Lecture Notes for **Machine Learning in Python**



Professor Eric Larson

Data Quality and Imputation

Class Logistics and Agenda

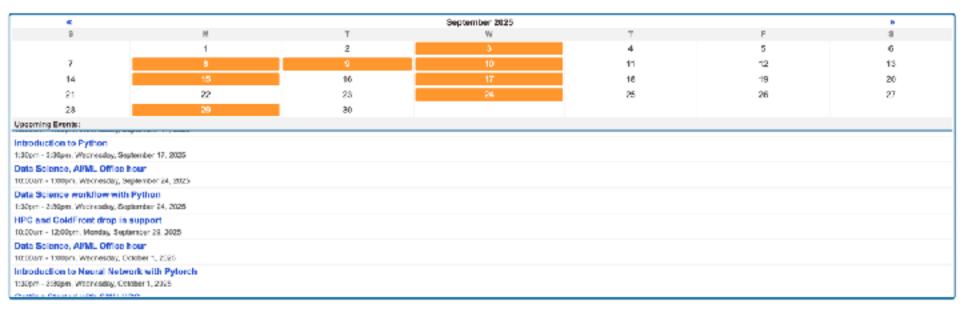
- Logistics:
 - Need help? canvas has links to various resources
 - the class GitHub is also a resource!
 - TA hours!
 - Team Forming Discussion sections
- Agenda:
 - Data Quality
 - Data Representations
 - Imputation methods

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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

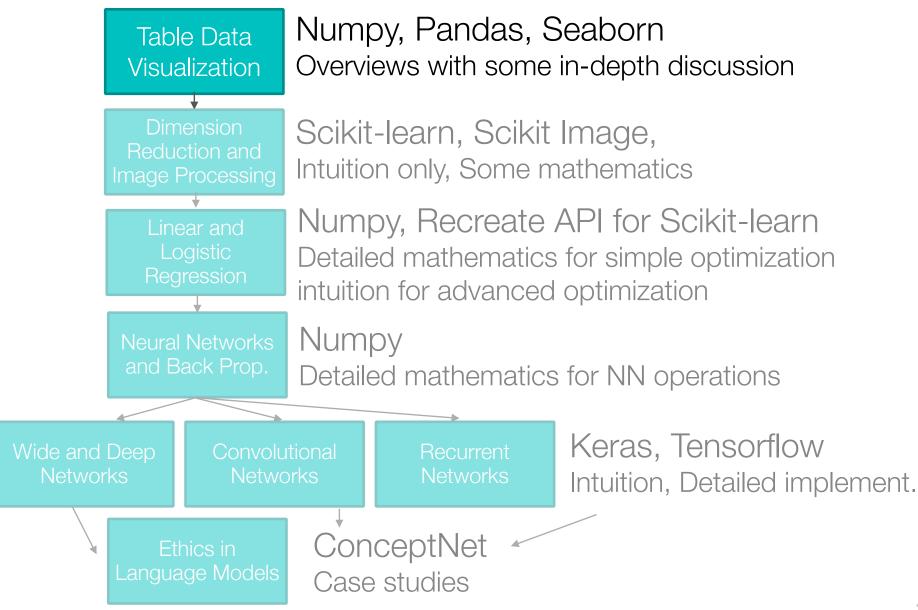
Using the SMU HPC

- Tutorials available for various types of analysis:
 - https://www.smu.edu/oit/research

Events This Month



Class Overview, by topic



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

	Nominal or Categorical	Variable could be one value in a set of categories. No ordering of values.	Allowed Transforms permuting values
Discrete		Example: Employee ID	boclean, one hot encoding, or hash function
Disc	Ordinal	Variable could be one value in a set of categories. Ordering matters. Example: Start Ratings, 1-5	Allowed Transforms $V_{new} = f_{mono} (V_{old}) + b$ integer (or bcolean)
STOTE	Interval or Numeric	Value is ocntinuous numerie valus. Could be in specified range. Example: BMI, Temperature, etc.	Allowed Transforms $V_{new} = f_{meno} (V_{old}) + b$ float
Continuous	Ratio or Numeric	Value is continuous numeric value. Zero is meaningful. Often not treated differently than interval. Example: Longtin, Elevation	Allowed Transforms $V_{new} = f_{meno} (V_{old})$ float

Split-Impute-Combine





split: pregnant split: BMI > 32

TID	Pregnant	BMI	Age	Diabetes
1	Y	>32	41-50	positive
8	Y	>32	7	regative
10	Y	>32	51-60	positive

Mode: none, can't impute

TAD	Prognant	DAN	Age	Diabetes
a	Y	132	7	positive
6	Y	c32	21-30	regative
7	Y	<32	21-30	positive

Mode: 21-30

TID	Hair Color	Height	Age	Arrested
1	Brown	5'2"	23	cn
2	Hazal	1.5m	12	na
3	BI	5	999	cn
4	Brown	5'2"	28	na

Self Test, Missing data

- Can all missing data be found by searching for NaNs?
 - A. Yes. Missing data should always be a NaN.
 - B. Yes. Pandas defaults all missing data to NaN.
 - C. No. This only works for floats, because that is the data type for NaN.
 - D. No. NaN only represents missing data that is already found.

K-Nearest Neighbors Imputation

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

$$d_k = \frac{1}{|F_{valid}|} \sum_{i \in F_{valid}} ||f_i^{(unk)} - f_i^{(k)}||$$
• May need to normalize ranges
• Weight neighbors differently?
• Have min # of valid features?
• Type: Euclidean, city-block, et

For k=3, find 3 closest neighbors

TID	Preg.	ВМІ	BMI Age Diab		Distance d_k
3	Υ	23.3	?	positive	0
6	Υ	25.6	21-30	negative	(0 + 2.3 + 1)/3
2	Ν	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

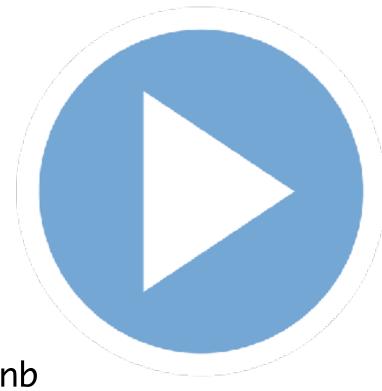
Distance can be calculated differently:

- Difference for valid features only
- May need to normalize ranges

- Type: Euclidean, city-block, etc.

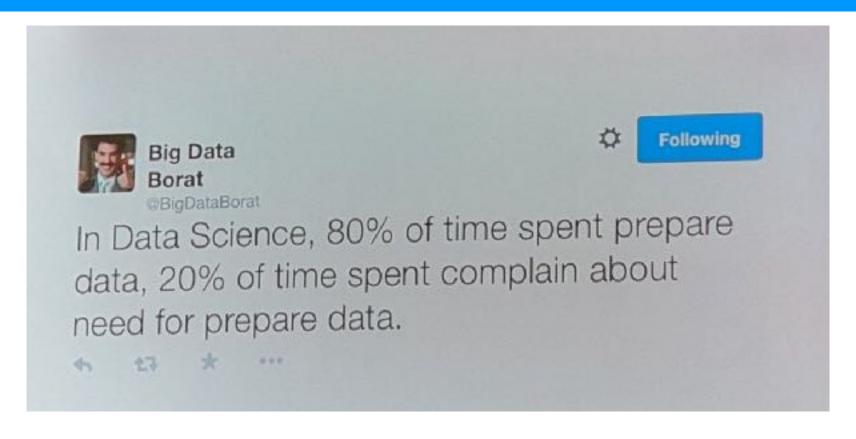
Demo

Pandas and Imputation Scikit-Learn



03. Data Visualization.ipynb

Data Representation and Documents



Data Tables as Variable Representations

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

Data Tables as Variable Representations

	TID	Pregnant	BMI	Age	Eye Color	Diabetes
	1	Y	33.6	41-50	brown	positive
<u>.</u>	2	N	26.6	31-40	hazel	negative
))	3	Y	23.3	31-40	blue	positive
•	4	Ν	28.1	21-30	brown	inconclusive
	5	N	43.1	31-40	blue	positive
	6	Y	25.6	21-30	hazel	negative
1	TID	Binary	Float	Ordinal	Object	Diabetes
<u>)</u>)	1	1	33.6	2	hash(0)	1
•	2	0	26.6	1	hash(1)	0
5	3	1	23.3	1	hash(2)	1
	4	0	28.1	0	hash(0)	2

0

Internal Rep.

5

6

hash(2)

hash(1)

43.1

25.6

Bag of words model

TID	Pregnant	BMI	Chart Notes	Diabetes
1	Υ	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

Bag of Words

Vocabulary

TID	Sleep	Fatigue	Weight	Rash	First	Sight
1	0	1	0	0	2	0
2	1	1	0	0 Imbor of	1	1 rences
3	1	1	0	2	1	1

Term-Frequency. Inverse-Document-Frequency **Stop Words** High Slee Stev TID Occurrence a, an, the .86 ().02 0 0.1 **Frequent Words** 0.1 ()Google, Python, Education γd "

inverse Occurrence

idf

Rare Words

Larson, Turing, Nobel

Small

Large

tfidf value

This is often used in RAG systems, for Keyword retrieval!!

Want to know more? If (t, d)

Take Natural Language Processing!

d

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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