An Evaluation of "Crash Prediction Networks" (CPN) for Autonomous Driving Scenarios in CARLA Simulator

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Agenda

1. **Why** safety monitors?

2. **What** is CPN?

3. **How** does it perform?

Safety

is a major impediment in the commercialization of Autonomous Vehicles [1]

"The question is not whether autonomous vehicles will be perfect (they won't). The question is when will we be able to deploy a fleet of fully autonomous driving systems that are actually safe enough to leave humans completely out of the driving loop.", Philip Koopman and Michael Wegner [2]

[1] McAllister, Rowan, et al. *"Concrete problems for autonomous vehicle safety: Advantages of bayesian deep learning."* International Joint Conferences on Artificial Intelligence, 2017.
[2] Koopman, Philip, and Michael Wagner. "Autonomous vehicle safety: An interdisciplinary challenge." IEEE Intelligent Transportation Systems Magazine 9.1 (2017): 90-96.

Safety Monitors / Safety Monitoring Framework (SMOF)

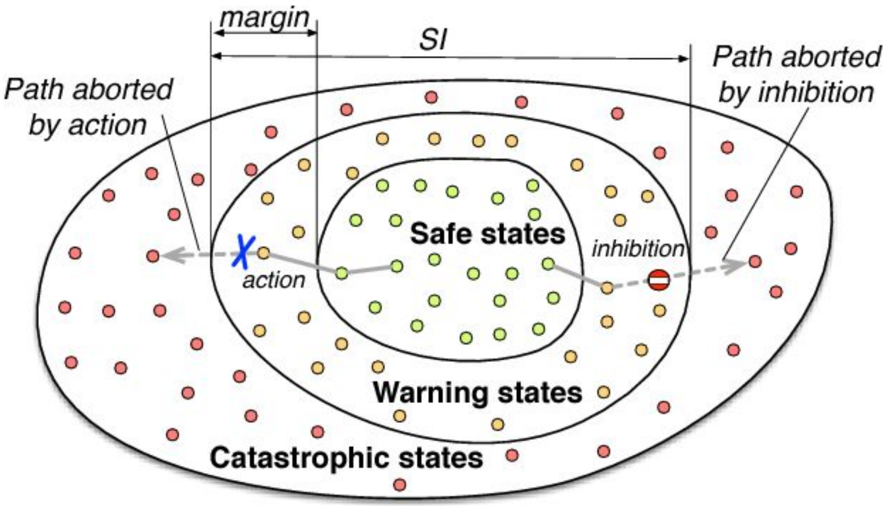


Fig. 1: Depiction of the states that an autonomous system can exist in and the corresponding response it exhibits [3]

[3] Machin, Mathilde, et al. "SMOF: A safety monitoring framework for autonomous systems." IEEE Transactions on Systems, Man, and Cybernetics: Systems 48.5 (2016): 702-715.

Proposed Approach: Crash Prediction Networks (CPN)

"an ensemble of neural networks that focus on different vehicle subsystems to reach a consensus of whether the chosen action in the current state would lead to a safe state or not"

Proposed Approach: Crash Prediction Networks (CPN)

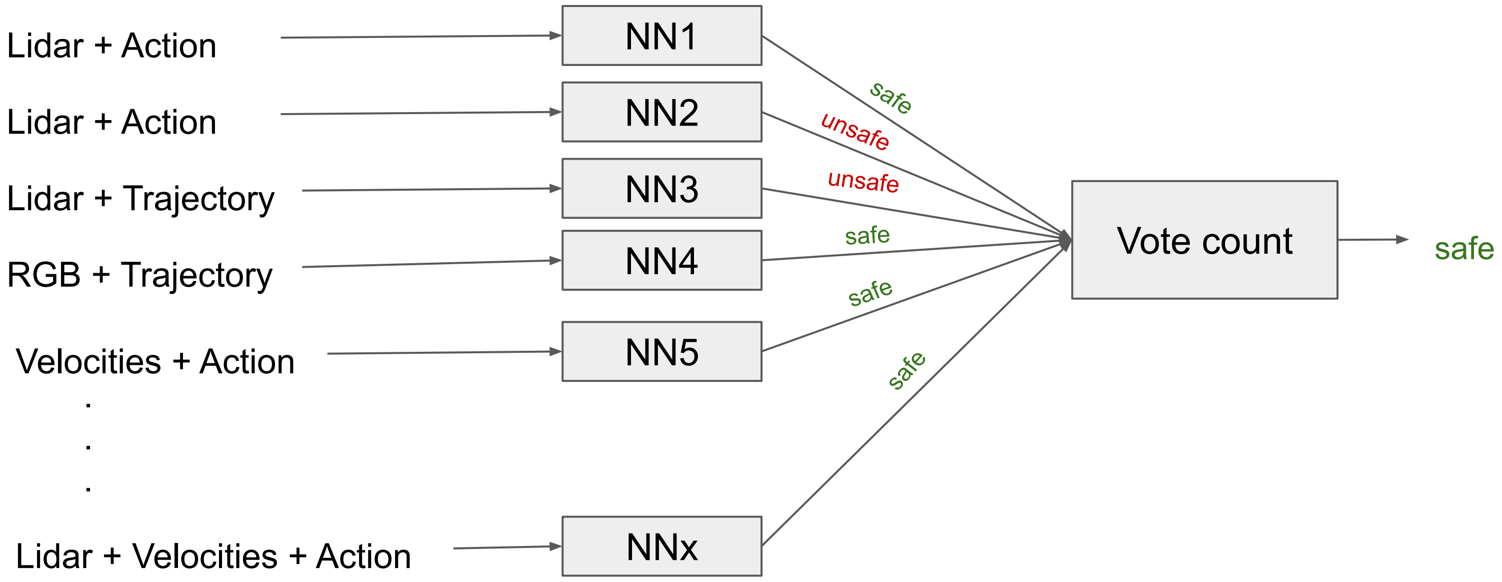


Fig. 2: An ensemble of different neural networks focusing on different subsystems to reach a consensus

Scope of the paper

- detect ‘locally avoidable’ catastrophes
- predict forward collisions
- only visual sensors as input to CPN

CPN (Vision): Two model variants

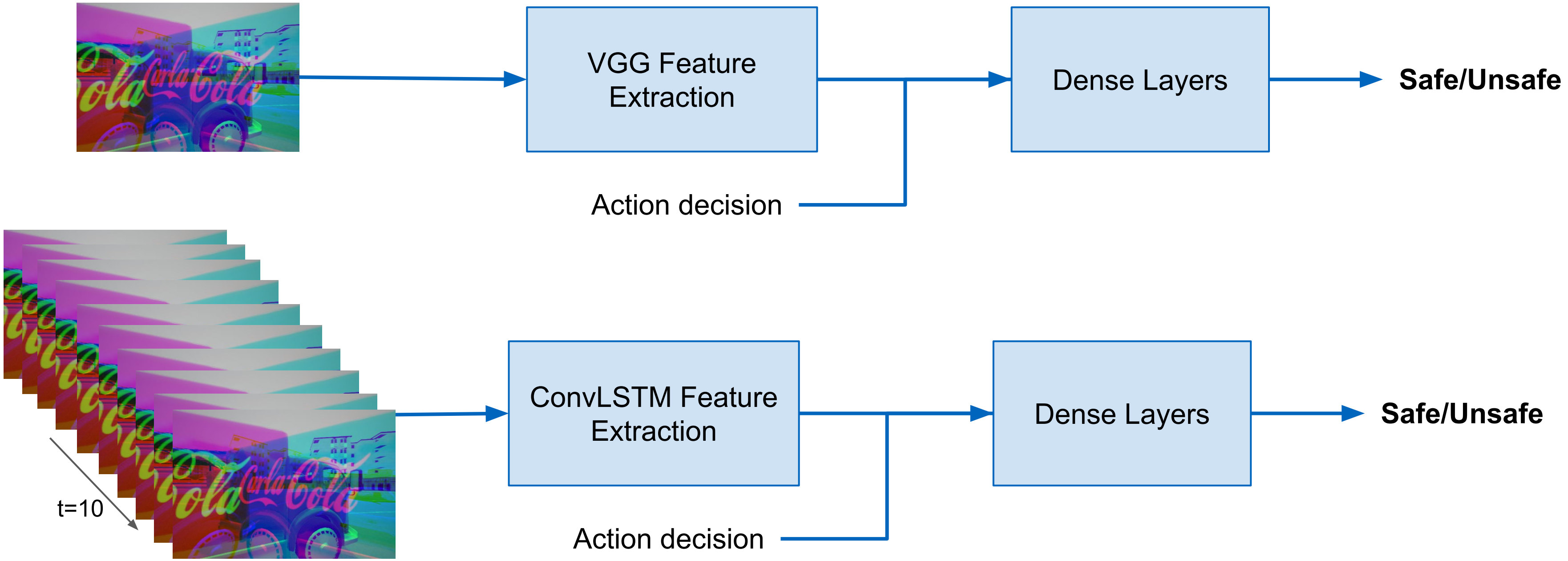


Fig. 3: Block diagram showing an abstraction of the two network architectures used: ***Simple CPN (top)*** *and* ***ST-CPN (bottom)***

Simple CPN vs ST-CPN

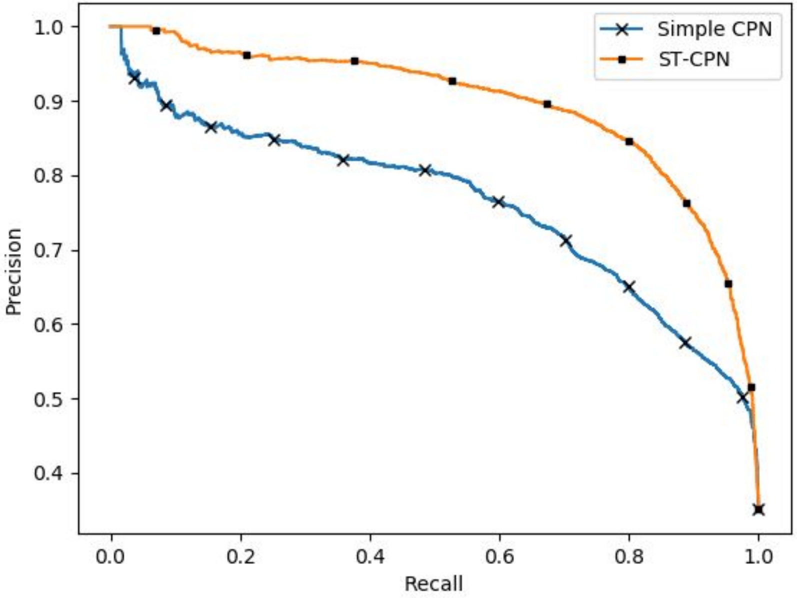
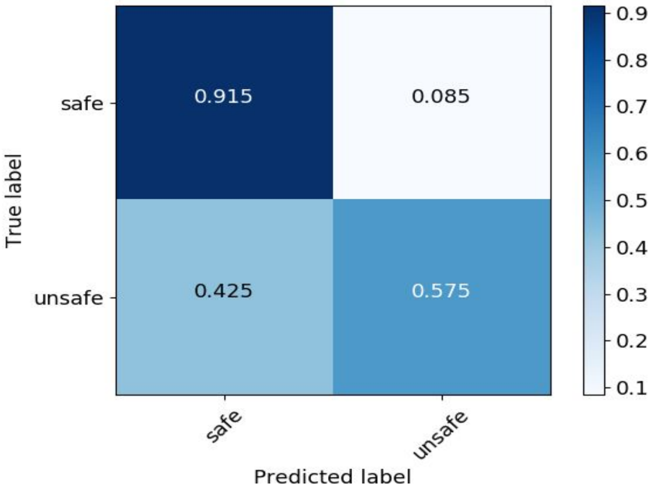


*Fig. 3: Precision-Recall Curve of **Simple CPN (blue)** vs **ST-CPN (orange)***

Simple CPN vs ST-CPN



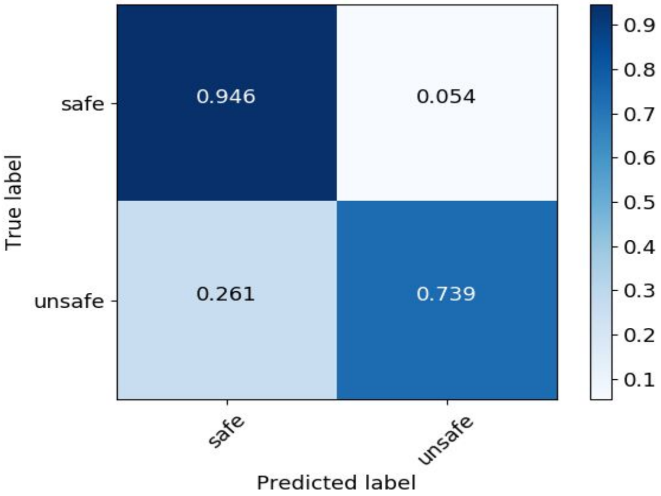


Fig. 4: Confusion matrix showing test time performance of ***Simple CPN (left)*** *and* ***ST-CPN (right)***

ST-CPN: Effect of changing weather conditions

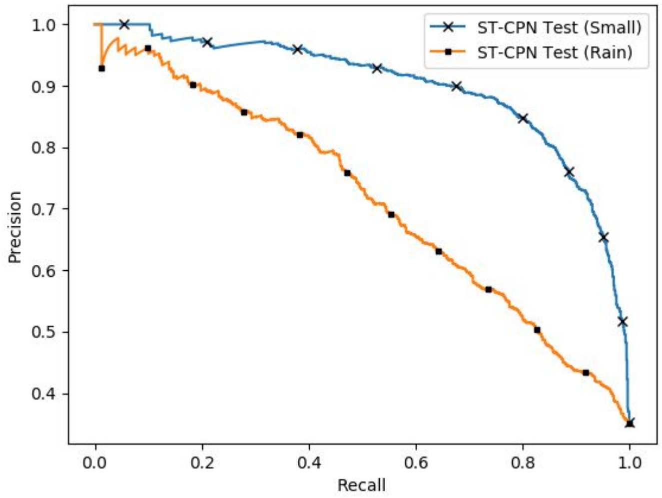


Fig. 5: Precision-Recall Curve comparing the performance of the ST-CPN model on the test set with clear weather vs rainy weather

ST-CPN: Ensembles allow for estimating uncertainty

Table1: Comparing the changes in the uncertainty estimates as the data moves further away in distribution from the data on which the model was trained

Dataset	AUC-PR	Uncertainty estimate
Training set with clear weather	0.9740	0.1391
Test set with clear weather	0.7679	0.0163
Test set with rainy weather	*0.5408*	*0.0212*

Conclusion

- ***Promising approach:*** potential to scale up to inputs from multiple sensors
- ***Temporal features*** play an important role
- ***Uncertainty estimates from*** ensembles could help detect distribution shift

Extra: CPN Dataset