

Deep Learning

MSDS 631

Tips and Tricks for
Deep Learning

Michael Ruddy

Questions?

- From last lecture?

Overview

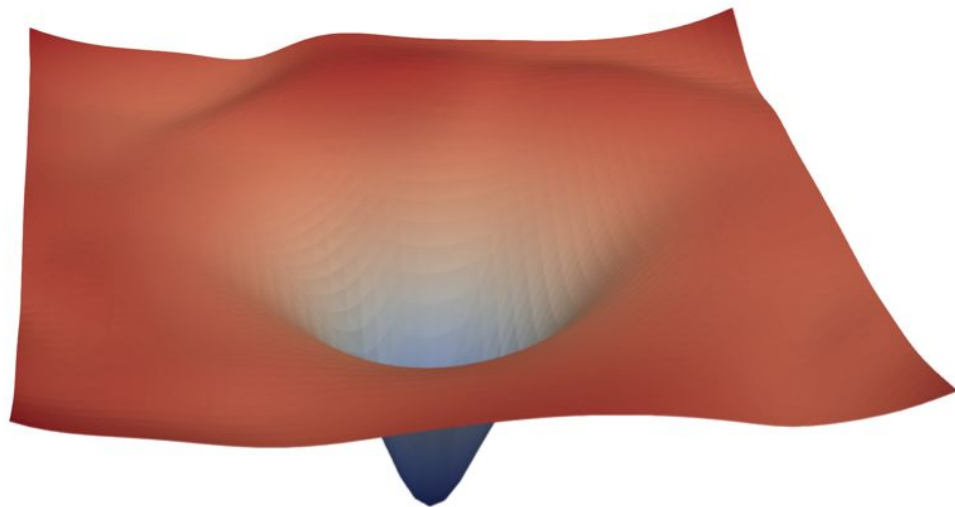
- What is training a model?
- Optimization
- Regularization
- Embeddings

What does it mean to train a model?

- Gradient Descent: Navigating through the space of possible models
 - Trying to find a “good” minimum for our loss function

What does it mean to train a model?

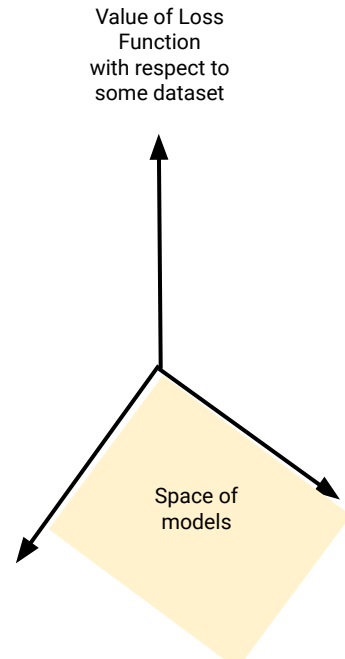
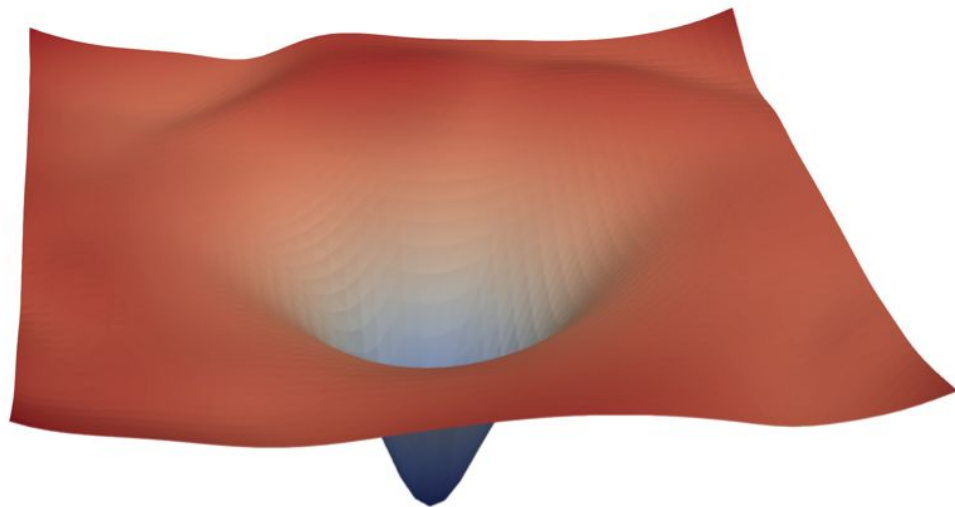
- Gradient Descent: Navigating through the space of possible models
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- Loss Landscape: The environment which informs our journey



From *Visualizing the Loss Landscape of Neural Nets* by
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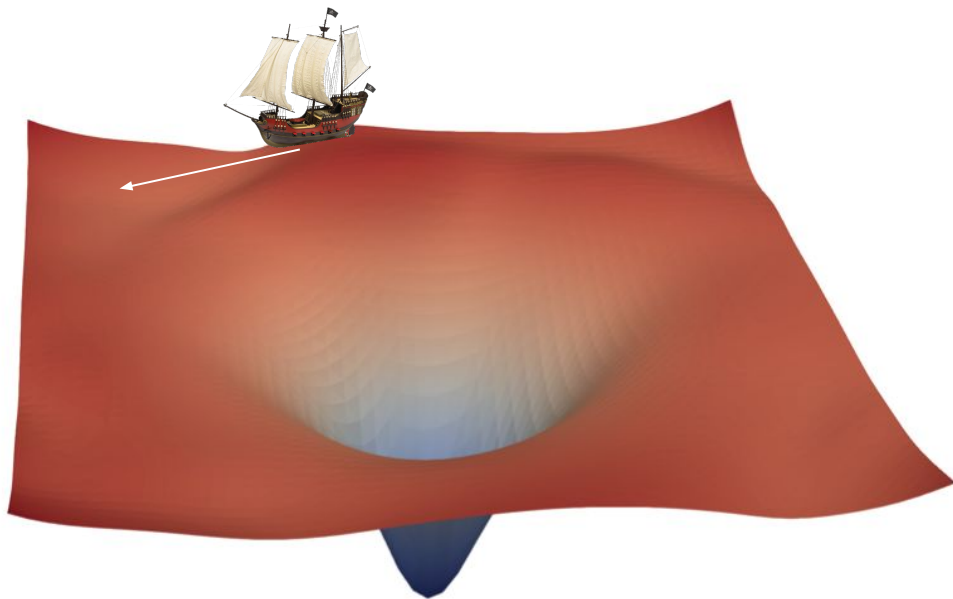
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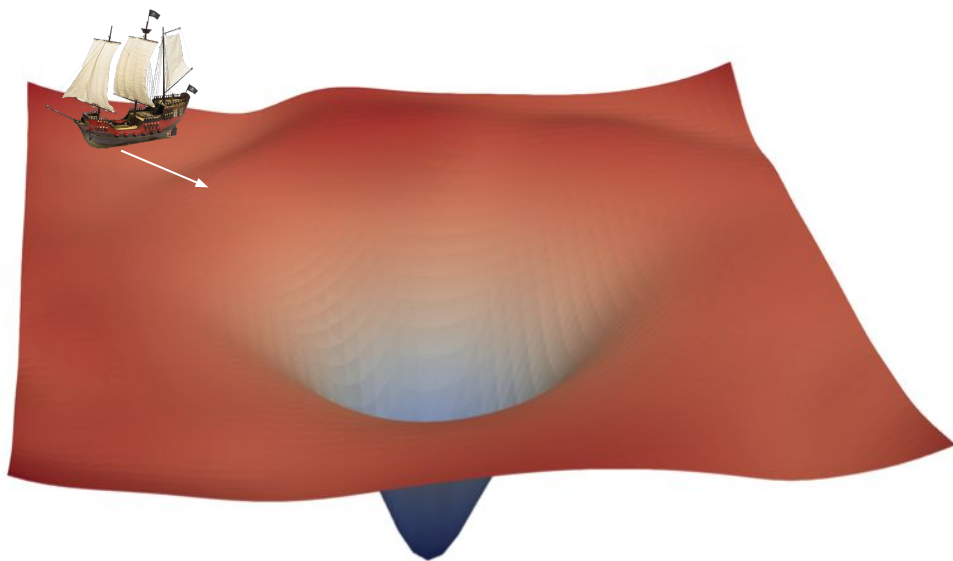
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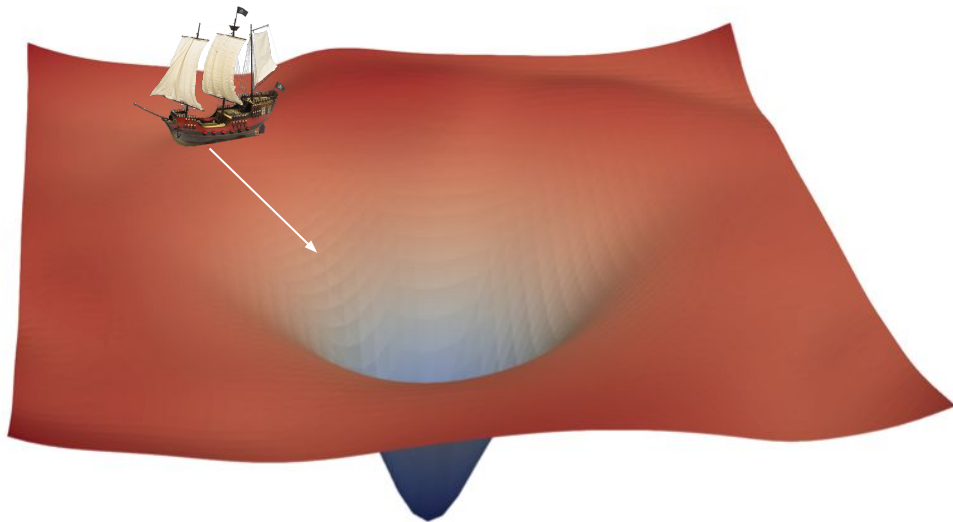
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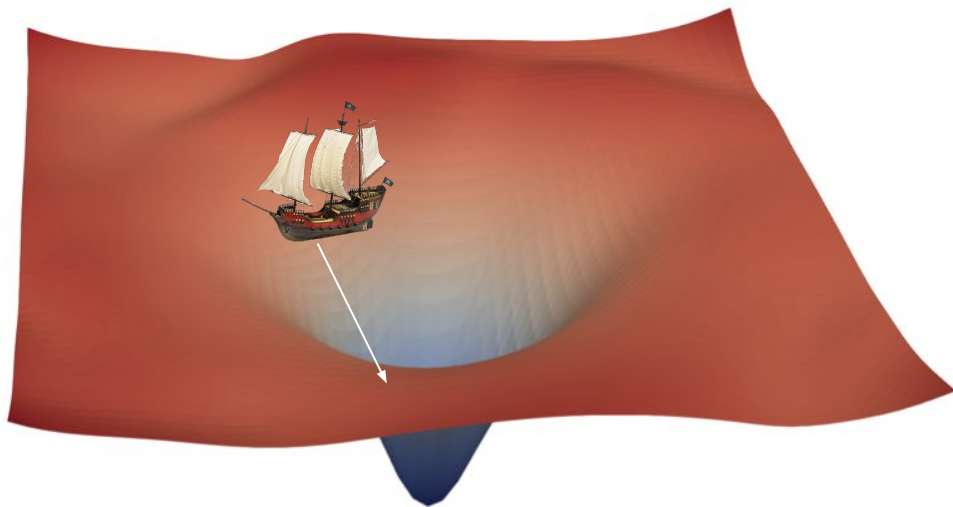
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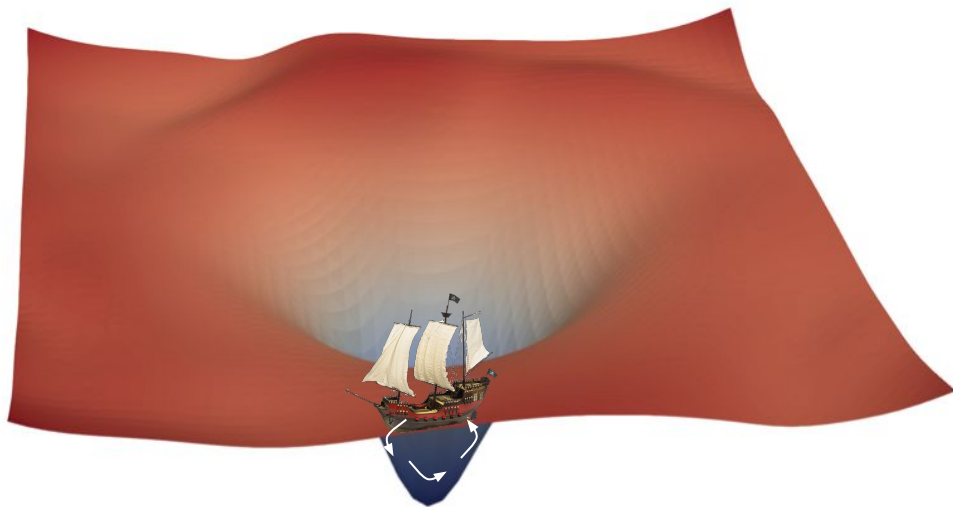
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 - Success!



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What does it mean to train a model?

- What can go wrong?
 - Too flat



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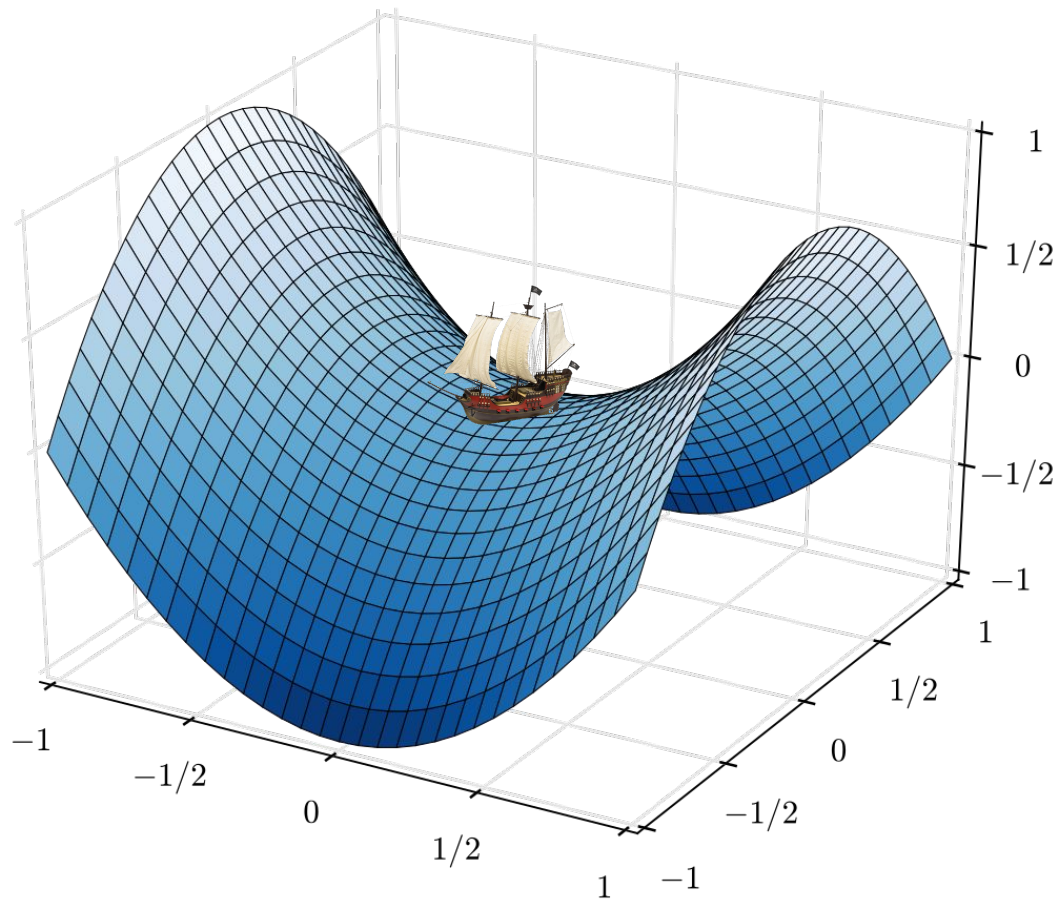
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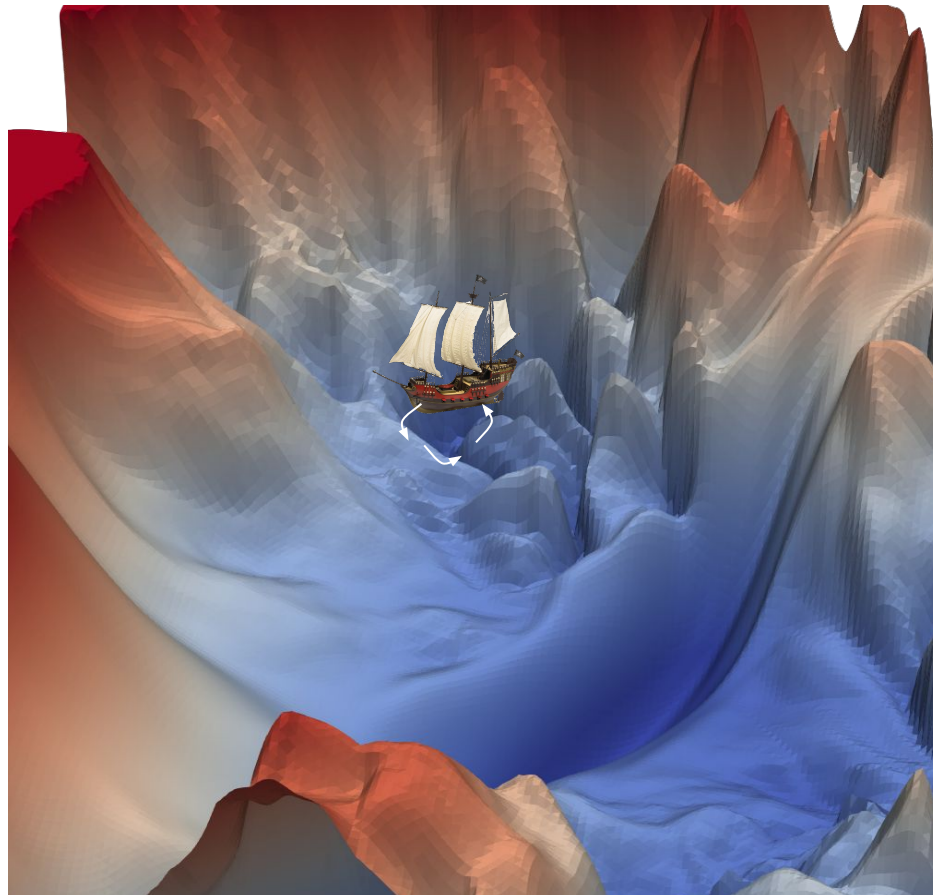
What does it mean to train a model?

- What can go wrong?
 - Too flat (or saddle point)



What does it mean to train a model?

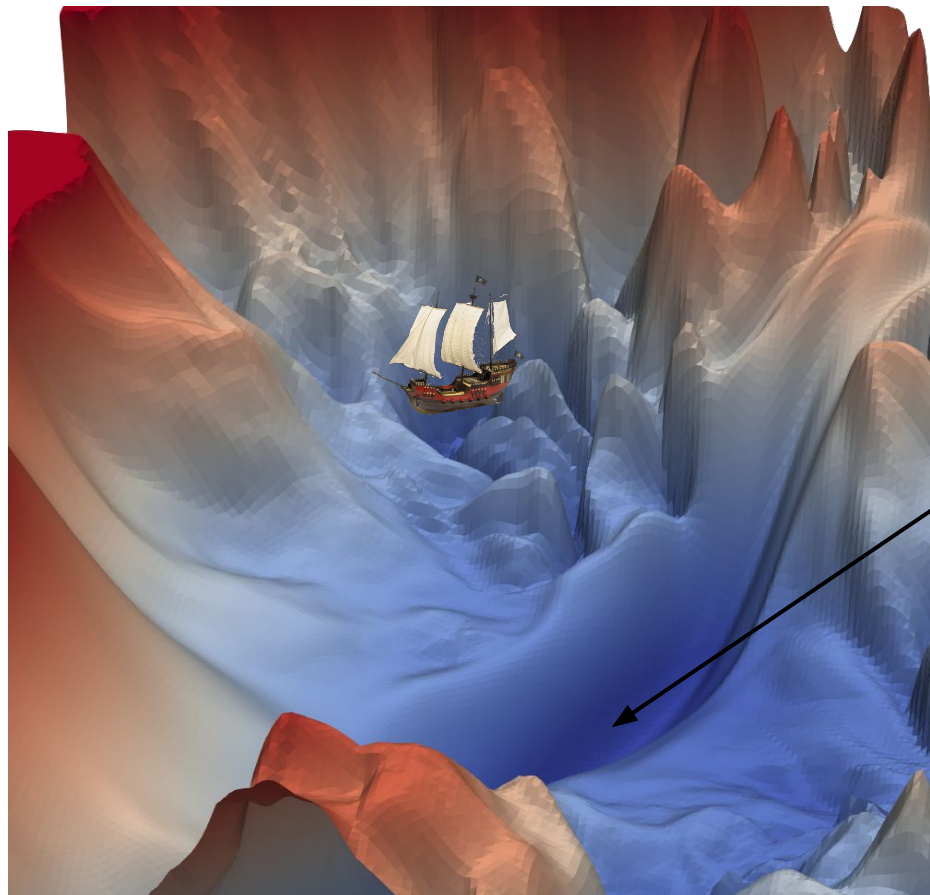
- What can go wrong?
 - Too flat
 - “Bad” minima



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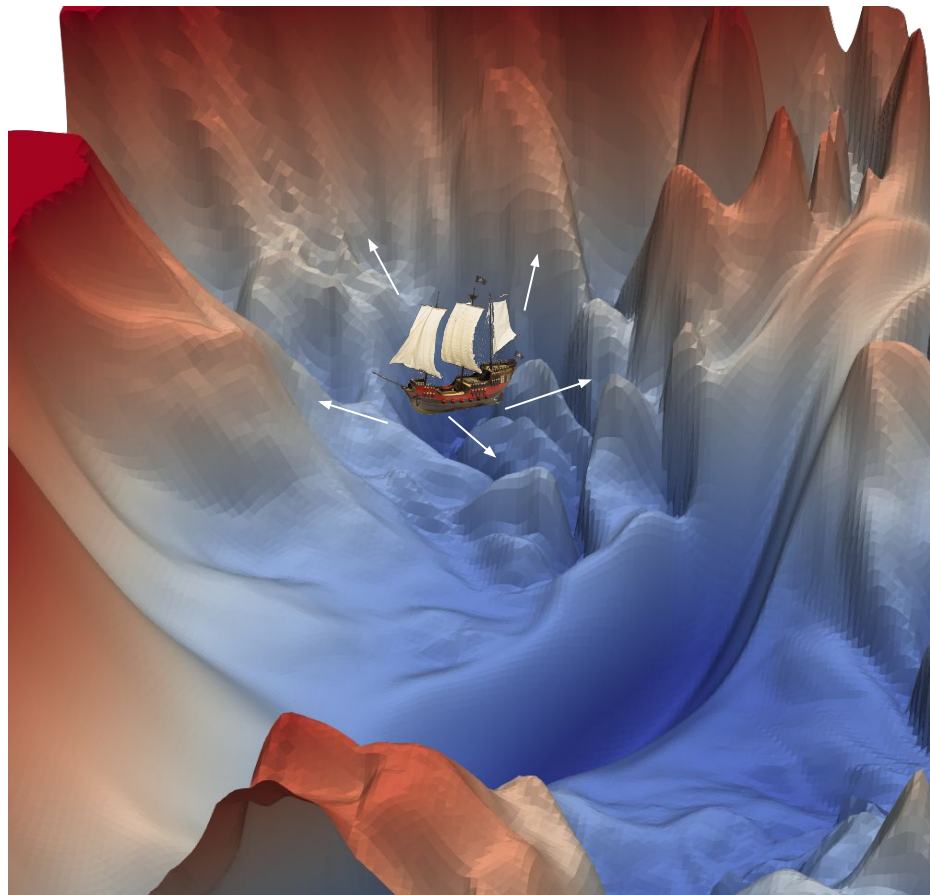


Better minima here

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- Unstable

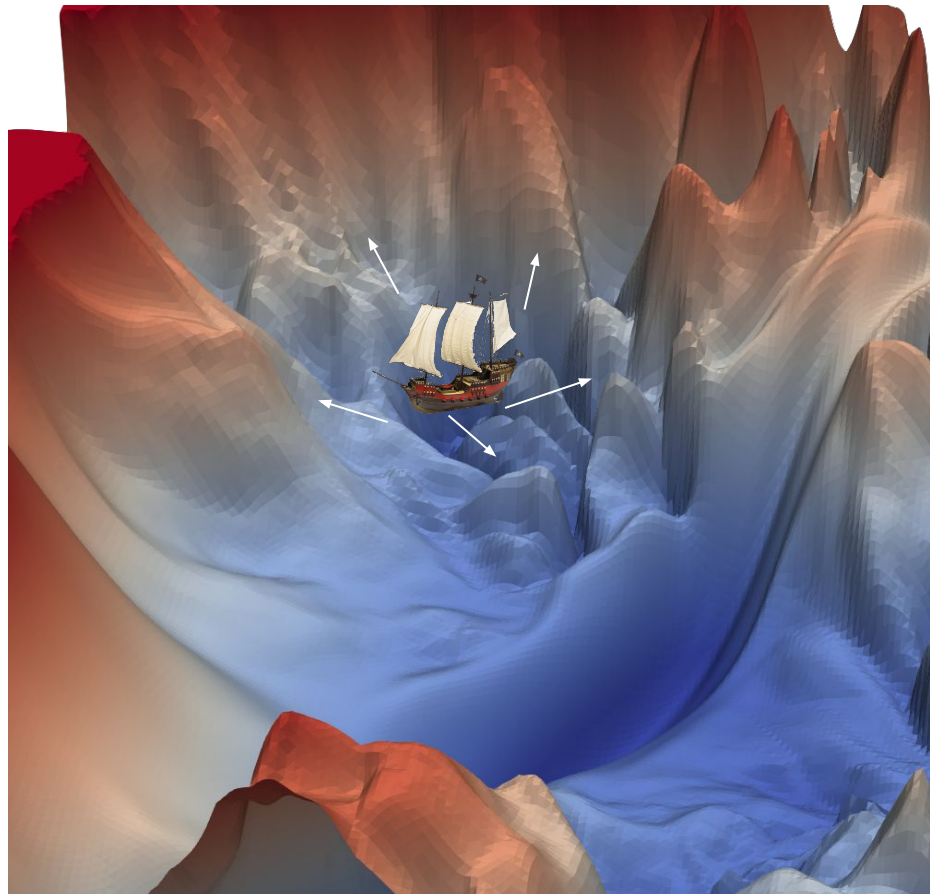


Small movement
may incur massive
loss increase

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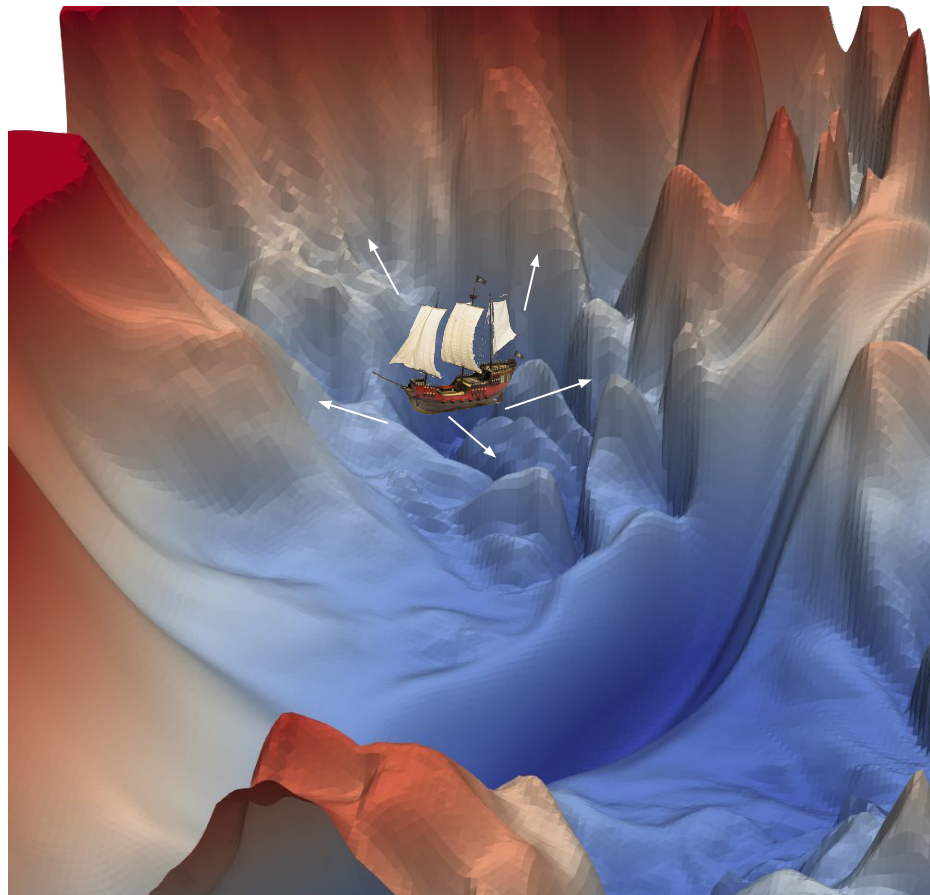


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- What can go wrong?
 - Too flat
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- Shallow
- Unstable
 - May not generalize well
- May not be as big as a problem as previously thought!

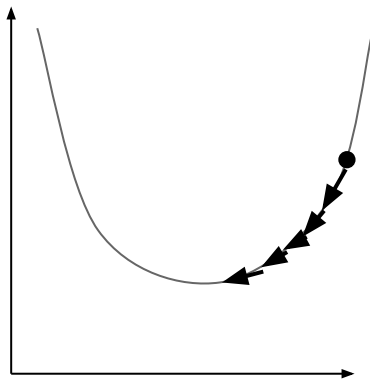


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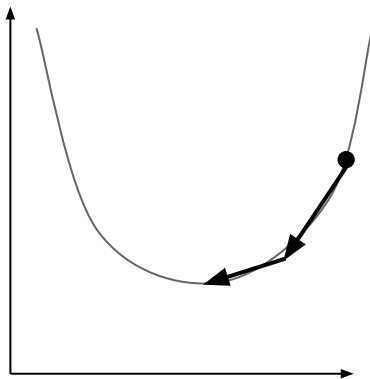
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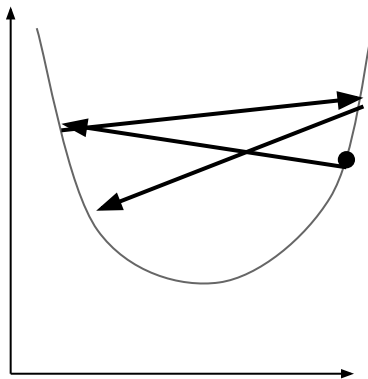
- Choosing a learning rate is an art-form



Low LR:
Too slow



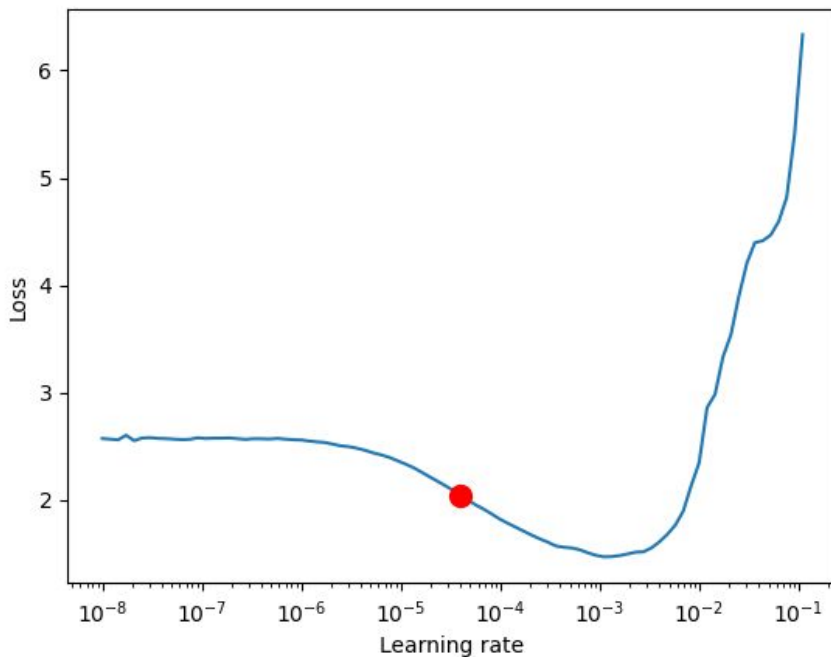
Just right:
Good
convergence



High LR:
diverges

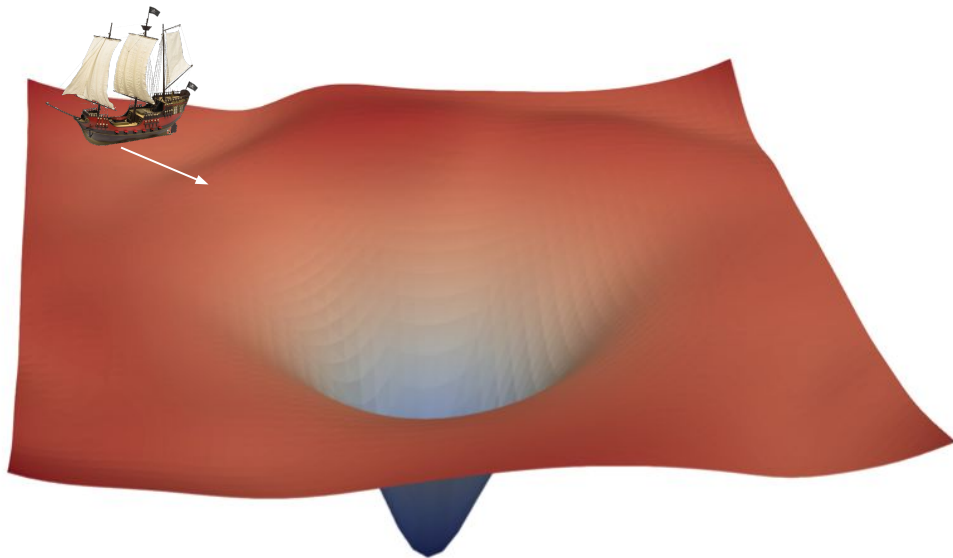
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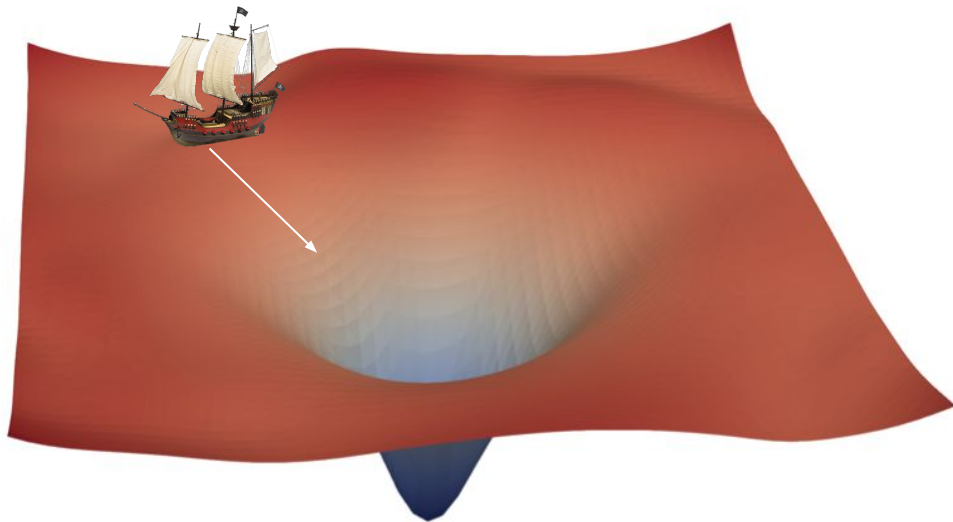
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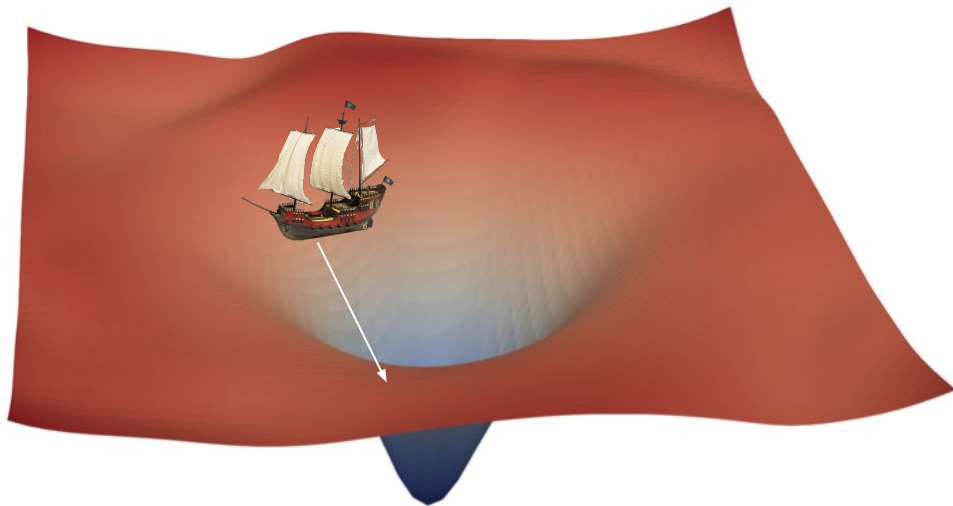
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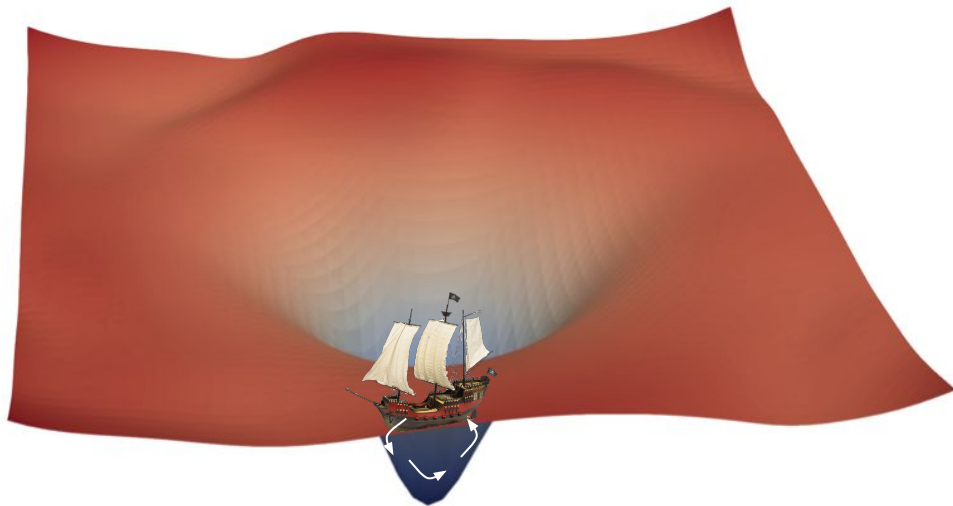
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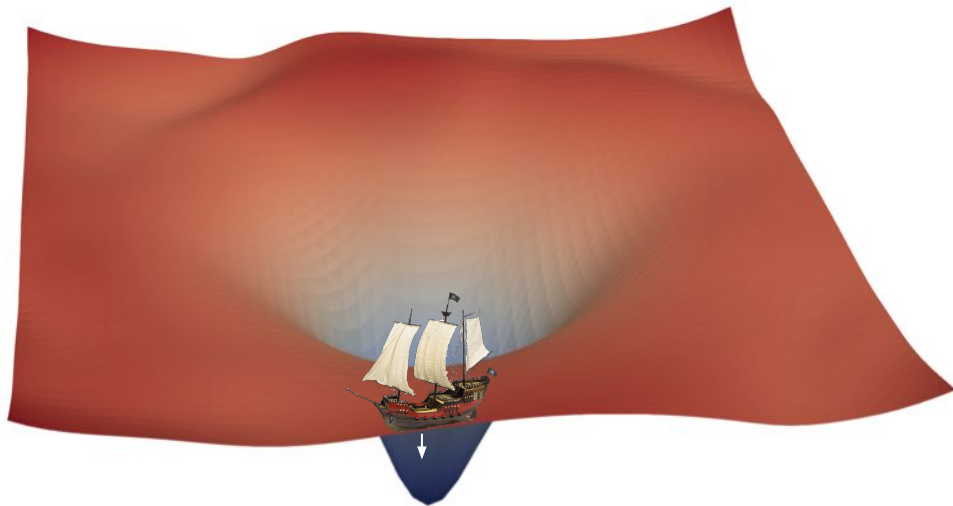
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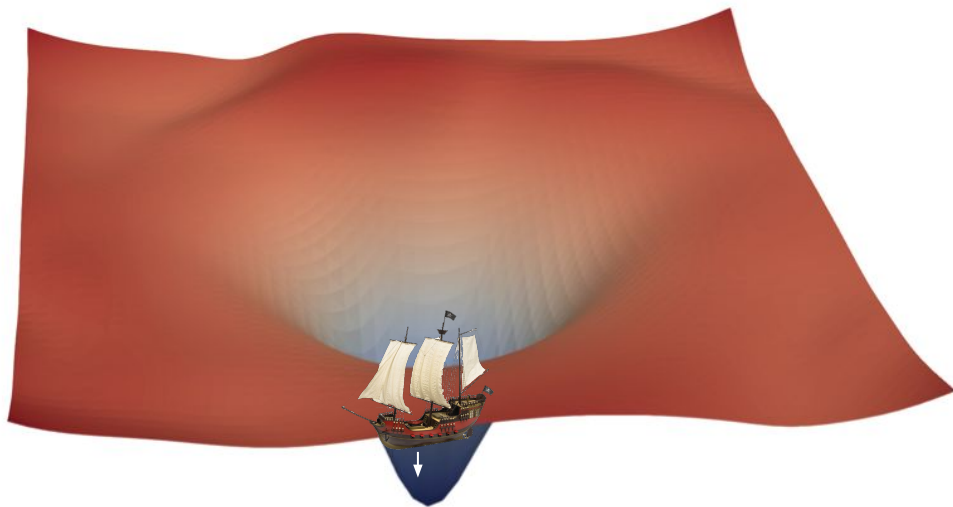
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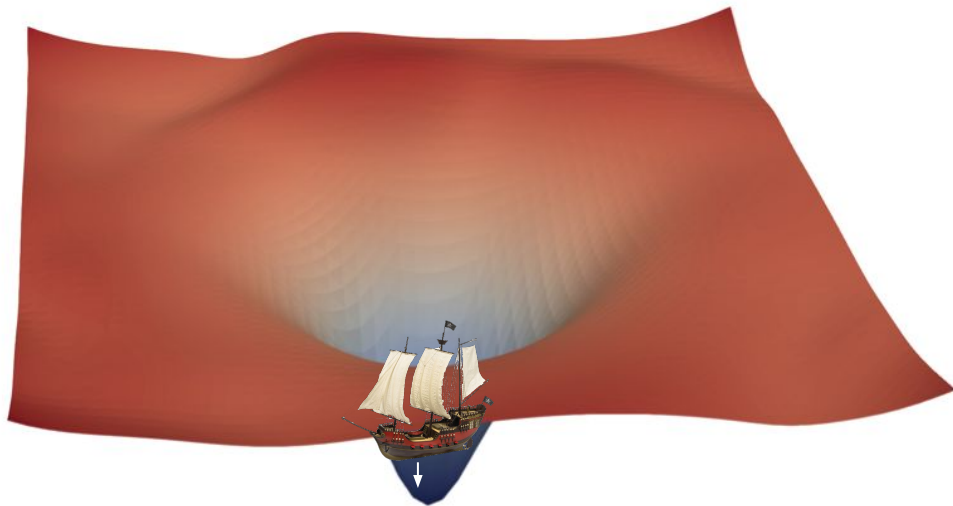
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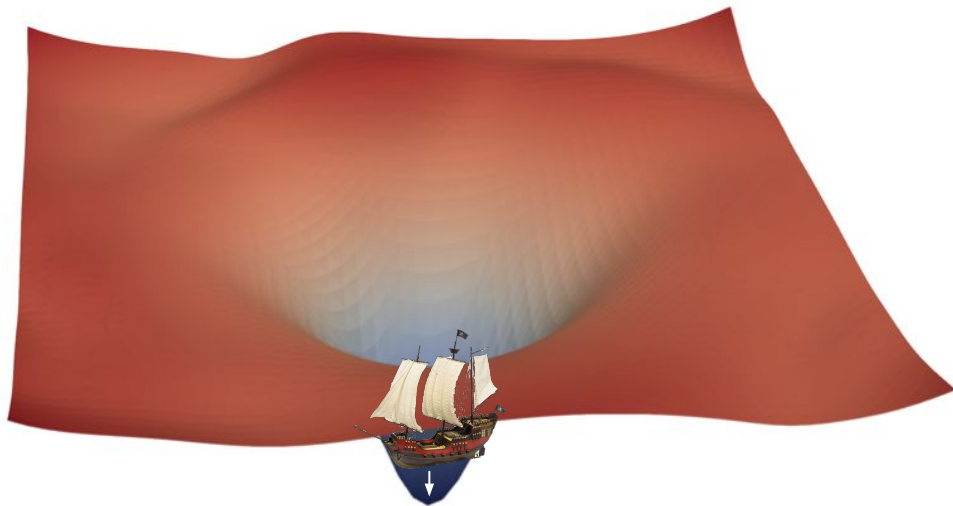
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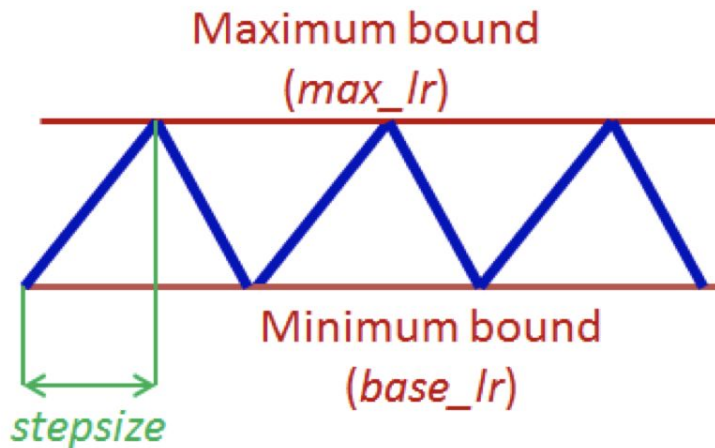
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- Cyclical LRs



*Cyclical Learning
Rates for Training
Neural Networks* by
Leslie Smith

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- Cyclical LRs
- And more!

Regularization

- There many techniques we can use to help prevent overfitting

Regularization

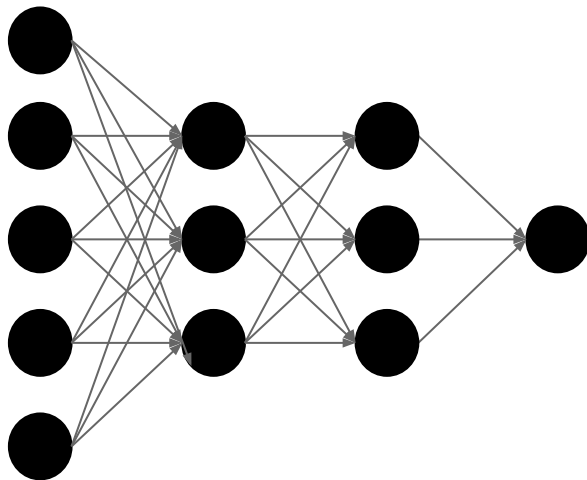
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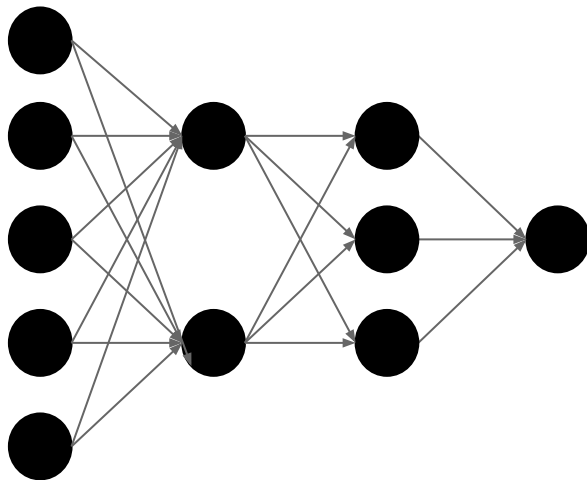
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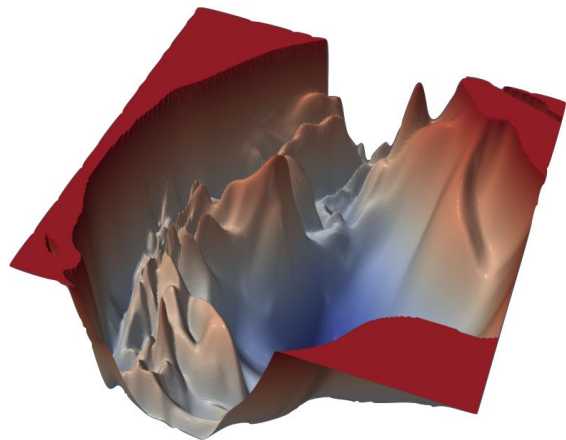
Regularization

- We usually train NN using *mini-batches*. (not a fixed loss landscape!)
 - Only compute gradient with respect to a small batch of your data
 - Data might be too big to load onto GPU
 - Form of regularization (adds noise)
 - Model updates more frequently

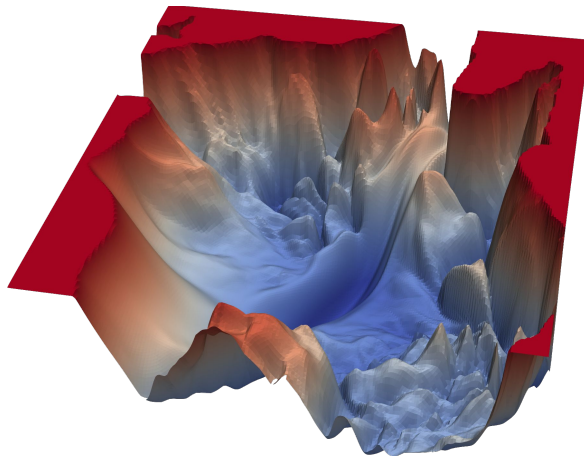
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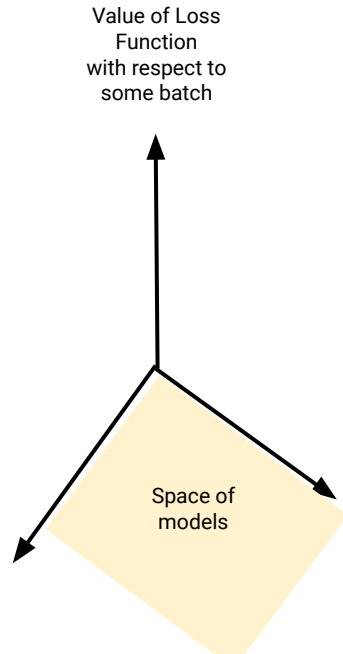
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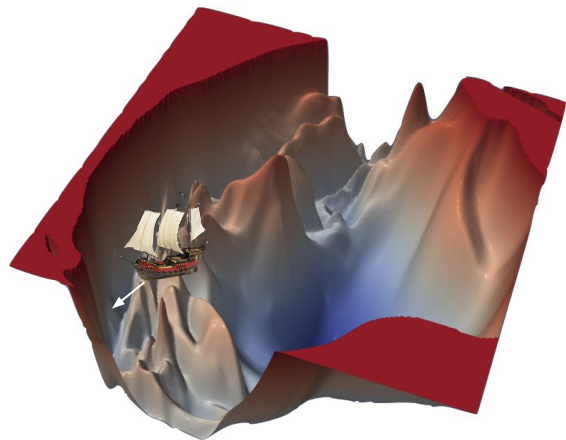
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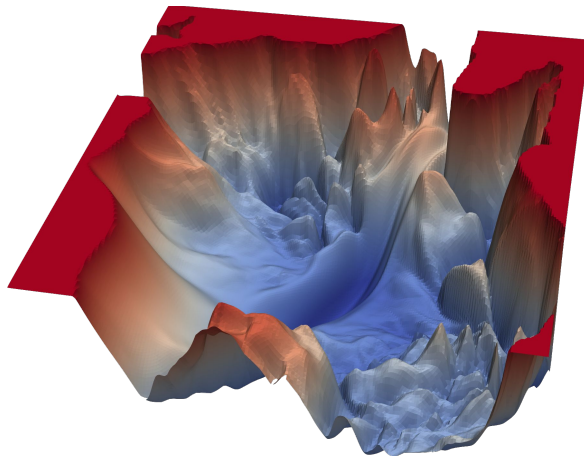
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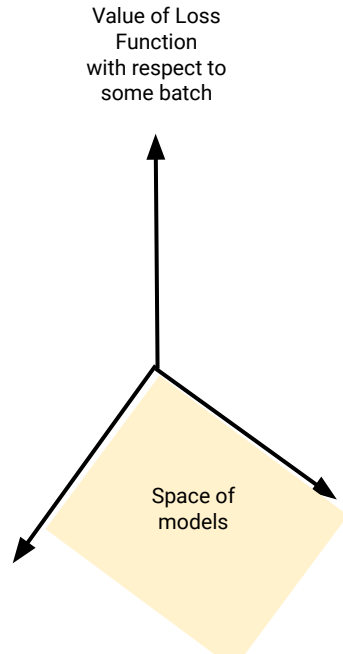
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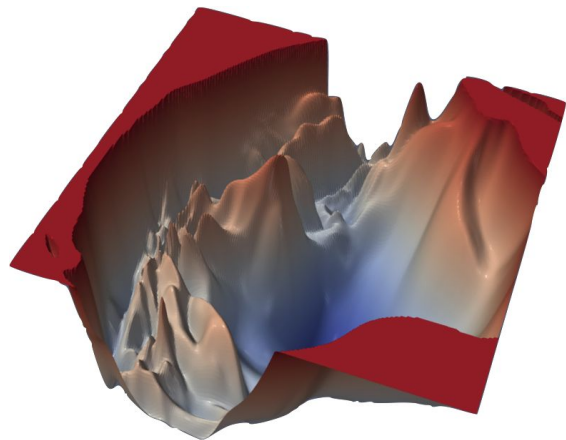
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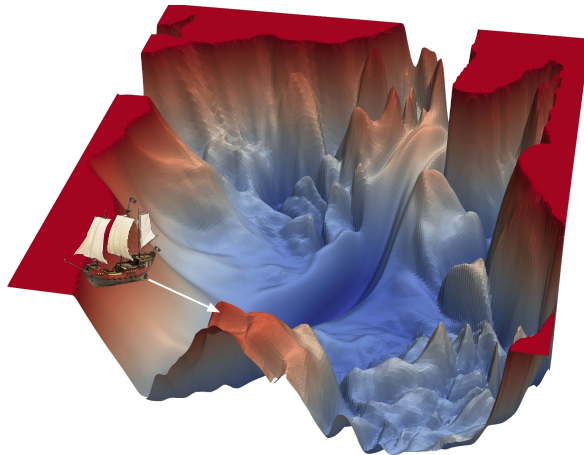
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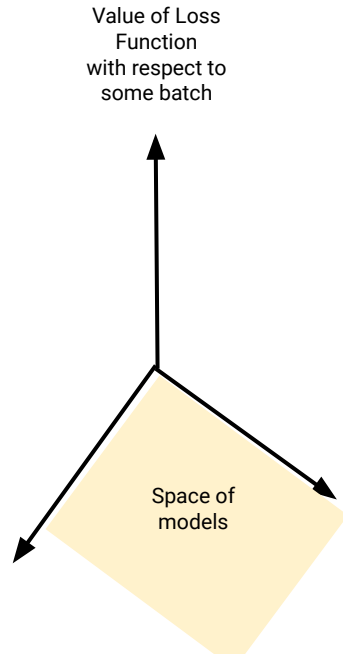
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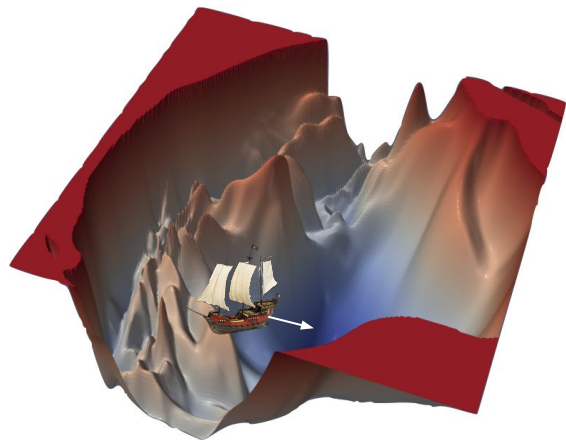
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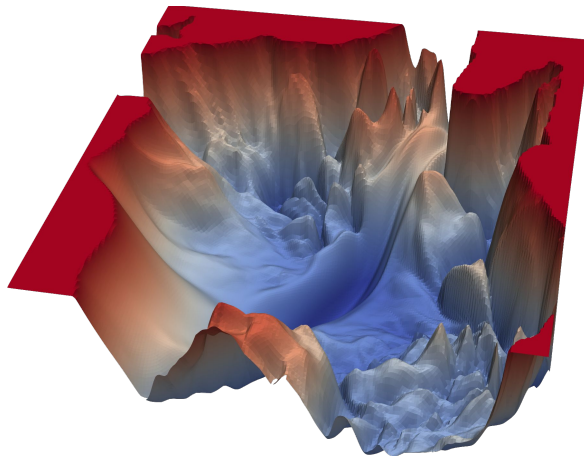
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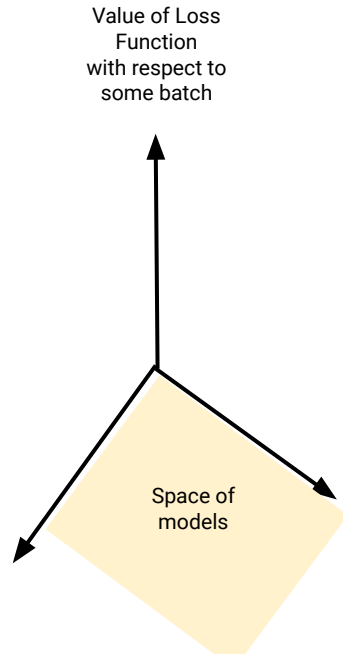
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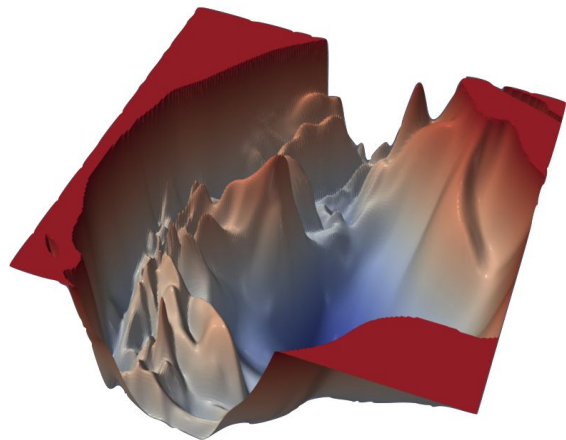
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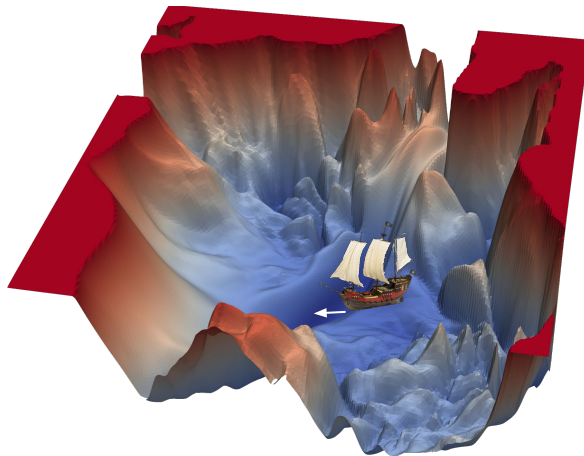
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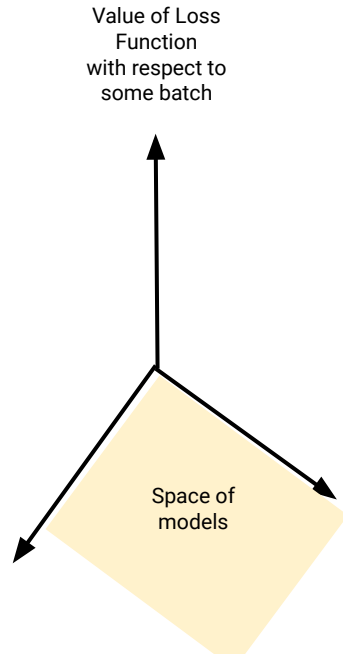
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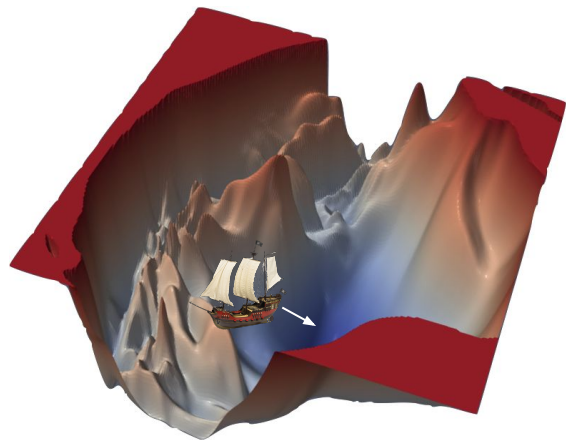
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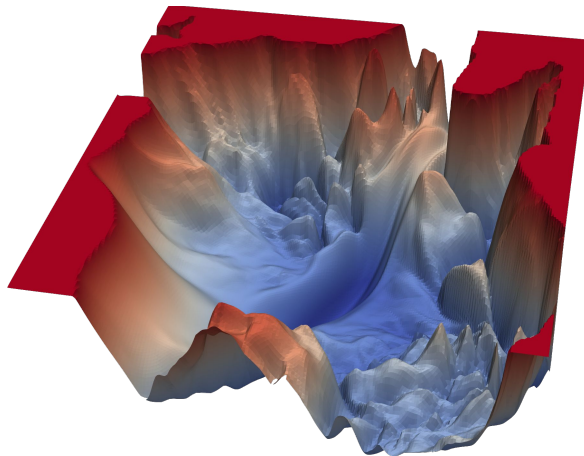
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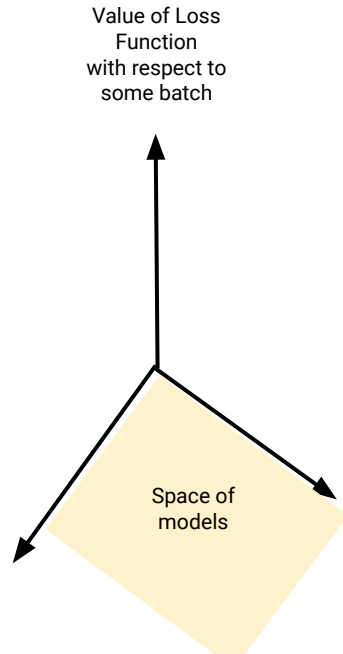
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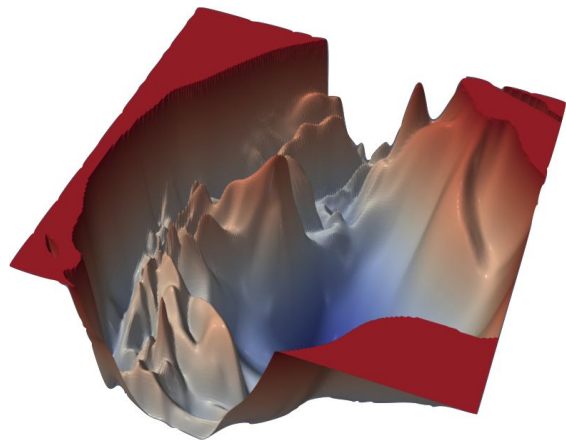
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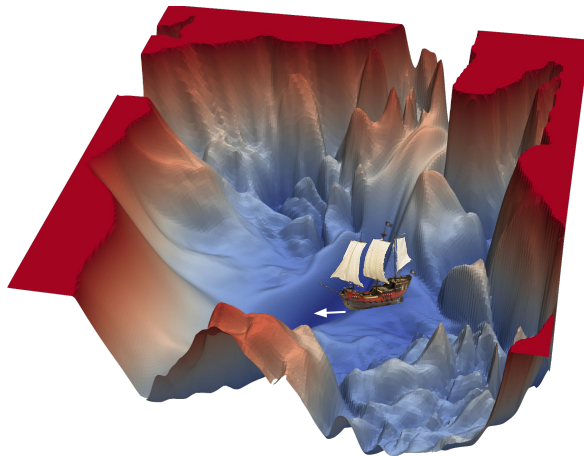
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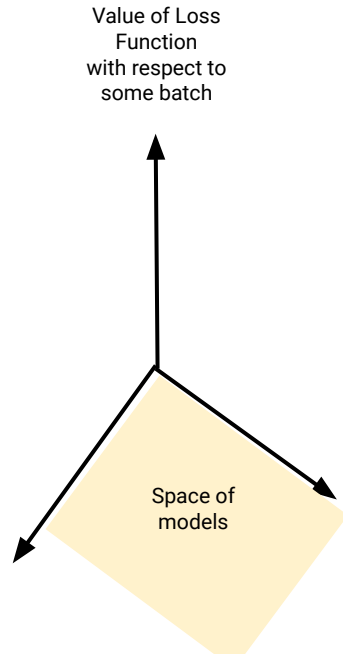
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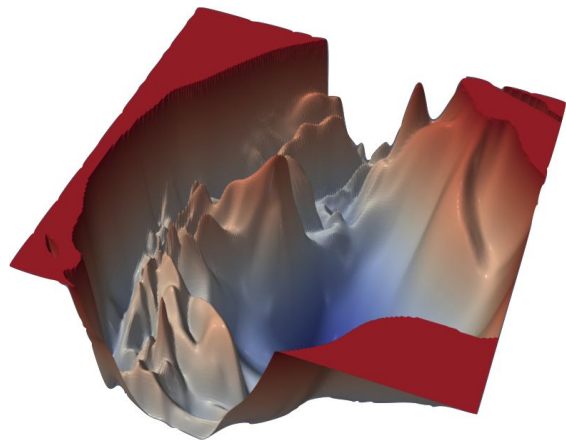
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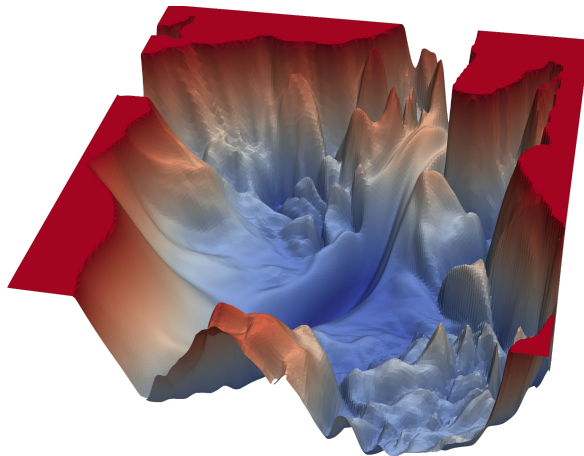
Regularization

Pictures from *Visualizing the Loss Landscape of Neural Nets* by
H. Li, Z. Xu, G. Taylor, C. Studer, T. Goldstein

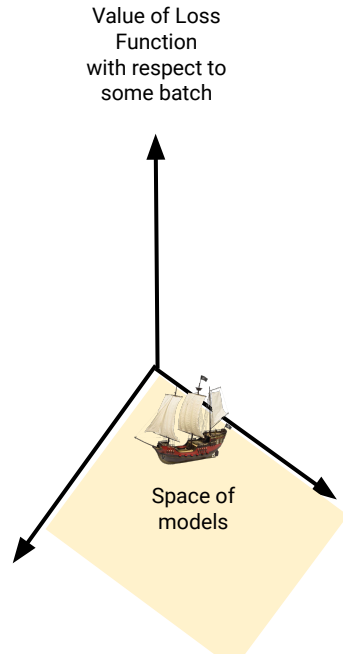
- We usually train NN using *mini-batches*. (not a fixed loss landscape!)
 - Only compute gradient with respect to a small batch of your data
 - Data might be too big to load onto GPU
 - Form of regularization (adds noise)
 - Model updates more frequently



Loss values for first batch



Loss values for second batch



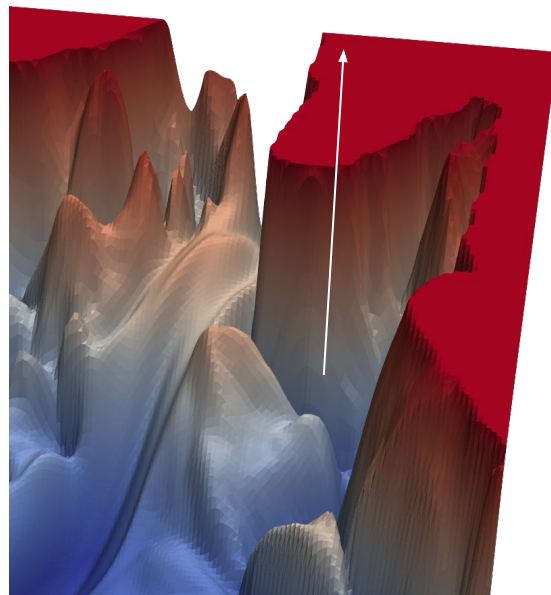
Normalization

- Normalization of continuous variables can be extremely helpful for optimization, particularly for deep neural networks
 - Puts features on a similar scale
 - Potentially avoid vanishing/exploding gradients

$$\bar{x} = \frac{x - \mu}{\sigma}$$

Normalization

- Vanishing/exploding gradients can become even worse in a deep network
 - Think chain rule



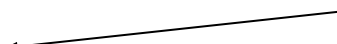
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Normalization

- Vanishing/exploding gradients can become even worse in a deep network
 - Think chain rule
- *Batch normalization* normalizes, in some sense, the output of each layer
 - “Normalizing along the way”

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

Output of some
hidden layer we will
apply batch
normalization to



Normalization

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$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$$

$$\overline{x} = \begin{bmatrix} \overline{x}_1 \\ \overline{x}_2 \\ \vdots \\ \overline{x}_n \end{bmatrix}$$

$$\overline{x}_i = \frac{x_i - \mu_i}{\sigma + \epsilon}$$

Normalization

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Normalize over the
mini-batch

↓

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Normalization

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$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad \bar{x} = \begin{bmatrix} \bar{x}_1 \\ \bar{x}_2 \\ \vdots \\ \bar{x}_n \end{bmatrix} \quad \gamma \bar{x} + \beta = \begin{bmatrix} \gamma_1 \bar{x}_1 + \beta_1 \\ \gamma_2 \bar{x}_2 + \beta_2 \\ \vdots \\ \gamma_n \bar{x}_n + \beta_n \end{bmatrix}$$

Normalization

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Gamma, beta
initialize as all ones
and zeros vectors
respectively!

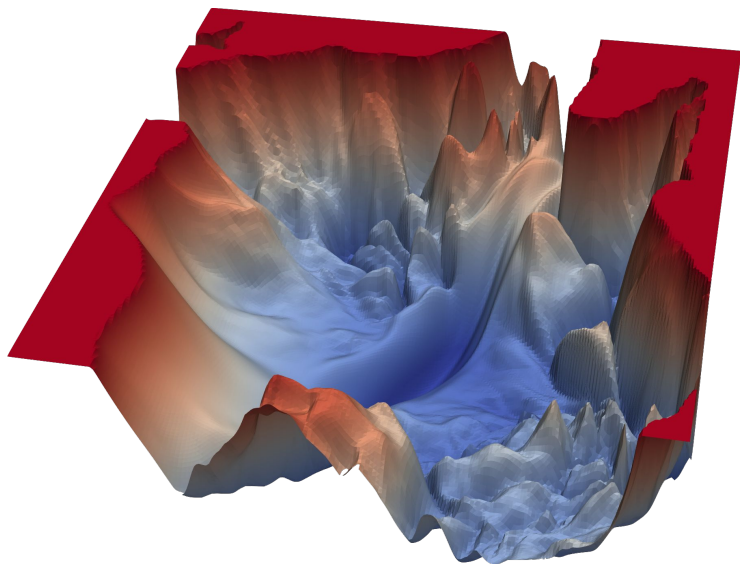
$$\gamma \bar{x} + \beta = \begin{bmatrix} \gamma_1 \bar{x}_1 + \beta_1 \\ \gamma_2 \bar{x}_2 + \beta_2 \\ \vdots \\ \gamma_n \bar{x}_n + \beta_n \end{bmatrix}$$

Smoothing the loss landscape

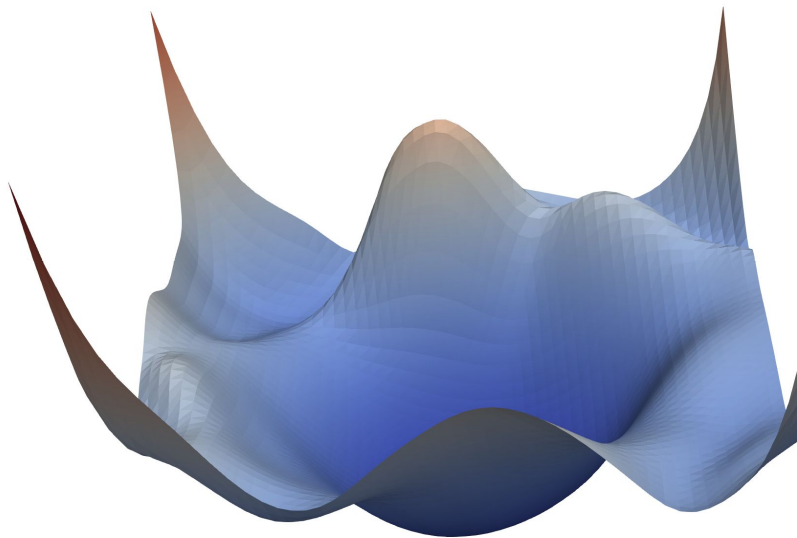
- Intuition: making the loss landscape easier to traverse

Smoothing the loss landscape

- Intuition: making the loss landscape easier to traverse
- Skip Connections (more on these later)



w/o skips



w/ skips

From *Visualizing the Loss Landscape of Neural Nets* by
H. Li, Z. Xu, G. Taylor, C. Studer, T. Goldstein

Other things to tweak

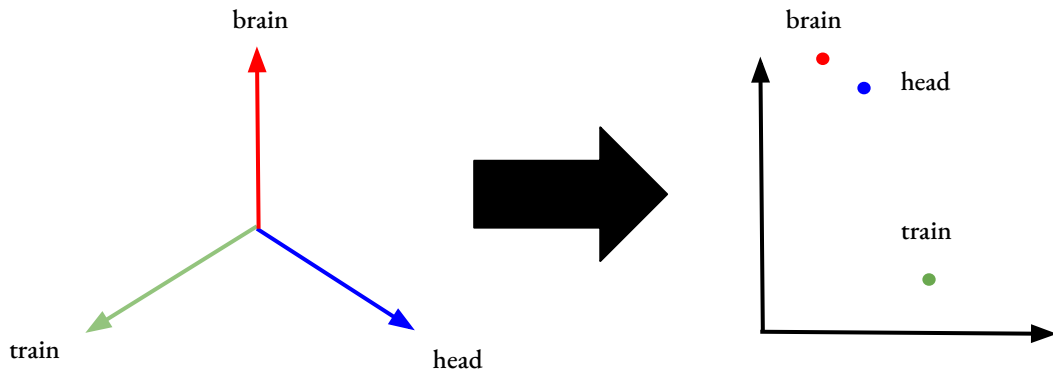
- Tons of different optimization algorithms
 - RMSprop
 - Adam
 - AdamW (adam with weight decay)
 - Adadelata
- Different methods for weight initialization
 - Idea: better/more stable starting points
- Change batch size
 - Spectrum from stochastic to one batch
 - Smaller batches usually results in noisier training

Embeddings

- For categorical variables we often use an *embedding* as a first step
- Categorical values can be one-hot encoded (meaning agnostic) then embedded into a meaningful feature space
- Similar to word embeddings
 - Go from one-hot encoded dictionary to word vectors

$$\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

brain head train

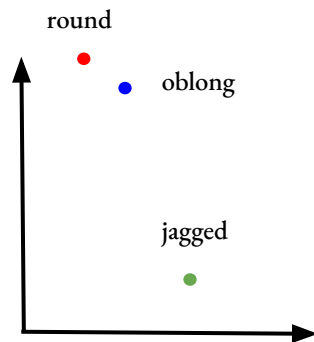
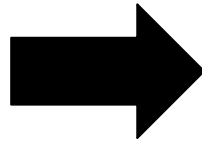
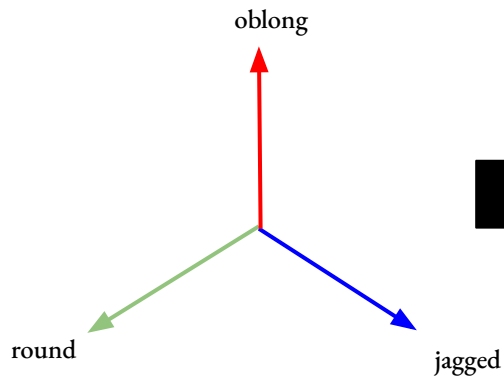


Embeddings

- For categorical variables we often use an *embedding* as a first step
- Categorical values can be one-hot encoded (meaning agnostic) then embedded into a meaningful feature space
- Doesn't have to be words
 - Go from one-hot encoded possible values to feature vectors

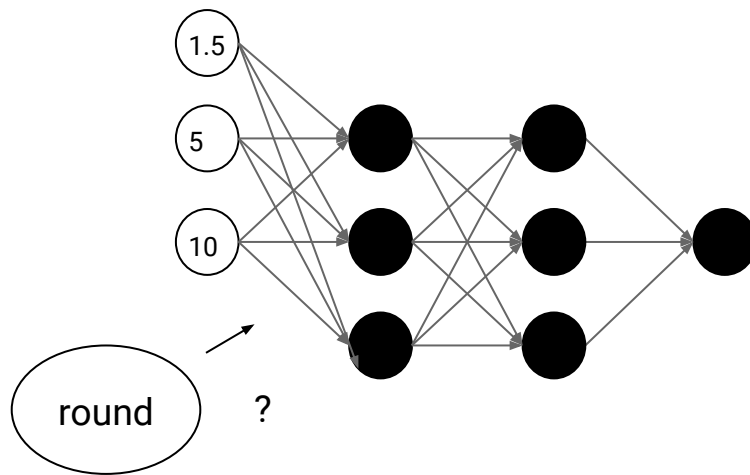
$$\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

round oblong jagged



Embeddings

- Suppose you have a mix of numerical and categorical variables for your input layer: $x = [1, .5, 10, \text{round}]$



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$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \end{bmatrix}$$

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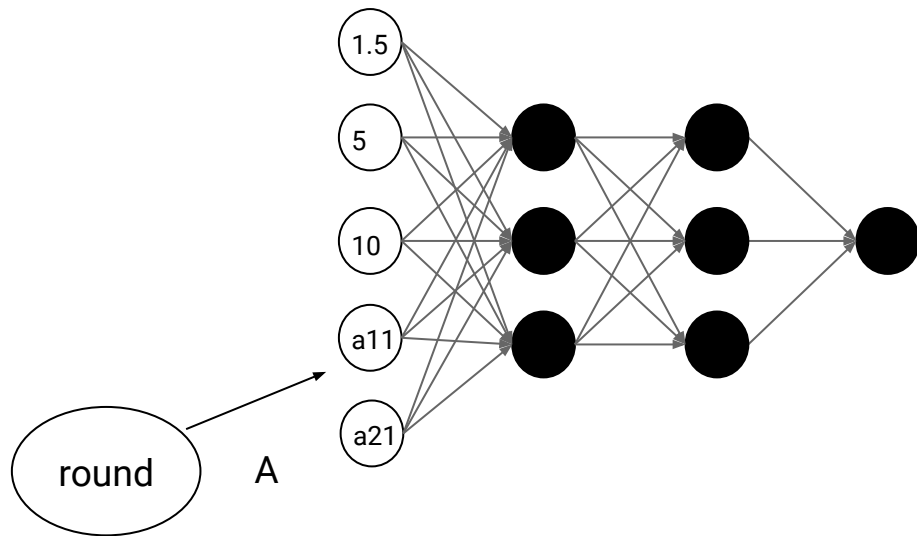
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Embedding of round

Embeddings

$\mathbf{x} = [1, .5, 10, \text{round}]$

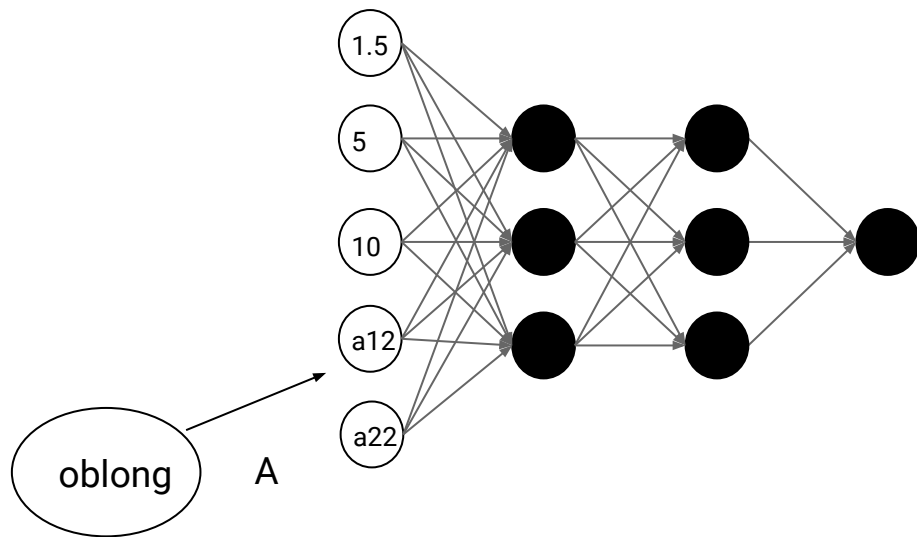
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Embeddings

$\mathbf{x} = [1, .5, 10, \text{oblong}]$

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \end{bmatrix}$$



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- What architecture you use and other hyperparameters you choose depend heavily on
 - The task
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- What architecture you use and other hyperparameters you choose depend heavily on
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 - How your model will be used
 - How interpretable you want your model to be
- The answer to “how many layers” or “how many nodes” is usually determined by
 - What other people have had success with
 - Your own experiments with different architectures

GPU Options for Final Project

- Option 1: Google Colab, Kaggle
- Option 2: USF Box 2
- Option 3: Extra GPU (email Alex)

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- Later in PyTorch: How to train on GPU