Clustering data at scale

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whoami

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- This work is my senior project
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Agenda

- Data
- Clustering
 - k-means
 - Improvements

- Large scale
 - k-means as a map-reduce
 - streaming k-means
 - MapReduce & Storm
- Results

Full version at http://goo.gl/n3n8S

Data

- Real-valued vectors (or anything that can be encoded as such)
- Think of rows in a database table
- Can be: documents, web pages, images, videos, users, DNA

The problem

Group **n d**-dimensional datapoints into **k** disjoint sets to minimize

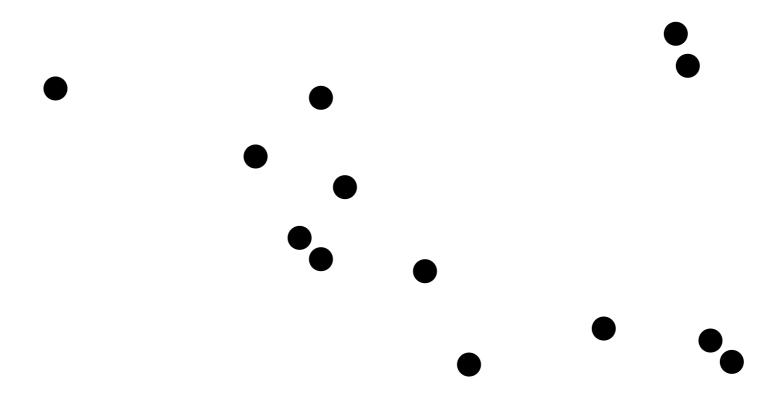
$$\sum_{\mathbf{c_1}}^{\mathbf{c_k}} \left(\sum_{\mathbf{x_{ij}} \in X_i} dist(\mathbf{x_{ij}}, \mathbf{c_i}) \right)$$

 X_i is the i^{th} cluster

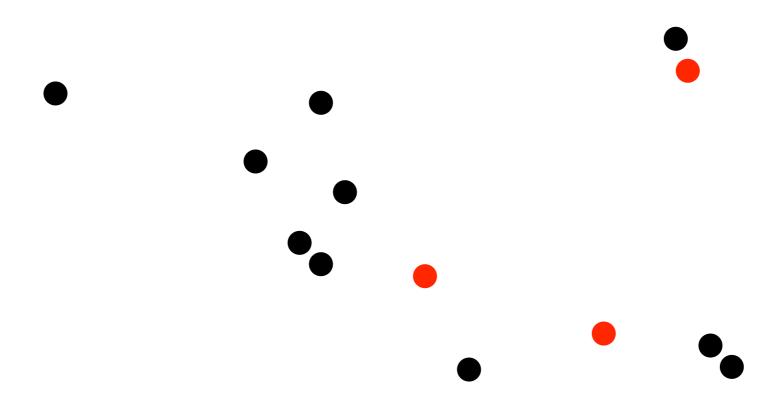
 $\mathbf{c_i}$ is the centroid of the i^{th} cluster

 $\mathbf{x_{ij}}$ is the j^{th} point from the i^{th} cluster

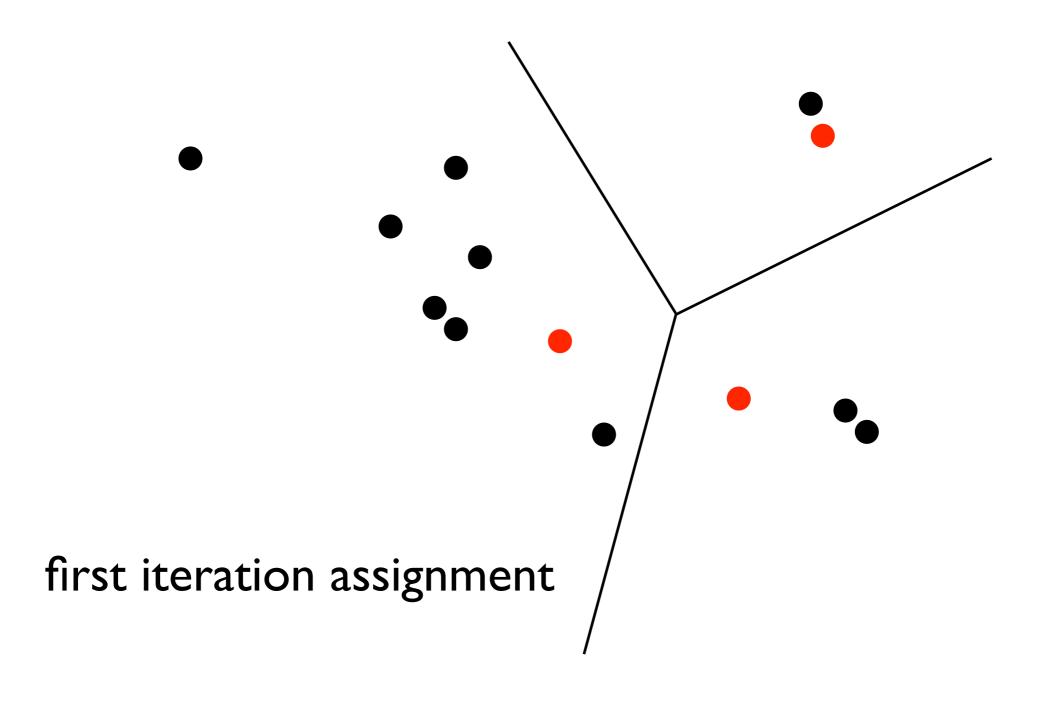
$$dist(\mathbf{x}, \mathbf{y}) = ||\mathbf{x} - \mathbf{y}||_2$$

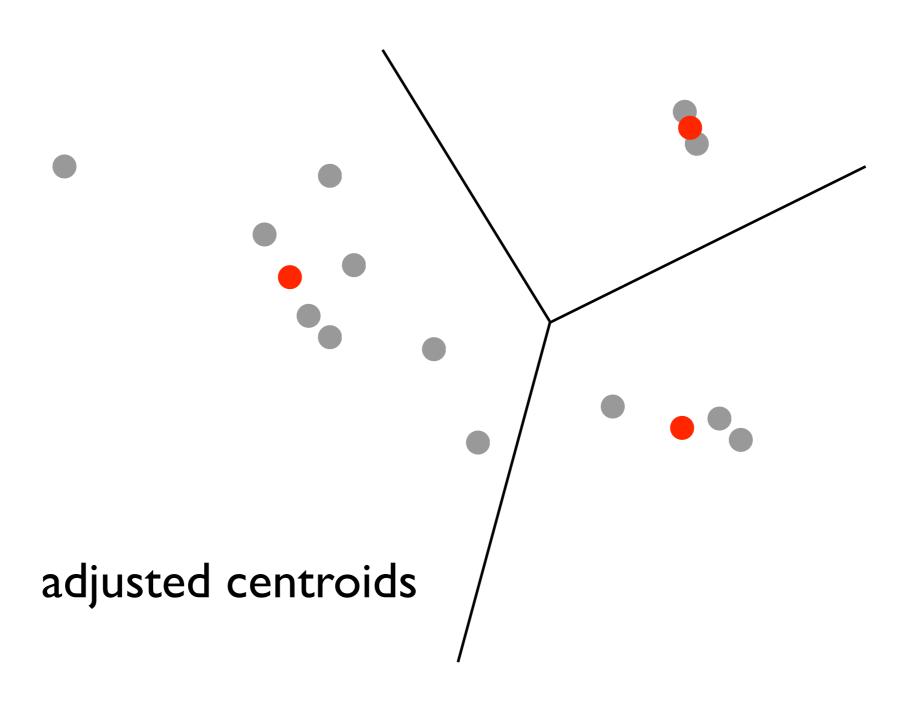


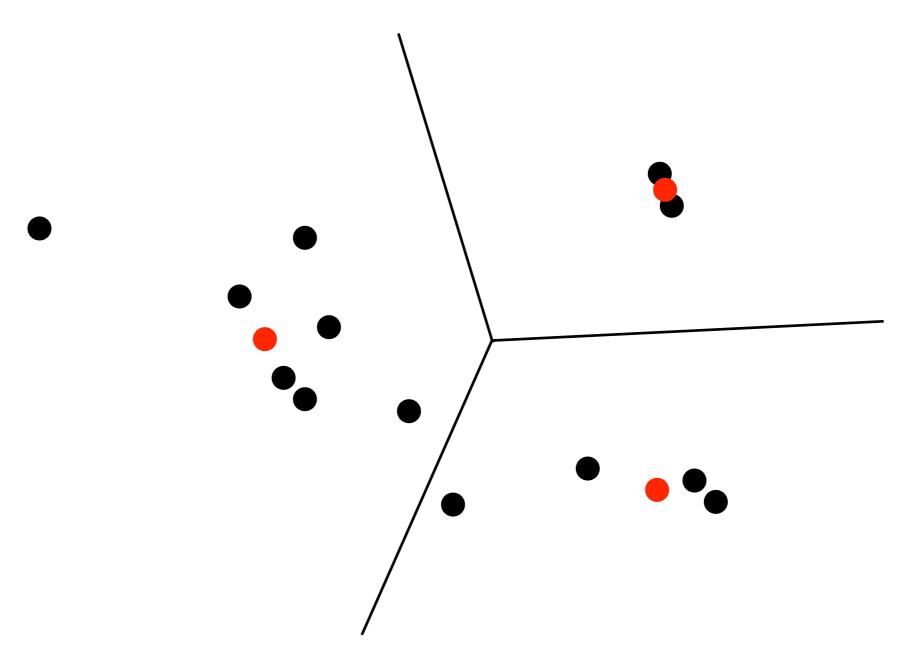
points to cluster



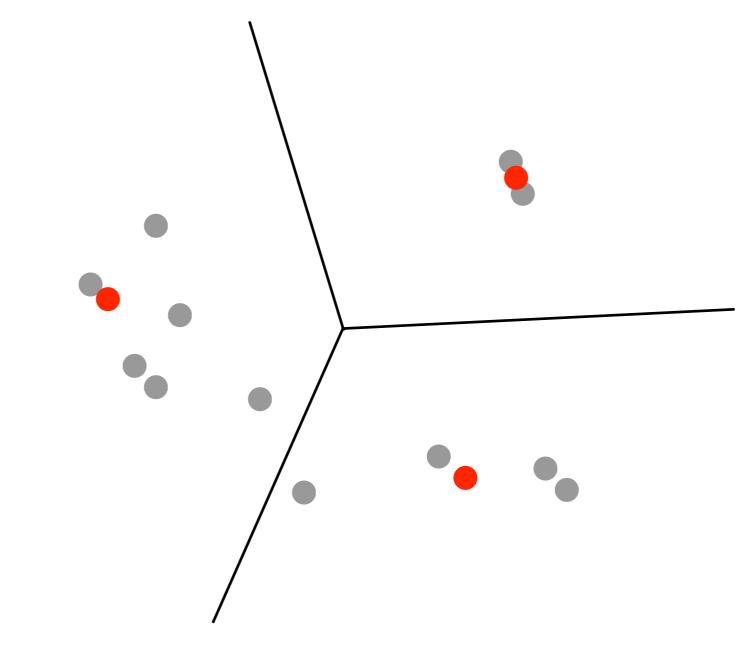
initial centroids







second iteration assignment



adjusted centroids

Details

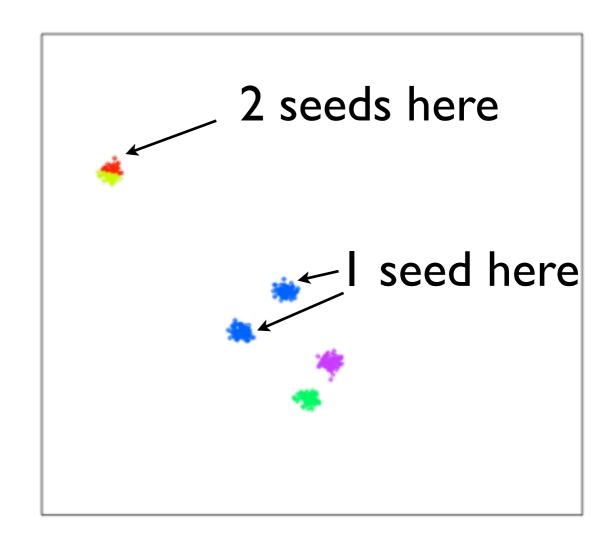
- Quality
 - How to initialize the centroids
 - When to stop iterating
 - How to deal with outliers
- Speed
 - Complexity of cluster assignment

Quality?

- Clustering is in the eye of the beholder
 - Total clustering cost and:
 - compact
 - well-separated
 - Dunn Index, Davies-Bouldin Index, etc.

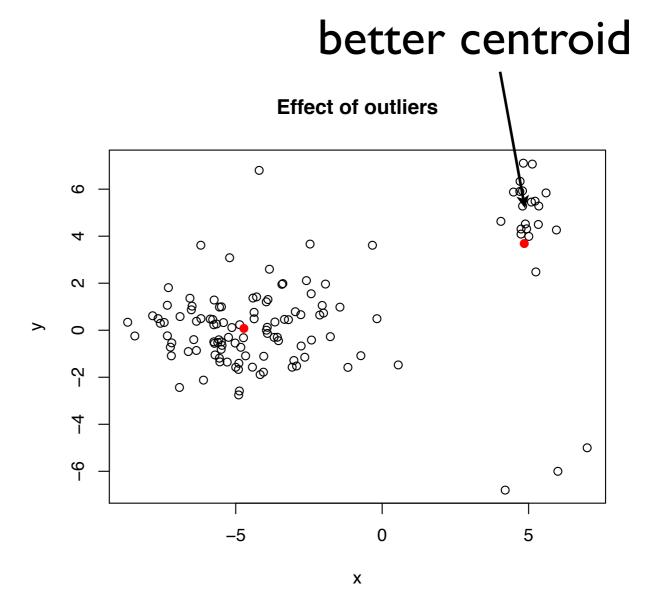
Centroid initialization

- Important for quick convergence and quality
- Randomly select k points as centroids
 - Clustering fails if two centroids are in the same cluster
- k-means++ addresses this



Outliers

- Real data is messy
- Outliers can affect k-means centroids

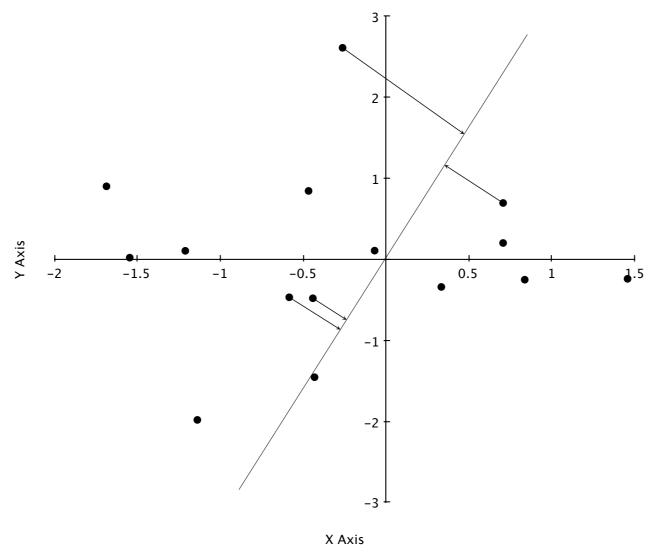


Closest cluster: reducing k

- Avoid computing the distance from a point to every cluster
 - Random Projections
 - projection search
 - locality-sensitive hashing search

Random Projections

Unit length vectors with normally distributed components



Closest cluster: reducing d

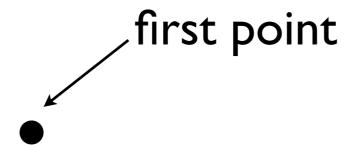
- Principal Component Analysis
 - compute SVD
- Random Projections
 - multiply data by projection matrix

k-means as a MapReduce

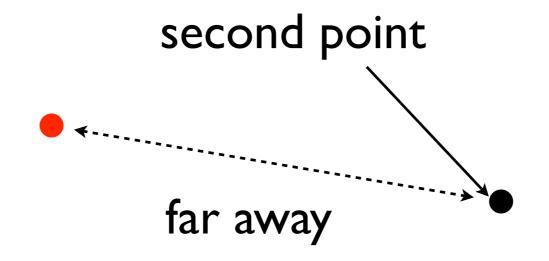
- Can't split k-means loop directly
- Must express a single k-means step as a MapReduce

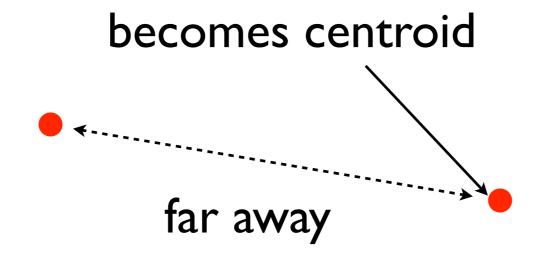
Now for something completely different

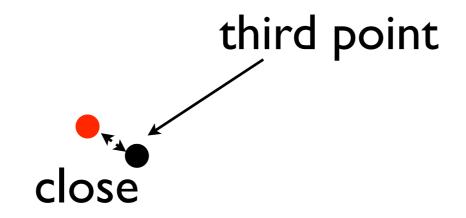
- Fast and Accurate k-means For Large Datasets
 M. Schindler, A. Wong, A. Meyerson
 - http://books.nips.cc/papers/files/nips24/NIPS2011_1271.pdf
- Attempt to build a "sketch" of the data in one pass
- O(k log n) intermediate clusters
- Can fit into memory
- Ball k-means on the sketch for k final clusters





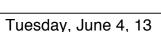






centroid is updated

close but becomes a new centroid



- for each point **p**, with weight **w**
 - find the closest centroid to **p**, call it **c** and let d be the distance between **p** and **c**
 - if an event with probability proportional to
 d * w / distanceCutoff occurs
 - create a new cluster with **p** as its centroid
 - else, merge **p** into **c**
 - if there are too many clusters, increase distanceCutoff and cluster recursively

The big picture MapReduce

- Can cluster all the points with just I MapReduce:
 - m mappers run streaming k-means
 - I reducer runs ball k-means to get k clusters

The big picture Storm

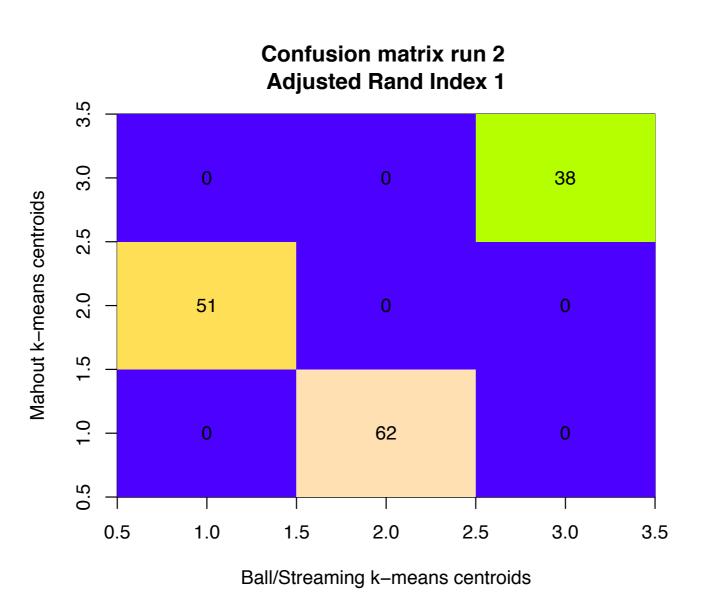
- Storm
 - streaming k-means bolt
 - Release the sketch when notified (e.g. tick tuples)
- Trident
 - streaming k-means partition aggregator
 - ball k-means aggregator



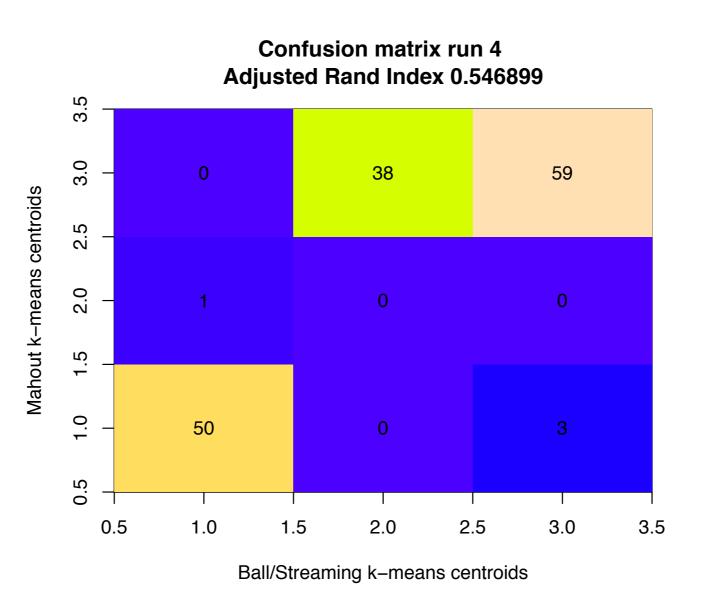
Quality

- Compared the quality on various small-medium UCI data sets
 - iris, seeds, movement, control, power
- Computed the following quality measures:
 - Dunn Index (higher is better)
 - Davies-Bouldin Index (lower is better)
 - Adjusted Rand Index (higher is better)
 - Total cost (lower is better)

iris randplot-2

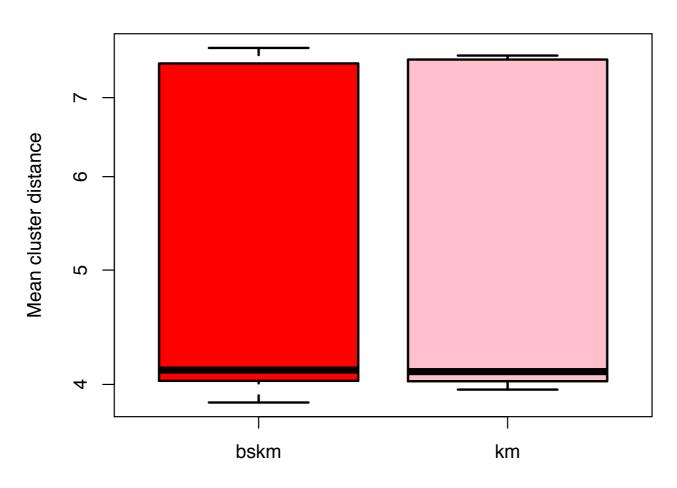


iris randplot-4



seeds compareplot

Clustering techniques compared all



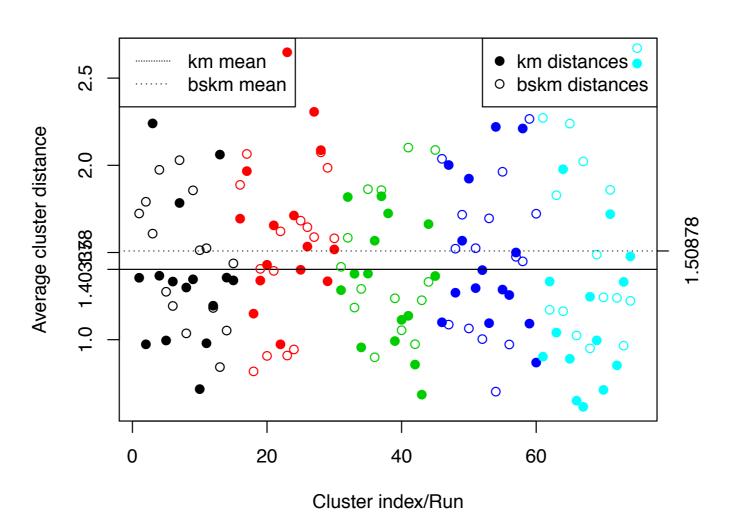
Clustering type / overall mean cluster distance

4.3116448

4.22126213333333

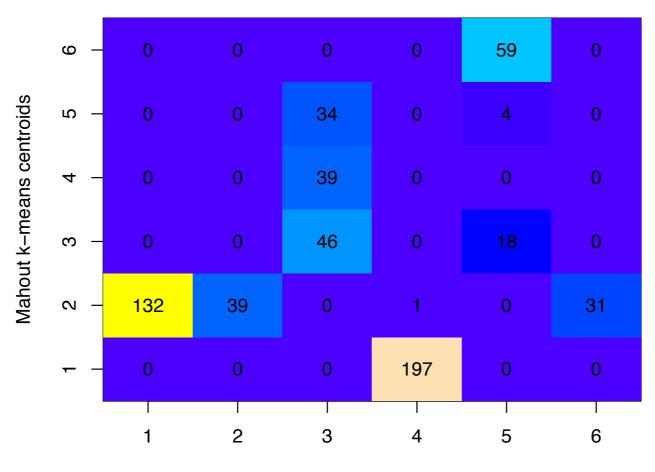
movement compareplot





control randplot-3

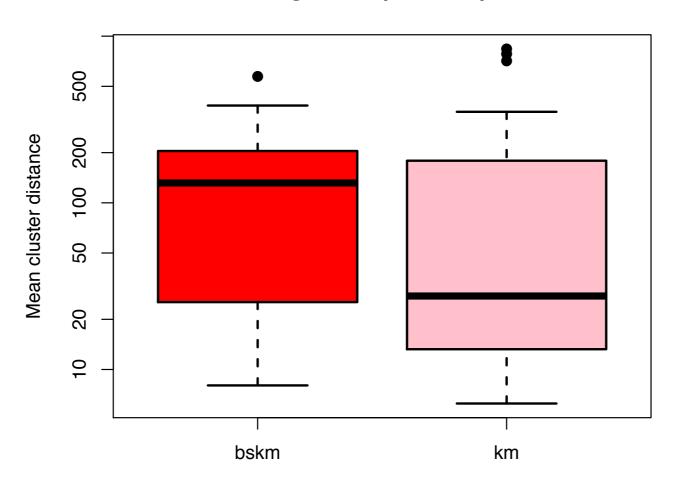
Confusion matrix run 3 Adjusted Rand Index 0.724136



Ball/Streaming k-means centroids

power allplot

Clustering techniques compared all



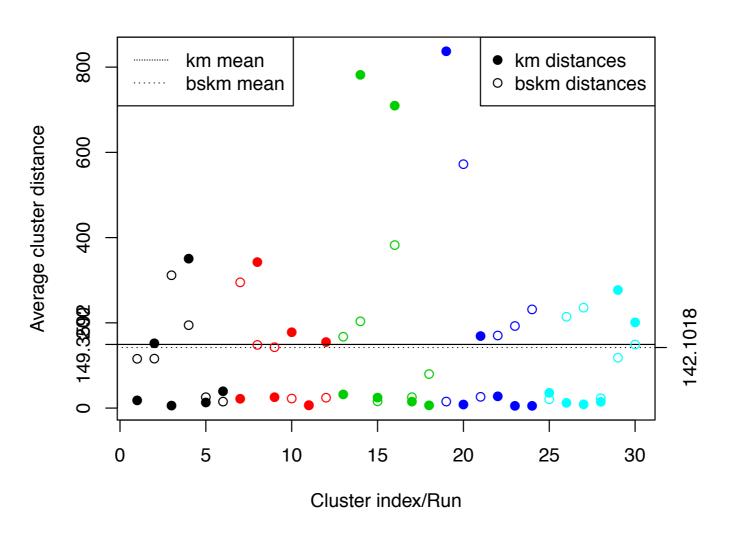
Clustering type / overall mean cluster distance

142.101769766667

149.3591672

power compareplot

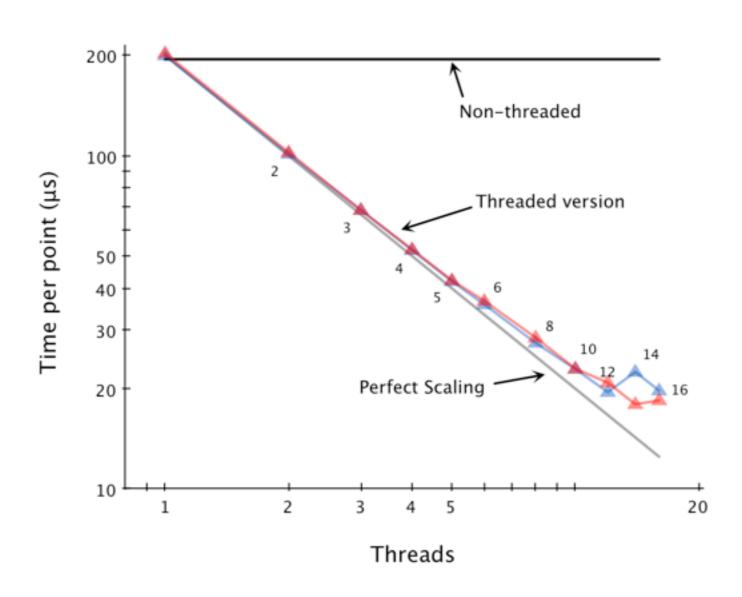




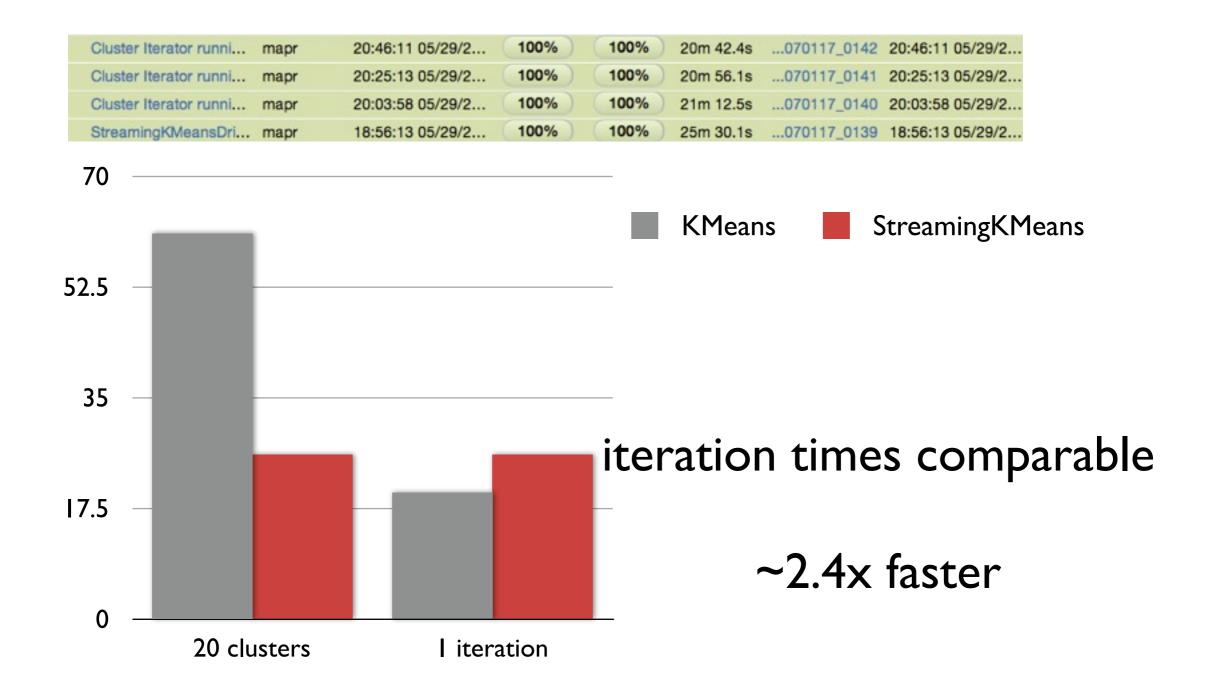
Overall (avg. 5 runs)

Dataset	Clustering	Avg. Dunn	Avg. DB	Avg. Cost	Avg.ARI
iris	km	9.161	0.265	124.146	0.905
	bskm	6.454	0.336	117.859	
seeds	km	7.432	0.453	909.875	0.980
	bskm	6.886	0.505	916.511	
movement	km	0.457	1.843	336.456	0.650
	bskm	0.436	2.003	347.078	
control	km	0.553	1.700	1014313	0.630
	bskm	0.753	1.434	1004917	
power	km	0.107	1.380	73339083	0.605
	bskm	1.953	1.080	54422758	

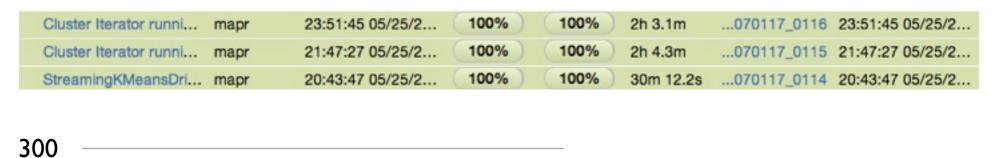
Speed (Threaded)

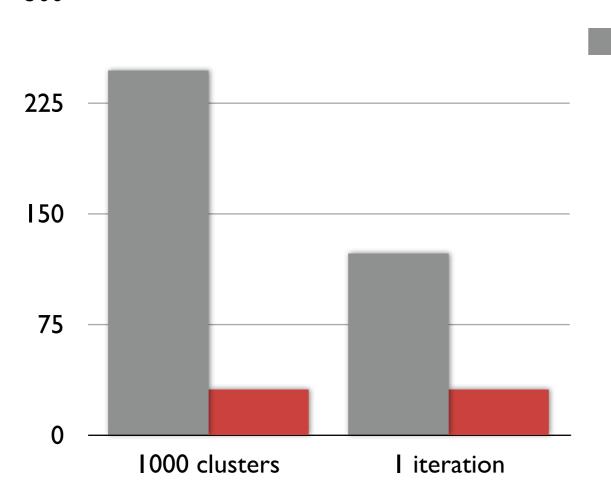


Speed (MapReduce)



Speed (MapReduce)





benefits from approximate nearest-neighbor search

StreamingKMeans

KMeans

~8x faster

Code

Clustering algorithms	BallKMeans StreamingKMeans	
Fast nearest-neighbor search	ProjectionSearch	
Quality metrics	ClusteringUtils	
MapReduce classes	StreamingKMeansMapper StreamingKMeansReducer	
Storm classes	StreamingKMeansBolt	

- Now available in Apache Mahout trunk
- Prototype for Storm <u>http://github.com/dfilimon/streaming-storm</u>

Thank you! Questions?

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