Active Collaborative Sensing for Energy Breakdown

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Worldwide Energy Consumption: Buildings

- The buildings sector, which includes residential and commercial structures, accounts for almost **21%** of the world's delivered energy consumption in 2015. (International Energy Outlook 2017)
- About **20%** of the energy could be avoided with efficiency improvements[1].

Worldwide Energy Consumption: Buildings

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Constructing efficient buildings

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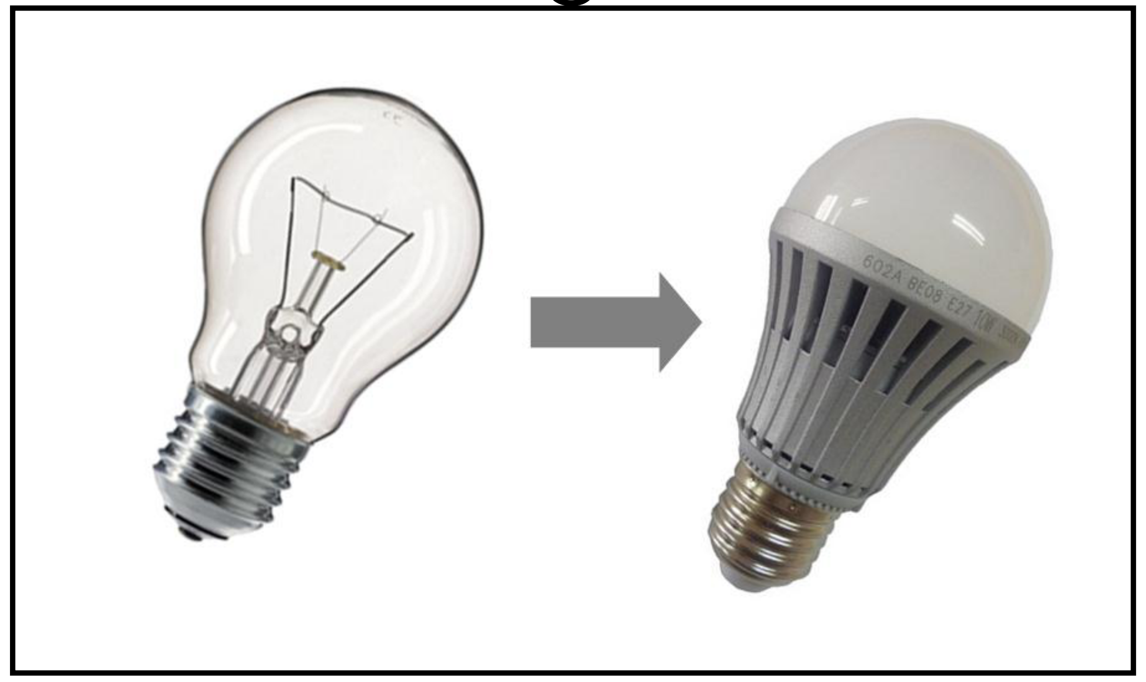
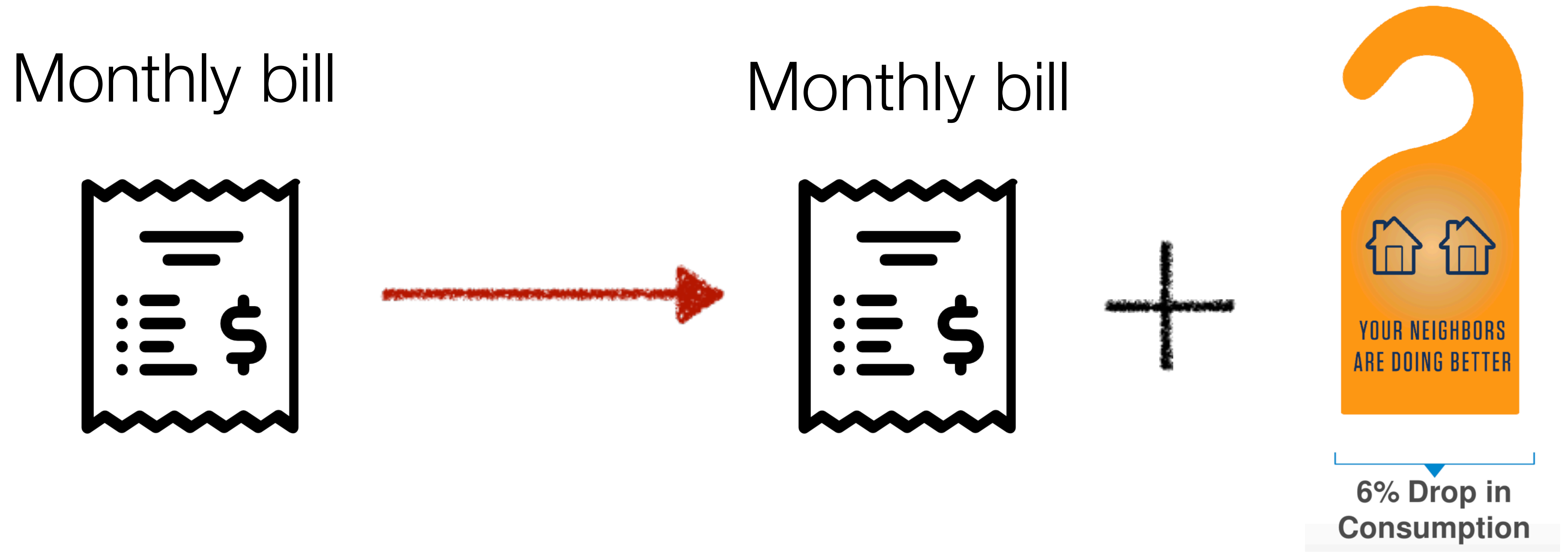


High Cost
The return is unclear before installation.

Improve Building Energy Efficiency

- Behavioral and operational efficiency.
  - Provide the more detailed energy feedback to customers.



Improve Building Energy Efficiency

- Behavioral and operational efficiency.
  - Provide the more detailed energy feedback to customers.
    - **Energy Breakdown: provide per-appliance energy readings.**

Save up to 15% energy[2]

Total energy consumption
e.g., monthly bills

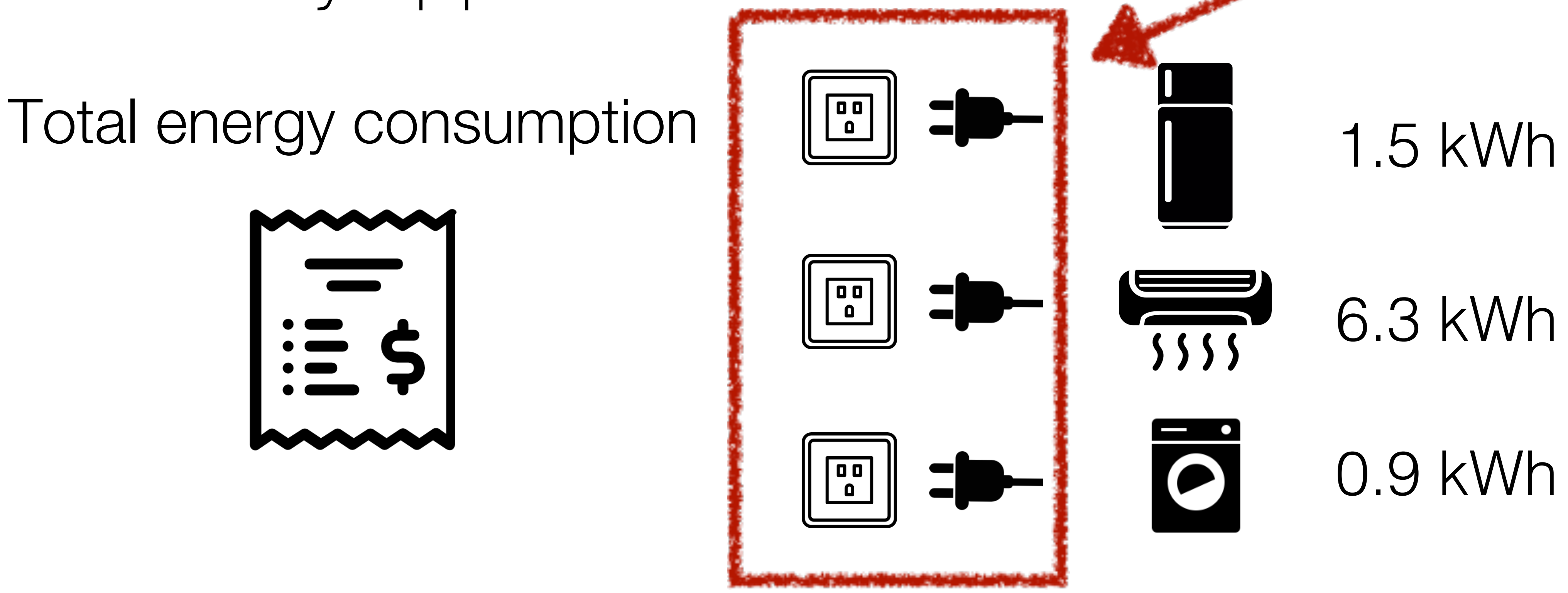
Total energy consumption

Appliance energy consumption

Related Work

- Direct Sensing System[3, 4]
  - Instrument every appliance in each home.

Plug load monitor

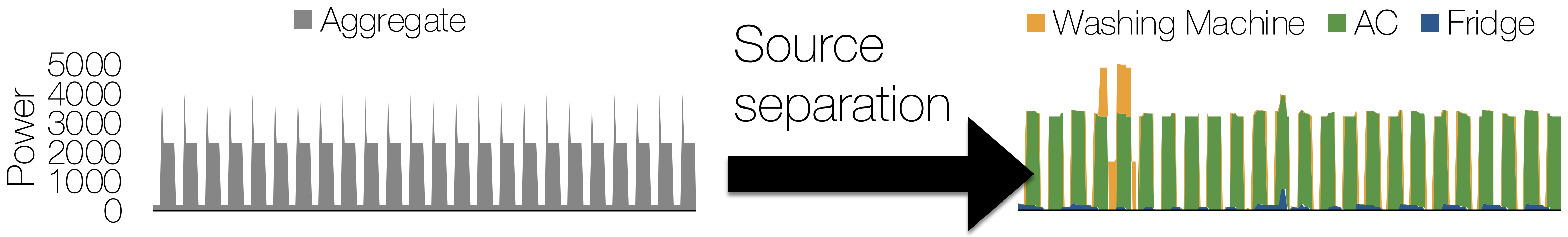


Expensive
Resource consuming
Poor Scalability

Related Work

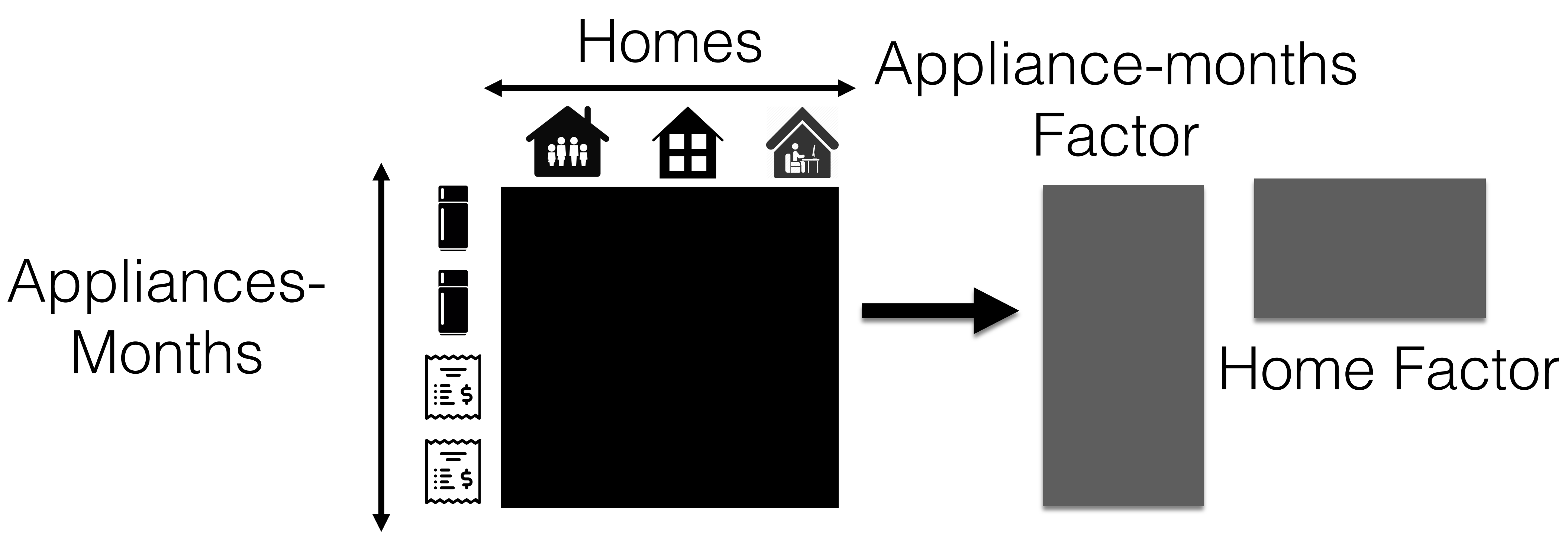
- Non-Intrusive Load Monitoring (NILM)
  - One smart sensor for each home.
  - Algorithms: Steady/transit state analysis[5], FHMM[6, 7], Neural Network[8, 9]

Expensive
Resource consuming
Poor Scalability

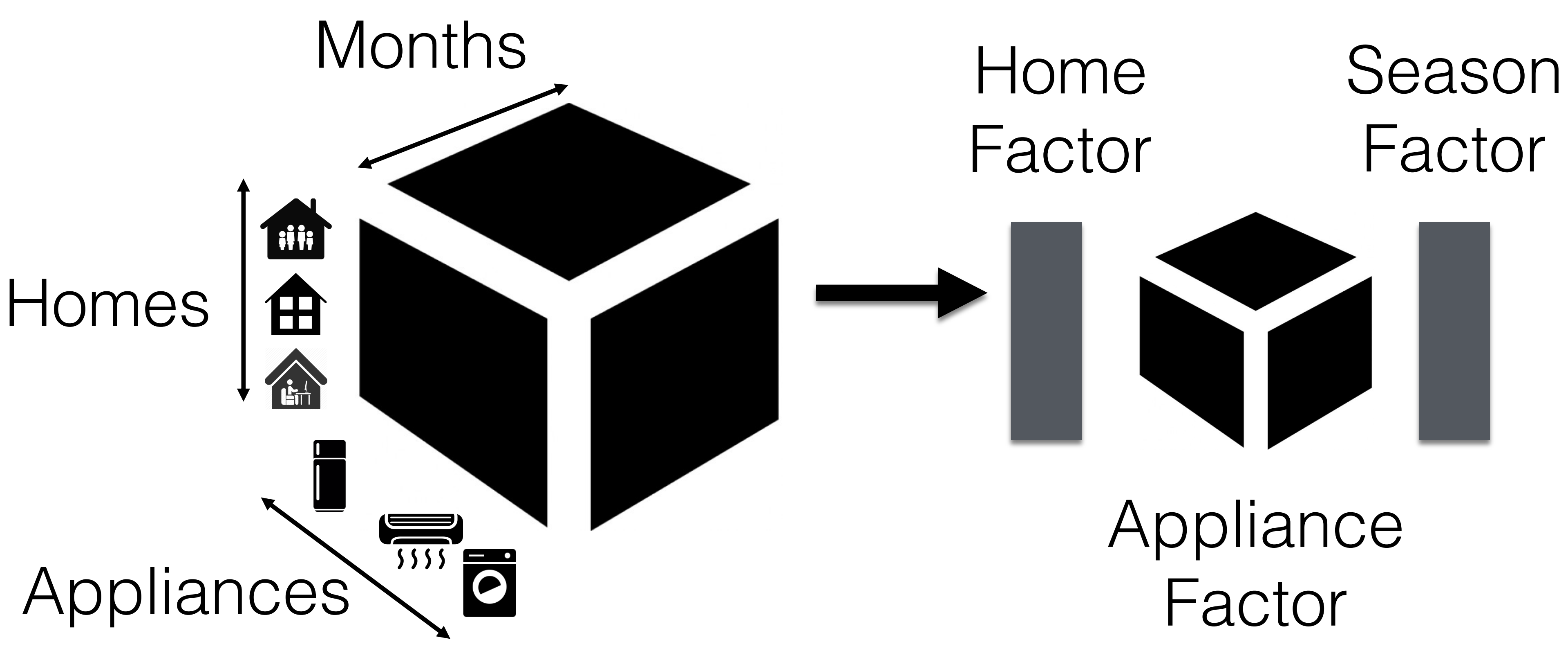


Related Work

- Collaborative Sensing[10, 11, 12]
  - No additional hardware installation in test homes.
  - Intuition:
    - Common design and construction patterns for homes create a repeating structure in energy data.



Scalable Energy Breakdown[10]



Scalable Energy Breakdown Across Regions[11]

Related Work

- Collaborative Sensing[10, 11, 12]
  - No additional hardware installation in test homes.
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				. . .				
Jan	20$	30$	10$		22$			
…	…	…	…		…			
Dec	25$	35$	15$		25$			
Jan	180$	—	250$		310$	200$	250$	210$
…	…	…	…		…	…	…	…
Dec	350$	380$	280$		480$	250$	—	350$

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Latent factor for months

	K1	K2
Jan	10	20
…	…	…
Dec	30	40
Jan	130	12020
…	…	…
Dec	120	110

… …

Latent factor for homes

		…	
K1	1	…	2
K2	2	…	3

Related Work

Limitation of Collaborative sensing

- Assume the existence of relevant training data, i.e., appliance-level energy readings from some fully instrumented homes.

Few buildings in the world have instrumented with sub-meters.

High cost of sub-meters instrumentation.

				. . .				
	?	30$			?			
	90$		?		?			
	10$	?	18$		20$			
		3	2		2		3	2

Related Work

Limitation of Collaborative sensing

- Assume the existence of relevant training data, i.e., appliance-level energy readings from some fully instrumented homes.

Few buildings in the world have instrumented with sub-meters.

High cost of sub-meters instrumentation.

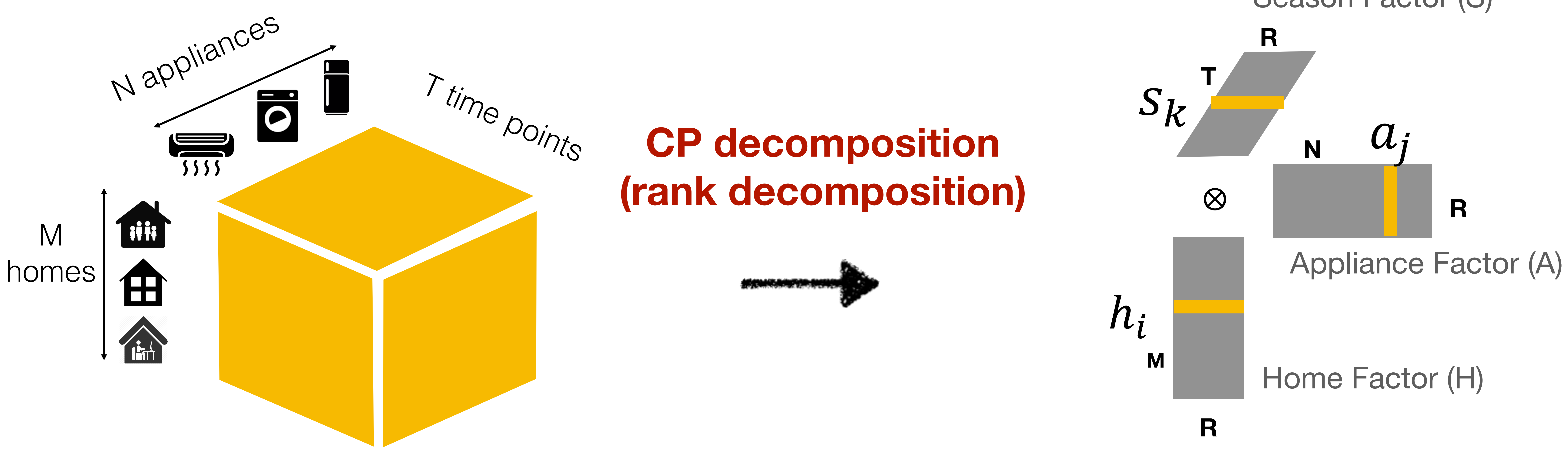
Can we minimize the deployment cost by selectively deploying sensors to a subset of homes and appliances while maximizing the reconstruction accuracy of sub-metered readings in non-instrumented homes?

Active sensor deployment for energy breakdown

Problem Statement

Active Sensor Deployment for Energy Breakdown

- Define the energy readings as a three-way tensor.



Active Tensor Completion

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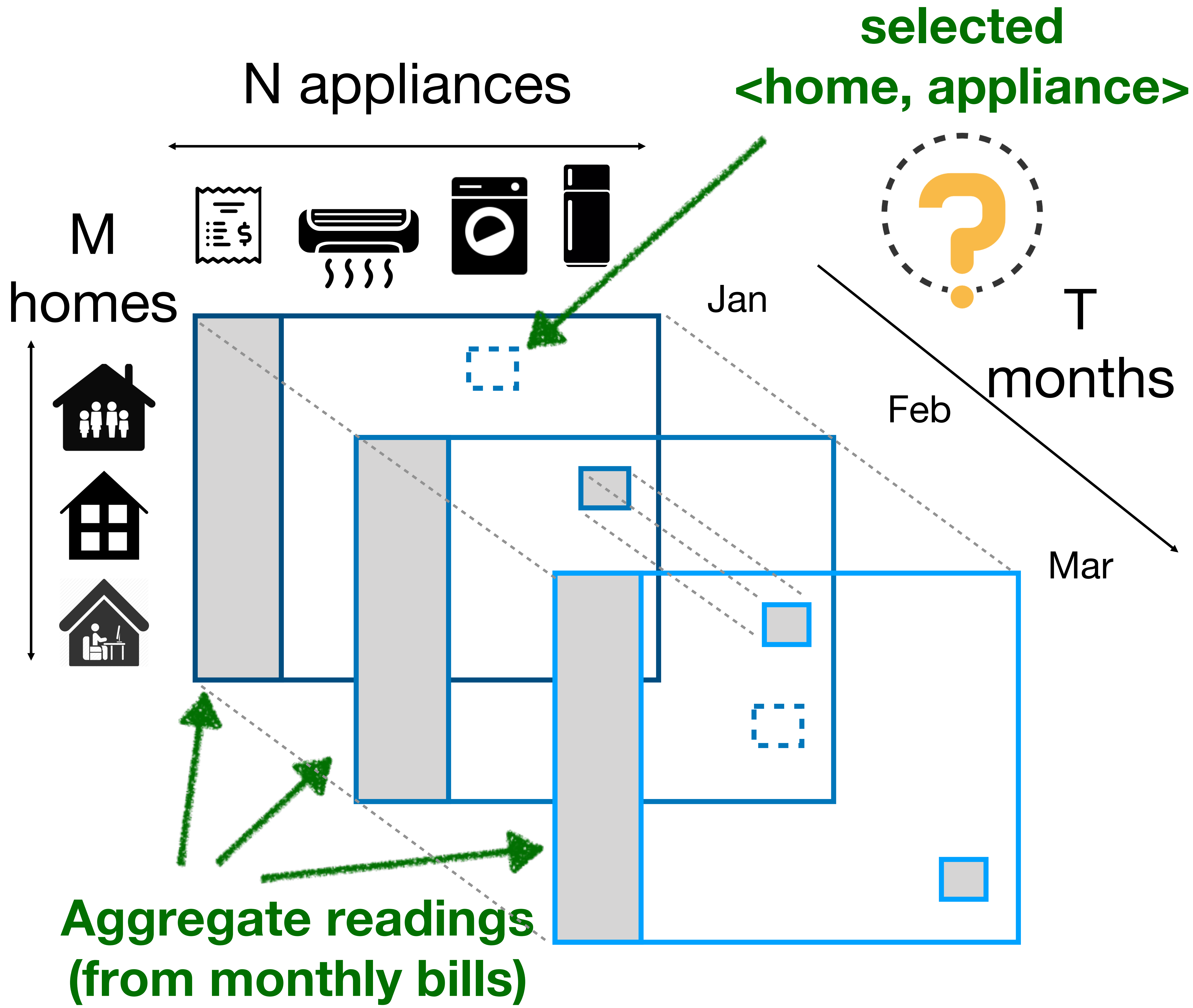
Special Properties of Energy Breakdown

- **Time-series data**
  - Energy data will be updated in every sampling cycle.
- **Combinatorial decision**
  - Select the <home, appliance> pairs.
- **Sensor Installation**
  - Once the sensor is installed, the readings will always be available thereafter.
  - Dilemma: balance the choice of instrumentation that focuses on the current reconstruction accuracy, and the accuracy for future predictions.



Active Selection

Uncertainty based active selection.

Select the one will reduce the reconstruction uncertainty the most rapidly.

Where does the uncertainty come from?

The observed energy readings are noisy.

- Hardware.
- Energy consumption in wire transition.
- Sub-meter readings.

For home i, appliance j, and month k

$$e_{ijk}^{obs} = e_{ijk}^{*} + \text{noise}$$

ground truth decomposition

$$e_{ijk}^{*} = < h_i^*, a_j^*, s_k^* >$$

True energy reading

approximate decomposition

$$e_{ijk}^{obs} \approx < \hat{h}_i, \hat{a}_j, \hat{s}_k >$$

? Uncertainty in parameter estimation

$$||h_i^* - \hat{h}_i|| \neq 0$$

$$||a_j^* - \hat{a}_j|| \neq 0$$

$$||s_k^* - \hat{s}_k|| \neq 0$$

?

Uncertainty in energy estimation

$$e_{ijk}^{*} = < h_i^*, a_j^*, s_k^* >$$

$$\hat{e}_{ijk} = < \hat{h}_i, \hat{a}_j, \hat{s}_k >$$

$$\boxed{||e_{ijk}^{*} - \hat{e}_{ijk}|| \neq 0}$$

Uncertainty Quantification

How to quantify the uncertainty in parameter estimation ?

Latent factor: h, a, s

$$e_{ijk}^{obs} = e_{ijk}^{*} + \eta_{ijk} \quad \eta_{ijk} \sim N(0, \delta^2)$$

noise

- In the tensor factorization, the objective function is:

$$L = \frac{1}{2}\sum_{k=1}^{t}\sum_{i,j}(e_{ijk}^{obs} - < h_i, a_j, s_k >)^2 + \frac{\lambda_1}{2}\sum_{i=1}^{M} h_i^T h_i + \frac{\lambda_2}{2}\sum_{j=1}^{N} a_j^T a_j + \frac{\lambda_3}{2}\sum_{k=1}^{t} s_k^T s_k$$

- Parameter Estimation: Alternating Least Square (ALS)

Home factor

$$h_i = A_{i,t}^{-1} b_{i,t} \quad A_{i,t} = \sum_{n=1}^{N}\sum_{l=1}^{t}(a_{n,t} \circ s_{l,t})(a_{n,t} \circ s_{l,t})^T + \lambda_1 I \quad b_{i,t} = \sum_{n=1}^{N}\sum_{l=1}^{t} e_{inl}(a_{n,t} \circ s_{l,t})$$

Uncertainty Quantification

How to quantify the uncertainty in parameter estimation?

It can be proved that, with probability at least $1-\delta$ **(Lemma 1 in paper)**

$$||\hat{\mathbf{h}}_i^t - \mathbf{h}_i^*||_{\mathbf{A}_i^t} \leq \sqrt{r\ln\frac{\lambda_1 r + |\Omega_t|Q^2R^2}{\lambda_1 \cdot r \cdot \delta}} + \sqrt{\lambda_1}P + \frac{2PQ^2R^2}{\sqrt{\lambda_1}}(G_2 + G_3)$$

$$G_1 = \frac{f_1(1-f_1^{|\Omega_t|})}{1-f_1} \qquad f_1 = q_1 + \epsilon_1$$

Uncertainty Quantification

How to quantify the uncertainty in parameter estimation?

It can be proved that, with probability at least $1-\delta$ **(Lemma 1 in paper)**

$$||\hat{\mathbf{h}}_i^t - \mathbf{h}_i^*||_{\mathbf{A}_i^t} \le \alpha_{h_i}^t \qquad ||\hat{\mathbf{a}}_j^t - \mathbf{a}_j^*||_{\mathbf{C}_j^t} \le \alpha_{a_j}^t \qquad ||\hat{\mathbf{s}}_k^t - \mathbf{s}_k^*||_{\mathbf{E}_k^t} \le \alpha_{s_k}^t$$

How the uncertainty in parameter estimation contributes to the uncertainty in energy estimation?

Uncertainty of home factor, and appliance factor estimation.

$$|\hat{\mathbf{e}}_{ijk} - \mathbf{e}_{ijk}^*| \le \alpha_{h_i}^t ||\hat{\mathbf{a}}_j^t \circ \hat{\mathbf{s}}_k^t||_{(\mathbf{A}_i^t)^{-1}} + \alpha_{a_j}^t ||\hat{\mathbf{h}}_i^t \circ \hat{\mathbf{s}}_k^t||_{(\mathbf{C}_j^t)^{-1}} + const$$

Upper bound of parameter estimation error

Uncertainty Quantification

How to quantify the uncertainty in parameter estimation?

It can be proved that, with probability at least $1 - \delta$ **(Lemma 1 in paper)**

$$||\hat{\mathbf{h}}_i^t - \mathbf{h}_i^*||_{\mathbf{A}_i^t} \leq \alpha_{h_i}^t \qquad ||\hat{\mathbf{a}}_j^t - \mathbf{a}_j^*||_{\mathbf{C}_j^t} \leq \alpha_{a_j}^t \qquad ||\hat{\mathbf{s}}_k^t - \mathbf{s}_k^*||_{\mathbf{E}_k^t} \leq \alpha_{s_k}^t$$

How the uncertainty in parameter estimation contributes to the uncertainty in energy estimation?

$$|\hat{\mathbf{e}}_{ijk} - \mathbf{e}_{ijk}^*| \boxed{\leq \alpha_{h_i}^t ||\hat{\mathbf{a}}_j^t \circ \hat{\mathbf{s}}_k^t||_{(\mathbf{A}_i^t)^{-1}} + \alpha_{a_j}^t ||\hat{\mathbf{h}}_i^t \circ \hat{\mathbf{s}}_k^t||}_{(\mathbf{C}_j^t)^{-1}} + const$$

$$Uncertainty(home_i, appliance_j, month_k)$$

Leverage Time Information

- **Sensor Installation**
  - Dilemma: balance the choice of instrumentation that focuses on the current reconstruction accuracy, and the accuracy for future predictions.

Could we prepare for the future?

Integrate temporal information to retrospect the history and foresee the future

$$(x, y) = argmax_{x \in [M], y \in [N]} \sum_{k=t-p}^{t+p} \rho_{k,t} \cdot Uncertainty(i, j, k)$$

Weight function to control the contribution

Evaluation: Theoretical analysis

Prediction Error with data selected by our proposed method, ActSense, $E_A(t)$

Prediction Error with any other data, $E_O(t)$

It can be proved that,

$$UB(E_A(t)) \leq UB(E_O(t))$$

Upper bound of the error

Empirical Evaluation: Setup

Datasets

- Dataport: the largest public residential home energy dataset.
  - Austin, 2014 (53), 2015 (93), 2016 (73), 2017 (44).
  - Aggregate, HVAC, Fridge, Washing Machine, Dishwasher, Furnace, Microwave.

- Evaluation Metric
  - Root Mean Square Error (RMSE) for appliance a. $RMSE(a) = \sqrt{\frac{\sum_i \sum_k (e_{ijk}^{obs} - \hat{e}_{ijk})^2}{M \times T}}$
  - Mean RMSE for each model. $MeanRMSE = \frac{\sum_a RMSE(a)}{N}$

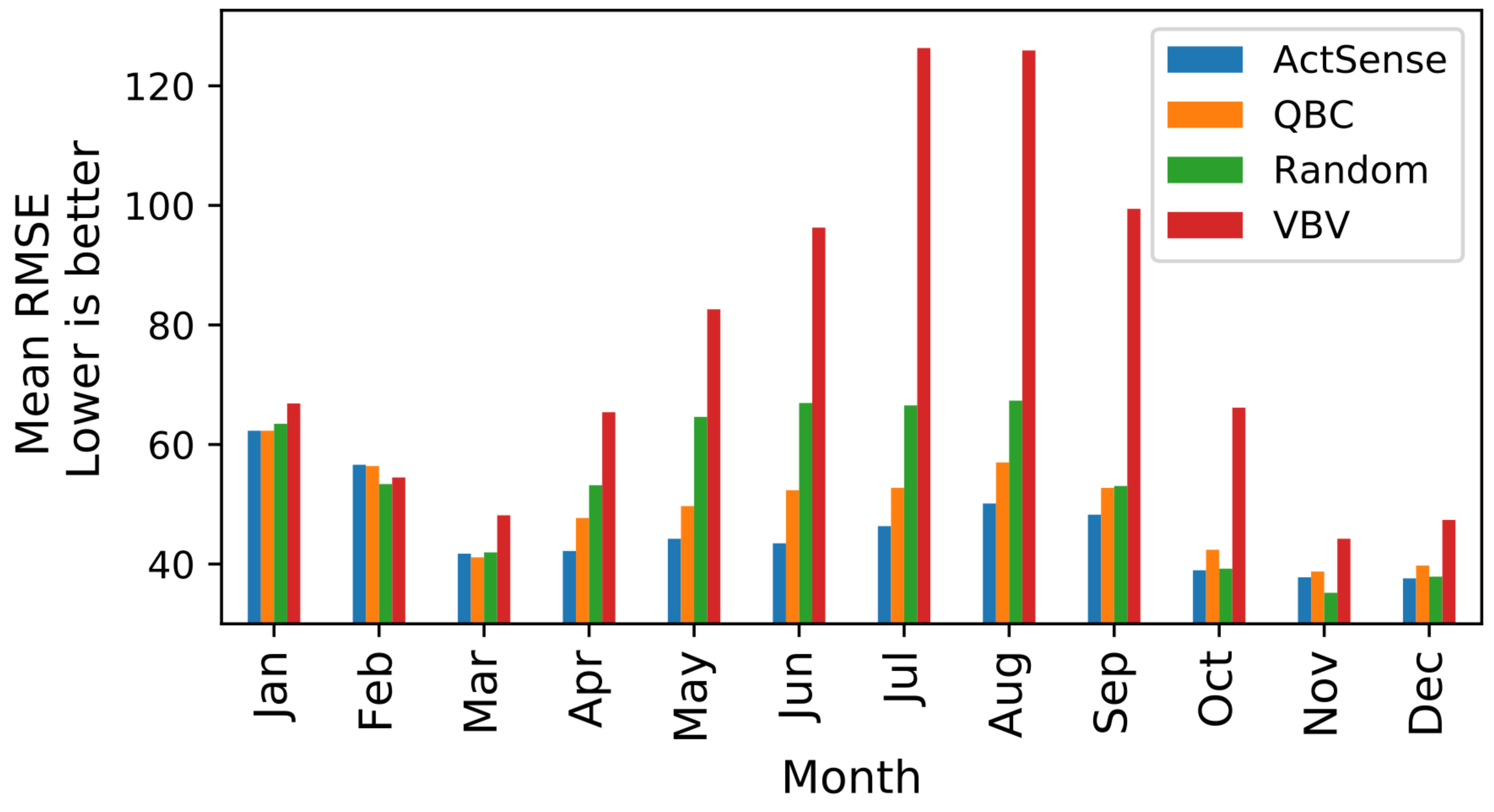
Empirical Evaluation: Baselines

- **Random Selection**
  - Perform CP decomposition with ALS
  - Select L <home, appliance> pairs **uniformly random from the candidates**.
- **Query By Committee (QBC)[13, 14]:**
  - Perform CP decomposition with ALS.
  - QBC quantifies the prediction uncertainty **based on the level of disagreement among a committee of trained models.**
  - We perform CP decomposition with different rank to form the committee. Uncertainty is computed by the variance across the estimate of the committee members.
- **Variational Bayesian - Variance (VBV)[15, 16]**
  - Perform CP decomposition with Variational Bayesian Inference.
  - Select the pairs **based on the variance of each estimation.**

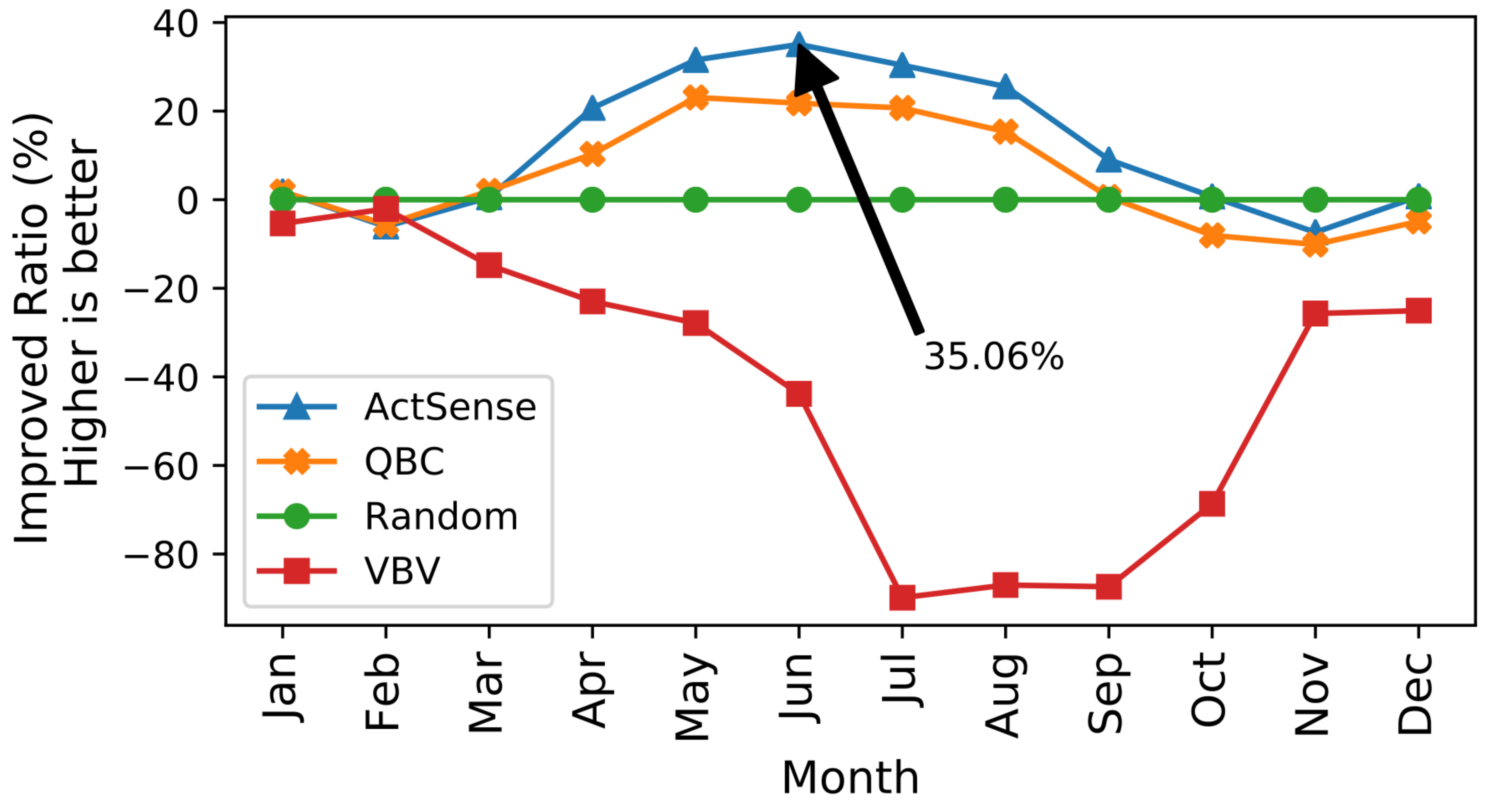
Empirical Evaluation

Quality of Energy Breakdown, Austin, 2015.

Select 5 pairs at each month.
At the end of the year, 10.75% <home, appliance> pairs are instrumented.



Mean RMSE performance across months



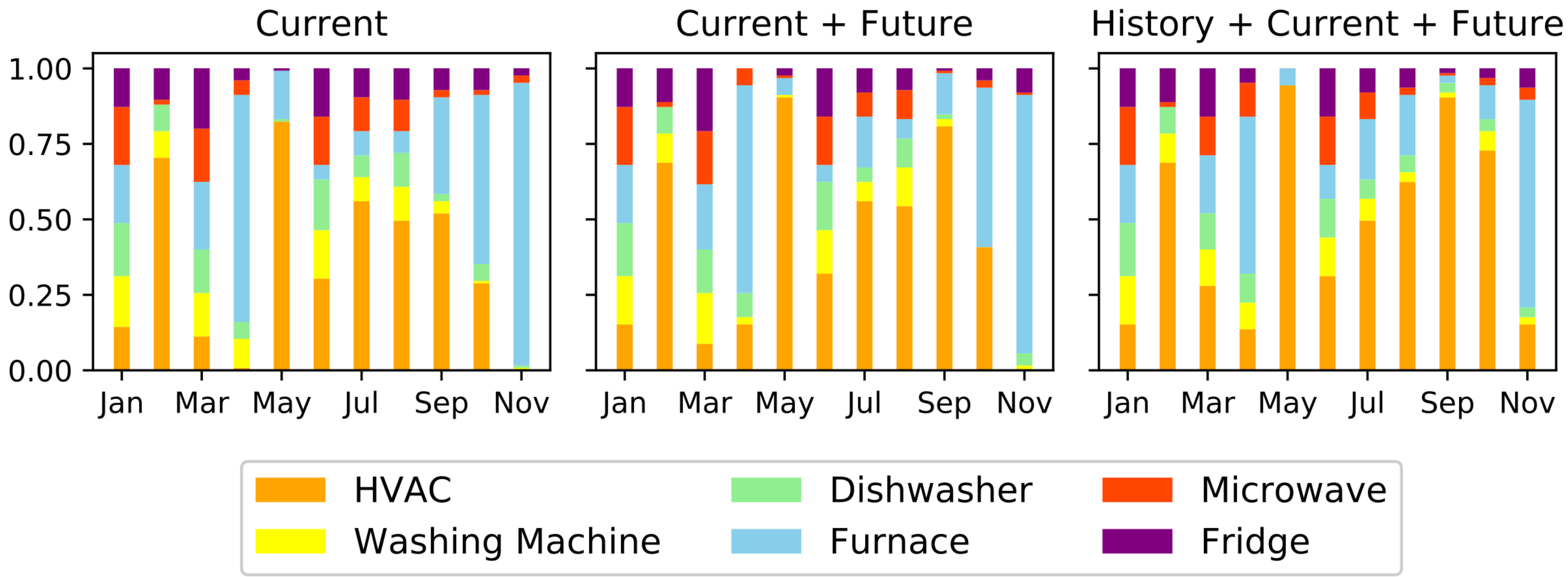
Relative Improvement compared with random method

Empirical Evaluation

Integrate temporal information

Table 2. Relative Improvement comparing to Random with different uncertainty estimation.

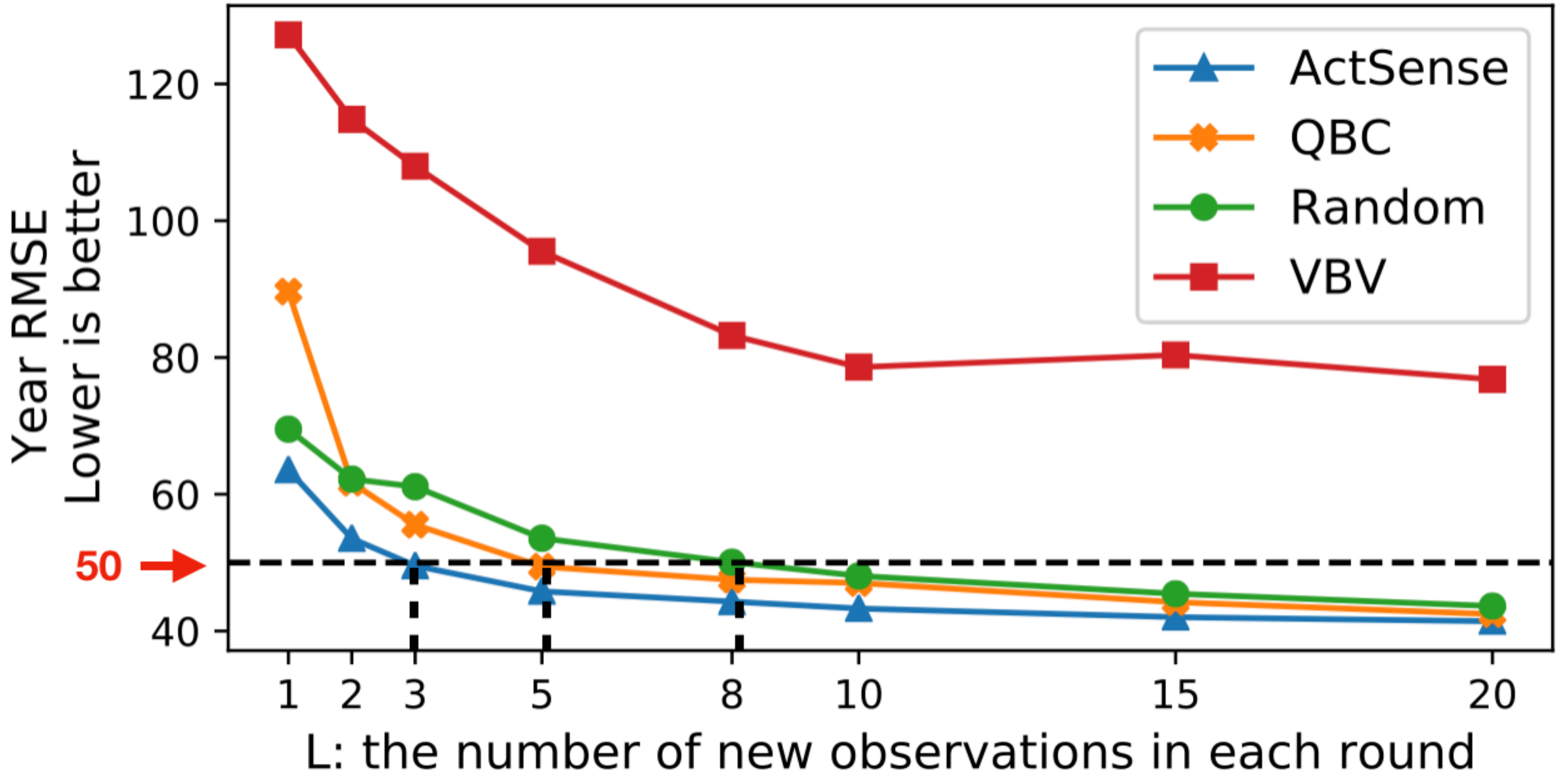
Uncertainty Estimation	Maximum	Mean
Current	34.38%	11.48%
Current + Future	34.89%	11.82%
History + Current + Future	35.06%	11.88%



Empirical Evaluation

Budget size, Austin, 2015.

$$\text{Year RMSE} = \frac{\sum_{t=1}^{12} Mean\ RMSE(t)}{12}$$



Summary

- Proposed an active collaborative sensing algorithm to actively deploy sensors for energy breakdown.
  - Utilize the uncertainty from the parameter estimation process to select the candidates.
  - Integrate the temporal information to retrospect the history and foresee the future.
- Provided rigorous theoretical analysis of the uncertainty reduction of the proposed algorithm.

- Future work
  - Active selection with budget constraint.
  - Active selection for transfer learning across regions.

Reference

[1] Gardner, G. T., & Stern, P. C. (2008). The short list: The most effective actions US households can take to curb climate change. *Environment: science and policy for sustainable development*, *50*(5), 12-25.
[2] Ehrhardt-Martinez, K., Donnelly, K. A., & Laitner, S. (2010, June). Advanced metering initiatives and residential feedback programs: a meta-review for household electricity-saving opportunities. Washington, DC: American Council for an Energy-Efficient Economy.
[3] Baechler, Michael C., and He Hao. *Business Case for Nonintrusive Load Monitoring*. No. PNNL-25425. Pacific Northwest National Lab.(PNNL), Richland, WA (United States), 2016.
[4] Laughman, Christopher, et al. "Power signature analysis." *IEEE power and energy magazine* 99.2 (2003): 56-63.
[5] Kolter, J. Zico, and Tommi Jaakkola. "Approximate inference in additive factorial hmms with application to energy disaggregation." *Artificial intelligence and statistics*. 2012.
[6] Lange, Henning, and Mario Bergés. "Efficient inference in dual-emission FHMM for energy disaggregation." *Workshops at the Thirtieth AAAI Conference on Artificial Intelligence*. 2016.
[7] Kelly, Jack, and William Knottenbelt. "Neural NILM: Deep neural networks applied to energy disaggregation." Proceedings of the 2nd ACM International Conference on Embedded Systems for Energy-Efficient Built Environments. ACM, 2015.
[8] Zhang, Chaoyun, et al. "Sequence-to-point learning with neural networks for non-intrusive load monitoring." *Thirty-Second AAAI Conference on Artificial Intelligence*. 2018.
[9] Batra, N., Wang, H., Singh, A., & Whitehouse, K. (2017, February). Matrix factorisation for scalable energy breakdown. In Proceedings of the... AAAI Conference on Artificial Intelligence.
[10] Batra, N., Jia, Y., Wang, H., & Whitehouse, K. (2018, April). Transferring Decomposed Tensors for Scalable Energy Breakdown Across Regions. In AAAI.

Reference

[11] Shubina, K., & Tsotsos, J. K. (2010). Visual search for an object in a 3D environment using a mobile robot. Computer Vision and Image Understanding, 114(5), 535-547.
[12] Chen, S. Y., & Li, Y. F. (2005). Vision sensor planning for 3-D model acquisition. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 35(5), 894-904.
[13] Li, Y. F., & Liu, Z. G. (2005). Information entropy-based viewpoint planning for 3-D object reconstruction. IEEE Transactions on Robotics, 21(3), 324-337.
[14] Banta, J. E., Wong, L. R., Dumont, C., & Abidi, M. A. (2000). A next-best-view system for autonomous 3-D object reconstruction. IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 30(5), 589-598.
[15] Beal, M. J. (2003). Variational algorithms for approximate Bayesian inference (p. 281). London: university of London.
[16] Silva, J., & Carin, L. (2012, August). Active learning for online bayesian matrix factorization. In Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 325-333). ACM.
[17] Sutherland, D. J., Póczos, B., & Schneider, J. (2013, August). Active learning and search on low-rank matrices. In Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 212-220). ACM.
[18] Chakraborty, S., Zhou, J., Balasubramanian, V., Panchanathan, S., Davidson, I., & Ye, J. (2013, December). Active matrix completion. In Data Mining (ICDM), 2013 IEEE 13th International Conference on (pp. 81-90). IEEE.
[19] Krishnamurthy, A., & Singh, A. (2013). Low-rank matrix and tensor completion via adaptive sampling. In Advances in Neural Information Processing Systems (pp. 836-844).

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Thanks!

Q & A

GitHub: https://github.com/yilingjia/ActSense