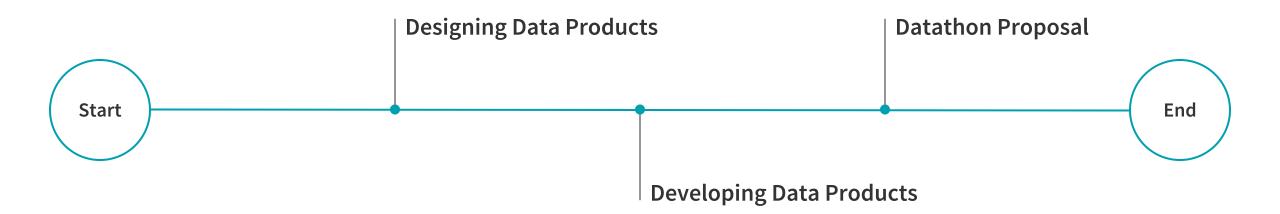
Building Data Products

Seminar Outline



Designing Data Products



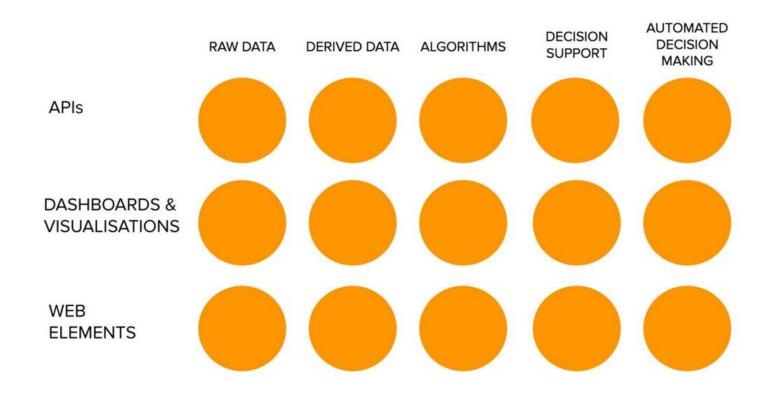
What is a Data Product?



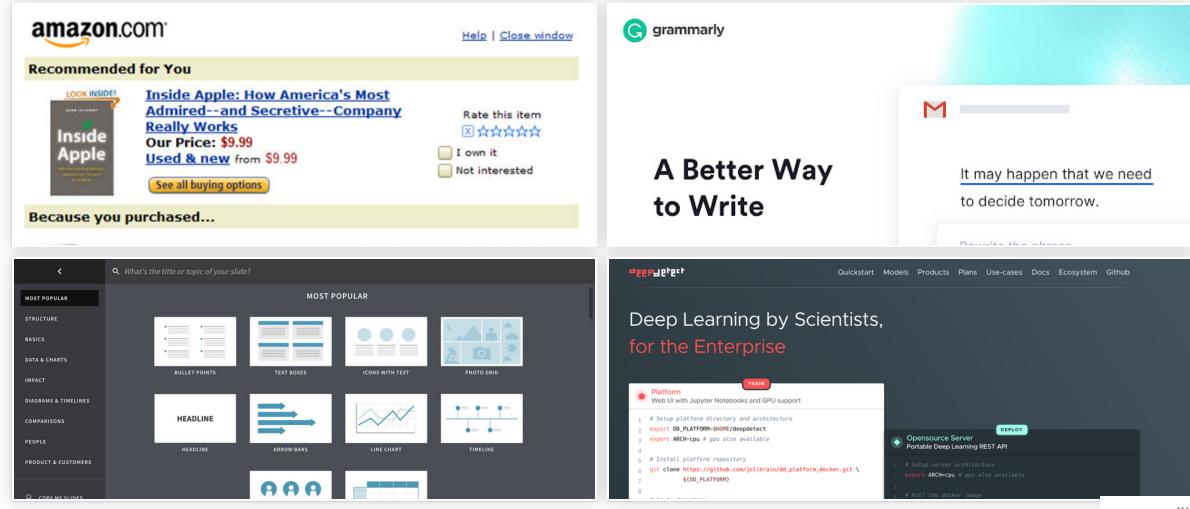
"A data product is a product that facilitates an end goal through the use of data"

DJ Patil, Former U.S Chief Data Scientist - Data Jujitsu

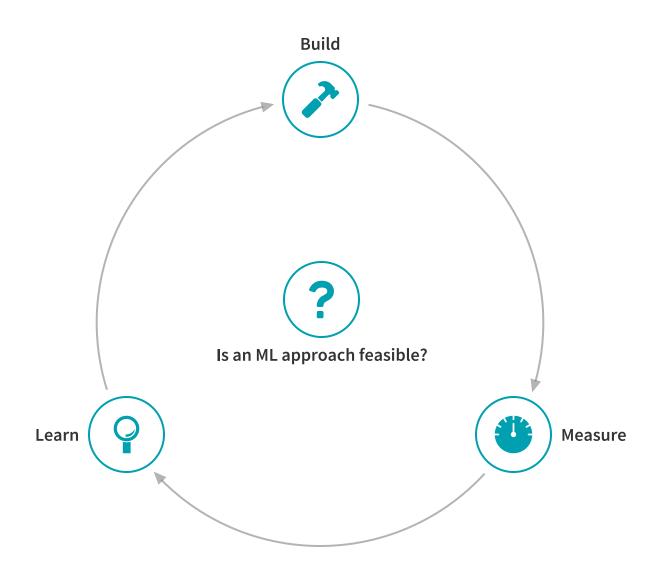
Types of Data Products



Examples of Data Products



MVP Cycle



Minimum Viable Data Product (MVDP)

Minimum Viable Implementation

Follow a customer-first approach.

Should support monitoring, feedback, and governance.

Minimum Viable Model

Forget about fancy papers and SOTA models.

Implement and baseline and iterate.

Minimum Viable Platform

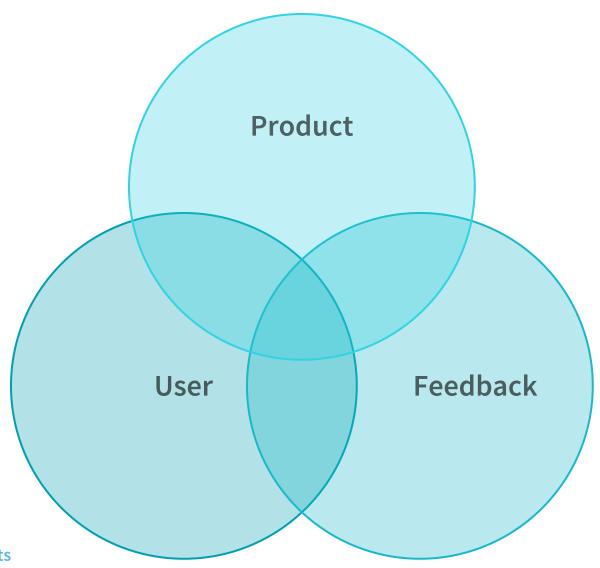








Principles for Data Product Design



Product Intrinsic Principles

- Build Trust with Transparency
- Invoke Discovery and Delight
- Visualize the Complex
- Blend in

Feedback-aware infrastructure

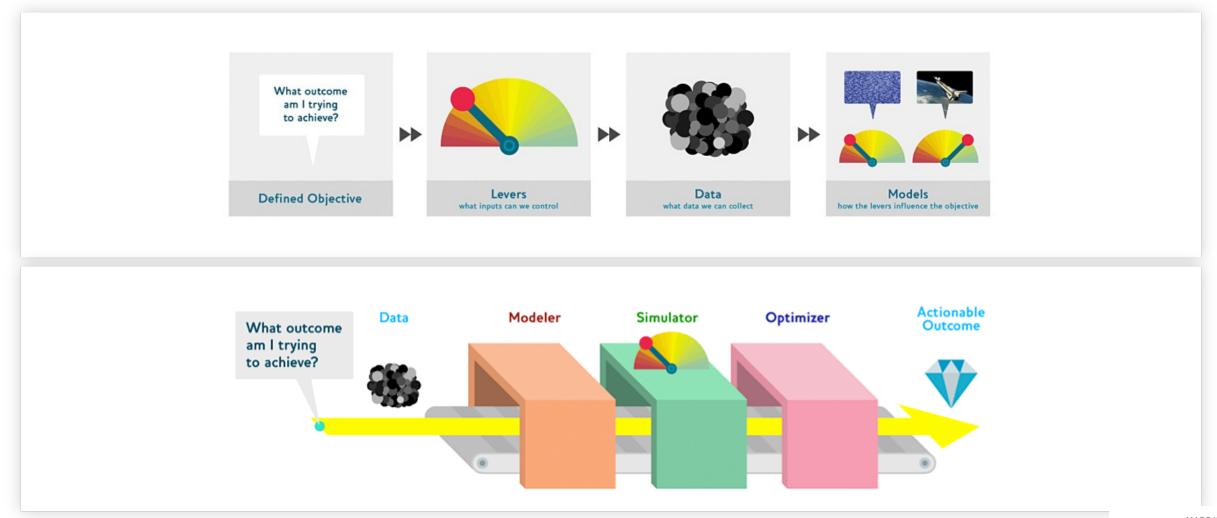
- Collect Data Passively
- Constantly Validate with Data

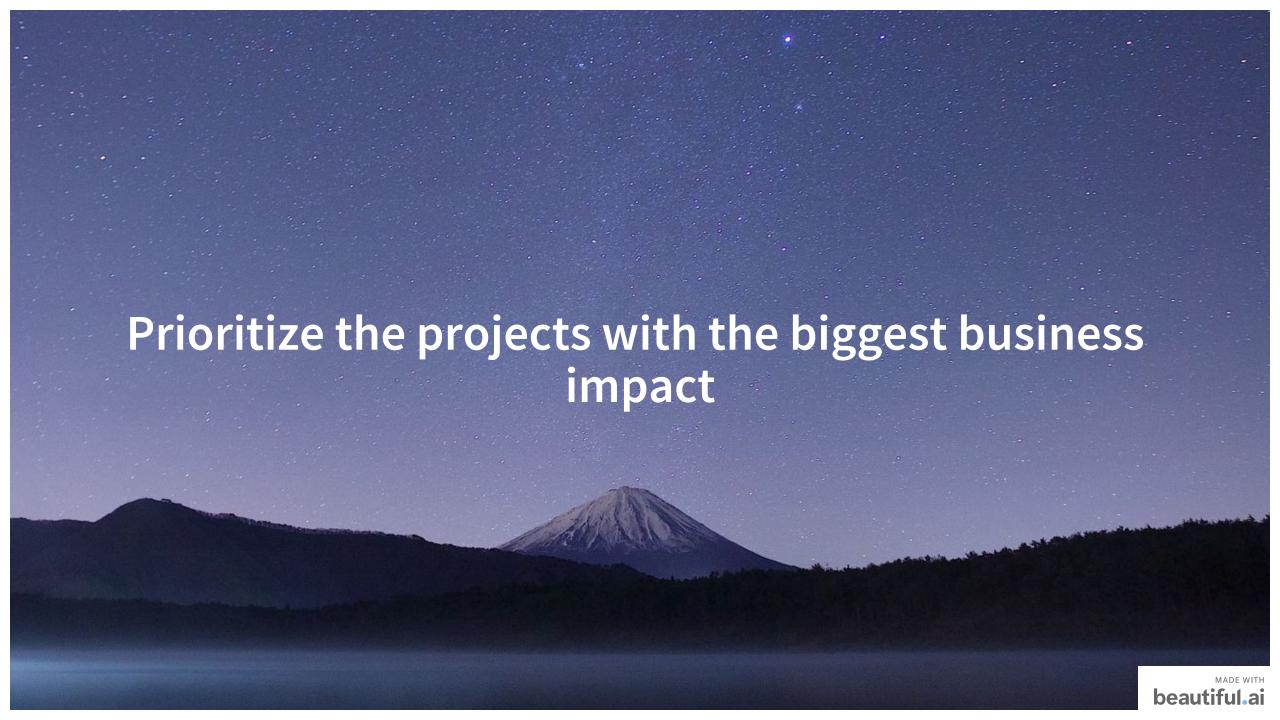
User-focused Principles

- Meet Unexpressed Needs
- Don't Exhaust the User
- Give Users Control

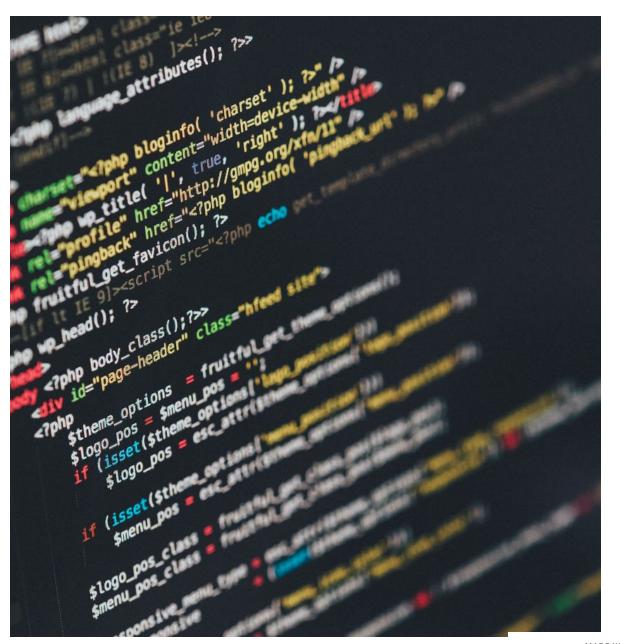
Drivetrain Approach

Designing Great Data Products

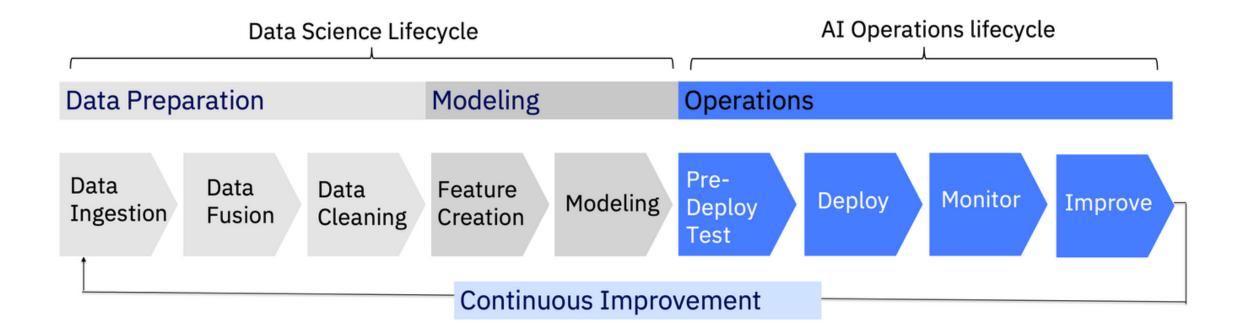




Developing Data Products



Data Science Process



Data Preparation

Master Data
Management and
Governance

Stewardship, Data quality, cleansing, etc.

Data Engineering

Pipeline design, ETL, etc.





Data Acquisition







Modeling



PYTÖRCH



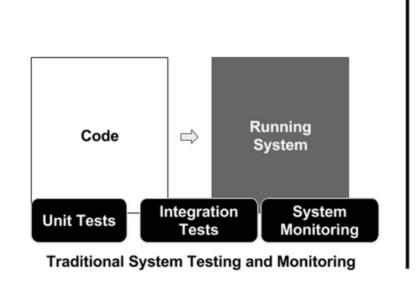


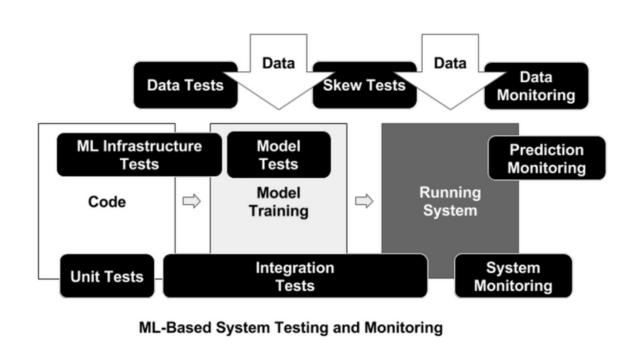




Testing

The ML Test Score: A Rubric for ML Production Readiness and Technical Debt Reduction





Deployment









Amazon SageMaker





Monitoring







Amazon SageMaker

Best Practices

Rules of Machine Learning: Best Practices for ML Engineering

Martin Zinkevich

This document is intended to help those with a basic knowledge of machine learning get the benefit of best practices in machine learning from around Google. It presents a style for machine learning, similar to the Google C++ Style Guide and other popular guides to practical programming. If you have taken a class in machine learning, or built or worked on a machine-learned model, then you have the necessary background to read this document.

Terminology

Overview

Before Machine Learning

Rule #1: Don't be afraid to launch a product without machine learning.

Rule #2: Make metrics design and implementation a priority.

Rule #3: Choose machine learning over a complex heuristic.

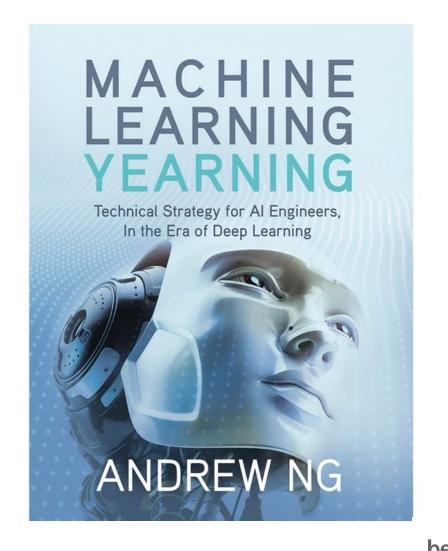
ML Phase I: Your First Pipeline

Rule #4: Keep the first model simple and get the infrastructure right.

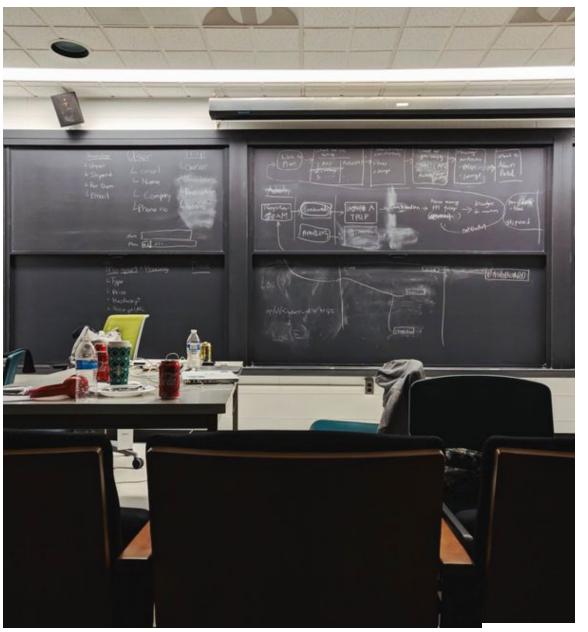
Rule #5: Test the infrastructure independently from the machine learning.

Rule #6: Be careful about dropped data when copying pipelines.

Rule #7: Turn heuristics into features, or handle them externally.



Datathon



Objetives

- Learn to design and implement a MVDP
- Understand the problems that DS can solve
- Understand the implications and problems that arises when applying DS

Proposed Projects

MNIST Online Tool

Example

Text Topic Classification

- Example 1
- Example 2

Movie Recommendation System

Example

Bitcoin Trading Bot

- Example 1
- Example 2
- Example 3

Hotdog - No hotdog App

- Example 1
- Example 2
- Example 3

MNIST Online Tool

- Data extraction: Download data from Keras datasets or similar
- Data preparation: Data augmentation
- Modelling: Recommended CNN with pretrained weights
- Evaluation: Accuracy metric
- Validation: Use a Logistic regression or a former SOTA model
- Model deployment: As microservice, as part of the backend, lambda, etc.

Movie Recommendation System

- Data extraction: MovieLens dataset. Netflix activity.
- Data preparation: Algorithm-dependent
- Modelling: Collaborative filtering algorithms
 - https://github.com/NicolasHug/Surprise
 - https://github.com/NVIDIA/DeepRecommender
 - https://github.com/benfred/implicit
 - https://github.com/zhenghaoz/gors
- Evaluation: Regression or classification metrics
- Validation: None
- Model deployment: As microservice, as part of the backend, lambda, etc.

Bitcoin Trading Bot

- Data extraction: Historical data of bitcoin prices
- Data preparation: Algorithm-dependent
 - Time series features (lags, cumsums, etc) for traditional algorithms
 - None for LSTM or Prophet
- Modelling: RNN, LSTM, traditional regression methods, Prophet (Recommended)
- Evaluation: Backtesting
- Validation: Against traditional methods like mean reversion, moving average, etc.
- Model deployment: Quantopian platform

Hotdog - No hotdog App

- Data extraction: Images of hotdog and not hotdogs
- Data preparation: Image preprocessing + Data augmentation
- Modelling: Pretrained CNN
- Evaluation: Accuracy
- Model deployment: As microservice, Tensorflow lite, CoreML, etc.

Resources

- Designing great data products
- The Fundamentals of Building Better Data Products
- · Data Jujitsu Ebook
- Rules of Machine Learning: Best Practices for ML Engineering
- Best MLOps Tools
- Monitoring Machine Learning Models in Production

- What is hardcore Data Science in practice?
- Applied Artificial Intelligence: An Introduction For Business Leaders - Book
- Machine Learning Yearning Book
- The Al Organization Book
- · Agile Data Science 2.0 Book
- Introducing MLOps Book

