EFFICIENT SPARSE MATRIX PROCESSING FOR NILM

NILM Workshop 2014

Stephen Makonin, PhD Candidate, ISP, smIEEE

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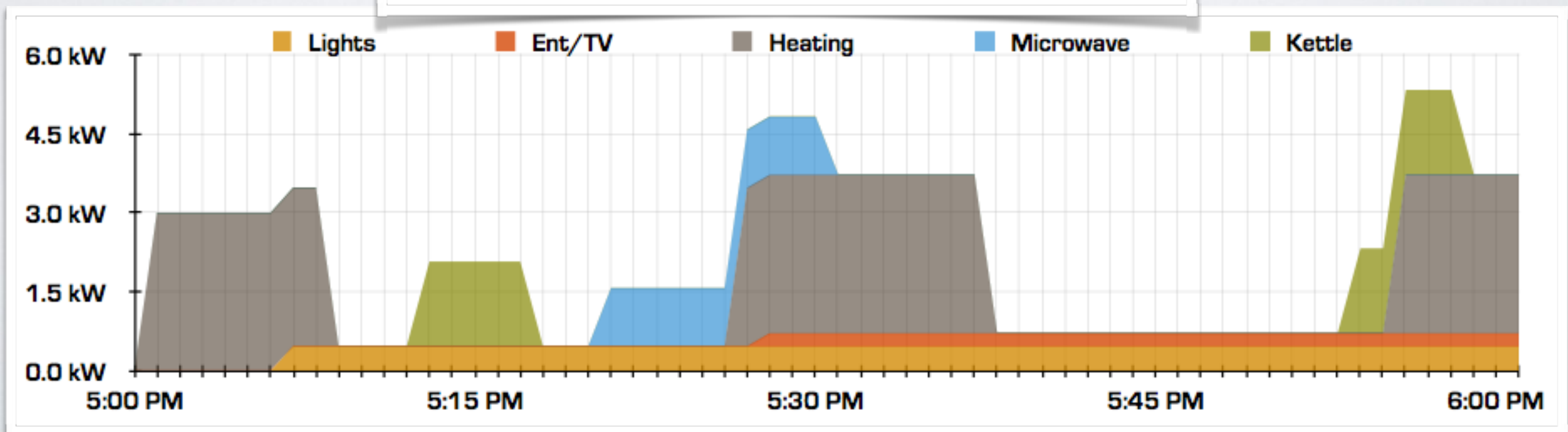
SFU

Simple Worked Example

- In Vancouver (BC, Canada) is a small 400 sq ft studio suite.

Appliance	Power	Description
Lights	480 W	8 Incandescent 60W Bulbs
Ent/TV	250 W	Panasonic 50 Plasma TV
Heating	3.0 kW	2 Cadet 1500W Baseboard
Microwave	1.1 kW	Panasonic Convection
Kettle	1.6 kW	Cuisinart Cordless 1.7L



Outline

1. Discuss the studio studio more
2. Discuss PMF and load states
3. Discuss super-state HMM

Training or Model Building Phase

4. Discuss the sparse Viterbi algorithm
5. Discuss estimation
6. Discuss test results

Testing and Evaluation Phase

Simple Worked Example

- At 6:01pm the aggregate power reading is 3.48kW

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$T = 61$
$M = 5$
$N = 15000$ (or $15\text{kW} = 120\text{V} \times 125\text{A}$ service)
$K = 2^5 = 32$ (super-states, since each load only has 2 states)

Our Very Small Dataset

Time	Mains	Lights	TV	Heat	Microwave	Kettle		Time	Mains	Lights	TV	Heat	Microwave	Kettle
5:00 PM	3000	0	0	3000	0	0		5:31 PM	3730	480	250	3000	0	0
5:01 PM	3000	0	0	3000	0	0		5:32 PM	3730	480	250	3000	0	0
5:02 PM	3000	0	0	3000	0	0		5:33 PM	3730	480	250	3000	0	0
5:03 PM	3000	0	0	3000	0	0		5:34 PM	3730	480	250	3000	0	0
5:04 PM	3000	0	0	3000	0	0		5:35 PM	3730	480	250	3000	0	0
5:05 PM	3000	0	0	3000	0	0		5:36 PM	3730	480	250	3000	0	0
5:06 PM	3480	480	0	3000	0	0		5:37 PM	730	480	250	0	0	0
5:07 PM	3480	480	0	3000	0	0		5:38 PM	730	480	250	0	0	0
5:08 PM	480	480	0	0	0	0		5:39 PM	730	480	250	0	0	0
5:09 PM	480	480	0	0	0	0		5:40 PM	730	480	250	0	0	0
5:10 PM	480	480	0	0	0	0		5:41 PM	730	480	250	0	0	0
5:11 PM	480	480	0	0	0	0		5:42 PM	730	480	250	0	0	0
5:12 PM	2080	480	0	0	0	1600		5:43 PM	730	480	250	0	0	0
5:13 PM	2080	480	0	0	0	1600		5:44 PM	730	480	250	0	0	0
5:14 PM	2080	480	0	0	0	1600		5:45 PM	730	480	250	0	0	0
5:15 PM	2080	480	0	0	0	1600		5:46 PM	730	480	250	0	0	0
5:16 PM	2080	480	0	0	0	1600		5:47 PM	730	480	250	0	0	0
5:17 PM	480	480	0	0	0	0		5:48 PM	730	480	250	0	0	0
5:18 PM	480	480	0	0	0	0		5:49 PM	730	480	250	0	0	0
5:19 PM	480	480	0	0	0	0		5:50 PM	730	480	250	0	0	0
5:20 PM	1580	480	0	0	1100	0		5:51 PM	730	480	250	0	0	0
5:21 PM	1580	480	0	0	1100	0		5:52 PM	730	480	250	0	0	0
5:22 PM	1580	480	0	0	1100	0		5:53 PM	2330	480	250	0	0	1600
5:23 PM	1580	480	0	0	1100	0		5:54 PM	2330	480	250	0	0	1600
5:24 PM	1580	480	0	0	1100	0		5:55 PM	5330	480	250	3000	0	1600
5:25 PM	1580	480	0	0	1100	0		5:56 PM	5330	480	250	3000	0	1600
5:26 PM	4580	480	0	3000	1100	0		5:57 PM	5330	480	250	3000	0	1600
5:27 PM	4830	480	250	3000	1100	0		5:58 PM	3730	480	250	3000	0	0
5:28 PM	4830	480	250	3000	1100	0		5:59 PM	3730	480	250	3000	0	0
5:29 PM	4830	480	250	3000	1100	0		6:00 PM	3730	480	250	3000	0	0
5:30 PM	3730	480	250	3000	0	0								

NILM sys_bootloader v1.01:

Loading dataset ... done!
Creating PMFs ... done!
Quantizing Load States … done!

(a) Lights, $m = 1$

n	0	...	480	...	15000
count(n)	6	0	55	0	0
$p_{Y_m}(n)$	0.10	0.00	0.90	0.00	0.00
$\mathbf{y}_{\mathrm{peak}}^{(m)}$	0	480			
$k^{(m)}$	0	1			
$p(k^{(m)})$	0.10	0.90			

(b) Ent/TV, $m = 2$

n	0	...	250	...	15000
count(n)	27	0	34	0	0
$p_{Y_m}(n)$	0.44	0.00	0.56	0.00	0.00
$\mathbf{y}_{\mathrm{peak}}^{(m)}$	0	250			
$k^{(m)}$	0	1			
$p(k^{(m)})$	0.44	0.56			

(c) Heating, $m = 3$

n	0	...	3000	...	15000
count(n)	36	0	25	0	0
$p_{Y_m}(n)$	0.59	0.00	0.41	0.00	0.00
$\mathbf{y}_{\mathrm{peak}}^{(m)}$	0	3000			
$k^{(m)}$	0	1			
$p(k^{(m)})$	0.59	0.41			

(d) Microwave, $m = 4$

n	0	...	1100	...	15000
count(n)	51	0	10	0	0
$p_{Y_m}(n)$	0.84	0.00	0.16	0.00	0.00
$\mathbf{y}_{\mathrm{peak}}^{(m)}$	0	1100			
$k^{(m)}$	0	1			
$p(k^{(m)})$	0.84	0.16			

(e) Kettle, $m = 5$

n	0	...	1600	...	15000
count(n)	51	0	10	0	0
$p_{Y_m}(n)$	0.84	0.00	0.16	0.00	0.00
$\mathbf{y}_{\mathrm{peak}}^{(m)}$	0	1600			
$k^{(m)}$	0	1			
$p(k^{(m)})$	0.84	0.16			

NILM sys_bootloader v1.01:

Loading dataset ... done!
Creating PMFs ... done!
Quantizing Load States … done!
Building super-state HMM … done!

Super-State HMM

$\mathbf{P}_0$ = [0, 0, 0, 0, 0.098, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0.115, 0.082, 0.098, 0, 0.033, 0, 0.016, 0, 0.262, 0.033, 0, 0, 0.164, 0.049, 0.049, 0]

A = {
val = [0.857, 0.714, 0.2, 0.5, 0.143, 0.8, 0.143, 0.833, 0.5, 0.143, 0.167, 0.938, 0.111, 0.063, 0.5, 0.889, 0.333, 0.333, 0.5, 0.667, 0.667, 1],
row_idx = [4, 16, 17, 20, 16, 17, 16, 18, 20, 4, 18, 24, 28, 24, 25, 28, 29, 30, 25, 29, 30, 22],
col_ptr = [0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 4, 6, 8, 8, 10, 10, 11, 11, 13, 15, 15, 15, 18, 20, 22, 22]
}
Note: *a full matrix would be 97.85% sparse*

B = {
val = [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
row_idx = [0, 8, 16, 24, 2, 10, 18, 1, 26, 9, 17, 25, 3, 11, 4, 19, 12, 27, 20, 28, 6, 14, 22, 5, 30, 13, 21, 29, 7, 15, 23, 31],
col_ptr = [0_{1}, 1_{250}, 2_{230}, 3_{250}, 4_{370}, 5_{250}, 6_{230}, 7_{20}, 8_{230}, 9_{20}, 10_{230}, 11_{250}, 12_{370}, 13_{250}, 14_{50}, 15_{180}, 16_{70}, 17_{180}, 18_{50}, 19_{250}, 20_{370}, 21_{250}, 22_{230}, 23_{20}, 24_{230}, 25_{20}, 26_{230}, 27_{250}, 28_{370}, 29_{250}, 30_{230}, 31_{250}, 32_{8571}]
}
Note: *a full matrix would be 99.99% sparse*

NILM sys_bootloader v1.01:

Loading dataset ... done!
Creating PMFs ... done!
Quantizing Load States … done!
Building super-state HMM … done!

Ready to disaggregate!

Appliance State Inference

Algorithm 3 SPARSE-VITERBI$(K, \mathbf{P}_0, \mathbf{A}, \mathbf{B}, y_{t-1}, y_t)$

1: $\mathbf{P}_{t-1}[k], \mathbf{P}_t[k] \leftarrow 0.0, k = 1, 2, ..., K$
2: **for** $(j, p_b) \in$ COLUMN-VECTOR$(\mathbf{B}, y_{t-1})$ **do**
3: $\quad \mathbf{P}_{t-1}[j] \leftarrow \mathbf{P}_0[j] \cdot p_b$
4: **end for**
5: **for** $(j, p_b) \in$ COLUMN-VECTOR$(\mathbf{B}, y_t)$ **do**
6: $\quad (i, p_a)[] \leftarrow$ COLUMN-VECTOR$(\mathbf{A}, j)$
7: $\quad \mathbf{P}_t[j] \leftarrow \max_{(i,p_a)}(\mathbf{P}_{t-1}[i] \cdot p_a \cdot p_b)$
8: **end for**
9: **return** $\arg\max(\mathbf{P}_t)$

$$y_{t-1} = 3730$$
$$y_t = 730$$

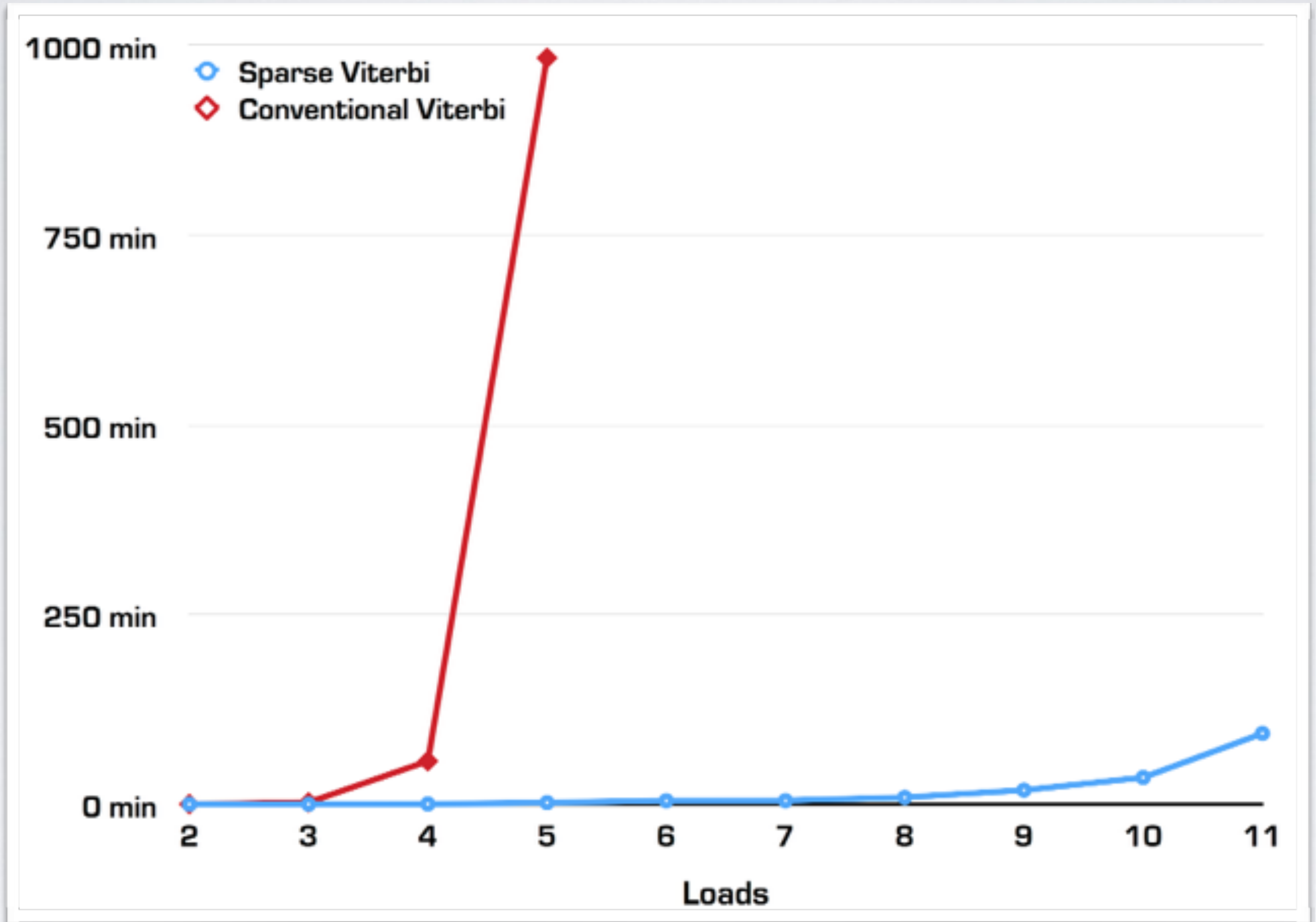
Line 1: previous time probability vector $\mathbf{P}_{t-1}$ of length K initialized to 0.0
Line 1: current time probability vector $\mathbf{P}_t$ of length K initialized to 0.0
Line 2: call to COLUMN-VECTOR$(\mathbf{B}, 3730)$ returns $[(28, 1.0)]$
Line 3: $\mathbf{P}_{t-1}[28] = \mathbf{P}_0[28] \cdot 1.0 = 0.164 \cdot 1.0 = 0.164$
Line 3: $\mathbf{P}_{t-1} = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0.164, 0, 0, 0]$
Line 5: call to COLUMN-VECTOR$(\mathbf{B}, 730)$ returns $[(24, 1.0)]$
Line 6: call to COLUMN-VECTOR$(\mathbf{A}, 24)$ returns $[(28, 0.111)]$
Line 7: $\mathbf{P}_t[24] = \max([0, 0.018]) = 0.018$
Line 7: $\mathbf{P}_t = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0.018, 0, 0, 0, 0, 0, 0, 0]$
Line 9: $k_t = \arg\max(\mathbf{P}_t) = 24$, which is the super-state or the state the studio suite is in
Line 9: $\widehat{S}_t =$ KTH-CARTESIAN$(24) = [1, 1, 0, 0, 0]$, determine the appliance states
Line 9: $k_t \equiv [1, 1, 0, 0, 0]$, meaning that only the appliances: lights and TV are ON

Estimating Consumption

$$
\begin{aligned}
\hat{y}_t &= \sum_m \mathbf{y}_{peak}^{(m)}[k_t^{(m)}] \\
&= \mathbf{y}_{peak}^{(m)}[1] + \mathbf{y}_{peak}^{(m)}[1] + \mathbf{y}_{peak}^{(m)}[0] + \mathbf{y}_{peak}^{(m)}[0] + \mathbf{y}_{peak}^{(m)}[0] \\
&= 480 + 250 + 0 + 0 + 0 \\
&= 730
\end{aligned}
$$

- Total consumption estimate is **730W**
  - the lights are consuming **480W**
  - the TV is consuming **250W**
  - all other loads are OFF with **0W** consumption

Runtime Test



time taken to disaggregate all 524,544 readings from 2 to 11 appliances (AMPds data)

Accuracy Measures

1. Finite-State f-score (FS f-score):

$$\mathrm{itp} = \frac{|\hat{x}_t^{(m)} - x_t^{(m)}|}{K^{(m)}}, \qquad \mathrm{atp} = 1 - \mathrm{itp}\,.$$

$$\mathrm{precision} = \frac{\mathrm{atp}}{\mathrm{atp} + \mathrm{itp} + \mathrm{fp}}, \quad \mathrm{recall} = \frac{\mathrm{atp}}{\mathrm{atp} + \mathrm{itp} + \mathrm{fn}}, \quad F_1 = 2 \cdot \frac{\mathrm{precision} \cdot \mathrm{recall}}{\mathrm{precision} + \mathrm{recall}},$$

2. Estimation Accuracy (Kolter & Johnson, 2011):

$$\mathrm{Est.Acc.} = 1 - \frac{\sum_{t=1}^{T} \sum_{m=1}^{M} |\hat{y}_t^{(m)} - y_t^{(m)}|}{2 \cdot \sum_{t=1}^{T} y_t}$$

Accuracy Results

Load	FS f-score	Estimation	ON	Events
Basement	53.6 / 40.2	99.0 / 69.3	23.0	6404
Dryer	99.7 / 99.6	90.8 / 92.2	100.0	1826
Washer	21.5 / 3.2	60.2 / 57.4	2.6	9961
Dishwasher	60.8 / 14.3	86.3 / 85.9	2.7	4394
Fridge	76.2 / 49.2	99.4 / 99.2	45.1	43500
HVAC/Fan	97.9 / 96.2	99.7 / 98.8	100.0	2531
Garage	99.9 / 99.9	99.8 / 99.9	100.0	228
Heat Pump	98.1 / 97.0	99.1 / 88.8	100.0	8291
Home Office	95.8 / 96.0	88.1 / 82.1	100.0	11044
Ent/TV	88.9 / 85.0	98.6 / 91.5	100.0	13314
Wall Oven	99.8 / 99.6	84.0 / 85.0	100.0	396
Overall	94.5 / 91.4	97.4 / 96.8	100.0	101889

$$\text{noise} = y_t - \sum_{m=1}^{M} y_t^{(m)},$$

40.9%

denoised test

noised test

state switches

Contact

Stephen Makonin, PhD Candidate, ISP, smIEEE

PhD Candidate, Computing Science, SFU

Researcher Associate, Applied Research, BCIT

email: stephen@makonin.com

website: http://makonin.com/

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