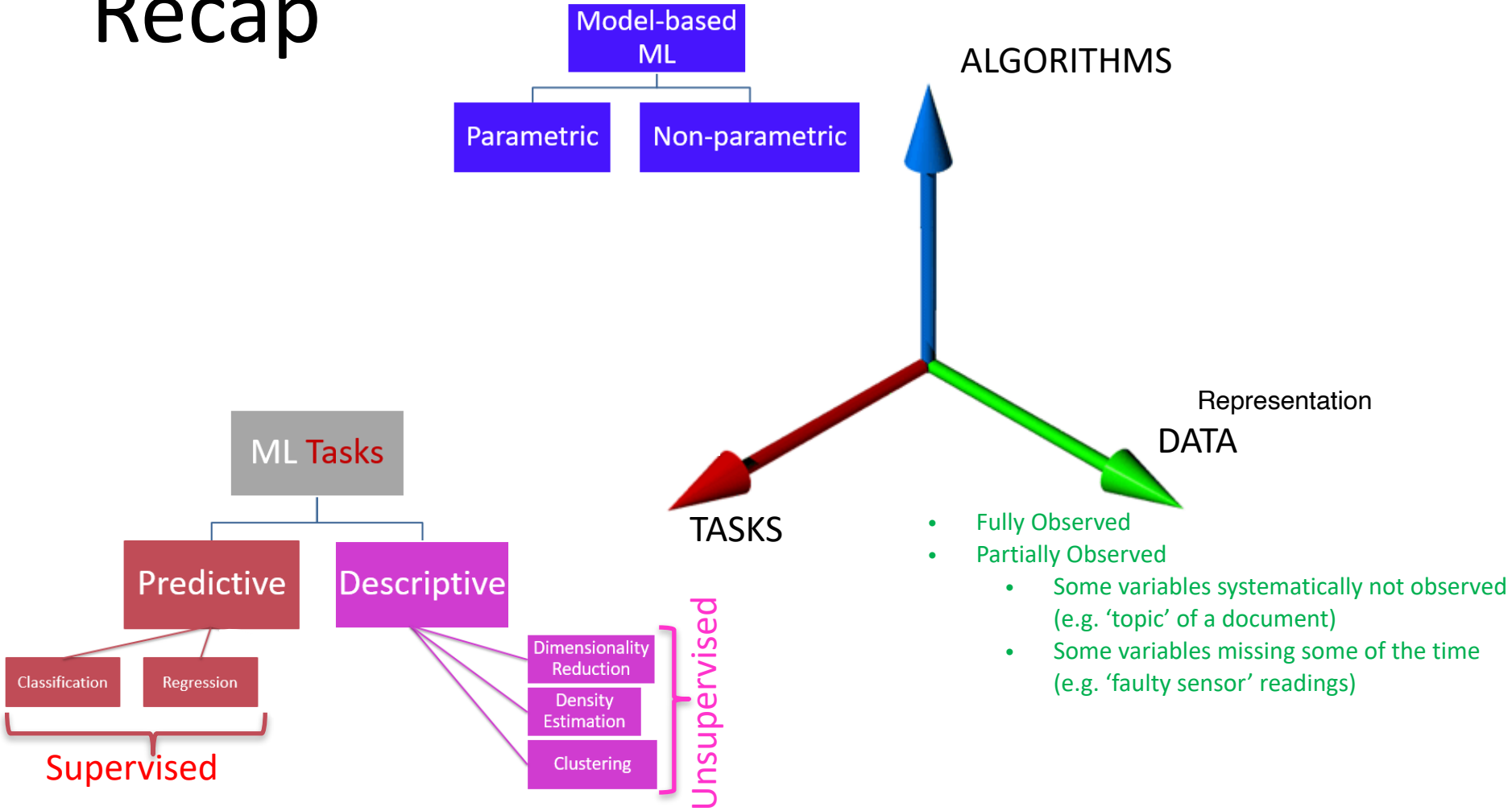
Additionally …

- Spending time <u>everyday</u> on material covered in class helps
  - Take notes
  - Revise
  - Reflect
- **Ask if you wish to take something down, but slide is no longer on screen**

Course TAs

1. Khushi Agarwal
2. Naimeesh Narayan Tiwari
3. Tathagato Roy
4. Nachiket Patil
5. Nitin Shrinivas
6. Vaibhav Agarwal
7. Naraharisetti Siddik Ayyappa
8. Kawshik Manikantan

Recap



- Fully Observed
- Partially Observed
  - Some variables systematically not observed (e.g. ‘topic’ of a document)
  - Some variables missing some of the time (e.g. ‘faulty sensor’ readings)

Lecture Outline

- ML Workflow
- Data Representations
- Basic Data Transformations
- Data Visualization

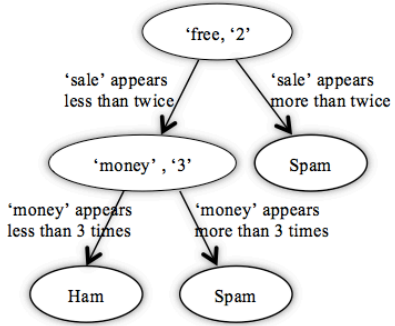
Machine Learning

Algorithmic methods that use data to improve their knowledge of a task

Task: Detect spam email

Data: Labelled emails (in inboxes of other users as well !)

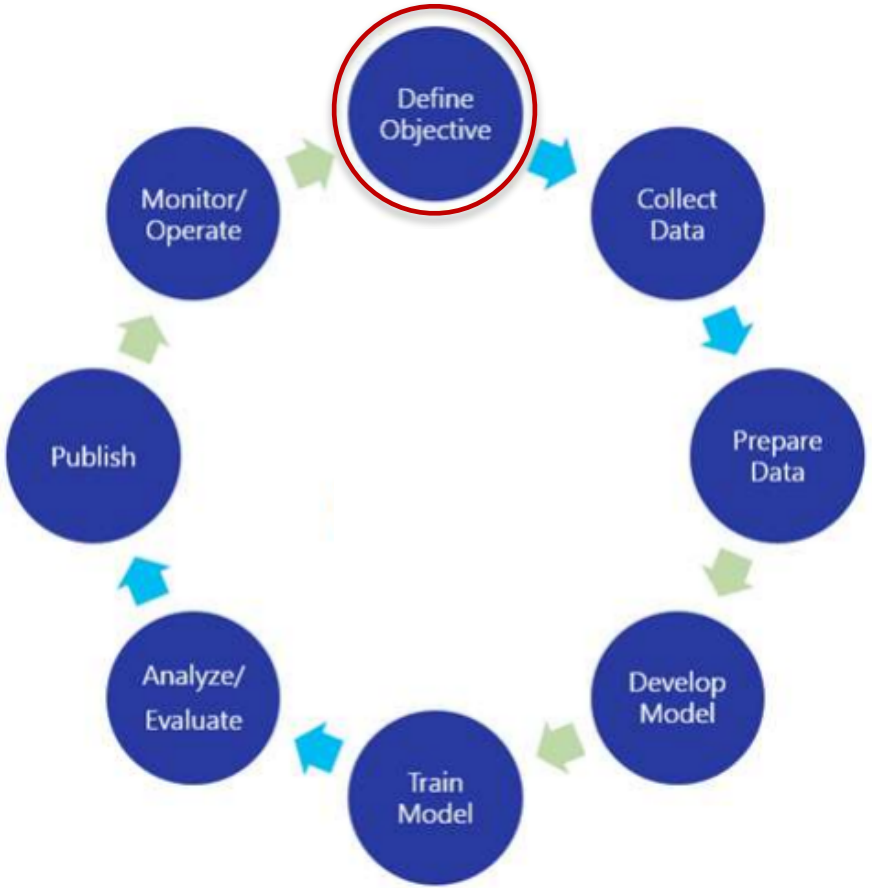
Knowledge:



Improve → 85% reduction of spam emails in Inbox over 3 months

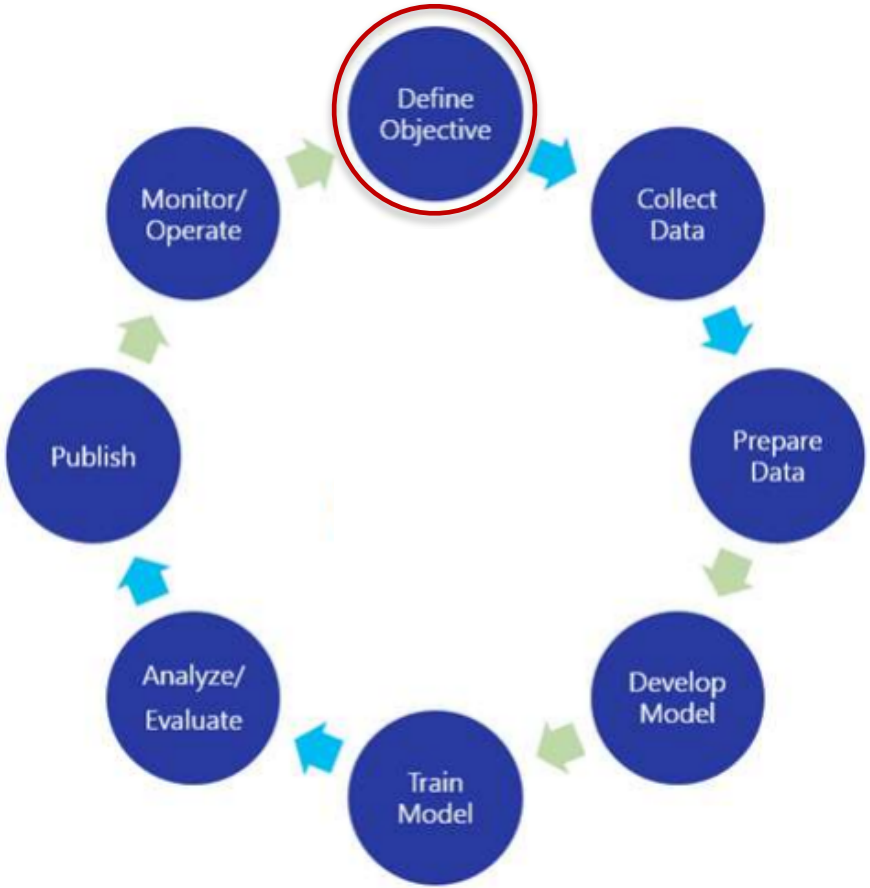
Algorithmic method: Decision Tree

Workflow of a Machine Learning Problem



- Detect spam email
- Predict value of a stock
- Predict effect of advertising on sales
- Drive car ‘safely’ without human intervention
- Translate text from one language to another
- Sentiment Analysis
- …

Workflow of a Machine Learning Problem



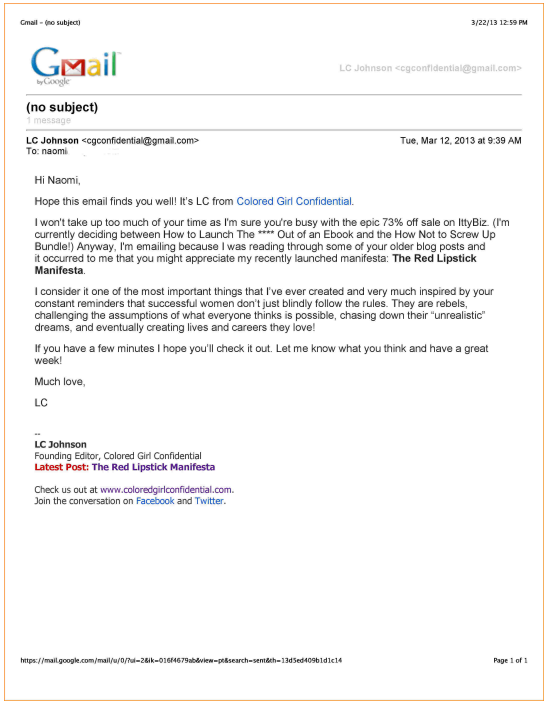
No Data, no ML !


Without data you're just another person with an opinion.
W. EDWARDS DEMING


"In God we trust, all others must bring data."
W. Edwards Deming
(c) iStockphoto / Thinkstock

Sources of data

- Detect spam email



Gmail – (no subject) 3/22/13 12:59 PM

Gmail by Google LC Johnson <cgconfidential@gmail.com>

(no subject)

1 message

LC Johnson <cgconfidential@gmail.com> Tue, Mar 12, 2013 at 9:39 AM
To: naomi

Hi Naomi,

Hope this email finds you well! It's LC from Colored Girl Confidential.

I won't take up too much of your time as I'm sure you're busy with the epic 73% off sale on IttyBiz. (I'm currently deciding between How to Launch The **** Out of an Ebook and the How Not to Screw Up Bundle!) Anyway, I'm emailing because I was reading through some of your older blog posts and it occurred to me that you might appreciate my recently launched manifesta: **The Red Lipstick Manifesta**.

I consider it one of the most important things that I've ever created and very much inspired by your constant reminders that successful women don't just blindly follow the rules. They are rebels, challenging the assumptions of what everyone thinks is possible, chasing down their "unrealistic" dreams, and eventually creating lives and careers they love!

If you have a few minutes I hope you'll check it out. Let me know what you think and have a great week!

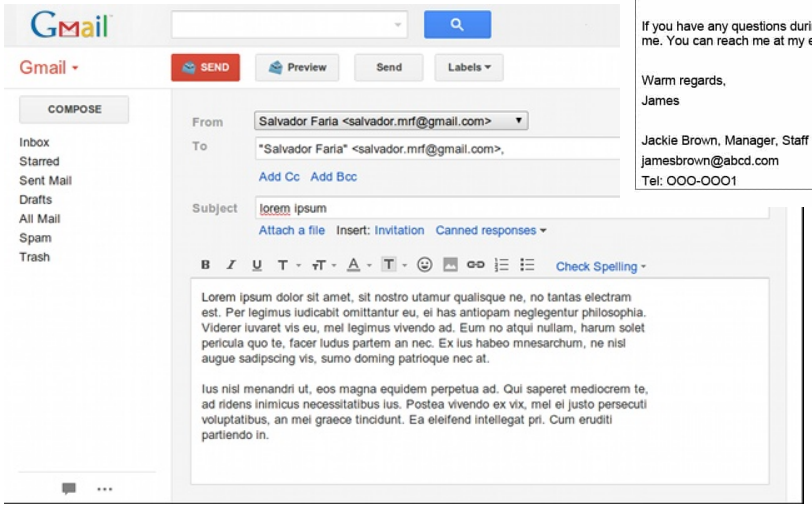
Much love,

LC

--
LC Johnson
Founding Editor, Colored Girl Confidential
Latest Post: The Red Lipstick Manifesta

Check us out at www.coloredgirlconfidential.com.
Join the conversation on Facebook and Twitter.

https://mail.google.com/mail/u/0/?ui=2&ik=016ff4679ab&view=pt&search=sent&th=13d5ed409b1d1c14 Page 1 of 1



Gmail

Gmail ▾ SEND Preview Send Labels ▾

COMPOSE

Inbox
Starred
Sent Mail
Drafts
All Mail
Spam
Trash

From Salvador Faria <salvador.mrf@gmail.com>
To "Salvador Faria" <salvador.mrf@gmail.com>,
Add Cc Add Bcc
Subject lorem ipsum
Attach a file Insert: Invitation Canned responses ▾
Check Spelling ▾

Lorem ipsum dolor sit amet, sit nostro utamur qualisque ne, no tantas electram est. Per legimus iudicabit omittantur eu, ei has antiopam neglegentur philosophia. Viderer iuvaret vis eu, mel legimus vivendo ad. Eum no atqui nullam, harum solet pericula quo te, facer ludus partem an nec. Ex ius habeo mnesarchum, ne nisl augue sadipscing vis, sumo doming patrioque nec at.

Ius nisl menandri ut, eos magna equidem perpetua ad. Qui saperet mediocrem te, ad ridens inimicus necessitatibus ius. Postea vivendo ex vix, mel ei justo persecuti voluptatibus, an mei graece tincidunt. Ea eleifend intellegat pri. Cum eruditi partiendo in.

Business Email Sample

To: "Anna Jones" <annajones@buzzle.com.>
CC: All Staff
From: "James Brown"
Subject: Welcome to our Hive!

Dear Anna,

Welcome to our Hive!
It is a pleasure to welcome you to the team of_____. We are excited to have you join our team, and we hope that you will enjoy Working with our Company.

On the last Saturday of each month we hold a special staff party to welcome any new employees. Please be sure to come next Week to meet all of our senior staff and any other new staff members who have joined_____ this month. You will receive an e-mail regarding the same with further details.

If you have any questions during your training period, please do not hesitate to contact me. You can reach me at my email address or on my office line at OOO-OOO1.

Warm regards,
James

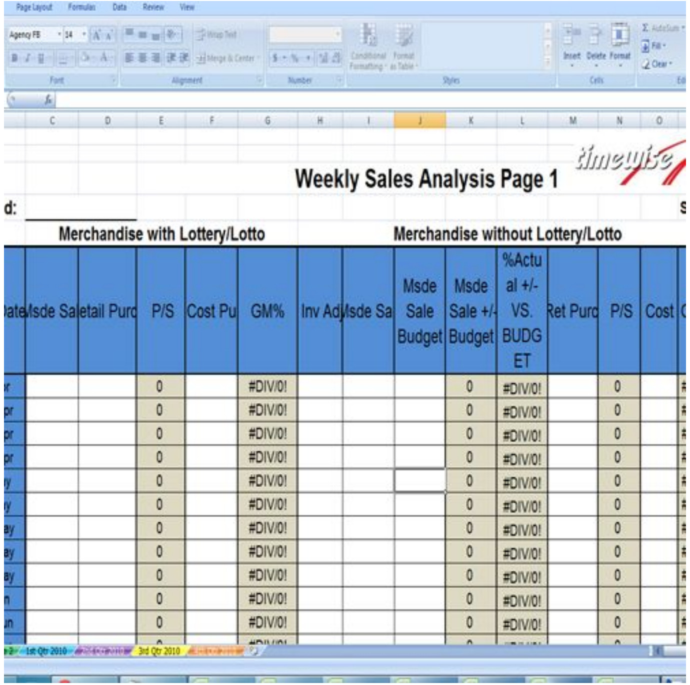
Jackie Brown, Manager, Staff
jamesbrown@abcd.com
Tel: OOO-OOO1

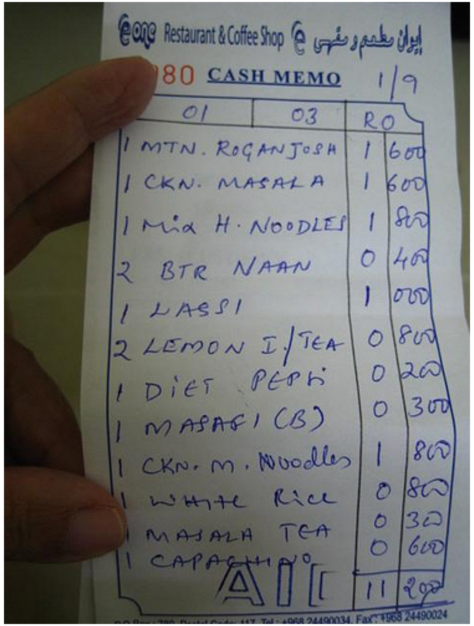
Sources of data

- Predict value of a stock

Sources of data

- Predict effect of advertising on sales

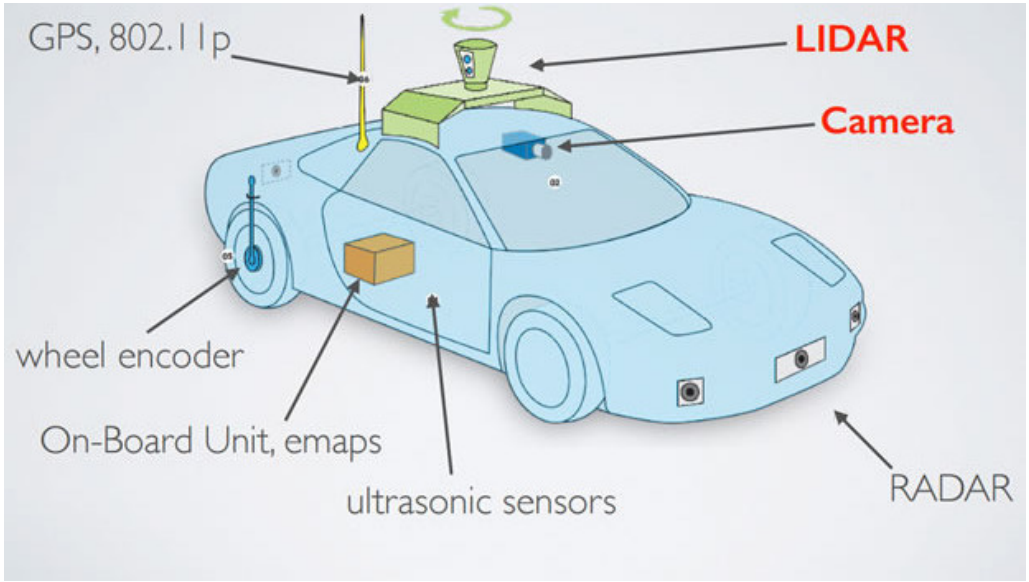




Raw Data may not always be digital in nature !

Sources of data

- Drive car safely without human intervention

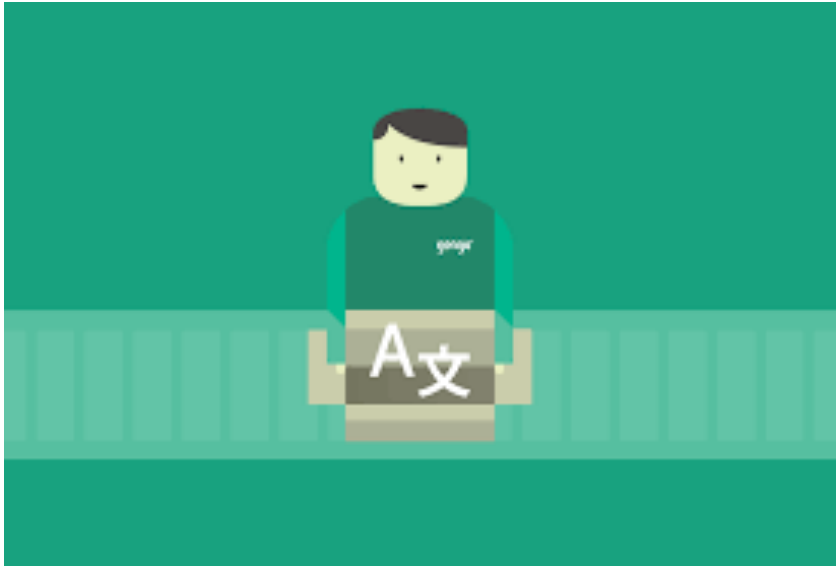


https://inai.iiit.ac.in/bodhyaan.html

Data can be multi-modal and may need to be 'synchronized'

Sources of data

- Translate text from one language to another



A human domain expert may be required to obtain raw data

Two fundamental questions

- What data to collect ?
- How to collect ?

Raw data

- May be too little in quantity

Raw data

- May be too much in quantity
  - Limitations on system end (compute, storage)

Raw data

- Not all of it relevant

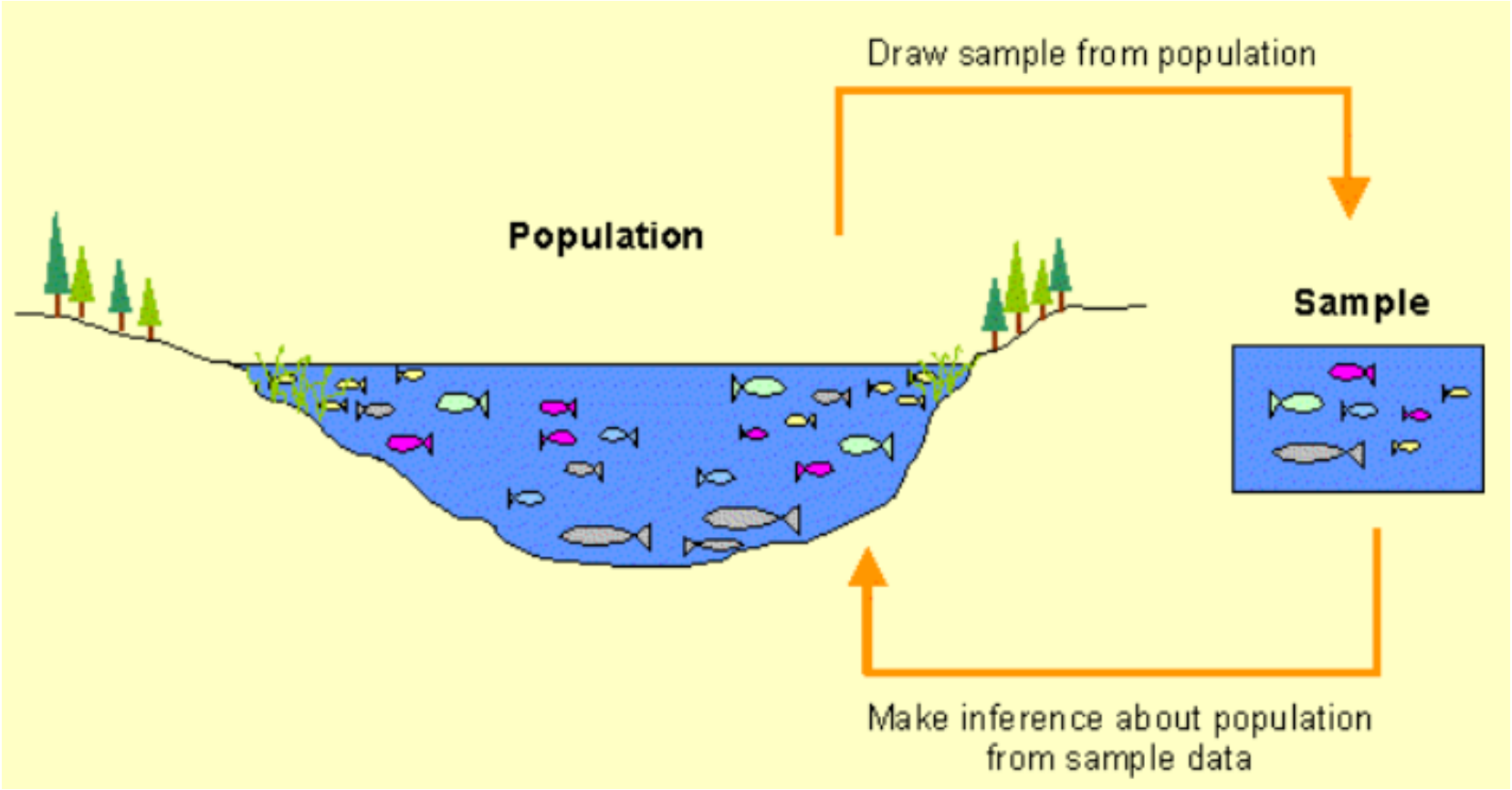
Raw data

- Often not directly usable
  - Filter (needed data)
  - **Transform (to numerical data)**

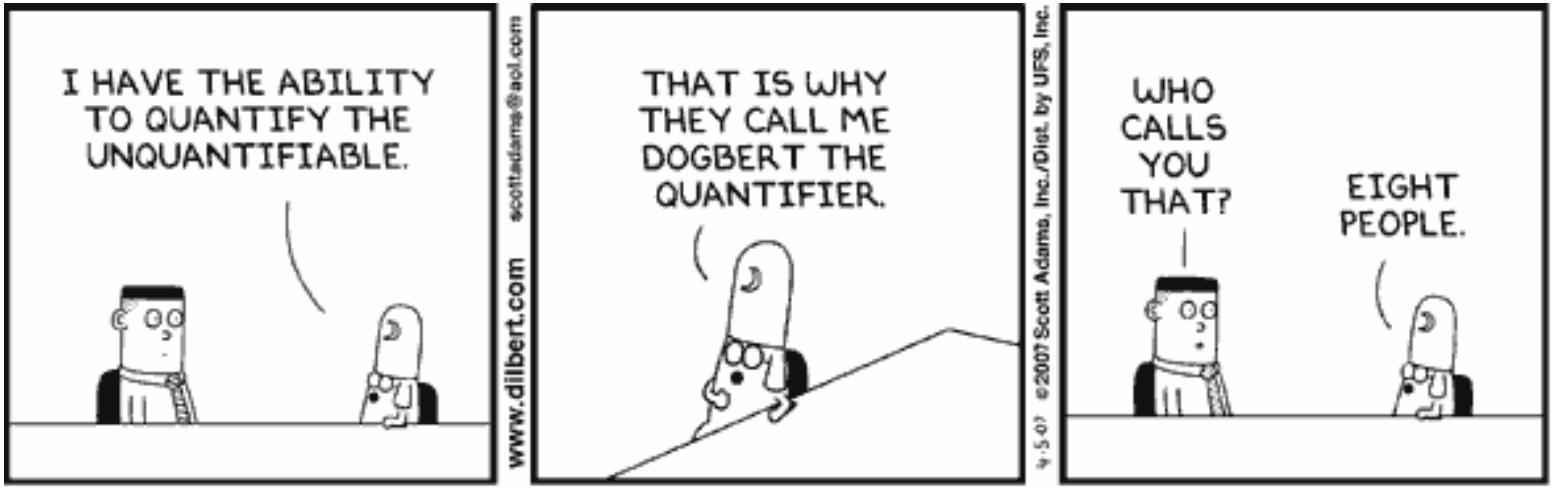
Two fundamental questions

- What data to collect ?
- How (much) to collect ?

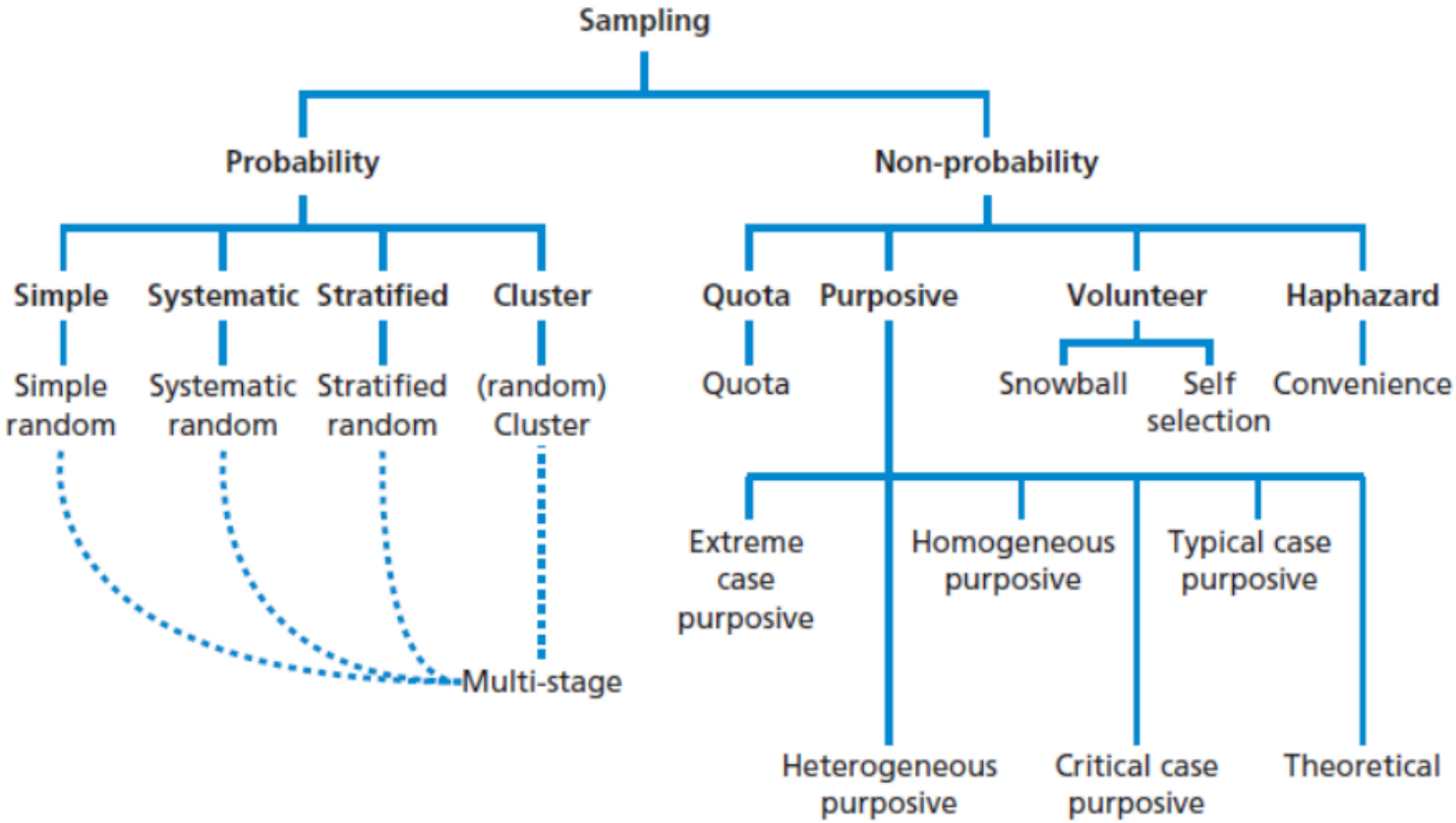
The Research Method



Are our samples ‘representative’ of the population?

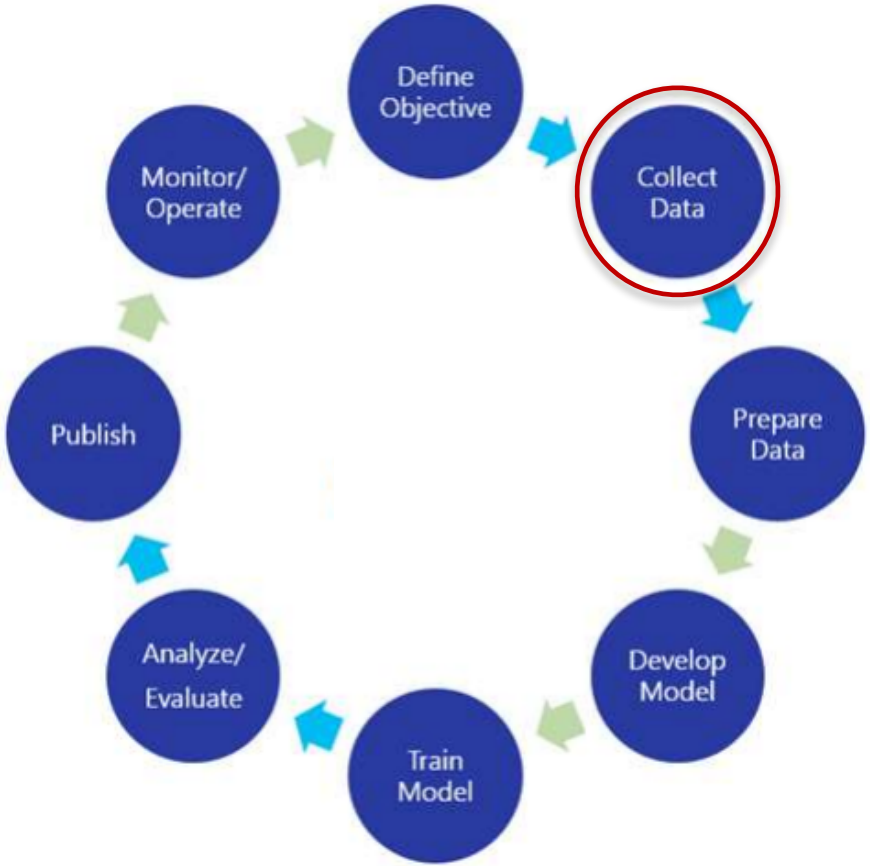


Sampling Techniques

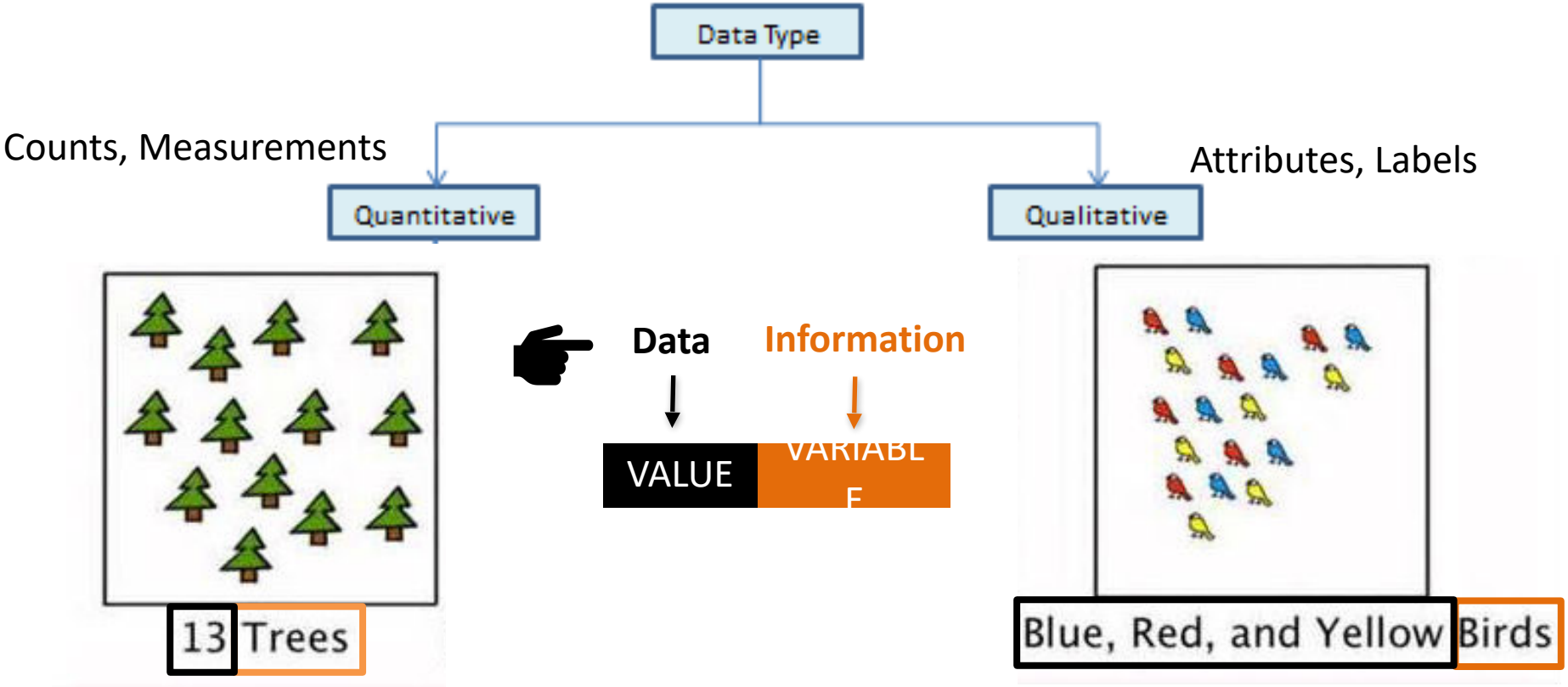


https://research-methodology.net/sampling-in-primary-data-collection/

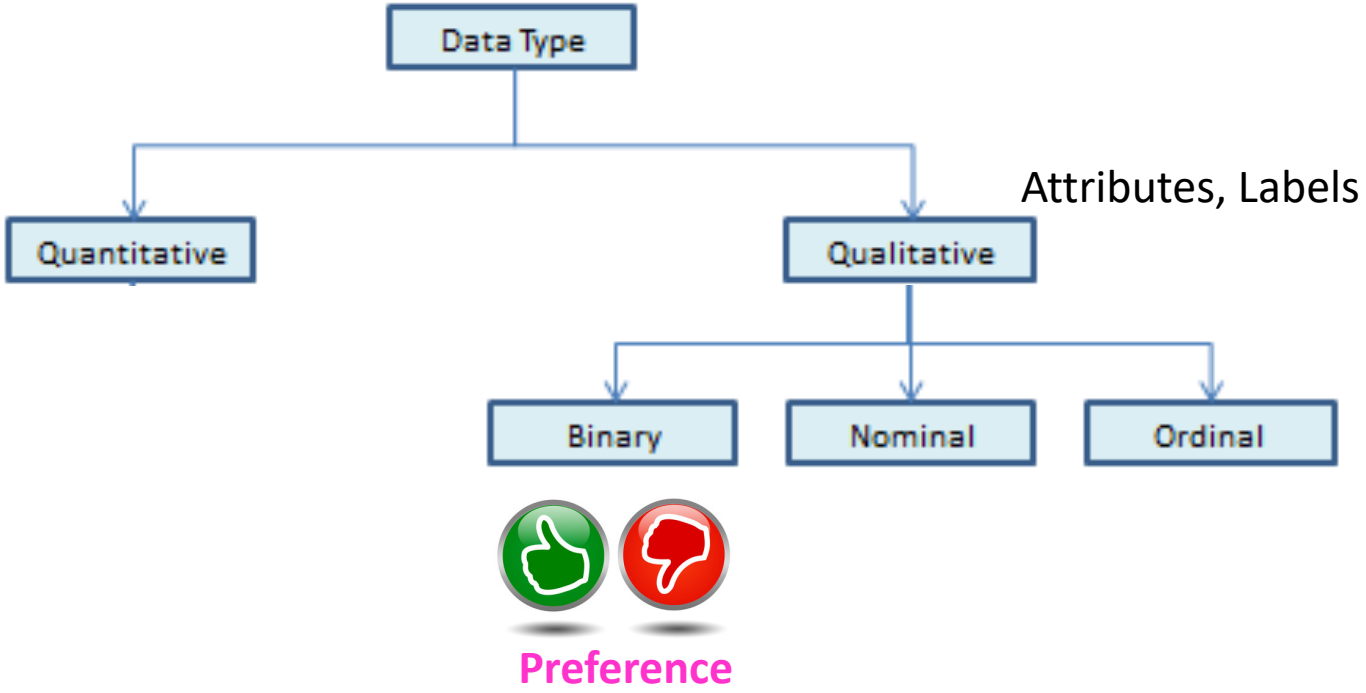
Workflow of a Machine Learning Problem



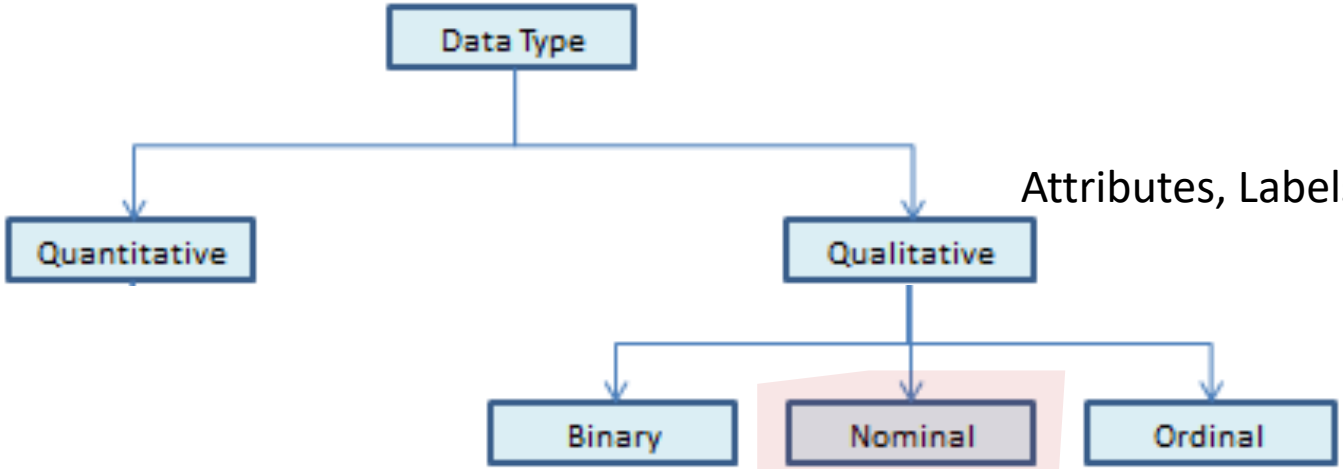
Taxonomy of data variables



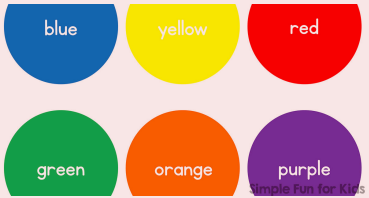
Taxonomy of data



Taxonomy of data



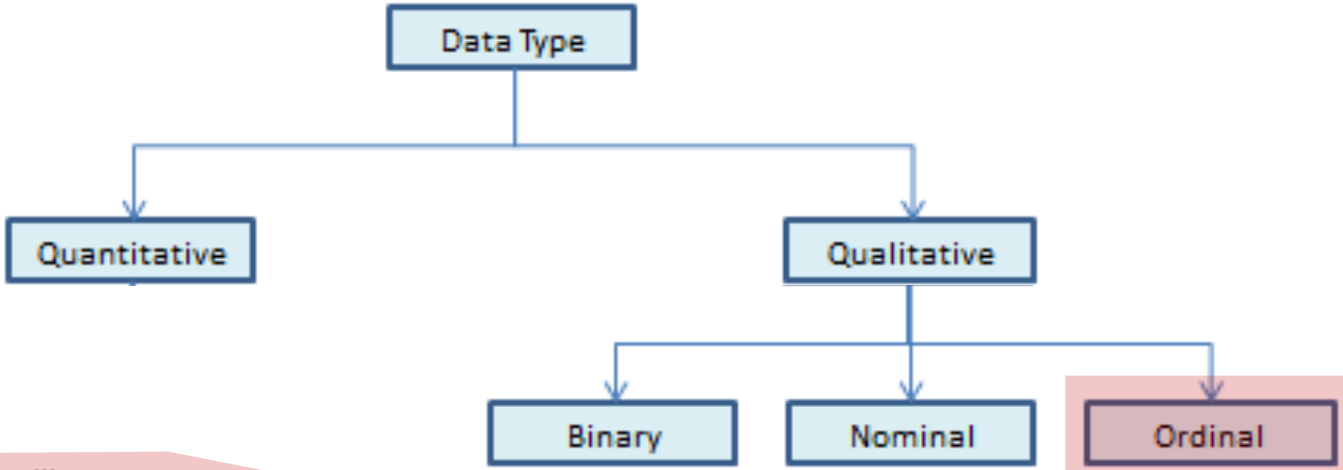
Attributes, Labels



Color

Make

Pin Code



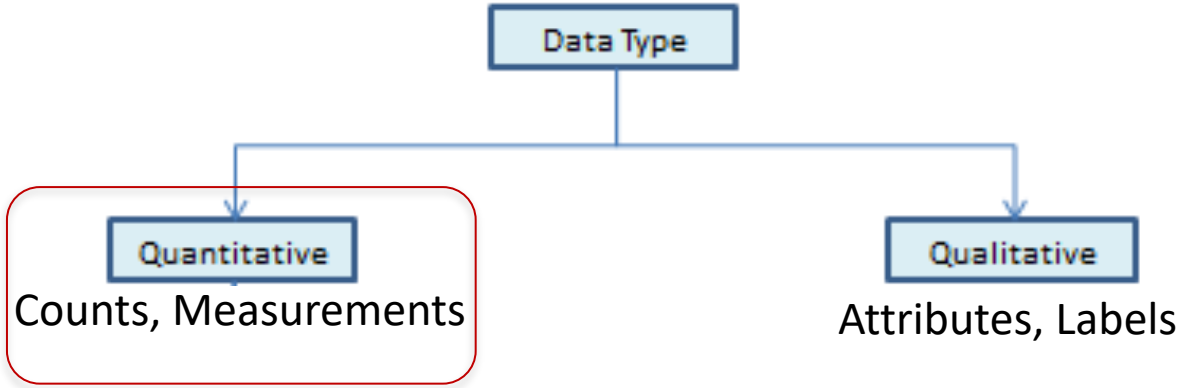
How comfortable are you with Python *

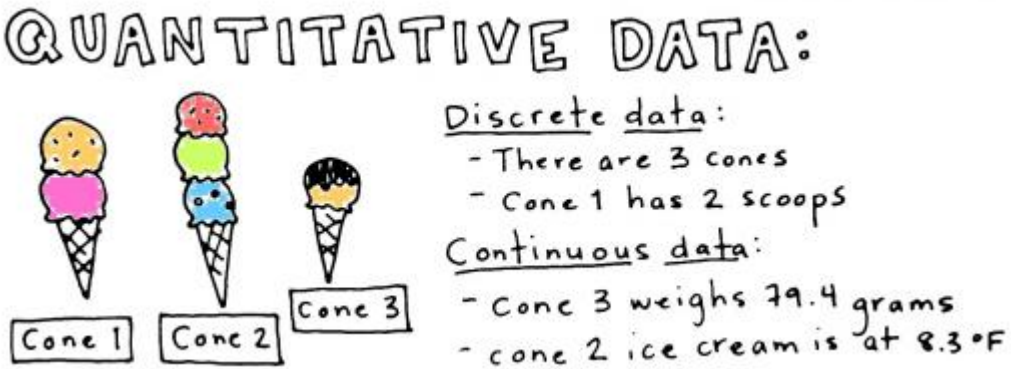
No knowledge ○ ○ ○ ○ ○ ○ Very comfortable

Letter grade
A +
A
A –
B +
B
B –
C +
C
C –
D +
D
E

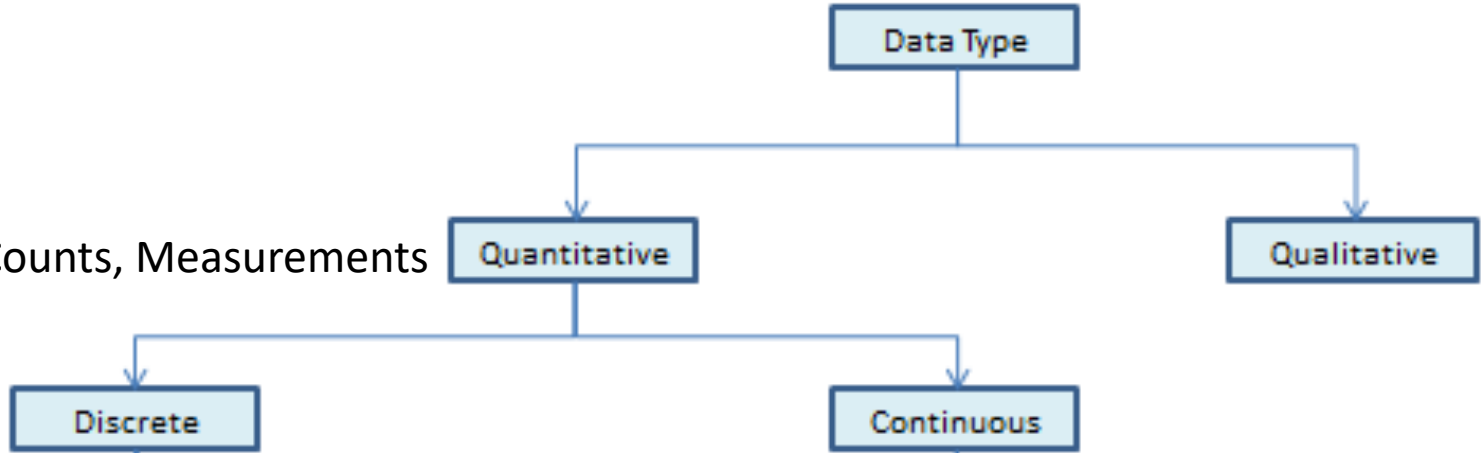
XS S M L XL XXL

Taxonomy of data





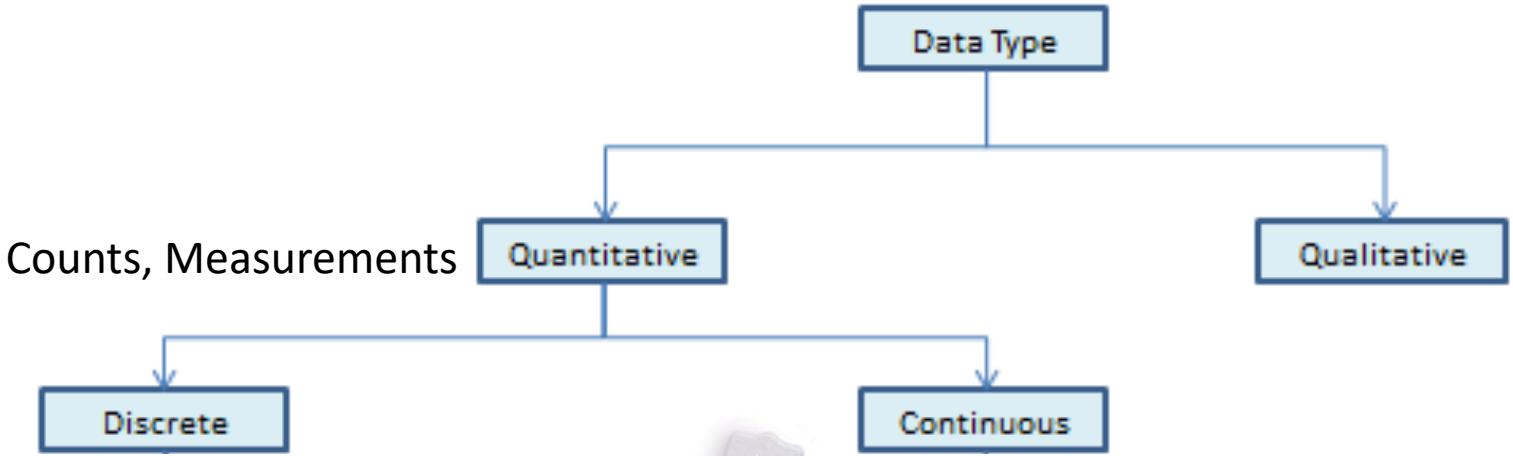
Taxonomy of data



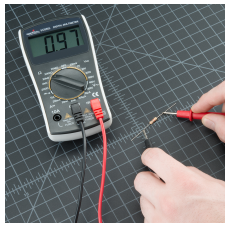
Counts, Measurements

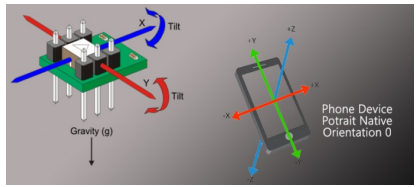
- # of CPU cores
- # of courses taken in a semester
- # of times word ‘sale’ appears in a doc

Taxonomy of data



Counts, Measurements



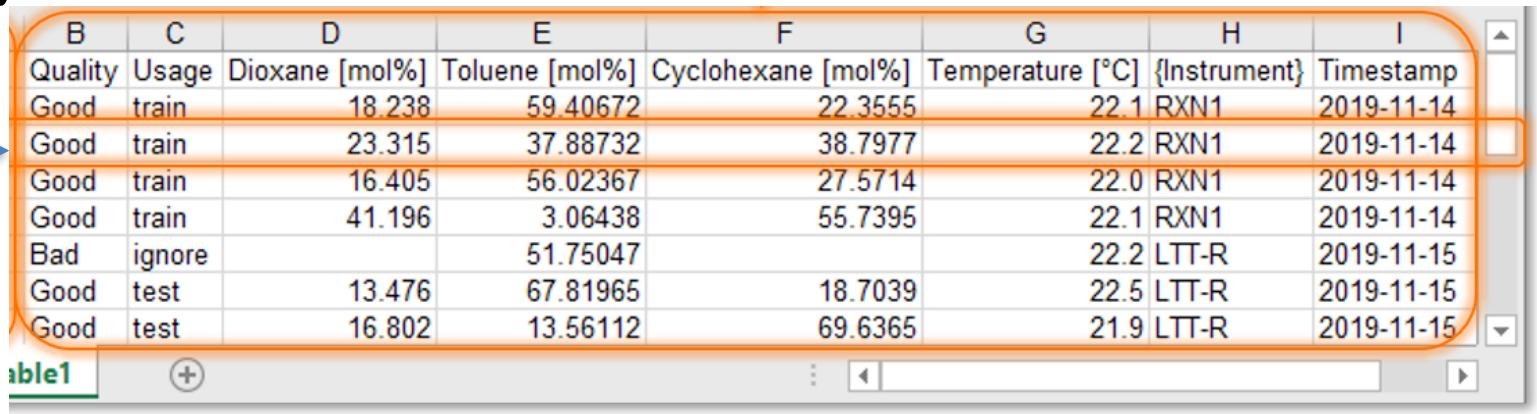


Samples and Features

Feature / Attribute

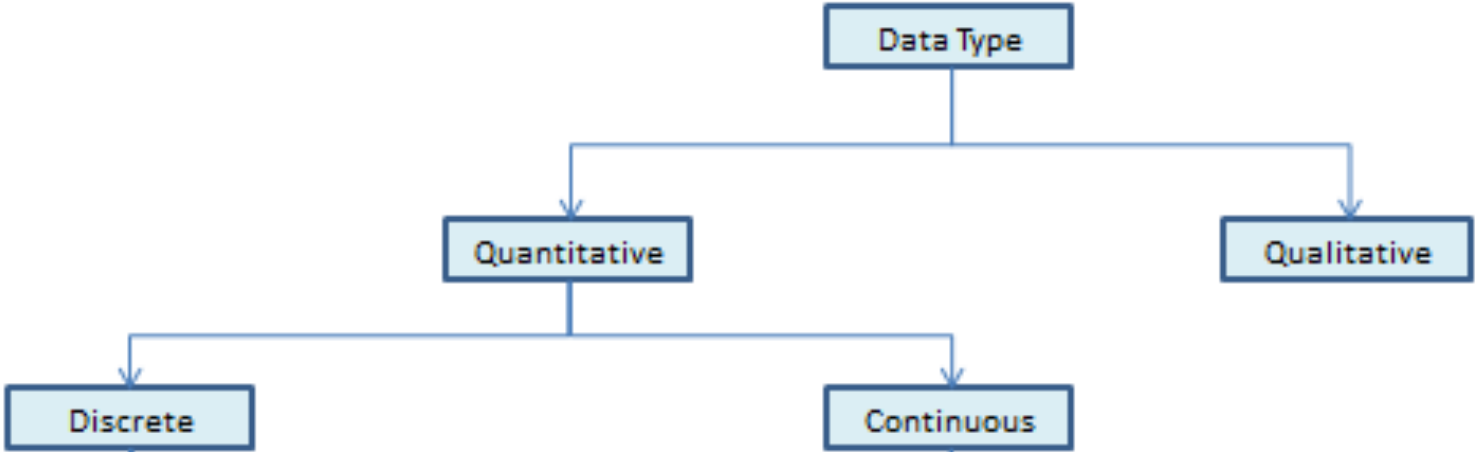
Dataset

Sample

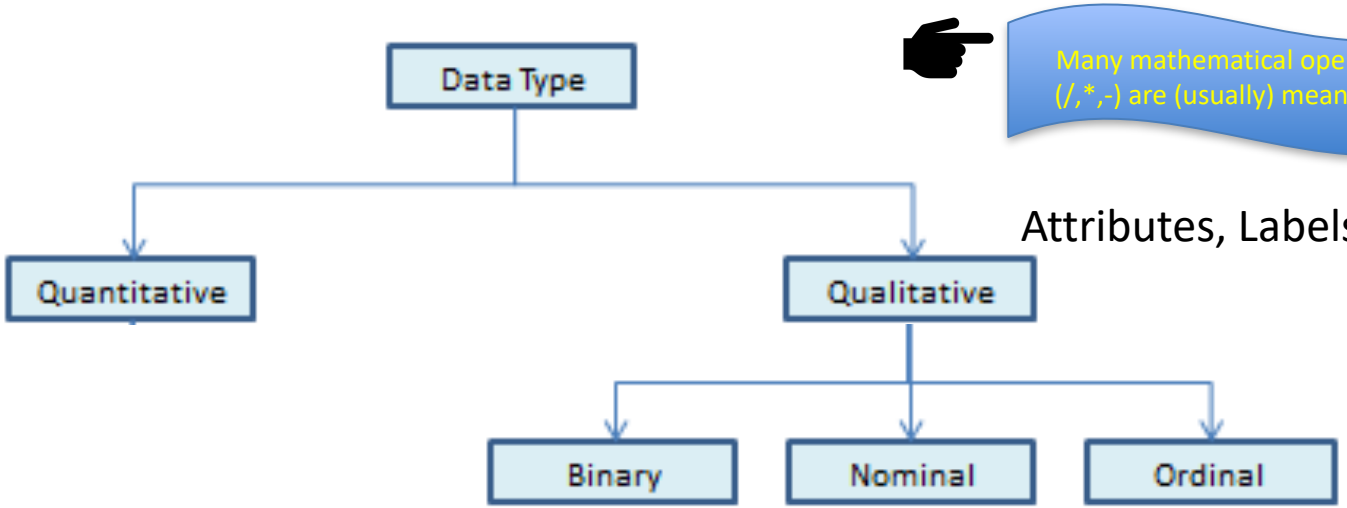


B	C	D	E	F	G	H	I
Quality	Usage	Dioxane [mol%]	Toluene [mol%]	Cyclohexane [mol%]	Temperature [°C]	{Instrument}	Timestamp
Good	train	18.238	59.40672	22.3555	22.1	RXN1	2019-11-14
Good	train	23.315	37.88732	38.7977	22.2	RXN1	2019-11-14
Good	train	16.405	56.02367	27.5714	22.0	RXN1	2019-11-14
Good	train	41.196	3.06438	55.7395	22.1	RXN1	2019-11-14
Bad	ignore		51.75047		22.2	LTT-R	2019-11-15
Good	test	13.476	67.81965	18.7039	22.5	LTT-R	2019-11-15
Good	test	16.802	13.56112	69.6365	21.9	LTT-R	2019-11-15

Ultimately, all data needs to be quantitative



Taxonomy of data: Qualitative → Quantitative



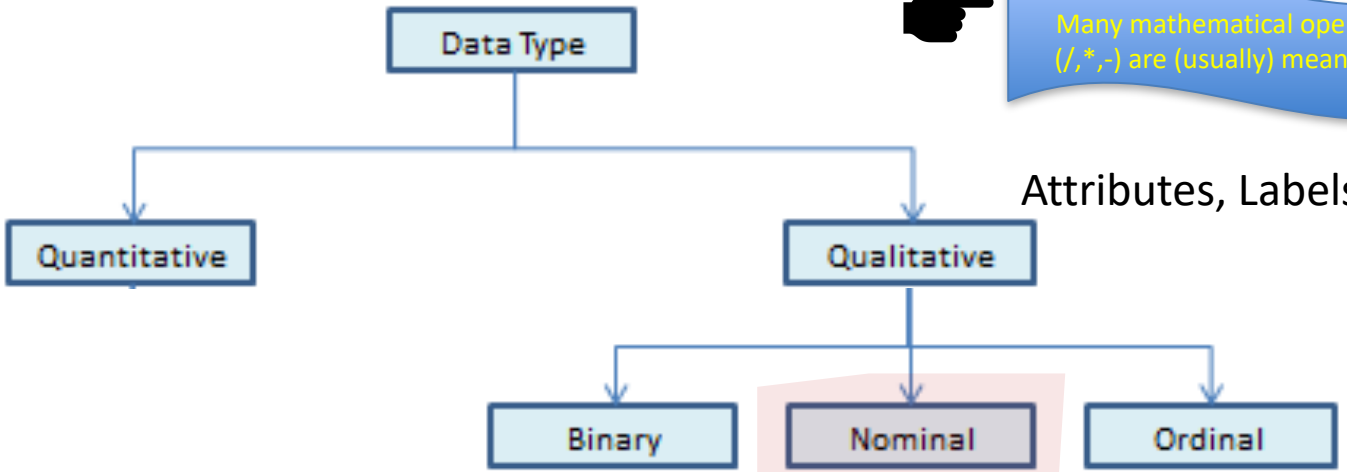
Many mathematical operations (/,*,-) are (usually) meaningless

Attributes, Labels

0/1 ; -1/1

Preference

Taxonomy of data: Qualitative → Quantitative



Many mathematical operations (/,*,-) are (usually) meaningless

Attributes, Labels

Color

Make

Pin Code

Numerical encoding of categorical variables

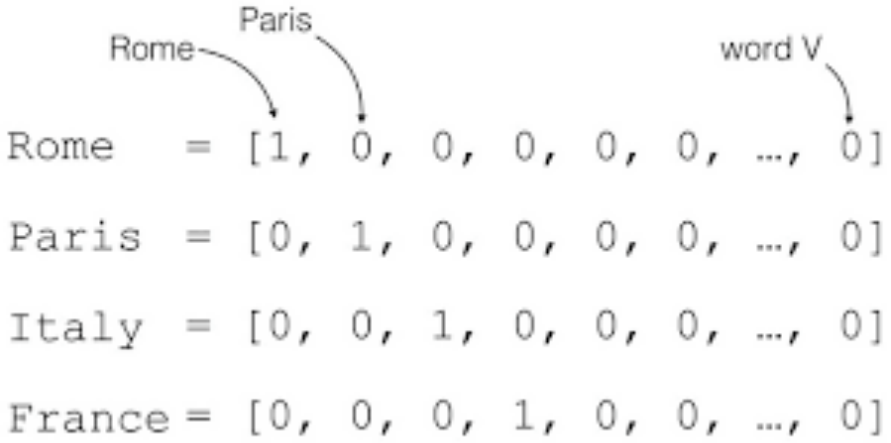
Original data:	
id	Color
1	White
2	Red
3	Black
4	Purple
5	Gold

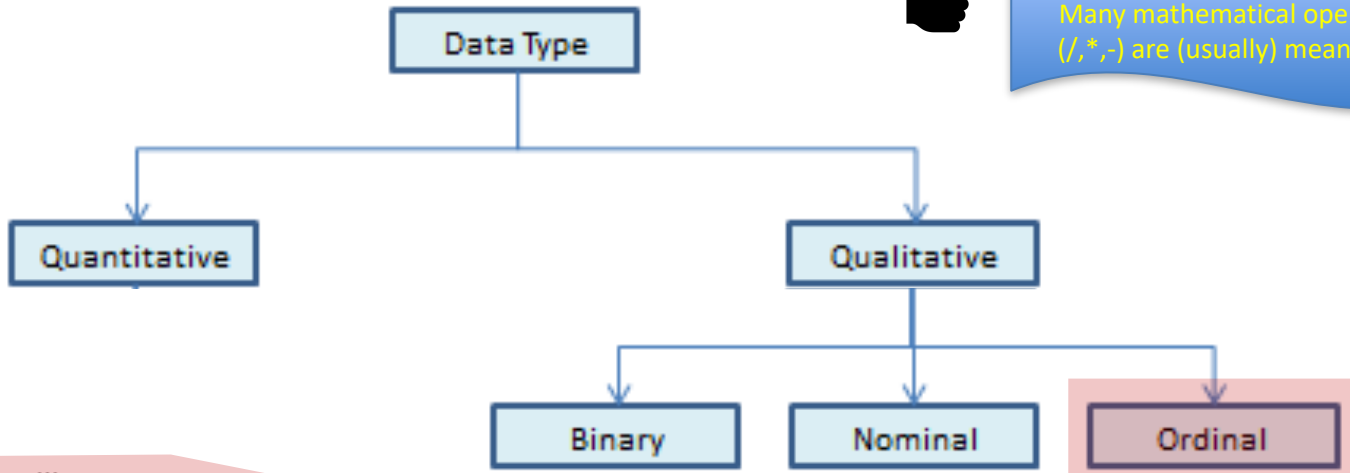
Numerical encoding of categorical variables

Original data:	
id	Color
1	White
2	Red
3	Black
4	Purple
5	Gold

One-hot encoding format:					
id	White	Red	Black	Purple	Gold
1	1	0	0	0	0
2	0	1	0	0	0
3	0	0	1	0	0
4	0	0	0	1	0
5	0	0	0	0	1

Numerical encoding of categorical variables





Many mathematical operations (/,*,-) are (usually) meaningless

How comfortable are you with Python *

	-2			+1		
No knowledge	○	○	○	○	○	○	Very comfortable

Letter grade
A +
A
A –
B +
B
B –
C +
C
C –
D +
D
E

XS S M L XL XXL

1 2 3 4 5

Example: Contact Lenses dataset

☛ No patient id

☛ Age is not a number !

Age	Spectacle prescription	Astigmatism	Tear production rate	Recommended lenses
Young	Myope	No	Reduced	None
Young	Myope	No	Normal	Soft
Young	Myope	Yes	Reduced	None
Young	Myope	Yes	Normal	Hard
Young	Hypermetrope	No	Reduced	None
Young	Hypermetrope	No	Normal	Soft
Young	Hypermetrope	Yes	Reduced	None
Young	Hypermetrope	Yes	Normal	hard
Pre-presbyopic	Myope	No	Reduced	None
Pre-presbyopic	Myope	No	Normal	Soft
Pre-presbyopic	Myope	Yes	Reduced	None
Pre-presbyopic	Myope	Yes	Normal	Hard
Pre-presbyopic	Hypermetrope	No	Reduced	None
Pre-presbyopic	Hypermetrope	No	Normal	Soft
Pre-presbyopic	Hypermetrope	Yes	Reduced	None
Pre-presbyopic	Hypermetrope	Yes	Normal	None
Presbyopic	Myope	No	Reduced	None
Presbyopic	Myope	No	Normal	None
Presbyopic	Myope	Yes	Reduced	None
Presbyopic	Myope	Yes	Normal	Hard
Presbyopic	Hypermetrope	No	Reduced	None
Presbyopic	Hypermetrope	No	Normal	Soft
Presbyopic	Hypermetrope	Yes	Reduced	None
Presbyopic	Hypermetrope	Yes	Normal	None

Example: PlayTennis dataset

Outlook	Temperature	Humidity	Windy	Play
Sunny	Hot	High	False	No
Sunny	Hot	High	True	No
Overcast	Hot	High	False	Yes
Rainy	Mild	Normal	False	Yes
...	...	...	...	...

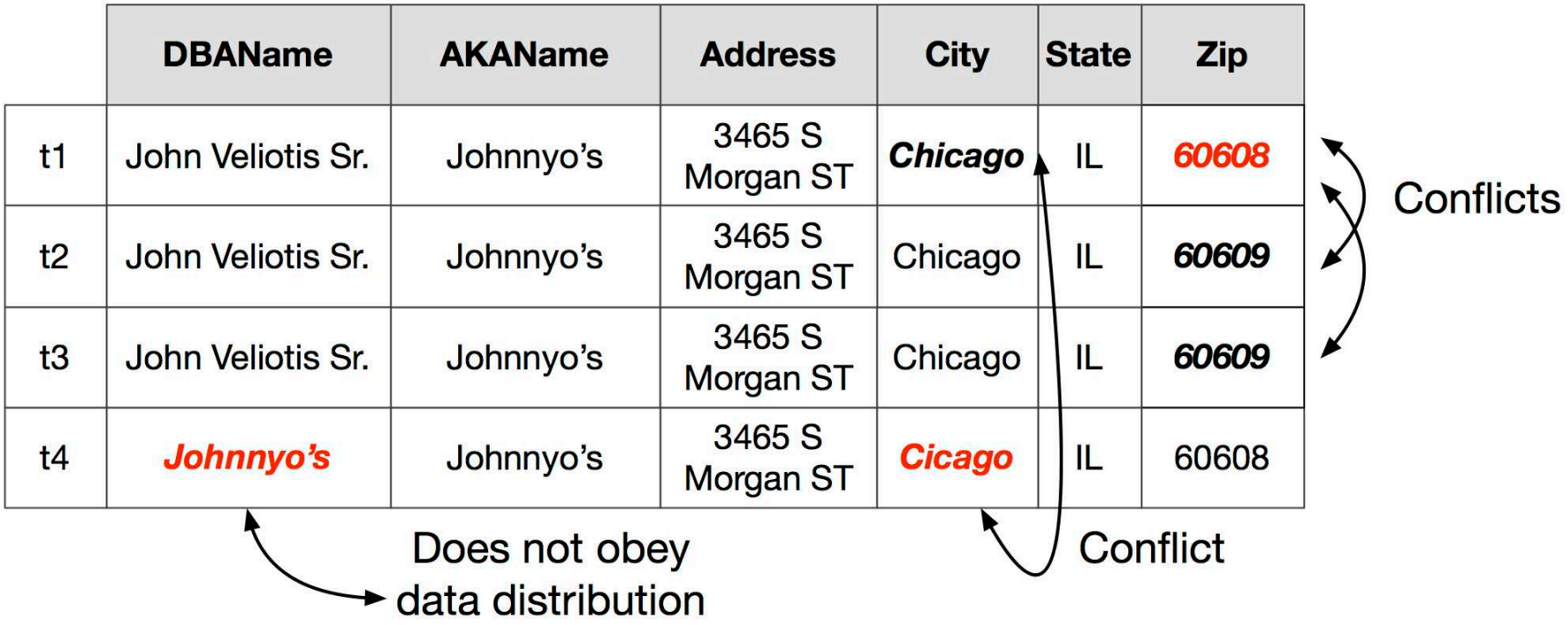
Outlook	Temperature	Humidity	Windy	Play
Sunny	85	85	False	No
Sunny	80	90	True	No
Overcast	83	86	False	Yes
Rainy	75	80	False	Yes
...	...	...	...	...

Sometimes data can be missing

Outlook	Temperature	Humidity	Windy	Play
Sunny	85	85	False	No
Sunny	80		True	No
Overcast	83	86	False	Yes
Rainy	75	80	False	Yes
...	...	...	...	...

→ Unknown or unrecorded

… or incorrect



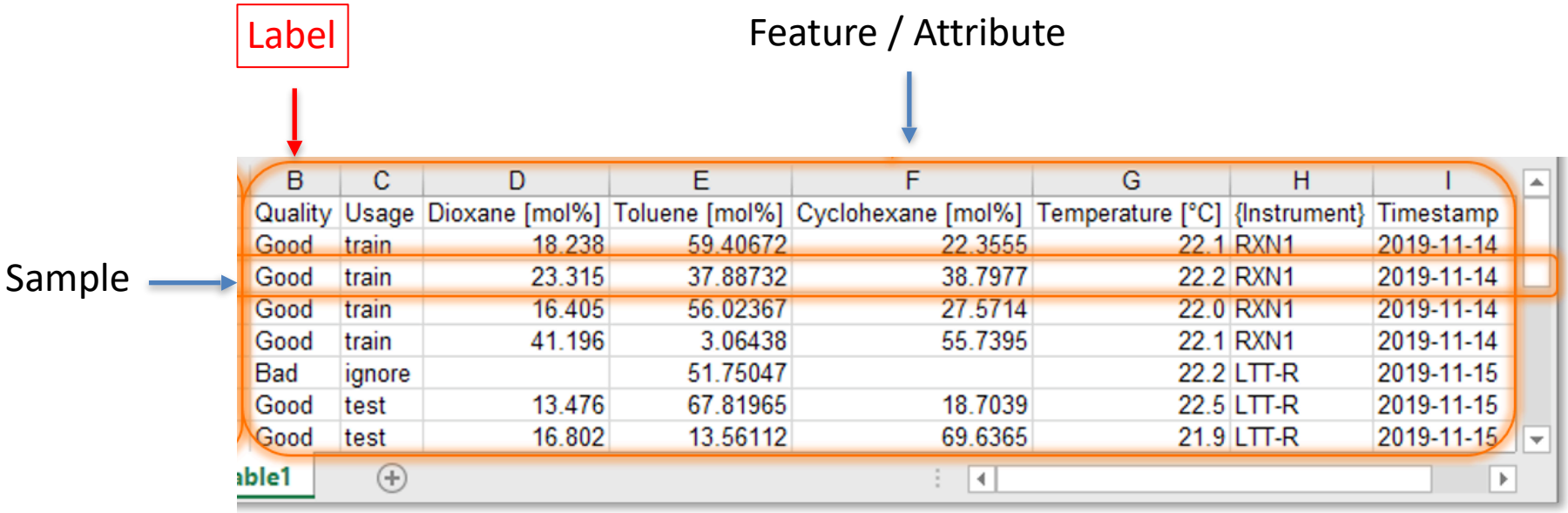
Data imputation

- Approaches that aim to estimate missing data
- Options
  - Remove sample
  - Fill with 0
  - Fill with constant
  - Fill with a statistical measure (mean, median, mode)
  - Do nothing. Use a learning method which can handle missing data.

Lecture Outline

- *ML Workflow*
- Data sample Representations
- Basic Data Transformations
- Data Visualization

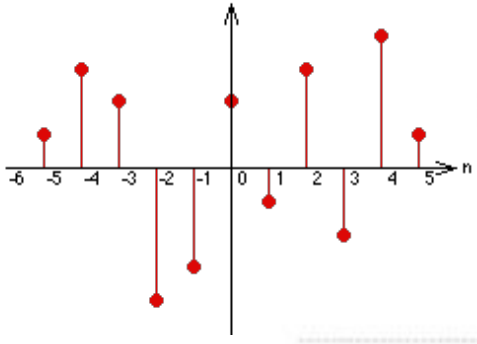
Samples, Features, Labels



B	C	D	E	F	G	H	I
Quality	Usage	Dioxane [mol%]	Toluene [mol%]	Cyclohexane [mol%]	Temperature [°C]	{Instrument}	Timestamp
Good	train	18.238	59.40672	22.3555	22.1	RXN1	2019-11-14
Good	train	23.315	37.88732	38.7977	22.2	RXN1	2019-11-14
Good	train	16.405	56.02367	27.5714	22.0	RXN1	2019-11-14
Good	train	41.196	3.06438	55.7395	22.1	RXN1	2019-11-14
Bad	ignore		51.75047		22.2	LTT-R	2019-11-15
Good	test	13.476	67.81965	18.7039	22.5	LTT-R	2019-11-15
Good	test	16.802	13.56112	69.6365	21.9	LTT-R	2019-11-15

able1

Data Sample Representations



Scalars

$$x$$

Vectors

$$x = \begin{bmatrix} x_1 \\ \vdots \\ x_N \end{bmatrix}$$

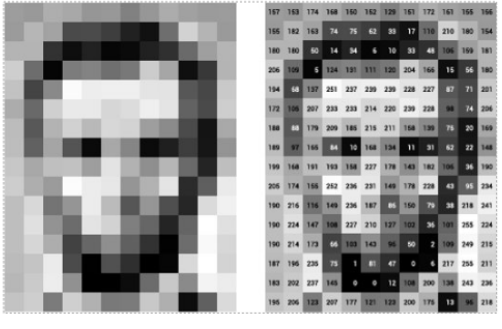
Matrix

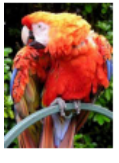
$$\mathbf{X} = \begin{bmatrix} \mathbf{x} & \cdots & \mathbf{x}_N \end{bmatrix} = \begin{bmatrix} x_{1,1} & & x_{N,1} \\ \vdots & \cdots & \vdots \\ x_{1,M} & & x_{N,M} \end{bmatrix}$$

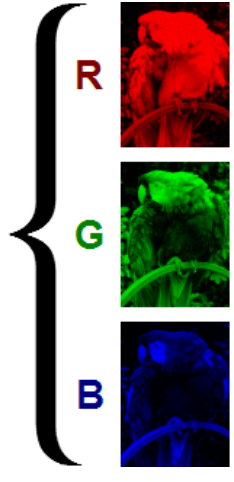
Tensor

$$\mathbf{X} = \{\mathbf{X}_1, \ldots \mathbf{X}_K\} = \begin{bmatrix} x_{1,1,1} & & x_{N,1,1} \\ \vdots & \cdots & \vdots \\ x_{1,M,1} & & x_{N,M,1} \end{bmatrix} \begin{bmatrix} \ddots & & \\ & & \\ & & \end{bmatrix} \begin{bmatrix} x_{1,1,K} & & x_{N,1,K} \\ \vdots & \cdots & \vdots \\ x_{1,M,K} & & x_{N,M,K} \end{bmatrix}$$

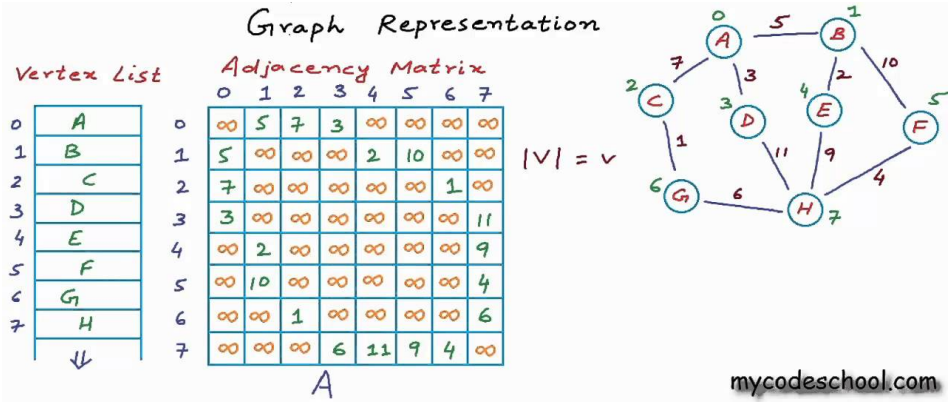
2-d image







Data Representations



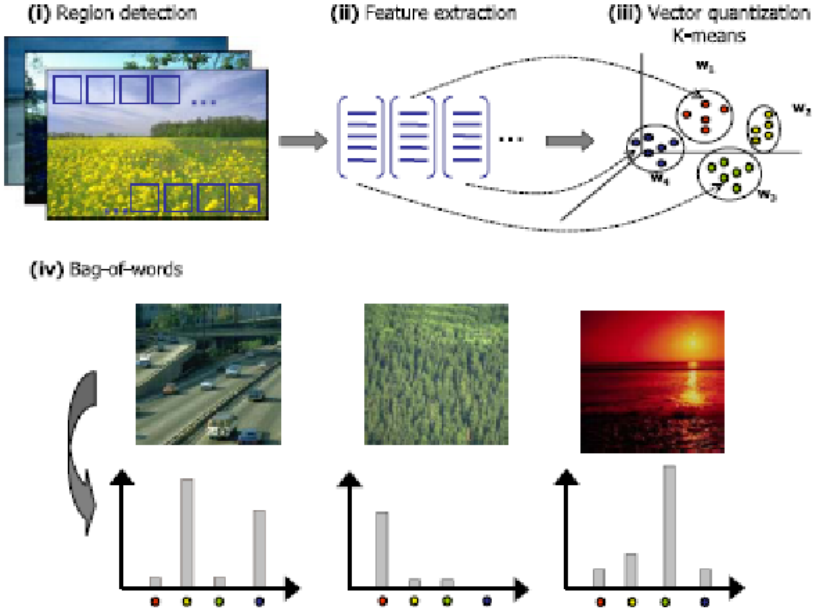
Feature Extraction (FE)

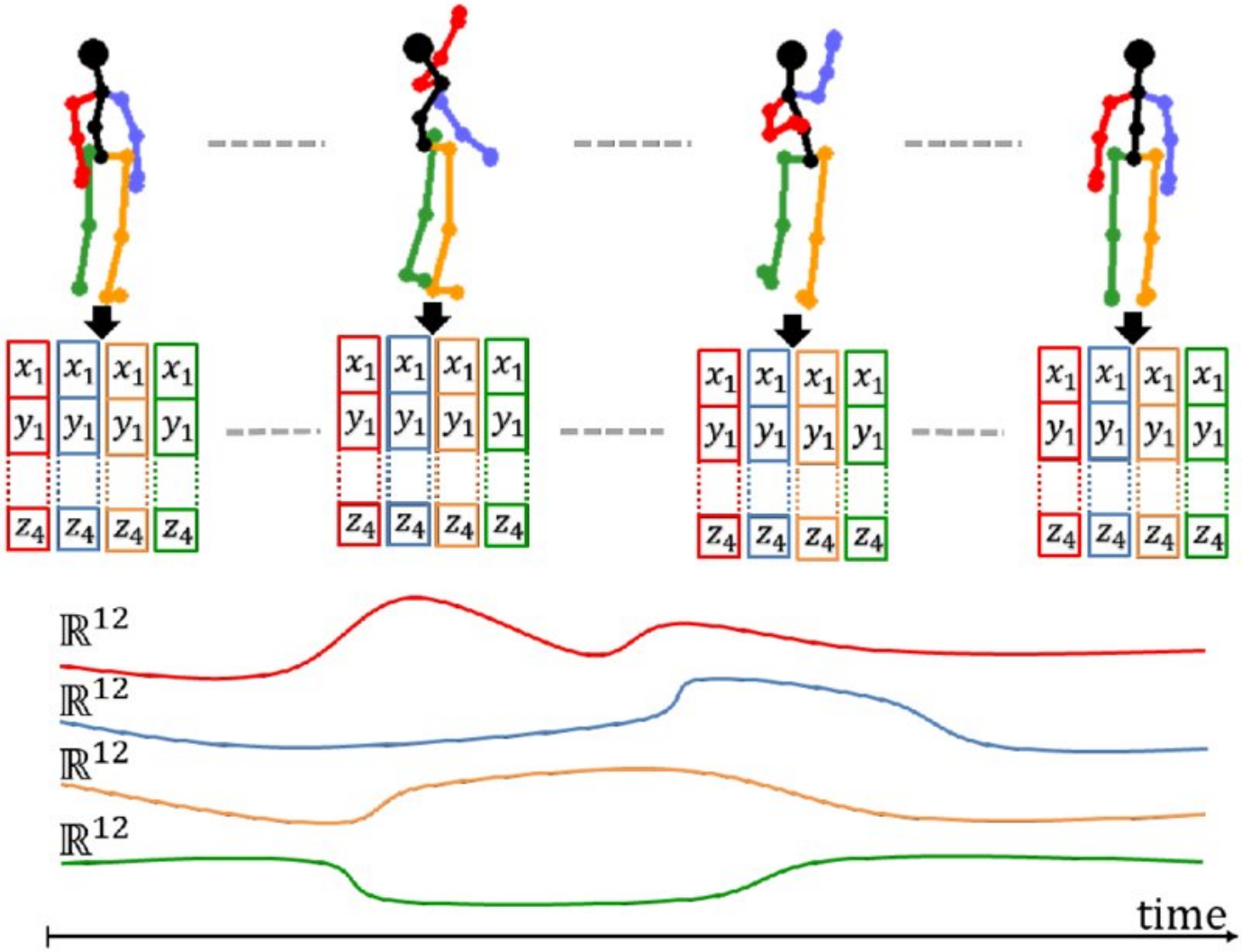
- Def: Feature Extraction (FE) is any algorithm that transformation raw data into features that can be used as an input for a learning algorithm.

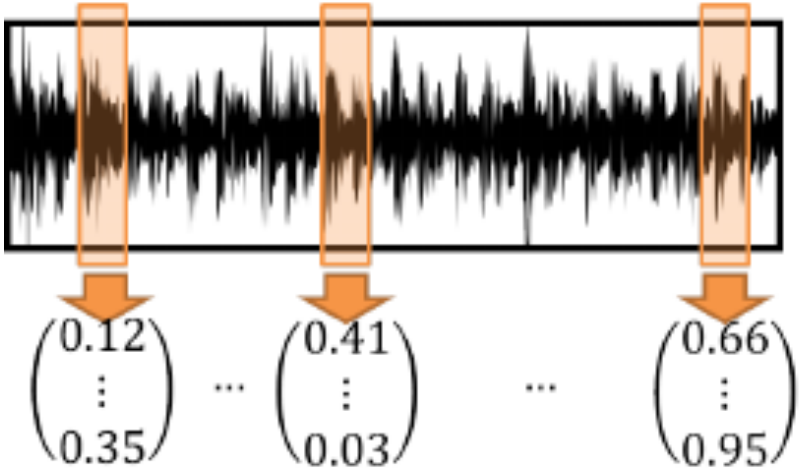
The Bag of Words Representation

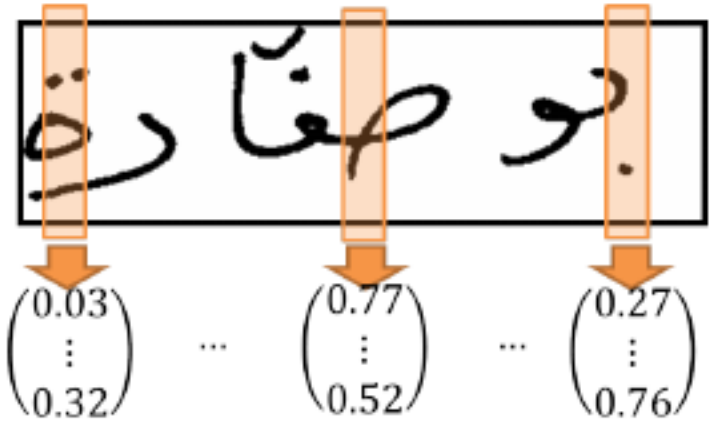
I love this movie! It's sweet, but with satirical humor. The dialogue is great and the adventure scenes are fun... It manages to be whimsical and romantic while laughing at the conventions of the fairy tale genre. I would recommend it to just about anyone. I've seen it several times, and I'm always happy to see it again whenever I have a friend who hasn't seen it yet!

it	6
I	5
the	4
to	3
and	3
seen	2
yet	1
would	1
whimsical	1
times	1
sweet	1
satirical	1
adventure	1
genre	1
fairy	1
humor	1
have	1
great	1
…	…

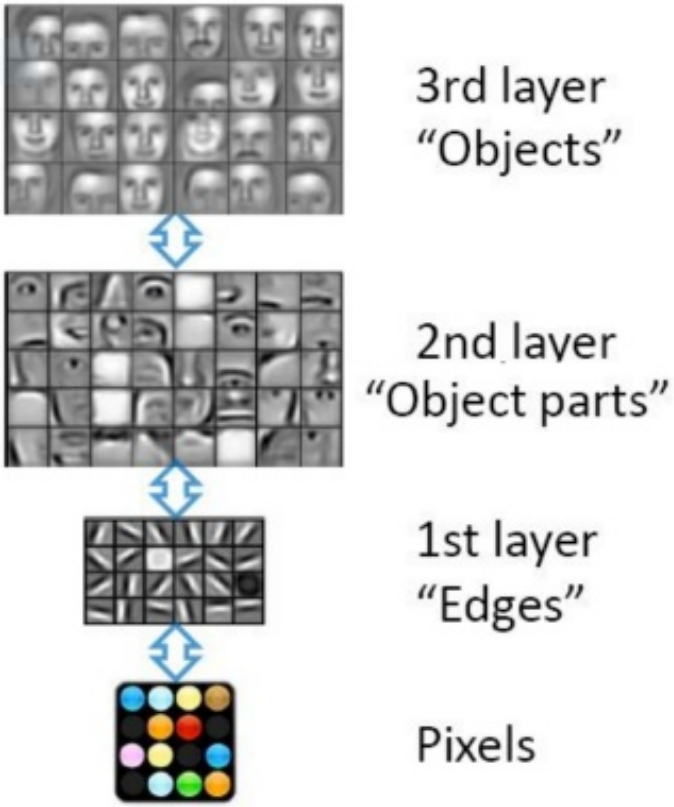


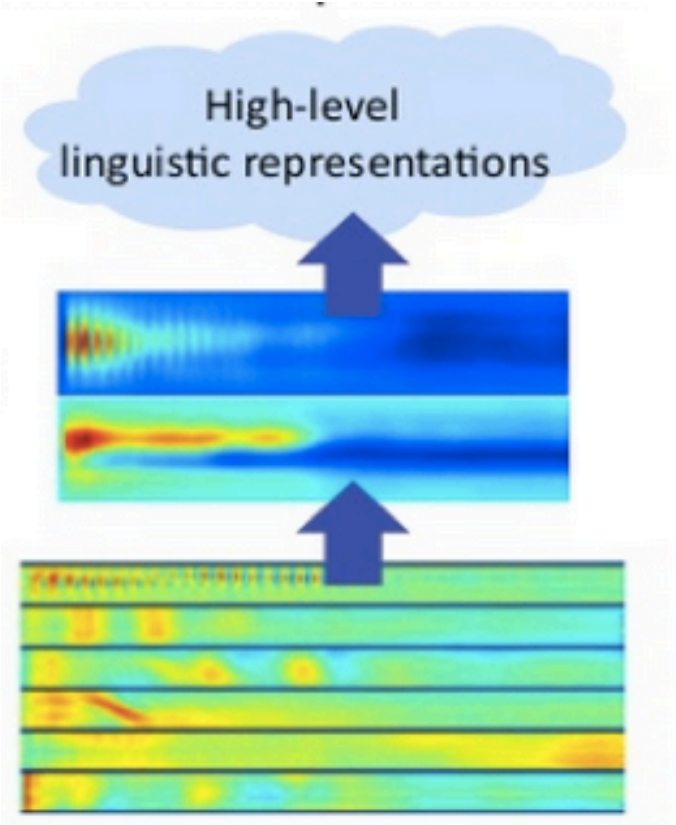

x_1 y_1 z_4
$\mathbb{R}^{12}$
$\mathbb{R}^{12}$
$\mathbb{R}^{12}$
$\mathbb{R}^{12}$
time


0.12
0.35
0.41
0.03
0.66
0.95


0.03
0.32
0.77
0.52
0.27
0.76

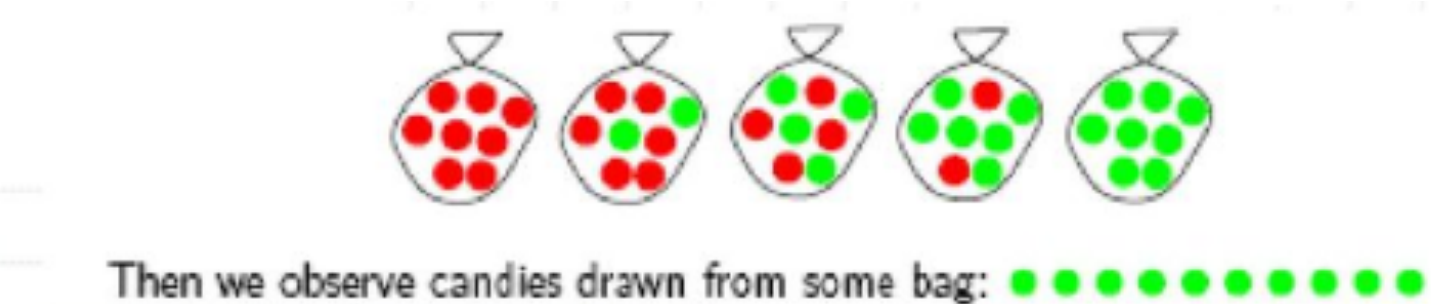
Feature-based, Hierarchical Data Representations





Data – a probability-based perspective

- The basis for Statistical Learning Theory



  - Domain described by random variables (r.v.)
    - X = {apple, grape}
    - $b_i \in [1,5]$
  - Data = Instantiation of some or all r.v.'s in the domain

Data: a probabilistic perspective

	DBAName	AKAName	Address	City	State	Zip
t1	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	***Chicago***	IL	***60608***
t2	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	Chicago	IL	***60609***
t3	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	Chicago	IL	***60609***
t4	***Johnnyo's***	Johnnyo's	3465 S Morgan ST	***Cicago***	IL	60608

Conflicts

Does not obey data distribution

Conflict

Output

Proposed Cleaned Dataset

	DBAName	Address	City	State	Zip
t1	John Veliotis Sr.	3465 S Morgan ST	Chicago	IL	60608
t2	John Veliotis Sr.	3465 S Morgan ST	Chicago	IL	**60608**
t3	John Veliotis Sr.	3465 S Morgan ST	Chicago	IL	**60608**
t4	**John Veliotis Sr.**	3465 S Morgan ST	**Chicago**	IL	60608

Marginal Distribution of Cell Assignments

Cell	Possible Values	Probability
t2.Zip	60608	0.84
	60609	0.16
t4.City	Chicago	0.95
	Cicago	0.05
t4.DBAName	John Veliotis Sr.	0.99
	Johnnyo's	0.01

Other important aspects of data

- Mode of collection
  - Passive (‘sense’)
  - Active (‘explore, sense, repeat’)

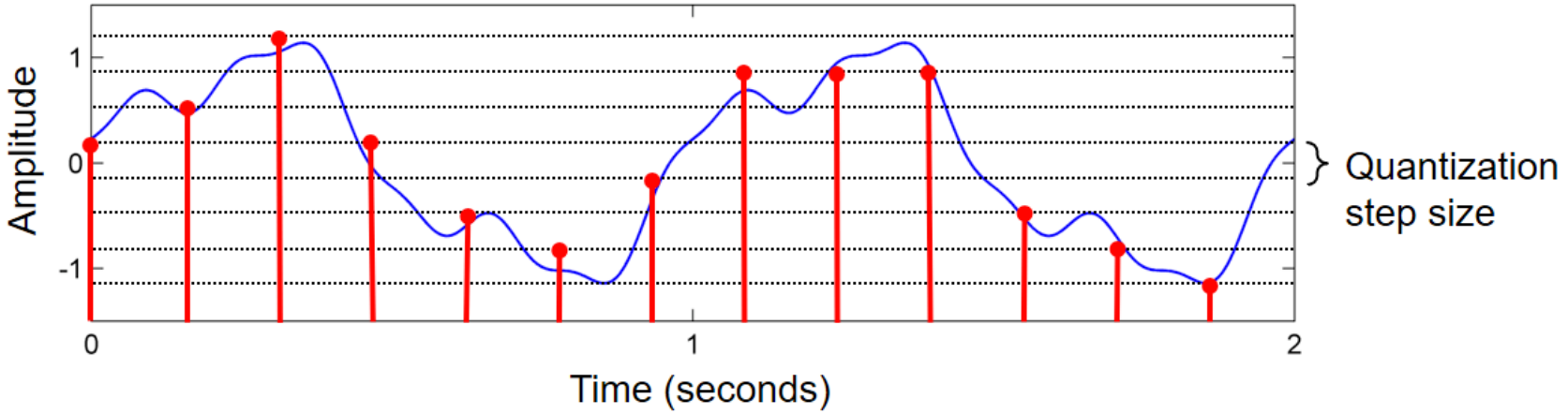
- Statistical assumptions on data
  - i.i.d (independent and identically distributed)
  - Online (e.g. time-series data)

Lecture Outline

- *ML Workflow*
- *Data Representations*
- Basic Data Transformations
- Data Visualization

Quantization

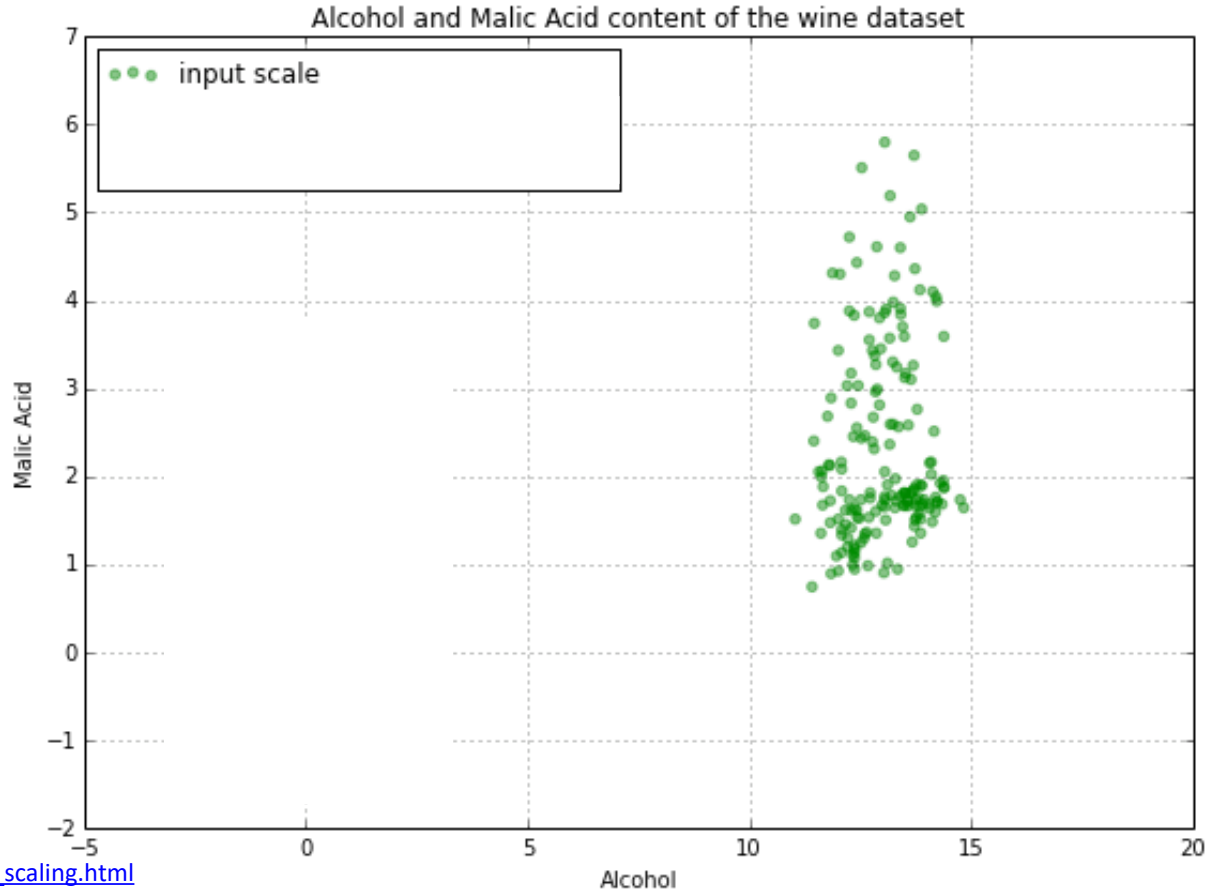
1. Continuous → Discrete (‘Rounding off’)



2. Binary Quantization (‘Thresholding’)

Data Normalization

	Class label	Alcohol	Malic acid
0	1	14.23	1.71
1	1	13.20	1.78
2	1	13.16	2.36
3	1	14.37	1.95
4	1	13.24	2.59



https://sebastianraschka.com/Articles/2014_about_feature_scaling.html

Popular normalization approaches

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

MinMax Scaling

Standardization
(Unit Normal Scaling)

$$z = \frac{x - \mu}{\sigma}$$

$$\mu = \frac{1}{N} \sum_{i=1}^{N} (x_i)$$

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2}$$

	Class label	Alcohol	Malic acid
0	1	14.23	1.71
1	1	13.20	1.78
2	1	13.16	2.36
3	1	14.37	1.95
4	1	13.24	2.59

Data Normalization (applied to each feature)

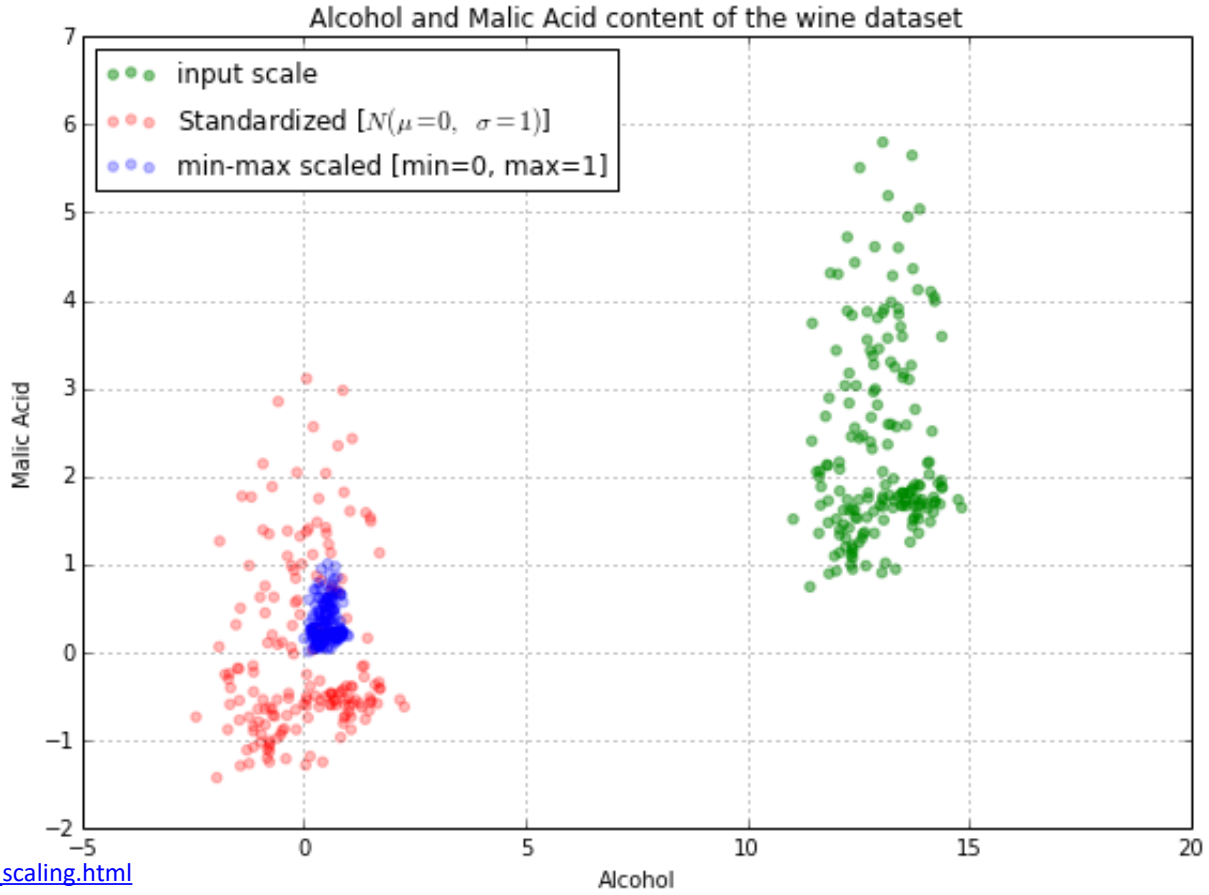
	Class label	Alcohol	Malic acid
0	1	14.23	1.71
1	1	13.20	1.78
2	1	13.16	2.36
3	1	14.37	1.95
4	1	13.24	2.59

- $X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$

  MinMax Scaling

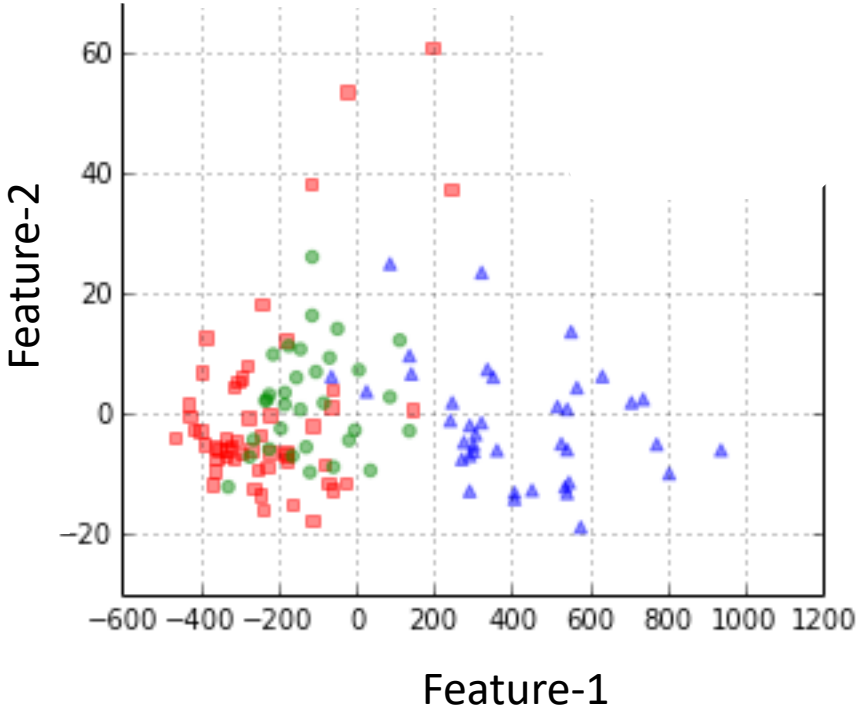
- Standardization (Unit Normal Scaling)

  $z = \frac{x - \mu}{\sigma}$

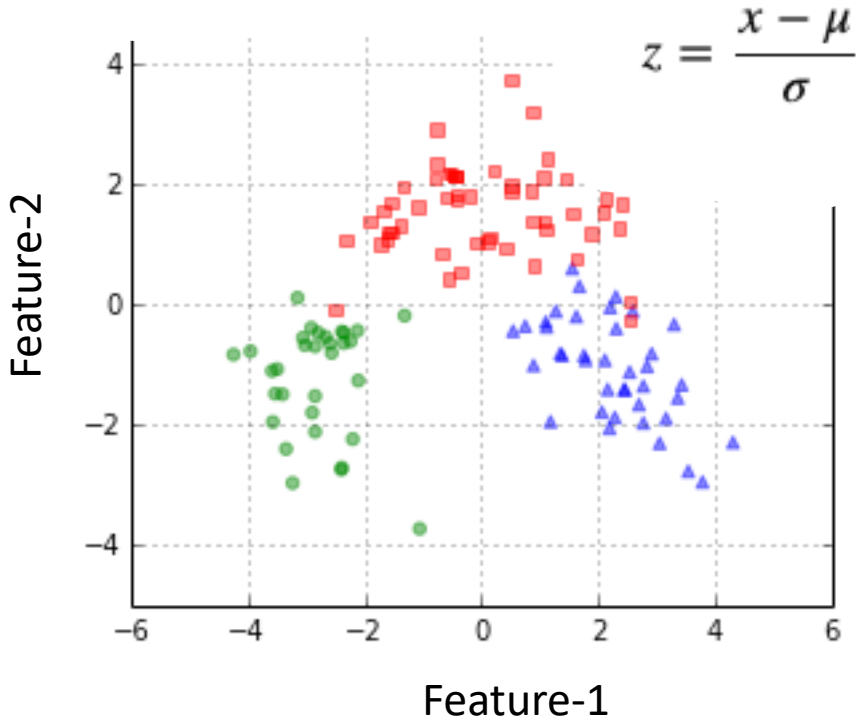


https://sebastianraschka.com/Articles/2014_about_feature_scaling.html

Before standardization



After standardization



https://sebastianraschka.com/Articles/2014_about_feature_scaling.html

Why normalize data ?

- Uniform treatment of all features
- (Empirically) Helps stabilize optimization and lead to faster convergence
- Disadvantages?

Workflow of a Machine Learning Problem