

Introduction

Defining Data Science

The application of data centric, computational, and inferential thinking to

understand solve the world problems
Science Engineering

> Data science is fundamentally interdisciplinary

# Reality of Data Science Today

- > Data is often not that big
- Substantial time spent in data cleaning and exploration
   Less time spent developing new models
- > Wide range of tools: SQL, R, Python, ...
- > Data science workflow is iterative (the lifecycle)
- > Discussed some ethical concerns of Data Science
- > Explored Food Safety data (not covered on exam)

Question Formulation

### Introduced QPR-V

- Question: construct a well formed question
   If I study will I do well on the exam → If I review X material will I get a grade that is above average.
- > Population: identify the population in the question Who or what are we studying ...
- > Representative: do the data reflect the population
  - Before collecting or analyzing the data Before collecting or analyzing in a Depends on the collection process
- > Validation:
  - verify conclusions through statistical inference and assess reproducibility

### Data Collection and Sampling

- > Census: the complete population
- > Survey: a sample of the population
- > Observational Studies: data collected without direct intervention
- Randomization: mechanism to control for external factors
   Simple random samples: drawing data from the population uniformly at random
  - Randomized Trial: randomly assign subjects to treatment and control groups

    ➤ gold standard in causal analysis

# **Data Wrangling**

Data wrangling is the process of cleaning and transforming data to enable subsequent analysis.





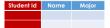
In Data Science, 80% of time spent prepare data, 20% of time spent complain about need for prepare data.

- > Structure: the "shape" of a data file
- > Granularity: how fine/coarse is each datum
- > Faithfulness: how well does the data capture "reality"
- > Temporality: how is the data situated in time
- > Scope: how (in)complete is the data

### Primary Keys and Functional Dependencies

- > A **primary key** is set of columns that uniquely identify each row. (e.g., student\_id)

  - > Can be composite: e.g. (City, State)
    > Each value occurrent Each value occurs at most once in the key column(s).
- > Functional Dependencies:









➤ Not just keys: (e.g., zipcode → State)

# Types of Data

- ➤ Quantitative (Numeric)
  - Continuous (e.g., health care expenditure)
  - Discrete (e.g., number of siblings)
- > Qualitative (Categorical)
  - Nominal (e.g., lane of traffic, country)
  - Ordinal (e.g., Yelp rating, education level)
- > Think about how you might visualize each kind of data

# Practice Types of Data

- > Age > Continuous
- Homework assignments in a class Discrete
- > Political party affiliation
- Nominal
- > Exam Grade Letter grade is ordinal
   Score is continuous
- ZIP-code (e.g., 94703)Nominal

Exploratory Data Analysis (EDA) and Visualization

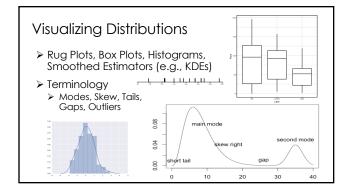
# **Exploratory Data Analysis**

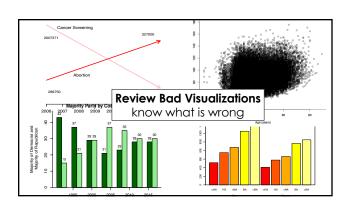


- ➤ Goals of EDA
  - > Validate the data collection and preparation
  - > Confirm understanding of the data
  - > Search for anomalies or where data is surprising
- ➤ Iterative Exploratory Process
  - > Analyze summary statistics and data distributions
  - > Transform and analyze relationships between variables
  - > Segment data across informative dimensions (granularity)
  - > Use <u>visualizations</u> to build a deeper understanding

### Several Case Studies in Class

- > Food safety in San Francisco
- Recall heavy use of aggregation and spatial visualization
- In class TaFeng shopping data analysis
   Data cleaning and outlier detection
- Data cleaning and outlier aetection
   You are required to be familiar with homework
- > Freeway traffic analysis
  - Visualizing distribution of flow for each lane
- Baby Names in Pandas
- Understanding popular baby names over time
- > You are not required to know these
  - reviewing may be helpful



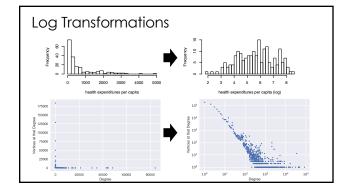


## Techniques of Visualization

- Scale: ranges of values and how they are presented
   Units, starting points, zoom, ...
- > Conditioning: breakdown visualization across a dimensions for comparison (e.g., income as function of education conditioned on gender)
- > Perception
  - Length: encode relative magnitude (best for comparison)
     Color: encode conditioning and additional dimensions and
- > Transformations: to linearize relationships highlight important trends(e.g., log-y & log-log plots)

  > Symmetrize distribution

  - Linearize relationships
- > Avoid stacking, chart junk, and over plotting



Numpy + Pandas

# Numpy

> Review basic slicing commands and Boolean indexing



- > Key functions: sum, mean, variance, arange
- > You will <u>not</u> be asked to <u>write complex python</u> programs on the exam.
  - You may need to <u>read</u> complex python expression...

### **Pandas**

- > Review column selection and Boolean slicing on rows
- > Be familiar with usage of basic commands: > sort\_values, head, read\_csv
- > Review *groupby* and merge syntax:
  - df.groupby (l'istate', 'gender')][('age', 'height')].mean()
     Know about mean(), sum(), count()
     df.A.merge(dfB, on='key', how='outer')
     be comfortable with inner and outer joins
- > Understand rough usage of basic plotting commands > plot, barh, histogram ...

Prediction and Inference

### Prediction and Inference

- ➤ Generalize beyond the data
  - make predictions: how much of this product will we sell?
  - infer properties of the population: what is the distribution of
- Relies on Models and Assumptions
  - Models: capture essential trends, laws, or patterns make predictions + reveal relationships
  - **Assumptions:** about the data and it's relationship to the quantities of interest
    - e.g., past reflects the future
- > Fundamental tool of science: test hypotheses

### Machine Learning

- > **Defn:** study of algorithms & programs that improve through experience
  - **Key enabling technology**: voice rec., spam detection, online advertising, fraud detection, content recommendation, self driving cars ...
  - Learning a function/program from Input(X) → Output(Y)

    > make predictions (ML & Stats)

    > make inferences about the population (Stats)

#### > Taxonomy of ML problems:

- Supervised Learning: given input (e.g., image) and output (e.g., Label)
  - Classification: output is nominal (e.g., spam/ham)
    Regression: output is continuous (e.g., price)
- Unsupervised Learning: given just the input (e.g., image)
  - > Clustering: output is nominal (e.g., day or night)
  - > Dimensionality Reduction: output is continuous (e.g., time of year)
- Reinforcement Learning: given input and rewards

  > Game Als and robotic controllers

## Practice Examples

- > Will it rain tomorrow? (Data: rainfall & season)
  - > Answer: Supervised, Classification
- > How much will it rain? (Data: rainfall & season)
  - Answer: Supervised, Regression
- > What are the kinds of micro-climates in SF? (Data: Rainfall)
  - > Answer: Unsupervised, Clustering
- > Plot the micro-climates in 2D according to their similarity?
  - > Answer: Dimensionality Reduction
- > Translate this sentence to Korean?
  - $\succ$  Answer: ... sequence of classification problems ... (not on exam)

Relational Algebra and SQL

### Relational Terminology

- > Database: Set of Relations
- > Relation: a table
  - **Schema:** the metadata including names, attribute names and types (and optional constraints)
  - Instance: tuples that satisfy the schema
- > Attribute: a column
- > Tuple: a row
- > Database Schema: the set of schemas of its relations.

Unary Operators: operate on single relation instance

- ightharpoonup Projection (  $\pi$  ): Retains only desired columns (vertical)
- $\succ$  Selection ( $\sigma$ ): Selects a subset of rows (horizontal)
- $\triangleright$  **Renaming (**  $\rho$  **):** Rename attributes and relations.

Binary Operators: operate on pairs of relation instances

- ➤ Union (∪): Tuples in r1 or in r2.
  - $\succ$  Intersection (  $\cap$  ): Tuples in r1 and in r2.
  - Set-difference ( ): Tuples in r1, but not in r2.
  - > Cross-product ( x ): Allows us to combine two relations.
  - ▶ Joins ( ⋈ , ⋈ ): Combine relations that satisfy predicates

Relational Algebra Operators Extensions: Not in the original relational algebra

 $\succ \gamma_{\text{age, AVG(rating)}}$  (Sailors): groupby operator

# Practice Question

Boats(bid,bname,color) Sailors(sid, sname, rating, age) Reserves(sid, bid, day)

For each boat color what is the average rating of sailors over 32 that reserved a boat of that color?

 $\gamma_{\text{color, AVG(rating)}}(\sigma_{\text{age}>32} \text{ (Sailors)} \bowtie_{\text{sid}} \text{Res} \bowtie_{\text{bid}} \text{Boats)}$ 

> Names of all pairs of sailors that reserved the same boat

 $\sigma_{\text{sname1}} = \text{sname}($ 

 $\pi_{\mathsf{sname1, sname}}$  (  $p_{\mathsf{T(name1,bid)}}$  (  $\pi_{\mathsf{sname,bid}}$  (  $\mathsf{Sailors} \bowtie_{\mathsf{sid}} \mathsf{Res}$  ))

⋈<sub>bid</sub> Res ⋈<sub>sid</sub> Sailors))

## SQL: Structured Query Language

- > Understand the basic structure of SQL queries:
  - > Be able to fill in the blanks
- ➤ Know base operators and agg.
   ➤ AND, OR, <>, IS NULL, AVG, COUNT, COUNT(DISTINCT...)
- > You should also know
  - > WITH r1(c1, c2) AS ( SELECT ...
- ➤ Look over HW4 ...

SELECT ...
FROM ...
[WHERE ...]
[GROUP BY ...]
[HAVING ...]
[ORDER BY ...]
[LIMIT ...];

### Practice Question

Boats(bid,bname,color) Sailors(sid, sname, rating, age) Reserves(sid, bid, day)

➤ For each boat color what is the average rating of sailors over 32 that reserved a boat of that color?

**SELECT** color, AVG(rating)

FROM Boats B, Reserves R, Sailors S
WHERE B.bid = R.bid AND R.sid = S.sid

AND S.age >32

**GROUP BY** color;

HAVING ORDER BY

### **Practice Question**

Boats(<u>bid</u>,bname,color) Sailors(<u>sid</u>, sname, rating, age) Reserves(<u>sid</u>, <u>bid</u>, <u>day</u>)

> Names of all pairs of sailors that reserved the same boat

SELECT DISTINCT \$1.name, \$2.name
FROM Sailors \$1, Reserves R1,
Sailors \$2, Reserves R2

WHERE S1.sid = R1.sid AND R2.sid = S2.sid

AND R1.bid = R2.bid AND S1.name < S2.name

# Extra Study Suggestions

- > You should be comfortable with filling in SQL expressions
- > What will not be covered on the midterm
  - Window functions
  - User defined functions and aggregates
  - > Table and View creation

Probability, Maximum Likelihood, and Priors Rules of Probability

 $\Omega$ : set of all possible outcomes from the chance process

A and B: collections of outcomes, AKA an event

- 1.  $P(\Omega) = 1$
- 2.  $0 \le P(A) \le 1$
- 3. If A and B disjoint, then P(A or B) = P(A) + P(B)
- ➤ If B is contained in A, then  $P(B) \le P(A)$
- $P(A^c) = 1 P(A)$
- $\triangleright$  P(A or B) = P(A) + P(B) P(A and B)
- $\triangleright$  P(A and B) = P(A) P(B) if A and B are independent
- $\triangleright$  Conditional Probability:  $P(A \mid B) = P(A \text{ and } B)/P(B)$  $\triangleright$  P(A and B and C) = P(A | B, C) P(B | C) P(C)

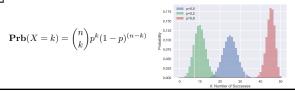
Distributions

>  $X \sim Bernoulli(p)$  distribution  $\rightarrow X \in \{0,1\}$ : > Example: flipping a coin (or a thumb tack)

$$\mathbf{Prb}(X = k) = p^{k} (1 - p)^{(1-k)} = \begin{cases} p & \text{if } k = 1\\ 1 - p & \text{if } k = 0 \end{cases}$$

>  $X \sim Binomial(n,p)$  distribution  $\rightarrow X \subseteq \{0,1,...,n\}$ :

Number of times the coin lands heads in n flips



Distributions Continued

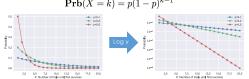
>  $X \sim DiscreteUniform(a,b)$  distribution  $\rightarrow X \in \{a, a+1, ..., b\}$ :

> Roll a fair dice

$$\mathbf{Prb}(X=k) = \frac{1}{b-a+1}$$

X ~ Geometric() distribution → X ∈ {1,2,3,...}:
 Number of times to flip a coin until it first lands heads

$$\mathbf{Prb}(X=k) = p(1-p)^{k-1}$$



### Distributions Continued

> You will not be required to know

Continuous distributions (e.g., Beta, Normal, Uniform)
 We will use them later and they may be final ®

Hypergeometric

Posterior estimation and conjugacy

# Summarizing Distributions

> Expectation

$$\mathbb{E}\left[X\right] = \sum_{x \in \Omega} x \, \mathbf{P}(x) \qquad \boxed{ \begin{split} \mathbb{E}\left[aX + b\right] = a\mathbb{E}\left[X\right] + b \\ \mathbb{E}\left[X + Y\right] = \mathbb{E}\left[X\right] + \mathbb{E}\left[Y\right] \end{split}}$$

> Variance

$$\begin{aligned} \mathbf{Var}\left[X\right] &= \sum_{x \in \Omega} \left(x - \mathbb{E}\left[X\right]\right)^2 \ \mathbf{P}(x) \\ &= \mathbb{E}\left[X^2\right] - \mathbb{E}\left[X\right]^2 \quad \begin{vmatrix} \mathbf{Var}\left[aX + b\right] = a^2\mathbf{Var}\left[X\right] \\ \mathbf{Var}\left[x + Y\right] &= \mathbf{Var}\left[X\right] + \mathbf{Var}\left[Y\right] \\ & \text{if independent} \end{vmatrix} \end{aligned}$$

### Method of Maximum Likelihood

➤ How do we estimate the parameters of a model? Maximize the likelihood of the data under the model

$$\hat{ heta}_{ ext{MLE}} = rg \max_{ heta} \mathbf{P}\left(\mathcal{D} \,|\, heta
ight)$$

Likelihood often written  $\mathcal{L}( heta)$ 

 $\triangleright$  How do we determine P(D |  $\theta$ )?

Often assume Independent and Identically Distributed Data (IID)

$$\hat{\theta}_{\text{MLE}} = \arg\max_{\theta} \prod^{n} \mathbf{P}(X = x_i \mid \theta)$$

 $\blacktriangleright$  Where D is the list of obs.  $(x_1, ..., x_n)$   $\stackrel{i=1}{}$  Likelihood for each record

 $\triangleright$  How do we determine P(D |  $\theta$ )?

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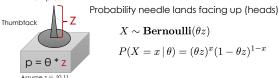
ightharpoonup Need to define the likelihood for each record (modeling!):

Probability needle lands facing up (heads)

 $X \sim \mathbf{Bernoulli}(\theta z)$ 

$$P(X = x \mid \theta) = (\theta z)^{x} (1 - \theta z)^{1-x}$$

> Need to define the likelihood for each record (modeling!):



 $X \sim \mathbf{Bernoulli}(\theta z)$ 

$$P(X = x \mid \theta) = (\theta z)^{x} (1 - \theta z)^{1-x}$$

Assume 
$$z = [0,1]$$

$$\hat{\theta}_{MLE} = \arg\max_{\theta} \prod_{i=1}^{n} \mathbf{P}(X = x_i \mid \theta) = \arg\max_{\theta} \prod_{i=1}^{n} (\theta z)^{x_i} (1 - \theta z)^{1 - x_i}$$

Toke the log [why?] 
$$= \arg\max_{\theta} \sum_{i=1}^{n} x_i \log(\theta z) + (1-x_i) \log(1-\theta z)$$

 $\hat{\theta}_{MLE} = \arg\max_{\theta} \prod_{i=1}^{n} \mathbf{P}(X = x_i \,|\, \theta) = \arg\max_{\theta} \prod_{i=1}^{n} (\theta z)^{x_i} (1 - \theta z)^{1 - x_i}$  Take the log (why?)

 $= \arg\max_{\theta} \sum_{i=1}^{n} x_{i} \log(\theta z) + (1 - x_{i}) \log(1 - \theta z)$ 

> Maximize by computing the derivative

$$\frac{\partial}{\partial \theta} \log \mathcal{L}(\theta) = \frac{\partial}{\partial \theta} \sum_{i=1}^{n} x_i \log(\theta z) + (1 - x_i) \log(1 - \theta z)$$
$$= \sum_{i=1}^{n} x_i \frac{\partial}{\partial \theta} \log(\theta z) + (1 - x_i) \frac{\partial}{\partial \theta} \log(1 - \theta z)$$

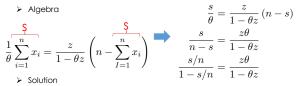
$$\begin{split} \frac{\partial}{\partial \theta} \log \mathcal{L}(\theta) &= \frac{\partial}{\partial \theta} \sum_{i=1}^n x_i \log(\theta z) + (1-x_i) \log(1-\theta z) \\ &= \sum_{i=1}^n x_i \frac{\partial}{\partial \theta} \log(\theta z) + (1-x_i) \frac{\partial}{\partial \theta} \log(1-\theta z) \\ &= \sum_{i=1}^n x_i \frac{z}{\theta z} + (1-x_i) \frac{-z}{1-\theta z} \quad \begin{bmatrix} \text{From calculus ("chain rule"):} \\ \frac{\partial}{\partial \theta} \log f(\theta) &= \frac{1}{f(\theta)} \frac{\partial}{\partial \theta} f(\theta) \end{bmatrix} \end{split}$$

 $\triangleright$  Set equal to zero and solve for  $\theta$ :

$$\sum_{i=1}^{n} x_i \frac{z}{\theta z} + (1 - x_i) \frac{-z}{1 - \theta z} = 0$$

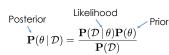
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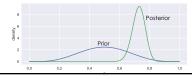
$$\hat{ heta}_{\mathrm{MLE}} = rac{1}{nz} \sum_{z} x$$
 How does this relate to the Bernoulli?

Bayes Rule and Priors



Used to estimate a distribution over possible parameters:

- > **Likelihood** determines likelihood of the data under the model
- Prior encodes our prior knowledge about the model
- > Posterior is our updated distribution over parameters



# Exam Review Review

- ➤ Extra Study suggestions
   ➤ Review lectures and section discussions
   ➤ Look over practice questions

  - > Go over this review lecture once more
- > Exam Details (see Piazza post for details)

  - ~80 Minutes
    ~1 page (front and back) answer sheet
    Allowed one page (front and back) cheat sheet
- ➤ Good Luck!