Computer Sciences Faculty, University of Murcia

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

FIWARE Global Summit 2022

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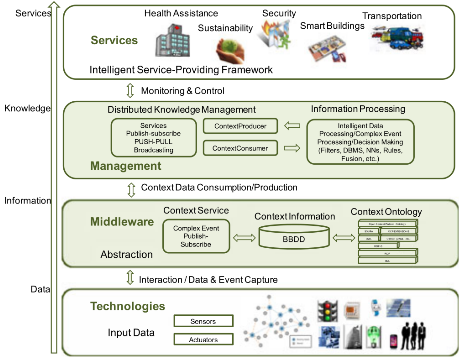
Content

Introduction and Motivation

Introduction and Motivation
IoT sensors

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



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

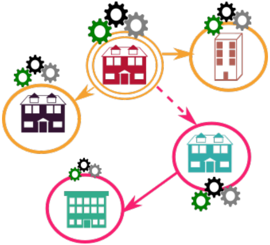
- Complete datasets are not always available
- Less developed cities can benefit from the paradigm

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

Resource optimisation:

- Sensor provision
- Sensor installation
- System maintenance



Background and related work

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.

Types of transfer learning

- Domain adaptation
- Domain confusion
- Multitask learning
- One-shot learning
- Zero-shot learning

What to transfer?

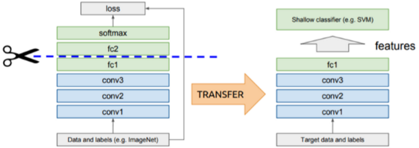
- Sample instances
- Feature mapping
- Muodel parameters
- Association rules

The two most popular deep transfer learning strategies are:

- Off-the-shelf Pre-trained Models as Feature Extractors

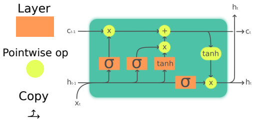
Idea: use outputs of one or more layers of a network trained on a different task as generic feature detectors. Train a new shallow model on these features.

Assumes that $D_S = D_T$

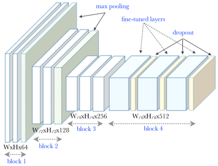


- Fine Tuning Off-the-shelf Pre-trained Models

LSTM and CNN



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



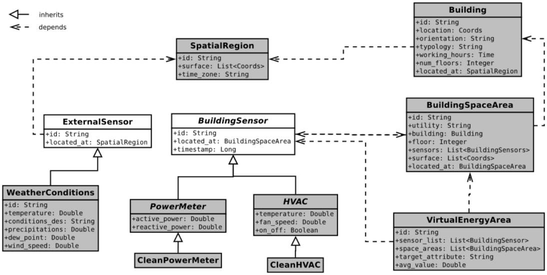
The LSTM approach has been combined with the convolution mechanisms, leading to the ConvLSTM which advantages have already been seen as superior in several recent applications [1] [2].

[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.

Use case: smart buildings

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

The source domain consists of the The Building non-residential Data Genome Project [1] (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

Use case: smart buildings

Source domain: meta-data

Variable	Labels	Freqs (% of valid)	Graphs	Valid	Missing
Heating type	1. (Empty string)	0 (0.0%)		124 (24.46%)	383 (75.54%)
	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%)		507 (100%)	0 (0%)
	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%)		124 (24.46%)	383 (75.54%)
	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	Valid	Missing
Primary space usage	1. College Classroom	81 (16.0%)		507 (100%)	0 (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%)		131 (25.84%)	376 (74.16%)
	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%)		507 (100%)	0 (0%)
	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%)		507 (100%)	0 (0%)
	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%)		313 (61.74%)	194 (38.26%)
	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

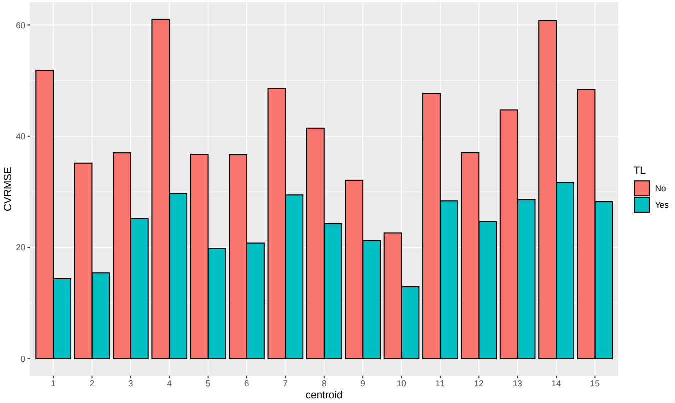
Source task

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-Julianna	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

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



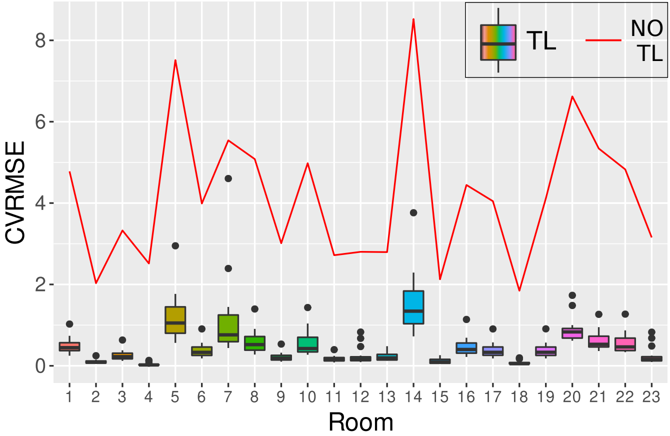
Use case: smart buildings

Target and task domain

[50] Dataset in[1] 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

[1] J. 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



Conclusions and future work

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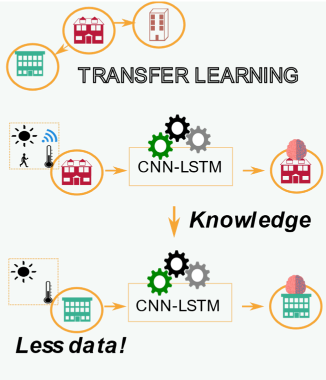

We have shown that transfer learning has the potential to improve the prediction accuracy in smart building related domains.

Conclusions and future work

Future work:

- Include knowledge from more than one building simultaneously and how the distance to the centroid influences the accuracy,
- 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.

Questions?

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

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