IN5550: Neural Methods in Natural Language Processing
Sub-lecture 2.3
Training as optimization

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Contents

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- It is averaged over all training instances and gives us estimation of the model 'fitness'.
- $\hat{\theta}$ is the best set of parameters:

$$\hat{\theta} = \arg\min_{\theta} \mathcal{L}(\theta) \tag{1}$$

Training as optimization

What is the intuition behind a loss function?

Training as optimization

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- Let's take a simple example

Training as optimization

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- WHITEBOARD EXAMPLE

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What are the main classes of NLP tasks?

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Training as optimization

What are the main classes of NLP tasks?

- regression
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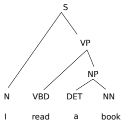
- structured prediction

Training as optimization

Given x,	predict y	
A sentence That's great!!!!!	**How positive is it** (from 1-10) 9.5	**regression** (scalar)
A sentence That's great!!!!!	**Pos. or Neg.?** Positive	**binary classification** (two choices)
A tweet That was fun. Vale la pena!	**Which langs.?** English Spanish	**multi-class classification** (many choices)
A question What is the most expensive spice in the world?	**A ranked list of searches** 1) Saffron-is-expensive 2) Truffles-are-crazy	**ranking** (ranked list of available choices)
A sentence I read a book	**Its syntactic parse**  	**structured prediction** (millions of choices)

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Training as optimization

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6. Ranking losses, etc, etc...

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- For that, we minimize both the loss and the regularization term $R(\theta)$:

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- Common regularization terms:
  1. L_2 norm (*Gaussian prior* or *weight decay*);
  2. L_1 norm (*sparse prior* or *lasso*)

Training as optimization

Now we can measure model performance. How can we change our parameters θ to improve?

1. We could just randomly change some of the parameters and see if the result is better (hill climbing algorithm)...

Training as optimization

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2. or we could be smarter about it (gradient-based methods).

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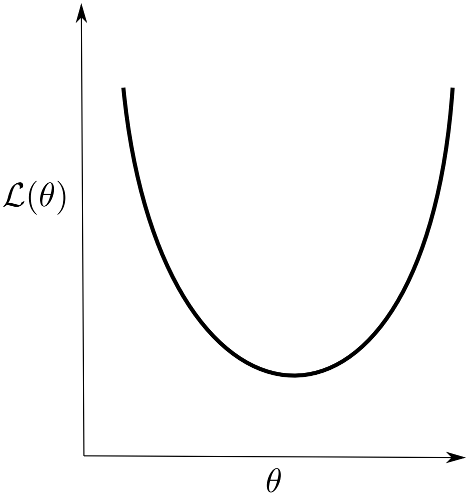
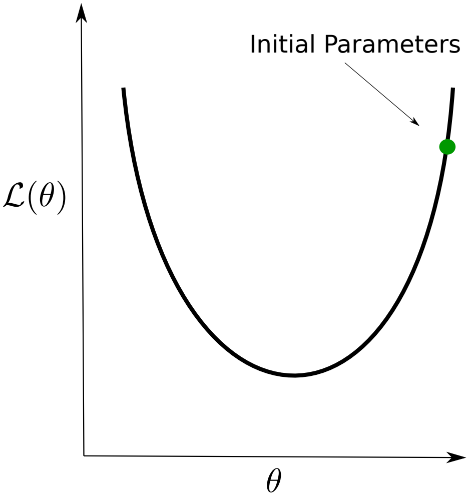
Convexity

- Convex functions: a single optimum point.
- Non-convex functions: multiple optimum points.

Training as optimization



Training as optimization



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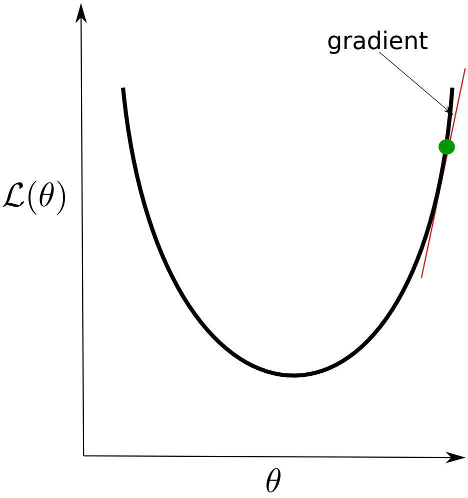

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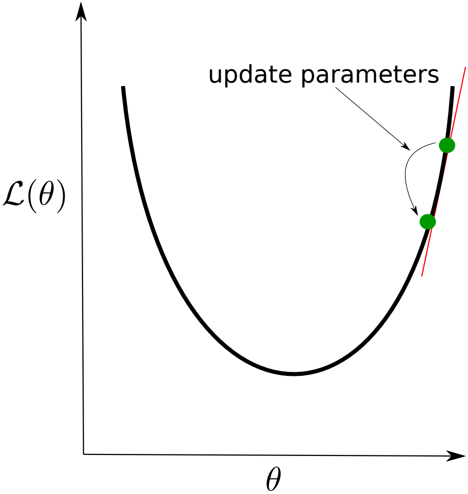

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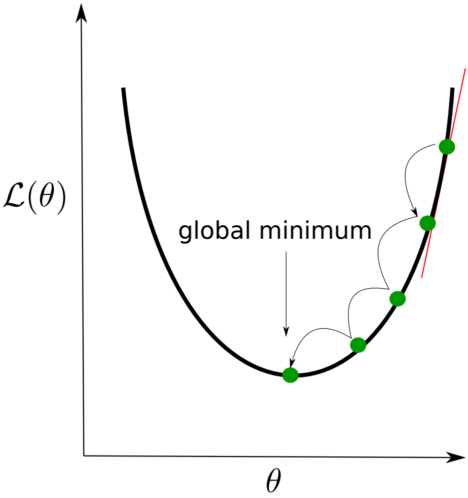
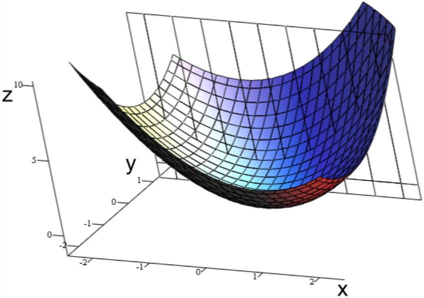
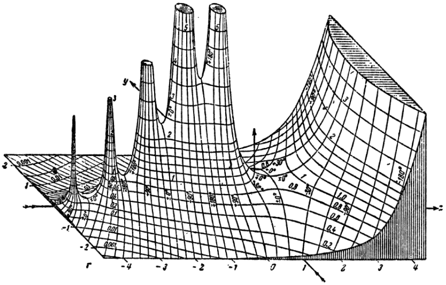


Error surfaces of convex and not-convex functions:



Convex function



Non-convex function

Training as optimization

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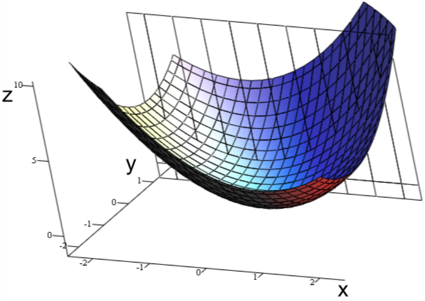

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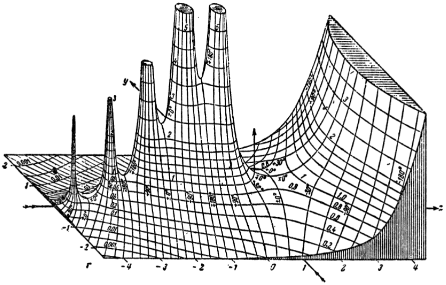

Non-convex function

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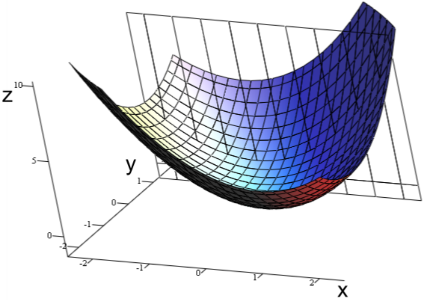

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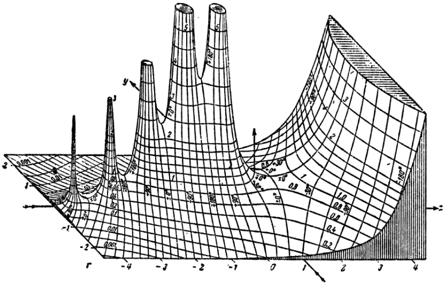

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- With non-convex functions, optimization can end up in a local optimum.
- Linear and log-linear models as a rule have convex error functions.

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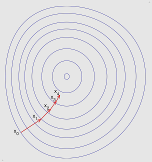
- the update is scaled by the learning rate n (can be decaying over the training time),
- repeat until convergence.



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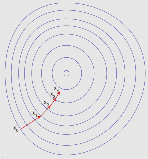

Instead of one instance, batches can be used (more stable and computationally efficient).

Training as optimization

Other gradient-based optimizers:

- Momentum
- AdaGrad
- RMSProp
- Adam
- AdamW
- etc...

All implemented in the libraries we are going to use: *PyTorch*, *Scikit-Learn*, *TensorFlow*, *Keras*, etc.

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So far so good. But what are the limitations of linear models? See the next sub-lecture 2.4!