



Participatory Sharing Economies via Decentralized Mobile and Cloud Computing

Evangelos Pournaras

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Motivation

Data Is the New Oil of the Digital Economy

SCIENCE

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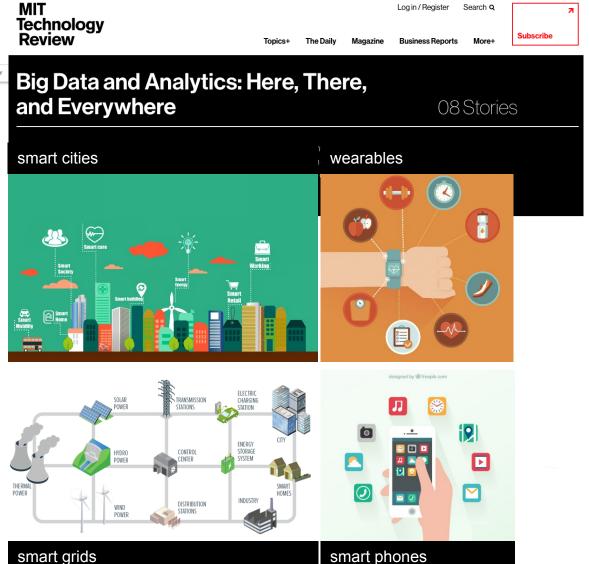
DATA IS THE NEW OIL OF THE **DIGITAL ECONOMY**



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.



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Threats & Challenges



"Your recent Amazon purchases, Tweet score and location history makes you 23.5% welcome here."



Autonomy



Commercial interests



Discriminatory big data analysis

Centralized Design *Beyond scalability*



Without detailed knowledge of appliance signatures, intuitive observation with power consumption variations indicates human activity.

Credit: "Private Memoirs of a Smart Meter," Molina-Markham, et.al., 2nd ACM Workshop On Embedded Sensing Systems For EnergyEfficiency In Buildines (Buildsys 2010), Zurich, Switzerland, November 2, 2010.

Time (Hours) vs Power Usage (kW)

Optimization & Learning

Data Analytics

Data Sharing

Privacy-intrusion, surveillance & profiling

Decentralized Participatory Design

Decentralization

- Scalability
- Participation: computational resources, sharing economies
- Informational self-determination
- Privacy-by-design
- Autonomy
- **Fairness**
- Services as public good by citizens for citizens



DEMOCRATIZATION OF MOBILE COMPUTING & INTERNET OF THINGS



Build digital democracy

Open sharing of data that are collected with smart devices would empower citizens and create jobs, say Dirk Helbing and Evangelos Pournaras.

☐ridges, coffee machines, toothbrushes, phones and smart devices are all now equipped with communicating sensors. In ten years, 150 billion 'things' will connect with each other and with billions of people. The 'Internet of Things' will generate data volumes that double every 12 hours rather than every 12 months, as is the case now.

Blinded by information, we need 'digital sunglasses'. Whoever builds the filters to monetize this information determines what we see - Google and Facebook, for example. Many choices that people consider their own are already determined by algorithms. Such remote control weakens responsible, self-determined decision-making and thus

The European Court of Justice's ruling on 6 October that countries and companies must comply with European data-protecour decisions, we need information systems that are transparent, trustworthy and user-controlled. Each of us must be able to choose, modify and build our own tools for winnowing information.

With this in mind, our research team at the Swiss Federal Institute of Technology in Zurich (ETH Zurich), alongside international partners, has started to create a distributed, privacy-preserving 'digital nervous system' called Nervousnet. Nervousnet uses the sensor networks that make up the Internet of Things, including those in smartphones, to measure the world around us and to build a collective 'data commons'. The many challenges ahead will be best solved using an open, participatory platform, an approach that has proved successful for projects such as Wikipedia and the open-source operating

predictable. Our behaviour is increasingly steered by personalized advertisements and search results, recommendation systems and emotion-tracking technologies. Thousands of pieces of metadata have been collected about every one of us (see go.nature. com/stogsu). Companies and governments can increasingly manipulate our decisions, behaviour and feelings1.

Many policymakers believe that personal data may be used to 'nudge' people to make healthier and environmentally friendly decisions. Yet the same technology may also promote nationalism, fuel hate against minorities or skew election outcomes2 if ethical scrutiny, transparency and democratic control are lacking - as they are in most private companies and institutions that use big data. The combination of nudging with big data about everyone's behaviour, feelings





Optimization & Learning

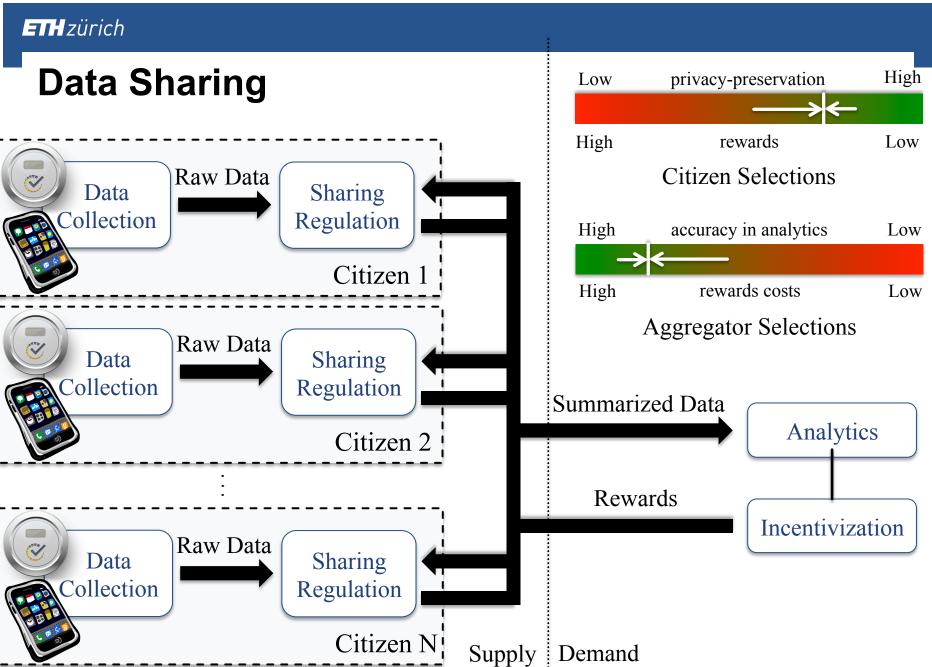
Data Analytics

Data Sharing



Data Sharing

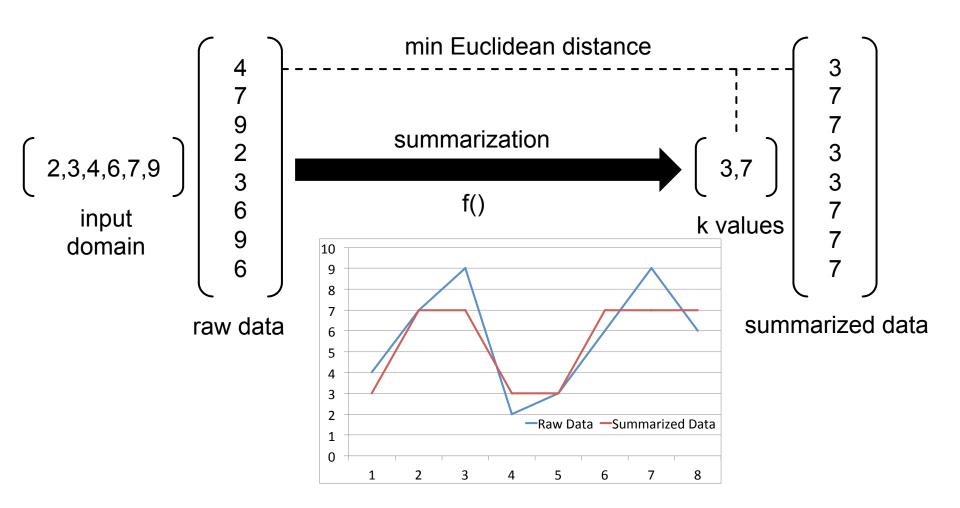
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Summarization





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.

ECBT - Smart Grid 6435 participants 1 sensor 1 year

Nervousnet 154 participants several sensors 4 days

Datasets

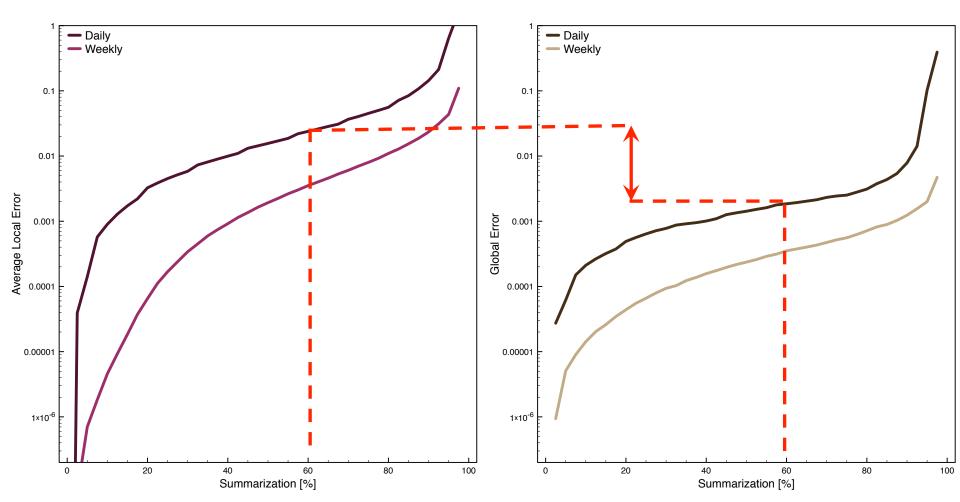




ECBT	Nervousnet
\checkmark	√
\checkmark	\checkmark
\checkmark	X
daily & weekly	daily
fixed, empirical & algorithmic	fixed & algorithmic
\checkmark	\checkmark
Χ	\checkmark
summation	average
	✓ ✓ ✓ daily & weekly fixed, empirical & algorithmic ✓



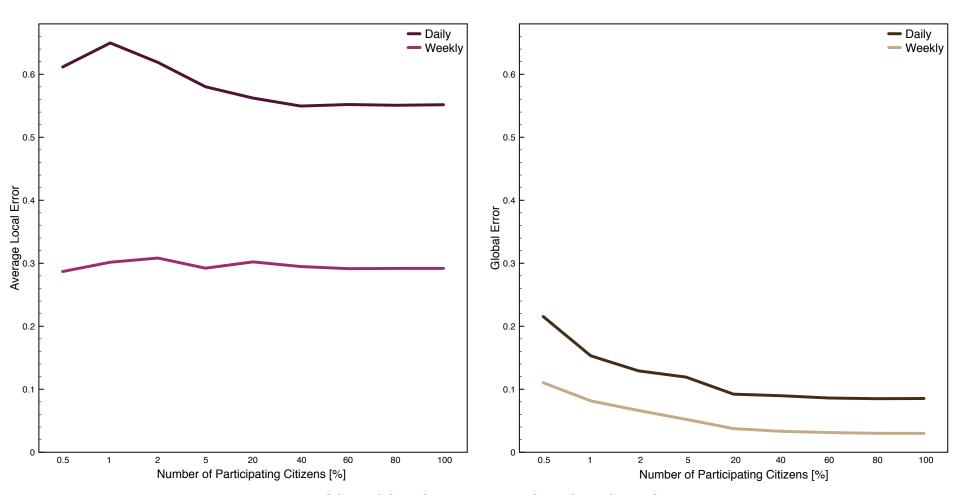
Privacy vs. Accuracy – Smart Grid



Fixed summarization levels



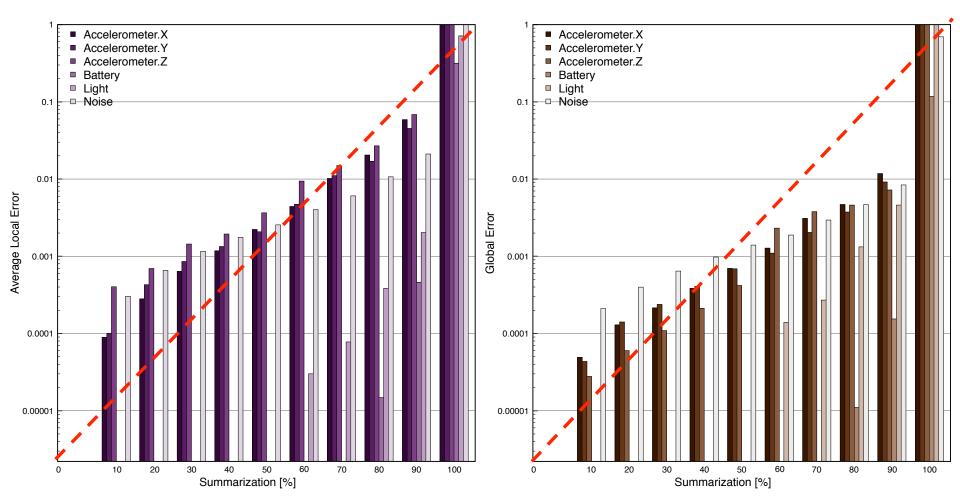
Privacy-preservation – Smart Grid



Algorithmic summarization levels



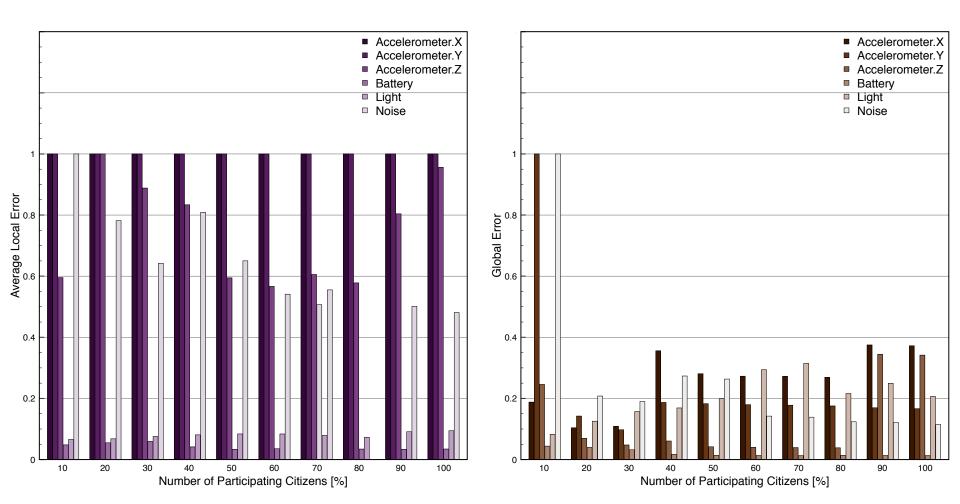
Privacy vs. Accuracy – Nervousnet



Fixed summarization levels



Privacy-preservation – Nervousnet



Algorithmic summarization levels



Social Norms & Human Decision-making

Companies

Governments

Educational Institutions

Non-Profitable/Non-Governmental Organizations

Data Collection Stakeholders

Model decision-making/privacy-perception in

data sharing

Novel mixed-mode social experiment at ETH Decision Science Lab

Social Networking

Training Health

Transport

Shopping

Environment

Social Networking

Health

Transport

Shopping

Finance Shopping

How (monetary) rewards steer human decision-making in information sharing?

Smartphone

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Microphone

Camera

Accelerometer

GPS

Proximity

Gyroscope

Thermometer

Air humidity

Battery

Barometer

Bluetooth

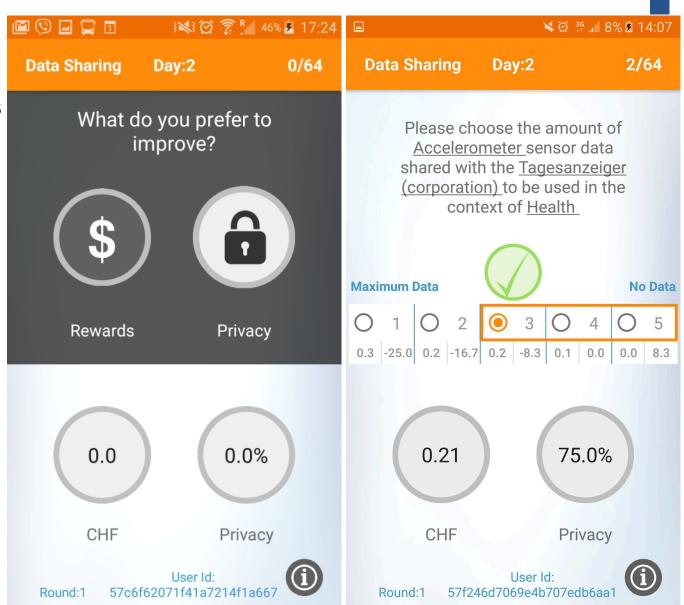
Ambient Light

Experiment

>100 users, >3 months

Real monetary incentives

Adherence to ethical & experimental protocols





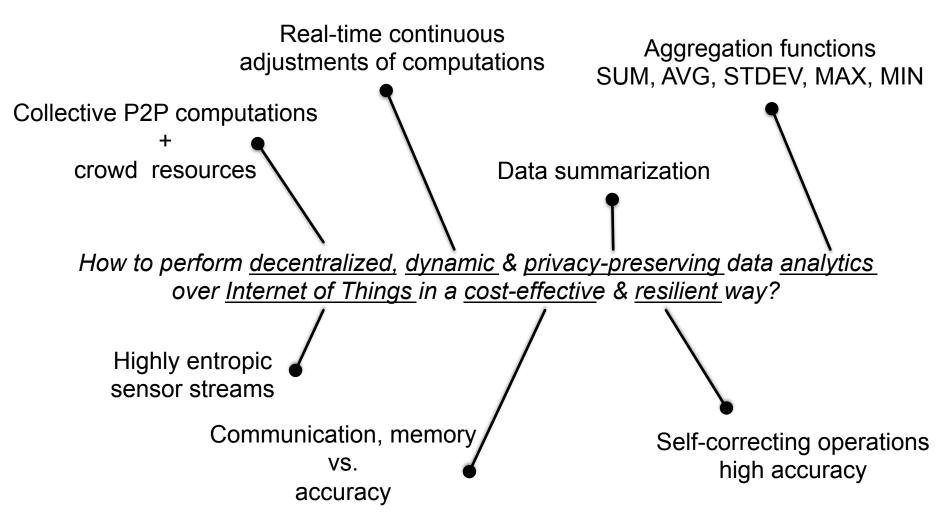
http://www.nervousnet.ethz.ch/hackathon/



Data Analytics

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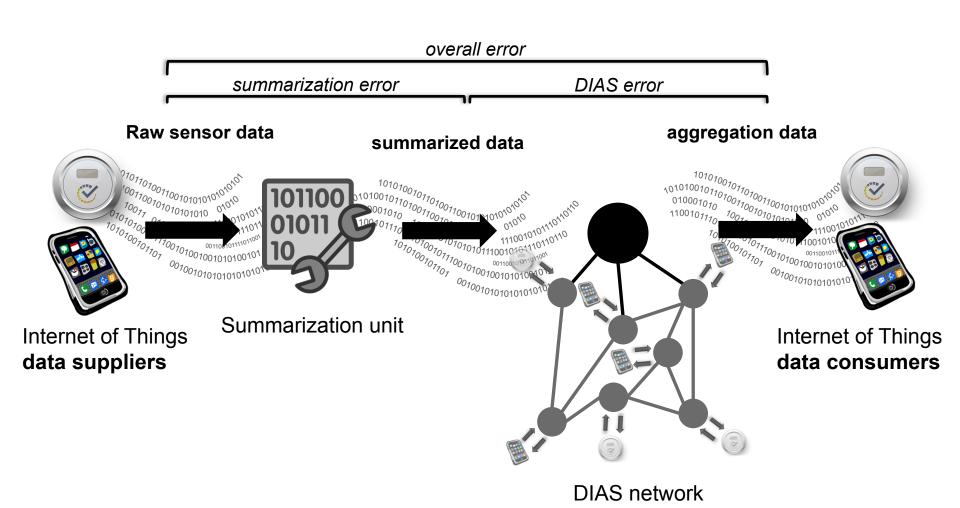
Research Question







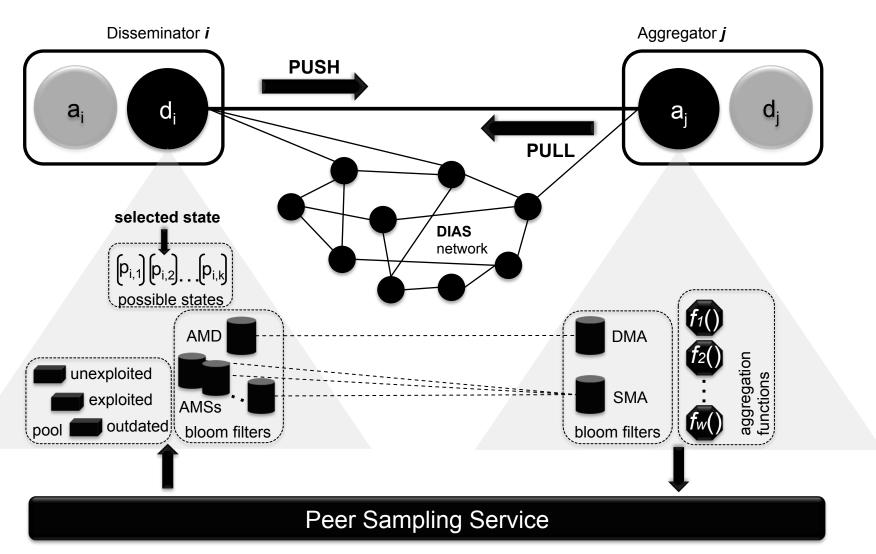
Decentralized Data Management



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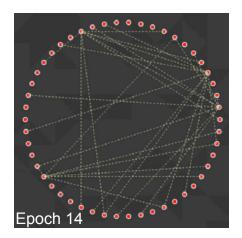


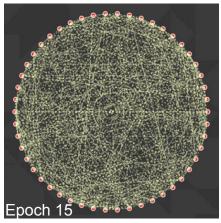
DIAS – How it works!

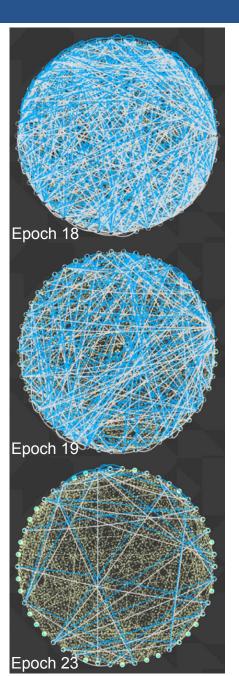


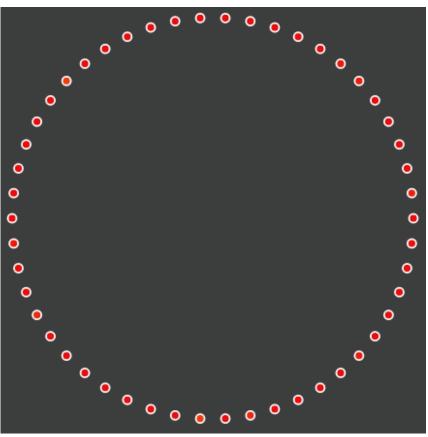


Visualization









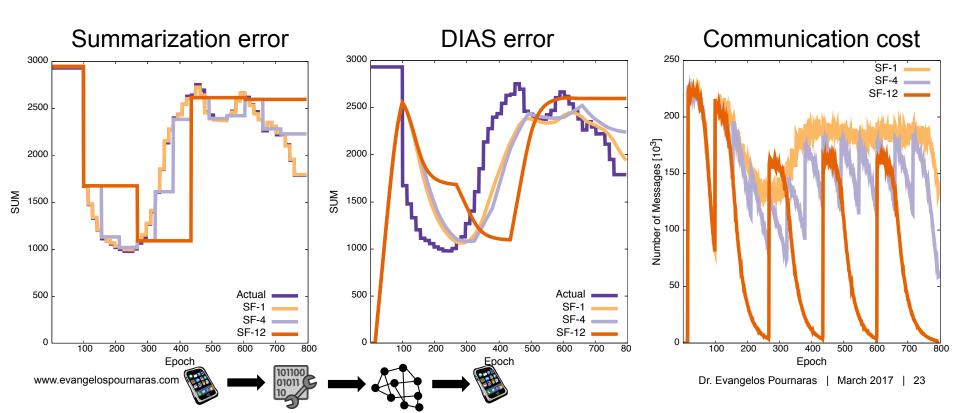


Experimental Evaluation

Implemented with the Protopeer distributed prototyping toolkit

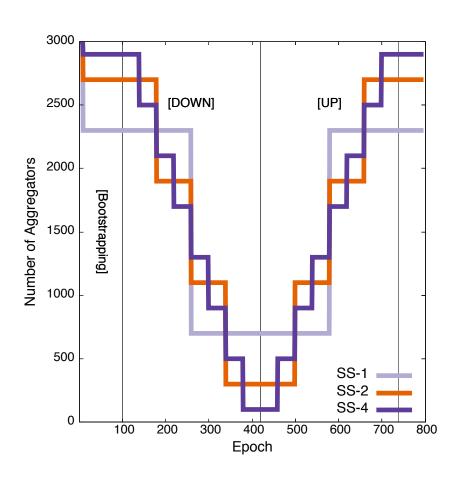
3000 nodes – Extreme scenario: all modes with a data suppliers & consumers

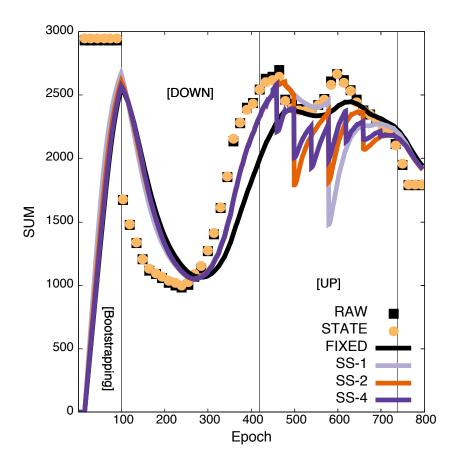
Real-world data: Electricity Customer Behavioral Trial





Dynamic Network Settings





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Optimization & Learning

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Smart Grids & Smart Cities

Local: make a shower, cook, laundry, charge EV

Global: prevent a blackout,

minimize production costs, maximize use of renewables

A computational design paradigm for truly decentralized participatory sharing economies?

Local: station to pick or leave a bicycle

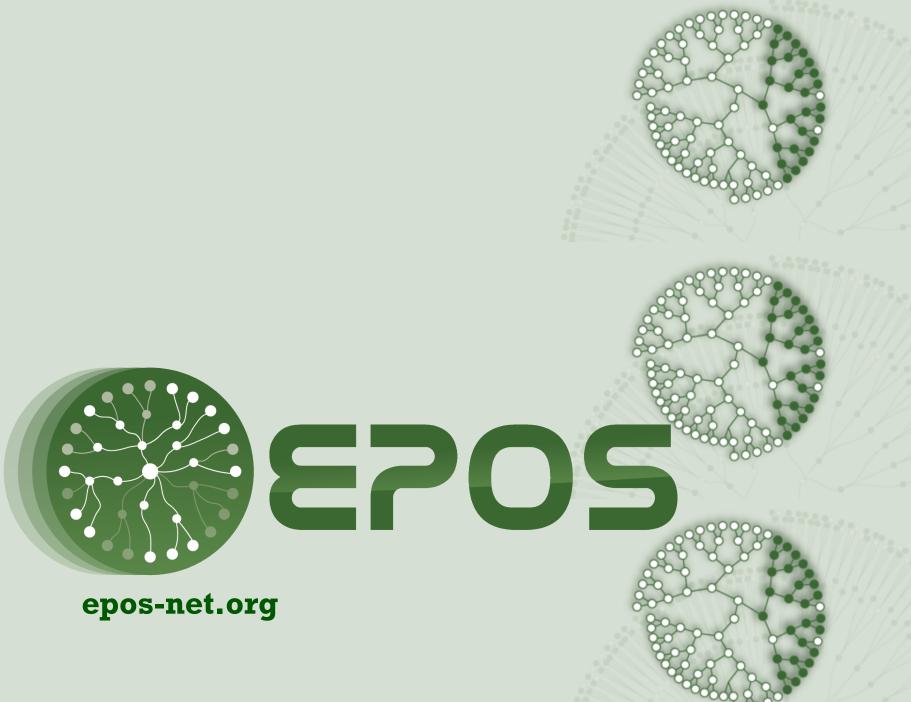
Global: prevent overload/underload of bicycle stations minimize manual bicycle relocations

minimize operational costs

minimize investment costs



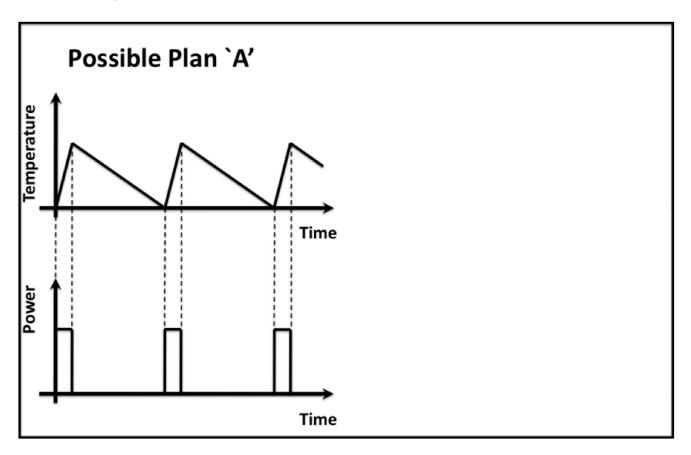






Participation Model

Planning alternative operations: possible plans





Technology

LG introduces its first Smart Grid-Ready Refrigerator the DIOS

Category: Environment Household - Tags: Household, Lg, Lge, Smart Adapt, Smart Grid, Wi-fi, Wifi



Barely 24 hours Samsung's <mark>Smart Grid Ready fridge</mark>, LG is now announcing its very own connected Smart Grid-Ready DIOS Fridge in Korea. The new smart refrigerator offers updates and information that can be accessed via smartphones and tablets. It offers three power the Smart Grid-ready.

The smart fridge also comes with Smart Adapt, with the latest upgrades, features and options." of daily schedules and dispenses regular weath

members can turn the fridge's LCD screen into a



Appliance controller developed at PNNL senses arid conditions by monitoring the frequency of the system and provides automatic demand

> Within the North American power disturbance of 60-Hz frequency

of disruption.

is an indicator of serious

between supply and demand that, if unarrested, leads to a blac can be installed in household appliances and turn them off for seconds to allow the grid to stabilize. The controllers can be pi in fractions of a second when a disturbance is detected, where come up to speed. They can even be programmed to delay rest after a power outage to ease power restoration.

- More reliable power grids are less costly to run
- Smaller electricity bills for consumers
- More efficient power plant use
- A foundation for future grid management



Grid Friendly Appliance™ Controller COOKING 13:00-21:00 13:00

Patent(s) Issued Available for licensing in all fields

The Grid Friendly response in times



researchers at Pacific Northwest National Laboratory may help solve the nation's overworked electricity grid. Called The Gri Friendly™ Appliance Controller, the circuit would turn normal household appliances in that would better regulate energy usage ar prevent local and national blackouts

A coin-sized integrated circuit developed I

00:00

13:00

COOKING 13:00-21:00 20:03

COOKING 13:00-21:00 20:08

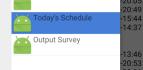
COOKING 13:00-21:00 14:49

COOKING 13:00-21:00 13:35

Set 21-03-2017's Schedule **Action Name** cooking TIME RANGE START TIME RANGE END

ADD

20-03-2017's Schedule Set Tomorrow's Schedule ACTION START - END OPTIMAL TIME Tomorrow's Schedule



14:41 14:53

◁

FLEXIBILITY

(Home) Charging SAE J1772

120/240V

Smart Charger Controller

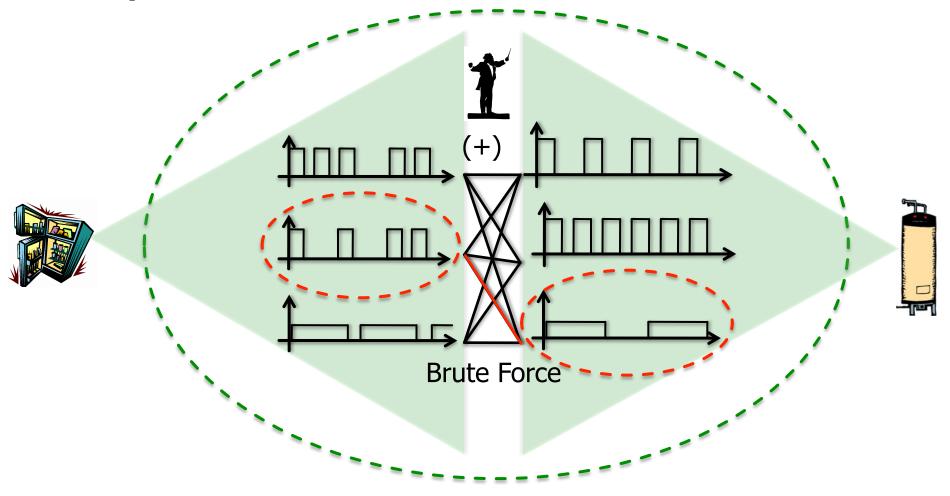
8881

4:51

0



Computational Model



Complexity = # of possible plans^{# of devices}

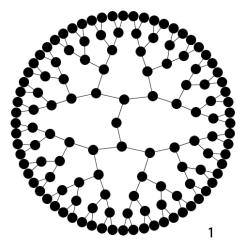
Decentralized Algorithm

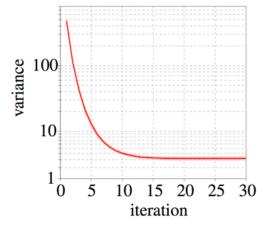
(Self-)organization in a tree topology bottom-up aggregation & decision-making



Selection function: e.g. Minimum variance, match target signal

- 1. Bottom-up phase: form candidate solutions
- 2. Top-down phase: back-propagate effective solutions
- 3. Repeat to learn





Monotonously improving/learning solutions

Local information



Experimental Evaluation



1000 households

Time: 11:00-23:00

13 plans, generated by load-shifting

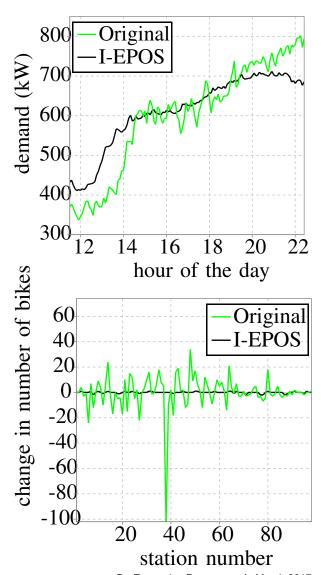




1000 users

Plan generation using historic trips

Time: 08:00-10:00

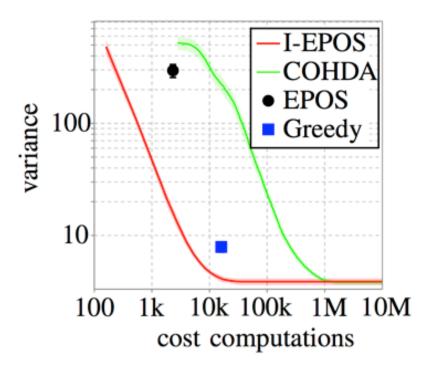




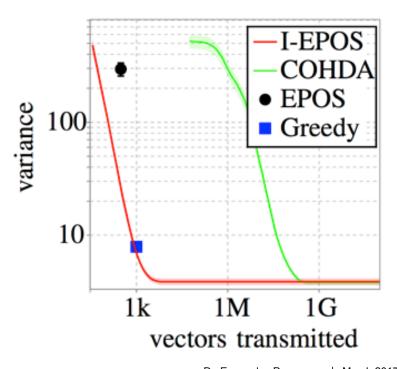
Comparison with Related Work

Superior performance even when compared to systems storing complete information & performing brute-force operations

Computational cost



Communication cost





Future Work & Research Direction

Living lab – Mobile social experiments, hackathons, smart city applications

Community-based cloud infrastructure personal data stores & public good services

Adaptive decentralized resource allocation in clouds with EPOS

Fully **decentralized deep learning** algorithms



References

General Relevance

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- **Evangelos Pournaras**, Jovan Nikolic, Alex Omerzel, Dirk Helbing, *Engineering Democratization in Internet of Things Data Analytics*, in the proceedings of the 31st IEEE International Conference on Advanced Information Networking and Applications-AINA-2017, Taiwan, March 2017 © IEEE
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Optimization & Learning

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Questions?

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nervousnet.info

dias-net.org

epos-net.org







The Trade-off of Data Sharing

		•	
Symbol	Interpretation	$\frac{k_{i,}}{2}$	<u>Entropy</u>
i	An agent index An apperblindex An apperblindex An apperblindex	$H(D_{i,e}) = -$	$\sum p_{i,e,j} \log_2 p_{i,e,j}$,
е	An epoch index		
t	A time index within an epoch $m{\eta}$	j=	:1 (
T	Epoch duration 1	$1 \stackrel{I}{\rightleftharpoons}$	1 if $c_{i,a,i} = d_{i,a,t}$
$R_{i,e}$	Sequence of raw data $\epsilon_{e,t} = -$	$p_{i,o,i} = \frac{1}{n} \sum_{i=1}^{n} p_{i,o,i}$	$a_t = \begin{cases} 1 & \text{if } c_{i,e,j} = d_{i,e,t}, \\ 0 & \text{if } c_{i,e,j} \neq d_{i,e,t}, \end{cases}$
$r_{i,e,t}$		$T \stackrel{Fi,e,j}{\smile} T$	$r_t = 1$
S _{i,e}	Sequence of summarized data $i=1$	t=1	$\bigcup \Pi \ c_{i,e,j} \neq u_{i,e,t},$
S _{i,e,t}	A record of summarized data ι – ι	[v, -c, -]	•
$f_{s}()$	Summarization function	$ r_{i,e,t} - s_{i,e,t} $	
j	An index for a possible summarization value $\epsilon_{i,e,t} = -$	$ r_{i,e,t}-s_{i,e,t} $	
$C_{i,e,j}$	A possible summarization value	$ r_{i,e,t} $	
k _{i,e}	The number of possible summarization values		
1	Number of epochs	Diversity	V
$lpha_{i,e}$	Summarization metric		
$D_{i,e}$	Sequence of raw or summarization data	$eta_{i,e} = rac{1}{T-1} \sum_{t=1}^{T-1} m_t, m_t = 0$	$11 \text{if } d_{i,a,t} = d_{i,a,t+1},$
$H(D_{i,e})$	Entropy	$\beta_{i,j} = \frac{1}{m_{i,j}} \sum_{i=1}^{n} m_{i,j} m_{i,j}$	
$p_{i,e,j}$	Probability of a possible value occurring in an epoch	T=1	_
n_t	Occurrence or not of possible value at time <i>t</i>	t=1	$0 \text{if } a_{i,e,t} \neq a_{i,e,t+1},$
$oldsymbol{eta_{i,e}}$	Diversity		
m_t	Change or not between two consecutive time periods t and t +	₁ Global error	
$\epsilon_{i,e,t}$	Local error	1 11	
$\varepsilon_{i,e}t$	Global error	$\frac{1}{1} r_{i,e,t} - \sum_{i=1}^{n} s_{i,e,t}$	
n	Number of participating citizens $c = \frac{1}{2} = \frac{1}{2}$	$i \mid l,e,l \mid l=1 \exists l,e,l \mid$	Rewards
$\epsilon_{e,t}$	Average local error among citizens - C, L	$\overline{\sum_{n}}$,	
γ_e	Total rewards that data aggregators are willing to provide	$ \rangle_{i=1} r_{i,e,t} $	$\gamma_* * P_*(\alpha_{**})$
$D \cap A$	Drabability density function for rewards		$1/ \times P_{*}(\Omega \cdot)$

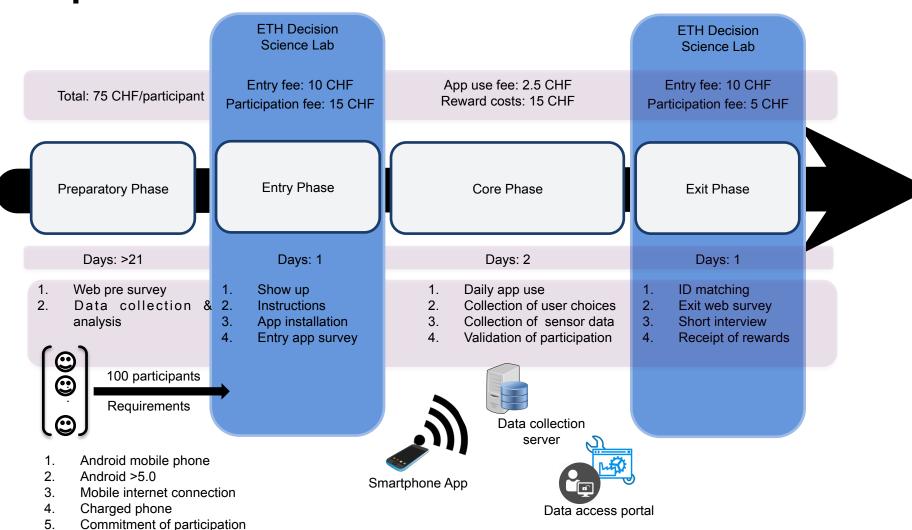
$$\gamma_{i,e} = \frac{\gamma_e * P_{\mathsf{r}}(\alpha_{i,e})}{n * P_{\mathsf{s}}(\alpha_{i,e})}.$$

Probability density function for rewards Number of discrete participation levels Probability density function for summarization

Rewards provided to agent i



Experimental Process



in entry, core & exit phases