

Imitative Planning for Autonomous Vehicles



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Q: Can robots **safely learn** to drive **suburban roads** in **interpretable** ways to **new goals** ?



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Without learning ?

Behavior cloning ?

Model-based RL ?

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(trains offline)

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Q: Can robots **safely learn** to drive **suburban roads** in **interpretable** ways to **new goals** ?

(trains offline)

(no rewards required)

(plans)

(dyn. model)

Without learning ?



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Model-based RL ?



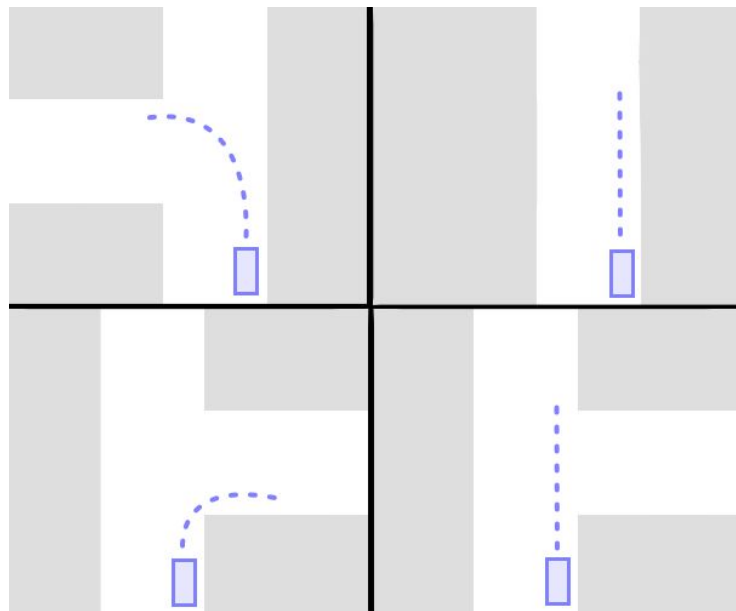
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	(trains offline)	(no rewards required)	(plans)	(dyn. model)
Without learning ?	✓	✗	✓	✓
Behavior cloning ?	?	✓	✗	✗
Model-based RL ?	?	✗	✓	✓

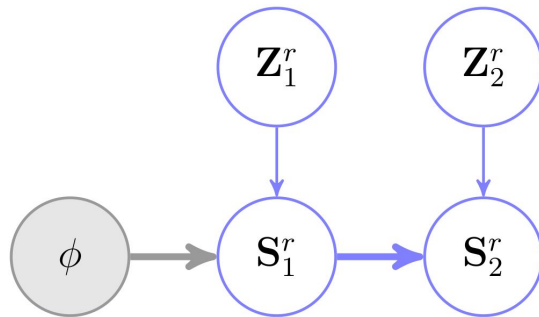
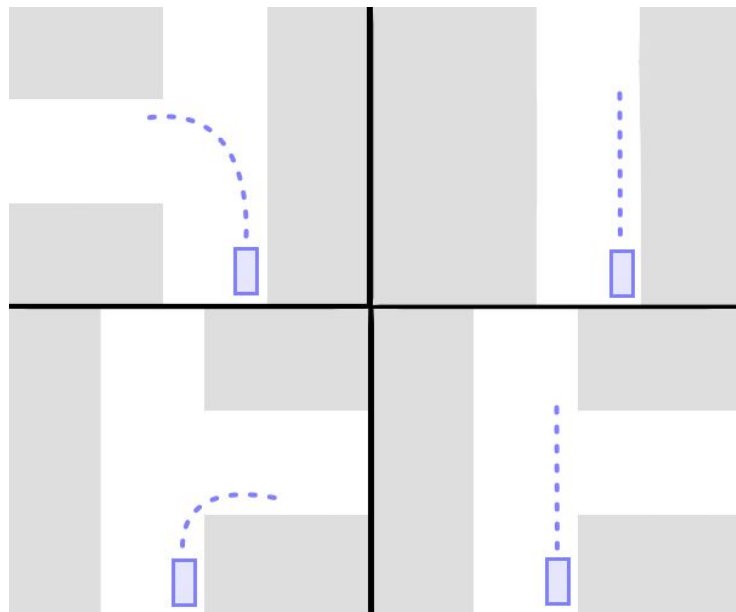
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Without learning ?	✓	✗	✓	✓
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Model-based RL ?	?	✗	✓	✓
Imitative Models (ours)	✓	✓	✓	✓

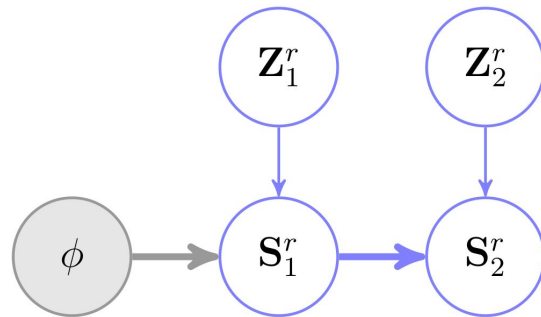
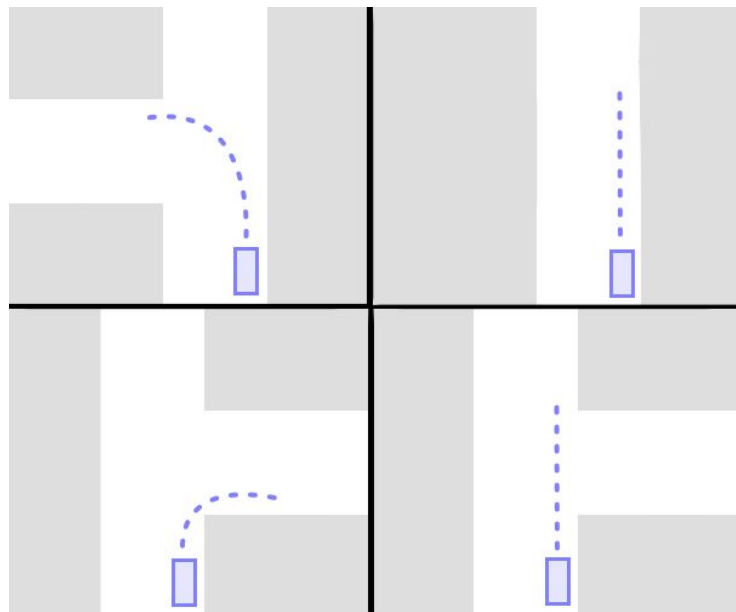
Modelling Expert Drivers



Modelling Expert Drivers

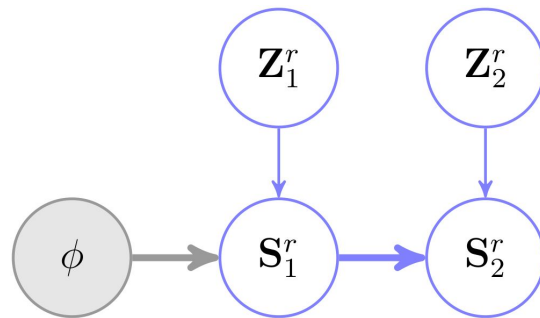
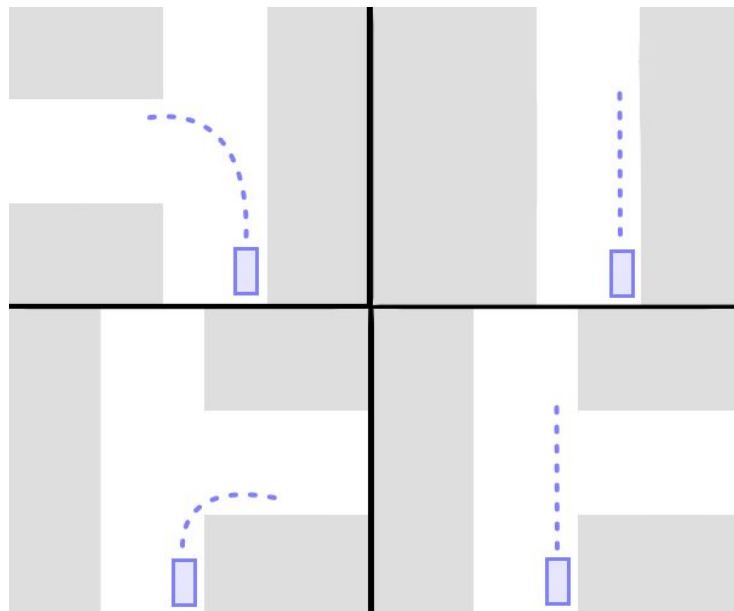


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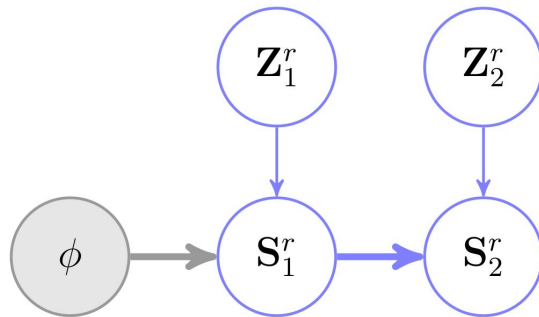
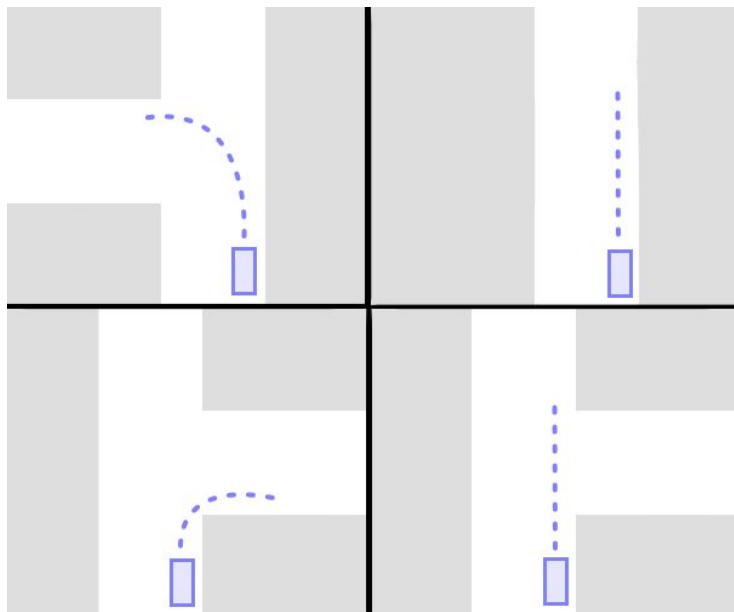
$$\text{states} = f(\text{latents}; \text{context})$$

Modelling Expert Drivers



$$\begin{aligned}\text{states} &= f(\text{latents}; \text{context}) \\ \text{latents} &= f^{-1}(\text{states}; \text{context})\end{aligned}$$

Modelling Expert Drivers

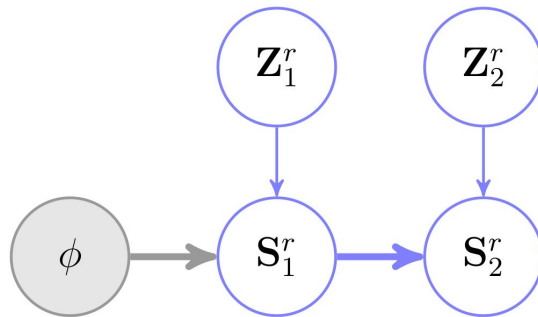
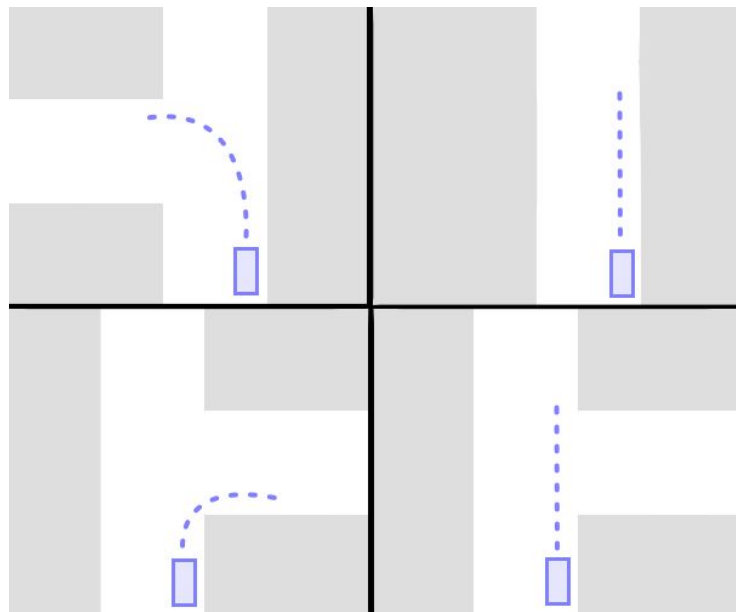


$$\mathbf{states} = f(\mathbf{latents}; \mathbf{context})$$

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$$q(\mathbf{states} | \mathbf{context}) = \frac{\mathcal{N}(\mathbf{latents}; 0, I)}{\left| \det \frac{\partial f}{\partial \mathbf{latents}} \right|}$$

Modelling Expert Drivers



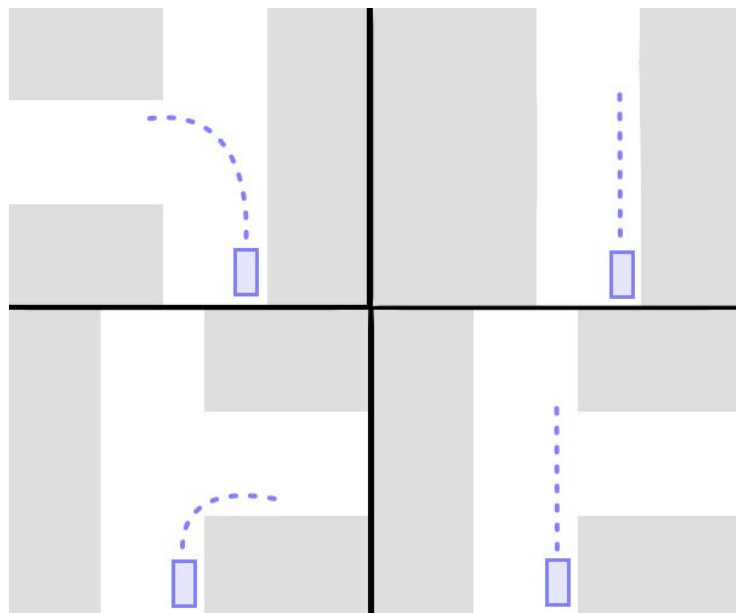
$$\begin{aligned}\text{states} &= f(\text{latents}; \text{context}) \\ \text{latents} &= f^{-1}(\text{states}; \text{context})\end{aligned}$$

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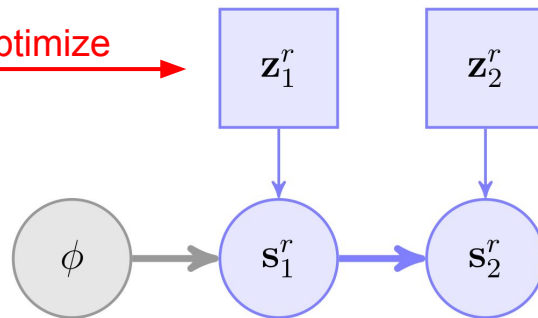
Can **plan** in this distribution!

new idea

Modelling Expert Drivers



optimize



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Can **plan** in this distribution!

new idea

Planning “Expert-like” Motions to our own Goals

$$\text{planned path} = \arg \max_{\text{states}} \log p(\text{states} \mid \text{goal}, \text{context})$$

Planning “Expert-like” Motions to our own Goals



$$\begin{aligned}\text{planned path} &= \arg \max_{\text{states}} \log p(\text{states} \mid \text{goal}, \text{context}) \\ &= \arg \max_{\text{states}} \log q(\text{states} \mid \text{context}) + \log p(\text{goal} \mid \text{states}, \text{context}) - \log p(\text{goal} \mid \text{context})\end{aligned}$$

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Drive safely...

Planning “Expert-like” Motions to our own Goals

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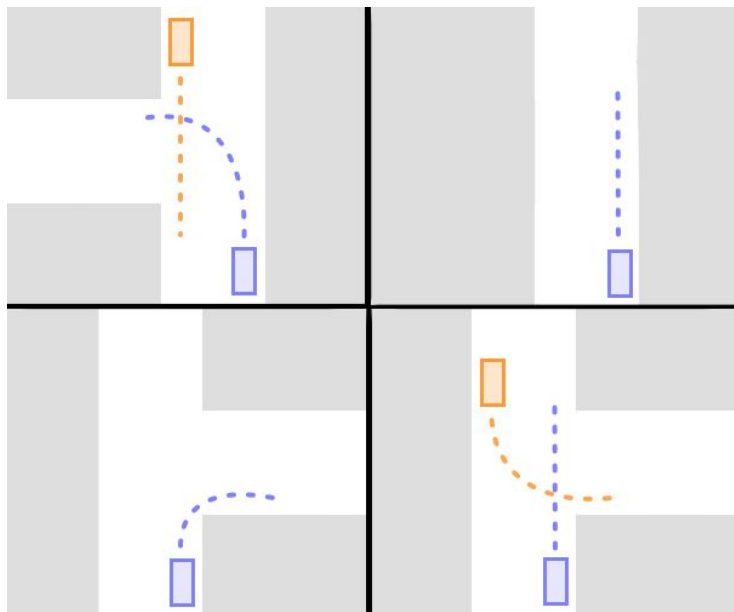
Drive safely...

...and get to our destination!

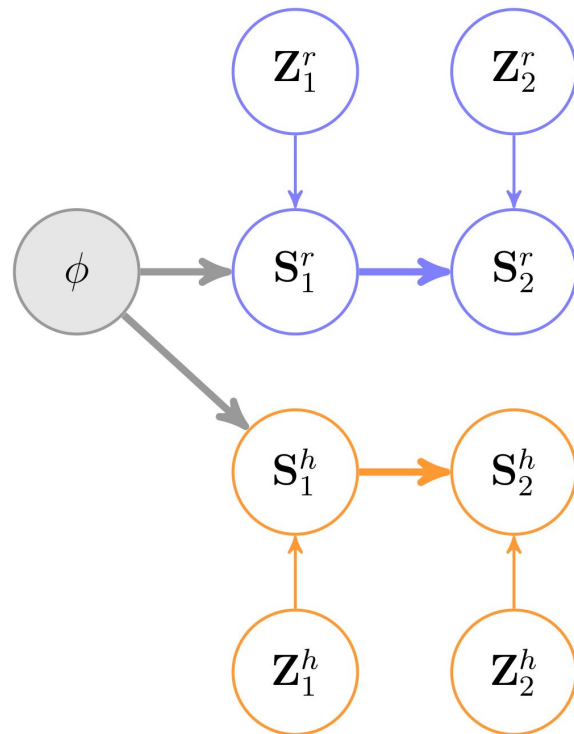
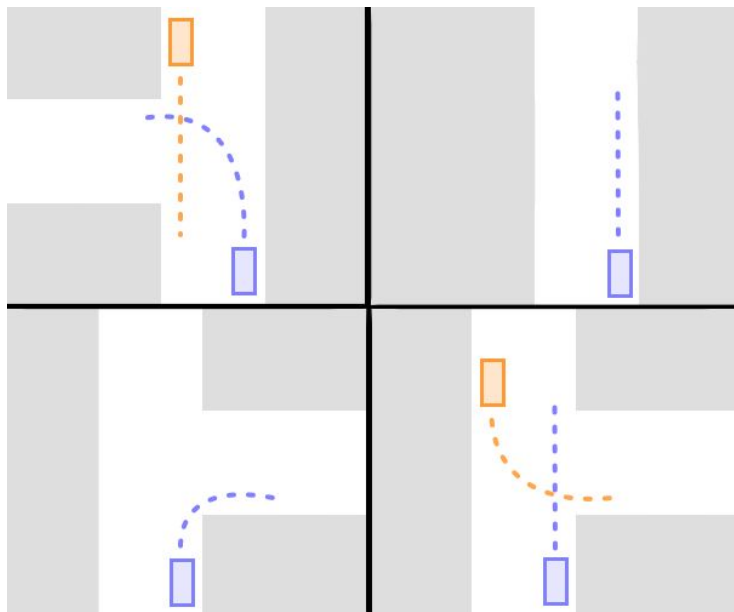




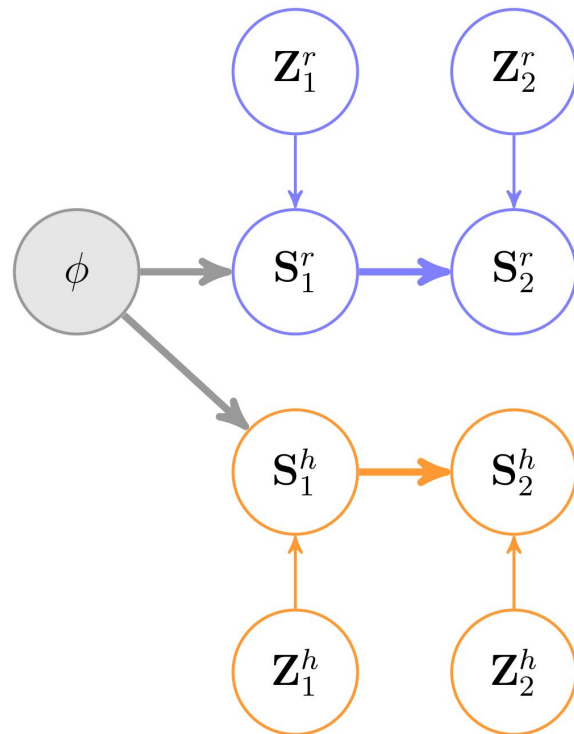
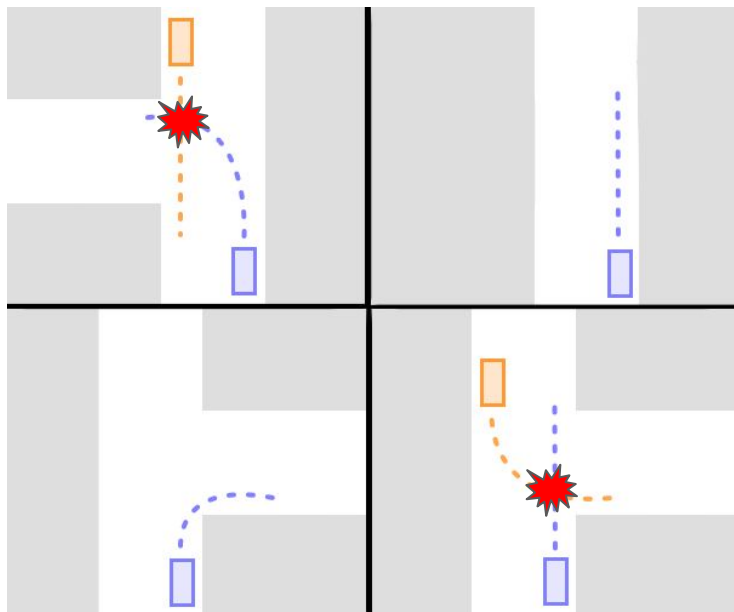
Modelling Multiple Expert Drivers



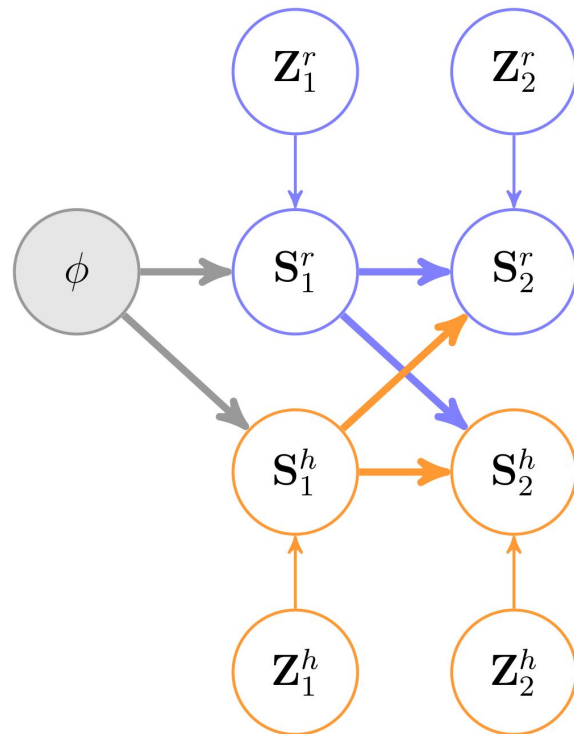
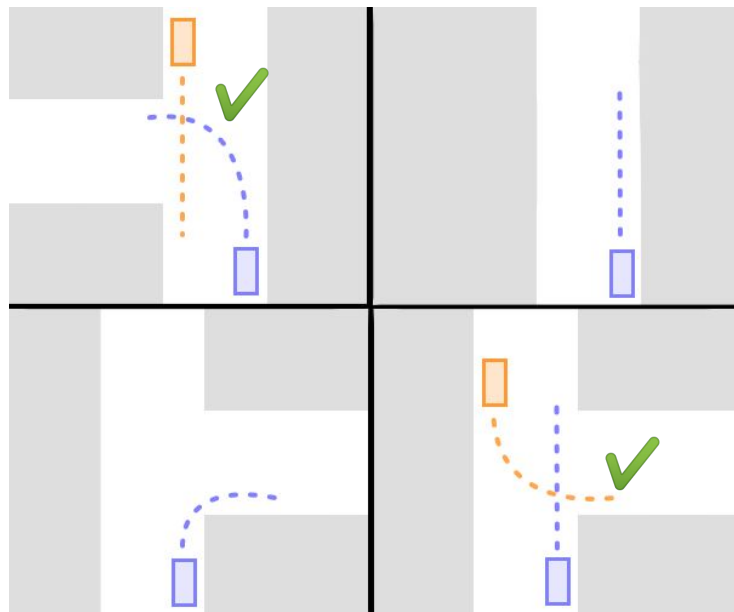
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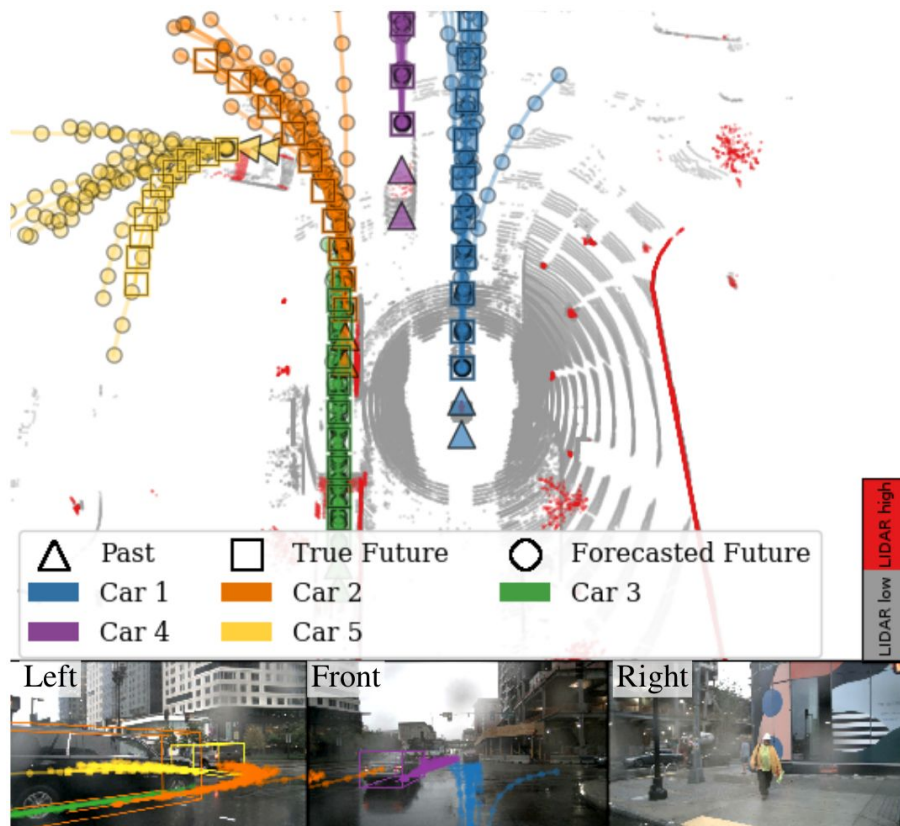
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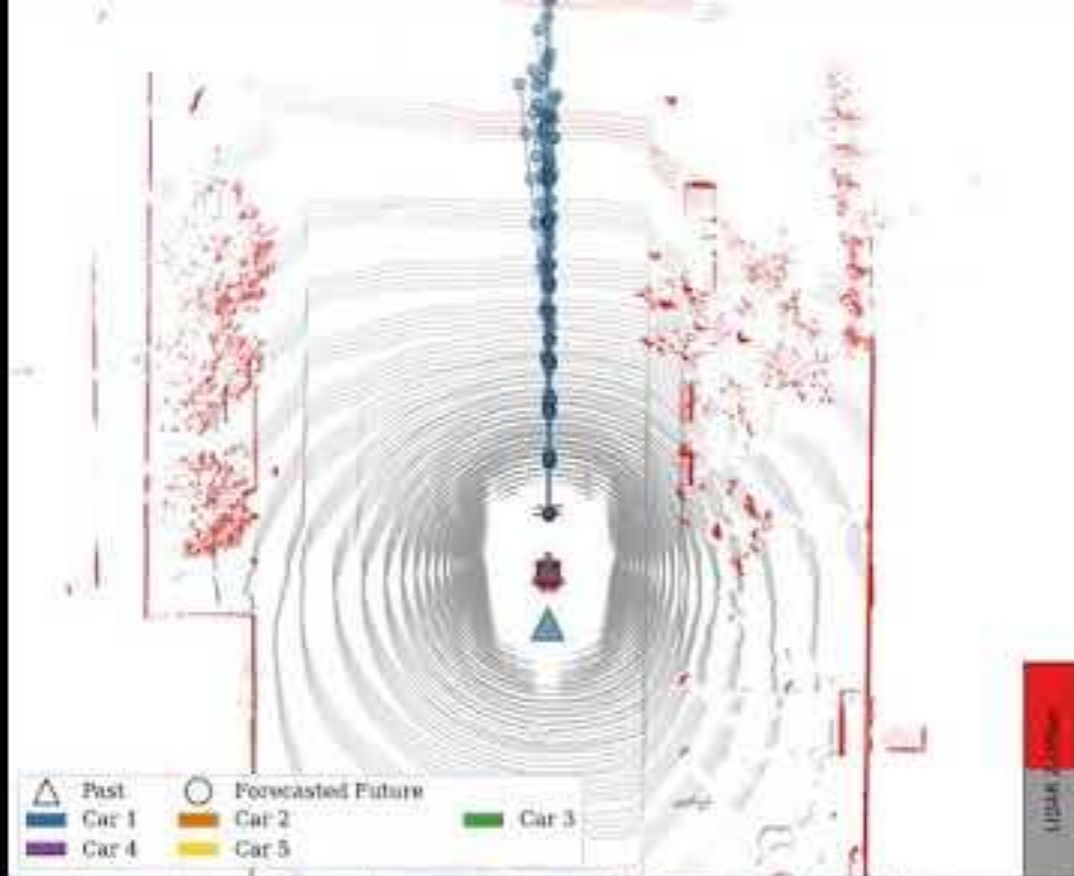


Modelling Multiple Expert Drivers



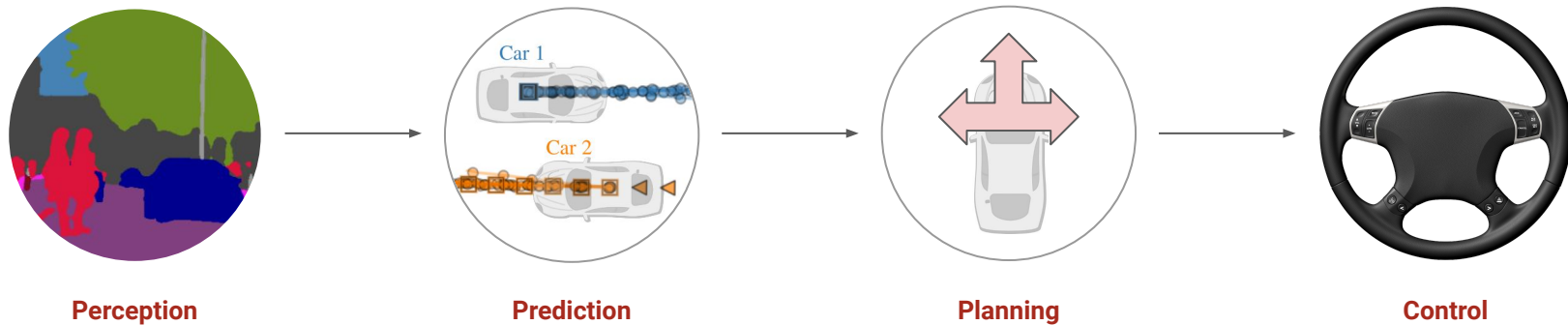
Forecasting with nuScenes data (Singapore + Boston)





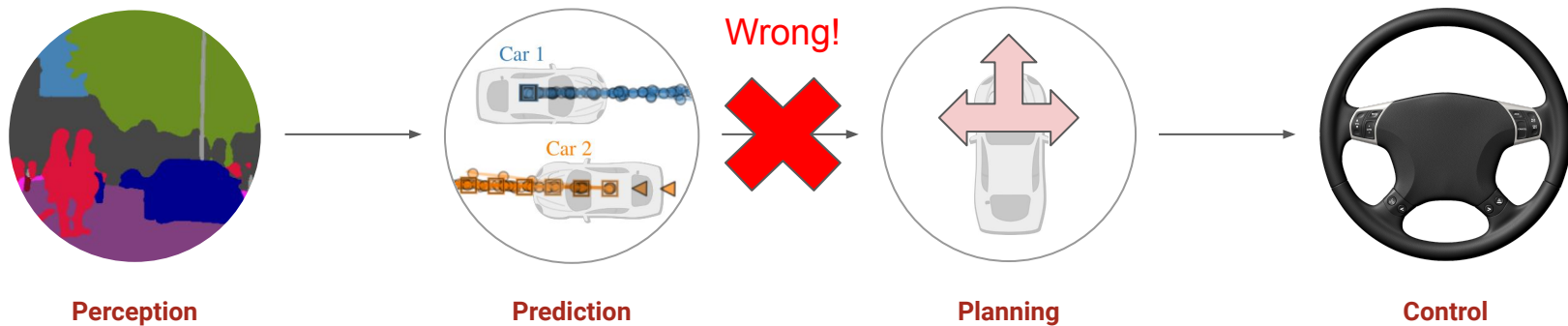
Multi-Agent Planning

Q: but how should ***autonomous vehicles*** predict other agents...**online**?



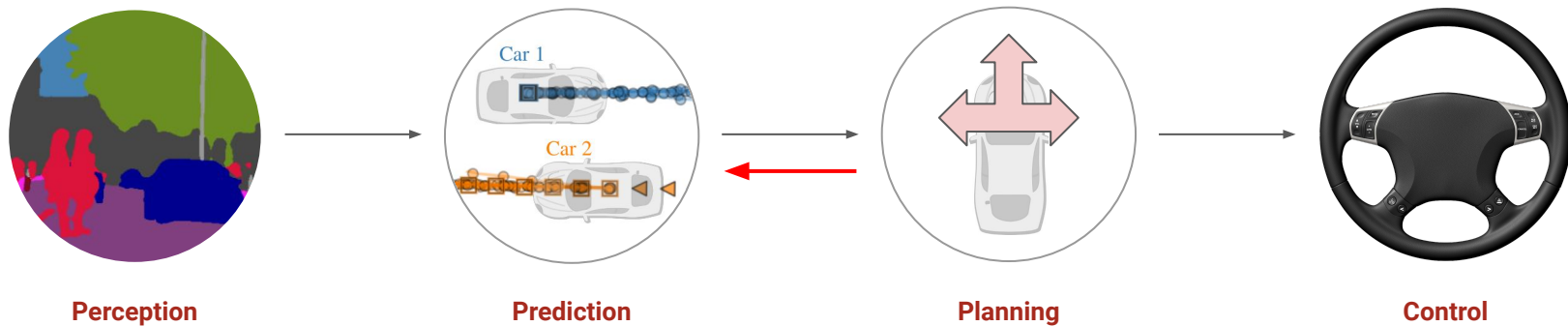
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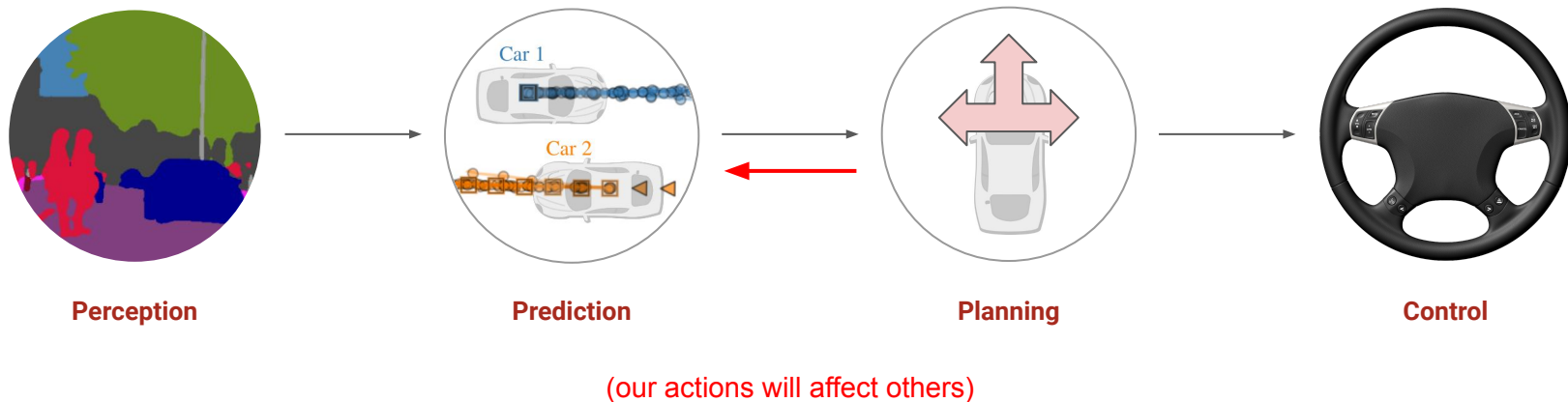
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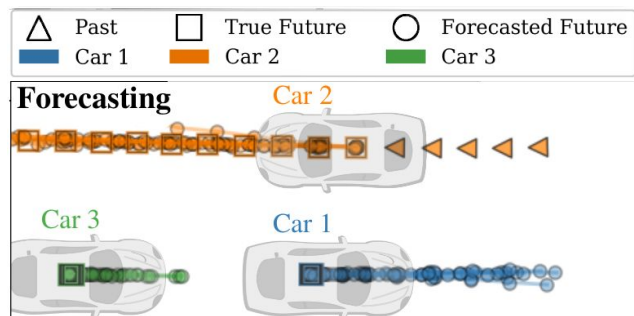


Multi-Agent Planning

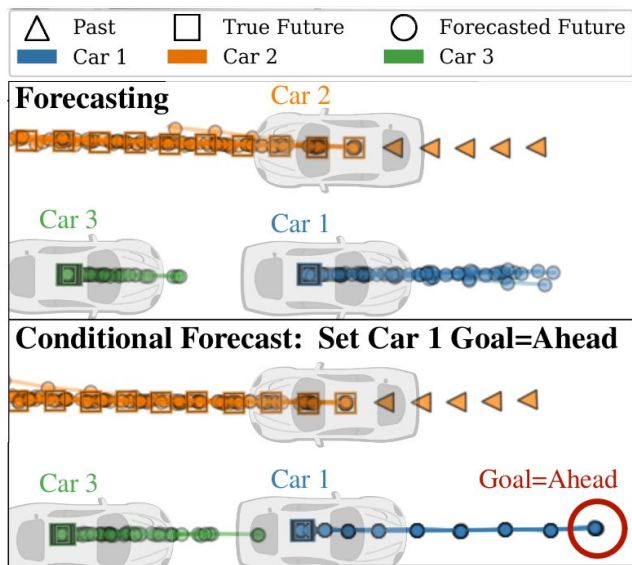
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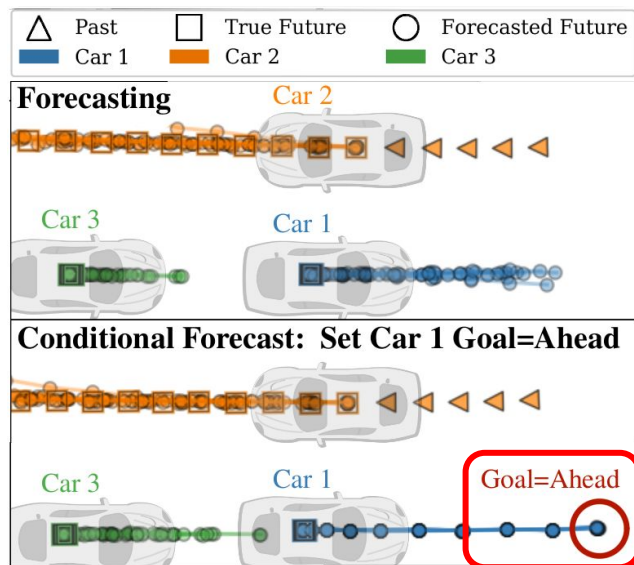
Goal-Conditioned Multi-Agent Forecasting



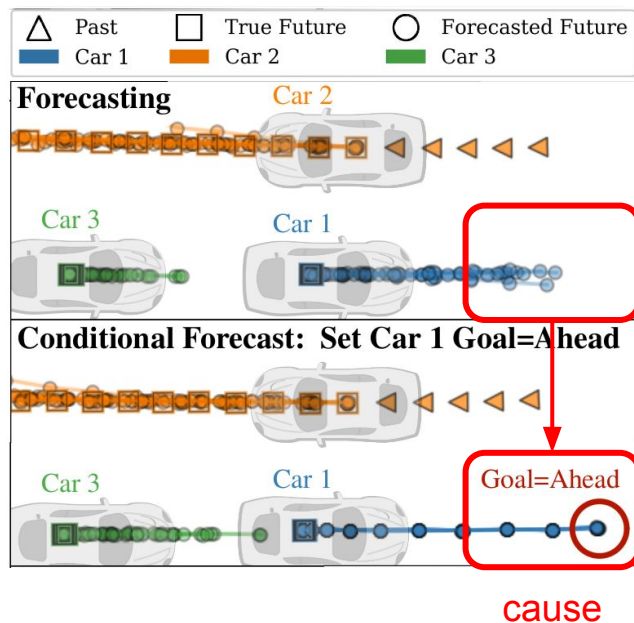
Goal-Conditioned Multi-Agent Forecasting



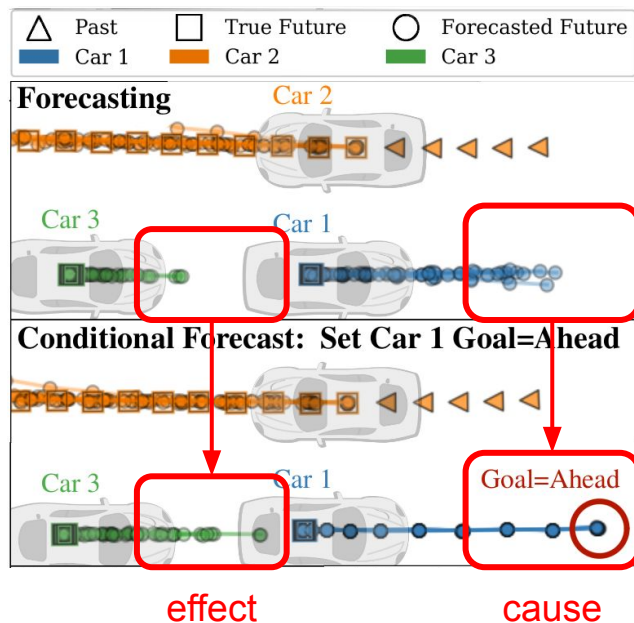
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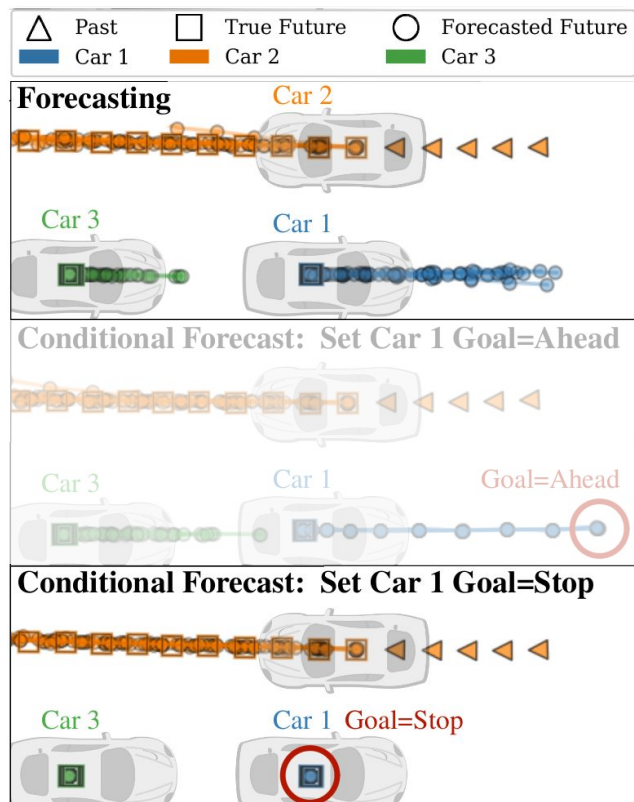
Goal-Conditioned Multi-Agent Forecasting



Goal-Conditioned Multi-Agent Forecasting



Goal-Conditioned Multi-Agent Forecasting



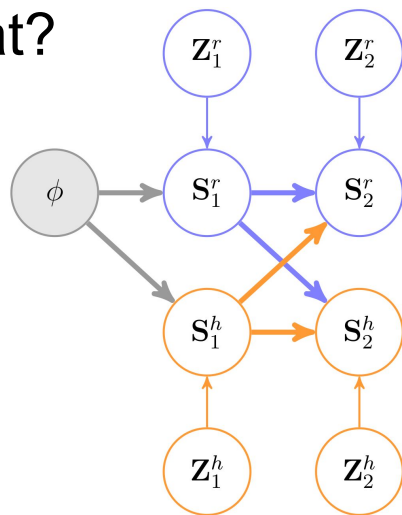
Goal-Conditioned Multi-Agent Forecasting

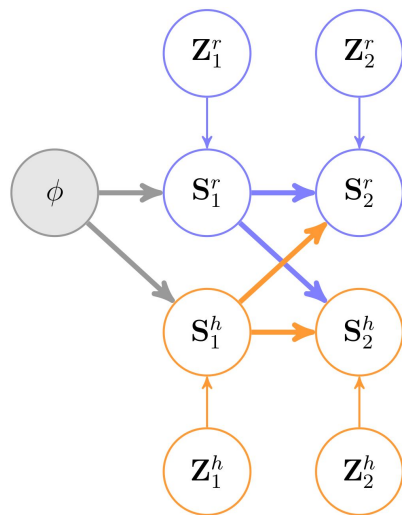


Goal-Conditioned Multi-Agent Forecasting



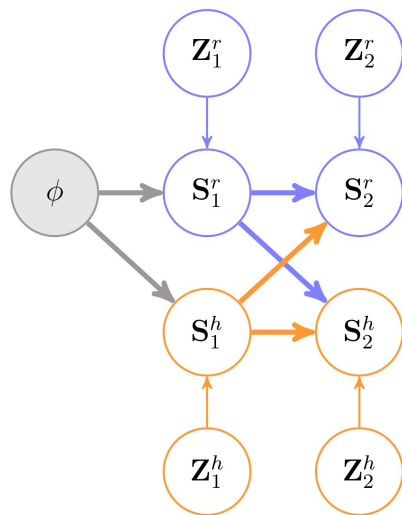
How did we do that?





Generating function:

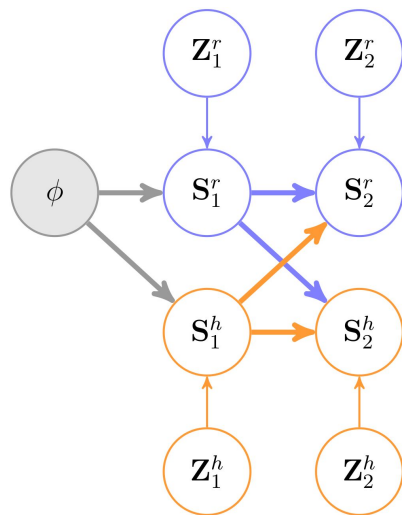
$$\text{states}, \text{states} = f(\text{latents}, \text{latents}; \text{context})$$



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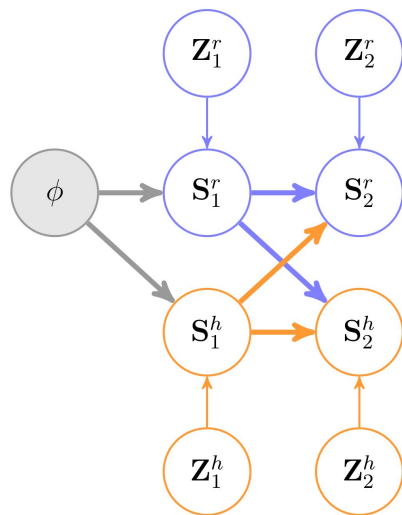
What is our Planning Objective?



Generating function:

$$\text{states}, \text{states} = f(\text{latents}, \text{latents}; \text{context})$$

$$p(\text{states}, \text{states} \mid \text{goal}, \text{context})$$

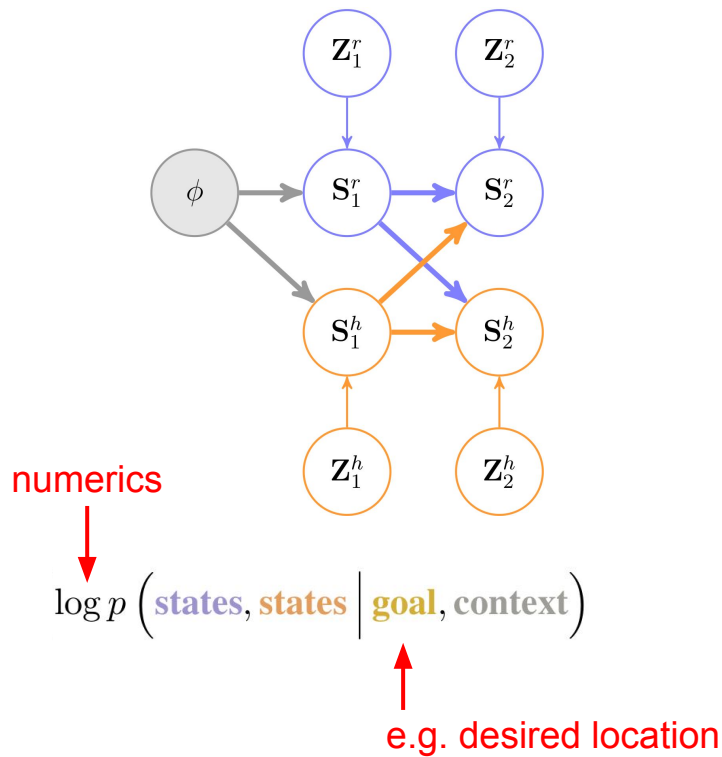


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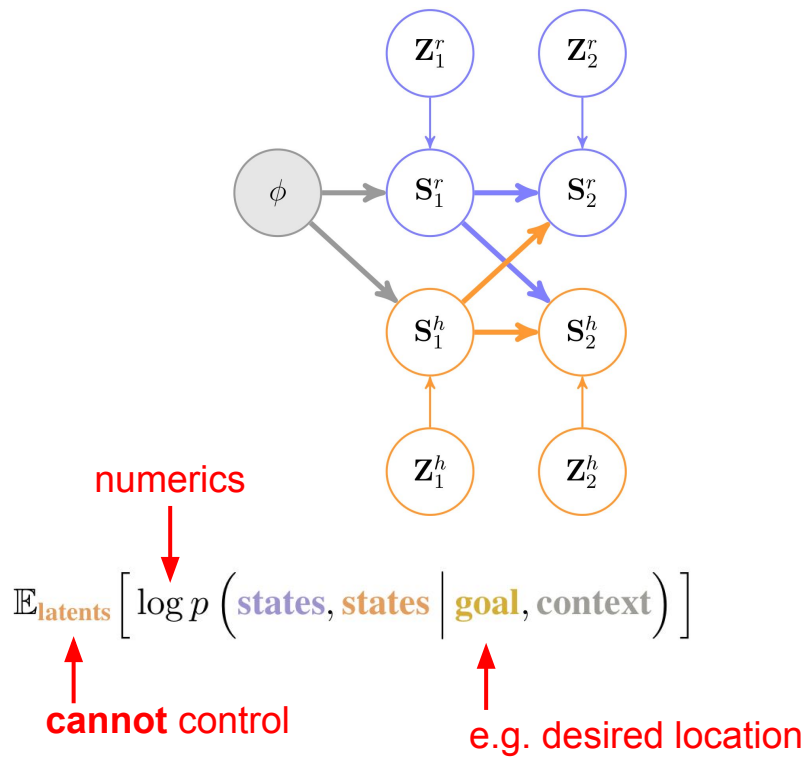
$$p(\text{states}, \text{states} \mid \text{goal}, \text{context})$$

↑
e.g. desired location



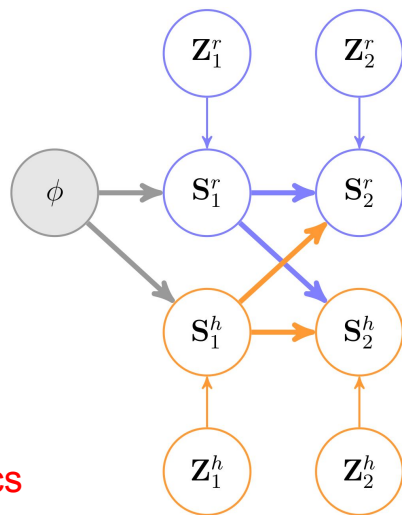
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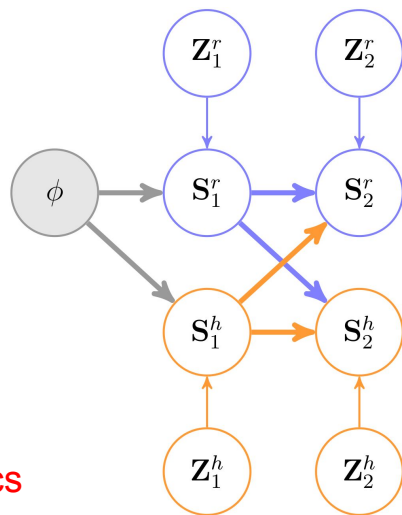


Generating function:

$$\text{states}, \text{states} = f(\text{latents}, \text{latents}; \text{context})$$

$$\arg \max_{\text{latents}} \mathbb{E}_{\text{latents}} \left[\log p \left(\text{states}, \text{states} \mid \text{goal}, \text{context} \right) \right]$$

numerics ↓
can control ↑ cannot control ↑ e.g. desired location ↑

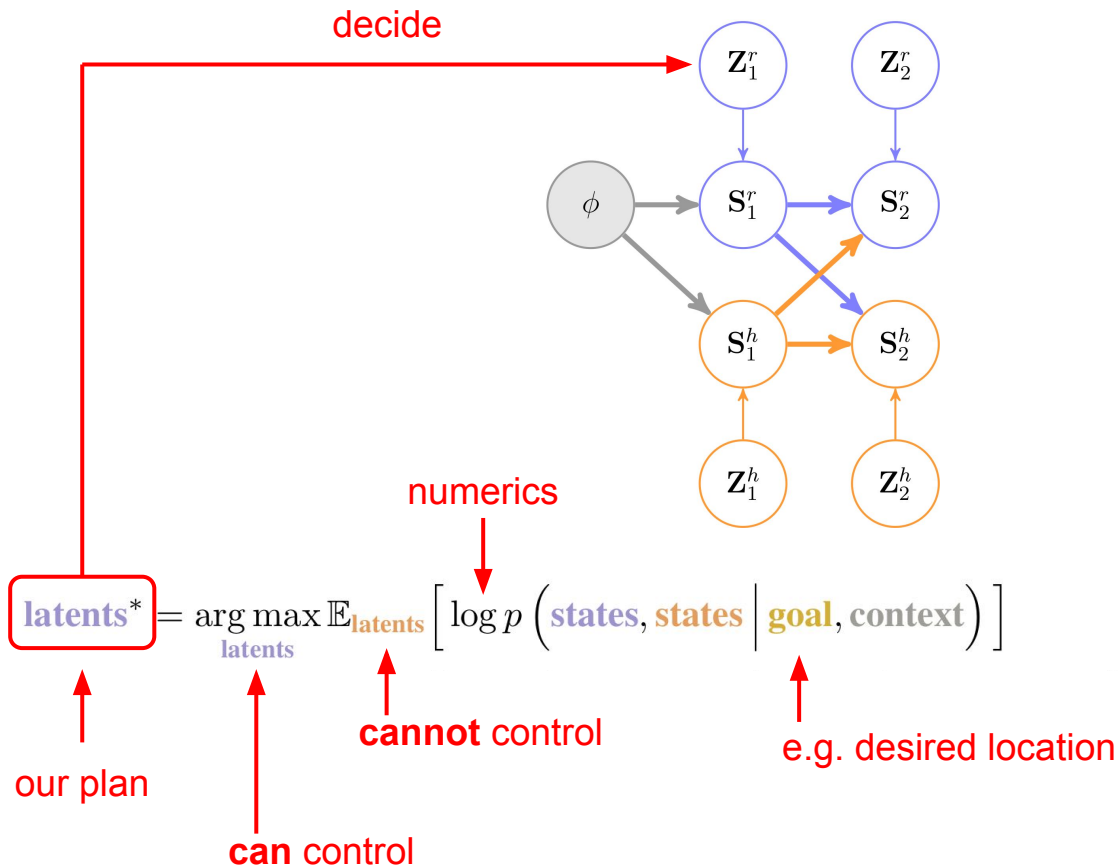


Generating function:

$$\text{states}, \text{states} = f(\text{latents}, \text{latents}; \text{context})$$

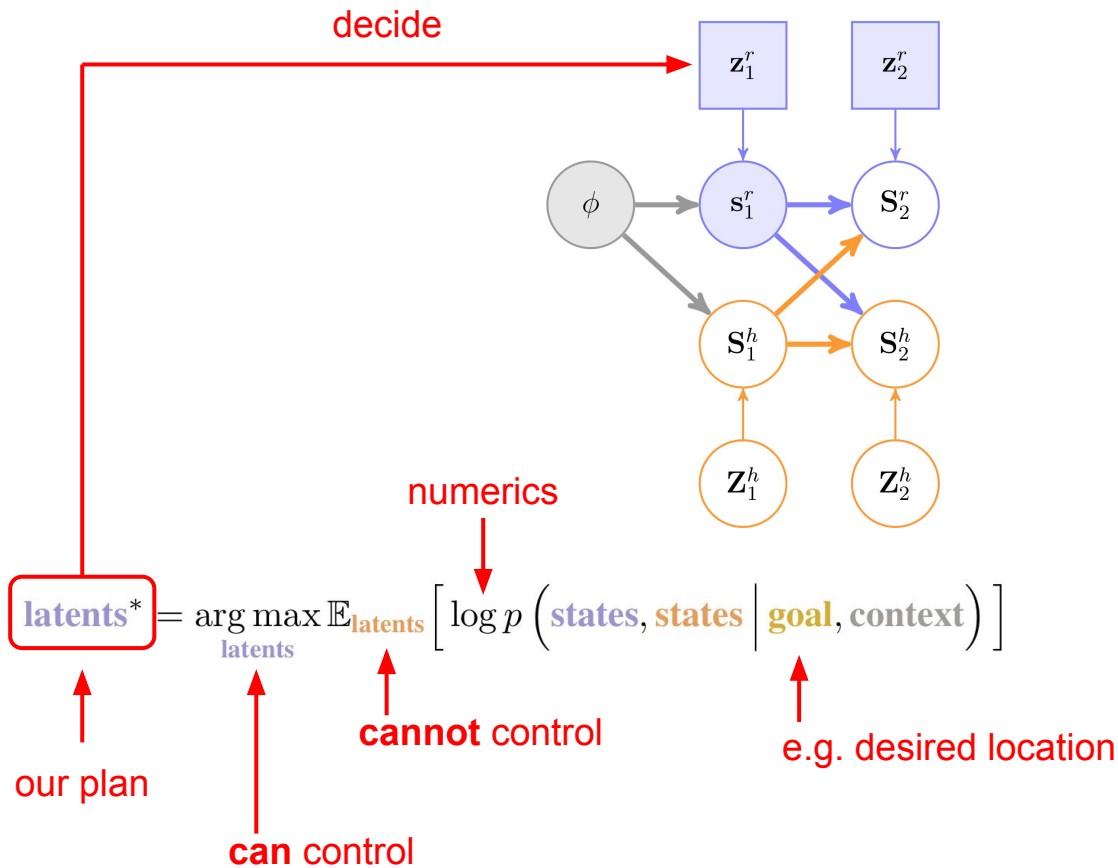
$$\text{latents}^* = \arg \max_{\text{latents}} \mathbb{E}_{\text{latents}} \left[\log p \left(\text{states}, \text{states} \mid \text{goal}, \text{context} \right) \right]$$

our plan \uparrow latents^*
 can control \uparrow latents
 cannot control \uparrow latents
 numerics \downarrow $\log p$
 e.g. desired location \uparrow goal



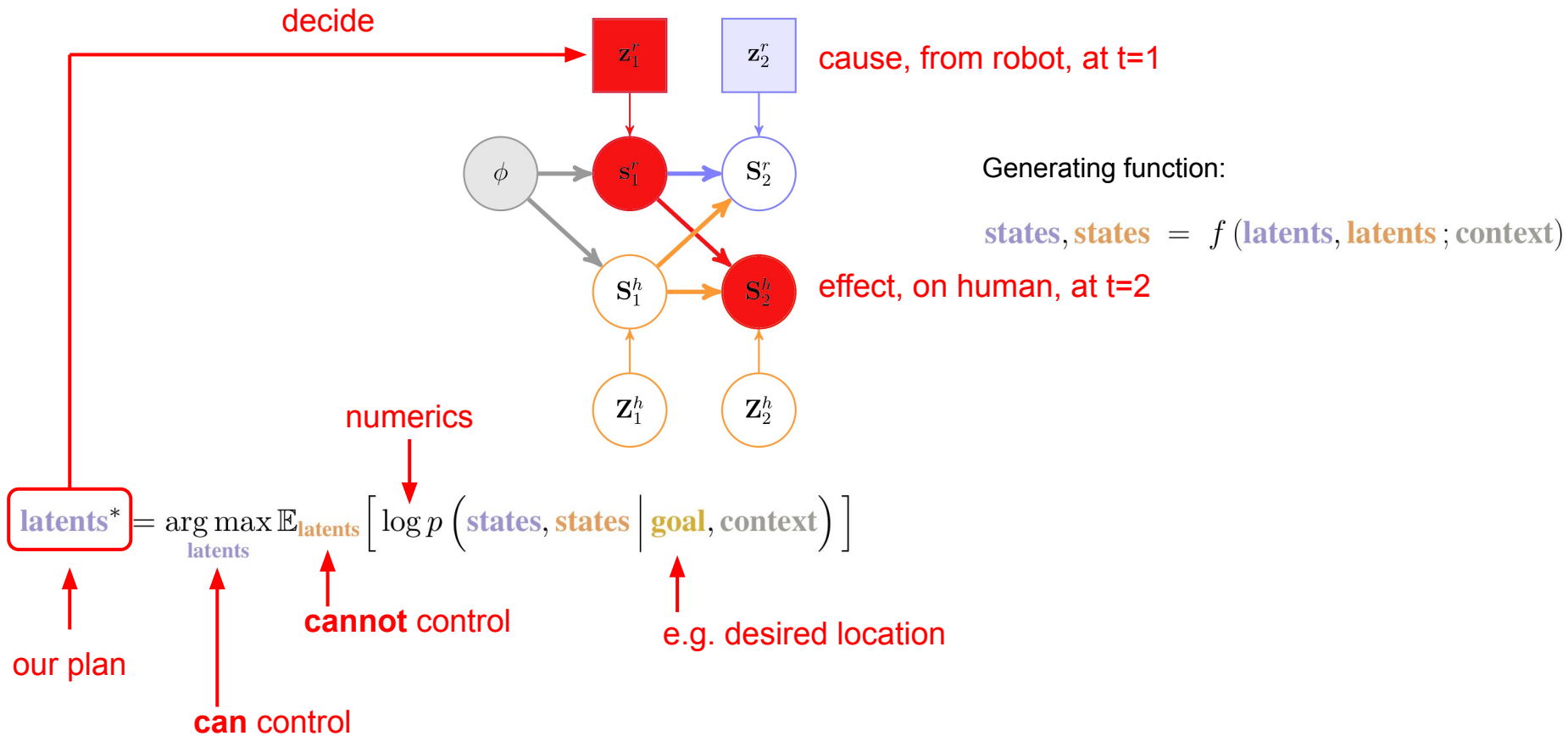
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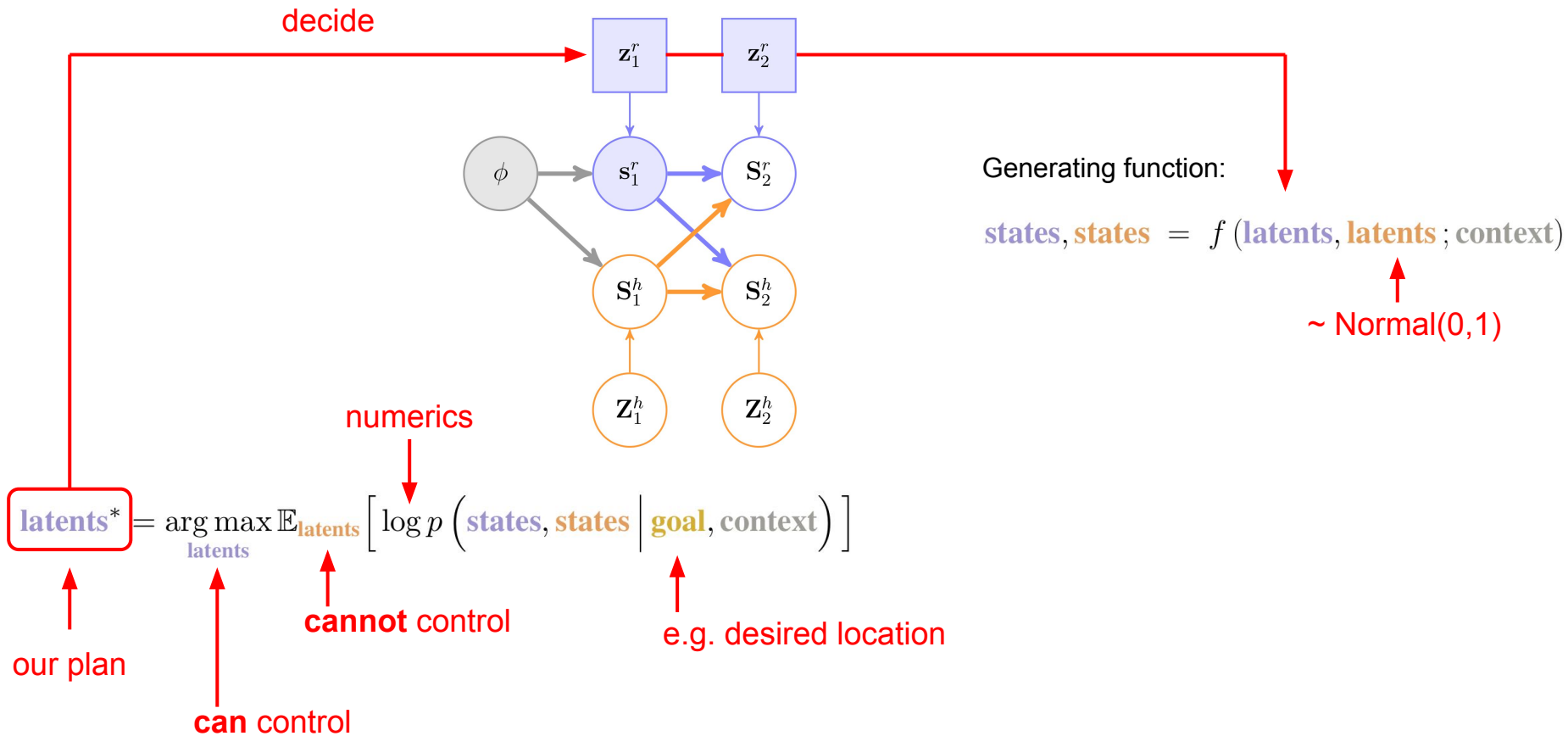
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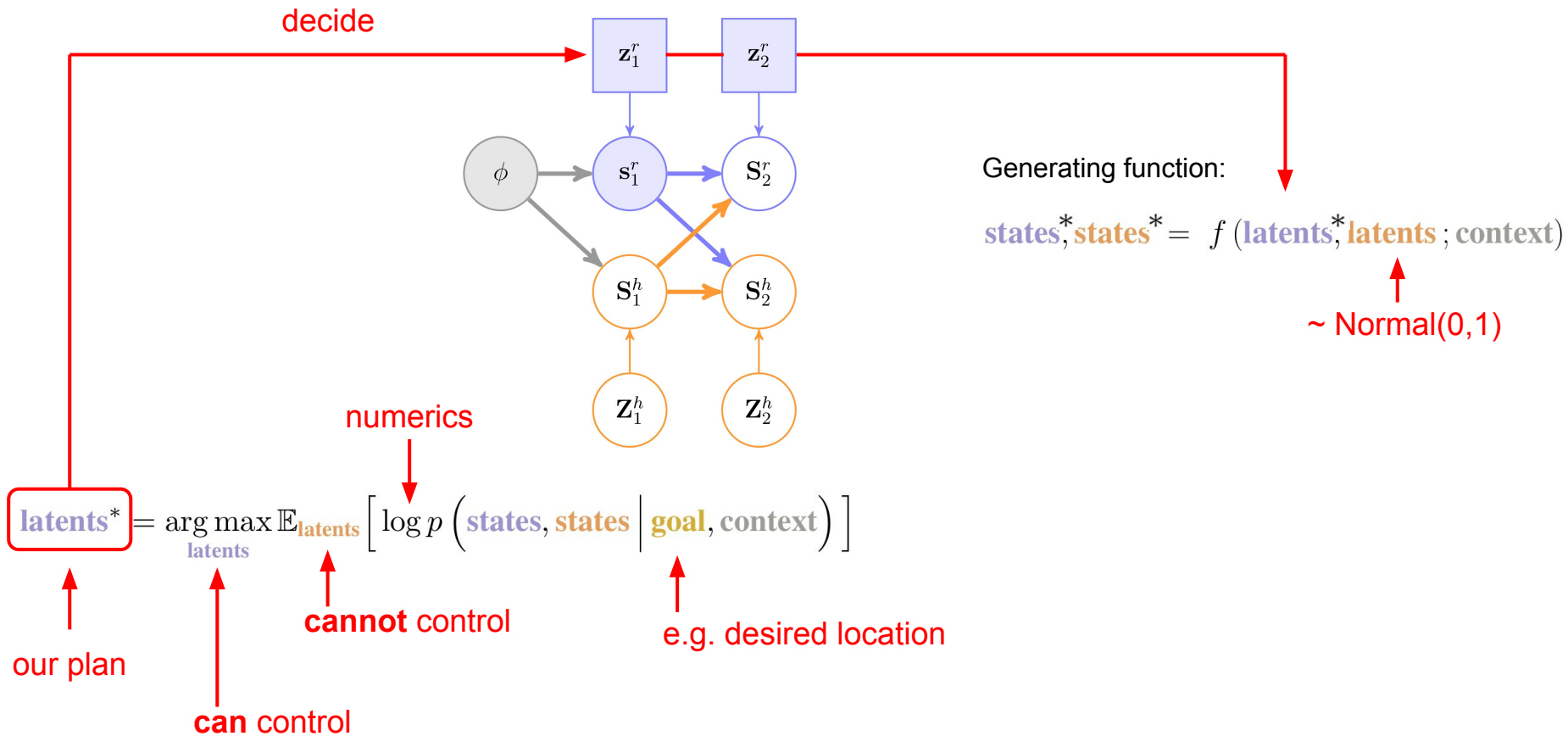


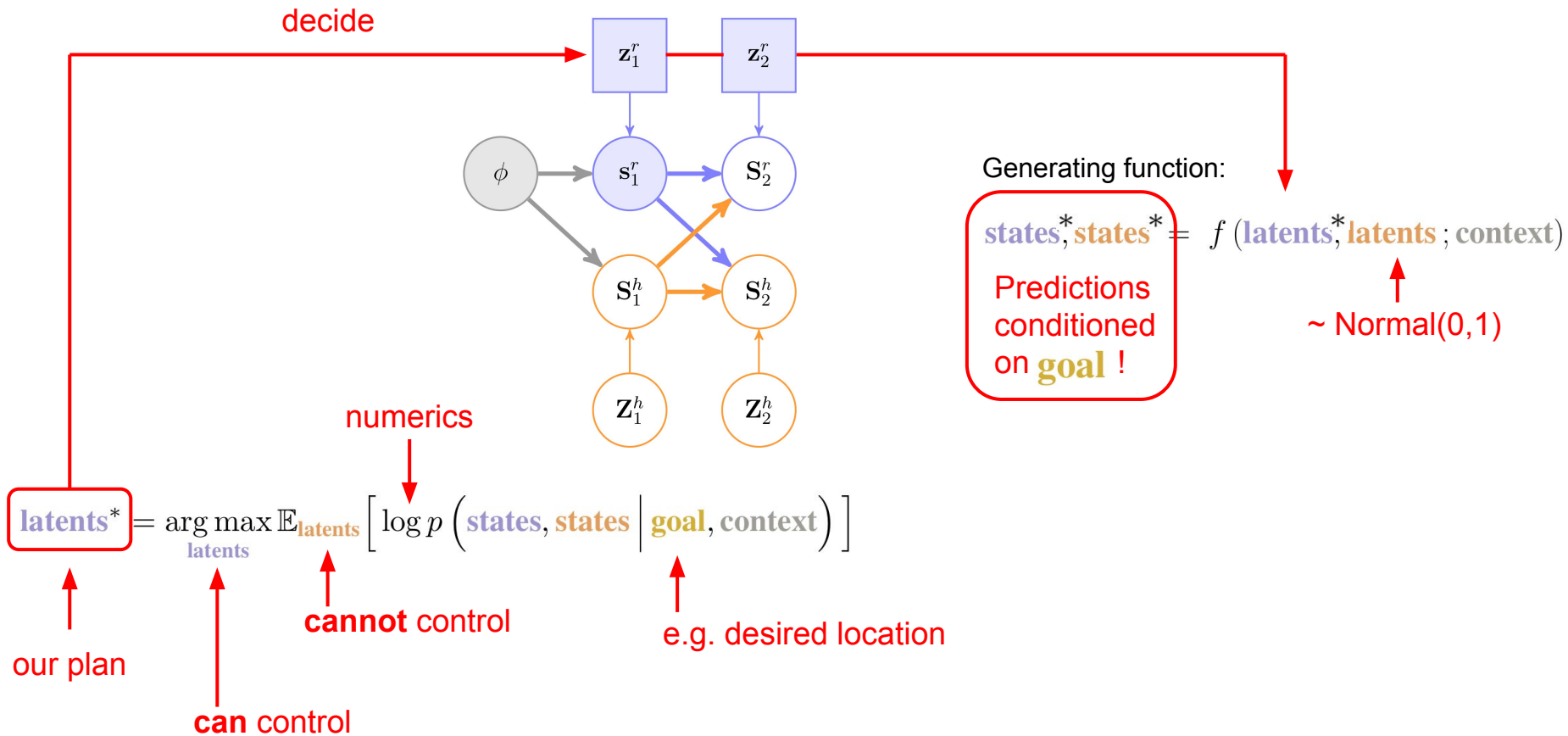
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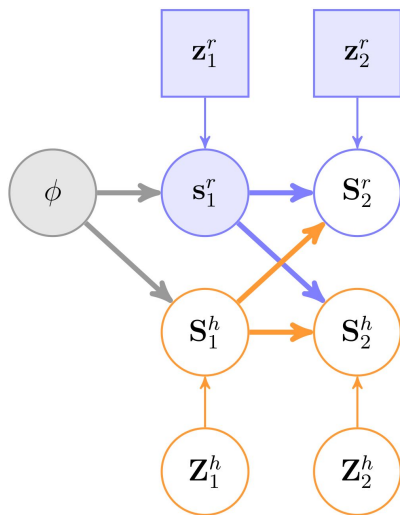
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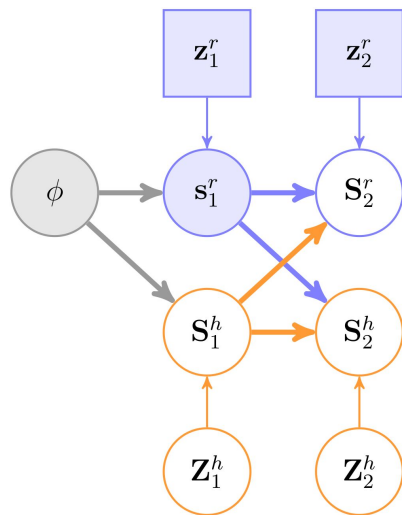




Generating function:

$$\text{states}, \text{states} = f(\text{latents}, \text{latents}; \text{context})$$

$$\begin{aligned} \text{latents}^* &= \arg \max_{\text{latents}} \mathbb{E}_{\text{latents}} \left[\log p \left(\text{states}, \text{states} \mid \text{goal}, \text{context} \right) \right] \\ &= \arg \max_{\text{latents}} \mathbb{E}_{\text{latents}} \left[\log q \left(\text{states}, \text{states} \mid \text{context} \right) + \log p(\text{goal} \mid \text{states}, \text{states}, \text{context}) - \log p(\text{goal} \mid \text{context}) \right] \end{aligned}$$



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 &= \arg \max_{\text{latents}} \mathbb{E}_{\text{latents}} \left[\log q \left(\text{states}, \text{states} \mid \text{context} \right) + \log p \left(\text{goal} \mid \text{states}, \text{states}, \text{context} \right) - \log p \left(\text{goal} \mid \text{context} \right) \right] \\
 &= \arg \max_{\text{latents}} \mathbb{E}_{\text{latents}} \left[\underbrace{\log q \left(\text{states}, \text{states} \mid \text{context} \right)}_{\text{multi-agent prior}} + \underbrace{\log p \left(\text{goal} \mid \text{states}, \text{states}, \text{context} \right)}_{\text{goal likelihood}} \right]
 \end{aligned}$$

Future work: how to respond to “out-of-distribution” scenes?



Thank you!

Single-agent forecasting + control

Deep Imitative Models for Flexible Inference, Planning, and Control

Nicholas Rhinehart, Rowan McAllister, Sergey Levine

arXiv 2018 <http://imitate.ml>

Multi-agent forecasting

PRECOC: PRediction Conditioned On Goals in Visual Multi-Agent Settings

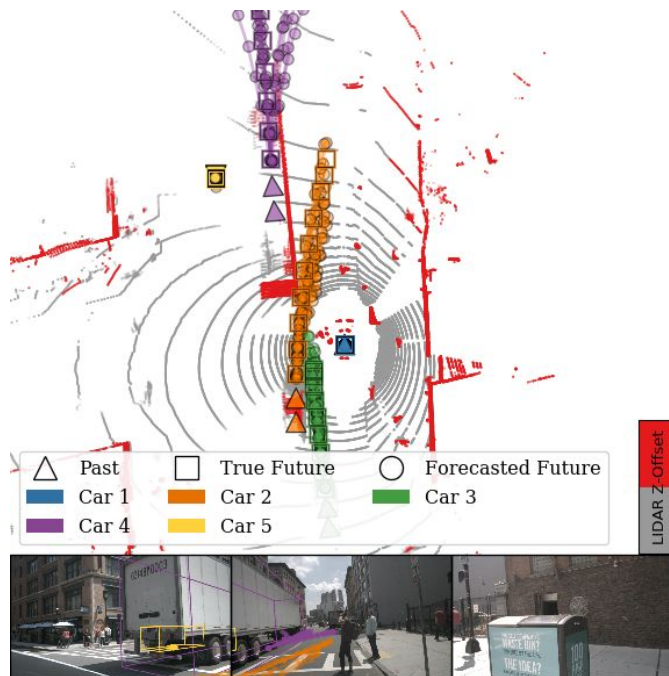
Nicholas Rhinehart, Rowan McAllister, Kris Kitani, Sergey Levine

ICCV 2019 <http://precog.ml>

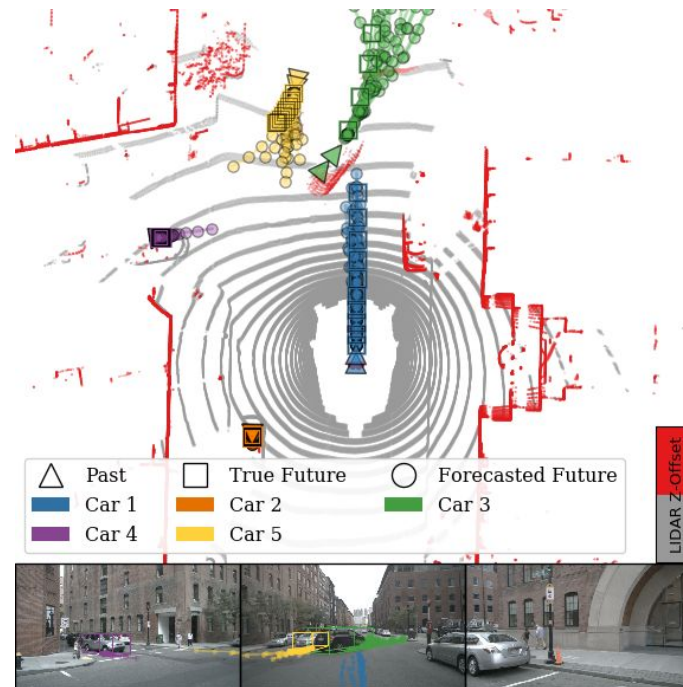
Bayesian single-agent forecasting + control

(in progress)

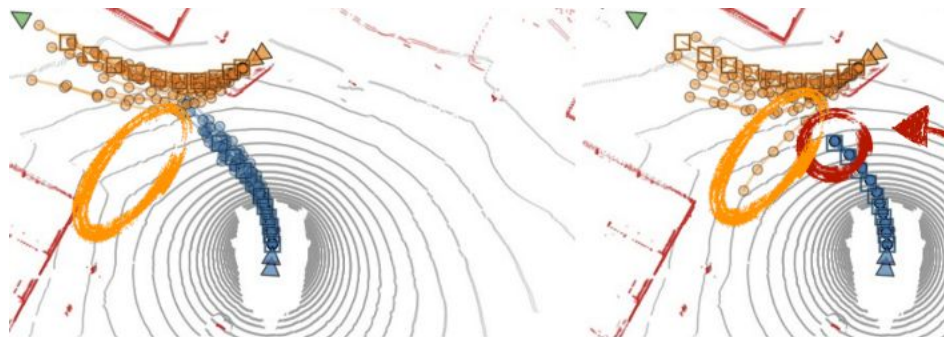
Forecasting with nuScenes data (Singapore + Boston)



Car 2 is predicted to overtake **Car 1**, which itself is forecasted to continue to wait for pedestrians and **Car 2**.

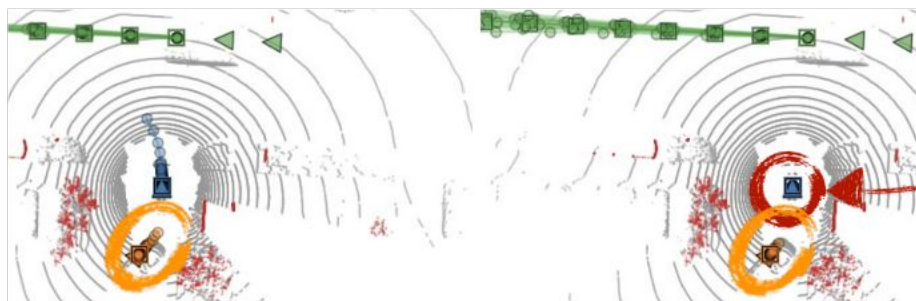


Car 4 is predicted to wait for a clear intersection, and **Car 5** is predicted to either start turning or continue straight.



Forecasting

PRECOG

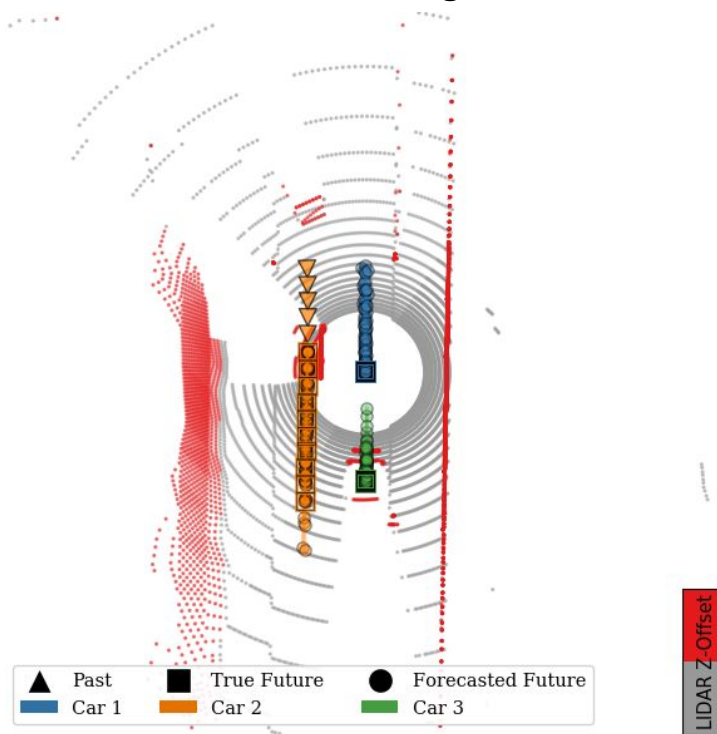


Forecasting

PRECOG

Goal-Conditioned Forecasting

Forecasting



Car 1 Forecasts Stopping

