Active Collaborative Sensing for Energy Breakdown

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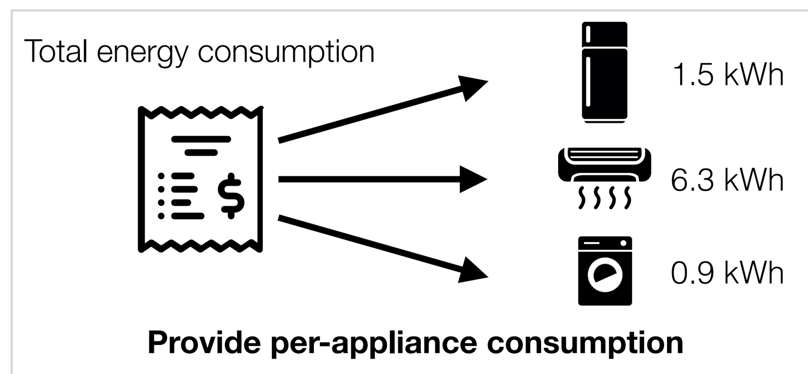
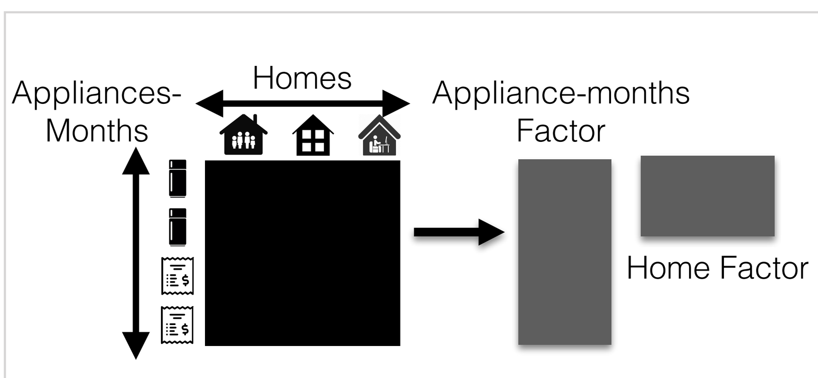
Motivation

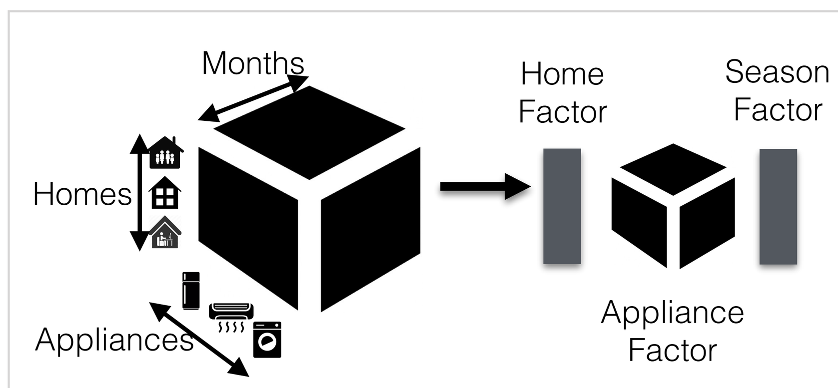
- **Energy breakdown**, i.e, providing per-appliance energy consumption, can increases residents' awareness and save up to 15% energy.



- **Collaborative Sensing**[1, 2]: reconstruct the sensor data of one building based on sensor data collected in other buildings.
  - common and repeated patterns of buildings.



Scalable Energy Breakdown[1]



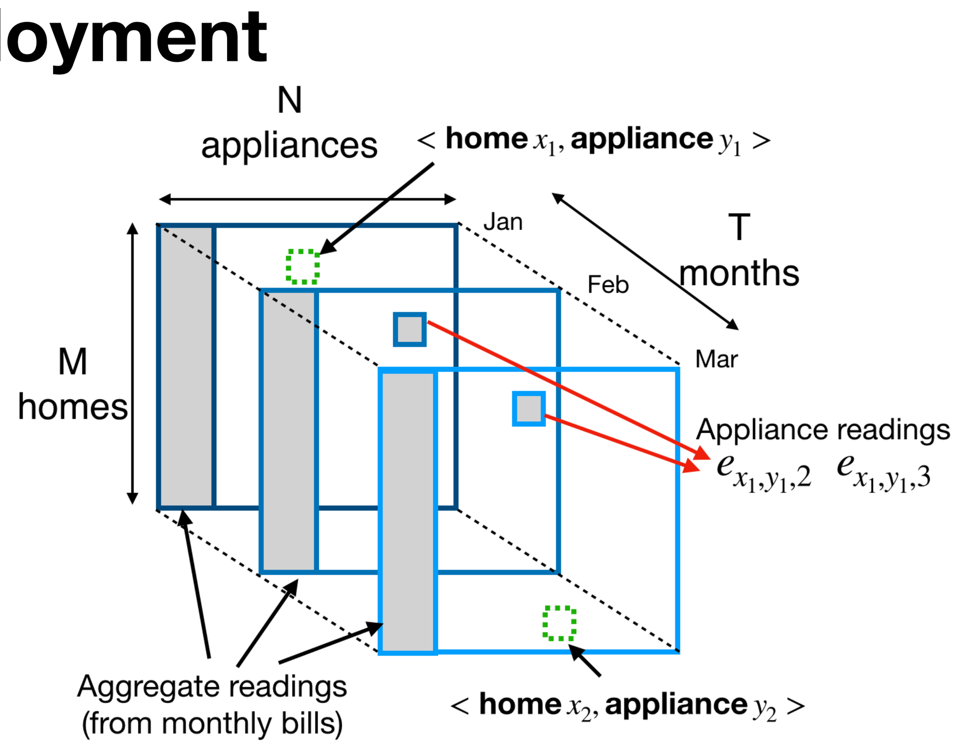
Scalable Energy Breakdown Across Regions[2]

- **Problem:** Very few homes in the world have been installed sub-meters; and the cost of retrofitting a home eats into the funds available for energy saving retrofits.

Active Sensing: strategically deploy sensing hardware to maximize the reconstruction accuracy while minimizing deployment cost.

Active Collaborative Sensing

- **Active Sensor Deployment**
  - Energy data is continuously generated and collected.
  - Once the sensor is installed, the readings are always available in the future.



- **Key Insights**

We model the energy readings as a three-way tensor and decompose the energy tensor with CP decomposition.

- Variance in energy use or error in sensor readings.

true energy reading

$$e^{obs} = e^* + noise$$

observed energy reading

- Uncertainty in parameter estimation.

$$e^{obs} \approx <\hat{h}, \hat{a}, \hat{s}>$$ estimated decomposition

$$e^* = <h^*, a^*, s^*>$$ true decomposition

- Uncertainty in data reconstruction.

$$\hat{e} = <\hat{h}, \hat{a}, \hat{s}> \neq e^* = <h^*, a^*, s^*>$$

Quantifying Uncertainty

- Uncertainty in data reconstruction comes from the uncertainty in parameter estimation.

Uncertainty of latent appliance factor estimation

$$\underbrace{|\hat{\mathbf{e}}_{ijk} - \mathbf{e}^*_{ijk}| \leq \boxed{\alpha^t_{h_i} || \hat{\mathbf{a}}^t_j \circ \hat{\mathbf{s}}^t_k ||_{(\mathbf{A}^t_i)^{-1}}} + \boxed{\alpha^t_{a_j} || \hat{\mathbf{h}}^t_i \circ \hat{\mathbf{s}}^t_k ||_{(\mathbf{C}^t_j)^{-1}}} + const}_{Uncertainty(i,j,t)}$$

Uncertainty of latent home factor estimation

- Combine uncertainties of historical and future months to select the <home, appliance> pairs.

$$(x, y) = \mathbf{argmax}_{x \in [M], y \in [N]} \sum_{l=t-p}^{t+p} \rho_l \cdot Uncertainty(i, j, l)$$

Weight function to control the contribution

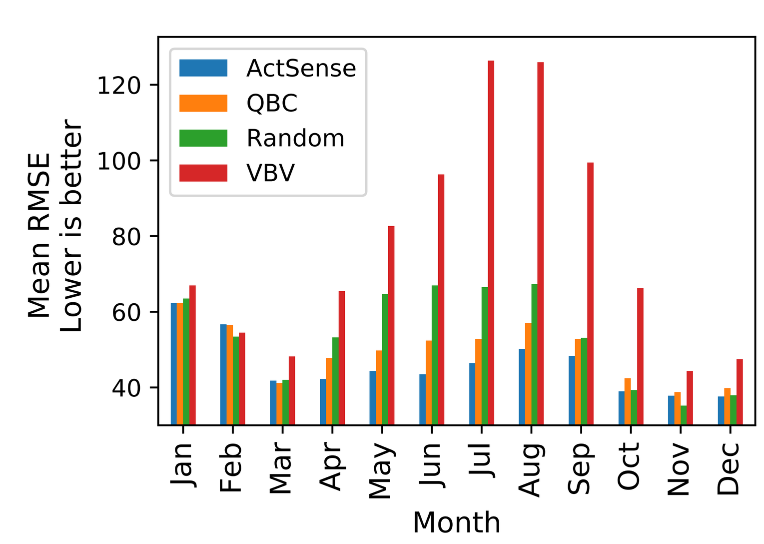
- **Analyzing Convergence**

With high probability, at each time t, the upper bound of the estimation error generated with **ActSense**, i.e., $UB(E_A(t))$, and the one generated with any other selection, i.e., $UB(E_O(t))$, satisfy: $UB(E_A(t)) \leq UB(E_O(t))$.

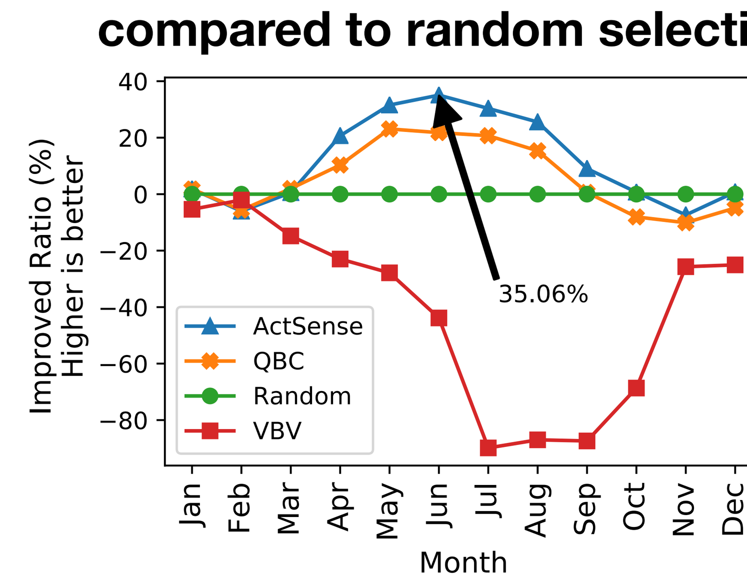
Empirical Evaluation

- We use the public **Dataport** dataset.
- Monthly energy data collected in Austin, U.S..

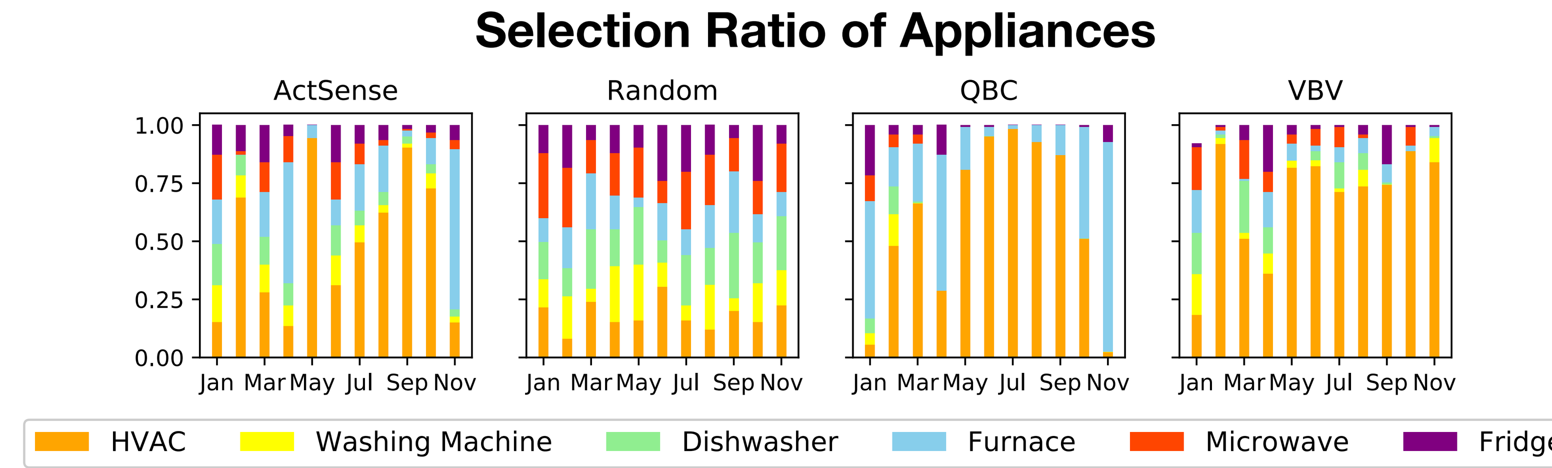
Mean RMSE performance



Relative improvement compared to random selection

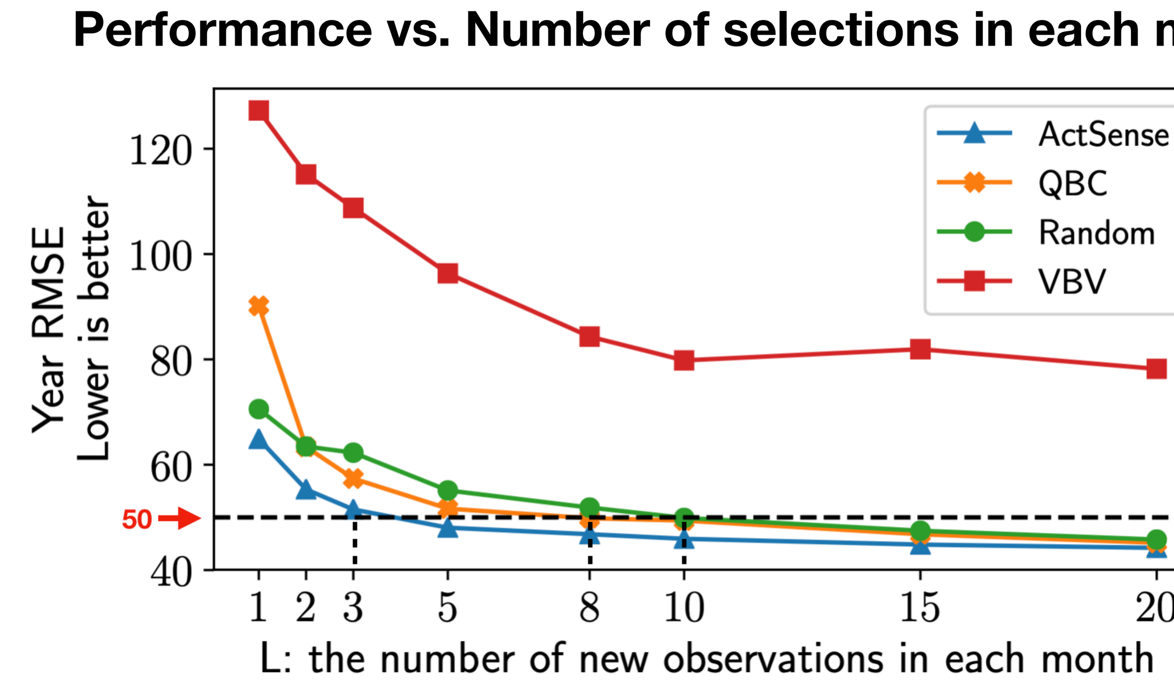


Selection Ratio of Appliances



- ActSense performs favorably compared to the baselines, and achieves the highest improvement.

Performance vs. Number of selections in each month.



- ActSense has the advantage in minimizing the cost of deployment for improving energy breakdown quality.

Reference

[1]Batra, N., Wang, H., Singh, A., & Whitehouse, K. Matrix factorisation for scalable energy breakdown AAAI 2017.
[2] Batra, N., Jia, Y., Wang, H., & Whitehouse, K. Transferring Decomposed Tensors for Scalable Energy Breakdown Across Regions. AAAI 2018.

Acknowledgements

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Reproducibility Our entire codebase, baselines, analysis and experiments can be found on Github, https://github.com/yilingjia/ActSense.