Data Replication in the Quality Space

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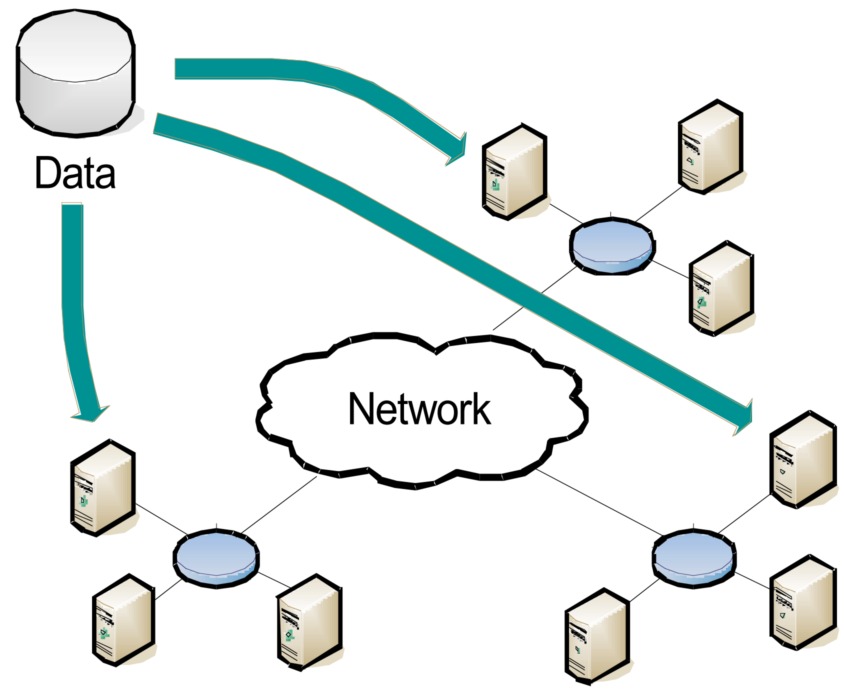
At Commnet USF

Roadmap

- Introduction
- Static data replication
- Dynamic data replication
- Experimental (simulation) results
- Summary

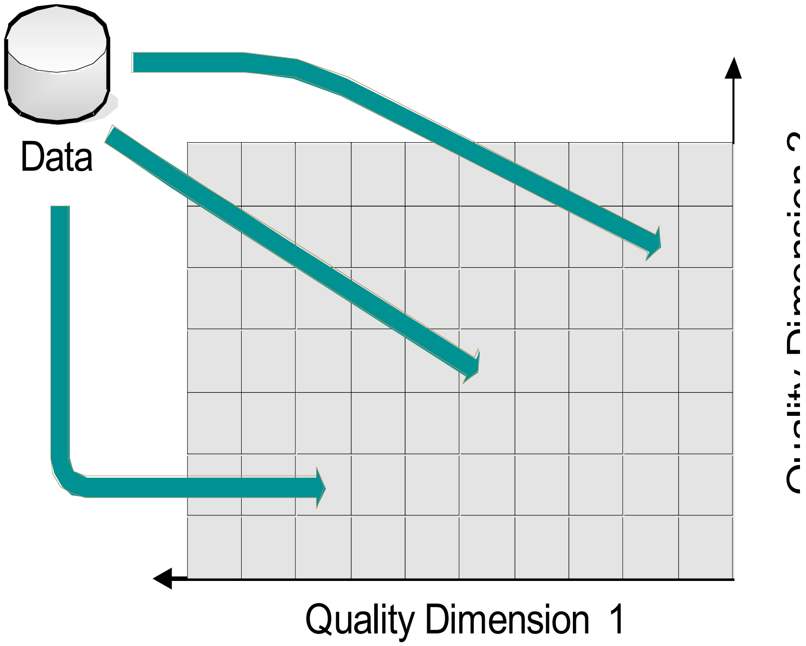
Data Replication

- The problem: given a data item and its popularity, determine *how many* replicas to put
- For writable data, *where* to put
- Destination: node(s) in a distributed environment
- Replicas are identical copies of the original data



Quality-Aware Replication

- Replicas are of different “quality”
- Destination: point(s) in a metric *quality space*
- Costs of transformation among different qualities are very high
- Applications
  - Multimedia
  - Materialized view
  - Biological structure
- Good news: read-only
- Bad news: too much storage needed

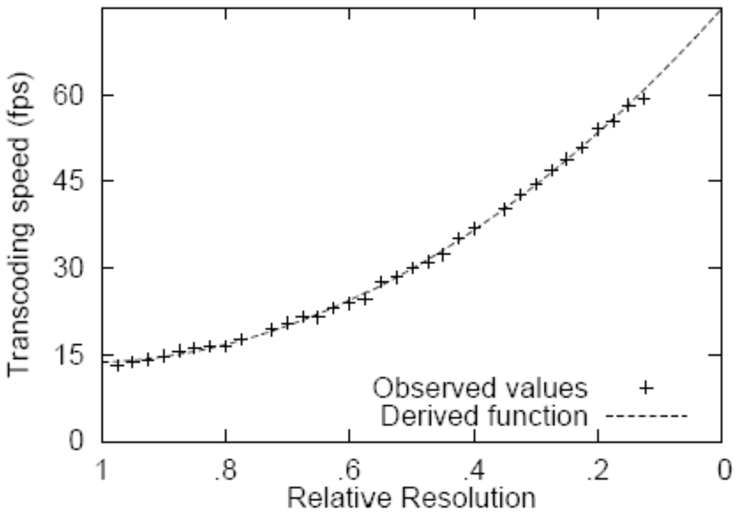


Delivery of Multimedia Data

- Quality (QoS) critical
  - Temporal/spatial resolution
  - Color
  - Format
- Varieties of user quality requirements
  - Determined by user preference and resource availability
  - Large number of quality combinations
- Adaptation techniques to satisfy quality needs
  - Dynamic adaptation: online transcoding
  - Static adaptation: retrieve precoded replica from disk

Dynamic adaptation

- Transcoding is very expensive in terms of CPU cost
- Online transcoding is not feasible in most cases
- Situation may improve in the future
- Layered coding
  - Not standardized yet.
  - Less popular than people expected



Static adaptation

- Little CPU cost
- Choice of many commercial service providers
- What about storage cost?
    - On the order of total number of quality points
    - Ignored in previous research assuming
        - Very few quality profiles
        - Storage is dirt cheap
    - Excessively high for service providers

$O(n^d)!$

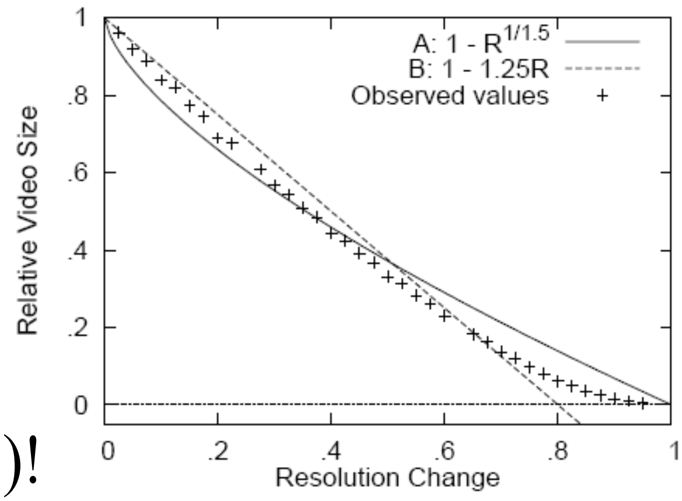


Table 2: Total relative storage in a 3D space.

n	5	10	15	20	25
Storage	20.23	117.7	354.8	755.9	1496.5

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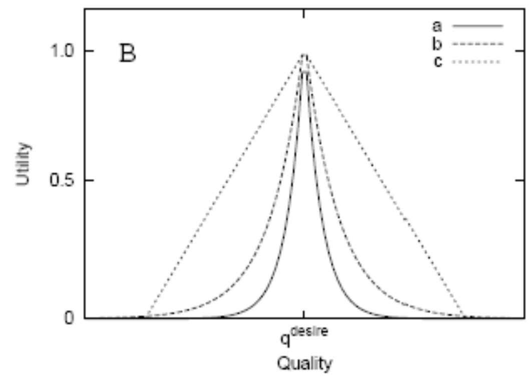
The *fixed-storage replica selection* (FSRS) Problem

- An optimization: get the highest *utility* given the popularity (f_k), storage cost (s_k) of all quality points under total storage S
  - $u(j,k)$: the utility when a request on quality j is served by replica of quality k
- *Utility* is given as a function of distance in quality space
  - Requests served by the closest replica

$$
\begin{array}{ll}
\text{maximize} & \sum_{j\in J}\sum_{k\in J} f_j u(j,k) Y_{jk} \\
\text{subject to} & \sum_{k\in J} X_k s_k \le S, \\
& \sum_{k\in J} Y_{jk} = 1, \\
& Y_{jk} \le X_k, \\
& Y_{jk} \in \{0,1\}, \\
& X_k \in \{0,1\}
\end{array}
$$



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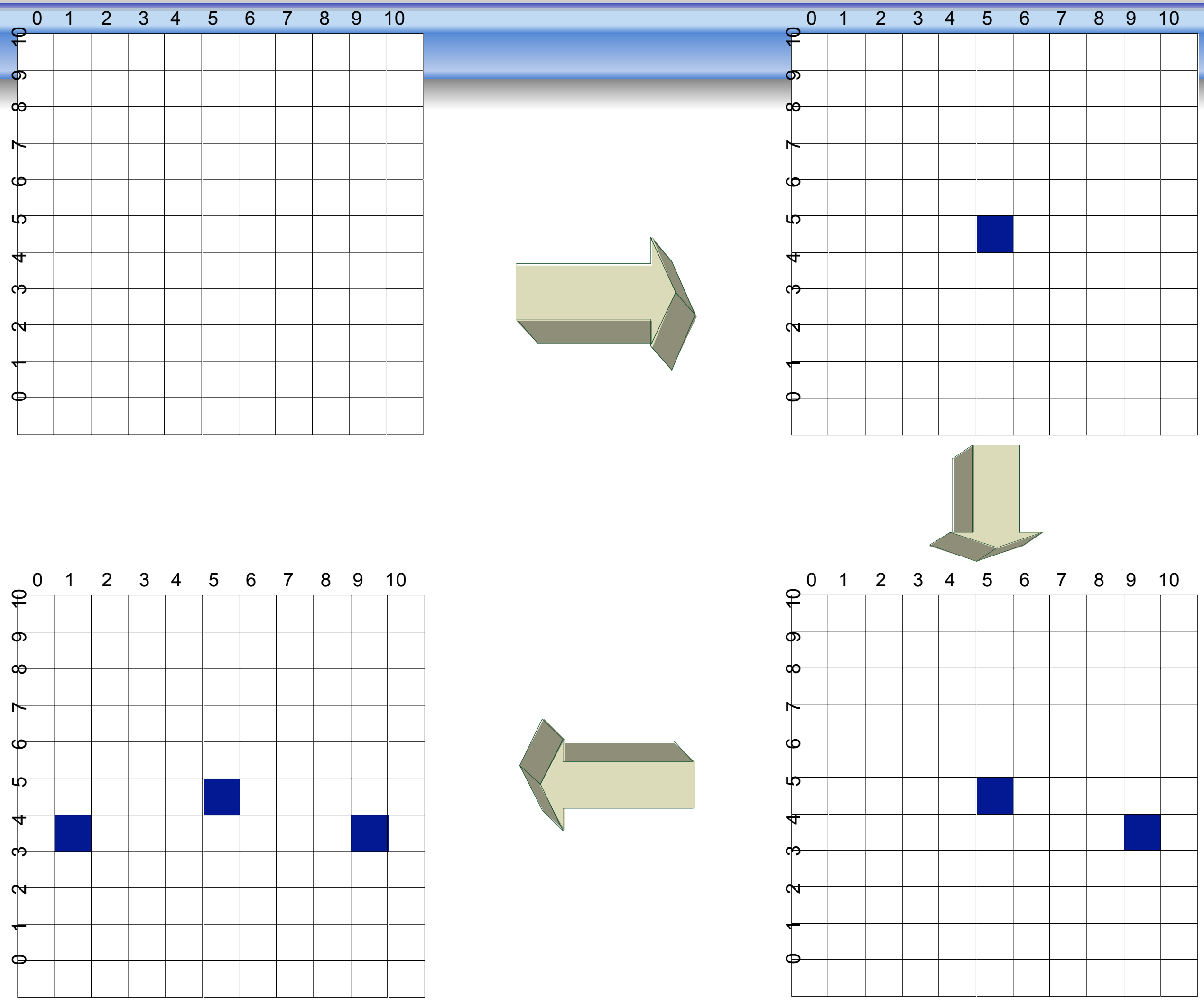
The FSRS Algorithms (I)

- Problem is NP-hard: a variation of the *k*-means problem
- We propose a heuristic algorithm named *Greedy*
  - Aggresively selects replicas based on the ratio of marginal utility gain (Δu) to cost (s_k)

```
selected replica set P := Φ
available storage s' := S
while s' > 0
    add the quality point that yields
    the largest Δu/s_k value to P
    decrease s' by s_k
return P
```

  - Time complexity: $O(m^2 I)$ where I is the # of replicas selected and m the total # of possible replicas

An illustration: *Greedy*



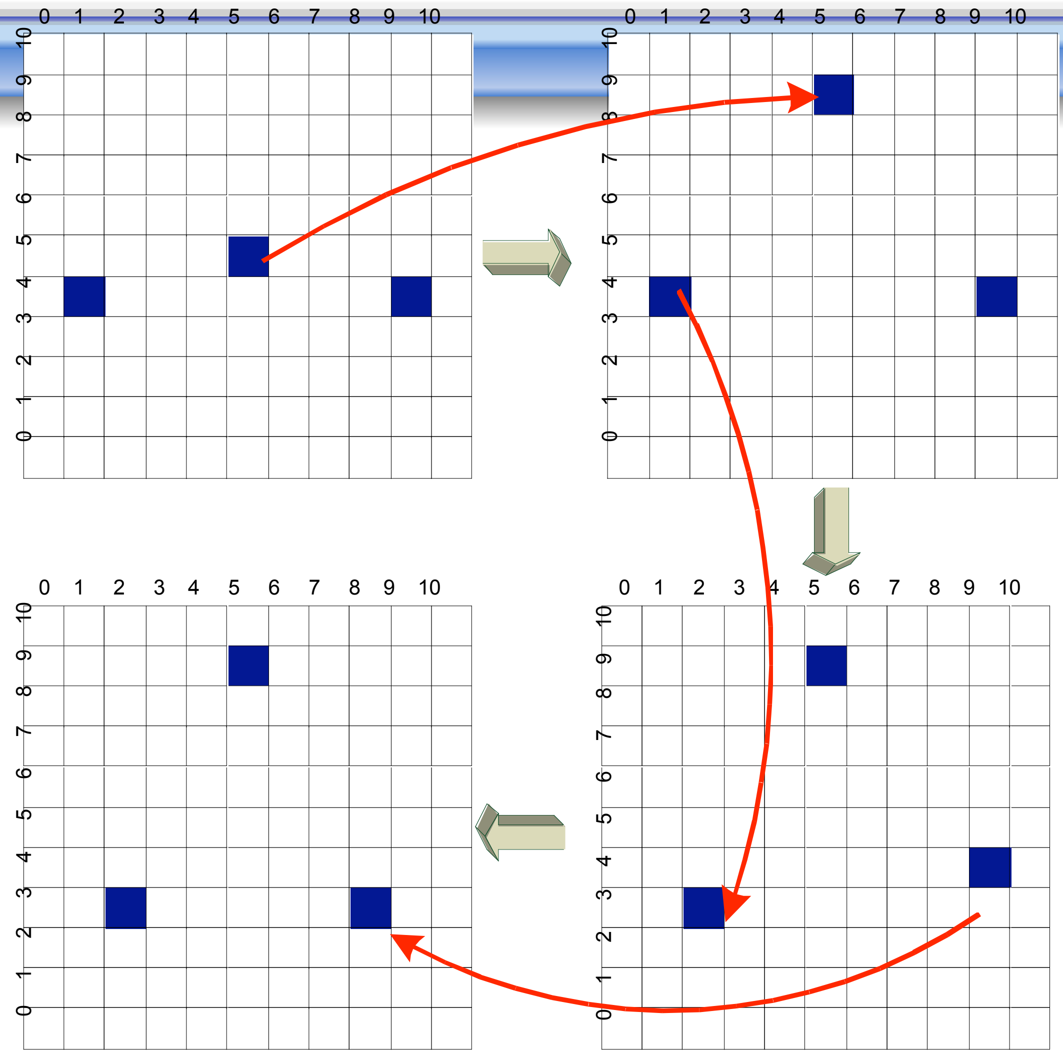
The FSRS Algorithms (II)

- *Greedy* could pick some bad replicas, especially the earlier selections
- Remedy*:* remove those bad choices and re-select
- The *Iterative Greedy a*lgorithm:

> $P \leftarrow$ a solution given by *Greedy*
>
> **while** there exists solution P' s.t. $U(P') > U(P)$
>
> **do** $P \leftarrow P'$
>
> **return** P

- Time complexity: same as *Greedy* with a larger coefficient

An illustration: *Iterative Greedy*



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Handling multiple media objects

- There are V ($V > 1$) media objects in the database, each with its own quality space and FSRS solution
- However, the storage constraint *S* is global
- Both *Greedy* and Iterative Greedy can be easily extended to solve FSRS for multiple media objects
- The trick: view the V physical media objects as replicas of a virtual object
- Model the difference in the *content* of the V objects as values in a new quality dimension.
- Time complexity: $O(IV^2m^2)$, can be reduced to $O(IVm^2)$ with some tweaks

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Dynamic replication

- Popularity f of replicas could change over time
- We only consider the situation where popularity of all replicas of a media object changes together
  - Reasonable assumption in many systems
  - Problem becomes competition for storage among media objects
  - Study of the more general case is underway
- Desirable dynamic replication algorithms:
  - Find solutions as optimal as those by static FSRS algorithms
  - Fast enough to make online decisions
- Naïve solution: run *Greedy* every time a change of f occurs

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Replication Roadmap (RR)

- Consider the order replicas are selected by *Greedy* – follow a predefined path (RR) for each media object
- RRs are all convex
- Exchanges of storage may happen between two media objects, triggered by the increase/decrease of *f*
  - The one that becomes more popular takes storage from the least popular one
  - The one that becomes less popular gives up storage to the most popular one
  - It is efficient to make exchanges at the *frontiers* of the RRs, no need to look inside

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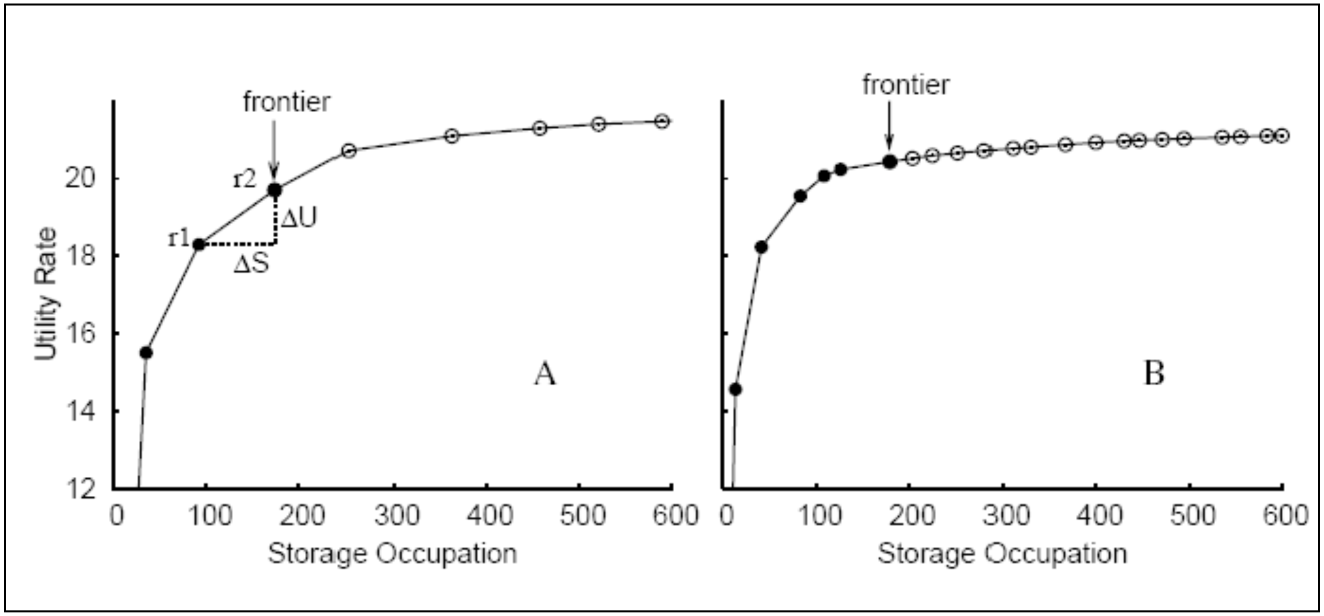
Replication Roadmap (continued)

- Storage exchanges, example:



Media *A* should take storage from media *B* as the slope of its current segment in RR is greater than that of *B*'s

Dynamic FSRS algorithm

- Based on the RR idea
- Proved performance: results given are as optimal as those chosen by *Greedy*
- Preprocess phase:
  - Build the RRs
- Online phase:
  - Performing exchanges till total utility converges
  - Time complexity: $O(I \log V)$ where I: # of storage exchanges occurs and V is the # of media objects

```
1   storage ← available storage
2   k ← 0, j ← V − 1
3   while k ≤ 0
4   do    r0 ← flist[k]
5         victims ← ∅
6         while storage < size of replica r0
7         do    r1 ← blist[j]
8               if r0 and r1 belong to the same video
9                 j ← j − 1
10                continue
11              if utility density of r1 > utility density of r0
12                k ← k + 1
13                rollback blist to its status on line 6
14                break
15              else append r1 to victims
16                   update and sort blist
17        if storage ≥ size of replica r0
18          EXCHANGE (r0, victims)
19          update and sort both flist and blist
```

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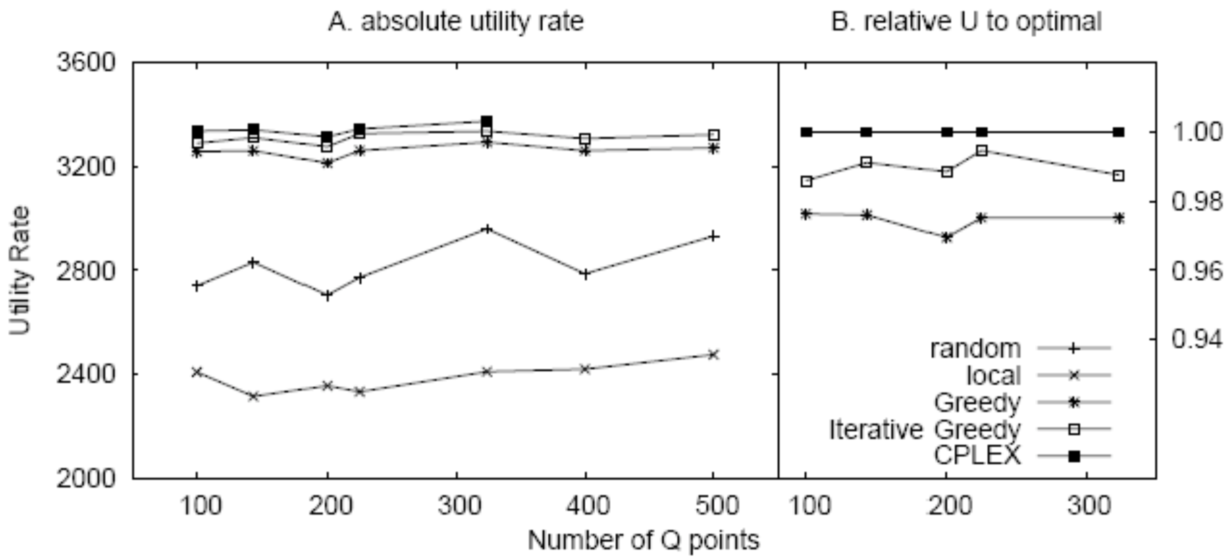
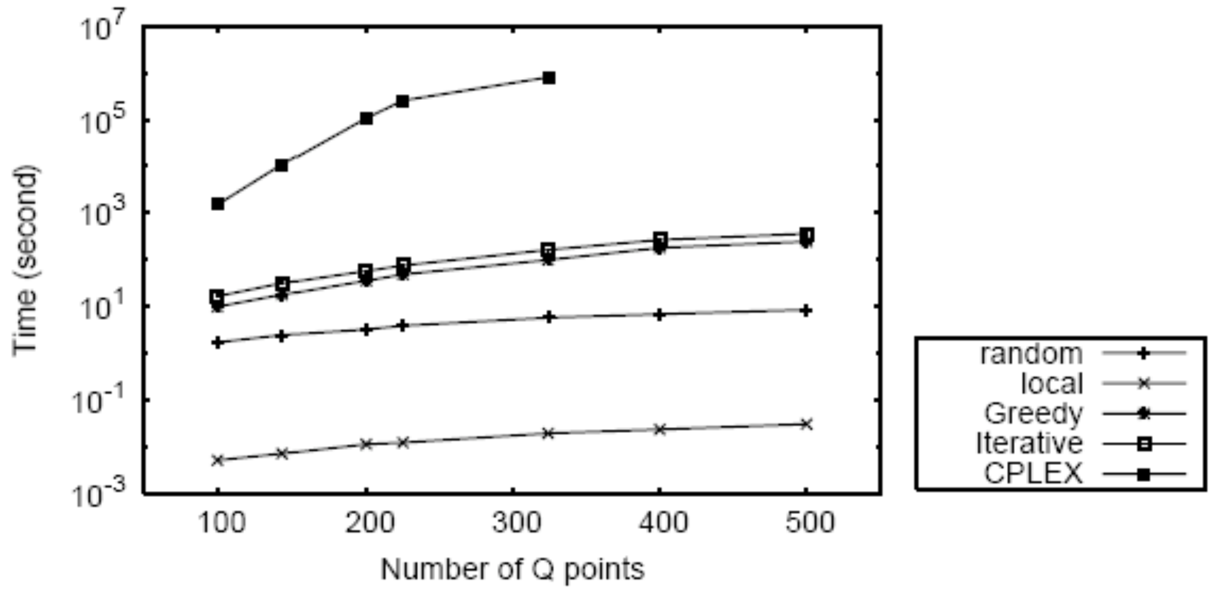
Effectiveness of algorithms

- For comparison:
  - The optimal solution (by CPLEX)
  - Random selections
  - Local popularity-based



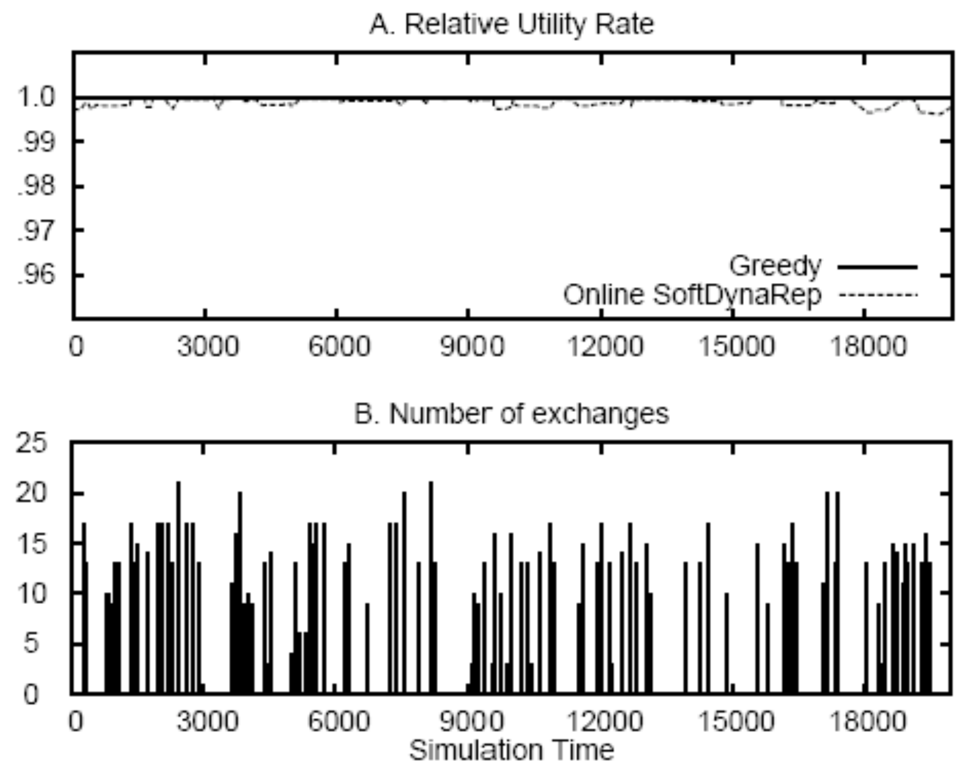
Efficiency of algorithms

- CPLEX < *Iterative Greedy* < *Greedy* < Random < Local
- Results on a P4 2.4 GHz CPU:



Dynamic replication

- Randomly generated changes of f
- Compare with *Greedy*
- Results with (almost) the same optimality as *Greedy*
- Reason: small number of storage exchanges



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Summary

- Storage cost in static adaptation prohibits replication of all qualities
- Need to optimize toward the highest utility given storage constraints
- Two heuristics are proposed for static replication that gives near-optimal choices
- Fast online algorithm for one dynamic replication problem
- Unsolved puzzles:
  - General case of dynamic replication
  - Is there a bound for the performance of *Greedy*?
    - Conjecture: *Greedy* is 4/3-competitive!

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Storage for replication

- Empirical formula to calculate storage after transcoding to a lower quality in one dimension: $F = F_0(1 - R^{\frac{1}{\beta}})$
- Sum of all replicas when there are *n* qualities

$$\begin{aligned}
\sum_{i=0}^{n} F_0(1 - R_i^{\frac{1}{\beta}}) &= F_0\left(n - \sum_{i=0}^{n}\left(\frac{i}{n}\right)^{\frac{1}{\beta}}\right) \\
&\approx F_0\left(n - \int_0^n \left(\frac{i}{n}\right)^{\frac{1}{\beta}}\right) \\
&= F_0\left(n - \frac{n\beta}{\beta+1}\right) \\
&= F_0\frac{n}{\beta+1} = F_0 O(n).
\end{aligned}$$

- Three dimensions: $F = \alpha F_0(1 - R_A^{\frac{1}{\beta}})(1 - R_B^{\frac{1}{\gamma}})(1 - R_C^{\frac{1}{\theta}})$, total storage is thus $O(n^3)$
- For d dimensions, $O(n^d)$

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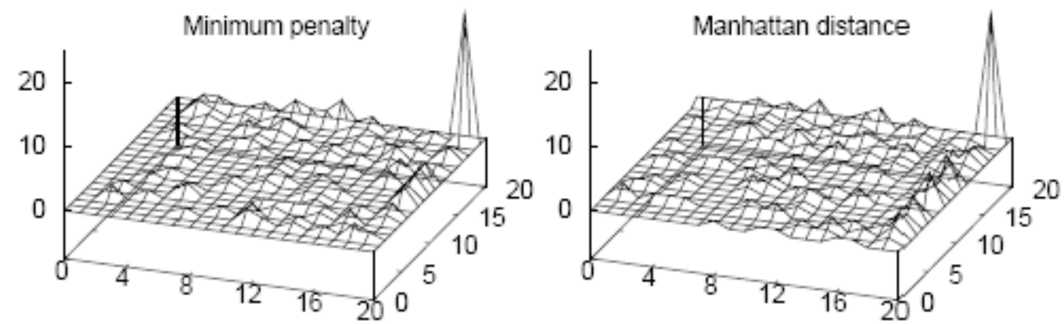
More experimental results

Selection of replicas by *Greedy*, 21X21 2-D quality space with larger number representing lower quality (i.e., point (20,20) is of the lowest quality), V = 30



Same inp … ly