Lecture 4 – Center and Spread, Other Loss Functions

DSC 40A, Spring 2023

Announcements

- Homework 1 is due **tomorrow at 11:59pm**.
  - LaTeX template provided if you want to type your answers.
  - Make sure to explain your answers! Don't just write a number; show how you got it.
  - Please come to office hours!
- Discussion section is on Wednesday.

Agenda

- Recap of empirical risk minimization.
- Center and spread.
- A new loss function.

Recap of empirical risk minimization

Empirical risk minimization

- **Goal**: Given a dataset $y_1, y_2, ..., y_n$, determine the best prediction h^*.

- Strategy:
  1. Choose a **loss function**, $L(h, y)$, that measures how far any particular prediction h is from the "right answer" y.

  2. Minimize **empirical risk** (also known as average loss) over the entire dataset. The value(s) of h that minimize empirical risk are the resulting "best predictions".

$$R(h) = \frac{1}{n} \sum_{i=1}^{n} L(h, y_i)$$

Absolute loss and squared loss

- General form of empirical risk:

$$R(h) = \frac{1}{n} \sum_{i=1}^{n} L(h, y_i)$$

- **Absolute loss**: $L_{\text{abs}}(h, y) = |y - h|$.
  - Empirical risk: $R_{abs}(h) = \frac{1}{n} \sum_{i=1}^{n} |y_i - h|$. Also called "**mean absolute error**".
  - Minimized by $h^* =$ **Median**$(y_1, y_2, ..., y_n)$.

- **Squared loss**: $L_{\text{sq}}(h, y) = (y - h)^2$.
  - Empirical risk: $R_{sq}(h) = \frac{1}{n} \sum_{i=1}^{n} (y_i - h)^2$. Also called "**mean squared error**".
  - Minimized by $h^* =$ **Mean**$(y_1, y_2, ..., y_n)$.

ex.) $y_1 = 1$, $y_2 = 5$, $h = 2$

Discussion Question

Consider a dataset $y_1, y_2, ..., y_n$.
Recall,

$$(x+y+z)^2 \neq x^2+y^2+z^2$$

$$R_{abs}(h) = \frac{1}{n} \sum_{i=1}^{n} |y_i - h|$$

$$R_{sq}(h) = \frac{1}{n} \sum_{i=1}^{n} (y_i - h)^2$$

$$R_{abs}(2) = \frac{1}{2}(1+3) = 2$$

$$R_{sq}(2) = \frac{1}{2}(1+9) = 5$$

Is it true that, for any h, $[R_{abs}(h)]^2 = R_{sq}(h)$?

a) True

b) False - give counterexample

$$2^2 \neq 5$$

Center and spread

What does it mean?

- General form of empirical risk:

$$R(h) = \frac{1}{n} \sum_{i=1}^{n} L(h, y_i)$$

- The input h^* that minimizes $R(h)$ is some measure of the **center** of the data set.
  - e.g. median, mean, mode.
- The minimum output $R(h^*)$ represents some measure of the **spread**, or variation, in the data set.

Absolute loss

mean abs dev from med

- The empirical risk for the absolute loss is

$$R_{abs}(h) = \frac{1}{n}\sum_{i=1}^{n} |y_i - h|$$

plug in median

- $R_{abs}(h)$ is minimized at $h^* = \text{Median}(y_1, y_2, \ldots, y_n)$.

- Therefore, the minimum value of $R_{abs}(h)$ is

$$\begin{aligned} R_{abs}(h^*) &= R_{abs}(\text{Median}(y_1, y_2, \ldots, y_n)) \\ &= \underbrace{\frac{1}{n}\sum_{i=1}^{n}}_{\text{average of}} \underbrace{|y_i - \text{Median}(y_1, y_2, \ldots, y_n)|}_{\text{each data point's distance to median}}. \end{aligned}$$

Mean absolute deviation from the median

- The minimum value of $R_{abs}(h)$ is the **mean absolute deviation from the median**.

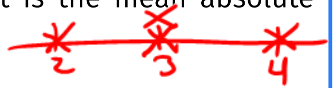
$$\frac{1}{n}\sum_{i=1}^{n}|y_i - \text{Median}(y_1, y_2, \dots, y_n)|$$

- It measures how far each data point is from the median, on average.

Discussion Question

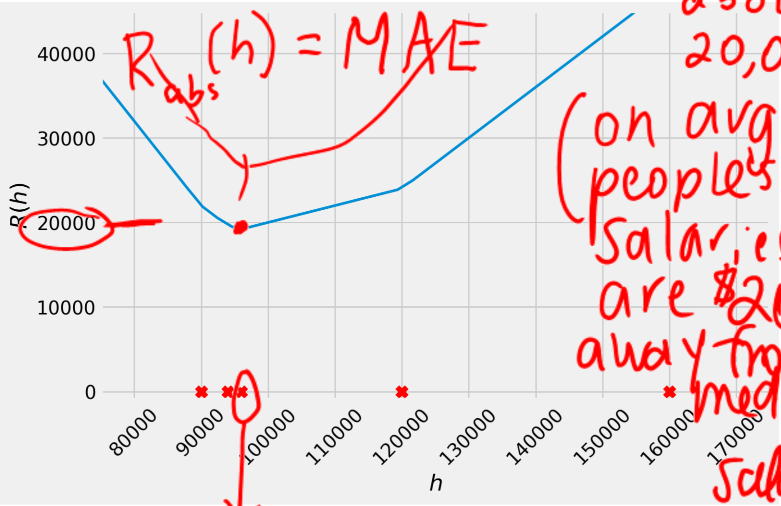
1 0 0 1

For the data set $2, 3, 3, 4$, what is the mean absolute deviation from the median? $= 3$



a) 0 b) $\boxed{\frac{1}{2}}$ c) 1 d) 2

Mean absolute deviation from the median



$R_{abs}(h) = MAE$

is about 20,000 (on avg, people's salaries are $20K away from median salary)

96,000 median

Squared loss

- The empirical risk for the squared loss is

$$R_{\text{sq}}(h) = \frac{1}{n}\sum_{i=1}^{n}(y_i - h)^2$$

plug in mean

- $R_{\text{sq}}(h)$ is minimized at $h^* = \text{Mean}(y_1, y_2, \dots, y_n)$.

- Therefore, the minimum value of $R_{\text{sq}}(h)$ is

$$\begin{aligned} \underline{R_{\text{sq}}(h^*)} &= R_{\text{sq}}(\text{Mean}(y_1, y_2, \dots, y_n)) \\ &= \underbrace{\frac{1}{n}\sum_{i=1}^{n}(y_i - \text{Mean}(y_1, y_2, \dots, y_n))^2}_{\text{variance!}}. \end{aligned}$$

Variance

- The minimum value of $R_{\text{sq}}(h)$ is the mean squared deviation from the mean, more commonly known as the **variance**.

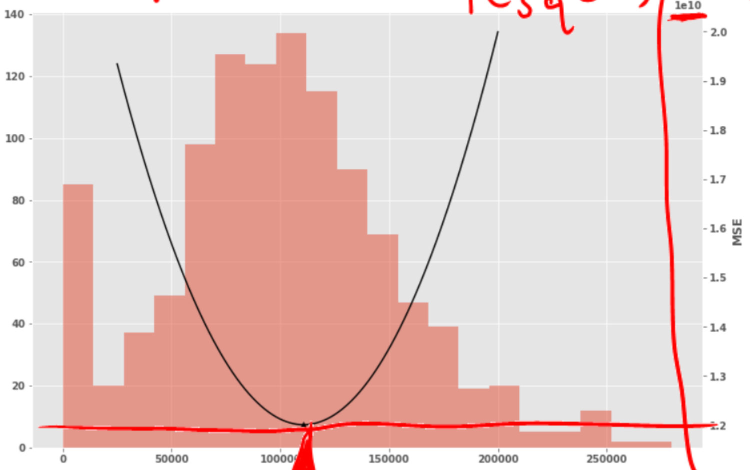
$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \text{Mean}(y_1, y_2, \ldots, y_n))^2$$

- It measures the squared distance of each data point from the mean, on average.
- Its square root is called the **standard deviation.**

Variance

is about 1.2×10^{10}

$R_{sq}(h) = \text{MSE}$

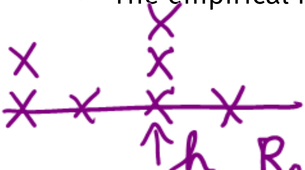


$h^* = \text{mean} \approx 110{,}000$

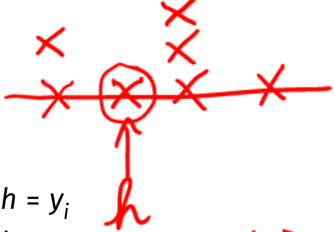
0-1 loss

- The empirical risk for the 0-1 loss is

$$R_{0,1}(h) = \frac{1}{n}\sum_{i=1}^{n}\begin{cases}0, & \text{if } h = y_i\\ 1, & \text{if } h \neq y_i\end{cases}$$



$R_{0,1}(h) = \frac{1}{7}(4) = 4/7$



$R_{0,1}(h) = \frac{1}{7}(6) = \frac{6}{7}$

- This is the proportion (between 0 and 1) of data points not equal to h.

- $R_{0,1}(h)$ is minimized at $h^* = \text{Mode}(y_1, y_2, \ldots, y_n)$.

- Therefore, $R_{0,1}(h^*)$ is the proportion of data points not equal to the mode.

measure of spread (clusteredness to mode)

A poor way to measure spread

- The minimium value of $R_{0,1}(h)$ is the proportion of data points not equal to the mode.
- A higher value means less of the data is clustered at the mode.
- Just as the mode is a very simplistic way to measure the center of the data, this is a very crude way to measure spread.

Summary of center and spread

- Different loss functions lead to empirical risk functions that are minimized at various measures of **center**.

  median, mean, mode

- The minimum values of these risk functions are various measures of **spread**.

  mean abs dev from median, variance

- There are many different ways to measure both center and spread. These are sometimes called **descriptive statistics**.

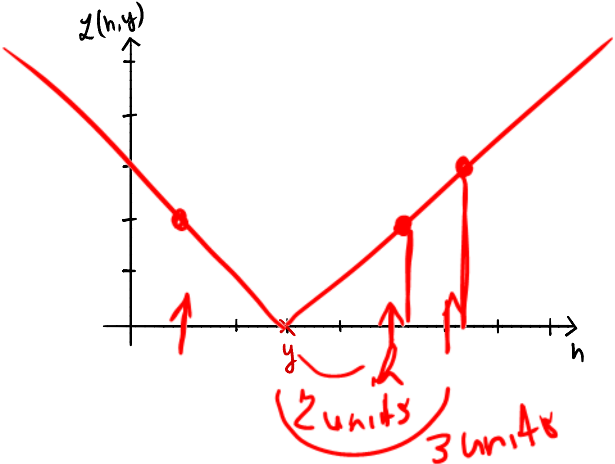
Prop. data

≠ mode

A new loss function

Plotting a loss function

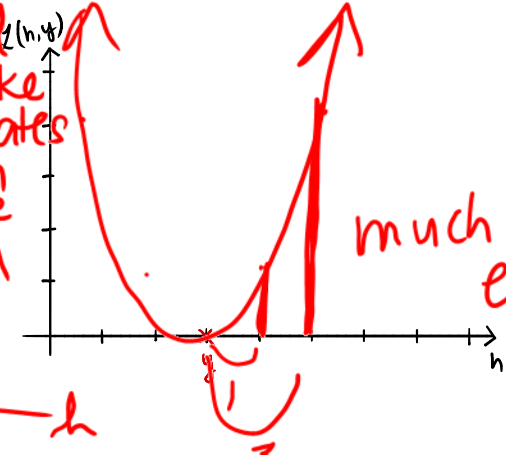
- The plot of a loss function tells us how it treats outliers.
- Consider y to be some fixed value. Plot $L_{\text{abs}}(h, y) = |y - h|$:



Plotting a loss function

- The plot of a loss function tells us how it treats outliers.
- Consider y to be some fixed value. Plot $L_{sq}(h, y) = (y - h)^2$:

asymmetrical loss fcn like this motivates prediction to be low



much bigger error incurred

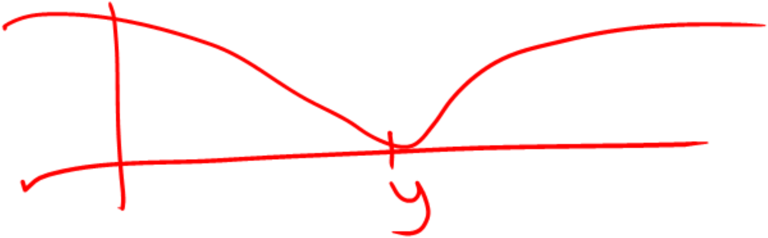
Discussion Question

Suppose L considers all outliers to be equally bad. What would it look like far away from y?

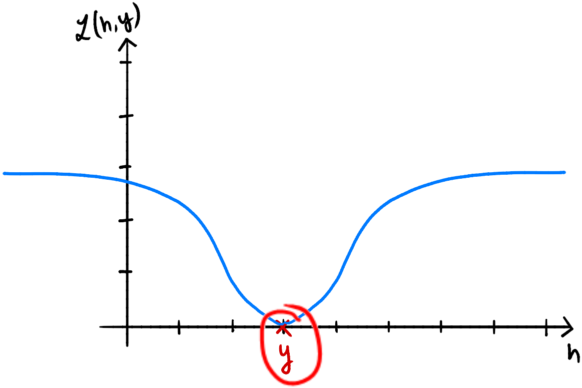
a) flat

b) rapidly decreasing

c) rapidly increasing



A very insensitive loss



- We'll call this loss L_{ucsd} because we made it up at UCSD.

Discussion Question

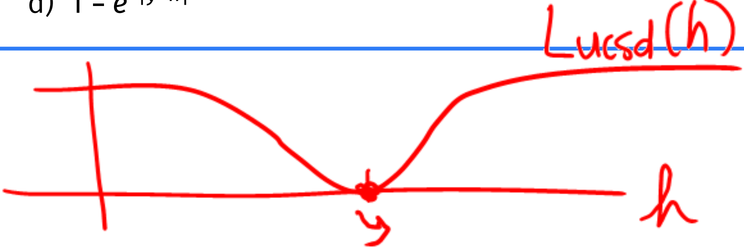
Which of these could be $L_{ucsd}(h, y)$?

a) $e^{-(y-h)^2}$ ← when $h = y$, $e^{-0^2} = 1$

b) $1 - e^{-(y-h)^2}$

c) $1 - (y - h)^2$ $\quad 1 - (0)^2 = 1$

d) $1 - e^{-|y-h|}$



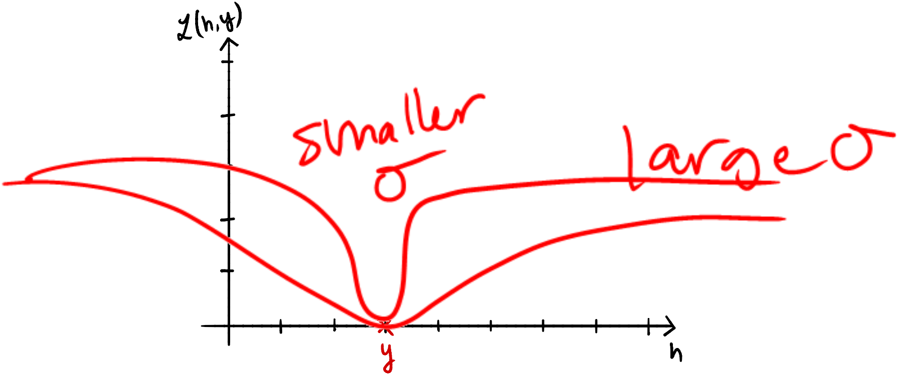
Adding a scale parameter

- Problem: L_{ucsd} has a fixed scale. This won't work for all datasets.
  - If we're predicting temperature, and we're off by 100 degrees, that's bad.
  - If we're predicting salaries, and we're off by 100 dollars, that's pretty good.
  - What we consider to be an outlier depends on the scale of the data.
- Fix: add a **scale parameter**, σ:

not SD, just some constant

$$L_{ucsd}(h, y) = 1 - e^{-(y-h)^2/\underline{\sigma^2}}$$

Scale parameter controls width of bowl



Empirical risk minimization

- We have salaries $y_1, y_2, \dots, y_n$.
- To find prediction, ERM says to minimize the average loss:

$$
\begin{aligned}
R_{ucsd}(h) &= \frac{1}{n}\sum_{i=1}^{n} L_{ucsd}(h, y_i) \\
&= \frac{1}{n}\sum_{i=1}^{n}\left[1 - e^{-(y_i - h)^2/\sigma^2}\right]
\end{aligned}
$$

Let's plot R_{ucsd}

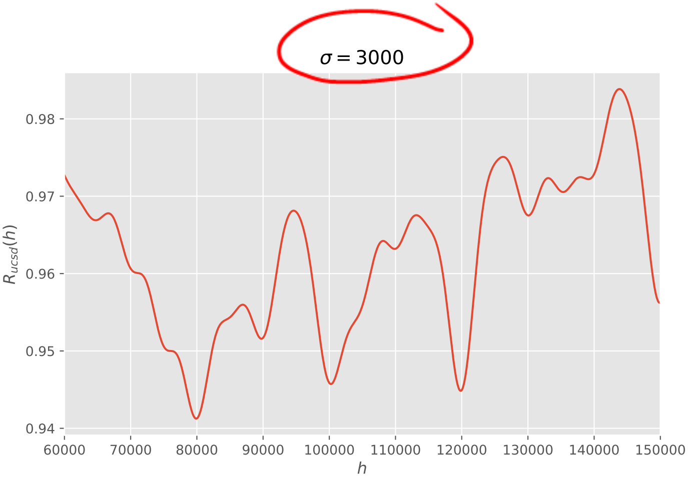
- Recall:

$$R_{ucsd}(h) = \frac{1}{n} \sum_{i=1}^{n} \left[1 - e^{-(y_i - h)^2/\sigma^2}\right]$$

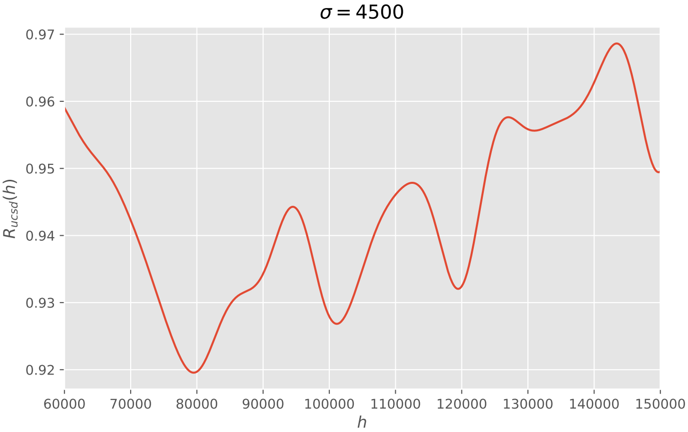
- Once we have data $y_1, y_2, ..., y_n$ and a scale σ, we can plot $R_{ucsd}(h)$.

- Let's try several scales, σ, for the data scientist salary data.

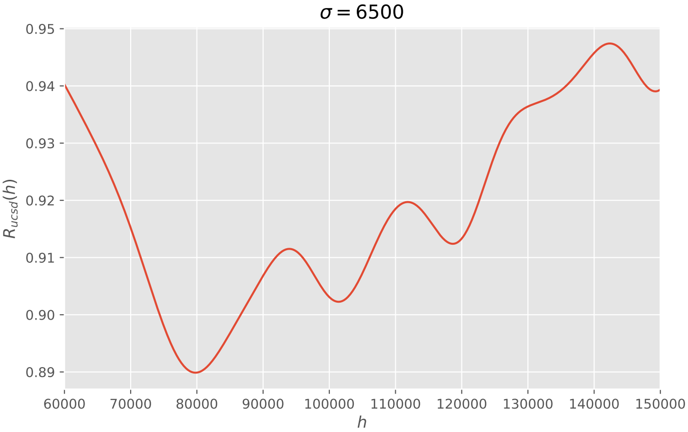
Plot of $R_{ucsd}(h)$



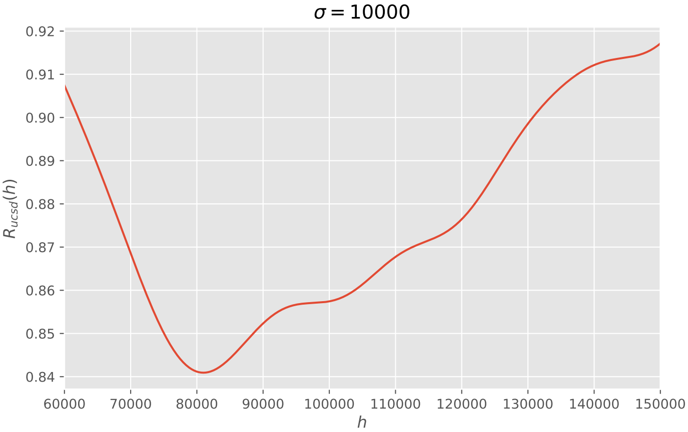
Plot of $R_{ucsd}(h)$



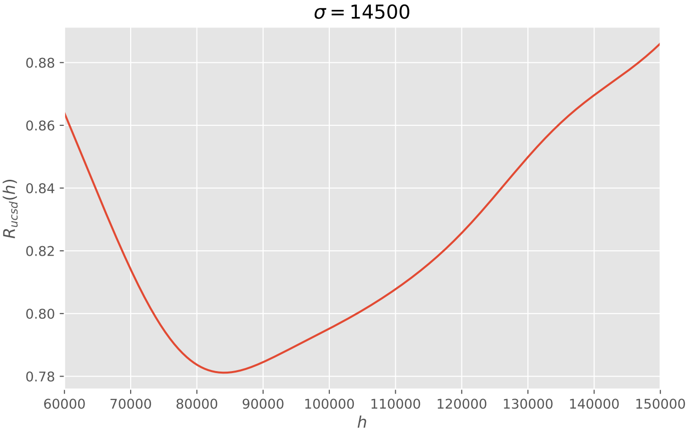
Plot of $R_{ucsd}(h)$



Plot of $R_{ucsd}(h)$



Plot of $R_{ucsd}(h)$



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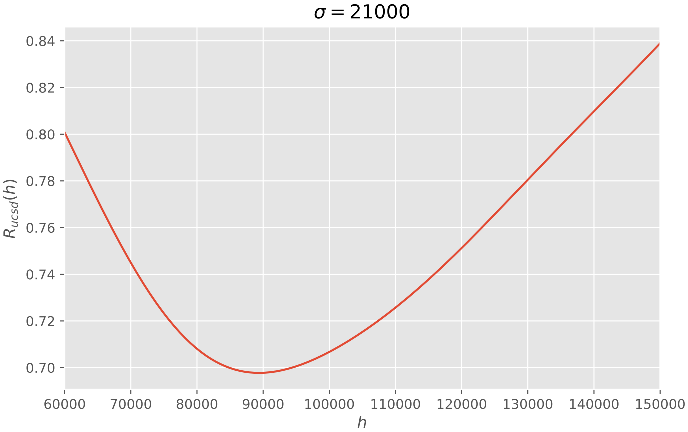
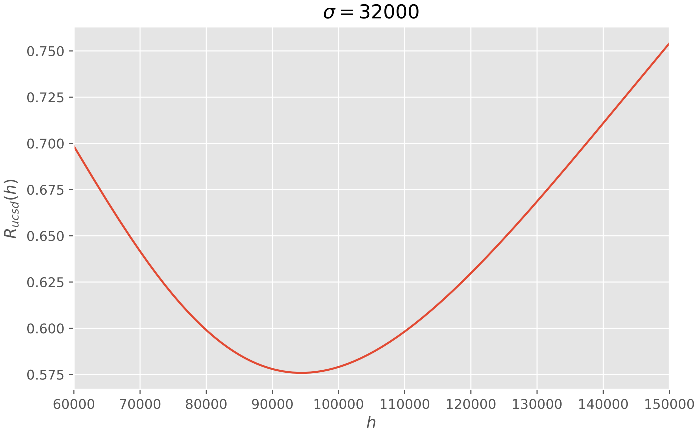


Plot of $R_{ucsd}(h)$



Minimizing R_{ucsd}

- To find the best prediction, we find h^* minimizing $R_{ucsd}(h)$.

- $R_{ucsd}(h)$ is **differentiable**.

- To minimize: take derivative, set to zero, solve.

Step 1: Taking the derivative

$$\frac{dR_{ucsd}}{dh} = \frac{d}{dh}\left(\frac{1}{n}\sum_{i=1}^{n}\left[1 - e^{-(y_i-h)^2/\sigma^2}\right]\right)$$

Step 2: Setting to zero and solving

- We found:

$$\frac{d}{dh} R_{ucsd}(h) = \frac{2}{n\sigma^2} \sum_{i=1}^{n} (h - y_i) \cdot e^{-(h-y_i)^2/\sigma^2}$$

- Now we just set to zero and solve for h:

$$0 = \frac{2}{n\sigma^2} \sum_{i=1}^{n} (h - y_i) \cdot e^{-(h-y_i)^2/\sigma^2}$$

- We **can** calculate derivative, but we **can't** solve for h; we're stuck again.

Summary

- Different loss functions lead to empirical risk functions that are minimized at various measures of **center**.
- The minimum values of these empirical risk functions are various measures of **spread**.
- We came up with a more complicated loss function, L_{ucsd}, that treats all outliers equally.
  - We weren't able to minimize its empirical risk R_{ucsd} by hand.
- **Next Time:** We'll learn a computational tool to approximate the minimizer of R_{ucsd}.