

FIWARE Global Summit

**Internet of Things, Artificial Intelligence
and Transfer learning for the realisation of
Smart Cities**

Aurora González-Vidal^{1,2} and Antonio F. Skarmeta¹

¹ Dept. of Information and Communication Engineering, University of Murcia, Spain

² ITI-CERTH, Salónica, Greece

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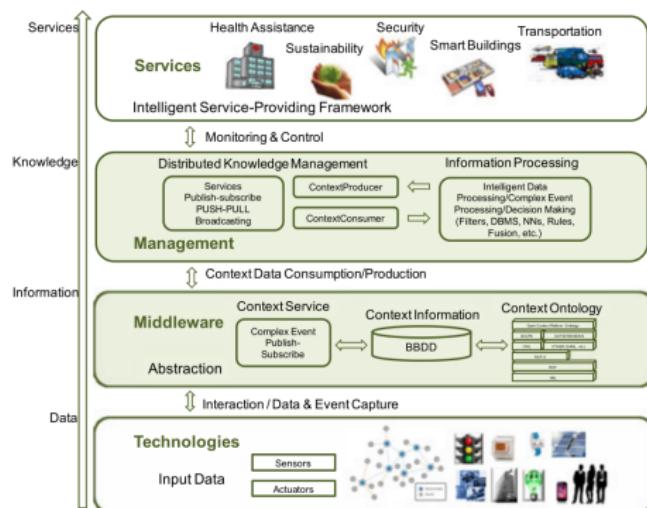
Introduction and Motivation

Introduction and Motivation

IoT sensors



Sensor provision, installation and system maintenance are essential for deploying IoT solutions and data-driven services.



Introduction and Motivation

City patterns and transfer learning



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Uncover city patterns to improve its smartness



Transfer learning can help in the achievement of scalable solutions towards the realisation of smart cities by sharing knowledge between similar domains.

- ▶ Complete datasets are not always available
- ▶ Less developed cities can benefit from the paradigm

Introduction

Objective



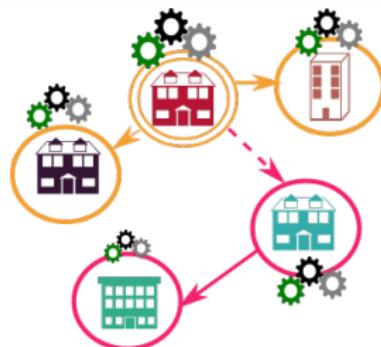
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Buildings are the foundation of cities

- ▶ Creation of a network of buildings according to their similarities
- ▶ Knowledge transfer between buildings with different levels of sensorisation for predictive problems

Resource optimisation:

- ▶ Sensor provision
- ▶ Sensor installation
- ▶ System maintenance





Background

Background

Transfer learning introduction



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Extensive research and work is being done in the context of transfer learning and on understanding how knowledge can be transferred among tasks. Learning a new task relies on the previous learned tasks.

What to transfer?

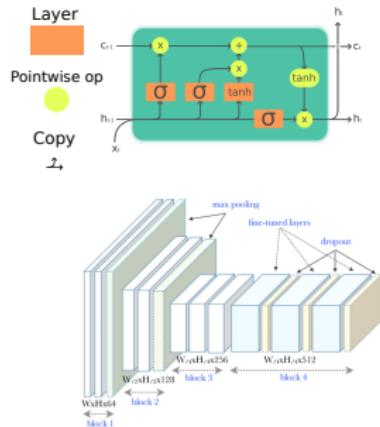
- ▶ Sample instances
- ▶ Feature mapping
- ▶ Model parameters
- ▶ Association rules

LSTM and CNN



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- ▶ Long-Short Term Memory networks
- ▶ Convolutional Neural Networks



The LSTM approach has been combined with the convolution mechanisms, leading to the ConvLSTM which advantages have already been seen as superior in several recent applications ^{1 2}.

¹ Wang, D., Yang, Y., & Ning, S. (2018, July). Deepstcl: A deep spatio-temporal convlstm for travel demand prediction. In 2018 international joint conference on neural networks (IJCNN) (pp. 1-8). IEEE.

² Hu, W. S., Li, H. C., Pan, L., Li, W., Tao, R., & Du, Q. (2020). Spatial-spectral feature extraction via deep ConvLSTM neural networks for hyperspectral image classification. *IEEE Transactions on Geoscience and Remote Sensing*, 58(6), 4237-4250.



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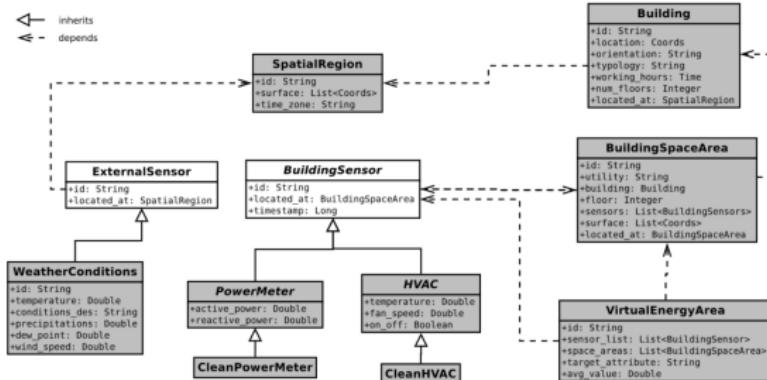
Use case: smart buildings

Use case: smart buildings

Data model



Data modelling and fusion using the FIWARE architecture. The used modules are Orion Context Broker (OCB) and COMET for NoSQL storage. NGSI-LD model that is entity-attribute



Use case: smart buildings

Source domain



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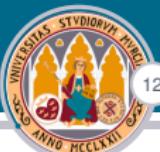
The source domain consists of the The Building non-residential Data Genome Project¹ (DGP). 1 year of data from 507 buildings:

- ▶ Hourly energy consumption
- ▶ Weather conditions
- ▶ Meta-data
- ▶ 156 Offices
- ▶ 105 primary/secondary school classrooms
- ▶ 95 university laboratories
- ▶ 81 university classrooms
- ▶ 70 university dormitories

C. Miller and F. Meggers, "The building data genome project: An open, public data set from non-residential building electrical meters," Energy Procedia, vol. 122, pp. 439–444, 201

Use case: smart buildings

Source domain: meta-data



Variable	Labels	Freqs (% of valid)	Graphs	Missing
				Valid
Heating type	1. (Empty string)	0 (0.0%)		
	2. Biomass	1 (0.8%)		
	3. District heating	1 (0.8%)		
	4. District Heating	1 (0.8%)		
	5. Electric	2 (1.6%)		
	6. Electricity	2 (1.6%)		
	7. Gas	112 (90.3%)		
	8. Heat network	2 (1.6%)		
	9. Heat network and steam	1 (0.8%)		
	10. Oil	2 (1.6%)		
Main heating type	1. (Empty string)	385 (75.9%)		
	2. Biomass	1 (0.2%)		
	3. Electric	2 (0.4%)		
	4. Electricity	2 (0.4%)		
	5. Gas	112 (22.1%)		
	6. Heat Network	2 (0.4%)		
	7. Heat Network And Steam	1 (0.2%)		
	8. Oil	2 (0.4%)		
Number of floors	1. 1	27 (21.8%)		
	2. 2	38 (30.6%)		
	3. 3	15 (12.1%)		
	4. 4	8 (6.5%)		
	5. 5	4 (3.2%)		
	6. 6	5 (4.0%)		
	7. 7	7 (5.6%)		
	8. 8	9 (7.3%)		
	9. 9	3 (2.4%)		
	10. 10	5 (4.0%)		
[3 others]		3 (2.4%)		

Variable	Labels	Freqs (%) of valid)	Graphs	Missing
				Valid
Primary space usage	1. College Classroom	81 (16.0%)		
	2. College Laboratory	95 (18.7%)		
	3. Dormitory	70 (13.8%)		
	4. Office	156 (30.8%)		
	5. Primary/Secondary Classro	105 (20.7%)		
Rating	1. (Empty string)	0 (0.0%)		
	2. B	5 (3.8%)		
	3. C	36 (27.5%)		
	4. D	44 (33.6%)		
	5. E	27 (20.6%)		
Subindustry	1. Bank/Financial Services	2 (0.4%)		
	2. Business Services	3 (0.6%)		
	3. City, County, State	13 (2.6%)		
	4. College/University	366 (72.2%)		
	5. Commercial Real Estate	4 (0.8%)		
	6. Corporate Office	2 (0.4%)		
	7. Other Government Building	12 (2.4%)		
	8. Primary/Secondary School	104 (20.5%)		
	9. Social Services	1 (0.2%)		
Timezone	1. America/Chicago	75 (14.8%)		
	2. America/Denver	3 (0.6%)		
	3. America/Los_Angeles	22 (4.3%)		
	4. America/New_York	151 (29.8%)		
	5. America/Phoenix	96 (18.9%)		
	6. Asia/Singapore	5 (1.0%)		
	7. Europe/London	143 (28.2%)		
	8. Europe/Zurich	12 (2.4%)		
Year built	1. (Empty string)	0 (0.0%)		
	2. 11th Century onwards	1 (0.3%)		
	3. 1754-1756	1 (0.3%)		
	4. 1800	1 (0.3%)		
	5. 1862-1875	1 (0.3%)		
	6. 1866	3 (1.0%)		
	7. 1871	1 (0.3%)		
	8. 1880	1 (0.3%)		
	9. 1887	1 (0.3%)		
	10. 1888	1 (0.3%)		
	[102 others]	302 (96.5%)		

Use case: smart buildings

Source task



Energy consumption (EC) prediction over a 24h horizon using weather data and past EC. We found the 15 most representative buildings by means of a k-prototypes clustering over the buildings meta-data and then trained a CNN-LSTM network over the data:

Centroid	RMSE	CVRMSE
1:PrimClass-Julianne	4.55	34.98
2:UnivClass-Anya	2.67	28.19
3:Office-Gustavo	40.79	18.15
4:PrimClass-Jaylin	1.19	49.73
5:UnivDorm-Marquis	18.67	7.94
6:PrimClass-Ervin	4.23	35.7
7:PrimClass-Jacquelyn	3.37	34.66
8:Office-Maximus	10.14	11.44
9:PrimClass-Johnathan	2.62	33.17
10:UnivLab-Marie	12.81	3.85
11:Office-Erik	3.43	30.6
12:PrimClass-Johnathon	5.61	31.55
13:UnivDorm-Alka	28.79	16.13
14:Office-Benthe	36.78	20.59
15:Office-Jude	58.89	15.01

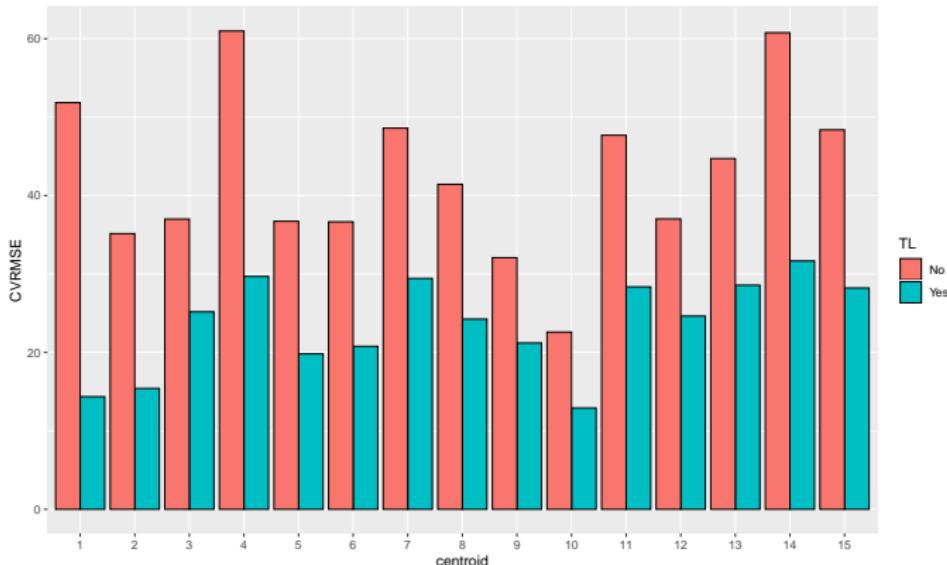
Use case: smart buildings

Target task



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Energy consumption prediction in the rest of buildings having only 2000 points of data (less than 3 months).



Use case: smart buildings

Target and task domain



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Dataset in¹ gathers occupants' energy behavior data collected amongst 23 office workers in Philadelphia, USA. It consists of a longitudinal comfort survey data collection together with continuous measurements of the weather, the local indoor environment around each subject, and certain of the subjects' behavioral actions. We have aggregated them in an hourly manner in order to extract the **hourly HVAC set point**.

Task domain: using only 2000 datapoints (very reduced dataset), predict the next 24h set point of the HVAC

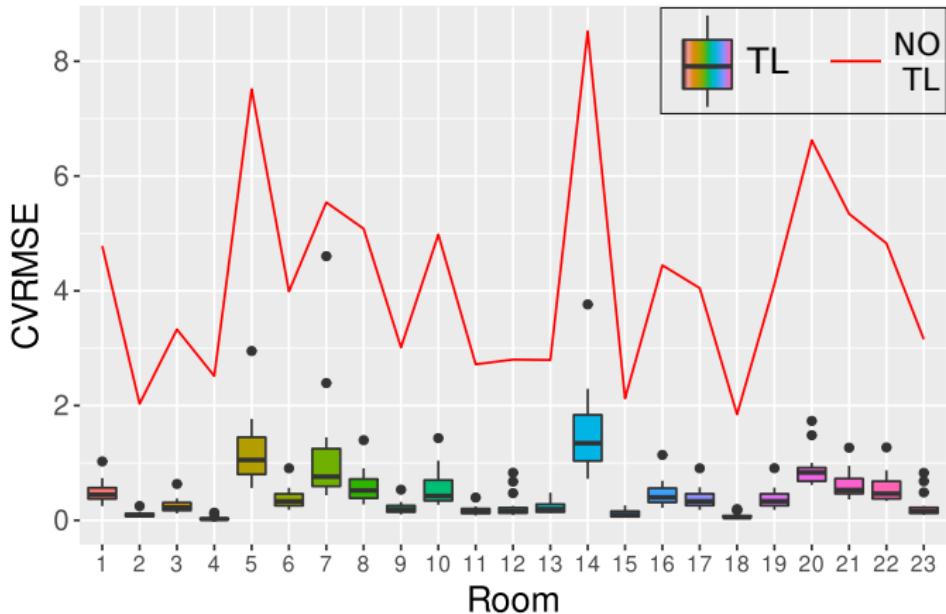
¹J. Langevin, P. L. Gurian, and J. Wen, "Tracking the human-building interaction: A longitudinal field study of occupant behavior in air-conditioned offices," *Journal of Environmental Psychology*, vol. 42, pp. 94–115, 2015.

Use case: smart buildings

Results



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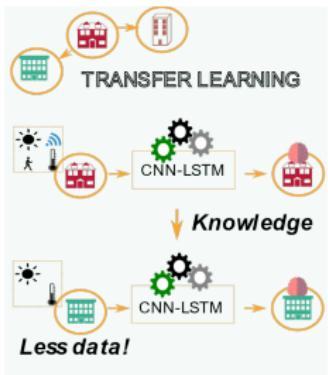


Conclusions, dissemination, acknowledgements



We have shown that transfer learning has the potential to improve the prediction accuracy in smart building related domains.

- ▶ Research publication: Gonzalez-Vidal, A., Mendoza-Bernal, J., Niu, S., Skarmeta, A. F., & Song, H. (2022). A Transfer Learning Framework for predictive energy-related scenarios in Smart Buildings. *IEEE Transactions on Industry Applications*.
- ▶ Code: <https://github.com/auroragonzalez/TLIAS>
- ▶ Interview (spanish): <https://internetdelascosas.xyz/articulo.php?id=771>
- ▶ Project acknowledgements: NGI explorers (g.a. 825183) + PHOENIX H2020 (g.a. 893079)





Questions?

Find this presentation at: github.com/auroragonzalez/presentations

Computer Sciences Faculty, University of Murcia

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Aurora González-Vidal, Antonio F. Skarmeta
aurora.gonzalez2@um.es, skarmeta@um.es



Open issues / future work

Open issues / future work



Future work:

- ▶ Include knowledge from more than one building simultaneously and how the distance to the centroid influences the accuracy,
- ▶ Use models with a different number of features
- ▶ Knowledge transfer between residential and non residential buildings,
- ▶ Optimal number of buildings that should be sensorised in order to achieve better accuracy and the cut-off point for the amount of data to be used in the target domain,
- ▶ Optimize the parameters of the Conv2DLSTM algorithm.



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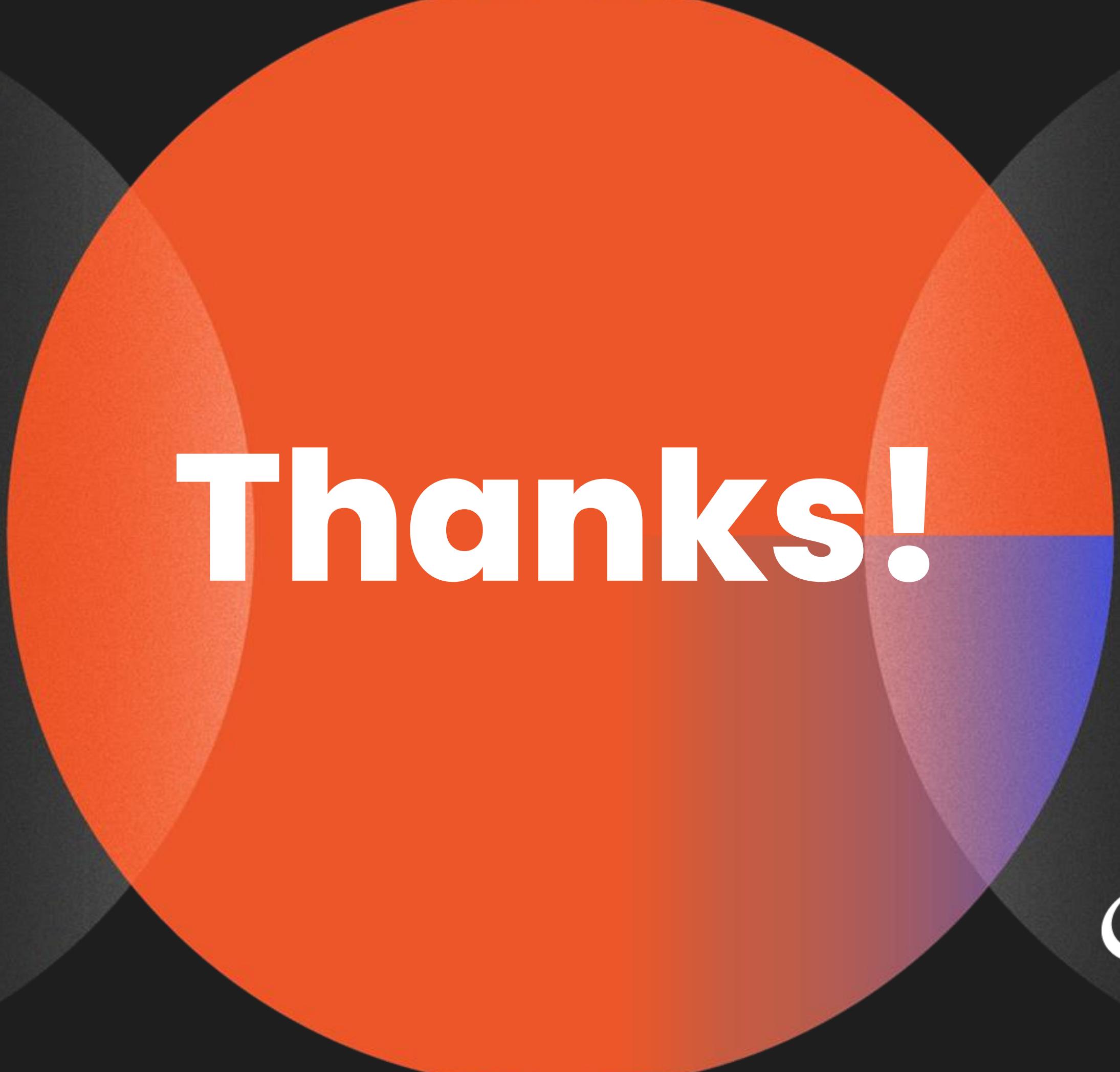
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