

HUMAN-POWERED DATA MANAGEMENT

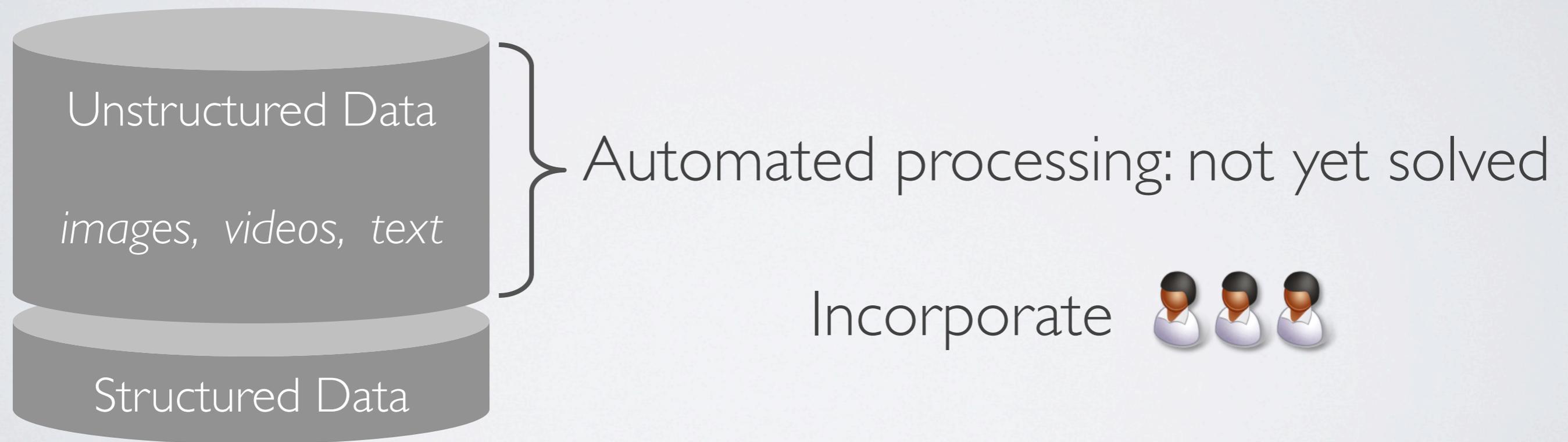
Aditya Parameswaran

with H. Garcia-Molina,
J. Widom, A. Polyzotis, M. Teh



Why should we (DM/DB folks) care?

Reason 1: Most data is unstructured



Why should we (DM/DB folks) care?

Reason 2: S/ware companies use crowds at scale

We undertook a survey of industry crowdsourcing users



use crowds!

*Often 10s+ of Millions of \$ / yr. / company
(on crowds + supervisors)*

Plenty of startups too!

Why should we (DM/DB folks) care?

Reason 3: Marketplaces are growing rapidly



20+ marketplaces

Big companies
have internal ones

Crowdsourcing Marketplaces

Size of these marketplaces have doubled in 2011 – 2013

Why should we (DM/DB folks) care?

Reason 1: Most data is unstructured

Reason 2: Software companies use crowds at scale

Reason 3: Marketplaces are growing rapidly

What is Human-Powered Data Management?

Data Processing
Algorithms

Data Processing
Systems

where humans act as “data processors”
e.g., compare, label, extract

Learning
accuracies

Machine Learning

Interfaces
Patterns

HCI

Incentives

Economics

Efficient Data Processing Algorithms & Systems

Data Processing Algorithms

Filter [SIGMOD12, VLDB14] Max [SIGMOD12]
Clean [KDD12, TKDD13] Categorize [VLDB11]
Search [ICDE14] Debugging [NIPS12]

Data Processing Systems

Deco [CIKM12, VLDB12, TR12, SIGMOD Record 12]
DataSift [HCOMP13, SIGMOD14] HQuery [CIDR11]

Auxiliary Plugins: Quality, Pricing

Confidence [KDD13, TR14] Eviction [TR12]
Pricing [VLDB15] Quality [HCOMP14]

Data Proc. Sys.: Crowd-Powered Search

Can your search engine handle this?

buildings in the vicinity of

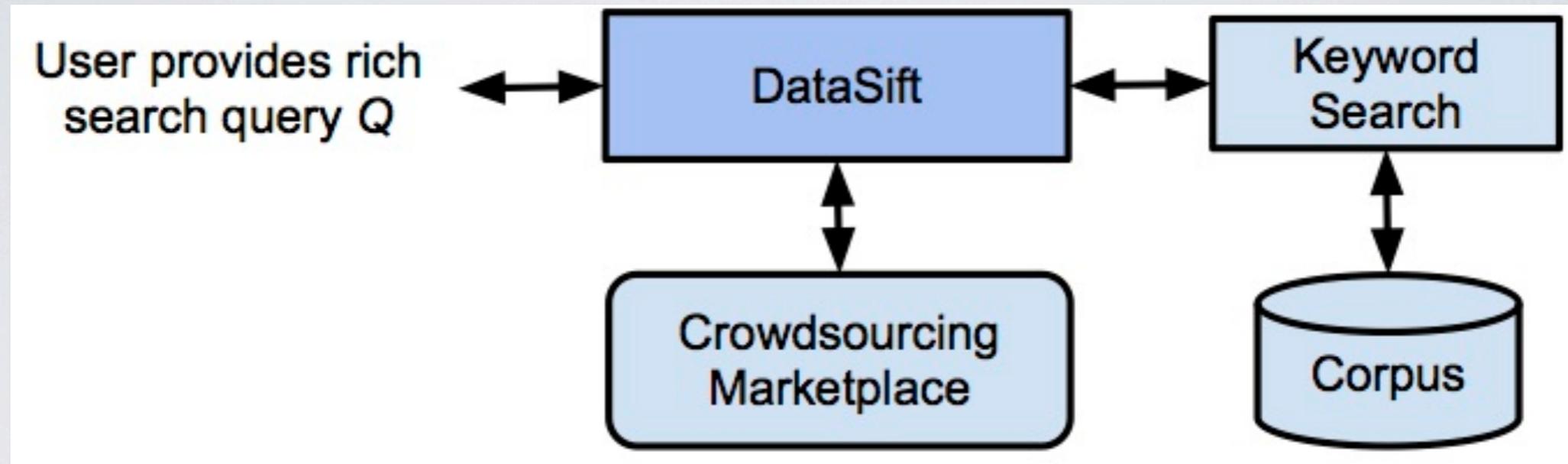


type of cable that connects to



*apartments in a good school district near
Urbana, with a bus stop near by*

DataSift: Crowd-Powered Search



- *Non-textual content:*
 - “cables that plug into ”
 - “funny pictures of cats with hats with captions”
- *Time-consuming:*
 - “find noise canceling headphones where the battery lasts 13 hrs”
 - “apartments in a nice area around urbana”

searched for **type of cable that connects to**



using Amazon Products

DataSift Rank	Thumbnail	Product Details
1		Mediabridge Hi-Speed USB 2.0 Cable - (6 Feet) Product page: http://www.amazon.co/dp/B001MXLD4G Price: USD 4.99
2		AmazonBasics USB 2.0 A-Male to B-Male Cable with Lighted Ends - Braided (6 Feet/1.8 Meters) Product page: http://www.amazon.co/dp/B003ES5ZQE Reviews: http://www.amazon.com/reviews/iframe?akid=AKIAJ... Price: USD 6.99
3		Epson Stylus USB Printer Cord NEW !! 2.0 A - B Cable 6' Product page: http://www.amazon.co/dp/B0032GO0SW Reviews: http://www.amazon.com/reviews/iframe?akid=AKIAJ... Price: USD 2.88
4		USB Printer Cable for HP DeskJet 1000 with Life Time Warranty Product page: http://www.amazon.co/dp/B004PRXM2C Reviews: http://www.amazon.com/reviews/iframe?akid=AKIAJ... Price: USD 4.95
5		Mediabridge Hi-Speed USB 2.0 Cable - (10 Feet) Product page: http://www.amazon.co/dp/B001MSU1HG Reviews: http://www.amazon.com/reviews/iframe?akid=AKIAJ... Price: USD 5.49
6		Mediabridge Hi-Speed USB 2.0 Cable - (16 Feet) Product page: http://www.amazon.co/dp/B001MSZBNA Reviews: http://www.amazon.com/reviews/iframe?akid=AKIAJ... Price: USD 7.49

Building DataSift: Challenges

Gather

Ask for text reformulations for query

Filter

Check if item satisfies query

Gather

Retrieve

Filter

Gather

Retrieve

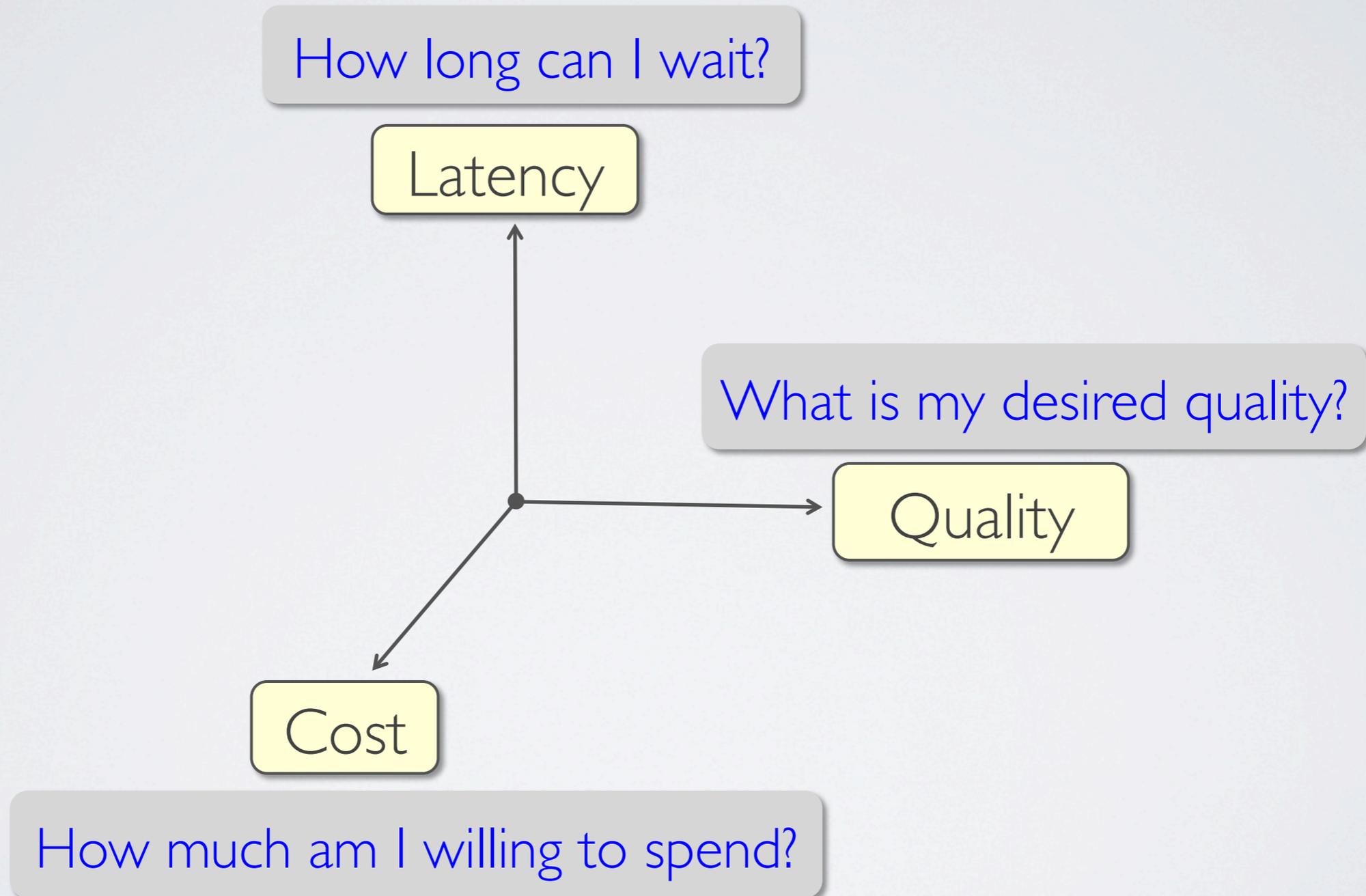
Filter

Retrieve

Filter

- *How many reformulations should we gather?*
- *How many items should we retrieve at each step?*
- *How do we filter items? How many people do we ask?*
- *How do we optimize the workflow?*
- *How do we guarantee correctness?*

Fundamental Tradeoffs



DataSift Summary

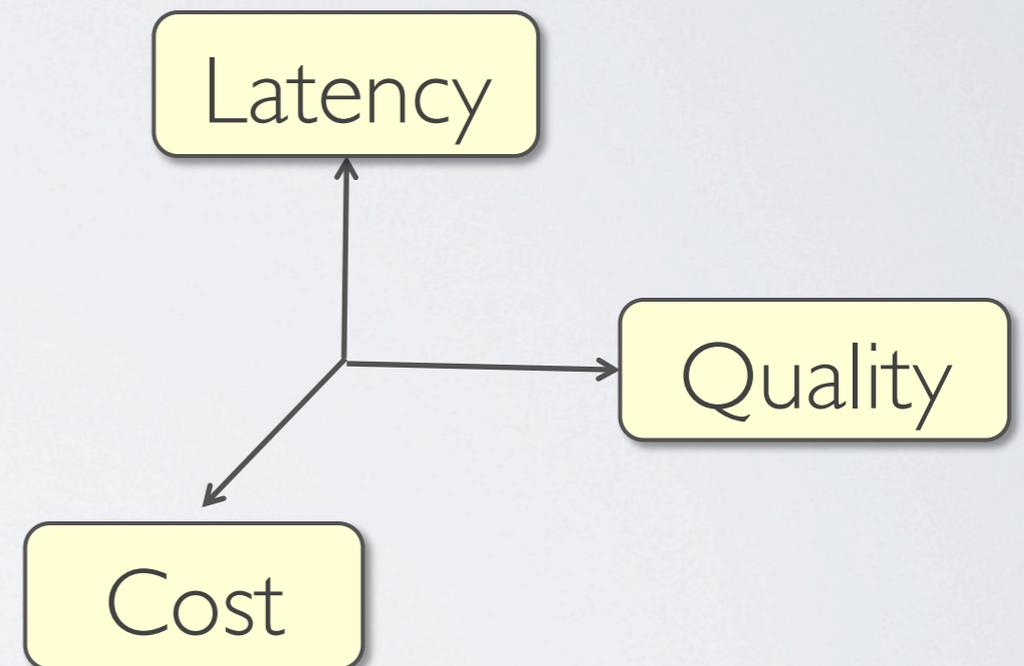
Sample applications:

education, social media, commerce, journalism, ...

Gather

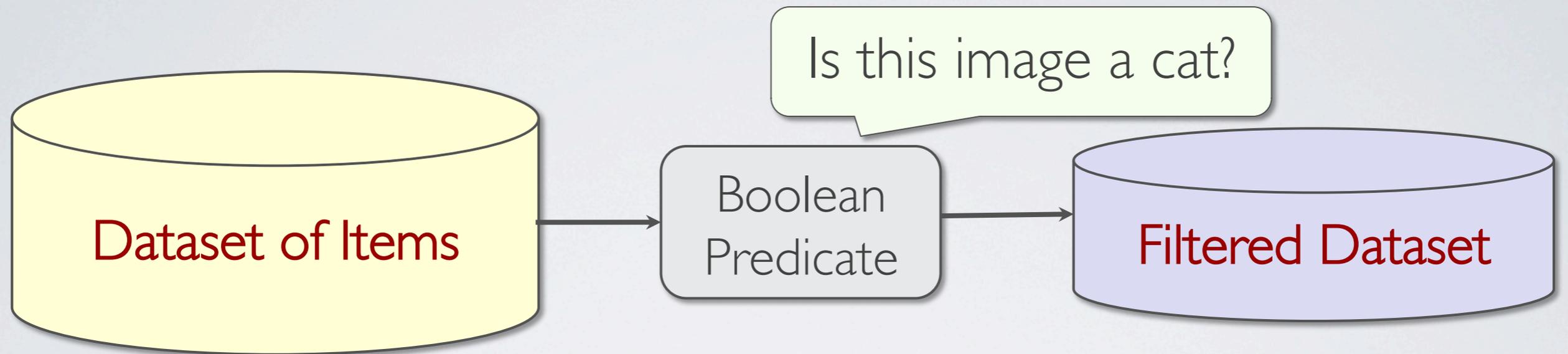
Retrieve

Filter

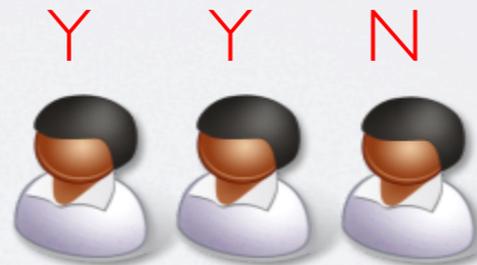


[SIGMOD | 4] DataSift: A Crowd-Powered Search Toolkit (demo)
[HCOMP | 3] An expressive and accurate crowd powered search

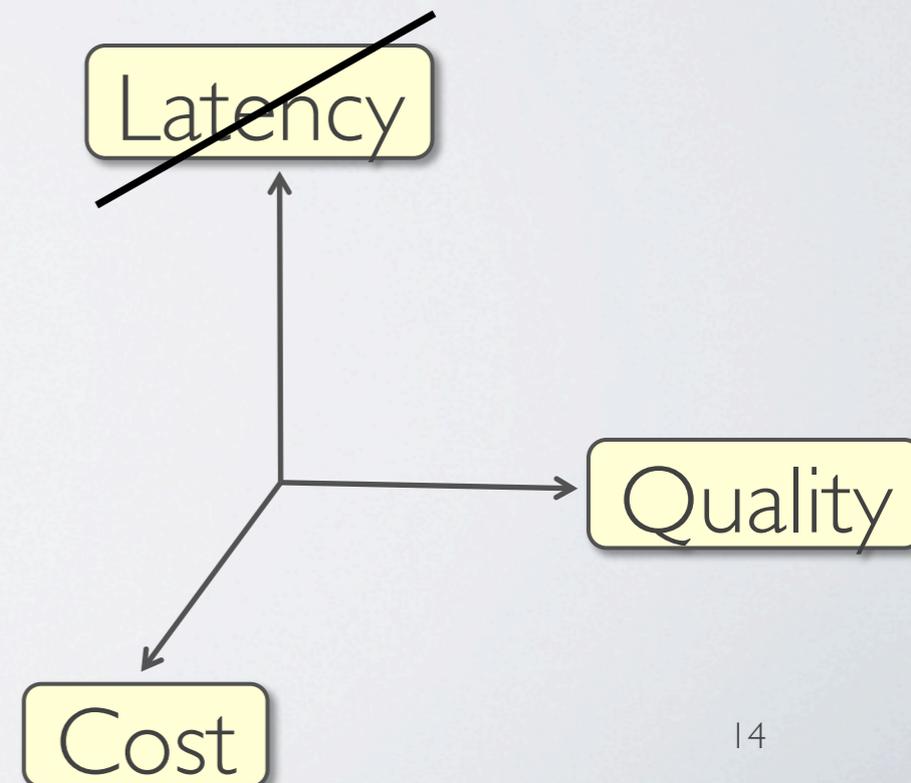
Filtering: The Simplest Version



Does X satisfy predicate?

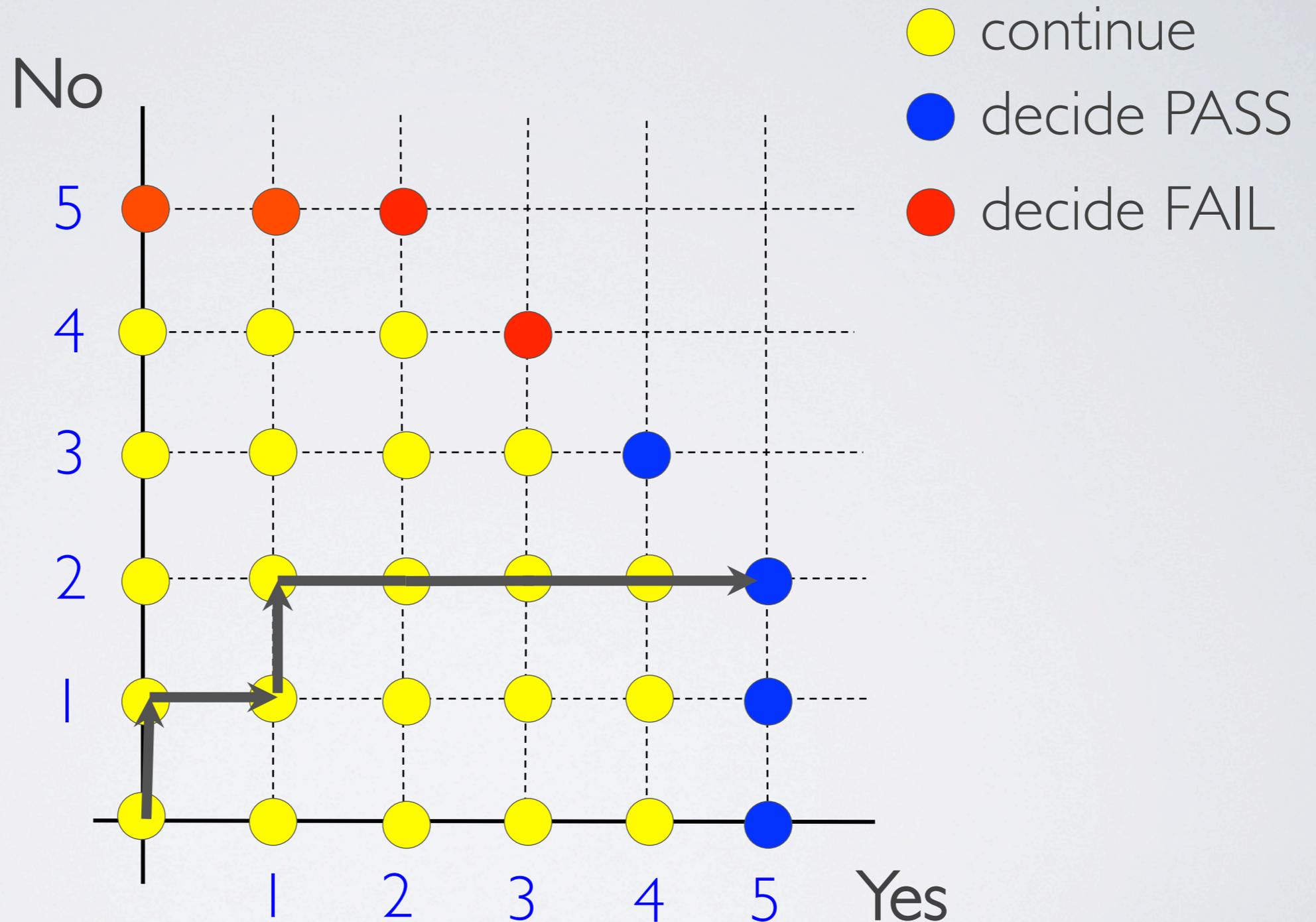


For now, all humans have same error rates

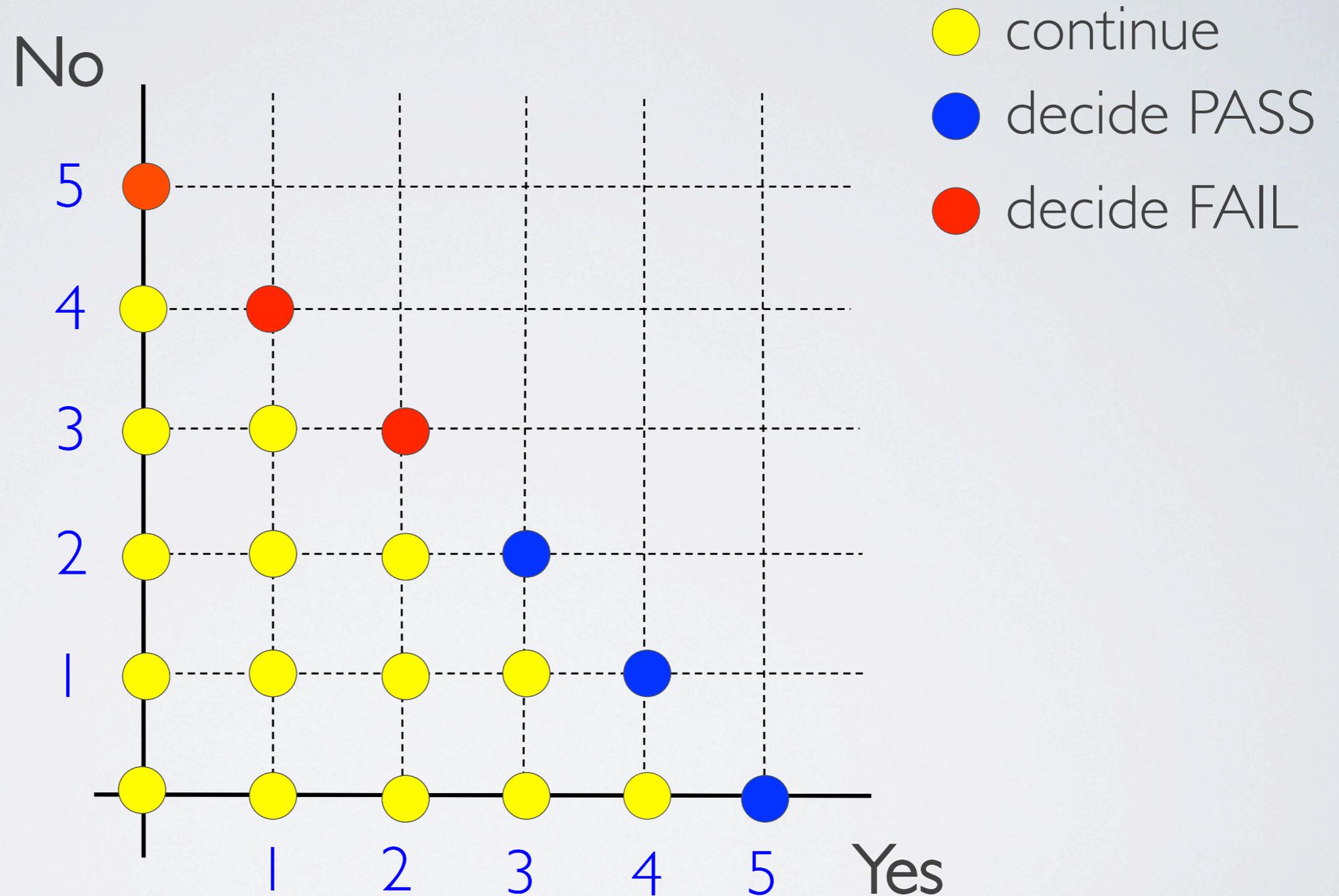


Our Visualization of Strategies

Markov
Decision
Process



Strategy Examples



Simplest Version

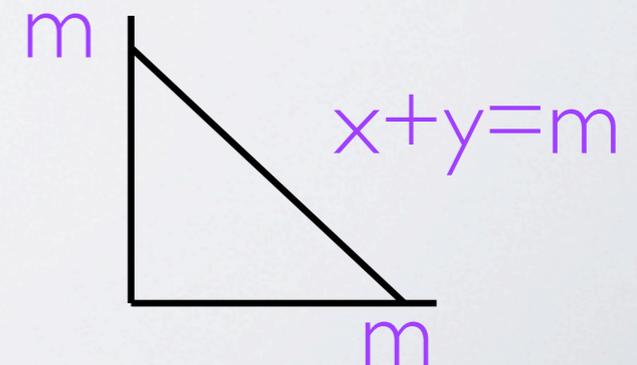
Given:

- Human error probability (FP/FN)
- $\Pr[\text{Yes} \mid 0]; \Pr[\text{No} \mid 1]$
- A-priori probability
- $\Pr[0]; \Pr[1]$

Via sampling,
prior history, or
gold standard

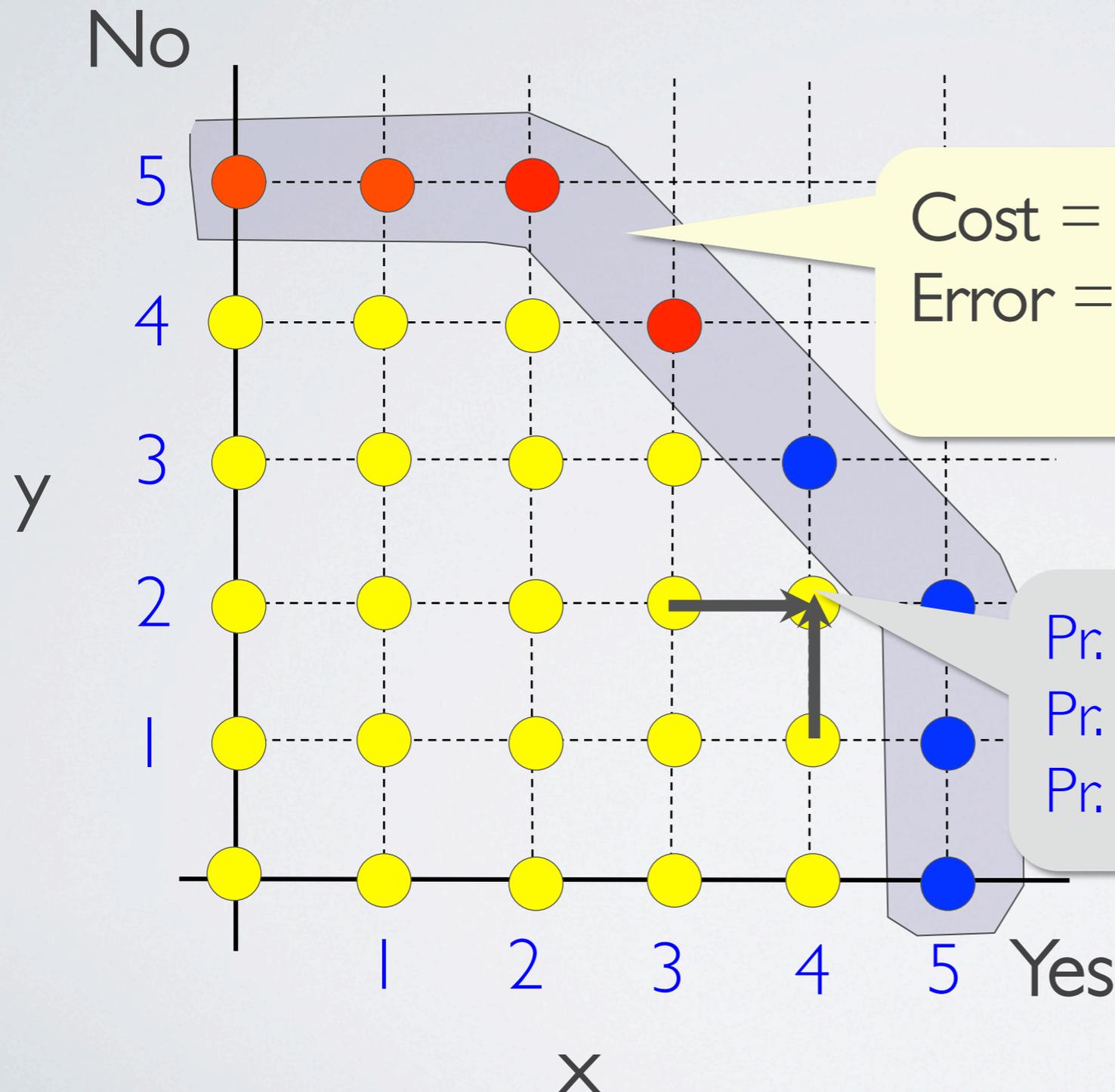
Find **strategy** with minimum expected cost (# of questions)

- Expected error $< t$ (say, 5%)
- Cost per item $< m$ (say, 20 questions)



Evaluating Strategies

- continue
- decide PASS
- decide FAIL



$$\text{Cost} = \sum (x+y) \text{Pr} [\text{reach}(x,y)]$$

$$\text{Error} = \sum \text{Pr} [\text{reach} \text{ ●} \wedge 1] + \sum \text{Pr} [\text{reach} \text{ ●} \wedge 0]$$

$$\text{Pr.} [\text{reach} (4, 2)] = \text{Pr.} [\text{reach} (4, 1) \ \& \ \text{get a No}] + \text{Pr.} [\text{reach} (3, 2) \ \& \ \text{get a Yes}]$$

Naïve Approach

For each grid point
Assign ●, ● or ●

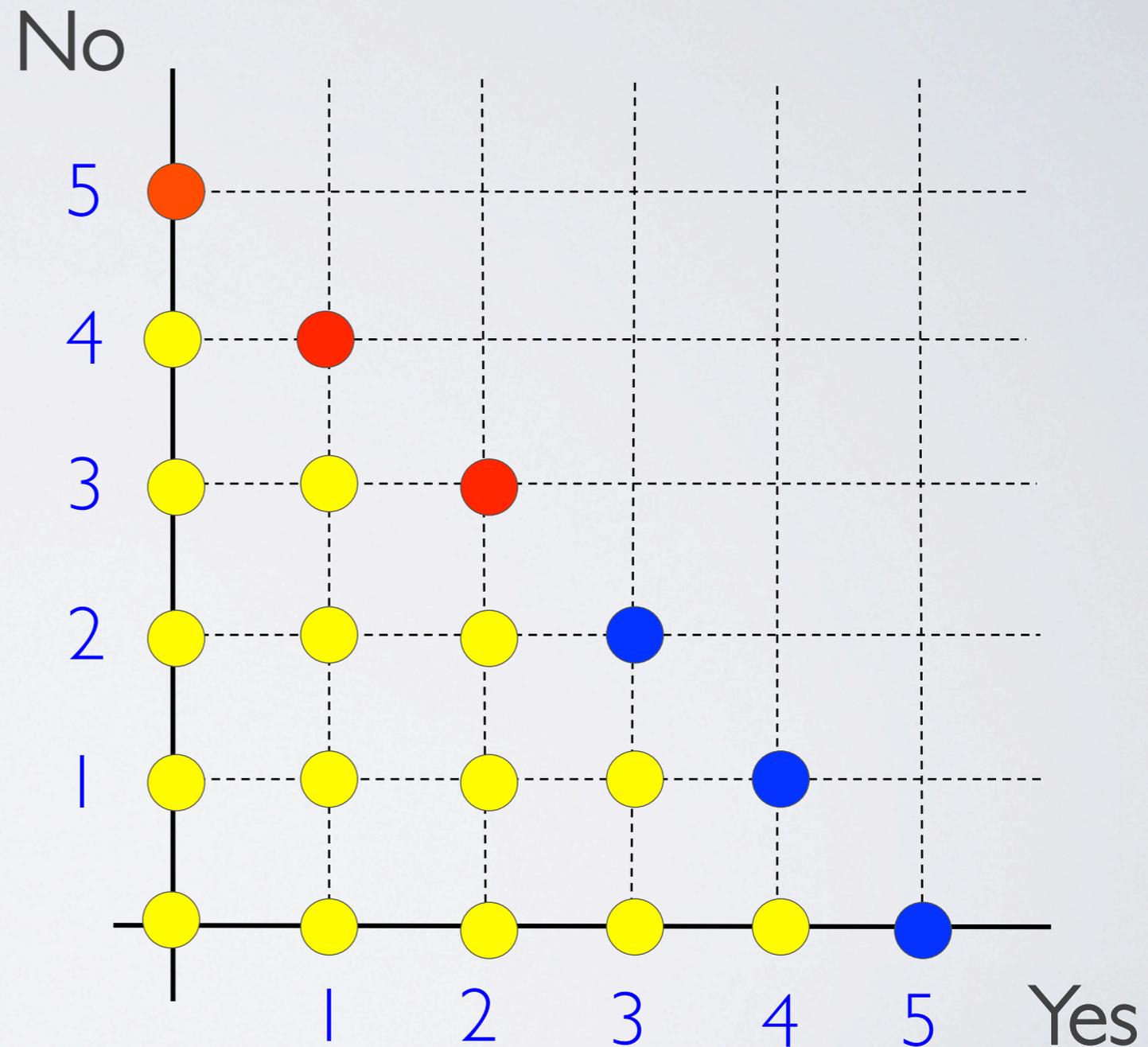
For all strategies:

- Evaluate cost & error

Return the best

$$O(3^g), g = O(m^2)$$

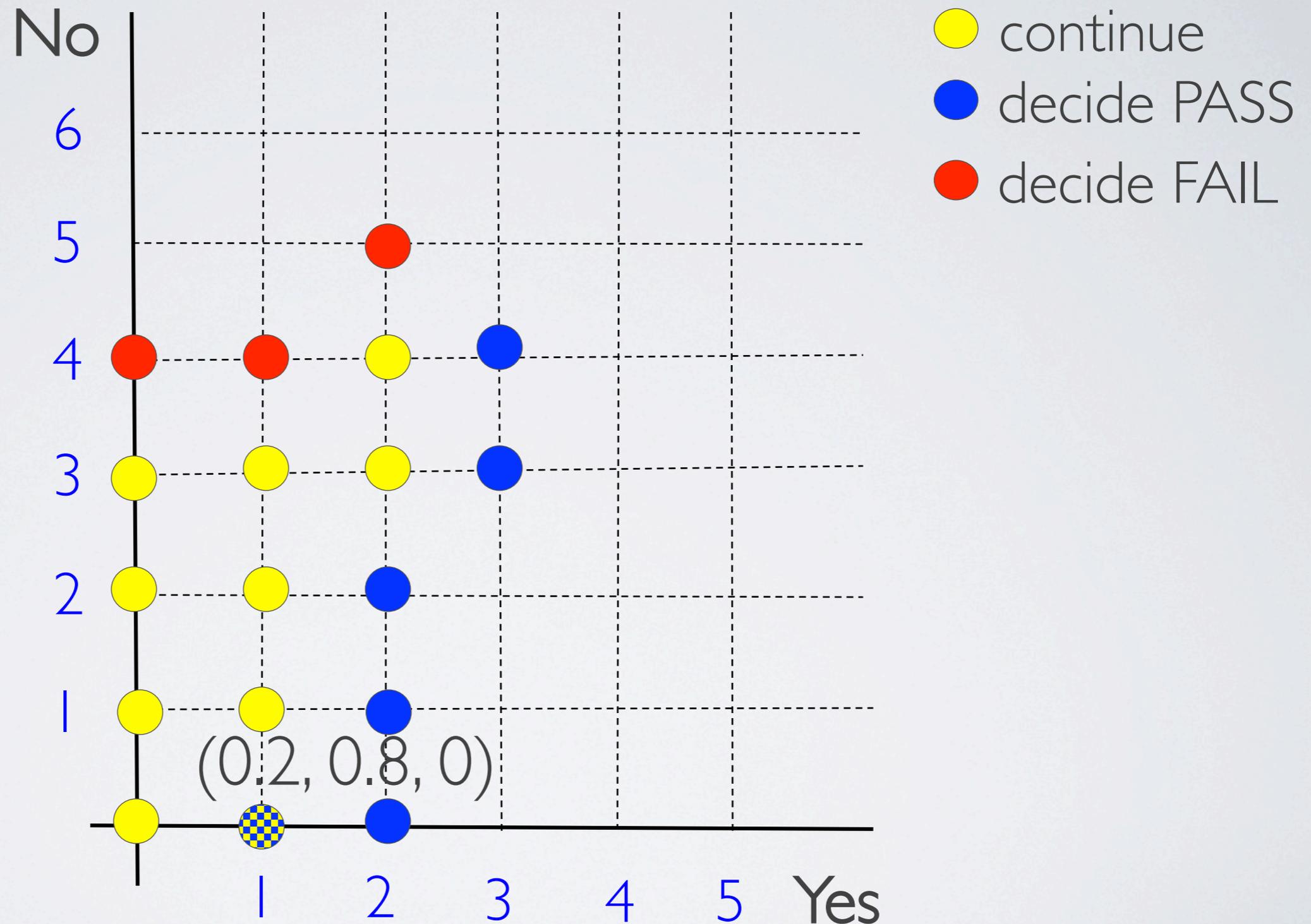
$$\text{If } m=5, g=21$$



Comparison

	Computing Strategy	Money
Naïve deterministic	Not feasible	\$\$
Our best deterministic	Exponential; feasible	\$\$\$

Probabilistic Strategy Example



Comparison

	Computing Strategy	Money
Naïve deterministic	Exponential; not feasible	\$\$
Our best deterministic	Exponential; feasible	\$\$\$
The best probabilistic THE BEST	Polynomial(m)	\$

Finding the Optimal Strategy

Simple: Use Linear Programming

- **variables:** “probabilistic decision per grid point”
- **constraints:**
 - probability conservation
 - boundary conditions

Generalizations

- Multiple answers (ratings, categories)
- Multiple independent filters
- Difficulty
- Different penalty functions
- Latency
- Different worker abilities
- Different worker probes
- A-priori scores

Doable

Hard!

Generalization: Worker Abilities

	Item 1	Item 2	Item 3
Actual	0	1	0
W_1	0	1	0
W_2	1	1	1
W_3	1	0	1

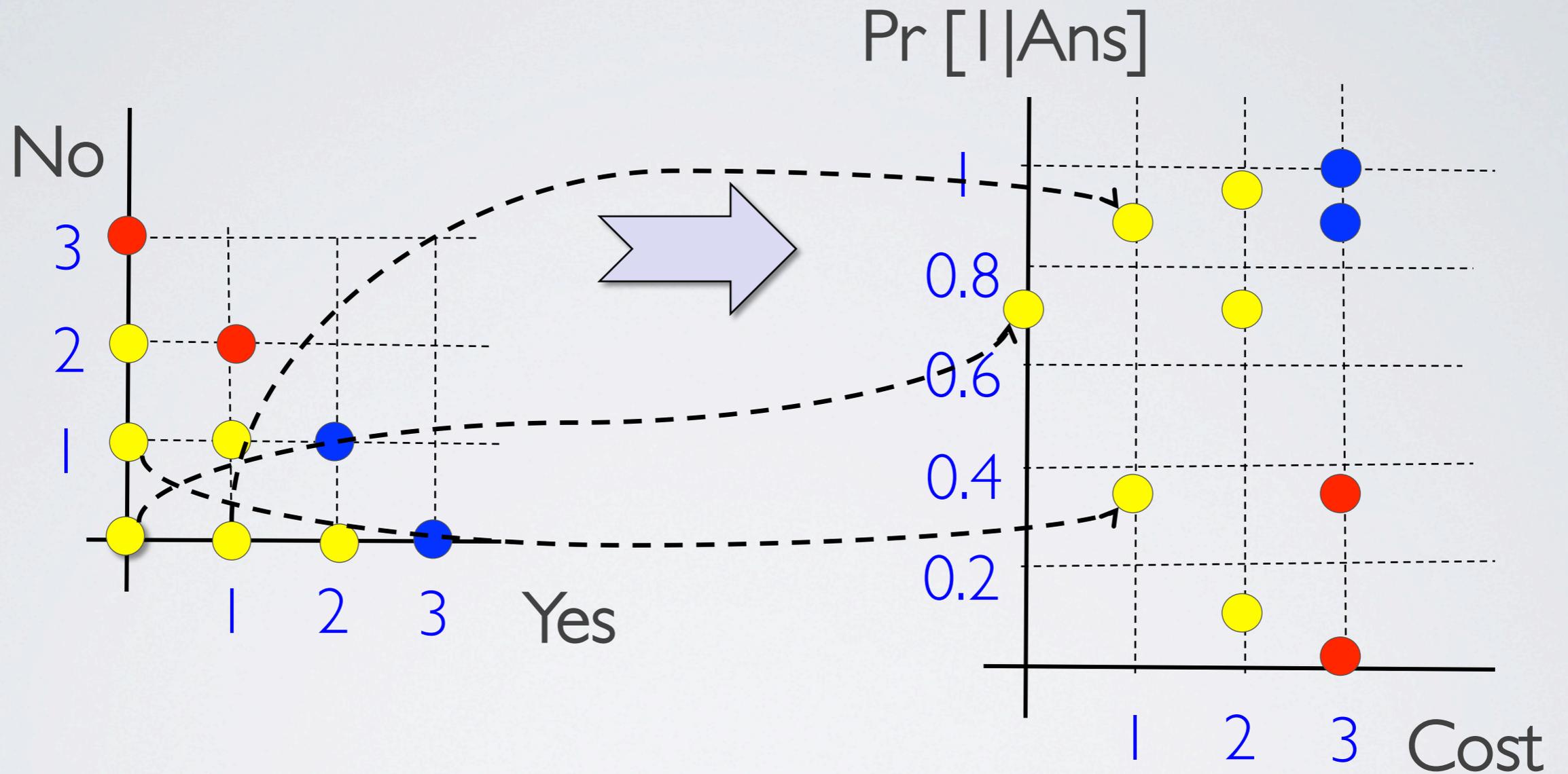
$(W_1 \text{ Yes}, W_1 \text{ No}, \dots, W_n \text{ Yes}, W_n \text{ No})$

$O(m^{2n})$ points

$n \approx 1000$

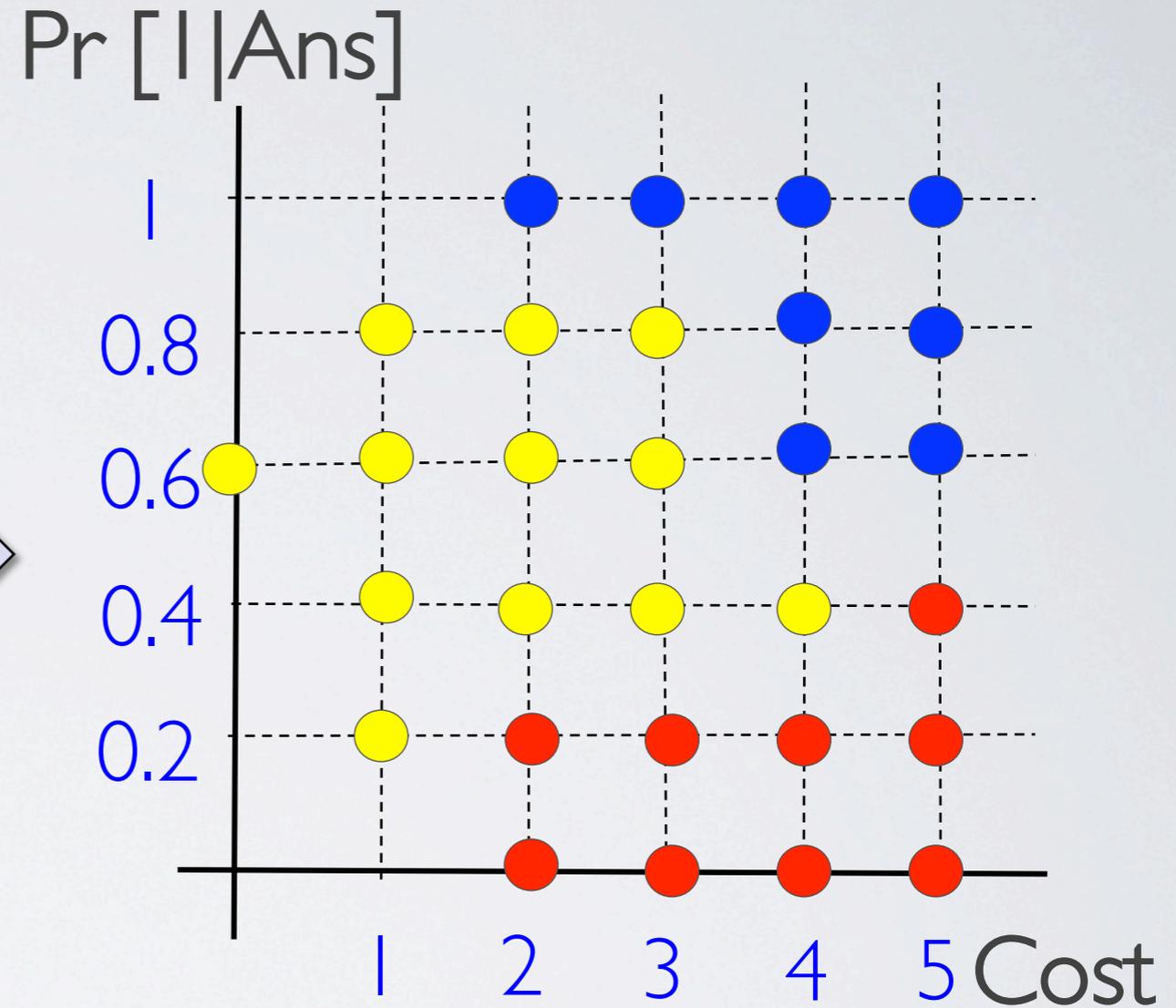
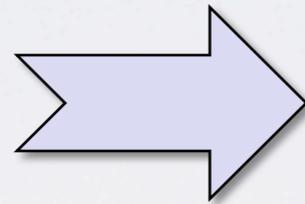
Explosion of state!

A Different Representation



Worker Abilities: Sufficiency

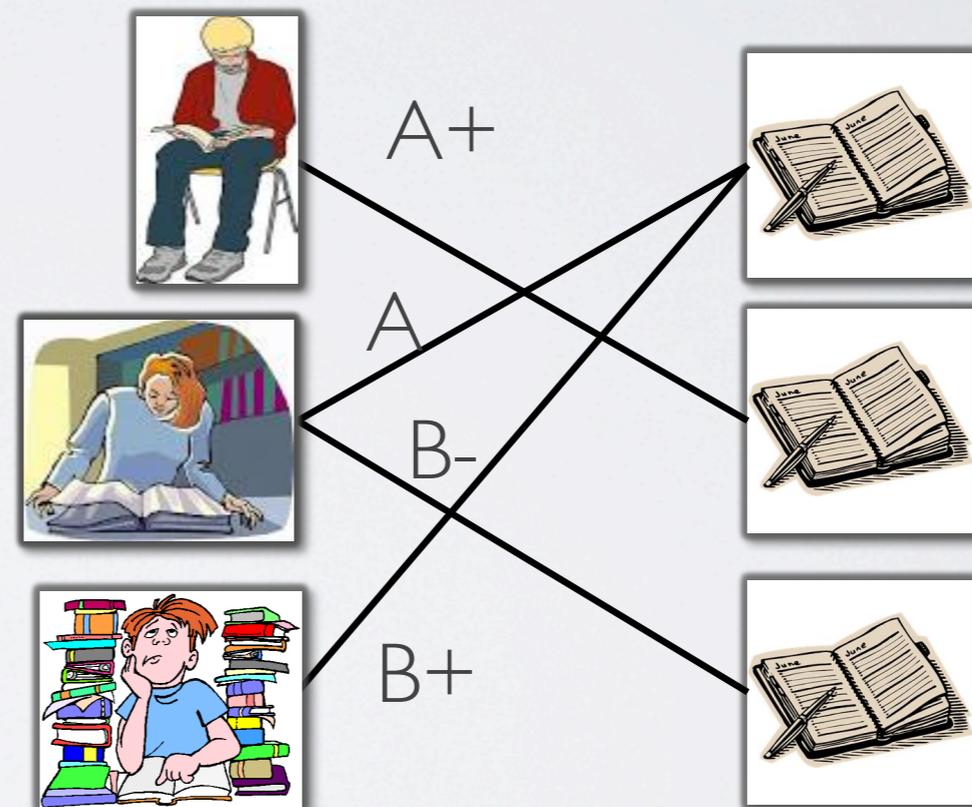
(W_1 Yes, W_1 No,
 W_2 Yes, W_2 No,
...,
 W_n Yes, W_n No)



Recording $\Pr[I | \text{Ans}]$ is sufficient:
Strategy \rightarrow Optimal

MOOCs: Application of Filtering

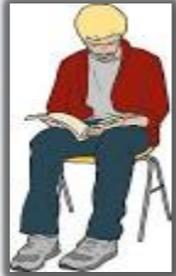
Peer Evaluation \approx Crowdsourcing
Required



Generalization of boolean
filtering to scoring [1-5]

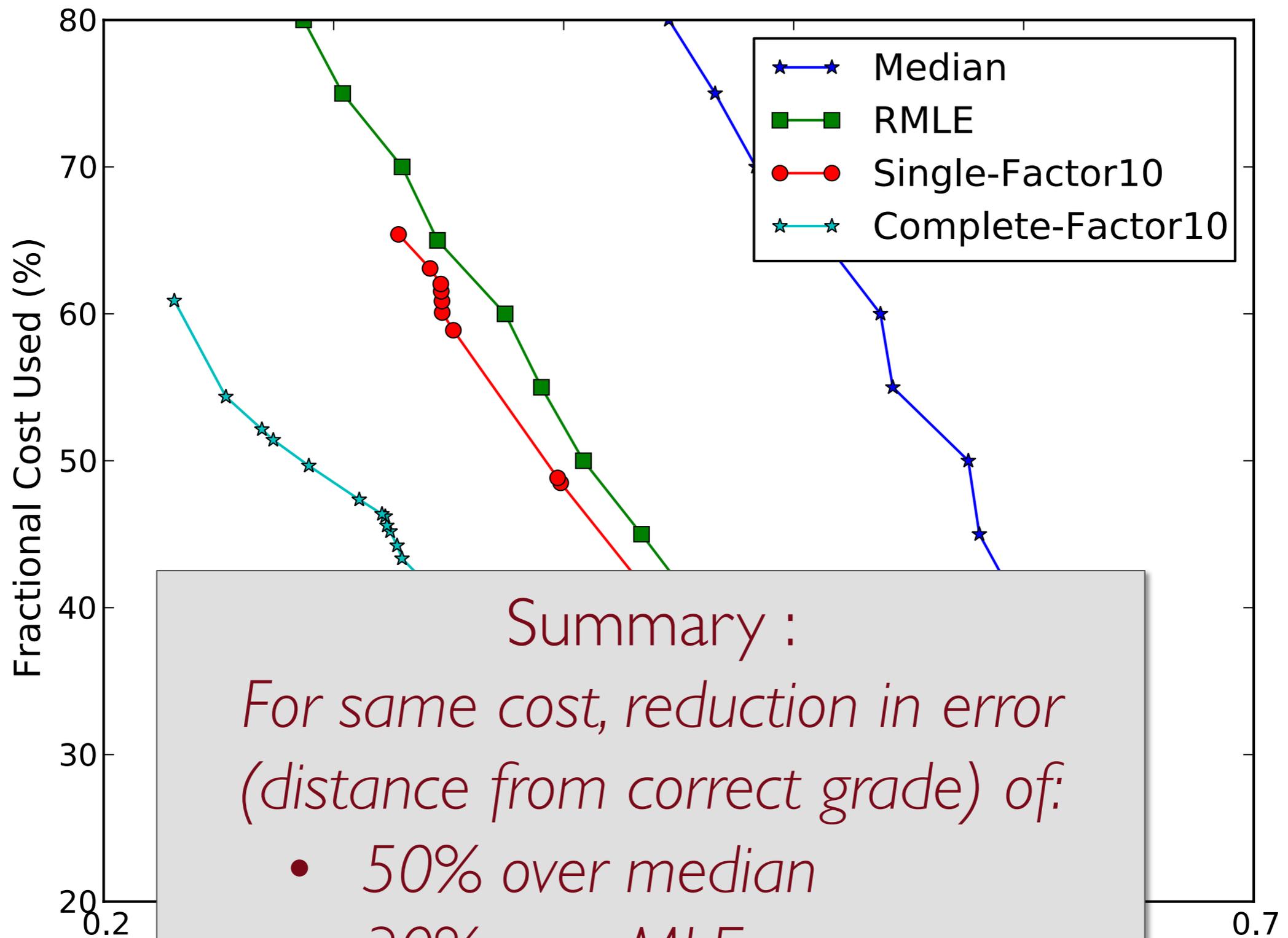
Experiments on MOOCs

Stanford HCI Course

1000  × 5  × 5 Parts = 25000 Parts

Graded by random peers with known error rates

To study: how much we can reduce error for fixed cost



Summary :

For same cost, reduction in error (distance from correct grade) of:

- *50% over median*
- *30% over MLE*
- *10-20% over same accuracy*

Efficient Data Processing Algorithms & Systems

Data Processing Algorithms

Filter [SIGMOD12, VLDB14] Max [SIGMOD12]
 Clean [KDD12, TKDD13] Categorize [VLDB11]
 Search [ICDE14] Debugging [NIPS12]

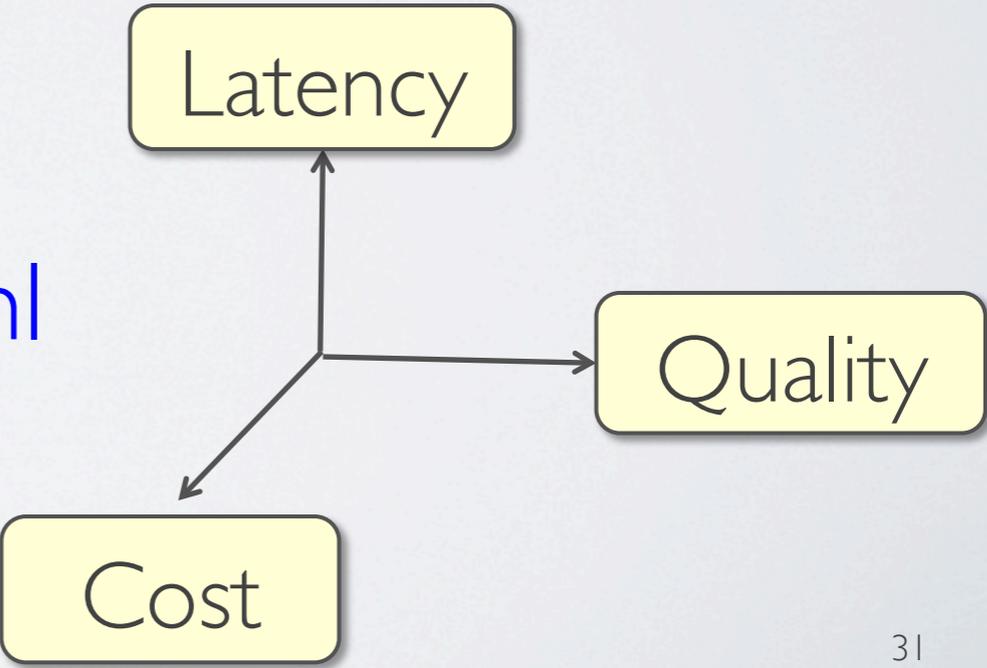
Data Processing Systems

Deco [CIKM12, VLDB12, TR12, SIGMOD Record 12]
 DataSift [HCOMP13, SIGMOD14] HQuery [CIDR11]

Auxiliary Plugins: Quality, Pricing

Confidence [KDD13, TR14] Eviction [TR12]
 Pricing [VLDB15] Quality [HCOMP14]

i.stanford.edu/~adityagp/scoop.html



VISUAL DATA MANAGEMENT with SeeDB

Aditya Parameswaran

with:

Hector Garcia Molina, Sam Madden,
Alkis Polyzotis, Manasi Vartak



Simplifying Data Analytics

Up to a million additional analysts will be needed to address data analytics needs in 2018 in the US alone.

--- *McKinsey Big Data Report, 2013*



How do we make it easier for novice data analysts to get insights from data?

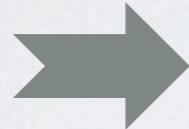
Data Analytics Workflow



All Products

All Products					

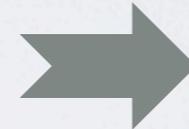
Query



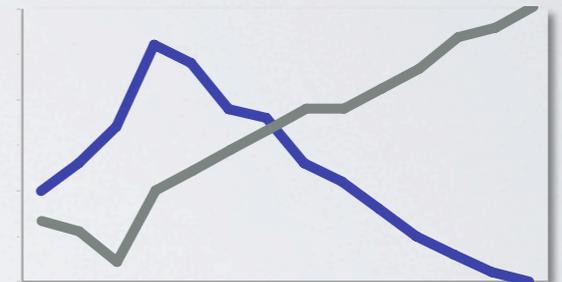
“Staplers”

“Staplers”					

Views



“Sales by Year”



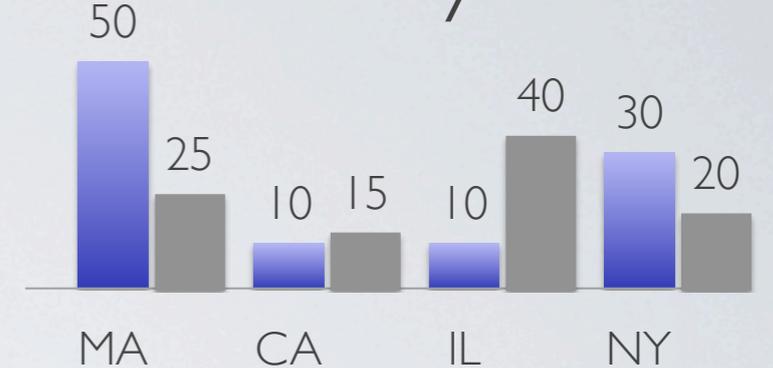
Laborious and Tiresome!
Can we automate this?

Similar issues with
Tableau, ShowMe, Profiler, Spotfire

“Production by Year”

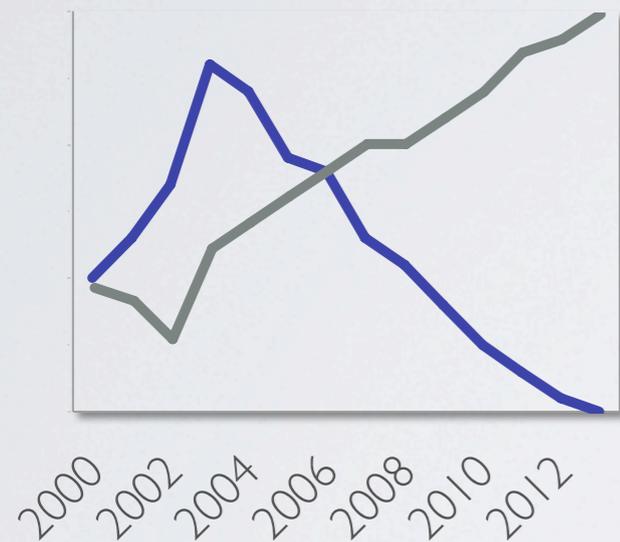


“Production by State”



Potentially Interesting Views(Visualizations)

“Sales by Year”

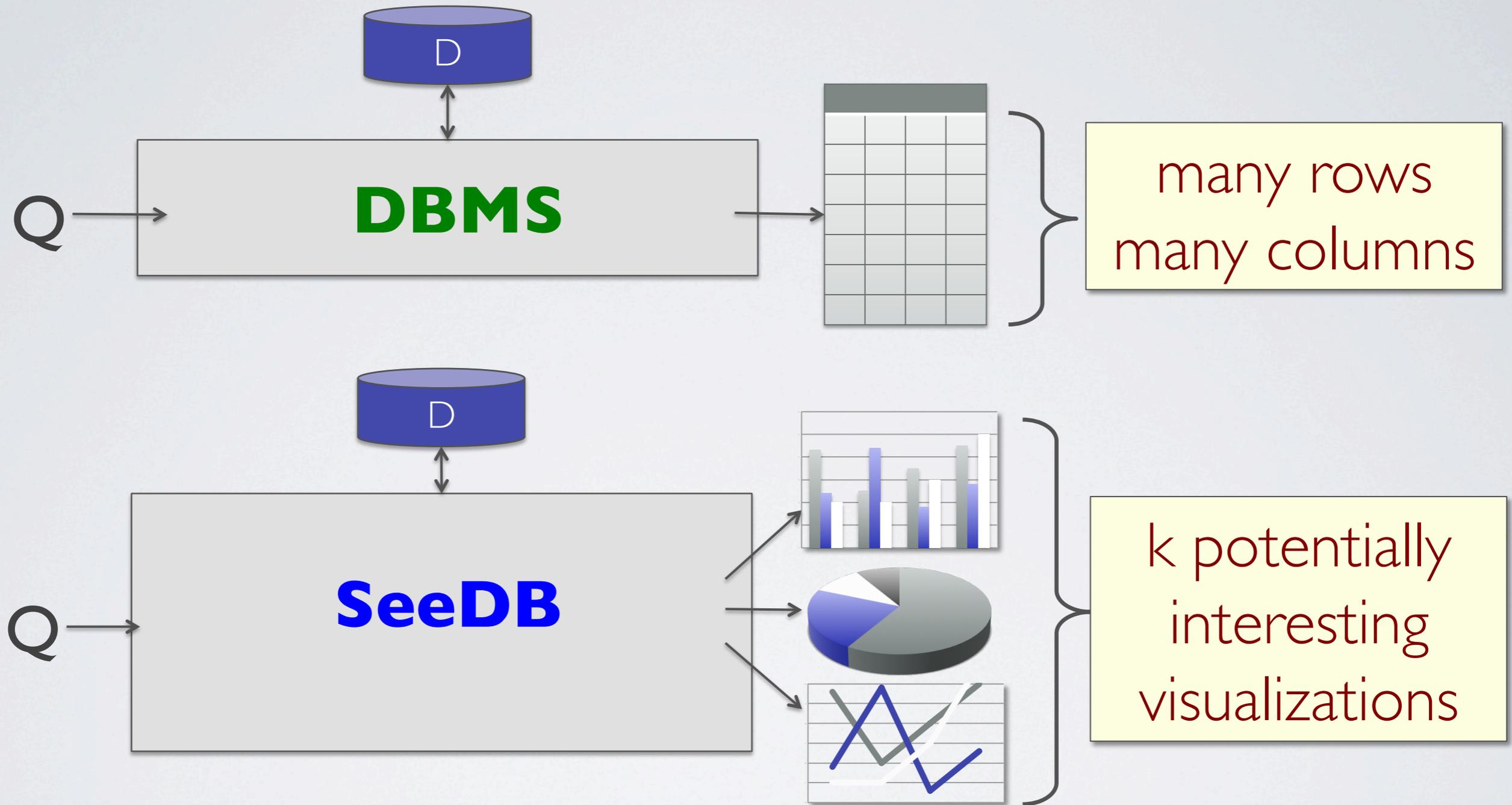


“Potentially interesting”: trend in subset that is not in overall data

Can we automatically highlight potentially interesting views?

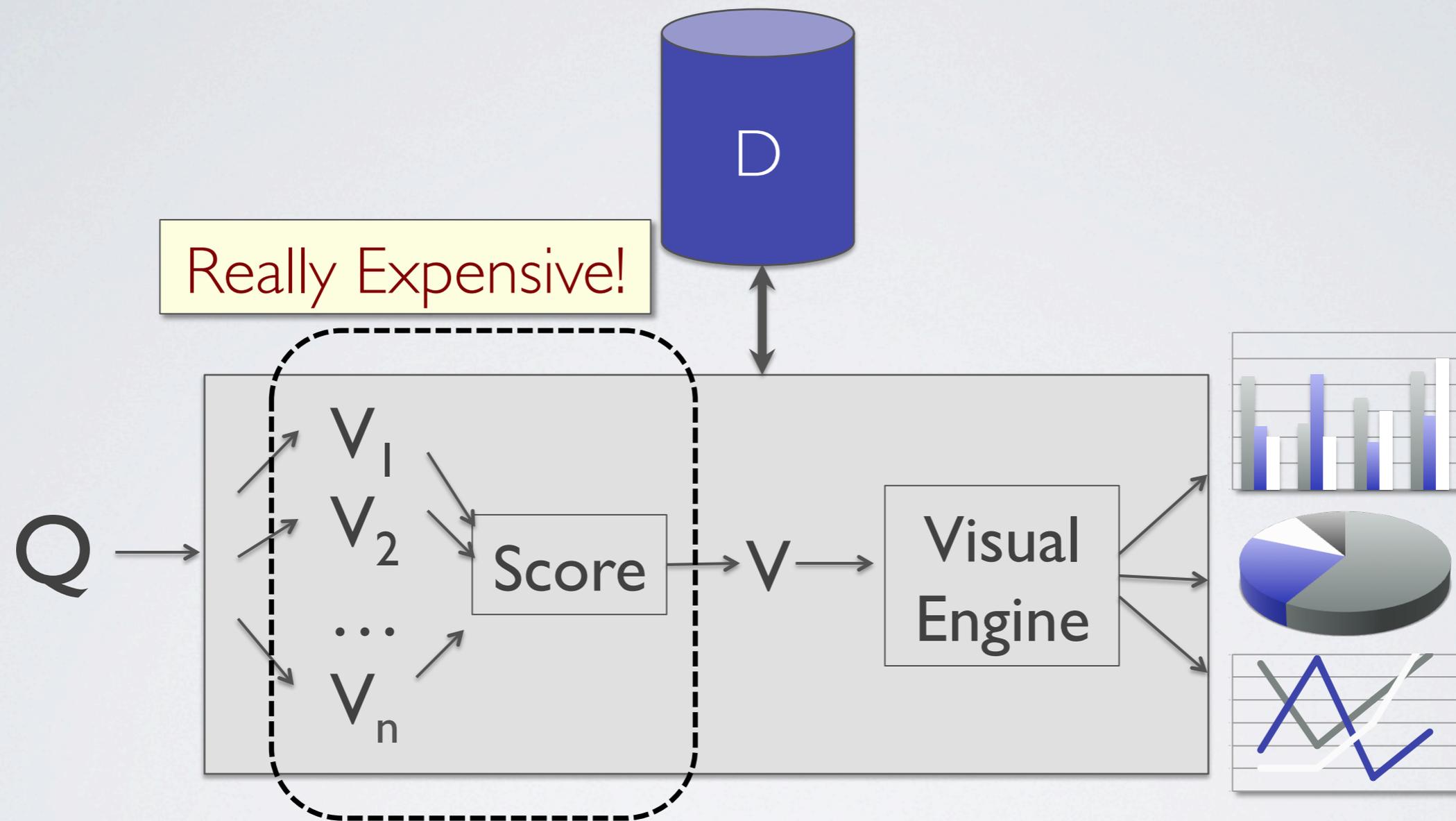
Saving: stepping through all views
now only potentially interesting ones!

Our Proposed System: SeeDB



[VLDB14] SeeDB: Visualizing Database Queries Efficiently (Vision)
[VLDB14] Automatically Generating Query Visualizations (Demo)

SeeDB: Conceptual Workflow

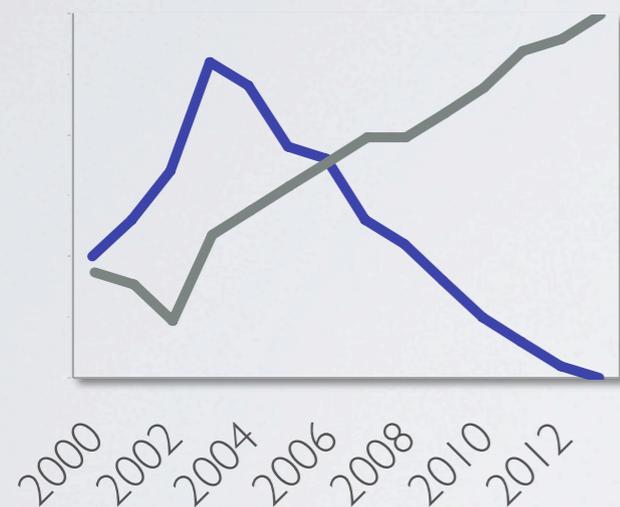


Objective : find k -best scoring views (or visualizations)

How do we score views?

This is a hard, domain-specific question!

“Sales by Year”



We are pursuing ways to learn this scoring function using crowds.

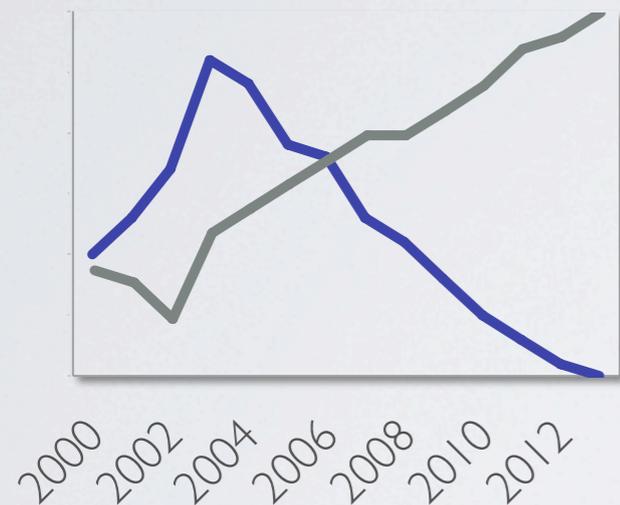
For now, a proxy that is “good-enough”
differences in “distribution”
e.g., *EMD, euclidean, KL-divergence*

Difference(Distribution of Sales by year overall,
Distribution of Sales by year for Staplers)
our techniques work with any scoring metric

How many views to consider?

Star Schema; Histogram Visualizations

“Sales by Year”



M measure attributes

A dimension attributes

F aggregation measures

One-dimensional visualizations:

$M \times A \times F$

If we consider binning:

$M \times A \times F \times B$

Building SeeDB: Concrete Directions

How do we minimize computation?

- Sharing computation
- Approximate visualizations
- Approximate scoring
- Visualization pruning

Technique 1: Sharing Computation

“Sales by Year”

“Production by Year”

“Sales and Production by Year”

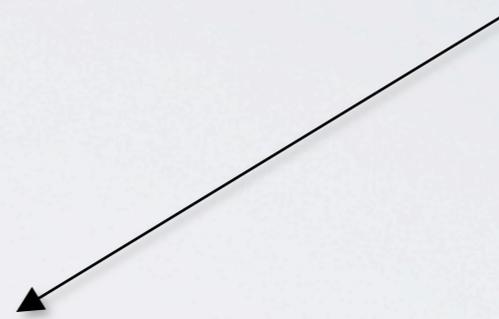
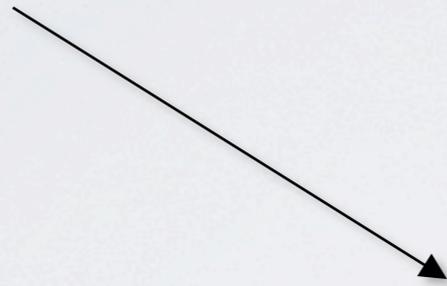
```
SELECT AGG(M1), AGG(M2), D,  
FROM R  
WHERE Prod = “Staplers”  
GROUP BY D
```

Linear
Speedup!

Technique 1: Sharing Computation

“Sales by Year”

“Sales by Region”



“Sales by Year, Region”

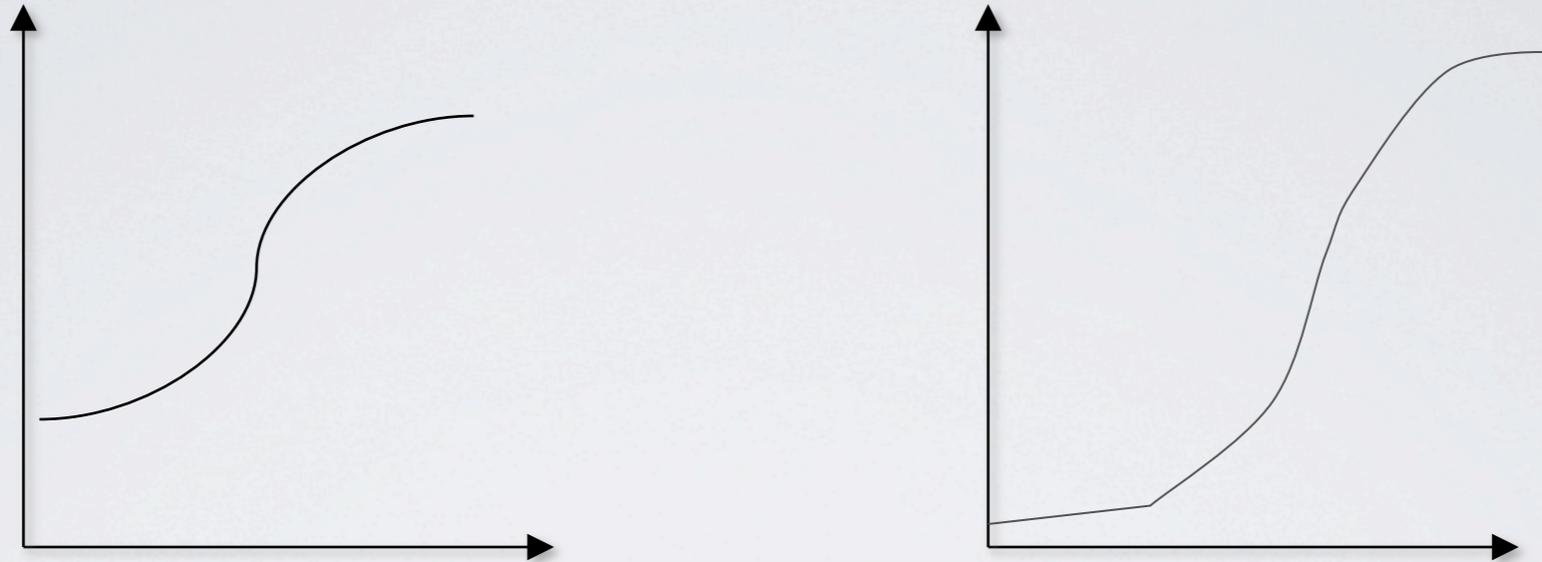
```
SELECT AGG(M), D1, D2
FROM R
WHERE Prod = “Staplers”
GROUP BY D1, D2
```

Problematic: # of
aggregates grow rapidly

Intractable!

Technique 2: Approximate Visualizations

“Production by Year”



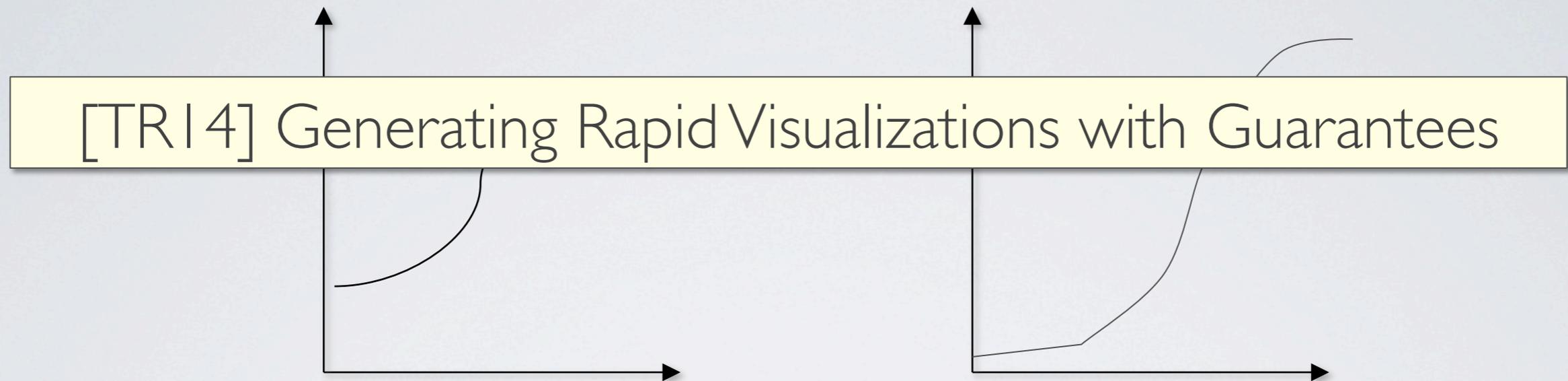
Analysts are only interested in trends, not absolutes

Limited also by resolution

*Can we provide visualizations that are **guaranteed** to look similar (e.g., similar order, similar differences) to actual ones, but at much lower cost?*

Technique 2: Approximate Visualizations

“Production by Year”



The answer is **yes!**

At a high-level, algorithm samples “more” from contentious areas

- Order of magnitudes saving compared to baselines
- Optimality guarantees
- Also of independent interest

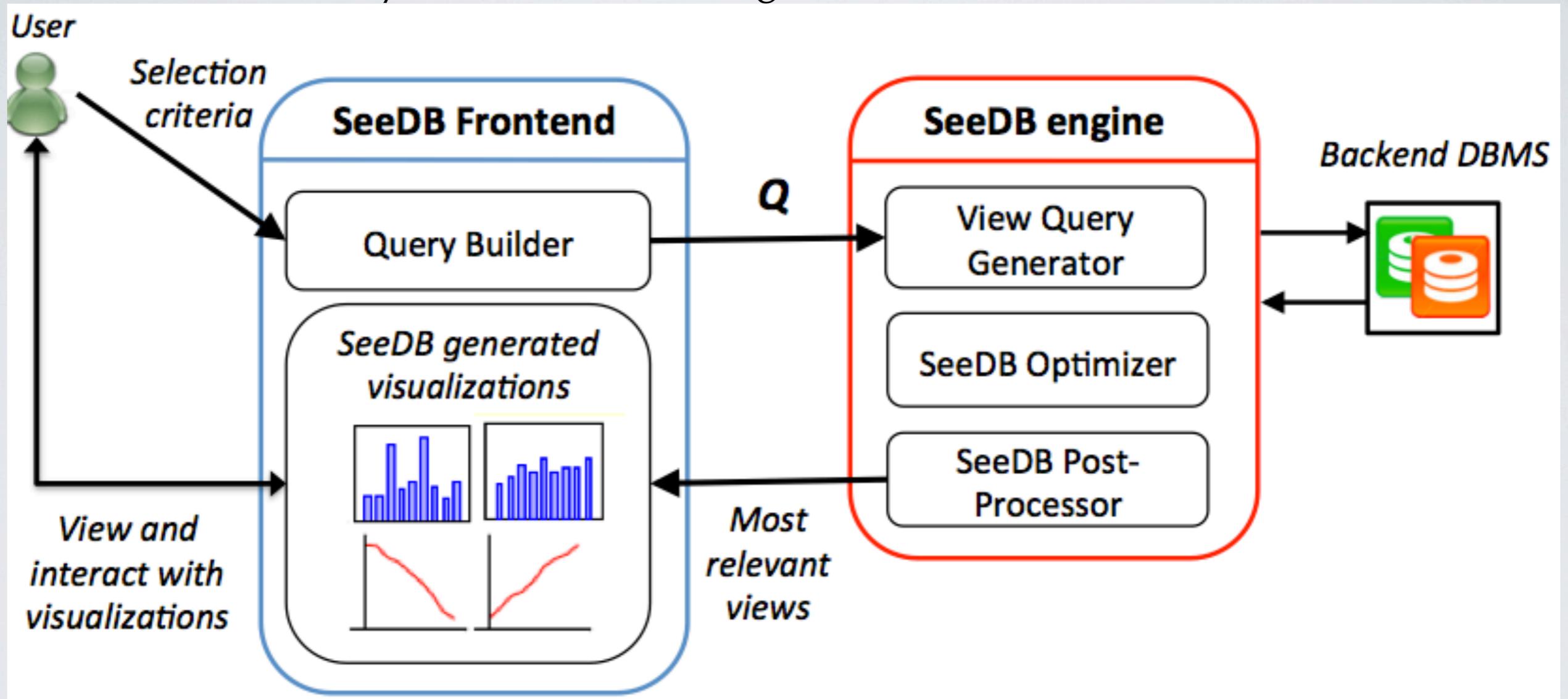
Building SeeDB: Concrete Directions

How do we minimize computation?

- ~~Sharing computation~~
- ~~Approximate visualizations~~
- Approximate utility computation
- Visualization pruning

Overall, a rich space of questions
generalizable beyond SeeDB!

Our Current Design



Interactive Query Builder

Query Builder

Table Name:

Predicates:

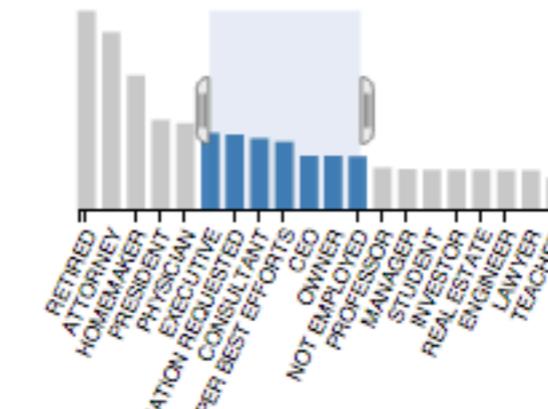
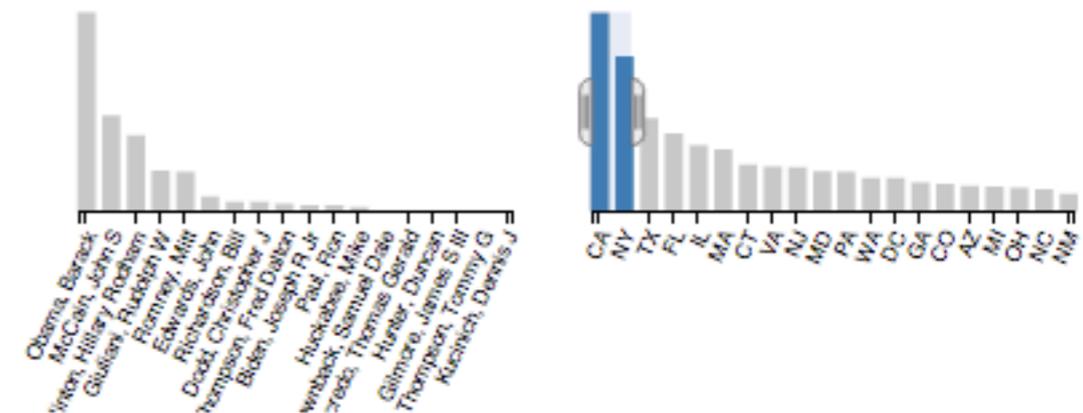
	Column Name	Operator	Value	
where	<input type="text" value="cand_nm"/>	<input "="" type="text" value="="/>	<input type="text" value="Obama, Barack"/>	<input type="button" value="X"/>
where	<input type="text" value="contbr_st"/>	<input type="text" value="in"/>	<input type="text" value="'CA', 'NY'"/>	<input type="button" value="X"/>

Distance Measure:

```
SELECT * FROM election_data_full WHERE (cand_nm = 'Obama, Barack')
AND (contbr_st in ('CA', 'NY'));
```

Distributions in data set

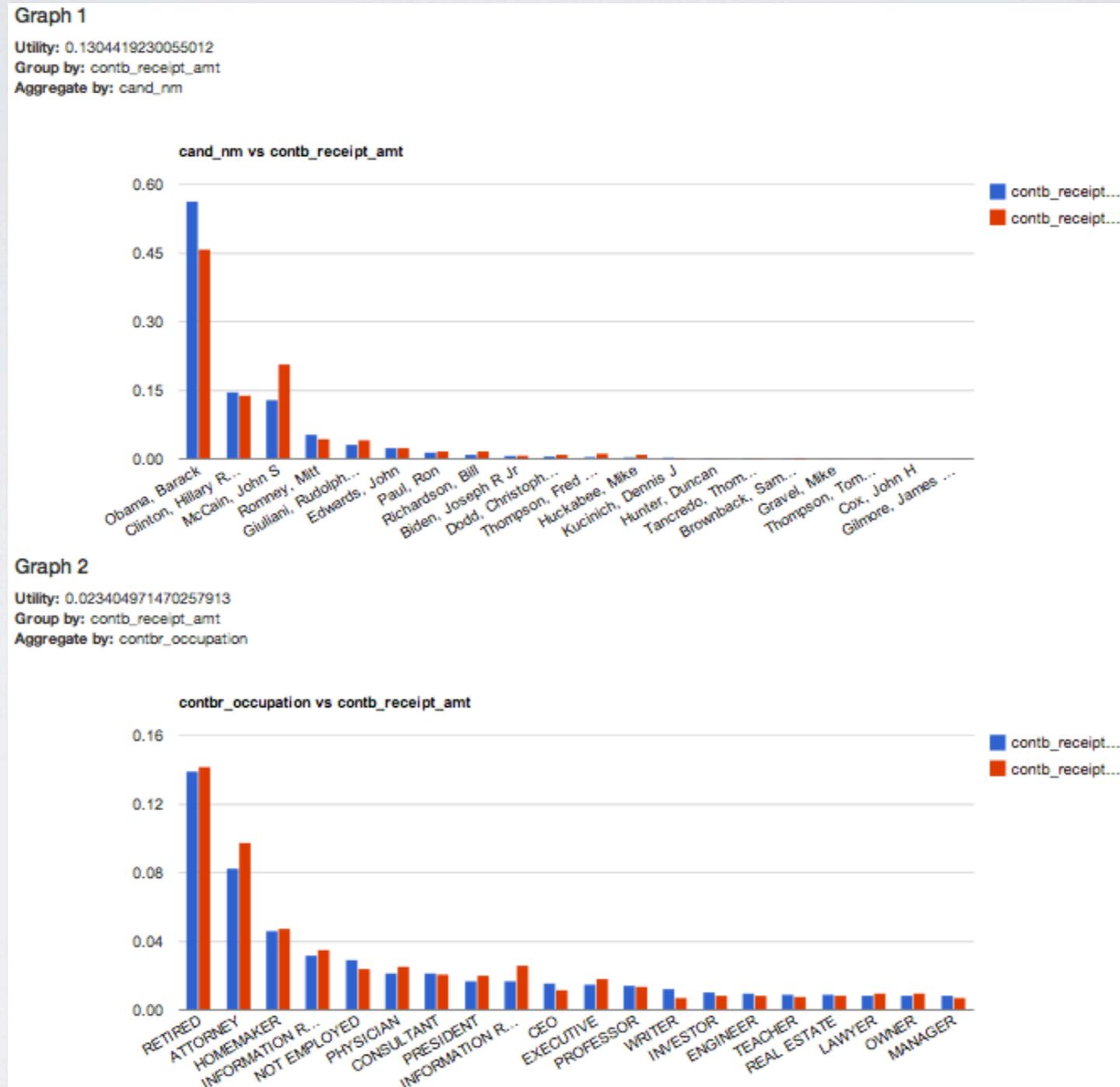
In the case of many unique values, only the 20 most common are displayed.



```
contbr_occupation in ('EXECUTIVE', 'INFORMATION REQUESTED', 'CONSULTANT', 'INFORMATION REQUESTED PER BEST EFFORTS', 'CEO', 'OWNER', 'NOT EMPLOYED')
```

```
contbr_st in ('CA', 'NY')
```

Top-k Visualizations



To summarize...

SeeDB has some ambitious goals...

*“show me all that’s interesting about the query result”
i.e., the holy grail of exploratory visual data analysis*

We’ve barely scratched the surface, yet!
... doesn’t mean we can’t build a useful tool