



INDRAPRASTHA INSTITUTE of  
INFORMATION TECHNOLOGY DELHI

UCLA



Imperial College  
London

UNIVERSITY OF  
Southampton

# NILMTK

An Open Source Toolkit for  
Non-intrusive Load Monitoring

# NILMTK team

Haimonti  
Dutta



Oliver  
Parson



Alex Rogers

Nipun Batra



Amarjeet Singh



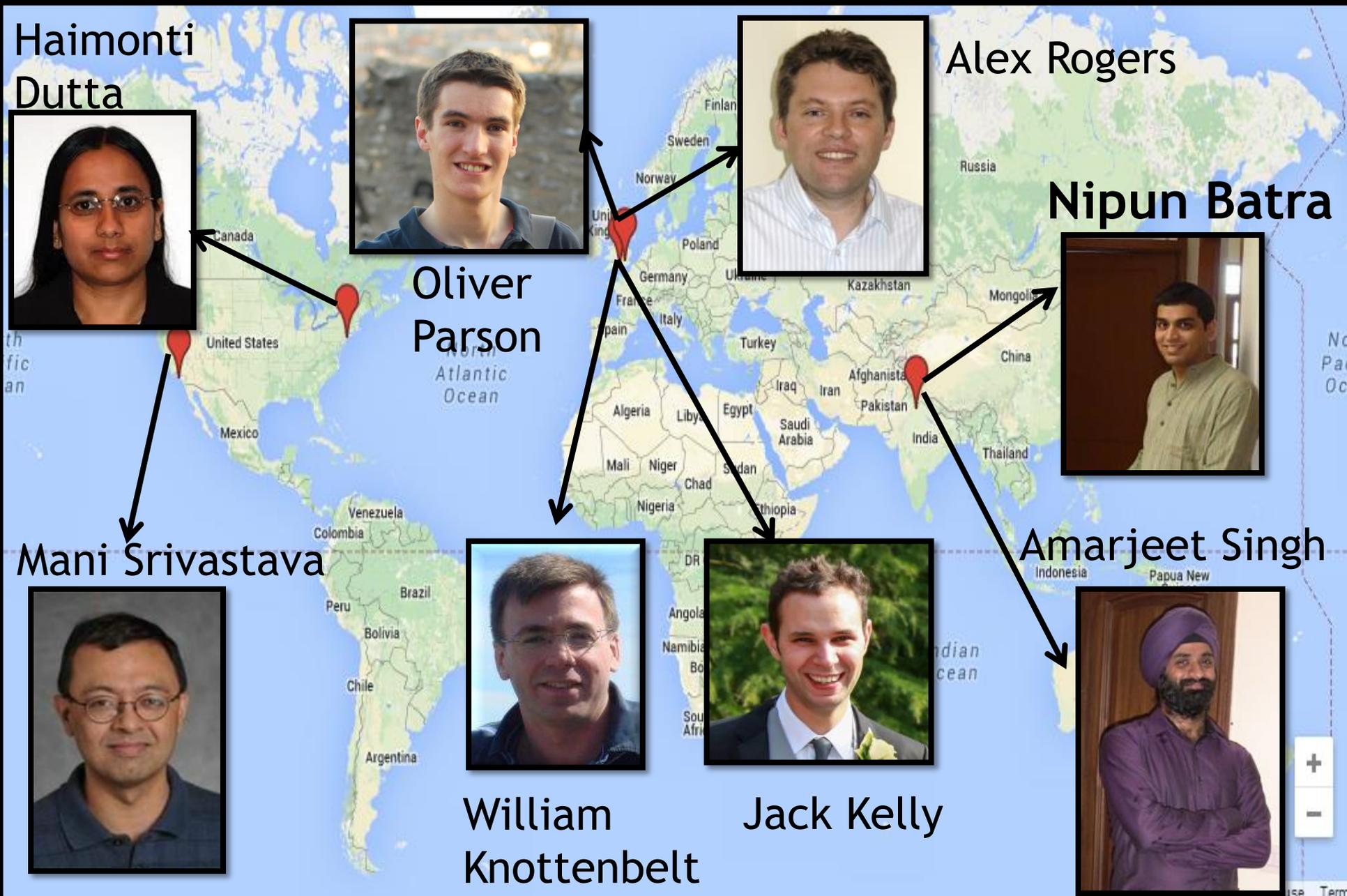
Mani Srivastava



William  
Knottenbelt

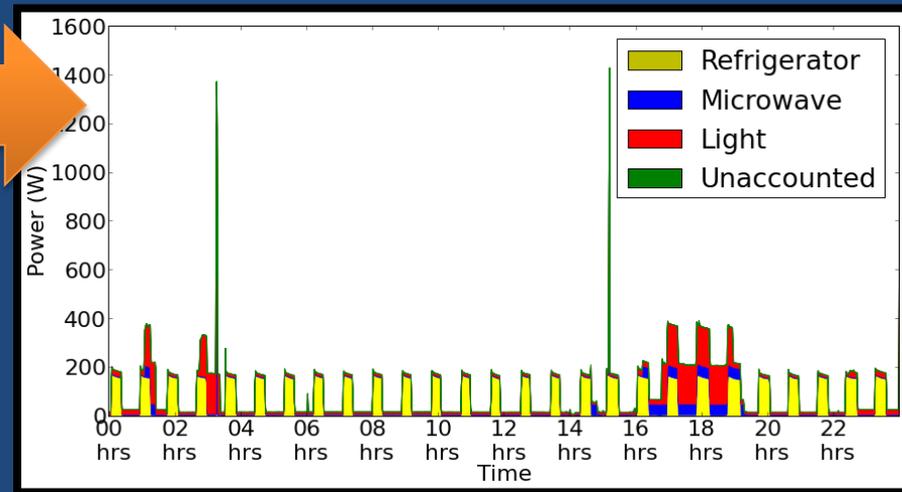
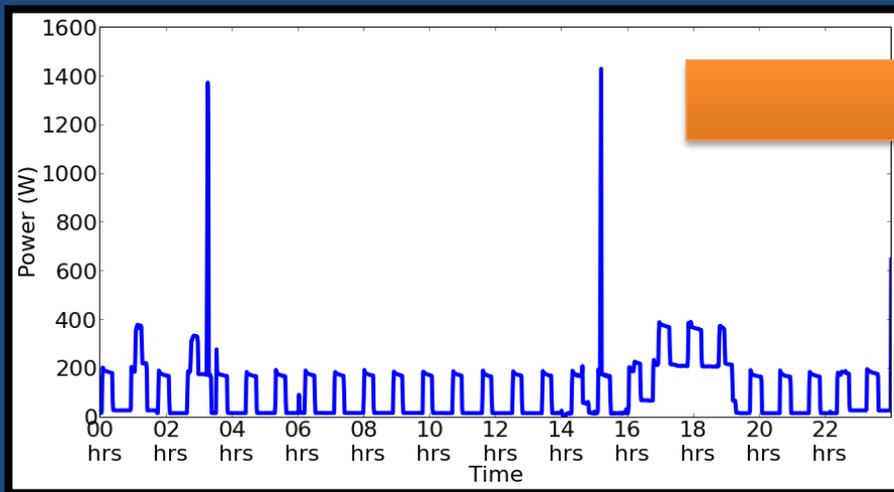


Jack Kelly



# Non-intrusive load monitoring (Energy disaggregation)

“Process of estimating the energy consumed by individual appliances given just a whole-house power meter reading”



Wait a minute! This  
sounds complicated  
Would it help?

# Jane goes to the market



Jane spends 200  
pounds on her  
purchases



Jane's husband John  
is worried with the  
expenses



He spends some time  
and looks at the  
purchase list



Do you think the  
itemized billing  
helped him?

NILM is the same, but for energy!

# Quiz time!

Identify this famous CS scientist



# Quiz time!

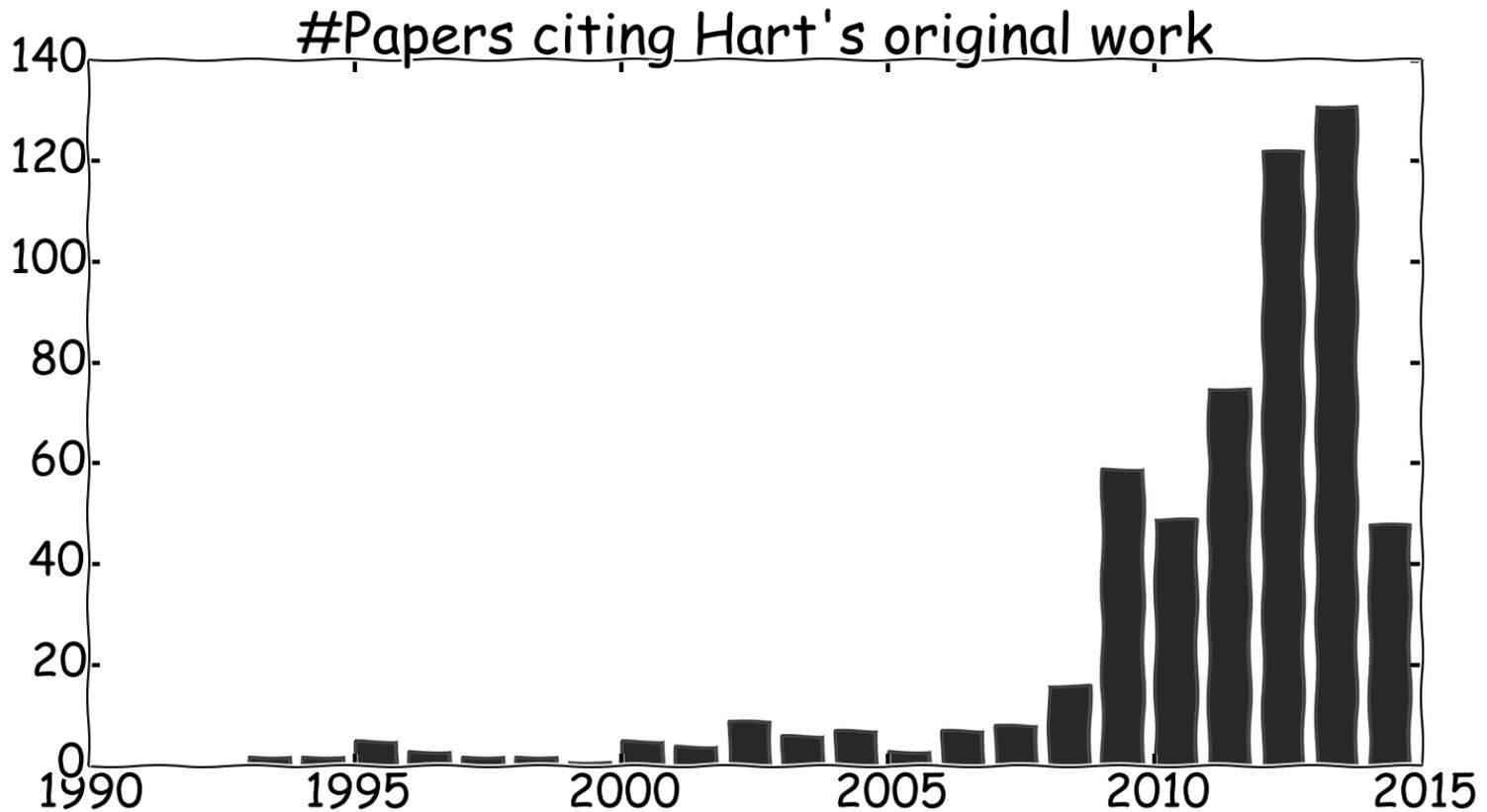
Identify this famous CS scientist



That ain't any great scientist. That's me on my first birthday in 1990...

This is not too far from the time when NILM was first discussed

# Giving credit where it is due



# NILM interest explosion

1. National smart meter rollouts
2. Reduced hardware costs
3. International meetings
  - NILM workshop 2012, 2014; EPRI NILM 2013
4. Public datasets
5. Startups

# “Data is the new oil”

- 9 NILM datasets and counting (few not specific to NILM)
- Across 6 countries (India, UK, US, Canada, EU)
- Measure aggregate and appliance level data
- Across 3 colors 😊
  - REDD
  - BLUED
  - GREEND

# The industry is interested!

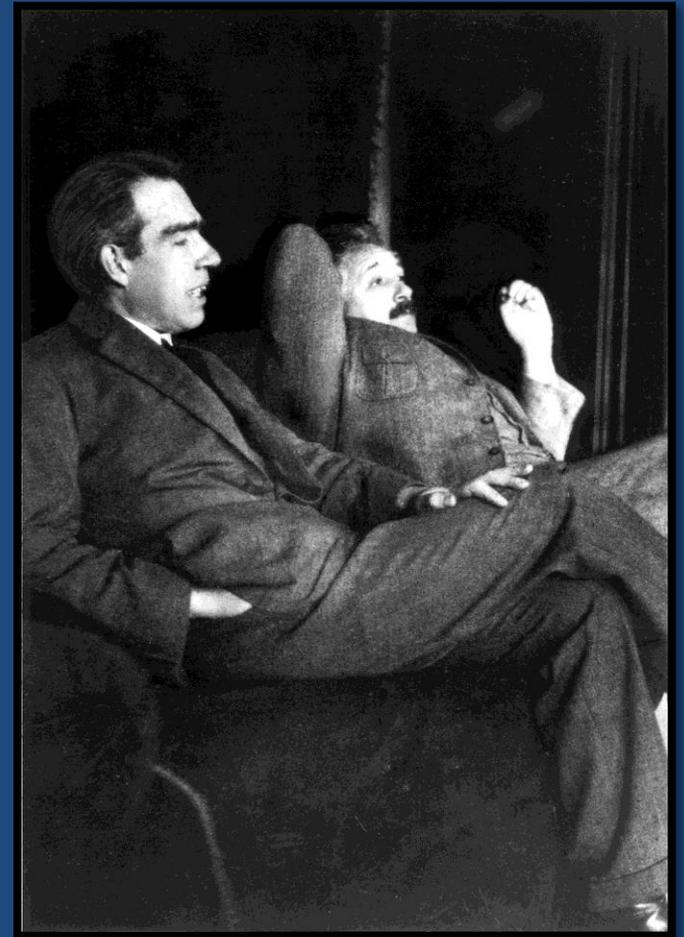


So, is everything so  
rosy?

Not quite! Else we  
won't be here

# The scientific method

“The scientific method is a body of techniques for investigating phenomena, acquiring new knowledge, or **correcting and integrating previous knowledge**” as per wiki



**3 core obstacles  
preventing comparison of  
state-of-the-art**

# 1. Hard to assess generality

- Subtle differences in aims of different data sets
- Previous contributions evaluated only on single dataset.
- Non-trivial to set up similar experimental conditions for direct comparison.



## 2. Lack of comparison against same benchmarks

- Newly proposed algorithms rarely compared against same benchmarks.
- Lack of “open source” reference algorithms → often lead to reimplementation.



# 3. “Inconsistent” disaggregation performance metrics

- Different performance metrics proposed in the past.
- Different formulae for same metric, eg. 4+ versions of “energy assigned”

$$\text{Acc} = 1 - \frac{\sum_{t=1}^T \sum_{i=1}^n |\hat{y}_t^{(i)} - y_t^{(i)}|}{2 \sum_{t=1}^T \bar{y}_t}$$

$$\sqrt{\left( \sum_{t,i} \|y_t^{(i)} - \hat{y}_t^{(i)}\|_2^2 \right) / \left( \sum_{t,i} \|y_t^{(i)}\|_2^2 \right)}$$

$$\left| \sum_t x_t^{(n)} - \sum_t \mu_{z_t^{(n)}}^{(n)} \right| / \sum_t x_t^{(n)}$$

$$MNE(n) = \frac{\sum_{t=1}^T |\theta_t^n - y_t^n|}{\sum_{t=1}^T \theta_t^n}$$

# What is NILMTK?

Open source NILM toolkit



# What does it do?

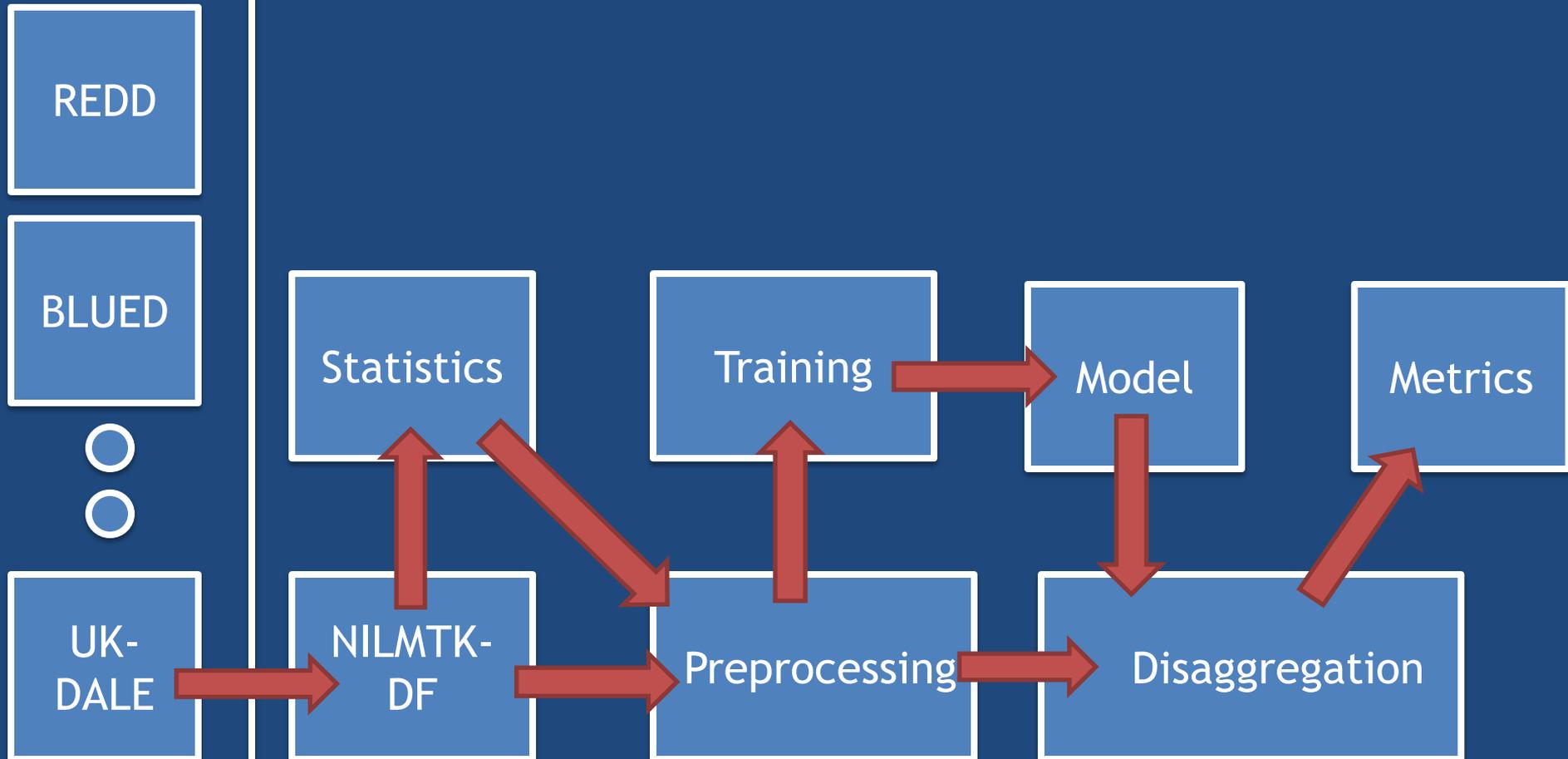
Enable easy comparative analysis of NILM algorithms across data sets.

# How does it do that?

Provides a pipeline from data sets to metrics to lower the entry barrier for researchers.

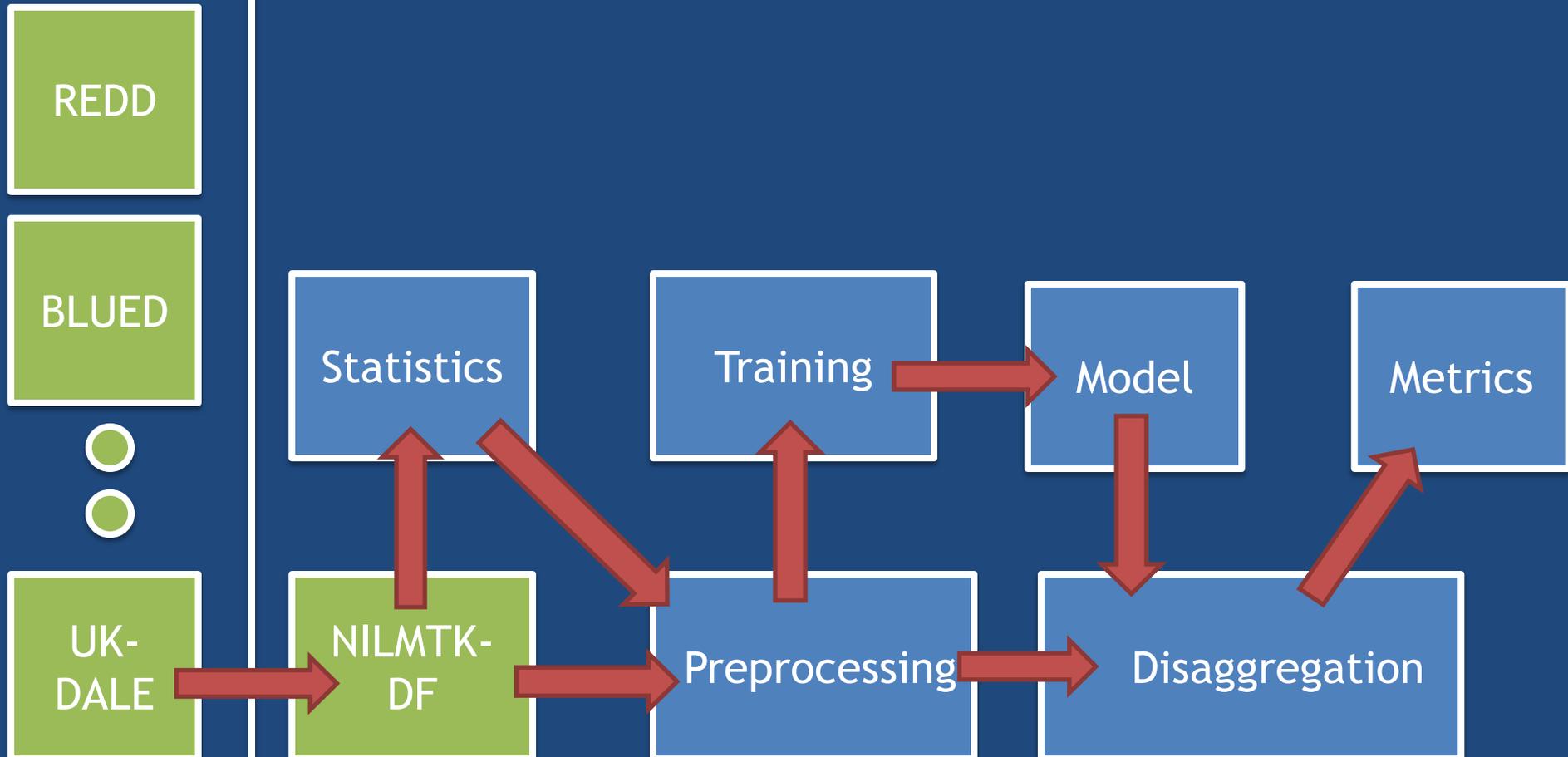
# NILMTK pipeline

Data interface



# Data Format

Data interface



# Data Format

- We propose NILMTK-DF: a common data format.
- Provide importers for 6 datasets: REDD, SMART\*, Pecan street, iAWE, AMPds, UK-DALE
- Both flat file and efficient binary storage format

# The fun of data!



**Big Data Borat**  
@BigDataBorat



+ Follow

In Data Science, 80% of time spent prepare data, 20% of time spent complain about need for prepare data.

↩ Reply ↻ Retweet ★ Favorite ⋮ More

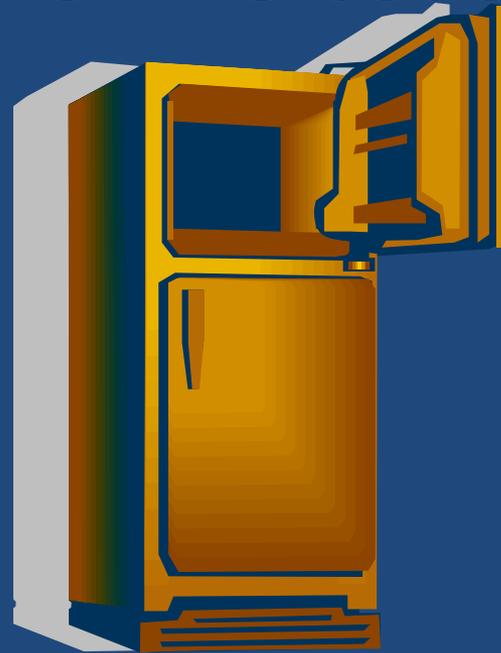
RETWEETS  
316

FAVORITES  
90



6:47 PM - 26 Feb 2013

# Standardizing nomenclature



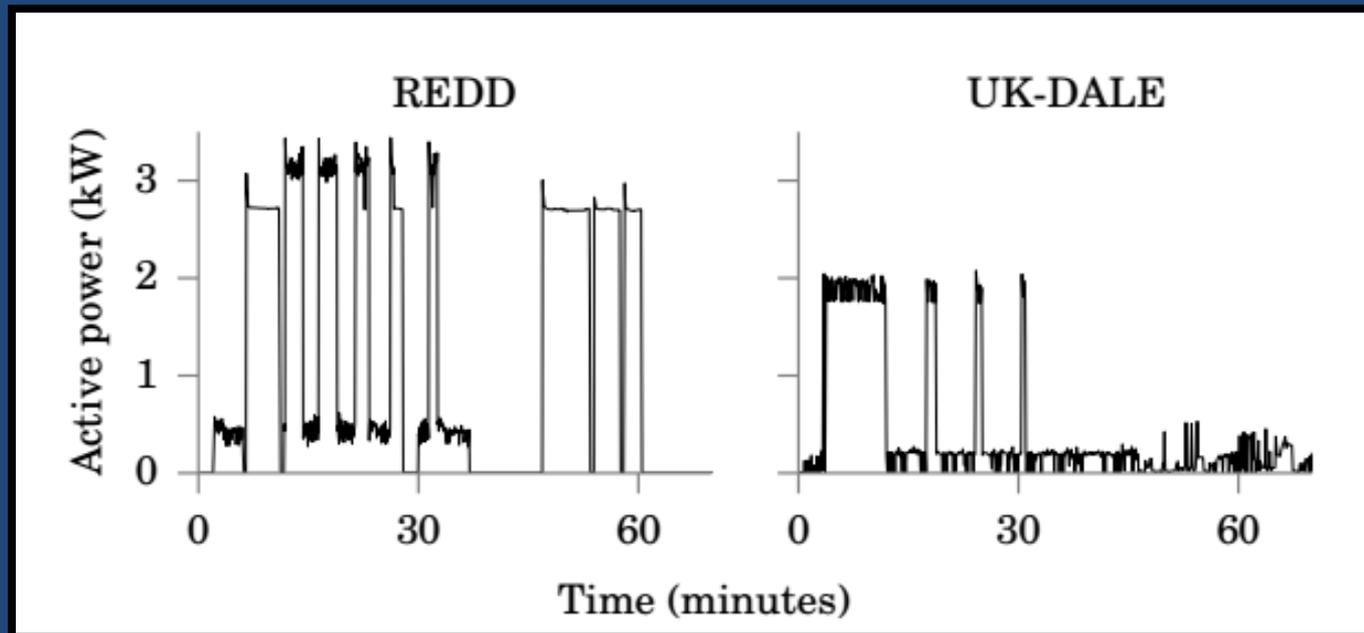
# Metadata

- Geographic coordinates
- Type of appliance- hot, cold, dry?
- Metering hierarchy
- Parameters measured

# Standard nomenclature + Metadata + Datasets =



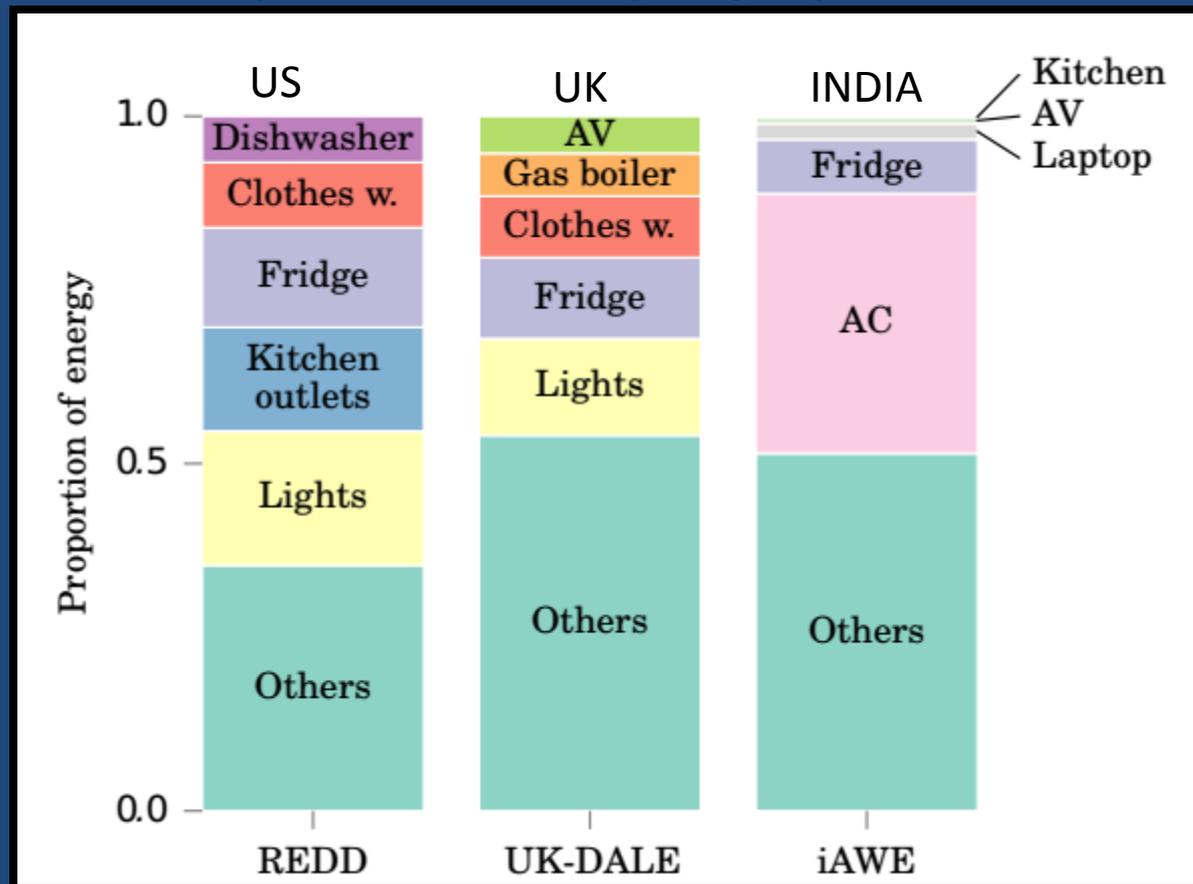
Comparing power draw of washing machines  
across US (REDD) and UK (UK-DALE)



# Standard nomenclature + Metadata + Datasets =

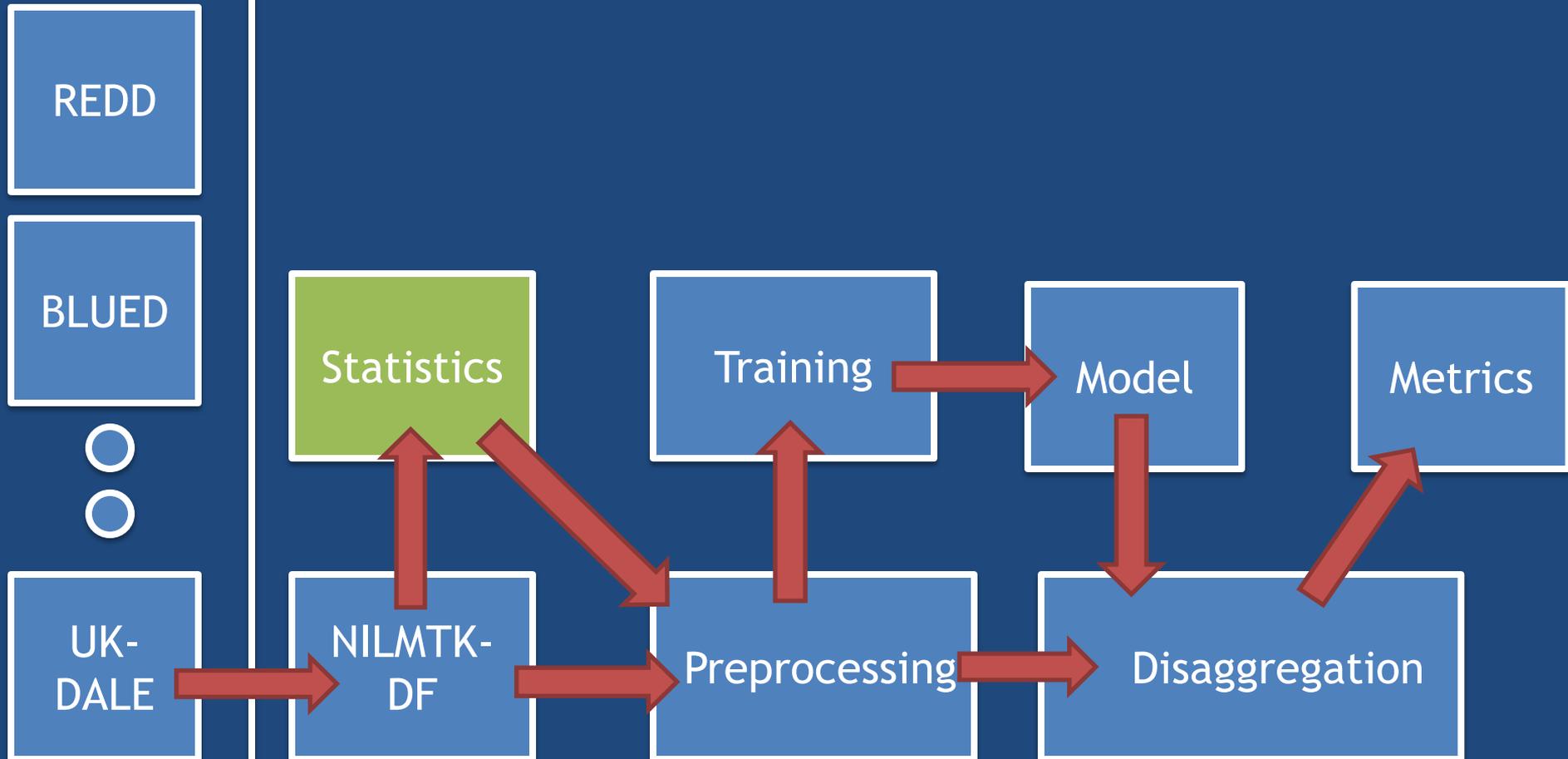


Top 5 appliance according to energy consumption across geographies



# NILMTK pipeline

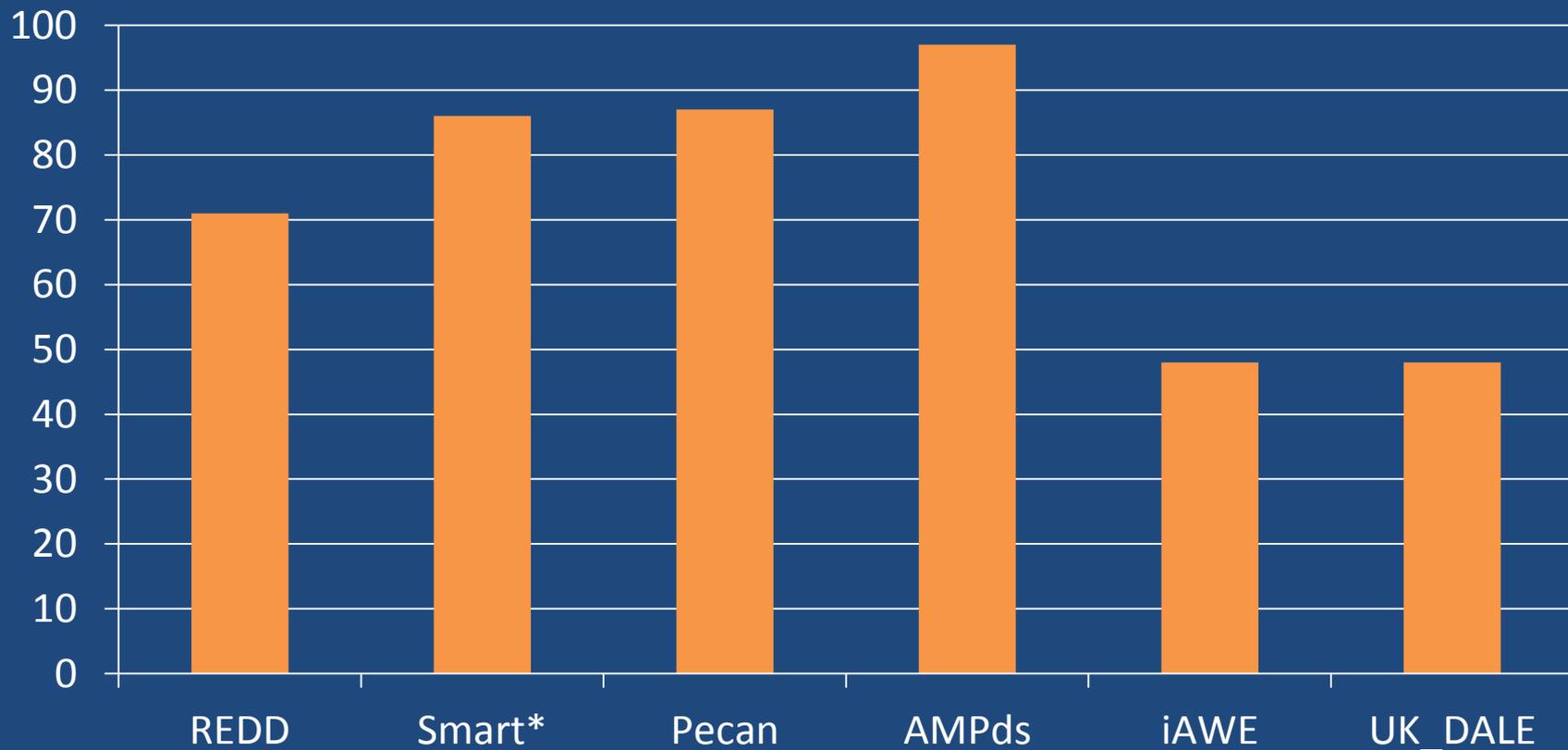
Data interface



# Statistics

- Energy submetered: Sum of energy of all appliance/Energy at mains level
- More energy submetered → More ground truth

% energy submetered

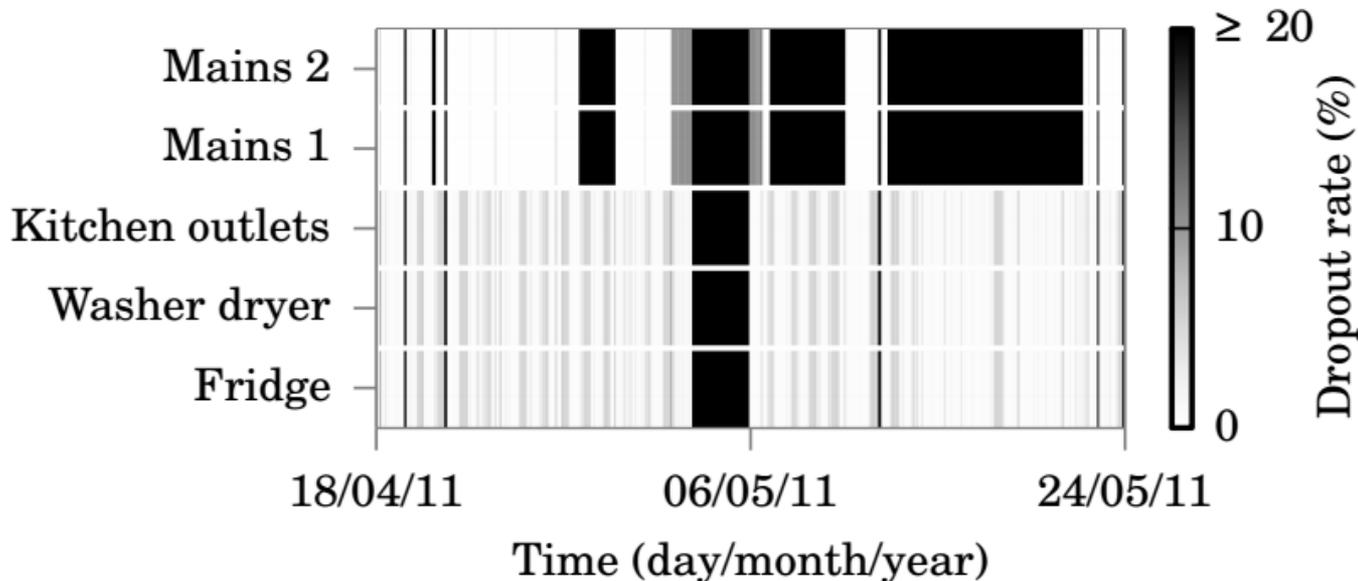


# Statistics

- Appliance usage patterns
- Correlations with weather
- Appliance power demands

# Diagnostics

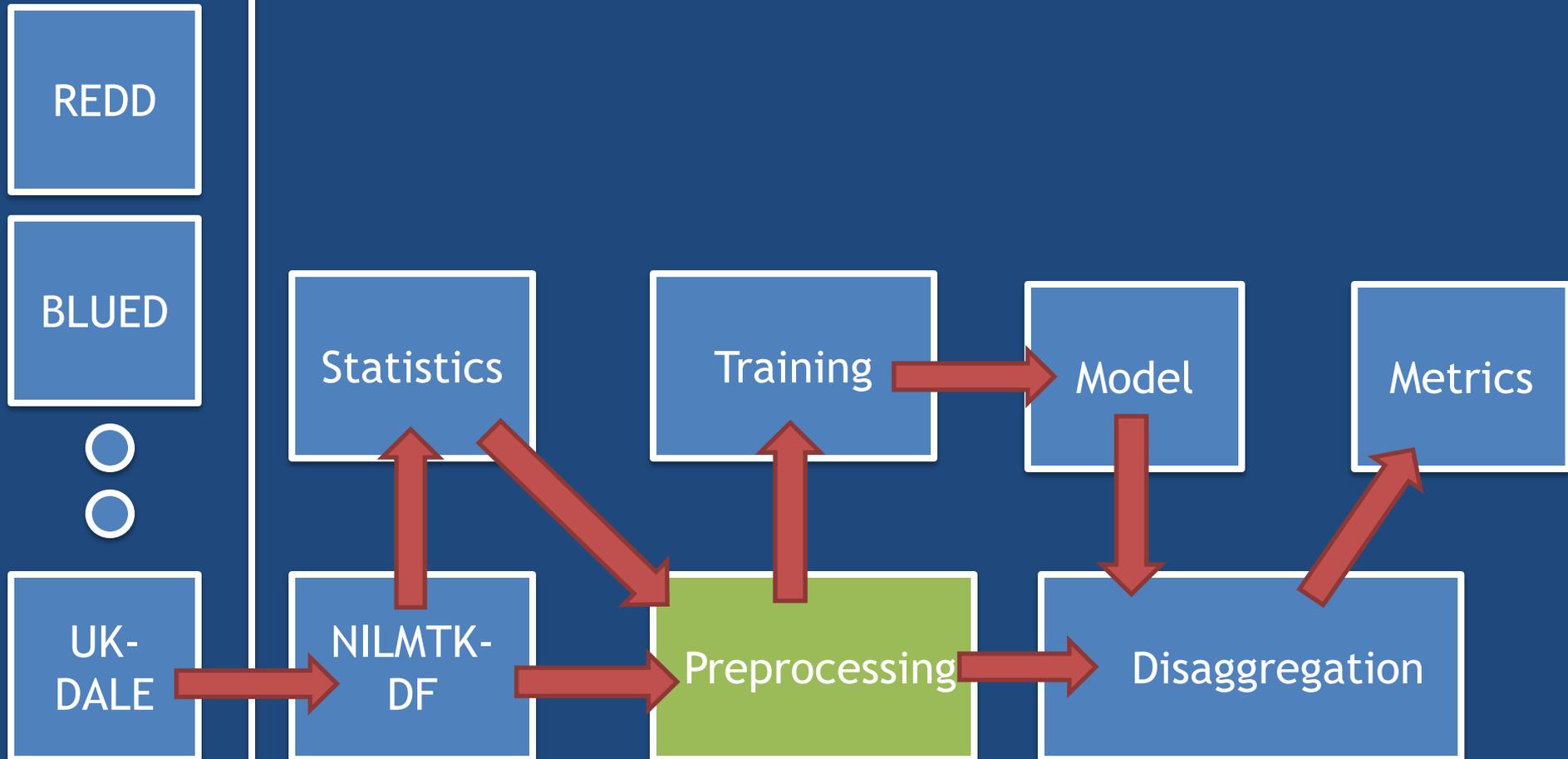
- Every data set has problems ☹️ NILMTK provides diagnostic functions for common problems.
- %Lost samples (per interval and whole), uptime



% lost samples in house 1 of REDD dataset

# Preprocessing

Data interface

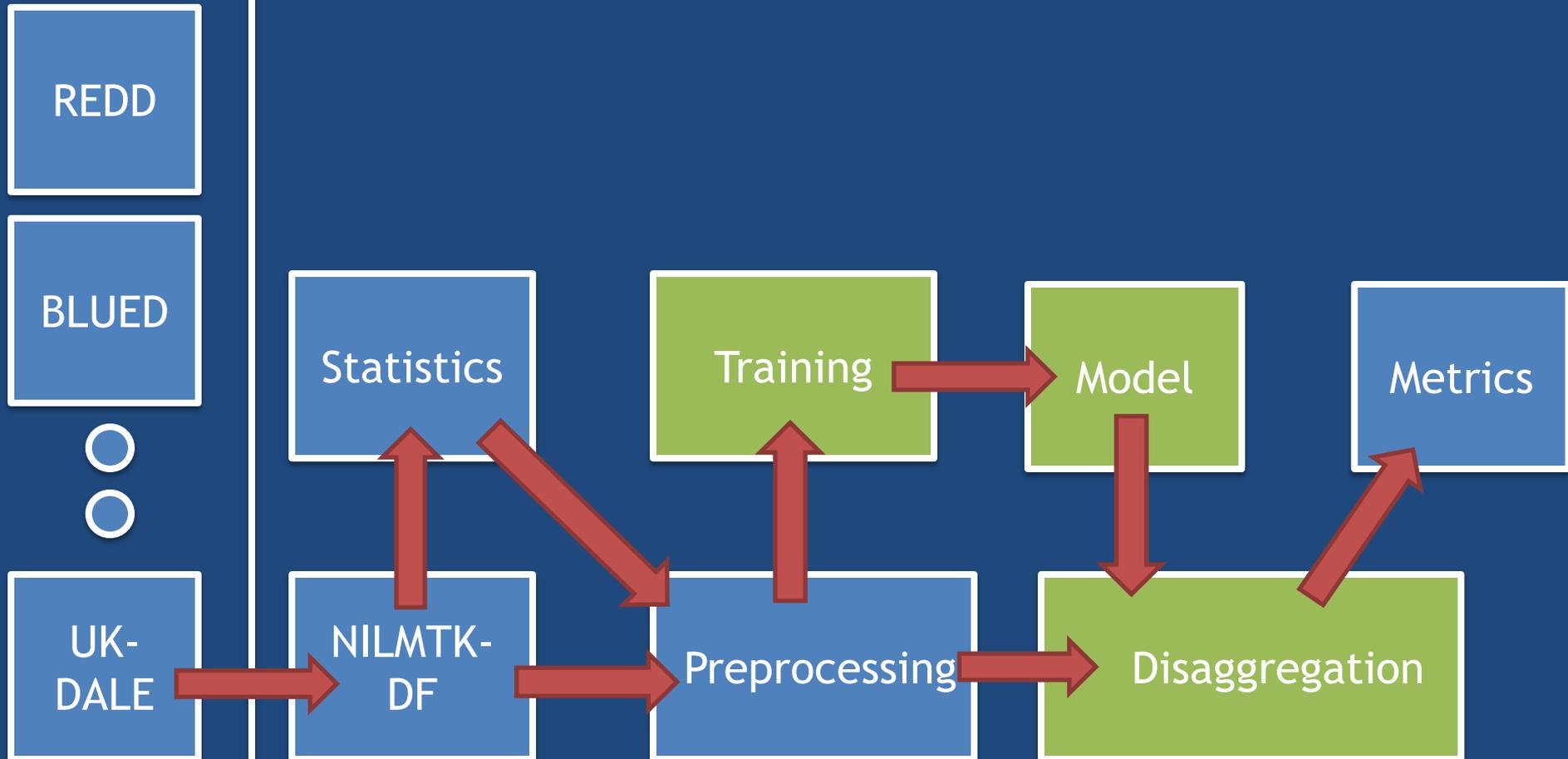


# Preprocessing

- Correct common problems (as per diagnosis).
- Other standard NILM preprocessors:
  - Interpolating, filtering implausible
  - Downsample to lower frequency
  - Select Top-k-appliances by energy consumption

# Heart of NILMTK

Data interface



# Training

- NILMTK provides two benchmark algorithms
  - Combinatorial optimization (CO)  
[Proposed by Hart]
  - Factorial hidden Markov model (FHMM)  
[More recent, more complex]

# Model

- Beyond the usual train and disaggregate, NILMTK allows importing and exporting learnt models
- Allows NILM to be deployed in “real world settings”
- Action speaks louder than words!! Demo follows!

# Disaggregate!

- Quite a bit of work before we disaggregate
- We performed
  - CO and FHMM based disaggregation across first home of each dataset
  - Detailed disaggregation analysis across the home in iAWE (dataset from India)



# Disaggregation across multiple datasets

- CO as good as FHMM across iAWE, UKPD, Pecan datasets
  - Space heating contributes 60% in Pecan and 35% in iAWE. Both approaches able to detect with fair ease



And I thought that CO was really outdated...

# Disaggregation across multiple datasets

- FHMM outperforms CO across REDD, Smart\*, AMPds
  - This is expected as FHMM models time variations.
- CO exponentially quicker than FHMM



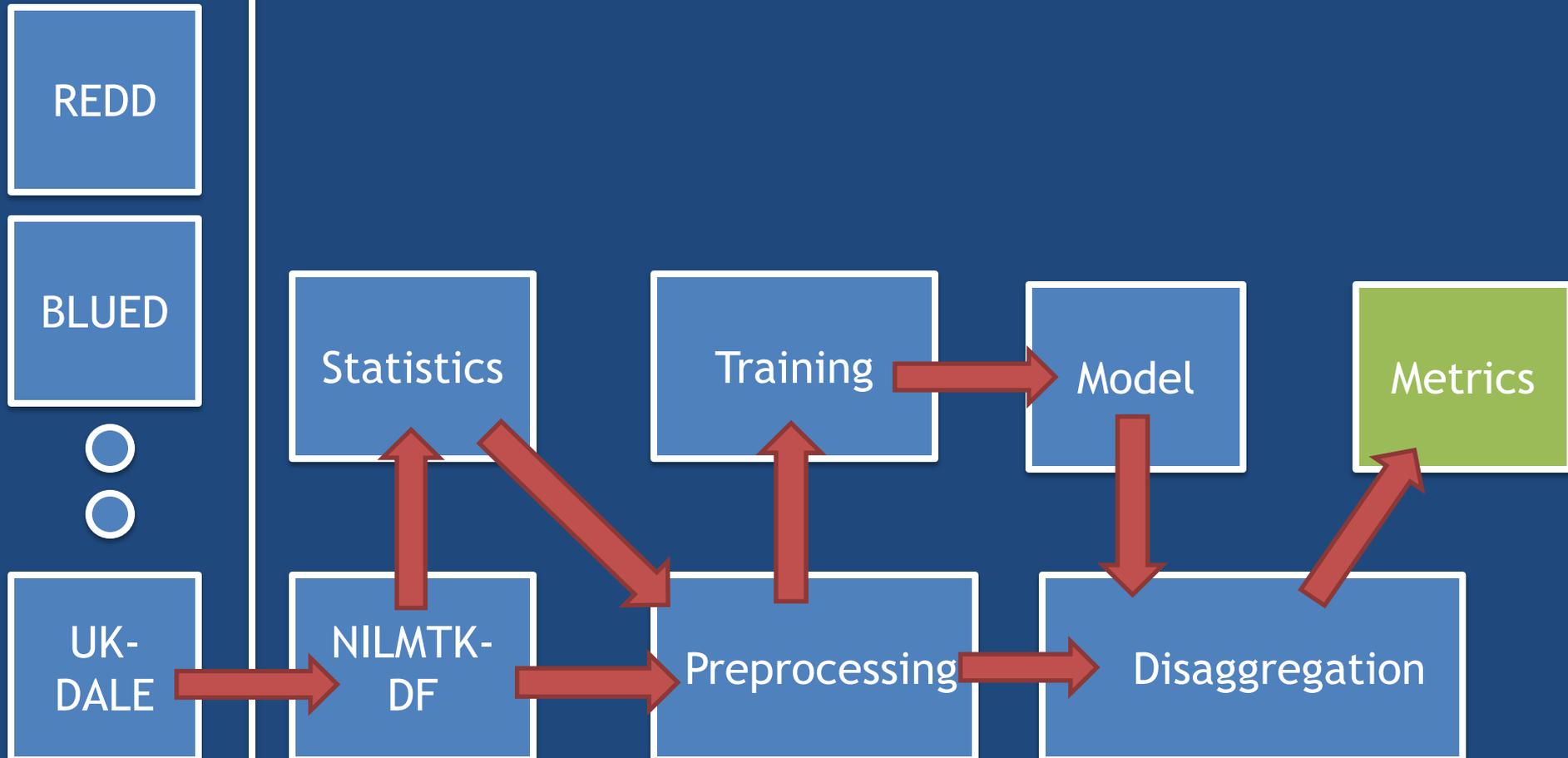
# Detailed disaggregation in iAWE dataset (India)

- CO and FHMM perform similar
- Appliances such as air conditioners way easier to disaggregate
- Complex appliances (laptops and washing machines) - not so good 😞



# NILMTK pipeline

Data interface



# Metrics

- NILMTK provides:
  - General machine learning metrics
    - Precision, Recall, F-score
  - Specialized metrics for NILM
    - Error in total energy assigned, RMS error in assigned power,..
  - Both event based and total power based NILM metrics.

# Demo time!!

# Conclusions

## Three core challenges in NILM research

1. Hard to address generality
2. Lack of comparison against same benchmarks
3. Inconsistent disaggregation performance metrics

## How NILMTK addresses these challenges

1. Standard input and output formats (Addresses #1)
2. Parsers for 6 NILM data sets (Addresses #1, #2)
3. Two benchmark NILM algorithms (Addresses #1, #2)
4. Statistics, diagnostics and preprocessing (Addresses #1, #2)
5. Metrics for different NILM use cases (Addresses #1)

# Backup

# Combinatorial optimization

- Seeks to find the optimal combination of appliances' power draw to minimize residual energy.
- Similar to subset-sum problem and thus NP-complete 😞
- Power draw is not related in time

# Combinatorial optimization

Appliance	Off power	On power
Air conditioner (AC)	0	2000
Refrigerator	0	200

If total power observed = 210  $\rightarrow$  AC is OFF and Refrigerator is ON

# Combinatorial optimization

Appliance	Off power	On power
Air conditioner (AC)	0	2000
Refrigerator	0	200

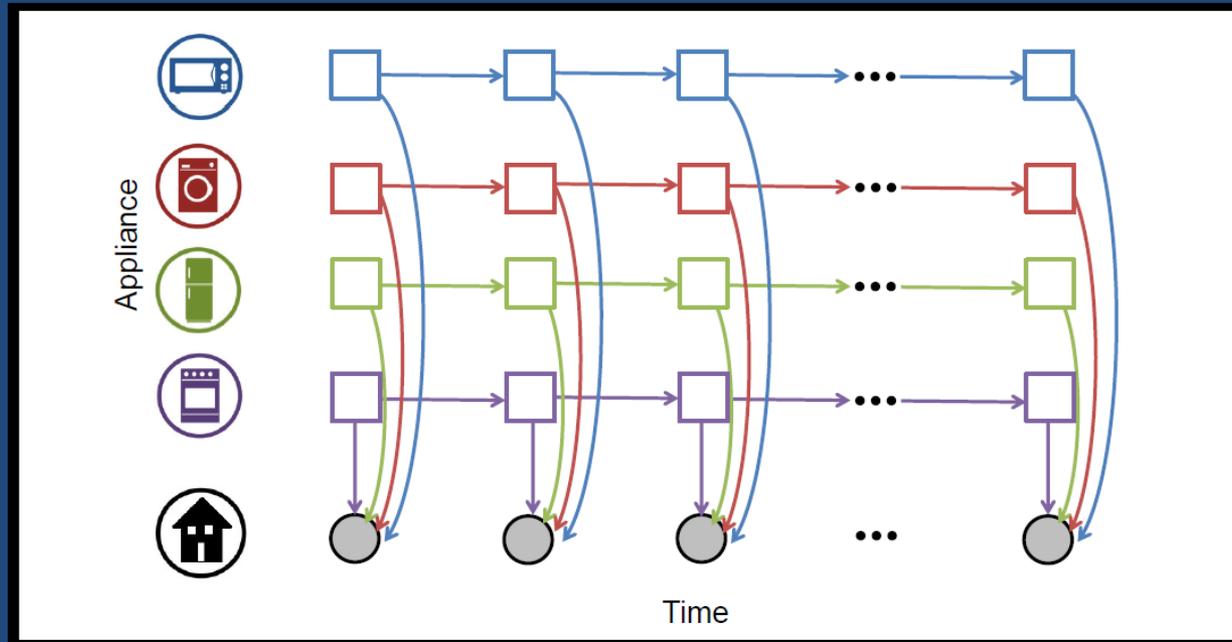
If total power observed = 2000  $\rightarrow$  AC is ON and Refrigerator is OFF

# Combinatorial optimization

Appliance	Off power	On power
Air conditioner (AC)	0	2000
Refrigerator	0	200

If total power observed = 2230  $\rightarrow$  AC is ON and Refrigerator is ON

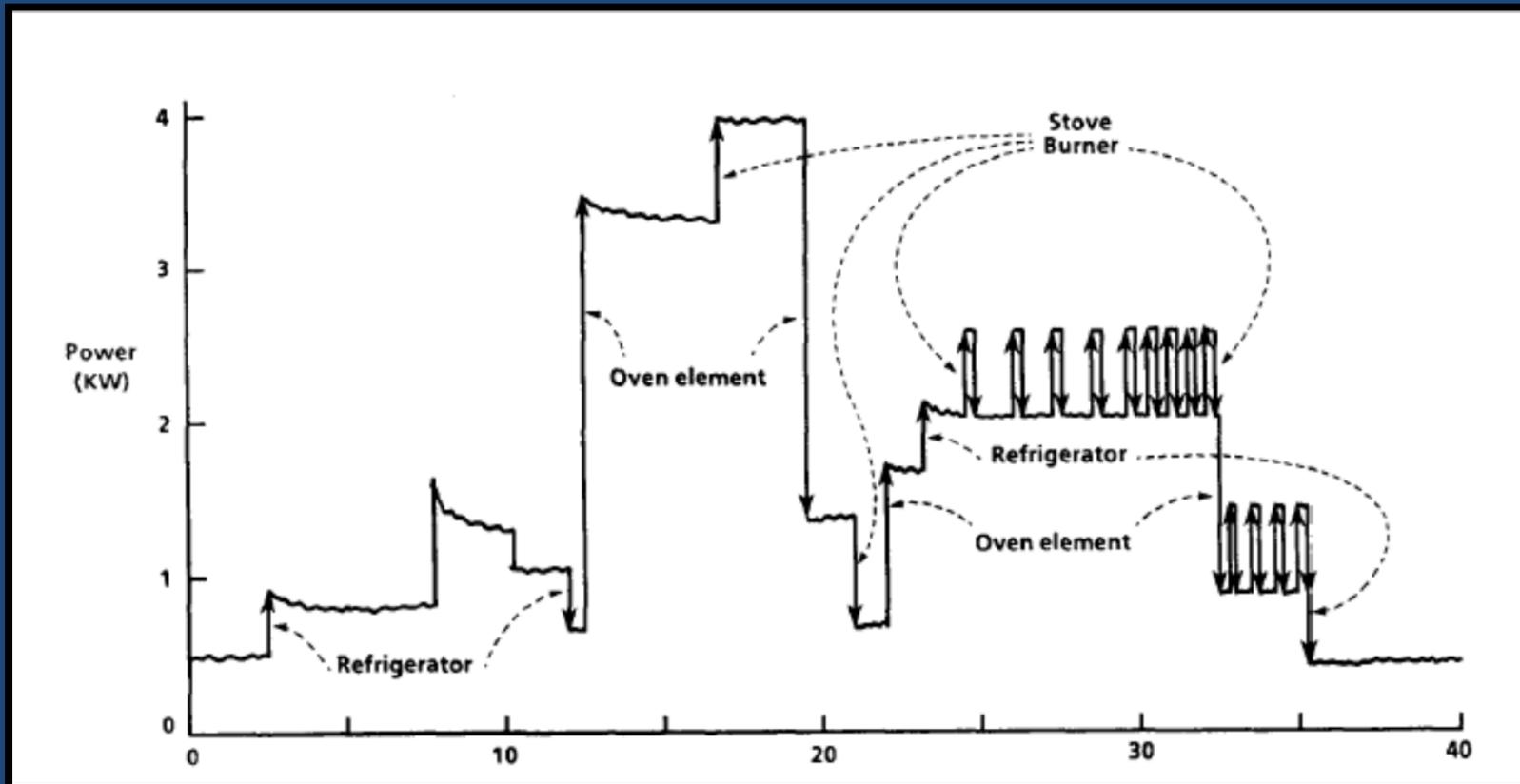
# FHMM



- Each appliance modeled as HMM
  - Power draw related in time → If TV is on right now, likely to be on next second.
- Exact inference scales worse than CO

# A bit of history

Seminal work on NILM done at MIT dates back to early 1980s - A good 6-7 years before I was born!



# Field progress

What happened here?

# Papers citing the seminal work per year

