Lecture Notes for

Machine Learning in Python

Professor Eric Larson

Data Quality and Imputation

Class Logistics and Agenda

- Agenda:
  - Data Quality
  - Data Representations
  - Imputation methods
- Needing some more help?
  - **fast.ai** has great, free resources

Class Overview, by topic

Table Data Visualization

Numpy, Pandas, Seaborn
Overviews with some in-depth discussion

Dimension Reduction and Image Processing

Scikit-learn, Scikit Image,
Intuition only, Some mathematics

Linear and Logistic Regression

Numpy, Recreate API for Scikit-learn
Detailed mathematics for simple optimization
intuition for advanced optimization

Neural Networks and Back Prop.

Numpy
Detailed mathematics for NN operations

Wide and Deep Networks | **Convolutional Networks** | **Recurrent Networks**

Keras, Tensorflow
Intuition, Detailed implement.

Ethics in Language Models

ConceptNet
Case studies

Data Quality

Review of Feature Data

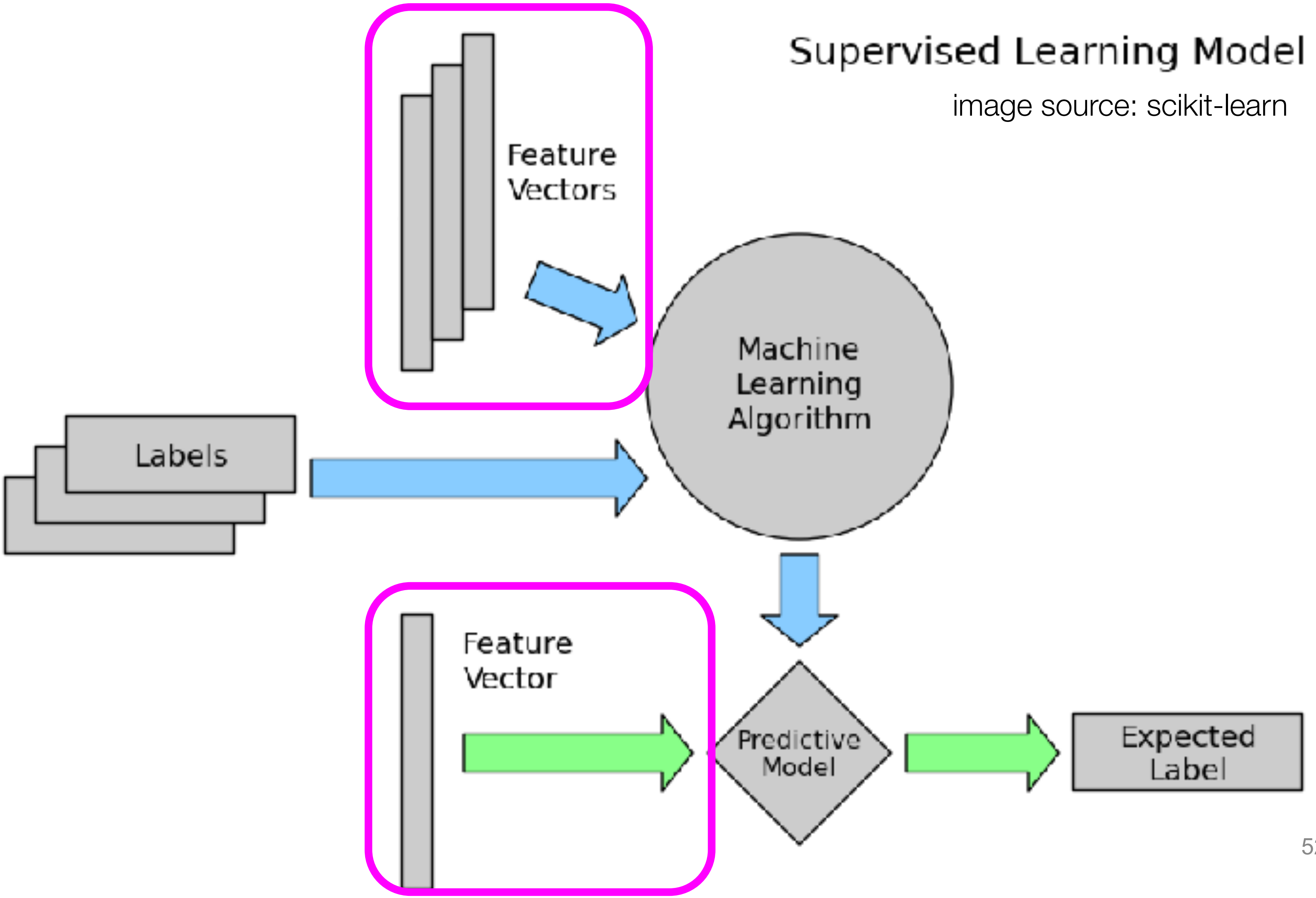


image source: scikit-learn

Data Quality Problems

- Missing
  - Easy to find, NaNs
- Duplicated
  - Easy to find, hard to verify
- Noise or Outlier
  - Hard to define
  - Hard to catch

Information is not collected (e.g., people decline to give their age and weight)

Features **not applicable** (e.g., annual income for children)

UCI ML Repository: 90% of repositories have missing data

TID	*Hair Color*	*Height*	*Age*	*Arrested*
1	Brown	5’2”	23	no
2	Hazel	1.5m	12	no
3	Bl	5	999	no
4	Brown	5’2”	23	no

Handling Issues with Data Quality

- **Eliminate** Instance or Feature
- **Ignore** the Missing Value During Analysis Replace with all possible values (talk about later)
- **Impute** Missing Values

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

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

K-Nearest Neighbors Imputation

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	?	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

For K=3, find 3 closest neighbors

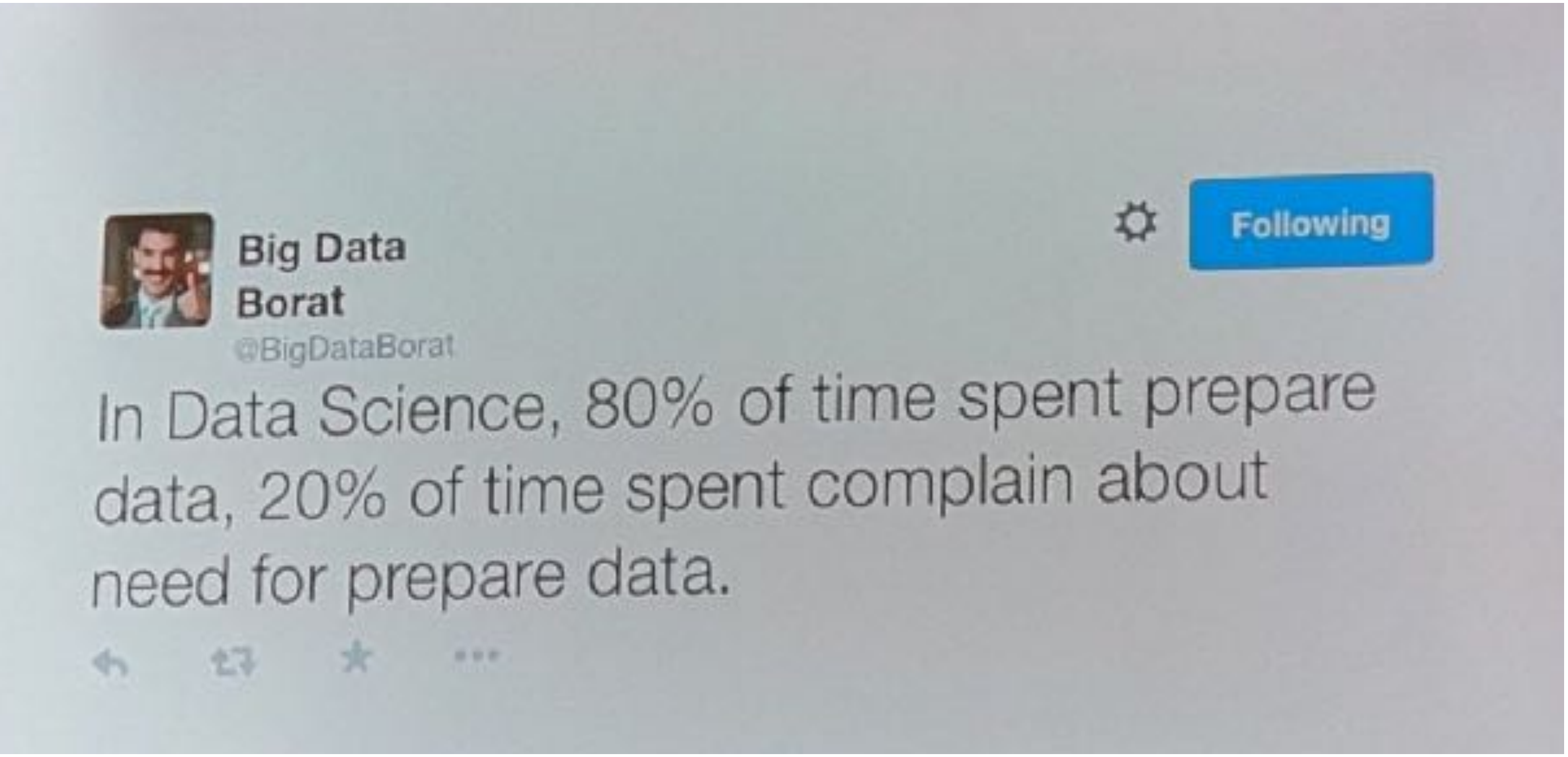
TID	Preg nant	BMI	Age	Diabetes	Distance
3	Y	23.3	?	positive	0
6	Y	25.6	21-30	negative	(0 + 2.3 + 1)/3
2	N	26.6	31-40	negative	(1 + 3.3 + 1)/3
4	?	28.1	21-30	negative	(4.8 + 1)/2

Imputed Age: 21-30

How to calculate distance?

- Difference for valid features only
- May need to normalize ranges
- Or weight neighbors differently
- Or have min # of valid features
- Euclidean, city-block, etc.

Data Representation and Documents



Feature Type Representation Review

	Attribute	Representation Transformation	Comments
Discrete	**Nominal**	Any permutation of values **one hot encoding or hash function**	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.

from Tan et al. Introduction to Data Mining

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

	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 hash:

(**want to** (1) minimize collisions **or** (2) make collisions meaningful)

Term-Frequency, Inverse-Document-Frequency

TID	Slee	Etc	Stev
1	0	.86	0
2	0.1	.02	0
3	0.1	.1	0

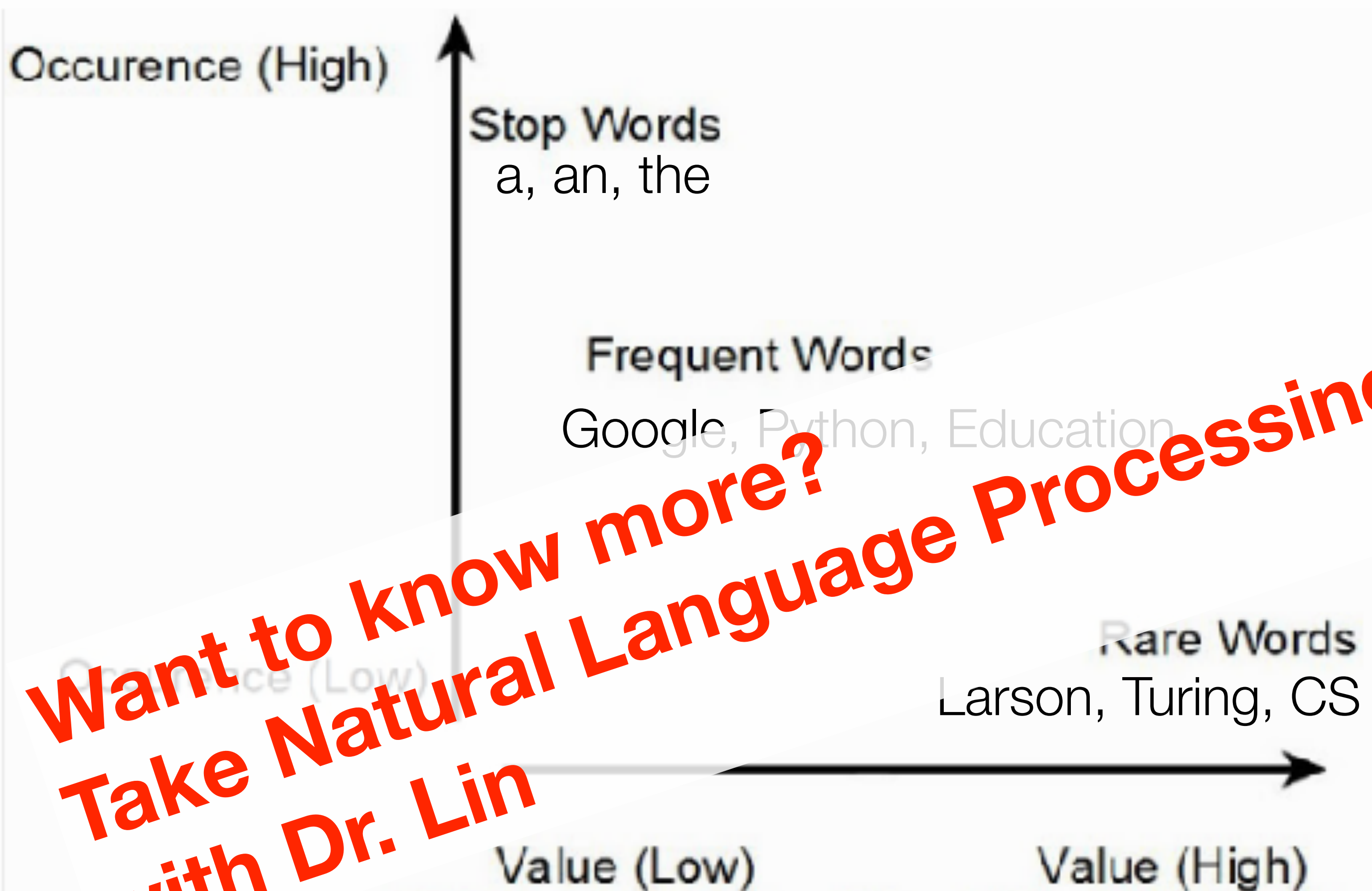
te … $\in D$

… in d"

inverse

idf(… $\in d$

… t"



https://www.kaggle.com/divsinha/sentiment-analysis-countvectorizer-tf-idf

Want to know more? Take Natural Language Processing with Dr. Lin

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

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

Demo

Pandas and Imputation

Scikit-Learn

Start the following:

`03. Data Visualization.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:
  - verify installation of seaborn, plotly, (and/or bokeh if you want)
  - look at pandas table data and additional tutorials

- Next time: Data Visualization

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