INFO 1998: Introduction to Machine Learning

CDS Education

We explore, learn, and educate big minds.

Lecture 2: Data Manipulation

INFO 1998: Introduction to Machine Learning

CDS Education

We explore, learn, and educate big minds.

Agenda

1. How to Define a Good Question
2. The Data Pipeline/Datasets
3. Data Manipulation Techniques
4. Data Imputation
5. Other Techniques

Creating A Good Question

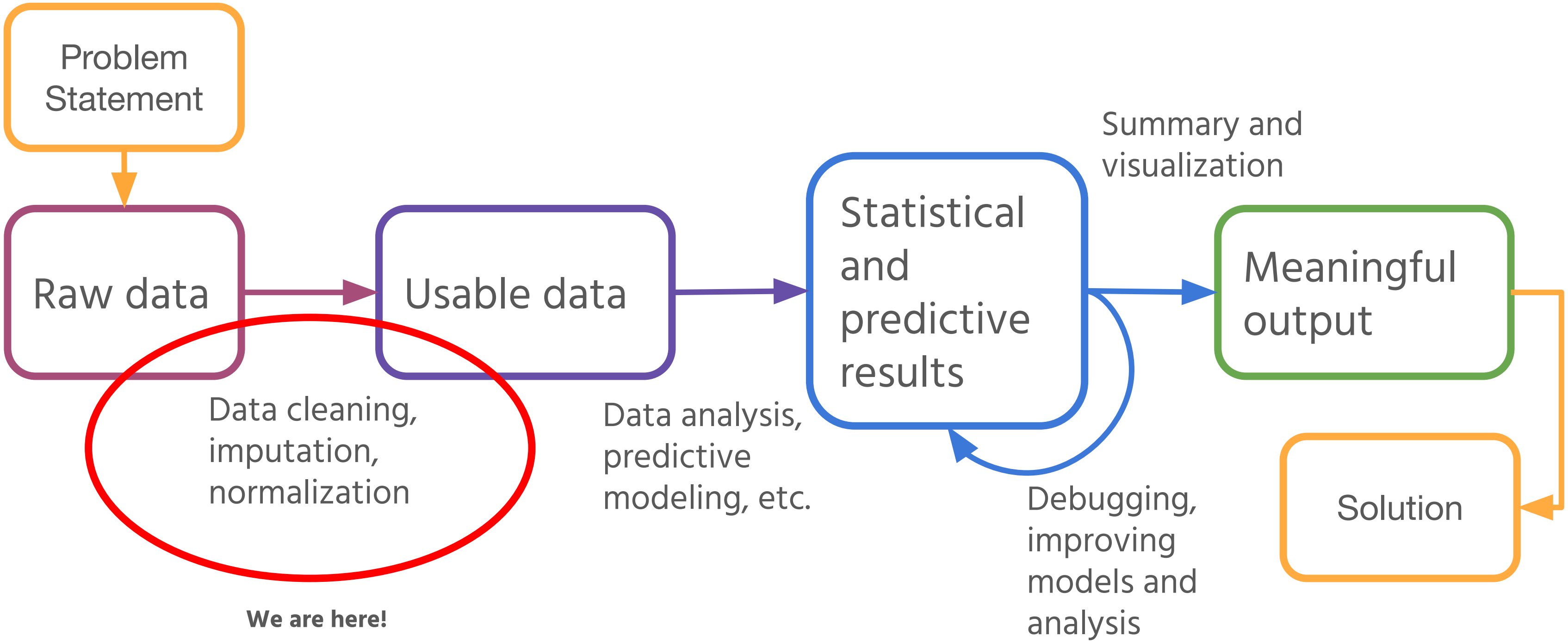
Good Examples:

- What work and lifestyle conditions greatly impact mental health, and in what way?
- Based on this data, what factors can be used to predict a candidate’s success within a Canadian election?
- What features best predict the amount of solar radiation the Earth gets based on data collected by NASA?

Poor Examples:

- What can the data tell me about mental health?
- Is there a relationship between the data and a candidate’s success in a Canadian election?
- Can we predict amount of solar radiation the earth gets?

The Data Pipeline



https://towardsdatascience.com/5-steps-of-a-data-science-project-lifecycle-26c50372b492

Acquiring data

- **Option 1:** Web scraping directly from web with tools like BeautifulSoup
- **Option 2:** Querying from databases
- **Option 3:** Downloading data directly (ex. from Kaggle/Inter-governmental organizations/Govt./Corporate websites)

…and more!

Finding a Relevant Dataset

Questions to Ask Yourself…

- Does the data measure what you care about?
- Is your data connected/related?
- Do you have a lot of data?

https://www.kaggle.com/datasets

How does input data usually look?

```
Timestamp,Class Year:,Major:,"On a scale 1 to 5 (1=unfamiliar, 5=proficient) , how well do you know Python?",How did you hear about this class?,"We will hold some
optional workshops to dive deeper into industry applications of advanced analytics, and any other topics that might be of interest to you (eg. Data Scraping).
What are some workshops you would like to attend? Anything goes.",What is a data problem that interests you the most?
2/9/20 0:26,2020,MBA,1,Referral by Friend,Tensorflow,A/B testing and setting up experiments
2/10/20 16:33,2023,Computer Science,1,In-class advertisement,"Website Analytics, Sentiment Analysis, Cleaning Data",How can we design efficient metrics to gauge
performance of any type of data?
2/11/20 8:26,2022,MechE,1,In-class advertisement,,I would like to know more about how computational methods are used in engineering or physics researches.
2/11/20 22:43,2023,ILR,1,Referral by Friend,,The ethics behind data sharing and privacy laws online
2/12/20 17:41,2023,Food Science,1,Referral by Friend,"artificial intelligence
human behavior
```

- Usually saved as .csv or .tsv files
- Known as **flat text files**, require parsers to load into code

	Timestamp	Class Year:	Major:	On a scale 1 to 5 (1=unfamiliar, 5=proficient) , how well do you know Python?	How did you hear about this class?	We will hold some optional workshops to dive deeper into industry applications of advanced analytics, and any other topics that might be of interest to you (eg. Data Scraping). What are some workshops you would like to attend? Anything goes.	What is a data problem that interests you the most?
0	2/9/20 0:26	2020	MBA	1	Referral by Friend	Tensorflow	A/B testing and setting up experiments
1	2/10/20 16:33	2023	Computer Science	1	In-class advertisement	Website Analytics, Sentiment Analysis, Cleanin...	How can we design efficient metrics to gauge p...
2	2/11/20 8:26	2022	MechE	1	In-class advertisement	NaN	I would like to know more about how computatio...
3	2/11/20 22:43	2023	ILR	1	Referral by Friend	NaN	The ethics behind data sharing and privacy law...
4	2/12/20 17:41	2023	Food Science	1	Referral by Friend	artificial intelligence \nhuman behavior\necon...	how to predict human behavior using internet d...
...	...	...	...	...	...	...	...

So…

Most datasets are **messy**.

Datasets can be **huge**.

Datasets **may not make sense**.

Question

What are some ways in which data can be “*messy*”?

Examples of Drunk Data

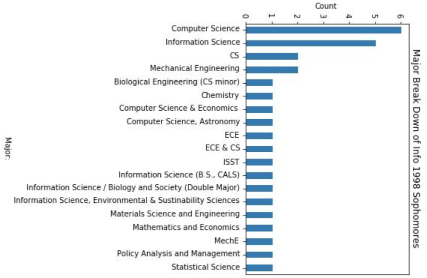
From the onboarding form!

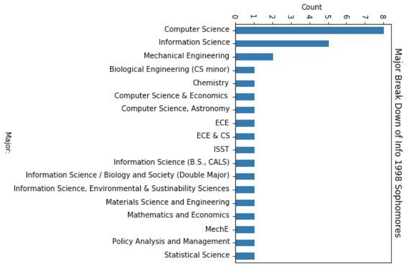
Example 1: Let's find CS majors in INFO 1998.

Different cases:

- Computer Science
- CS
- Cs
- computer science
- CS and Math
- OR/CS

…goes on





Example 2: From INFO 1998 (Fall '18)

Answers for 'What Year Are You?'

- 1999
- 1st Master
- Junor
- INFO SCI

…goes on

Why we manipulate data?

Ease of Use

Prevent calculation errors

Improve memory efficiency

DataFrames!

- **Pandas** (a Python library) offers **DataFrame** objects to help manage data in an orderly way
- Similar to Excel spreadsheets or SQL tables
- DataFrames provides functions for selecting and manipulating data

```
import pandas as pd
```

Data Manipulation Techniques

- Filtering & Subsetting
- Concatenating
- Joining
- *Bonus*: Summarizing

Filtering vs. Subsetting

- Filters **rows**
- Focusing on data entries

Name	Age	Major
Chris	21	Sociology
Tanmay	21	Information Science
Sam	18	ECE
Dylan	20	Computer Science

Filtering

- Subsets **columns**
- Focusing on characteristics

Name	Age	Major
Chris	21	Sociology
Tanmay	21	Information Science
Sam	18	ECE
Dylan	20	Computer Science

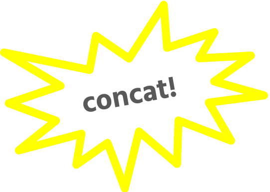
Subsetting

Concatenating

Joins together two data frames, either row-wise or column-wise

Name	Age	Major
Chris	21	Sociology
Jiunn	20	Statistics

Name	Age	Major
Lauren	19	Physics
Sam	17	ECE



Name	Age	Major
Chris	21	Sociology
Ethan	20	Statistics
Lauren	19	Physics
Sam	18	ECE

Joining

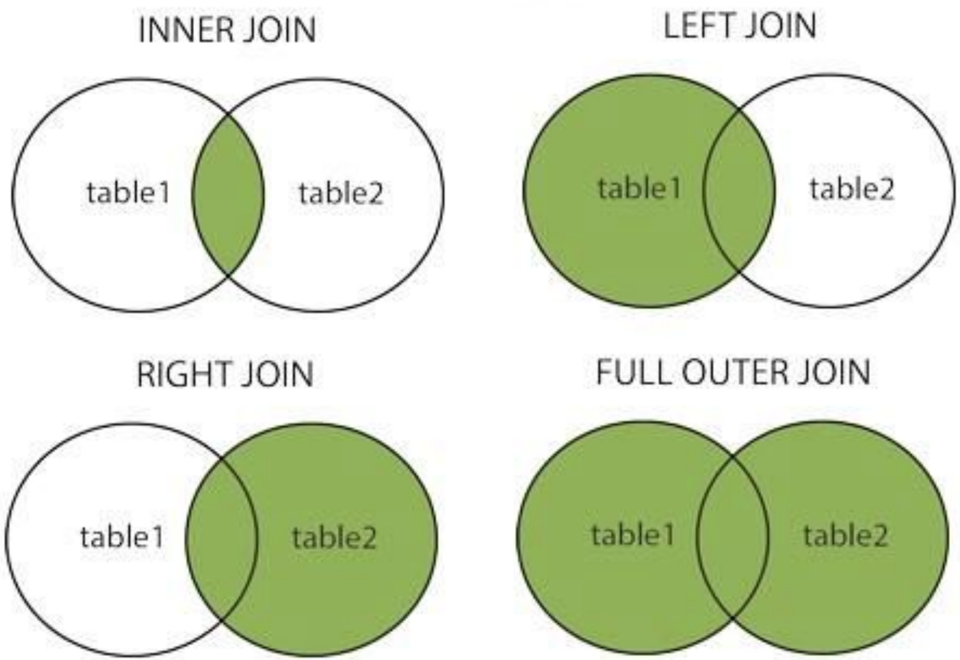
Joins together two data frames on any specified key (fills in NaN otherwise). The index is the key here.

	Name
0	Ann
1	Chris
2	Dylan
3	Camilo
4	Tanmay

	Age	Major
0	19	Computer Science
1	20	Sociology
2	19	Computer Science

	Name	Age	Major
0	Ann	19	Computer Science
1	Chris	20	Sociology
2	Dylan	19	Computer Science
3	Camilo	NaN	NaN
4	Tanmay	NaN	NaN

Types of Joins



Bonus: Summarizing

- Gives a quantitative overview of the dataset
- Useful for understanding and exploring the dataset!

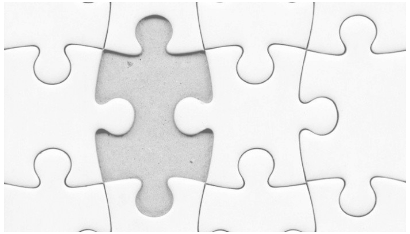
```
>>> s = pd.Series([1, 2, 3])
>>> s.describe()
count    3.0
mean     2.0
std      1.0
min      1.0
25%      1.5
50%      2.0
75%      2.5
max      3.0
dtype: float64
```

```
>>> s = pd.Series(['a', 'a', 'b', 'c'])
>>> s.describe()
count      4
unique     3
top        a
freq       2
dtype: object
```

Above: stats made easy

Dealing with missing data

Datasets are usually incomplete. We can solve this by:



Leaving out samples with missing data

Data imputation

Randomly Replacing NaNs

Using summary statistics

Using predictive models

1: Leaving out samples with missing values

- Option: Remove NaN values by removing specific samples or features
- **Beware** not to remove too many samples or features!
    - Information about the dataset is lost each time you do this
- Question: How much is too much?

2: Data Imputation

3 main techniques to impute data:

1. Randomly replacing NaNs
2. Using summary statistics
3. Using regression, clustering, and other advanced techniques

2.1: Randomly replacing NaNs

- **This is not good - don’t do it**
- Replacing NaNs with random values adds unwanted and unstructured noise

2.2: Using summary statistics (non-categorical data)

- Works well with small datasets
- Fast and simple
- Does not account for correlations & uncertainties
- Usually does **not** work on categorical features

```
>> an_array.mean(axis=1) # computes means for each row
```

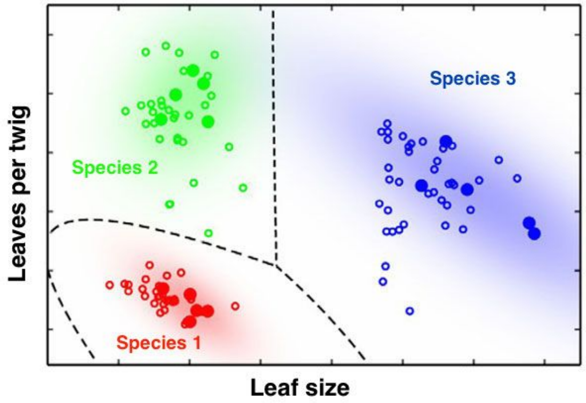
```
>> an_array.median() # default is axis=0
```

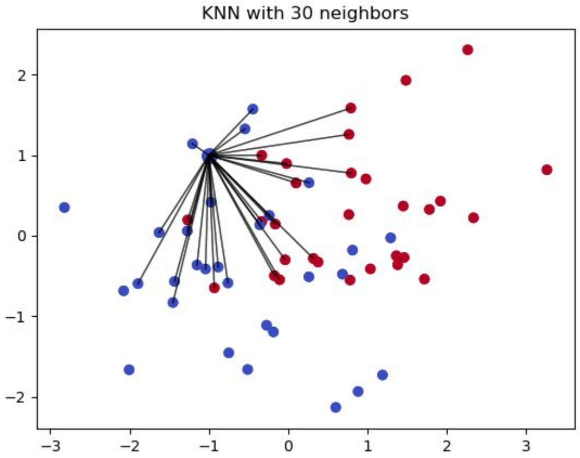
2.2: Using summary statistics (categorical data)

- Using mode works with categorical data (only theoretical)
- But it introduces **bias** in the dataset

2.3: Using Regression / Clustering

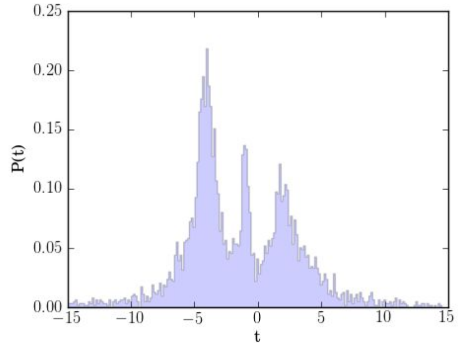
- Use other variables to predict the missing values
  - Through either regression or clustering model
- Doesn't include an error term, so it's not clear how confident the prediction is

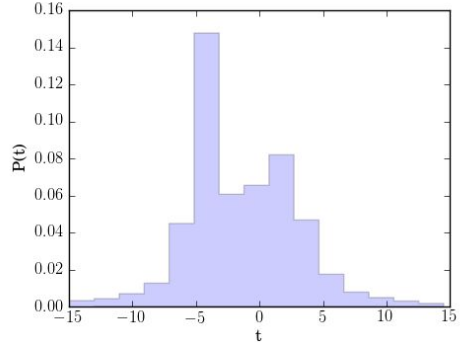




Technique 1: Binning

What?	Makes continuous data categorical by lumping ranges of data into discrete "levels"
Why?	Applicable to problems like (third-degree) price discrimination





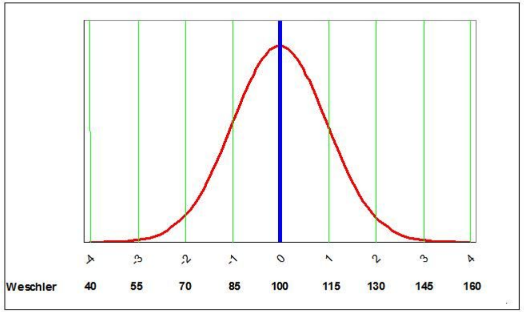
Technique 2: Normalizing

What?	Turns the data into values between 0 and 1
Why?	Easy comparison between different features that may have different scales

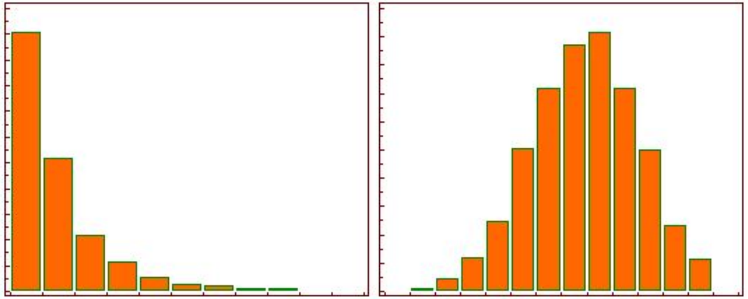
Technique 3: Standardizing

What?	Turns the data into a normal distribution with mean = 0 and SD = 1
Why?	Meet model assumptions of normal data; act as a benchmark since the majority of data is normal; wreck GPAs

Standardizing



Log transformation



Others include square root, cubic root, reciprocal, square, cube...

Technique 4: Ordering

What?	Why?	Example
Converts categorical data that is inherently ordered into a numerical scale	Numerical inputs often facilitate analysis	January → 1 February → 2 March → 3 …

Technique 5: Dummy Variables

What?

Creates a binary variable for each category in a categorical variable

plant	is a tree
aspen	1
poison ivy	0
grass	0
oak	1
corn	0

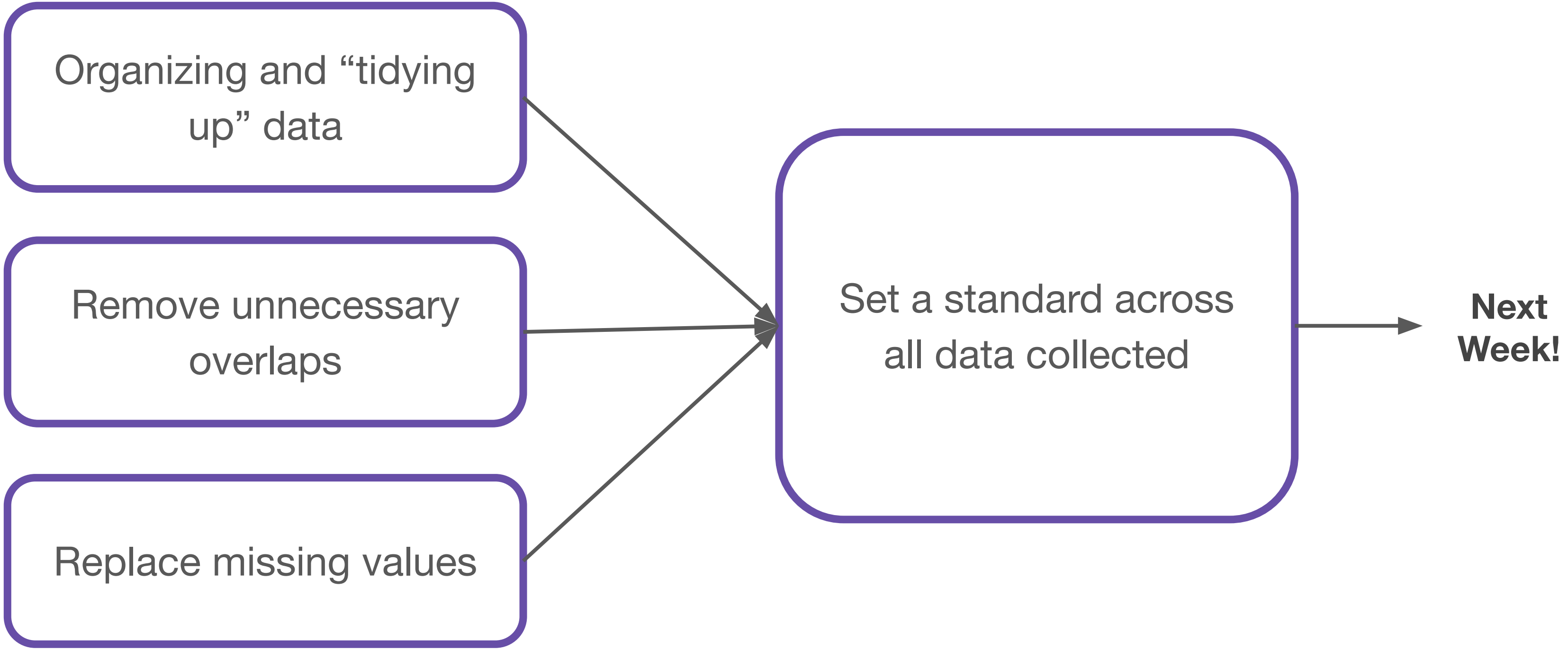
Technique 6: Feature Engineering

What?	Generates new features which may provide additional information to the user and to the model
Why?	You may add new columns of your own design using the assign function in pandas

ID	Num
0001	2
0002	4
0003	6

ID	Num	Half	SQ
0001	2	1	4
0002	4	2	16
0003	6	3	36

Summary


Organizing and "tidying up" data
Remove unnecessary overlaps
Replace missing values
Set a standard across all data collected
Next Week!

Demo

Coming Up

- **Assignment 2**: Due at 4:30pm on March 17, 2020
- **Next Lecture**: Data Visualization (no lecture next week due to wellness days)

CDS Education

We explore, learn, and educate big minds.