Stanford University

CS 329P : Practical Machine Learning (2021 Fall)

1.1 Course Introduction

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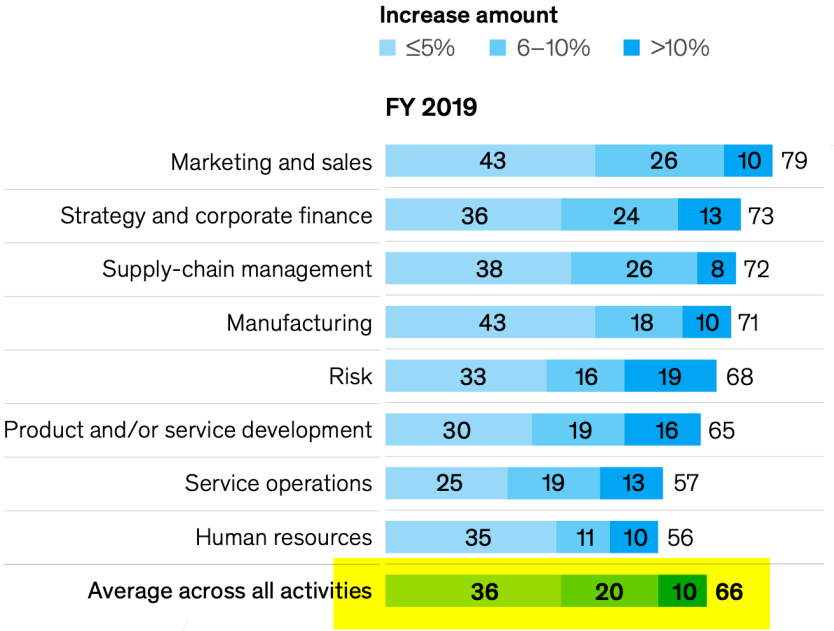
https://c.d2l.ai/stanford-cs329p

Machine Learning (ML) in Industry

- A decade ago ML was mainly used by "Big Tech"
- It's common for companies using ML to drive revenues
  - Top segments are: high-tech, automotive, manufacturing, retail, finance, healthcare
  - Covid-19 accelerated this process

Revenue increase from AI adoption in the previous year (source McKinsey)

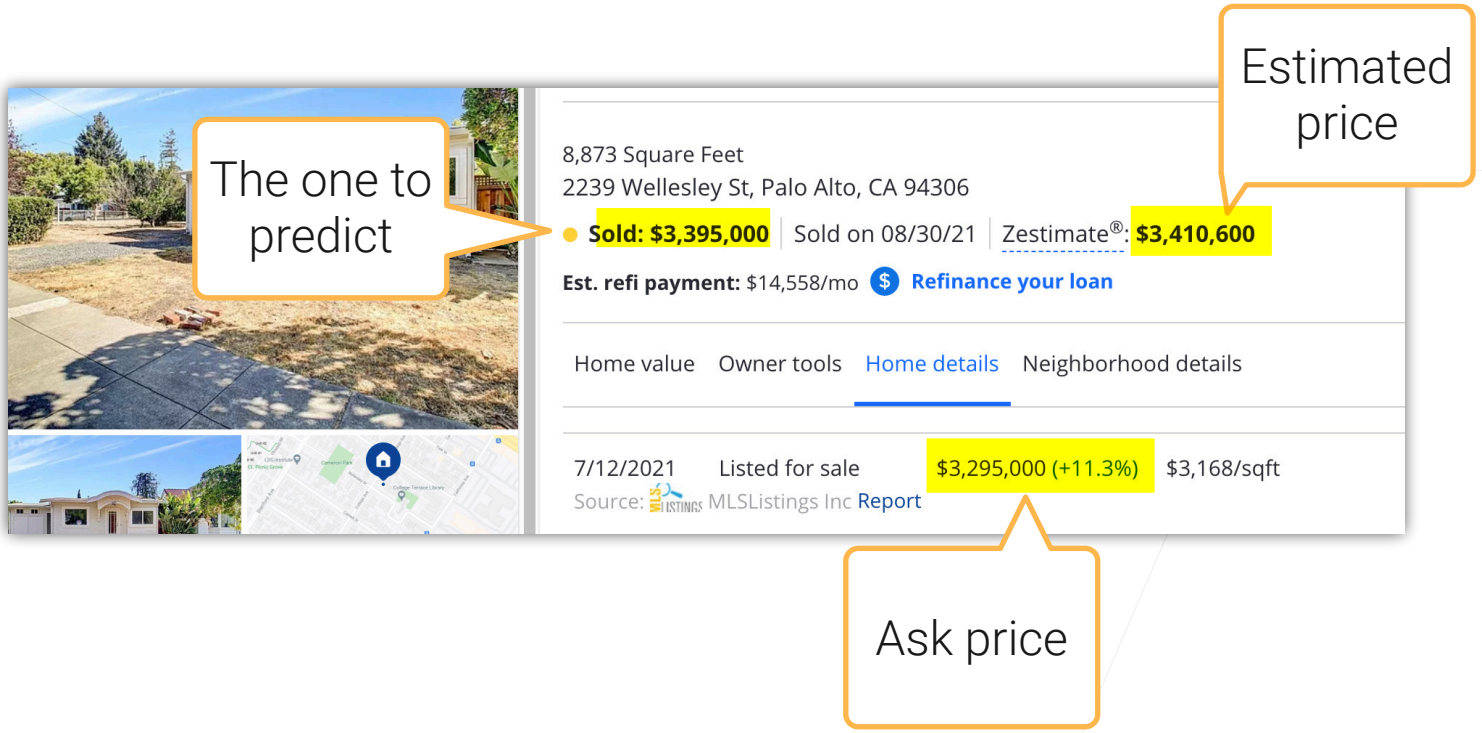


Industrial ML Applications

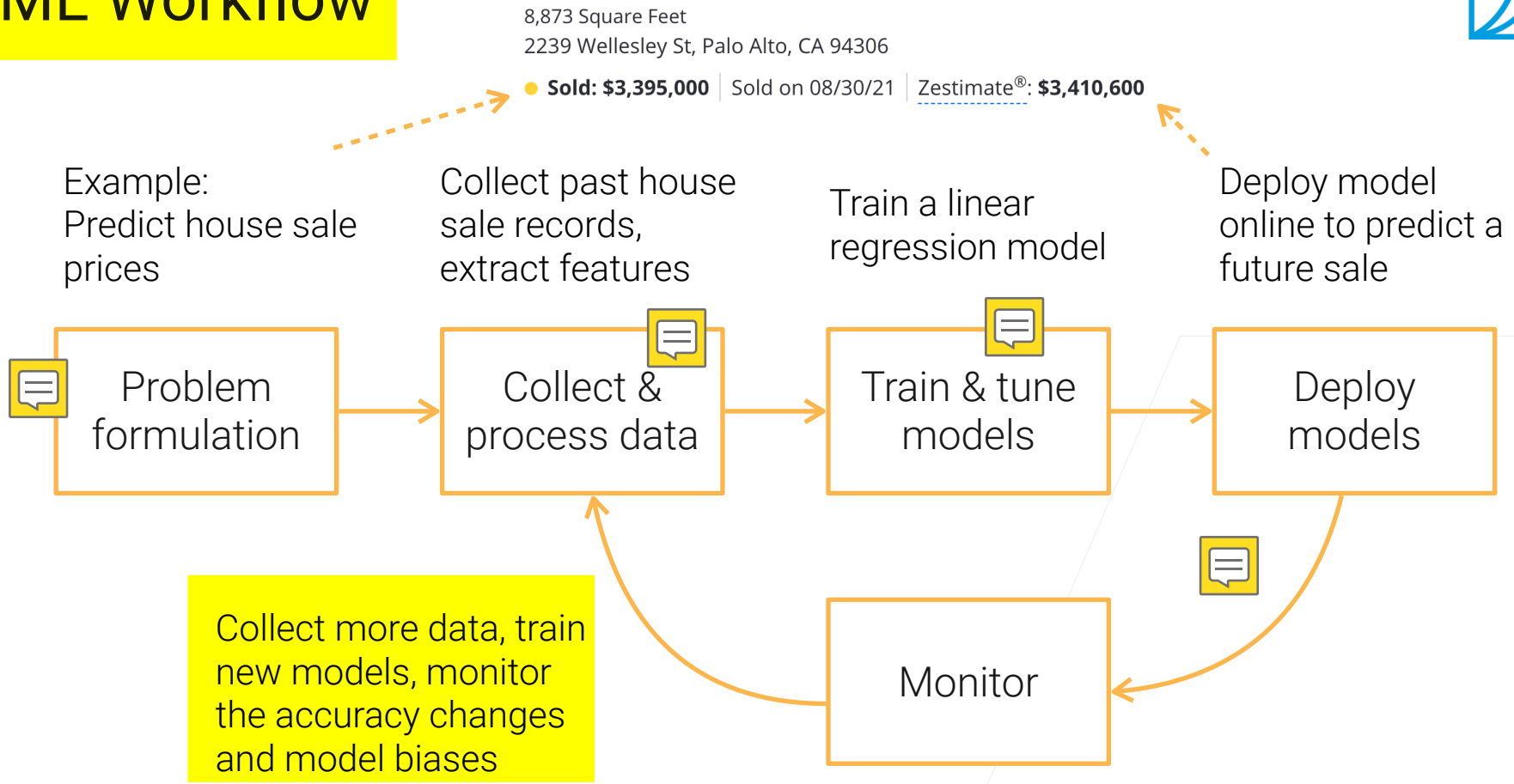
Manufacturing		Predictive maintenance, quality control
Retail		Recommendation, chatbot, demand forecasting
Healthcare		Alerts from real-time patient data, disease identification
Finance		Fraud detection, application processing
Automobile		Breakdown prediction, self-driving

House Sales Prediction

- The goal is to predict the bid price for the winning buyer



ML Workflow


8,873 Square Feet
2239 Wellesley St, Palo Alto, CA 94306
Sold: $3,395,000 | Sold on 08/30/21 | Zestimate®: $3,410,600
Example: Predict house sale prices
Collect past house sale records, extract features
Train a linear regression model
Deploy model online to predict a future sale
Problem formulation
Collect & process data
Train & tune models
Deploy models
Monitor
Collect more data, train new models, monitor the accuracy changes and model biases

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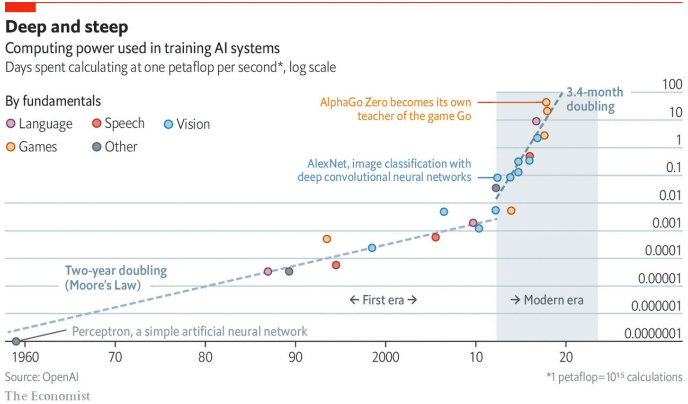
Challenges at ML stages

- Formulate problem: focus on the most impactful industrial problems
- Data: high-quality data is scarce, privacy issues
- Train models: ML models are more and more complex, data-hungry, expensive
- Deploy models: heavy computation is not suitable for real-time inference
- Monitor: data distributions shifts, fairness issues



Course Topics

- Techniques a data scientist needs but often not taught in university ML/stats/programming courses

Data

- Collect/ preprocess data
- Covariate/ concepts/label shifts
- Data beyond IID

Train

- Model validation/ combinations/ tuning
- Transfer learning
- Multi-modality

Deploy

- Model deployment
- Distillation

Monitor

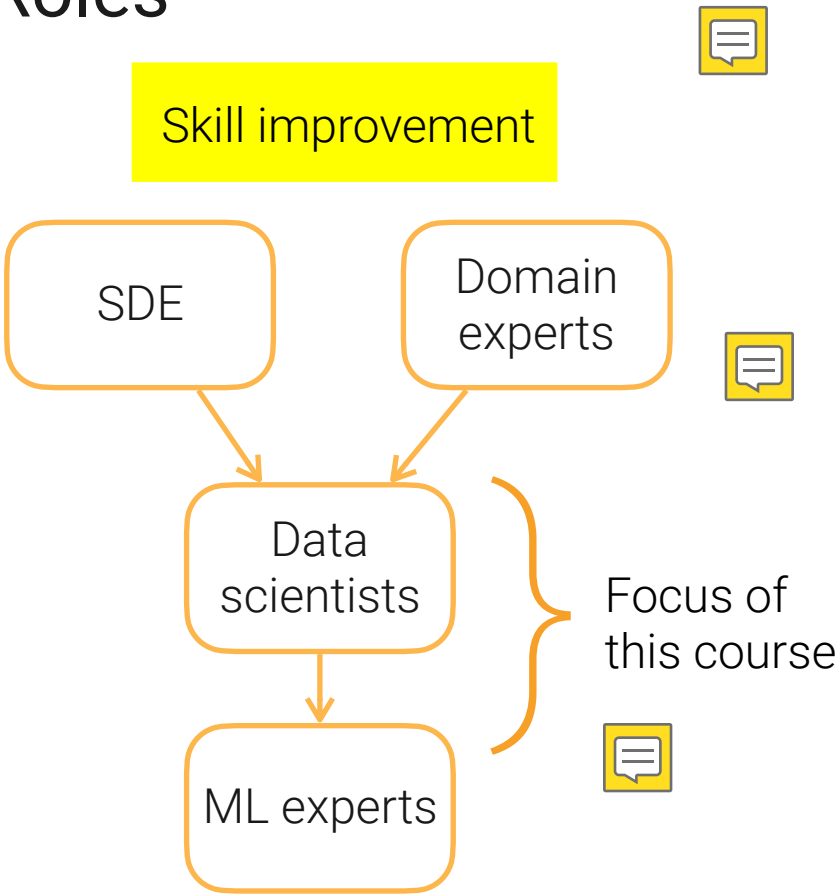
- Fairness
- Explainability

Roles

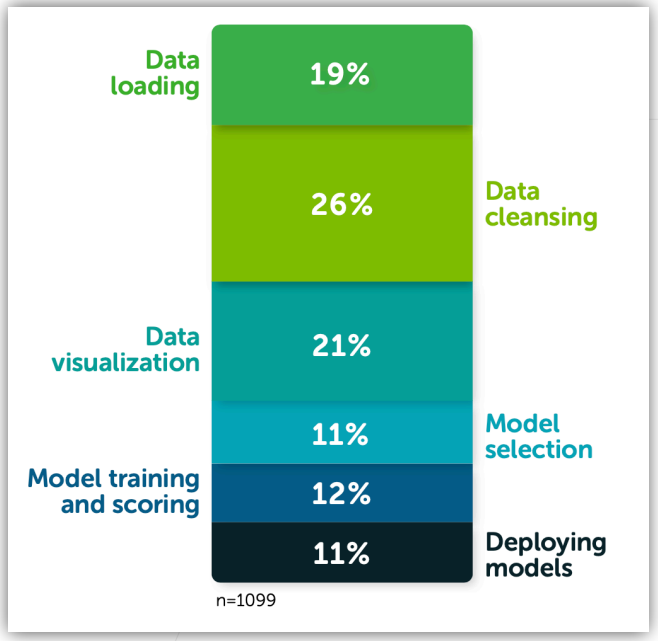
- Domain experts: have business insights, know what data is important and where to find it, identify the real impact of a ML model
- Data scientists: full stack on data mining, model training and deployment

- ML experts: customize SOTA ML models
- SDE: develop/maintain data pipelines, model training and serving pipelines

Roles



How data scientists spent their time (source: Anaconda survey 2020)



Summary

- ML has become a staple of modern business.
- A ML workflow includes: formulating the problem, preparing data, training and deploying ML models, monitoring
- This course will teach technologies a data scientist needs in each ML workflow stage