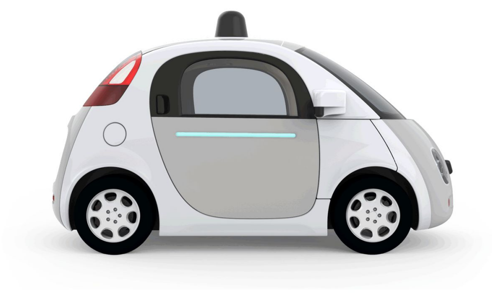
Safe Reinforcement Learning via Formal Methods

Nathan Fulton and André Platzer

Carnegie Mellon University

Safety-Critical Systems

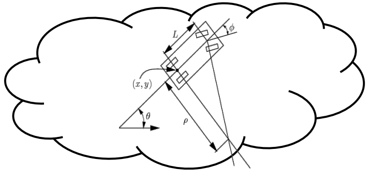


"How can we provide people with cyber-physical systems they can bet their lives on?" - Jeannette Wing

Autonomous Safety-Critical Systems

How can we provide people with **autonomous** cyber-physical systems they can bet their lives on?

Model-Based Verification Reinforcement Learning



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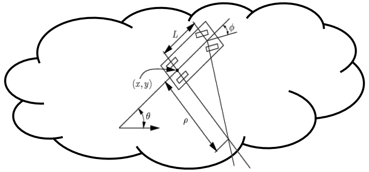
Model-Based Verification

Reinforcement Learning



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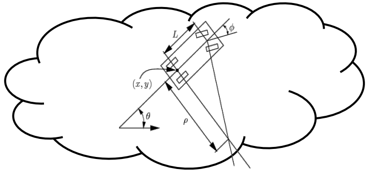

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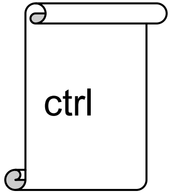

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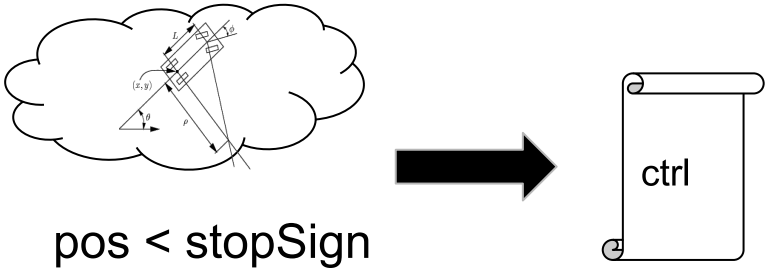

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Approach: prove that control software achieves a specification with respect to a model of the physical system.

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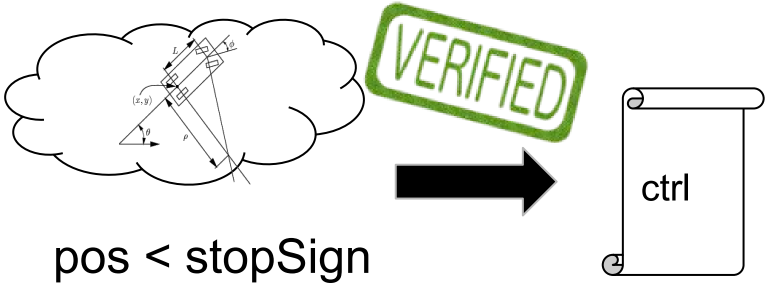

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Benefits:

- Strong safety guarantees
- Automated analysis

Reinforcement Learning

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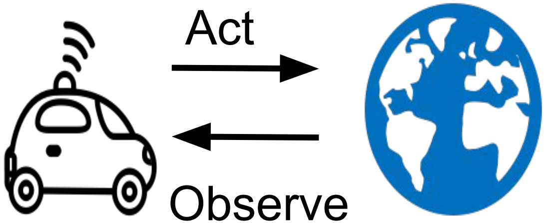

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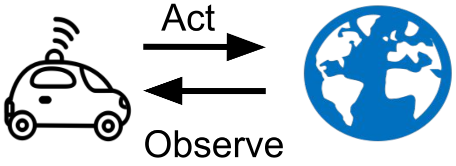

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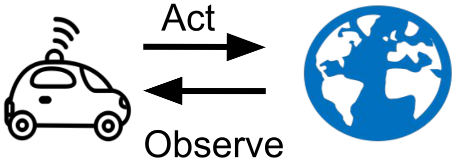

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- Formal proofs = decades-long proof development

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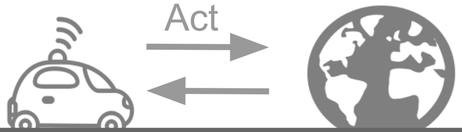

Goal: Provably correct reinforcement learning

Bene

- S ... del
- A ... s

Draw

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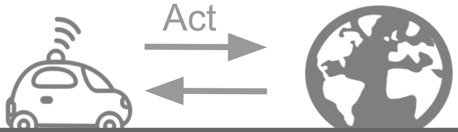

Goal: Provably correct reinforcement learning

1. **Learn Safety**
2. **Learn a Safe Policy**
3. **Justify claims of safety**

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Model-Based Verification

Accurate, analyzable models often exist!

```
{
   {?safeAccel;accel ∪ brake ∪ ?safeTurn; turn};
   {pos’ = vel, vel’ = acc}
}*
```

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Continuous motion

discrete control

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Continuous motion

discrete, ***non-deterministic*** control

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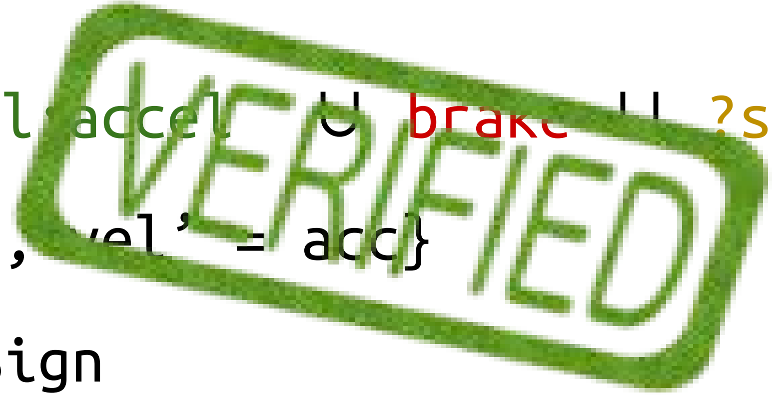

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- **Computer-checked proofs of safety specification.**

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- **Computer-checked proofs of safety specification**
- **Formal proofs mapping model to runtime monitors**

Model-Based Verification Isn't Enough

Perfect, analyzable models don't exist!

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How to implement?

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Only accurate sometimes

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    { ?safeAccel;accel  ∪  brake ∪  ?safeTurn; turn};
    {dx'=w*y, dy'=-w*x, ...}
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Our Contribution

Justified Speculative Control is an approach toward provably safe reinforcement learning that:

1. learns to resolve non-determinism without sacrificing formal safety results

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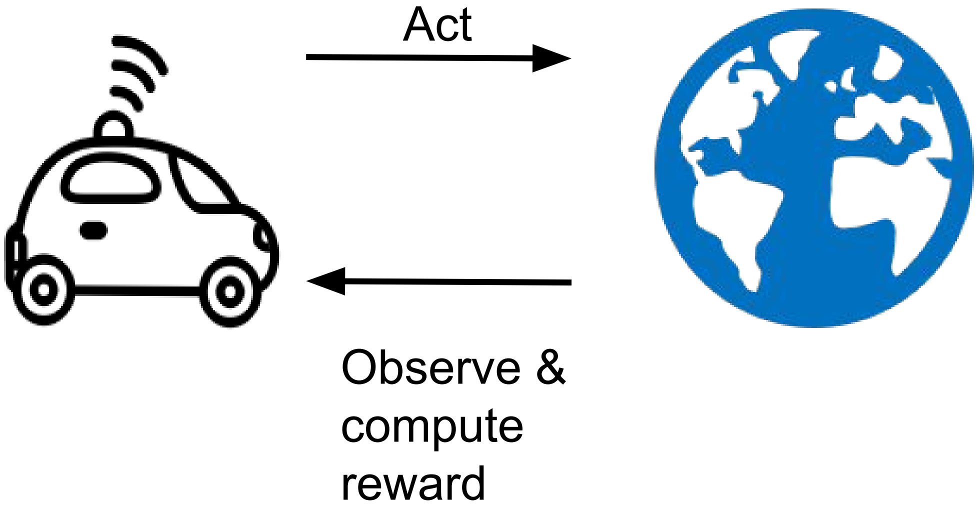
Justified Speculative Control is an approach toward provably safe reinforcement learning that:

1. learns to resolve non-determinism without sacrificing formal safety results
2. allows and directs speculation whenever model mismatches occur

Learning to Resolve Non-determinism



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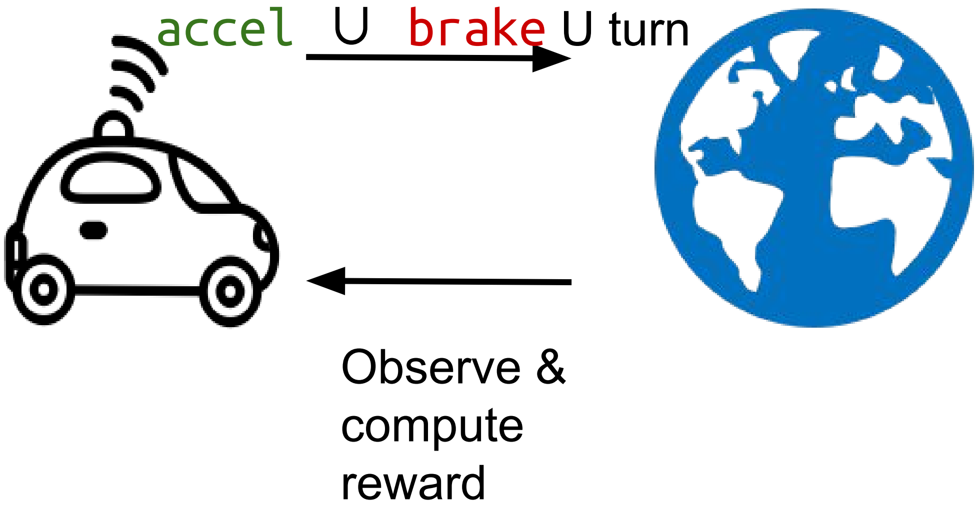

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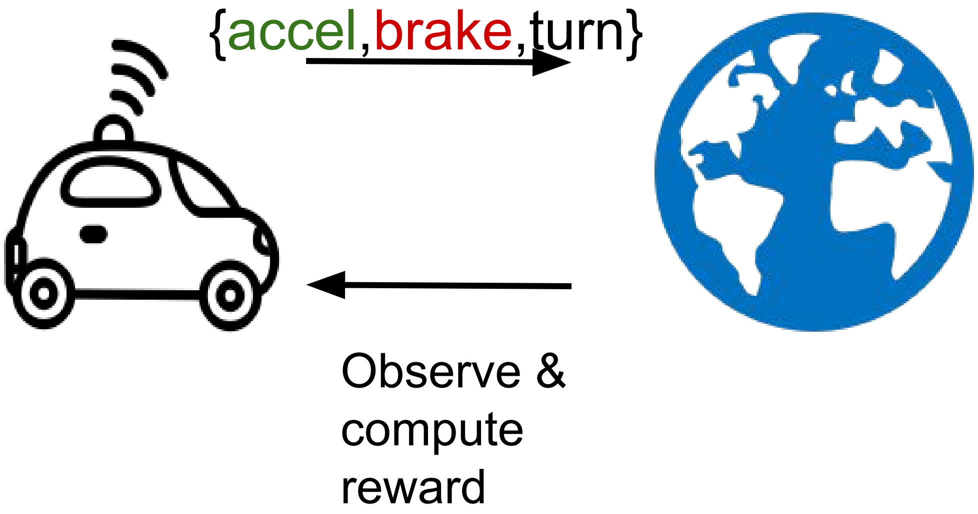

Learning to Resolve Non-determinism

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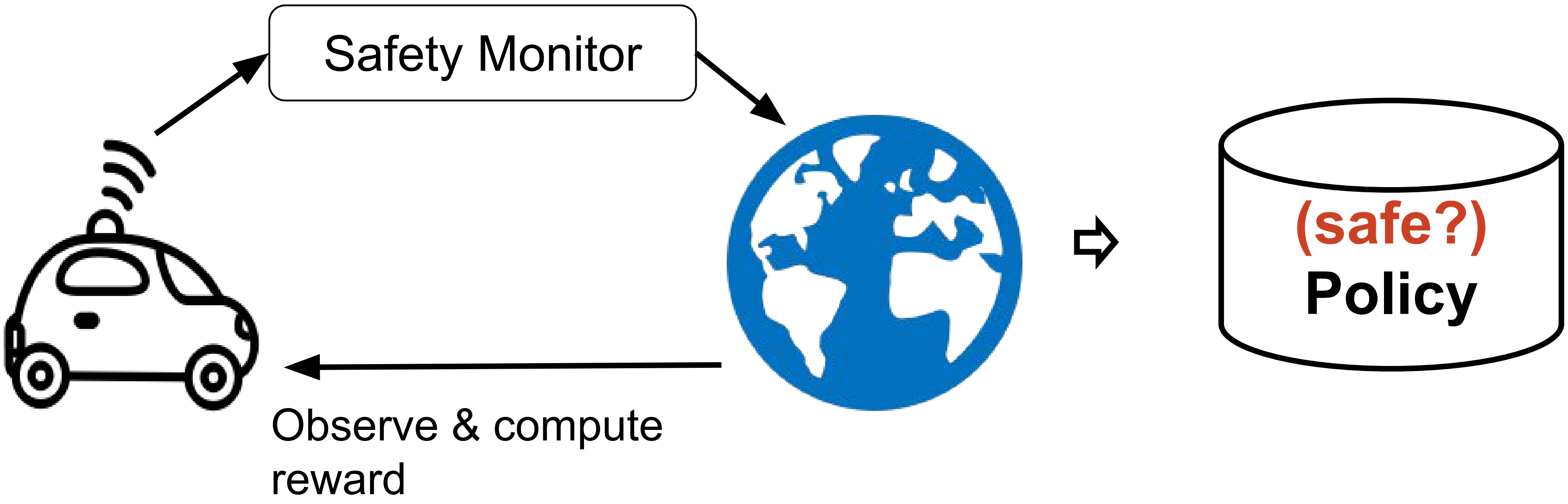
Learning to **Safely** Resolve Non-determinism



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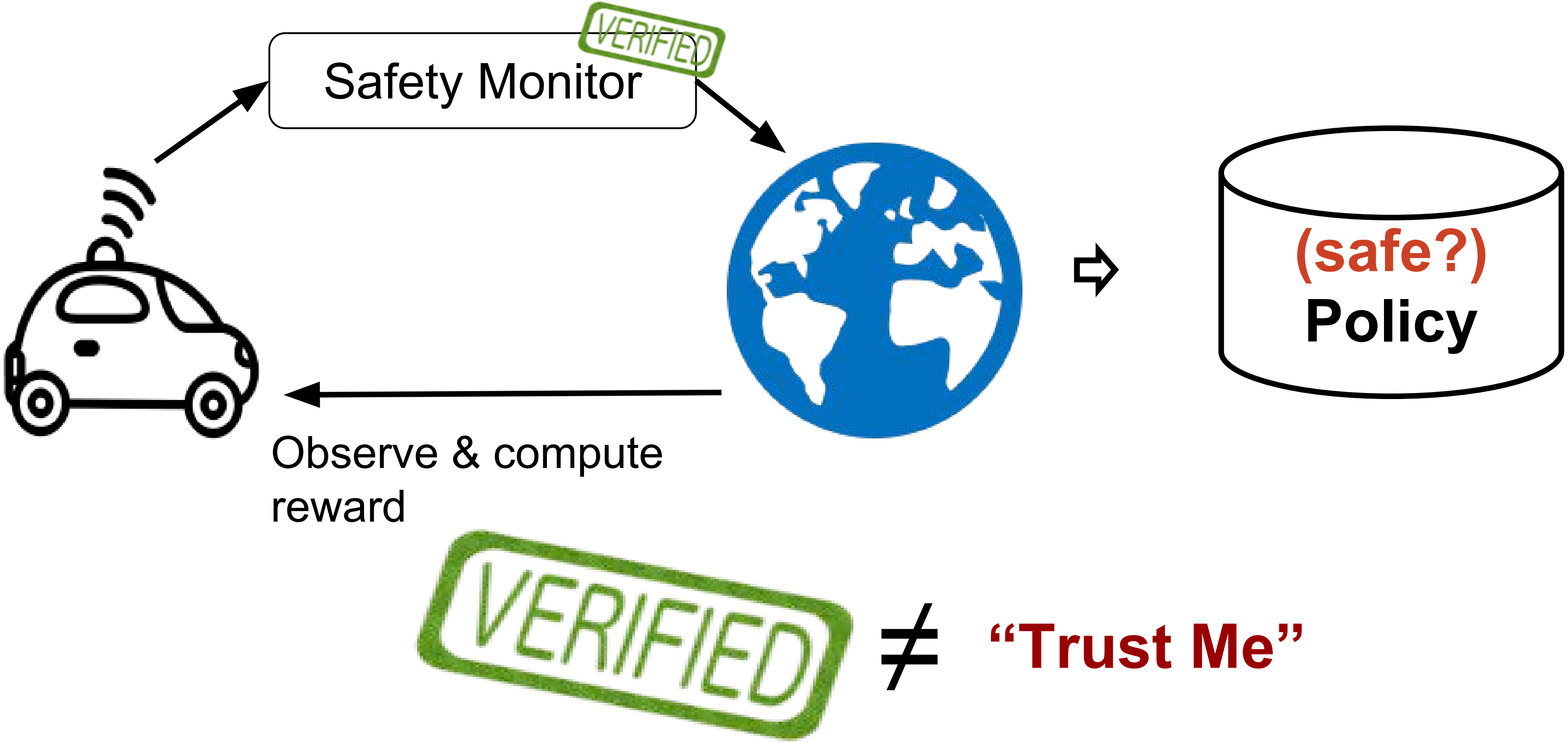

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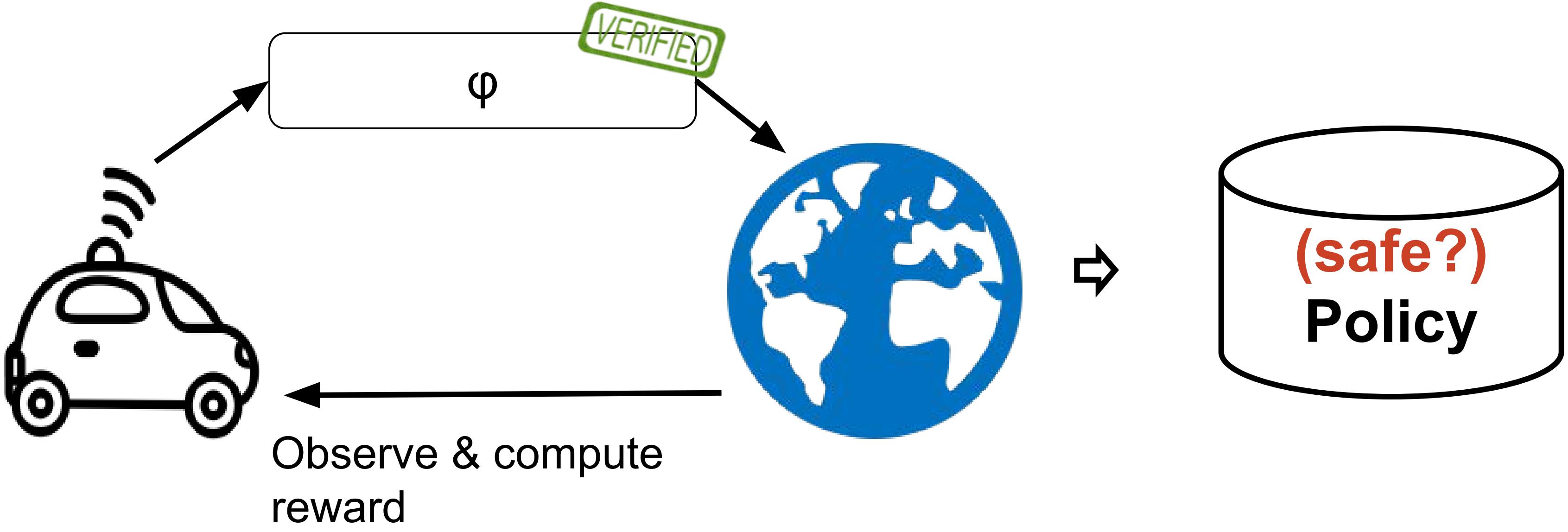
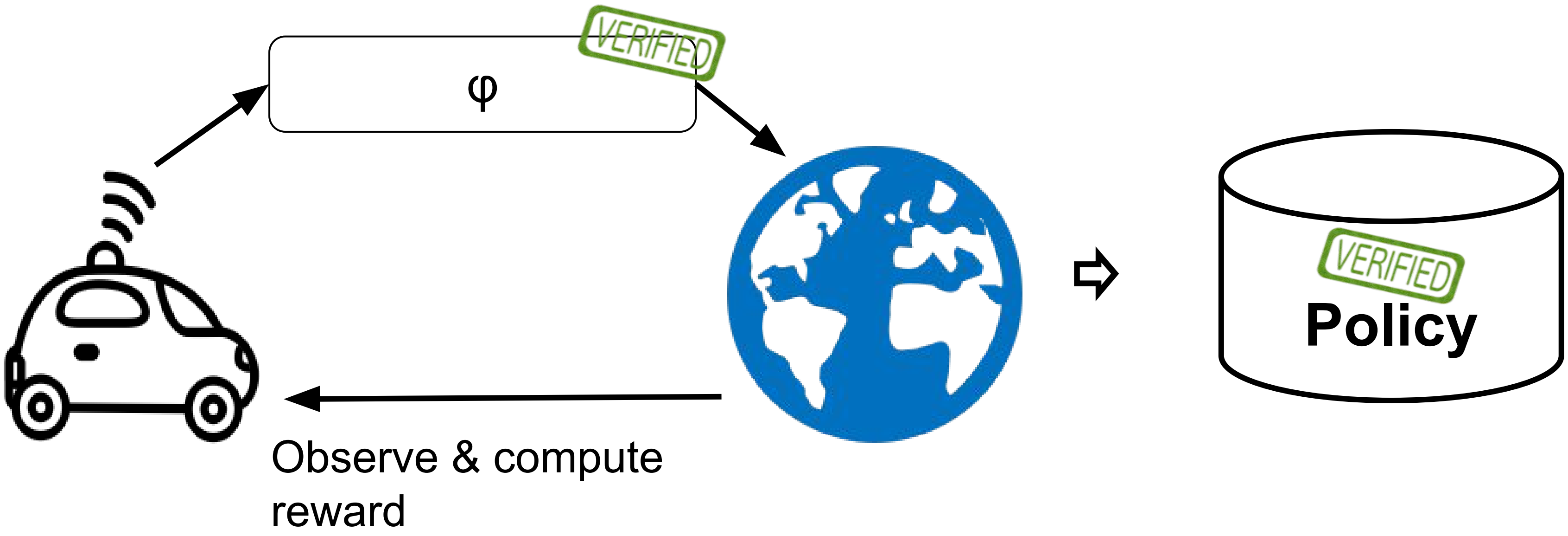


Use a theorem prover to prove:

$$(\mathit{init} \rightarrow [\{\{\mathit{accel} \cup \mathit{brake}\};\mathit{ODEs}\}^*](\mathit{safe})) \leftrightarrow \varphi$$

Learning to **Safely** Resolve Non-determinism



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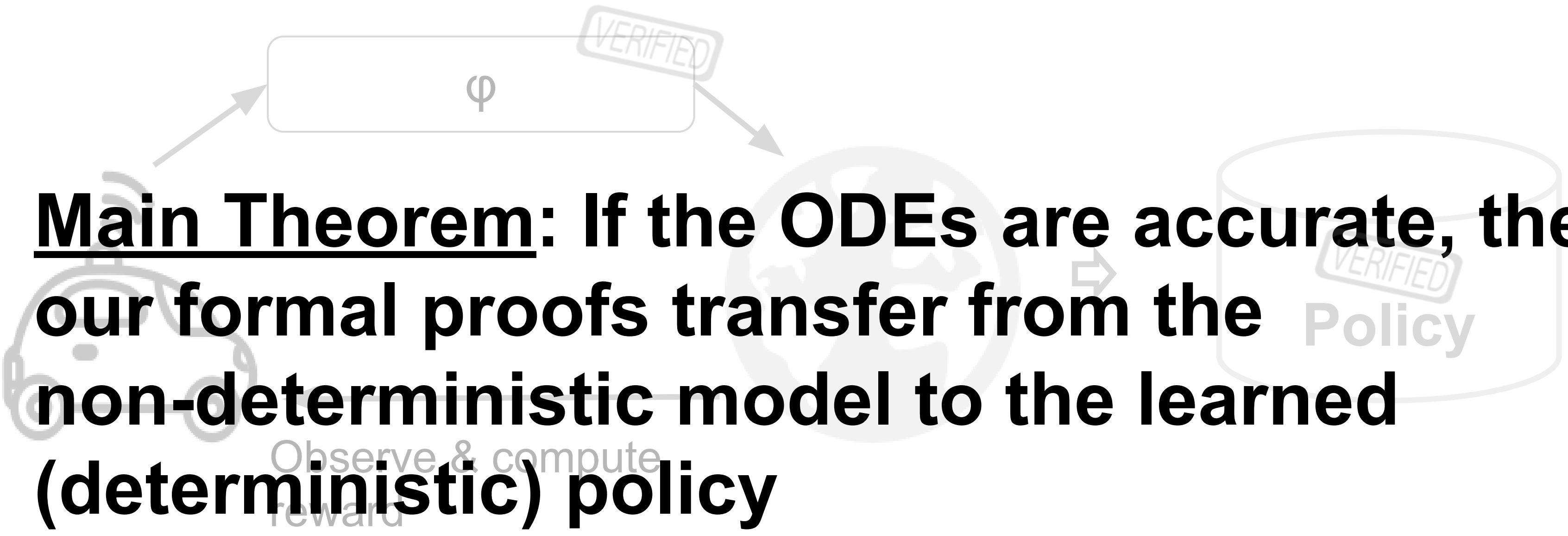

<u>Main Theorem</u>: If the ODEs are accurate, then our formal proofs transfer from the non-deterministic model to the learned (deterministic) policy

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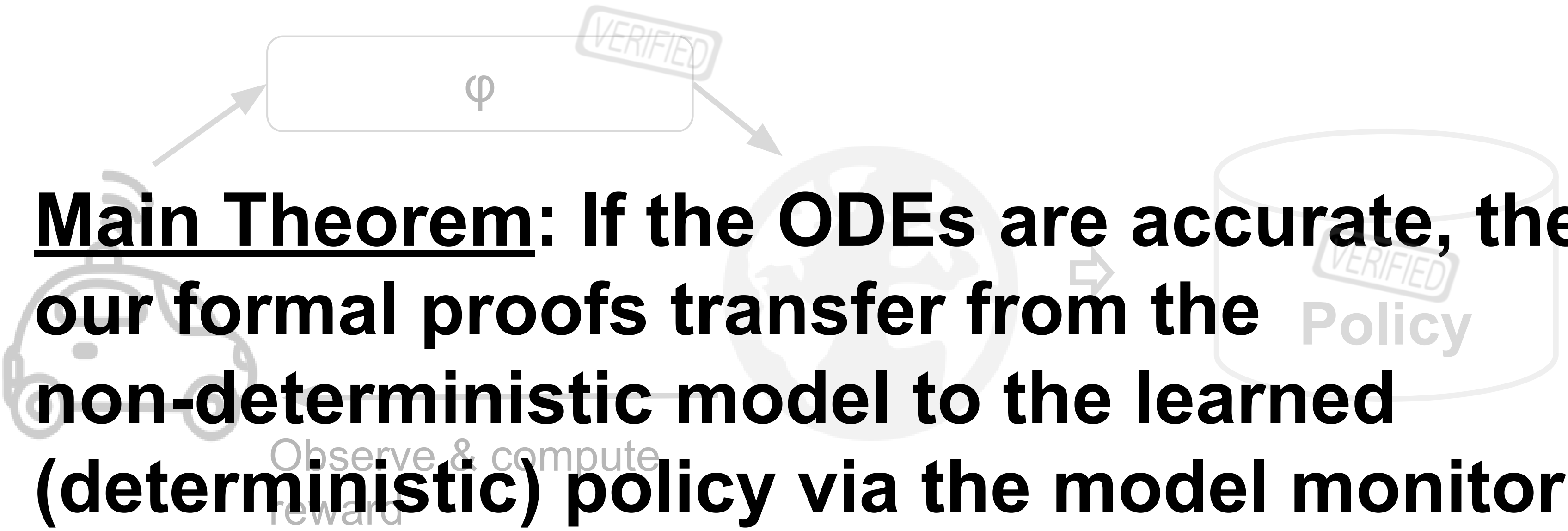
Learning to **Safely** Resolve Non-determinism

<u>Main Theorem</u>: If the ODEs are accurate, then our formal proofs transfer from the non-deterministic model to the learned (deterministic) policy via the model monitor.



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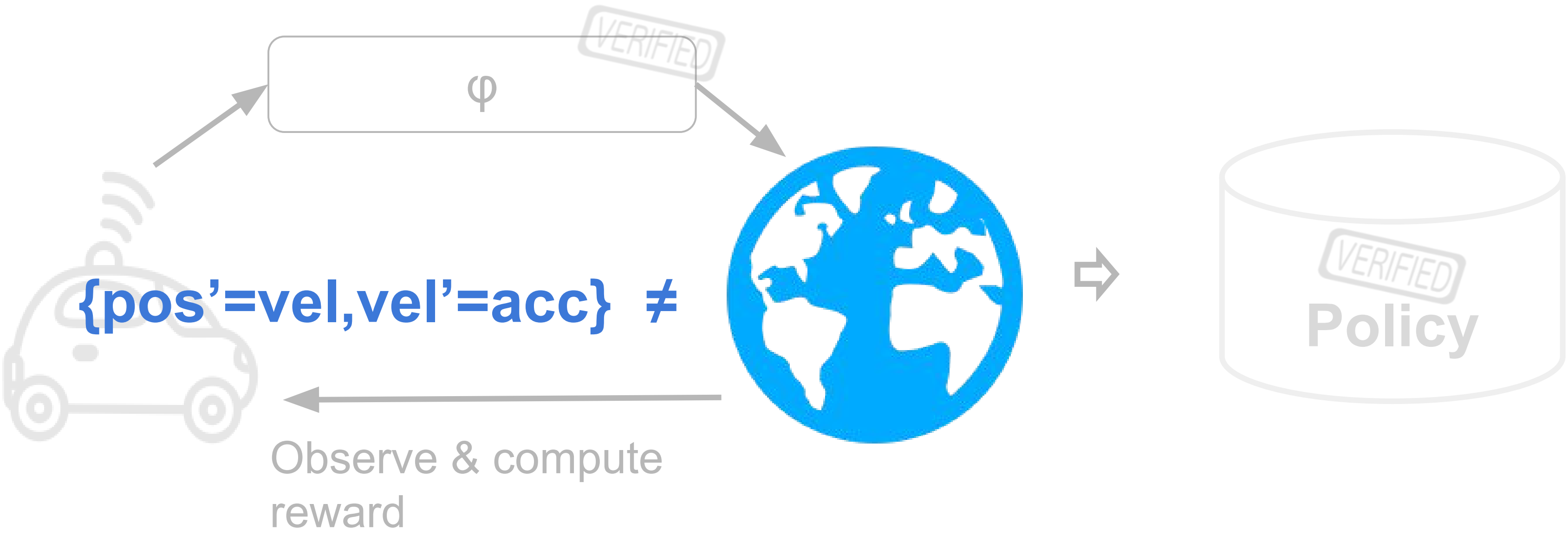

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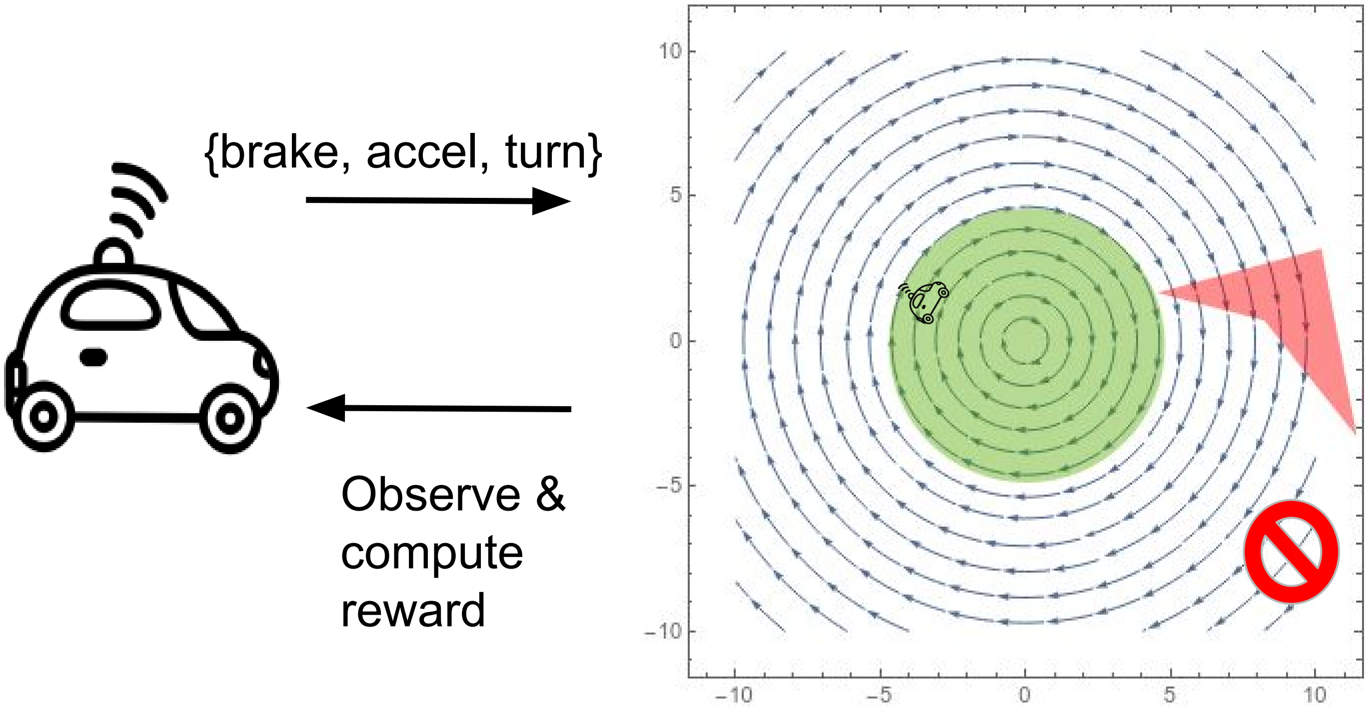

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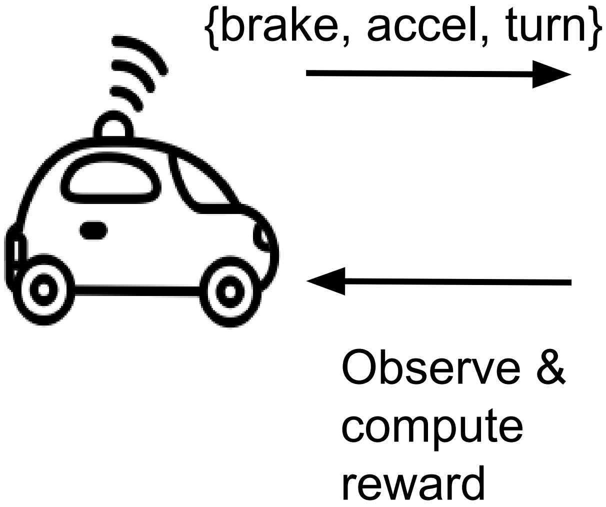
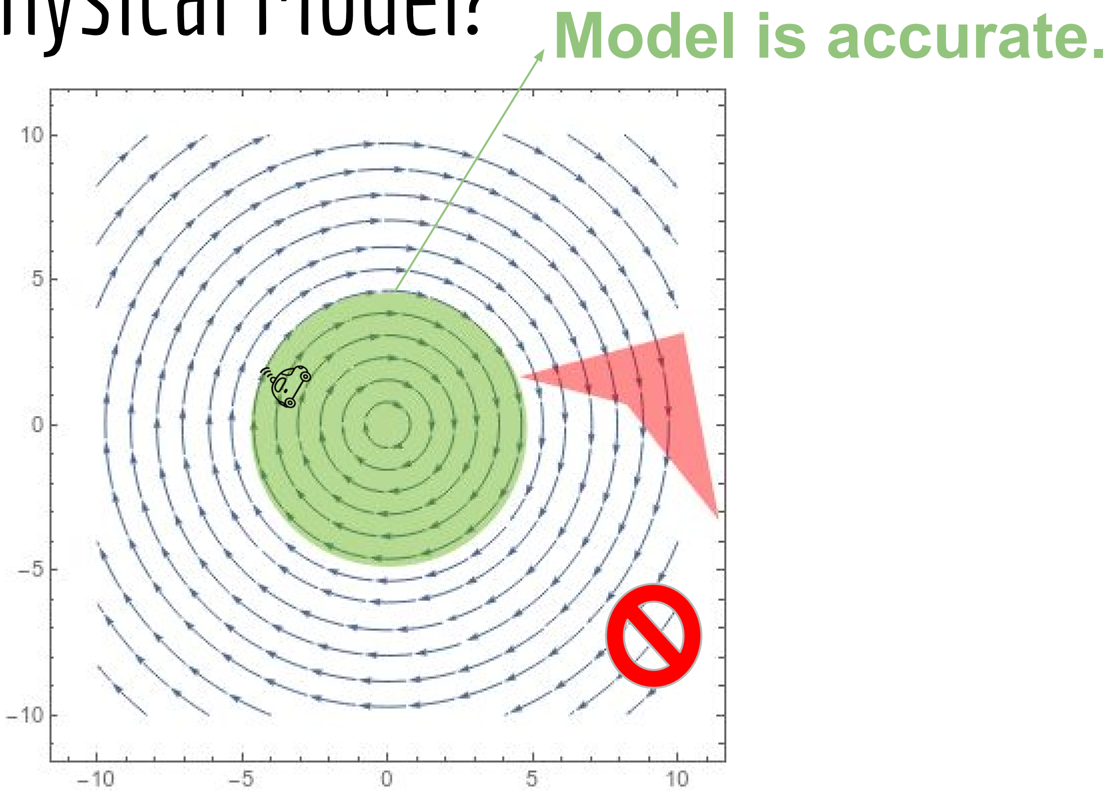
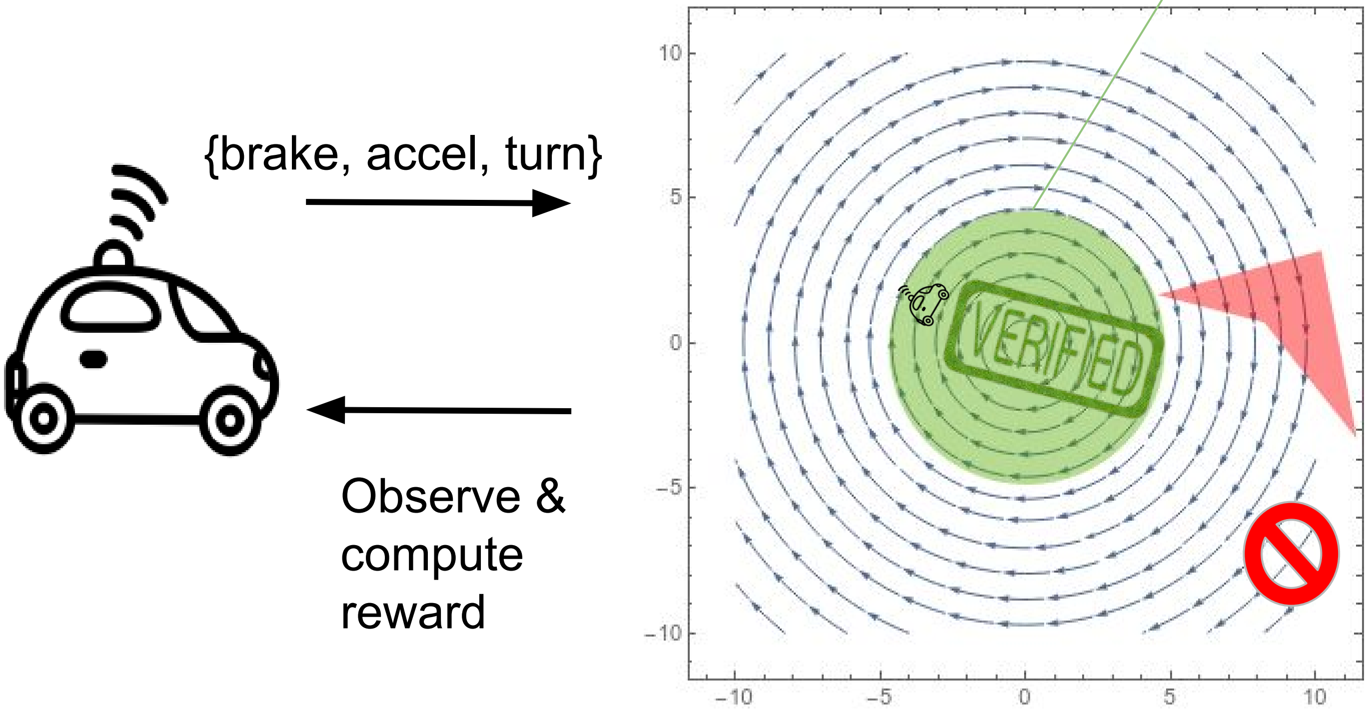




What About the Physical Model?

Model is accurate.



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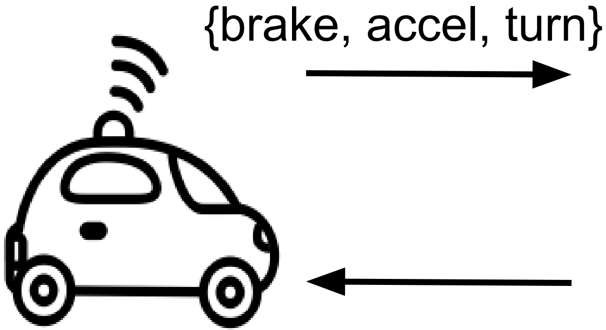
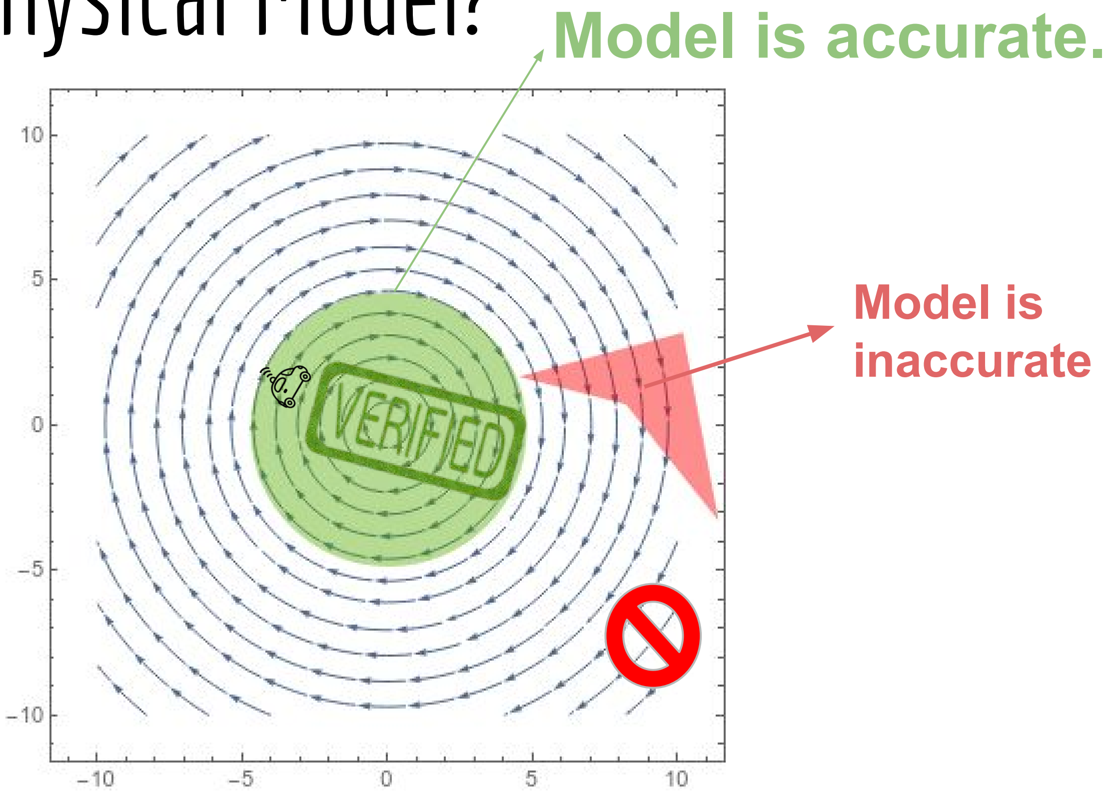


Observe & compute reward



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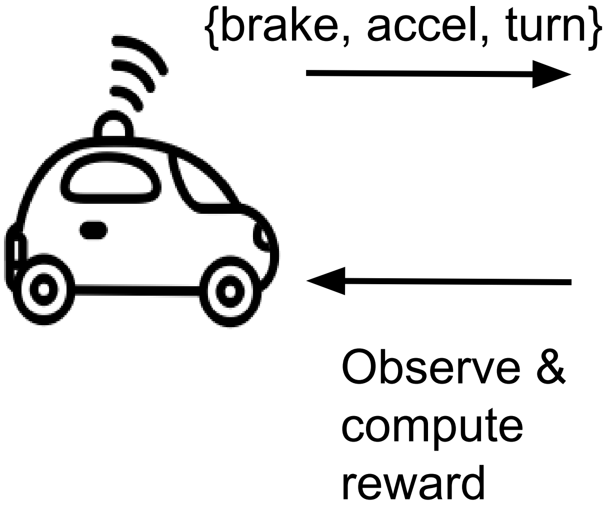

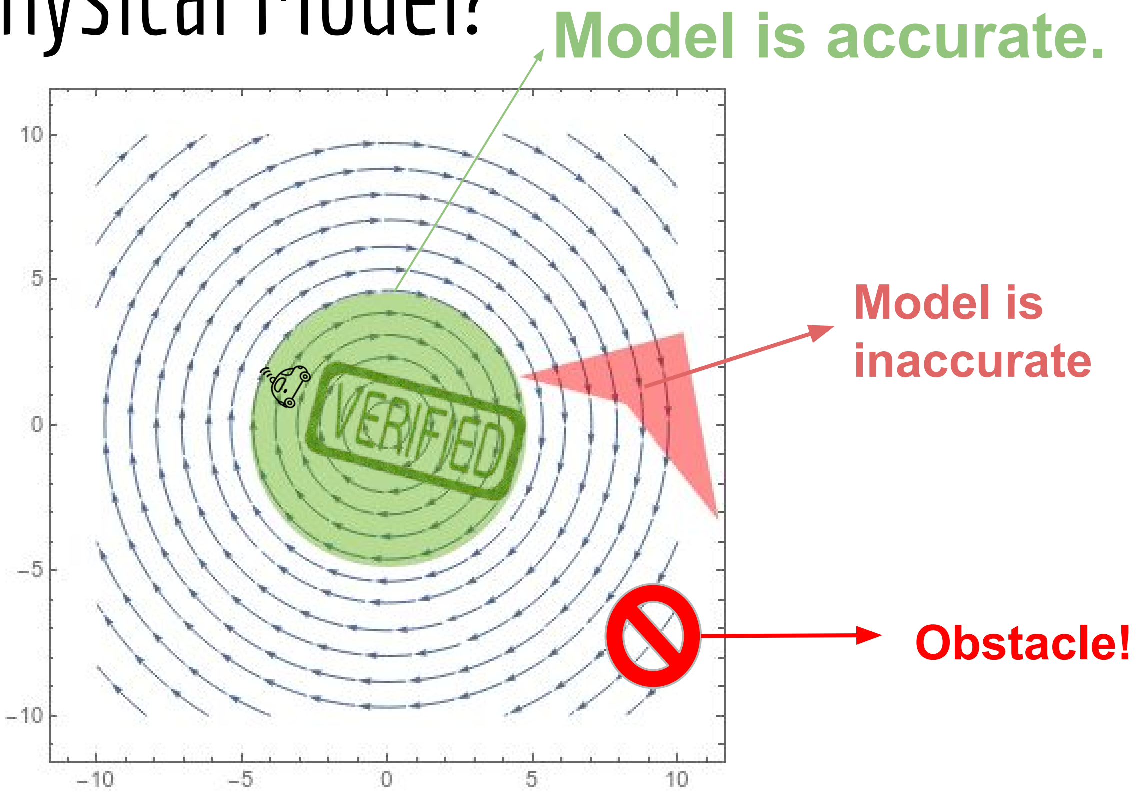

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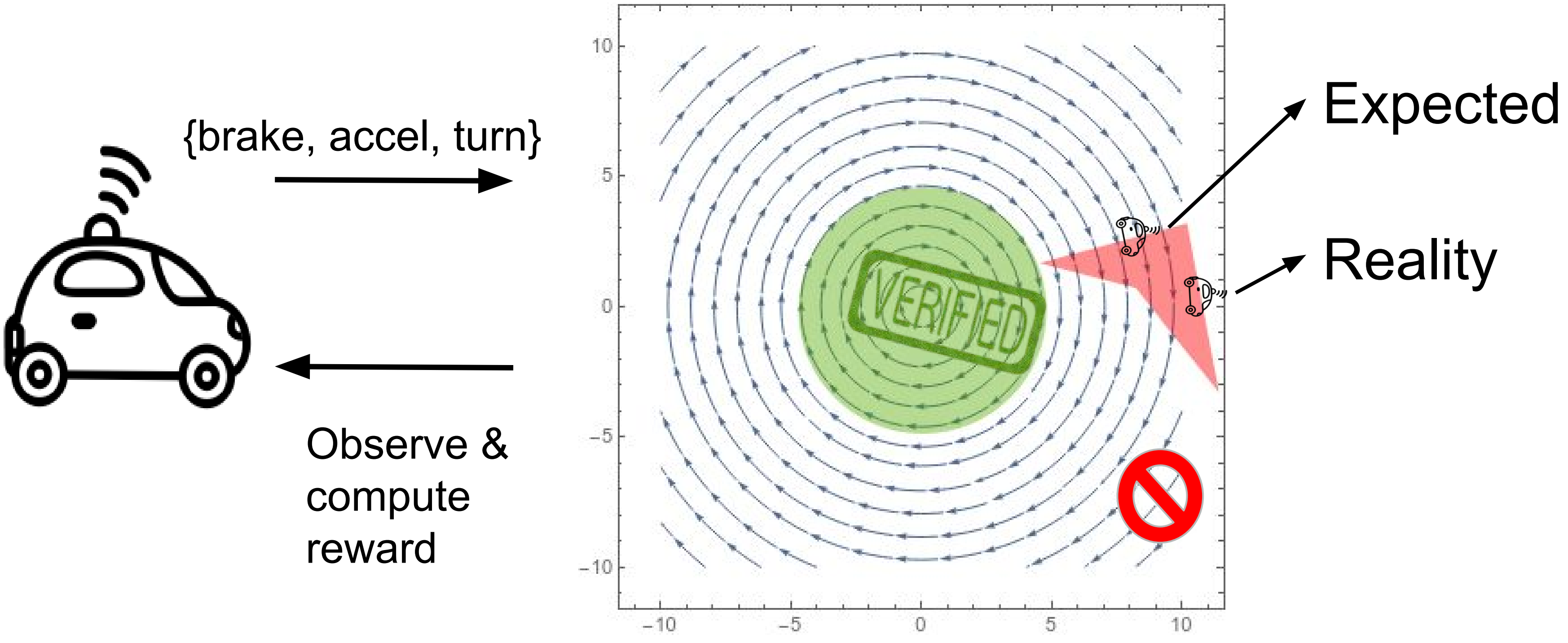
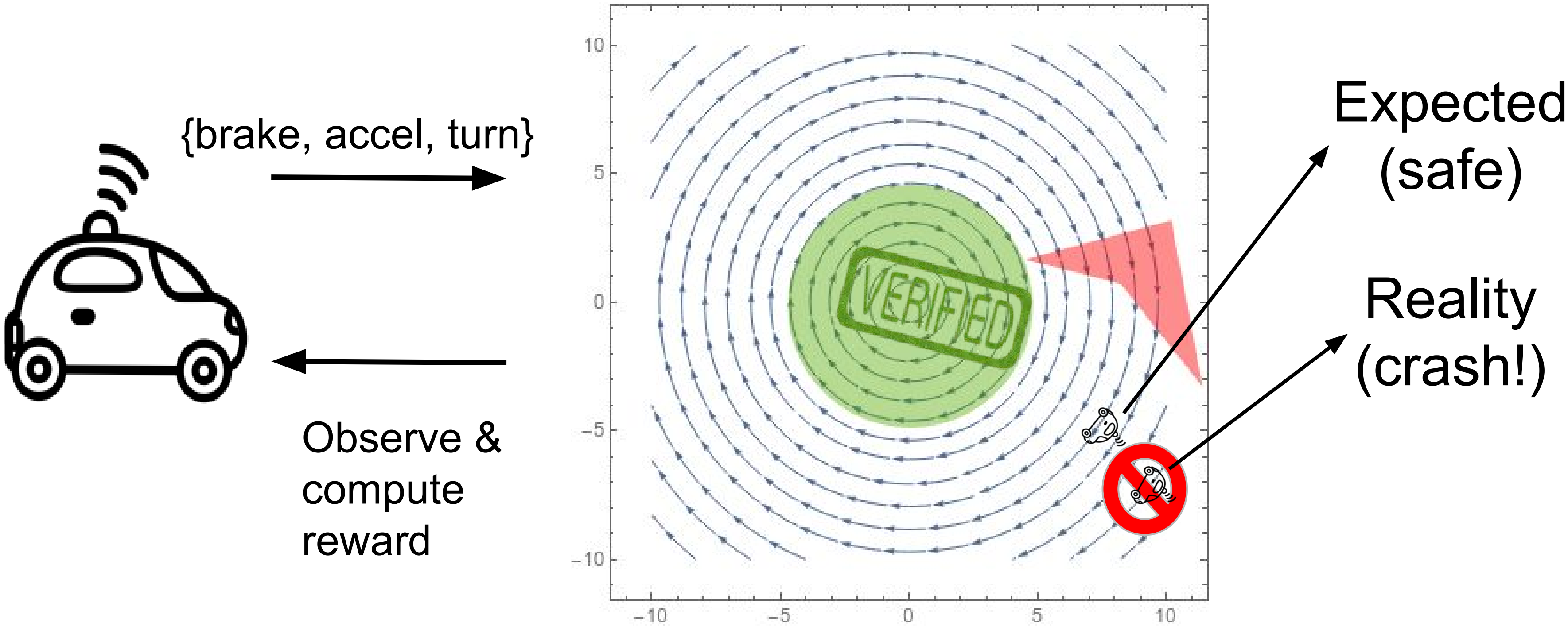


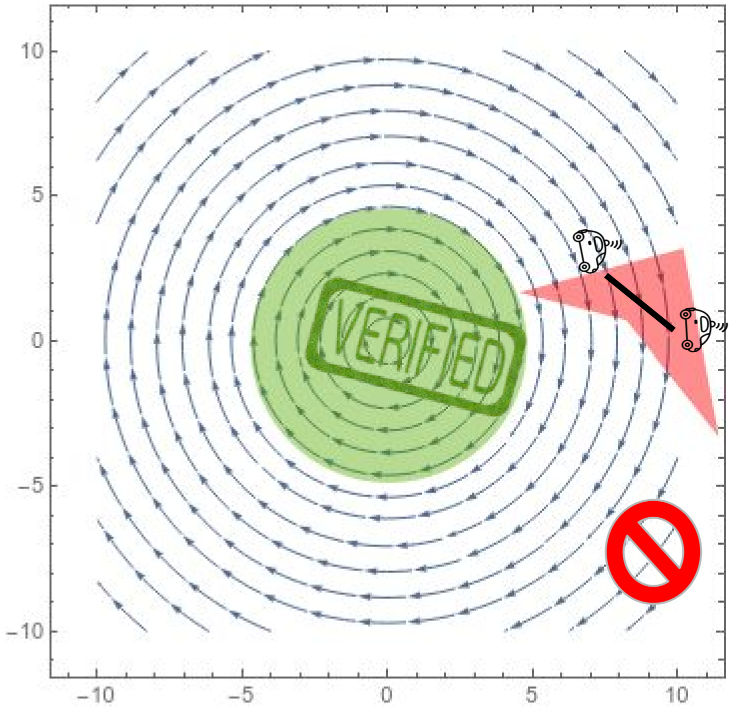
Speculation is Justified



Leveraging Verification Results to Learn Better

{brake, accel, turn}

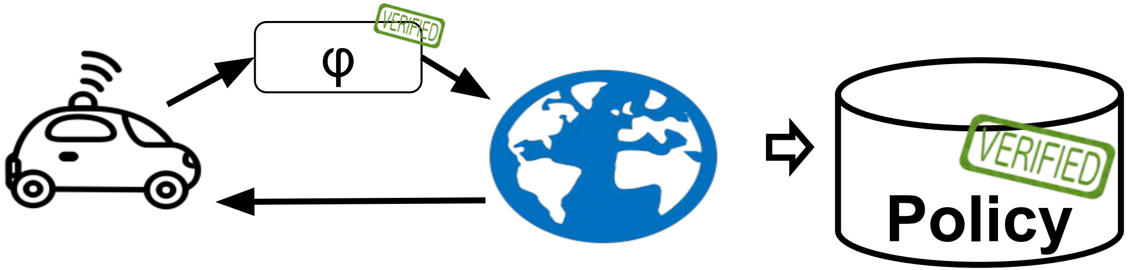
Observe &
compute
reward



Use a real-valued version of the model monitor as a reward signal

Conclusion

Justified Speculative Control provides the best of logic and learning:



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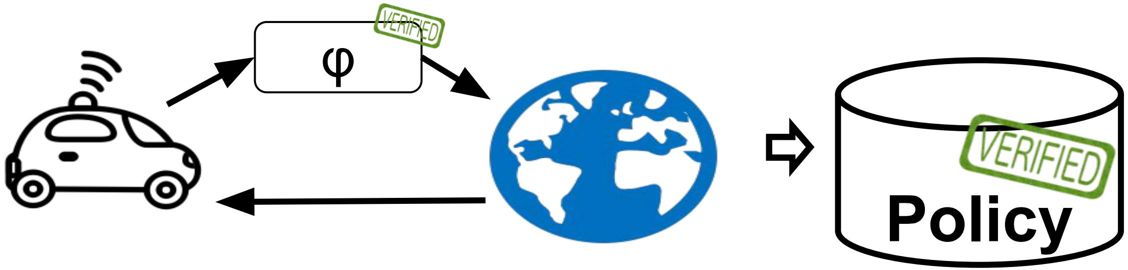

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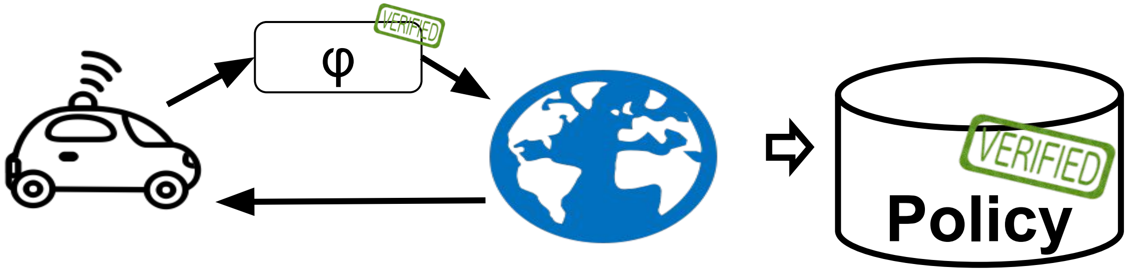

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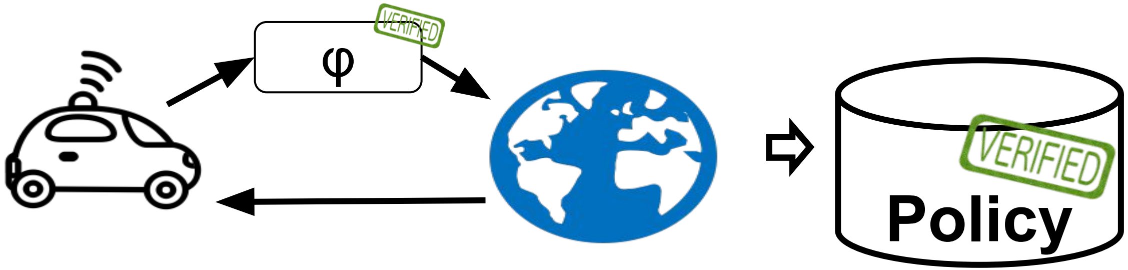

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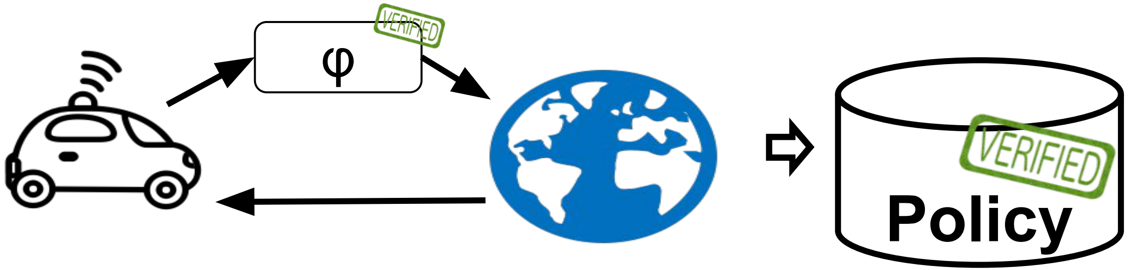

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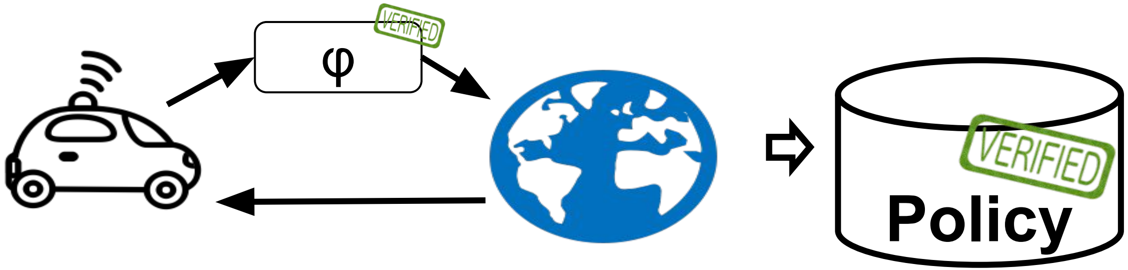

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