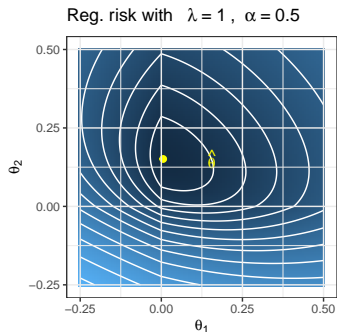
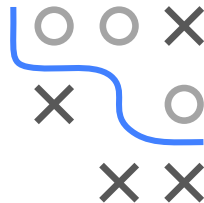


Optimization in Machine Learning

Optimization Problems

Unconstrained problems



Learning goals

- Definition
- Max. likelihood
- Linear regression
- Regularized risk minimization
- SVM
- Neural network

UNCONSTRAINED OPTIMIZATION PROBLEM

$$\min_{\mathbf{x} \in \mathcal{S}} f(\mathbf{x})$$

with objective function

$$f : \mathcal{S} \rightarrow \mathbb{R}.$$



The problem is called

- **unconstrained**, if the domain \mathcal{S} is not restricted:

$$\mathcal{S} = \mathbb{R}^d$$

- **smooth** if f is at least $\in \mathcal{C}^1$
- **univariate** if $d = 1$, and **multivariate** if $d > 1$.
- **convex** if f convex function and \mathcal{S} convex set

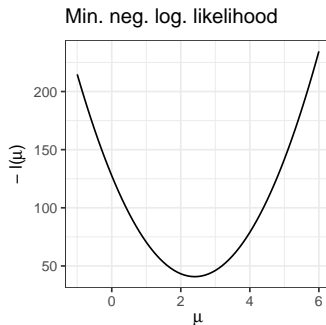
EXAMPLE 1: MAXIMUM LIKELIHOOD / 2

- **Likelihood:**

$$\mathcal{L}(\mu \mid \mathcal{D}) = \prod_{i=1}^n f(\mathbf{x}^{(i)} \mid \mu, 1) = (2\pi)^{-n/2} \exp\left(-\frac{1}{2} \sum_{i=1}^n (\mathbf{x}^{(i)} - \mu)^2\right)$$

- **Neg. log-likelihood:**

$$-\ell(\mu, \mathcal{D}) = -\log \mathcal{L}(\mu \mid \mathcal{D}) = \frac{n}{2} \log(2\pi) + \frac{1}{2} \sum_{i=1}^n (\mathbf{x}^{(i)} - \mu)^2$$



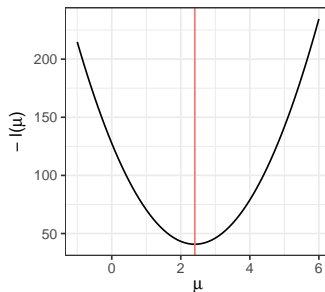
EXAMPLE 1: MAXIMUM LIKELIHOOD / 3

$$\min_{\mu \in \mathbb{R}} -\ell(\mu, \mathcal{D}).$$

can be solved analytically (setting the first deriv. to 0) since it is a quadratic form:

$$-\frac{\partial \ell(\mu, \mathcal{D})}{\partial \mu} = \sum_{i=1}^n (\mathbf{x}^{(i)} - \mu) = 0 \Leftrightarrow \hat{\mu} = \frac{1}{n} \sum_{i=1}^n \mathbf{x}^{(i)}$$

Min. neg. log. likelihood



EXAMPLE 1: MAXIMUM LIKELIHOOD / 4

Note: The problem was **smooth, univariate, unconstrained, convex**.

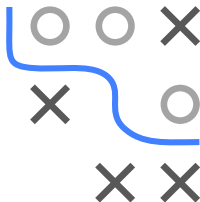
If we had optimized for σ as well

$$\min_{\mu \in \mathbb{R}, \sigma \in \mathbb{R}^+} -\ell(\mu, \mathcal{D}).$$

(instead of assuming it is known) the problem would have been:

- bivariate (optimize over (μ, σ))
- constrained ($\sigma > 0$)

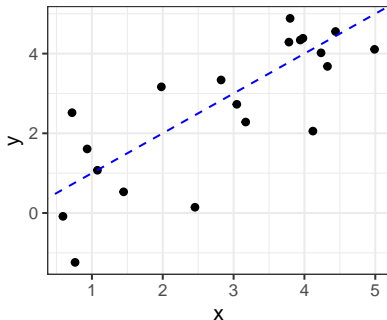
$$\min_{\mu \in \mathbb{R}, \sigma \in \mathbb{R}^+} -\ell(\mu, \mathcal{D}).$$



EXAMPLE 2: NORMAL REGRESSION

Assume (multivariate) data $\mathcal{D} = ((\mathbf{x}^{(1)}, y^{(1)}), \dots, (\mathbf{x}^{(n)}, y^{(n)}))$
and we want to fit a linear function to it

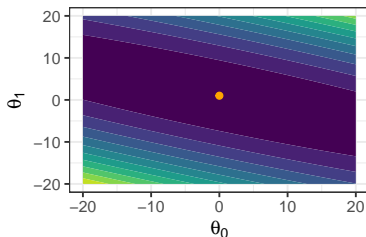
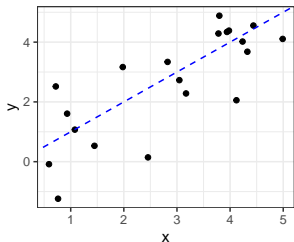
$$y = f(\mathbf{x}) = \theta^\top \mathbf{x}$$



EXAMPLE 2: LEAST SQUARES LINEAR REGR.

Find param vector θ that minimizes SSE / risk with L2 loss

$$\min_{\theta \in \mathbb{R}^d} \sum_{i=1}^n \left(\theta^\top \mathbf{x}^{(i)} - y^{(i)} \right)^2$$



- **Smooth, multivariate, unconstrained, convex** problem
- Quadratic form
- Analytic solution: $\theta = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{y}$, where \mathbf{X} is design matrix

RISK MINIMIZATION IN ML

In the above example, if we exchange

$$\min_{\theta \in \mathbb{R}^d} \sum_{i=1}^n \left(\theta^\top \mathbf{x}^{(i)} - y^{(i)} \right)^2$$

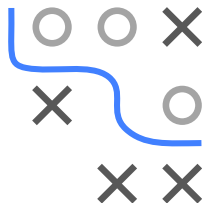
- the linear model $\theta^\top \mathbf{x}$ by an arbitrary model $f(\mathbf{x} \mid \theta)$
- the L2-loss $(f(\mathbf{x} \mid \theta) - y)^2$ by any loss $L(y, f(\mathbf{x}))$

we arrive at general **empirical risk minimization** (ERM)

$$\mathcal{R}_{\text{emp}}(\theta) = \sum_{i=1}^n L\left(y^{(i)}, f\left(\mathbf{x}^{(i)} \mid \theta\right)\right) = \min!$$

Usually, we add a regularizer to counteract overfitting:

$$\mathcal{R}_{\text{reg}}(\theta) = \sum_{i=1}^n L\left(y^{(i)}, f\left(\mathbf{x}^{(i)} \mid \theta\right)\right) + \lambda J(\theta) = \min!$$



EXAMPLE 3: REGULARIZED LM

ERM with L2 loss, LM, and L2 regularization term:

$$\mathcal{R}_{\text{reg}}(\theta) = \sum_{i=1}^n \left(\theta^\top \mathbf{x}^{(i)} - y^{(i)} \right)^2 + \lambda \cdot \|\theta\|_2^2 \quad (\text{Ridge regr.})$$

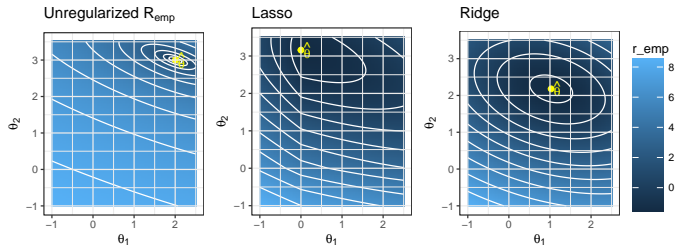
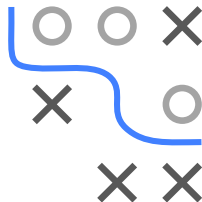
Problem **multivariate**, **unconstrained**, **smooth**, **convex** and has analytical solution

$$\theta = (\mathbf{X}^\top \mathbf{X} + \lambda \mathbf{I})^{-1} \mathbf{X}^\top \mathbf{y}.$$

ERM with L2-loss, LM, and L1 regularization:

$$\mathcal{R}_{\text{reg}}(\theta) = \sum_{i=1}^n \left(\theta^\top \mathbf{x}^{(i)} - y^{(i)} \right)^2 + \lambda \cdot \|\theta\|_1 \quad (\text{Lasso regr.})$$

The problem is still **multivariate**, **unconstrained**, **convex**, but **not smooth**.

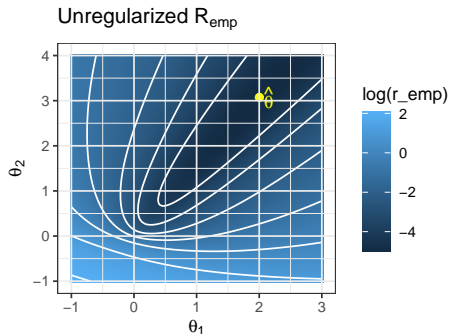


EXAMPLE 4: (REGULARIZED) LOG. REGRESSION

For $y \in \{0, 1\}$ (classification), logistic regression minimizes
log / Bernoulli / cross-entropy loss over data

$$\mathcal{R}_{\text{emp}}(\boldsymbol{\theta}) = \sum_{i=1}^n \left(-y^{(i)} \cdot \boldsymbol{\theta}^\top \mathbf{x}^{(i)} + \log(1 + \exp(\boldsymbol{\theta}^\top \mathbf{x}^{(i)})) \right)$$

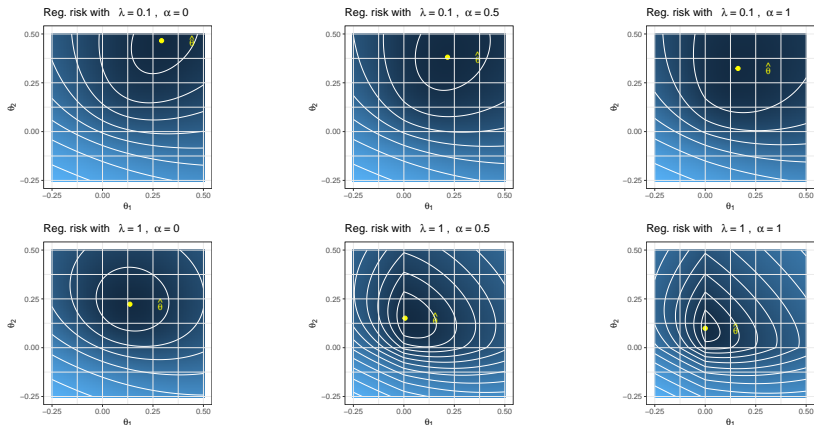
Multivariate, unconstrained, smooth, convex, not analytically solvable.



EXAMPLE 4: (REGULARIZED) LOG. REGRESSION

/ 2
Elastic net regularization is a combination of L1 and L2 regularization

$$\frac{1}{2n} \sum_{i=1}^n L(y^{(i)}, f(\mathbf{x}^{(i)} | \theta)) + \lambda \left[\frac{1-\alpha}{2} \|\theta\|_2^2 + \alpha \|\theta\|_1 \right], \lambda \geq 0, \alpha \in [0, 1]$$



The higher λ , the closer to the origin, L1 shrinks coeffs exactly to 0.

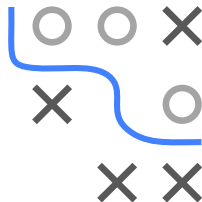
EXAMPLE 4: (REGULARIZED) LOG. REGRESSION

/ 3

$$\frac{1}{2n} \sum_{i=1}^n L\left(y^{(i)}, f\left(\mathbf{x}^{(i)} \mid \boldsymbol{\theta}\right)\right) + \lambda \left[\frac{1-\alpha}{2} \|\boldsymbol{\theta}\|_2^2 + \alpha \|\boldsymbol{\theta}\|_1 \right], \lambda \geq 0, \alpha \in [0, 1]$$

Problem characteristics:

- Multivariate
- Unconstrained
- If $\alpha = 0$ (Ridge) problem is smooth; not smooth otherwise
- Convex since L convex and both L1 and L2 norm are convex

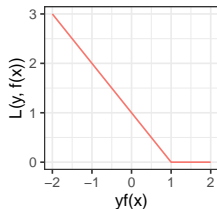
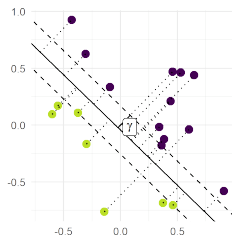


EXAMPLE 5: LINEAR SVM

- $\mathcal{D} = ((\mathbf{x}^{(i)}, y^{(i)}))_{i=1, \dots, n}$ with $y^{(i)} \in \{-1, 1\}$ (classification)
- $f(\mathbf{x} \mid \boldsymbol{\theta}) = \boldsymbol{\theta}^\top \mathbf{x} \in \mathbb{R}$ scoring classifier:
Predict 1 if $f(\mathbf{x} \mid \boldsymbol{\theta}) > 0$ and -1 otherwise.

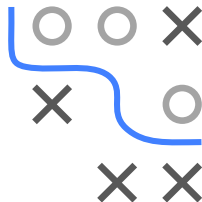
ERM with LM, hinge loss, and L2 regularization:

$$\mathcal{R}_{\text{reg}}(\boldsymbol{\theta}) = \sum_{i=1}^n \max(1 - y^{(i)} f^{(i)}, 0) + \lambda \boldsymbol{\theta}^\top \boldsymbol{\theta}, \quad f^{(i)} := \boldsymbol{\theta}^\top \mathbf{x}^{(i)}$$



Loss
— Hinge

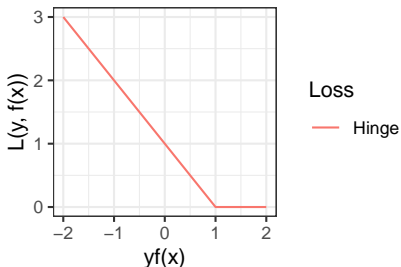
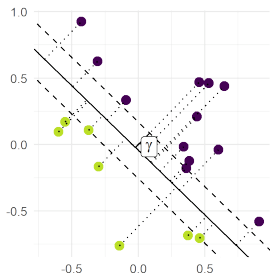
This is one formulation of the **linear SVM**. Problem is: **multivariate**, **unconstrained**, **convex**, but **not smooth**.



EXAMPLE 5: LINEAR SVM / 2

Understanding hinge loss $L(y, f(\mathbf{x})) = \max(1 - y \cdot f(\mathbf{x}), 0)$

y	$f(\mathbf{x})$	Correct pred.?	$L(y, f(\mathbf{x}))$	Reason for costs
1	$(-\infty, 0)$	N	$(1, \infty)$	Misclassification
-1	$(0, \infty)$	N	$(1, \infty)$	Misclassification
1	$(0, 1)$	Y	$(0, 1)$	Low confidence / margin
-1	$(-1, 0)$	Y	$(0, 1)$	Low confidence / margin
1	$(1, \infty)$	Y	0	—
-1	$(-\infty, -1)$	Y	0	—



EXAMPLE 6: KERNELIZED SVM

Kernelized formulation of the primal^(*) SVM problem:

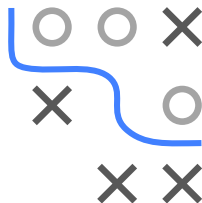
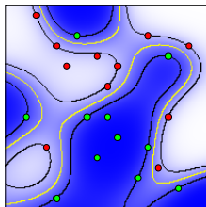
$$\min_{\theta} \sum_{i=1}^n L\left(y^{(i)}, \mathbf{K}_i^{\top} \theta\right) + \lambda \theta^{\top} \mathbf{K} \theta$$

with $k(\cdot, \cdot)$ pos. def. kernel function, and

$\mathbf{K}_{ij} := k(\mathbf{x}^{(i)}, \mathbf{x}^{(j)})$, $n \times n$ psd kernel matrix, \mathbf{K}_i i -th column of \mathbf{K} .

Kernelization

- allows introducing nonlinearity through projection into higher-dim. feature space
- without changing problem characteristics (convexity!)



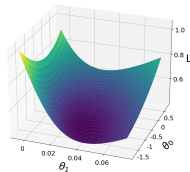
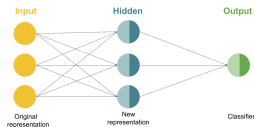
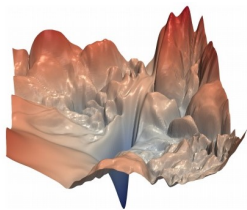
^(*) There is also a dual formulation to the problem (comes later!)

EXAMPLE 6: NEURAL NETWORK

Normal loss, but complex f defined as computational feed-forward graph. Complexity of optimization problem

$$\arg \min_{\theta} \mathcal{R}_{\text{reg}}(\theta),$$

so smoothness (maybe) or convexity (usually no) is influenced by loss, neuron function, depth, regularization, etc.



Loss landscapes of ML problems.

Left: Deep learning model ResNet-56, right: Logistic regression with cross-entropy loss

Source: <https://arxiv.org/pdf/1712.09913.pdf>