15-319 / 15-619 Cloud Computing

Recitation 12

November 12th 2019

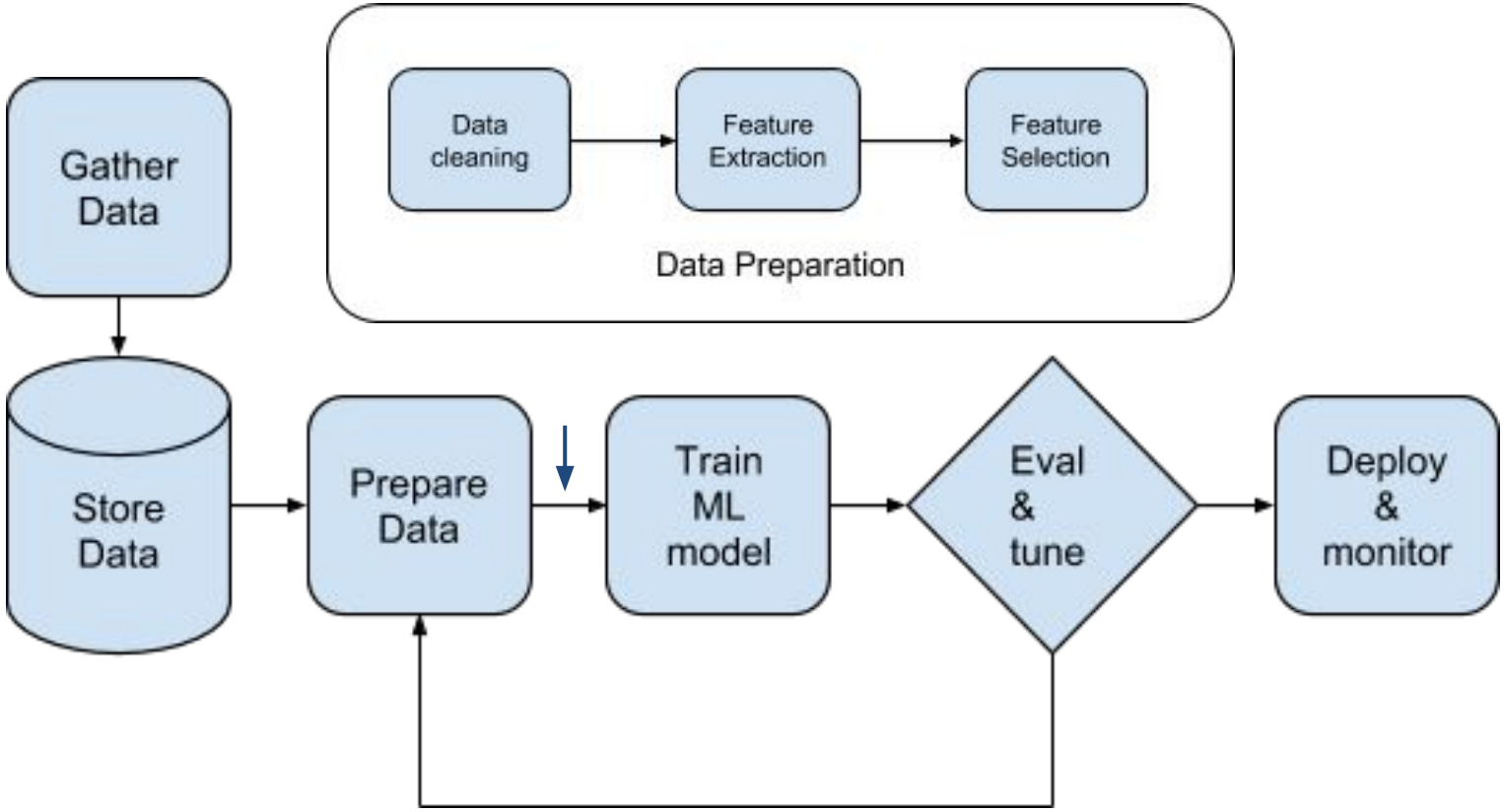
Overview

- **Last week's reflection**
  - Team Project Phase 2, Live Test
  - Quiz 10

- **This week's schedule**
  - Project 4.2
  - Quiz 11
  - **Twitter Analytics: The Team Project**
    - Phase 3
      - Managed Services

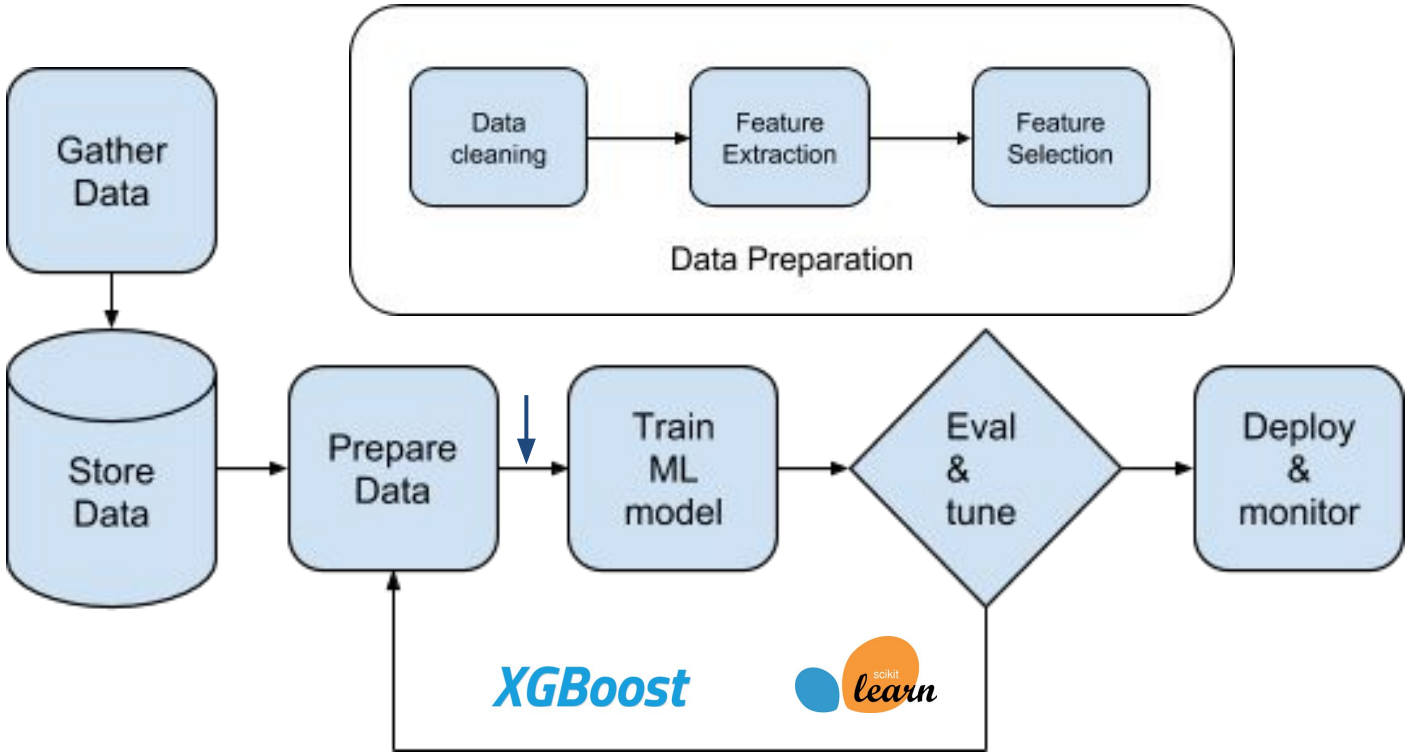
Machine Learning in Production

- A typical end-to-end process for Machine Learning



Machine Learning in Production

- A proliferation of tools on the Cloud

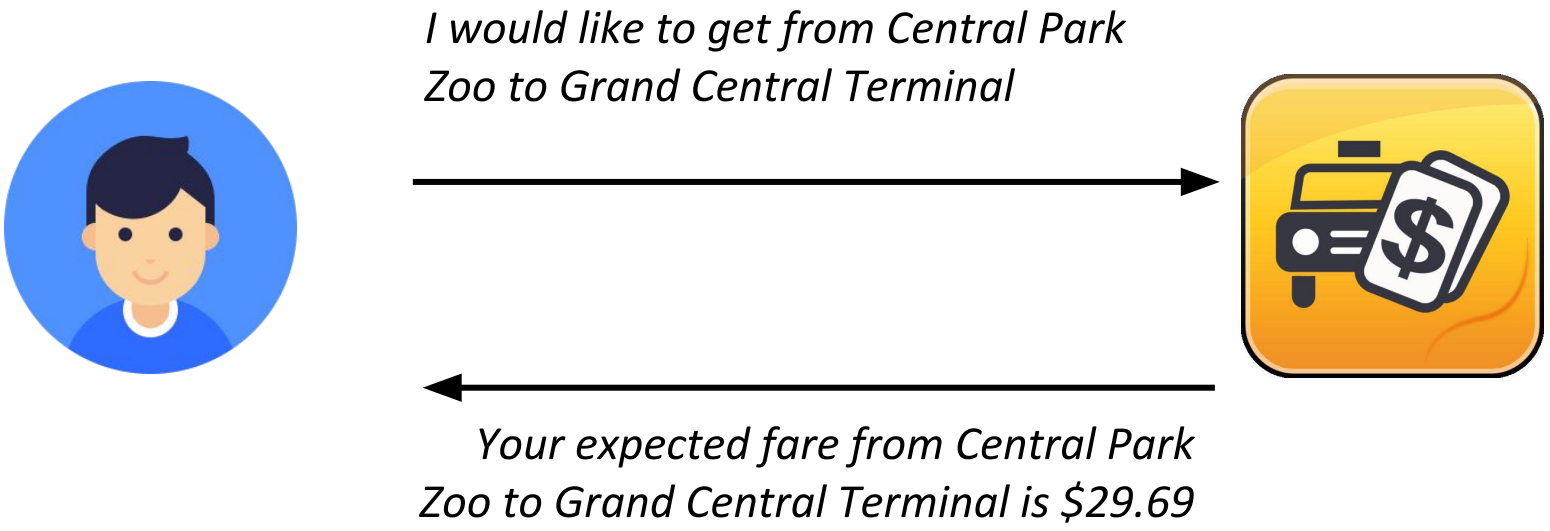


ML on Managed Services

- Machine learning training on large datasets tend to be computationally intensive
- An increasingly affordable option for users without specialized IT infrastructure is to process ML workloads on the cloud with Managed Services like Google AI Platform.
- Benefits:
  - No need to provision and configure virtual machines
  - Horizontal and vertical scaling is possible
  - No need to write custom logic to orchestrate multiple workers and achieve parallel training
  - Deploy your model to the cloud

P4.2 - Taxi Fare Prediction Application

- Accepts speech queries to get the fare estimate to get from point to point (based on historical data), and returns the result as speech



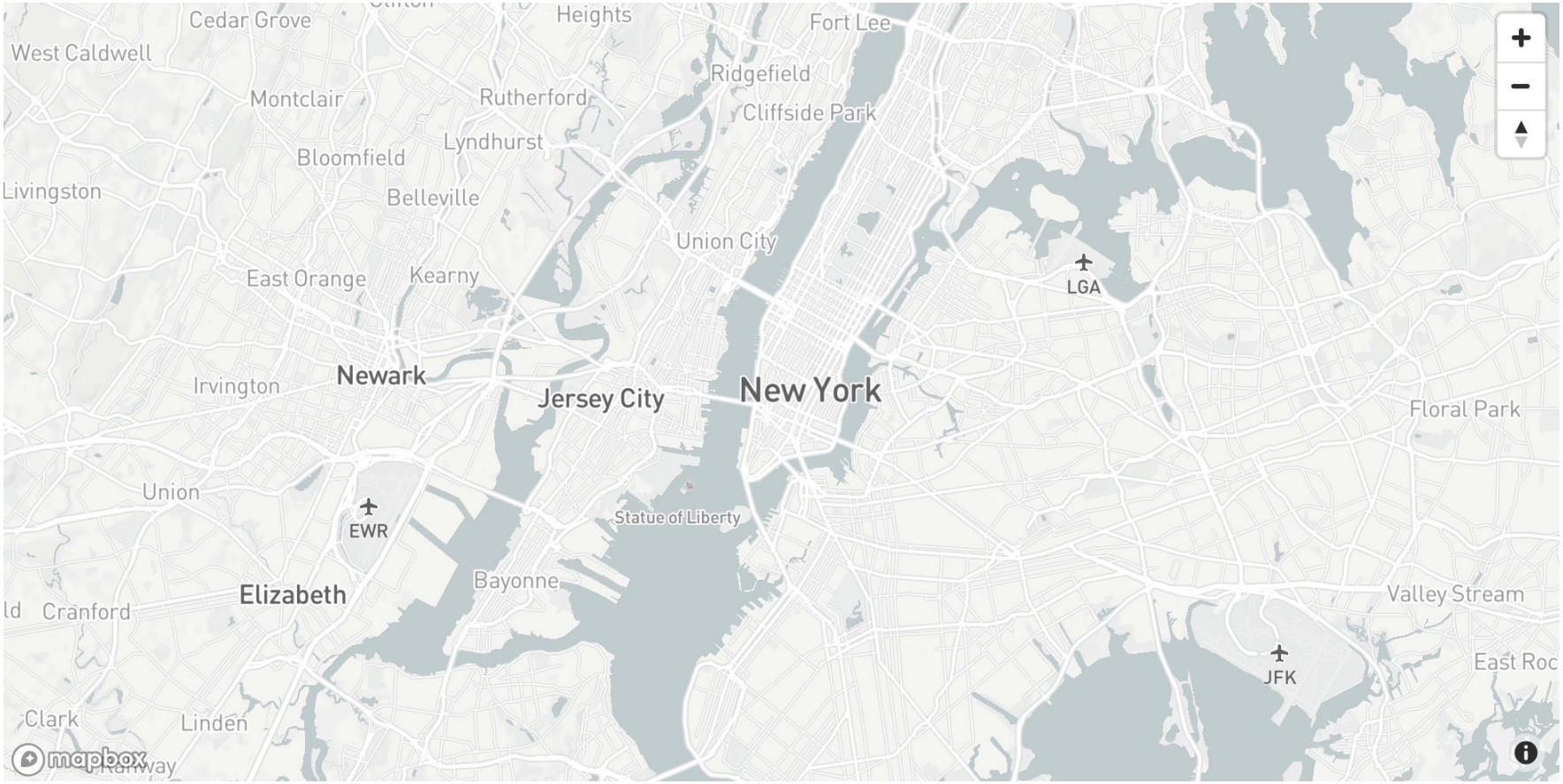
P4.2 - Overview of Tasks

- Task 1: Data Visualization and Feature Engineering
- Task 2: Training, hyperparam tuning, deploying your model using the Google AI Platform and serving queries.
- Task 3: Stitch together services into a pipeline to build a user-facing interface for fare predictions.
- Bonus:
  - Use Cloud Vision API to identify NYC landmarks
  - Use AutoML to train a custom model that accepts custom landmarks as input for prediction

Task 1: Feature Engineering - Data Viz

- You are given a small training dataset containing historical data of fare prices in New York City.
- Steps to perform
  - Data exploration and visualization
  - Understand the data for Feature Engineering with regards to feature construction, data cleaning, etc.

Task 1: Feature Engineering - Data Viz



Task 1: Feature Engineering

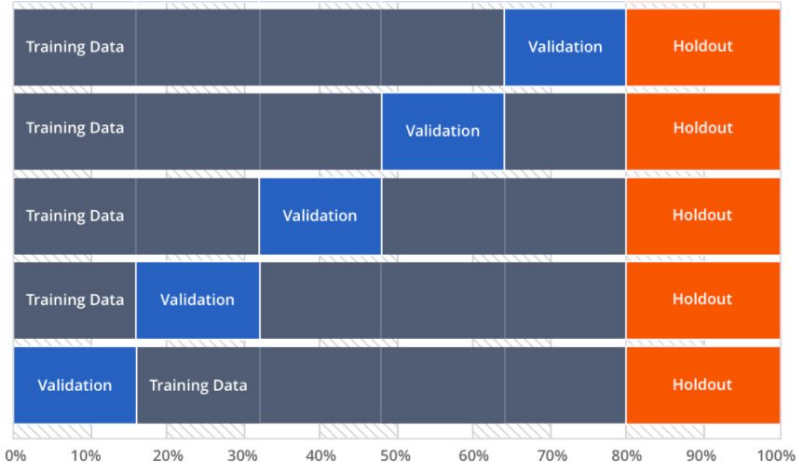
- You are given a small training dataset containing historical data of fare prices in New York City
- Steps to perform
  - Clean data and remove outliers
    - Consider what you learned from the data visualization task
  - Extract or construct meaningful features that will improve performance over the baseline model (which uses raw features with no transformations)

Task 1: Feature Engineering

- Feature engineering = transforming domain knowledge into better features
- Some ideas for feature engineering
  - Calculate distance from the geo-coordinates
  - Calculate distance to landmarks
  - What are good proxies for traffic conditions?

Task 1: Feature Engineering

- Evaluating your model
  - Metric: Root Mean Squared Error (RMSE)
  - K-fold Cross Validation
    - Used to assess the predictive performance of the model outside the training sample on unseen data



  - Plot feature importance

Task 2: Training, Tuning & Deploying

- Build a complete model with the training dataset. We will leverage Google AI Platform to perform model training.
- Deploy the trained model to AI Platform.
- Deploy a Flask application that accepts web requests and returns fare predictions
  - Transform raw features from web requests using the feature engineering solution developed in Task 1.
  - Make API calls to the model hosted on AI Platform
  - Format and return a web response

Task 2: Tuning with Google AI Platform

- **Hyperparameter Tuning**
- Parameters v/s. Hyperparameters
  - Parameters: internal, often not set by the practitioners
  - Hyperparameters: external, often set by the practitioners before training
    - Basically, configuration parameters that impact the training process
- Finding optimal hyperparameters with exhaustive Grid Search is expensive

Task 2: Tuning with GCP HyperTune

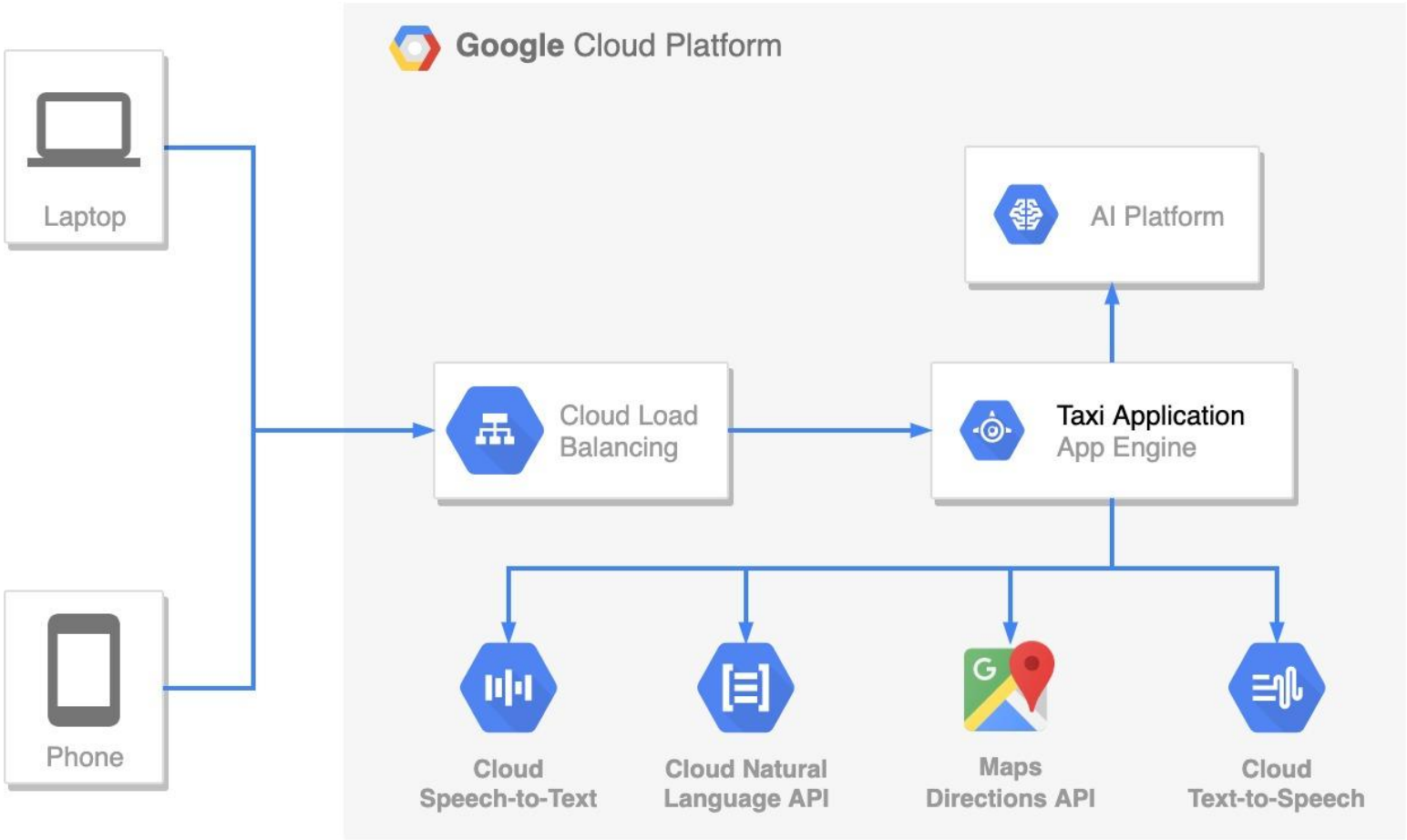
- Black box optimization service (does not need access to the underlying model)
- Need to specify a config yaml file that describes which hyperparameters to tune
- Uses a method called Bayesian Optimization to efficiently search through different combinations of hyperparameters
- An example of a HyperTune configuration file: hptuning_config.yaml

Task 2: Deploying Model to AI Platform

- **To get a full score in this task, you need to:**
  - Enable HyperTune, add at least 3 additional parameters to tune, run the hypertuning job and create a model on Google AI Platform.
  - Deploy the fare prediction application to GAE that uses the model created above and serves web requests correctly.
  - The predictions should achieve a target accuracy, measured by RMSE.

Task 3: ML Application Pipeline

- Build an end-to-end application pipeline to predict car fare requests using the following architecture.



Task 3: ML Application Pipeline

- Your application will include multiple APIs
  - Functional APIs to be implemented
    - **/predict -** Generate fare predictions for a JSON array of rides
    - **/speechToText -** Convert WAV audio to text string
    - **/textToSpeech -** Convert text string to WAV audio
    - **/namedEntities** - Identify landmarks in a given sentence
    - **/directions** - For two given NYC landmarks, determine the latitude / longitude for each pickup and drop off pair

Task 3: ML Application Pipeline

Putting it together:

- **/farePrediction** - Given a WAV audio ride request, determine the predicted fare
  - **Response**
    - { "**predicted_fare**": "23.78",
      "**entities**": ["Charging Bull", "Carnegie Hall"],
      "**text**": "Your expected fare from Charging Bull to Carnegie Hall is $23.78",
      "**speech**": <BASE64 ENCODED AUDIO> }

- General solution flow
  - Speech to text ride request (/speechToText)
  - Extract entities from text ride request (/namedEntities)
  - Get the coordinates of the pickup and drop off locations (/directions)
  - Query the AI Platform model to get the predicted fare (/predict)
  - Convert the text response to speech (/textToSpeech)

Bonus: Landmark Recognition

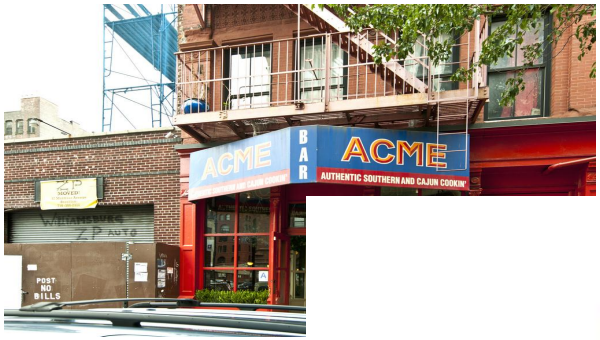
- (5 points) Use Cloud Vision to identify NYC landmarks
- (5 points) Add unique destinations using AutoML

- **/farePredictionVision**
  - Unlike **/farePrediction**, the ride request will not be sent as WAV audio
  - The API will accept the source and destination as images of NYC landmarks
  - Must query the Cloud Vision API and custom AutoML model to determine the landmark names
  - Continue with the same request as **/farePrediction**

Bonus: Landmark Recognition

. . . .

Bonus: Landmark Recognition



Cloud AutoML Vision

. . . .

Hints

- Task 1: Feature transformation
    - The exact same feature transformations must be applied to the training and the test set
    - Cannot share code if stateful functions are used, for example:
        - get_dummies()
        - df.qcut()
    - Store state like bin ranges and categorical values to apply the transformation consistently
    - Jupyter: command not found (use virtualenv)

Hints

- Task 2: HyperTune
  - Read the XGBoost hyperparameter doc to understand which hyperparameters can help most.
  - You can change the number of workers for the AI Platform training job to parallelize the training process.
  - Learn to make good estimates for the cost for each run
    - Cost = Consumed ML Units * $0.49

Issues to Consider

- Overfitting
  - RMSE on training data is much lower than test data
  - You should not filter outliers just because it makes your cross validation scores look better, since some of these records may be representative of the patterns in the real world.
    - Students who do this may pass Task 1, but will fail Task 2.
    - You should make sure you have good features first, before trying to play around with filtering outliers.

TEAM PROJECT
Twitter Data Analytics

Team Project Phase 2 Live Test
Top Q1 Teams

HeartInTheWork	48653.85
Let'sDoIt!	45176.35
SleeplessCoders	45035.20
TeamRocket	39800.38
We Are Not Special	38465.16

Q1H

LiverExplosion	61178.44
Let'sDoIt!	49342.10
YJZ	49142.40
Invictus	47239.21
MakeTwitterGreatAgain	47116.48

Q1M

Congrats to **Let'sDoIt!** for top performance for both HBase and MySQL tests.

Team Project Phase 2 Live Test
Top Q2 Teams

Tritter	11381.92
LiverExplosion	11086.91
CarnegieAnalytica	9667.79
YJZ	9498.33
Team Rocket	7117.90

Q2H

YJZ	27552.07
BareMetalAlchemist	23757.92
CarnegieAnalytica	21597.64
MakeTwitterGreatAgain	20245.92
Tritter	19962.12

Q2M

Congrats to **Tritter, CarnegieAnalytica and YJZ** for top performance for both HBase and MySQL tests.

Team Project Phase 2 Live Test
Top Q3 Teams

Team Rocket	1247.2

Q3H

YJZ	6391.36
StayUpForCC	4885.50
BareMetalAlchemist	4389.00
YiQiGanCC	4020.50
MakeTwitterGreatAgain	3839.80

Q3M

Team Project - Phase 3

- Use only **AWS managed services** for all queries.
- Development budget: $100
  - Penalty for lavishness: >$150
- Live test:
  - Per-hour-budget: $1.28 (included in $100)
- Perform ETL on your beloved GCP and Azure

Cloud Managed Services

- Managed services remove the burden from having to operate the provisioned cloud infrastructure.

- Management of the tools such as monitoring, patching, security, backup are offered as part of the service.

Team Project - Phase 3

- RPS targets have been changed →
  - Q1: 38000
  - Q2: 12000
  - Q3: 6000
- Teams should NOT use any EC2 VMs or EBS volumes.
- Rule of thumb:
  - If you see anything in EC2 dashboard, stop.
  - If you are doing `sudo apt install mysql-server`, stop.
- Teams should explore the managed services provided by AWS to come up with a solution.
- Teams are required to use Terraform (unless Terraform does not have support for your particular managed service)

Team Project General Hints

- No EC2 VMs and EBS volumes in the live test!
  - Nonetheless, you can use those to do verification or comparison to the hosted service you built before in the development process.

- You can check the EC2 web console after launching the managed service to verify if the managed service is allowed
  - Example 1: Lambda is allowed since it there will be no EC2 instances visible in the web console while using.
  - Example 2: EMR is not allowed because there are master and slave machines in the web console.

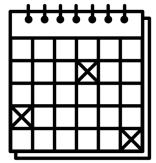
Team Project General Hints

- One option would be to split the services into web-tier and storage-tier and choose different managed services.
  - If so, the compatibility of these two services should be taken into account.

- Consider the different characteristics of queries to decide what kind of managed services to use.

- High performance/cost ratio is valued.
  - Try your best to achieve the highest possible ratio.

Team Project Time Table



Phase (and query due)	Start	Deadlines	Code and Report Due
Phase 1 • Q1, Q2	Monday 10/07/2019 00:00:00 ET	**Checkpoint 1, Report: Sunday 10/13/2019 23:59:59 ET** **Checkpoint 2, Q1: Sunday 10/20/2019 23:59:59 ET** **Phase 1, Q2: Sunday 10/27/2019 23:59:59 ET**	Phase 1: Tuesday 10/29/2019 23:59:59 ET
Phase 2 • Q1, Q2,Q3	Monday 10/28/2019 00:00:00 ET	Sunday 11/10/2019 15:59:59 ET	
Phase 2 Live Test (Hbase **AND** MySQL) • Q1, Q2, Q3	Sunday 11/10/2019 17:00:00 ET	Sunday 11/10/2019 23:59:59 ET	**Tuesday 11/12/2019 23:59:59 ET**
Phase 3 • Q1, Q2, Q3 (Managed services)	**Monday 11/11/2019 00:00:00 ET**	**Sunday 11/24/2019 15:59:59 ET**	
Phase 3 Live Test • Q1, Q2, Q3 (Managed services)	Sunday 11/24/2019 17:00:00 ET	Sunday 11/24/2019 23:59:59 ET	Tuesday 11/26/2019 23:59:59 ET

Upcoming Deadlines

- Project 4.2: Machine Learning on the Cloud
  - Due Sunday, November 17, 2019, 11:59 PM ET
- Team Project : Phase 3
  - Live-test at: Sunday November 24, 2019 3:59 PM ET
  - Code and report due: Tuesday November 26, 2019 11:59 PM ET

Questions?