

Uber AI Labs

**AMPLIFY**i

# Probabilistic Machine Learning

or...the importance of modeling unknowns

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# Machine Learning is HOT

Many application domains in almost all verticals of tech

Speech and Language Technologies,  
automatic speech recognition,  
machine translation, question-answering,  
dialog systems



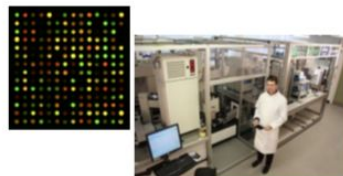
"When is the world going to end?"  
Not to end.  
As long as you keep me  
charged, we should be just  
fine.

**AMPLIFY**

Computer Vision:  
Object, Face and Handwriting  
Recognition, Image Captioning



Scientific Data Analysis  
(e.g. Bioinformatics, Astronomy)



Recommender Systems



Self-driving cars

Autonomous driving

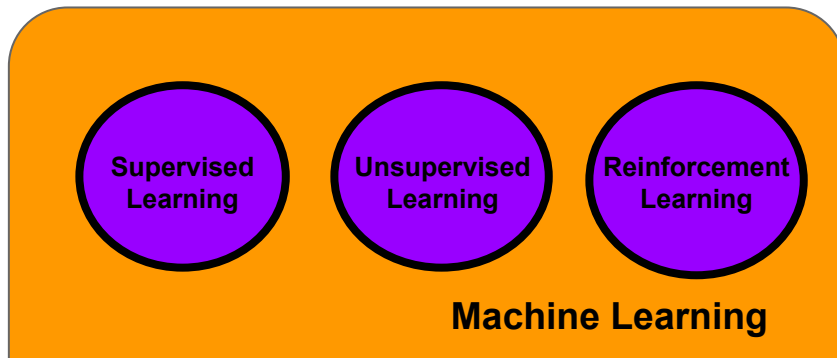
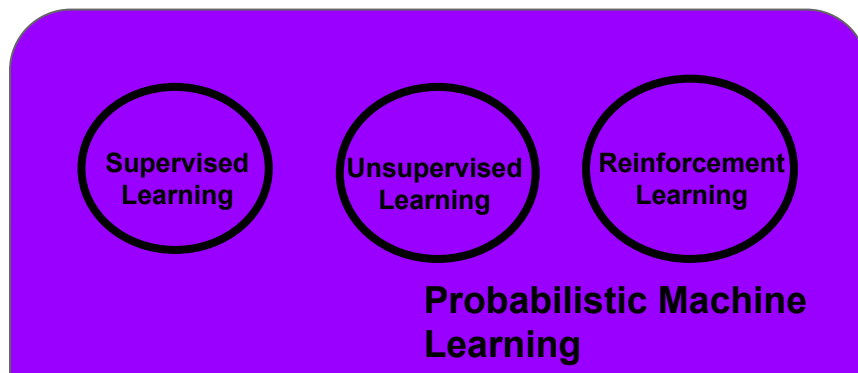
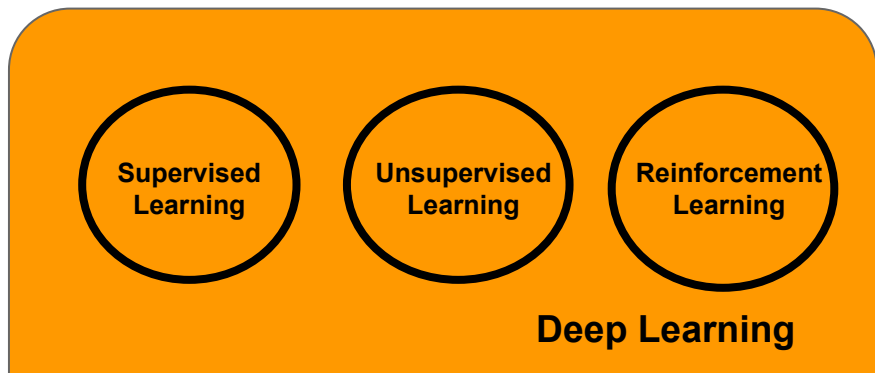


Financial Prediction and  
Automated Trading



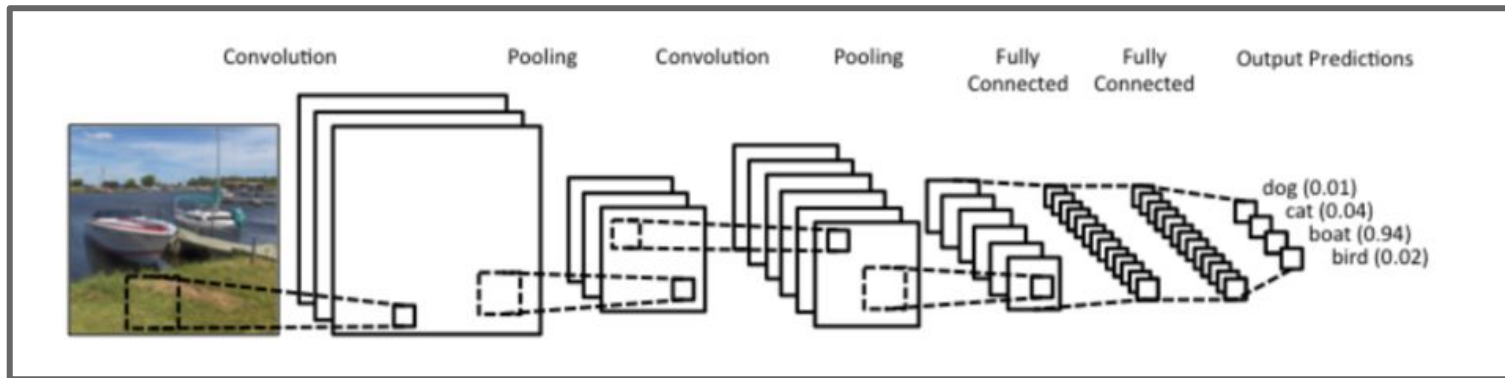
# Machine Learning Concept Map

As of 2018...



# Deep (Supervised) Learning

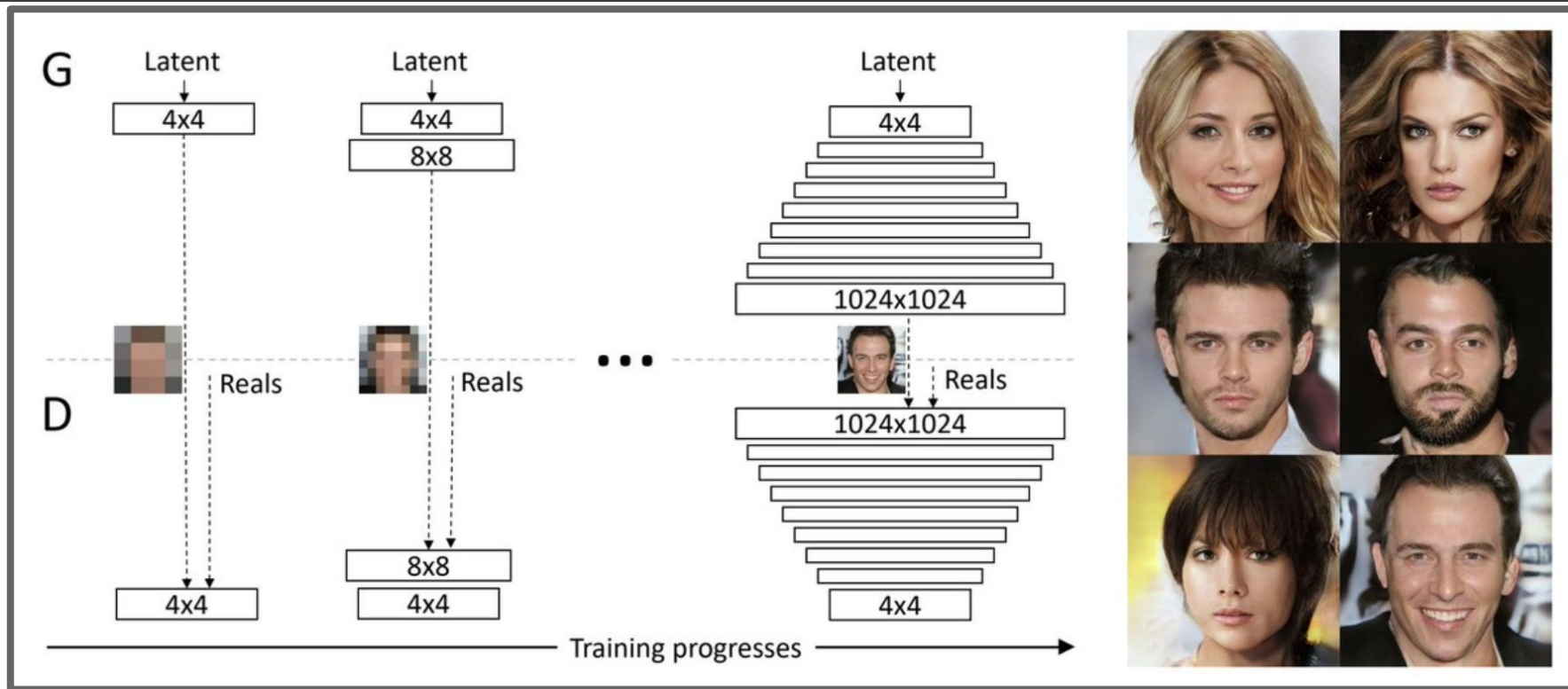
The darling child of Machine Learning



- Actually invented in the 80s and 90s!
- Become popular after a landmark paper by Krizhevsky et al. demonstrating state-of-art computer vision results. Key idea: Train it on a lot of data!
- Works very well with web-scale data.
- And a lot of computation.
- And some very good autodiff libraries: e.g. PyTorch, TensorFlow and MXNet.

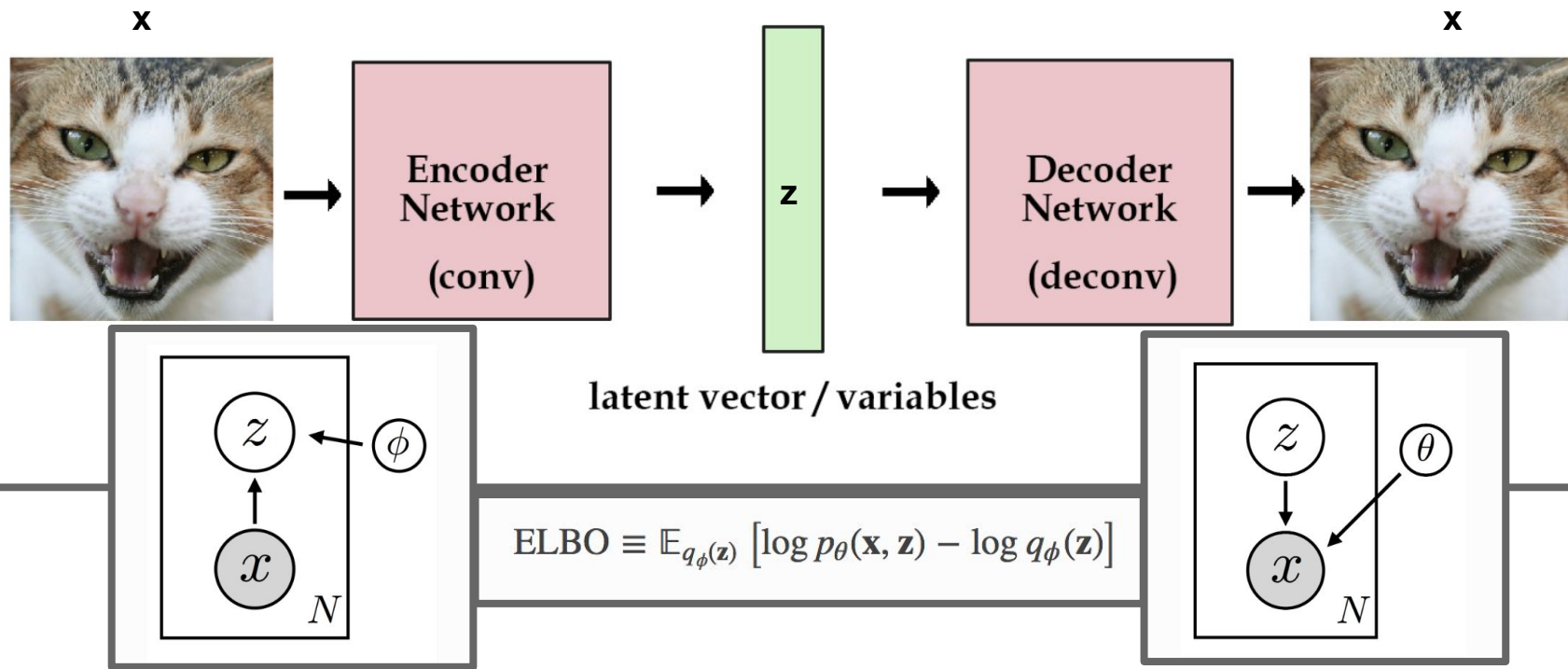
# Deep Unsupervised/Semi-supervised Learning

## Generative Adversarial Networks



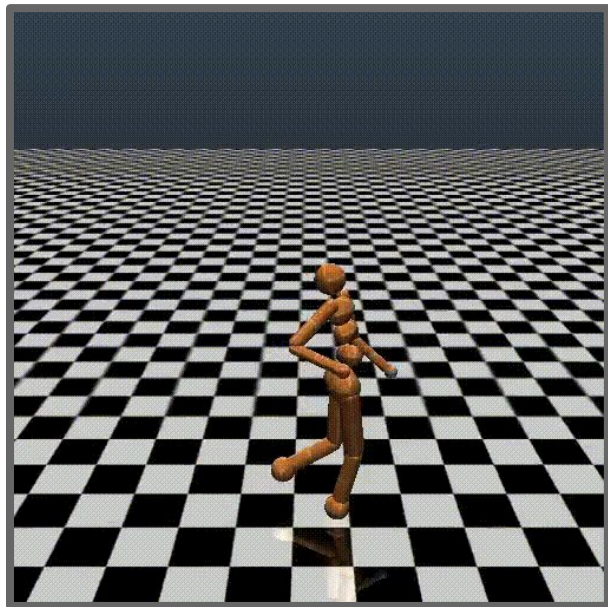
# Deep Unsupervised/Semi-supervised Learning

## Variational Autoencoders



# Deep Reinforcement Learning

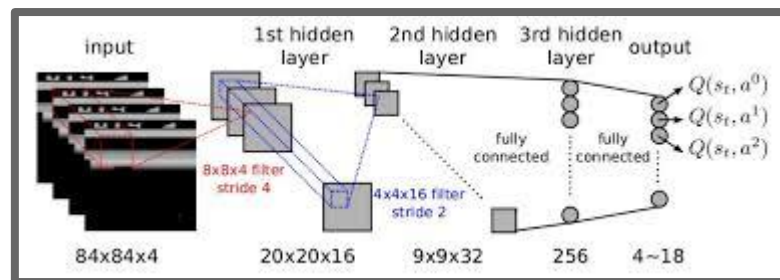
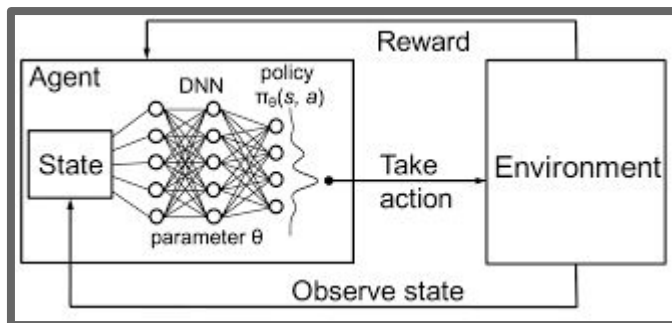
And the art of machine learning hype using games





# Deep Reinforcement Learning

And the art of machine learning hype using games



$$Q^{\pi}(s_t, a_t) = \underline{E}[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \dots | s_t, a_t]$$

Q value for that state given that action

Expected discounted cumulative reward ...

given that state and that action



# Deep Reinforcement Learning

But not all games...

**BRAINS VS. ARTIFICIAL INTELLIGENCE**  
Be sure to tweet @WinBigRivers and @SCSatCMU using #BrainsvsAI

**JANUARY 11-30 | 11AM-7PM**

**WE ARE LIFTING THE ANTE!**  
120,000 HANDS NO-LIMIT HOLD 'EM

Each hand starts with each player having 200 big blinds.  
One big blind is \$100, and one small blind is \$50.

**Hands Dealt: 115,756/120,000**

<b>BRAINS : (\$1,560,189)</b>	<b>LIBRATUS : \$1,560,189</b>
<b>DONG KIM : (\$84,054)</b> <b>LIBRATUS : \$84,054</b>	<b>JASON LES : (\$862,347)</b> <b>LIBRATUS : \$862,347</b>
<b>JIMMY CHOU : (\$338,347)</b> <b>LIBRATUS : \$338,347</b>	<b>DANIEL MCAULAY : (\$275,441)</b> <b>LIBRATUS : \$275,441</b>

Parentheses indicate a negative number.

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PG-3

# Probabilistic Machine Learning

In one slide

*Everything follows from two simple rules:*

**Sum rule:**  $P(x) = \sum_y P(x, y)$

**Product rule:**  $P(x, y) = P(x)P(y|x)$

**Learning:**

$$P(\theta|\mathcal{D}, m) = \frac{P(\mathcal{D}|\theta, m)P(\theta|m)}{P(\mathcal{D}|m)}$$

$P(\mathcal{D}|\theta, m)$  likelihood of parameters  $\theta$  in model  $m$   
 $P(\theta|m)$  prior probability of  $\theta$   
 $P(\theta|\mathcal{D}, m)$  posterior of  $\theta$  given data  $\mathcal{D}$

**Prediction:**

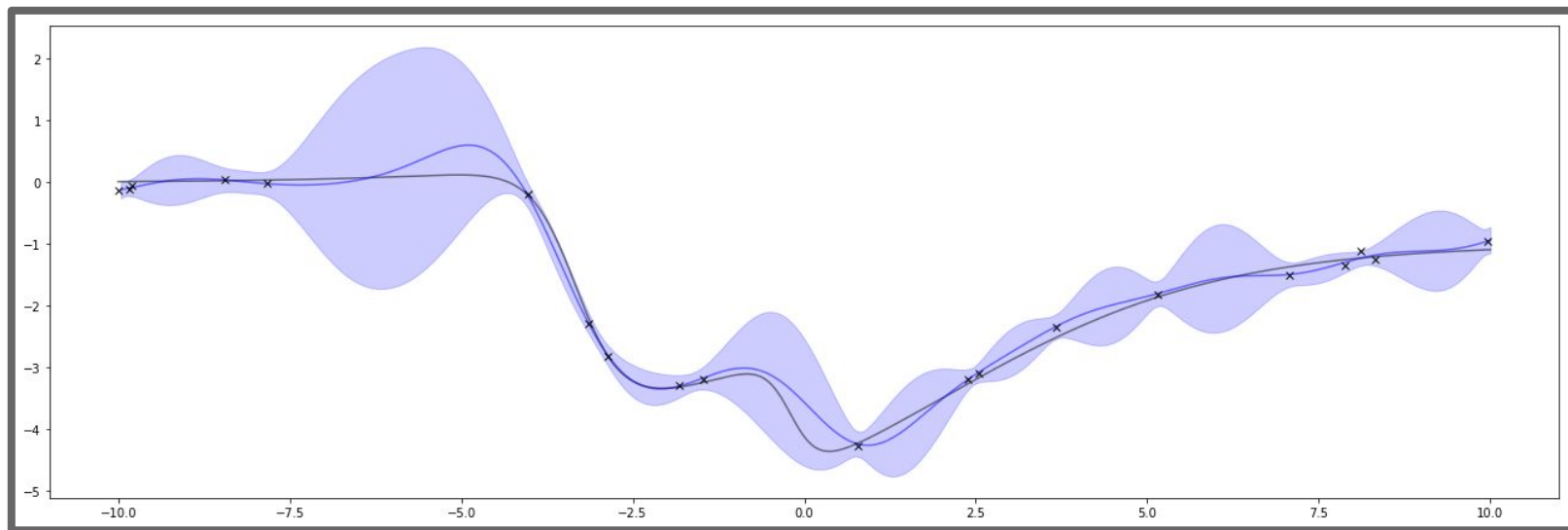
$$P(x|\mathcal{D}, m) = \int P(x|\theta, \mathcal{D}, m)P(\theta|\mathcal{D}, m)d\theta$$

**Model Comparison:**

$$P(m|\mathcal{D}) = \frac{P(\mathcal{D}|m)P(m)}{P(\mathcal{D})}$$

# Probabilistic Supervised Learning

Example: Gaussian Processes



$$p(y|x, \mathcal{D})$$

# Probabilistic Unsupervised Learning

## Probabilistic Graphical Models & Probabilistic Programming

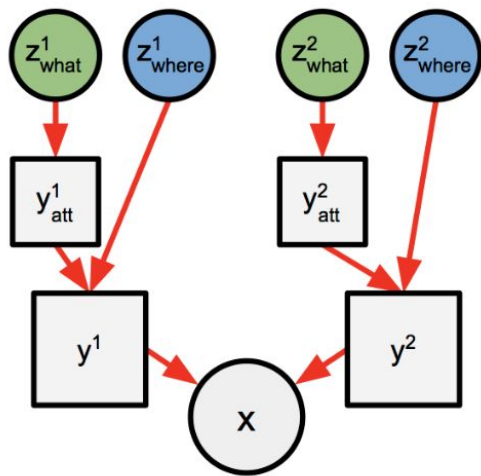
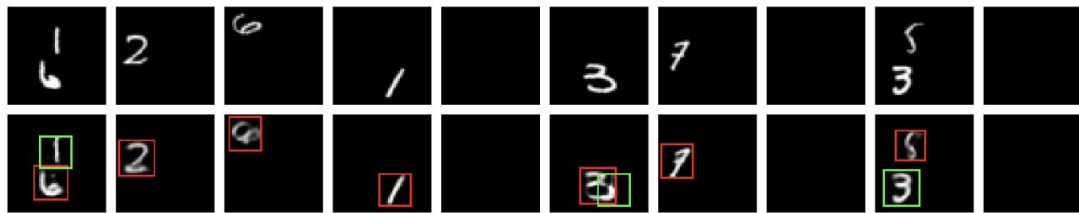


Figure 1: Two steps of the generative process.

```
data = mnist.view(-1, 50 * 50)

svi = SVI(model,
            guide,
            optim.Adam({'lr': 1e-4}),
            loss=TraceGraph_ELBO())

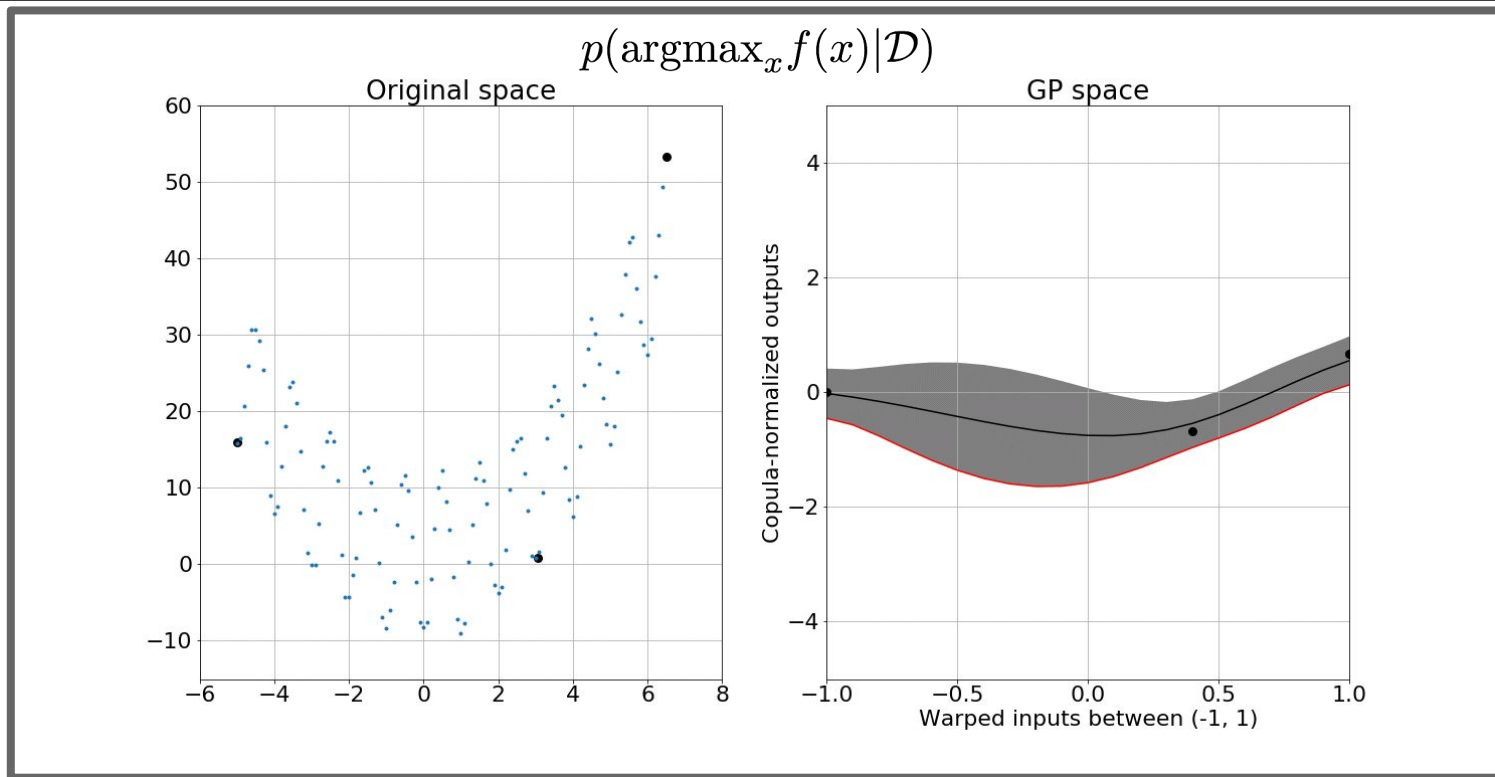
for i in range(5):
    loss = svi.step(data)
    print('i={}, elbo={:.2f}'.format(i, loss / data.size(0)))
```



$$p(x|\mathcal{G})$$

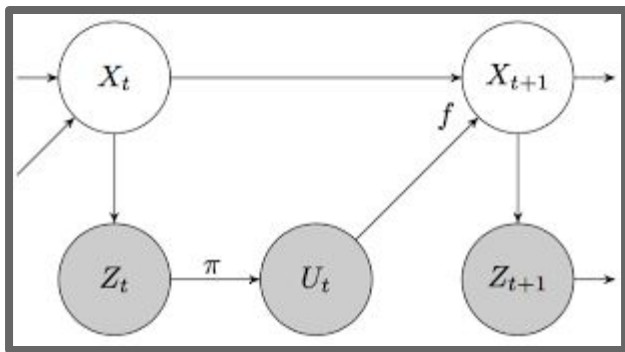
# Probabilistic Reinforcement Learning

## Gaussian Processes & Bayesian Optimization



# Probabilistic Reinforcement Learning

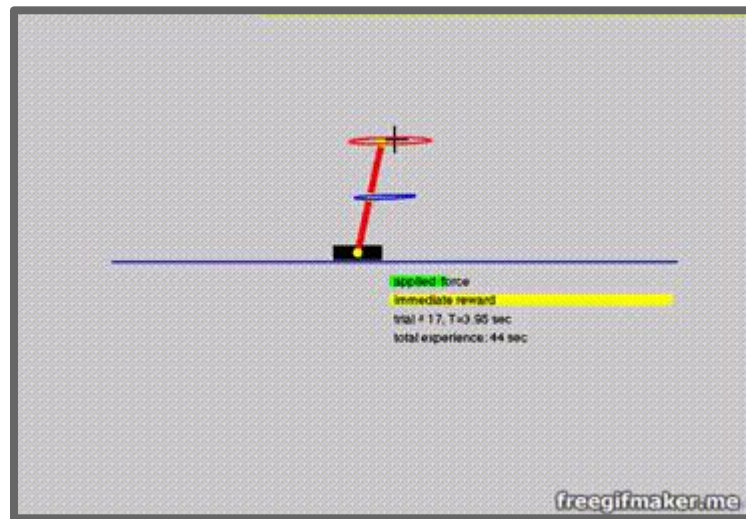
## Model-based Reinforcement Learning



$$\operatorname{argmax}_{\theta} \mathbb{E} \left( \left( \sum_{t=0}^T \gamma^t r_t \right) \middle| \pi(a|s, \theta) \right)$$

using

$$p^{\pi} \left( \sum_t \gamma^t r_t \middle| s_t, a_t \right)$$



# The Future is Deep + Probabilistic ML

***Use deep learning as a powerful tool for inference  
in complicated probabilistic models of the real  
world***



# Come help build the Future at Amplyfi!



*are on the hunt for exceptional talent...*

## *Current vacancies:*

- DevOps Engineer
- Software Architects
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## *Interested to hear more?*

Contact Chloe Murray, Talent Manager  
[chloe.murray@amplyfi.com](mailto:chloe.murray@amplyfi.com)  
[www.amplyfi.com](http://www.amplyfi.com)