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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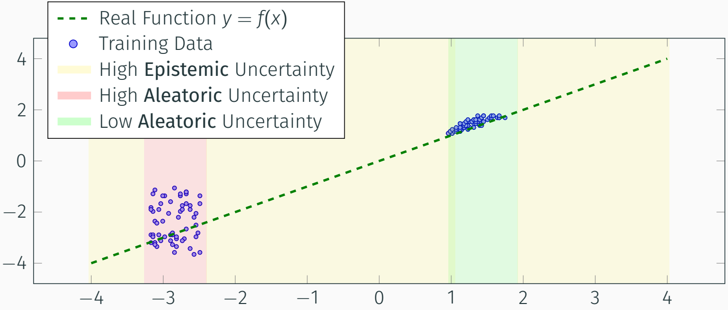
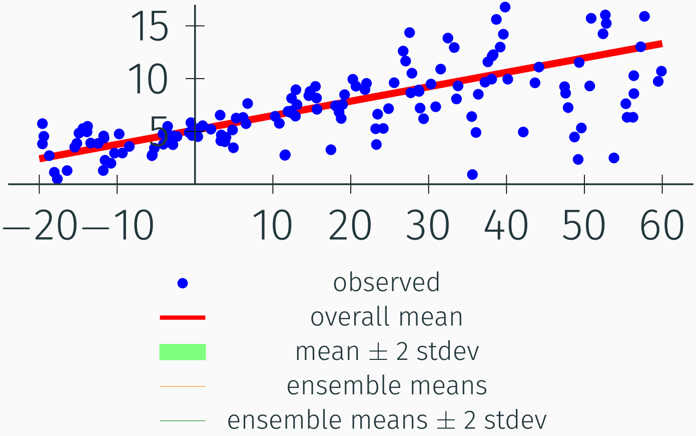
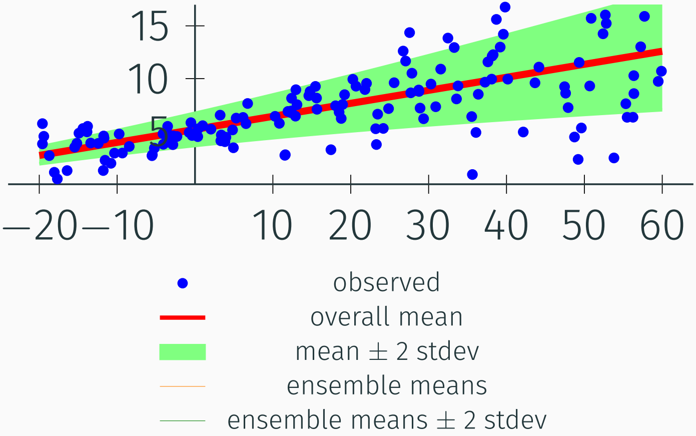


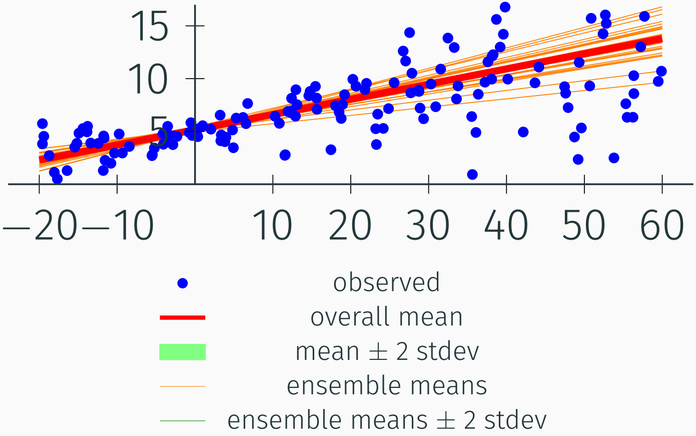
No Uncertainty (linear regression)



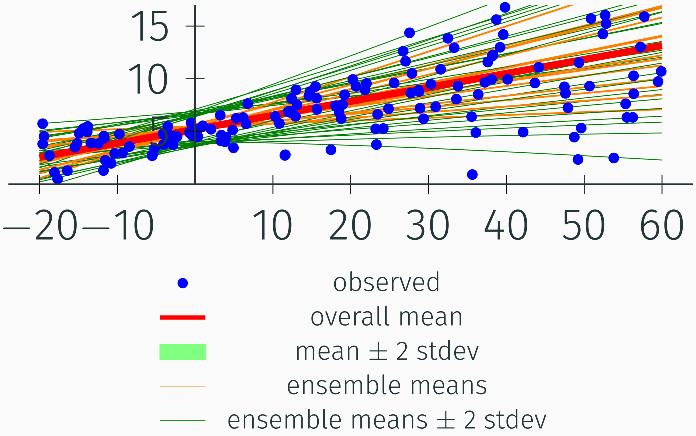
Aleatoric Uncertainty



Epistemic Uncertainty



Aleatoric and Epistemic Uncertainty



Concept

Workflow

1. Sample data from noisy Cartpole Environment

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2. Learn neural network for one-step dynamics

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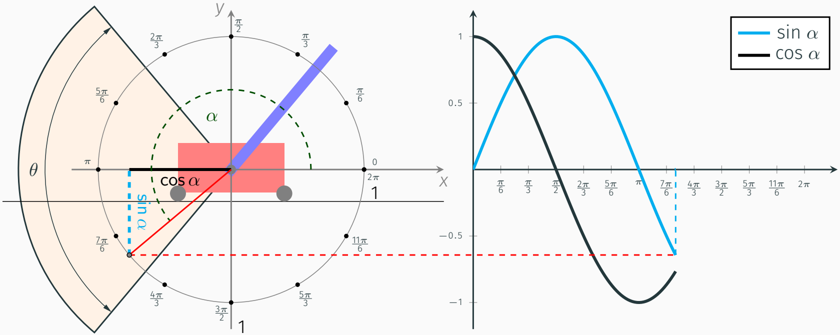
2. Learn neural network for one-step dynamics
3. Train RL policy against dynamics model


y
$\frac{\pi}{2}$
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α
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π
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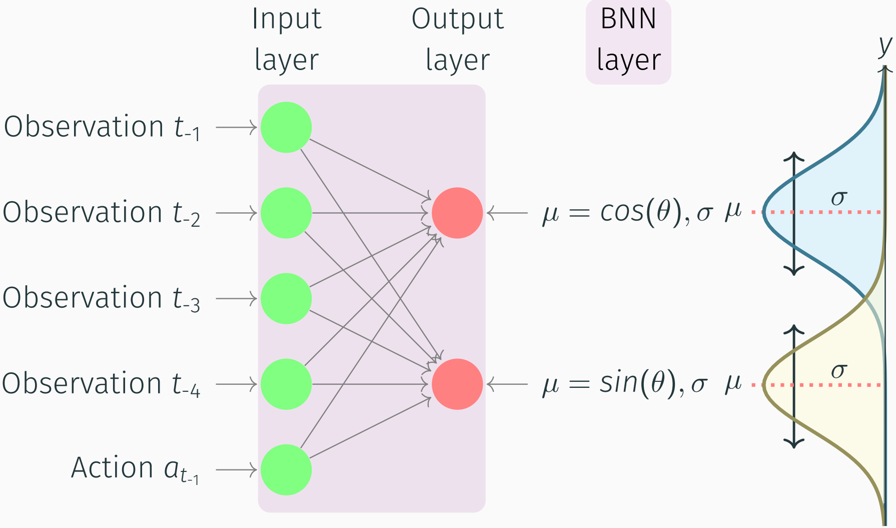
x
$\cos\alpha$
$\sin\alpha$
1
$\frac{7\pi}{6}$
$\frac{11\pi}{6}$
$\frac{4\pi}{3}$
$\frac{5\pi}{3}$
$\frac{3\pi}{2}$
1
1
0.5
-0.5
-1
$\frac{\pi}{6}$ $\frac{\pi}{3}$ $\frac{\pi}{2}$ $\frac{2\pi}{3}$ $\frac{5\pi}{6}$ π $\frac{7\pi}{6}$ $\frac{4\pi}{3}$ $\frac{3\pi}{2}$ $\frac{5\pi}{3}$ $\frac{11\pi}{6}$ 2π
$\sin\alpha$
$\cos\alpha$

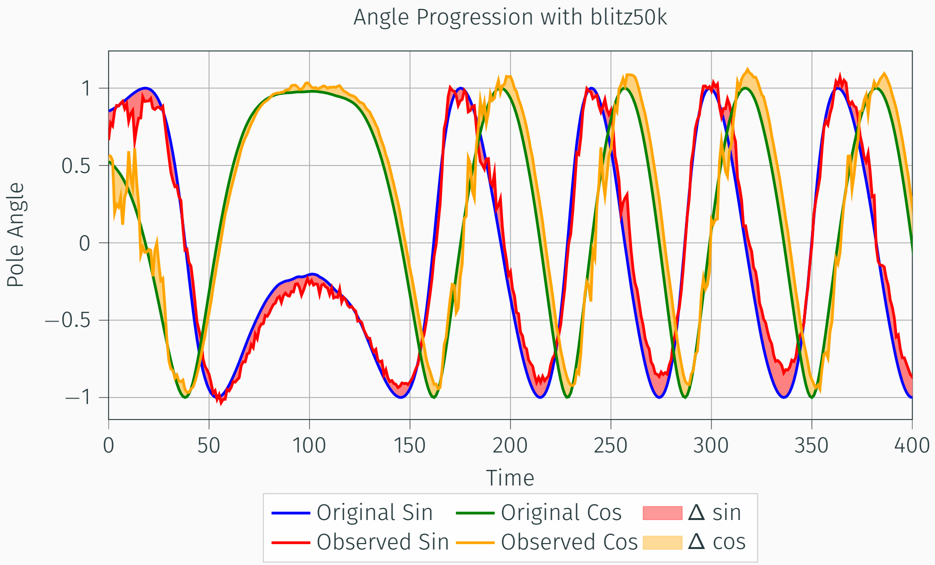
Neural Network Architecture



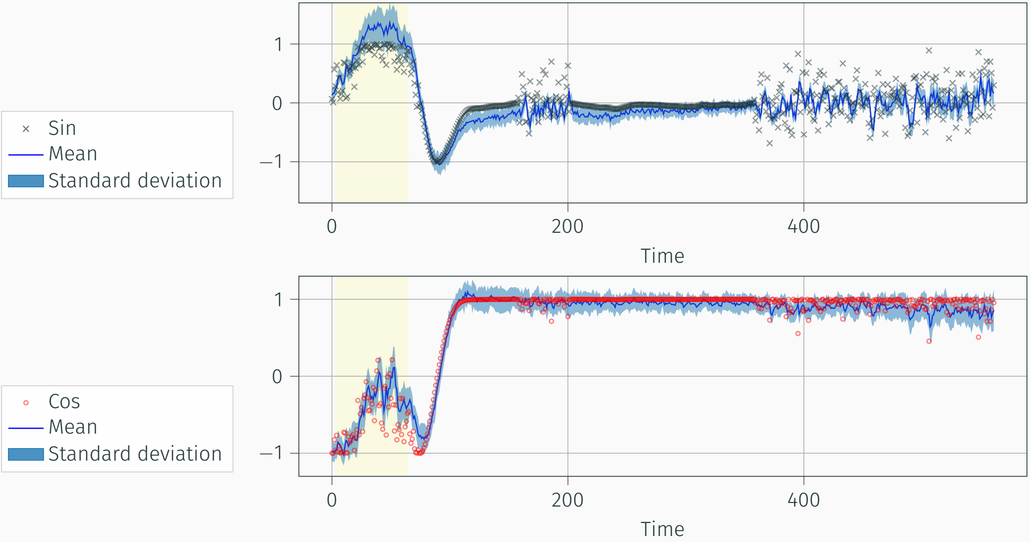
Experiments & Results

BNN predictions: 1k time series

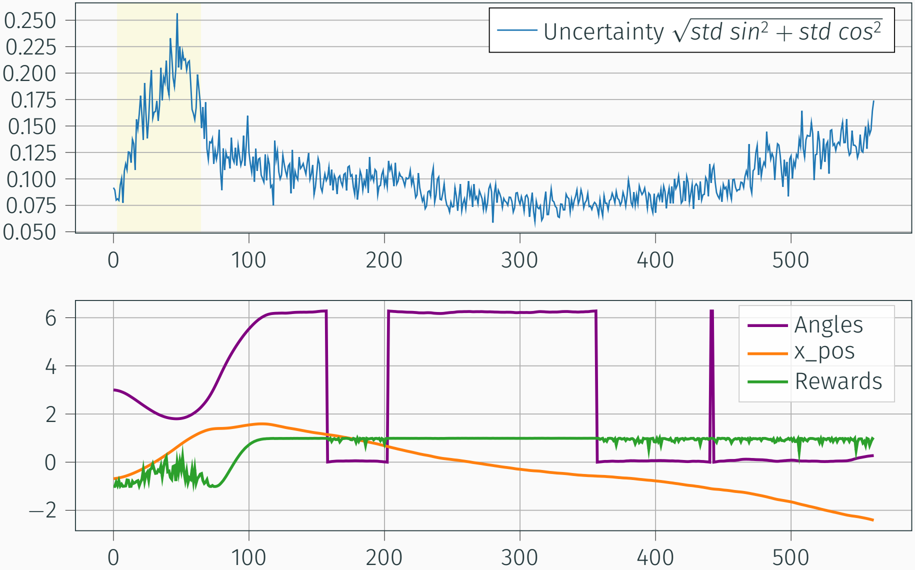
BNN predictions: 50k time series



BNN Uncertainty: 75k time series



BNN Uncertainty: 75k time series



Video Demo Links

With Uncertainty

Without uncertainty

LIVE DEMO

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?

References

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Backup Slides

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

```
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()
```