Lecture Notes for
Machine Learning in Python

Professor Eric Larson

Introduction, Syllabus, Data Types

Class Logistics and Agenda

- Syllabus
- Overview of Machine Learning
- Types of Data and Representation

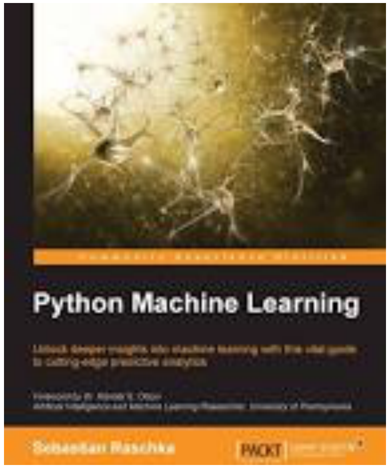
Course Syllabus

Introductions

- Me
  - Eric Larson
- You
  - Name, department, grad/ugrad
  - Something true or false
- My approach to this course
  - programming
  - math
  - **applications** and **analytics**

FAQ

- Text: None
  - Recommended: Python Machine Learning, Sebastian Raschka, Second edition
- Use Canvas for posted course material
- Prerequisite:
  - Linear Algebra, Calculus
  - Basic statistics and probability
  - Python programming
- Version of python: 3.X
  - install through anaconda
  - use virtual environments
- Deep Learning Library: Keras over Tensorflow



How will you grade participation?

- Participation will be graded in the course:
    - Distance students will answer these questions via canvas upload
    - must upload the questions throughout semester for full credit

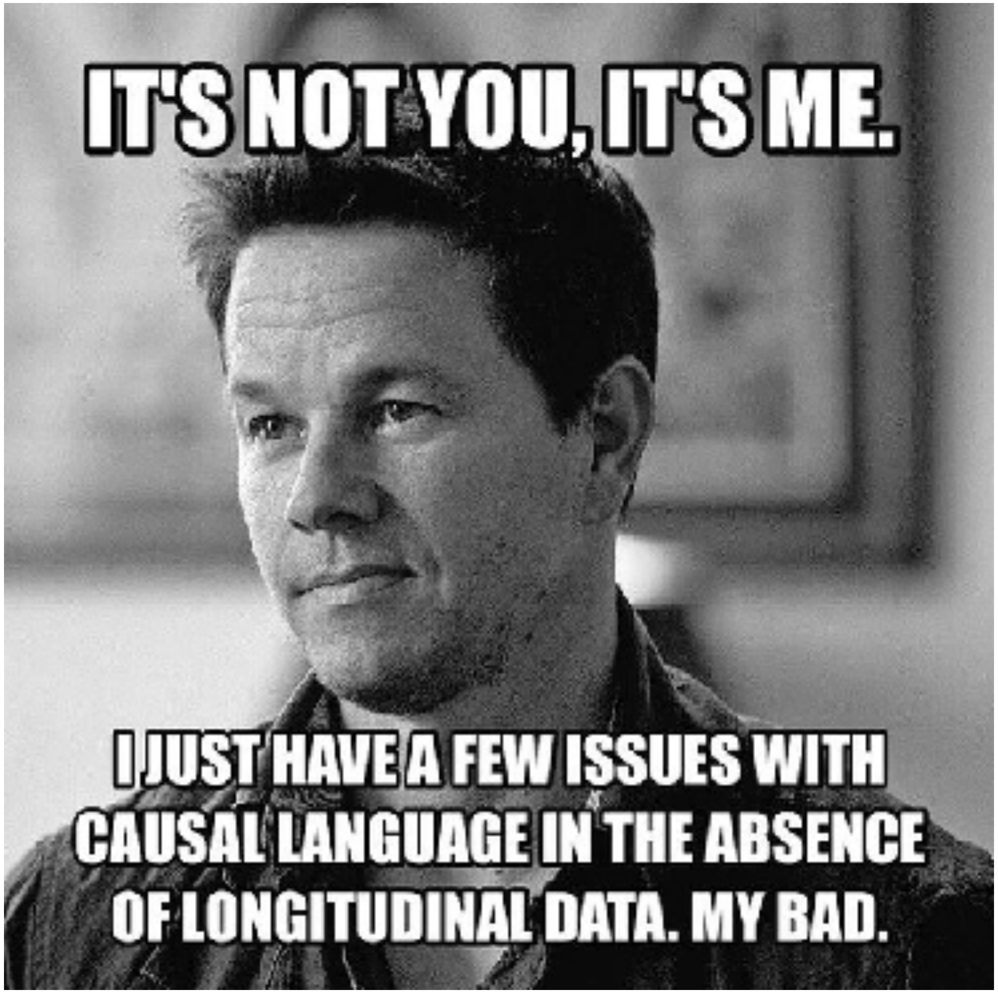
- Choose to respond to the question:
    - Do you think this will work?
        - A: **Yes** this is going to work
        - B: This is **not** going to work
        - C: I am **not even here**

Question ML1a

Canvas Syllabus

- Assignments
- Grading Rubrics
- Participation
- Course Schedule
- In-Class Assignments
- Difference between 5000 and 7000

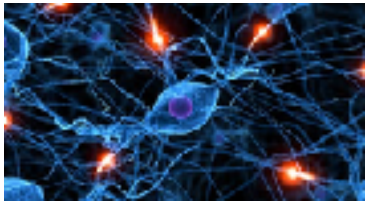
Machine Learning Overview

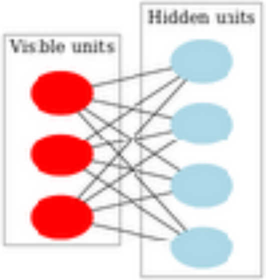

IT'S NOT YOU, IT'S ME.
I JUST HAVE A FEW ISSUES WITH CAUSAL LANGUAGE IN THE ABSENCE OF LONGITUDINAL DATA. MY BAD.

A History of Machine Learning

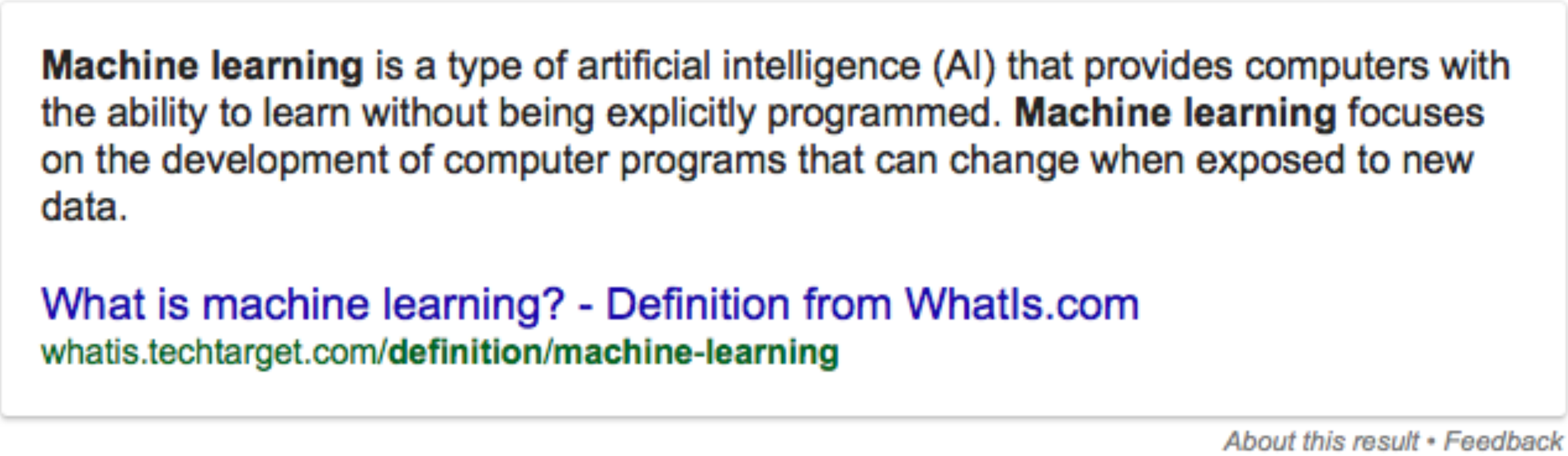
- Historically builds from disciplines statistics and computer science (algorithms)
- Its really just algorithms for optimizing weights 🤠

- **1952**: Arthur Samuel IBM creates checker program
- **1957**: Rosenblatt, Neural Network Perceptron
- **1967**: Nearest Neighbor Pattern Recognition
- **1970's**: AI Winter
- **1990's**: Volley of "New" Machine learning Algorithms
- **2001**: Breiman's Random Forests
- ~**2004**: Modern Support Vector Machines with Kernels
- **2005**: Second AI Winter
- ~**2010**: Deep Learning Convolutional Networks
- **2015**: Deep Learning becomes buzz word, you hear about it and take this course



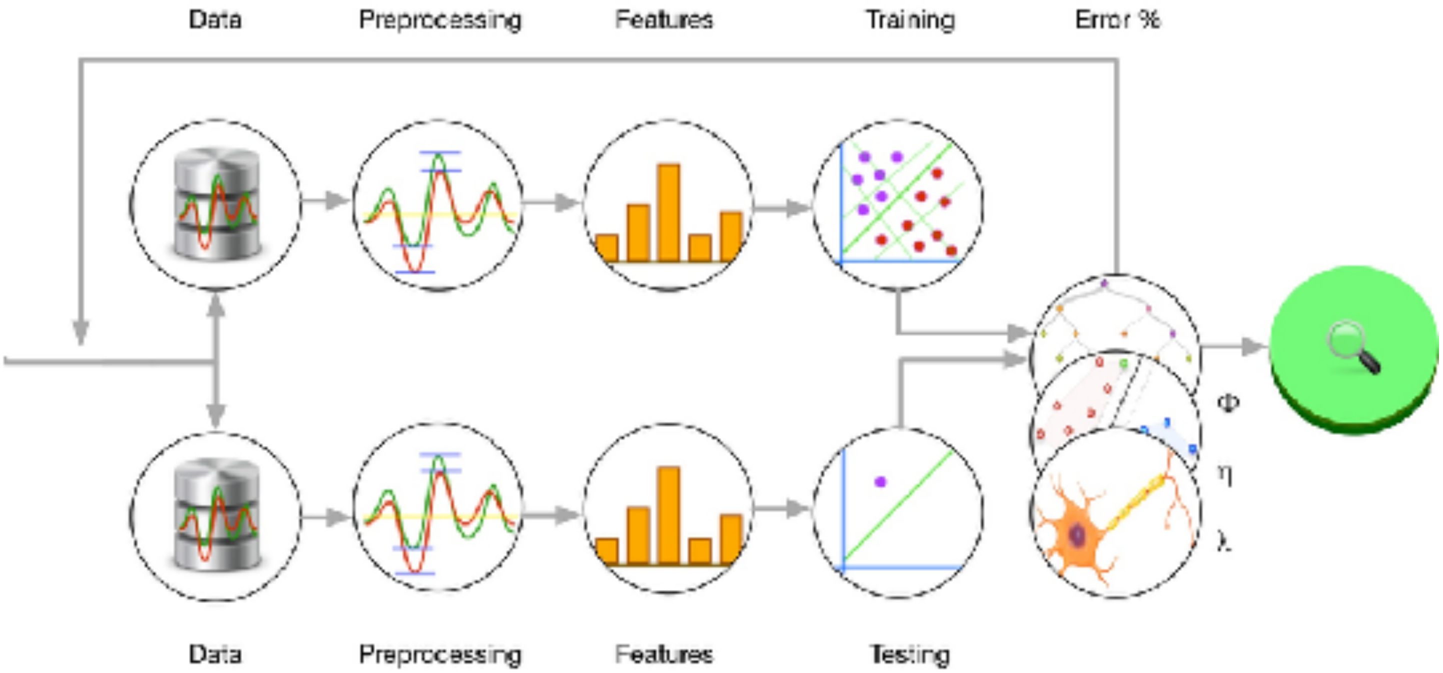


What is Machine Learning?

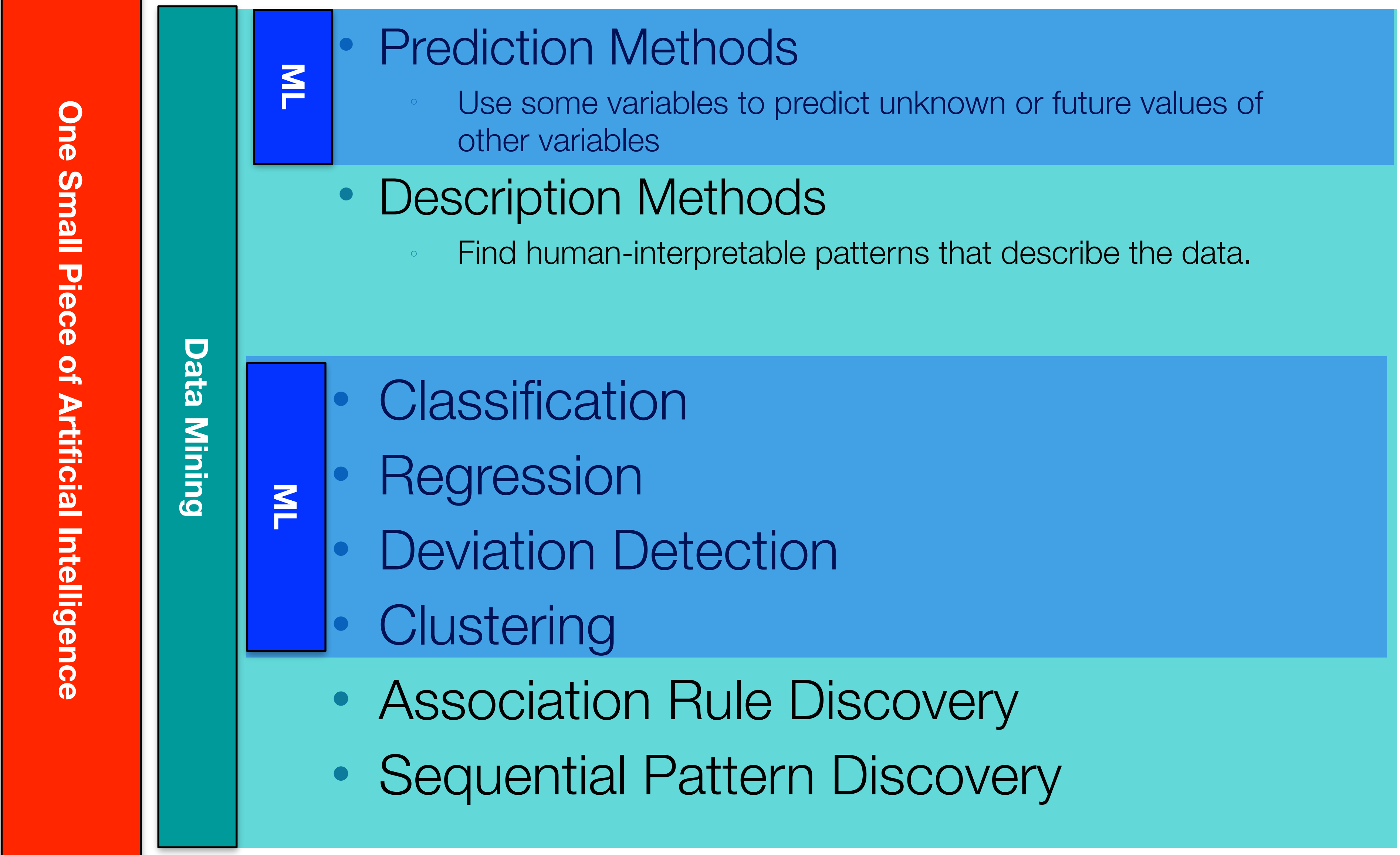


Machine learning is a type of artificial intelligence (AI) that provides computers with the ability to learn without being explicitly programmed. **Machine learning** focuses on the development of computer programs that can change when exposed to new data.

What is machine learning? - Definition from WhatIs.com
whatis.techtarget.com/**definition/machine-learning**



Machine Learning is part of Data Mining



One Small Piece of Artificial Intelligence

Data Mining

ML

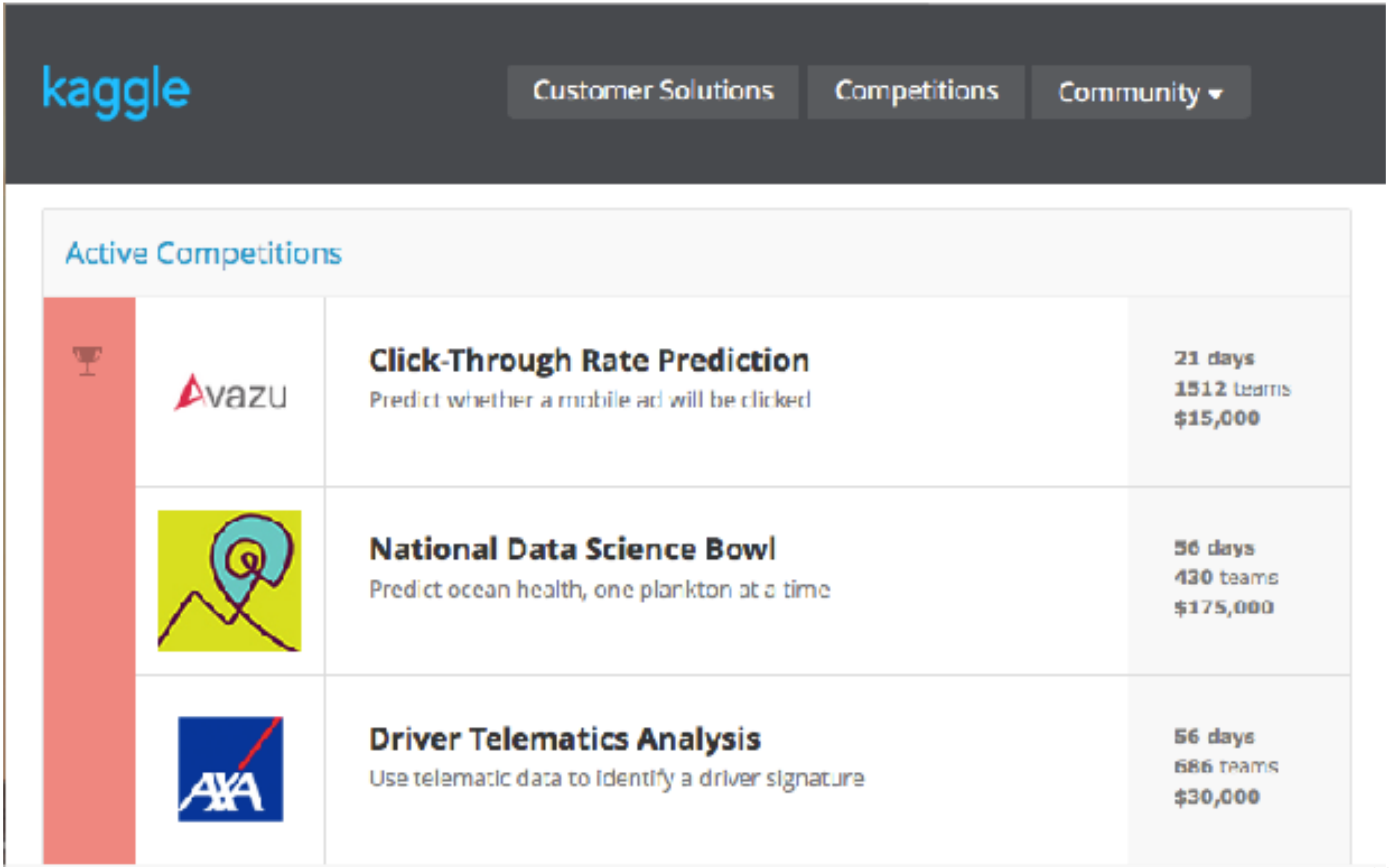
- Prediction Methods
  - Use some variables to predict unknown or future values of other variables
- Description Methods
  - Find human-interpretable patterns that describe the data.

ML

- Classification
- Regression
- Deviation Detection
- Clustering
- Association Rule Discovery
- Sequential Pattern Discovery

section 1, manipulated from Tan et al. Introduction to Data Mining

Problem Types in Machine Learning

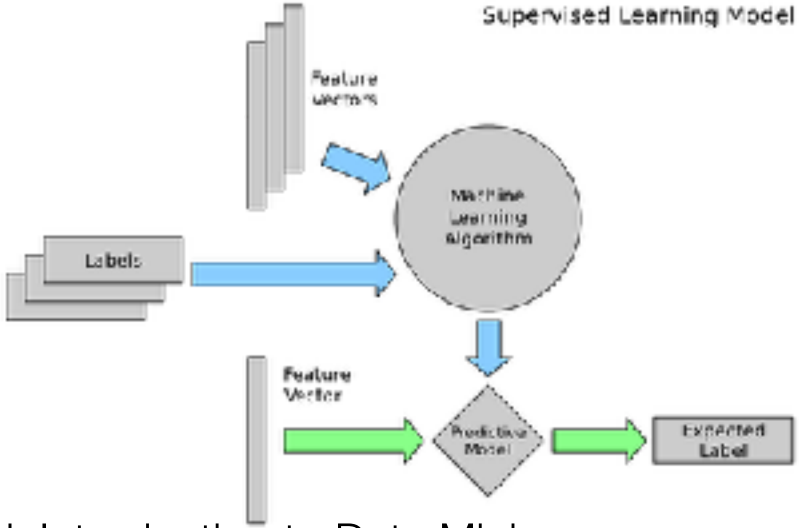


Active Competitions

Avazu	**Click-Through Rate Prediction** Predict whether a mobile ad will be clicked	21 days 1512 teams $15,000
	National Data Science Bowl Predict ocean health, one plankton at a time	56 days 430 teams $175,000
AXA	**Driver Telematics Analysis** Use telematic data to identify a driver signature	56 days 686 teams $30,000

Classification: Definition

- Given a collection of instances (*training set*)
    - Each instance contains a set of *features*, one of the features is the *class*.
- Find a *model* for class as a function of the values of features.
- Goal: <u>previously unseen</u> instances should be assigned a class as accurately as possible.



section 1, from Tan et al. Introduction to Data Mining

Classification: Definition

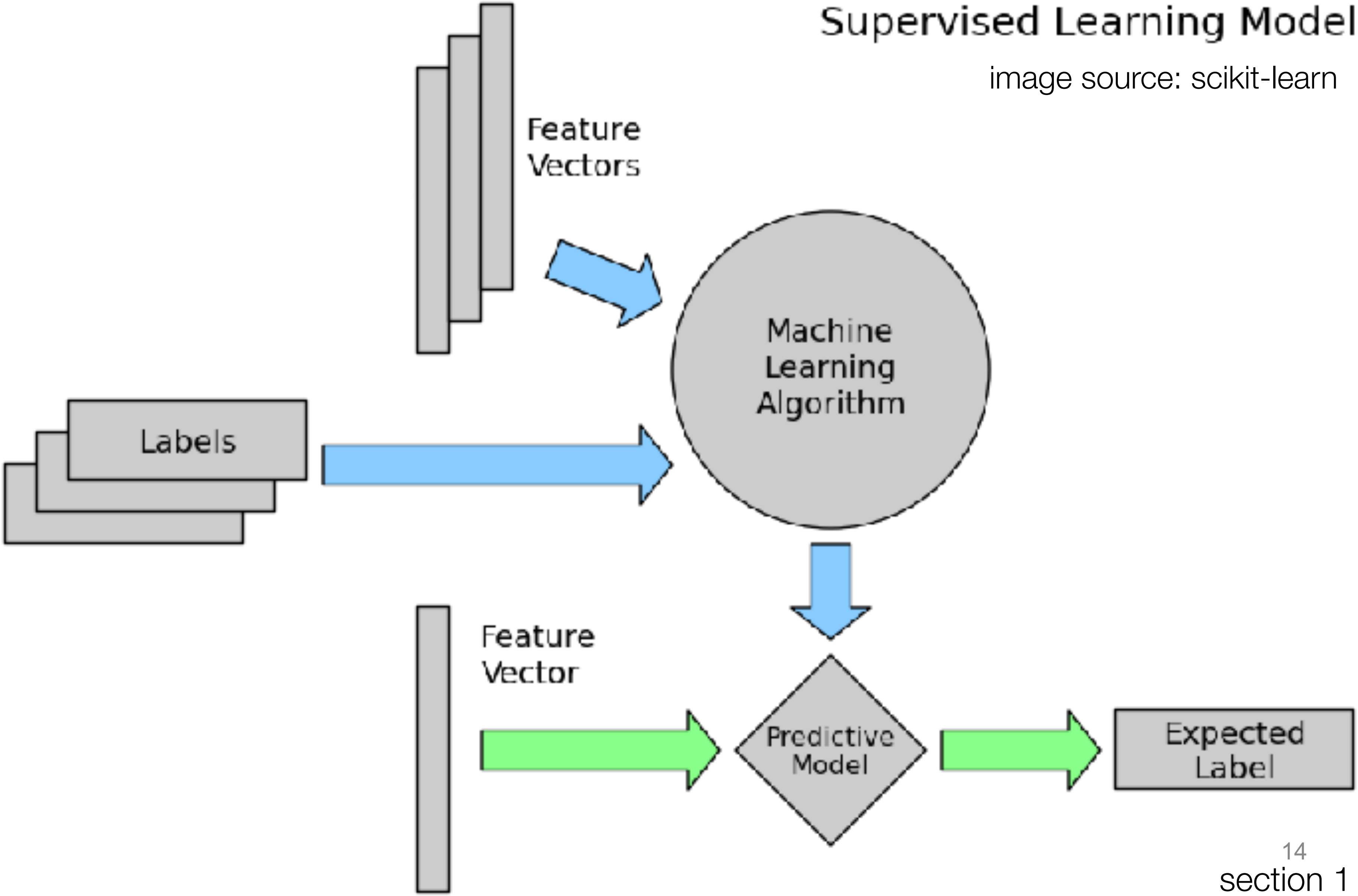


image source: scikit-learn

Classification: Malware

- Goal: classify files as malware based on structure, size, and naming.
- Approach:
  - Use already classified malware files.
  - ***{malware, not malware}*** decision forms the ***class attribute***.
  - Collect various malware examples and a number of safe files, providing labels for each and a set of features.

Training Set

TID	Name	Size	Class
1	erte.dll	916 b	not
2	fufu.bin	1M	yes
3	exe.exe	1G	not
4	ex.py	113 b	not

Unknown

TID	***Name***	***Size***
1	asdf.dll	11b

Classifying: Objects in Images

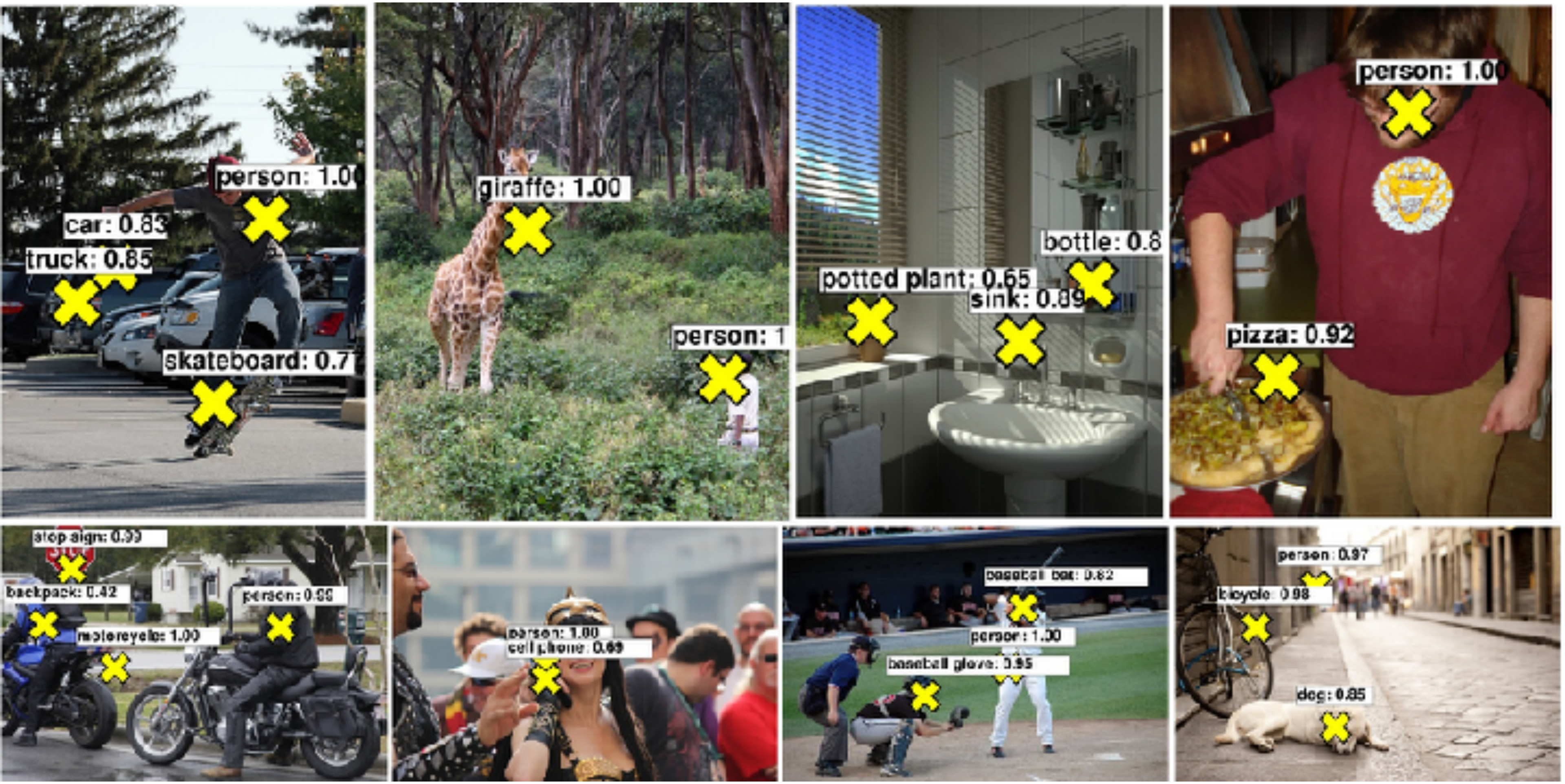


Image Net:

- 14 million images
- 200 Labeled Categories
- 1000 Location Labels

Attributes:

- Images

Regression

- Predict a value of a given *continuous valued* variable based on the values of other variables
- Examples:
    - Predicting sales amounts of new product based on advertising expenditure.
    - Predicting wind velocities as a function of temperature, humidity, air pressure, etc.
    - Predicting lung function as a function of gender, weight, height

Training Set

TI	Gend.	Weight	Asthma	LF
1	M	175lbs	N	85%
2	F	150lbs	N	87.3%
3	F	155lbs	Y	90%
4	M	225lbs	Y	65.2%

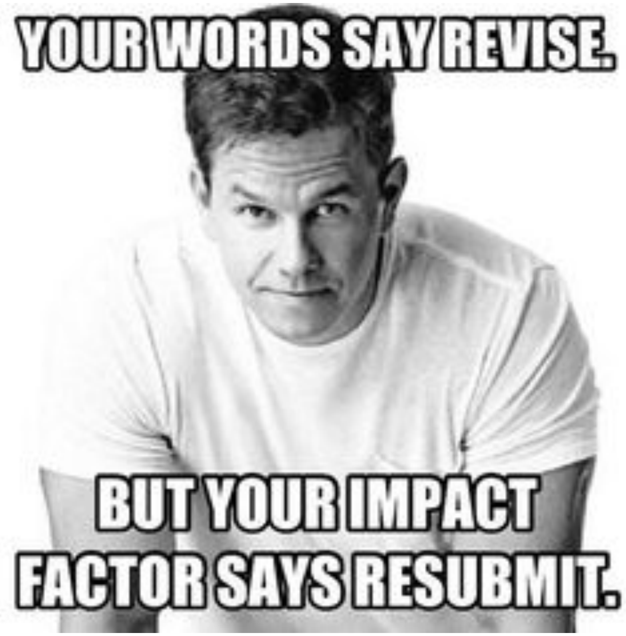
Unknown

TI	Gend.	Weight	Asthma
1	M	160lbs	N

Self Test

- (**A. classification)**
  (B. regression)
  (C. not Machine Learning)
  - Dividing up customers by potential profitability?
    - classification/regression
  - Extracting frequency of sound?
    - NOT ML
  - Finding someone's adipose tissue measure from waist circumference?
    - regression
  - Deciding if a person has diabetes based upon their history and diet?
    - classification
  - Finding the genre of an online article based on the words in it?
    - classification

Types of Data and Categorization



What is Table Data?

- Collection of data **instances** and their **features**

- A **feature** is a property or characteristic of an object
  - Examples: eye color of a person, temperature, etc.

- A collection of features describe an **instance**

Attributes, variables, fields, characteristics, **Features**

Objects, records, points, samples, cases, entities, **Instances**

TID	*Pregnant*	*BMI*	*Age*	*Diabetes*
1	Y	33.6	41-50	positive
2	N	26.6	31-40	negative
3	Y	23.3	31-40	positive
4	N	28.1	21-30	negative
5	N	43.1	31-40	positive
6	Y	25.6	21-30	negative
7	Y	31.0	21-30	positive
8	Y	35.3	21-30	negative
9	N	30.5	51-60	positive
10	Y	37.6	51-60	positive

section 2, from Tan et al. Introduction to Data Mining

Types of Attributes

- **Nominal**
- Examples: ID numbers, eye color, zip codes
- **Ordinal**
- Examples: rankings (e.g., taste of potato chips on a scale from 1-10), grades, height in {tall, medium, short}
- **Interval**
- Examples: calendar dates, temperatures in Celsius or Fahrenheit.
- **Ratio**
- Examples: temperature in Kelvin, length, time, counts

Distinctness:	= ≠
Order:	< >
Addition:	+ -
Multiplication:	* /

Nominal attribute: distinctness

Ordinal attribute: distinctness & order

Interval attribute: distinctness, order, & addition

Ratio attribute: all properties

section 2, from Tan et al. Introduction to Data Mining

Feature Type Representation

	Attribute	Representation Transformation	Comments
Discrete	**Nominal**	Any permutation of values one hot encoding	If all employee ID numbers were reassigned, would it make any difference?
	Ordinal	An order preserving change of values, i.e., new_value = f(old_value) where f is a monotonic function. integer	An attribute encompassing the notion of good, better best can be represented equally well by the values {1, 2, 3} or by { 0.5, 1, 10}.
Continuous	**Interval**	new_value =a * old_value + b where a and b are constants float	Thus, the Fahrenheit and Celsius temperature scales differ in terms of where their zero value is and the size of a unit (degree).
	Ratio	new_value = a * old_value float	Length can be measured in meters or feet.

Self Test

- Are these **A. interval or B. ratio**:
  - Angle measured 0-360 degrees
    - ratio
  - Height above sea level
    - interval or ratio depending on if sea level is considered arbitrary
- Are these **A. ordinal, B. nominal, or C. binary**?
  - military rank
    - ordinal
  - coat check number
    - nominal
  - time as AM or PM
    - binary

Before Next Lecture

- Before next class:
  - install python on your laptop
  - install anaconda distribution of python

- Look at Python primer if you need review
  - I made ~4 hours of YouTube content…
  - https://www.youtube.com/playlist?list=PL7lPdRN5E0YKCnVl-fvx8jOOCWVeGTsrV

Demo

If time:
Jupyter Notebooks
and Numpy

`01_Numpy and Pandas Intro.ipynb`

Lecture Notes for
Machine Learning in Python

Professor Eric Larson

Numpy, Pandas, Document Features

Class Logistics and Agenda

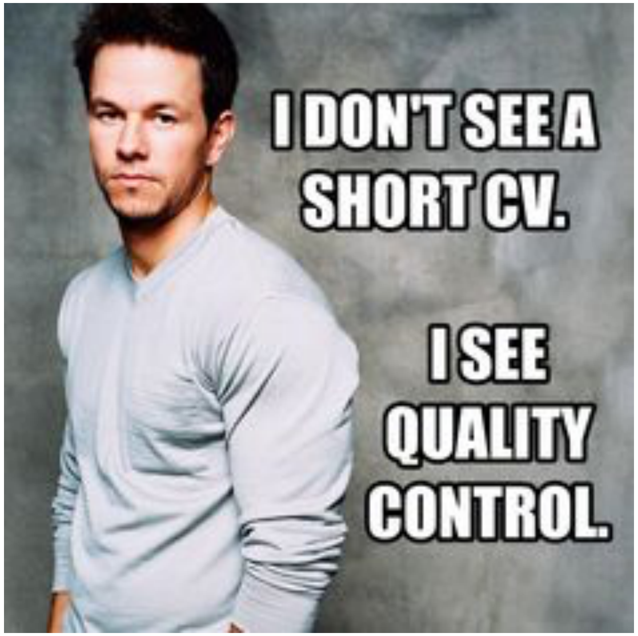
- Canvas? Anaconda Installs?
- Distance transfers?
- Agenda:
  - Numpy
  - Data Quality
  - Attributes Representation
    - documents
  - The Pandas eco-system
    - loading and manipulating attributes

Demo

“Finish”
Jupyter Notebooks
and Numpy

`01_Numpy and Pandas Intro.ipynb`

Data Quality



Review of Feature Data

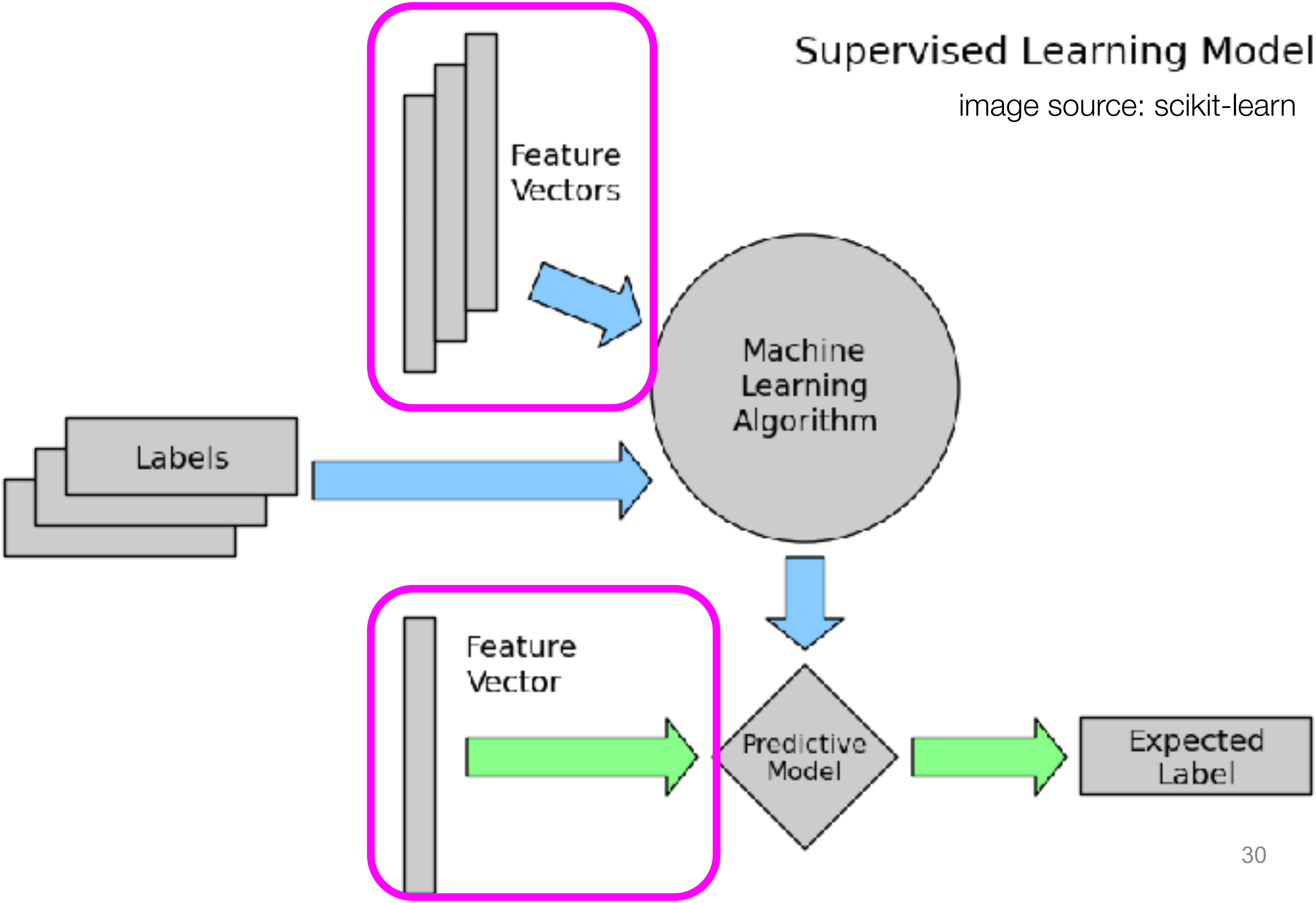


image source: scikit-learn

Data Quality Problems

- Noise and outliers
  - remove if you know its noise/outlier
- Missing values
  - replace or ignore
- Duplicate data
  - clean entries or merge

Missing Values

- Reasons for missing values
  - Information is **not collected** (*e.g.*, people decline to give their age and weight)
  - Features may **not be applicable** to all cases (*e.g*., annual income for children)
  - **UCI ML Repository**: 90% of repositories have missing data

- Handling missing values
  - **Eliminate** Data Objects
  - **Impute** Missing Values
  - **Ignore** the Missing Value During Analysis
  - Replace with all possible values (talk about later)

How?

Stats:
mean
median
mode

Imputation

- When is it probably fine to impute missing data:
  - [✓ (A) When there is not much missing data]
  - [✓ (B) When the missing feature is mostly predictable from another feature]
  - [✓ (C) When there is not much missing data for each subgroup of the data]
  - (D) When it is the class you want to predict

self test ML1b.1

Split-Impute-Combine

TID	Pregnant	BMI	Age	Diabetes
1	Y	33.6	41-50	positive
2	N	26.6	31-40	negative
3	Y	23.3	?	positive
4	N	28.1	21-30	negative
5	N	43.1	31-40	positive
6	Y	25.6	21-30	negative
7	Y	31.0	21-30	positive
8	Y	35.3	?	negative
9	N	30.5	51-60	positive
10	Y	37.6	51-60	positive

split: pregnant
split: BMI > 32

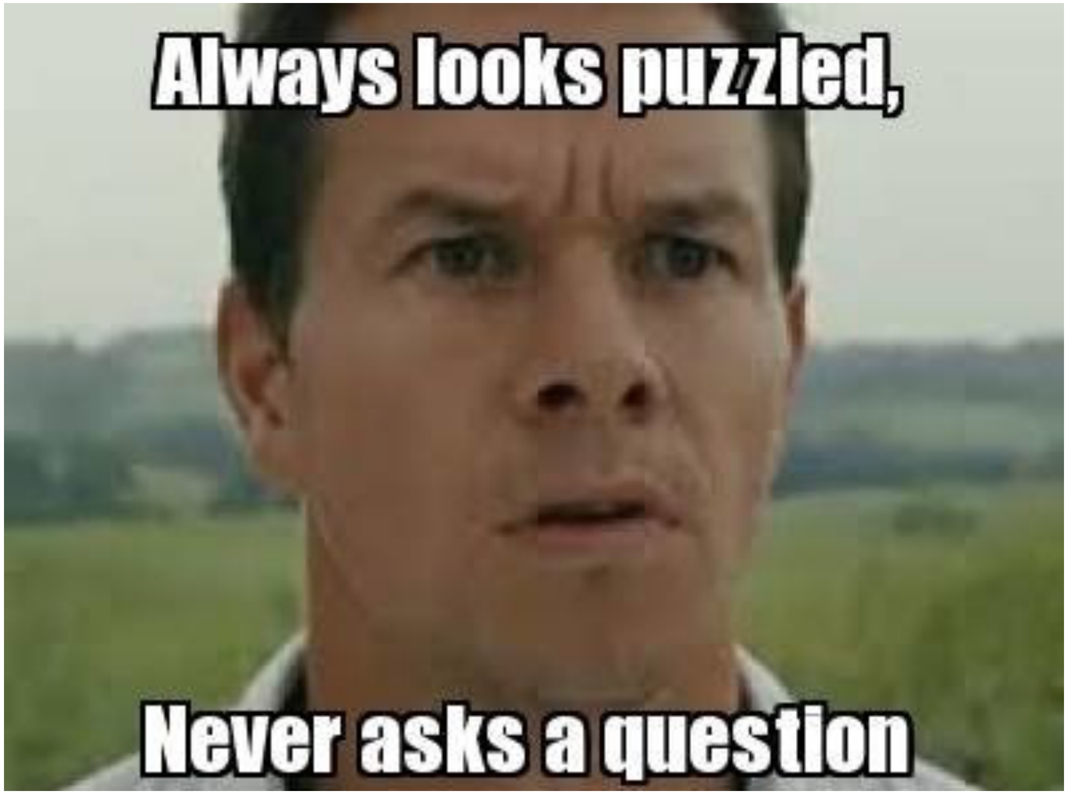
TID	Pregnant	BMI	Age	Diabetes
1	Y	>32	41-50	positive
8	Y	>32	?	negative
10	Y	>32	51-60	positive

Mode: none, can’t impute

TID	Pregnant	BMI	Age	Diabetes
3	Y	<32	?	positive
6	Y	<32	21-30	negative
7	Y	<32	21-30	positive

Mode: 21-30

Data Representation



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Continuous	**Interval**	new_value =a * old_value + b where a and b are constants float	Thus, the Fahrenheit and Celsius temperature scales differ in terms of where their zero value is and the size of a unit (degree).
	Ratio	new_value = a * old_value float	Length can be measured in meters or feet.

Data Tables as Variable Representations

Table

TID	Pregnant	BMI	Age	Eye Color	Diabetes
1	Y	33.6	41-50	brown	positive
2	N	26.6	31-40	hazel	negative
3	Y	23.3	31-40	blue	positive
4	N	28.1	21-30	brown	inconclusive
5	N	43.1	31-40	blue	positive
6	Y	25.6	21-30	hazel	negative

Internal Rep.

TID
1
2
3
4
5
6

Data Tables as Variable Representations

Table

TID	***Pregnant***	***BMI***	***Age***	***Eye Color***	***Diabetes***
1	Y	33.6	41-50	brown	positive
2	N	26.6	31-40	hazel	negative
3	Y	23.3	31-40	blue	positive
4	N	28.1	21-30	brown	inconclusive
5	N	43.1	31-40	blue	positive
6	Y	25.6	21-30	hazel	negative

Internal Rep.

TID	***Binary***	***Float***	***Ordinal***	***Object***	***Diabetes***
1	1	33.6	2	hash(0)	1
2	0	26.6	1	hash(1)	0
3	1	23.3	1	hash(2)	1
4	0	28.1	0	hash(0)	2
5	0	43.1	1	hash(2)	1
6	1	25.6	0	hash(1)	0

Bag of words model

TID	*Pregnant*	*BMI*	*Chart Notes*	*Diabetes*
1	Y	33.6	Complaints of fatigue wh…	positive
2	N	26.6	Sleeplessness and some…	negative
3	Y	23.3	First saw signs of rash o…	positive
4	N	28.1	Came in to see Dr. Steve…	inconclusive
5	N	43.1	First diagnosis for hospit…	positive
6	Y	25.6	N/A	negative

Vocabulary

Bag of Words

TID	Sleep	Fatigue	Weight	Rash	First	Sight
1	0	1	0	0	2	0
2	1	1	0	0	1	1
3	1	1	0	2	1	1

number of occurrences

Feature Hashing

what happens when we get more words?

TID	Slee	Fati	Wei	Ras	First	Sigh	Why	Fox	Bro	Lazy	Dog	Etc	Stev
1	0	1	0	0	2	0	0	0	0	1	0	2	0
2	1	1	0	0	1	1	0	0	4	0	1	3	0
3	1	1	0	2	1	1	1	0	1	0	0	1	0

or we could have a hashing function, h(x) = y

TID	h(x)=1	h(x)=2	h(x)=3	h(x)=4	h(x)=5	h(x)=6
1	0	1	0	1	2	0
2	1	1	4	0	2	1
3	2	1	1	2	1	1

multiple words mapped to one feature (want to minimize collisions)

Term-Frequency, Inverse-Document-Frequency

TID	Slee	Fati	Wei	Ras	First	Sigh	Why	Fox	Bro	Lazy	Dog	Etc	Stev
1	0	0.05	0	0	0.34	0	0	0	0	1	0	0.86	0
2	0.1	0.05	0	0	0.12	0.25	0	0	1.21	0	1	1.02	0
3	0.1	0.05	0	0.27	0.12	0.25	0.02	0	0.45	0	0	0.1	0

term frequency $\mathrm{tf}(t,d) = f_{td},\ t \in T \text{ and } d \in D$

"num occurrences of *t* in doc *d*"/"words in *d*"

inverse document frequency: normalize occurrences

$$\mathrm{idf}(t,d) = \log\frac{|D|}{|n_t|},\ \text{where } n_t = d \in D \text{ with } t \in d$$

"total docs"/"num docs with *t*"

$$\text{tf-idf}(t,d) = \mathrm{tf}(t,d) \cdot \mathrm{idf}(t,d)$$

$$\text{tf-idf}(t,d) = \mathrm{tf}(t,d) \cdot (1 + \mathrm{idf}(t,d))$$ smoothed

TF-IDF

- The tf-idf value can never be greater than one.
  - (A) true
  - (B) false
  - (C) it depends on IDF normalization

term frequency $\mathrm{tf}(t,d) = f_{td},\ t \in T \text{ and } d \in D$

"num occurrences of *t* in doc *d*"/"words in *d*"

inverse document frequency: normalize occurrences

$$\mathrm{idf}(t,d) = \log \frac{|D|}{|n_t|},\ \text{where } n_t = d \in D \text{ with } t \in d$$

"total docs"/"num docs with *t*"

$$\text{tf-idf}(t,d) = \mathrm{tf}(t,d) \cdot \mathrm{idf}(t,d)$$

self test ML1b.2

Demo

Sklearn and Pandas

TF-IDF

DataFrames

Loading

Indexing

Imputing

```
02_Document Feature Engineering.ipynb
```

Other Tutorials:

http://vimeo.com/59324550

http://pandas.pydata.org/pandas-docs/version/0.15.2/tutorials.html

For Next Lecture

- Before next class:
    - install seaborn
    - install plotly
    - mess with pandas and look at additional tutorials

- Next Week: Data Visualization
- End of Next Week: **Lab One Due, Table Data**