Module 5
Evaluating and presenting results

DAV-6300-1: Experimental Optimization

David Sweet // 20240926

Review: LLN, CLT, A/B Testing

- As $N \to \infty$
  - LLN: $\mu \to E[y]$, estimate approaches “true” BM
  - CLT: $\mu \sim \mathcal{N}(E[y], VAR[y]/N)$, normal, narrows w/N
- **Design**: $N \geq \left(\frac{2.5\hat{\sigma}_\delta}{PS}\right)^2$
- **Measure**: Randomize, $\delta = \mu_B - \mu_A$, $se = \sigma_\delta/\sqrt{N}$
- **Analyze**: If $\delta > PS$ and $\frac{\delta}{se} \geq 1.64$, then accept B.

Review: False Positive Traps

- **Don't stop early**, even if t-stat looks good
- **Beware multiple comparisons** in A/B/C/… tests
  - Use Bonferroni correction: p = 0.05 / (K-1)
  - Then accept if: $\mu > PS$ and $t = \dfrac{\delta}{se} \geq 1.64$

Where have we used the iid assumption so far in this class?

Standard Errors

- Poorly-estimated se will ruin an experiment
- Usually se gets underestimated:
  - Thus, $t = \dfrac{\delta}{se} \geq 1.64$, t is overestimated
- Generates false positives

Standard Errors

- iid - independent, identically distributed
- Ex, $\sigma^2 = \dfrac{\sum_i^N (y_i - \bar{y})^2}{N}$ assumes
    - $cov(y_i, y_j) = 0$ <== independent
    - $E[y_i] = E[y_j]$, $var[y_i] = var[y_j]$, ... <== identically distributed

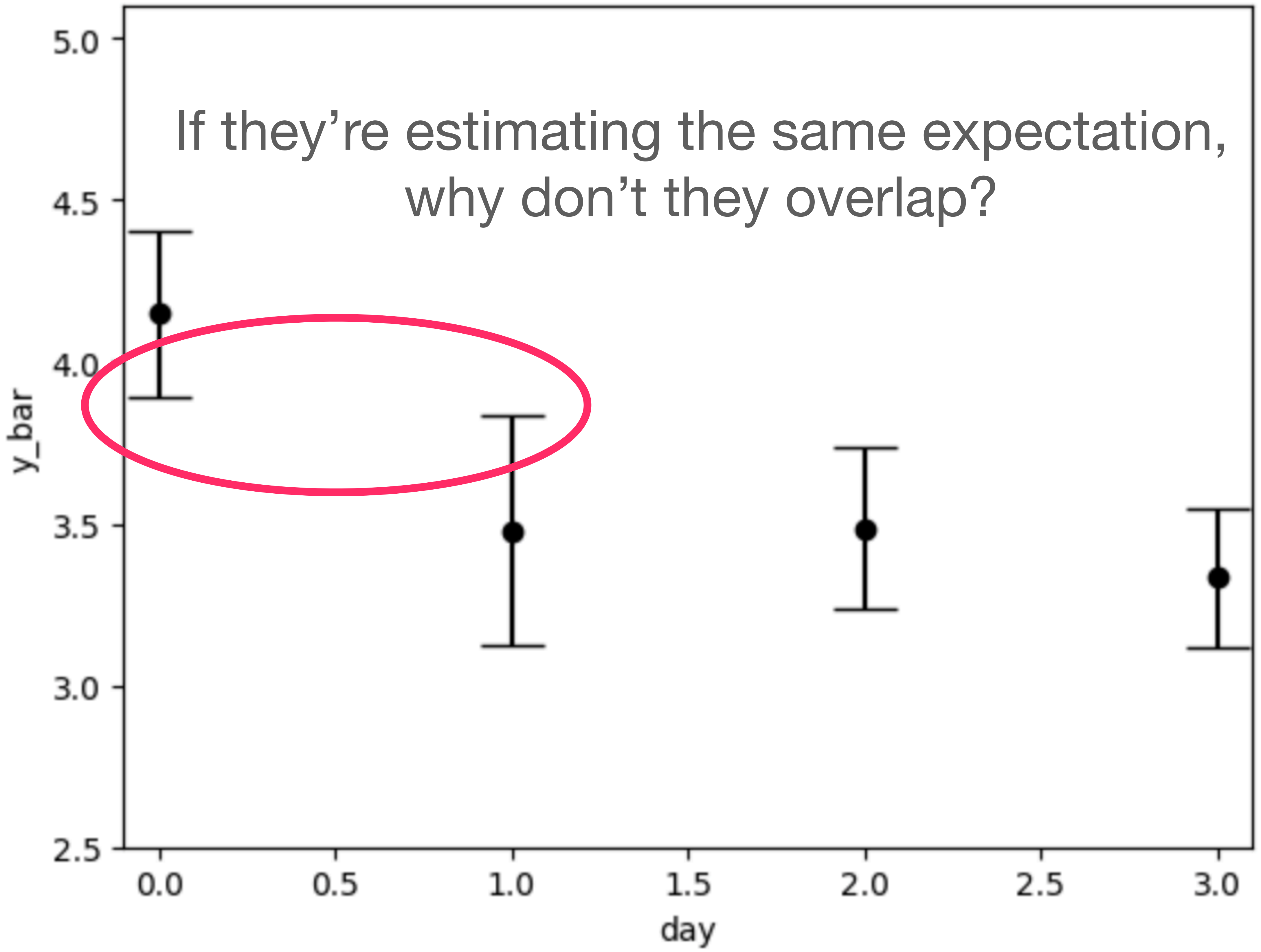
Standard Errors: iid violations

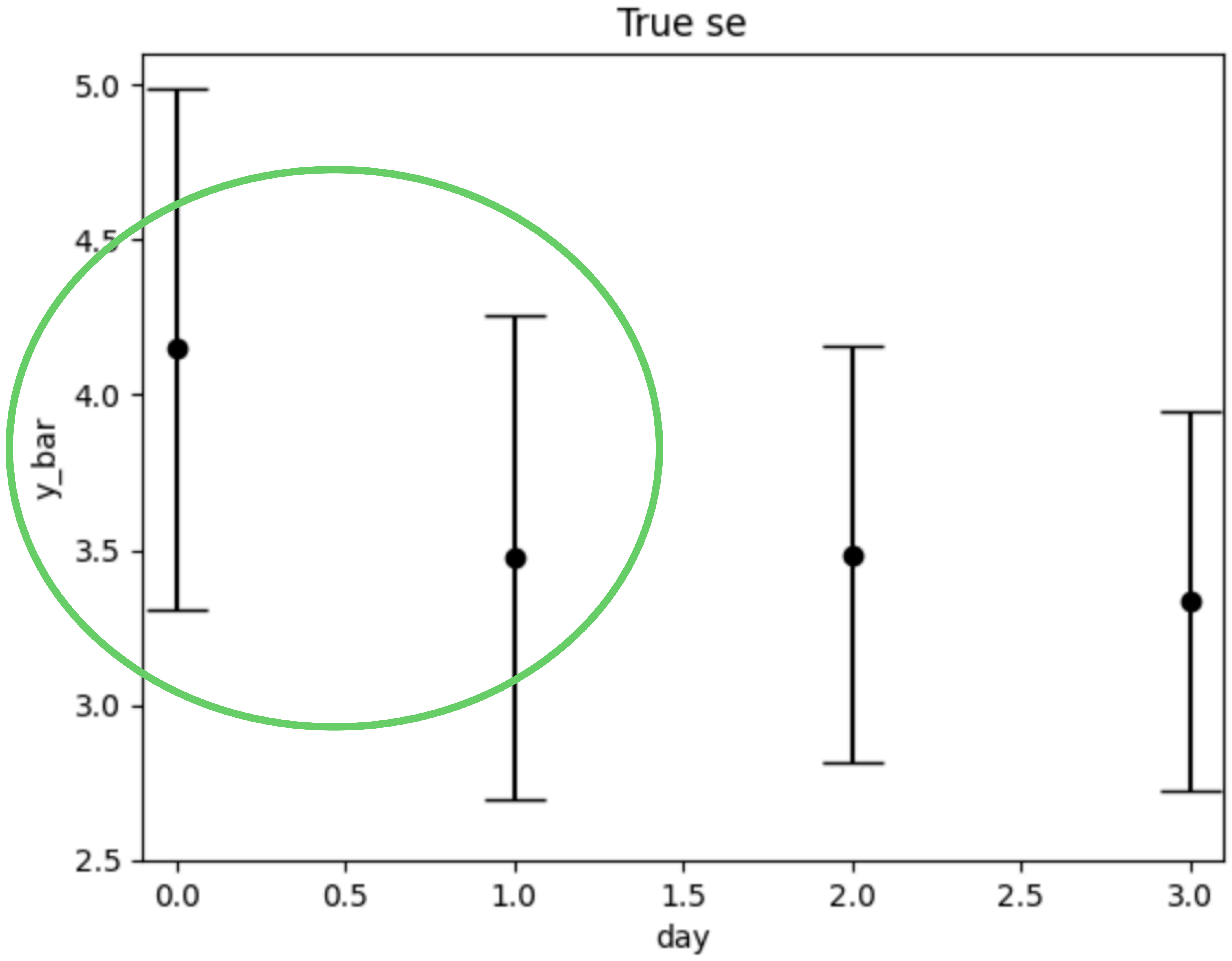
- $cov(y_i, y_j) = 0$ violations:
  - timeseries autocorrelation
  - correlated behavior across users
  - correlated behavior across stocks
- Common problem, big problem

Timeseries data are often autocorrelated.
What could give rise to this? Gives examples.

Standard Errors: iid violations

- $cov(y_i, y_j) = 0$ violation





Standard Errors: iid violations

- $E[y_i] = E[y_j]$ violation
- Expectation can vary with
  - Yser, stock, time of day, day of week, genre of song, industry of stock, age of user, length of tweet, … (confounders)
  - Transient effects (nonstationarity)
  - Passage of time (nonstationarity)
- When running an experiment we try to isolate the effect of A/B on y_i

Standard Errors: iid violations

- $var[y_i] = var[y_j]$ violation
- Called heteroscedasticity
- Variance can vary with
  - User, stock, time of day, day of week, genre of song, industry of stock, age of user, length of tweet, …
  - Any feature that might predict y_i might also predict $var[y_i]$

What is a holdout test and what is it used for?

Validation of Results

- Replication: Measure again
- No other tricks
- Replication crisis: Independent re-experiments don’t reproduce original
  https://en.wikipedia.org/wiki/Replication_crisis
- Avoid crisis

Validation of Results

- Industry replication techniques
- Reverse A/B: Switch to B, but run small portion as A for a while
- Holdout
  - Start of quarter: Fix a set of users, NE, no experimentation
  - During quarter: Monitor difference between NE and rest of users
    - Is the difference growing as expected?
  - End of quart: Run A/B test comparing NE to “all changes from this quarter”

Recap

- Underestimating se increases false positives
  - Look for non-overlapping error bars, autocorrelation
- Replication is the only check on results
  - Reverse A/B
  - Holdout

Evaluating results

Present to stakeholders

- Stakeholders
  - You
  - Your team
  - Other affected teams (ex., dependencies, tradeoffs)
- Usually evaluating multiple metrics (ex., revenue, clicks, time spent)
- Stakeholders may value metrics differently

Evaluating results

Approval

- Create an approval process to follow for each experiment, ex:
  - Present to stakeholders
  - Discuss
  - Final decision: manager, designated committee, vote (?)
  - Document decision (people disagree, forget)
- Standardized process helps remove experimenter bias, reduce conflict

A/B test presentation

Ad serving system

- You work on an ad-serving team for a website
- Your pages all show a single ad, the one with the highest predicted probability of getting a click
- You earn revenue when users click on ads
- You just completed an A/B test …

A/B test review #28364

- A: Currently displaying the one, best ad on each page
- B: Try displaying the two best ads on each page
- BM: Increase clicks/page
    - How? P{click on either of two} > P{click on just one}
- Guardrails: sessions/day, pages/session, time/session

session = one site visit,
potentially multiple pages

A/B test review #28364

- Design:
  - $\hat{\sigma}_\delta = 0.12$ (estimated from logs)
  - PS = 0.003 clicks/page (from data science group report, 2021Q4)
  - $N > (\frac{2.5 \times \hat{\sigma}_\delta}{PS})^2 \sim 10{,}000$
- Need at least N = 10,000 pages

A/B test review #28364

- Measurement:
  - Allocated 1% of users to A and 1% to B; randomly-chosen users
  - Ran for 5 days
  - Collected measurements from 10,452 sessions with A and 10,896 sessions with B
  - (!) Entire system was down for 1.5 hours on the second day

A/B test review #28364

- Analysis:
  - A clicks/page = .017
  - B clicks/page = .021
  - $\delta = .004 \pm .0017$ clicks/page
  - $t = 2.35$

- Both criteria for switching to B are met
  - $\delta >$ PS $= 0.003$
  - $t > 1.64$

A/B test review #28364

- Guardrails: no change

	A	B
• sessions/day/user	0.403 +/- .03	0.39 +/- .03
• pages/session	2.2 +/- .015	2.4 +/- .013
• time/session	24.1s +/- 5.7s	22.1s +/- 5.9s

A/B test review #28364

- Summary:
  - Clicks/page increases by 0.004 when we show two ads/page
  - This number is both statistically and practically significant
  - No guardrail metrics are worsened
- **Recommendation: Show two ads/page**

Presenting results

- Describe the system
  - ex., ad server, fraud detector, recommender system
- Describe the business metric
  - ex., revenue, fraud accuracy, user engagement
- What part of the system is being modified? ex., the ML predictor
- How was it modified? ex., a new feature was added
- How/why do you think your “version B” will improve the BM?

Presenting results

- How did you take an individual measurement?
  - One presentation of an ad, and Was it clicked?
  - One day's revenue
  - Time spent on your app by a single user in a single session
  - One presentation of a post, and Was it liked?
  - One play of a song, and Was it skipped?

Presenting results

- The value of N, the number of individual measurements you took
- How long should did it take to collect all N (ex., 1 week, 1 month)?
- How did you monitor the business metric(s)? (ex., a URL to a dashboard)
- What is PS? What was your rationale for choosing this value?
- How was σ_δ estimated?
- Display $\hat{\sigma}_\delta$, PS, N

Presenting results

- How did you perform randomization?
  - Did you assign users (randomly) beforehand to “A” or “B”?
  - Did you randomly choose A or B on every event?
  - Did you randomly choose A or B at time intervals?
- Discuss possible confounders

Presenting results

- Were there any system problems during measurement?
  - System problems might introduce sampling or confounder bias
  - Ex: “West-cost system outage”, sampling bias
  - Ex: B code failed on Monday, but was fixed; confounder bias if measurements from A on Monday are included

Presenting results

- Were there any broad-scale, unusual events during measurement?
  - COVID-19 discovered, markets go nuts
  - Election day, Twitter very active with election-specific tweets
  - Taylor Swift releases new album on Spotify, activity is high and focused
  - Blackout on East Coast, activity is low for those users
- Measurement may not be a good predictor of “most of the time”
- May introduce sampling bias (in blackout case)

Presenting results

A/B test analysis

- Clearly define the business metric, BM, being used to evaluate this experiment
  - Ex: “pnl” not enough; “pnl measured daily at 4pm, net of exchange fees, marked to prices from Bloomberg” is better
  - Describe the in-house technology used to measure the business metric; “the Python function pnl_3a() in pnl_metrics.py”
- Display δ, t and conditions required to accept B

Presenting results

- Discuss other relevant business metrics even if not the one used to evaluate
- Would switching to B reduce other metrics, even if it increases BM?
  - Often the case
  - Ex: Users retweet more, but post less
  - Ex: Profit increases, but so does risk
- Stakeholders may value metrics differently
  - Ex: Ad team wants more ads shown, but song-recommender team wants more songs played

Summary

- Create an experimentation process to reduce bias and conflict
- Include all stakeholders in decision-making
- Presenting results:
  - Describe BM, guardrails, design (N), measurement (randomization)
  - Report unusual events / problems
  - Report analysis: δ, t, guardrails
  - Interpret and recommend an action