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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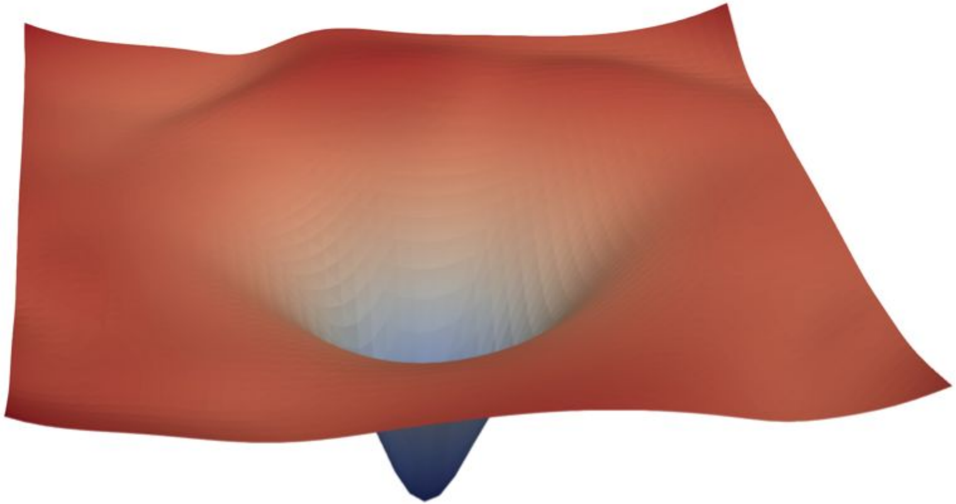
- Loss Landscape: The environment which informs our journey



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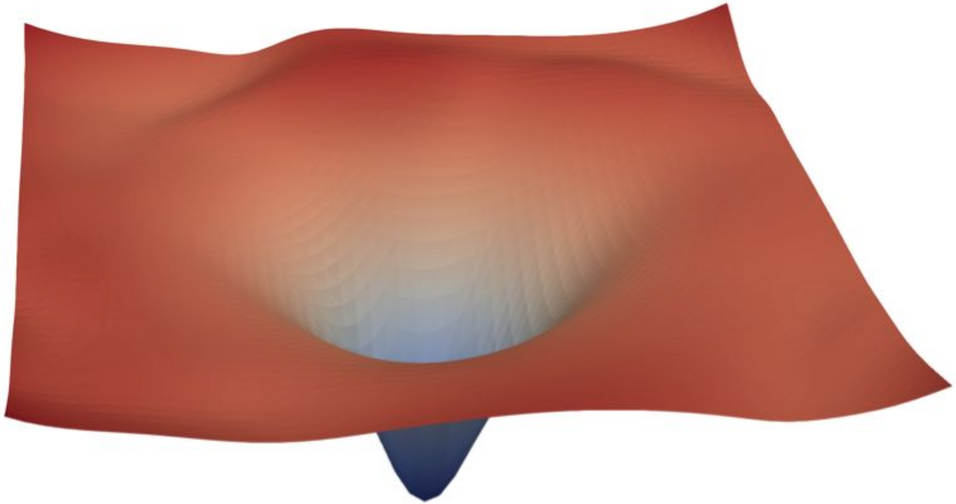

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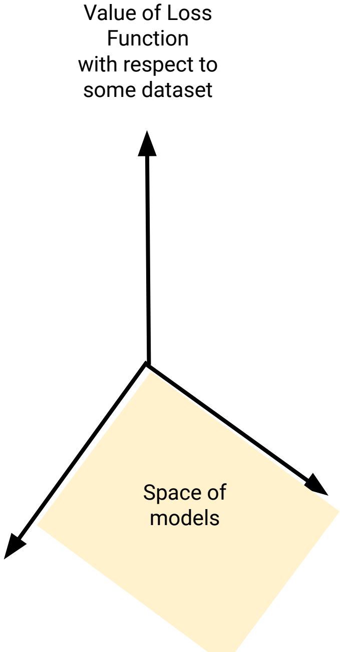

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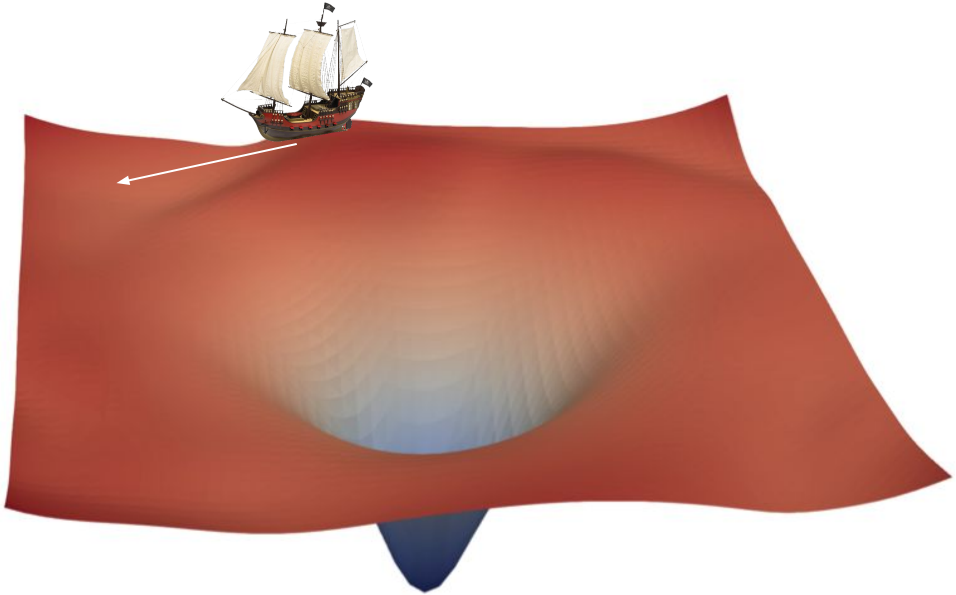

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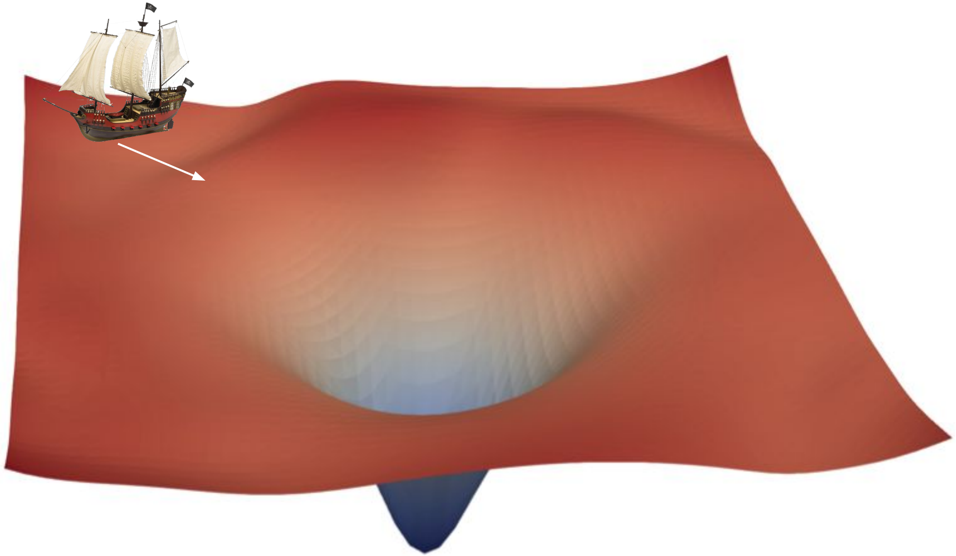

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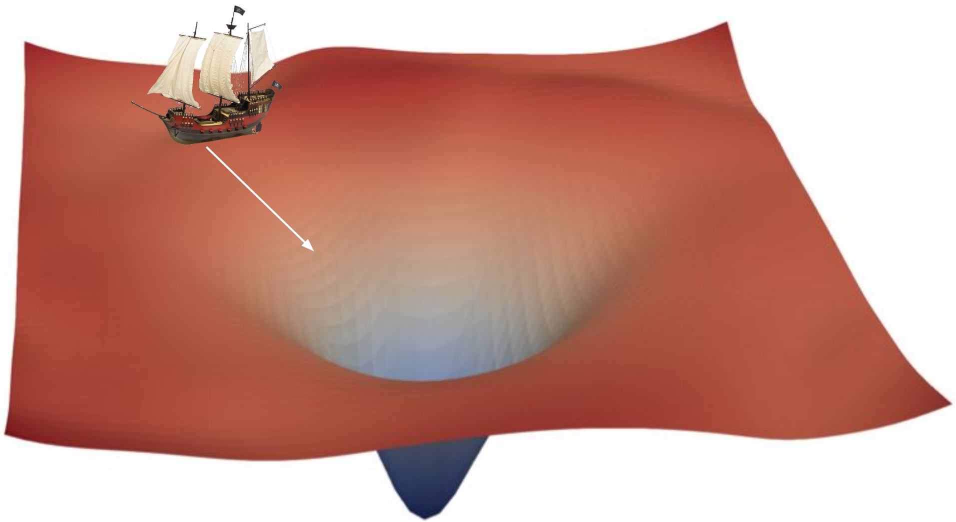

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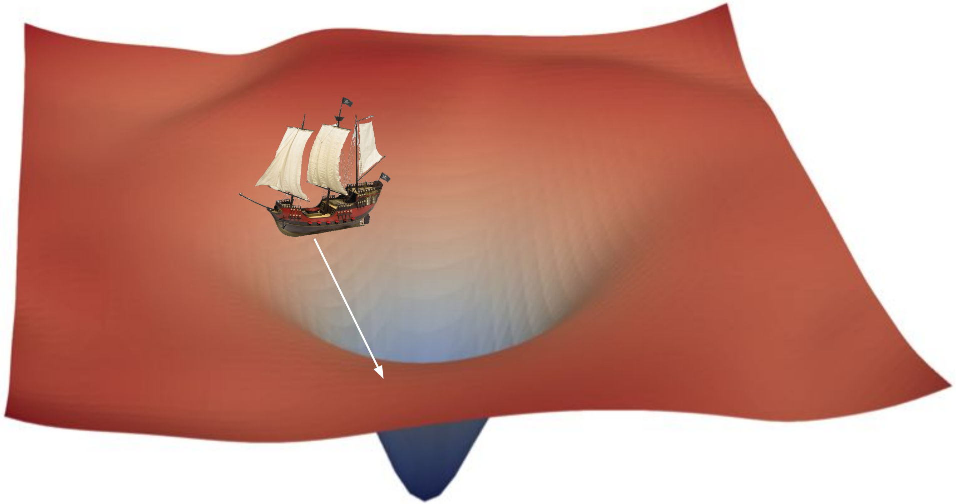

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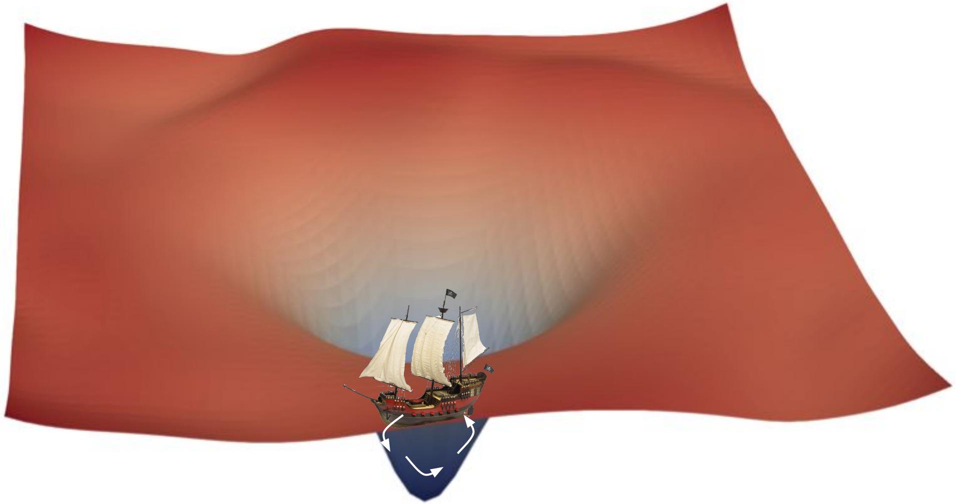
  - Success!



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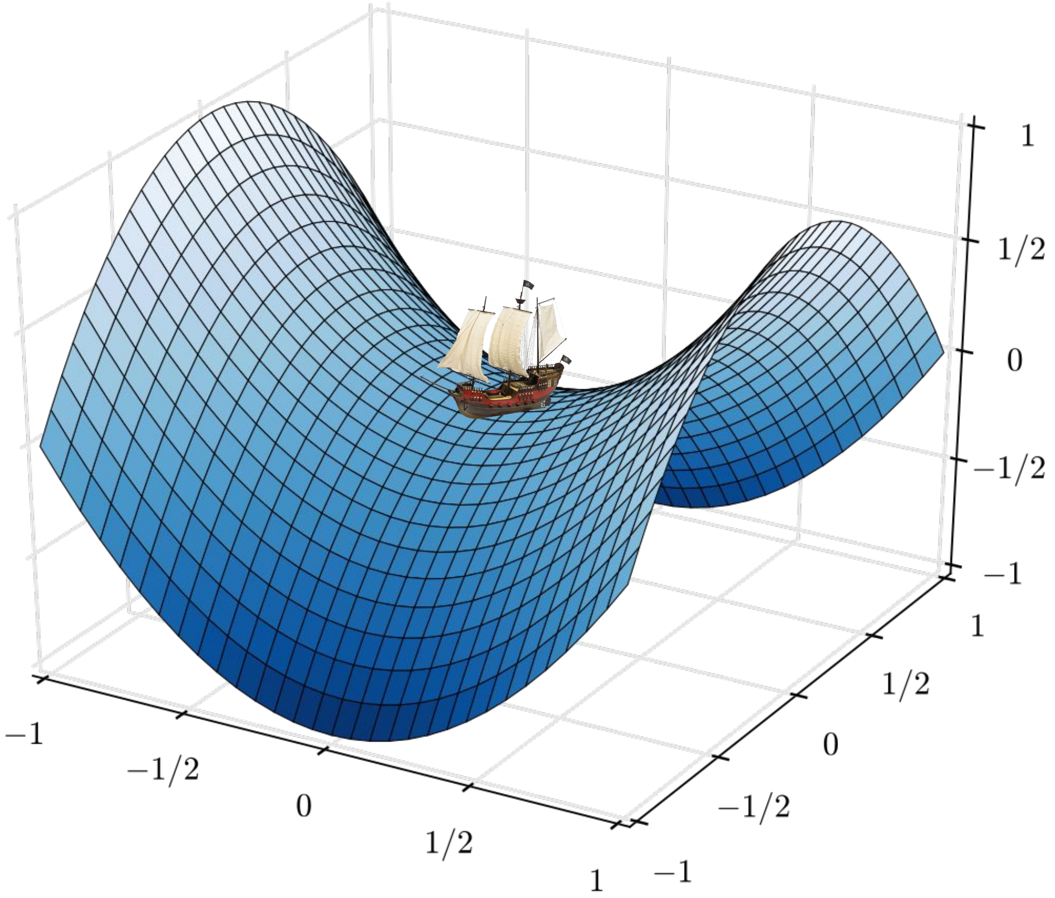
What does it mean to train a model?

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



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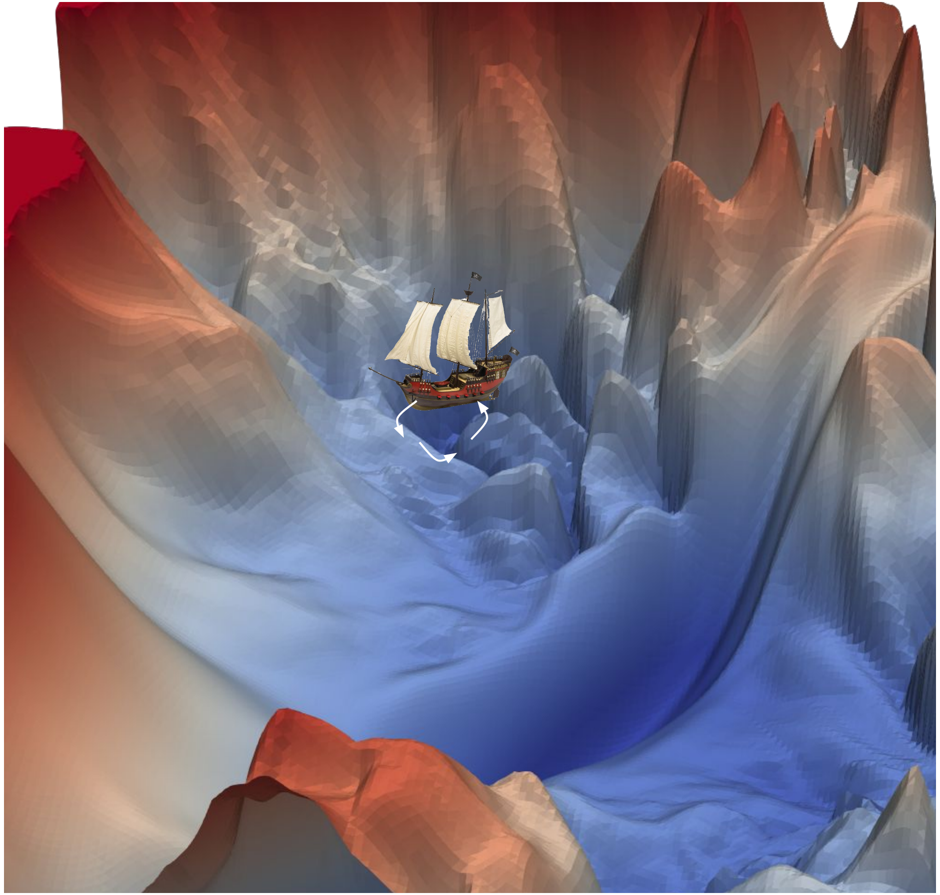
  - “Bad” minima



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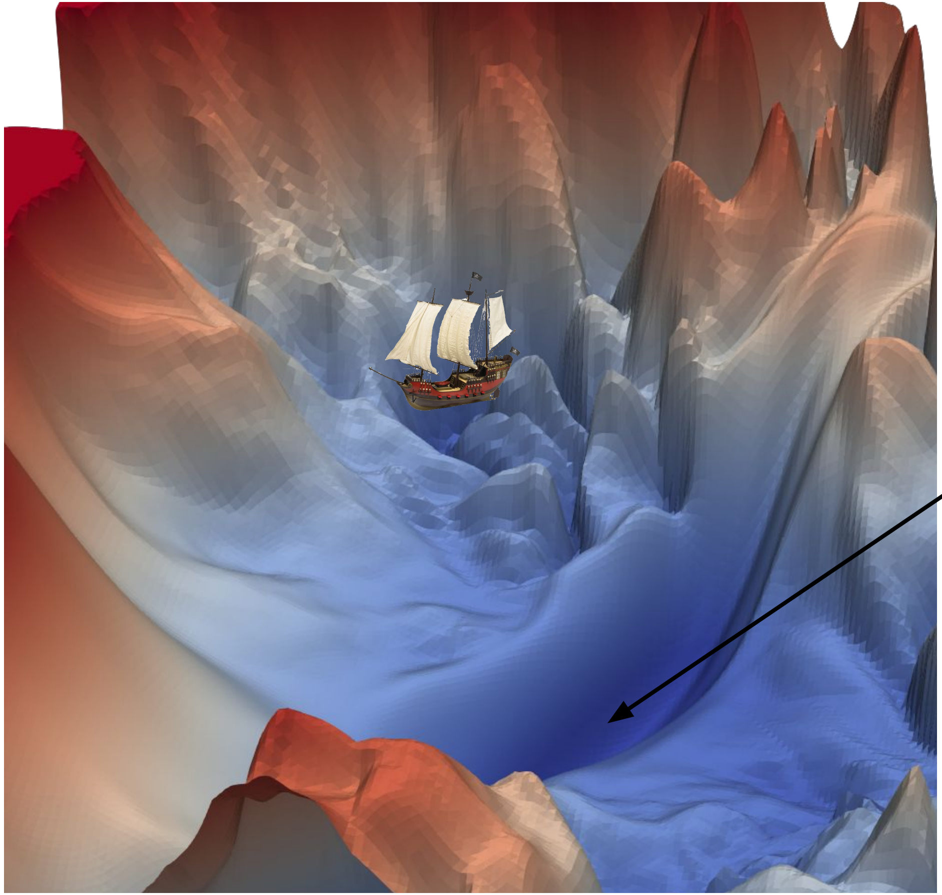

Better minima here

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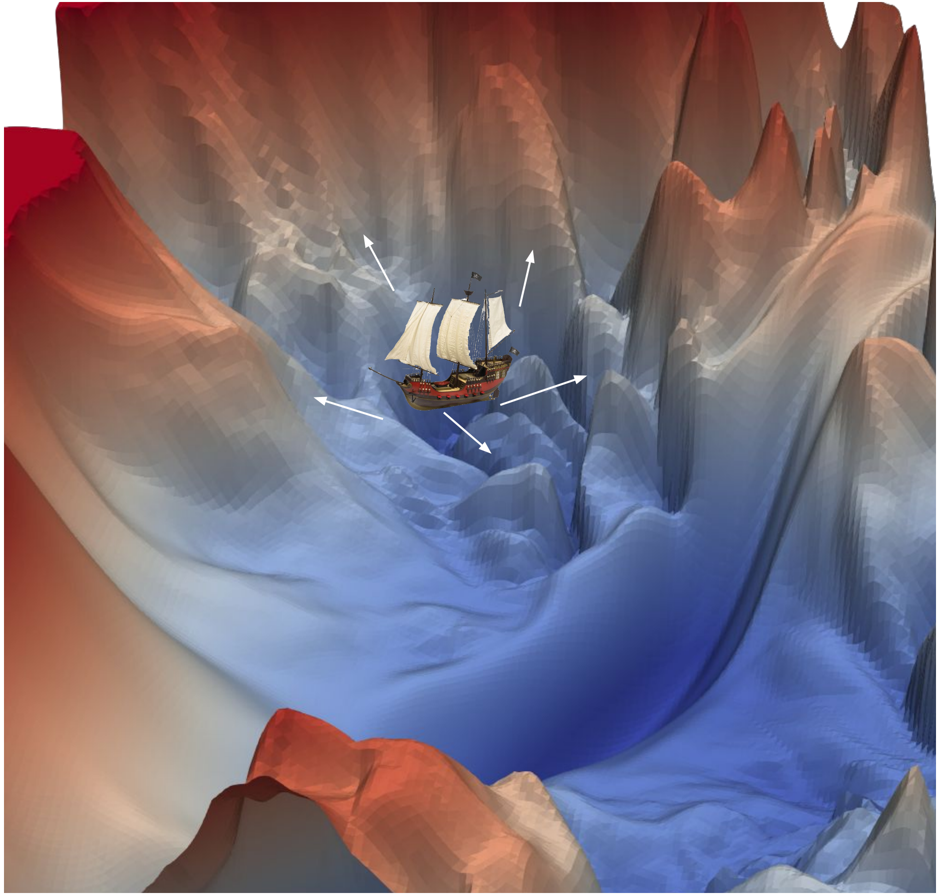

Small movement may incur massive loss increase

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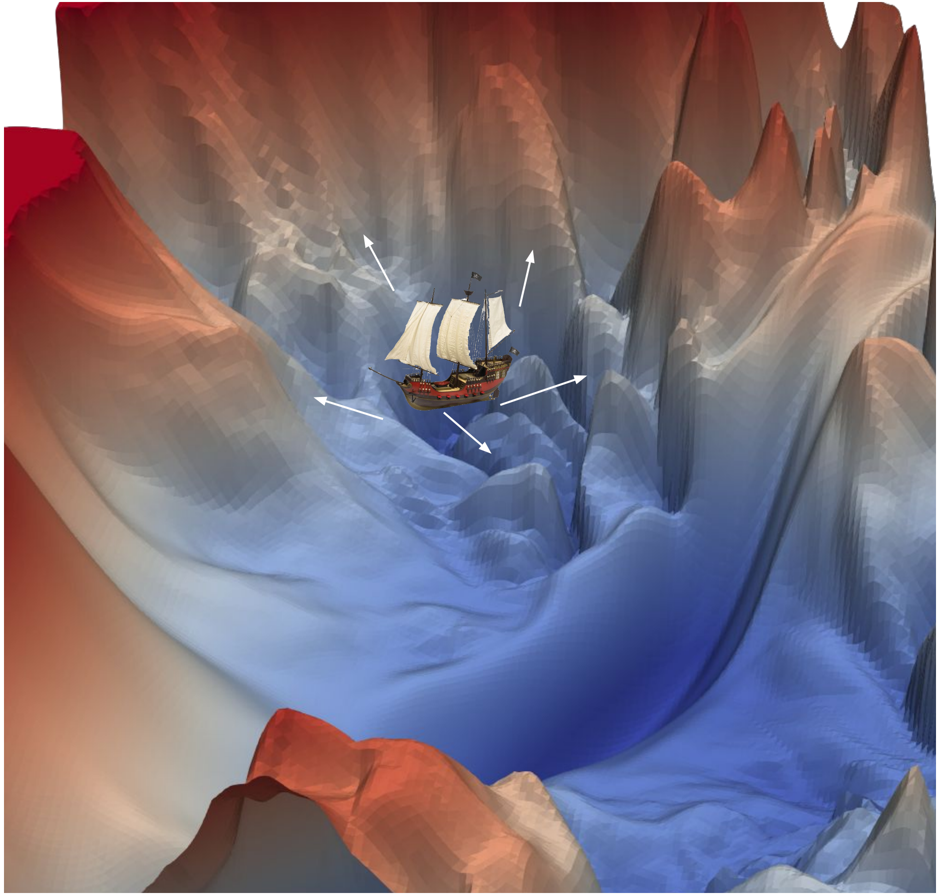

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  - Too flat
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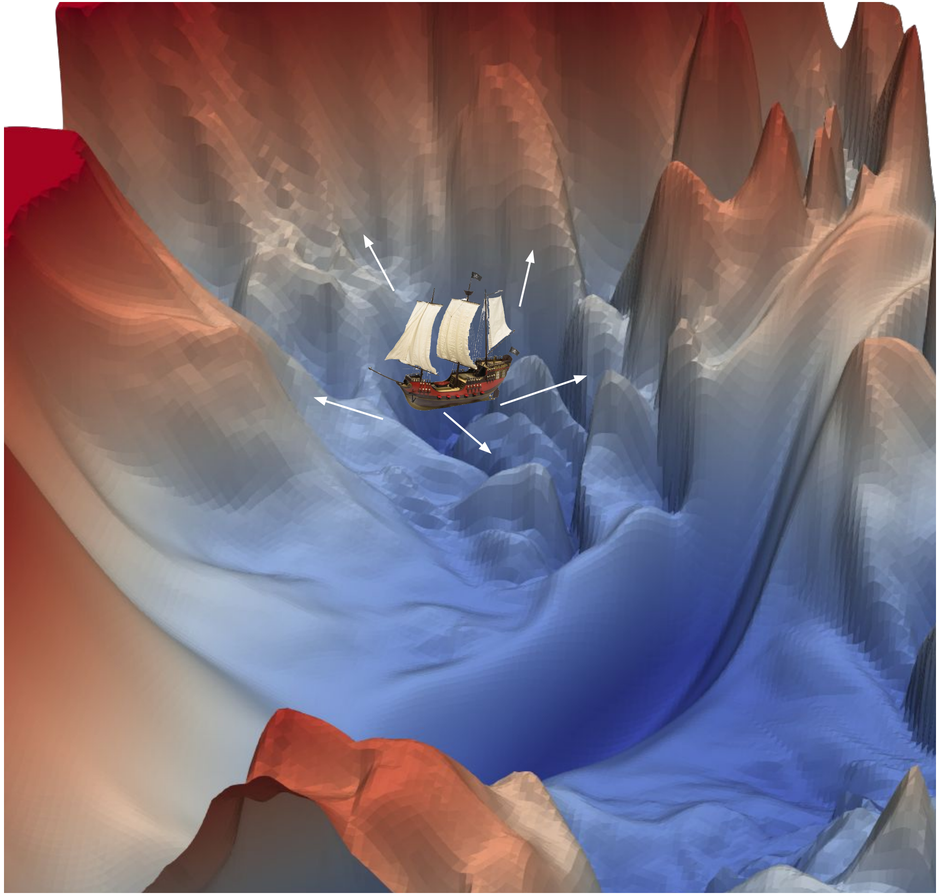
- Shallow
- Unstable
  - May not generalize well
- May not be as big as a problem as previously thought!



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Adjusting Learning Rates

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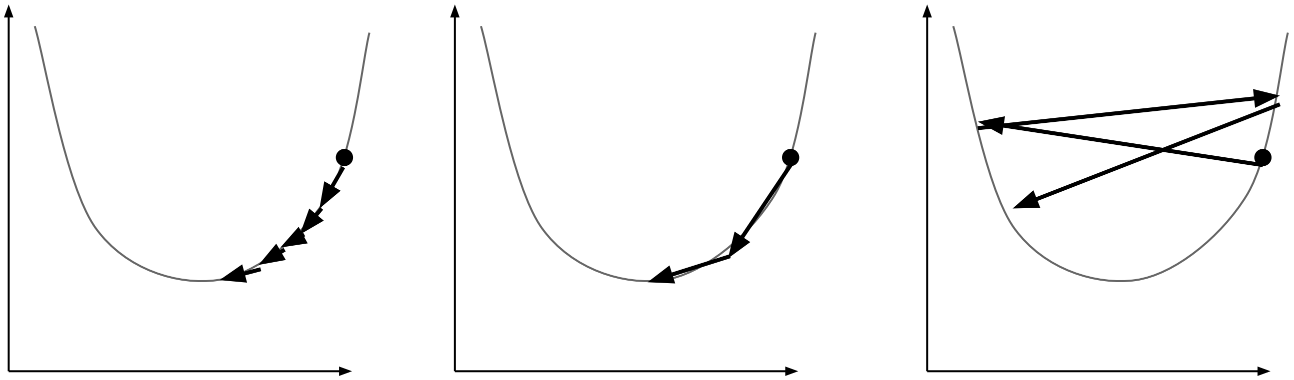

Low LR:
Too slow

Just right:
Good
convergence

High LR:
diverges

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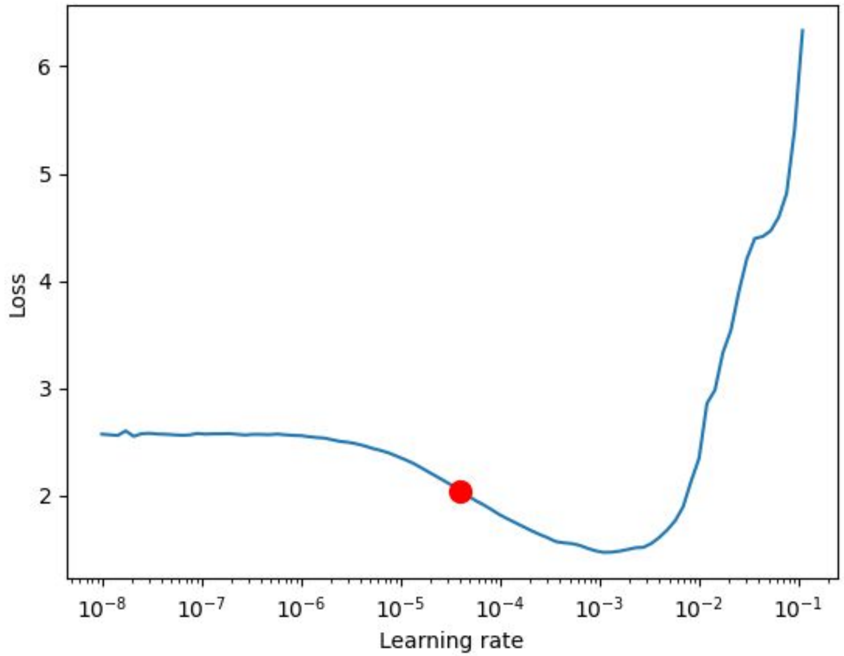

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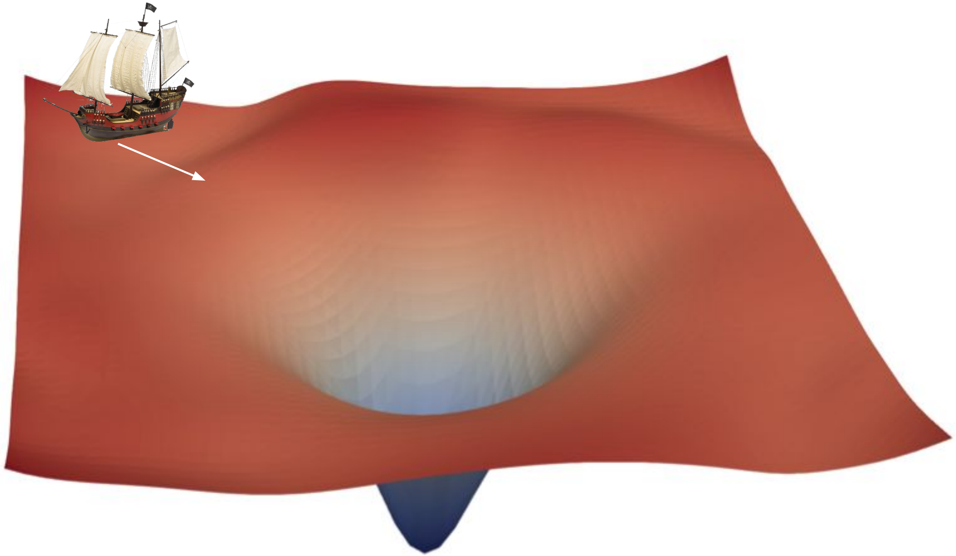

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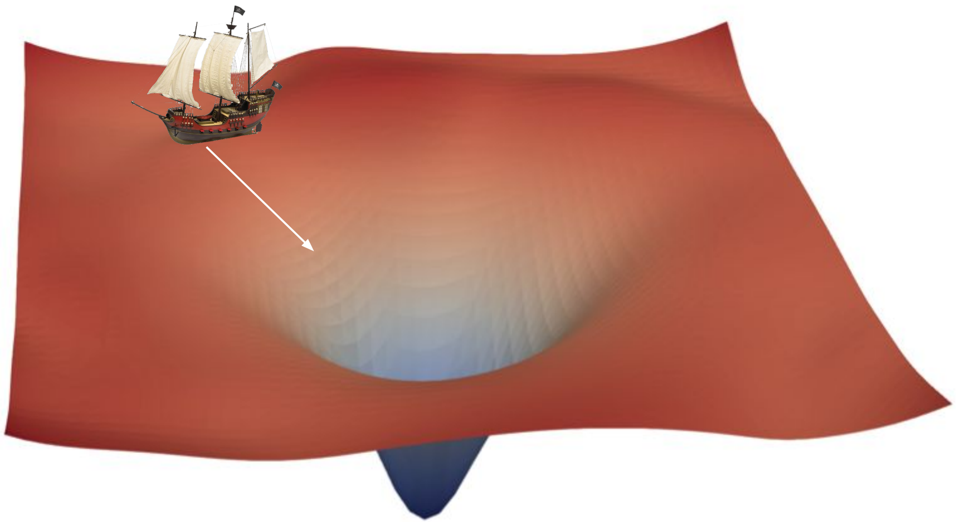

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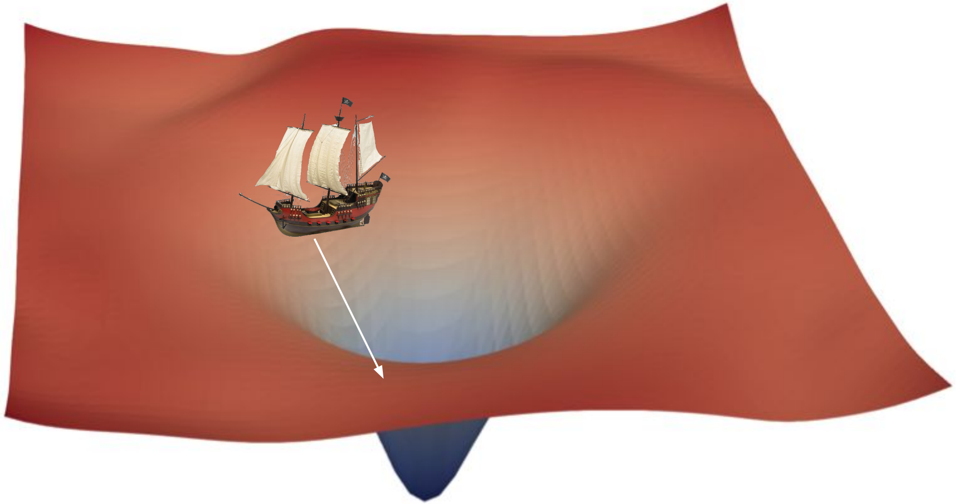

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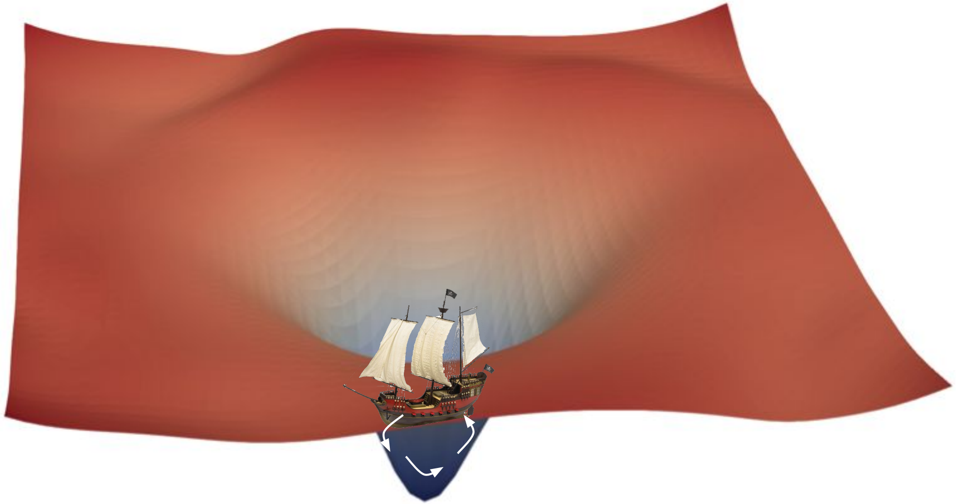

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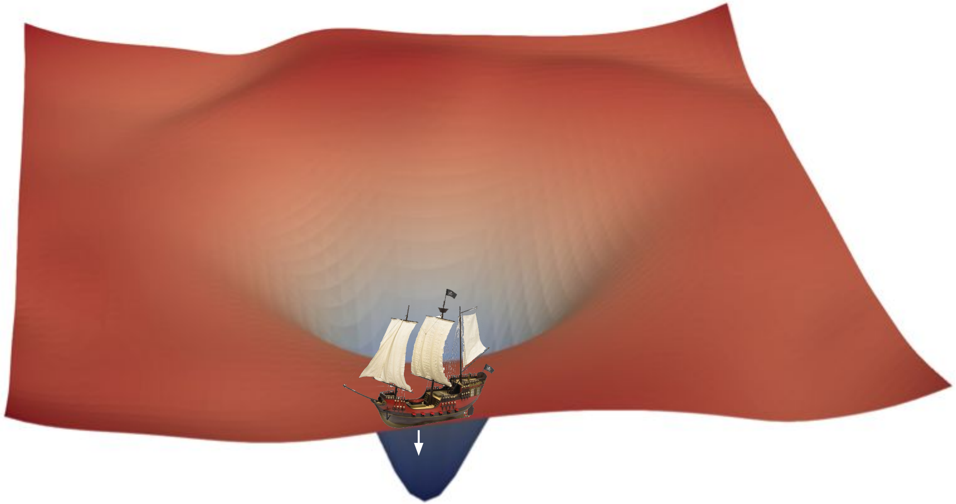

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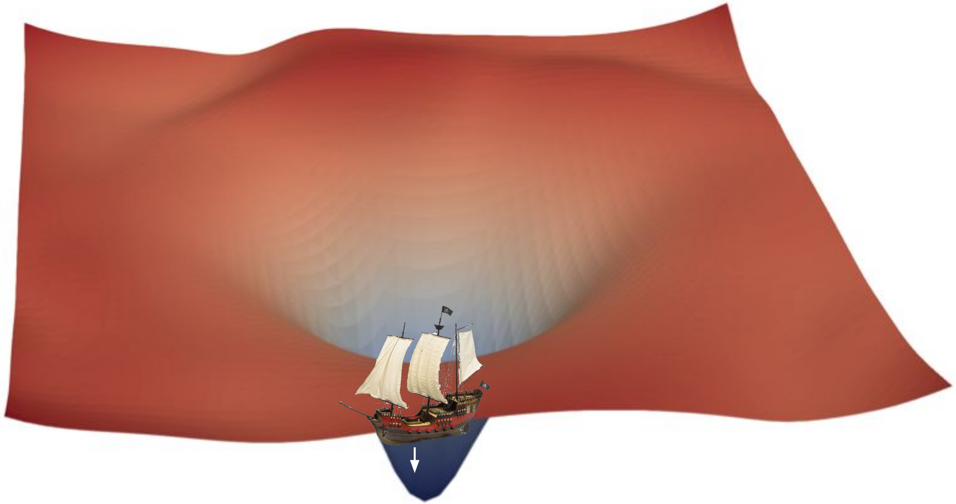

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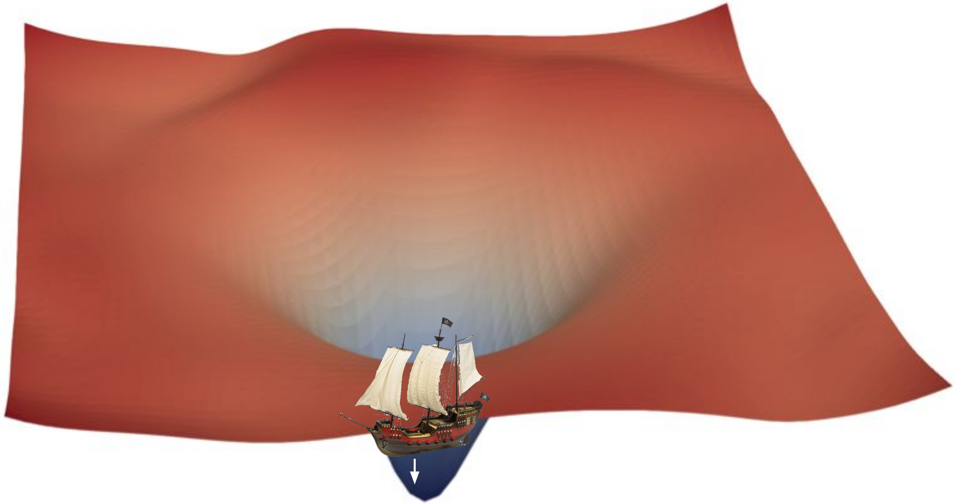

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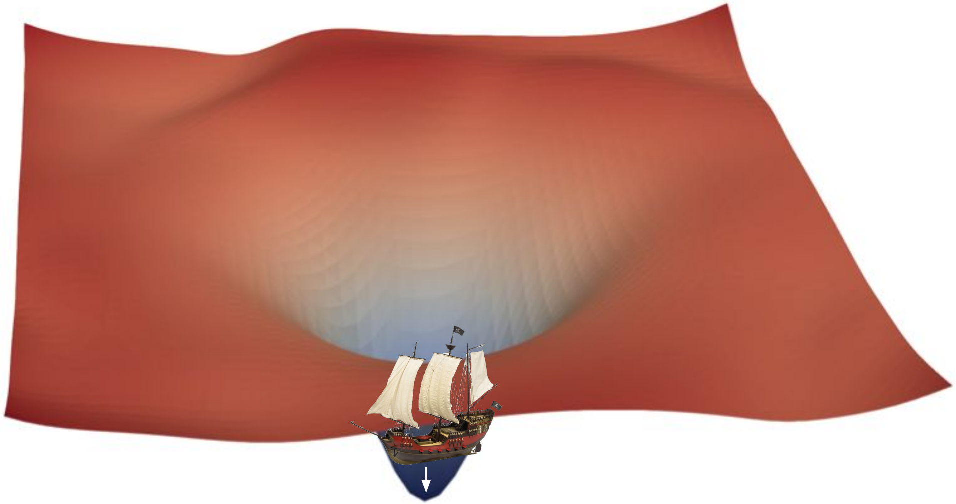

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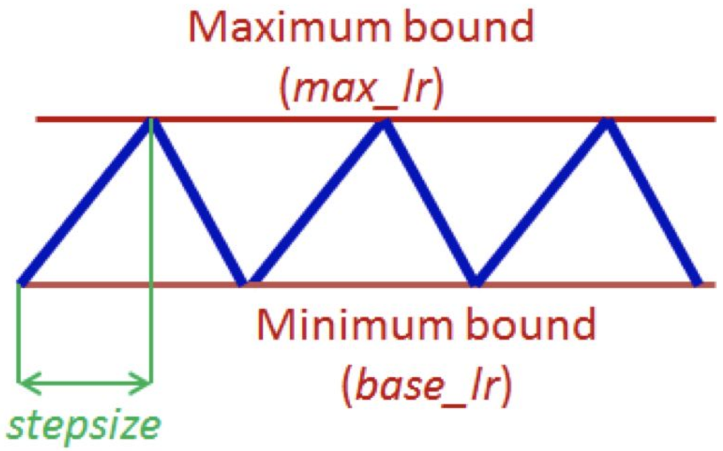

Cyclical Learning Rates for Training Neural Networks by Leslie Smith

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- Cyclical LRs
- And more!

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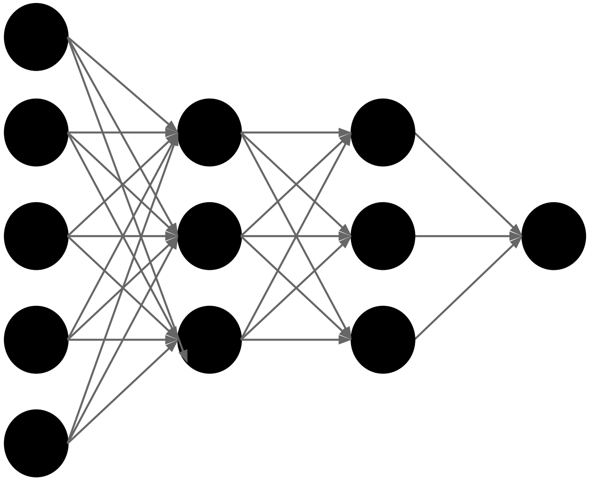

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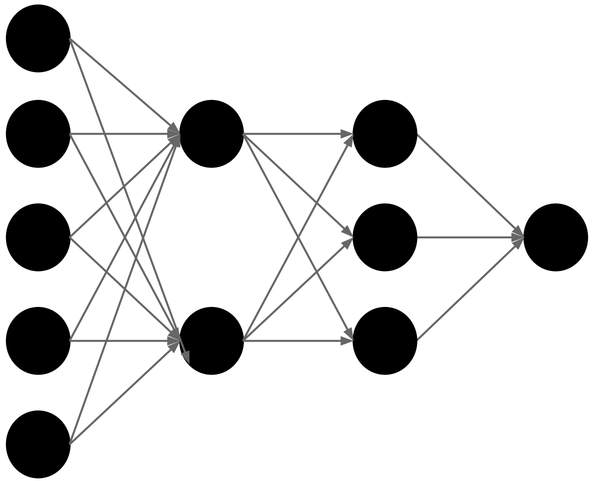

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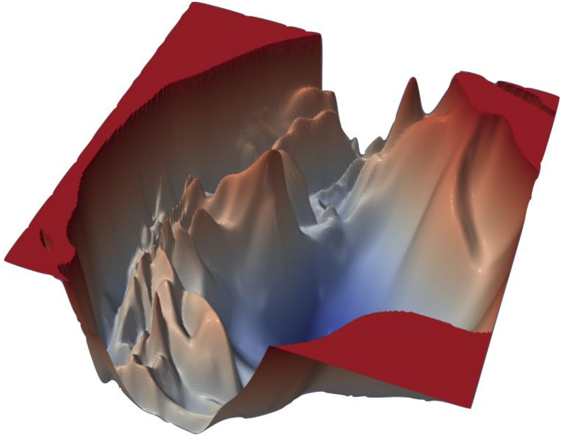

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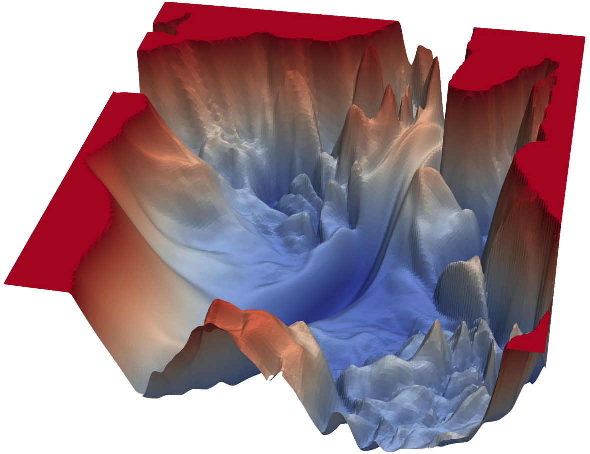

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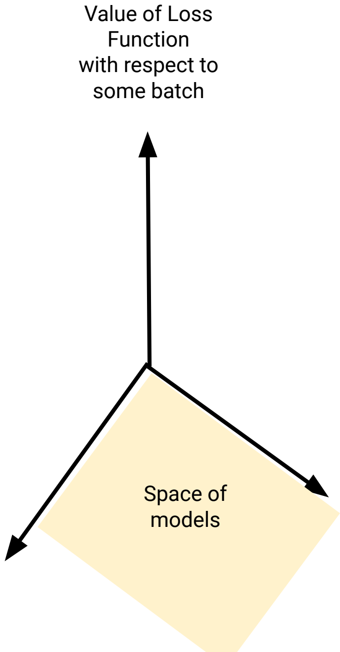

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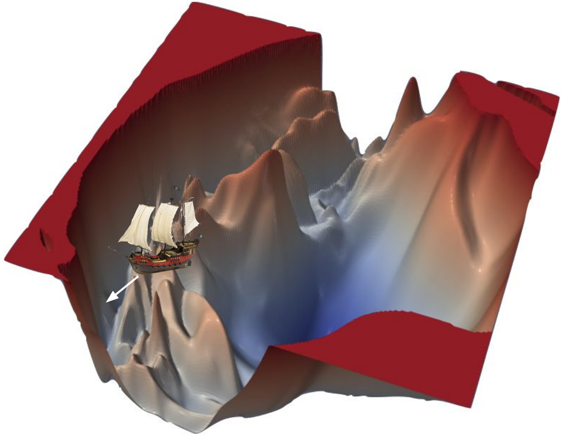

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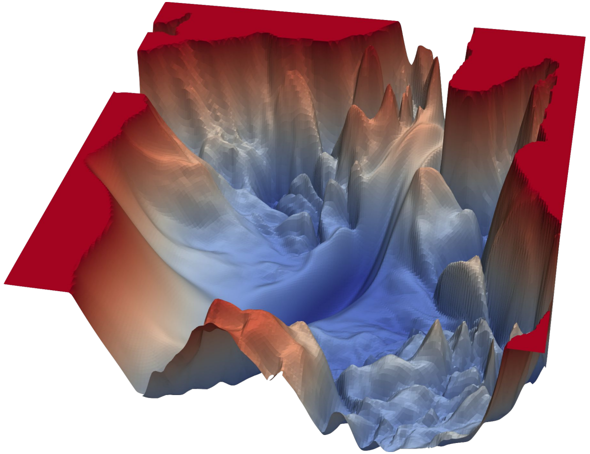

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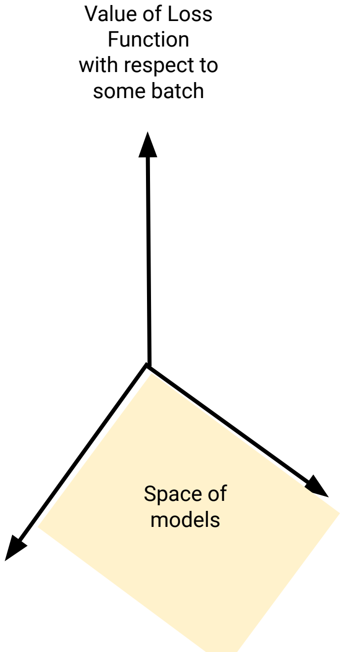

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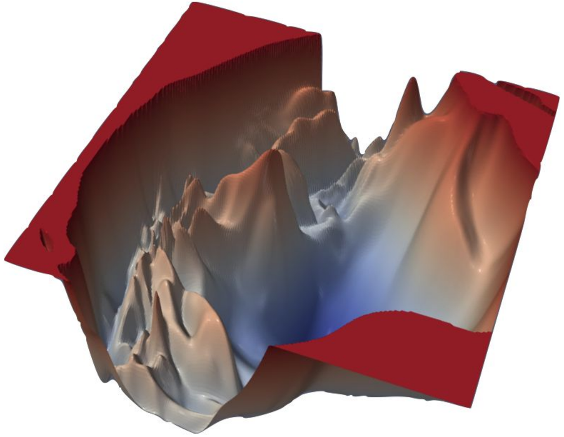

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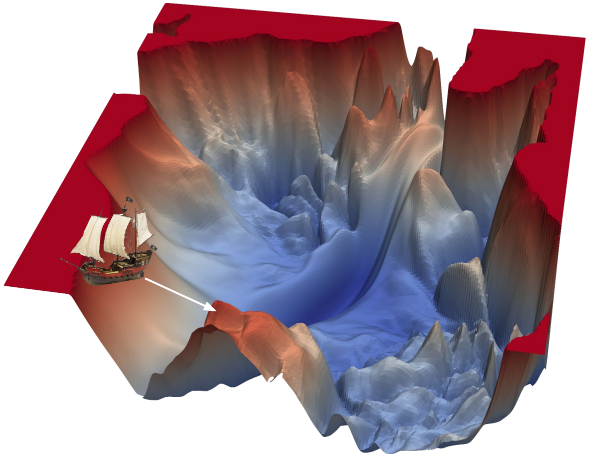

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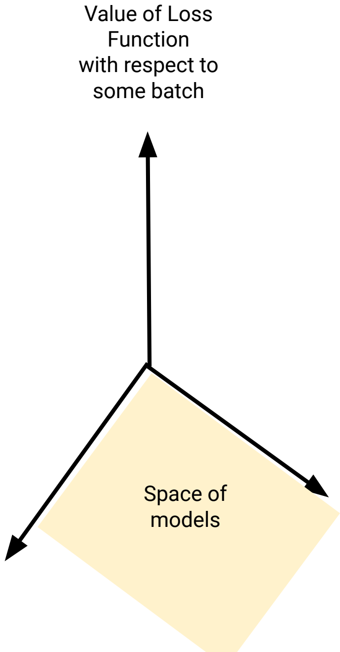

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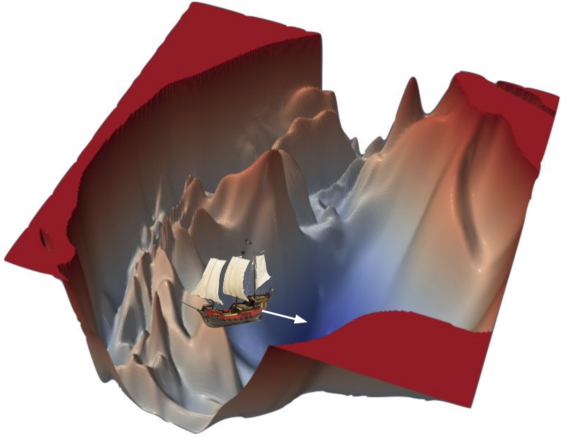

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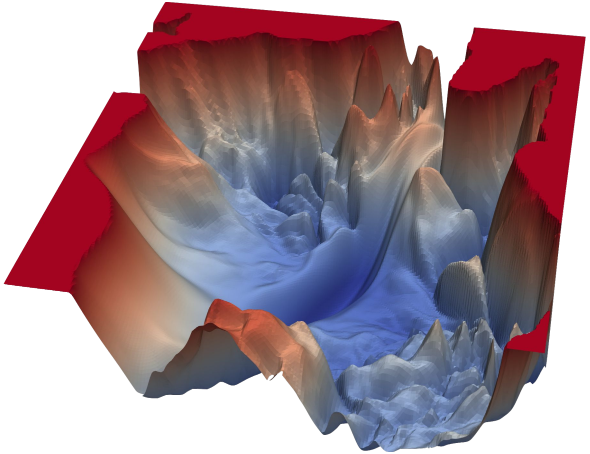

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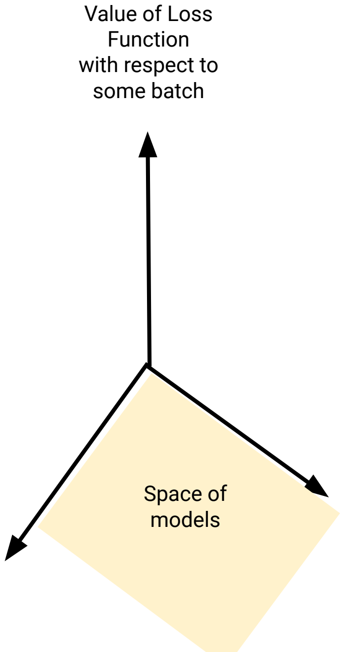

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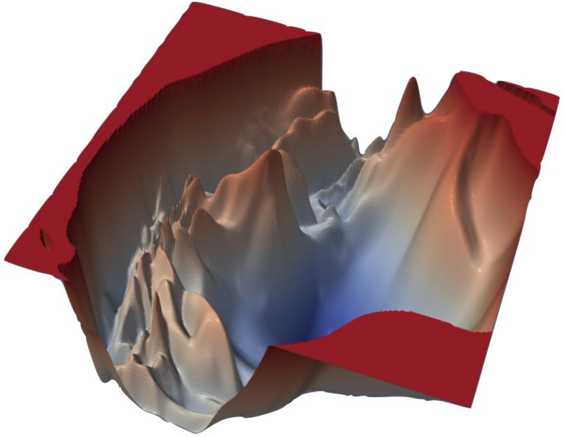

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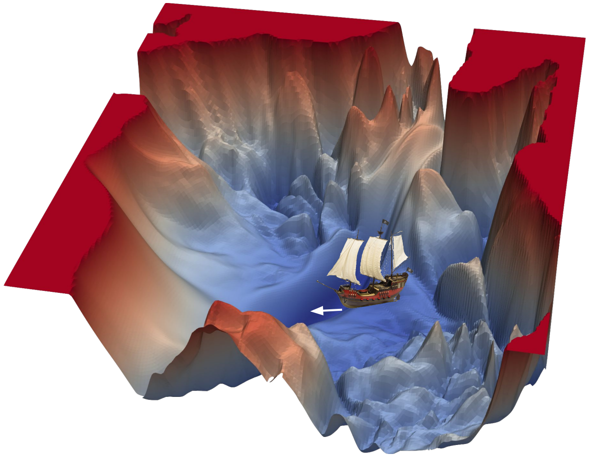

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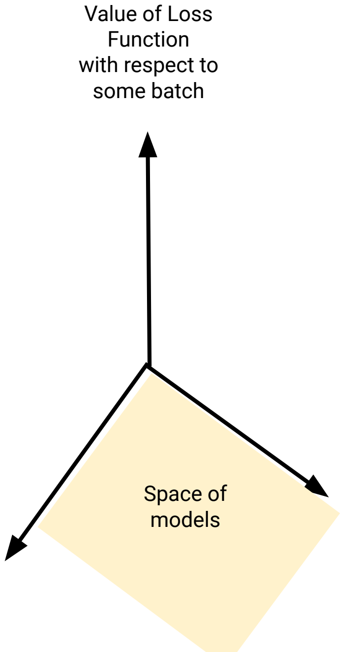

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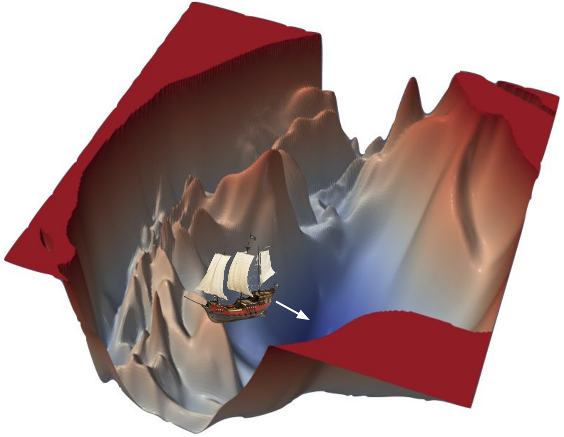

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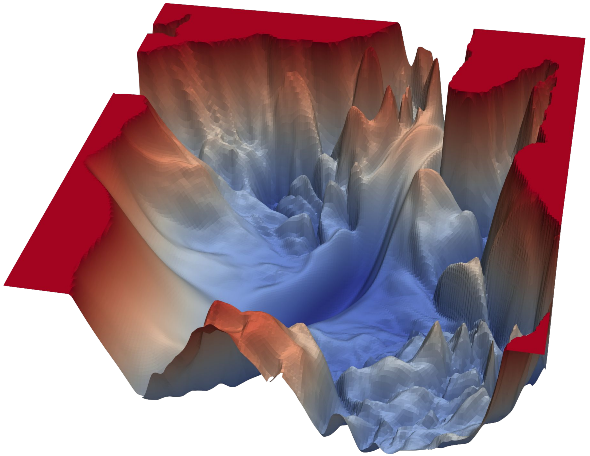
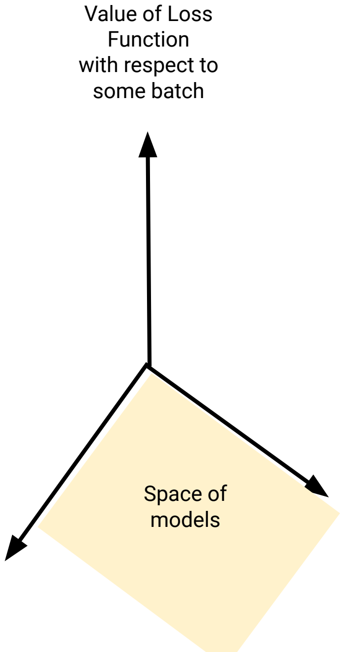


Loss values for second batch



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
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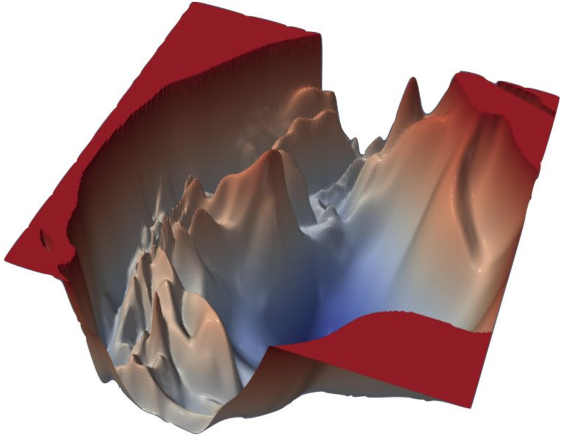
  - Form of regularization (adds noise)
  - Model updates more frequently



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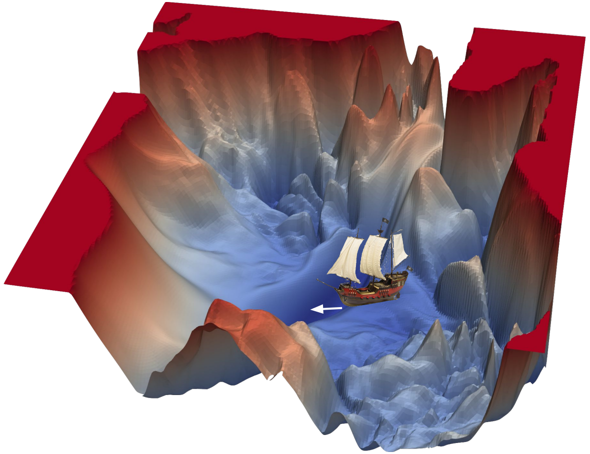

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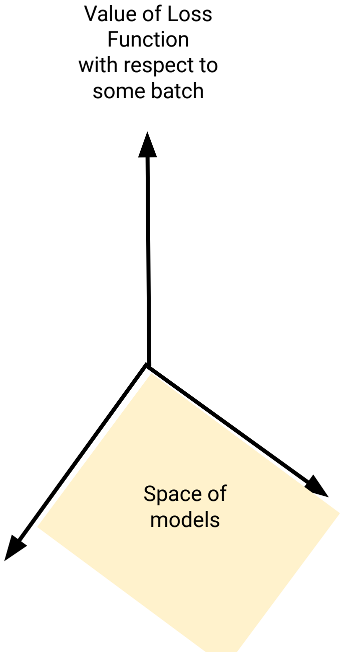

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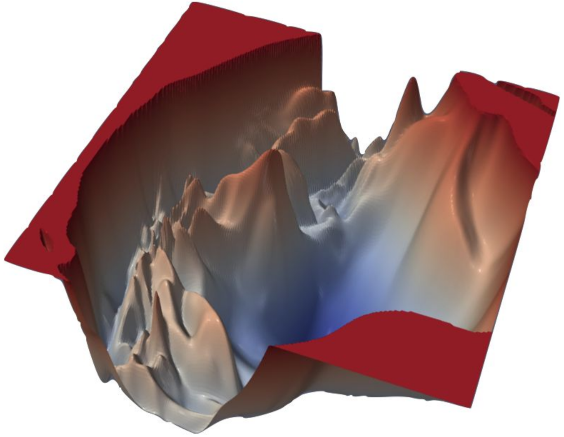

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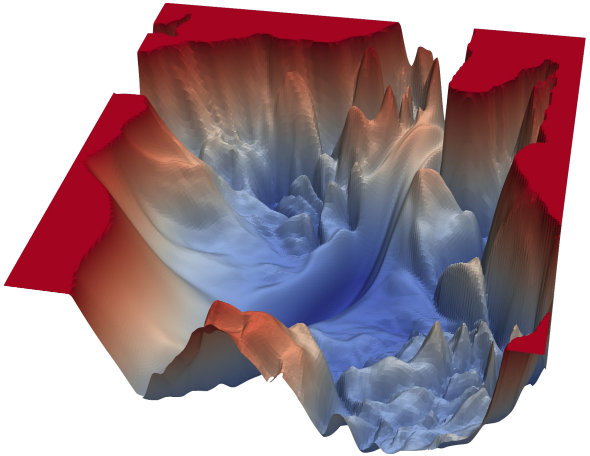

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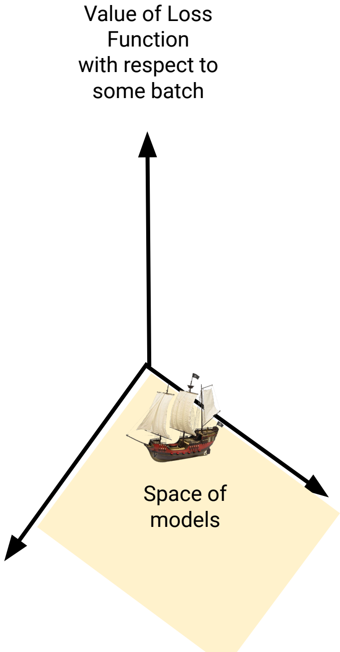


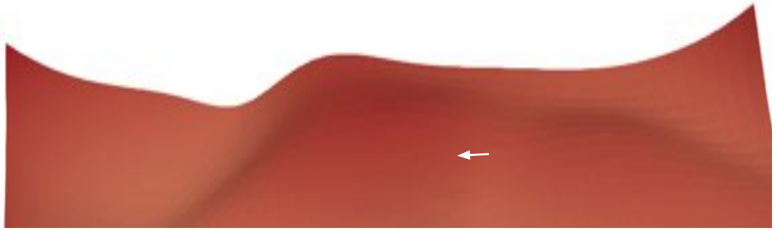
Normalization

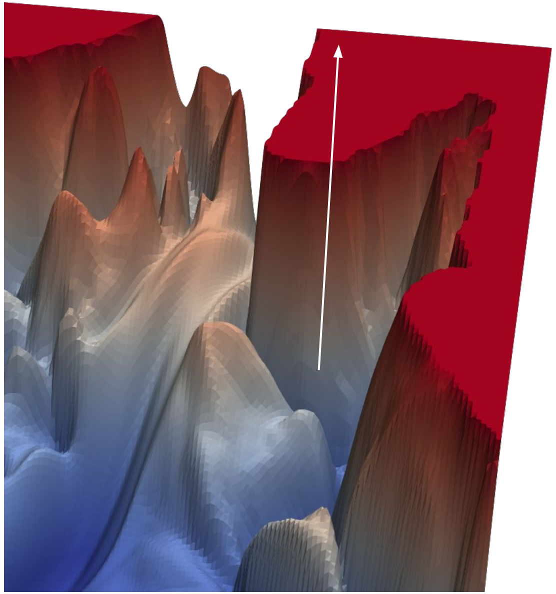
- Normalization of continuous variables can be extremely helpful for optimization, particularly for deep neural networks
  - Puts features on a similar scale
  - Potentially avoid vanishing/exploding gradients

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

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

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

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

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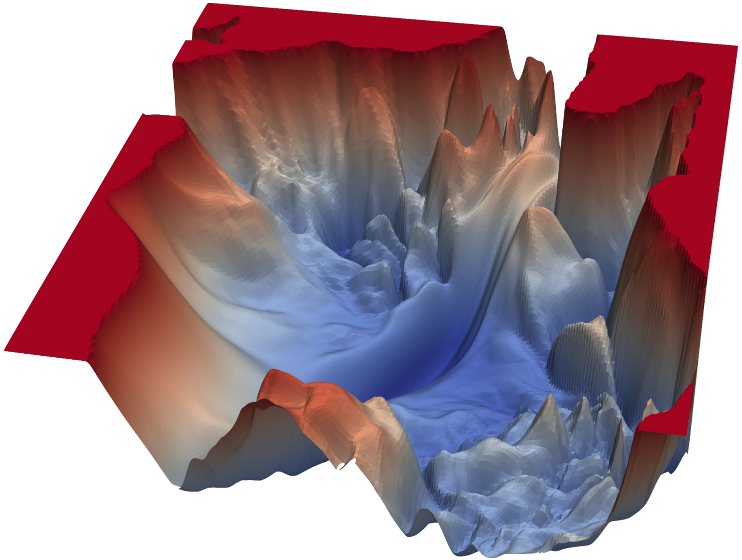
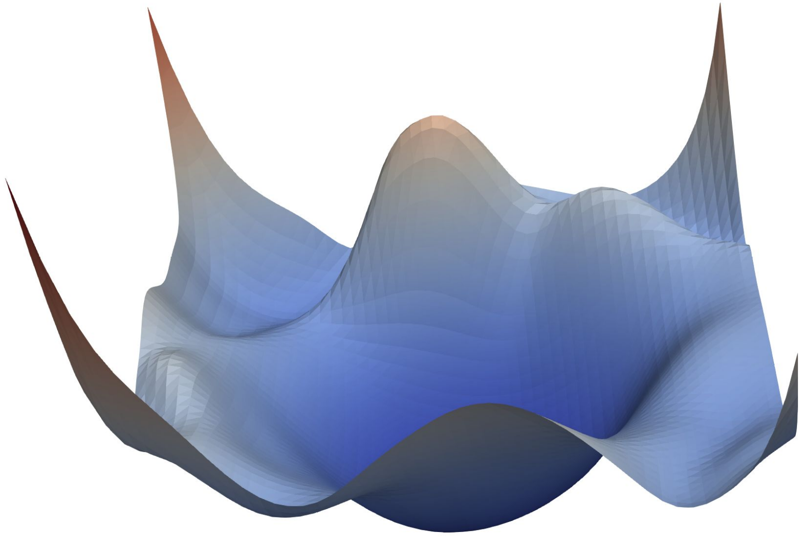
- Skip Connections (more on these later)



w/o skips



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Other things to tweak

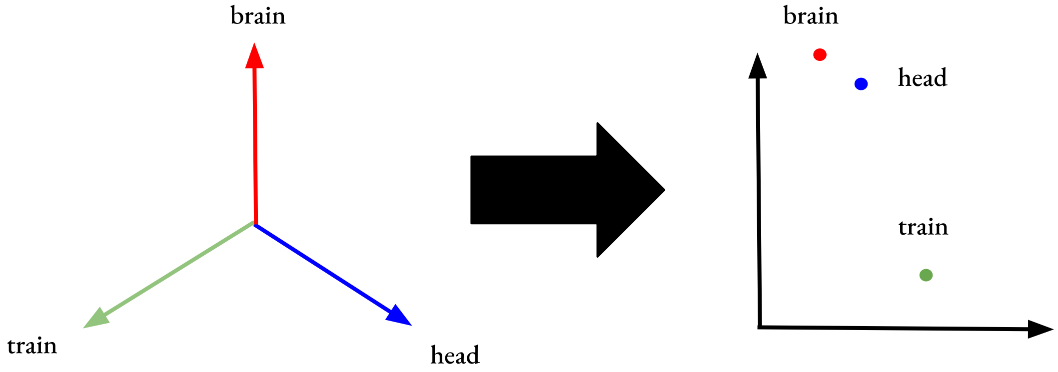
- Tons of different optimization algorithms
  - RMSprop
  - Adam
  - AdamW (adam with weight decay)
  - Adadelta
- Different methods for weight initialization
  - Idea: better/more stable starting points
- Change batch size
  - Spectrum from stochastic to one batch
  - Smaller batches usually results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

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

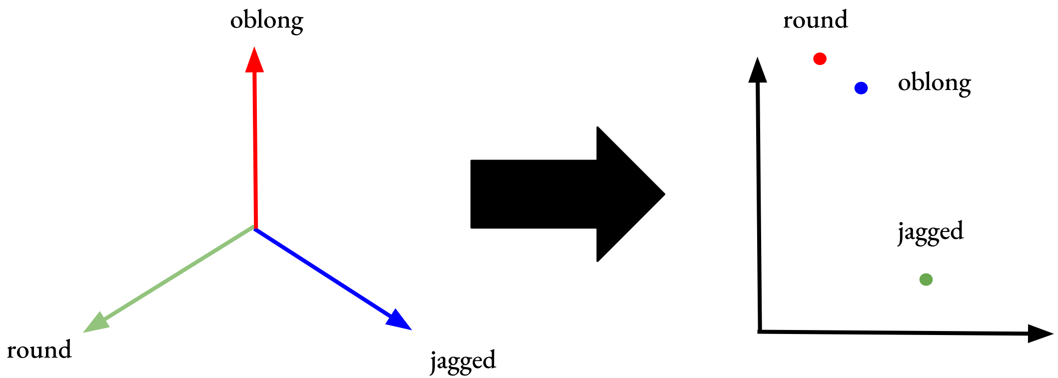
brain head train



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

$$\underset{\text{round}}{\begin{bmatrix}1\\0\\0\end{bmatrix}} \quad \underset{\text{oblong}}{\begin{bmatrix}0\\1\\0\end{bmatrix}} \quad \underset{\text{jagged}}{\begin{bmatrix}0\\0\\1\end{bmatrix}}$$



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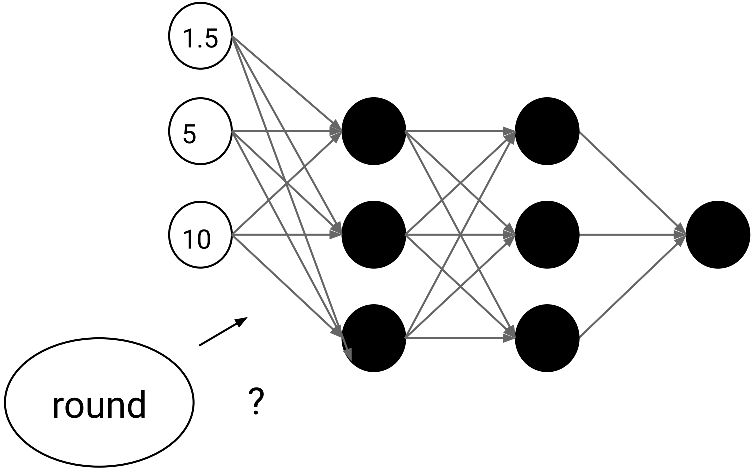

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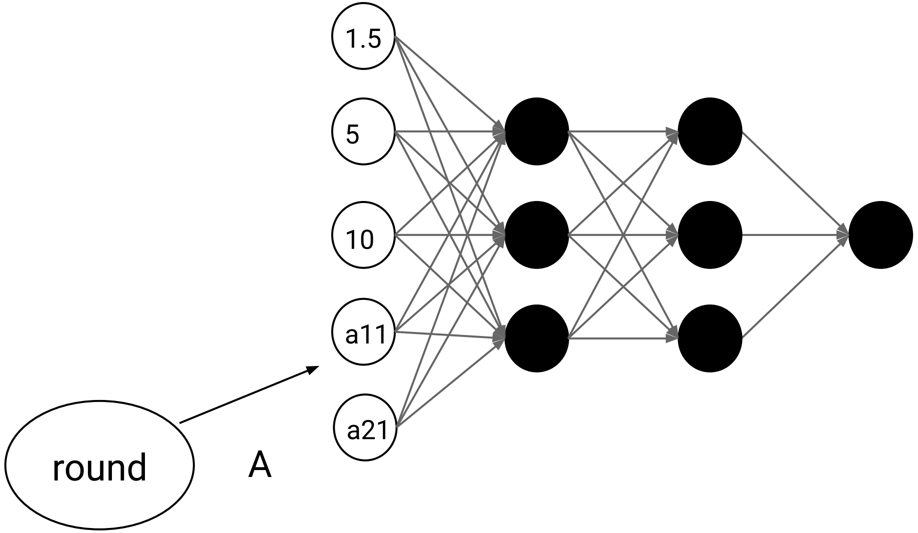

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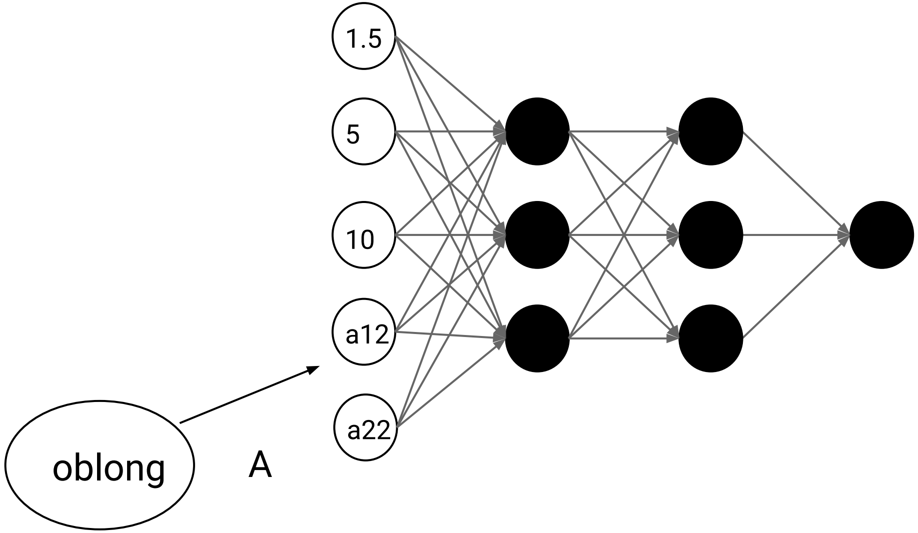

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  - How your model will be used
  - How interpretable you want your model to be
- The answer to “how many layers” or “how many nodes” is usually determined by
  - What other people have had success with
  - Your own experiments with different architectures

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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