UNCERT

PyTorch Based Implementation of Semi-Model-Based Reinforcement Learning with Uncertainty

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Motivation

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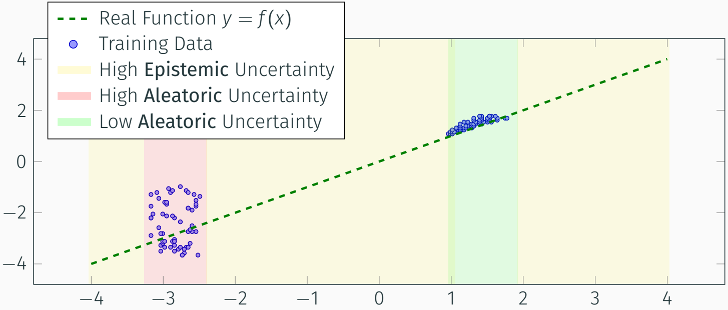
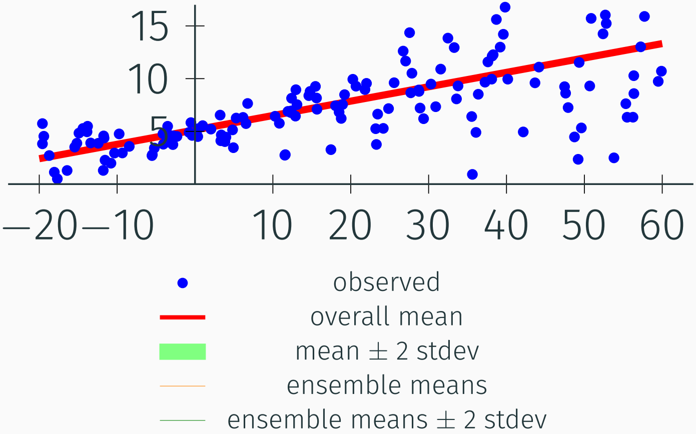
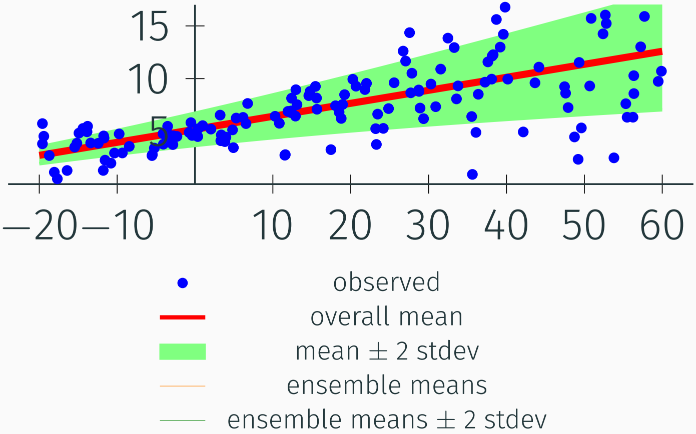
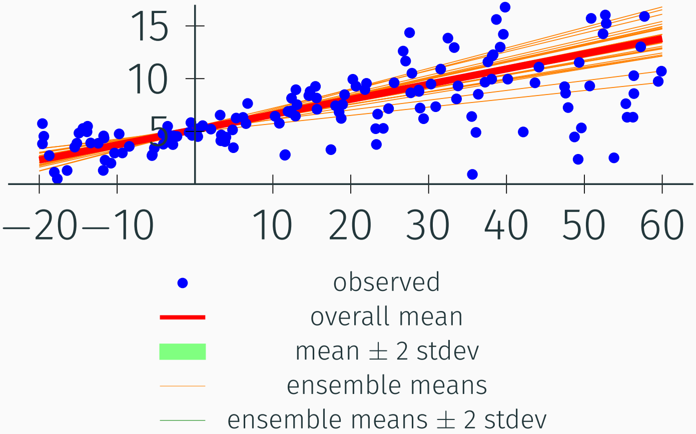


No Uncertainty (linear regression)

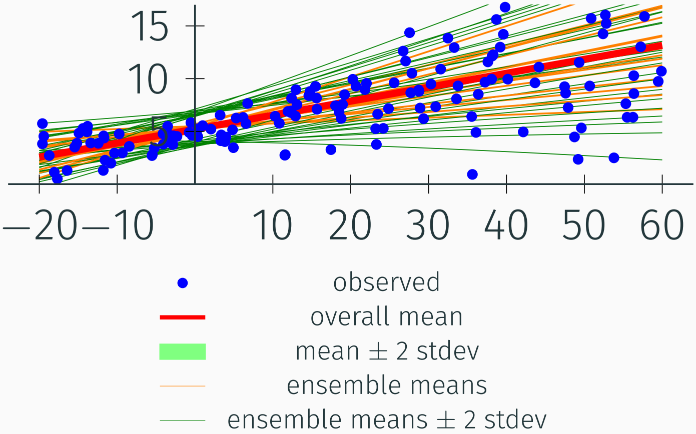



15
10
5
−20
−10
10
20
30
40
50
60
observed
overall mean
mean ± 2 stdev
ensemble means
ensemble means ± 2 stdev

Epistemic Uncertainty



Aleatoric and Epistemic Uncertainty



Convolutional Neural Network (CNN) vs. Bayesian Neural Network (BNN)

BNN has weights and biases that are probability distributions instead of single fixed values. These are updated during every output calculation.

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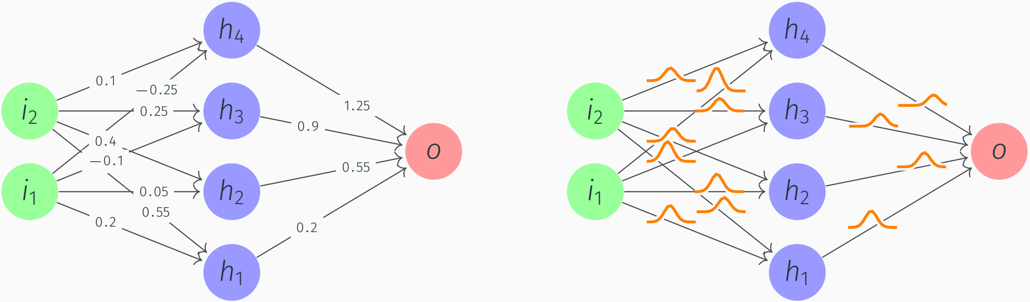

Concept

Workflow

1. Sample data from noisy Cartpole Environment

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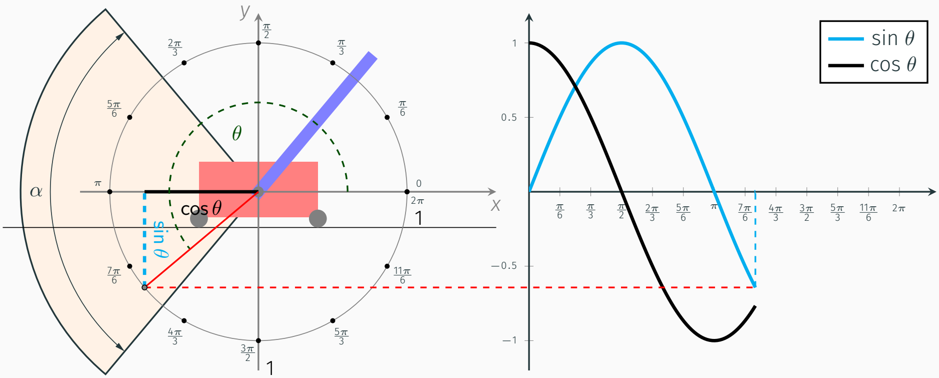
2. Learn neural network for one-step dynamics
3. Train RL policy against dynamics model

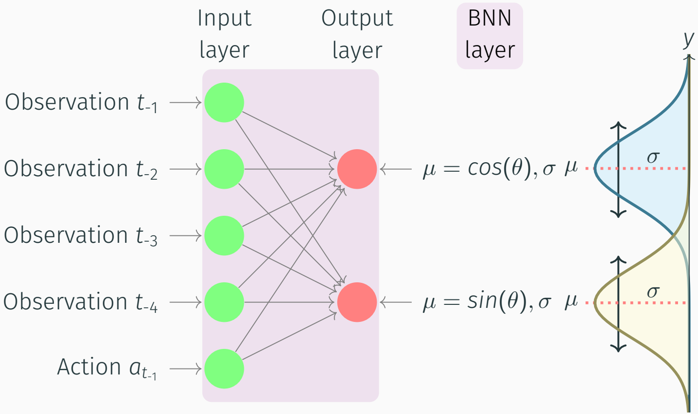
Data Sampling

CartPole superimposed with the unit circle.[1] α is the noisy section. The angle of the pole θ can be decomposed into sine and cosine. Action space is quantized.



[1]Actual environment has the circle turned 90° anti-clockwise.

Bayesian Neural Network Architecture



Observation includes x position of the cart, its velocity, the angle of the pendulum θ and its angular velocity. 21 input nodes (5 oberservation parameters $* 4$ time steps $+ 1$ action $= 21$) and two outputs. Action $a_{t_{-1}}$ will take the agent from observation t_{-1} to observation t_0.

Experiments & Results

Experiment Configuration

Table 1: Hyperparameter used to run the experiments.

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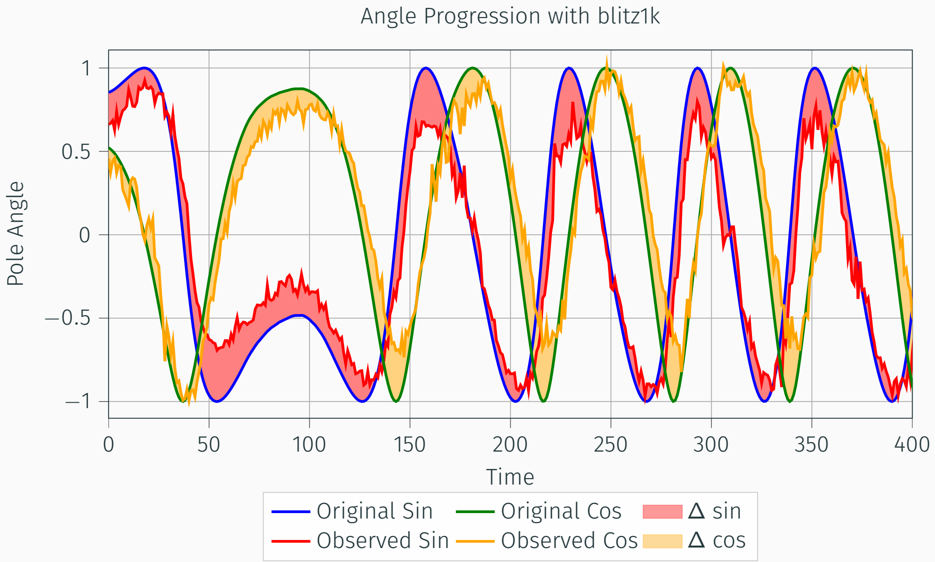
`RL algorithms`	PPO

Experiments & Results

Bayesian Neural Network.
Random actions.

BNN predictions: 1k time series, random actions



BNN predictions: 50k time series, random actions

Video Demo Links

With Uncertainty

https://youtu.be/vAIEon3I5lw

Without Uncertainty

https://youtu.be/Xuhp5B6EwWY

Experiments & Results

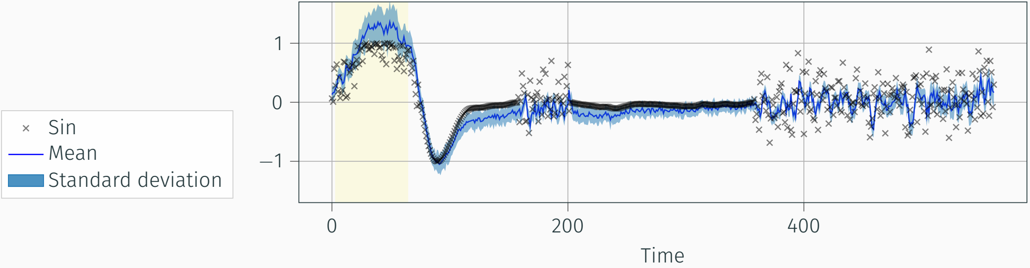
Well-trained PPO agent.
50k time series training data.
75k time steps learning.

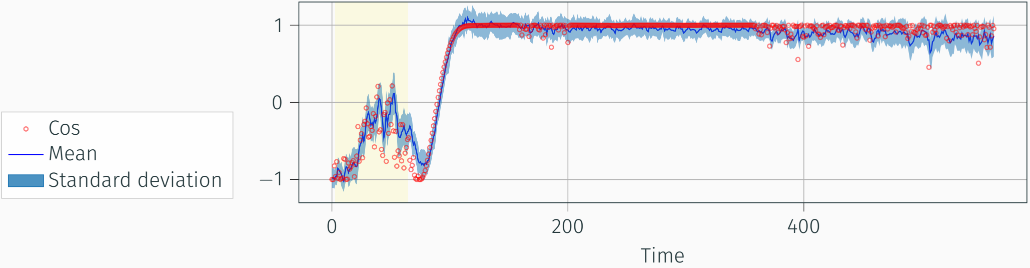
Reward function

$$reward = \cos(\alpha) - \left(\sqrt{{\sigma_{sin}}^2 + {\sigma_{cos}}^2} * \epsilon\right)$$

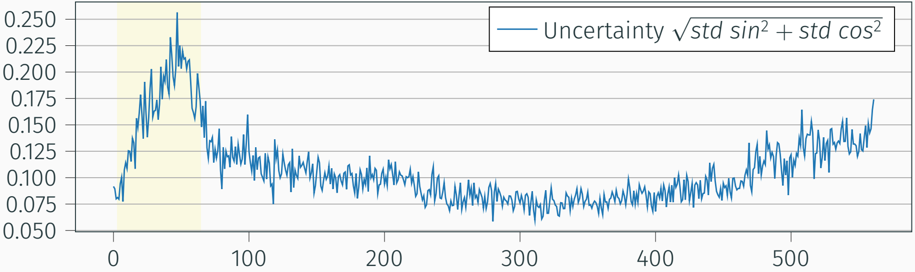
```
reward = cosine - (math.sqrt(std_sin ** 2 + std_cos ** 2)*factor)
```

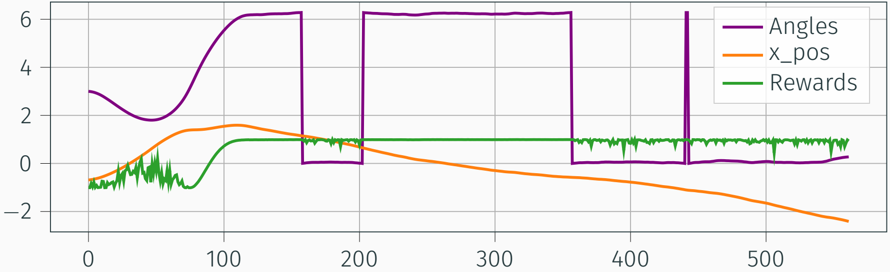
BNN Uncertainty: 75k time series





BNN Uncertainty: 75k time series





Implementation

> “Talk is cheap. Show me the code.”
>
> *Linus Torvalds*

Conclusion

Take Aways

1. RL agent detects noisy sector and avoids it

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2. RL agent is able to ”solve” the environment even with uncertainty

Take Aways

1. RL agent detects noisy sector and avoids it
2. RL agent is able to "solve" the environment even with uncertainty
3. Use PyTorch ;-)

Questions?[2]

[2] Source code, presentation and an exhaustive report are at github.com/github-throwaway/ARL-Model-RL-Unsicherheit

References

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Backup Slides

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BLiTZ Implementation

Creating a variational regressor class

```python
@variational_estimator
class BayesianRegressor(nn.Module):
    def __init__(self, input_dim, output_dim):
        super().__init__()
        self.blinear = BayesianLinear(input_dim, output_dim)

    def forward(self, x):
        return self.blinear(x)
```

Defining a confidence interval evaluating function

```python
def evaluate_regression(regressor, x, y, samples=25, std_multiplier=2):
    preds = [regressor(x) for i in range(samples)]
    preds = torch.stack(preds)
    means = preds.mean(axis=0)
    stds = preds.std(axis=0)
    ci_upper = means + (std_multiplier * stds)
    ci_lower = means - (std_multiplier * stds)
    ic_acc = (ci_lower <= y) * (ci_upper >= y)
    ic_acc = ic_acc.float().mean()
    return ic_acc, (ci_upper >= y).float().mean(), (ci_lower <= y).float().mean()
```

Creating our regressor and loading data

```
optimizer = optim.Adam(regressor.parameters(), lr=0.01)
criterion = torch.nn.MSELoss()
complexity_cost_weight = 1. / x_train.shape[0]
```

Main training and evaluating loop

```python
losses = []
for epoch in tqdm(range(100)):
    new_epoch = True
    for i, (datapoints, labels) in enumerate(dataloader_train):
        optimizer.zero_grad()

        loss = regressor.sample_elbo(
            inputs=datapoints,
            labels=labels,
            criterion=criterion,
            sample_nbr=3,
            complexity_cost_weight=complexity_cost_weight
        )

        loss.backward()
        optimizer.step()
```

Backup Slides

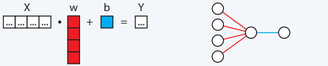
Cheatsheet

Cheatsheet[3]

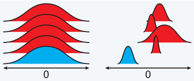
function | matrices | computational graph | priors | posteriors

linear regression

$$Y = f(X, w_1, b_1)$$
$$f(x, w, b) = x \cdot w + b$$

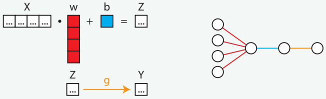


$$w_{1,i} \sim N(0, 100)$$
$$b_1 \sim N(0, 100)$$



logistic regression (classification)

$$Z = f(X, w_1, b_1)$$
$$Y = g(Z)$$
$$g(x) = \frac{1}{1 + e^{-x}}$$



$$w_{1,i} \sim N(0, 100)$$
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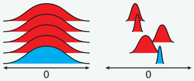
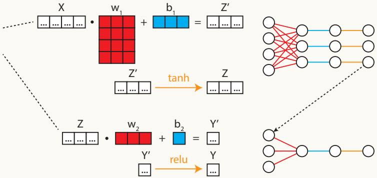
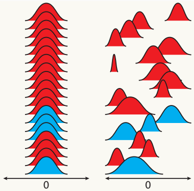


deep net regressor

$$Z = \tanh(f(X, w_1, b_1))$$
$$Y = \mathrm{ReLu}(f(Z, w_2, b_2))$$
$$\mathrm{ReLu}(x) = \max(x, 0)$$
$$\tanh x = \frac{e^{2x} - 1}{e^{2x} + 1}$$



$$w_{1,i} \sim N(0, 1)$$
$$b_{1,i} \sim N(0, 1)$$
$$w_{2,i} \sim N(0, 1)$$
$$b_{2,i} \sim N(0, 1)$$



[3] https://github.com/ericmjl/bayesian-deep-learning-demystified