Spatial-Temporal K Nearest Neighbors Model on MapReduce for Traffic Flow Prediction

A. Agafonov, A. Yumaganov

Samara National Research University

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Task definition

- Forecast the traffic flow in 10 minutes ahead
- Take into account spatial and temporal characteristics of the traffic flow
- Develop a distributed forecasting model
- Efficiently process large-scale traffic data

Task

- Real-time processing
- High accuracy

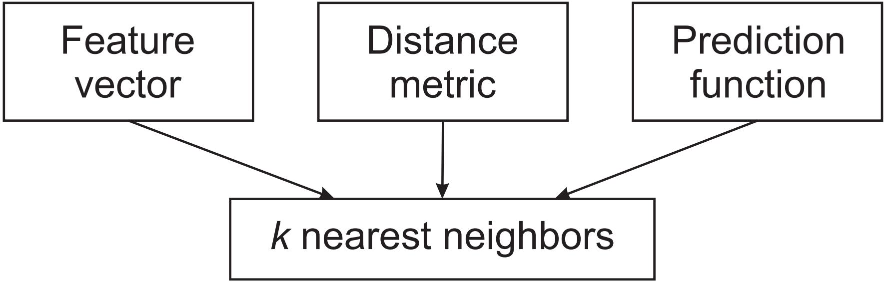
Problem formulation

- $G = (N, E)$ is a directed graph representing the road network;
- N is a node representing the road intersection;
- E is an edge denoting the road segment;
- V_t^j is an observed traffic flow characteristic on an edge $j \in E$ in a time moment t.

Given a graph $G(N, E)$ and traffic flow data $V_t^j, j \in E, t = 1, 2, \ldots T$, predict the traffic flow characteristic at a time interval $(t + \Delta)$ for a predefined prediction horizon Δ.

Proposed model

A short-term traffic flow forecasting model based on non-parametric regression *k* nearest neighbors algorithm is proposed.



Feature vector

Time-Domain Upstream / Downstream (TDUD) feature-vector:

$$(V^j_{t-T}, \ldots, V^j_{t-1}, V^j_t, V^{j-1}_{t-T}, \ldots, V^{j-1}_{t-1}, V^{j-1}_t V^{j+1}_{t-T}, \ldots, V^{j+1}_{t-1}, V^{j+1}_t)$$

Proposed feature vector:

- Partition the transportation network graph into several spatially compact clusters $\{G_i\}$ and define the cluster feature vector

$$\{V^j_t\}, j \in G_i, t = t_{cur} - T, \ldots, t_{cur}$$

- Reduce the dimensionality of the cluster feature vector using PCA procedure

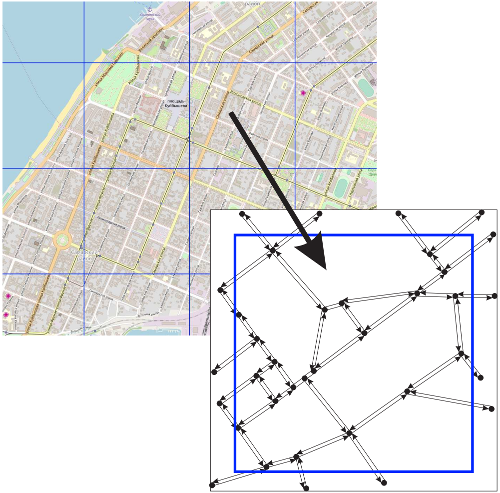
$$\{X_n\}^i, n = 1, \ldots, N$$

- Define the result feature vector for each road segment $j \in E$

$$S_j = (\{V^j_t\}, \{X_n\}^i), \quad i : j \in G_i, \quad t = t_{cur} - T, \ldots, t_{cur}, \quad n = 1, \ldots, N.$$

Graph partitioning

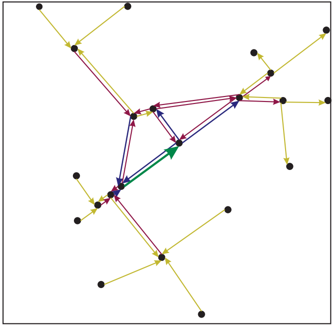
Partitioning by area G^{area}



Partitioning by distance G^{dist}

$$G_i^{dist} = \{j \in E : r(i,j) <= R\},$$

where $r(i,j)$ is the distance, $i \in E, j \in E$



Proximity measure

Weighted Euclidean distance with the trend adjustment:

$$d(S, \bar{S}^i) = d^{link}(V, \bar{V}^i) + \gamma d^{pca}(X, \bar{X}^i),$$

$$d^{link}(V, \bar{V}^i) = \alpha \sqrt{\sum_{t=1}^{T} \beta^{T-t+1} \left(V_t - \bar{V}_t^i\right)^2} + (1-\alpha) \sqrt{\sum_{t=2}^{T} \sum_{\delta=1}^{t-1} \left((V_t - V_\delta) - \left(\bar{V}_t^i - \bar{V}_\delta^i\right)\right)^2},$$

$$d^{pca}(X, \bar{X}^i) = \sqrt{\sum_{n=1}^{N} \left(X_n - \bar{X}_n^i\right)^2}.$$

Prediction function

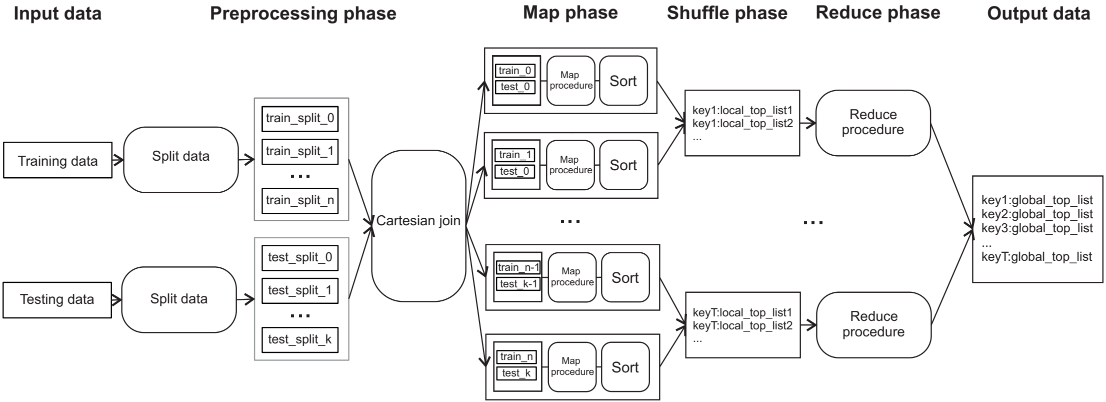
Prediction function by the weighted average:

$$\hat{V}_{T+1} = \sum_{k=1}^{K} \frac{d_k^{-1}}{\sum_{k=1}^{K} d_k^{-1}} V_{T+1}^{k}$$

Prediction function that combines the weighted average and the trend adjustment:

$$\hat{V}_{T+1} = \partial \sum_{k=1}^{K} \frac{d_k^{-1}}{\sum_{k=1}^{K} d_k^{-1}} V_{T+1}^{k} + (1 - \partial)\left(V_T + \frac{1}{KT} \sum_{k=1}^{K} \sum_{t=1}^{T} \left(V_{T+1}^{k} - V_t^{k}\right)\right)$$

MapReduce-based implementation



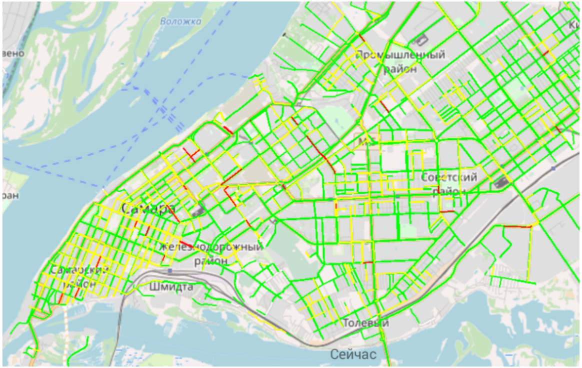
Model analysis

Comparison:

- proposed kNN model
- TDUD-KNN
- SARIMA

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}|V_t - \hat{V}_t|,$$

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|V_t - \hat{V}_t|}{V_t} \times 100\%$$



Data set:

- Transportation network with 26018 road segments
- Average speed in a period of 60 days
- New data each 10 minutes

Model analysis. MAE / MAPE

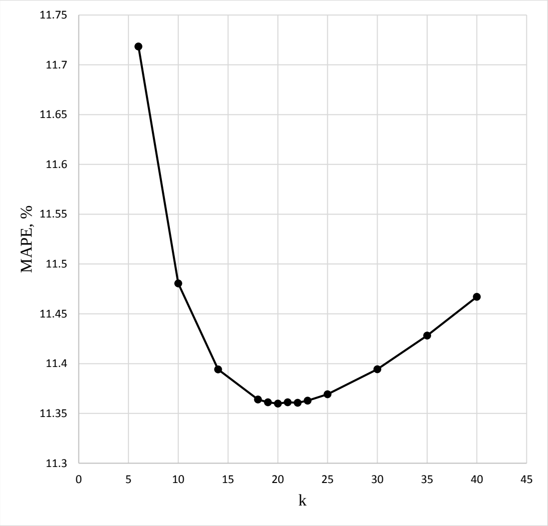
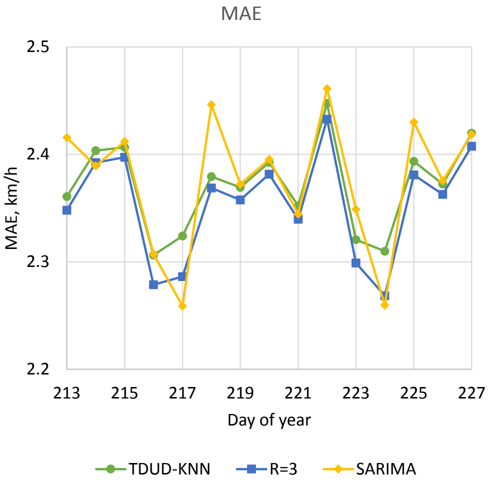
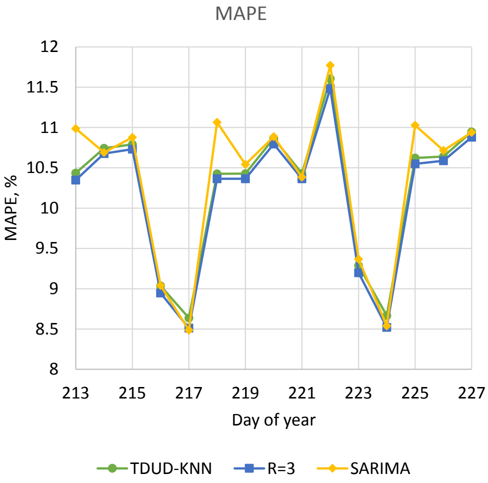


Table: Algorithms Comparison

	MAE	MAPE
$R = 1$	2.378	10.61
$R = 2$	2.374	10.598
$R = 3$	**2.372**	**10.593**
G^{area}	2.379	10.596
TDUD-KNN	2.387	10.611
SARIMA	2.399	10.77

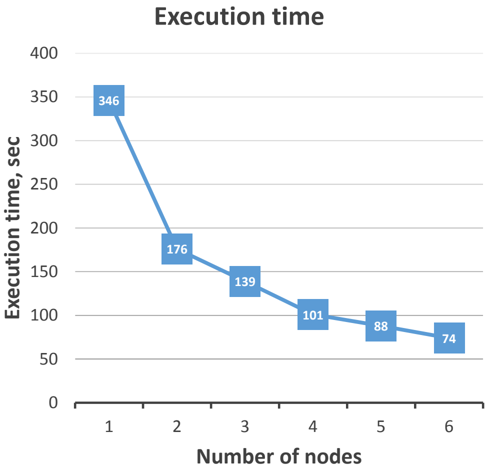
Model analysis. MAE / MAPE by days

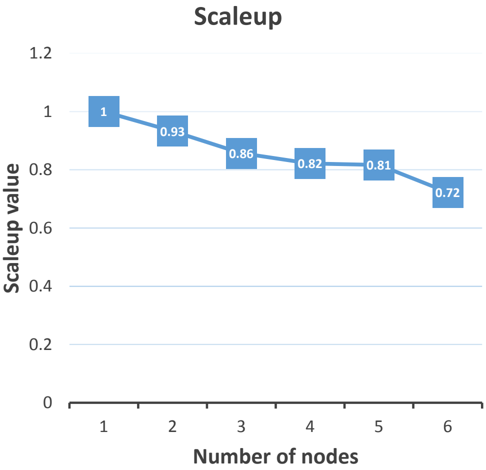




Model analysis. Execution time

Cluster up to 6 PC: Intel Core i5-3740 3.20 GHz, 8 GB RAM





Conclusion

The distributed spatial-temporal model of short-term traffic flow forecasting has the following advantages:

- The model takes into account spatial and temporal characteristics of the traffic flow.
- The implementation is based on MapReduce processing model in the open-source cluster-computing framework Apache Spark for distributed Big Data processing.
- The proposed model has a high prediction accuracy and reasonable execution time, sufficient for real-time prediction.

Thank you!

Anton Agafonov
ant.agafonov@gmail.com

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