

Agile Data Science

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Same as Engineering?

- Both involve technical work, writing code, and interacting with businesspeople!
- Effort usually not foreseeable
- Achievable results usually not foreseeable
- Most work is exploration which is discarded



“Data science”?

- Warehousing
 - Business Intelligence & Reporting
 - Offline Modelling
 - Algorithm Development
 - Research
-
- This presentation will motivate guidelines by following our hapless data protagonist through numerous bad decisions.



Examples for Presentation

- We work at a company which sells lots of distinct products to consumers or small business.
 - Self-service purchase
 - Search functionality prominent on site
 - Email signup
 - Repeat customers
- We thought up two possible projects:
 - Spelling Correction on Searches
 - Personalized Recommendations



Can we ask for priorities?

- Let's go ask somebody in the business which project to do.
- They might need some information in order to decide...
 - “How long will it take?” “Sorry, don't know.”
 - “What benefits will it produce?” “Uh....”
- They say: Do whatever will best maximize sales.
- Lesson: **Data science projects are fungible.**



Failure by Success

- I built a state of the art spelling correction system...
- It supports English, French, Italian, German, and Spanish...
- It includes heuristics for keyboard distance...
- It outperformed the other spelling correction systems in an online competition...
- It took four months to build and integrate...
- It turns out that 0.3% of our searches involve misspellings and the revenue is negligible...
- Lesson: **Know your best case results and benefits.**



Estimating Spelling Correction Benefits

- Do we *have* a log of what the user typed?
- How do we tell when it's a mistake?
- How many searches have spelling mistakes?
- What's the downstream consequence of a misspelling on sales?
- How many of the mistakes can we correct?
- Result: estimate that spelling correction will make \$\$\$\$ /week in new sales.



Implementing Spellcorrect

- OK, I verified my benefits, so NOW I can take months and build my super-duper spelling correction system, right?
- Oops! It turns out that 95% of the people who made spelling mistakes fixed them and did a new search themselves anyway.
- or... Oops! It turns out that 90% of our spelling corrections were on mobile and mobile traffic converts much less than the average we used.
- Lesson: **You never fully understand the dynamics.**



Implementing Intelligently

- What's the easiest implementation we can possibly do which will get a measurable fraction of the result?
 - Time to do some stats on what's measurable...
 - Lookup table for most common mistakes?
 - Single character correction in our search engine?
- Deploy the minimum viable feature and measure it!



Prioritization

- OK, my test worked, so NOW I can finally build my nice system, right?
- Wrong! Can you get 80% of the benefit in 20% of the time with the lookup table or another simple solution?
- We haven't even started looking at recommendations, after all!
- Lesson: You have more good ideas than time.



Quick Test for Recs

- How can we evaluate the benefits and test as quickly as possible?
 - Unlike spelling, there's no clear post-hoc assessment.
- Deploy a quick test?
 - For popular searches, where there's plenty of data, show what people ultimately bought
 - Engineering release cycle - could be weeks
- How about those email subscribers?



More Recommender Tests

- Verified on email, so now do the engineering.
- Good results on the first test, so now we want to expand who sees recommendations... go through the engineering cycle all over again?
- Instead of one fixed implementation, deploy a system for reading recommendation from a file or DB which can be updated with a faster process.
- Lesson: **Design for fast iteration**



A/B Tests

- We got great results when we rolled out our recommender, but it turns out we also introduced a new product line the same week, so how do we attribute the gains? Both teams claim credit...
- Longitudinal tests are difficult and ambiguous to interpret.
- We need to show the recommender to some people and not to others, who are otherwise identical, to get clean results.
- Lesson: **Need A/B tests, AKA randomized trials.**



Team Structure

- Who's going to do the engineering to make the A/B tests or a recommender?
 - Can you do it yourselves? May you do it yourselves?
- Do you have engineers allocated?
 - Now you're the product owners
- None of the above?
- Lesson: **Know where your engineering is**



Implementation Quality

- We wrote this to throw away, but it turns out it worked. Now what?
- Write it again, better
 - Design it for fast iteration
- Reliability and robustness? Think 9s
 - How often does it fail?
 - What does that failure cost?
 - How does reducing that failure cost compare against the next best project?



Managing the Backlog

- Recurring areas: do we work on recommendations or spelling?
- Now it's time to record your estimates and compare against the actual result to calibrate.
- A likely productivity curve:
 - Increases at beginning with increasing domain knowledge and tooling
 - Decreases again after best and easiest ideas have been implemented
- Analogies: A^* , multi-armed bandit



Opening New Areas

- Would be convenient to start on new areas when returns diminish on existing projects
 - Context switching has costs
- Collecting new data has a long lead time
 - Need to start collecting well in advance
- Adding new features will have business and product interactions
- Manage a pool of exploitable domains
 - Kanban-style



Other Business Goals

- **Special projects**
 - “We’re now also selling things for partners. Figure out where to show them to maximize profit while keeping our partners happy.”
- **Strategic goal changes**
 - “This quarter, we care about time on site and number of page views in addition to profit.”



Software Testing & Maintenance

- **Data validation**
 - Do we have the right amount?
 - Are certain cases for which we KNOW we should have data covered?
 - Does the data pass some sanity tests (smoke tests)?
- **Holdbacks**
 - Keep 1% to 10% of users/arrivals/etc permanently out of the feature.
 - When rolled out, it produced X% profit lift. Does it still produce that compared to the baseline?



Summary of Lessons (1)

- The team should get the desired result(s) from the business, and then choose the most effective path.
- Estimate your best case outcome at each stage, using what you have measured and learned.
- Proceed incrementally, doing the minimum possible work to observe the next set of unknowns.



Summary of Lessons (2)

- After each step, be willing to say “good enough” or “not worth it” and prioritize a different project.
- Build for fast iteration.
- Demand an A/B test (controlled trial) framework.
- Engineering work is critical.



Questions? rotten fruit?

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If you're reading an archive of this presentation,
I'm happy answer questions by email.

