LEARNING IN CYCLES

IMPLEMENTING SUSTAINABLE MACHINE LEARNING MODELS IN PRODUCTION

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City of Boston
Mayor Martin J. Walsh

Innovation & Technology

GETTING STARTED

MY BACKGROUND

Chief Data Officer for the City of Boston, leading our Analytics Team and steering the city's overall plans for using data.

Other resume highlights:

- *PhD in poli-sci from NYU*
- *Post-doc at Vanderbilt*
- *Data science consultant*
- *Director of Data Science at the Democratic National Committee (2014 - 2016)*

WHICH MEANS

I've made lots of models.

I've also made LOTS of mistakes.

Fortunately, at least some of what I've learned along the way should be useful to others.

WHAT'S IN THIS TALK

This talk's about ***sustainable machine learning models*** - iterative models that use outputs of one iteration to generate data for future runs.

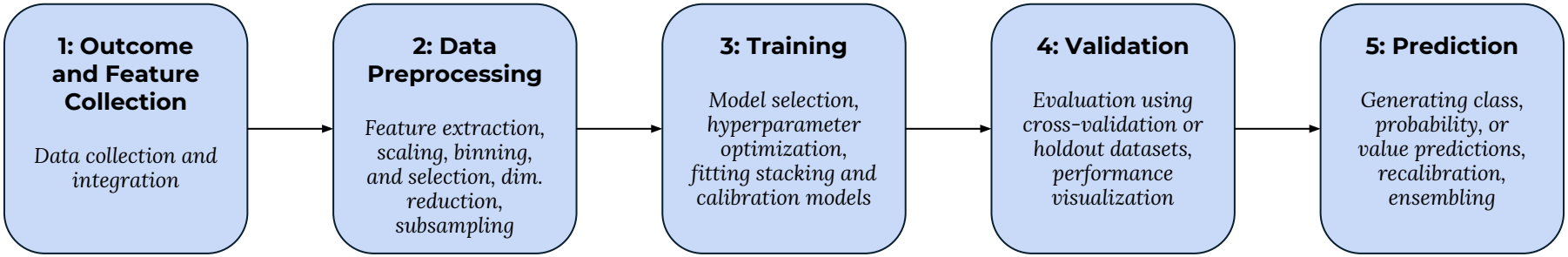
Example use cases:

- *Direct marketing*
- *Recommendation engines*
- *Ad customization*
- *QA and compliance audits*

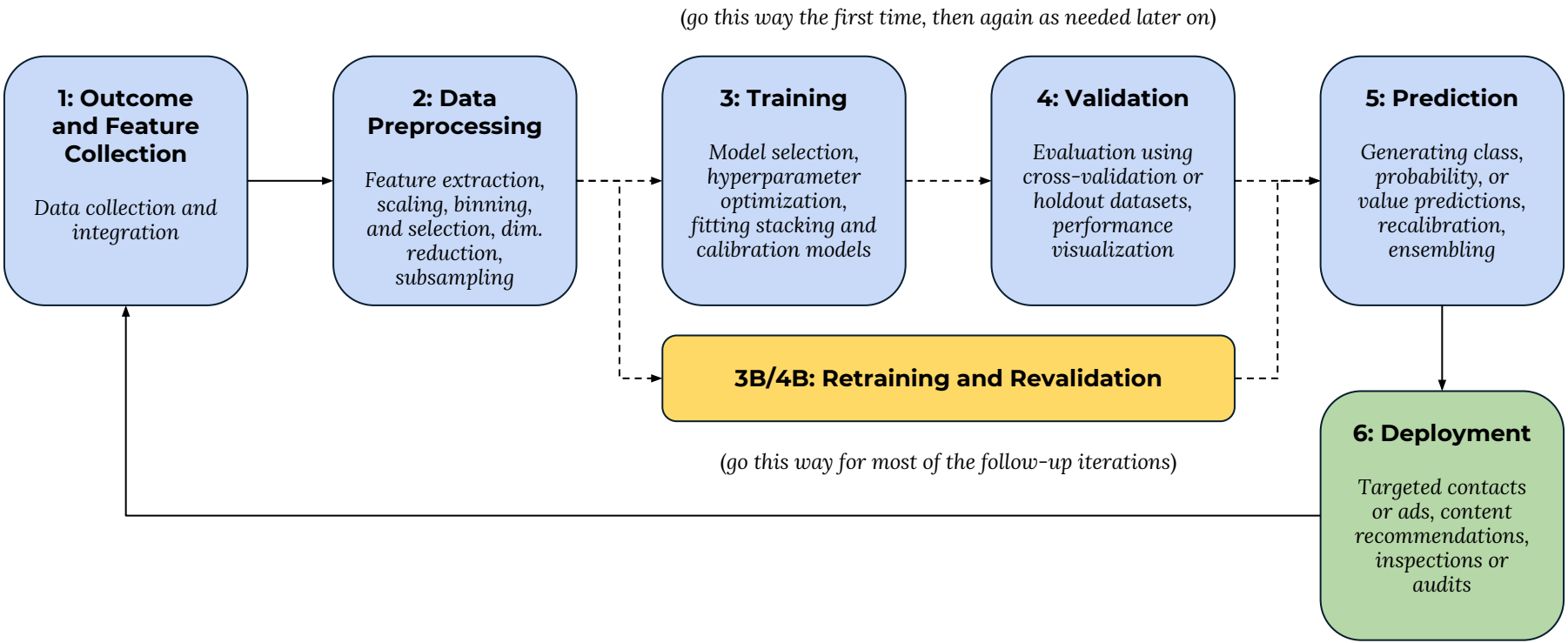
We'll focus on practical approaches and considerations for data scientists, analysts, and engineers working on these kinds of models in the wild.

WHAT'S DIFFERENT ABOUT SUSTAINABLE MACHINE LEARNING MODELS?

A TRADITIONAL MACHINE LEARNING MODEL DESIGN



A SUSTAINABLE MACHINE LEARNING MODEL DESIGN



SO WHAT'S THE BIG DEAL?

PICKING OPTIMIZATION METRICS

A single-run model can have a clear technical goal, but a sustainable model has a systemic goal that's harder to translate to a simple metric

EXPLORATION OR EXPLOITATION?

There are benefits to targeting sub-optimally in a given iteration, both to learn more and to preserve future value, but the cost is lower performance now

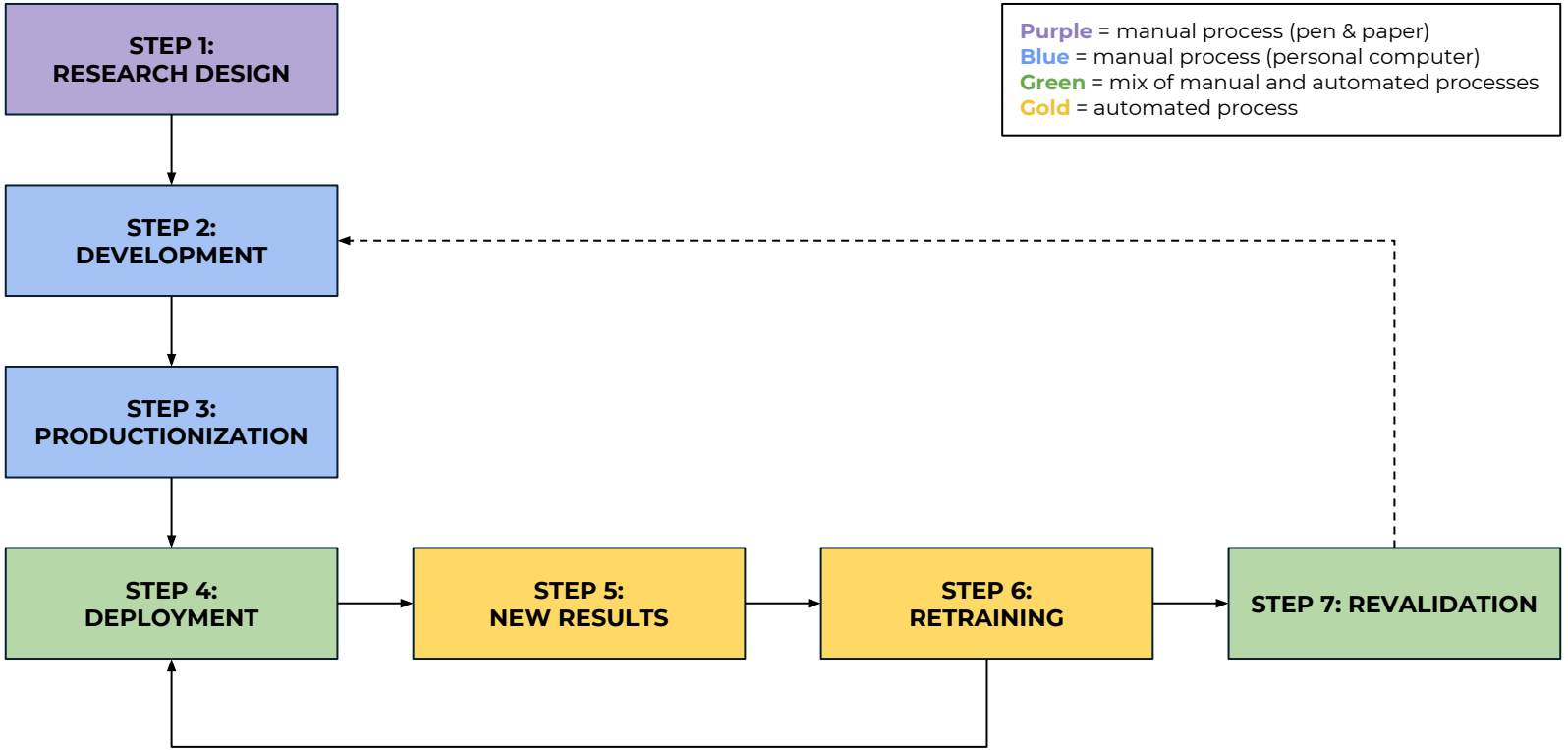
OFTEN NO FORMAL SOLUTION

It's tempting to try to come up with a mathematical solution for the repeated optimization problem, but that's not feasible for most complex models

WE'RE MAKING SOFTWARE NOW

Running a model repeatedly is an obvious case for automation, so we need to think about things like version control, scheduling, monitoring, alerts, etc.

MY RECOMMENDED APPROACH TO SUSTAINABLE ML MODELING



THE IMPORTANCE OF DIVERSE DATA

WHY DOES DIVERSE DATA MATTER FOR SUSTAINABILITY?

THE TRADEOFF

The key benefit of a sustainable ML model: using organic data for model updates, **new info is gathered at little or no cost**.

The downside of this approach: unlike data from a distinct research process (surveys, experimental tests, etc.), **this information will be biased.**

What makes a model "sustainable": when the data collected is sufficiently diverse, **biases can often be overcome.**

DATA COVERAGE

The most obvious problem with organic data is that it will only cover a narrow subset of the total possibilities (potential customers, ad variations, etc.).

When that happens, you don't learn anything new about the rest of the universe of options.

That matters because **without new information about alternatives, it's hard to learn anything that will suggest changing course.**

DATA RELIABILITY

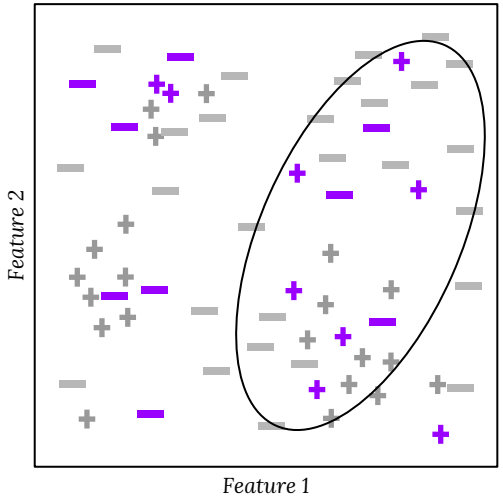
Even worse, having an unrepresentative sample of data can lead you to bad inferences about the rest of the universe.

This is the same selection bias problem that shows up in other fields, most notably survey research.

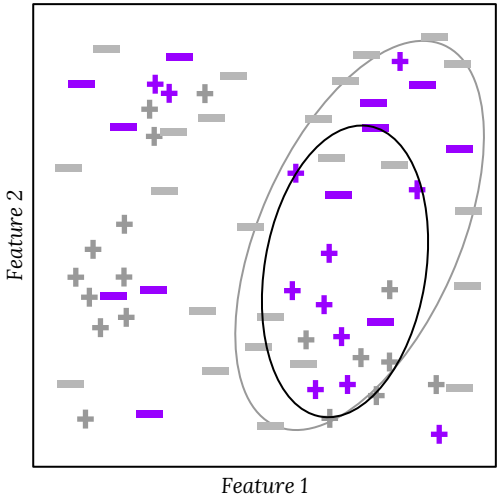
Even when we know the data generating process, **models often can't recognize outliers without some examples of "normal" observations to compare to.**

WHAT NOT TO DO #1: TUNNELING DOWN TOO NARROWLY

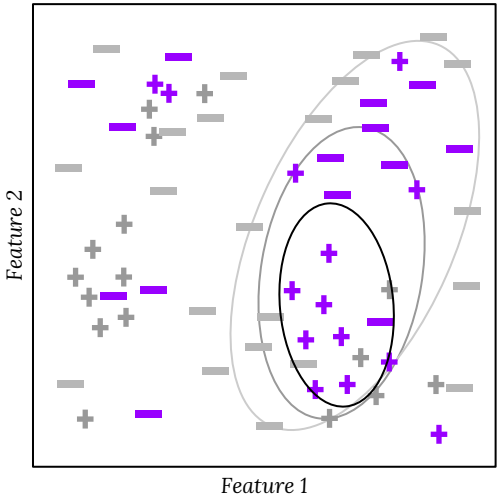
Initial data and targets selected by 1st model run
(purple = observed, gray = unobserved)



Data after some new results, targets selected by 2nd model run



Data after more new results, targets selected by 3rd model run



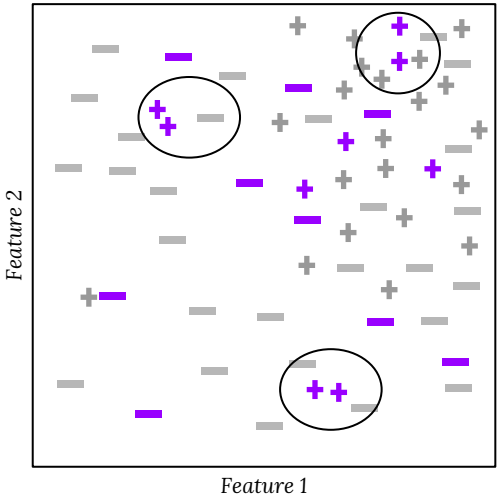
While this gives us a very high-propensity target universe by the time you get to the third run, it's a **very** narrow part of the overall universe and misses a lot of potential good targets. This will only get worse over time

Real-world example: Age filtering in direct mail fundraising

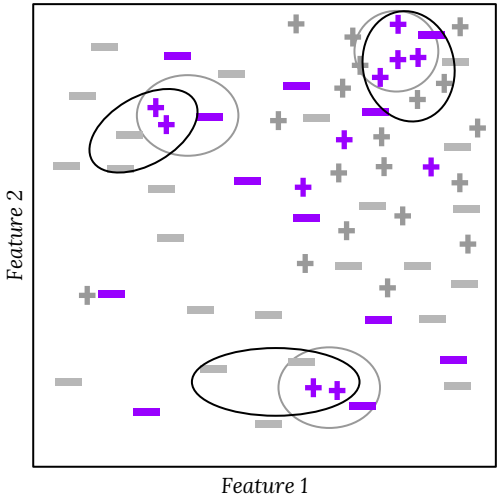
WHAT NOT TO DO #2: PUTTING TOO MUCH TRUST IN BIASED DATA

Initial data and target universe selected by 1st model run

(purple = observed, gray = unobserved)



Data after some new results, and target universe selected by 2nd model run



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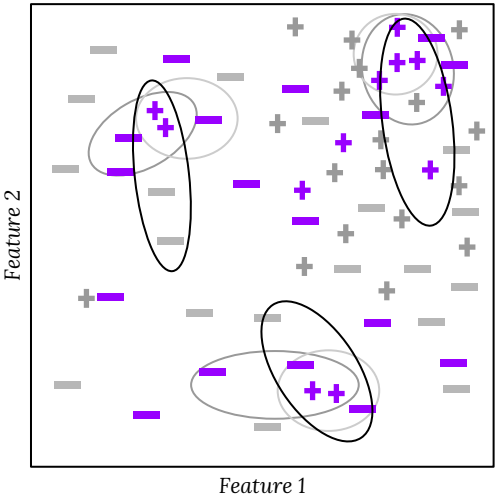

Knowing that bias is built-in to your data generating process, it's important to approach your data with a bit of skepticism and be ready to change course when the model's not working the way you expect

Real-world example: Republicans targeted by a Democratic volunteer recruitment model

FIVE STRATEGIES FOR KEEPING YOUR DATA DIVERSE

BROAD-BASED SAMPLING	Deliberately collect new data from outside your optimal universe, in order to ensure wide coverage. *Real-world example: Annual restaurant inspections*
SUPPLEMENTATION	Bring in comparable data from other sources to expand coverage to a broader universe. *Real-world example: Shared fundraising lists*
WEIGHTING TO LEARN	Adjust your optimization calculations so that higher priority is given to options which are uncertain. *Real-world example: Direct mail prospecting ensembles*
ROUGH TARGETING	Add noise to your final predictions so that a wider range of options is tried. *Real-world example: Rounding volunteer propensity scores*
HIGH-CHURN MODELING	Build your model in such a way that it will quickly update its recommendations and try out a wider range of possibilities. *Real-world example: Phone quality scores*

RECOMMENDATIONS FOR MODEL DESIGN

BUILDING FEATURES FOR SUSTAINABLE MODELS

CYCLICAL PATTERNS

Add hour of day, day of week, time until/since important events, flags for specific periods of time, etc., as features so that the model's predictions will account for when they're being generated

DYNAMIC FEATURES

Bring in external sources of data that change over time, such phone / address / email validations or histories with other organizations or programs, so that you're not in an entirely-closed system

COMPONENT MODEL OUTPUTS

Predictions from other models (supervised or unsupervised) of fundamental characteristics that are regularly updated can keep your model fresh without drowning it in individually-weak features

INDIVIDUAL HISTORIES

Include results from prior contacts or assignments, exposure to previous treatments, behavior after treatments, and other history data so that the model can adapt over time on an individual level

Common theme: Use features that create heterogeneity in predictions across model runs and directly incorporate the results of previous iterations so that your predictions improve at the individual level

MODEL SELECTION AND TUNING

BUILD IN HETEROGENEITY

Models that allow complex interactions (random forests, boosted trees) will give more variety within and across iterations than simpler models (linear regression, naive bayes)

EMBRACE ENSEMBLES

Tree ensembles, models with varied hyperparameter values, bagging and stacking, novel ensemble combination methods

RETRAIN FREQUENTLY

Not every time you predict necessarily, but often enough for new results to be incorporated quickly

ROTATE YOUR DATA

As you add new data, start rotating out older data once you have a sufficient amount to keep the model from getting increasingly stale

Common theme: Choose a modeling approach that will allow for complex relationships between features & outcomes and quickly respond to changes in observed results between iterations

EVALUATING AND MONITORING PERFORMANCE

OUT-OF-CONTEXT VALIDATION

Don't just look at random holdout set, hold out batches of results by time period or group - for example, use most recent results as test set to proxy for next batch's performance

TRACK CHANGE OVER TIME

Be on the lookout for sudden changes in performance, feature importances, or recommendation patterns, as these can be signs of problems with the model or data

HOLD YOURSELF ACCOUNTABLE

Keep archives of predictions and go back later on and see how they did, to make sure that your validation strategy is giving you realistic expectations and to find opportunities for improvement

STAY ON TOP OF THINGS

Set up automated monitoring and alerts for both the models and incoming results - for example, keep a Jupyter notebook of all the things you check frequently and automate it with nbconvert

Common theme: Because there are so many ways for sustainable models to go wrong, make sure you thoroughly validate your models in BOTH development and production

FINAL ADVICE

KNOW YOUR DATA

Your model is only as good as its data, and when you're relying on data you know is biased, it's critical to know specifically how so that you can adjust for it.

Spend some time understanding the data generating process, from a human perspective, away from your IDE or notebooks.

Talk to the subject matter experts, log on to the app or website, and **make sure you understand what the data you're relying on really means.**

DO SANITY CHECKS

The main benefit of these models is not that they deliver mysterious insights, but that they can synthesize a lot of obvious things at scale.

Make a habit of inspecting feature importances, looking at top/bottom tiers' summary stats, and spot-checking individual predictions to see if they make sense .

Even if the calculations aren't directly interpretable, **the overall patterns should still pass the smell test.**

BE OPEN TO CHANGE

Don't expect to get your model right the first time: more likely than not, things will go wrong somehow, and even if not there's always room for improvement.

Though you can automate the periodic updates, plan to routinely go back to the model and make changes by hand.

Just because a model is "sustainable" doesn't mean it does all the work on its own.

For more information about the City of Boston's Analytics Team, go to boston.gov/analytics.

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THANK YOU!