An investigation into membership inference attacks on location data

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Problem statement

Can we use the valuable data that is collected by online services without giving up peoples private information?

Privacy for location data

- Every point can be sensitive, and may or may not be unique to an individual.
- Classical anonymization methods (k-anonymization, pseudonymization) fall short.
- **The classical notions of anonymization need to be redefined and measured differently.**

Aggregate statistics for location data

Definition: *Aggregate statistic*

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (1)$$

- Don't *directly* reveal information about any one person.
- Have been put into practice by companies who release data about their customers [**?**].
- But ...

Pyrgelis et al. 2017 [?]

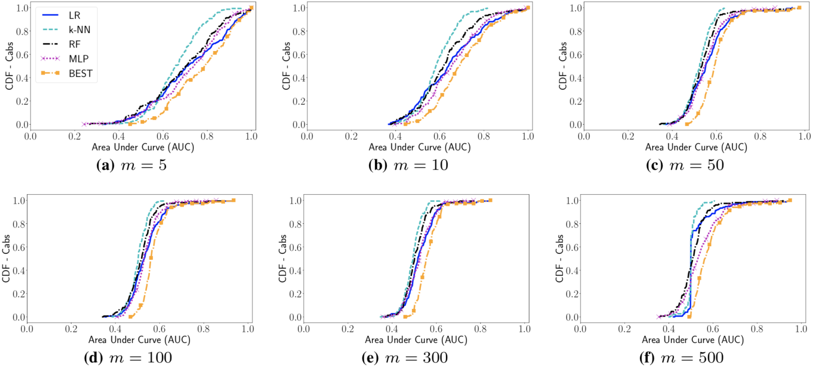


Figure: Different locations than released prior against the SFC data set: Adversary's performance for different group sizes.

Contributions

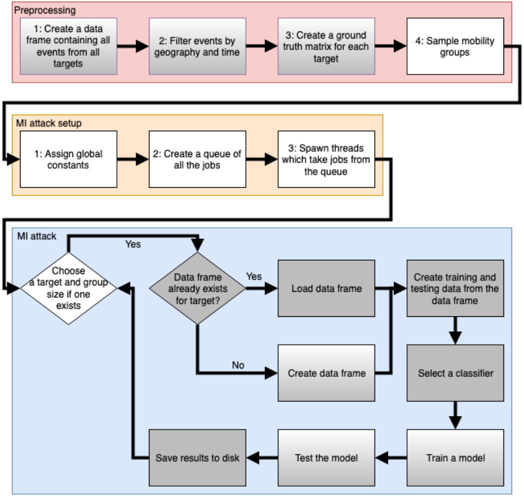
We look at . . .

1. Aggregation size vs accuracy of MI;
2. Defenses;
3. Attack profile;
4. 75 % run time reduction;
5. No need for geo-coordinates.

Data sets

	San Francisco cabs (SFC)	Call detail records (CDR)
Users	534	153,997
Span	1 month	1 month
Geography	Downtown San Fran	1 city
ROIs	100	220
Reports	`(Lat, Long)`	Antenna ID

Attack overview



Attack overview

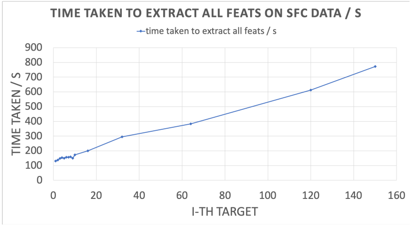
Name	**Adversary knowledge**
SUBSET OF LOCATIONS	Real locations of a subset of individuals
SAME LOCATIONS	Participation in groups also used in T_I.
DIFFERENT LOCATIONS	Participation in groups not used in T_I.

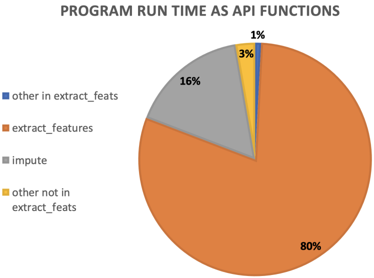
Modifications

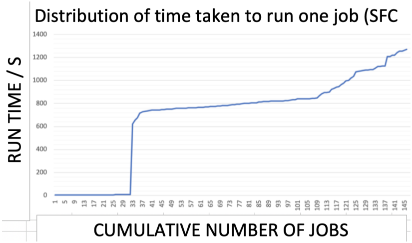
Why profile?

- Understand the resource constraints;
- Understand how the attack works;
- Identify potential problems in advance.

Profile of the original attack







Optimizations

What did we learn?

1. The program is CPU bound;
2. Data frame operations are expensive;
3. The program scales poorly for big data sets.

Optimizations

How can we improve the attack?

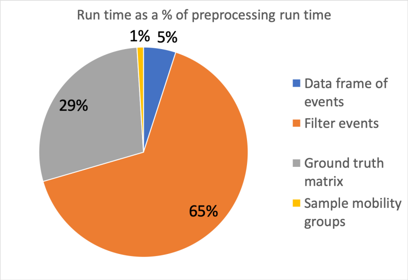
1. Introducing multithreading (attack) and multiprocessing (preproc);
2. Choosing the optimal number of threads and processes;
3. Optimizing data frame operations.

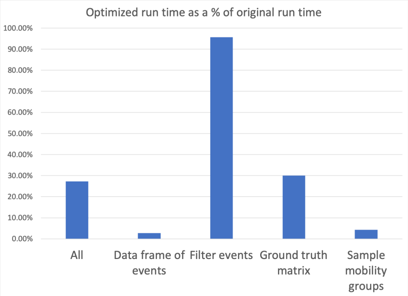
Evaluating our optimizations

Either:

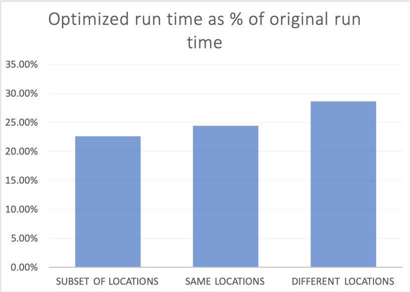
1. The attack runs "fast enough" to collect enough good results;
2. The program bottleneck is due to hardware, not badly optimized code.

Evaluating our optimizations





Evaluating our optimizations



Functions which take up the longest run time:

- `threading.wait`
- `thread.lock.acquire`

$\Longrightarrow$ the program is now IO bound.

Extending the input space

Pyrgelis et al.'s attack code needs geo-coordinates in order to work.
But the CDR data set uses anonymized locations.

Therefore:

1. Make config files specific to the data set;
2. Branch in preprocessing for data frame operations;

Measuring success

1. Type checking;
2. Unit testing;
3. Dummy data;
4. Real life.

Reimplementation

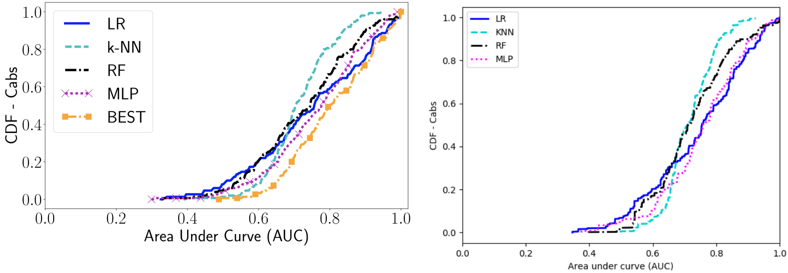


Figure: SAME LOCATIONS on SFC data with $m = 5$

Reimplementation

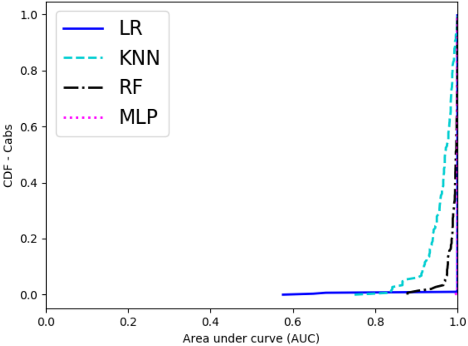
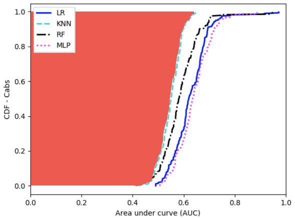


Figure: SUBSET OF LOCATIONS on SFC data with $m = 50$

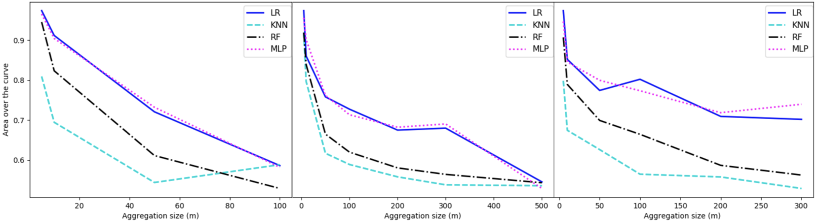
Measuring attack power

Definition: *Area over the curve (AOC)*

$$\mathrm{AOC}(x) = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{2}$$



Attack power and aggregation size



(a) SUBSET OF LOCATIONS (b) SAME LOCATIONS (c) DIFFERENT LOCATIONS

Figure: AOC of different classifiers against aggregation size for attacks on SFC data.

Attack power and aggregation size

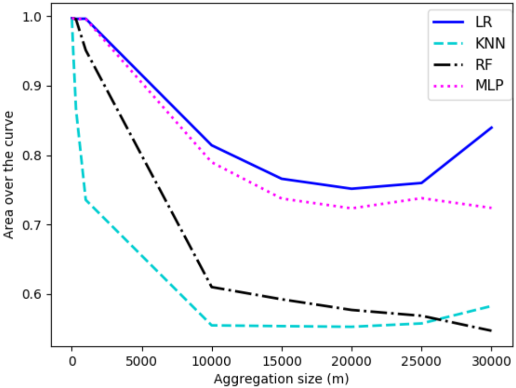
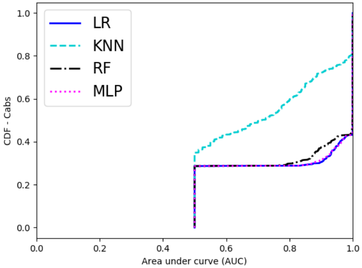
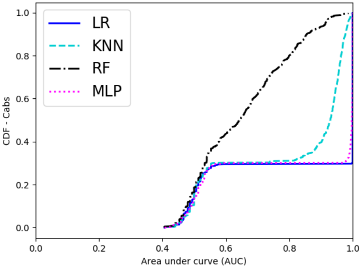


Figure: AOC of different classifiers against aggregation size for attacks on CDR data.

Defenses (SFC)



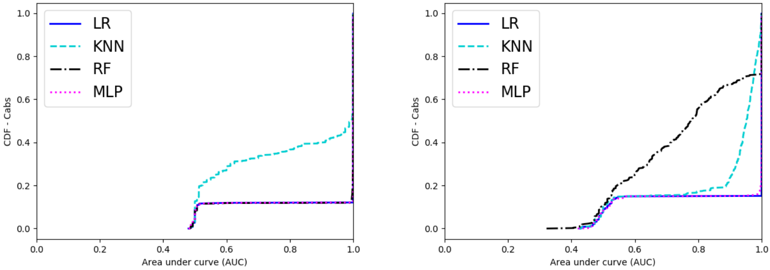
(a) $m = 5$



(b) $m = 100$

Figure: Modal ROI reports (WINNER TAKES ALL) per epoch.

Defenses (SFC)

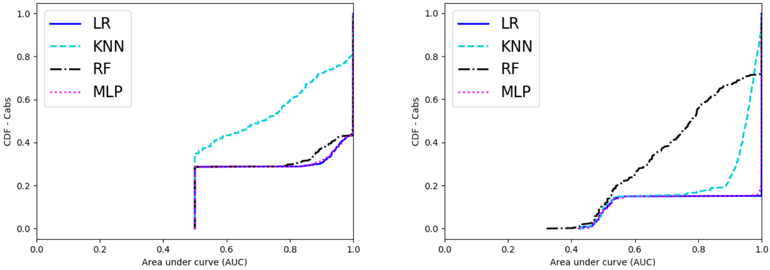


(a) $m = 5$

(b) $m = 100$

Figure: Random ROI reports per epoch.

Defenses (SFC)



(a) $m = 5$ (b) $m = 100$

Figure: Comparison between modal and random ROI reports.

Defenses (SFC)

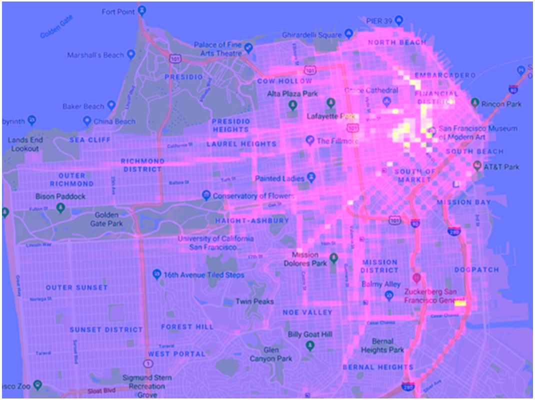


Figure: Aggregate taxi traffic on the San Francisco area between May 19 and June 10, 2008 [?]

Defenses (SFC)

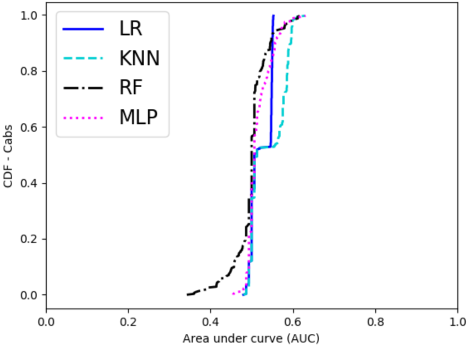


Figure: $N(0, 10^2)$, $m = 5$

Defenses (SFC)

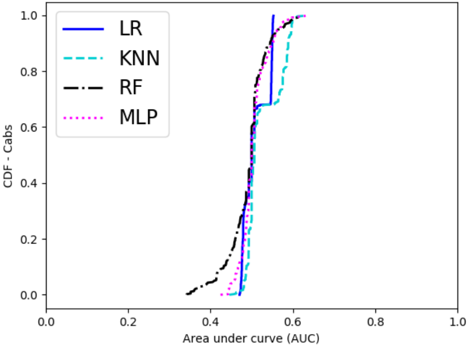


Figure: $Lap(0, \Delta/\epsilon), \epsilon = 0.1, m = 5$

Defenses (SFC)

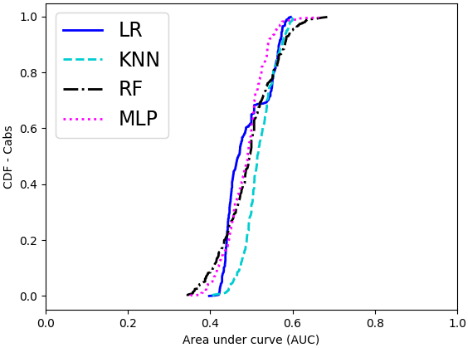
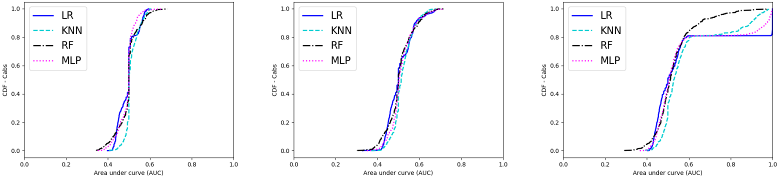


Figure: $Lap(0, 1/\epsilon), \epsilon = 0.1, m = 5$

Defenses (SFC)



(a) $m = 5$ (b) $m = 10$ (c) $m = 100$

Figure: Low count suppression with threshold $= 10$.

Defenses (SFC)

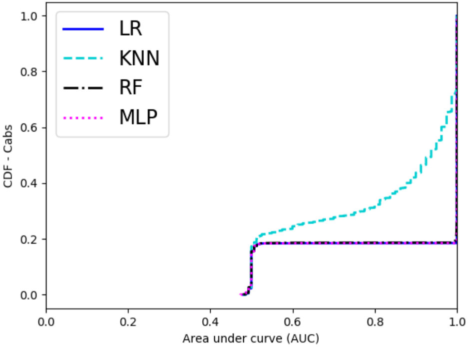
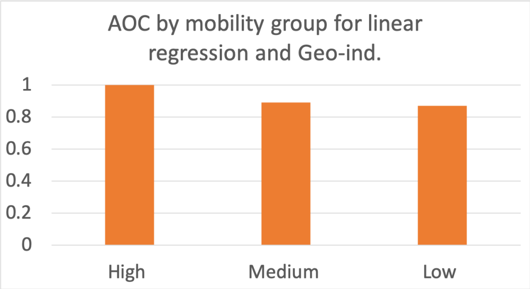


Figure: Geo-indistinguishablity, $m = 5, \epsilon = 0.1$

Defenses (SFC)



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Self-assessment

Strengths:

- Run time
- Scalability of preprocessing
- Extents of analysis

Limitations:

- Extensibility using defenses;
- Analysis across data sets;
- Assumptions in the formalization of membership inference

Future work

- Do longer observation periods increase the power of MI?
- What factors are behind the trend of AOC vs aggregation size?
- Membership inference on internet browsing data;
- Improving the scalability of Python's APIs.

References

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