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Conquering the Divide: Continuous Clustering of Distributed Data Streams

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Outline

- Motivation in Data Streams
- Continuous Distributed Model
- Our CD Clustering Algorithms
- Experiments
- Extensions and conclusion

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Data Streams

- Modern data acquisition generates large distributed data coming as distributed streams
  - Environmental sensors
  - Web/blog crawlers
  - Soldier locations on battlefield
  - Different mail servers collate their mails over time
  - Repositories on book, audio, video evolve on their own
- Need support not provided in traditional DBMS

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Monitoring Challenges

- Need real-time monitoring of data properties
  - To help identify any problem of the data (collection): network attack detection, performance debugging
  - To help understand the nature of the data distribution: classification, distinct count, etc.
- Clustering is a foundational monitoring problem
  - Web crawlers cluster pages into groups to monitor traffic load
  - Underwater fish tracking monitors the clusters of schools to quickly deploy attracting or dispelling devices

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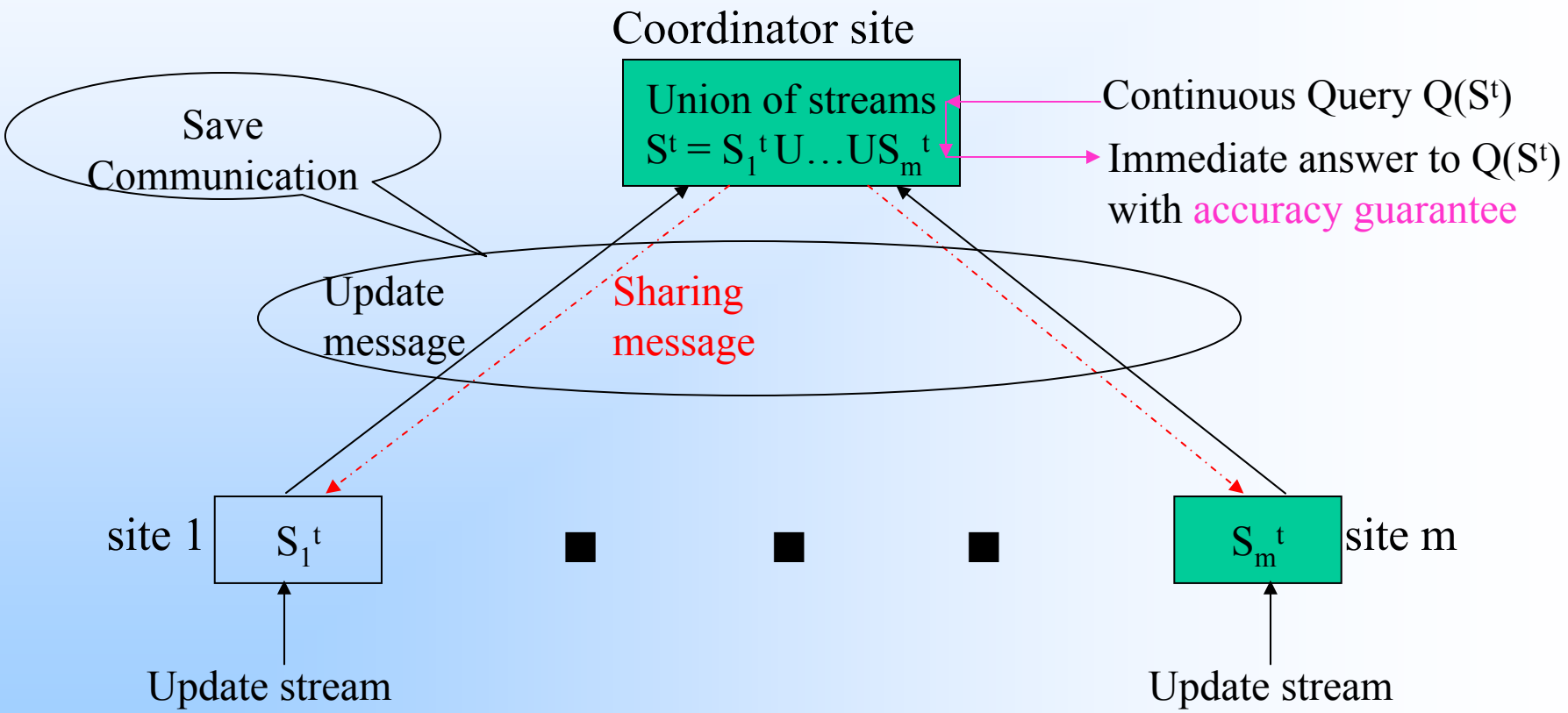
Continuous Distributed (CD) Model



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  - Global algorithms
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Our Contribution

- We provide several k-center clustering algorithms that
  - Monitor distributed dynamic streams
  - Answer continuous query
  - Achieve constant factor approximation as good as centralized algorithm
  - Minimize the communication between sites

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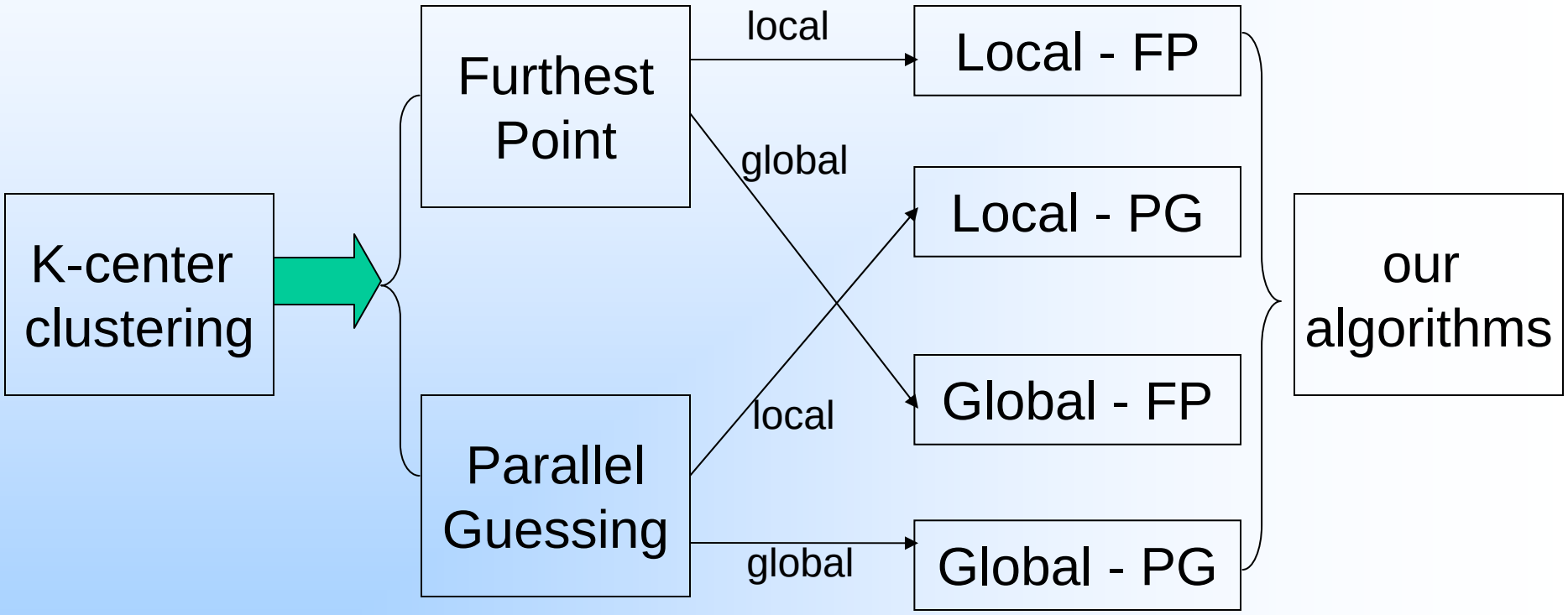

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K-center clustering

- Given
  - a set P of n points
  - a distance function $d(p,q)$ between pairs of points
- Find a set $C \subset P$ of $k<n$ points as centers
- Minimize the radius $r = \max_{p \in P} d(p, C(p))$
  - $C(p) = \text{argmin}_{c \in C} d(c,p)$, distance of p to closest center

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"Furthest Point" (FP) Algorithm

- Furthest Point (FP) (Gonzalez '85)
  - Pick an arbitrary point as the first center, $C_1 = \{c_1\}$
  - Given i centers in C_i, find the point p to maximize $d(p, C_i(p))$, set $C_{i+1} = C_i \cup \{p\}$.
  - Stop after k iterations with k centers C_k.
- Analysis:
  - Factor 2 approximation to the optimal clustering
  - k passes, $O(kn)$ distance computations

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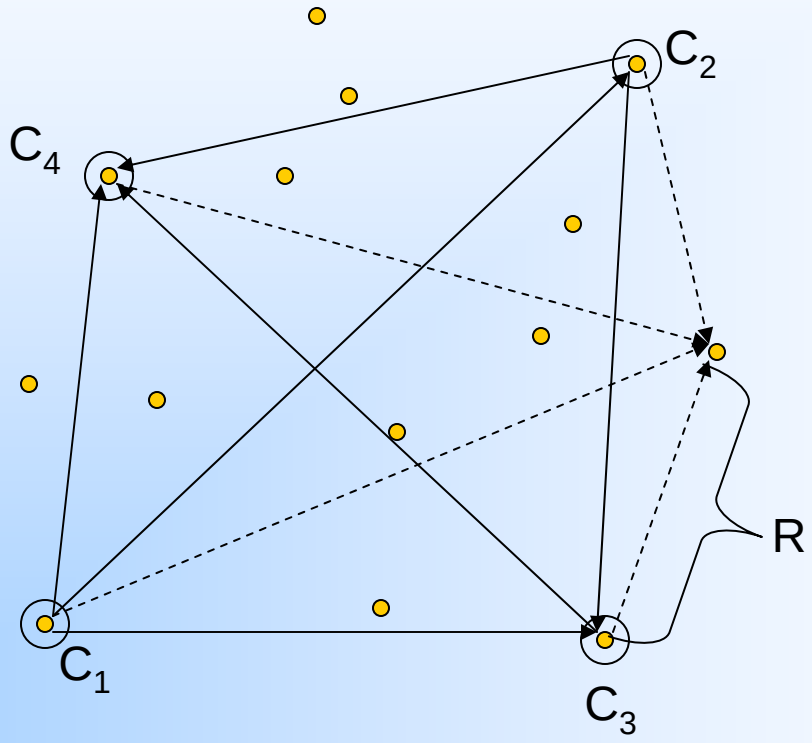
An example



- A 4-center clustering using FP algorithm

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"Parallel Guessing" (PG) Algorithm

- Assume R is a lower bound on the optimal radius
- Pick an arbitrary first center, $C = \{c_1\}$
- For each point p, if $d(p, C(p)) > R$, then $C = C \cup \{p\}$
- In parallel, guess $R = (1+ \varepsilon/2), (1+ \varepsilon /2)^2, (1+ \varepsilon /2)^3, \ldots$
- Use result for smallest R that generates k or fewer centers

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Analysis of PG Algorithm

- Makes one pass over the input
- Gives $(2+\varepsilon)$ approximation
- If the ratio $\max_{p,q} d(p,q) / \min_{p,q} d(p,q) = \Delta$, the number of parallel guesses is $O(1/\varepsilon \log \Delta)$
- Stores $O(k/\varepsilon \log \Delta)$ points, and each update needs $O(k/\varepsilon \log \Delta)$ distance computations

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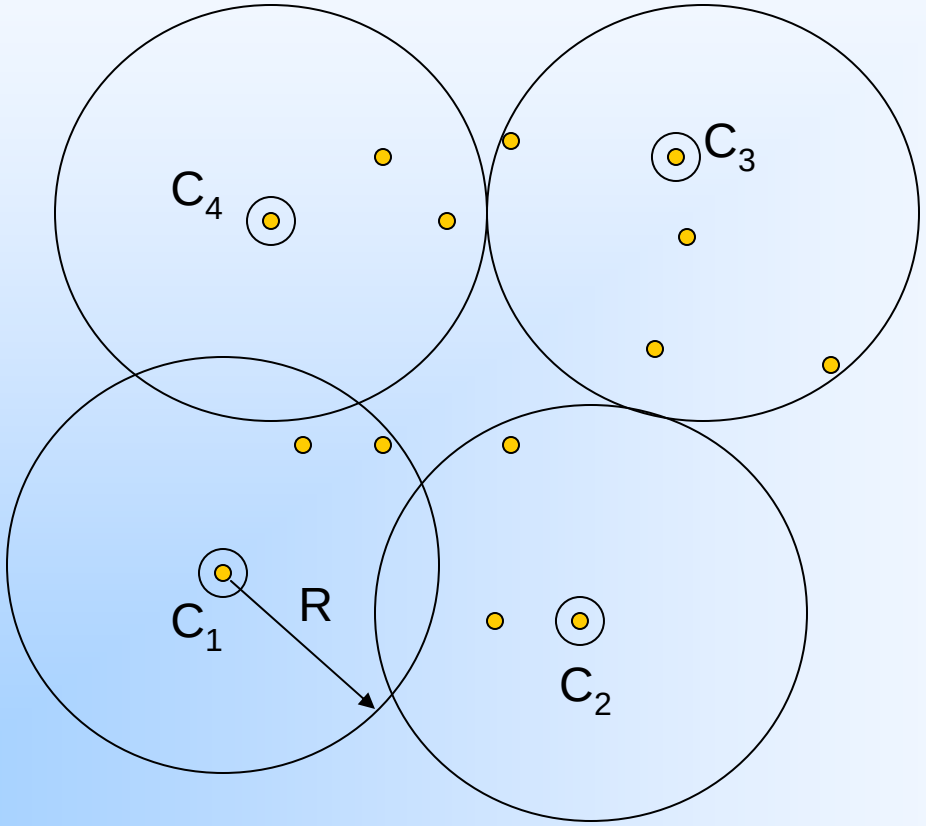
An example



- A 4-center clustering using PG algorithm

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Merging Local Clusterings

- Local-FP: each site runs FP on its points, send k-centers to coordinator on recluster.
- Local-PG: each site runs PG on its points, shares centers for current good guess R with coordinator
- Both have variants which share more or less data:
  - Coordinator does not share cluster information
  - Coordinator broadcasts the global cluster radius
  - Coordinator lazily shares radius (when contacted by site)
- All versions guarantee a $(4+\varepsilon)$ approximation

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Space and Communication Cost — Local Algorithms

- Local-FP: each local reclustering sends $O(k)$ points
  - No tight bounds on worst case number of reclusterings.
- Local-PG: one pass over the input, each site sends up to k points for each guess.
  - Total communication is at most $O(km/\varepsilon \log \Delta)$.
  - Space required at each site is $O(k/\varepsilon \log \Delta)$.

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Cluster Merging

- Clusters can be merged by clustering the cluster centers
- Given point set P_i, $i=1,\ldots,m$, let $C_i \subseteq P_i$ be the k centers of α-approximate k-center clustering of P_i
- Run a β-approximate k-center clustering on union of C_i's
- Result: the resulting k centers C form an $(\alpha+\beta)$ clustering of the point set $P = P_1 \cup P_2 \cup \ldots \cup P_m$

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Global-FP Clustering

- Distributed collaboration to find k global centers using FP:
  - In round i, each site sends its furthest point from current centers C_i
  - Coordinator picks furthest point as a center and sends it to all sites
- Each remote client monitors its local points, recluster if some point is more than $(1+ \varepsilon/2)R$ from the global centers
- Alternate collaborating and monitoring phrases
- Each reclustering sends $O(mk)$ points

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Global-PG Clustering

- Coordinator maintains a global PG clustering, shares the current good guess and centers with all clients
  - Client sends new point p if $\exists i$, $d(p,C_i(p)) > R_i$
  - Coordinator shares new centers with all clients
- Total communication bounded by $O(km/\varepsilon \log \Delta)$
- Coordinator always has a $(2+\varepsilon)$-approximation

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Comparison

- A summary of the algorithms:

Algorithm	Guarantee	Space	Communication
Local-FP	**4 + ε**	**O(n)**	**—**
Local-PG	**4 + ε**	**O(k/ε log Δ)**	**O(km/ε log Δ)**
Global-FP	**2 + ε**	**O(n)**	**—**
Global-PG	**2 + ε**	**O(k/ε log Δ)**	**O(km/ε log Δ)**

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Experimental Data Sets

- US Census 2005 (TIGER) data
  - N = 600k 2-D points
  - State of New Jersey, m = 21
- Stock price series
  - Price series of a stock with n = 330k values
  - Simulate 100-D vectors
- Measure communication cost as ratio compared to sending complete data

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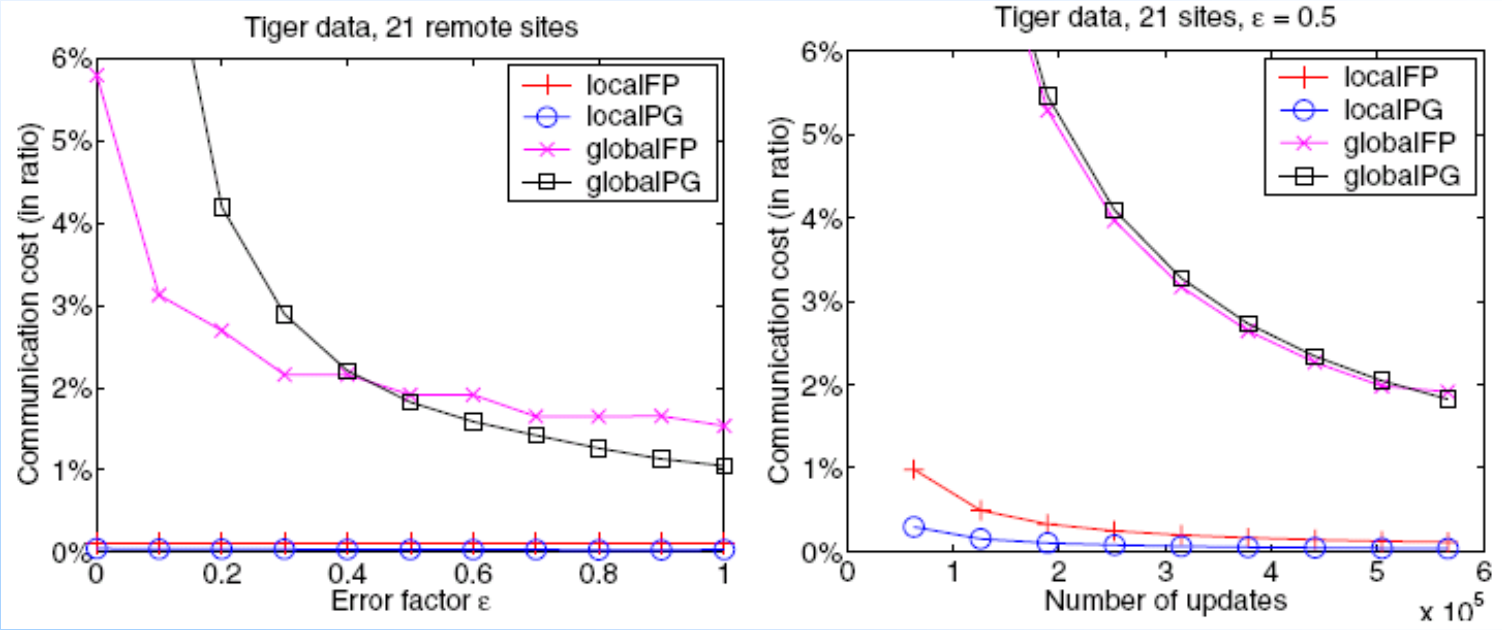
Experimental Results — Communication cost

- Fix sites m and clusters k, vary ε: compare communication



- The local algorithms are more cost effective than naive global implementations of distributed algorithms

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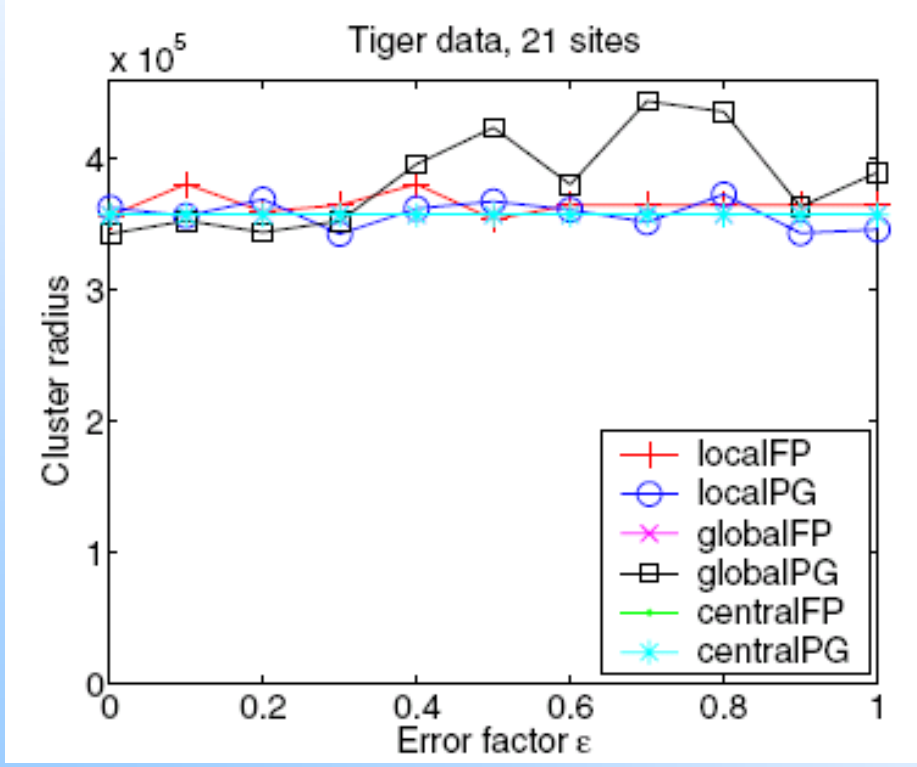
Experimental Results — Cluster Quality

- Fix m, k, vary ε, compare radius: smaller is better



- Not much to choose between algorithms in terms of accuracy
- Choice of ε seems not very sensitive – can choose a large value and not suffer

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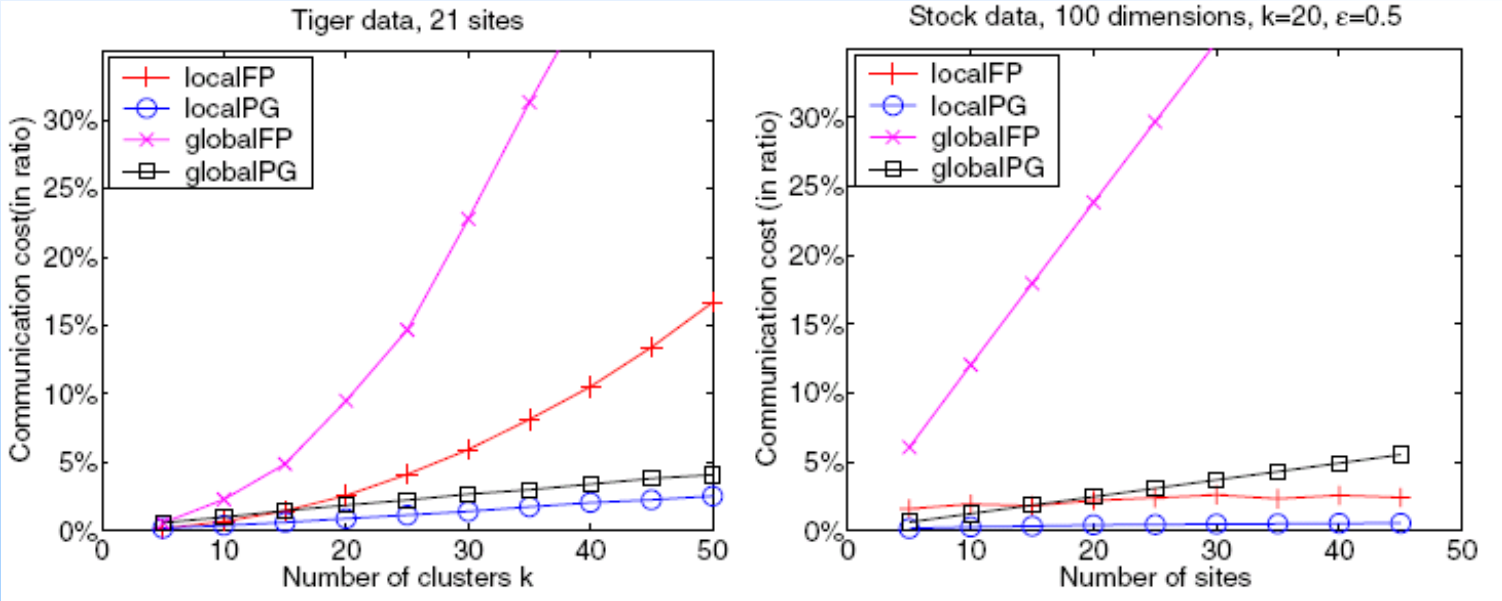
Experimental Results — Other Dependence

- Varying number of clusters k and sites m



- Analysis of cost seems a good predictor: all algorithms very close to linear on *m*, quadratic on *k* for FP algorithms

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Extensions

- Deletions: run same algorithms as before. Monitor the (k+1) points which are 'proof' of current clustering and recluster if any get deleted.
- Moving Points: can treat as deletion of old point, reinsertion at new location if possible.
- Sliding window: treat the point that is no longer in the window as a deletion of point

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Variable number of clusters

- Although we built a k-center clustering, we can get any k'-clustering for $k' \leqslant k$
  - For FP algorithms, pick the first k' centers
  - For PG algorithms, the k' clustering is the smallest guess that generates at most k' centers
- 1-center problem is a special case, and we can get a stronger $(1+\varepsilon)$-approximation

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Conclusion

- Introduced distributed continuous clustering
- Shown local and global k-center algorithms
  - Minimize communication, guarantee clustering quality
- Experimental results show
  - local and parallel guessing uses least communication
  - clustering quality is similar to centralized algorithm
  - space needed independent of the input size
- Open to study other popular clustering algorithms, and other settings

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- Thank you!