04.01.2019

Statistical Methods in AI (CSE/ECE 471)

Lecture-2: ML Workflow, Data Representations, Supervised Learning, Intro to Classification

Ravi Kiran

Center for Visual Information Technology (CVIT), IIIT Hyderabad

Announcements

- IMPORTANT: All assignments/projects will need to be in Python.
- Tutorial on Python, Pandas, Jupyter notebook this Saturday. **Bring your laptops**.
- Ask questions.

Announcements

- Assignments – Questions involving equations/ mathematical derivation
  - Write up in latex [overleaf.com] → submit
  - Write neatly on paper → scan as photo/pdf [camscanner] → submit
- TA office hours, locations will be announced shortly.

Lecture Outline

- ML Workflow
- Intro to Supervised Learning
  - Taxonomy
  - Data Representations
  - Models

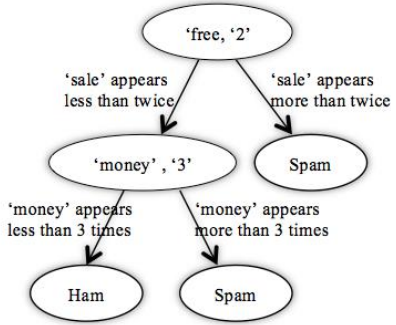
Machine Learning

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 !)

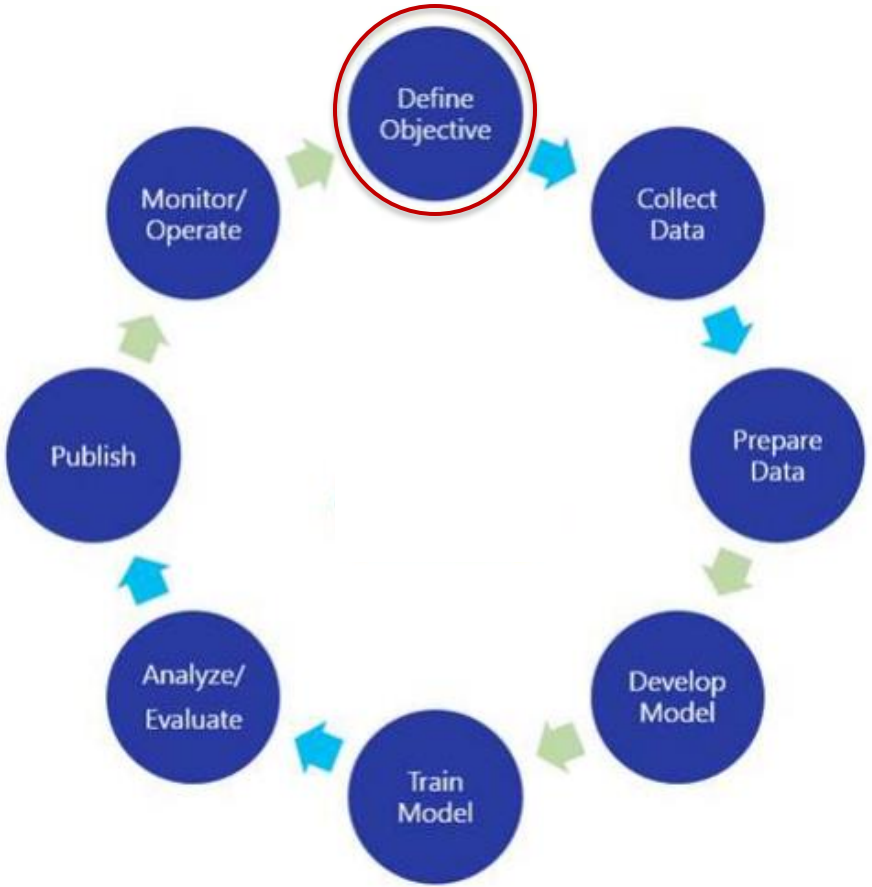
Knowledge:



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

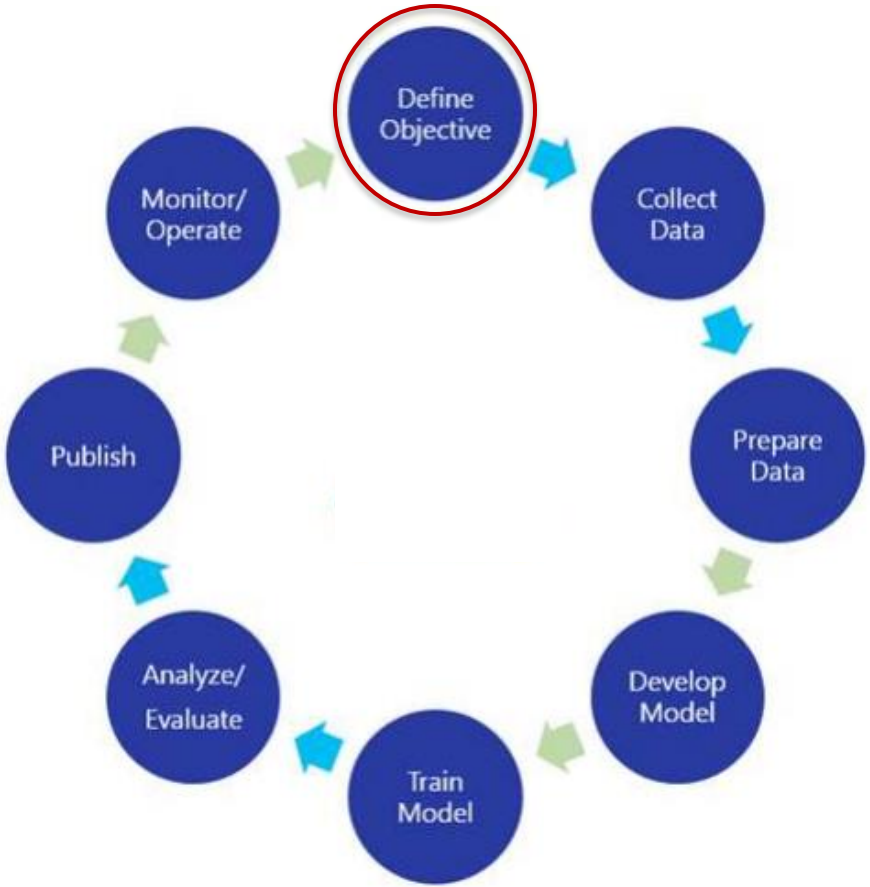
Algorithmic method: Decision Tree

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



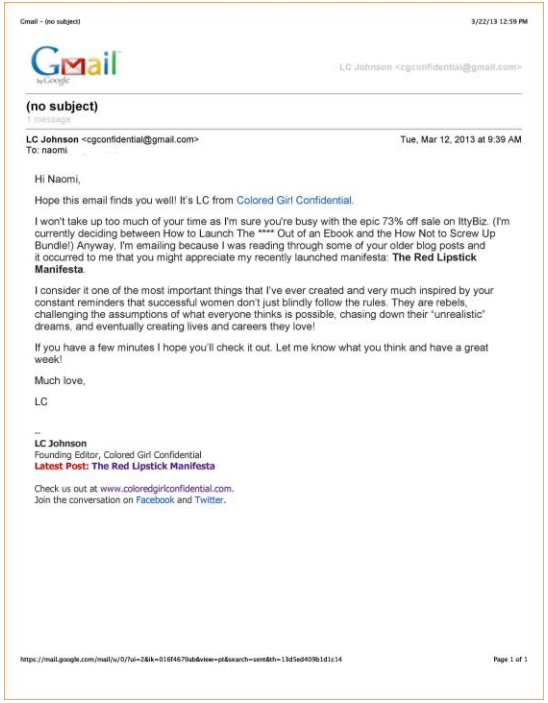
No Data, no ML !


“
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

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!

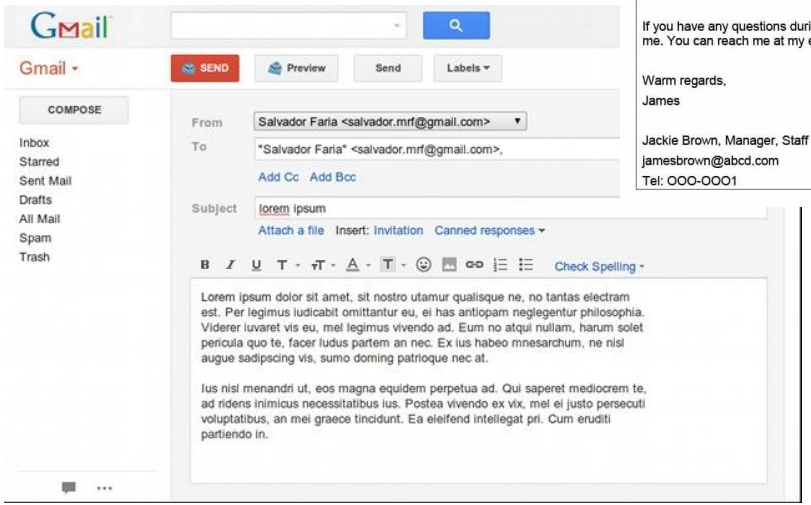
Much love,

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=016f4679ab&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 ▾
B I U T ▾ ▾ A ▾ 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

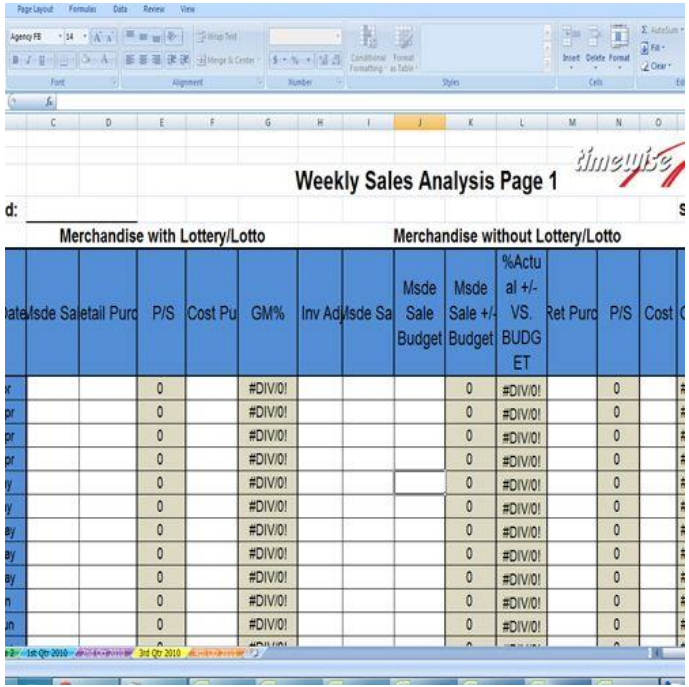
Jackie Brown, Manager, Staff
jamesbrown@abcd.com
Tel: OOO-OOO1

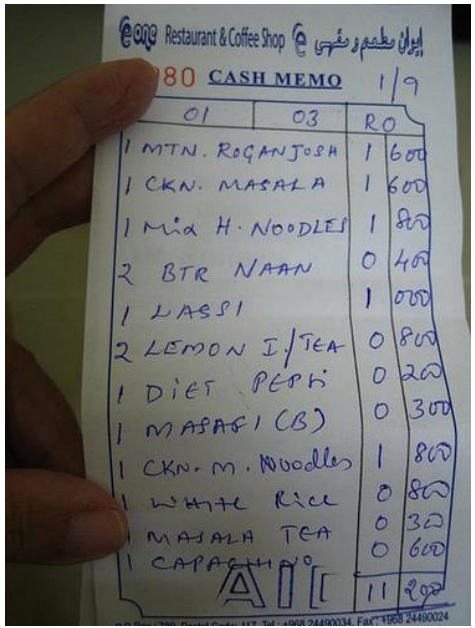
Sources of data

- Predict value of a stock

Sources of data

- Predict effect of advertising on sales

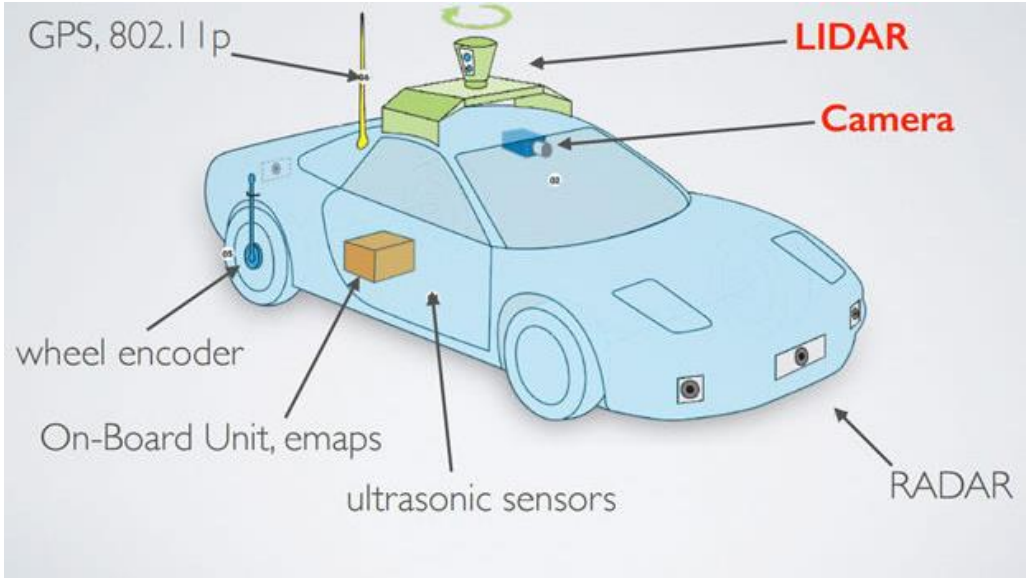




Raw Data may not always be digital in nature !

Sources of data

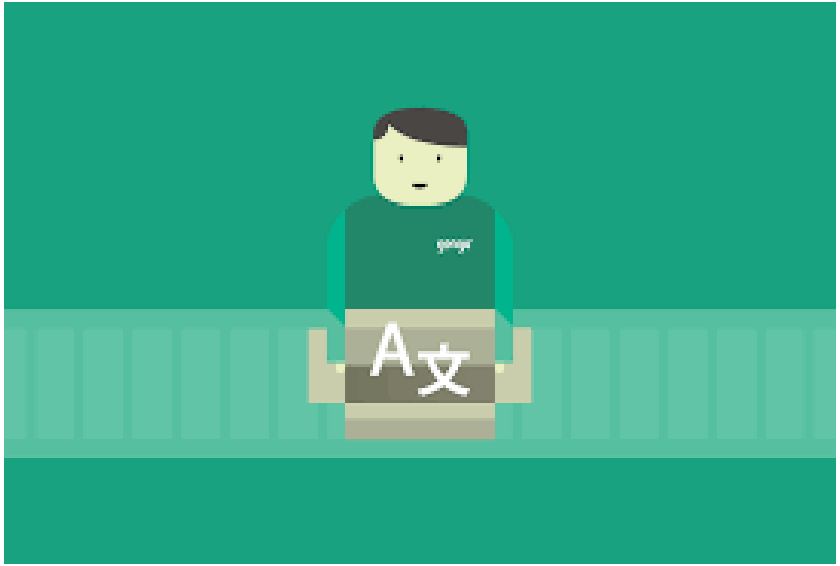
- Drive car safely without human intervention



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

Raw data

- Not all of it relevant

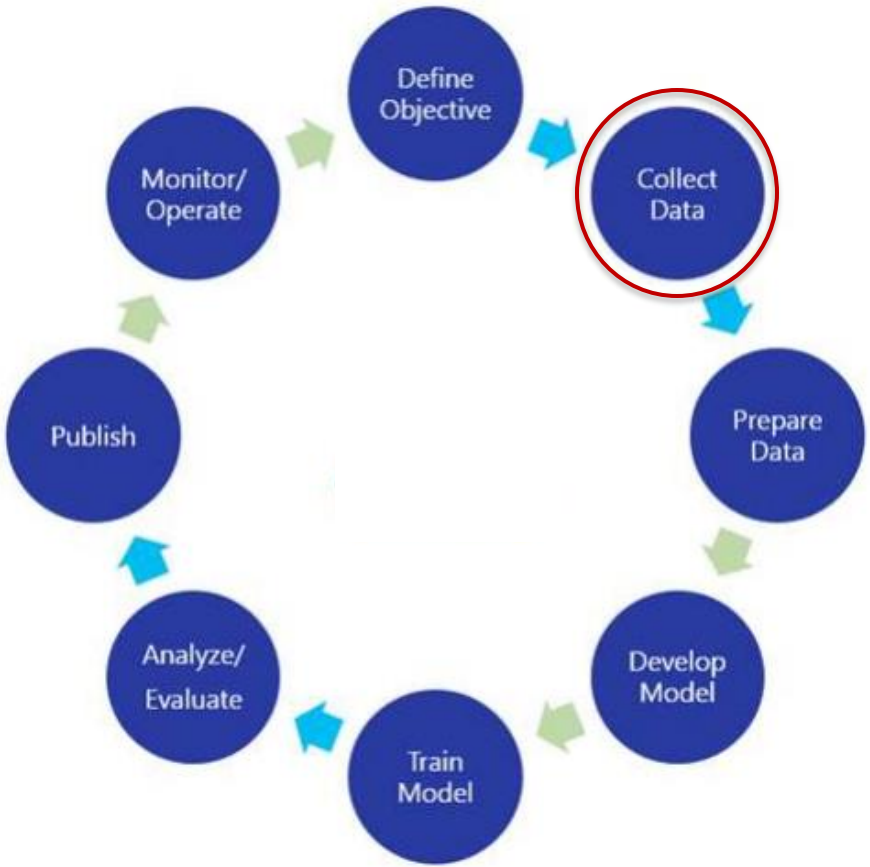
Raw data

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

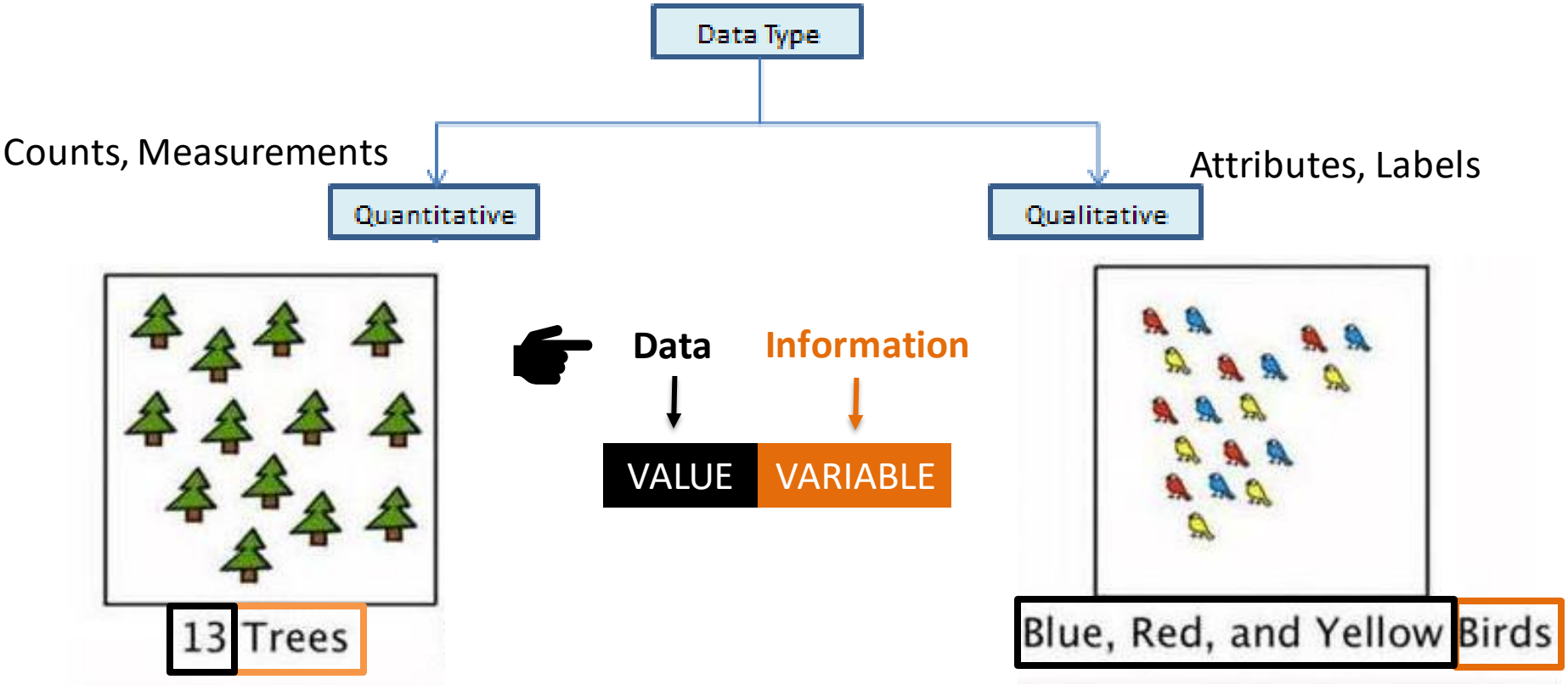
Raw data

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

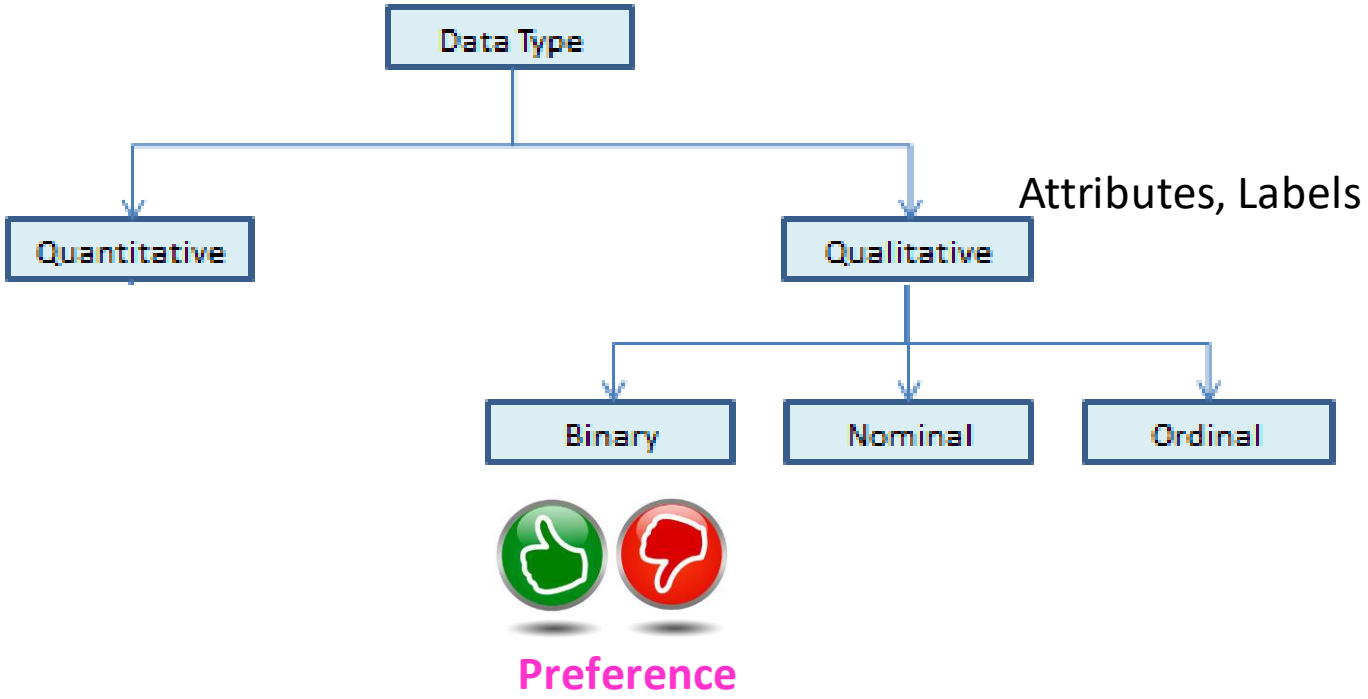
Workflow of a Machine Learning Problem



Taxonomy of data variables



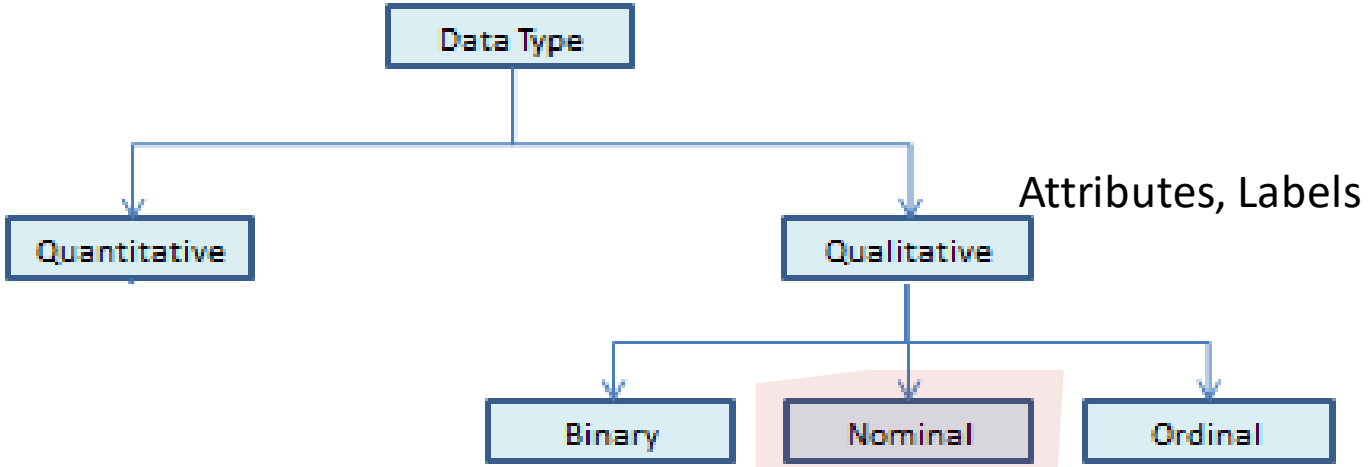
Taxonomy of data



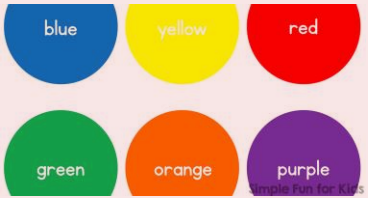
Attributes, Labels

Preference

Taxonomy of data



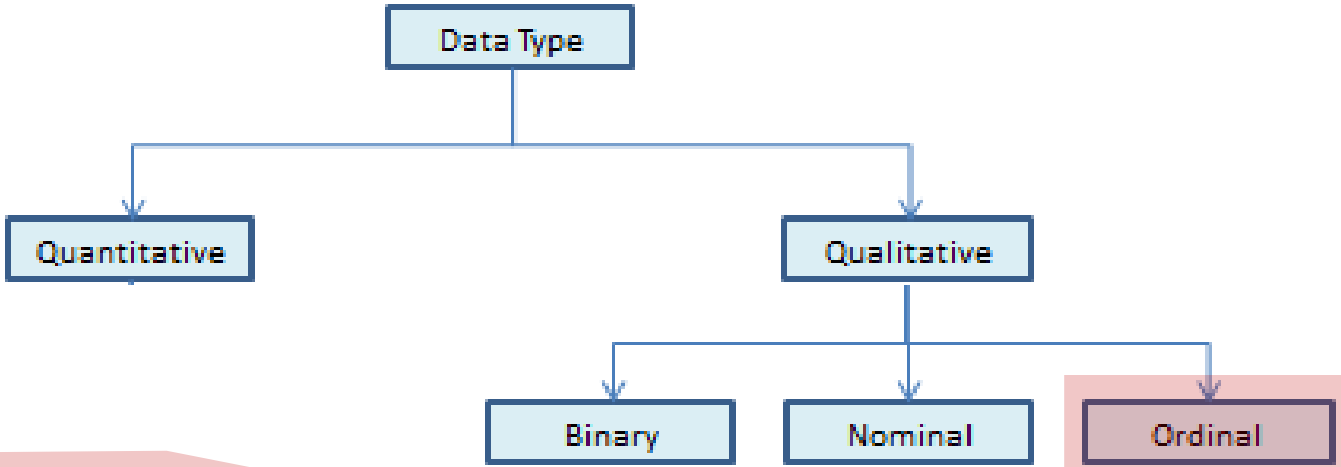
Attributes, Labels



Color

Make

Pin Code



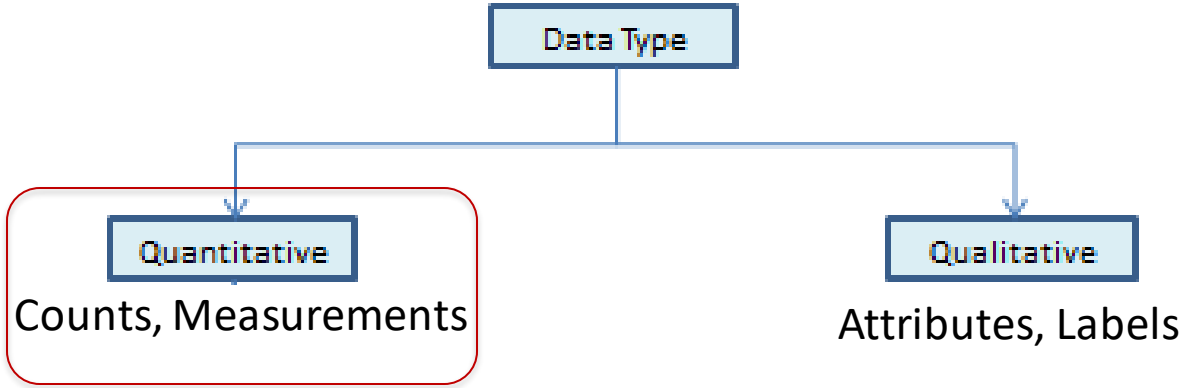
How comfortable are you with Python *

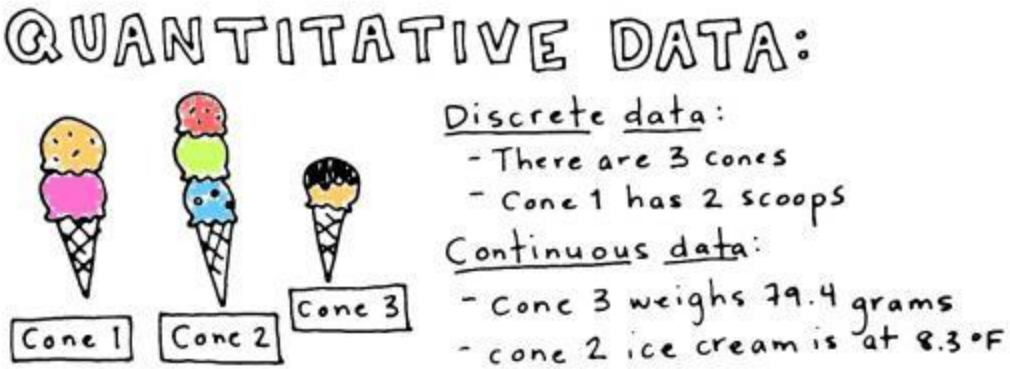
No knowledge ○ ○ ○ ○ ○ ○ Very comfortable

XS S M L XL XXL

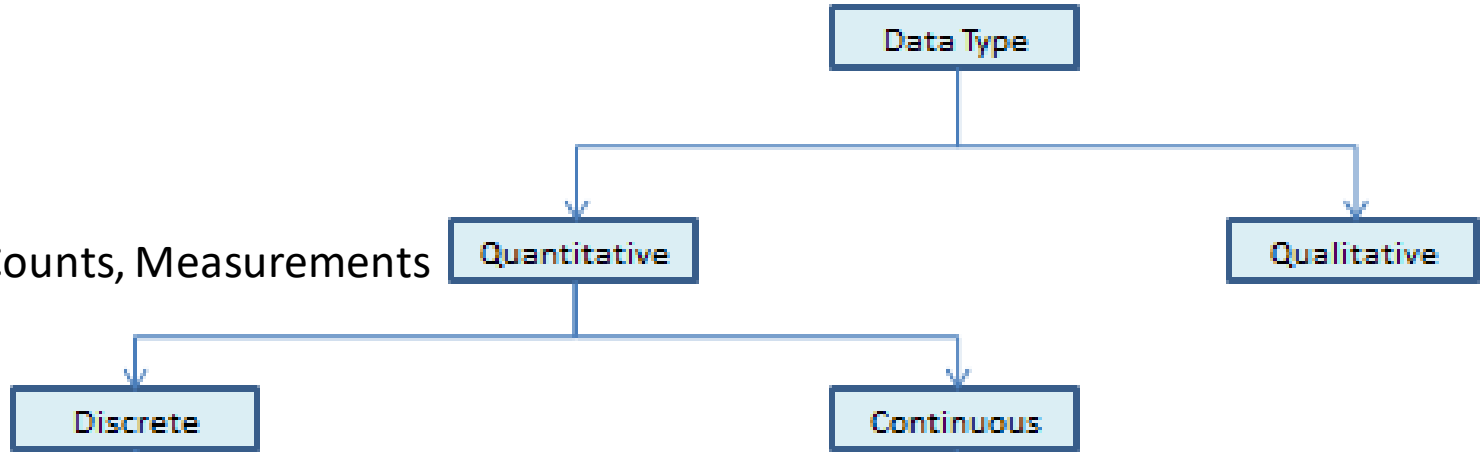
Letter grade
A +
A
A –
B +
B
B –
C +
C
C –
D +
D
E

Taxonomy of data





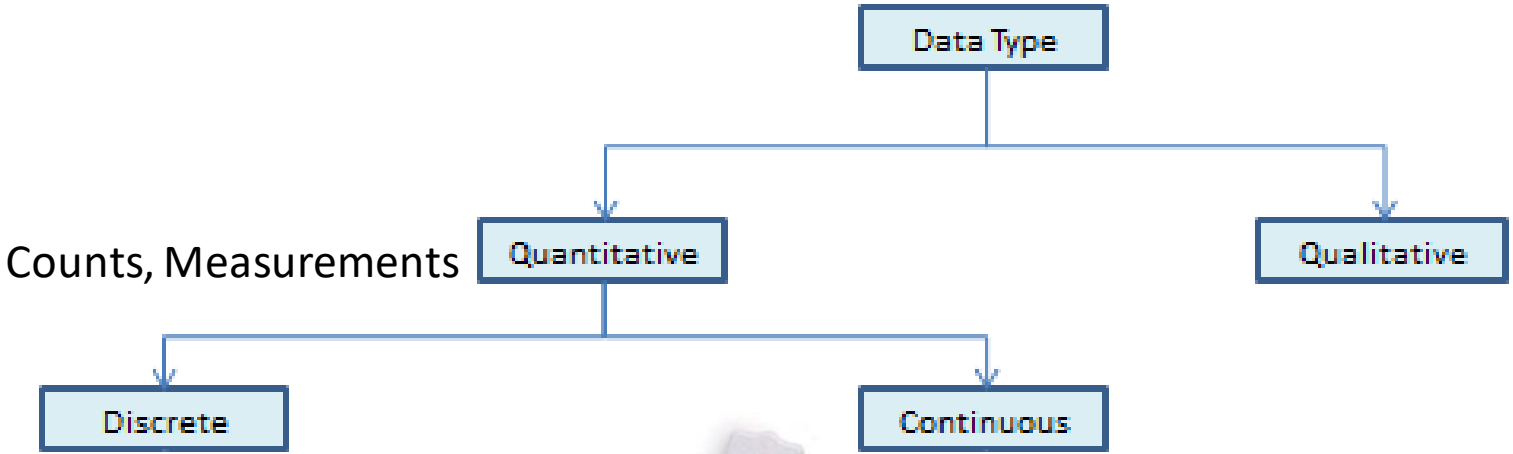
Taxonomy of data



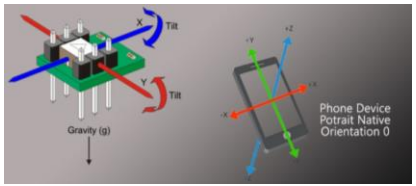
Counts, Measurements

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

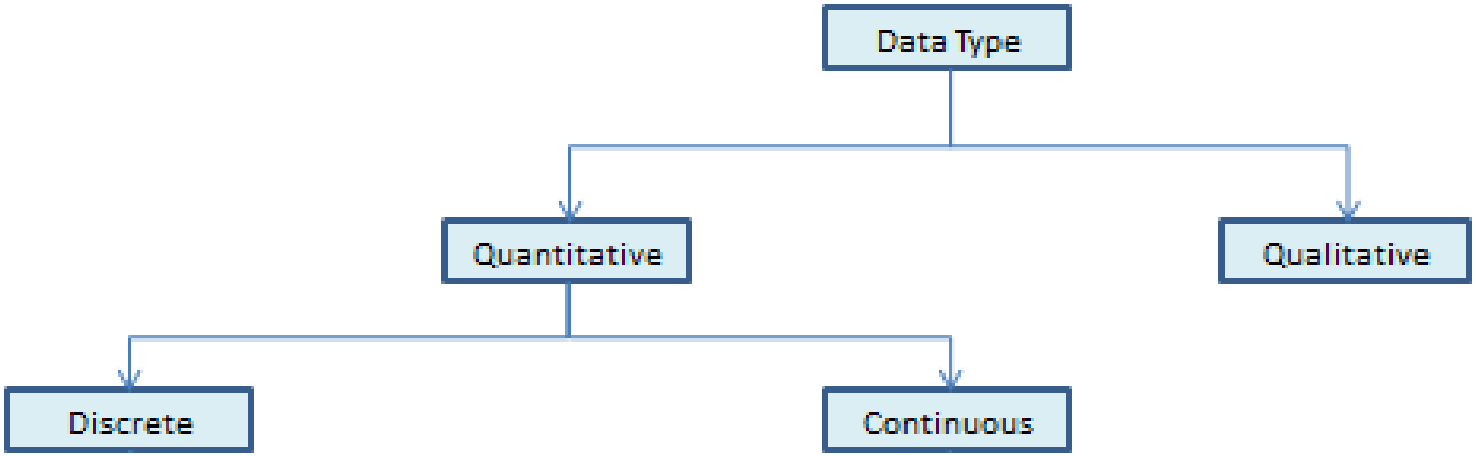
Taxonomy of data

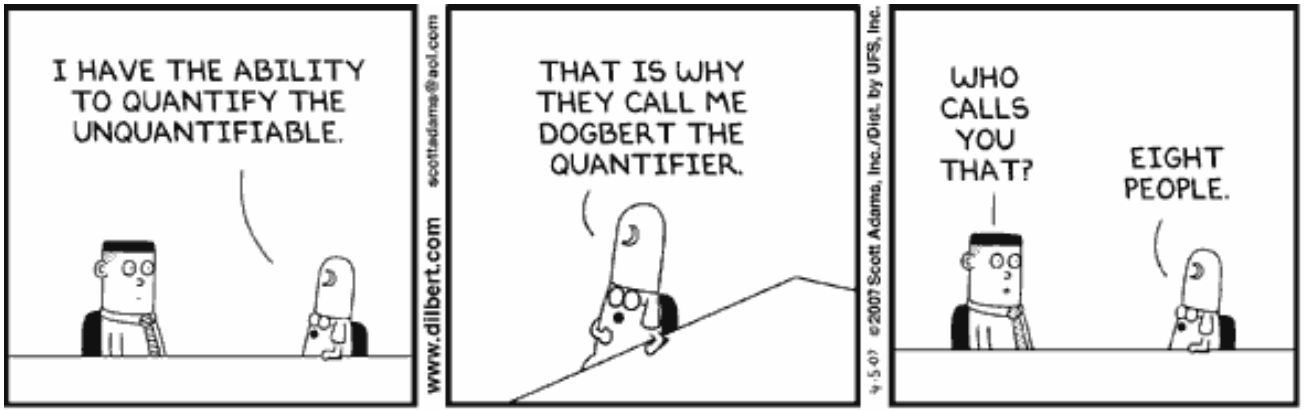


Counts, Measurements

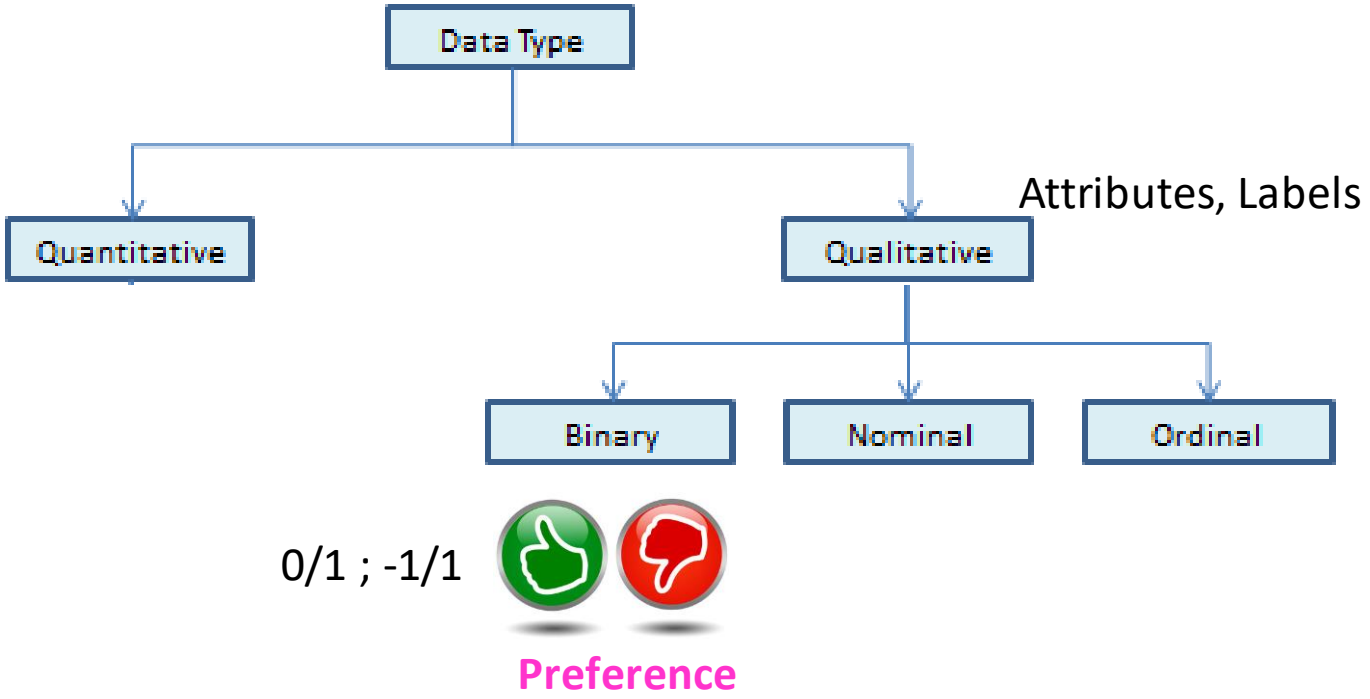


Ultimately, all data needs to be quantitative

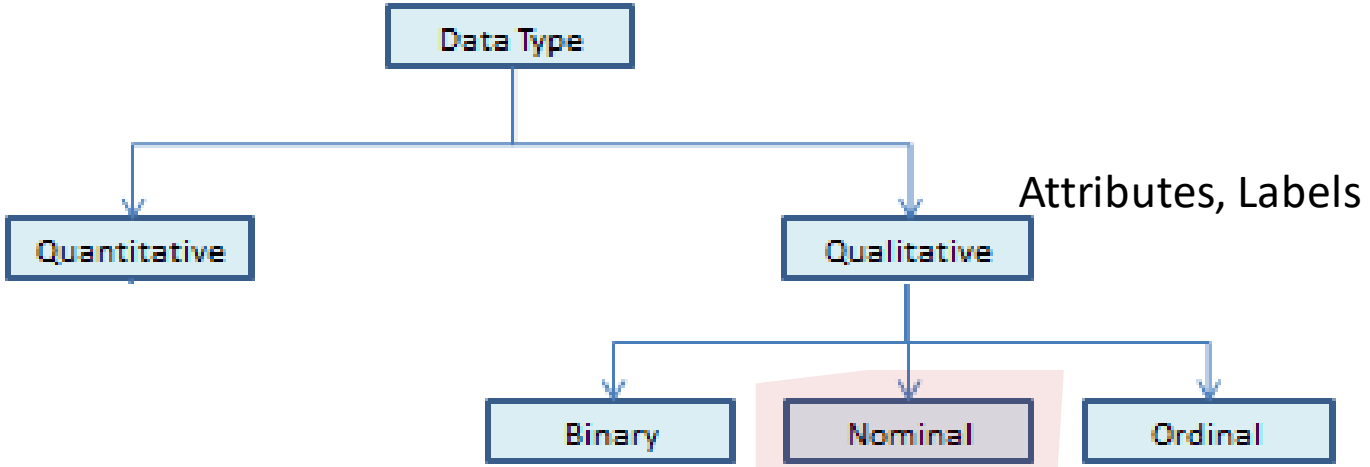




Taxonomy of data: Qualitative → Quantitative



Taxonomy of data: Qualitative → Quantitative

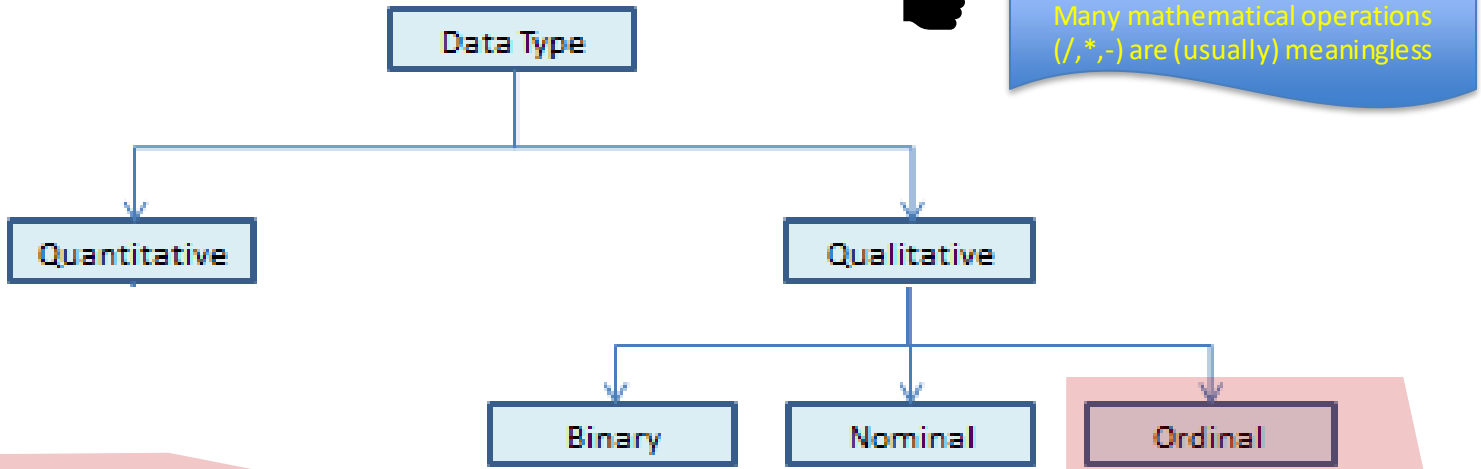


Attributes, Labels

Color

Make

Pin Code



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
...	...	...	...	...

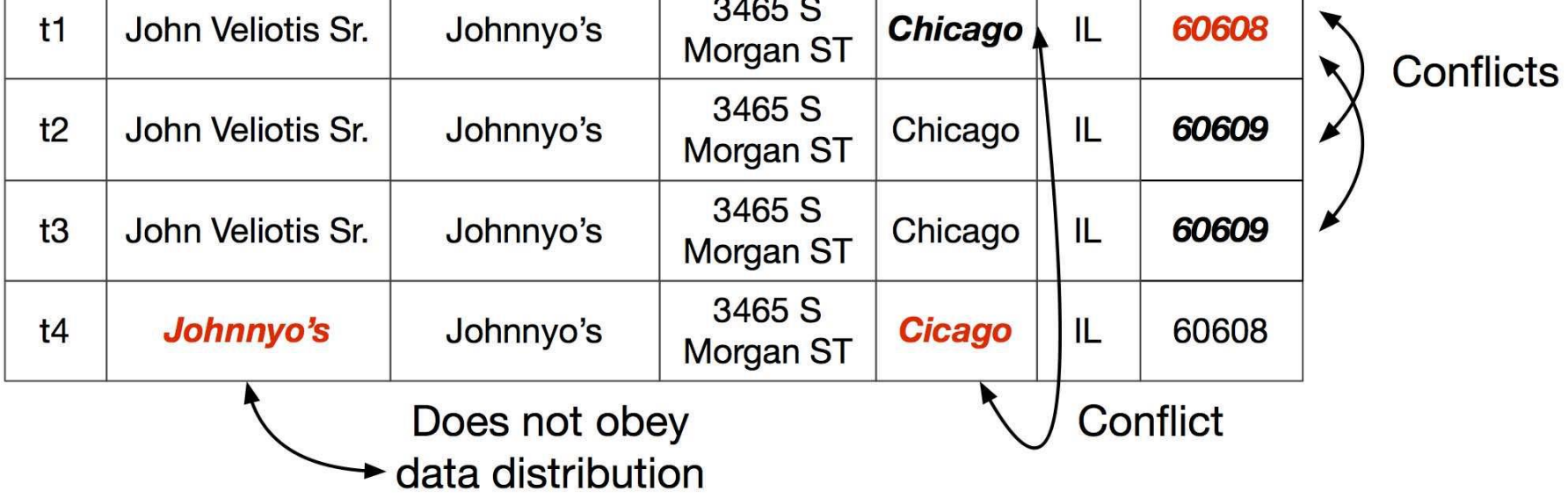
Sometimes data can be missing

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

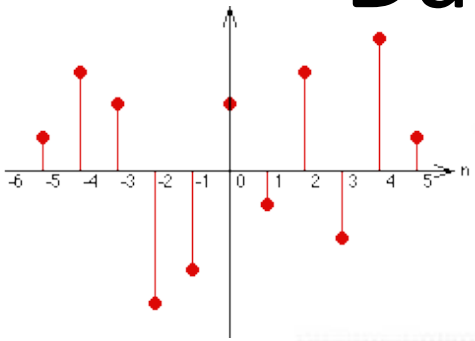
	DBAName	AKAName	Address	City	State	Zip
t1	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	***Chicago***	IL	***60608***
t2	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	Chicago	IL	***60609***
t3	John Veliotis Sr.	Johnnyo's	3465 S Morgan ST	Chicago	IL	***60609***
t4	***Johnnyo's***	Johnnyo's	3465 S Morgan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



Data imputation

- Approaches that aim to estimate missing data

Data Representations



Scalars

$$x$$

Vectors

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

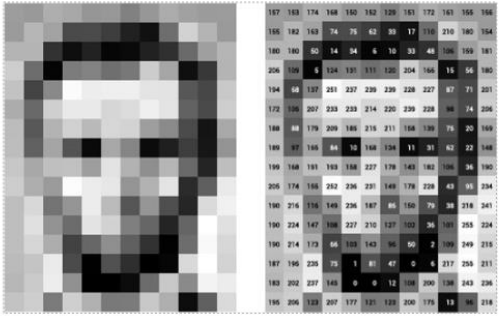
Matrix

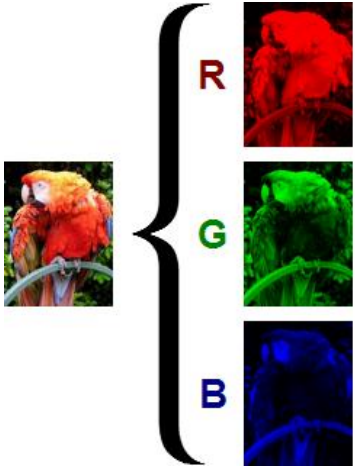
$$\mathbf{X} = \begin{bmatrix} \mathbf{x} & \cdots & \mathbf{x}_N \end{bmatrix} = \begin{bmatrix} x_{1,1} & & x_{N,1} \\ \vdots & \cdots & \vdots \\ x_{1,M} & & x_{N,M} \end{bmatrix}$$

Tensor

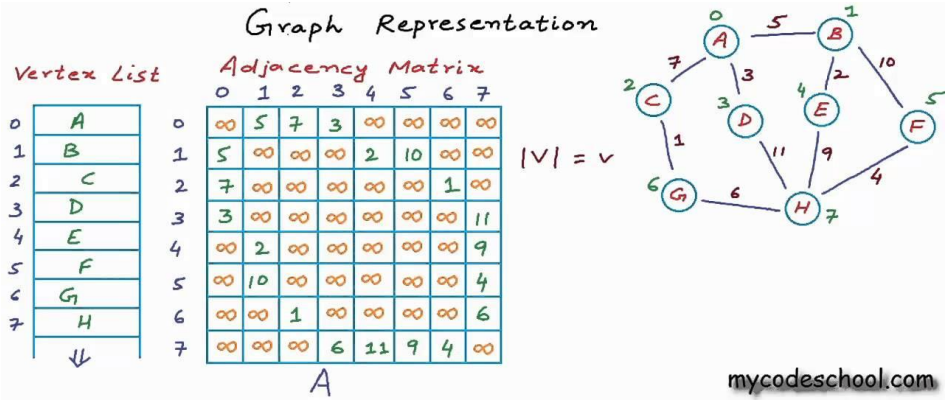
$$\mathbf{X} = \{\mathbf{X}_1, \ldots \mathbf{X}_K\} = \begin{bmatrix} x_{1,1,1} & & x_{N,1,1} \\ \vdots & \cdots & \vdots \\ x_{1,M,1} & & x_{N,M,1} \end{bmatrix} \begin{bmatrix} \ddots & & \\ & & \\ & & \end{bmatrix} \begin{bmatrix} x_{1,1,K} & & x_{N,1,K} \\ \vdots & \cdots & \vdots \\ x_{1,M,K} &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

2-d image



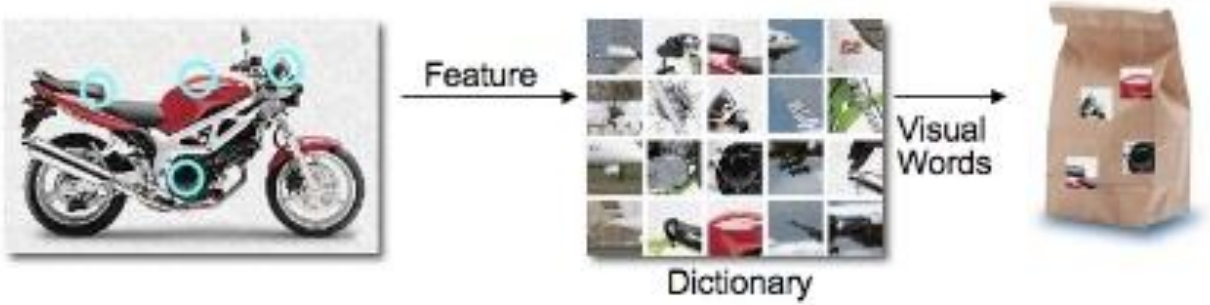


Data Representations



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.

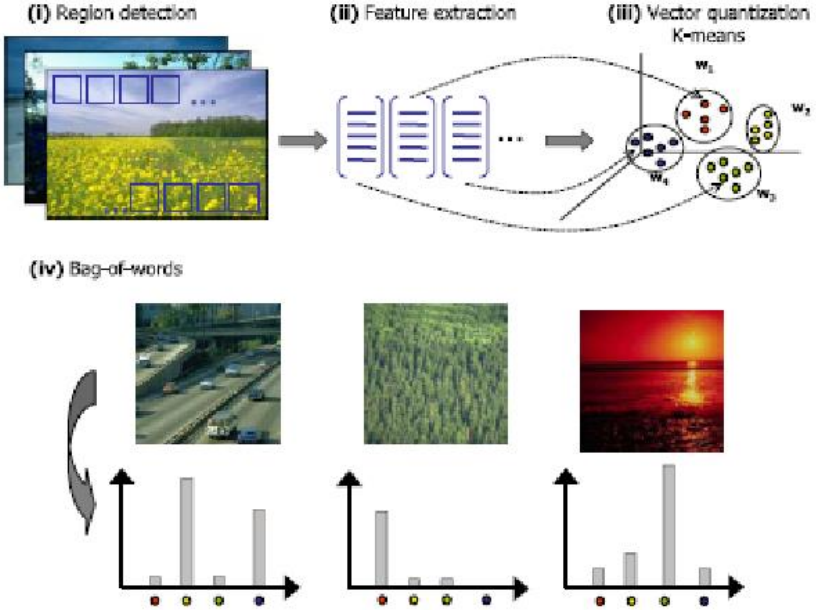


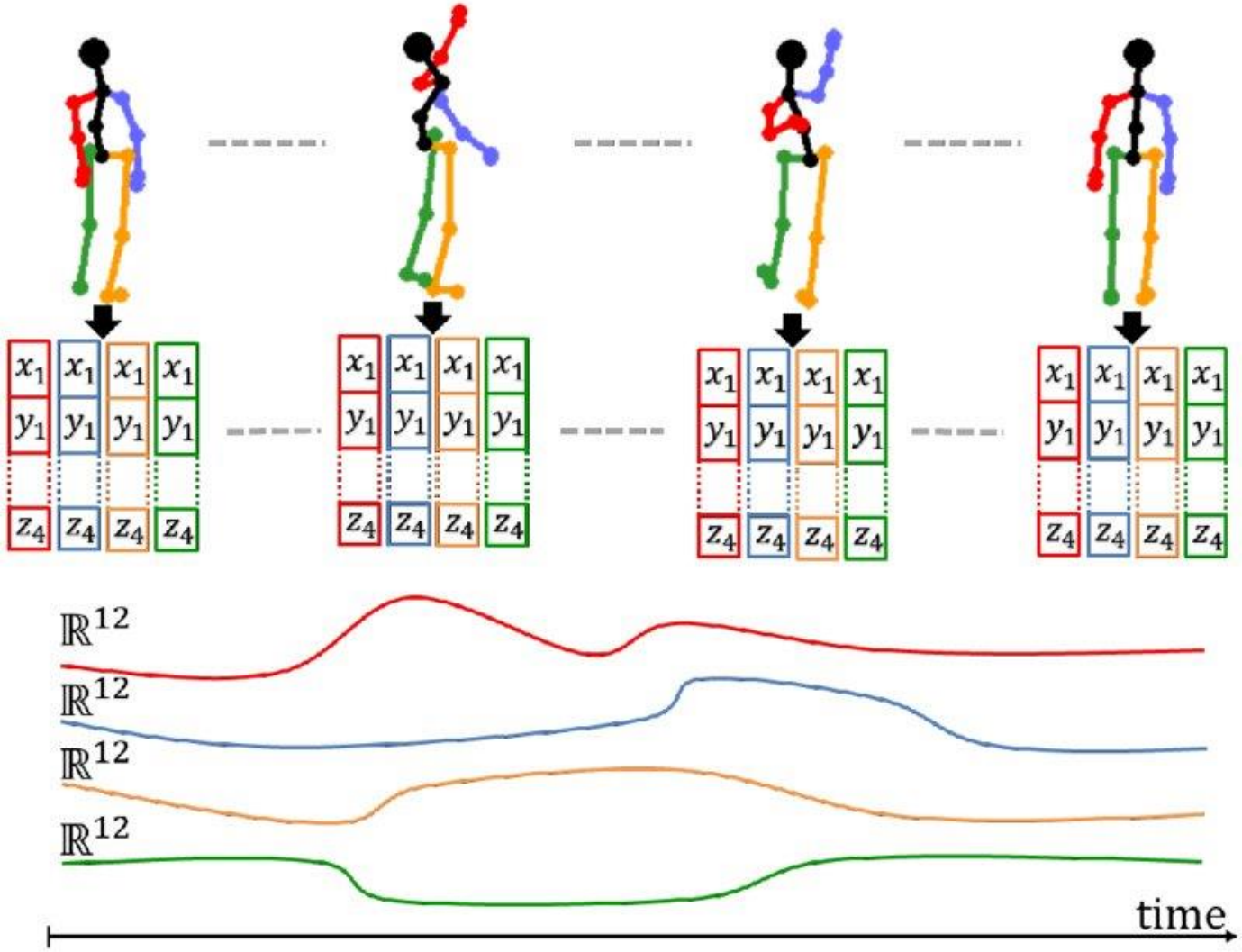
- Examples
  - Construct bag-of-words vector from an email
  - Remove stopwords in a sentence
  - Apply PCA projection to high-dimensional data

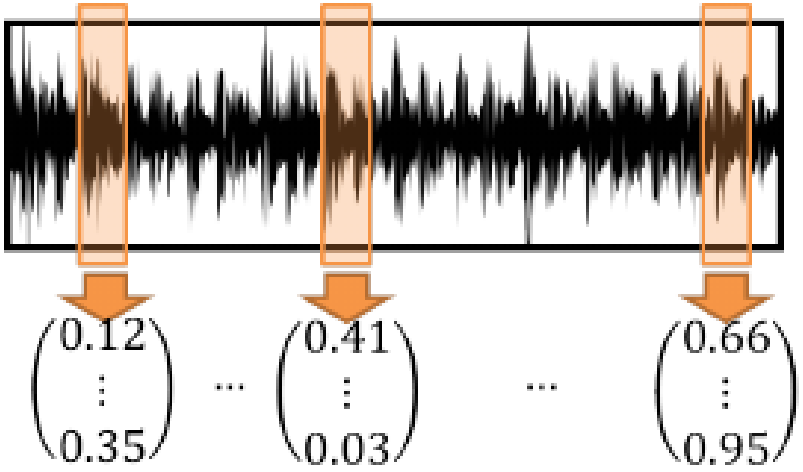
The Bag of Words Representation

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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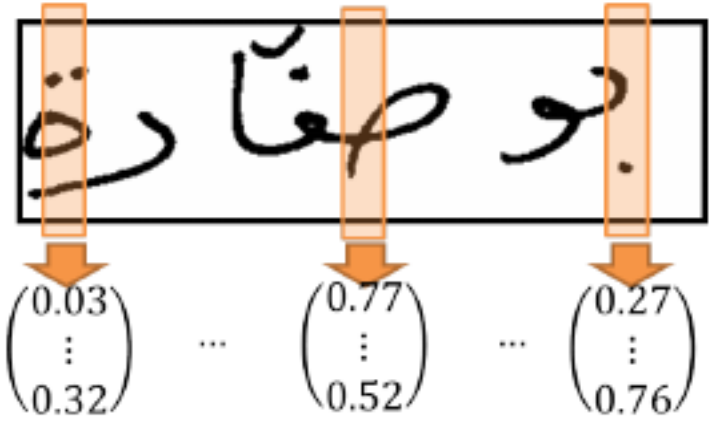
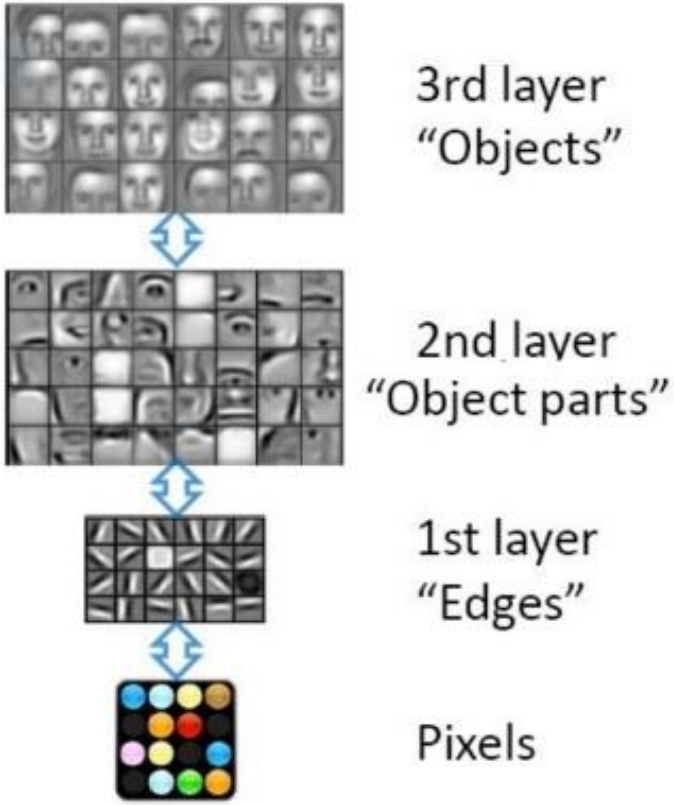
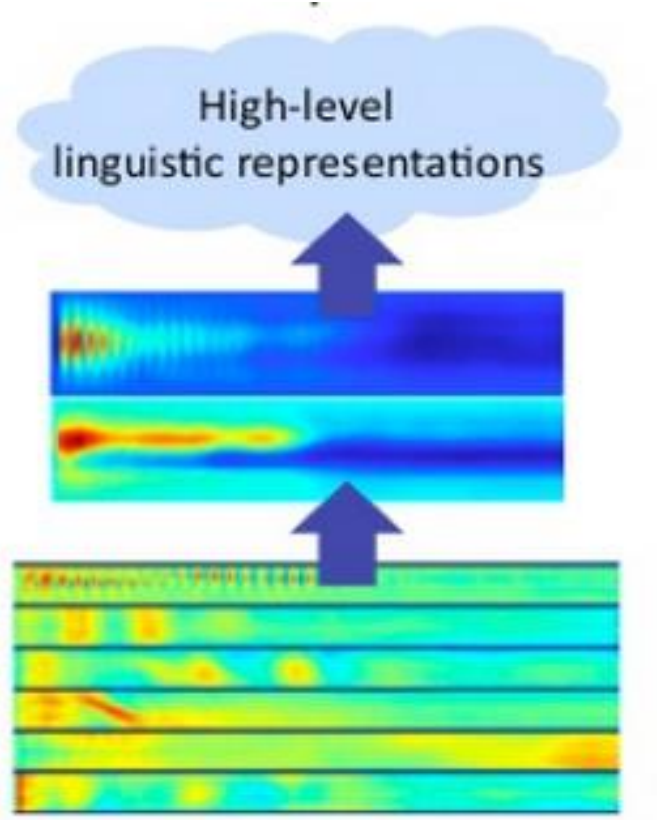
0.35
0.41
0.03
0.66
0.95


0.03
0.32
0.77
0.52
0.27
0.76

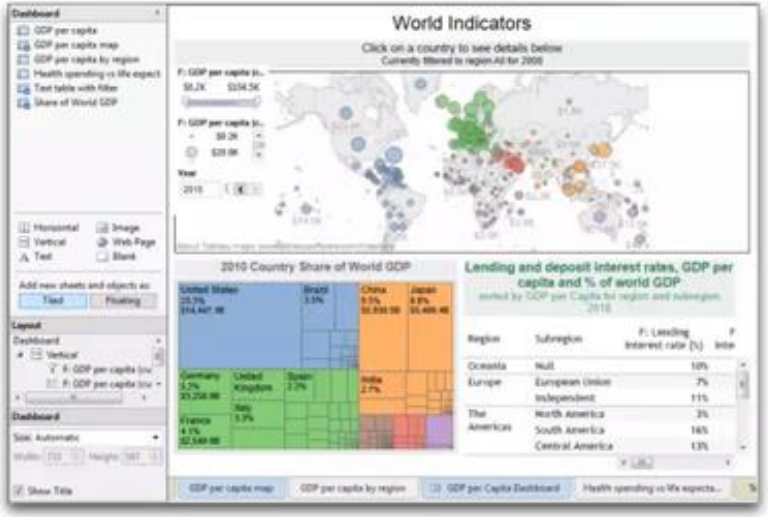
Feature-based, Hierarchical Data Representations



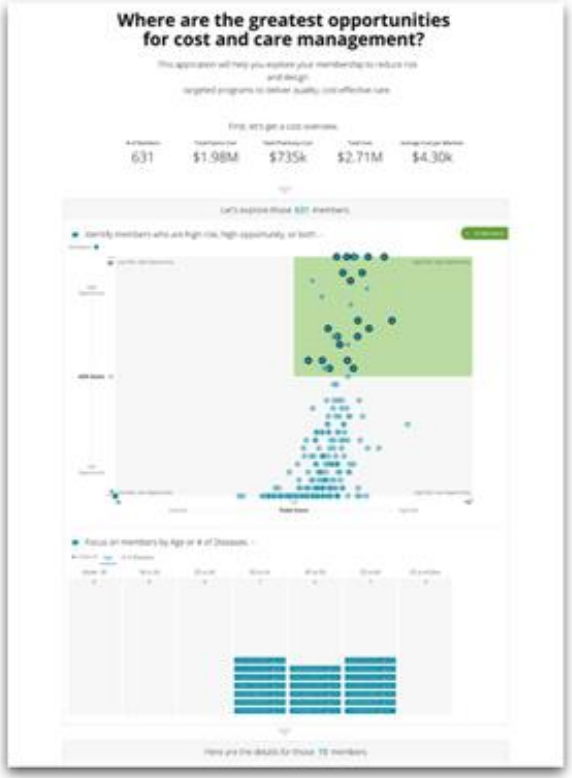


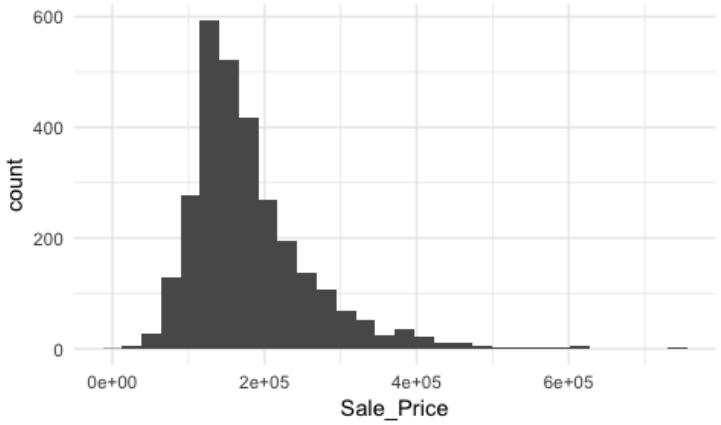
Gazing at Data: Data visualization

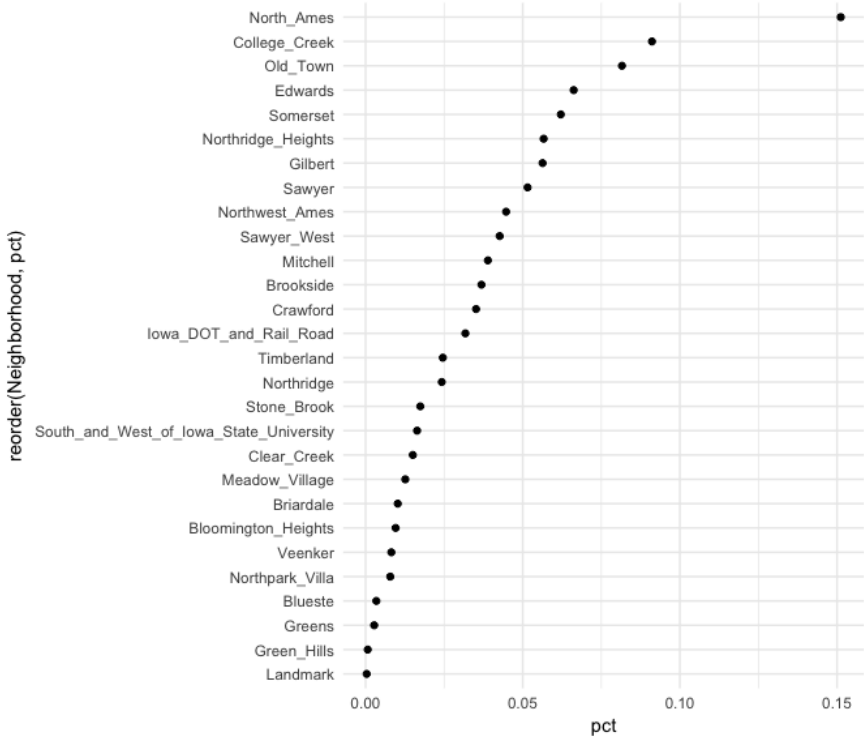
data exploration

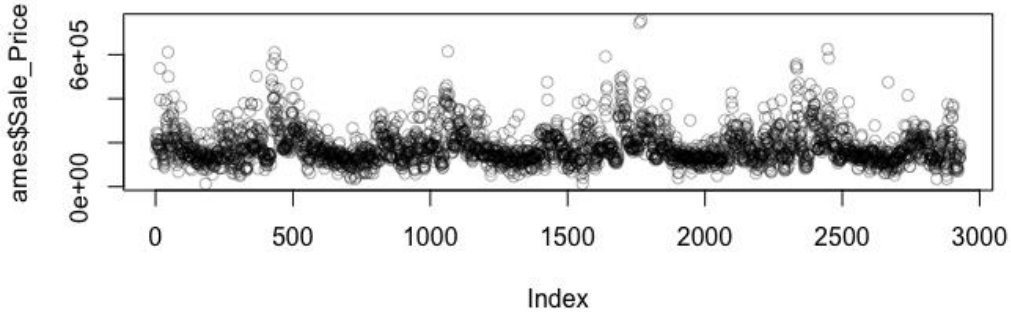


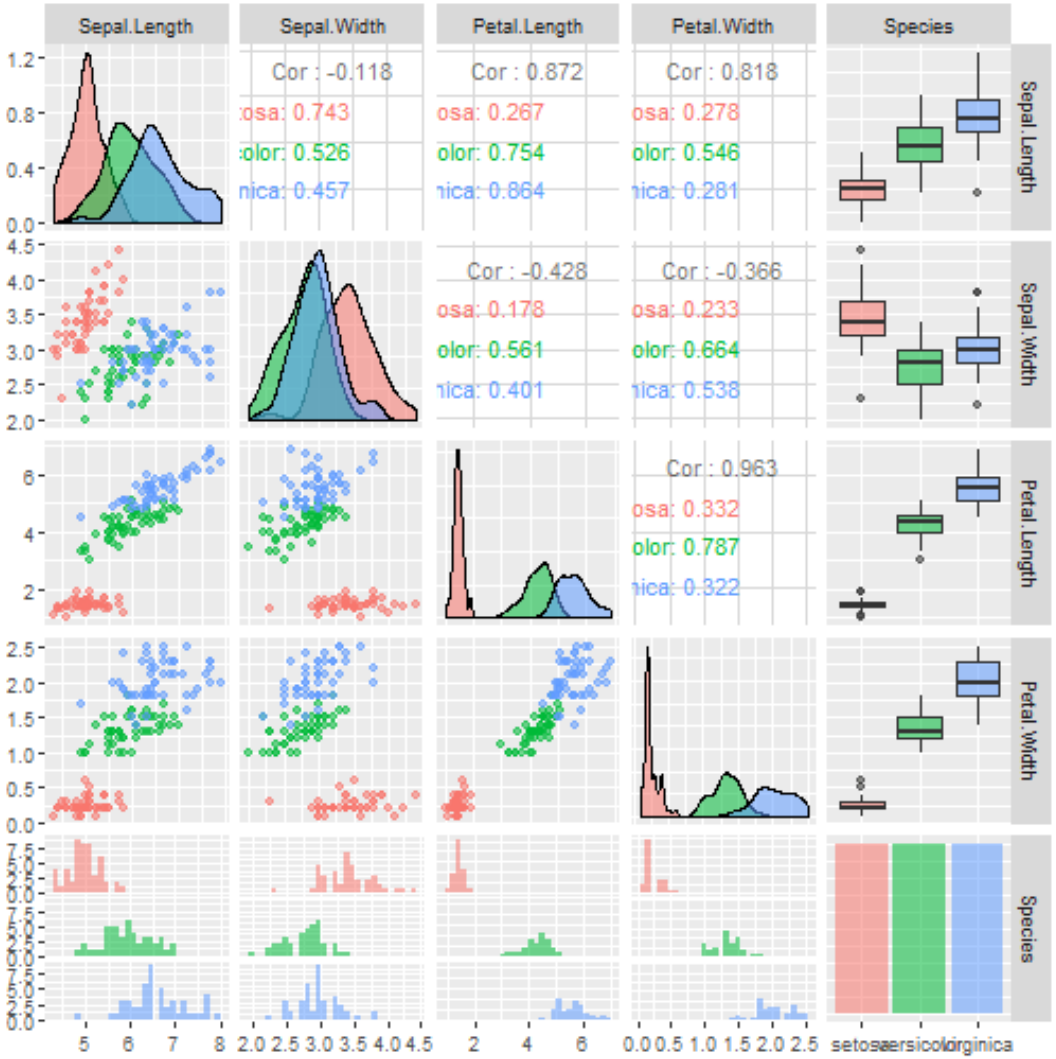
data presentation




600
400
200
0
count
0e+00
2e+05
4e+05
6e+05
Sale_Price

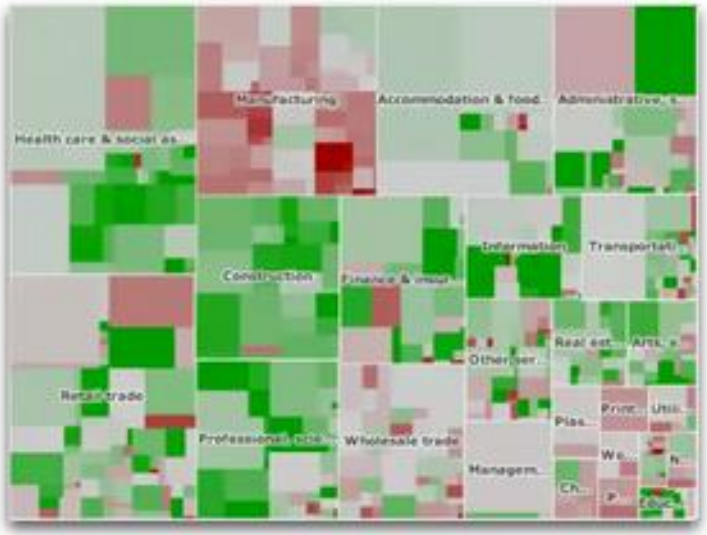

North_Ames
College_Creek
Old_Town
Edwards
Somerset
Northridge_Heights
Gilbert
Sawyer
Northwest_Ames
Sawyer_West
Mitchell
Brookside
Crawford
Iowa_DOT_and_Rail_Road
Timberland
Northridge
Stone_Brook
South_and_West_of_Iowa_State_University
Clear_Creek
Meadow_Village
Briardale
Bloomington_Heights
Veenker
Northpark_Villa
Blueste
Greens
Green_Hills
Landmark
reorder(Neighborhood, pct)
0.00
0.05
0.10
0.15
pct


ames$Sale_Price
0e+00
6e+05
0
500
1000
1500
2000
2500
3000
Index


Sepal.Length
Sepal.Width
Petal.Length
Petal.Width
Species
Cor : -0.118
Cor : 0.872
Cor : 0.818
Cor : -0.428
Cor : -0.366
Cor : 0.963
osa: 0.743
olor: 0.526
nica: 0.457
osa: 0.267
olor: 0.754
nica: 0.864
osa: 0.278
olor: 0.546
nica: 0.281
osa: 0.178
olor: 0.561
nica: 0.401
osa: 0.233
olor: 0.664
nica: 0.538
osa: 0.332
olor: 0.787
nica: 0.322
setosa
versicolor
virginica

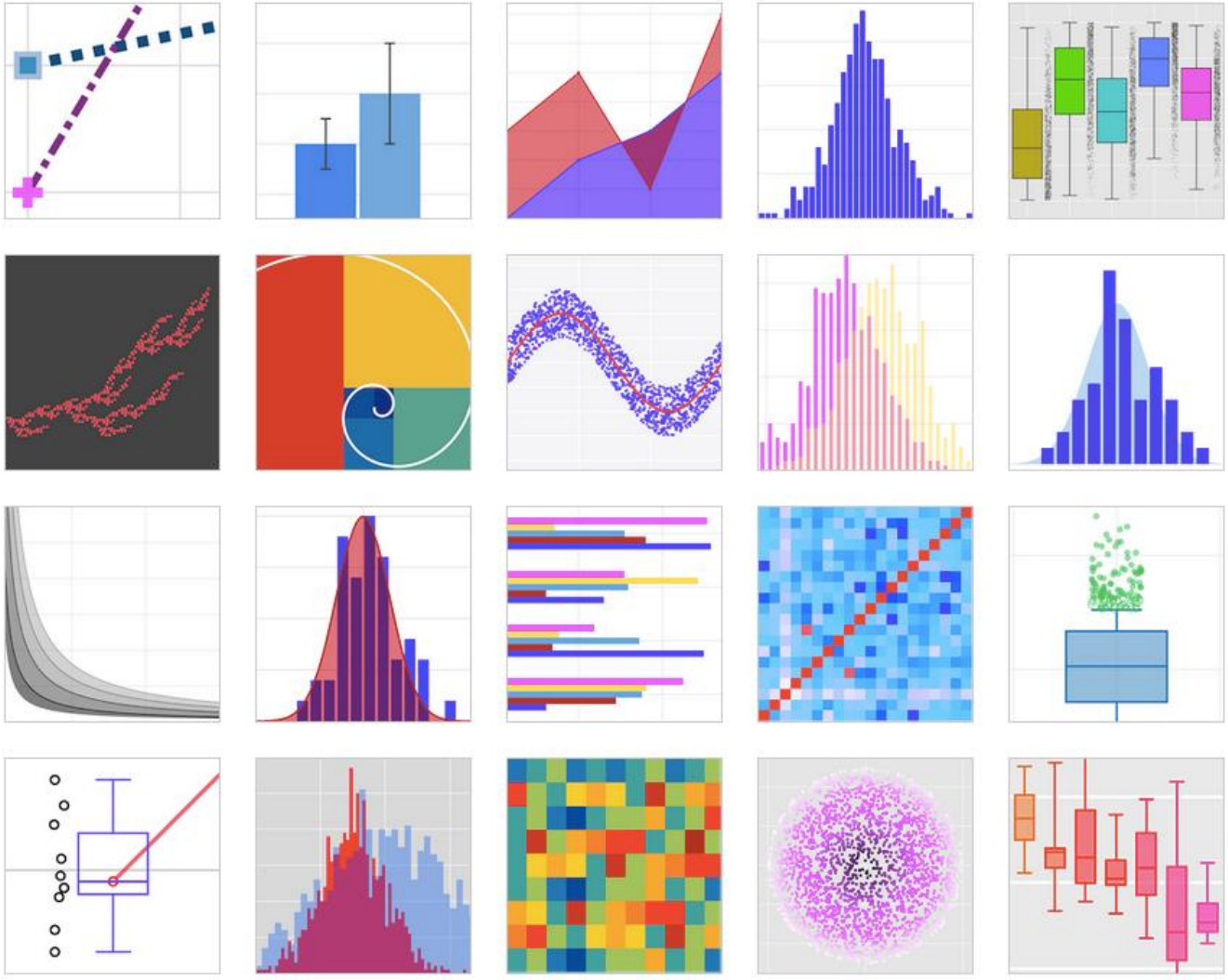
Data visualization

treemap

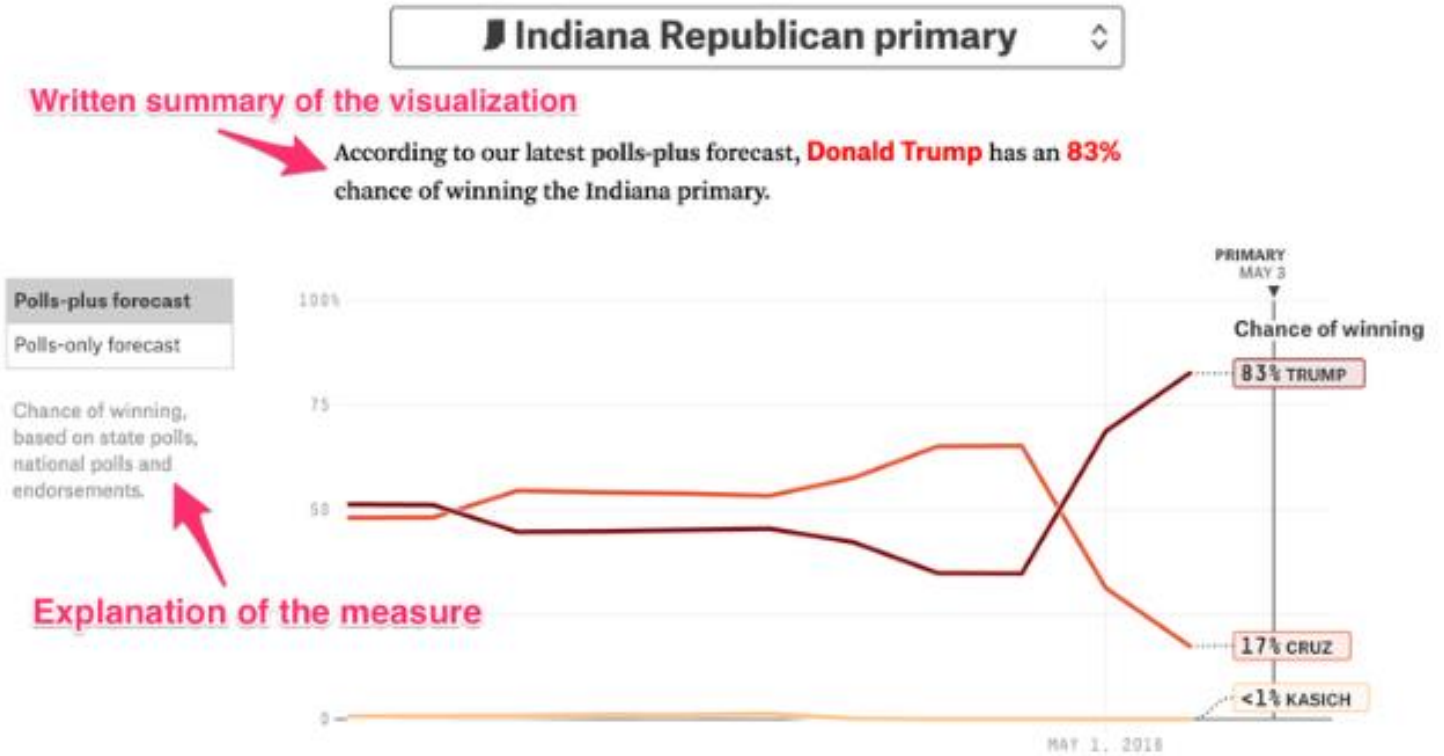


leaderboard

Shuttle		40 Yard		Bench Press		Vert Leap (in)		Broad Jump (in)	
Jordan Jeffer...	4.06	Tol Robert Griffin	4.41	Jordan Jeffer...	14	Tol Robert Griffin	39	Andrew Luck	124
Russell Wilson	4.09	Russell Wilson	4.55	Darron Thomas	14	Jacory Harris	37	Darron Thomas	121
Austin Davis	4.11	Jordan Jeffer...	4.65	Robert Griffin	---	Jordan Jeffer...	37	Tol Robert Griffin	120
Chandler Harr...	4.15	Andrew Luck	4.67	Russell Wilson	---	Darron Thomas	36	Russell Wilson	118
Andrew Luck	4.28	Aaron Corp	4.72	Andrew Luck	---	Andrew Luck	36	Jordan Jeffer...	116
Darron Thomas	4.28	Jacory Harris	4.72	Aaron Corp	---	Russell Wilson	34	Jacory Harris	113
Aaron Corp	4.30	Chandler Harr...	4.76	Jacory Harris	---	Chandler Harr...	33	Tyler Hansen	113
Patrick Witt	4.37	Tyler Hansen	4.78	Chandler Harr...	---	Case Keenum	33	Chandler Harr...	112
B.J. Coleman	4.38	Darron Thomas	4.80	Tyler Hansen	---	Aaron Corp	32	Nick Foles	112
Jacory Harris	4.40	Case Keenum	4.82	Case Keenum	---	Patrick Witt	32	Austin Davis	109



Data Exploration and Visualization



Fivethiryeight provides explanation surrounding their visualization to ensure readers understand what they are looking at.

Data Exploration and Visualization

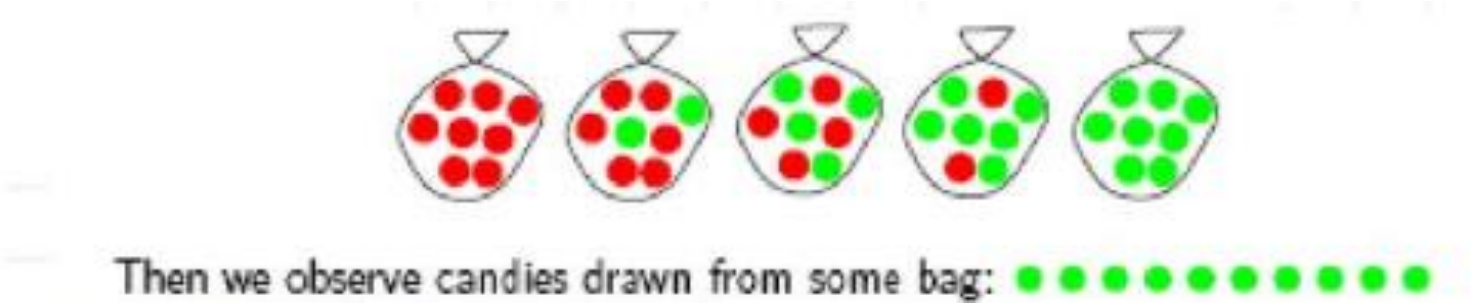
.. To be covered in next week’s tutorial

"In good information visualization, there are no rules, no guidelines, no templates, no standard technologies, no stylebooks ... You must simply do whatever it takes."

—Edward Tufte

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

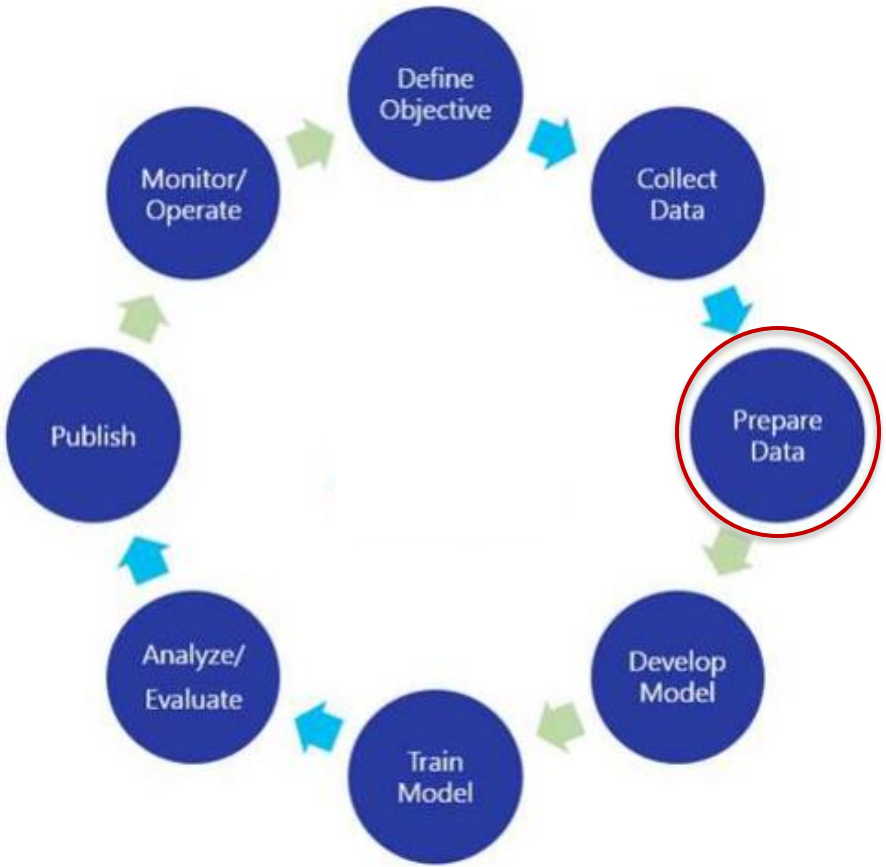
Cell	Possible Values	Probability
t2.Zip	60608	0.84
	60609	0.16
t4.City	Chicago	0.95
	Cicago	0.05
t4.DBAName	John Veliotis Sr.	0.99
	Johnnyo's	0.01

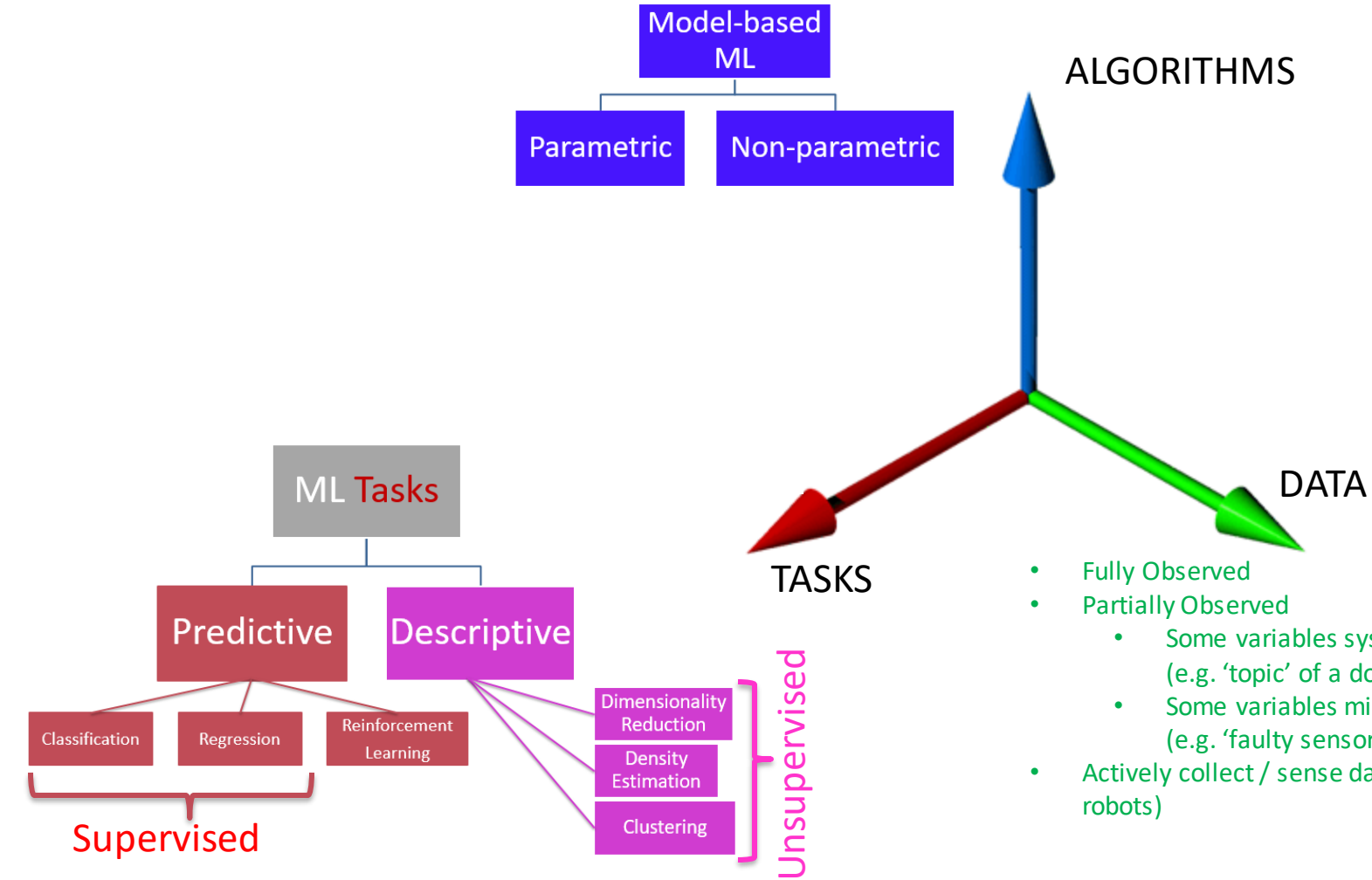
Other important aspects of data

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

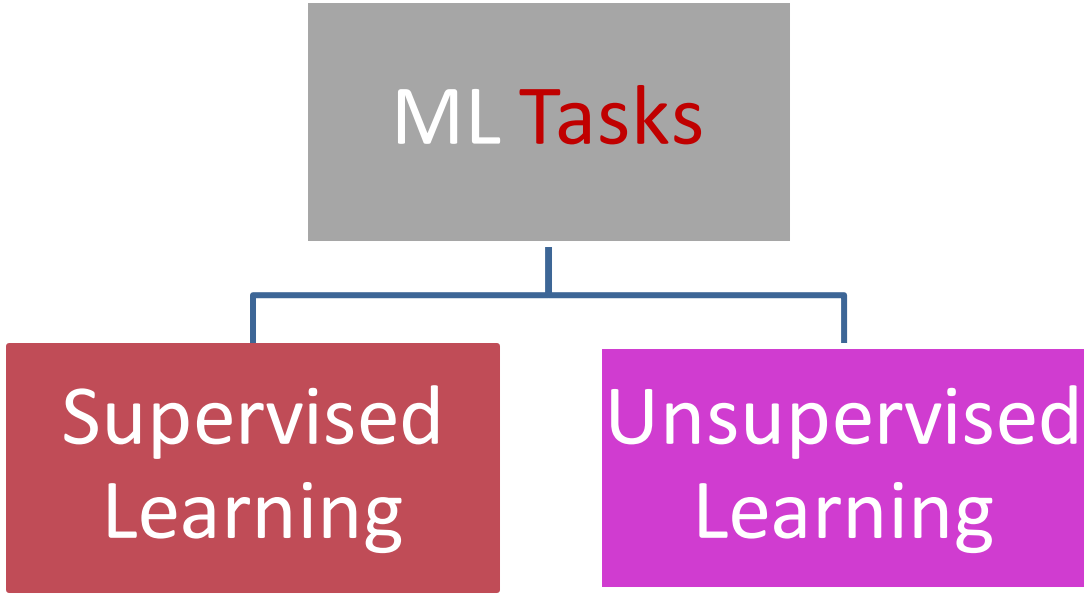
- Statistical assumptions on data
  - i.i.d (independent and identically distributed)
  - Online (e.g. time-series data)

Workflow of a Machine Learning Problem



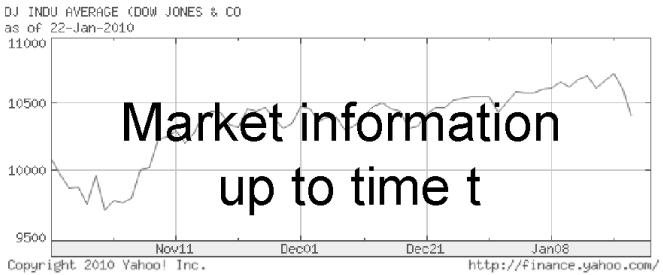


- Fully Observed
- Partially Observed
  - Some variables systematically not observed (e.g. 'topic' of a document)
  - Some variables missing some of the time (e.g. 'faulty sensor' readings)
- Actively collect / sense data (e.g. exploration robots)


ML Tasks
Supervised Learning
Unsupervised Learning
Given an input, estimate output

ML::Tasks → Predictive

Feature Space $\mathcal{X}$



Label Space $\mathcal{Y}$

"Sports"
"News"
"Science"
…

Share Price
"$ 24.50"

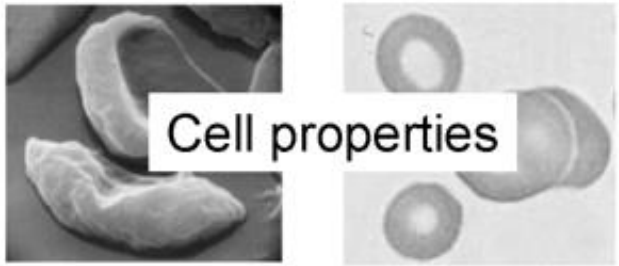
Task: Given $X \in \mathcal{X}$, predict $Y \in \mathcal{Y}$.

ML::Tasks → Predictive → Classification

Feature Space $\mathcal{X}$

Label Space $\mathcal{Y}$

"Sports"
"News"
"Science"
...



"Anemic cell"
"Healthy cell"

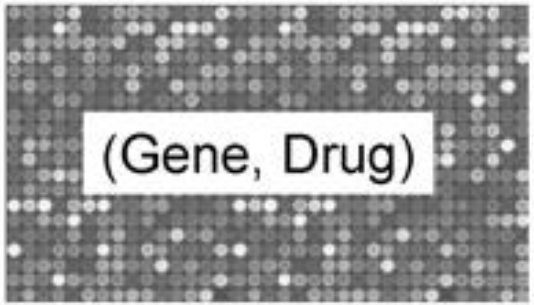
Discrete Labels

ML::Tasks → Predictive → Regression

Feature Space $\mathcal{X}$

Label Space $\mathcal{Y}$

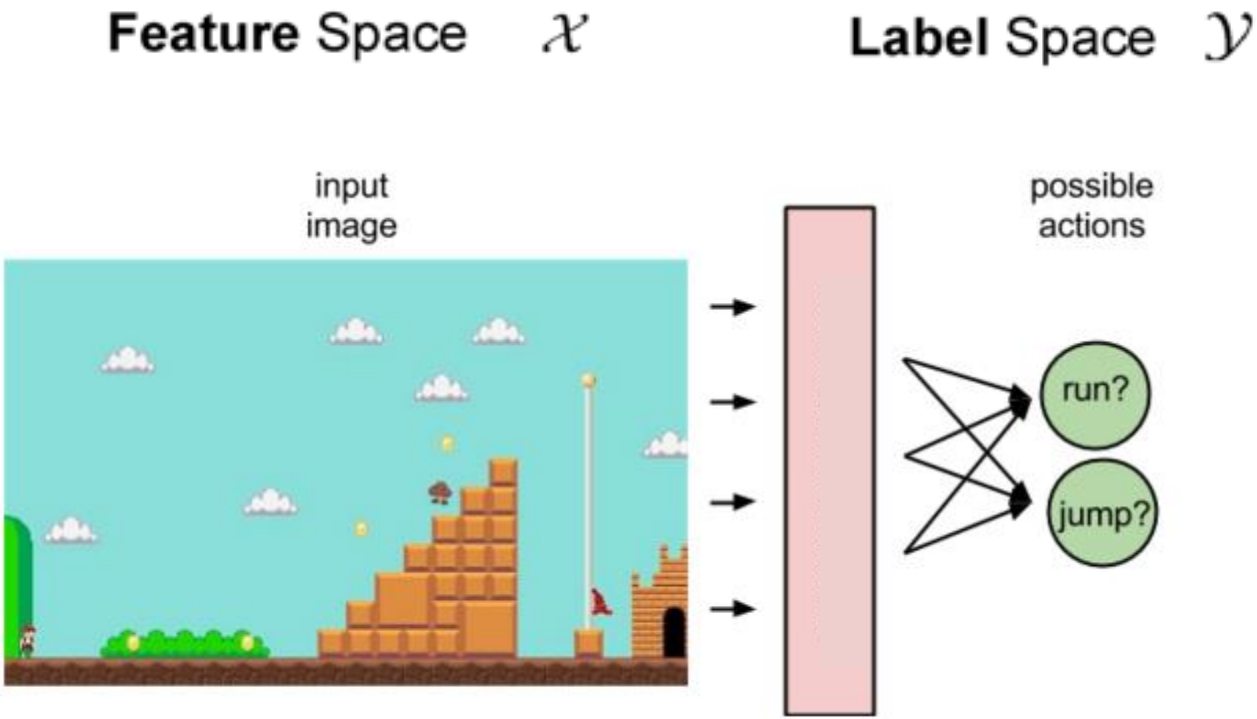
→ Share Price
"$ 24.577"



→ Expression level
"6.88"

Continuous Labels

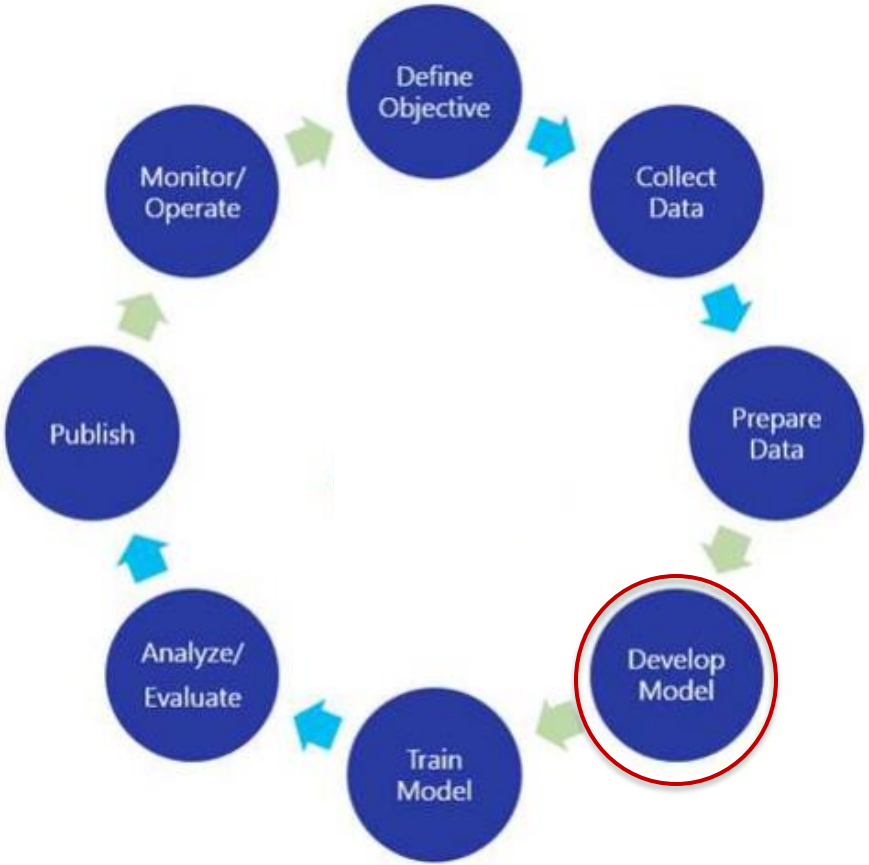
ML::Tasks → Predictive → Reinforcement Learning

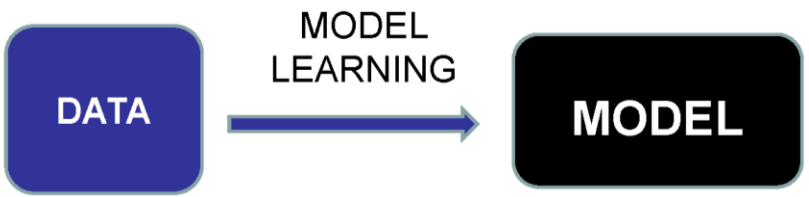


ML::Tasks → Predictive → Reinforcement Learning

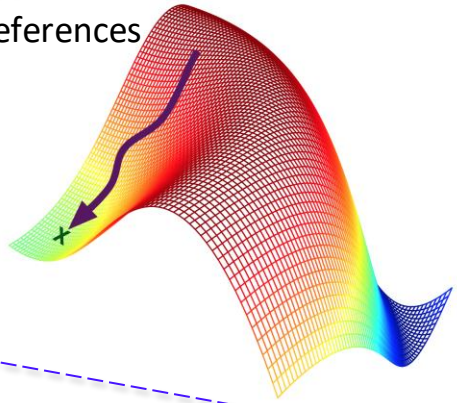
Feature Space $\mathcal{X}$ **Label** Space $\mathcal{Y}$

Workflow of a Machine Learning Problem





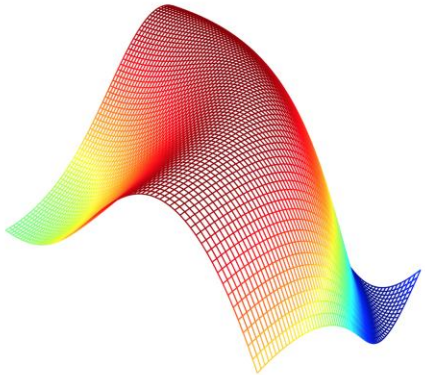
Strategy for fulfilling preferences



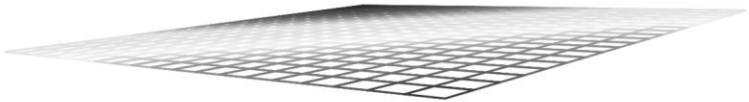
Optimization

Evaluation

Representation



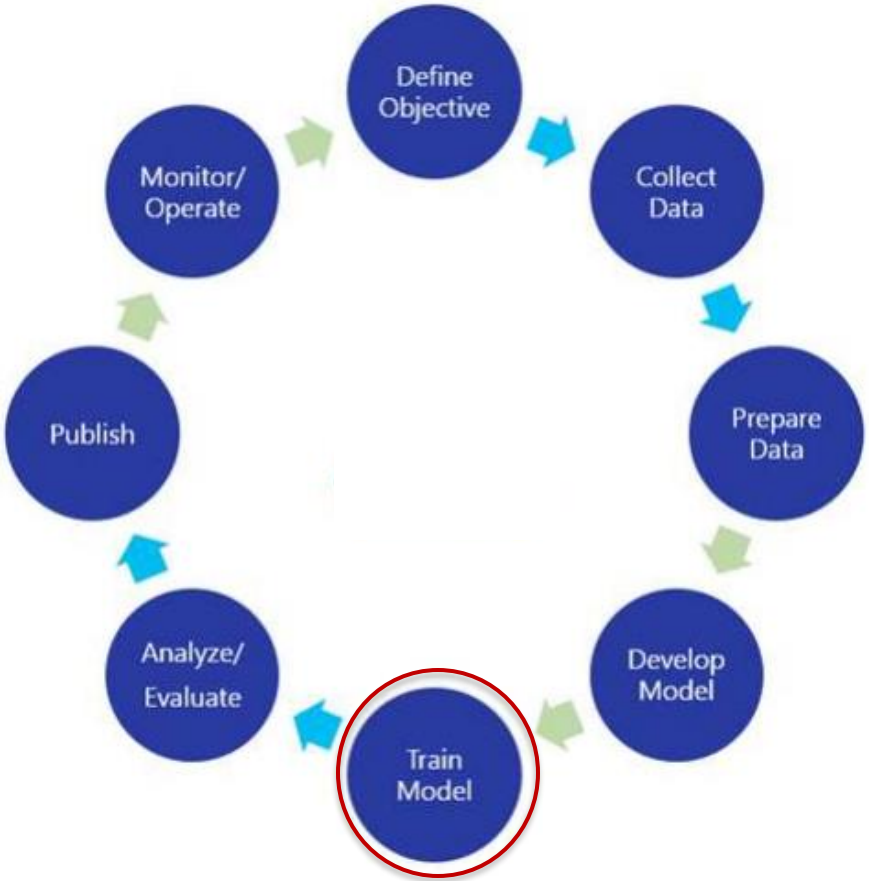
Preferences over the landscape



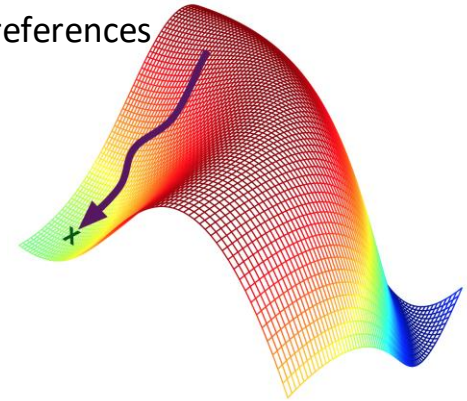
The landscape of allowed models

https://medium.com/@devnag/machine-learning-representation-evaluation-optimization-fc7b26b38fdb

Workflow of a Machine Learning Problem



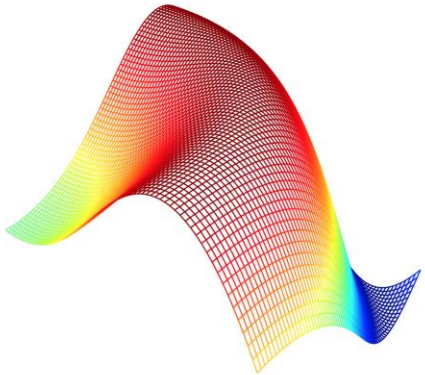
Strategy for fulfilling preferences



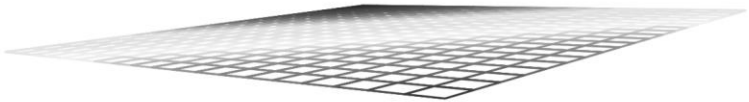
Optimization

Evaluation

Representation



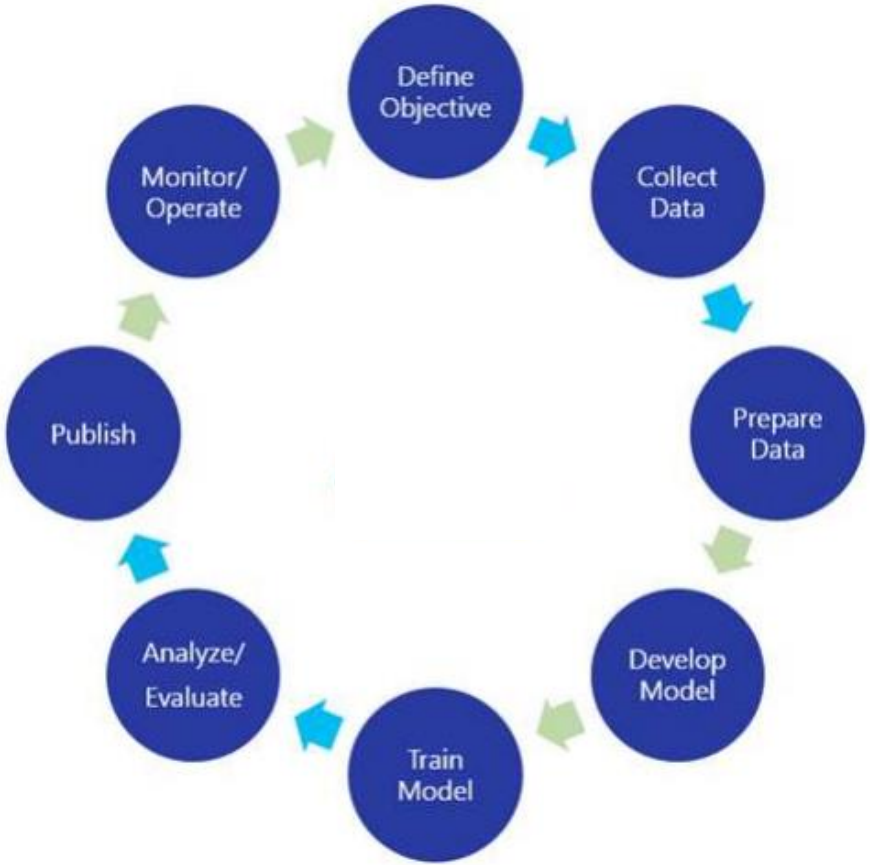
Preferences over the landscape

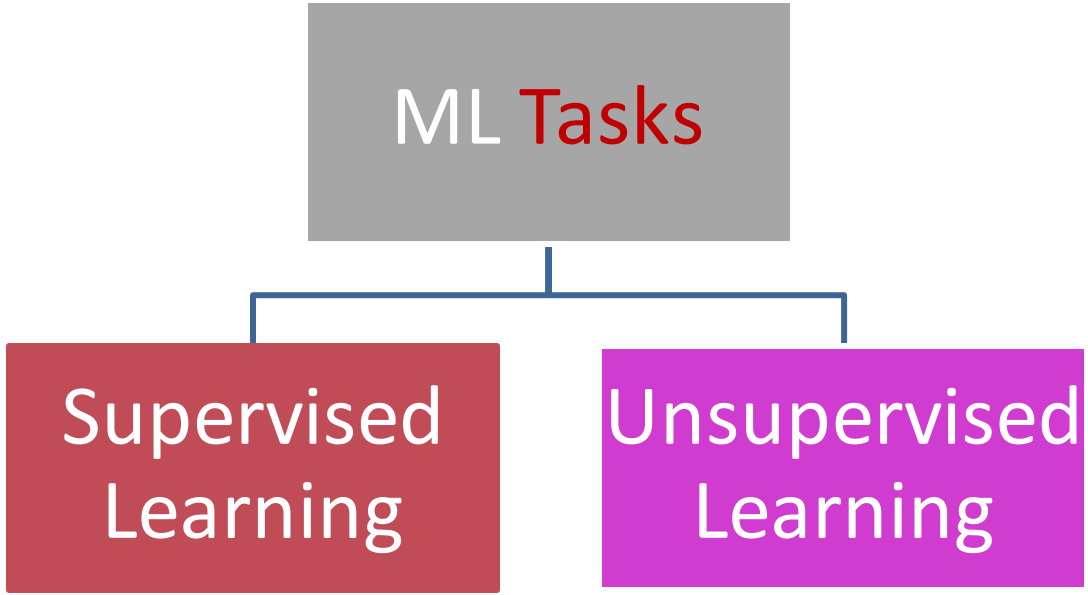


The landscape of allowed models

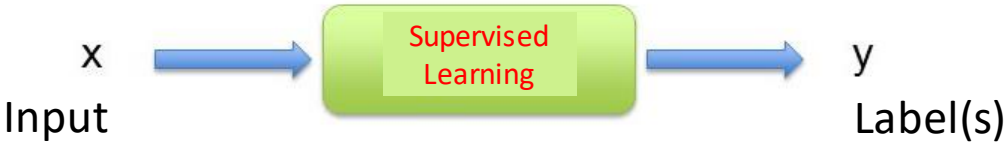
https://medium.com/@devnag/machine-learning-representation-evaluation-optimization-fc7b26b38fdb

Workflow of a Machine Learning Problem




ML Tasks
Supervised Learning
Unsupervised Learning
Given an input, estimate output

Supervised Learning



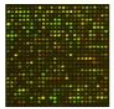
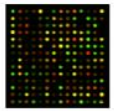
Data

Space of inputs (or, predictors): $\mathcal{X}$

▷ e.g. $x \in \mathcal{X} \subset \{0, 1, \ldots, 2^{16}\}^{64}$ is a string of pixel intensities in an 8×8 image.

▷ e.g. $x \in \mathcal{X} \subset \mathbb{R}^{33,000}$ is a set of gene expression levels.

$x_1 =$  $x_2 =$  $\ldots$

$x_1 =$  $x_2 =$  $\ldots$

$$x_1 = \begin{bmatrix} 5 \\ 1 \\ 22 \\ \vdots \end{bmatrix} \qquad x_2 = \begin{bmatrix} 1 \\ 0 \\ 17 \\ \vdots \end{bmatrix}$$

\# cigarettes/day

\# drinks/day

BMI

Space of outputs (or, responses): $\mathcal{Y}$

- e.g. $y \in \mathcal{Y} = \{0, 1\}$ is a binary label ($1 =$ "cat")
- e.g. $y \in \mathcal{Y} = [0, 200]$ is life expectancy

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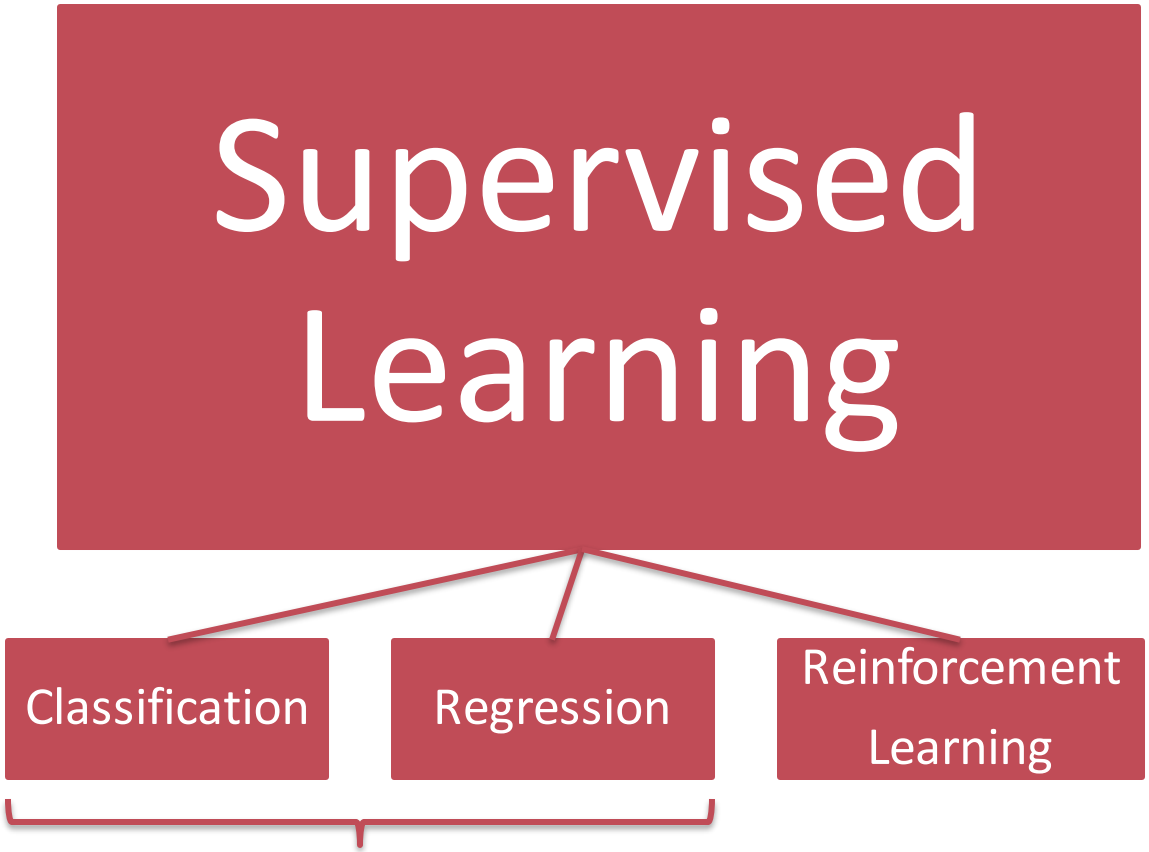
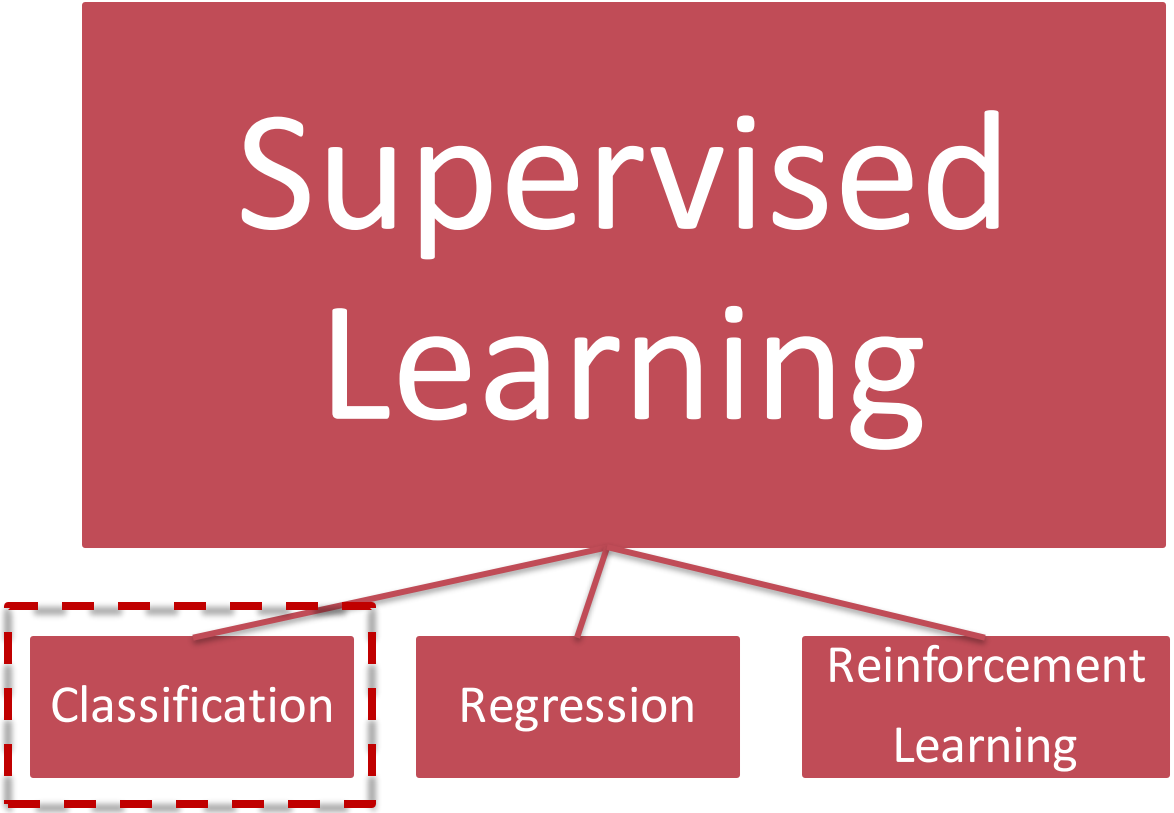
Dataset (or *training data*): examples $\{(x_1, y_1), \ldots, (x_n, y_n)\}$

- e.g. a collection of images labeled according to the presence or absence of a face


Supervised Learning
Classification
Regression
Reinforcement Learning
We'll focus on these two


Supervised Learning
Classification
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Classification

Binary

Multi-class

Multi-label

Structure

{0,1}

1-of-K

n-of-K

E.g. graph/sequence