

Edge Analytics for Privacy & Performance

Hamed Haddadi

Queen Mary University of London

The Data Ecosystem

Data about us:



Data generated by us:



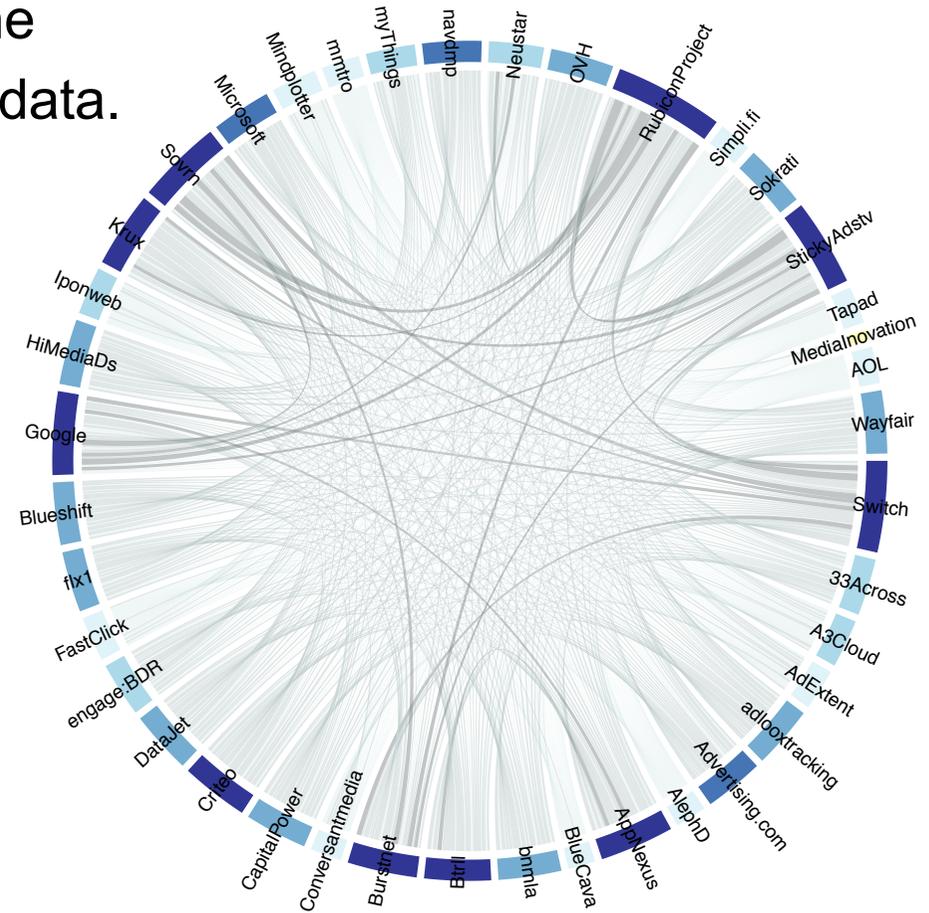
Data around us:



Data About Us

We found **thousands** of trackers across the world who follow our clicks and trade our data.

Our digital footprint include data we are not even aware of. Hence Provenance is a major issue.

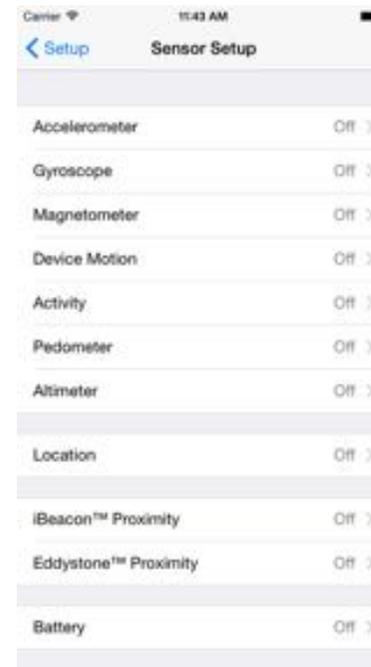
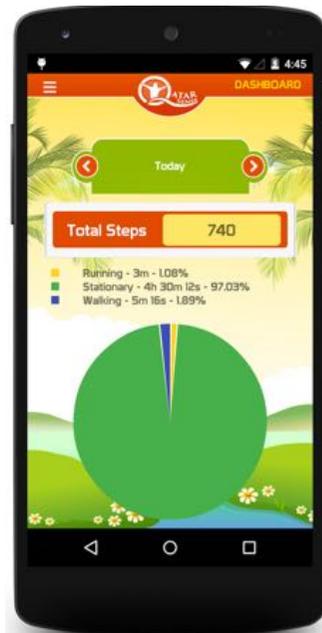


TMA 2014, PAM 2016 and “Anatomy of the Third-Party Web Tracking Ecosystem” on MIT TR 2014.

- Ad Blocking is not the long-term solution, see: “Ad-Blocking and Counter Blocking: A Slice of the Arms Race”, USENIX 2016.

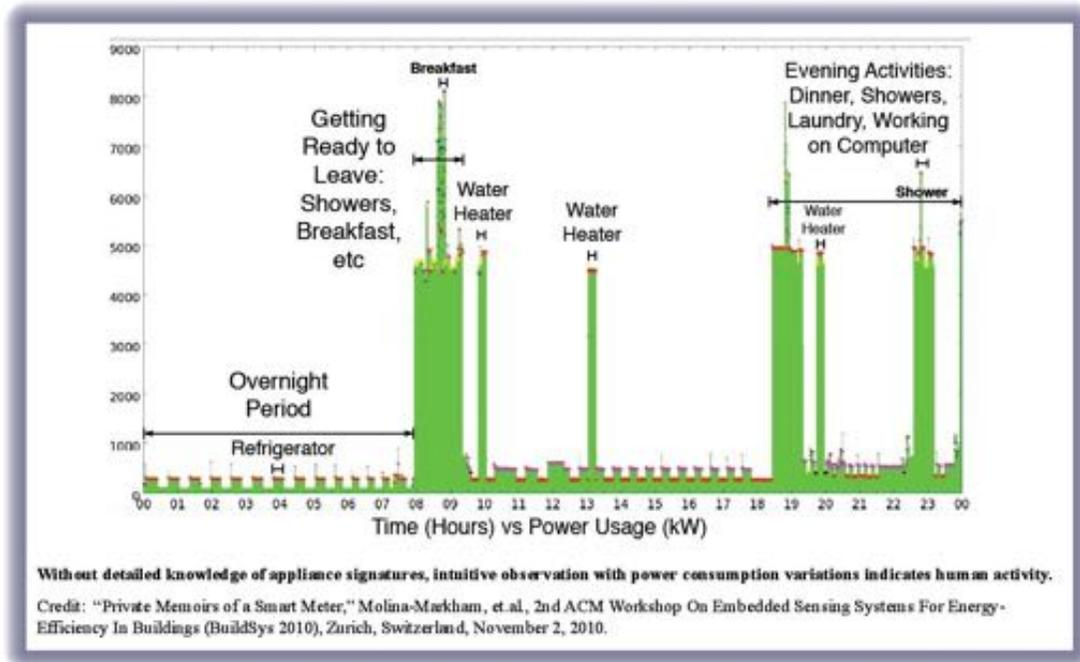
Data Generated by Us

- Online Social media
- Wearable devices
 - Signals indicative of physical & mental health
 - Largely suffering from data isolation and poor user interaction (see publications: qmwearables.eecs.qmul.ac.uk)



Data around us

- IoT devices
- Cyber Physical Systems



www.connectedseeds.org/about/sensors



CPS Applications and Challenges

- Opportunities
 - Infrastructure monitoring
 - Understanding individuals' wellbeing & public health
 - Enabling personalised services
- Challenges
 - Real-time control & adaptation
 - Accountability & liability
 - Algorithmic bias, price discrimination, public exposure,...
 - Same with IoT/mobile data: see "Privacy Leakage in Mobile Computing: Tools, Methods, and Characteristics" 2014.

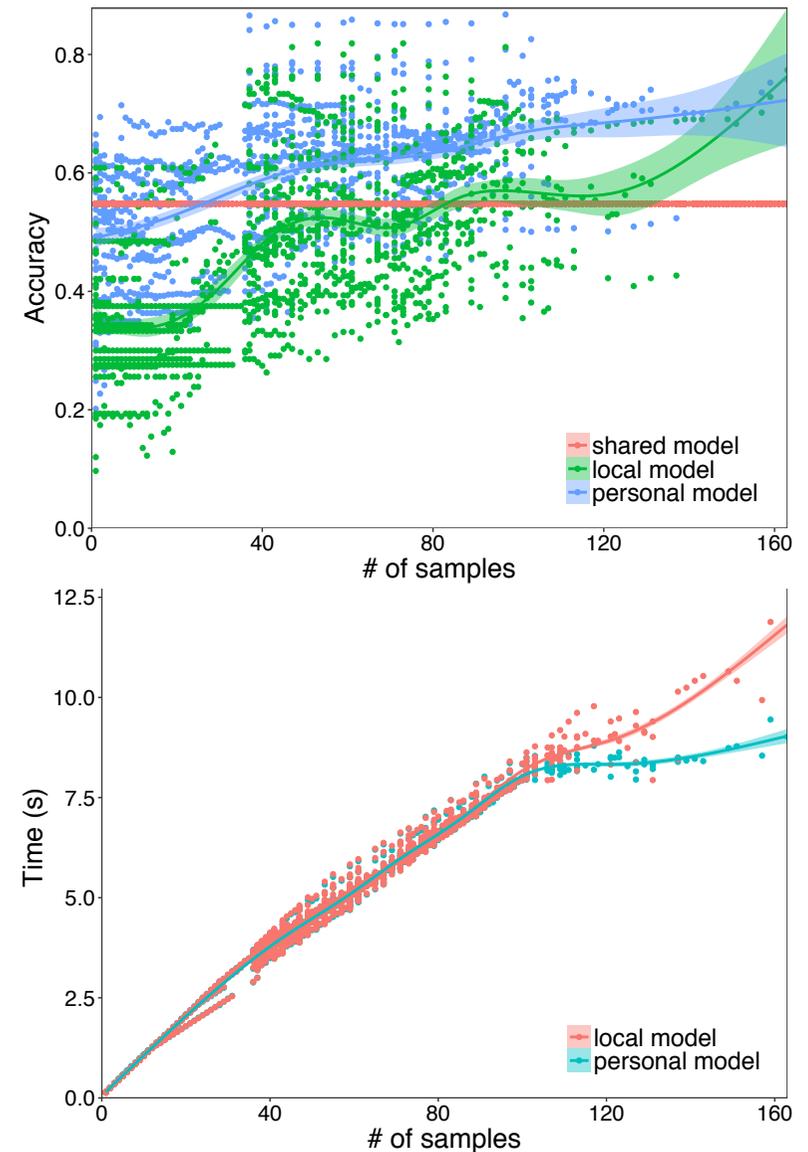
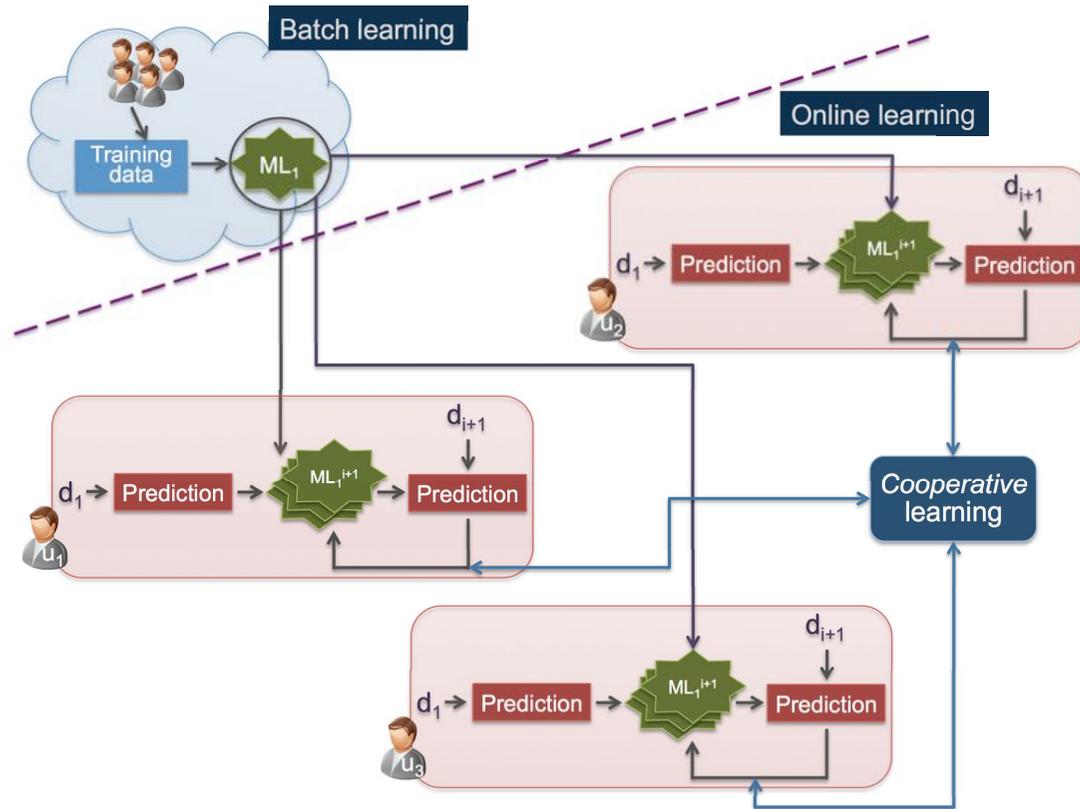
Can we do detailed, user-centric, contextual analytics without privacy disasters and legal challenges?

Outline

- CPS introduction & Motivations
- Privacy-preserving sensing & analytics
- The Databox platform

Cooperative learning

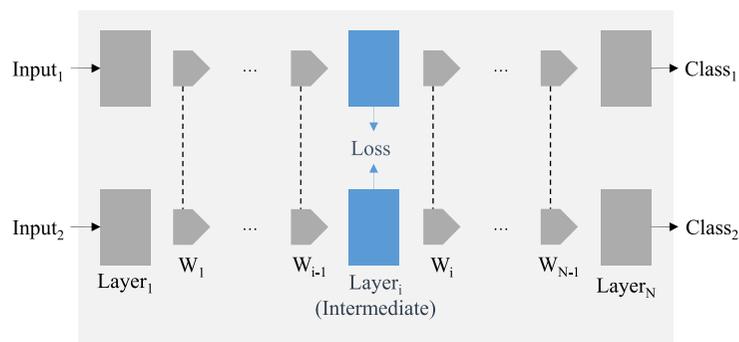
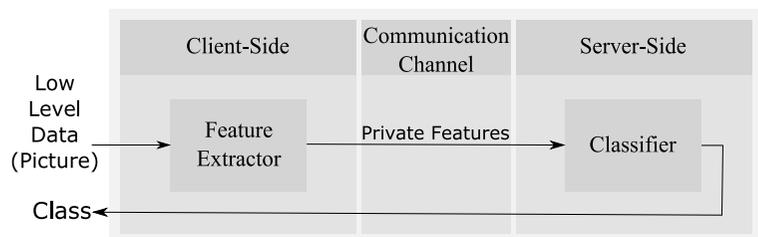
Case study: smartphone activity recognition



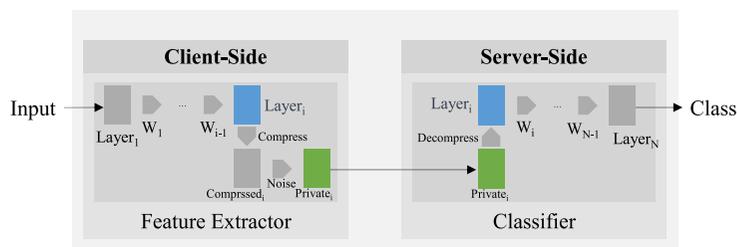
“Personal Model Training under Privacy Constraints”, on ArXiv 2017

Edge computing paradigm

Case study: can we do gender detection without face recognition?

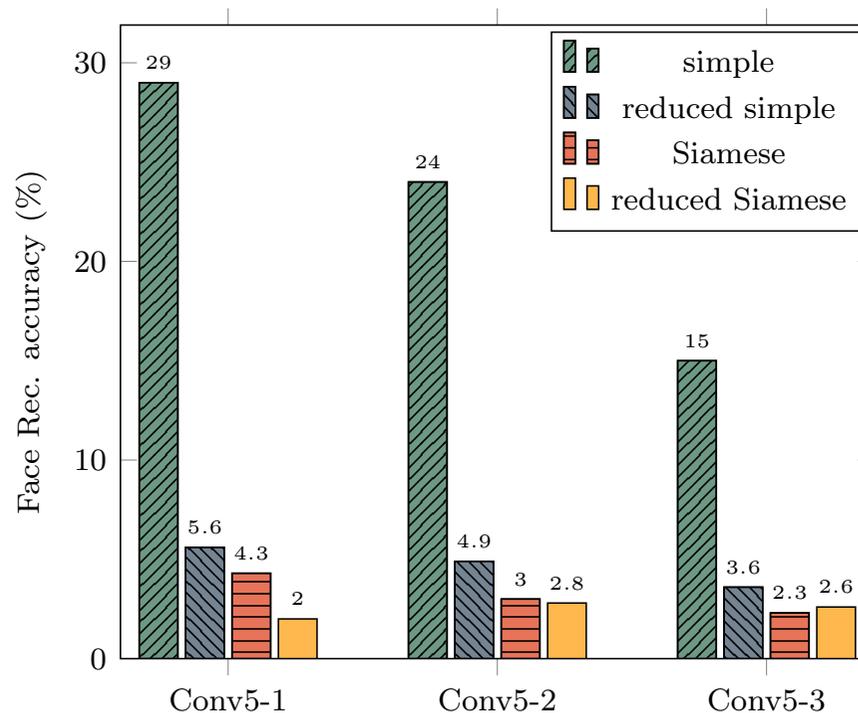


(a) Training advanced embedding with Siamese structure where we have identical network structure and weights connected by dashed lines are equal.



(b) Using advanced embedding (with PCA projection and noise addition in client side and reconstruction and classification in server side)

Accuracy on LFW			
	Conv5-1	Conv5-2	Conv5-3
simple	94%	94%	94%
reduced simple	89.7%	87%	94%
Siamese	92.7%	92.7%	93.5%
reduced Siamese	91.3%	92.9%	93.3%



“A Hybrid Deep Learning Architecture for Privacy-Preserving Mobile Analytics” on ArXiv 2017

Outline

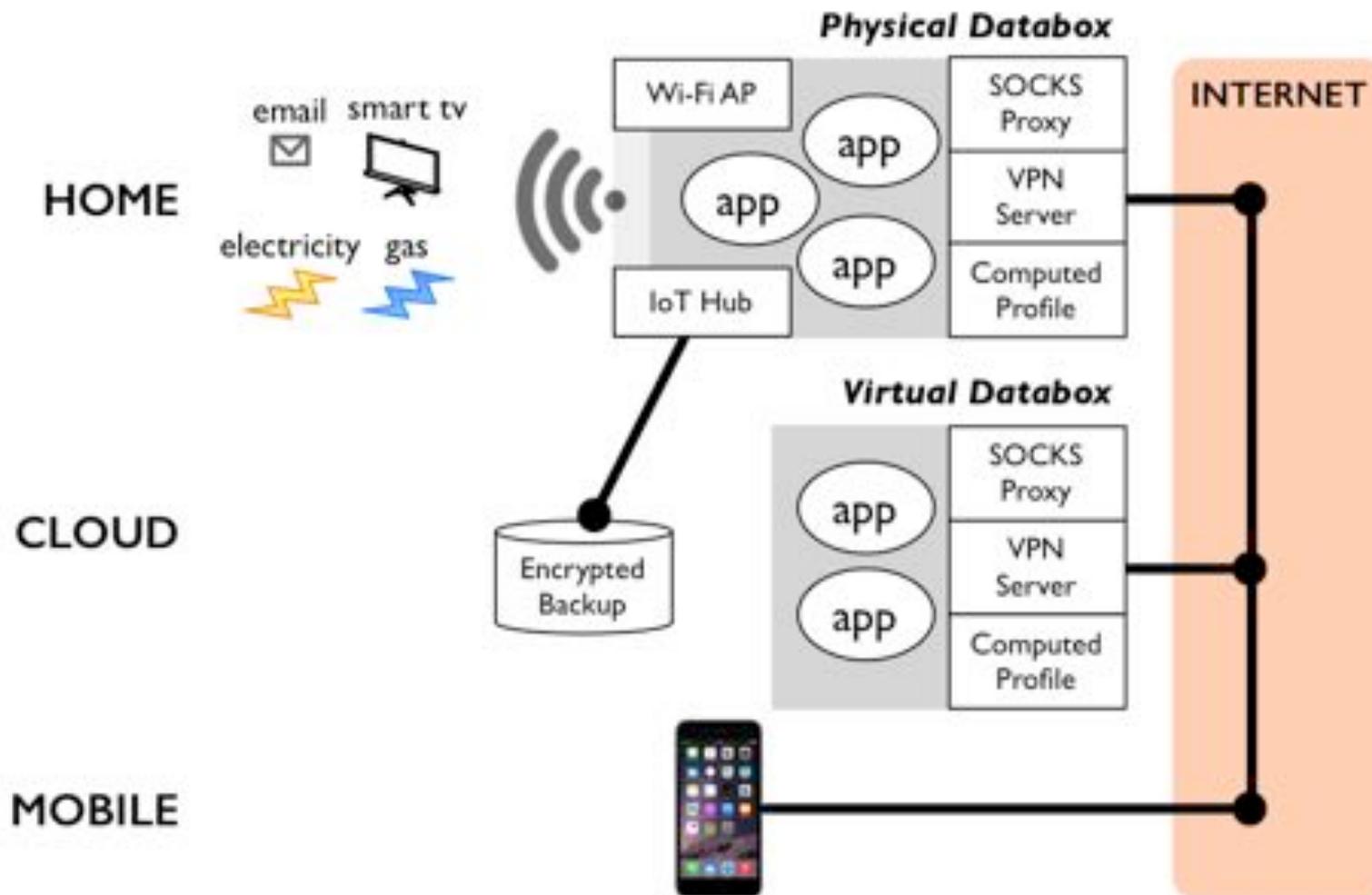
- CPS introduction & Motivations
- Privacy-preserving sensing & analytics
- **The Databox platform**

Databox vision

- An open-source personal networked system:
 - collates, curates, and mediates access to our personal data.
 - Enables interaction, sense-making, and privacy-preserving analytics on personal data, with potential wider societal benefits (Haddadi et al., CCR 2013)
- **Not yet another data silo:**
 - cooperative design approach, involving engagement with **all** stakeholders (sources, collectors, processors, organisations, and subjects)

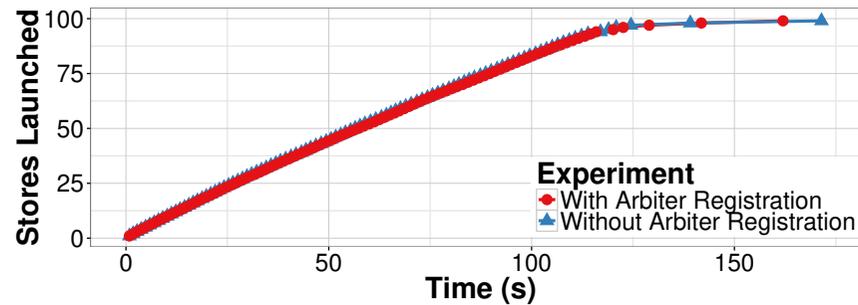
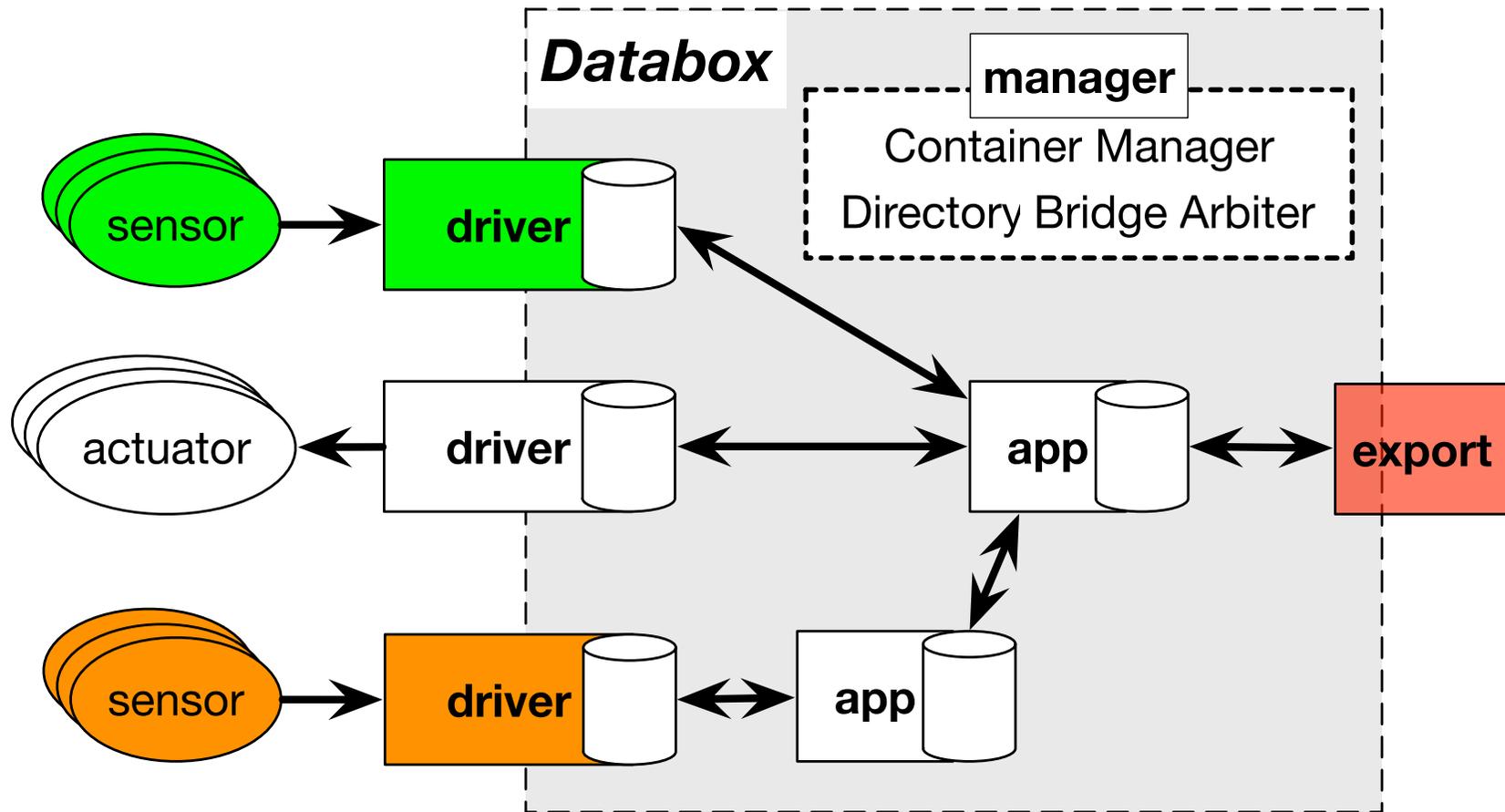
See Haddadi et al., "Personal Data: Thinking Inside the Box", (MIT-TR, Aarhus 2015)

Privacy-Aware Personal Data Platform

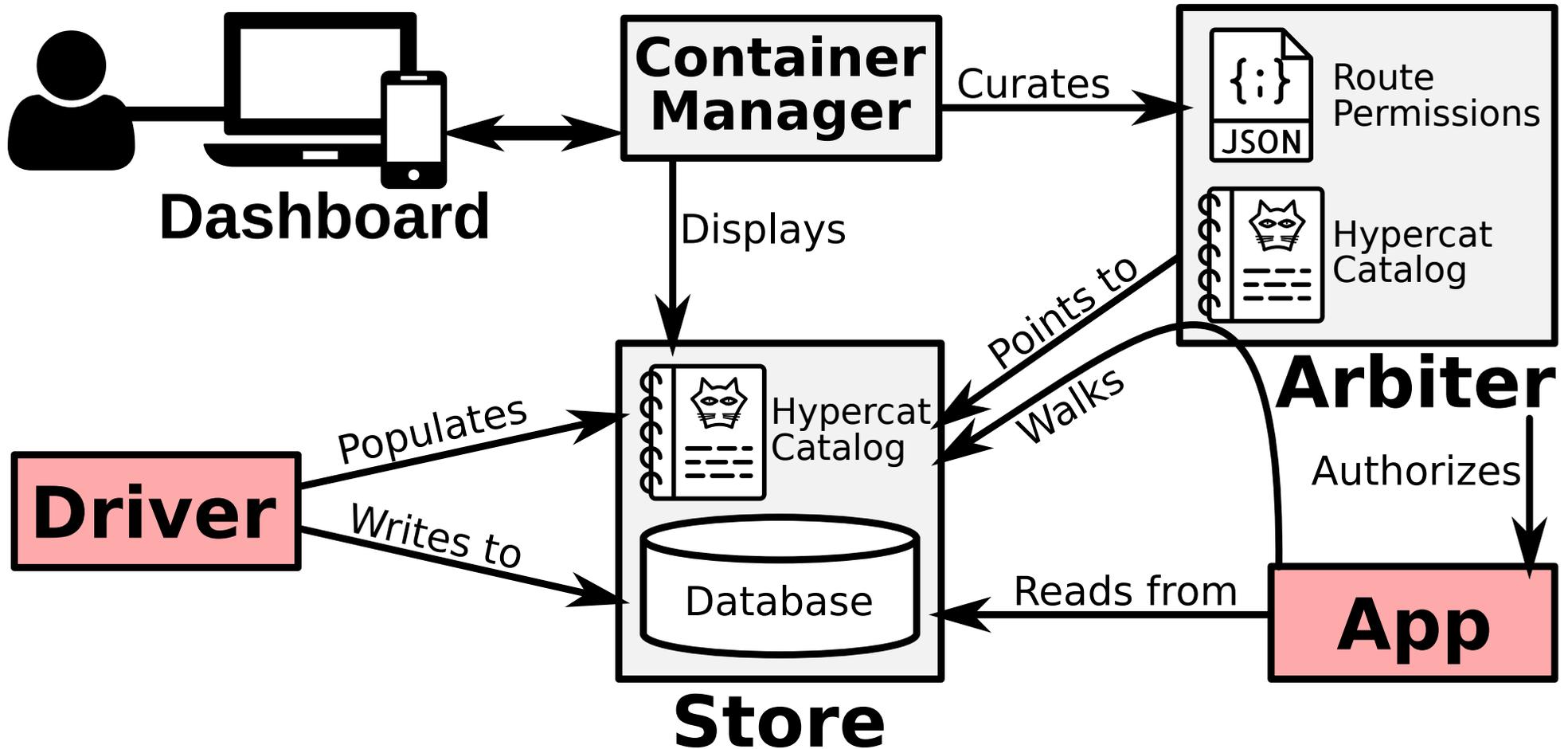


EPSRC [Databox](http://www.databoxproject.uk): Privacy-Aware Infrastructure for Managing Personal Data
3-years, started October 2016: www.databoxproject.uk

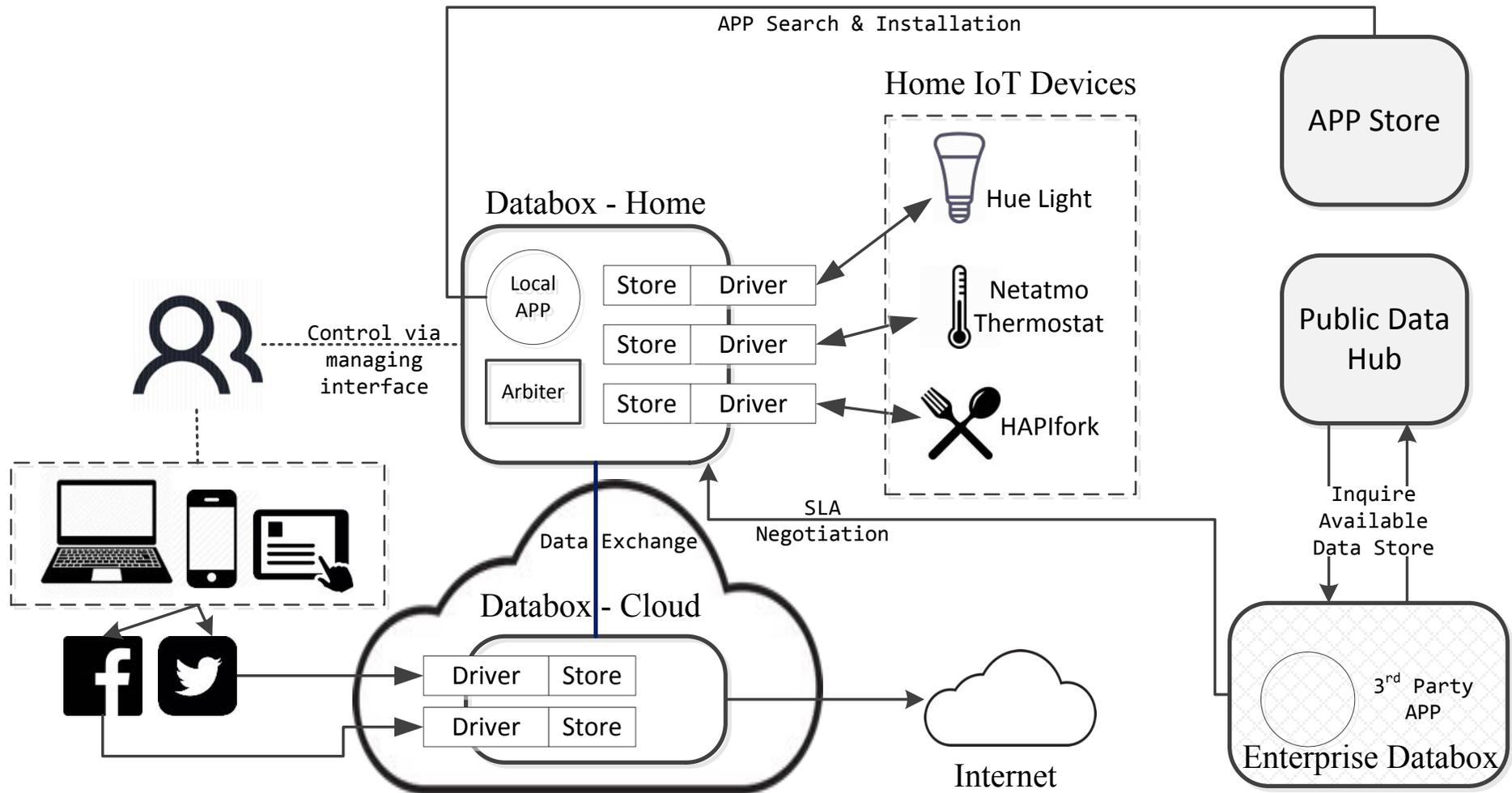
System architecture



Interaction between the components

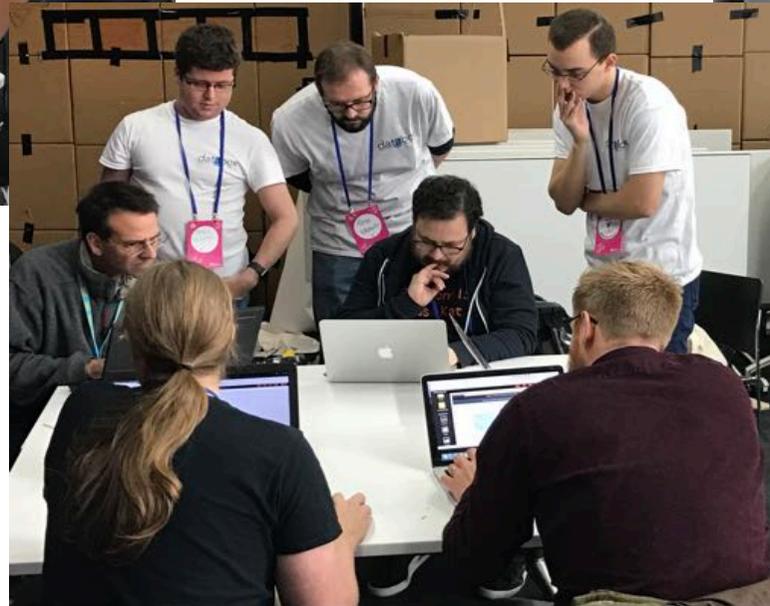


Databox and apps ecosystem



Code available on <https://github.com/me-box/>

Developer Community Engagement



www.databoxproject.uk



Conclusions

- Personal Data analytics face complex challenges and we need new approaches for data utilisation.
- Databox, edge-computing, and user-centric processing methods are timely enablers in this direction
- Interesting new approaches for personal data, ambient sensing, actuation, and HDI

For more information, software, and papers:

<http://www.eecs.qmul.ac.uk/~hamed/>