Reasoning with Data Notes

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Contents

Course Summary

- see `lecture1written.pdf`

Exploratory Data Analysis

EDA for 1-variable categorical data

- population: complete set on interest (eg all US workers). can't be measured perfectly
- sample: subset of pop that can actually be obtained
- parameter: summary of population (eg average weight). also can't be measured
- statistic: estimation of parameter using sample.
- inference: specifying estimate of a parameter (ie gving estimate and measure of how far off it is)
- individuals/units/cases: objects described in dataset
- variable: column of spreadsheet, something measured
- quantitative: numerical (eg age)
- categorical/qualitative: not numerical (eg ethnicity)
- frequency table: show how often each *categorical* variable shows up
  - relative freq. table: how percent often they show up, adding up to 1 or 100%: best summary of a categorical variable
- frequency/percent/relative (add to 1) frequency bar graphs: to visualize categorical data. v. similar to their freq table variants.
- pie graph: to visualize a *single* categorical variable, with each slice being a category.

EDA for 1-variable quantitative data

- grouped frequency/grouped relative frequency table: for one quantitative var. boring version of a histogram.
- histogram: for one quantitative variable. visualizes a grouped (rel.) freq table.
- distribution of one quantitative var (anal. doesn't really hold up for qualitative)
  - modality: how many 'clusters'? (eg unimodal/bimodal/etc)
  - symmetric/skewness? (skew right means tail is to right)
  - center: mean ($\overline{x}$)
    * median if heavy outliers. using mode is cursed but you do you
  - spread: standard deviation (S) (usually, $\frac{2}{3}$ of values are 1 stddev away from mean)
    * interquartile range (IQR) if heavy outliers.
  - outliers?
- fun facts: variance: square of std dev. easier in formulas because it removes the square root, but in real world, std dev is preferred because it has same units as the data
- box plot: other way to graph quantiative data (using min, first quartile, median, third quartile, max)
  - interquartile range (IQR): difference between quartiles, a measure of spread. is rough, not as useful as stddev.
  - shows less data than histogram, so best for concise comparison of *multiple* distributions (see section on 2-variable EDA)

EDA for 2-variable data

- relationship/association: one variable can tell you about another
- explanatory variable: "input" variable, the x-axis
- response variable: "output" variable, the y-axis
- if we need analysis from explanatory $\rightarrow$ response
  - categorical $\rightarrow$ quantiative: side by side boxplots
    - more difference if boxes are futher apart on "y-axis"
    - summaries: numerical summaries of response for each category
  - categorical $\rightarrow$ categorical: contingency table
    - summaries: conditional percents of responses, conditioned on explanatory (ie what percent of people from Cali are stat majors?)
  - quantitative $\rightarrow$ quantiative: scatterplots
    - describe: direction, form, outliers
    - summaries (only if reasonably linear): correlation coefficient (R), least squares regression line ($\hat{y} = b_0 + b_1 X$)
  - quantiative $\rightarrow$ categorical: outside scope of this course

Study Design

- no matter what, we want to consider and get…
    - reliability, statistical significance: low random variation/error
        - use a large sample size
        - can be measured with stddev
    - validity: trustworthy estimates and predictions
        - consider and declare outliers. remove them if needed, but with caution!
        - beware extrapolation outside range of data that produced the model
        - validate model (eg check for linearity if you use linear regression)
    - generalizability: no bias aka systemic error
        - called instrument bias if instrument is set wrong (can be social instrument such as misleading survey)
            - remove via resetting instrument (reset scale, rewrite survey)
        - called sampling bias if sample is systematically not representative
            - remove via random sampling. such as simple random sampling (SRS): every individual has same chance to be chosen as any other; every pair same chance as other pair; etc
- and if we have 2 or more variable relationships…
    - causality: no lurking/confounding variables; if we want to find causation and not just correlation
        - use randomized assignment of explanatory variable
        - experimental study: study where lurking/confounding variables are removed
        - observational study: not experimental. subjects decided which treatments to get (eg survey vitamin c usage vs flu symptoms)
        - placebo control group: 'non-active' treatment to avoid placebo effect
        - 'double blind': neither the researchers nor the subjects know which treatment they are receiving

good luck on exam 1 <3

Elementary Probability

- probablility: measure of variation due to a random phenomenon
- random: produced so that probability applies. satisfies:
  - equal likelihood (A's selection is as likely as B's)
  - independence (A's selection doesn't influence B's)
- coin: P(heads)= 0.5
- relative frequency: if selections are random (eq likelihood and independent),

$$\text{P(outcome)} = \frac{\text{\# of ways outcome occurs}}{\text{\# of possible outcomes}}$$

  - long-run approx. can be as precise as desired: Law of Large Numbers
  - not replacing violates independence
    * consider a bag with a blue and red ball. selecting blue and not putting it back makes P(red) = 1.
    * but this is common—a pollster doesn't survey two houses twice
  - not replacing is fine if population $\geq$ 10 or 20 times the sample
    * consider 2000 blue, 2000 red. selecting blue makes P(red) $\approx$ 0.5
- probablility experiment: an outcome's success/failure varies
  - eg flipping a coin: outcome (like get heads) varies
  - trials: different "runs" of a probability experiment
- disjoint/mutually exclusive: $A \cap B$ is empty
- elementary outcomes: irreducible for assigning probabilities. mutually disjoint.
- sample space: S, the set of all elementary outcomes in a probability experiment
- complement: A^C, "opposite" of a probability. $A + A^C = 1$.
- intersection: $\cap$, "and" of two probabilities. middle of venn diagram.
- union: $\cup$, "or" of two probabilities. all circles' overlap area.
  - $\text{P}(A \cup B) = \text{P}(A) + \text{P}(B) - \text{P}(A \cap B)$
- joint probability tables
  - each inner box is an elementary outcome (and a joint probability like $A \cap B$)
  - rows sum to row marginal probabilities, same with columns
  - 2x2 tables can represent venn diagrams

- conditional probability (A, if we know that B):
  - $\mathrm{P}(A \text{ given } B) = \mathrm{P}(A \mid B) = \mathrm{P}(A \cap B) \div \mathrm{P}(B)$
  - for a d20, $\mathrm{P}(4 \mid \text{even}) = 0.1$
  - take from box and margin of a joint probability table
- statistically independent: unassociated events. if you know the outcome of one event, it doesn't change the probability of the other.
  - with variables: association b/t A and B is nearly what is expected from chance
  - with sampling: any person similarly likely to be selected, regardless of previous selection
  - A and B are independent
    - iff $\mathrm{P}(A \mid B) = \mathrm{P}(A)$
    - iff $\mathrm{P}(A \mid B) = \mathrm{P}(A \mid B^C)$
    - iff $\mathrm{P}(A \cap B) = \mathrm{P}(A) \cdot \mathrm{P}(B)$

Probability Models of Data

- random variable: outcome of randomness that takes on numerical values
- discrete rv: takes on "separated" outcomes. modeled with table or rel-freq histogram
- continuous rv: takes on an interval of outcomes. modeled with density curve
- rv example: cars occupancy
  1. define prob. experiment: randomly select car on road
  2. define rv: let X = number of people in car
  3. assign probabilites to X. denote prob. of $X = 1$ as $\mathrm{P}(X = 1)$
- Binomial Counts "Experiment"/Study/Trial
  - conditions:
    - (a) fixed sample size n for every run of study
    - (b) two categories (success/failure) for each observation
    - (c) observations must succeed or fail independantly
    - (d) fixed prob p of success for each observation
  - conditions c and d are guaranteed if selections are random
  - the count of successes in n trials is a discrete rv X, and follows the Binomial Distribution (ie, X is binomial. see by graphing the histogram)
  - $\mathrm{P}(X = x) = {}_nC_x \cdot p^x \cdot (1-p)^{n-x}$
  - binomial coefficient ${}_nC_k = C_k^n = \binom{n}{k} = \frac{n!}{x!(n-x)!}$ (recall $0! = 1$)
  - eg: 8 rand selected lab animals get vaccine w/ prevention rate of 40% and then are infected. Then X = surviving animals out of $n = 8$ with $p = 0.4$.

- distributions (density curves)
  - graph a histogram, imagine a idealized curve fitting it
    * idealized curve means true populations, so variables are greek letters
    * mean = μ (mu)
    * stddev = σ (sigma)
  - area = proportion of observations = relative freq = probability
  - total area = 1
  - exponential distribution
    * let X be the time until the next event, with events occuring randomly with a mean waiting time λ.
    * denoted $X \sim \mathrm{Exp}(\lambda)$
    * fun fact: this is graphed $f(x) = \lambda e^{-\lambda x}$
    * eg: time until next earthquake, time until a phone call ends
  - uniform distribution
    * a process produces values $\in [a, b]$ with equal likelihood.
    * denoted $X \sim \mathrm{Uniform}(a, b)$
    * fun fact: this is graphed $f(x) = \frac{1}{b-a}$ for $x \in [a, b]$, $f(x) = 0$ elsewhere
    * eg: result of dice roll
  - normal/gaussian distribution
    * models result of mixing many independant factors and Central Lim Thrm
    * denoted $X \sim \mathrm{N}(\mu = u, \sigma = s)$
    * fun fact: these are variations on the graph $f(x) = e^{-x^2}$
    * eg: human height
    * points of inflection are 1 stddev away from mean
    * 68/95/99.7 percent of population falls within 1/2/3 stddev of mean
  - standard normal distribution
    * for discussing probability on normal distributions: on all normal curves, portions with the same Z score have the same area.
    * standardized/Z score: stddevs from mean for a number
      · $Z = \frac{\text{observation}-\mu}{\sigma}$
    * $\mathrm{N}(\mu = 0, \sigma = 1)$ is already standardized. we may denote $Z \sim \mathrm{N}(0, 1)$
    * eg: consider adult male weight X.
      · we know $X \sim \mathrm{N}(\mu = 165, \sigma = 30)$
      · if P weighs 202 pounds, how unusual are they?
      · $Z = \frac{202-165}{30} = 1.23$ and $\mathrm{P}(X < 202) = \mathrm{P}(Z < 1.23) = 0.8907$.
    * Z score tables and such exist for these calculations
    * be able to calculate: Z score to prob, prob to Z score, stdizing to find prob, unstdizing to find score (see Lecture 14 notes)

Sampling Distribution of a Statistic

- population distribution: eg how long it takes for literally every lightbulb to burn out
- (sample) data distribution: eg how long it takes for this random sample of $n = 1000$ lightbulbs to burn out
- sampling distribution of a statistic: the probability distribution of all possible values of a statistic (from taking many samples of same sample size from same population)
- sampling distribution of $\overline{X}$, the mean
  - center: if sampling is random, then mean of sample is the population mean. ie,
    $$\mu_{\overline{x}} = \mu \text{ if sampling is random}$$
  - spread: if sampling is random and outcomes are statistically independant (eg sampling with replacement or infinitely large pop), then
    $$\sigma_{\overline{x}} = \frac{\sigma}{\sqrt{n}}$$
  - shape: if sample is large ($n \geq 30$), then by the Central Limit Theorem, the sampling distribution of $\overline{X}$ approaches the normal distribution. (resembles population otherwise)
  - lightbulb example problem in Lecture 16. Note AFSOC for inference.
- sampling distribution of $\hat{P}$, proportion
  - consider a binomial study (in particular, random and independant) with sample size n and success probability p. then,
  - center:
    $$\mu_{\hat{p}} = p$$
  - spread:
    $$\sigma_{\hat{p}} = \sqrt{\frac{p(1-p)}{n}}$$
  - shape: if np and $n(1-p)$ both ≥ 10, then by the Central Limit Theorem, $\hat{P}$ approaches the normal distribution. (resembles population otherwise?? maybe?)
  - coinflip example problem in Lecture 18.

good luck on exam 2 <3

Formal Inference (Confidence Intervals, Hypo. Testing)

- we study two branches of formal inference:
  - confidence intervals: what are most likely values of a parameter?
  - hypothesis/significance testing: what is the likelihood of a parameter to be a value?
- Confidence Intervals
  - Theory: $\overline{x}$ is "probably" somewhat "close" to μ.
    * how probable? confidence level
    * how close? margin of error
  - if random sampling, stat. independant, normal, then the confidence interval is

$$\overline{X} \pm Z_{\text{critical}} \frac{\sigma}{\sqrt{n}}$$

    * where n = sample size, $\overline{X}$ = sample mean, σ = assumed population stdddev, $Z_{\text{c}} = 1.645$ for $C = 90\%$, $Z_{\text{c}} = 2$ for $C = 95\%$, $Z_{\text{c}} = 3$ for $C = 99.7\%$, etc
    * eg: $\approx 95\%$ of $\overline{x}$'s are within $\pm 2\sigma_{\overline{x}}$
  - similarly, if binomial (in particular, random sampling and independent) and normal, the confidence interval is

$$\hat{p} \pm Z_{\text{critical}} \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

- Hypothesis Testing
  1. State Hypotheses
     - null (H_0): μ = value
     - alt (H_a): $\mu <, >$, or $\neq$ value
  2. choose α (usually 0.01 or 0.05)
  3. perform study, get sample statistic, get p value of that sample statistic
  4. conclusion: if $p < \alpha$, this is very unlikely. we reject the null hypothesis
  5. state in context: what does parameter represent? what is the likely value/why?
- Note: '$\neq$' confidence test with significance α is equiv to making a confidence interval with level $1 - \alpha$ ie α^C
  - ie: Hypothesis test says do not reject $H_0 \Leftrightarrow H_0$ value is inside confidence interval