Consiglio Nazionale
delle Ricerche

STS-EPR

A mechanistic approach for modelling spatial, temporal and social aspects of human mobility

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09-04-2021

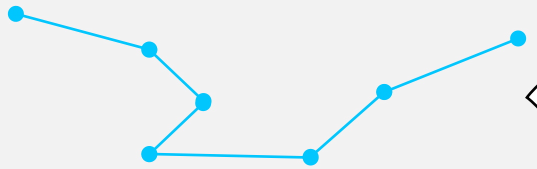
Introduction

- **Human mobility** is the discipline that studies the movements of individuals in **space** and **time**.

- The increase of GPS devices and location-based services allows to collect **digital footprints** of human's movements.

Trajectory

Definition

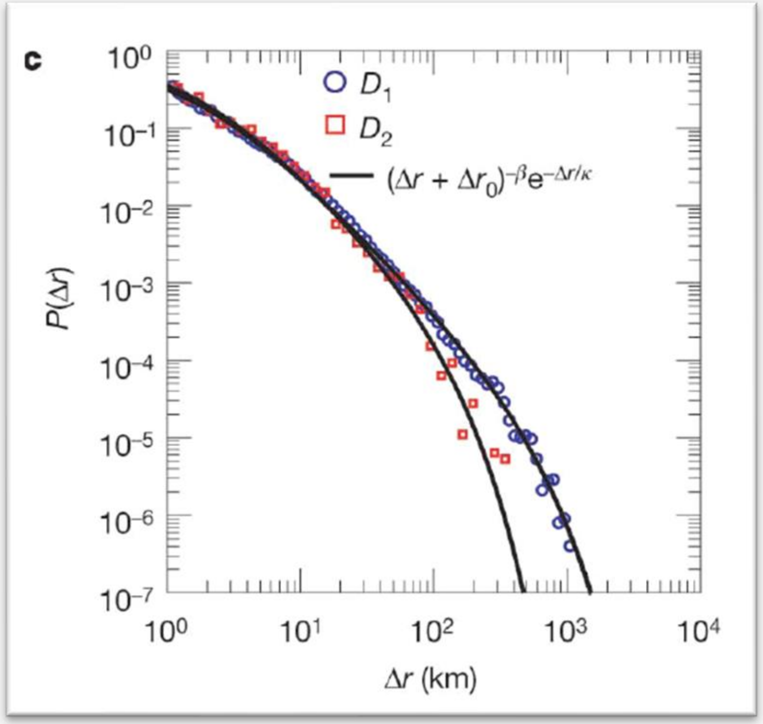


$$T = < (r_0, t_0), (r_1, t_1), \dots, (r_n, t_n) >$$

Introduction

- The large avaliability of digital traces of our displacements, offers the possibility to study human movements at a **large scale** and in **detail**.

- Several mobility patterns emerge [1, 2]:
  - **Power-law** behavior of Δr, r_g, and Δt
  - Tendency to **return** to few location visited before
  - Move at **specific times** of the day



[1] Brockmann, D., Hufnagel, L., Geisel, T., 2006. The scaling laws of human travel. Nature 439, 462–5.
[2] Gonzalez, M.C., Hidalgo, C., Barabasi, A.L., 2008. Understanding individual human mobility patterns. Nature 453, 779–82.

Introduction

- Mobility trajectory data are of **fundamental** importance in different disciplines [3]:

Epidemic modeling

Traffic optimization

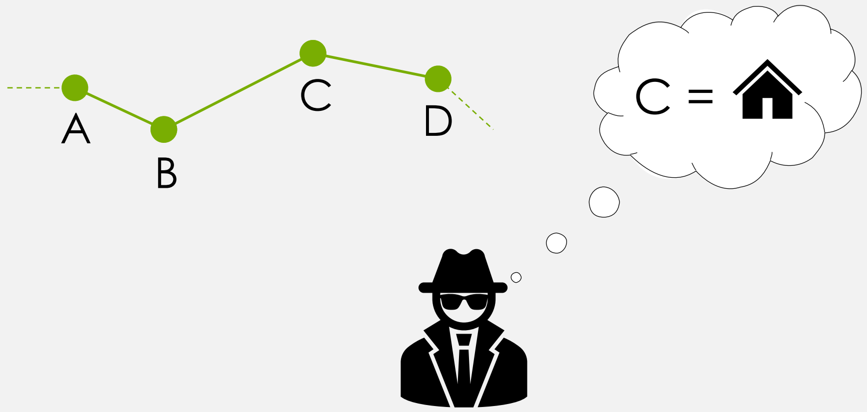
What-if analysis

[3] Barbosa-Filho et al. 2018. Human mobility: Models and applications.

Introduction

Problem

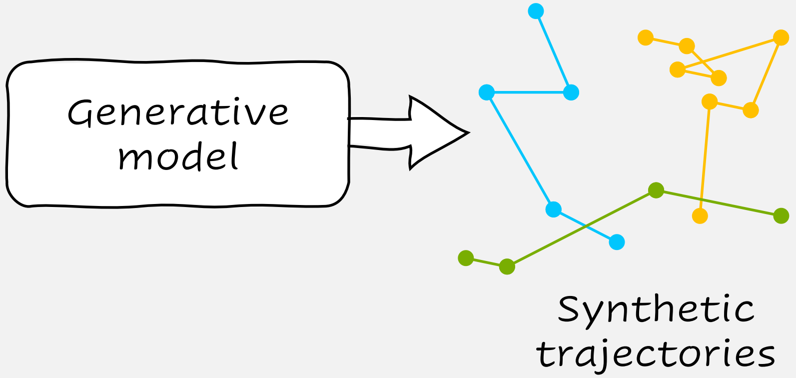
- Mobility trajectory data are sensitive: they suffer from **privacy attacks** [4]



- Companies **cannot** make mobility data freely available

Solution

- **Generative models**
  - Generate **synthetic** yet **realistic** trajectories
  - **Reduce** the cost of the data collection phase (time and money)
  - Produce trajectories for new scenarios



[4] Montjoye, Y.A., Hidalgo, C., Verleysen, M., Blondel, V., 2013. Unique in the crowd: The privacy bounds of human mobility. Scientific reports 3, 1376.

Introduction

- A mechanistic model assumes that a complex system can be understood by examining the workings of its individual parts and the way they are coupled.

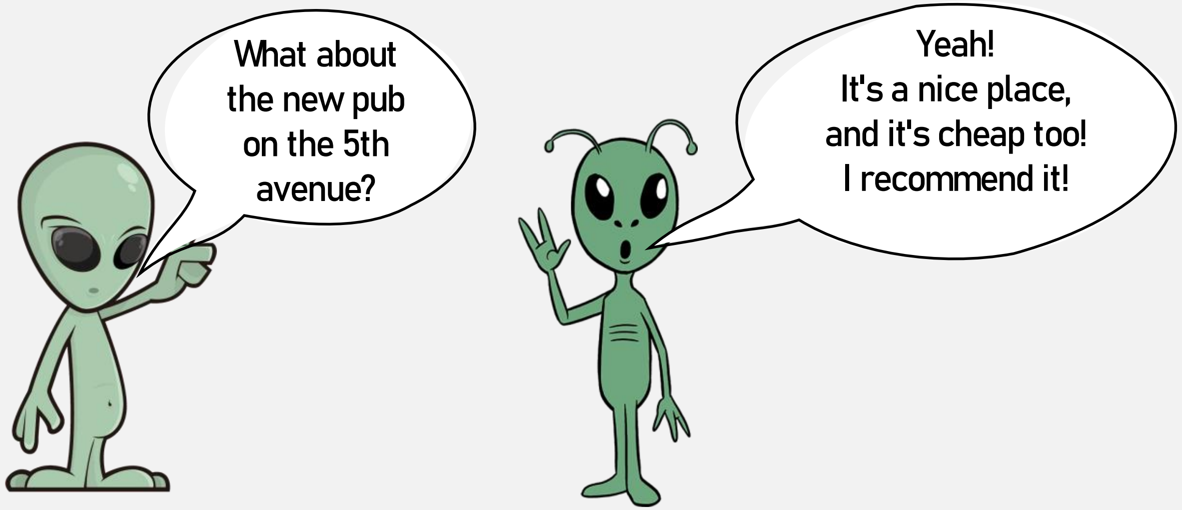
- They use **pre-calculated statistical functions** based on prior knowledge of human mobility.

- **PROS**
  - \+ Explainability
  - \+ Transferability

- **CONS**
  - – Cannot capture all the aspects of mobility

Introduction

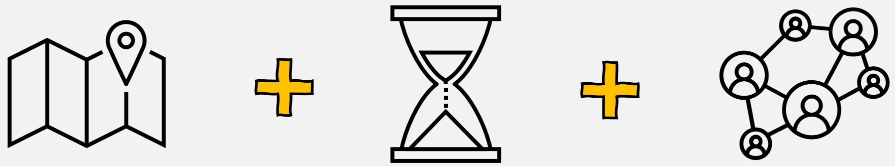
- Most of the generative models focus only on the **spatial** and **temporal** dimensions of mobility.
- What about the **social** dimension?
  - ≈ **30%** of an individual's movements are taken for **social** purposes [8].
  - Individuals are more likely to visit a location if it has been **recommended** by a friend.



[8] Cho, E., Myers, S., Leskovec, J., 2011. Friendship and mobility: User movement in location-based social networks, pp. 1082–1090.

STS-EPR

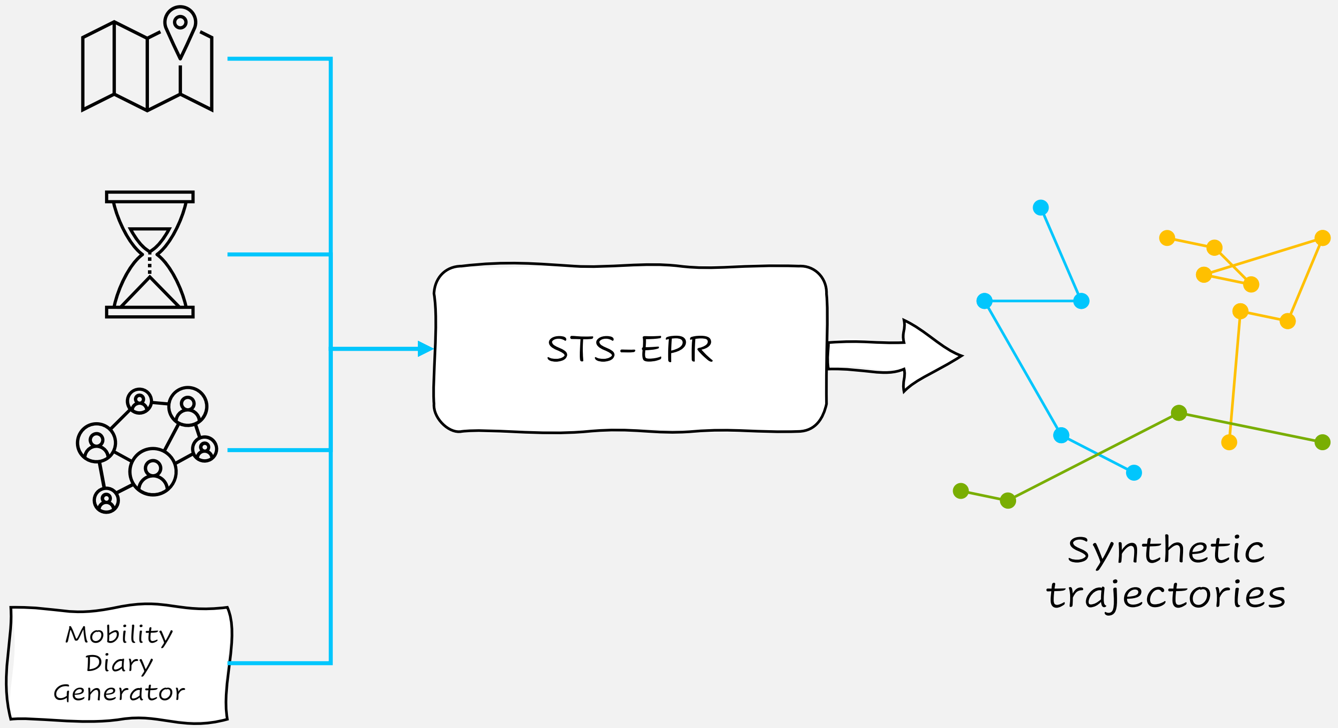
- STS-EPR (Spatial, Temporal, and Social EPR) is a **mechanistic** generative model that embeds mechanisms to capture the **spatial**, **temporal** and **social** aspects of mobility together.



- STS-EPR couples the advantages of two state-of-the-art generative models:
  - **GeoSim [5]**: it considers the social dimension, but its spatial and temporal realism is limited.
  - **DITRAS [6]**: it is able to capture the individual's circadian rhythm using a **Mobility Diary Generator** (MDG), as well as the spatial aspects of mobility, but it does not take into account the sociality of individuals.

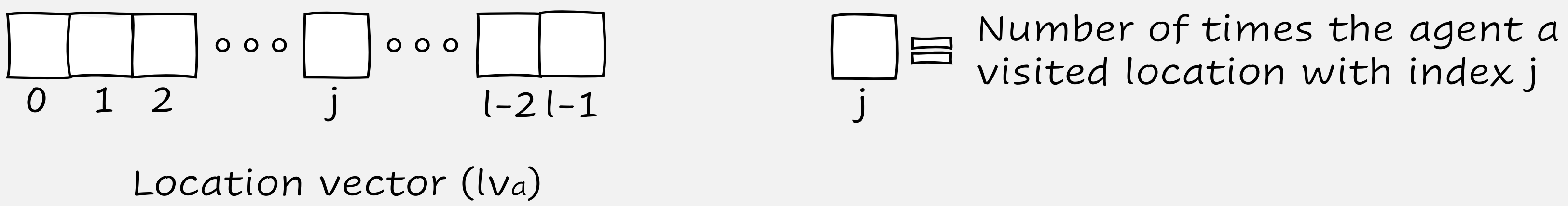
[5] Toole, J., Herrera-Yague, C., Schneider, C., Gonzalez, M.C., 2015. Coupling human mobility and social ties. Journal of the Royal Society.
[6] Pappalardo, L., Simini, F., 2017. Data-driven generation of spatio-temporal routines in human mobility. Data Mining and Knowledge Discovery, 32.

STS-EPR



STS-EPR

- Location Vector [5]

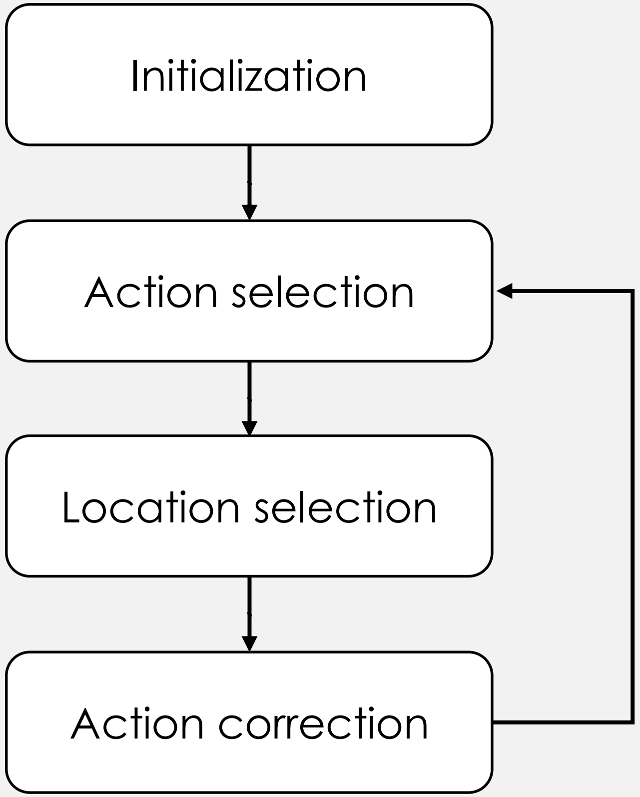


- Mobility Similarity [5]
  - The **mobility similarity** (mob_{sim}) between two agents is defined as the **cosine similarity** of their **location vectors**.

[5] Toole, J., Herrera-Yague, C., Schneider, C., Gonzalez, M.C., 2015. Coupling human mobility and social ties. Journal of the Royal Society.

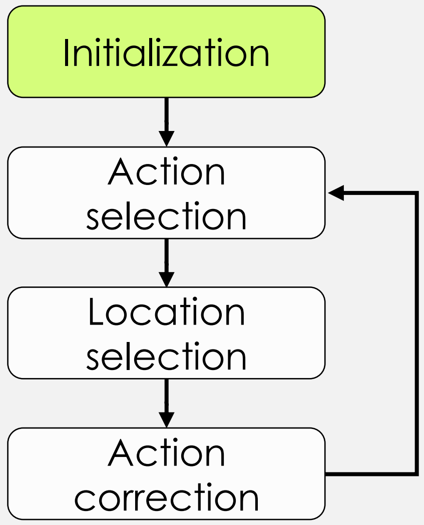
STS-EPR

- STS-EPR is composed of **four** phases:



STS-EPR: Initialization phase

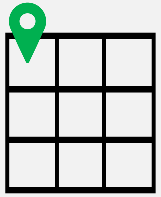
- The N synthetic individuals are connected in an undirected graph G. Each edge's **weight** represents the **mobility similarity** of the linked agents.



- The model assigns at each agent a **mobility diary** produced by the MDG.

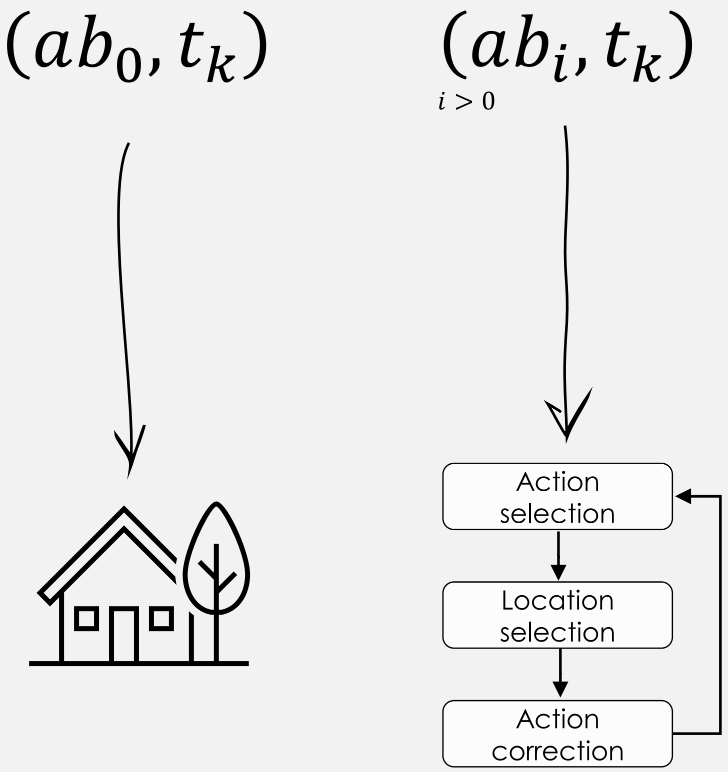
$$< (ab_0, t_0), (ab_1, t_1), \dots, (ab_0, tj) \dots >$$

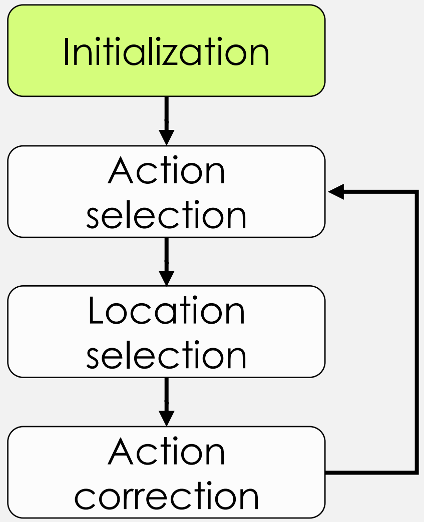
- The agents are assigned to a starting location i with a probability $p(i) \propto w_i$, where w_i is the **relevance** of location i.



STS-EPR: Initialization phase

- Each agent moves according to its mobility diary's entries at the time specified.

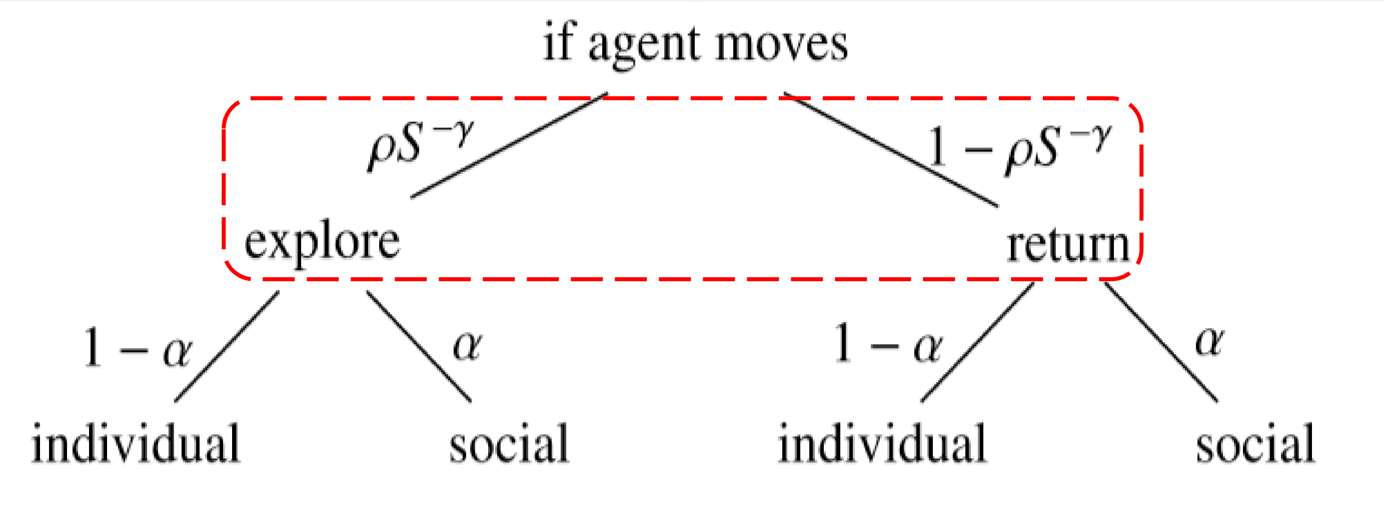


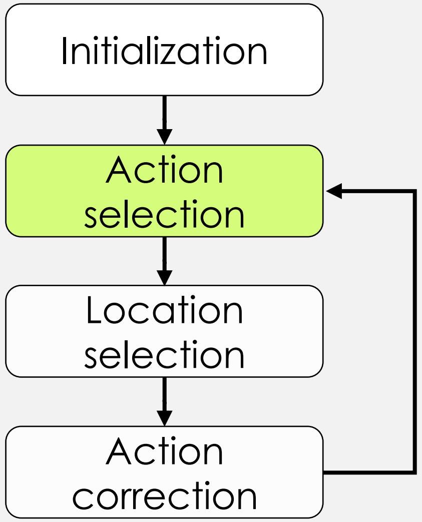


STS-EPR: Action Selection phase

- In this phase the agent selects with **which mechanisms** to move.
- First, the agent selects between two competing **spatial** mechanisms: **exploration** and **preferential return**.

$\rho = 0.6$
$\gamma = 0.21$
$S = number\ of\ unique\ visited\ locations$

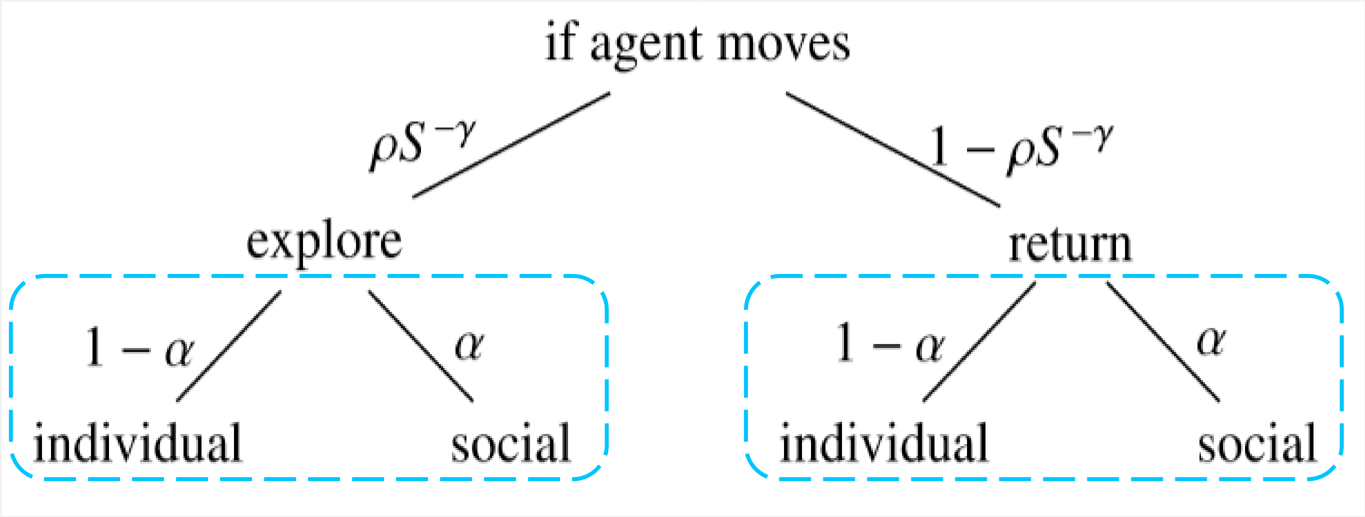


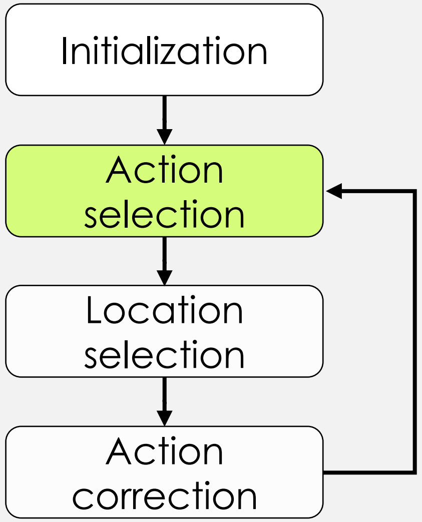


STS-EPR: Action Selection phase

- Then, the agent selects between two competing **social** mechanisms: **individual** and **social influence**.

$\alpha = 0.2$



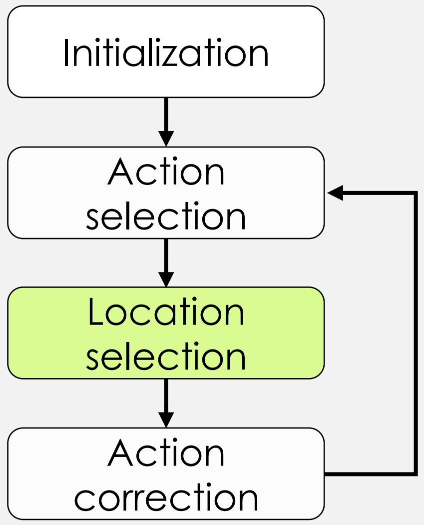


STS-EPR: Location Selection phase

- During the location selection phase, the agent decides **which location** will be the **destination** of its next displacement, according to the combinations of the **spatial** and **social** mechanisms picked.

- There are **four** possible combinations:

1. **Individual** – **Exploration**
2. **Individual** – **Return**
3. **Social** – **Exploration**
4. **Social** – **Return**



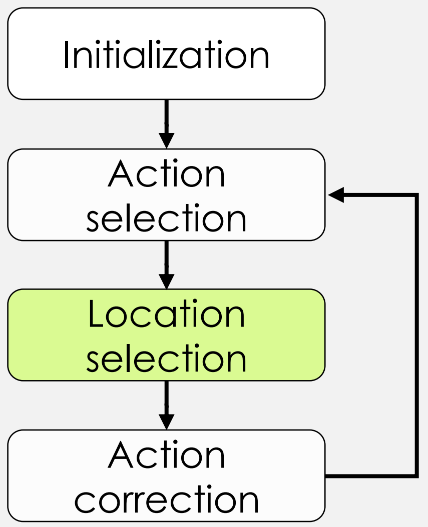
STS-EPR: Location Selection phase

Individual – **Exploration:**

- The agent selects to visit an **unvisited** location **without the influence** of its social contacts.
- If the agent is currently at location i it selects an **unvisited** location j with probability

$$p(j) \propto \frac{w_i\, w_j}{d_{ij}^2}$$

- d_{ij} is the distance between locations i and j.
- The relevance of a location k is w_k.



STS-EPR: Location Selection phase

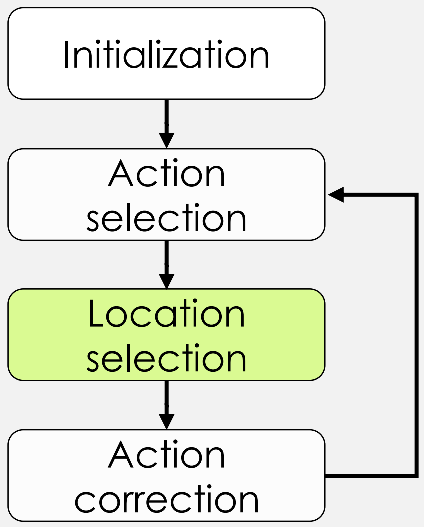
Individual – **Return:**

- The agent selects to **return** to a **visited** location **without the influence** of its social contacts.

- The agent, currently at location i, decides to return to location j with probability

$$p(j) \propto f_a(j)$$

- Where $f_a(j)$ is defined as: $\frac{lv_a[j]}{\sum_{j=1}^{|L|} lv_a[i]}$



STS-EPR: Location Selection phase

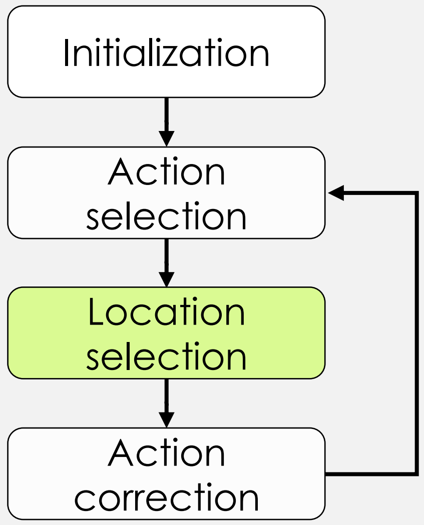
Social – {**Exploration**, **Return**}:

- The agent selects a **visited** (**Return**) **or unvisited** (**Exploration**) location to return **with the influence** of its social contacts.

- The agent a selects a **social contact**; the probability of a social contact c to be selected is

$$p(c) \propto mob_{sim}(a, c)$$

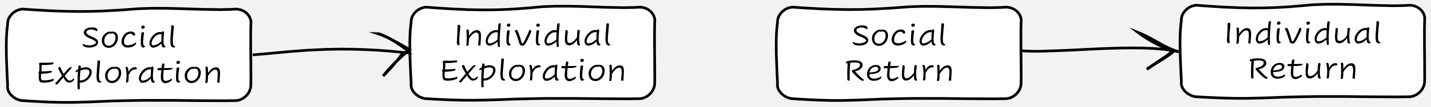
- After the social contact c il selected, the agents a selects **the proper location** i, according to the spatial mechanism picked, with probability $p(i) \propto f_c(i)$

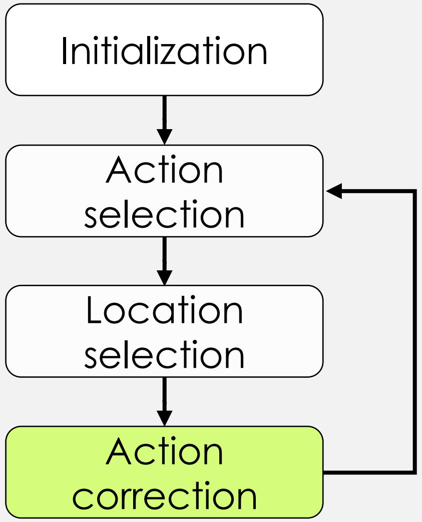


STS-EPR: Action Correction phase

The set of possible locations an agent can reach **is limited**.

- **No location in social choices:** if no location visited by a social contact c is feasible for the agent a, the action is corrected from **Social** – {**Exploration**, **Return**} to **Individual** – {**Exploration**, **Return**}



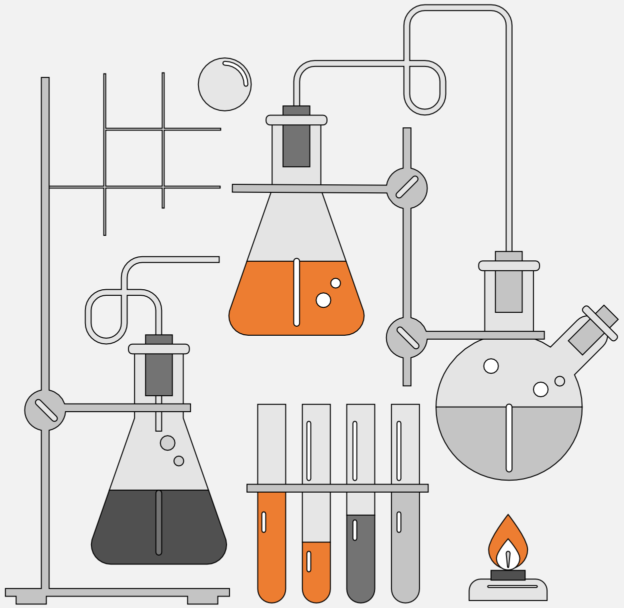


- **No new location to explore:** when an agent decides to explore but it visited all the locations at least once we force the agent to make an **Individual** – **Return**.

Experiments

Experiments

- We validate **STS-EPR** using as baselines **DITRAS** and **GeoSim**.
- For each city, we **compare** the **synthetic** trajectories with **real** ones extracted from Foursquare's checkins [7].
- The similarity between the two sets of trajectories is computed with respect to the mobility patterns that characterize human mobility, and it is quantified with the **Kullback-Leibler divergence**.



[7] Yang, D., Qu, B., Yang, J., Cudre-Mauroux, P., 2019. Revisiting user mobility and social relationships in lbsns: A hypergraph embedding approach, pp. 2147–2157

Results

	Model	Δr	r_g	$f(r_i)$	Vl	Δ_t	$t(h)$	E_{unc}	mob_{sim}
London	GeoSim	0.5036 ±0.0075	4.9381 ±0.0932	**0.0016 ±0.0001**	4.427 ±0.0069	0.1962 ±0.0043	0.281 ±0.0003	8.5182 ±0.0003	0.6097 ±0.0079
	DITRAS	0.0221 ±0.0022	**0.1813 ±0.0239**	0.1094 ±0.0	0.1428 ±0.006	0.166 ±0.0031	0.0119 ±0.0004	3.8816 ±0.1897	0.4347 ±0.0516
	STS-EPR	**0.0108 ±0.0016**	0.4609 ±0.233	0.0097 ±0.0003	**0.1032 ±0.0126**	**0.1626 ±0.0035**	**0.0116 ±0.001**	**2.6749 ±0.1169**	**0.2543 ±0.01**
Tokyo	GeoSim	0.7257 ±0.002	4.8165 ±0.0042	**0.0002 ±0.0**	3.0957 ±0.0148	0.2354 ±0.0003	0.2837 ±0.0006	7.1242 ±0.0593	0.0931 ±0.0017
	DITRAS	0.0628 ±0.0025	**0.2417 ±0.0171**	0.1409 ±0.0	0.1101 ±0.0048	0.2007 ±0.003	**0.0074 ±0.0001**	5.0034 ±0.2708	0.923 ±0.0375
	STS-EPR	**0.0485 ±0.0013**	0.2504 ±0.0746	0.0108 ±0.0002	**0.0226 ±0.0019**	**0.2001 ±0.0024**	0.0076 ±0.0001	**4.8717 ±0.2247**	**0.014 ±0.0009**
New York City	GeoSim	0.5947 ±0.0062	5.3913 ±0.0051	**0.0071 ±0.0004**	3.6418 ±0.0069	0.1973 ±0.0004	0.18 ±0.0005	8.0483 ±0.0579	0.5879 ±0.0149
	DITRAS	**0.0091 ±0.0006**	**0.2987 ±0.0359**	0.193 ±0.0026	0.1281 ±0.0044	**0.1665 ±0.0032**	**0.0066 ±0.0003**	**4.8881 ±0.0248**	0.5425 ±0.038
	STS-EPR	0.0188 ±0.0015	0.3886 ±0.0284	0.0318 ±0.0008	**0.0531 ±0.004**	0.1705 ±0.0047	0.0071 ±0.0005	5.028 ±1.1511	**0.3066 ±0.0044**

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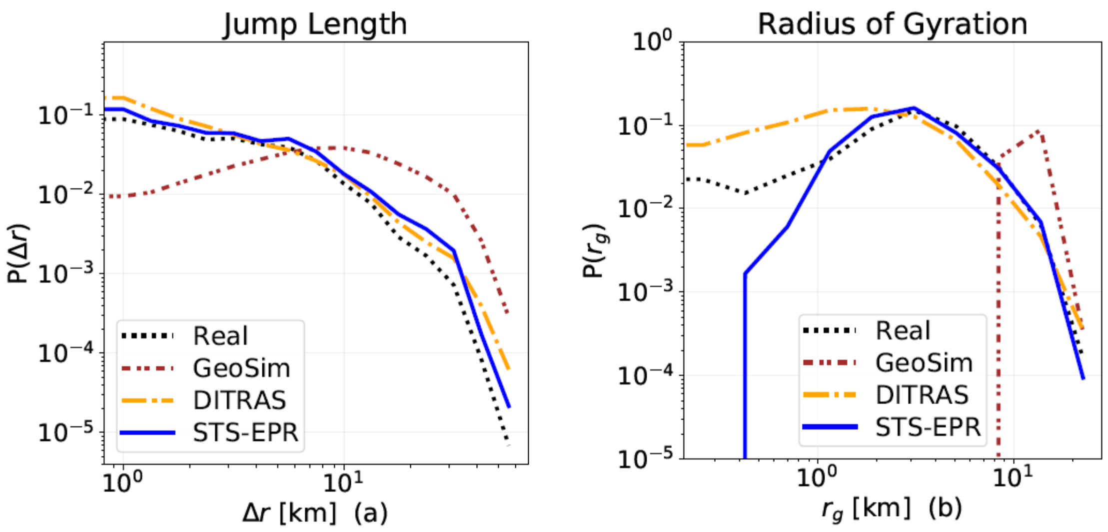

- GeoSim **cannot** reproduce neither Δr nor r_g
- STS-EPR generally better than DITRAS w.r.t. Δr
- DITRAS generally better than STS-EPR w.r.t. r_g

Results

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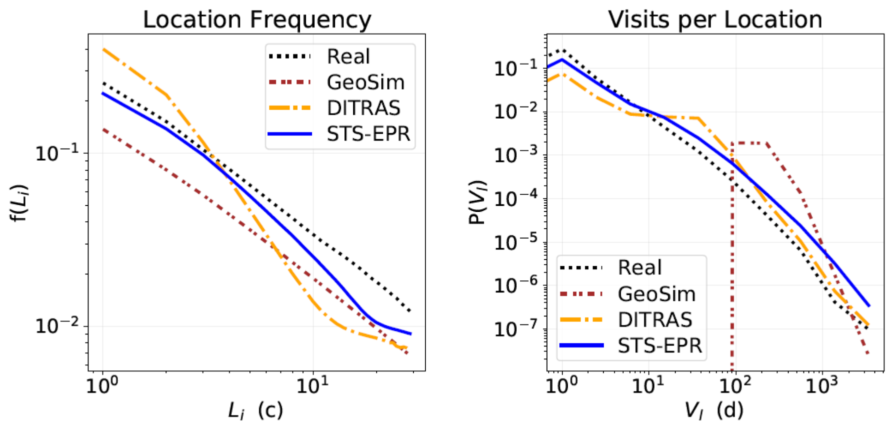
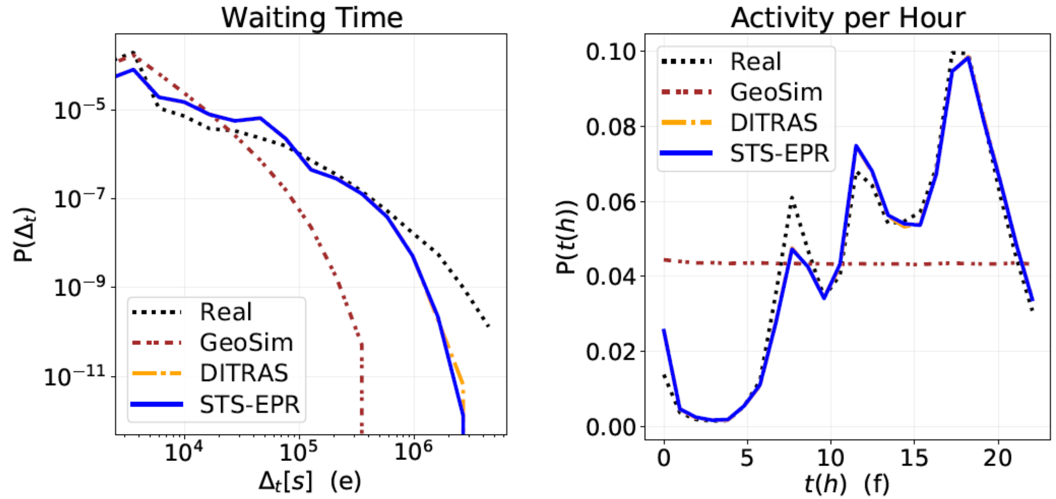


- GeoSim is the best model w.r.t. $f(r_i)$ but cannot reproduce V_l
- STS-EPR is better than DITRAS w.r.t. both $f(r_i)$ and V_l: the inclusion of the sociality produces better trajectories

Results



- The temporal measures are better captured by STS-EPR and DITRAS thanks to the MDG.

	Δ_t	$t(h)$	E_{unc}	mob_{sim}
London	0.1962 ±0.0043	0.281 ±0.0003	8.5182 ±0.0003	0.6097 ±0.0079
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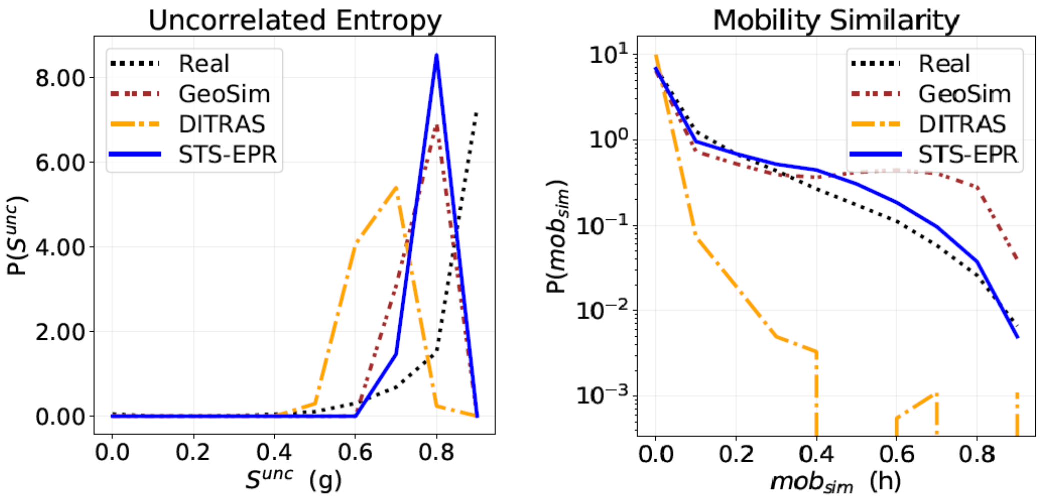

- STS-EPR is able to capture the social aspect of mobility better than GeoSim and DITRAS
- None of the presented models can replicate the distribution of E_{unc}

Open Source

scikit mobility

```python
from skmob.models import sts_epr

STS_epr = sts.STS_epr()

start = pandas.to_datetime('22-03-2021')
end = pandas.to_datetime('25-03-2021')
social_graph, spatial_tessellation, diary = load_parameters()

syn_trajectories = STS_epr.generate(start, end, social_graph = social_graph,
                                    spatial_tessellation = spatial_tessellation,
                                    diary_generator = diary)
```

https://github.com/scikit-mobility

Conclusions

- STS-EPR can generate **realistic** trajectories for all the **three dimensions**, improving the state-of-the-art models GeoSim and DITRAS
- The inclusion of the social dimension in STS-EPR help improving the realism with respect to the spatial and temporal measures.
- The model can be applied to **different geographic regions** without loss of generative capability.

Future directions

- Use of Deep Learning methods (e.g., GANs)
- External/Ausiliar information
- Include a dynamic social graph

THANKS FOR THE ATTENTION!

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https://github.com/GiulianoCornacchia

References

- [1] Brockmann, D., Hufnagel, L., Geisel, T., 2006. The scaling laws of human travel. Nature 439, 462–5.
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