



Mobility modeling through mobile data: generating an optimized and open dataset respecting privacy

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1. Introduction

Human mobility modelling:

- · Mobile data:
 - ✓ Scientific progress: Urban planning, business development, optimization [1, 2].
 - rivacy concerns: tracking individuals location, privacy threats (sensitive data).
- Orange Flux Vision® (FV®) [3] publishes statistical indicators respecting privacy wrt european GDPR (General Data Protection Regulation) [4].
- · Objectives:
 - Privacy of the raw data is critical [5].
 - Improve the utility of these data solving challenges due to data anonymization.
 - Generate a synthetic dataset of Virtual Humans (VHs) to reconstruct the improved mobility scenario.

Mobility models orange





2. Case study and data analysis

Festival International de Musique Universitaire (FIMU) [6]:

- · Modeling n=7 days: Identify people's mobility patterns in the week of the festival.
- FV® mobility model: Volume of users (resident, french and foreign tourists) per day and per cumulative days (union).

Number of unique users per socio-categorical profile (geoLife)

Date geoLife		Visitor Category	Cumulative Days	Volume	
2017-06-01	popular	French Tourist	6 days	4,000	
2017-06-02	NR	Foreign Tourist	2 days	971	
2017-06-03	rural worker	Resident	3 days	1,359	







2. Case study and data analysis

Challenges

- · Data acquisition (many files volume of users per sensitive data):
 - Generalization (age ranges, socio-professional categories, region, ...).
 - \circ *k*-anonymity (indistinguishability among *k*=20 users) -> data masking (#).
 - Extrapolation of Orange's customers to estimate the real population.

Aggregation of French unique visitors present over three FIMU's days

Label	Cum. Days FR_geoLife FR_gender		FR_gender	FR_age	FR_region	
Th1	01 day	23,816	23,811	23,810	23,598	
Fr1	01 day	27,145	27,144	27,142	26,945	
Fr2	02 days	36,917	36,915	36,915	36,758	

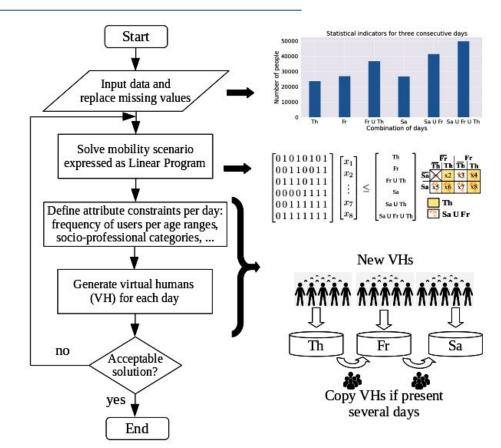




3. Proposed approach

Random search optimization:

- Input mobility data and randomly replace # with range(1,20).
- Model the improved mobility scenario as a linear program.
- Define user's attributes constraints.
- Generate Virtual Humans (VHs) and define the combination of days constraints.



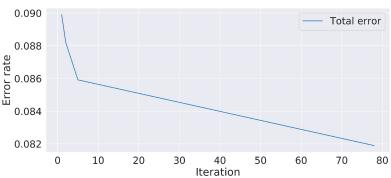




4. Results: mobility scenario

Improved mobility scenario:

- Allows learning more insights about users' mobility patterns.
- Fast convergence: 100 iterations in 22 minutes (best result found in iter. 79).
- Final dataset: low error rate (~ 8.1%).



			Fr			Fr					
Days combination		Th		Th		$\overline{\mathbf{Th}}$		Th			
			We	We	We	We	We	We	We	We	
00	<u> </u>	Su	Sa	-	4851	4378	1527	1801	1701	786	3450
			Sa	4791	234	87	266	1748	48	417	893
	Mo	C	Sa	9695	228	199	508	341	92	506	1220
$\overline{ ext{Tu}}$		Su	Sa	2171	287	74	73	4237	103	1109	1229
Tu	1	$\overline{\mathbf{Su}}$	Sa	5937	183	49	207	97	36	67	233
	Mo		Sa	592	100	103	42	63	116	63	80
	Мо	Su	$\overline{\mathbf{Sa}}$	7380	71	34	56	71	89	77	22
8		Su	Sa	256	51	96	49	27	52	94	61
		Su	Sa	7052	446	213	787	1163	35	679	775
	$\overline{\text{Mo}}$		Sa	441	59	104	71	62	94	106	99
	MIO	Su	Sa	1004	110	53	70	85	87	52	53
Tu	1	Su	Sa	42	94	50	91	93 38	38	51	36
		Su	Sa	159	309	72	325	442	67	396	94
	Mo		Sa	111	76	89	35	71	34	102	434
	IVIO	Su	Sa	434	84	71	41	112	67	89	149
	Su	Sa	4176	61	71	93	211	74	506	176	





4. Results: synthetic dataset

Final Generated Dataset

Index	ex Person ID Date ID		Visit Duration		
1	55385	2	6h		
2	234	5	4h		

Number of users per dataset and absolute error for sub-categories of Age on the 1st FIMU day

Age range	Real data	Synthetic data	Absolute error	
18-24	2,312	2,319	7 (0.3%)	
35-44	3,230	3,215	15 (0.46%)	
>65	3,483	3,439	44 (1.26%)	

Sensitive personal data

Person ID Name		Gender	Age	GeoLife	Vis. Cat.	Region	Sleeping Area
7645	A. Berry		NR	NR	Foreign T.	UK	city of Belfort
10589	A. Maillet	М	<18	rural worker	French T.	Rhône-Alpes	rest of Doubs





5. Conclusion

- Efficiently generates a synthetic dataset with low error rate.
- Few iterations are required to satisfy all user constraints.
- Overcomes challenges due to data anonymization techniques.

• Future work:

- Improve the dataset with more (virtual) sensitive information.
- Design privacy-preserving algorithms to collect mobile data.
- Use this dataset to evaluate the designed algorithms.





6. References

[1] T. Kashiyama, Y. Pang, and Y. Sekimoto. *Open PFLOW: Creation and evaluation of an open dataset for typical people mass movement in urban areas.* DOI: 10.1016/j.trc.2017.09.016

[2] V. Caiati, L. Bedogni, L. Bononi, F. Ferrero, M. Fiore, and A. Vesco. *Estimating urban mobility with open data: A case study in bologna*. DOI: 10.1109/isc2.2016.7580765

[3] Flux Vision: real time statistics on mobility patterns. orange-business.com/en/products/flux-vision

[4] General Data Protection Regulation (GDPR). gdpr-info.eu/

[5] Y-A. de Montjoye, C. A. Hidalgo, M. Verleysen, and V. D. Blondel. *Unique in the Crowd: The privacy bounds of human mobility*. DOI: 10.1038/srep01376.

[6] FIMU Belfort 2017: le festival parfait pour bouger à la Pentecôte. leparisien.fr/culture-loisirs/fimu-belfort-2017-le-festival-parfait-pour-bouger-a-la-pentecote-23-05-2017-6976476.php





Thank you!

The dataset is freely available at -> github.com/hharcolezi/OpenMSFIMU

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