Machine Learning in Real-Time

Predicting taxi fares in NYC with Dataiku

Alex COMBESSIE

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Intro: Why Real-Time is the New Black

REAL-TIME ANSWERS: Google

REAL-TIME TRANSPORT: UBER

REAL-TIME MACHINE LEARNING:

Agenda

1. In Search of Good Features
2. **Traaaaaaining Time!**
3. Exposing our Model to Users... In a Real-Time App

Outro: Lessons Learned & a Few More Things

In Search of Good Features

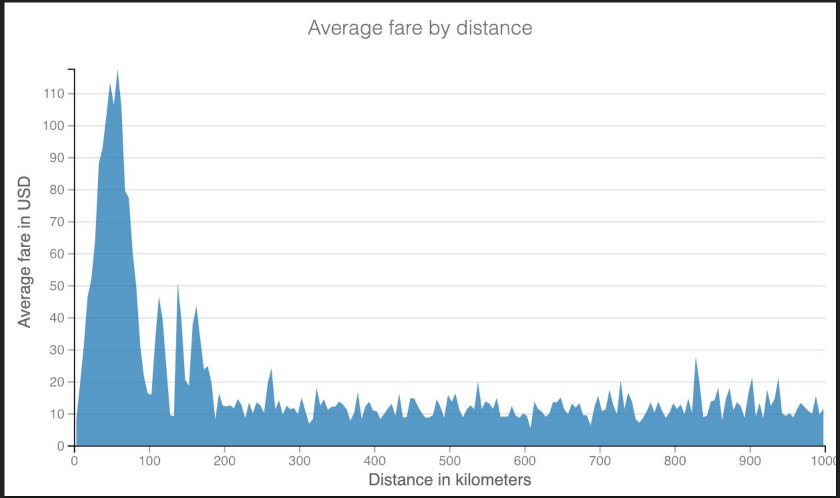
Discovering the Data at Hand

Poor, Dirty Data

www.kaggle.com/c/new-york-city-taxi-fare-prediction/data

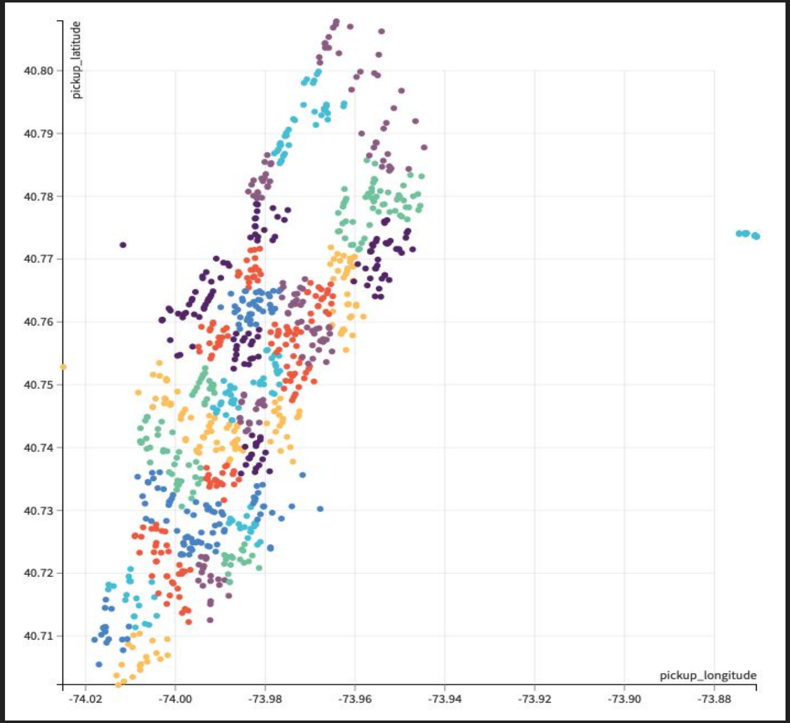
- **Only 4 raw features:** pickup time and location, drop-off location, number of passengers
- **Weird stuff:**
  - 1.9M rides < 100 meters?
  - 100K rides > 300 km??
  - To the bottom of the Hudson???

Non Linear Relationships



Making Features by the Hundred

What Do You See?

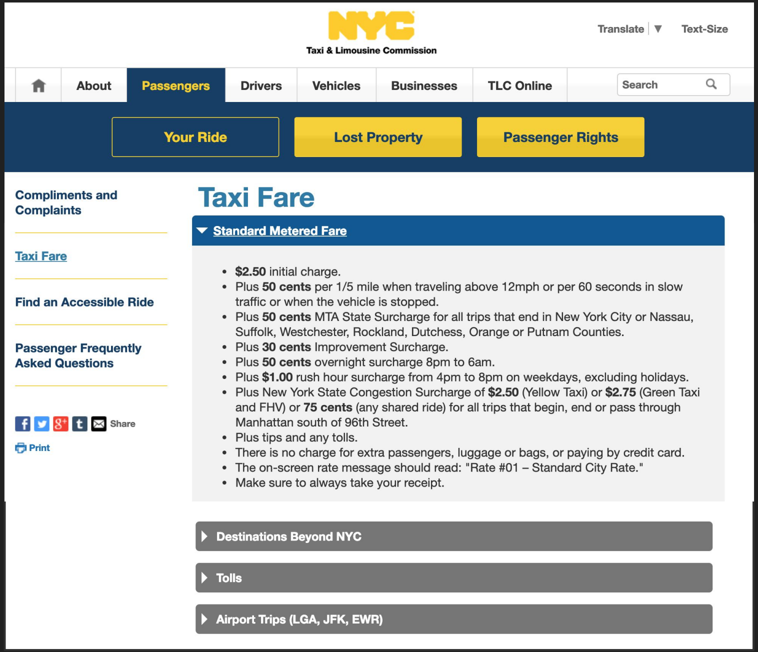


Feature Engineering x Many Iterations

1. **Start simple:** geometrical distances, time seasonalities
2. **Build up with unsupervised learning:** Clustering on GPS coordinates to assign pickup/drop-off to neighborhoods
3. **Finish with windowing:** aggregate features like avg/max fare from one cluster to another in the last 10/100/… rides

Going Back to the Root Cause

The Not-So-Secret Formula



Last Round of Enrichment

- **Convert the formula into features**
  - Flags for specific areas and hours
  - Tolls & airport trips
  - Traffic conditions → the here API

Focus on What Matters

- **Too many features: 4 ↗ 500 ↘ 100** (highest correlated features)


Traaaaaining Time!

Choose Your ~~Weapon~~ Algorithm

The Arsenal

Random Forest	ON
Gradient tree boosting	ON
Ordinary Least Squares	
Ridge Regression	
Lasso Regression	
XGBoost	
Decision Tree	

Support Vector Machine	ON
Stochastic Gradient Descent	ON
KNN	ON
Extra Random Trees	ON
Neural Network	ON
Lasso Path	ON

+ ADD CUSTOM PYTHON MODEL

Microsoft

LightGBM

- Better = – 0.3 RMSE
- Faster = x 3 speed
- Stronger = not Out of Memory

Fighting the Evil Dr. Overfitting

By Feature

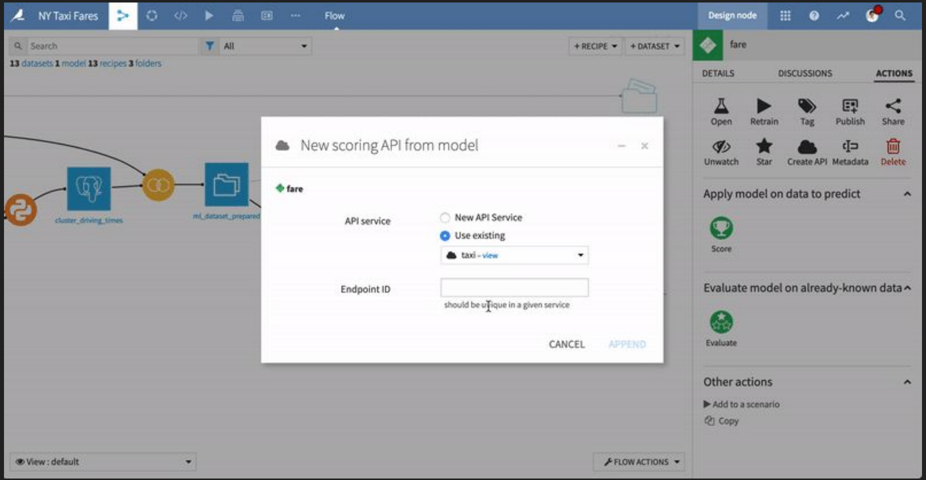
- Balanced view of all features <u>VS</u> always learning from the most predictive
- Reduce “colsample_bytree” parameter to a lower percentage of 60% instead of 100% - a.k.a. Bagging
- Grid-Search

By Observation

- Generalize to the entire dataset <u>VS</u> specific to a small group of observations
- Limit tree growth by setting a “min_split_gain” threshold in addition to “max_depth”
- MOAR Grid-Search

Exposing our Model to Users...
In a Real-Time App

From Batch to Real-Time (API)



Turning a model into an API,
as easy as pie!

API Service Structure

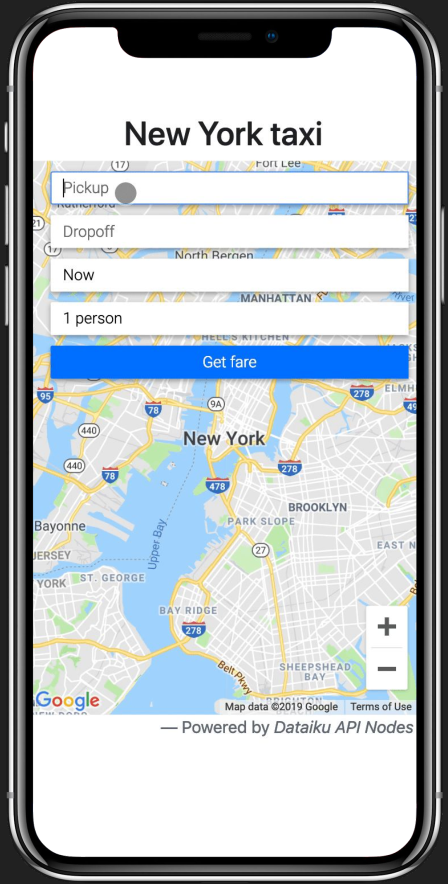
predict_fare: Python endpoint to take raw features and output the fare prediction, a "wrapper" to call...

A. **_cluster**: Python endpoint to assign pickup and dropoff to neighbourhood clusters

B. **_traffic**: Python endpoint to get traffic data from the HERE API

C. **_fare**: our predictive model using both raw features and traffic data

Just Demo



taxifare.dss-demo.dataiku.com

Outro

4 Things You Can Learn by Doing

1. Understand the problem before building models
2. Do not add features for the sake of features
3. Try as many algorithms as possible
4. Simplify your pipeline before deployment

データ
育

From English *data*
and Japanese affix *-iku* (育)
“To raise or bring up; to grow up”

Literally, *"Data Education"*
or *"Let's Grow the Data skills"*

Join Us at EGG LDN

The Human-Centered AI Conference

July 2, 2019

london.egg.dataiku.com

Early Bird Discount: MancML

Thanks!

Questions?

Try it yourself

dataiku.com/dss/trynow

... or any Linux server/container

Learn and stay in touch

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