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FACULTEIT INGENIEURSWETENSCHAPPEN

Model identification and learning control in autonomous driving

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Thesis voorgedragen tot het behalen
van de graad van Master of Science
in de ingenieurswetenschappen:
elektrotechniek, optie Elektronica en
geïntegreerde schakelingen

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Preface

I would like to thank my family in the first place. During the history of my studies they always have been my biggest fans and I want to show my gratitude for the opportunities they have given me. I also want to thank my promoter Professor Swevers at the KU Leuven and Dr. Tong my mentor at Siemens for the professional discussions and tips they have given me in order to improve results.

Stijn Staring

Contents

Abstract

The `abstract` environment contains a more extensive overview of the work. But it should be limited to one page.
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Samenvatting

In dit `abstract` environment wordt een al dan niet uitgebreide Nederlandse samenvatting van het werk gegeven. Wanneer de tekst voor een Nederlandstalige master in het Engels wordt geschreven, wordt hier normaal een uitgebreide samenvatting verwacht, bijvoorbeeld een tiental bladzijden.
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List of Figures and Tables

List of Figures

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List of Abbreviations and Symbols

Abbreviations

LoG	Laplacian-of-Gaussian

Symbols

42	"The Answer to the Ultimate Question of Life, the Universe, and Everything" according to [**?**]
c	Speed of light

Chapter 1

Introduction

1.0.1 Importance of topic

"Society expects autonomous vehicles to be held to a higher standard than human drivers." [10] This quote is setting the tone of the technology in autonomous driving. In order to be accepted to the public, autonomous vehicles should perform as least as good as the conventional human driver on parameters as for example safety. Despite widespread research on self-driving vehicles the acceptance by the user stays only limited.[1] The purchase behaviour of customers can be directly linked with comfort. Also in order to gain more trust by the public it is clear that the challenge of making autonomous vehicles as comfortable as possible, should be tackled. This immediately leads to the questions what comfort during driving exactly is and how to measure it. A survey was conducted by researchers of the university of Warwick with as research question: Do passengers prefer autonomous vehicles be driven as full efficiency machines or in a way that emulates averaged human behaviour? [13] The result suggested that a blend of both is appealing the most confidence by user of a autonomous vehicle.
Driving comfort is a personal experience and also depend on the current emotional state of the driver. This means that more than one driving style for autonomous vehicle-driving should be identified for a certain vehicle. [15] The state of the driver can be communicated with the vehicle at the start of each ride and different driving styles can be obtained by changing the parameters in the path planning algorithm.

FIGURE 1.1: Concept visualization of autonomous driving. (source: [4])

1.0.2 Link with previous studies and problem formulation

In order to identify the specific comfort preferences of the driver that are quantized by these parameters, the vehicle should be able to learn them by demonstration. [7] Despite that each driver has its own preferences, they are based on a common notion of comfort where only different trade-offs are made. For example some drivers prefer more aggressive driving behaviour than others which will manifests itself in a different trade-offs of different comfort criteria than for example a defensive drivers. This will later in this thesis be translated into a comfort objective where different weights are used in order to quantify different comfort trade-offs made. This approach is in literature called inverse optimal control because it is learning the objective function of the comfort optimization. The lower the outputted value of this comfort objective, the higher the measurement of attained comfort will be in the later path planning algorithm.

In order to find comfort criteria which can be used to distinguish different drivers, research about the common notion of comfort is necessary. Passenger surveys in public road transport about carsickness [12] have identified lateral acceleration as the primarily responsible for motion sickness. It is explained that drive style is a main factor to influence the amount of sickness and it was found that sickness is higher when drivers drove with a higher average magnitude of fore-and-aft and lateral motion. These effect were found far more significant than the effect of vertical vibrations. There is also a consensus reached about the contribution of continuous trajectories to the prevention of motion sickness and the natural feel of paths.[5] This means that higher order kinematic variables like accelerations and jerks also should be considered when measuring comfort.

1.0.3 Thesis objective

The goal of this thesis is to build further on the research of learning by demonstration [7] and to refine this idea in a good working practical application. The thesis is more concretely focussed in the ability to explain driver data and the practical implementation and validation of a learning algorithm that is able to capture user specific driving preferences in weights of a comfort objective function. The learning process is to be done offline and is based on an inverse optimal control approach. A comfort objective will be derived from literature to describe the common notion of comfort and this will be fitted on individual driver data to produce driver specific parameters. In the next step this objective function will be used in a path planning MPC formulation which will be calculating online feasible and comfortable paths whereafter an tracking MPC algorithm will follow it.

To conduct the inverse learning control there is first look at data generated by simulations where it is assumed that the vehicle is driving on an straight road and high way speed when executing manoeuvrers as lane changes and longitudinal accelerations.

An example lane change can be seen in Figure 1.2. Assumptions made during this manoeuvre To be able to make the generated data of high quality an MPC approach with a 15 degree of freedom vehicle model is used. Also in the learning algorithm itself a three degree of freedom non-linear bicycle model is used in order to adequately capture the different kinematic signals e.g. jerks and accelerations. Further there were comparisons made of different methods to learn from multiple datasets.

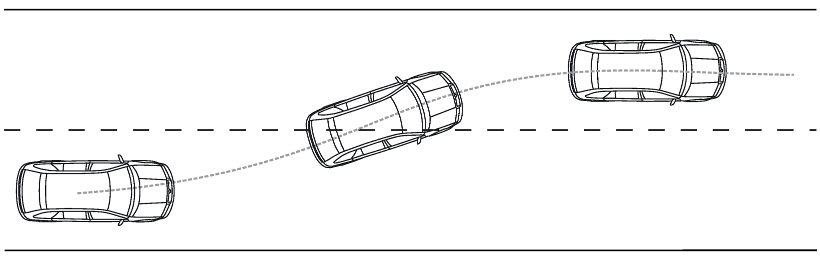

FIGURE 1.2: Example lane change as used as input in the inverse optimal control algorithm.

The execution of this research is conducted with the support of "Siemens Digital Industries Software - NVH R&D engineering department" located in Leuven which made it possible to preserve the direct link with reality. Software was made available e.g. Simcenter Amesim and the possibility to validate the obtained algorithms with real driver data made it possible to make the results that could be obtained more significant.

Chapter 2

State of the art modelling of comfort

As discussed in the introduction the goal of the thesis is to learn and implement a method to capture personal experience of comfort in autonomous driving. This will be done by using an inverse optimal control approach where the weights are learned from demonstration. To be able to do this it is necessary that a literature study is done about how to define comfort in a vehicle and to gain information about inverse optimal control.
This chapter will give an overview of the literature that is available and will show how the thesis will fit in earlier conducted research.

2.1 What are the parameters that define comfort during driving?

In the following US patent [3] the idea is to assess the amount of comfort by calculating a value for carsickness. This value is calculated by a weighted sum of the sway motion, surge motion and heave motion of the vehicle. These motions are being directly calculated from the lateral acceleration, fore-aft acceleration and the vertical acceleration of the vehicle.

In the paper 'Investigating ride comfort measures in autonomous cars' [5], it is explained that due to the introduction of autonomous vehicles there will be an other perception of comfort. Figure 2.1 indicates in blue the claimed traditional comfort factors and in red the new ones that also have to be taken into account in when driving in autonomous vehicles. Concretely this can be translated into the preference of smooth trajectories and low lateral motions when the roads are assumed to be sufficiently smooth. A hypotheses is that motion sickness will be more prominent in autonomous driving due to the loss of control. Is is also argued that the amount of travel time and the distance to an obstacle are naturally parameters that contribute to a comfortable feeling.

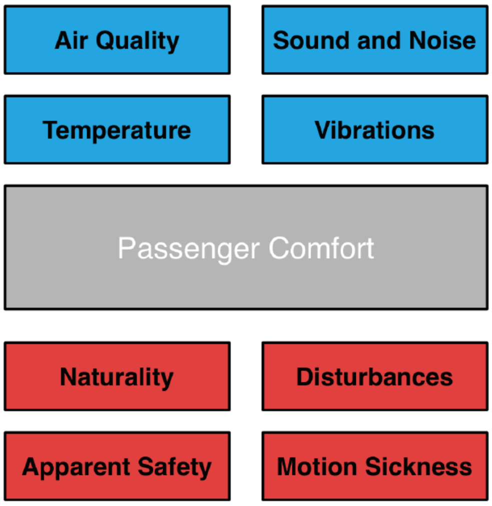

Figure 2.1: Overview of comfort parameters in autonomous vehicle with old parameters (blue) and new ones (red).(Source: [5])

In 'Analysis of Driving Style Preference in Automated Driving' [2] three studies are conducted in order to capture the definition of comfortable driving in autonomous vehicles. In the first study drivers drove manually with their own driving styles and this data was used in order to look for relevant metrics that could be used in defining distinct driver styles.

In a second study are the main metrics found from study one varied in order

2.1.1 Conclusion

sectionModelling of comfort

2.1.2 Machine learning

2.1.3 Inverse optimal control

2.1.4 How to model a driver and trajectory

2.1.5 Why do we use the entropy distribution?

2.1.6 RPROP

2.2 Conclusion

Chapter 3

The Learning Algorithm

Herinner de lezer nog even de structuur die gaat worden gevolgd. Learning, planning, tracking, validatie. Dit hoofdstuk zal over de learning gaan. Hoe is algorithm opgebouwd? Wrm wordt dit zo gedaan? Welke vehicle modellen wordt er gebruikt? Wrm mag men hier een simple vehicle mode gebruiken? Dit is gemachtigd omdat men hier de omgeving wil scannen voor een feasible pad –> dit wordt trager gedaan dan de tracking.(tracking zal gebruik maken van een meer complex model) Path planning ligt focus vooral op de omgeving. Goed refereren naar het rapport en VS rapport Wat zijn de assumpties die werden genomen?
Hoe zal de methode gevalideerd worden? Leg de twee methodes uit: code generatie en kijken of de wegings factoren terug gevonden kunnen worden? Mappen de feature values met de values van het geobserveerde pad? –> is het doel dat gevolgd probeert te worden haalbaar?
Ga hier niet meer te diep in op de entropie. Leg het hier meer intuitief uit om de lezer niet te verwaren.
Vermeld afleiding van algortihm. Leg uit in Thesis hoe komt aan gradient die gebruikt. Zie papers: Ziebart et al and Kretzschmar et al.
Modeleer een andere bestuurder. Can try to reproduce a data set with a change of parameters which represents a different driver. Can check that the learned model is also different. Hiermee aantonen dat er ook echt andere wegingsfactoren worden gegenereerd en dat de specifieke driving characteristics worden meegenomen.
Ligt een tipje van de sluier op : hoe zal de data gegenereerd worden? Plot simulink model en duidt de blokken aan die zullen worden ingevuld. Hier gaat dieper in gegaan worden in de volgende hoofdstukken.
Maak een vermelding dat men het menselijke gedrag van het geleerde model kan nagaan met een Turing test.

Maak een plotje zoals paper Learning to Predict Trajectories of Cooperatively Navigating Agents –> feature variance afwijking en average error. (zelfde plotjes als al de papers)

Schrijf een paragraaf over hoe de data gegenereerd wordt. –> leg kort het gebruik

van de verschillende vehicle modellen uit.
Schrijf een paragraaf over de theta update –> zie RPROP methode –> beschrijf wrm beter is dan andere methodes die gezien werden. Bespreek hoe de parameters werden gekozen.
Kan vermelding maken dat in deze thesis de features zijn gekozen met de hand –> men kan proberen om de features ook te leren van date (Characterizing Driving Styles with Deep Learning)

3.1 The First Topic of this Chapter

Chapter 4

Background in optimal control problems

This chapter gives some background information of the theory behind optimal control (OCP). After a global introduction and the discussion about the time discretization and shooting option, the chapter is being specified into model predictive control (MPC).

4.0.1 Optimal control problem (OCP)

An optimal control problem determines the desired inputs and corresponding state trajectories to change the system from an initial state to a desired final state in an optimal way while satisfying some input and state constraints [8].

$$
\begin{aligned}
\min_{\boldsymbol{q}(.),\boldsymbol{u}(.)} \quad & \int_0^T l(\boldsymbol{q}(t), \boldsymbol{u}(t))dt + E(\boldsymbol{q}(T)) \\
\text{s.t.} \quad & \dot{\boldsymbol{q}}(t) = \boldsymbol{f}(\boldsymbol{q}(t), \boldsymbol{u}(t)) \\
& \boldsymbol{q}(0) = \boldsymbol{q}_0, \;\; \boldsymbol{q}(T) = \boldsymbol{q}_T \\
& h(\boldsymbol{q}(t), \boldsymbol{u}(t)) \geq 0 \\
& \boldsymbol{q}(t) \in Q, \quad \boldsymbol{u}(t) \in U, \quad t \in [0, T]
\end{aligned}
\tag{4.1}
$$

$\boldsymbol{q}$ is called contains all the states of the system and $\boldsymbol{u}$ containing the controls. In the context of vehicle control states are often kinematic variables like positions and velocities of the centre of gravity of the vehicle. $\boldsymbol{u}$ is containing the controls which are typically steerwheelangle and the amount of throttle which can be directly linked the amount of propulsion force. The objective function l of the optimization problem is integrated over the desired control horizon T. The objective function indicates what should be minimized and is a function of the different states and controls. The terminal cost is represented by $E(\boldsymbol{q}(T))$ and can be needed to assure certain conditions of the system at the end of the control horizon. $\dot{\boldsymbol{q}}(t)$ describes the dynamics of the system by an explicit ordinary differential equation. Furthermore there are also constraints possible on states and inputs, represented by h, Q and

U respectively. The results that come out of an OCP indicate which states will be visited by the system and which controls have to be applied in order to do this with respect to the constraints on an optimal manner. [9]

There is a difference between soft and hard constraints. Soft constraints are placed in the objective function l. If the constraint is better fulfilled a more optimal solution will be obtained. A hard constraint, represented by h in equation 4.1, is explicitly put in the constraints and defines the feasible solution set of the optimization [14].

4.0.2 Time discretization

The optimal control problem (equation 4.1) is continuous in time which means that it has infinite dimensions. To be able to run the optimization problem on digital systems there is need for discretization. There are several ways to do this which are summarized in Figure 4.1.

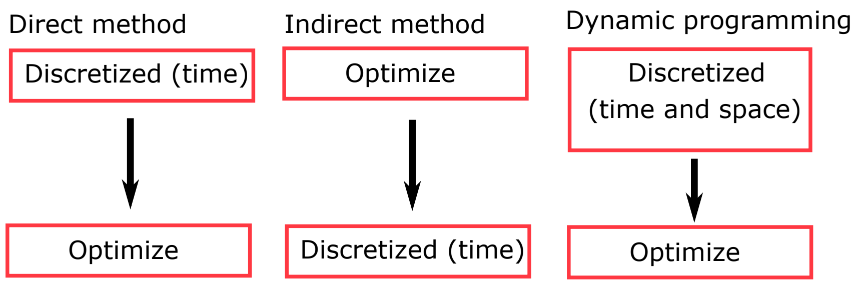

Figure 4.1: Overview of different discretization methods.

Since direct methods are best suited to solve practically relevant OCPs [8], this thesis is following the direct method. To implement the discretization of time when using the Direct method, a time shooting approach can be used.

Time shooting

A shooting approach makes use of a time grid. This means that time will be sampled and on every time instant the optimal control problem is assessed. Constraints will only be not violated on these time instants but no limits are set between different time samples. To bound the system to the constraints a high enough sampling rate is desired. [8] Two different shooting approaches exist:

1. Multiple shooting (MS)
   During multiple shooting $ns \in \mathbb{N}$ new states and $nc \in \mathbb{N}$ new controls are defined on every new time sample and are taken as optimization variables. Because input changes are only allowed on the time samples this will often lead to a piece wise control input signal. This is indicated by the blue bars in Figure 4.2 (left). The red dots in Figure 4.2 (left) indicate the condition

of the states on the discrete time samples. In order to make the connection $\boldsymbol{q}(k+1) = \boldsymbol{f}(\boldsymbol{q}(k), \boldsymbol{u}(k))$ from the previous state to the next, time integration is used. The constraints introduced in this way are called in literature 'path closing constraints' [6].

2. Single shooting (SS)
   In the single shooting or sequential approach only the initial state and control points are optimization variables. This is achieved by replacing the state variable by the integration result from the previous state [6]. This approach is show in equation 4.2. Figure 4.2 (right) gives a visualization with the green dots indicating the result of one integration step from the previous state.

$$\begin{aligned} \boldsymbol{q}(1) &= \boldsymbol{f}(\boldsymbol{q}(0), \boldsymbol{u}(0)) \\ \boldsymbol{q}(2) &= \boldsymbol{f}(\boldsymbol{f}(\boldsymbol{q}(0), \boldsymbol{u}(0)), \boldsymbol{u}(1)) \\ \boldsymbol{q}(3) &= \boldsymbol{f}(\boldsymbol{f}(\boldsymbol{f}(\boldsymbol{q}(0), \boldsymbol{u}(0)), \boldsymbol{u}(1)), \boldsymbol{u}(2)) \\ &\ldots \end{aligned} \tag{4.2}$$

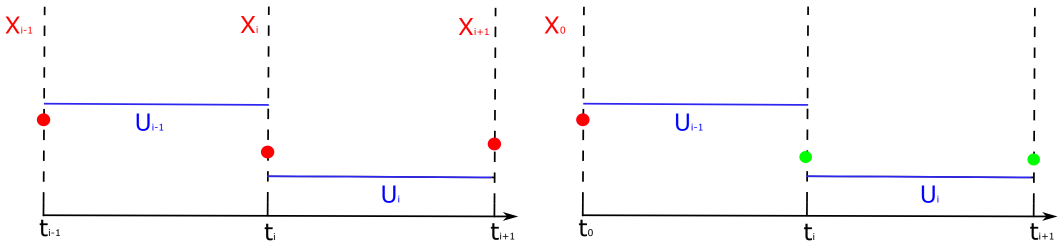

FIGURE 4.2: Schematic view of the time shooting approaches (left: multiple shooting; right: single shooting).

In this thesis a multiple shooting approach is used together with the use of a Runge-Kutta integration scheme. Runge-Kutta is an explicit integration scheme which has a higher calculation cost than a standard Euler scheme but is more reliable for non-linear systems and has a higher stability with respect to the chosen time-step [8].

Multiple shooting will lead to a larger Hessian of the objective function and a larger Jacobian of the constraints in comparison with the single shooting approach due to the fact that more optimization variables are introduced. But on the other hand, multiple shooting has a sparse Hessian which can be solved very effectively. Single shooting would instead often produce a smaller fully populated Hessian because of the very non-linear way that the states depend on the begin state and the different controls.

4.0.3 Model predictive control

MPC is already a mature approach in slow changing environments such as a chemical plant, but has more recently made also his breakthrough to the fast dynamic systems due to an increase of computational power and the implementation of new algorithms [8].

In order to be able to deal with model-plant mismatch and disturbances, MPC uses in this paper a moving control horizon. The time horizon is divided in discreet steps T_s and inputs are calculated over the finite prediction horizon $N \cdot T_s$ by solving an OCP. The decision on the amount of samples taken to define the control horizon is based on a trade off between calculation effort and accuracy [11, 8]. Figure 4.3 depicts the solving of the OCP on time sample $t+1$. In Figure 4.4 it can be seen how only the first control sample of the calculated control signal will be applied to the system and a new OCP is solved.

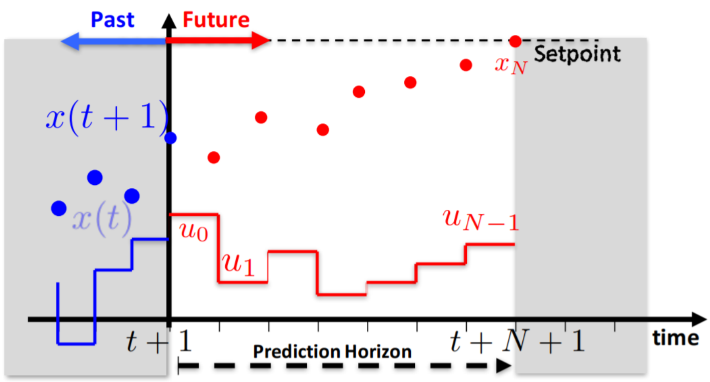

Figure 4.3: Visualization of the optimal control problem solved in one iteration of the MPC (Source: [9]).

Equation **??** is a representation of the solved discrete system OCP during one iteration of the MPC. It is a discretized version of equation 4.1. The Runge-Kutta integration is embedded in $\boldsymbol{f}$. The hard constraints are represented by h. It is worth noticing that the constraints can be violated in-between the different time sample points.

MPC has no direct feedback loop, but through the iterative way of solving the OCPs it can still deal with model mismatch or a changing environment. The downside of this approach is that it requires a bigger computational load, which makes efficiently written software a necessity.

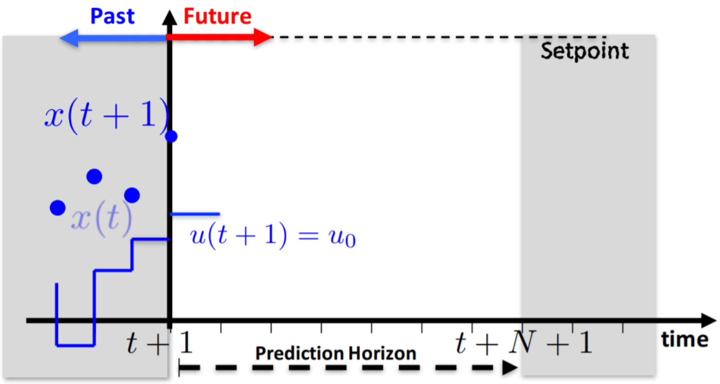

FIGURE 4.4: Visualization of the application of the first step of the calculated control signal during one iteration of the MPC (Source:[9]).

Chapter 5

Path Planning MPC

MPC –> path planning met het gevonden model.
Ga hier volledig in op wat MPC is. Valideer de MPC code door na te gaan wat de invloed is bij het varieren van de gevonden parameters. Hoeveel zal het verschillen? Ga in op het gebruikte point model/non-linear model en bespreek de gelijkenissen en de verschillen van het learning algorithm. (zie ook notes VS en verbeteringen NAETS)

Chapter 6

Path tracking MPC

MPC –> path tracking met non lin model. Bespreek non lin model Bespreek resultaten. Valideer de resultaten. Wat gebeurd er als de parameteres iets anders worden geschat? Zeker de parameters voor de banden zijn moeilijk om te schatten. Bespreek de tekort komingen van de het model en valideer het model hoe de referencie wordt getrackt met andere parameter values. hoe robuust is de mpc? (Zei paper VS)

Hier kan men praten over de implementatie in het simulink model. Het zou goed zijn om het ACADO model te vervangen door een tracking MPC die in CasADi geschreven is. (reference path to follow wordt niet geupdated maar blijft constant in model –> dit is niet hoe het werkt in de realiteit.) Kan als echt tegoei wilt doen ook inladen in de template die gekregen heb van Flavia –> PID vervangen door MPC en path planner. Een simulink model is nodig om er het 15 dof vehicle model in te kunnen verwerken.

6.1 The First Topic of this Chapter

6.1.1 Item 1

Sub-item 1

Sub-item 2

6.1.2 Item 2

6.2 The Second Topic

6.3 Conclusion

Chapter 7

Validatie

Bespreek de validatie van de methode. Implementeer similaties in prescan. Bespreek de verschillende software tools bij Siemens –> Amesim, simulink, prescan. Hoe werken ze samen en hoe wordt de validatie precies gedaan? Wat zijn de resultaten? Install amesim and write a chapter about how the dataset is generated. How is the amesim model defined etc.

7.1 The First Topic of this Chapter

7.1.1 Item 1

Sub-item 1

Sub-item 2

7.1.2 Item 2

7.2 The Second Topic

7.3 Conclusion

Chapter 8

Conclusion

The final chapter contains the overall conclusion. It also contains suggestions for future work and industrial applications.

Appendices

Appendix A

The First Appendix

Appendices hold useful data which is not essential to understand the work done in the master's thesis. An example is a (program) source. An appendix can also have sections as well as figures and references[**?**].

Appendix B

The Last Appendix

Appendices are numbered with letters, but the sections and subsections use arabic numerals, as can be seen below.

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