Managing NLP Experiments

Intro lecture

17.04.2025

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Course Goal

and some small goals

The main goal of this course is to help you to get a nice job.

Some other goals

Helping with obligatory classes

As a side effect, this course should help with other classes (mainly SNLP 2).

Helping with the projects for other classes

Treating ML projects from an end-to-end point of view will help you to make projects for other classes.

Helps you to create a portfolio of projects

02

How will we ~~try to~~ achieve our goals?

Our plan

01 Orientation on end-to-end ML

02 Versatility

03 Interview-driven approach

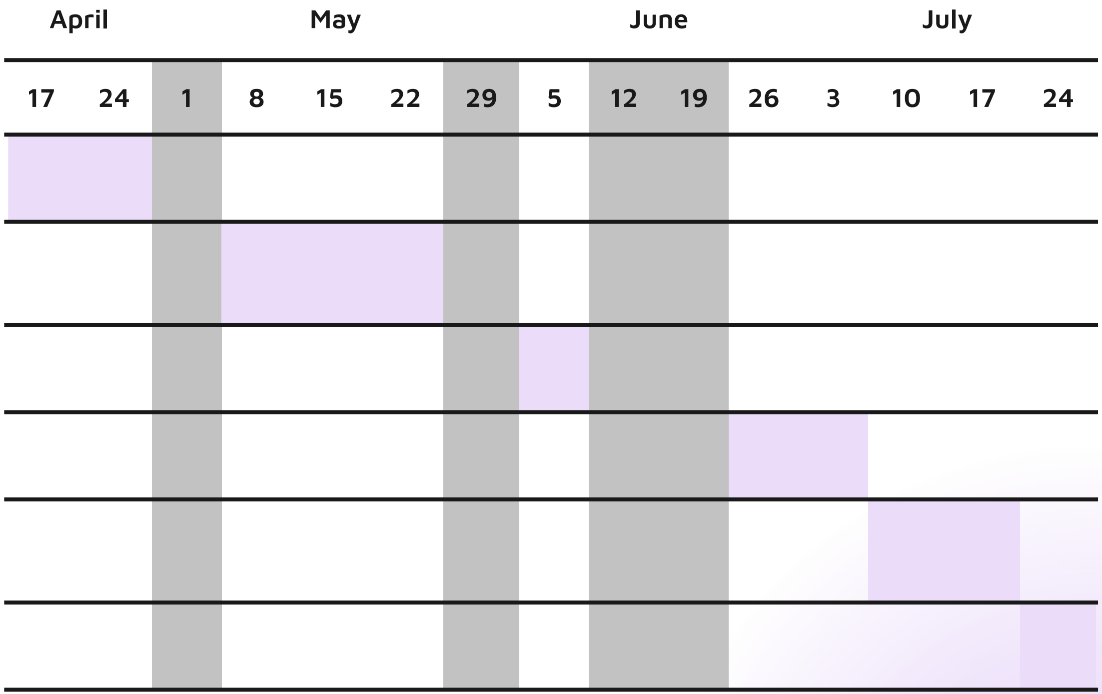
04 Work towards strong project portfolio

05 Course readjustment and targeting

03

Course Structure and Topics

Course Plan



Course Plan

		April		May					June				July			
Module	**Topics**	17	24	1	8	15	22	29	5	12	19	26	3	10	17	24
Introduction	Course Overview, ML Project Design															

Module 0. Introduction

Course Overview

- Overview of the entire course structure.
- Grading.
- Course workflow.
- Comparison of Machine Learning in research versus in production.
- Machine learning use cases.

ML Project Life Cycle

- Requirements for ML Systems.
- Machine learning life cycle and its stages.
- Different tasks in the cycle.
- Skills and knowledge required for solving those tasks.
- Explore various machine learning roles, including ML engineer, applied scientist, data scientist, and other positions.

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Training Data	Sampling, Labeling, Class Imbalance															

Module I. Training Data

Sampling

- Nonprobability Sampling.
- Simple Random Sampling.
- Weighted Sampling.
- Reservoir Sampling.
- Importance Sampling.

Labeling

- Hand Labels (label multiplicity, data lineage).
- Natural Labels.
- Handling the Lack of Labels (weak supervision, semi-supervision, transfer learning, active learning)

Class Imbalance

- Challenges of Class Imbalance
- Handling Class Imbalance (using right evaluation metrics, resampling, algorithm-level methods)

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Data Analysis, Data Visualization	Exploratory Data Analysis, Data Visualization															

Module II. Data Analysis

Exploratory Data Analysis

- Understanding different data types
- Descriptive statistics
- Identifying patterns and relationships (outliers, trends, dependencies)
- Data profiling tools

Data Visualization

- Basics of data visualization
- Most common techniques (histograms, box plots, scatter plots, correlation heatmaps)

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Module III. Feature Engineering

Common Feature Engineering Operations

- Handling Missing Values (deletion, imputation).
- Scaling.
- Discretization.
- Encoding Categorical Features.
- Feature Crossing.
- Discrete and Continuous Positional Embeddings.

Data Leakage

- Common Causes for Data Leakage (time-correlated data, scaling, filling missing values, group leakage, data generation)
- Detecting Data Leakage

Engineering Good Features

- Feature Importance
- Feature Generalization

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Model Development, Offline Evaluation	Model Development, Offline Evaluation															
Exam																

Module IV

Model Development

- Evaluating ML Models
- Ensembles
- Experiment Tracking and Versioning
- Distributed Training
- AutoML

Offline Evaluation

- Baselines
- Evaluation Methods

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Grading

Exam

- Exam is obligatory.
- The exam will be based on theoretical questions which you will be getting for every individual topic.
- You get 3 CP.
- You entire grade for the course is based on the exam.

Project

- You can get extra 3 CP.
- It is a programing project based on the skills which you learn in this course.
- You will have to write a short paper about it (4-5 pages) in latex.
- You grade for the course will be based both on the exam (1/2) and on the project (1/2).

04
Course Workflow

Course Workflow

Materials

- Questions about the topic.
- Topic cheat sheet.
- Notes about the lecture in Markdown (strongly recommended to use Obsidian)
- Lecture slides.
- Practical examples.

Lecture

- Topic presentation.
- Practical showcases.

05

ML in Research Versus in Production

	Research	Production
Requirements	State-of-the-art model performance on benchmark datasets	Different stakeholders have different requirements
Computational priority	Fast training	Fast inference, low latency
Data	Static	Constantly shifting
Fairness	Often not a focus	Must be considered
Interpretability	Often not a focus	Must be considered

Case

Mobile app that recommends restaurants to users:

- Makes money by charging restaurants a 10% service fee.
- The project involves ML engineers, salespeople, product managers, infrastructure engineers, and a manager.

Different stakeholders

ML engineers

- Want a model that recommends restaurants that users will most likely order from.
- Believe they can do so by using a more complex model with more data.

Different stakeholders

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Sales team

- Wants a model that recommends the more expensive restaurants since these restaurants bring in more service fees.

Different stakeholders

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Product team

- Notices that every increase in latency leads to a drop in orders through the service.
- They want a model that can return the recommended restaurants in less than 100 milliseconds.

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ML platform team

- As the traffic grows, this team has been woken up in the middle of the night because of problems with scaling their existing system.
- They want to hold off on model updates to prioritize improving the ML platform.

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Manager

- Wants to maximize the margin, and one way to achieve this might be to let go of the ML team.

ML platform team

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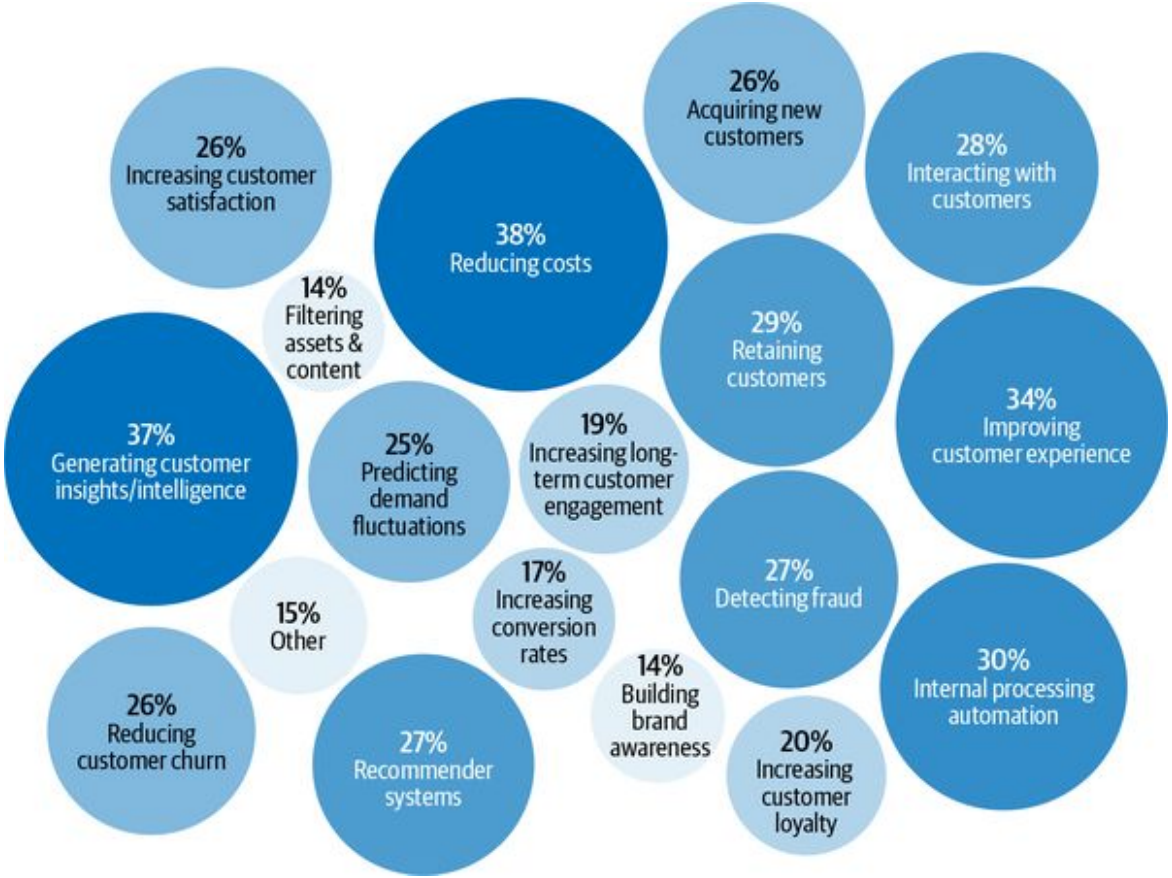
ML Use Cases in the enterprise

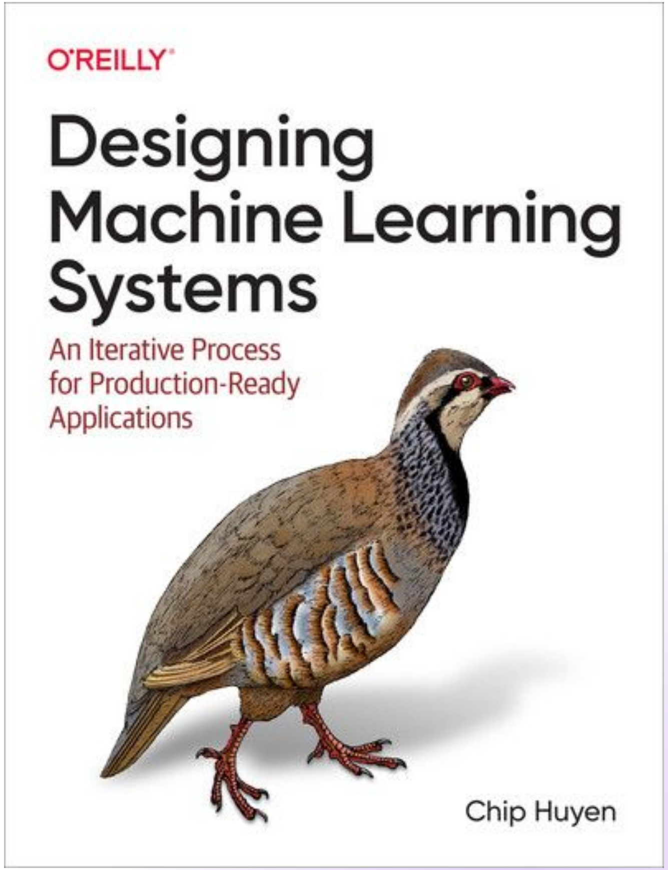


2020 state of enterprise machine learning. Source: Adapted from an image by Algorithmia

06
Literature

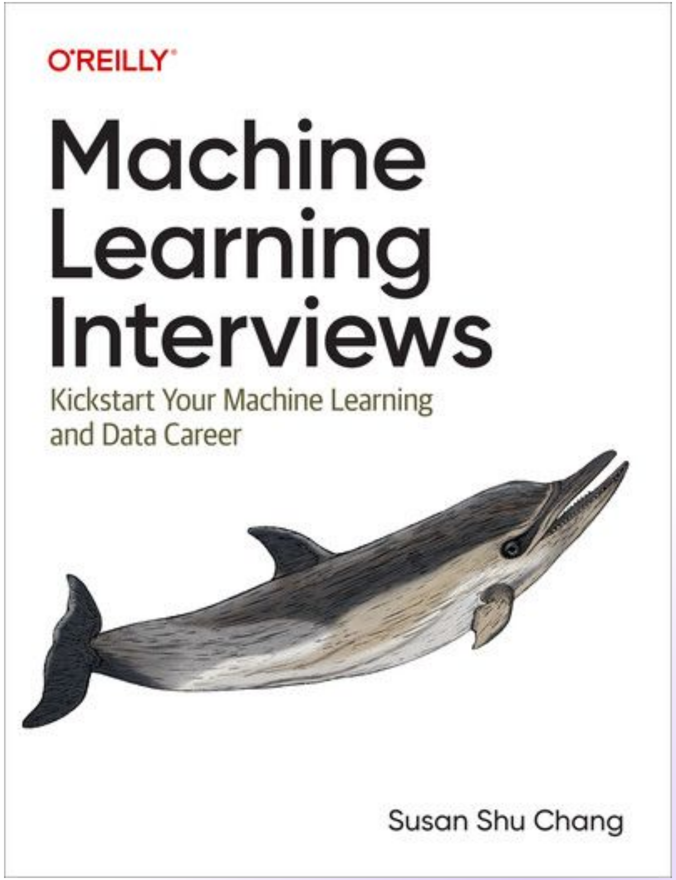
Topics

- Data Engineering Fundamentals
- Training Data
- Feature Engineering
- Model Development And Offline Evaluation
- Model Deployment And Prediction Service
- Data Distribution Shifts and Monitoring
- Continual Learning And Test in Production
- Infrastructure and tooling for ML Ops



Topics

- Machine Learning Roles And The Interview Process
- Machine Learning Job Application And Resume
- Technical Interview: Machine Learning Algorithms
- Technical Interview: Model Training And Evaluation
- Technical Interview: Coding
- Technical Interview: Model Deployment And End-To-End ML
- Behavioral Interviews
- Tying It All Together: Your Interview Roadmap
- Post-Interview And Follow-Up



Thanks!