# Concurrent K-Means Algorithm

Implementation

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# K-Means Algorithm

**Project:** 

Implement single-threaded and 2 methods for "parallelization"

1) Single Threaded Version

2) Distributed Memory Approach

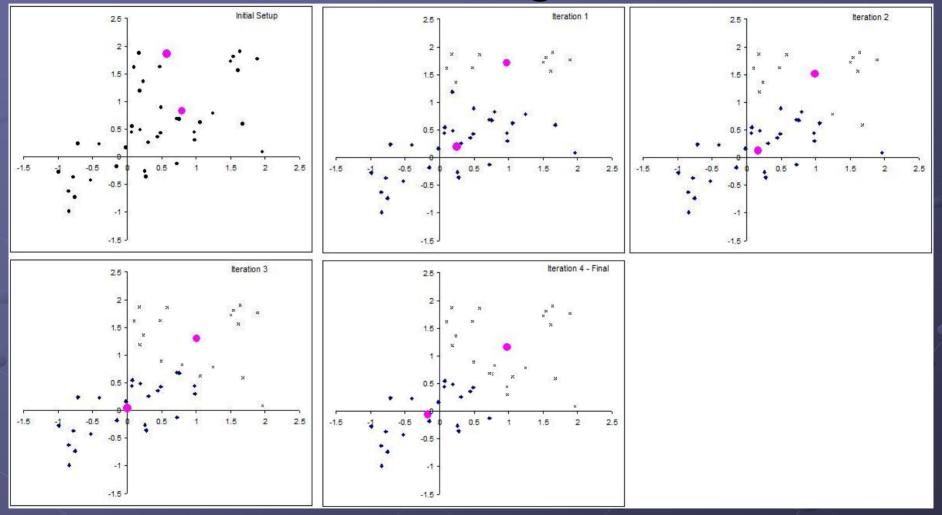
3) Shared Memory Approach

# K-Means Algorithm

- Randomly assign cluster centers (e.g. select random points from within the dataset)
- For each point calculate the distance to the cluster centers and assign the point to the closest "cluster".
- Based on the membership calculated in step (2) calculate the center of the new clusters.
- Repeat steps (2) and (3) until stopping criteria are met (e.g. no point change cluster membership).

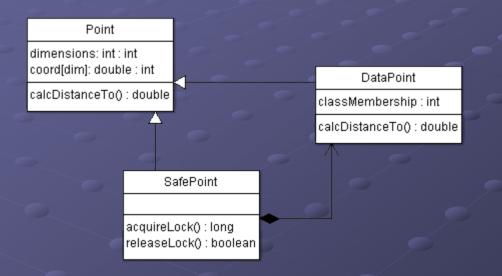
MacQueen, 1967 [1]

#### k-means Algorithm



Brute Force:  $549,755,813,800 = 5.5*10^{11}$  possible 2-cluster arrangements

#### Data Structures



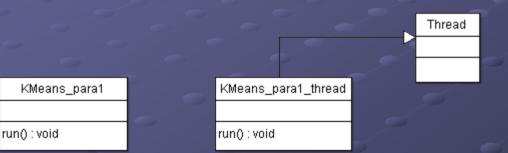
#### **Data Structures**

Vector

PointVector

genUniform(parameters : void) : void importFrom(fileName : String) : void exportAsCSV(fileName : String) : void

#### **Data Structures**



# "Distributed" Model Approach

Exploit the "data" parallelism:

- Subdivide the data into equal "chunks": copies points references to a local Vector (otherwise, whole Vector locked)
- Copy cluster centers to a local Vector
- Code very similar to the single-threaded version

// calculate cluster membership

P(mutex\_locked); V(mutex\_membership); processed = true;

V(mutex\_locked);

However, data storage and processing are in different objects.

```
// get a lock on the point
public long acquireLock() {
    long dataLock = 0;
    try {
        mutex locked.acquire();
        if (!locked && !processed) {
            //give the lock only when the point has not been processed
            locked = true:
            mutex locked.release();
            while (dataLock == 0) { // do not allow a "zero" lock
                dataLock = rand.nextLong();
            this.randDataLock = dataLock:
            mutex membership.acquire(); //lock up the membership calculation
        } else {
            mutex locked.release();
        return dataLock:
    } catch (InterruptedException e) {
        System.out.println("SafePoint.aquireLock(): " + e.getMessage());
        return 0;
```

Point can only be locked for processing once (flag reset between iterations) Lock exclusivity accomplished though a randomized "key".

```
// release the lock on the point
public boolean releaseLock(long dataLock) {
   boolean lock released = false;
    try {
        mutex locked.acquire();
        if (randDataLock != 0 && this.randDataLock == dataLock) {
            if (locked) { // release the lock only if it has previously been acquired
                locked = false:
                processed = true;
                lock released = true;
                randDataLock = 0;
                mutex membership.release();
        mutex locked.release();
        return lock released;
    } catch (InterruptedException e) {
        System.out.println("SafePoint.releaseLock(): " + e.getMessage());
        return false:
```

"mutex\_membership" forces waiting for the result. "key" required to release the lock.

```
public boolean setClusterMembership(long dataLock, int newValue) {
    boolean valueSet = false;
    try {
        mutex_locked.acquire();
        if (randDataLock != 0 && this.randDataLock == dataLock) {
            if (locked) { // allow changes to the cluster membership only if locked
                point.setClusterMembership(newValue);
                valueSet = true;
            }
            mutex_locked.release();
            return valueSet;
        } catch (InterruptedException e) {
            System.out.println("SafePoint.setClusterMembership(): " + e.getMessage());
            return false;
        }
    }
}
```

"key" required to change value.

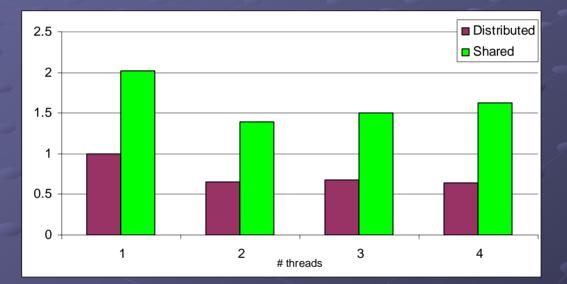
#### "Shared" Memory Approach

Multiple threads are potentially accessing the same data points; therefore, need to lock points while calculating cluster centers.

```
for (Iterator iPt = dataPoints.iterator(); iPt.hasNext();) {
    SafePoint point = (SafePoint) iPt.next();
   long dataLock = point.acquireLock();
   if (dataLock != 0) {
        int newCluster = -1:
        double newMinDistance = 10E38:
        for (int iCtr=0; iCtr < clusterCenters.size(); iCtr++) {</pre>
            Point center = (Point) clusterCenters.elementAt(iCtr);
            double dist = point.calcDistanceTo(center);
            if (dist < newMinDistance) { // closer center found
                newCluster = iCtr:
                newMinDistance = dist:
        // assign the new cluster center, if it has changed
        if (point.getClusterMembership() != newCluster) {
            point.setClusterMembership(dataLock, newCluster);
            safeChangedMembership.write(true);
        point.releaseLock(dataLock);
```

#### Results

Processing time with respect to single-threaded version

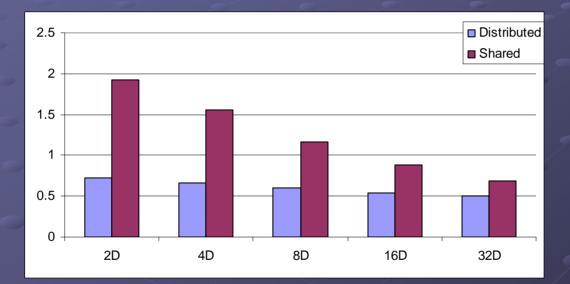


There is a lot of variability in processing time; but, the ratio of processing times is relatively constant.

(on dual core processor)

#### Results

Processing time with respect to single-threaded version (2 threads)



As the amount of parallelized work increases the ratio of the "locking overhead" to the work done decreases.

(on dual core processor)

#### Conclusions

- Important to determine if the problem size justifies concurrent implementation.
- Match the number of threads to the number of cores.
- Do not use locks where it is not necessary (pretty high cost).
   For example, if parts of the code are intended to be run single-threaded, adapt the data structures for such.

#### Future developments

- Increase the amount of work done in parallel (currently only the cluster assignment is done in parallel; can also put parts of the recalculation of new cluster centers).
- Check other problem characteristics and how they affect the processing time w.r.t. single-threaded version (e.g. total number of points, number of clusters, cluster shape, etc.).
- Compare approach/results to other research.

#### References

[1] MacQueen, J. Some methods of classification and analysis of multivariate observations, Proceedings of the fifth Berkeley symposium on mathematical statistic and probability (Vol. 1, pp. 281-297) Berkeley: University of California Press.

#### Thank You!

#### Questions?