DHBW Ravensburg

Intelligence Engineering

Solving Real World Problems At Scale

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LECTURE II

Introduction to Machine Learning Systems Design

This lecture in one slide

II Introduction to Machine Learning Systems Design

Business and ML Objectives

Requirements for ML Systems

Iterative Process

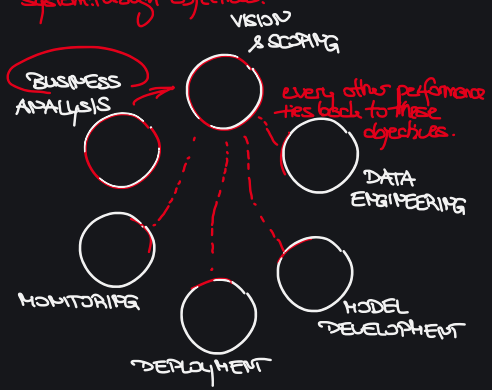
Framing ML Problems

Mind Versus Data

1

Business and ML Objectives

First Guidance on Developing the System through Objectives.



"The sole purpose of a business is to maximize profits for shareholders." – Milton Friedman

VISION & SCOPING
BUSINESS ANALYSIS
DATA ENGINEERING
MODEL DEVELOPMENT
DEPLOYMENT
MONITORING

There is vested interest in the AI hype. Expectation management is crucial.
VISION & SCOPING
BUSINESS ANALYSIS
Starting here AI adoption is hard work and an investment.
DATA ENGINEERING
MONITORING
MODEL DEVELOPMENT
DEPLOYMENT
Returns on investment heavily depend on maturity of adoption.
Development cycles and skills don't develop over-time.

2

Requirements for ML Systems



- **RELIABILITY**
  Correct function at desired level of performance in the face of adversity.
- **SCALABILITY**
  With respect to complexity, throughput, and other types of growth.
- **MAINTAINABILITY**
  Structure workload, infrastructure and tool landscape so that you can keep up.
- **ADAPTABILITY**
  Capacity to discuss potentials for performance improvement and allowing updates without service interruptions.

3

Iterative Process

Developing ML systems is a cycle with a lot of back and forth!
#ITERATIVE.
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BUSINESS ANALYSIS
DATA ENGINEERING
MODEL DEVELOPMENT
DEPLOYMENT
MONITORING

Objectives
Key Results
Constraints
VISION & SCOPING

Stakeholders: users, managers, humanity

We learn from data, so this is where we start with our craftmanship.
Different services, modalities, formats. for samples x
DATA ENGINEERING

It is all about the labels

Training Data
This requires the most ML specific knowledge.
ML
MODEL DEVELOPMENT

Training Data
X
This requires the most ML specific knowledge.
ML
MODEL
DEVELOPMENT
• Feature Engineering
• Model Selection
• Training
• Evaluation
ŷ

Deployment: expose your system

Monitoring: stay adaptive

Business analysis closes the loop

4

Framing ML Problems

FRAMING
"The art of simplifying problems before solving them."
- cite me.
Not everything is an ML problem.
But a lot can be framed as one.
VISION & SCOPING
DATA ENGINEERING
MODEL DEVELOPMENT

Classification versus regression

CLASSIFICATION
0.2
0.8
class 1
class 2
REGRESSION
0.3
Great to enforce classes in X.
Threshold to class
Usually you want to reframe in this direction.
binary
multiclass
#Cardinality
Reframe in this direction if possible.

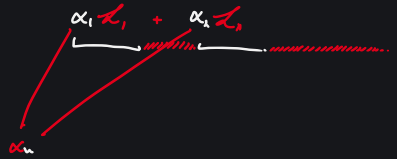
!! Restrain from „buying" this with an increasing number of models.

Hierarchical & Sequential systems are sophisticated but hard to maintain.

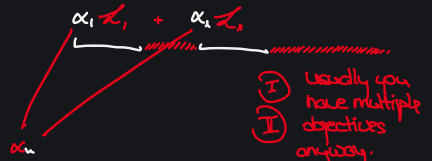
→ Talk is cheap. Go and try those things on MNIST to sharpen your own intuition.

The objective function defines what optimal is

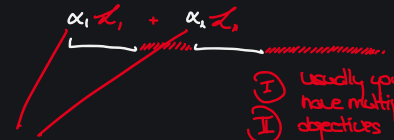
THE EFFECTIVENESS OF DECOUPLING OBJECTIVES.



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THE EFFECTIVENESS OF DECOUPLING OBJECTIVES.



I) Usually you have multiple objectives anyway.

II) This is a clean way to state them explicitly.

Pareto Optimization

Trivial to weight objectives while training.

Everytime you touch is a retrain.

Beautiful opportunity to train two models and adaptively weight during inference.

! Objective Functions require gradients.
For everything else we still need metrics.

5

Mind Versus Data

As data flows through models. During the infrastructure is key
Intelligent architectural designs frozen within the current paradigm. Data-centric.
MODEL success heavily depends on data.
DATA utilization again is tied to compute.
Biggest leverage in managing and improving data Quality and Quantity.

"We don't have better algorithms. We just have better data." - Norvig (Director Search @Google)



Remember how more data is a regularization method, driving generalization of your models?

References