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
- Logistics:
  - need help? canvas has links to various resources
    - the class GitHub is also a resource!
  - TA hours posted!

Course Github Page:	https://github.com/eclarson/MachineLearningNotebooks
Other Useful Guides:	Helpful Links and Guides for Semester
Participation For Distance Students	Turn in answers to questions here: Participation

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

Last Time

Data Quality Problems

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

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

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	Pregnant	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.

K-Nearest Neighbors Imputation

TID	Pregnant	BMI	Age	Diabetes
1	Y	33.6	31-40	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	21-30	positive

$$d_k = \frac{1}{|F_{valid}|} \sum_{i \in F_{valid}} \|f_i - f_i^{(k)}\|$$

i^{th} feature, f, in row

For $k = 3$, find 3 closest neighbors

TID	Preg.	BMI	Age	Diabetes	Distance d_k
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

… repeat for all rows, select 3 closest …

Imputed Age: 21-30

Distance can be calculated differently:

- Difference for valid features only
- May need to normalize ranges
- Weight neighbors differently?
- Have min # of valid features?
- Type: Euclidean, city-block, etc.

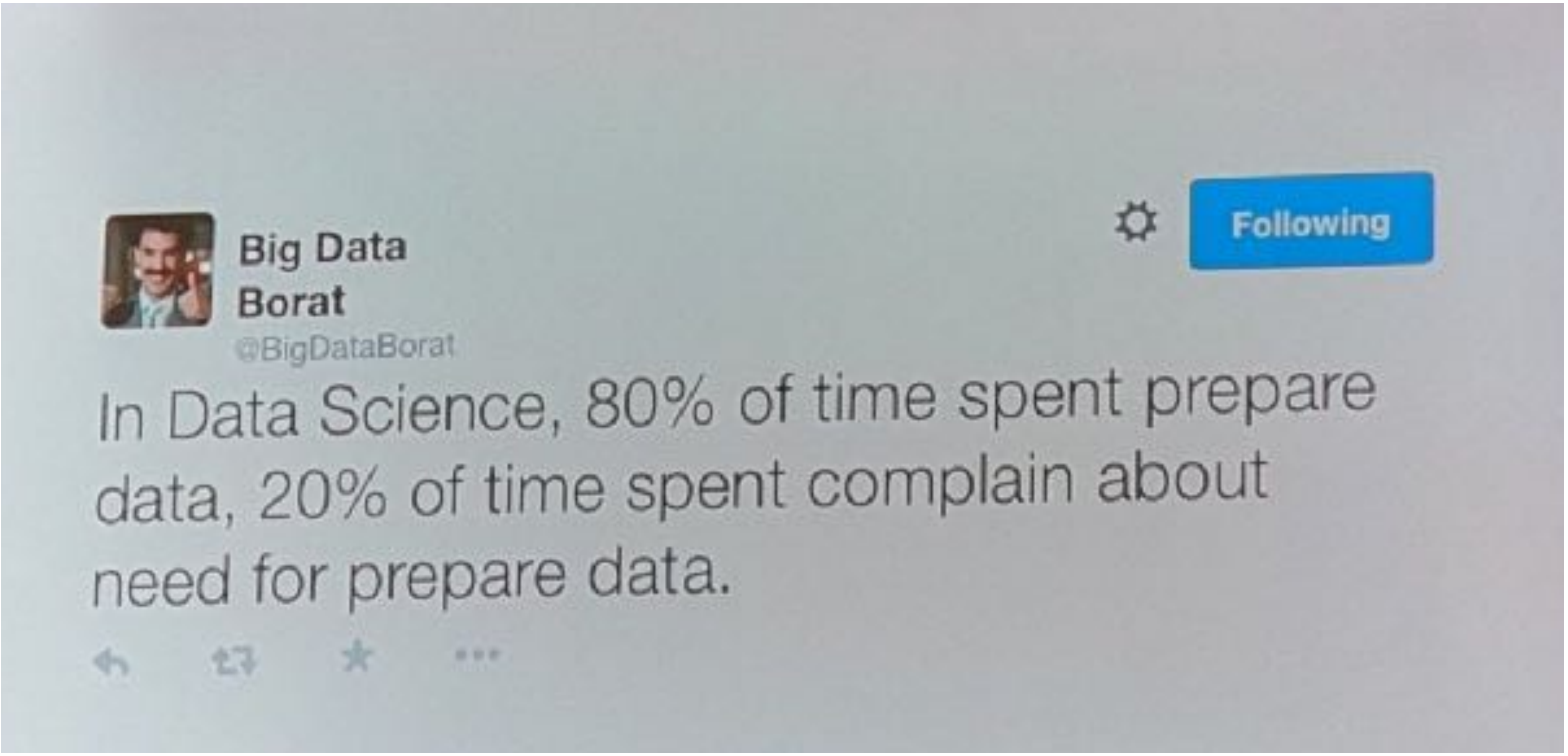
Demo

Pandas and Imputation

Scikit-Learn

`03. Data Visualization.ipynb`

Data Representation and Documents



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

Term-Frequency, Inverse-Document-Frequency

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

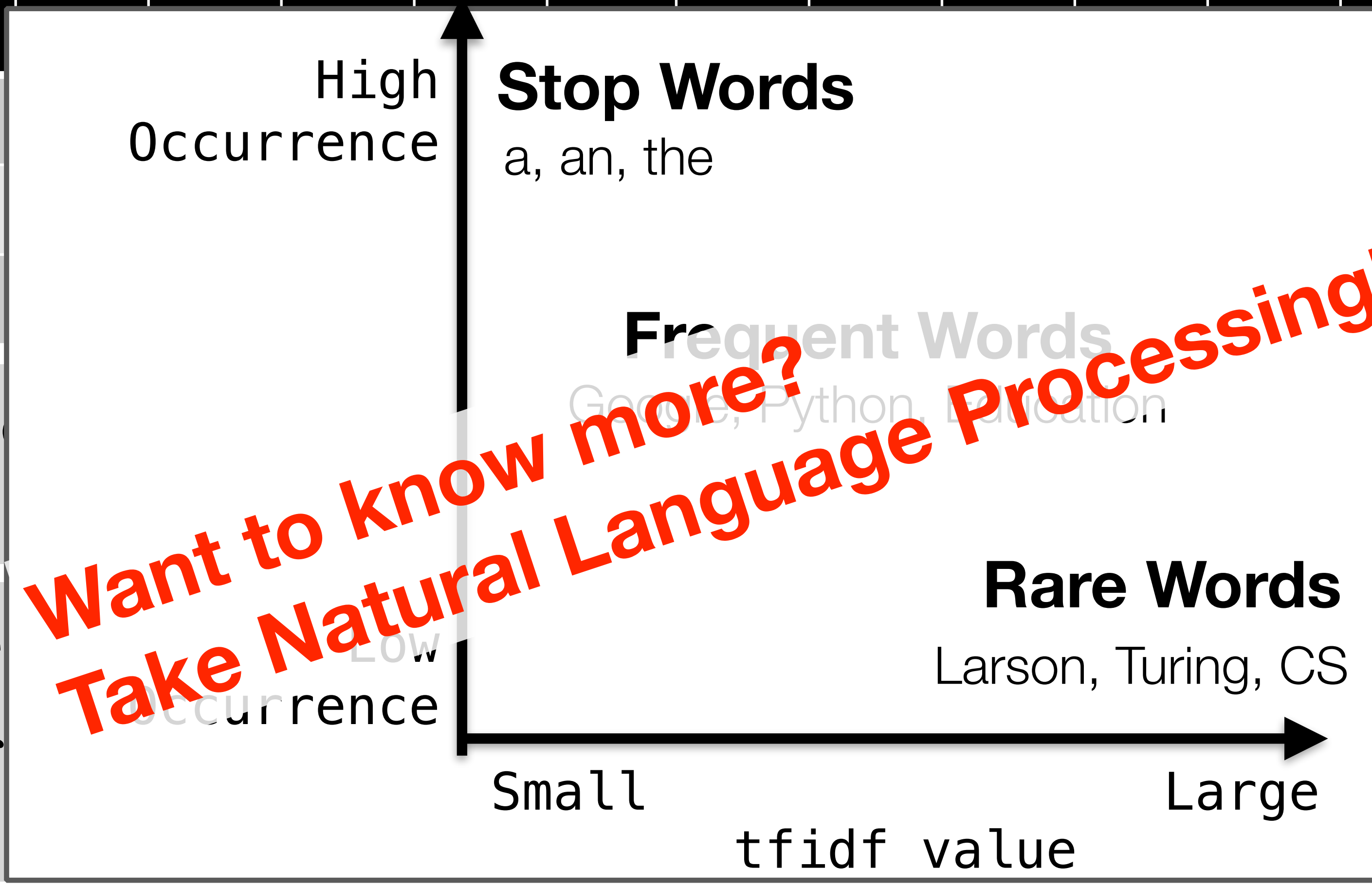
t … $\in D$

… n d”

inverse …

idf … $\in d$

…”



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

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

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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