
Why Great Models Fail

LESSONS FROM 9 YEARS OF DEPLOYING ML MODELS

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- **Chief Machine Learning Engineer - MegRob DSA**
- **9+ years experience in data science and machine learning**
 - **Building products to support stakeholder and business strategy**
 - **Intersection between technical and non-technical teams**



**“FAILURES” ARE A LEARNING
OPPORTUNITY**

HOW DO I KNOW THIS?

SOCIAL MEDIA ANALYSIS



What are the target
customers talking about?



What are the trending
topics of conversations?

SOCIAL MEDIA ANALYSIS



SHORTCOMINGS



Minimal Stakeholder
Consultation



Expensive Data

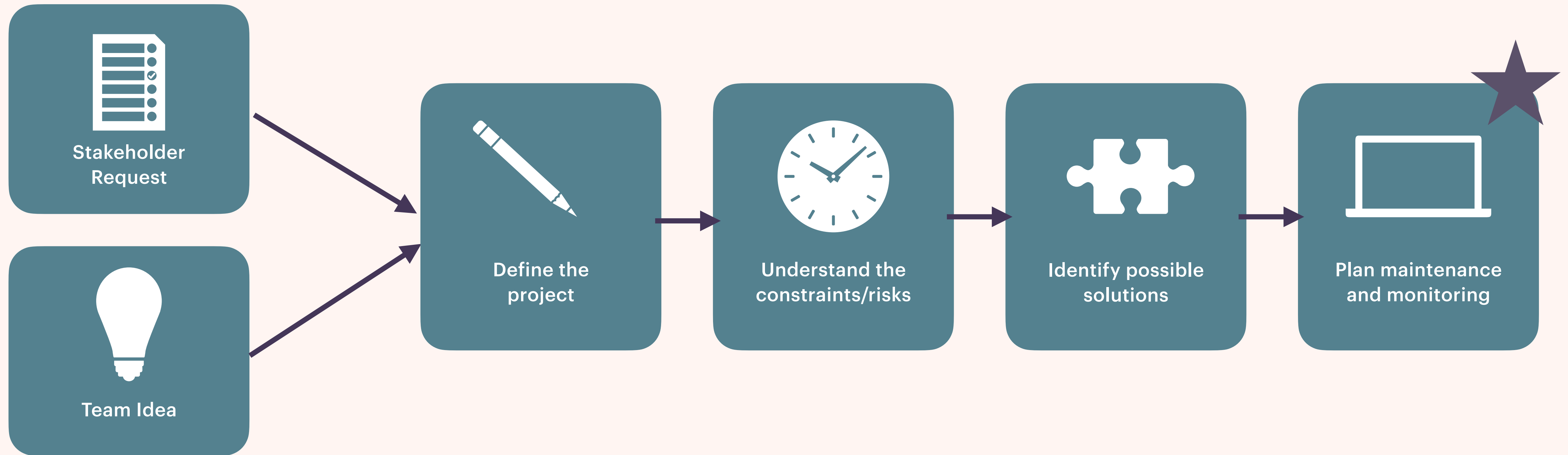


WHY DO MODELS FAIL?

1. **Scope of work not fully defined**
2. **The world changes over time**

**PROPER SCOPE IS THE
FOUNDATION OF A SUCCESSFUL
PROJECT**

SCOPING A PROJECT



What is your value add?

DEFINE THE PROJECT

Identify the stakeholders and end users

Identify the problem or pain point

Define success

Identify the project goals and objectives

Identify the project risks and constraints

Identify the project resources and budget

Identify the project timeline and milestones

Identify the project communication and reporting structure

IDENTIFY STAKEHOLDERS AND END USERS

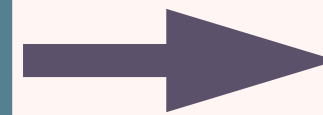
- Who will act on the predictions from the model?
 - Who owns the decisions that are informed by the model?
 - What workflows does this model touch/affect?
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IDENTIFY PROBLEM TO SOLVE

- How does this ask help you?
 - What do you wish you knew about your customer?
 - What manual or semi-manual tasks takes up a lot of time?
 - Do you feel like you're guessing anywhere?
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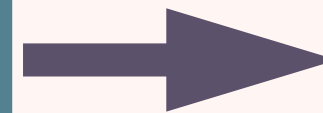
DEFINE SUCCESS

We want better marketing campaigns.



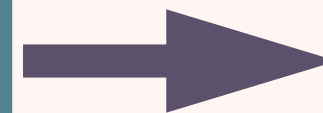
Unsubscribe rate, bounce rate, conversion rate

We need to keep users engaged in the app.



Daily active users, churn rate

We need more users to like our content.



Click-through rate (CTR), time on page

COMMON PITFALLS



Building what is cool
to you



Evaluating on vibes

There isn't a stakeholder to use the model
outputs.

The contribution of the model does not outweigh
the costs of its maintenance.

You are unable to quantify the contributions of
your model.

You cannot justify the cost of maintaining your
model.

UNDERSTAND CONSTRAINTS AND RISKS

Identify available budget and bandwidth

Brainstorm effects of bad predictions or recommendations



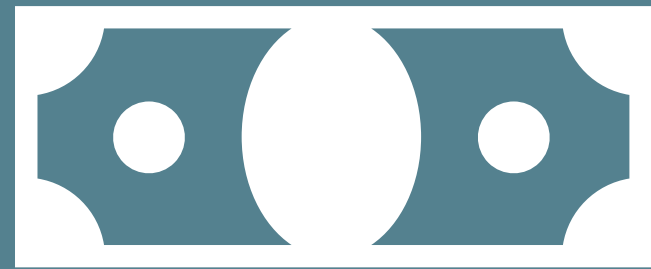
IDENTIFY BUDGET AND BANDWIDTH

- What is the expected compute power needed?
 - Is there a cost to acquire any additional data?
 - How long will it take to build the model?
 - What are the team's other priorities and how does this project compare?
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BRAINSTORM BAD OUTCOMES

- What population is harmed by a bad prediction?
 - When is it “ok” for the model to be wrong? (Type I vs. Type II errors)
 - What are the risks of an incorrect prediction - monetary, life/death, etc?
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COMMON PITFALLS



Ignoring budget and
bandwidth

The cost of the best performing model exceeds
the computing resources available.

The team doesn't have the capacity to scale this
into production.



Underestimating
risks

A small mistake in the model can cause big harm
to the company or customers.

The risk is not worth the model payoff.

IDENTIFY POSSIBLE SOLUTIONS

Understand existing capabilities and solutions

Define the minimum viable product

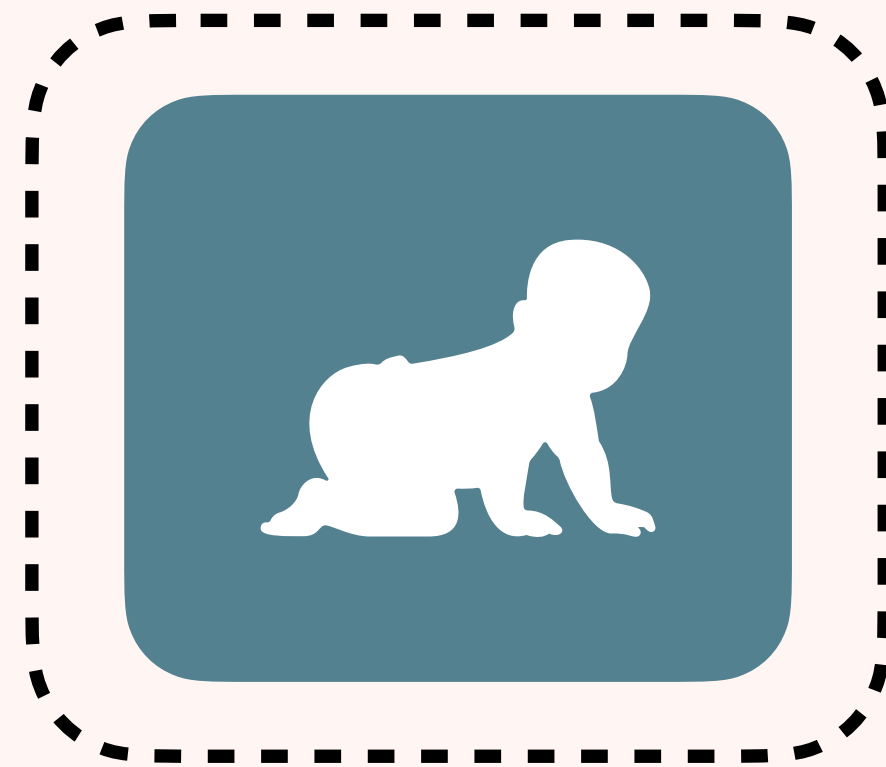


UNDERSTAND EXISTING CAPABILITIES

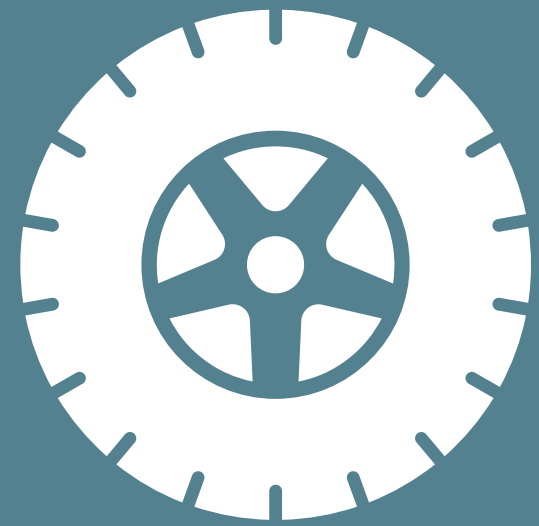
- Has someone tried to solve this problem before?
 - What can you learn from previous attempts?
 - Is there an existing tool that you can adapt?
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DEFINE THE MVP

- What is the most basic solution?
- What would convince stakeholders this is working?
- How will the output be consumed?

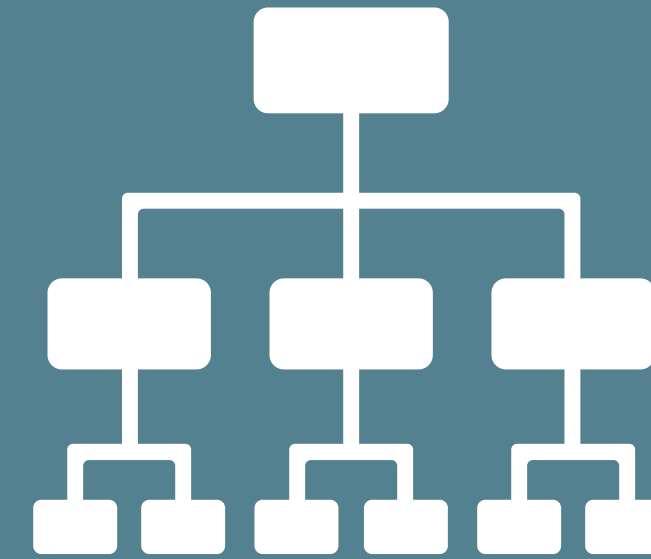


COMMON PITFALLS



Reinventing the
wheel

You waste resources and time without
providing any value above existing
projects.



Overcomplicated
solutions

It takes too long to build a model and
launch it into production. You introduce
risk and cost.

MAINTENANCE AND MONITORING

Know where the model pipeline can fail

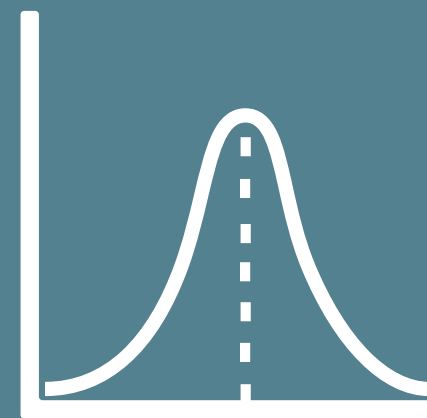
Plan robust monitoring system

Strategy for fixing failures

IDENTIFY FAILURE POINTS



Data Ingestion



Feature Generation



Model Training



Predictions and
Inference



Serving

- Broken pipelines
- Schema changes
 - Duplicates
 - Delayed jobs

- Feature drift
- Timeout errors

- Data leakage
- Overfitting

- Model drift
- Corrupt files

- Compute availability
- Latency issues

Dependency failure

ROBUST MONITORING SYSTEM

Data Issues



- Summary metrics
- Distribution changes (Chi-square, Kolmogorov-Smirnoff)
- Missing values

Model Issues



- MAE, MSE, AUC
- Precision, recall, F1 score
- Semantic similarity, prompt injections

Infrastructure



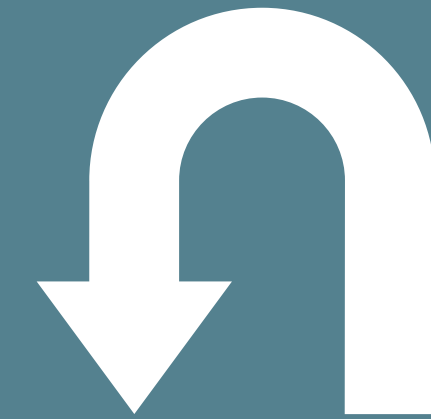
- Timeout rate
- Latency summary
- SLA comparison

COMMON PITFALLS



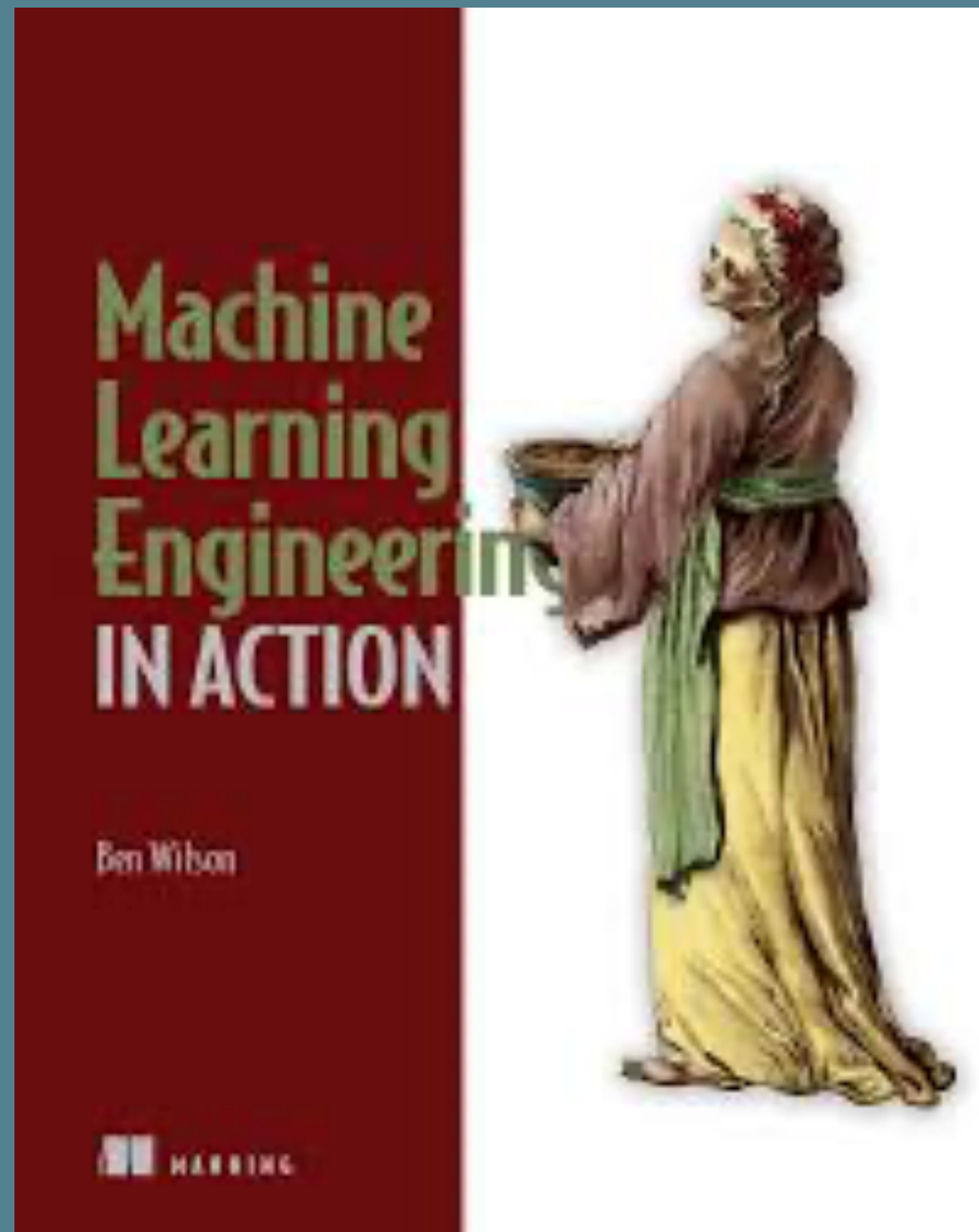
Lack of adequate
monitoring

You are unable to catch any error before it grows into a bigger problem. You lose stakeholder or customer trust in your team and model.



Ignoring model drift

Data changes over time - especially if you are using the model for intervention. The model only represents one point in time.



**“MODELS WILL DRIFT.
THERE IS NO SUCH
THING AS STATIC
IMPLEMENTATION.”**

WHY DO MODELS DRIFT?

Concept: Divergence between input and target variables

Data: Change in underlying distributions of features

Label: Distribution of target variables change over time

Reality:



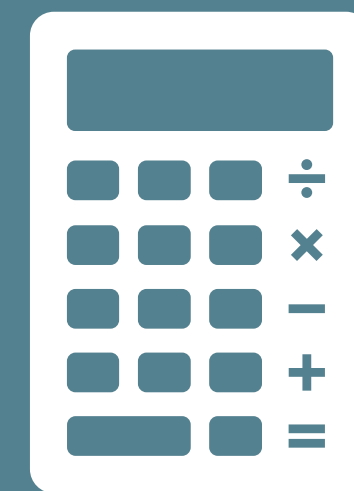
ADDRESSING MODEL DRIFT



**Feature
engineering**



**Retrain
model**



**New
algorithm**



**Retire the
model**

KEY TAKEAWAYS

- **A highly predictive model is not enough to succeed in industry.**
 - **Stakeholders and subject matter experts should play a key role in project scope.**
 - **A model represents a point in time, and the world changes over time.**
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