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A Denoising Hybrid Model for Anomaly Detection in Trajectory Sequences

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CHANGE

ΕΥΡΩΠΑΪΚΗ ΕΝΩΣΗ
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ΕΠΑνΕΚ 2014-2020
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ανάπτυξη - εργασία - αλληλεγγύη

Με τη συγχρηματοδότηση της Ελλάδας και της Ευρωπαϊκής Ένωσης

Introduction

Anomaly detection in trajectory data

What is trajectory?

$T_i = \{(x_1,y_1), (x_2,y_2),\ldots.., (x_m,y_m)\}$

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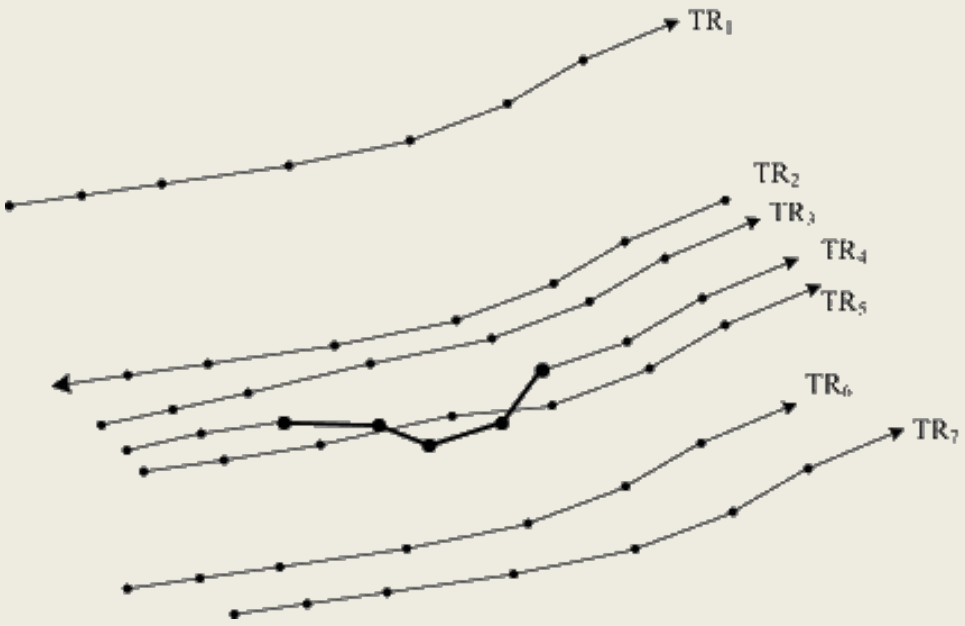
What is an anomalous trajectory?

One that is different compared to others with respect to some kind of similarity

- not uniformly defined
- context dependent



[Meng et al., 2019]

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Applications:

- traffic monitoring and management
- public safety
- surveillance

Related Work

Most trajectory anomaly detection methods rely on
[Gupta et al., 2013; Bhowmick & Narvekar, 2018] :

- Distance (trajectories with not many neighbors)
  [Lee at al., 2008]
- Density (trajectories with low density)
  [Fontes at al., 2013]
- Historical similarity (temporal outlier detection)
  [Li at al., 2009]
- Classification (machine learning classification models – e.g. Isolation Forest, Neural Autoencoders)
  [Zhang et al., 2011; Bouritsas et al., 2019]

Problem Definition

Given a set of trajectories $T_i = \{(x_1,y_1), (x_2,y_2),\ldots\ldots, (x_m,y_m)\}$:

Our goal:

The unsupervised spatiotemporal detection of anomalies in the dataset

- without explicit description of normal patterns
- capturing the temporal dependencies of trajectory data

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Our contributions:

- A hybrid architecture: a sequential denoising autoencoder with a density-based model
- two variants of LSTM autoencoders trained by minimizing a Haversine distance-based weighted loss function

Methodology

Models

Denoising LSTM Autoencoders

- Aim: reproduce the input sequence by minimizing the reconstruction error
- Anomalies: instances with high reconstruction error

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Two components:

- *encoder*–sequence compression into a latent vector
- *decoder*–input reconstruction from the latent representation

Methodology

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Denoising LSTM Autoencoders

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Two components:

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Two variants of denoising LSTM Autoencoders:

- **LSTM:** Encoder → Encoder's output → Copy m times → LSTM decoder → Dense layer → Final output
- **SEQ:** Encoder → Hidden state vector updated at every timestep → LSTM decoder → Dense layer → Final output

Methodology

Loss function

$$L_{HVR} = \frac{1}{2|I|}\sum_{i}\sum_{t}[(xi(t) - xir(t))^2 + \left(y_i(t) - yir(t)\right)^2] * w_i$$

w_i: log haversine distance covered by trajectory

Methodology

Loss function

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Anomaly detection

Apply two methods on the reconstruction errors of unseen trajectories:

- **AVG**: Trajectories ranked by the average of their reconstruction errors
- **LOF**: We propose applying Local Outlier Factor algorithm on error sequences

Methodology

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How does LOF work?

- Density-based outlier detection
- Anomalies have much lower local densities than the average of their *k* nearest neighbors

Experiments

Dataset

Porto Taxi Dataset [Mendes-Moreira & Moreira-Matias, 2015]

442 taxis; 01/07/2013 - 30/06/2014 (1.7M trips)

Finally, 1.2M sequences of 9 pairs of (longitude, latitude)

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Test set

- 10% of dataset
- 1% of test set altered to generate synthetic anomalies

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Method	Variant	Description	Pattern
DSTRT	$DSTRT_c$	Complete noise	[0,8,1,7,2,6,3,5,4]
	$DSTRT_p$	Light noise	[0,1,2,4,3,5,6,7,8]
CYCLE	$CYCLE_c$	Same route twice	[0,1,2,3,0,1,2,3,4]
	$CYCLE_b$	Back and forth	[3,4,5,4,3,4,5,4,3]

Experiments

Model Comparison

<u>Models</u>

- $LSTM_m$ & SEQ_m (MSE loss)
- $LSTM_h$ & SEQ_h (weighted MSE loss)
- Baselines: Naïve Random Ranking (NRR); LOF; Feed-Forward Autoencoder (FF)

Experiments

Model Comparison

Models

- ➢ $LSTM_m$ & SEQ_m (MSE loss)
- ➢ $LSTM_h$ & SEQ_h (weighted MSE loss)
- ➢ Baselines: Naïve Random Ranking (NRR); LOF; Feed-Forward Autoencoder (FF)

Evaluation

- ➢ Rank-based
- ➢ Trajectories ranked by anomaly factor
  - o Autoencoders: rank reconstruction errors (MSE) using AVG or LOF method
  - o LOF: rank LOF scores of trajectories
- ➢ Artificially generated outliers should be ranked higher
- ➢ F1 measure at k=5%

Results

Trajectory Reconstruction

Models	FF	$LSTM_m$	SEQ_m	$LSTM_h$	SEQ_h
MSE	$8.726*10^{-6}$	$4.112*10^{-6}$	$4.968*10^{-6}$	$\mathbf{3.908*10^{-6}}$	$4.286*10^{-6}$

- Sequential models have better reconstruction ability than FF
- Haversine-weighted loss function decreases error

Results

Anomaly Detection

F1 Measure (%)

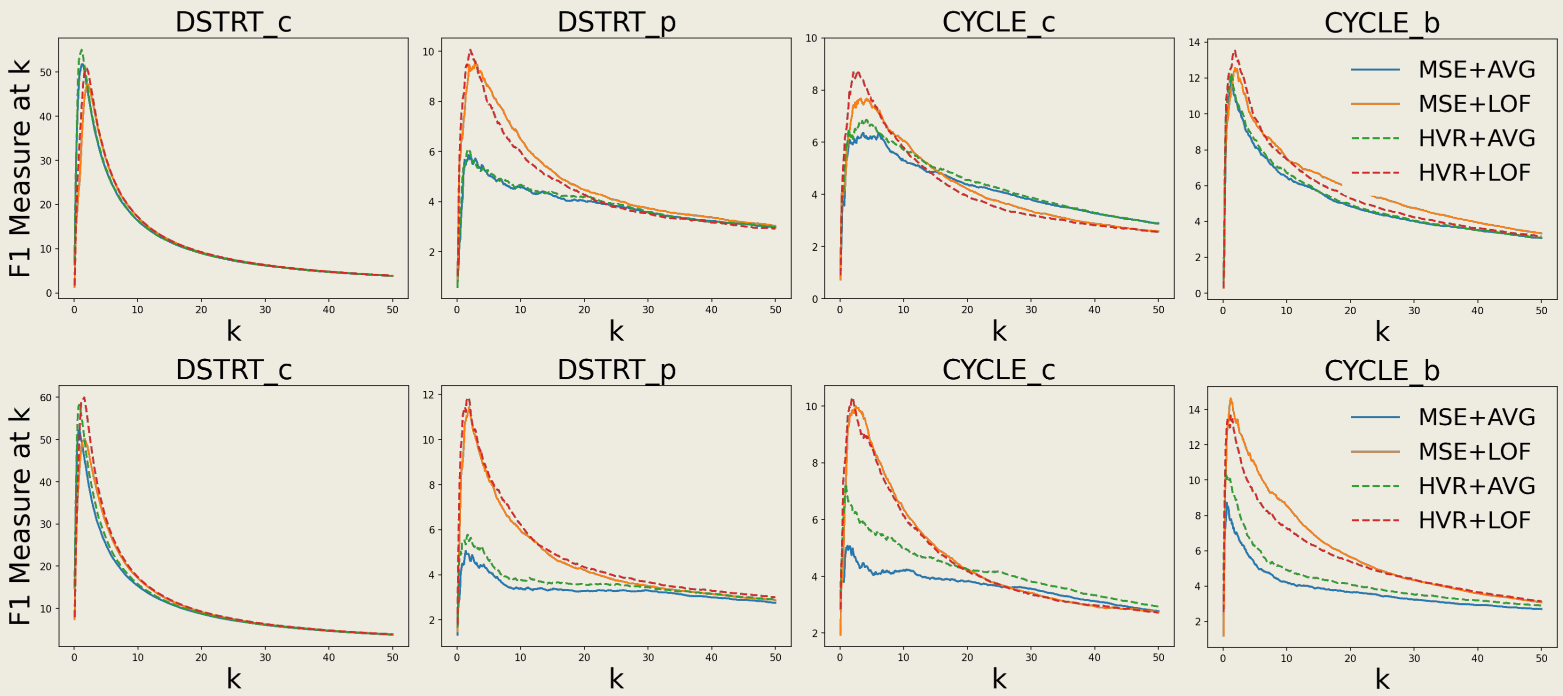
	DSTRT				CYCLE			
	$DSTRT_c$		$DSTRT_p$		$CYCLE_c$		$CYCLE_b$	
	AVG	**LOF**	**AVG**	**LOF**	**AVG**	**LOF**	**AVG**	**LOF**
NRR	1.67	1.67	1.67	1.67	1.67	1.67	1.67	1.67
LOF	-	28.72	-	4.49	-	7.39	-	7.39
FF	18.30	27.38	2.90	5.88	1.56	5.96	2.87	15.48
$LSTM_m$	27.88	30.37	5.03	**8.59**	6.13	7.36	8.18	9.55
SEQ_m	25.14	30.20	4.13	8.23	4.13	**8.70**	5.25	**10.89**
$LSTM_h$	**28.18**	**30.64**	**5.17**	7.88	**6.67**	**7.60**	**8.54**	**9.77**
SEQ_h	**26.70**	**31.30**	**4.65**	**8.43**	**5.55**	8.51	**6.26**	9.25

- Sequential models outperform FF & LOF in most cases
- The Hybrid architecture (LOF applied on reconstruction errors) improves performance in all autoencoders
- Haversine-weighted function outperforms MSE in 13 of 16 cases

Results

Anomaly Detection

Variation of F1 measure over k (for LSTM & SEQ models)



- The Hybrid architecture HVR+LOF gives better results in most cases than MSE+AVG approach

Results

Qualitative Analysis

- SEQ_m + AVG compared to SEQ_h + LOF on our real test set
- One set of the top 0.1% of the trajectories wrt reconstruction error for each model
- Two annotators annotated the trajectories predicted by only one model

Results

Qualitative Analysis

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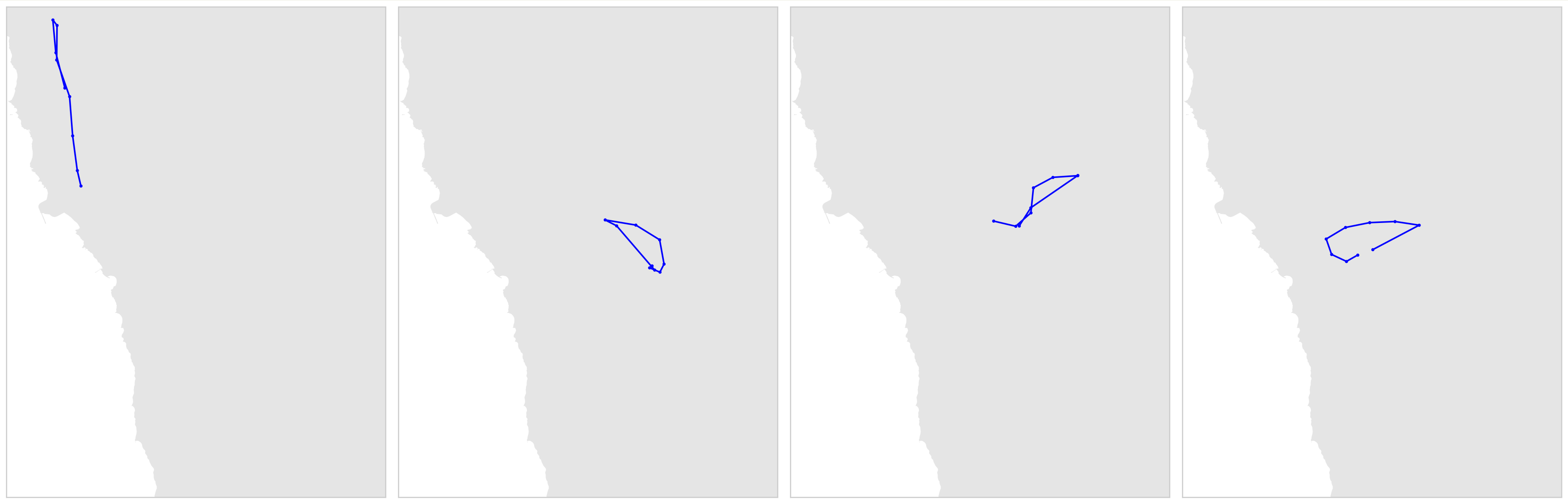
Models	Accuracy
SEQ_m + AVG	9.5%
SEQ_h + LOF	51.7%

Results

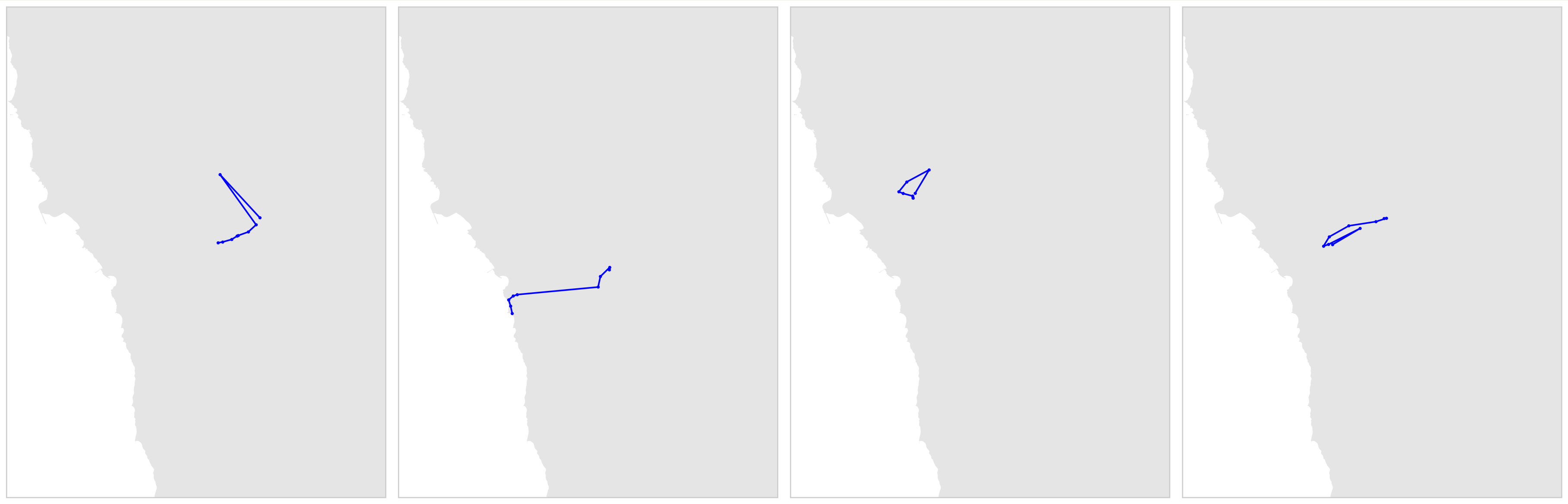
Qualitative Analysis



Anomalies detected only by SEQ_m + AVG method

Results

Qualitative Analysis



Anomalies detected only by SEQ_h + LOF method

- Our Hybrid approach captures different patterns of anomalies

Conclusion

Summary

- Hybrid approach: Sequential denoising autoencoder + density-based algorithm
- Haversine-weighted loss function
- Rank-based evaluation

Conclusion

Summary

- Ensemble approach: Sequential denoising autoencoder + density-based algorithm
- Haversine-weighted loss function
- Rank-based evaluation

Future Work

- More datasets (e.g. bike sharing data)
- Annotated real data
- Transfer learning across different datasets

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