Big Data Experiments as Data Pipelines

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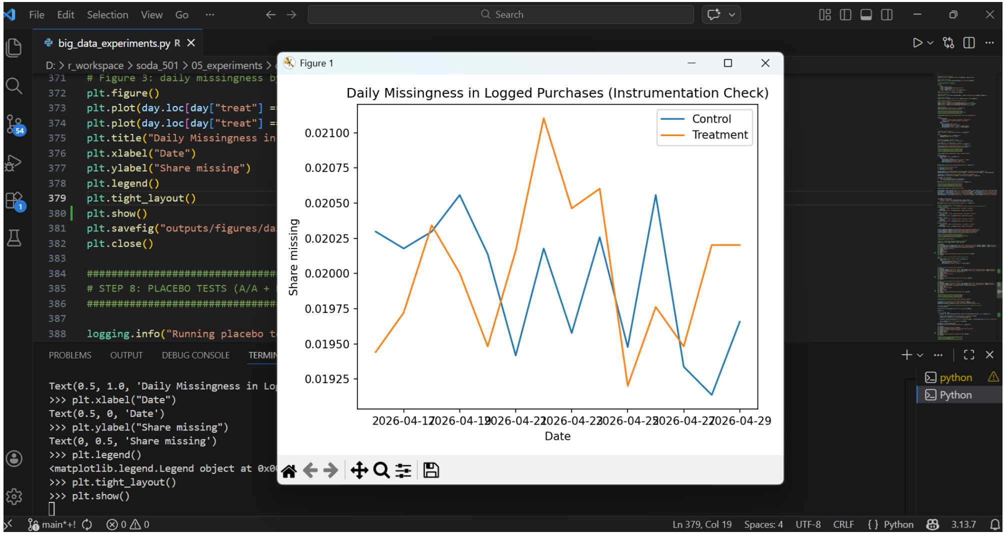
18 february 2026

Start Off: Verifying Your Environment

1. **Environment check (required).** Submit proof that you successfully ran the full tutorial code on your machine. You may submit *one* of the following:
   - A screenshot or text file showing console output that includes the printed representation shapes (document–term matrix, Word2Vec document vectors, and transformer embeddings).



```
# Figure 3: daily missingness b
plt.figure()
plt.plot(day.loc[day["treat"] =
plt.plot(day.loc[day["treat"] =
plt.title("Daily Missingness in
plt.xlabel("Date")
plt.ylabel("Share missing")
plt.legend()
plt.tight_layout()
plt.show()
plt.savefig("outputs/figures/da
plt.close()

##################################
# STEP 8: PLACEBO TESTS (A/A +
##################################

logging.info("Running placebo t
```

```
Text(0.5, 1.0, 'Daily Missingness in Lo
>>> plt.xlabel("Date")
Text(0.5, 0, 'Date')
>>> plt.ylabel("Share missing")
Text(0, 0.5, 'Share missing')
>>> plt.legend()
<matplotlib.legend.Legend object at 0x0
>>> plt.tight_layout()
>>> plt.show()
```

   - A screenshot of your `figures/` directory showing generated plots with timestamps.
   - A Git commit (hash or screenshot) that includes at least one generated figure or output file.
   - A short log file (e.g., `run_log.txt`) containing printed diagnostics and evaluation metrics.

Conceptual Questions

Please write three to ten sentence explanations for each of the following questions. **You are only required to answer ONE of the two questions below.**

2. **Estimands at scale (ITT vs "product impact").** In a platform A/B test, the treatment may (i) fail to deliver to some users, (ii) deliver but users may not engage, and (iii) outcomes may be measured through fragile logs.
   - Define the ITT estimand in this setting.
   - Give one reason ITT is the default for decision-making in production experiments.

- Explain one case where ITT is not the estimand a research audience wants, and what additional assumptions you would need to target an alternative estimand.

  Answer: ITT in a platform A/B test is the average effect of being assigned to the treatment condition on some outcome measured through logs, comparing all assigned-treatment users to all assigned-control users, regardless of whether the treatment actually delivered or the user engaged with it. ITT is the default for production decisions because it reflects the real-world rollout scenario - when someone ships a feature to everyone, some users will always fail to receive it or ignore it, so ITT tells the actual business impact of flipping the switch. A research audience often wants the effect among users who actually received and engaged with the treatment, because they care about the mechanism - does the feature work when used - not just the average diluted effect across everyone including people who never saw it. To target that alternative estimand (LATE/TOT), we would need to use treatment assignment as an instrumental variable for actual engagement, which requires assuming that assignment only affects the outcome through engagement and not through any other path. We would also need to assume monotonicity - meaning every user either always complies with their assignment or never does, so nobody would paradoxically refuse the treatment when assigned to it but seek it out on their own when assigned to control - and this is still an assumption we must defend, not something randomization gives us for free.

3. **Measurement as part of the design.** Large experiments rely on instrumentation and event logs (missing events, changing definitions, bots).
   - Give two concrete examples of how logging changes can create "fake treatment effects".
   - Explain why randomization does not protect you from measurement drift.
   - Propose one monitoring strategy that would detect instrumentation problems early (what would you plot or test?).

Applied Exercises

Use the code in the week's code tutorial and the lecture slides to answer the following questions. **You are only required to answer TWO of the three questions below.**

Response: This week's work is here: `https://github.com/yasinshafi/soda501/tree/main/05_experiments/problem_set`

4. **Add a retention-style outcome and estimate its ATE.** Extend the pipeline so that, in addition to the existing outcomes, you compute a user-level retention / activity measure.
   - From the user-day logs, create `days_active` = the number of days with `active == 1` for each user (ignore missing days).
   - Create `retained_any` = 1 if `days_active` ≥ 1, else 0.
   - Add both outcomes to the analysis-ready dataset and estimate the ATE using:
     (a) difference in means, and
     (b) regression adjustment with `factor(block)` and cluster-robust SEs clustered at `cluster_id`.
   - Save your results as `outputs/tables/ate_retention.csv`.
5. **Simulate noncompliance and compare ITT vs TOT (IV).** Modify the experiment so that treatment assignment does not always translate into treatment receipt.

- Create a variable `received` such that:
  - all controls have `received = 0`,
  - treated units have `received = 1` with probability $p < 1$ (choose and report your p),
  - (optional) let p depend on `platform` or `baseline_activity`.
- Redefine the outcome generation so that the treatment effect operates through `received` rather than `treat`.
- Compute:
  (a) ITT: regress the outcome on `treat` (your original approach),
  (b) TOT / LATE using IV: treat `treat` as an instrument for `received`.
- Report the ITT and TOT estimates side-by-side and explain (2–5 sentences) why TOT is typically larger in magnitude than ITT in your simulation.
- Save your results as `outputs/tables/itt_vs_tot.csv`.

6. **Multiple outcomes + multiple testing (BH/FDR).** In big experiments, it is easy to "find significance" by testing many outcomes.
   - Create 10 outcome variables at the user level:
     - 1 outcome with a real treatment effect (use one of your existing outcomes),
     - 9 placebo outcomes with **no** treatment effect (simulate them so they depend on baseline covariates but not `treat`).
   - For each outcome k, estimate the treatment effect with robust SEs and extract a p-value.
   - Apply Benjamini–Hochberg (BH) correction to control the false discovery rate.
   - Create a table with columns: outcome name, $\hat{\tau}$, p-value, BH-adjusted p-value, and an indicator for whether it is significant at $q = 0.05$.
   - Save your results as `outputs/tables/multiple_testing.csv`.

Challenge Question (Optional — if you finish early)

Choose **ONE** option.

(a) **Randomization inference.** Implement a randomization-inference (permutation) p-value for the treatment effect on `converted`.
   - Keep the outcomes fixed.
   - Permute `treat` within blocks (or explain why you permuted globally).
   - Compute the null distribution of the difference-in-means estimator and report a two-sided p-value.
   - Plot the null distribution and mark the observed estimate.

(b) **Interference / spillover simulation.** Simulate spillovers within `cluster_id` so that control users' outcomes depend on the fraction of treated users in their cluster.
   - Define an exposure variable, e.g., `exposure` = share treated in cluster.
   - Modify outcome generation so that outcomes depend on both `treat` and `exposure`.
   - Show (briefly) how naive user-level analysis can mis-estimate the direct effect when interference exists.