ML Lifecycle Management

Effective Management of the ML Pipeline

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Agenda

- ML Design
- Why it Matters
- ML Product Design and Planning
- ML Systems Design
- Templates
- Q&A

ML Design

Intuition:

Before we start developing any machine learning models, we need to first motivate and design our application.

Why it matters?

- e2e view of all components of the project
- Clearly defined value proposition
- Reduce *I said, she said, they said*
- Define where to stop

ML Product Design

Intuition:

Motivate the need for the product and outline the objectives and impact.

- Looks at the *What* and *Why*

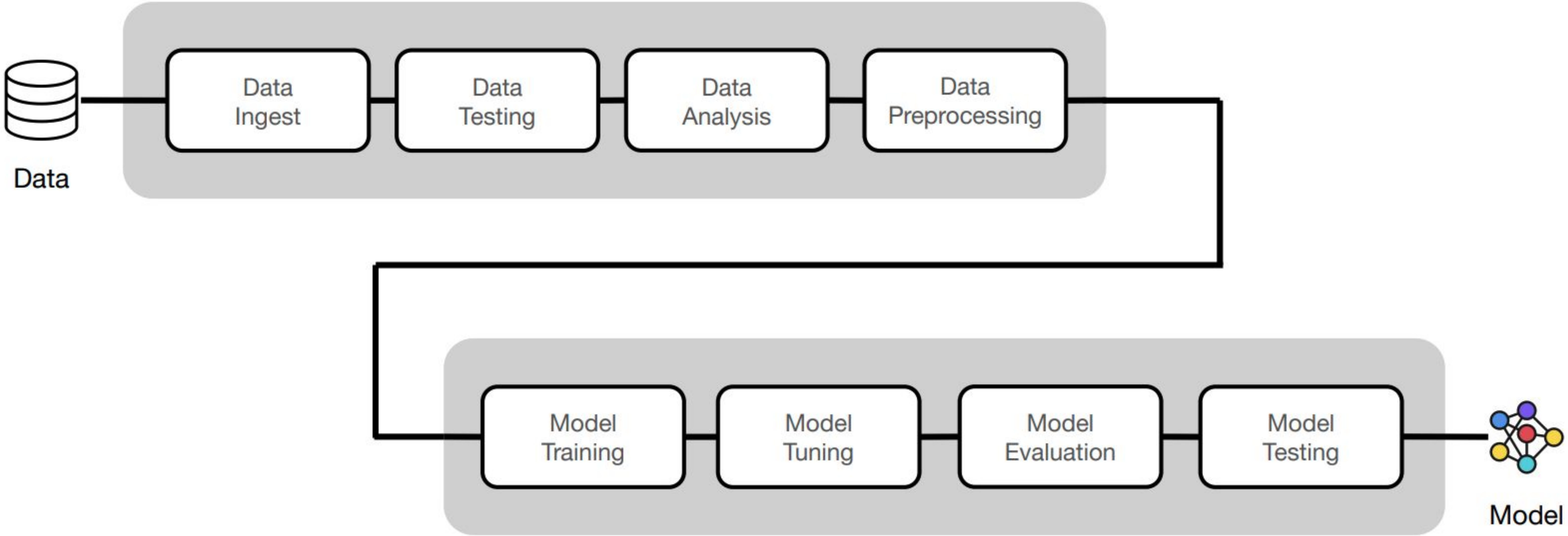
ML System Design

Intuition:

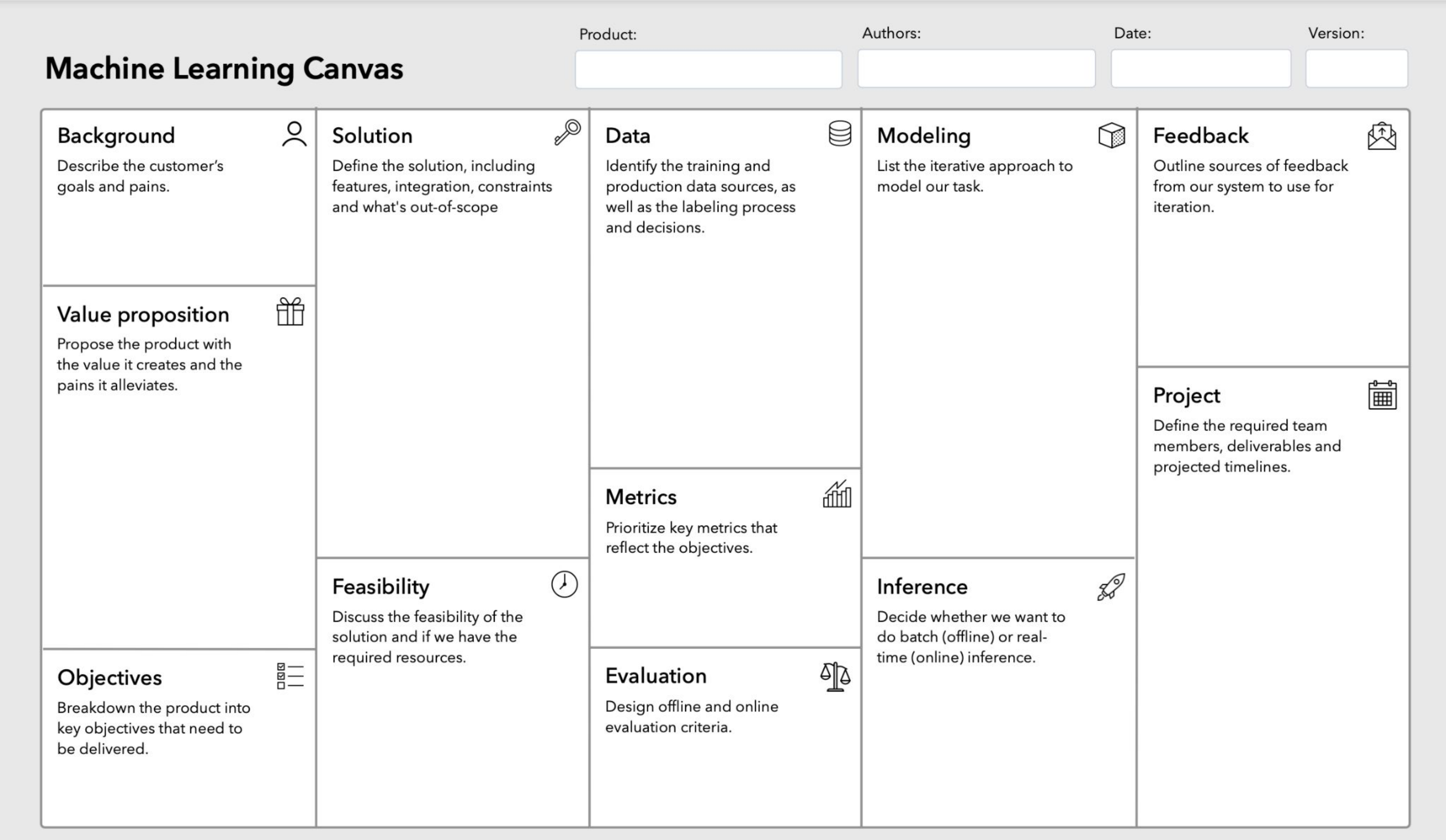
How can we engineer our approach for building the product?

- Looks at the *How*
- We account for everything from data ingestion to model serving.

ML System Design



Templates


Machine Learning Canvas
Product:
Authors:
Date:
Version:
Background
Describe the customer's goals and pains.
Solution
Define the solution, including features, integration, constraints and what's out-of-scope
Data
Identify the training and production data sources, as well as the labeling process and decisions.
Modeling
List the iterative approach to model our task.
Feedback
Outline sources of feedback from our system to use for iteration.
Value proposition
Propose the product with the value it creates and the pains it alleviates.
Project
Define the required team members, deliverables and projected timelines.
Metrics
Prioritize key metrics that reflect the objectives.
Feasibility
Discuss the feasibility of the solution and if we have the required resources.
Inference
Decide whether we want to do batch (offline) or real-time (online) inference.
Objectives
Breakdown the product into key objectives that need to be delivered.
Evaluation
Design offline and online evaluation criteria.

ML Product Design - Background

Intuition:

Set the scene for what we're trying to do through a user-centric approach:

- users : profile/persona of our users
- goals : our user's main goals
- pains : obstacles preventing our users from achieving their goals

ML Product Design - Value Prop.

Intuition:

Propose the value we can create through a product-centric approach:

- product : what needs to be built to help our users reach their goals?
- alleviates : how will the product reduce pains?
- advantages : how will the product create gains?

ML Product Design - Objectives

Intuition:

Breakdown the product into key objectives that we want to focus on.

Example:

- Kera Health's Face Verification System

ML Product Design - Solution

Intuition:

Describe the solution required to meet our objectives, including its:

- core features : key features that will be developed
- integration : how the product will integrate with other services
- alternatives : alternative solutions that we should consider
- constraints : limitations that we need to be aware of
- out-of-scope : features that we will not be developing for now

ML Product Design - Feasibility

Intuition:

- How feasible is our solution and do we have the required resources to deliver it (data, $, infrastructure, team, etc.)

ML Product Design - Data

Intuition:

Describe the training and/or production (batches/streams) sources of data:

- training:
  - access to training data and testing (holdout) data
  - sampling techniques applied to create dataset
  - any other considerations
- production :
  - access to batches or real-time streams of data
  - how can we trust this stream of data

ML Product Design - Labeling

Intuition:

Describe the labeling process and how we decided on the features and labels.

- assumptions : what assumptions exist about the labeling process
- reality : what exists in the data on investigation
- decisions : what labeling process we finalise on based on features.

ML Product Design - Metrics

Intuition:

Hardest but most rewarding part of ML systems. We try to tie our core objectives (from the product design stage) - many of which may be qualitative, with quantitative metrics that our model can optimize towards.

- deciding which metrics to prioritize?

ML Product Design - Evaluation

Intuition:

Allows us think about when and how we'll evaluate our model.

- offline : test (holdout) datasets - usually done before deployment.
- online : ensures continuous high performance in production, using manual labels or proxy signals.

ML Product Design - Modeling

Intuition:

While the specific methodology we employ can differ based on the problem, there are core principles we always want to follow:

- end-to-end utility : end results from every iteration should deliver minimum end-to-end utility for benchmarking purposes
- manual before ml : try a simple rule-based approach before ml
- augment vs. automate : allow systems to supplement decision making processes as opposed to making actual decisions
- internal vs. external : not all releases have to be end user facing
- thorough : test well (code, data + models), benchmark different approaches.

ML Product Design - Inference

Intuition:

Once we have a model we're satisfied with, we need to think about whether we want to perform batch (offline) or real-time (online) inference:

- batch inference : store results in a database for use.
- online inference : provide an api endpoint for inference.

ML Product Design - Feedback

Intuition:

How do we receive feedback on our system and incorporate it into the next iteration?

Can involve human-in-the-loop feedback as well as automatic feedback via monitoring, etc.

- batch inference : store results in a database for use.
- online inference : provide an api endpoint for inference.

Conclusion

- Summary: Documentation of the why and how we are building any ML process is essential to avoid deviating from original plans without a clear understanding or pathway for achieving usable results.
- Next Steps: Explore the tools and techniques introduced today.

Q&A

Thank You!