Applying geospatial data for Machine Learning
with a focus on social good

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DSSG Webinar
30th June 2020

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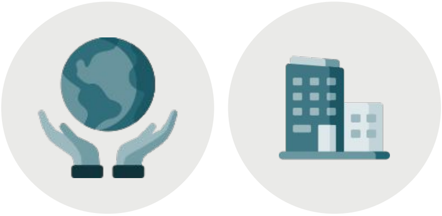

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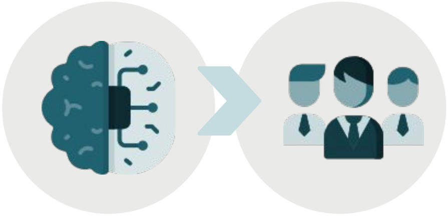

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01

Spatiotemporal data types

Spatiotemporal data?

Spatiotemporal (ST) data is defined as data with both a **spatial and temporal component.**

Examples

- Remote Sensing Data
- Route taken by a transport
- Measurements done by a sensor in the street
- Medical imaging (fMRI exam)
- Videos

These are applicable in several domains, such as **environmental and climate, public safety and human mobility.**

Sources: https://arxiv.org/pdf/1906.04928.pdf

Why we should treat ST data differently

Traditional Machine Learning methods (based on tabular data) **don't work as well in spatiotemporal data.**

- Typically, spatiotemporal (ST) data is in **continuous space**
- Patterns of ST data typically contain **spatial and temporal properties** - hard to capture by traditional methods
- Data samples are **not independently generated**
- Traditional methods are very reliant on **manual feature engineering**, which is hard to do on spatiotemporal data.

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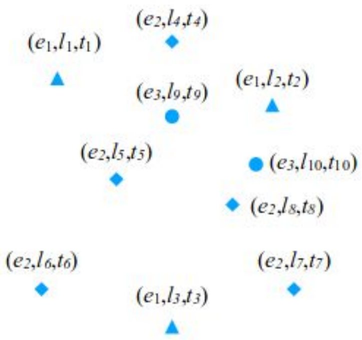
Sources: https://arxiv.org/pdf/1906.04928.pdf

Data Types - Event



Discrete events occurring at **point locations and times**

(crime events, traffic accidents, disease outbreaks, social events and trending topics, civil protection)

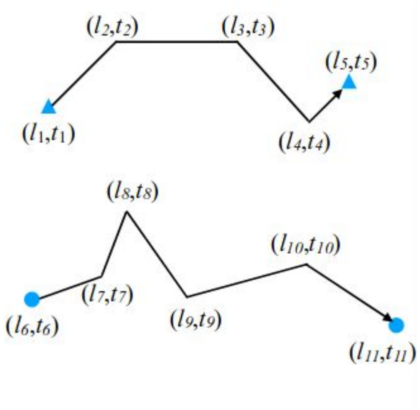
e_i - Event type
l_i - Location
t_i - Time

Events | Operatives | Ground assets | Aerial Assets | Important events | Today's Events | Advanced search

Event Nr.	Status	District	Municipality	Parish	Locality	Day/Time	Nature			
2020130093053		PORTO	PENAFIEL	Termas de São Vicente	TERMAS DE SÃO VICENTE	2020.06.26 14:56	Trauma	2	1	0
2020130093050		PORTO	GONDOMAR	Fânzeres e São Pedro da Cova	FÂNZERES E SÃO PEDRO DA COVA	2020.06.26 14:55	Patrulhamento, Reconhecimento e Vigilância	5	1	0
2020130093041		PORTO	MATOSINHOS	Custóias, Leça do Balio e Guifões	MATOSINHOS	2020.06.26 14:46	Detritos não confinados	12	3	0

Sources: http://www.prociv.pt/en-us/SITUACAOOPERACIONAL/Pages/default.aspx?cID=14, https://arxiv.org/pdf/1906.04928.pdf

Data Types - Trajectory

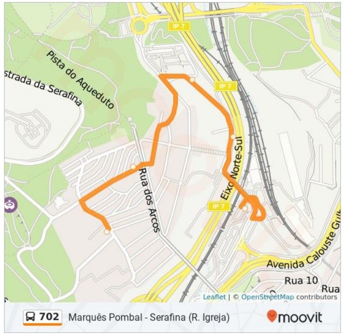


Denote the paths traced by **bodies moving in space over time** (moving route of transports).

Collected by **sensors in a moving object**, for instance.

Represented by a sequence:

(l_i, t_i) where **l_i** is the location and **t_i** is the time.



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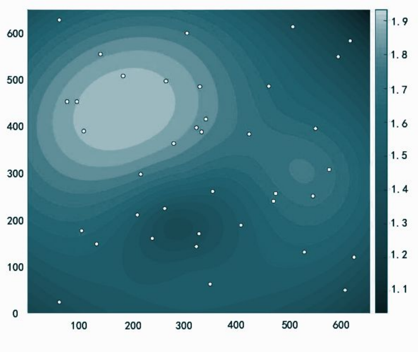
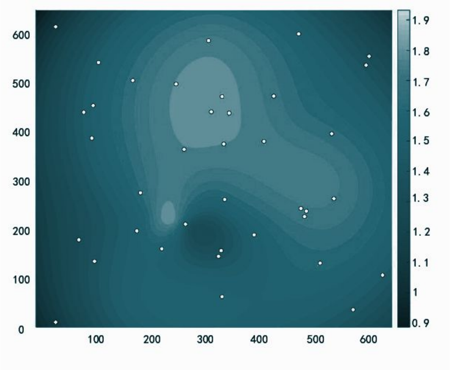
Sources: https://carris.tecmic.com/index.html, https://arxiv.org/pdf/1906.04928.pdf

Data Types - Point Reference





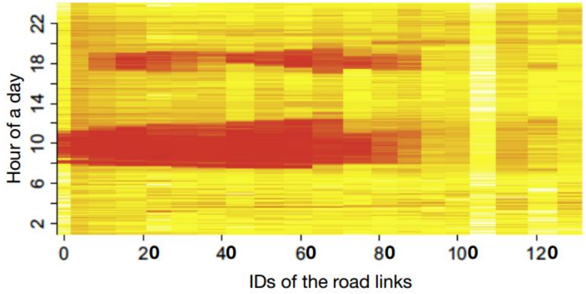
Measurements of a **continuous ST field** (temperature, vegetation, population) over a **set of moving reference points in space and time** - e.g. weather balloons.

Tuple $(\mathbf{r}_i, \mathbf{l}_i, \mathbf{t}_i)$ with measurement value **m**

$\mathbf{r}_i$ - Sensor
$\mathbf{l}_i$ - Location
$\mathbf{t}_i$ - Time

Sources: https://arxiv.org/pdf/1906.04928.pdf

Data Types - Raster Data



ST fields recorded at **fixed locations and time points** (the previous datatype - point reference - had **changing locations**)

e.g. air quality data, traffic flow/car speed

For *m* fixed locations and *n* timestamps, we can present the data as a matrix R (*mxn*).

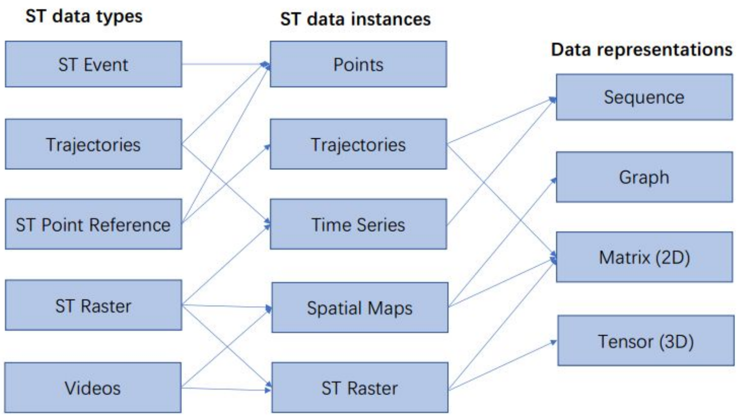
Each entry $\mathbf{r_{ij}}$ is the measurement at location $\mathbf{s_i}$ at timestamp $\mathbf{t_j}$.

Sources: https://qualar1.apambiente.pt/qualar/index.php?page=2, https://arxiv.org/pdf/1906.04928.pdf

02

Treating this data

Representation types



There is not a **best** way of representing ST data.

Traffic Flow Prediction

- Traffic flow graph
- Cell region-level traffic flow matrix

Wind Forecasting

- Represent sensor data as 2D matrices containing wind intensity: (location, timesteps)
- Can also represent as 3D tensor: row region sensor ID, column region sensor ID, timestamp.

Sources: https://arxiv.org/pdf/1906.04928.pdf

Modeling approaches in the literature

	Trajectories	Time Series	Spatial Maps (Image-like data & Graphs)	ST Raster
CNN	[24], [67], [103], [117], [150]		[11], [154], [199], [152], [100], [31], [139], [148], [184], [80], [69], [15], [72], [200], [113], [54], [68]	[188], [12], [123], [141], [106], [74], [131], [149], [116], [128], [128], [76], [78]
GraphCNN			[85], [155], [94], [111], [144], [22], [92], [175], [44], [8], [85], [155]	
RNN(LSTM,GRU)	[42], [77], [165], [99], [91], [163], [35], [159], [64], [38], [135], [181], [88], [81], [190], [37], [169], [166], [41], [65], [192]	[126], [27], [177], [90], [23], [89], [178], [17], [179], [101], [97], [14], [34]	[125], [107], [156], [2], [3], [39], [62], [162]	[23]
ConvLSTM			[1], [98], [161], [198], [151], [73], [201], [70], [147]	
AE/SDAE	[115], [197], [13]	[55], [167], [104]	[32], [16], [191], [48], [52], [182]	
RBM/DBN	[117]	[136]		[140], [58], [66]
Seq2Seq	[82], [170], [20], [171]	[90], [89]		
Hybrid	[164], [142], [108]	[96], [59]	[189], [30], [19], [6], [174], [187], [84], [109], [134], [49], [176]	[105], [127]
Others	[36], [10], [46], [195], [26], [193], [168]	[124], [93]	[133], [145], [202], [21], [183], [146], [79], [43], [185], [186], [132]	[122], [63], [71]

Recurrent Networks
- Mostly used for trajectories and time series

CNNs
- Mostly used for map-like data (spatial maps/ST Raster)

GraphCNN
- Used for graph data

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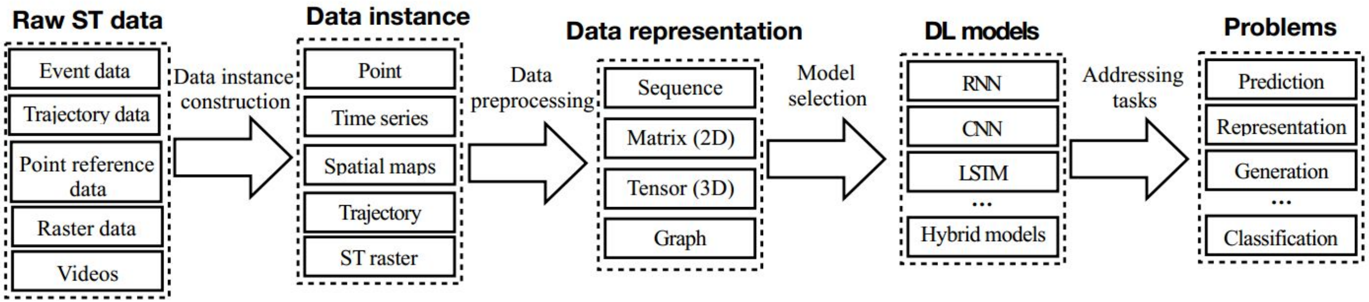
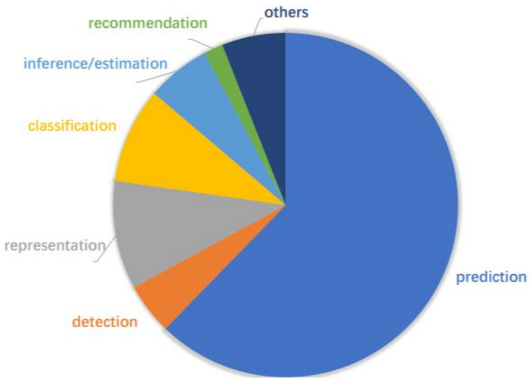
Sources: https://arxiv.org/pdf/1906.04928.pdf

Pipeline for (most) ST data problems





Prediction: predict the future observations of the ST data based on its historical data.

Representation: learn the abstract and useful representations of the input data to facilitate downstream data mining or machine learning tasks.

Classification: separate geospatial data in classes.

Estimation: information inference.

Sources: https://arxiv.org/pdf/1906.04928.pdf

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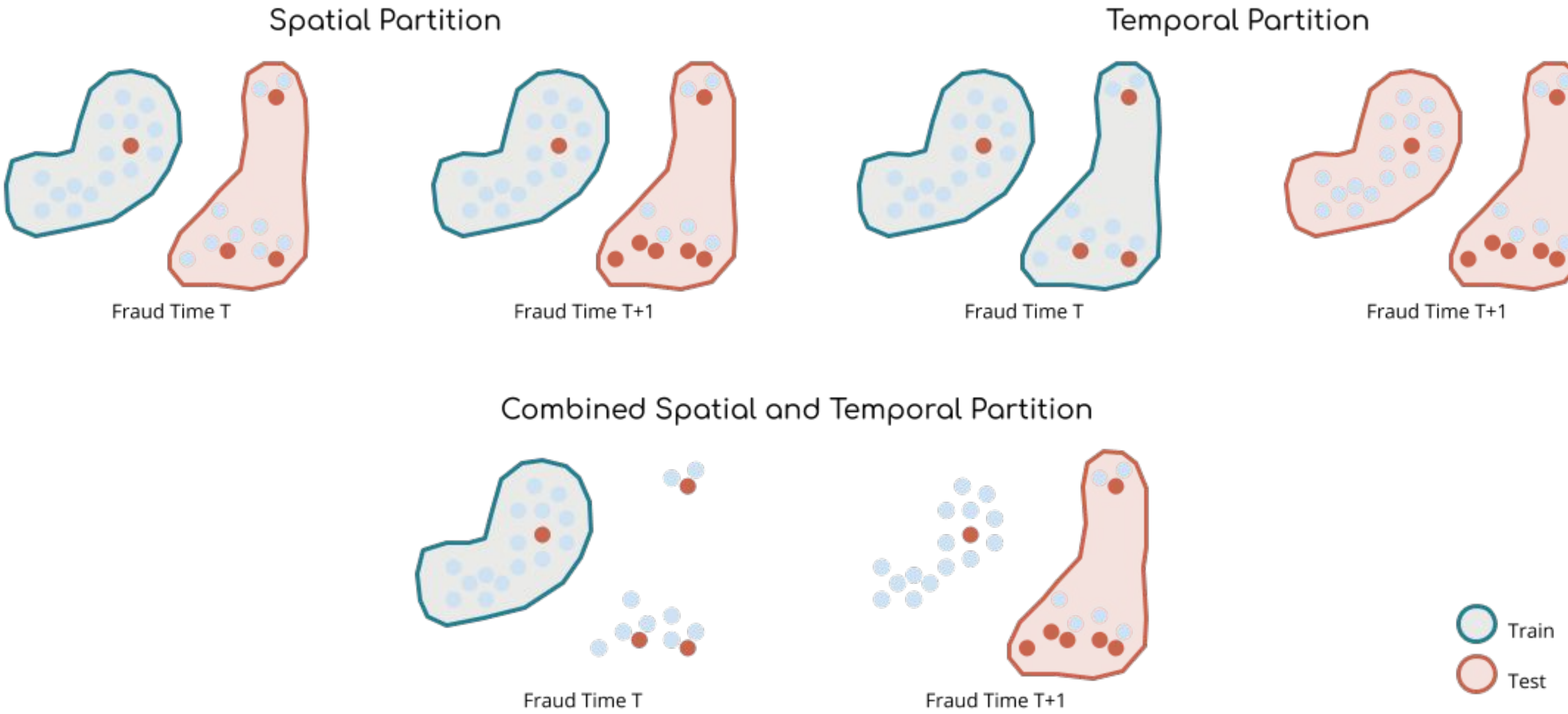
Model evaluation for geospatial problems

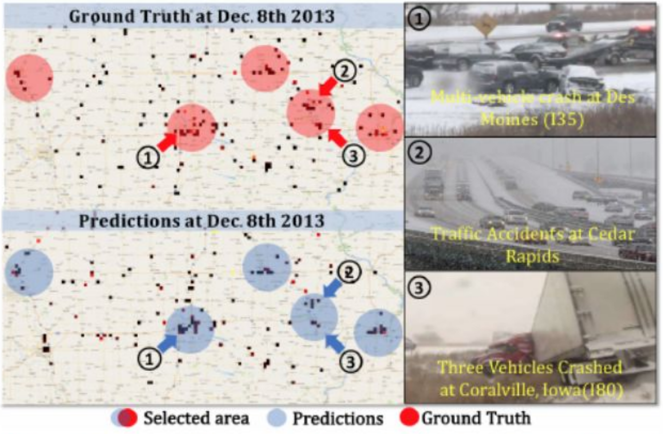


Sources: https://nilg.ai/blog/202006/who-is-tampering-your-meters-fraud-detection-in-utilities/

02

Use Cases

Traffic Accident Count Prediction (i)



- Has the goal of improving transportation, public safety and safe routing.
- Challenging:
  - **Rareness** of accidents in space and time
  - **Spatial heterogeneity** (rural vs urban environment have different accident factors).
- Commonly formulated as a **classification** or **regression** problem
  - Will there be an accident in (e_i, t_i)?
  - Accident count in (e_i, t_i)?

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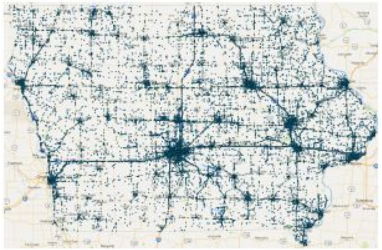
Sources: https://dl.acm.org/doi/pdf/10.1145/3219819.3219922

Traffic Accident Count Prediction (ii)



(a) Visualization of Traffic Accidents

(b) Rainfall Map

(c) RWIS Observation Stations

Data Sources

- **Target:** Crash Data
- **Auxiliary:** Road Networks
- **Features:**
  - Satellite Images
  - Traffic Camera Data (i.e. number of vehicles)
  - Rainfall Data
  - RWIS Stations (Temperature and Wind)

Formulation

- **Data Instances**
  - Map is partitioned in a square spatial grid S (elements $\mathbf{s}_i$).
  - Data Sources above are saved as 3D tensor ($\mathbf{s}_i$, $\mathbf{t}_i$)
  - Map is masked according to road networks
- **Target**
  - Predict the total number of accidents in a given time window, for cell $\mathbf{s}_i$.

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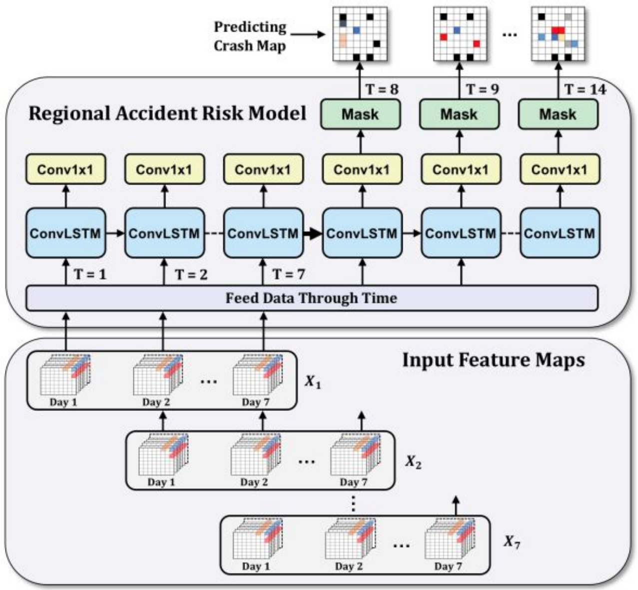
Sources: https://dl.acm.org/doi/pdf/10.1145/3219819.3219922

Traffic Accident Count Prediction (iii)



Regional ConvLSTM Model

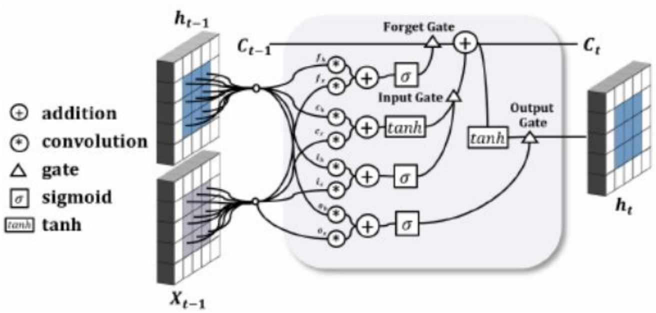


Figure 3: The inner structure of a ConvLSTM cell.

Training and Testing

The last 7 days are predicted based on the data in the first 7 days.

Amount of days chosen is related with the human activity **weekly pattern.**

The first 7 years are used for **training** the model, and the last **year** for testing (partition by time)

Sources: https://dl.acm.org/doi/pdf/10.1145/3219819.3219922

Traffic Accident Count Prediction (iv)

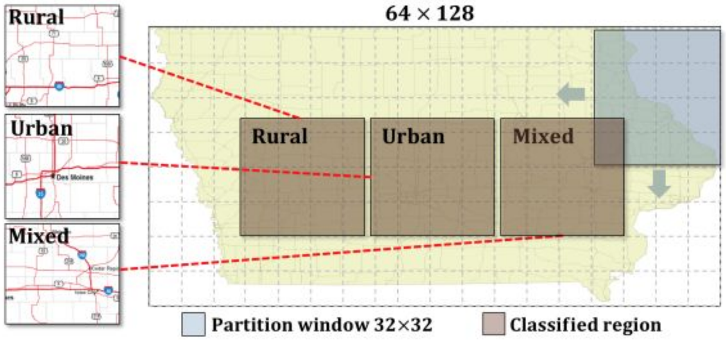


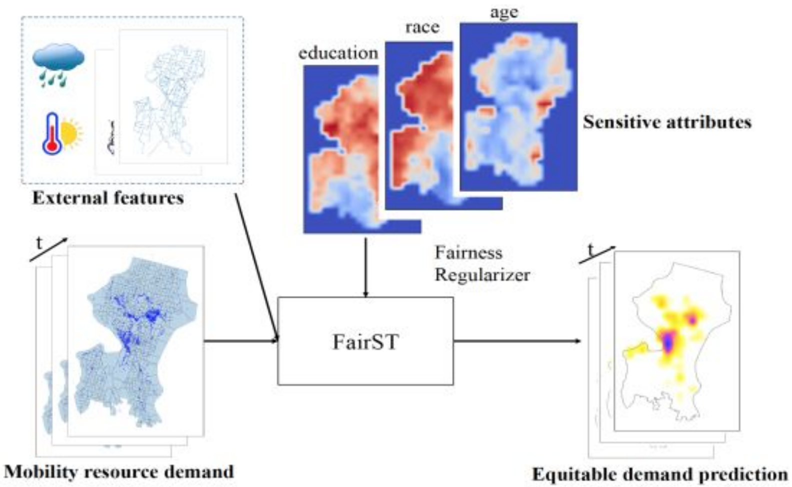
Figure 5: Map partitioning of spatial ensemble model (stride=16).

For dealing with spatial heterogeneity, the authors **learn a model for each window**, and ensemble all the predictions.

Sources: https://dl.acm.org/doi/pdf/10.1145/3219819.3219922

Fair Demand Prediction in Mobility Systems (i)

- New mobility systems (e.g. bike-sharing) offer affordable transport options for citizens.
- Current demand prediction models do not deal with social disparities: less demand **might not mean less interest**, but an area with **disadvantaged groups**!



Sources: https://dl.acm.org/doi/pdf/10.1145/3347146.3359380

Fair Demand Prediction in Mobility Systems (ii)

- How do we incorporate fairness in this approach?

Individuals of different groups must have access to the same resources.

Group Fairness: The disadvantaged group must experience similar predicted outcomes as the advantaged group

Vertical Equity: Transportation policies must favor the disadvantaged groups

Two fairness metrics added, measuring the **gap** between **mean demand per capita** across two groups, over a certain period of time.

Region-based Fairness Gap: each geographic region has a categorical label (e.g. Caucasian)

Individual-based Fairness Gap: the group label is numeric (e.g. % of Caucasian)

Sources: https://dl.acm.org/doi/pdf/10.1145/3347146.3359380

Fair Demand Prediction in Mobility Systems (iii)

- Loss Function is Modified to add the following terms:

Regression Loss, for penalizing wrong predictions in terms of **demand value** (Mean Absolute Error)

Region Fairness Loss, for penalizing the model when the demand per capita in a region containing both groups **is not the same**

Individual Fairness Loss, for penalizing the model when the demand per capita in a region containing both groups **does not favor the disadvantaged group** (weighted).

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Sources: https://dl.acm.org/doi/pdf/10.1145/3347146.3359380

City Inflow/Outflow Prediction (i)

- Crowd flow prediction is important for managing **traffic and public safety.**
  - Measured by the number of pedestrians + cars + people traveling on public transportation systems.
  - This paper uses **GPS data** for measuring the number of pedestrians.

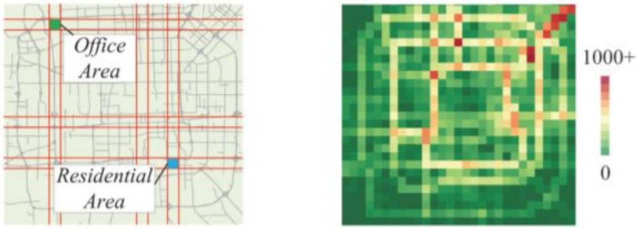
- **Challenging** problem due to:
  - **Spatial dependencies** (outflow in a region affects inflow in another)
  - **Temporal dependencies** (traffic congestion at 8 am affects typical traffic at 9 am, and people's routine changes throughout the year)
  - **External factors** (e.g. weather)

(a) Inflow and outflow (b) Measurement of flows

Source: https://www.aaai.org/ocs/index.php/AAAI/AAAI17/paper/viewPaper/14501

City Inflow/Outflow Prediction (ii)

- Problem and label definition



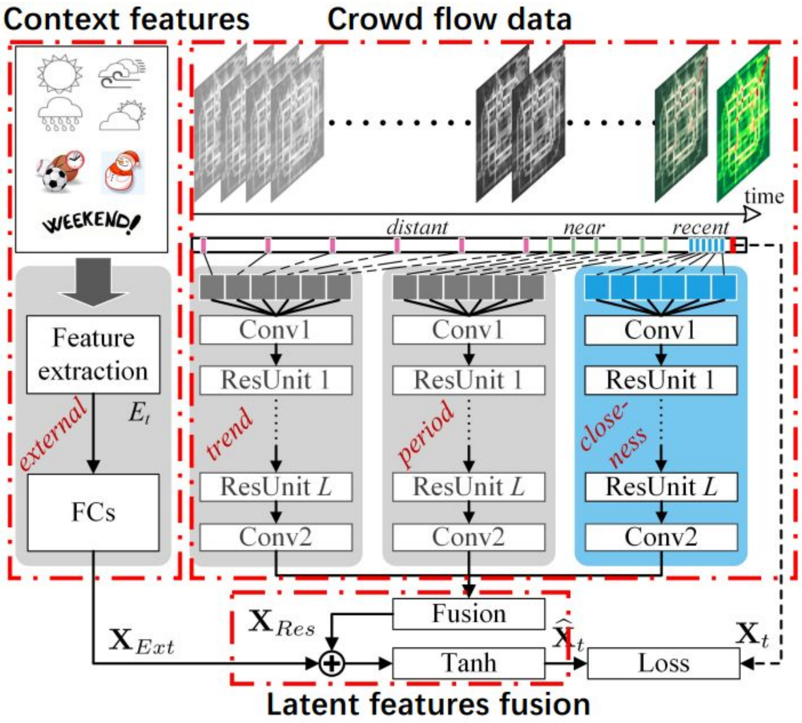
(a) Grid-based map segmentation (b) Inflow matrix

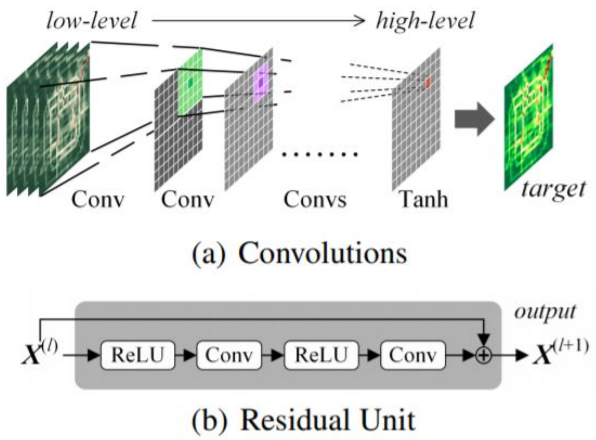
The authors define an **inflow** and **outflow** 2D matrix, for each **timestep**, after dividing the map in a grid.

Given the **historical observations** up to point **T-1**, they want to predict the count of inflow and outflow at point **T**.

Source: https://www.aaai.org/ocs/index.php/AAAI/AAAI17/paper/viewPaper/14501

City Inflow/Outflow Prediction (iii)





Spatiotemporal ResNet

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Source: https://www.aaai.org/ocs/index.php/AAAI/AAAI17/paper/viewPaper/14501

Concluding…

There are **many ways** spatiotemporal data can be used for AI applications.

There is not much (if any?) research done using open data in Portugal. **So why not start with it?**

http://centraldedados.pt/

DADOS ABERTOS
em Portugal

http://dadosabertos.pt/

I'm sure **DSSG** would give you some exposure and help you find **motivated volunteers**.

(well, I'm biased)

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