



SMART BUILDINGS

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Predicting building occupancy



UvA HvA WiFi network

Hogeschool van Amsterdam – Universiteit van Amsterdam 75 buildings One WiFi HvA-UvA-netwerk for approx. 90.000 users, Normal day use: 40.000+ simultaneous wifi-connections.





WiFi Data use: monitoring





WiFi Data use: communication

https://uva.mapiq.net/



WiFi data use: predicting occupancy

How many connections per hour tomorrow?





WiFi data use: no history is available Project involves collection of data over a sufficient long time period



$n_{h} = \frac{1}{4}$	$(t_{12}+t_3+t_6+t_9)$

15-11-2018 06:00	16
15-11-2018 07:00	21
15-11-2018 08:00	70
15-11-2018 09:00	627
15-11-2018 10:00	1094
15-11-2018 11:00	1753
15-11-2018 12:00	1845
15-11-2018 13:00	2023
15-11-2018 14:00	1897
15-11-2018 15:00	1998
15-11-2018 16:00	1739
15-11-2018 17:00	1733
15-11-2018 18:00	1231
15-11-2018 19:00	949
15-11-2018 20:00	484
15-11-2018 21:00	313
15-11-2018 22:00	104

n_h

h



WiFi data use project: occupancy prediction





WiFi data use project: cloud version





Use cases: UB en REC







Time series





REC

UB



Mathematics 4 predicting occupancy

Linear regression Neural network Time series modelling





Linear regression

 $Y = \alpha + \beta X + \varepsilon$

- Y regressor
- X explainable variables (?)
- α constant
- ε error

<u>Traditional X values:</u> building schedules special events etc (# WiFi connections per hour)



Linear regression

 $Y = \alpha + \beta X + \varepsilon$

- Y regressor
- X explainable variables (?)
- α constant
- ε error

We used base line explainable variables:
holiday(yes/no)day of the week(Monday, ..., Sunday)hour of the day(0,1,2,...,23)

(# WiFi connections per hour)



Results linear regression (REC)





Neural network non linear relation input and output





Results recurrent neural network (REC)





Time series modelling

Linear regression

$$Y = α + β X + ε$$

R-Sarima

$$Y_t = \alpha + \beta X_t + \eta_t$$

with

$$\eta_{t} = \frac{\Theta_{o}(LS)\Theta_{a}(L)}{\Phi_{p}(LS)\psi_{p}(L)\Delta_{s}^{D}\Delta^{d}} \epsilon_{t}$$

Models seasonality, regularity patterns and white noise

- L Lag (how far back do we need to look)
- S Seasonality



Results (REC)





Results





Rolling window time series approach





Conclusion

Data logging is important

Stable data connections real time monitoring systems to data platforms are needed

Simple models don't work (if you have one data source)





Use of modelling 1: Smart (HVAC) systems

REAL TIME connection to HVAC systems

- Shut down airco in under-used areas
- Decrease heat in busy areas

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PREDICTED values for slow responding systems



USE of modelling: smart communication

Real time communication (current busy areas)

Forward communication (tomorrow is expected to be busy)





USE of modelling: Smart service planning

Planning of cleaning services



Planning of maintenance





TRANSFER of METHODOLOGY

Aggregation level: room, are, floor, building



TRANSFER OF METHODOLOGY

Aggregation level: room, are, floor, building

SENSOR TECHNIQUES



TRANSFER OF METHODOLOGY

Aggregation level: room, are, floor, building

SENSOR TECHNIQUES

OTHER OCCUPANCY modelling:

- bikes in the street,
- cars in carparks,
-



WHY CWI?

INTELLIGENT SYSTEMS NEW STATE OF THE ART MODELLING COMPLEX

NEXT GENERATION

SMART



cybersecurity

54141281 BUILDEU

complex data

quantum software quantum software

Societal relevance

scientific computing

neuroscience

A

MATIOPIE

digital finance

חוסכאכרושות

Curctions