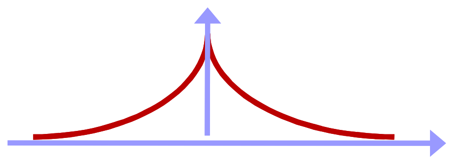

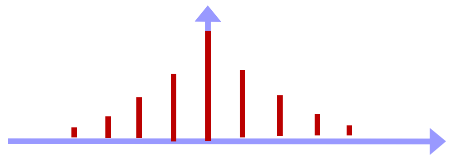

Data-driven concerns in privacy

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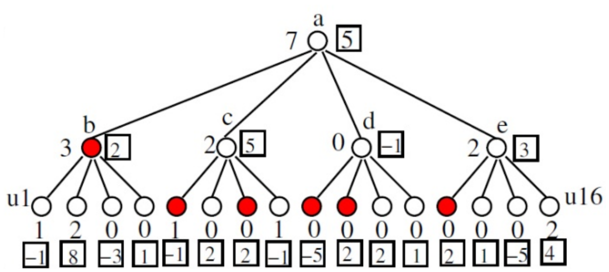
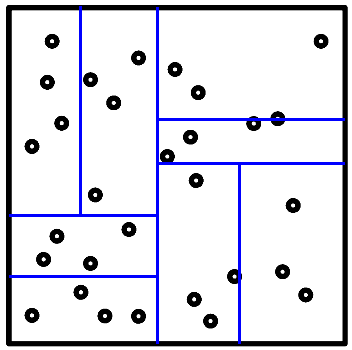
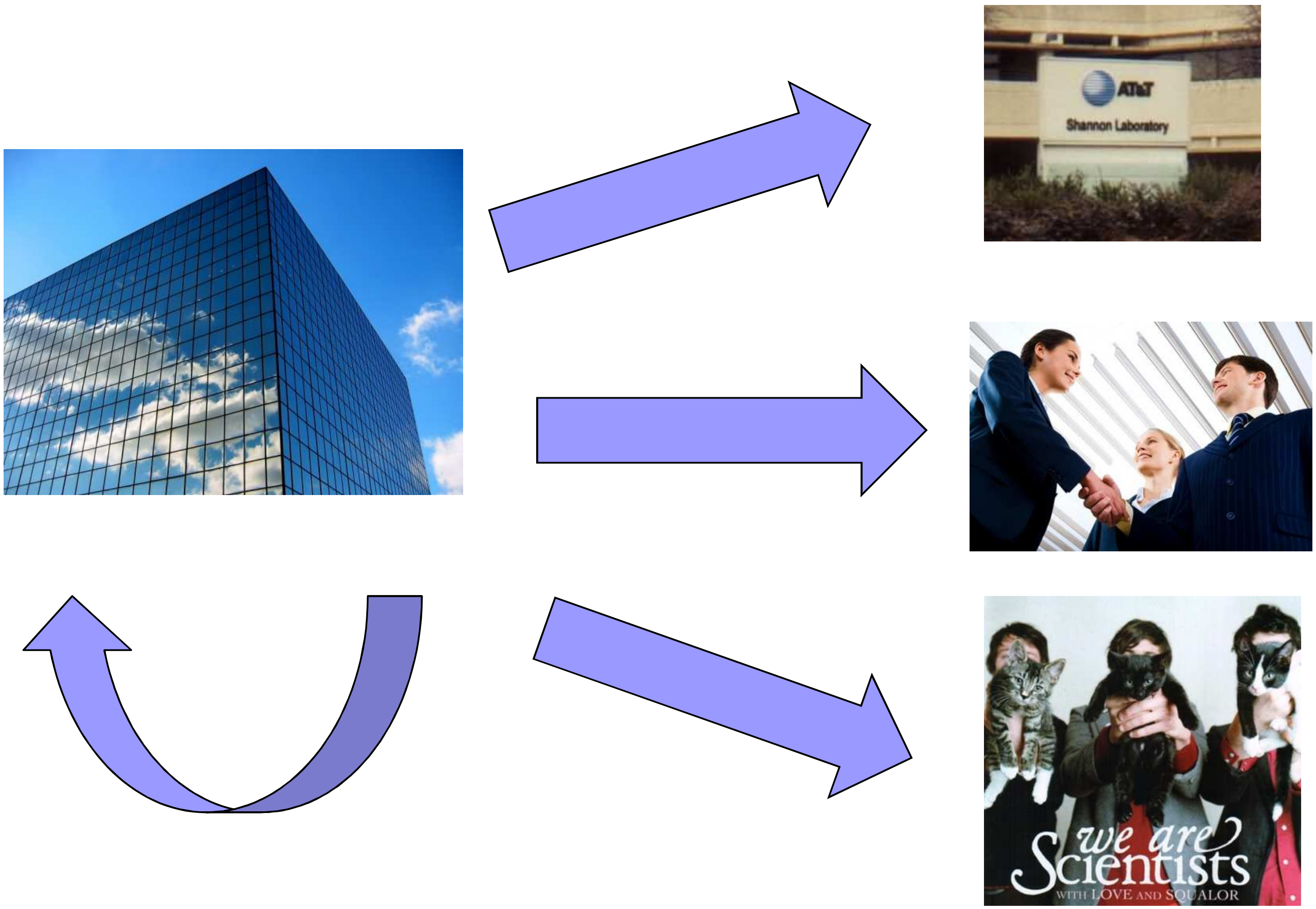




Outline

- Anonymization and Privacy models
- Non-uniformity of data
- Optimizing linear queries
- Predictability in data

The anonymization scenario



Data-driven privacy

- Much interest in private data release
  - Practical: release of AOL, Netflix data etc.
  - Research: hundreds of papers
- In practice, many data-driven concerns arise:
  - Efficiency / practicality of algorithms as data scales
  - How to interpret privacy guarantees
  - Handling of common data features, e.g. sparsity
  - Ability to optimize for known query workload
  - Usability of output for general processing
- This talk: outline some efforts to address these issues

Differential Privacy [Dwork 06]

- Principle: released info reveals little about any individual
  - Even if adversary knows (almost) everything about everyone else!
- Thus, individuals should be secure about contributing their data
  - What is learnt about them is about the same either way
- Much work on providing differential privacy
  - Simple recipe for some data types e.g. numeric answers
  - Simple rules allow us to reason about composition of results
  - More complex for arbitrary data (exponential mechanism)
- Adopted and used by several organizations:
  - US Census, Common Data Project, Facebook (?)

Differential Privacy

The output distribution of a differentially private algorithm changes very little whether or not any individual's data is included in the input – so you should contribute your data

A randomized algorithm K satisfies ε-differential privacy if:

Given any pair of neighboring data sets,

D_1 and D_2, and S in Range(K):

$$\Pr[K(D_1) = S] \le e^{\varepsilon} \Pr[K(D_2) = S]$$

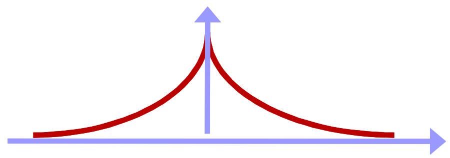
Achieving ε-Differential Privacy

(Global) Sensitivity of publishing:

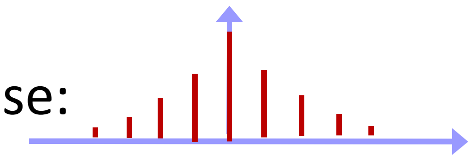
$s = \max_{x,x'} |F(x) - F(x')|$, x, x' differ by 1 individual

E.g., count individuals satisfying property P: one individual changing info affects answer by at most 1; hence $s = 1$

For every value that is output:



- Add Laplacian noise, $Lap(\varepsilon/s)$:
- Or Geometric noise for discrete case:



Simple rules for composition of differentially private outputs:

Given output O_1 that is ε_1 private and O_2 that is ε_2 private

- (Sequential composition) If inputs overlap, result is $\varepsilon_1 + \varepsilon_2$ private
- (Parallel composition) If inputs disjoint, result is $\max(\varepsilon_1, \varepsilon_2)$ private

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- Anonymization and Privacy models
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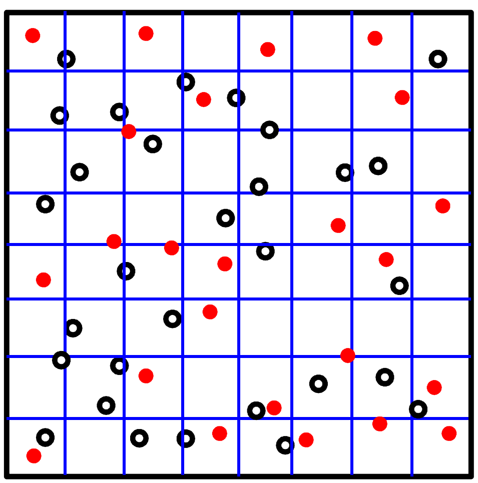
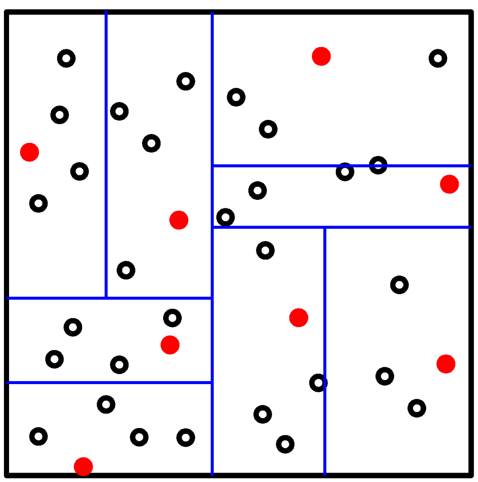
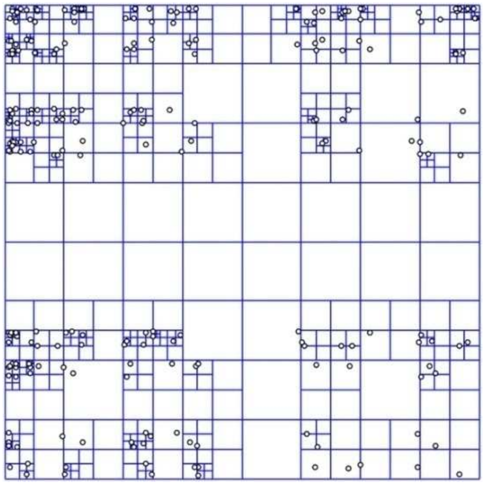
Sparse Spatial Data [ICDE 2012]

- Consider location data of many individuals
  - Some dense areas (towns and cities), some sparse (rural)
- Applying DP naively simply generates noise
  - lay down a fine grid, signal overwhelmed by noise
- Instead: compact regions with sufficient number of points

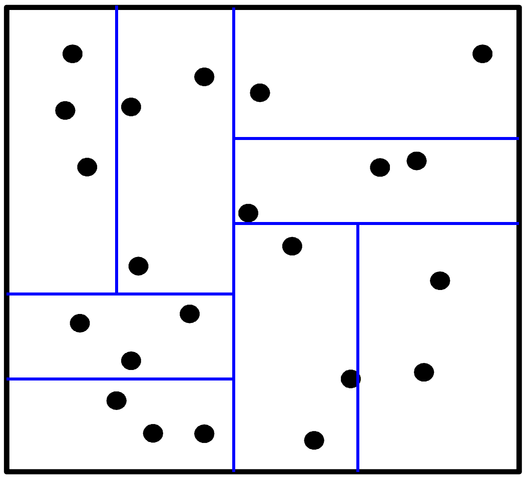




Private Spatial decompositions



quadtree



kd-tree

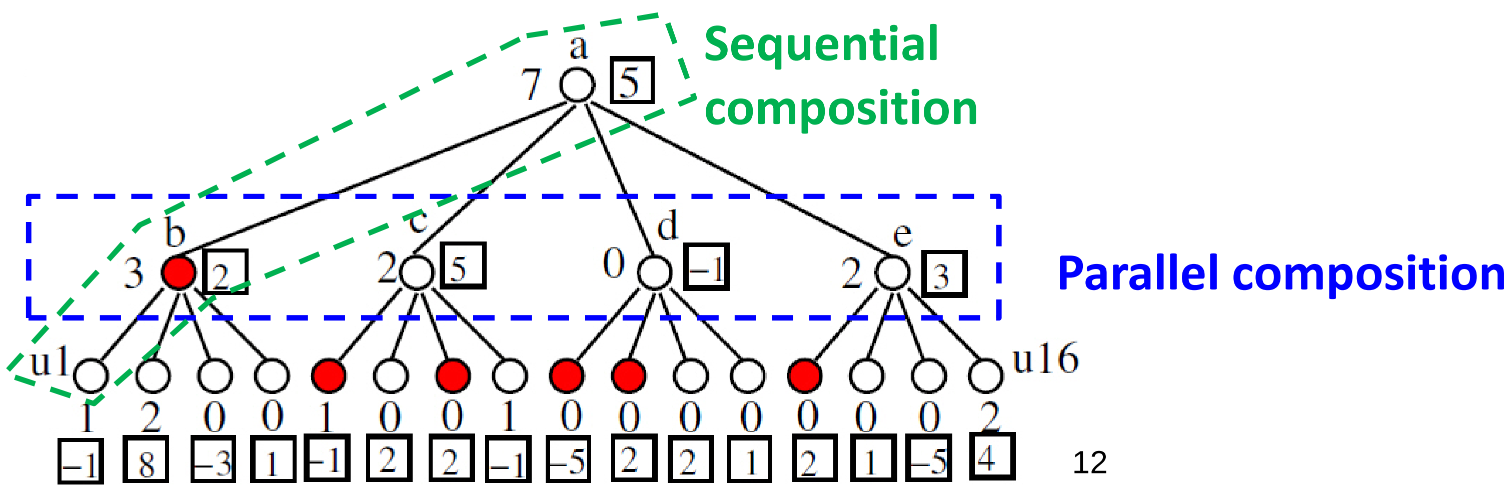
- Build: adapt existing methods to have differential privacy
- Release: a private description of data distribution
  (in the form of bounding boxes and noisy counts)

Building a Private kd-tree

- Process to build a private kd-tree
  - Input: maximum height *h*, minimum leaf size *L*, data set
  - Choose dimension to split
  - Get (private) median in this dimension
  - Create child nodes and add noise to the counts
  - Recurse until:
    - Max height is reached
    - Noisy count of this node less than *L*
    - Budget along the root-leaf path has used up
- The entire PSD satisfies DP by the composition property

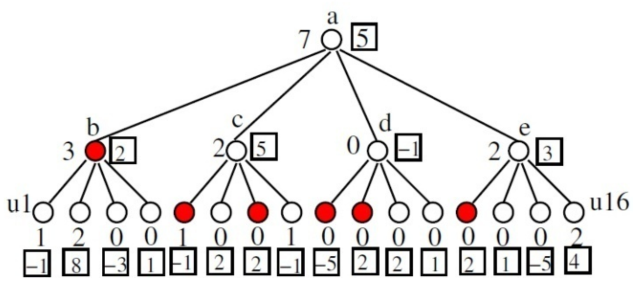
Building PSDs – privacy budget allocation

- Data owner specifies a total budget reflecting the level of anonymization desired
- Budget is split between medians and counts
  - Tradeoff accuracy of division with accuracy of counts
- Budget is split across levels of the tree
  - Privacy budget used along any root-leaf path should total ε



Privacy budget allocation

- How to set an ε_i for each level?
  - Compute the number of nodes touched by a 'typical' query
  - Minimize variance of such queries
  - Optimization: min $\sum_i\ 2^{h-i} / \varepsilon_i^2$ s.t. $\sum_i \varepsilon_i = \varepsilon$
  - Solved by $\varepsilon_i \propto (2^{(h-i)})^{1/3}\varepsilon$: more to leaves
  - Total error (variance) goes as $2^h/\varepsilon^2$



- Tradeoff between noise error and spatial uncertainty
  - Reducing h drops the noise error
  - But lower h increases the size of leaves, more uncertainty

Post-processing of noisy counts

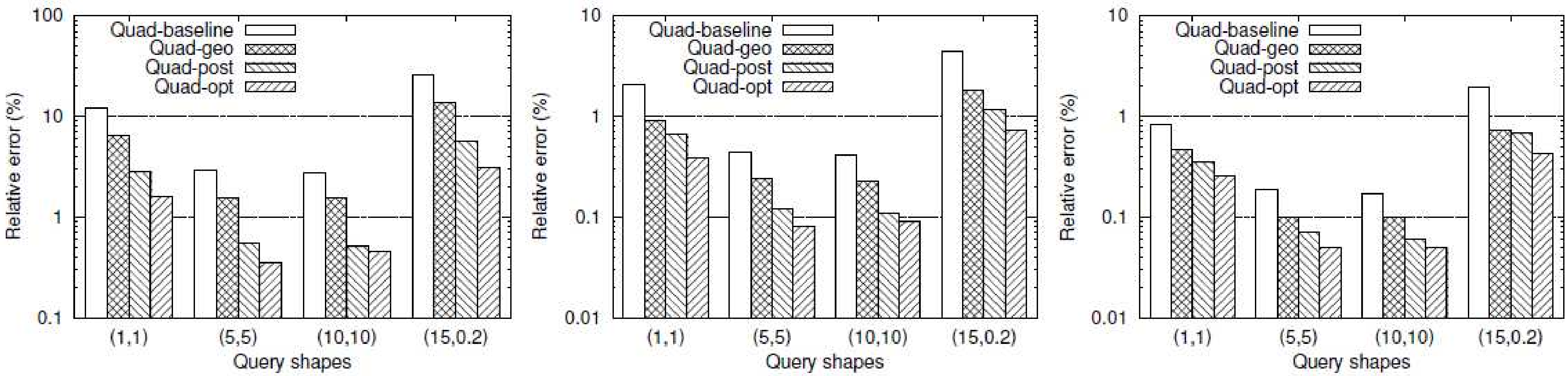
- Can do additional post-processing of the noisy counts
  - To improve query accuracy and achieve consistency
- Intuition: we have count estimate for a node and for its children
  - Combine these independent estimates to get better accuracy
  - Make consistent with some true set of leaf counts
- Formulate as a linear system in n unknowns
  - Avoid explicitly solving the system
  - Expresses optimal estimate for node v in terms of estimates of ancestors and noisy counts in subtree of v
  - Use the tree-structure to solve in three passes over the tree
  - Linear time to find optimal, consistent estimates

Experimental study

- 1.63 million coordinates from US TIGER/Line dataset
  - Road intersections of US States
- Queries of different shapes, e.g. square, skinny
- Measured median relative error of 600 queries for each shape

Experimental study

- Effectiveness of geometric budget and post-processing



(a) $\varepsilon = 0.1$ (b) $\varepsilon = 0.5$ (c) $\varepsilon = 1.0$

  - Relative error reduced by up to an order of magnitude
  - Most effective when limited privacy budget

Outline

- Anonymization and Privacy models
- Non-uniformity of data
- **Optimizing linear queries**
- Predictability in data

Optimizing Linear Queries [ICDE 2013]

- Linear queries capture many common cases for data release
  - Data is represented as a vector x
  - Want to release answers to linear combinations of entries of x
  - E.g. contingency tables in statistics
  - Model queries as matrix Q, want to know y=Qx

$$Q = \begin{pmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{pmatrix} \qquad x = \begin{matrix} 3 \\ 5 \\ 7 \\ 0 \\ 1 \\ 4 \\ 9 \\ 2 \end{matrix}$$

Answering Linear Queries

- Basic approach:
  - Answer each query in Q directly, and add uniform noise
- Basic approach is suboptimal
  - Especially when some queries overlap and others are disjoint
- Several opportunities for optimization:
  - Can assign different scales of noise to different queries
  - Can combine results to improve accuracy
  - Can ask different queries, and recombine to answer Q

$$Q = \begin{pmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{pmatrix}$$

The Strategy/Recovery Approach

- Pick a strategy matrix S
  - Compute z = Sx + v
    noise vector
    strategy on data
  - Find R so that Q = RS
  - Return y = Rz = Qx + Rv as the set of answers
  - Measure accuracy based on var(y) = var(Rv)
- Common strategies used in prior work:

I: Identity Matrix	C: Selected Marginals
Q: Query Matrix	H: Haar Wavelets
F: Fourier Matrix	P: Random projections

Step 1: Error Minimization

- Given Q, R, S, ε want to find a set of values $\{\varepsilon_i\}$
  - Noise vector v has noise in entry i with variance $1/\varepsilon_i^2$
- Yields an optimization problem of the form:
  - Minimize $\sum_i b_i / \varepsilon_i^2$ (minimize variance)
  - Subject to $\sum_i |S_{i,j}| \varepsilon_i \leq \varepsilon$ (guarantee ε differential privacy)
- The optimization is convex, can solve via interior point methods
  - Costly when S is large
  - We seek an efficient closed form for common strategies

Grouping Approach

- We observe that many strategies S can be broken into groups that behave in a symmetrical way
  - Rows in a group are disjoint (have zero inner product)
  - Non-zero values in group i have same magnitude C_i
- All common strategies meet this grouping condition
  - Identity (I), Fourier (F), Marginals (C), Projections (P), Wavelets (H)
- Simplifies the optimization:
  - A single constraint over the ε_i's
  - New constraint: $\sum_{\text{Groups } i} C_i \varepsilon_i = \varepsilon$
  - Closed form solution via Lagrangian

$$
\left(\begin{array}{cccccccc}
\frac{1}{2\sqrt{2}} & \frac{1}{2\sqrt{2}} & \frac{1}{2\sqrt{2}} & \frac{1}{2\sqrt{2}} & \frac{1}{2\sqrt{2}} & \frac{1}{2\sqrt{2}} & \frac{1}{2\sqrt{2}} & \frac{1}{2\sqrt{2}} \\
\hline
\frac{1}{2\sqrt{2}} & \frac{1}{2\sqrt{2}} & \frac{1}{2\sqrt{2}} & \frac{1}{2\sqrt{2}} & -\frac{1}{2\sqrt{2}} & -\frac{1}{2\sqrt{2}} & -\frac{1}{2\sqrt{2}} & -\frac{1}{2\sqrt{2}} \\
\hline
\frac{1}{2} & \frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} & -\frac{1}{2} & -\frac{1}{2} \\
\hline
\frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}}
\end{array}\right)
$$

Step 2: Optimal Recovery Matrix

- Given Q, S, $\{\varepsilon_i\}$, find R so that $Q=RS$
  - Minimize the variance $Var(Rz) = Var(RSx + Rv) = Var(Rv)$
- Find an optimal solution by adapting Least Squares method
- This finds x' as an estimate of x given $z = Sx + v$
  - Define $\Sigma = Cov(z) = diag(2/\varepsilon_i^2)$ and $U = \Sigma^{-1/2} S$
  - OLS solution is $x' = (U^T U)^{-1} U^T \Sigma^{-1/2} z$
- Then $R = Q(S^T \Sigma^{-1} S)^{-1} S^T \Sigma^{-1}$
- Result: $y = Rz = Qx'$ is consistent—corresponds to queries on x'
  - R minimizes the variance
  - Special case: S is orthonormal basis ($S^T = S^{-1}$) then $R=QS^T$

Overall Process

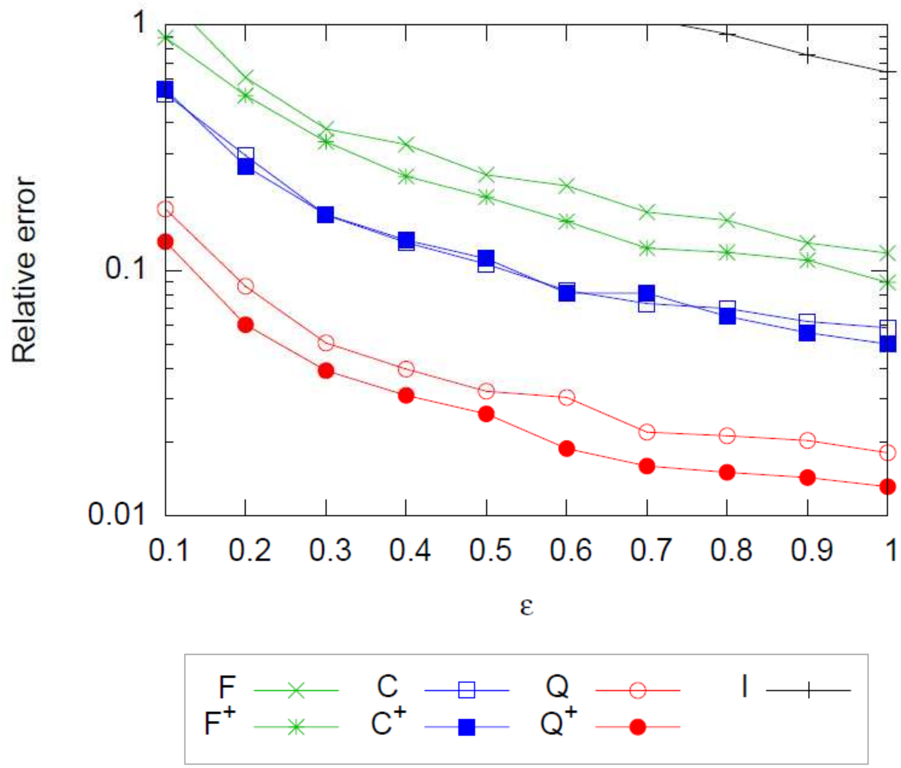
- Ideal version: given query matrix Q, compute strategy S, recovery R and noise budget $\{\varepsilon_i\}$ to minimize $Var(y)$
  - Not practical: sets up a rank-constrained SDP
  - Follow the 2-step process instead
- Given query matrix Q decomposed into $Q=(RS)$, compute optimal noise budgets $\{\varepsilon_i\}$ to minimize $Var(y)$ (Step 1)
- Given query matrix Q, strategy S and noise budgets $\{\varepsilon_i\}$, compute new recovery matrix R to minimize $Var(y)$ (Step 2)
- Fairly fast (matrix multiplications and inversions)
  - Faster when S is e.g. Fourier, since can use FFT

Experimental Study

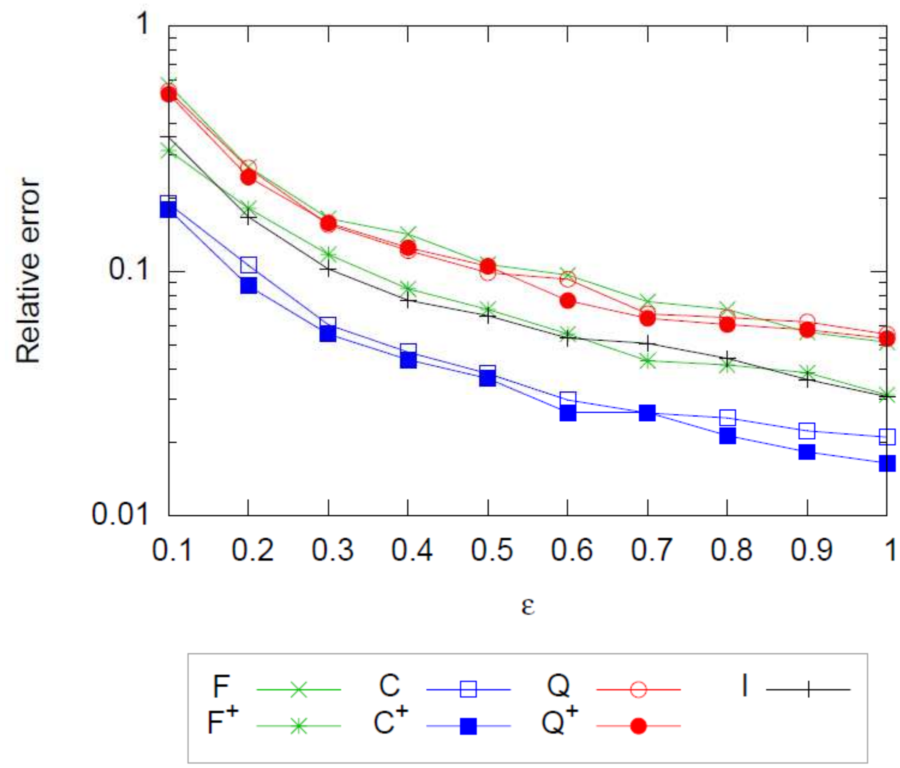
- Used two real data sets:
  - ADULT data – census data on 32K individuals
  - NLTCS data– binary data on 21K individuals
- Tried a variety of query workloads Q over these
  - Based on low-degree k-way marginals
- Compared the original and optimized strategies for:
  - Original queries, Q / Q^+
  - Fourier strategy F/F^+ [Barak et al. 07]
  - Clustered sets of marginals C/C^+ [Bing et al. 11]
  - Identity basis I

Experimental Results

ADULT, 1- and 2-way marginals



NLTCS, 2- and 3-way marginals



- Optimized error gives constant factor improvement
- Time cost for the optimization is negligible on this data

Outline

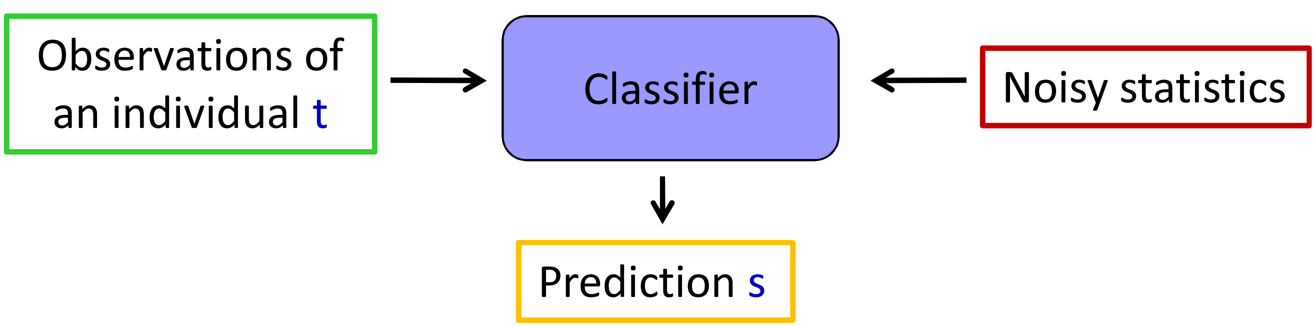
- Anonymization and Privacy models
- Non-uniformity of data
- Optimizing linear queries
- **Predictability in data**

Revisiting the privacy definition [KDD 2011]

- Differential privacy guarantees that what I learn about an individual from the released data is about the same whether or not they are in the data
- So I can't learn much about an individual from the released data, right?
- WRONG!
  - Will show how differentially private output can still allow us to draw accurate conclusions about individuals

Use Machine Learning to Perform Inference

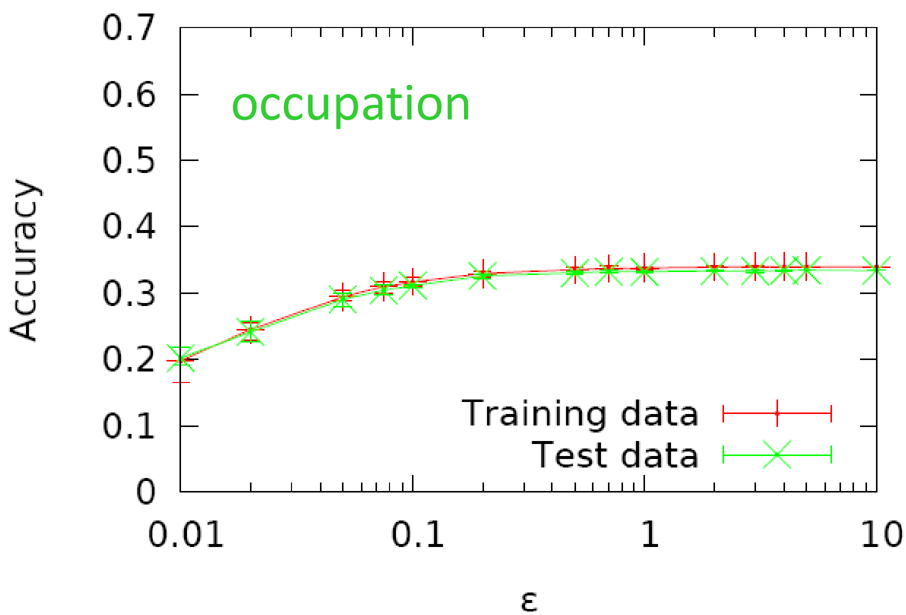
- Key idea: build an accurate classifier under DP
- Data model: target ("sensitive") attribute $s \in SA$
  - Think disease status, salary band, etc.
- "Observable" attributes $t_1, t_2 \ldots t_m$
  - Think age, gender, postal code, height etc.
- Goal: build a classifier that given $(t_1, t_2, \ldots t_m)_i$ predicts s_i
  - An accurate classifier reveals the private information

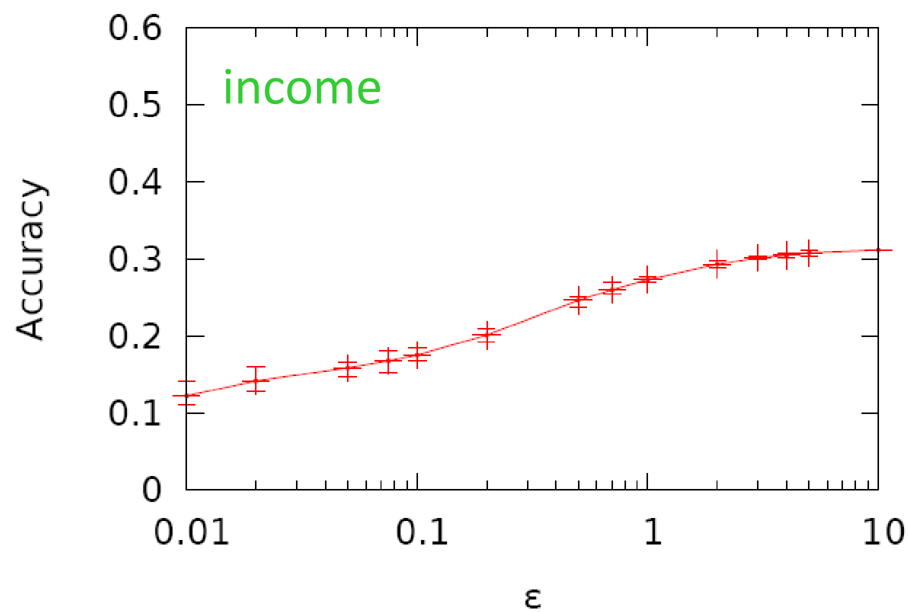


Building the Classifier

- Build a naïve Bayes classifier for s:
  - Prediction is $s' = \arg\max_{s \in SA} \Pr[s] \, \Pi_{j=1}^{m} \Pr[t_i \mid s]$
- Parameters are the marginal distributions
  $\Pr[t_i | s] = \Pr[t_i \cap s]/\Pr[s] \approx |\{r \in T : r_i = t_i \cap r_s = s\}| / |\{ r \in T : r_s = s\}|$
- Just need the counts $\forall s \in SA, i, v \in T_i \; |\{r \in T : t_i = v \cap r_s = s\}|$
  - Can obtain "noisy" versions of these under differential privacy
  - Noise is small compared to most counts
- Minor corrections: add 1 to counts (Laplacian correction), round up to 1 if negative due to noise

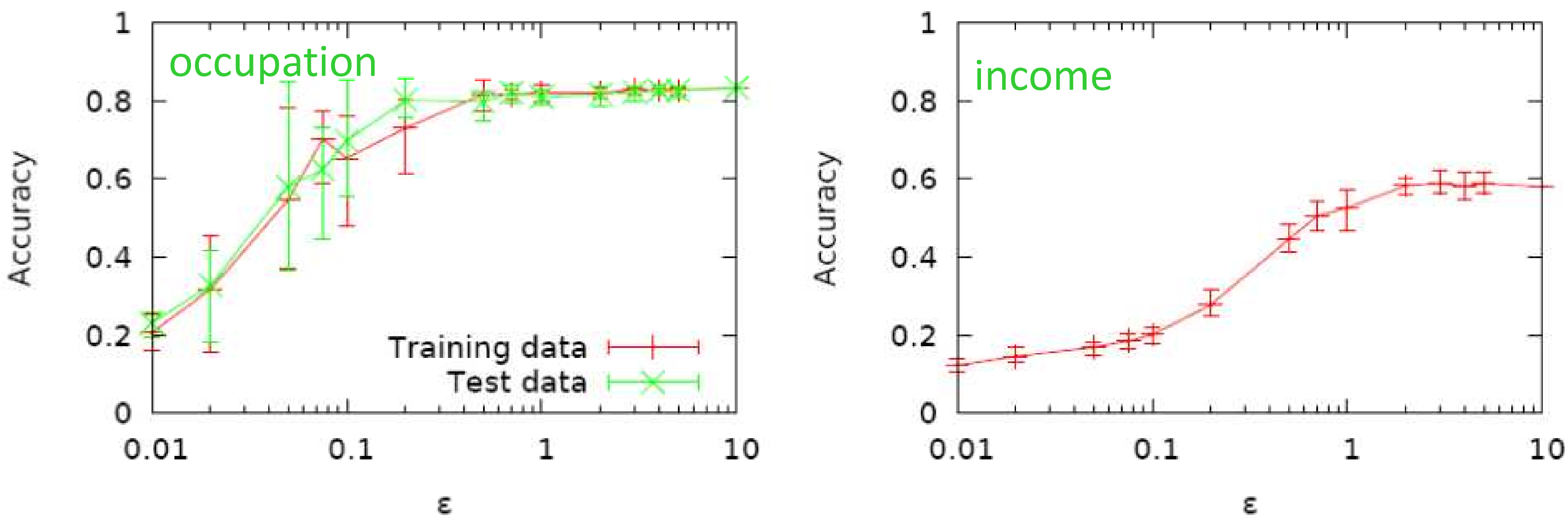
Experimental Study





- Tested accuracy of predicting
  - ‘occupation’ (14 options) in UCI Adult data
  - ‘income’ (9 options) in UCI Internet-usage data
- Clear improvement in accuracy over baseline methods
  - E.g. just predict most common attribute value

High Confidence Results



- When restricting to high-confidence predictions (~ 10% of the data), accuracy is yet higher

Discussion

- Why does this work?
  - The classifier is based on correlations between the observable attributes and the target attribute
  - These are *population statistics*: they arise from the coarse behavior of the whole population
  - One individual has almost no influence on them
  - More directly, the noise added to mask an individual does not substantially change them until the noise is very large
- Differential privacy is behaving as advertised
  - What we learn about the individual really is the same whether they are there or not

Enabling Disclosure

- Should we be worried? Correlations are inherent in the data?
  - An 'attacker' might never be able to collect such data
  - But almost 'for free' they can use released "privatized" statistics and potentially compromise an individual's privacy
- "If the release of the statistic *S* makes it possible to determine the (microdata) value more accurately than without access to *S*, a disclosure has taken place" – T. Dalenius, 1977
  - DP does not prevent disclosure, even when the attacker has no other information
  - Attempts to remove correlation in data may destroy utility!
  - Urges caution when releasing data under any privacy definition

Concluding Remarks

- Differential privacy can be applied effectively for data release
- Care is still needed to ensure that release is allowable
  - Can't just apply DP and forget it: must analyze whether data release provides sufficient privacy for data subjects
- Many open problems remain:
  - Transition these techniques to tools for data release
  - Want data in same form as input: private synthetic data?
  - Allow joining anonymized data sets accurately
  - Obtain alternate (workable) privacy definitions

Thank you!