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Self-regulatory Information Sharing in Participatory Social Sensing

Evangelos Pournaras, Jovan Nikolic, Pablo Velasquez, Marcello Trovati, Nik Bessis, Dirk Helbing

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Big Data and Analytics: Here, There, and Everywhere

08 Stories

In this content collection, MIT Technology Review looks at the data explosion from multiple angles. Editors and contributors examine how big data is revolutionizing shale-oil production—and how the big-data boom may be leaving poorer nations behind. They also look at the growing role of data analytics in everything from increasing crop production to gauging driving efficiency.

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Researchers trained a computer to recognize the behavior that precedes a particular maneuver.

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Major wireless carriers have begun testing a technology that can double the capacity of any wireless data connection.

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WIRED

Data Is the New Oil of the Digital Economy

BUSINESS CULTURE DESIGN GEAR SCIENCE SECURITY

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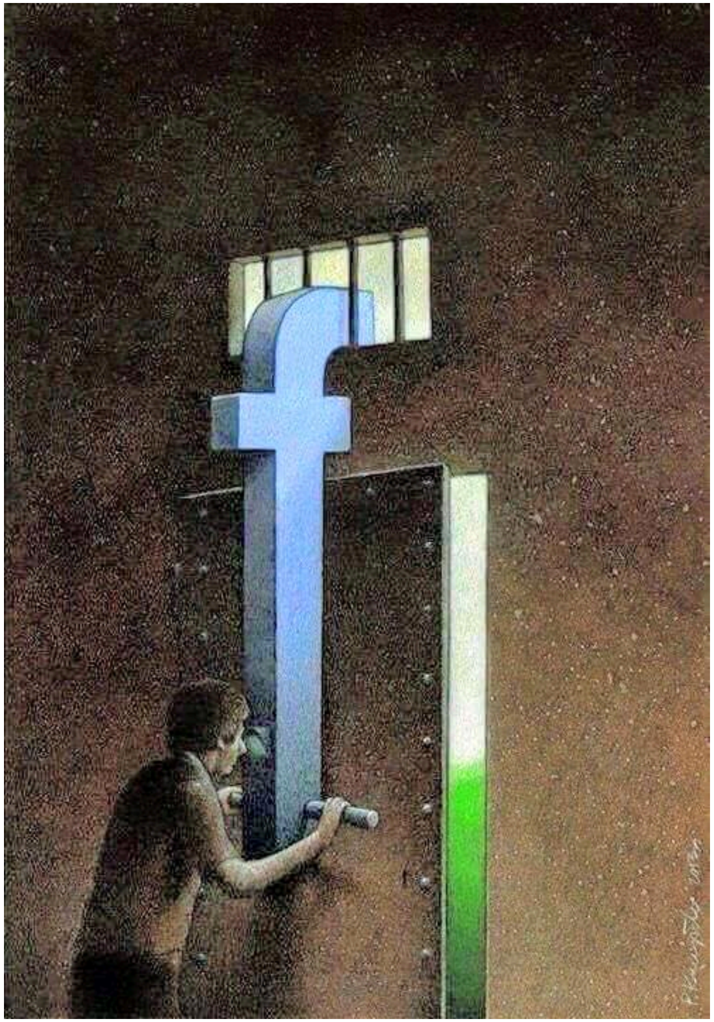
DATA IS THE NEW OIL OF THE DIGITAL ECONOMY

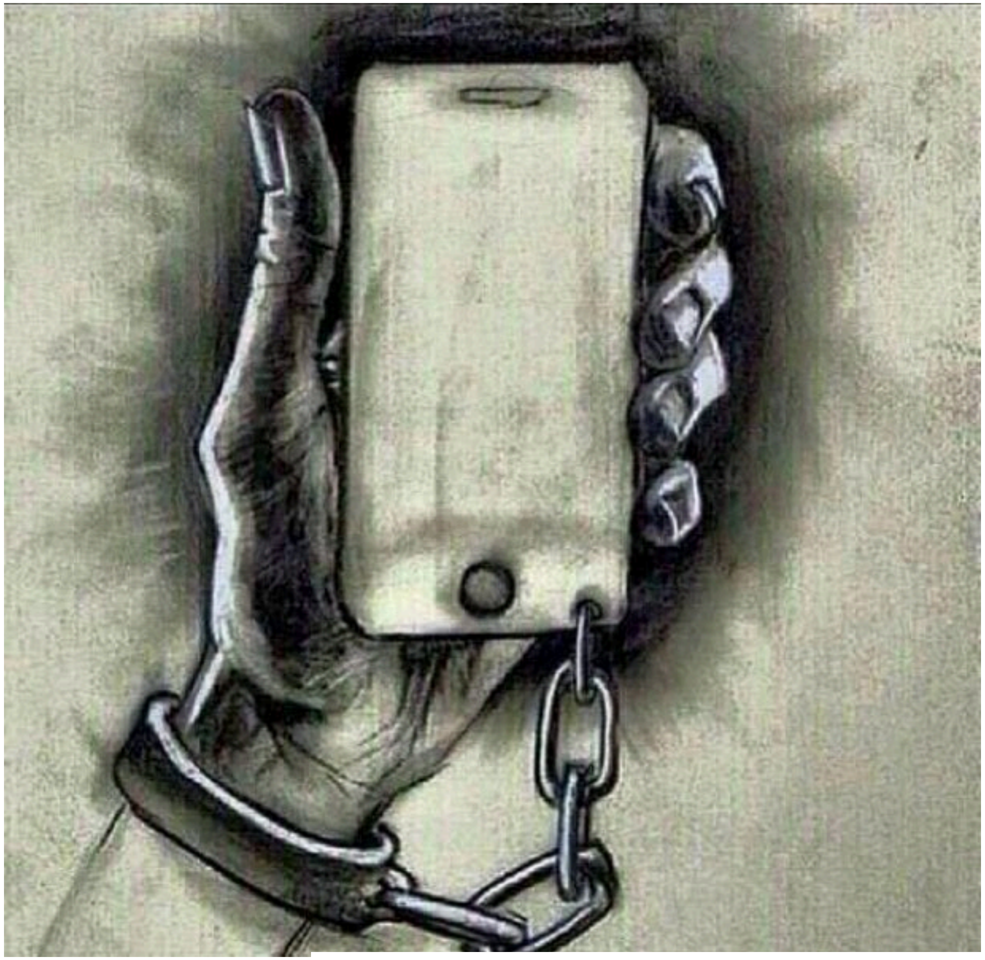
Image: verifex/Flickr

DATA IN THE 21st Century is like Oil in the 18th Century: an immensely, untapped valuable asset. Like oil, for those who see Data's fundamental value and learn to extract and use it there will be huge rewards.

We're in a digital economy where data is more valuable than ever. It's the key to the smooth functionality of everything from the government to local companies. Without it, progress would halt.

Challenges





Challenges

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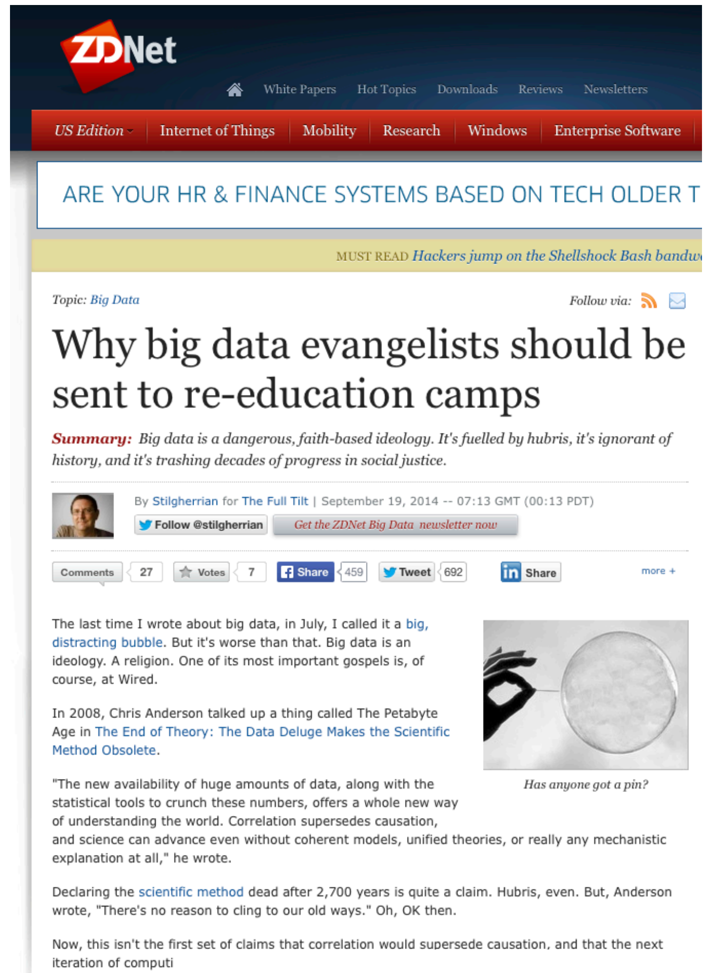
Big Data's Dangerous New Era of Discrimination

by Michael Schrage | 8:00 AM January 29, 2014

Comments (30)

Congratulations. You bought into Big Data and it's paying off Big Time. You slice, dice, parse and process every screen-stroke, clickstream, Like, tweet and touch point that matters to your enterprise. You now know exactly who your best — and worst — customers, clients, employees and partners are. Knowledge is power. But what kind of power does all that knowledge buy?

Big Data creates Big Dilemmas. Greater knowledge of customers creates new potential and power to discriminate. Big Data — and its associated analytics — dramatically increase both the dimensionality and degrees of freedom for detailed discrimination. So where, in your corporate culture and strategy, does value-added personalization and segmentation end and harmful



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Topic: Big Data *Follow via:*

Why big data evangelists should be sent to re-education camps

Summary: *Big data is a dangerous, faith-based ideology. It's fuelled by hubris, it's ignorant of history, and it's trashing decades of progress in social justice.*

By Stilgherrian for The Full Tilt | September 19, 2014 -- 07:13 GMT (00:13 PDT)

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The last time I wrote about big data, in July, I called it a big, distracting bubble. But it's worse than that. Big data is an ideology. A religion. One of its most important gospels is, of course, at Wired.

In 2008, Chris Anderson talked up a thing called The Petabyte Age in The End of Theory: The Data Deluge Makes the Scientific Method Obsolete.

Has anyone got a pin?

"The new availability of huge amounts of data, along with the statistical tools to crunch these numbers, offers a whole new way of understanding the world. Correlation supersedes causation, and science can advance even without coherent models, unified theories, or really any mechanistic explanation at all," he wrote.

Declaring the scientific method dead after 2,700 years is quite a claim. Hubris, even. But, Anderson wrote, "There's no reason to cling to our old ways." Oh, OK then.

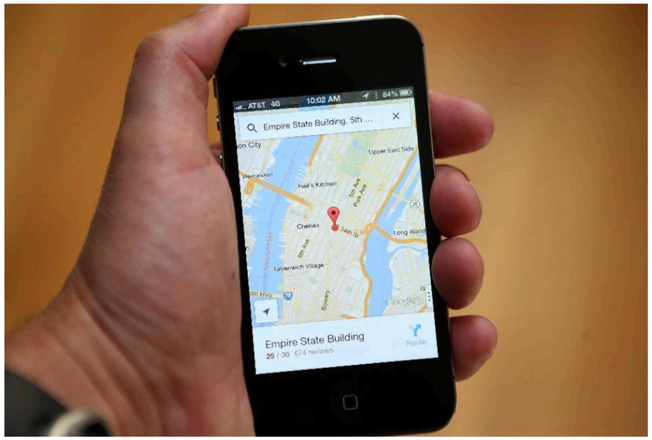
Now, this isn't the first set of claims that correlation would supersede causation, and that the next iteration of computi

Challenges

Existing **social mining** practices
threaten **social cohesion**

“*surveillance has become increasingly privatized, commercialized and participatory***”,** Julie E. Cohen

Recent Views



We may think Google Maps is free, but we actually pay by giving it access to valuable data—our geo locations. (Photo by Justin Sullivan/Getty Images)

How The Citizen Data Scientist Will Democratize Big Data

Bernard Marr
CONTRIBUTOR

I write about big data, analytics and enterprise performance

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FULL BIO >

Opinions expressed by Forbes Contributors are their own.

The rise of the citizen data scientist is a subject which is creating a lot of excitement at the moment. Put simply (and a bit bluntly) businesses, particularly larger ones with more mature Big Data analytical operations, are finding that it is too important to be left solely in the hands of the data scientists.

For a start – one reason is that there simply aren't enough of them. That isn't to say that data scientists – by which I mean staff with a formal education in business intelligence, statistics and roles purely involving data analytics – are no longer needed. They are, and I believe people with these backgrounds will continue to play a crucial role. But there is an ever growing plethora of tools and services designed to facilitate Big Data analytics outside of the IT lab and across the organization as a whole.

This is enabling the rise of what has been termed the "Citizen Data Scientist". In fact, last year analysts at Gartner IT +1.38% predicted that the demand for these people will increase five times more quickly than the demand for "traditional", highly skilled data scientists.

Retailer Sears, for example, recently empowered 400 staff from its business intelligence (BI) operations to carry out advanced, Big Data driven customer segmentation – work which would previously have been carried out by specialist Big Data analysts, probably with PhDs. The move is said to have created hundreds of thousands of dollars' worth of efficiencies in data preparation costs alone. Exploratory analysis, visualization and putting insights into action is also taken care of by this new class of Citizen Data Scientist.

Sears used tools provided by Platfora to allow its BI staff to effectively retrain and repurpose themselves as Big Data analysts. Platfora VP of products Peter Schlamp told me "customer segmentation is a very complex problem. It is not something your average Excel user can do.

Citizen Data Scientists (Source: Shutterstock)

Forbes / Opinion

APR 1, 2016 @ 03:48 PM 2,051 VIEWS

Privacy Is The New Money, Thanks To Big Data

Omri Ben-Shahar
CONTRIBUTOR

I write about law, economics, and consumer markets

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Opinions expressed by Forbes Contributors are their own.

The Apple/FBI showdown was the recent installment in an unfolding legal battle over privacy protection. Beginning with the Snowden revelations, it is widely thought that the major threat to our privacy in the digital era comes from the power of Big Government to access personal information stored in devices and websites. As this debate rages, we are losing sight of the other enterprise of personal data collection—known as "Big Data"—which is subject to less popular interest, but is far grander in scope, involves higher stakes and numerous ongoing legal battles.

The FBI or NSA data collection is Small Data. It focuses on meta-data or on few targeted individuals under investigation. In contrast, Big Data business is *really* big. I am talking about the collection of personal data by websites, mobile apps, retailers, insurance companies – any commercial entity that receives information from people. In the old brick-and-mortar world, firms had Pendaflex files about their customers, neatly tucked away in file cabinets. If you walked into a supermarket or bookstore and browsed the shelves, there would be no record of this activity. In the digital world, people leave their prints everywhere. The sum of our activities – where we browse, shop, or drive; what we read, eat, or own; who we chat with, like or love – is collected, neatly organized by algorithms, smartly analyzed by sophisticated software, and used or sold primarily for marketing purposes. It does not decay or gather dust, and it is never forgotten.

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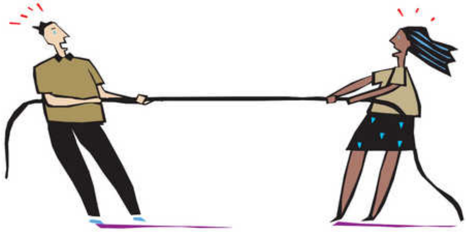
Opposing Views in Information Sharing

Big Data Analytics vs. Privacy-preservation

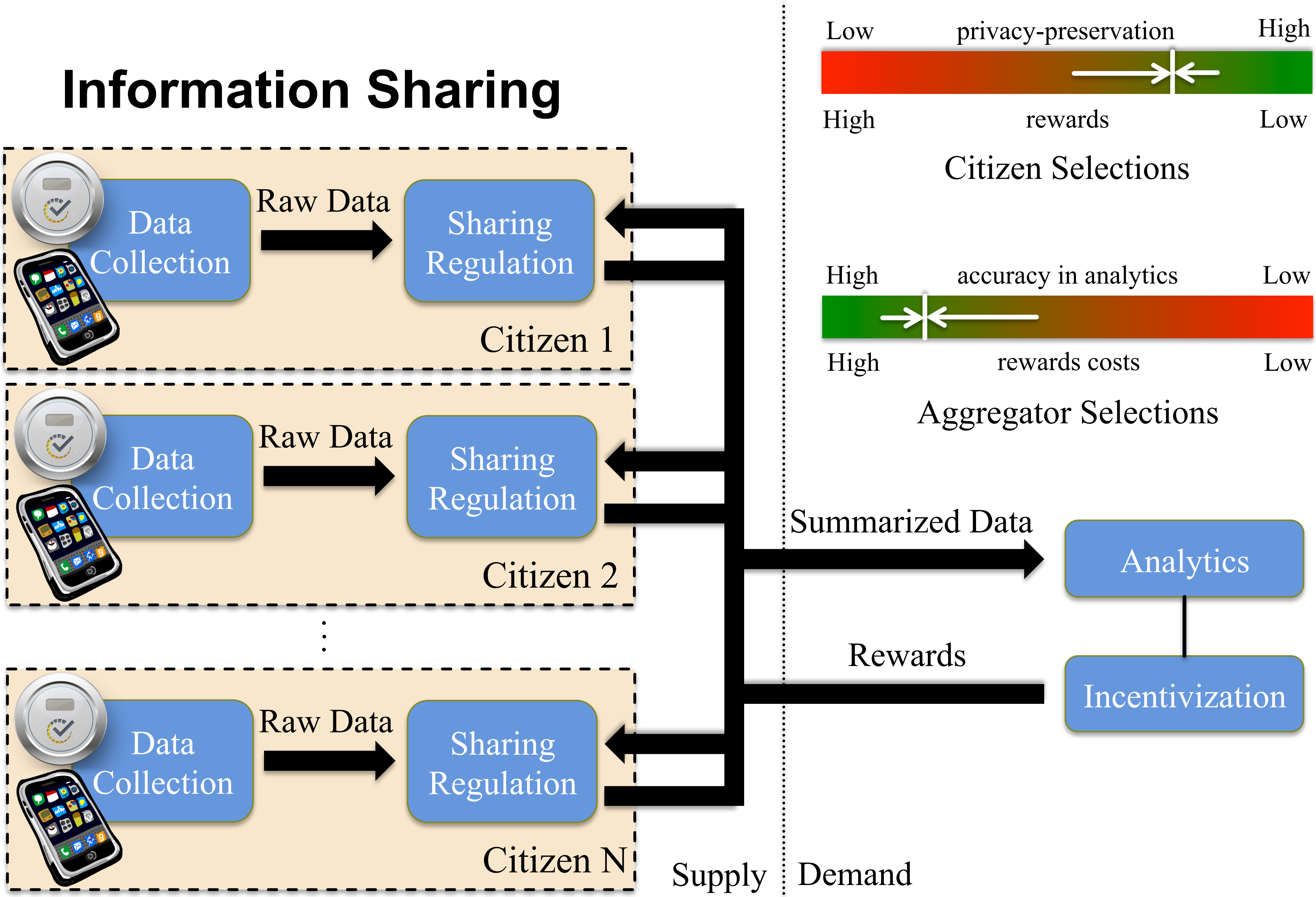


More data,
more information, more knowledge, more security, more business opportunities,
more prosperity

Less data,
less information, less surveillance, less discrimination, more freedom/justice, more social cohesion,
more prosperity

How to bridge this gap?

Information Sharing



Summarization

min Euclidean distance

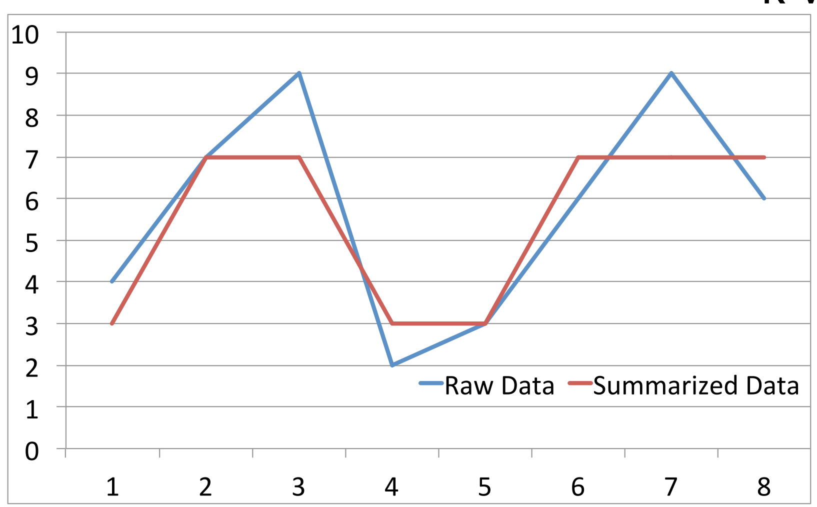
$$\begin{pmatrix} 2,3,4,6,7,9 \end{pmatrix} \quad \begin{pmatrix} 4 \\ 7 \\ 9 \\ 2 \\ 3 \\ 6 \\ 9 \\ 6 \end{pmatrix} \xrightarrow[f()]{\text{summarization}} \begin{pmatrix} 3,7 \end{pmatrix} \quad \begin{pmatrix} 3 \\ 7 \\ 7 \\ 3 \\ 3 \\ 7 \\ 7 \\ 7 \end{pmatrix}$$

input domain

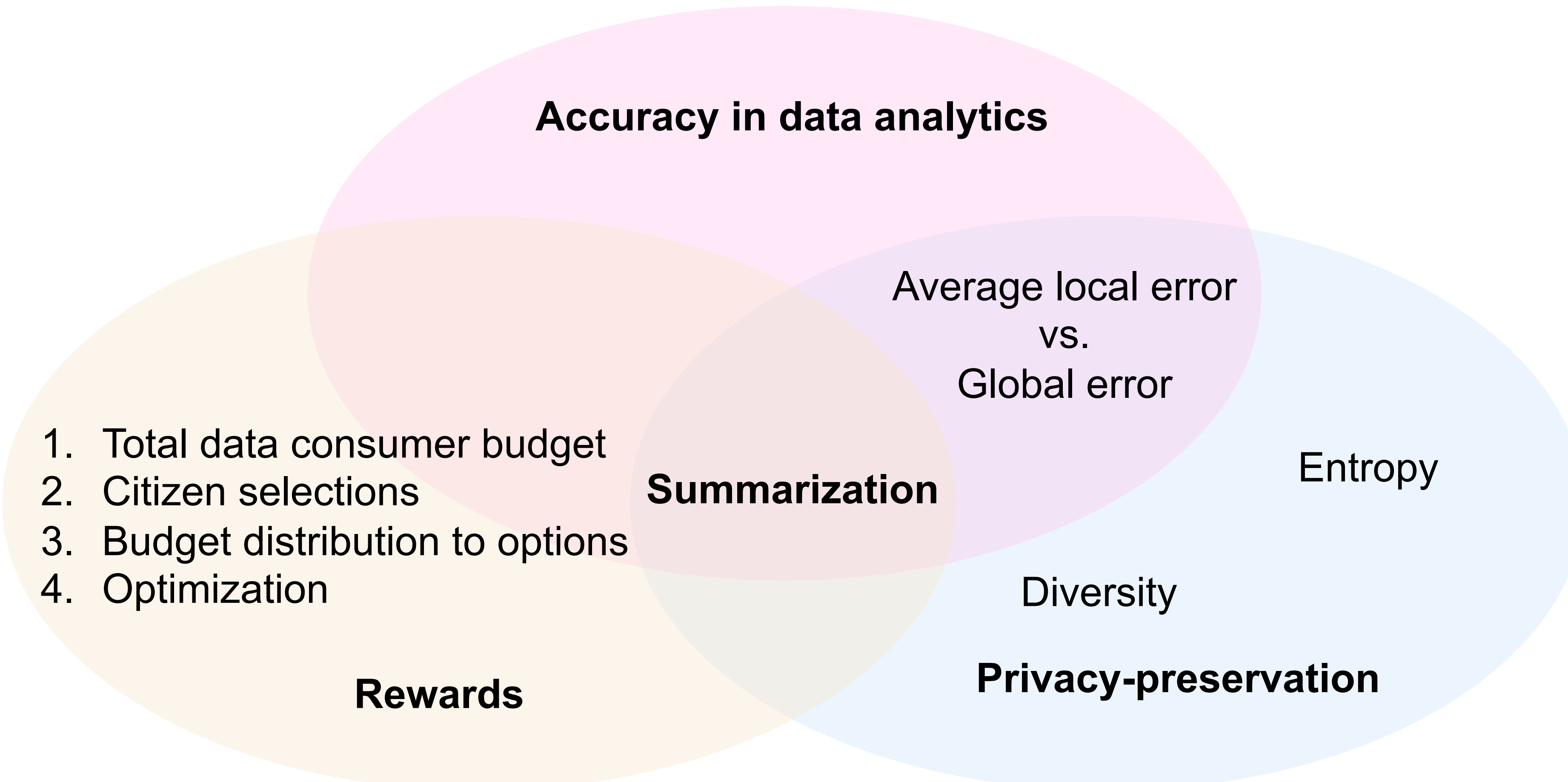
raw data

k values

summarized data



The Trade-offs of Information Sharing



The Trade-offs of Information Sharing

Symbol	Interpretation
i	An agent index
e	An epoch index
t	A time index within an epoch
T	Epoch duration
$R_{i,e}$	Sequence of raw data
$r_{i,e,t}$	A record of raw data
$S_{i,e}$	Sequence of summarized data
$s_{i,e,t}$	A record of summarized data
$f_s()$	Summarization function
j	An index for a possible summarization value
$c_{i,e,j}$	A possible summarization value
$k_{i,e}$	The number of possible summarization values
l	Number of epochs
$\alpha_{i,e}$	Summarization metric
$D_{i,e}$	Sequence of raw or summarization data
$H(D_{i,e})$	Entropy
$p_{i,e,j}$	Probability of a possible value occurring in an epoch
n_t	Occurrence or not of possible value at time t
$\beta_{i,e}$	Diversity
m_t	Change or not between two consecutive time periods t and $t+1$
$\epsilon_{i,e,t}$	Local error
$\varepsilon_{i,e}t$	Global error
n	Number of participating citizens
$\epsilon_{e,t}$	Average local error among citizens
γ_e	Total rewards that data aggregators are willing to provide
$P_r()$	Probability density function for rewards
z	Number of discrete participation levels
$P_s()$	Probability density function for summarization
$\gamma_{i,e}$	Rewards provided to agent i

Entropy

$$H(D_{i,e}) = -\sum_{j=1}^{k_{i,e}} p_{i,e,j} \log_2 p_{i,e,j},$$

$$p_{i,e,j} = \frac{1}{T}\sum_{t=1}^{T} n_t, \quad n_t = \begin{cases} 1 & \text{if } c_{i,e,j} = d_{i,e,t}, \\ 0 & \text{if } c_{i,e,j} \neq d_{i,e,t}, \end{cases}$$

Average local error

$$\epsilon_{e,t} = \frac{1}{n}\sum_{i=1}^{n} \epsilon_{i,e,t}$$

$$\epsilon_{i,e,t} = \frac{|r_{i,e,t} - s_{i,e,t}|}{|r_{i,e,t}|}$$

Diversity

$$\beta_{i,e} = \frac{1}{T-1}\sum_{t=1}^{T-1} m_t, \quad m_t = \begin{cases} 1 & \text{if } d_{i,e,t} = d_{i,e,t+1}, \\ 0 & \text{if } d_{i,e,t} \neq d_{i,e,t+1}, \end{cases}$$

Global error

$$\varepsilon_{e,t} = \frac{|\sum_{i=1}^{n} r_{i,e,t} - \sum_{i=1}^{n} s_{i,e,t}|}{|\sum_{i=1}^{n} r_{i,e,t}|},$$

Rewards

$$\gamma_{i,e} = \frac{\gamma_e * P_r(\alpha_{i,e})}{n * P_s(\alpha_{i,e})}.$$

Implementation

Unsupervised learning

Several implementation algorithms

Summarization - Clustering

Fixed: Manual selection

Empirical: Citizens' preferences, semi-automated

Customizable – number of clusters

Algorithmic: Fully-automated, data-driven

Survey questions

Privacy preferences

Survey answers ➔ summarization range

My household may decide to be more aware of the amount of electricity used by appliances we own or buy.

Datasets

ECBT - Smart Grid
6435 participants
1 sensor
1 year

Nervousnet
154 participants
several sensors
4 days

Measurements & variables	ECBT	Nervousnet
Privacy	✓	✓
Accuracy	✓	✓
Costs & Rewards	✓	X
Epoch length	daily & weekly	daily
Summarization level	fixed, empirical & algorithmic	fixed & algorithmic
Number of citizens	✓	✓
Several sensor types	X	✓
Analytics	summation	average

Evaluation & Research Questions

Does summarization improve privacy?

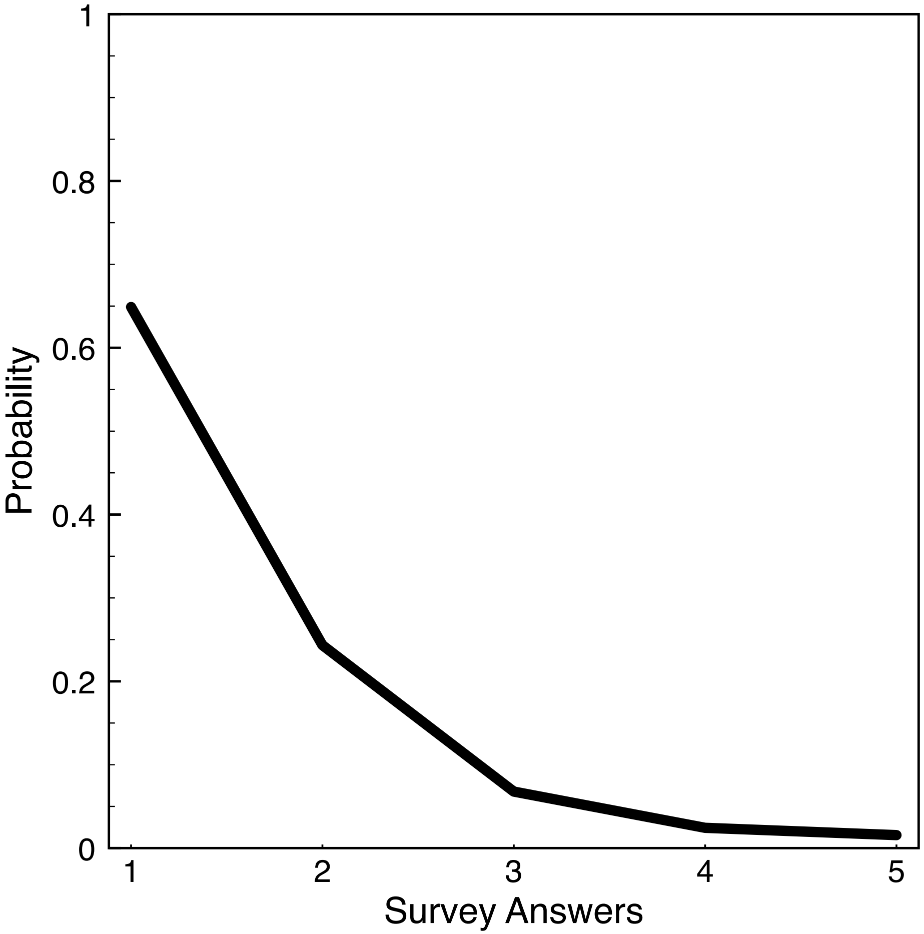
How does participation level influence privacy?

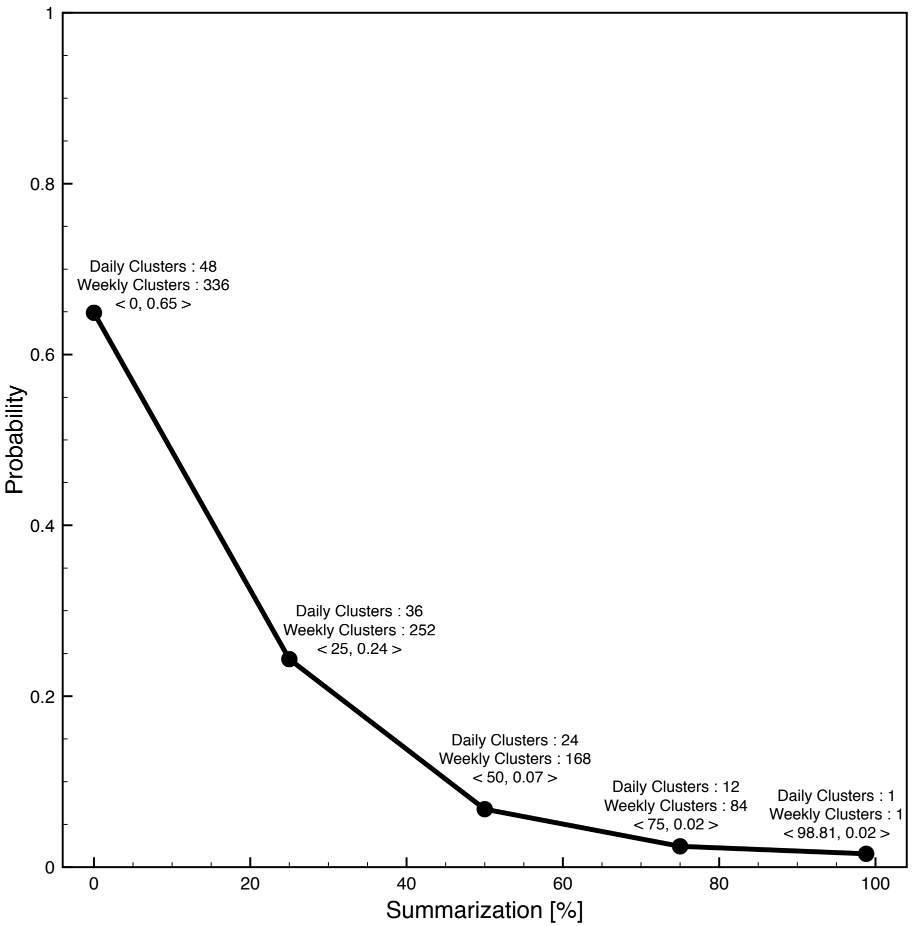
Which are the trade-offs between privacy & accuracy in analytics?

Does sensor/information type influence these trade-offs?

How rewards can be fairly distributed given citizens' selections?

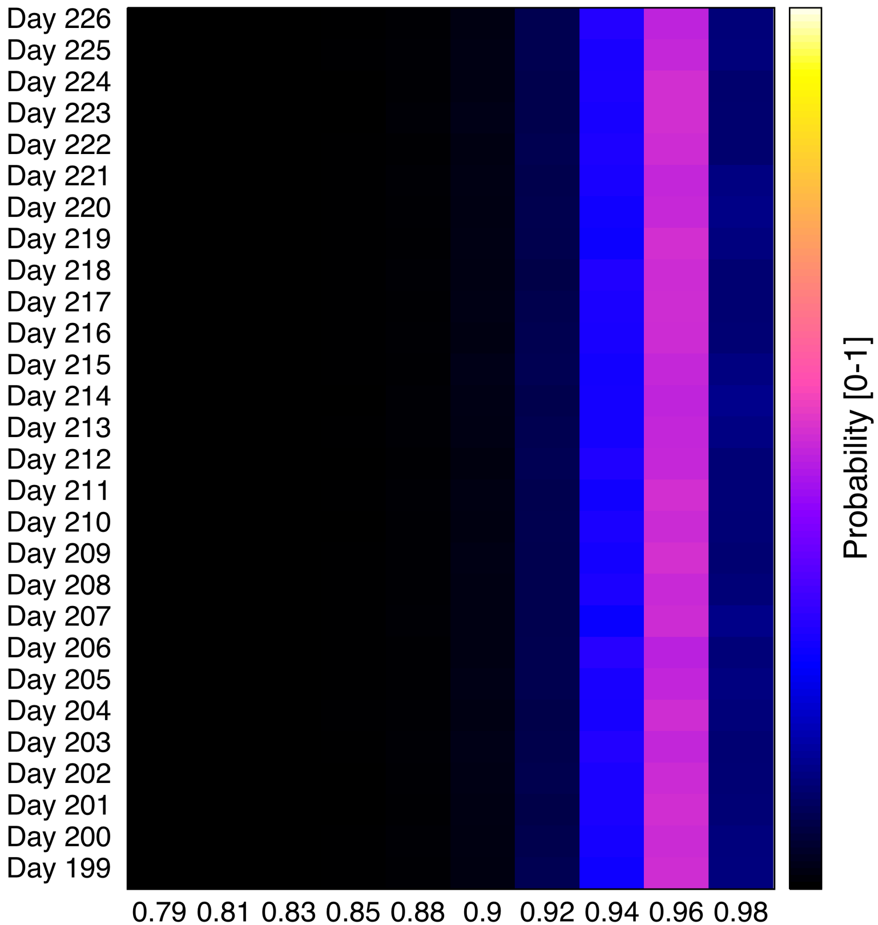
Empirical Summarization Values – Smart Grid



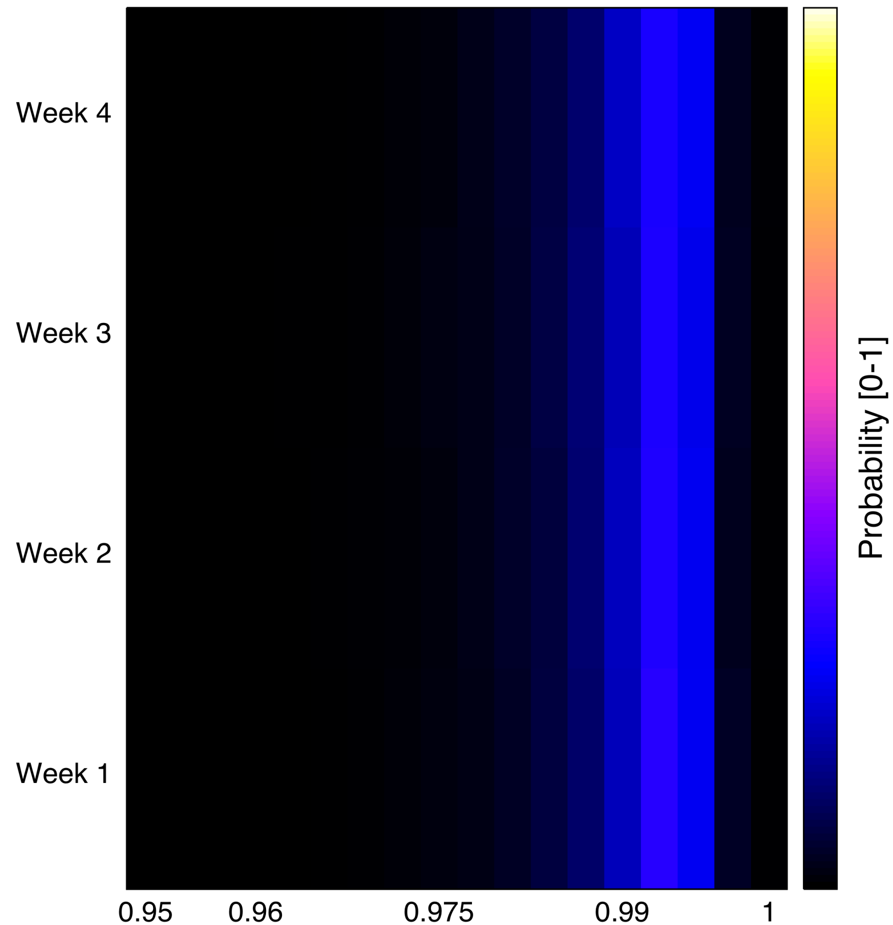


Daily summarization

Algorithmic Summarization Values – Smart Grid

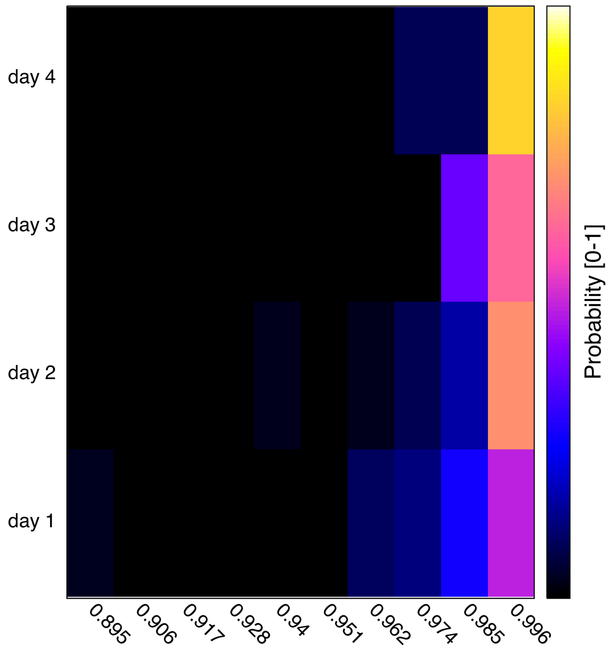


Daily

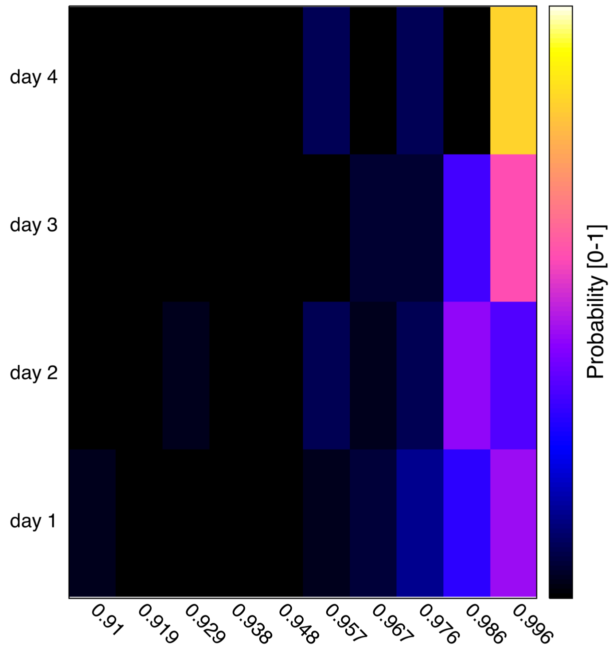


Weekly

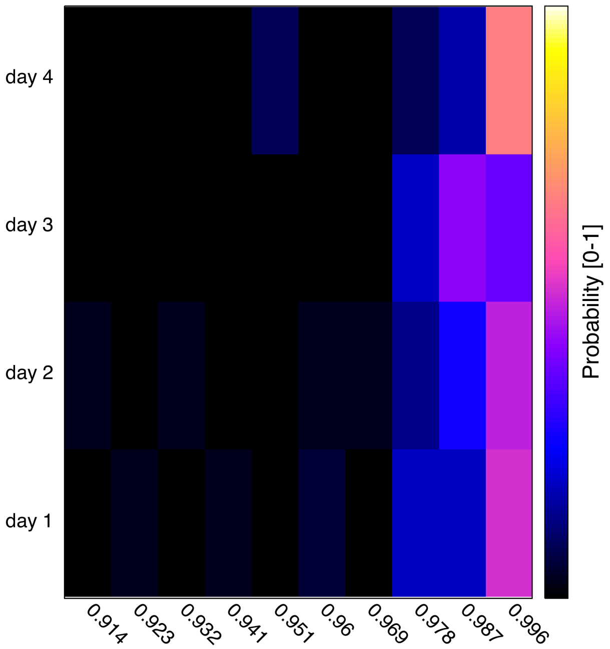
Algorithmic Summarization Values - Nervousnet



Accelerometer.X

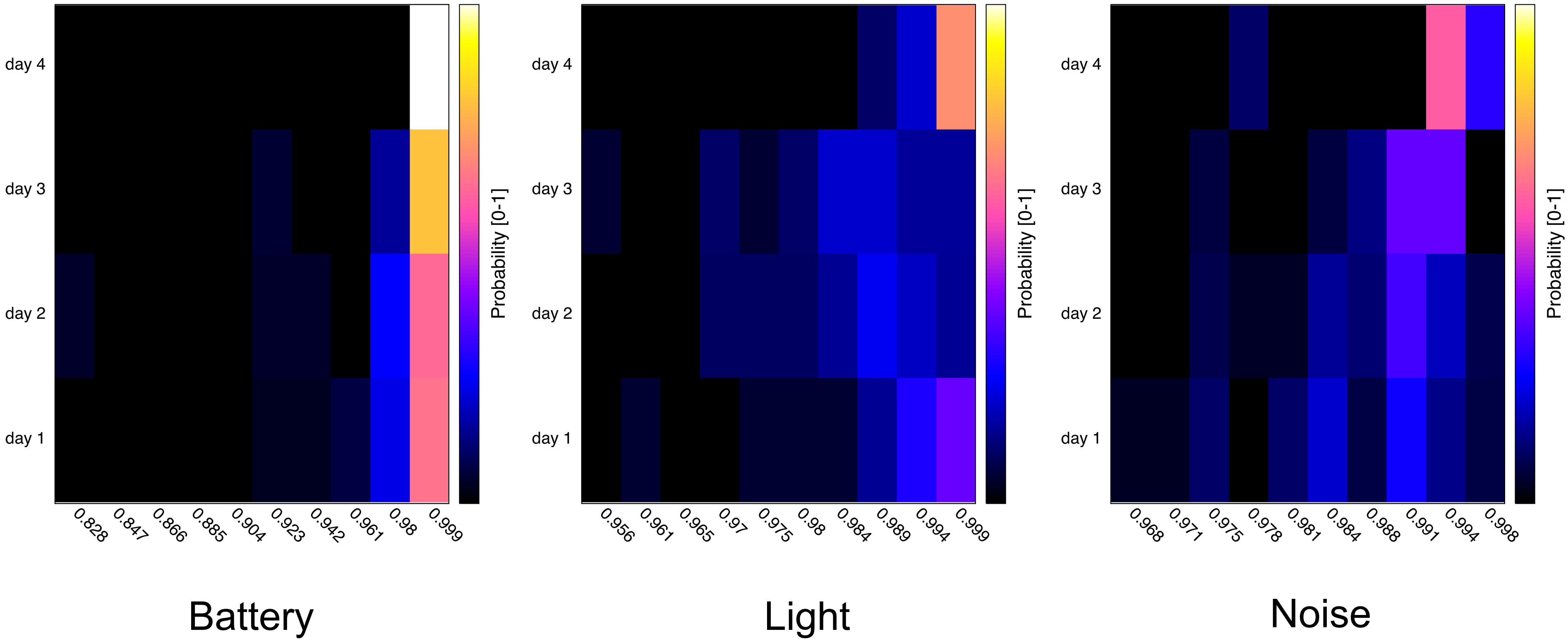


Accelerometer.Y



Accelerometer.Z

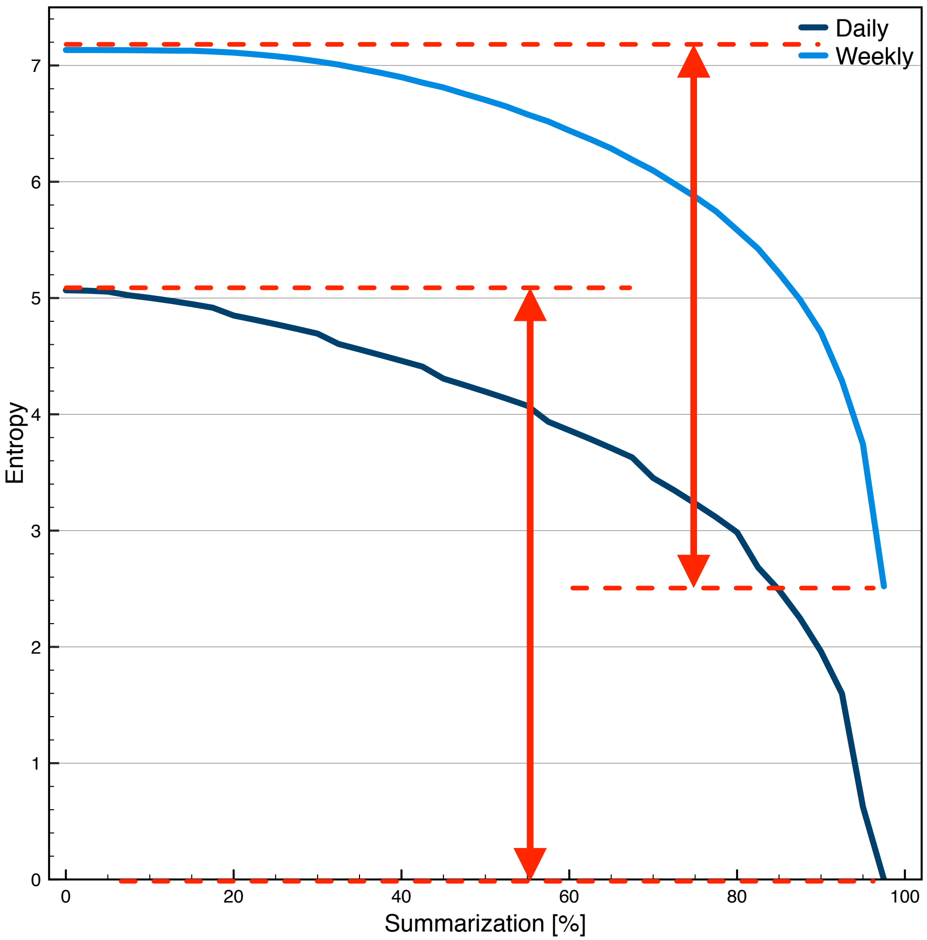
Algorithmic Summarization Values - Nervousnet

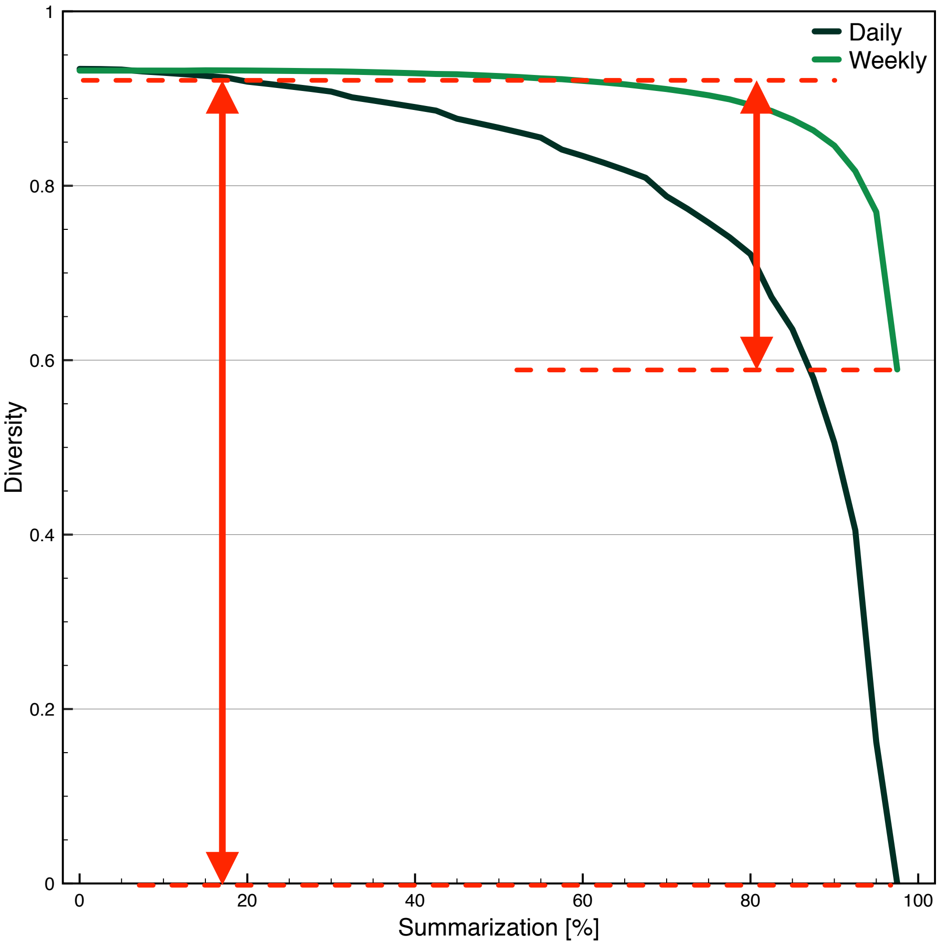


Does summarization improve privacy?

Does sensor/information type influence these trade-offs?

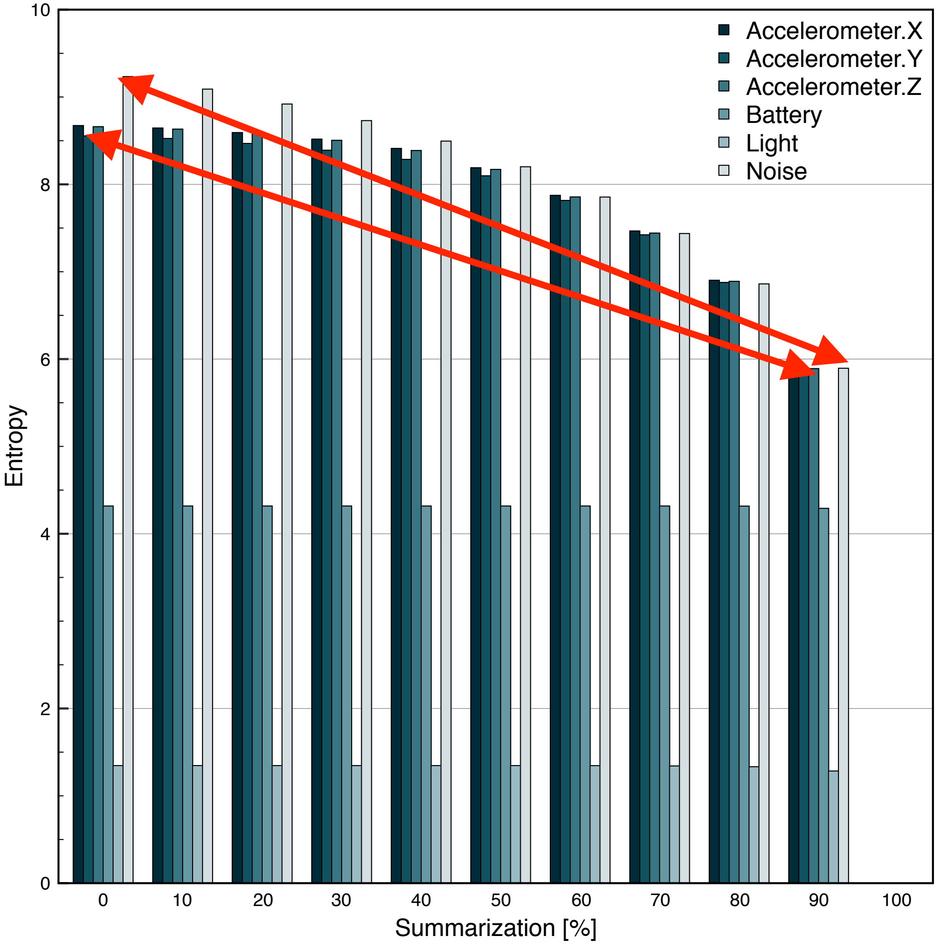
Privacy-preservation – Smart Grid

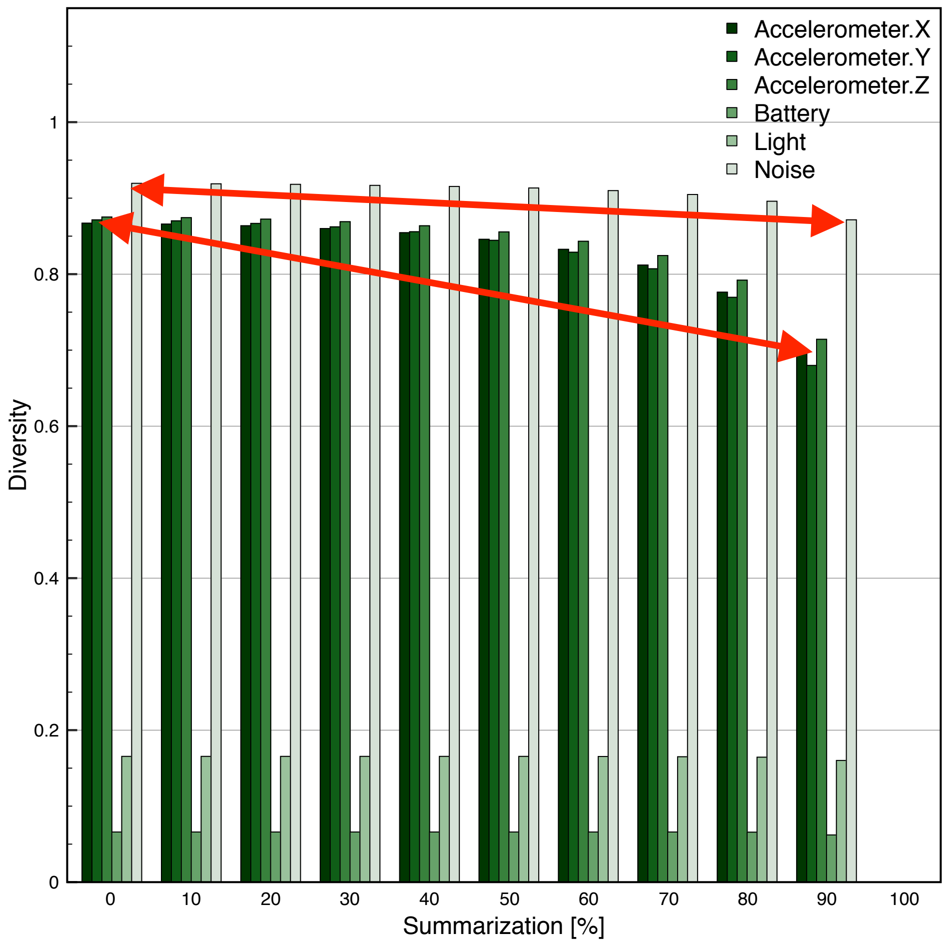




Fixed summarization levels

Privacy-preservation – Nervousnet





Fixed summarization levels

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How does participation level influence privacy?

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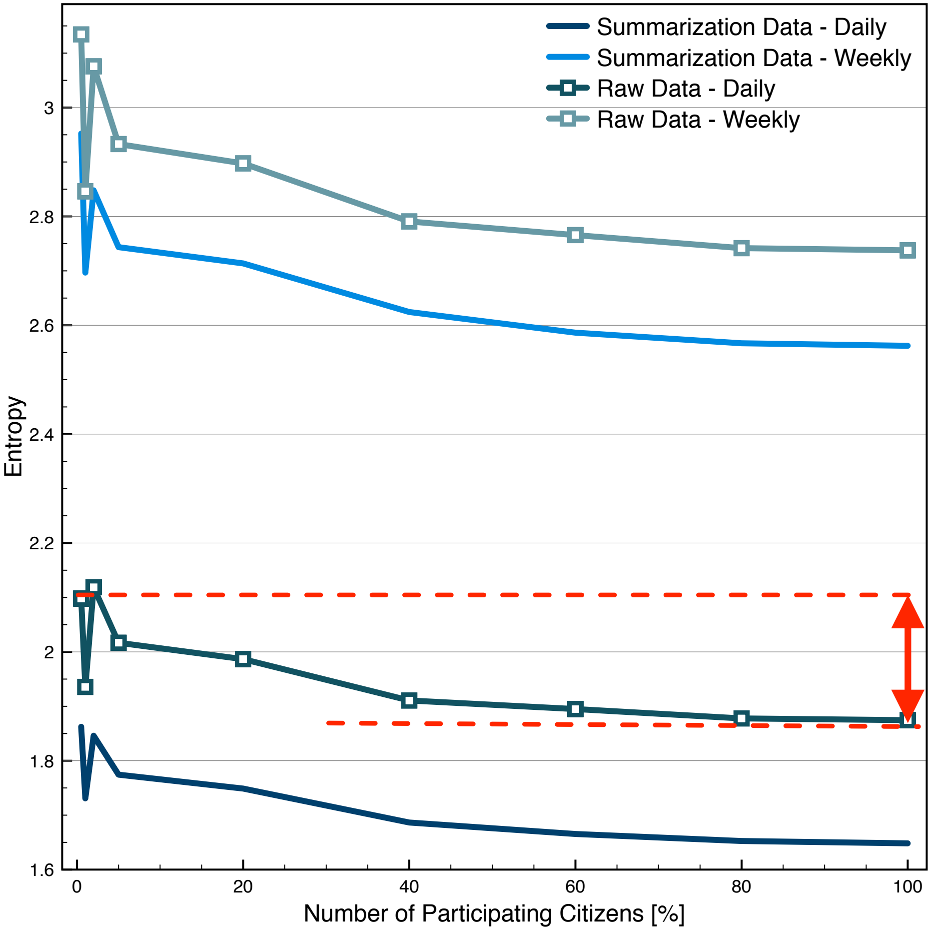
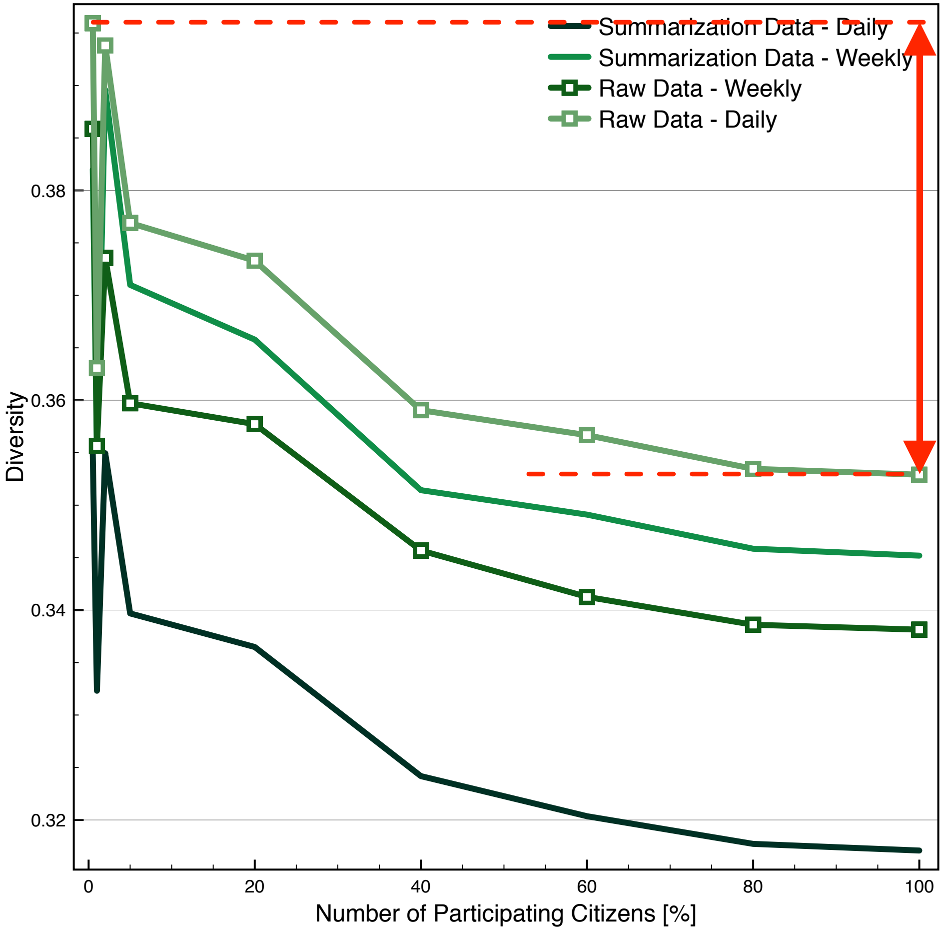
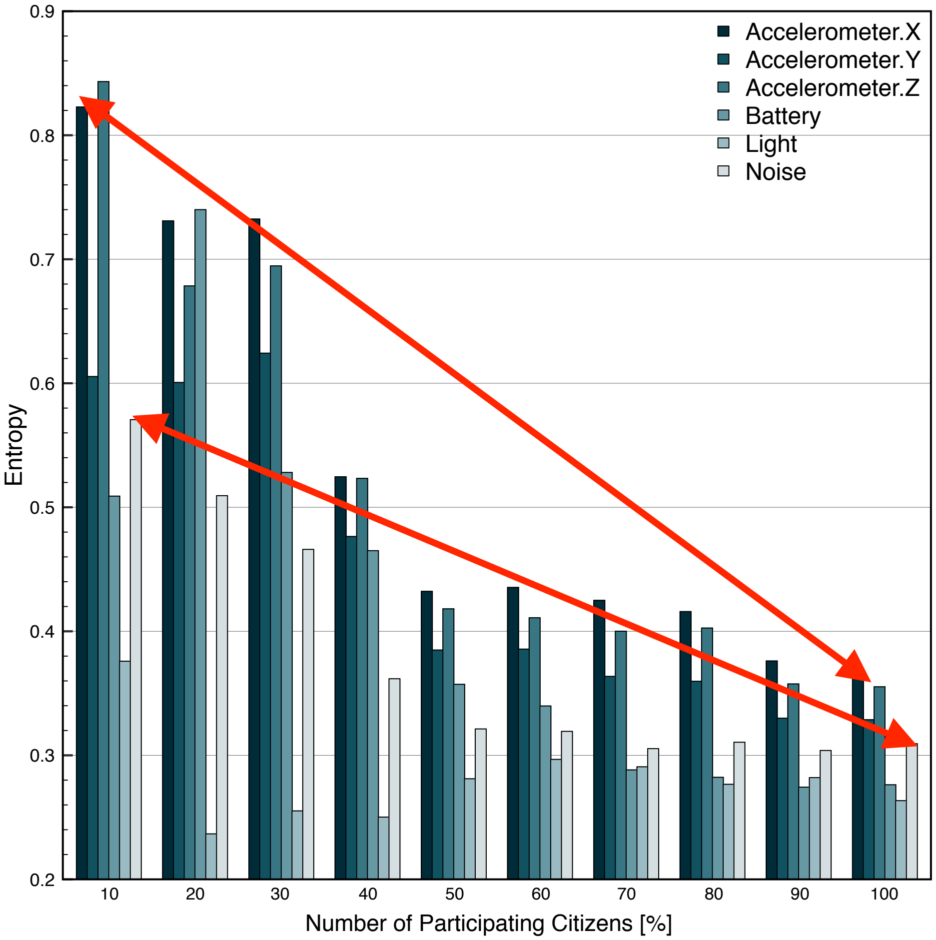
Privacy-preservation – Smart Grid

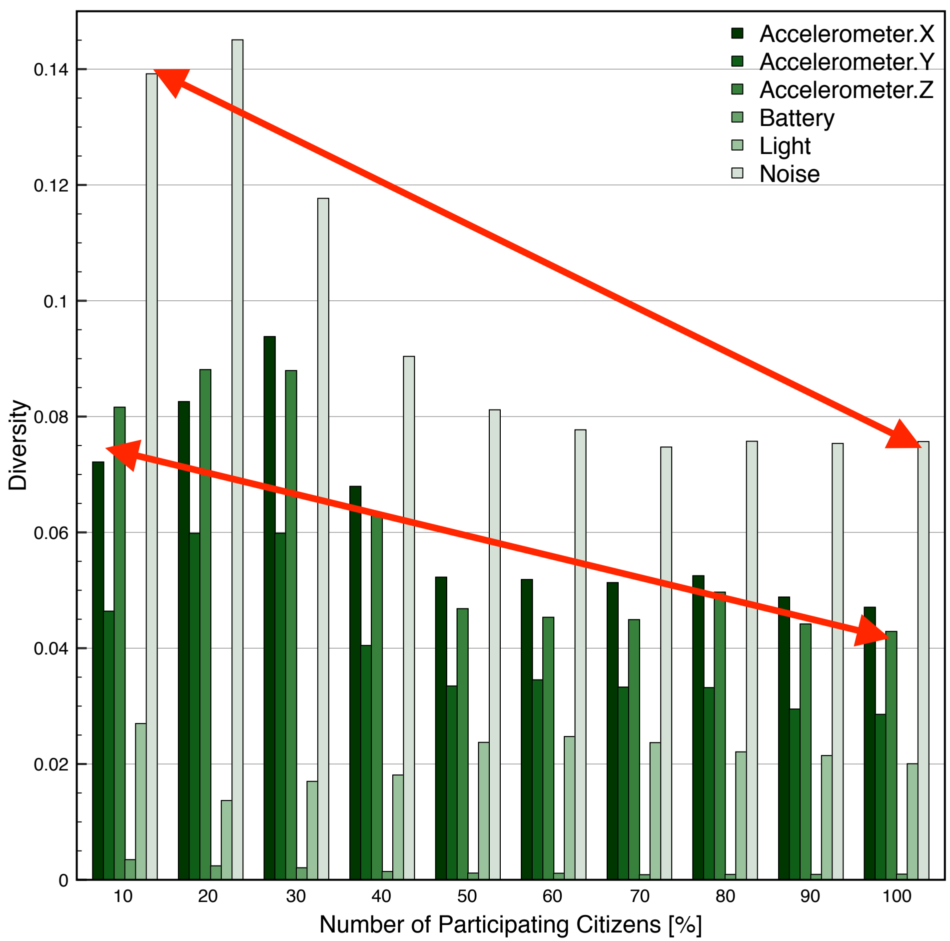




Empirical summarization levels

Privacy-preservation – Nervousnet

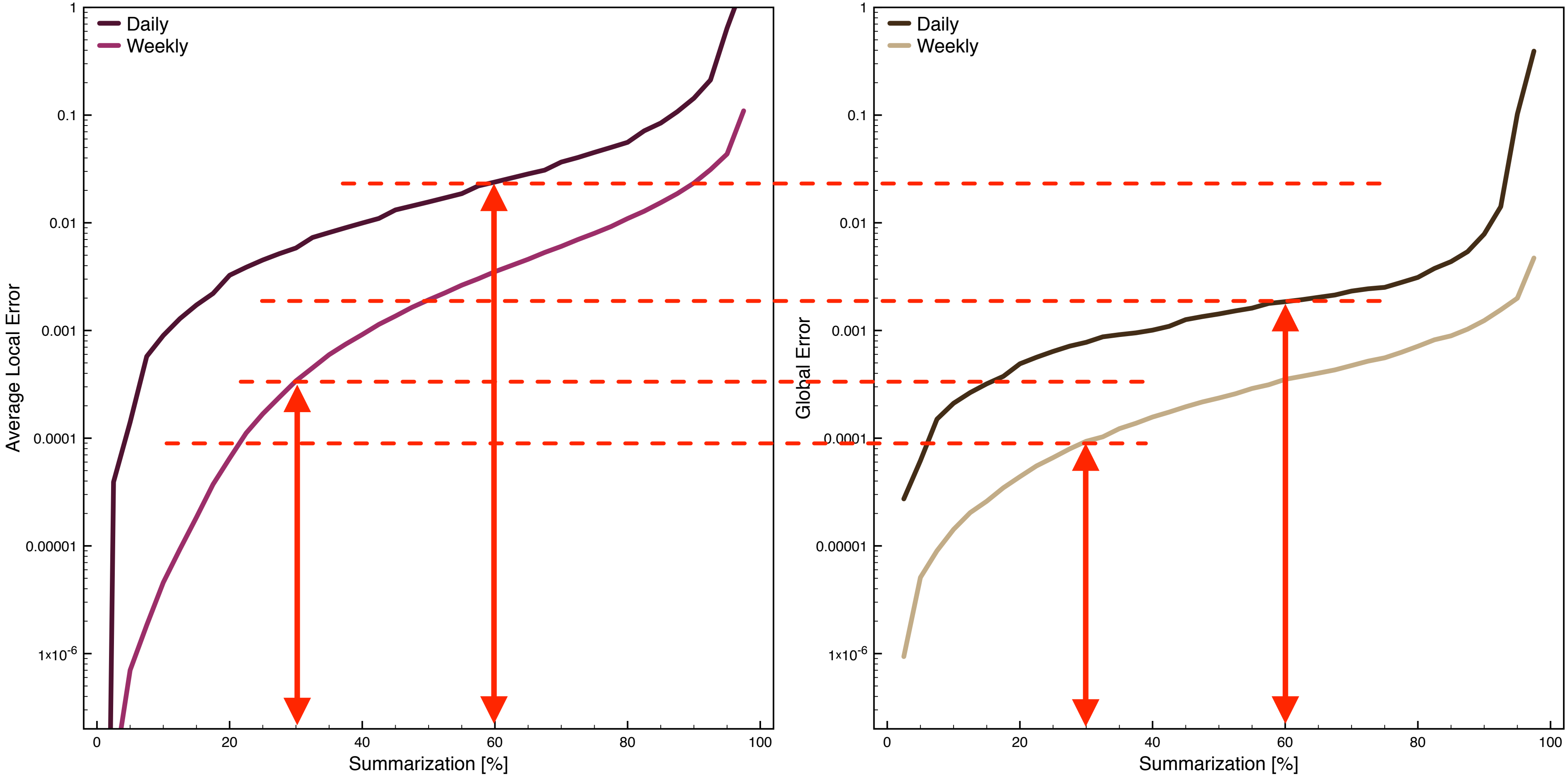




Algorithmic summarization levels

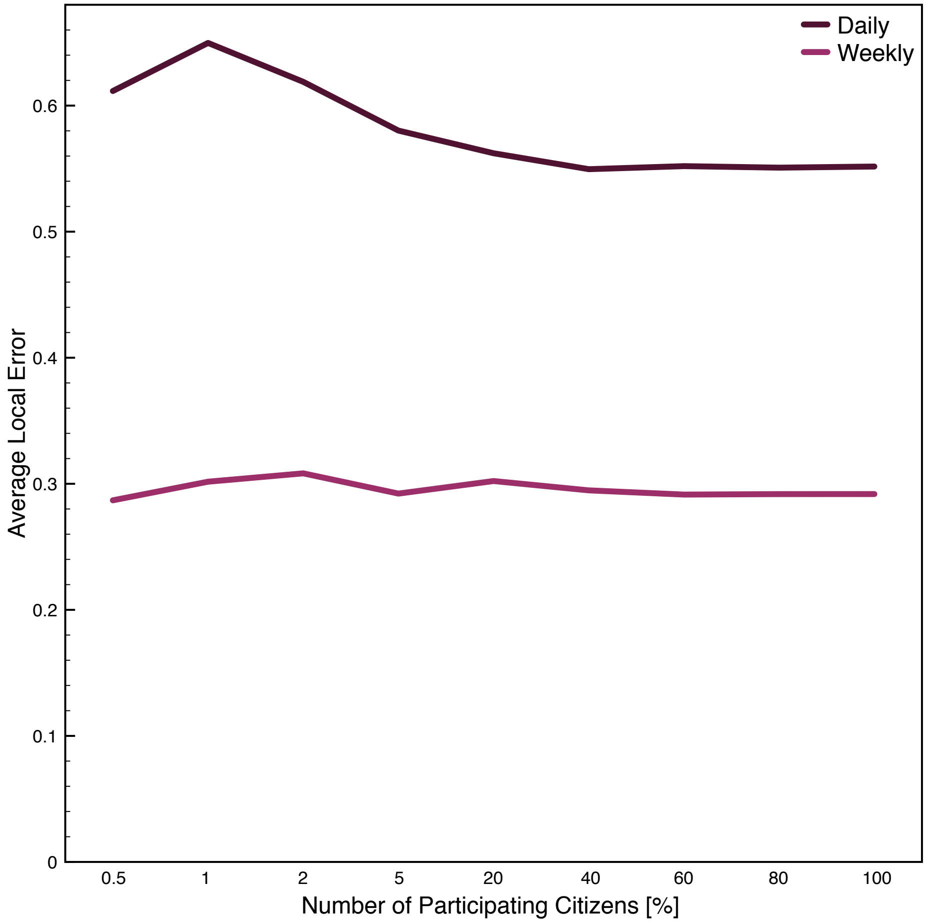
Which are the trade-offs between privacy & accuracy in analytics?

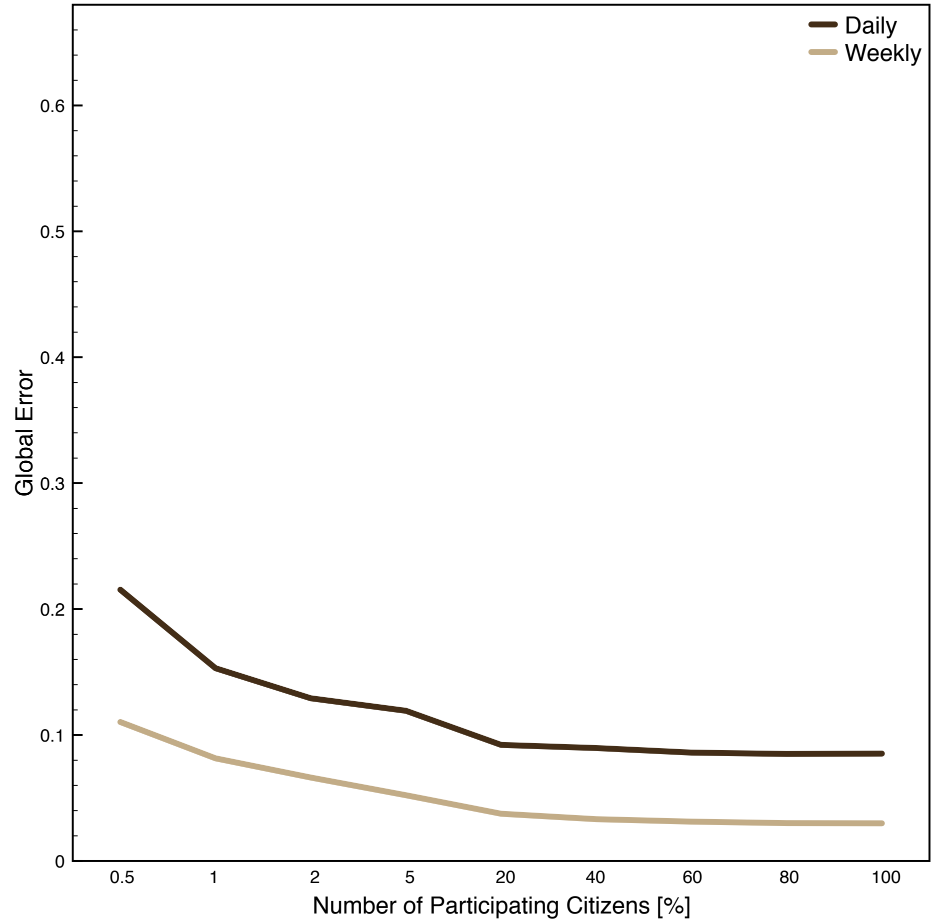
Privacy vs. Accuracy – Smart Grid



Fixed summarization levels

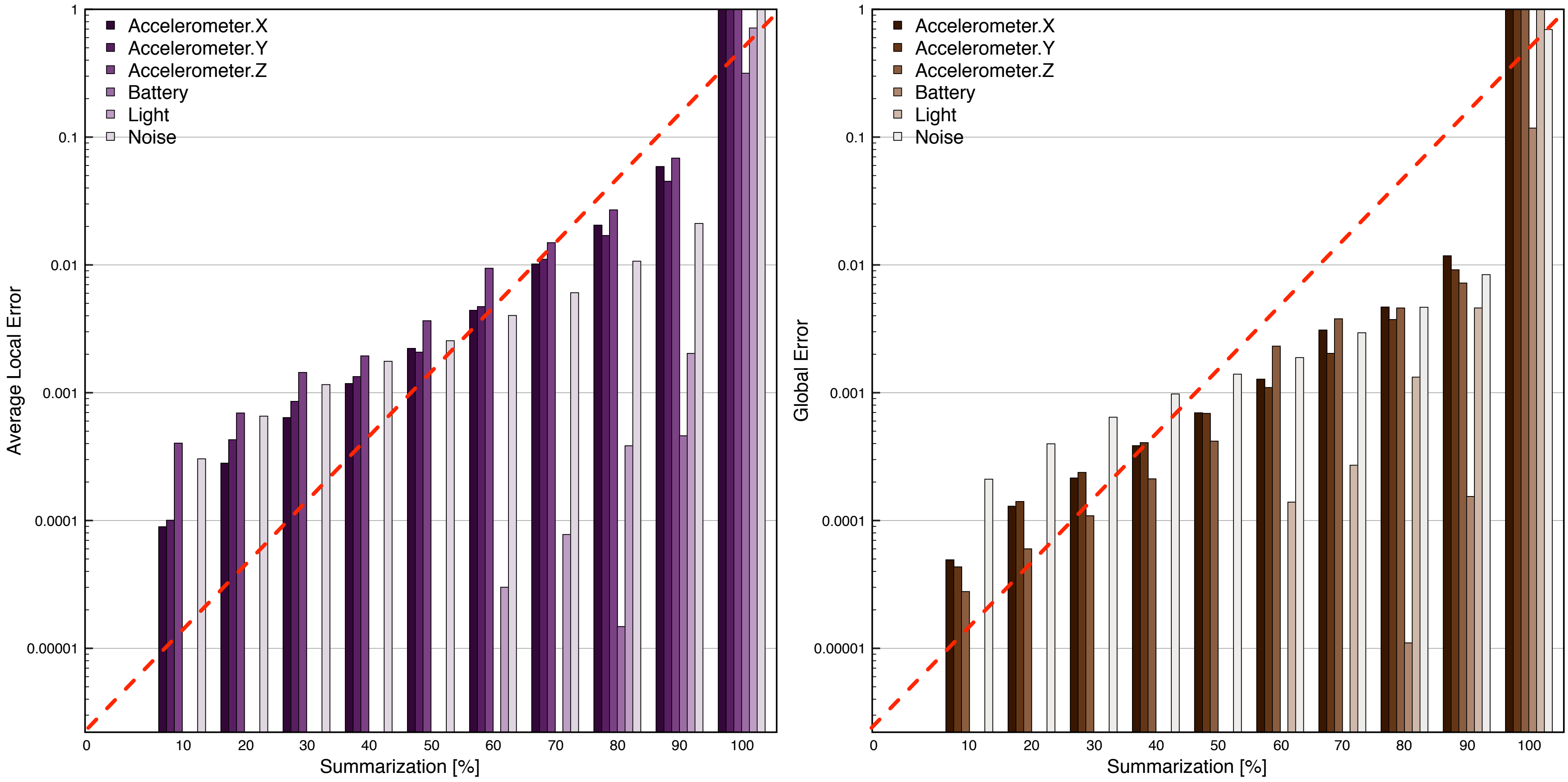
Privacy vs. Accuracy – Smart Grid





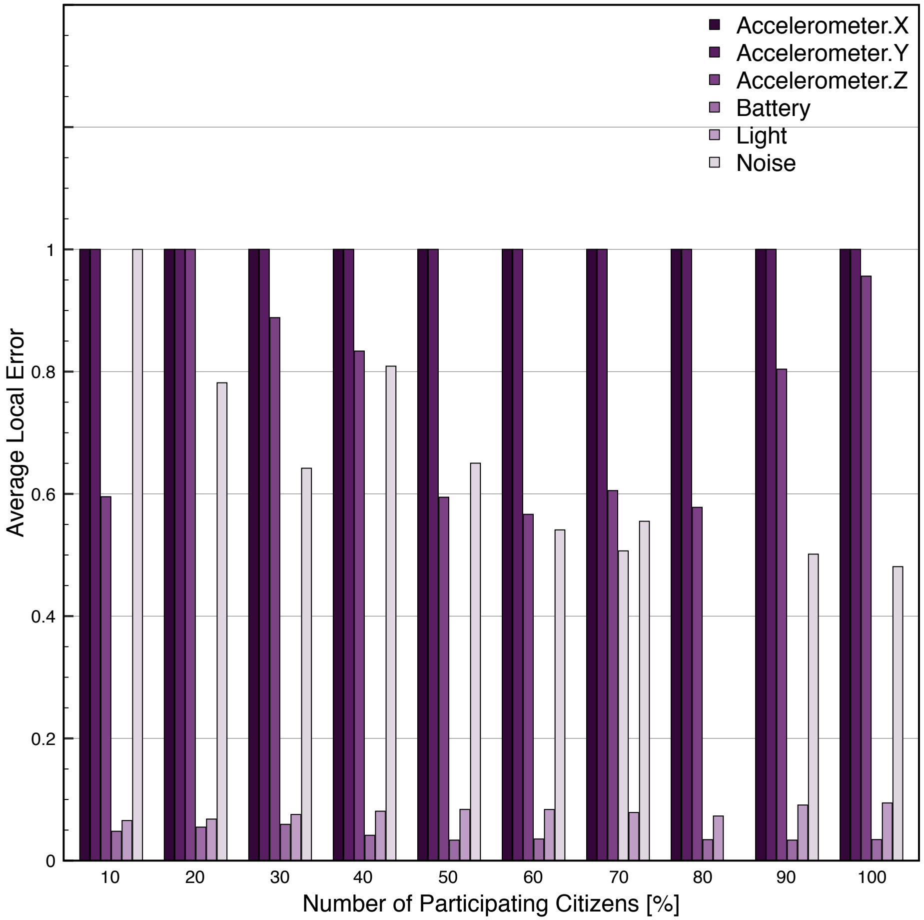
Algorithmic summarization levels

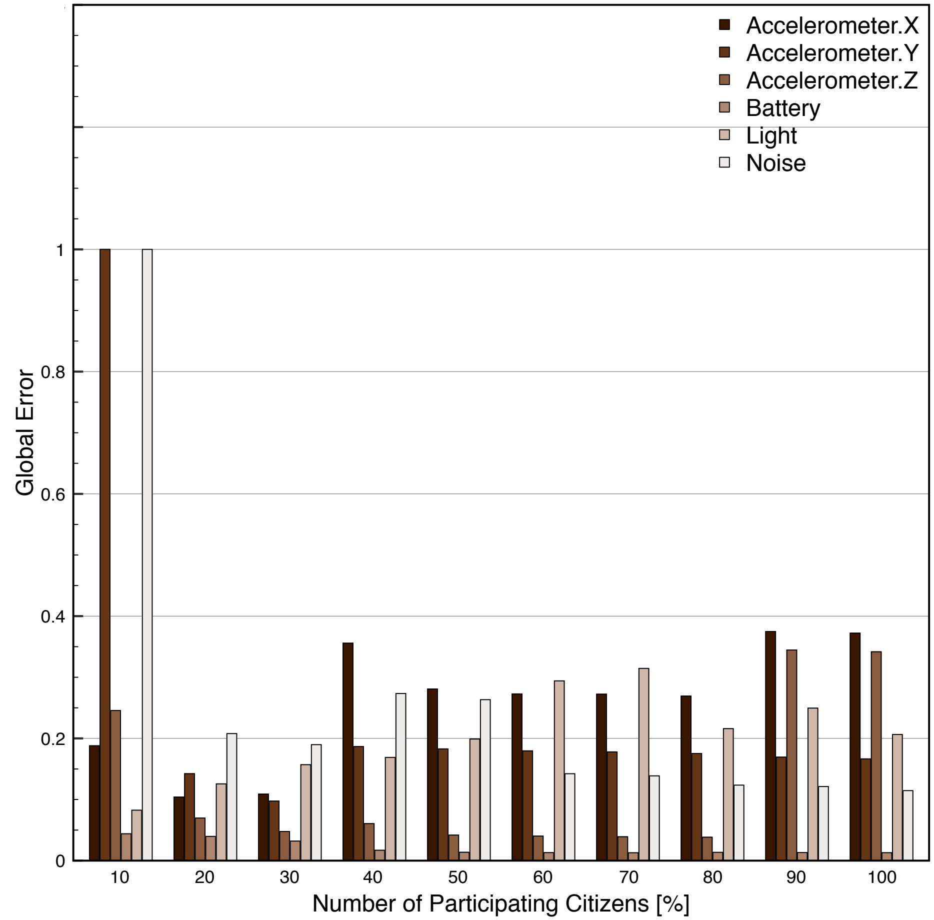
Privacy vs. Accuracy – Nervousnet



Fixed summarization levels

Privacy vs. Accuracy – Nervousnet

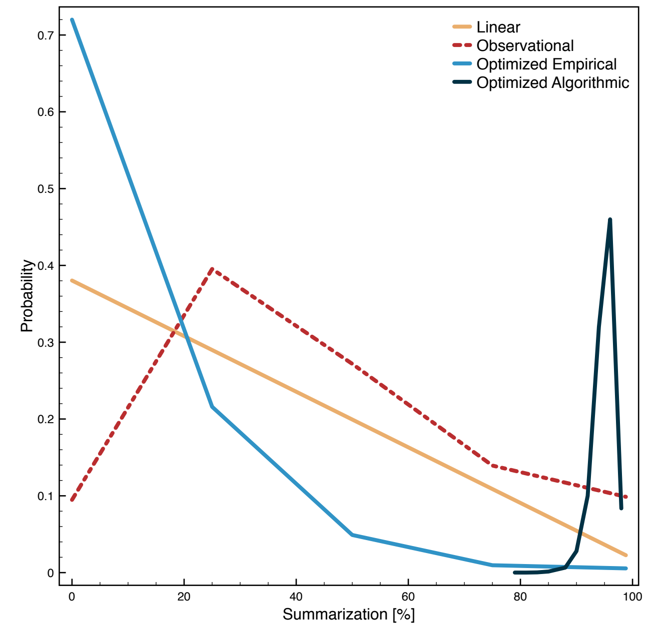


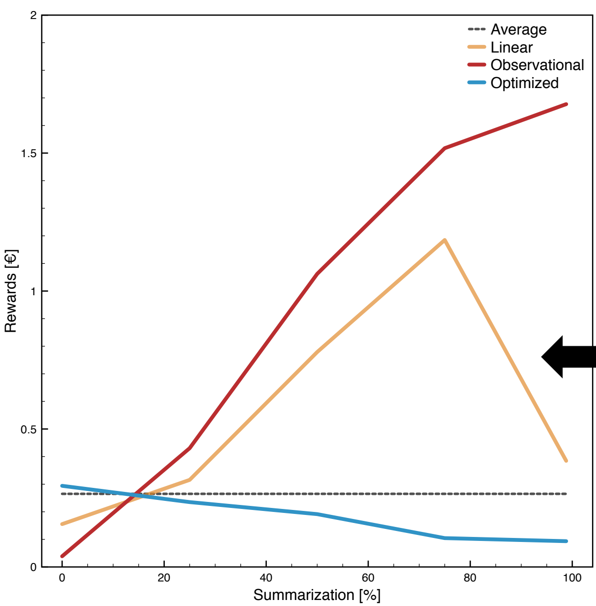


Algorithmic summarization levels

How rewards can be fairly distributed given citizens' selections?

Rewards – Smart Grid

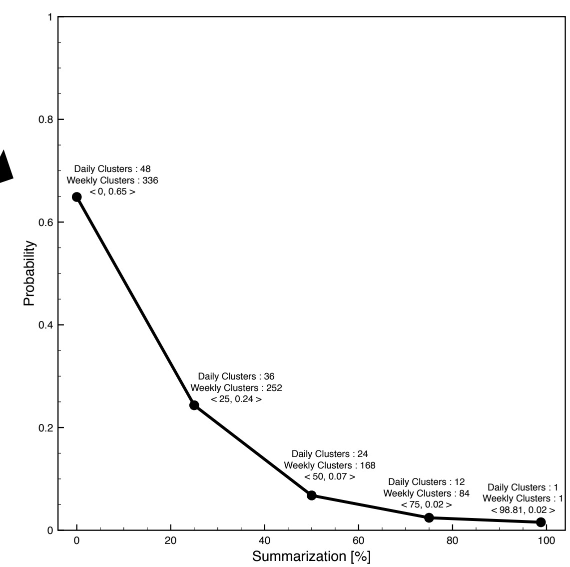




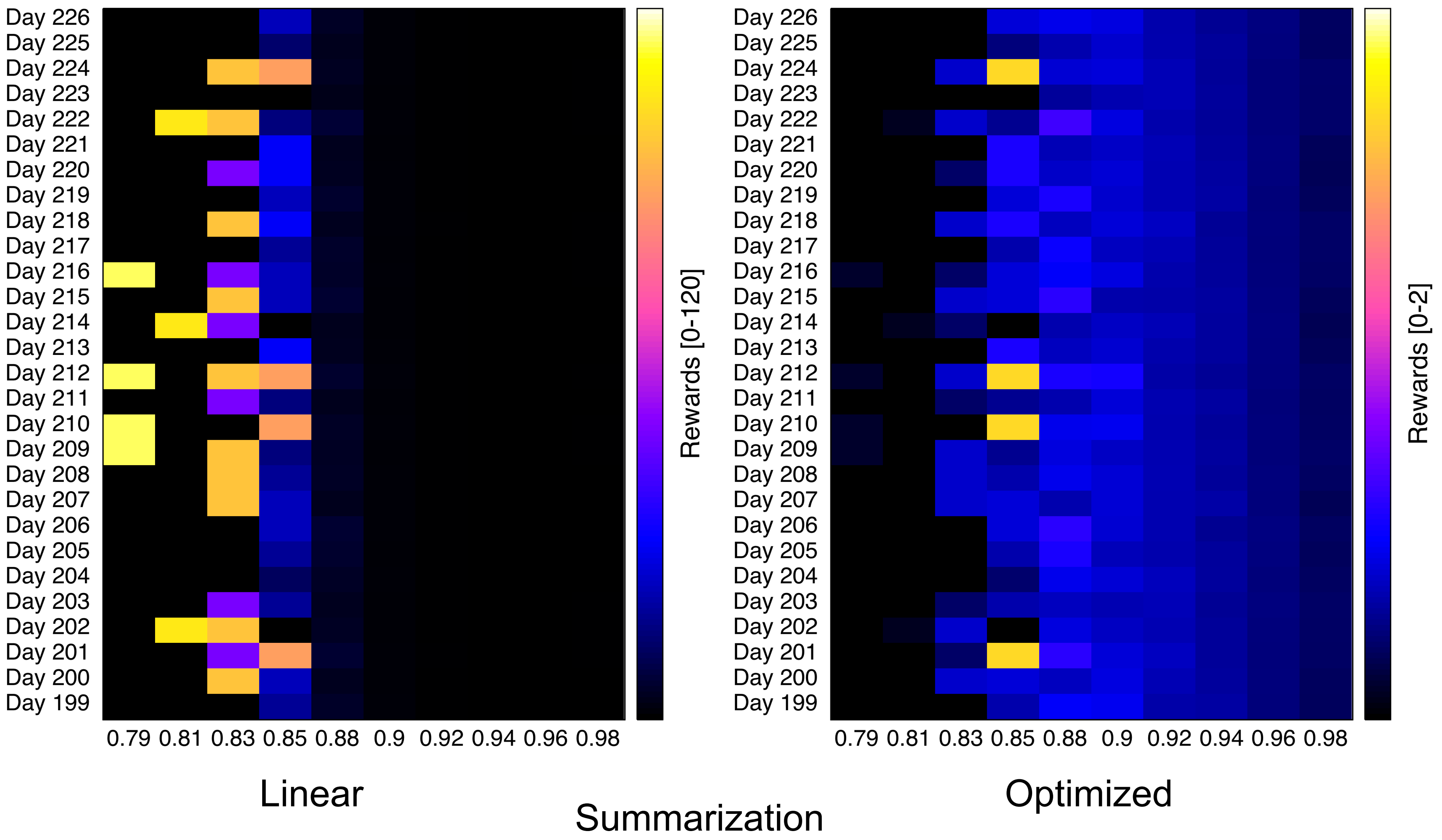
Total budget

$$\gamma_{i,e} = \frac{\gamma_e * P_{\mathrm{r}}(\alpha_{i,e})}{n * P_{\mathrm{s}}(\alpha_{i,e})}.$$

Number of citizens



Rewards – Smart Grid



Conclusions

Higher summarization, higher privacy-preservation

More participants, higher privacy-preservation

Sensor types influence privacy-preservation & accuracy

Local errors cancel out resulting in low global errors

Incentivization can be optimized to be fair

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Questions?

Evangelos Pournaras, Jovan Nikolic, Pablo Velasquez, Marcello Trovati, Nik Bessis and Dirk Helbing, *Self-regulatory Information Sharing in Participatory Social Sensing*, The European Physical Journal Data Science, 5:14, 2016

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