Appliance Detection Using Very Low-Frequency Smart Meters Time Series

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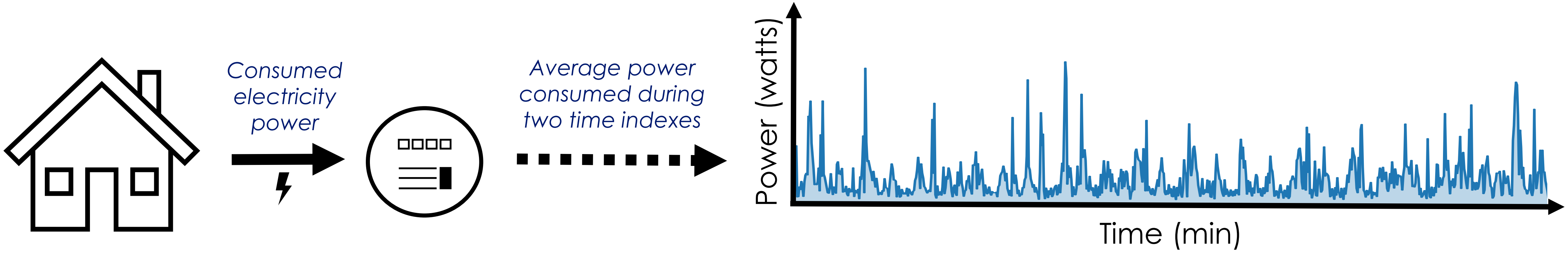
We proposed an extensive ***benchmark*** *of actual state-of-the-art* ***time series classifiers*** *applied to detect various appliances using different* ***very low-frequency*** *smart meters consumption datasets.*

Motivation: widespread adoption of Smart Meters

- **Individual Smart Meters are mainly adopted around the worlds**

More than half (56%) electricity customers in the European Union, had a **smart meter installed** in their home:

- To **bill more accurately** the clients 
- To better manage the **smart grids** 

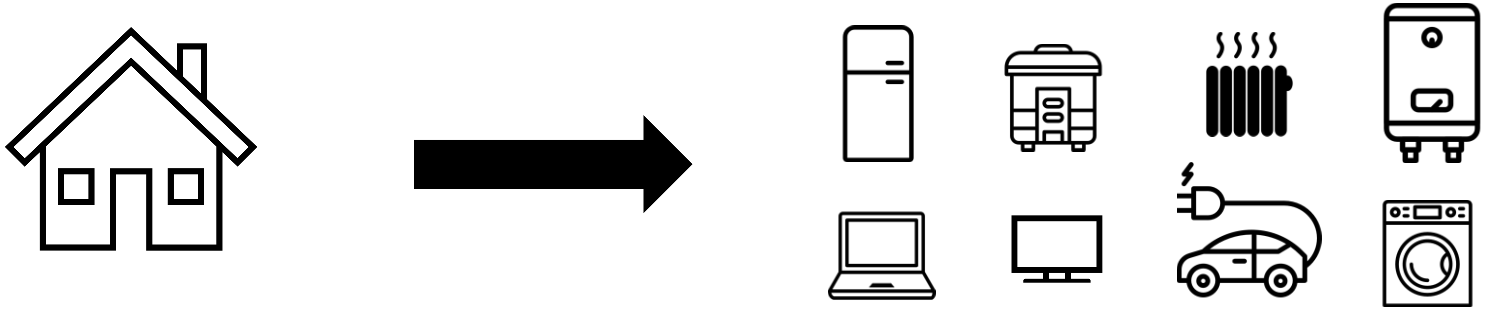


Smart Meter **Electricity consumption time series**

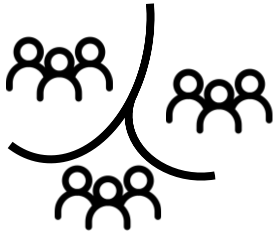
- Individual Smart Meters record electricity consumption at a **very-low frequency (>1min)**, in average, one data point recorded every **15min** or **30min**.

Challenge: Appliance Detection Problem

- **Detecting automatically appliances owned by customers**



- **It's become crucial for electricity suppliers to know this information**



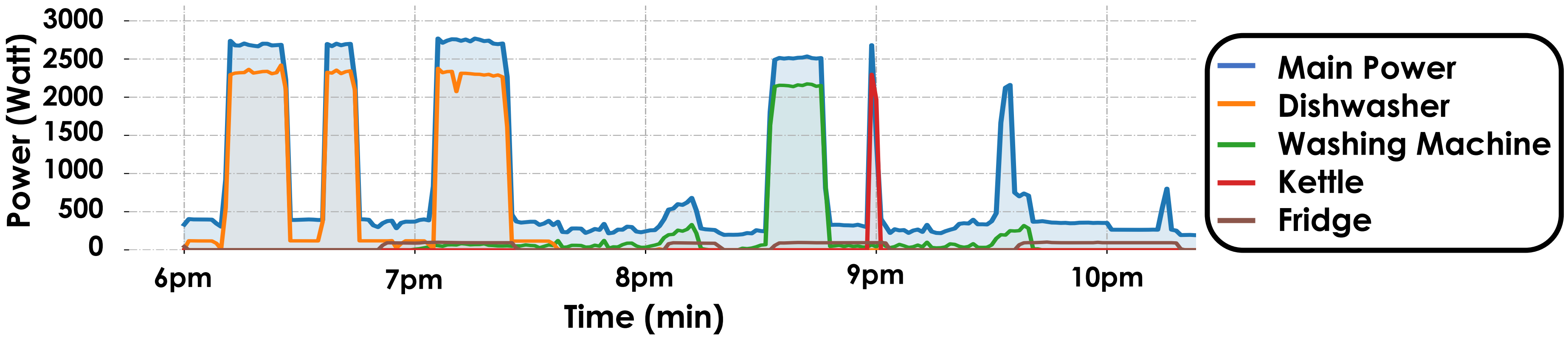
1. To **segment** the consumer base and therefore propose **personalized offers** that meets the client's need (increase client retention/statisfcation).

2. To **advise** customers to **rationalize their electricity consumption** and help them toward the energy transition.

Challenge: Appliance Detection Problem

- **Challenge related to NILM (Non-Intrusive Load Monitoring):**

A problem well studied in the literature, it aims to **identify the power consumption, pattern, or on/off state activation** of individual appliances using only the **main consumption series**.



- **However, appliance detection differs from NILM studies in two main aspects:**

1. Our problem concerns knowing **if** a household owns a specific appliance, not **when** the appliance is in an « on » state.

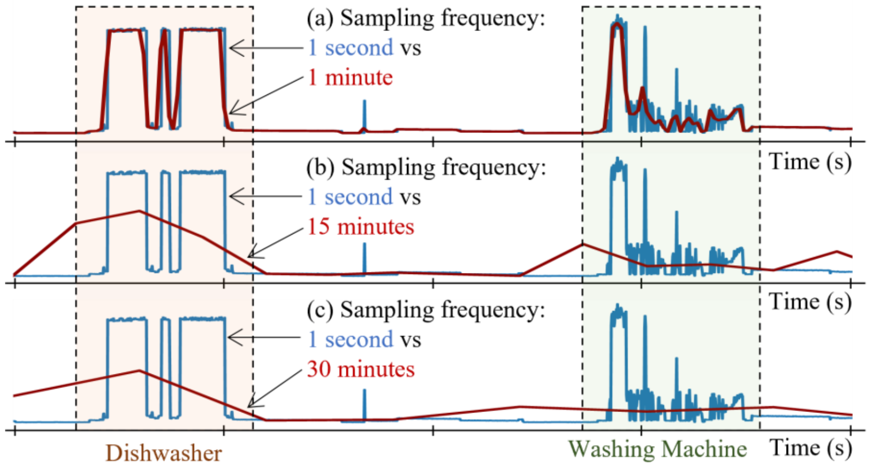
2. Most of the studies related to NILM are conducted at a **high-frequency** sampling level (one point every second or even more).

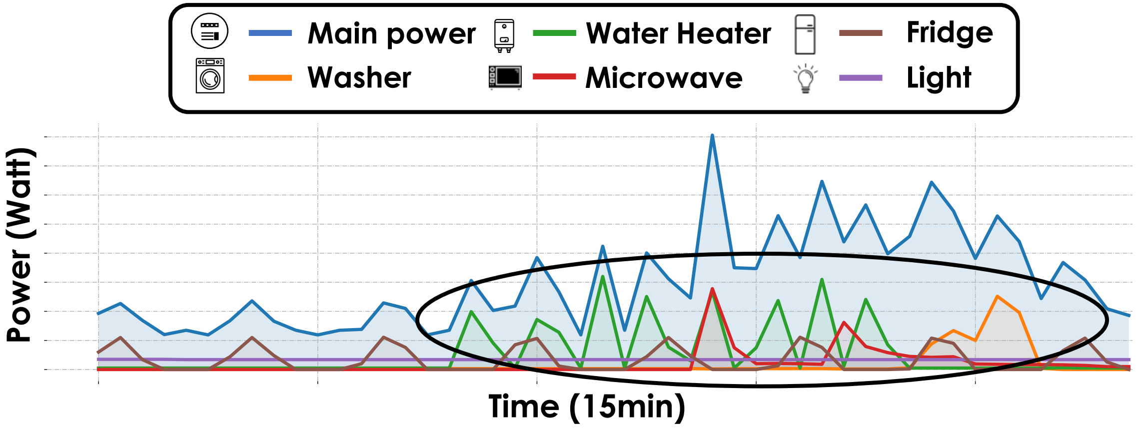
Challenge: Appliance Detection Problem

- **Impact of the smart meters reading**

  1. Loss of **unique appliance patterns**: usual pattern recognition algorithms are not usable at a **very-low sampling frequency**.

  2. Consumption time series aggregate **multiple appliance signals** that run simultaneously, making it hard to distinguish different signatures.



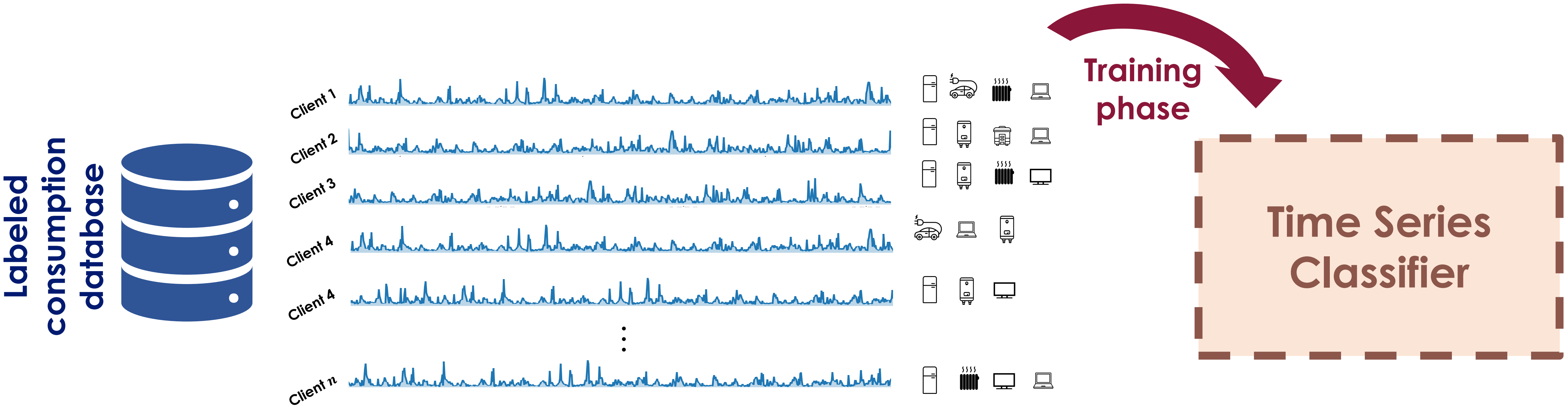


- Given the **proliferation of very-low frequency meters** and the **need to detect appliances**, we want to study the **effectiveness** of existing approaches on this problem.

Proposed Methodology

- **Idea : cast this challenge in a time series classification problem**

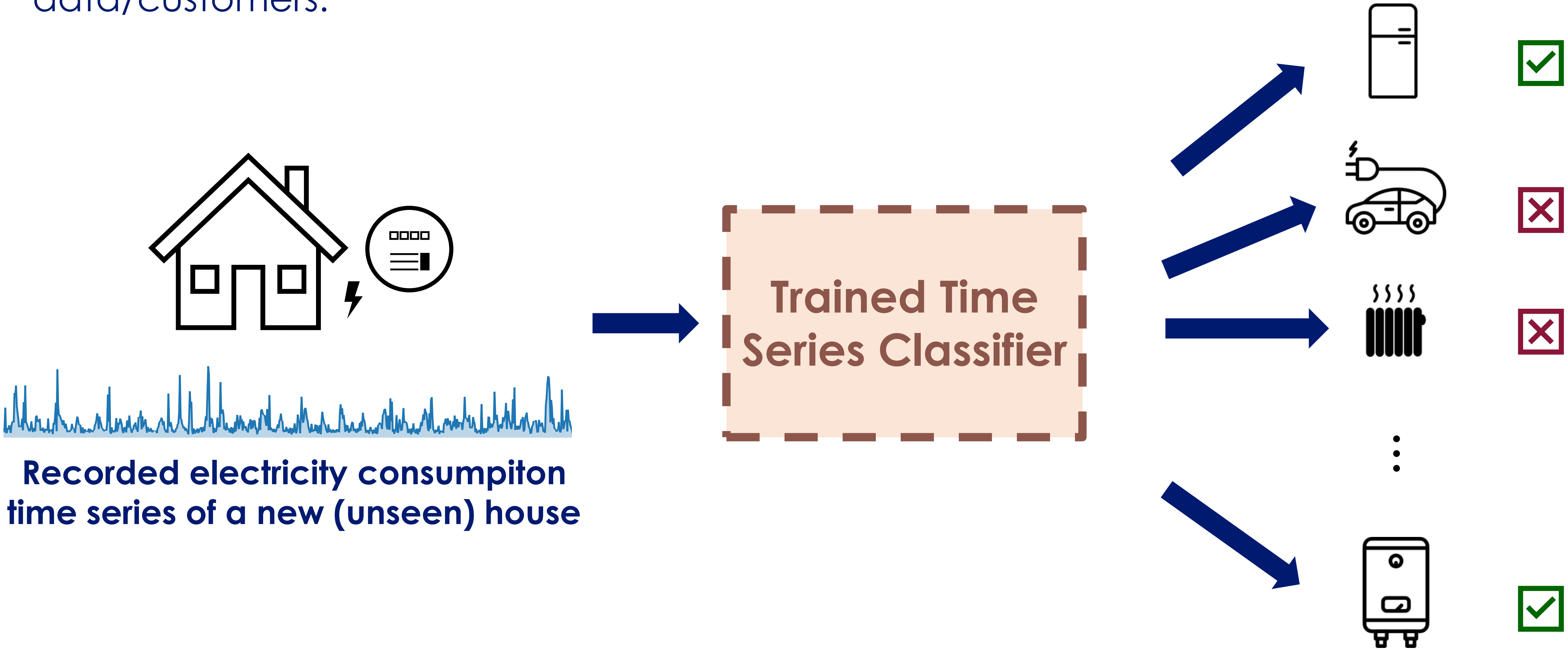
Electricity suppliers conduct surveys on subsets of customers, using these data to train a **Machine Learning model** to extract relevant features and detect **appliances automatically**.



Proposed Methodology

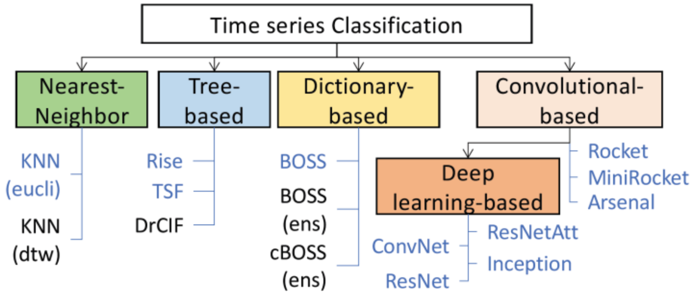
- **Idea : cast this challenge in a time series classification problem**

These algorithms can then be used on new (unlabeled) electricity consumption data/customers.

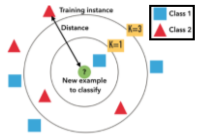


Proposed Methodology: Time Series Classifiers

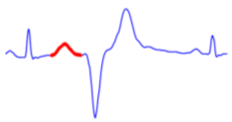
- **Various time series classifiers exists in the litterature, based on different approaches**



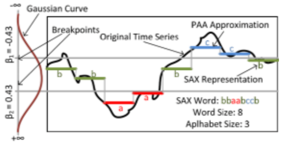
- **Nearest-Neighbor based classifiers**
  KNN with Euclidian distance
  KNN with Dynamic Time Warping



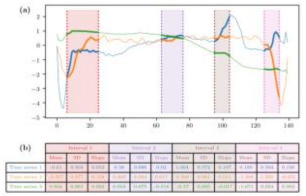
- **Motifs discovery based classifiers**
  Shapelets Transform Classifier



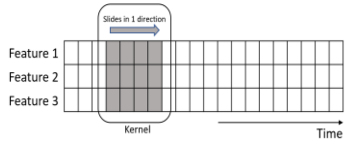
- **Dictionnary based classifiers**
  BOSS
  BOSS ensemble
  cBOSS ensemble



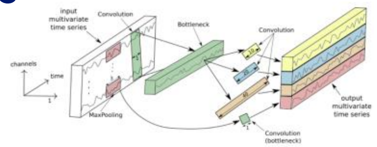
- **Tree based classifiers**
  Time Series Forest
  RISE
  DrCIF



- **Random Convolutional based classfiers**
  Rocket
  MiniRocket
  Arsenal



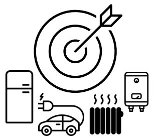
- **Deep-learning based classifiers**
  ConvNet
  ResNet/ResNetAtt
  InceptionTime



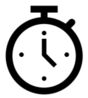
Proposed Methodology: Our Framework

- **We implemented a framework to assess the following interrogations**

1. According to the variety of **time series classifiers** in the literature, which **is the best** to **detect appliances**? Is there one classifier better for a particular type of appliance?



2. Wich appliances can be accurately detected at **30min sampling frequency**?

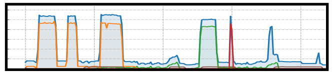


3. More generally, how does the Smart Meters **reading impact the appliance detection score**?

4. What is the impact of the **data size** on the **detection quality**?

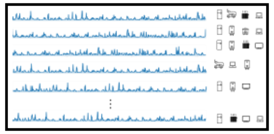
Datasets

- **Selected datasets for the benchmark**

NILM datasets 

REFIT
- High frequency (6sec)
- 20 houses
- 7 different appliances

UKDALE
- High frequency (8sec)
- 5 houses
- 4 different appliances

Survey datasets
(labeled) 

ISSDA – CER dataset
- Very low-frequency (30min)
- 4335 houses
- 6 different appliances

EDF 1
- Very low-frequency (30min)
- 1553 houses
- 9 different appliances

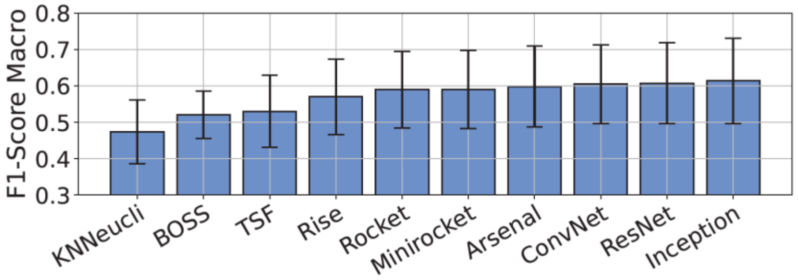
EDF 2
- Very low-frequency (10min)
- 1260 houses
- 6 different appliances

- Total of **13 different types** of appliances through the different datasets.

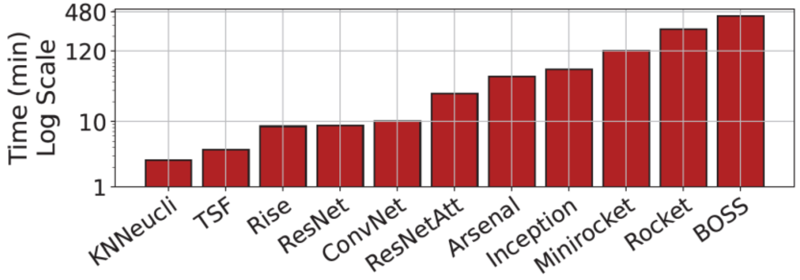
Results: Overall results at 30min sampling frequency

- **Global results for all classifiers, using 30min resampled data**

Average detection score (F1-Score Macro)



Average running Time (Training + Inference)



- **Best classifiers**
  - **InceptionTime** (detection quality)
  - **ConvNet/ResNet** (balance between detection quality and running time)

- **Most detectable appliances at 30min**

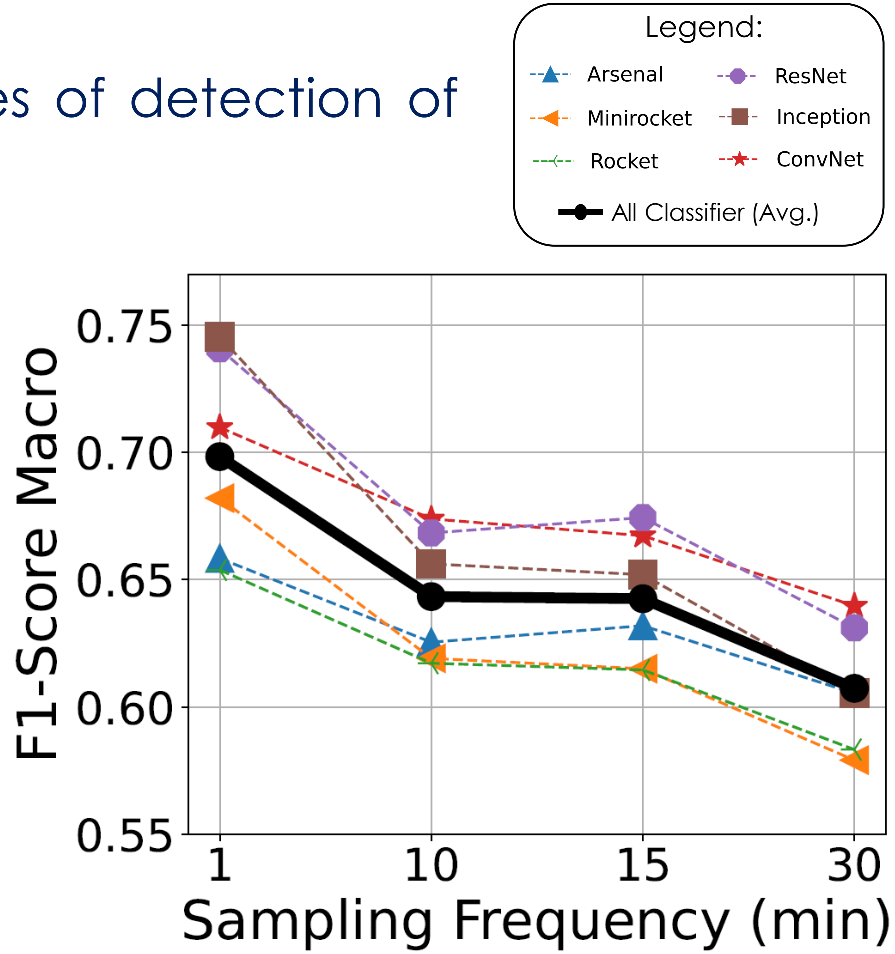
  - Heater
  - Water Heater
  - Electric vehicle
  - Cooker

  - Type of heater
  - Dishwasher
  - Tumble Dryer
  - Computer/Television

  - Microwave
  - Kettle
  - Oven
  - Washing Machine

Results: Influence of sampling rate

- Average impact of the sampling frequency on all cases of detection of the **REFIT** and **EDF 2** datasets.



  - **In average** ≃ **10 points** when the sampling rate drops from **1min** to **30min.**

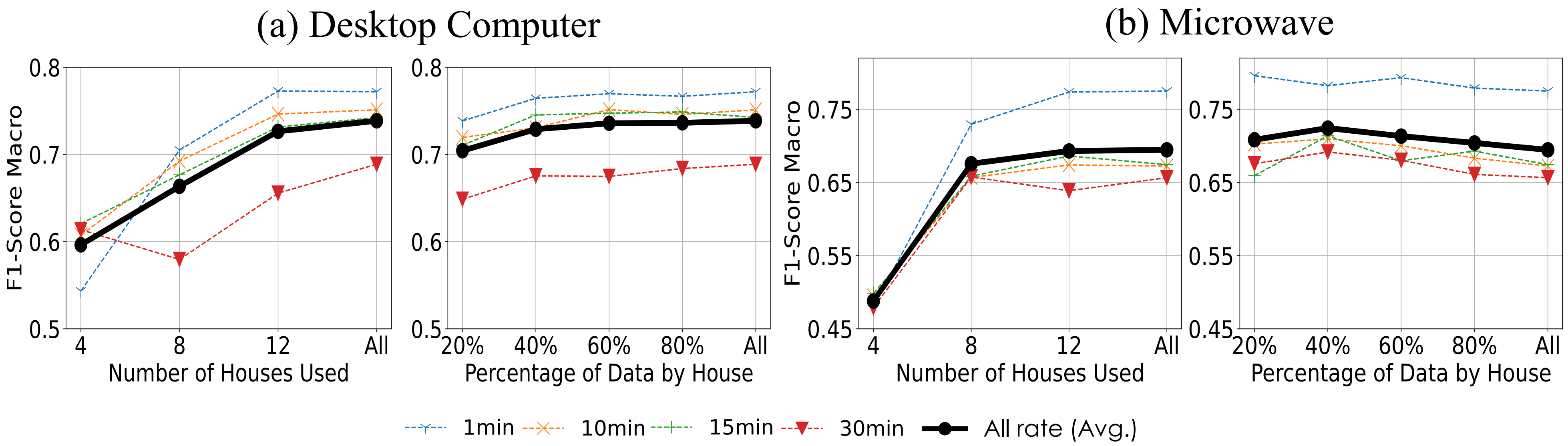
  - ≃ **4 points** drop between **15min and 30min.**

- Using **1min** sampled data improved the detection score **drastically**, using **15min** sampled data help to detect many appliances better.

Results: Influence of data size

- Average impact of data size on different appliance detection cases using the **REFIT** dataset.

For different appliances and sampling frequencies, we compared the influence of the data size: number of houses **vs.** percentage of data used by houses.



- Using **different sources** (i.e., houses) is more reliable than many data from a few houses.

Conclusions

- We proposed and implemented a **framework** for assessing the performance of **wide variety** of time series classifiers across **many different datasets** and **appliance detection cases**.
- **Deep-learning based classifiers outperform** other approaches regarding accuracy and scalability.
- Certain appliances can be **accurately detected, even at 30min sampling frequency**. EDF, the main French electricity supplier, already uses these algorithms.
- However, using **1min sampled data** improved the detection score **drastically,** and suppliers need to target a minimum of **15min** for the Smart Meter reading to detect many appliances better.

Thank you !

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Appendix A: Datasets description

- **Datasets description:** Left side : datasets characteristics (number of time series, sampling frequency, time series length). Right side : selected appliance detection cases through the five datasets; for each case, the table summarizes the number of time series available (♯TS)and the imbalance degree of the test set for the case (IB Ratio). A slash indicate that no data are available for this case/dataset.

Datasets	Tot. TS	TS Length 1min	TS Length 10min	TS Length 15min	TS Length 30min
REFIT	9091	1440	144	96	48
UKDALE	4767	1440	144	96	48
CER	4225	/	/	/	25728
EDF 1	2611	/	/	/	17520
EDF 2	1553	/	26208	17472	8736

	Appliance case	REFIT ♯TS	REFIT IB Ratio	UKDALE ♯TS	UKDALE IB Ratio	CER ♯TS	CER IB Ratio	EDF 1 ♯TS	EDF 1 IB Ratio	EDF 2 ♯TS	EDF 2 IB Ratio
Tech	Desktop Computer	5190	0.56	/		3286	0.47	1402	0.38	3740	0.62
Tech	Television	1134	0.92	/		/		/		/	
Kitchen	Cooker	/		/		1682	0.76	/		/	
Kitchen	Kettle	4790	0.72	1222	0.84	/		/		/	
Kitchen	Microwave	7434	0.55	1678	0.77	/		324	0.91	/	
Kitchen	Electric Oven	/		/		/		510	0.85	1152	0.91
Washer	Dishwasher	7798	0.44	2378	0.32	2350	0.66	224	0.93	2846	0.75
Washer	Tumble Dryer	3466	0.22	/		2214	0.68	1534	0.41	3470	0.42
Washer	Washing Machine	7422	0.54	2830	0.38	/		/		/	
Heating	Water Heater	/		/		3070	0.56	1336	0.66	548	0.86
Heating	Electric Heater	/		/		1348	0.19	1624	0.58	1538	0.56
Heating	Convector/Heat Pump	/		/		/		506	0.69	/	
Other	Electric Vehicule	/		/		/		140	0.3	/	

Appendix B: Overall results at 30min sampling frequency

Quality detection results (F1-Score Macro)

Appliance	Dataset	Arsenal	Minirocket	Rocket	ConvNet	ResNet	ResNetAtt	InceptionTime	BOSS	TSF	Rise	KNNeucli	Avg. Score
Desktop Computer	CER	0.618	0.617	0.606	0.602	0.614	0.530	0.608	0.516	0.580	0.586	0.491	0.579
	EDF 1	0.571	0.564	0.570	0.489	0.560	0.459	0.555	0.491	0.533	0.543	0.469	0.528
	EDF 2	0.603	0.576	0.582	0.579	0.620	0.514	0.601	0.519	0.570	0.592	0.520	0.571
	REFIT	0.697	0.683	0.674	0.715	0.740	/	0.623	0.542	0.525	0.600	0.548	0.635
Appliance Average Score		0.622	0.610	0.608	0.596	**0.634**	/	0.597	0.517	0.552	0.580	0.507	0.578
Television	REFIT	0.656	0.647	0.645	0.695	0.699	/	0.718	0.485	**0.737**	0.664	0.513	0.646
Cooker	CER	0.680	0.673	0.676	0.661	0.689	0.541	**0.710**	0.526	0.566	0.584	0.440	0.613
Kettle	REFIT	0.368	0.376	0.381	0.522	0.477	/	0.415	0.536	0.359	0.428	0.421	0.428
	UKDALE	0.540	0.502	0.522	0.428	0.432	/	0.583	0.504	0.353	0.442	0.446	0.475
Appliance Average Score		0.454	0.439	0.452	0.475	0.454	/	0.499	**0.520**	0.356	0.435	0.434	0.452
Microwave	REFIT	0.656	0.598	0.588	0.745	0.679	/	0.673	0.563	0.540	0.717	0.529	0.629
	UKDALE	0.446	0.498	0.460	0.532	0.526	/	0.541	0.435	0.459	0.430	0.378	0.471
	EDF 1	0.480	0.471	0.475	0.534	0.510	0.409	0.474	0.454	0.400	0.429	0.457	0.463
Appliance Average Score		0.527	0.522	0.508	**0.604**	0.572	/	0.563	0.484	0.466	0.525	0.455	0.521
Oven	EDF 1	0.513	0.498	0.499	0.512	0.512	0.472	0.523	0.506	0.429	0.497	0.437	0.491
	EDF 2	0.557	0.584	0.553	0.571	0.562	0.560	0.576	0.495	0.459	0.491	0.397	0.528
Appliance Average Score		0.535	0.541	0.526	0.542	0.537	0.516	**0.550**	0.500	0.444	0.494	0.417	0.509
Dishwasher	REFIT	0.650	0.599	0.619	0.580	0.605	/	0.590	0.557	0.519	0.584	0.515	0.582
	UKDALE	0.458	0.465	0.465	0.419	0.380	/	0.384	0.399	0.429	0.554	0.525	0.448
	CER	0.699	0.720	0.700	0.730	0.728	0.594	0.737	0.586	0.609	0.648	0.488	0.658
	EDF 1	0.454	0.441	0.450	0.528	0.522	0.383	0.535	0.430	0.418	0.421	0.211	0.436
	EDF 2	0.753	0.760	0.741	0.799	0.801	0.585	0.835	0.596	0.603	0.600	0.512	0.690
Appliance Average Score		0.603	0.597	0.595	0.611	0.607	/	**0.616**	0.514	0.516	0.561	0.450	0.563
Tumble Dryer	REFIT	0.493	0.503	0.502	0.468	0.448	/	0.441	0.506	0.416	0.434	0.461	0.467
	CER	0.634	0.641	0.628	0.606	0.612	0.550	0.623	0.549	0.578	0.602	0.474	0.591
	EDF 1	0.619	0.578	0.607	0.624	0.607	0.475	0.636	0.550	0.537	0.563	0.487	0.571
	EDF 2	0.733	0.714	0.714	0.757	0.769	0.475	0.769	0.560	0.593	0.681	0.493	0.660
Appliance Average Score		**0.620**	0.609	0.613	0.614	0.609	/	0.617	0.541	0.531	0.570	0.479	0.572
Washing Machine	REFIT	0.605	0.572	0.592	0.581	0.586	/	0.614	0.520	0.562	0.557	0.529	0.572
	UKDALE	0.475	0.505	0.478	0.535	0.530	/	0.454	0.408	0.581	0.549	0.509	0.502
Appliance Average Score		0.540	0.538	0.535	0.558	0.558	/	0.534	0.464	**0.572**	0.553	0.519	0.537
Water Heater	CER	0.625	0.613	0.613	0.610	0.612	0.465	0.637	0.527	0.596	0.584	0.462	0.577
	EDF 1	0.835	0.821	0.827	0.814	0.828	0.768	0.841	0.670	0.713	0.805	0.591	0.774
	EDF 2	0.733	0.685	0.724	0.731	0.685	0.591	0.759	0.658	0.580	0.666	0.617	0.675
Appliance Average Score		0.731	0.706	0.721	0.718	0.708	0.608	**0.746**	0.618	0.630	0.685	0.557	0.675
Heater	CER	0.522	0.532	0.514	0.533	0.508	0.477	0.565	0.459	0.492	0.527	0.397	0.502
	EDF 1	0.784	0.783	0.789	0.777	0.778	0.713	0.800	0.643	0.758	0.777	0.638	0.749
	EDF 2	0.591	0.566	0.578	0.626	0.637	0.527	0.648	0.497	0.591	0.605	0.451	0.574
Appliance Average Score		0.603	0.597	0.595	**0.659**	0.607	0.572	0.616	0.514	0.516	0.561	0.450	0.609
Type of Heater	EDF 1	0.632	0.622	0.631	0.597	0.638	0.534	**0.651**	0.539	0.556	0.625	0.467	0.590
Electric Vehicle	EDF 1	0.689	**0.730**	0.670	0.681	0.699	0.553	0.720	0.541	0.456	0.725	0.556	0.638
Classifiers Average Score		0.601	0.593	0.592	0.609	0.610	/	**0.617**	0.521	0.531	0.574	0.474	/
Classifiers Average Rank		3.773	4.697	4.758	4.303	3.697	/	**2.864**	7.939	7.924	6.197	8.848	/