One Model to Drift Them All: Conditional Diffusion Model for Driving at the Limits

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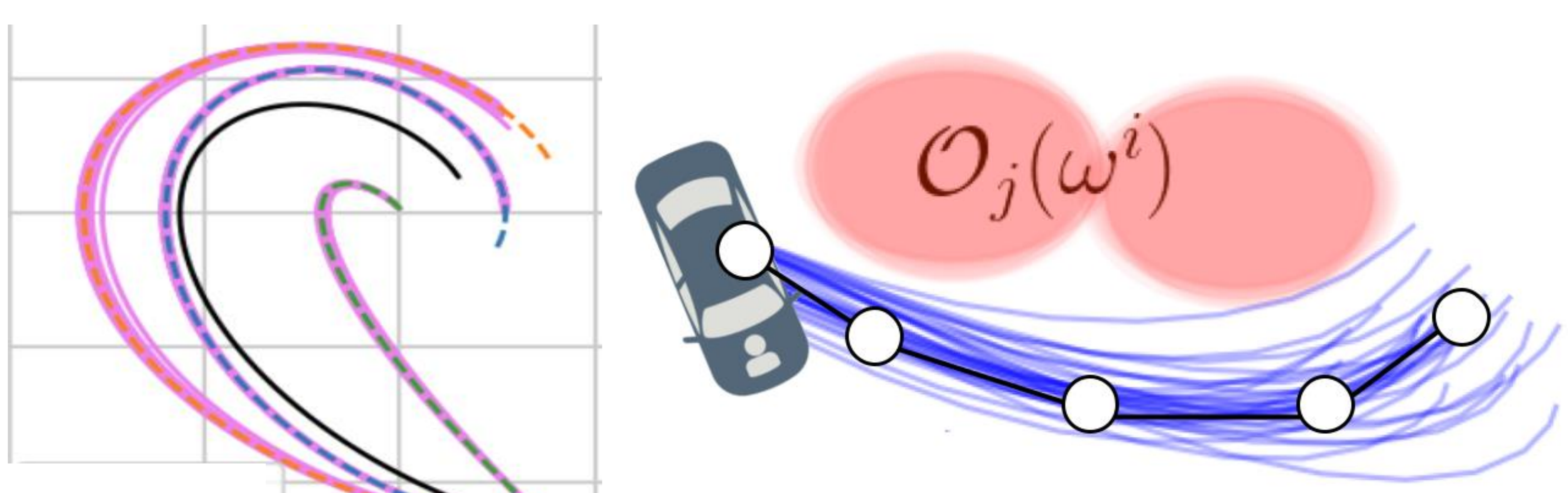
Driving at the limits of handling

Expert-level **racing** and **drifting** are challenging tasks due to their highly **dynamic** and **unstable** nature

Challenges:

- *Sensitivity to model mismatch*
- *Unrealistic data assumptions*
- *Limited vehicle responses characterization*

Objectives: *Offline learn a* ***single model***, able to predict multimodal trajectories **on the fly** from **context** and useful for **high-frequency** control, given unlabeled dataset of trajectories from different vehicles in various environments



$L_{nll}(\theta, \tau_{t:T_f}) := \mathbb{E}_{\tilde{x}^{\theta}_{t:T_f}}\left[\sum_{s=t}^{t+T_f} \|x_s - \tilde{x}^{\theta}_s\|^2_{(\Sigma^{\theta}_s)^{-1}} + \log(\det(\Sigma^{\theta}_s))\right],$

Our conditional denoising diffusion vehicle model

Key idea: Predict physics-constrained model parameters, instead of trajectories or actions

Given a *context as state-action history*, sample *latent variable* θ from

$$p_{\Psi}(\theta \mid x_{T_p:t}, u_{T_p:t})$$

Denoising model score function

State-action history of fixed length

First principles enforced via a neural SDE parameterized by θ

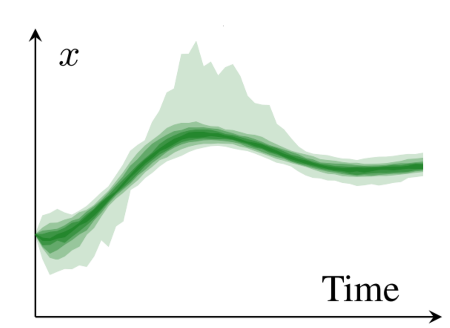
$$dx = M^{\theta}(x,u)F^{\theta}(x,u)dt + \Sigma^{\theta}(x,u)dW$$

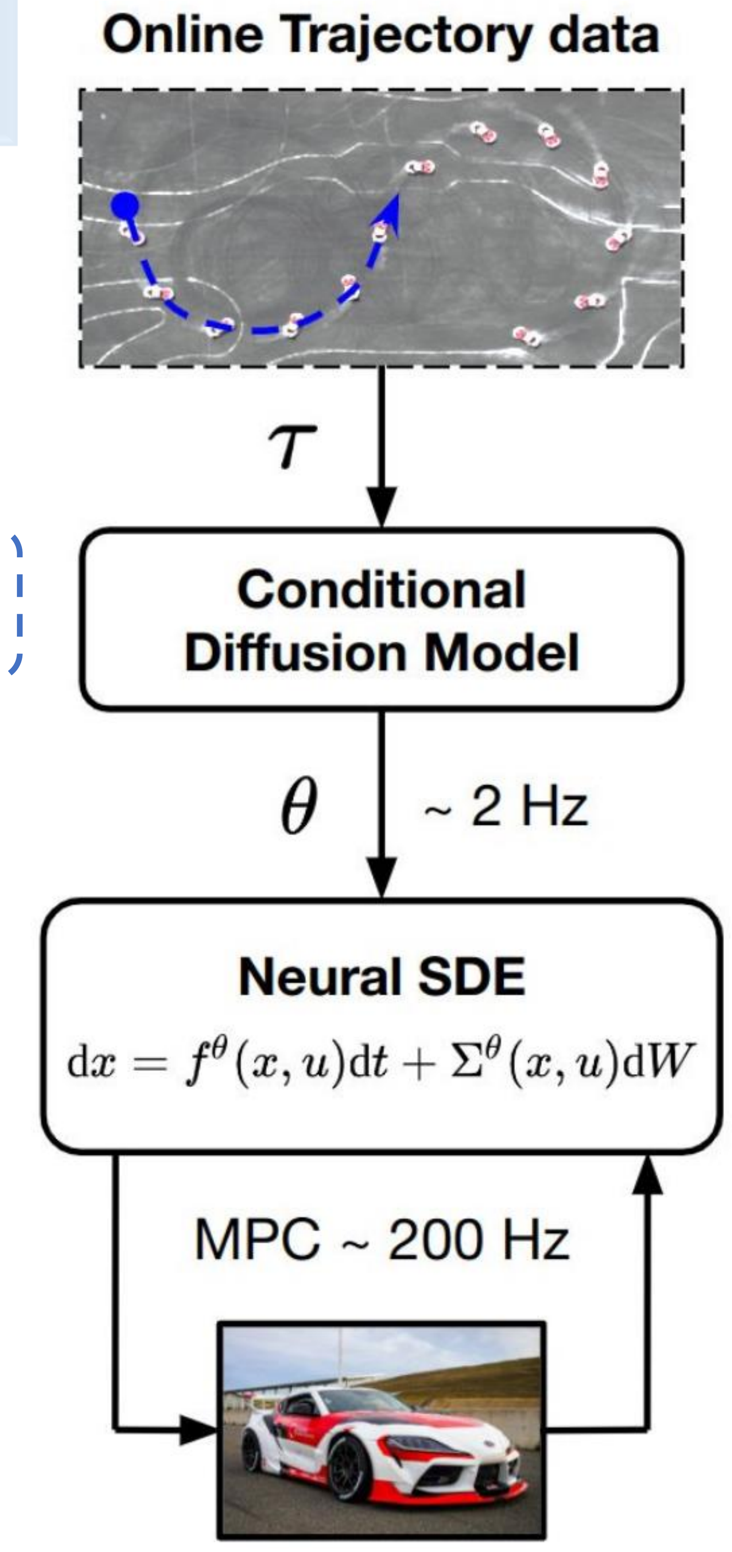
Kinetics + Kinematics + Tire forces qualitative knowledge

Brownian disturbances

A fixed θ contains unknown parameters without or with physical meaning such as

$m^{\theta}, I_z^{\theta}, I_w^{\theta}, R^{\theta}, a^{\theta}, b^{\theta}$

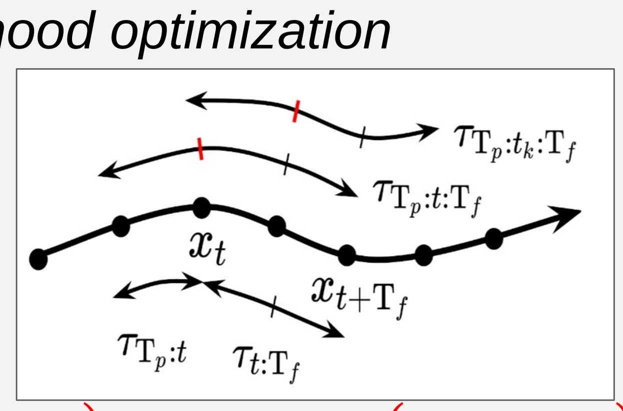




How to train your diffusion vehicle model?

Stage 1: Local estimation of θ via nonconvex log-likelihood optimization

Look near a random state-action sequence $\tau_{T_p:t} = \{x_{T_p:t}, u_{T_p:t}\}$



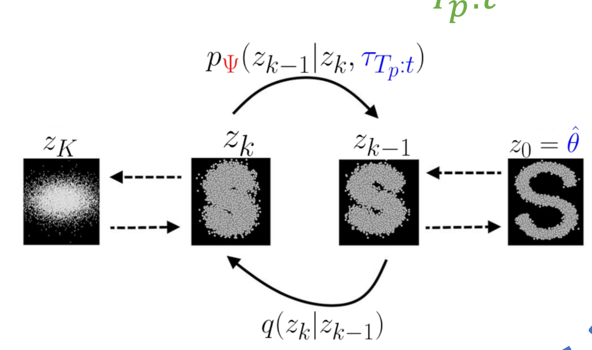
$\hat{\theta} = argmin_{\theta}\ L_{nll}(\theta, \tau_{t:T_f}) + \boldsymbol{E}_{t_k \sim t}[L_{nll}(\theta, \tau_{T_p:t_k:T_f})]$

Unlabelled *dataset*

$\{\hat{\theta}, \tau_{T_p:t}\}$

Stage 2: Update diffusion model parameter Ψ by denoising $\hat{\theta}$ parameter conditioned on $\tau_{T_p:t}$

Model update from batch of $\{\hat{\theta}, \tau_{T_p:t}\}$



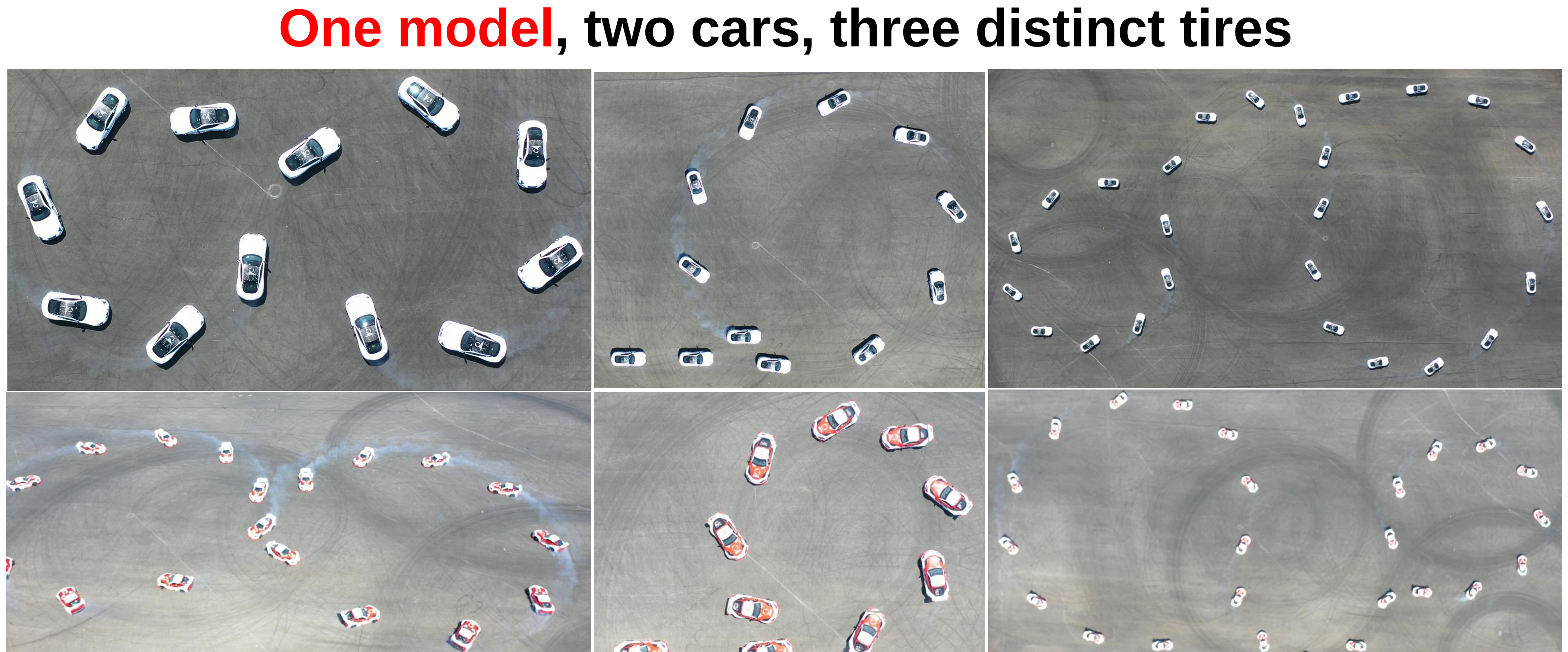
Initialize nonconvex optimizer by sampling from $p_{\Psi}(\theta \mid x_{T_p:t}, u_{T_p:t})$

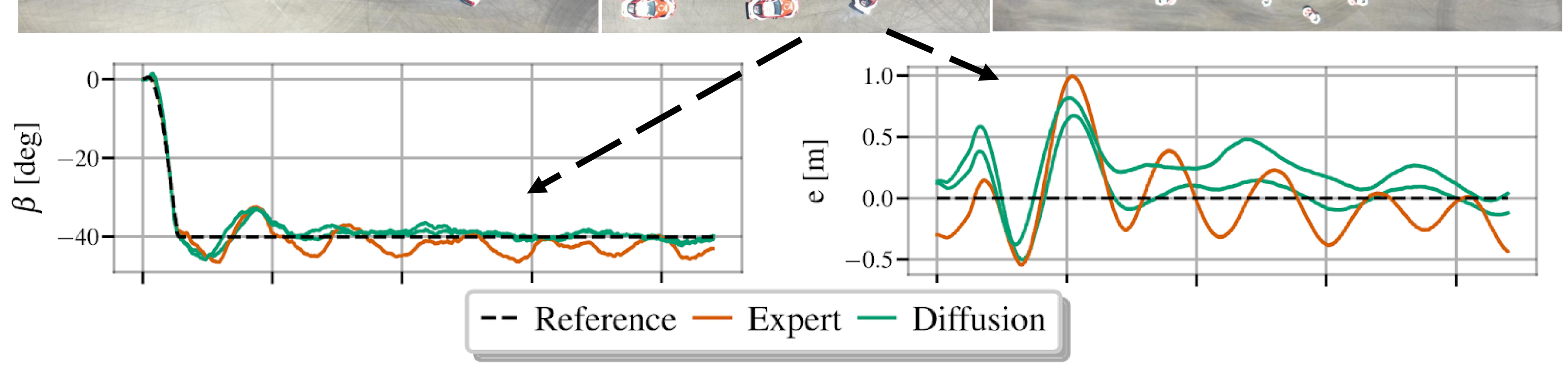
A single model used on a Supra and Lexus

- Multimodal model parameters' predictions
- Online adaptation capabilities
- Generalization to unseen task and vehicle setup, e.g., tires, gear,…
- Tracking performance on par with environment-specific expert model

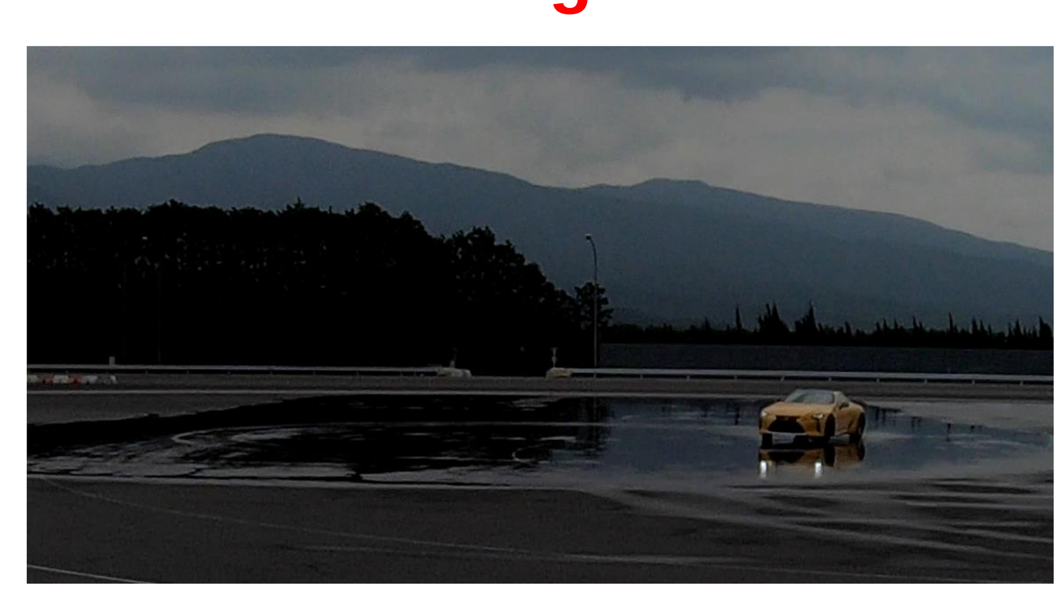
Vehicles with completely distinct specs and behavior at the limits of handling

One model, two cars, three distinct tires





Drifting on wet surfaces



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Key takeaways

- *A hierarchical approach combining diffusion model expressivity and high-rate replanning and reliability of MPC*
- *Can exploit physics knowledge or other inductive biases in the lower-level mode*
- *Capturing complex distributions allows to draw on prior experience to quickly adapt on the fly without having to perform system identification*