Encouraging Acceptance of Smart Meters Through Privacy Preserving Machine Learning

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Motivation (Climate Change)

- Smart meter data contains an enormous amount of potential predictive power that will aid the **transition away from fossil fuel technologies** to cleaner and renewable technologies [1].
- Reliable forecasting will provide opportunity for more efficient optimisation of electricity grids to cope with **varying energy demand** and **increasing contributions of renewables in the energy mix**.
- Accurate forecasting is important here to understand how **demand is evolving with consumer behaviour change** (e.g. EV charging, electric heating and cooling).

Motivation (Privacy)

- Smart meter installation in most countries is an opt-in process and levels of adoption of smart meters remains low.
- **Data privacy and security concerns** are among the most cited reasons consumers give for **rejecting a smart meter** installation [2].
- High-resolution smart meter data is particularly sensitive as it can easily enable inference about household occupancy, lifestyle habits or even what and when specific appliances are being used in a household.
- The privacy concerns include **surveillance, selling data and illegal data acquisition & use.**

Proposed Solution

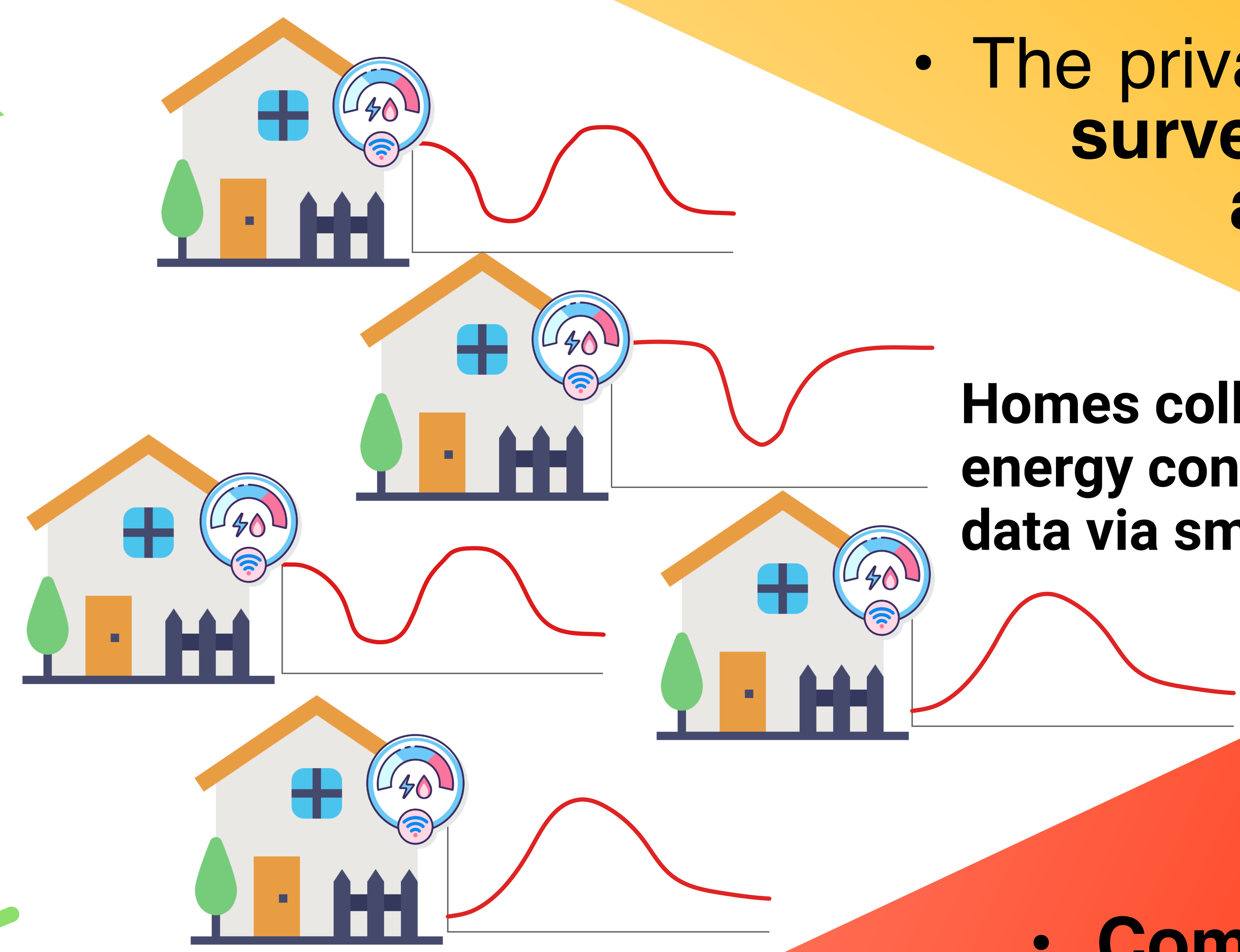
(Federated learning applied to energy demand forecasting)

Global model shared with clients

The datacenter orchestrates a training procedure whereby each smart meter (client) partially trains a **local forecasting model on its own data** and iteratively communicates its local model back to the datacenter to be **aggregated with other households**. Communication continues back and forth until the model converges. The **raw energy consumption data remains private** as it is never shared - only the model updates are.

Local models aggregated to form new global model

Partially trained local models shared back to the datacenter



Dataset

- Public dataset from the Low Carbon London project, led by UK Power Networks [3].
- Contains half-hourly energy consumption readings for **5,567 households** in London, UK between **2011 and 2014**.
- Data can be combined with historic weather data such as **temperature and humidity** - adds valuable signals into the forecasting model to improve accuracy.
- We aim to show that **short-term, medium-term and long-term forecasting models** trained using federated learning can compete with centralised learning whilst also preserving the privacy of consumers' energy consumption data.

Challenges

- **Communicating large models between rounds of training** - there is a significant increase in bandwidth in order to train a model using federated learning. This can be tackled by compressing the model updates prior to communication without much loss in model performance.
- **Lack of compute on current smart meters** - could be tackled by performing the machine learning tasks on more capable devices such as connected in-home display units.
- **Heterogeneity among clients** - federated learning works best when the data distribution among clients is similar. We'll make use of our previous work [4] to tackle issues of varying household energy consumption behaviours.

References

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