Artificial Neural Networks Applied to Taxi Destination Prediction

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Table of contents

1. Challenge setup

- . Task
- . Datasets
- . Features

2. Winning approach

- . Inputs and output structure
- . Winning Architecture

3. Alternative approaches

- . Recurrent Neural Networks
- . Bidirectional Recurrent Neural Networks
- . Memory-Network-like Architecture
- 4. Experimental Results
- . Results
- . Analysis of the learnt embeddings

Task



- City of Porto
- Evaluation score: Haversine distance
- Improve the dispatch system of the taxis

Datasets

Training:

- 1.7 million training complete trajectories,
- (Mean, Std) path length: (12min, 11min),
- Longest ride: 16h 10min,
- Taxi lost in Iran.



Testing:

- Kaggle testing: 320 testing prefixes,
- Custom testing dataset: 20 000 testing prefixes.

Features

- the complete taxi ride: a sequence of GPS positions (latitude and longitude) measured every 15 seconds.
- metadata associated to the taxi ride:
 - client ID,
 - stand ID,
 - ► taxi ID,
 - timestamp of the beginning of the ride.



-2. Winning approach

Embeddings for meta-data

Timestamp ightarrow (Week of the year, Day of the week, quarter hour of the day)



Metadata	Number of possible values	Embedding size	
Client ID	57106	10	
Taxi ID	448	10	
Stand ID	64	10	
Quarter hour of the day	96	10	
Day of the week	7	10	
Week of the year	52	10	

Structure of the outputs



2. Winning approach

Winning Architecture



Training

- Training data is composed of complete trajectories, whereas our model processes prefixes.
- Training and Testing data distributions.
- Equirectangular approximation of the Haversine distance as the training cost:

$$d(x,y) = R\sqrt{\left(\left(\lambda_y - \lambda_x\right)\cos\left(\frac{\phi_y - \phi_x}{2}\right)\right)^2 + (\phi_y - \phi_x)^2}$$

• SGD with momentum.

RNN



Bidirectional RNN



-3. Alternative approaches

Memory-Network-like Architecture



Results

	Model	Custom Test	Kaggle Test
1	MLP, clustering (winning model)	2.81	1.87
2	MLP, clustering, no embeddings	2.93	2.17
3	MLP, clustering, embeddings only	4.29	3.76
4	RNN	3.14	2.39
5	Bidirectional RNN	3.01	2.33
6	Bidirectional RNN with window	2.60	2.06
7	Memory network	2.87	2.20
	Second-place team	-	2.09
	Third-place team	-	2.11
	Average competition scores ¹	-	3.11
	Constant predictor (center of Porto)	4.71	4.19

¹Only the scores better than the center of Porto predictor are selected. 381 teams.

Confidence of the models

Null hypothesis: the errors of the models have the same mean.

Model	1	2	4	5	6
2	$4.0 \cdot 10^{-2}$				
4	$1.4 \cdot 10^{-6}$	$1.6 \cdot 10^{-3}$			
5	$2.2 \cdot 10^{-3}$	$1.4 \cdot 10^{-1}$	$2.9 \cdot 10^{-2}$		
6	$3.8\cdot 10^{-4}$	$6.5 \cdot 10^{-8}$	$0.0 \cdot 10^{+0}$	$4.2 \cdot 10^{-11}$	
7	$1.9 \cdot 10^{-1}$	$1.6 \cdot 10^{-1}$	$1.9 \cdot 10^{-5}$	$1.6 \cdot 10^{-2}$	$2.1 \cdot 10^{-6}$

- 1 MLP, clustering
- 2 MLP, clustering, no embeddings
- 4 RNN

- 5 Bidirectional RNN
- 6 Bidirectional RNN with window
- 7 Memory network

4. Experimental Results

t-SNE: Quarter of Hour



4. Experimental Results

t-SNE: Weeks



Softmax output





Conclusion

- Almost fully automated compared to other published solutions,
- Raw GPS points, no discretization,
- Use of meta-data,
- Little preprocessing,
- No post-processing,
- No ensembling.

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https://github.com/adbrebs/taxi