

# Lecture Notes for **Machine Learning in Python**

Professor Eric Larson  
**Numpy, Pandas, Document Features**

# Class Logistics and Agenda

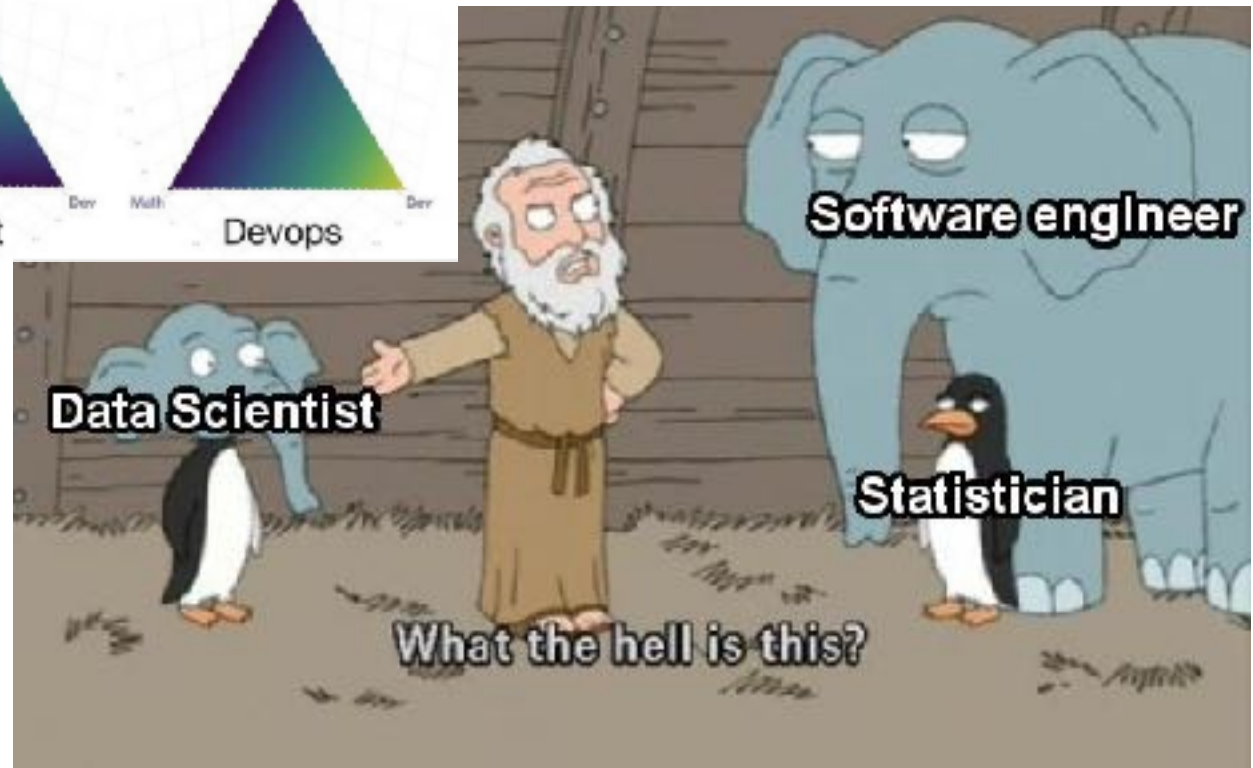
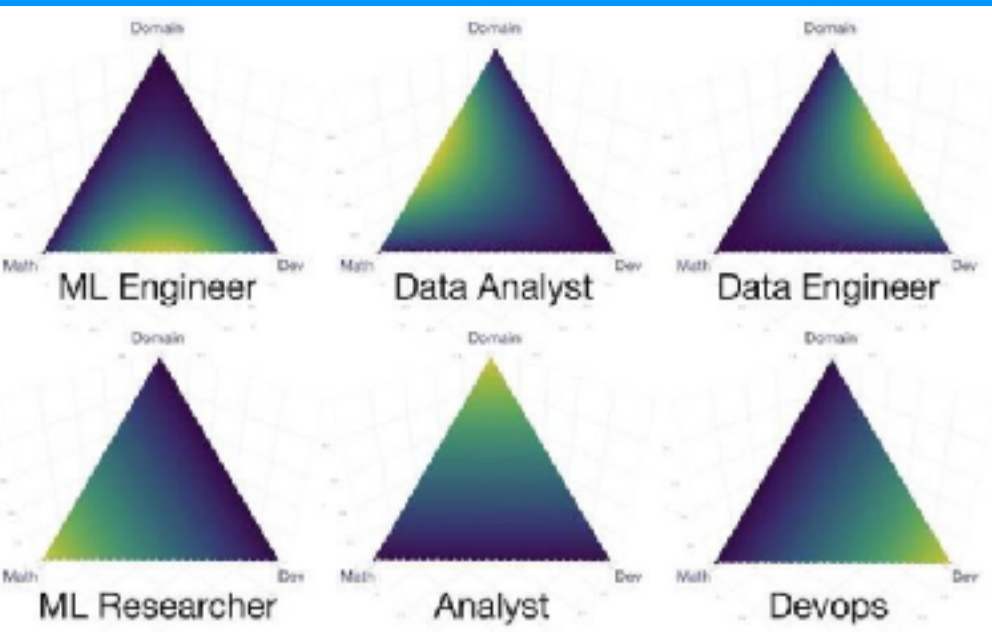
- ❑ Canvas? Anaconda Installs?
- ❑ Red/Blue/Distance
- ❑ Agenda:
  - ❑ Finish Numpy
  - ❑ Data Quality
  - ❑ Attributes Representation
    - ❑ documents
  - ❑ The Pandas eco-system
    - ❑ loading and manipulating attributes
- ❑ Needing some more help?
  - ❑ **fast.ai** has great, free resources

## **“Finish” Jupyter Notebooks and Numpy**

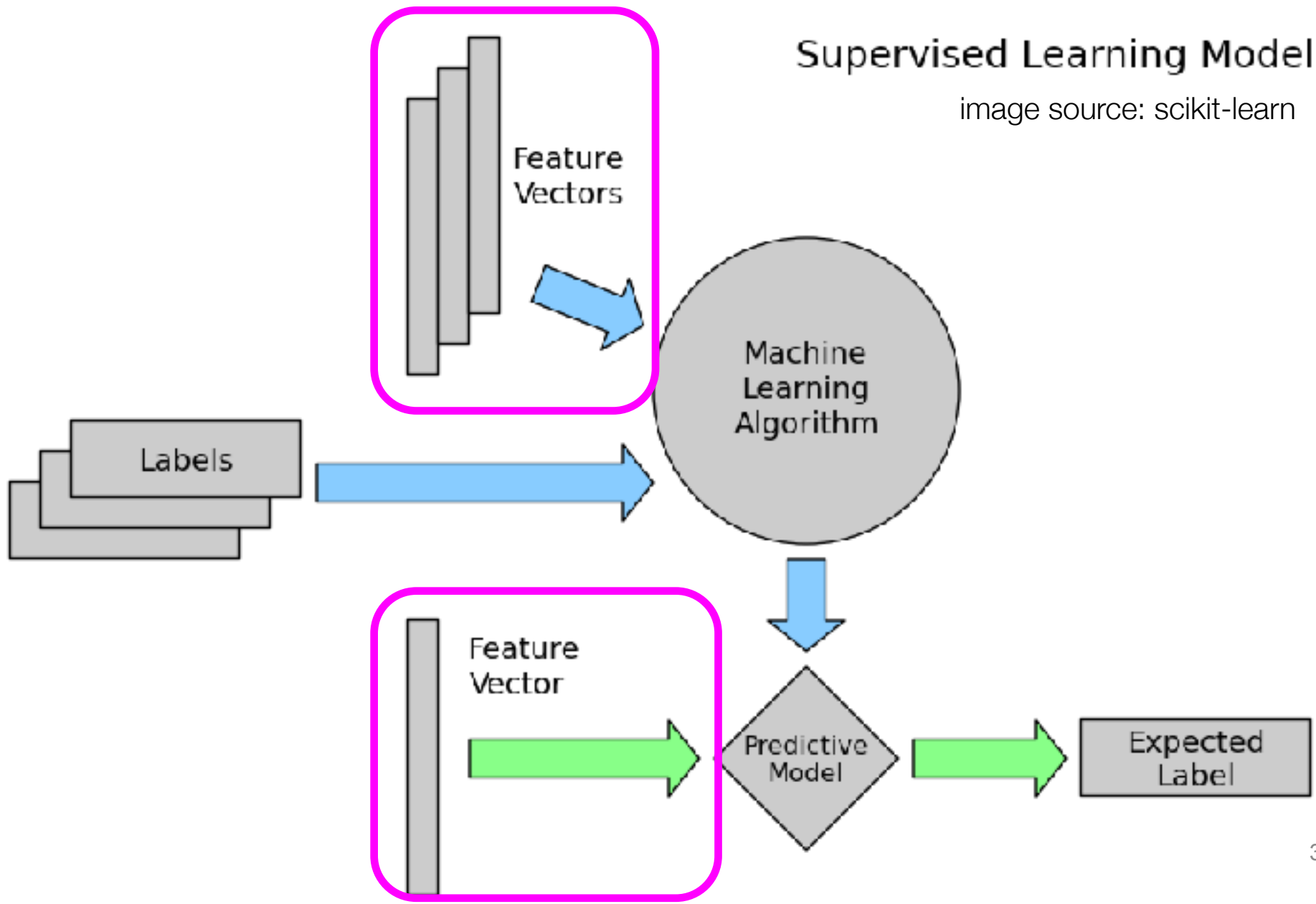


`01_Numpy and Pandas Intro.ipynb`

# Data Quality



# Review of Feature Data



# 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

<i>TID</i>	<i>Hair Color</i>	<i>Height</i>	<i>Age</i>	<i>Arrested</i>
<b>1</b>	Brown	5'2"	23	no
<b>2</b>	Hazel	1.5m	12	no
<b>3</b>	Bl	5	999	no
<b>4</b>	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?**

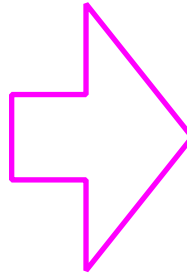
**Stats?**  
**mean**  
**median**  
**mode**

# 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



<i>TID</i>	<i>Pregnant</i>	<i>BMI</i>	<i>Age</i>	<i>Diabetes</i>
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

<i>TID</i>	<i>Pregnant</i>	<i>BMI</i>	<i>Age</i>	<i>Diabetes</i>
1	Y	>32	41-50	positive
8	Y	>32	?	negative
10	Y	>32	51-60	positive

Mode: none, can't impute

<i>TID</i>	<i>Pregnant</i>	<i>BMI</i>	<i>Age</i>	<i>Diabetes</i>
3	Y	<32	?	positive
6	Y	<32	21-30	negative
7	Y	<32	21-30	positive

Mode: 21-30

# K-Nearest Neighbors Imputation

For K=3, find 3 closest neighbors

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

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.