

# $\ell_1$ and $\ell_2$ Regularization

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# Tikhonov and Ivanov Regularization

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# Hypothesis Spaces

- We've spoken vaguely about “bigger” and “smaller” hypothesis spaces
- In practice, convenient to work with a **nested sequence** of spaces:

$$\mathcal{F}_1 \subset \mathcal{F}_2 \subset \mathcal{F}_n \cdots \subset \mathcal{F}$$

## Polynomial Functions

- $\mathcal{F} = \{\text{all polynomial functions}\}$
- $\mathcal{F}_d = \{\text{all polynomials of degree } \leq d\}$

# Complexity Measures for Decision Functions

- Number of variables / features
- Depth of a decision tree
- Degree of polynomial
- How about for **linear** decision functions, i.e.  $x \mapsto w^T x = w_1 x_1 + \dots + w_d x_d$ ?
  - $\ell_0$  complexity: number of non-zero coefficients  $\sum_{i=1}^d 1(w_i \neq 0)$ .
  - $\ell_1$  “lasso” complexity:  $\sum_{i=1}^d |w_i|$ , for coefficients  $w_1, \dots, w_d$
  - $\ell_2$  “ridge” complexity:  $\sum_{i=1}^d w_i^2$  for coefficients  $w_1, \dots, w_d$

# Nested Hypothesis Spaces from Complexity Measure

- Hypothesis space:  $\mathcal{F}$
- Complexity measure  $\Omega : \mathcal{F} \rightarrow [0, \infty)$
- Consider all functions in  $\mathcal{F}$  with complexity **at most**  $r$ :

$$\mathcal{F}_r = \{f \in \mathcal{F} \mid \Omega(f) \leq r\}$$

- Increasing complexities:  $r = 0, 1.2, 2.6, 5.4, \dots$  gives nested spaces:

$$\mathcal{F}_0 \subset \mathcal{F}_{1.2} \subset \mathcal{F}_{2.6} \subset \mathcal{F}_{5.4} \subset \dots \subset \mathcal{F}$$

# Constrained Empirical Risk Minimization

## Constrained ERM (Ivanov regularization)

For complexity measure  $\Omega : \mathcal{F} \rightarrow [0, \infty)$  and fixed  $r \geq 0$ ,

$$\begin{aligned} \min_{f \in \mathcal{F}} \quad & \frac{1}{n} \sum_{i=1}^n \ell(f(x_i), y_i) \\ \text{s.t.} \quad & \Omega(f) \leq r \end{aligned}$$

- Choose  $r$  using validation data or cross-validation.
- Each  $r$  corresponds to a different hypothesis spaces. Could also write:

$$\min_{f \in \mathcal{F}_r} \frac{1}{n} \sum_{i=1}^n \ell(f(x_i), y_i)$$

# Penalized Empirical Risk Minimization

## Penalized ERM (Tikhonov regularization)

For complexity measure  $\Omega : \mathcal{F} \rightarrow [0, \infty)$  and fixed  $\lambda \geq 0$ ,

$$\min_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n \ell(f(x_i), y_i) + \lambda \Omega(f)$$

- Choose  $\lambda$  using validation data or cross-validation.
- (Ridge regression in homework is of this form.)

# Ivanov vs Tikhonov Regularization

- Let  $L: \mathcal{F} \rightarrow \mathbf{R}$  be any performance measure of  $f$ 
  - e.g.  $L(f)$  could be the empirical risk of  $f$
- For many  $L$  and  $\Omega$ , Ivanov and Tikhonov are “equivalent”.
- What does this mean?
  - Any solution  $f^*$  you could get from Ivanov, can also get from Tikhonov.
  - Any solution  $f^*$  you could get from Tikhonov, can also get from Ivanov.
- In practice, both approaches are effective.
- Tikhonov convenient because it's *unconstrained* minimization.

Can get conditions for equivalence from Lagrangian duality theory – details in homework.



# Ivanov vs Tikhonov Regularization (Details)

Ivanov and Tikhonov regularization are equivalent if:

- 1 For any choice of  $r > 0$ , any Ivanov solution

$$f_r^* \in \arg \min_{f \in \mathcal{F}} L(f) \text{ s.t. } \Omega(f) \leq r$$

is also a Tikhonov solution for some  $\lambda > 0$ . That is,  $\exists \lambda > 0$  such that

$$f_r^* \in \arg \min_{f \in \mathcal{F}} L(f) + \lambda \Omega(f).$$

- 2 Conversely, for any choice of  $\lambda > 0$ , any Tikhonov solution:

$$f_\lambda^* \in \arg \min_{f \in \mathcal{F}} L(f) + \lambda \Omega(f)$$

is also an Ivanov solution for some  $r > 0$ . That is,  $\exists r > 0$  such that

$$f_\lambda^* \in \arg \min_{f \in \mathcal{F}} L(f) \text{ s.t. } \Omega(f) \leq r$$

## $\ell_1$ and $\ell_2$ Regularization

# Linear Least Squares Regression

- Consider linear models

$$\mathcal{F} = \{f : \mathbf{R}^d \rightarrow \mathbf{R} \mid f(x) = w^T x \text{ for } w \in \mathbf{R}^d\}$$

- Loss:  $\ell(\hat{y}, y) = (y - \hat{y})^2$
- Training data  $\mathcal{D}_n = ((x_1, y_1), \dots, (x_n, y_n))$
- Linear least squares regression is ERM for  $\ell$  over  $\mathcal{F}$ :

$$\hat{w} = \arg \min_{w \in \mathbf{R}^d} \frac{1}{n} \sum_{i=1}^n \{w^T x_i - y_i\}^2$$

- Can **overfit** when  $d$  is large compared to  $n$ .
- e.g.:  $d \gg n$  very common in Natural Language Processing problems (e.g. a 1M features for 10K documents).

# Ridge Regression: Workhorse of Modern Data Science

## Ridge Regression (Tikhonov Form)

The ridge regression solution for regularization parameter  $\lambda \geq 0$  is

$$\hat{w} = \arg \min_{w \in \mathbb{R}^d} \frac{1}{n} \sum_{i=1}^n \{w^T x_i - y_i\}^2 + \lambda \|w\|_2^2,$$

where  $\|w\|_2^2 = w_1^2 + \dots + w_d^2$  is the square of the  $\ell_2$ -norm.

## Ridge Regression (Ivanov Form)

The ridge regression solution for complexity parameter  $r \geq 0$  is

$$\hat{w} = \arg \min_{\|w\|_2^2 \leq r^2} \frac{1}{n} \sum_{i=1}^n \{w^T x_i - y_i\}^2.$$

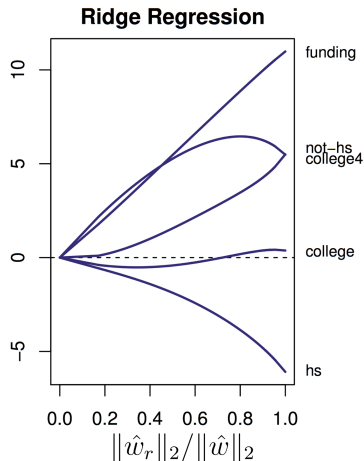
## How does $\ell_2$ regularization induce “regularity”?

- For  $\hat{f}(x) = \hat{w}^T x$ ,  $\hat{f}$  is **Lipschitz continuous** with Lipschitz constant  $L = \|\hat{w}\|_2$ .
- That is, when moving from  $x$  to  $x+h$ ,  $\hat{f}$  changes no more than  $L\|h\|$ .
- So  $\ell_2$  regularization controls the maximum rate of change of  $\hat{f}$ .
- Proof:

$$\begin{aligned} \left| \hat{f}(x+h) - \hat{f}(x) \right| &= \left| \hat{w}^T (x+h) - \hat{w}^T x \right| = \left| \hat{w}^T h \right| \\ &\leq \|\hat{w}\|_2 \|h\|_2 \text{ (Cauchy-Schwarz inequality)} \end{aligned}$$

- Since  $\|\hat{w}\|_1 \geq \|\hat{w}\|_2$ , an  $\ell_1$  constraint will also give a Lipschitz bound.

# Ridge Regression: Regularization Path



$$\hat{w}_r = \arg \min_{\|w\|_2^2 \leq r^2} \frac{1}{n} \sum_{i=1}^n (w^T x_i - y_i)^2$$
$$\hat{w} = \hat{w}_\infty = \text{Unconstrained ERM}$$

- For  $r = 0$ ,  $\|\hat{w}_r\|_2 / \|\hat{w}\|_2 = 0$ .
- For  $r = \infty$ ,  $\|\hat{w}_r\|_2 / \|\hat{w}\|_2 = 1$

Modified from Hastie, Tibshirani, and Wainwright's *Statistical Learning with Sparsity*, Fig 2.1. About predicting crime in 50 US cities.

# Lasso Regression: Workhorse (2) of Modern Data Science

## Lasso Regression (Tikhonov Form)

The lasso regression solution for regularization parameter  $\lambda \geq 0$  is

$$\hat{w} = \arg \min_{w \in \mathbb{R}^d} \frac{1}{n} \sum_{i=1}^n \{w^T x_i - y_i\}^2 + \lambda \|w\|_1,$$

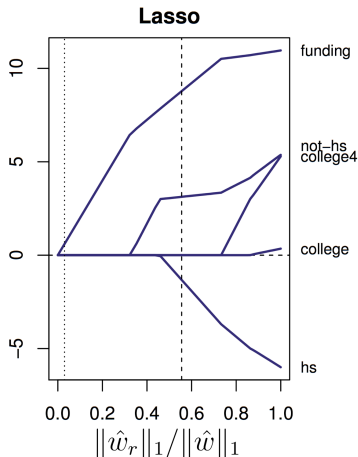
where  $\|w\|_1 = |w_1| + \dots + |w_d|$  is the  $\ell_1$ -norm.

## Lasso Regression (Ivanov Form)

The lasso regression solution for complexity parameter  $r \geq 0$  is

$$\hat{w} = \arg \min_{\|w\|_1 \leq r} \frac{1}{n} \sum_{i=1}^n \{w^T x_i - y_i\}^2.$$

# Lasso Regression: Regularization Path



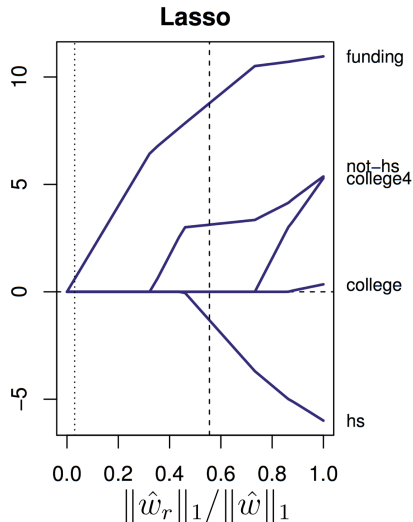
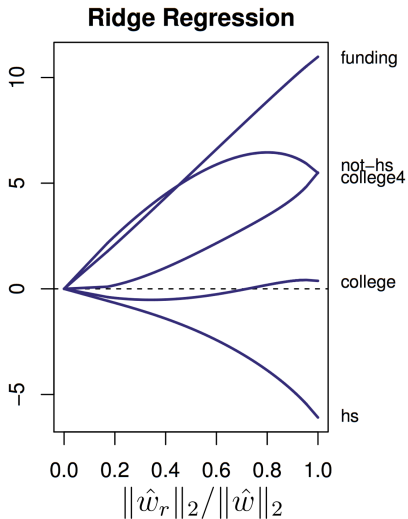
$$\hat{w}_r = \arg \min_{\|w\|_1 \leq r} \frac{1}{n} \sum_{i=1}^n (w^T x_i - y_i)^2$$
$$\hat{w} = \hat{w}_\infty = \text{Unconstrained ERM}$$

- For  $r = 0$ ,  $\|\hat{w}_r\|_1 / \|\hat{w}\|_1 = 0$ .
- For  $r = \infty$ ,  $\|\hat{w}_r\|_1 / \|\hat{w}\|_1 = 1$

Modified from Hastie, Tibshirani, and Wainwright's *Statistical Learning with Sparsity*, Fig 2.1. About predicting crime in 50 US cities.



# Ridge vs. Lasso: Regularization Paths



Modified from Hastie, Tibshirani, and Wainwright's *Statistical Learning with Sparsity*, Fig 2.1. About predicting crime in 50 US cities.

# Lasso Gives Feature Sparsity: So What?

Coefficient are 0  $\implies$  don't need those features. What's the gain?

- Time/expense to compute/buy features
- Memory to store features (e.g. real-time deployment)
- Identifies the important features
- Better prediction? sometimes
- As a feature-selection step for training a slower non-linear model

# Ivanov and Tikhonov Equivalent?

- For ridge regression and lasso regression (and much more)
  - the Ivanov and Tikhonov formulations are equivalent
  - [Optional homework problem, upcoming.]
- We will use whichever form is most convenient.

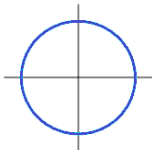
Why does Lasso regression give sparse solutions?

- Illustrate affine prediction functions in parameter space.

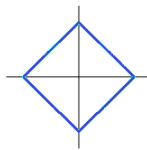
# The $\ell_1$ and $\ell_2$ Norm Constraints

- For visualization, restrict to 2-dimensional input space
- $\mathcal{F} = \{f(x) = w_1x_1 + w_2x_2\}$  (linear hypothesis space)
- Represent  $\mathcal{F}$  by  $\{(w_1, w_2) \in \mathbf{R}^2\}$ .

- $\ell_2$  contour:  
 $w_1^2 + w_2^2 = r$



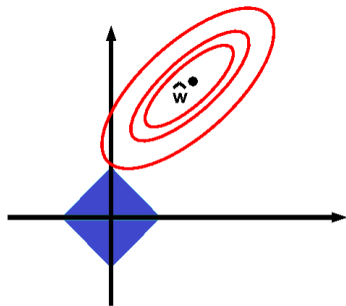
- $\ell_1$  contour:  
 $|w_1| + |w_2| = r$



Where are the “sparse” solutions?

# The Famous Picture for $\ell_1$ Regularization

- $f_r^* = \arg \min_{w \in \mathbb{R}^2} \frac{1}{n} \sum_{i=1}^n (w^T x_i - y_i)^2$  subject to  $|w_1| + |w_2| \leq r$



- Blue region: Area satisfying complexity constraint:  $|w_1| + |w_2| \leq r$
- Red lines: contours of  $\hat{R}_n(w) = \frac{1}{n} \sum_{i=1}^n (w^T x_i - y_i)^2$ .

KPM Fig. 13.3

# The Empirical Risk for Square Loss

- Denote the empirical risk of  $f(x) = w^T x$  by

$$\hat{R}_n(w) = \frac{1}{n} \|Xw - y\|^2,$$

where  $X$  is the **design matrix**.

- $\hat{R}_n$  is minimized by  $\hat{w} = (X^T X)^{-1} X^T y$ , the OLS solution.
- What does  $\hat{R}_n$  look like around  $\hat{w}$ ?



# The Empirical Risk for Square Loss

- By “completing the square”, we can show for any  $w \in \mathbf{R}^d$ :

$$\hat{R}_n(w) = \frac{1}{n} (w - \hat{w})^T X^T X (w - \hat{w}) + \hat{R}_n(\hat{w})$$

- Set of  $w$  with  $\hat{R}_n(w)$  exceeding  $\hat{R}_n(\hat{w})$  by  $c > 0$  is

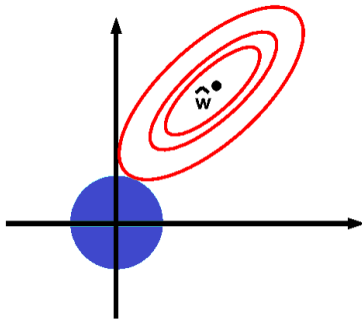
$$\left\{ w \mid \hat{R}_n(w) = c + \hat{R}_n(\hat{w}) \right\} = \left\{ w \mid (w - \hat{w})^T X^T X (w - \hat{w}) = nc \right\},$$

which is an **ellipsoid centered at  $\hat{w}$** .

- We'll derive this in homework.

# The Famous Picture for $\ell_2$ Regularization

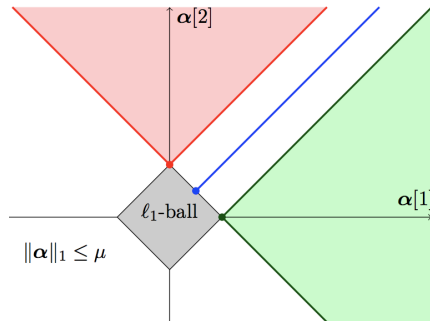
- $f_r^* = \arg \min_{w \in \mathbb{R}^2} \sum_{i=1}^n (w^T x_i - y_i)^2$  subject to  $w_1^2 + w_2^2 \leq r$



- Blue region: Area satisfying complexity constraint:  $w_1^2 + w_2^2 \leq r$
- Red lines: contours of  $\hat{R}_n(w) = \sum_{i=1}^n (w^T x_i - y_i)^2$ .

KPM Fig. 13.3

# Why are Lasso Solutions Often Sparse?

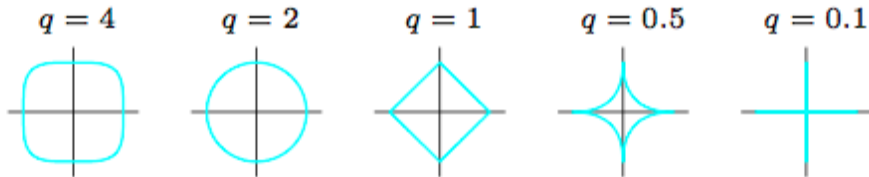


- Suppose design matrix  $X$  is orthogonal, so  $X^T X = I$ , and contours are circles.
- Then OLS solution in green or red regions implies  $\ell_1$  constrained solution will be at corner

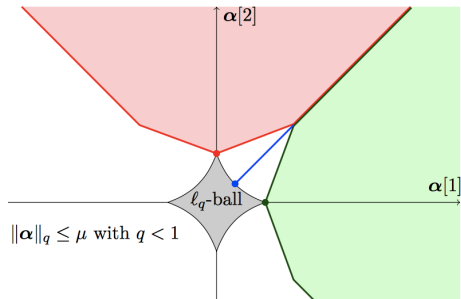
Fig from Mairal et al.'s [Sparse Modeling for Image and Vision Processing](#) Fig 1.6

# The $(\ell_q)^q$ Constraint

- Generalize to  $\ell_q$  :  $(\|w\|_q)^q = |w_1|^q + |w_2|^q$ .
- Note:  $\|w\|_q$  is a norm if  $q \geq 1$ , but not for  $q \in (0, 1)$
- $\mathcal{F} = \{f(x) = w_1 x_1 + w_2 x_2\}$ .
- Contours of  $\|w\|_q^q = |w_1|^q + |w_2|^q$ :



## $\ell_q$ Even Sparser



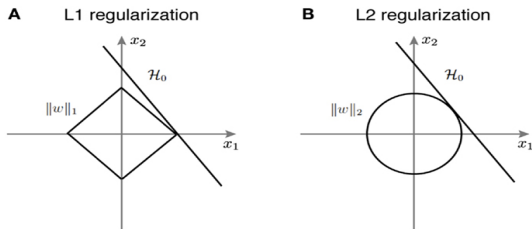
(b)  $\ell_q$ -ball with  $q < 1$ .

- Suppose design matrix  $X$  is orthogonal, so  $X^T X = I$ , and contours are circles.
- Then OLS solution in green or red regions implies  $\ell_q$  constrained solution will be at corner

$\ell_q$ -ball constraint is not convex, so more difficult to optimize.

# The Quora Picture

- From Quora: “Why is L1 regularization supposed to lead to sparsity than L2? [sic]” (google it)



- Does this picture have any interpretation that makes sense? (Aren't those lines supposed to be ellipses?)
- Yes... we can revisit.

Figure from <https://www.quora.com/Why-is-L1-regularization-supposed-to-lead-to-sparsity-than-L2>.

## Finding the Lasso Solution: Lasso as Quadratic Program

# How to find the Lasso solution?

- How to solve the Lasso?

$$\min_{w \in \mathbf{R}^d} \sum_{i=1}^n (w^T x_i - y_i)^2 + \lambda \|w\|_1$$

- $\|w\|_1 = |w_1| + |w_2|$  is not differentiable!



# Splitting a Number into Positive and Negative Parts

- Consider any number  $a \in \mathbf{R}$ .
- Let the **positive part** of  $a$  be

$$a^+ = a1(a \geq 0).$$

- Let the **negative part** of  $a$  be

$$a^- = -a1(a \leq 0).$$

- Do you see why  $a^+ \geq 0$  and  $a^- \geq 0$ ?
- How do you write  $a$  in terms of  $a^+$  and  $a^-$ ?
- How do you write  $|a|$  in terms of  $a^+$  and  $a^-$ ?

# How to find the Lasso solution?

- The Lasso problem

$$\min_{w \in \mathbf{R}^d} \sum_{i=1}^n (w^T x_i - y_i)^2 + \lambda \|w\|_1$$

- Replace each  $w_i$  by  $w_i^+ - w_i^-$ .
- Write  $w^+ = (w_1^+, \dots, w_d^+)$  and  $w^- = (w_1^-, \dots, w_d^-)$ .

# The Lasso as a Quadratic Program

We **will show**: substituting  $w = w^+ - w^-$  and  $|w| = w^+ + w^-$  gives an **equivalent** problem:

$$\begin{aligned} \min_{w^+, w^-} \quad & \sum_{i=1}^n \left( (w^+ - w^-)^T x_i - y_i \right)^2 + \lambda \mathbf{1}^T (w^+ + w^-) \\ \text{subject to} \quad & w_i^+ \geq 0 \text{ for all } i \quad w_i^- \geq 0 \text{ for all } i, \end{aligned}$$

- Objective is **differentiable** (in fact, **convex and quadratic**)
- $2d$  variables vs  $d$  variables and  $2d$  constraints vs no constraints
- A “**quadratic program**”: a convex quadratic objective with linear constraints.
  - Could plug this into a generic QP solver.

## Possible point of confusion

**Equivalent** to lasso problem:

$$\begin{aligned} \min_{w^+, w^-} \quad & \sum_{i=1}^n \left( (w^+ - w^-)^T x_i - y_i \right)^2 + \lambda \mathbf{1}^T (w^+ + w^-) \\ \text{subject to} \quad & w_i^+ \geq 0 \text{ for all } i \quad w_i^- \geq 0 \text{ for all } i, \end{aligned}$$

- When we plug this optimization problem into a QP solver,
  - it just sees  $2d$  variables and  $2d$  constraints.
  - Doesn't know we want  $w_i^+$  and  $w_i^-$  to be positive and negative parts of  $w_i$ .
- Turns out – they will come out that way as a result of the optimization!
- But to eliminate confusion, let's start by calling them  $a_i$  and  $b_i$  and prove our claim...

# The Lasso as a Quadratic Program

Lasso problem is trivially equivalent to the following:

$$\begin{aligned} \min_w \min_{a,b} \quad & \sum_{i=1}^n \left( (a-b)^T x_i - y_i \right)^2 + \lambda \mathbf{1}^T (a+b) \\ \text{subject to} \quad & a_i \geq 0 \text{ for all } i \quad b_i \geq 0 \text{ for all } i, \\ & a - b = w \\ & a + b = |w| \end{aligned}$$

- Claim: Don't need constraint  $a + b = |w|$ .
- $a' \leftarrow a - \min(a, b)$  and  $b' \leftarrow b - \min(a, b)$  at least as good
- So if  $a$  and  $b$  are minimizers, at least one is 0.
- Since  $a - b = w$ , we must have  $a = w^+$  and  $b = w^-$ . So also  $a + b = |w|$ .

# The Lasso as a Quadratic Program

$$\begin{aligned} & \min_w \min_{a,b} \sum_{i=1}^n \left( (a-b)^T x_i - y_i \right)^2 + \lambda \mathbf{1}^T (a+b) \\ & \text{subject to } a_i \geq 0 \text{ for all } i \quad b_i \geq 0 \text{ for all } i, \\ & \quad a - b = w \end{aligned}$$

- Claim: Can remove  $\min_w$  and the constraint  $a - b = w$ .
- One way to see this is by switching the order of minimization...

# The Lasso as a Quadratic Program

$$\begin{aligned} \min_{a,b} \min_w \quad & \sum_{i=1}^n \left( (a-b)^T x_i - y_i \right)^2 + \lambda 1^T (a+b) \\ \text{subject to} \quad & a_i \geq 0 \text{ for all } i \quad b_i \geq 0 \text{ for all } i, \\ & a - b = w \end{aligned}$$

- For any  $a \geq 0, b \geq 0$ , there's always a single  $w$  that satisfies the constraints.
- So the inner minimum is always attained at  $w = a - b$ .
- Since  $w$  doesn't show up in the objective function,
  - nothing changes if we drop  $\min_w$  and the constraint.

# The Lasso as a Quadratic Program

- So lasso optimization problem is equivalent to

$$\begin{aligned} \min_{a,b} \quad & \sum_{i=1}^n \left( (a-b)^T x_i - y_i \right)^2 + \lambda 1^T (a+b) \\ \text{subject to} \quad & a_i \geq 0 \text{ for all } i \quad b_i \geq 0 \text{ for all } i, \end{aligned}$$

where at the end we take  $w^* = a^* - b^*$  (and we've shown above that  $a^*$  and  $b^*$  are positive and negative parts of  $w^*$ , respectively.)

- Has constraints – how do we optimize?



$$\min_{w^+, w^- \in \mathbf{R}^d} \sum_{i=1}^n \left( (w^+ - w^-)^T x_i - y_i \right)^2 + \lambda \mathbf{1}^T (w^+ + w^-)$$

subject to  $w_i^+ \geq 0$  for all  $i$

$w_i^- \geq 0$  for all  $i$

- Just like SGD, but after each step
  - Project  $w^+$  and  $w^-$  into the constraint set.
  - In other words, if any component of  $w^+$  or  $w^-$  becomes negative, set it back to 0.

## Finding the Lasso Solution: Coordinate Descent (Shooting Method)

# Coordinate Descent Method

- **Goal:** Minimize  $L(w) = L(w_1, \dots, w_d)$  over  $w = (w_1, \dots, w_d) \in \mathbf{R}^d$ .
- In gradient descent or SGD,
  - each step potentially changes all entries of  $w$ .
- In each step of **coordinate descent**,
  - we adjust only a single  $w_i$ .
- In each step, solve

$$w_i^{\text{new}} = \arg \min_{w_i} L(w_1, \dots, w_{i-1}, w_i, w_{i+1}, \dots, w_d)$$

- Solving this argmin may itself be an iterative process.
- Coordinate descent is great when
  - it's easy or easier to minimize w.r.t. one coordinate at a time

# Coordinate Descent Method

## Coordinate Descent Method

**Goal:** Minimize  $L(w) = L(w_1, \dots, w_d)$  over  $w = (w_1, \dots, w_d) \in \mathbf{R}^d$ .

- **Initialize**  $w^{(0)} = 0$
- **while** not converged:
  - Choose a coordinate  $j \in \{1, \dots, d\}$
  - $w_j^{\text{new}} \leftarrow \arg \min_{w_j} L(w_1^{(t)}, \dots, w_{j-1}^{(t)}, \mathbf{w}_j, w_{j+1}^{(t)}, \dots, w_d^{(t)})$
  - $w_j^{(t+1)} \leftarrow w_j^{\text{new}}$  and  $w^{(t+1)} \leftarrow w^{(t)}$
  - $t \leftarrow t + 1$
- Random coordinate choice  $\implies$  **stochastic coordinate descent**
- Cyclic coordinate choice  $\implies$  **cyclic coordinate descent**

In general, we will adjust each coordinate several times.

# Coordinate Descent Method for Lasso

- Why mention coordinate descent for Lasso?
- In Lasso, the coordinate minimization has a **closed form solution!**

# Coordinate Descent Method for Lasso

## Closed Form Coordinate Minimization for Lasso

$$\hat{w}_j = \arg \min_{w_j \in \mathbf{R}} \sum_{i=1}^n (w^T x_i - y_i)^2 + \lambda |w|_1$$

Then

$$\hat{w}_j = \begin{cases} (c_j + \lambda)/a_j & \text{if } c_j < -\lambda \\ 0 & \text{if } c_j \in [-\lambda, \lambda] \\ (c_j - \lambda)/a_j & \text{if } c_j > \lambda \end{cases}$$

$$a_j = 2 \sum_{i=1}^n x_{i,j}^2$$

$$c_j = 2 \sum_{i=1}^n x_{i,j} (y_i - w_{-j}^T x_{i,-j})$$

where  $w_{-j}$  is  $w$  without component  $j$  and similarly for  $x_{i,-j}$ .

# Coordinate Descent: When does it work?

- Suppose we're minimizing  $f : \mathbf{R}^d \rightarrow \mathbf{R}$ .
- Sufficient conditions:
  - ①  $f$  is continuously differentiable and
  - ②  $f$  is strictly convex in each coordinate

- But lasso objective

$$\sum_{i=1}^n (w^T x_i - y_i)^2 + \lambda \|w\|_1$$

is not differentiable...

- Luckily there are weaker conditions...

# Coordinate Descent: The Separability Condition

## Theorem

*<sup>a</sup>If the objective  $f$  has the following structure*

$$f(w_1, \dots, w_d) = g(w_1, \dots, w_d) + \sum_{j=1}^d h_j(w_j),$$

*where*

- $g : \mathbf{R}^d \rightarrow \mathbf{R}$  is differentiable and convex, and
- each  $h_j : \mathbf{R} \rightarrow \mathbf{R}$  is convex (but not necessarily differentiable)

*then the coordinate descent algorithm converges to the global minimum.*

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<sup>a</sup>Tseng 2001: “Convergence of a Block Coordinate Descent Method for Nondifferentiable Minimization”



## Coordinate Descent Method – Variation

- Suppose there's no closed form? (e.g. logistic regression)
- Do we really need to fully solve each inner minimization problem?
- A single projected gradient step is enough for  $\ell_1$  regularization!
  - Shalev-Shwartz & Tewari's "Stochastic Methods..." (2011)

# Stochastic Coordinate Descent for Lasso – Variation

- Let  $\tilde{w} = (w^+, w^-) \in \mathbf{R}^{2d}$  and

$$L(\tilde{w}) = \sum_{i=1}^n \left( (w^+ - w^-)^T x_i - y_i \right)^2 + \lambda (w^+ + w^-)$$

## Stochastic Coordinate Descent for Lasso - Variation

**Goal:** Minimize  $L(\tilde{w})$  s.t.  $w_i^+, w_i^- \geq 0$  for all  $i$ .

- **Initialize**  $\tilde{w}^{(0)} = 0$ 
  - **while** not converged:
    - Randomly choose a coordinate  $j \in \{1, \dots, 2d\}$
    - $\tilde{w}_j \leftarrow \tilde{w}_j + \max \{ -\tilde{w}_j, -\nabla_j L(\tilde{w}) \}$