

# Representer Theorem

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<sup>1</sup>Slides based on Lecture 5a from David Rosenberg's [course material](#).

# SVM solution is in the “span of the data”

- We found the SVM dual problem can be written as:

$$\begin{aligned} \sup_{\alpha \in \mathbb{R}^n} \quad & \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j=1}^n \alpha_i \alpha_j y_i y_j x_j^T x_i \\ \text{s.t.} \quad & \sum_{i=1}^n \alpha_i y_i = 0 \\ & \alpha_i \in \left[0, \frac{c}{n}\right] \quad i = 1, \dots, n. \end{aligned}$$

- Given dual solution  $\alpha^*$ , primal solution is  $w^* = \sum_{i=1}^n \alpha_i^* y_i x_i$ .
- Notice:  $w^*$  is a linear combination of training inputs  $x_1, \dots, x_n$ .
- We refer to this phenomenon by saying “ $w^*$  is in the **span of the data**.”
  - Or in math,  $w^* \in \text{span}(x_1, \dots, x_n)$ .

## Ridge regression solution is in the “span of the data”

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

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

- This has a closed form solution (Homework #3):

$$w^* = (X^T X + \lambda I)^{-1} X^T y,$$

where  $X$  is the design matrix, with  $x_1, \dots, x_n$  as rows.

## Ridge regression solution is in the “span of the data”

- Rearranging  $w^* = (X^T X + \lambda I)^{-1} X^T y$ , we can show that (also Homework #3):

$$\begin{aligned} w^* &= X^T \underbrace{\left( \frac{1}{\lambda} y - \frac{1}{\lambda} X w^* \right)}_{\alpha^*} \\ &= X^T \alpha^* = \sum_{i=1}^n \alpha_i^* x_i. \end{aligned}$$

- So  $w^*$  is in the span of the data.
  - i.e.  $w^* \in \text{span}(x_1, \dots, x_n)$

## If solution is in the span of the data, we can reparameterize

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

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

- We now know that  $w^* \in \text{span}(x_1, \dots, x_n) \subset \mathbb{R}^d$ .
- So rather than minimizing over all of  $\mathbb{R}^d$ , we can minimize over  $\text{span}(x_1, \dots, x_n)$ .

$$w^* = \arg \min_{w \in \text{span}(x_1, \dots, x_n)} \frac{1}{n} \sum_{i=1}^n \{w^T x_i - y_i\}^2 + \lambda \|w\|_2^2.$$

- Let's reparameterize the objective by replacing  $w$  as a linear combination of the inputs.

## If solution is in the span of the data, we can reparameterize

- Note that for any  $w \in \text{span}(x_1, \dots, x_n)$ , we have  $w = X^T \alpha$ , for some  $\alpha \in \mathbb{R}^n$ .
- So let's replace  $w$  with  $X^T \alpha$  in our optimization problem:

$$\text{[original]} \quad w^* = \arg \min_{w \in \mathbb{R}^d} \frac{1}{n} \sum_{i=1}^n \{w^T x_i - y_i\}^2 + \lambda \|w\|_2^2$$

$$\text{[reparameterized]} \quad \alpha^* = \arg \min_{\alpha \in \mathbb{R}^n} \frac{1}{n} \sum_{i=1}^n \{(X^T \alpha)^T x_i - y_i\}^2 + \lambda \|X^T \alpha\|_2^2.$$

- To get  $w^*$  from the reparameterized optimization problem, we just take  $w^* = X^T \alpha^*$ .
- We changed the dimension of our optimization variable from  $d$  to  $n$ . Is this useful?

## Consider very large feature spaces

- Suppose we have a 300-million dimension feature space [very large]
  - (e.g. using high order monomial interaction terms as features, as described last lecture)
- Suppose we have a training set of 300,000 examples [fairly large]
- In the original formulation, we solve a 300-million dimension optimization problem.
- In the reparameterized formulation, we solve a 300,000-dimension optimization problem.
- This is why we care about when the solution is in the span of the data.
- This reparameterization is interesting when we have more features than data ( $d \gg n$ ).

# What's next?

- For SVM and ridge regression, we found that the solution is in the span of the data.
  - derived in two rather ad-hoc ways
- Up next: The Representer Theorem, which shows that this “span of the data” result occurs far more generally, and we prove it using basic linear algebra.



# Math Review: Inner Product Spaces and Hilbert Spaces

# Hypothesis spaces we've seen so far

Finite-dimensional vector space (linear functions):

$$\mathcal{H} = \{f: \mathcal{X} \rightarrow \mathbb{R} \mid f(x) = w^T x, \quad w, x \in \mathbb{R}^d\} .$$

To consider more complex input spaces (e.g. text, images), we use a feature map  $\phi: \mathcal{X} \rightarrow \mathcal{F}$ :

$$\mathcal{H} = \{f: \mathcal{X} \rightarrow \mathbb{R} \mid f(x) = w^T \phi(x)\} .$$

- $\phi$  does not have to be linear.
- The feature space  $\mathcal{F}$  can be  $\mathbb{R}^d$  (Euclidean space) or an infinite-dimensional vector space.
- We would like more structure on  $\mathcal{F}$ .

# Inner Product Space (or “Pre-Hilbert” Spaces)

An **inner product space** (over reals) is a vector space  $\mathcal{V}$  with an **inner product**, which is a mapping

$$\langle \cdot, \cdot \rangle : \mathcal{V} \times \mathcal{V} \rightarrow \mathbb{R}$$

that has the following properties:  $\forall x, y, z \in \mathcal{V}$  and  $a, b \in \mathbb{R}$ :

- Symmetry:  $\langle x, y \rangle = \langle y, x \rangle$
- Linearity:  $\langle ax + by, z \rangle = a \langle x, z \rangle + b \langle y, z \rangle$
- Positive-definiteness:  $\langle x, x \rangle \geq 0$  and  $\langle x, x \rangle = 0 \iff x = 0_{\mathcal{V}}$ .

To show a function  $\langle \cdot, \cdot \rangle$  is an inner product, we need to check the above conditions.

Exercise: show that  $\langle x, y \rangle \stackrel{\text{def}}{=} x^T y$  is an inner product on  $\mathbb{R}^d$ .

# Norm from Inner Product

Inner product is nice because it gives us notions of “size”, “distance”, “angle” in the vector space.

For an inner product space, we can define a norm as

$$\|x\| \stackrel{\text{def}}{=} \sqrt{\langle x, x \rangle}.$$

## Example

$\mathbb{R}^d$  with standard Euclidean inner product is an inner product space:

$$\langle x, y \rangle := x^T y \quad \forall x, y \in \mathbb{R}^d.$$

Norm is

$$\|x\| = \sqrt{x^T x}.$$

# Orthogonality (Definitions)

## Definition

Two vectors are **orthogonal** if  $\langle x, x' \rangle = 0$ . We denote this by  $x \perp x'$ .

## Definition

$x$  is orthogonal to a set  $S$ , i.e.  $x \perp S$ , if  $x \perp s$  for all  $s \in S$ .

# Pythagorean Theorem

## Theorem (Pythagorean Theorem)

If  $x \perp x'$ , then  $\|x + x'\|^2 = \|x\|^2 + \|x'\|^2$ .

## Proof.

We have

$$\begin{aligned}\|x + x'\|^2 &= \langle x + x', x + x' \rangle \\ &= \langle x, x \rangle + \langle x, x' \rangle + \langle x', x \rangle + \langle x', x' \rangle \\ &= \|x\|^2 + \|x'\|^2.\end{aligned}$$



# Hilbert Space

- A pre-Hilbert space is a vector space equipped with an inner product.
- We need an additional technical condition for Hilbert space: **completeness**.
- A space is **complete** if all Cauchy sequences in the space converge to a point in the space.

## Definition

A **Hilbert space** is a complete inner product space.

## Example

Any finite dimensional inner product space is a Hilbert space.

# The Representer Theorem



# Generalize from SVM Objective

- SVM objective:

$$\min_{w \in \mathbb{R}^d} \frac{1}{2} \|w\|^2 + \frac{c}{n} \sum_{i=1}^n \max(0, 1 - y_i [\langle w, x_i \rangle]).$$

- Generalized objective:

$$\min_{w \in \mathcal{H}} R(\|w\|) + L(\langle w, x_1 \rangle, \dots, \langle w, x_n \rangle),$$

where

- $w, x_1, \dots, x_n \in \mathcal{H}$  for some Hilbert space  $\mathcal{H}$ . (We typically have  $\mathcal{H} = \mathbb{R}^d$ .)
- $\|\cdot\|$  is the norm corresponding to the inner product of  $\mathcal{H}$ . (i.e.  $\|w\| = \sqrt{\langle w, w \rangle}$ )
- $R: [0, \infty) \rightarrow \mathbb{R}$  is nondecreasing (**Regularization term**), and
- $L: \mathbb{R}^n \rightarrow \mathbb{R}$  is arbitrary (**Loss term**).

# General Objective Function for Linear Hypothesis Space (Details)

- **Generalized objective:**

$$\min_{w \in \mathcal{H}} R(\|w\|) + L(\langle w, x_1 \rangle, \dots, \langle w, x_n \rangle)$$

- We can map  $x_i$  to a feature space.
- The prediction/score function  $x \mapsto \langle w, x \rangle$  is linear in  $w$ .

# General Objective Function for Linear Hypothesis Space (Details)

- **Generalized objective:**

$$\min_{w \in \mathcal{H}} R(\|w\|) + L(\langle w, x_1 \rangle, \dots, \langle w, x_n \rangle)$$

- Ridge regression and SVM are of this form. (Verify this!)
- What if we penalize with  $\lambda\|w\|_2$  instead of  $\lambda\|w\|_2^2$ ? Yes!
- What if we use lasso regression? No!  $\ell_1$  norm does not correspond to an inner product.

# The Representer Theorem: Quick Summary

- Generalized objective:

$$w^* = \arg \min_{w \in \mathcal{H}} R(\|w\|) + L(\langle w, x_1 \rangle, \dots, \langle w, x_n \rangle)$$

- Representer theorem tells us we can look for  $w^*$  in the span of the data:

$$w^* = \arg \min_{w \in \text{span}(x_1, \dots, x_n)} R(\|w\|) + L(\langle w, x_1 \rangle, \dots, \langle w, x_n \rangle).$$

- So we can reparameterize as before:

$$\alpha^* = \arg \min_{\alpha \in \mathbb{R}^n} R\left(\left\|\sum_{i=1}^n \alpha_i x_i\right\|\right) + L\left(\left\langle \sum_{i=1}^n \alpha_i x_i, x_1 \right\rangle, \dots, \left\langle \sum_{i=1}^n \alpha_i x_i, x_n \right\rangle\right).$$

- Our reparameterization trick applies much more broadly than SVM and ridge.

# The Representer Theorem

## Theorem (Representer Theorem)

Let

$$J(w) = R(\|w\|) + L(\langle w, x_1 \rangle, \dots, \langle w, x_n \rangle),$$

where

- $w, x_1, \dots, x_n \in \mathcal{H}$  for some Hilbert space  $\mathcal{H}$ . (We typically have  $\mathcal{H} = \mathbb{R}^d$ .)
- $\|\cdot\|$  is the norm corresponding to the inner product of  $\mathcal{H}$ . (i.e.  $\|w\| = \sqrt{\langle w, w \rangle}$ )
- $R: [0, \infty) \rightarrow \mathbb{R}$  is nondecreasing (**Regularization term**), and
- $L: \mathbb{R}^n \rightarrow \mathbb{R}$  is arbitrary (**Loss term**).

Then it **has a minimizer of the form**  $w^* = \sum_{i=1}^n \alpha_i x_i$ .

# The Representer Theorem (Proof sketch)

## Reparameterizing our Generalized Objective Function

## Rewriting the Objective Function

- Define the training score function  $s : \mathbb{R}^d \rightarrow \mathbb{R}^n$  by

$$s(w) = \begin{pmatrix} \langle w, x_1 \rangle \\ \vdots \\ \langle w, x_n \rangle \end{pmatrix},$$

which gives the **training score vector** for any  $w$ .

- We can then rewrite the objective function as

$$J(w) = R(\|w\|) + L(s(w)),$$

where now  $L : \mathbb{R}^{n \times 1} \rightarrow \mathbb{R}$  takes a column vector as input.

- This will allow us to have a slick reparameterized version...



# Reparameterize the Generalized Objective

- By the Representer Theorem, it's sufficient to minimize  $J(w)$  for  $w$  of the form  $\sum_{i=1}^n \alpha_i x_i$ .
- Plugging this form into  $J(w)$ , we see we can just minimize

$$J_0(\alpha) = R\left(\left\|\sum_{i=1}^n \alpha_i x_i\right\|\right) + L\left(s\left(\sum_{i=1}^n \alpha_i x_i\right)\right)$$

over  $\alpha = (\alpha_1, \dots, \alpha_n)^T \in \mathbb{R}^{n \times 1}$ .

- With some new notation, we can substantially simplify
  - the norm piece  $\|w\| = \|\sum_{i=1}^n \alpha_i x_i\|$ , and
  - the score piece  $s(w) = s(\sum_{i=1}^n \alpha_i x_i)$ .

# Simplifying the Reparameterized Norm

- For the norm piece  $\|w\| = \|\sum_{i=1}^n \alpha_i x_i\|$ , we have

$$\begin{aligned}\|w\|^2 &= \langle w, w \rangle \\ &= \left\langle \sum_{i=1}^n \alpha_i x_i, \sum_{j=1}^n \alpha_j x_j \right\rangle \\ &= \sum_{i,j=1}^n \alpha_i \alpha_j \langle x_i, x_j \rangle.\end{aligned}$$

- This expression involves the  $n^2$  inner products between all pairs of input vectors.
- We often put those values together into a matrix (Gram/Kernel matrix).

## Example: Gram Matrix for the Dot Product

- Consider  $x_1, \dots, x_n \in \mathbb{R}^{d \times 1}$  with the standard inner product  $\langle x, x' \rangle = x^T x'$ .
- Let  $X \in \mathbb{R}^{n \times d}$  be the **design matrix**, which has each input vector as a row:

$$X = \begin{pmatrix} -x_1^T - \\ \vdots \\ -x_n^T - \end{pmatrix}.$$

- Then the Gram matrix is

$$\begin{aligned} K &= \begin{pmatrix} x_1^T x_1 & \cdots & x_1^T x_n \\ \vdots & \ddots & \vdots \\ x_n^T x_1 & \cdots & x_n^T x_n \end{pmatrix} = \begin{pmatrix} -x_1^T - \\ \vdots \\ -x_n^T - \end{pmatrix} \begin{pmatrix} | & \cdots & | \\ x_1 & \cdots & x_n \\ | & \cdots & | \end{pmatrix} \\ &= XX^T \end{aligned}$$

# Simplifying the Reparametrized Norm

- With  $w = \sum_{i=1}^n \alpha_i x_i$ , we have

$$\begin{aligned}\|w\|^2 &= \langle w, w \rangle \\ &= \left\langle \sum_{i=1}^n \alpha_i x_i, \sum_{j=1}^n \alpha_j x_j \right\rangle \\ &= \sum_{i,j=1}^n \alpha_i \alpha_j \langle x_i, x_j \rangle \\ &= \alpha^T K \alpha.\end{aligned}$$

# Simplifying the Training Score Vector

- The score for  $x_j$  for  $w = \sum_{i=1}^n \alpha_i x_i$  is

$$\langle w, x_j \rangle = \left\langle \sum_{i=1}^n \alpha_i x_i, x_j \right\rangle = \sum_{i=1}^n \alpha_i \langle x_i, x_j \rangle$$

- The training score vector is

$$\begin{aligned} s \left( \sum_{i=1}^n \alpha_i x_i \right) &= \begin{pmatrix} \sum_{i=1}^n \alpha_i \langle x_i, x_1 \rangle \\ \vdots \\ \sum_{i=1}^n \alpha_i \langle x_i, x_n \rangle \end{pmatrix} = \begin{pmatrix} \alpha_1 \langle x_1, x_1 \rangle + \cdots + \alpha_n \langle x_n, x_1 \rangle \\ \vdots \\ \alpha_1 \langle x_1, x_n \rangle + \cdots + \alpha_n \langle x_n, x_n \rangle \end{pmatrix} \\ &= \begin{pmatrix} \langle x_1, x_1 \rangle & \cdots & \langle x_1, x_n \rangle \\ \vdots & \ddots & \vdots \\ \langle x_n, x_1 \rangle & \cdots & \langle x_n, x_n \rangle \end{pmatrix} \begin{pmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{pmatrix} \\ &= K \alpha \end{aligned}$$

## Reparameterized Objective

- Putting it all together, our reparameterized objective function can be written as

$$\begin{aligned} J_0(\alpha) &= R\left(\left\|\sum_{i=1}^n \alpha_i x_i\right\|\right) + L\left(s\left(\sum_{i=1}^n \alpha_i x_i\right)\right) \\ &= R\left(\sqrt{\alpha^T K \alpha}\right) + L(K\alpha), \end{aligned}$$

which we minimize over  $\alpha \in \mathbb{R}^n$ .

- All information** needed about  $x_1, \dots, x_n$  is summarized in the Gram matrix  $K$ .
- We're now minimizing over  $\mathbb{R}^n$  rather than  $\mathbb{R}^d$ .
- If  $d \gg n$ , this can be a big win computationally (at least once  $K$  is computed).

# Reparameterizing Predictions

- Suppose we've found

$$\alpha^* \in \arg \min_{\alpha \in \mathbb{R}^n} R\left(\sqrt{\alpha^T K \alpha}\right) + L(K\alpha).$$

- Then we know  $w^* = \sum_{i=1}^n \alpha_i^* x_i$  is a solution to

$$\arg \min_{w \in \mathcal{H}} R(\|w\|) + L(\langle w, x_1 \rangle, \dots, \langle w, x_n \rangle).$$

- The prediction on a new point  $x \in \mathcal{H}$  is

$$\hat{f}(x) = \langle w^*, x \rangle = \sum_{i=1}^n \alpha_i^* \langle x_i, x \rangle.$$

- To make a new prediction, we may need to touch all the training inputs  $x_1, \dots, x_n$ .

- It will be convenient to define the following column vector for any  $x \in \mathcal{H}$ :

$$k_x = \begin{pmatrix} \langle x_1, x \rangle \\ \vdots \\ \langle x_n, x \rangle \end{pmatrix}$$

- Then we can write our predictions on a new point  $x$  as

$$\hat{f}(x) = k_x^T \alpha^*$$



## Summary So Far

- Original plan:
  - Find  $w^* \in \arg \min_{w \in \mathcal{H}} R(\|w\|) + L(\langle w, x_1 \rangle, \dots, \langle w, x_n \rangle)$
  - Predict with  $\hat{f}(x) = \langle w^*, x \rangle$ .
- We showed that the following is equivalent:
  - Find  $\alpha^* \in \arg \min_{\alpha \in \mathbb{R}^n} R(\sqrt{\alpha^T K \alpha}) + L(K\alpha)$
  - Predict with  $\hat{f}(x) = k_x^T \alpha^*$ , where

$$K = \begin{pmatrix} \langle x_1, x_1 \rangle & \cdots & \langle x_1, x_n \rangle \\ \vdots & \ddots & \vdots \\ \langle x_n, x_1 \rangle & \cdots & \langle x_n, x_n \rangle \end{pmatrix} \quad \text{and} \quad k_x = \begin{pmatrix} \langle x_1, x \rangle \\ \vdots \\ \langle x_n, x \rangle \end{pmatrix}$$

- Every element  $x \in \mathcal{H}$  occurs inside an inner products with a training input  $x_i \in \mathcal{H}$ .

# Kernelization

## Definition

A method is **kernelized** if every feature vector  $\psi(x)$  only appears inside an inner product with another feature vector  $\psi(x')$ . This applies to both the optimization problem and the prediction function.

- Here we are using  $\psi(x) = x$ . Thus finding

$$\alpha^* \in \arg \min_{\alpha \in \mathbb{R}^n} R\left(\sqrt{\alpha^T K \alpha}\right) + L(K\alpha)$$

and making predictions with  $\hat{f}(x) = k_x^T \alpha^*$  is a **kernelization** of finding

$$w^* \in \arg \min_{w \in \mathcal{H}} R(\|w\|) + L(\langle w, x_1 \rangle, \dots, \langle w, x_n \rangle)$$

and making predictions with  $\hat{f}(x) = \langle w^*, x \rangle$ .

# Summary

- We used duality for SVM and bare hands for ridge regression to find their kernelized version.
- Our principle tool for kernelization is reparameterization by the representer theorem.
- Once kernelized, we can apply the kernel trick: doesn't need to represent  $\phi(x)$  explicitly.