#### Estimating congestion and traffic patterns when planning road work

Literature study





# Subjects

- 1. Theoretical background
  - 1. Different traffic models
  - 2. LWR model
  - 3. Fundamental relations
  - 4. The Godunov scheme
- 2. Combining ML and FR
- 3. Planning
- 4. Results





# 1. Theoretical background

- Internship at CGI (november 2022 march 2023)
  - iAMLAB
  - SPIN
    - Systeem Planning en Informatie Nederland



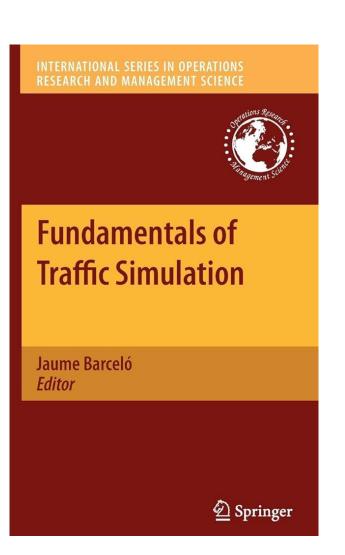


How can mathematical models, specifically the combination of traffic models and machine learning algorithms, be used to improve estimates of the effect of road work on traffic?



### 1.1 Different traffic models





### 1.1 Different traffic models

Macroscopic model
Microscopic model



Kesting, Arne et al. "Agents for Traffic Simulation." *Multi-Agent Systems* (2008).

M. J. Lighthill and G. B. Whitham, *On kinematic waves. ii. a theory of traffic flow on long crowded roads*, Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences, 229 (1955), pp. 317-345

P. I. Richards, Shock waves on the highway, Operations research, 4 (1956), pp. 42-51



$$\frac{\partial q}{\partial t} + \frac{\partial \phi}{\partial x} = 0$$

Conservation law



 $\frac{\partial q}{\partial t} + \frac{\partial \phi}{\partial x} = 0$ 

**Conservation law** 

 $\phi(q)$ 

**Fundamental relation** 



$$\frac{\partial q}{\partial t} + \frac{\partial \phi}{\partial x} = 0$$

#### Conservation law

 $\phi(q)$  $u(q) \qquad \phi = qu$ 

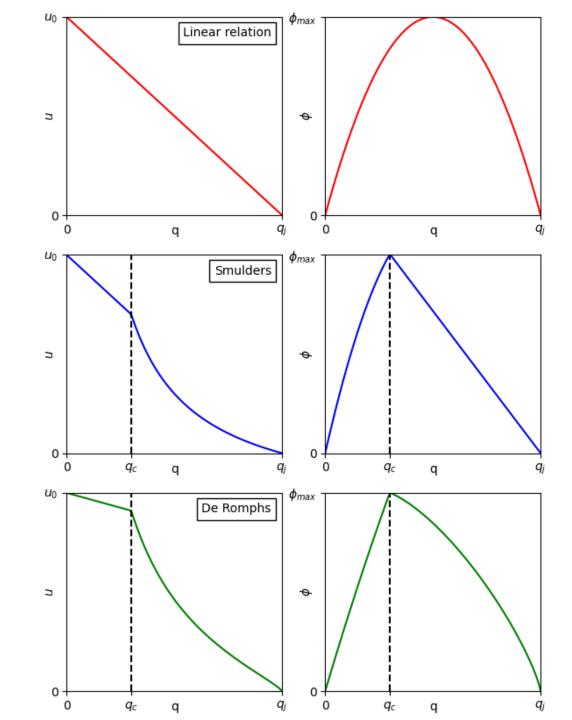
**Fundamental relation** 



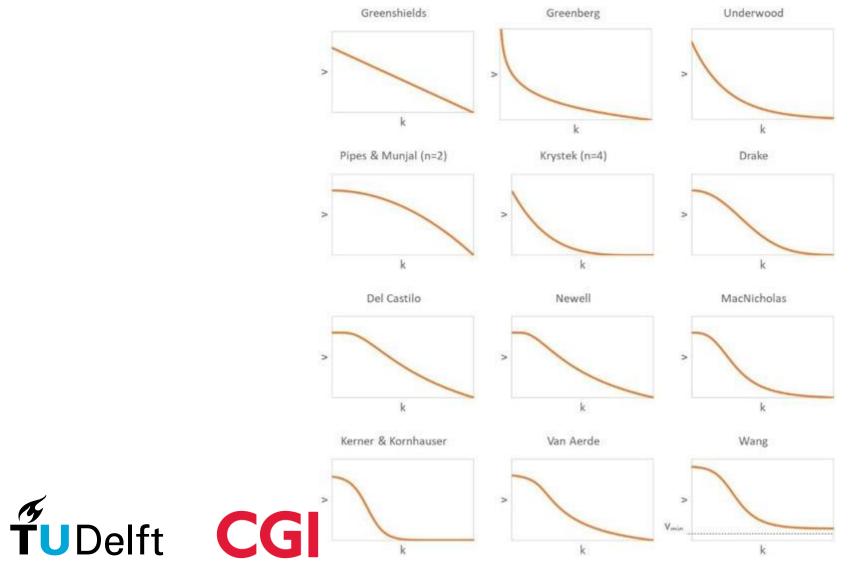
### 1.3 Fundamental relations

$$u_{\text{linear}}(q) = u_0(1 - \frac{q}{q_j})$$

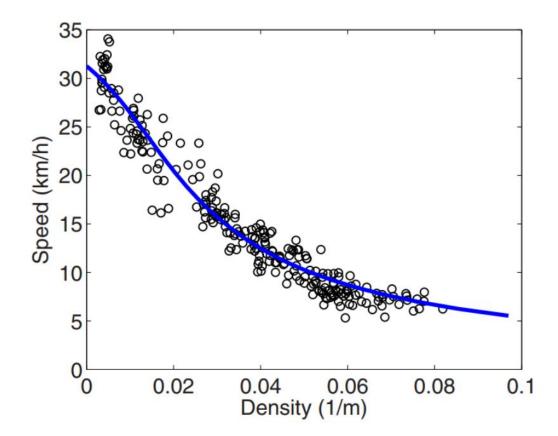
$$u_{\mathsf{Sm}}(q) = \begin{cases} u_0(1 - \frac{q}{q_j}), & \text{for } q < q_c \\ \gamma(\frac{1}{q} - \frac{1}{q_j}), & \text{for } q > q_c \end{cases}$$
$$u_{\mathsf{DR}}(q) = \begin{cases} u_0(1 - \alpha q), & \text{for } q < q_c \\ \gamma(\frac{1}{q} - \frac{1}{q_j})^{\beta}, & \text{for } q > q_c \end{cases}$$



# **1.3 Fundamental relations**



### **1.3 Fundamental relations**



Dirk Helbing. "Derivation of a fundamental diagram for urban traffic flow". In: *The European Physical Journal B* 70 (2009), pp. 229–241.





**Definition 6 (Cauchy problem)** The problem

$$q_t + \phi(q)_x = 0, \quad x \in \mathbb{R}, \quad t > 0,$$
  
$$q(x, 0) = q_0(x), \quad x \in \mathbb{R},$$

for some function  $\phi : \mathbb{R} \to \mathbb{R}$  is called a Cauchy problem [4]. In this context, **Cauchy data** represents the initial conditions  $q_0(x)$  from which a unique solution can be found.



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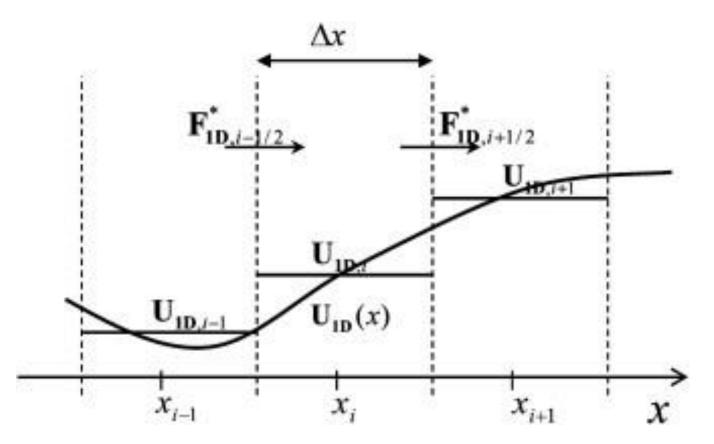
Definition 7 (Riemann problem) A Cauchy problem with initial values

$$q_0(x) = \begin{cases} q_l & \text{ for } x < 0\\ q_r & \text{ for } x \ge 0 \end{cases}$$
(2.11)

where  $q_l, q_r \in \mathbb{R}$  is called a Riemann problem. [8]

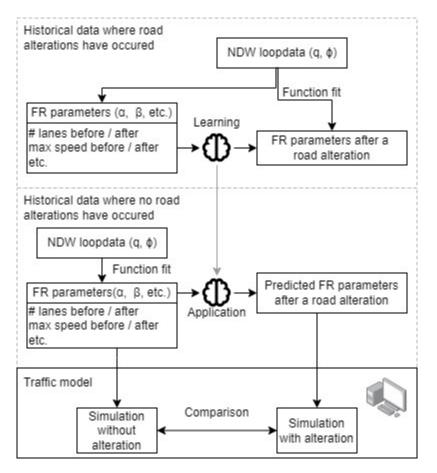


- Finite volume method
- Conserved implicitly
- Shockwaves stay intact

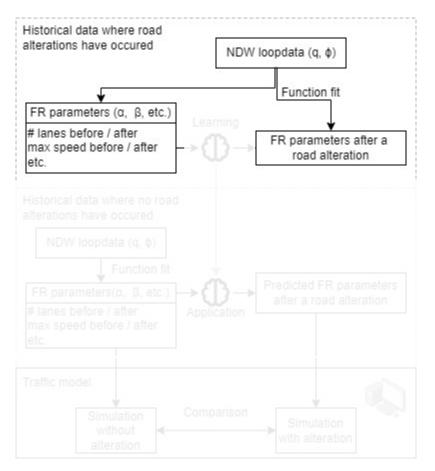


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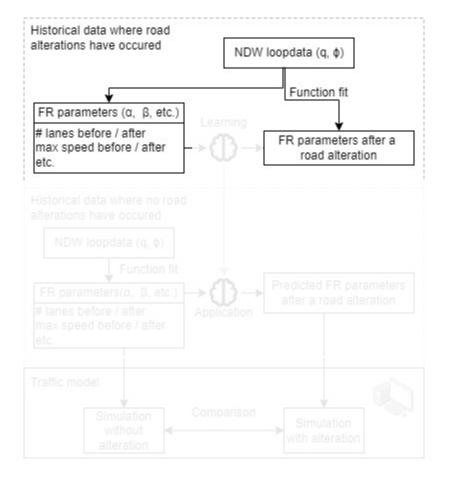






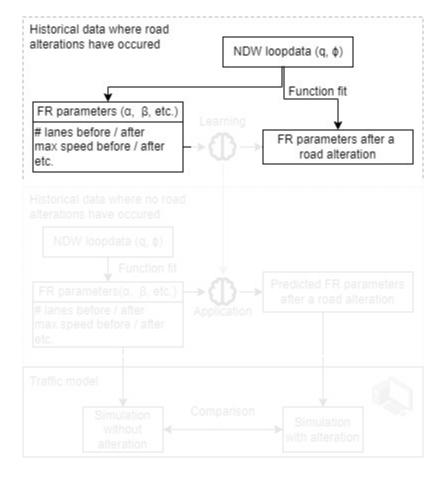


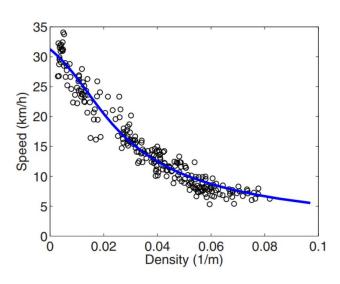












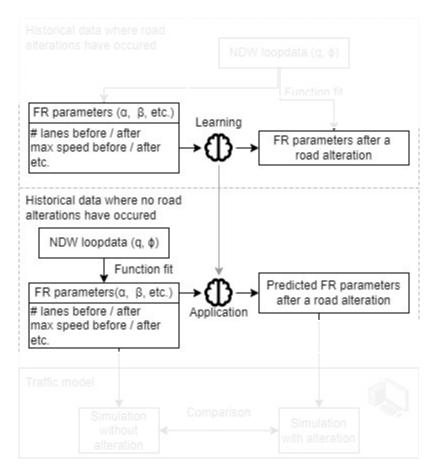
Dirk Helbing. "Derivation of a fundamental diagram for urban traffic flow". In: *The European Physical Journal B* 70 (2009), pp. 229–241.

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FR parameters (α, β, etc.) # lanes before / after max speed before / after etc.	Learning →∰→	Function fit FR parameters after a road alteration
Historical data where no road alterations have occured NDW loopdata (q, ø)		

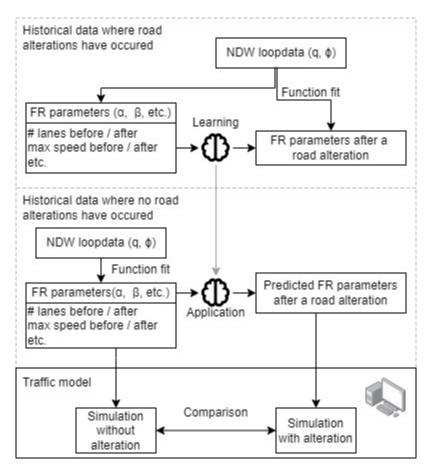




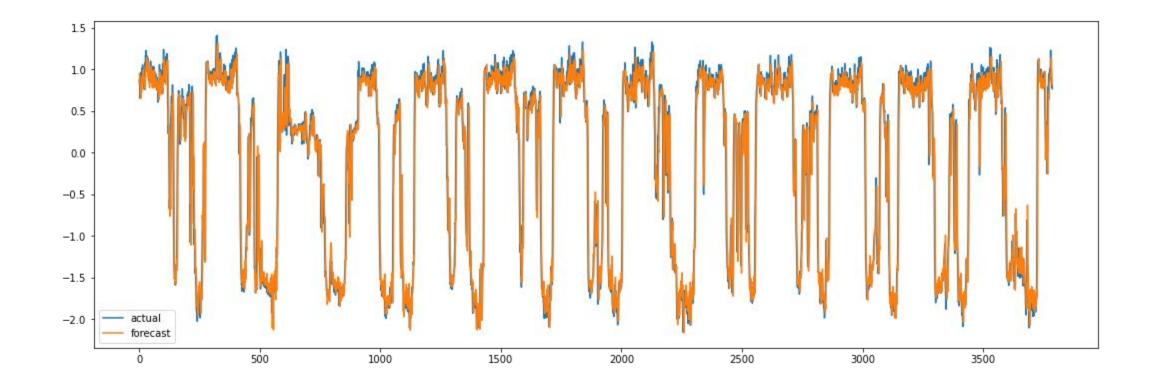


Function fit	Destinted CD assembles	
FR parameters( $\alpha$ , $\beta$ , etc.) $\rightarrow$	Predicted FR parameters     after a road alteration	
# lanes before / after App max speed before / after etc.		
Traffic model Simulation without alteration	parison Simulation with alteration	











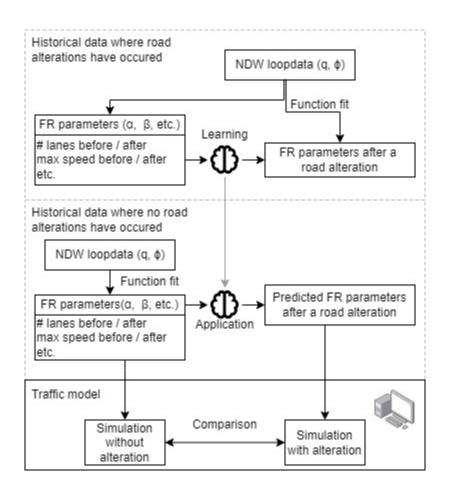
Traffic forecasting using graph neural networks and LSTM (keras.io)

Table 2. ML – based traffic analysis summary		
	Technique used	Objectives
Sommer and Paxson	Machine learning	ML methods have been applied to spam detection more effectively than
.[13]	technique	intrusion detection because the detection of anomalies is best for finding
		different forms of known attacks.
Zhang et al.[24]	Artificial neural network using	Extract out the protocol features from feature words that are extracted by VE
	Voting Experts (VE) algorithm	algorithm.
Wang et al [25]	Machine learning (SVM)	Classification the energy that is used in data flows.
Furno et al. [26]	Machine learning using	Spatial structure analysis and bridge the temporal to mobile traffic data by
	Exploratory factor analysis	using EFA technique
	(EFA)	
Mirsky et al.[27]	Artificial neural network using Kitsune	Detection of malicious traffic entering and leaving the network
Suthaharan et	Machine learning	Classification of network intrusion traffic by learning the network
al.[28]	Using supervised learning	characteristics
	technique	
Blowers et al.[29]	Machine learning use a	Anomaly detection based on clustering
	DBSCAN clustering	
Laskov et al[21].	Machine learning (SVM),(kNN)	Compare both supervised and unsupervised learning for detecting malicious
	γ-algorithm, k-means	activities
Mukkamala et al[9]	Machine learning (SVM)	To discover patterns or features that describe user behaviours to build
		classifiers for recognizing anomalies
Zamani et al [16]	artificial immune algorithm	Intrusion detection in distributed systems.
Bujlow et al.[30]	Machine learning using C5.0	Classification of traffic in network
	algorithm	
Amuna and Vinoth	Machine learning using Decision	Classification of traffic in network
[31]	Tree and Naïve Bayes ML	
	algorithms	
Bartos et al. [32]	Machine learning	Detect both known and previously unseen security threats
	Using supervised learning	
	technique	

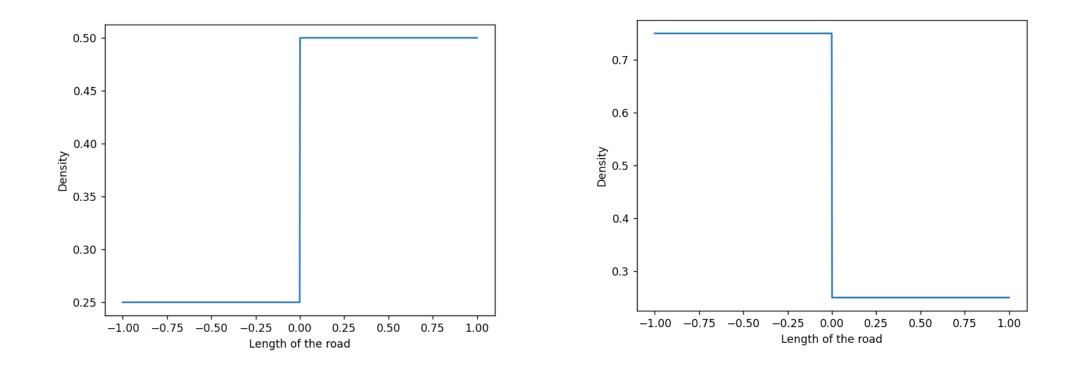


Alqudah, Nour, and Qussai Yaseen. "Machine learning for traffic analysis: a review." Procedia Computer Science 170 (2020): 911-916.

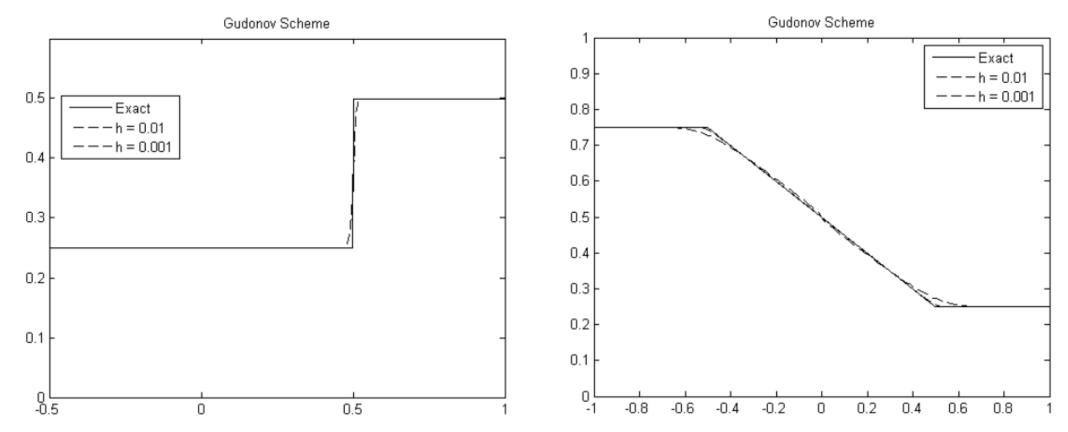
# 3. Planning









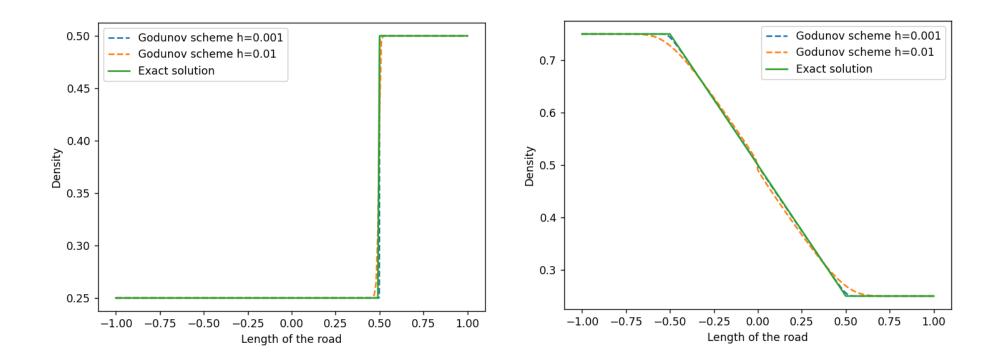


Godunov Scheme for a shock solution at T = 2 (left) and Rarefraction at T = 1 (right). k = 0.001.



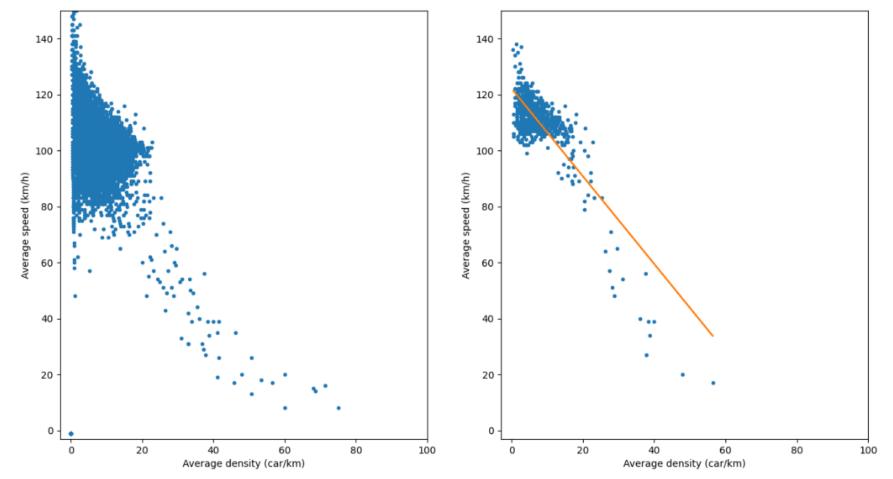
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Numerical Solutions of Traffic Flow on Networks (ntnu.no)



Godunov Scheme for a shock solution at T = 2 (left) and Rarefraction at T = 1 (right). k = 0.001.







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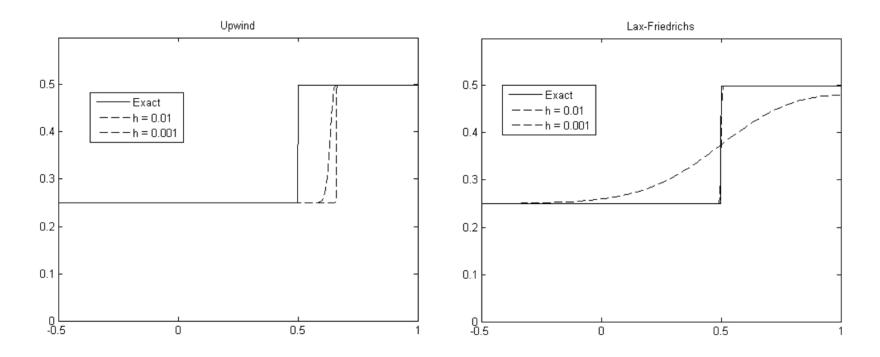
### Subquestions

- 1. What is a **measure of performance** of different traffic models and ML algorithms in terms of their ability to accurately estimate the effects of road work on traffic?
- 2. How can **macroscopic traffic** models be used as a **framework** to estimate the effect of road work on traffic using ML?
- 3. How can we use **ML algorithms** to identify and predict the **impact** of road work based on historical data?
- 4. How can the **insights** gained from the traffic model be used to **improve the efficiency** of road work planning processes?



# FEM around shock waves

Figure 6.2.1: Exact and numerical solutions for the inviscid Burger equation using the upwind scheme(6.2.2)(left) and the Lax-Friedrichs scheme(6.2.3)(right). k = 0.001.





https://ntnuopen.ntnu.no/ntnuxmlui/bitstream/handle/11250/259317/730608\_FULLTEXT 01.pdf?sequence=3&isAllowed=y

# FEM around shock waves

CGI

**T**UDelft

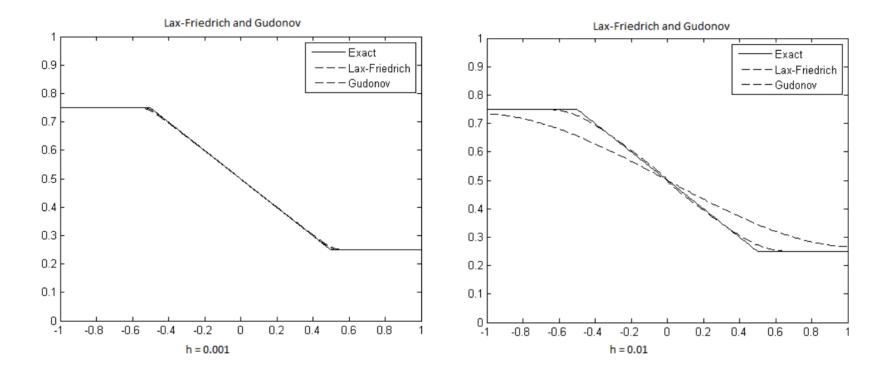


Figure 7.1.2: Godunov and Lax-friedrich for a Rarefraction solution h = 0.001 (left) and h = 0.01 (right). k = 0.001 and T = 1.

https://ntnuopen.ntnu.no/ntnuxmlui/bitstream/handle/11250/259317/730608\_FULLTEXT 01.pdf?sequence=3&isAllowed=y

#### Pseudocode for the Godunov scheme

1.  $q_l = q_r$  gives the constant solution  $q(x, t) = q_0(x)$  and  $\phi(q(0)) = 0$ .

2.  $q_l < q_r$  means that there is a higher density of traffic on the right than on the left. This higher density on the right leads to lower speeds. As traffic moves from left to right, it follows that the shockwave will stay a discontinuity. It is concluded that the solution has the form:

$$q(x,t) = \begin{cases} q_l & \text{for } x < st \\ q_r & \text{for } x \ge st \end{cases}$$
(2.12)

where the shock speed *s* is found to be

$$s = \frac{\phi(q_l) - \phi(q_r)}{q_l - q_r}.$$
 (2.13)

This choice for *s* is called the Rankine-Hugoniot condition [4]. This means the value of  $\phi(q(0))$  depends on the value of *s*; if s > 0, then the shock moves to the right and  $q(0) = q_l$ , while s < 0 yields  $q(0) = q_r$ . s = 0 is impossible in this situation, as that implies  $\phi(q_l) = \phi(q_r)$  which is only possible if  $q_l = q_r$ .

3.  $q_l > q_r$  has multiple weak solutions, but only one physically meaningful solution; the rarefraction wave. This means the shock will not stay a discontinuity, but it will spread out. This type of rarefraction wave is the correct solution in this situation as it satisfies the entropy condition as defined in [4] and [8]. Mathematically, this looks like this:

$$q(x,t) = \begin{cases} q_l & \text{for } x < \phi'(q_l)t \\ (\phi')^{-1}(\frac{x}{t}) & \text{for } \phi'(q_l)t \le x \le \phi'(q_r)t \\ q_r & \text{for } x > \phi'(q_r)t \end{cases}$$
(2.14)

For the Godunov method, we will need  $\phi(q(0))$ . This can be found from this equation:

$$q(0) = \begin{cases} q_l & \text{if } \phi'(q_l) > 0\\ (\phi')^{-1}(0) & \text{if } \phi'(q_l) \le 0 \le \phi'(q_r) < 0\\ q_r & \text{if } \phi'(q_r) < 0 \end{cases}$$
(2.15)

In the case of traffic models,  $\phi(q)$  is a concave function and  $(\phi')^{-1}(0)$  is the unique solution to  $\phi'(q) = 0$  which represents the point of maximum flux. [4, 8]

### Pseudocode for the Godunov scheme

**T**UDelft

```
Data: Some initial q_0(x), a fundamental relation \phi(q) with maximum flux \phi(q_{max}), a domain x
          and boundary values Q_{\text{boundary point}}(t).
Result: An approximation of the traffic flow over time.
begin
     Discretize t as t_n size k, and x as x_i size h
     Discretize q_0(x) as q_i^0 = \frac{1}{h} \int_{x-\frac{h}{2}}^{x+\frac{h}{2}} q_0(x) dx
     for n in timerange do
          for all i do
                We will find q_i^* at the interface between x_i and x_{i+1}
                if \phi'(q_i^n) \ge 0 and \phi'(q_{i+1}^n) \ge 0 then q_i^* \longleftarrow q_i^n;
                if \phi'(q_i^n) < 0 and \phi'(q_{i+1}^n) < 0 then q_i^* \longleftarrow q_{i+1}^n;
                 \begin{array}{c} \text{if } \phi'(q_i^n) \geq 0 \text{ and } \phi'(q_{i+1}^n) < 0 \text{ then} \\ s \leftarrow \frac{\phi(q_i^n) - \phi(q_{i+1}^n)}{q_i^n - q_{i+1}^n} \end{array} 
                    if s \ge 0 then q_i^* \longleftarrow q_i^n;
                  if s < 0 then q_i^* \longleftarrow q_{i+1}^n;
               if \phi'(q_i^n) < 0 and \phi'(q_{i+1}^n) \ge 0 then q_i^* \longleftarrow q_{max};
          for all interior i do
             | q_i^{n+1} = q_i^n - \frac{k}{h}(\phi(q_i^*) - \phi(q_{i-1}^*))
          for all boundary points i do

\lfloor q_i^{n+1} = Q_i(t_{n+1})
```

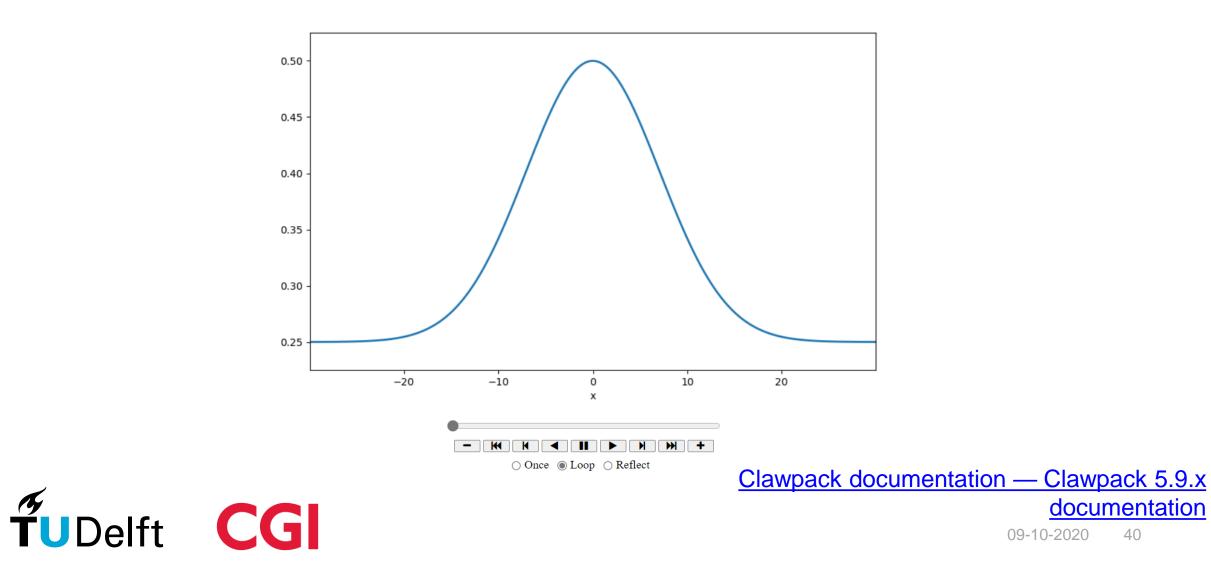
### 2.1 NDW data

- Loopdata
- Incidents instead of (planned) road work





Time t = 0.0



Time t = 40.0

