

QARTA: An ML-based System for Accurate Map Services

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Qatar road network increased three times between 2013-18: Ashghal

24 Apr 2018 - 11:58





QARTA leverages **big spatio-temporal data** and **machine learning**, to build a **map engine** that understands routes, **traffic**, and **drivers**.

+4% Accuracy -70% Pricing

Fleet-aware Car | buses | motorcycles

QARTA in production



All 4k taxis in Qatar



RAFEEQ 3k delivery motorbikes

Services: https://qarta.io

- In-traffic navigation
- Travel time estimation
- Complex route planning
- OD matrices

2M requests/week 1M GPS point/day





Fare estimation

Taxi Dispatching

General Architecture



DL (I): Rule-based Data Cleaning

Existing efforts for data cleaning and wrangling do not support spatial and spatio-temporal data



"After analyzing all your data, I think we can safely say that none of it is useful."

Deployed Rules in QARTA

- Trajectories with a stop
 Split the trajectory
 - Split the trajectory
- Unrealistic points Remove the point
- Missing pointsSplit the trajectory

DL(II): Trajectory Imputation



Low sampling rates

- ~400m
- Save energy & bandwidth

Need densification

- Use the wisdom of the crowd to impute each trajectory





General Architecture: MapMaking Layer



MM Layer (I): Edge weights



Each trip: $d_i \approx w(e_1) + w(e_2) + ... + w(e_k)$

Solve system of equations $\Sigma_i[w(e_1) + w(e_2) + ... + (e_k) - d_i]^2$

\rightarrow Introduce constraints with Ridge Reg. \rightarrow

-	9-1-19 <mark>-</mark> 4	4:05	51.61527	25.26012	51.40927	25.24814	30.8	31
	9-1-19 <mark></mark> 4	4:06	51.61497	25.2602	51.53813	25.32512	20.4	20



MM Layer (II): Metadata imputation

- Need rich metadata (annotation) for road networks
 - Speed limit
 - Number of lanes
 - Road type
 - 0 ...
- Metadata inference in QARTA is framed as a supervised learning problem
 - **Step 1**: Find the best models that would map road features to certain metadata
 - **Step 2**: Use these models to predict the missing metadata values

Public maps have very poor metadata coverage



General Architecture: Calibration



Cal. Layer (I) : Estimated time of arrival

Important for:

- Route planning
- Logistics | Deliveries
- Fare estimation

Depends on:

Google Maps OSRM Estimated travel time (mins) Estimated travel time (mins) 50 50 40 30 20 10 20 30 40 50 10 50 GT - travel time (mins) GT - travel time (mins)

60

- Time | Location
- Route
- Vehicle type
- Weather

Can we learn the <u>per-trip</u> **ETA offset** (error) **distribution** for each map service, and use that to calibrate our queries?

Cal. Layer (I): Supervised Learning of ETA offsets

	free flow features			Te	Spatial features				
ETA_OFFSET(s,d,t) ~) ~ f (osrm_tt(s,c	l), distance,	hour_of_day,	day_of_week,	hour_of_week,	zone(s),	zone(d))
		+5	17	12.5	8	2	32	'14'	'53'
		+2	15	9.8	22	6	142	'03'	'12'
Trips		-7	32	11.2	7	1	7	'51'	'63'



Experimental evaluation

• Data

- Qatar taxi fleet
- 250k trips

• ML models

- Trained on 200k trips
- Tested on 50k trips

• Underlying algorithms

- OSRM for shortest path
- OSM map
- Off-the-shelf kNN&Range queries

Shortest Path



k-NN Queries

- Precision: Number of items in KNN list that overlap with ground truth
 - All very similar performance

 NDCG: A ranking quality measure that takes into account the order if items in the list



Thank You! Do not forget to attend our demo

7 A Demonstration of QARTA: An ML-based System for Accurate Map Services

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