Deep Learning
MSDS 631

Tips and Tricks for Deep Learning

Michael Ruddy

Some Thoughts

- Final Project Reminders
- Tips
  - Loss Function Documentation (output? average?)
  - What is true for this dataset may not be true for another
  - For experiments, make sure you are re-initializing parameters
- Only small penalty for submitted lab on time
  - Come see me today for issues!
- Please put your name on your lab
- Isn't it enough to know how to use software for DL? Why peak "under the hood"?

Questions?

- From last lecture?
- From the lab assignment?

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

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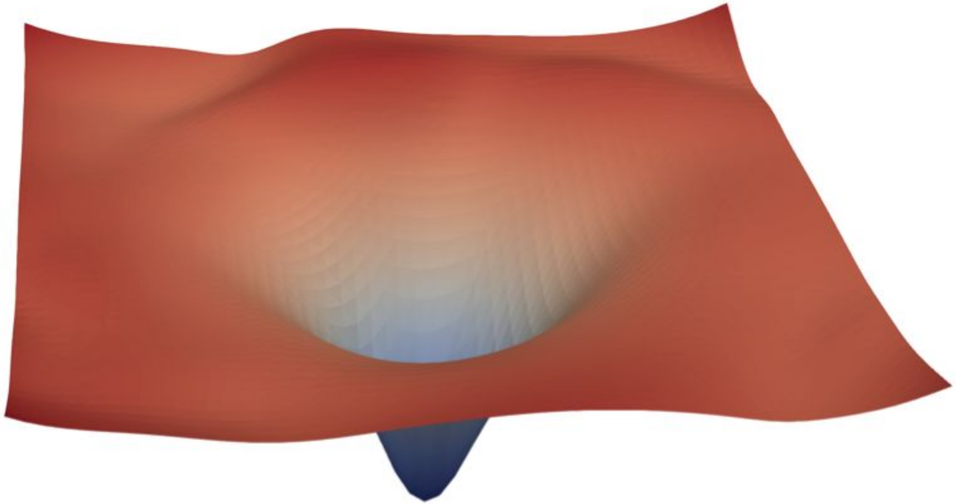

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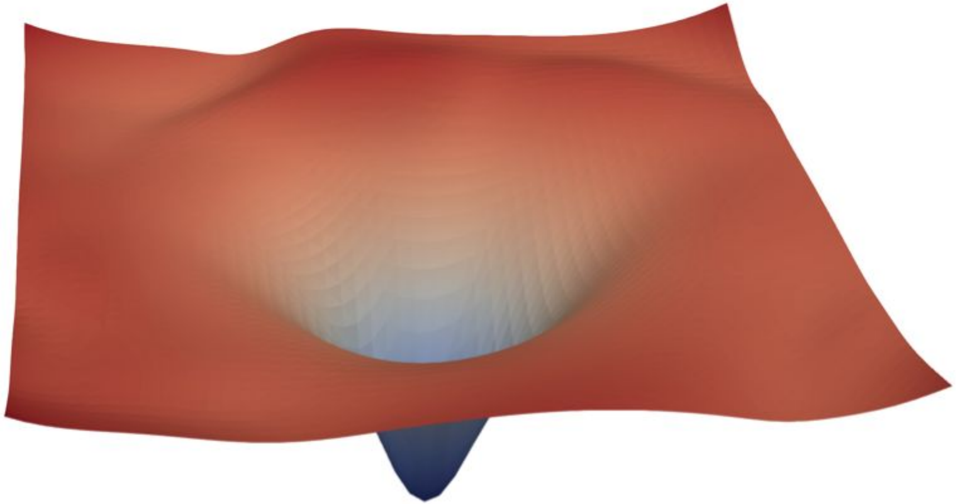

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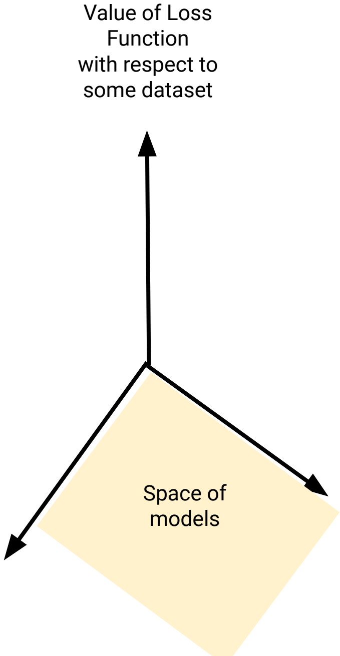

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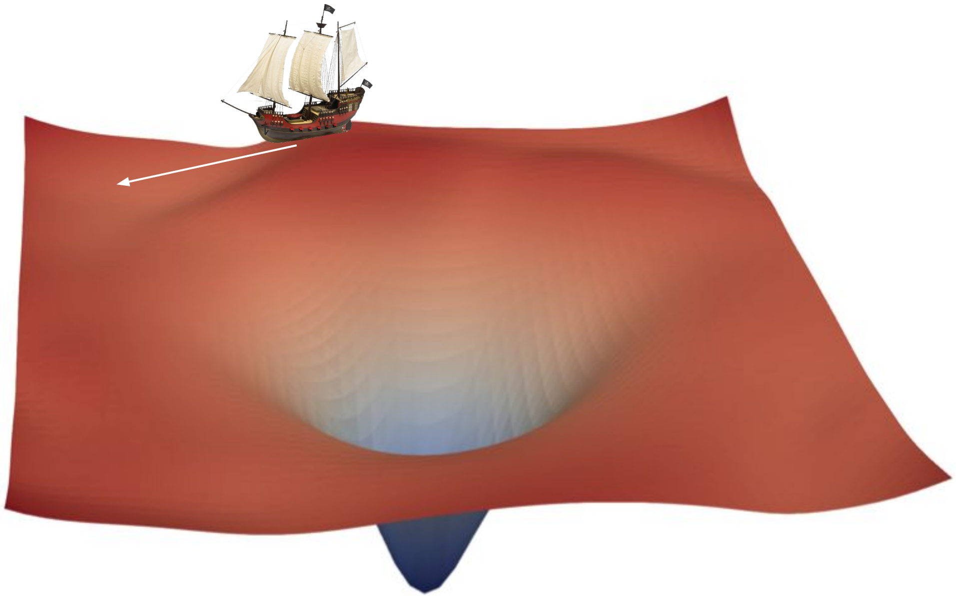

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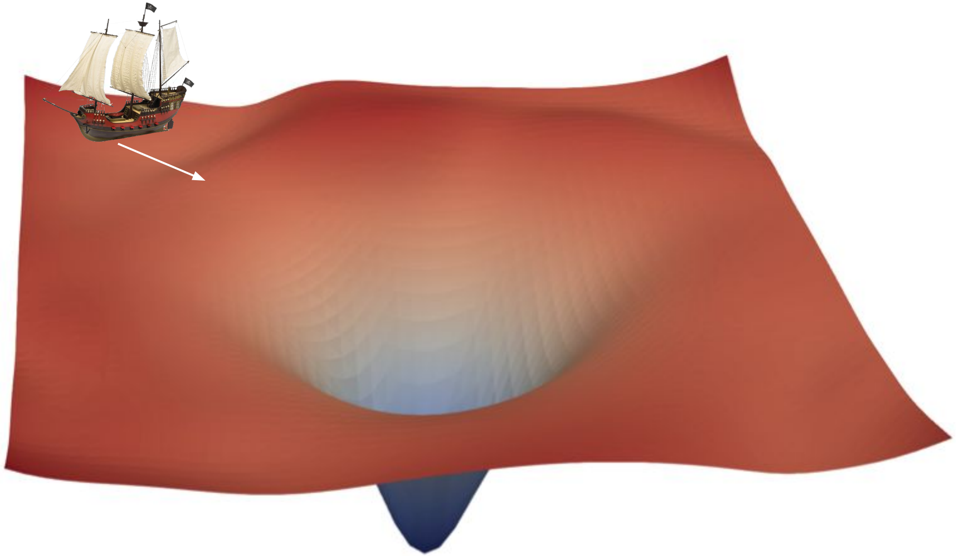

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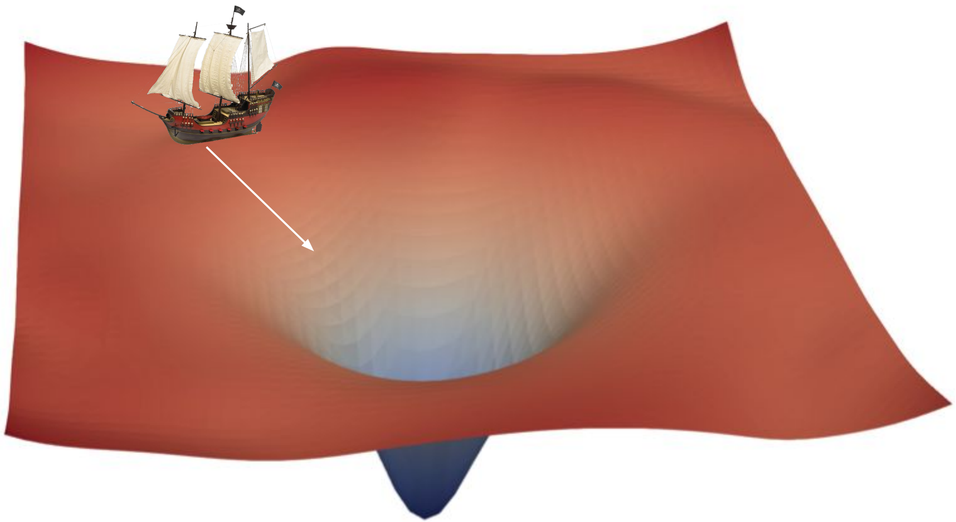

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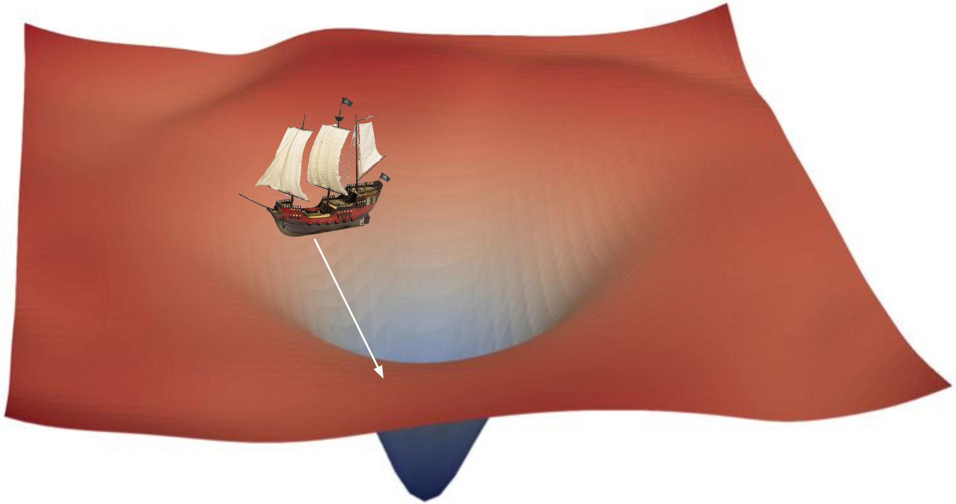

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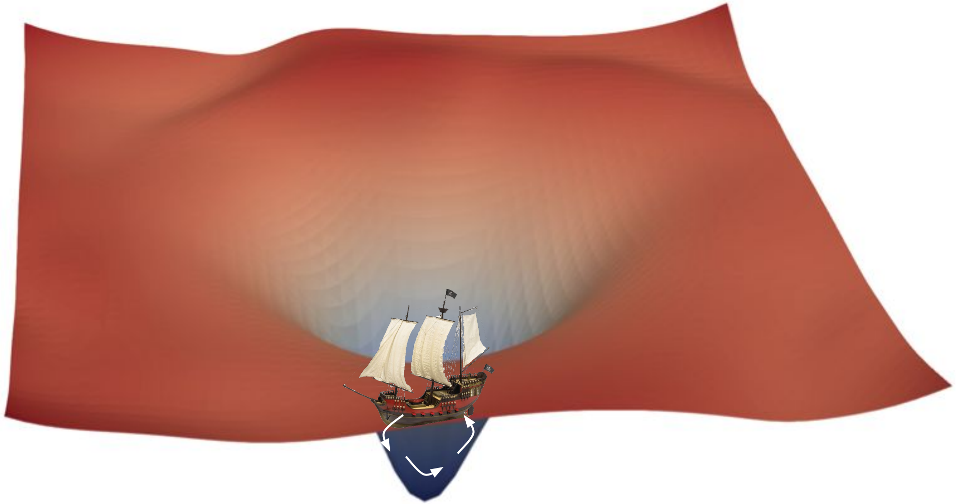
    - Success!



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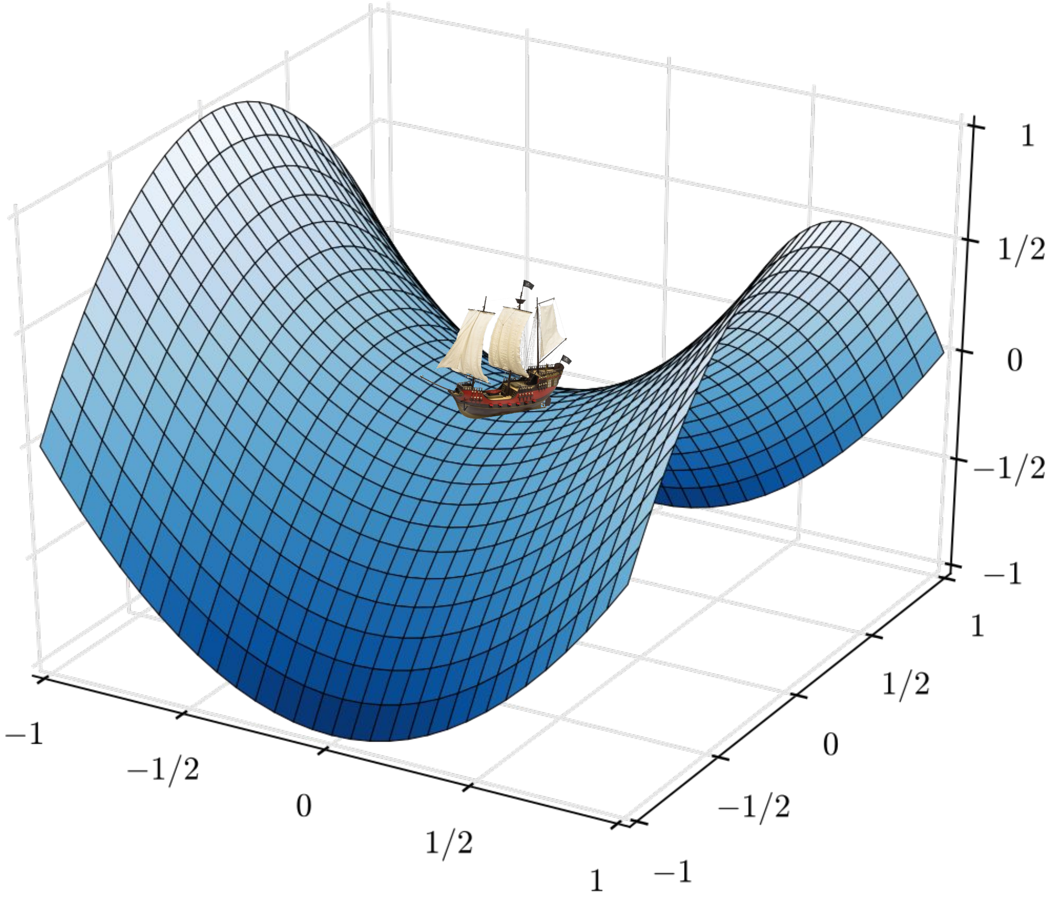
    - Too flat (or saddle point)



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- What can go wrong?
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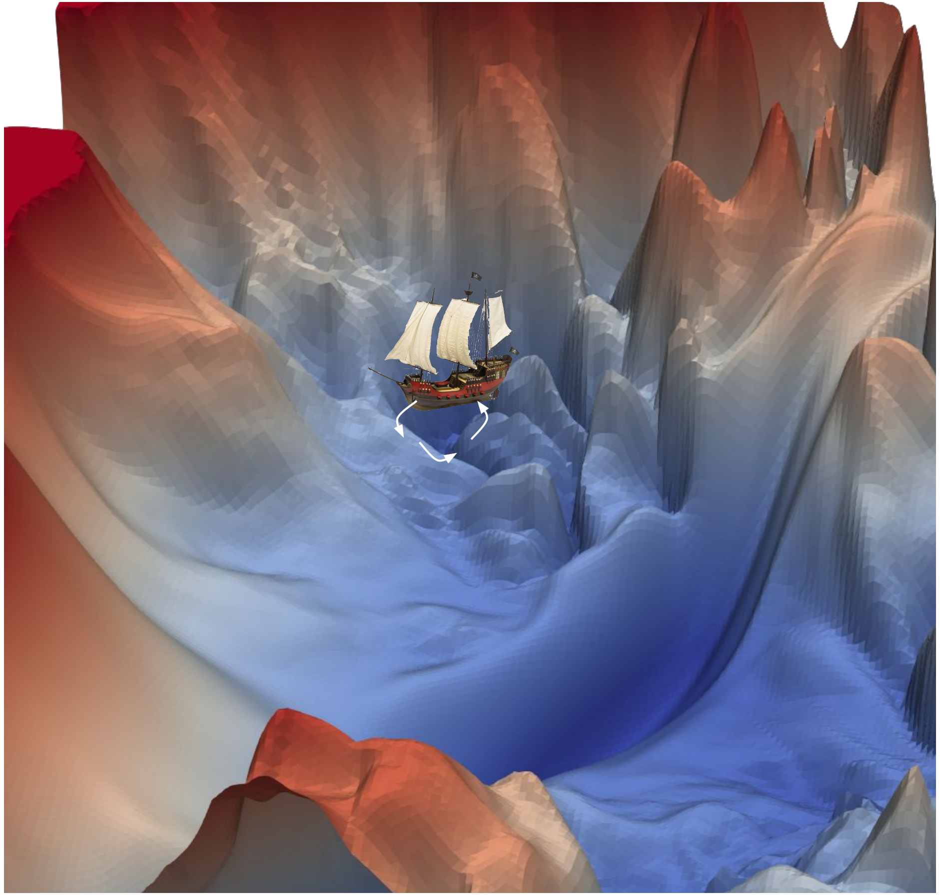

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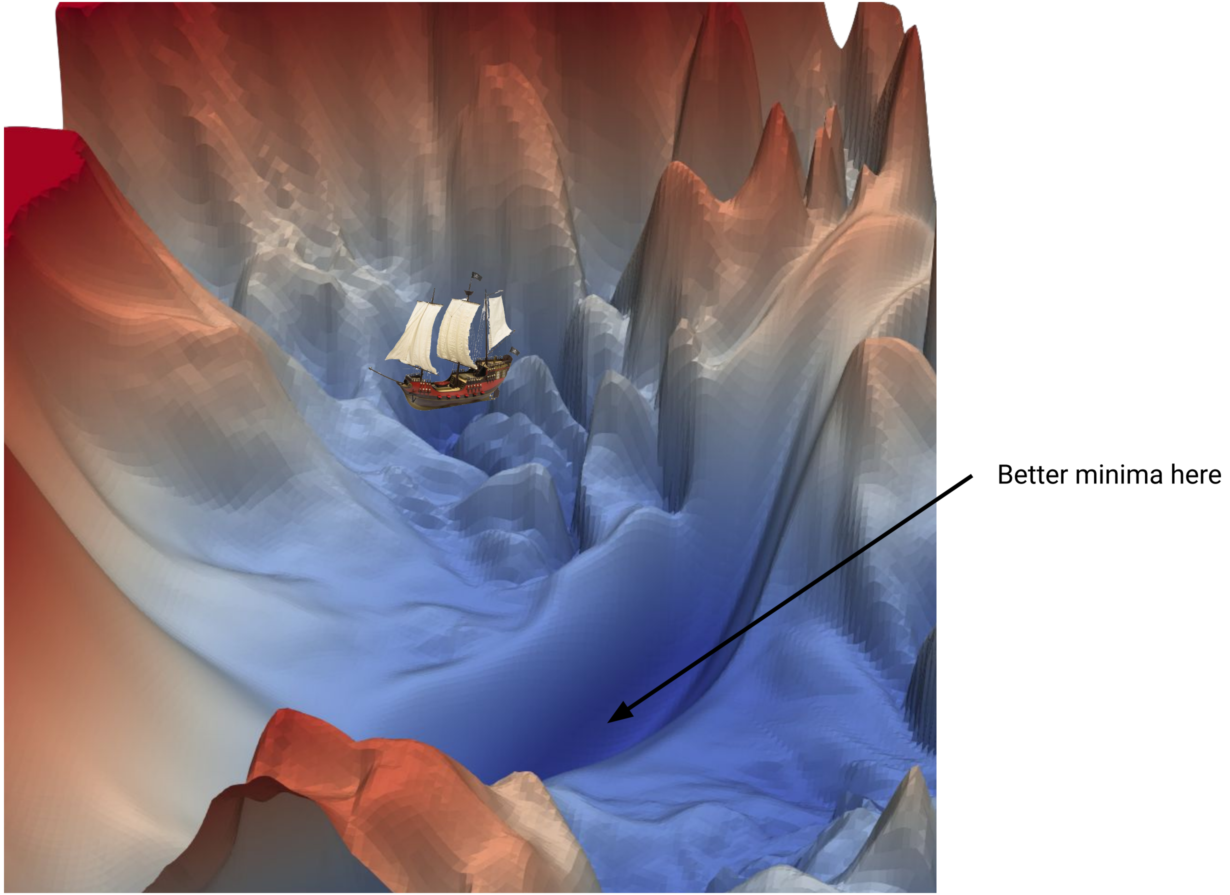

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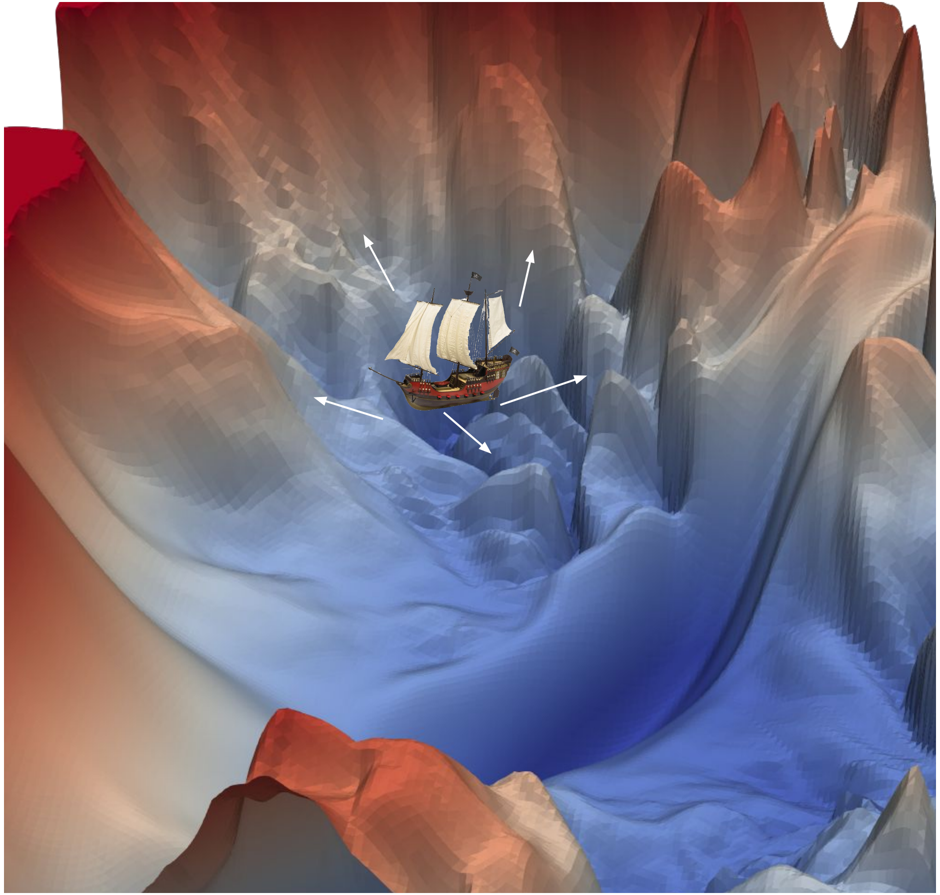

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Small movement may incur massive loss increase

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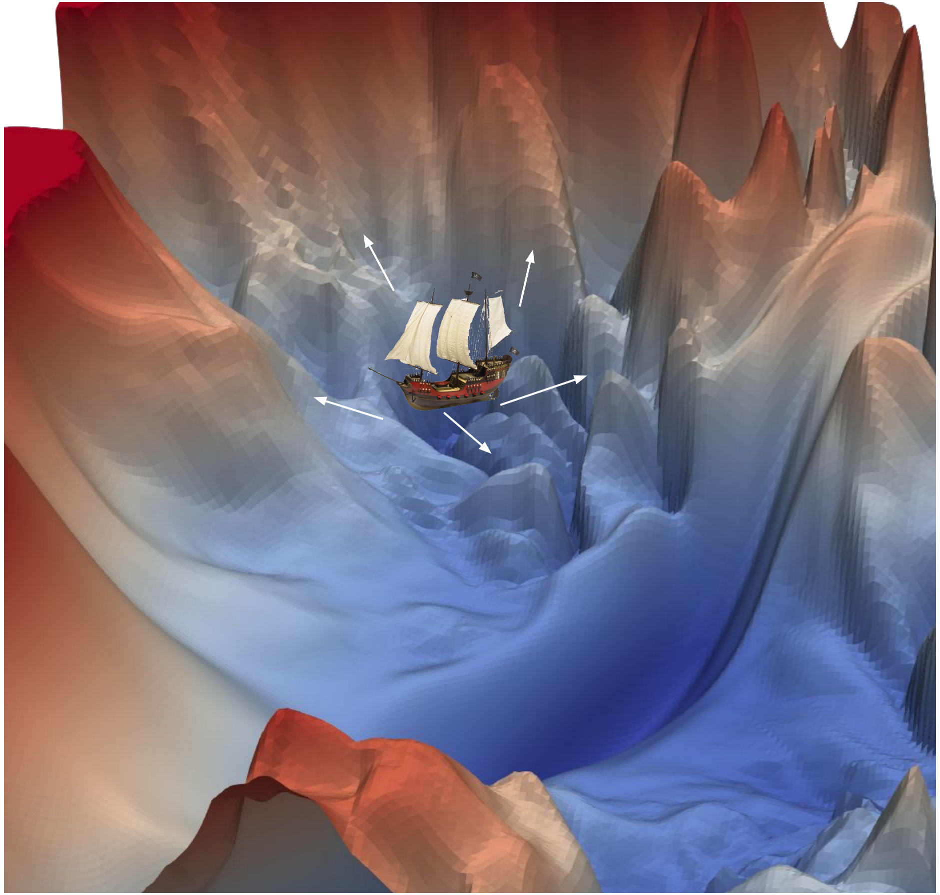
  - May not generalize well



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    - Too flat
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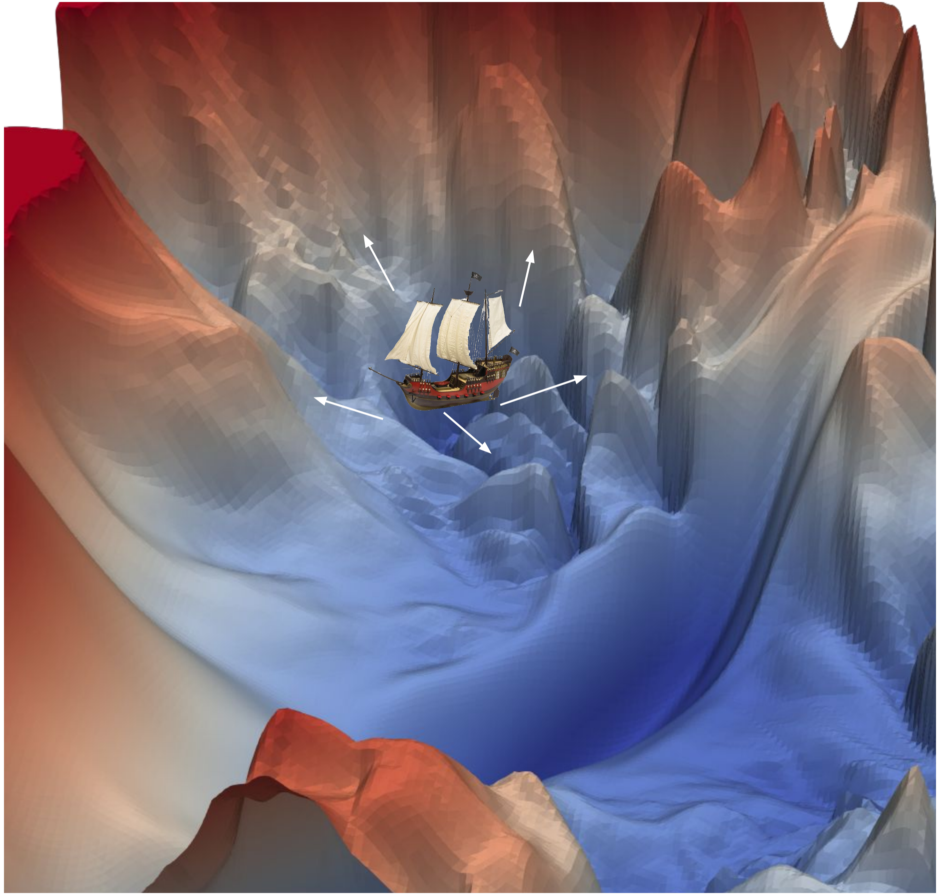
- Shallow
- Unstable
    - May not generalize well
- May not be as big as a problem as previously thought!



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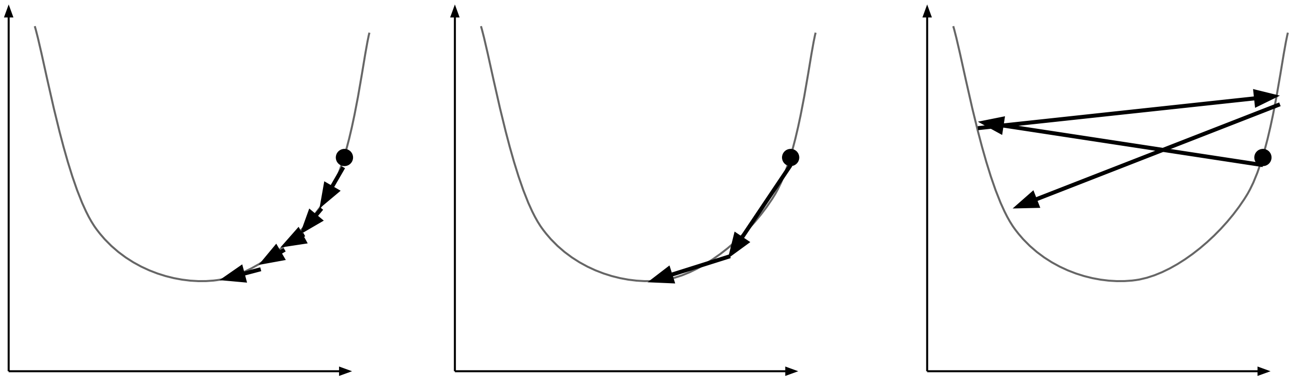

Low LR:
Too slow

Just right:
Good
convergence

High LR:
diverges

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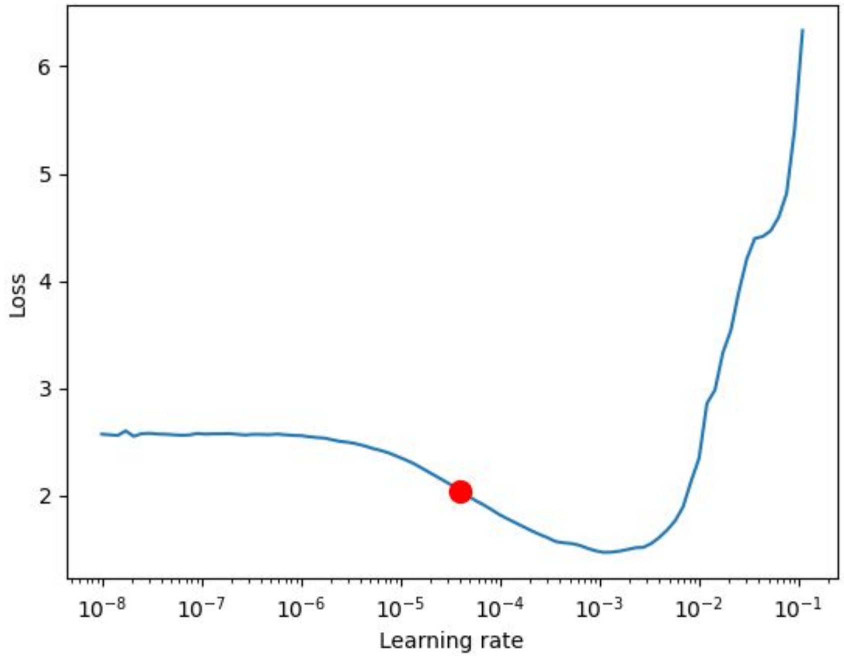

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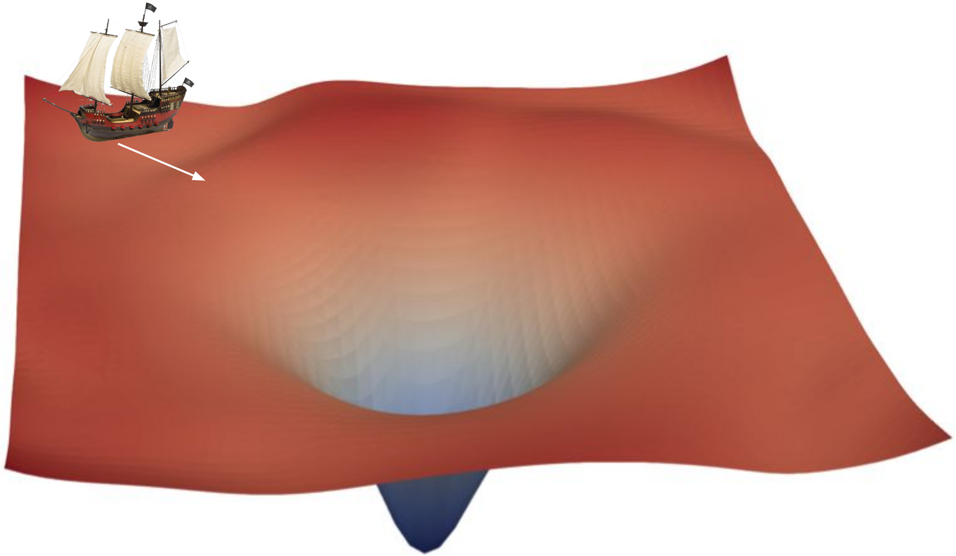

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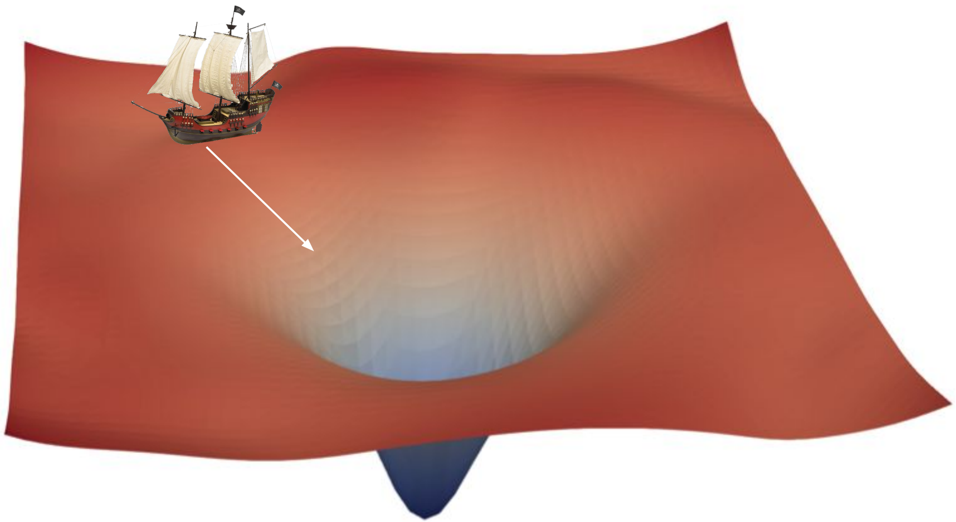

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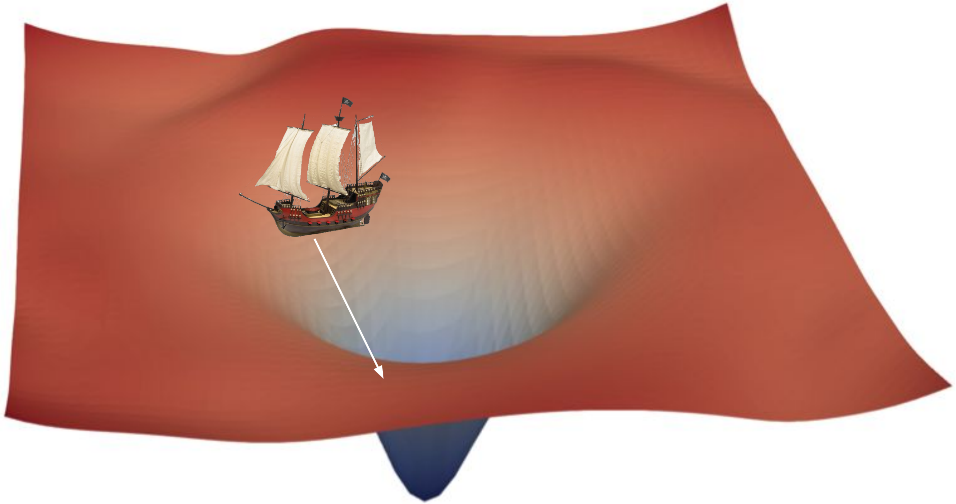

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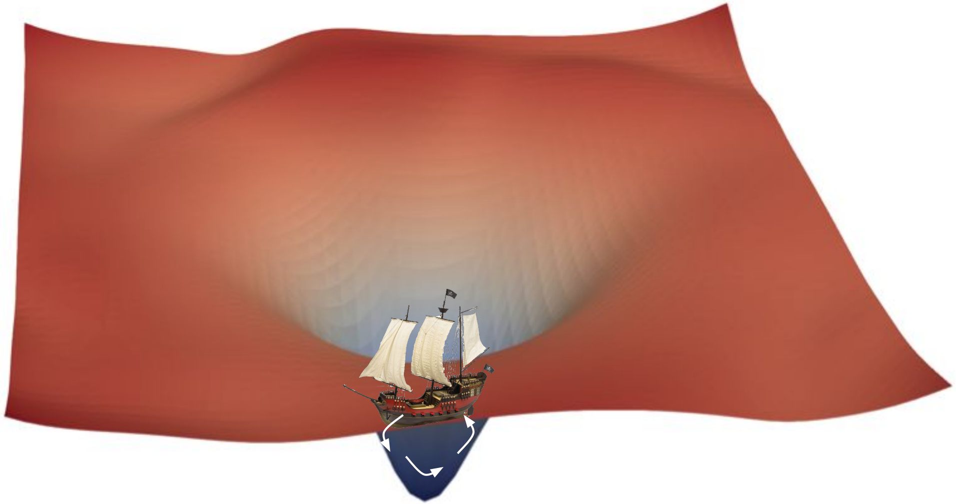

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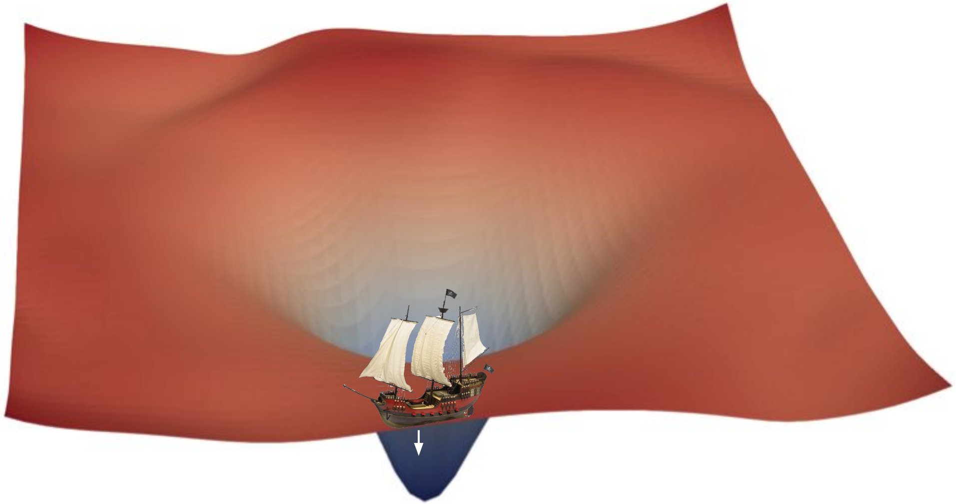

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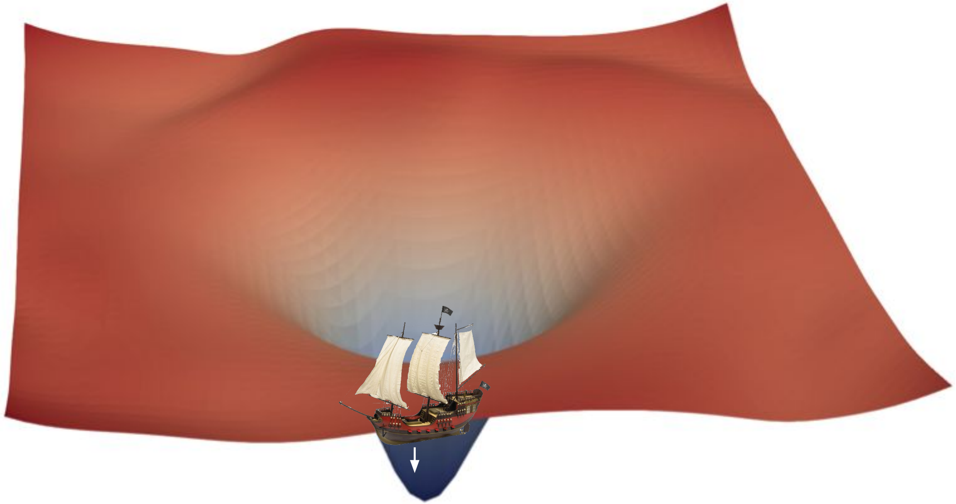

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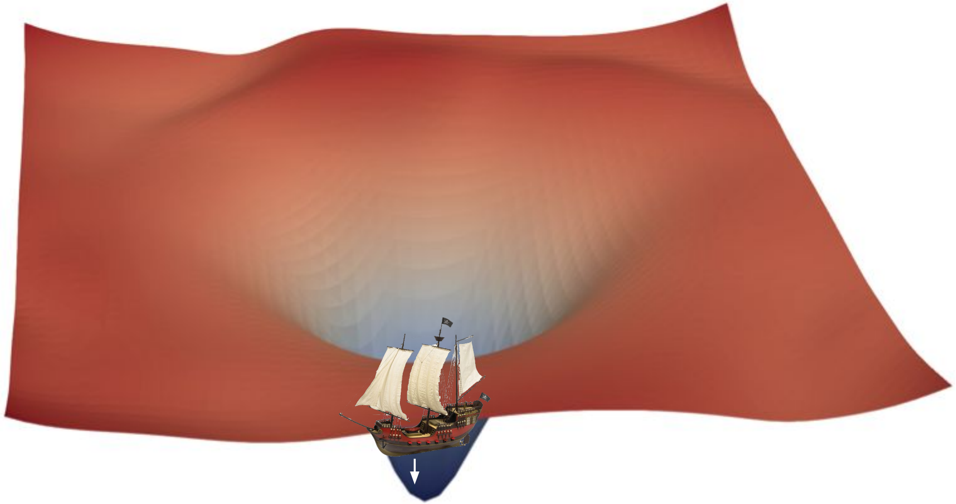

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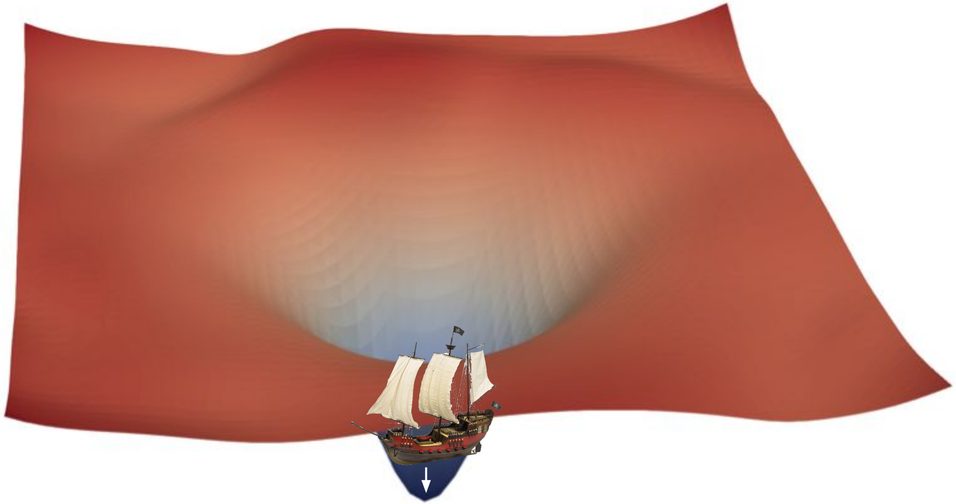

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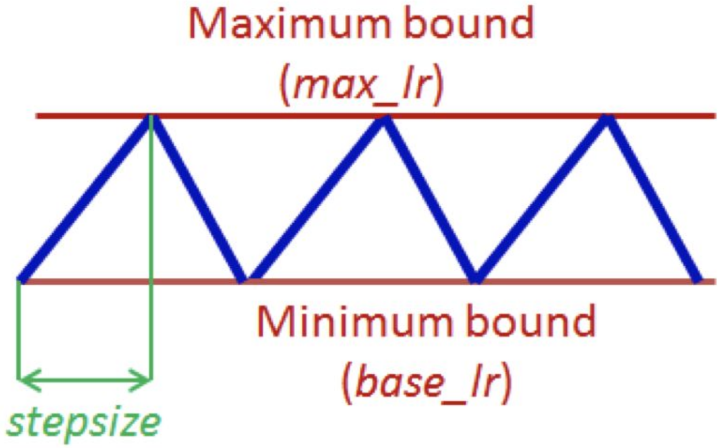

Cyclical Learning Rates for Training Neural Networks by Leslie Smith

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- Cyclical LRs
- And more!

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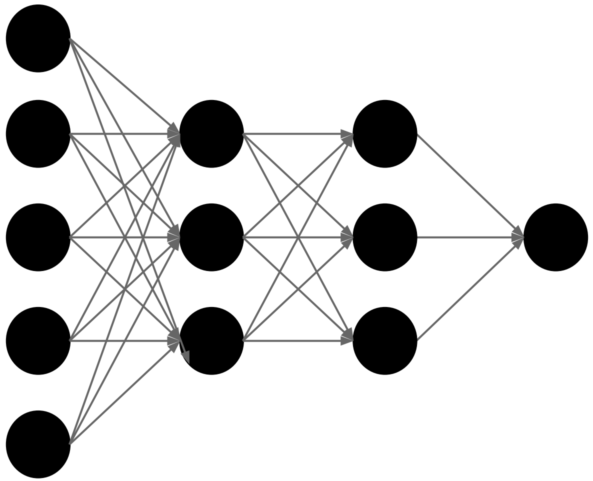

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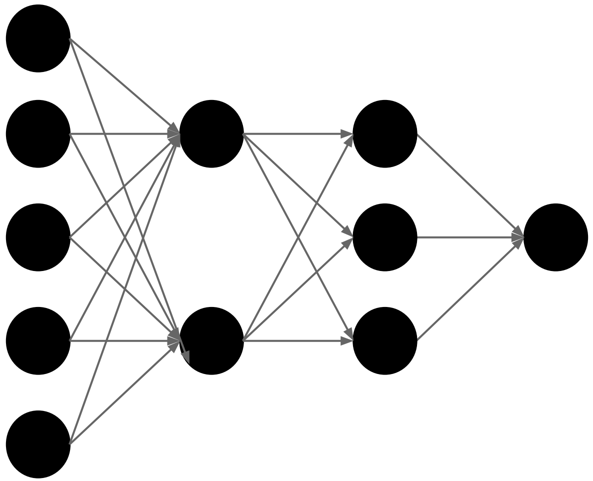

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- We usually train NN using *mini-batches*. (not a fixed loss landscape!)
  - Only compute gradient with respect to a small batch of your data
  - Data might be too big to load onto GPU
  - Form of regularization (adds noise)
  - Model updates more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

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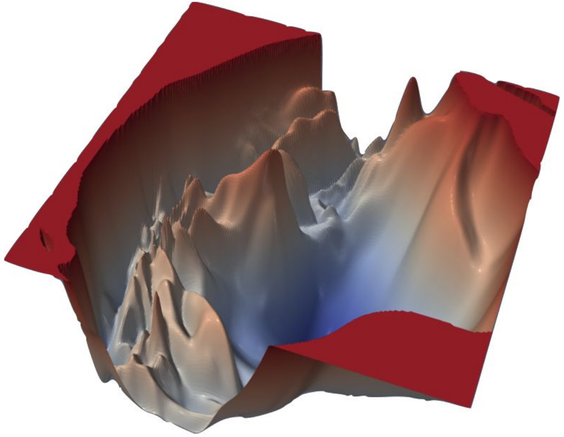

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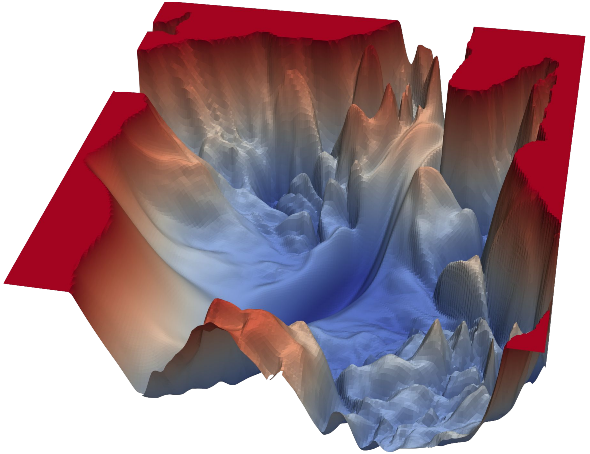

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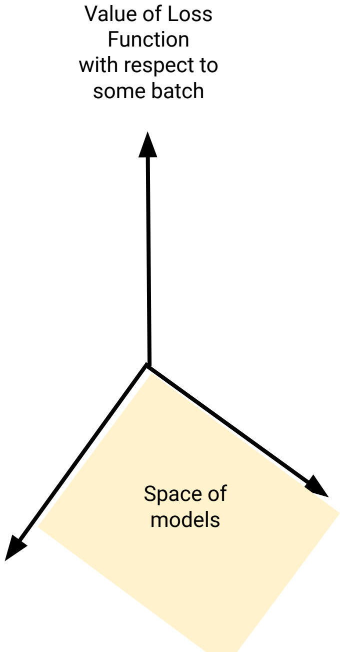

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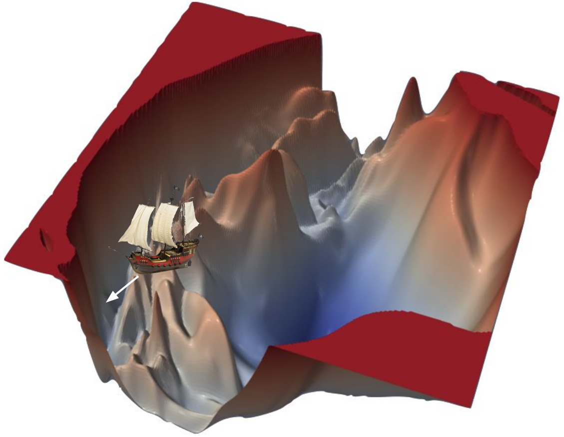

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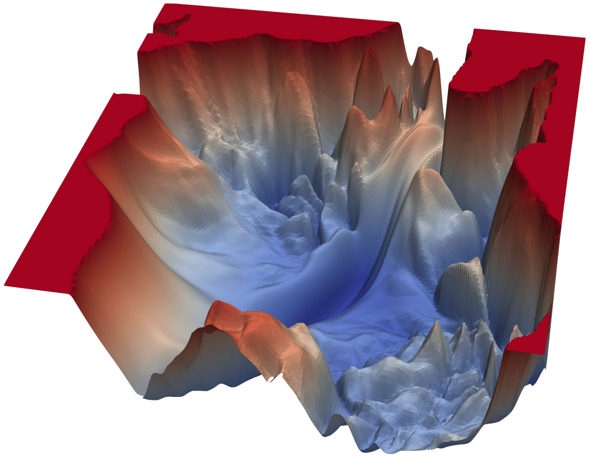

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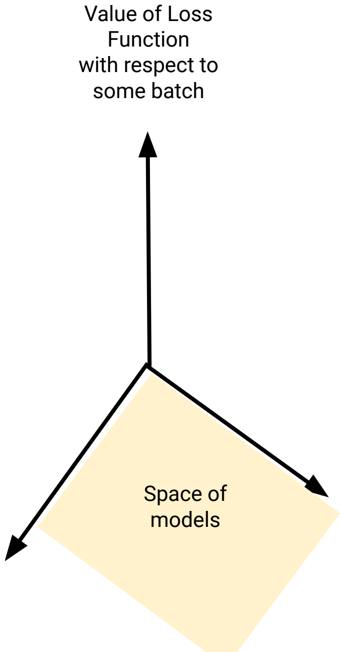

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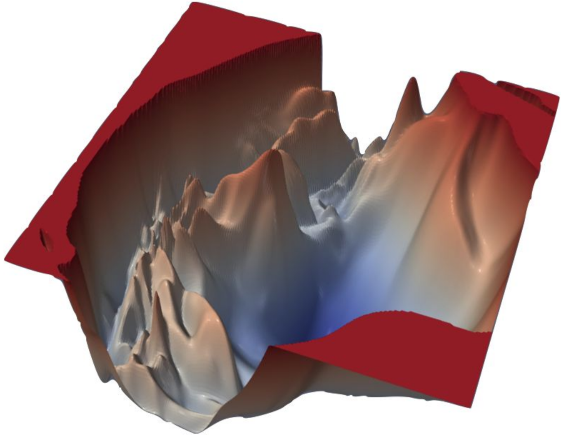

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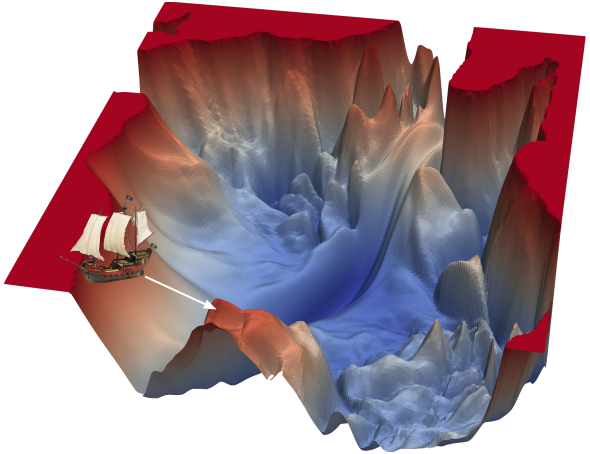

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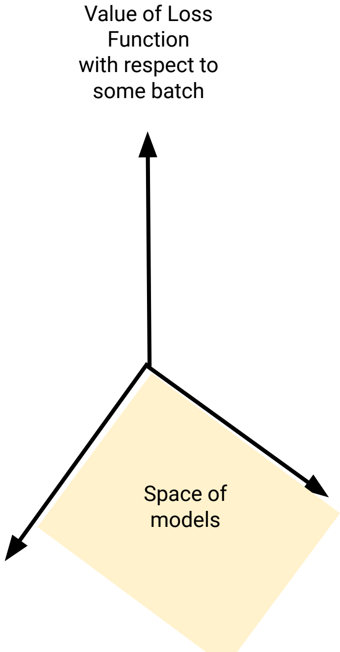

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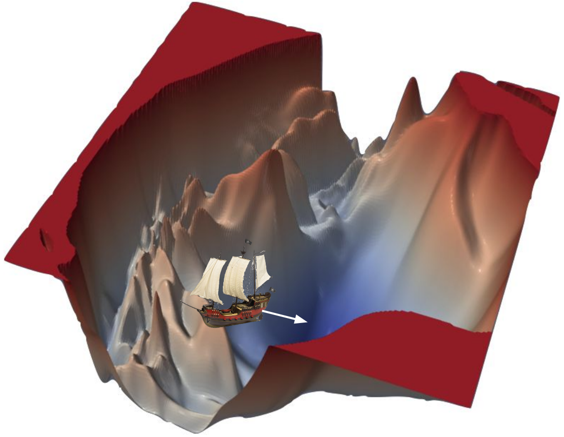

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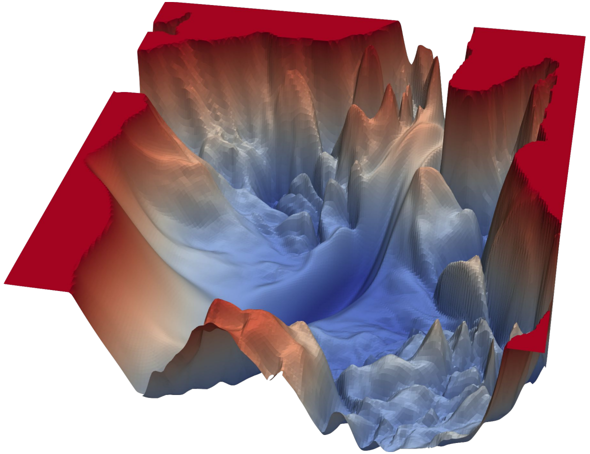

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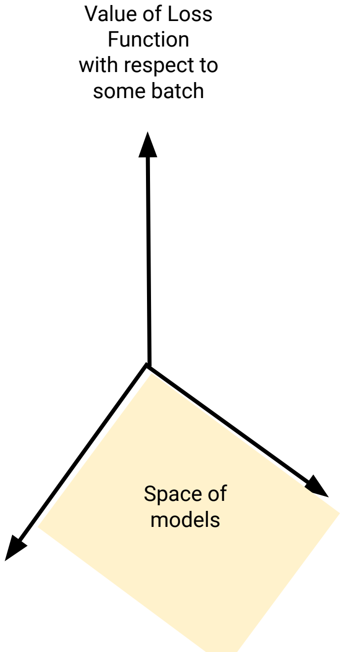

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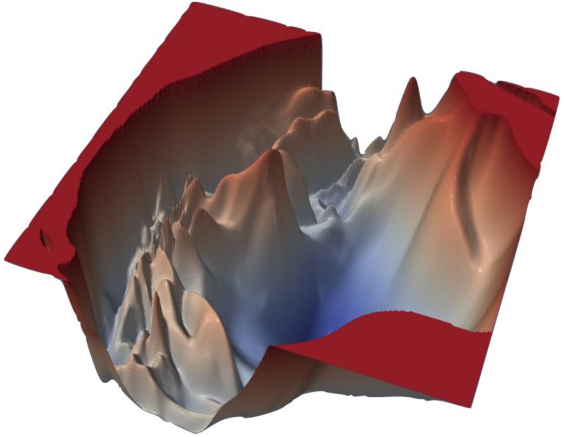

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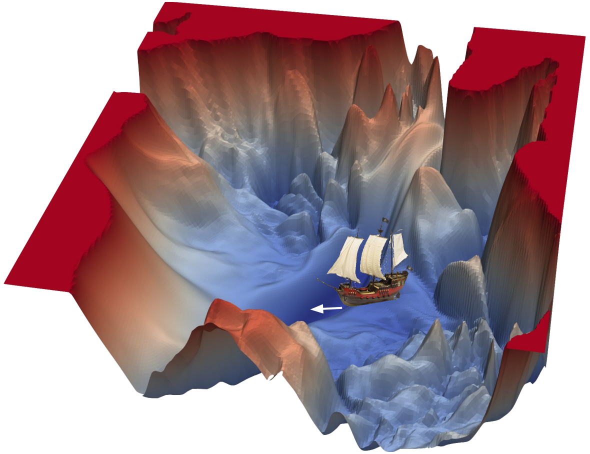

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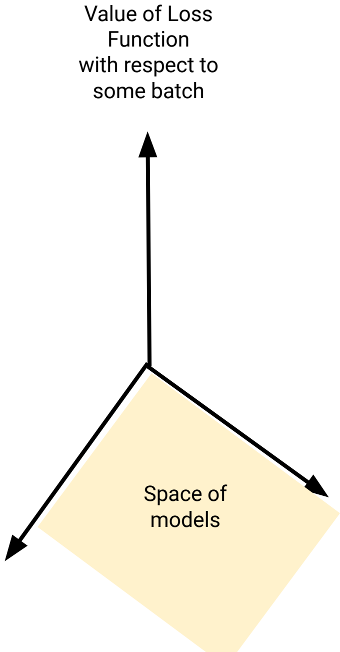

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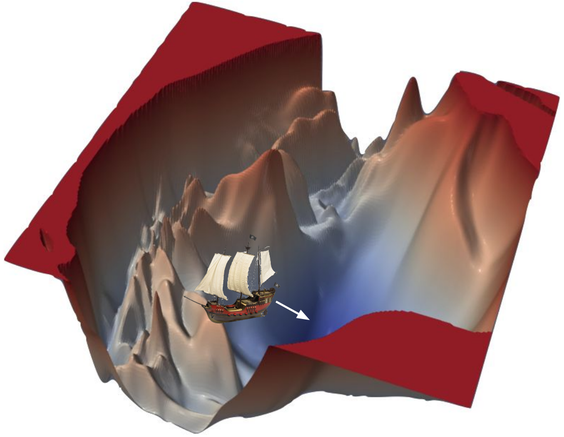
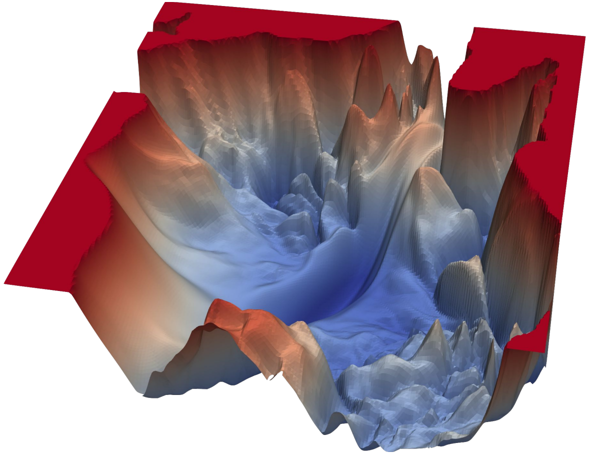
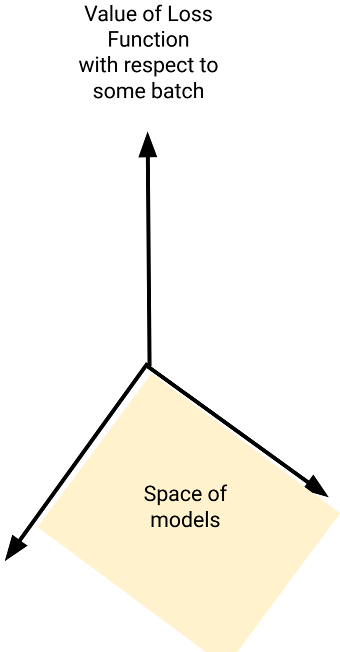


Loss values for first batch



Loss values for second batch



Regularization

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

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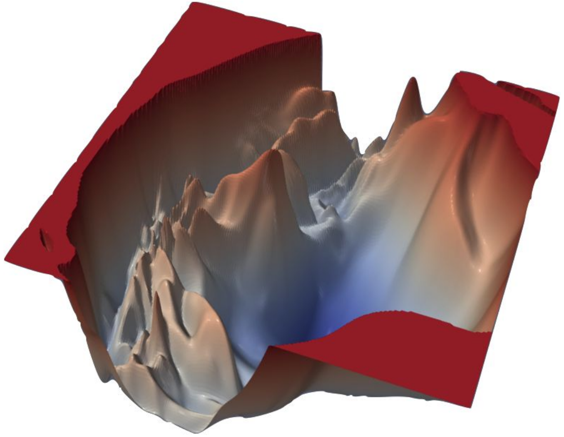

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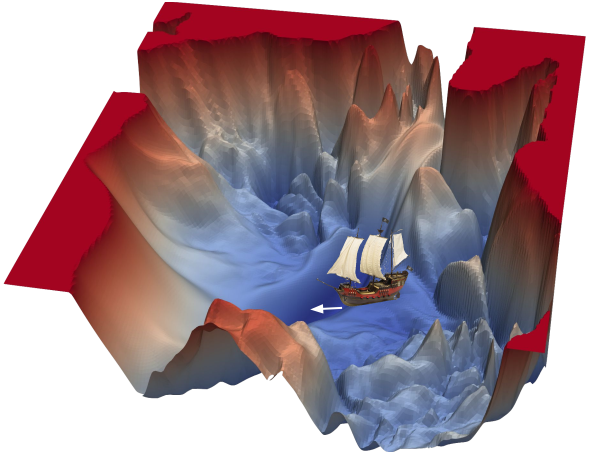

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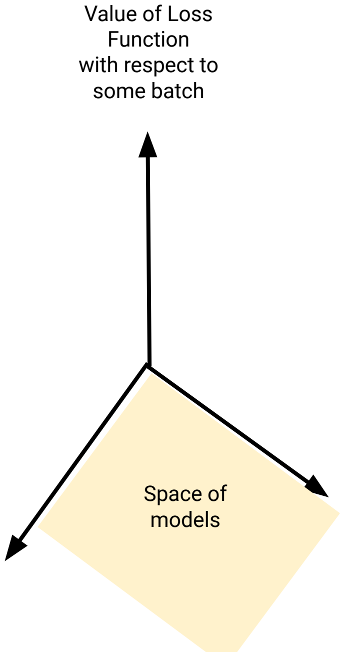

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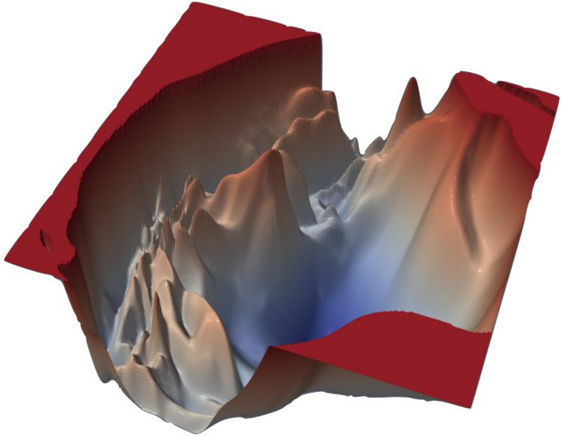

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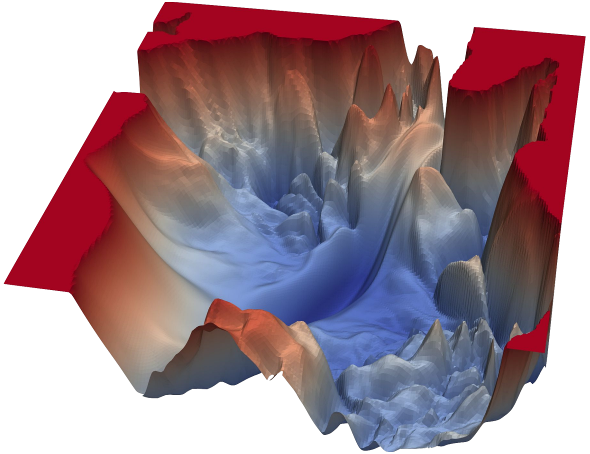

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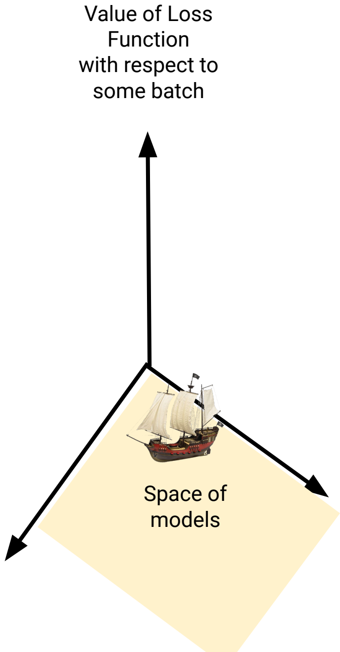


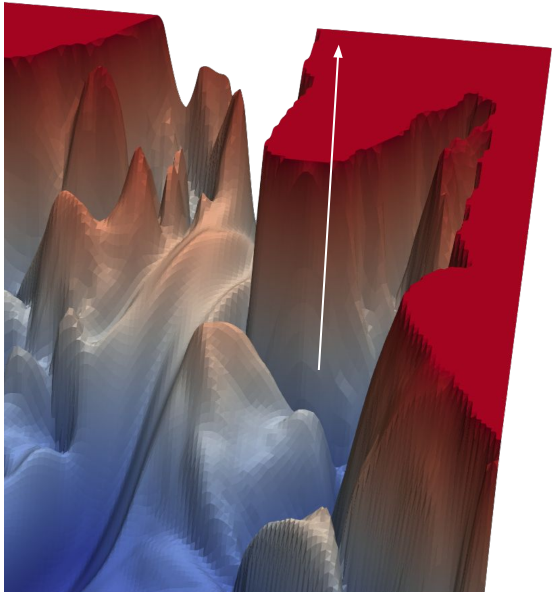
Normalization

- 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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- 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

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Normalize over the mini-batch

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \qquad \overline{x} = \begin{bmatrix} \overline{x}_1 \\ \overline{x}_2 \\ \vdots \\ \overline{x}_n \end{bmatrix} \qquad \overline{x}_i = \frac{x_i - \mu_i}{\sigma + \epsilon}$$

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Normalization

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

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

Smoothing the loss landscape

- Intuition: making the loss landscape easier to traverse

Smoothing the loss landscape

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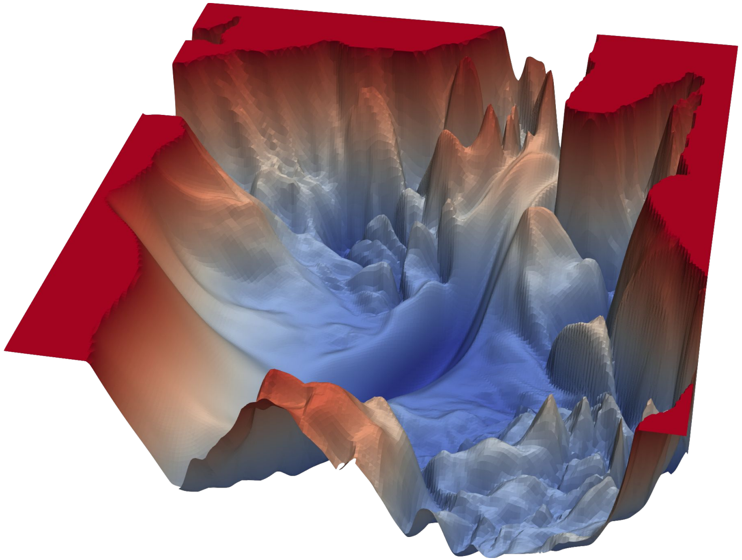
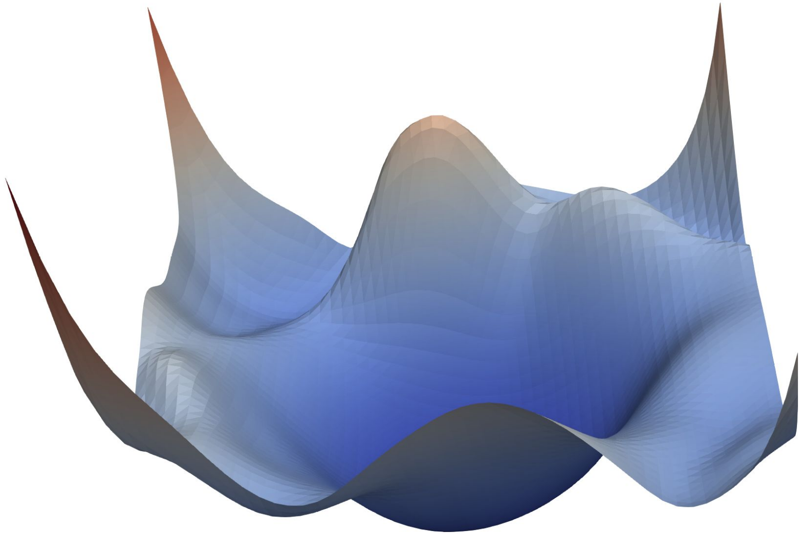
- Skip Connections (more on these later)



w/o skips



w/ skips

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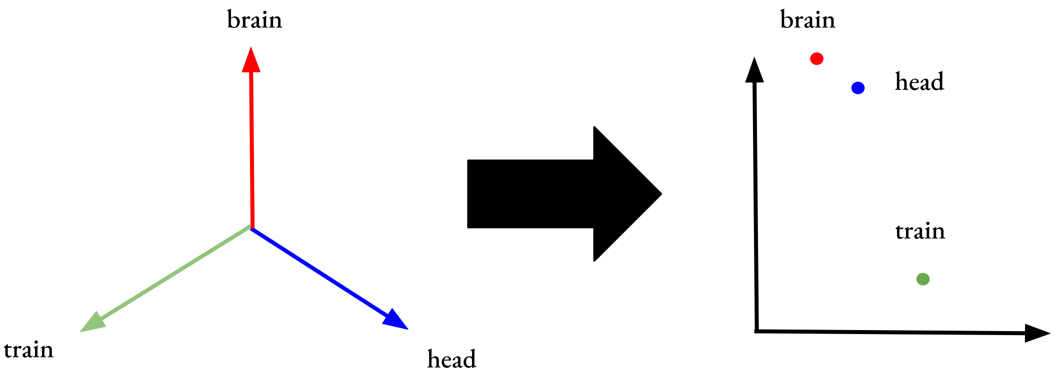
Other things to tweak

- Tons of different optimization algorithms
  - RMSprop
  - Adam
  - AdamW (adam with weight decay)
  - Adadelta
- 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

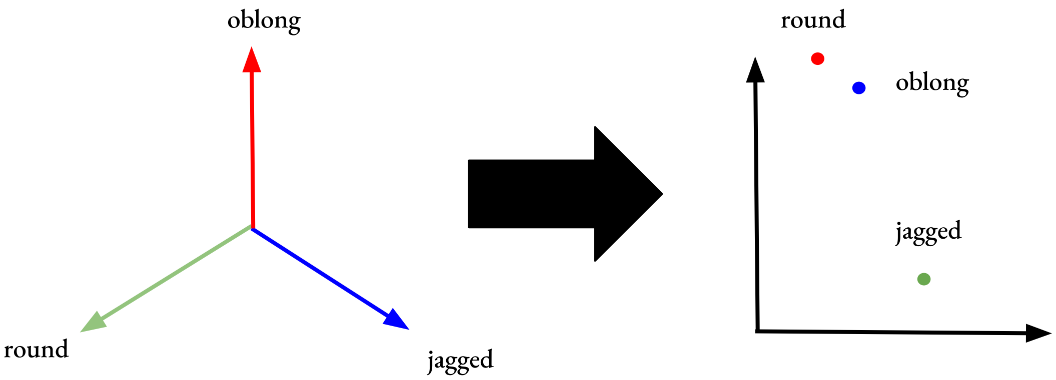
$$\begin{array}{ccc} \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} & \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} & \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \\ \text{brain} & \text{head} & \text{train} \end{array}$$



Embeddings

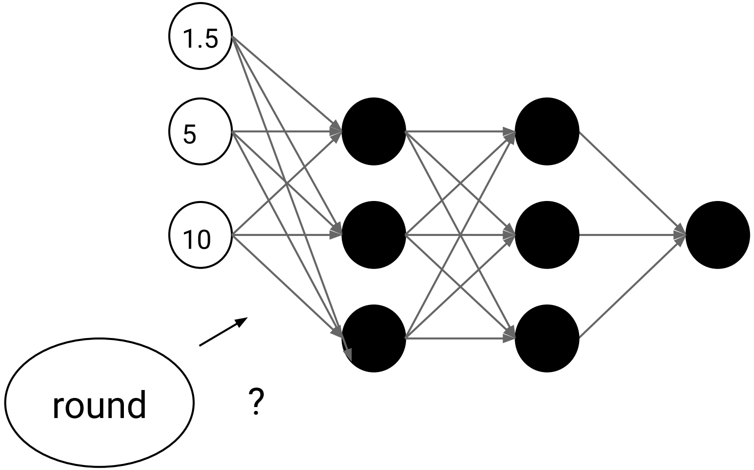
- For categorical variables we often use an *embedding* as a first step
- Categorical values can be one-hot encoded (meaning agnostic) then embedded into a meaningful feature space
- Doesn't have to be words
    - Go from one-hot encoded possible values to feature vectors

$$\begin{array}{ccc} \begin{bmatrix}1\\0\\0\end{bmatrix} & \begin{bmatrix}0\\1\\0\end{bmatrix} & \begin{bmatrix}0\\0\\1\end{bmatrix} \\ \text{round} & \text{oblong} & \text{jagged} \end{array}$$



Embeddings

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



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Embedding of round

Embeddings

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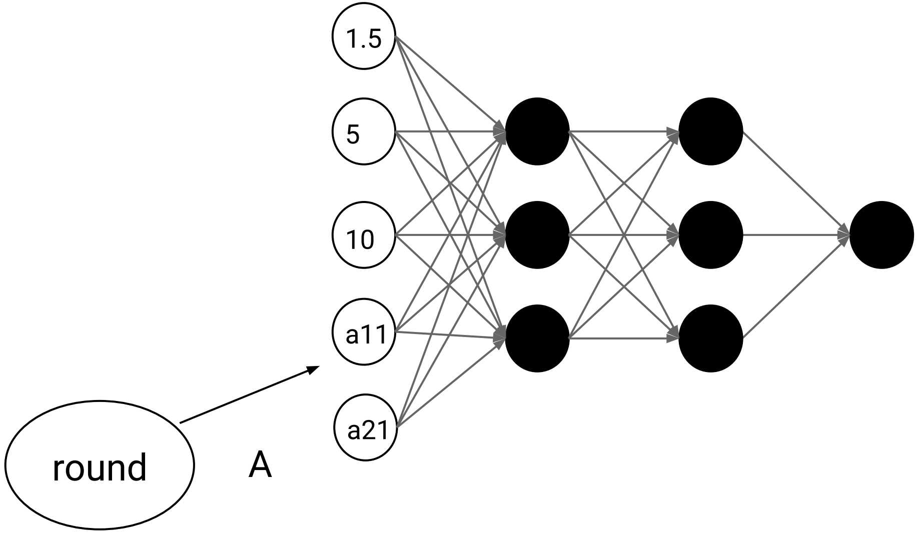

Embeddings

x = [1, .5, 10, oblong]

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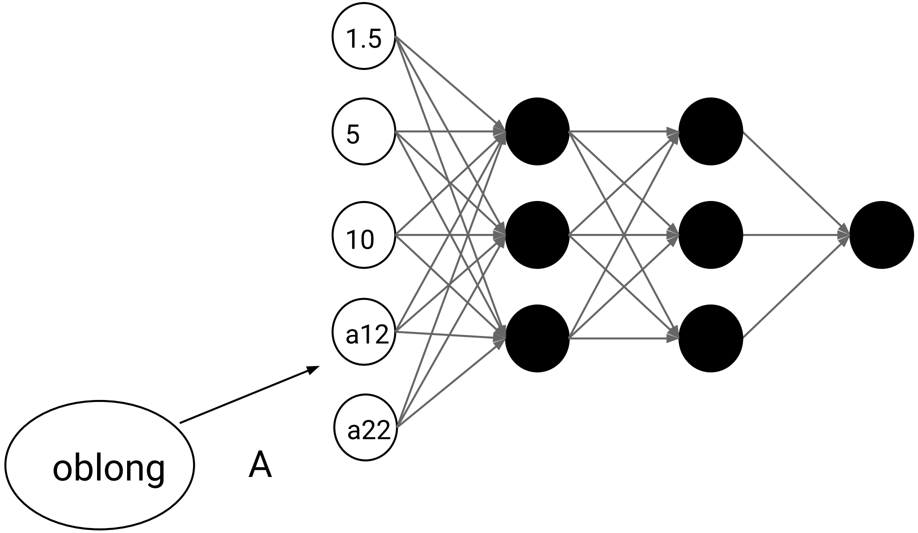

Why this or that architecture for a given problem?

- What architecture you use and other hyperparameters you choose depend heavily on
  - The task
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  - 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