WOGAN at the SBST 2022 CPS Tool Competition

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Joint work with F. Spencer and I. Porres

WOGAN

- WOGAN is a general test suite generation algorithm which utilizes generative adversarial networks and neural networks.

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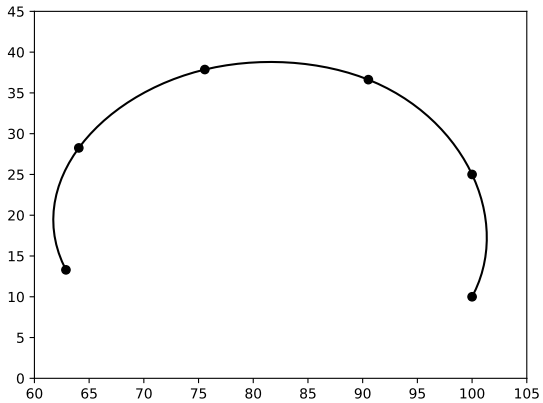
- We fix the roads to have 6 points (5 curvature values).



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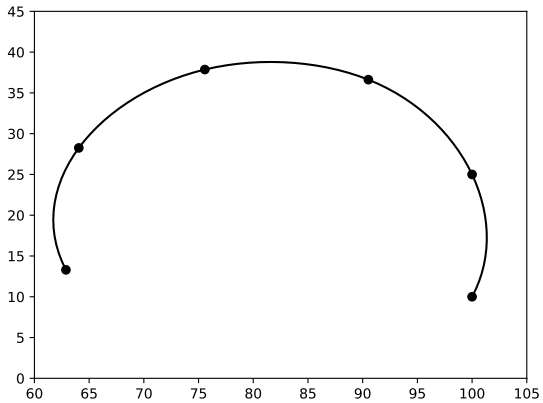

  - This is an arbitrary decision. Small dimension makes learning with NNs easier, but higher dimensions allow more varied roads.

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  - Signal output and distances to lane edges also available, but we did not use them.

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- Such a generator is trained based on a sample from A.
- WOGAN trains online a generator on

$$\{t \in \mathcal{I} : \mathrm{BOLP}(t) > 1 - \varepsilon\}$$

for some small ε.

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  - Add t to T.
- N.B. We execute the best test t on the SUT in order to find more training data for A. Without this the estimates of A can be unreliable.

Intuition

- The intuition is that over time A gets more accurate and thus more high-BOLP tests get included in the training batch of G. Thus G should be able to learn a distribution on high-BOLP tests.

Some Further Details

- We train the generator as a Wasserstein generative adversarial network (WGAN) as it is empirically known to be able to produce varied samples (should be good for road diversity).

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- WOGAN is a general-purpose algorithm the only domain knowledge we use is the input representation.

Experimental Validation

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- WOGAN among the best performing entries (better in BeamNG.AI and not so good in DAVE-2).
- We are quite satisfied: WGAN enabled us diverse tests and we got good results without much domain knowledge.