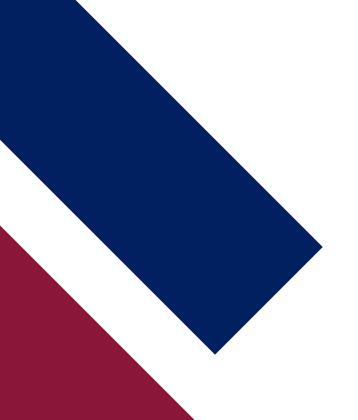
Few labels are all you need: A Weakly Supervised Framework for Appliance Localization in Smart-Meter Series





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May21st, 2025



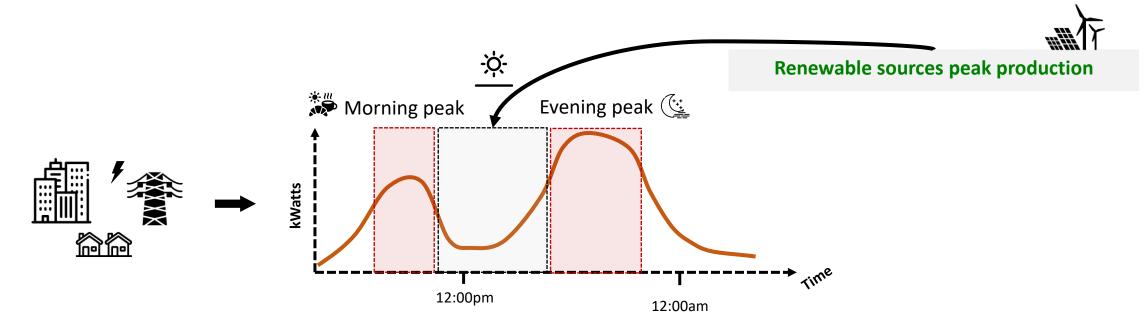




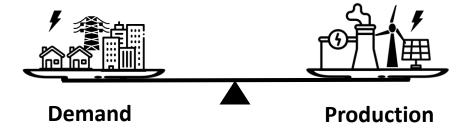


Context: From Renewable Surge to the Flexibility Challenge

Typical daily electricity grid domestic demand

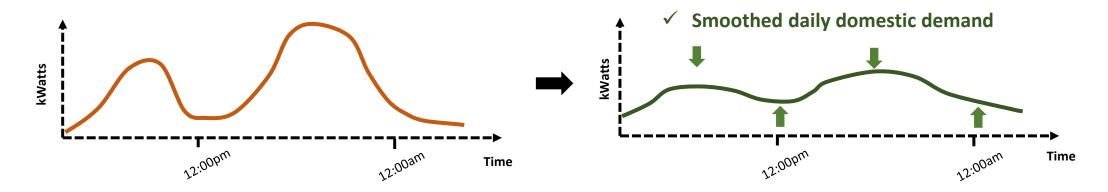


The Flexibility Challenge = real-time ability to match variable supply & demand



Context: The Flexibility Challenge

Reducing peak demand: shifting parts of the consumption to off-peak hours



Electricity suppliers (as EDF) need to play an active role in this process

How convince clients to change their consumption behaviors?

1. Personalized contracts





Lower off-peak pricing, for charging your Electric Vehicle at night

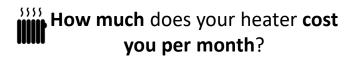
2. Dynamic pricing





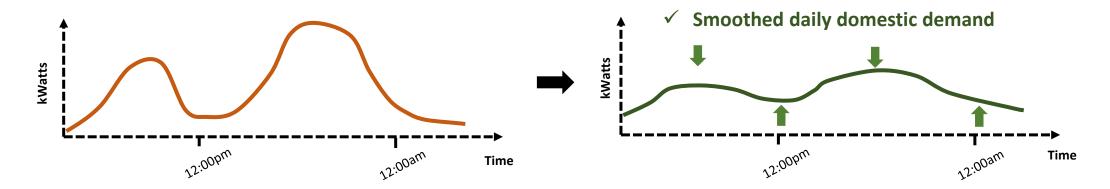
Criticial Peak Pricing Peak Time Rebeat

3. Appliance-level feedback



Context: The Flexibility Challenge

Reducing peak demand: shifting parts of the consumption to off-peak hours



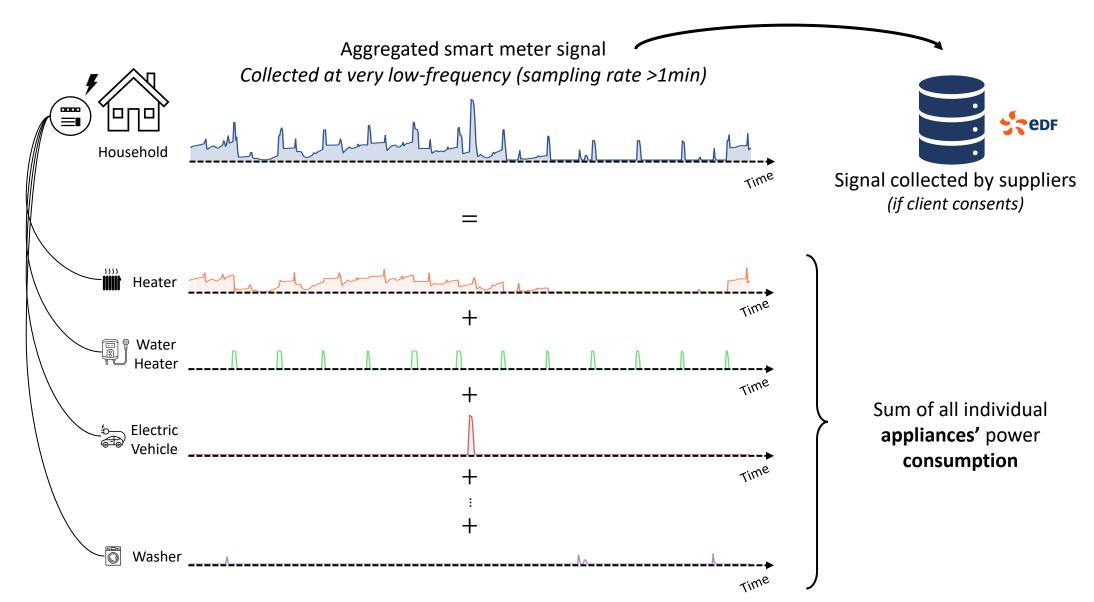
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How convince clients to change their consumption behaviors?



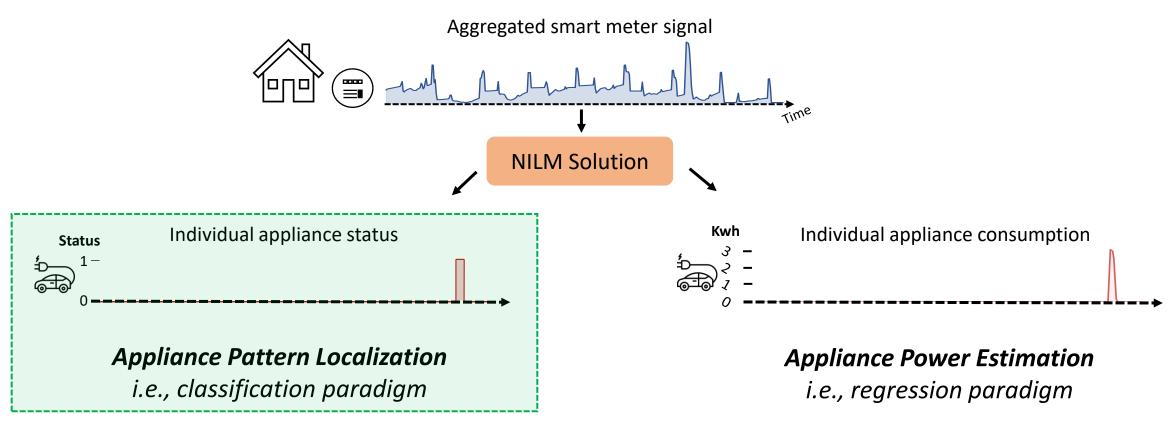
Context: Smart Meter Deployement

Millions of Smart Meters deployed in individual households



Background: Smart Meter Data Analytics

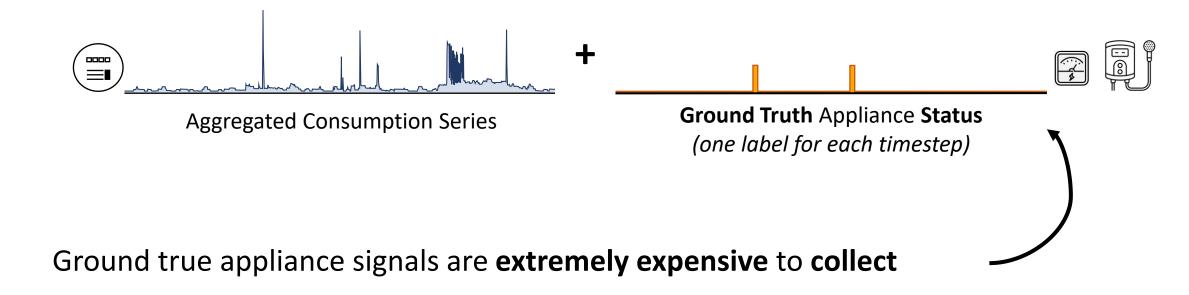
Non-Intrusive Load Monitoring (NILM): estimates **power consumption**, operational **patterns**, or **on/off state** of individual appliances using **only the total aggregated signal**



Background: Smart Meter Data Analytics

Appliance Pattern Localization = when the appliance is used?

SotA solutions require **large number** of **strong labels**





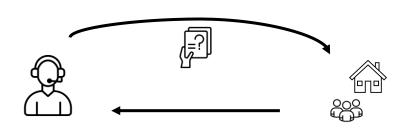
1000\$ to instrument an household with dedicated sensors!

Lever: Weak labels

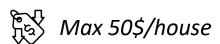
We already have weak labels

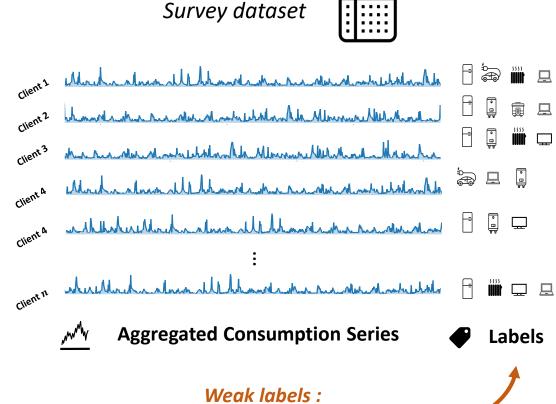
Can we use weak labels for accurate appliance localization?

"Is the appliance **X** present in your household?"



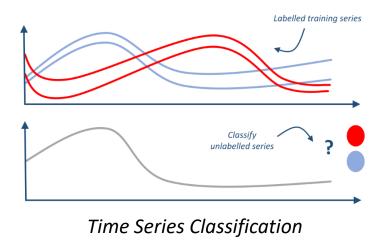
Customers fill out a **questionnaire** in exchange for a small reward

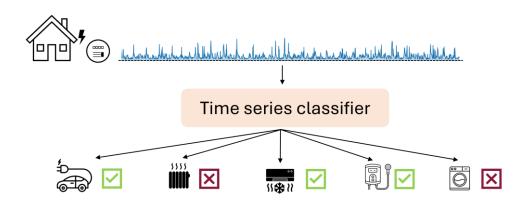




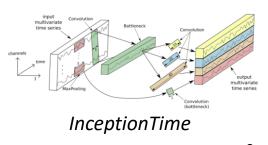
Lever: Appliance Detection in Consumers Household

Detecting appliances in consumers households can be cast as a **Time Series** Classification Problem¹.





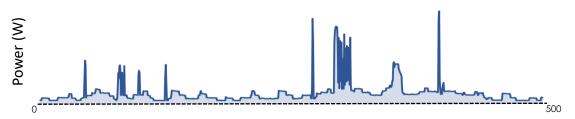
Recent studies demonstrate that **deep learning** (including CNNs) are the most **accurate** solutions for **tackling this task**^{1,2}.



Can we tackle the **Appliance Pattern Localization** problem using **minimal supervision**?

Challenges

Aggregate electricity consumption series

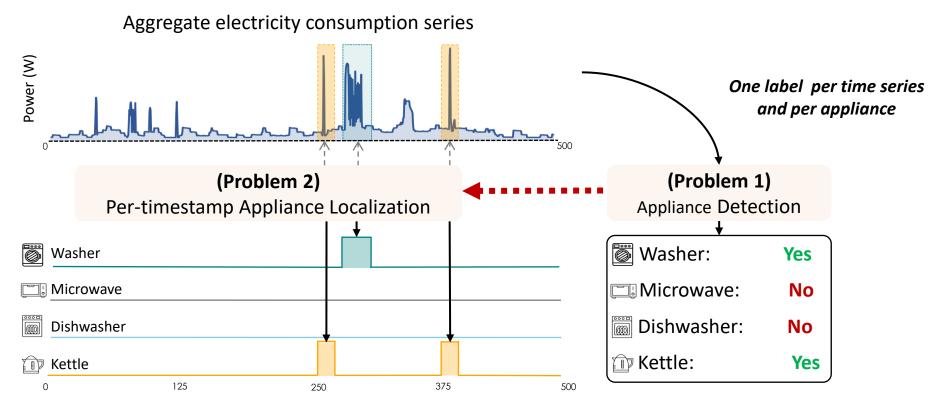


Can we tackle the **Appliance Pattern Localization** problem using **minimal supervision**?

Challenges Aggregate electricity consumption series One label per time series and per appliance (Problem 1) **Appliance Detection Washer:** Yes **Microwave:** No Dishwasher: No M Kettle: Yes

Can we tackle the **Appliance Pattern Localization** problem using **minimal supervision**?

Challenges



Can we tackle the **Appliance Pattern Localization** problem using **minimal supervision**?

Challenge

Aggregate electricity consumption series One label per time series and per appliance (Problem 2) (Problem 1) Per-timestamp Appliance Localization **Appliance Detection Washer** Washer: Yes ■ Microwave: No Microwave Dishwasher Dishwasher: No Yes Markettle: M Kettle 250

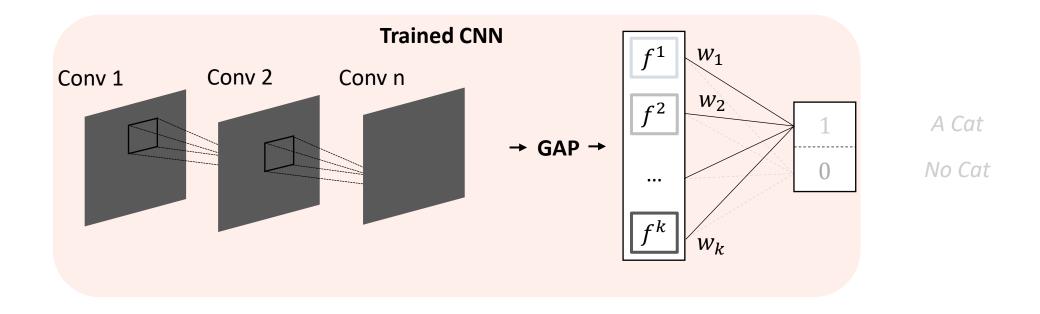
Solution

✓ CamAL

Class Activation Map based Appliance Localization

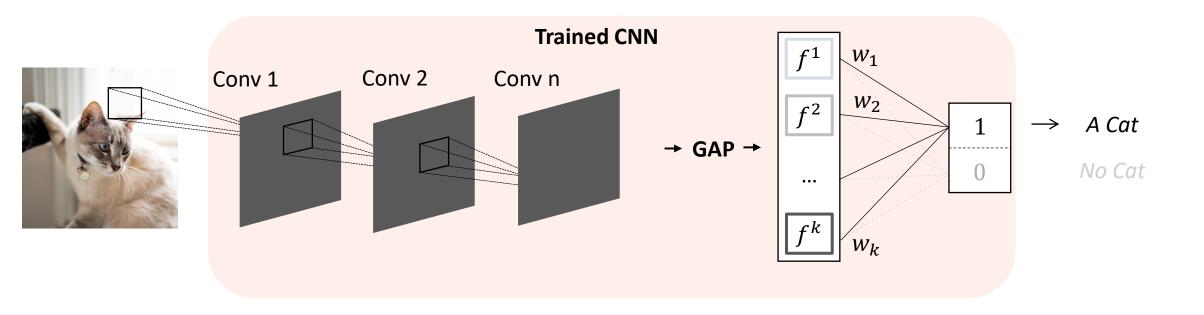
Background: Weakly Supervised Localization

Explainable AI - Class Activation Map (CAM)



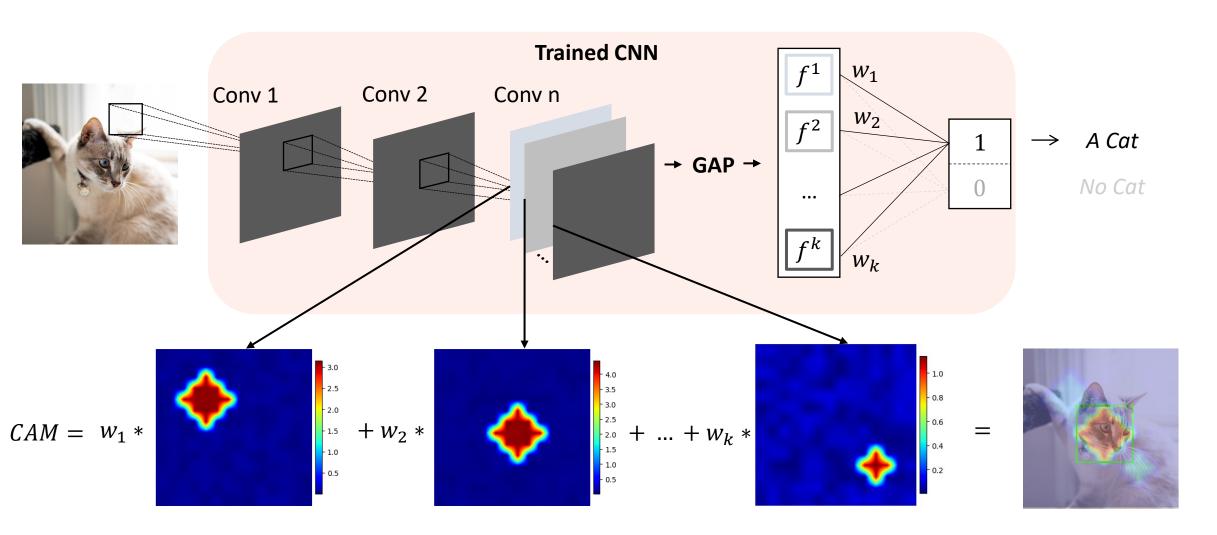
Background: Weakly Supervised Localization

Explainable AI - Class Activation Map (CAM)

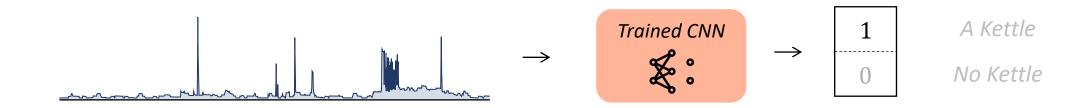


Background: Weakly Supervised Localization

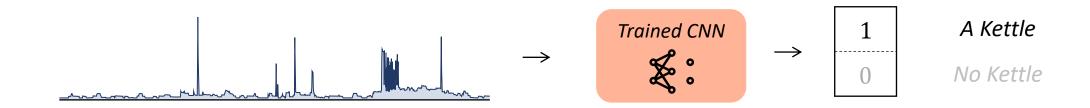
Explainable AI - Class Activation Map (CAM)



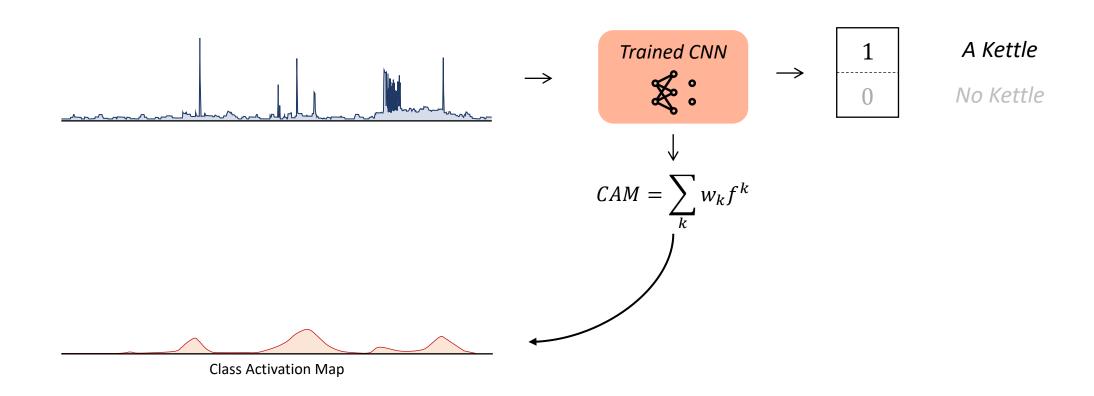
CNNs (ResNet, Inception) perform well on the Appliance Detection task



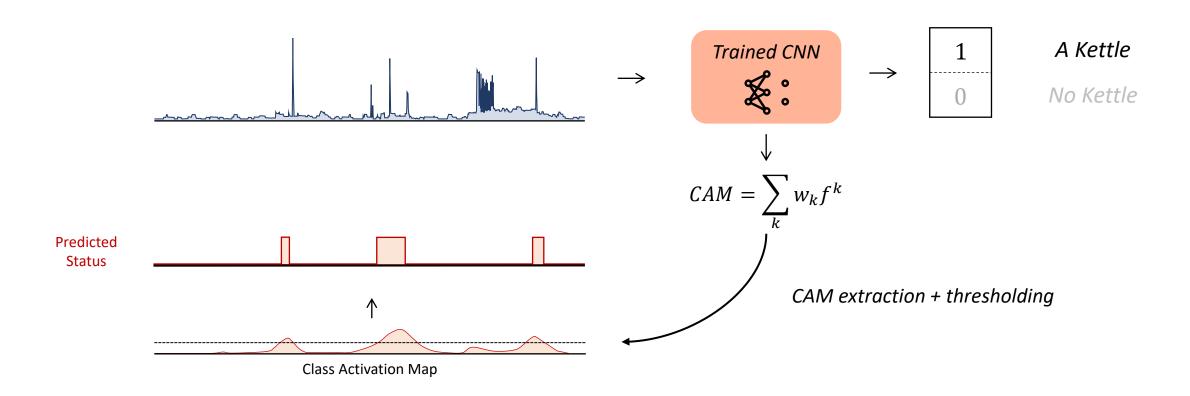
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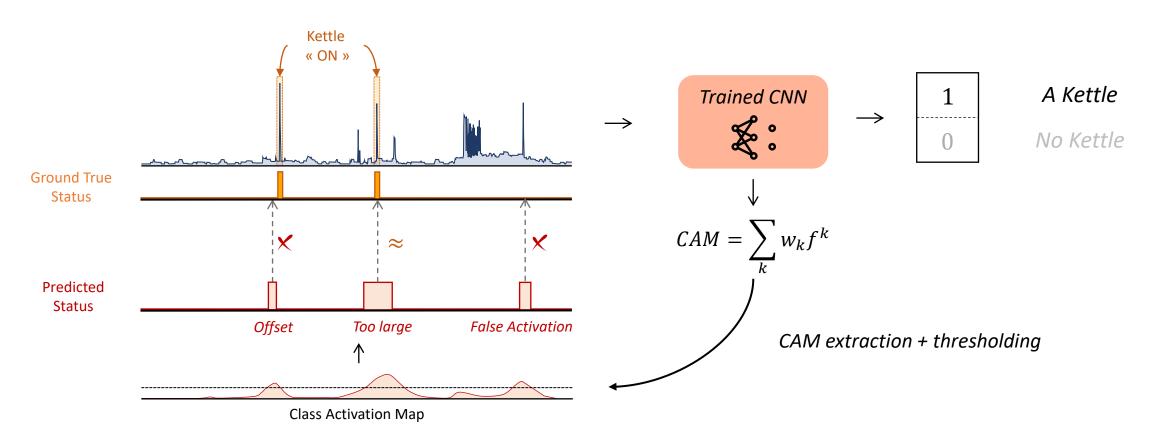
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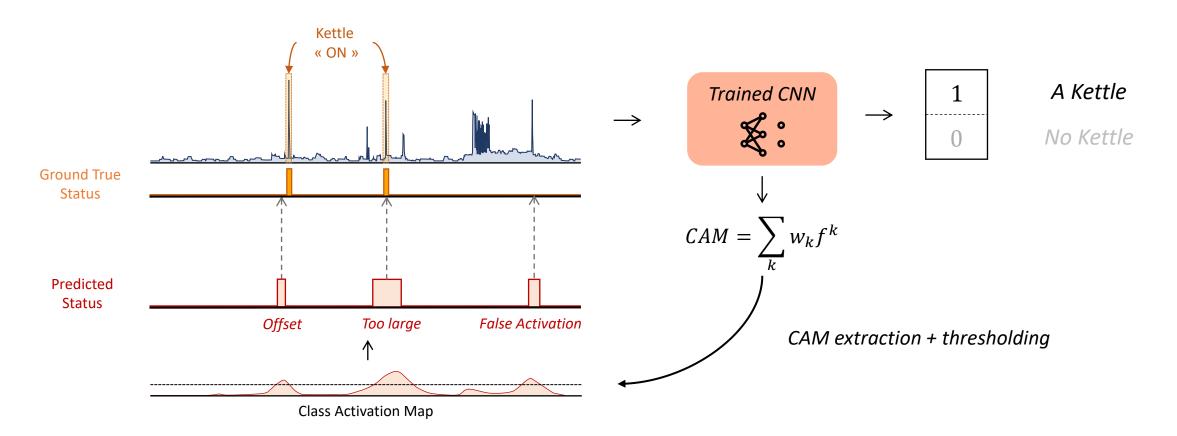
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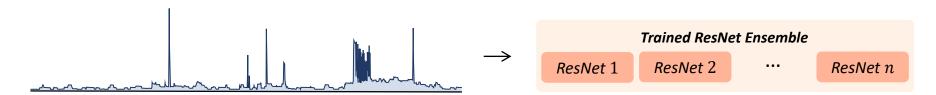
CNNs (ResNet, Inception) perform well on the Appliance Detection task

Is CAM a « Free Lunch » for **Appliance-Pattern Localization**?

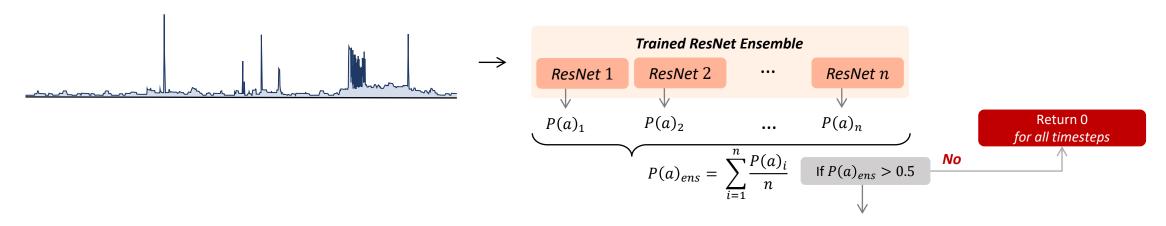
Not that simple...



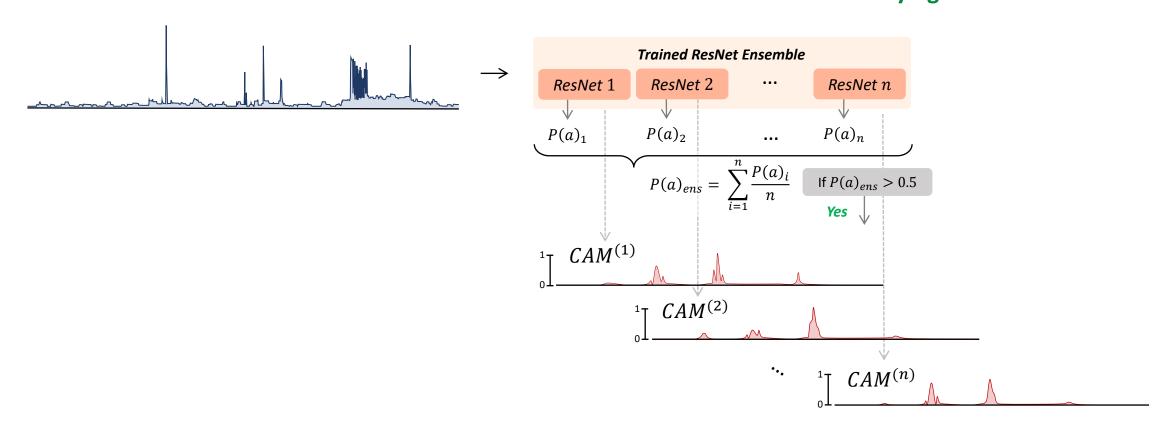
Improving CAM for Appliance Localization



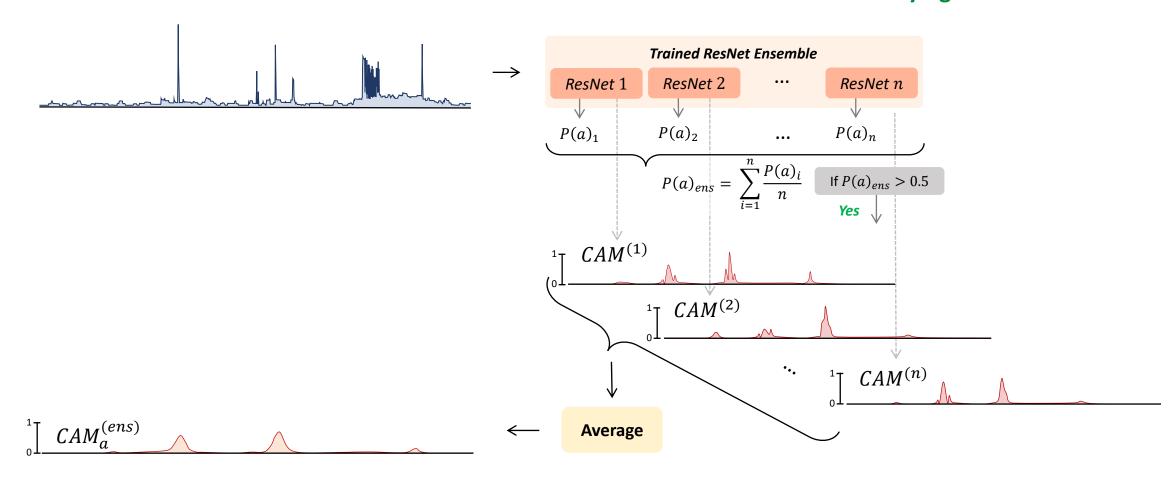
Improving **CAM** for **Appliance Localization**



Improving **CAM** for **Appliance Localization**



Improving **CAM** for **Appliance Localization**



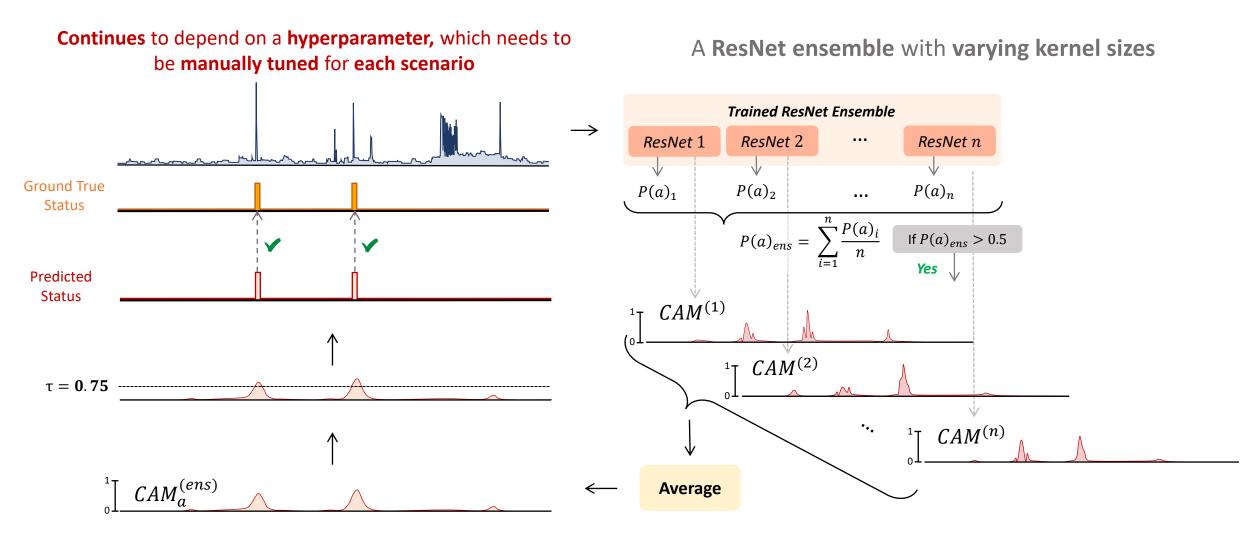
Improving CAM for Appliance Localization

A ResNet ensemble with varying kernel sizes **Trained ResNet Ensemble** ResNet 1 ResNet 2 ResNet n $P(a)_2$ $P(a)_n$ $P(a)_1$ If $P(a)_{ens} > 0.5$ Yes Predicted Status $CAM^{(1)}$ ¹T CAM⁽²⁾ $CAM^{(n)}$ **Average**

Improving CAM for Appliance Localization

Trained ResNet Ensemble ResNet 1 ResNet 2 ResNet n **Ground True** $P(a)_n$ $P(a)_1$ $P(a)_2$ Status If $P(a)_{ens} > 0.5$ Yes \ Predicted **Status** $CAM^{(1)}$ ¹T CAM⁽²⁾ $CAM^{(n)}$ **Average**

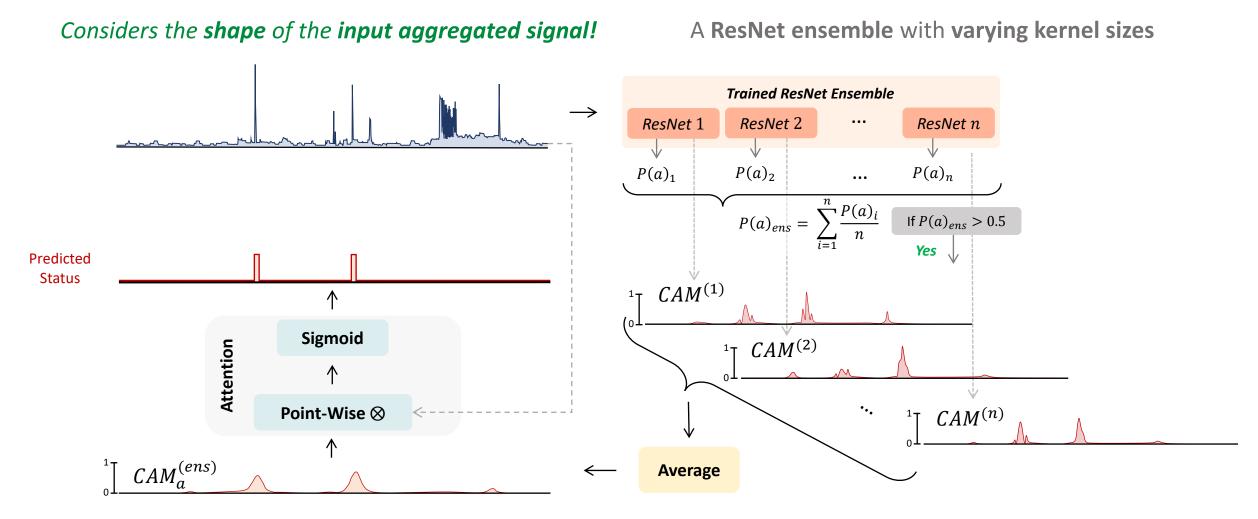
Improving CAM for Appliance Localization



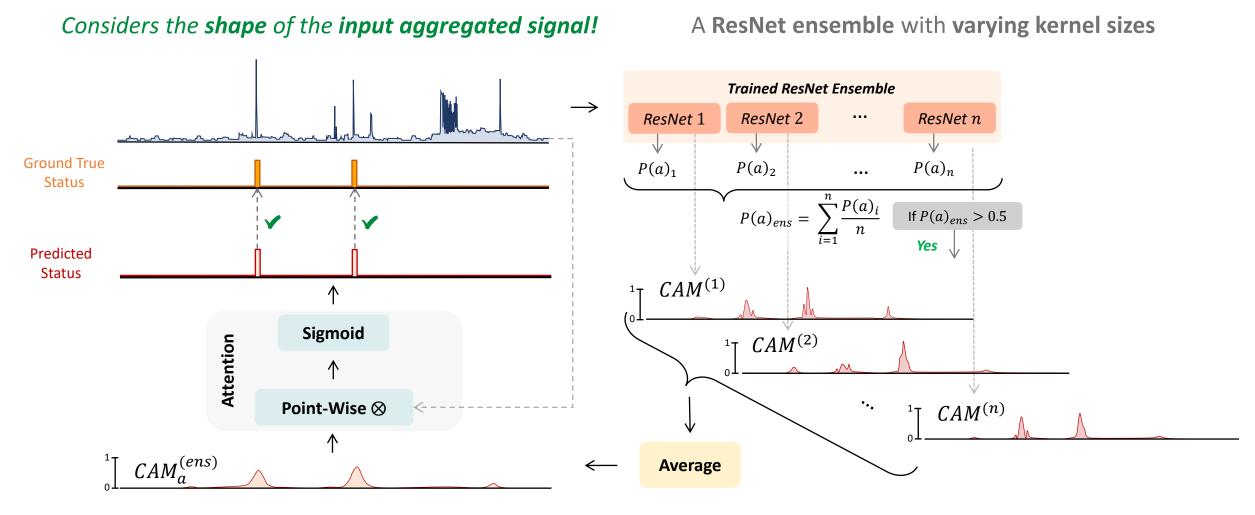
Improving CAM for Appliance Localization

A ResNet ensemble with varying kernel sizes Considers the **shape** of the **input aggregated signal! Trained ResNet Ensemble** ResNet 1 ResNet 2 ••• ResNet n $P(a)_2$ $P(a)_n$ $P(a)_1$ If $P(a)_{ens} > 0.5$ Yes | $CAM^{(1)}$ ¹T *CAM*⁽²⁾ $CAM^{(n)}$ $CAM_a^{(ens)}$ **Average**

Improving CAM for Appliance Localization

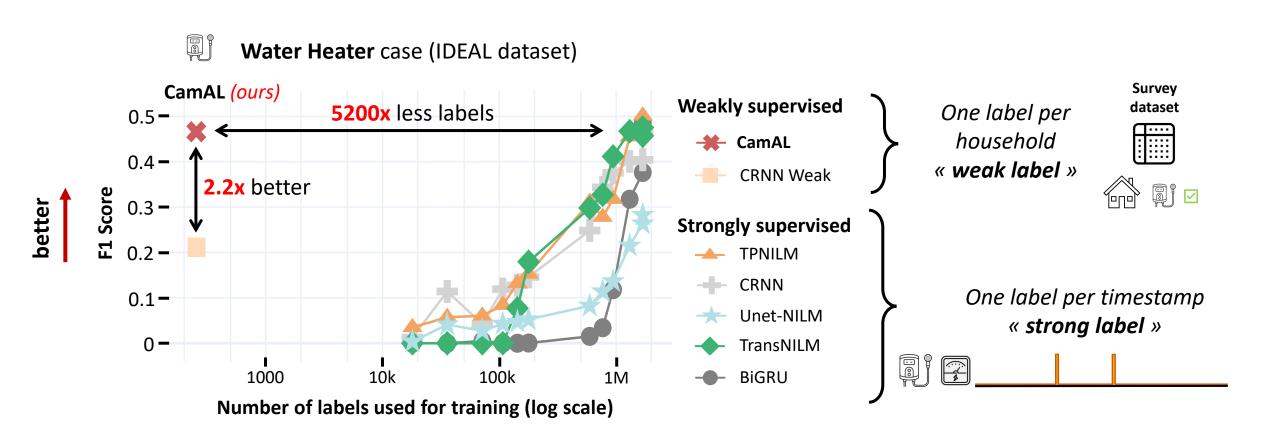


Improving CAM for Appliance Localization



Experimental Evaluation: Results

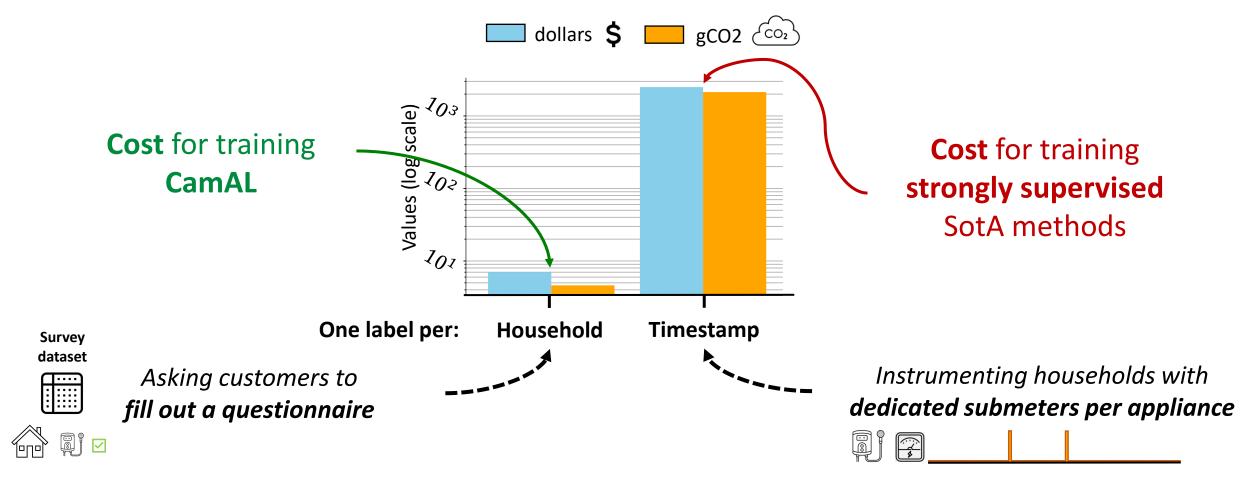
How does CamAL perform compared to strongly-supervised baselines?



2.2x more accurate for same number of labels! Up to **5200x less labels** for same accuracy!

Experimental Evaluation: Results

How do label-collection costs vary between approaches?



Conclusion

- CamAL (Class Activation Map based Appliance Localization)
 - Leverage explainable AI to tackle appliance-pattern localization using weak labels
 - Achieve near-strongly supervised method's accuracy while drastically reducing labeling costs
- CamAL is the first "frugal" yet accurate method for identifying appliance-usage patterns in smart-meter data.
- Promising open research direction: generate softly labeled sub-meter activation signals to train sequence-to-sequence approaches.

Thank you!

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41st IEEE International Conference on Data Engineering

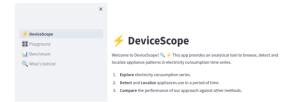
— HONG KONG SAR, CHINA I MAY 19 – 23, 2025 —

Want to learn more about our work?





Github repo





Online demo