Predicting Humans around Robots

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The story thus far ...

- ✅ Decision-making
- ✅ Perception
- ☐ Models of humans
  - ✅ Aligning robots to human values
  - Today-> ☐ Predicting humans around robots

Today's class

- Why do we need prediction / forecasting?
- Forecasting as a Machine Learning problem
  - Model?
  - Loss?
  - Data?
- Connection between Forecasting and Model-based RL

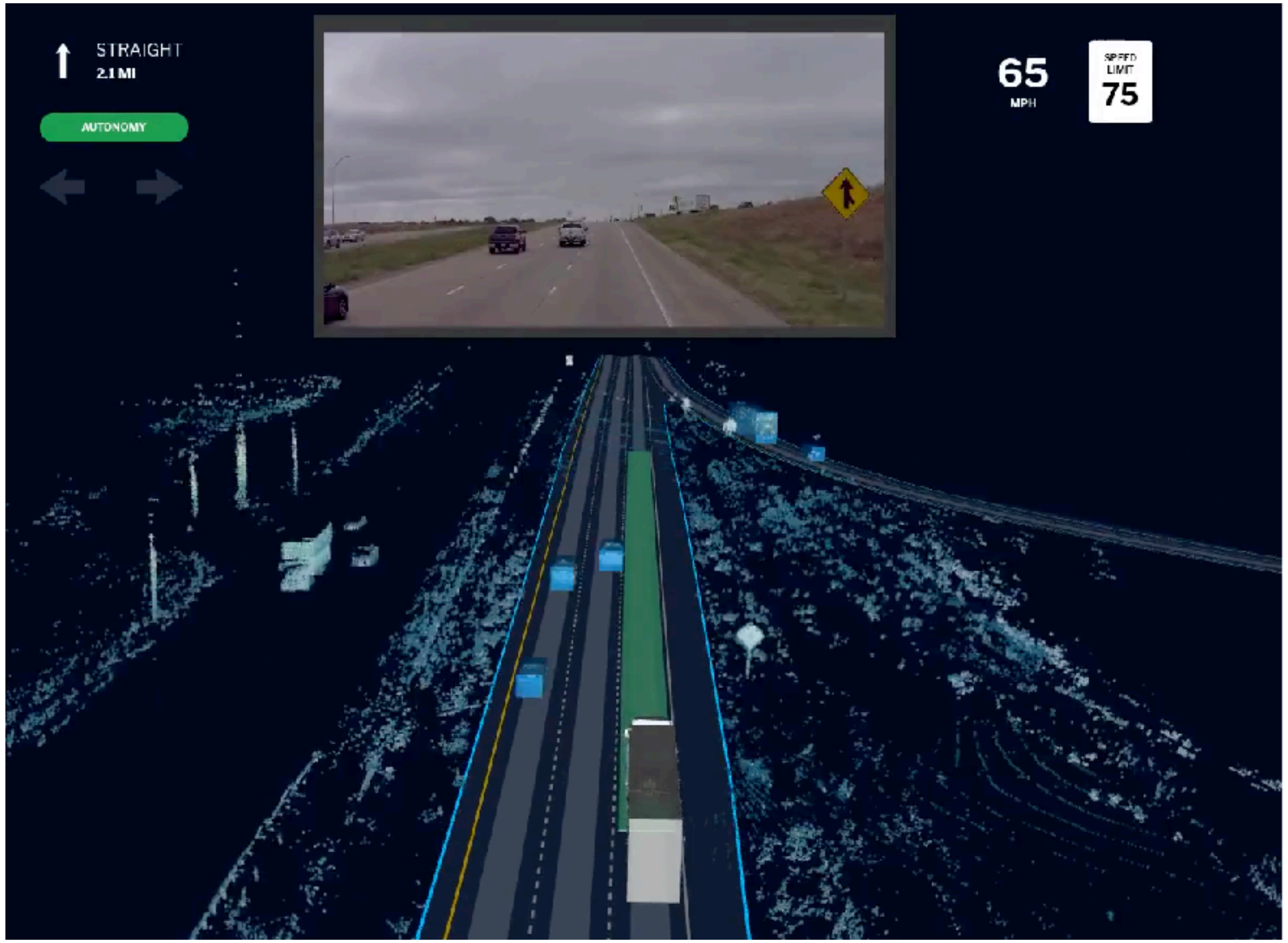
Why do robots need to *forecast* humans?

Two motivating applications

Collaborative Cooking

PORTAL

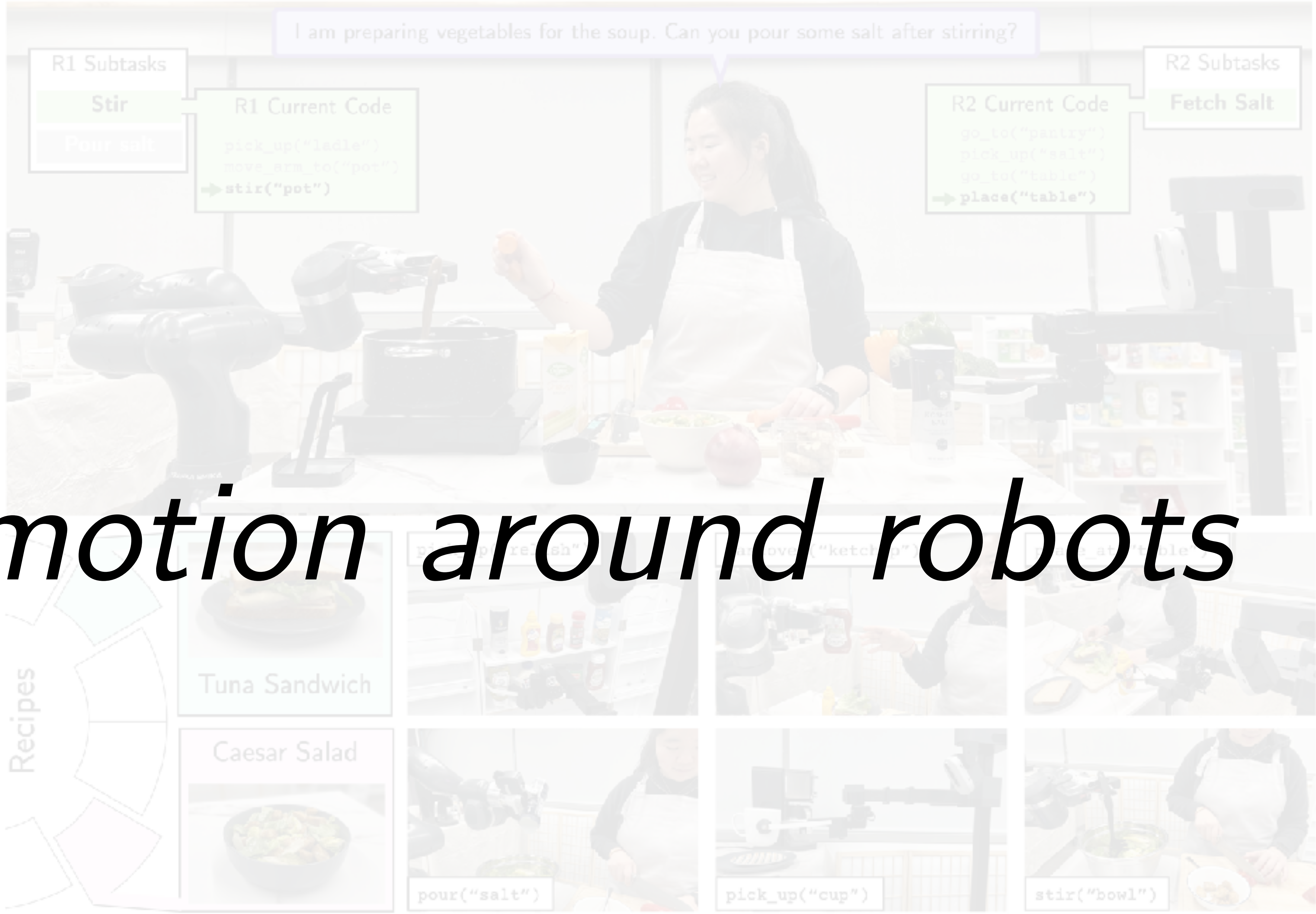
Two motivating applications



Self-driving

Collaborative Cooking

What do these have in common?

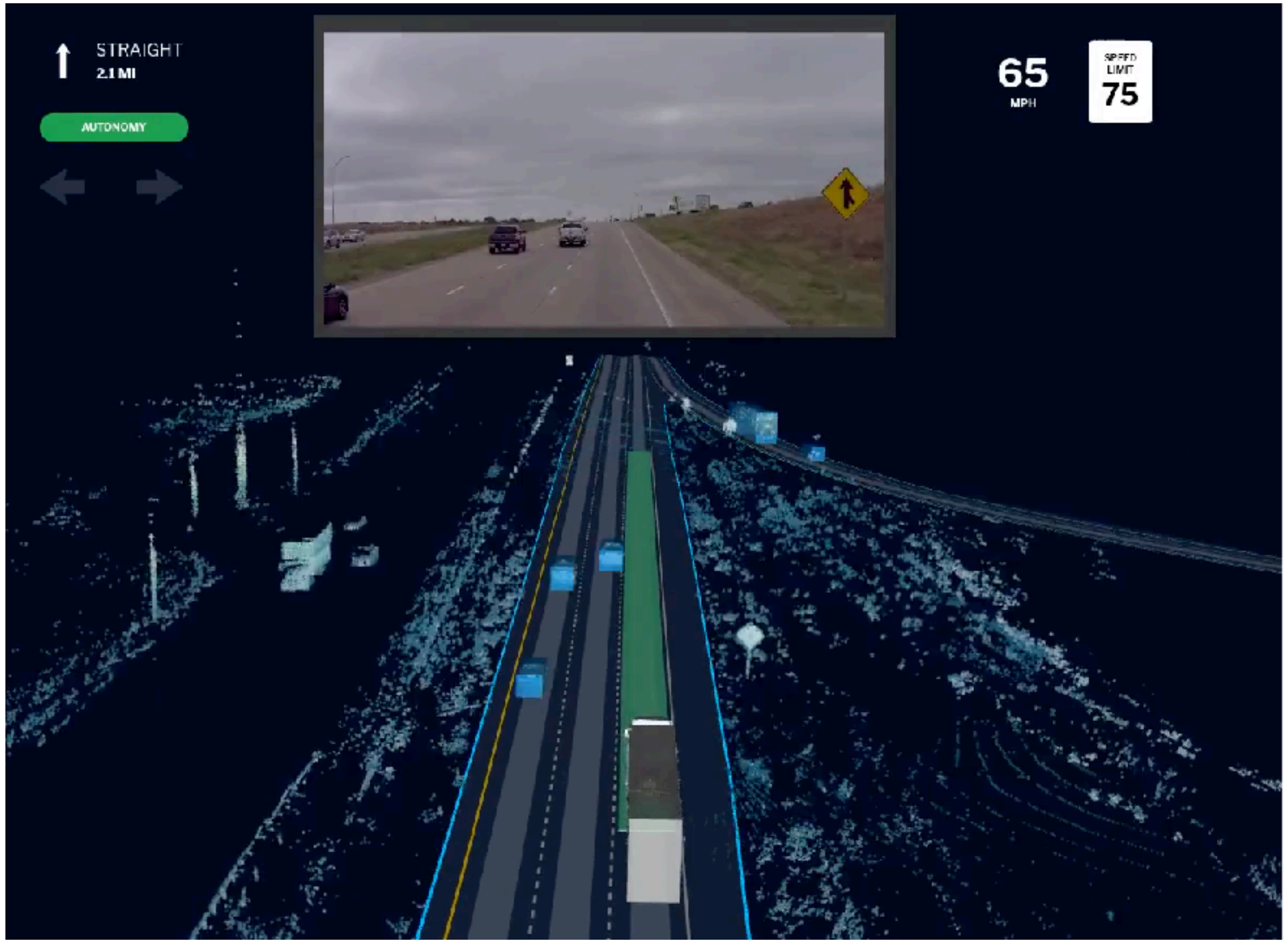


Forecasting human motion around robots

Self-driving

Collaborative Cooking

Two motivating applications



Self-driving

Aurora

Collaborative Cooking

PORTAL


30.0 m
20.0 m
10.0 m
1541016641.475 20181031.175444Z.mkz-07.mkz.V0-592_MDC

Why do robots need to *forecast* humans?

To enable **safe**, **responsive**, and **interpretable** actions

Two motivating applications

Self-driving

Collaborative Cooking

Forecasting human motion is essential

No human prediction:

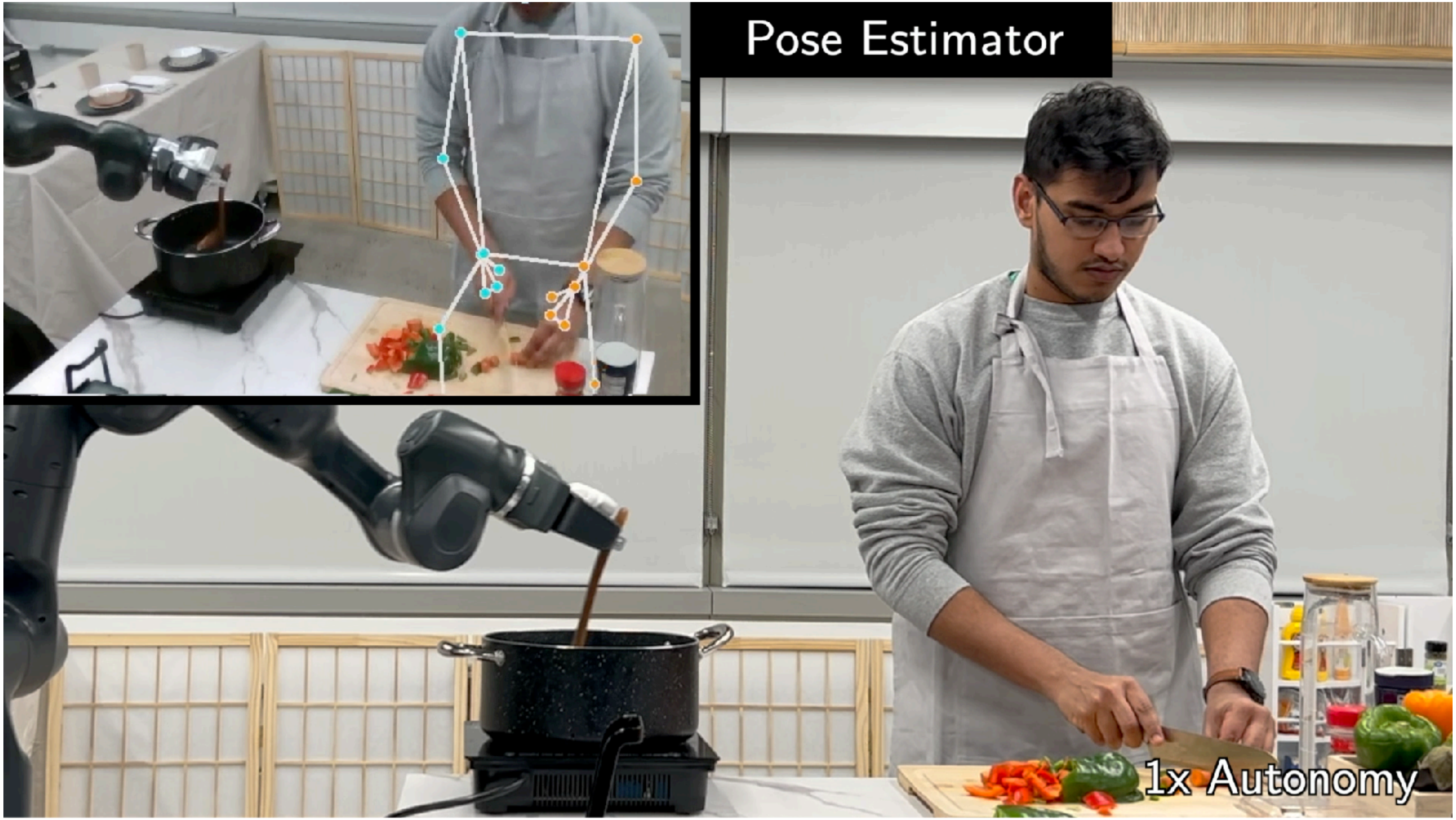
Unresponsive robots are discomforting

Forecasting human motion is essential

No human forecast:
Unresponsive robots are discomforting

Human forecast:
Robot anticipates human and makes room

Forecasting human motion is essential



Why do robots need to *forecast* humans?

To enable safe, responsive, and interpretable actions

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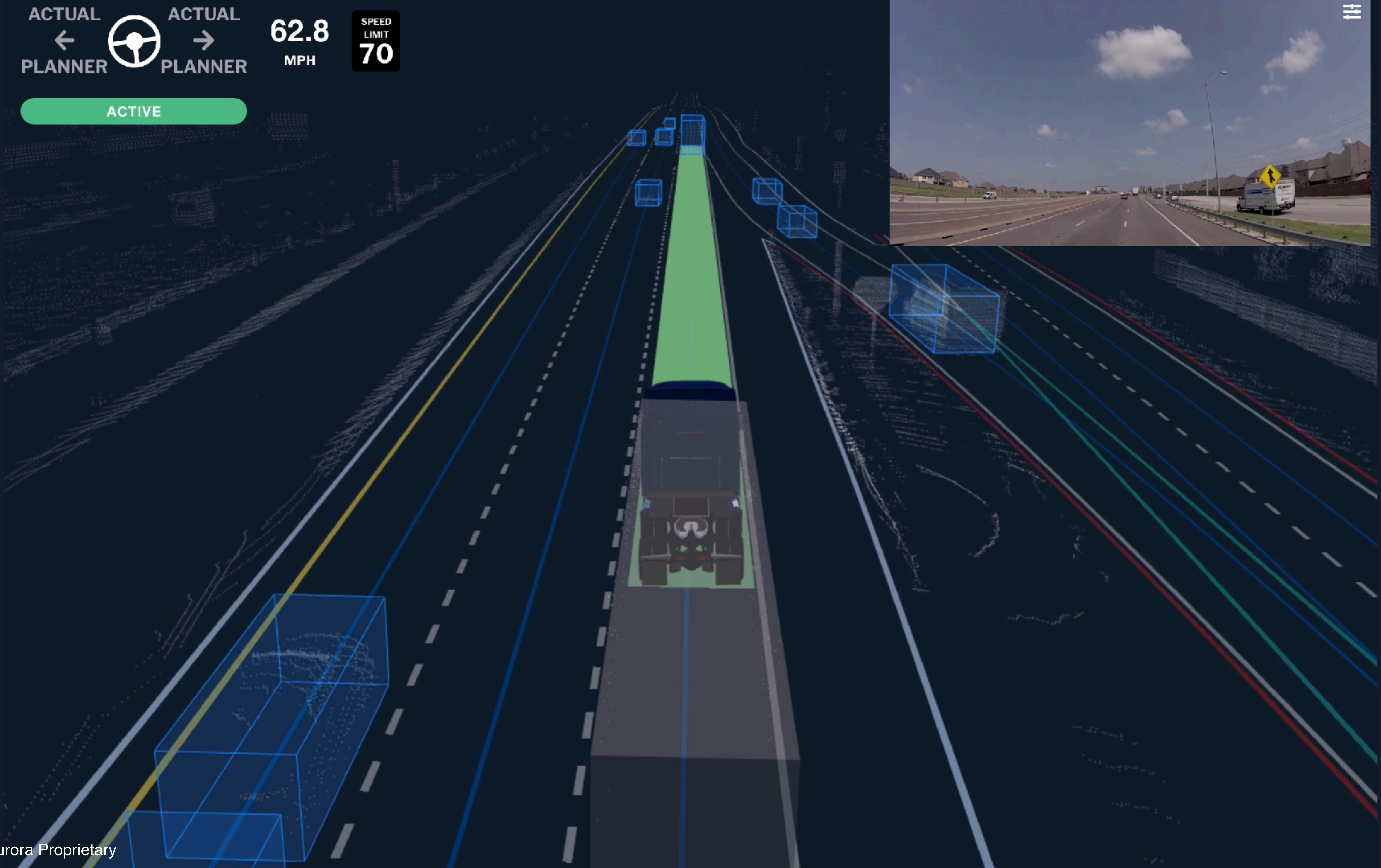
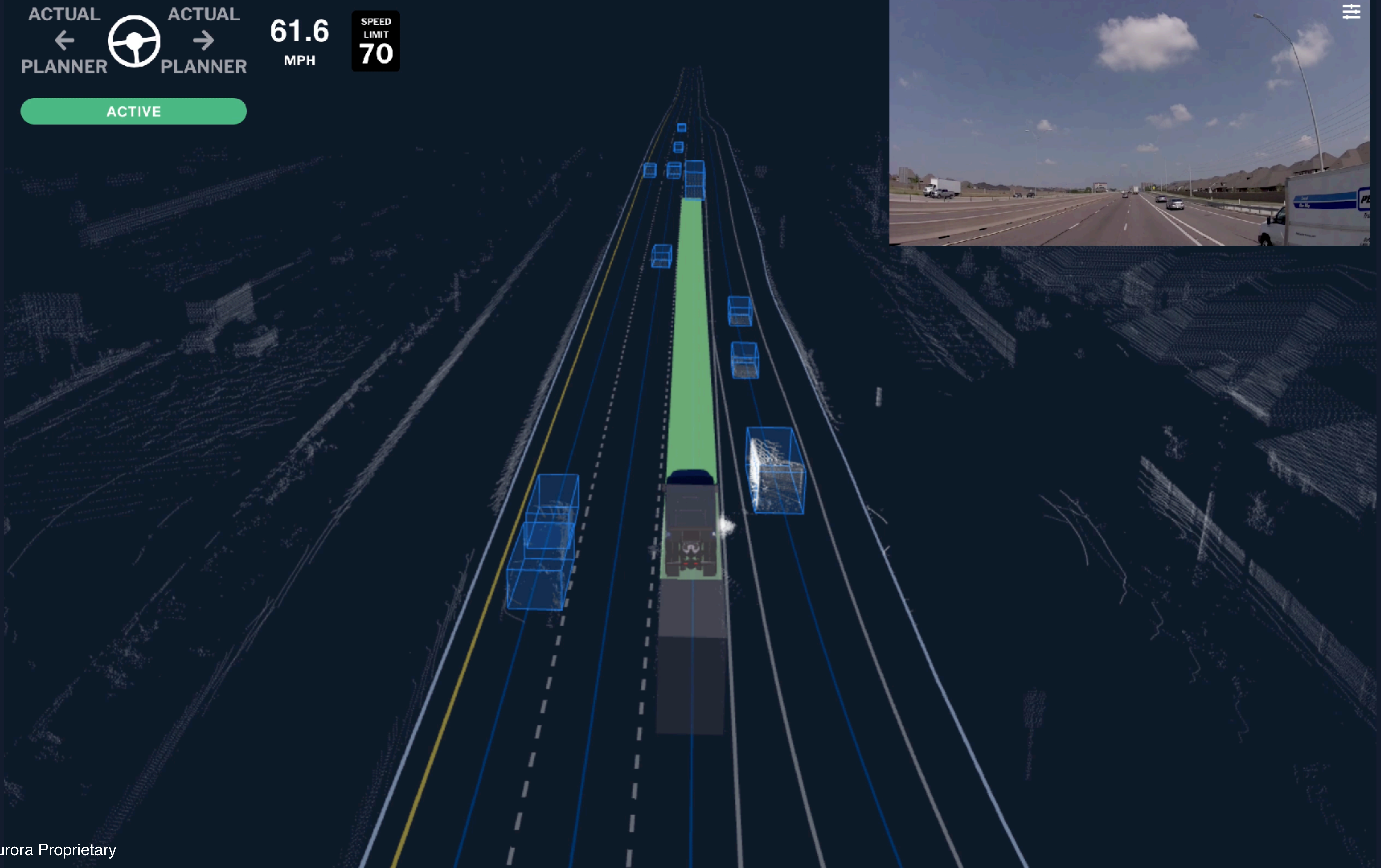
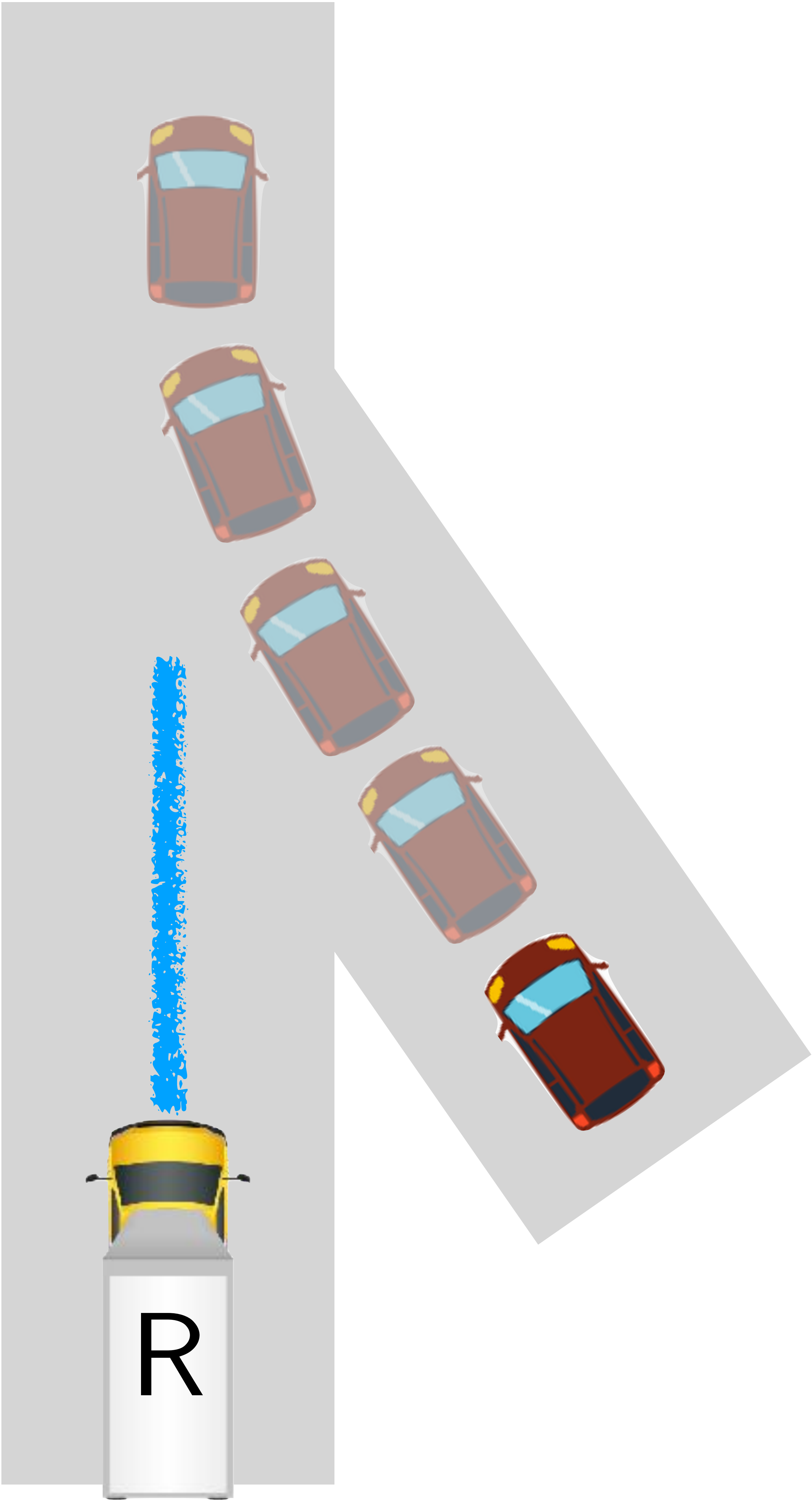
Merging on the Highway


ACTUAL
PLANNER
ACTUAL
PLANNER
62.8
MPH
SPEED
LIMIT
70
ACTIVE


ACTUAL
PLANNER
ACTUAL
PLANNER
61.6
MPH
SPEED LIMIT
70
ACTIVE

Think-Pair-Share

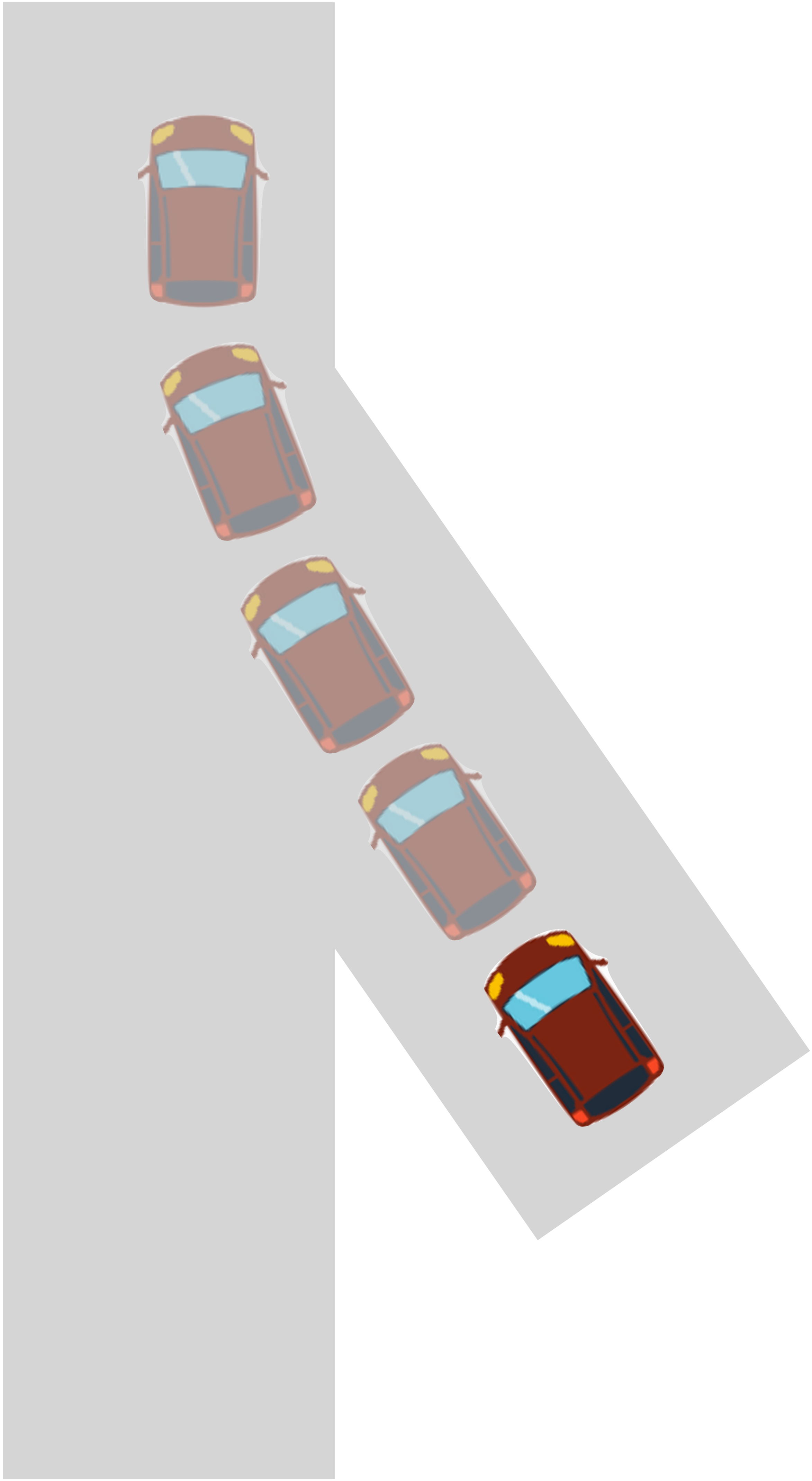
Learn forecasts for merging actors



Forecast 5s future trajectory

Once we have the forecast, we can plan to merge safely

Train a learner to forecast 5s future.



Model: Input / Output?

Data?

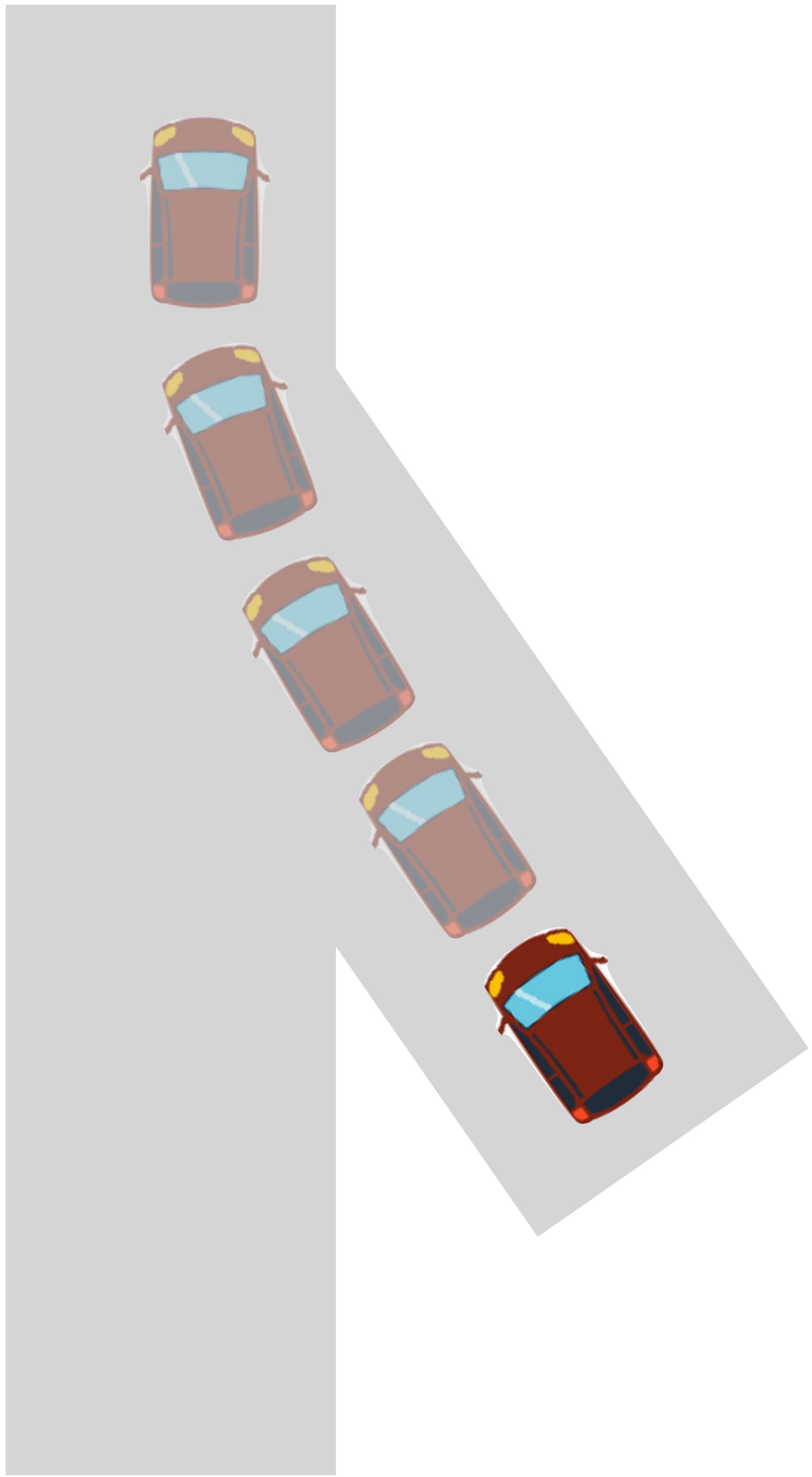
Loss?

Think-Pair-Share!

Think (30 sec): Train a learner to forecast 5s future.

Pair: Find a partner

Share (45 sec): Partners exchange ideas



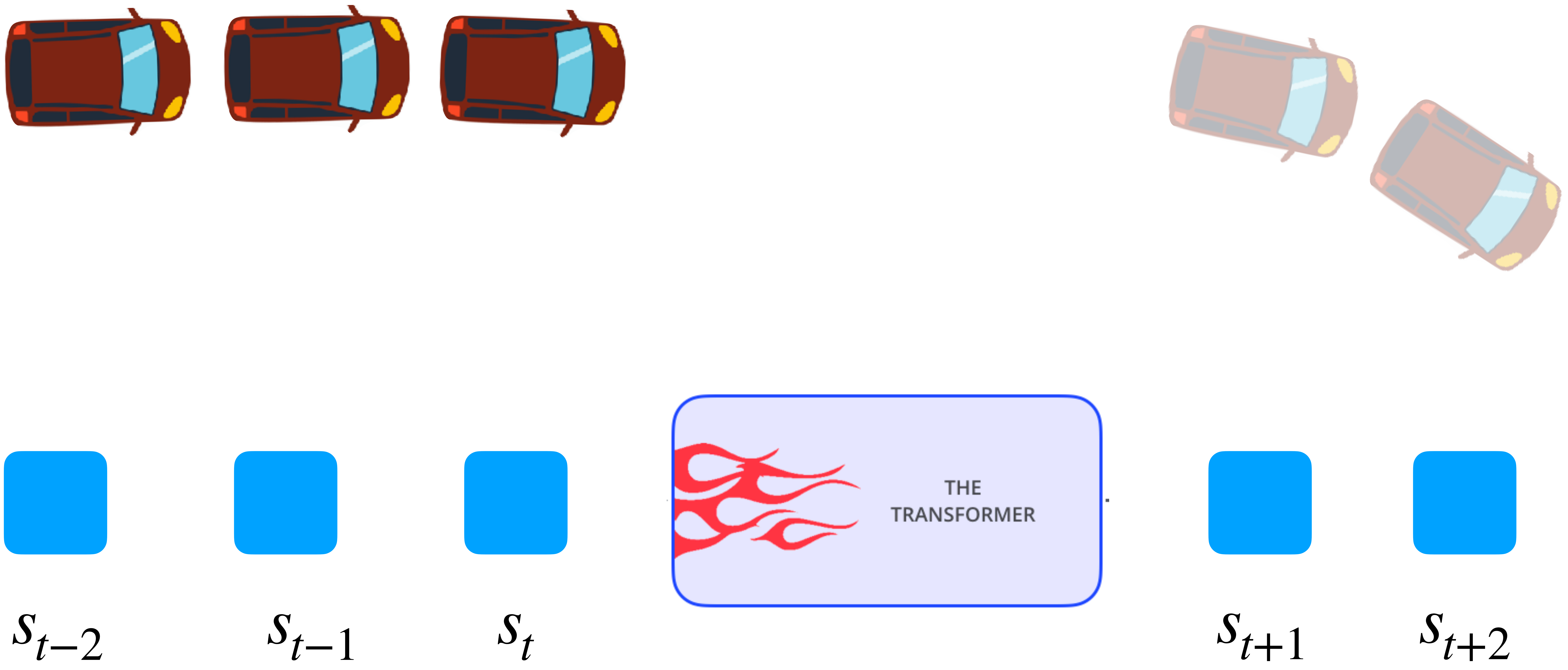
Model: Input / Output?

Data?

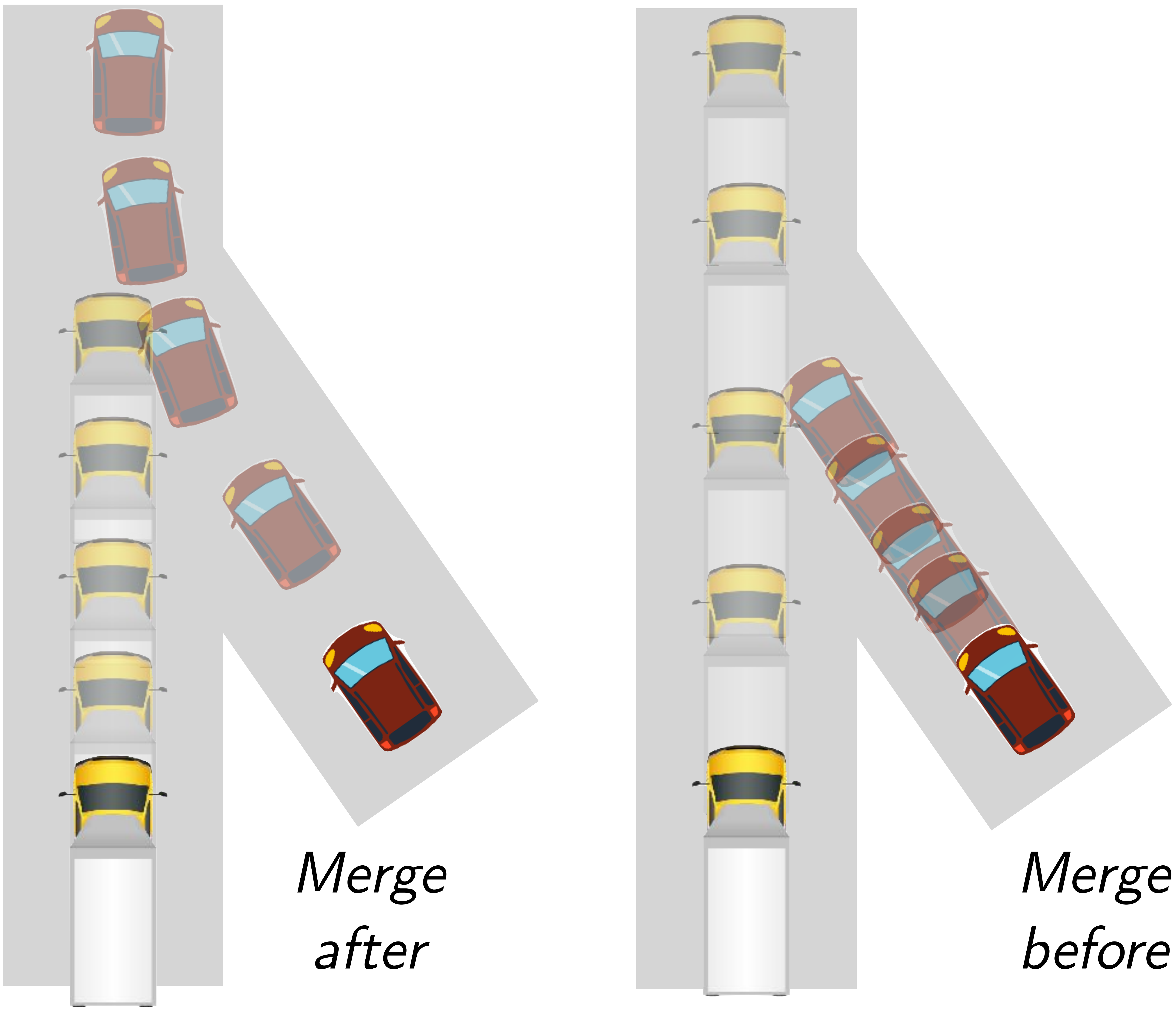
Loss?

A first attempt at model, data, and loss

Model: Use a *sequence* model that maps past sequence (input) to future sequence (output)

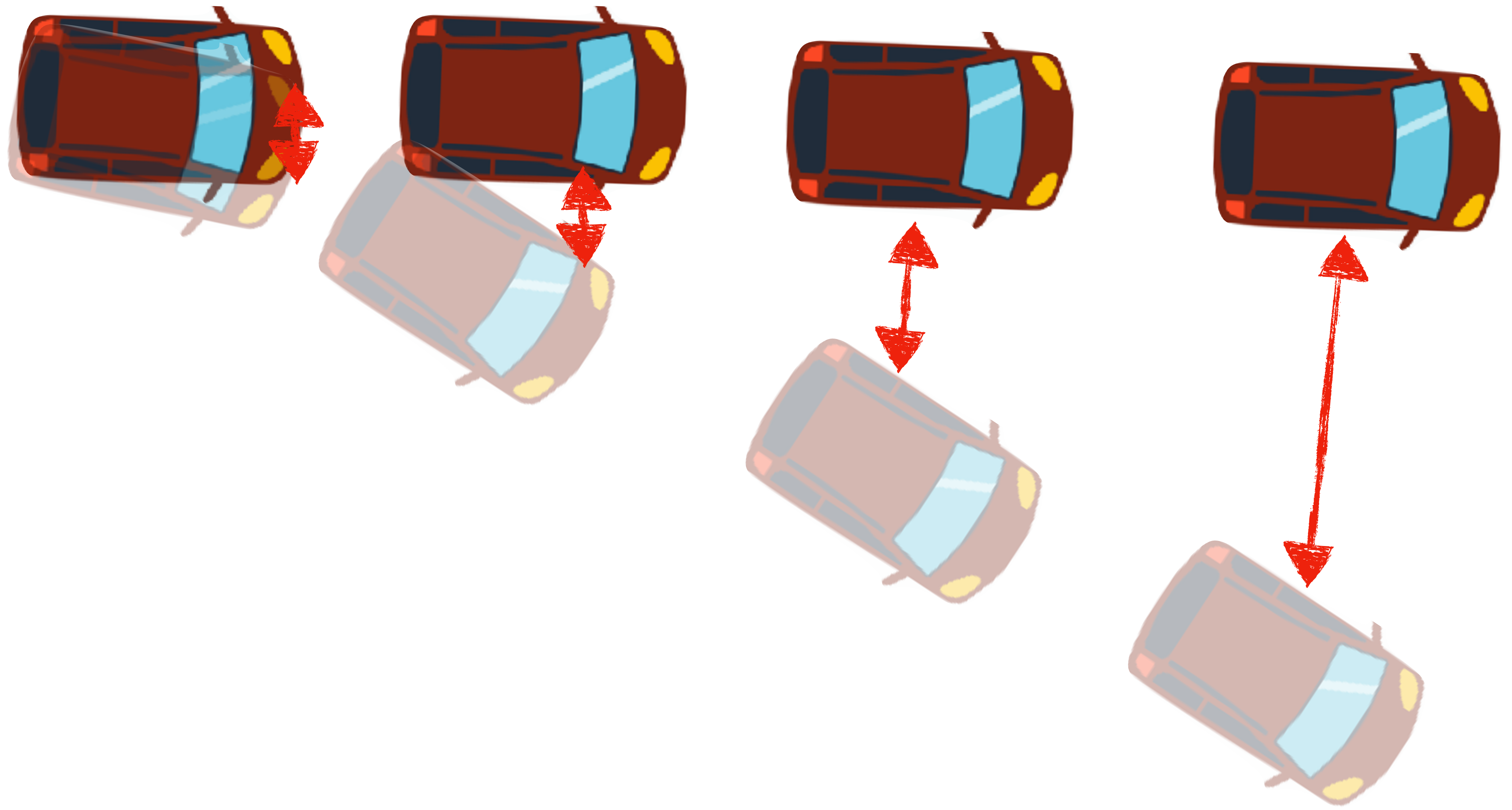


Data: Drive around the car and collect data



Loss: L2 Loss from Ground Truth

Ground Truth: $s_{t+1}, s_{t+2}, \ldots, s_{t+k}$

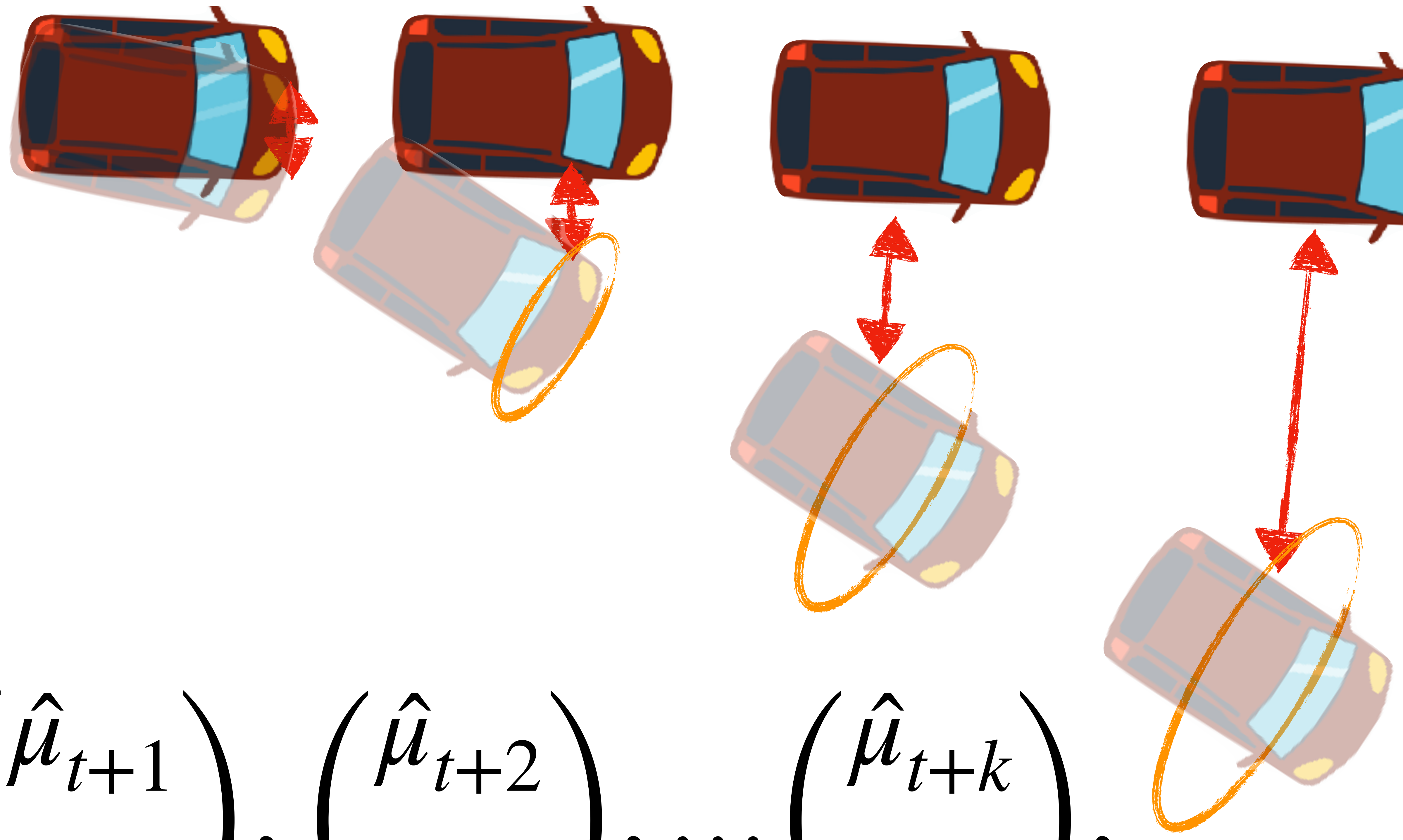


Loss: $\sum_{\tau=t}^{t+k} (s_\tau - \hat{s}_\tau)^2$

Forecast: $\hat{s}_{t+1}, \hat{s}_{t+2}, \ldots, \hat{s}_{t+k}$

Loss: L2 Loss from Ground Truth

Ground Truth: $s_{t+1}, s_{t+2}, \ldots, s_{t+k}$



Suppose I am predicting both mean and variance

Loss: $$\sum_{\tau=t}^{t+k} \frac{(s_\tau - \hat{\mu}_\tau)^2}{\hat{\sigma}_\tau}$$

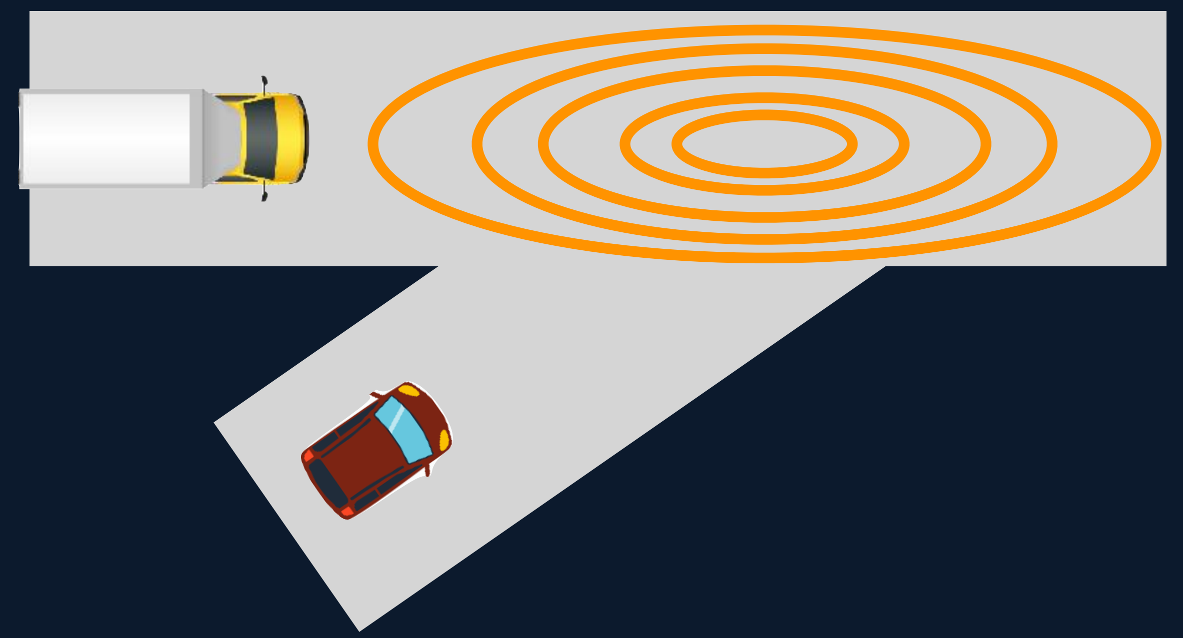
Forecast: $$\begin{pmatrix} \hat{\mu}_{t+1} \\ \hat{\sigma}_{t+1} \end{pmatrix}, \begin{pmatrix} \hat{\mu}_{t+2} \\ \hat{\sigma}_{t+2} \end{pmatrix}, \ldots \begin{pmatrix} \hat{\mu}_{t+k} \\ \hat{\sigma}_{t+k} \end{pmatrix},$$

Today's class

- ☑ Why do we need prediction / forecasting?
  (Enable safe, responsive, and interpretable robot actions)
- ☐ Forecasting as a Machine Learning problem (First attempt)
  - ☐ Model?
  - ☐ Loss?
  - ☐ Data?
- ☐ Connection between Forecasting and Model-based RL

We have model, data, loss.

Let's deploy the model!



Forecasts have huge variance!

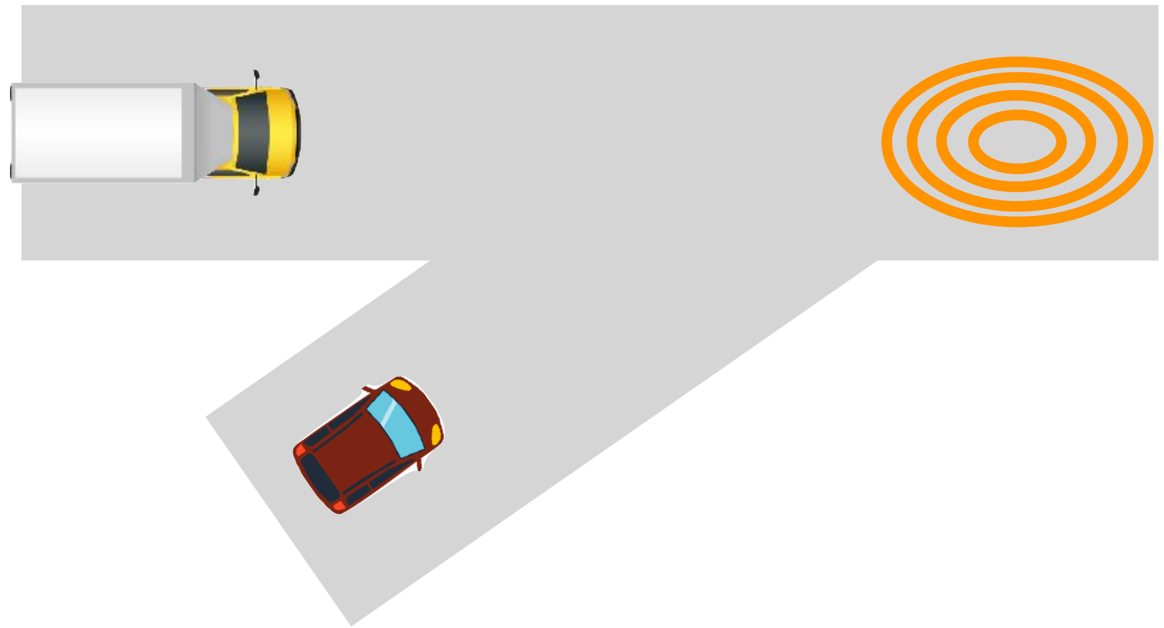
Forces robot to brake aggressively!

Why is the forecast so whacky?

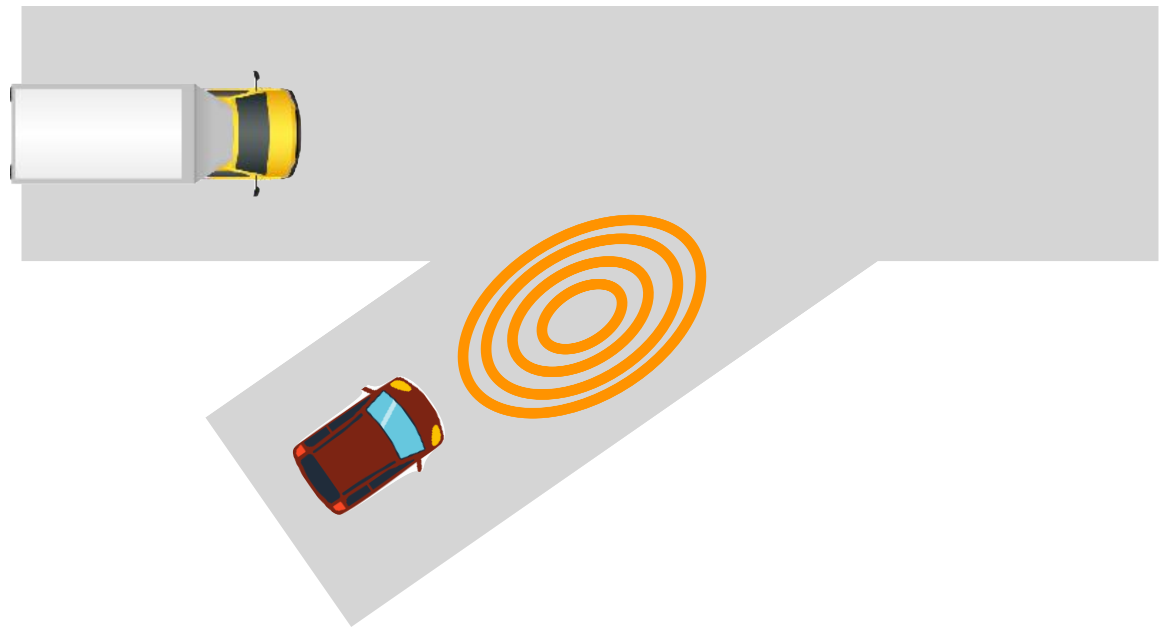
Why is the forecast so whacky?

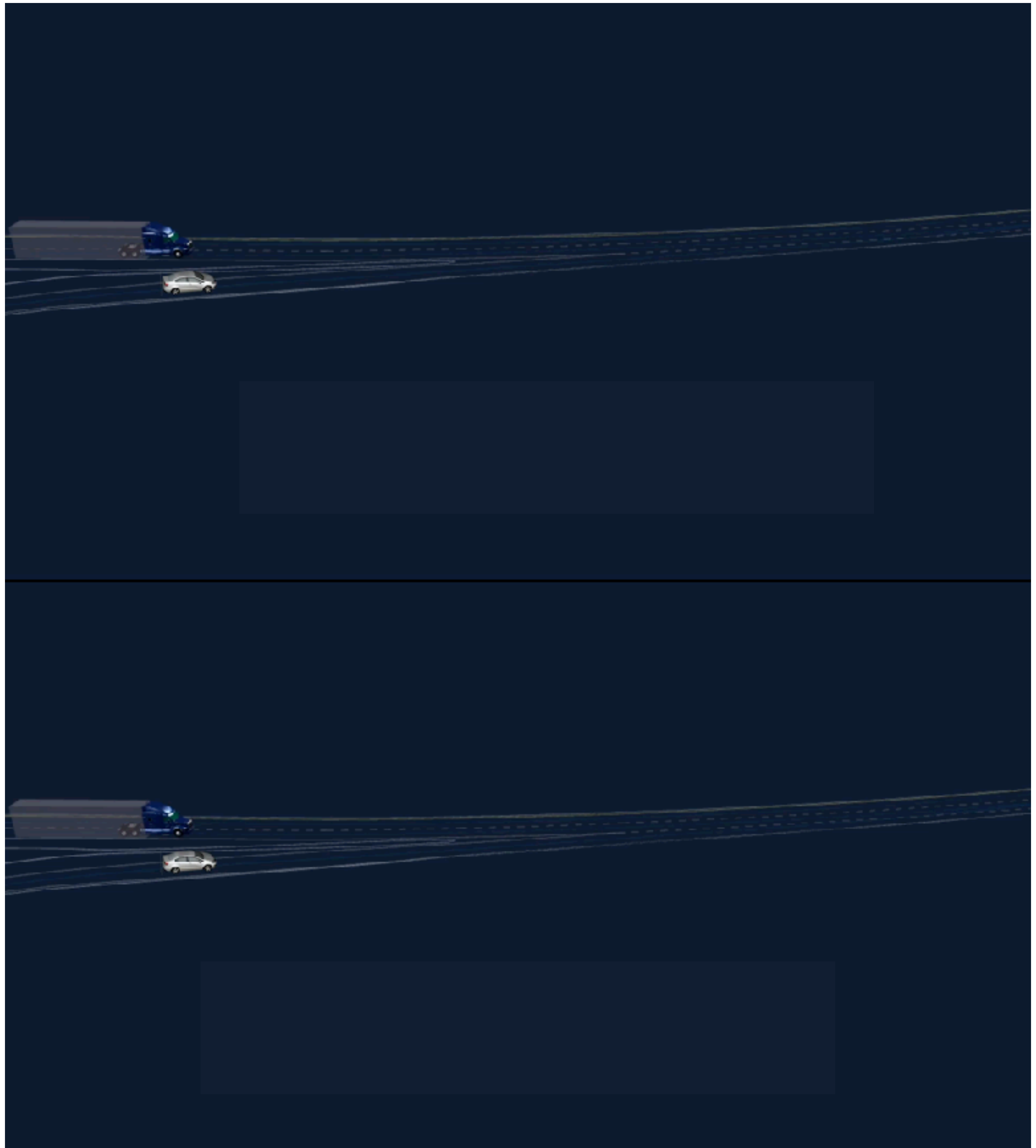
There are two modes in the data

Mode A:
Robot merges
after



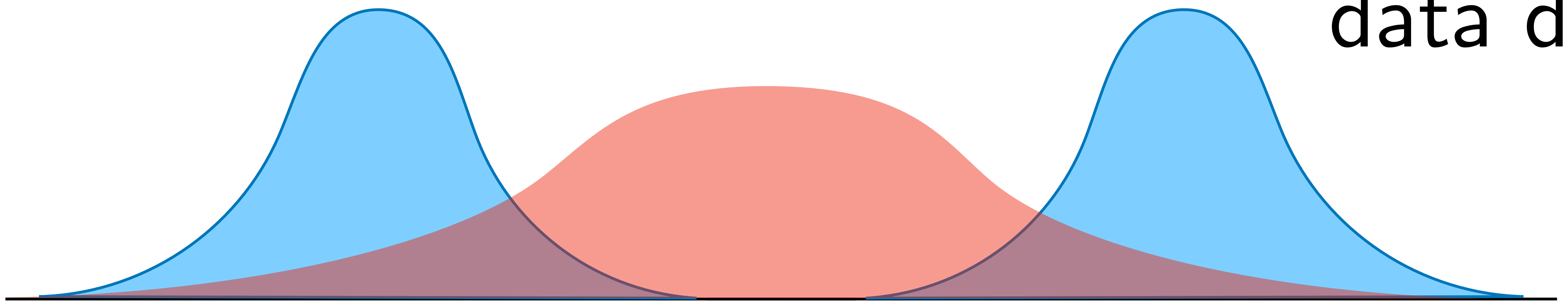
Mode B:
Robot merges
before





What happens when you try to fit a single Gaussian on multi-modal data?

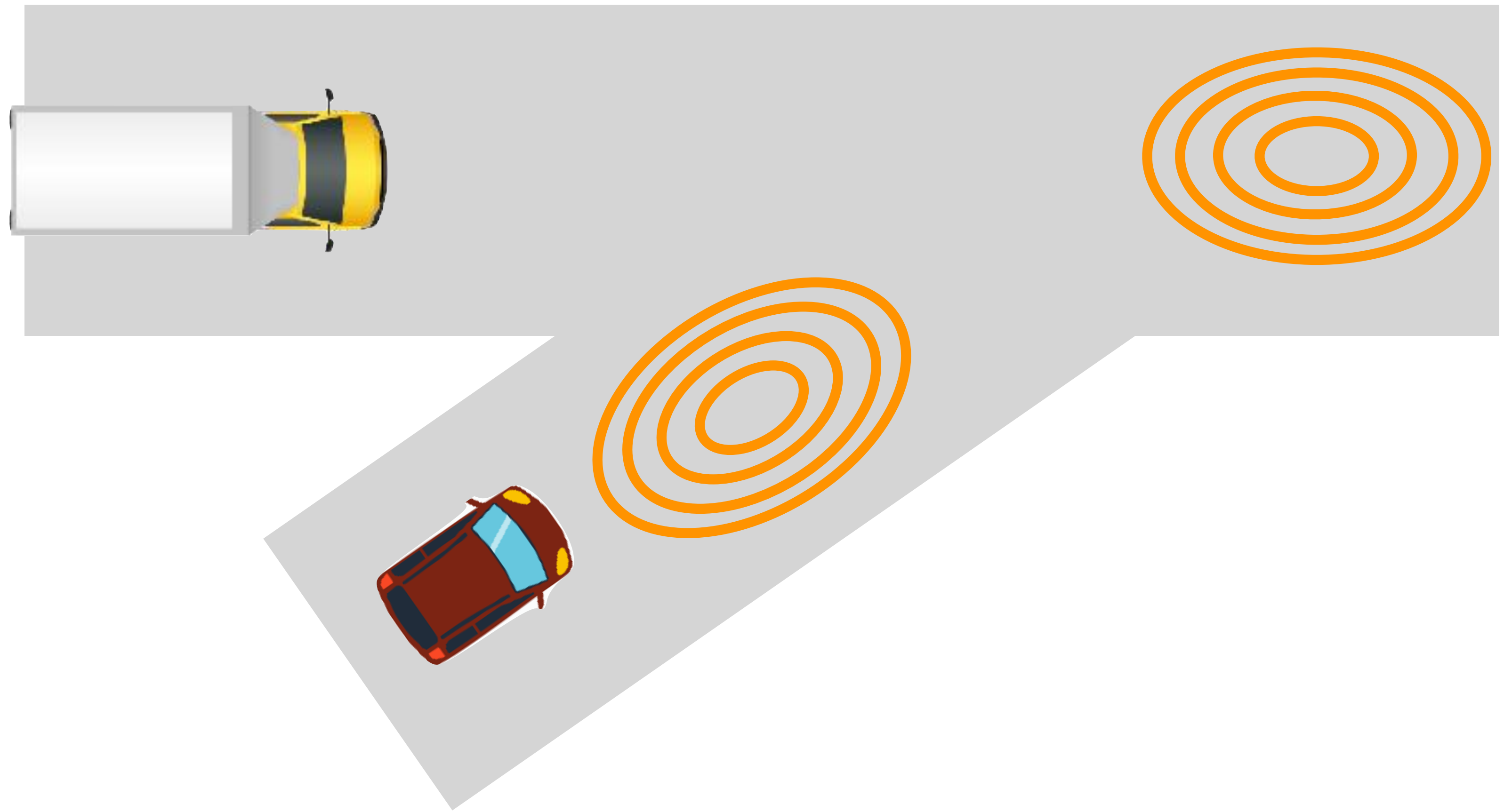
Ground truth data distribution



Gaussian averages (marginalizes) over both modes

Okay .. so why can't we just predict multi-modal distributions?

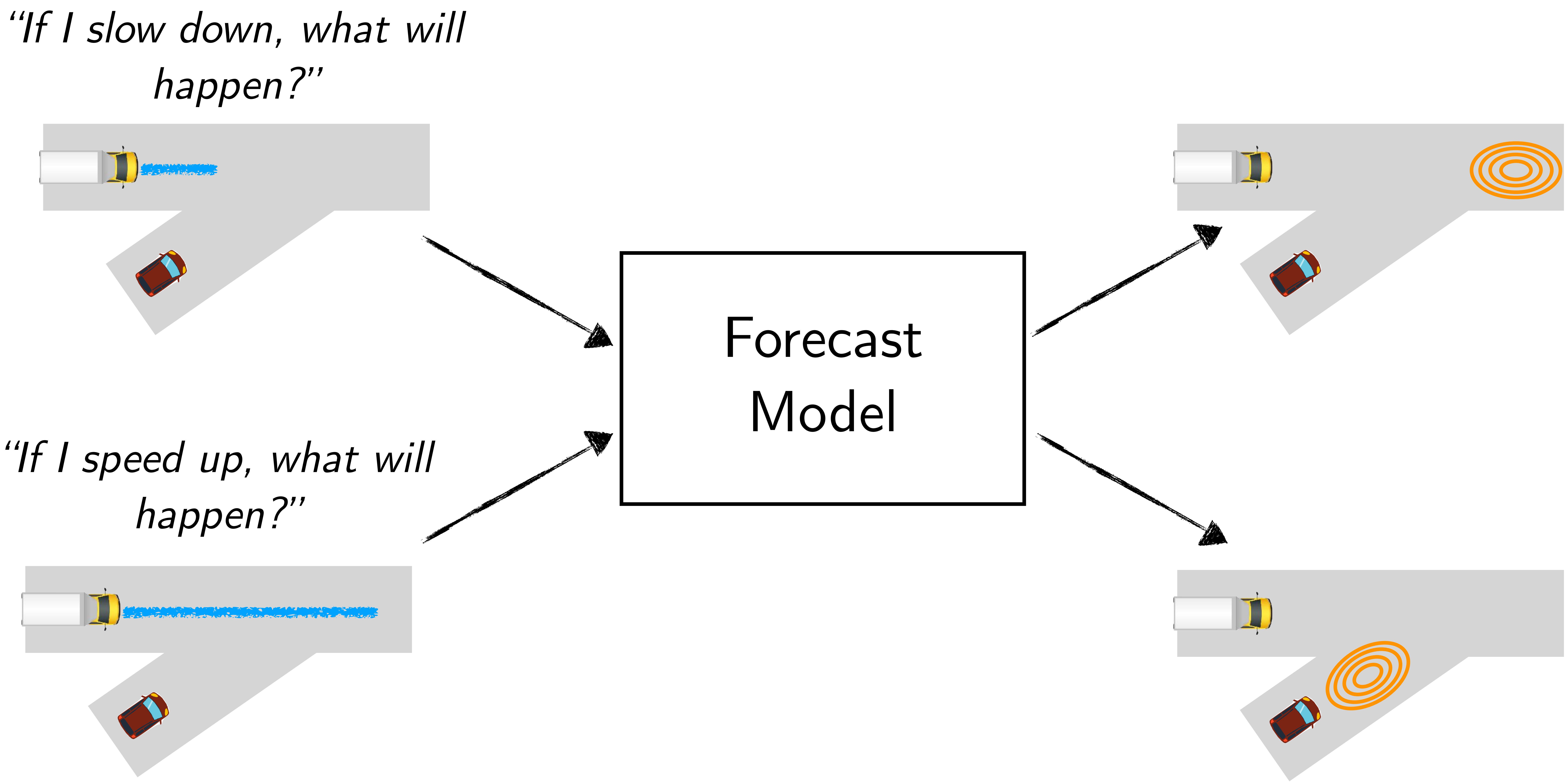
Multi-modal forecasts do not solve the issue



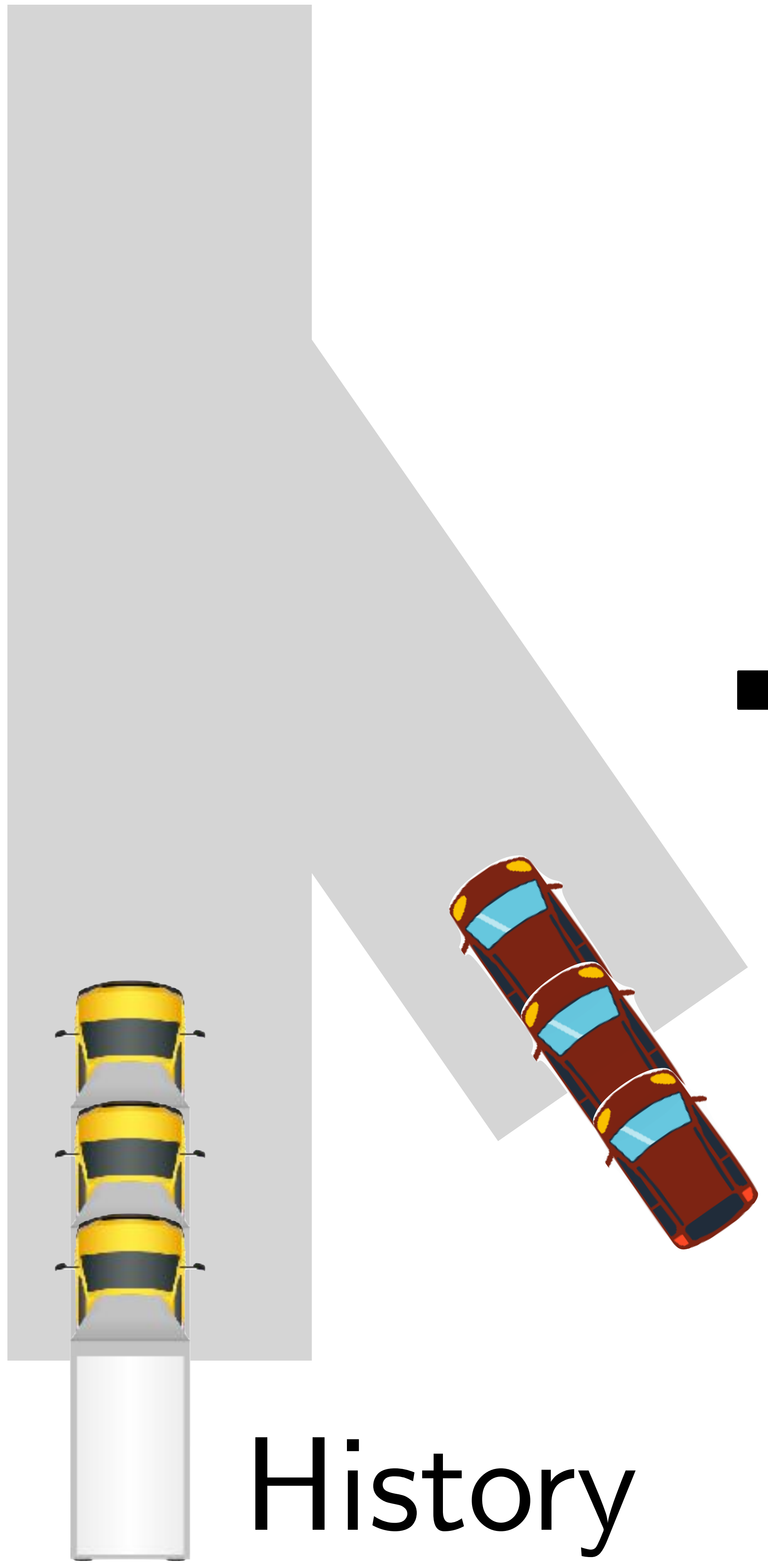
We are (incorrectly) telling the planner
both modes can happen simultaneously

Forecast humans conditioned on what the robot will do

Solution: Train a conditional forecast

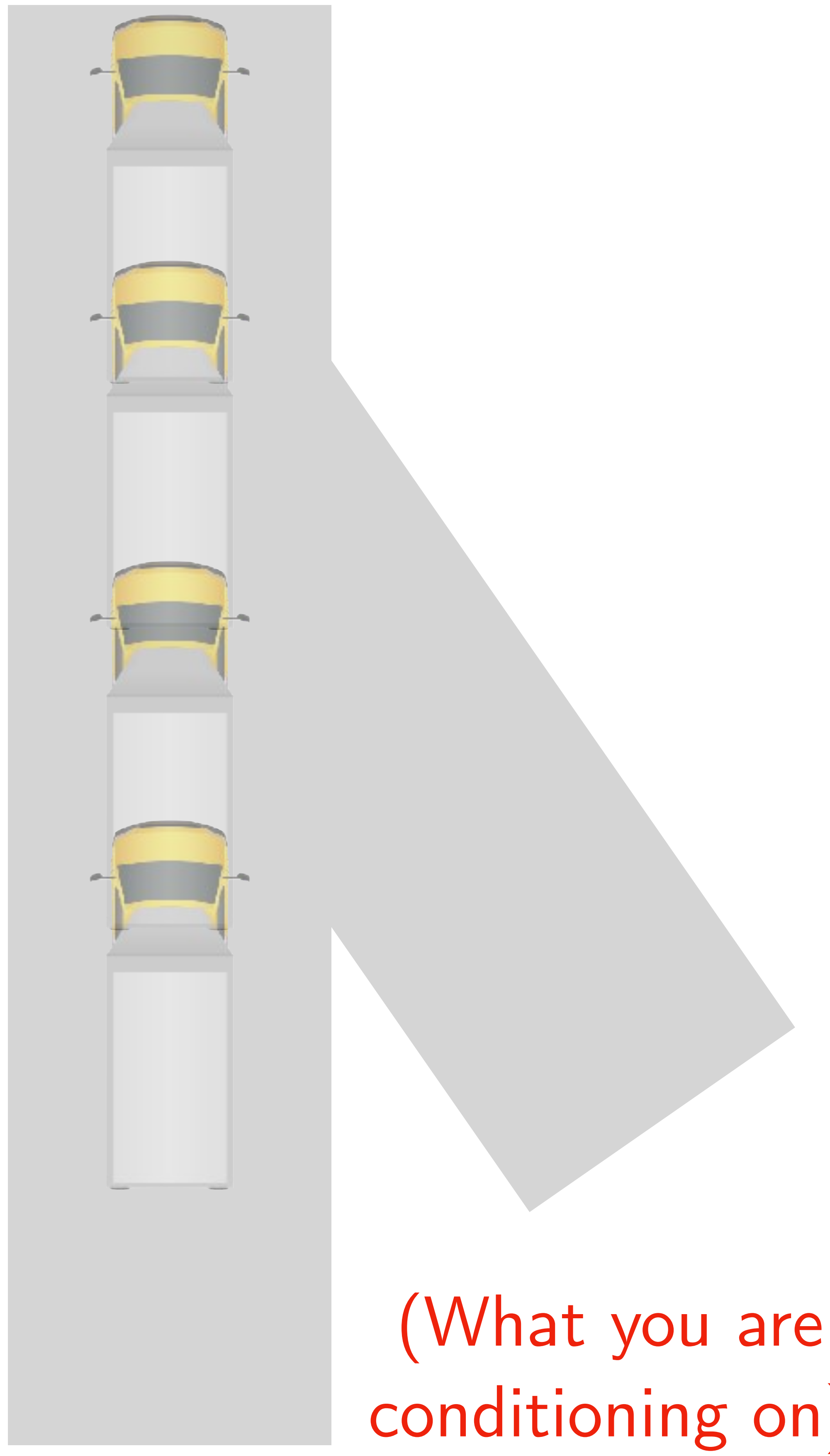


Solution: Train a conditional forecast



History

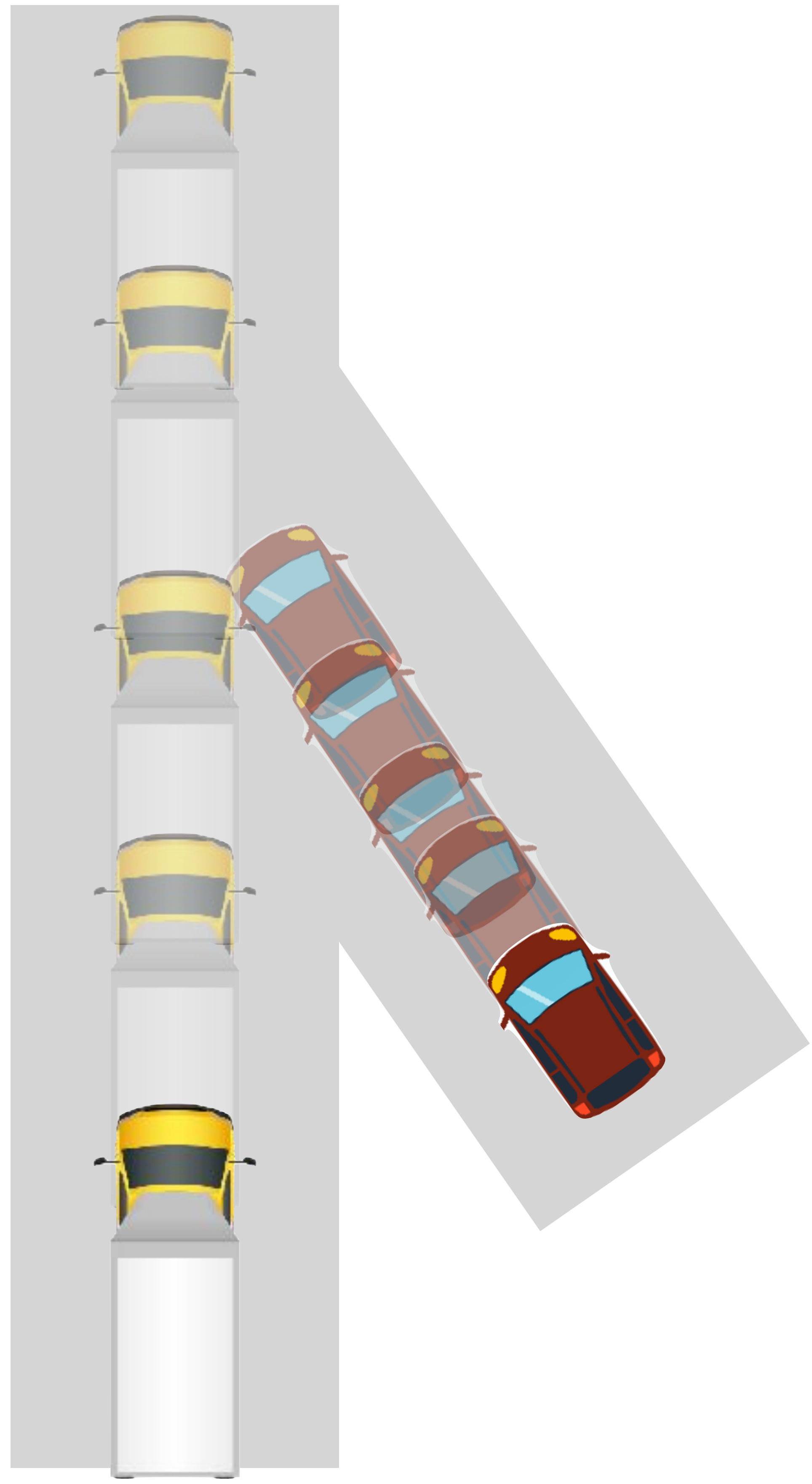
$\ldots, s_{t-2}, s_{t-1}, s_t$



(What you are conditioning on)

Plan

$a_{t_1}, a_{t+2}, a_{t+3}$



Forecast

$s_{t+1}, s_{t+2}, s_{t+3}, s_{t+4}$

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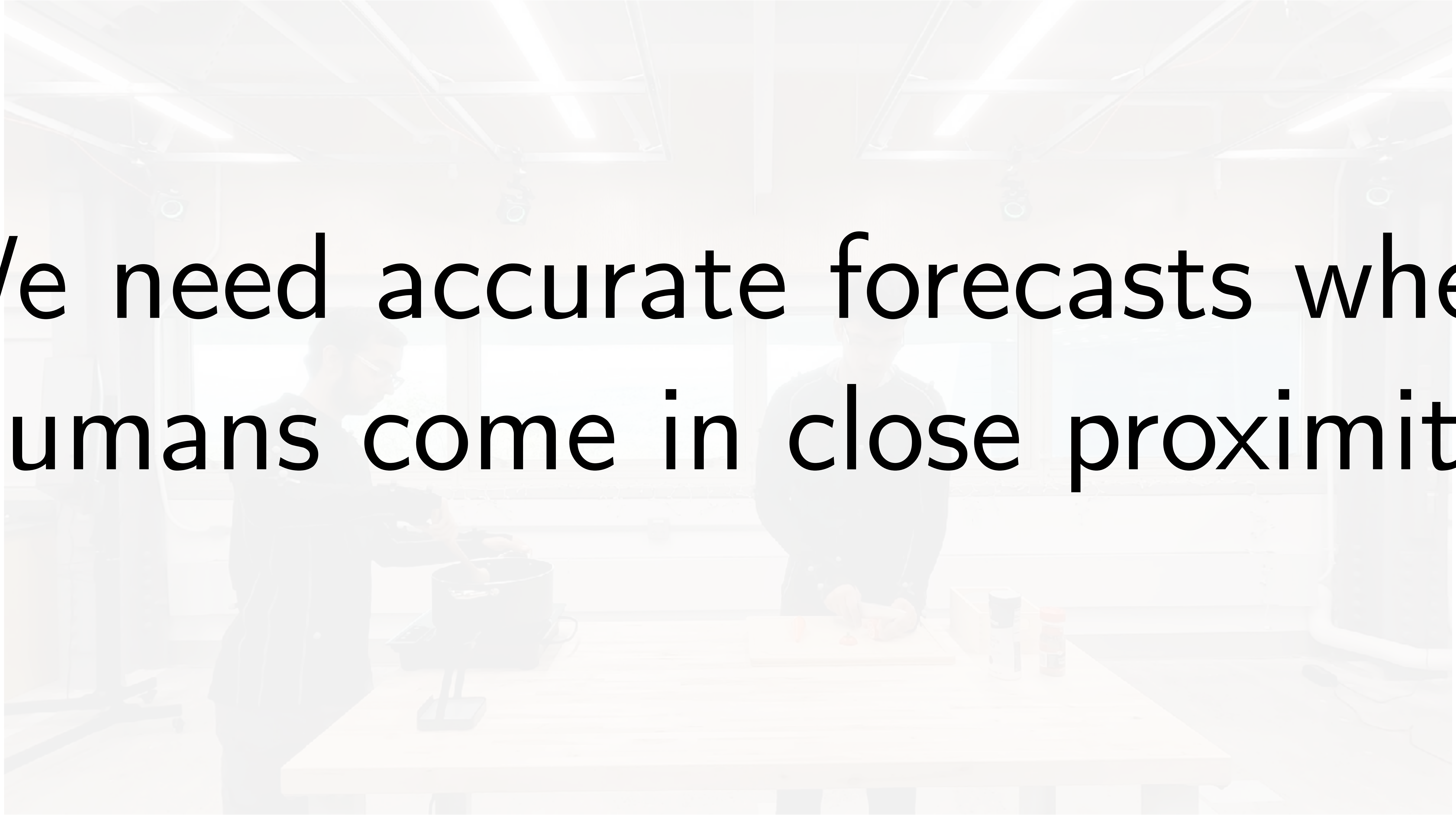
Two motivating applications

Self-driving

Collaborative Cooking

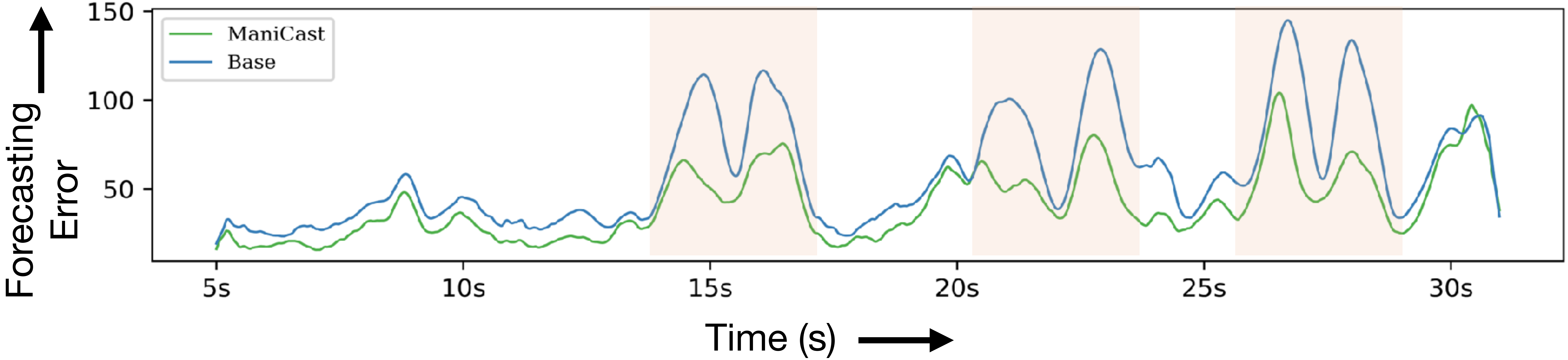
Are all time steps equally important in the loss?

Are all time steps equally important?

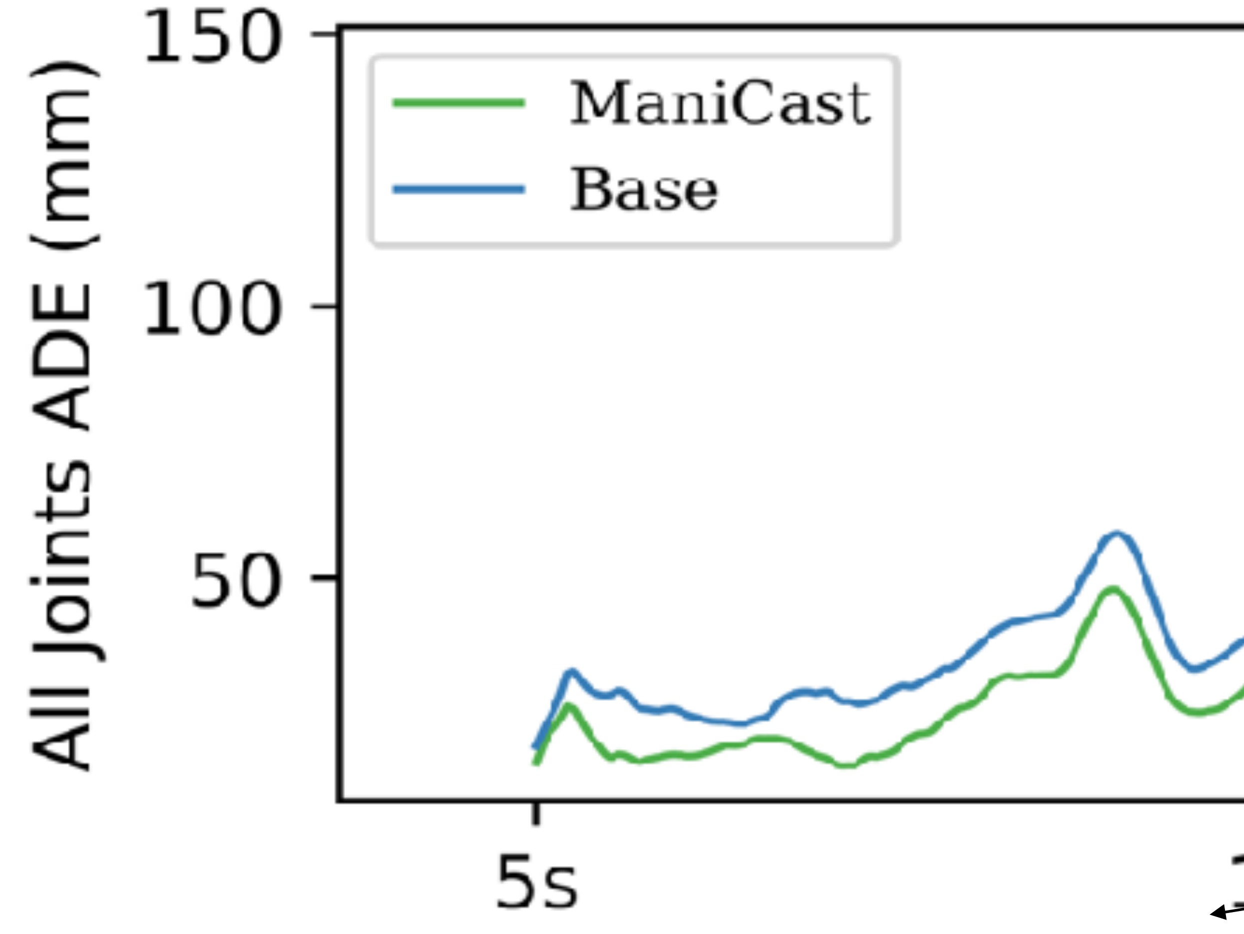


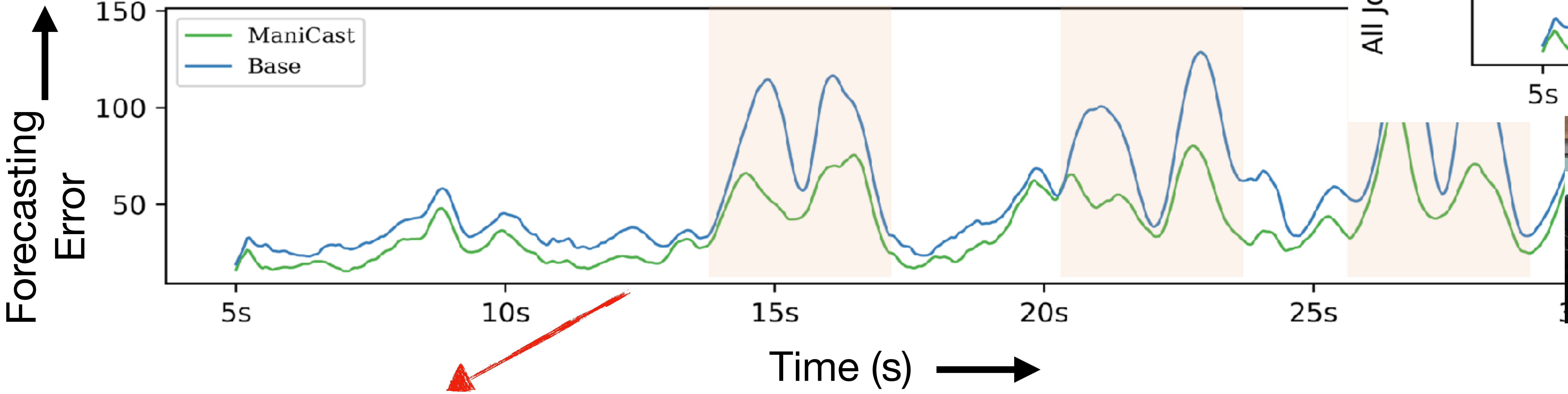
We need accurate forecasts when humans come in close proximity

How does forecasting error vary over time?



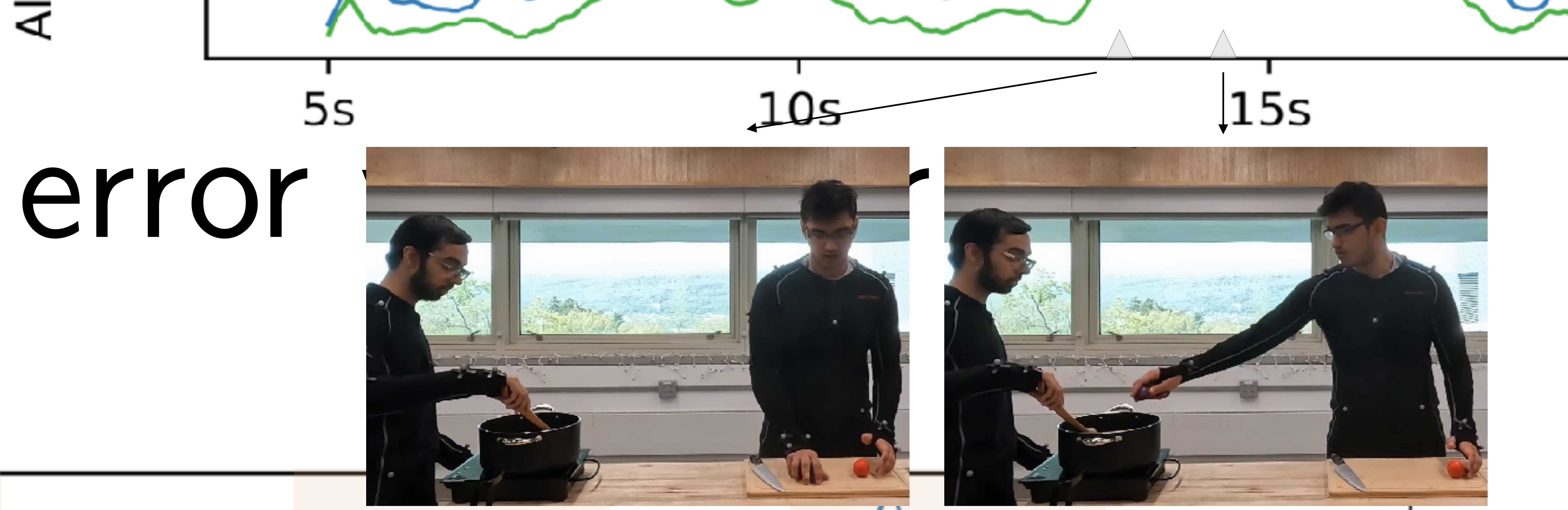
How does forecasting error vary ov

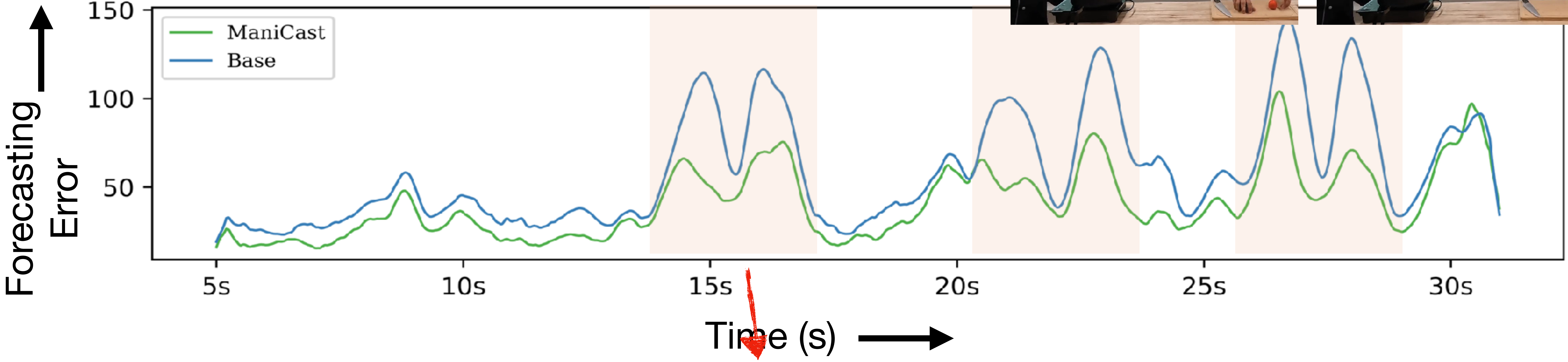




Error is low here.
But this is not a critical state as humans are far apart.

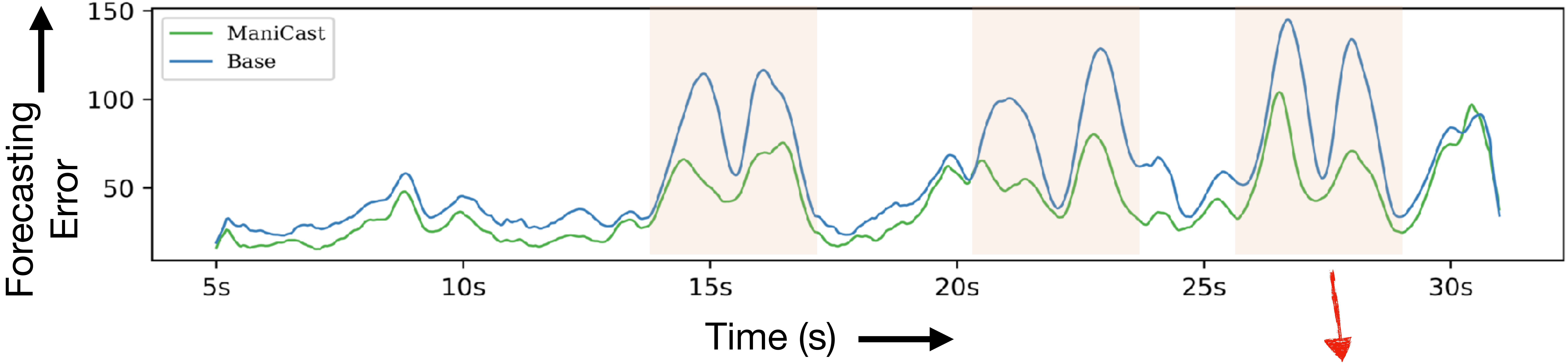
How does forecasting error

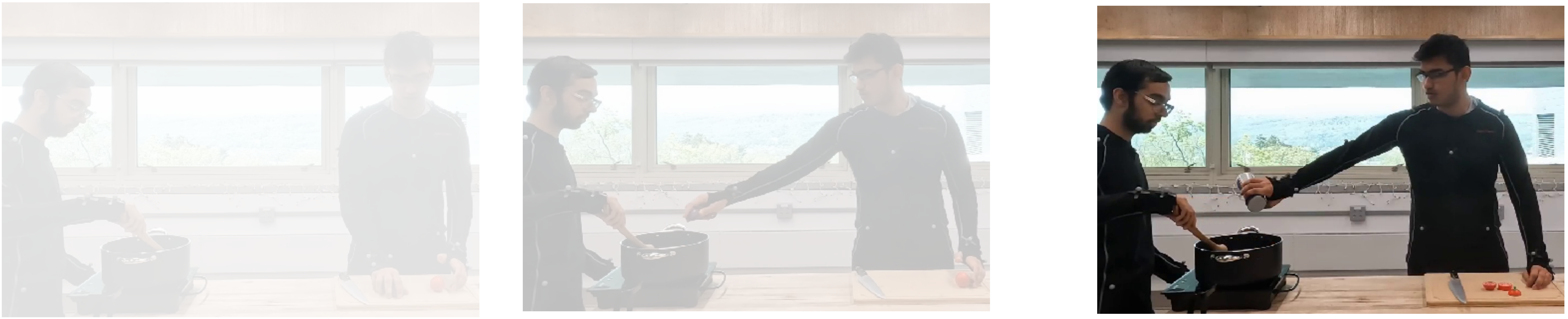




Error shoots up here!
And it's a very important state as humans in close proximity!

How does forecasting error vary over time?





Why is the error low here

but higher here?

A simple fix: Upweight critical transition points

Importance Sampling

Identify "transitions" when the human comes into the robot's workspace

Task 1

Task 2

Task 3

Importance Sampling

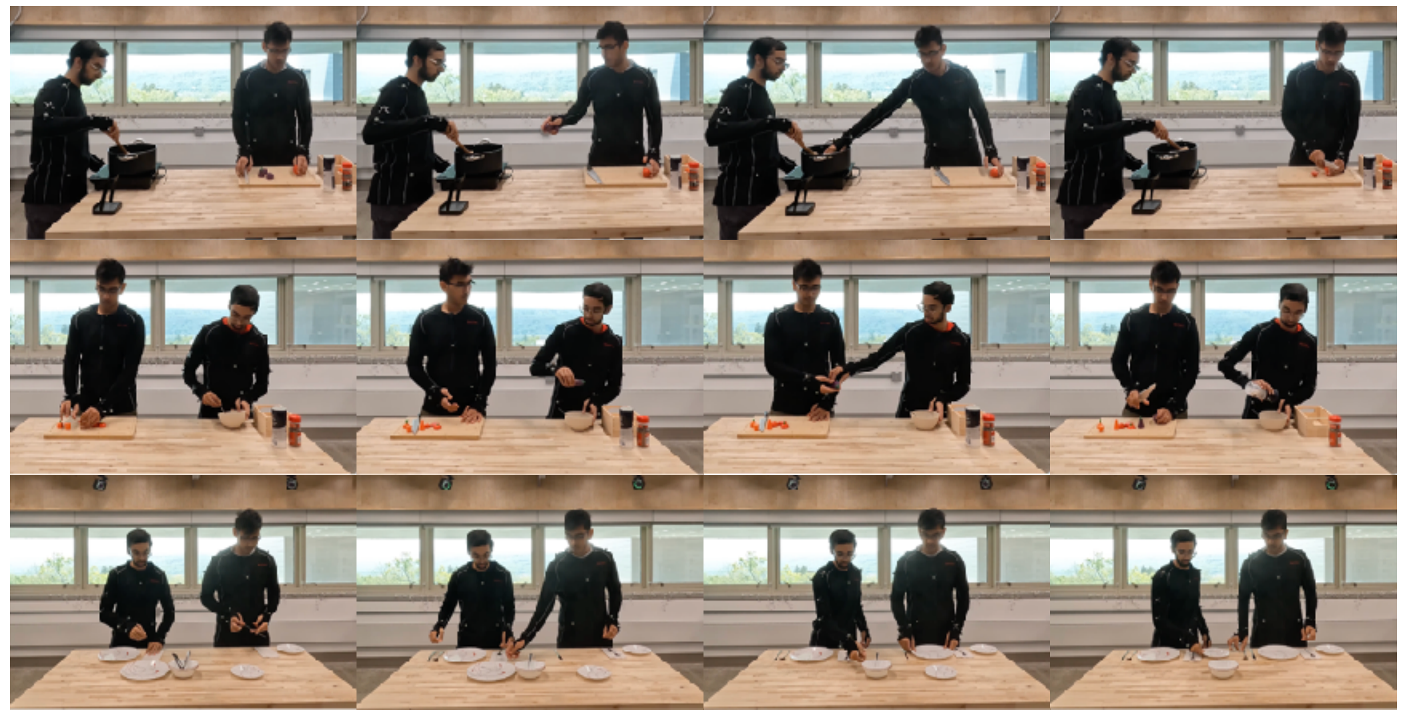
Identify "transitions" when the human comes into the robot's workspace

Task 1

Task 2

Task 3

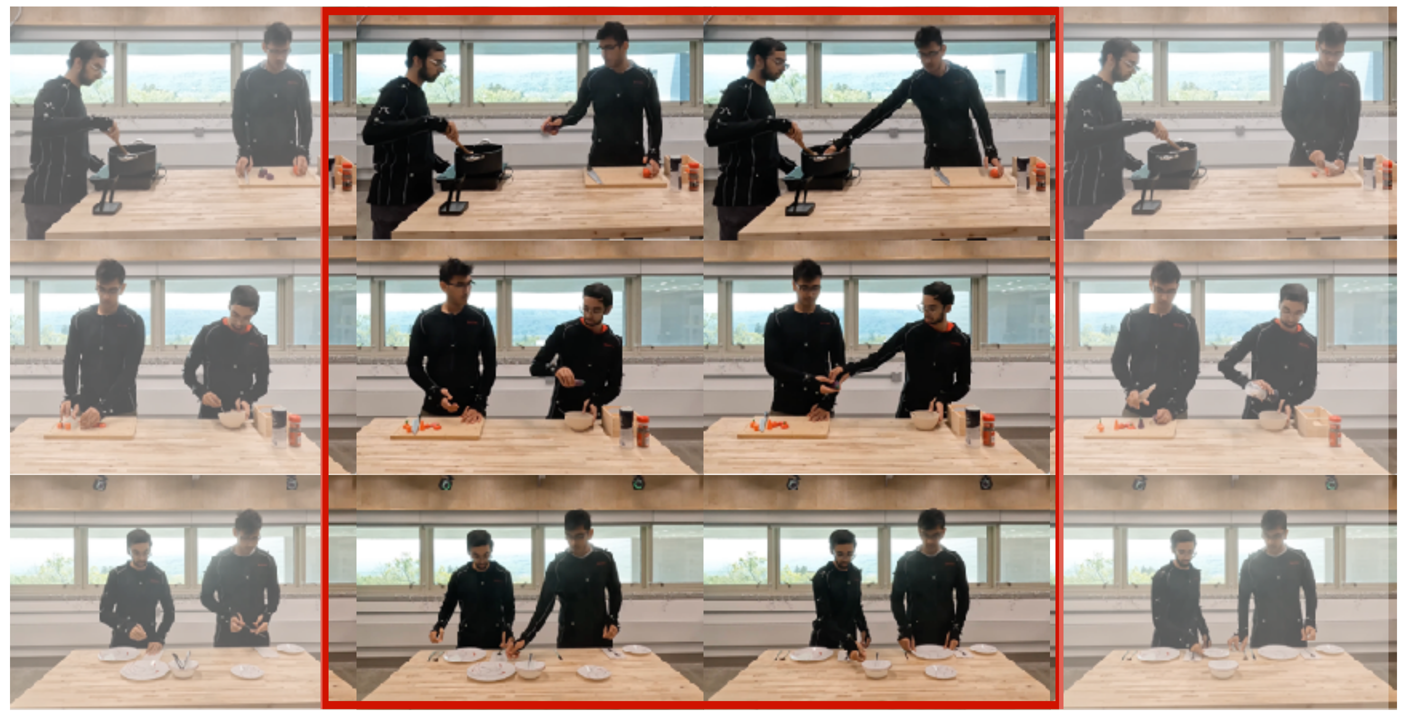
Train equally on all data + transition data



All Data

$\forall \xi_R, \xi_H$

Train equally on all data + transition data



All Data

$\forall\, \xi_R, \xi_H$

Sample Equally

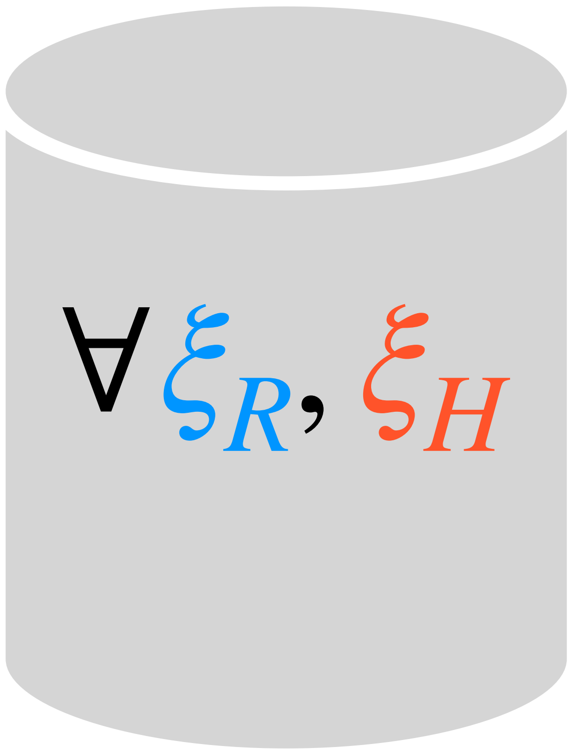
$\forall\, \xi_R, \xi_H$

Transition Data

Generalization of the idea:

Forecasts should match the ground truth in terms of the cost it induces

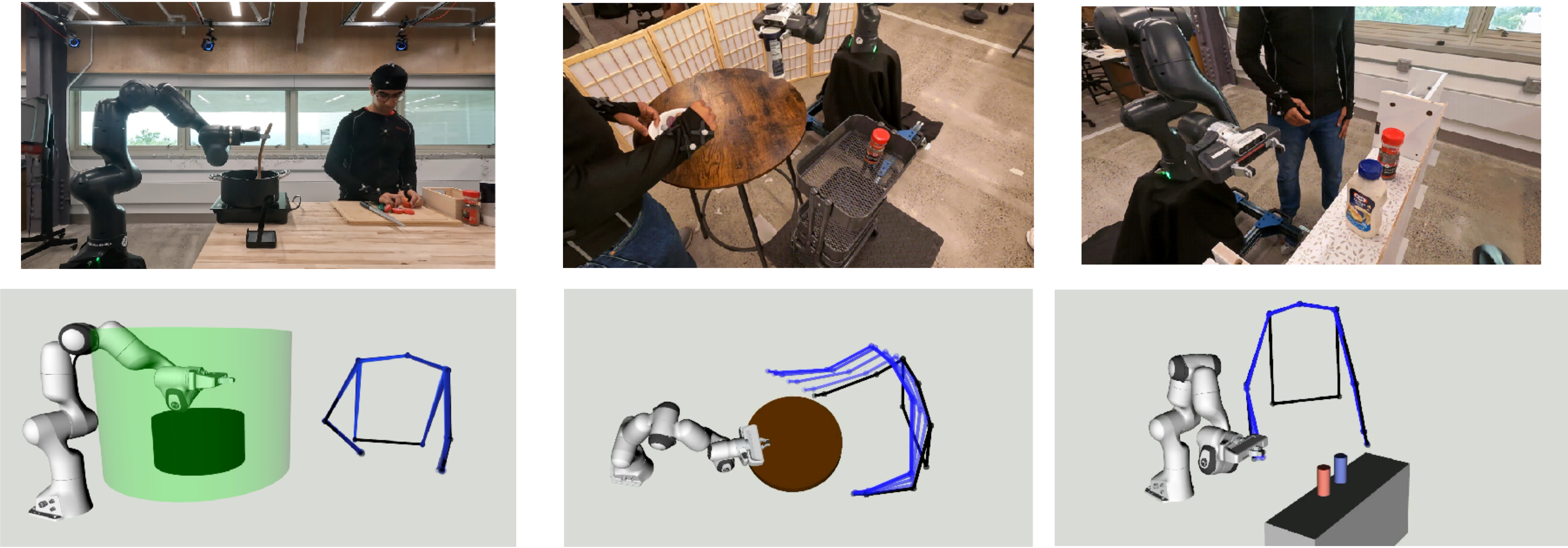
Solution: Replace L2 loss with cost weighted loss



minimize $\mathbb{E}\left[\left| C(\xi_R, \xi_H) - C(\xi_R, \hat{\xi}_H) \right|\right]$

where, ξ_H is the observed future human motion
and, $\hat{\xi}_H$ is the predicted / forecasted human motion
and, ξ_R is the planned robot trajectory

Evaluation across different tasks



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- ☐ Connection between Forecasting and Model-based RL

Quiz

Refresher on Model-based RL

In model-based RL, what data distribution should we train transition models on?

When poll is active respond at **PollEv.com/sc2582**

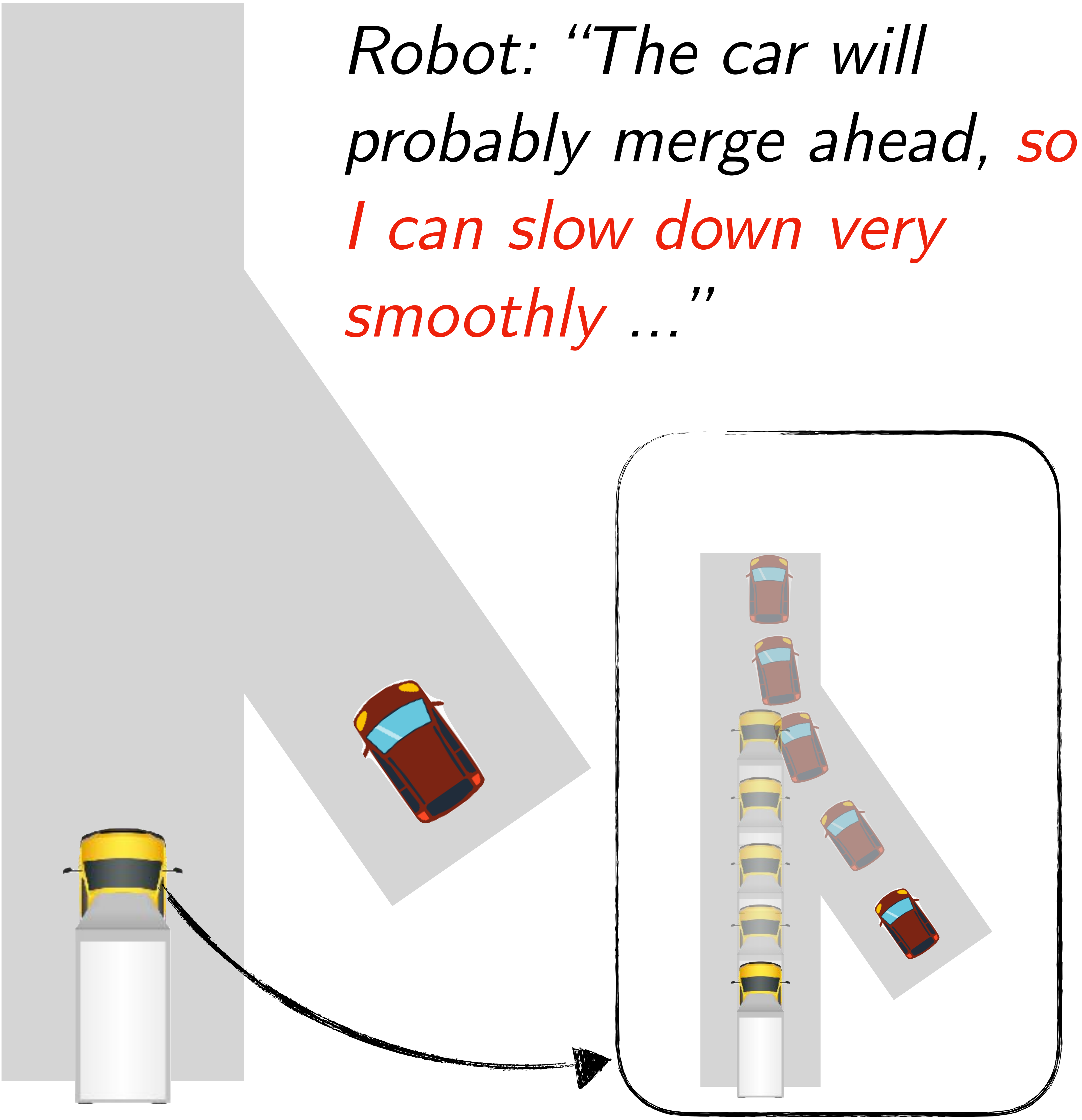
Send **sc2582** to **22333**

What happens when we deploy model?

What went wrong?

What went wrong?

Robot: "The car will probably merge ahead, so I can slow down very smoothly ..."



Humans never drive in such an ambiguous manner during merges!

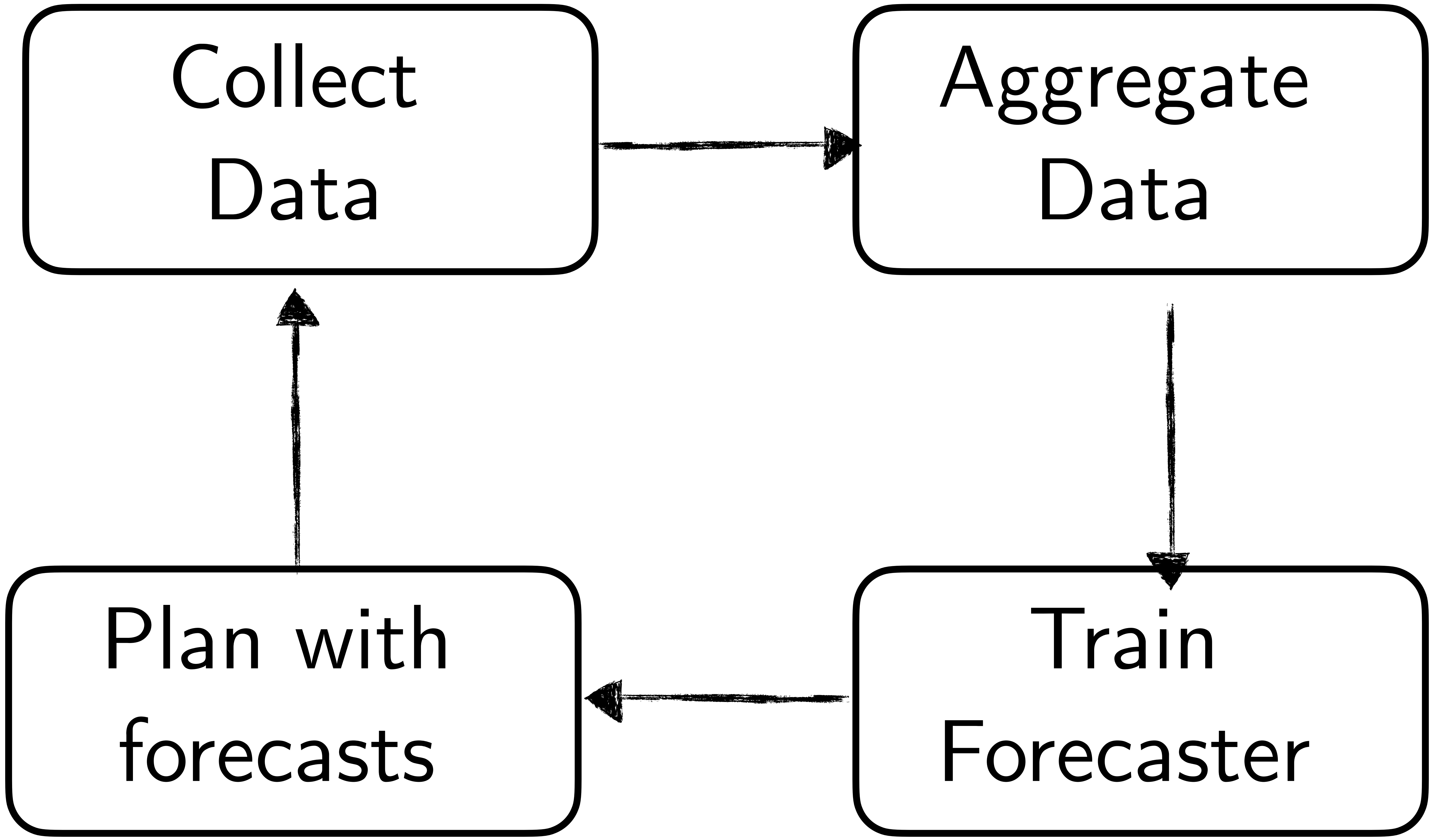
We trained on data when human was driving

We trained on human driving data

We are testing on robot driving

If robot driving is different from human driving, we have a train-test mismatch

DAGGER for Forecasting!



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Forecasts are really just transition models

Forecasting <-> Model-based RL

Conditional Forecasts

$$P(s_{t:t+k} \mid s_{t:t-k}, a_{t:t+k})$$

Model

$$M(s_{t+1} \mid s_t, a_t)$$

We know how to solve model-based RL (previous lecture!)

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