Software Engineering for ML/AI

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Administrivia

- Homework 3 out

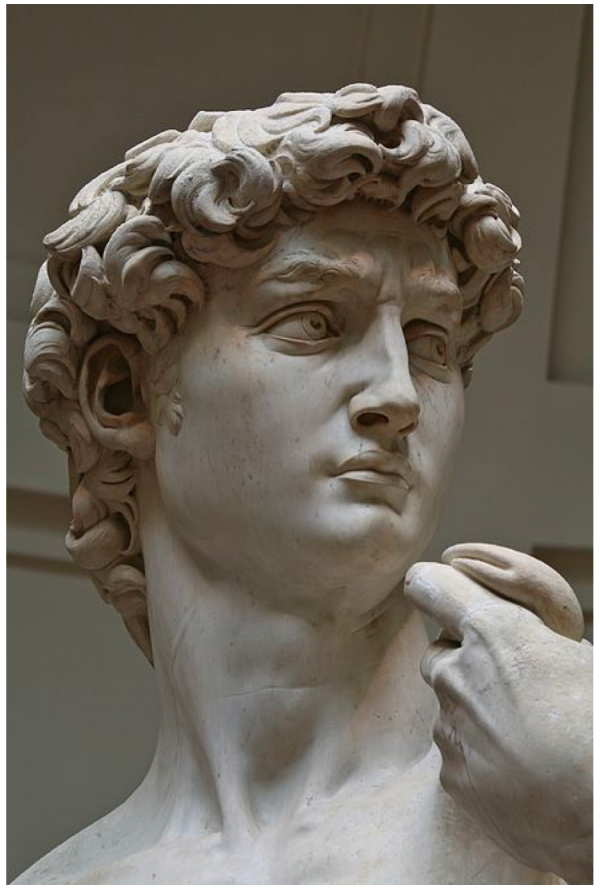
Interview: Josh Gardner

Software Engineering and ML

Traditional Software Development

"It is easy. You just chip away the stone that doesn't look like David."

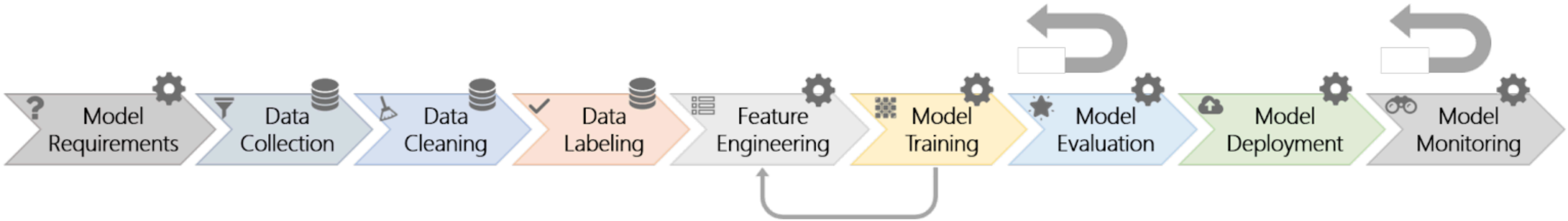
–(probably not) Michelangelo



ML Development

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

Microsoft's view of Software Engineering for ML



Three Fundamental Differences:

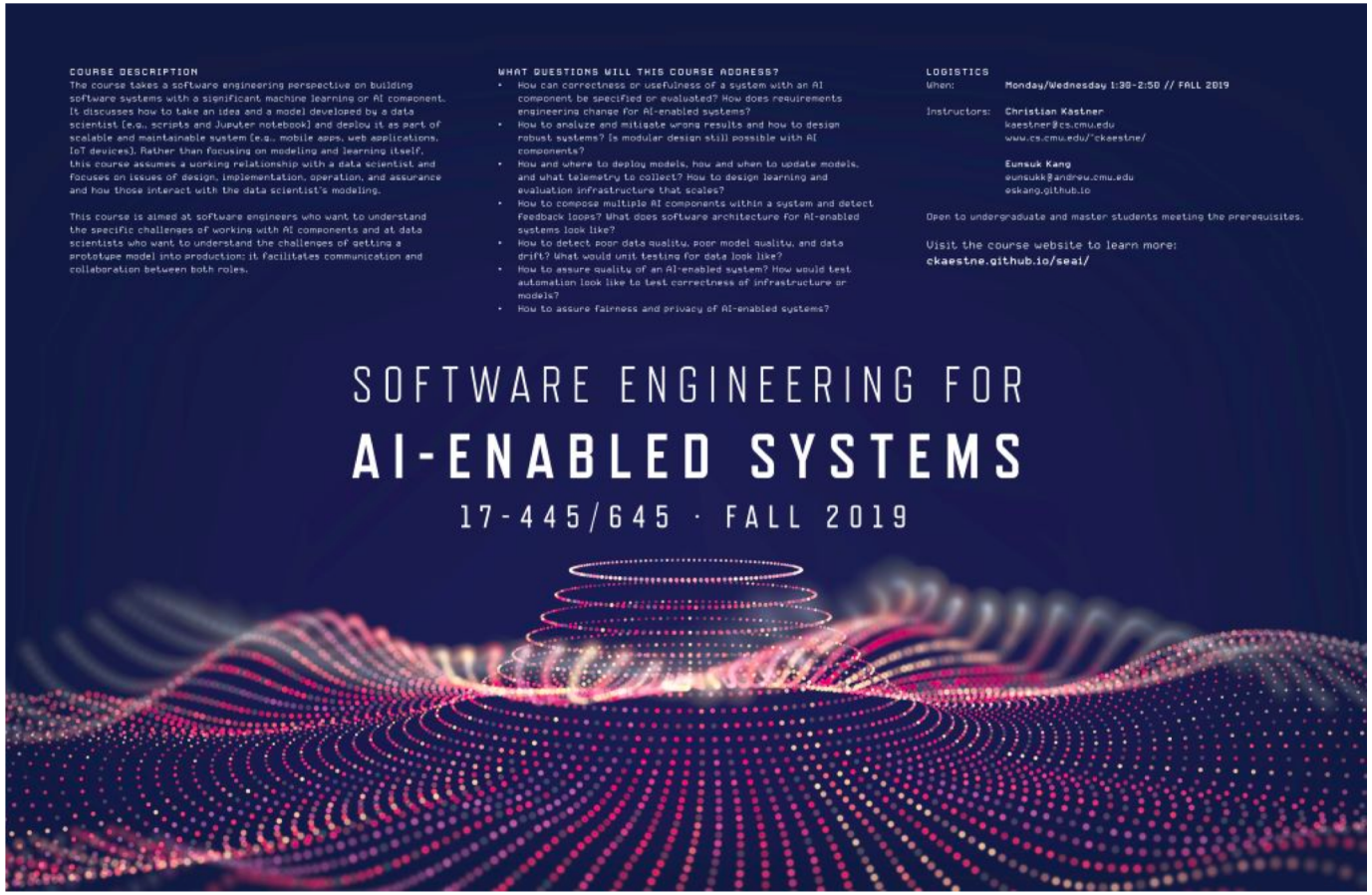
- Data discovery and management
- Customization and Reuse
- ML Modularity

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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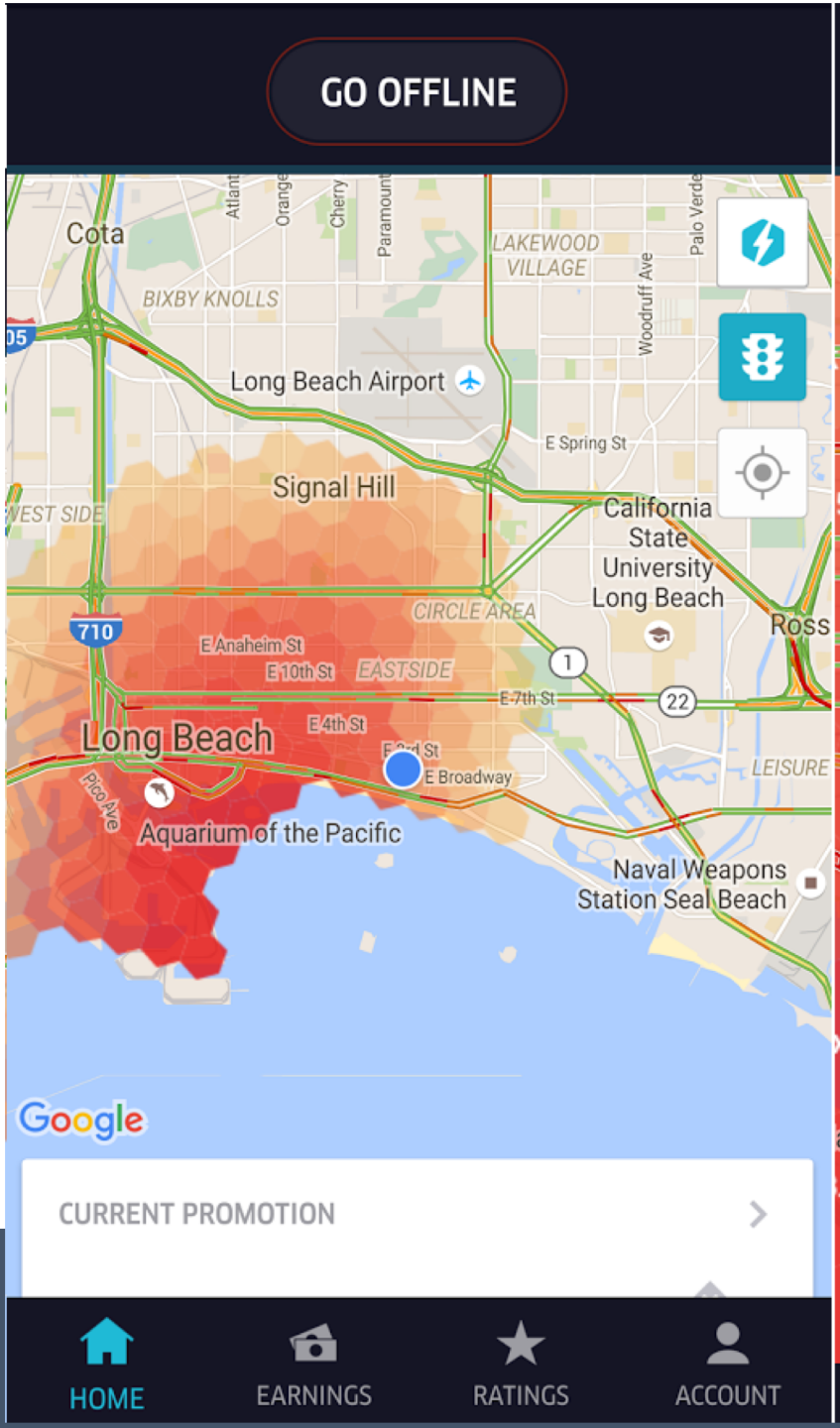
Qualities of Interest?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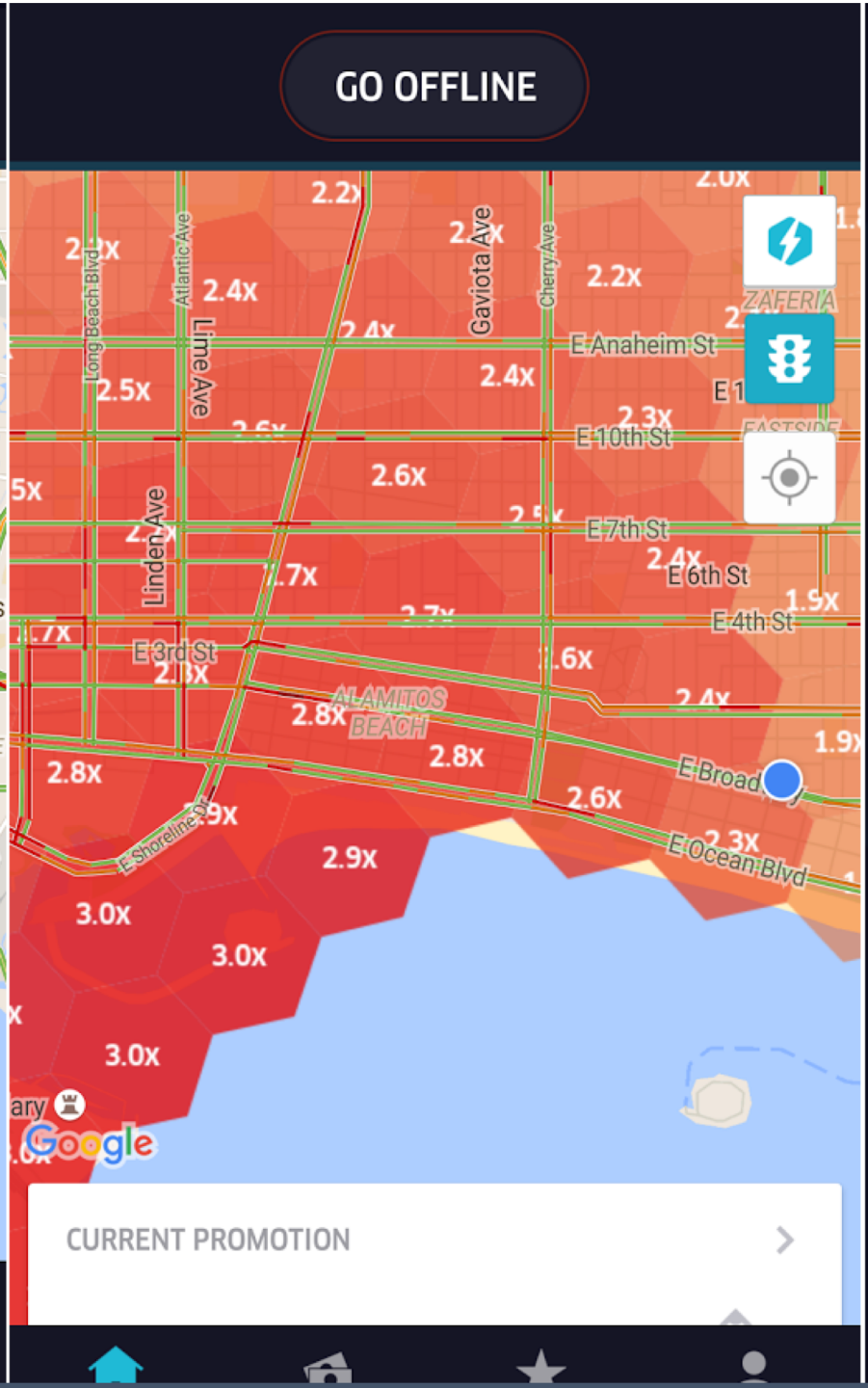
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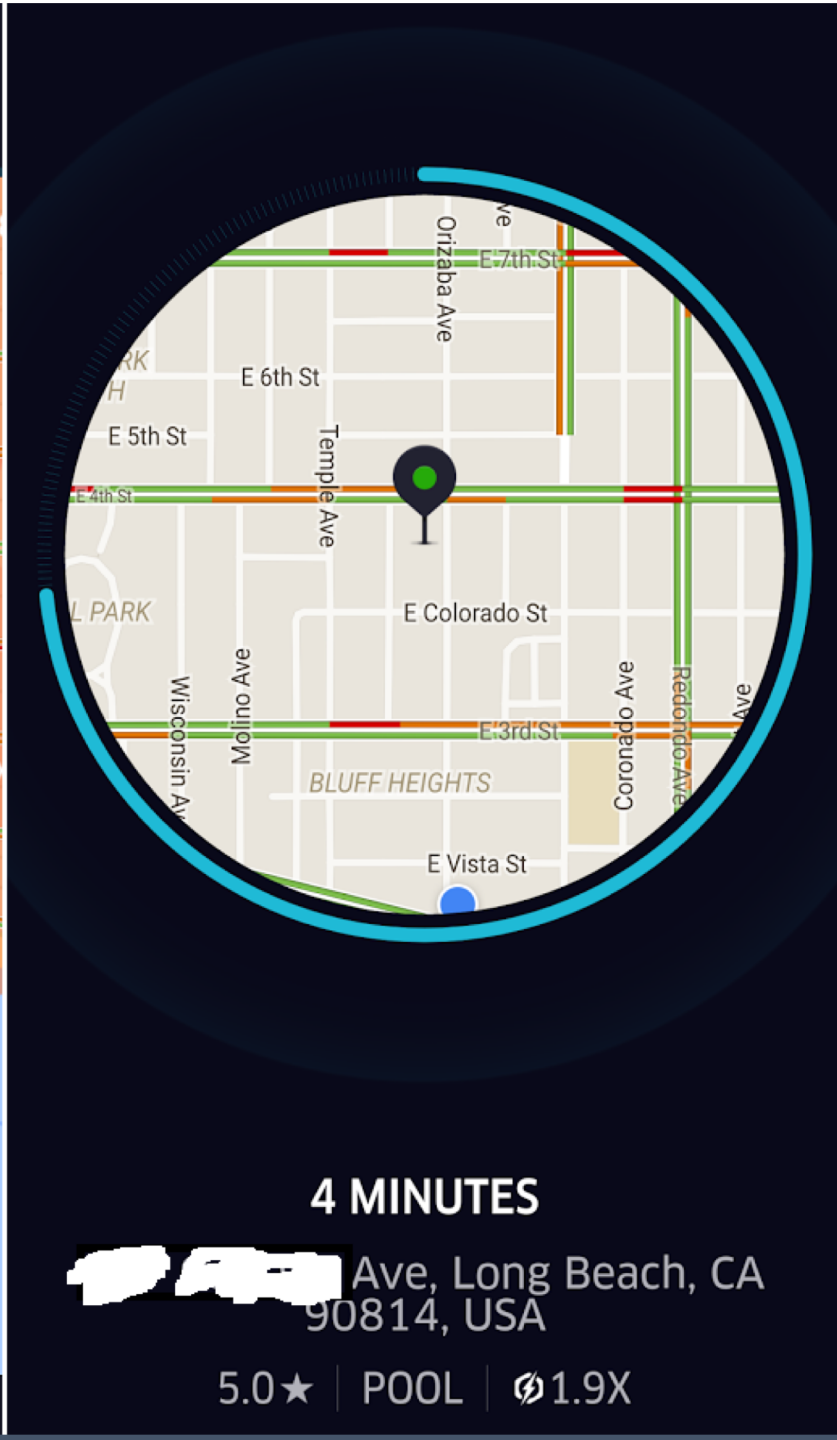
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Qualities of Interest?

MACHINE LEARNING PIPELINE

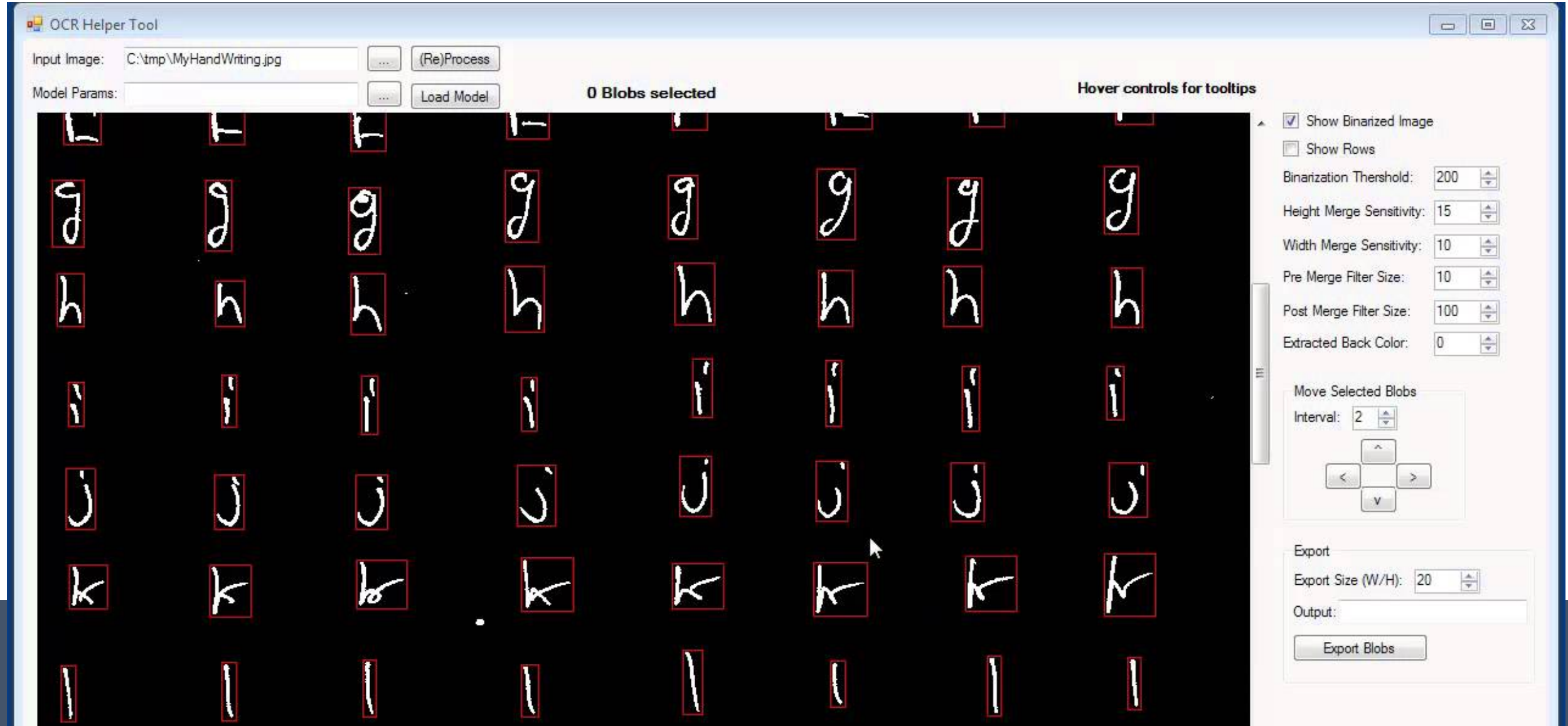
Typical ML Pipeline

- Static
  - Get labeled data
  - Identify and extract features
  - Split data into training and evaluation set
  - Learn model from training data
  - Evaluate model on evaluation data
  - Repeat, revising features
- With production data
  - Evaluate model on production data; monitor
  - Select production data for retraining
  - Update model regularly

Example Data

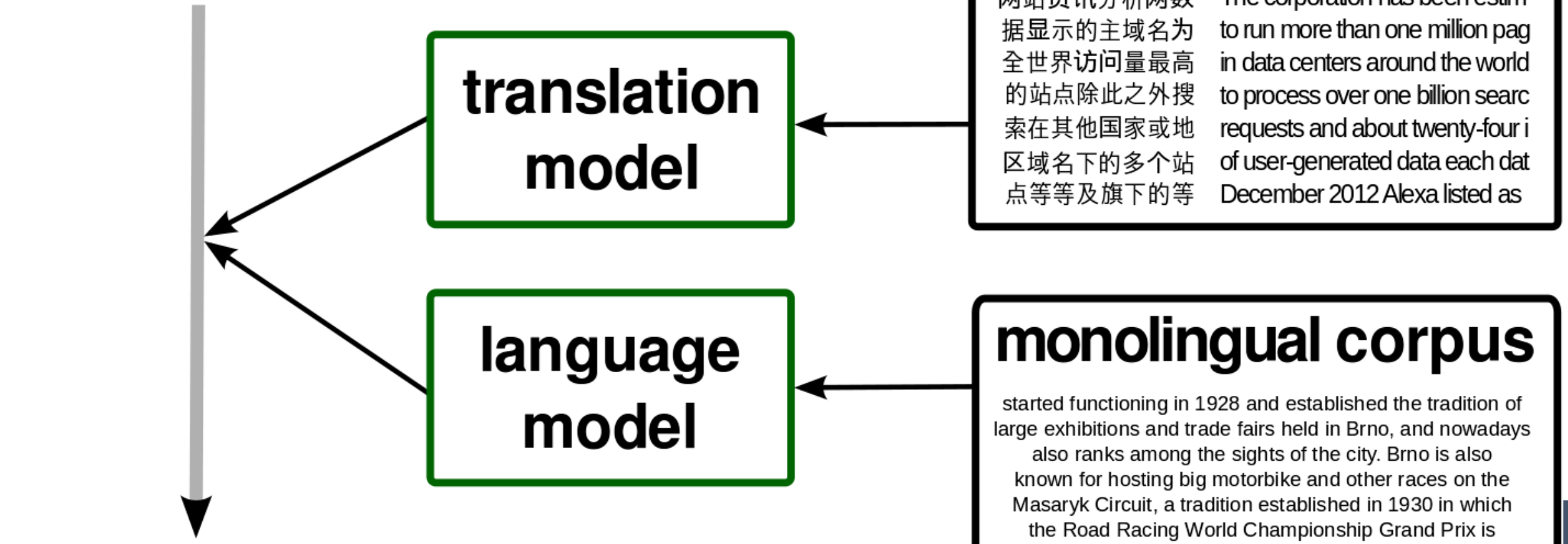
UserId	PickupLocation	TargetLocation	OrderTime	PickupTime
5	….	…	18:23	18:31
…				

Example Data



Learning Data

似乎格式有問題



English output

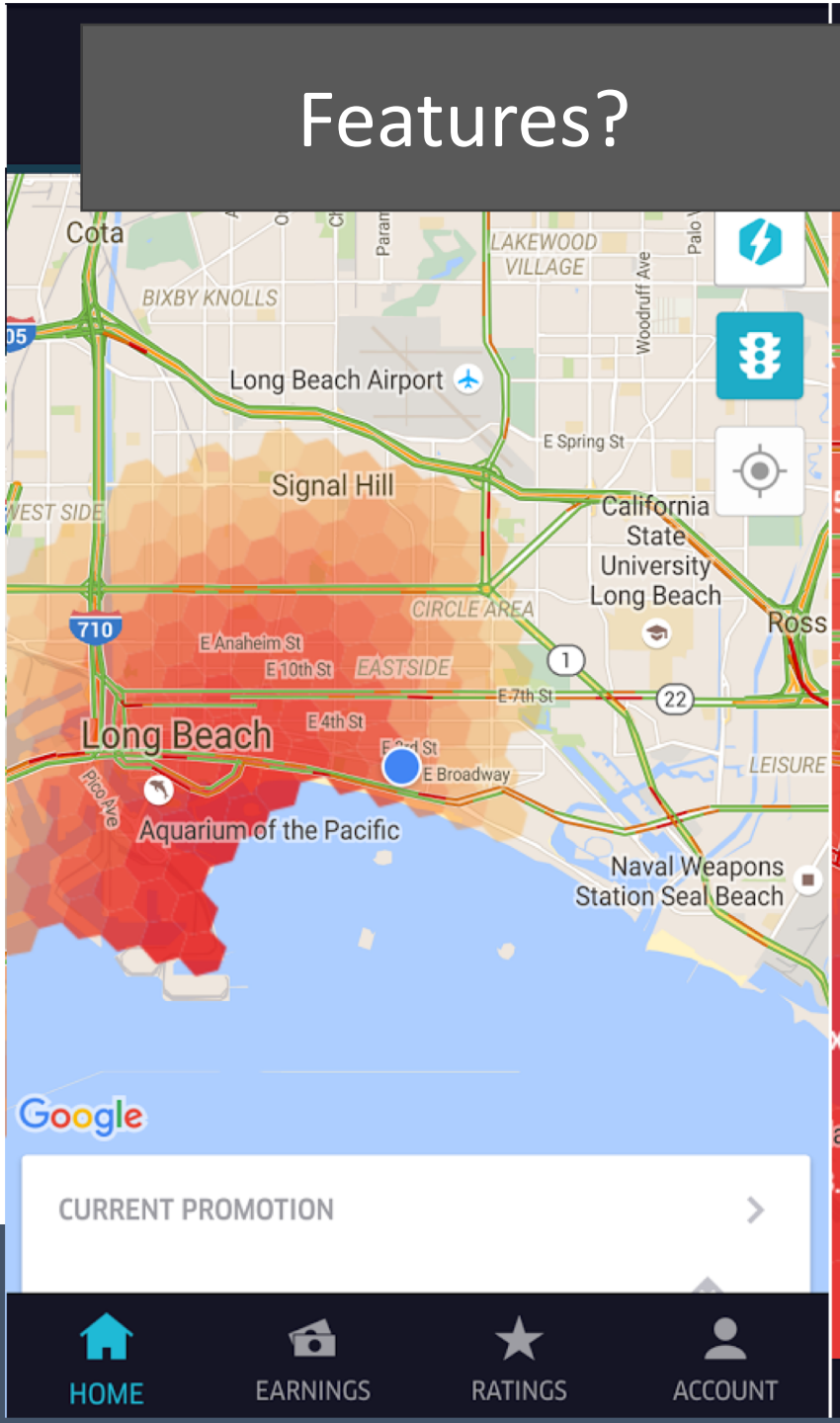
Training Data

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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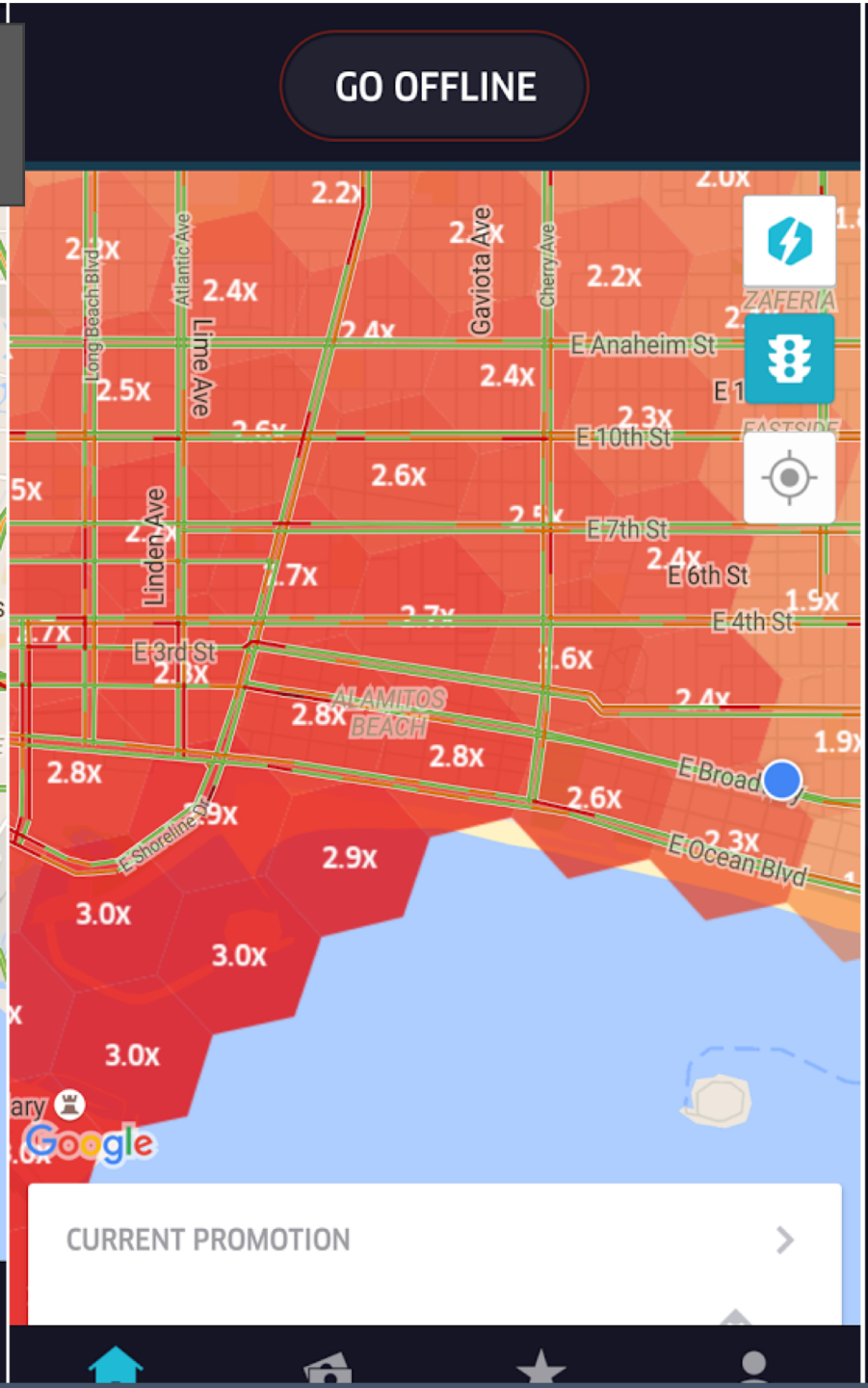
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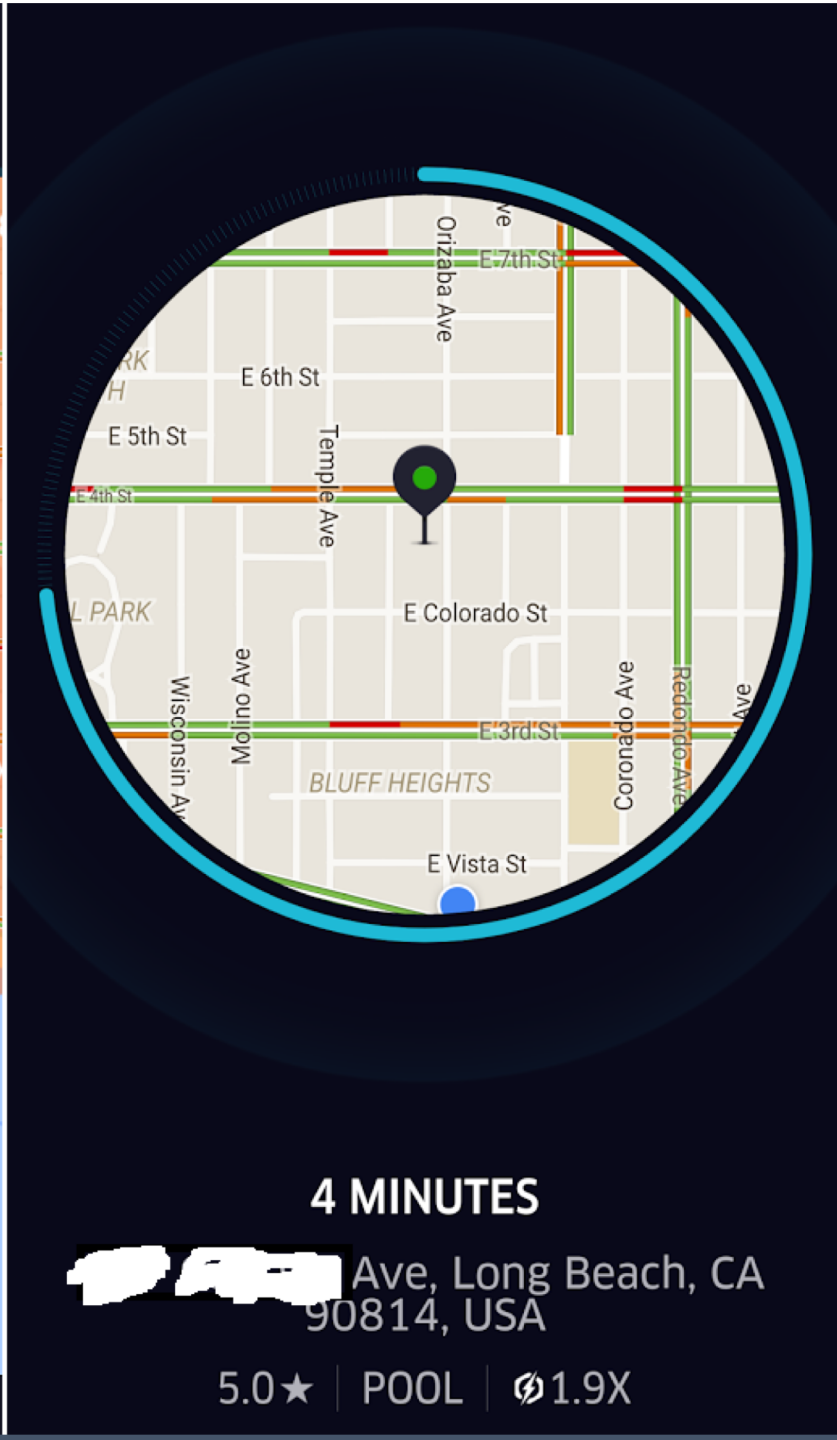
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Feature Extraction

- 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

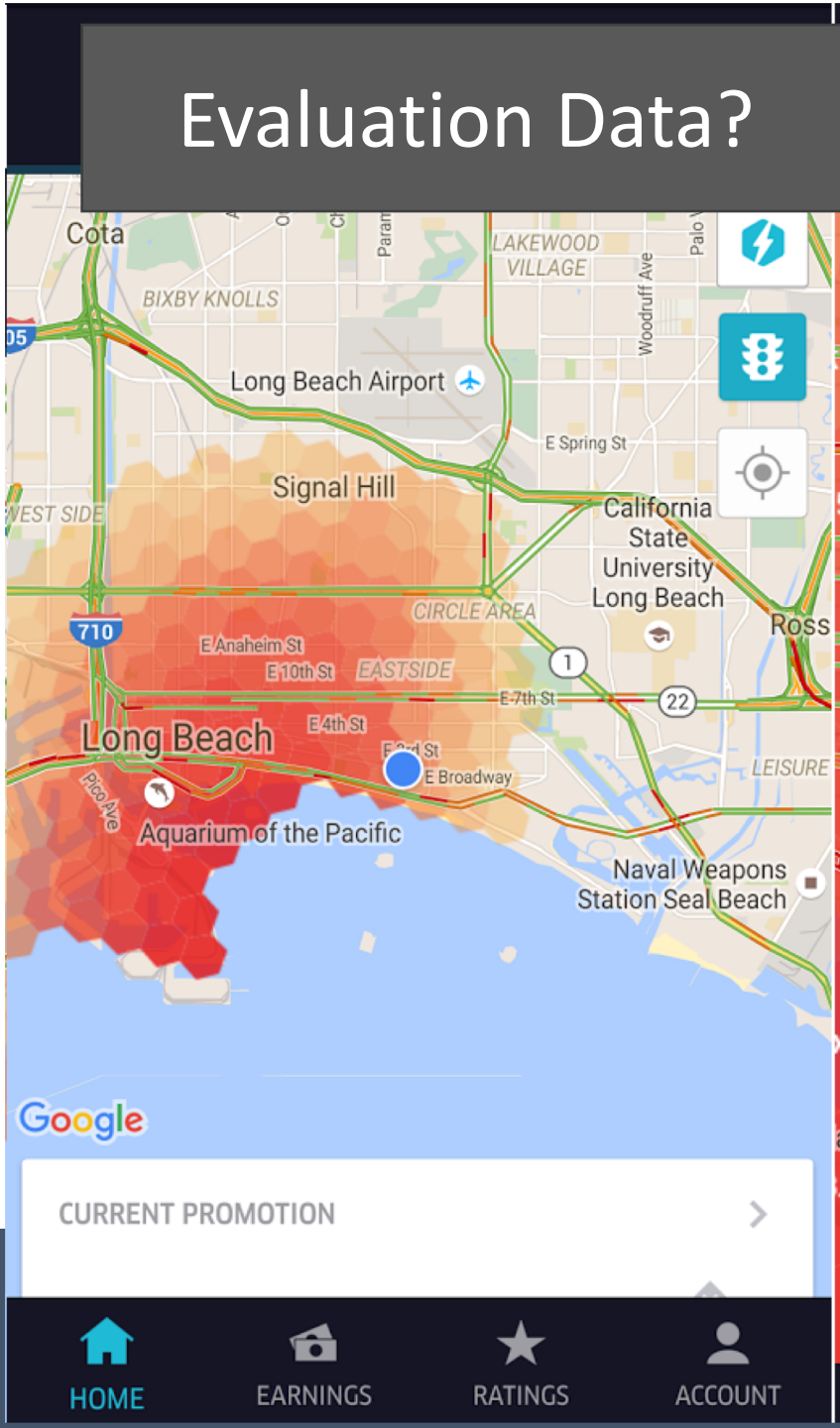
Evaluation

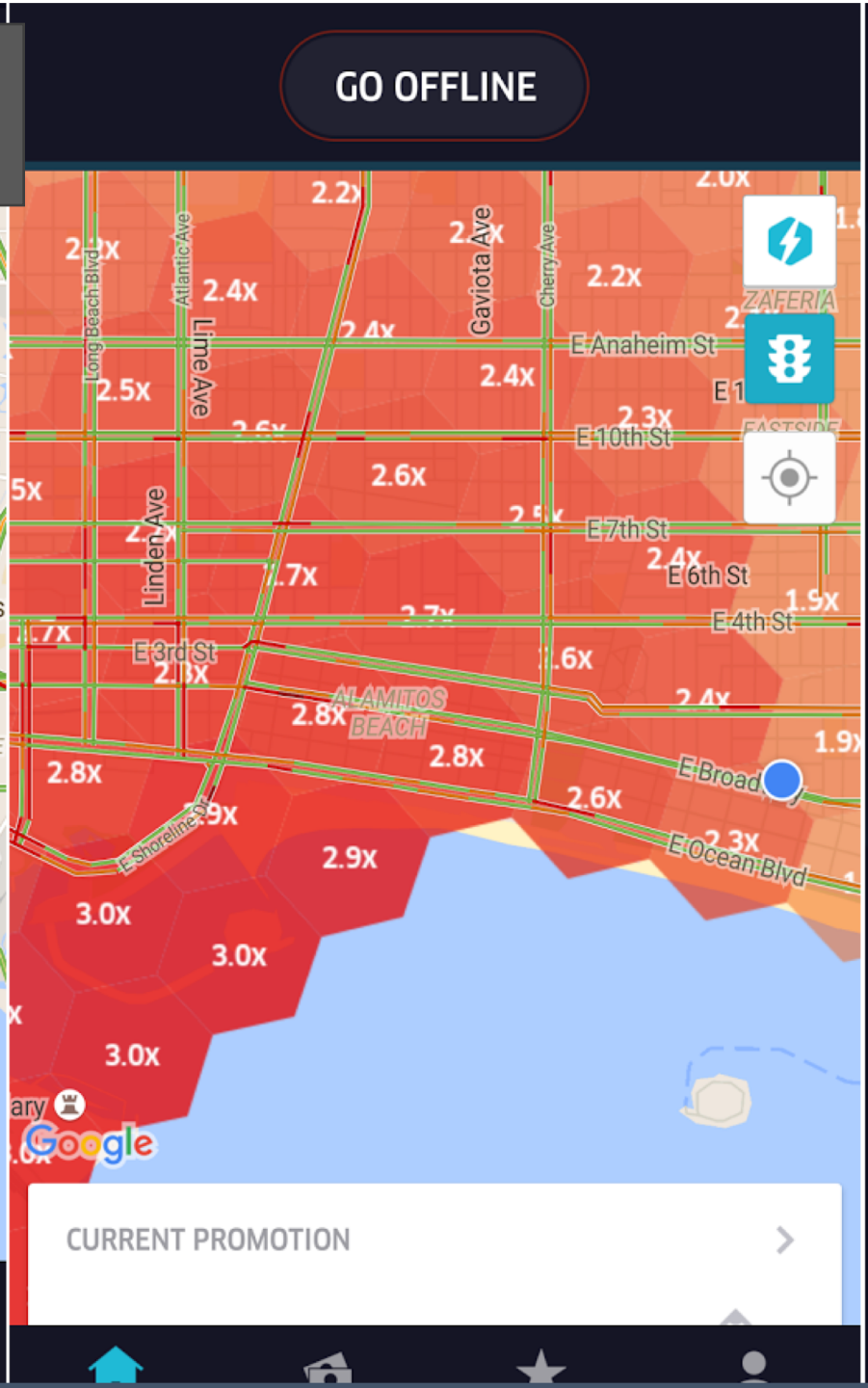
- Prediction accuracy on learned data vs
- Prediction accuracy on unseen data
  - Separate learning set, not used for training

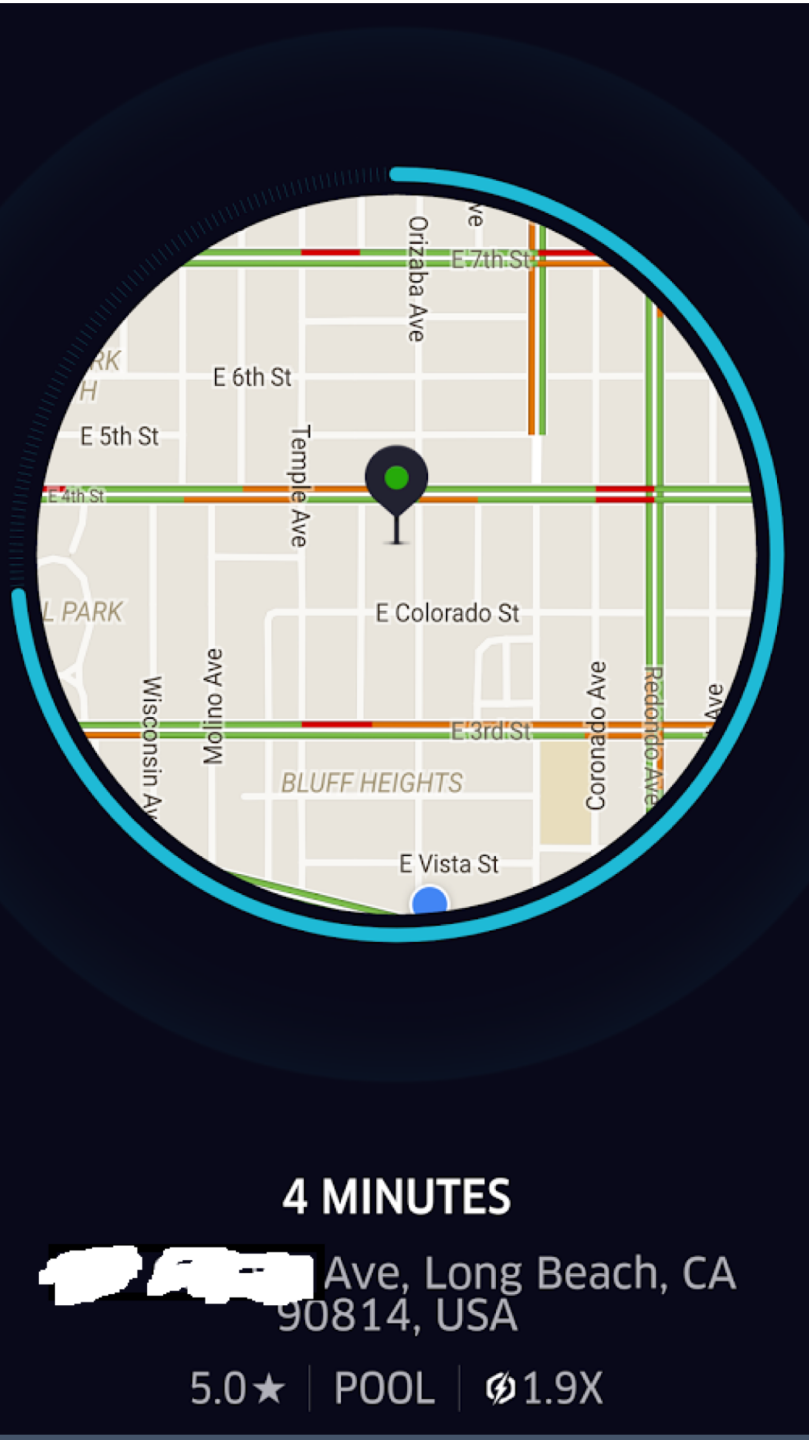
- For binary predictors: false positives vs false negatives, recall, precision
- For numeric predictors: average (relative) distance between real and predicted value
- For ranking predictors: topK etc

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

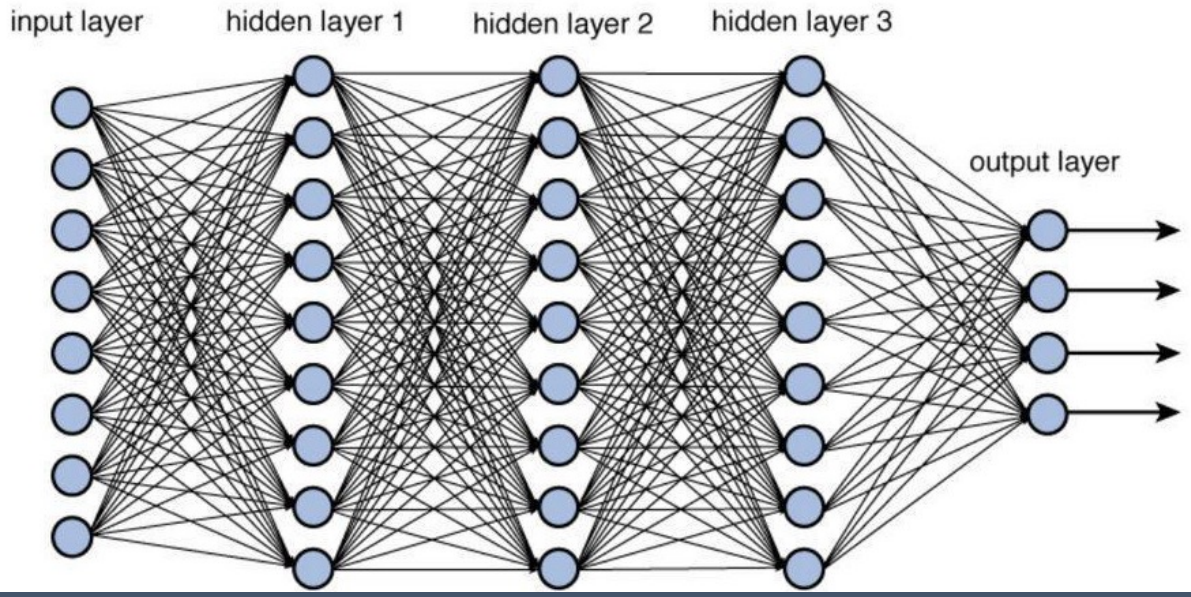
ML COMPONENT TRADEOFFS

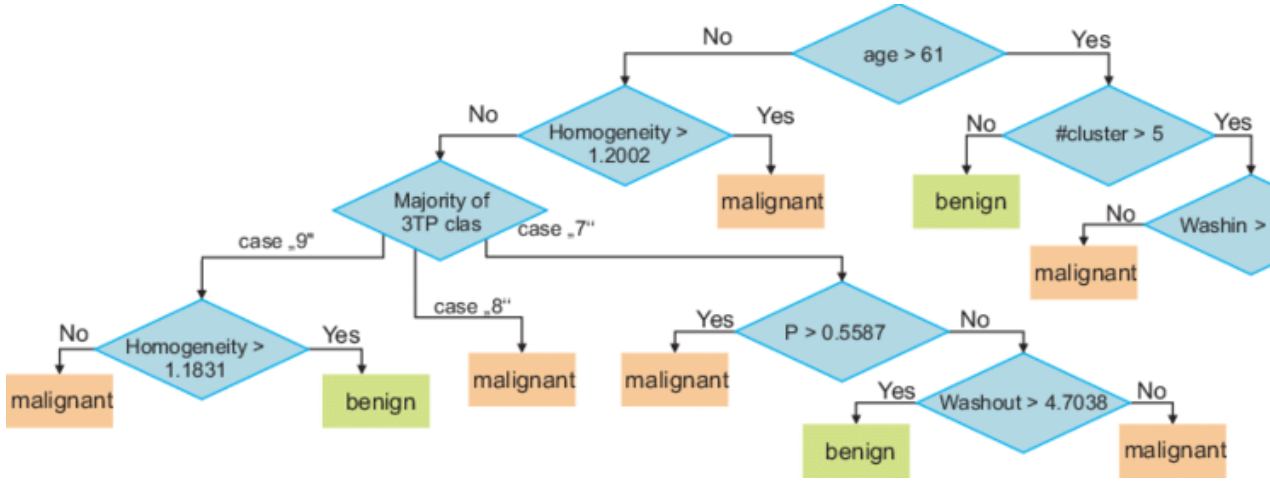
Qualities of ML Components

- 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”

Making Decisions

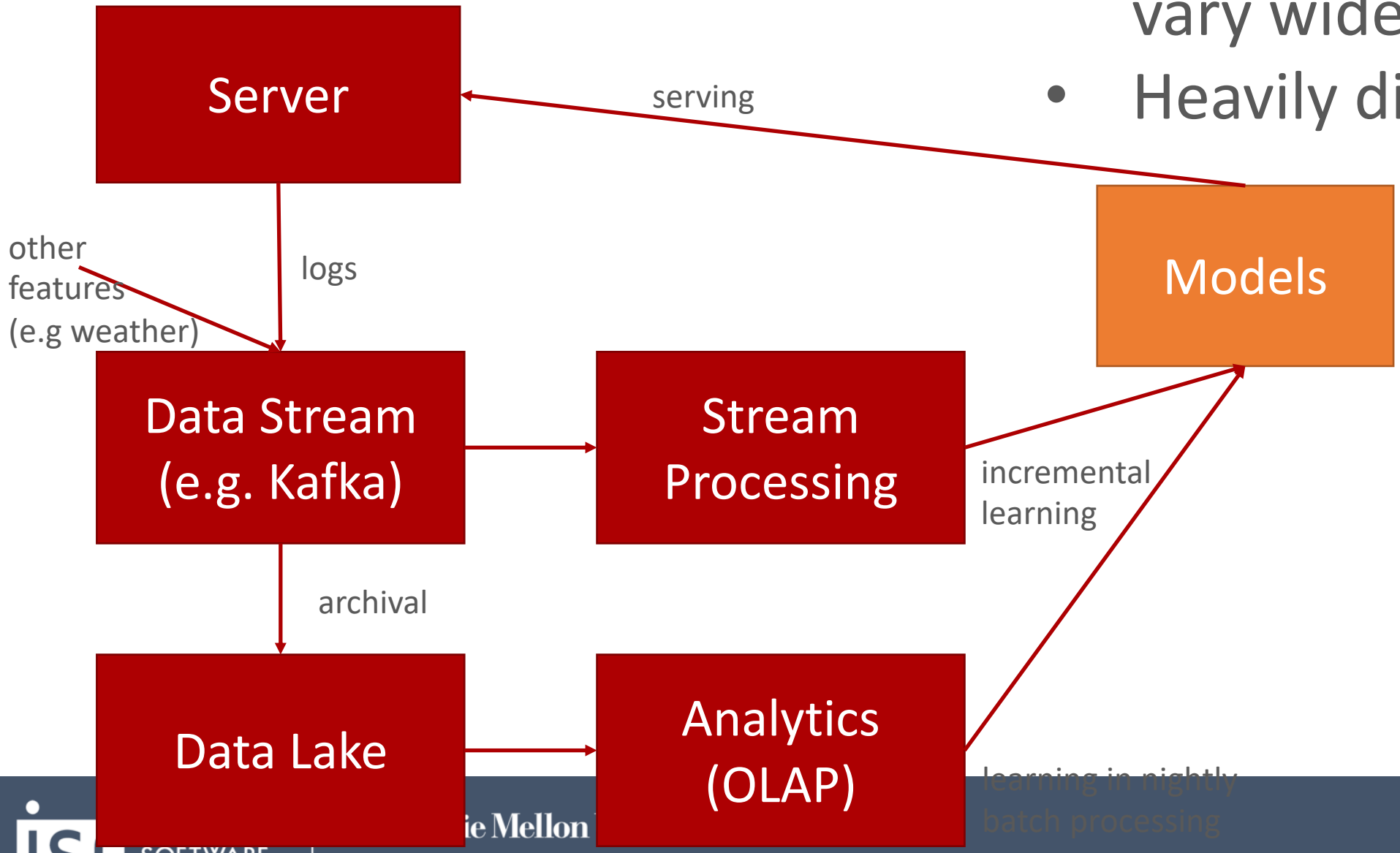
- What steps to take?
- What information to collect?

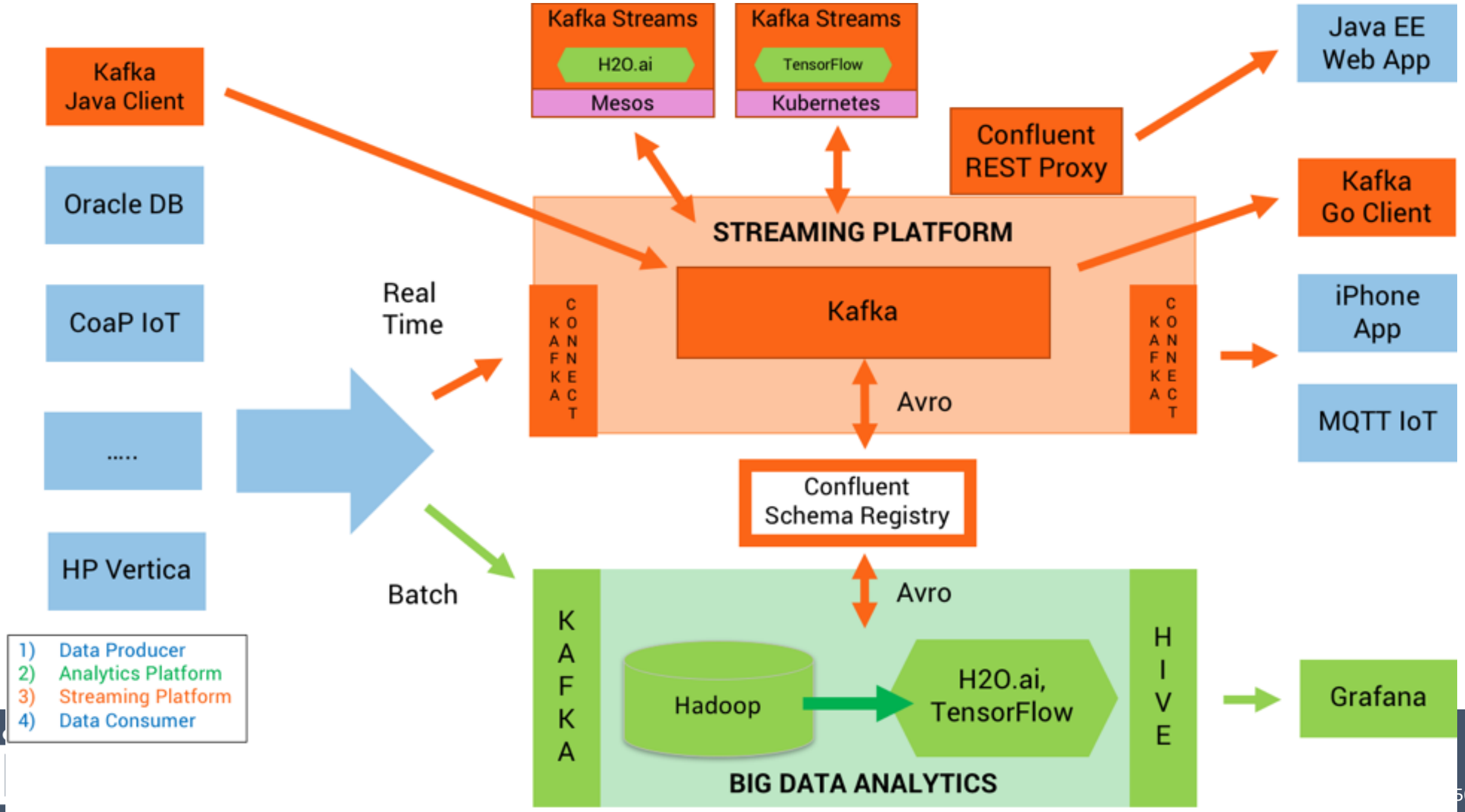
UPDATING MODELS

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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HIVE
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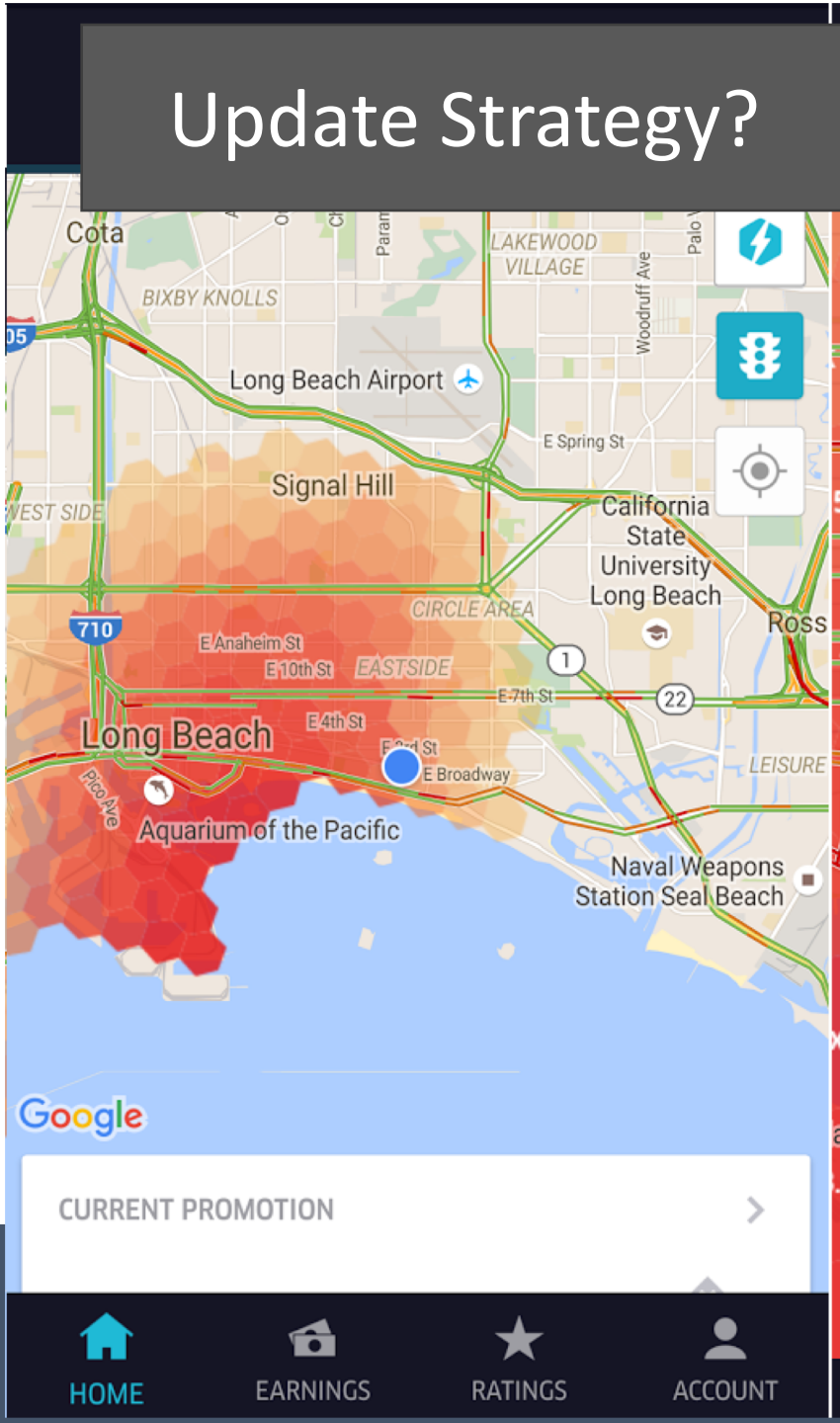
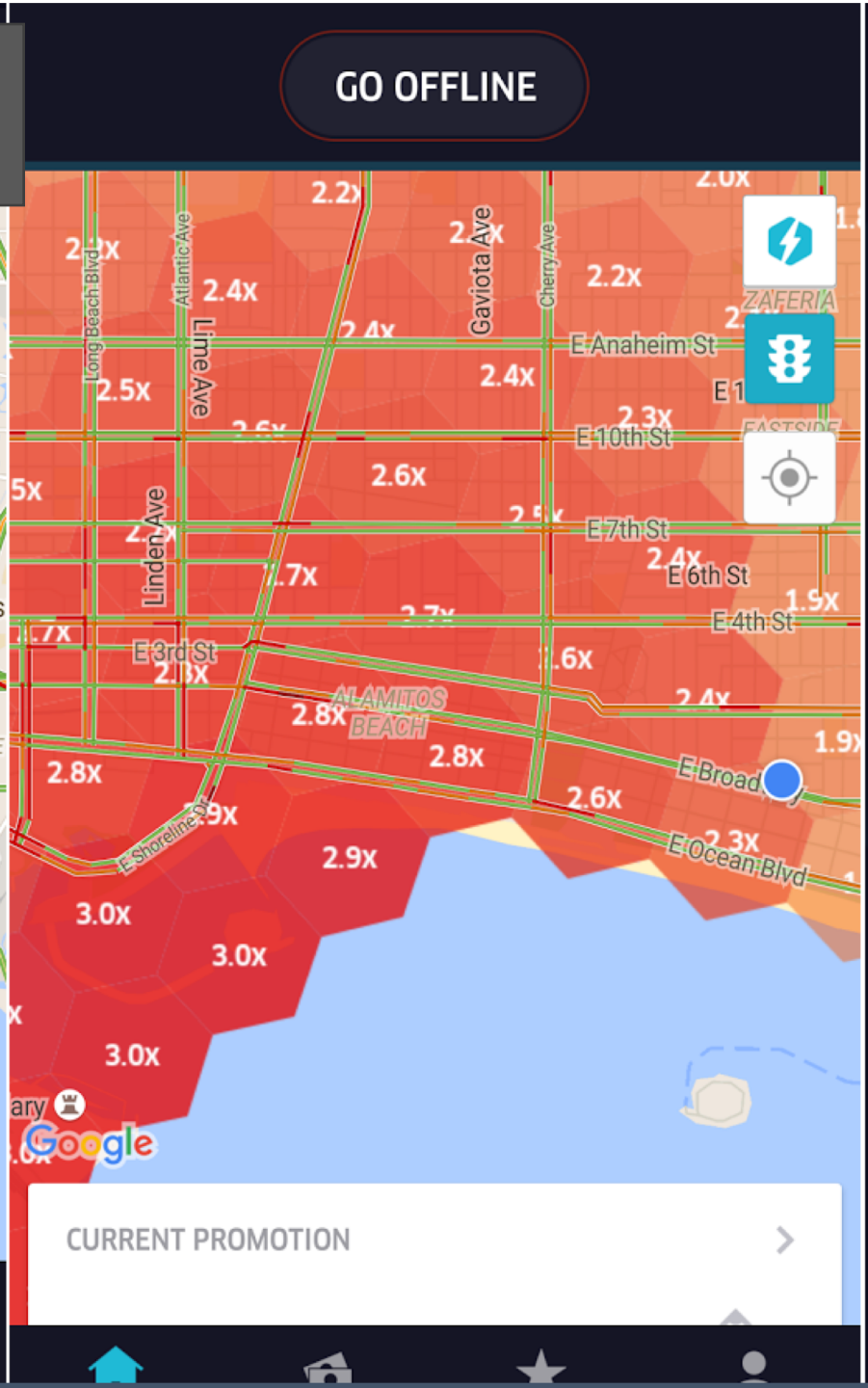
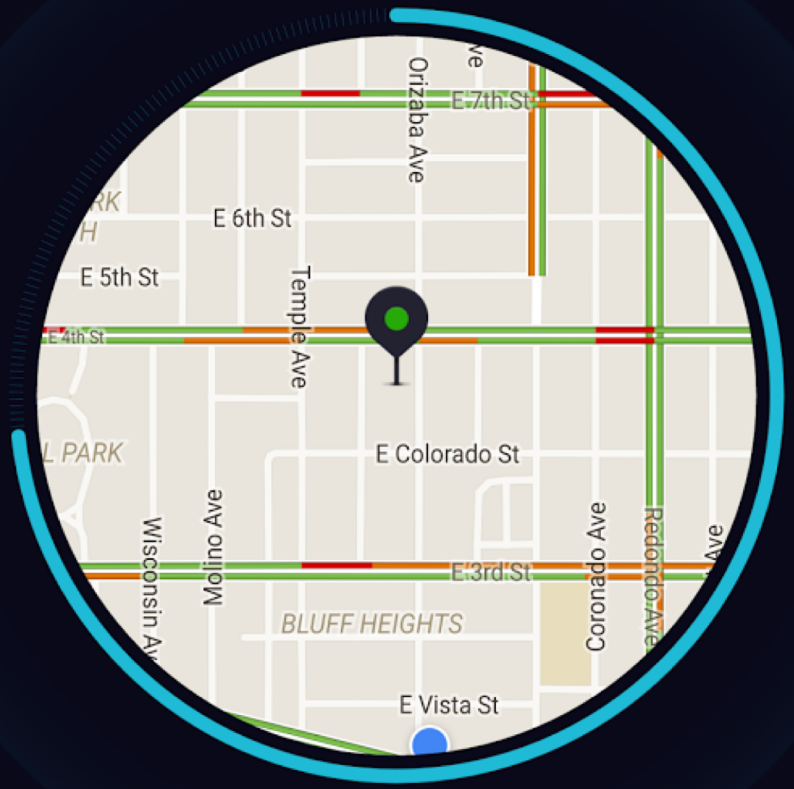
iPhone App
MQTT IoT
Grafana
1) Data Producer
2) Analytics Platform
3) Streaming Platform
4) Data Consumer

Update Strategy?

Update Strategy?







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Making Decisions

- What steps to take?
- What information to collect?

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

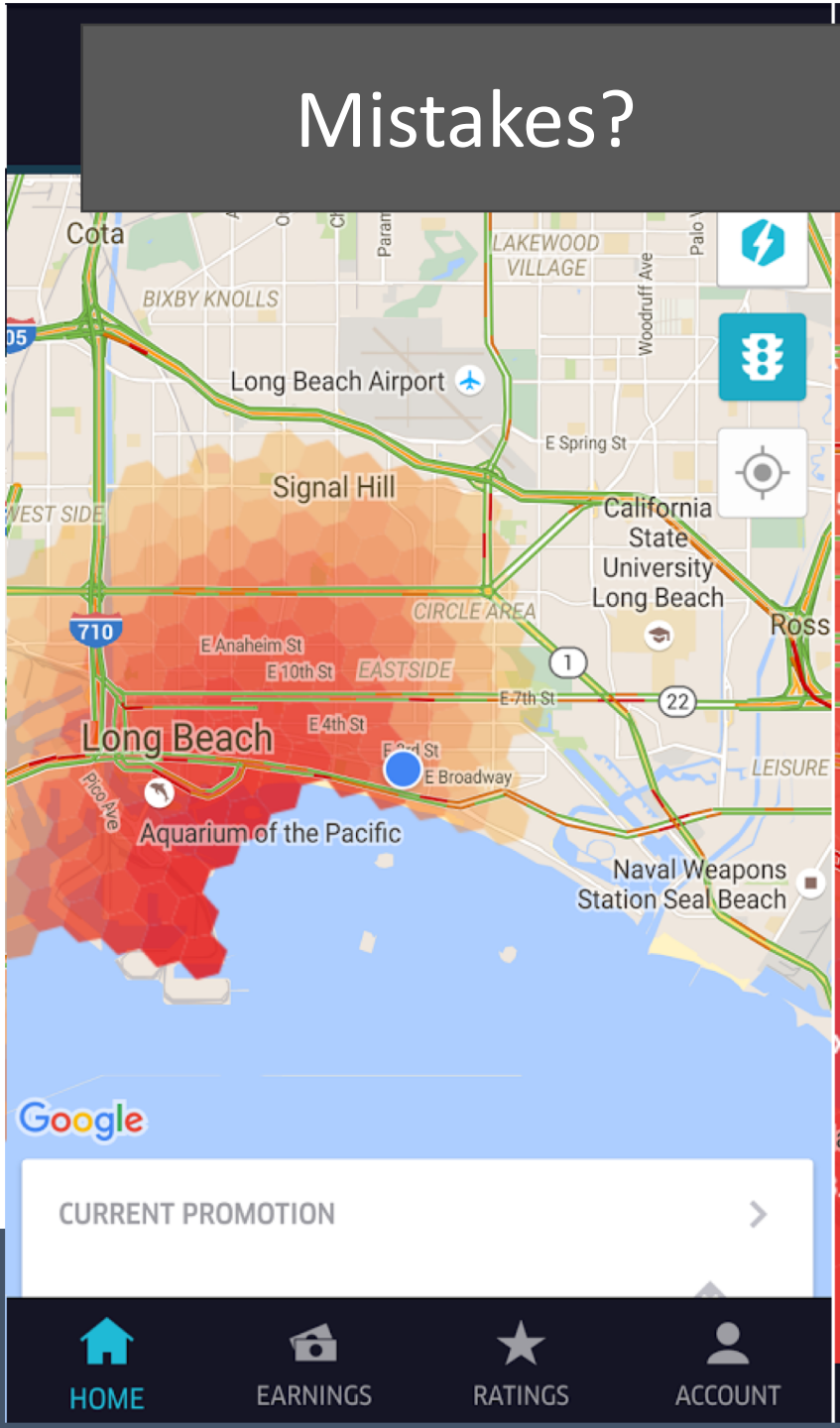
- Worst thing that can happen?
- Backup strategy? Undoable? Nontechnical compensation?

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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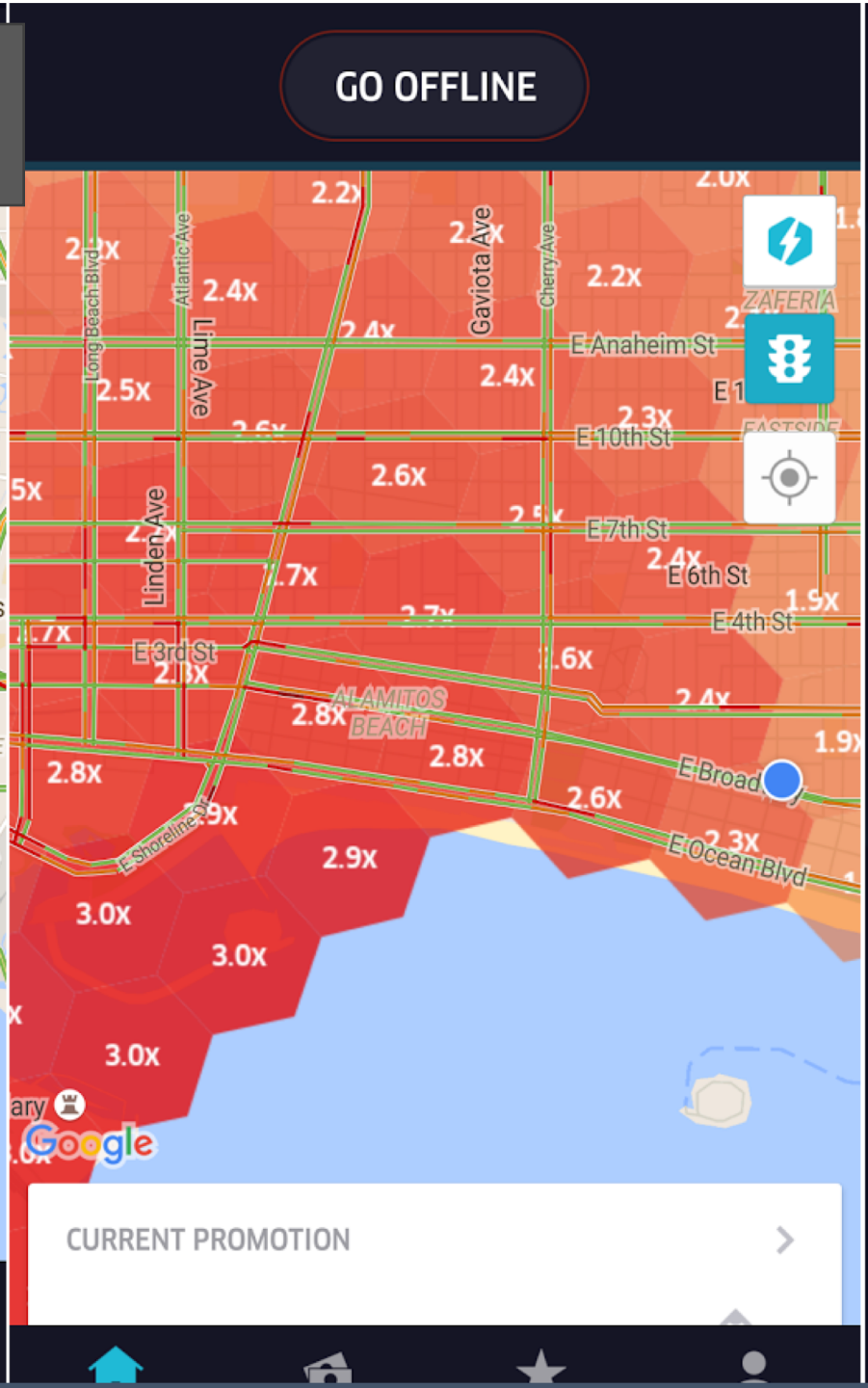
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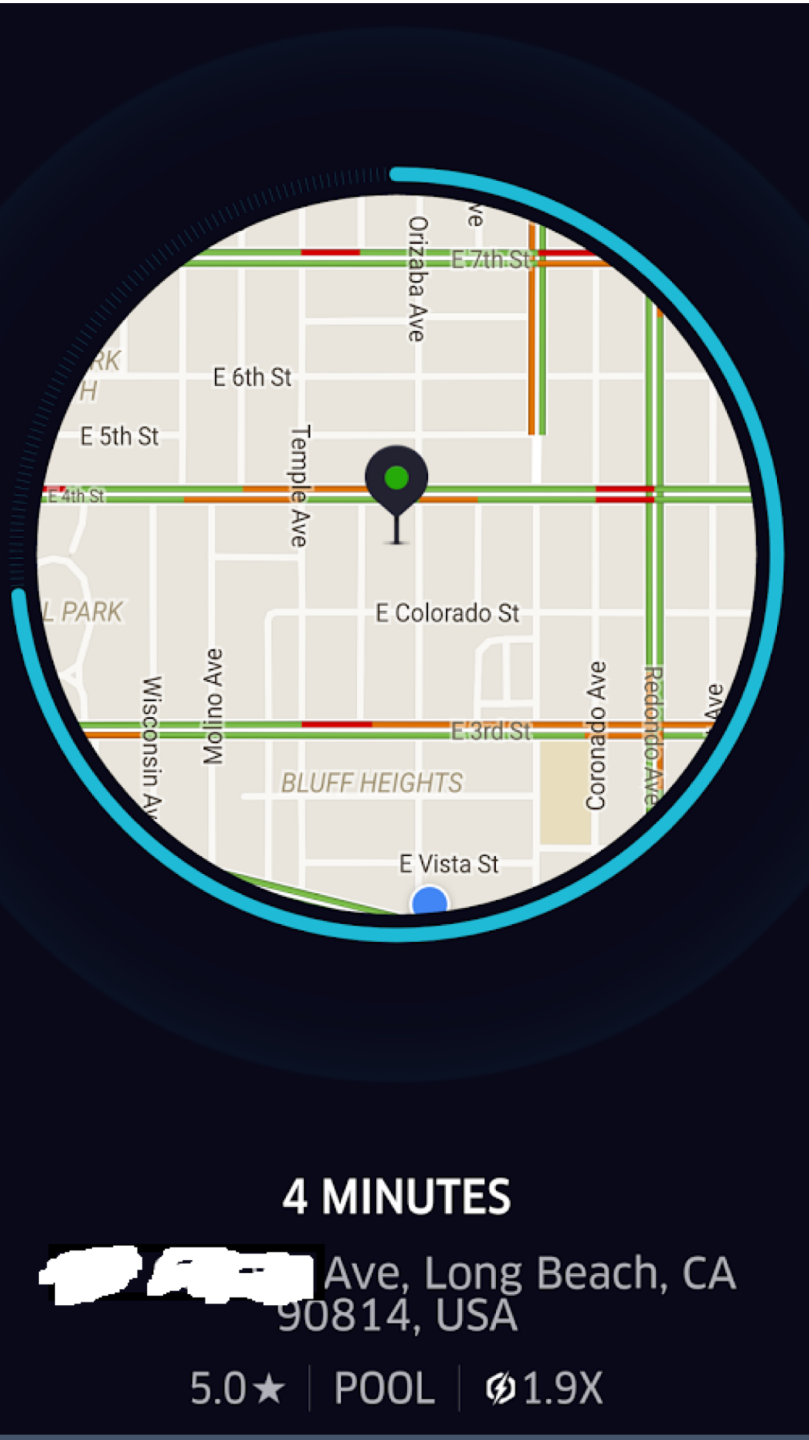
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Telemetry

- 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

Model Orchestration

- Multiple models work together
  - ORC + statistical translation
  - driver activity predictor + demand predictor + event predictor + weather model
  - model + railguards
- Many different composition strategies
  - ensemble learning
  - integrated models
  - model sequencing
  - partitioning

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