Deep Learning Tutorial

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Agenda

- **Day 1:**

  Introduction to Machine Learning

  Symbolic Computation with Theano

- **Dia 2**

  Convolutional Neural Networks

  Dia 3

  Transfer Learning

Introduction to Machine Learning

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Learning functions from data

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- **Supervised Learning**
  - Classification: SPAM classification, object recognition
    - Categorical output: $y = f(\mathbf{x}) \qquad y \in \mathcal{Y}$

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    - Real output: $y = f(\mathbf{x}) \qquad y \in \mathbb{R}$

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  - Regression: House pricing, forecasting
    - Real output: $y = f(\mathbf{x}) \qquad y \in \mathbb{R}$

- **Unsupervised Learning**
  - Density estimation, clustering, anomaly detection

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y **is the correct class**

The objective is to learn a mapping (function) from x to y:

$$y_{\text{pred}} = f(x)$$

That generalizes to unseen examples

Supervised learning - classification

Toy example:

2-class problem: classify fish between bass and salmon

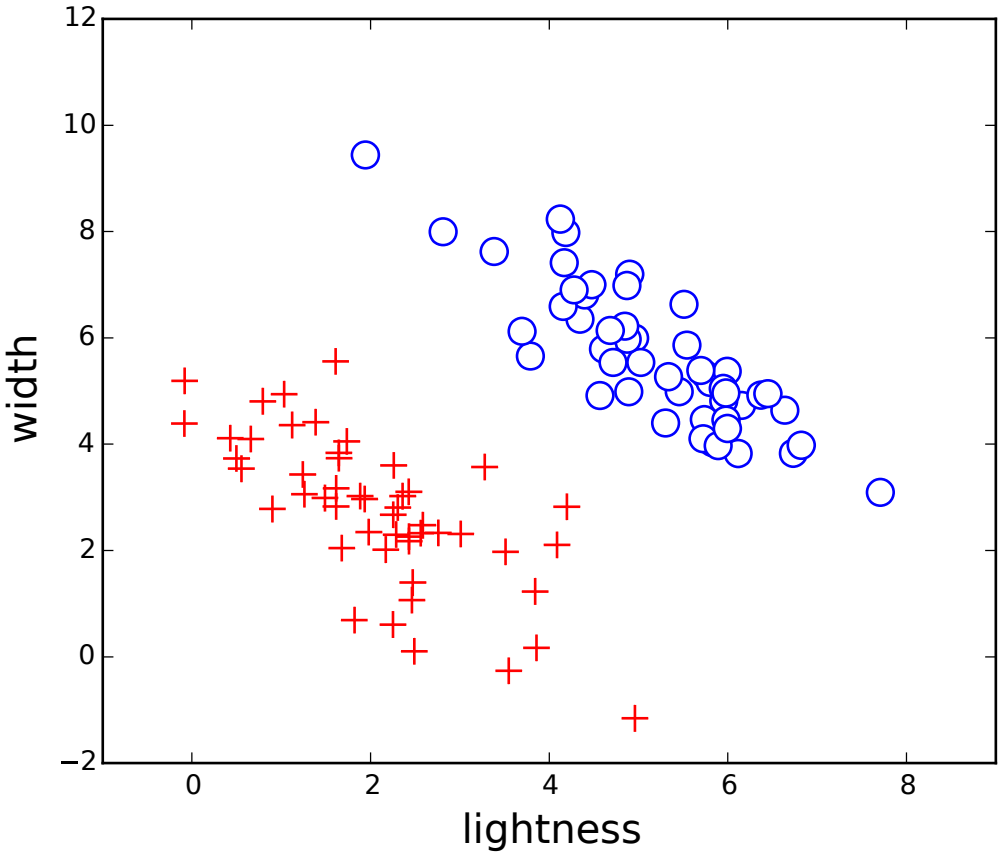
$$y \in \{\text{bass}, \text{salmon}\}$$

Two measurements: width and lightness

$$\mathbf{x} = \{x_1, x_2\}$$

Supervised Learning – toy example

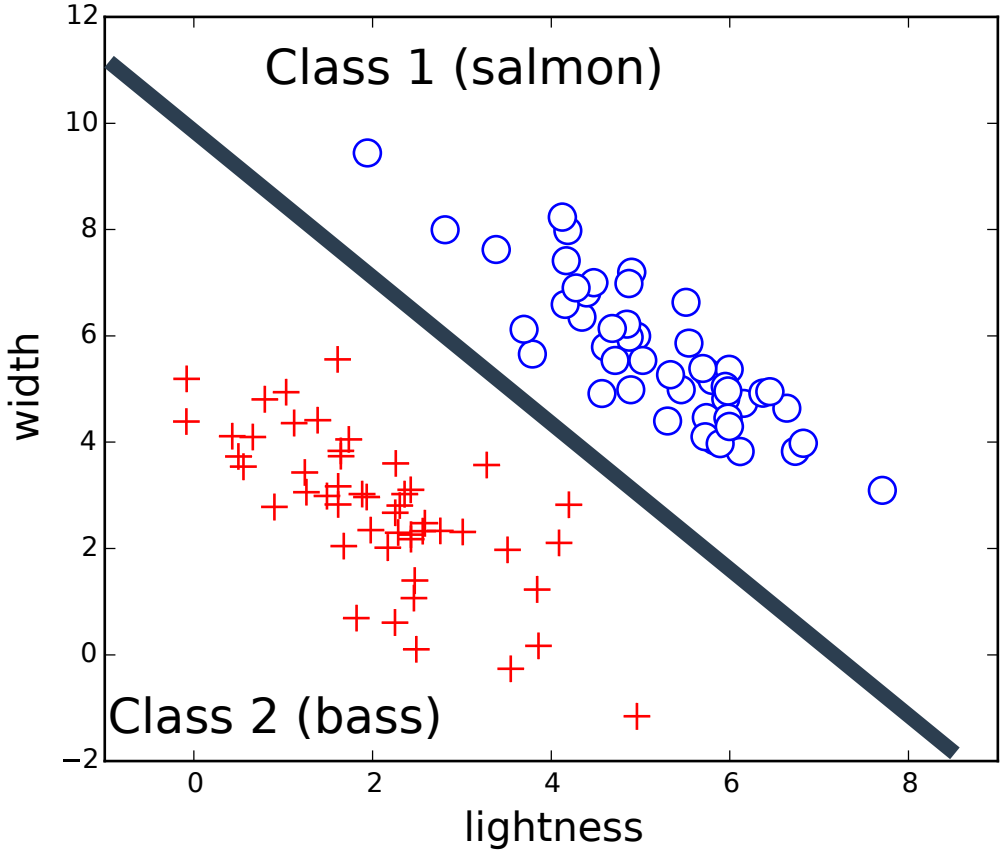
Acquired 50 examples from each class:



Supervised Learning – toy example

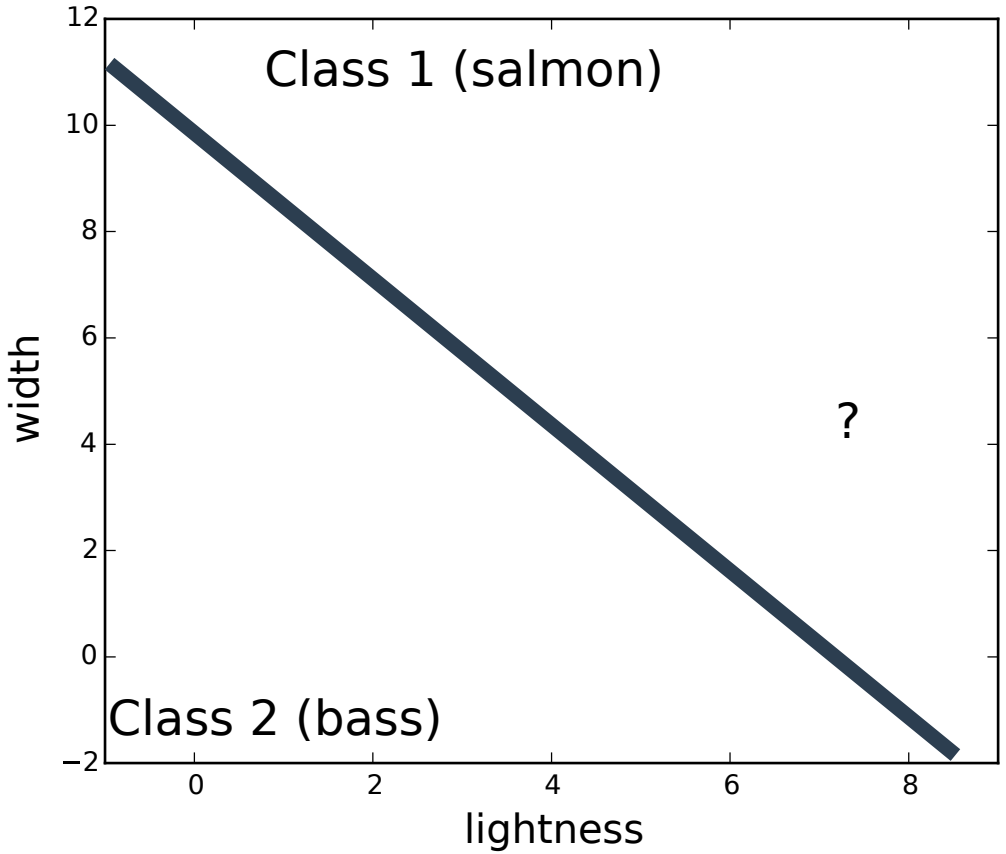
Learn a model

(in this case: a parametric linear model)

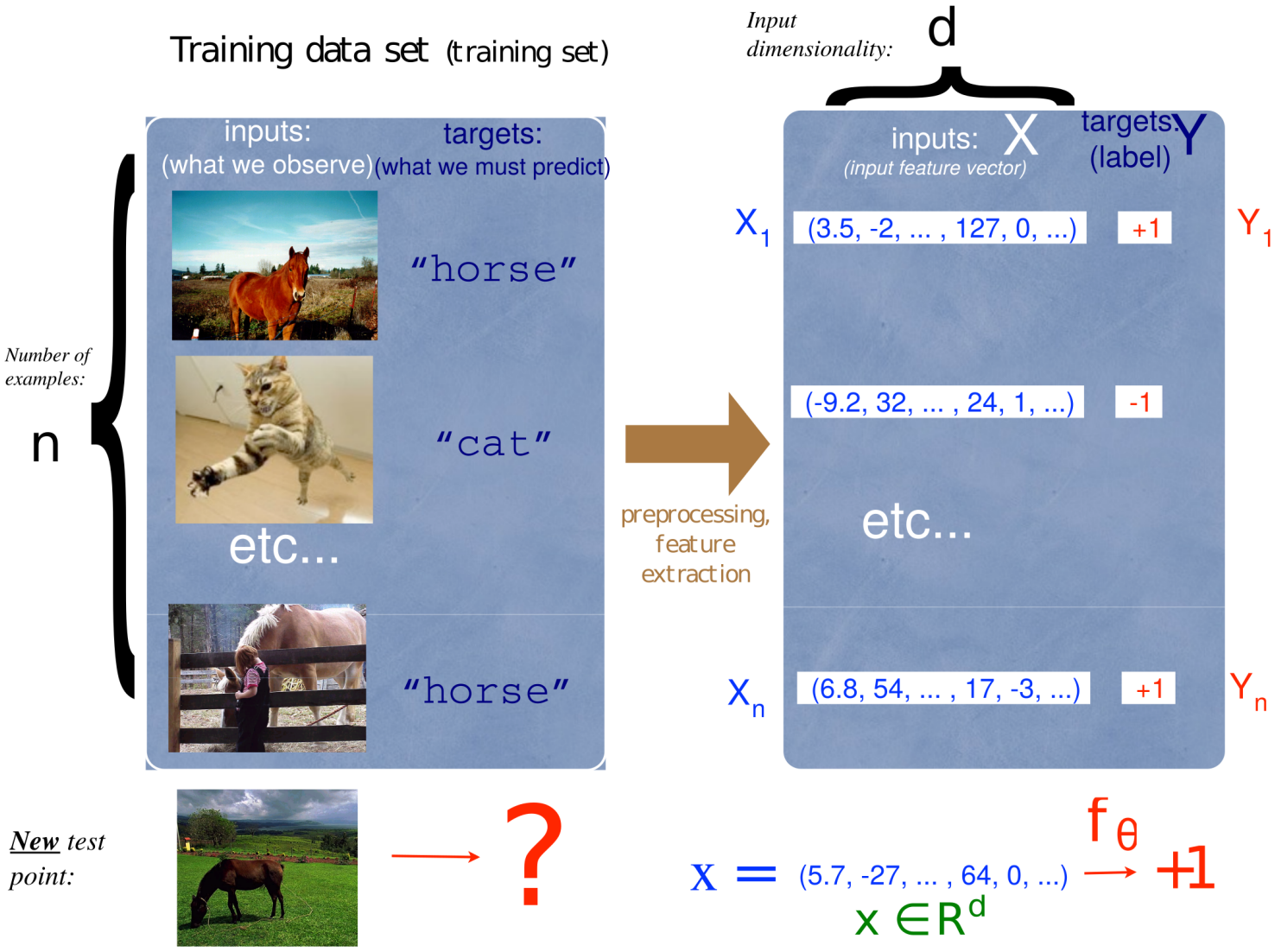


Supervised Learning – toy example

Generalize to new examples



Supervised Learning



Slide from Pascal Vincent

Supervised Learning

PLANE

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PLANE

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Slide de
Yann Lecun

3 basic elements for Machine Learning

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Usually a parametric family (e.g. “Logistic Regression”)

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A way to evaluate the quality of f

Loss function → the lower, the better is the model

A way to search for the best f

Optimization procedure → how to change the parameters to get a lower loss

Logistic Regression

Logistic Regression

Function family:

linear: $w_1 x_1 + w_2 x_2 ... w_m x_m$

Use a non-linear function to get results between [0,1]

$$P(y|x) = \sigma(\mathbf{w}^\intercal \mathbf{x})$$

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Optimization:

Gradient descent: Start with random w, do small steps that reduce the loss

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$$L = -\frac{1}{N}\sum \log P(y|x)$$

$$L = -\frac{1}{N}\sum_{i=1}^{N} y^{(i)} \log \hat{y}^{(i)} + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)})$$

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For T iterations:

$$\mathbf{w}^{(t+1)} = \mathbf{w}^{(t)} - \alpha \nabla_{\mathbf{w}} L$$

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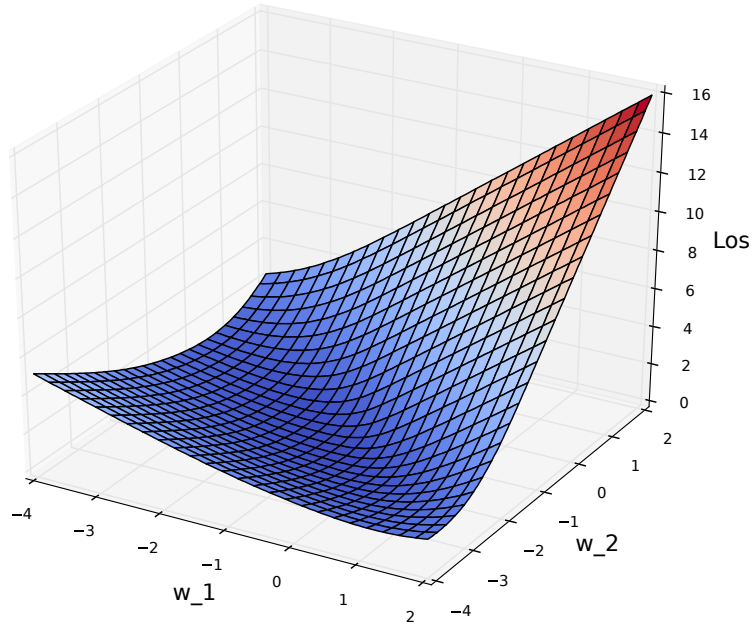
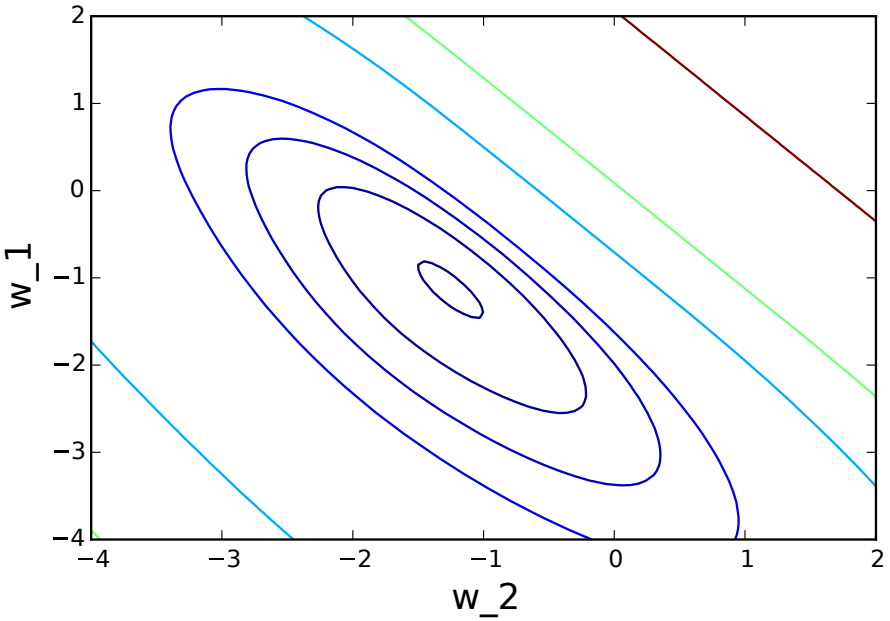
Calculating $\nabla_{\mathbf{w}} L$:

Use chain rule. Or use software that does it for you (e.g. Theano)

Visualizing the loss function

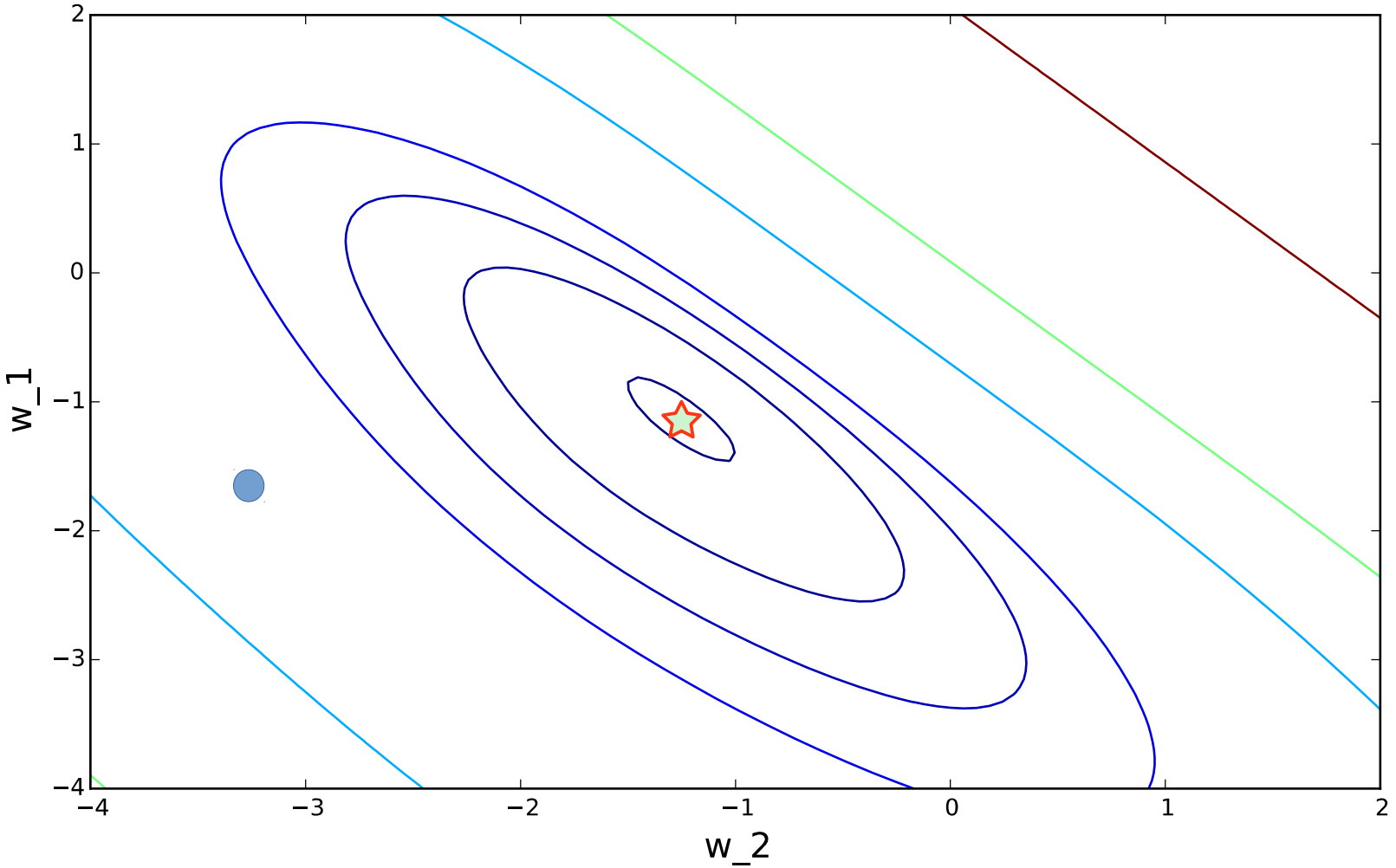
Loss as a function of w_1, w_2:





Gradient descent

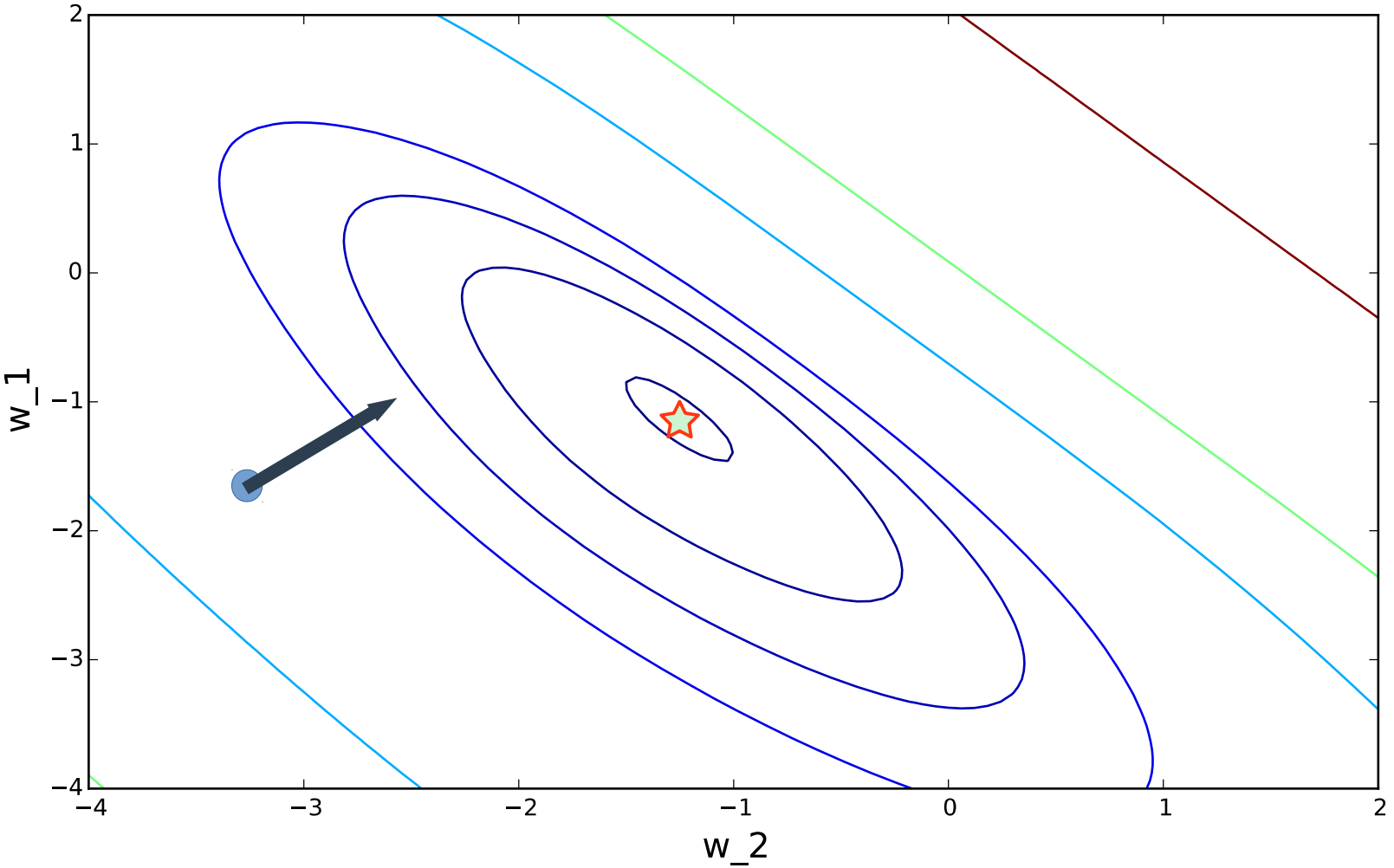
$\mathbf{w}^{(0)}$
(random)



Descida de gradiente

$\mathbf{w}^{(0)}$

Gradiente
$-\nabla_{\mathbf{w}} L$



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$\mathbf{w}^{(0)}$

$\mathbf{w}^{(1)}$

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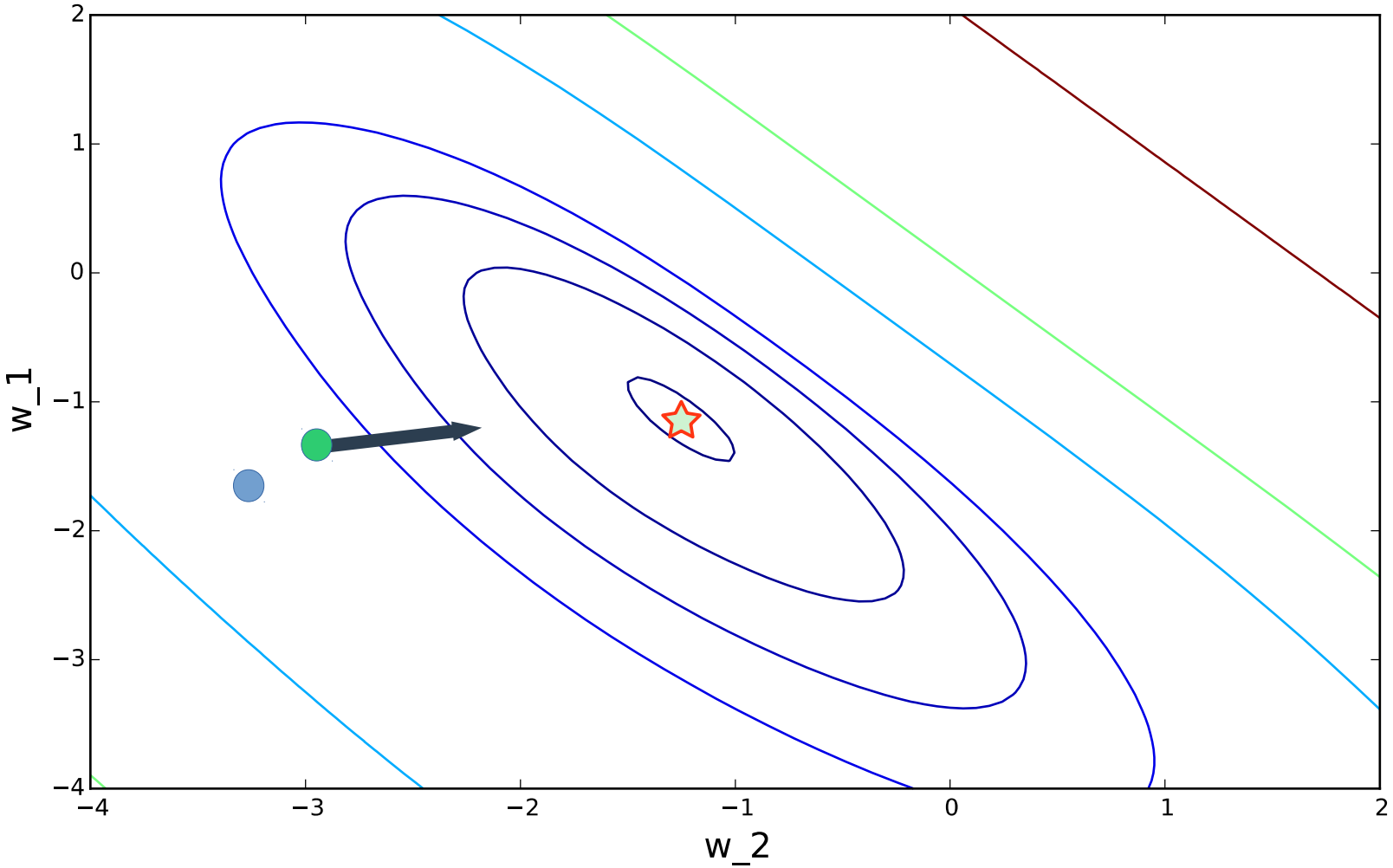

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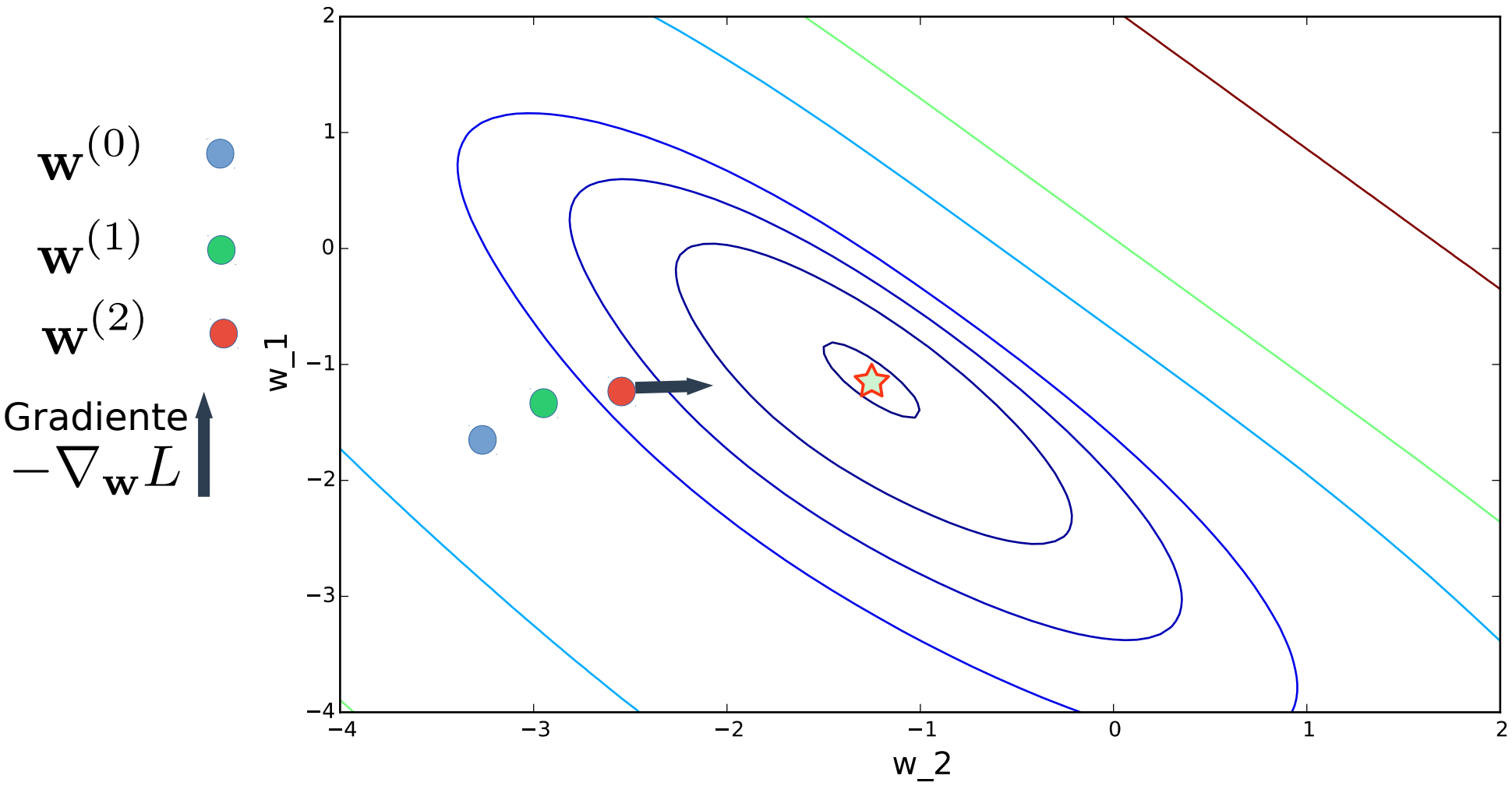
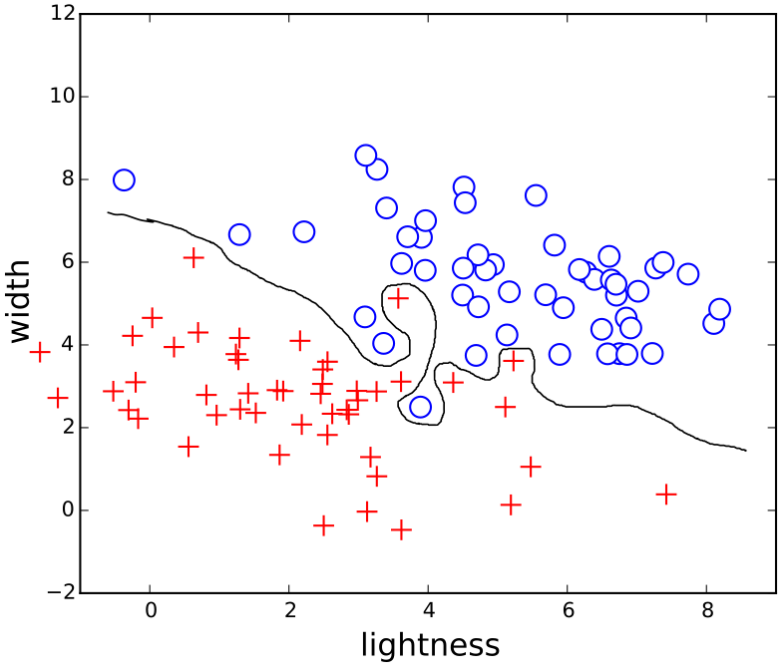


Overfitting

What matters is generalization error, but we minimize training error

If our model is too complex, it may overfit



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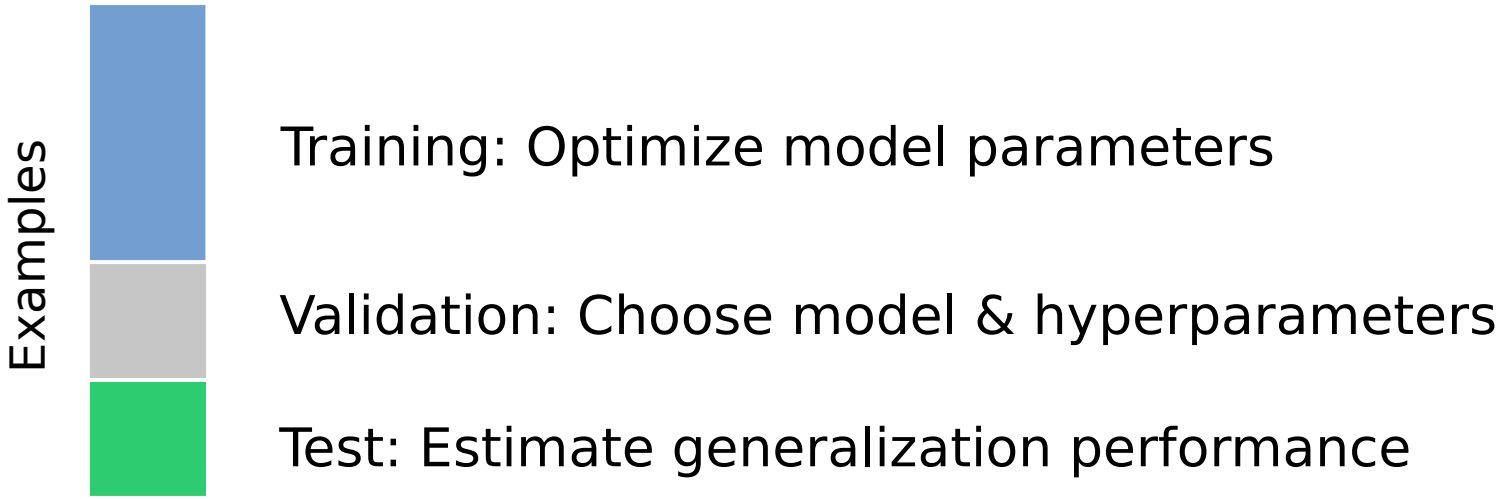
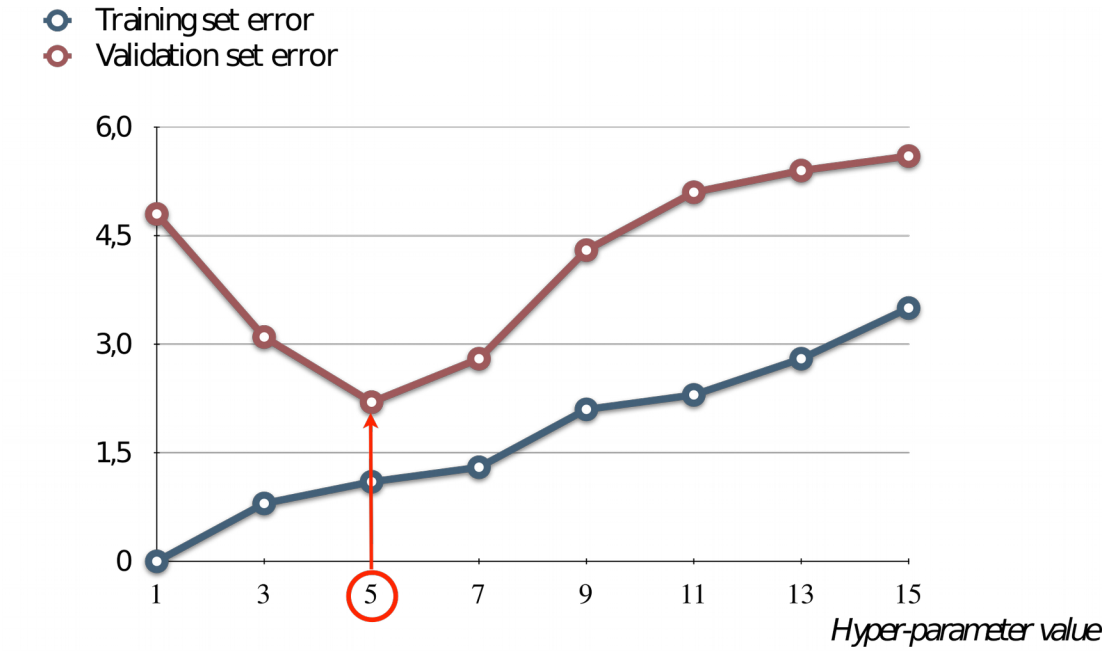


Model selection and overfitting

Train different models on the training set

Evaluate performance on validation. Pick best model

Test model performance on test set

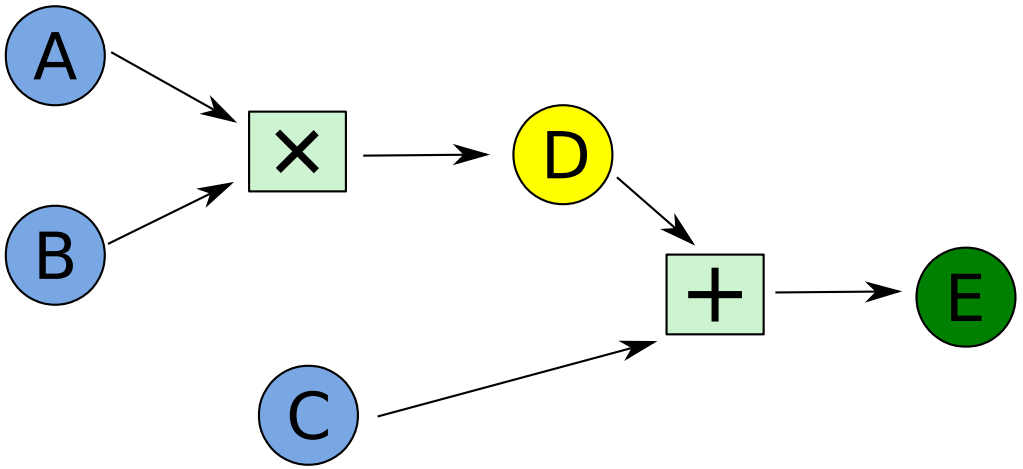


Hyper-parameter value which yields smallest error on validaiton set is 5
(it was 1 for the training set)

Introduction to Theano

Symbolic Computation

Expressions are defined as a graph



Blue: inputs

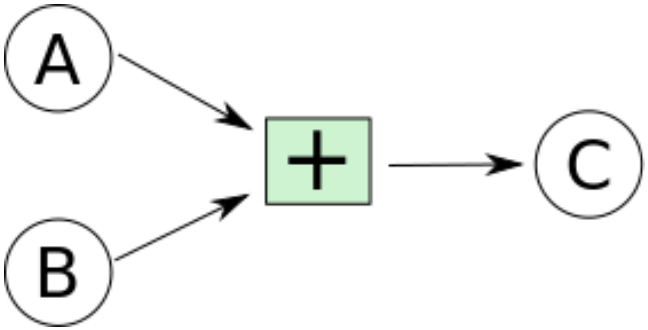
Yellow: intermediate nodes

Green: output

Introduction to Theano

Expressions need to be compiled

```
a = T.scalar()
b = T.scalar()
c = 3*a + 2*b
f = theano.function([a,b],c)
f(2,2) #returns 10
```



Enable automatic differentiation:

```
df_da = T.grad(c, a)
g = theano.function([a,b], df_da)
g(2,2) # returns 3
```

Ipython Notebook

DEMO