

Decision Making *in Robots and Autonomous Agents*

Security and Privacy: Introducing the Issues

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Correctness vs. Security

- Program or system **correctness**:
program satisfies specification
 - For reasonable input, get reasonable output
- Program or system **security**:
program properties preserved in the face of attack
 - For unreasonable input, output not completely disastrous
- Main difference: **adversary**
 - Active interference from a malicious agent
 - It is very difficult to come up with a model that captures all possible adversarial actions
 - Hence the need for discussion around models

An Ongoing Situation

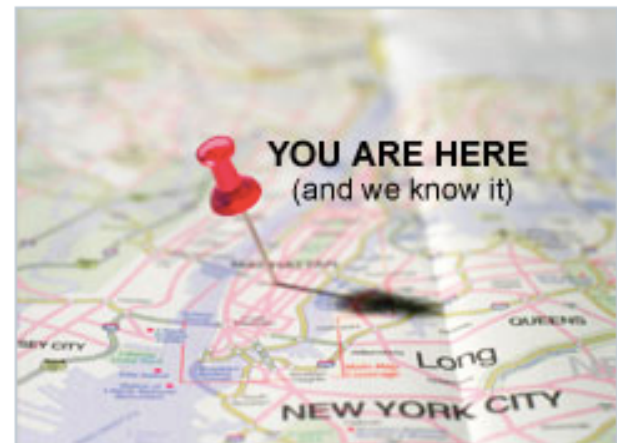
Senate introduces mobile location privacy bill

Consumer Reports News: June 16, 2011 02:23 PM

Yesterday, two U.S. senators proposed a bill that would require companies to obtain consent from mobile device users before sharing location-based information with third parties.

The bill, called the Location Privacy Protection Act of 2011, is sponsored by Senators Al Franken (D-Minn.) and Richard Blumenthal (D-Conn.). It would require companies to tell consumers when information about their location is being collected, and allow consumers to decide if they want that information to be shared, according to a press release on Franken's official website.

The legislation seeks to close a loophole in the Electronic Communications Privacy Act that allows smartphone companies, app companies, and phone companies that offer wireless Internet to disclose consumers' location information to third parties.



What kinds of data does Microsoft collect?

Microsoft collects data to help you do more. To do this, we use the data we collect to operate and improve our software, services, and devices, provide you with personalized experiences and to help keep you safe. These are some of the most common categories of data we collect.

Information from device sensors

Places you go



Windows 10 phones, tablets, and PCs come with sensors. That can be your phone's microphone or camera; an internal GPS sensor, and more.

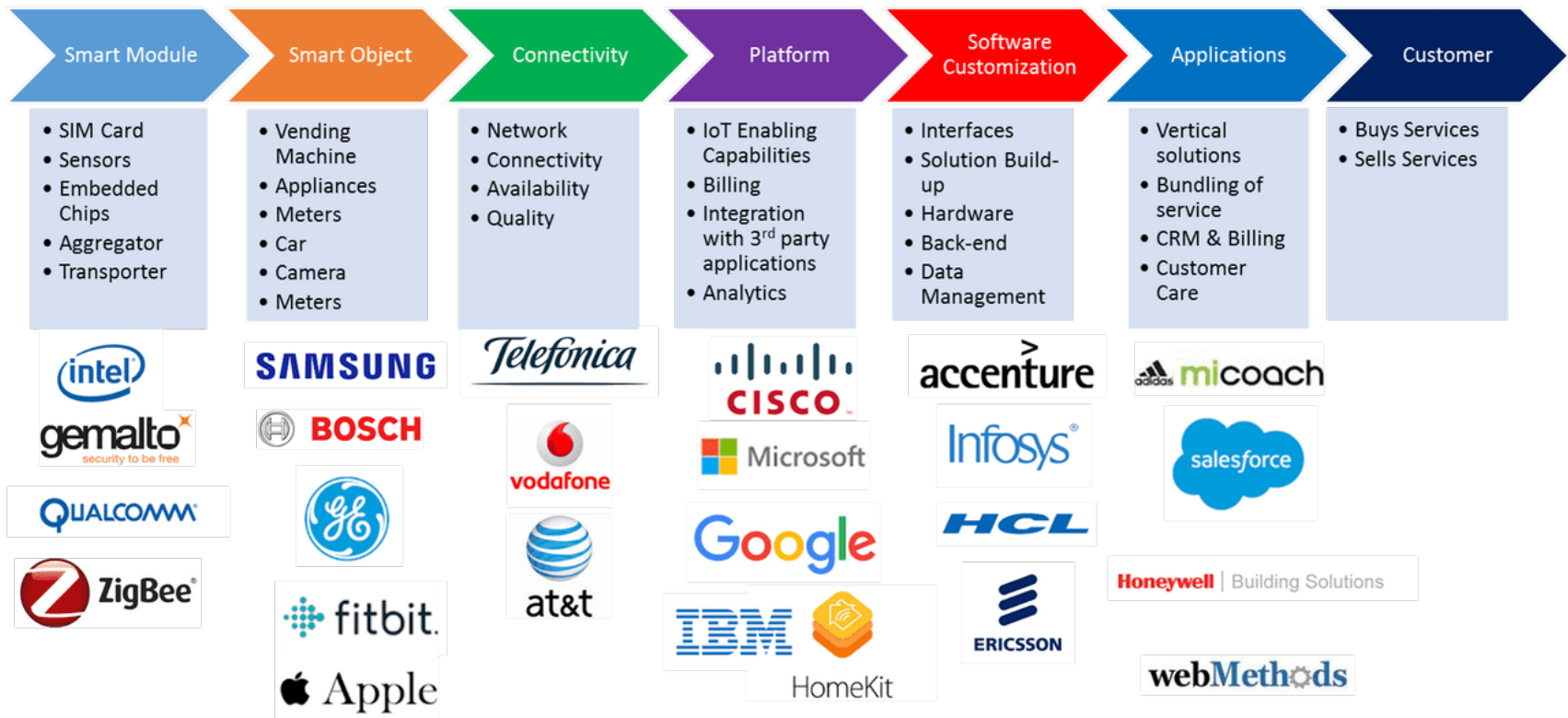
Location information helps us give you directions to the places you want to go and show you info relevant to where you are. For this, we use the locations you provide or that we've detected using technologies like GPS or IP addresses.

Detecting location also helps us protect you. For example, if you almost always sign in from Tokyo, and suddenly you're signing in from London, we can check to make sure it's really you.

Why do we Give it Away?!

Location Based Services

Internet of Things Value Chain



Note, the above is not an exhaustive list of companies and any company may have play in more than one component of value chain
 Copyright: Telecomcircle.com

Robots are Becoming Connected too!

What are the implications?



[<http://blog.ncpad.org/wp-content/uploads/2011/05/carebot.jpg>]

Already in your home:

<https://www.youtube.com/watch?v=H0h20jRA5M0>

Discuss...

1. What is “privacy”? How will you model it?
2. How will you ensure it through computational means?
 - We’ll say a bit about computational approaches to ensuring privacy
 - We will not spend much time discussing regulation, social engineering, etc. – topic of a whole other course!

Typical Situation: Location Privacy

- “... the ability to prevent other parties from learning one’s current or past location” [Beresford + Stajano]
- Principle is that the person whose location is being measured should control who can know it
- Many ways in which location information can be revealed:
 1. *When*: A subject may be more concerned about current or future location being revealed than past locations
 2. *How*: User may be comfortable if friends can manually request location but not want alerts sent automatically
 3. *Extent*: User may prefer to have location reported as ambiguous region rather than precise point

Computational Threats

- Consequences of location leak can range from uncomfortably creepy (being watched), to unwanted revelation (e.g., AIDS clinic, political locations), to actual physical harm.
- Computational attacks include:
 - Analysis of movement patterns, e.g., GPS traces
 - “Inference” attacks
 - Context inference
 - etc. (hard to make a finite list)

Analysis of Movement Patterns

Examples (often benign) from the literature:

- Look for places where GPS signal is lost three or more times within a given radius
 - Often happens because a building blocks the signal, so prompt user to enter location
 - Cluster such places and treat as labels
- Look for combinations of dwell time, breaks in time or distance, and periods of low GPS accuracy – treat as potentially significant locations
- Fingerprinting through the use of repeatable sets of in-range GSM and Wi-Fi base stations

“Inference Attacks”

Use inference algorithms (e.g., Bayesian inference) to go from evidence (observed traces of movement) to latent variables (e.g., locations of interest acting as goals)

Examples of how attacks get carried out:

- Using location measurements from an indoor sensor, examine where people in an office building spent their time, including e.g., who spent more time than anyone else at a given desk?
- Using week-long GPS traces from drivers in a city, algorithmically determine the home locations of drivers
 - Can be done to up to 85% accuracy

“Context” Inference

We can infer many more things beyond home location

Examples:

- Use GPS traces to infer, in real time, a moving person's mode of transportation (bus/foot/car)
- Predict their route based on historical movement data
- Very common to predict potential routes and target destinations (highly developed due to Uber, etc.)
- Can look at multi-agent data to identify events such as meetings and stopover locations

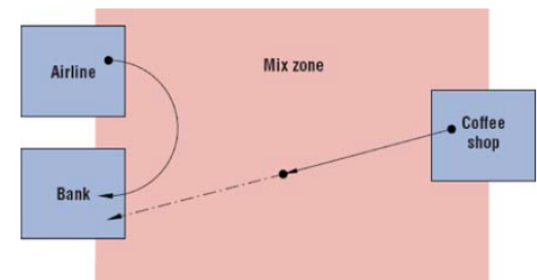
Computational Countermeasures: What could One Do?

Four main routes:

- Regulatory strategies: government rules on what is OK
- Privacy policies: trust-based agreements between individuals and those receiving the data
- Anonymity: use a pseudonym and create ambiguity by grouping with other people
- Obfuscation: reduce the quality of location data

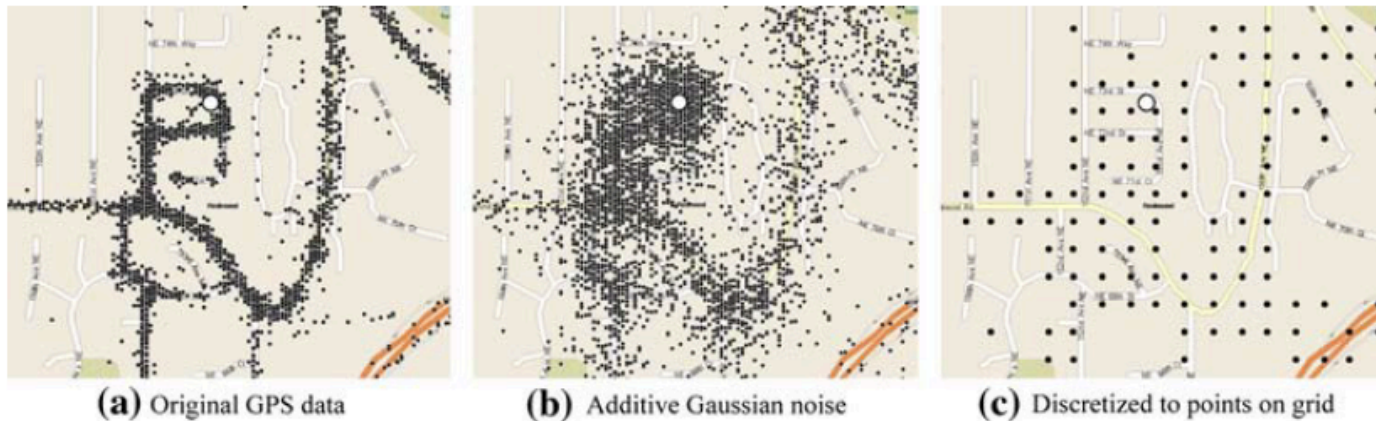
Anonymity

- Replace associated name with an untraceable ID, i.e., pseudonym (could be long-term or frequently changing)
 - What is the benefit of frequent change?
 - What is the practicality of using this as protection?
- Algorithmic ideas:
 1. K-anonymity: Instead of pseudonymously reporting exact location, person reports a region containing $k-1$ other people
 - Person can not be distinguished from $k-1$ other people
 - May need historical k-anonymity (when attacker can use traces)
 2. Mix zones: Give new pseudonym in regions
 - Defined as outside of well known labelled areas
 - Hard for attacker to guess identity in this zone



Obfuscation

- Degrading the quality of location measurements may reduce threats to location privacy
- Inaccuracy: give measurement different from actual
- Add additive noise and/or quantization
 - Is this enough? Discuss when and how much...



[J. Krumm, Inference attacks on location tracks. In Pervasive 2007, pp 127–143]

Modelling Location Privacy

What to include in the model:

- Set of mobile users
- Set of all possible traces (motion trajectories)
- Location Privacy Preserving Mechanism (LPPM) – the protocol
- Set of all observable traces

- Specification of the “Adversary”
- Specification of an evaluation metric, i.e., when is an adversary considered to have succeeded

Location Privacy Preserving Mechanisms

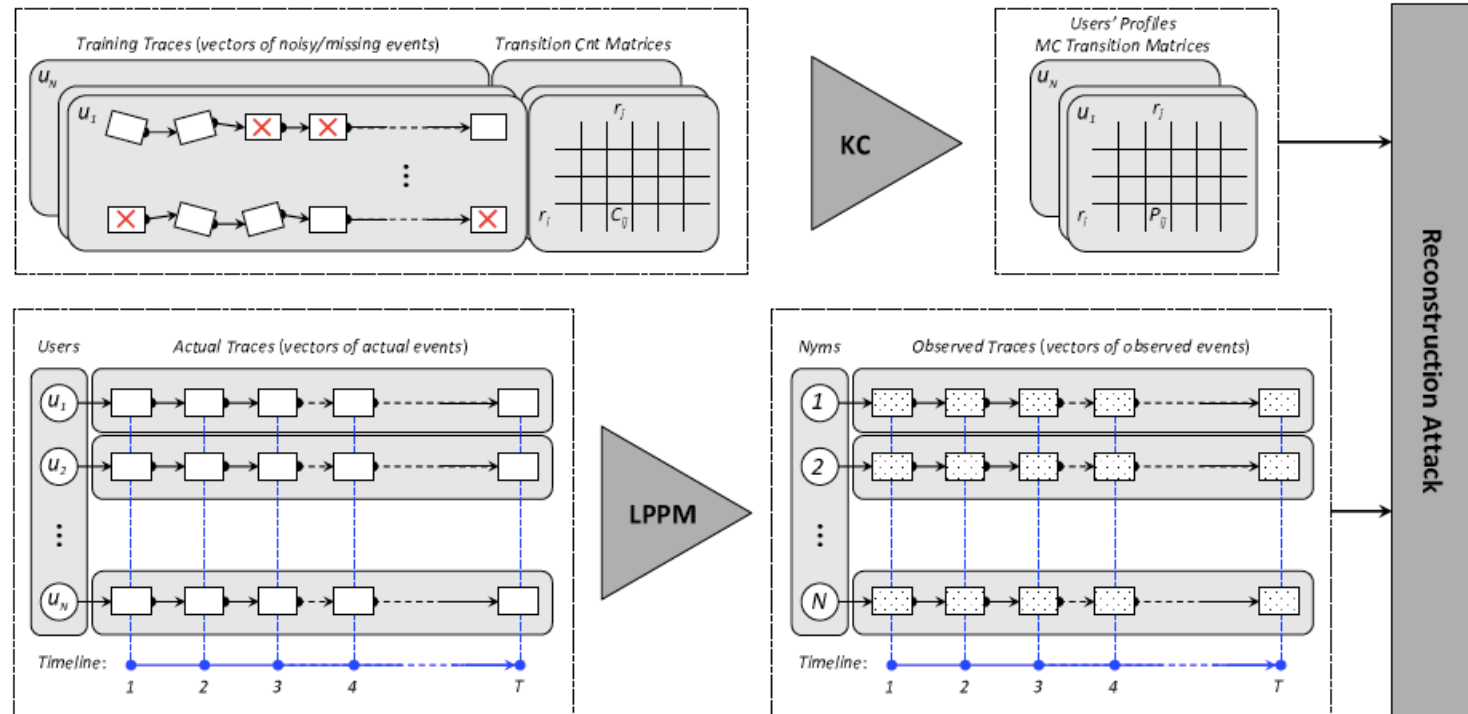
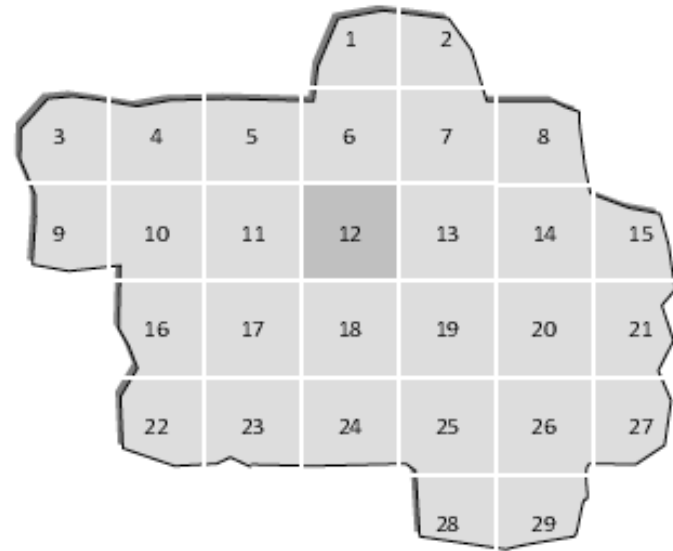


Figure 1. Elements of the proposed location-privacy framework. The users produce actual traces, which are then anonymized and obfuscated by the LPPM to produce anonymous observed traces. The attacker uses a set of training traces to create, via the knowledge construction (KC) mechanism, a mobility profile for each user in the form of a Markov Chain transition probability matrix. Having the user mobility profiles and the observed traces, the adversary tries to reconstruct (infer) the actual traces. The only element of the framework not shown here is the metric that evaluates the success of the adversary's reconstruction attack by comparing the results of the attack with the users' actual traces.

[R. Shokri et al., Quantifying location privacy, IEEE Symp. Sec. Privacy 2011]

Obfuscating Location

- Consider user u whose actual location is region r_{12}
- Different obfuscation methods will replace r_{12} with a different location pseudonym r'
 - Perturbation: $r' = \{14\}$
 - Add dummy regions: $r' = \{12, 15, 26\}$
 - Reduce precision, $r' = \{9, 10, 11, 12, 13, 14, 15\}$
 - Location hiding, $r' = \emptyset$



Main Inference Problem in Tracking Attacks

- Attacker has partial traces of location, possibly after some kind of obfuscation
- They need to solve an inference problem (for parameters of a Markov Chain, P), which involves first completing the traces
- Direct computation is intractable (sum of terms whose number grows exponentially with length of trace)
 - Use sampling based approximations

$$\Pr(P|TT, TC) = \sum_{ET} \Pr(P, ET|TT, TC).$$

Training traces

Transition counts

Estimated Completion of TT

Tools for Inference

- Gibbs sampling, create a homogeneous Markov Chain on the state space of P and ET in an iterative procedure:

$$\begin{aligned} P^{\{l\}} &\sim \Pr(P|ET^{\{l-1\}}, TT, TC) \\ ET^{\{l\}} &\sim \Pr(ET|P^{\{l\}}, TT, TC) \end{aligned}$$

- How them to sample from these?
 - Dirichlet prior or similar for rows of P
 - Bayes filter type mechanism for ET

Many Variations on this Theme of Inference Attacks

- Tracking attacks: Maximize a quantity of the form,

$$\arg \max_{\sigma, A} \Pr(\sigma, A | O).$$

to determine pseudonym permutation assignments (σ) and actual traces (A) given observed traces (O)

- Localization attack: More specifically, determine the probability of a user being at a location at a specific time (given some knowledge of user profile P^u),

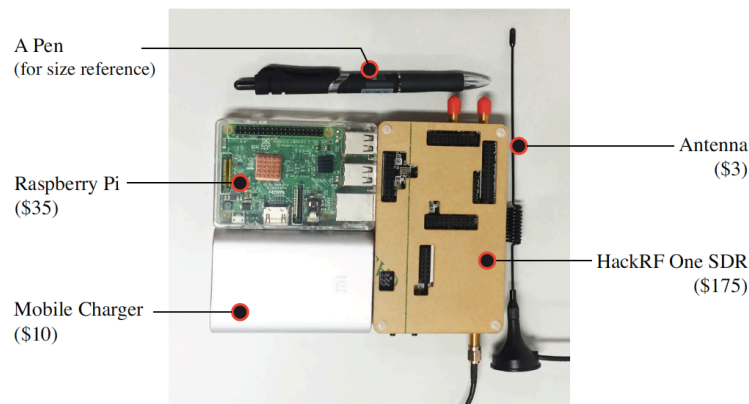
$$\Pr\{a_u(t) = r | o_u, P^u\}$$

Other Kinds of Attacks on Navigation Systems: Sensor Spoofing

- Spoofing attack: a situation in which a person or program successfully masquerades as another by falsifying data, to gain an illegitimate advantage.
 - Example is with GPS signals – used for localization
- GPS spoofing attack: attempts to deceive a GPS receiver by broadcasting incorrect GPS signals, structured to resemble a set of normal GPS signals, or by rebroadcasting genuine signals captured elsewhere or at a different time.
- These spoofed signals may be modified in such a way as to cause the receiver to estimate its position to be somewhere other than where it actually is, or to be located where it is but at a different time, as determined by the attacker.

Examples of Attacks

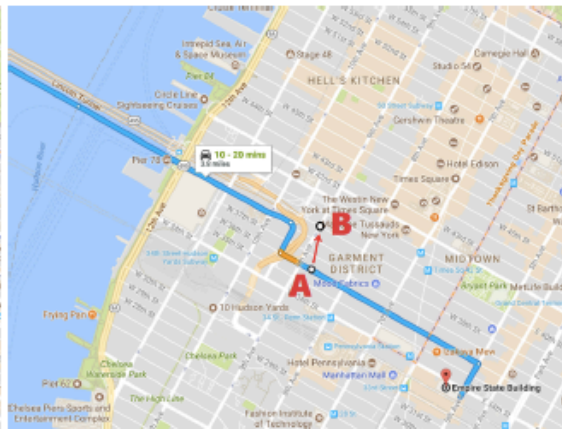
- Targeting drones and ships that depend on GPS for path planning, e.g., Humphreys et al. demonstrated a successful GPS spoofing attack against drones in 2012.
- In 2013, a luxury yacht was intentionally diverted from Monaco to Greece by spoofing its receiving GPS signals.
- Recent works have targetted systems in the open environment (e.g., open air/water) such as drones and ships where a simple GPS change could (stealthily) steer their navigation.



An Attack Example



(a) Original navigation route $\Gamma : P \rightarrow D$



(b) Ghost location B



(c) Actual path of the victim $A \rightarrow C$

The victim's original navigation route is P to D ;
At location A , the spoofer sets the GPS to a ghost location B which forces the navigation system to generate a new route B to D .
Following the turn-by-turn navigation, the victim actually travels from A to C in the physical world.

[Zeng et al., USENIX Security Symp. 2018]