Trajectory Outlier Detection

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About me

- B.S in Computer Engineering
- Data Science Intern – Progos Tech (2017)
- M.Sc in Computer Science (University of Minnesota Duluth)
- Currently – Software Developer (Data Science) OATI (Open Access Technology International)
- Towards Data Science Medium Contributor

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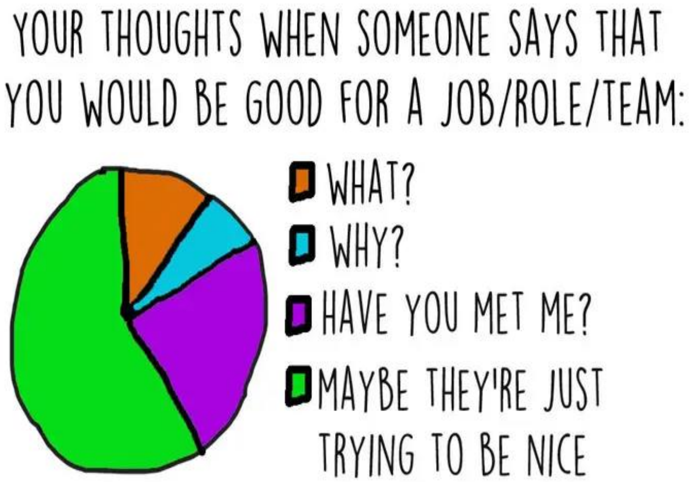
Outline

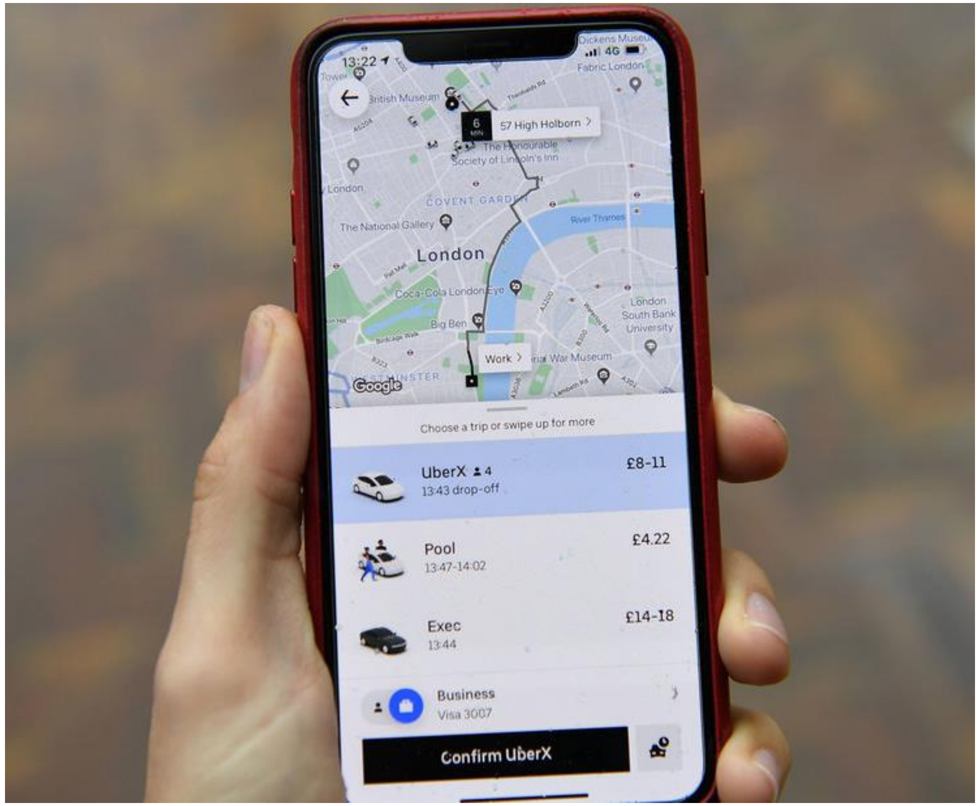
- Introduction
- DBSCAN
- Methodology
- Results
- Conclusion & Q/A

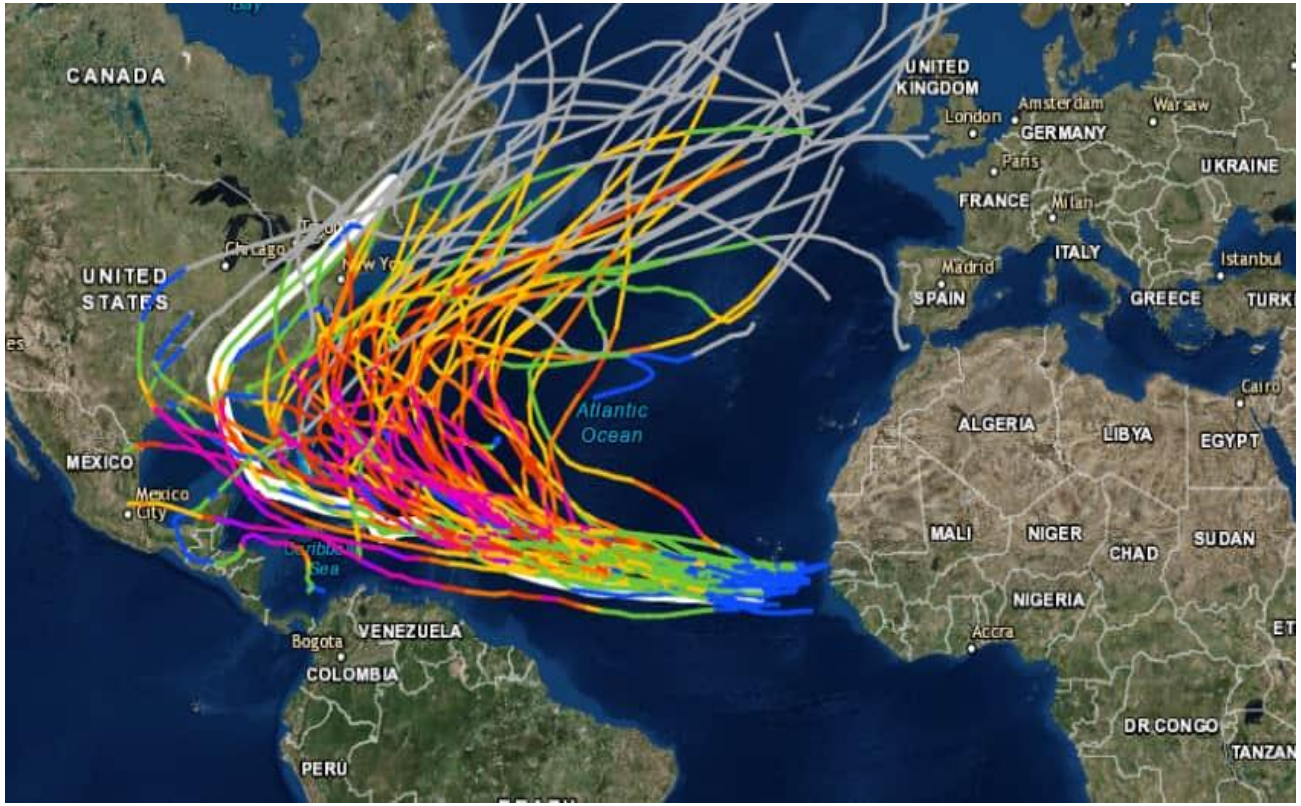
Goal


THOUGHTS YOU HAVE ON THE FIRST DAY OF A NEW JOB:
MY BOSS IS GOING TO REALIZE I WAS A HUGE MISTAKE.
MY BOSS IS GOING TO REALIZE I WAS A HUGE MISTAKE.


IT'S
Easy


YOUR THOUGHTS WHEN SOMEONE SAYS THAT YOU WOULD BE GOOD FOR A JOB/ROLE/TEAM:
WHAT?
WHY?
HAVE YOU MET ME?
MAYBE THEY'RE JUST TRYING TO BE NICE





What is a Trajectory?

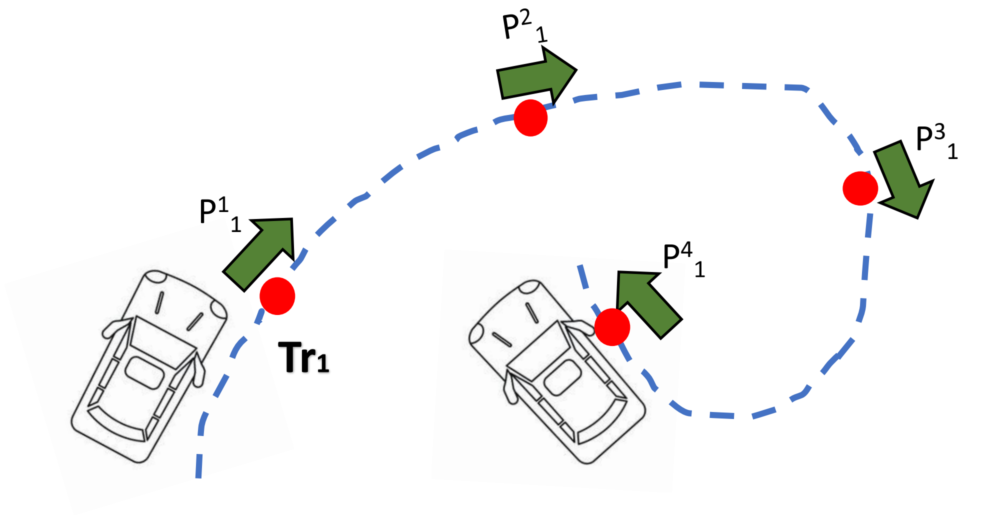
- Informally, a trajectory is a path an object takes over time
- Or even simply, a record of the movement of an object

Meet a Trajectory

- A single multidimensional point P^j_i generated from a moving object *O*, using a tracking device, at time-bin *tj*, is called a trajectory point of the trajectory T_{ri}

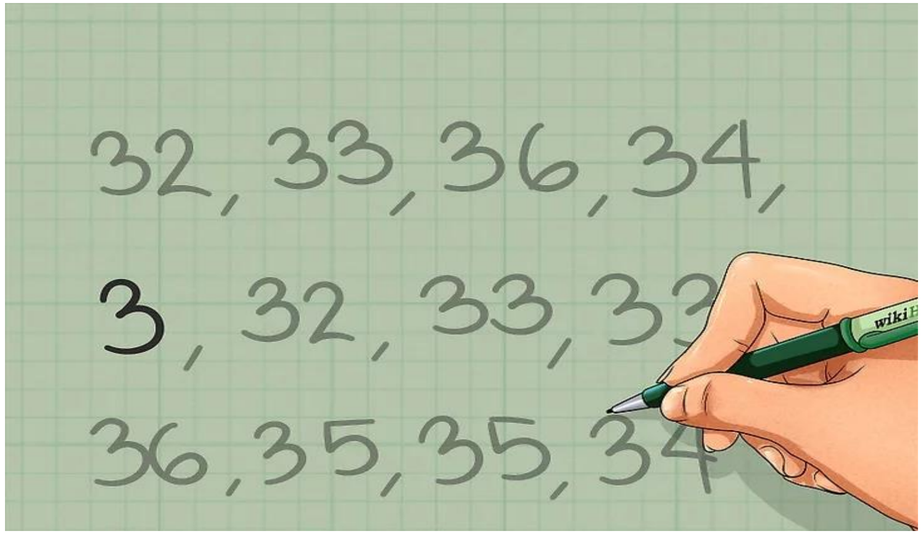
- The trajectory of a moving object *O* is then defined as a sequence of such trajectory points produced at time-bins $\{t_1, t_2 \ldots\ldots t_j\}$ denoted as $T_{ri} = \{P^1_{i,} P^2_{i,} \ldots\ldots P^j_i\}$ as shown on the right

- A time-bin is the most smallest unit of time interval for a trajectory which can consist of a single or multiple points that record its movements



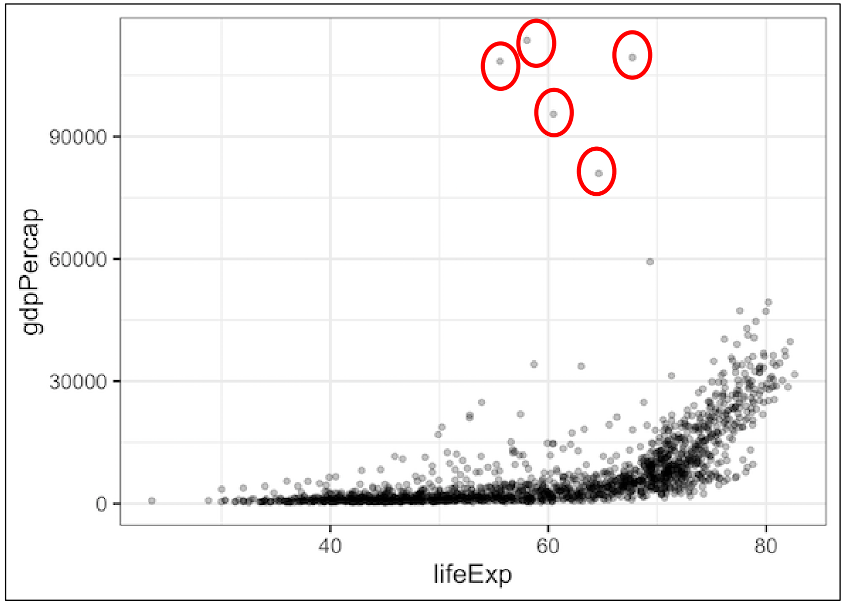
Meet the Outlier

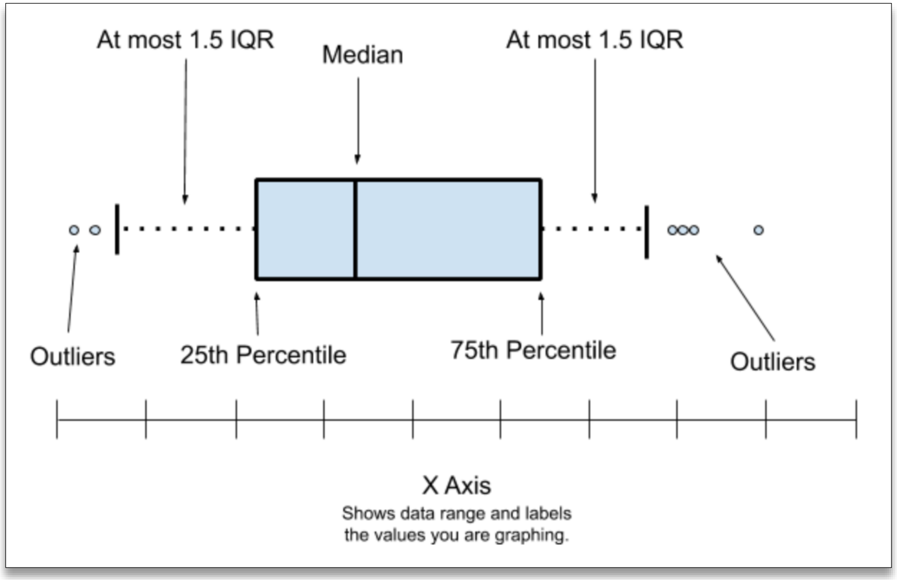
- In statistics, it is simply an observation that is different from other observations (Wiki)
- It could be textual data, image etc.



Find the Outlier

Formally, any point in the data that does not conform to the overall underlying pattern in the data

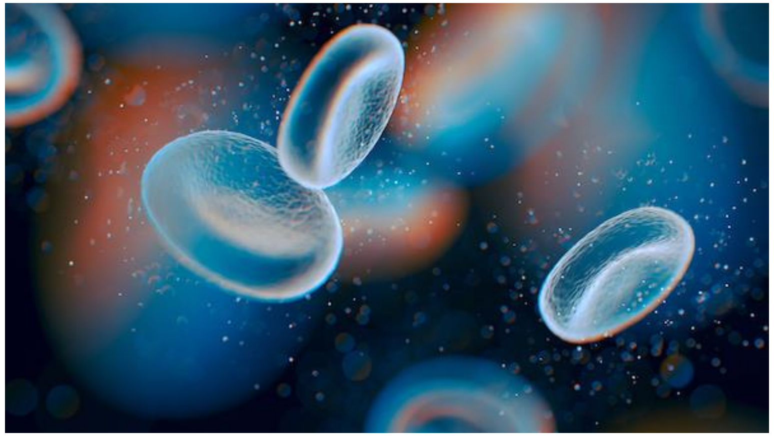




Good or Bad?

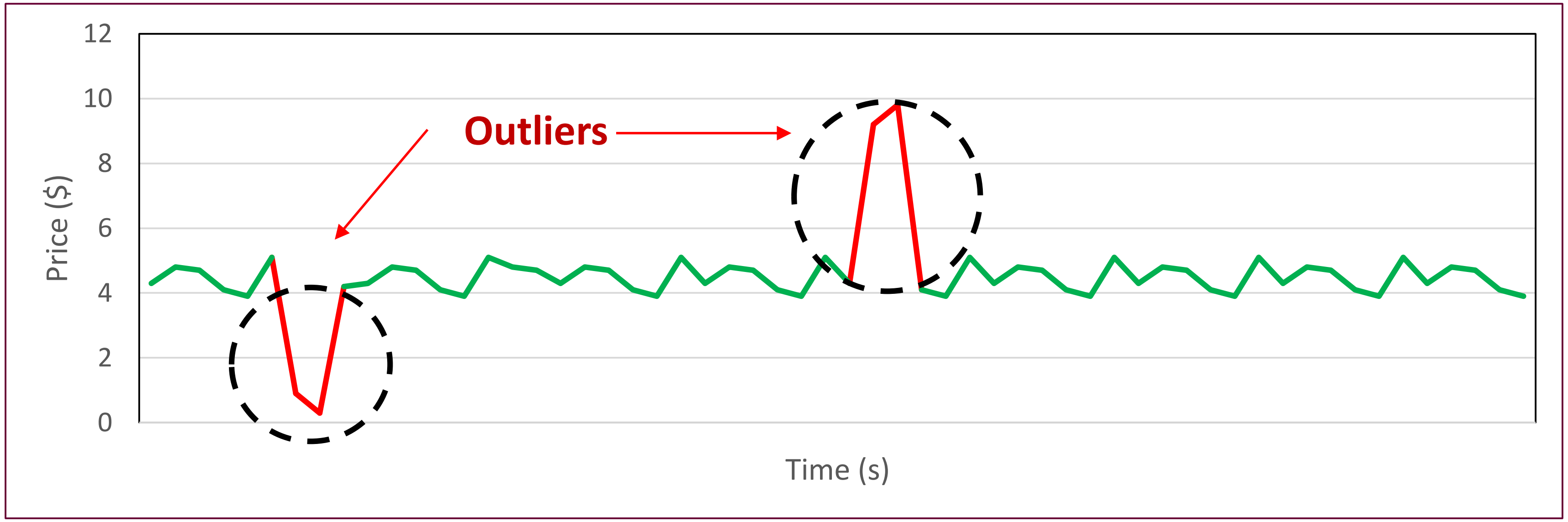
- Credit Card Fraud Detection
- Cancerous Cell Detection through imagery
- Interesting information about the data (Machine failing)

- Sway your prediction model e.g. in regression
- Reduce accuracy
- Loss of data



What are Trajectory Outliers?

- Outliers are data points that behave inconsistently compared to the general pattern of data points in the all the trajectories in the window
- Example below shows two outliers in a stock price “trajectory”



Applications

- Real time outlier detection is a time-critical process
- Applications include traffic management, stock-price monitoring

Source: Google Images

Imperative that outliers are detected in a timely fashion!!

Source: Google Images

Outline

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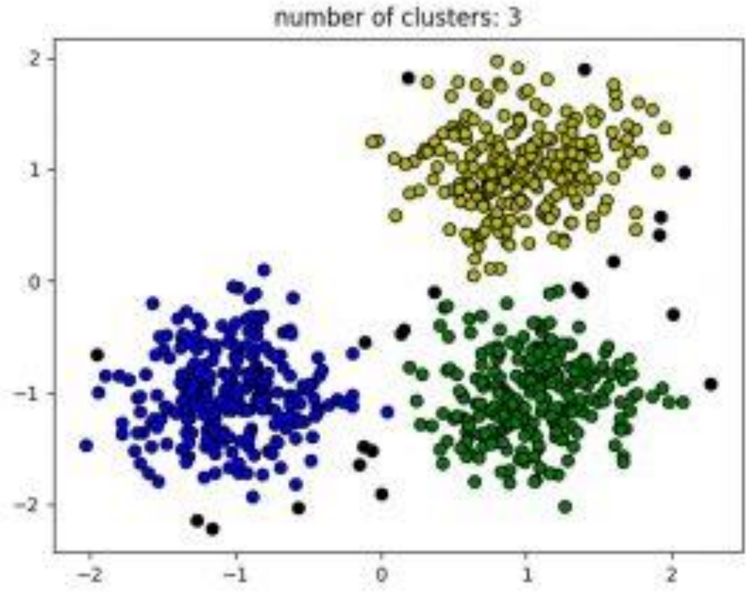
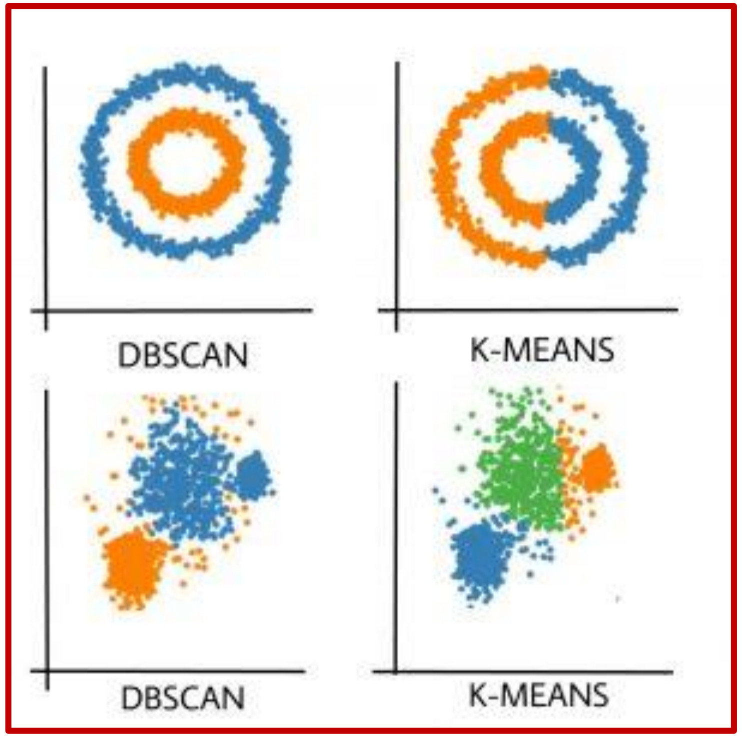
- Literature Review
- Methodology
- Results
- Conclusion & Future Work

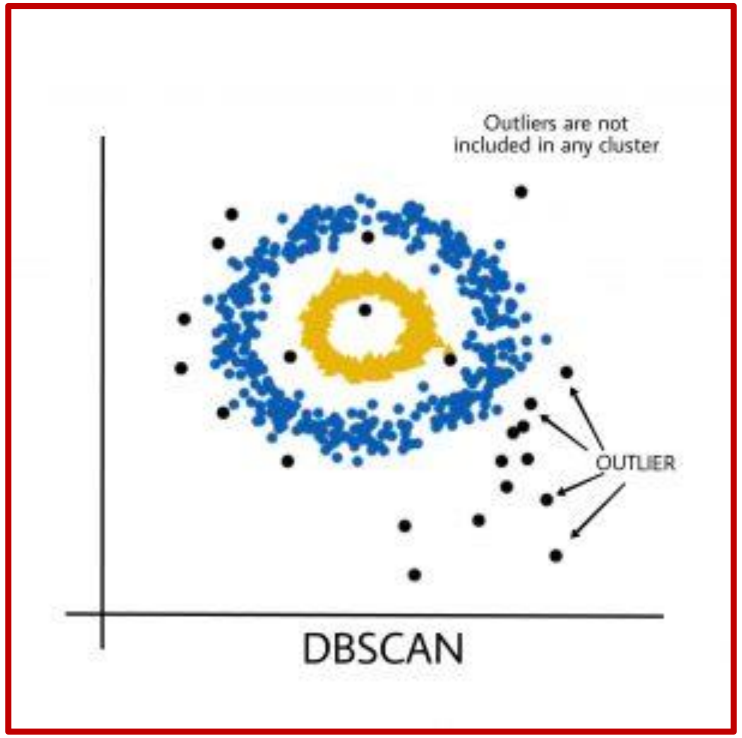
DBSCAN

- Clustering algorithm (similar to K-means)
- Clusters points based on density
- Algorithm as two parameters:
    1) Eps (Distance threshold between two points)
    2) MinPoints (Equal to number of Dimensions + 1)

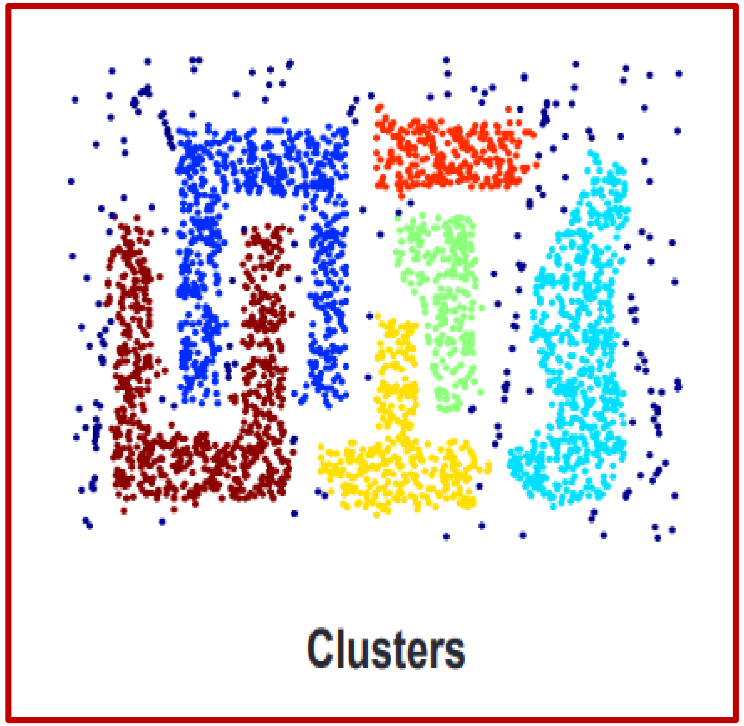




1) K-Means form spherical clusters only



2) K-Means skewed by outliers

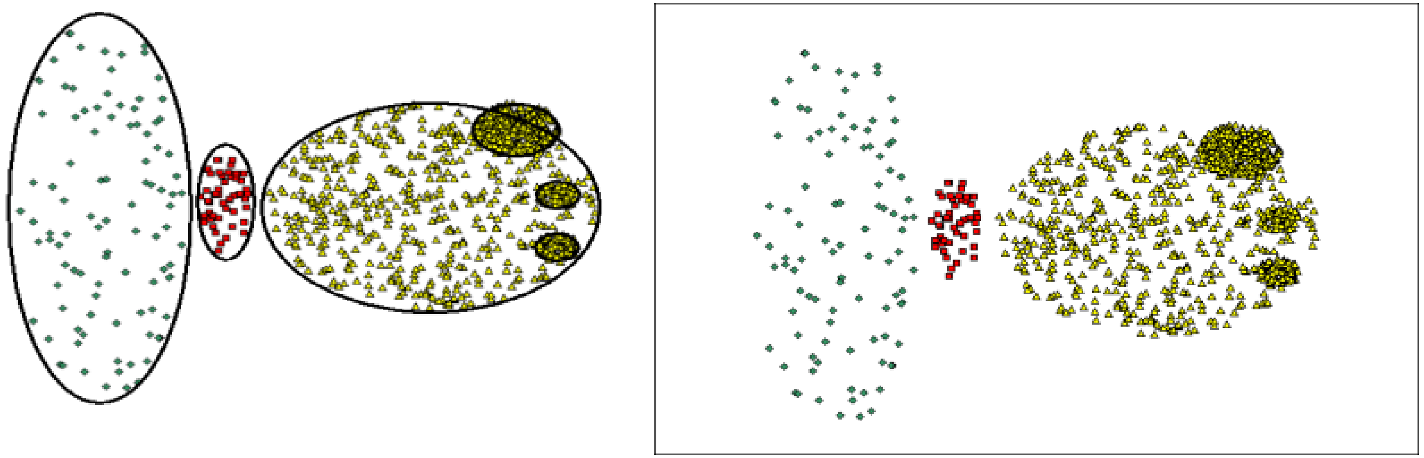


3) Can handle clusters of various shapes

DBSCAN vs K-Means

DBSCAN Disadvantages

- Cannot handle varying densities
- Sensitive to parameters
- Can’t apply directly to trajectories

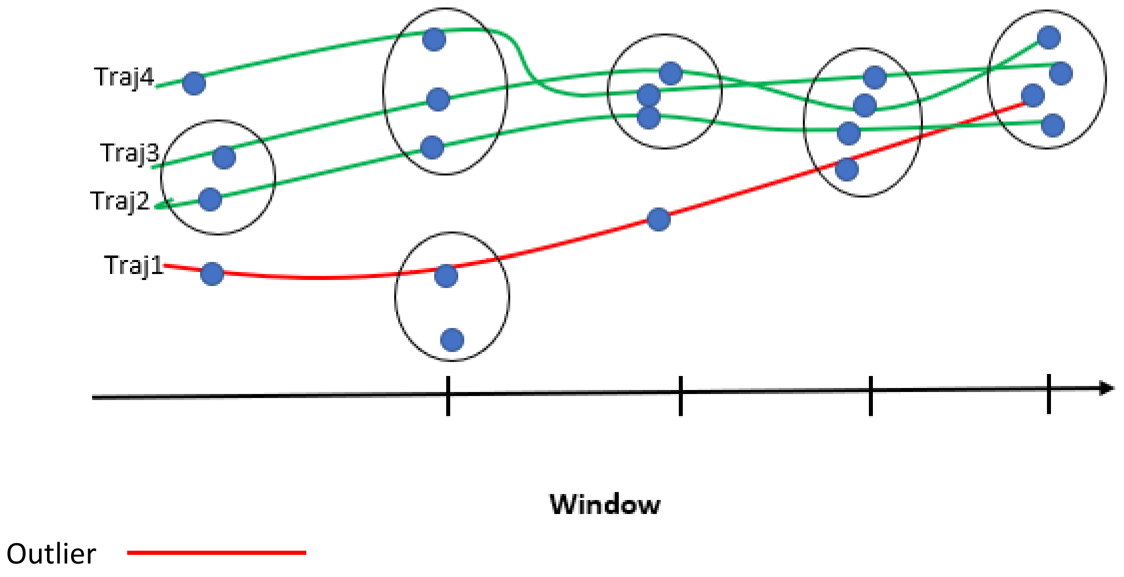


Original Points

(ε =9.92, MinPts=4)

Objectives

Outlier Detection over Massive-Scale Trajectory Streams



Parameters:

- Distance Threshold *d*
- Neighbor Count Threshold *k*
- Time-Bin Count *thr*

Definition:

Given a distance threshold *d*, neighbor count threshold *k* and time-bin count threshold *thr*, a trajectory is an outlier in the window if it has fewer than k trajectory neighbors i.e.

$$|TN(Tri,d,thrj)| < k$$

Haversine Approximation

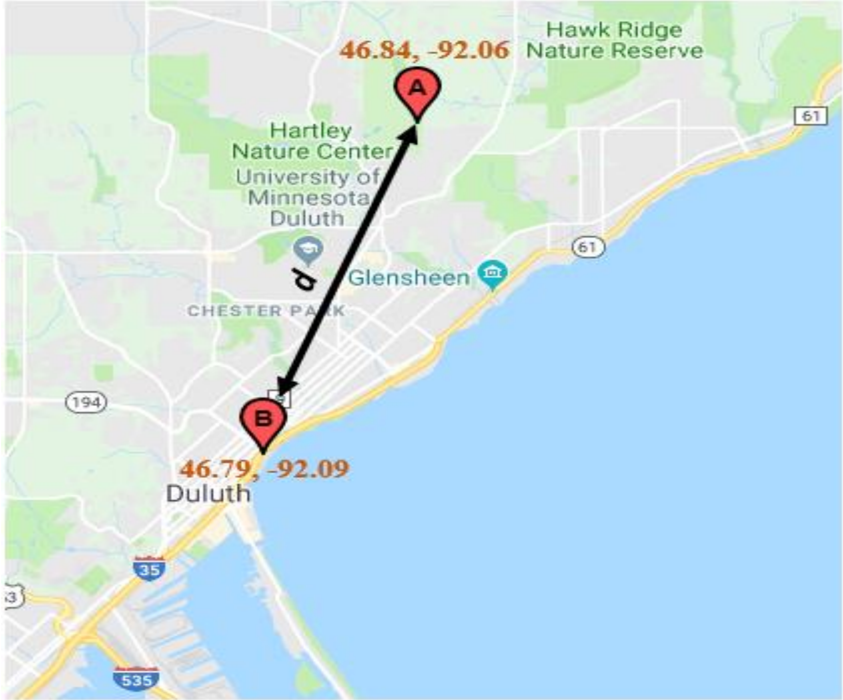
- Calculates the shortest distance between two points on a sphere given the latitude and the longitude

$$a = sin^2\left(\frac{\Delta\phi}{2}\right) + sin^2\left(\frac{\Delta\gamma}{2}\right) * \cos(\theta_1) * \cos(\phi_2)$$

$$c = 2 * \text{atan2}(\sqrt{a}, \sqrt{1-a})$$

$$d = R * c$$

where ϕ, γ, R is the latitude, longitude and the radius of the query search respectively



Data Structures of ODMTS

Parameters

thr
K
d

Tr_i. NT

Neighbors	Time-bins

Stores the information of all trajectories that share at least one point neighbor with Tr_i

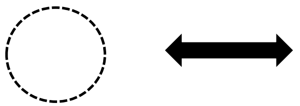
Tr_i. TList

Stores the IDs of neighboring timebins

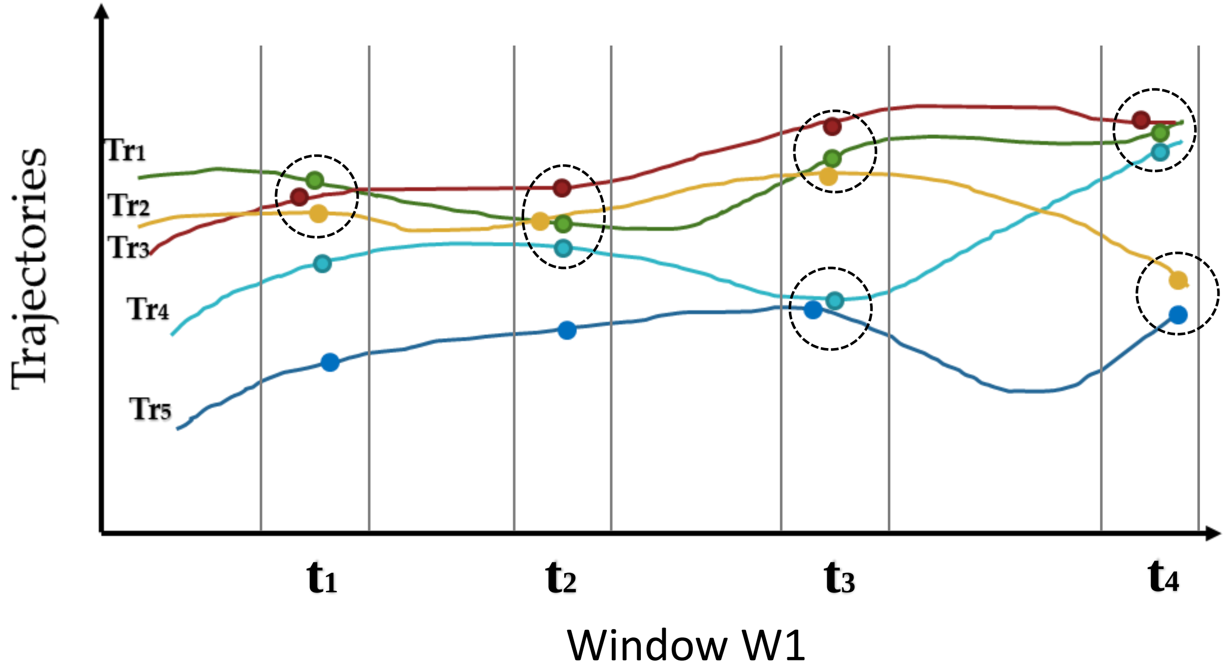
Range Query (Neighbors)

Find all neighbors of each point in each time-bin

D = 500m
Thr = 2
K = 3



Point Neighbor
(d < ε)



ODMTS Example

Tr3. NT

Neighbors	Time-bins
Tr1	*t1*
Tr2	*t1*

|Time-bins| > thr ?

Tr3. Tlist

t1

Tr4. NT

Neighbors	Time-bins
Null	*Null*

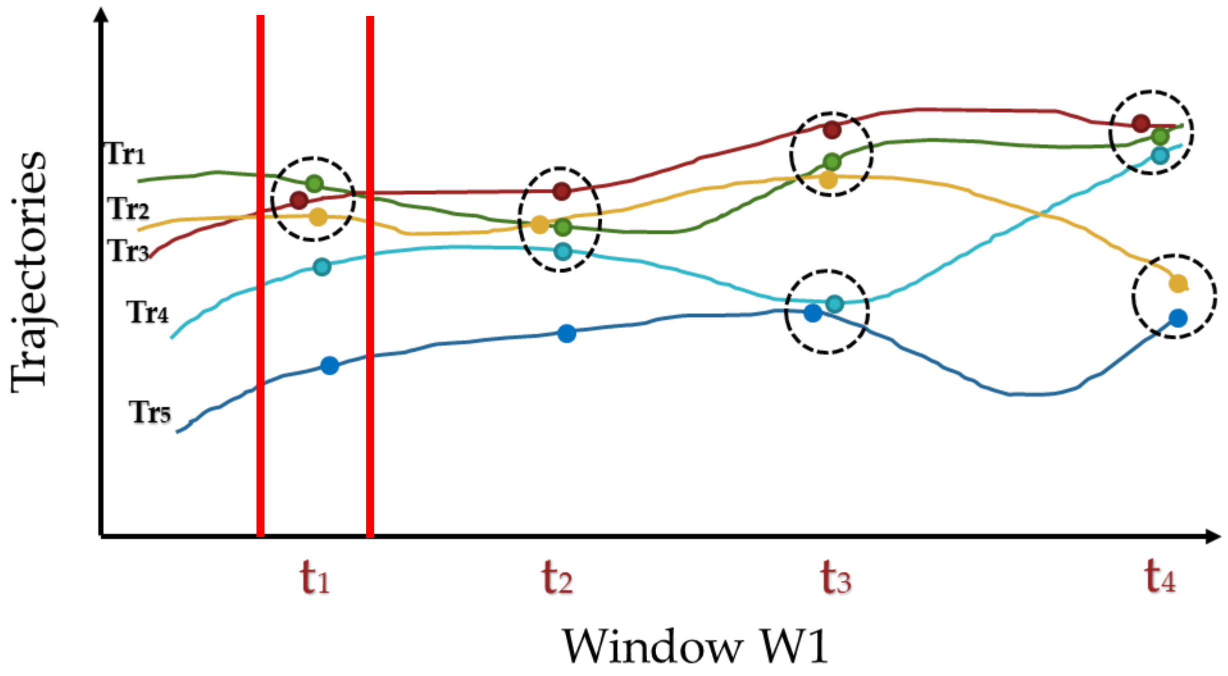
|Time-bins| > thr ?

Tr1. Tlist

Null

Time-bin t1

Time-bin t1



ODMTS Example

Tr3. NT

Neighbors	Time-bins
Tr1	*t1, t2*
Tr2	*t1, t2*
Tr4	*t2*

Tr4. NT

Neighbors	Time-bins
Tr1	*t2*
Tr2	*t2*
Tr3	*t2*

Tr3. Tlist

t1, t2

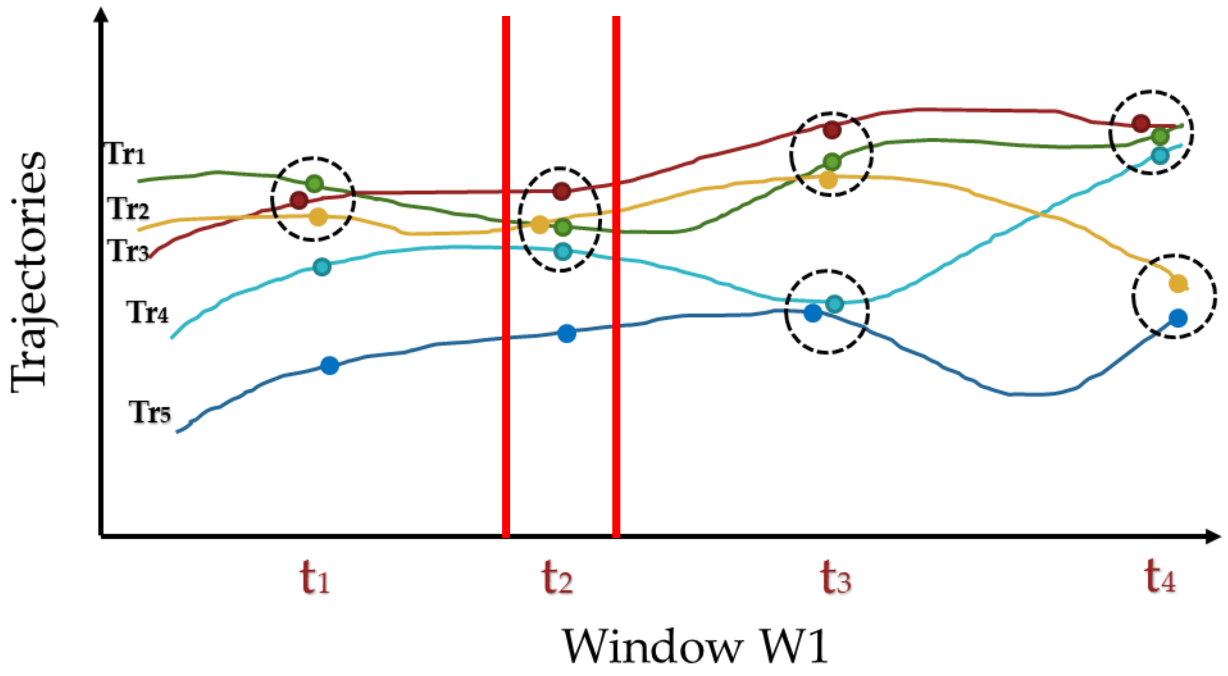
Tr4. Tlist

t2

Time-bin t2

t1, t2

Time-bin t2



ODMTS Example

Tr3. NT

Neighbors	Time-bins
Tr1	*t1, t2, t3*
Tr2	*t1, t2, t3*
Tr4	*t2*

|Time-bins| > thr ?

Tr3. Tlist

t1, t2, t3

Tr4. NT

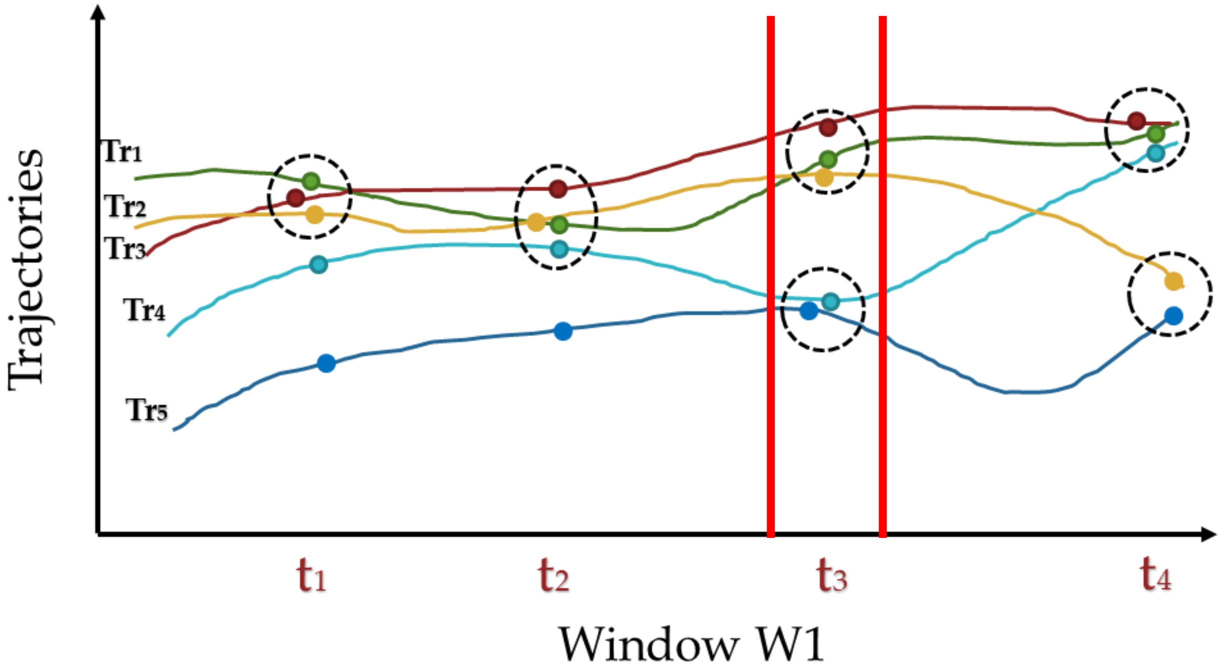
Neighbors	Time-bins
Tr1	*t2*
Tr2	*t2*
Tr3	*t2*
Tr5	*t3*

Tr4. Tlist

t2

Time-bin t3

Time-bin t3



ODMTS Example

Tr3. NT

Neighbors	Time-bins
Tr1	*t1, t2, t3, t4*
Tr2	*t1, t2, t3*
Tr4	*t2, t4*

|Time-bins| > thr ?

Tr3. Tlist

t1, t2, t3, t4

Tr4. NT

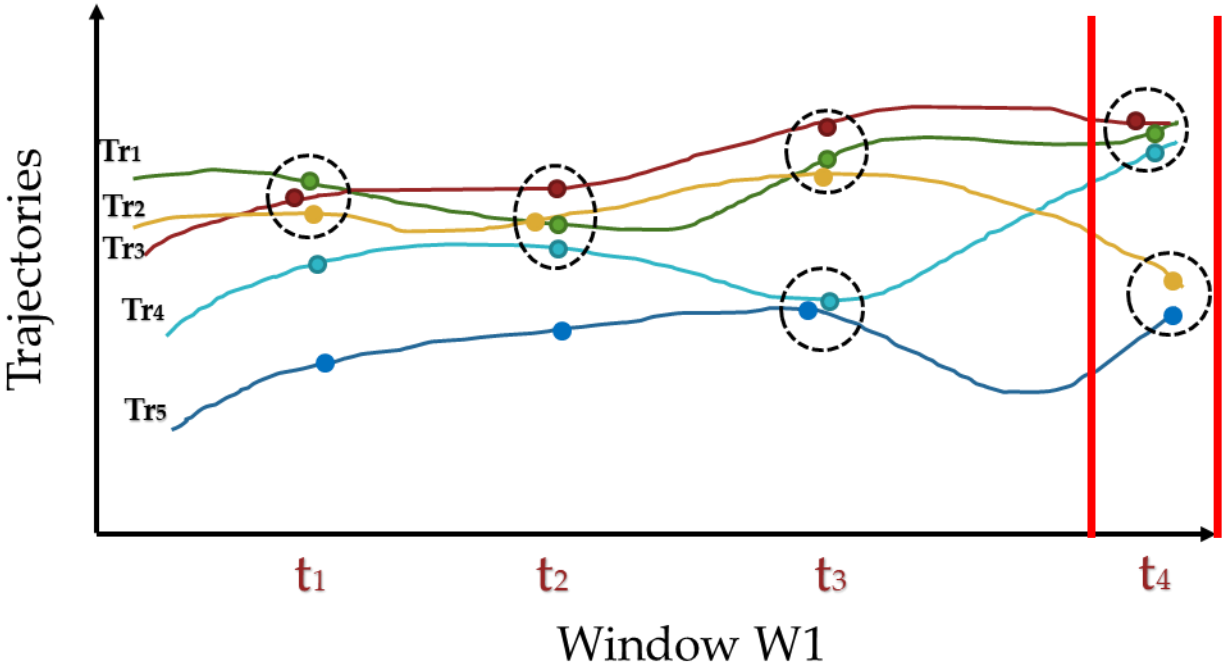
Neighbors	Time-bins
Tr1	*t2, t4*
Tr2	*t2*
Tr3	*t2, t4*
Tr5	*t3*

Tr4. Tlist

t2, t4

Time-bin t4

Time-bin t4



ODMTS Example

- Check each entry of Tr_i.NT:

  Are |time-bins| > = Thr_j ?

- If at least K entries fulfill the above condition, Trajectory is inlier.
- Else otherwise

- Hence, Tr_3 is an inlier and Tr_4 is an outlier

Outlier Test

Tr3. NT

Neighbors	Time-bins
Tr_1	*t1, t2, t3, t4*
Tr_2	*t1, t2, t3*
Tr_4	*t2, t4*

Tr4. NT

Neighbors	Time-bins
Tr_1	*t2, t4*
Tr_2	*t2*
Tr_3	*t2, t4*
Tr_5	*t3*

Tr3. Tlist

t1, t2, t3, t4

Tr4. Tlist

t2, t4

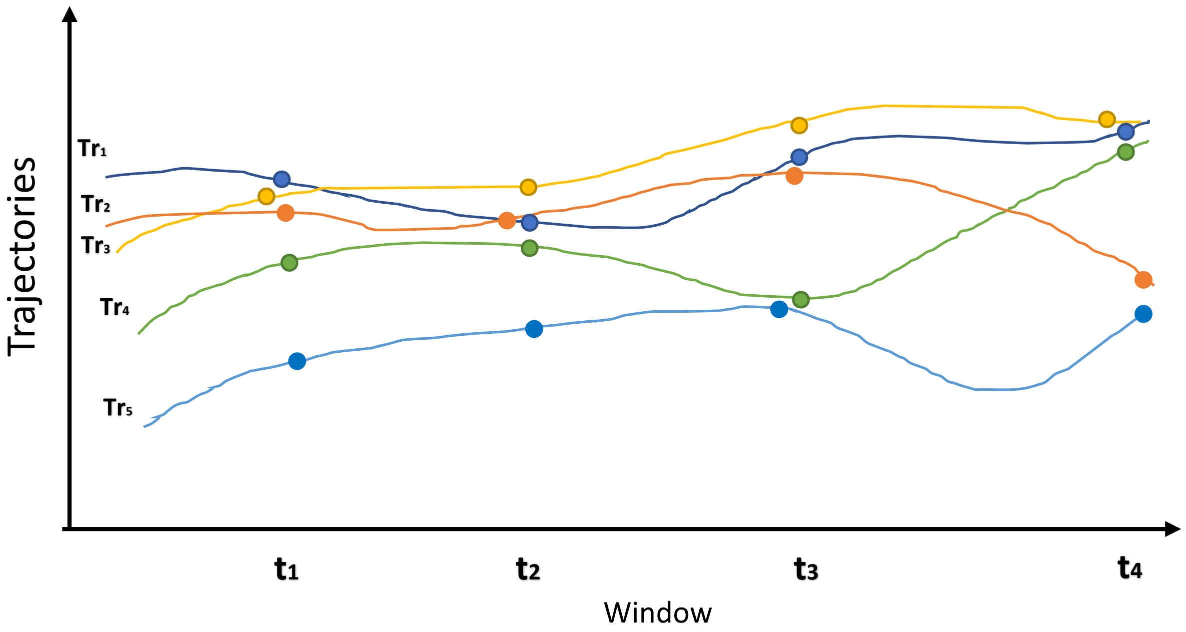
Time-bin t4

Pseudocode of ODMTS

Algorithm 1 Distance Based Outlier Detection (ODMTS)

Input Set of Trajectories, parameters: d, k, thr_i
Output Trajectory Outliers

for *each* TR_i **do**
  for *each* TR_k **do**
    if $dist(p_i^j, p_k^j) < d$ **then**
      $TR_i.NT.\text{insert}(TR_k)$
    end if
  end for
  if $TR_i.Count(t_{bin}) > thr$ **then**
    $TR_i.Tlist.\text{insert}(t_{bin})$
  end if
  if $TR_i.\text{size} < \text{k}$ **then**
    TR_i is an Outlier
  end if
end for



Experimental Setup

Hardware

- 40 cores
- 512 GB RAM

Performance Measures

- Total Execution Time

Software

- Python

Datasets

Dataset	No. of Trajectories	No. of Points (million)	No. of Attr.	Duration	Distance	Area
T-Drive	10357	15	2	7 days	9 million	Beijing
Geolife	17621	23.6	7	5 years	1.2 million	Beijing
Porto	1710671	-	9	1 year	-	Porto

Result of ODMTS

Outline

- Introduction
- Literature Review
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- Results
- Conclusion & Future Work

Approach 1: Use Spatial Data Structures for Speed

Goal & Motivation:

- Use k-d trees and r-trees to improve running performance of ODMTS
- Compare the performances for both the trees
- Good for multi-dimensional points as in our case (latitude, longitude geo-coordinates)
- Our initial experiments revealed search query to be the slowest
- Suitable for range query search in large datasets

Key Idea Behind Approach 1

- Evaluated using python’s cProfiler

Algorithm 1 Distance Based Outlier Detection (ODMTS)

Input Set of Trajectories, parameters: d, k, thr_i
Output Trajectory Outliers

for *each* TR_i **do**
  for *each* TR_k **do**
    if $dist(p_i^j, p_k^j) < d$ **then**
      $TR_i.NT.\text{insert}(TR_k)$
    end if
  end for
  if $TR_i.Count(t_{bin}) > thr$ **then**
    $TR_i.Tlist.\text{insert}(t_{bin})$
  end if
  if $TR_i.\text{size} < \text{k}$ **then**
    TR_i is an Outlier
  end if
end for

Pseudocode

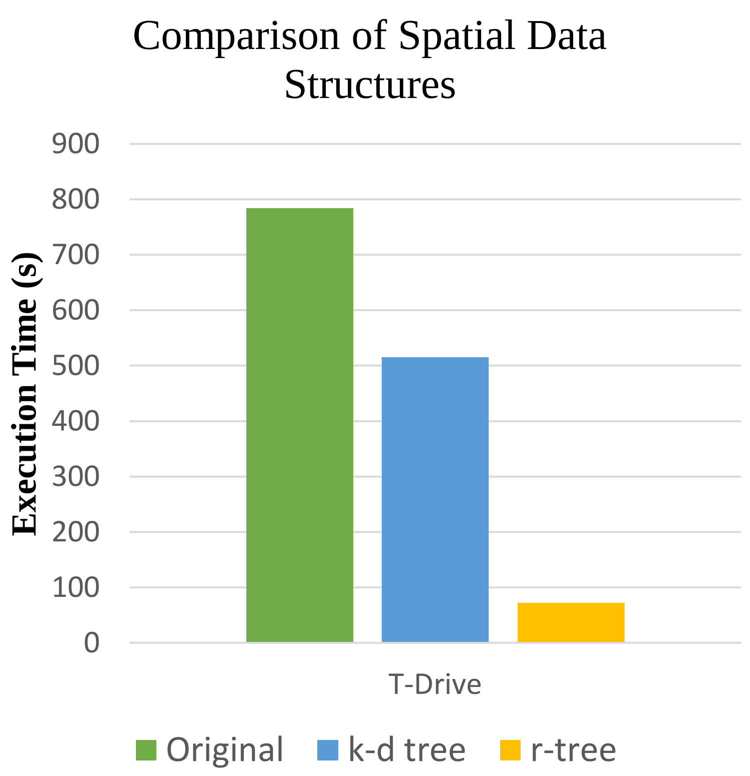
- No change in pseudocode except insertion and search query
- Insert all geo-coordinates in tree
- Use a range query to retrieve neighbors in a radius *r*

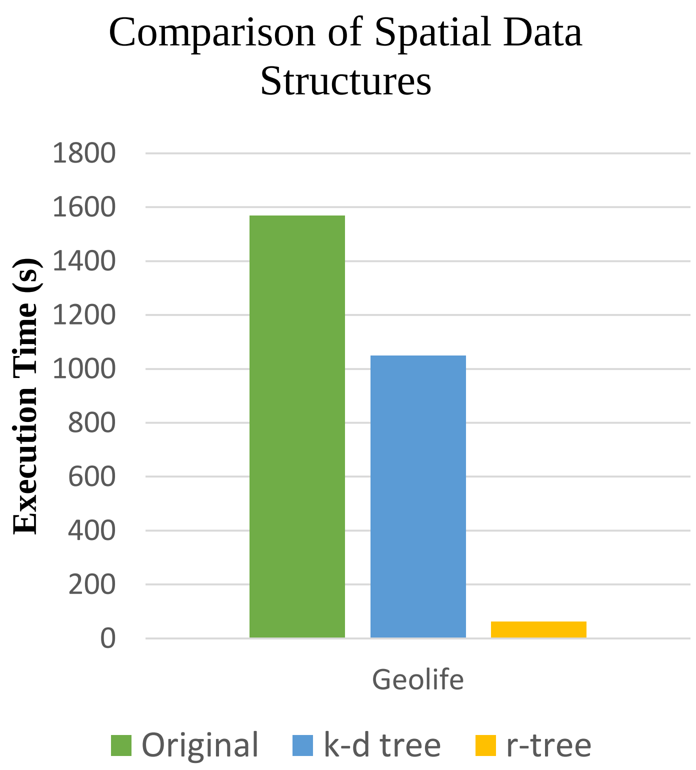
Algorithm 1 Distance Based Outlier Detection (ODMTS)

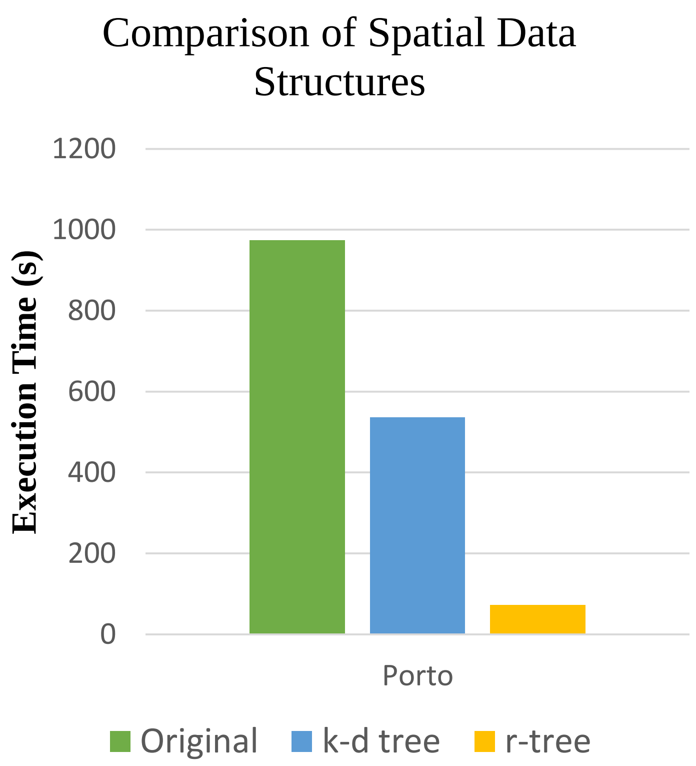
Input Set of Trajectories, parameters: d, k, thr_i
Output Trajectory Outliers

for *each* TR_i **do**
    for *each* TR_k **do**
        if $dist(p_i^j, p_k^j) < d$ **then**
            $TR_i.NT.\text{insert}(TR_k)$
        end if
    end for
    if $TR_i.Count(t_{bin}) > thr$ **then**
        $TR_i.Tlist.\text{insert}(t_{bin})$
    end if
    if $TR_i.\text{size} < \text{k}$ **then**
        TR_i is an Outlier
    end if
end for

Results of Approach 1







The experiments showed that using an R-tree improved the execution time performance of the ODMTS algorithm by 10x!!

Approach 2: Parallelization Strategy

Goal & Motivation:

- Propose parallelization strategy for ODMTS
- Study scalability in terms of execution time
- Study memory usage vs performance gain

- Our initial experiments revealed search query to be the slowest
- Harness the computing power of modern machines

Pseudocode

- Divide the workload among cores
- Single tree, passed to each core
- Each core performs search query on a subset of the dataset

Algorithm 2 Parallel - Distance Based Outlier Detection (ODMTS)

Input Set of Trajectories, parameters: d, k, thr_i
Output Trajectory Outliers

Insert all trajectory points in K-D/R Tree
Divide the Trajectory Dataset into Count(cores)
Insert divided Datasets in separate TR_iList
for each core **do**
    Run a Ball-Point Query Search on all Trajectories in TR_iList
    Insert query search result in $Neighbor_iList$
    for each in $Neighbor_iList$ **do**
        if $Count(Neighbor_iList[TR_i]) < k$ **then**
            TR_i is an Outlier
        end if
    end for
end for

Experimental Setup

Hardware

- Akka
- 40 cores
- 512 GB RAM

Performance Measures

- Total Execution Time

Software

- Python
- Multiprocessing

Datasets

Dataset	No. of Trajectories	No. of Points (million)	No. of Attr.	Duration	Distance	Area
T-Drive	10357	15	2	7 days	9 million	Beijing
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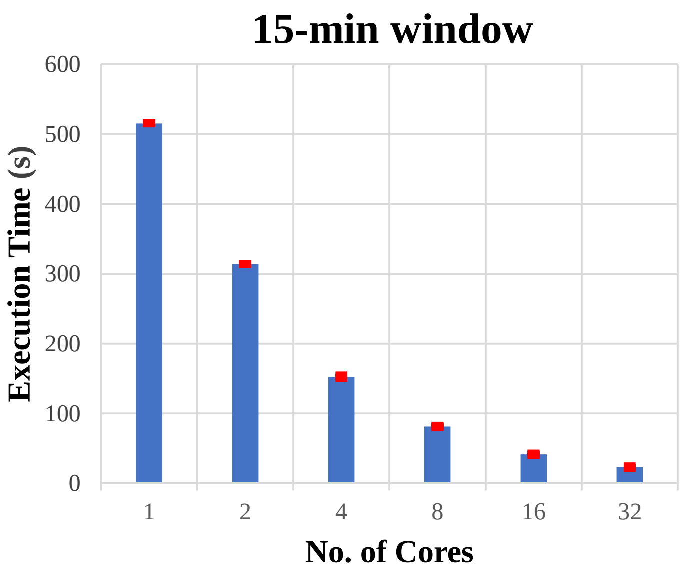
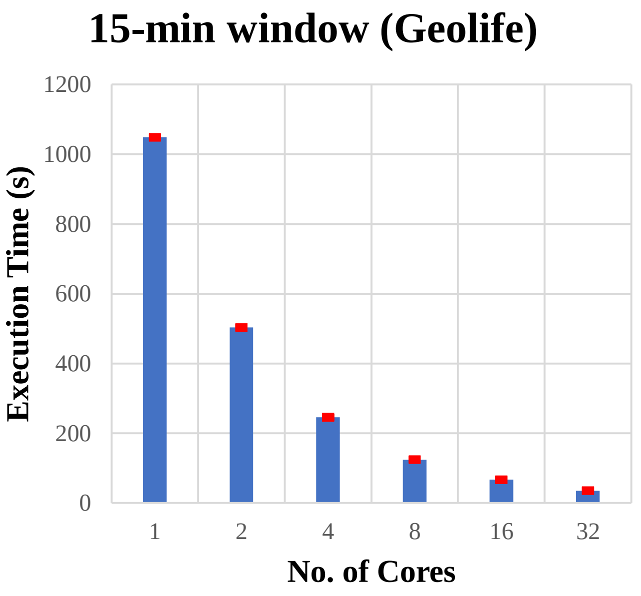
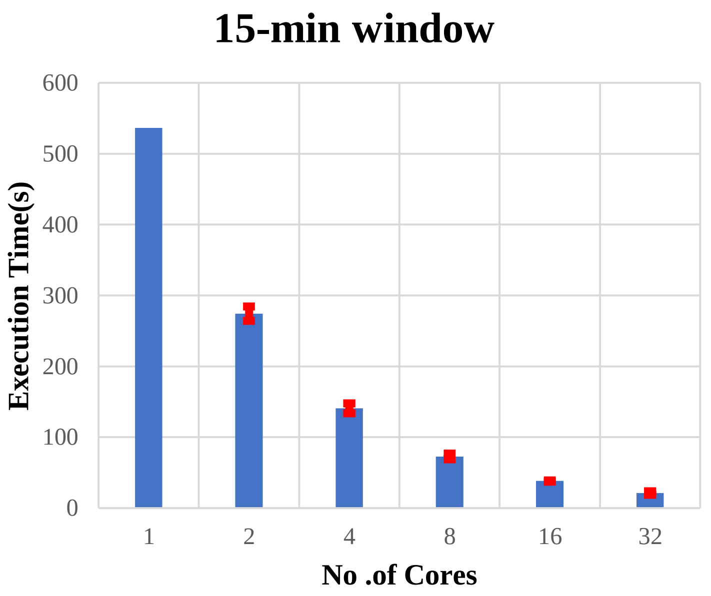
Results of Parallelization Strategy



T-Drive



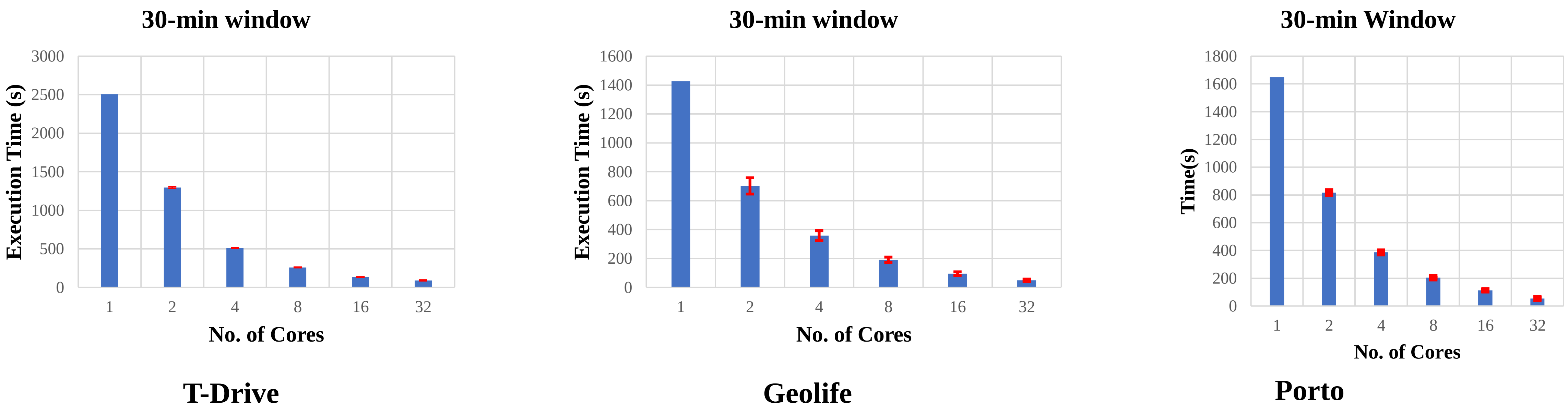
Geolife



Porto

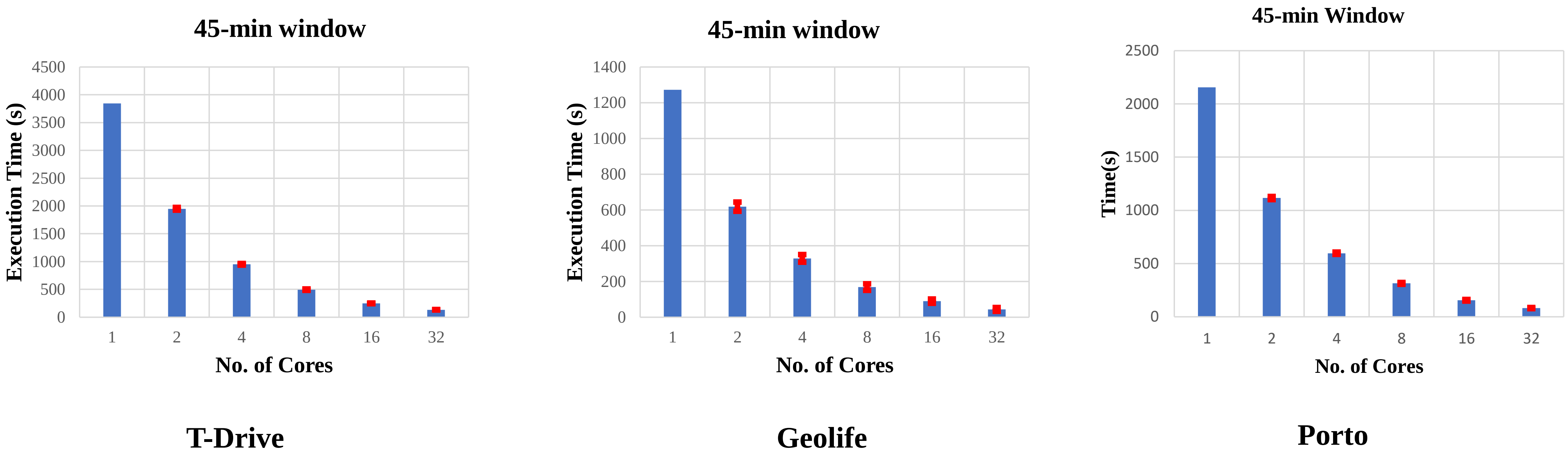
The experiments showed a linear decrease in execution time for k-d trees as the number of cores are increased!

Results of Parallelization Strategy



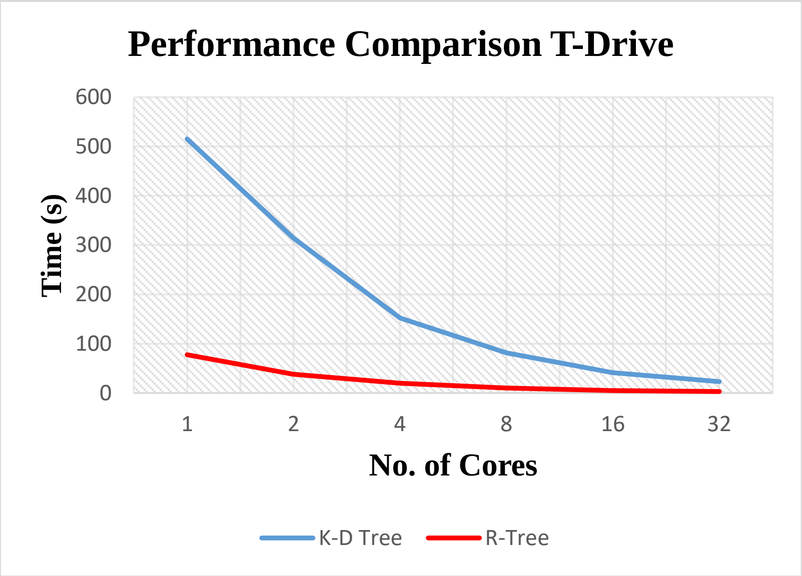
Workload is perfectly balanced among cores and the algorithm scales!!

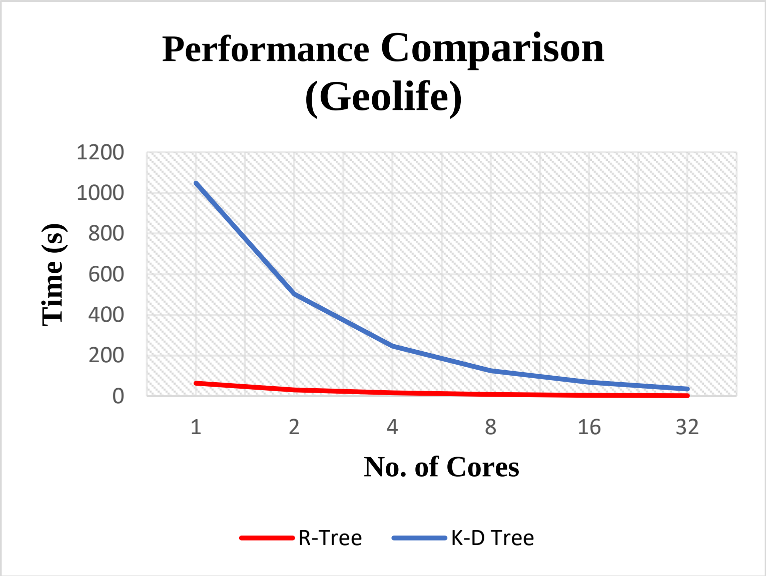
Results of Parallelization Strategy

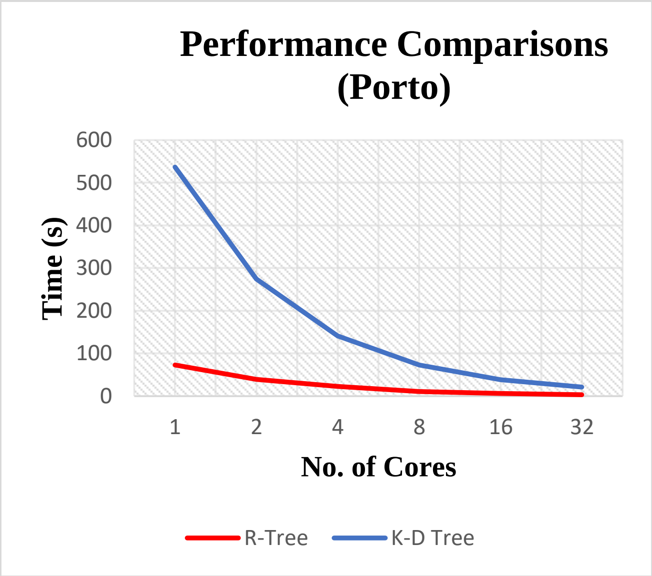


Scales linearly with the number of cores. In our case 32X decrease!

Results of Parallelization Strategy

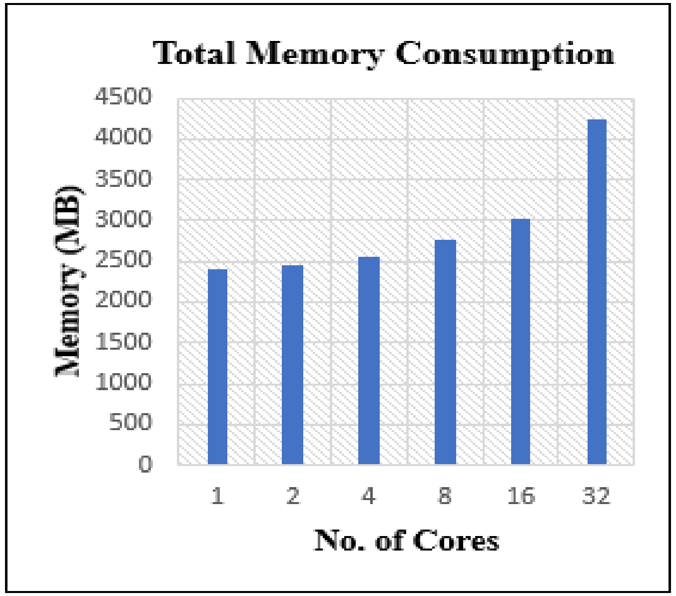




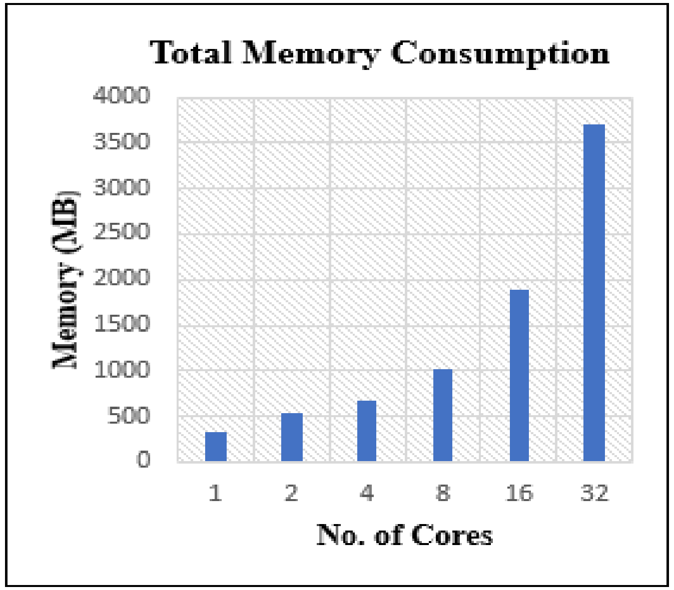


However, R-trees do not scale linearly in terms of execution times as the number of cores are increased, unlike k-d trees!!

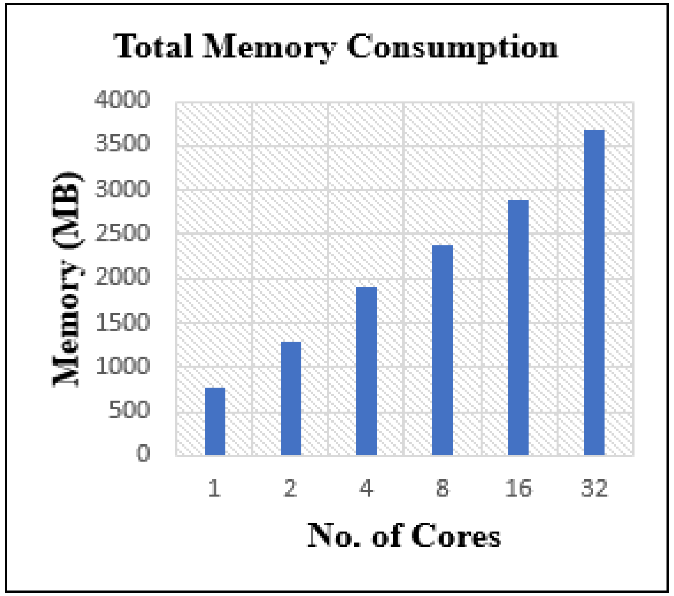
Results of Parallelization Strategy



T-Drive



Geolife



Porto

Total Memory Consumption shows an almost linear increase as number of cores are increased. This is because each core keeps a separate copy of the tree whilst having the same number of trajectory points!!

Approach 3: PDMTS

Goal & Motivation:

- Propose partition based streaming algorithm PDMTS
- Aim to detect trajectories that are significantly different but for a small period of the overall time of the trajectory
- Introduce windowing and temporal comparisons against other trajectories in the window

- Some outliers only hidden as sub-trajectories and not as a whole

Pseudocode

- Modifying TRAOD and Outlier Detection over Massive-Scale Trajectory Stream
- Detect outliers that are significantly different from the rest of the dataset but only for a small period of the trajectory
- Introduce windowing and temporal comparisons against other trajectories in the window
- First partition trajectory as in TRAOD then detect outliers using ODMTS
- Evaluate using Precision, Recall and F-Score

Algorithm 3 Streaming TRAOD (S-TRAOD)

Input Set of Trajectories, parameters: d, k, thr_i
Output Trajectory Outliers

—* Partioning Phase *—
for each TR_i **do**
    Partition TR_i at coarse granularity using MDL (L_i)
end for
—* Detection Phase *—
for each partition L_i **do**
    for each partition L_j **do**
        if $dist(p_i^j, p_k^j) < d$ **then**
            $TR_i.NT.\text{insert}(TR_k)$
        end if
    end for
    if $TR_i.Count(t_{bin}) > thr$ **then**
        $TR_i.Tlist.\text{insert}(t_{bin})$
    end if
    if $TR_i.\text{size} <$ k **then**
        TR_i is an Outlier
    end if
end for

Experimental Setup

Hardware

- Akka
- 40 cores
- 512 GB RAM

Performance Measures

- Precision
- Recall
- F-Score

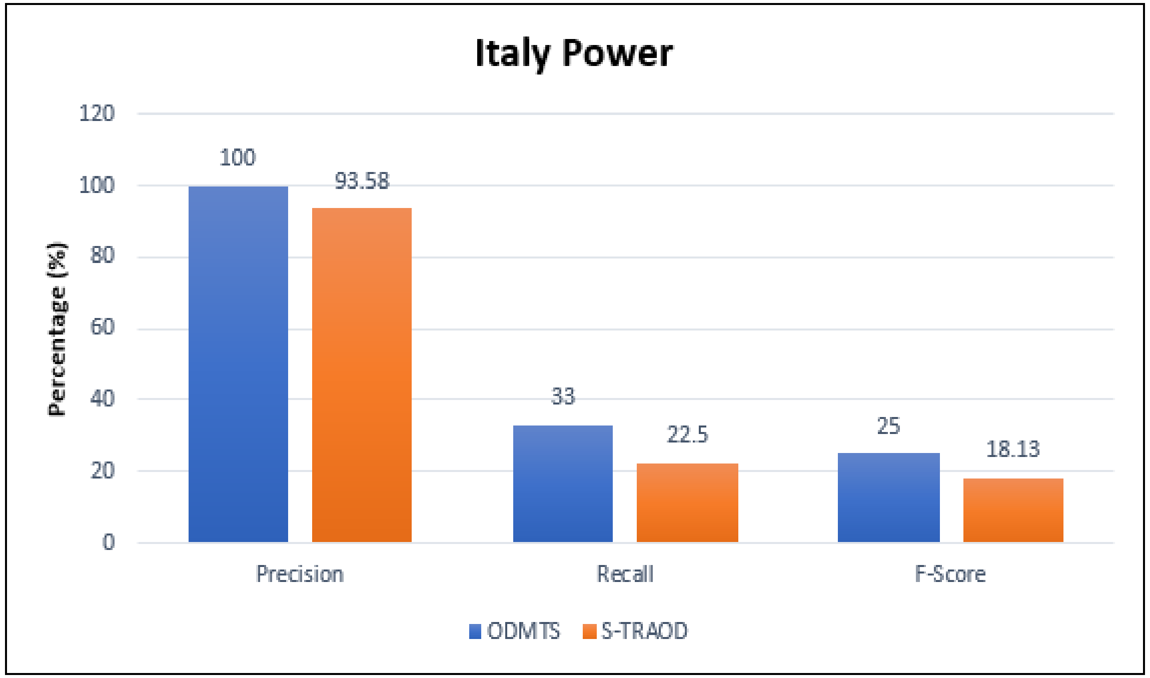
Software

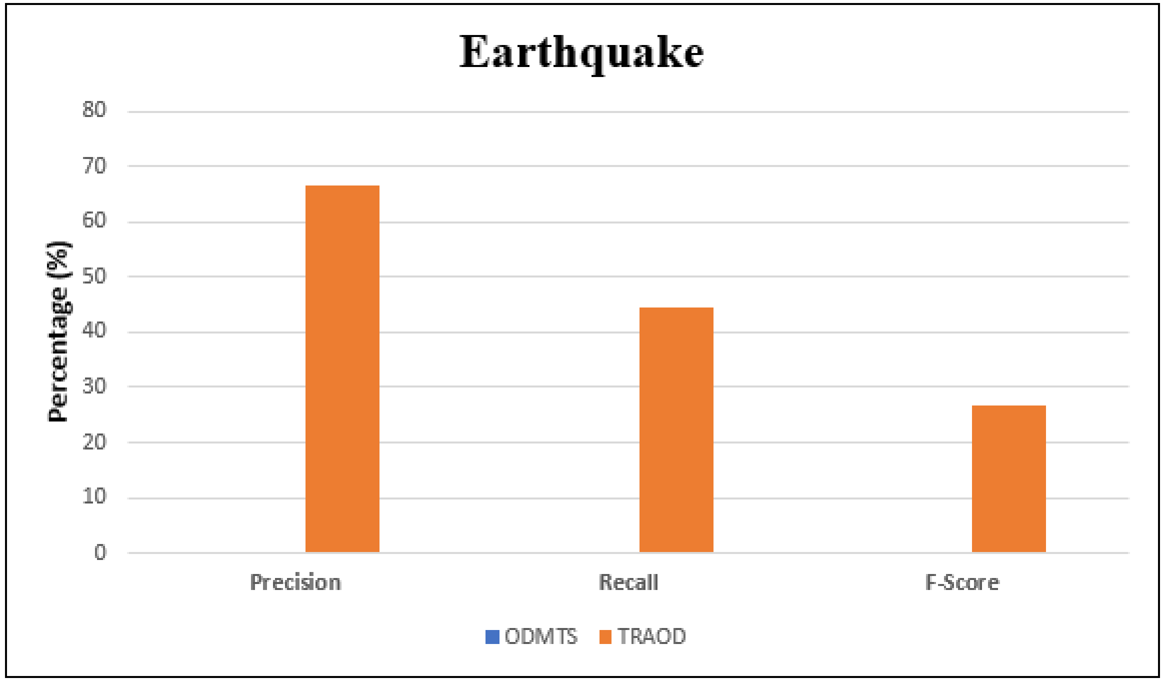
- Python

Datasets

Dataset	No. of Trajectories	No. of Points (million)	No. of Attr.	Duration	Area
Earthquake	322	512	1	36 years	California
Italy Power	67	24	1	1 year	Italy

Results of Approach 3





ODMTS fails to detect any outlier on Earthquake dataset!!
Performs similarly on Italy Power!!

Outline

- Introduction
- Literature Review
- Methodology
- Results
- Conclusion

Conclusions for Approach 1

- Slowest block of our pseudocode was the range query for the neighbor search.
- To address this, we used k-d trees and r-trees, which are spatial data structures, to improve range queries
- The experiments showed that using an R-tree improved the execution time performance of the ODMTS algorithm by 10x compared to without them

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QUESTIONS?