## Sampling from Databases

CompSci 590.04 Instructor: AshwinMachanavajjhala



## Recap

- Given a set of elements, random sampling when number of elements N is known is easy if you have random access to any arbitrary element
  - Pick n indexes at random from 1 ... N
  - Read the corresponding n elements
- Reservoir Sampling: If N is unknown, or if you are only allowed sequential access to the data
  - Read elements one at a time. Include t<sup>th</sup> element into a reservoir of size n with probability n/t.
  - Need to access at most  $n(1+\ln(N/n))$  elements to get a sample of size n
  - Optimal for any reservoir based algorithm



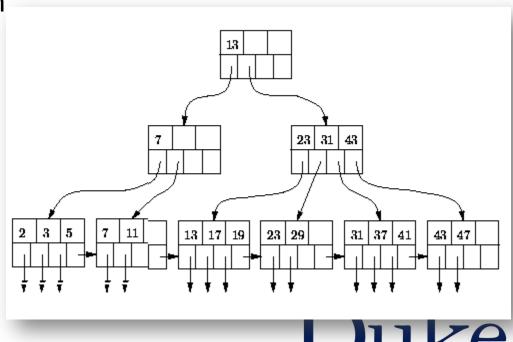
# Today's Class

- In general, sampling from a database where elements are only accessed using indexes.
  - B+-Trees
  - Nearest neighbor indexes
- Estimating the number of restaurants in Google Places.



### B+ Tree

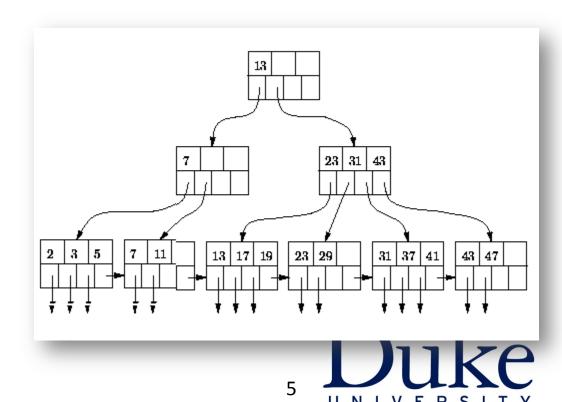
- Data values only appear in the leaves
- Internal nodes only contain keys
- Each node has between f<sub>max</sub>/2 and f<sub>max</sub> children
  - $f_{max} = maximum fan-out of the tree$
- Root has 2 or more children





## Problem

How to pick an element uniformly at random from the B<sup>+</sup> Tree?

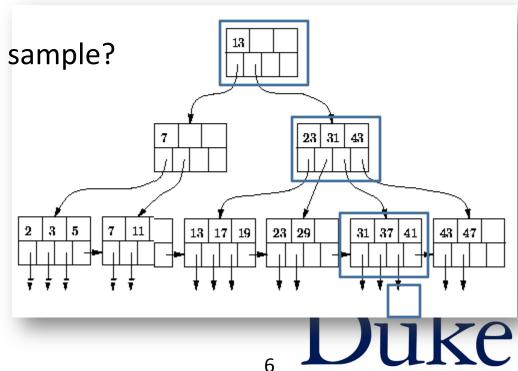


## Attempt 1: Random Path

#### Choose a random path

- Start from the root
- Choose a child uniformly at random
- Uniformly sample from the resulting leaf node

Will this result in a random sample?



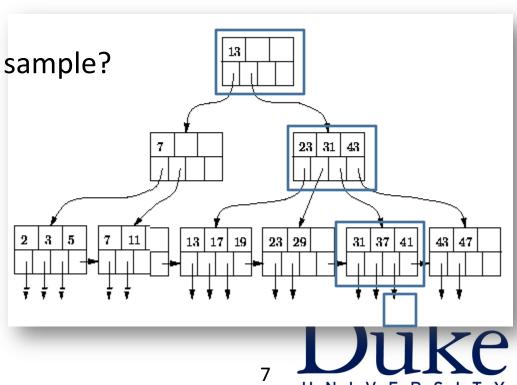
## **Attempt 1: Random Path**

#### Choose a random path

- Start from the root
- Choose a child uniformly at random
- Uniformly sample from the resulting leaf node
- Will this result in a random sample?

#### NO.

Elements reachable from internal nodes with low fanout are more likely.



## Attempt 2: Random Path with Rejection

- Attempt 1 will work if all internal nodes have the same fan-out
- Choose a random path
  - Start from the root
  - Choose a child uniformly at random
  - Uniformly sample from the resulting leaf node
- Accept the sample with probability  $\prod_{i \in path} f_i/f_{max}$



## Attempt 2 : Correctness

• Any root to leaf path is picked with probability:  $\prod_{i \in path}^{f_i/f_{max}}$ 

 The probability of including a record given the path:

$$\prod_{i \in nath} \frac{1}{f_i}$$



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$$\prod_{i \in path} 1/f_i$$

$$\prod_{f \in nath} \frac{1}{f_{max}} = \frac{1}{f_{max}^h}$$



## Attempt 3: Early Abort

Idea: Perform acceptance/rejection test at each node.

- Start from the root
- Choose a child uniformly at random
- Continue the traversal with probability:  $f_i/f_{max}$
- At the leaf, pick an element uniformly at random, and accept it with probability : # of elements in leaf

  # of elements in leaf

Proof of correctness: same as previous algorithm



 Repeatedly sampling n elements will require accessing the internal nodes many times.



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#### Perform random walks simultaneously:

- At the root node, assign each of the n samples to one of its children uniformly at random
  - $n \rightarrow (n_1, n_2, ..., n_k)$
- At each internal node,
  - Divide incoming samples uniformly across children.
- Each leaf node receives s samples. Include each sample with acceptance probability  $\mathbf{r}_{f_{s,t}}$



 Problem: If we start the algorithm with n, we might end up with fewer than n samples (due to rejection)



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- Solution: Start with a larger set
- $n' = n/\beta^{h-1}$ , where  $\beta$  is the ratio of average fanout and  $f_{max}$

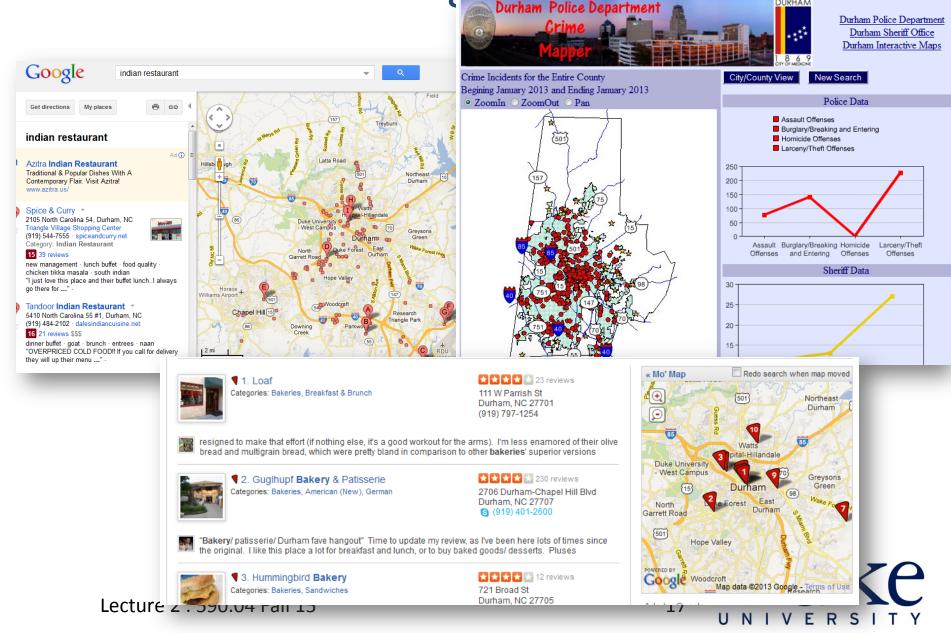


# Summary of B<sup>+</sup>tree sampling

- Randomly choosing a path weights elements differently
  - Elements in the subtree rooted at nodes with lower fan-out are more likely to be picked than those under higher fan-out internal nodes
- Accept/Reject sampling helps remove this bias.



Nearest Neighbor indexes



## **Problem Statement**

#### Input:

- A database D that can't be accessed directly, and where each element is associated with a geo location.
- A nearest neighbor index (elements in D near <x, y>)
  - Assumption: index returns k elements closest to the point <x,y>

#### Output

• Estimate 
$$\frac{1}{|D|} \sum_{d \in D} f(d)$$



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#### **Applications**

- Estimate the size of a population in a region
- Estimate the size of a competing business' database
- Estimate the prevalence of a disease in a region



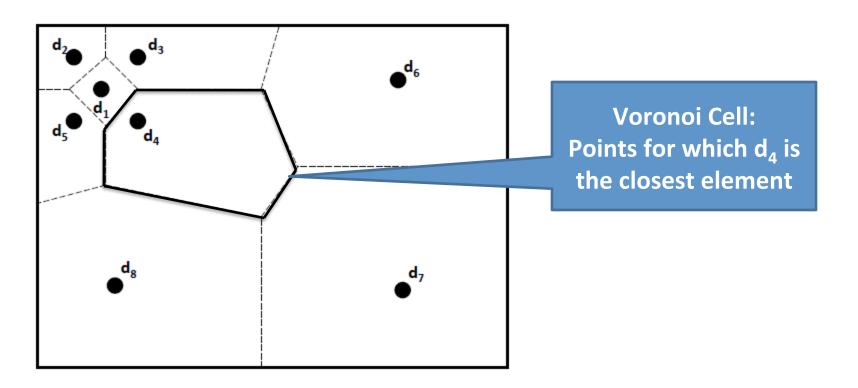
# Attempt 1: Naïve geo sampling

For i = 1 to N

- Pick a random point  $p_i = \langle x, y \rangle$
- Find element  $d_i$  in D that is closes to  $p_i$  Return  $\hat{f}(D) = \frac{1}{N} \sum_i f(d_i)$



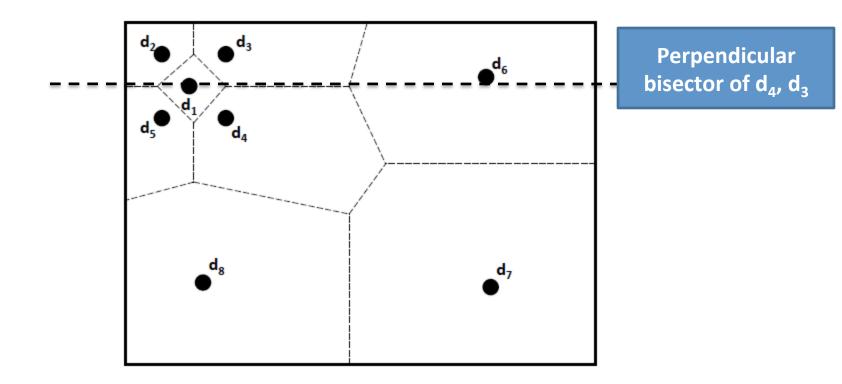
## Problem?



Elements d<sub>7</sub> and d<sub>8</sub> are much more likely to be picked than d<sub>1</sub>



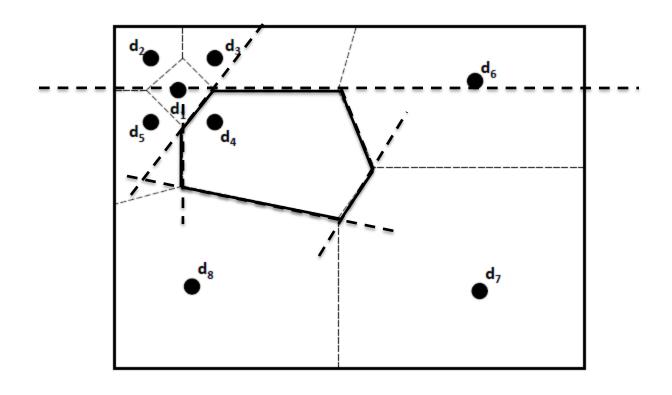
# Voronoi Decomposition





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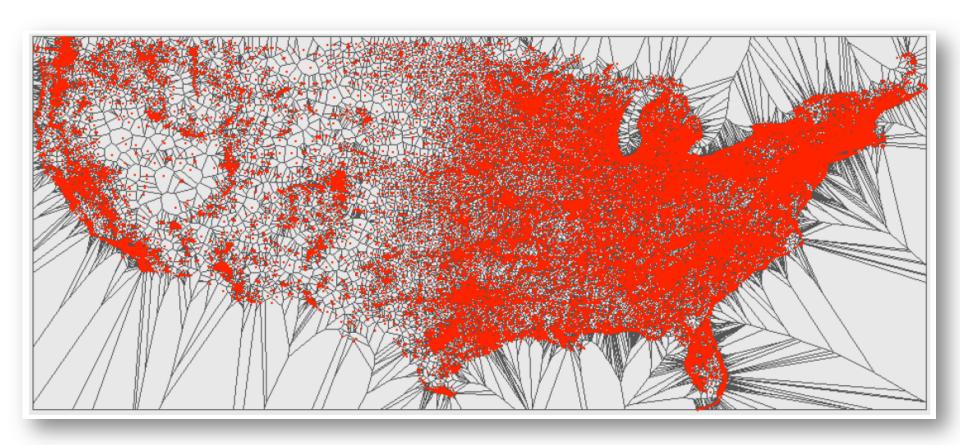
# Voronoi Decomposition



$$P[sampling d_i] = \frac{area(Vor(d_i))}{total \ area}$$



# Voronoi decomposition of Restaurants in US





# Attempt 2: Weighted sampling

For i = 1 to N

- Pick a random point  $p_i = \langle x, y \rangle$
- Find element d<sub>i</sub> in D that is closes to p<sub>i</sub>

• Return 
$$\hat{f}(D) = \frac{1}{N} \sum_{i} \left( f(d_i) \cdot \frac{total\ area}{area(Vor(d_i))} \right)$$



# Attempt 2: Weighted sampling

#### For i = 1 to N

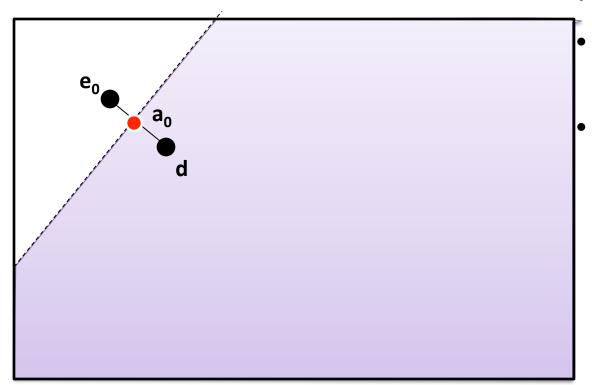
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#### Problem:

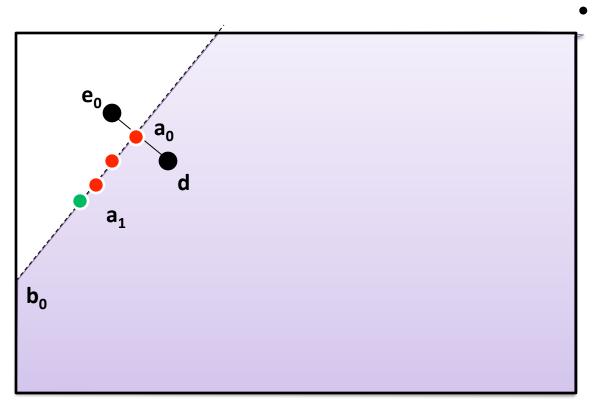
We need to compute the area of the Voronoi cell. We do not have access to other elements in the database.





- Find nearest point
- Compute perpendicular bisector
- a0 is a point on the Voronoi cell.



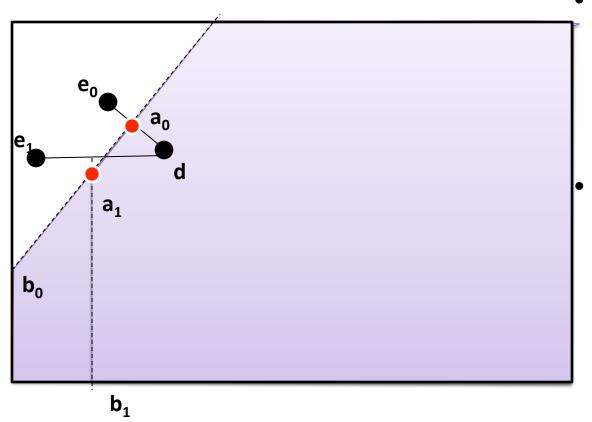


- Find a point on  $(a_0, b_0)$  which is just inside the Voronoi cell.
  - Use binary search

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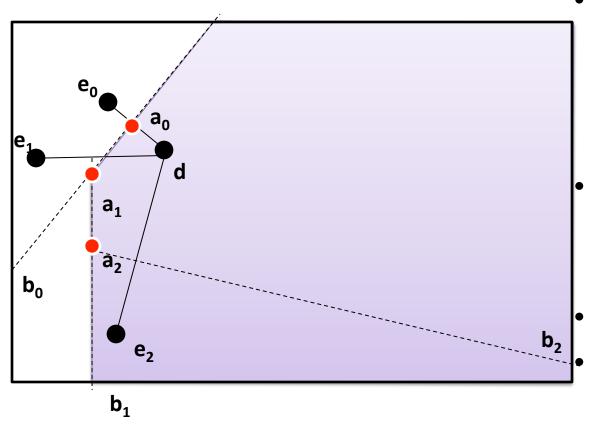
Recursively check
 whether mid point is in
 the Voronoi cell





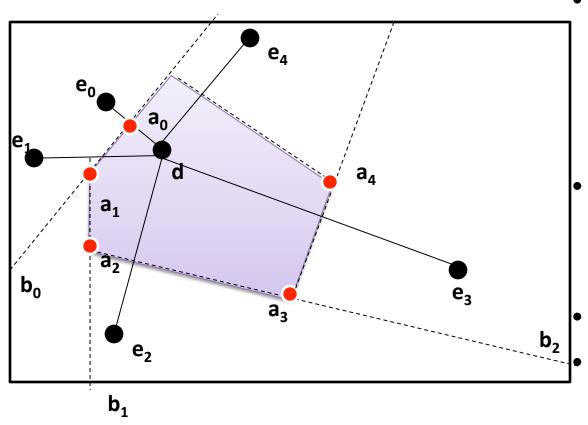
- Find nearest points to a<sub>1</sub>
  - $a_1$  has to be equidistant to one point other than  $e_0$  and d
- Next direction is perpendicular to (e<sub>1</sub>,d)





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  - ... and so on ...





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- Find next point ...
  - ... and so on ...



## Number of samples

- Identifying each a<sub>i</sub> requires a binary search
  - If L is the max length of (ai, bi), then  $a_{i+1}$  can be computed with ε error in O(log (L/ε)) calls to the index
- Identifying the next direction requires another call to the index
- If number of edges of Voronoi cell = k, total number of calls to the index =  $O(K \log(L/\epsilon))$
- Average number of edges of a Voronoi cell < 6</li>
  - Assuming general position ...



## Summary

- Many web services allow access to databases using nearest neighbor indexes.
- Showed a method to sample uniformly from such databases.
- Next class: Monte Carlo Estimation for #P-hard problems.



## References

- F. Olken, "Random Sampling from Databases", PhD Thesis, U C Berkeley, 1993
- N. Dalvi, R. Kumar, A. Machanavajjhala, V. Rastogi, "Sampling Hidden Objects using Nearest Neighbor Oracles", KDD 2011

