Panel session: Energy Efficiency and Smart Cities

Machine learning to estimate energy demands and user behavior related to buildings in the smart grid context

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Outline

• Introduction
• Machine Learning
• Deep Learning
• Numerical results
• What comes next?
• Conclusion.
Building level

Energy demand profiles
Smart Grid level

Building layer

Neighborhood layer

SG layer
Machine Learning

• Given observations
  \[ D_{\text{Energy}} = \{u^{(i)}, v^{(i)}\}_{i=1}^l \]

• Learn a predictive function

• Goal: Minimize the empirical loss

\[
\text{Distance} \left( p_{\text{model}}(V|\Gamma; \Theta) \parallel p_{\text{empirical}}(V|\Gamma) \right)
\]
MIT technology review 2013

**Deep Learning**
With massive amounts of computational power, machines can now recognize objects and translate speech in real time. Artificial intelligence is finally getting smart.

**Temporary Social Media**
Messages that quickly self-destruct could enhance the privacy of online communications and make people freer to be spontaneous.

**Prenatal DNA Sequencing**
Reading the DNA of fetuses will be the next frontier of the genomic revolution. But do you really want to know about the genetic problems or musical aptitude of your unborn child?

**Additive Manufacturing**
Skeptical about 3-D printing? GE, the world’s largest manufacturer, is on the verge of using the technology to make jet parts.

**Baxter: The Blue-Collar Robot**
Rodney Brooks’s newest creation is easy to interact with, but the complex innovations behind the robot show just how hard it is to get along with people.

**Memory Implants**
A maverick neuroscientist believes he has deciphered the code by which the brain forms long-term memories. Next-testing a prosthetic implant for people suffering from long-term memory loss.

**Smart Watches**
The designers of the Pebble watch realized that a mobile phone is more useful if you don’t have to take it out of your pocket.

**Ultra-Efficient Solar Power**
Doubling the efficiency of a solar cell would completely change the economics of renewable energy. Nanotechnology just might make it possible.

**Big Data from Cheap Phones**
Collecting and analyzing information from simple cell phones can provide surprising insights into how people move about and behave—and even help us understand the spread of diseases.

**Supergrids**
A new high-power circuit breaker could finally make highly efficient DC power grids practical.
Success stories

- 2010, Stanford University Artificial Intelligence Lab have switched their main focus to Deep Learning.
- 2011, IDSIA, Switzerland, won traffic sign recognition competition and their method was the only one which outperformed humans.
- 2012, Microsoft: “...most dramatic change in accuracy since 1979...” for speech recognition, by Richard Rashid, Chief Research Officer.
- 2012, Google Brain, a cluster of 16000 processors and 1 billions connections successfully trained itself to recognize cats on Youtube (lead by Andrew Ng).
- 2013, Google acquired DNNResearch from Geoffrey Hinton.
- 2013, Baidu is setting up a machine learning facility in California, next to Google, dedicated to Deep Learning (lead by Andrew Ng from 2014).
What is Deep Learning?

- 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.
What is Deep Learning?

Restricted Boltzmann Machines

Inference

\[
P(h_j=1|v) = \frac{1}{1 + \exp(-\sum_i w_{ij} v_i - b_j)}
\]

\[
P(v_i=1|h) = \frac{1}{1 + \exp(-\sum_j w_{ij} h_j - a_i)}
\]

Advantages

- Unsupervised learning
- Automatically features extraction
- Stochastic models
- Generative power
What is Deep Learning?
Contrastive Divergence

Learning in RBMs [Geoffrey Hinton, 2002]

Markov Chain

K times

Weights Update

\[ \Delta W_{ij} = E_{P_{data}}[v_i h_j] - E_{P_K}[v_i h_j] \]

The other parameters can be trained in a similar manner.
What is Deep Learning?

Generic architecture
1. Conditional RBMs

**CRBM: Building Energy prediction**

**Inference for CRBM**

\[
\rho(h = 1 | u, v) = \text{sig}(u^T W^{uh} + v^T W^{vh} + b^h)
\]

\[
\rho(v | h, u) = \mathcal{N}(W^{uv^T} u + W^{vh} h + b^v, \sigma^2)
\]

**Total energy**

\[
E(v, h, u; W) = -v^T W^{vh} h - v^T b^v - u^T W^{uv} v - u^T W^{uh} h - h^T b^h
\]
1. Conditional RBMs

**CRBM: Building Energy prediction**

\[ E(v, h, u; W) = -v^T W^{vh} h - v^T b^v - u^T W^{uv} v - u^T W^{uh} h - h^T b^h \]

**Weight updates**

\[ W^{uh}_{\tau+1} = W^{uh}_\tau + \alpha \left( \langle uh^T \rangle_{data} - \langle uh^T \rangle_{recon} \right) \]

\[ W^{uv}_{\tau+1} = W^{uv}_\tau + \alpha \left( \langle uv^T \rangle_{data} - \langle uv^T \rangle_{recon} \right) \]

\[ W^{vh}_{\tau+1} = W^{vh}_\tau + \alpha \left( \langle vh^T \rangle_{data} - \langle vh^T \rangle_{recon} \right) \]

**Biases updates**

\[ b^v_{\tau+1} = b^v_{\tau} + \alpha \left( \langle v \rangle_{data} - \langle v \rangle_{recon} \right) \]

\[ b^h_{\tau+1} = b^h_{\tau} + \alpha \left( \langle h \rangle_{data} - \langle h \rangle_{recon} \right) \]
1. Conditional RBMs

CRBM: Building Energy prediction

<table>
<thead>
<tr>
<th>Model</th>
<th>Lighting consumption</th>
<th>Total energy consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RMSE</td>
<td>R</td>
</tr>
<tr>
<td>ANN (NAR)</td>
<td>2.24</td>
<td>0.93</td>
</tr>
<tr>
<td>ANN (NARX)</td>
<td>1.22</td>
<td>0.96</td>
</tr>
<tr>
<td>HMM</td>
<td>1.23</td>
<td>0.95</td>
</tr>
<tr>
<td>CRBM</td>
<td>1.11</td>
<td>0.96</td>
</tr>
</tbody>
</table>

2. Three Way Conditional RBMs

eFCRBM: People detection
2. Three Way Conditional RBMs  

**eFCRBM: People detection**

Utility:

- Multi dimensional time series classification and prediction.

2. Three Way Conditional RBMs

Classification Procedure

\[ y = \arg \min_{\gamma \in \mathcal{Y}} \left[ d \left( PV(v_{<t}, y), TV_t \right) \right] \]
2. Three Way Conditional RBMs eFCRBM: People detection

Time response of all sensor integrated in MIST1431, for Scenario2.

<table>
<thead>
<tr>
<th>Localization -16 classes (8 moving / 8 sitting position)</th>
<th>SVM</th>
<th>NB</th>
<th>AdaB.</th>
<th>GMM</th>
<th>eFCRBM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>71.56%</td>
<td>64.81%</td>
<td>40.21%</td>
<td>74.07%</td>
<td><strong>88.72%</strong></td>
</tr>
</tbody>
</table>
What comes next?

Deep reinforcement learning

Can we replace discrete actions with continuous actions?

Infusing these new methods could improve buildings automation systems in the smart grid context?

Conclusions

• Machine learning is a good solution in order to quantify the energy variations in the smart grid context

• Deep learning methods increase the accuracy of the estimated building energy demands and user behavior

• There is theoretical and empirical evidence in favor of multiple levels of representation