Lecture Notes for

Machine Learning in Python

[👨‍🏫, 👨‍💻, 🐍, 👨‍🔬]

Professor Eric Larson

Table Data using Numpy, Pandas

Class Logistics and Agenda

- Canvas. Python Installs.
- Participation. Zoom. Attendance.
- Agenda:
  - Data Encodings
  - Demo: Table Data, Numpy
  - Data Quality
  - Attributes Representation
    - documents
  - The Pandas eco-system
    - loading and manipulating attributes

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

Types of Data and Categorization

Table Data

- **Table Data**: Collection of data **instances** and their **features**
  - **Python:** Pandas Dataframe
  - **R:** Data.frame
  - **Matlab:** Table Class
  - **C++**: Make yourown, `std::vector<Record>`

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

Objects, records, rows, 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

Feature Vector Representation

$f_{mono}(\cdot)$
monotonic function

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

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

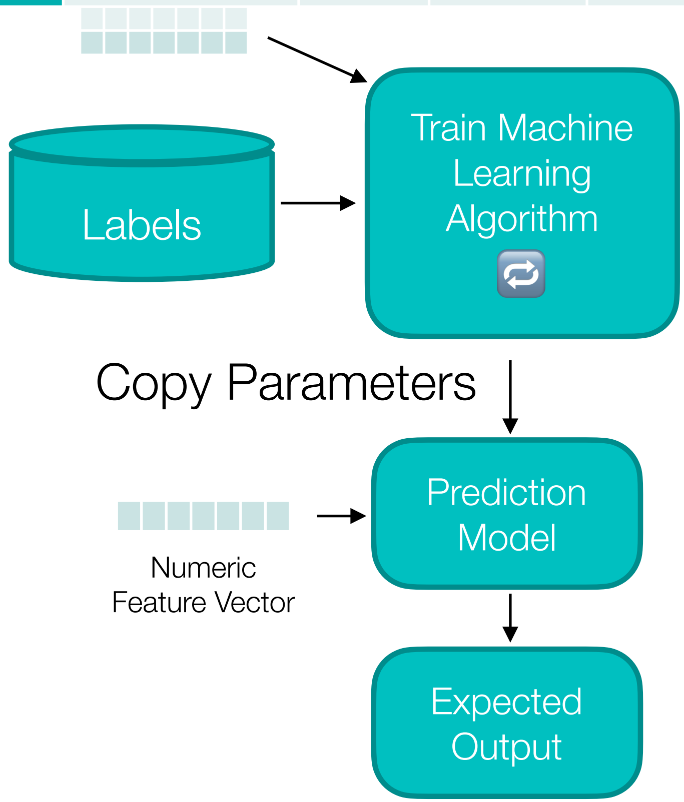
“Finish”
Jupyter Notebooks

`01_Numpy and Pandas Intro.ipynb`

Data Quality

Data Quality Problems

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



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

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

Lecture Notes for

Machine Learning in Python

Professor Eric Larson

Table Data using Numpy, Pandas