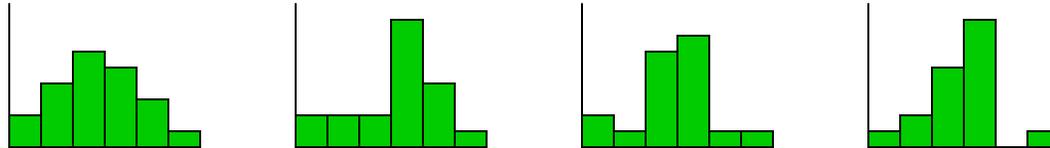


# Histograms and Wavelets on Probabilistic Data



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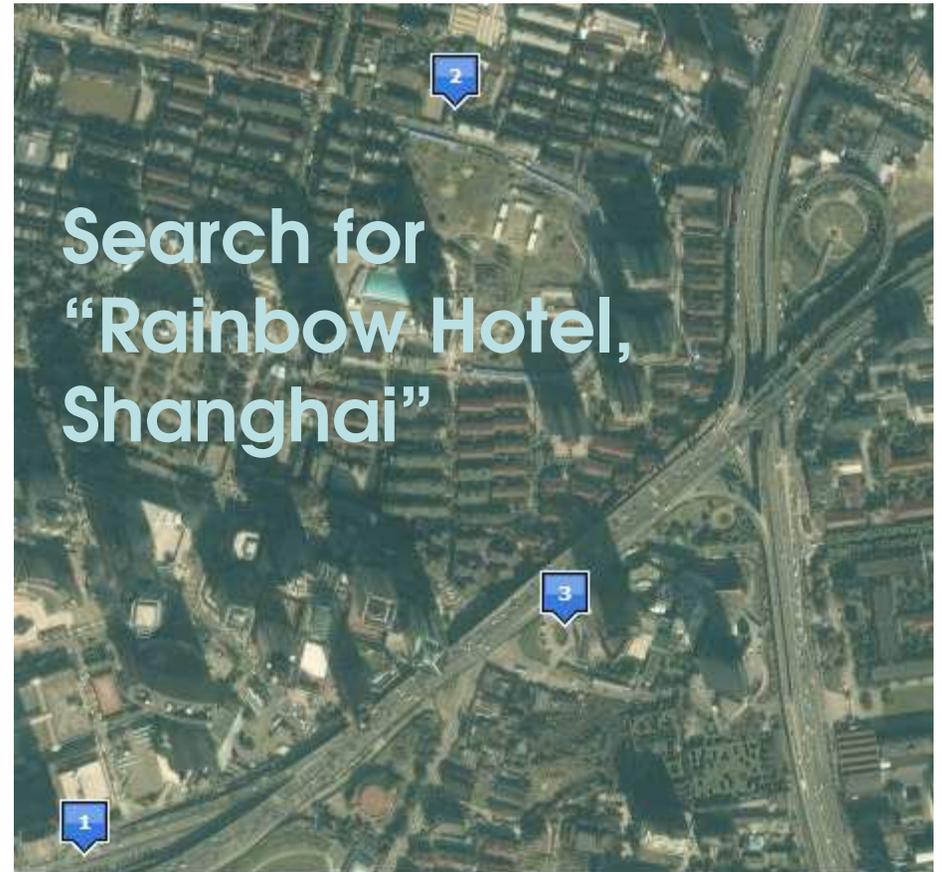
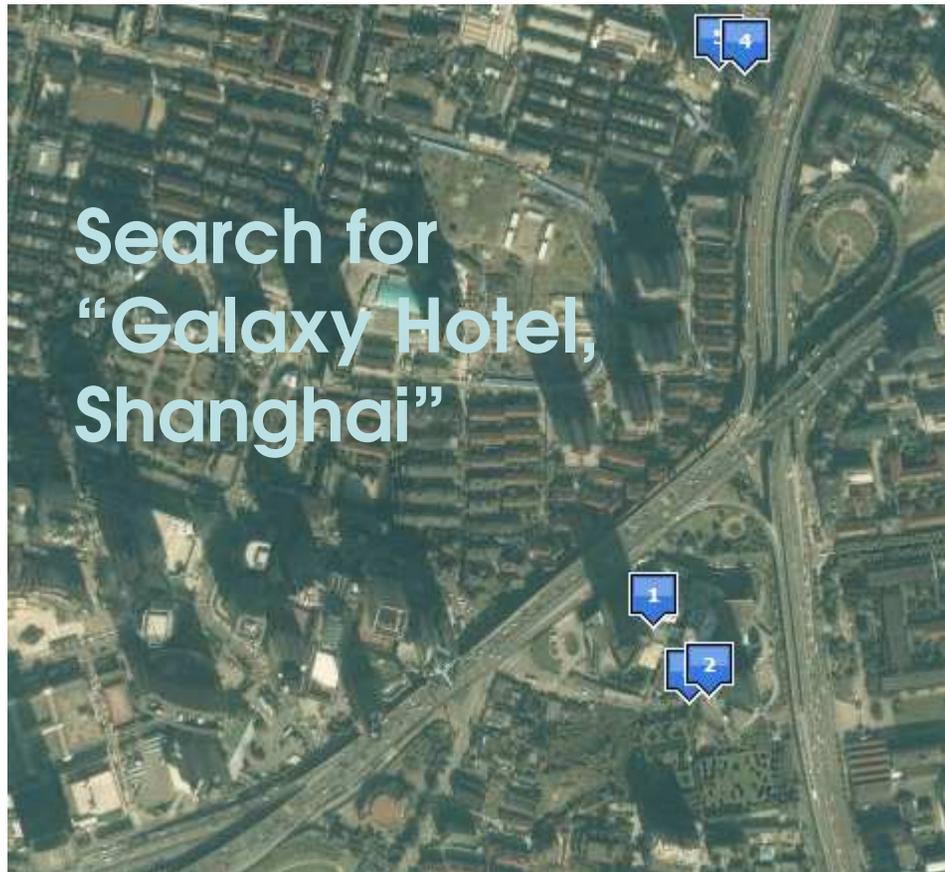
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# Sources of Probabilistic Data

- ◆ Increasingly data is *uncertain* and *imprecise*
  - Data collected from sensors has errors and imprecisions
  - Record linkage has confidence of matches
  - Learning yields probabilistic rules
- ◆ Recent efforts to build uncertainty into the DBMS
  - Mystiq, Trio and MayBMS projects
  - Model uncertainty and correlations within tuples
  - Aim to allow general purpose queries over uncertain data

# Uncertain Data



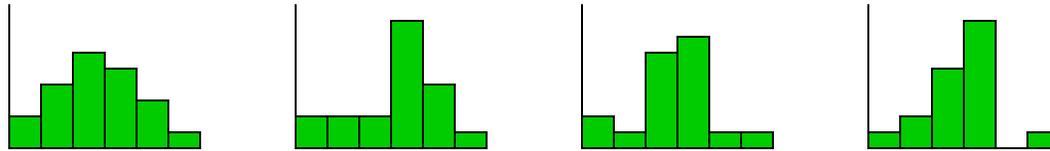
**Query:** How close is Galaxy Hotel to Rainbow Hotel?

# Probabilistic Data Reduction

- ◆ Probabilistic data can be difficult to work with
  - Even simple queries can be #P complete [Dalvi, Suciu '04]
  - Want to avoid materializing all possible worlds
- ◆ Seek compact representations of probabilistic data
  - Data synopses which capture key properties
  - Can perform expensive operations on compact summaries
  - Histograms and wavelets used in traditional systems
- ◆ **Challenge:** how to build optimal synopses?

# Models of Data

- ◆ Model defines a distribution over possible worlds,  $W$
- ◆ Limit correlations to keep models compact
- ◆ Value pdf model:
  - Each item has independent distribution of frequencies



- ◆ Tuple pdf model:
  - Each tuple has a distribution of possible values
  - Can interpret as non-independent Value pdf model

# Histograms for Probabilistic Data

- ◆ A histogram partitions a domain into buckets
  - All values within a bucket behave similarly
  - Can be represented by a single value
- ◆ Apply same idea to probabilistic data
  - Partition domain to minimize *expected* error
  - Key problem is finding cost of a given bucket
  - Use **dynamic programming** to find overall cost

# Sum Squared Error Histograms

- ◆ Given a bucket  $b=(s,e)$ , choose representative value  $r$ 
  - Pick  $c$  to minimize expected squared error
  - Frequency of item  $i$  in world  $W$  is  $g_i(W)$
  - (Expected) cost =  $\sum_{i=s}^e \sum_{\text{worlds } W} \text{Pr}[W] \cdot (g_i(W) - r)^2$
- ◆ Cost minimized by  $r =$  mean value in the bucket
  - Mean given by  $r = \sum_{i=s}^e \sum_{\text{worlds } W} \text{Pr}[W] \cdot g_i(W)$
  - Generalizes the deterministic case
  - Cost of a bucket is sum of expected sum of squares, less scaled expected square of sums
- ◆ How to compute the **cost** efficiently on demand?

# Sum Squared Error Histograms

- ◆ Use the fact that  $E[X^2] = \text{Var}[X] + E[X]^2$  to simplify
  - Apply independence and summation of variance
  - Rewrite cost of a bucket in terms of sums of values per item
  - Keep prefix sums of these values to find sum of any range
- ◆ With precomputation, **find bucket cost in  $O(1)$  time**
  - Find optimal B-bucket histogram in time  $O(Bn^2)$  via DP
- ◆ Holds for both tuple and value pdf models
  - Linearity of expectation handles dependencies for tuple pdf

# Sum Squared Relative Error

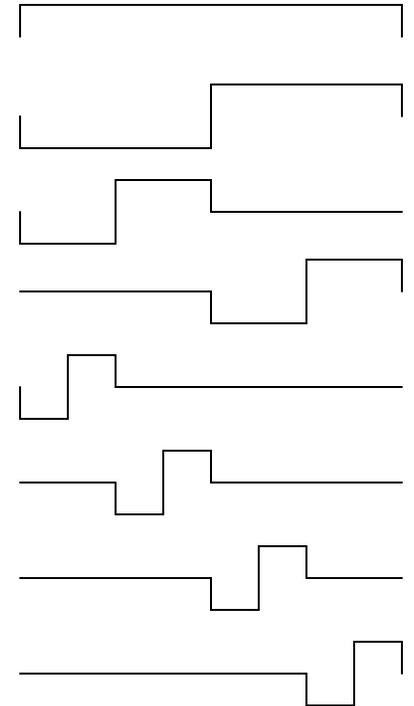
- ◆ Cost of bucket is  $E_W[\sum_{i=s}^e (g_i(W) - r)^2 / \max(c^2, g_i^2(W))]$ 
  - For representative value  $r$ , and constant  $c$
- ◆ Expand out the quadratic numerator
  - Observe that denominator is fixed in any world  $W$
  - Differentiate to find optimal value of  $r$
- ◆ Gives bucket cost in terms of three expectations:
  - $\sum_i 1/\max(c^2, g_i^2)$  ;  $\sum_i g_i/\max(c^2, g_i^2)$  and  $\sum_i g_i^2/\max(c^2, g_i^2)$
  - Use prefix sums to find bucket cost in constant time
- ◆ Find optimal B-bucket SSRE histogram in time  $O(Bn^2)$

# Sum of Absolute Error

- ◆ Cost of bucket is  $E_W[\sum_{i=s}^e | g_i(W) - r |]$ 
  - Break into sum of values above  $r$ , and those below
  - Minimize when  $r$  is some value with non-zero probability
  - As  $r$  varies, cost decreases to a minimum, then increases
- ◆ Can precompute prefix sums for different  $r$  values
  - Ternary search to find best choice of  $r$  for a bucket
  - Takes  $O(\log |V|)$  steps over  $|V|$  different values
- ◆ Find opt B-bucket SAE histogram in  $O(n^2(B+\log |V|))$

# Wavelets for Probabilistic Data

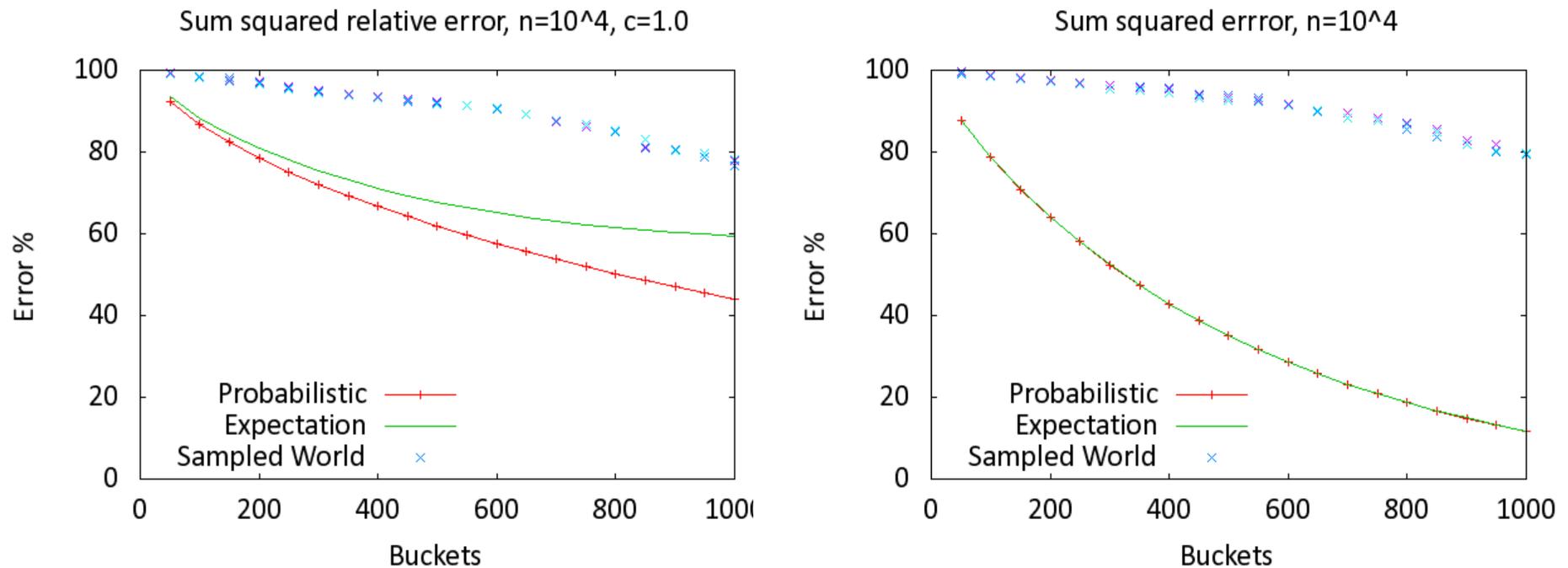
- ◆ Express data via  $B$  Haar basis functions
  - Seek to minimize expected squared error
- ◆ Use **linearity of wavelet transform**
  - Optimal to take expected coefficient values
  - Error due to dropping  $i$ 'th coefficient = square of expected value
  - Best to pick  $B$  largest expected coefficients
- ◆ More complex under other error metrics
  - Perform DP over tree structure and coefficient values



# Experimental Study

- ◆ Evaluated on two probabilistic data sets
  - Real data from Mystiq Project (10K items)
  - Synthetic data from MayBMS generator (30K items)
- ◆ Compare to naïve methods to generate summaries:
  - Build wavelets/histograms over sampled possible world
  - Build wavelets/histograms over expected values
- ◆ Plot fraction of cost of 1 bucket – cost of n buckets

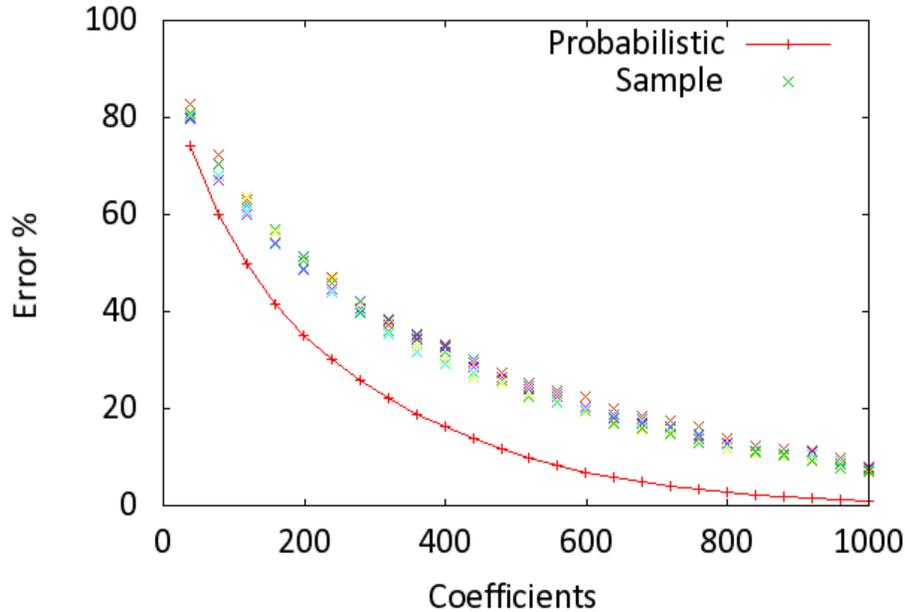
# Sum Squared Error Histograms



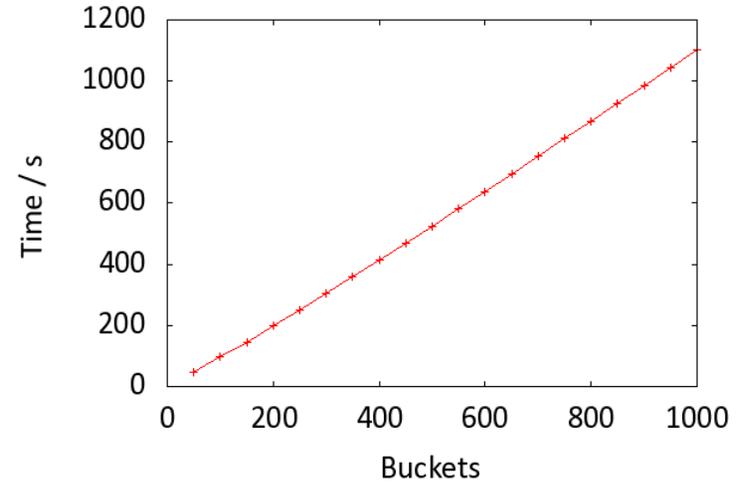
- ◆ Clear benefit for relative error over naïve methods
- ◆ Histograms on expected values almost as good for SSE

# Time and Wavelets

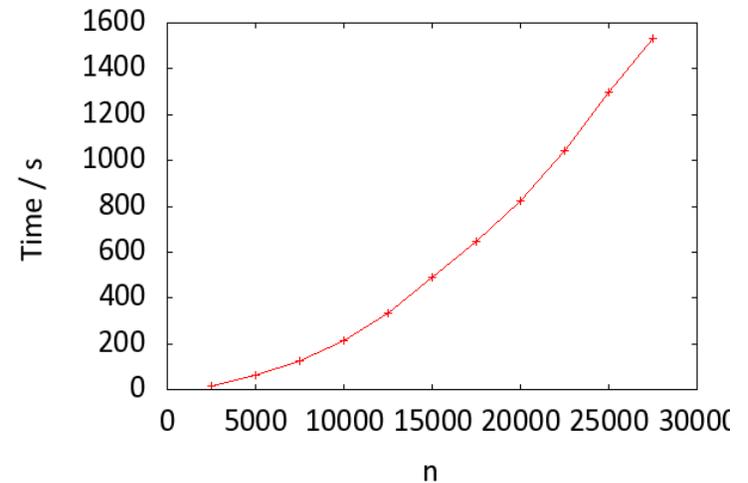
SSE Wavelets, Synthetic Data,  $n=2^{15}$



Sum Squared Relative Error Time Cost,  $n=10^4$



Sum Squared Relative Error Time Cost,  $B=200$



- Time cost is linear in  $B$ , quadratic in  $n$ 
  - ◆ Same cost for histogram of sample
- Expected coefficients shows clear benefit over sampling possible worlds

# Concluding Remarks

- ◆ Can build synopses for probabilistic data

## Advantages:

- ◆ Histograms and wavelets are familiar objects
- ◆ Leverage existing methods for processing summaries

## Disadvantages:

- ◆ Dynamic programming can be slow (quadratic cost)
  - Can approximate using standard techniques
- ◆ Representation loses probabilistic semantics
  - Look for summaries that are more like pdfs?