Adding Neural Network Controllers to Behavior Trees without Destroying Performance Guarantees

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Abstract—In this paper, we show how controllers created using data driven designs, such as neural networks, can be used together with model based controllers in a way that combines the performance guarantees of the model based controllers with the efficiency of the data driven controllers. The considered performance guarantees include both safety, in terms of avoiding designated unsafe parts of the state space, and convergence, in terms of reaching a given beneficial part of the state space. Using the framework Behavior Trees, we are able to show how this can be done on the top level, concerning just two controllers, as described above, but also note that the same approach can be used in arbitrary sub-trees. The price for introducing the new controller is that the upper bound on the time needed to reach the desired part of the state space increases. The approach is illustrated with an inverted pendulum example.

Index Terms—Neural Networks, Machine Learning, Performance guarantees, Safety, Behavior Trees

I. INTRODUCTION

The use of artificial neural networks (ANN) in machine learning has shown remarkable success in a variety of applications, ranging from playing board games [1] to transferring the artistic style of paintings [2]. Now with computational resources being more capable than ever before, training of ANNs with multiple hidden layers has become feasible, which have shown significant potential in complicated control tasks [3].

Although promising strides have been made in the application of ANNs to models of real-world mission-critical systems with complicated dynamics, such as spacecraft [4], there remains an obstruction: lack of safety guarantees. Many interesting robotic applications that require a high level of autonomy in remote environments, such as underwater vehicles and spacecraft, could benefit from ANNs, but are disenfranchised by their inherent uncertainty.

In this paper we seek to find a way to combine the ability of ANNs to learn complicated control tasks, namely optimal control, with the safety guarantees of a model based controller. We focus on the task of optimally swinging up and stabilizing an inverted pendulum.

In order to render this combination of safety and performance, we attempt to combine multiple controllers into one with the use of behaviour trees [5], which have been shown to enable task switching in a reactive and modular fashion. Specifically we combine an ANN controller, that has learned an optimal control policy, with two other controllers, one with safety guarantees and one with convergence guarantees, see Figure 1.

It is well known that learning algorithms might cause unsafe behavior. Both during training, and possibly even after training, as it can be hard to guarantee performance in all cases. Therefore, safety of learning approaches is a very active research area, [6]–[10].

In [8] Constrained Markov Decision Problems (CMDPs) were used, and the cumulative cost was replaced by a stepwise one, which was then transferred into the admissible control set leading back to a standard MDP formulation.

There is also a set of approaches using Lyapunov ideas, originating in control theory. In [9] a Lyapunov approach was used to guarantee stability of an RL agent. The agent was allowed to switch between a given set of controllers that were designed to be safe no matter what switching strategy was used. Then, in [10], Lyapunov concepts were used to iteratively estimate the region of attraction of the policy, i.e., the region that the state is guaranteed not to leave, when applying the controller at hand. At the same time, while being in this safe region, the estimate of the region, as well as performance, was improved. Finally, Chow et al. used the CMDPs to construct Lyapunov functions using linear programming, [7]. The approach is guaranteed to provide feasible, and under certain assumptions, optimal policies.

Our approach differs from all of the above by using the properties of the switching structure, Behavior Trees (BTs), to combine the properties of the three different controllers, instead of focusing on endowing the learning controller itself with safety.

Fig. 1: The Behavior Tree that governs the switching between the controllers. If Safety is not ok, the emergency controller will be executed. Else, if the execution time is not ok, the model based controller will be executed. If neither of those problems occur, the neural network controller will be executed.
The main contribution of this paper is that we show how BTs can be used to combine the efficiency of an ANN controller with the convergence of a model based controller, and the safety of a hand crafted controller.

The outline of the paper is as follows. In Section II we present background material. Then, in Section III we formulate the problem as well as our proposed solution. The safety and convergence of the approach is analyzed in Section IV and the efficiency in Section V. Finally, conclusions are drawn in Section VI.

II. BACKGROUND

A. Optimal Control and Databases of Optimal Trajectories

In this paper we focus on the normalised state equations of motion of an inverted pendulum, as adapted from [11], given by the following first order system,

\[ \dot{s} = \begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} v \\ u \\ \omega \end{bmatrix} = f(x,u), \quad (1) \]

where the variables are: \( x \) cart position, \( v \) cart velocity, \( \theta \) pole angle (clockwise from upright), \( \omega \) pole angular velocity, and \( u \in [-\bar{u}, \bar{u}] \) control input with \( \bar{u} \) its maximum magnitude.

We define a trajectory cost functional

\[ J = \int_{0}^{T_f} u^2 d\tau \quad (2) \]

and using Pontryagin’s minimum principle [12] define the Hamiltonian

\[ \mathcal{H} = -\lambda_\omega (u \cos(\theta) - \sin(\theta)) + \lambda_\theta \omega + \lambda_v u + \lambda_x v + u^2. \quad (3) \]

We minimize the Hamiltonian and retrieve the optimal control as a function of both states and costates

\[ u^* = \frac{\lambda_\omega \cos(\theta)}{2} - \frac{\lambda_v}{2}. \quad (4) \]

Lastly, we compute the costate equations of motion

\[ \dot{\lambda} = -\nabla_u \mathcal{H} = \begin{bmatrix} 0 \\ -\lambda_x \\ -\lambda_\omega (u \sin(\theta) + \cos(\theta)) \end{bmatrix}. \quad (5) \]

Considering the task of swinging up the pendulum, we nominate initial and terminal state constraints

\[ s(t_0) = \begin{bmatrix} 0 & 0 & \pi & 0 \end{bmatrix}^T, \quad (6) \]

\[ s(t_f) = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}^T, \quad (7) \]

as well as the free-time condition

\[ \mathcal{H}(s(\tau), \lambda(\tau), u(\tau)) = 0. \quad (8) \]

The trajectory optimization problem then becomes: choose \( \tau_1 \) and \( \lambda(\tau_0) \) such that the constraints are satisfied.

We first solve for a nominal trajectory, then execute random-walks, exploiting the homotopy of the state dynamics by resolving the problem from randomly perturbed states along the trajectory, see [4]. Through this process we are able to generate large databases of optimal control trajectories, whose state-control pairings can be used to train a universal function approximator, namely a neural network, to supply the optimal control in real-time. Examples of these databases are shown in Figure 2 and Figure 3.

![Fig. 2: A plot of 354918 state trajectories, illustrating the position of both the cart and the pole. Note that the cart moves horizontally at \( y = 0 \), and the tip of the pole ends at \( x = 0, y = 1 \) in an upright position for all trajectories.](image1)

![Fig. 3: The control trajectories over time for the 354918 state trajectories of Figure 2.](image2)

B. Model based controller for inverted pendulum

For the safe controller used in this paper, we implement the globally asymptotically stable controller of [13]. Using the normalized pendulum dynamics of Equation (1), the control law reads:

\[ u = \frac{\omega k_\omega + k_\theta (\theta - \theta_i) + k_\theta \tan^{-1} (k_v v + k_x x)}{\cos(\theta)} \quad (9) \]

\[ u = \min (\max (u, -\bar{u}), \bar{u}) \quad (10) \]

where the reference angle is

\[ \theta_{i,j+1} = \begin{cases} \theta_{i,j} - 2\pi & \text{if } -\pi \leq \theta_i - \theta_{i,j} \leq -\bar{\theta} \\ \theta_{i,j} & \text{if } -\bar{\theta} < \theta_i - \theta_{i,j} < \bar{\theta} \\ \theta_{i,j} + 2\pi & \text{if } \bar{\theta} \leq \theta_i - \theta_{i,j} \leq \pi \end{cases} \quad (11) \]

and \( \bar{\theta} \) is the smallest positive value that satisfies

\[ k_\theta (-\theta_i + \bar{\theta}) + k_\theta \tan^{-1} (\pi k_v u_m + \pi^2 k_x (u_m + \pi)) - \pi u_m \cos(\bar{\theta}) + \sin(\bar{\theta}) = 0. \quad (12) \]

With a proper choice of controller gains

\[ k_\theta > (1 + k_\omega) \quad (13) \]

\[ k_\theta, k_\omega \gg k_x, k_v > 0 \quad (14) \]

the state \( \theta = \theta_i, \omega = x = v = 0 \) is globally asymptotically stable.
C. Classical Formulation of BTs

A BT [14]–[20] is a directed rooted tree where the internal nodes are called control flow nodes and leaf nodes are called execution nodes. For each connected node we use the common terminology of parent and child. The root is the node without parents; all other nodes have one parent. The control flow nodes have at least one child. Graphically, the children of a node are placed below it, see Figure 1.

A BT starts its execution from the root node that generates signals called Ticks with a given frequency. These signals allow the execution of a node and are propagated to one or several of the children of the ticked node. A node is executed if and only if it receives Ticks. The child immediately returns Running to the parent, if its execution is under way, Success if it has achieved its goal, or Failure otherwise.

In the classical formulation, there exist two main categories of control flow nodes (Sequence and Fallback) and two categories of execution nodes (Action and Condition).

The Sequence node routes the Ticks to its children from the left until it finds a child that returns either Failure or Running, then it returns Failure or Running accordingly to its own parent. It returns Success if and only if all its children return Success. Note that when a child returns Running or Failure, the Sequence node does not route the Ticks to the next child (if any). The symbol of the Sequence node is a box containing the label “→”.

The Fallback node routes the Ticks to its children from the left until it finds a child that returns either Success or Running, then it returns Success or Running accordingly to its own parent. It returns Failure if and only if all its children return Failure. Note that when a child returns Running or Success, the Fallback node does not route the Ticks to the next child (if any). The symbol of the Fallback node is a box containing the label “?”.

When an Action node receives Ticks, it executes a command. It returns Success if the action is successfully completed or Failure if the action has failed. While the action is ongoing it returns Running.

When a Condition node receives Ticks, it checks a proposition. It returns Success or Failure depending on if the proposition holds or not. Note that a Condition node never returns a status of Running.

D. Theoretical Results and Statespace Formulation of BTs

In this section we will briefly review some results from [5] that will be needed to prove the overall properties of the behavior tree. To follow the notation of [5], in this section, \( x \) and \( x_0 \) denote the complete state of the system, whereas in the rest of the paper, \( s \) denotes the complete state and \( x \) denotes the position of the cart.

**Definition 1 (Behavior Tree):** A BT is a three-tuple
\[
\mathcal{T} = \{f_i, r_i, \Delta t\}, \tag{15}
\]
where \( i \in \mathbb{N} \) is the index of the tree, \( f_i : \mathbb{R}^n \to \mathbb{R}^n \) is the right hand side of an ordinary difference equation, \( \Delta t \) is a time step and \( r_i : \mathbb{R}^n \to \{R, S, F\} \) is the return status that can be equal to either Running (R), Success (S), or Failure (F).

Let the Running/Activation region \( (R_i) \), Success region \( (S_i) \) and Failure region \( (F_i) \) correspond to a partitioning of the state space, defined as follows:
\[
\begin{align*}
R_i &= \{ x : r_i(x) = R \} \tag{16} \\
S_i &= \{ x : r_i(x) = S \} \tag{17} \\
F_i &= \{ x : r_i(x) = F \}. \tag{18}
\end{align*}
\]

Finally, let \( x_k = x(t_k) \) be the system state at time \( t_k \), then the execution of a BT \( \mathcal{T} \) is a standard ordinary difference equation
\[
x_{k+1} = f_i(x_k), \tag{19}
\]
\[
t_{k+1} = t_k + \Delta t. \tag{20}
\]

The return status \( r_i \) will be used when combining BTs recursively, as explained below.

**Definition 2 (Sequence compositions of BTs):** Two or more BTs can be composed into a more complex BT using a Sequence operator,
\[
\mathcal{T}_0 = \text{Sequence}(\mathcal{T}_1, \mathcal{T}_2). \tag{26}
\]

Then \( r_0, f_0 \) are defined as follows
\[
\begin{align*}
\text{If } x_k &\in S_1 & \text{ then } r_0(x_k) &= r_2(x_k) \tag{21} \\
\text{ and } \text{ else } & & f_0(x_k) &= f_2(x_k) \tag{23}
\end{align*}
\]

\[
\begin{align*}
\text{If } x_k &\in S_1 & \text{ then } r_0(x_k) &= r_1(x_k) \tag{24} \\
\text{ and } \text{ else } & & f_0(x_k) &= f_1(x_k). \tag{25}
\end{align*}
\]

\( \mathcal{T}_1 \) and \( \mathcal{T}_2 \) are called children of \( \mathcal{T}_0 \). Note that when executing the new BT, \( \mathcal{T}_0 \) first keeps executing its first child \( \mathcal{T}_1 \) as long as it returns Running or Failure. The second child is executed only when the first returns Success, and \( \mathcal{T}_0 \) returns Success only when all children have succeeded, hence the name Sequence.

For notational convenience, we write
\[
\text{Sequence}(\mathcal{T}_1, \text{Sequence}(\mathcal{T}_2, \mathcal{T}_3)) = \text{Sequence}(\mathcal{T}_1, \mathcal{T}_2, \mathcal{T}_3), \tag{26}
\]
and similarly for arbitrarily long compositions.

**Definition 3 (Fallback compositions of BTs):** Two or more BTs can be composed into a more complex BT using a Fallback operator,
\[
\mathcal{T}_0 = \text{Fallback}(\mathcal{T}_1, \mathcal{T}_2). \tag{27}
\]

Then \( r_0, f_0 \) are defined as follows
\[
\begin{align*}
\text{If } x_k &\in F_1 & \text{ then } r_0(x_k) &= r_2(x_k) \tag{28} \\
\text{ and } \text{ else } & & f_0(x_k) &= f_2(x_k) \tag{29}
\end{align*}
\]

\[
\begin{align*}
\text{If } x_k &\in F_1 & \text{ then } r_0(x_k) &= r_1(x_k) \tag{30} \\
\text{ and } \text{ else } & & f_0(x_k) &= f_1(x_k). \tag{31}
\end{align*}
\]
Note that when executing the new BT, \( T_1 \) first keeps executing its first child \( T_2 \) as long as it returns Running or Success. The second child is executed only when the first returns Failure, and \( T_0 \) returns Failure only when all children have tried, but failed, hence the name Fallback.

For notational convenience, we write

\[
\text{Fallback}(T_1, \text{Fallback}(T_2, T_3)) = \text{Fallback}(T_1, T_2, T_3),
\]

and similarly for arbitrarily long compositions.

**Definition 4 (Finite Time Successful):** A BT is Finite Time Successful (FTS) with region of attraction \( R' \), if for all starting points \( x(0) \in R' \subseteq R \), there is a time \( \tau \), and a time \( \tau'(x(0)) \) such that \( \tau'(x) \leq \tau \) for all starting points, and \( x(t) \in R' \) for all \( t \in [0, \tau'] \) and \( x(t) \in S \) for \( t = \tau' \).

Note that exponential stability implies FTS, given the right choices of the sets \( S, F, R \), since a BT for which \( x_i \) is a globally exponentially stable equilibrium of the execution [19], and \( S \supset \{ x : ||x-x_i|| \leq \epsilon \} \), \( \epsilon > 0 \), \( F = \emptyset \), \( R = \mathbb{R}^n \setminus S \), is FTS.

**Lemma 1:** (Robustness and Efficiency of Sequence Compositions) If \( T_1, T_2 \) are FTS, with \( S_1 = R_1' \cup S_2 \), then \( T_0 = \text{Sequence}(T_1, T_2) \) is FTS with \( \tau_0 = \tau_1 + \tau_2 \), \( R_0' = R_1' \cup R_2' \) and \( S_0 = S_1 \cap S_2 = S_2 \).

Proof: See [5].

By **safety** we denote the ability to avoid a particular part of the statespace, which we for simplicity denote the **Obstacle Region**.

**Definition 5 (Safe):** A BT is safe, with respect to the obstacle region \( O \subseteq \mathbb{R}^n \), and the initialization region \( I \subseteq R \), if for all starting points \( x(0) \in I \), we have that \( x(t) \notin O \), for all \( t \geq 0 \).

In order to make statements about the safety of composite BTs, we also need the following definition.

**Definition 6 (Safeguarding):** A BT is safeguarding, with respect to the step length \( d \), the obstacle region \( O \subseteq \mathbb{R}^n \), and the initialization region \( I \subseteq R \), if it is safe, and FTS with region of attraction \( R' \supset I \) and a success region \( S \), such that \( I \) surrounds \( S \) in the following sense:

\[
\{ x \in X \subset \mathbb{R}^n : \inf_{s \in S} ||x-s|| \leq d \} \subset I,
\]

where \( X \) is the reachable part of the statespace \( \mathbb{R}^n \). This implies that the system, under the control of another BT with maximal state steplength \( d \), cannot leave \( S \) without entering \( I \), and thus avoiding \( O \); see Lemma 2 below.

**Lemma 2 (Safety of Sequence Compositions):** If \( T_1 \) is safeguarding, with respect to the obstacle \( O_1 \) initial region \( I_1 \), and margin \( d \), and \( T_2 \) is an arbitrary BT with \( \max_{x} ||x-f_2(x)|| < d \), then the composition \( T_0 = \text{Sequence}(T_1, T_2) \) is safe with respect to \( O_1 \) and \( I_1 \).

Proof: See [5].

### III. Problem and Proposed Approach

In this paper we will address the following problem:

**Problem 1:** Given three controllers, one reliable model based controller, a high performing neural network controller, and a safe emergency controller, can we use a behavior tree to combine the three so as to achieve safety, robustness and efficiency?

The proposed approach is built upon the structure depicted in Figure 1, which is also given with labels for the different sub-trees in Figure 4, where one should note the addition of a “near goal” condition. Since there is no advantage to using the ANN controller very close to the goal state, we default to the model based controller so as to ensure safe maintenance of the goal configuration. Pseudocode for the different components of the BT can be found in Algorithms 1-5.

**Algorithm 1:** Safety OK?

```plaintext
1 Function Tick()
2    if \(|x| \leq d_{safe} \) and ResettingPosition == False then
3        return Success
4    else
5        return Failure
```

where the safety distance \( d_{safe} \geq \pi^2(\pi+\bar{u}) \), where \( \bar{u} \) is the maximal acceleration of the cart, see [13], Eq (28). This is to make sure the model based controller has enough space.

**Algorithm 2:** Apply Emergency Controller

```plaintext
1 Function Tick()
2    if \(|x| > d_{safe} \) then
3        \( u = -\bar{u}\text{sgn}(x) \)
4    else
5        \( u = -k_x x - k_v v \)
6        \( k_x, k_v > 0 \)
7    if \( x \equiv 0 \) and \( v \equiv 0 \) then
8        ResettingPosition == False
9        return Success
10    else
11        ResettingPosition == True
12        return Running
13 return Running
```
Algorithm 3: Progress OK?
1 Function Tick()
2 if $\tau < T$ then
3 return Success
4 else
5 return Failure

Algorithm 4: Apply Model Based Controller
1 Function Tick()
2 Let $u$ be given by Equation [10]
3 return Running

Algorithm 5: Apply Neural Network Controller
1 Function Tick()
2 Let $u$ be given by an ANN trained on the data of Section II-A.
3 return Running

IV. SAFETY AND CONVERGENCE

In this section we prove that the proposed approach is indeed safe and FTS, i.e., converges to the goal configuration in finite time. Since the BT is running in discrete time, we let the equations of motion of the BT be the discretization of Eq. [1], i.e., $f_i(s) = s + f(s, u_i)\Delta \tau$, with different $u_i$ for the different controllers.

Looking at BT 1, first we let $S_1 = \{s : ||x|| \leq d_{safe}\}$ be the success region, where we allow the other controllers to execute. In order to be able to stop a cart that has been accelerated all across $S_1$, we must have some space between $S_1$ and $O_1$. Thus we let $O_1 = \{s : ||x|| > 3d_{safe} + d_1\}$ be the obstacle region, that we guarantee the state will never reach.

The initialization region, where we are sure to avoid crashing into $O_1$ is then $I_1 = \{s : d_{safe} + d_1 > ||x|| > d_{safe}\}$. Finally, let $R_1' \supset I_1$ be the region of attraction which we do not need to compute explicitly, as long as it contains $I_1$, which it does by the construction above (avoiding the obstacle is possible from $I_1$).

Furthermore we set the upper bound on the step length to satisfy $d_1 = \max_{s, i}||s - f_i(s)||$ which can be computed based on the max input $\bar{u}$ and the equations of motion in [1].

Now we will present a series of Lemmas, ending with Lemma 6 concluding that the overall controller is safe, and Lemma 8 concluding that it is finite time successful, which means that the overall system will converge to a neighbourhood of the goal in finite time.

**Lemma 3:** BT 1 is FTS with some region of attraction $R_1' \subset I_1$.

**Proof:** Looking at BT 1 it is clear that it for all starting points $s(0) \in I_1$, it will reach $S_1$ in finite time. \[\square\]

**Lemma 4:** BT 1 is safe with respect to the obstacle region $O_1$, and the initialization region $I_1$.

**Proof:** Looking at BT 1 it is clear that it for all starting points $s(0) \in I_1$, it will reach $S_1$ in finite time. \[\square\]
Fig. 8: The states over time for the scenario in Figure 7.

Fig. 9: At \( x \leq -4 \) the emergency controller is invoked to avoid getting too far from the origin.

Proof: Looking at BT 1 it is clear that it for all starting points \( s(0) \in I_1 \), we have that \( s(\tau) \notin O \), for all \( \tau \geq 0 \).

Lemma 5: BT 1 is safeguarding with respect to the obstacle region \( O_1 \) and the step length \( d_1 \).

Proof: According to Lemma 4 BT 1 is safe. We also have that \( R' \supset I \) and finally
\[
\{ s \in X : \inf_{z \in S} ||s - z|| \leq d \} \subset I,
\]
by construction, where \( X \) is the reachable part of the state space \( \mathbb{R}^n \).

Lemma 6: BT 123 is safe, independently of the content of BT2 and BT3.

Proof: First note that \( \max_s ||s - f_i(s)|| < d_1 \) for all controllers used by construction. Then the conclusion follows from Lemma 2 given the properties of Lemma 5 where we let \( \mathcal{F}_2 = \text{Sequence}(BT2, BT3) \).

Lemma 7: BT 2 is FTS when \( \tau > T \).

Proof: When \( \tau > T \) BT 2 always executes Eq. (10), which is known to be globally asymptotically stable, thus it is also FTS for any success region around the equilibrium point.

Lemma 8: BT 123 is FTS.

Proof: First note that if \( \tau > T \) then BT12 is equivalent to BT123, since BT3 is never executed. BT12 is FTS due to Lemma 1 considering the properties concluded in Lemma 3, Lemma 7 and the fact that \( S_2 = R'_2 \cup S_2 \). The later is a consequence from \( d_{safe} \) being chosen with respect to the region of attraction of BT 2. Furthermore, since BT 123 is safe, and is equivalent to BT12 when \( \tau > T \), we conclude that BT 123 is FTS.

V. EFFICIENCY AND SIMULATIONS

First we run a few simulations to illustrate the approach and then derive a table to assess the efficiency of it.

In Figures 5 and 6, the effects of the \textbf{Near goal?} condition can be seen. In Figures 7 and 8, the effect of the \textbf{Execution time Ok?} condition can be seen, and in Figures 9 and 10, the effect of the \textbf{Safety Ok?} condition can be seen.

We assess the performance of our behaviour tree and its ancillary controllers on the nominal swing up task described by the constraints in Equation (6). Considering the cost functional in Equation (2), from which the trajectory database in Fig 2 and 3 was generated, we nominate absolute impulse \( \int_0^T |u|dt \) as our primary performance metric. The absolute impulse, as well as convergence time, are supplied for each controller in Table I.

As expected, the Neural network controller has the best performance, in fact it is nearly optimal; however it still lacks safety guarantees. The model based controller had the worst performance, although it is formally guaranteed to converge. The behaviour tree, combining both the neural network and model based controller, not only has acceptable performance with respect to the nominal optimal trajectory, it is also guaranteed to converge and be safe.

| Control           | Average convergence time | Average impulse |
|-------------------|--------------------------|-----------------|
| Optimal           | 10.249                   | 3.696           |
| Neural network    | 10.253                   | 3.734           |
| Model based       | 20.161                   | 8.402           |
| Behaviour tree    | 14.785                   | 4.479           |

TABLE I: Swing up performance analysis of controllers with respect to nominal optimal control trajectory, averaged over 20 simulations.

VI. CONCLUSIONS

In this paper we have shown how Behavior Trees can be used to provide task switching between different controllers in a theoretically sound way. Enabling performance guarantees for the combined controller when the properties of the different parts satisfy certain conditions.
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