UNIVERSITY OF CAMBRIDGE
Department of Engineering

Harry Fieldhouse
and David Cole

Uncertainty-Aware Modeling of Learned Human Driver Steering Behaviors on High-Difficulty Maneuvers: Comparing BNNs and GPs

Introduction

Human drivers behave in a complex and adaptable way. Understanding this is invaluable to better designing vehicles for the real-world.

Specific objectives are:

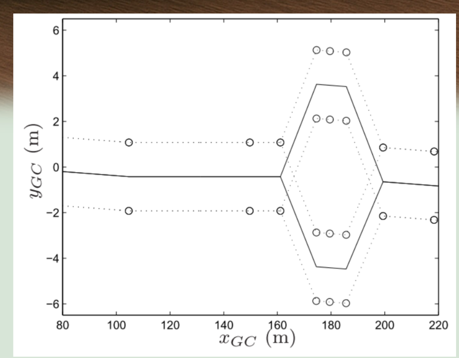
- Utilize a driver model representing human learning and typical behavioural characteristics;
- Compare behavioural replication with Gaussian Processes (GP) and Bayesian Neural Networks (BNN) as internal models.

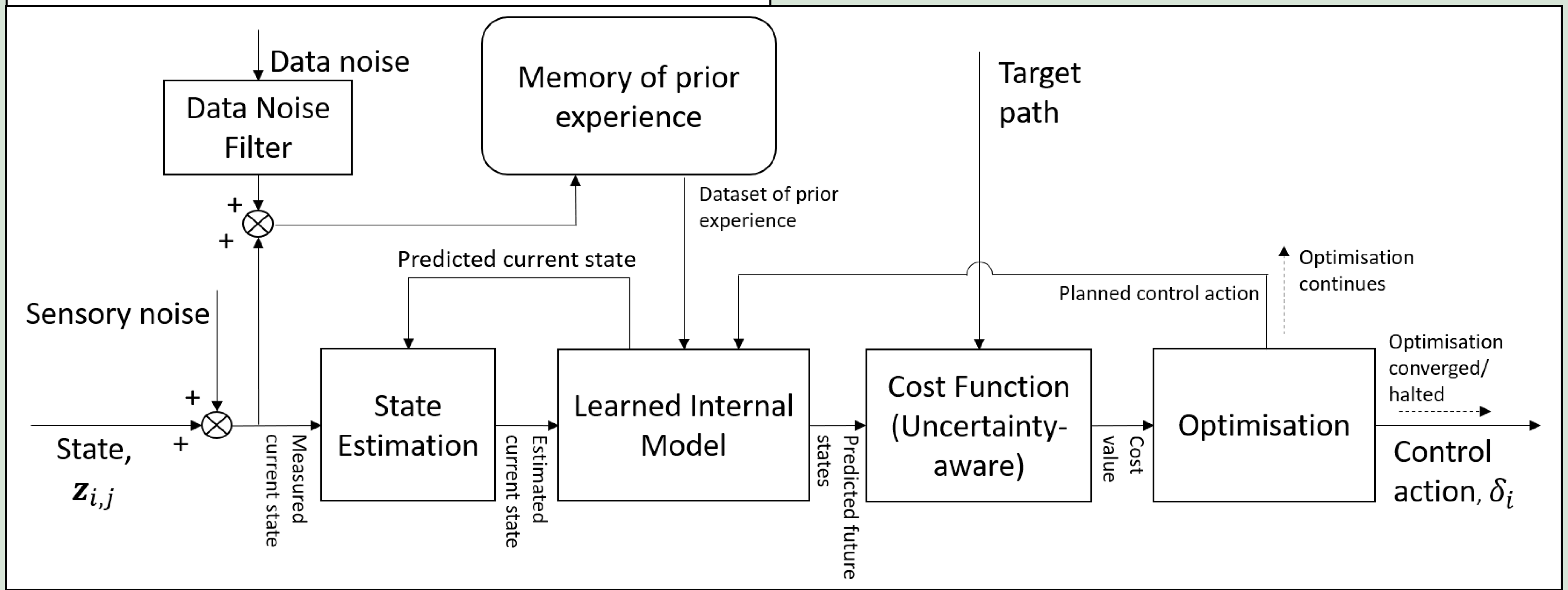
Driver Model

Previous work developed the driver model used here [1][2].

The model is based on the following elements:

- Learnt internal model of vehicle dynamics, capturing confidence in predictions, here GP or BNN;
- State estimation, with Extended Kalman Filter (EKF);
- Uncertainty-aware Model Predictive Control (MPC).





Cost Function

$$C = \underbrace{\sum_{j=i}^{i+H}}_{\text{Sum over timesteps to prediction horizon}} \overbrace{w_y \mathbb{E}(y_j - y_j^*)^2}^{\text{Lateral path error}} + \overbrace{w_\theta \mathbb{E}(\theta_j - \theta_j^*)^2}^{\text{Yaw path error}} + \overbrace{w_c \mathbb{I}_{x_j \in \mathbf{c}} \mathbb{E}(y_j - y_j^*)^4}^{\text{Constraint enforcement}} + \underbrace{w_{\dot{\delta}} \mathbb{E}(\dot{\delta}_j)^2}_{\text{Steering rate}} + \underbrace{w_{\ddot{\delta}} \mathbb{E}(\ddot{\delta}_j)^2}_{\text{Steering second derivative}} + \underbrace{w_\sigma \mathrm{Var}(y_j)}_{\text{Prediction variance}}$$

Modeling Individuals

Predictions can be specified to observed driver characteristics:

- Ability can be matched by adjusting training data and accuracy of prior beliefs about the vehicle dynamics,
- Behaviors can be replicated by changing cost function weightings.

Simulation

The driver model is run within a simulated environment.

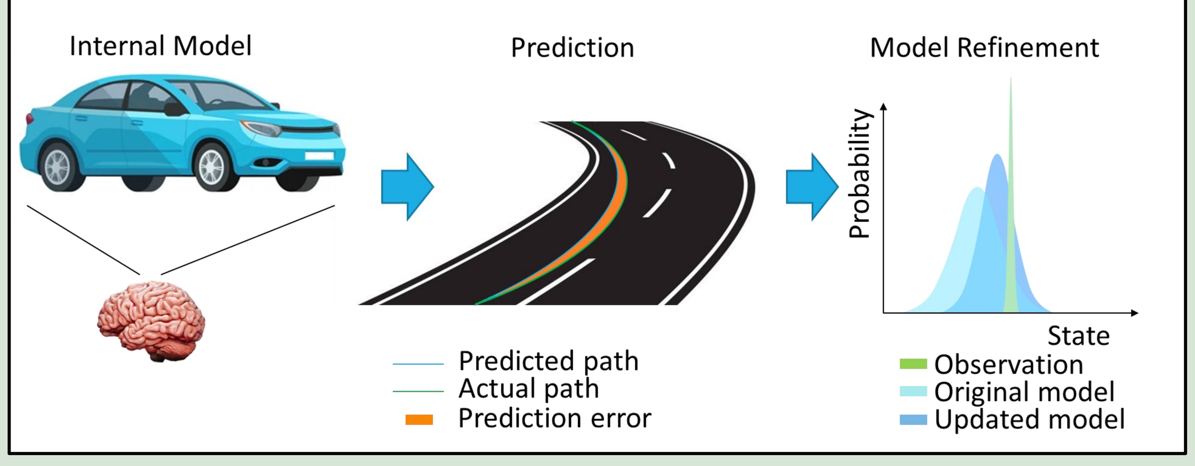
Testing is performed using a 'Moose Test' to compare against experimental data [3]. Environment parameters are set to match the vehicle and road conditions identified from testing of the experimental setup.

Human Learning

In human control of a system, learning behaviour can be observed when repeat actions are analysed. In skilled tasks, such as path following in driving, this learning is clearly apparent in the early stages before slowing as performance converges.

Internal Model

Improvements observed are believed to be due to the human learning an internal model of the system which gets better with experience [4].



Internal Model Format

Gaussian Process

Non-parametric method for system learning.

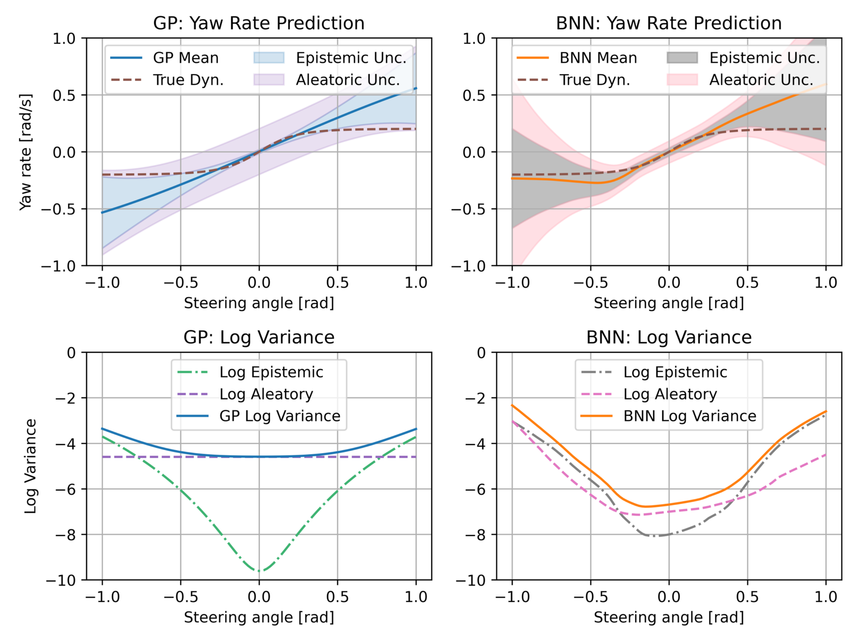
Assumes all samples will follow a multivariate Gaussian distribution with covariance determined by a specified kernel function with learnt hyperparameters [5].

Bayesian Neural Network

Parametric neural network method for system learning.

Prediction variance is derived by treating network weights as random variables and learning a variance in addition to the mean [6].

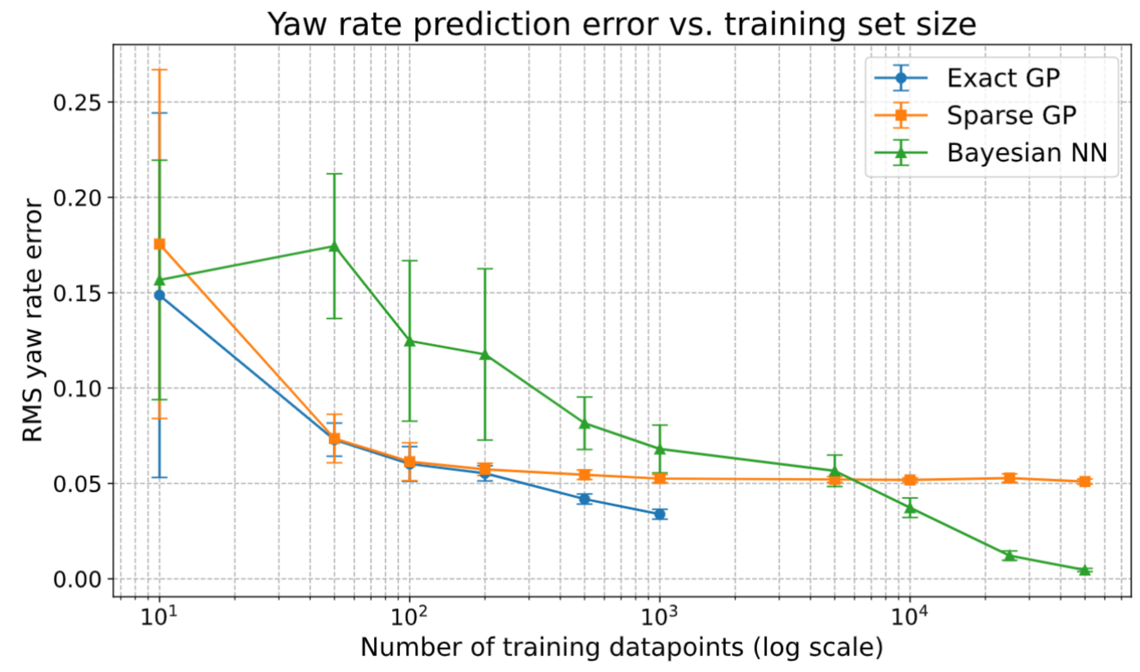
Predictions can be approximated by Monte Carlo sampling or forward propagation of mean and variance [7].



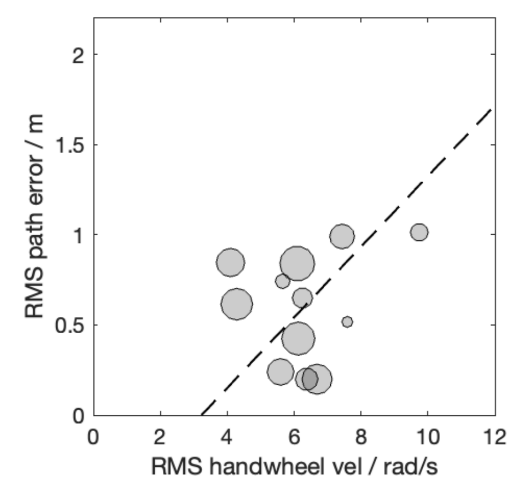
GP vs. BNN Comparison

Component	Gaussian Process	Bayesian Neural Network
Computational Efficiency	Full GP [5]: O(N^3), O(N), O(N^2) Sparse [8]: O(NM^2), O(M), O(M^2)	O(NP), O(P), O(P) [6] (train, infer mean, infer variance)
Prediction Accuracy	Good data efficiency, performance comparatively higher for small data sets.	With large datasets and sufficient model size, very high accuracy can be achieved.
Robustness	+ Guaranteed smoothness [5]. + Variance increases away from data [5]. - Hyperparameter overfitting. - Kernel [9].	+ When high accuracy is achieved. - No guarantees on variance away from data [10]. - Extrapolation unpredictable.
Overall	Better with small dataset sizes (efficiency and accuracy). Provides more guarantees on output.	Scales better with larger dataset sizes. Can achieve very high modelling accuracy.

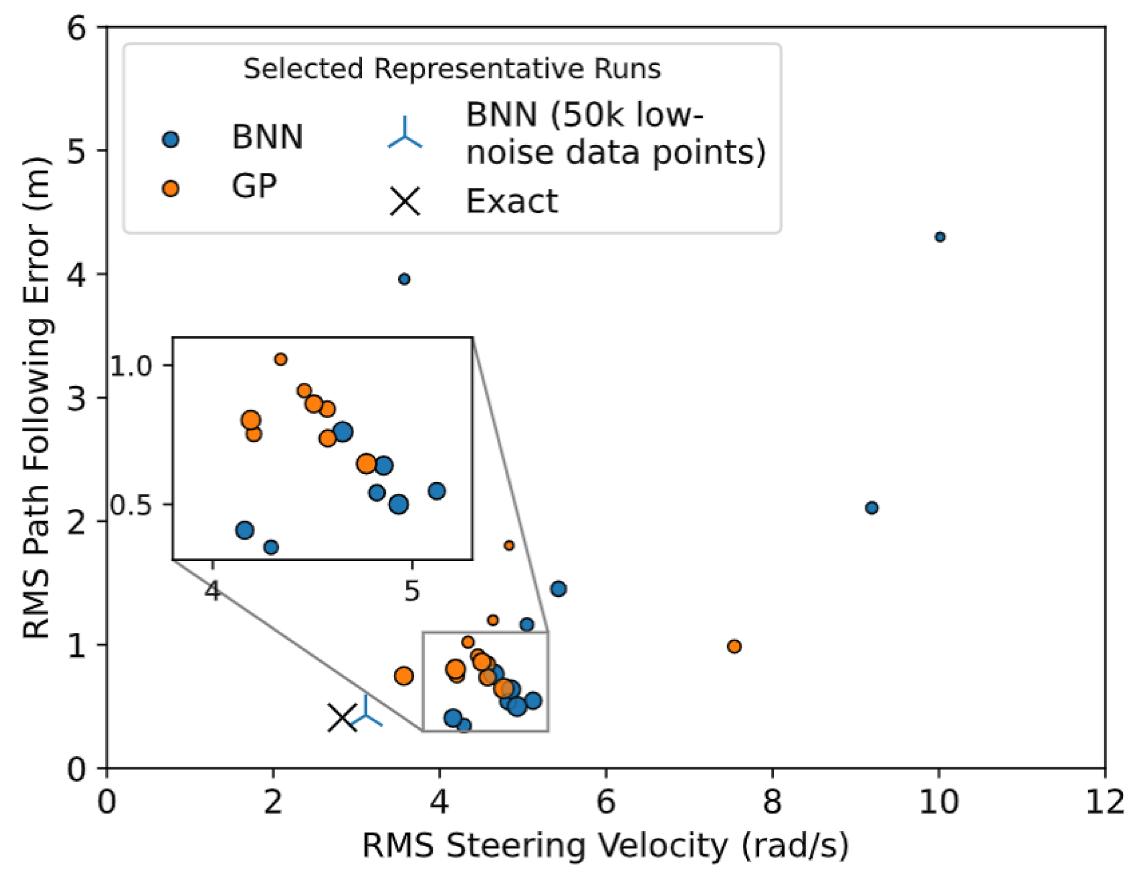
Results



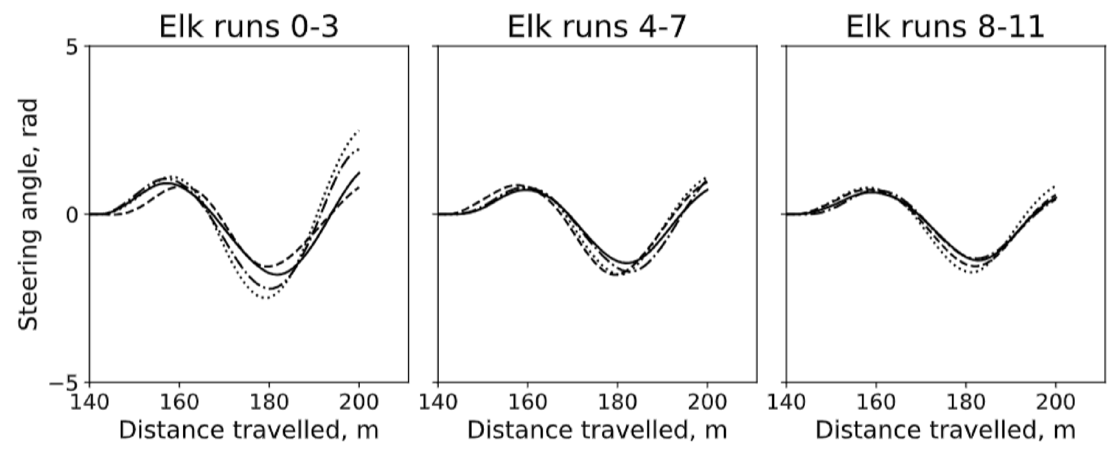
Model prediction accuracy comparison over dataset size.



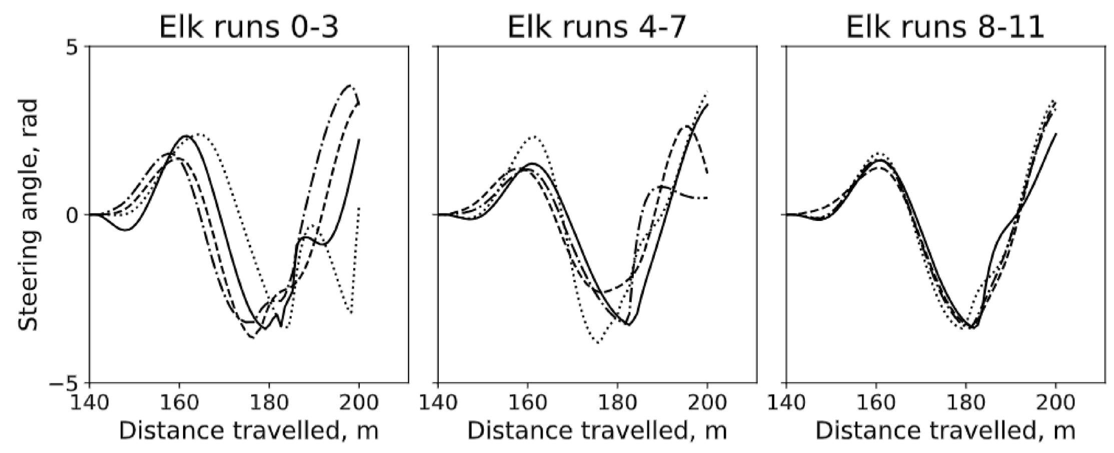
[1][3] Performance of human participant in experiment with repeated elk test maneuvers (see maneuver layout to left). Run number indicated by increasing marker size. Driver learning apparent as both metrics improve and behavior seen in run-to-run variability and trade-off in prioritisation between metrics. This participant was adventurous with high run-to-run variability and often high control effort (RMS steering velocity).



Driver model performance over 12 repeats of an elk test maneuver.



Cautious control on elk test maneuvers, with high ω_σ (using BNN).



Adventurous control on elk test maneuvers, with low ω_σ (using BNN).

Conclusions

The choice between the two approaches depends on the specific application context:

- For small-scale applications or when interpretability is key, a GP-based internal model is attractive.
- For large-scale or high-dimensional problems, BNNs perform well.

Further Work

Explore hybrid approaches that combine the strengths of both methods.

Paper & references
https://sites.google.com/view/icra-lhmp-hamf-djc

This work was supported by Toyota Motor Europe (TME), grant number G116038. The industrial supervisor is Xabier Carrera Akutain of TME.