

# Computing Inconsistency Measures Under Differential Privacy

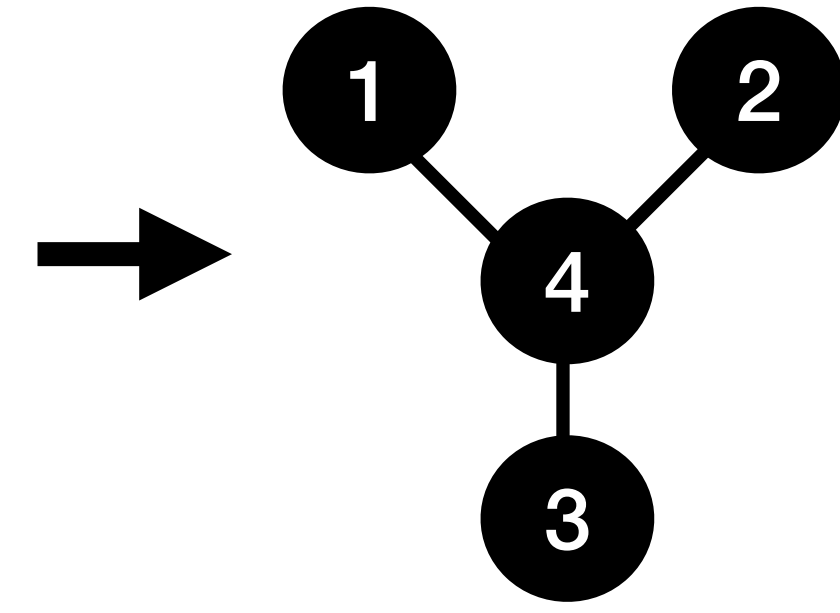
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## Background

### Denial Constraints and Conflict Graphs

ID	Capital	Country
1	Ottawa	Canada
2	Ottawa	Canada
3	Ottawa	Canada
4	Ottawa	Kanada



$\sigma$  : Capital  $\rightarrow$  Country

“country of two tuples must be the same if their capital is the same”

### Inconsistency Measures [1]

Given, dataset  $D$  and constraint set  $\Sigma$ , inconsistency measures are of the form  $I(D, \Sigma) \rightarrow \mathbb{R}$ :

1. Drastic Measure  $I_D(G)$  = existence of an edge ✗
2. Minimal inconsistency measure  $I_{MI}(G)$  = number of edges ✓
3. Problematic measure  $I_P(G)$  = number of vertices with positive degree ✓
4. Maximal consistency measure  $I_{MC}(G)$  = number of maximal independent sets ✗
5. Optimal repair measure  $I_R(G)$  = minimum vertex cover size ✓

✓ = our work

### Differential Privacy [2]

A randomized algorithm  $A: \mathcal{G} \rightarrow \mathcal{R}$  satisfies  $\epsilon$ -differential privacy (DP) if for any two adjacent graphs  $G, G' \in \mathcal{G}$  that differ in a node and for any subset of outputs  $o \subseteq \mathcal{R}$  it holds that :

$$\Pr[A(G) \in o] \leq e^\epsilon \Pr[A(G') \in o]$$

## Experiments

### Setup

- Inconsistency: Random typo to 1% rows
- Privacy:  $\epsilon = 1$
- Measure: True vs private by adding one typo at a time

### Datasets

- Five real-world datasets with varying conflict graph densities
- We experiment on subset of 10k and repeat for 10 times and average

Dataset	#Tuples	#Attributes	#Constraints	Graph density
Adult	32k	15	3	9635
Flight	500k	20	13	1520
Hospital	114k	15	7	793
Stock	122k	7	1	1
Tax	1M	15	9	373

### References:

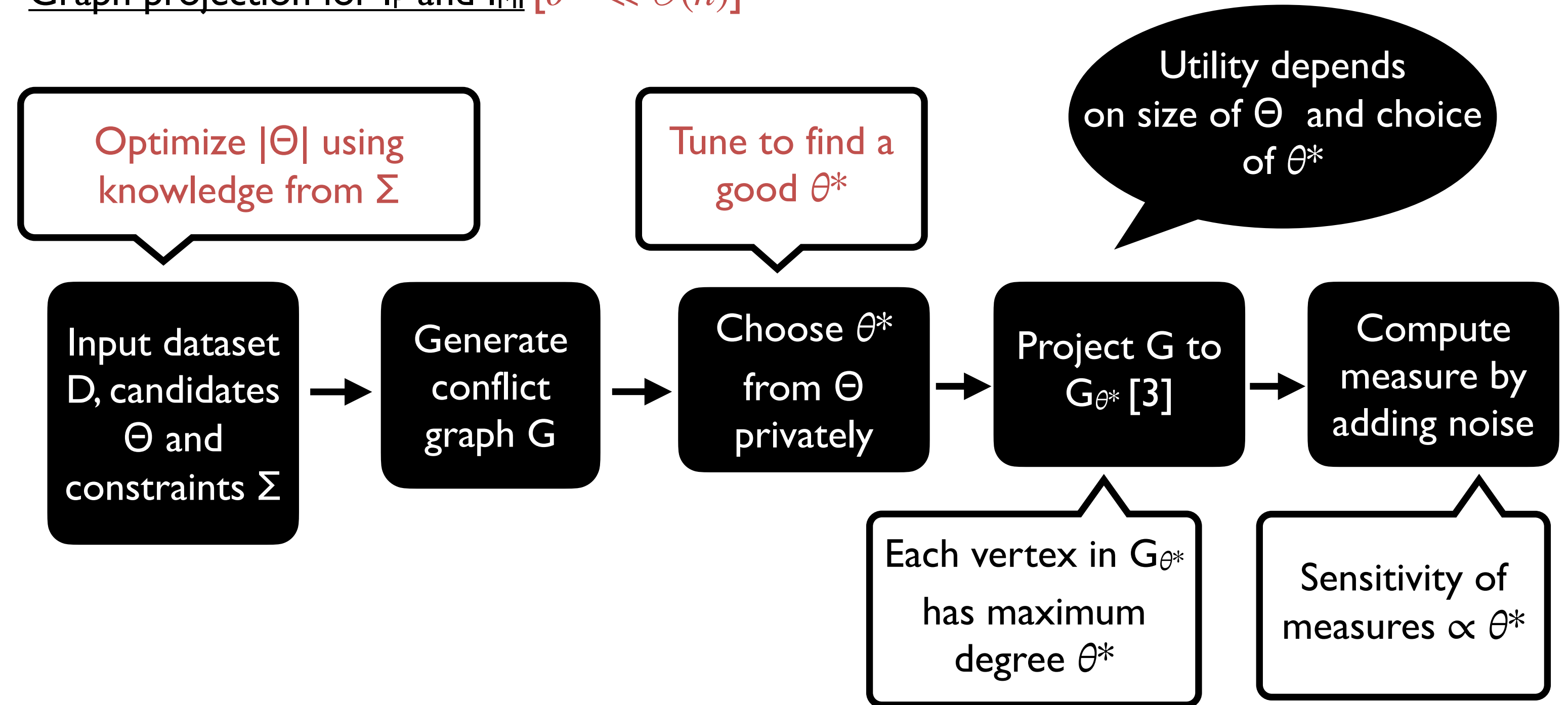
1. Livshits, Ester, et al. "Properties of inconsistency measures for databases." *International Conference on Management of Data*. 2021.
2. Dwork, Cynthia, et al. "Calibrating noise to sensitivity in private data analysis." *TCC 2006*
3. Day, Wei-Yen, et al. "Publishing graph degree distribution with node differential privacy." *International Conference on Management of Data* 2016.
4. Dong, Wei, et al. "R2T: Instance-optimal Truncation for Differentially Private Query Evaluation with Foreign Keys." *ACM SIGMOD 2023*

## Differentially Private Inconsistency Measures

### Challenges

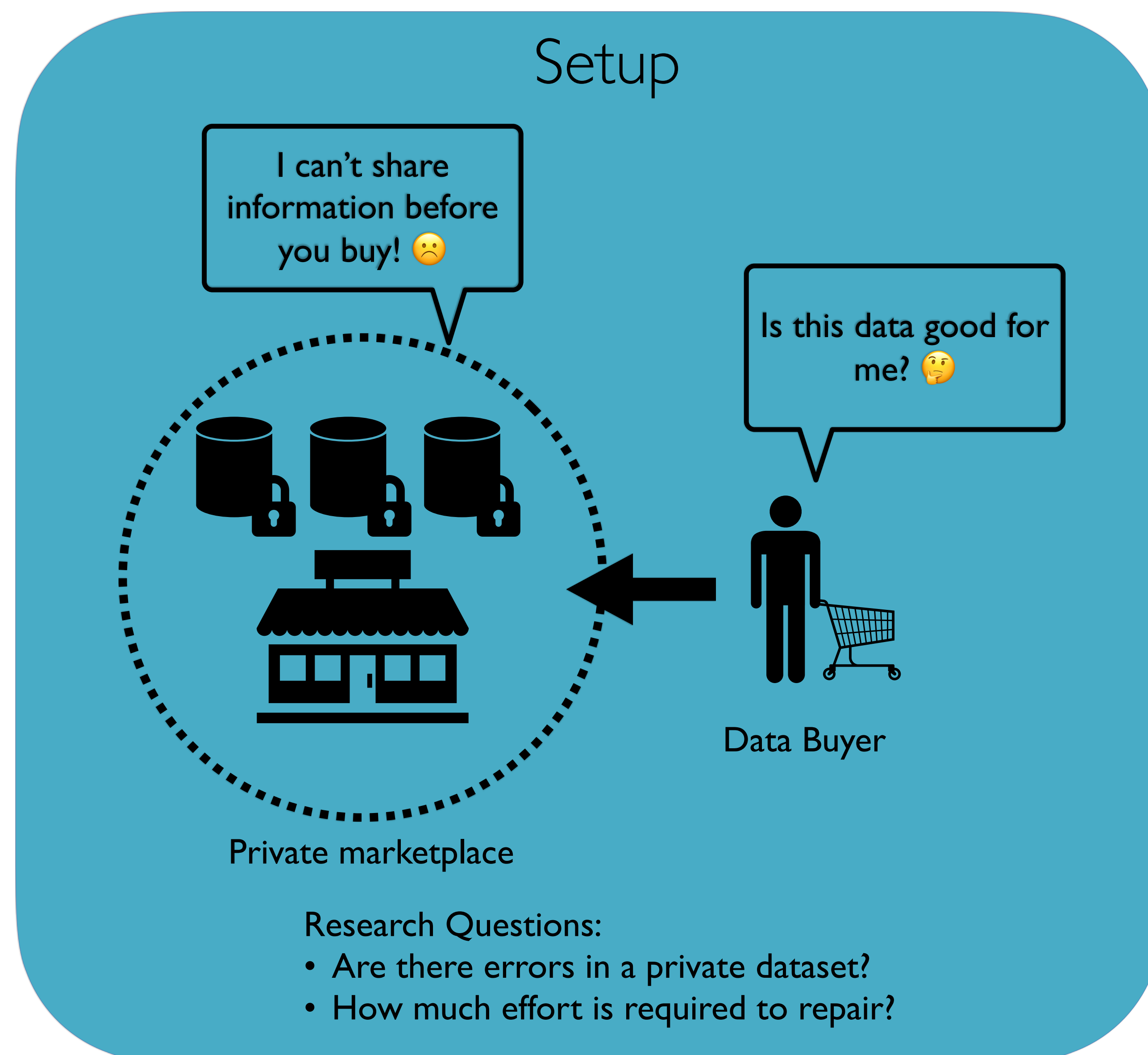
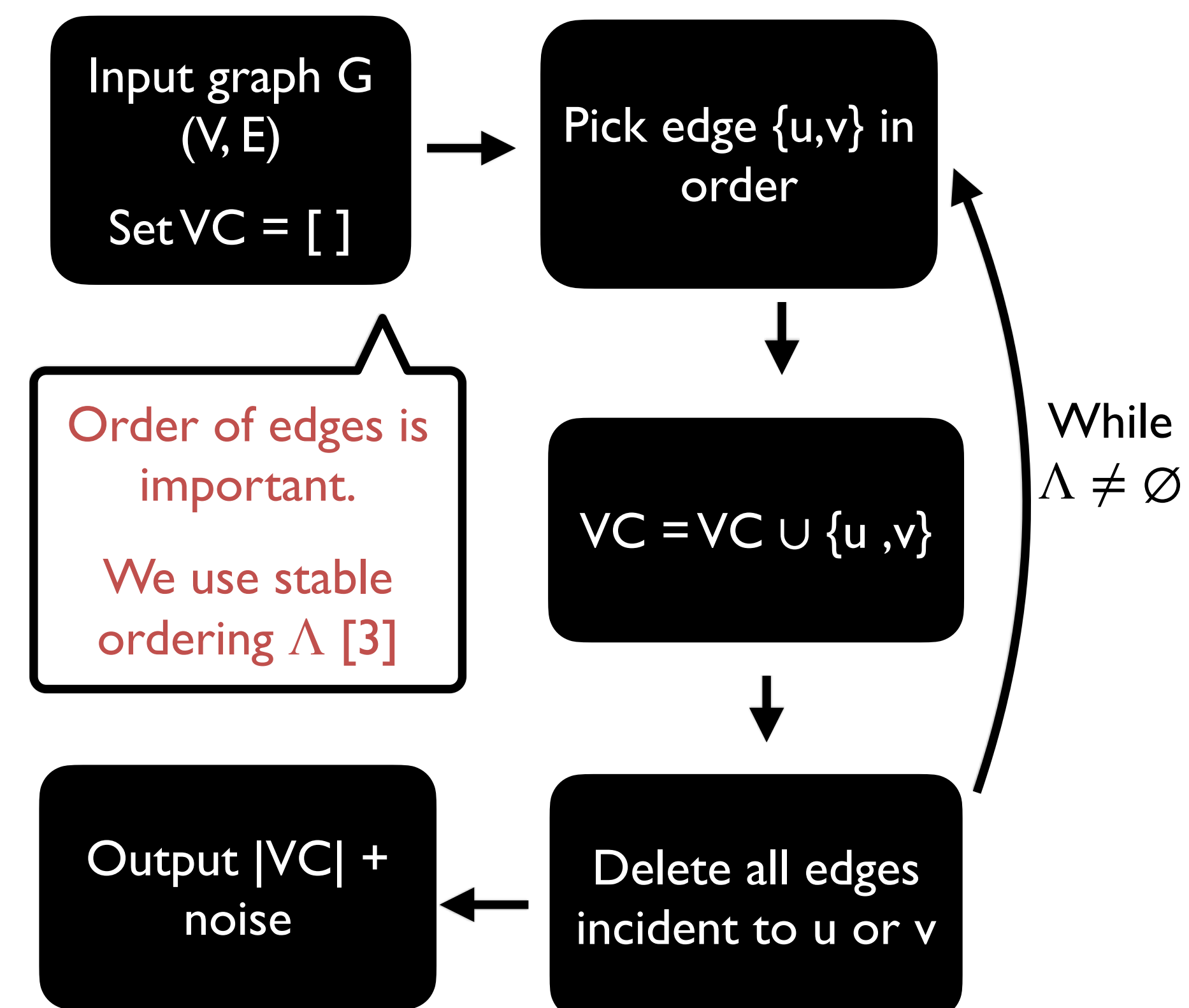
1. Computational hardness: Minimum vertex cover ( $I_R$ ) and #maximal independent sets ( $I_{MC}$ ) are NP hard problems
2. High sensitivity: Maximum change in output when  $G$  is replaced by  $G'$  is  $\mathcal{O}(n)$ , where  $n$  is the number of nodes

### Graph projection for $I_P$ and $I_{MI}$ [ $\theta^* \ll \mathcal{O}(n)$ ]

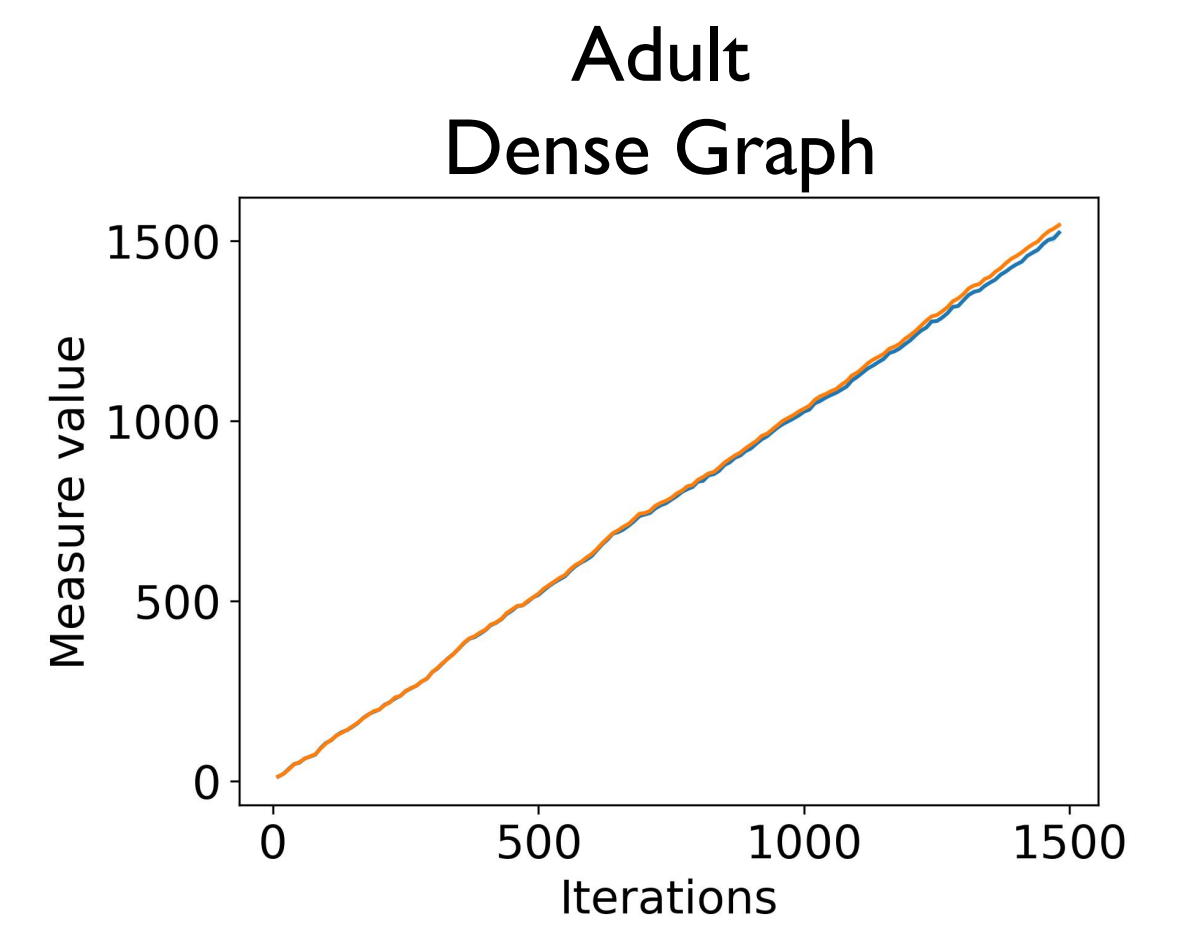
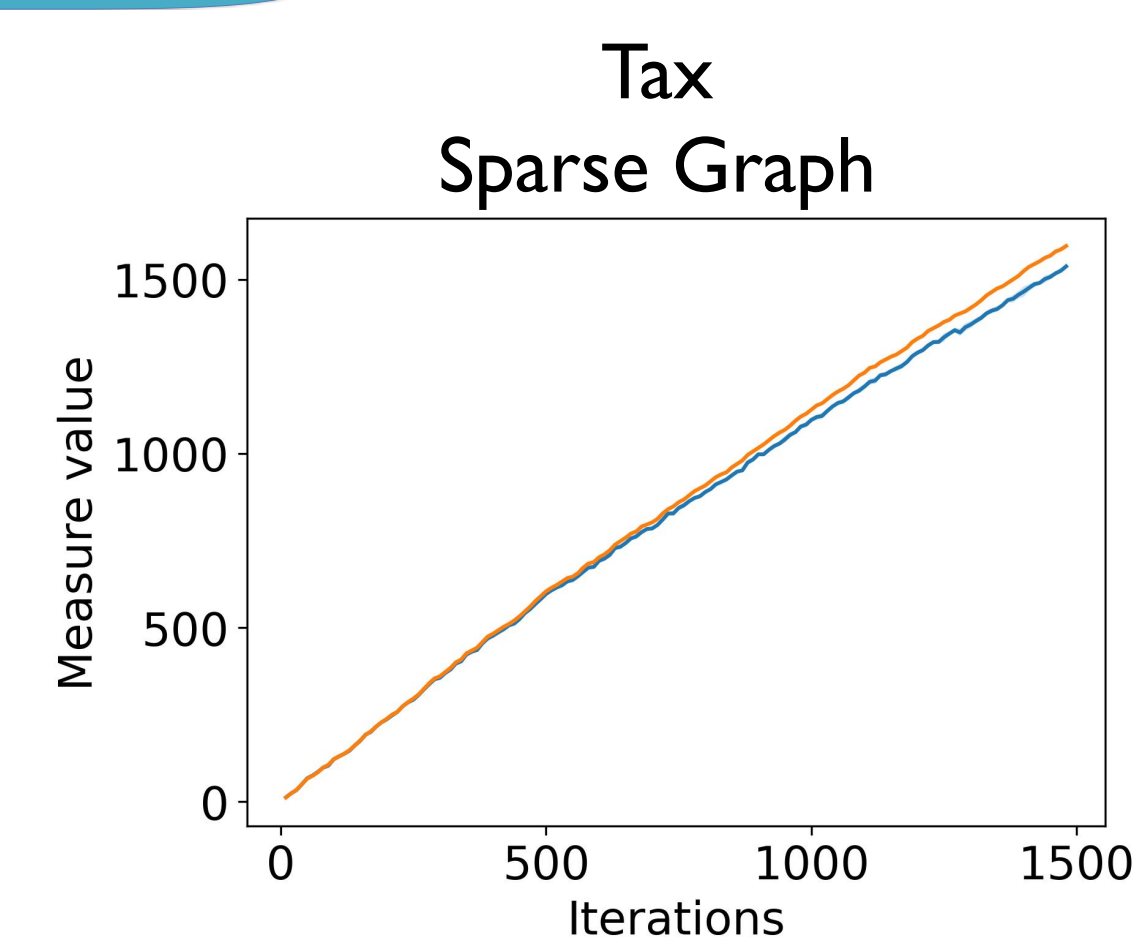


### DP vertex cover size for $I_R$ [ $2 \ll \mathcal{O}(n)$ ]

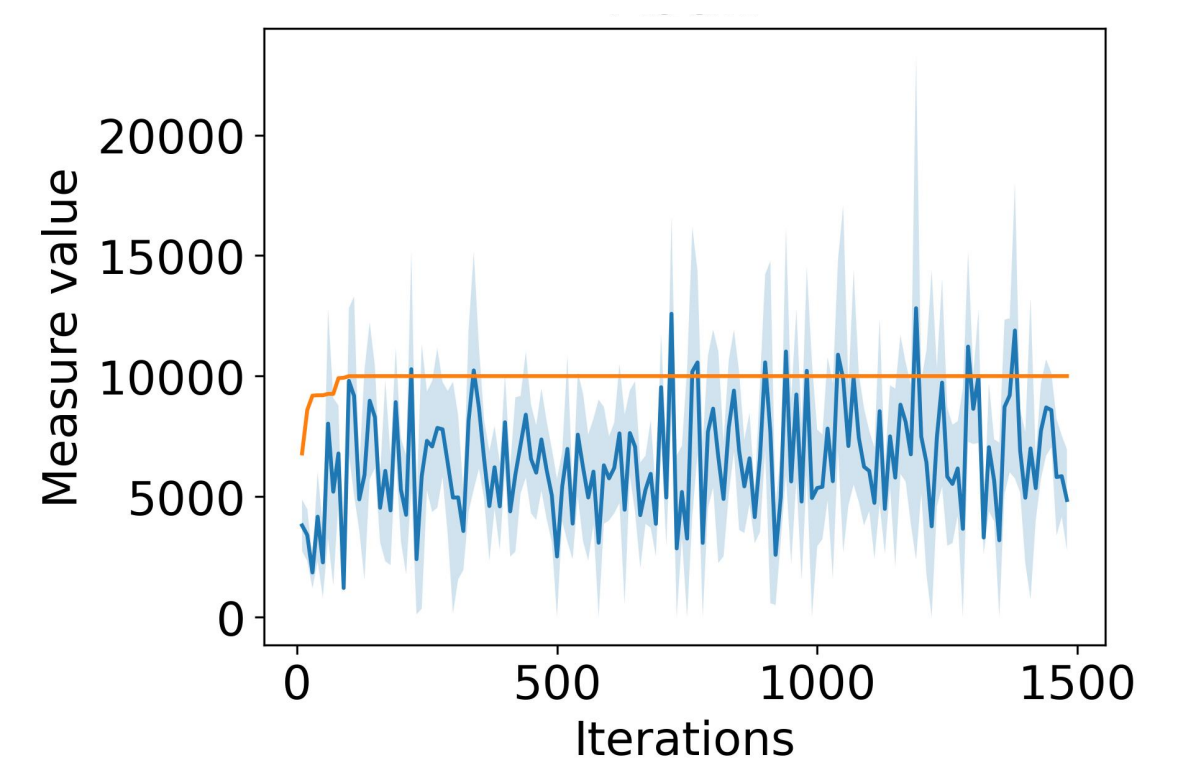
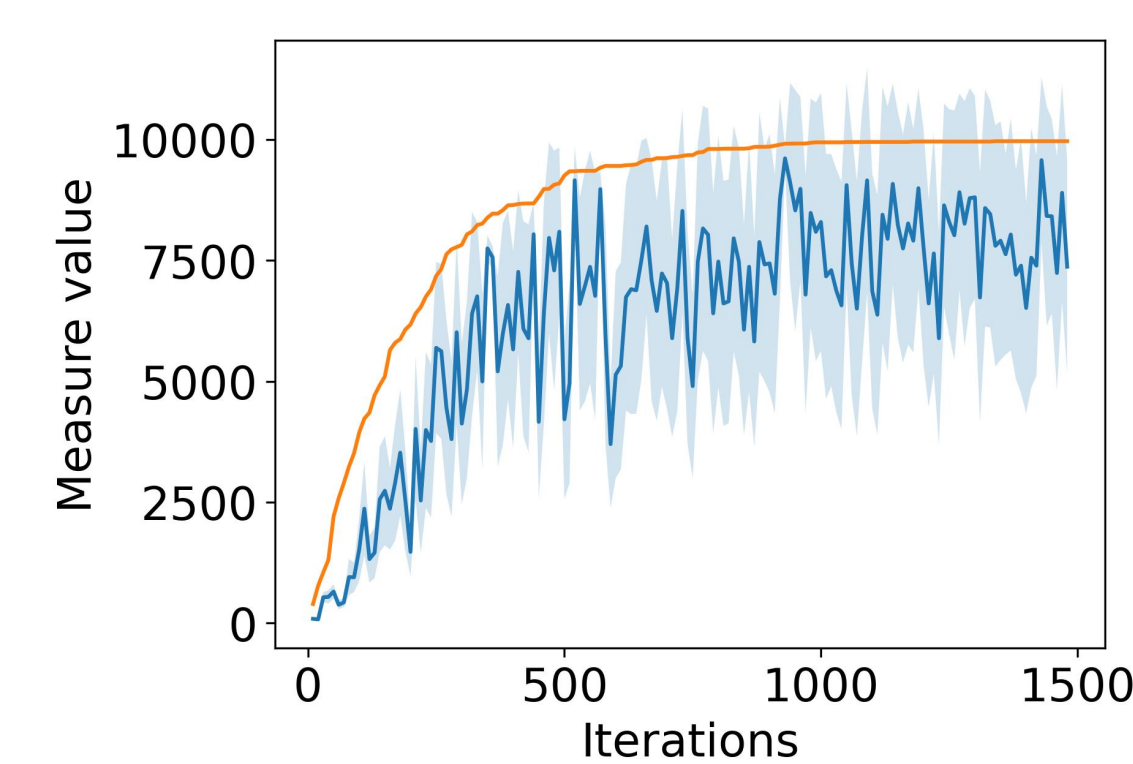
We analyse the 2-approximate vertex cover size algorithm and show that it has sensitivity of 2.



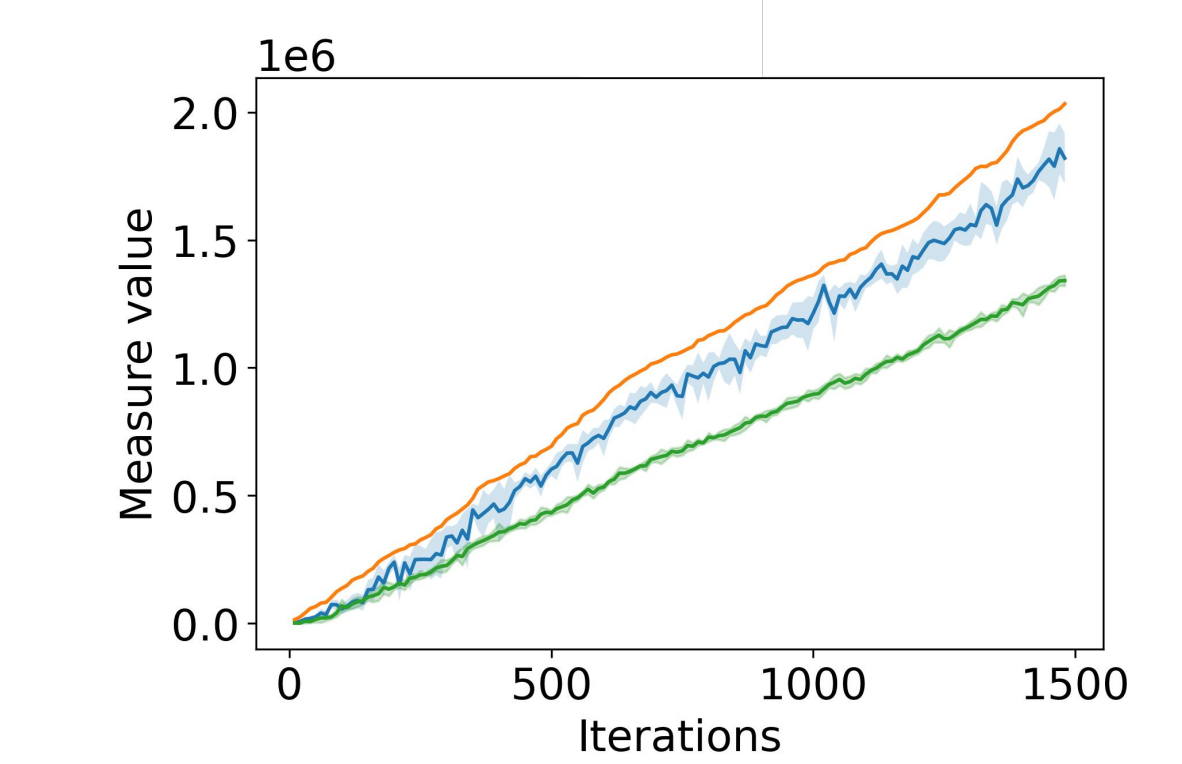
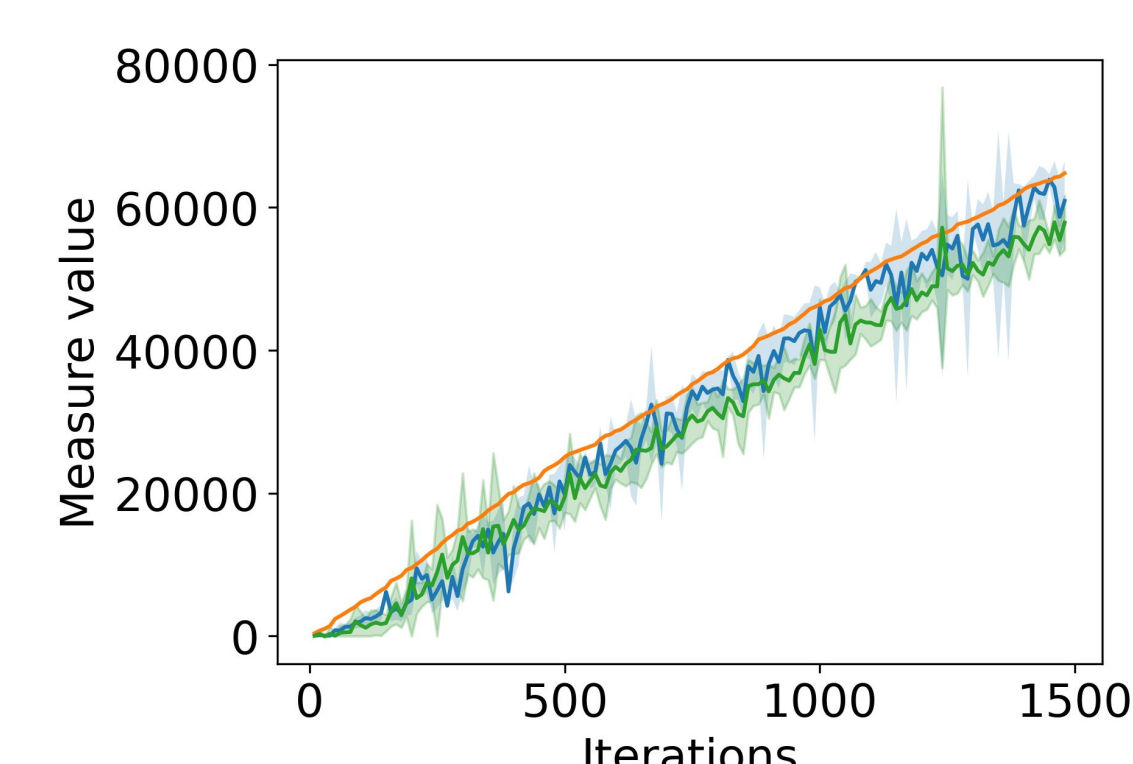
### Repair ( $I_R$ )



### Problematic ( $I_P$ )



### Minimum Inconsistency ( $I_{MI}$ )



— Our approach — True value — R2T