UNCERT

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

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28.09.2021

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Motivation

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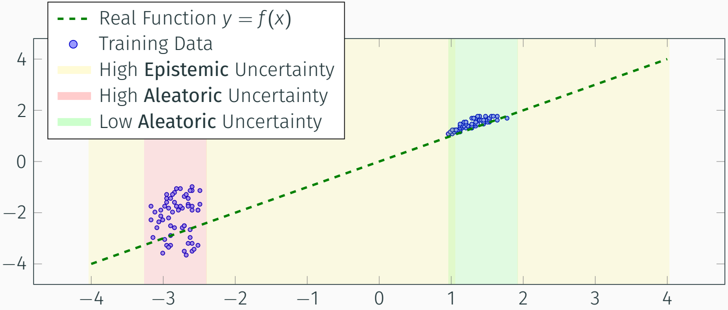
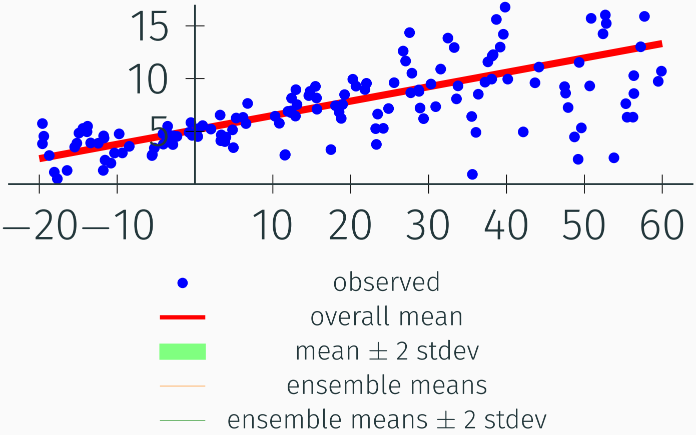


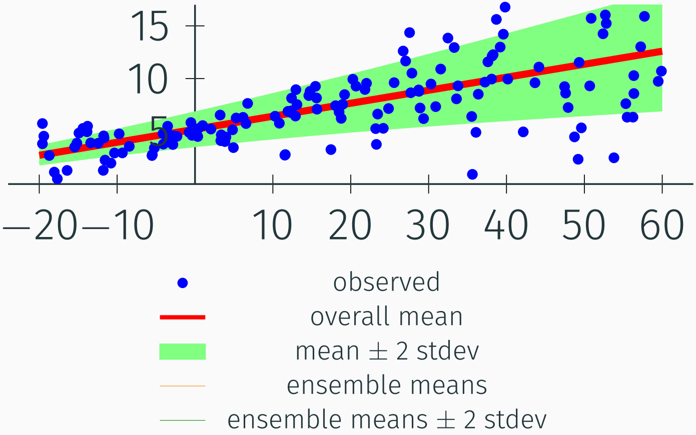
No Uncertainty (linear regression)

Mean captures the overall trend, but misses that y becomes more variable as x becomes larger.



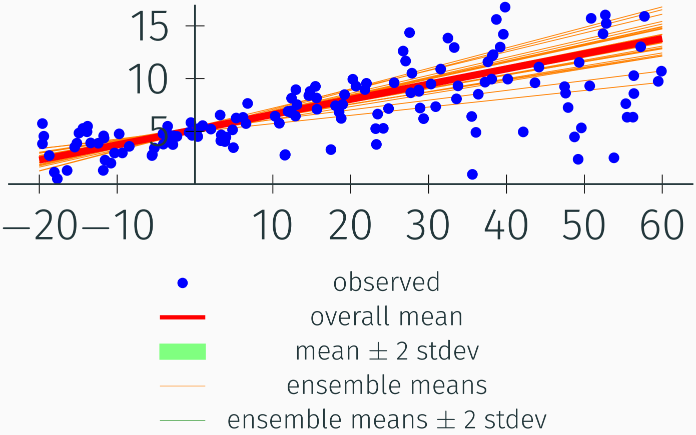
Aleatoric Uncertainty

Standard deviation represents variation inherent to the underlying process. This uncertainty can not be reduced.



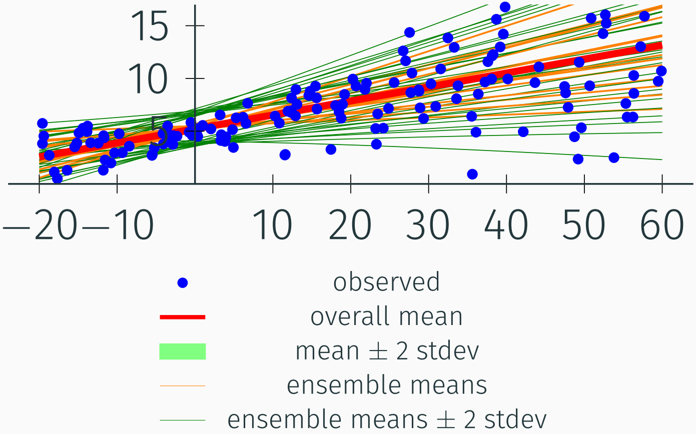
Epistemic Uncertainty

Each line represents a different random draw of the model parameters from the posterior distribution. Model is uncertain about the linear relationship.



Aleatoric and Epistemic Uncertainty

This model correctly predicts more variability as towards the extremes of x.



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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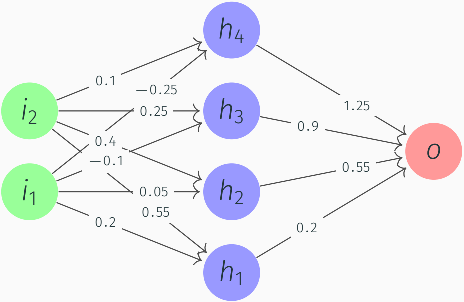

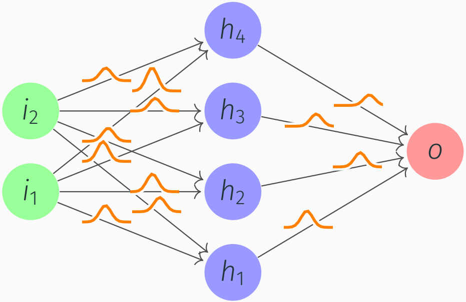

Concept

Workflow

1. Sample data from noisy Cartpole Environment

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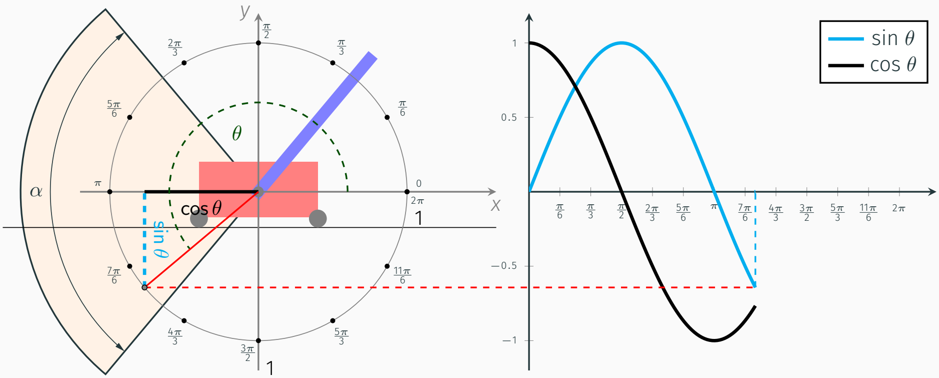
2. Learn neural network for one-step dynamics
3. Train RL policy against dynamics model

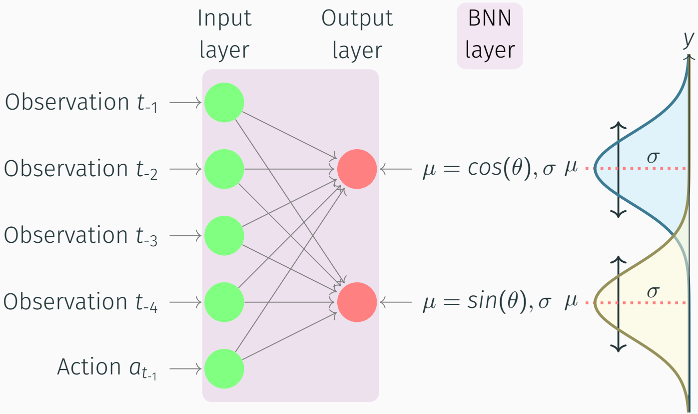
Data Sampling

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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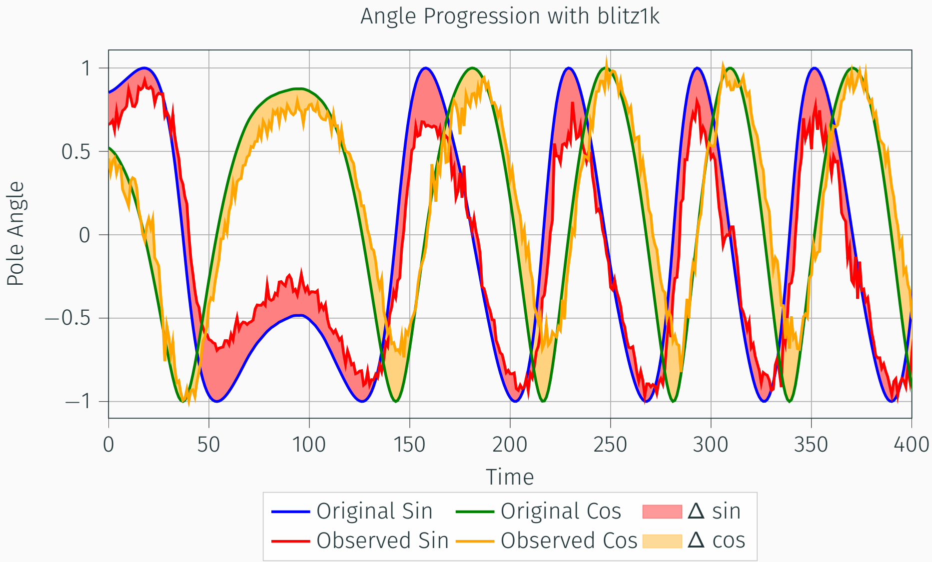
`RL algorithms`	PPO

Experiments & Results

Bayesian Neural Network.
Random actions.

BNN predictions: 1k time series, random actions



BNN predictions: 50k time series, random actions

Experiments & Results

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

Video Demo Links

Without Uncertainty

https://youtu.be/Xuhp5B6EwWY

With Uncertainty

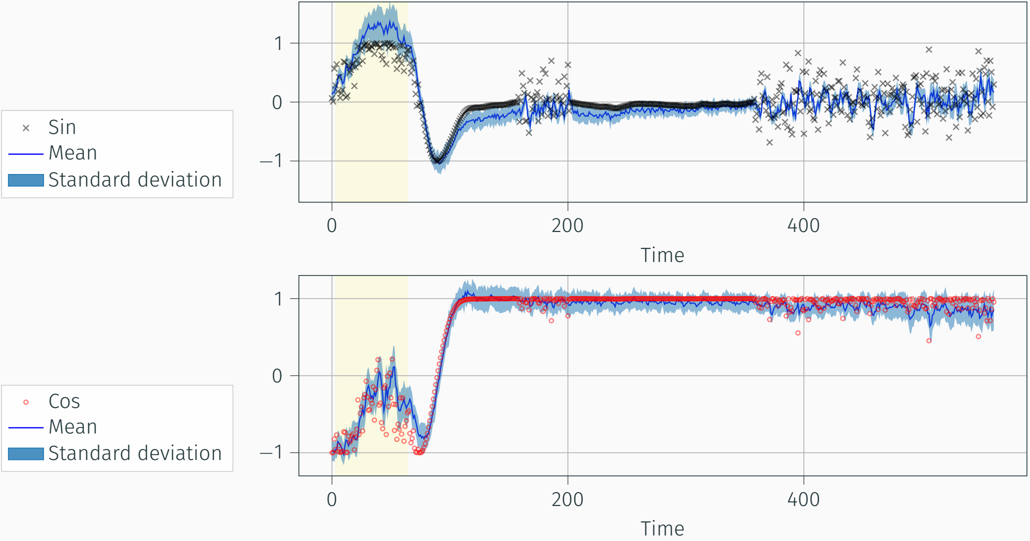
https://youtu.be/vAIEon3I5lw

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



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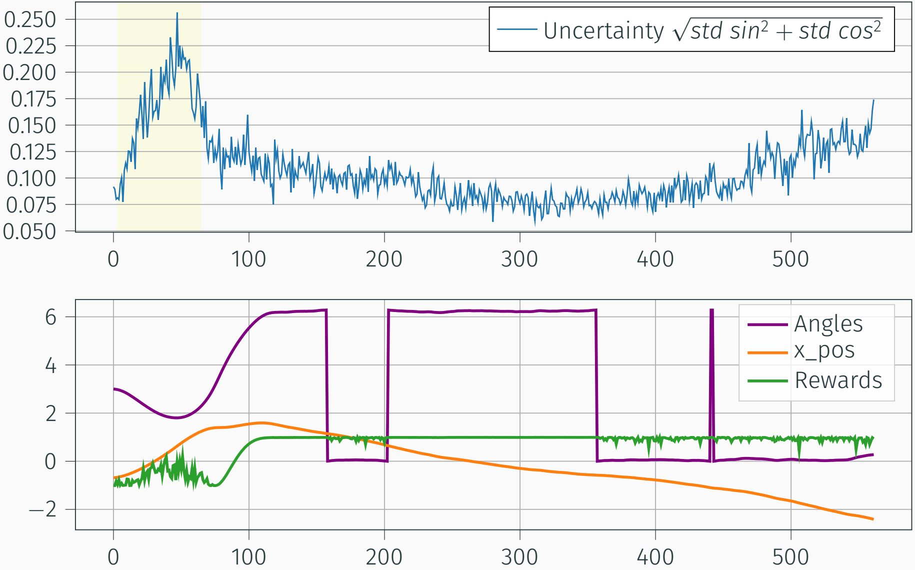

Implementation

“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

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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]
```

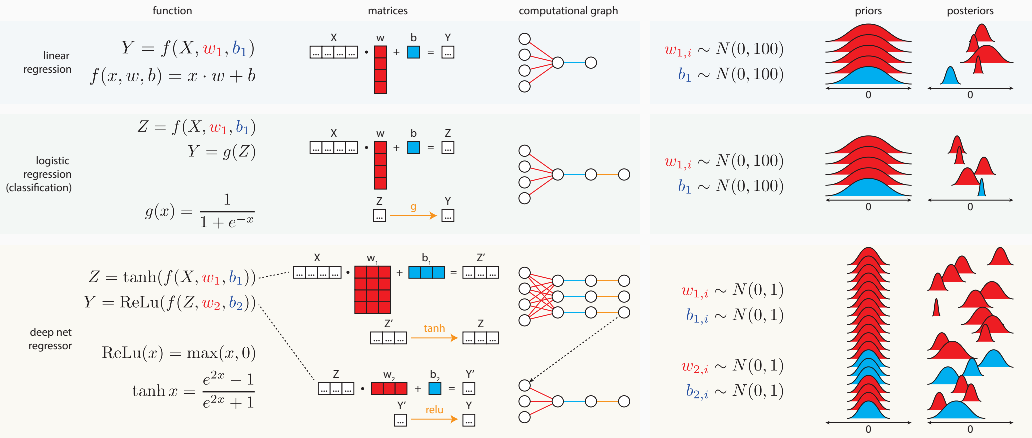
Main training and evaluating loop

```
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]



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

Backup Slides

Distributions

Probability distributions entangled by Bayes' rule

$$P(\mathbf{w} \mid \mathcal{D}) = \frac{P(\mathcal{D} \mid \mathbf{w})P(\mathbf{w})}{P(\mathcal{D})} \quad \text{where } \mathcal{D} = (x_i, y_i)$$