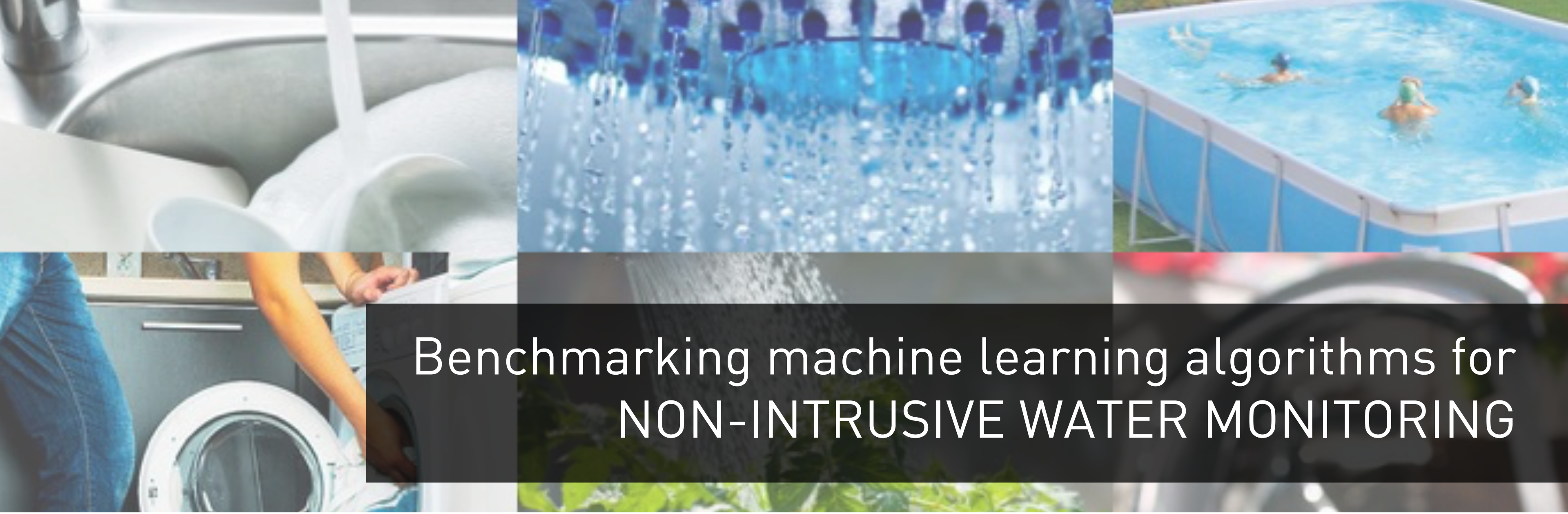


Benchmarking machine learning algorithms for NON-INTRUSIVE WATER MONITORING

Andrea Cominola[1,2], Marie-Philine Becker[1,2], Riccardo Taormina[3]

[1] Technische Universität Berlin | [2] Einstein Center Digital Future | [3] Delft University of Technology

MOTIVATION & BACKGROUND

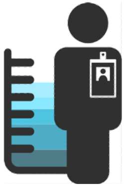
DEMAND MANAGEMENT STRATEGIES

. technological
. financial
. legislative
. operation and maintenance
. education

CONSUMER COMMUNITY

USER MODELLING

Toilet
Shower
Dishwasher
Washing machine
Garden
Swimming pool



END-USES CHARACTERIZATION

CONSUMPTION MONITORING

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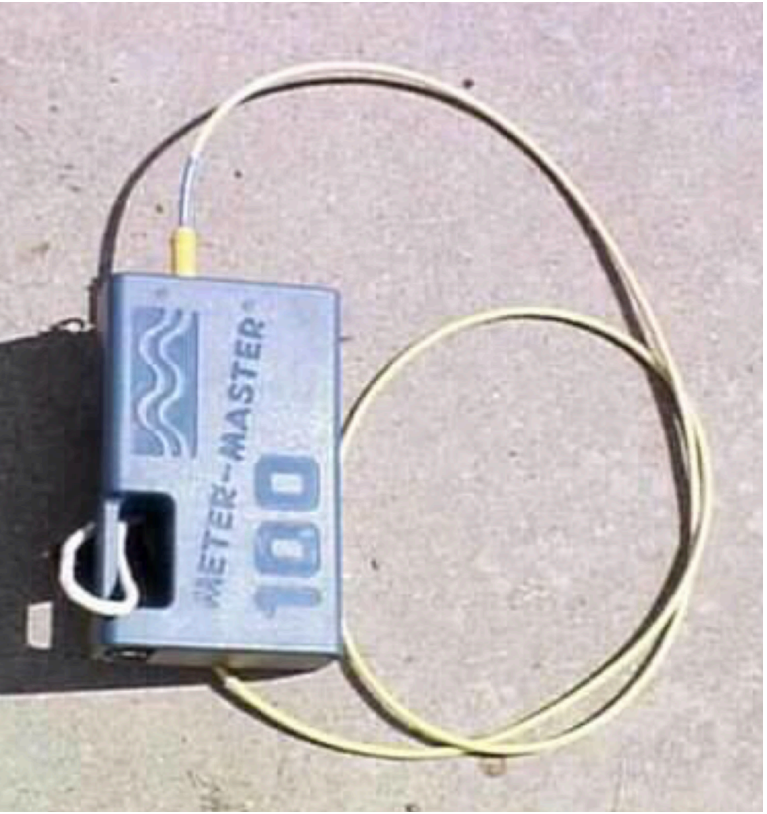
Cominola et al., 2015

MOTIVATION & BACKGROUND



Increasing amount of residential water demand management studies over the last 25 years

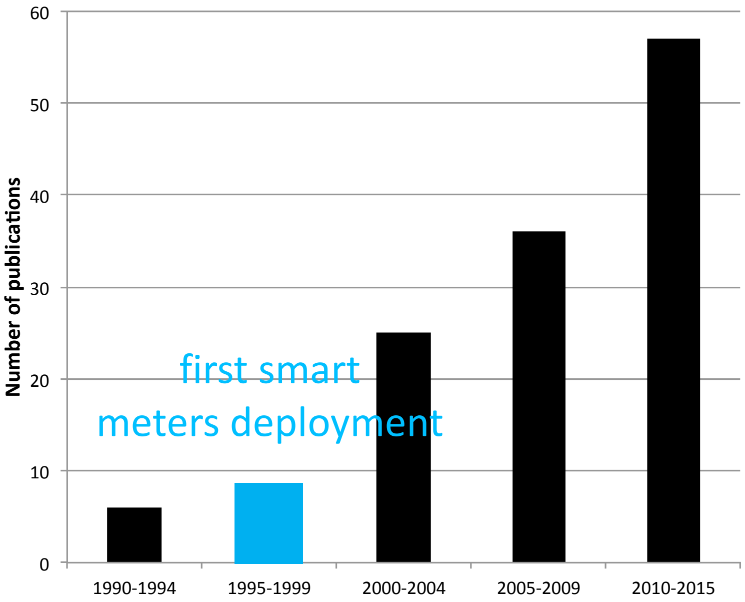


Figure source (left): Mayer, P. W., DeOreo, W. B., Opitz, E. M., Kiefer, J. C., Davis, W. Y., Dziegielewski, B., & Nelson, J. O. (1999). Residential end uses of water.
Figure source(right): Cominola et al., 2015.

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FROM PIONEERING STUDIES ...

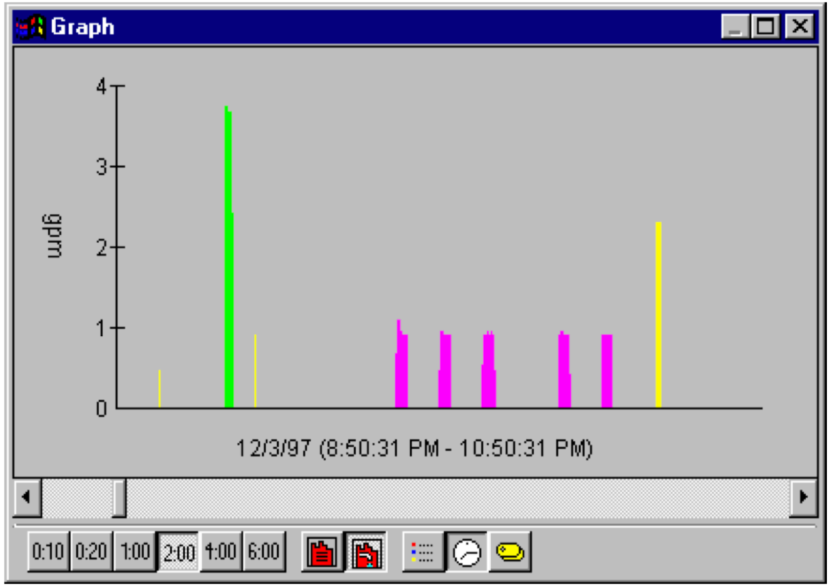

Figure 3.8 Sample flow trace from Trace Wizard showing a two hour view. Water events depicted include a toilet flush, a five cycle dishwasher, and various faucet uses.

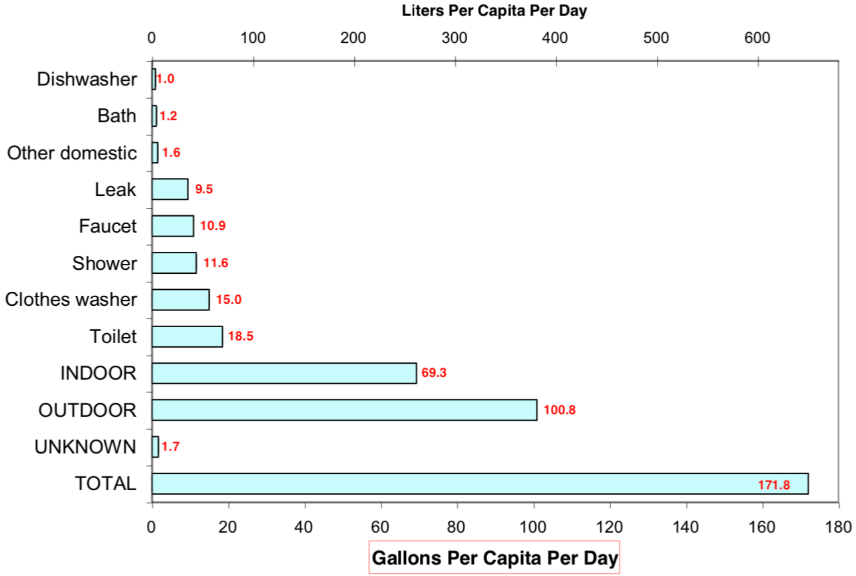

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Figure source: Mayer, P. W., DeOreo, W. B., Opitz, E. M., Kiefer, J. C., Davis, W. Y., Dziegielewski, B., & Nelson, J. O. (1999). Residential end uses of water.

NIWM – Non-Intrusive Water Monitoring

. We define **Non-Intrusive Water Monitoring** as the problem of deriving individual end use water consumption traces from the composite signal recorded by a single-point meter installed at the inlet of a household.

. The concept takes inspiration from the Non-Intrusive Load Monitoring of electricity demand.

??????????????????????????????????????

??? Which ML algorithms can enable ???????

??? accurate NIWM end use classification? ???????

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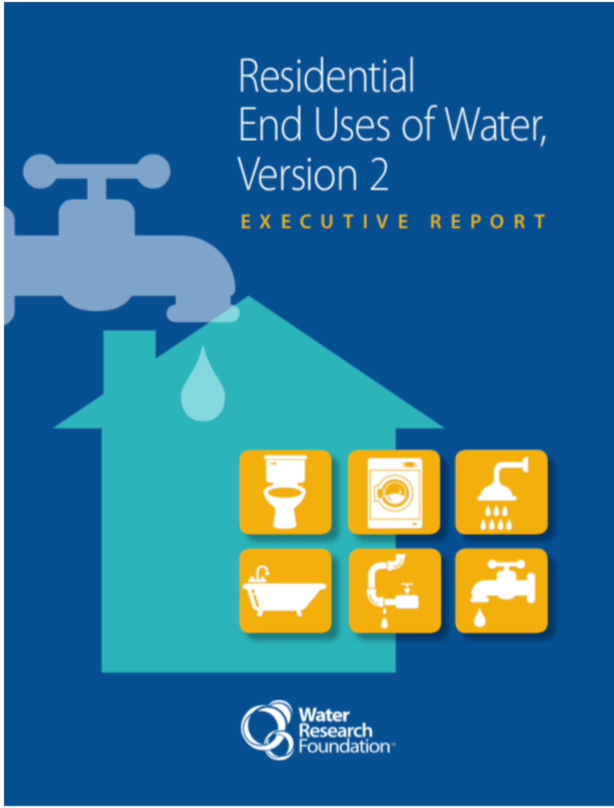
CASE STUDY

REU2016 – Residential End Uses of Water 2016

- Residential end-uses monitored for a period of **2 weeks**, with a **10s resolution**, in **762 households** spread across **9 study sites** in the USA and Canada
- Starting date: 06.03.2012
- Ending date: 29.01.2013
- **13 End-use labels** obtained via flow trace analysis with Trace Wizard
- Total Number of events: 2 981 053
- Usable Number of events: **1 912 994**



Source: https://www.waterrf.org/research/projects/residential-end-uses-water-version-2

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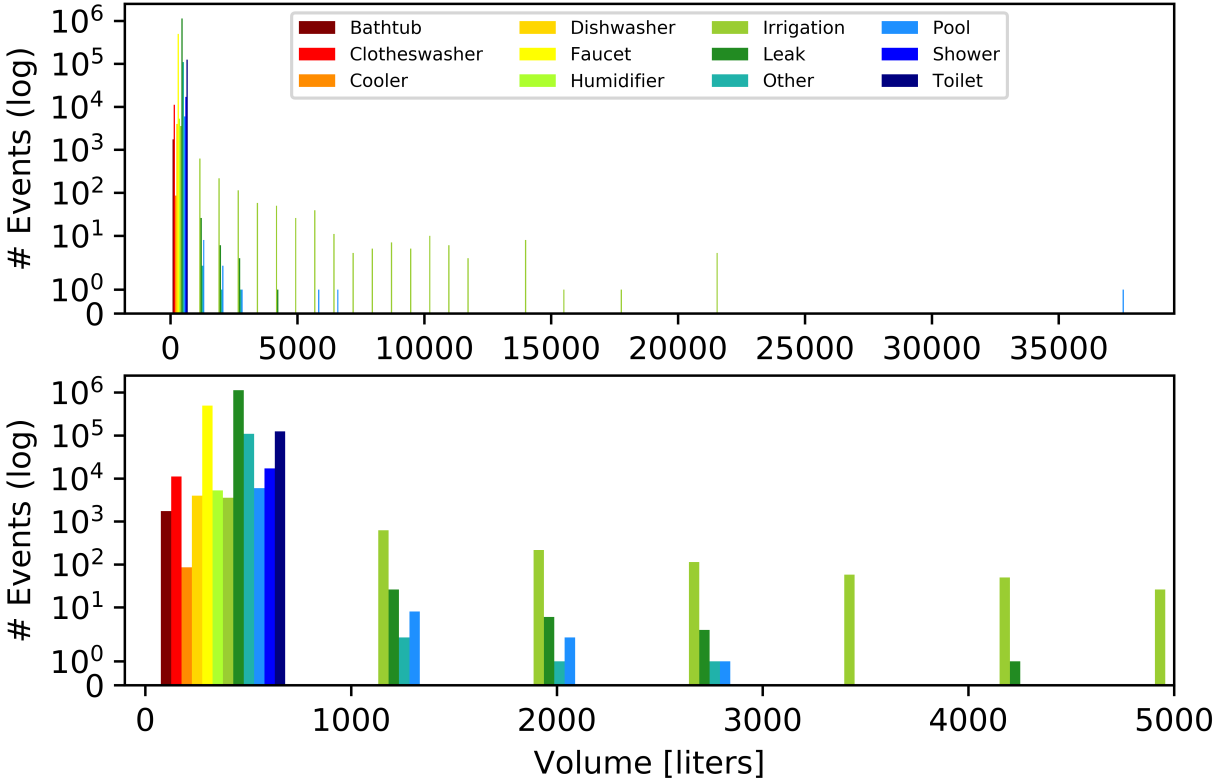
DATASET CHARACTERISTICS

13 end use categories:

. Bathtub
. Washing machine
. Cooler
. Dishwasher
. Faucet
. Humidifier
. Irrigation
. Leak
. Pool
. Shower
. Toilet
. Treatment
. Other



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DATASET CHARACTERISTICS

6 water usage features:

. Event duration

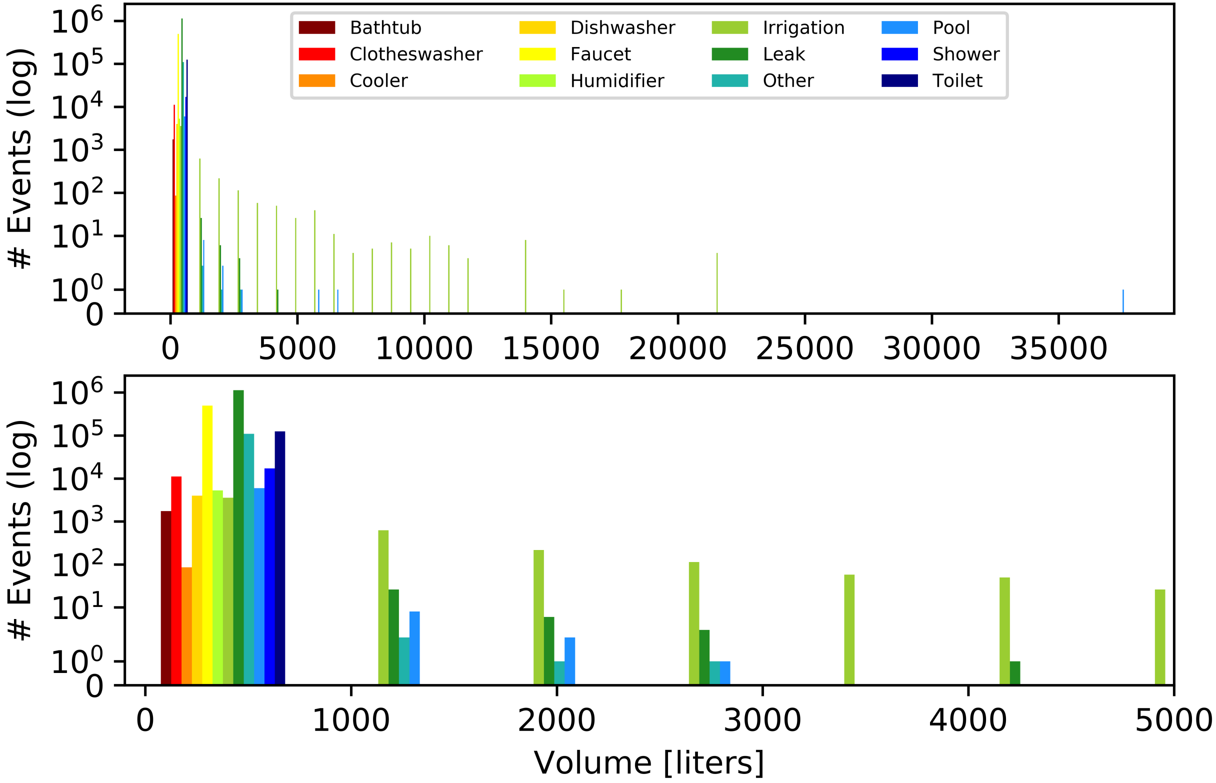
. Event volume

. Event flow peak

. Mode

. Time of day

. Day of week



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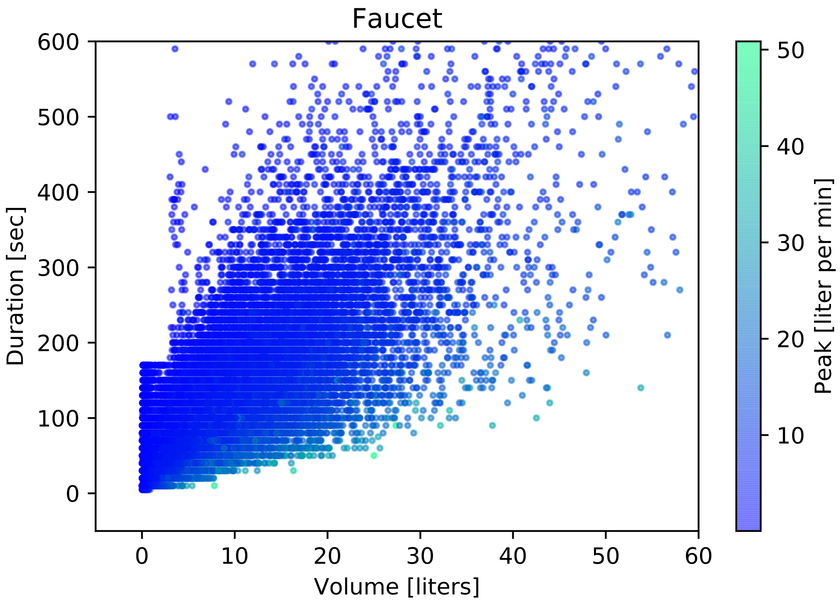
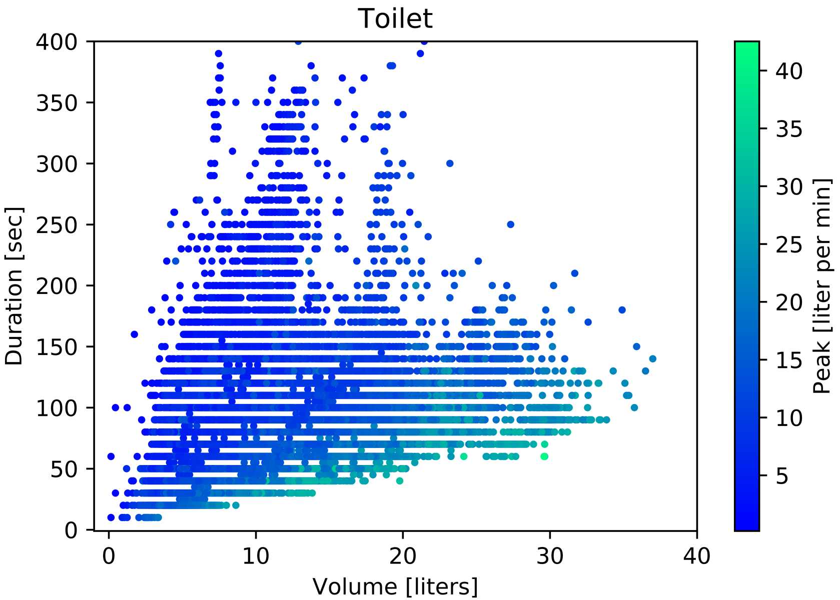
DATASET ANALYSIS

Correleation of event volume, duration, and peak



. Many events have a low peak. This might indicate the usage of faucet aerators



. Events with low volume, low peak and long duration can probably be attributed to high-efficiency toilets (built after 1992)

. Green points can be categorized as ‘old’ toilets, as they have higher peak values.

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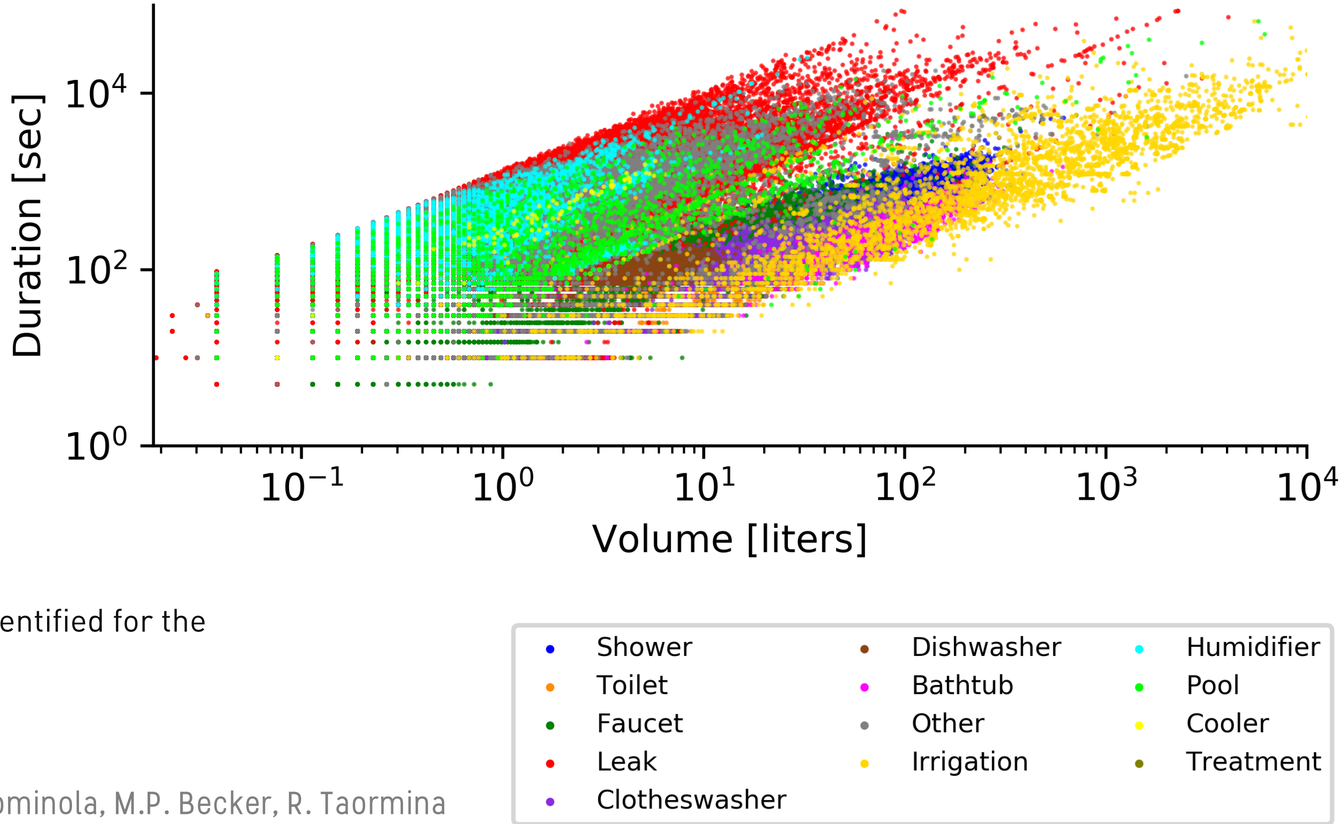
DATASET ANALYSIS

Correleation of event volume and duration for different end uses



Volume-duration ranges can be identified for the different end uses.

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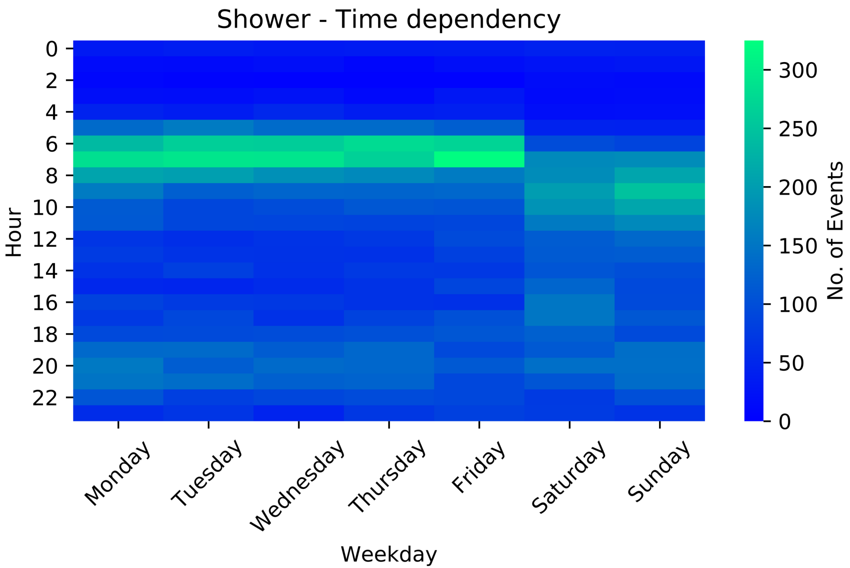
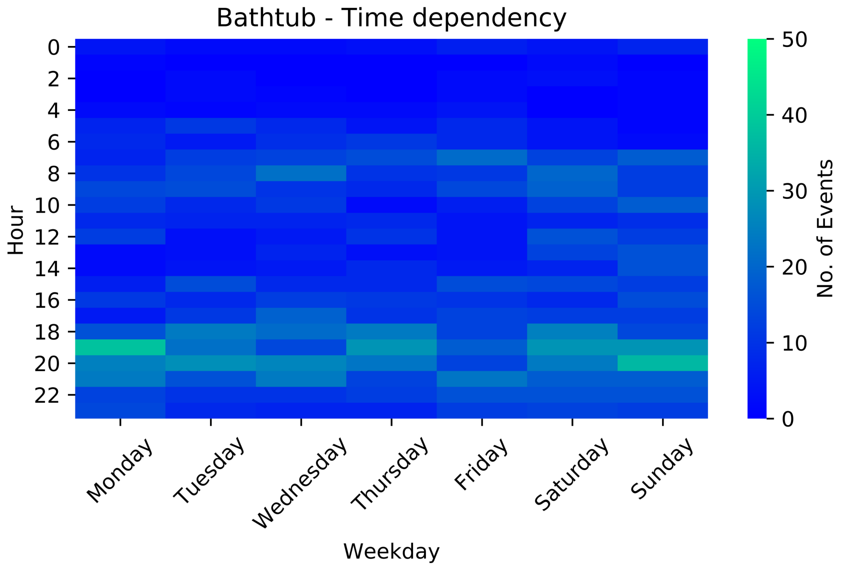
DATASET ANALYSIS

Time-of-day and day-of-week analysis





. **Weekday routine**: most **shower events** are visible in the early morning. Working hours clearly visible

. **Weekend routine**: routines are less regular and delayed start time with respect to weekdays is observed.

. Most **bathtub events** are observed during the late afternoon and evening

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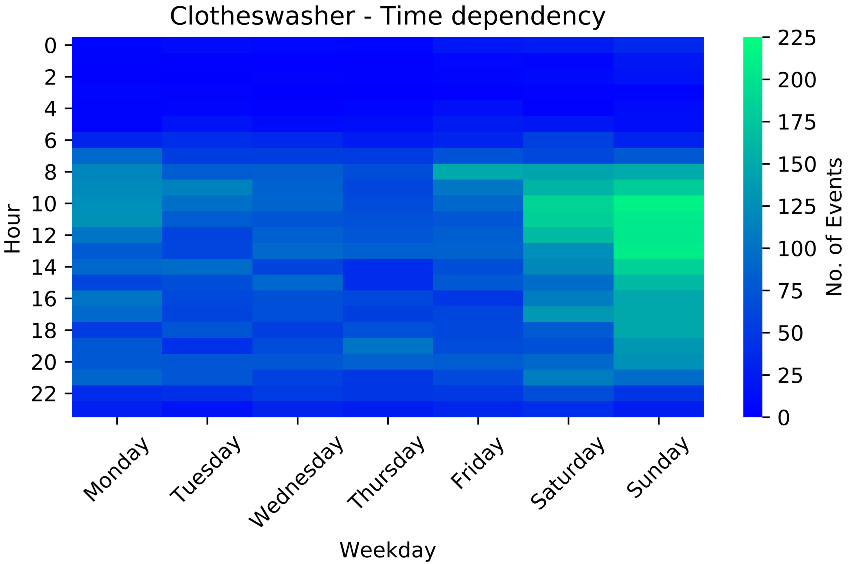
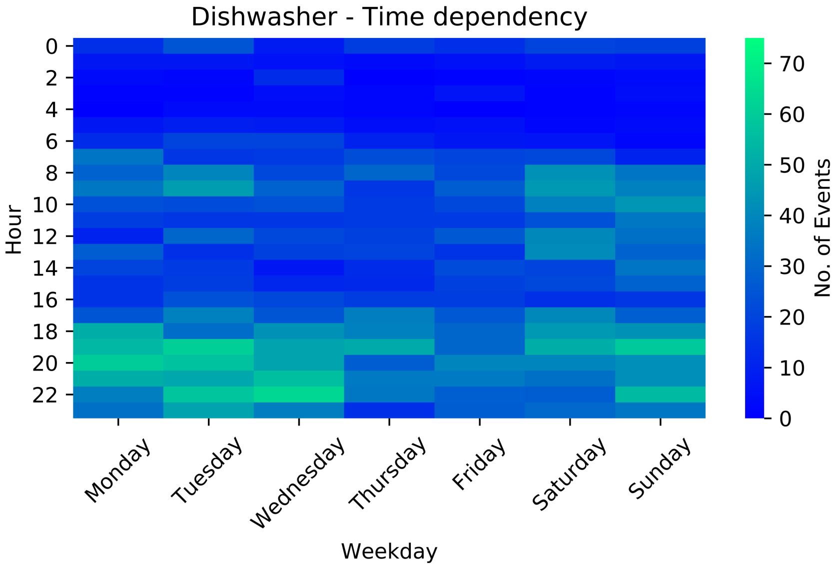
DATASET ANALYSIS

Time-of-day and day-of-week analysis





. Most **clothes washing events** are observed during the weekend

. Most **dishwasher events** are observed during the late afternoon and evening

. Routines appear to be more regular in specific days (e.g., Mon-Wed and Sun) and can happen late at night (programmable device).

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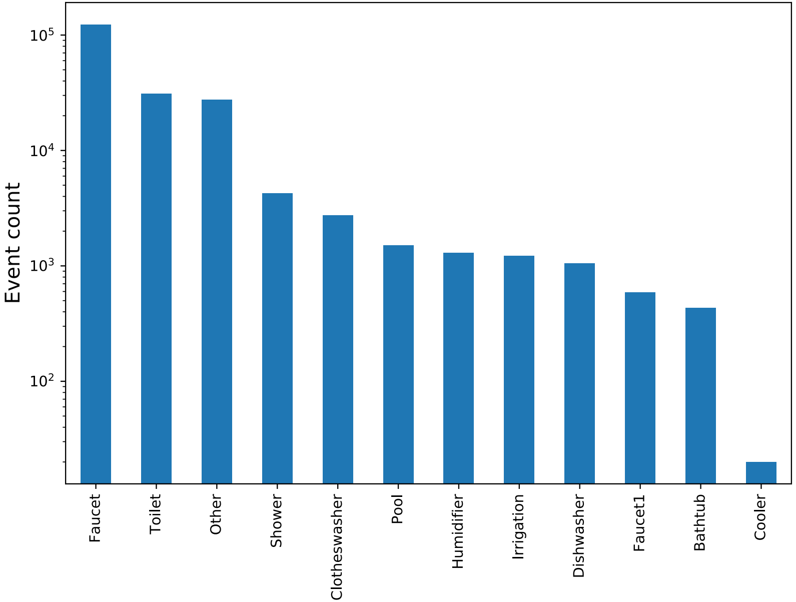
Random forest classifier - PRELIMINARY RESULTS



	Faucet	Toilet	Other	Shower	Clotheswasher	Pool	Humidifier	Irrigation	Dishwasher	Faucet1	Bathtub	Cooler
Faucet	96%	3%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Toilet	11%	89%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Other	8%	0%	91%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Shower	10%	3%	0%	83%	4%	0%	0%	0%	0%	0%	0%	0%
Clotheswasher	24%	27%	1%	11%	36%	0%	0%	0%	0%	0%	1%	0%
Pool	9%	0%	32%	0%	0%	58%	0%	1%	0%	0%	0%	0%
Humidifier	9%	0%	81%	0%	0%	0%	10%	0%	0%	0%	0%	0%
Irrigation	7%	8%	5%	9%	7%	1%	0%	60%	0%	0%	3%	0%
Dishwasher	87%	4%	0%	0%	0%	0%	0%	0%	9%	0%	0%	0%
Faucet1	46%	14%	37%	2%	0%	0%	1%	0%	0%	0%	0%	0%
Bathtub	1%	15%	0%	12%	43%	0%	0%	8%	0%	0%	21%	0%
Cooler	0%	0%	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%

Predicted label

. Most categories contributing to the largest amount of events can be accurately identified (see **confusion matrix** on the right).

. However, classes are very imbalanced (see plot on the left)

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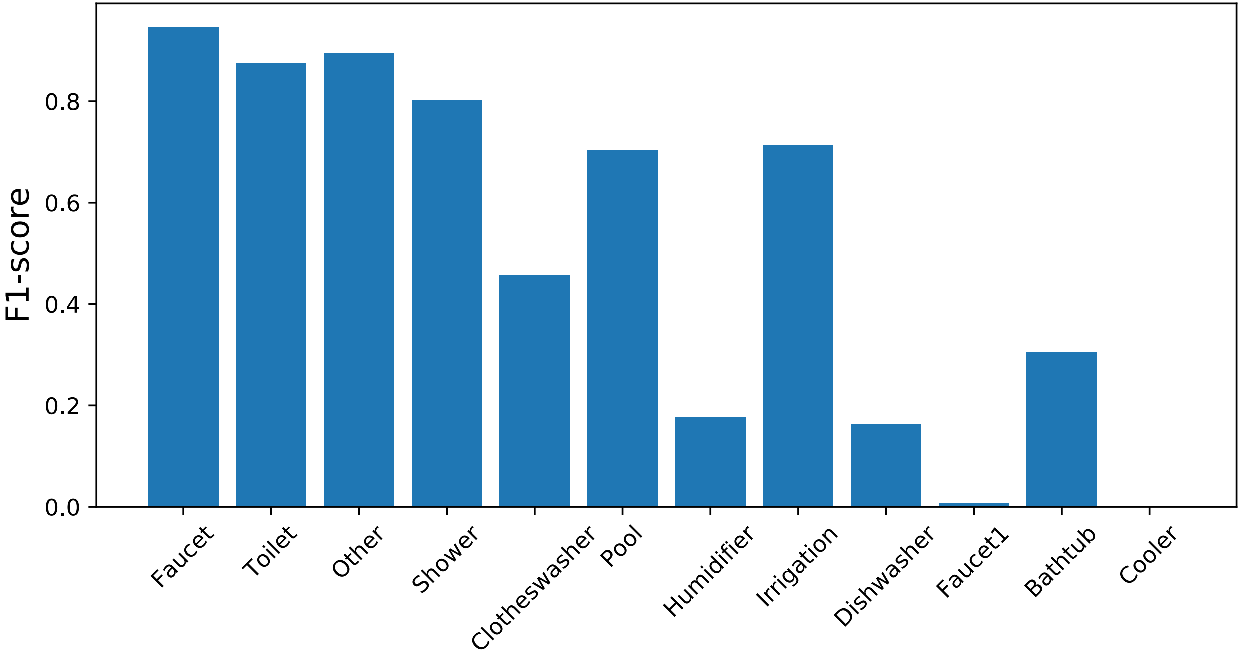
Random forest classifier - PRELIMINARY RESULTS



Classification results are more accurate for:

. End uses contributing the **largest number of events** (e.g., faucet, toilet)

. End uses with **long durations and/or large volumes** per event (e.g., pool, irrigation).

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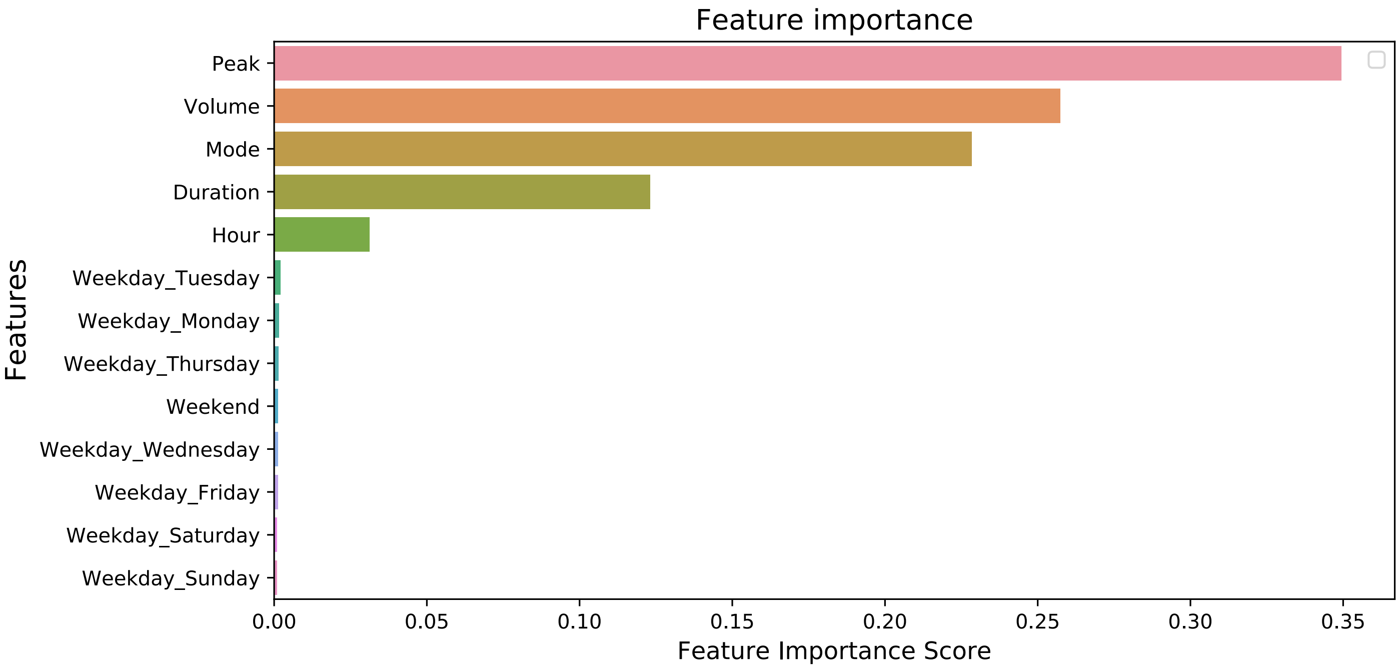
Random forest classifier - PRELIMINARY RESULTS



Event **peak, volume, mode, duration, and hour of day** emerged as the most relevant features for training our Random forest classifier. This is confirmed by other studies in the literature. However, we expect this feature set to potentially change when other methods or more balanced categories will be considered.

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NEXT STEPS

. Data processing: analysis of different subsets and **resampling** for more balanced categories.

. Extensive testing with other **machine learning classification algorithms** (e.g., LightGBM, XGBoost, ANNs, logistic regression)

. Comparative testing on **synthetic datasets** generated via STREaM (https://github.com/acominola/STREaM)

. Comparative analysis with other **real-world datasets**?

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