# The Neural Energy Decoder

## Energy Disaggregation by Combining Binary Subcomponents


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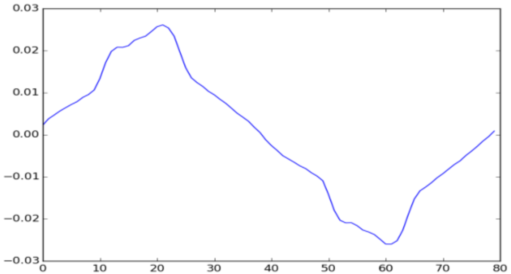
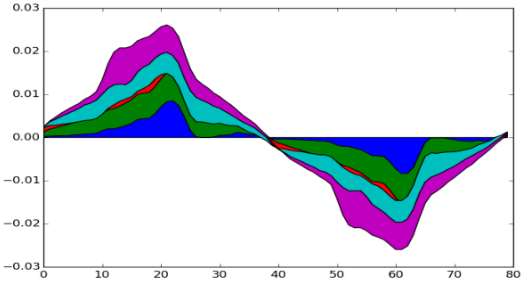
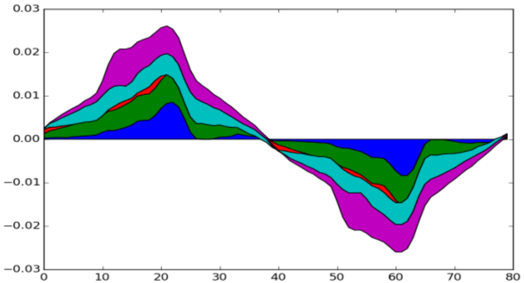
# Introduction: Disaggregation in two steps

1) Find recurring building blocks in the aggregate current waveforms




2) Combine inferred subcomponents into appliances

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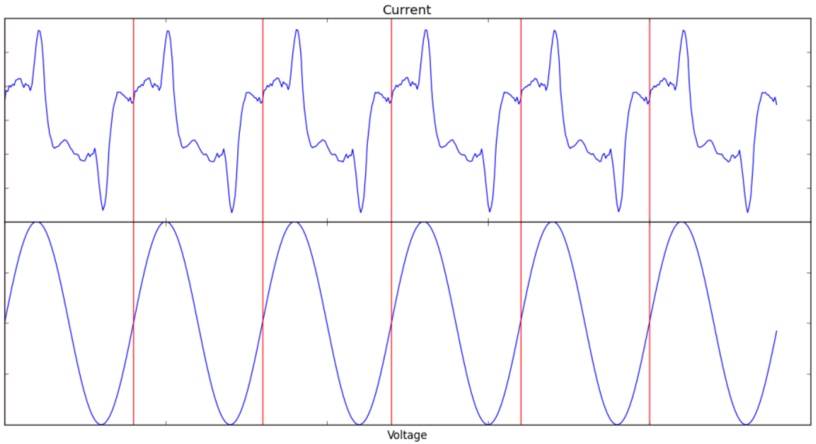
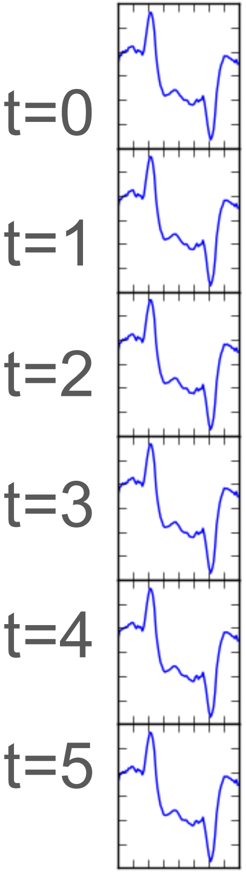
# Step 1: Inferring additive subcomponents
- Fully unsupervised

# Step 1: Data pre-processing

Preserving phase info by slicing current according to zero-crossings in voltage:




Matrix containing current $Y \in \mathbb{R}^{T \times N}$:

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# Step 1: Identifying sub-components

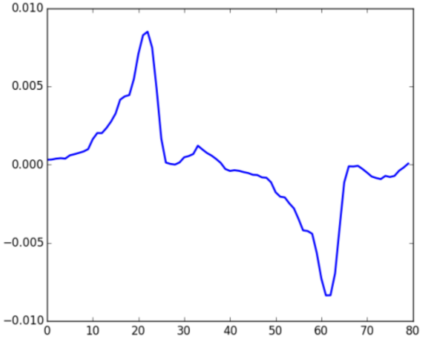
- Fully unsupervised
- Binary Matrix Factorization: minimize $||XG - Y||$
  - $X \in \{0,1\}^{T \times C}$: temporal information
  - $G \in \mathbb{R}^{C \times N}$: shape of component waveform
  - $Y \in \mathbb{R}^{T \times N}$: matrix containing aggregate waveforms
- BMF is NP-complete problem

# Step 1: One slice of X and G

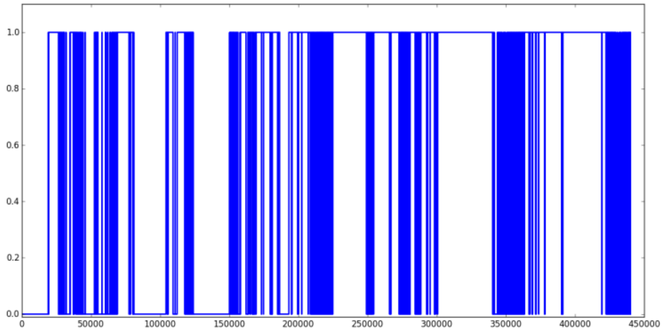
- minimize ||XG - Y||

- Let’s consider the *i*th row of X and the *i*th column of G

What: $G_i$

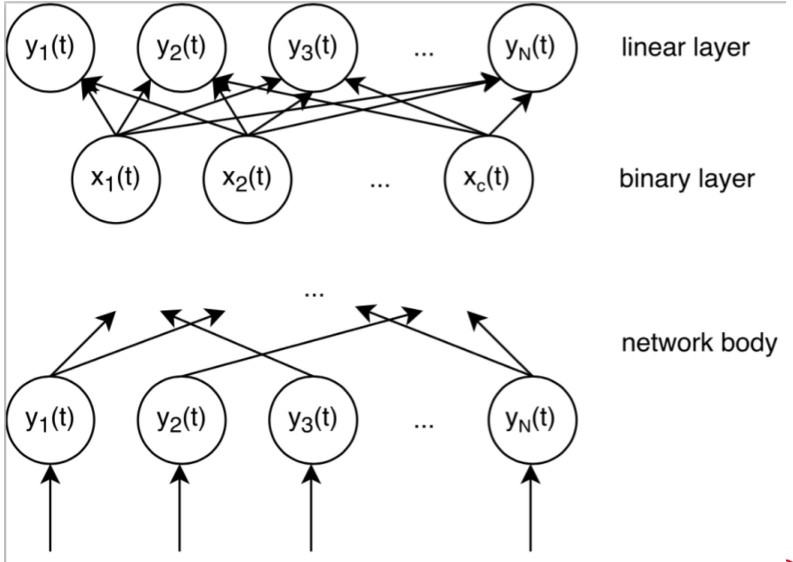



When: $X_i$



# Step1: Neural Binary Matrix Factorization

- Approximation using Neural Network
  - special topology
  - Autoencoder
  - Output: XG with X being binary
  - Learning: minimize ||XG - Y|| given some input




- ng on GPU possible
ecommended)

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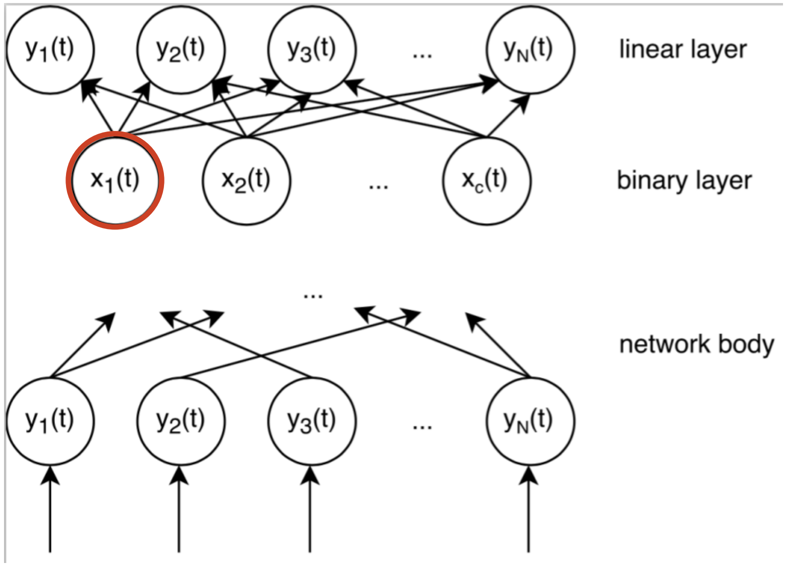
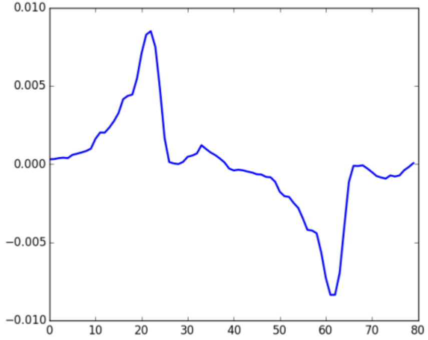
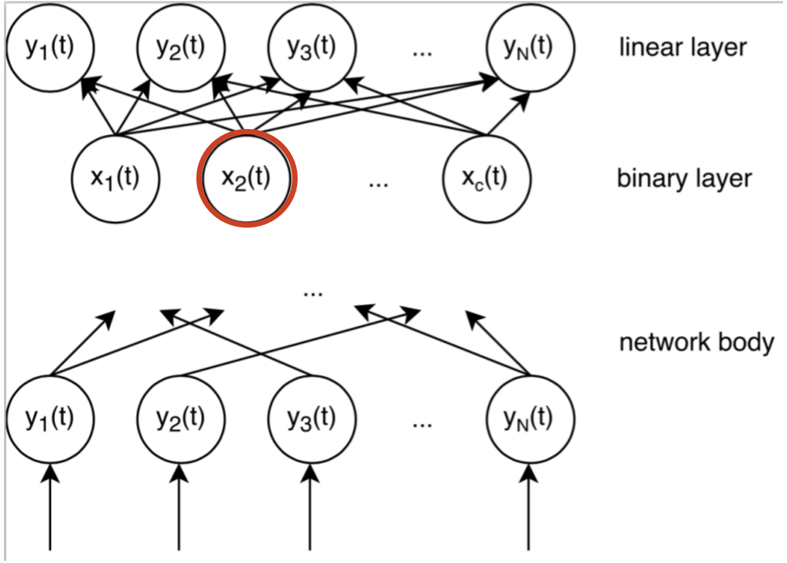
# Step1: Neural Binary Matrix Factorization



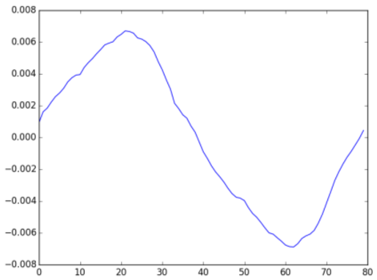

$G_1$:



# Step1: Neural Binary Matrix Factorization




$G_2$:



# Step1: Application to Phase B of BLUED

- BLUED: sampling frequency of 12kHz but resampled to 4.8kHz, i.e N=80
- 5 layer neural network created with keras*
  - 60 cycles fed into network at once in freq domain
  - layers: 4800 -> 2000 -> 1000 -> 100 -> 4800
- C = 100, i.e. 100 inferred subcomponents

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* http://keras.io

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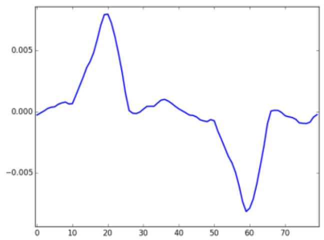
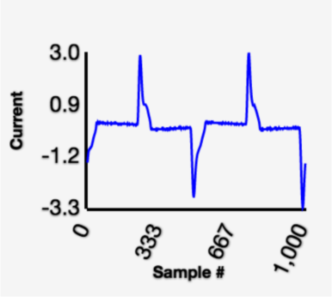
# Step1: Application to Phase B of BLUED

Component 63:




Laptop: *




AC-DC converter?

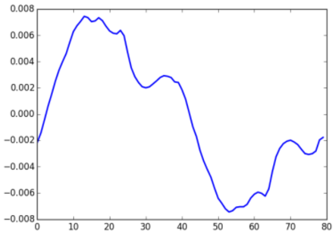
- Electronics
    - Computer
    - Laptop
    - ...



* taken from PLAID (www.plaidplug.com)

# Step1: Application to Phase B of BLUED

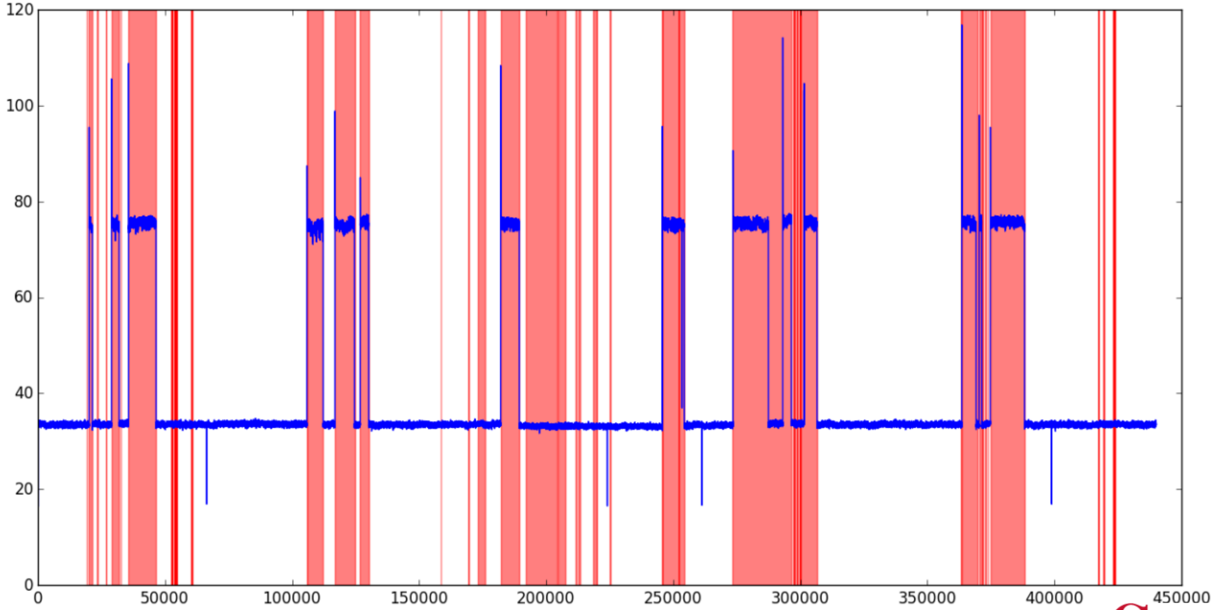
Component 34:




$X_{34}$:

DVR:

F1 Score: 0.85




= component 34 is turned on

Note: DVR and TV have a temporal correlation of 1

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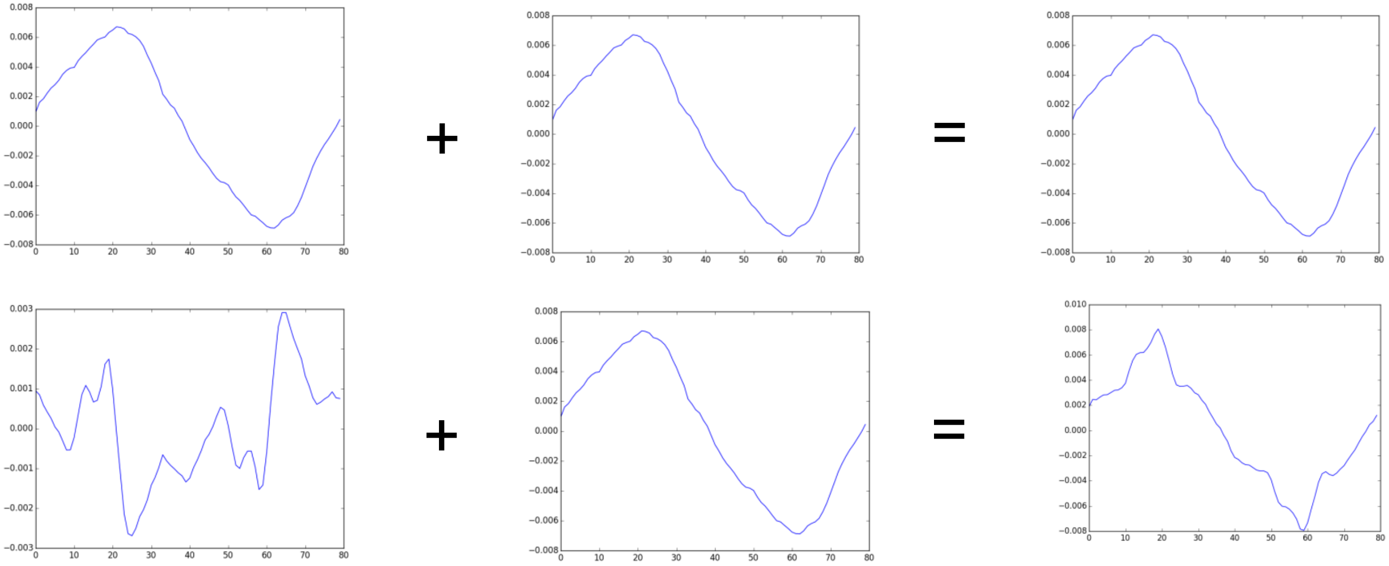
# Step 1: Some components cannot be appliances

- A single appliance as a superposition of components

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Step 2: Combining additive subcomponents

- supervised
- unsupervised

# Step 2: Supervised Re-Aggregation

- Assuming knowledge $Q \in \{0,1\}^{T \times A}$ containing ground truth of appliance
  - 2-state appliances: *on* or *off*
- Find mapping between X and Q
  - Logistic Regression


[0, 1, 0, 1, 1, 0, …] -> [0, 1, …]

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# Results: Logistic Regression

$$mde(p, \hat{p}) = \sum_{i,t} \frac{|p_i(t) - \hat{p}_i(t)|}{p_i(t)}$$

| Appliance | Active | Boolean F1 | Logit F1 | MDE($\hat{p}$) | MDE($p$) |
|---|---|---|---|---|---|
| A/V LR | 60% | 0.89 | 0.98 | 0.04 | 0.009 |
| Computer 1 | 27.3% | 0.88 | 0.99 | 0.05 | 0.042 |
| Desk Lamp | 21.4% | 0.84 | 0.95 | 0.06 | 0.013 |
| DVR | 20.7% | 0.94 | 0.99 | 0.006 | 0.005 |
| Socket LR | $> 0.1\%$ | 0.96 | 0.92 | 0.09 | 0.089 |
| Garage Door | 0.4 % | 0.49 | 0.89 | 0.07 | 0.063 |
| Iron | 0.1 % | 0.74 | 0.92 | 0.12 | 0.115 |
| Laptop 1 | 33.3% | 0.75 | 0.92 | 0.34 | 0.272 |
| LCD Monitor | 16.2% | 0.73 | 0.94 | 0.12 | 0.029 |
| Monitor 2 | 17.3% | 0.80 | 0.92 | 0.20 | 0.089 |
| Printer | 0.1% | 0.45 | 0.70 | 0.05 | 0.045 |
| Tall Desk Lamp | 21.4% | 0.84 | 0.95 | 0.06 | 0.008 |
| TV Basement | 20.7% | 0.94 | 0.99 | 0.05 | 0.029 |
| Random | 30% | 0 | 0 | - | - |
| Overall | | | | 0.058 | 0.037 |

TABLE I

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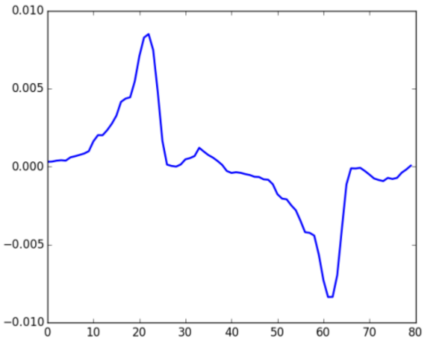
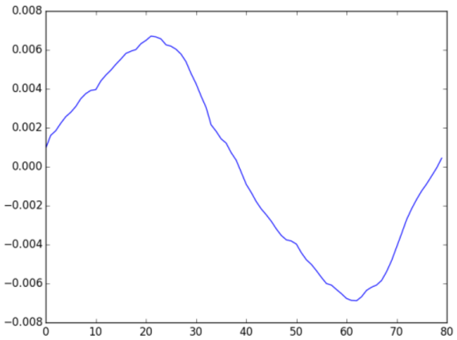
TABLE I

# Step 2: Unsupervised Re-Aggregation

- Waveform clustering by 'appliance type' conceivable
  - Electronics
  - Resistive loads, etc ..



# Step 2: Best component for each appliance

- For each appliance, the component that resulted in highest F1 score
- Random baseline:
    - 0.3

| Appliance | Active | Lower Bound F1 | Naïve F1 |
|---|---|---|---|
| A/V LR | 60% | 0.85 | 0.85 |
| Computer 1 | 27.3% | 0.67 | 0.74 |
| Desk Lamp | 21.4% | 0.70 | 0.70 |
| DVR | 20.7% | 0.85 | 0.85 |
| Socket LR | > 0.1% | 0.0 | 0.0 |
| Garage Door | 0.4 % | 0.24 | 0.3 |
| Iron | 0.1 % | 0.09 | 0.30 |
| Laptop 1 | 33.3% | 0.71 | 0.71 |
| LCD Monitor | 16.2% | 0.63 | 0.63 |
| Monitor 2 | 17.3% | 0.67 | 0.70 |
| Printer | 0.1% | 0.07 | 0.07 |
| Tall Desk Lamp | 21.4% | 0.70 | 0.70 |
| TV Basement | 20.7% | 0.85 | 0.85 |

TABLE IV

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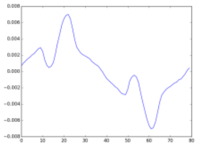
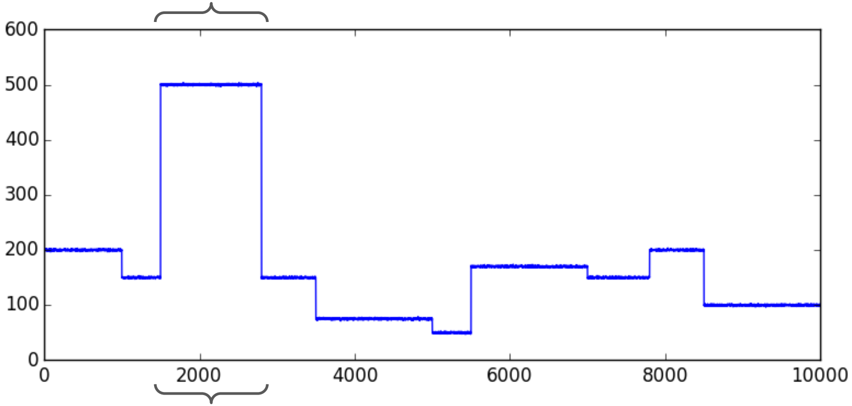
# Step 2: Augmenting existing approaches

- Existing NILM systems can be improved using NED

- A hypothesis could ... ced:






?

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# Conclusion

- Supervised: a single cycle of current sufficient to infer activity of appliance with decent precision
- Unsupervised:
  - Cluster according to waveform type?
  - Combine components in an unsupervised way possible?
  - Augment existing approaches with waveform information?
  - Regularization, sparse coding?

e computationally very cheap, carried out by smart meter

nsmission problems circumvented: 100 additional bits per cy

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# Thank you!

- Special thanks to Jack Kelly and Jingkun Gao for the feedback in our Skype calls :)
- Code for image and sound disaggregation available at:
  - http://henning.inferlab.org/neural-bmf/
- BLUED dataset can be found here:
  - http://portoalegre.andrew.cmu.edu:88/BLUED/
- Interested in a dump of the inferred matrices X, G and ground truth Q?

ningl@andrew.cmu.edu

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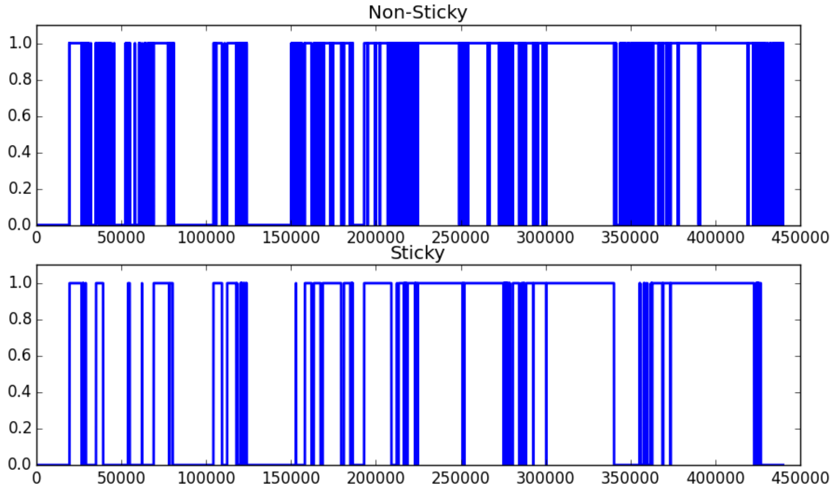
# Step 1: Factorial HMMs and BMF

- Inference in additive FHMMs can be represented as a BMF problem with some temporal regularization

- minimize ||XG - Y|| + f(X)

  - f(X) temporal regularization

  - makes states 'sticky'

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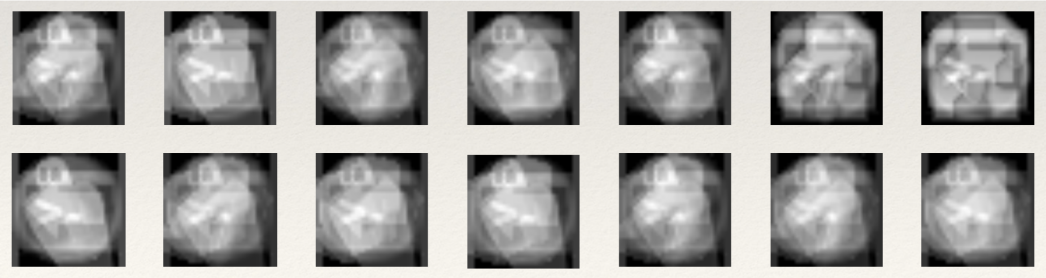
# Disentangling Images

Source images:


Grayscale superpositions of images:

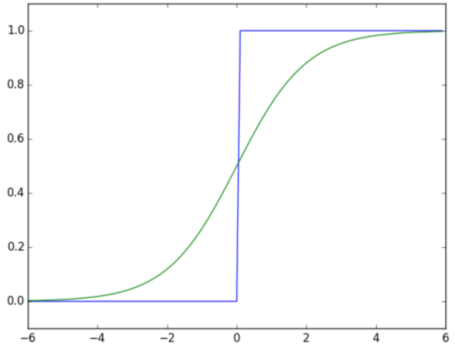


# Disentangling Images

Weights of the components inferred by Neural BMF:

# Non-Smoothness

- Binary Units: Output of the network is non-smooth
- Aggregate power trace is also non-smooth
  - Jumps or drops when appliance is turned on/off
- Stochastic Gradient Descent requires gradients to be defined
  - f(x) = 1 iff x > 0, 0 else: gradient either 0 or not defined (x=0)




approximation: Set gradient of binary
lerivative of $(1 - \exp(-x))^{-1}$

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