



# Deep Learning

Dr. Mehran Safayani

safayani@iut.ac.ir

safayani.iut.ac.ir



<https://www.aparat.com/mehran.safayani>



[https://github.com/safayani/deep\\_learning\\_course](https://github.com/safayani/deep_learning_course)



# Hyperparameter tuning

Tuning process

# Hyper parameters

①  $\alpha$

momentum  $\beta = 0.9$

Adam  $\underbrace{\beta_1}_{0.9}, \underbrace{\beta_2}_{0.999}, \underbrace{\varepsilon}_{10^{-8}}$

③ #layers

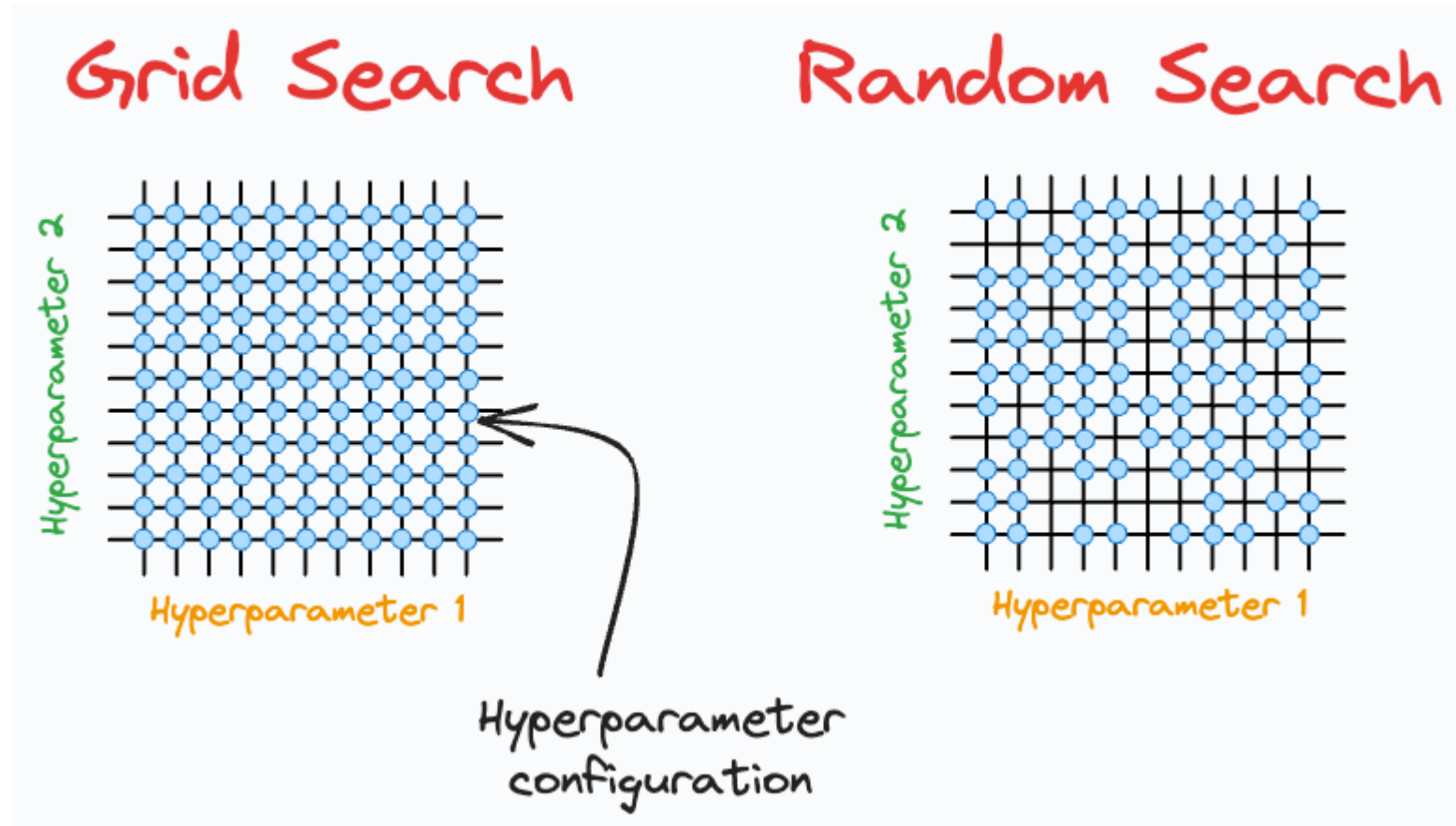
② #hidden units

③ Learning rate decay

② mini-batch size

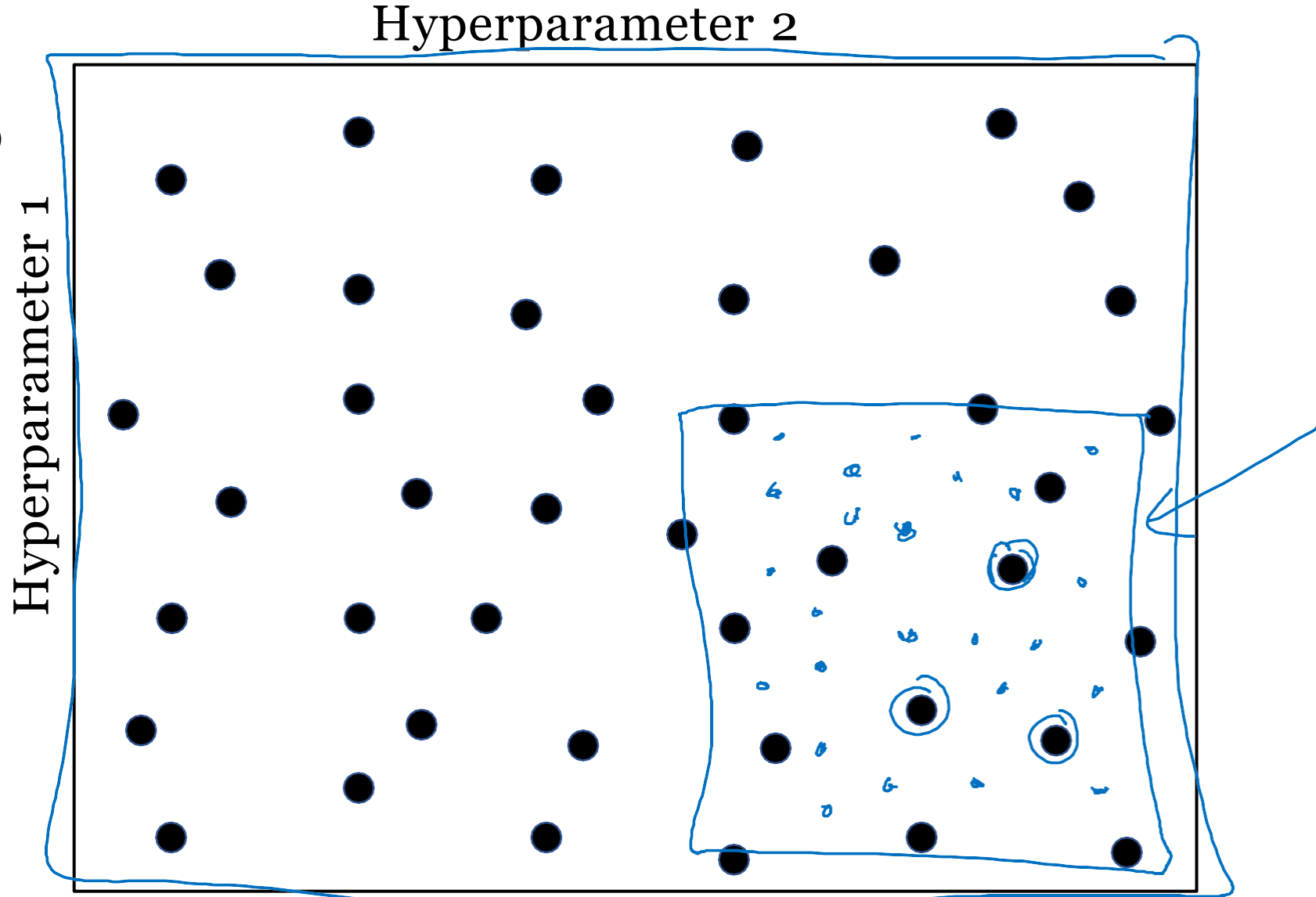
# Hyperparameter tuning

- Grid Search
- Random search



# Coarse to fine

- $n^{[l]} = 50, \dots, 100$



# Using an appropriate scale to pick hyperparameters

$$n^{[l]} = 50, \dots, 100$$



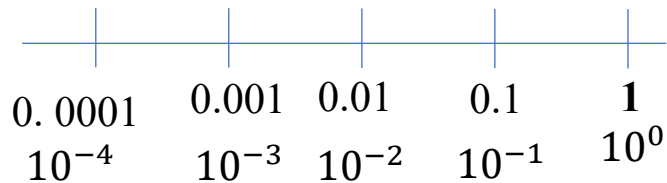
- #Layers

L: 2 – 4

2,3,4

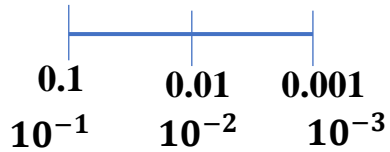
- $\alpha = 0.0001, \dots, 1$

$$\alpha = 10^r \quad r = -1 * np \cdot random \cdot randint(4)$$



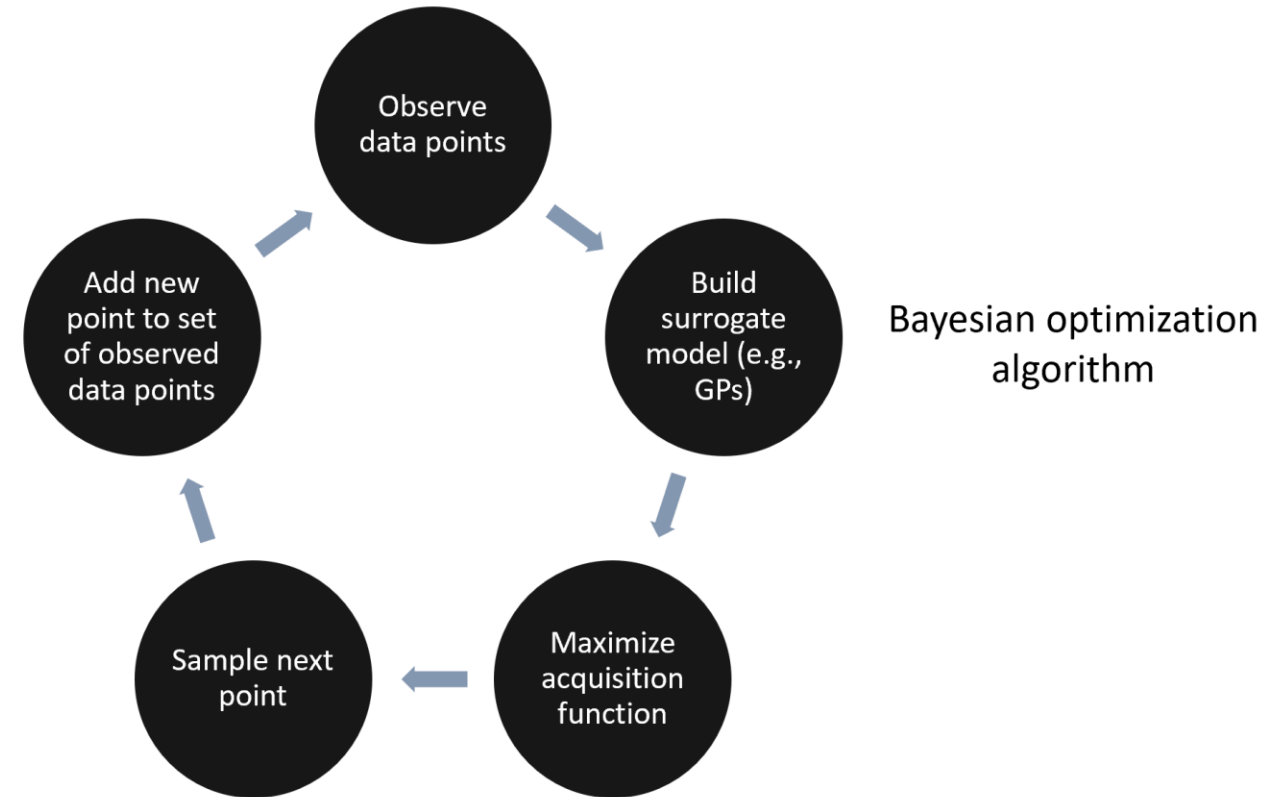
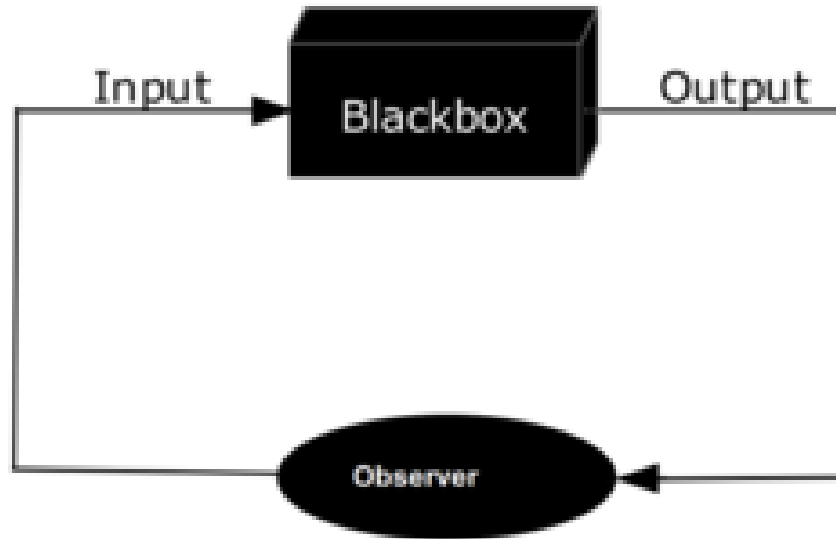
# Using an appropriate scale to pick hyperparameters

- $r = -4 * np \cdot random \cdot rand()$      $r \in [-4, 0]$
- $\alpha = 10^r$
- $\beta = 0.9 \cdots 0.999$
- $1 - \beta = 0.1 \cdots 0.001$

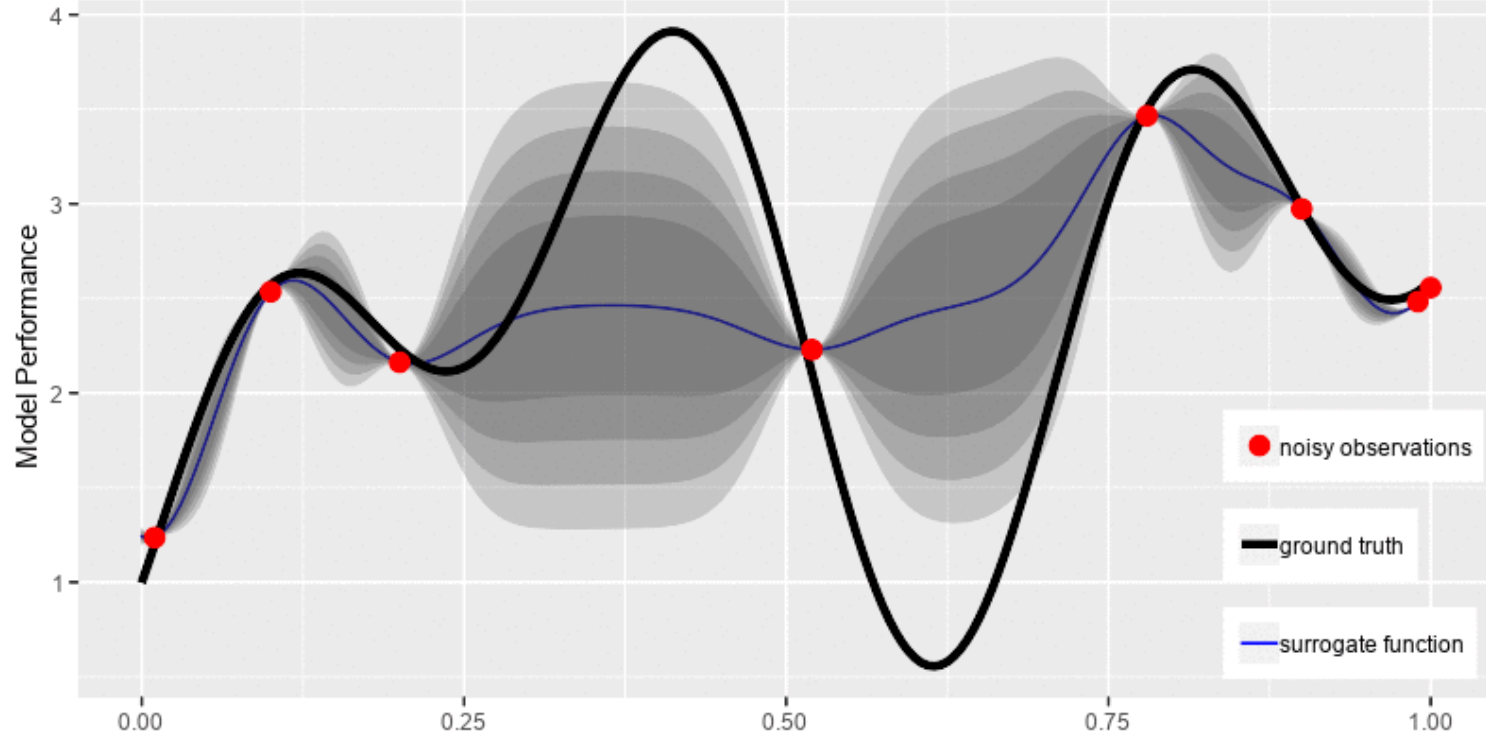


- $r \in [-3, -1]$   
 $1 - \beta = 10^r$   
 $\beta = 1 - 10^r$

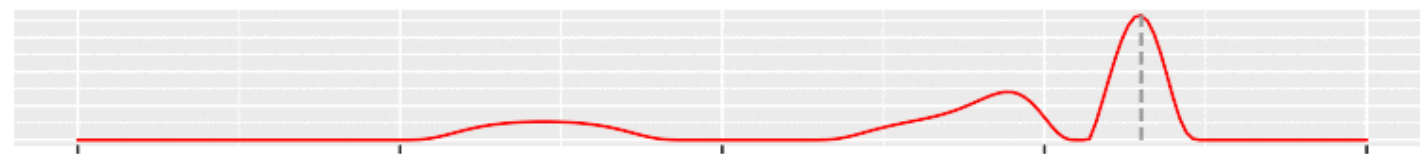
# Bayesian Optimization







Expected improvement



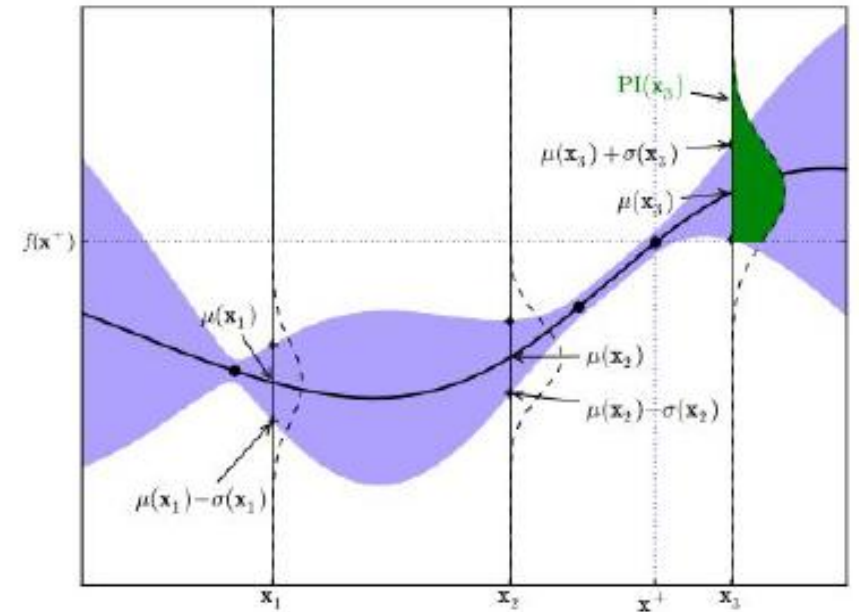
Suppose that we'd like to maximize  $f(x)$ , and the best solution we have so far is  $x^*$

$$EI(x) = (\mu - f(x^*)) \Phi \left( \frac{\mu - f(x^*)}{\sigma} \right) + \sigma \varphi \left( \frac{\mu - f(x^*)}{\sigma} \right)$$

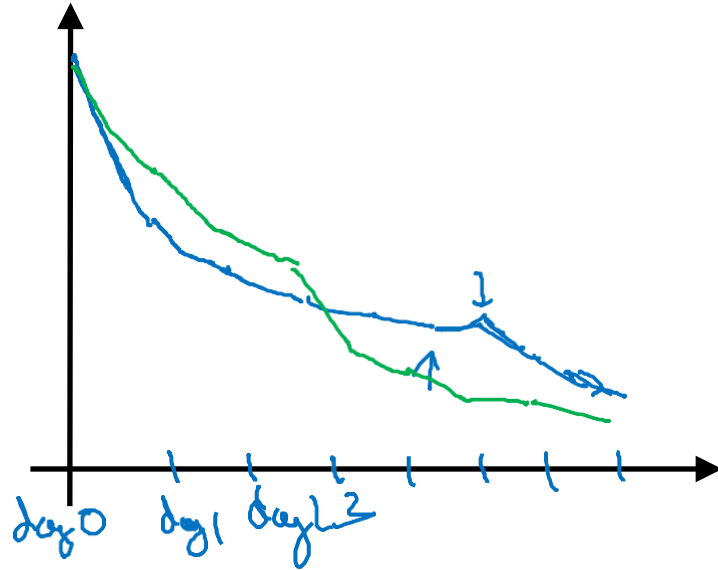
Where  $\varphi(z)$  is the probability density function of the normal distribution  $\mathcal{N}(0,1)$ ,

$\Phi(z) \equiv \text{CDF}(z)$

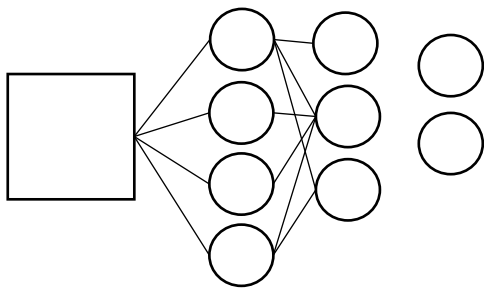
Expected Improvement function



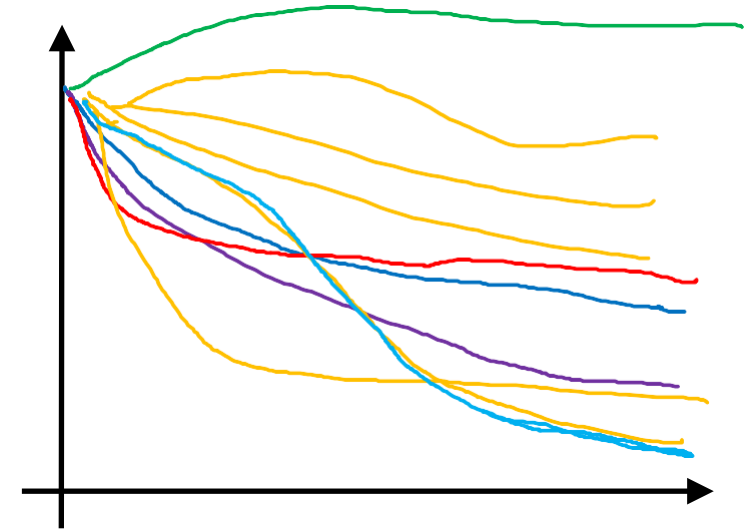
# Babysitting one model



Panda



# Training many models in parallel



Caviar