2019 Vehicle Technology International Conference

Traffic Aware Dynamic Routing

Ying Ying Liu, Ziyue Wang and Parimala Thulasiraman

Department of Computer Science

University of Manitoba

October 1, 2019

Outline

MOTIVATION

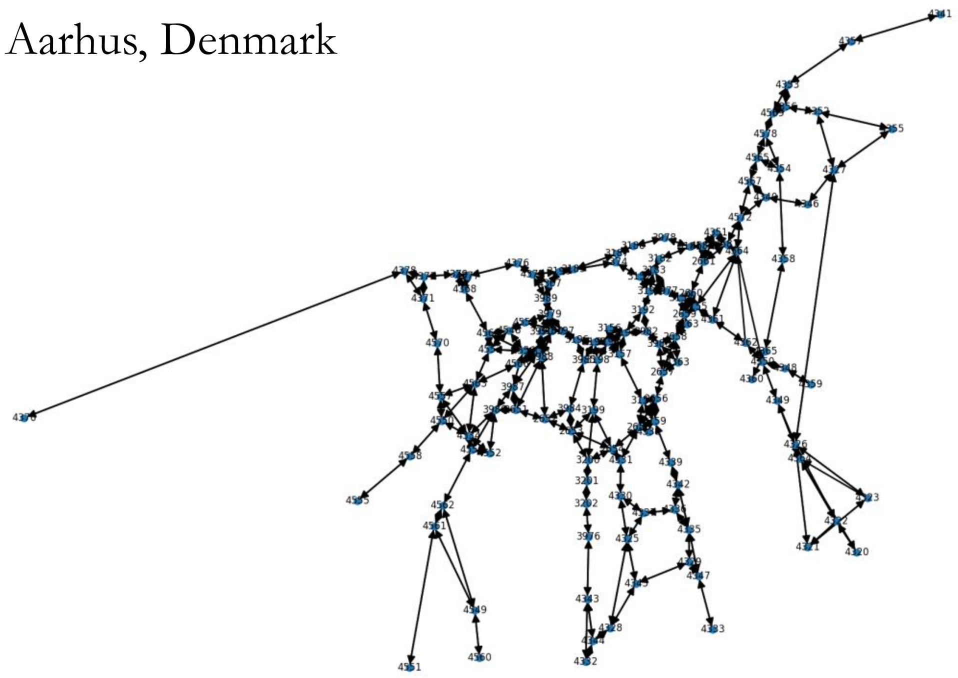
DYNAMIC TRAFFIC CLUSTERING AND PREDICTION

MANY-OBJECTIVE PATH FINDING

CONCLUSION

Motivation

Aarhus, Denmark



Traffic Aware Dynamic Path Finding from A to B:

- Shortest distance
- Fastest arrival
- Least emission
- Least turns (easy driving)

Questions:

1. How to be traffic aware?

2. Can we achieve all the objectives at the same time?

Part I

Understand Traffic Through Clustering

Motivation

Traffic is complex

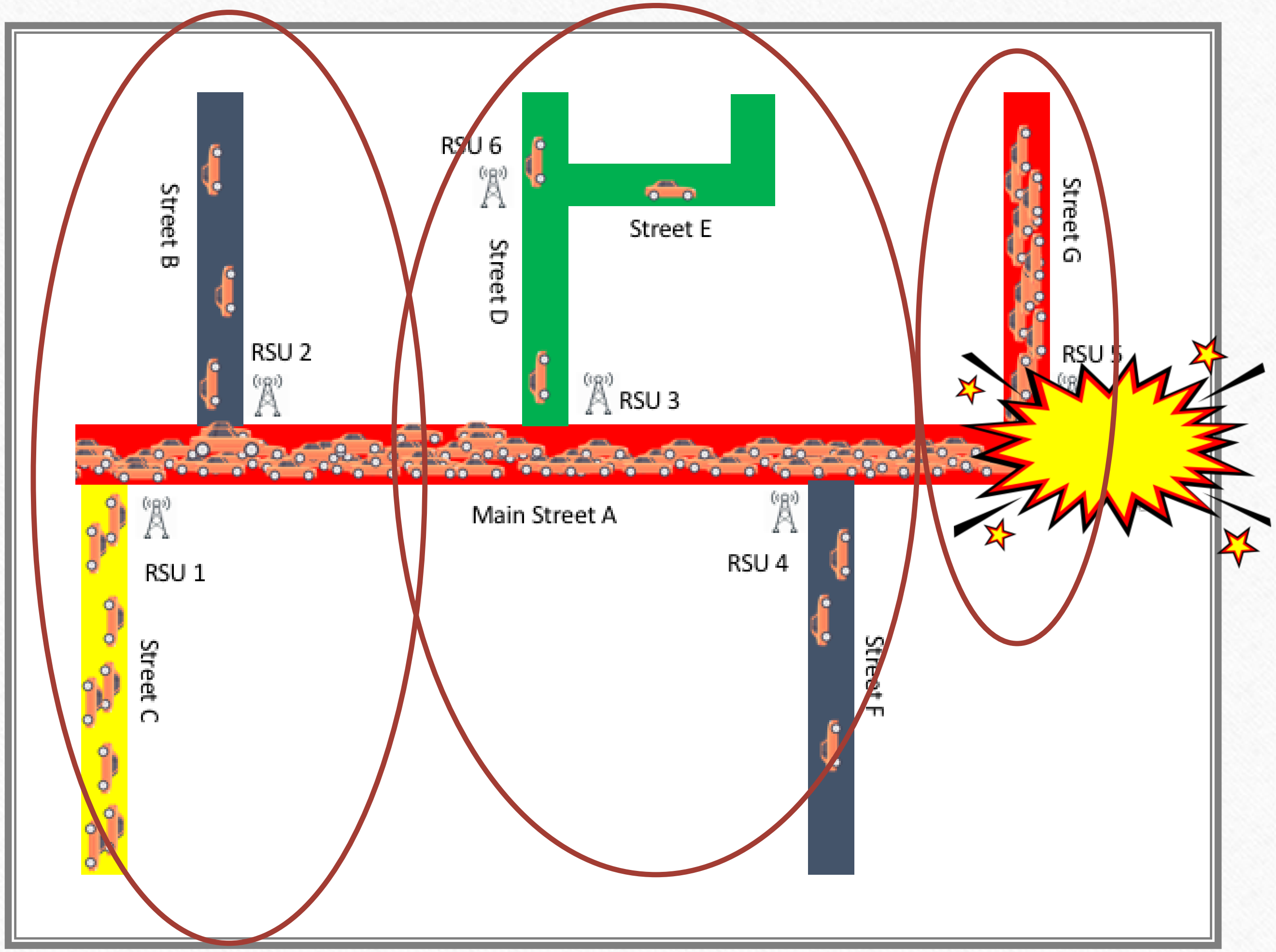
Complex network/peak-hours/accidents

Intelligent transportation system (ITS) studies in this domain

ITS aims to build a smart city

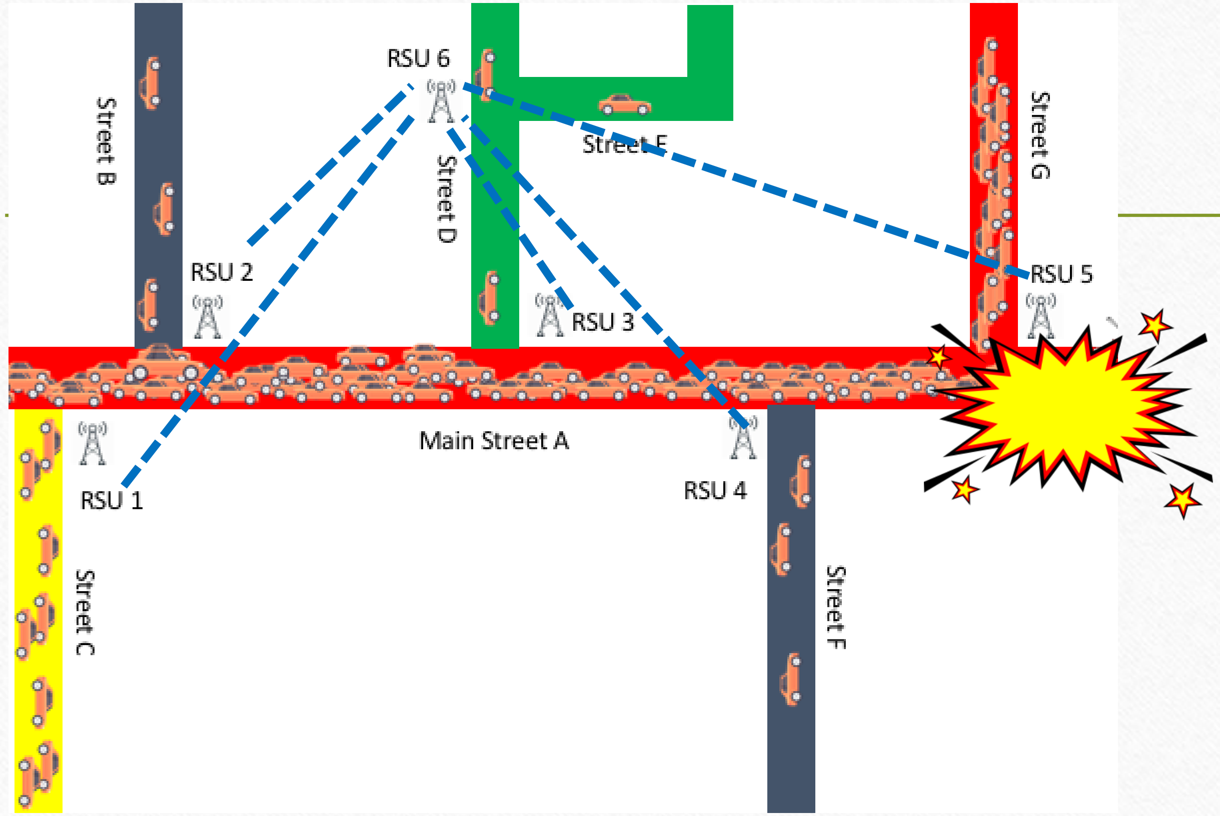
Smart City

Smart City uses many IoT technology to solve the problems related to city



The Domino Effect of Congestion

- Assume there is an accident somewhere towards the end of main street A.
- Is street G affected?
- How about street E and F?
- How about street B and C?



Observation

- Streets are spatially and temporally correlated
- The sensors record real-time traffic data and communicate with each other
- Clustering is used to study the relationship between the road points

Contributions

We propose a dynamic traffic clustering system – Spatial Locality

We improve the solution quality of prediction by using neural network with clustered traffic data – Temporal Locality

Affinity Propagation Clustering

- No central control
  - Run on each RSU (road side unit)
  - Based on distributive message passing
- Dynamic
  - The algorithm can run without termination
- Main Computation:
  - Pair-wise similarity
  - Responsibility
  - Availability

Pari-wise Similarity for Clustering

In order to find the real-time traffic clusters, I need to define the similarity, that is, how an object is similar/dissimilar to another.

Traditional method of define dissimilarity between road points by using Euclidean distance, however, it is static.

Some existing work use real-time traffic speed to cluster the traffic network.

- It does not represent the traffic influence directly
- It is not as easy collect as traffic flow data
- It is not as accurate as traffic flow data

Thus I propose to use traffic flow data to represent the relationship between road points.

Pair-wise Traffic Flow Similarity

Assumption: if traffic flow from A to B is very high (a lot of vehicles from A to B), point A has high influence on road point B

1. Count the flow from A to B on shortest path

2. Normalize the similarity by the from A to B over total flow into B

$$Similarity\ (A, B) = \frac{Flow\ A\ to\ B}{Total\ flow\ into\ B}$$

Thus all similarity will be normalized from 0 to 1

3. In order to make the similarity work for most clustering algorithm, it must be symmetric

$$s\ (A, B) = \frac{Similarity(A, B) + \ Similarity(B, A)}{2}$$

Responsibility and Availability

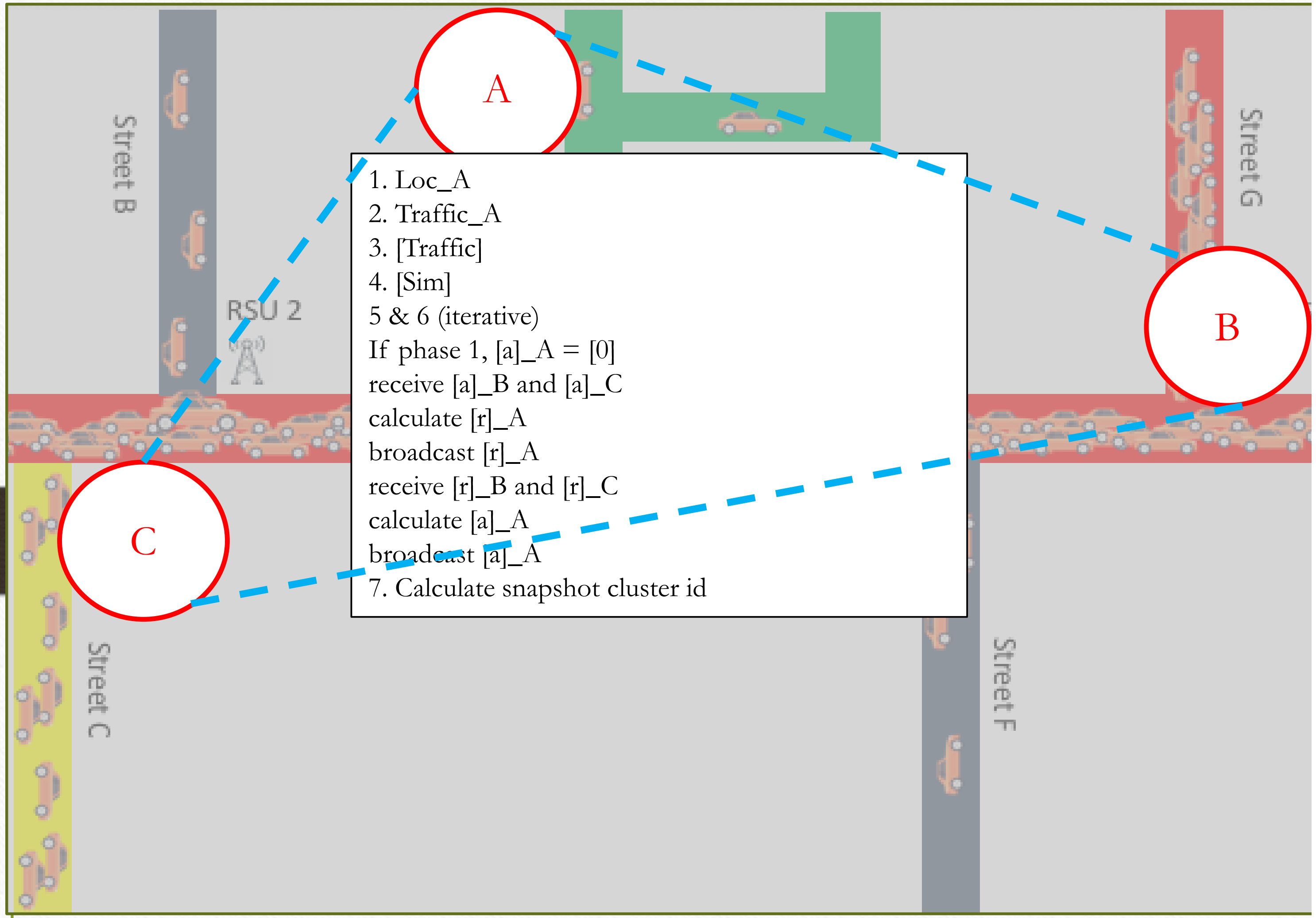
- Initially, every node consider itself as a cluster
- Every phase, compute two local variables: responsibility (*r*), and availability (*a*)
  - *r(i, k)*: how well k is the center of i
  - *a(i, k)*: how well *i* is a member of *k*
- Update and communicate *a* and *r* at each iteration

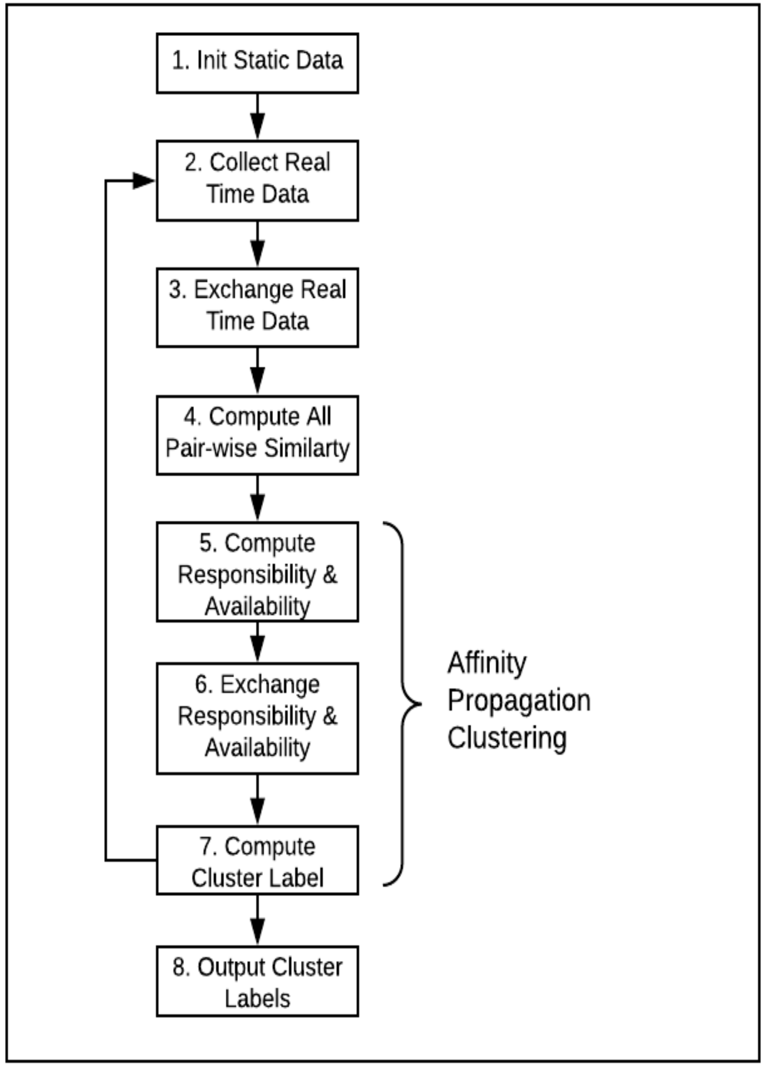
$$r(i,k) = s(i,k) - \max_{k' s.t. k' \neq k} \{a(i,k') + s(i,k')\}$$

$$a(i,k) = \min\{0, r(k,k) + \sum_{i' s.t. i' \notin \{i,k\}} \max\{0, r(i',k)\}\}$$

$$a(k,k) = \sum_{i' s.t. i' \neq k} \max\{0, r(i',k)\}$$

- Point *i* belongs to the center *k* that gives maximum *a(i, k)* + *r(i, k)*


A
B
C
Street B
RSU 2
Street G
Street C
Street F
1. Loc_A
2. Traffic_A
3. [Traffic]
4. [Sim]
5 & 6 (iterative)
If phase 1, [a]_A = [0]
receive [a]_B and [a]_C
calculate [r]_A
broadcast [r]_A
receive [r]_B and [r]_C
calculate [a]_A
broadcast [a]_A
7. Calculate snapshot cluster id


1. Init Static Data
2. Collect Real Time Data
3. Exchange Real Time Data
4. Compute All Pair-wise Similarty
5. Compute Responsibility & Availability
6. Exchange Responsibility & Availability
7. Compute Cluster Label
8. Output Cluster Labels
Affinity Propagation Clustering

Evaluation

We measure solution quality and number of clusters

We use data set from Citypulse: Aarhus, Denmark (Open Data Aarhus)

Muhammad Intizar Ali, Feng Gao and Alessandra Mileo, **"CityBench: A Configurable Benchmark to Evaluate RSP Engines Using Smart City Datasets"**, The Semantic Web - ISWC 2015 - 14th International Semantic Web Conference, October 11-15, 2015, Bethlehem, PA, USA

Evaluation Metrics

Silhouette Coefficient:

- How an item is similar to current cluster over other clusters
- The higher the better

Similarity Mean:

- The mean of the inter-cluster similarity
- The higher the better
- For some situation, intra-cluster similarity is not considered

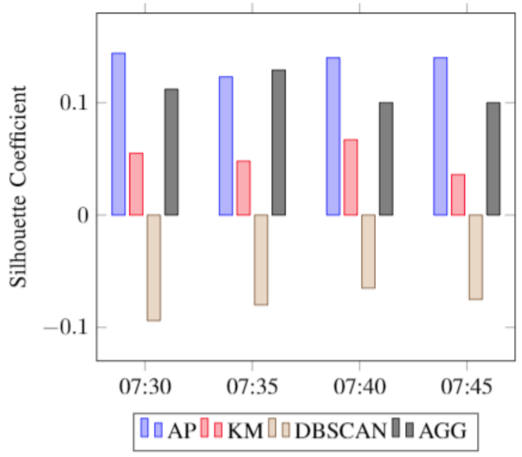


Fig. 2. Peak Hour Silhouette

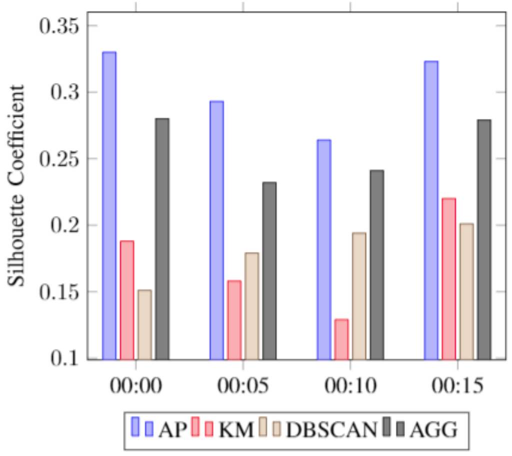


Fig. 4. Non-Peak Hour Silhouette

Silhouette Coefficient

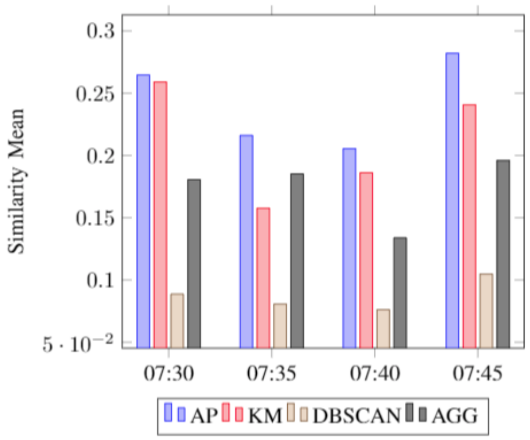


Fig. 3. Peak Hour Similarity Mean

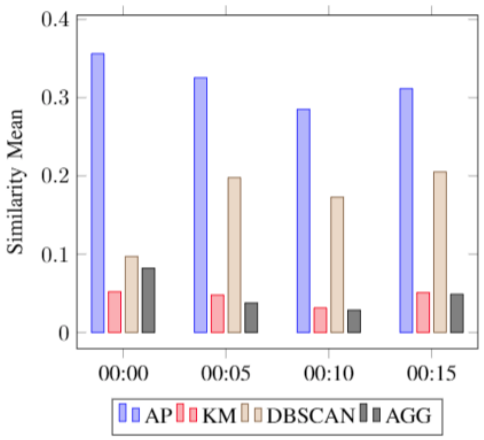
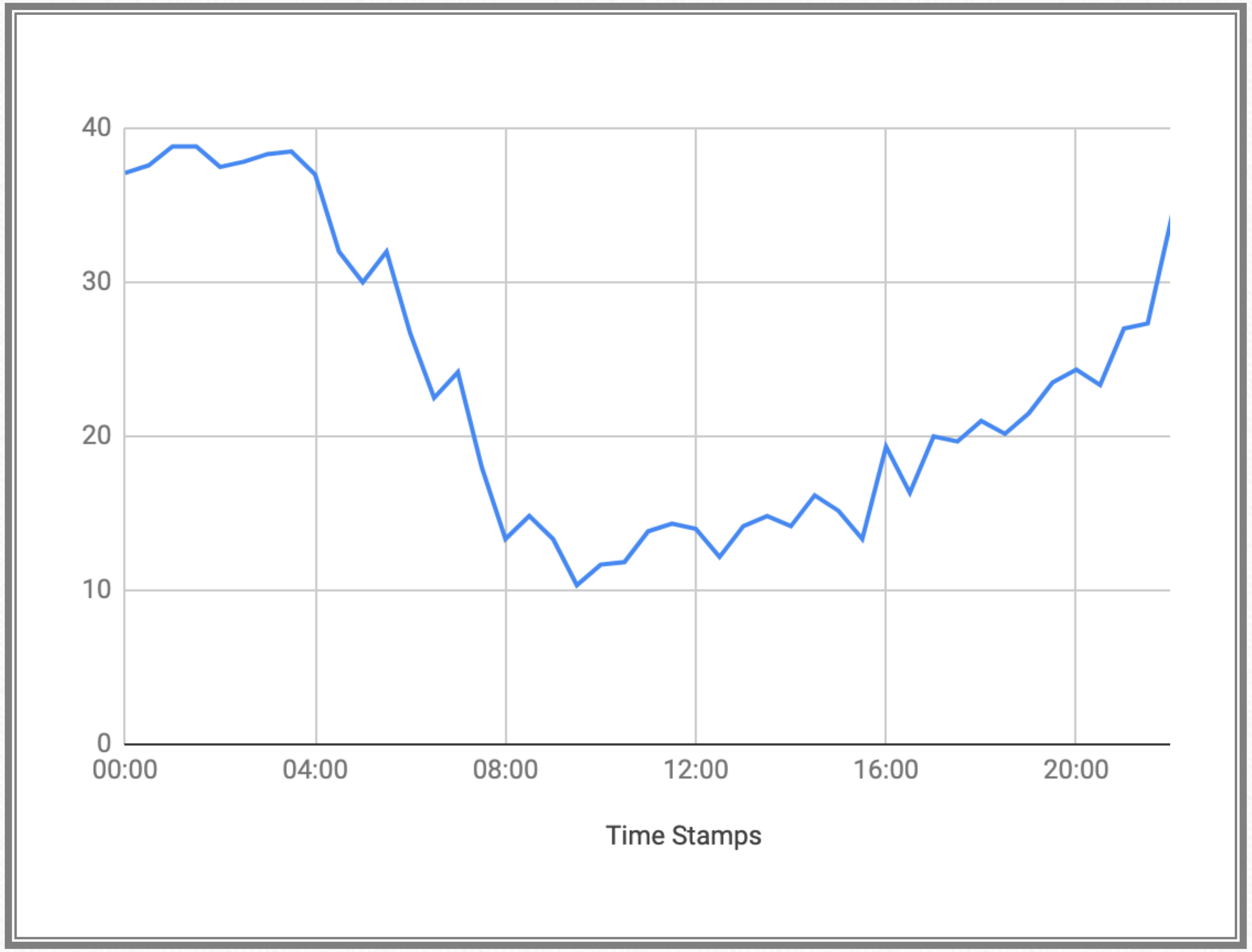


Fig. 5. Non-Peak Hour Similarity Mean

Similarity Mean



Number of Clusters

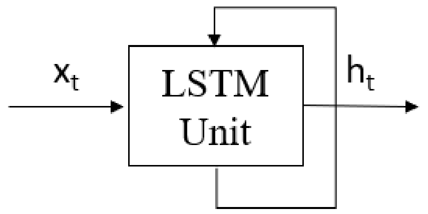
- A lot of clusters at midnight due to low traffic flow
- In peak hours, the number of clusters increases
- 9:00 A.M. is not peak hour but low number of clusters due to smooth and steady traffic flow

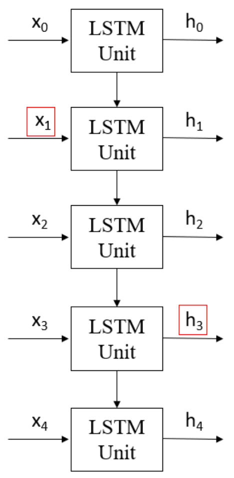
Contributions

We propose a dynamic traffic clustering system – Spatial Locality

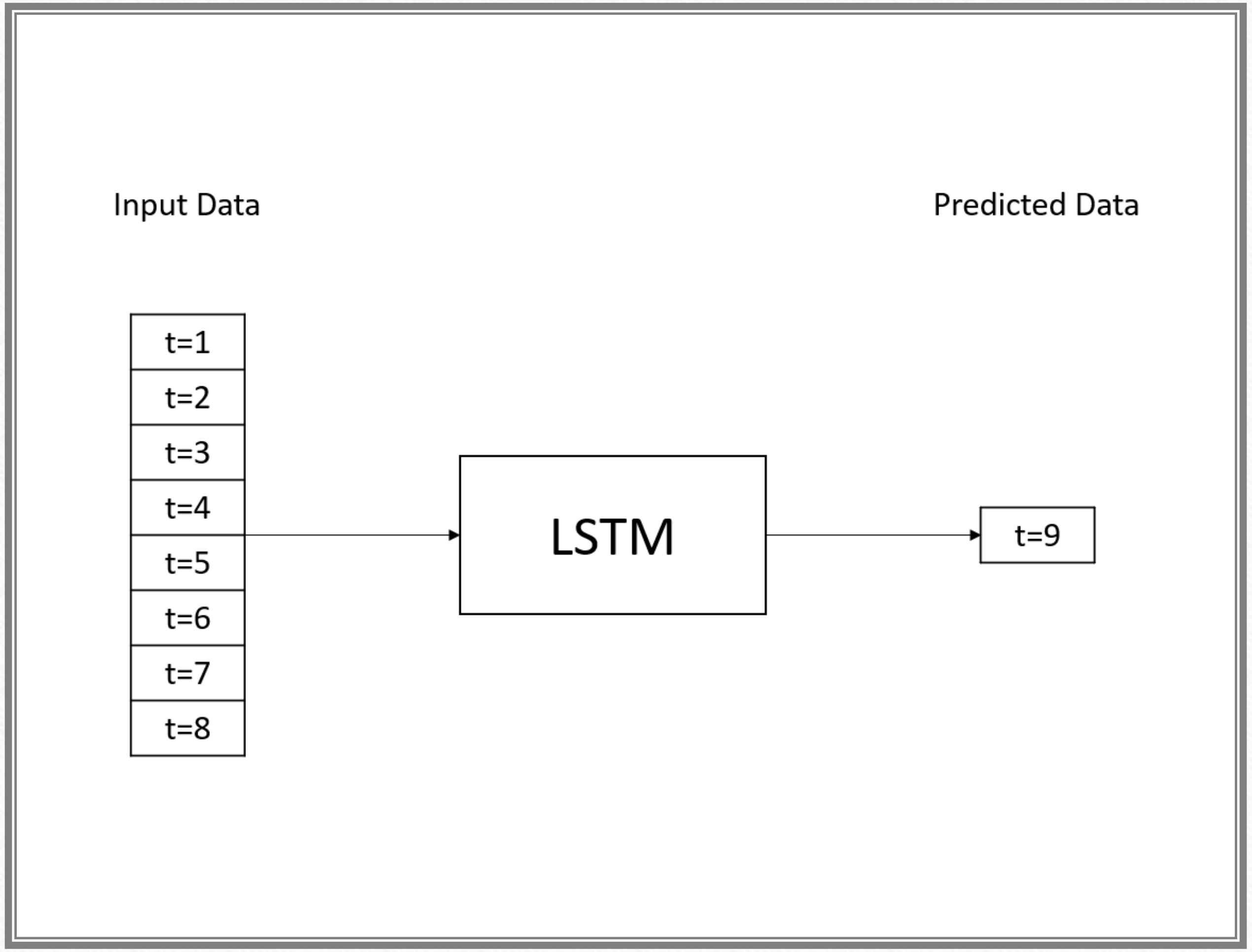
We improve the solution quality of prediction by using neural network with clustered traffic data – Temporal Locality

Long-short term memory



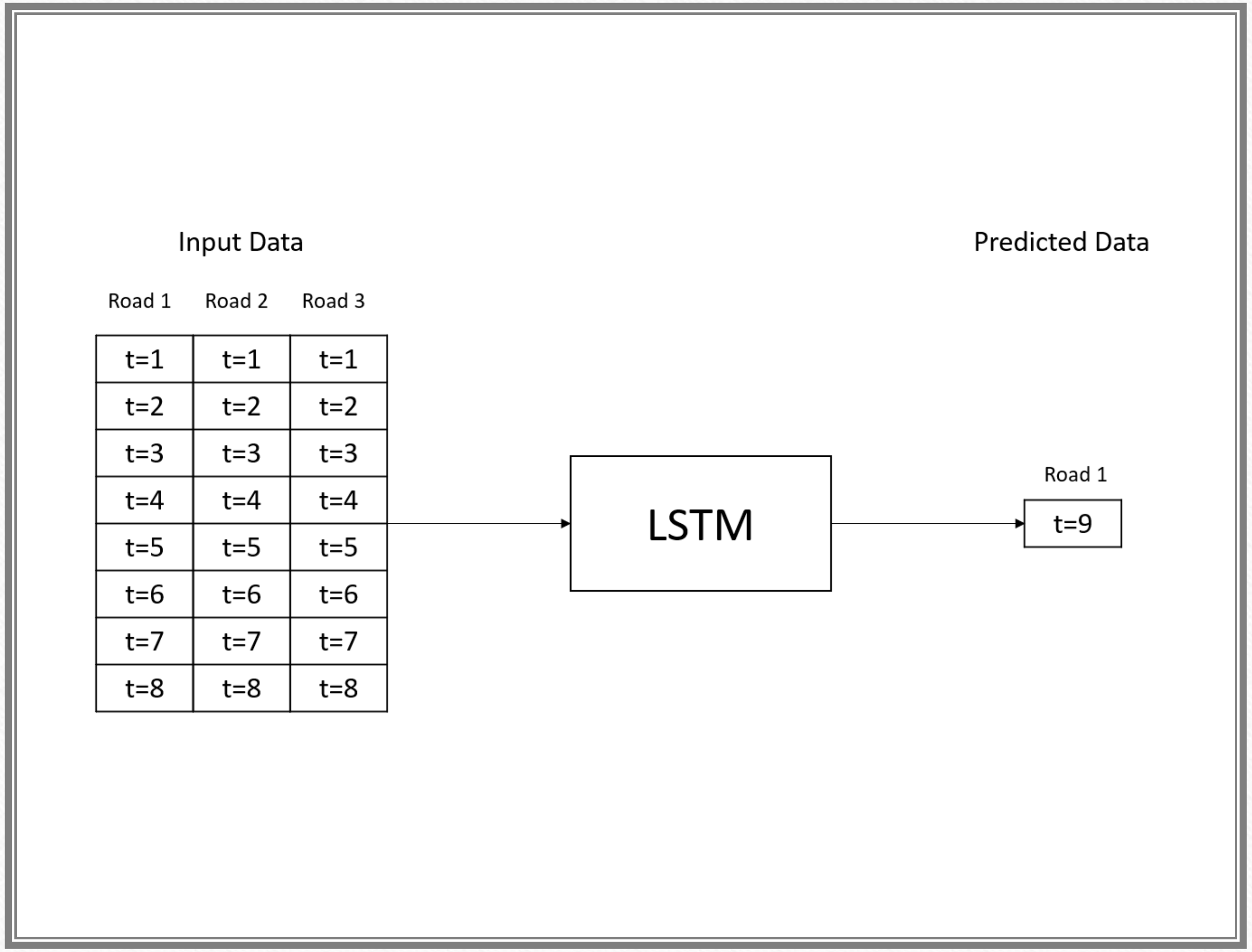


- Recurrent neural network is an extension of ANN
- LSTM is an implementation of RNN
- Hidden layer has feedback connections to itself
- Time-stamped input
- Previous data can be take into next iteration



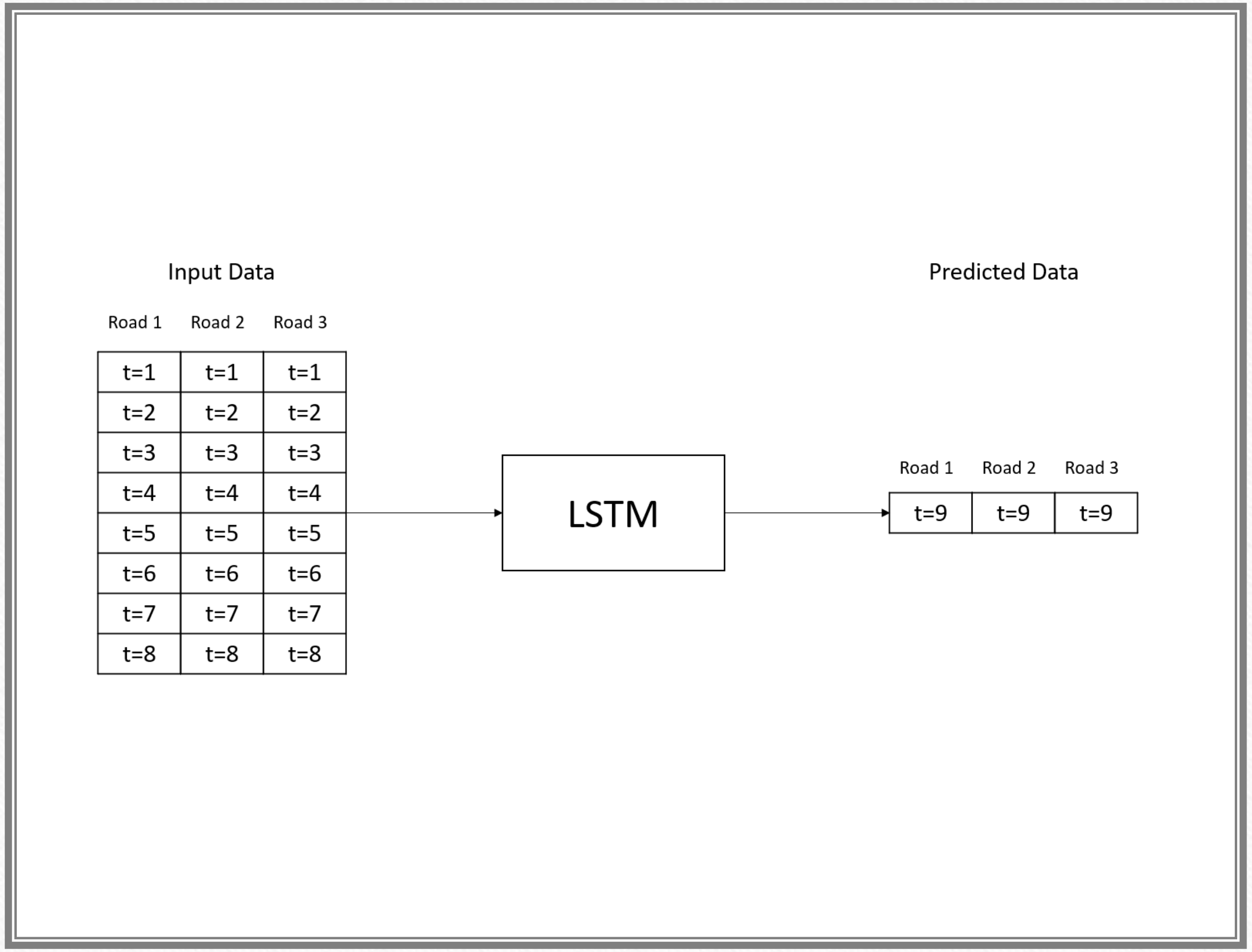
One to One Prediction

- Existing solution
- One time-series data is to predict one result
- Only just the road itself to predict itself



Many to One Prediction

- Use more than one roads to predict
- Use the roads in same cluster
- Potential computation overhead
- Potential higher prediction quality



Many to Many Prediction

- Use cluster data to predict entire cluster
- Potential computation overhead single prediction
- High throughput: more efficient in large predictions

Static Clustering

- In order to make the prediction work, we need static clusters
- That is, the clusters work well for any time-stamp (both peak and non-peak)
- Non-peak hours should have same weight with peak hours
- Proposed cluster merge algorithm

Algorithm 3: Cluster Merge

Data : Clustering Algorithm $A(x)$, Time stamp similarities

$$TS = \{ts_0, ts_1, \ldots ts_T\}$$

Result: Cluster labels: $C(i), i \in N$

```
s[N, N] = 0;   Init similarity
for t ∈ T do   For each time stamp
    C_t = A(ts_t);   Clustering the graph
    ∀i, j ∈ N : if C_t(i) == C_t(j) then   If two nodes are in same cluster
        s[N, N]+ = 1;   Increase their similarity by 1
    end
end
s[N, N] = (s[N,N] − min(s[N,N])) / max(s[N,N]);   Normalize the similarity
C = A(s);   Final clustering
Return C;
```

Experiment

- Data set from Citypulse: Aarhus, Denmark (Open Data Aarhus)
- Default Adam optimizer parameters from Keras
- Our LSTM design has 4 hidden layers:
  - Layer 1: LSTM layer of 64 units
  - Layer 2: LSTM layer of 64 units
  - Layer 3: Dropout layer of 64 units, dropout rate = 0.2
  - Layer 4: Dense layer of output size units, all apply sigmoid function.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - p_i)^2$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - p_i|$$

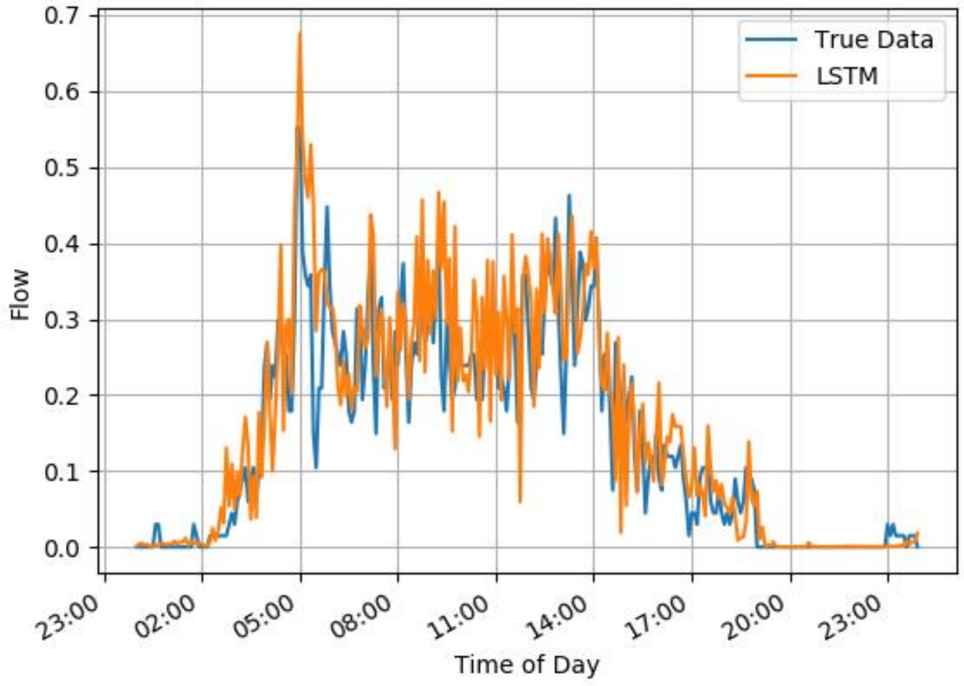
$$EV = 1 - \frac{Var(y-p)}{y}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - p_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Evaluation Metrics

- mean square error (MSE)
- mean absolute error (MAE)
- explained variance (EV)
- R^2 (R2)

Many to One Prediction



- 52 roads are in the cluster, 52 time-series data is used to predict one of them
- The prediction is very close to the real traffic flow value and the floating pattern
- One to one, many to one, many to many have no difference in performance

Evaluation

- MSE is reduced by 30%, MAE is reduced by 21%, the errors are clearly decreased
- EV and R2 has increased by about 7%
- 52 times higher throughput in many to many prediction

Models	MSE	MAE	EV	R2
One to One	0.006501	0.051743	0.779400	0.779377
Many to One	0.004556	0.042653	0.810834	0.810533
Many to Many	**0.004004**	**0.039840**	**0.836513**	**0.833502**

Benefits of Clustering

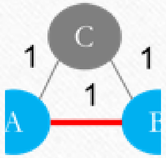
- Spatial locality is captured by real-time distributive Clustering
    - Results can be used to avoid paths in the same cluster of congestion sites for real-time path finding
- Temporal locality is captured by LSTM
    - Many to one prediction considers spatial locality and outperforms traditional one to one prediction
    - Many to many prediction has highest throughput (e.g. predict 52 roads at the same time)
    - Prediction can be used for path finding that avoids congestion sites

Part 2

Plan the Path

Motivation

Can we achieve all the objectives at the same time?



Shortest Distance

Least Emission

Least Turns

Fastest Arrival

Motivation

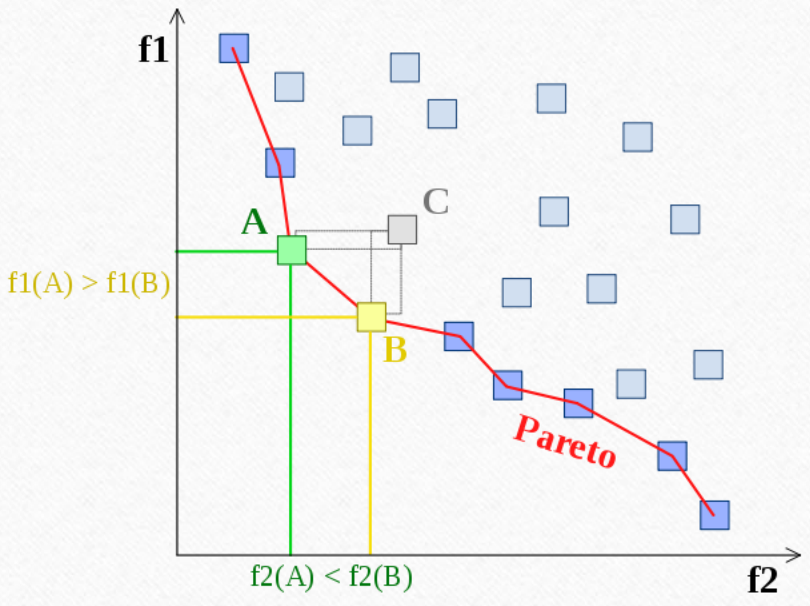


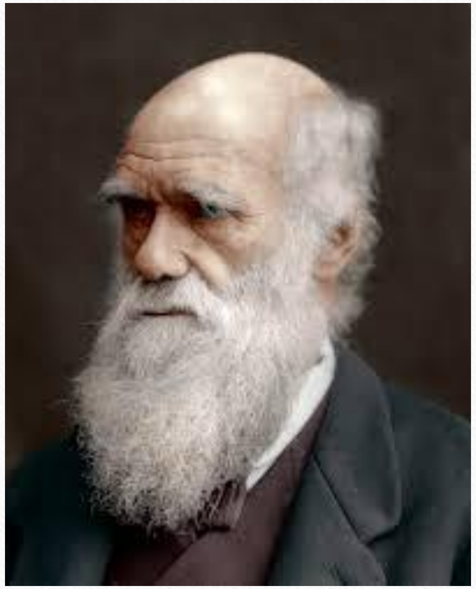
Image: Wikipedia

- In Many-Objective Optimization problems, if minimization functions contradict with each other, then it is not possible to minimize all functions at the same time
- Approach 1: minimize a composite function with user defined weights
- Approach 2: Find a set of solutions that are on the Pareto Front

Contributions

We solve the 4-objective traffic-aware dynamic path finding problem with genetic algorithm

Primer: Genetic Algorithm



Charles Darwin
1809 - 1882

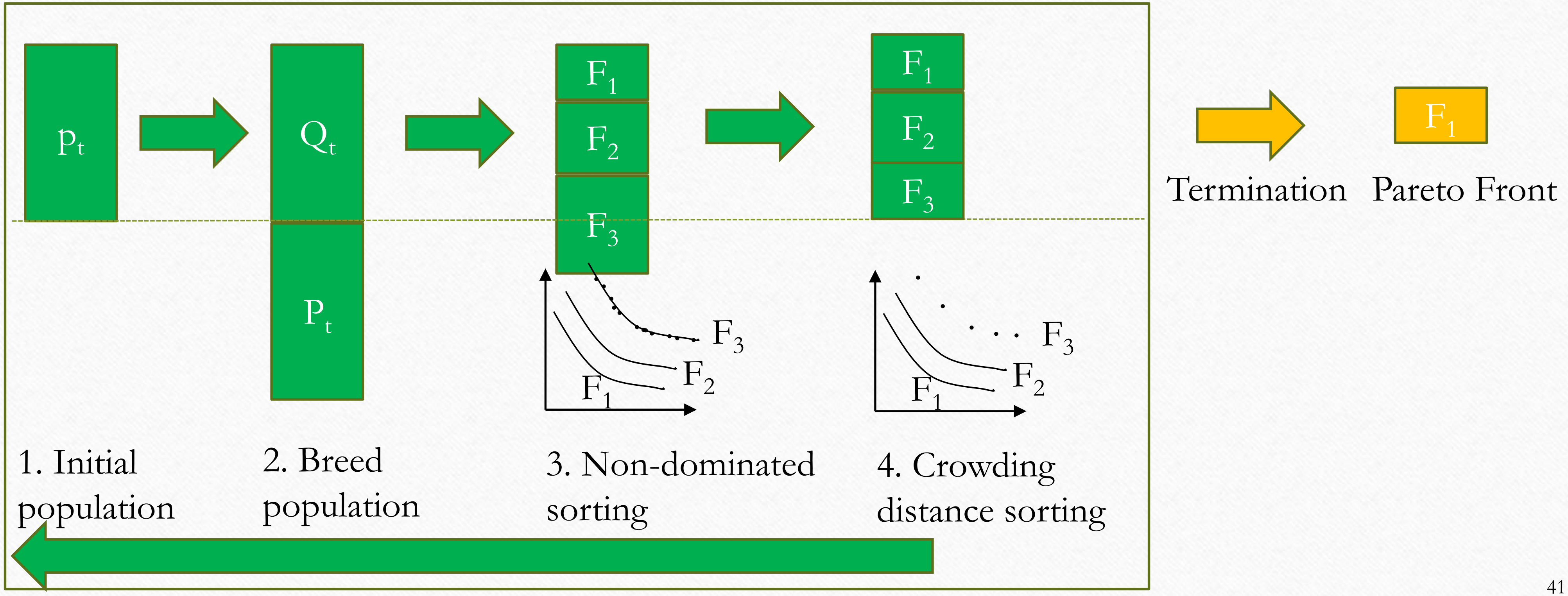
- Essentials of Darwinian evolution:
  - Organisms reproduce in proportion to their fitness in the environment
  - Offspring inherit traits from parents
  - Traits are inherited with some variation, via mutation and sexual recombination

Primer: Genetic Algorithm

- Essentials of Genetic Algorithm:
  - A population of candidate solutions evolves over time, with the fittest at each generation contributing the most offspring to the next generation
  - Offspring are produced via crossover between parents, along with random mutation
- Why GA?
  - Successful method of searching large space for good solutions
  - Massive parallelism
  - Adaptation to change

Nondominated Sorting Genetic Algorithm-II for Multi-Objective Optimization

[Deb et al. 2002]



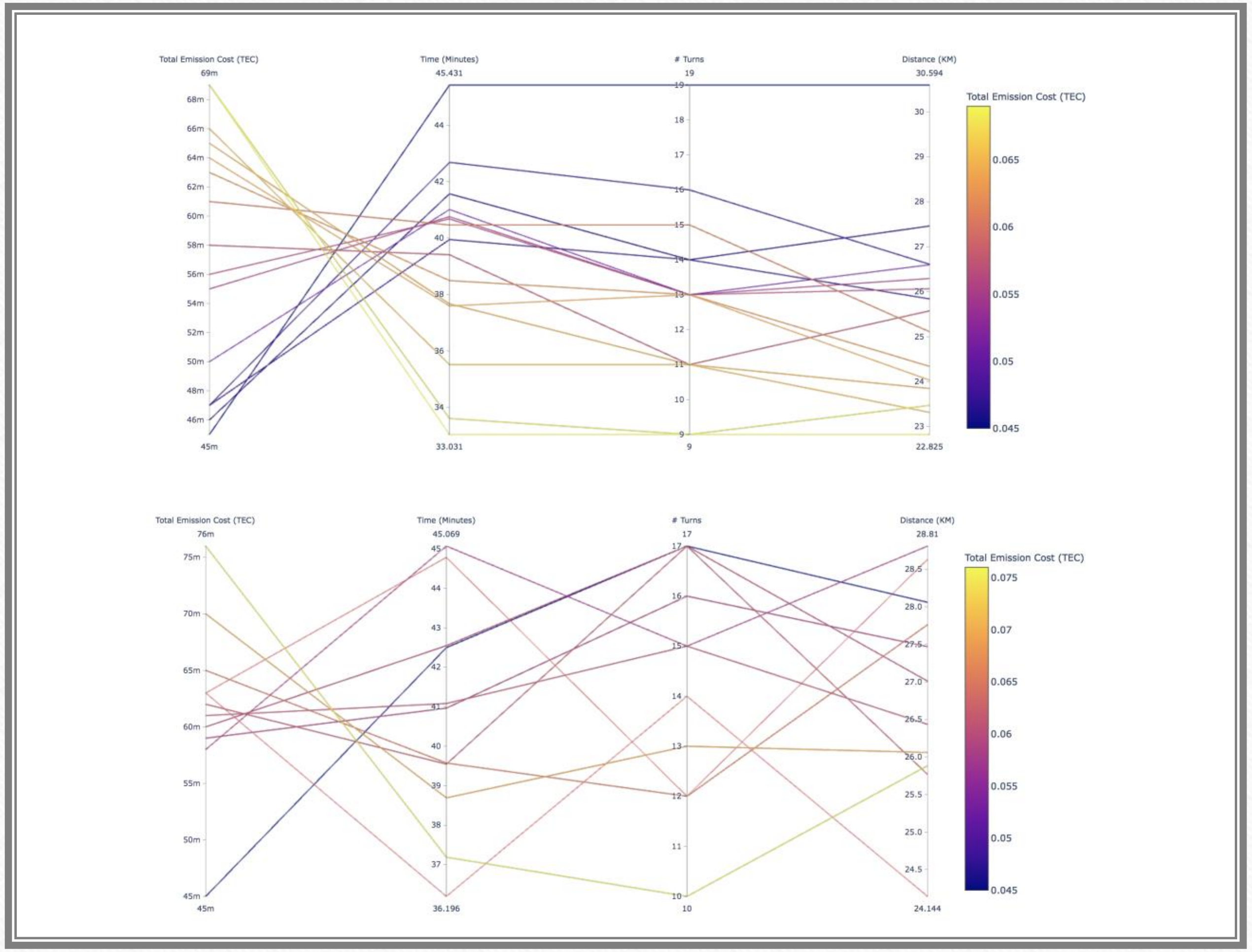
NSGA-II For Path Finding

Objectives	Unit	Traffic and Time Dependent	Formula
1. TEC (Total Vehicle Emission Cost)	$/hour	Yes	$TECPerHour = \sum_p \sum_e \phi^p \cdot \frac{A^p \cdot e^{B^p \cdot \tilde{S}_e(TimeIdx))}}{C^p \cdot \tilde{S}_e(TimeIdx)} \cdot l_e \cdot f_e$ $TimeIdx = \begin{cases} \lfloor \frac{TravelTime}{5} \rfloor & \text{if } v_i \neq S \\ 0 & \text{otherwise} \end{cases}$ $f1(TEC) = TECPerHour \cdot (\frac{TravelTime}{60})$
2. Time	Minute	Yes	$f2(Time) = \sum_e \frac{l_e}{\bar{S}_e(TimeIdx) \cdot 60}, \forall e$
3. Turns	#	No	$HasTurn_e = \begin{cases} 1 & \text{if } StreetName(v_i) \neq StreetName(v_j) \\ 0 & \text{otherwise} \end{cases}$ $f3(Turns) = \sum_e HasTurn_e, \forall e$
4. Distance	km	No	$f4(Distance) = \sum_e l_e, \forall e$
Contraints	N/A	No	Valid and loop-free path

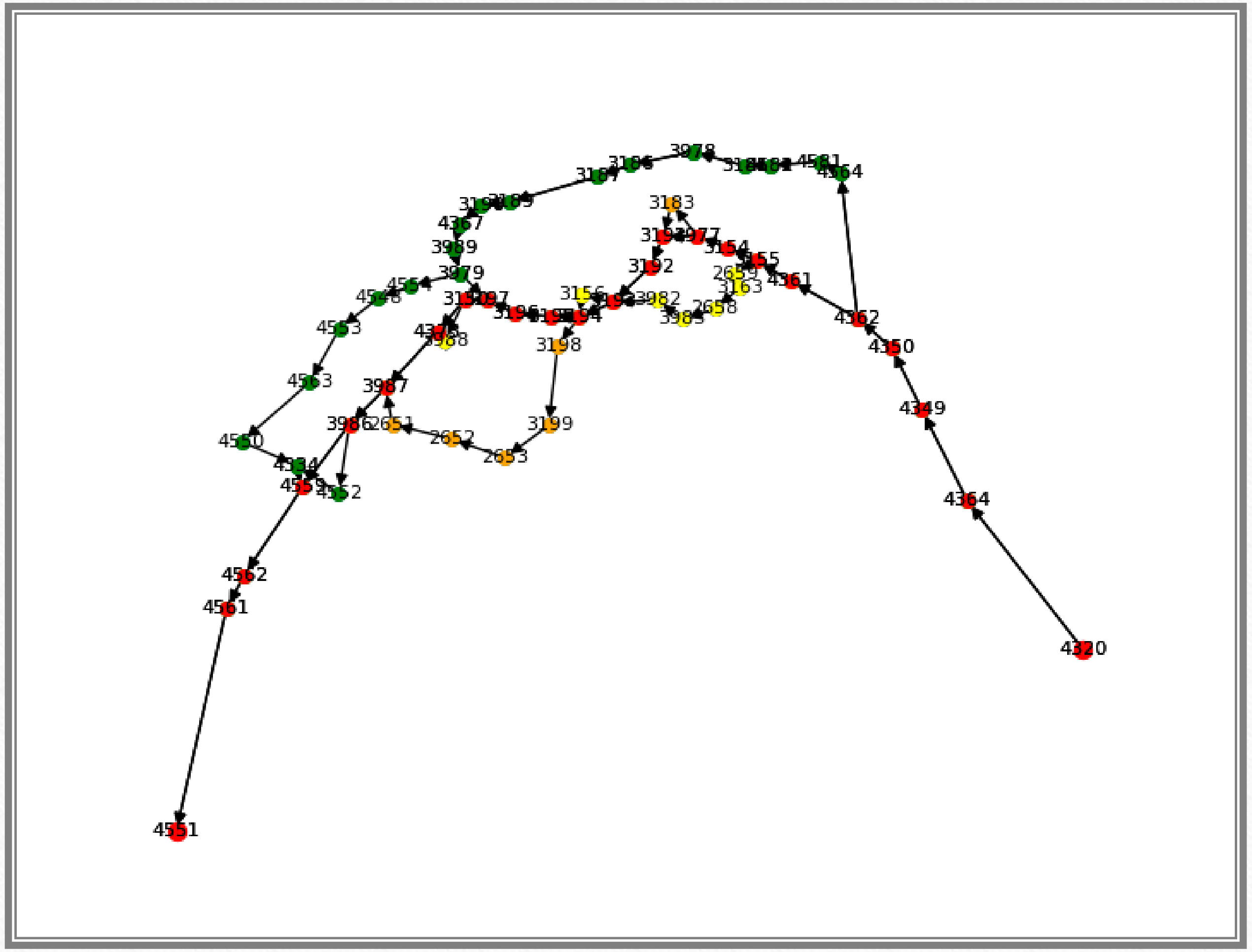
Experiment

- Data set from Citypulse: Aarhus, Denmark (Open Data Aarhus):
  - 136 nodes and 443 edges.
  - Population size: 100
  - Generations: 50
  - Parent selection: tournament selection of 2
  - Crossover sites: maximum 5
  - Mutation rate: 0.8
  - beginning timestamp 2014-02-13T11:30:00

Evaluation



- From city Hinnerup to city Hasselager
- Travel time, Number of turns, Distance are generally aligned with each other with fluctuations caused by traffic conditions
- TEC is more difficult to predict



Multiple Path Finding

- Red: shortest path
- Green: least TEC
- Orange: least time and distance

Benefits of Many-Objective Path Finding

- Practical and realistic
- Can be modified and expanded with different objectives
- Is traffic aware: optimization automatically by using traffic as objective function variable
- Is dynamic: optimization automatically by using time as objective function variable

Publications

1. Ziyue Wang, Parimala Thulasiraman and Ruppa K. Thulasiram, *A Dynamic Traffic Awareness System for Urban Driving* , The IEEE International Conference on Internet of Things, Atlanta, USA, July 14-July 17, 2019.
2. Ying Ying Liu, Fatemeh Enayatollahi and Parimala Thulasiraman, *Traffic Aware Many-Objective Dynamic Route Planning*, To Appear on 2019 IEEE Symposium Series on Computational Intelligence, Xiamen, China, December 6-9, 2019

Future Work

01

Improve many-objective path finding with many-many cluster-level traffic prediction

02

Improve similarity measurement

03

Implement affinity propagation on real IoT devices

04

Experiment on larger and many datasets with more comparisons

Questions?