Data Science Bootcamp, 10th January 2017

Gradient Descent

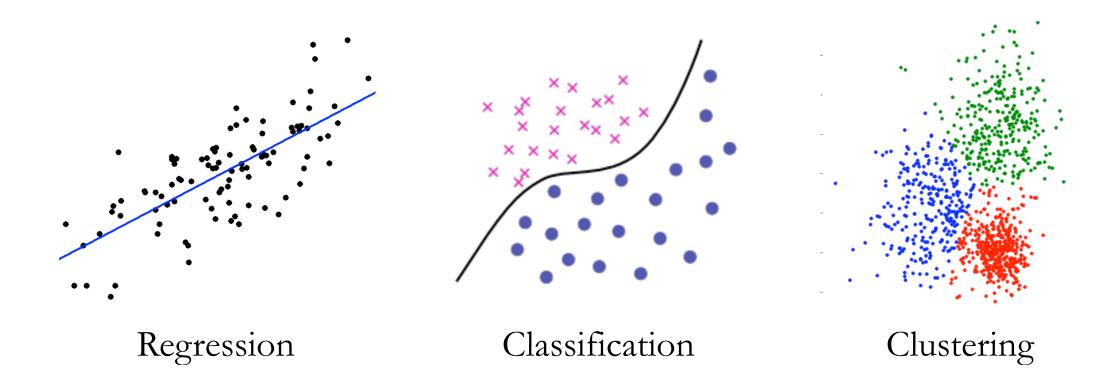
Francisco J. R. Ruiz





Introduction

• What do these problems have in common?

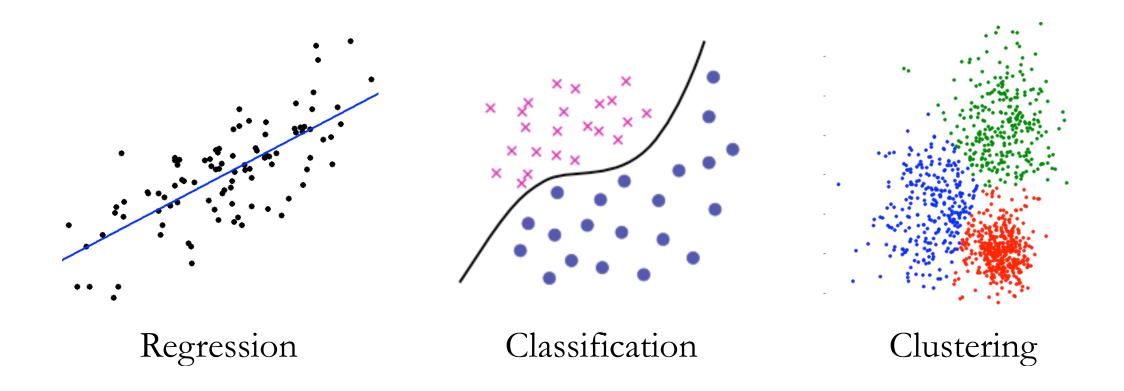






Introduction

• In all of them, we define and minimize an error function

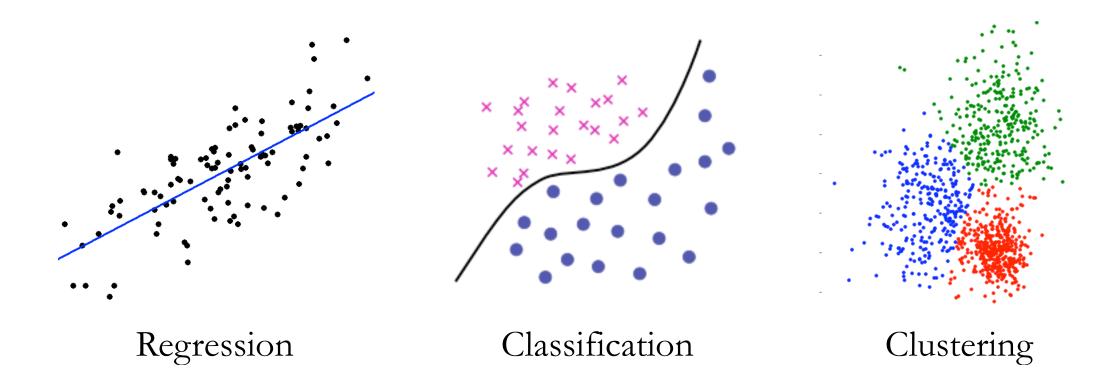






Introduction

Error function = Loss







- Optimization appears in many machine learning algorithms
 - Supervised and unsupervised learning
 - Basic and advanced methods





• Optimization: Minimize an objective function

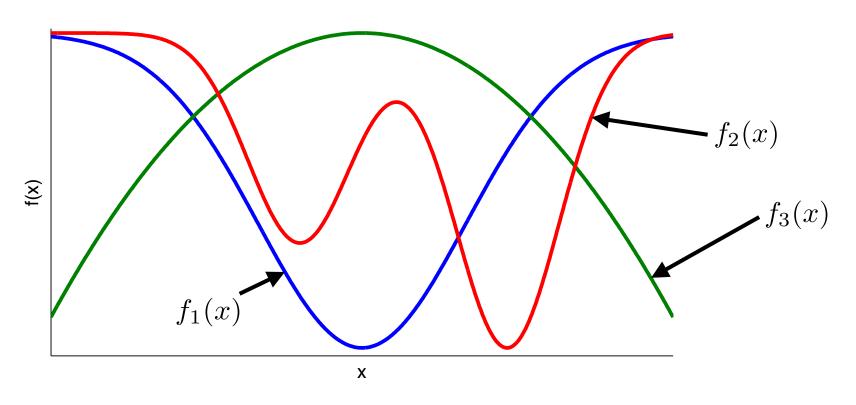
$$\mathbf{x}^{\star} = \min_{\mathbf{x}} f(\mathbf{x})$$

- Example: Linear regression
 - The function is the sum of squared errors
 - Find the coefficients that minimize the function





• The function can have one, multiple of none local optima







- In some cases, we can find the optima analytically
 - Example: linear regression

- In most practical cases, we need an iterative algorithm
 - Example: logistic regression





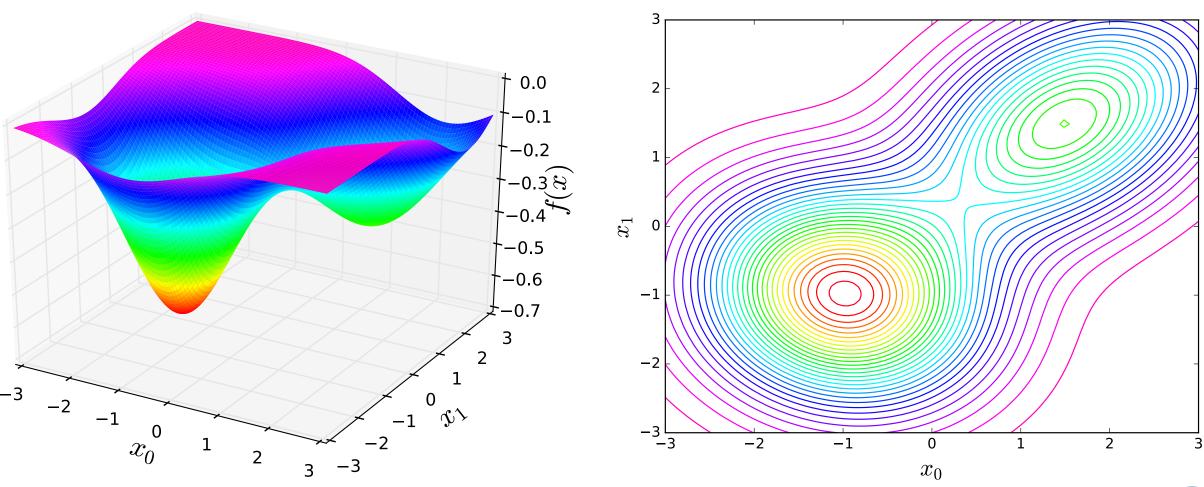
Gradient Descent

- Gradient descent is an algorithm for optimization
 - Simple to implement
 - Intuitive interpretation
 - Works also in high dimensions





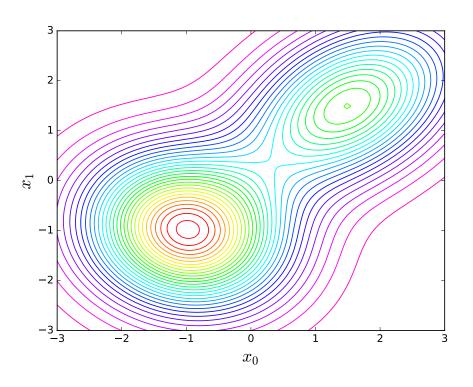
Gradient

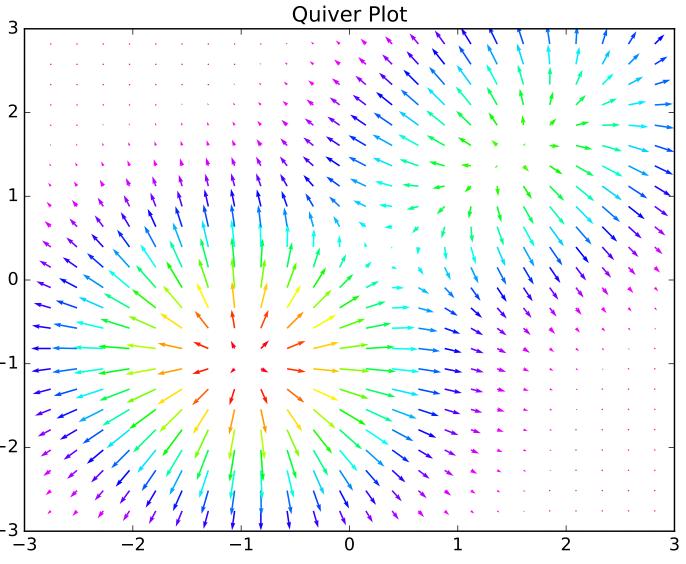






Gradient



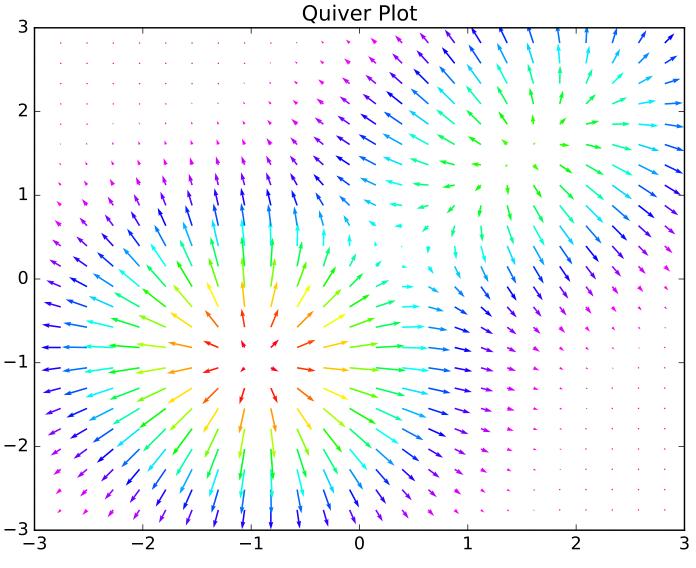






Gradient

The gradient gives the direction of steepest ascent







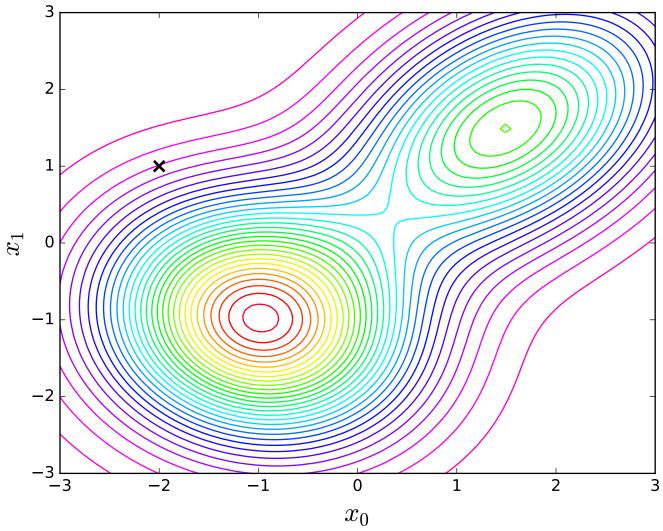
Algorithm:

- 1. Set **x** to initial guess
- 2. Refine the current value of x
- 3. If not converged, go back to step 2

• In step 2, follow the negative gradient

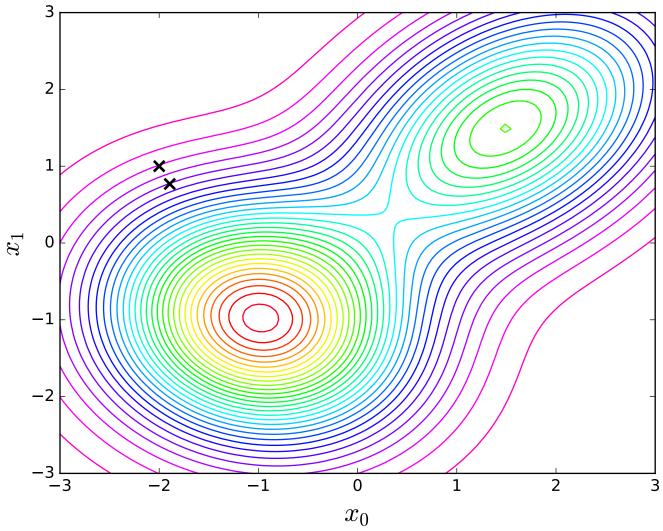






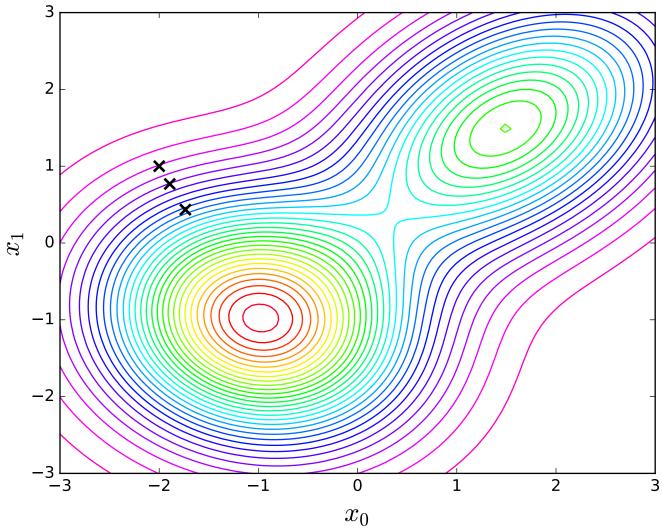






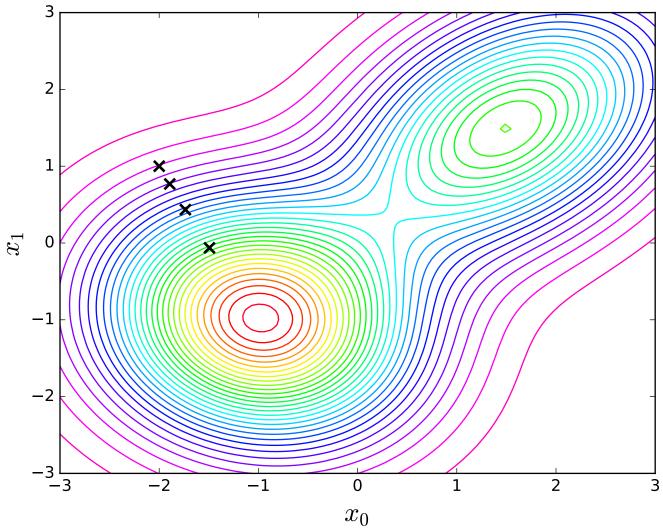






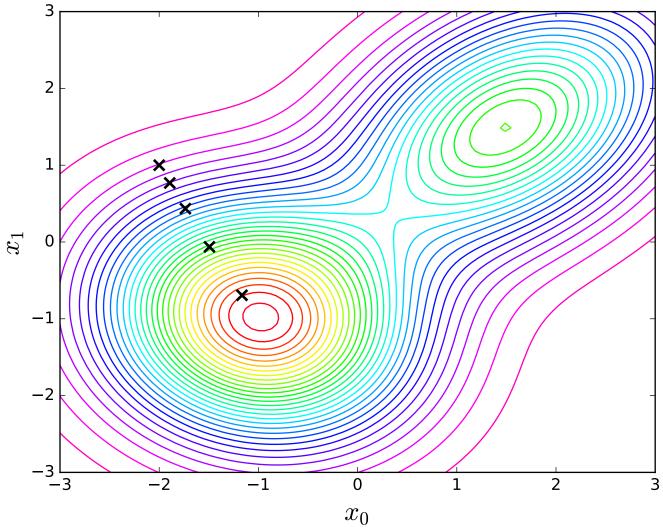






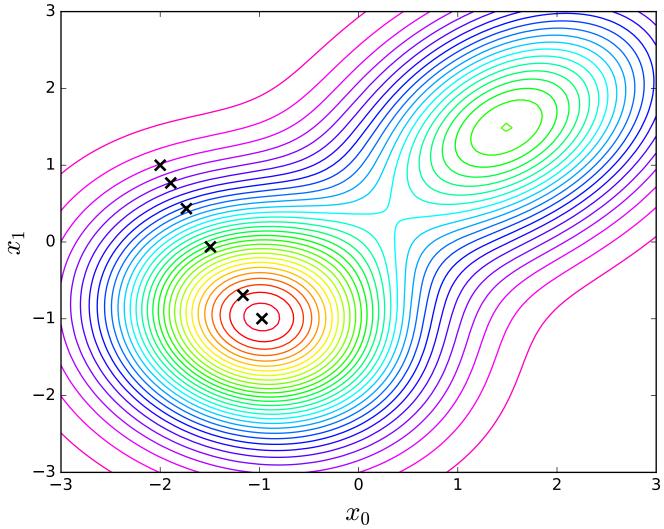






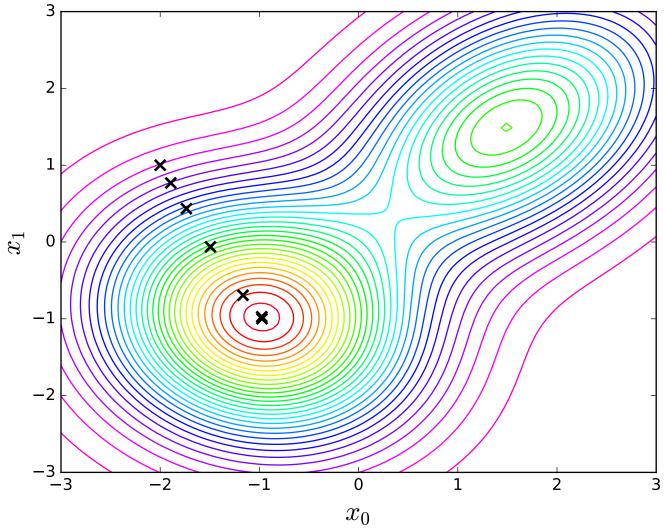
















• Each update is:

$$\mathbf{x}^{\text{new}} = \mathbf{x}^{\text{old}} + \rho \cdot \nabla_{\mathbf{x}} f(\mathbf{x}^{\text{old}})$$
 (Maximization)

$$\mathbf{x}^{\text{new}} = \mathbf{x}^{\text{old}} - \rho \cdot \nabla_{\mathbf{x}} f(\mathbf{x}^{\text{old}})$$
 (Minimization)





• Each update is:

$$\mathbf{x}^{ ext{new}} = \mathbf{x}^{ ext{old}} + \rho \cdot \nabla_{\mathbf{x}} f(\mathbf{x}^{ ext{old}})$$
 (Maximization)
$$\mathbf{x}^{ ext{new}} = \mathbf{x}^{ ext{old}} - \rho \cdot \nabla_{\mathbf{x}} f(\mathbf{x}^{ ext{old}})$$
 (Minimization) Gradient Step size





Convergence

- We stop the algorithm:
 - When **x** does not change much
 - When the gradient is small
 - After a fixed number of iterations





Limitations

- Not guaranteed to find the global optimum
- Choosing the step size is a nuisance
- Only takes into account gradient information





Today's Session

• Implement gradient descent

• Explore different step sizes and initial points

• Understand the effect of the step size

• IPython Notebook: GradientDescent





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