Lecture Notes for

# Machine Learning in Python

[👨‍🏫, 👨‍💻, 🐍, 👨‍🔬]

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## Table Data using Numpy, Pandas

# Class Logistics and Agenda

- Canvas? Anaconda Installs?
- In-person versus Zoom and other classes
- 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++**: Trick Question

**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

| | Attribute | Representation Transformation | Comments |
|---|---|---|---|
| Discrete | **Nominal** | Permutation of values only. **one hot encoding or hash function** | If all **employee ID** numbers were reassigned, would it make any difference? |
| | **Ordinal** | Order must be preserved `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 =f(old_value) + b` $f$ is monotonic through origin **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 = f(old_value)` $f$ is monotonic through origin **float** | **Length** can be measured in meters or feet, but **zero is zero** |

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 |

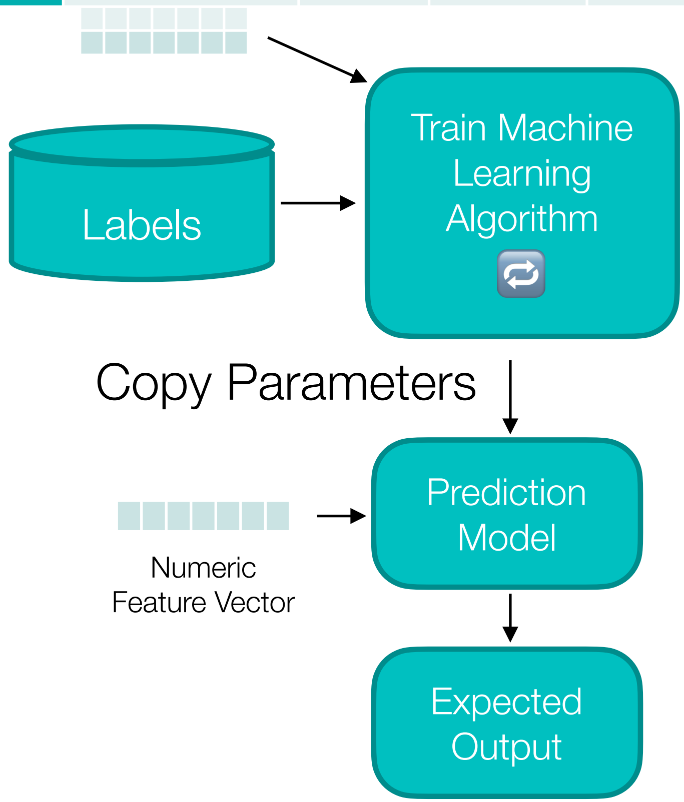
# “Finish”
# Jupyter Notebooks

`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 | no |
| 3 | Bl | 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

# 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 |

$$d_{i,j} = \frac{1}{|F_{valid}|} \sum_{f \in F_{valid}} \|f_i - f_j\|$$

For K=3, find 3 closest neighbors

| TID | Preg. | 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.

# 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: Documents, Data Imputation Demo