

# Deep learning methods for on-line flexibility prediction and optimal resource allocation in smart buildings

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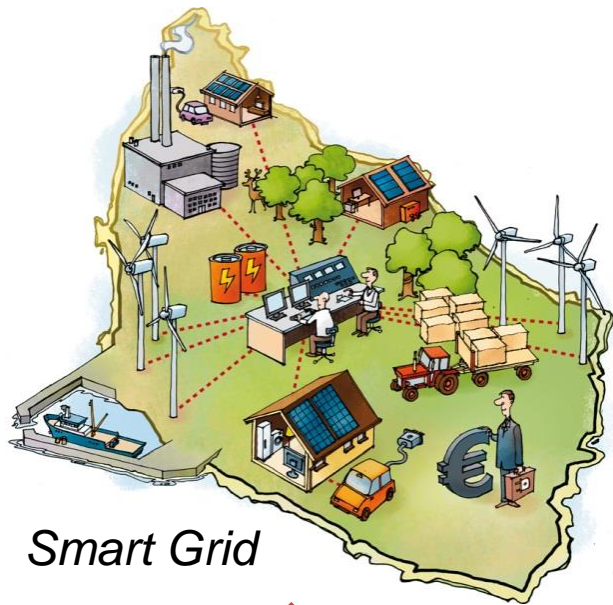
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# Machine learning methods for on-line flexibility prediction and optimal resource allocation in smart buildings

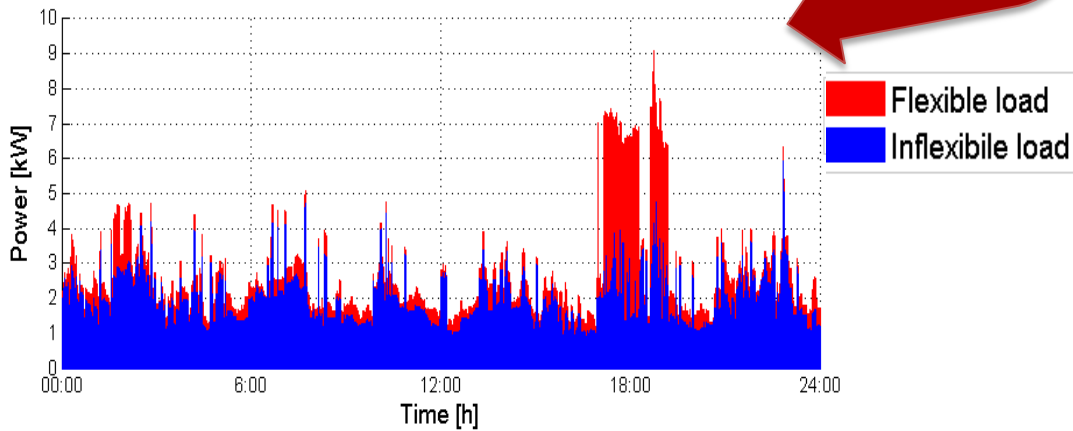
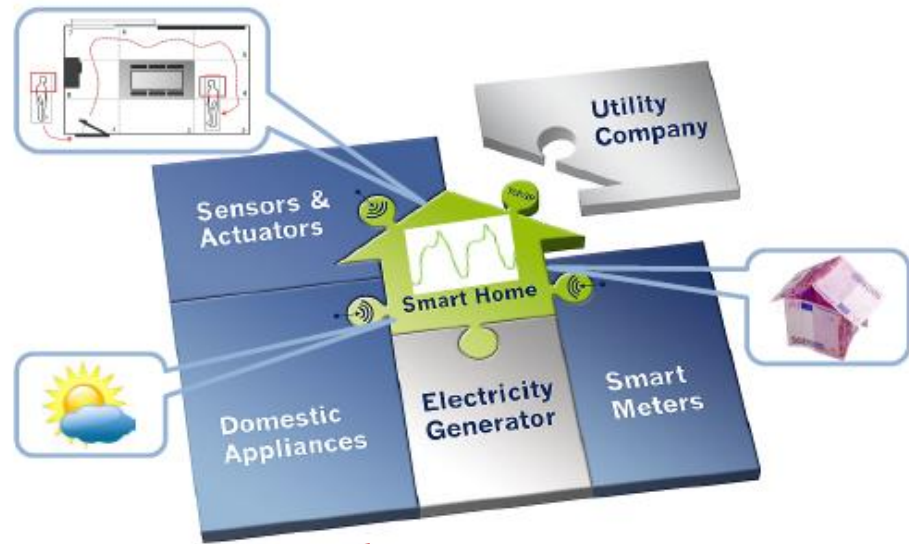
Elena Mocanu, Phuong H. Nguyen,  
Madeline Gibescu, J.G. Slootweg

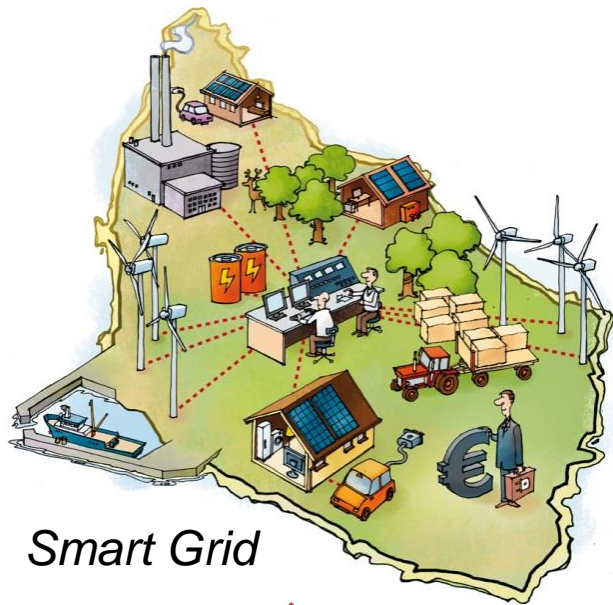
# Outline

- Introduction
- Machine learning → Deep learning
- 1) On-line flexibility prediction
  - Flexibility identification
  - Flexibility prediction
- 2) Optimal resource allocation
  - Deep reinforcement learning
- Conclusion and future work

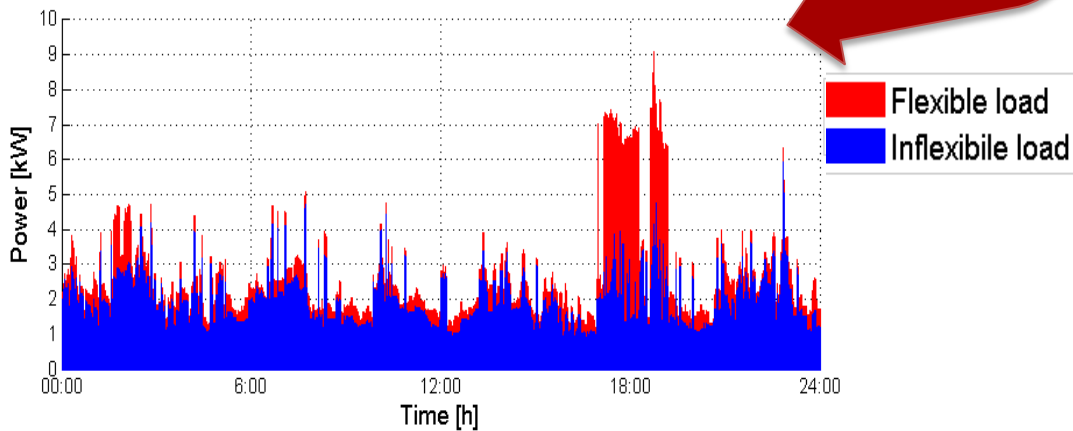
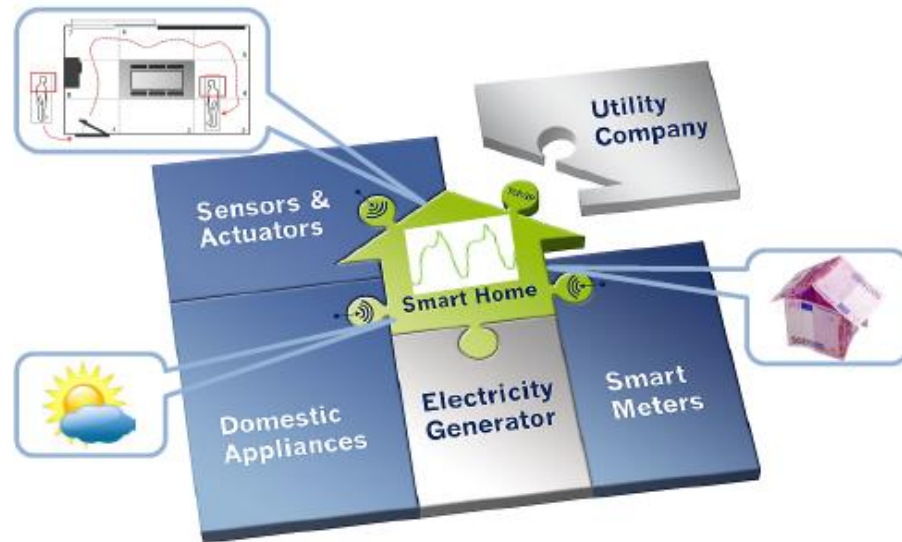


Smart Grid

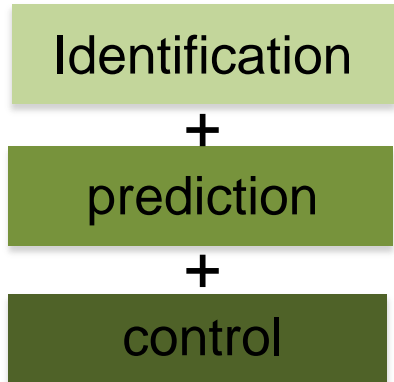




Smart Grid



Building energy flexibility



# Problem formulation

1) *Energy disaggregation*: **Given** a set of observation  $\mathbf{D}^{(t)} \in \mathbb{R}^{d \times n}$  learn a model for every electrical device,  $\hat{d}$ .

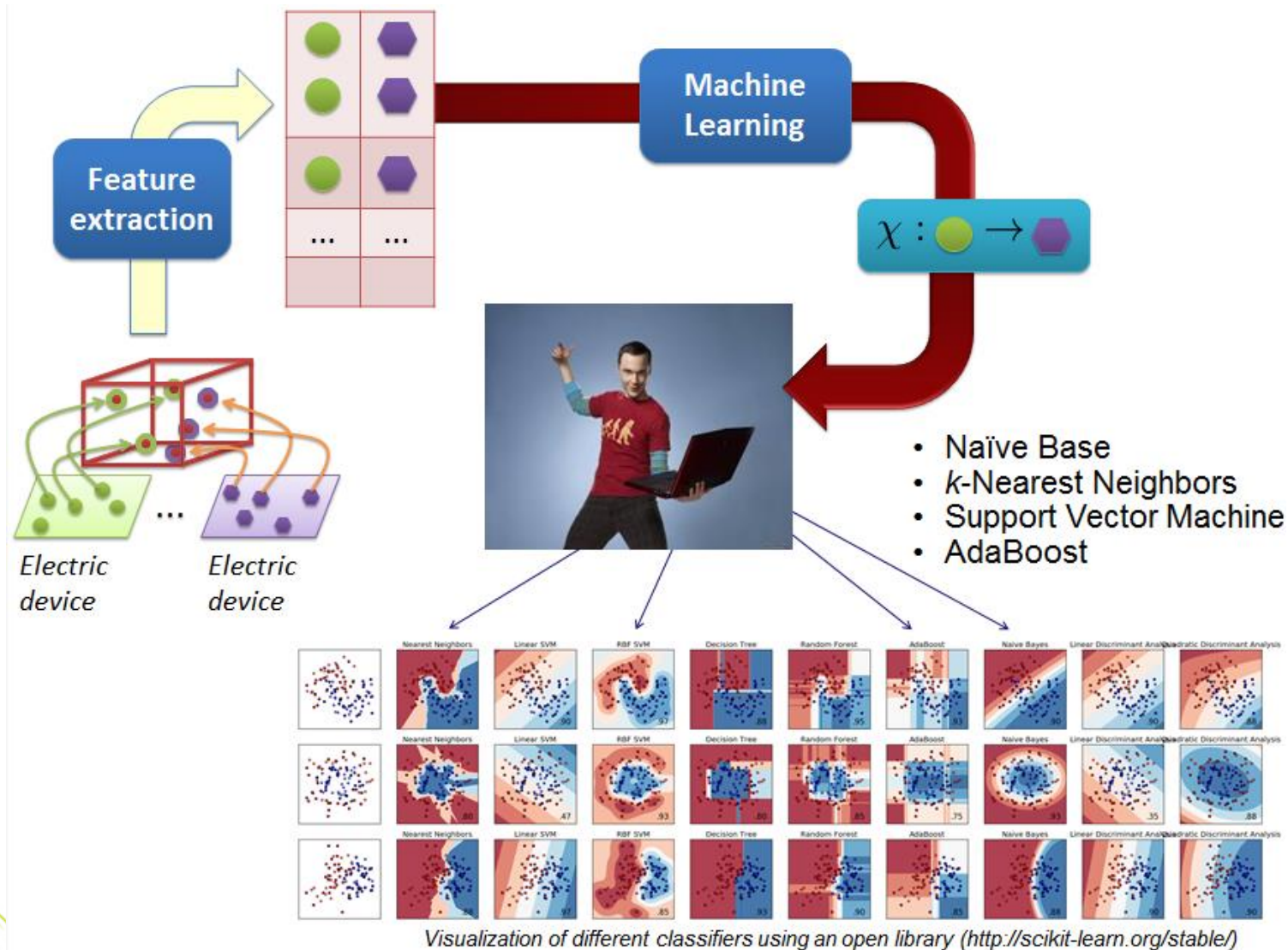
**Traditional** versus **Big data era**

2) *Flexibility identification*: **Given** the set of building demand energy profiles  $\mathbf{B}^{(t)}$  and their corresponding sum of disaggregated electrical parts  $\sum_{i=1}^d \hat{d}$  classified at every moment in time find how many devices are operating in the building.

3) *Flexibility prediction*: **Given** the set of building demand energy profiles,  $\mathbf{B}^{(t)}$  learn the *time-of-use* (ToU) predictive function (or the power consumption) for every device such that the empirical loss is minimized,

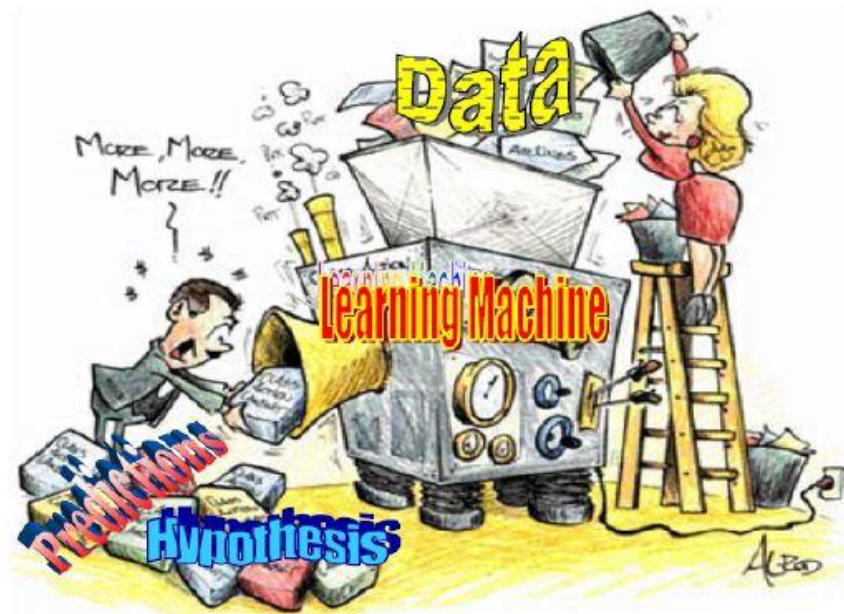
$$\min \|ToU_{\hat{d}}(d|\hat{d}, \mathbf{B}) \wedge ToU_{empirical}(d|\mathbf{D})\|$$

# Building flexibility identification



# Machine learning

- ▶ Given observations  
 $\mathcal{D}_{Energy} = \{\mathbf{U}^{(i)}, \mathbf{v}^{(i)}\}_{i=1}^I$
- ▶ Learn a predictive function
- ▶ Goal: Minimize the empirical loss





# Why Deep Learning?

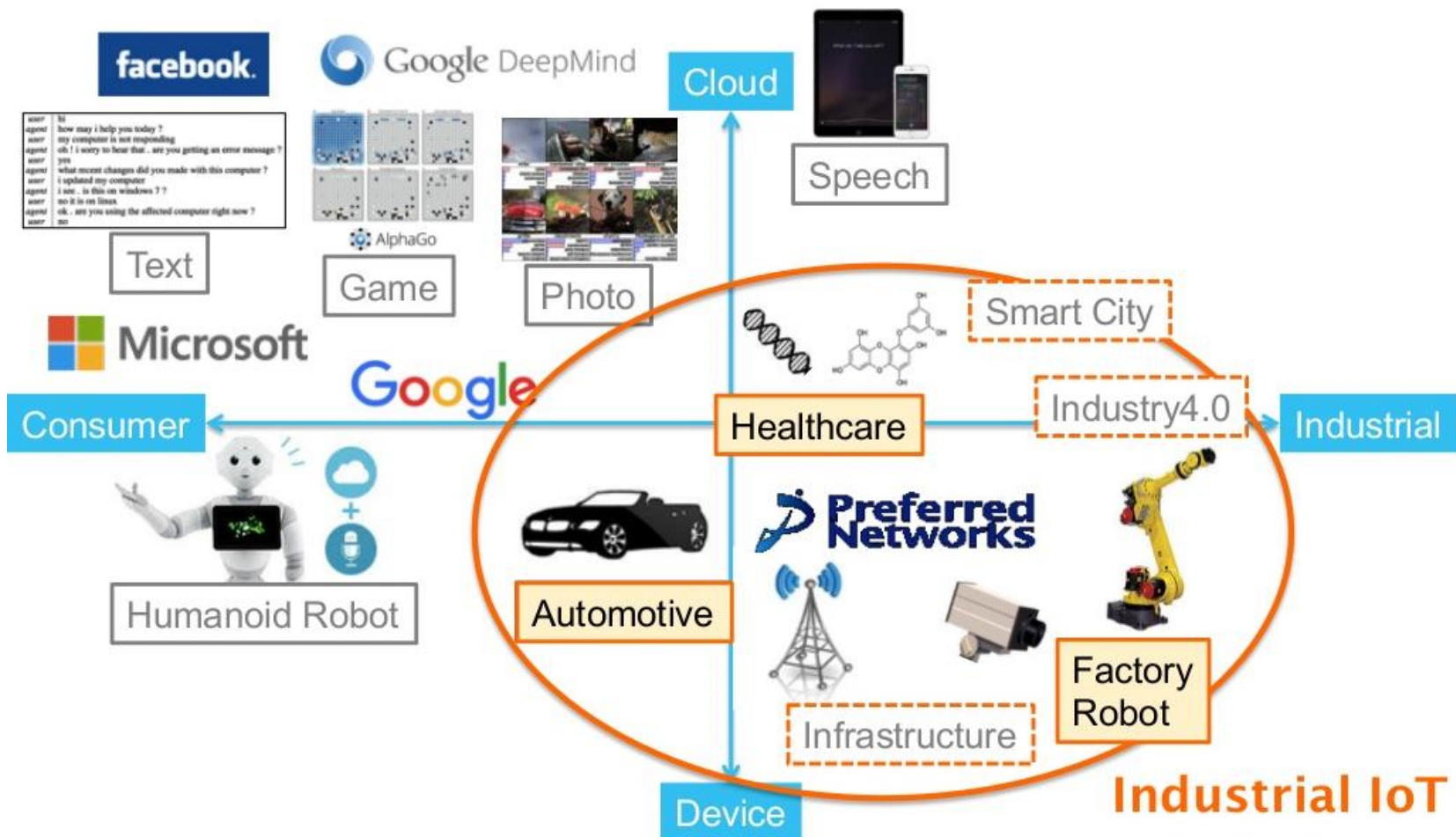


Image Source: Yahoo Japan, 20 March 2016

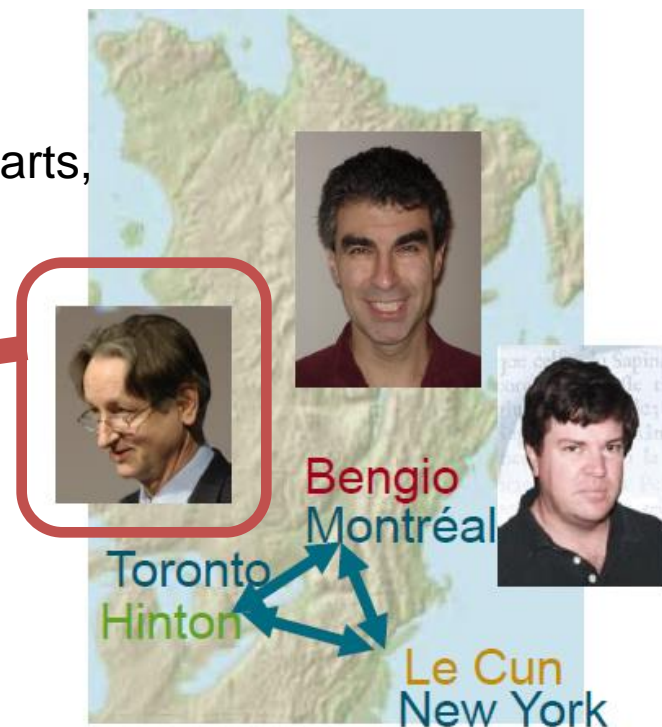
# What is Deep Learning ?

## Origins (1980-1990) :

- Boltzmann Machines, Restricted Boltzmann Machines. (Smolensky ,1986, called them “harmoniums”)
- Successful on simple test cases.
- People: Geoffrey Hinton, Terry Sejnowski, Emile Aarts, Jan Korst.

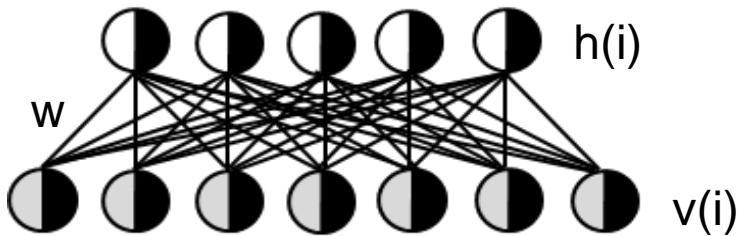
## Breakthrough in 2006:

- Ability to train deep architectures by using layer-wise unsupervised learning, whereas previous purely supervised attempts had failed.

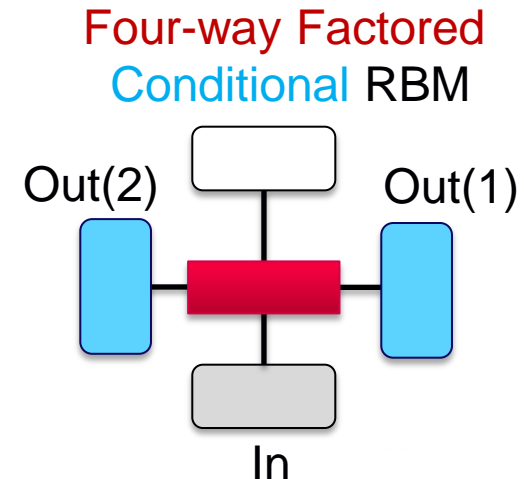
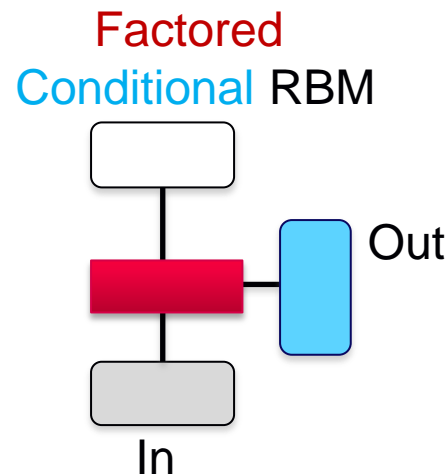
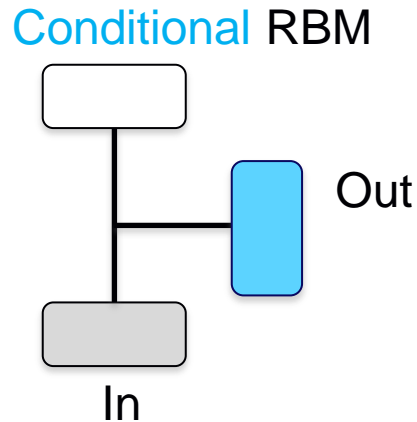
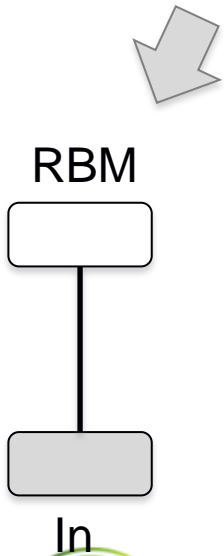
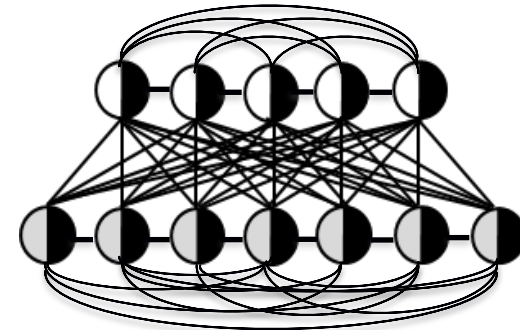


# The intuition behind our proposed method

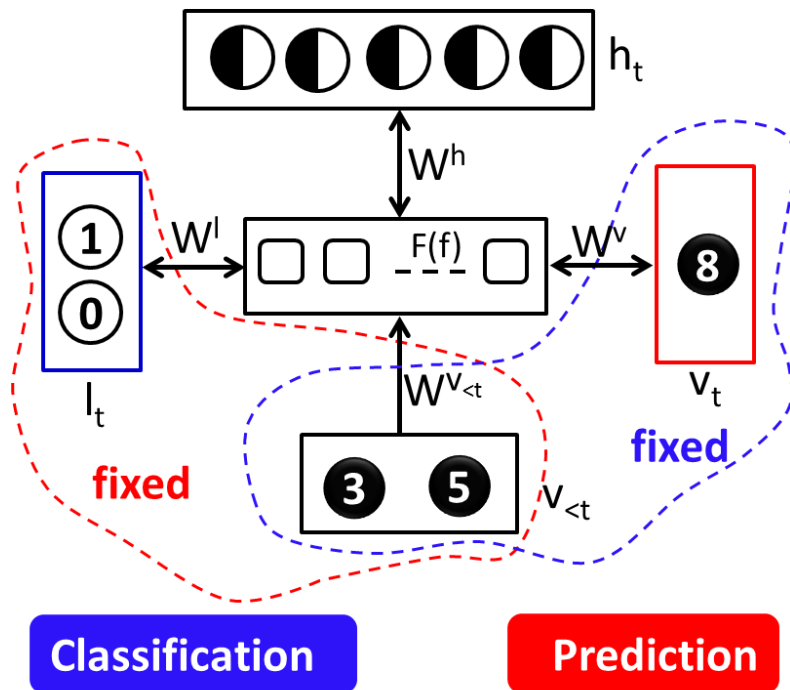
Restricted Boltzmann Machine



Boltzmann Machine

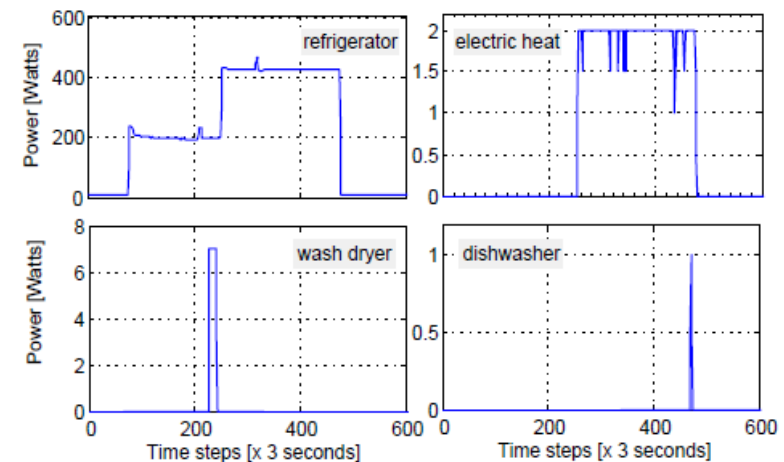
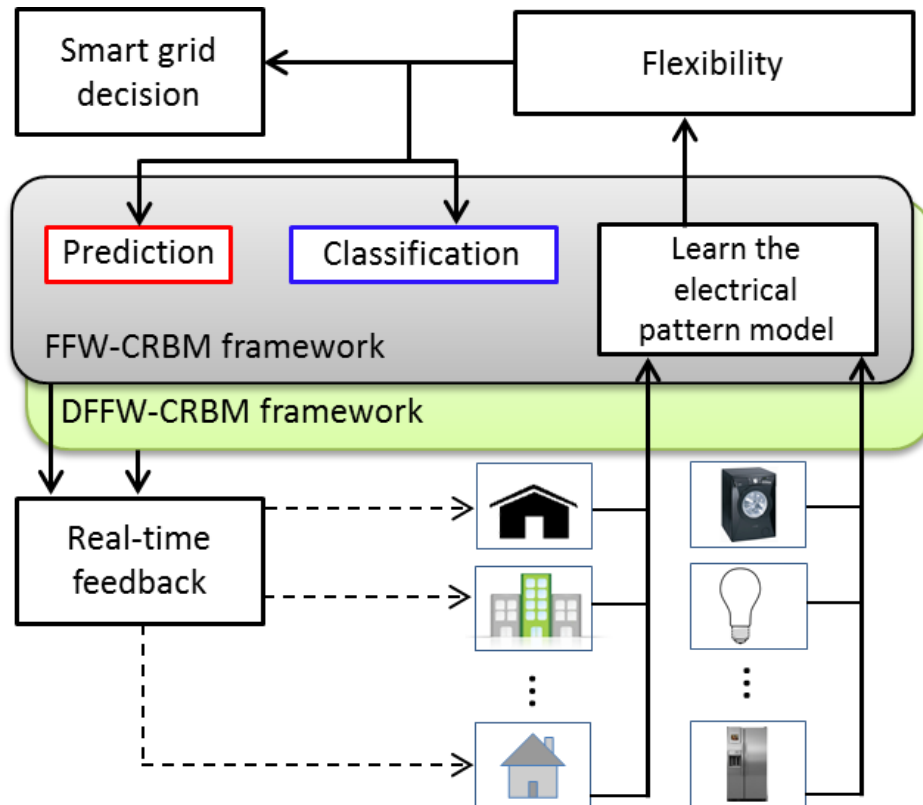


# Factored four way conditional restricted Boltzmann machine (FFW-CRBM)



*Classification and prediction schemes for FFW-CRBM*

# IoT architecture used for the real-time identification and prediction procedure of the buildings energy flexibility



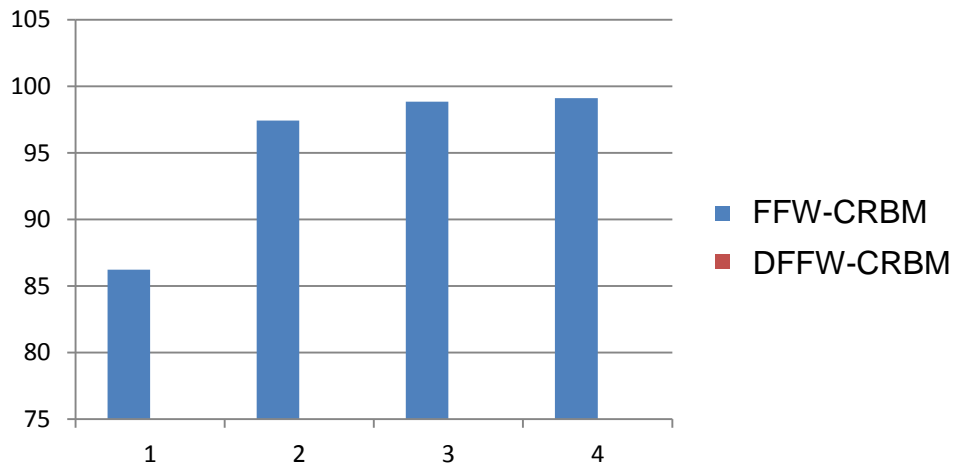
REDD: A Public Data Set  
for Energy Disaggregation  
Research

*[Kolter and Johnson]*

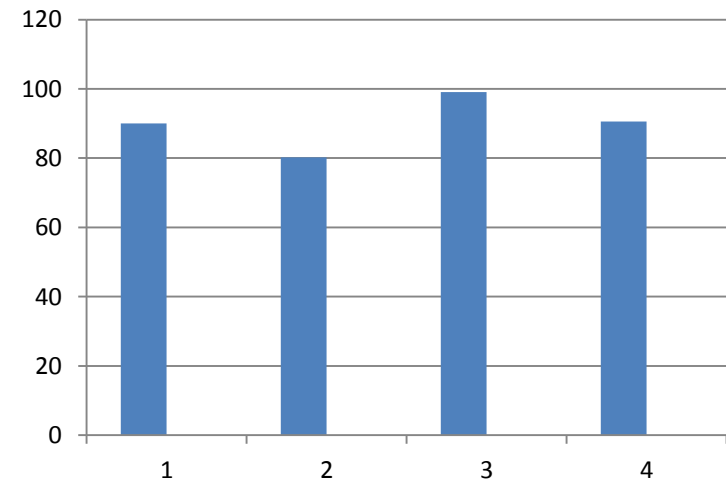
# Results – flexibility identification

Appliance	Method	Accuracy [%]	Balanced accuracy [%]
refrigerator	FFW-CRBM	86.23	90.05
	DFFW-CRBM	83.10	91.27
dishwasher	FFW-CRBM	97.42	80.21
	DFFW-CRBM	97.26	87.06
washer dryer	FFW-CRBM	98.83	99.03
	DFFW-CRBM	99.06	92.16
electric heater	FFW-CRBM	99.10	90.58
	DFFW-CRBM	99.03	92.05

## Accuracy [%]



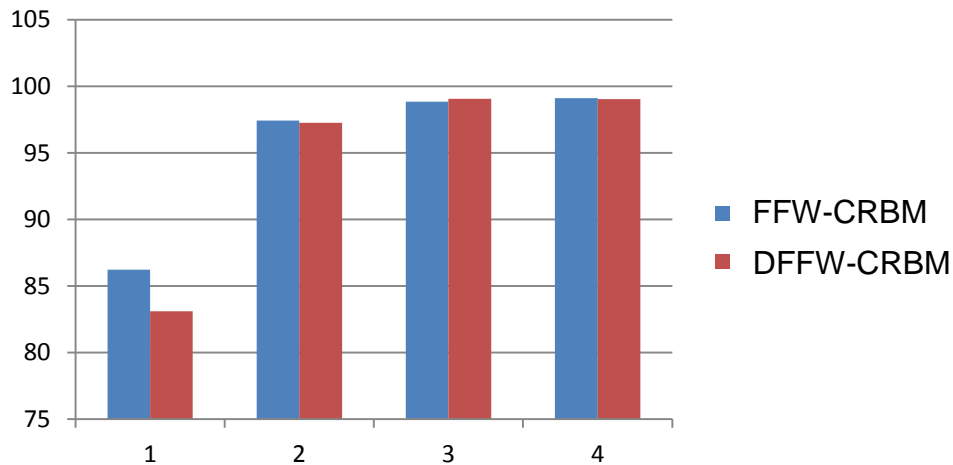
## Balanced accuracy [%]



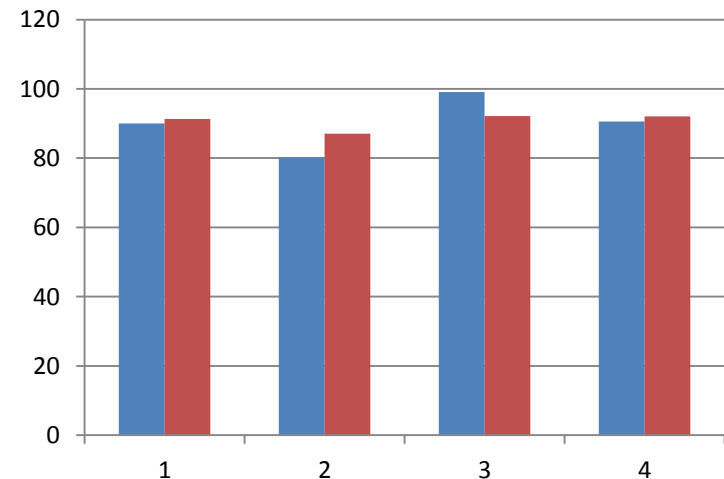
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Accuracy [%]



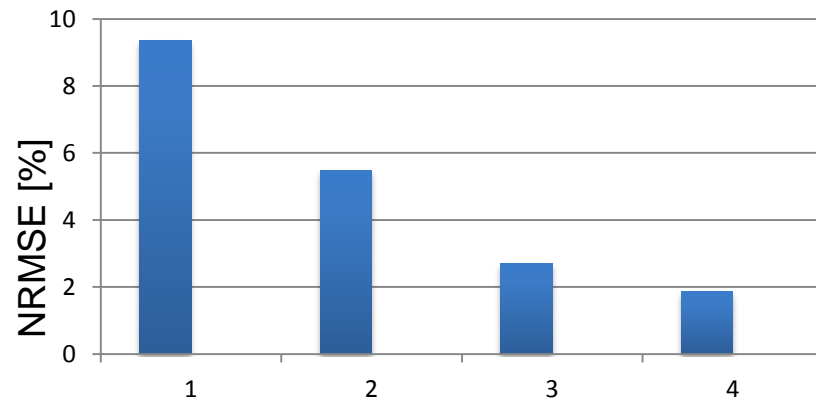
Balanced accuracy [%]



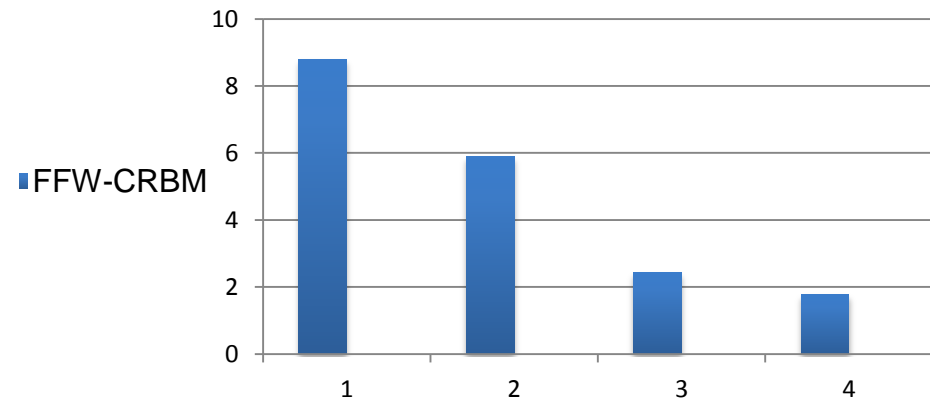
# Results – flexibility prediction

Appliance	Method	Power NRMSE [%]	Time-of-use NRMSE [%]
refrigerator	FFW-CRBM	9.36	8.79
	DDFW-CRBM	9.27	8.71
dishwasher	FFW-CRBM	5.49	5.89
	DDFW-CRBM	5.41	5.87
washer dryer	FFW-CRBM	2.70	2.43
	DDFW-CRBM	2.59	2.44
electric heater	FFW-CRBM	1.86	1.78
	DDFW-CRBM	1.85	1.77

## Power

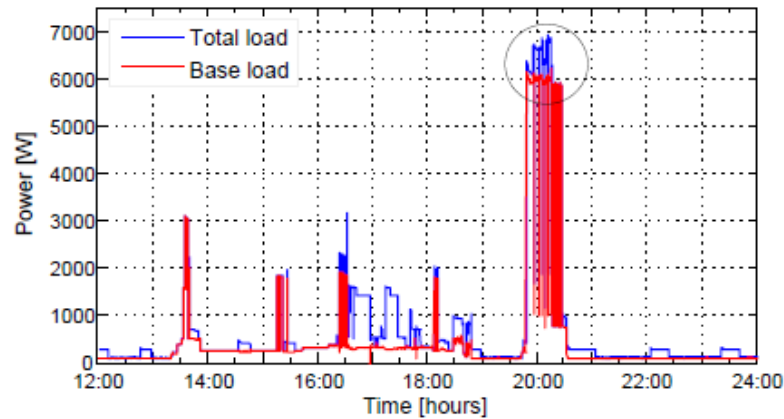


## Time-of-Use





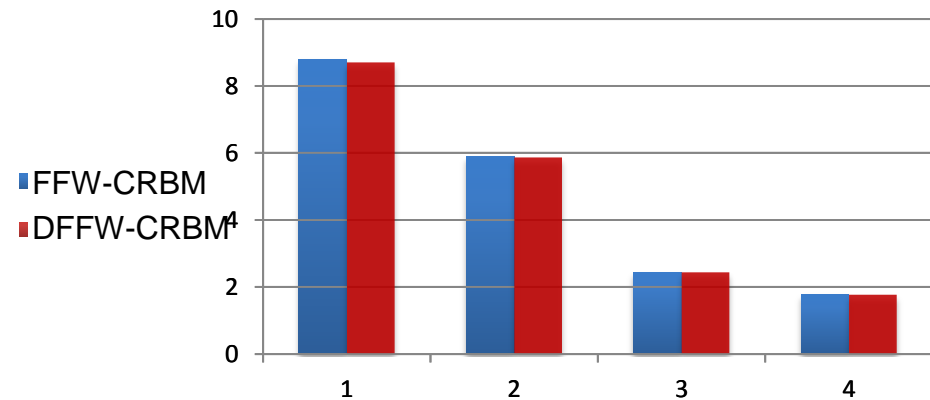
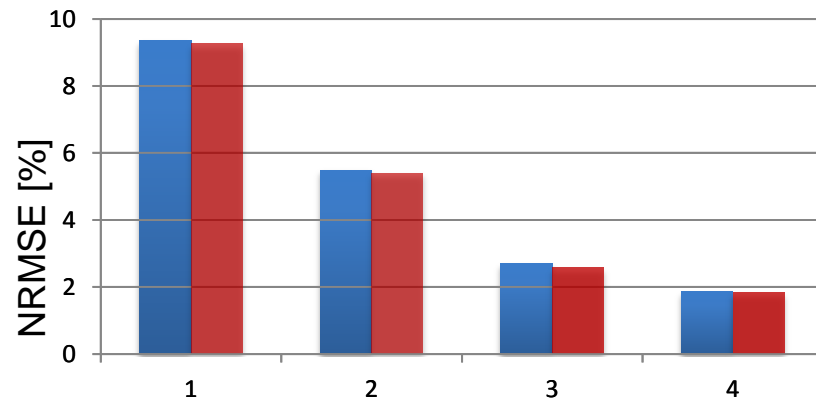
# Results – flexibility prediction



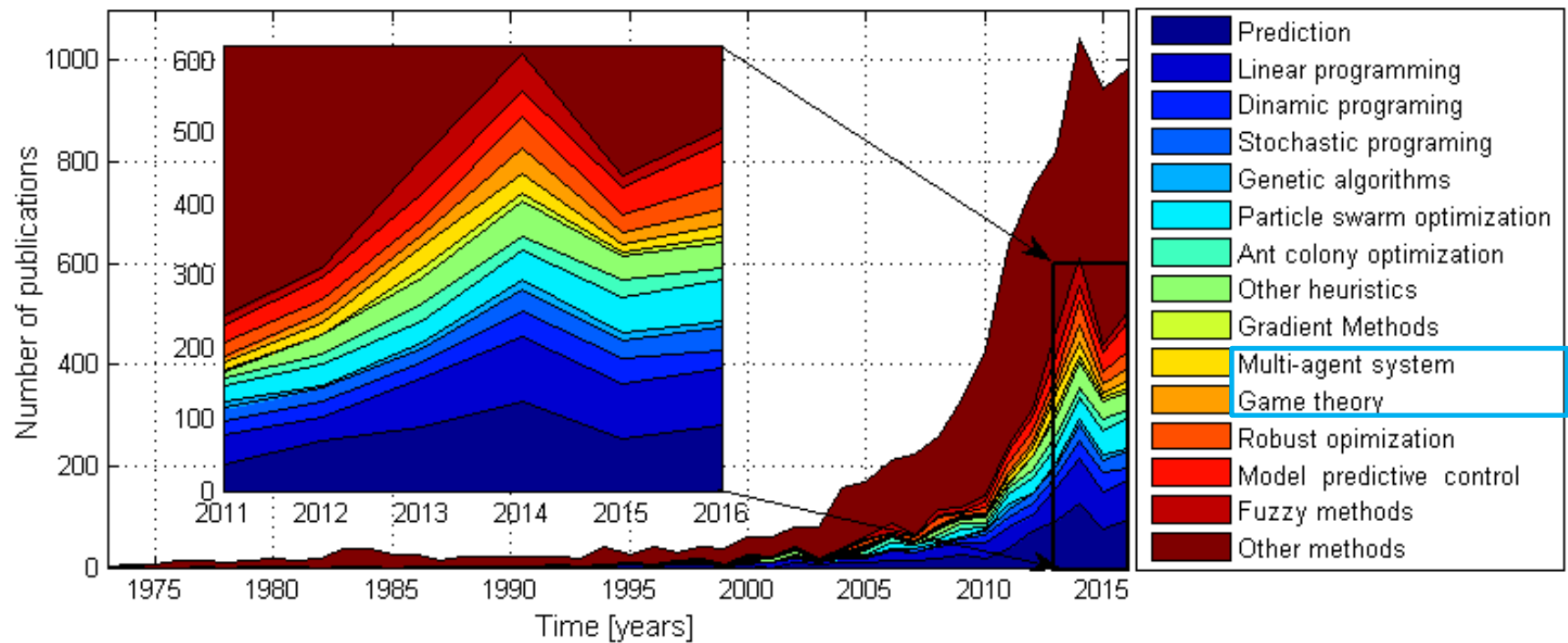
Power

Appliance	Method	Power NRMSE [%]	Time-of-use NRMSE [%]
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electric heater	FFW-CRBM	1.86	1.78
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Time-of-Use



# On-line resource allocation



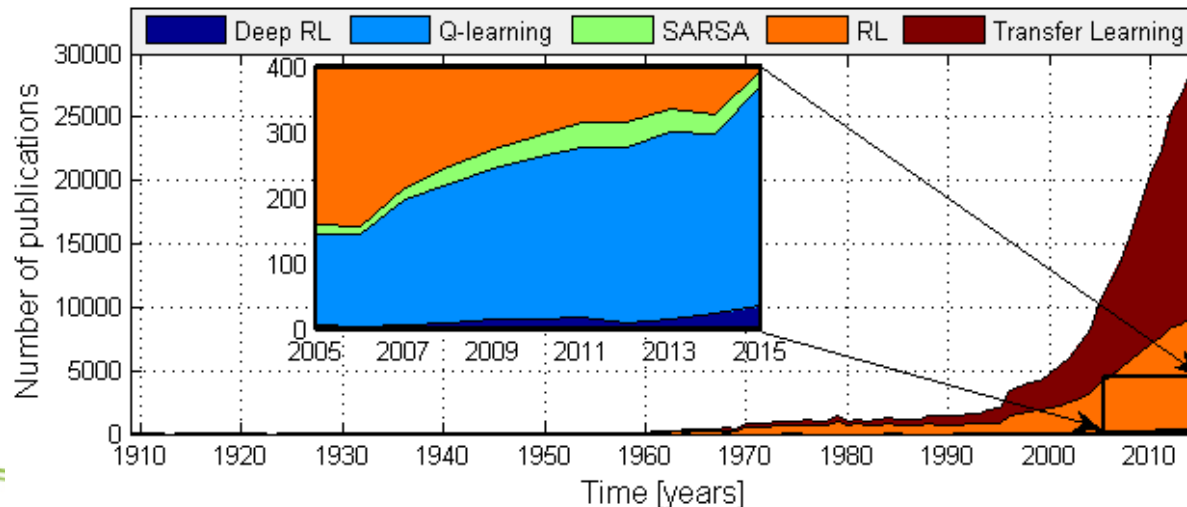
# On-line resource allocation

[2015] Human-level control through **deep reinforcement learning**, *Minh et al*, Nature

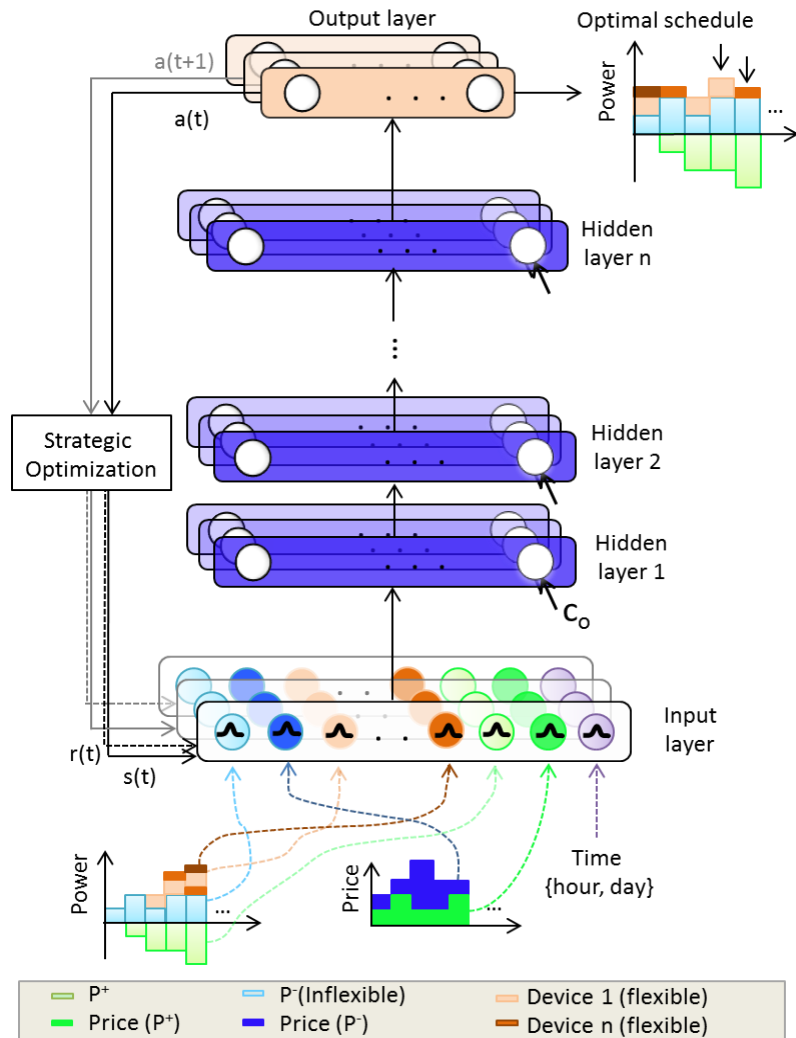
*“This work bridges the divide between high-dimensional sensory inputs and actions, resulting in the first artificial agent that is capable of learning to excel at a diverse array of challenging tasks.”*

[2016] AlphaGO versus Lee Sedol - professional Go player

$\sim 10^{170}$  compared to  $\sim 10^{50}$  for chess (Kasparov, 1997)



# Optimal resource allocation



*Reinforcement learning*

$$\{s, a\} \rightarrow Q(s, a)$$

*Deep learning*

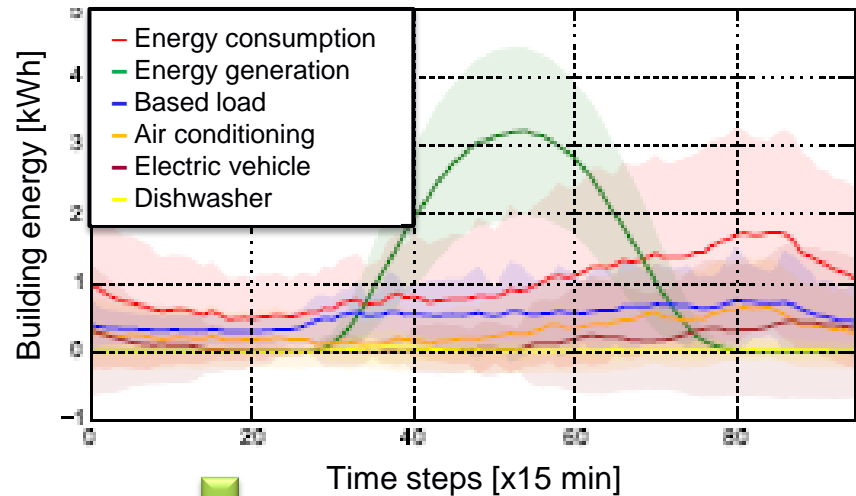
$$\frac{\text{Input data}}{\text{data}} \rightarrow DNN_{(k)} \xrightarrow{\text{Output}} \text{Data estimation}$$

*Deep reinforcement learning*

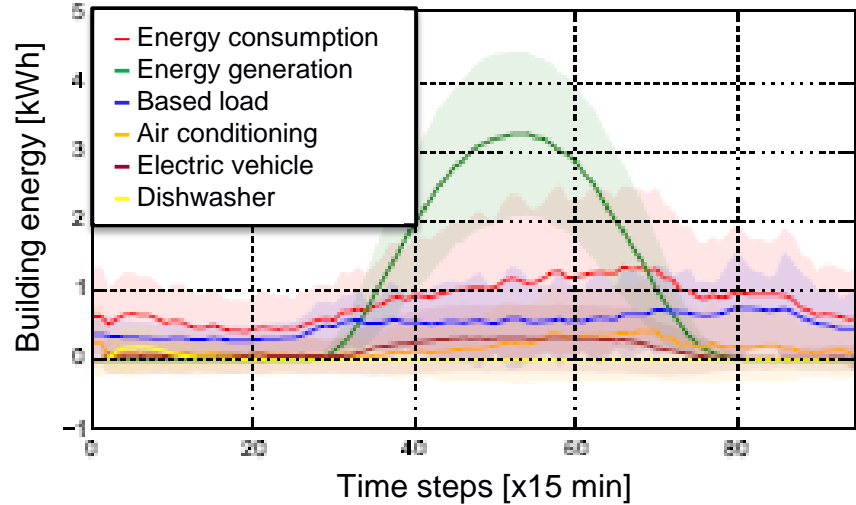
$$\left\{ \begin{array}{l} \frac{\text{Input states}}{\text{states}} \rightarrow DNN_{(k)} \xrightarrow{\text{Output}} Q(s, a) \\ \frac{\text{Input states}}{\text{states}} \rightarrow DNN_{(k)} \xrightarrow{\text{Output}} p(a|s) \end{array} \right. \begin{array}{l} \text{Deep Q-learning} \\ \text{Deep Policy Gradient} \end{array}$$

# Optimal resource allocation

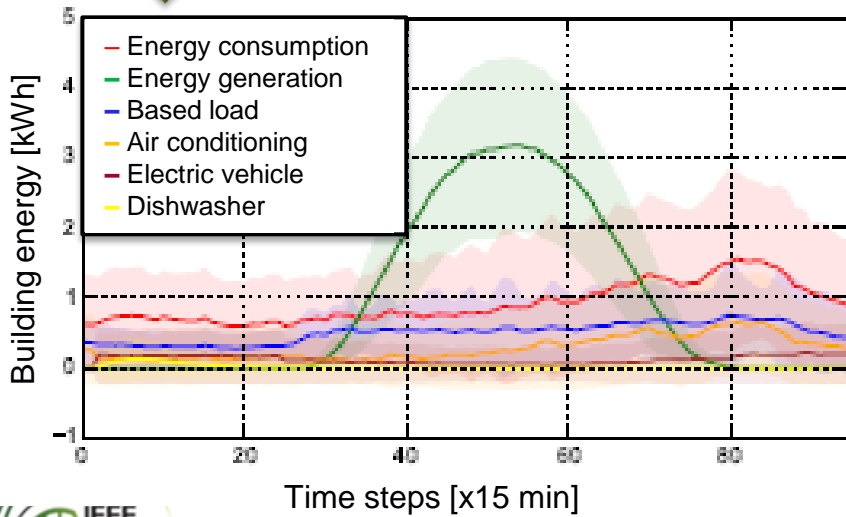
*Deep  
reinforcement  
learning*



↓ Peak reduction

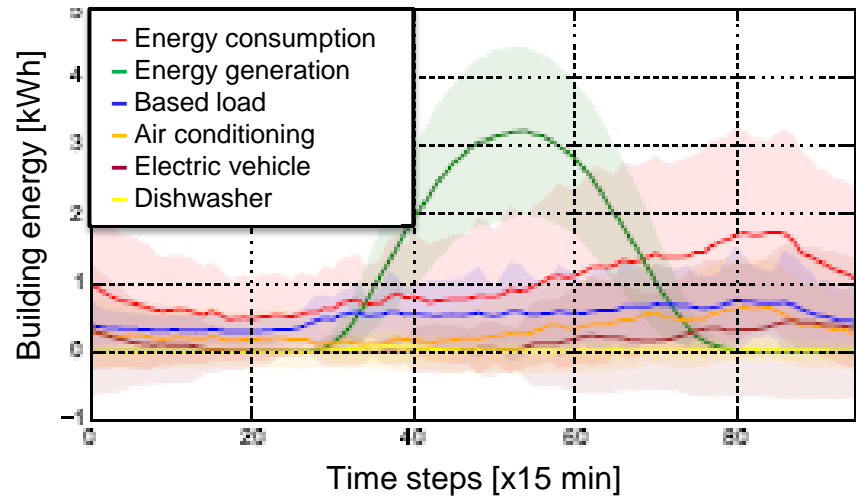


↓ Cost minimization

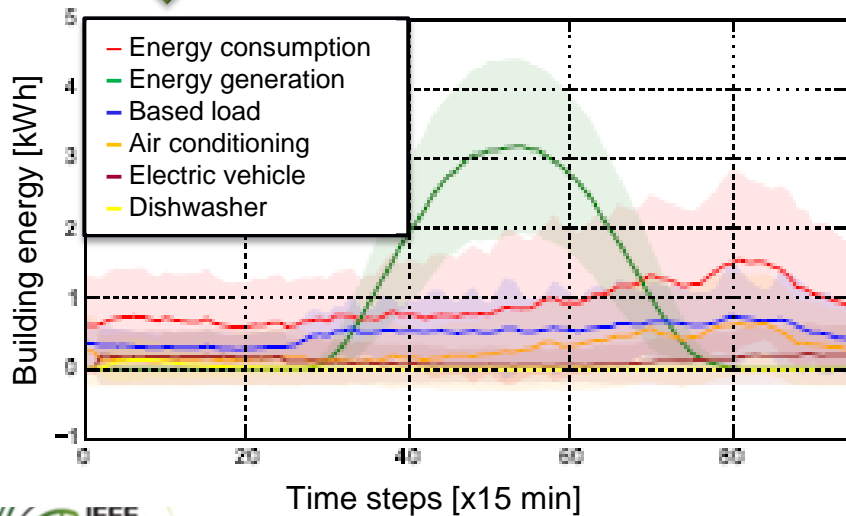


# Optimal resource allocation

*Deep  
reinforcement  
learning*



Cost minimization



Results: 27% cost reduction

Pecan Street dataset

- Building level
- Aggregated level

# Conclusions

## Part I

- We proposed a novel IoT framework using FFW-CRBMs and DFFW-CRBMs to perform simultaneously and in real-time flexibility identification and prediction
- The evaluation on the REDD dataset shows that:
  - Both models perform very well, reaching a similar performance with state-of-the-art models on flexibility identification
  - Both models are capable of performing also flexibility prediction (i.e. real-time estimation of the power consumption and time-of-use of the flexible appliances)

## Part II

- We introduce Deep Reinforcement Learning for on-line resource allocation at both building and aggregated level
- The evaluation on the Pecan Street dataset shows that
  - We are able to minimize the peak consumption, as well as to reduce the building energy cost with approximately 27%.

- References

## Part I

[1] Mocanu E., Nguyen P.H. and Gibescu M. *Energy disaggregation for real-time building flexibility detection*. IEEE Power and Energy Society General Meeting, 2016, Boston, USA.

[2] Mocanu D.C., Mocanu E., Nguyen H.P., Gibescu M. and Liotta A. *Big IoT data mining for real-time energy disaggregation in buildings*. Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics (IEEE SMC), 2016, Hungary.

## Part II

[3] Mocanu E., Mocanu D.C., Nguyen H.P., Liotta A. , Webber M.E., Gibescu M. and Sloomweg J.G. *On-line Building Energy Optimization using Deep Reinforcement Learning*, CoRR, 2017, (submitted for journal publication)

**Thank you for your attention! Questions?**