ABSENCE: Usage-based Failure Detection in Mobile Networks

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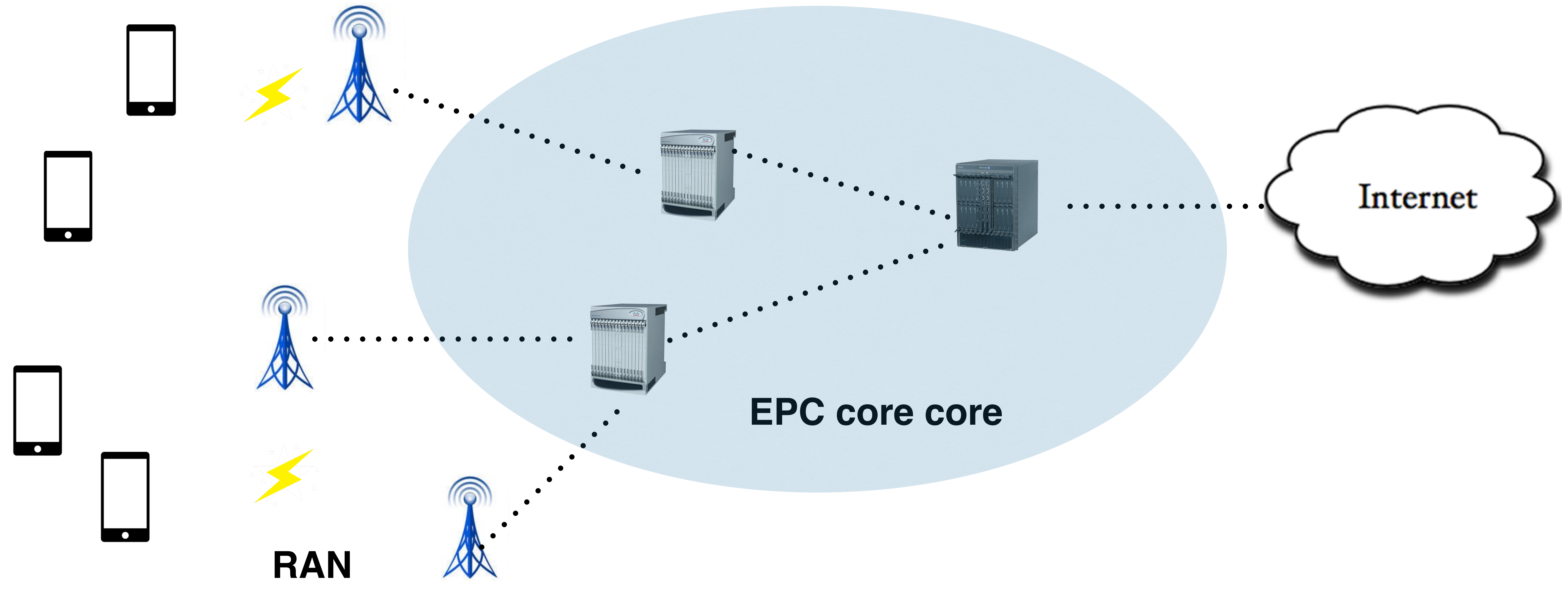
THE UNIVERSITY OF UTAH

AT&T Labs Research
The Science Behind The Service

Silent failures



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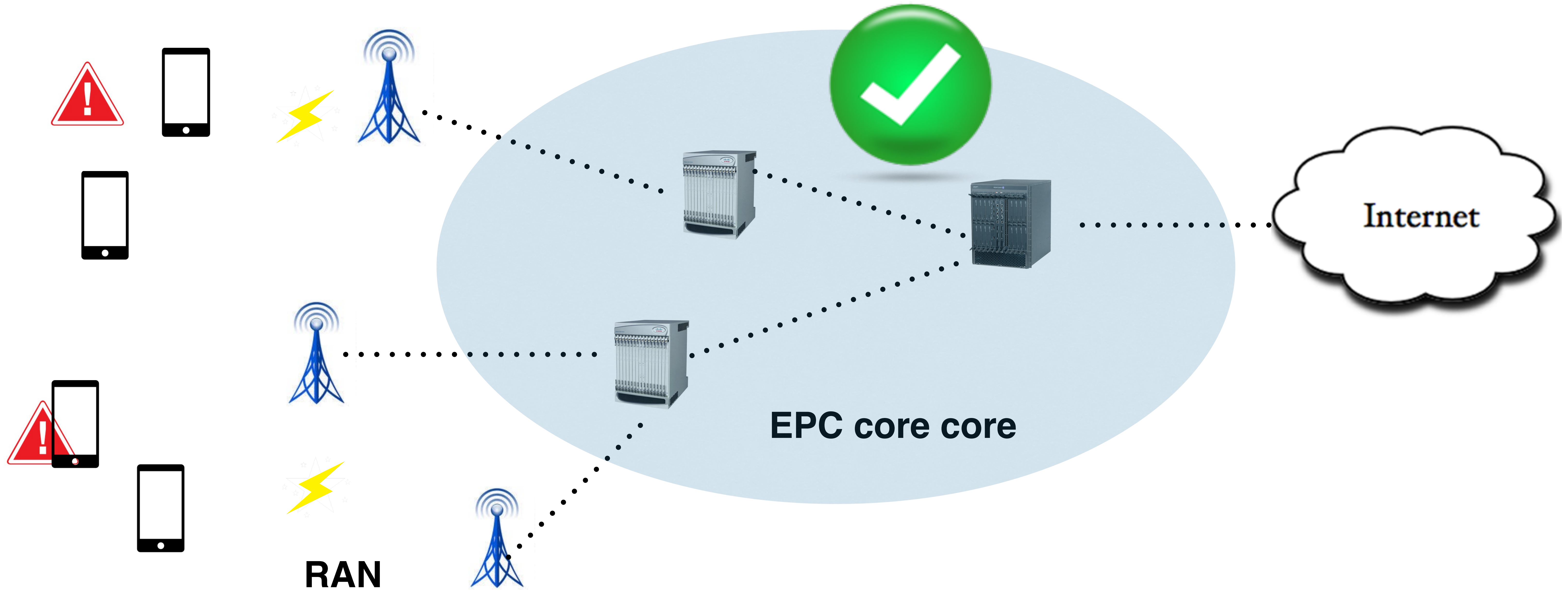

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- New features rolled out, bugs on devices, or combination of both.

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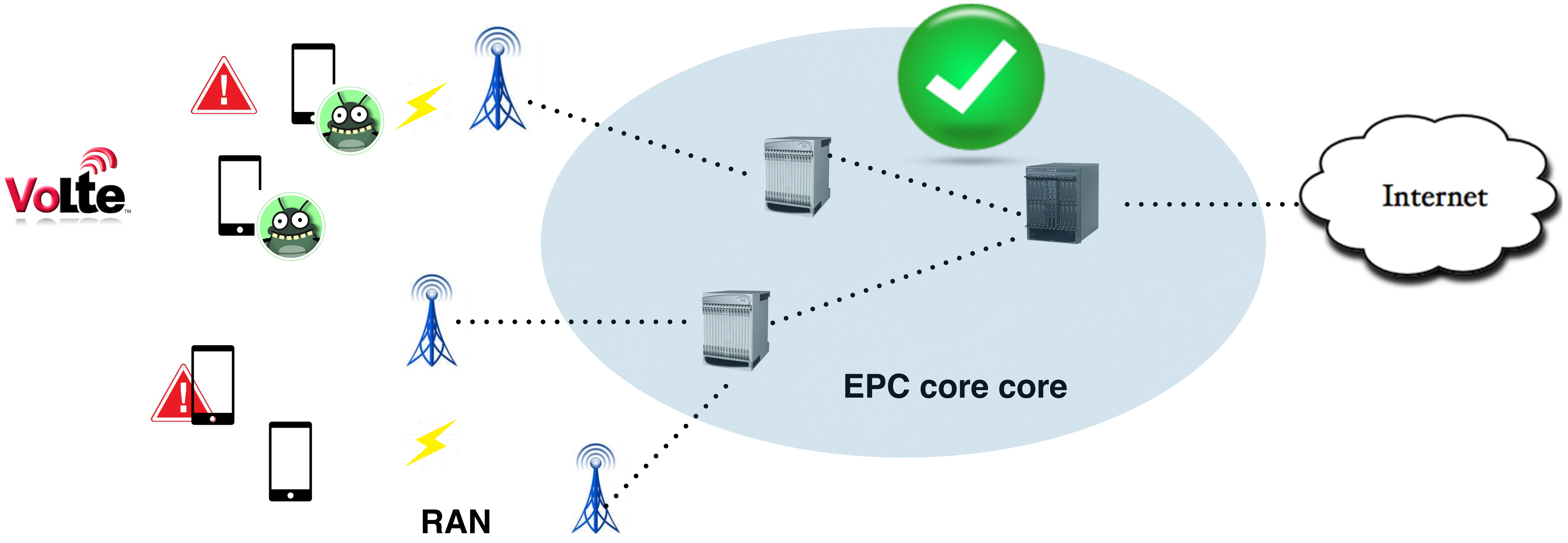

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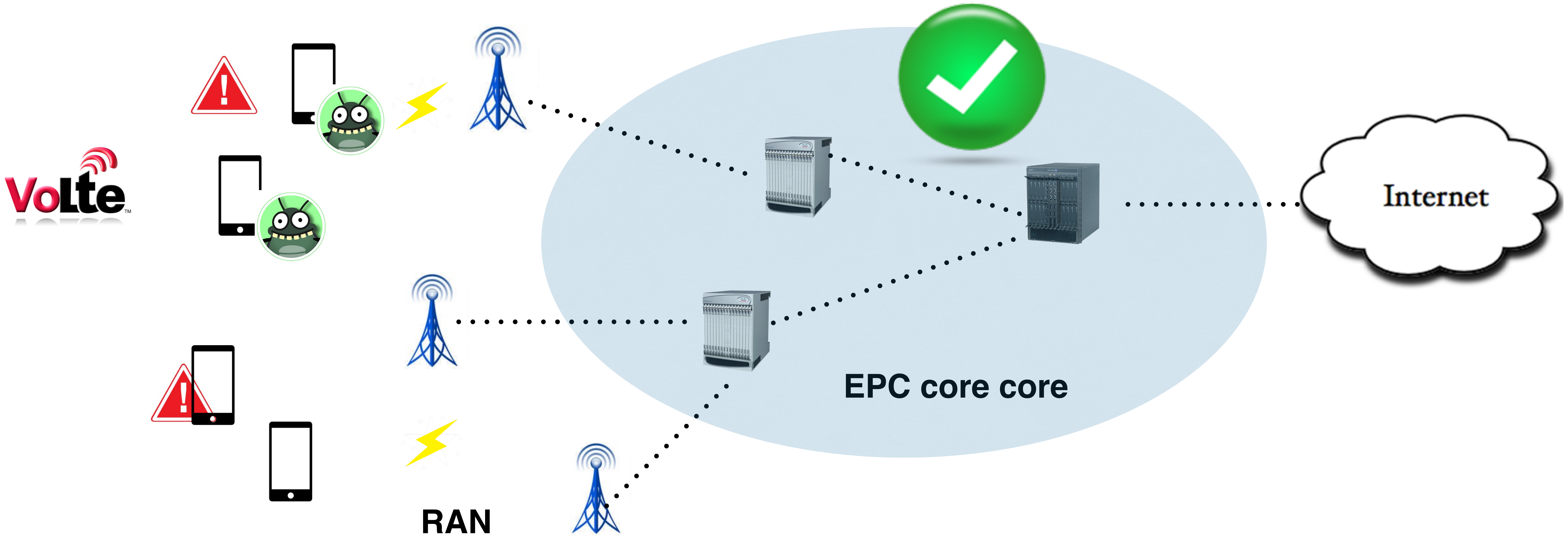

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Detecting silent failures is challenging!

Detecting silent failures is difficult - passive network monitoring

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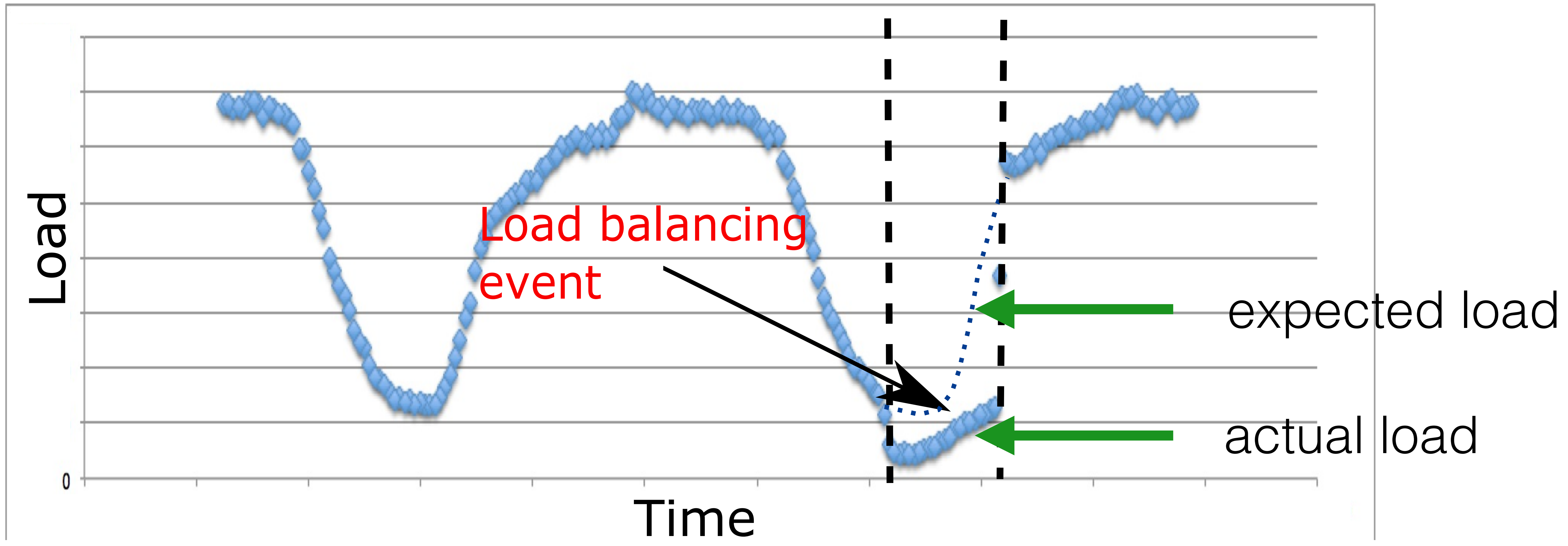
  - Load balancing/maintenance activities.
  - Dynamic routing/Self-Organizing Network (SON).



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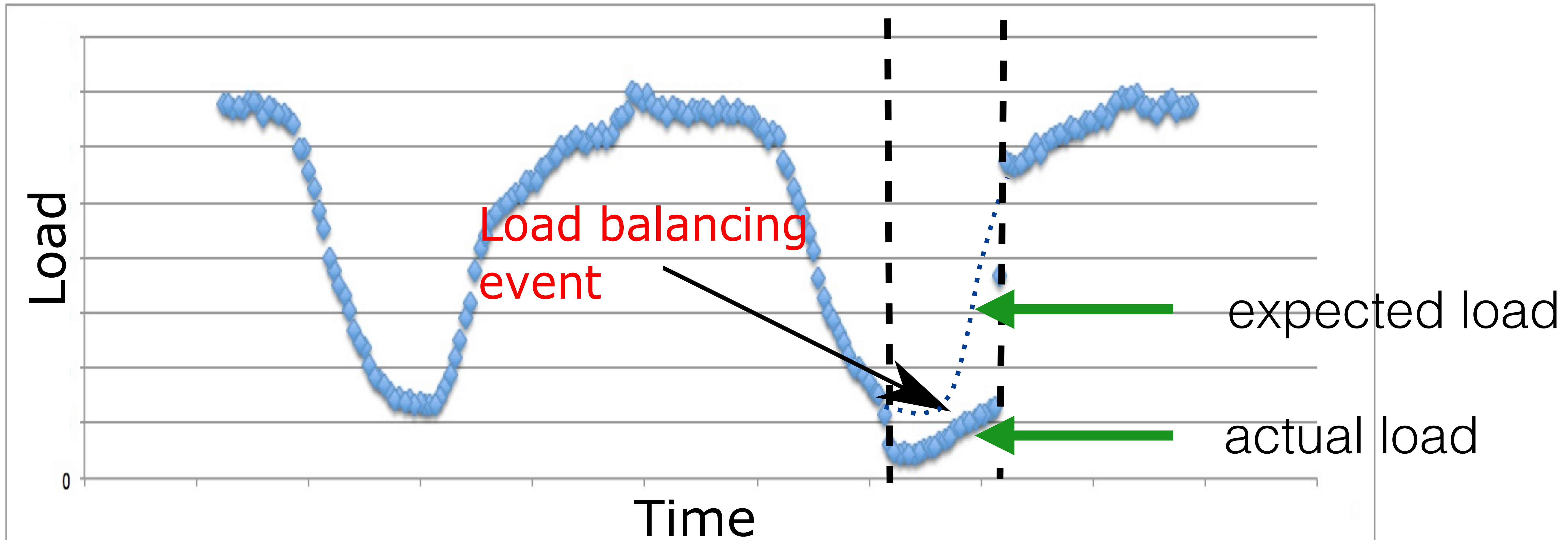
  - Load balancing/maintenance activities.
  - Dynamic routing/Self-Organizing Network (SON).
- Key Performance metric Indicators (KPI) **may not** reflect service issues:
  - E.g., accessibility KPI looks good even when only a subset of users can access the network.



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  - Load balancing/maintenance activities.
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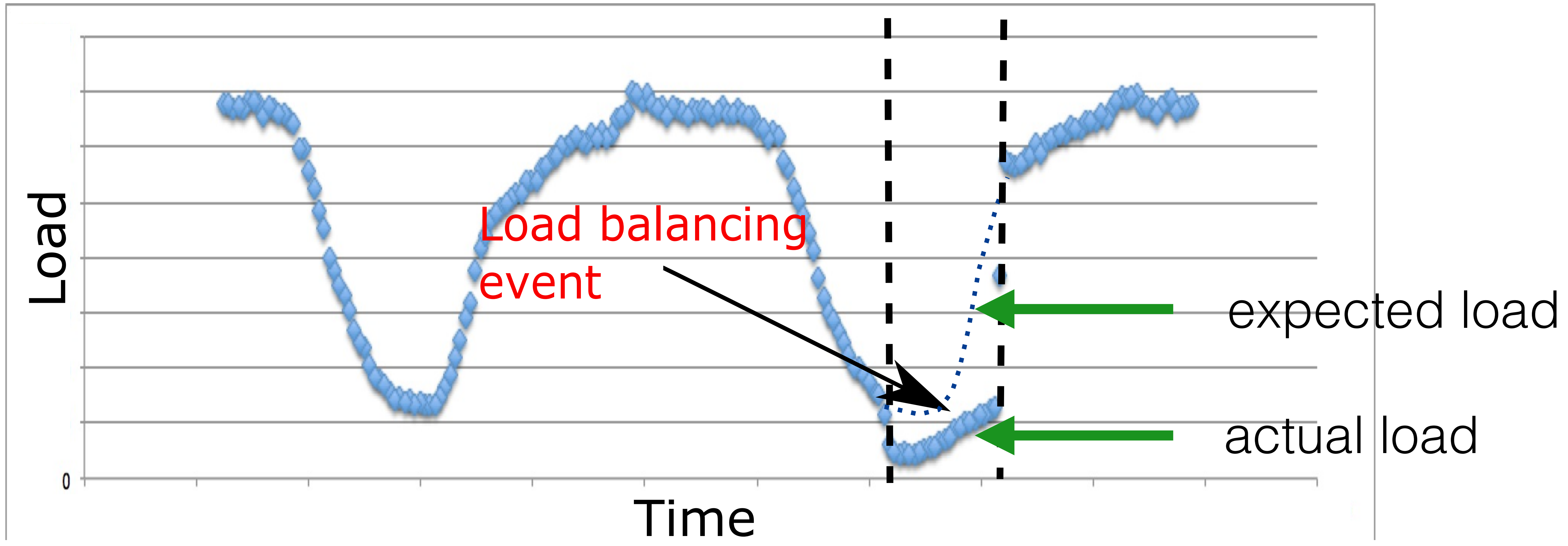
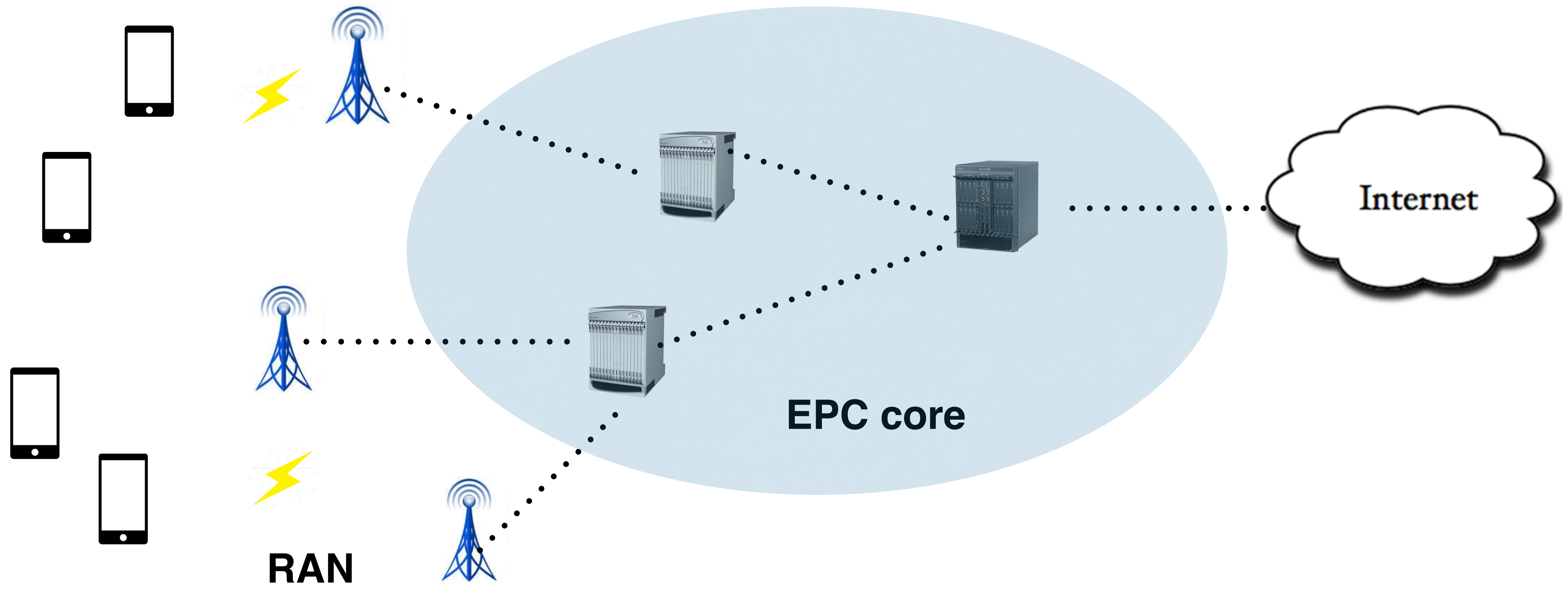
A "healthy network" (from a monitoring perspective) does not guarantee service experience of users!

  - E.g., accessibility KPI looks good even when only a subset of users can access the network.

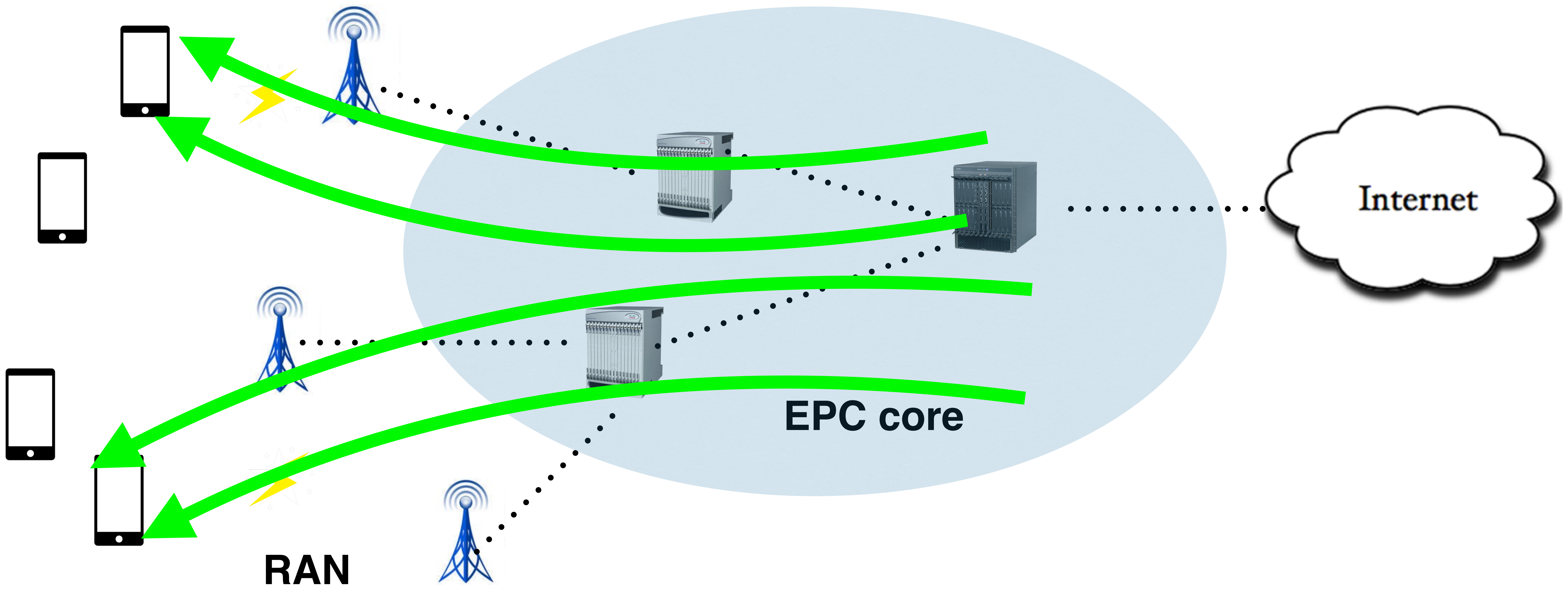


Detecting silent failures is difficult - active service monitoring



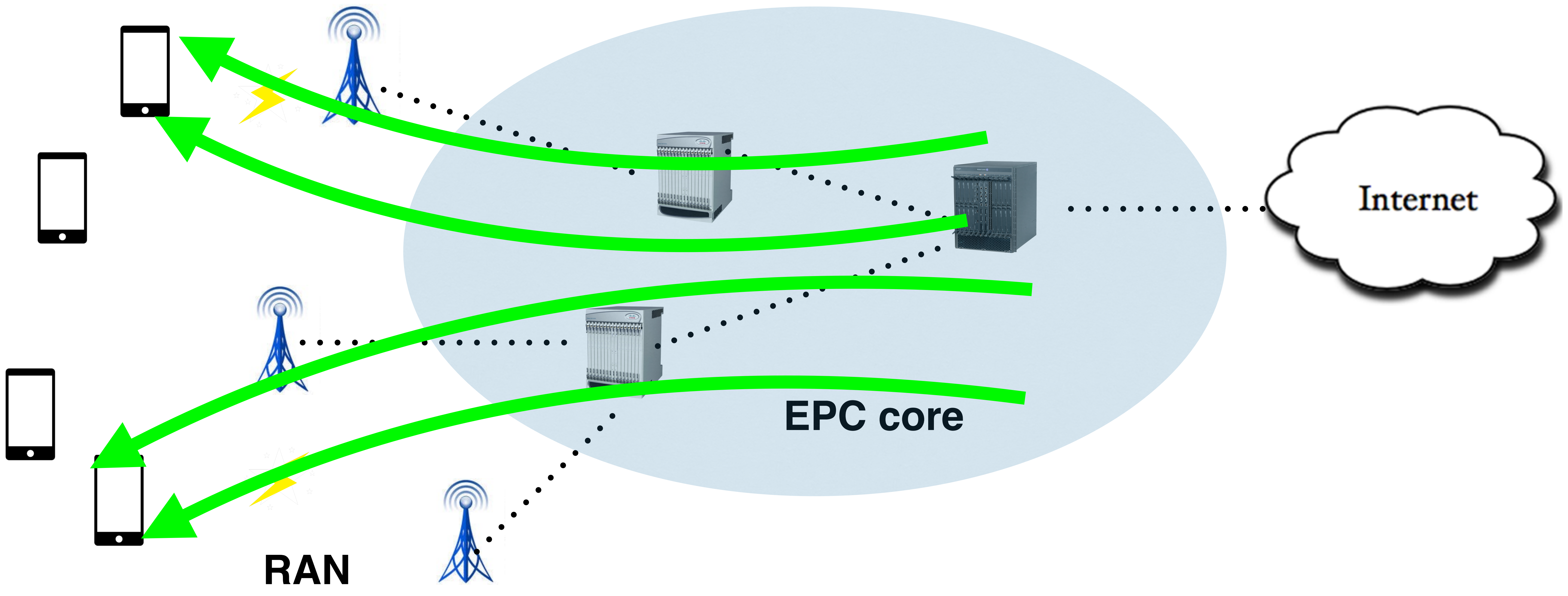
Detecting silent failures is difficult - active service monitoring

- Sending test traffic across the network on **all** service paths.



Detecting silent failures is difficult - active service monitoring

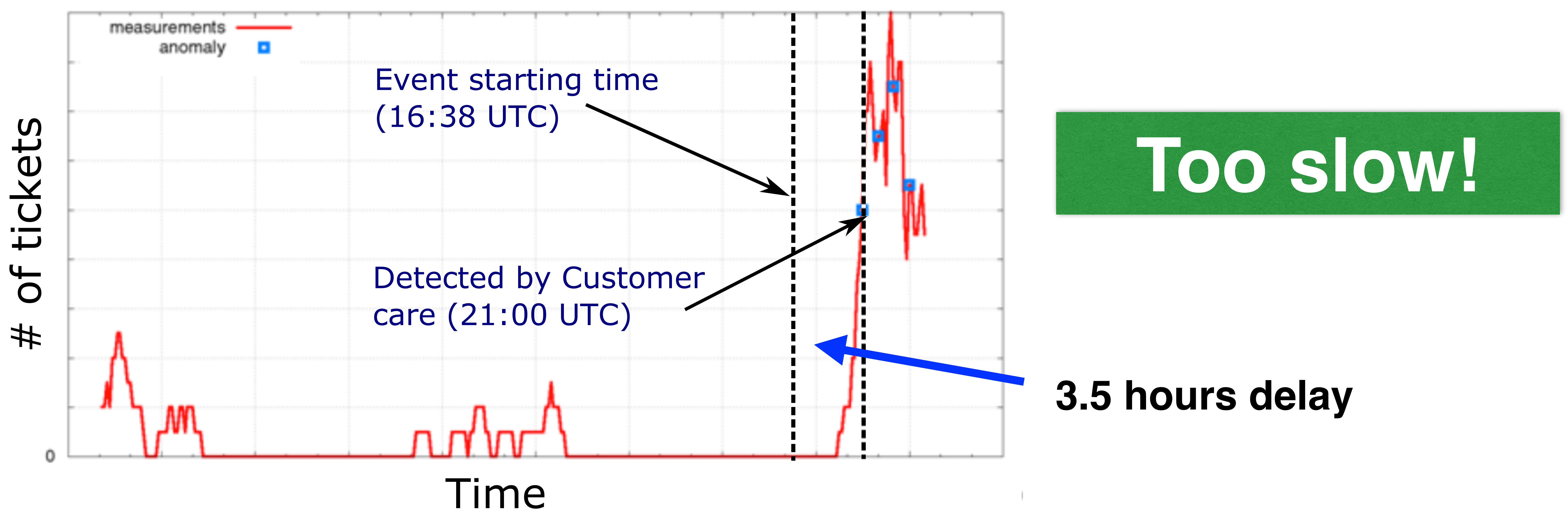
- Sending test traffic across the network on **all** service paths.
- Many types of customer devices, applications, huge geographic environment to probe.



Active monitoring does not scale!

Relying on customer feedback

- It takes time for customers to give feedback.
- Relying on customer feedback is **too slow**: hours of delay.
  - E.g., failure happens at **16:38 UTC** but manifests in customer feedback at **21:00 UTC**, **3.5 hours of delay**.



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- ABSENCE: **Passive service monitoring** approach - monitor usage of users in a passive manner.

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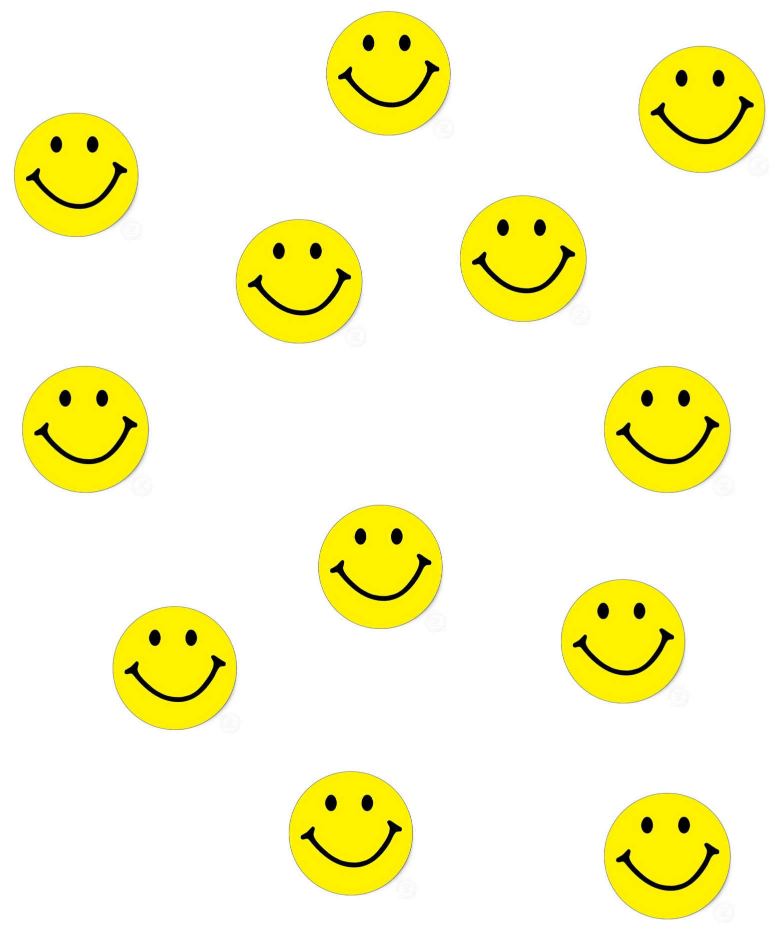
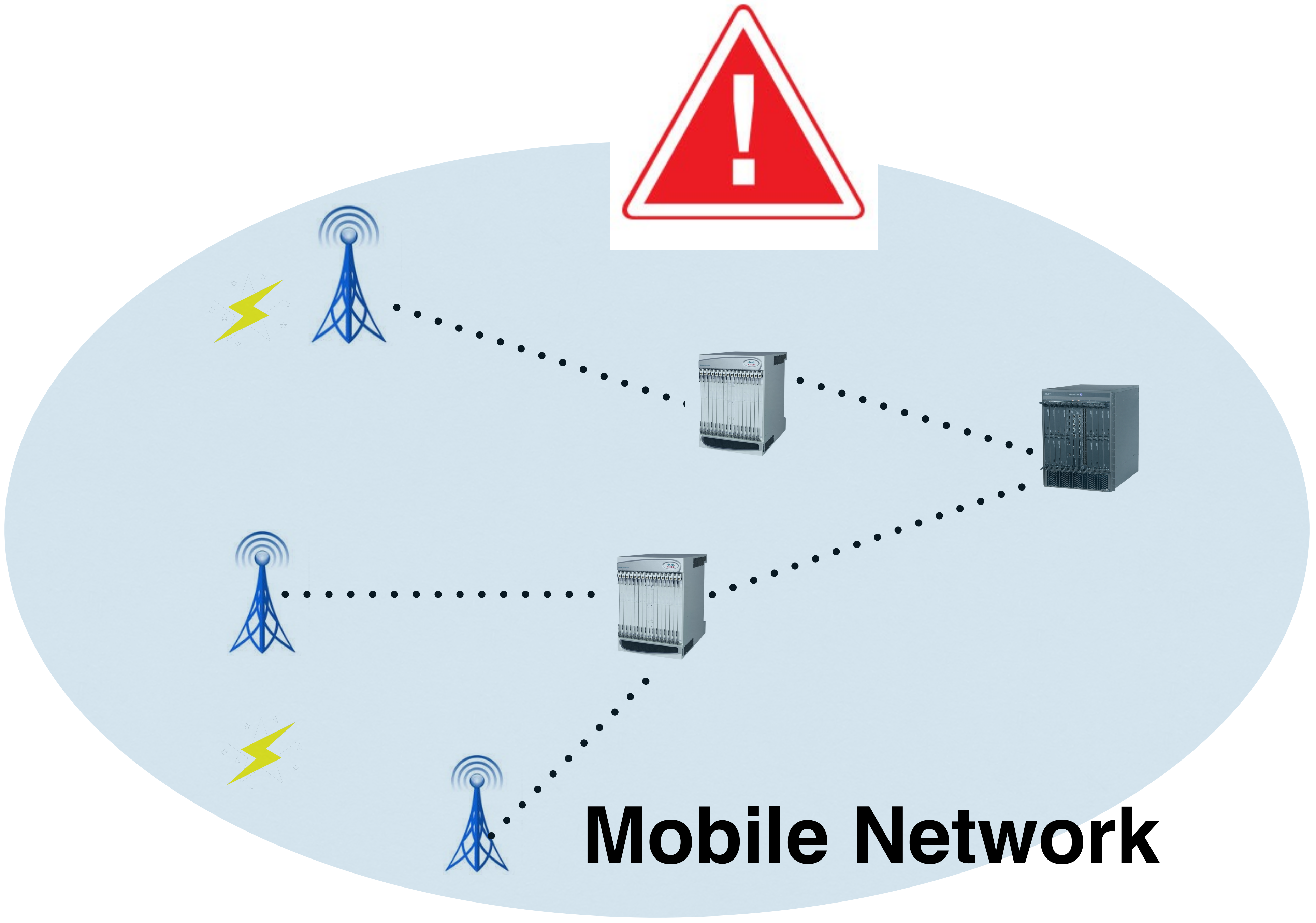
- ABSENCE: **Passive service monitoring** approach - monitor usage of users in a passive manner.
- ***Absence of customer usage*** is a reliable indicator of service disruptions in a mobile network.

ABSENCE’s key ideas



A group of users

Usage



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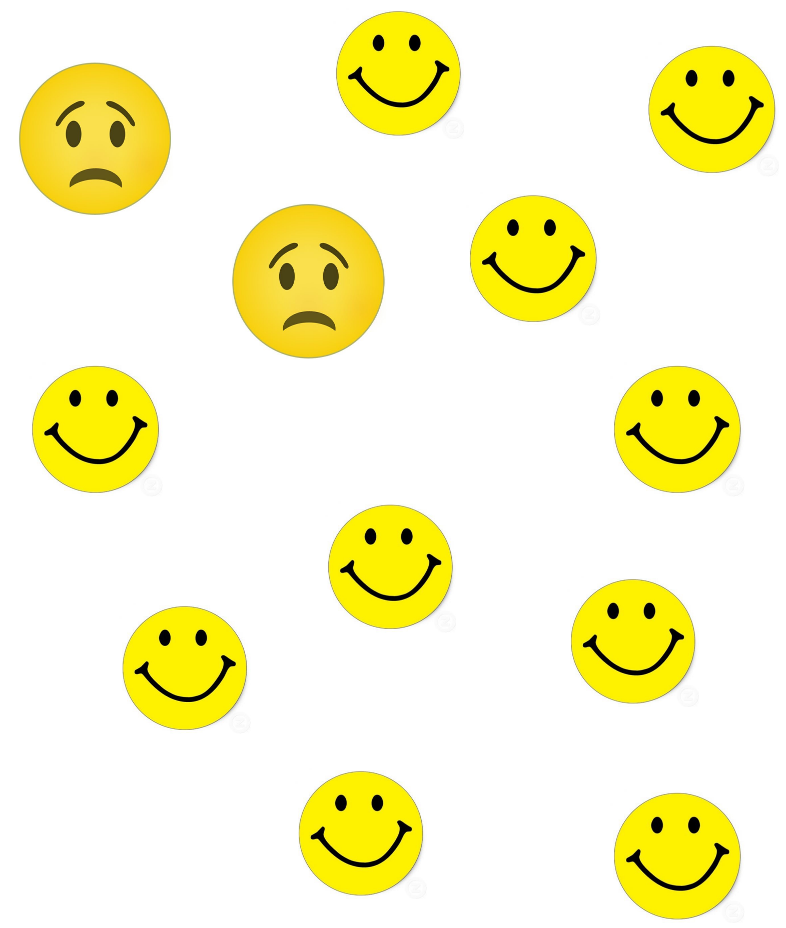

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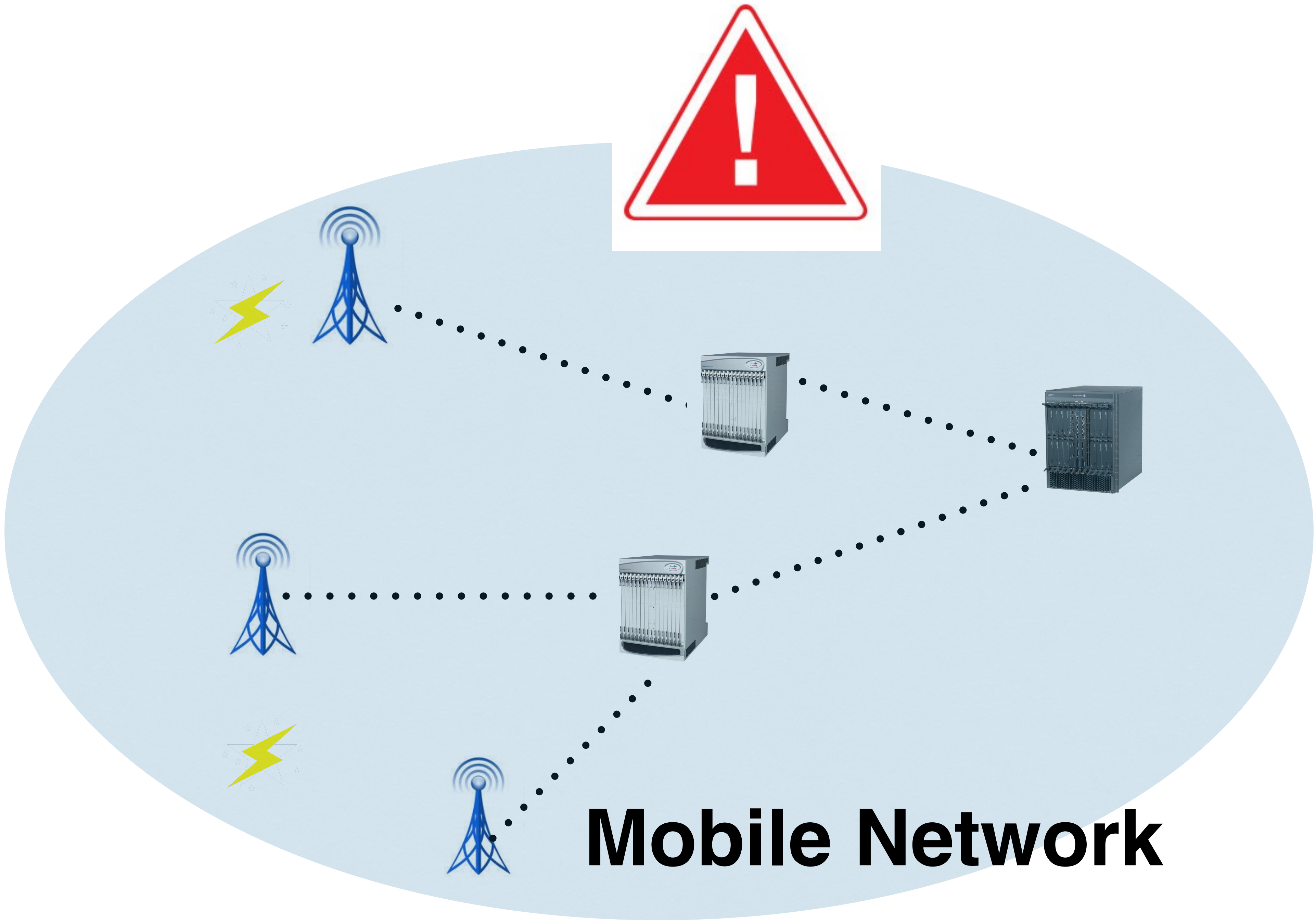

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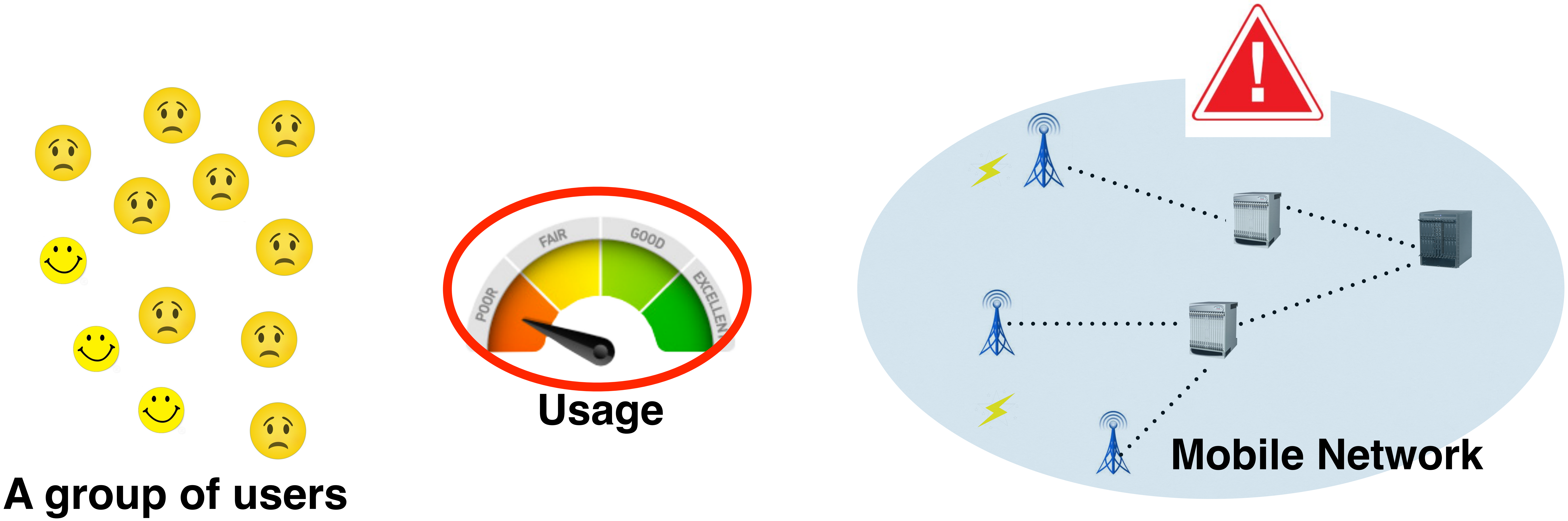
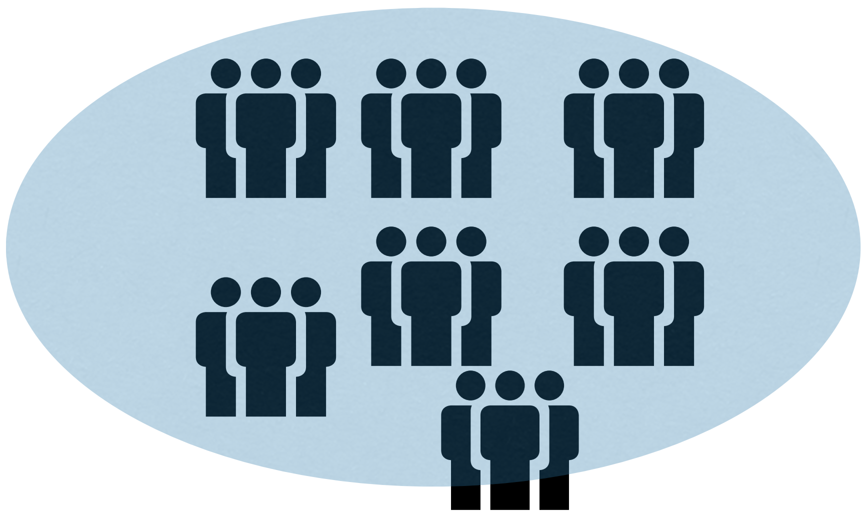


- If failure happens, users are not able to use the network as normal.
- Large number of users cannot use the network leads to a drop in usage.
- Could detect both hard failures (outages) and performance degradations.

ABSENCE overview

Use anonymized and aggregated Call Detail Record (CDR) collected in real time from an U.S. operator.



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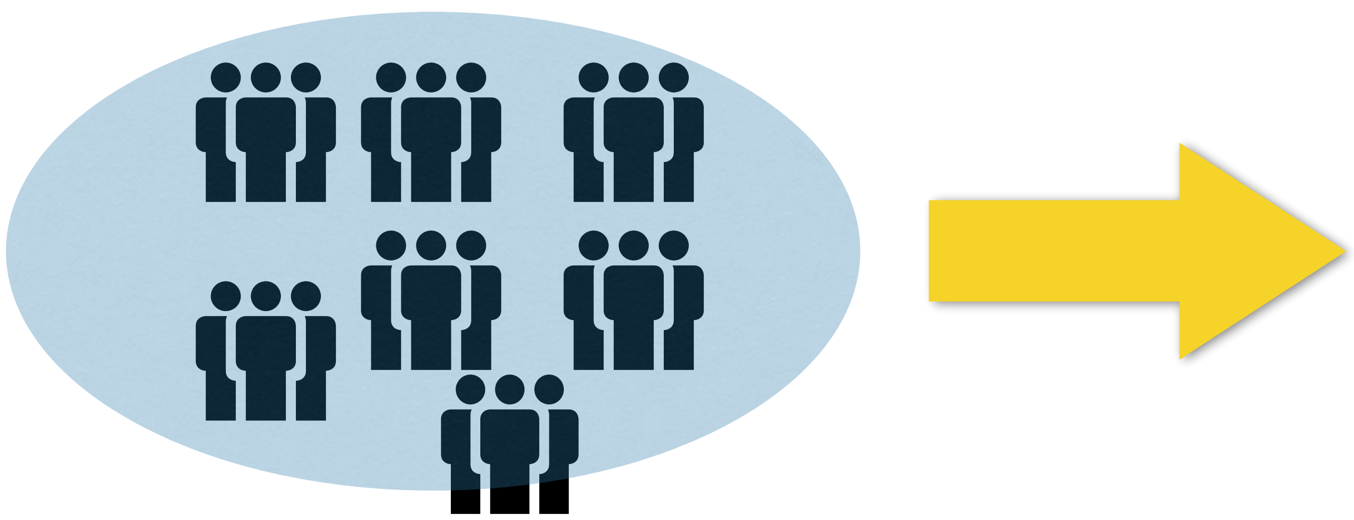

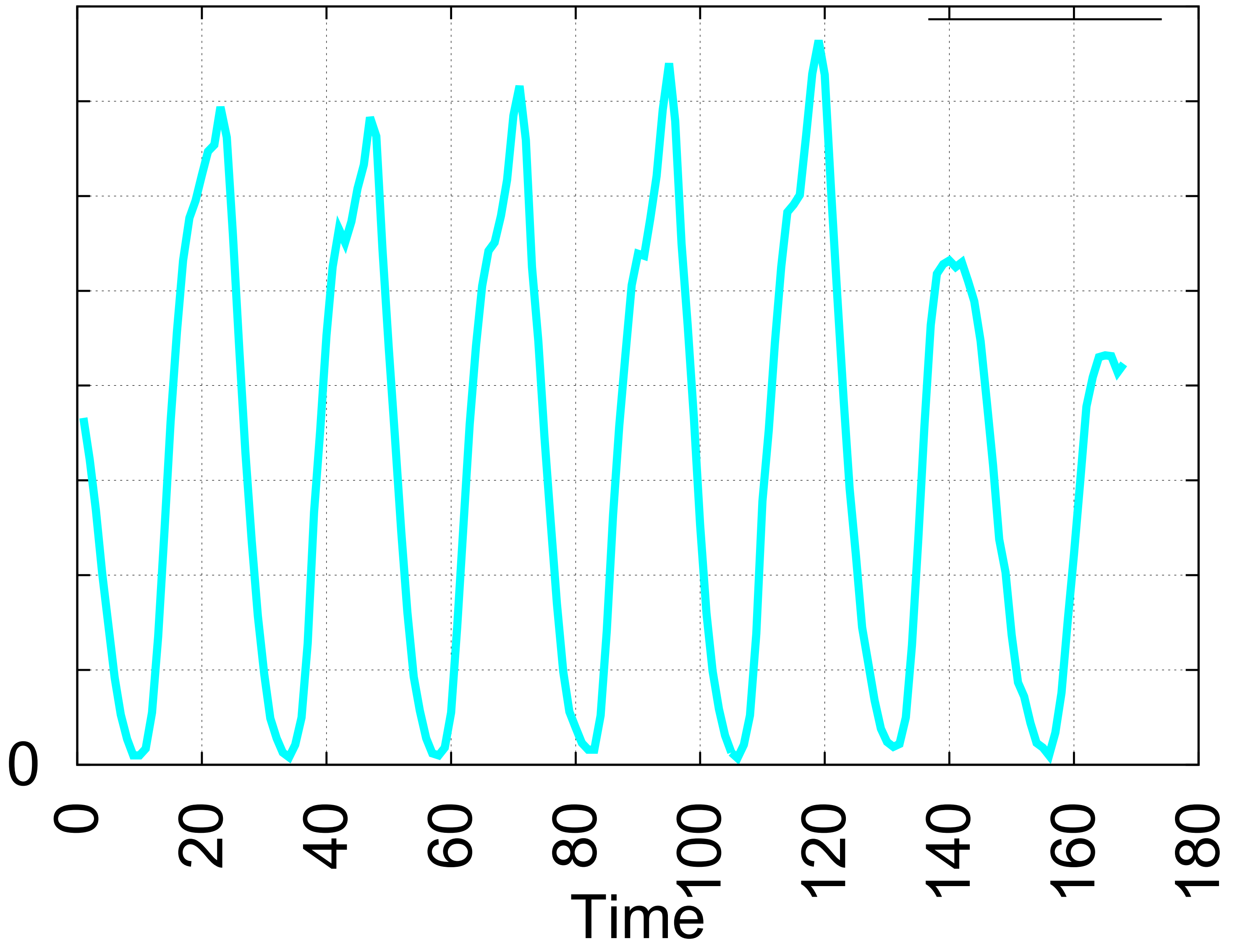

Week 1

ABSENCE overview

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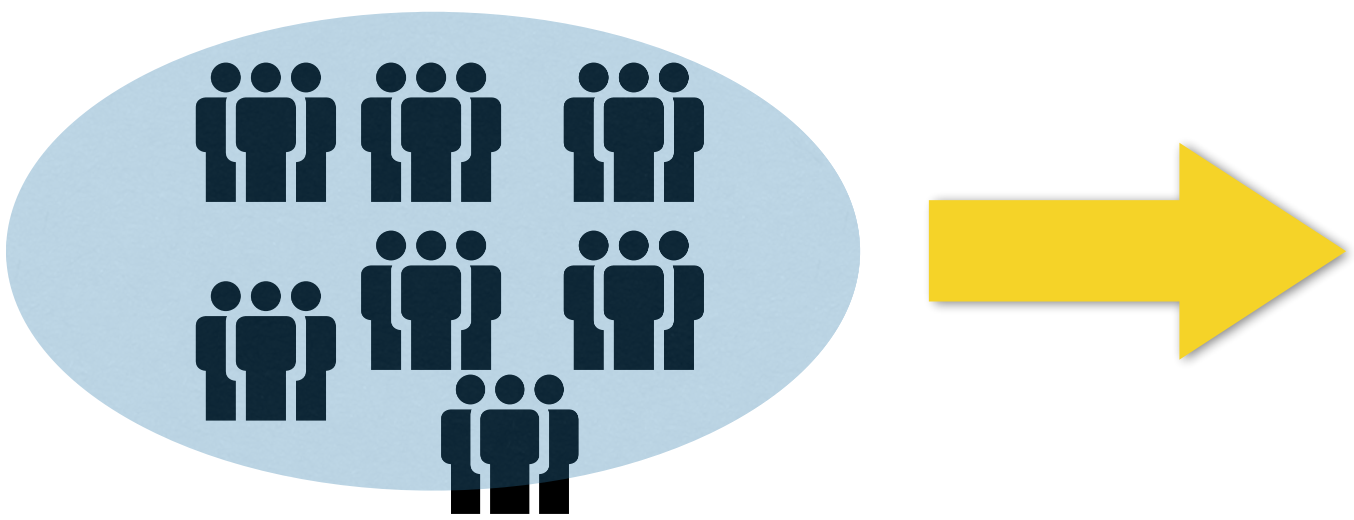

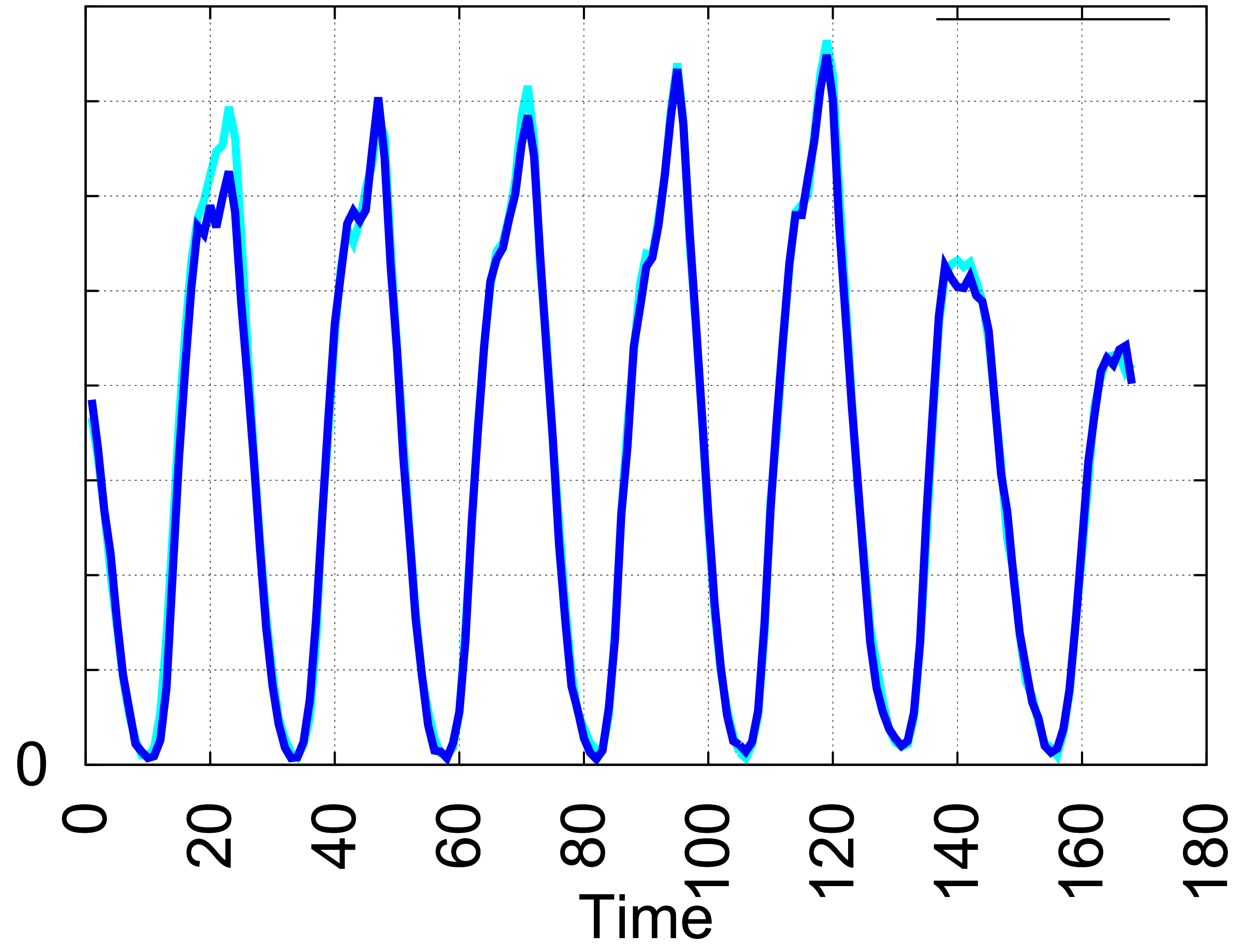

Week 2

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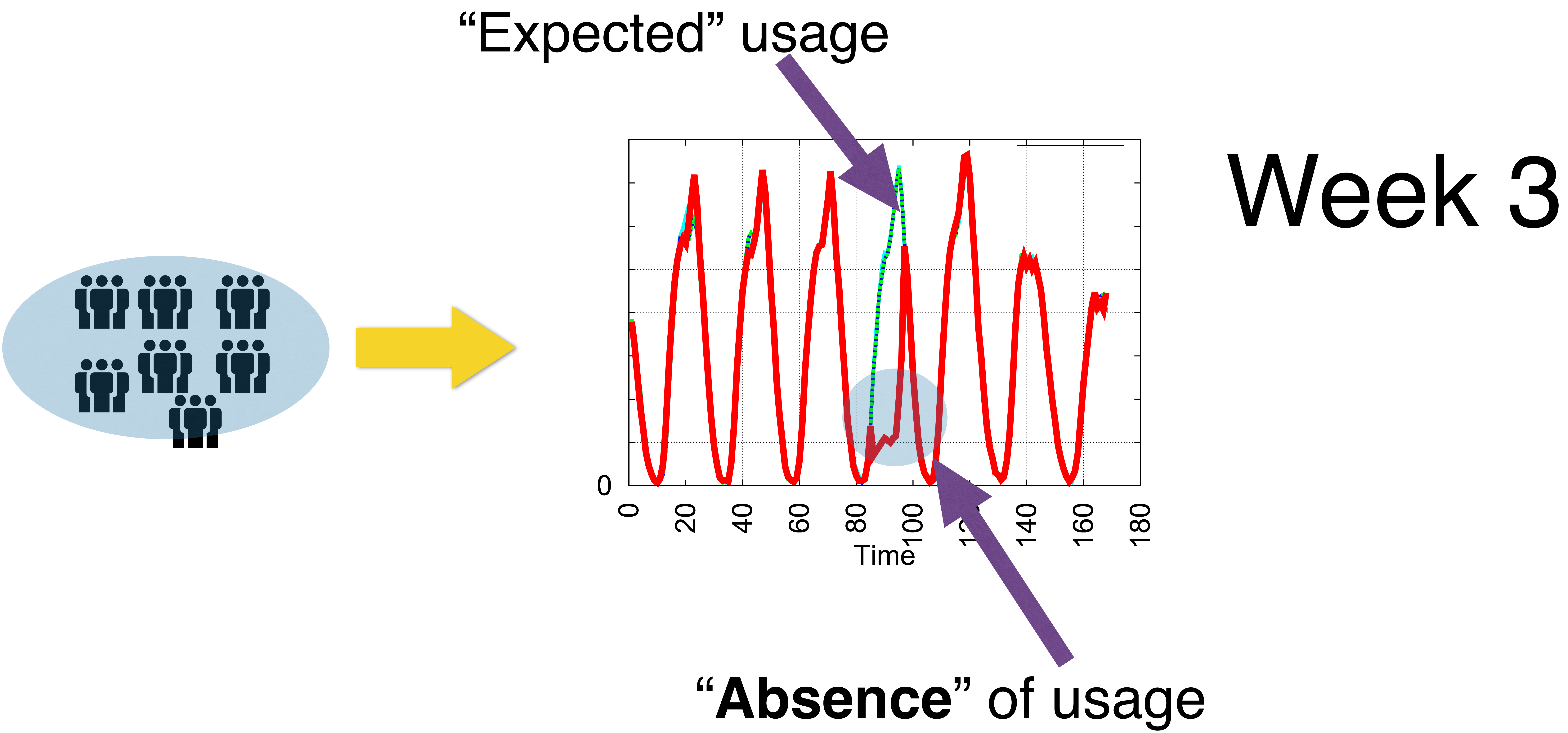

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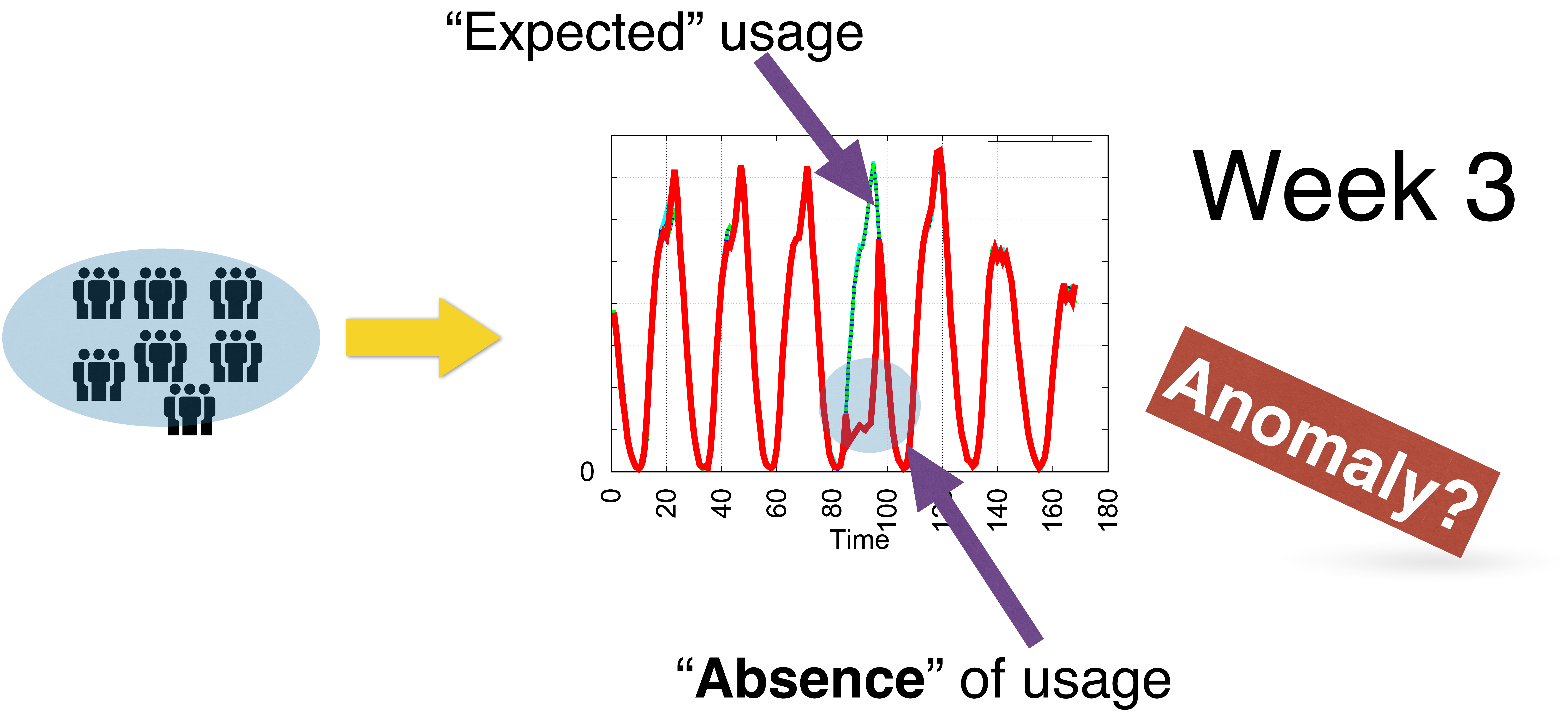

Outline

- Motivation.
- ABSENCE overview.
- **Is ABSENCE feasible?**
- ABSENCE's challenges.
- ABSENCE's event detection.
- Synthetic workload evaluation.
- Operational validation.

Is ABSENCE feasible?

Is usage predictable enough for anomaly detection?

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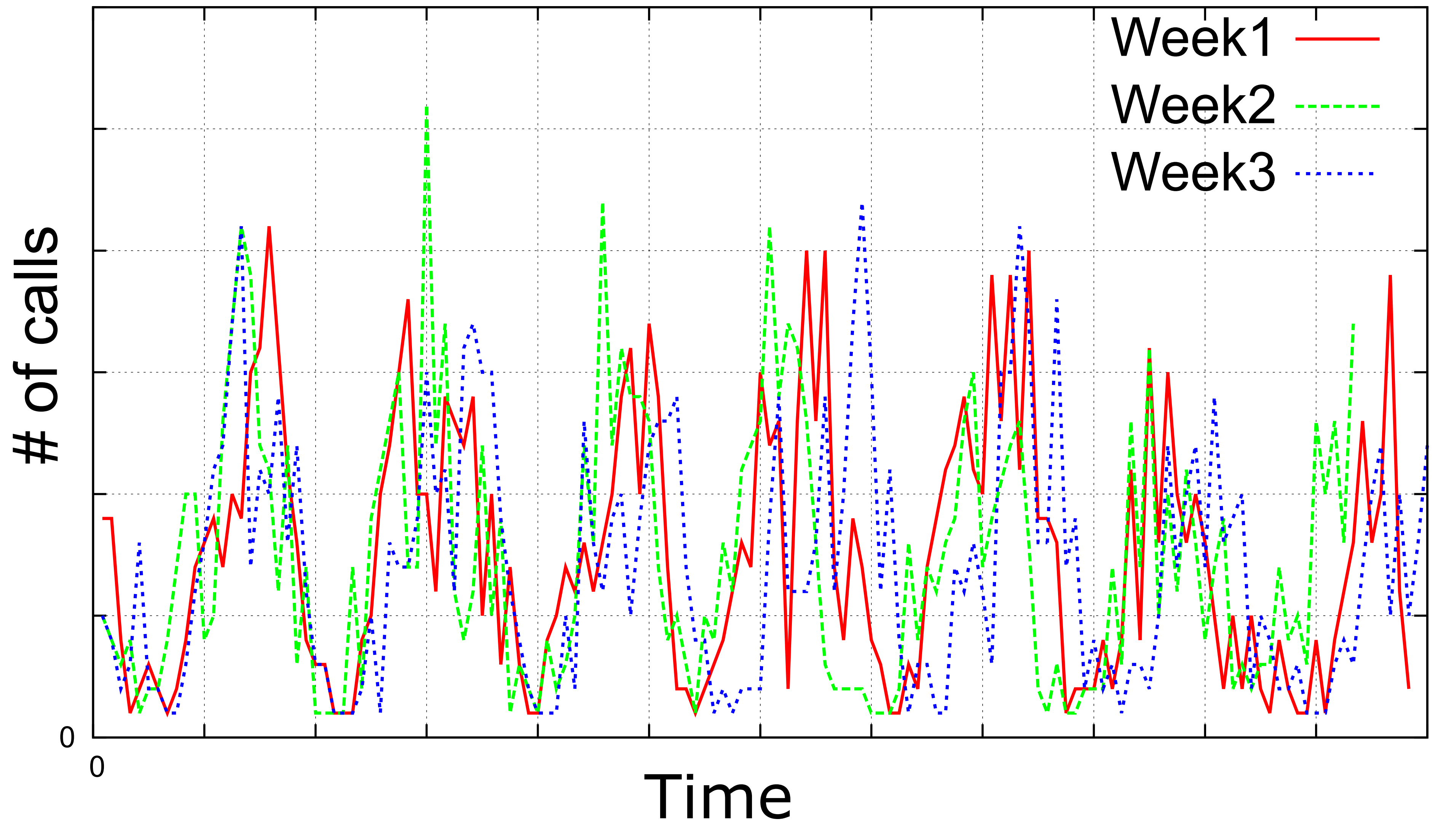
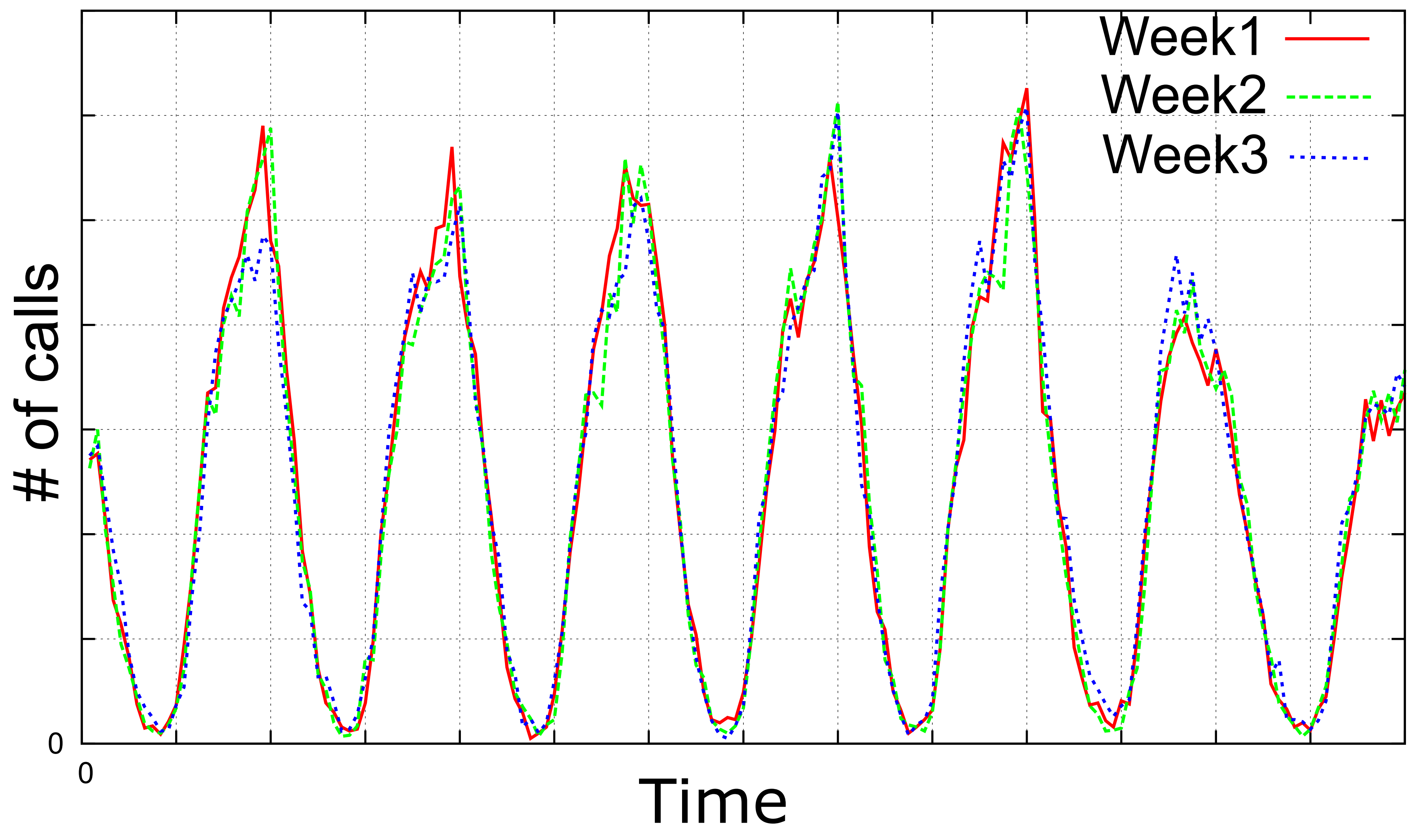


70 users



3000 users

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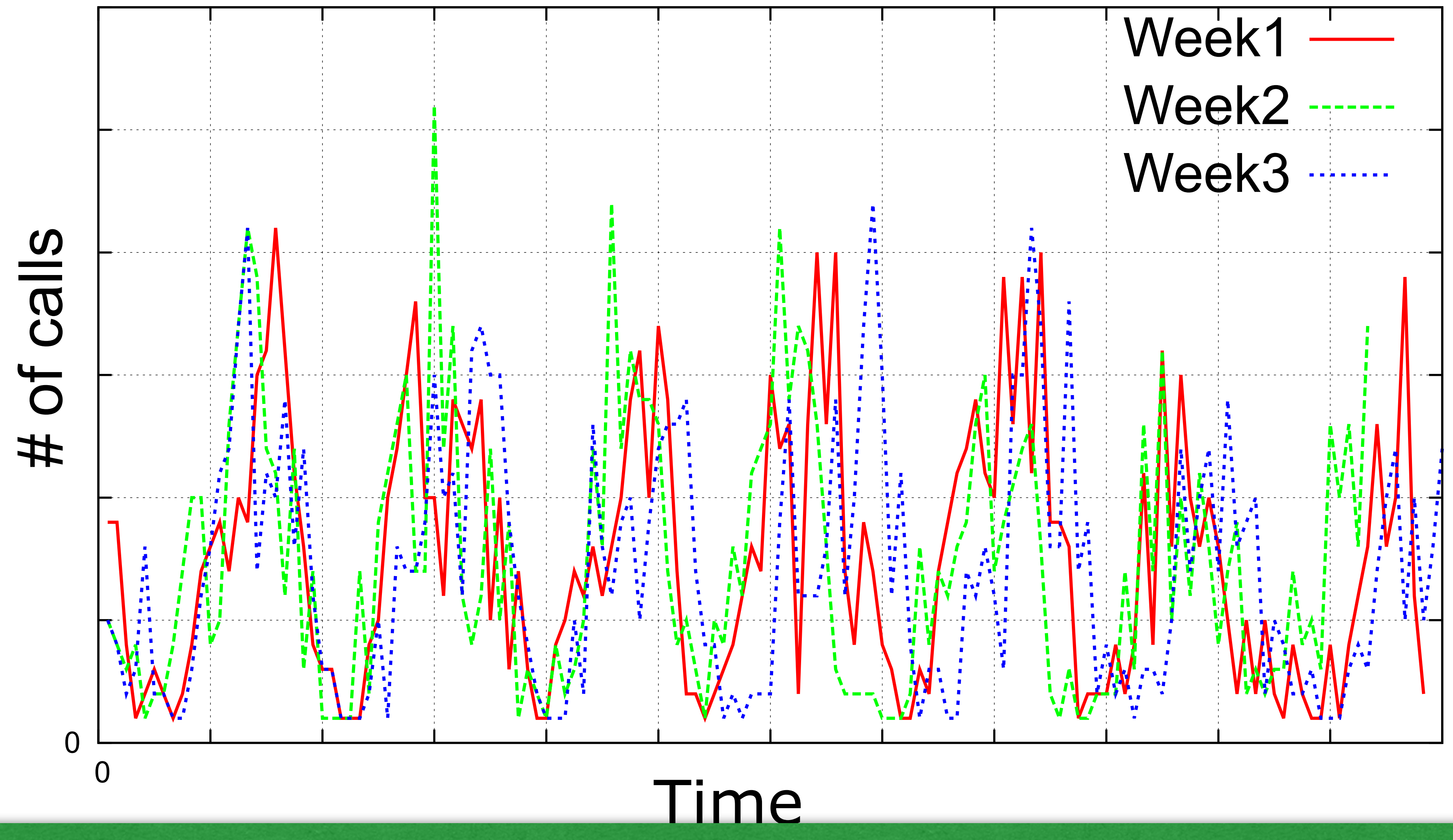

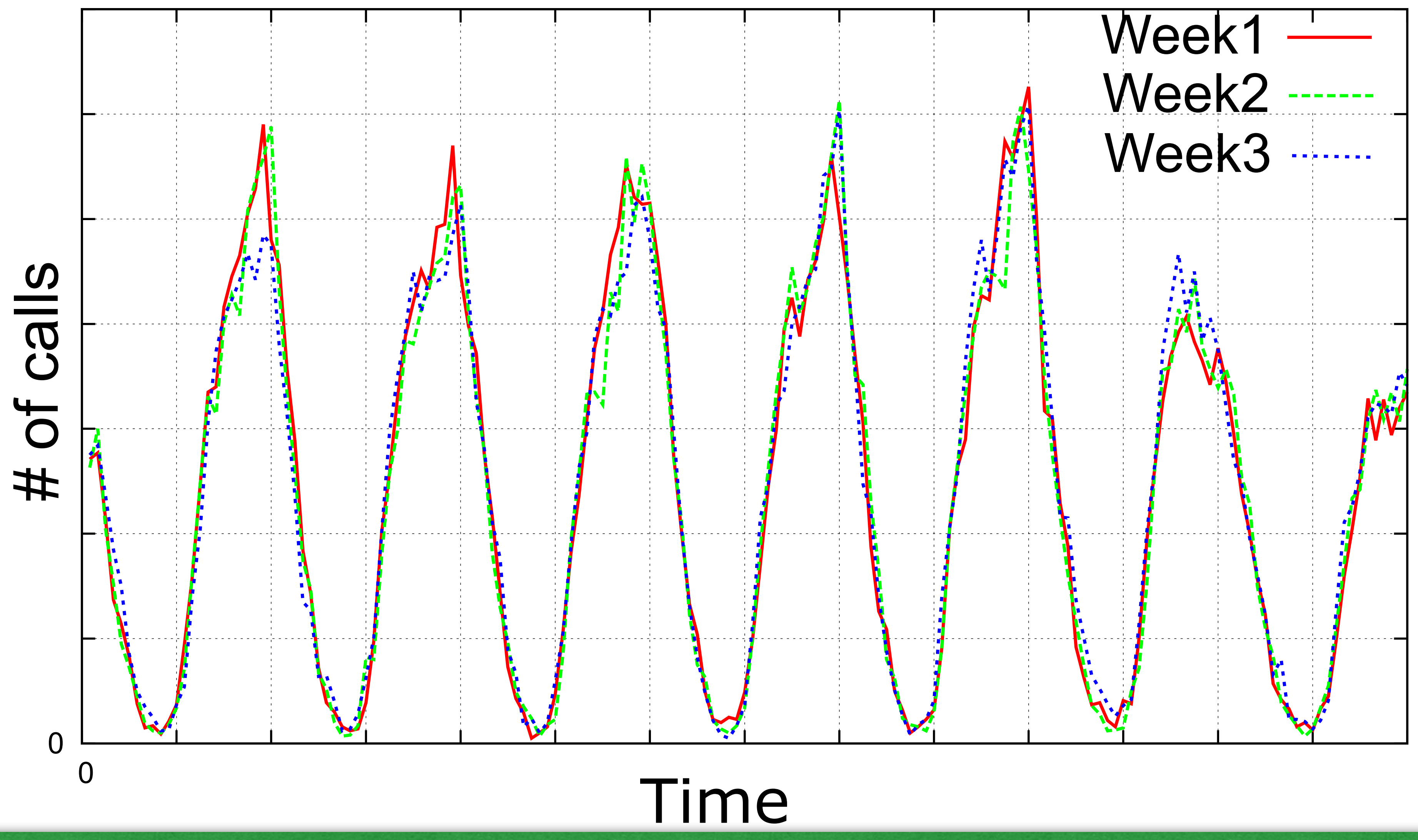

Yes, usage of a large enough group of users is predictable!

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Challenges

- Failures happens to different scopes: geo-area, device makes/models, service types.

- How to deal with users mobility?

- How to improve predictability of aggregate usage?

- How to make ABSENCE scalable, given a large amount of data in the network?

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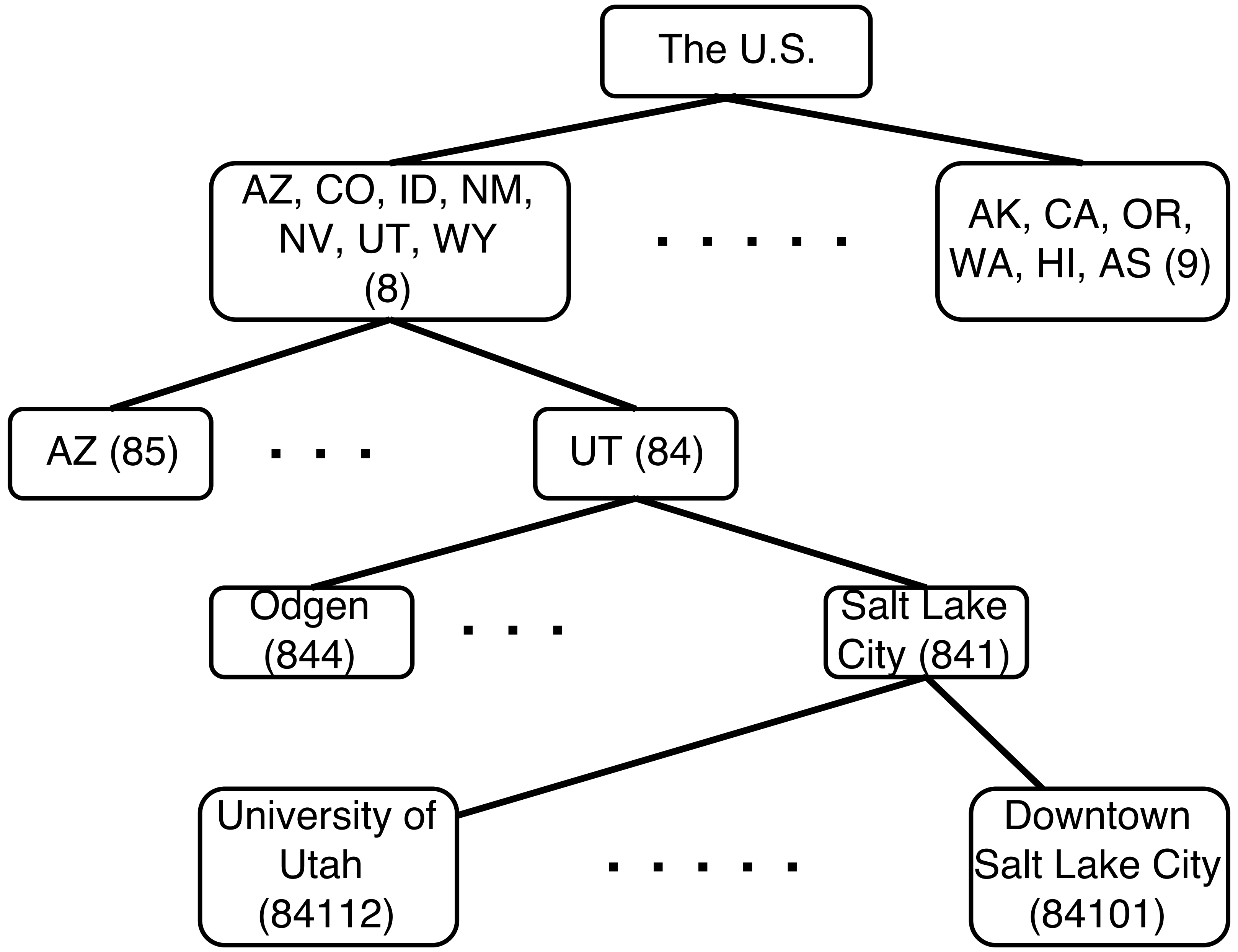

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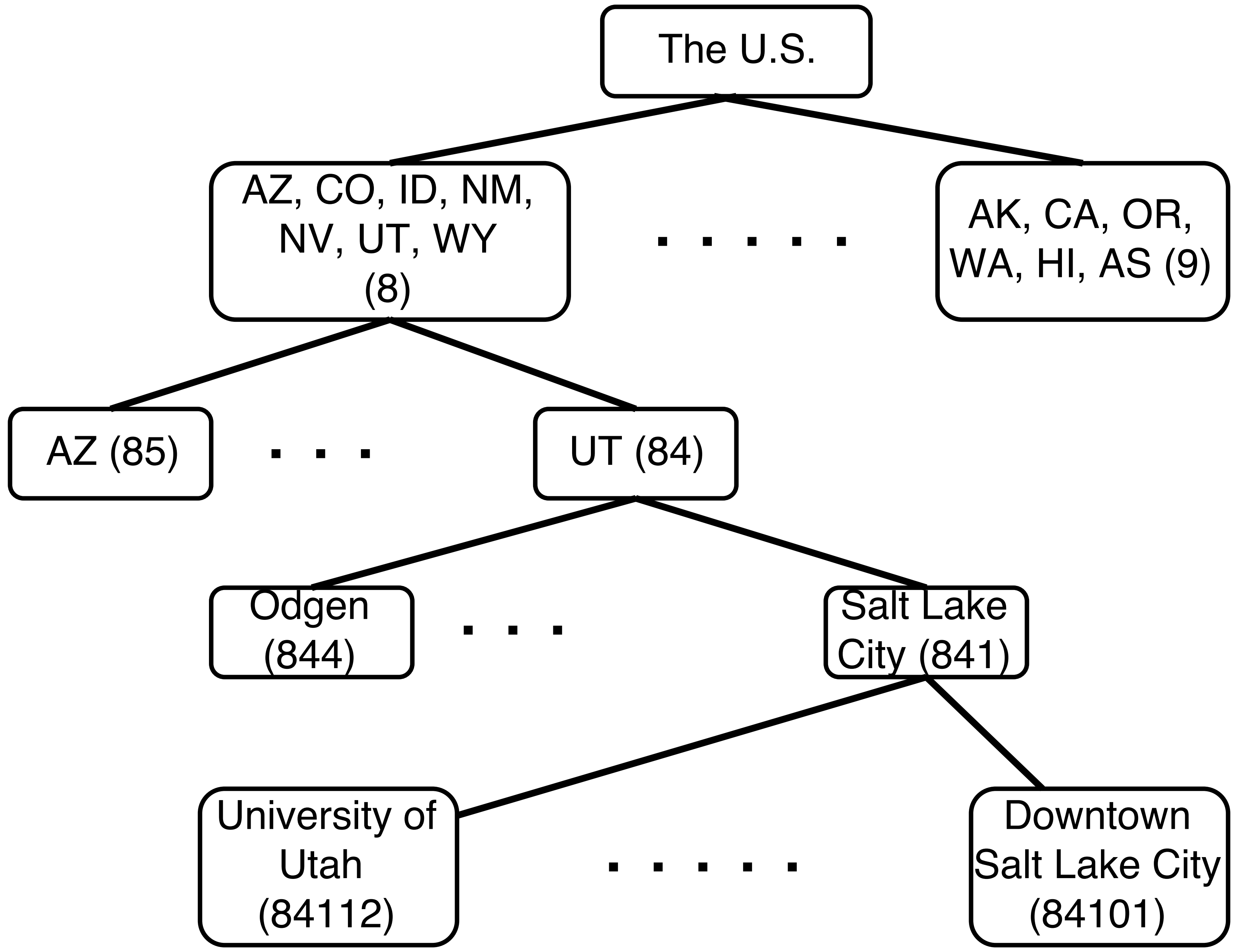

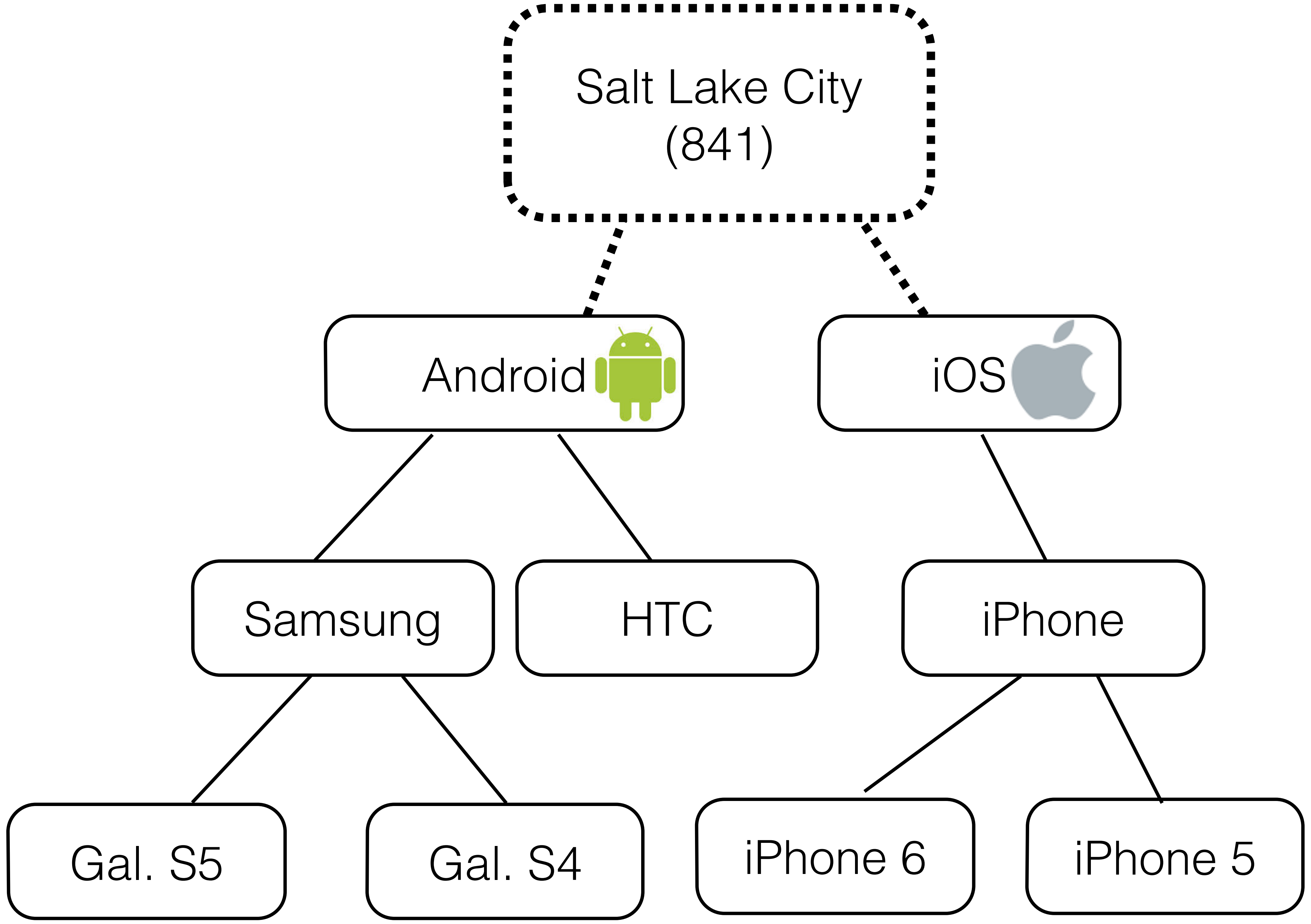

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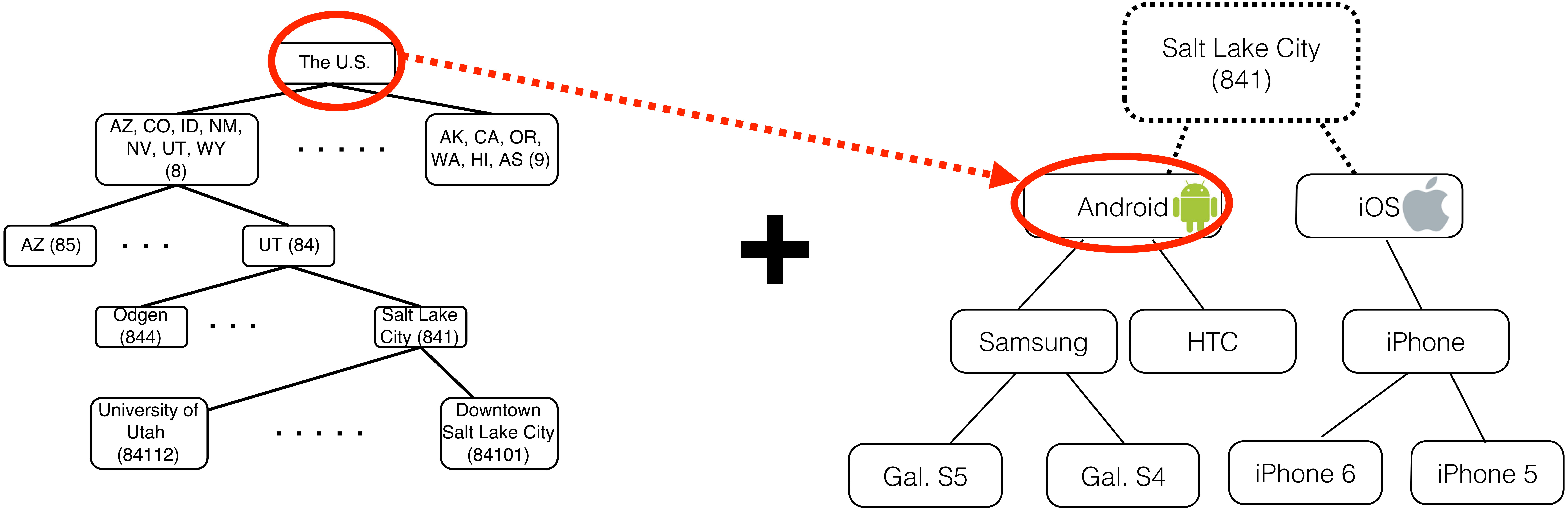

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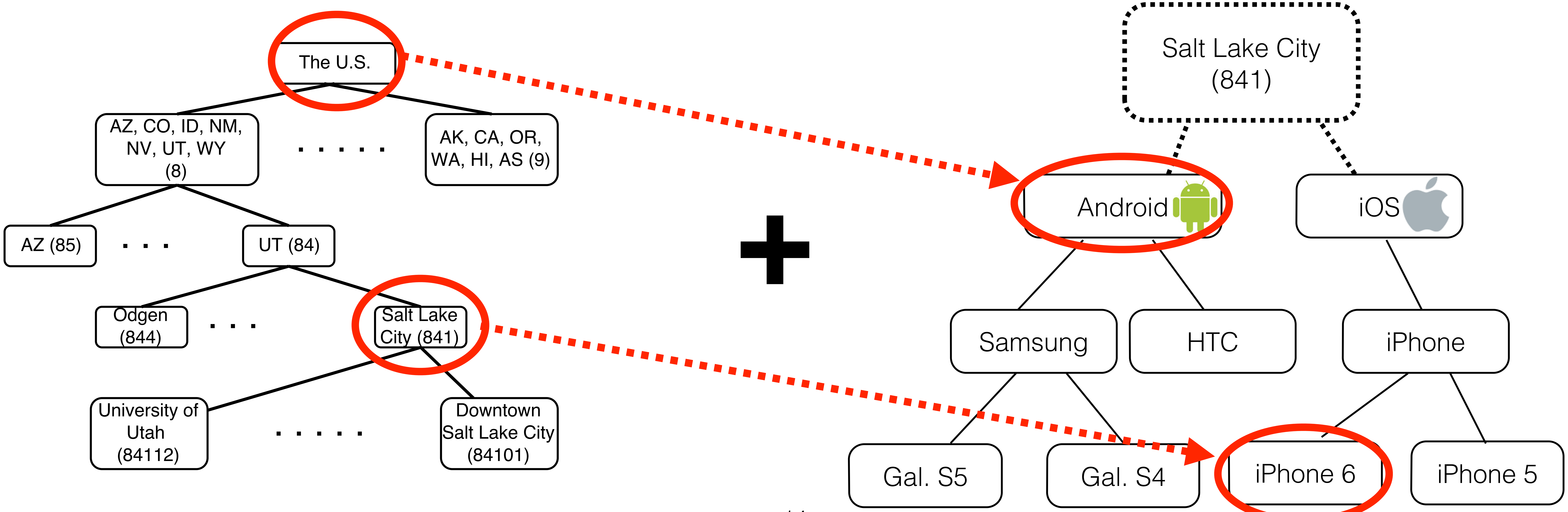

Timestamp	Usage	State	City	Area	OS	Make	Model
2016/05/10 10:00	5000	Utah	Salt Lake City	U. Of Utah	Android	Samsung	Galaxy S6

Hierarchical attributes

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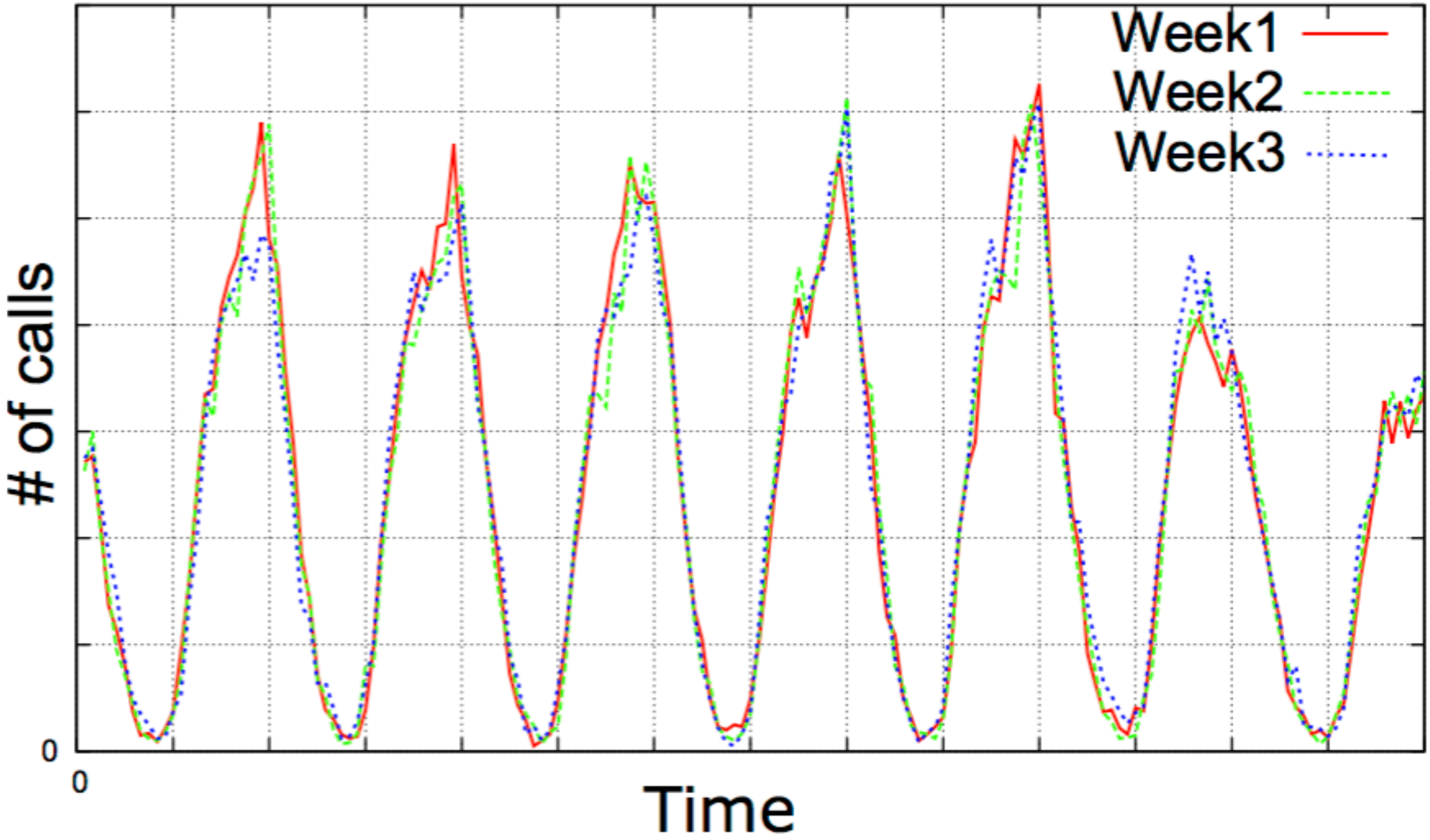

Need temporal aggregation to deal with sparse data during

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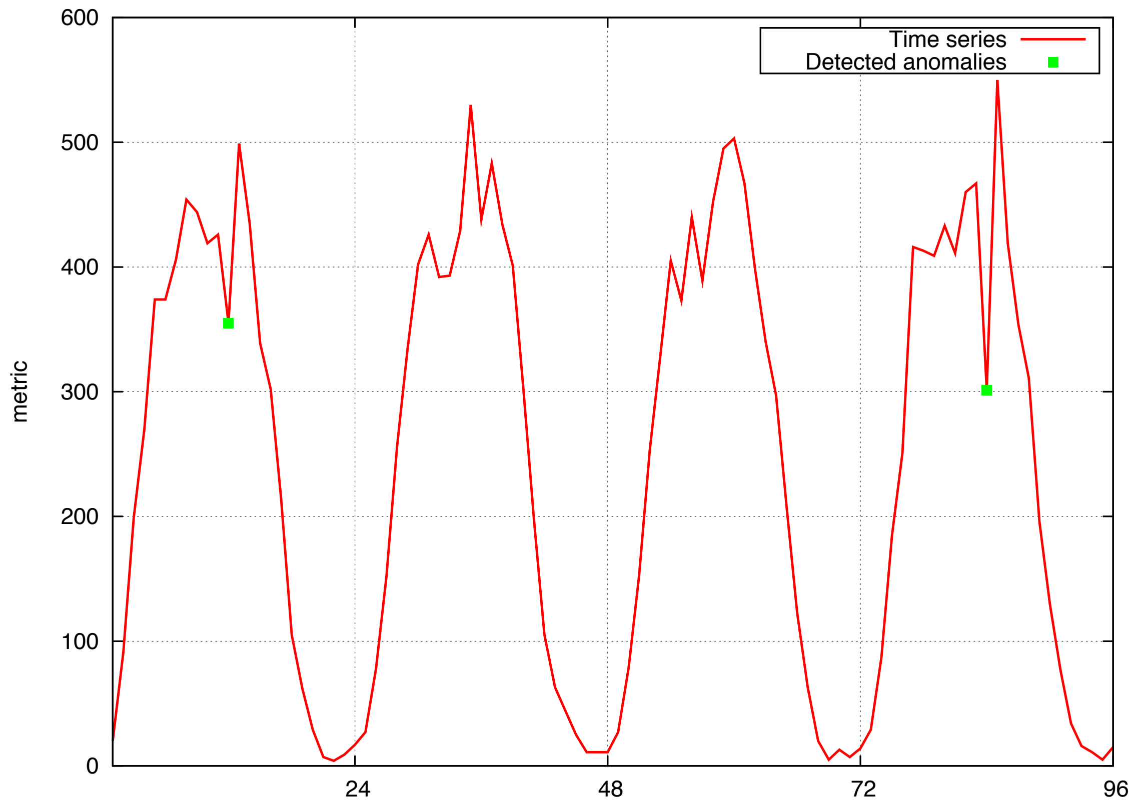
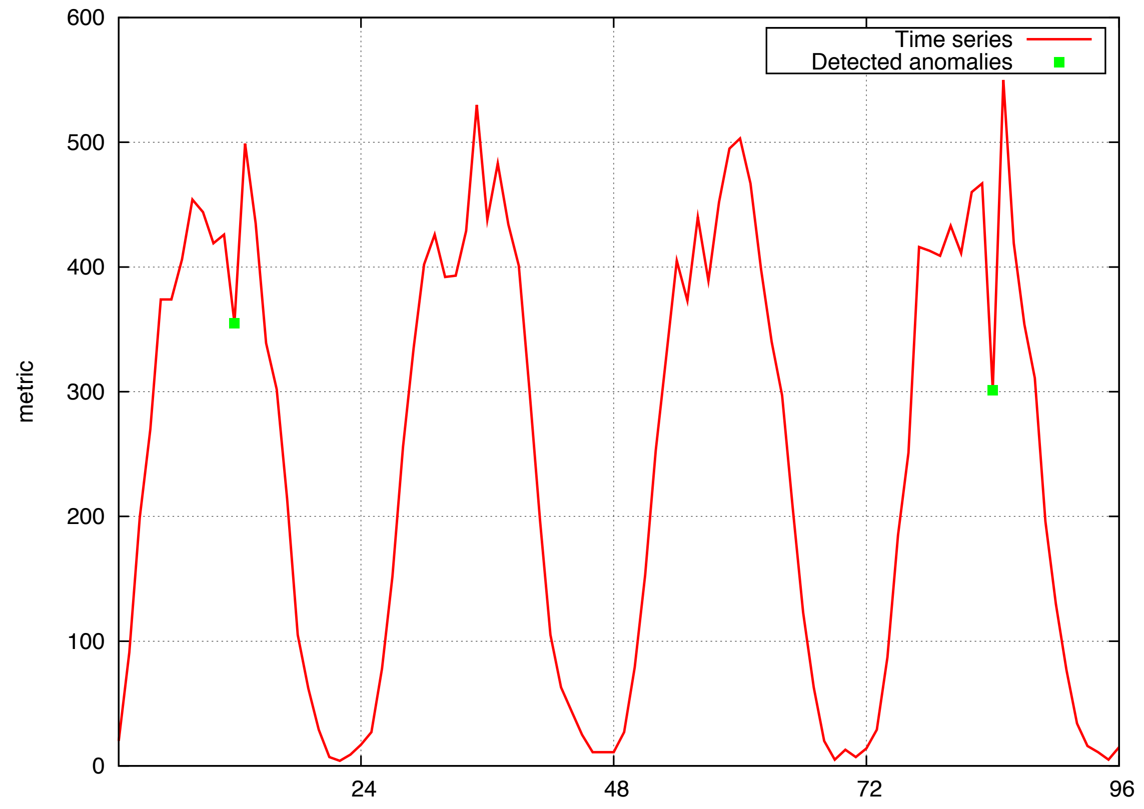
Event detection algorithm



Usage's time series

Event detection algorithm



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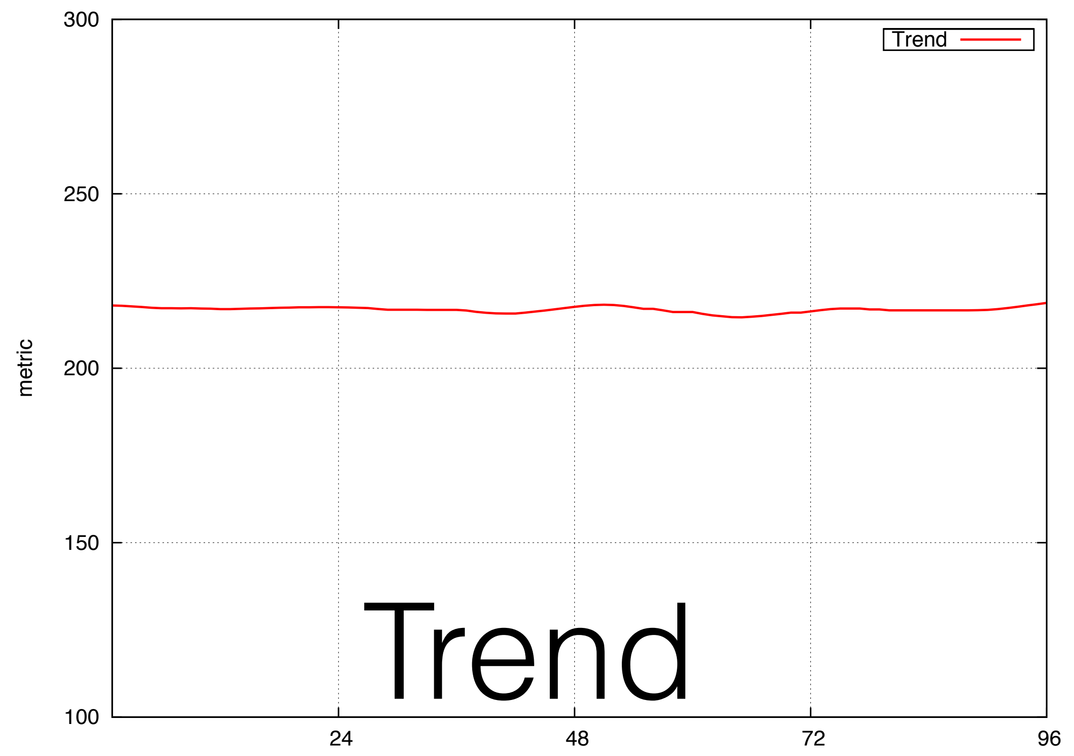
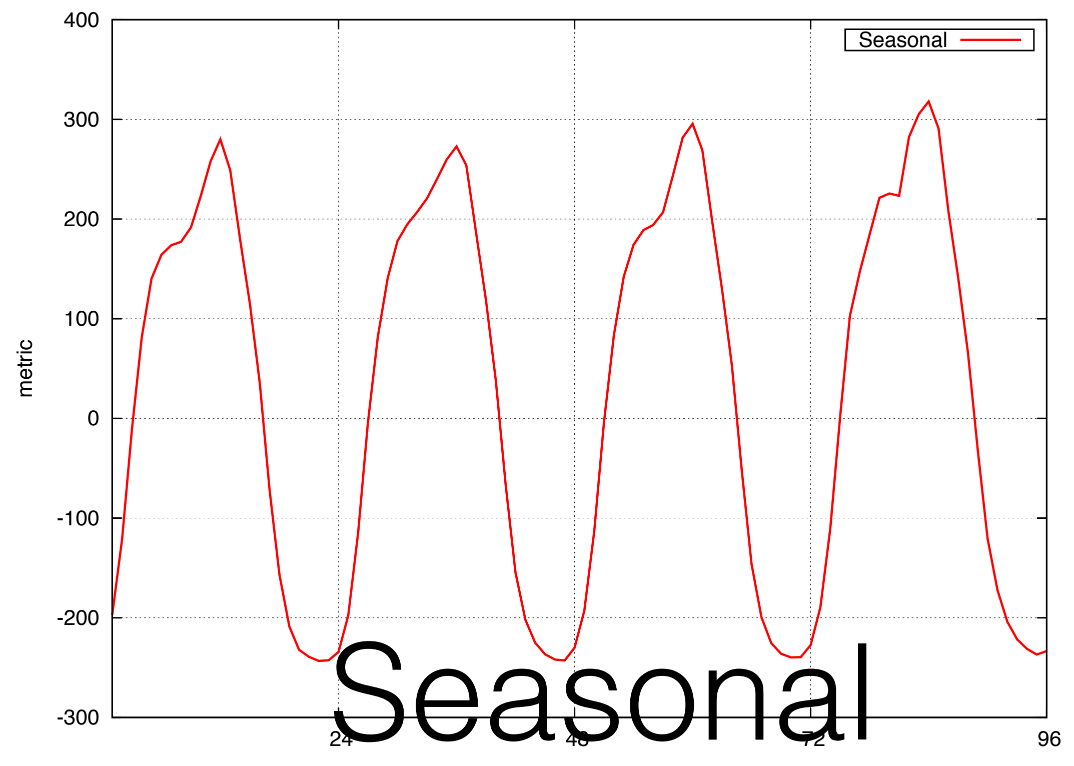
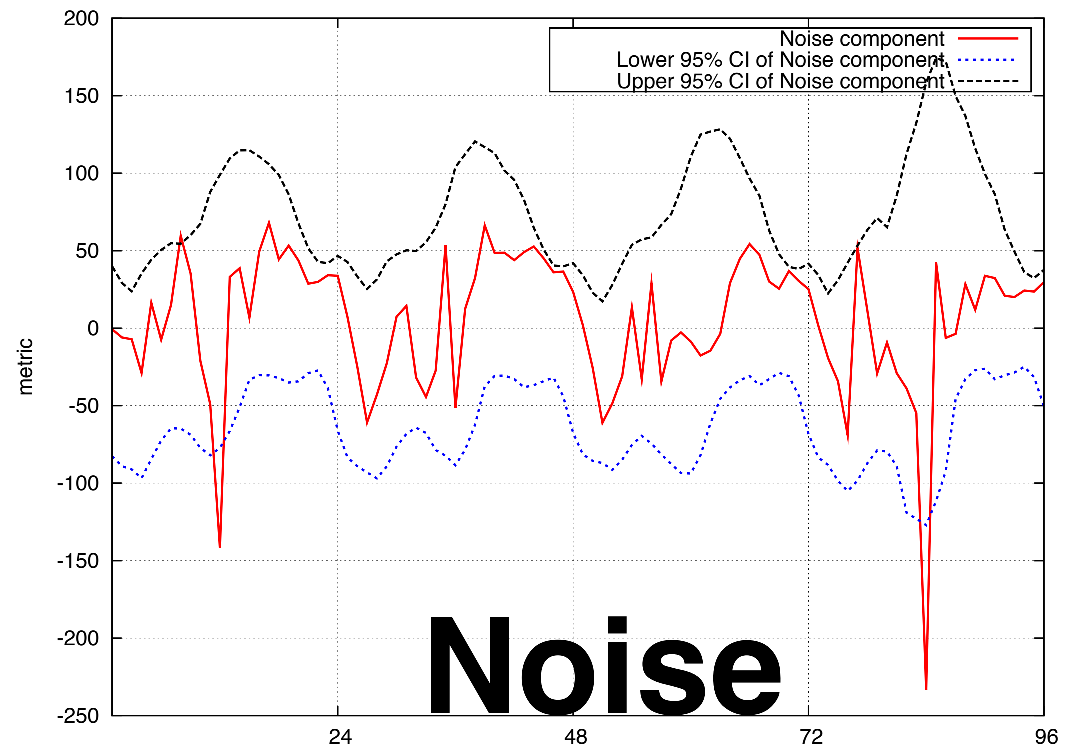
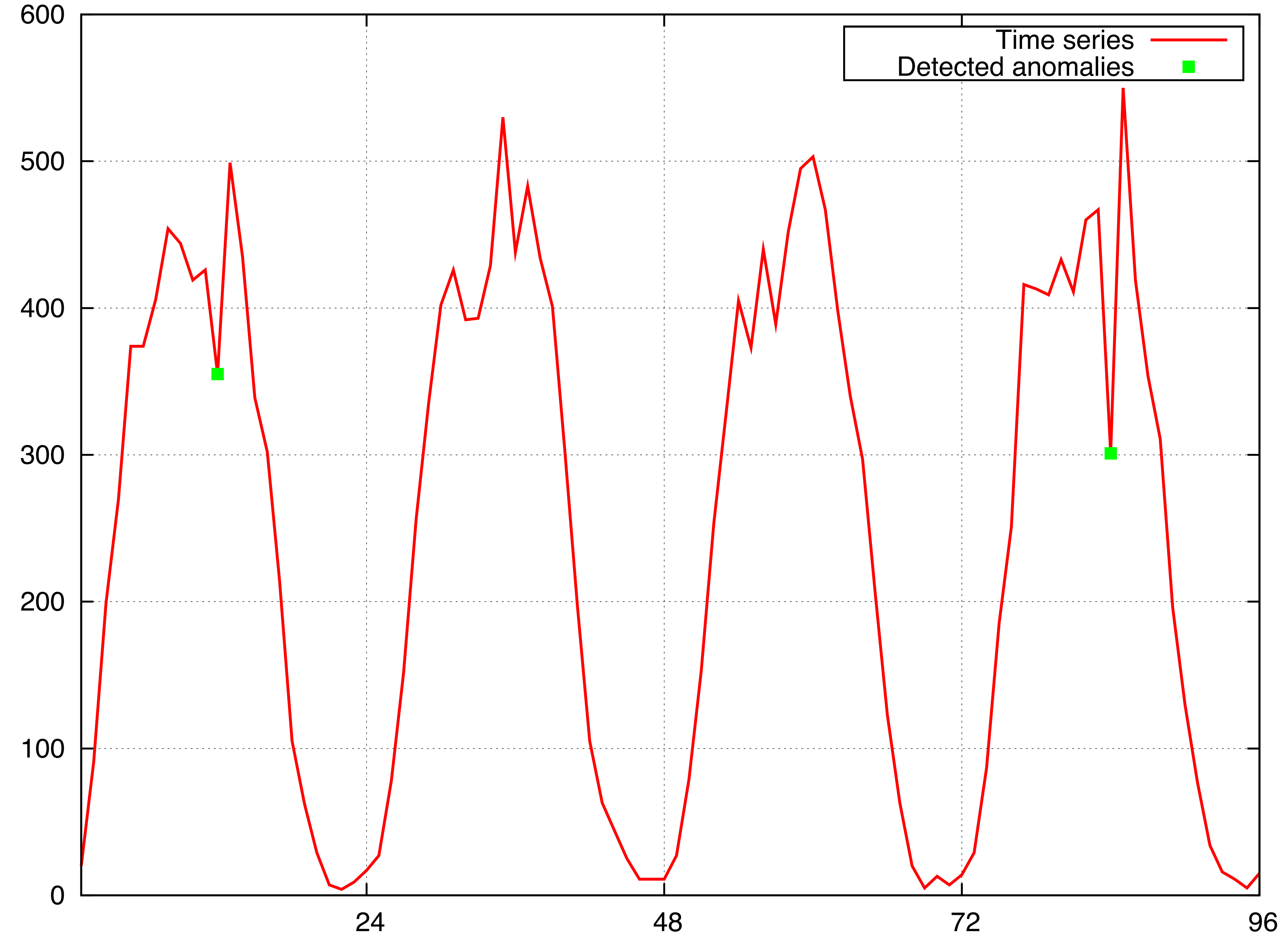






- Decompose time series: trend, seasonal, noise
- *Trend*: moving average.
- *Seasonal*: average of phasing values.
- ***Noise*** = *Time series - Trend - Seasonal*

Event detection algorithm



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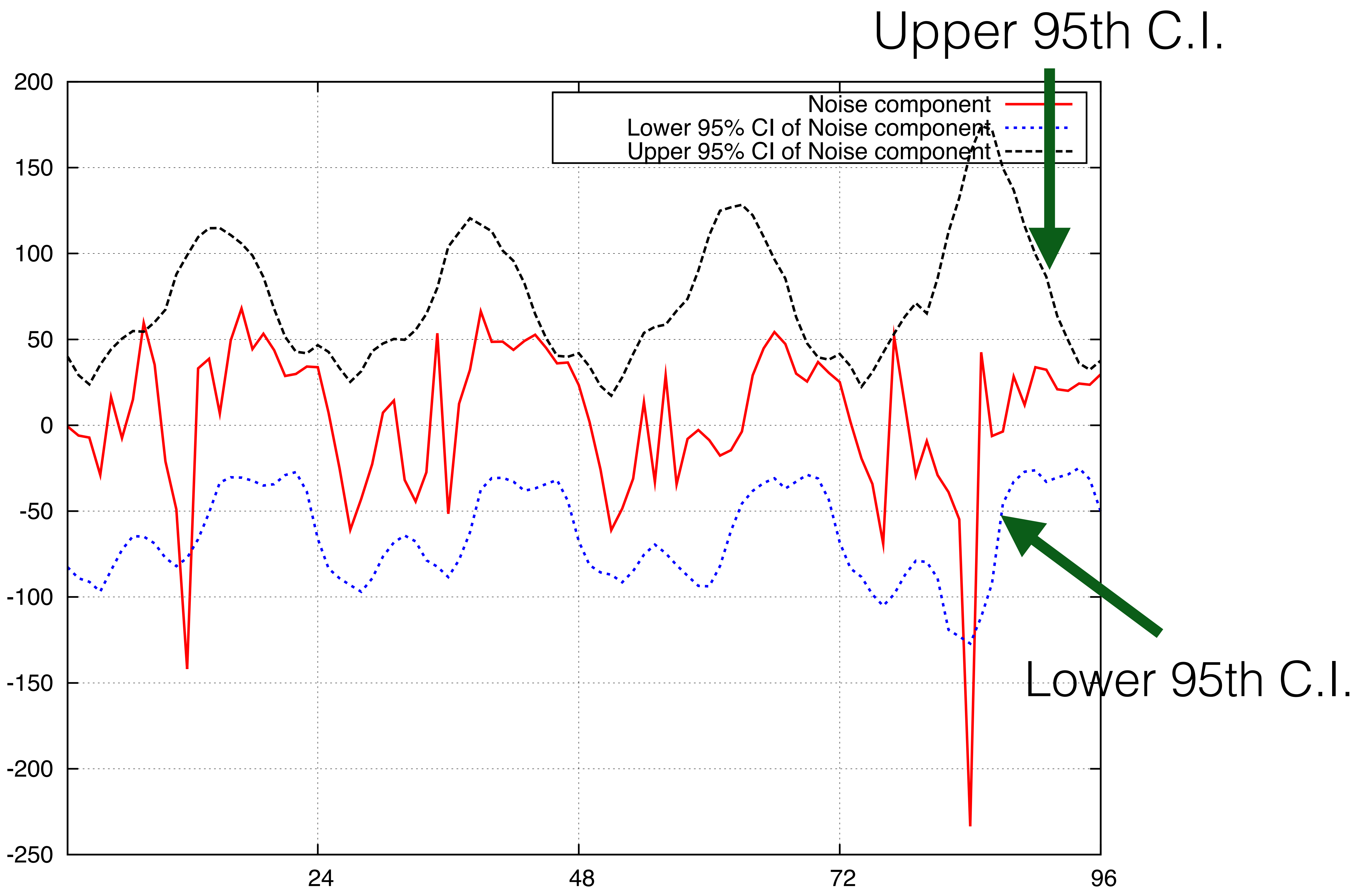
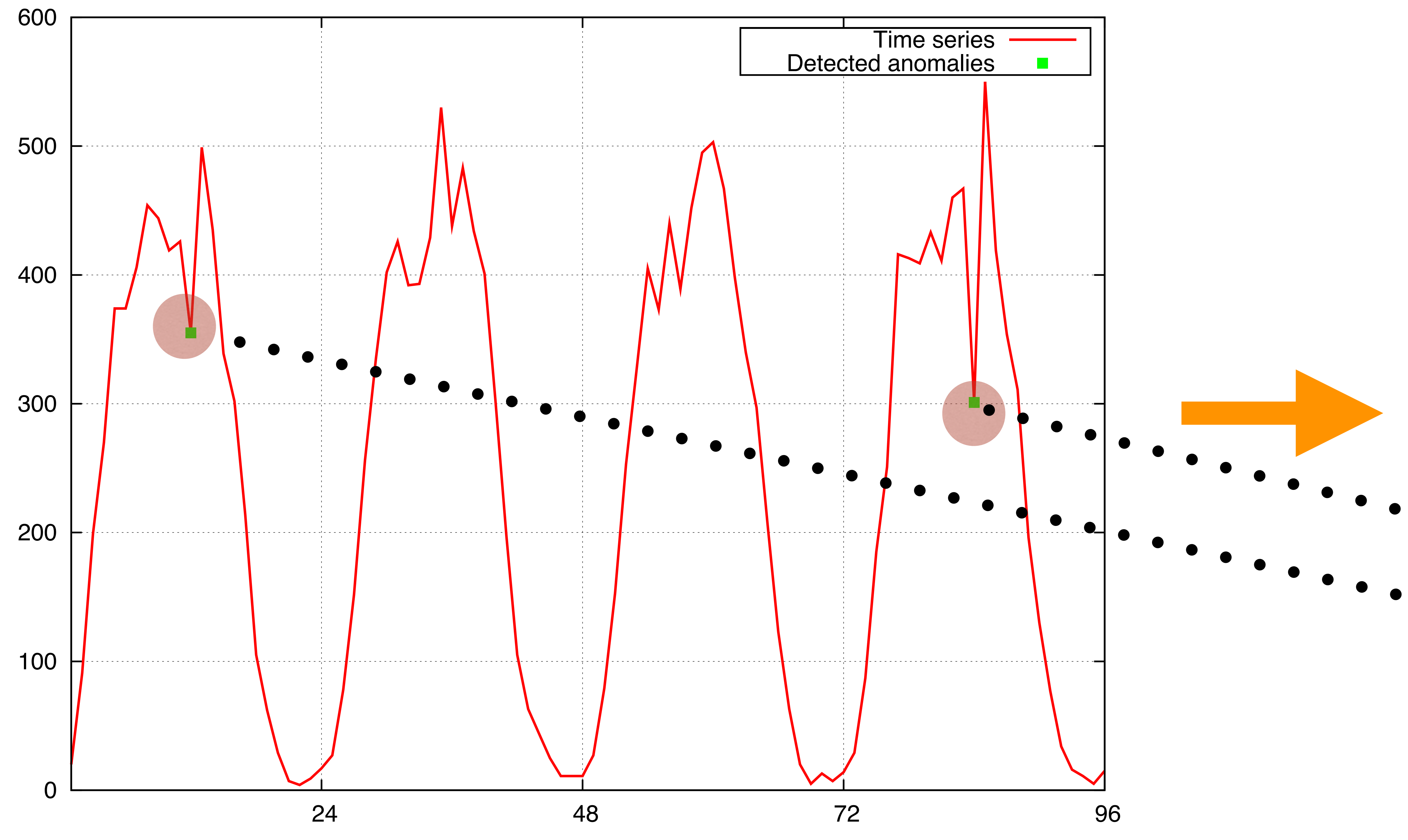


Noise component

Event detection algorithm

- If noise is out of the 95th percent Confidence Interval (CI) of noise component => anomaly.



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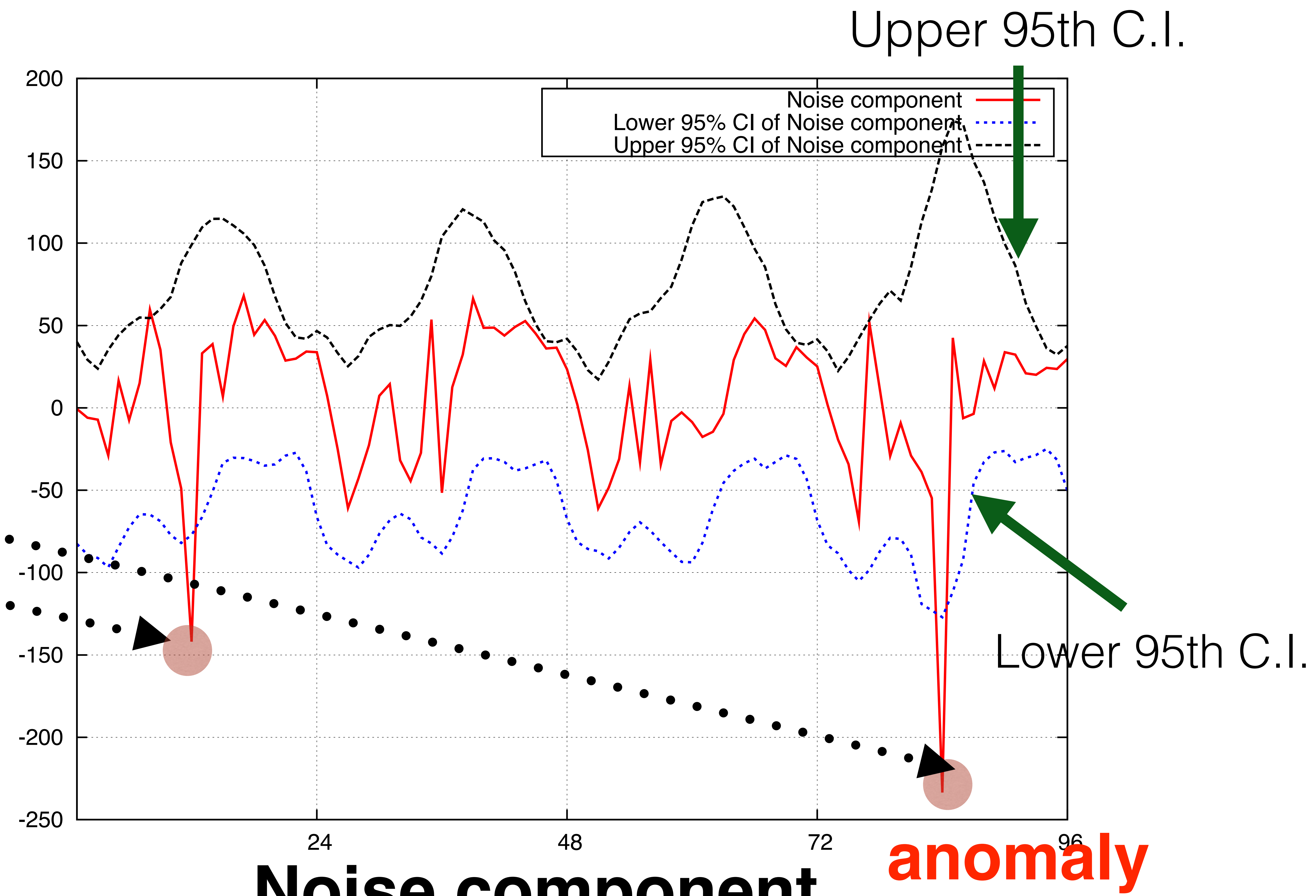

Noise component

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- **Synthetic workload evaluation.**
- Operational validation.

Synthetic workload evaluation

- 6 months of **real CDR** from an U.S operator.
- Synthetically introduce failures:
  - Network failures: remove usage on base stations.
  - Device failures: remove usage on devices.

Parameters and metrics

Parameters

- **11,000 failures generated.**
- 100 ZIPs, 10 cities.
- Two popular device types.
- LTE/Voice.
- Duration: 1,2,3,6,12 hours.
- Quiet and busy hours.
- Impact degree: 0 - 55%.

(total usage reduction)/(total normal usage) for a given aggregation

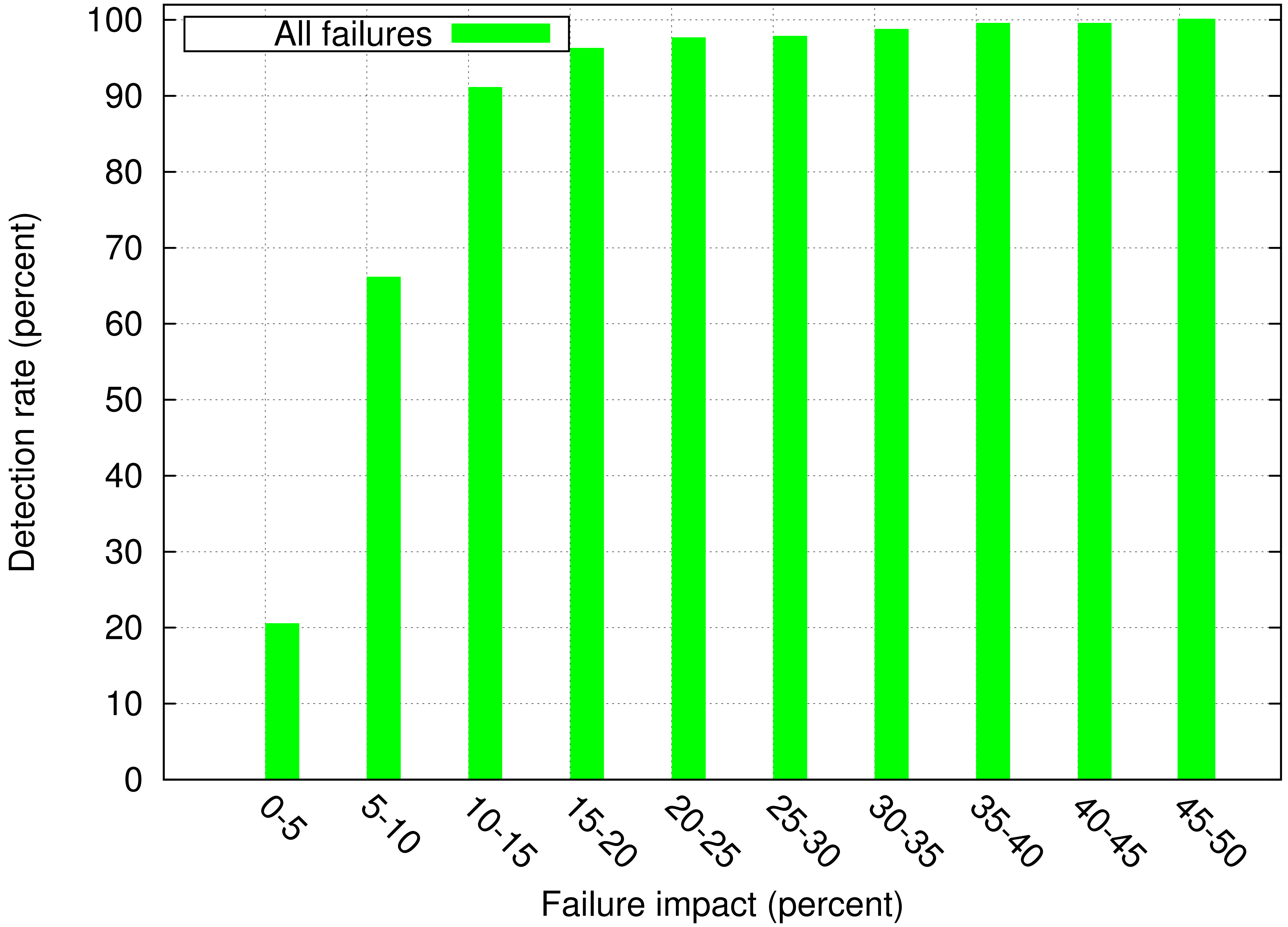
Metrics

- Detection rate = detected events/introduced events.
- Loss ratio = loss until detected/normal usage.

Example of failure scenarios:

- All Android devices in Los Angeles fail.
- All Iphone5 devices in Downtown Los Angeles fail.

Overall detection rate



- With the 11,000 introduced failures:
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  - ABSENCE tends to miss events that are <10% of impact.

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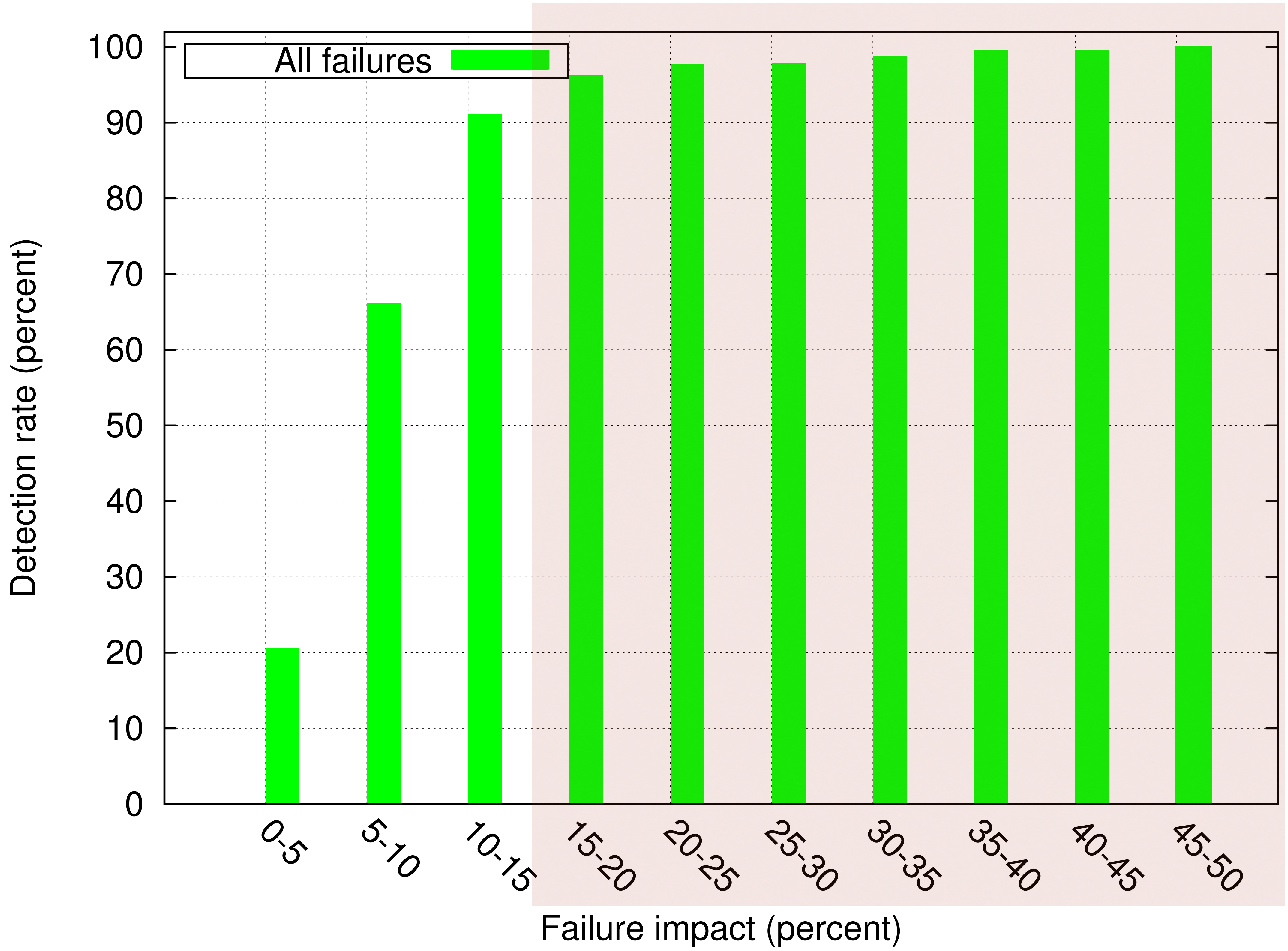

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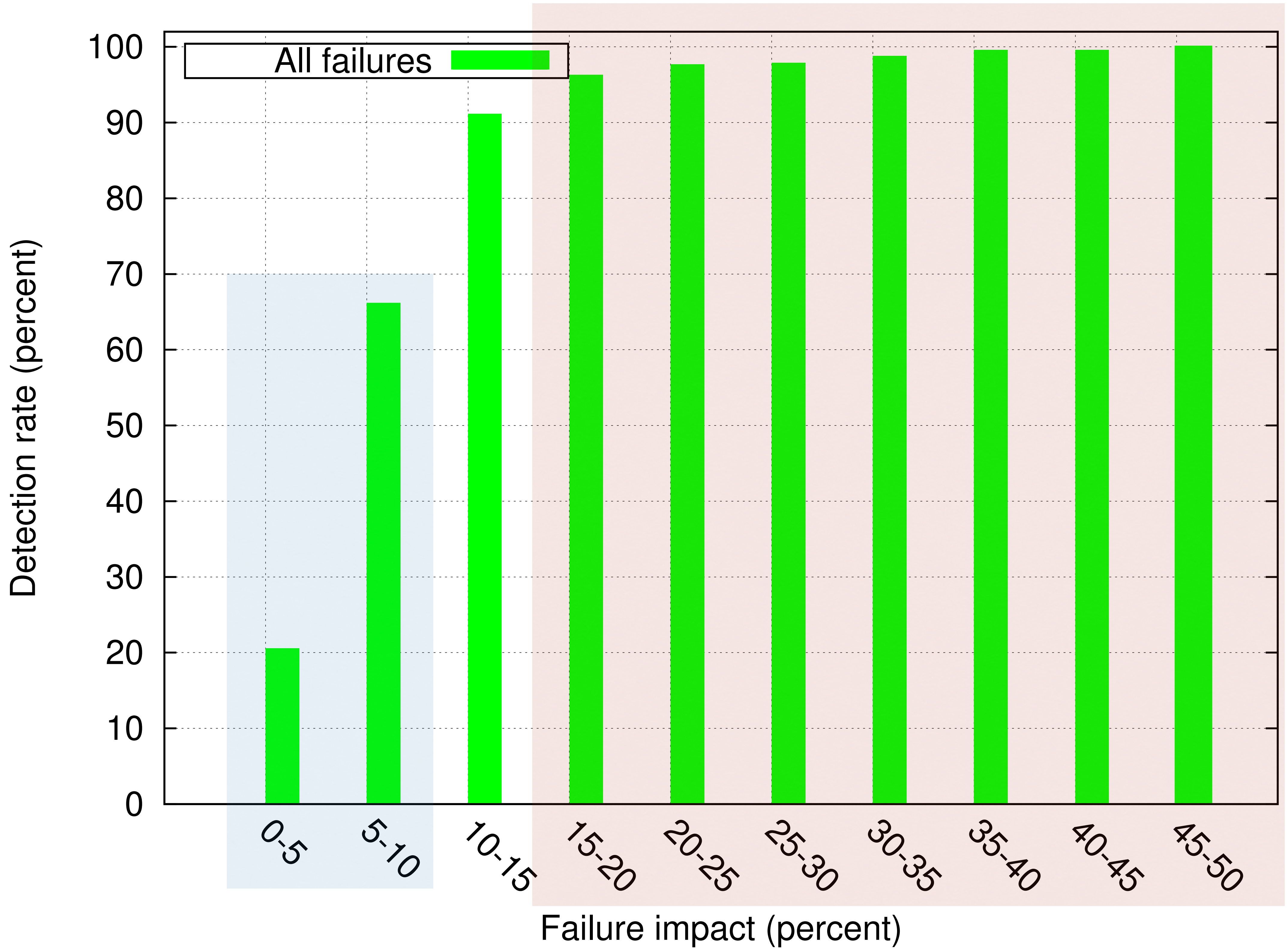

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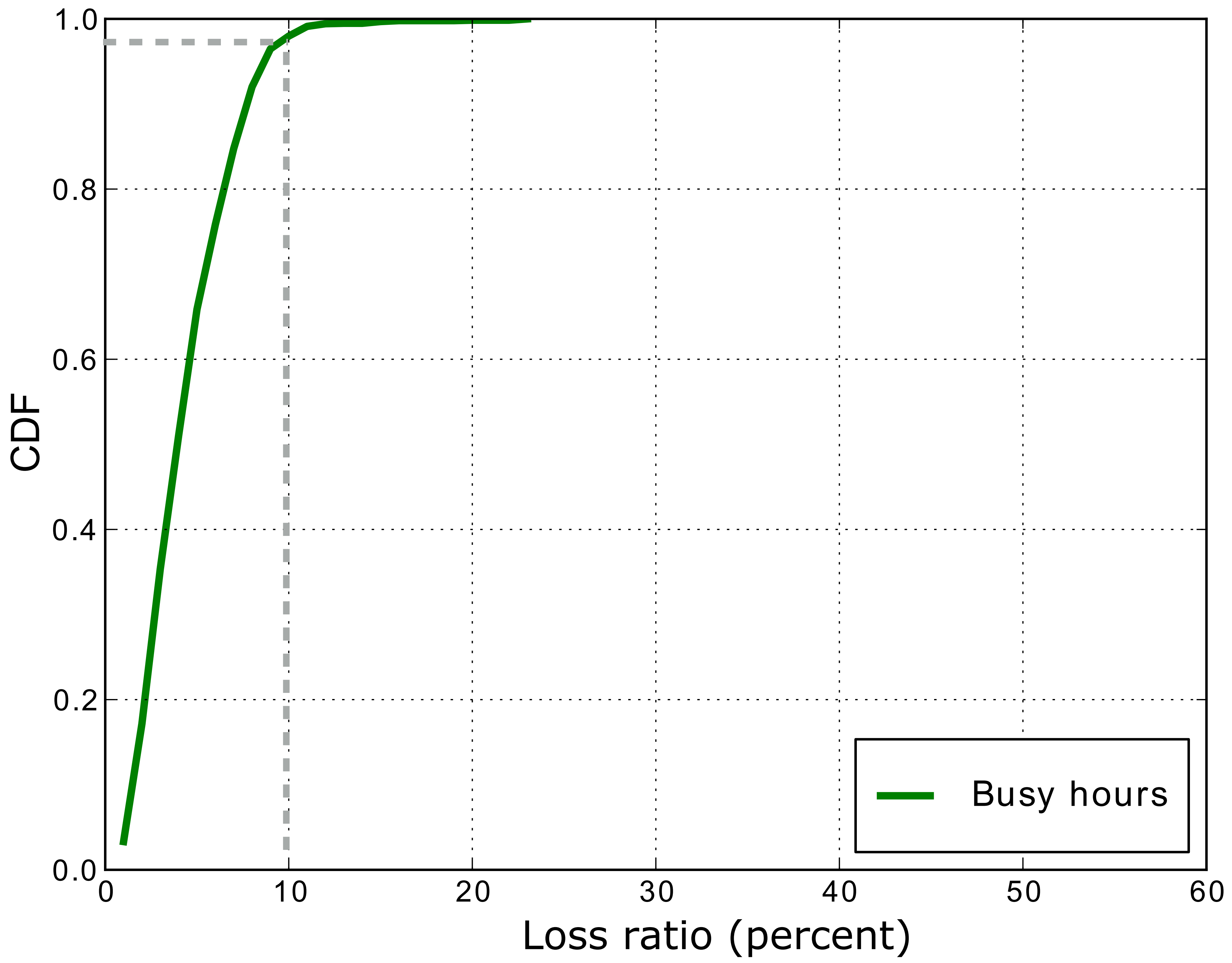
Loss ratio of detected failures



Loss Ratio= (usage loss until detection)/(normal usage during the failure period)

- All detected failures:
    - ~97% of them are detected when <10% of usage is lost (during busy hours).

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- **Operational validation.**

Evaluate against known silent failures from the operator

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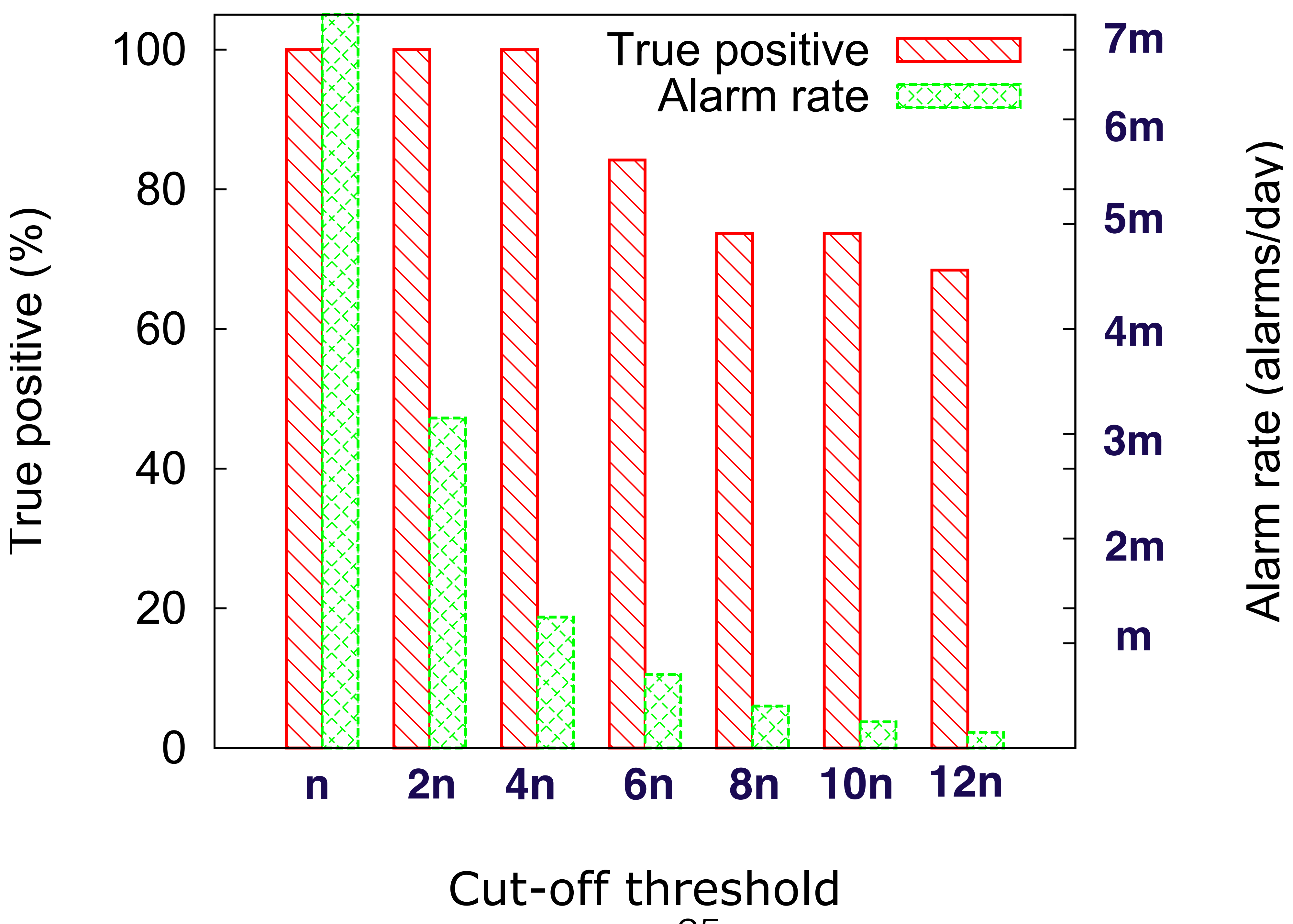
- 19 silent failure events: not known by the network operator when they happened.
- **Detected19/19, 100% true positive.**

Alarm rate and true positive

- Use the 19 known events from operator.
- Alarm rate (**m**): average number of alarms per day that an operation team needs to handle.
- Cut-off threshold (**n**): filter out events that less impactful.
- Increase cut-off threshold could reduce alarm rate while maintaining true positive rate of ABSENCE



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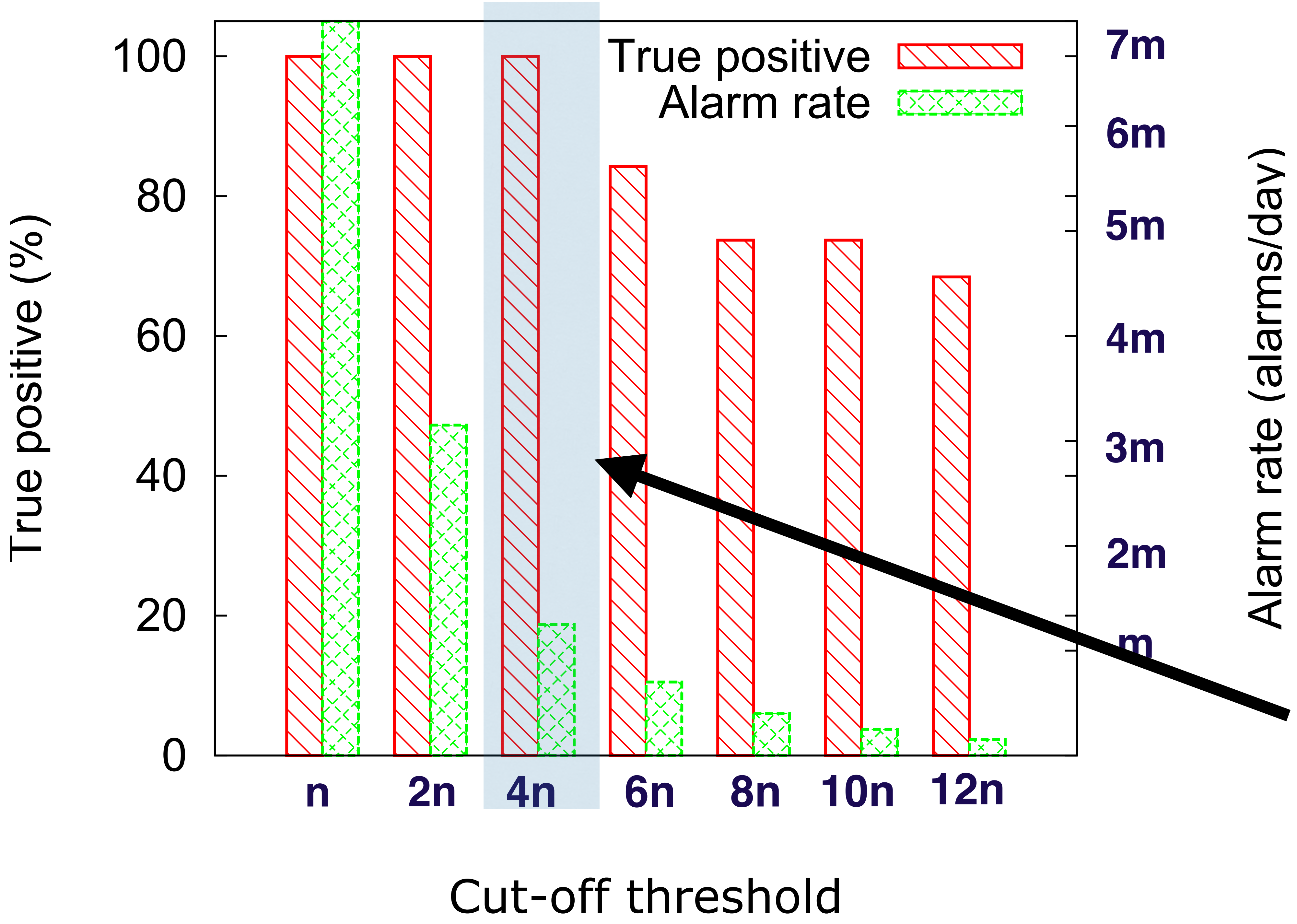

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m alarms per day
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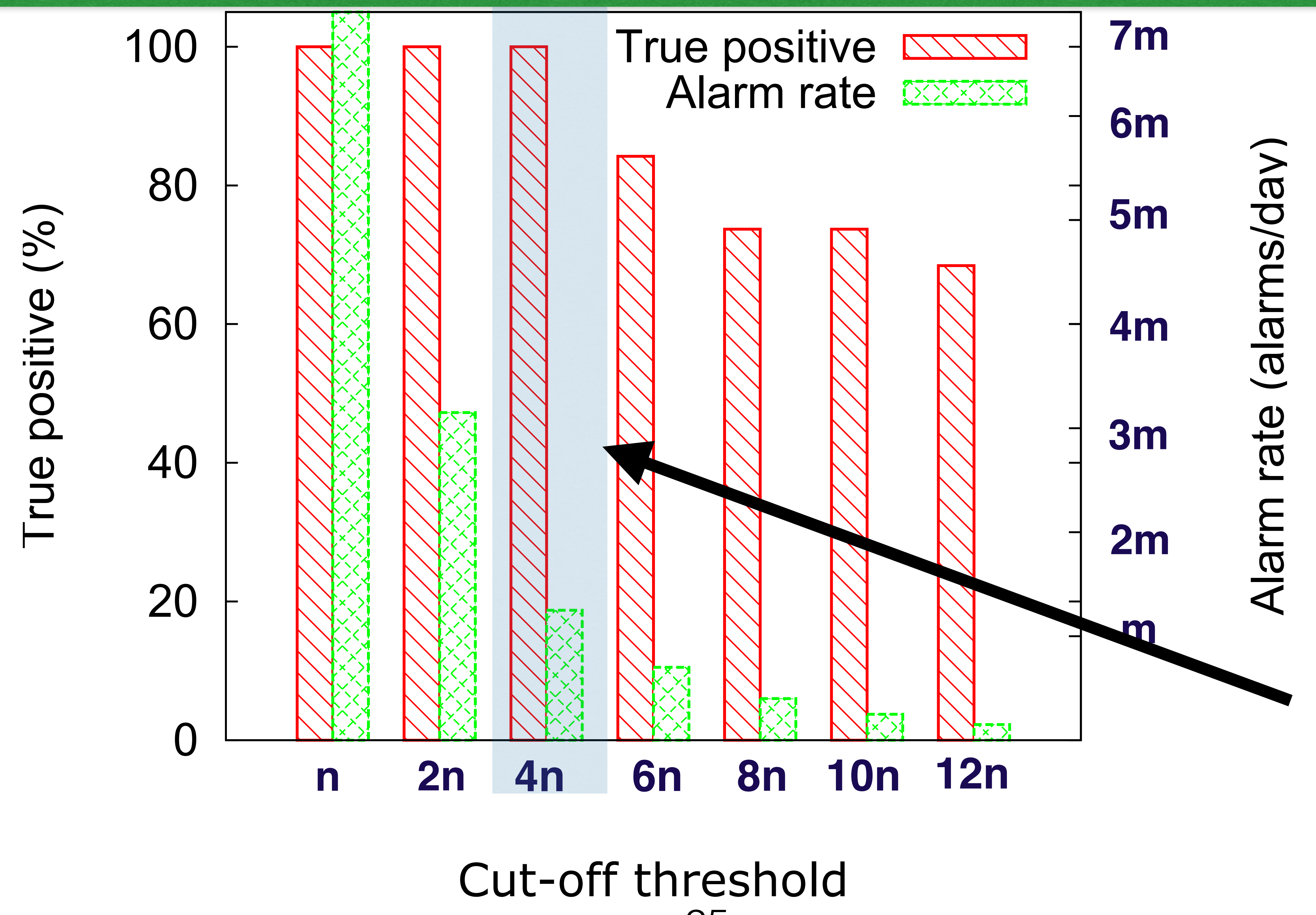
ABSENCE's alarm rate is reasonable for practical!



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Conclusions

- ***Absence of customer usage*** is a reliable indicator of service disruptions a mobile network.
- Appropriate grouping users results in predictable usage and high fidelity for anomaly detection.
- Synthetic evaluation and operational validation.
- Practical in an operational environment.

Thank you!

ABSENCE: Usage-based Failure Detection in Mobile Networks

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