Benchmarking machine learning algorithms for NON-INTRUSIVE WATER MONITORING

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DEMAND MANAGEMENT STRATEGIES

- technological
- financial
- legislative
- operation and maintenance
- education

MOTIVATION & BACKGROUND

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END-USES CHARACTERIZATION

Toilet
Shower
Dishwasher
Washing machine
Garden
Swimming pool

User Modelling

Cominola et al., 2015
MOTIVATION & BACKGROUND

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

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.

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?
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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13 end use categories:

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

DATASET CHARACTERISTICS

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DATASET CHARACTERISTICS

6 water usage features:

. Event duration
. Event volume
. Event flow peak
. Mode
. Time of day
. Day of week
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.

Many events have a low peak. This might indicate the usage of faucet aerators.
Volume-duration ranges can be identified for the different end uses.
. **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.
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).
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).
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).
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.
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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