



# Spatio-Temporal Traffic Anomaly Detection Methods on the Urban Road Network: A Literature Review

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**Kvalifikacijski doktorski ispit**

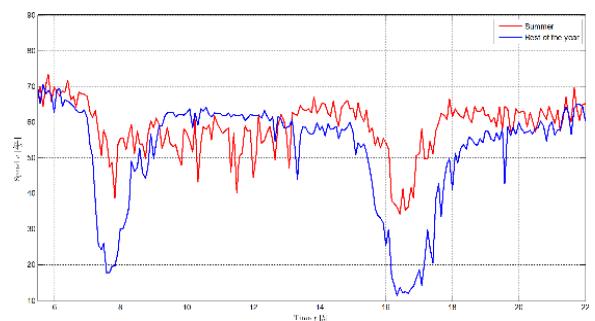
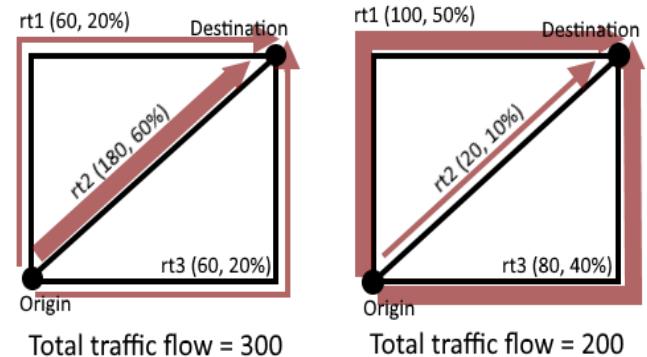
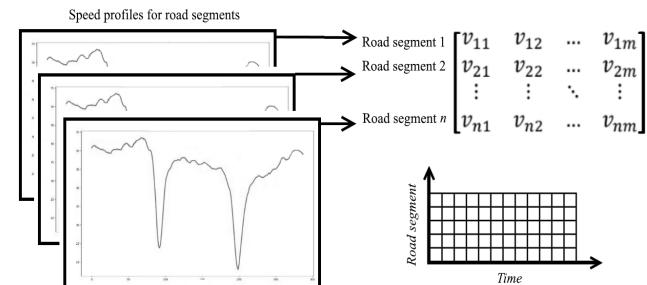
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Fakultet prometnih znanosti

**Mentor:** Prof. dr. sc. Tonči Carić

Rujan, 2019.

# SADRŽAJ

1. Uvod
2. Prostorno-vremenski podaci
3. Prostorno-vremenske anomalije
4. Metode detekcije anomalija
5. Zaključak



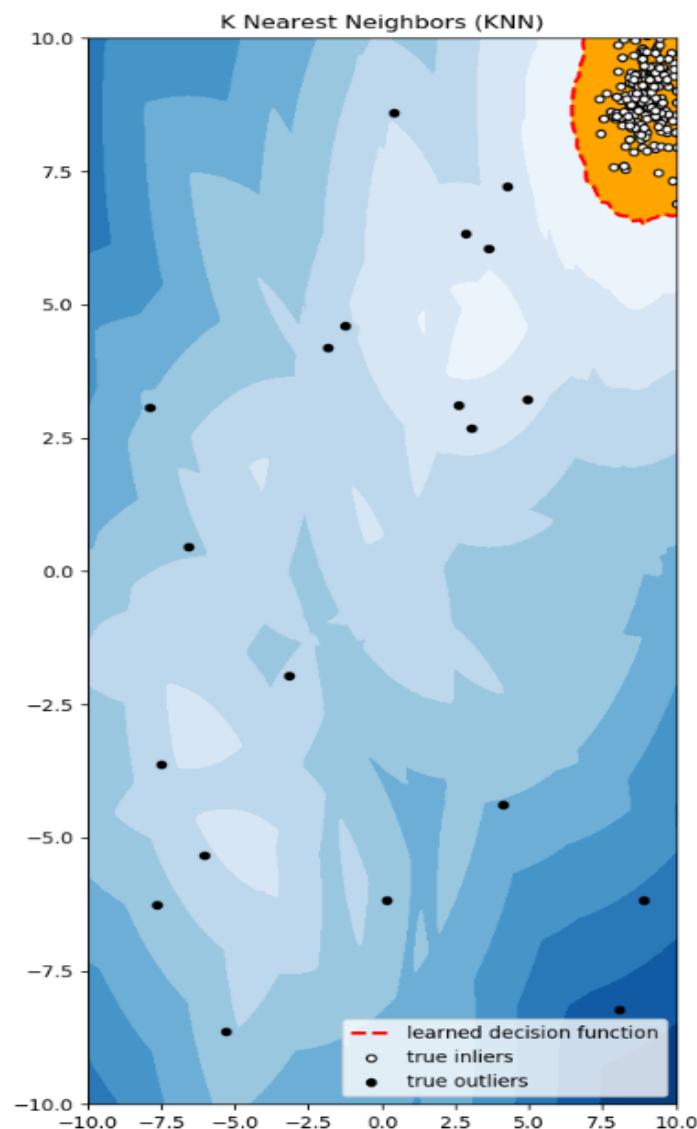
# UVOD - ANOMALIJE

## DETEKCIJA ANOMALIJA

problem pronašlaska  
neočekivanog “ponašanja”  
podataka

## JEDNA OD PRVIH DEFINICIJA

anomalija je podatak koji se  
toliko razlikuje od ostalih  
podataka, da postoji  
opravdana sumnja da je  
generiran iz nekog drugog  
izvora [1]



[1] D. M. Hawkins, *Identification of Outliers*. London: Springer Science, 1980.

# UVOD – MOTIVACIJA

## SUSTAVI ZA DETEKCIJU ANOMALIJA SU VAŽAN DIO INTELIGENTNIH TRANSPORTNIH SUSTAVA (ITS)

aplikacije definirane nekim od jedanaest funkcionalnih područja ITS-a zahtijevaju neku vrstu sustava za detekciju anomalija [2]



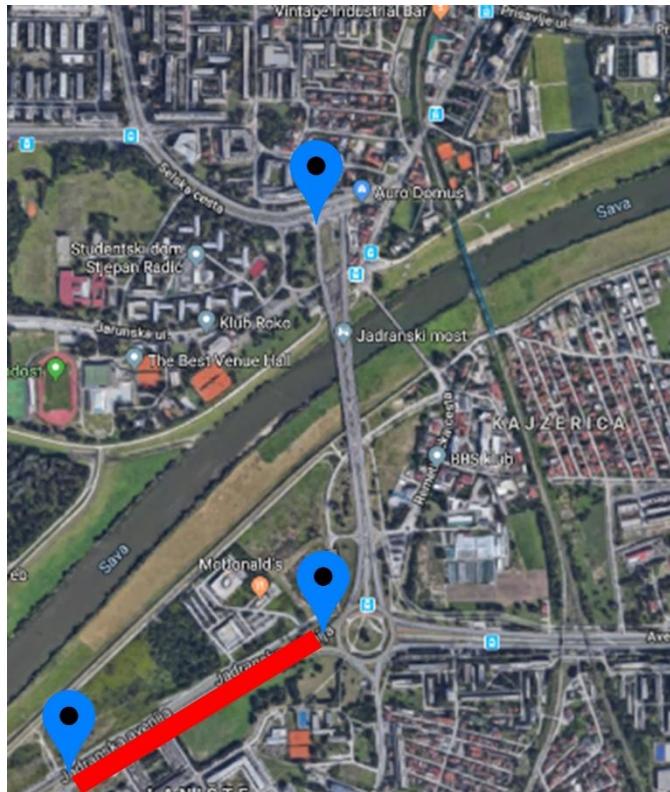
# PROSTORNO-VREMENSKI PODACI

## KOMBINACIJA

PROSTORNIH

I

VREMENSKIH



# PROSTORNO-VREMENSKI PODACI

## IZVORI PODATAKA

Globalni Navigacijski Satelitski Sustavi (GNSS) – privatne osobe, javni gradski prijevoz, taxi

*id\_korisnika, x\_korisnika, y\_korisnika, timestamp, ...*

## Mobilne mreže

*id\_korisnika, timestamp, x\_stanice, y\_stanice, ...*

## Senzori na prometnicama

*br\_vozila, brzina, timestamp, ...*

## Društvene mreže

[3] X. Kong, X. Song, F. Xia, H. Guo, J. Wang, and A. Tolba, “LoTAD : Long-Term Traffic Anomaly Detection Based on Crowdsourced Bus Trajectory Data,” World Wide Web, vol. 21, no. 2018, pp. 825–847, 2018.

[4] F. Lipan and A. Groza, “Mining Traffic Patterns from Public Transportation GPS Data,” in Proceedings of the 2010 IEEE 6th International Conference on Intelligent Computer Communication and Processing, 2010.

# PROSTORNO-VREMENSKI PODACI

## UZ DETEKCIJU ANOMALIJA, PROSTORNO-VREMENSKI PODACI NALAZE SVOJU PRIMJENU U RAZNIM PODRUČJIMA VEZANIM ZA TRANSPORT

- Predviđanje stanja prometne mreže [5]
- Detekcija propagacije zagušenja [6]
- Pronalazak uzroka zagušenja [7]
- ...

[5] X. Ma, Z. Dai, Z. He, J. Ma, Y. Wang, and Y. Wang, “Learning traffic as images: A deep convolutional neural network for large-scale transportation network speed prediction,” Sensors, vol. 17, no. 4, pp. 1–16, 2017.

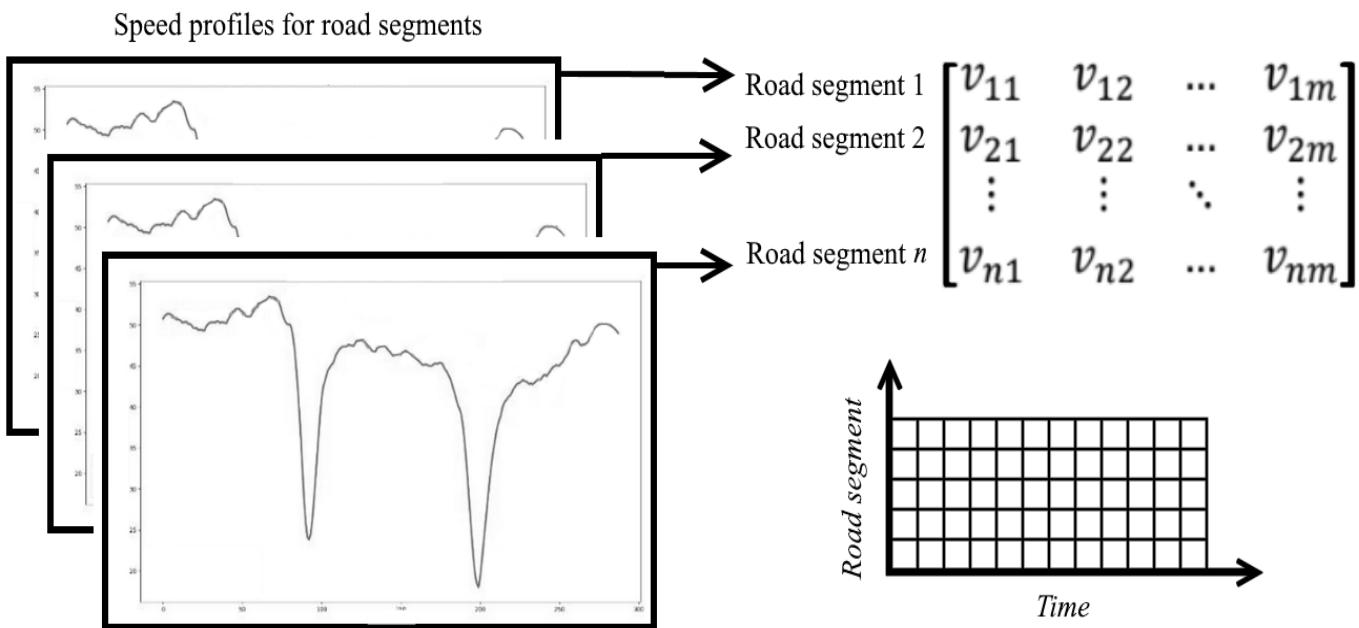
[6] H. Nguyen, W. Liu, and F. Chen, “Discovering Congestion Propagation Patterns in Spatio-Temporal Traffic Data,” IEEE Trans. Big Data, vol. 3, no. 2, pp. 169–180, 2017.

[7] F. Sun, A. Dubey, and J. White, “DxNAT - Deep neural networks for explaining non-recurring traffic congestion,” in Proceedings - 2017 IEEE International Conference on Big Data, Big Data 2017, 2018, vol. 2018-January

# PROSTORNO-VREMENSKI PODACI

## NAČIN PRIKAZA PODATAKA - PROFILI BRZINA

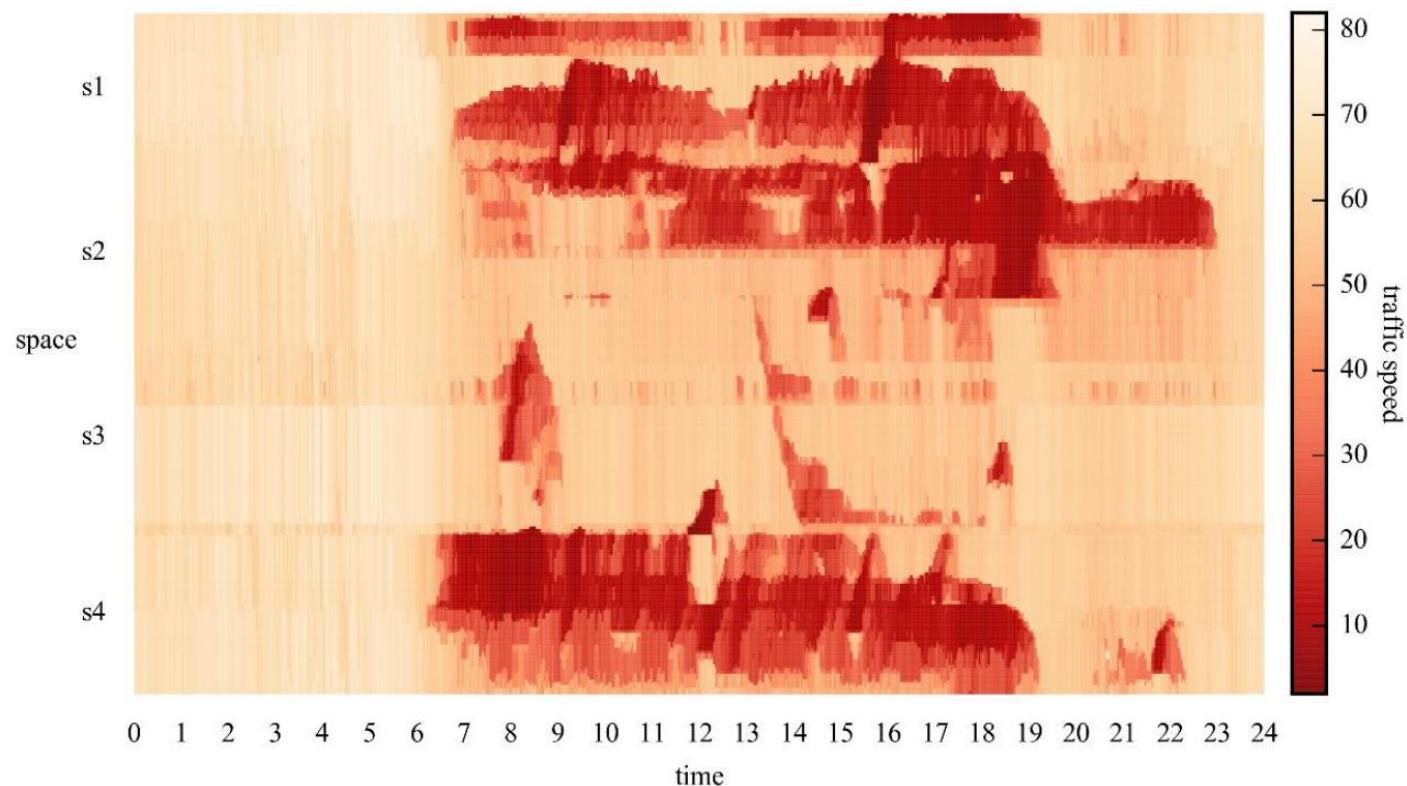
$$M = \begin{bmatrix} SP_1 \\ SP_2 \\ \vdots \\ SP_n \end{bmatrix}$$



# PROSTORNO-VREMENSKI PODACI

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# PROSTORNO-VREMENSKI PODACI

## NAČIN PRIKAZA PODATAKA

Profili prometnog toka [8]

$$V = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1m} \\ v_{21} & v_{22} & \dots & v_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ v_{n1} & v_{n2} & \dots & v_{nm} \end{bmatrix}$$

Proizvoljna struktura [3]

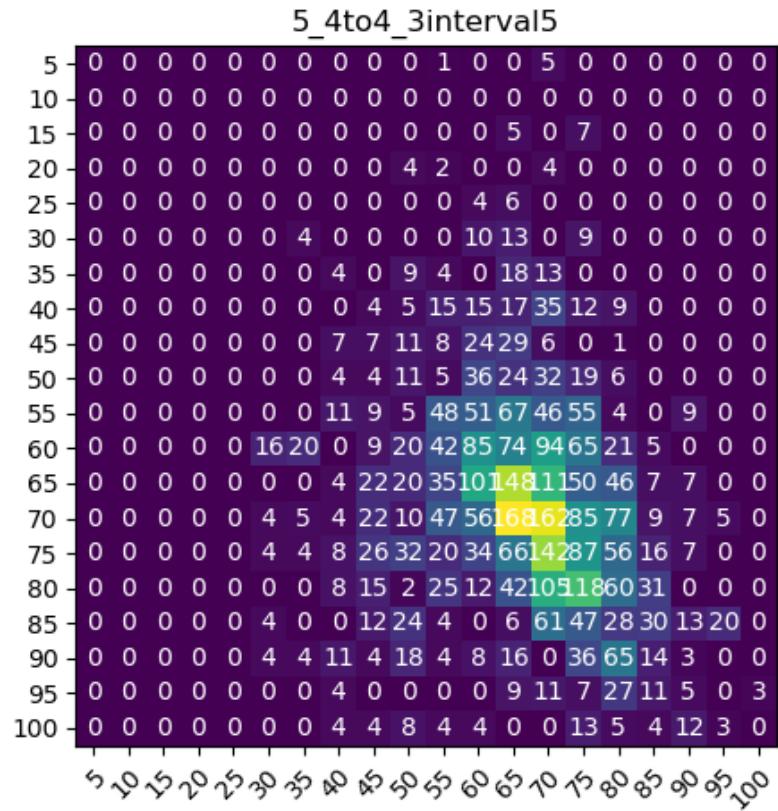
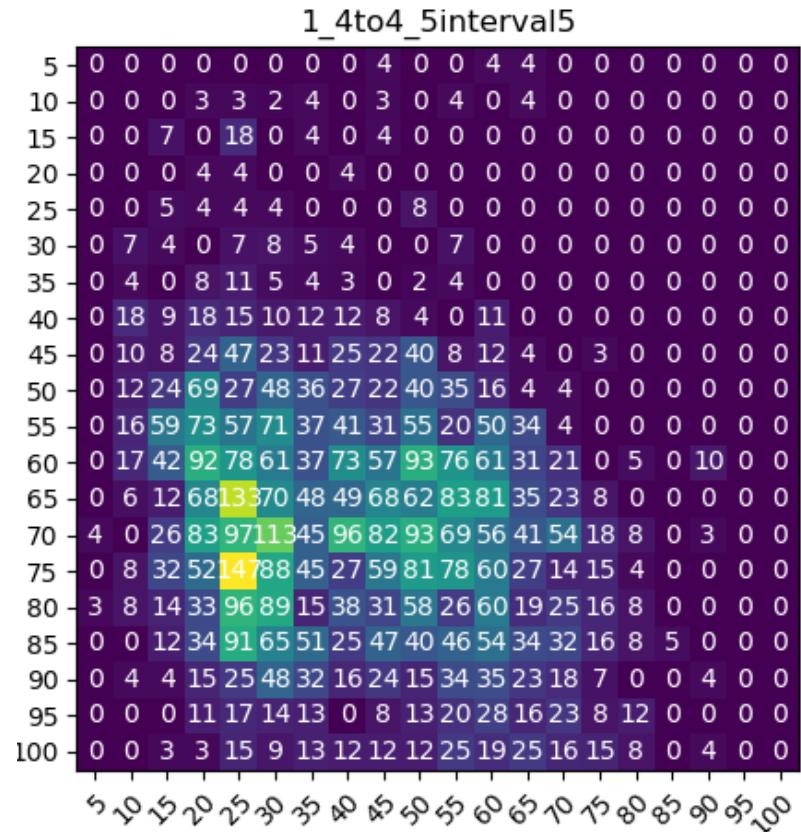
$$M = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1m} \\ a_{21} & a_{22} & \dots & a_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nm} \end{bmatrix}$$

$$a_{ij} = (\bar{v}, \bar{t}_{stop})$$

$i \in 1, 2, \dots, n$  Cestovni segmenti  
 $j \in 1, 2, \dots, m$  Vremenski intervali

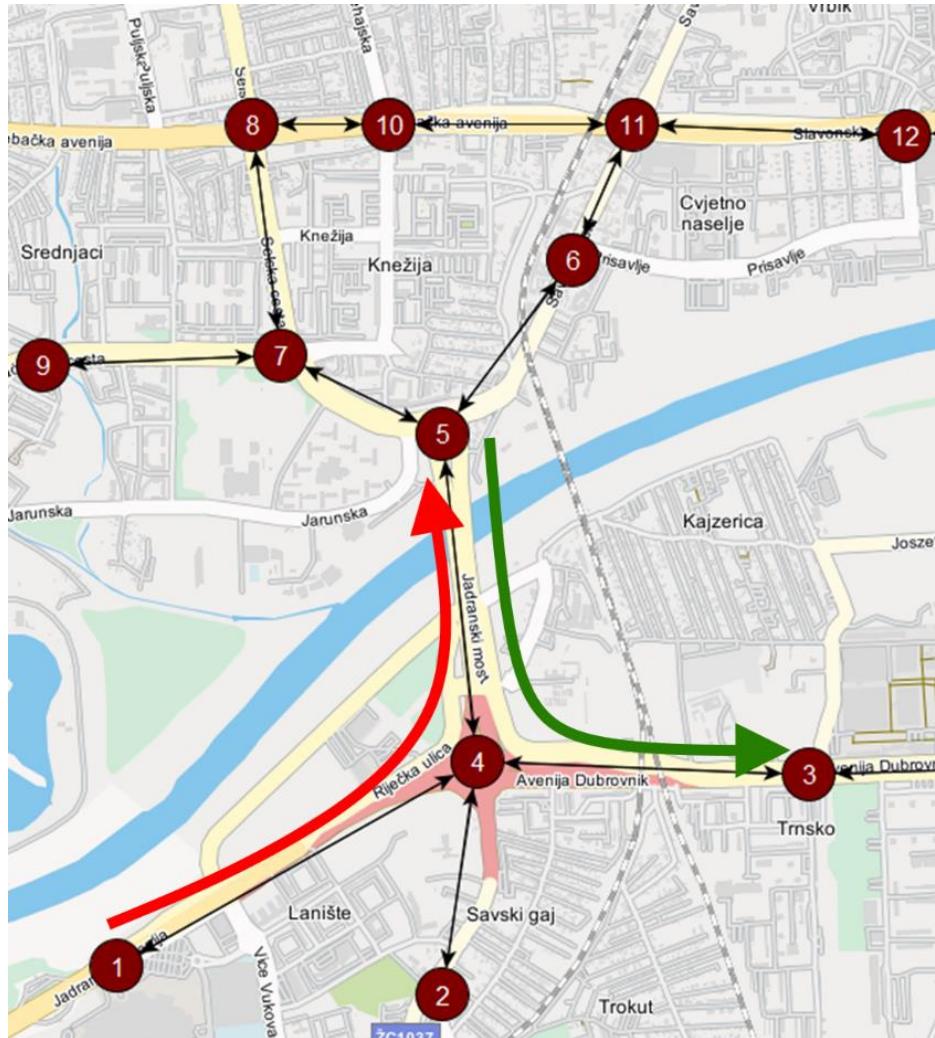
# PROSTORNO-VREMENSKI PODACI

## NAČIN PRIKAZA PODATAKA (PRIJELAZNE MATRICE)



# PROSTORNO-VREMENSKI PODACI

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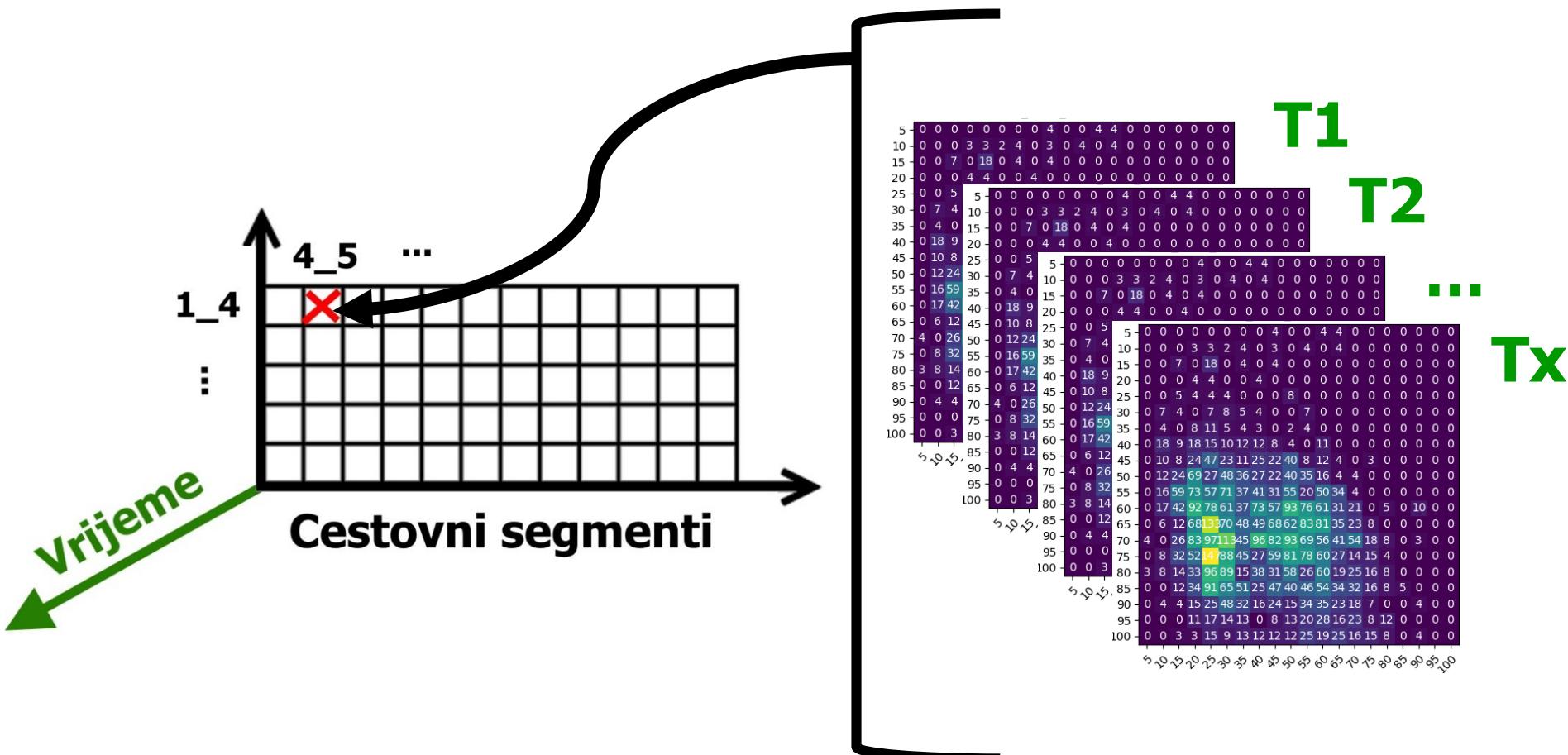


1\_4 → 4\_5

5\_4 → 4\_3

# PROSTORNO-VREMENSKI PODACI

# NAČIN PRIKAZA PODATAKA (PRIJELAZNE MATRICE)



# PODJELA PRISTUPA

GENERALNA  
PODJELA

Anomalije u trajektorijama  
(engl. *Trajectory anomaly*)

Anomalije u prometnom  
toku  
(engl. *Traffic anomaly*)

PREMA  
METODAMA

Zasnovane na  
modelu  
(engl. *Model  
based*)

Zasnovane na  
udaljenosti  
(engl. *Proximity  
based*)

Zasnovane na  
gustoći  
(engl. *Density  
based*)

PREMA  
IMPLEMENTACIJI

Uzorak  
usmjerenja  
(engl. *Routing  
patterns*)

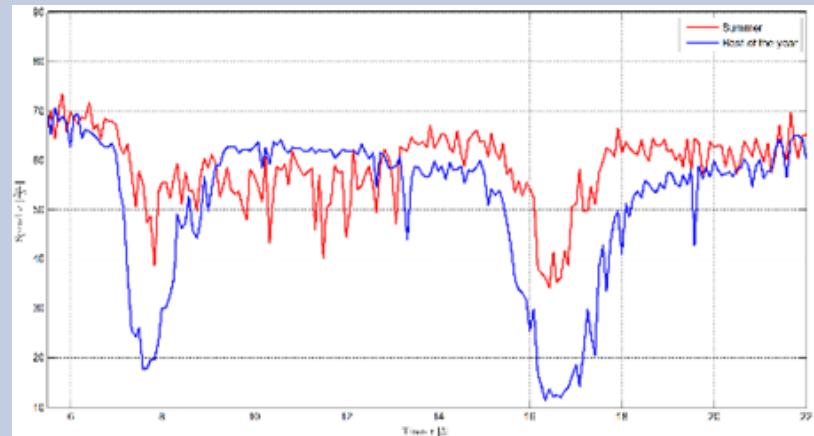
Razina anomalije  
(engl. *Anomaly  
scoring*)

Podjela na regije  
(engl. *Region-  
based methods*)

# PODJELA PRISTUPA



Anomalije u trajektorijama



Anomalije u prometnom toku

### ANOMALIJE U TRAJEKTORIJI

odnose se na detekciju anomalija koje su vezane za trajektoriju jednog vozila

Primjeri:

- Detekcija prevare prilikom vožnje taksijem [10]
- Detekcija opasnih vozača [11]

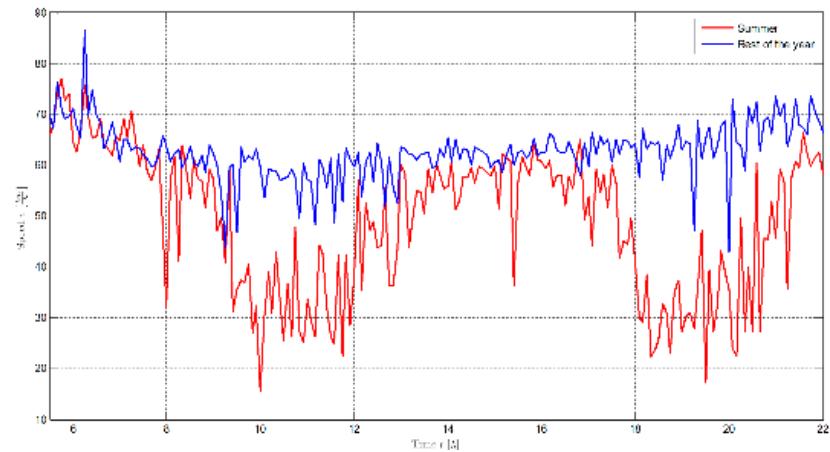
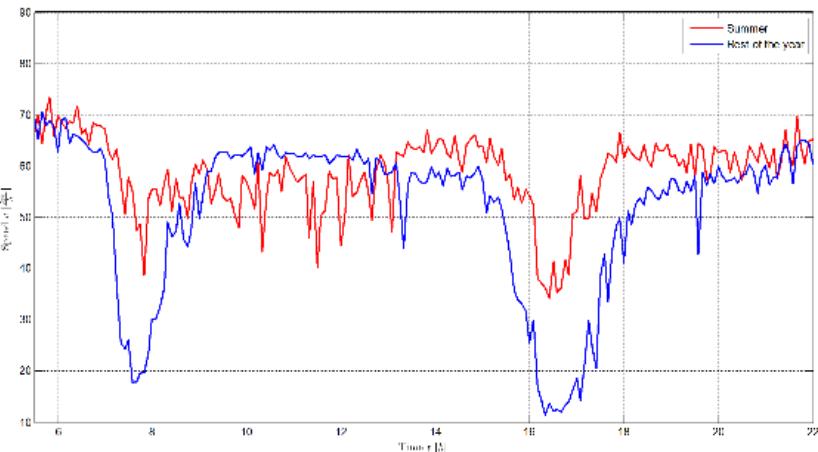
[10] C. Chen, D. Zhang, P. S. Castro, N. Li, L. Sun, and S. Li, “Real-Time Detection of Anomalous Taxi Trajectories from GPS Traces,” in *Mobile and Ubiquitous Systems: Computing, Networking, and Services*, 2012, pp. 63–64.

[11] Y. U. Zheng, “Trajectory Data Mining : An Overview,” *ACM Trans. Intell. Syst. Technol.*, vol. 6, no. 3, pp. 1–41, 2015.

# PODJELA PRISTUPA

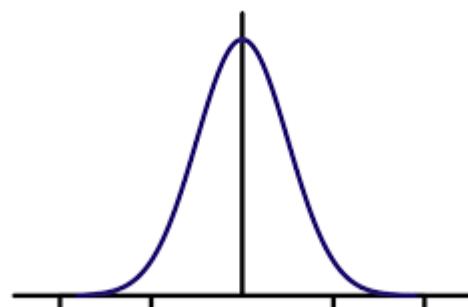
## PROMETNE ANOMALIJE

vezane za anomalije nekog od prometnih parametara (npr. brzina, volumen...) [6][12]

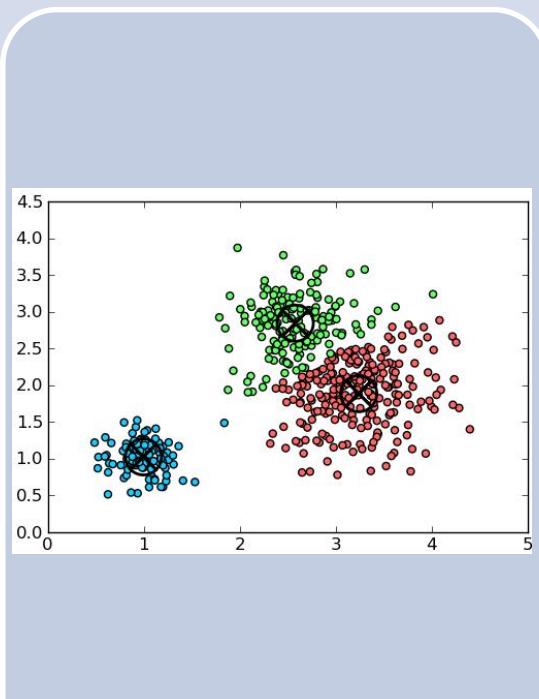


[12] W. Liu, Z. Yu, S. Chwala, J. Yuan, and X. Xie, "Discovering Spatio-Temporal Causal Interactions in Traffic Data Streams," in Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2011, pp. 1010–1018.

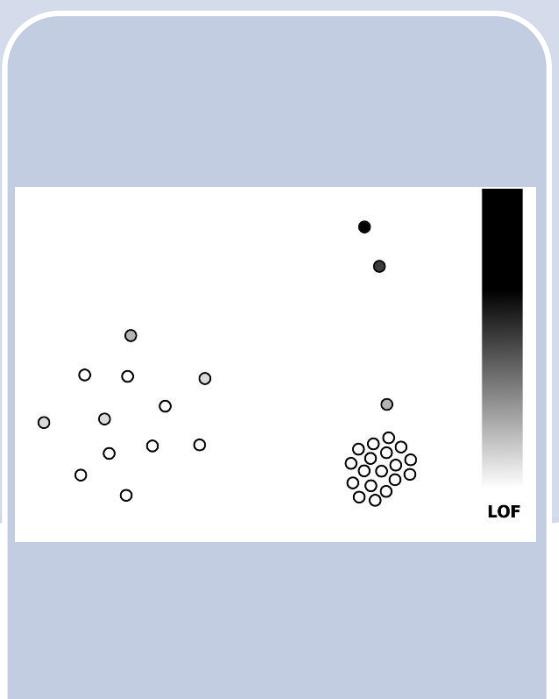
# PODJELA PRISTUPA - METODE



Zasnovane na  
modelu



Zasnovane na  
udaljenosti



Zasnovane na  
gustoći

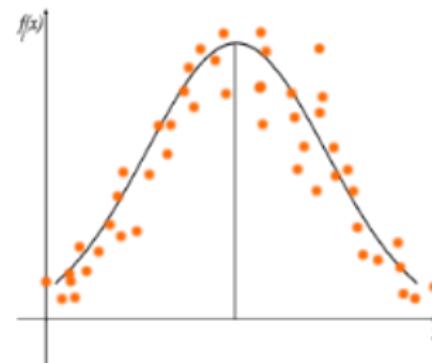
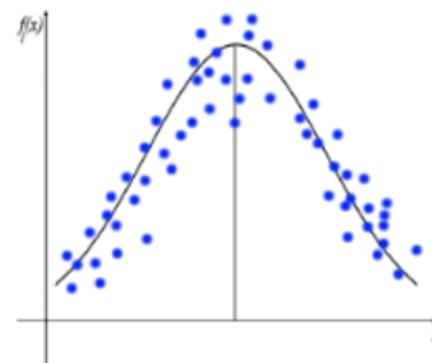
# PODJELA PRISTUPA - METODE

## ZASNOVANE NA MODELU

opisivanje podataka  
nekom od distribucija  
(npr. normalna)

Novi set podataka se  
uspoređuje s modelom.

Najčešća upotreba je u  
svrhu klasifikacije



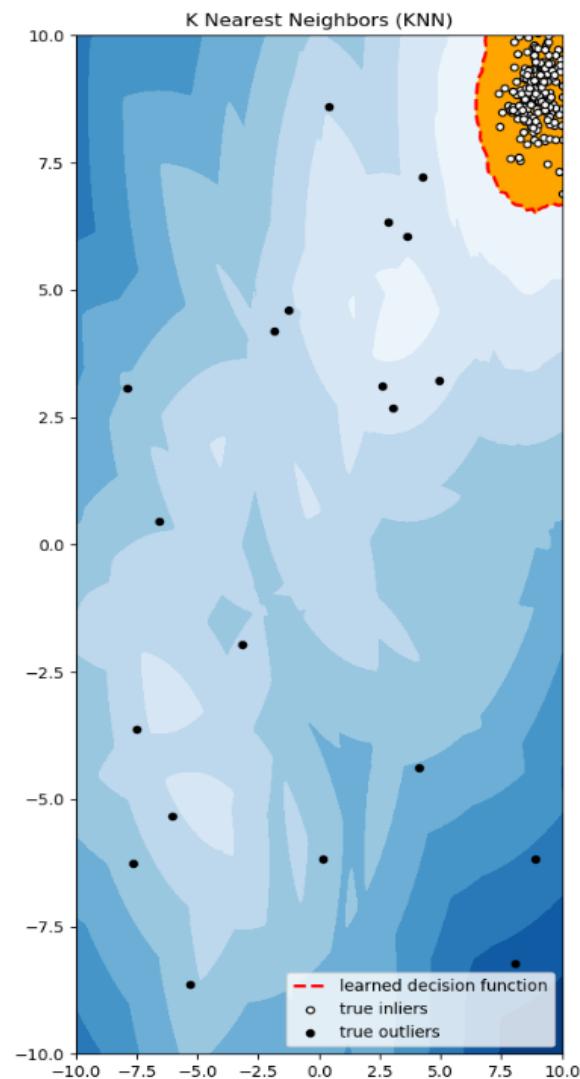
# PODJELA PRISTUPA - METODE

## ZASNOVANE NA UDALJENOSTI

anomalije su one vrijednosti koje su najudaljenije od vrijednosti koje se smatraju očekivanima

Npr. k-means algoritam

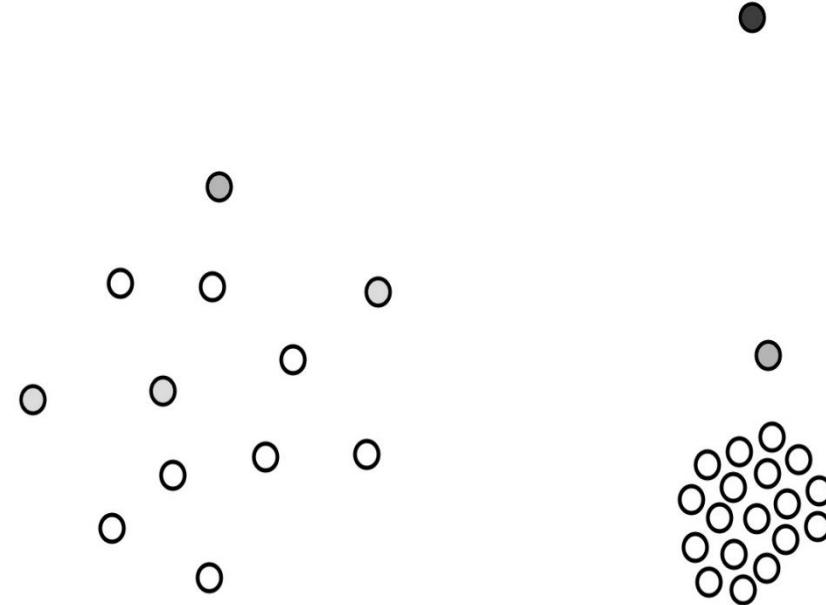
$$J = \sum_{j=1}^k \sum_{i=1}^n \|x_i^{(j)} - c_j\|^2$$



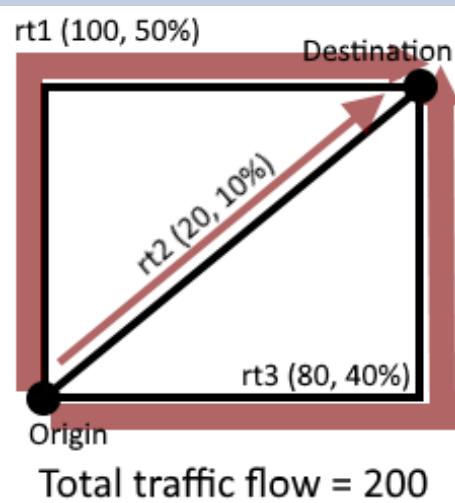
# PODJELA PRISTUPA - METODE

## ZASNOVANE NA GUSTOĆI

anomalije su one vrijednosti koje su najraspršenije u odnosu na vrijednosti koje se smatraju očekivanima



# PODJELA PRISTUPA - IMPLEMENTACIJA

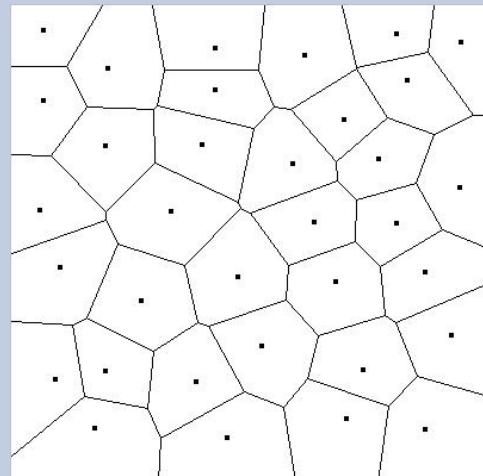


Uzorak  
usmjerenja (engl.  
*Routing patterns*)

$$O = [o_1, o_2, \dots, o_n]$$

$$S(o_i) > S(o_j)$$

for every  $o_j \in O$



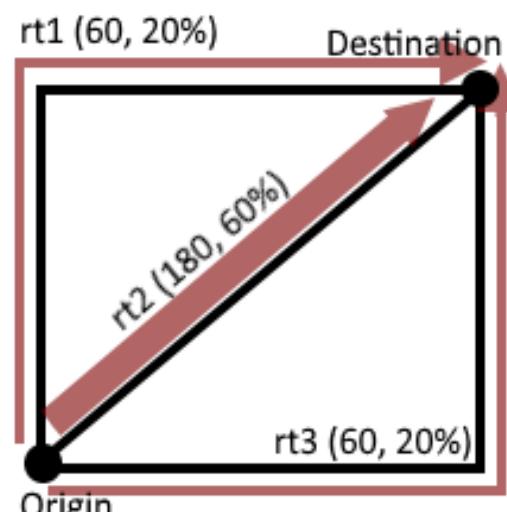
Razina anomalije  
(engl. *Anomaly scoring*)

Podjela na regije  
(engl. *Region-based methods*)

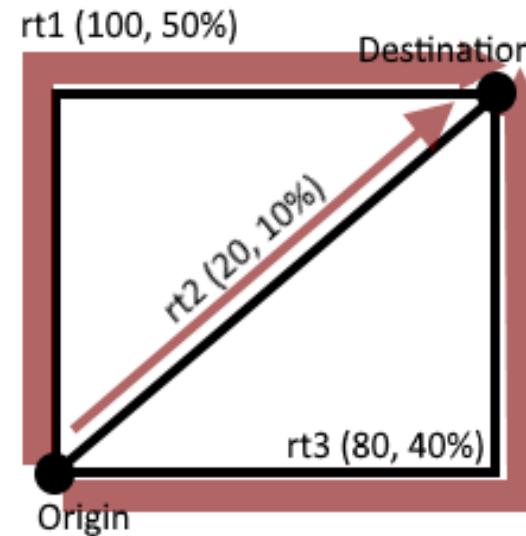
# PODJELA PRISTUPA - IMPLEMENTACIJA

## PREMA UZORKU USMJERAVANJA

### Primjer 1 [13]



Total traffic flow = 300



Total traffic flow = 200

$$[f_1, p_1, f_2, p_2, \dots, f_n, p_n]$$

[13] B. Pan, D. Wilkie, and C. Shahabi, "Crowd Sensing of Traffic Anomalies based on Human Mobility and Social Media Categories and Subject Descriptors," *ACM International Symposium on Advances in Geographic Information Systems*, 2013, pp. 344–353.

### PREMA UZORKU USMJERAVANJA

Primjer 1 [13]

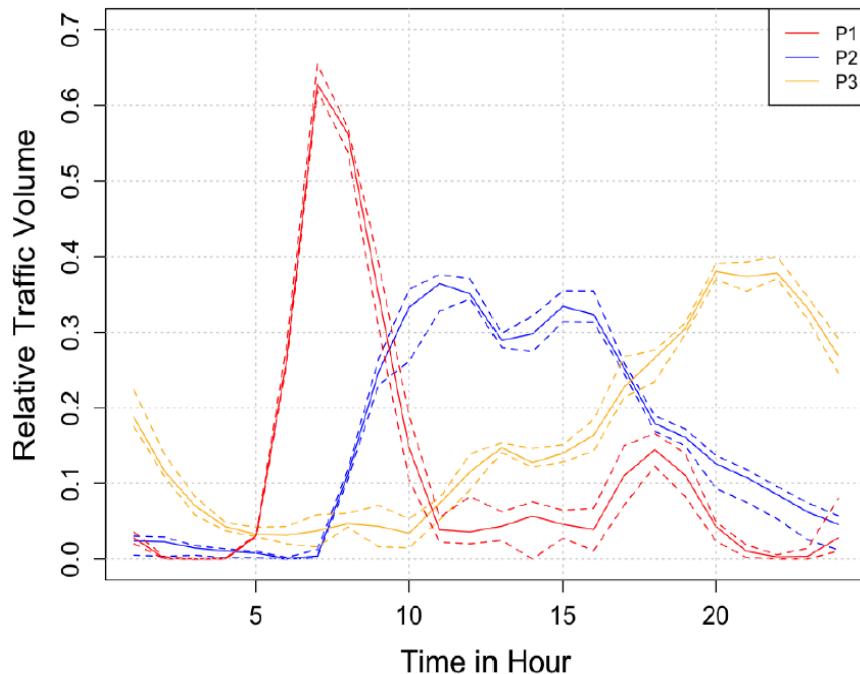
Anomalija je detektirana ako je udaljenost između uzorka usmjerenja i srednjeg uzorka usmjerenja veća za 3 standardne devijacije:

$$d_M(RP_{t1}, \mu_{[t_0, t_1]}) \geq 3 \sqrt{\frac{1}{N} \sum_{t \in [t_0, t_1]} (RP_t - \mu_{[t_0, t_1]})^2}$$

# PODJELA PRISTUPA - IMPLEMENTACIJA

## PREMA UZORKU USMJERAVANJA

### Primjer 2 [8]



Nonnegative Matrix Factorization (NMF)

$$V = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1m} \\ v_{21} & v_{22} & \dots & v_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ v_{n1} & v_{n2} & \dots & v_{nm} \end{bmatrix}$$

$$V \approx CP$$

$C \in \mathbb{R}^{n \times r}$  Matrica koeficijenata

$P \in \mathbb{R}^{r \times m}$  Matrica uzoraka

$r$  Broj uzoraka

## PODJELA PRISTUPA - IMPLEMENTACIJA

### RAZINA ANOMALIJE

ne postoji jednoznačna definicija anomalije, stoga postoji mnogo načina određivanja razine anomalije

$$S_{it}^d = \beta P_a^T(v_{it}^d) + (1 - \beta)P_r(v_{it}^d) \quad [8]$$

$$AI_i = \frac{\sum_{j \in M} \frac{density_i}{density_j}}{size(M)} \quad [3]$$

$$d_M(RP_{t1}, \mu_{[t_0, t_1]}) \geq 3 \sqrt{\frac{1}{N} \sum_{t \in [t_0, t_1]} (RP_t - \mu_{[t_0, t_1]})^2} \quad [13]$$

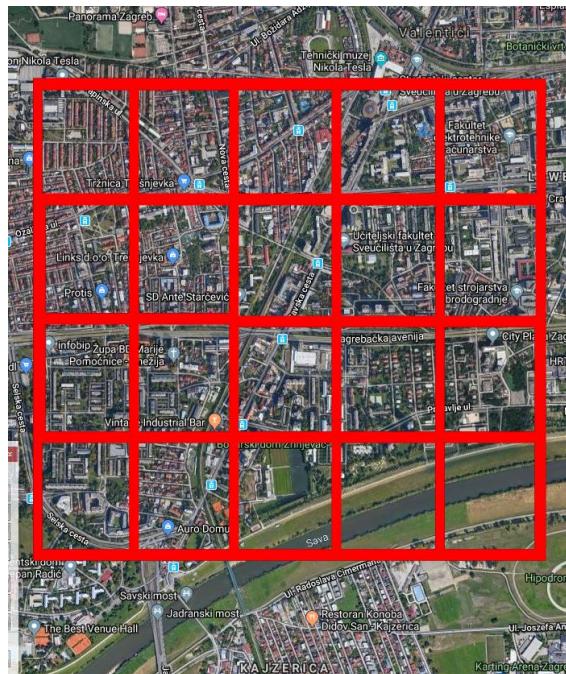
# PODJELA PRISTUPA - IMPLEMENTACIJA

## PODJELA NA REGIJE

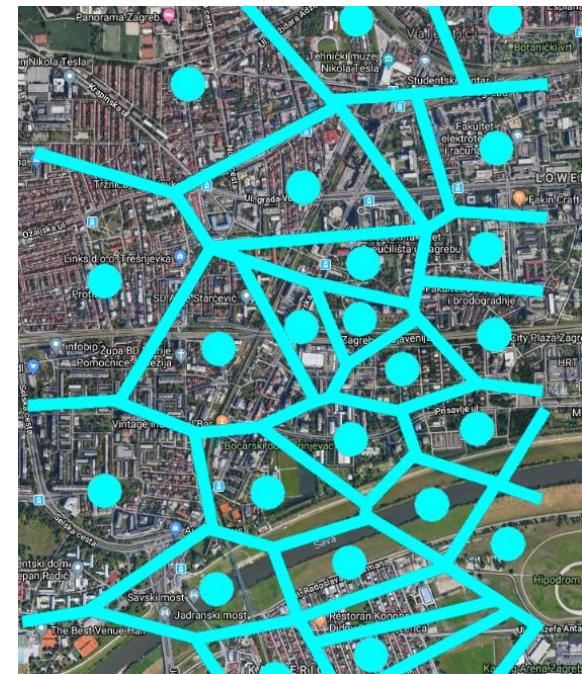
najčešće se određuje razina anomalije za geografski definirano područje



Heksagonalne ćelije



Raster polja



Voronoeve ćelije

# ZAKLJUČAK

Detekcija anomalija vrlo je važan dio mnogih ITS aplikacija (putno informiranje, upravljanje prometom, ...)

Buduća istraživanja:

- 1) NOVA STRUKTURA PROSTORNO VREMENSKIH PODATAKA I ALGORITMI ZA DETEKCIJU ANOMALIJA**
- 2) OPISIVANJE UZROKA NASTANKA ANOMALIJA**
- 3) RAZVOJ METODA ZA DETEKCIJU ANOMALIJA KORIŠTENJEM METODA DUBOKOG UČENJA**

**HVALA VAM NA PAŽNJI!**



# LITERATURA

- [1] D. M. Hawkins, *Identification of Outliers*. London: Springer Science, 1980.
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- [3] X. Kong, X. Song, F. Xia, H. Guo, J. Wang, and A. Tolba, "LoTAD : Long-Term Traffic Anomaly Detection Based on Crowdsourced Bus Trajectory Data," *World Wide Web*, vol. 21, no. 2018, pp. 825–847, 2018.
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- [10] C. Chen, D. Zhang, P. S. Castro, N. Li, L. Sun, and S. Li, "Real-Time Detection of Anomalous Taxi Trajectories from GPS Traces," in *Mobile and Ubiquitous Systems: Computing, Networking, and Services*, 2012, pp. 63–64.
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- [14] L. Tišljarić, M. Erdelić, T. Erdelić, T. Carić, „Traffic State Estimation Using Speed Profiles and Convolutional Neural Networks,” MIPRO 2019, Opatija, 2019.