Software Engineering for ML/AI

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Administrivia

- Homework 2 (Code Artifacts) due today.

Learning goals

- Identify differences between traditional software development and development of ML systems.
- Understand the stages that comprise the typical ML development pipeline.
- Identify challenges that must be faced within each stage of the typical ML development pipeline.

Participation Survey

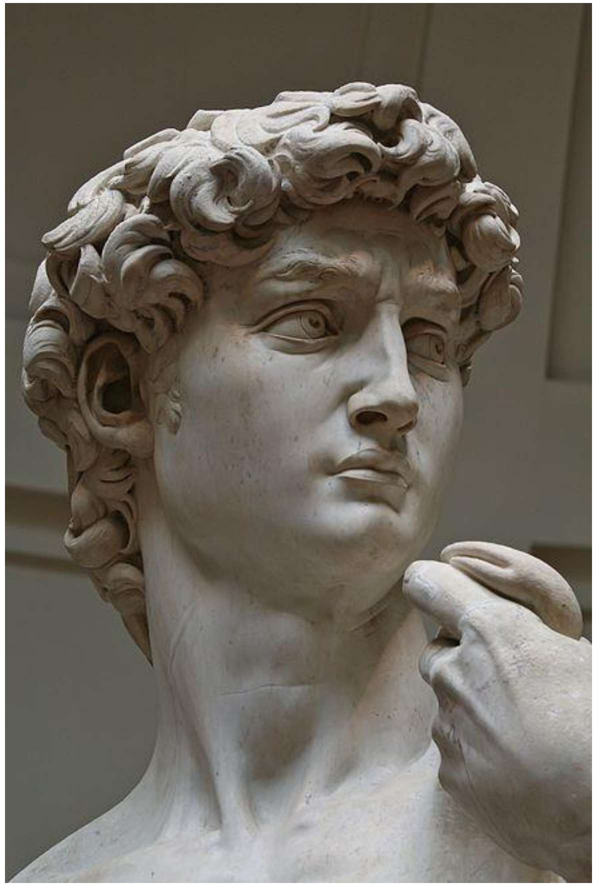
- **YES** in Zoom:
  "I've a taken machine learning course."

- **NO** in Zoom:
  "I have not taken a machine learning course."

Software Engineering and ML

Traditional Software Development

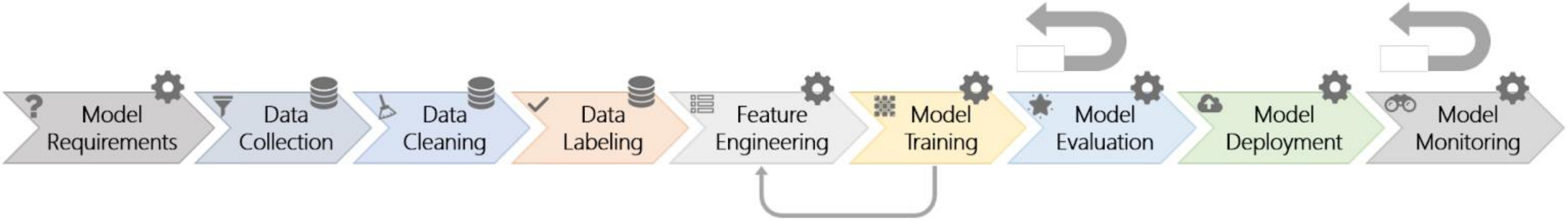
"It is easy. You just chip away the stone that doesn't look like David." – (probably not) Michelangelo



ML Development

- Observation
- Hypothesis
- Predict
- Test
- Reject or Refine Hypothesis

Microsoft's view of Software Engineering for ML



Three Fundamental Differences:

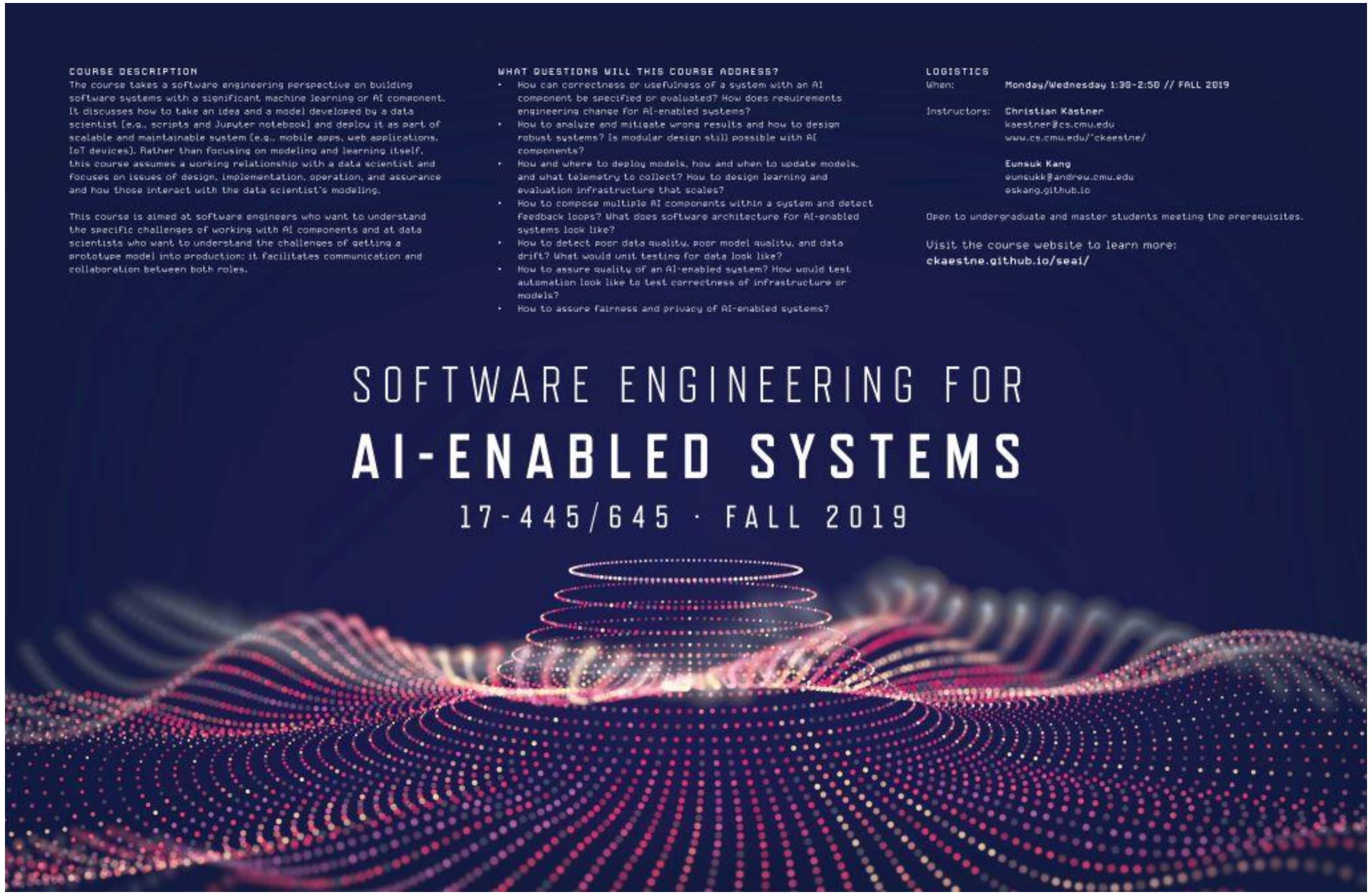
- Data discovery and management
- Customization and Reuse
- No incremental development of model itself

Case study developed by

Christian Kästner

https://ckaestne.github.io/seai/

CASE STUDY



WHAT CHALLENGES ARE THERE IN BUILDING AND DEPLOYING ML?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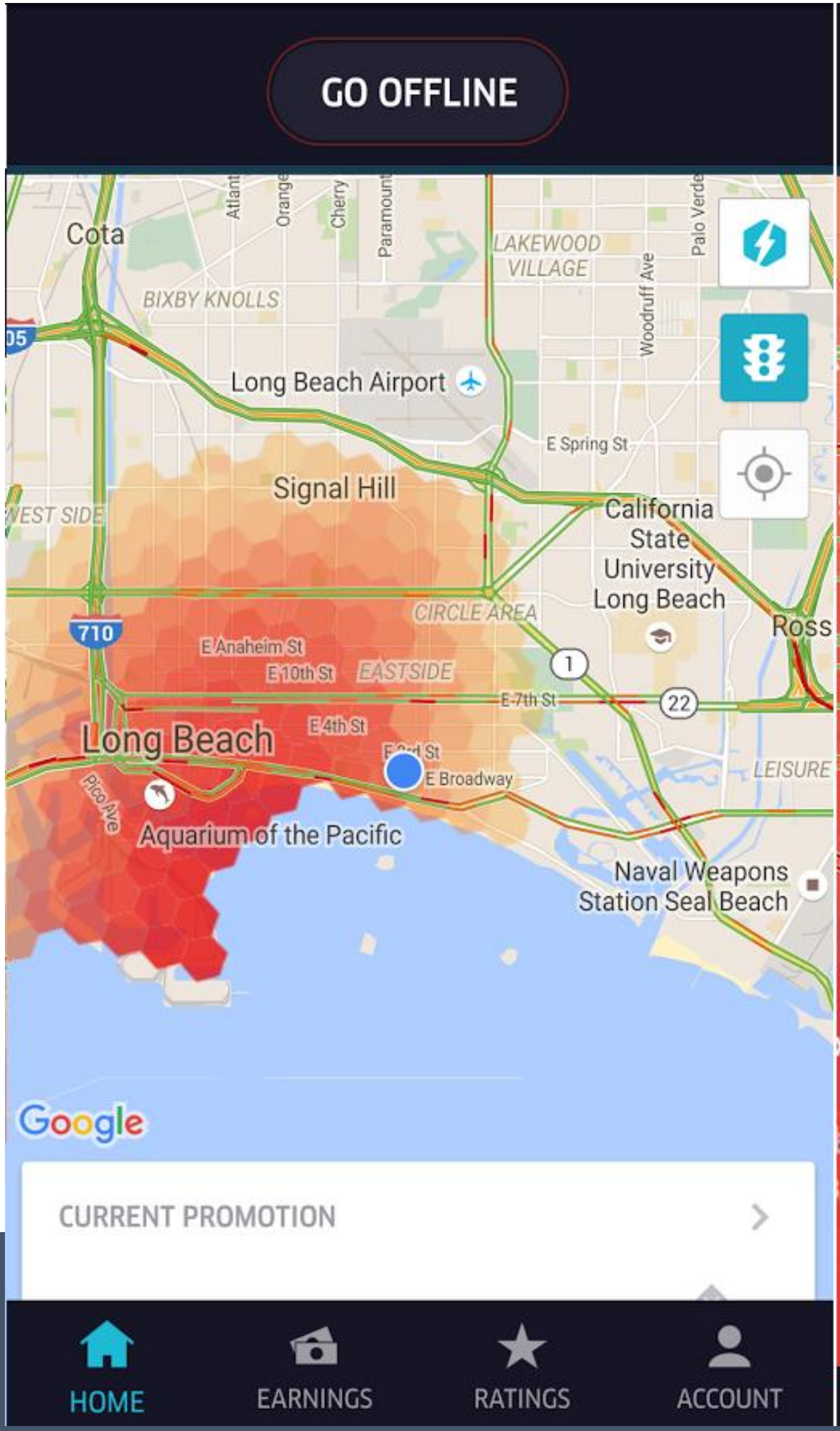
TIBETAN INDIAN NEPALI FOOD
POTALA
명동교자
아하 노래방
POTALA RESTAURANT
빤달빤달
鸡肋
タッカルビ
DAKGALBI
명동본점 2F
제임스 치즈 등갈비
MINI BEER PUB
LE PIANO
홍콩반점
부대찌개
정성본
김밥
명동교자
수제 돈까스
Homemade pork cutlet
SKIN
노래방

Qualities of Interest?

A

B

C



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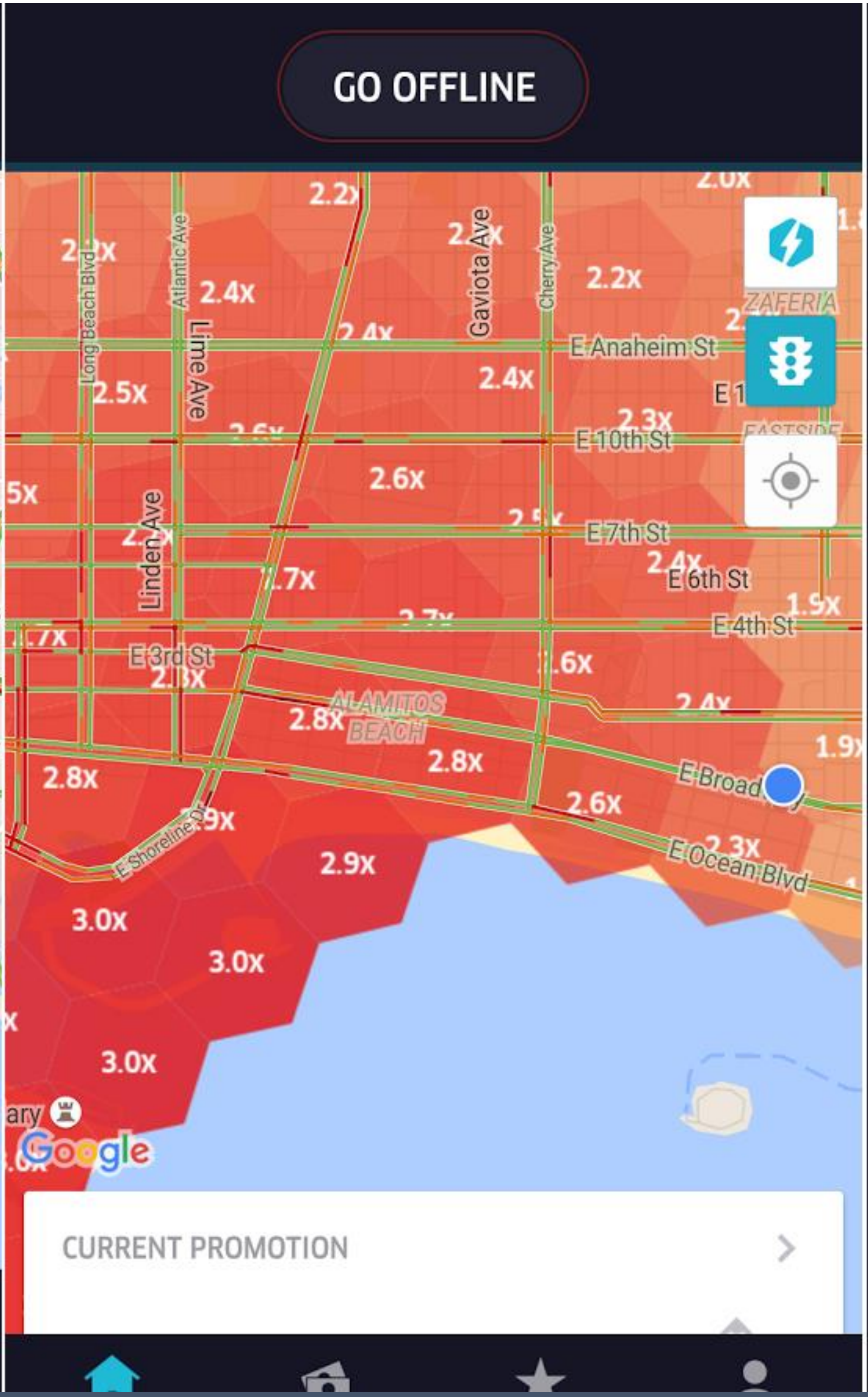

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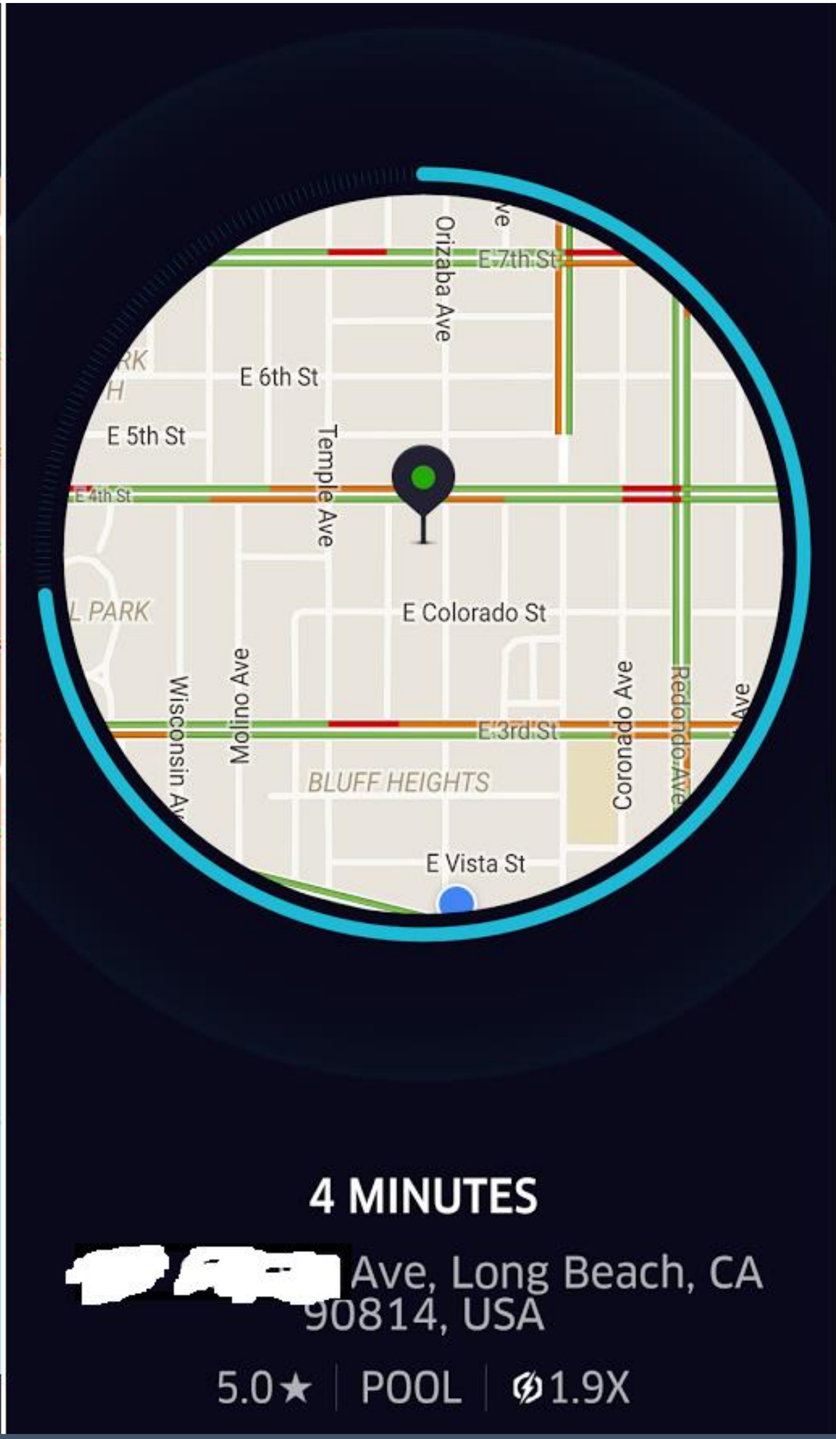

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E Vista St
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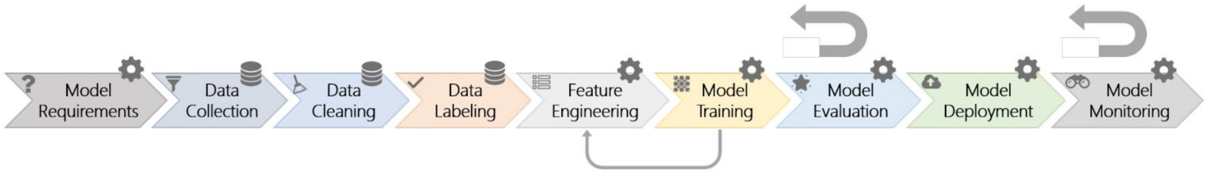
5.0★ | POOL | 1.9X

Qualities of Interest?

MACHINE LEARNING PIPELINE

Typical ML Pipeline

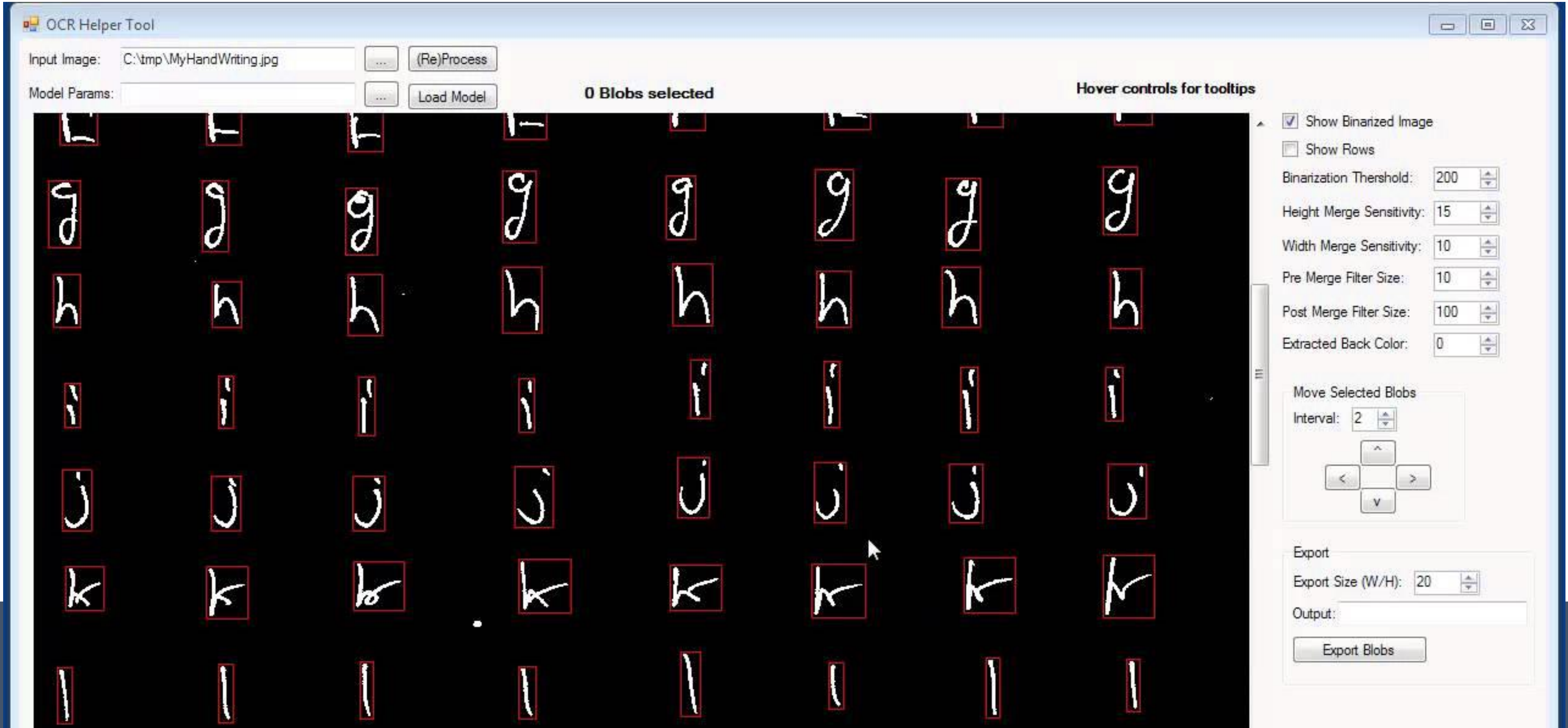


- Static
  - Get labeled data (data collection, cleaning and, labeling)
  - Identify and extract features (feature engineering)
  - Split data into training and evaluation set
  - Learn model from training data (model training)
  - Evaluate model on evaluation data (model evaluation)
  - Repeat, revising features
- with production data
  - Evaluate model on production data; monitor (model monitoring)
  - Select production data for retraining (model training + evaluation)
  - Update model regularly (model deployment)

Example Data

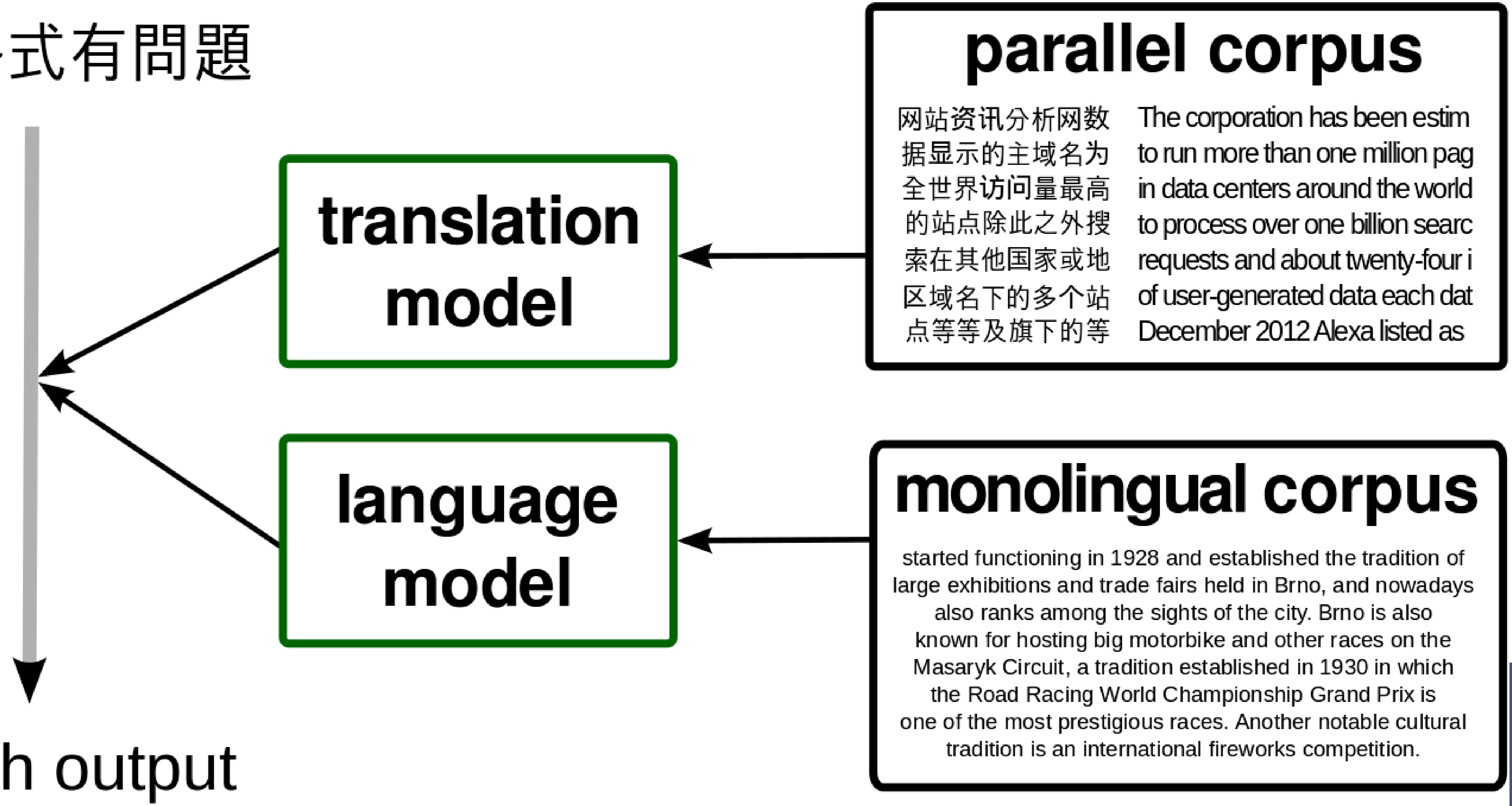
UserId	PickupLocation	TargetLocation	OrderTime	PickupTime
5	….	…	18:23	18:31
…				

Example Data



Learning Data

似乎格式有問題

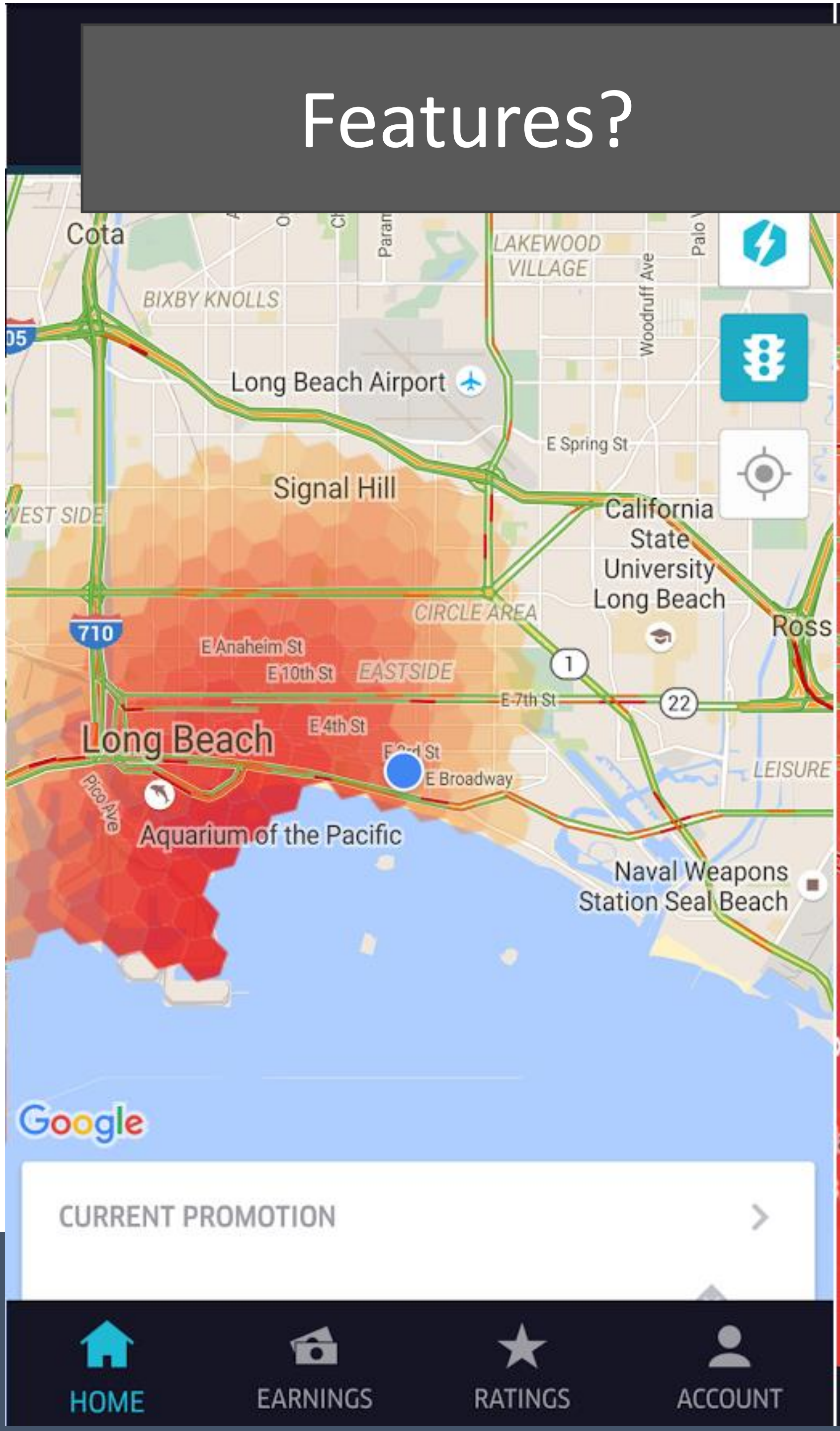


Feature Engineering

- Identify parameters of interest that a model may learn on
- Convert data into a useful form
- Normalize data
- Include context
- Remove misleading things
- In OCR/translation:

Features?

Features?



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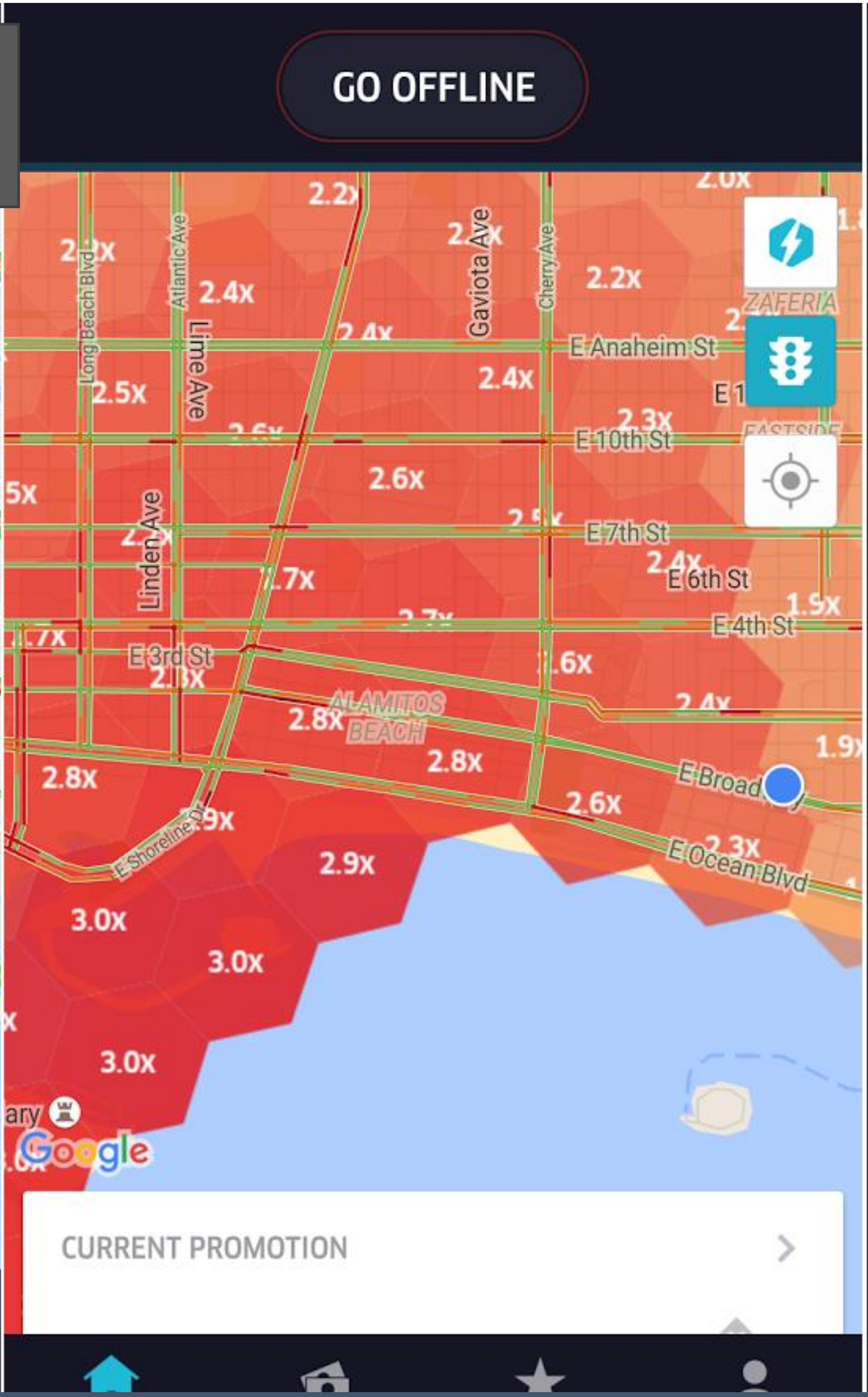

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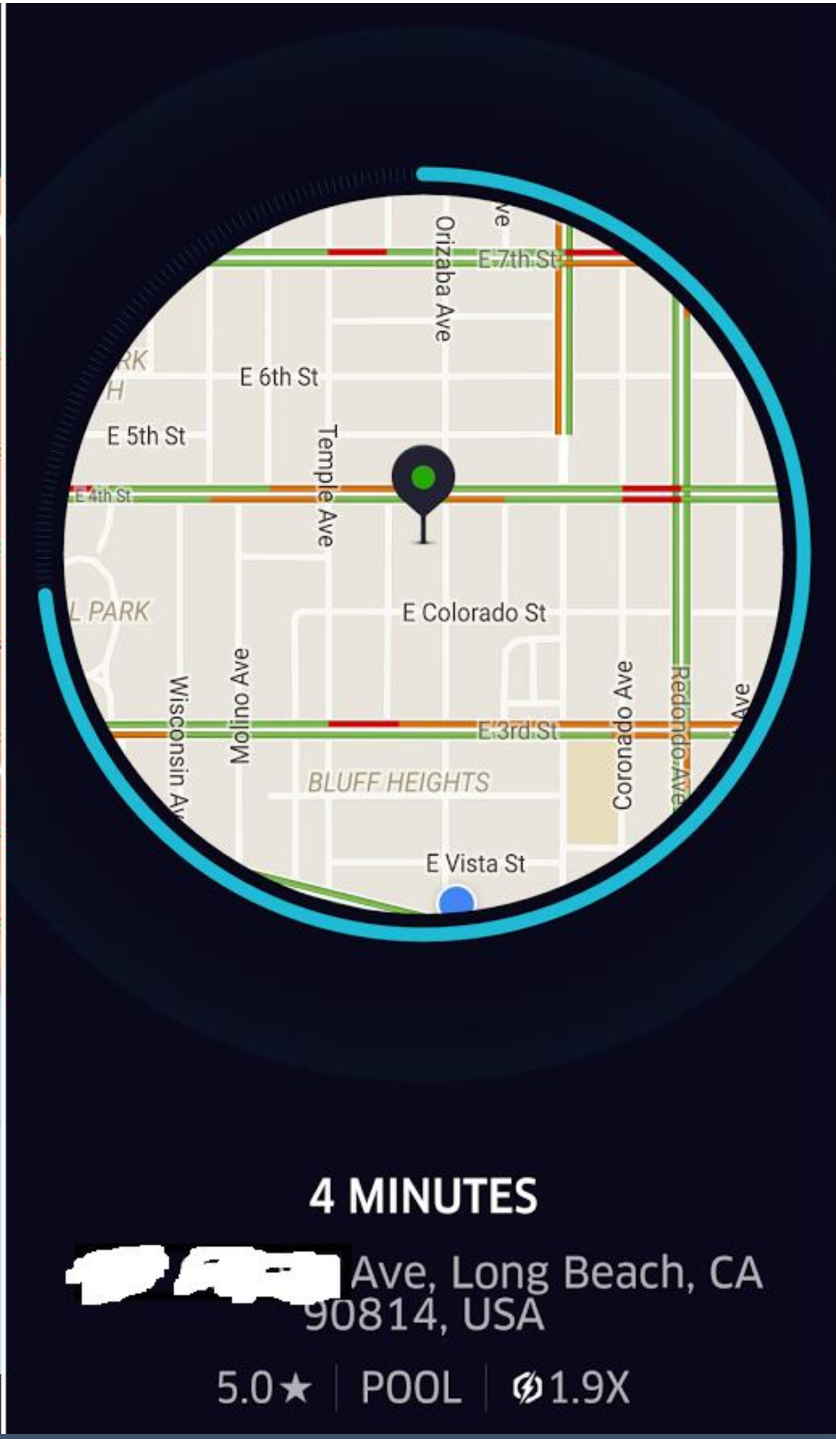

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Feature Extraction

- In surge prediction:
  - Location and time of past surges
  - Events
  - Number of people traveling to an area
  - Typical demand curves in an area
  - Demand in other areas

Data Cleaning

- Removing outliers
- Normalizing data
- Missing values
- …

Learning

- Build a predictor that best describes an outcome for the observed features

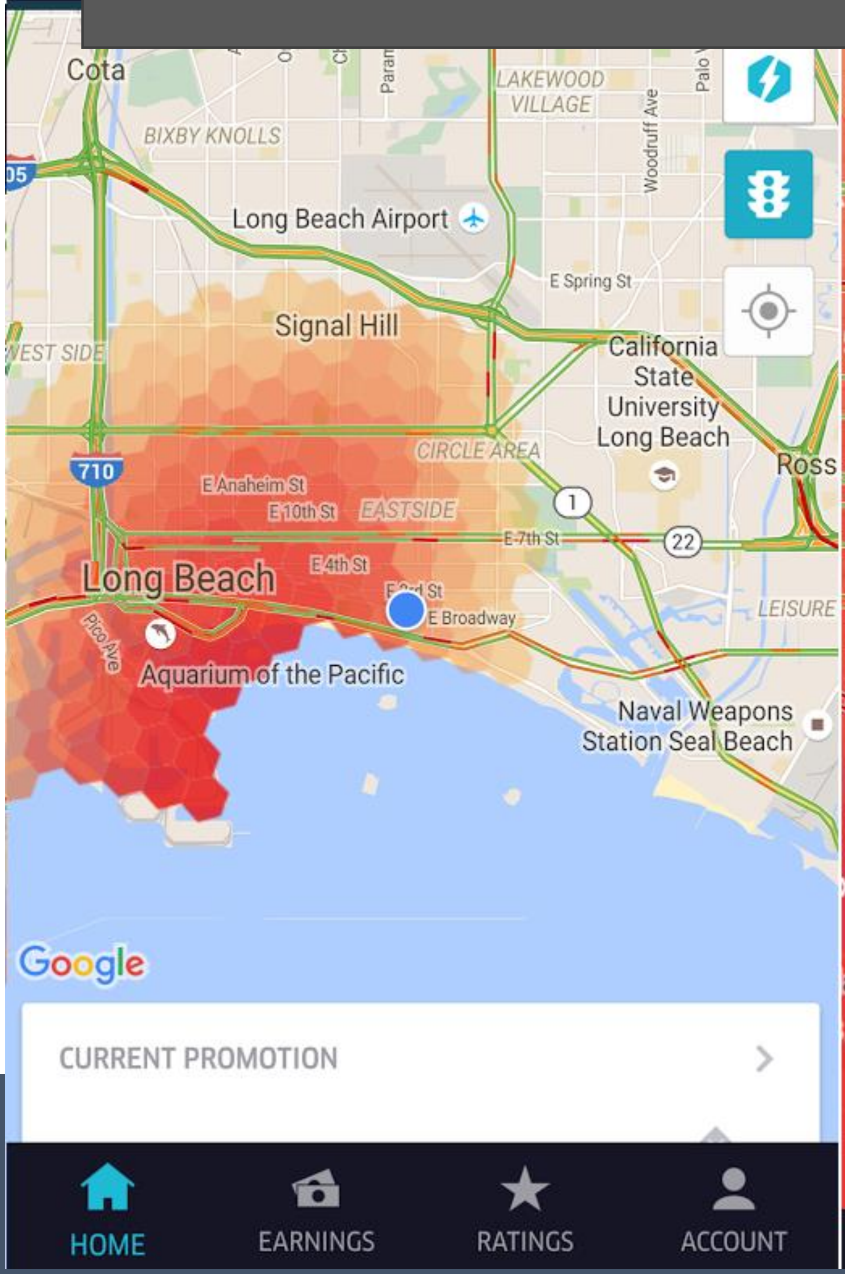
Evaluation

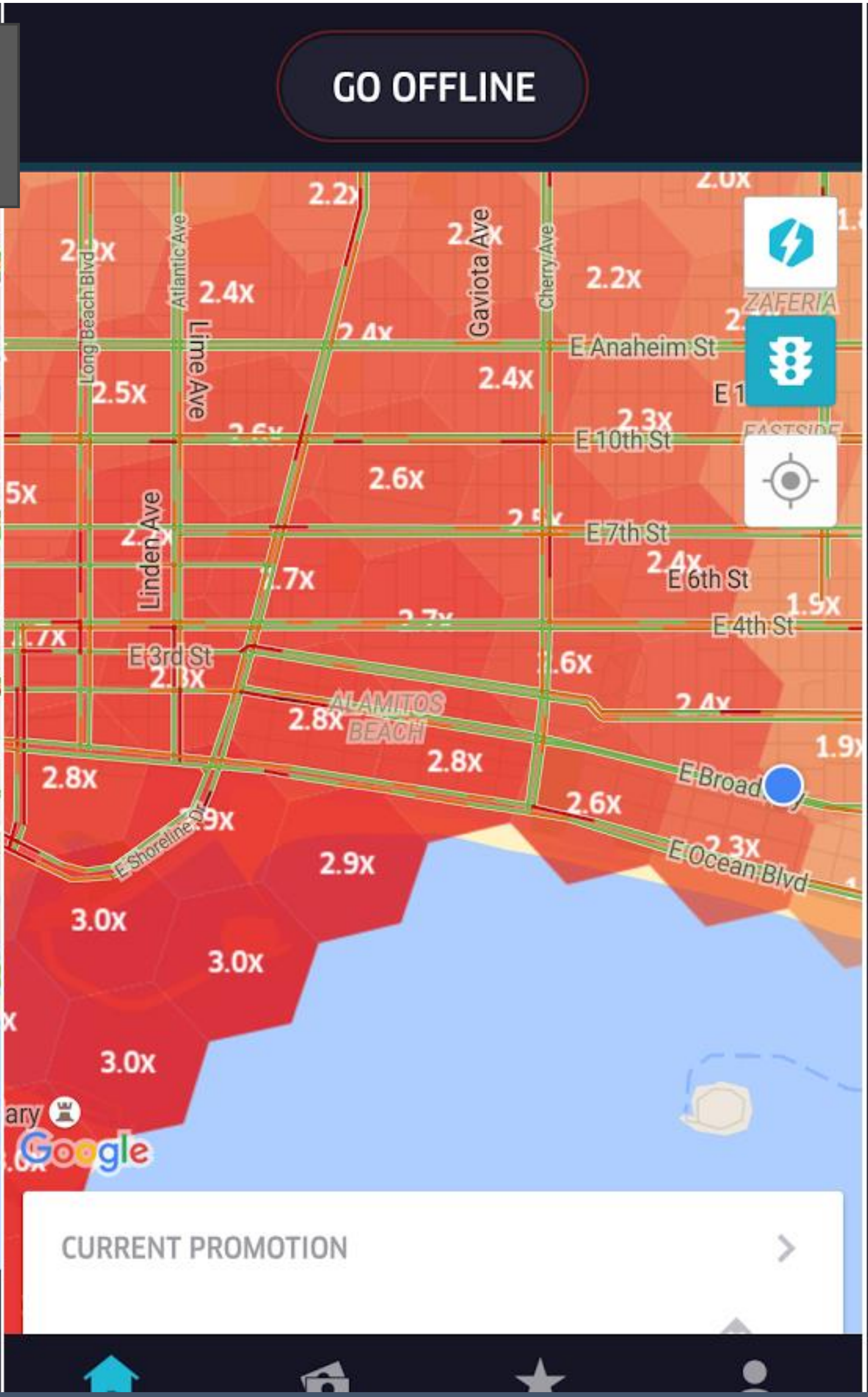
- Prediction accuracy on learned data vs
- Prediction accuracy on unseen data
  - Separate learning set, not used for training

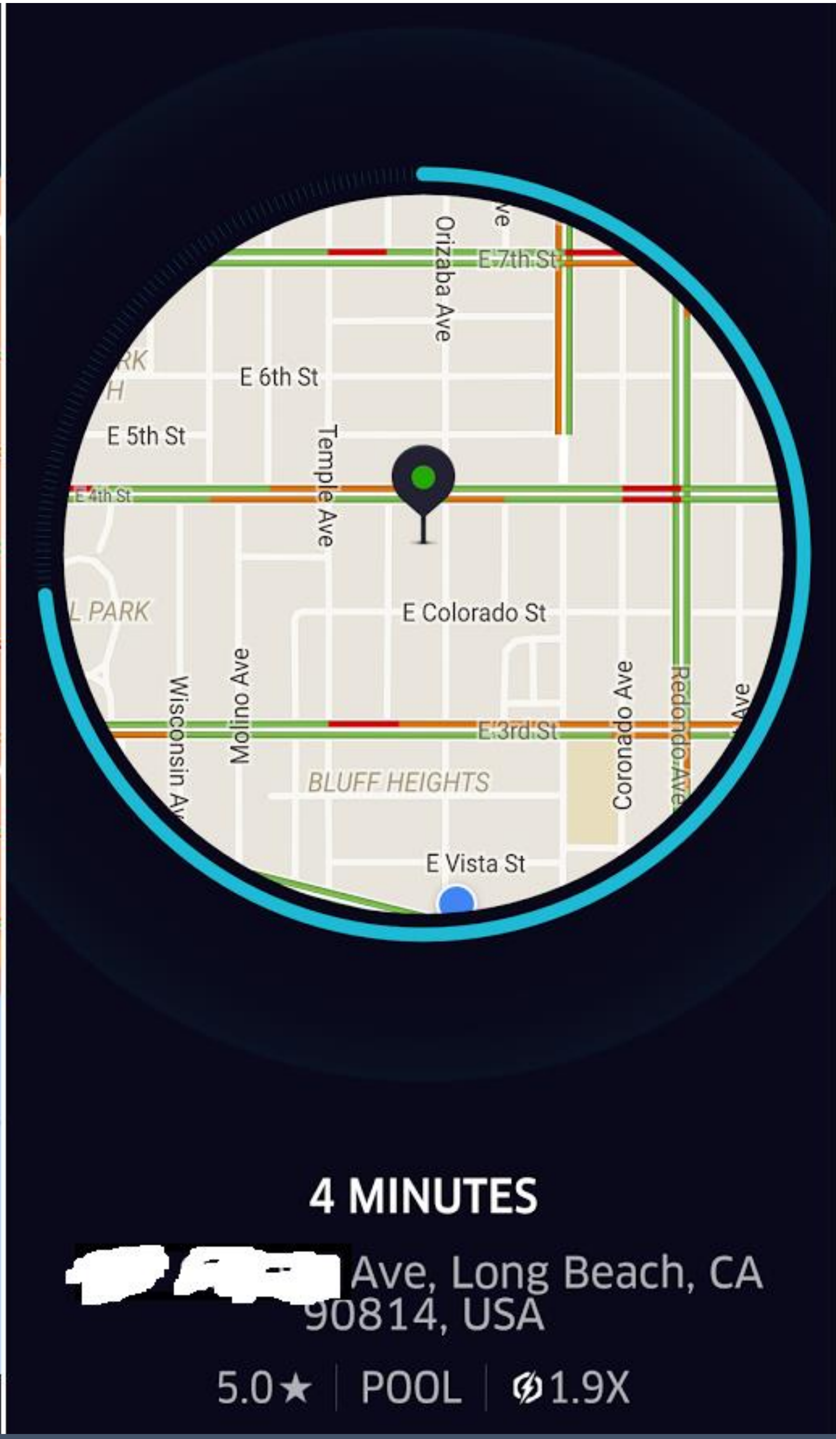
- For binary predictors: false positives vs. false negatives, precision vs. recall
- For numeric predictors: average (relative) distance between real and predicted value
- For ranking predictors: topK etc

Evaluation Data?

Evaluation Data?







Learning and Evaluating in Production

- Beyond static data sets, **build telemetry**
- Design challenge: identify mistakes in practice

- Use sample of live data for evaluation
- Retrain models with sampled live data regularly
- Monitor performance and intervene

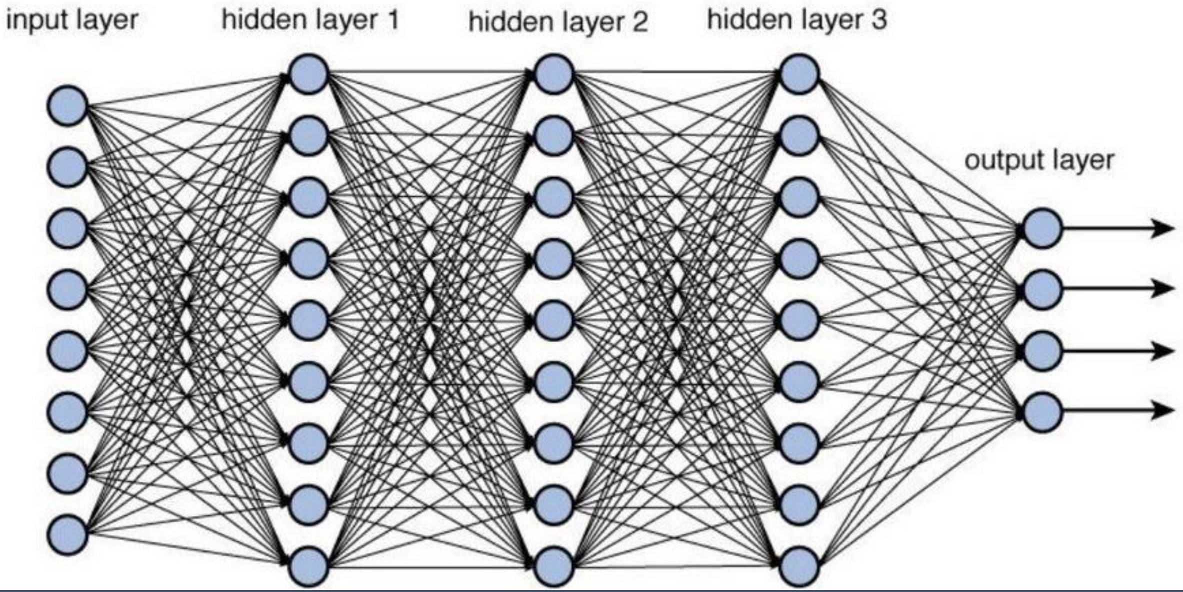
ML COMPONENT TRADEOFFS

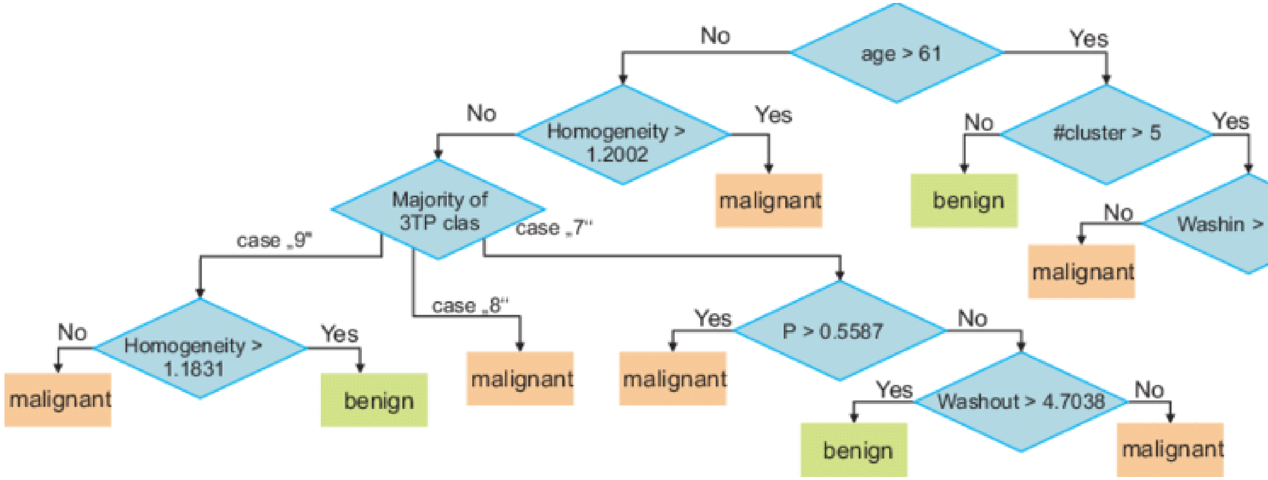
Qualities of ML Components

- Accuracy
- Capabilities (e.g. classification, recommendation, clustering…)
- Amount of training data needed
- Inference latency
- Learning latency; incremental learning?
- Model size
- Explainable? Robust?
- …

Understanding Capabilities and Tradeoffs

- Deep Neural Networks
- Decision Trees





SYSTEM ARCHITECTURE CONSIDERATIONS

Where should the model live?

Glasses

Phone

Cloud

OCR Component

Translation Component

Where should the model live?

Car

Phone

Cloud

Surge Prediction

Considerations

- How much data is needed as input for the model?
- How much output data is produced by the model?
- How fast/energy consuming is model execution?
- What latency is needed for the application?
- How big is the model? How often does it need to be updated?
- Cost of operating the model? (distribution + execution)
- Opportunities for telemetry?
- What happens if users are offline?

Typical Designs

- Static intelligence in the product
  - difficult to update
  - good execution latency
  - cheap operation
  - offline operation
  - no telemetry to evaluate and improve
- Client-side intelligence
  - updates costly/slow, out of sync problems
  - complexity in clients
  - offline operation, low execution latency

Typical Designs

- Server-centric intelligence
  - latency in model execution (remote calls)
  - easy to update and experiment
  - operation cost
  - no offline operation
- Back-end cached intelligence
  - precomputed common results
  - fast execution, partial offline
  - saves bandwidth, complicated updates
- Hybrid models

Other Considerations

- Coupling of ML pipeline parts
- Coupling with other parts of the system
- Ability for different developers and analysists to collaborate
- Support online experiments
- Ability to monitor

Reactive System Design Goals

- Responsive
  - consistent, high performance
- Resilient
  - maintain responsive in the face of failure, recovery, rollback
- Elastic
  - scale with varying loads

Common Design Strategies

- Message-driven, lazy computation, functional programming
  - asynchronous, message passing style
- Replication, containment, supervision
  - replicate and coordinate isolated components, e.g. with containers
- Data streams, “infinite data”, immutable facts
  - streaming technologies, data lakes

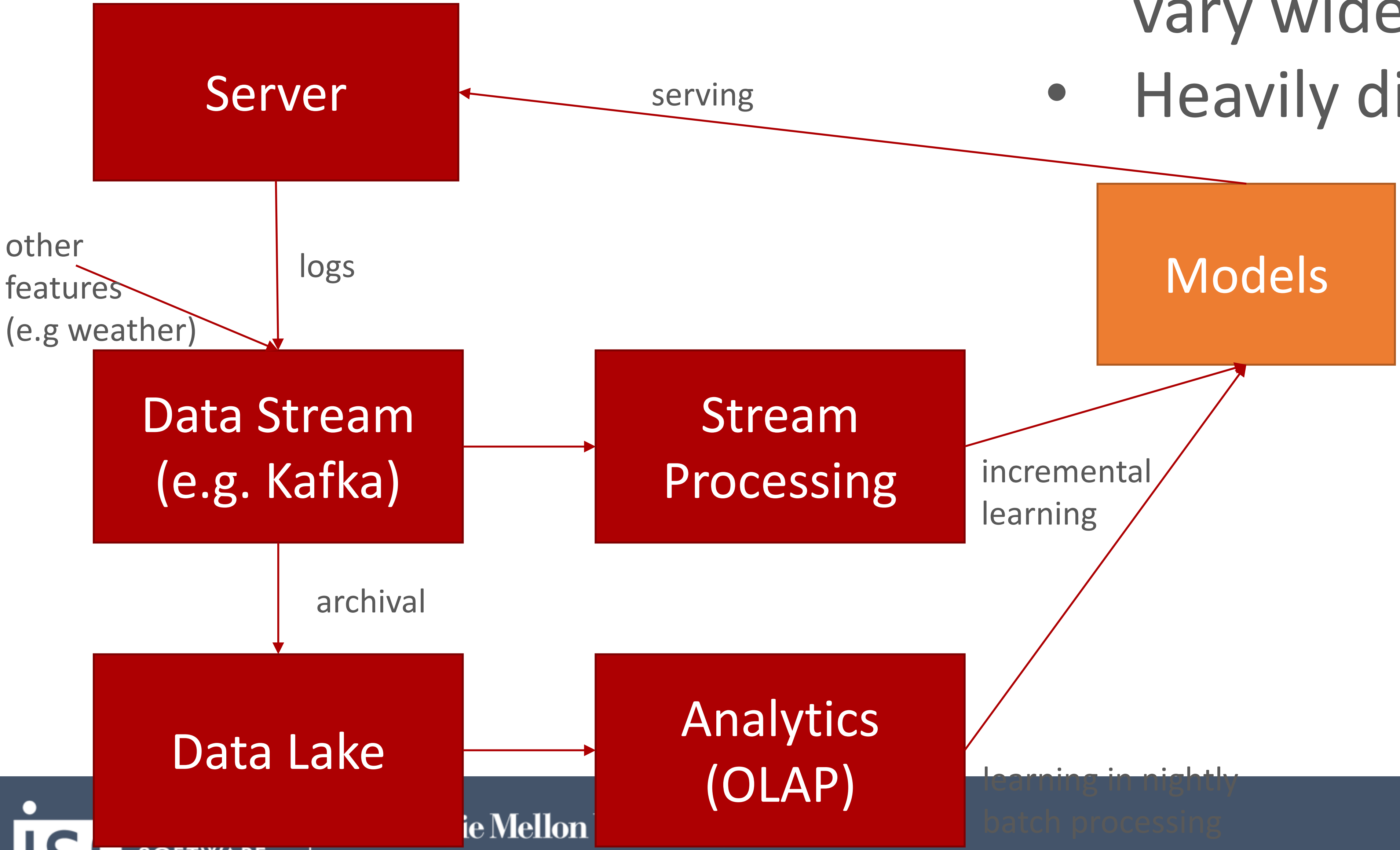
- See “big data systems” and “cloud computing”

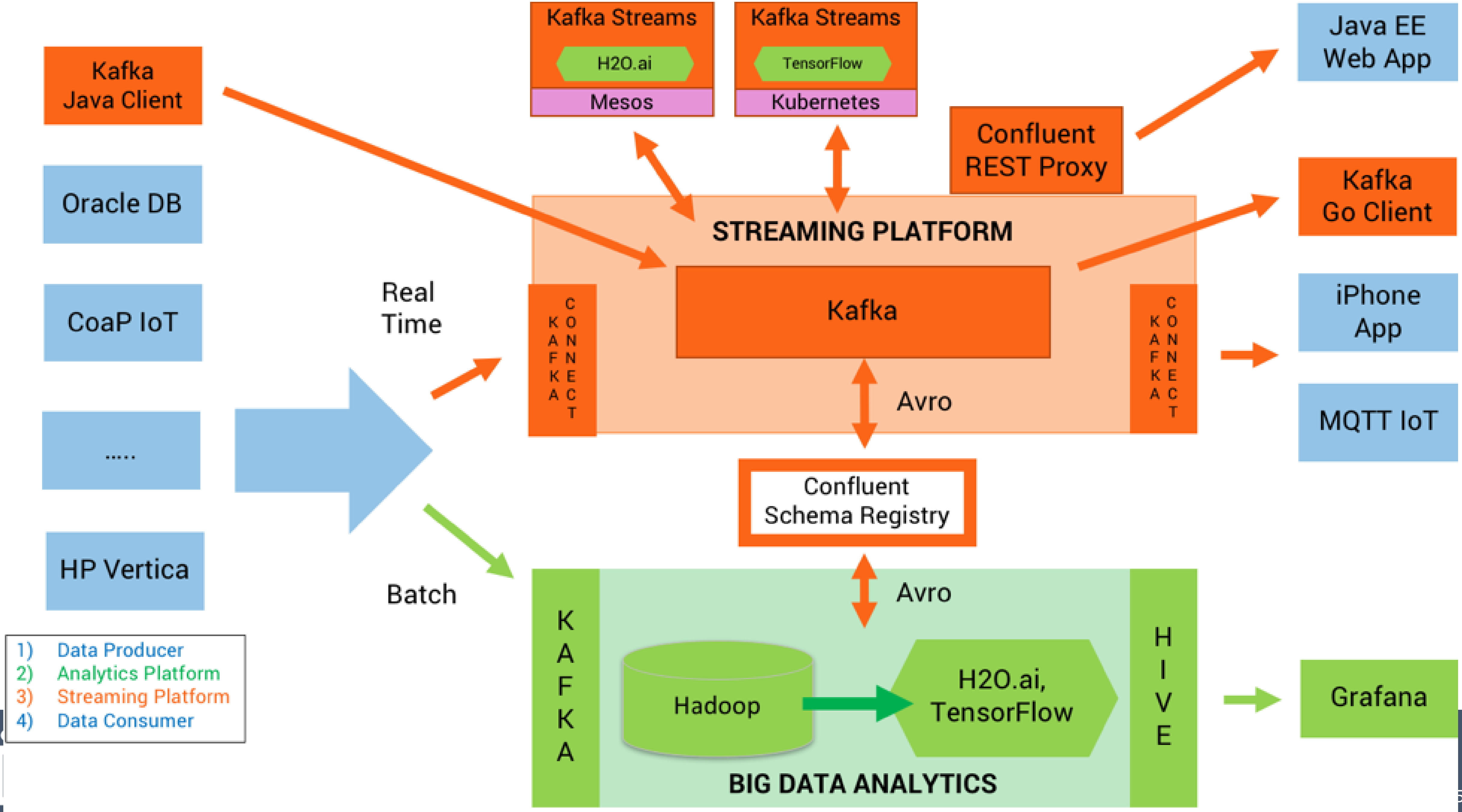
UPDATING MODELS

Updating Models

- Models are rarely static outside the lab
- Data drift, feedback loops, new features, new requirements
- When and how to update models?
- How to version? How to avoid mistakes?

- Latency and automation vary widely
- Heavily distributed

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Confluent Schema Registry
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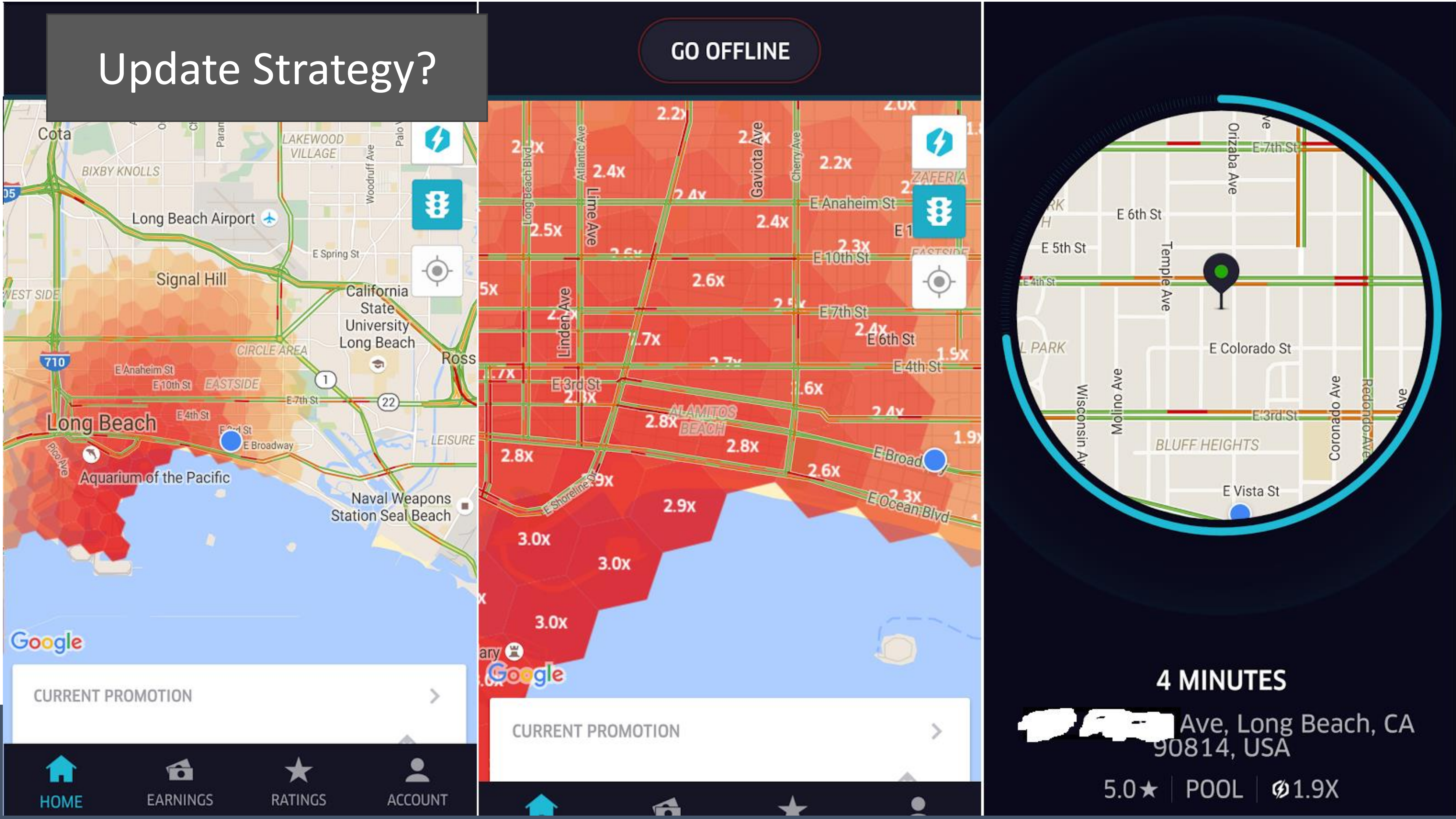
Hadoop
H2O.ai, TensorFlow
HIVE
BIG DATA ANALYTICS
Java EE Web App
Kafka Go Client
iPhone App
MQTT IoT
Grafana
1) Data Producer
2) Analytics Platform
3) Streaming Platform
4) Data Consumer

Update Strategy?

Update Strategy?



PLANNING FOR MISTAKES

Mistakes will happen

- No specification
- ML components detect patterns from data (real and spurious)
- Predictions are often accurate, but mistakes always possible
- Mistakes are not predicable or explainable or similar to human mistakes
- Plan for mistakes
- Telemetry to learn about mistakes?

How Models can Break

- System outage
- Model outage
  - model tested? deployment and updates reliable? file corrupt?
- Model errors
- Model degradation
  - data drift, feedback loops

Hazard Analysis

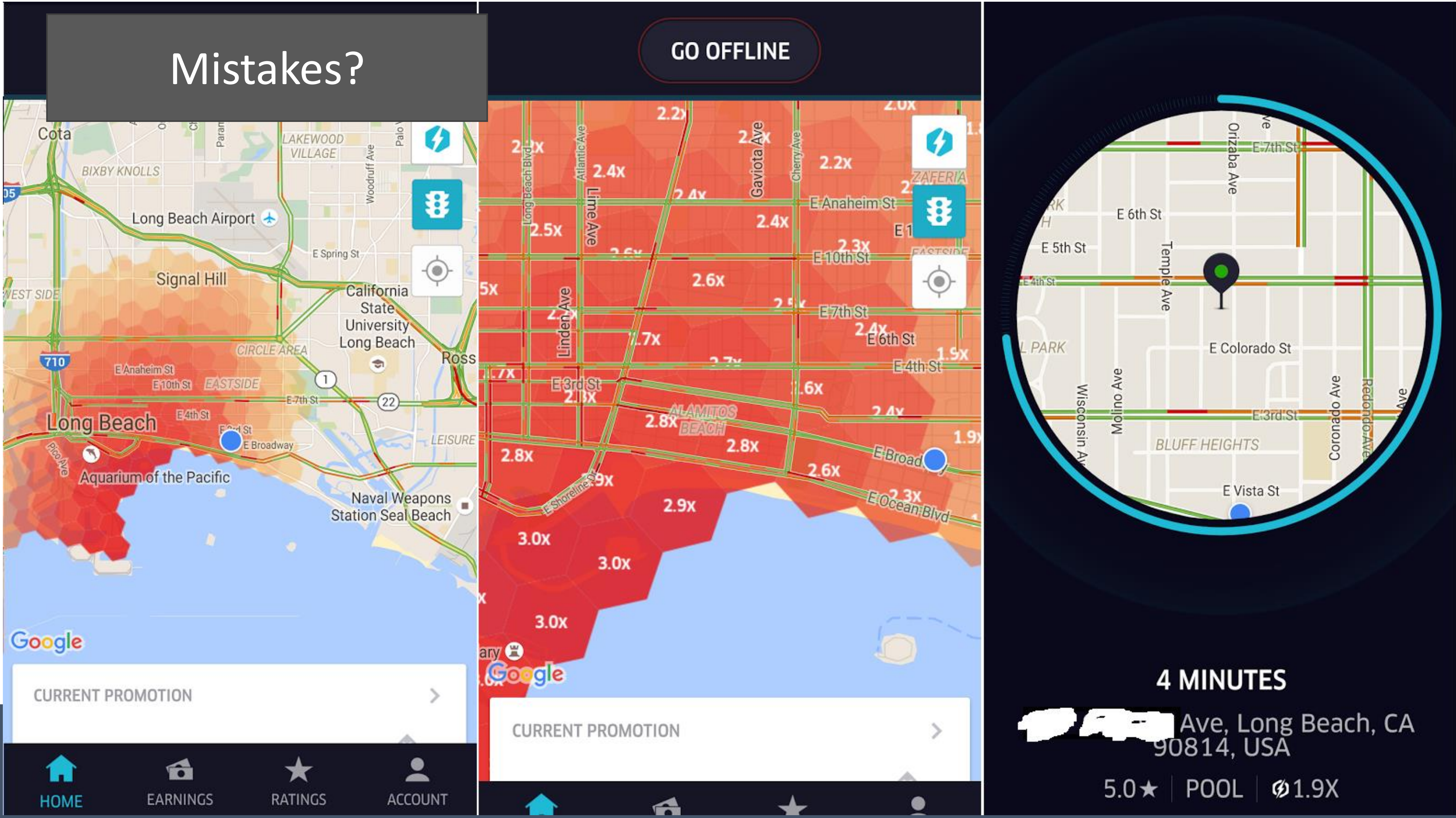
- Worst thing that can happen?
- Backup strategy? Undoable? Nontechnical compensation?

Mitigating Mistakes

- Investigating in ML
  - e.g., more training data, better data, better features, better engineers
- Less forceful experience
  - e.g., prompt rather than automate decisions, turn off
- Adjust learning parameters
  - e.g., more frequent updates, manual adjustments
- Guardrails
  - e.g., heuristics and constraints on outputs
- Override errors
  - e.g., hardcode specific results

Mistakes?

Mistakes?



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Telemetry

- Purpose:
  - monitor operation
  - monitor success (accuracy)
  - improve models over time (e.g., detect new features)
- Challenges:
  - too much data – sample, summarization, adjustable
  - hard to measure – intended outcome not observable? proxies?
  - rare events – important but hard to capture
  - cost – significant investment must show benefit
  - privacy – abstracting data

Summary

- Machine learning in production systems is challenging
- Many tradeoffs in selecting ML components and in integrating them in larger system
- Plan for updates
- Manage mistakes, plan for telemetry