2024

Data Science Methodology

From System Design to Deployment

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OUTLINE

1. Problem Framing
2. Data and Feature Engineering
3. Modeling Techniques
4. Model Validation and Evaluation

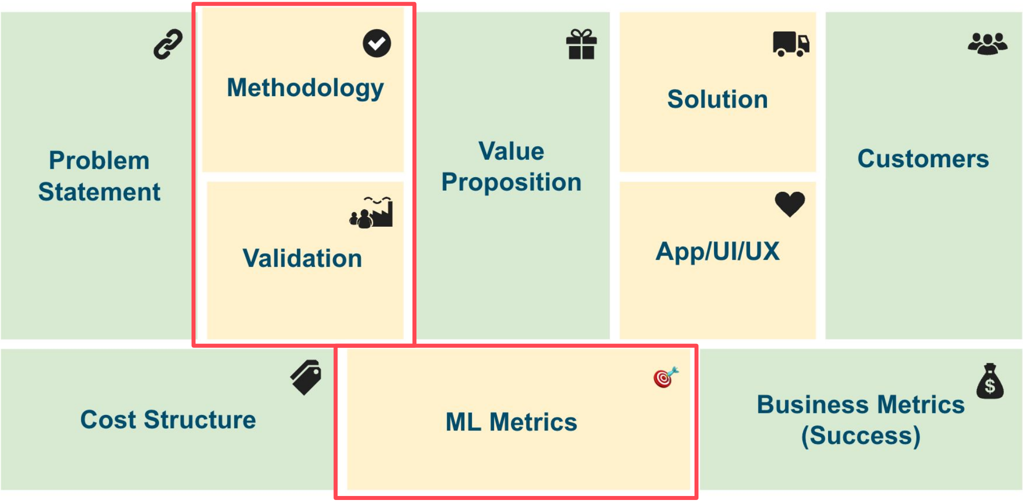
4.x – Data Science Methodology

Purpose

- Frame the ML problem

Guiding questions:

- How do we frame this as a machine learning problem? What ML metric should we optimize?



MODULE DETAILS

Goals

- Understand how to approach ML problems systematically
- Learn to make informed decisions about data and modeling techniques
- Develop skills to evaluate ML models effectively

Learning Outcomes

- Frame ML problems effectively
- Perform data and feature engineering
- Select appropriate modeling techniques
- Design robust evaluation frameworks

HANDS-ON ACTIVITIES

Exercise

- Create a clear understanding of ML task to solve to adhere to **Solution Design** created earlier
- Goal: Understand requirements for ML Pipeline

Output

1. Drafting the next part of a design document: **DS Methodology**
   a. Problem Framing and Approach
   b. Data and Feature Engineering
   c. Modeling Techniques and Algorithms
   d. Model Validation and Evaluation

Problem Framing and Approach

ML Product Design

> Guide: 4.1 - Problem Framing and Approach

4.1 – Problem Framing and Approach

How do we frame this as a machine learning problem?

Purpose

- To ensure the ML approach aligns with the business problem and leverages appropriate techniques.

Guiding questions:

- How do we frame this as a machine learning problem?
- What ML metric we should optimize?
- Why is this approach the most suitable?
- What is the simplest solution? Can we solve the problem without ML?
- What is a feasible baseline solution?

Case: NewPizza - long waiting time

How do we frame this as a machine learning problem?

Let’s recall business metrics we fixed for this task

Possible approaches:

- Regression?
- Classification?
- Unsupervised learning?

Given a business metrics to optimize, you can frame ML problem in different forms

Case: NewPizza - long waiting time

How do we frame this as a machine learning problem?

Let's recall business metrics we fixed for this task

Let's talk about baselines:

- Regression
- Classification

You can have no-ML baselines of various complexity

Case: shop queue detection

How do we frame this as a machine learning problem?

Possible approaches

- Object detection?
- Applying multi-modal LLM?
- Other ideas?

Your overall solution may consist from several ML problems/models

Case: shop queue detection

How do we frame this as a machine learning problem?

Let’s talk about baselines:

- Object detection
- Applying multi-modal LLM

Sometimes no-ML baseline for a chosen solution isn’t possible.
How can we get a baseline then?

Exercise: Problem Framing and Approach

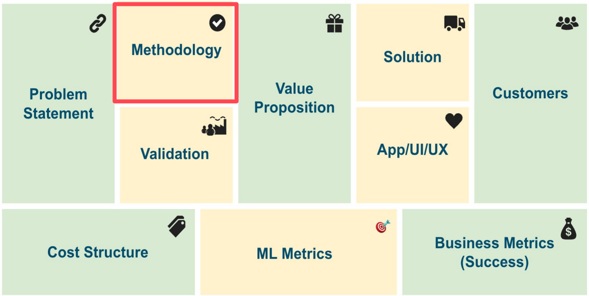
How does the solution look for our customers?

Group task:

- Brainstorm and complete the ML Product Design sections:
  - 4.1 - Problem Framing and Approach
- 5 min

Key points:

- ML problem type (e.g., classification, regression)
- Potential alternative approaches
- Baseline solution (without ML)



Practice

4.1 - Problem Framing and Approach

How do we frame this as a machine learning problem?

Overview:

- The business problem of inaccurate trip duration predictions is framed as a regression problem. The approach involves using historical trip data to train a model that predicts trip duration

Key points:

- Problem Type: Regression.
- Approach: Supervised learning with historical data.
- Baseline Solution: Current provider's predictions.

Example

ML Product Design: EasyRide Taxi

Problem Statement

- High MAPE > 30%.
- External provider's prediction service (we can't improve).
- Competitive market with accurate pricing as a differentiator.
- Critical to EasyRide's strategy of superior customer service.

Methodology

- Problem Type: Regression.
- Approach: Supervised learning.
- Metric: MAPE.
- Baseline: Current predictions.

Validation

- Validation Methodology: Shadow deployment, A/B testing.
- Pilot Scope: 1 week
- Success Criteria: Lower MAPE, higher booking rates.

Value Proposition

- Minimize revenue loss
- Improve customer retention
- Improve driver retention

Solution

- Target: trip duration in minutes
- Format: a float number
- Components: Taxi App, Data Ingestion, ML Solution, Backend

App/UI/UX

- UI: ETA, trip duration and cost/earnings.
- UX: Requesting a ride, viewing the predicted cost, booking the ride.

Customers

- Taxi app customers
- Taxi drivers

Cost Structure

- Initial Development: $214,083
- Annual Operations: $386,000
- Annual Benefit: $15,147,500
- ROI: First Year: 2,424% / Subsequent Years: 3,825%

Performance / ML Metrics

- Prediction accuracy (MAPE) < 15%
- Prediction latency < 100ms
- Business Metrics: Booking rate, Revenue Increase
- Timeline: Daily metric evaluation.

Business Metrics (Success)

- Daily Revenue Increase by $24,000
- Pricing Loss Reduction by $17,000
- Booking Rate Improvement by 6%
- Evaluate metrics daily, with quarterly reviews

Data and Feature Engineering

ML Product Design

› Guide: 4.2 - Data and Feature Engineering

Case: shop queue detection

What data do we need?

- Where can we find a dataset?
- How can we collect one?
- How can we label one?

Collecting and labeling can be expensive, but will deliver you high-quality data

- What is the size of the dataset you may need here?
- How to ensure you collected enough data?

4.2 – Data and Feature Engineering

What data do we need?

Purpose

- To ensure the ML system has access to high-quality, relevant data.

Guiding questions:

- What data will you use to train your model?
- What input data is needed during serving?
- How will we ensure data quality?
- How will you clean and prepare the data (e.g., excluding outliers) - consider important edge cases

Exercise: Data and Feature Engineering

What data do we need?

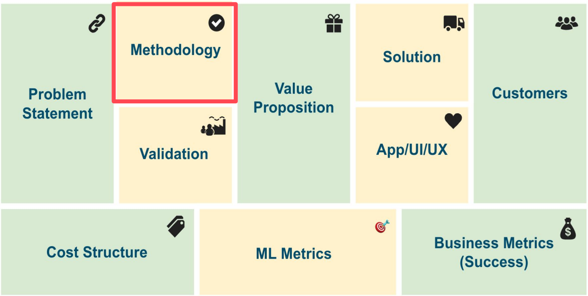
Group task:

- Brainstorm and complete the ML Product Design sections:
    - 4.1 - Problem Framing and Approach
- 5 min

Key points:

- Data sources and collection methods
- Data preprocessing and feature engineering
- Data quality assurance processes
- Data Labeling

Practice



4.2 – Data and Feature Engineering

What data do we need?

Overview:

- Data is sourced from the NY Taxi dataset, including features such as pickup and dropoff locations, trip distance, time of day, and day of the week.
- Data File format: Parquet

Key points:

- Data Sources: NY Taxi dataset (TLC Trip Record Data)

Data fields:

- **id** - a unique identifier for each trip
- **pickup_datetime** - date and time when the meter was engaged
- **dropoff_datetime** - date and time when the meter was disengaged
- **passenger_count** - the number of passengers in the vehicle (driver entered value)
- **pickup_longitude** - the longitude where the meter was engaged
- **pickup_latitude** - the latitude where the meter was engaged
- **dropoff_longitude** - the longitude where the meter was disengaged
- **dropoff_latitude** - the latitude where the meter was disengaged
- **trip_duration** - duration of the trip in seconds

Example

Modeling Techniques and Algorithms

ML Product Design

> Guide: 4.3 - Modeling Techniques and Algorithms

4.3 – Modeling Techniques and Algorithms

What it the best modelling approach?

Purpose

- To provide a clear understanding of the technical approach and its rationale

Guiding questions:

- Which ML algorithms are most suitable for our problem?
- How will we optimize model performance?
- What are the trade-offs between different modeling approaches?
- What feature engineering techniques you need to consider for selected ML model?

Case: NewPizza - long waiting time

What it the best modelling approach?

- Selected algorithms and rationale
  - Time-series models (frameworks?)
  - GBDT predicting the delta (frameworks?)
- Hyperparameter tuning strategy
  - Manual - try this first
  - Optuna - you still need to understand what hyperparameters matter

Case: shop queue detection

What it the best modelling approach?

- Selected algorithms and rationale
  - YOLO
  - Multi-modal LLM
- Model architecture details
  - ?
- Hyperparameter tuning strategy
  - ?

Exercise: 4.3 - Modeling Techniques

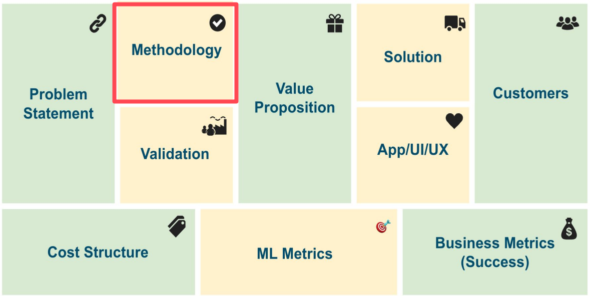
What it the best modelling approach?

Group task:

- Brainstorm and complete the ML Product Design sections:
  - 4.3 - Modeling Techniques and Algorithms
- 5 min

Key points:

- Selected algorithms and rationale
- Model architecture details (for DL)



Practice

4.3 – Modeling Techniques

What it the best modelling approach?

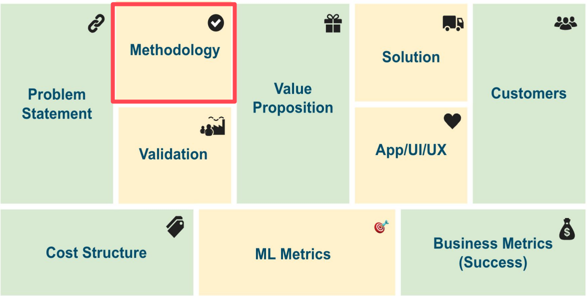
Overview:

- After evaluating various regression algorithms, Gradient Boosting Decision Trees (GBDT), specifically XGBoost, is chosen as the primary model for its balance of accuracy and computational efficiency in predicting trip durations.
- XGBoost is chosen for its:
  - Superior handling of non-linear relationships in geo-temporal data
  - Robustness to outliers common in urban traffic patterns
  - Ability to capture complex feature interactions
  - Scalability to large datasets typical in taxi operations
  - Balance between prediction accuracy and inference speed

Example

Key points:

- **Selected algorithm**: XGBoost
  Alternatives considered: Linear Regression, Random Forest



Model Validation and Evaluation Framework

ML Product Design

> Guide: 4.4 - Model Validation and Evaluation Framework

4.4 – Model Validation and Evaluation

How to ensure generalization and robustness?

Purpose

- To ensure the model's performance can be reliably measured and meets business requirements

Guiding questions:

- Which metrics do you need to calculate?
- How will we split our data to validate the model effectively?
- How will we ensure the evaluation process is unbiased and thorough?

Case: shop queue detection

How to ensure generalization and robustness?

What if we have just 100 samples?

- Cross-validation and data split:
  - K-fold
  - Holdout
  - or something else?

Case: NewPizza - long waiting time

How to ensure generalization and robustness?

- ML Metrics: Performance metrics specific to the validation and test phases. Evaluation metrics should be relevant to business metrics.
    - Classification:
        - Precision at Recall.
        - Other ideas?
    - Regression:
        - RMSE. Then what?

Exercise: Model Validation and Evaluation

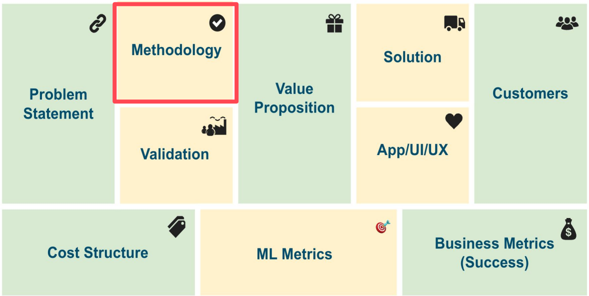
How to ensure generalization and robustness?

Group task:

- Brainstorm and complete the ML Product Design sections:
    - How to ensure generalization and robustness?
- 5 min

Key points:

- **Techniques**: Cross-validation (e.g., k-fold cross-validation), holdout validation, stratified sampling.
- **Data Splits**: Training set, validation set, and test set.
- **Metrics**: Performance metrics specific to the validation and test phases. Evaluation metrics should be relevant to business metrics.



Practice

4.4 – Model Validation and Evaluation

How to ensure generalization and robustness?

Overview:

- The model's performance is rigorously validated using a combination of time-based cross-validation and geospatial holdout validation, with evaluation metrics directly tied to business impact.
- Time-based Cross-validation:
  - Weekly data chunks
  - Rolling window approach
- Geospatial Holdout (suitable if we want to introduce new city/neighbourhood):
  - Reserve specific NYC neighborhoods
  - Test model generalization

Key points:

- MAPE: Target <15% (Current: 30%)
- RMSLE: Penalize underestimation
- Latency: <500ms response time
- Time-based split for cross-val

Example

Assignment

Start with ML System Design!

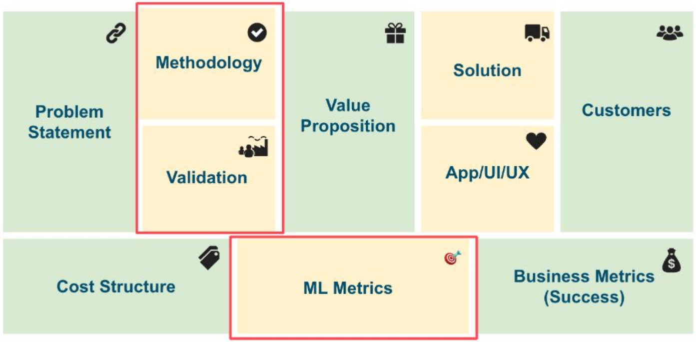
Prerequisites

- Draft of the ML Product Design: Business Understanding
- Draft of the ML Product Design: Solution

Practice: Methodology

If … else … LLM …

- Frame DS methodology for your project
- Follow the guide to describe each section
- Summarise Methodology blocks on the canvas
- Update Cost Structure & Solution (if needed)



Materials & Links

- Course Materials: Google Drive
- Practice - EasyRide Taxi - Day 3 - PUBLIC
- Guide - ML System Design - Canvas