

Data Driven Smartphone Energy Level Prediction

- Five centuries in the life of BlackBerry users

**Earl Oliver, Ph.D. Candidate
University of Waterloo**

Take-aways

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- ✦ Built a comprehensive dataset that contains over **five centuries** of user-interaction and energy consumption behaviour from over **13500** BlackBerry users.

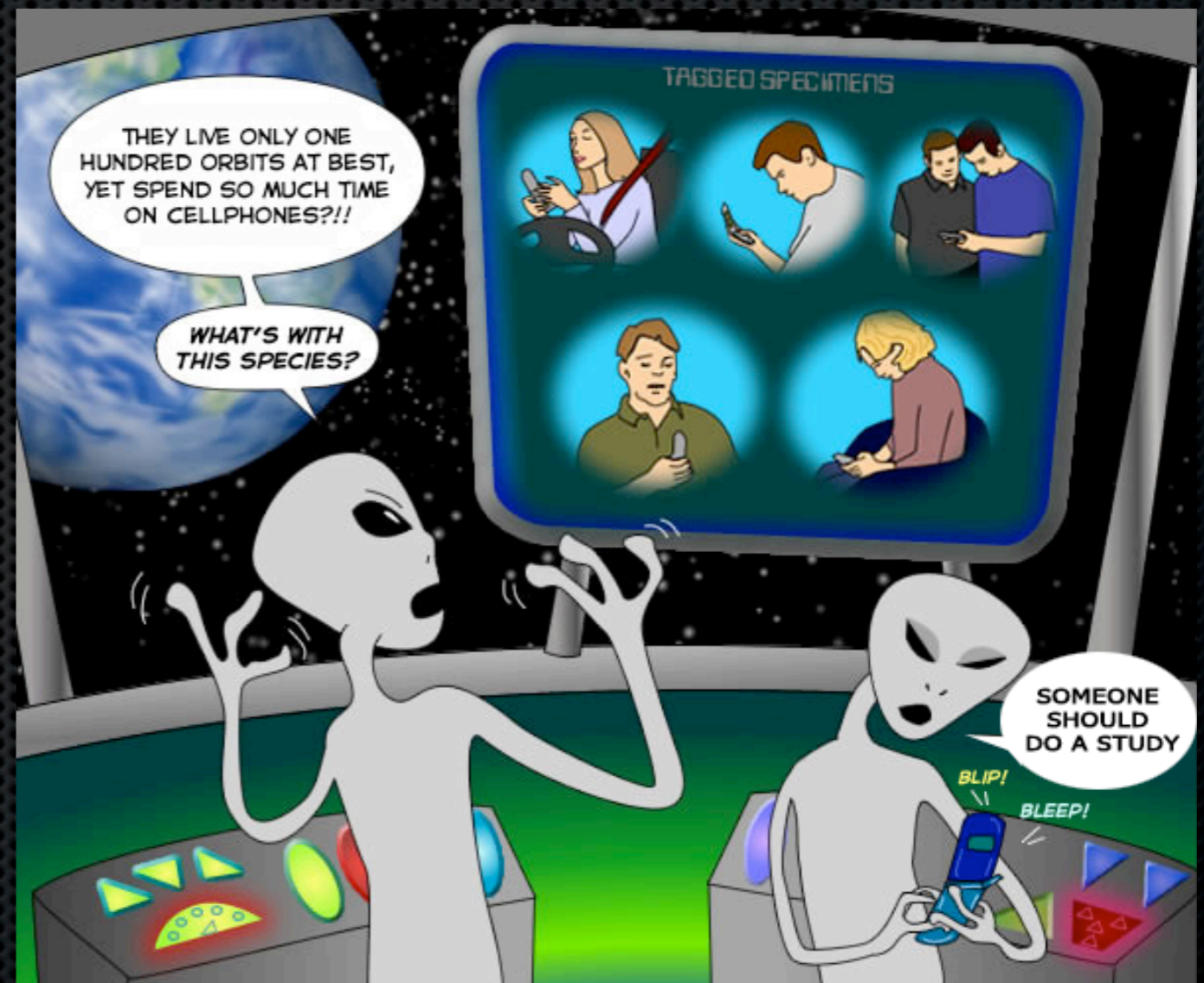
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- ✦ Demonstrate that clustering users by energy consumption characteristics can improve battery level prediction by **~54%** over long durations.

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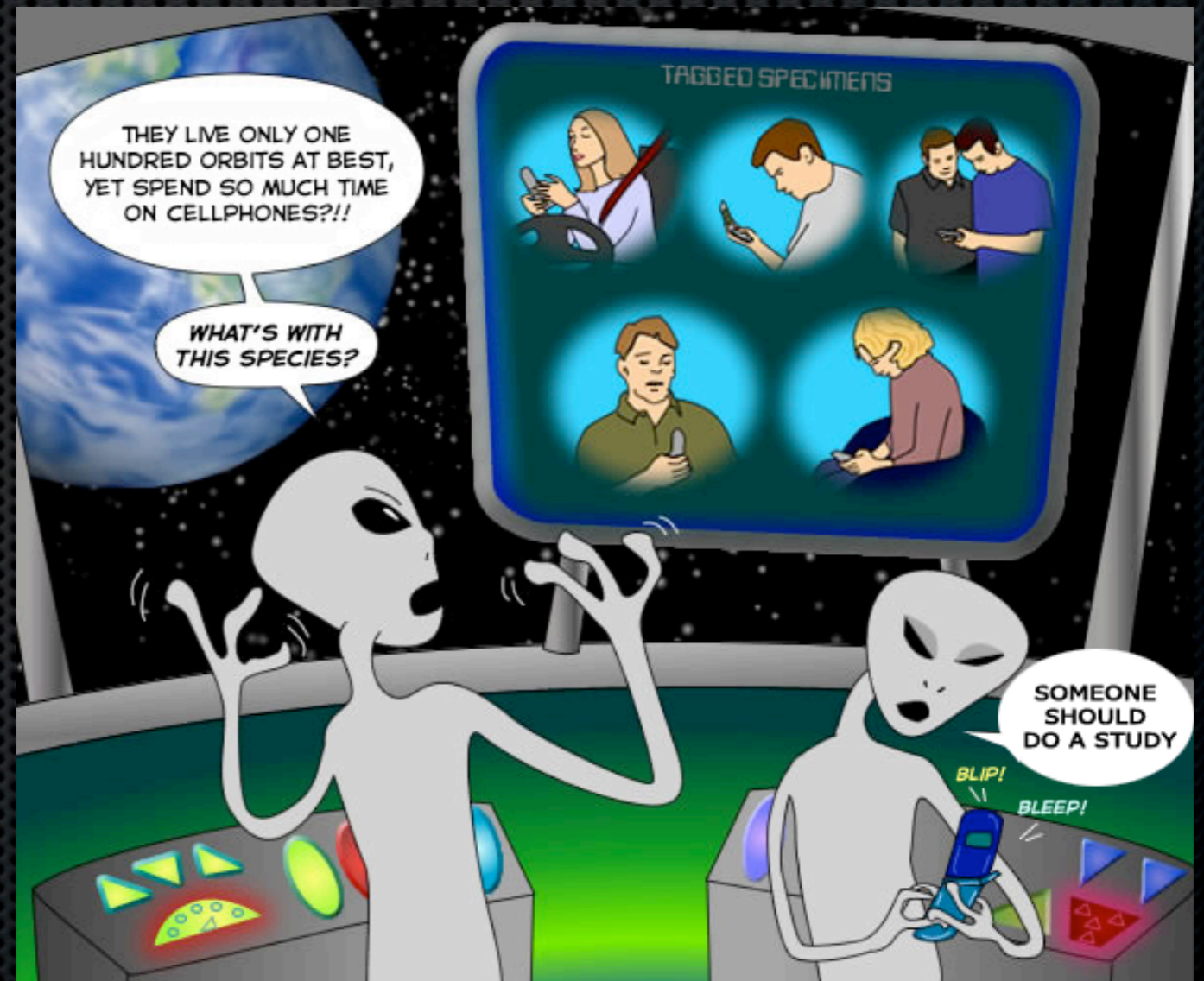
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- ✦ Demonstrate that clustering users by energy consumption characteristics can improve battery level prediction by **~54%** over long durations.
- ✦ Constructed the ***App-Predict*** tool to simulate the successful execution rate of energy intensive mobile applications.

Outline



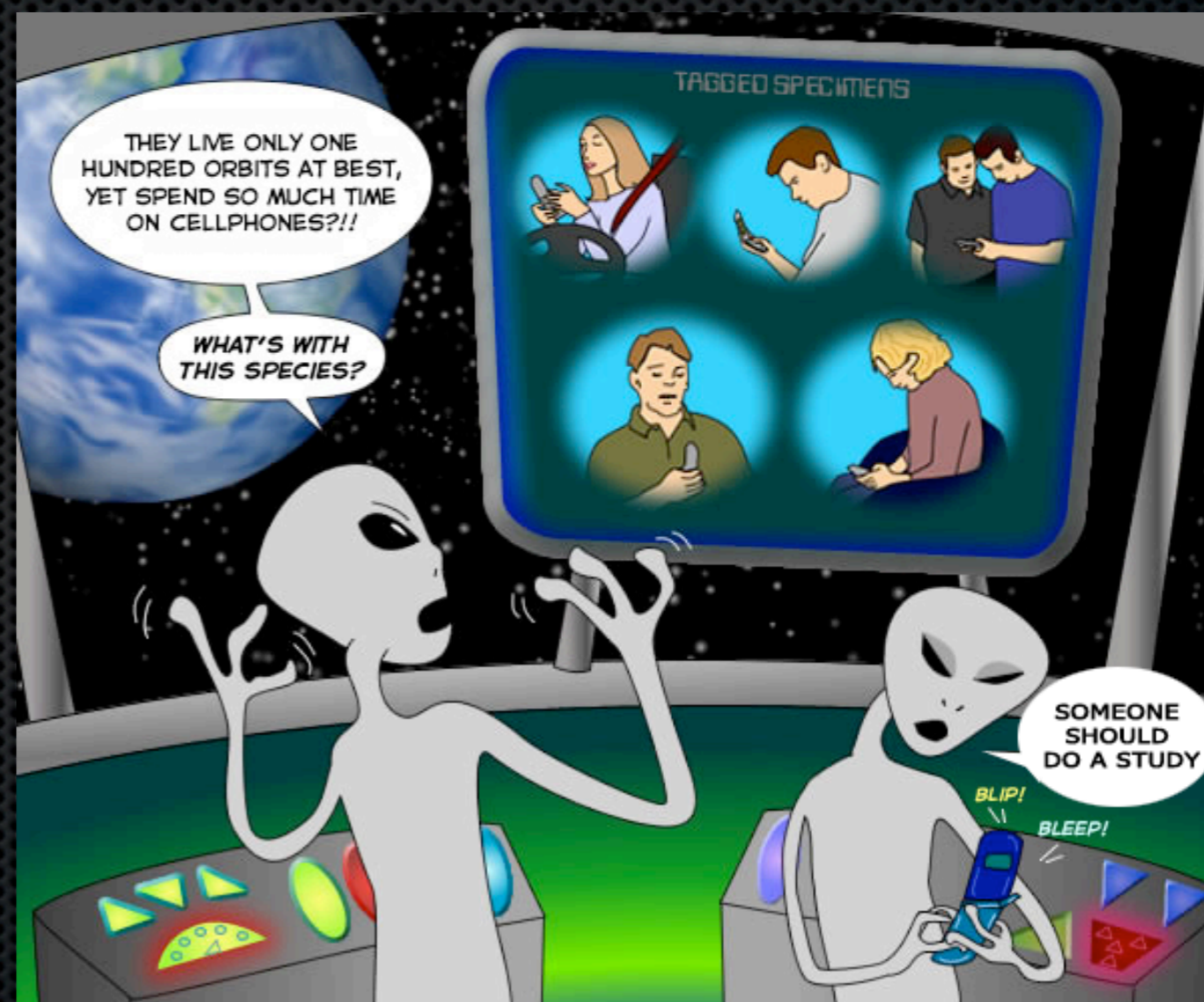
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- ✦ Motivation



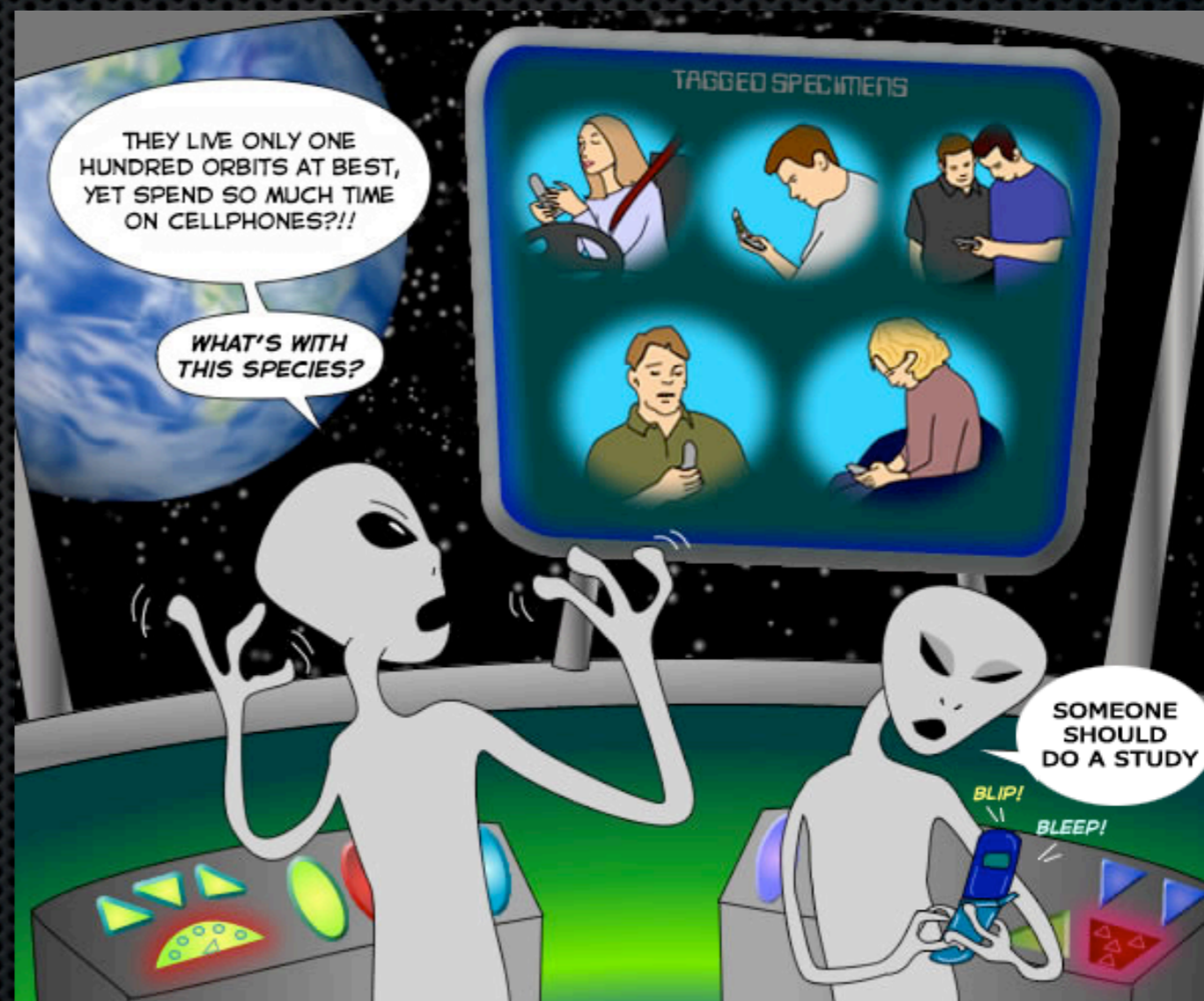
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- ✦ Smartphone usage study
 - ✦ Challenges



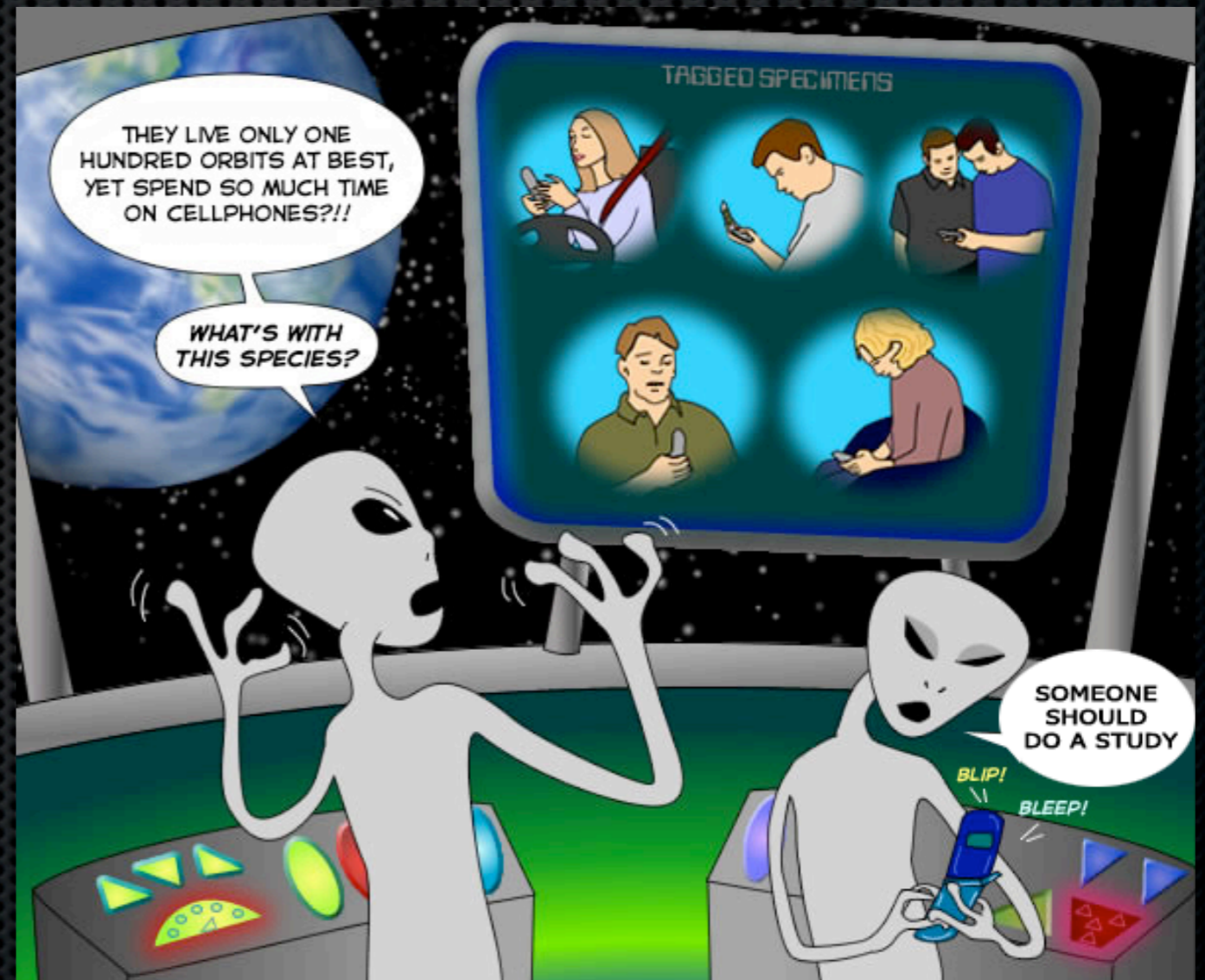
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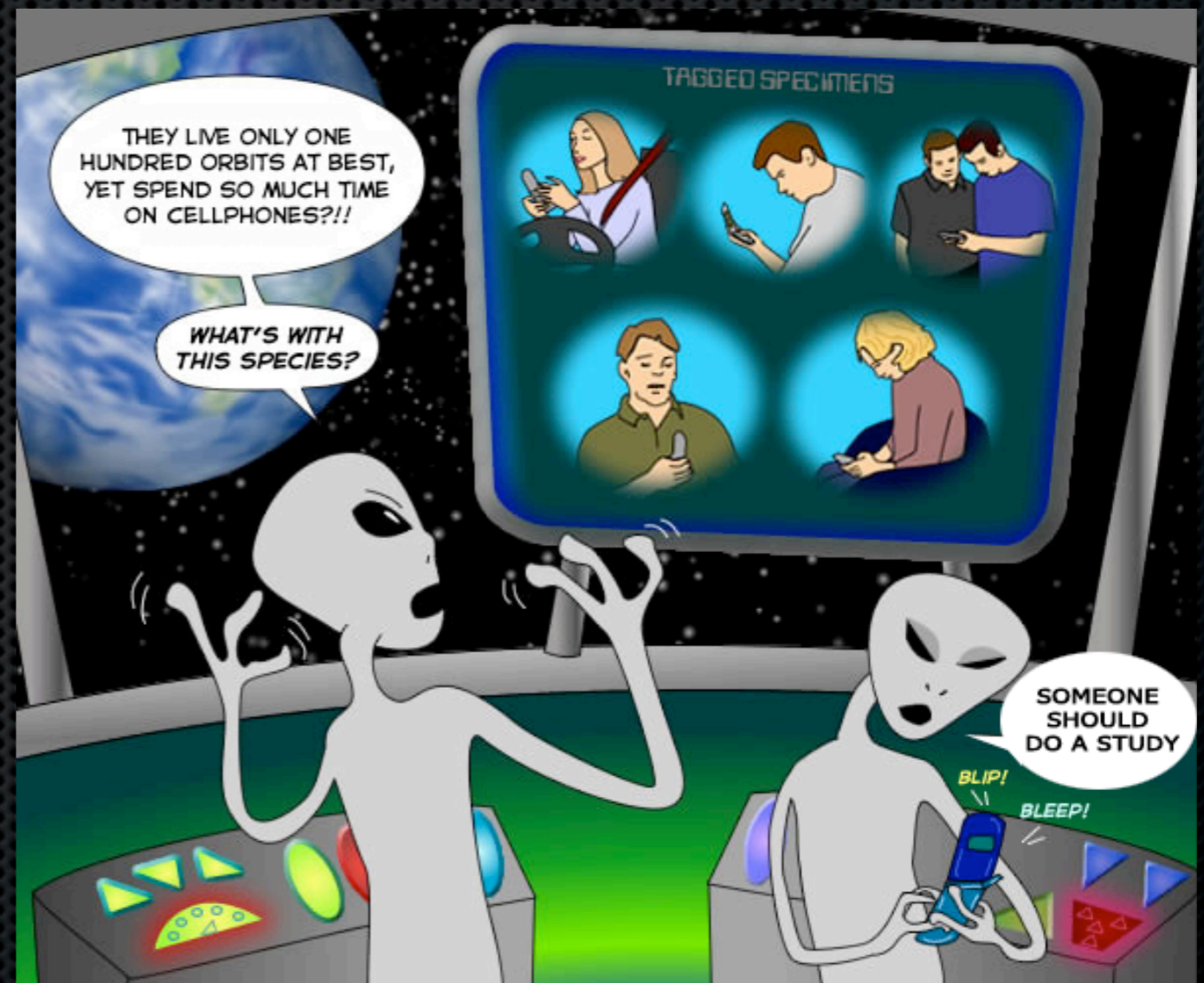
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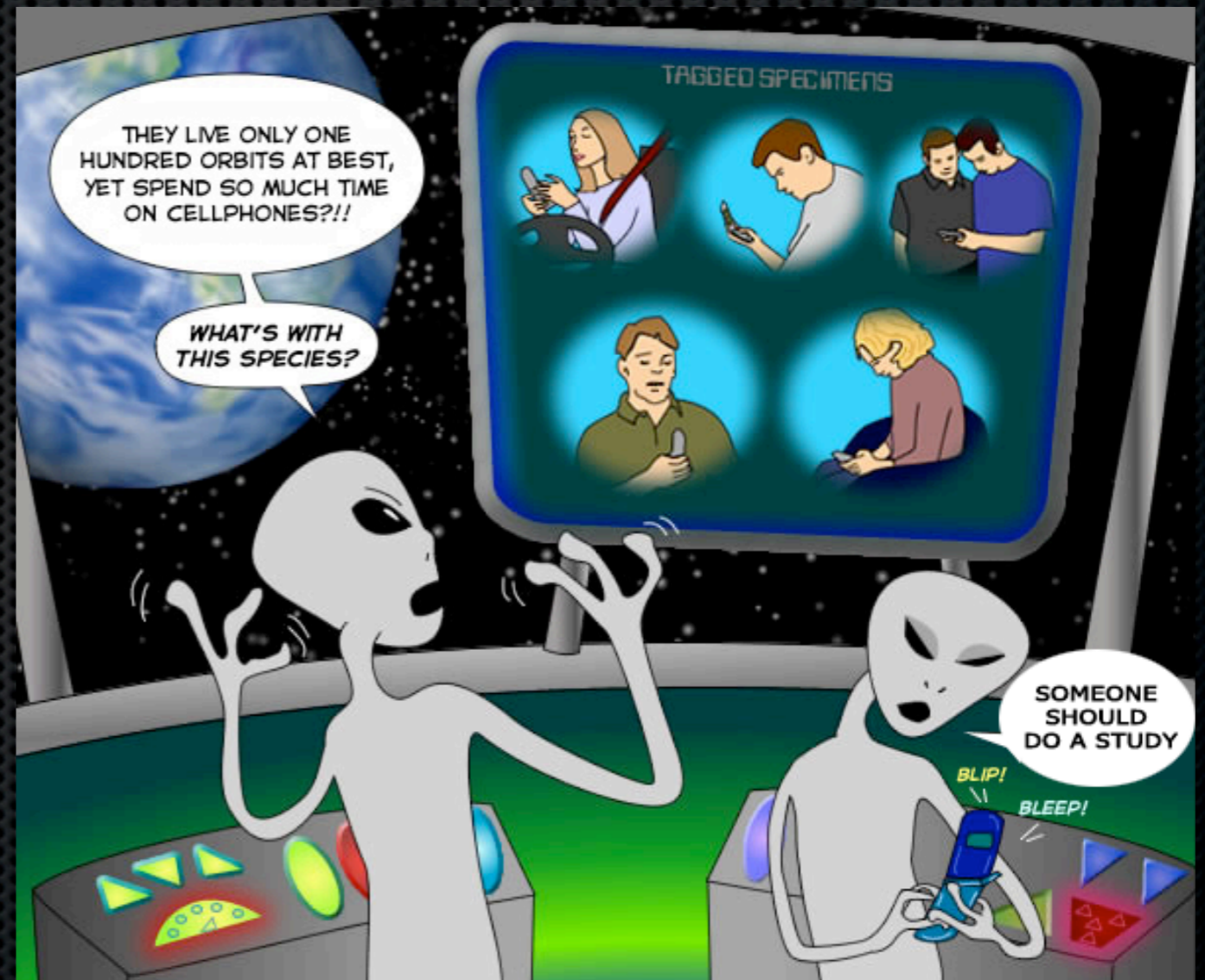
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- ✦ Successful application execution prediction
- ✦ Future work



Motivation

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Mobile
applications

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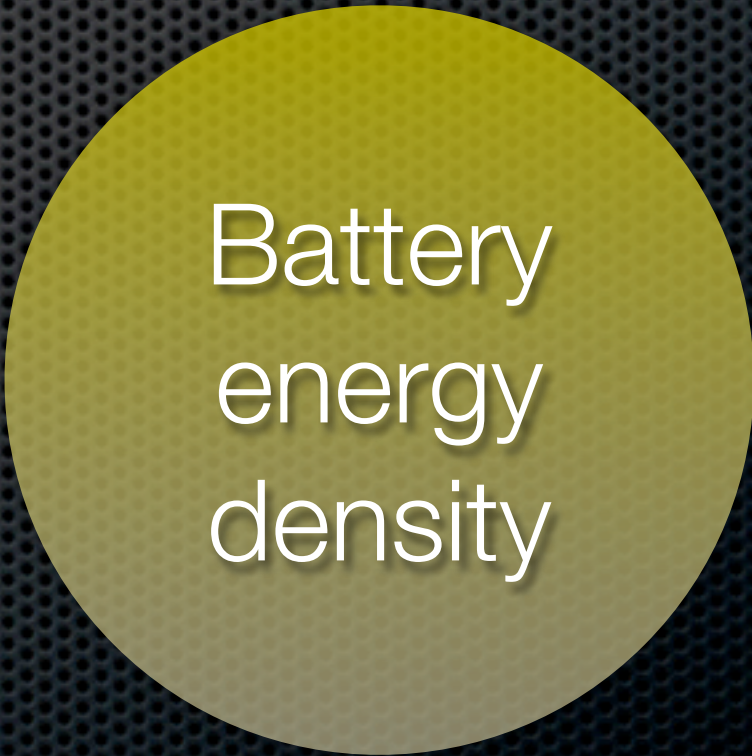
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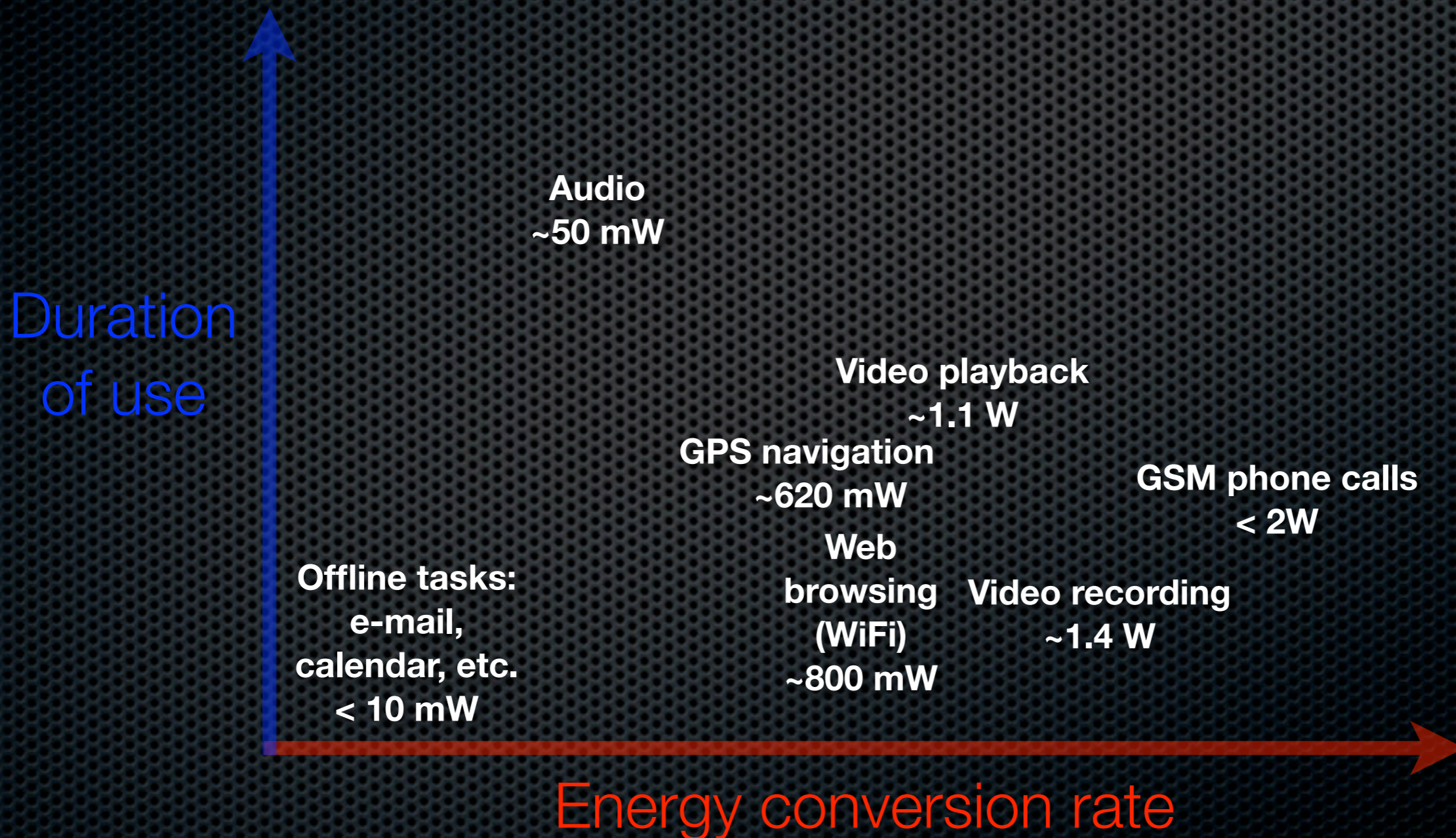


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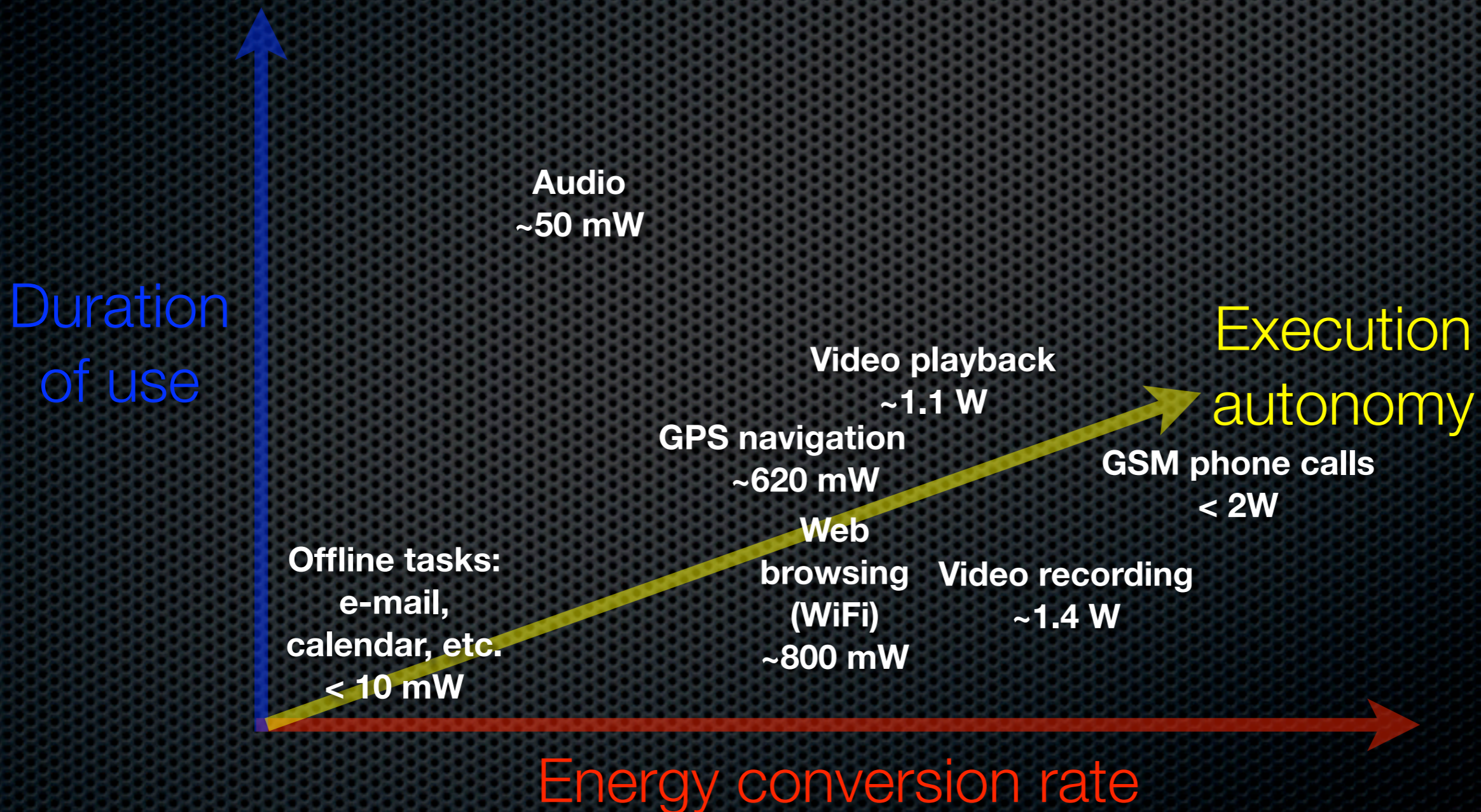


Battery
energy
density

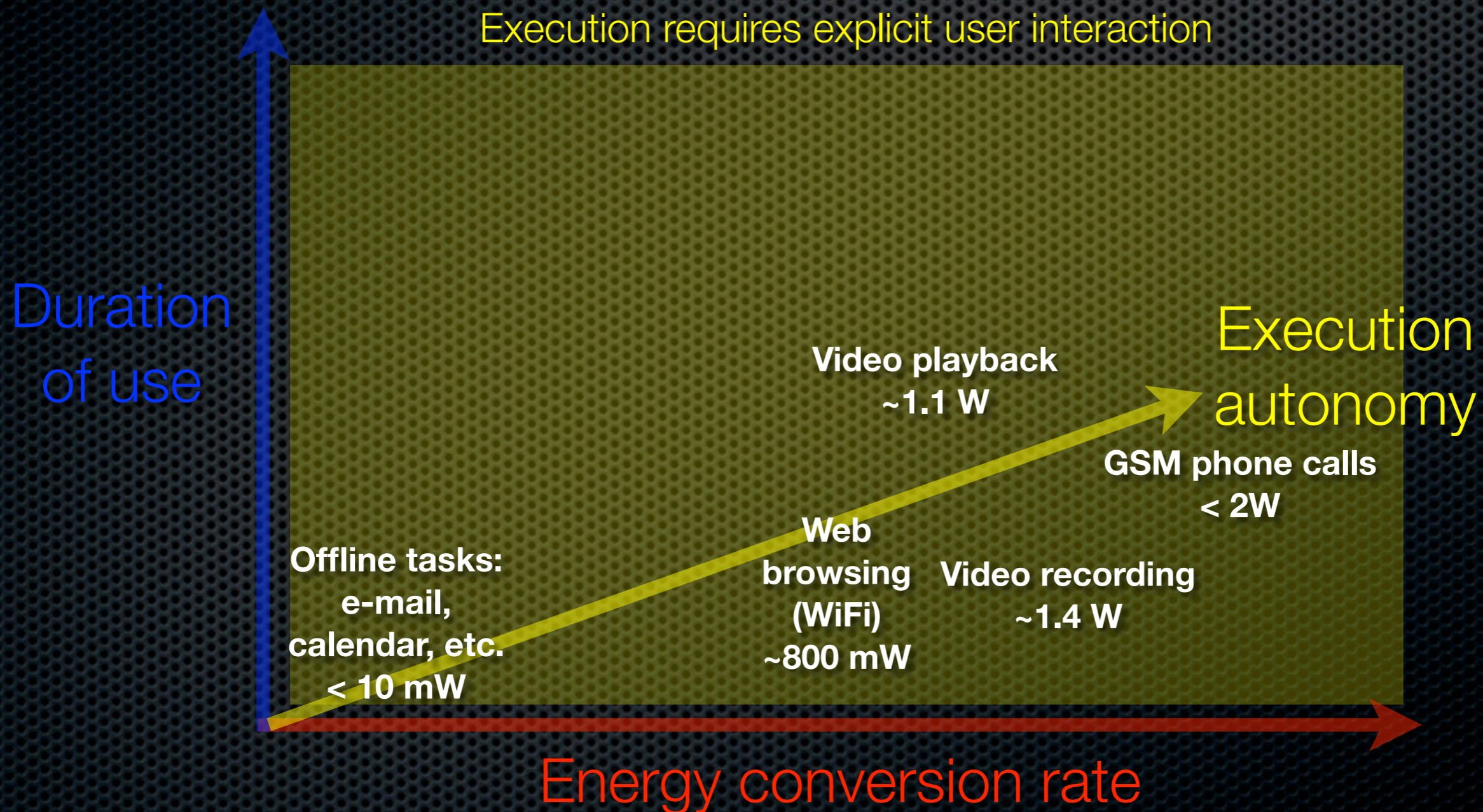
Execution continuum



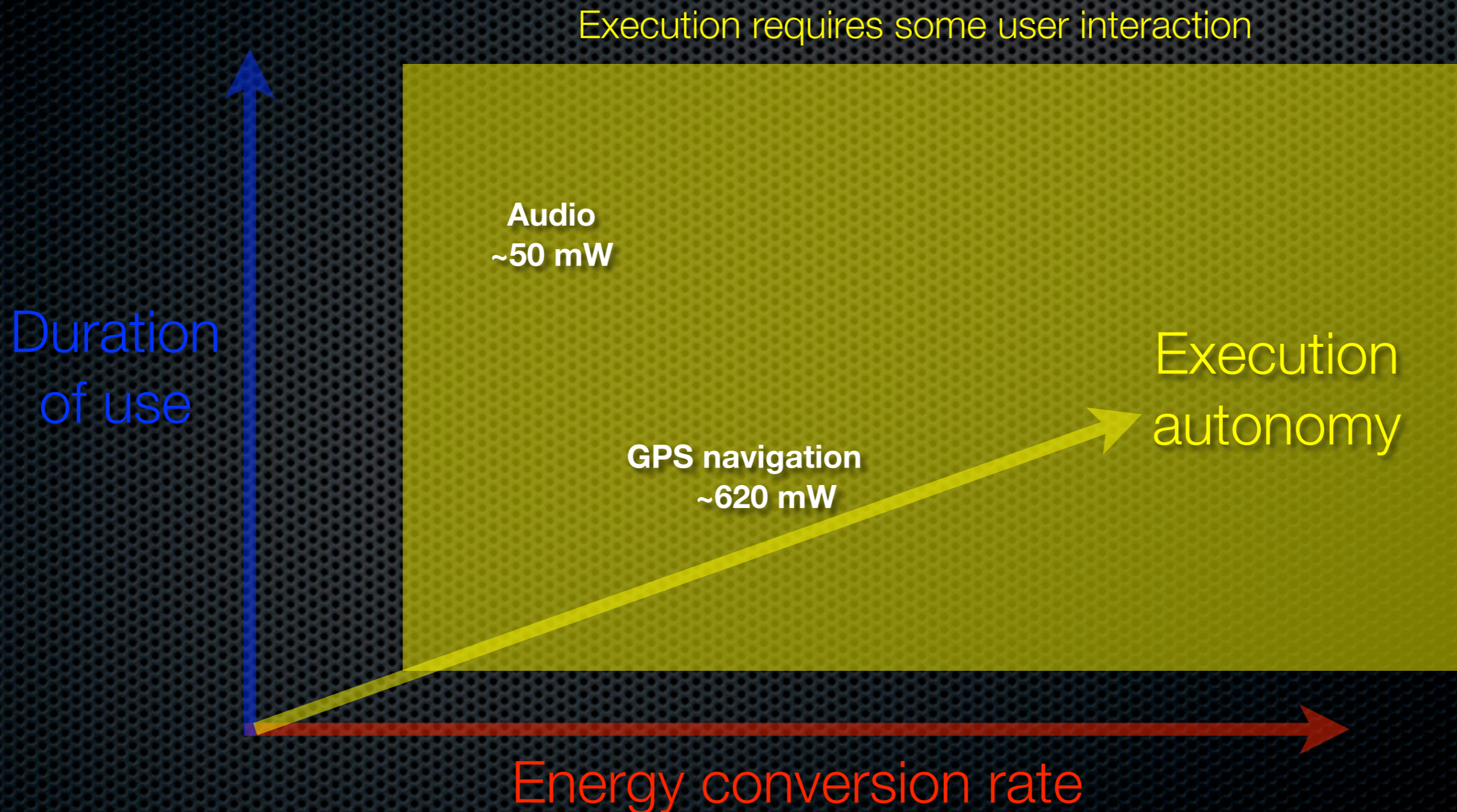
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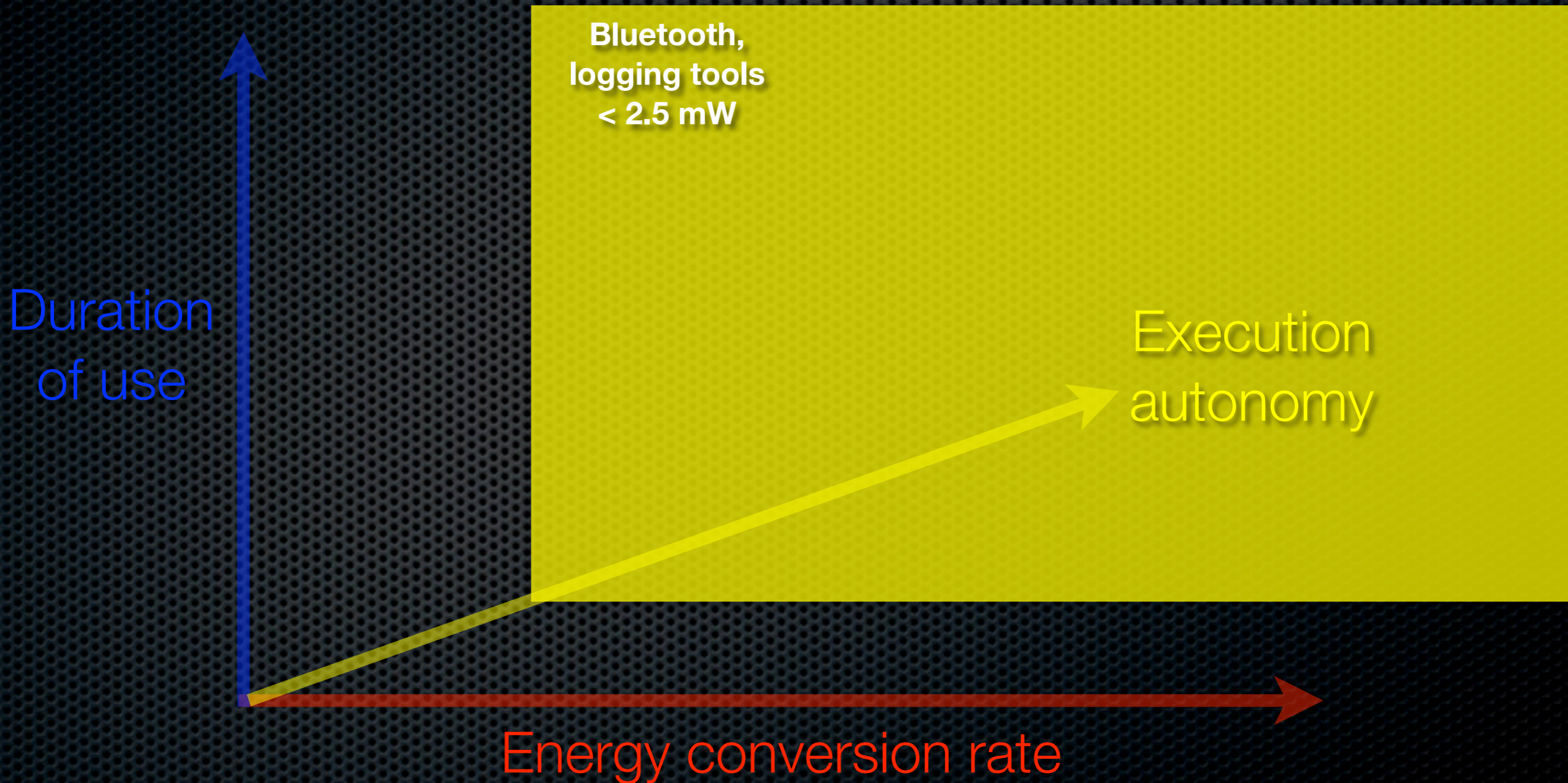


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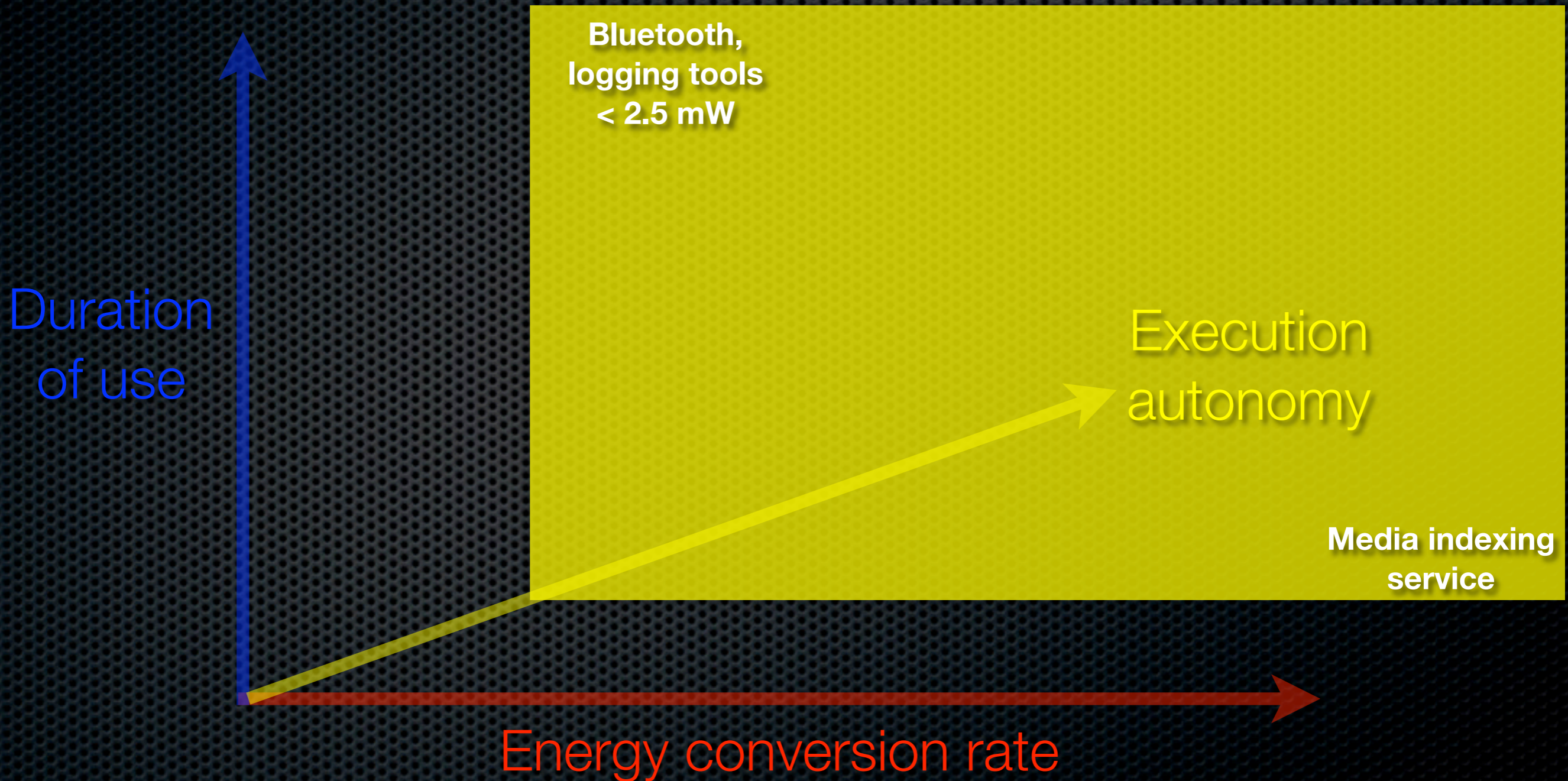
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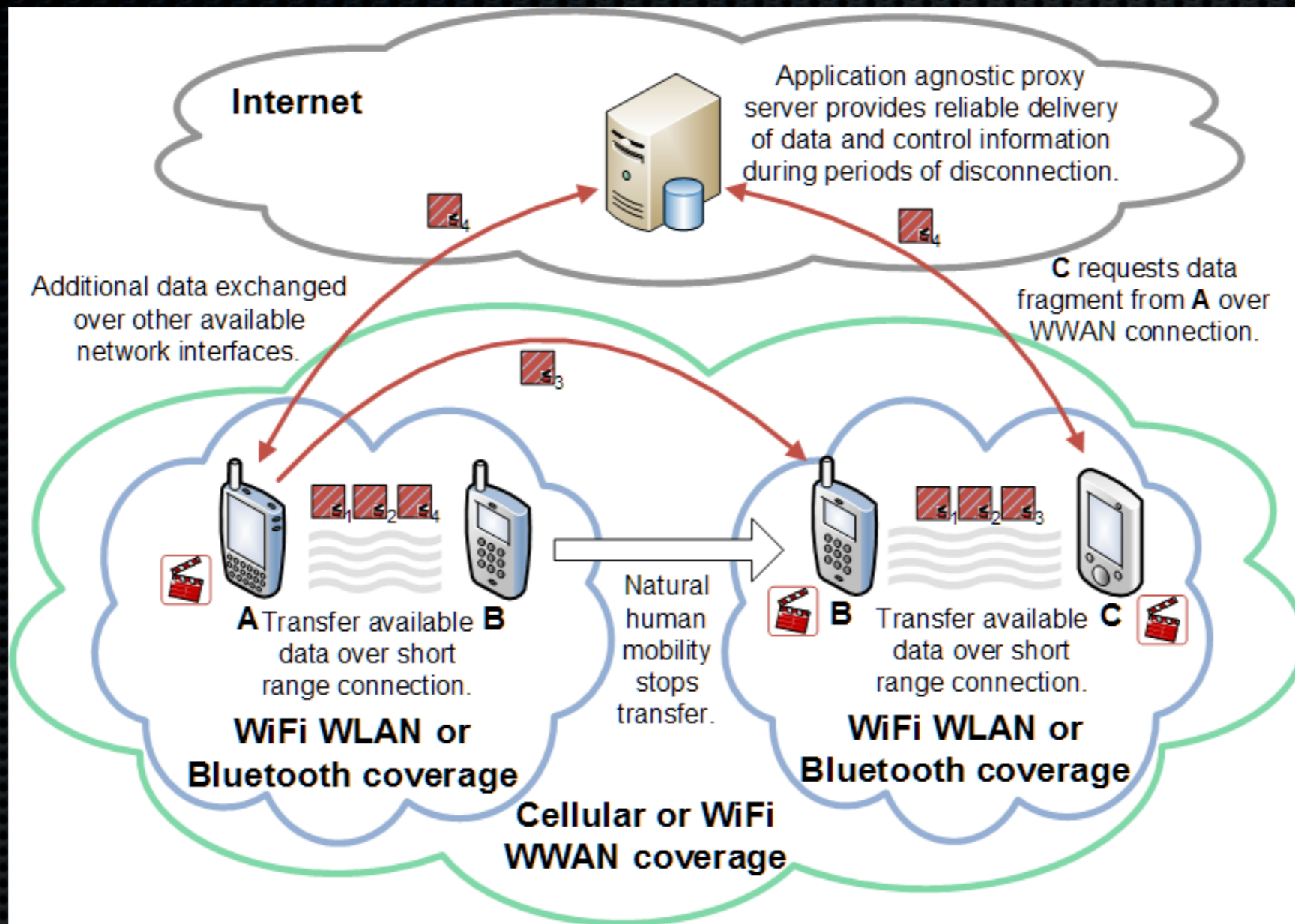
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The next frontier in mobile applications:
MyTube, PocketBay, etc.

Duration
of use

Execution
autonomy

Energy conversion rate



The next frontier in mobile applications

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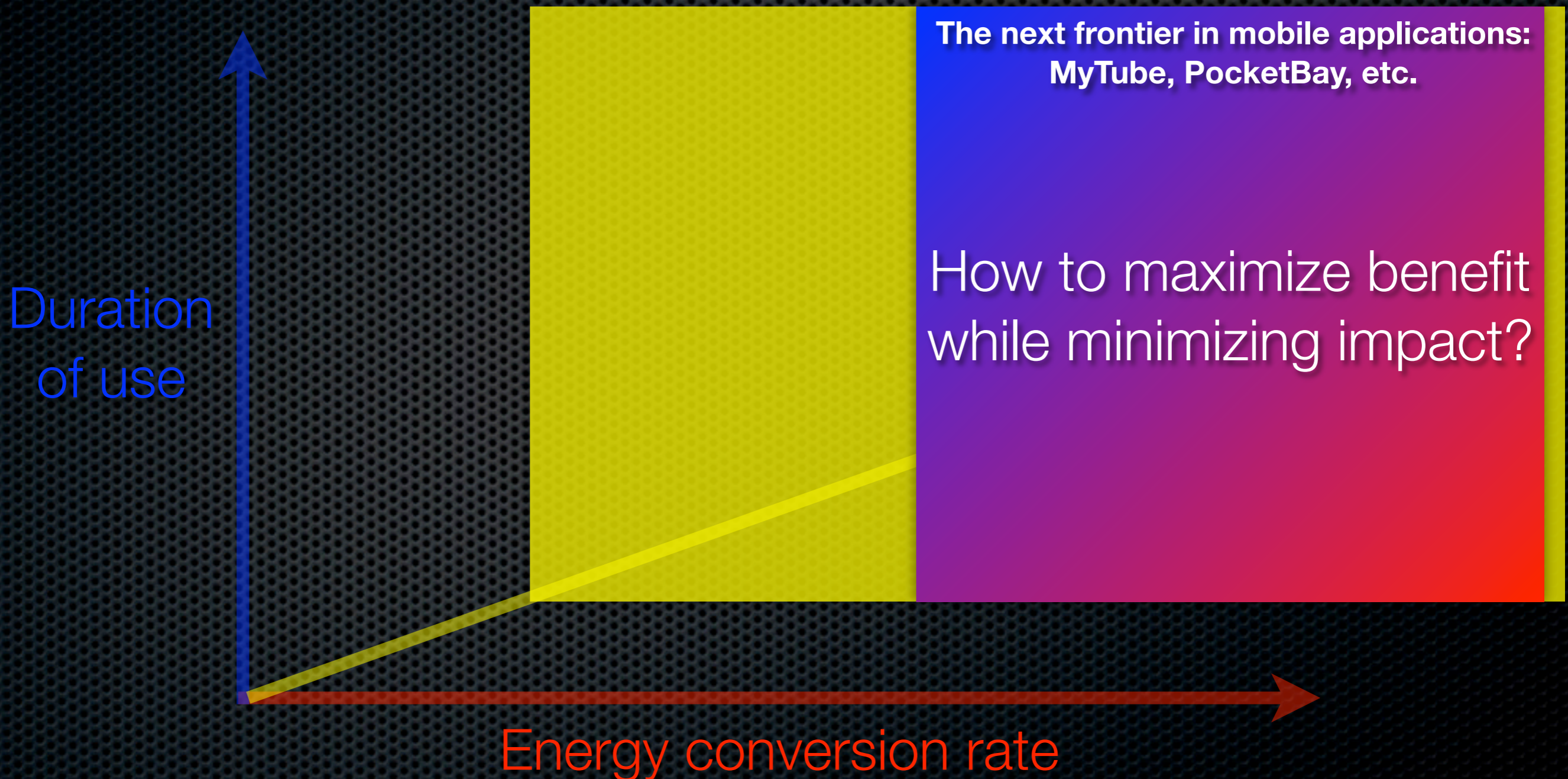
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The next frontier in mobile applications

- ✦ Wireless opportunistic communication
 - ✦ **requires autonomous execution**
- ✦ Continuous execution maximize connection opportunities
- ✦ Unfettered energy consumption can deplete finite energy resources
 - ✦ **Unacceptable**

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- ✦ Two goals:
 - ✦ Regulate mobile application execution based on a **predicted future battery level.**
 - ✦ **Predict the successful execution rate** of energy intensive applications given known consumption

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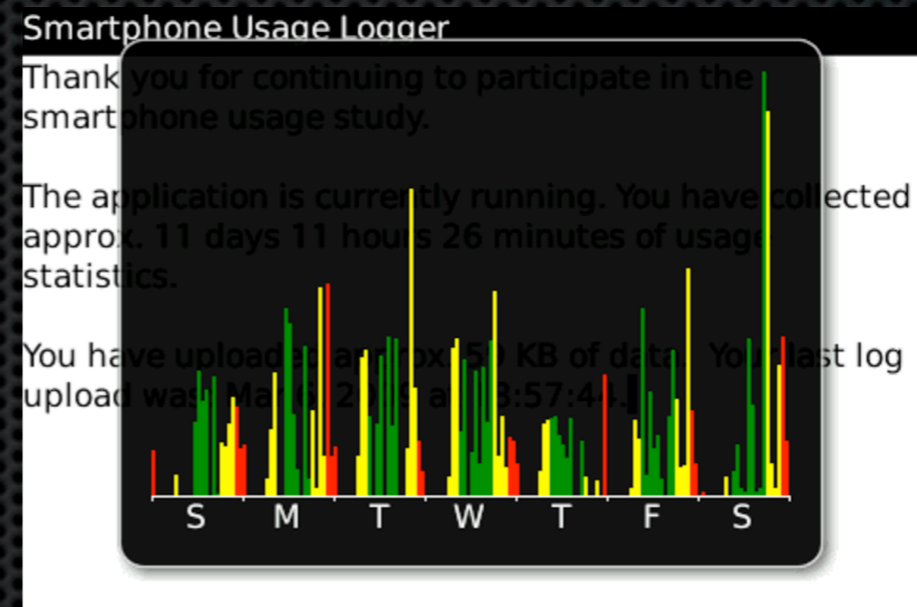
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 - ✦ Impact -> uninstallation

Design of the usage logger

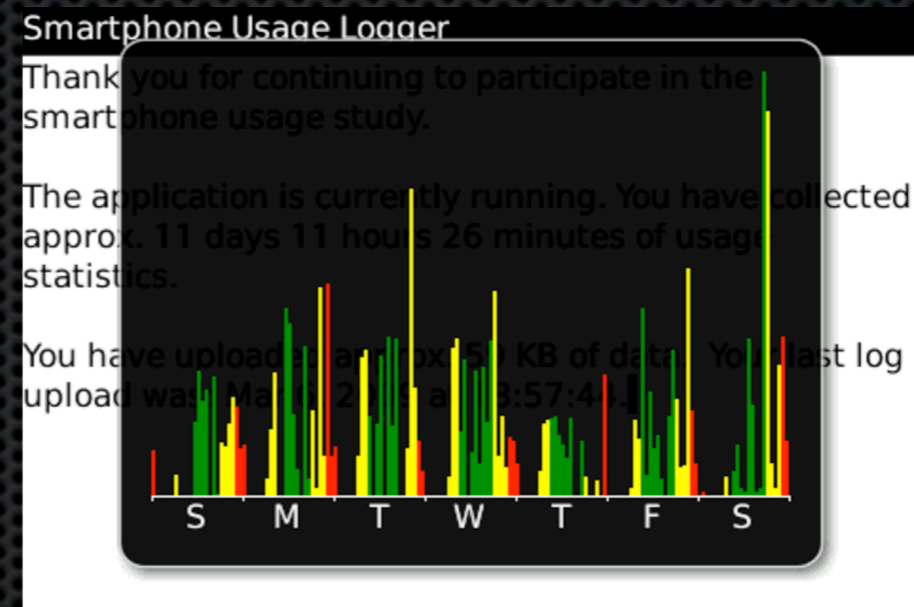
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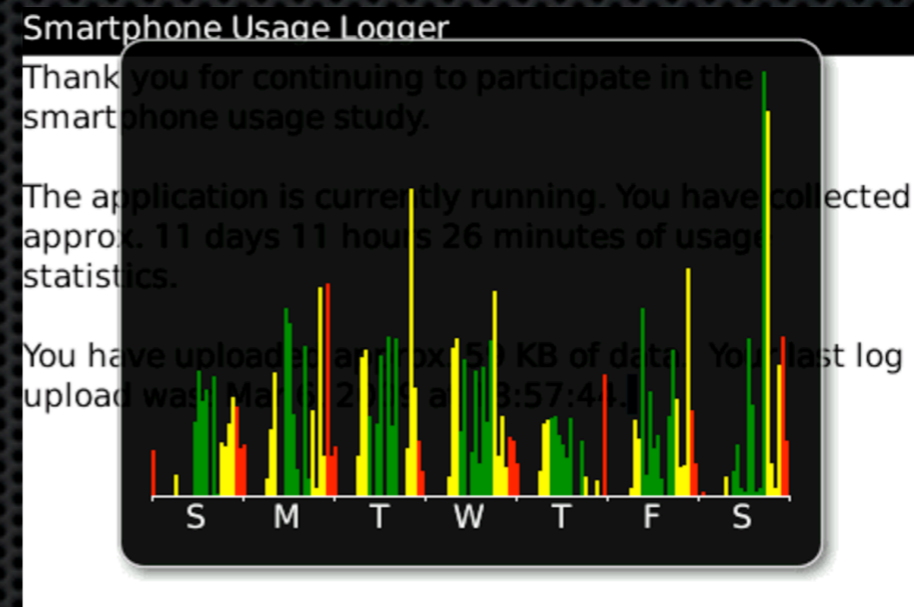
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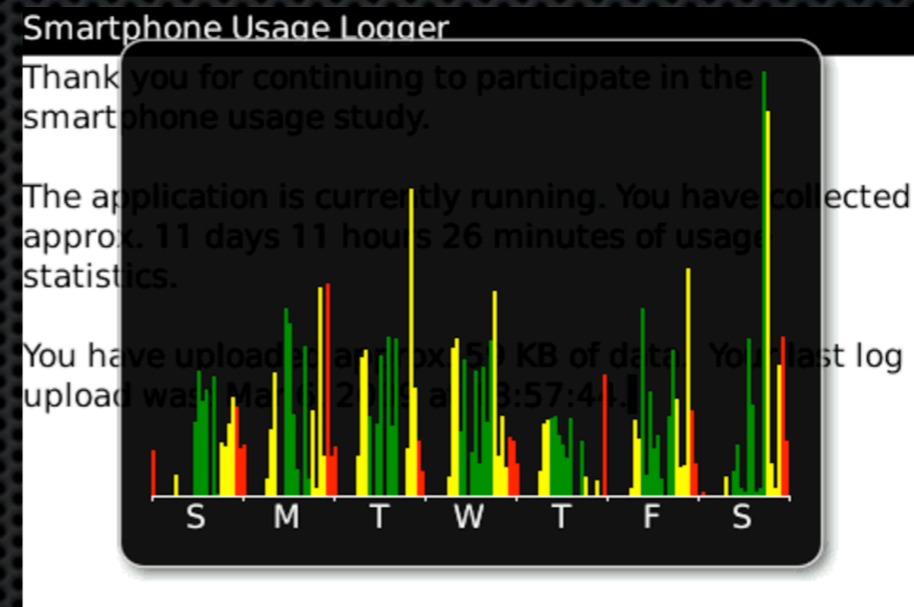
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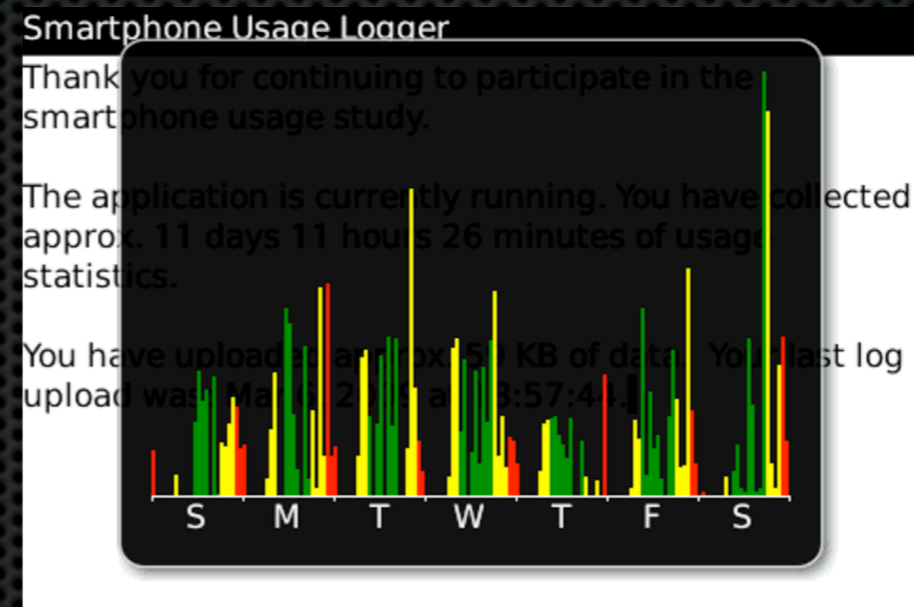
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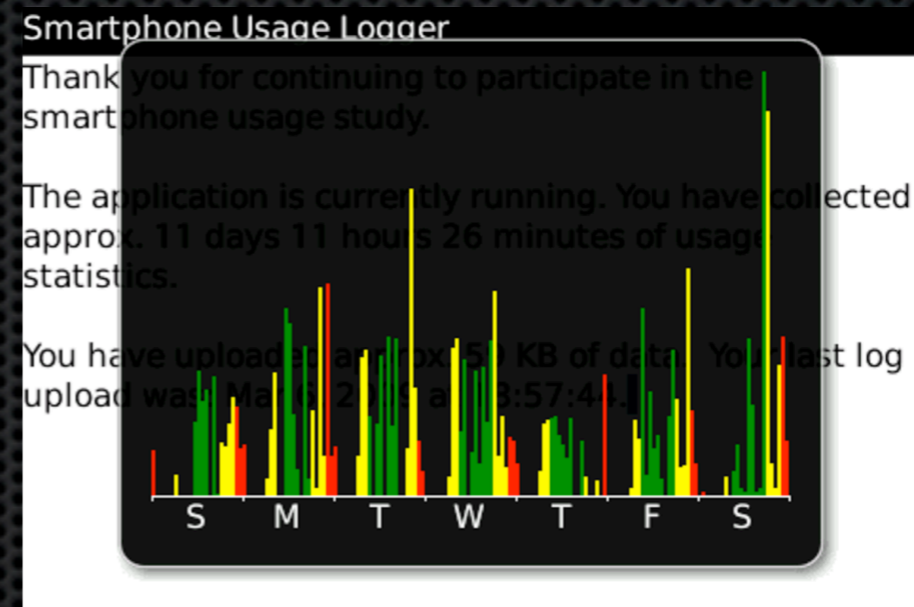
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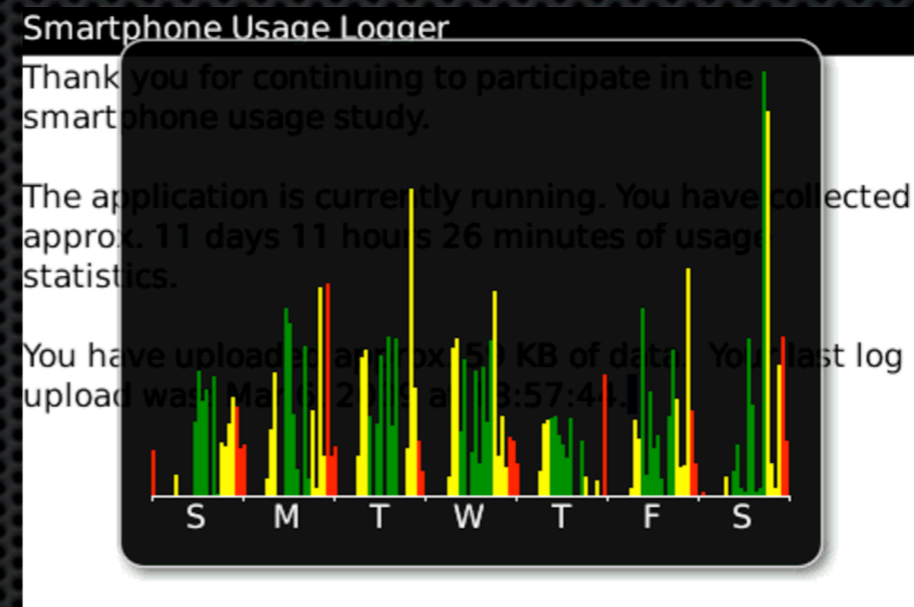
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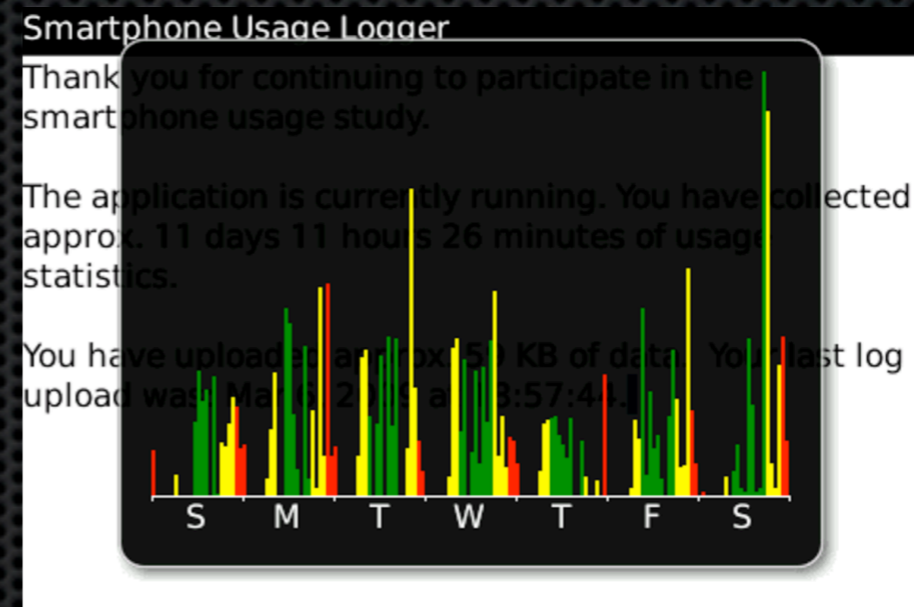
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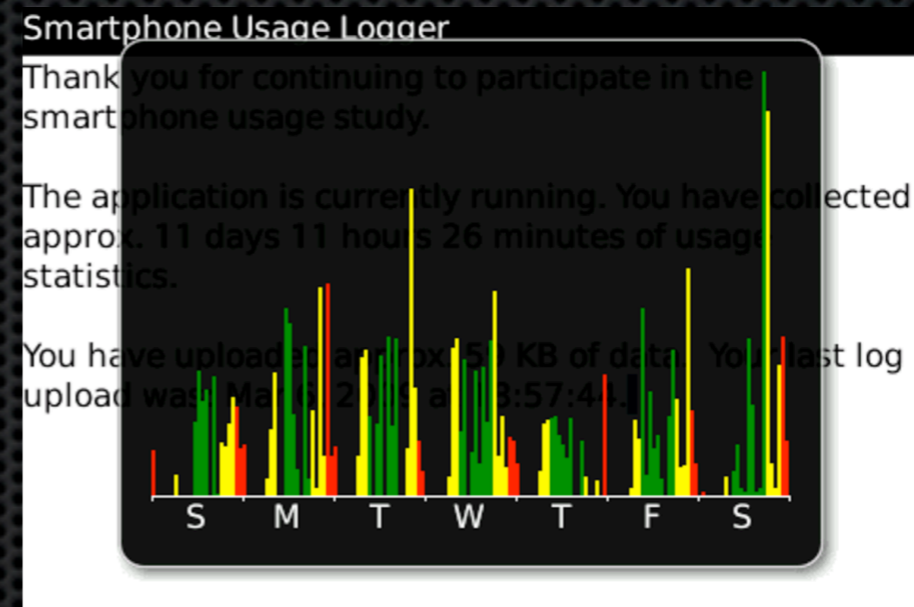
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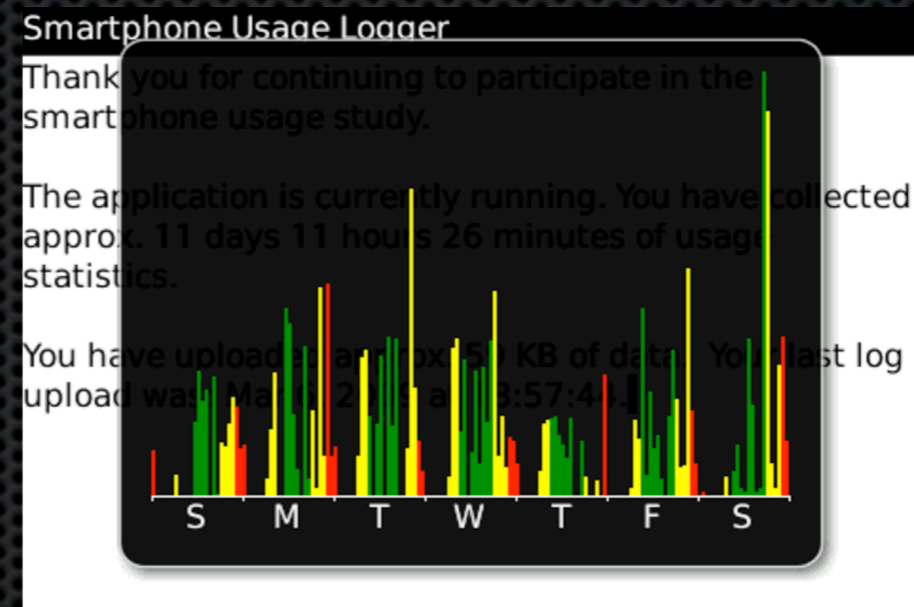
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 - Clusters of download in Apache logs
 - ~65% of data collected by standard logger was questionable and discarded

Hardware characteristics



- All BlackBerry devices since Q2 2006

Hardware characteristics



- ✦ All BlackBerry devices since Q2 2006
- ✦ Radios
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- ✦ Screen sizes from: 240x260px to 360x480px
- ✦ Isomorphic to other devices from other manufactures.

Dataset

* As of 16:00h February 2, 2010

Dataset

- 3.5 years of cumulative smartphone usage as of September 2009

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Dataset

- ✦ 3.5 years of cumulative smartphone usage as of September 2009
- ✦ 0.512 millennium of usage as of February 2010

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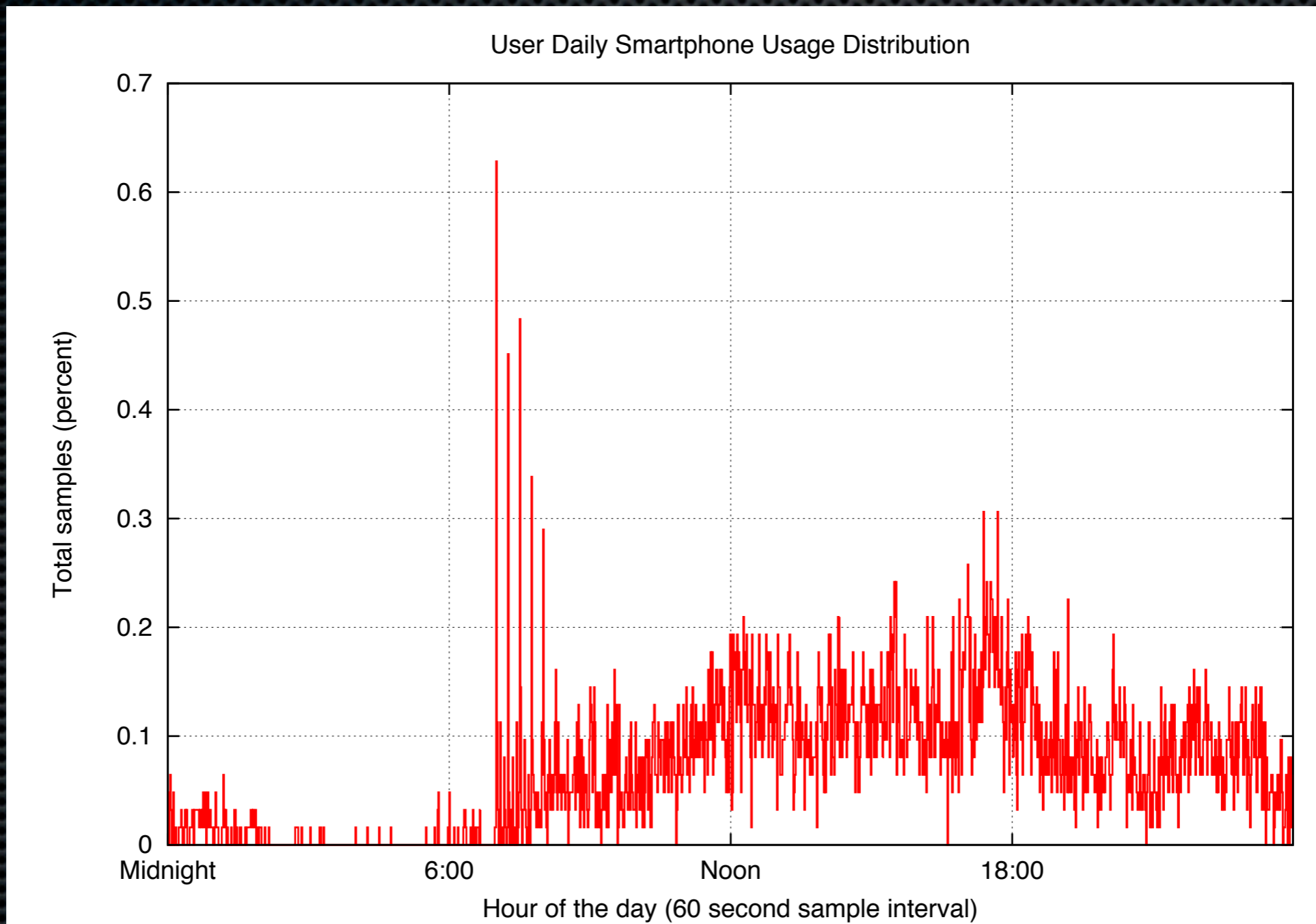
* As of 16:00h February 2, 2010

Dataset

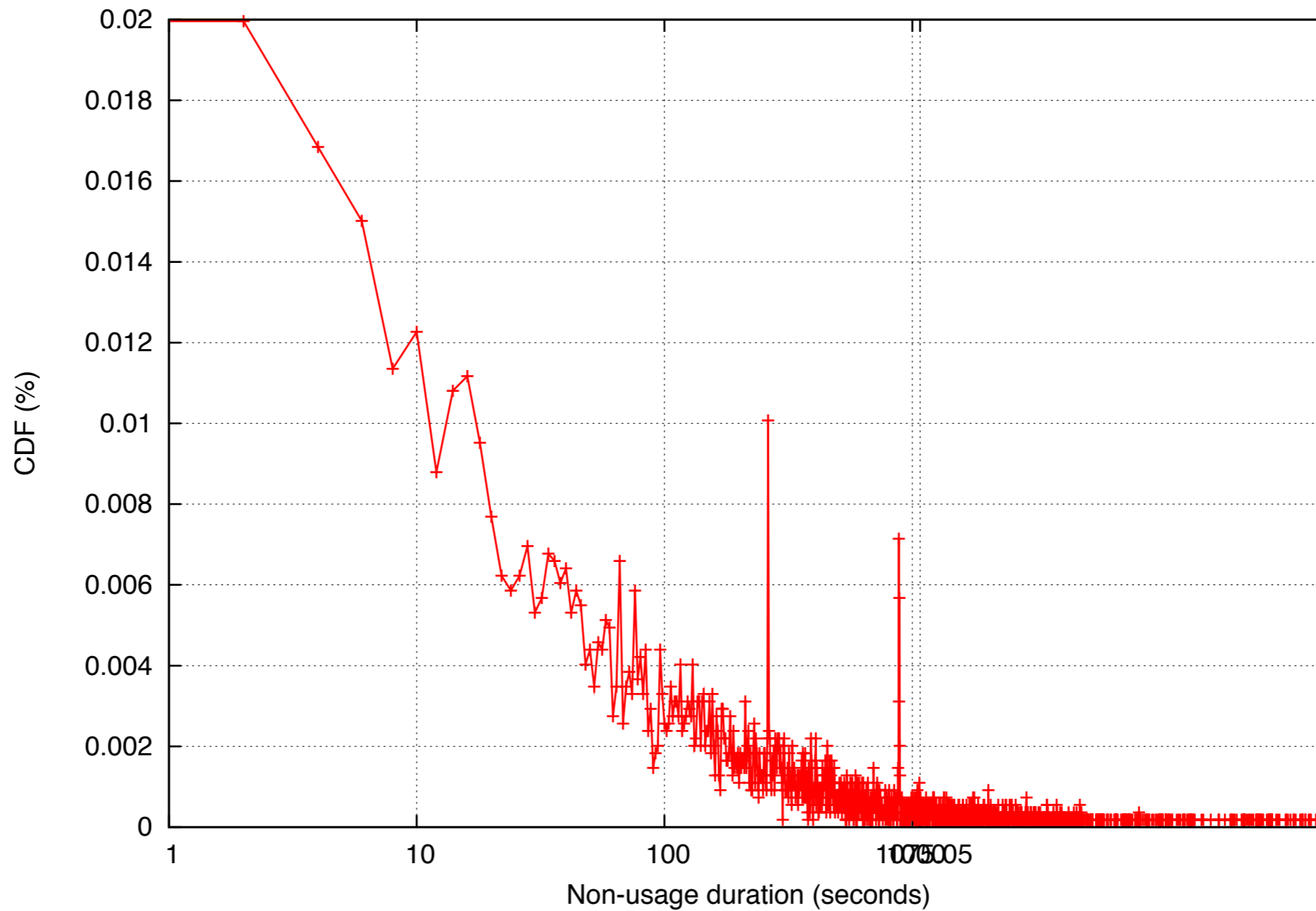
- ✦ 3.5 years of cumulative smartphone usage as of September 2009
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 - ✦ 13523 BlackBerry users
 - ✦ Spanning 11 types of devices, 23 timezones
- ✦ Mean/median user contribution: 13.8/15.3 days

* As of 16:00h February 2, 2010

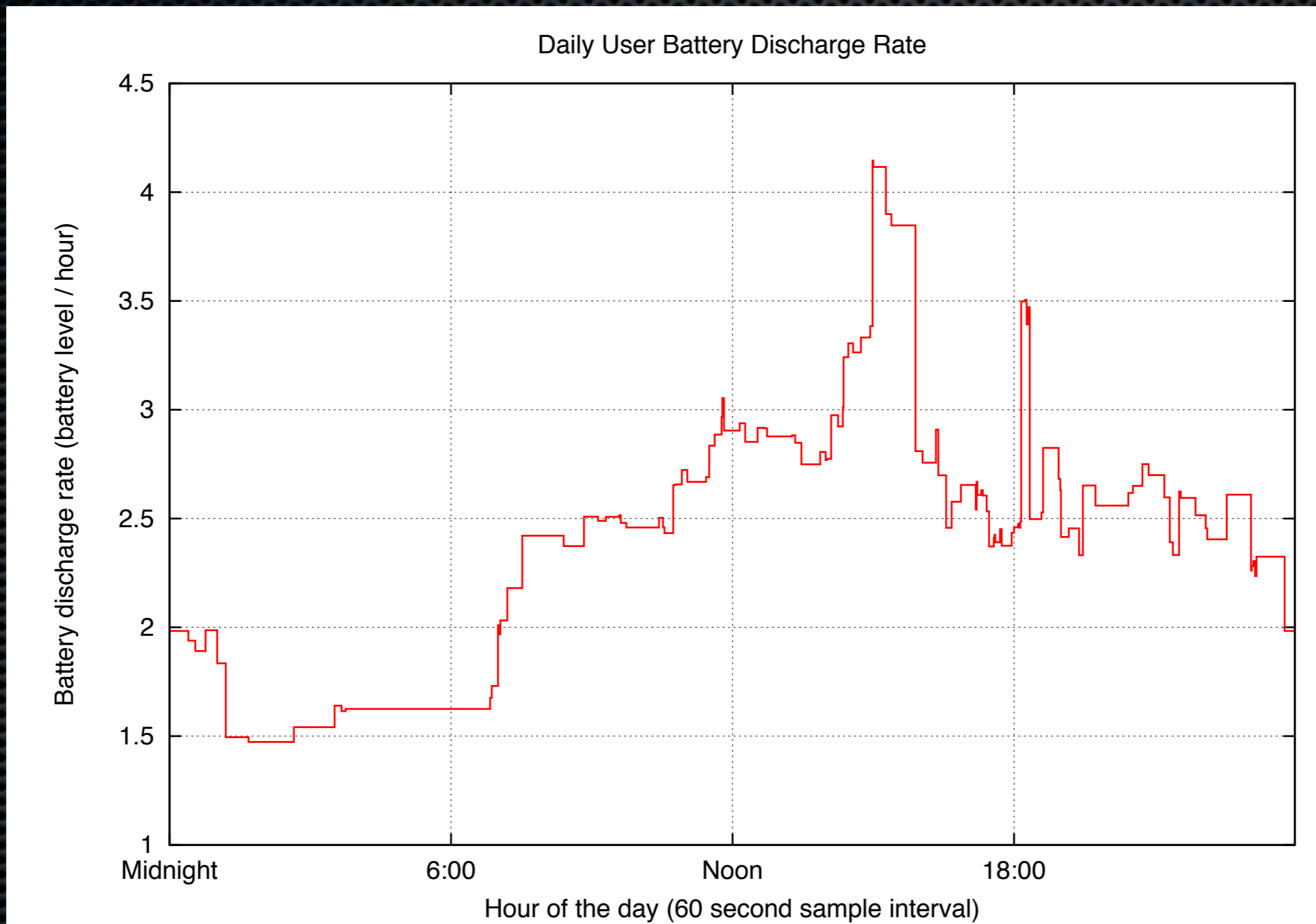
Sample usage traces

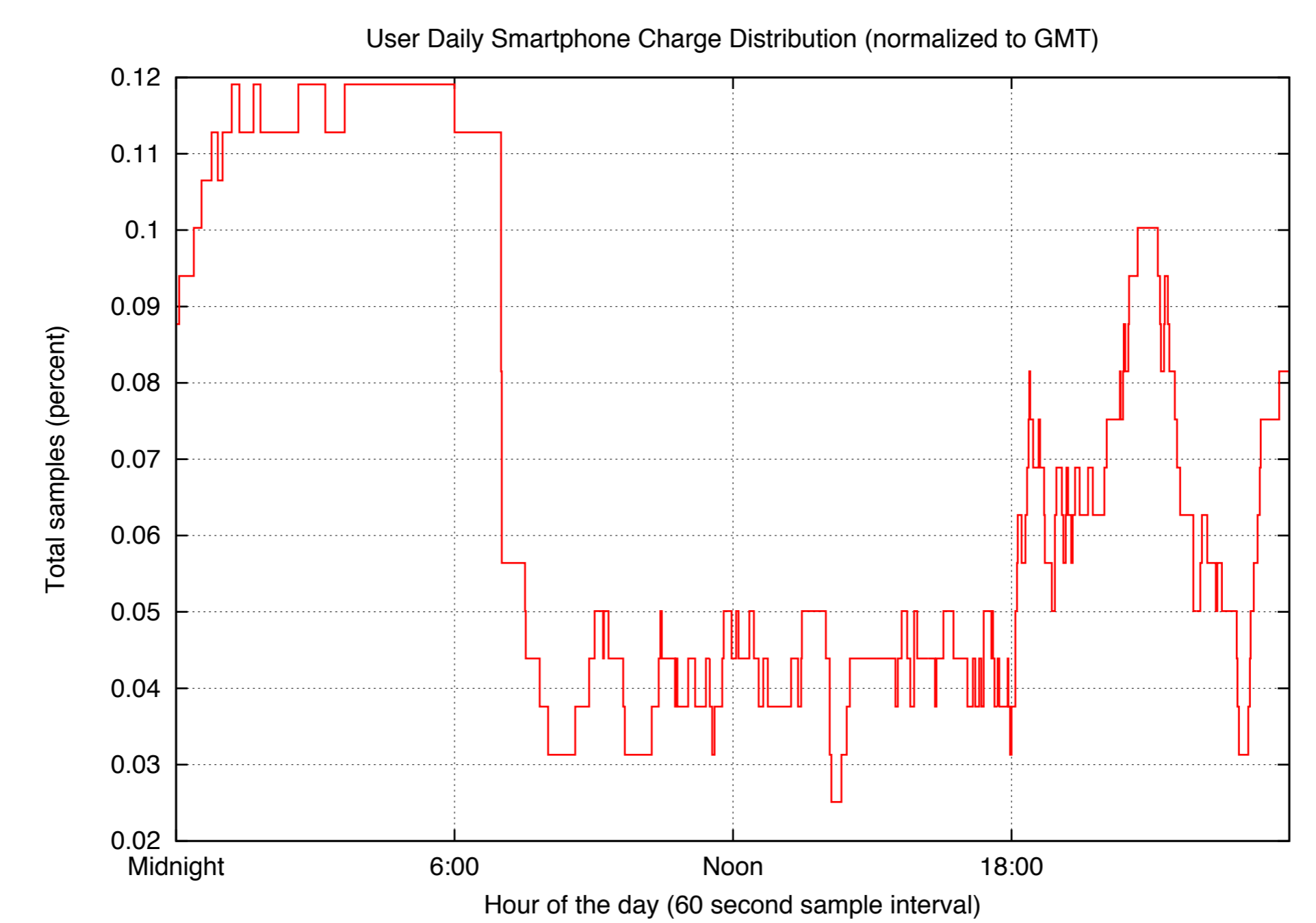


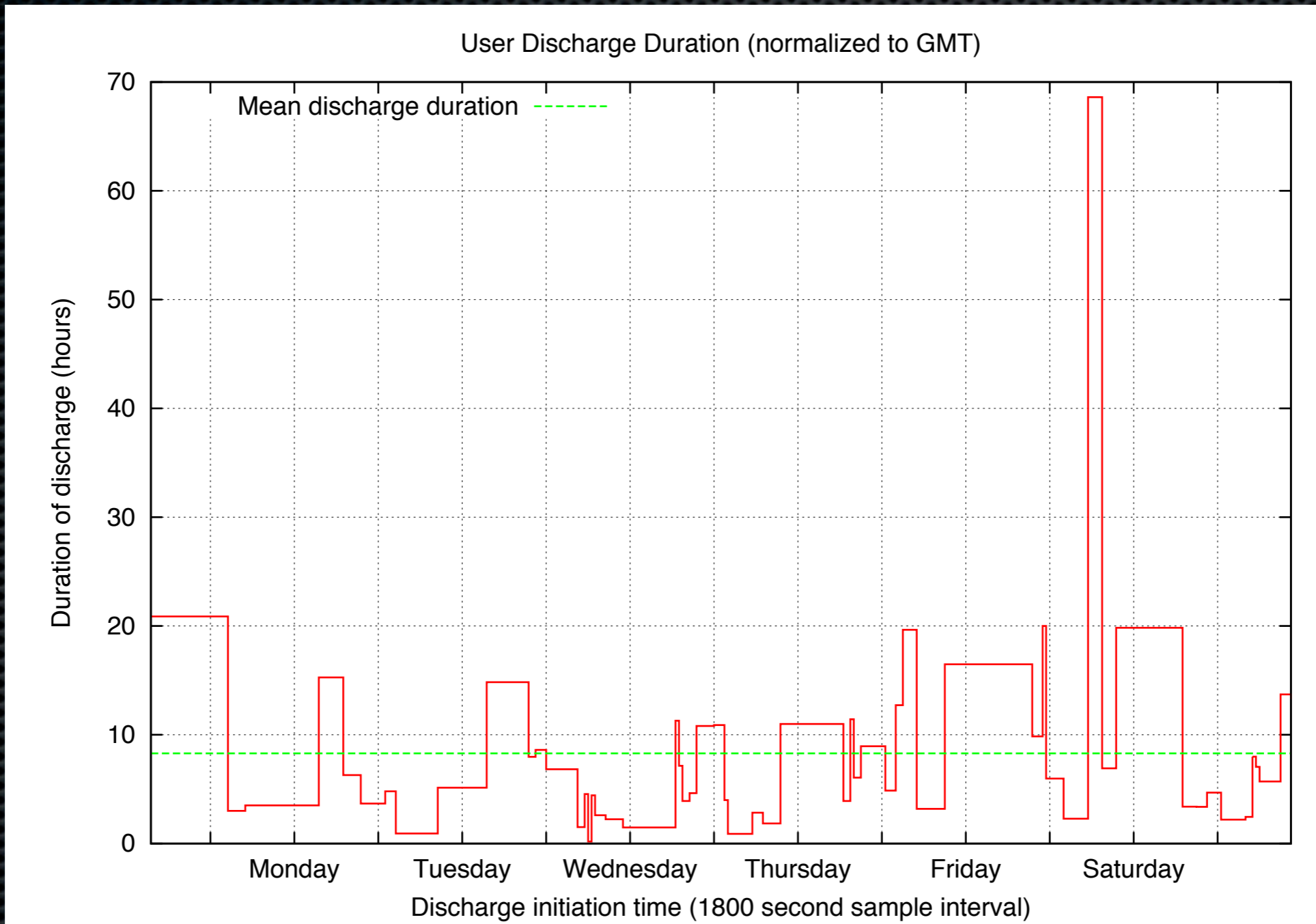
User Smartphone Inactivity Duration PDF



Sample energy traces







Energy level prediction

Half way!

**You're doing
great!**

Energy level prediction

- Variables of interest:



Energy level prediction

- ✦ Variables of interest:
 - ✦ charge duration

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Energy level prediction

- ✦ Variables of interest:
 - ✦ charge duration
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Energy level prediction

- ✦ Variables of interest:
 - ✦ charge duration
 - ✦ discharge duration
 - ✦ battery level when a charge is initiated

Half way!

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Energy level prediction

- ✦ Variables of interest:
 - ✦ charge duration
 - ✦ discharge duration
 - ✦ battery level when a charge is initiated
 - ✦ charge rate

Half way!

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Energy level prediction

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Energy level prediction

- ✦ Variables of interest:
 - ✦ charge duration
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 - ✦ charge rate
 - ✦ discharge rate
 - ✦ device type

Half way!

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Energy level prediction

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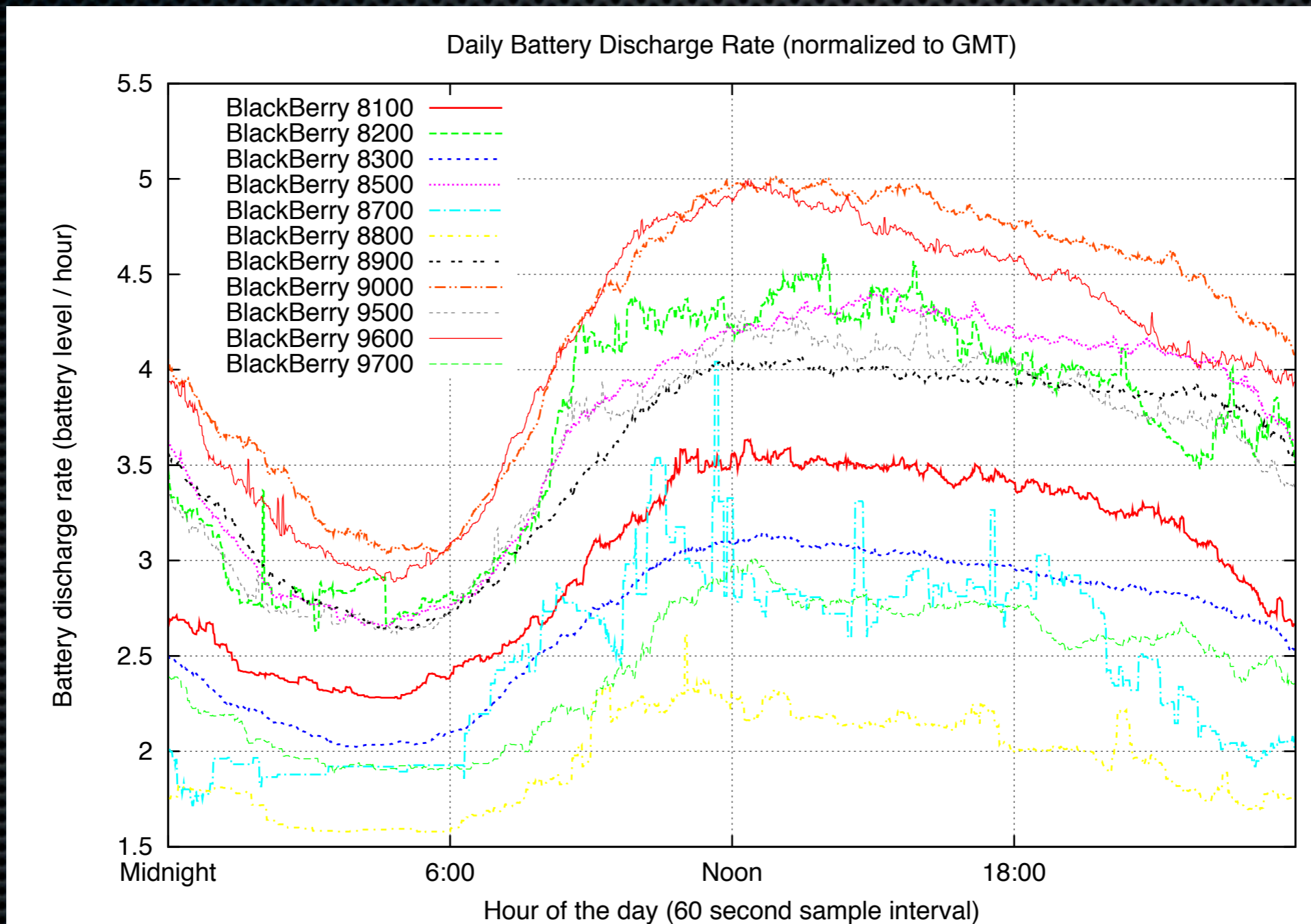
Time of the
day/week

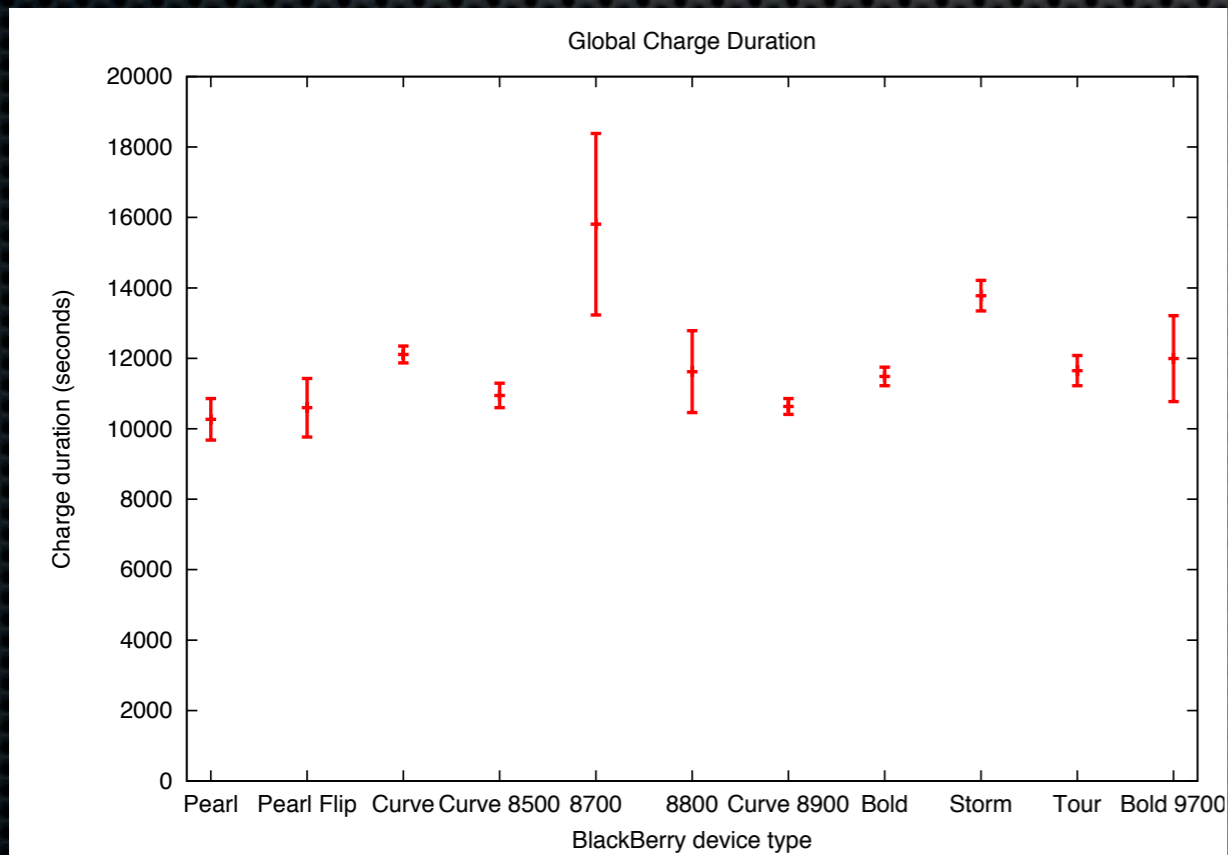
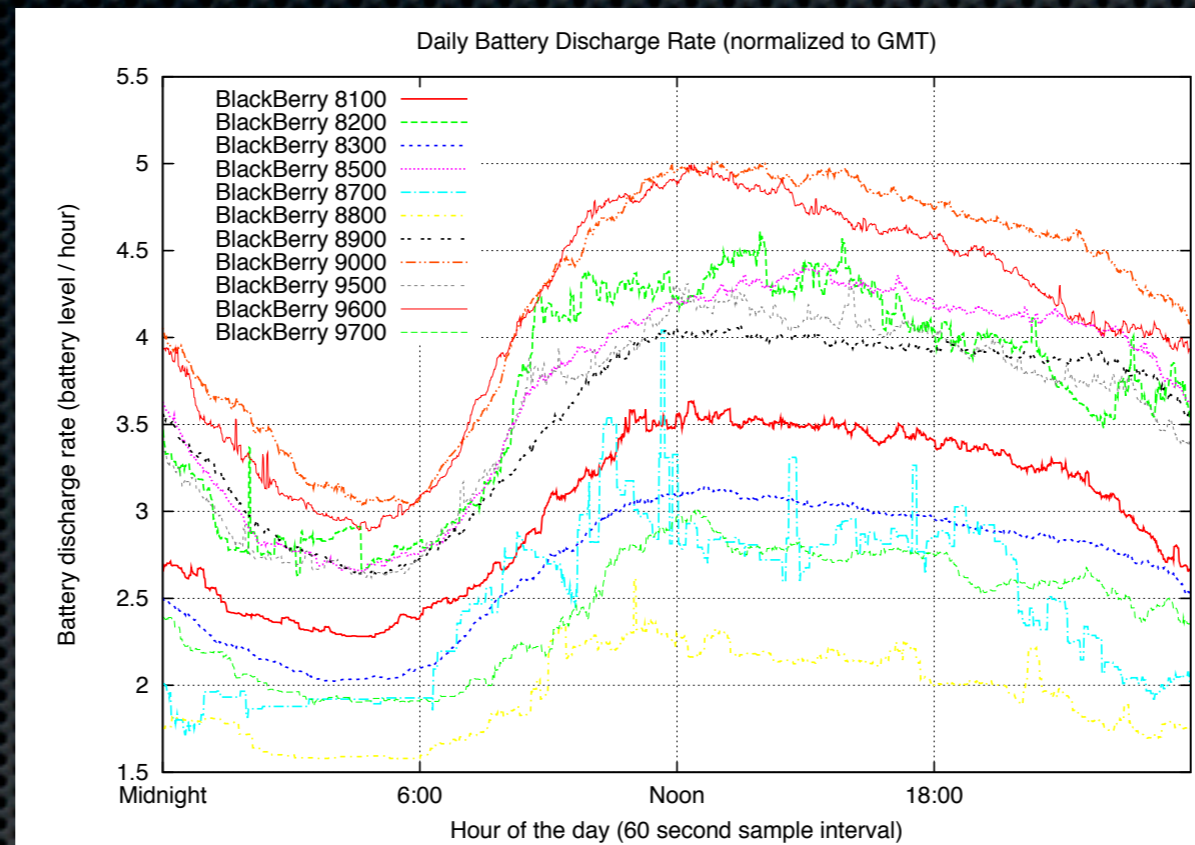
Half way!

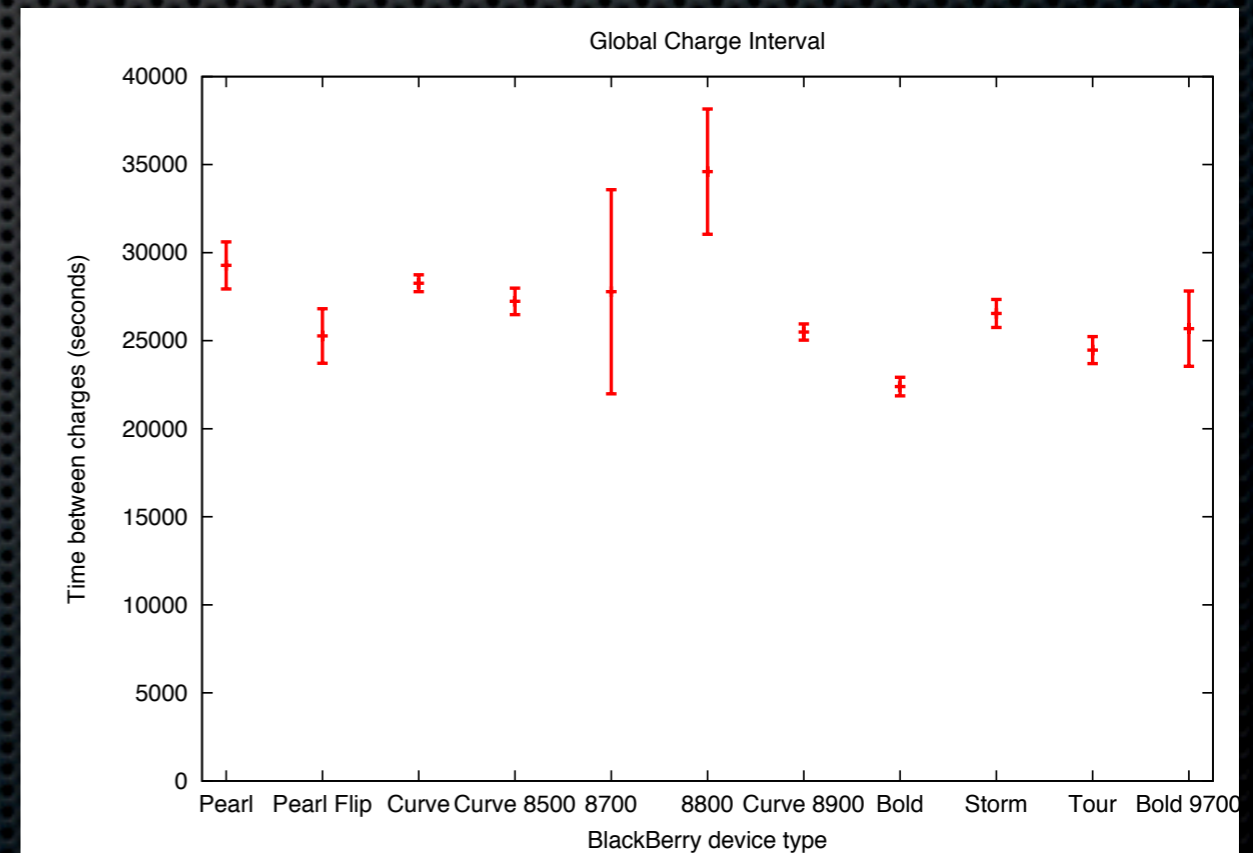
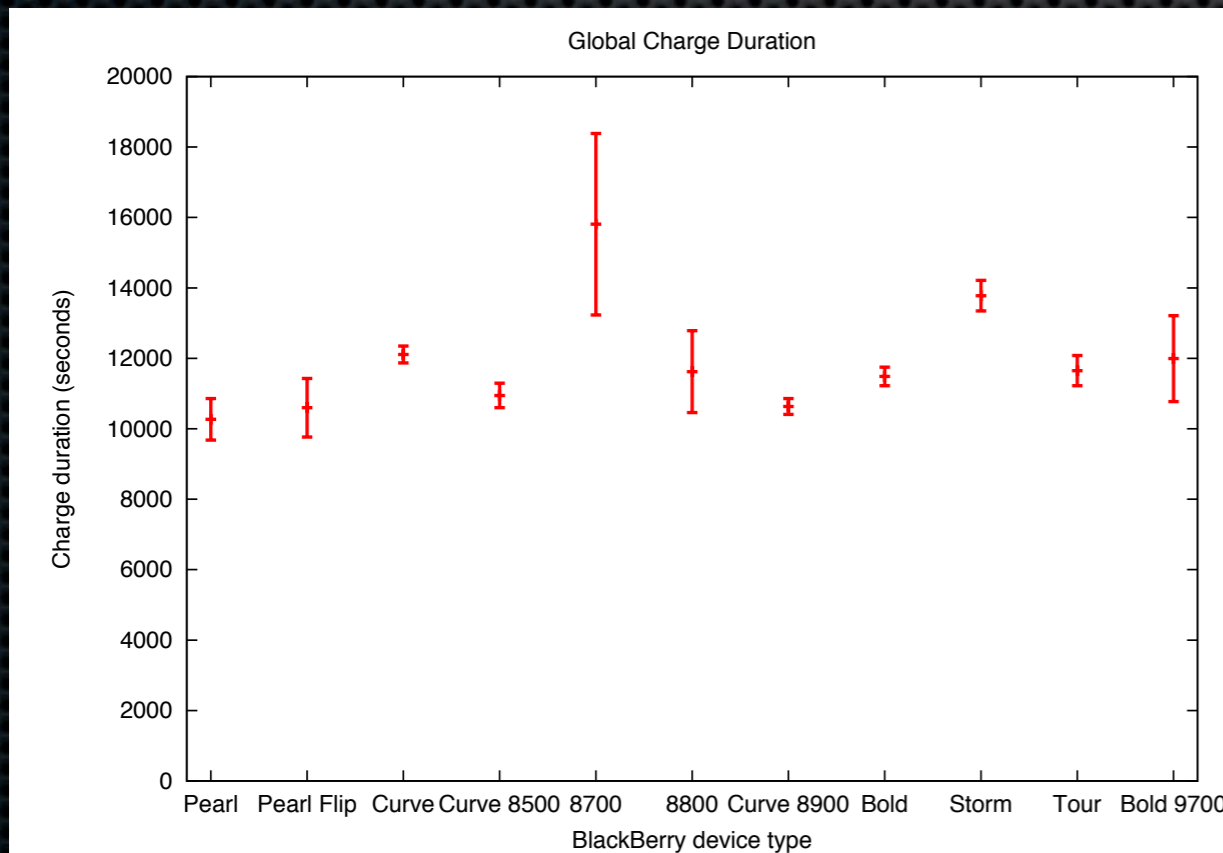
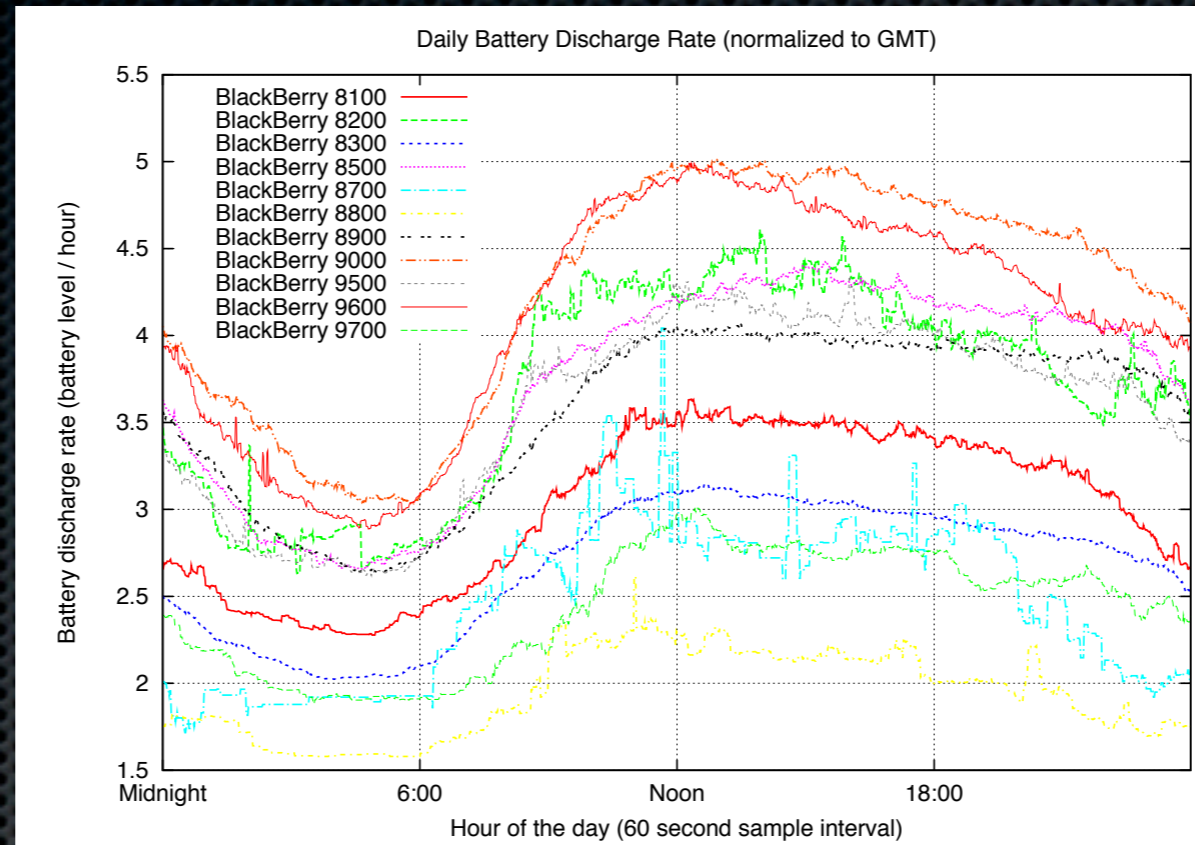
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User classification

- ✦ Cluster by device







User classification

User classification

- ✦ Cluster by device
- ✦ Cluster by energy consumption/replenishment characteristics

User classification

- ✦ Cluster by device
- ✦ Cluster by energy consumption/replenishment characteristics
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User classification

- ✦ Cluster by device
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 - ✦ The set that yield the best prediction results.

Prediction algorithm

Algorithm 1 Calculate future battery level

Require: $\delta_{charge|discharge}$, $\rho_{charge|discharge}$, b_{curr} , β , γ ,
 t_{last} , $t_{predict}$
 $i \leftarrow 0$
for $i < t_{predict}$ **do**
 if $\gamma \wedge t_{curr} < t_{last} + \delta_{charge}(t_{last})$ **then**
 $\gamma \leftarrow \text{false}$ {The charge period has ended.}
 $t_{last} \leftarrow t_{last} + \delta_{charge}(t_{last})$
 else if $\neg\gamma \wedge t_{curr} < t_{last} + \delta_{discharge}(t_{last})$ **then**
 $\gamma \leftarrow \text{true}$ {The discharge period has ended.}
 $t_{last} \leftarrow t_{last} + \delta_{discharge}(t_{last})$
 end if
 if γ **then**
 $b_{future} \leftarrow b_{future} + \rho_{charge}(\beta, t_{curr})$
 else
 $b_{future} \leftarrow b_{future} - \rho_{discharge}(\beta, t_{curr})$
 end if
 $i \leftarrow i + \text{BUCKET_SIZE}$
 $t_{curr} \leftarrow t_{curr} + \text{BUCKET_SIZE}$
end for
return b_{future}

Prediction algorithm

t_{last} = last time that the device began charging or discharging

δ_{charge_t} = mean charge duration of a charge initiated during $bucket(t)$

$\delta_{discharge_t}$ = mean discharge duration of a discharge initiated during $bucket(t)$

ρ_{charge_t} = mean charge rate during $bucket(t)$

$\rho_{discharge_t}$ = mean charge rate during $bucket(t)$ bucket size = 30 minutes

Prediction algorithm

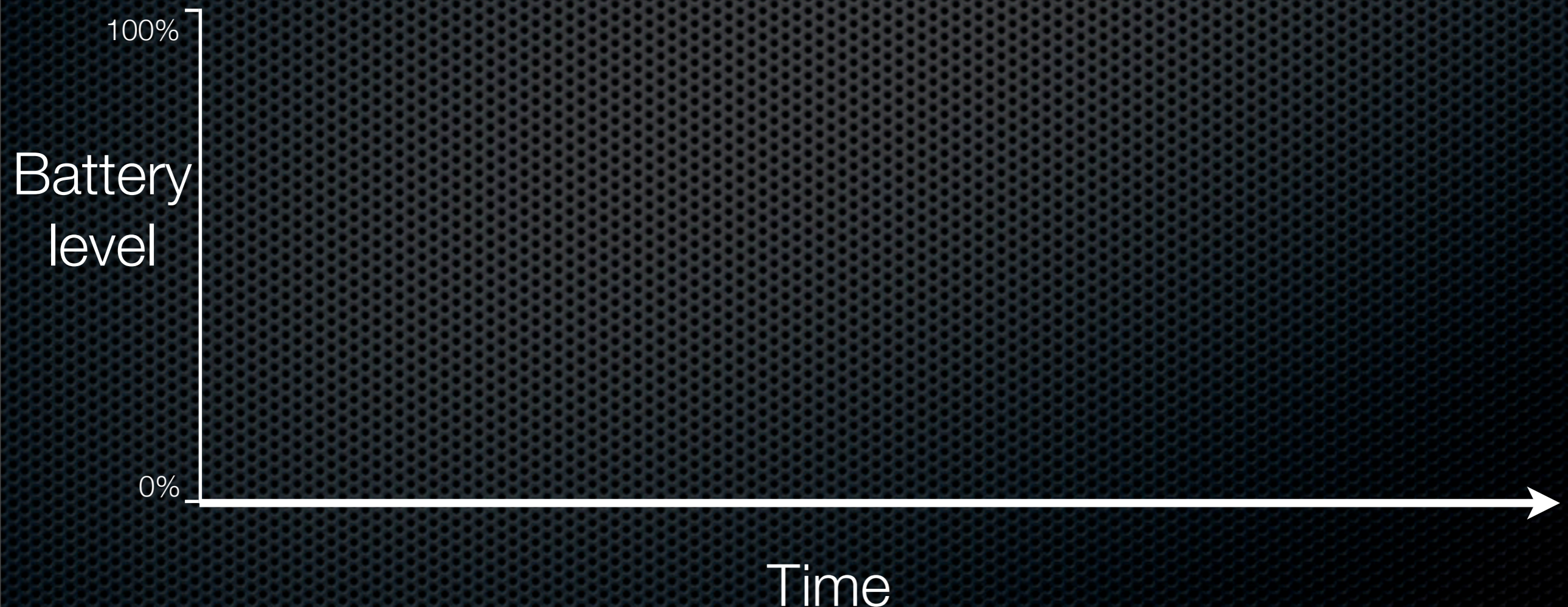
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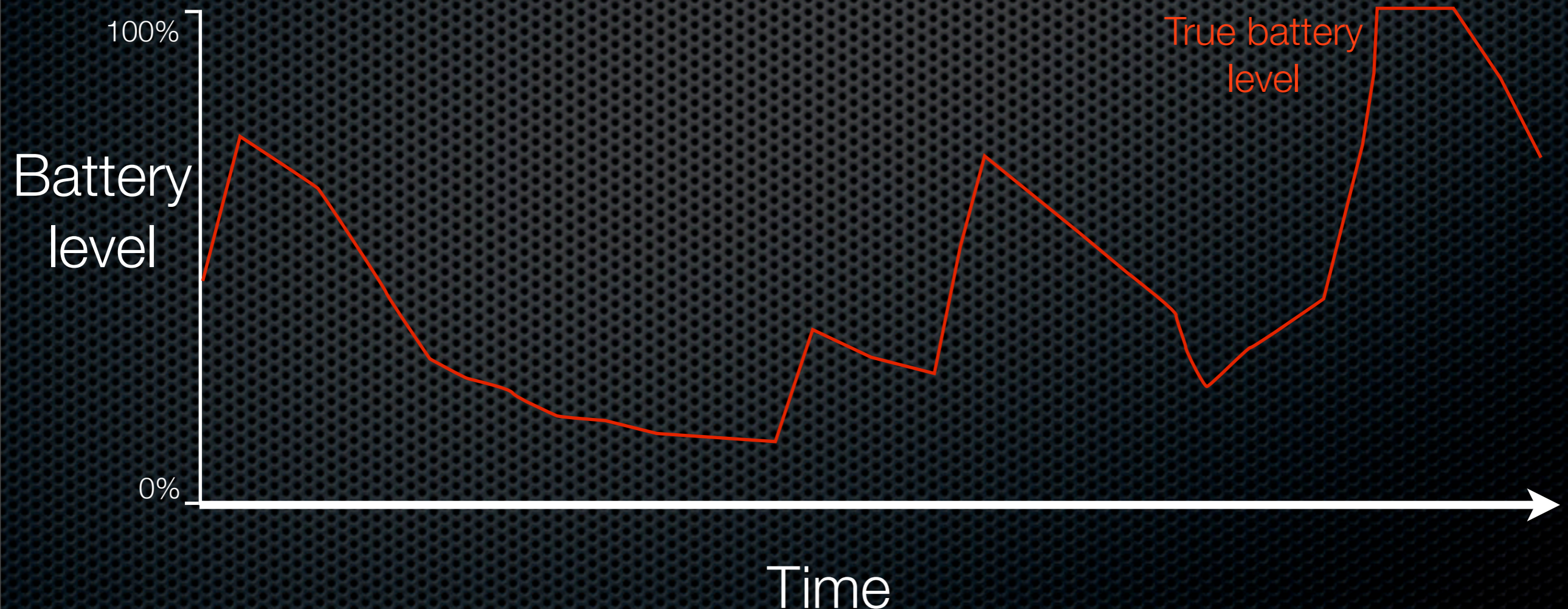
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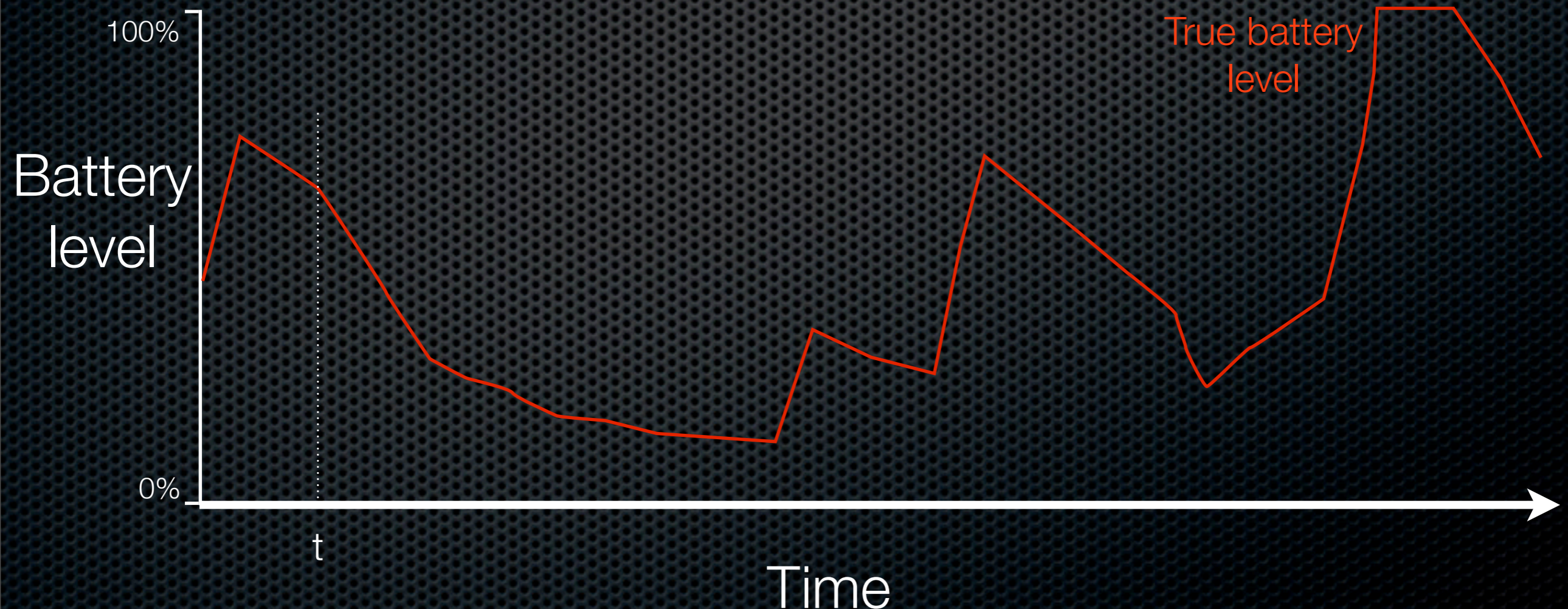
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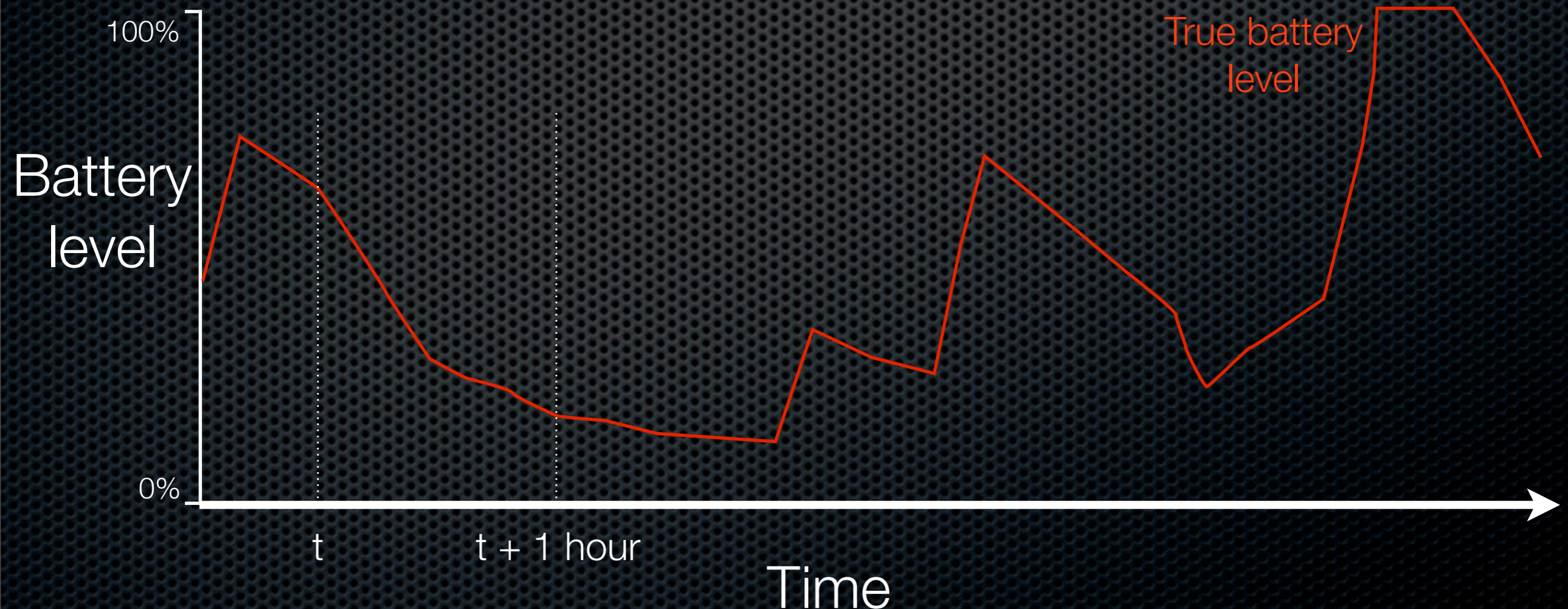
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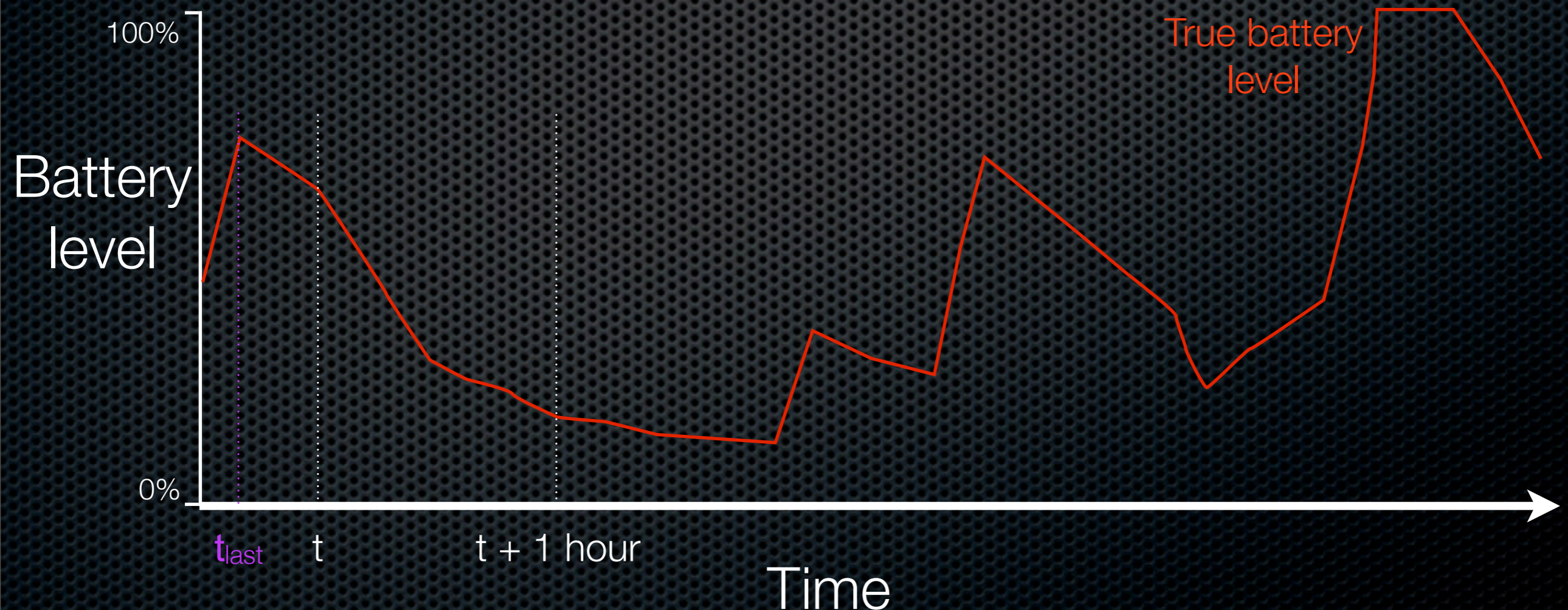
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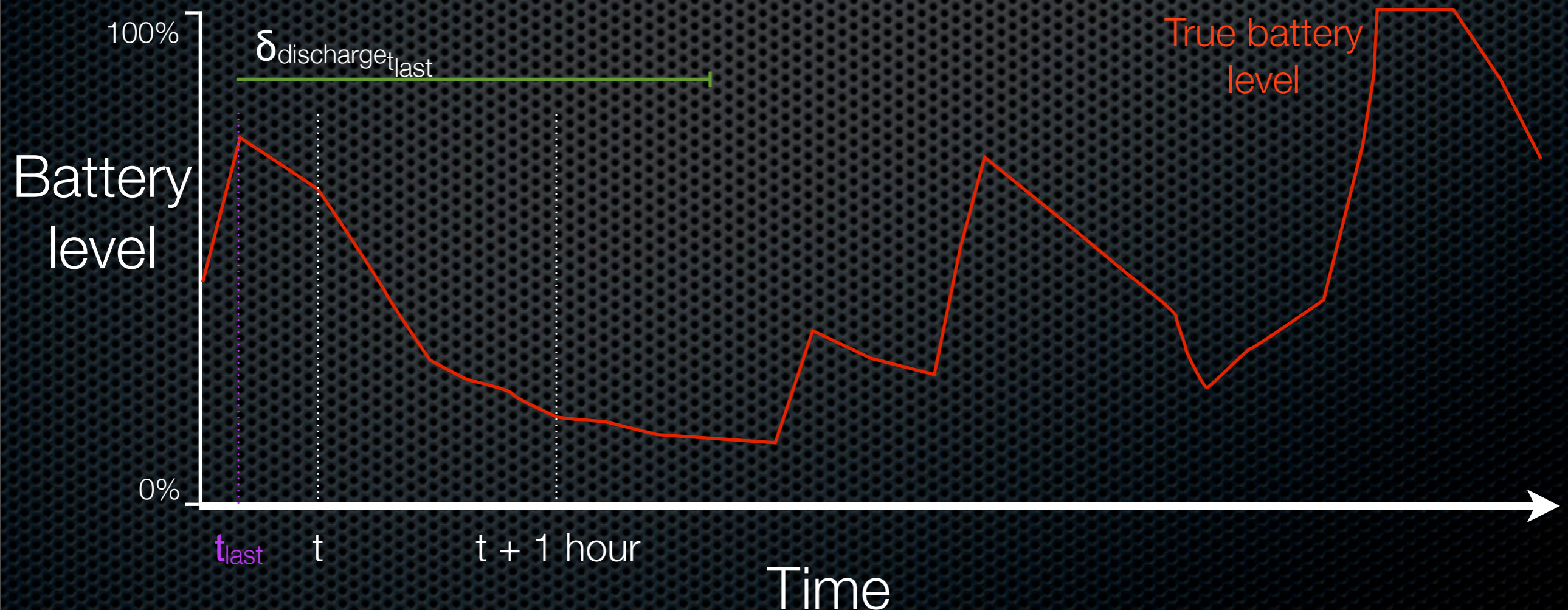
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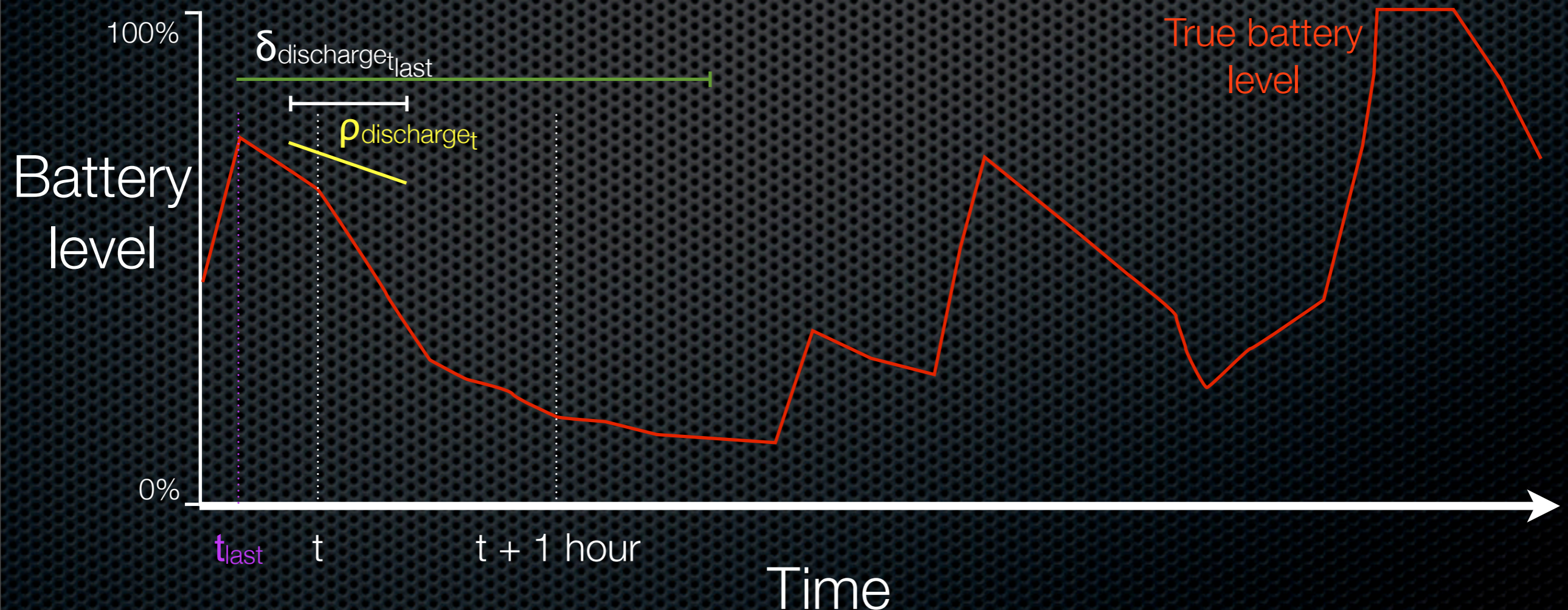
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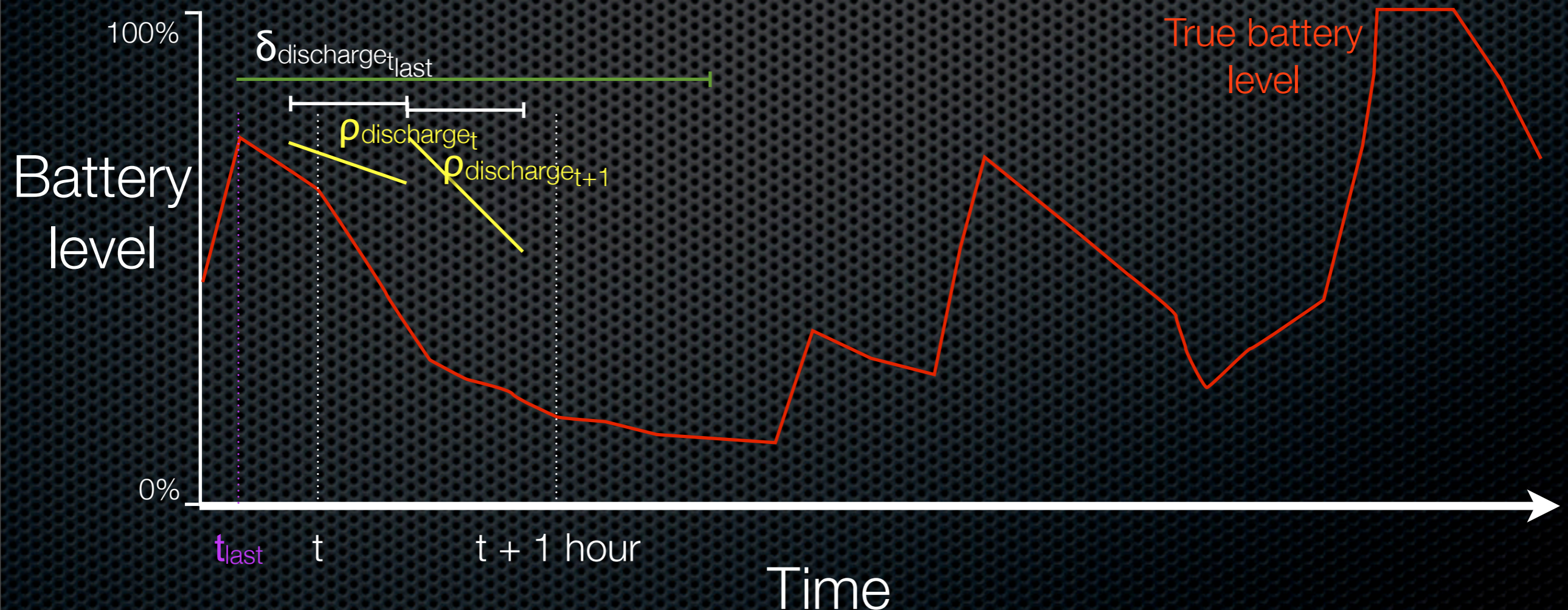
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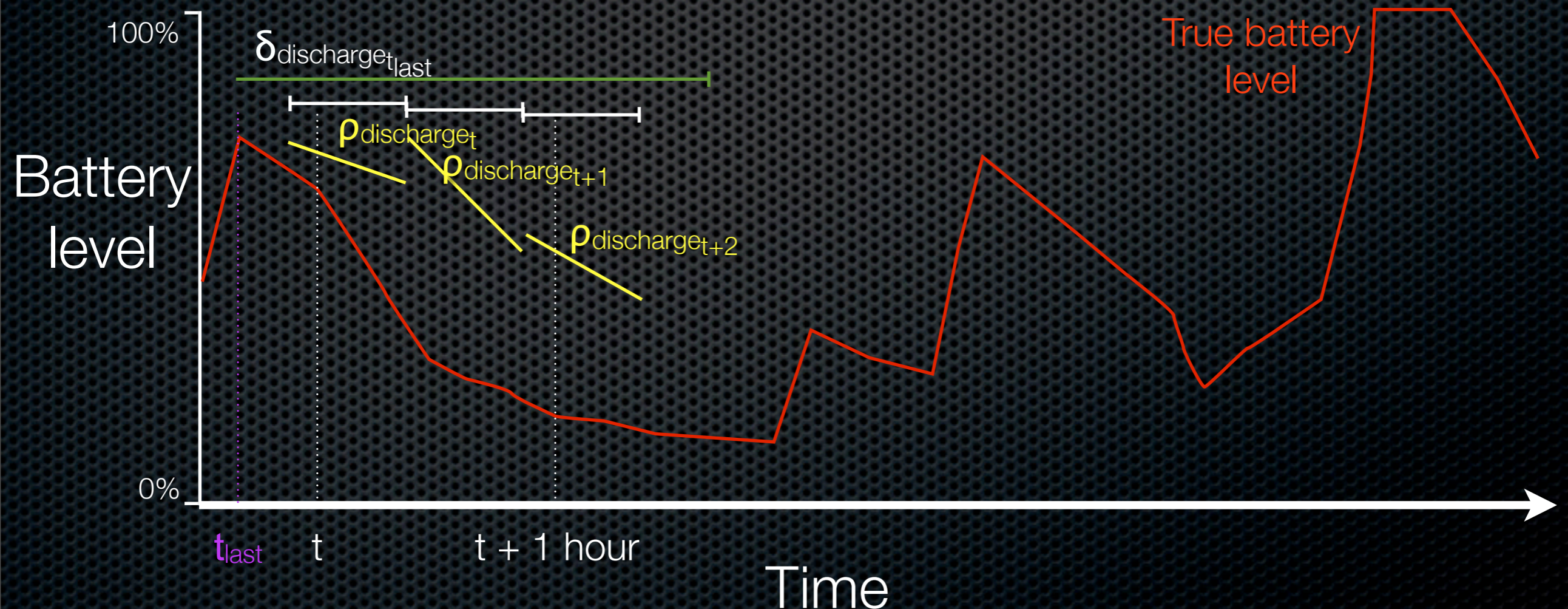
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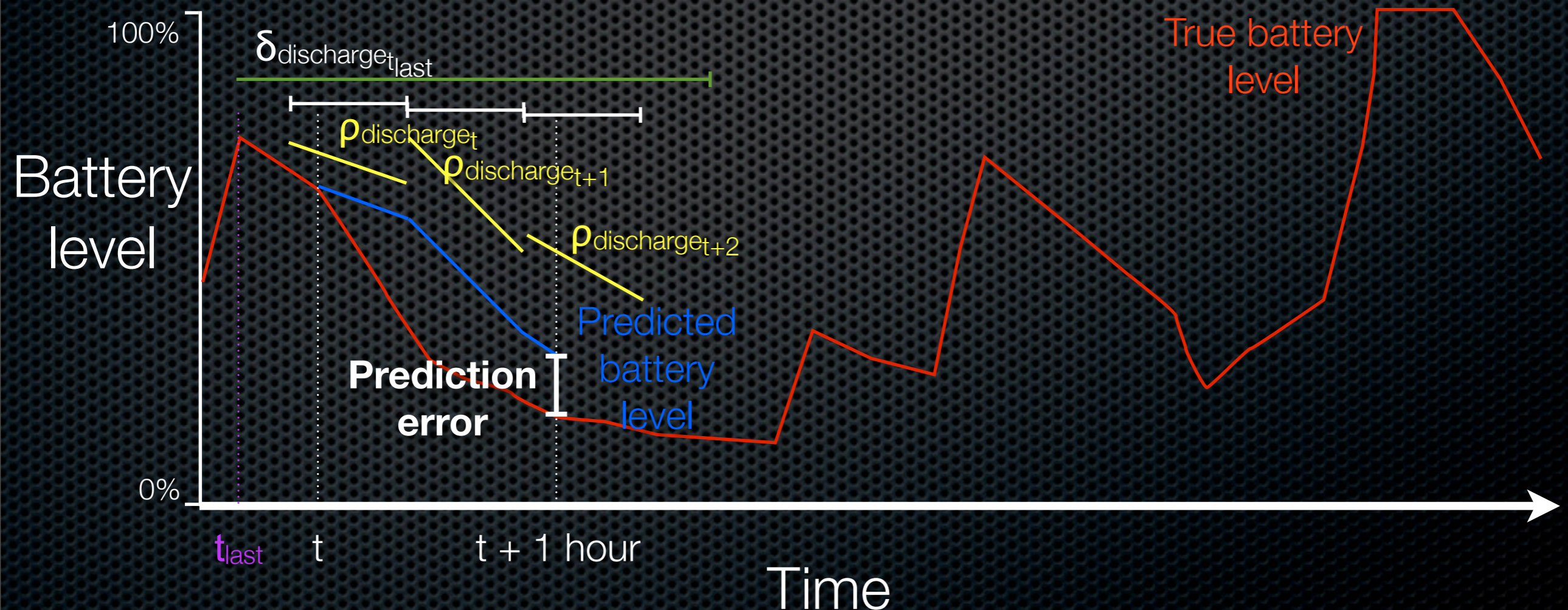
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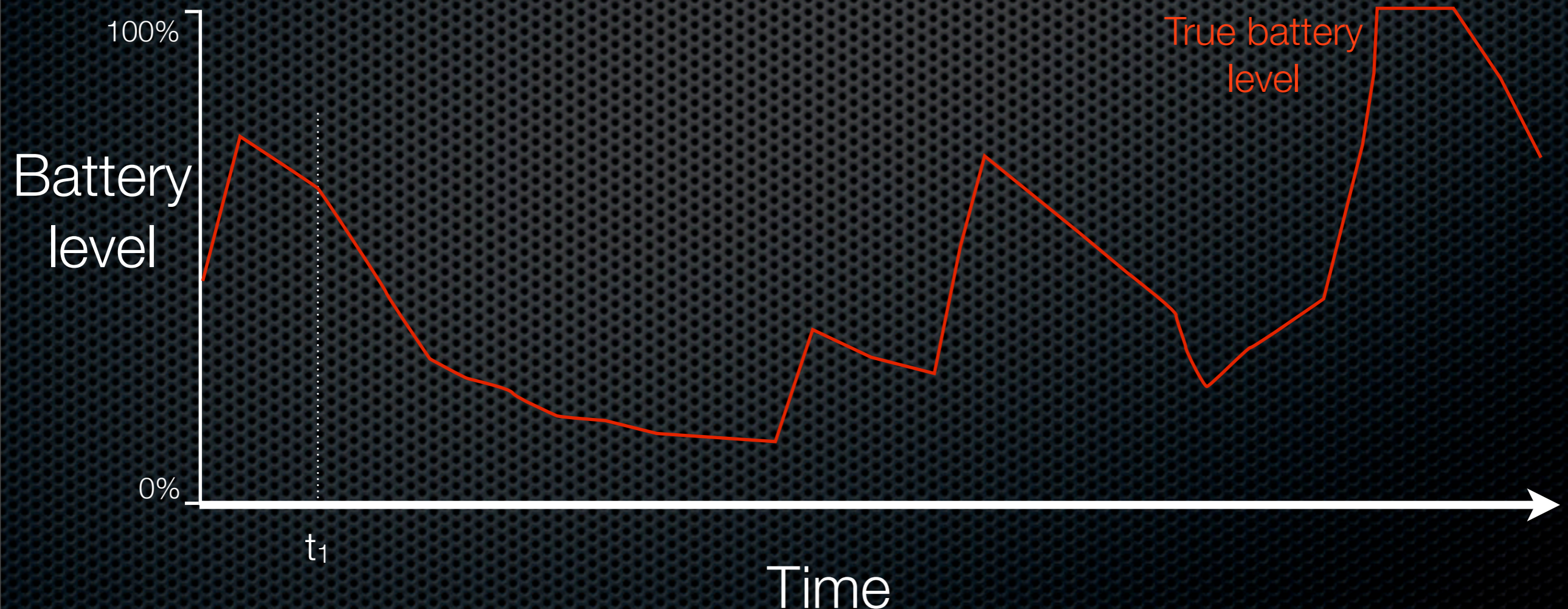
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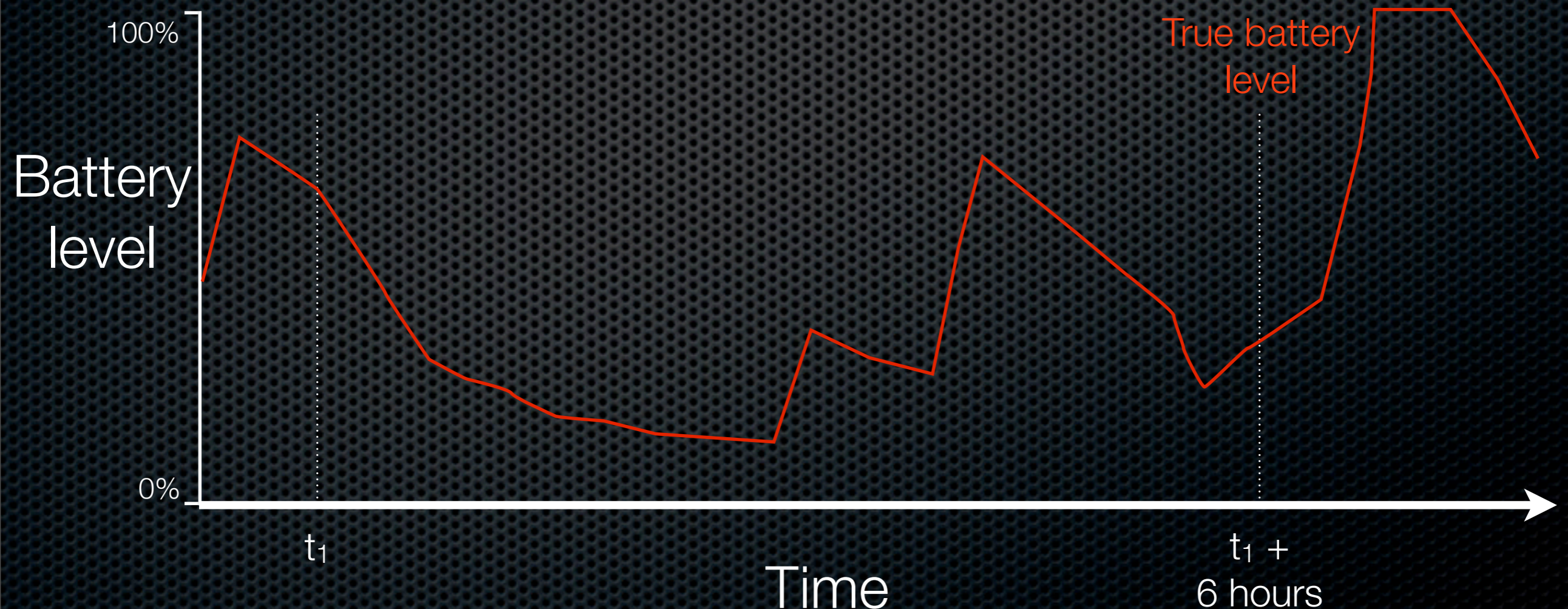
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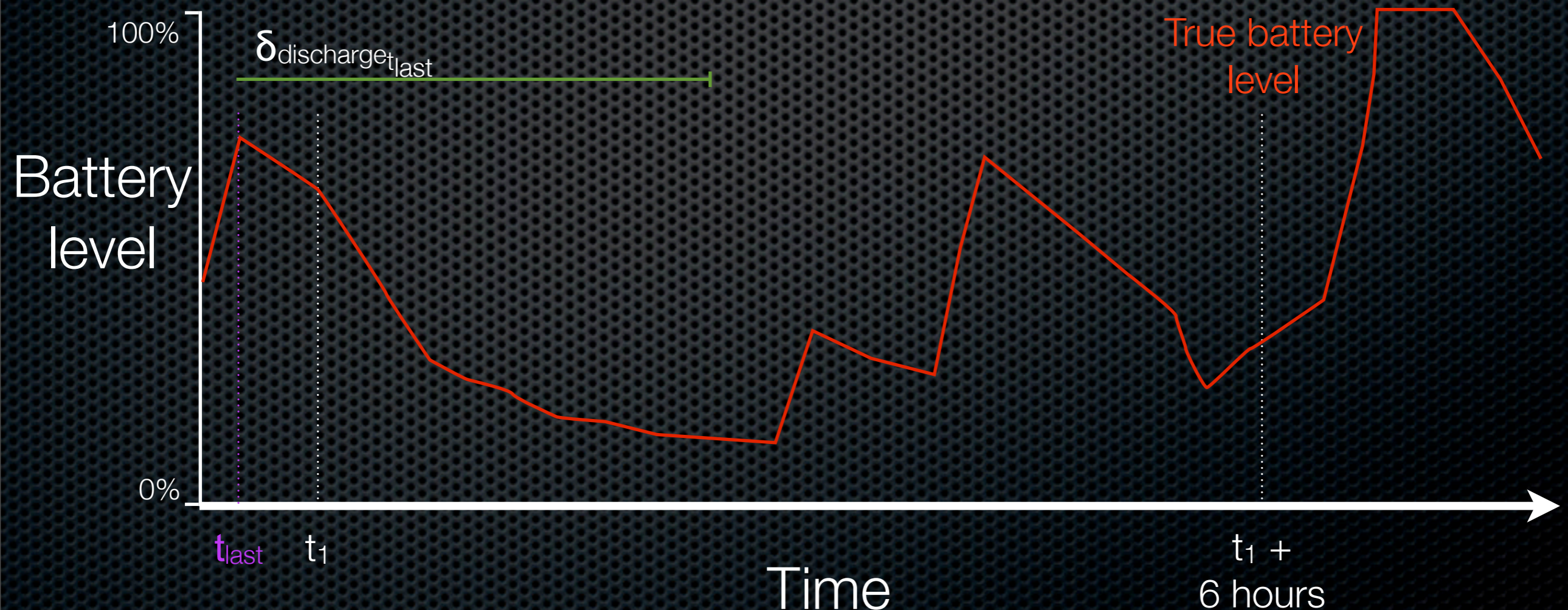
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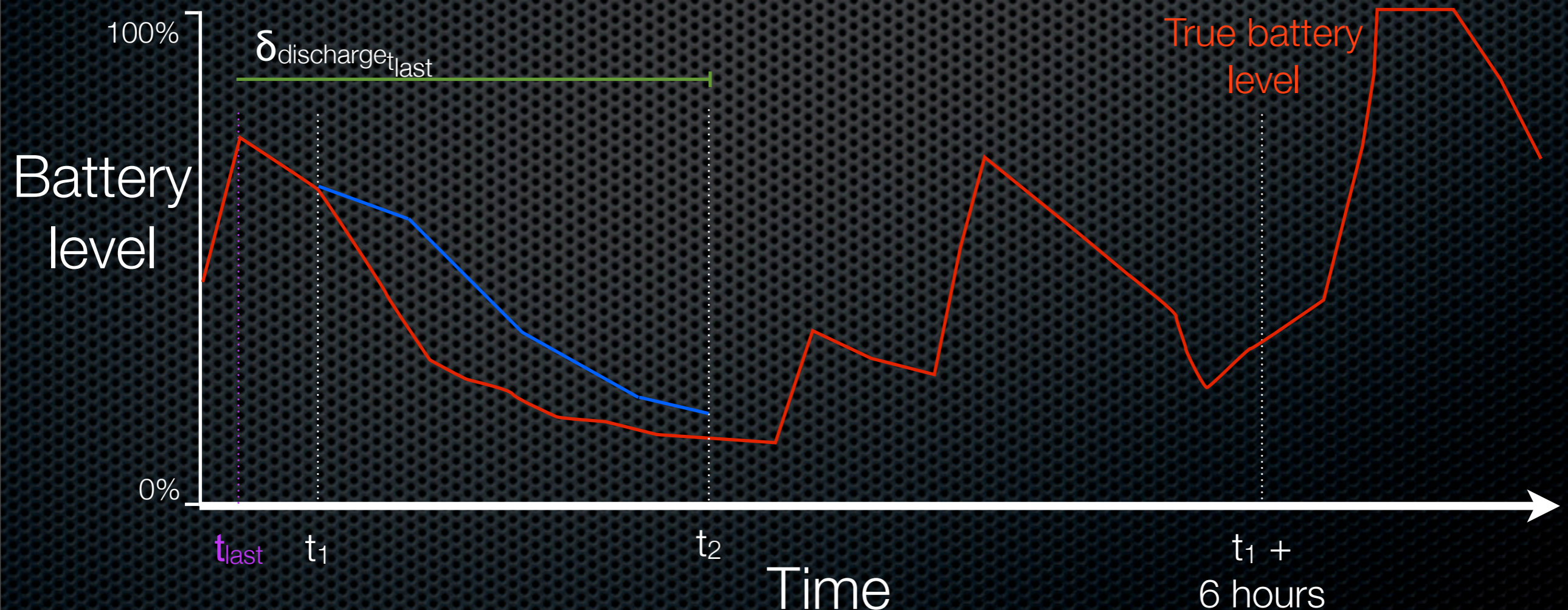
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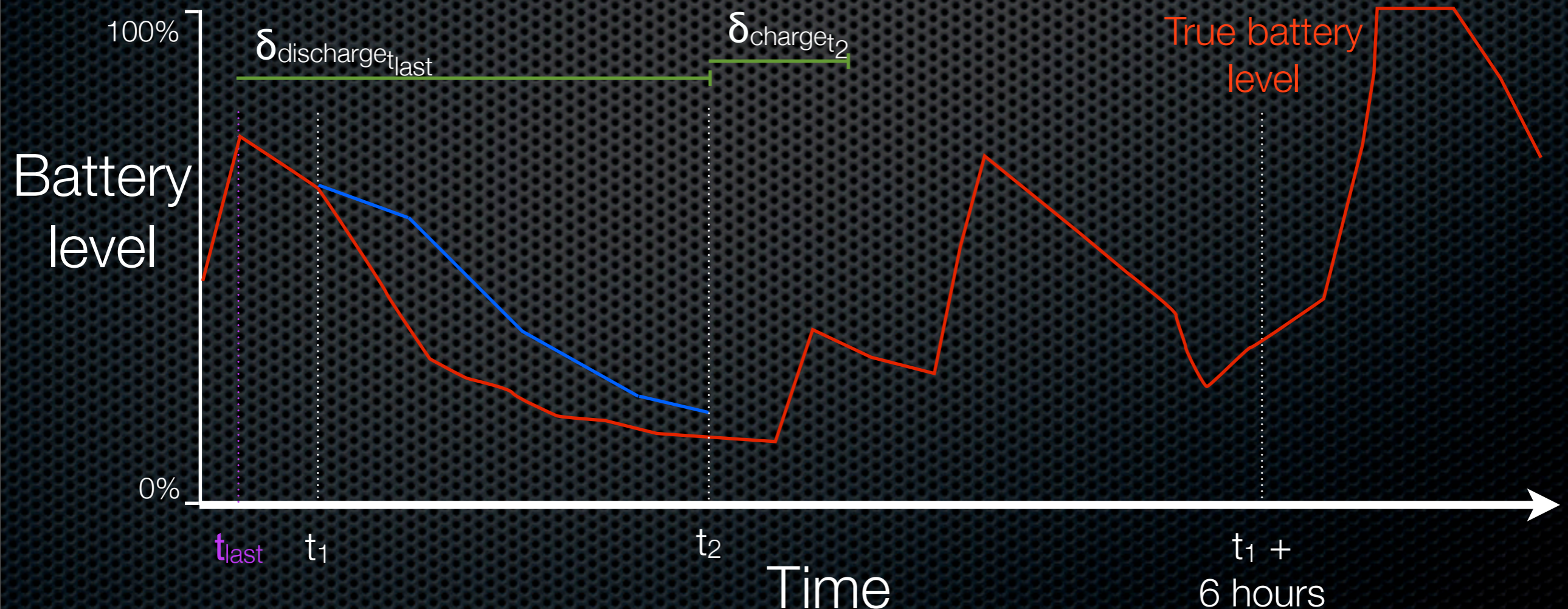
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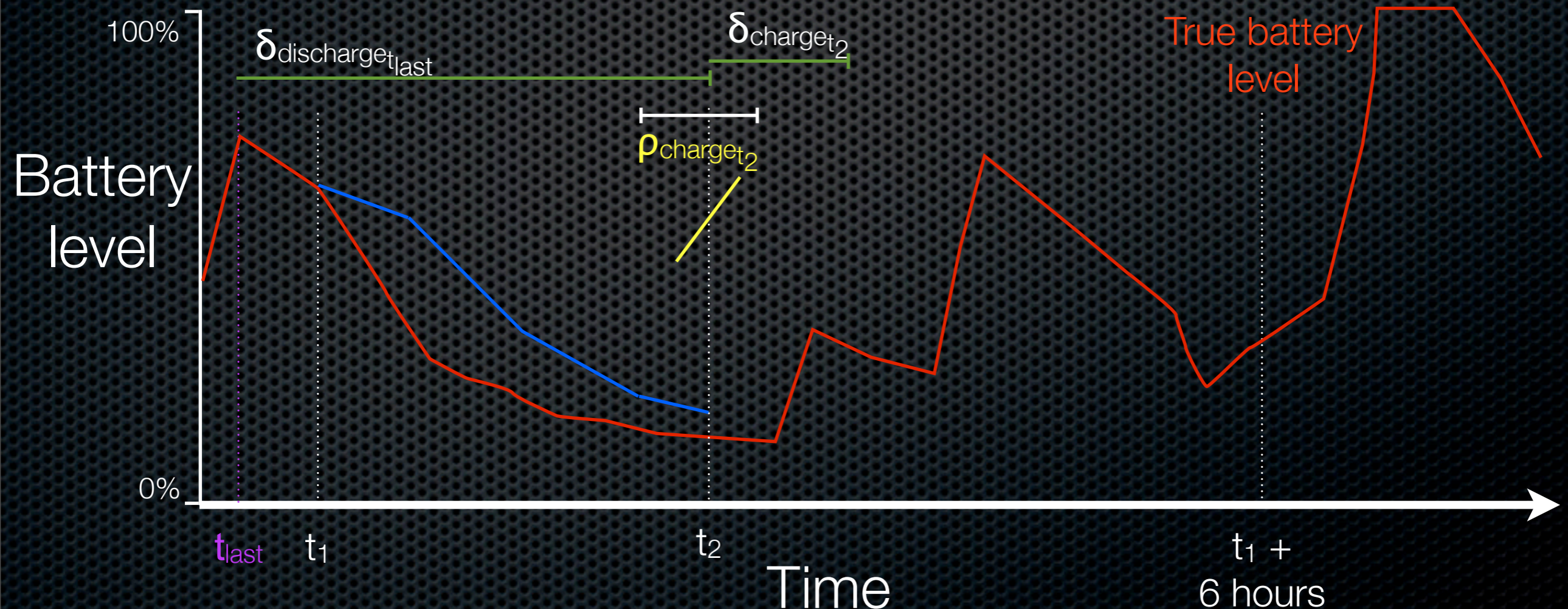
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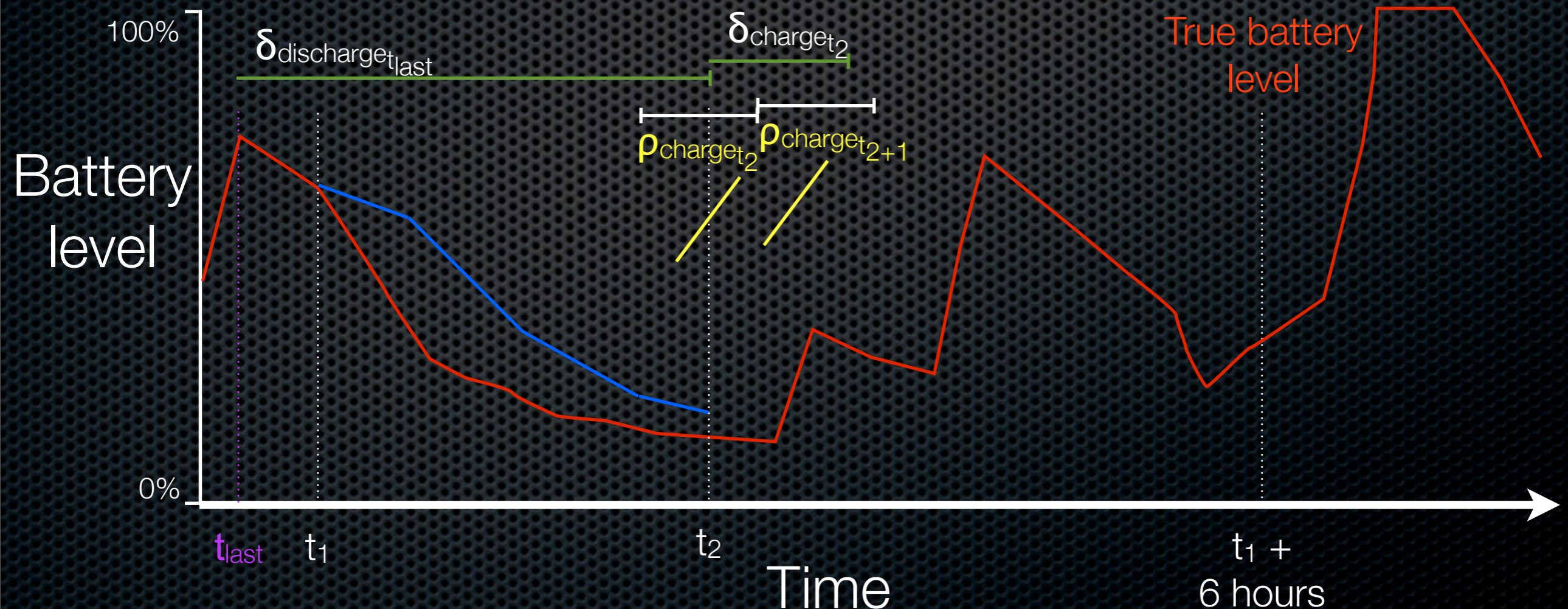
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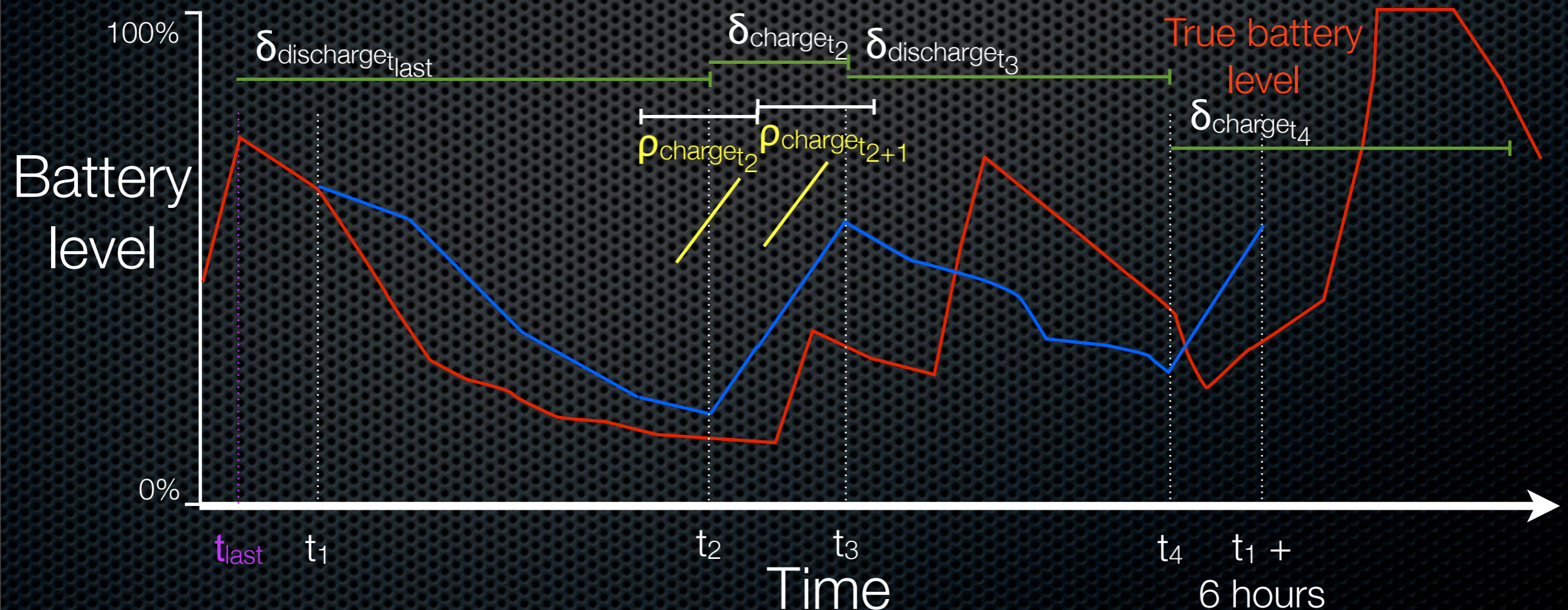
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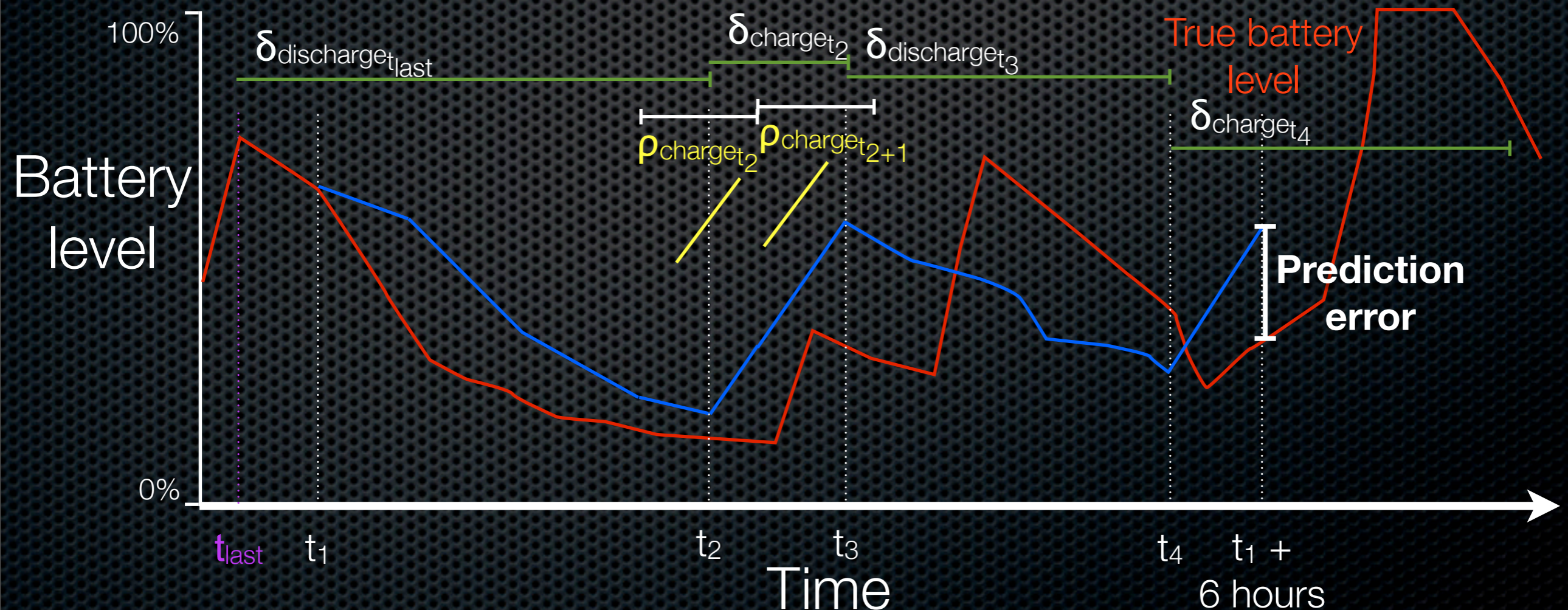
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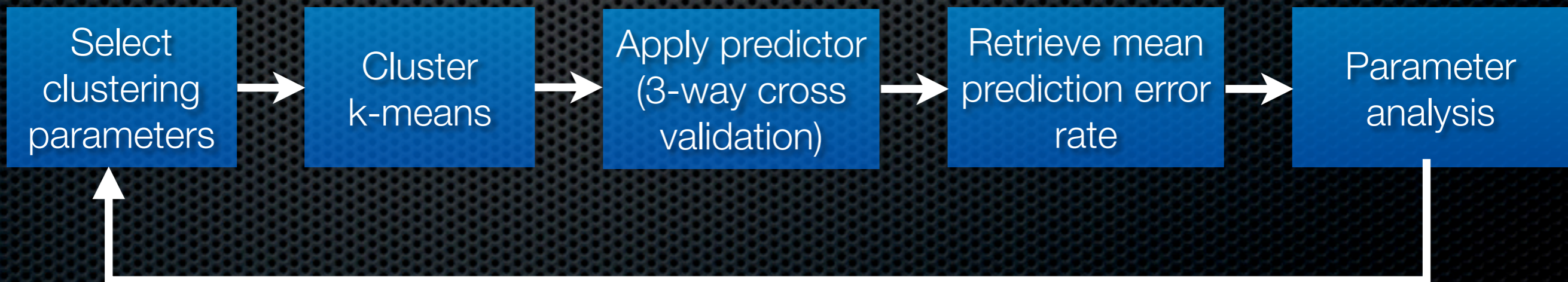
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User classification

- ✦ Cluster by device
- ✦ Cluster by energy consumption/replenishment characteristics
 - ✦ Which set of characteristics are best?
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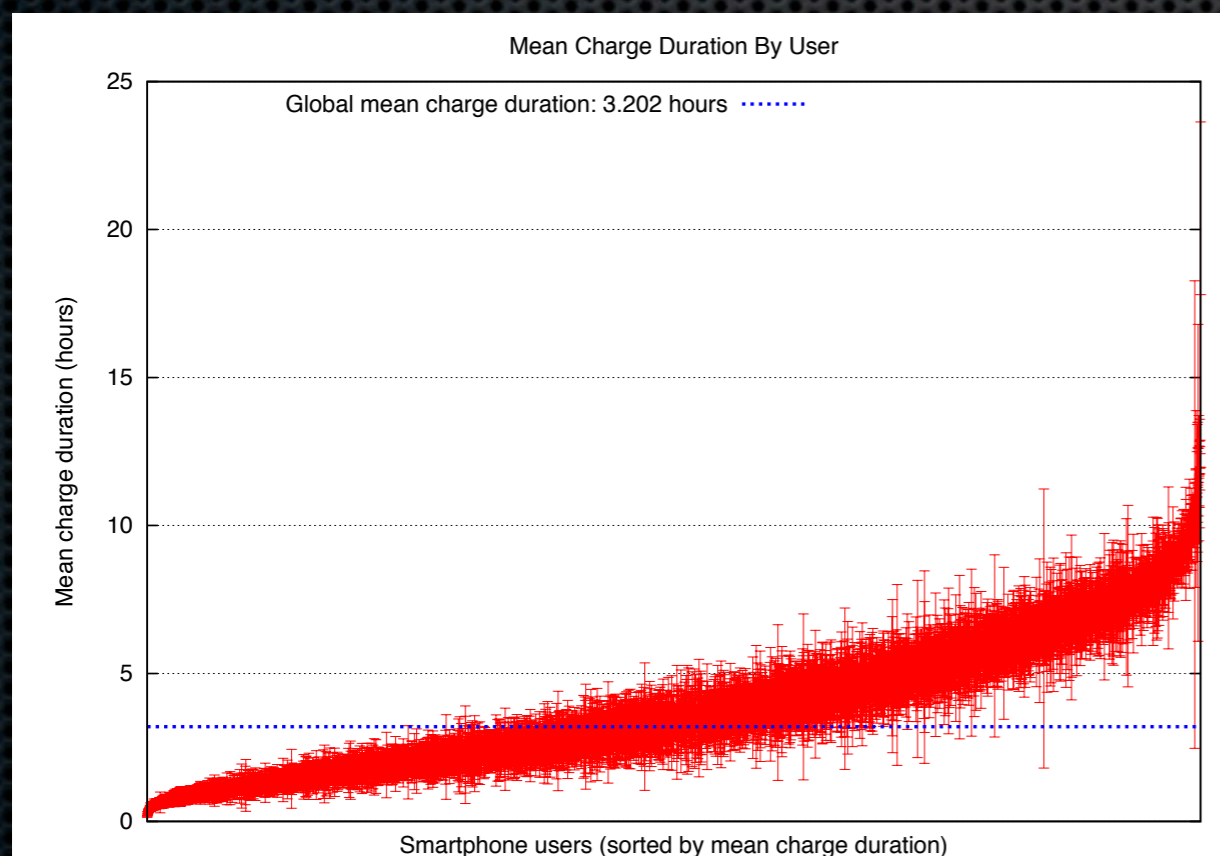


Clustering parameters

$$\left\{ \begin{array}{l} \text{Mean charge duration} \\ \text{Mean discharge duration} \end{array} \right\} \times \left\{ \begin{array}{l} \text{weekday} \\ \text{weekend} \end{array} \right\}$$

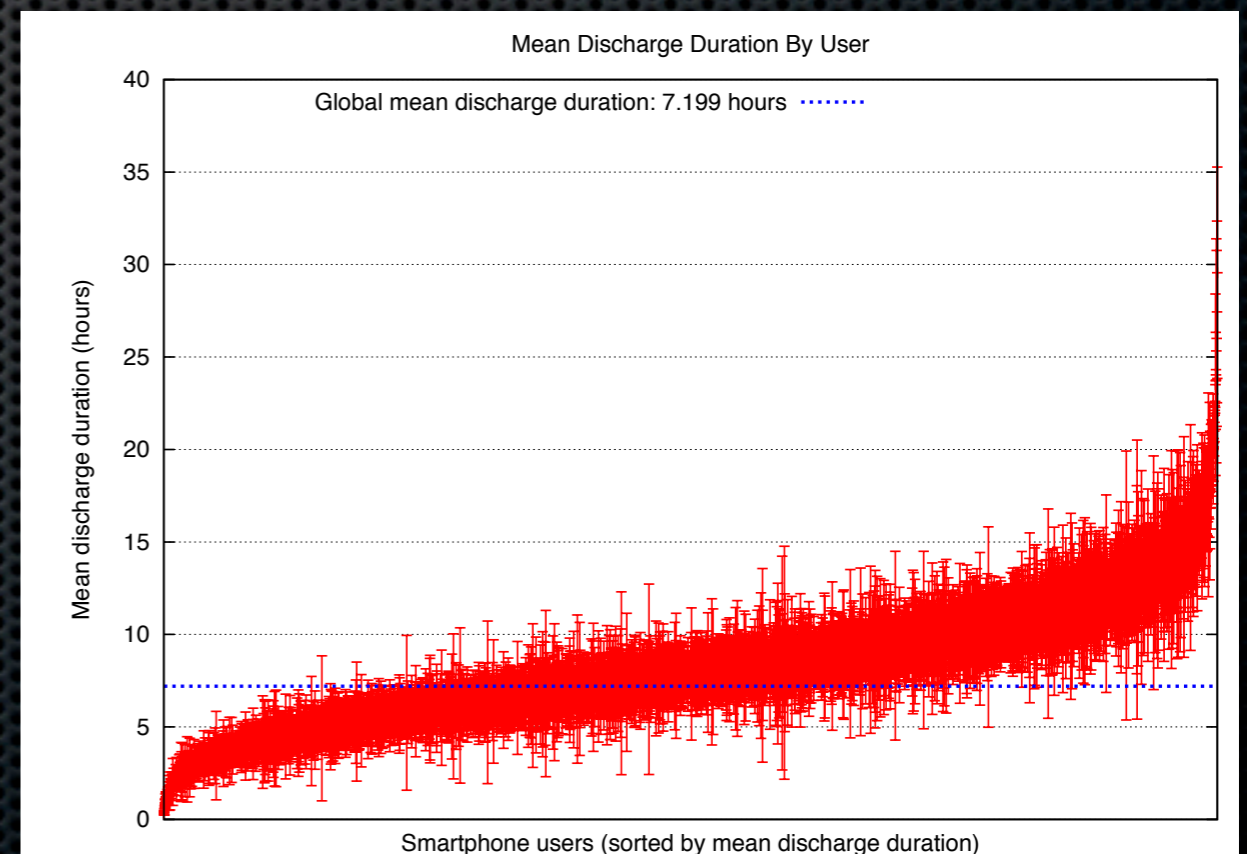
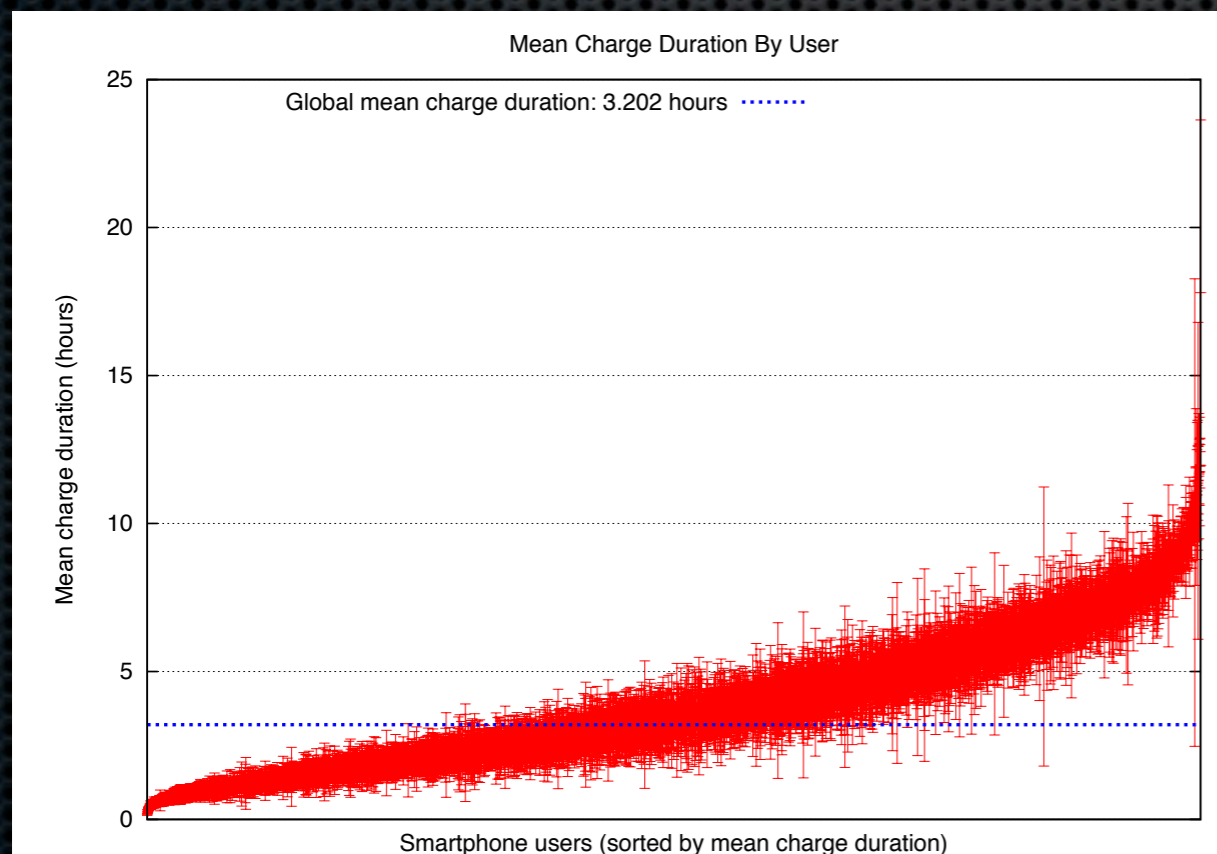
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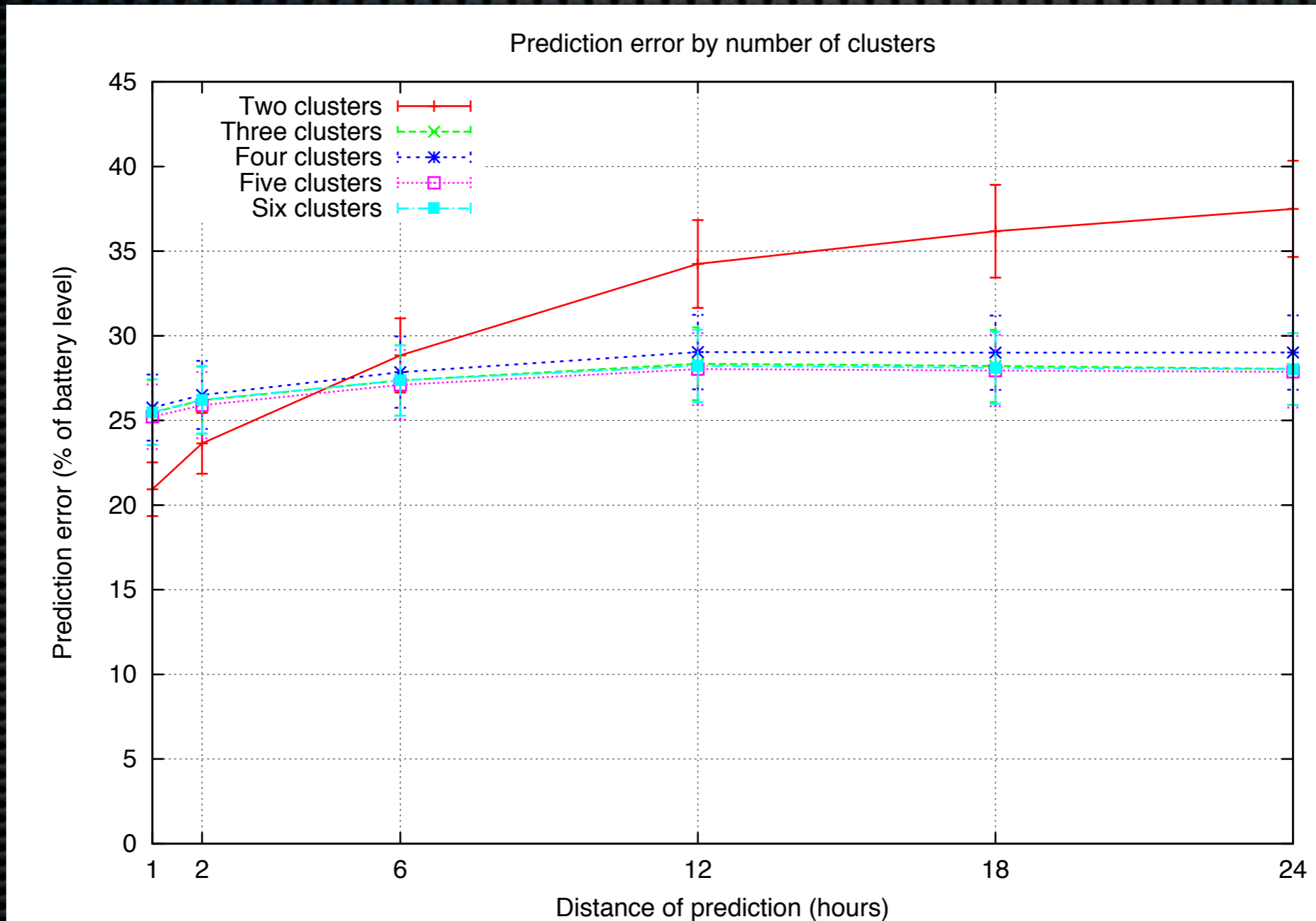


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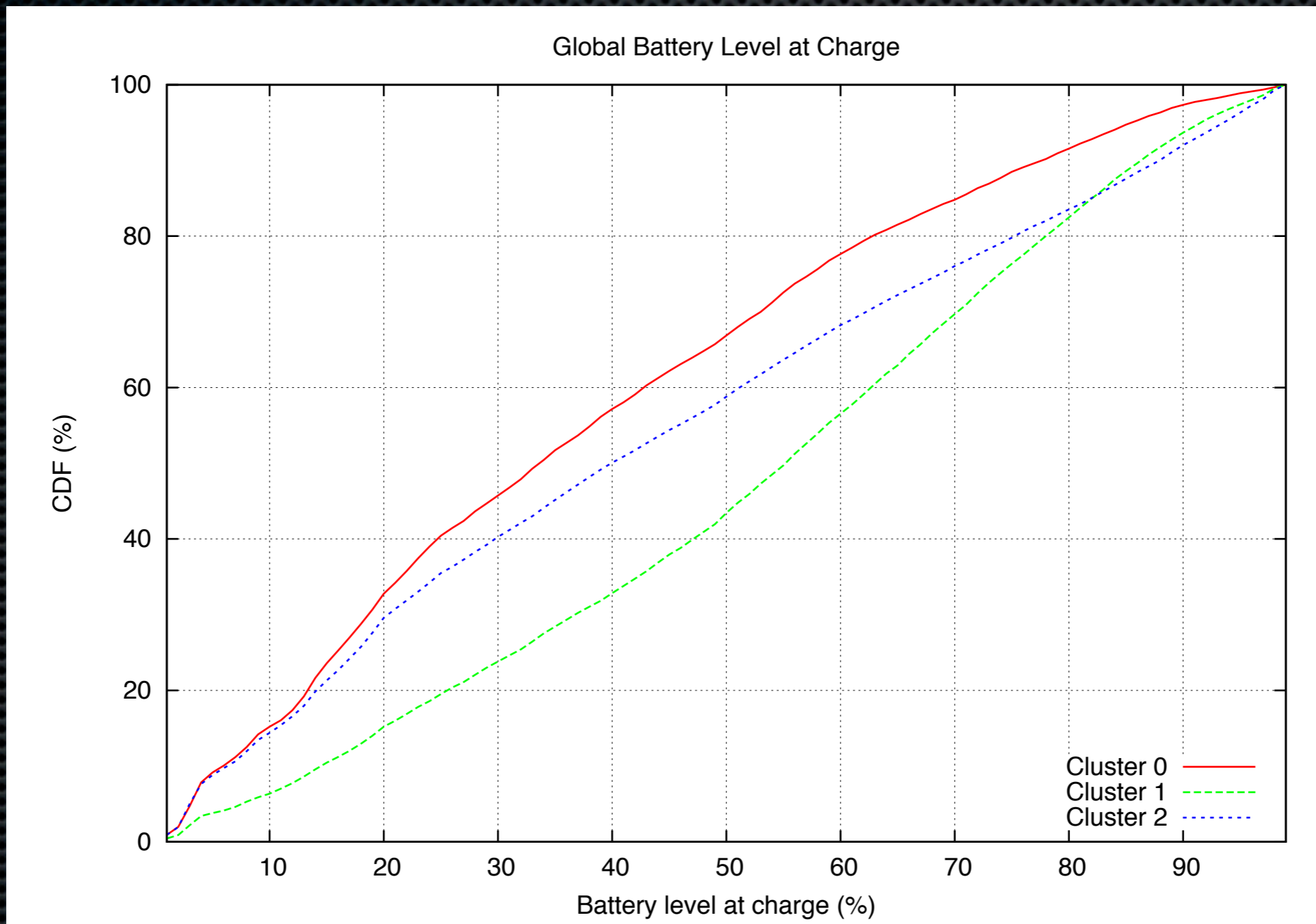
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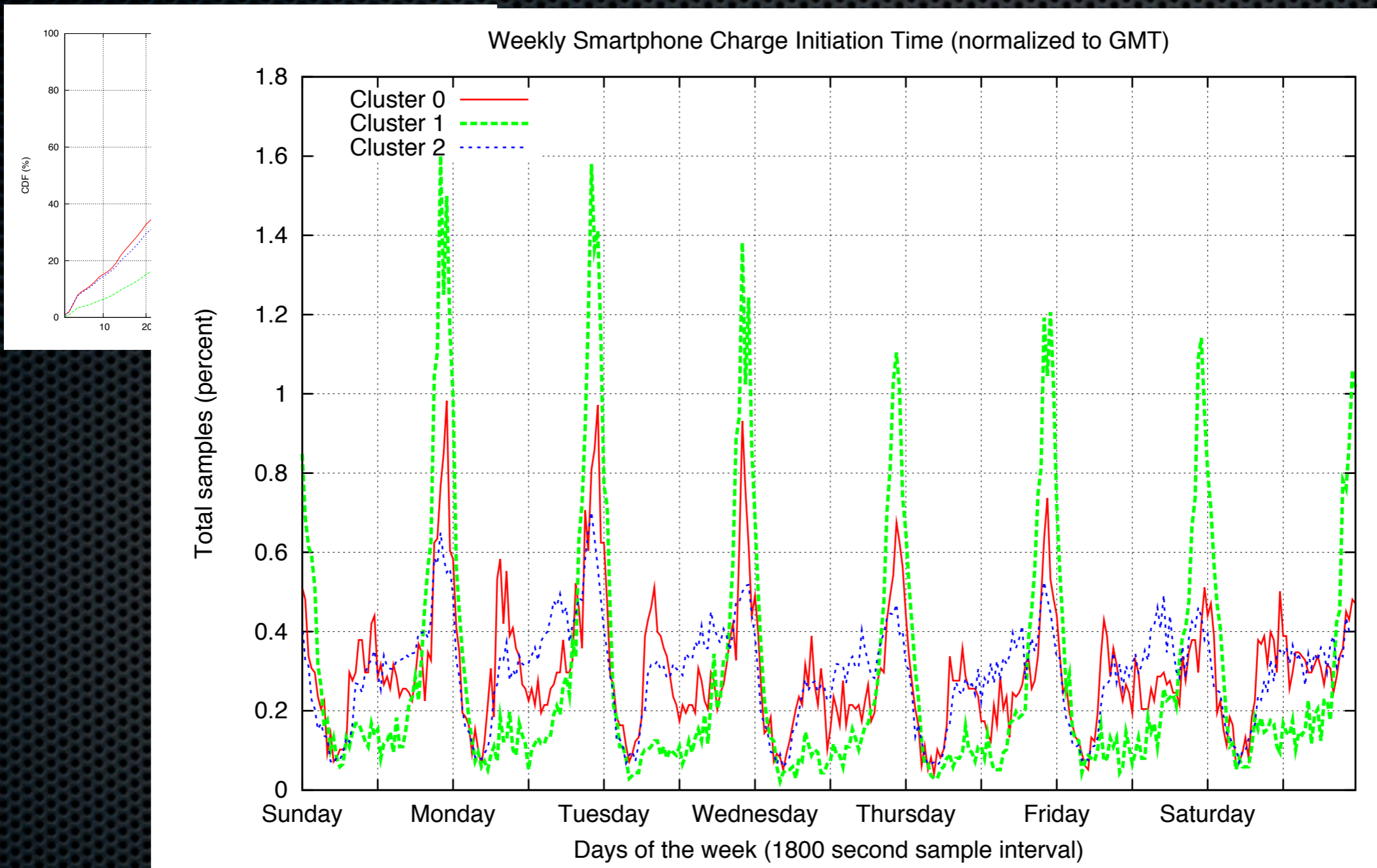
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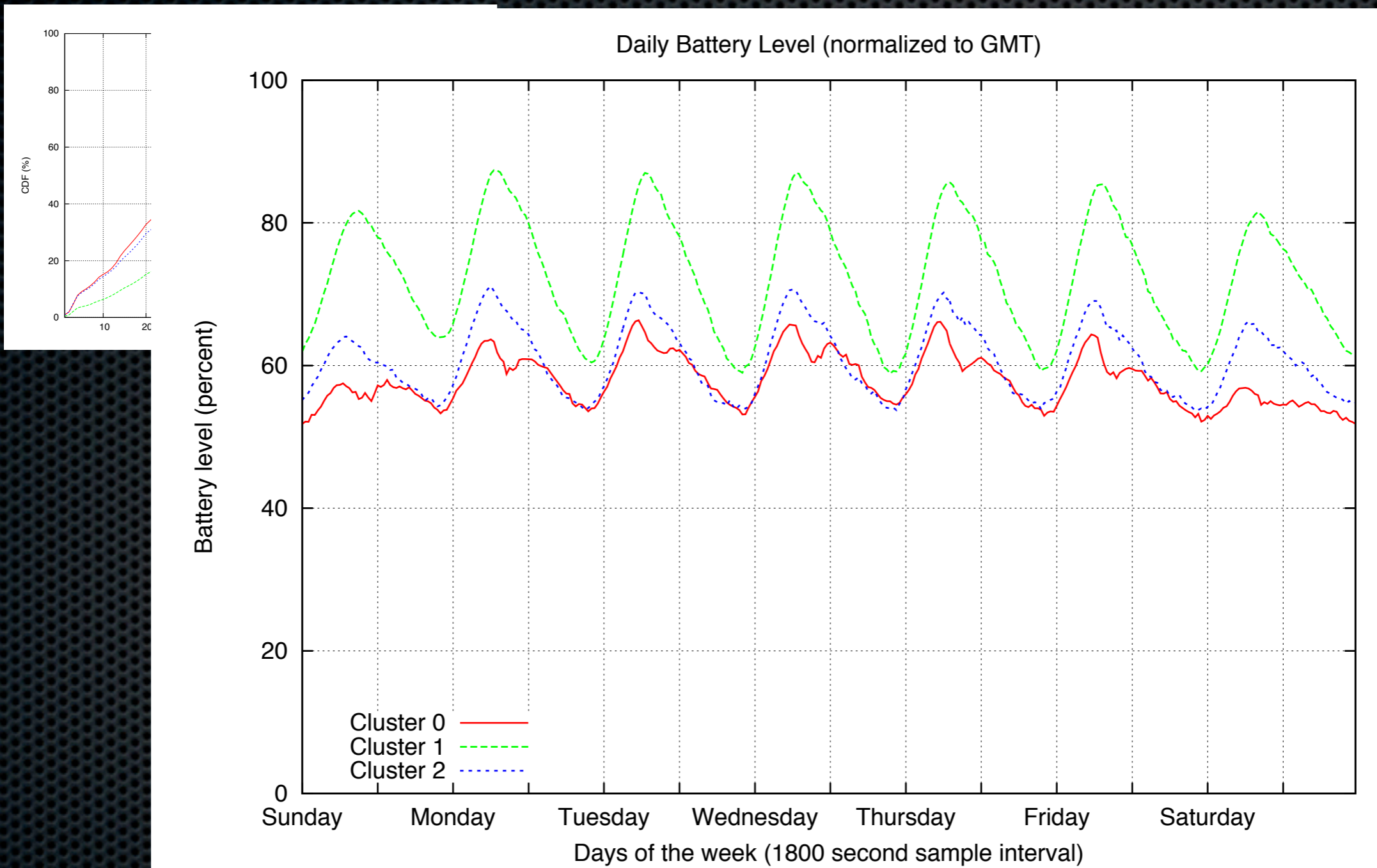
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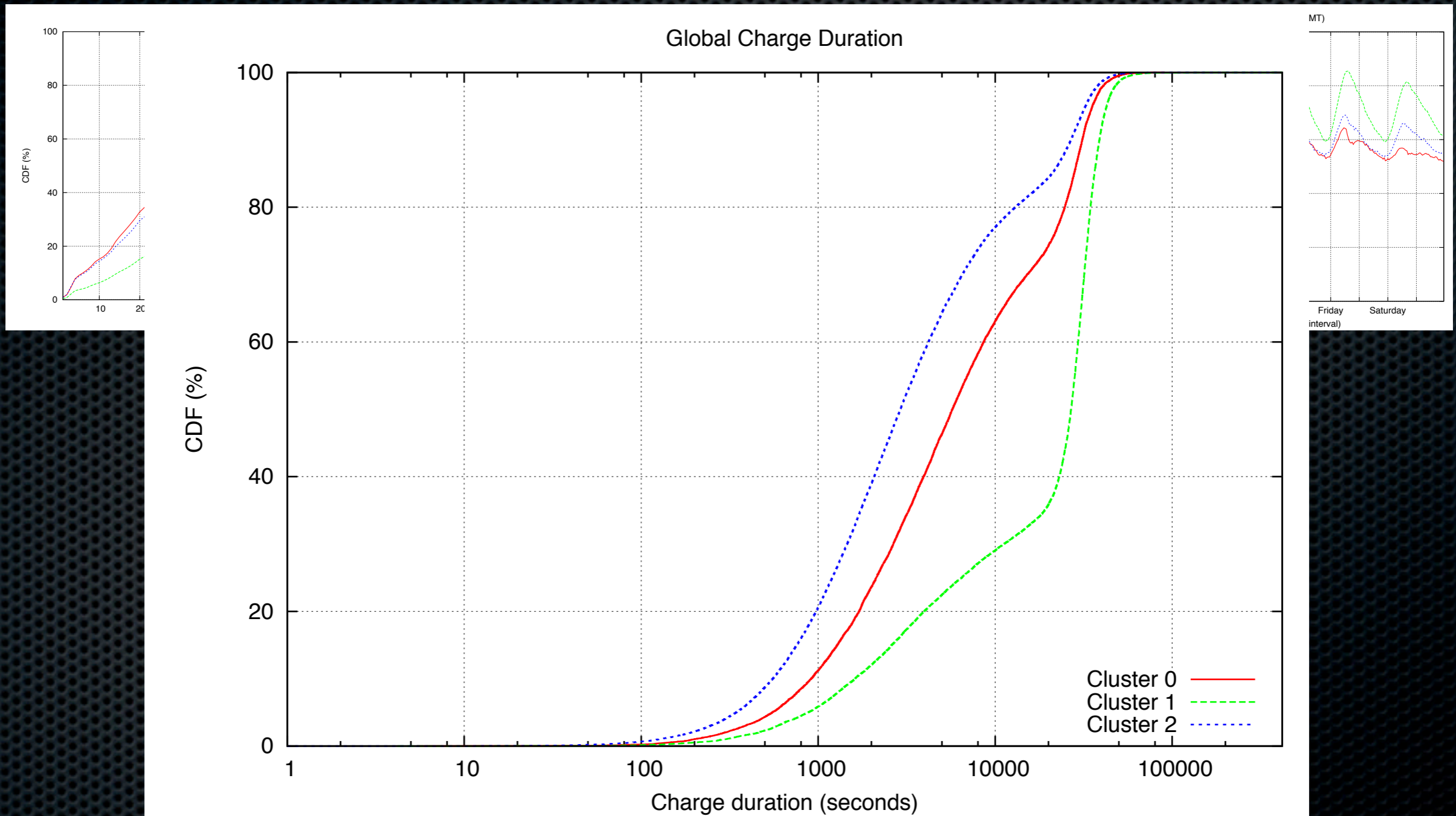
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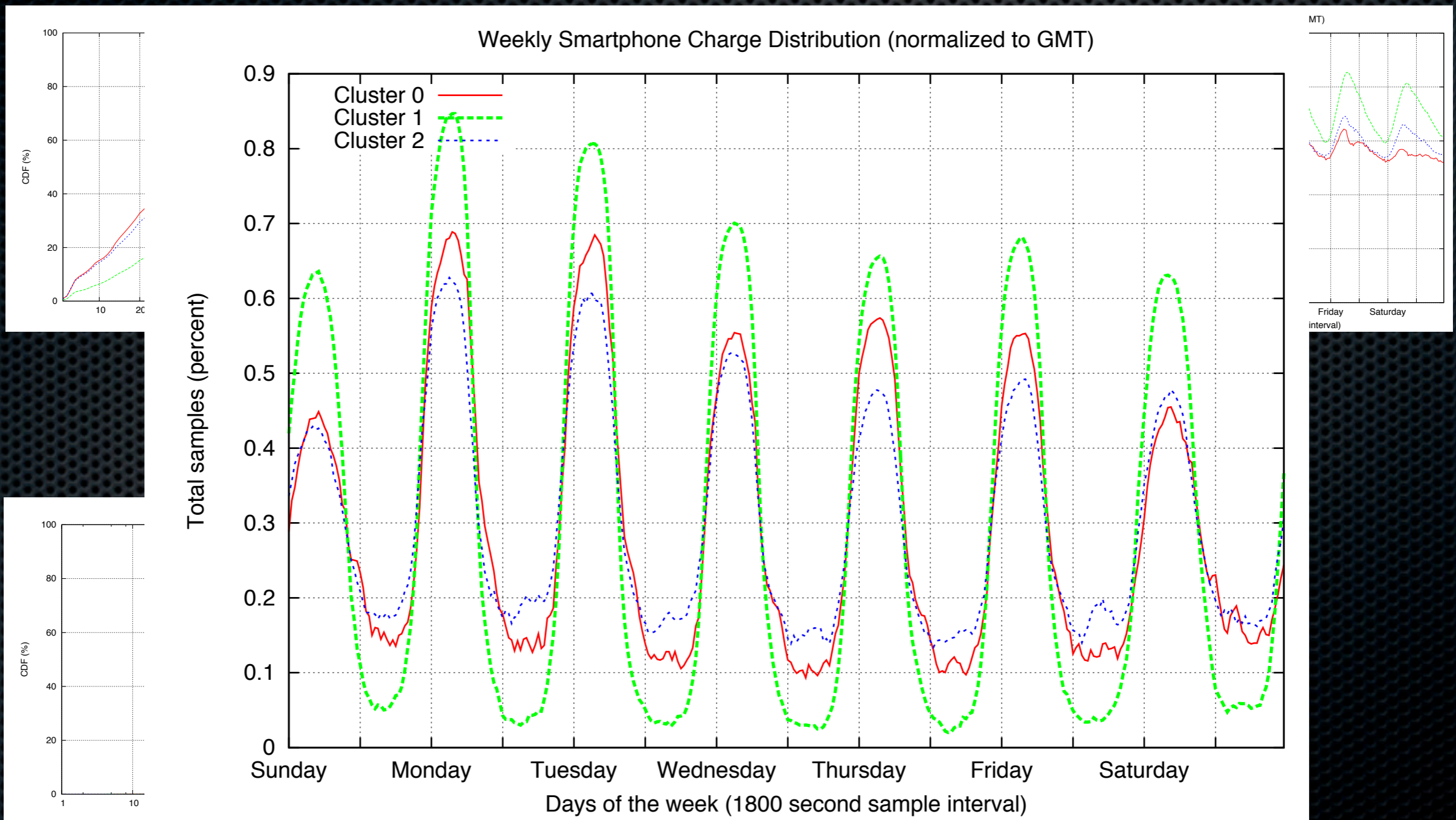
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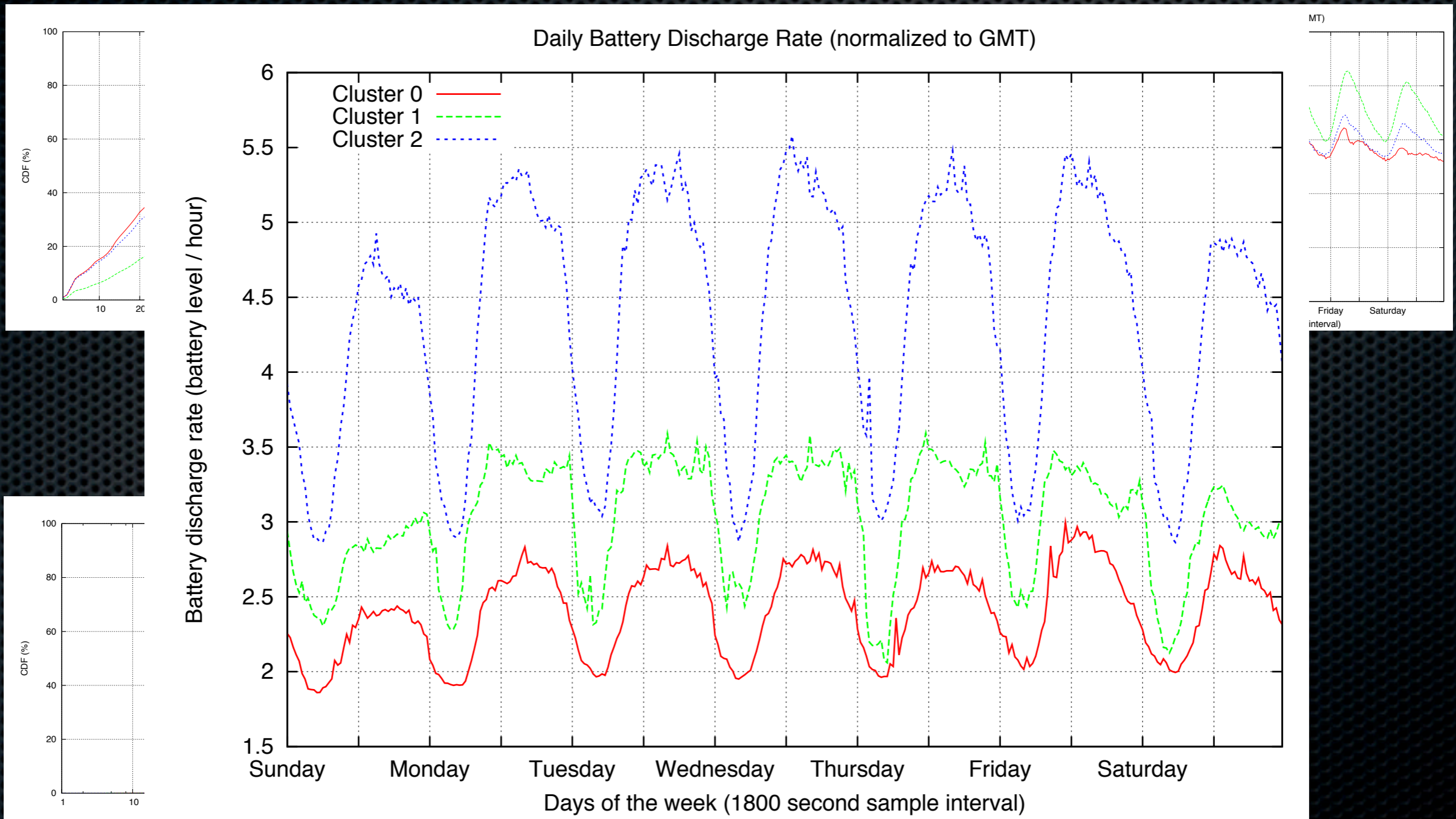
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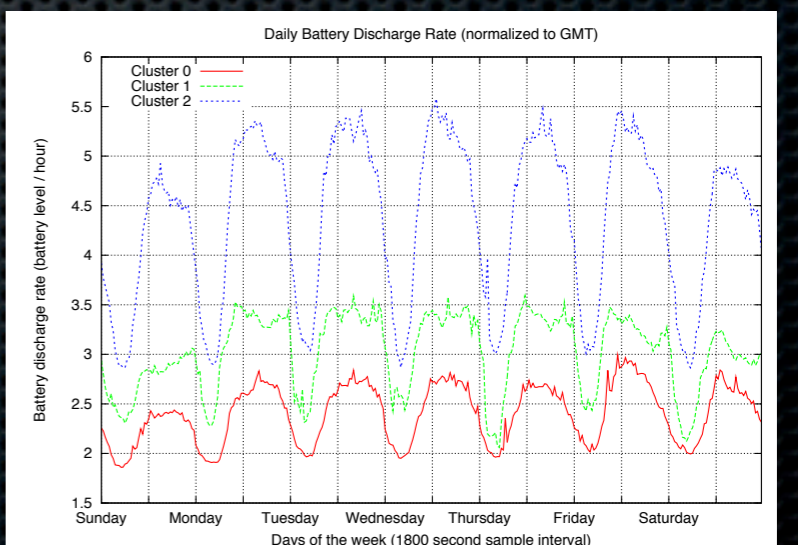
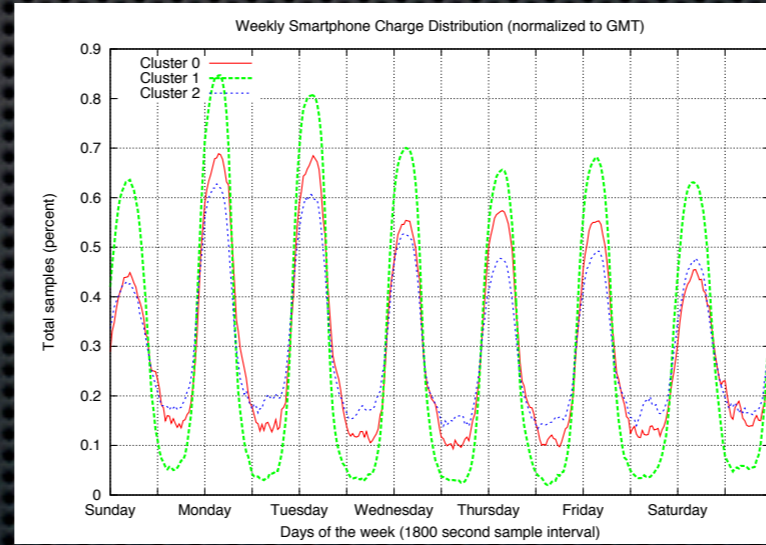
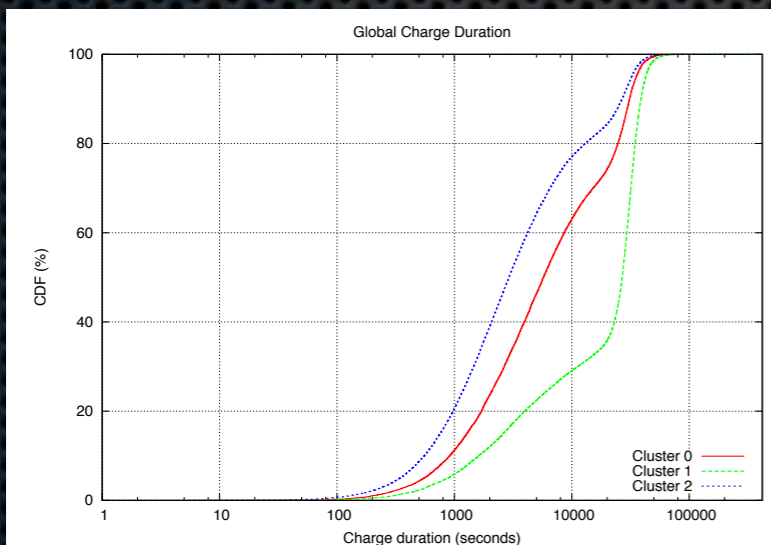
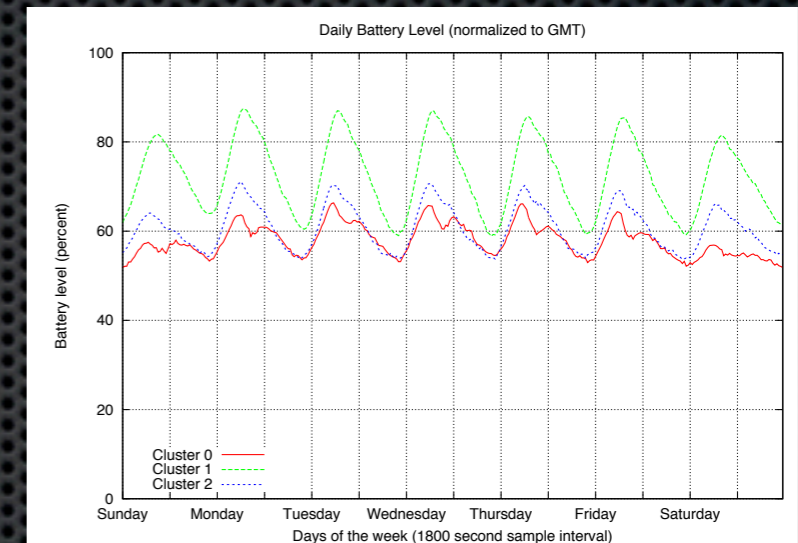
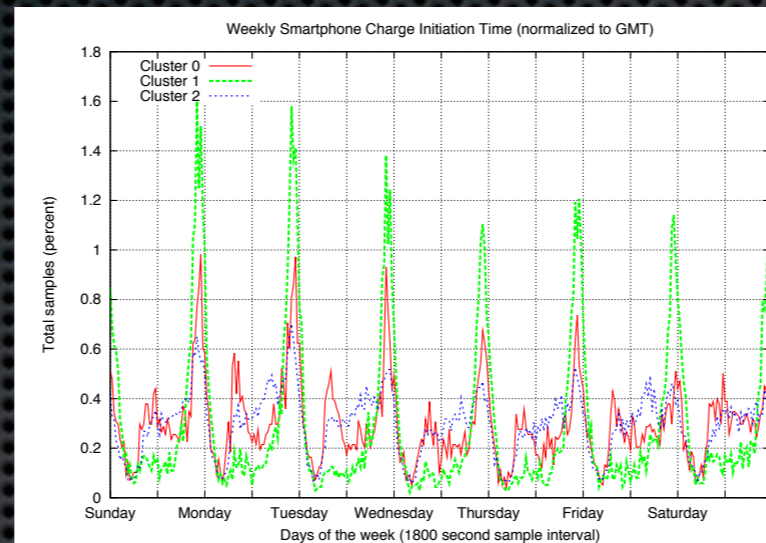
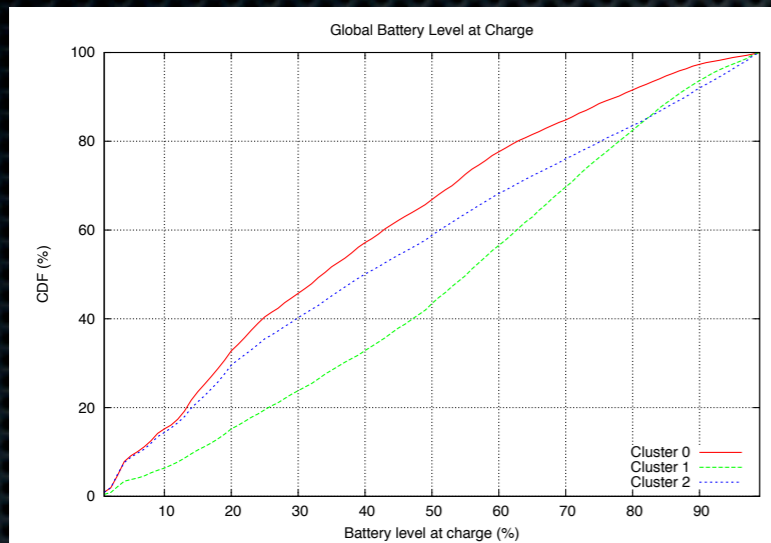
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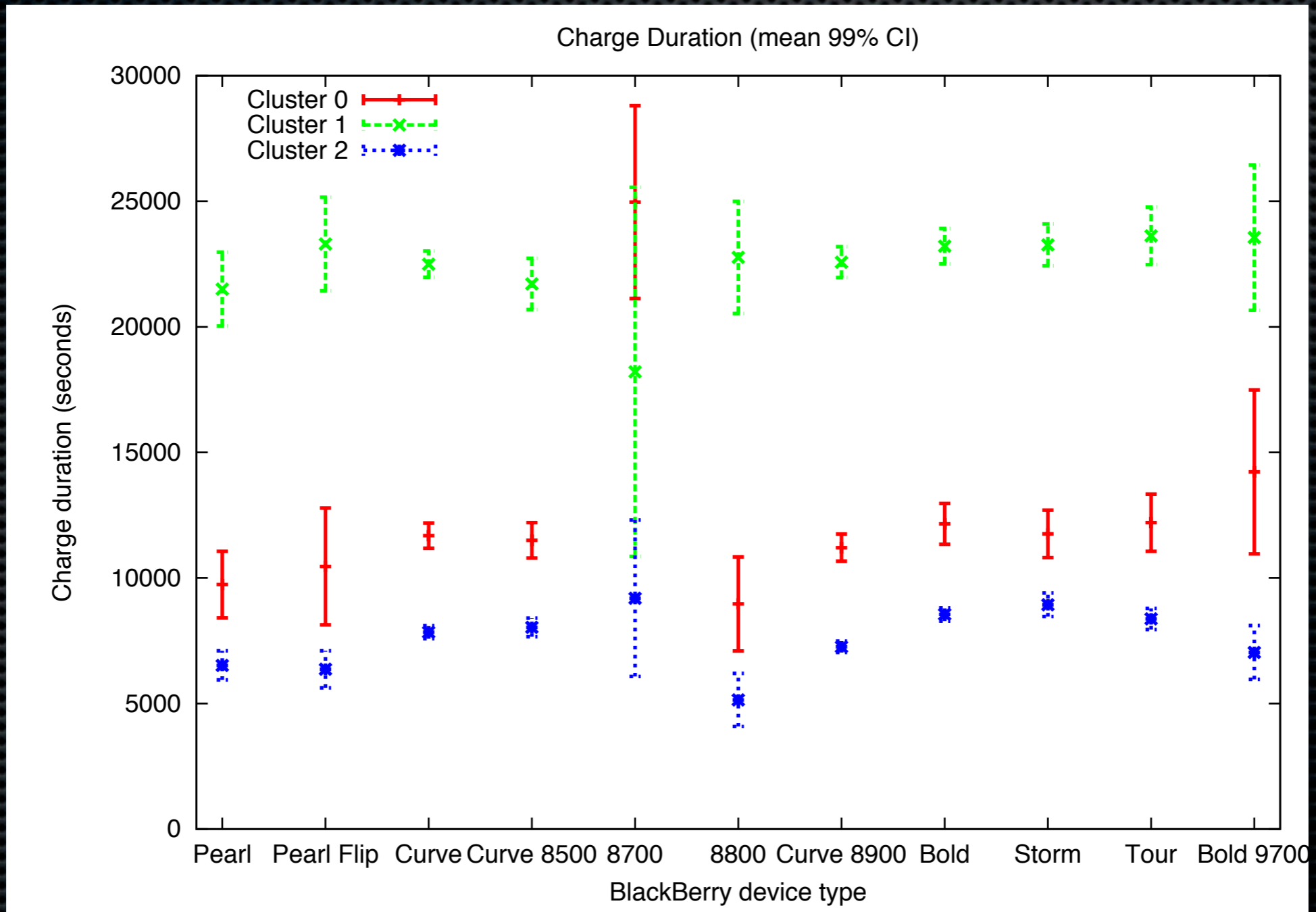
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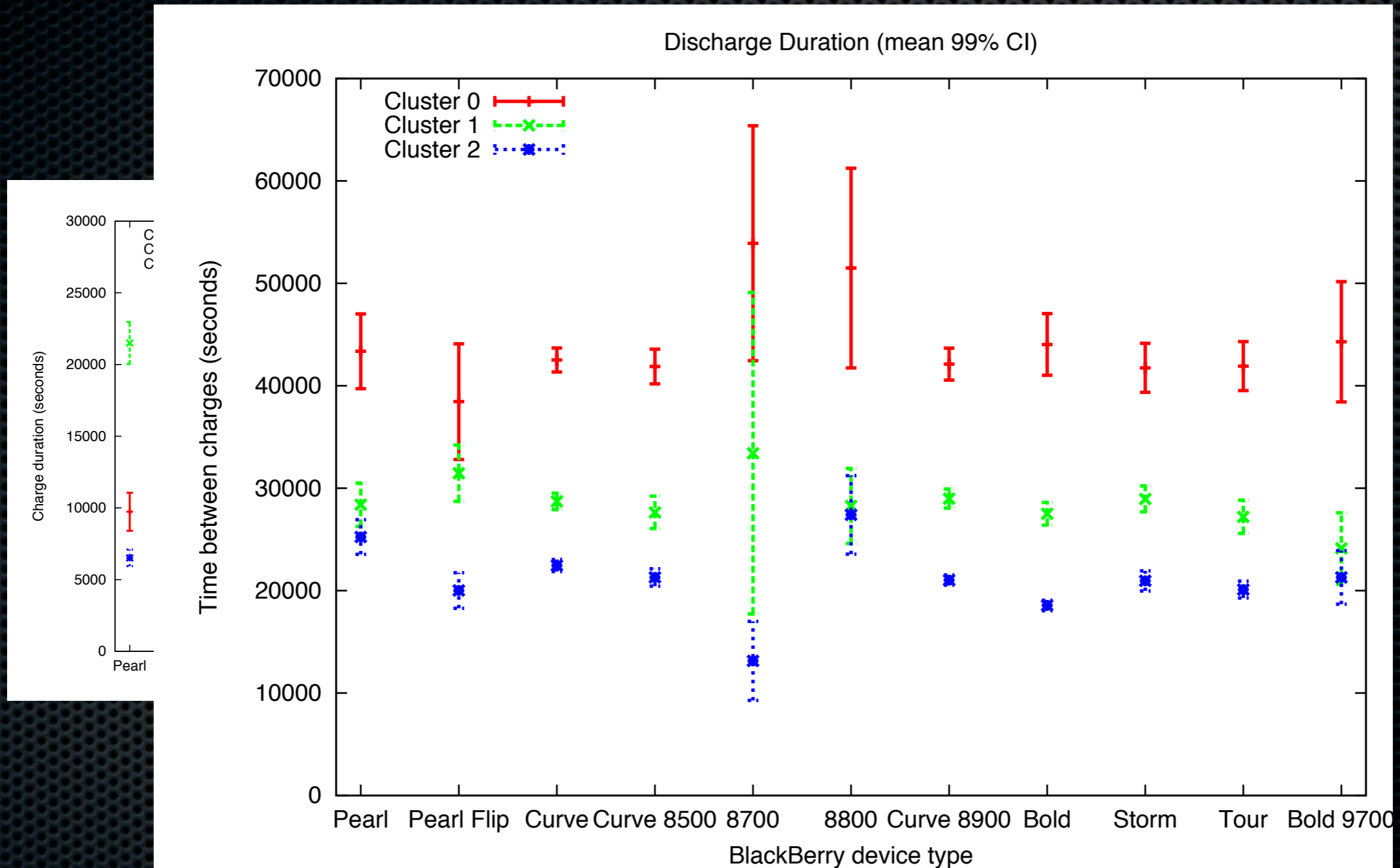
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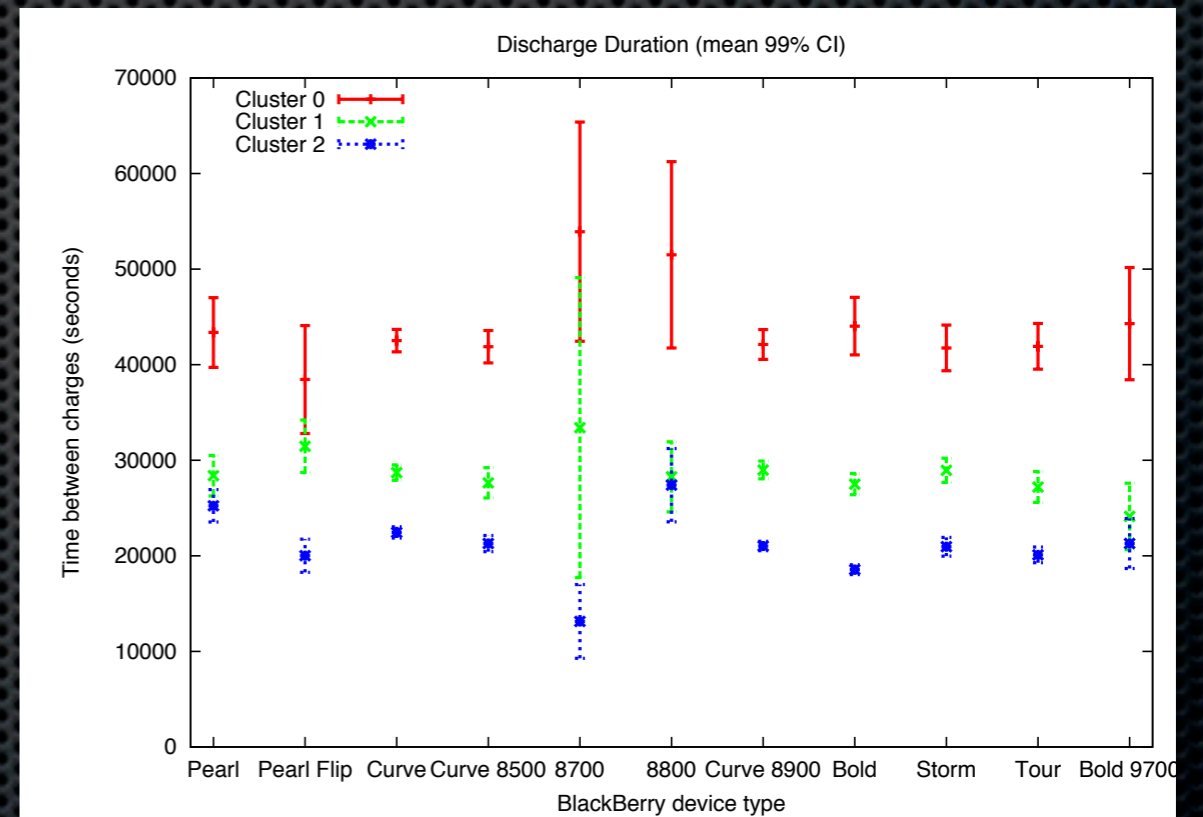
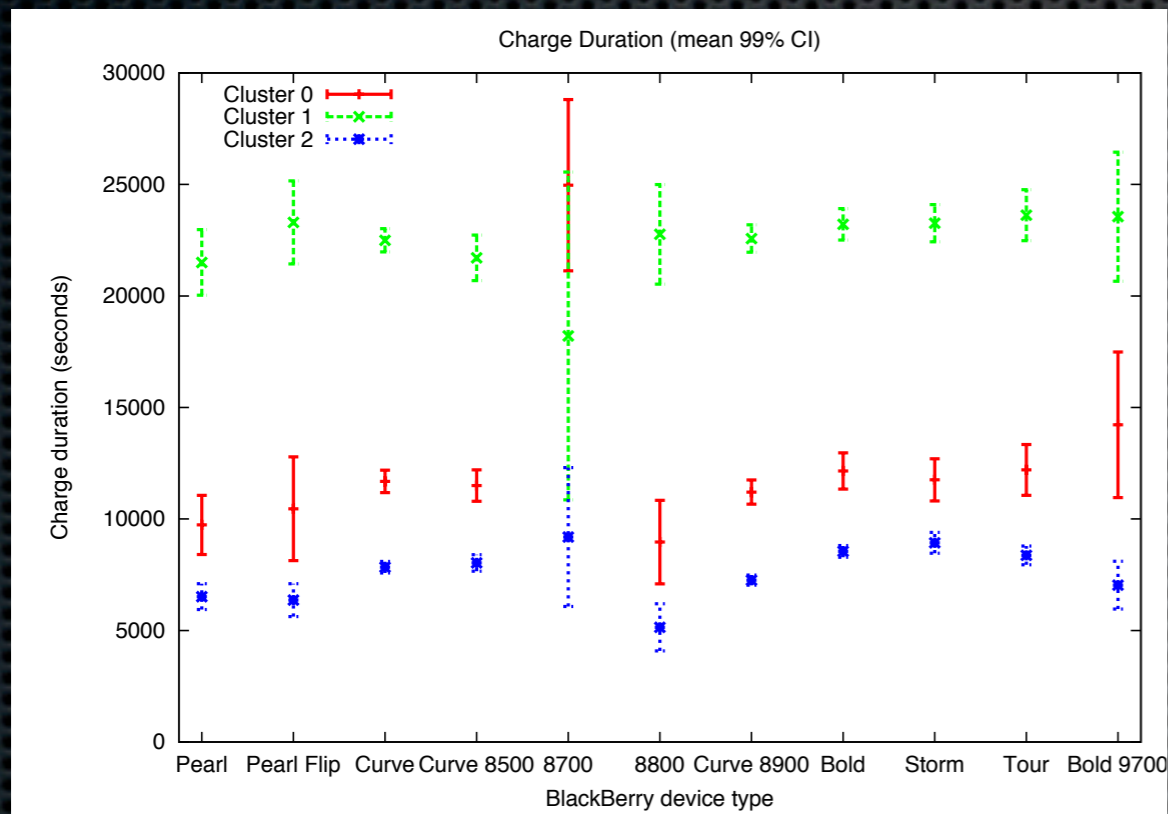
User/device classification



User/device classification

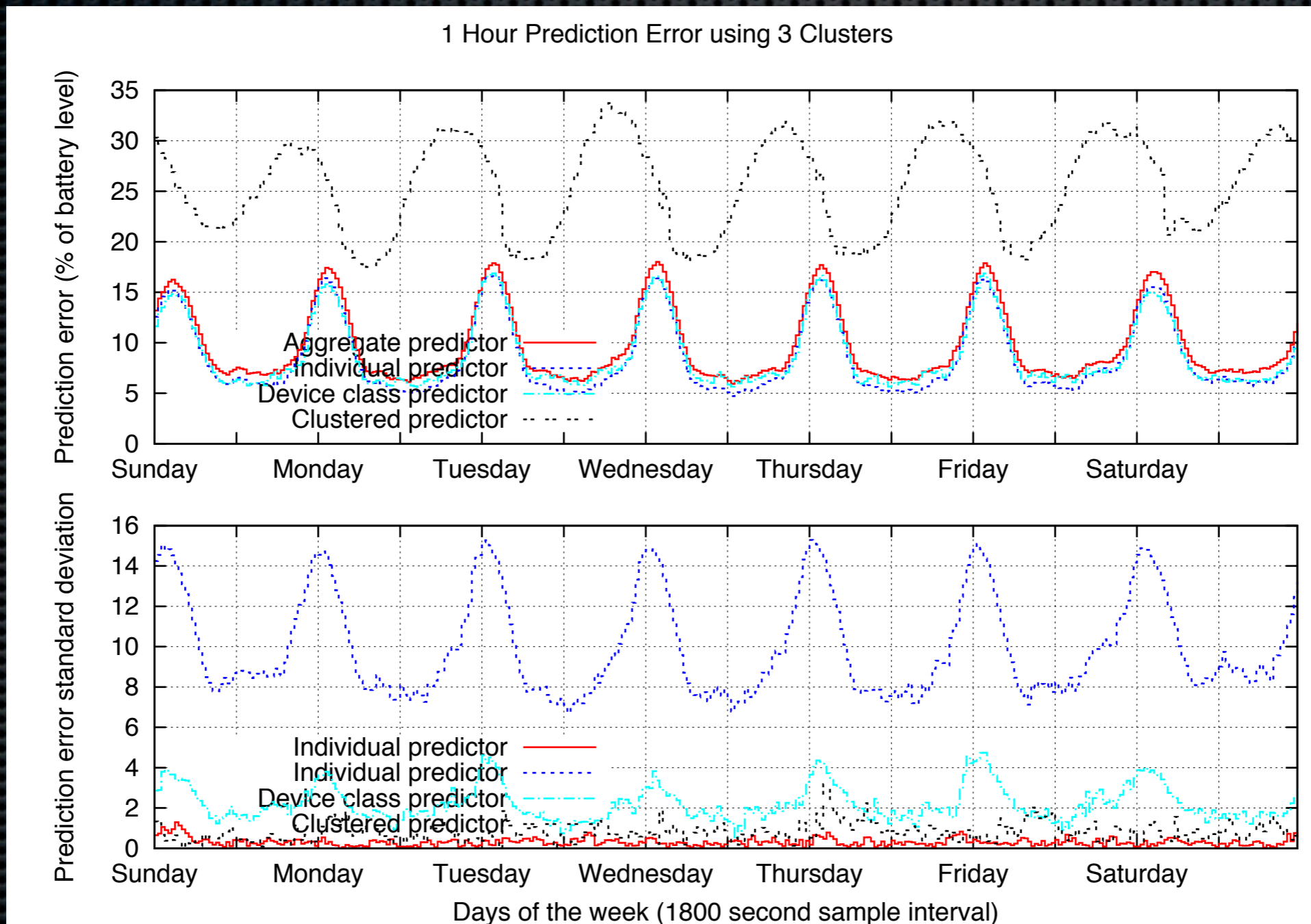


User/device classification

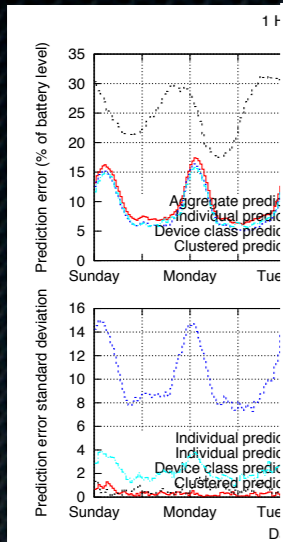


- ✦ Can you guess which user type has the most predictable battery level?

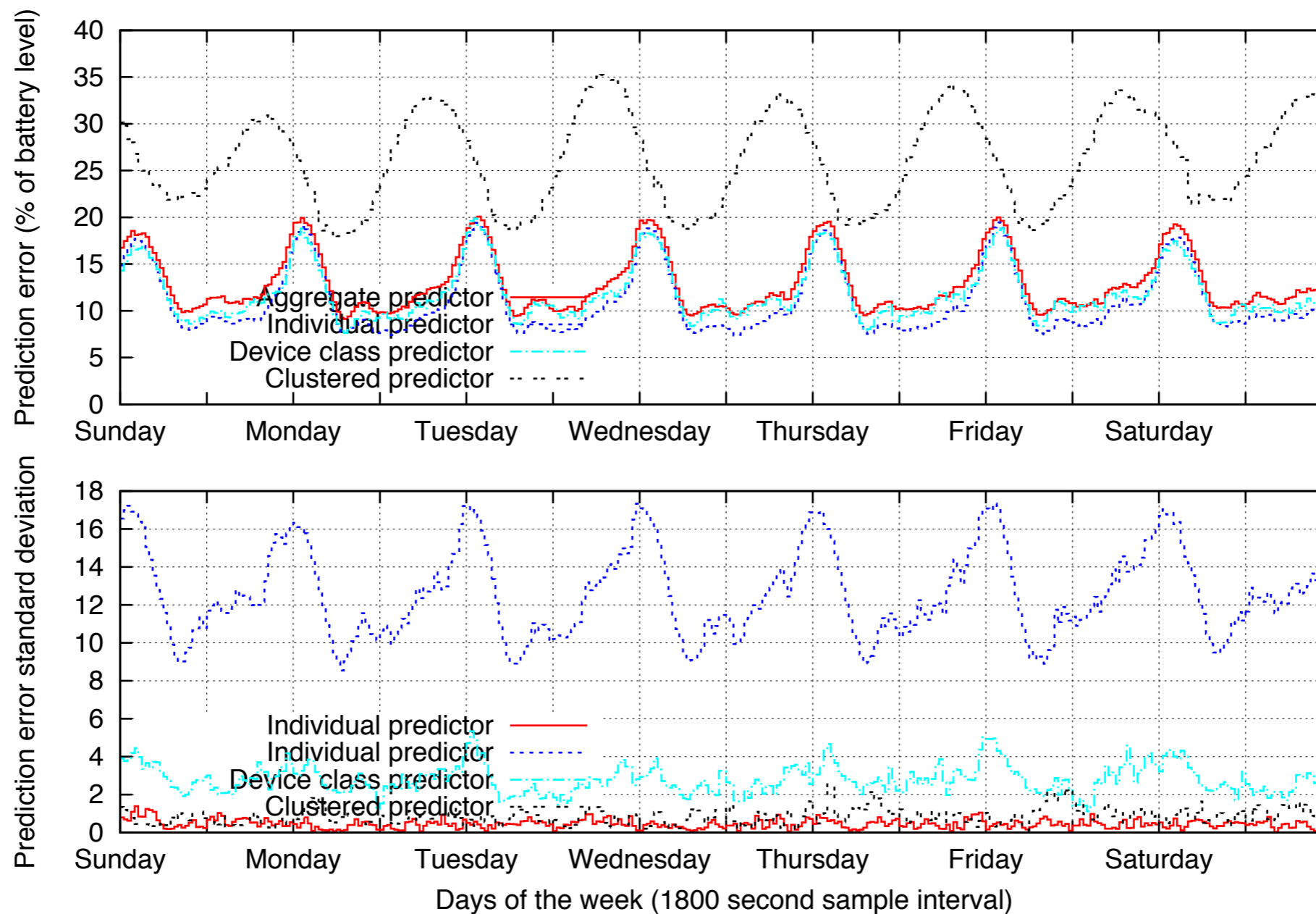
Battery prediction rate



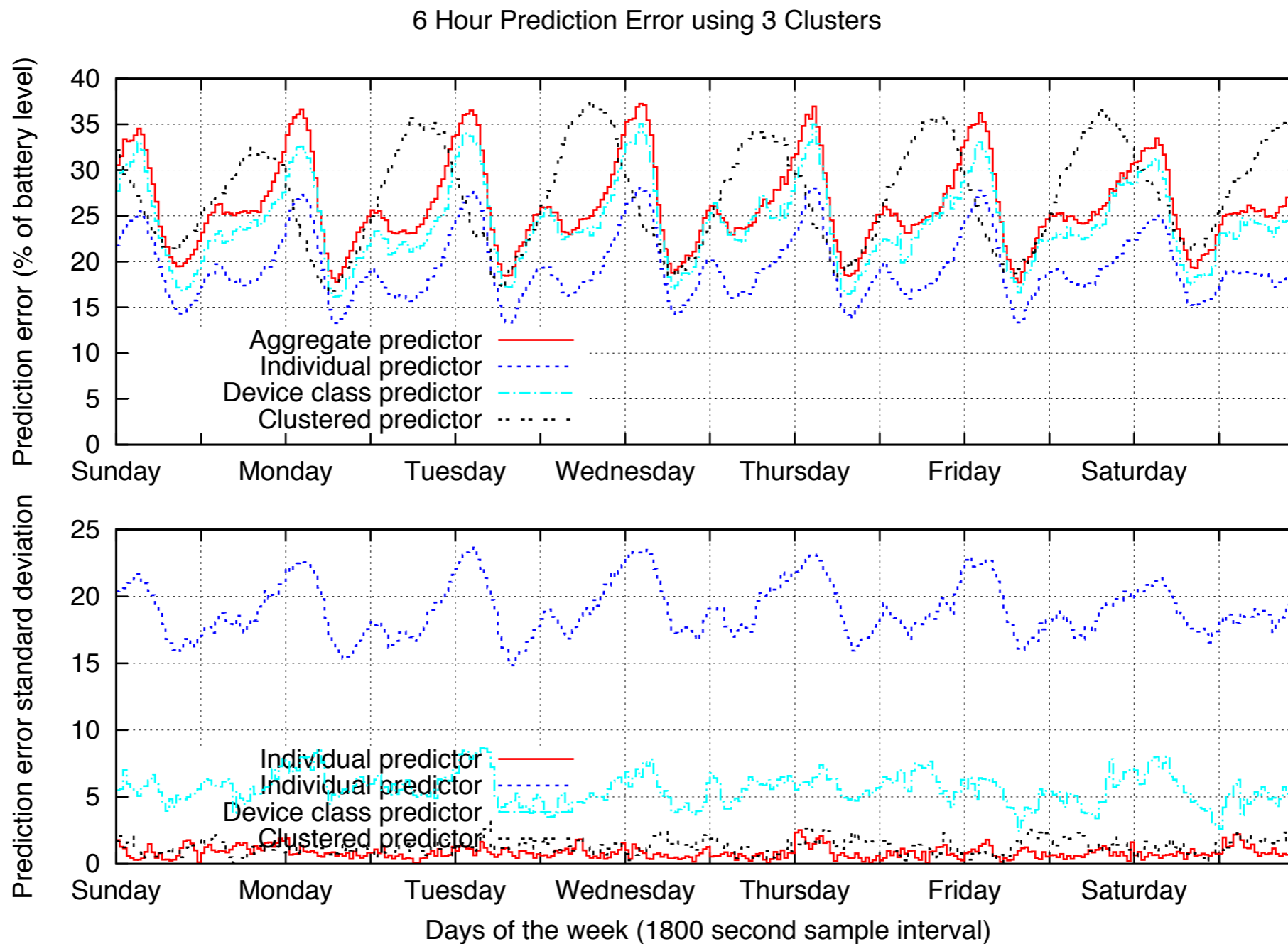
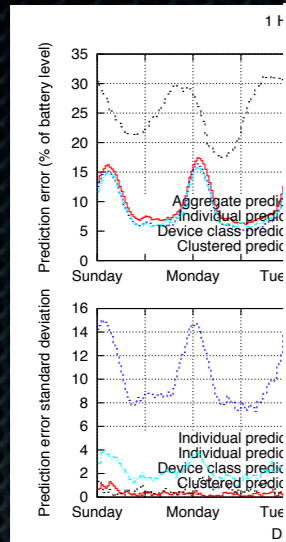
Battery prediction rate



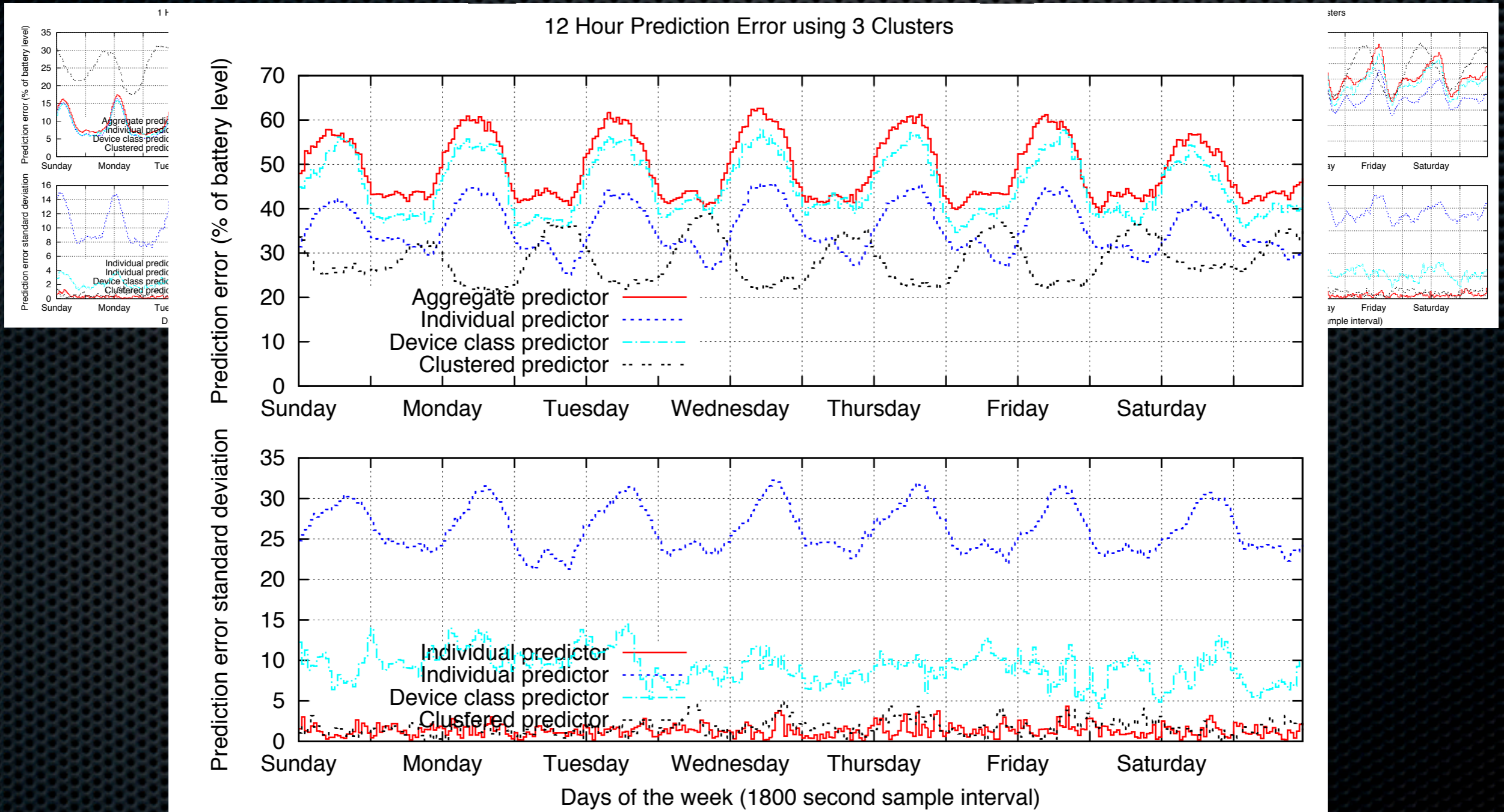
2 Hour Prediction Error using 3 Clusters



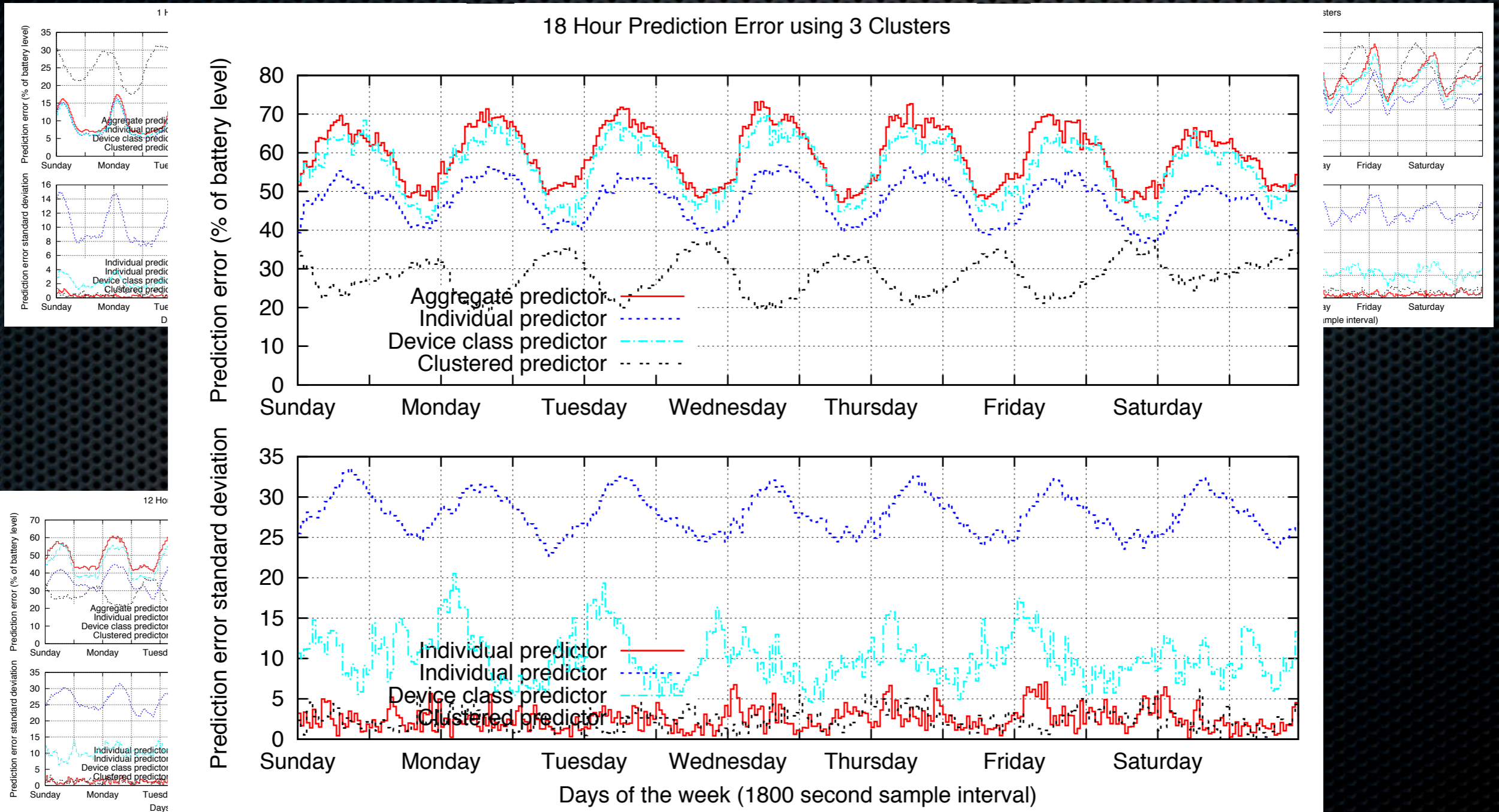
Battery prediction rate



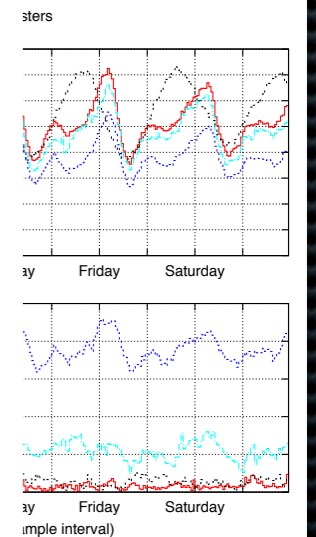
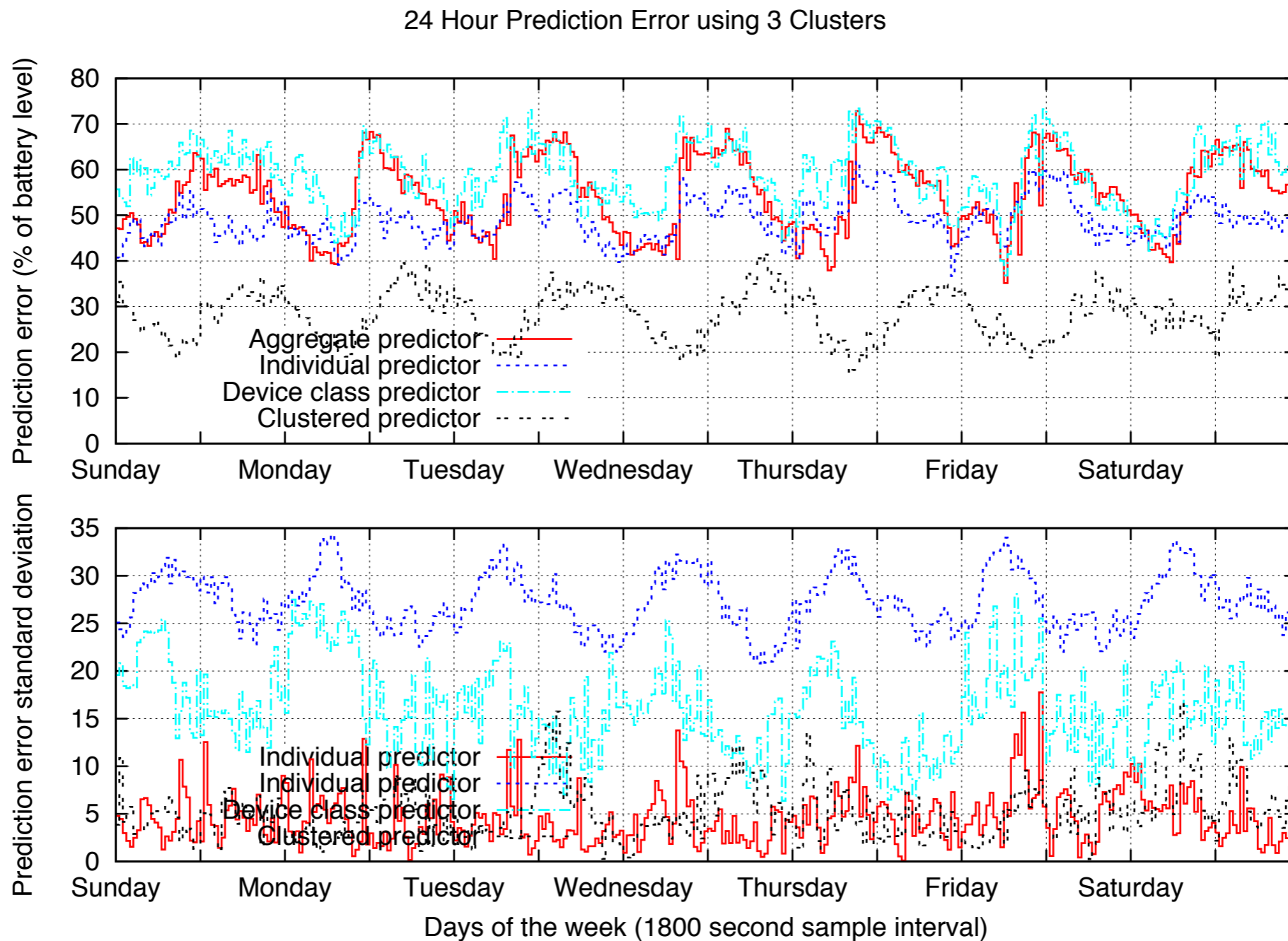
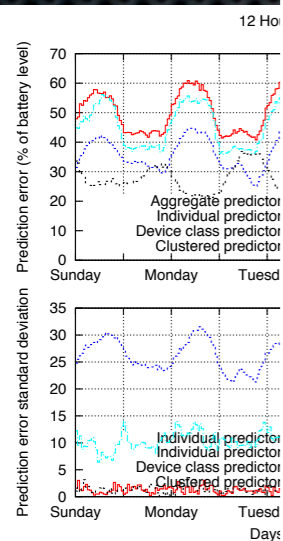
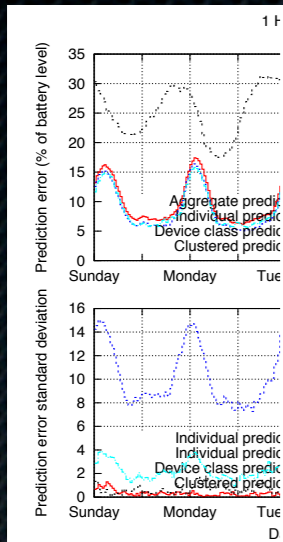
Battery prediction rate



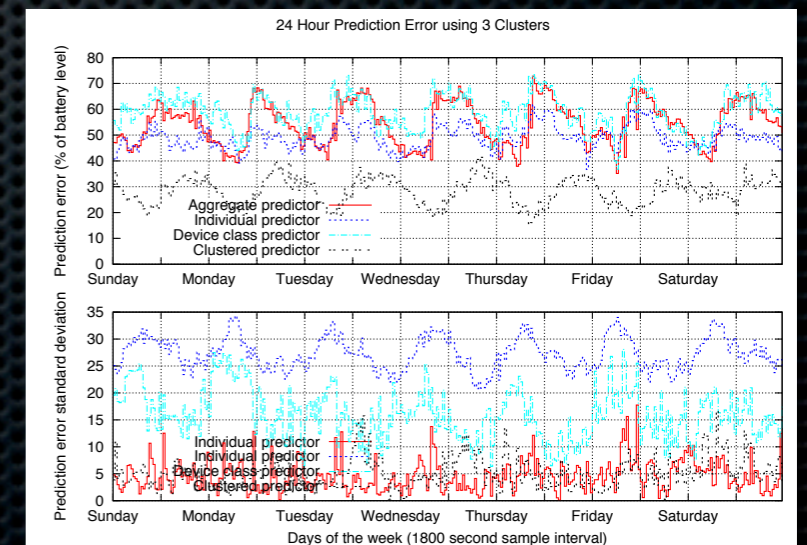
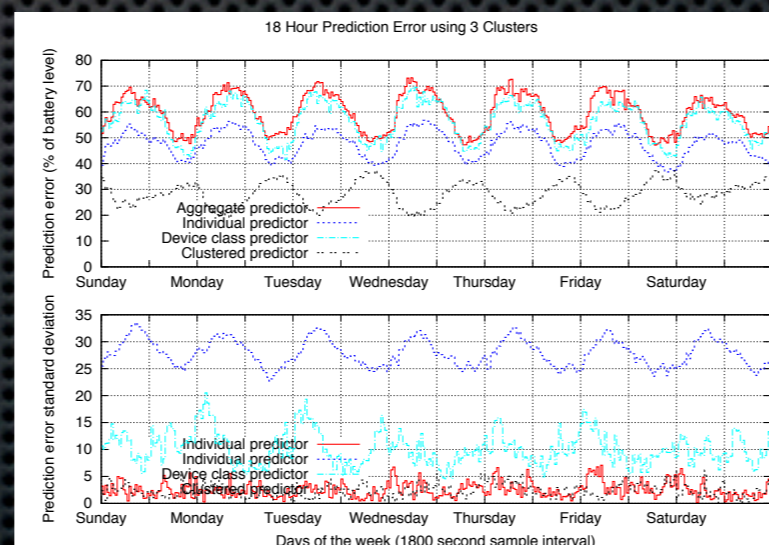
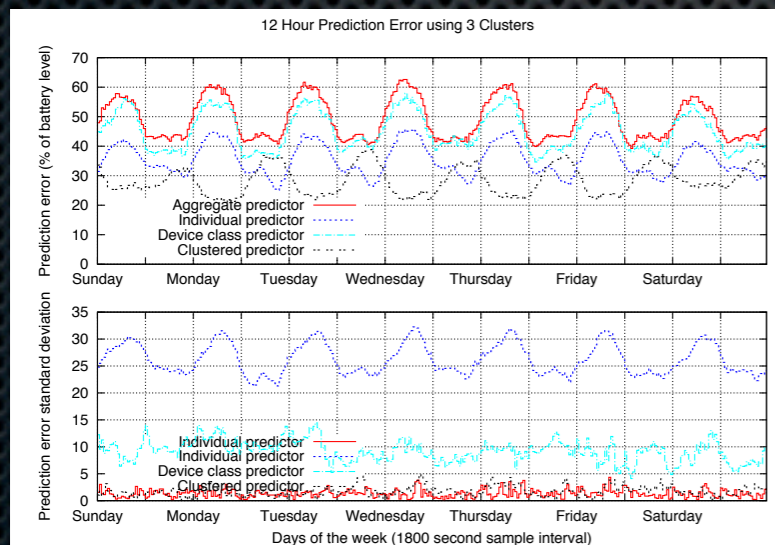
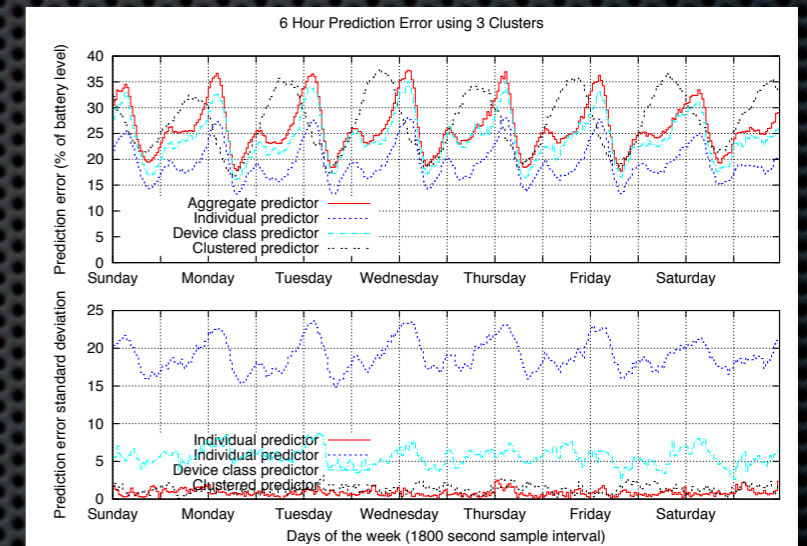
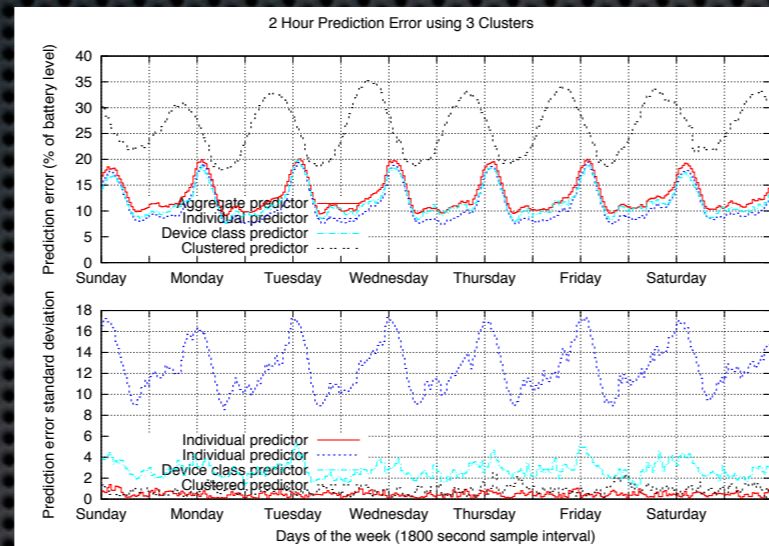
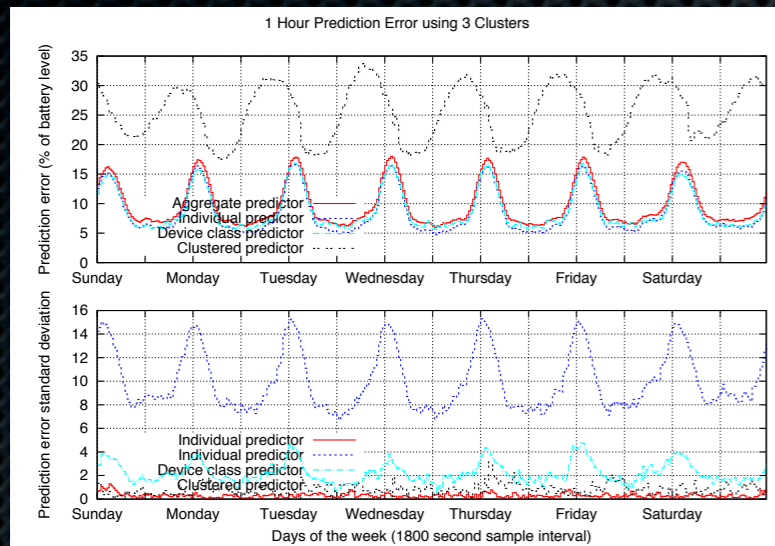
Battery prediction rate



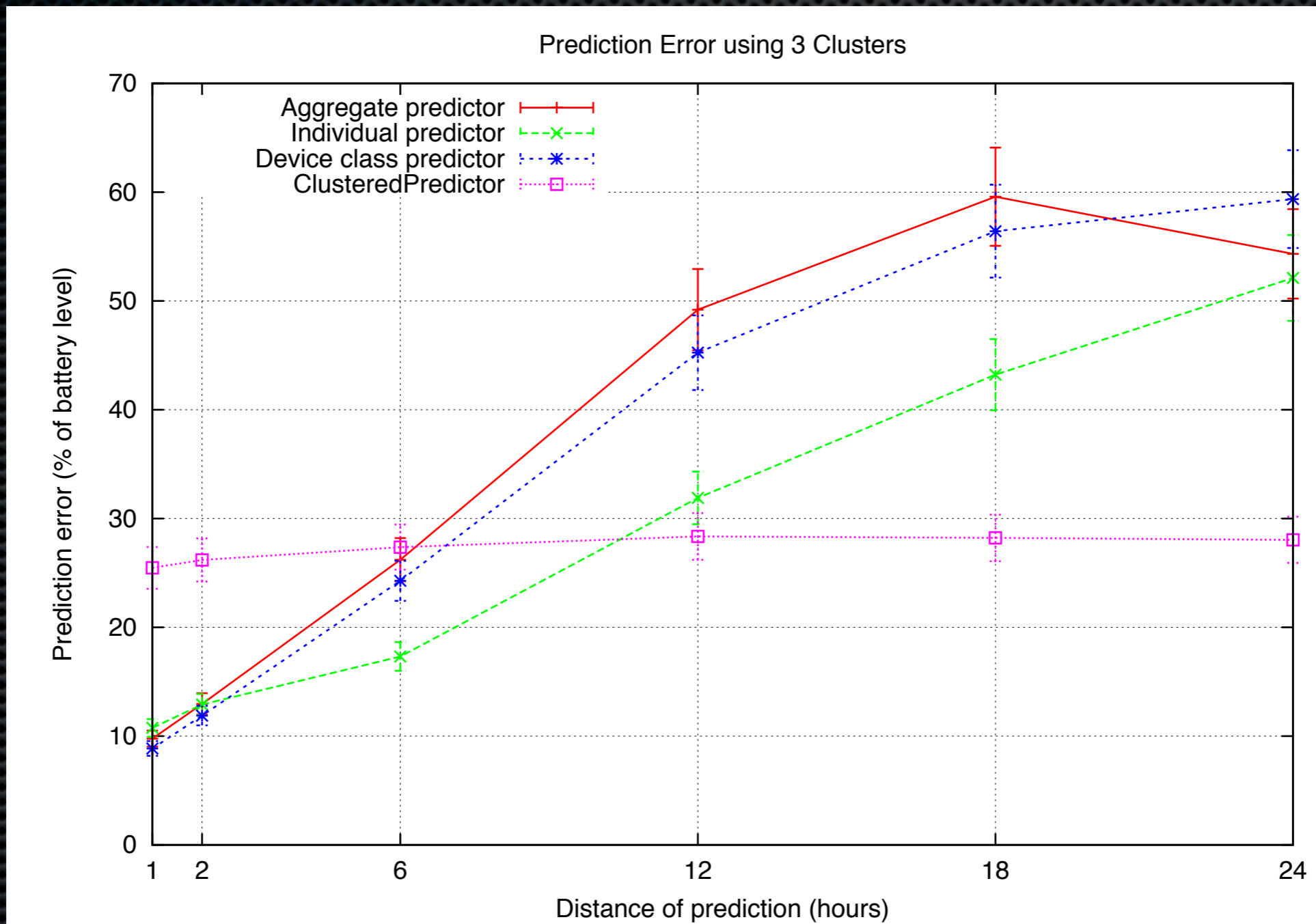
Battery prediction rate



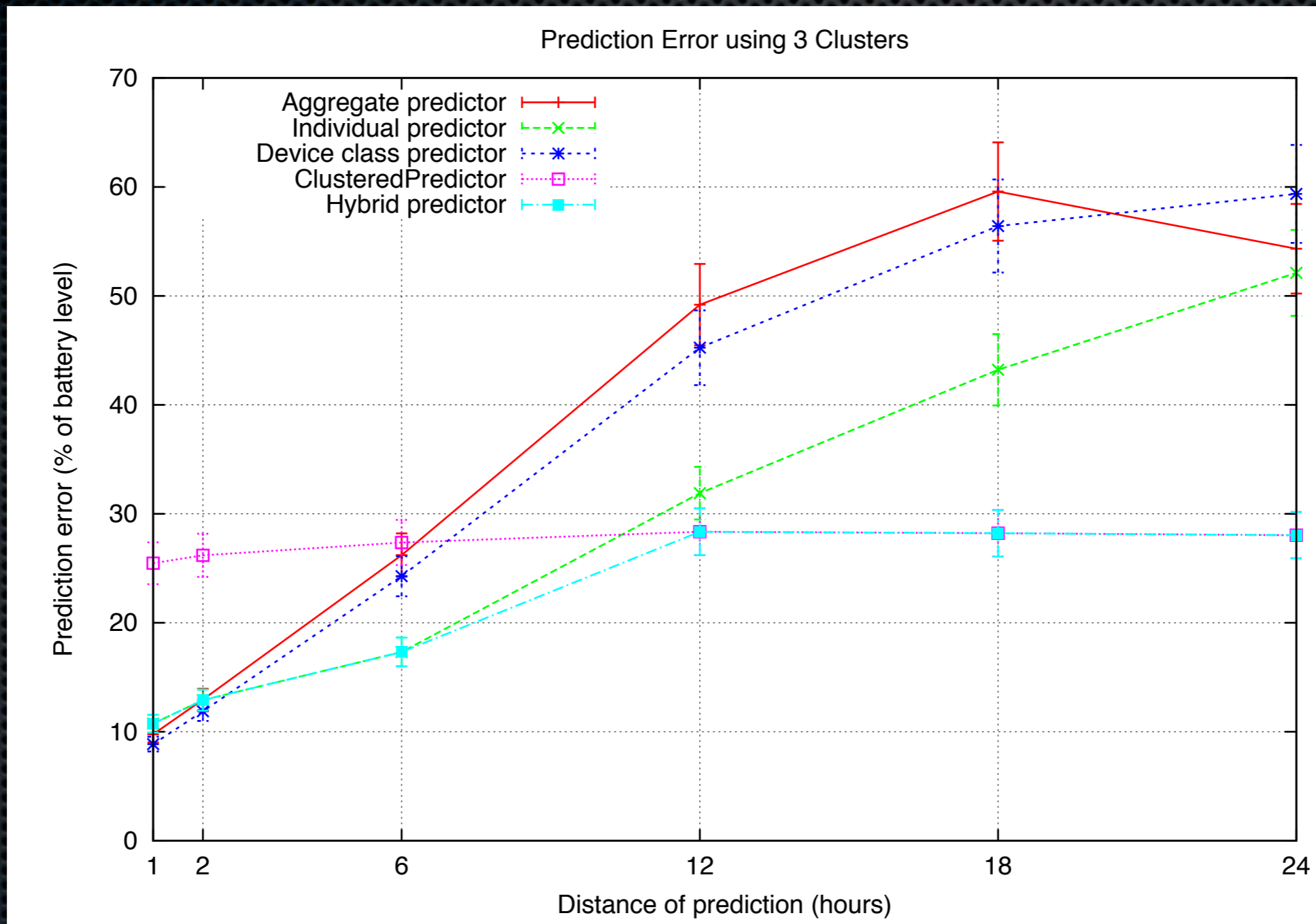
Battery prediction rate



Battery prediction rate



Hybrid battery predictor



Successful execution prediction

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- Built **App-Predict** tool to simulate an application's execution against known traces.

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 - ✦ specific user types

Use of App-Predict

Device	Capacity	Voltage
8100	900 mAh	3.7V
8200	900 mAh	3.7V
8300	1100 mAh	3.7V
8500	1150 mAh	3.7V
8700	1000 mAh	3.7V
8800	1400 mAh	3.7V
8900	1400 mAh	3.7V
9000	1500 mAh	3.7V
9500	1400 mAh	3.7V
9600	1400 mAh	3.7V
9700	1500 mAh	3.7V

Use of App-Predict

- Energy capacities of all devices in the dataset are 'known'

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- Energy capacities of all devices in the dataset are 'known'
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Use of App-Predict

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 - WiFi data transfer (from memory and file)

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- Energy capacities of all devices in the dataset are 'known'
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Use of App-Predict

- Energy capacities of all devices in the dataset are 'known'
- Measured the energy consumption of basic applications
 - Bluetooth scanning
 - WiFi data transfer (from memory and file)
 - File I/O
 - Video playback

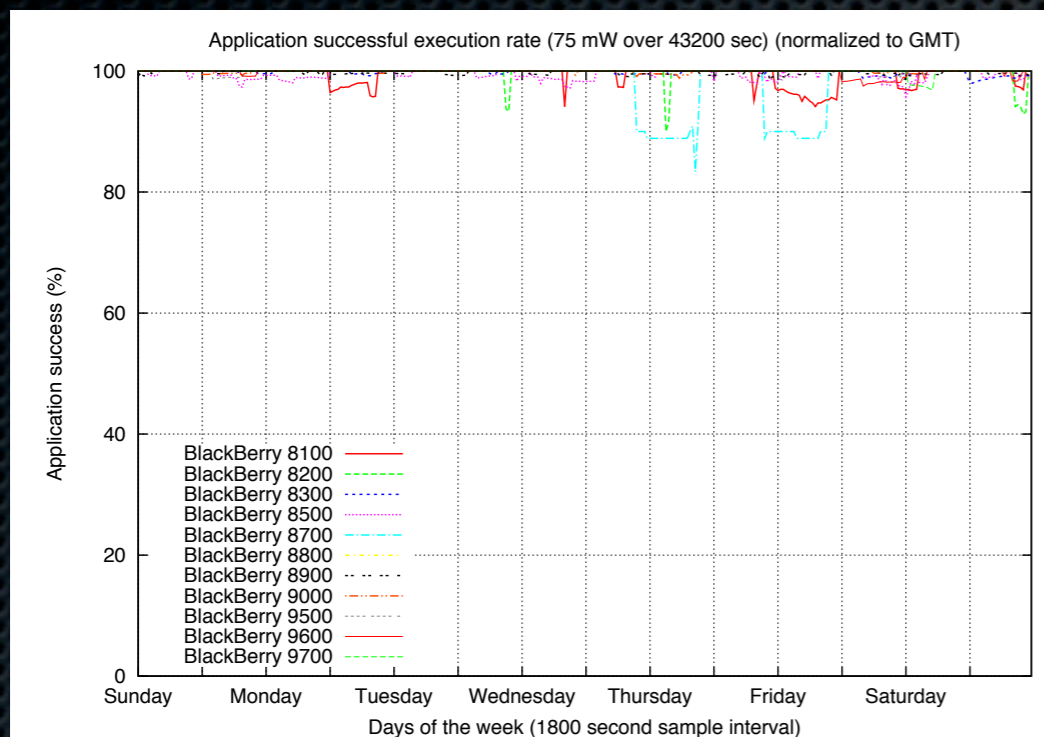
Device	Capacity	Voltage
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Use of App-Predict

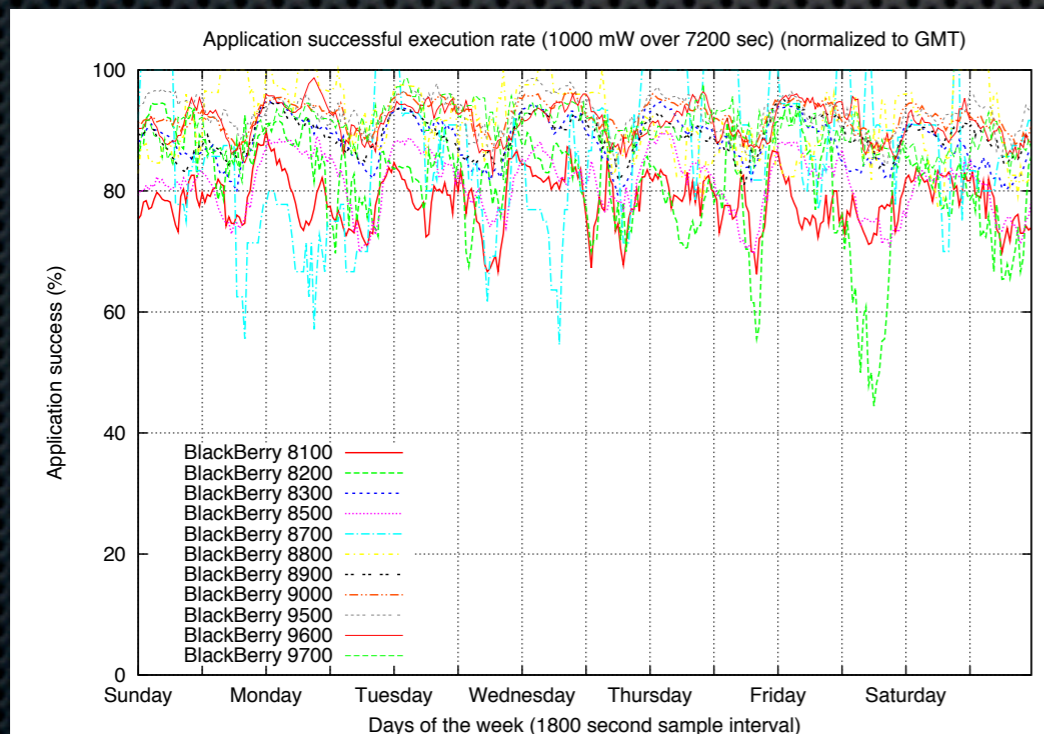
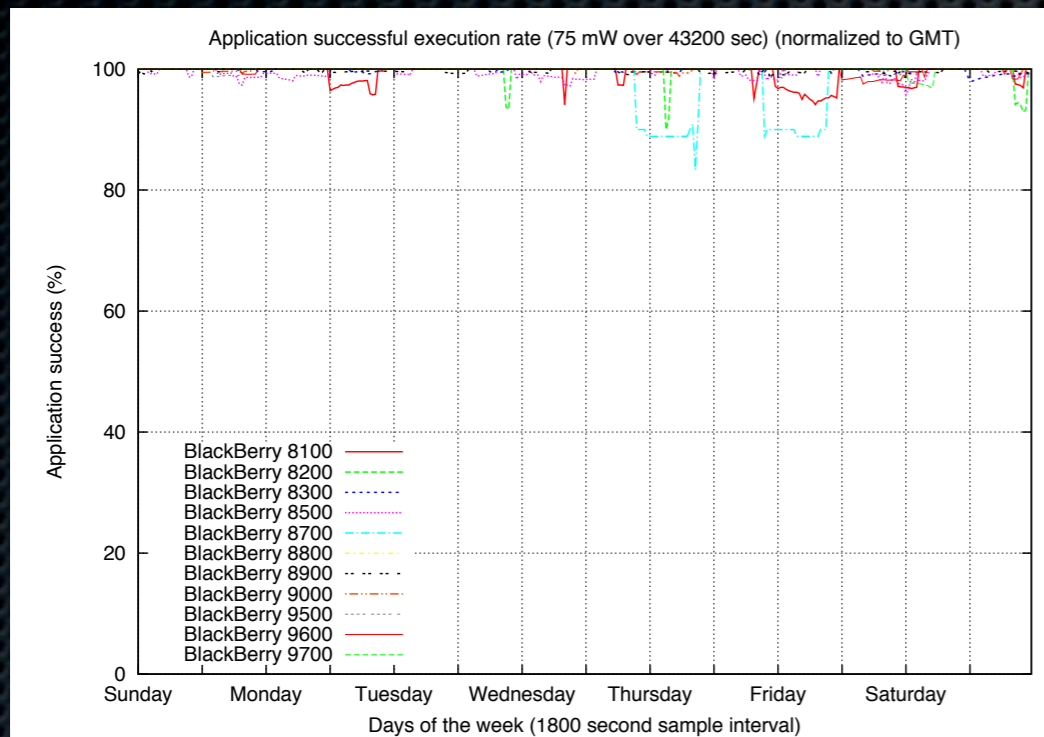
- Energy capacities of all devices in the dataset are 'known'
- Measured the energy consumption of basic applications
 - Bluetooth scanning
 - WiFi data transfer (from memory and file)
 - File I/O
 - Video playback
 - GSM phone calls

Device	Capacity	Voltage
8100	900 mAh	3.7V
8200	900 mAh	3.7V
8300	1100 mAh	3.7V
8500	1150 mAh	3.7V
8700	1000 mAh	3.7V
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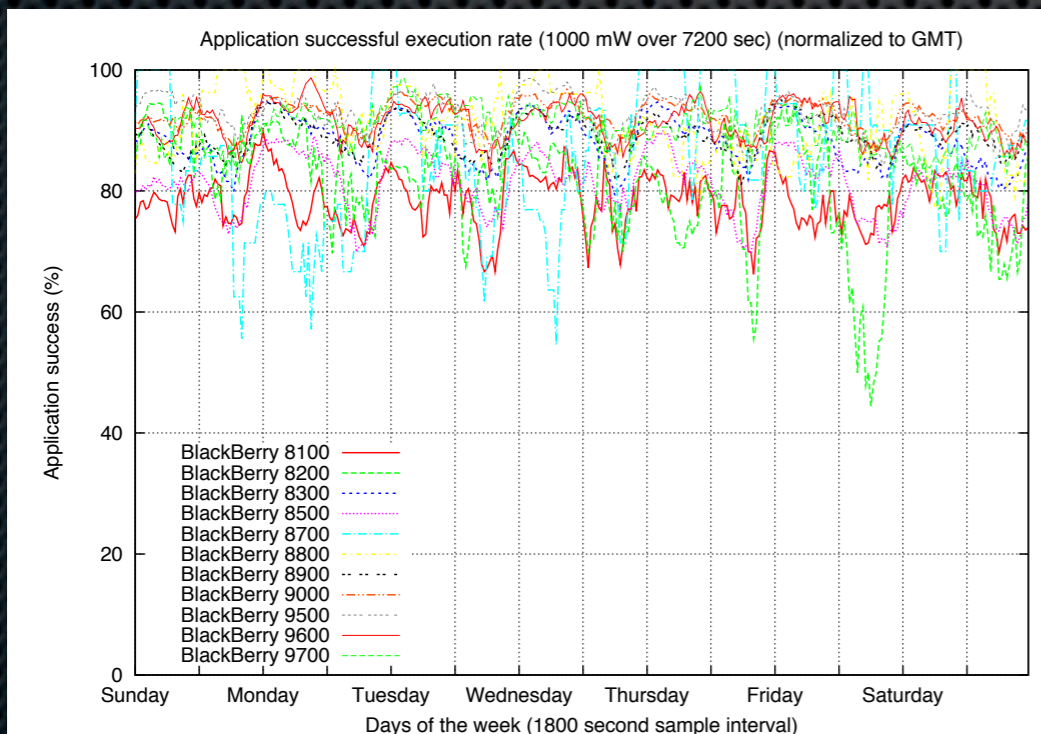
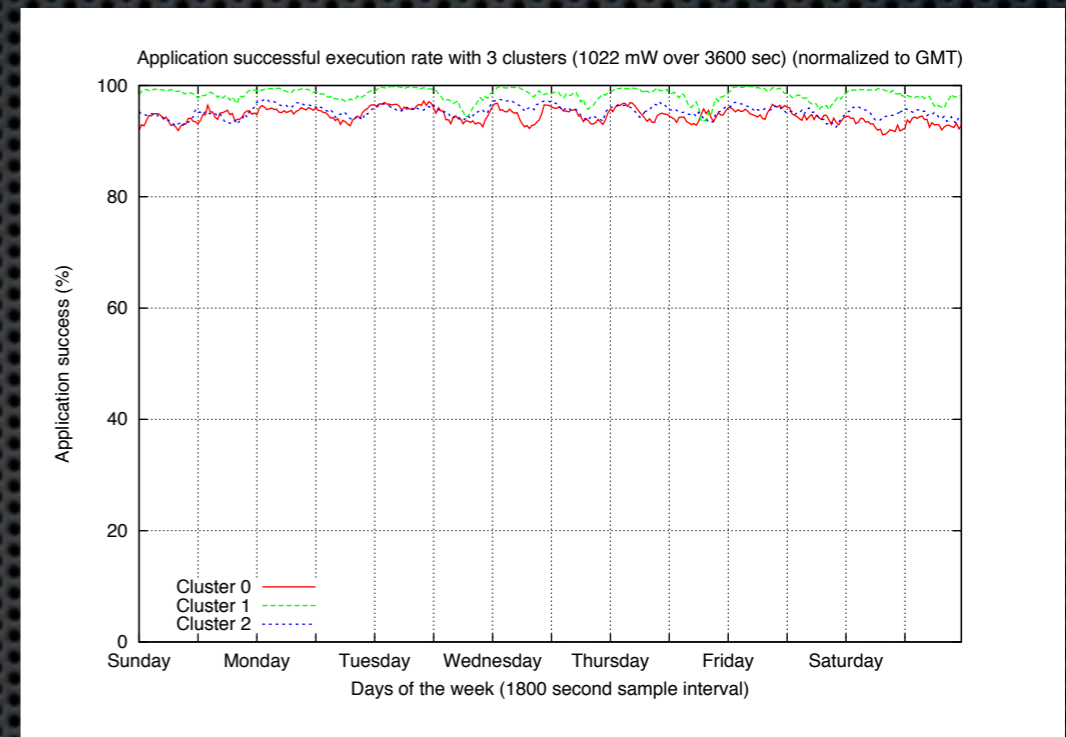
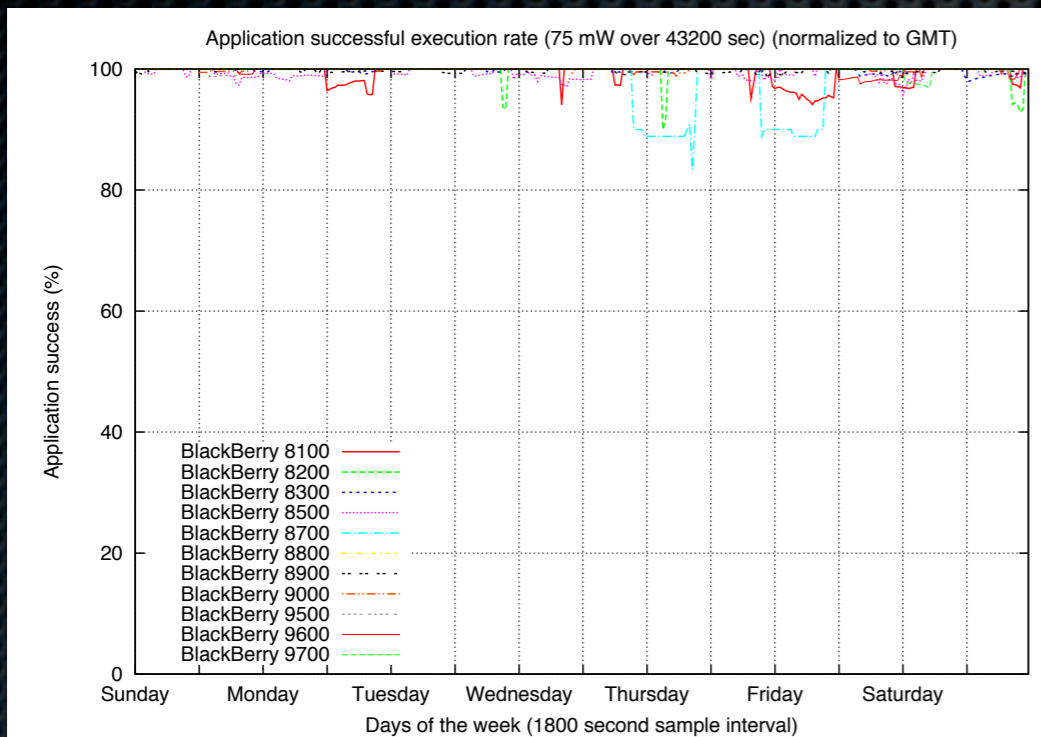
Examples



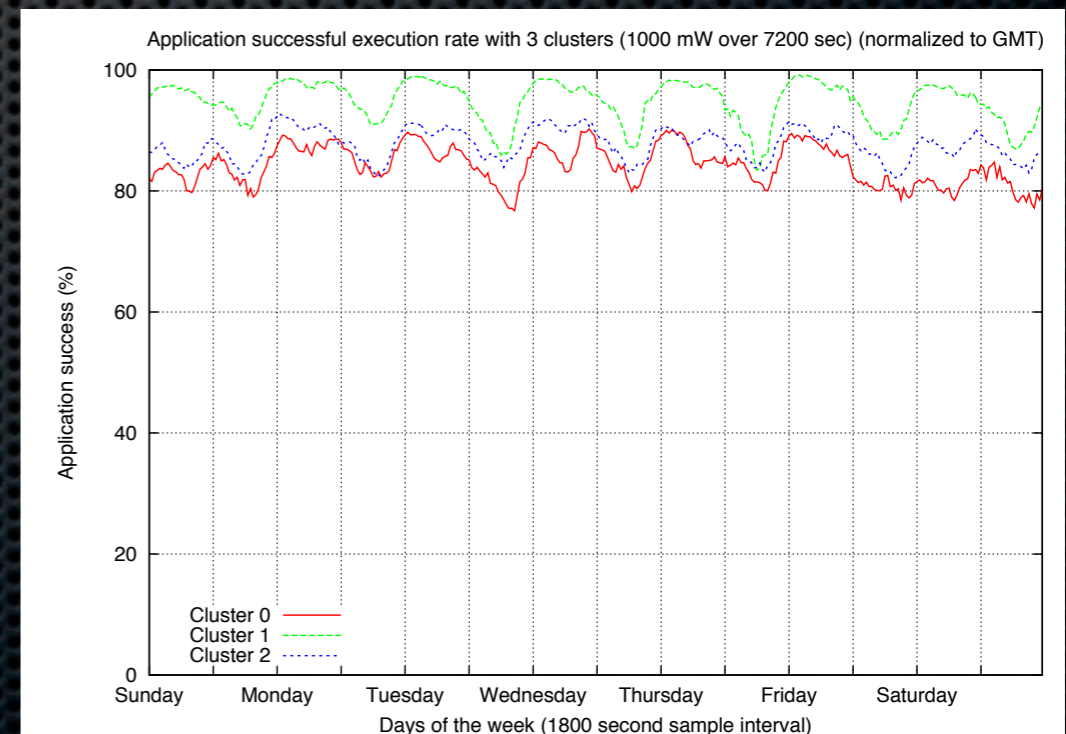
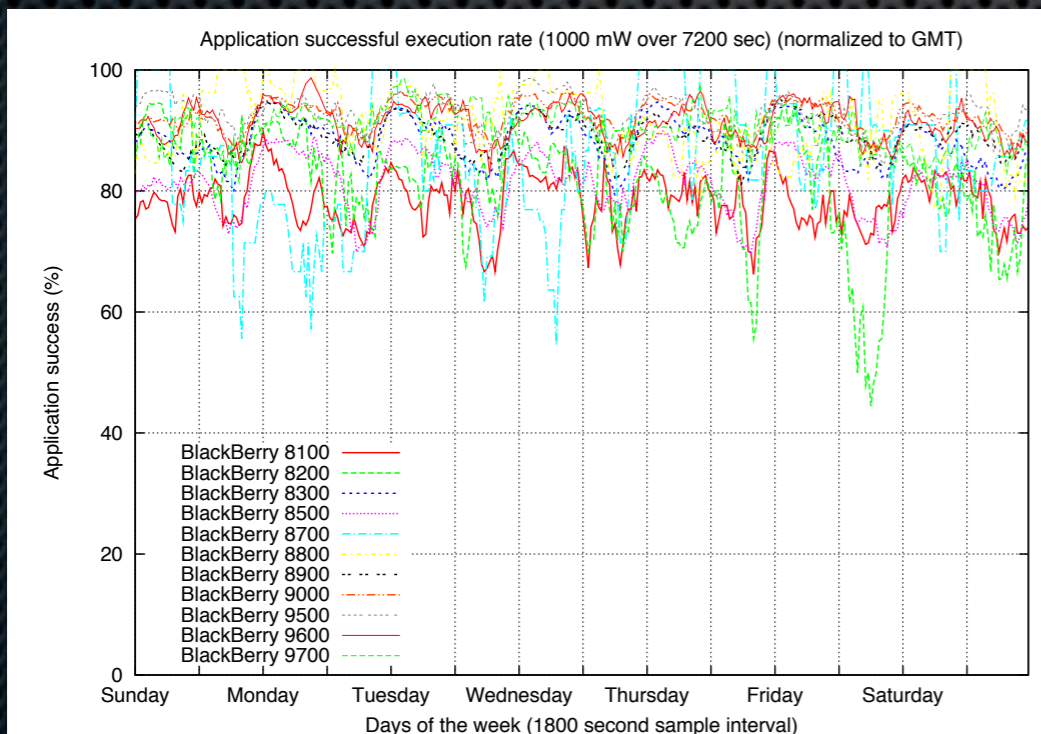
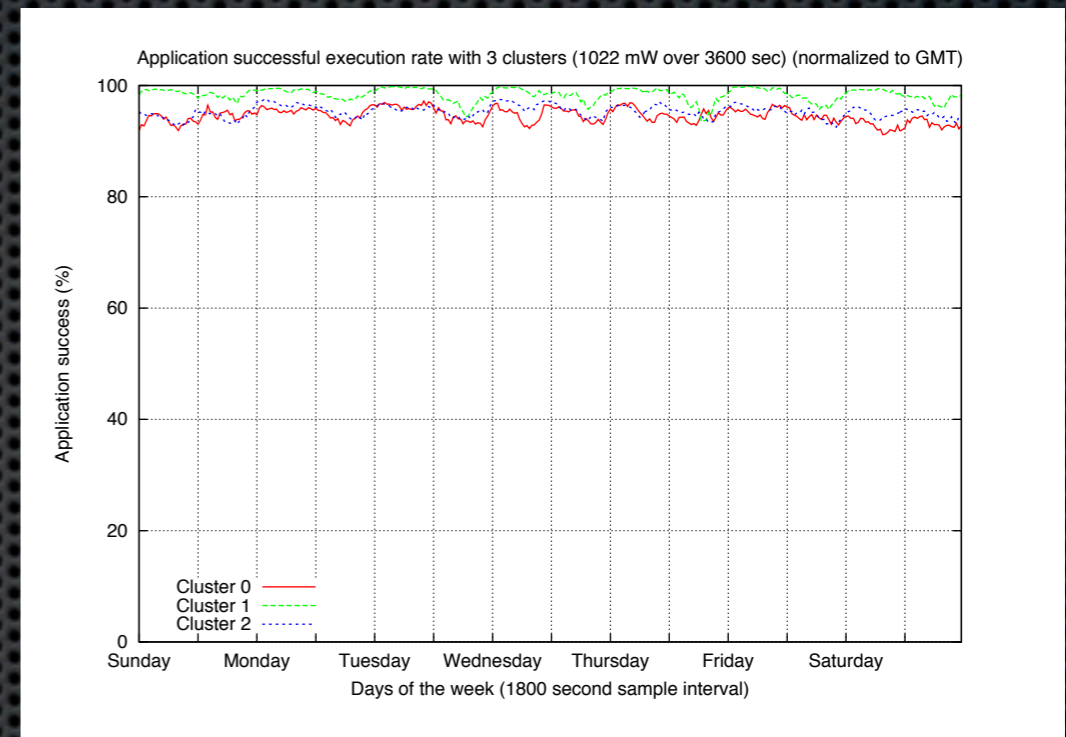
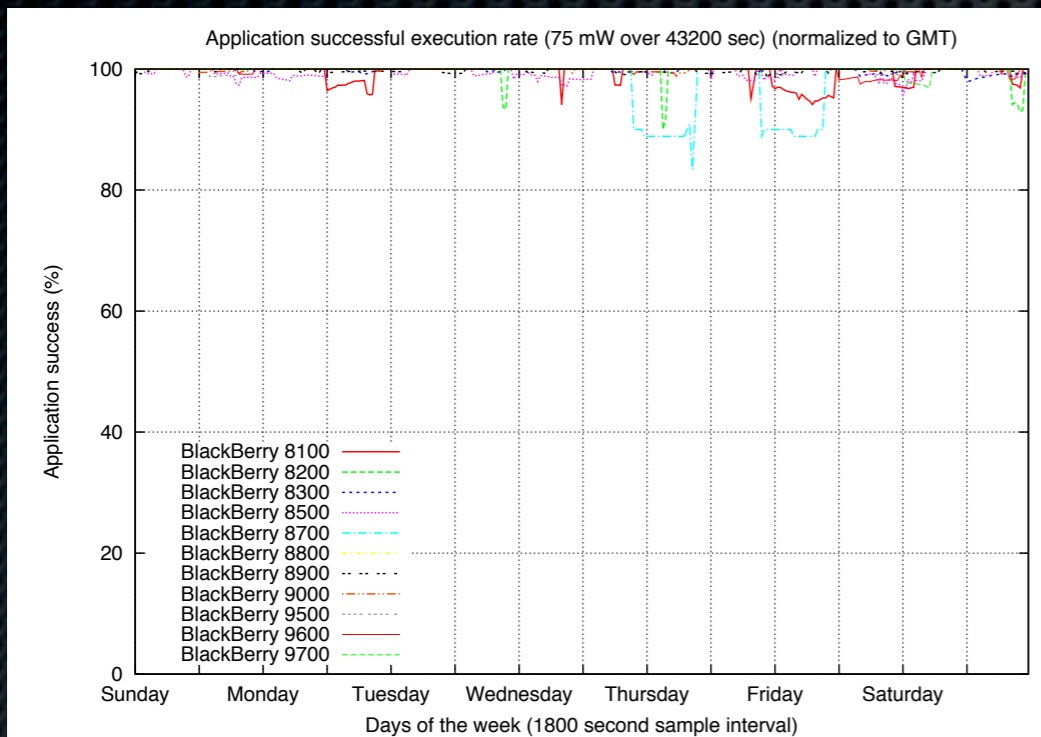
Examples



Examples



Examples



More complex scenarios

More complex scenarios

- ✦ Scenario 1

More complex scenarios

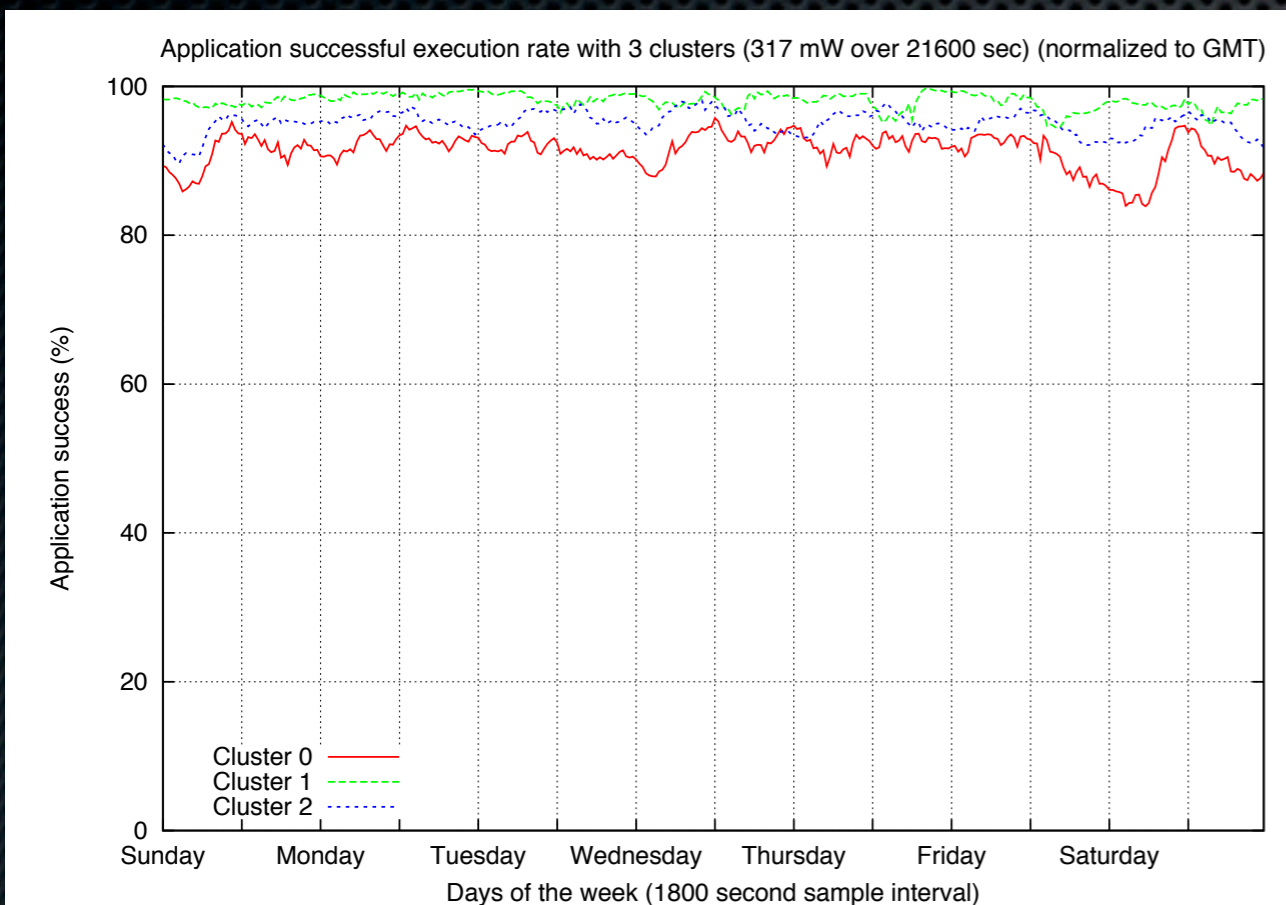
- ✦ Scenario 1
 - ✦ Scan for neighbouring Bluetooth device every minute

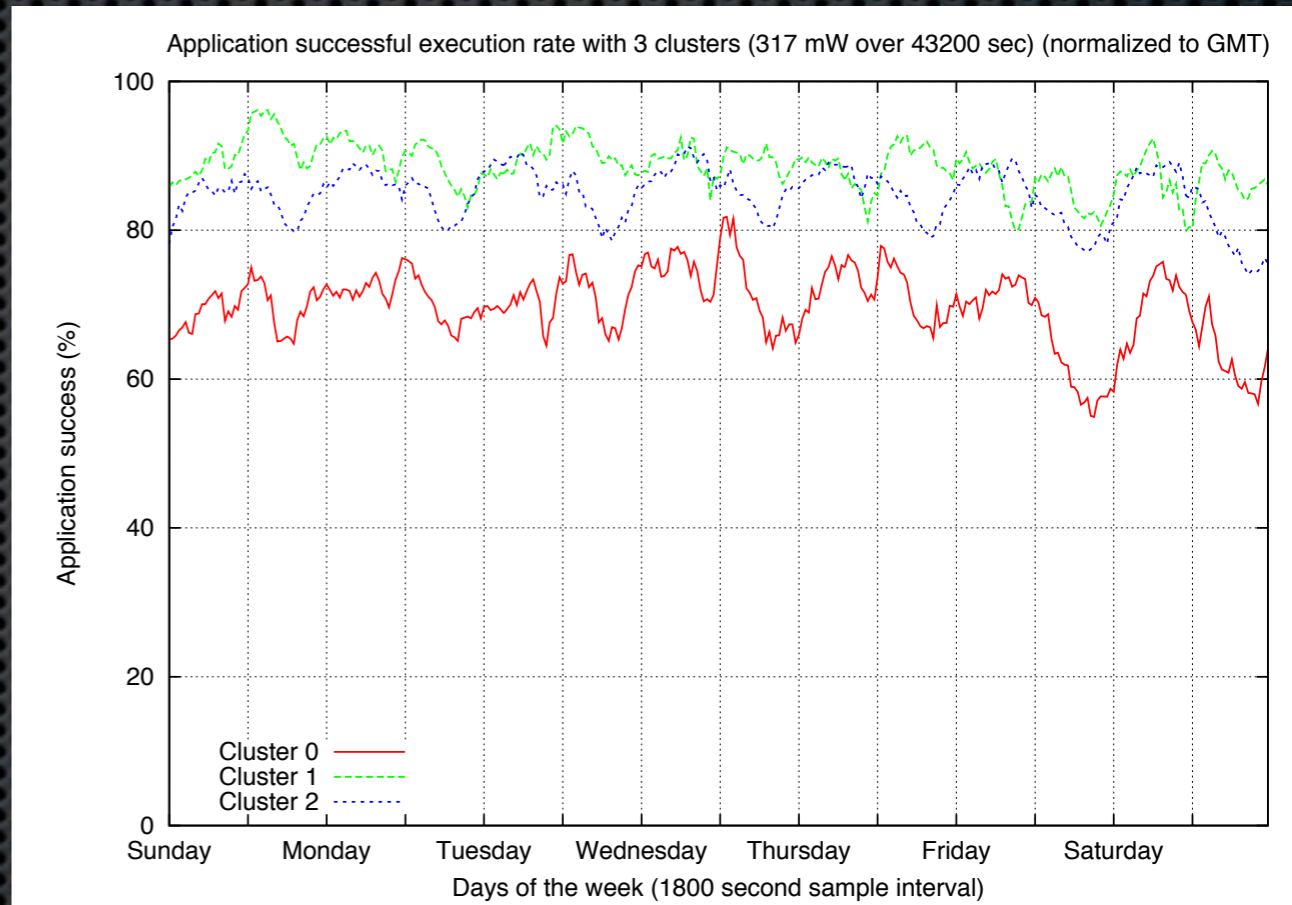
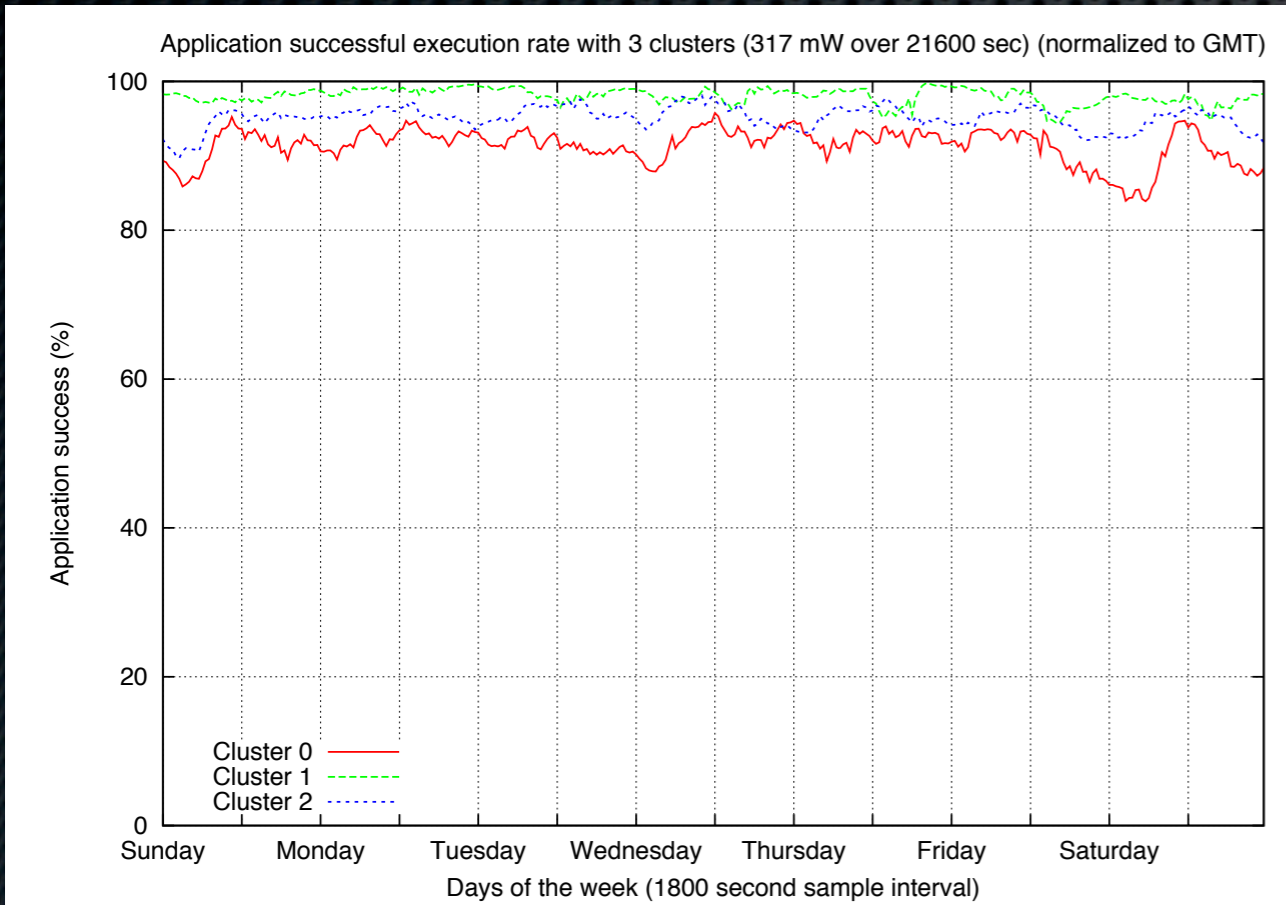
More complex scenarios

- ✦ Scenario 1
 - ✦ Scan for neighbouring Bluetooth device every minute
 - ✦ Upload 50 KB of memory resident data over WiFi after every scan.

More complex scenarios

- ✦ Scenario 1
 - ✦ Scan for neighbouring Bluetooth device every minute
 - ✦ Upload 50 KB of memory resident data over WiFi after every scan.
 - ✦ Upload 100 MB of Flash-resident data over WiFi once per hour.



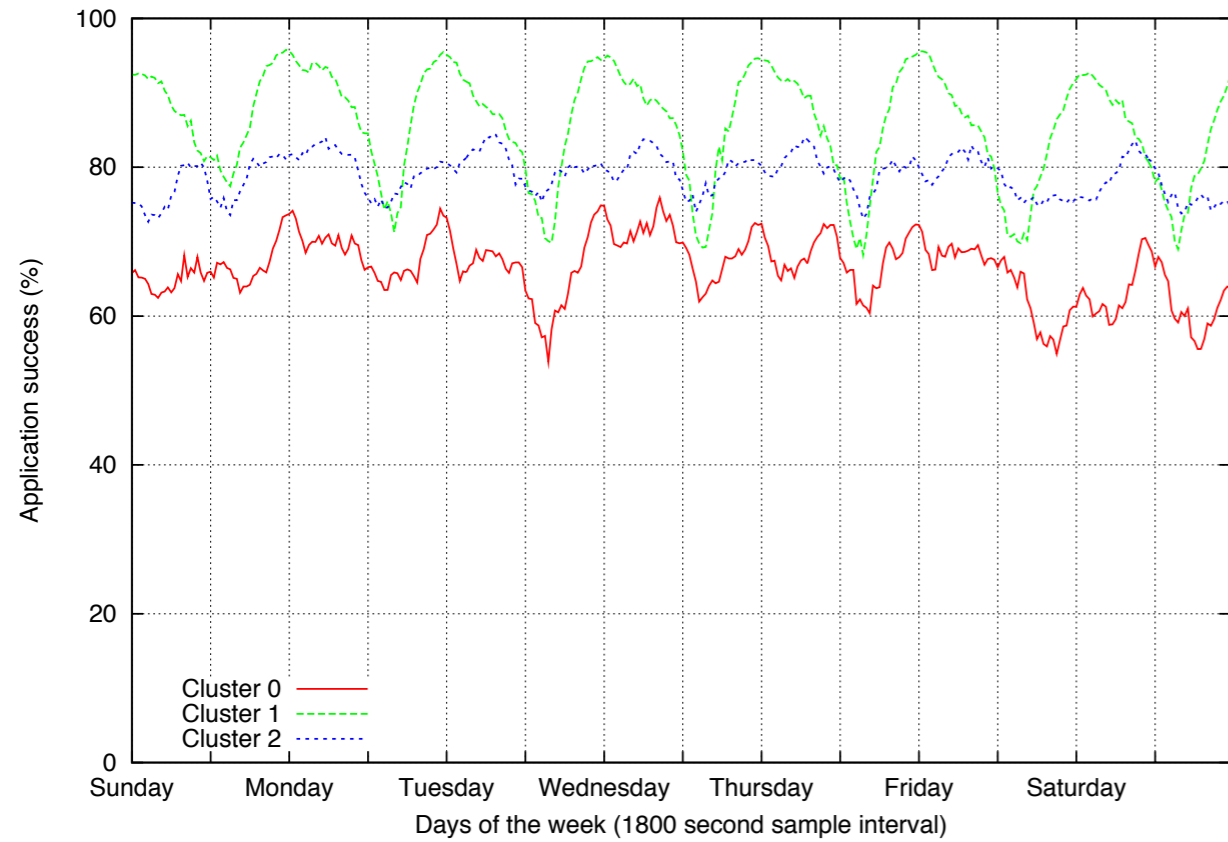


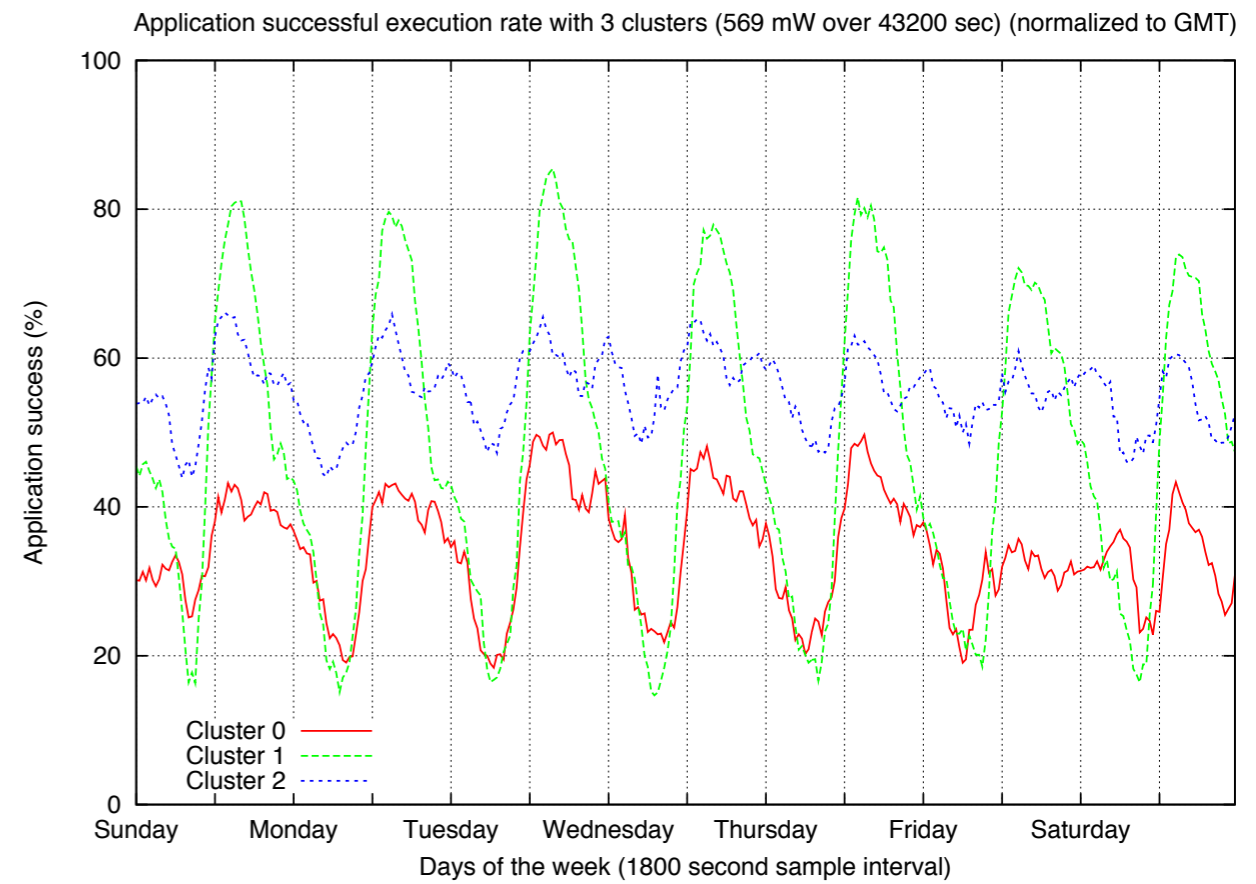
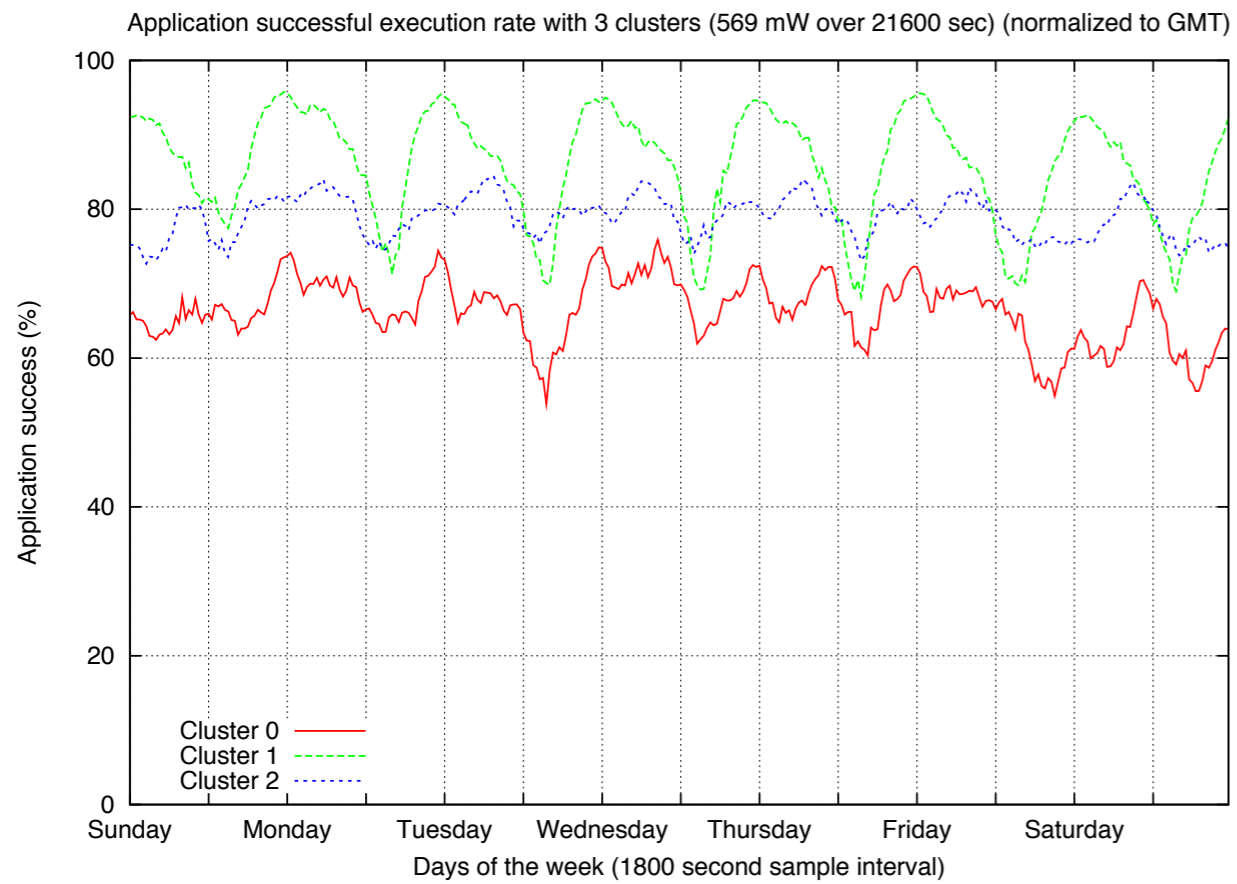
- ✦ Scenario 2
 - ✦ Scan for neighbouring Bluetooth device every minute
 - ✦ Upload 50 KB of memory resident data over WiFi after every scan.
 - ✦ Upload 100 MB of Flash-resident data over WiFi once per hour.

- ✦ Scenario 2

- ✦ Scan for neighbouring Bluetooth device every minute
- ✦ Upload 50 KB of memory resident data over WiFi after every scan.
- ✦ Upload 100 MB of Flash-resident data over WiFi once per hour.
- ✦ Download 100 MB of data over WiFi once per hour and write it to Flash.

Application successful execution rate with 3 clusters (569 mW over 21600 sec) (normalized to GMT)





Future work

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- Runtime profiling of applications' energy consumption.

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- ✦ Runtime profiling of applications' energy consumption.
- ✦ Creation of an energy supervisor

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- ✦ Runtime profiling of applications' energy consumption.
- ✦ Creation of an energy supervisor
 - ✦ Uses future predicted battery level to enable/disable energy intensive applications to preserve device usability.

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- Clustering users by energy consumption characteristics can improve battery level prediction by ~**54%** over long durations.
- ***App-Predict*** tool to simulate the successful execution rate of energy intensive mobile applications.

Questions?

Trivia questions

