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

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# Table of Contents

# Introduction

# Motivation

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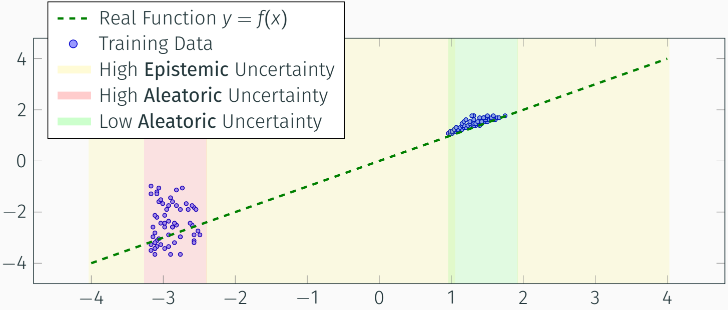
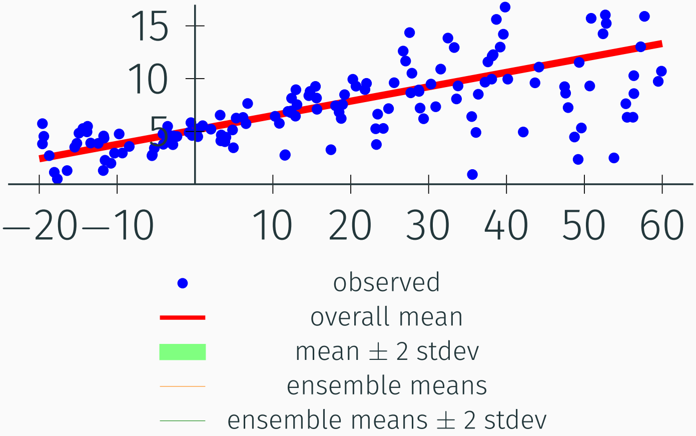
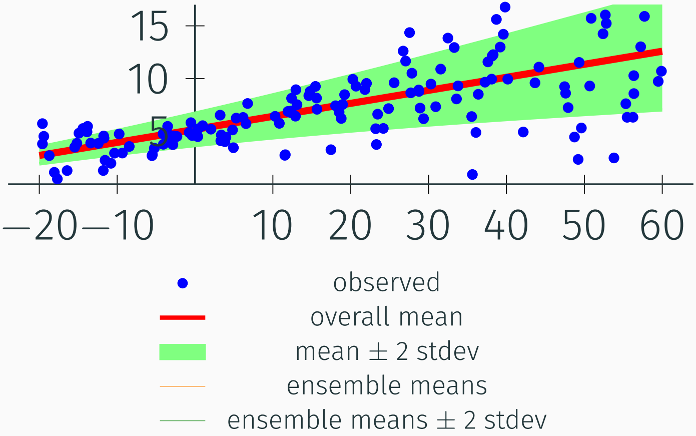


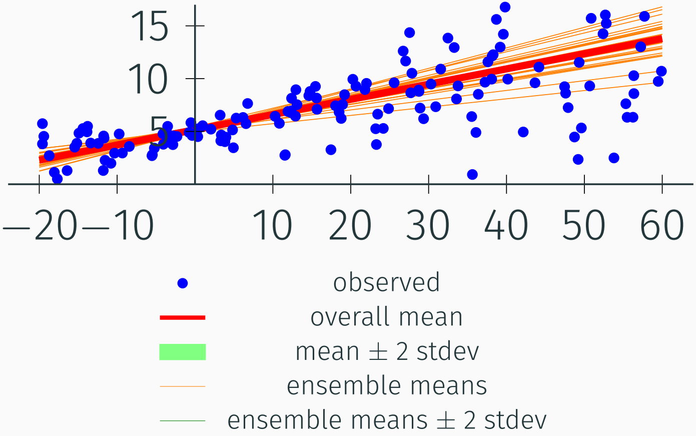
# No Uncertainty (linear regression)



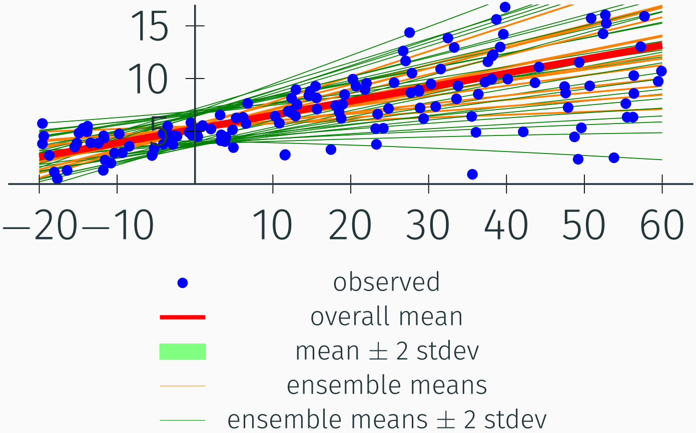
# Aleatoric Uncertainty



# Epistemic Uncertainty



# Aleatoric and Epistemic Uncertainty



# Concept

# Workflow

1. Sample data from noisy Cartpole Environment

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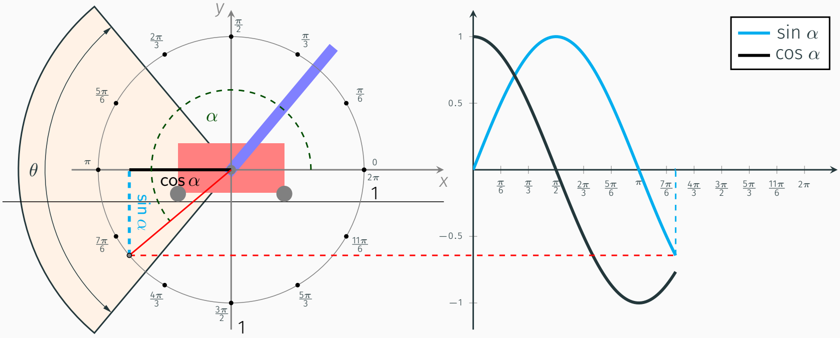
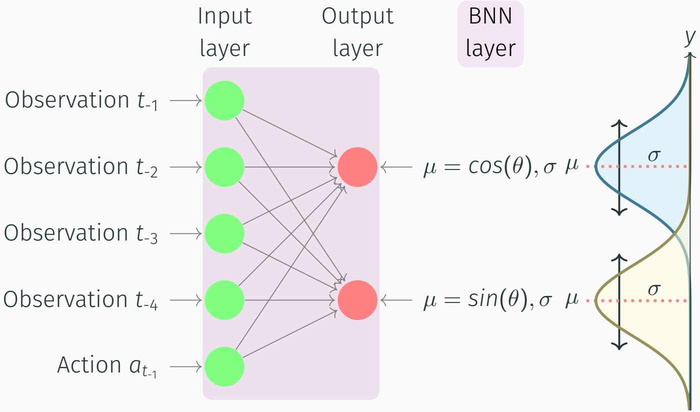
2. Learn neural network for one-step dynamics
3. Train RL policy against dynamics model

# Data Sampling



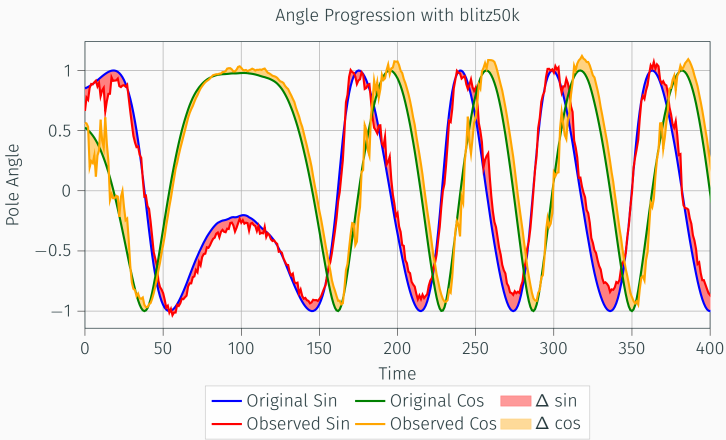
# Neural Network Architecture



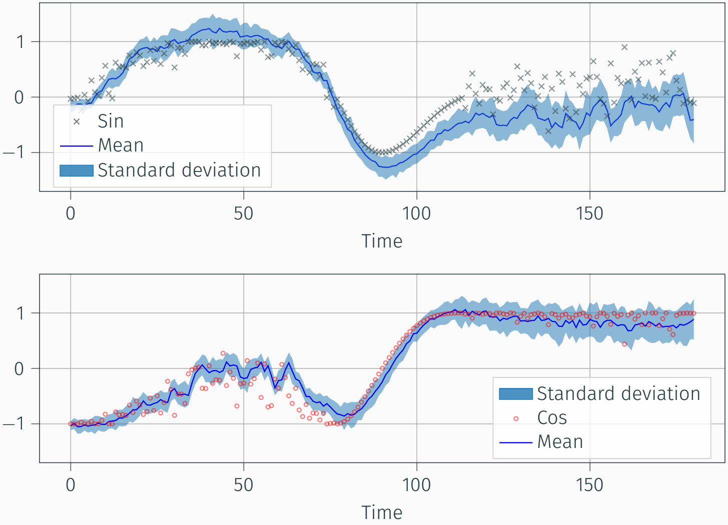
# Experiments & Results

# BNN predictions: 1k time series

# BNN predictions: 50k time series



# BNN Uncertainty: 75k time series



DEMO TIME

# Conclusion

# Take Aways

1. RL agent detects noisy sector and avoids it

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1. RL agent detects noisy sector and avoids it
2. RL agent has trouble solving both environments
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

```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()
```