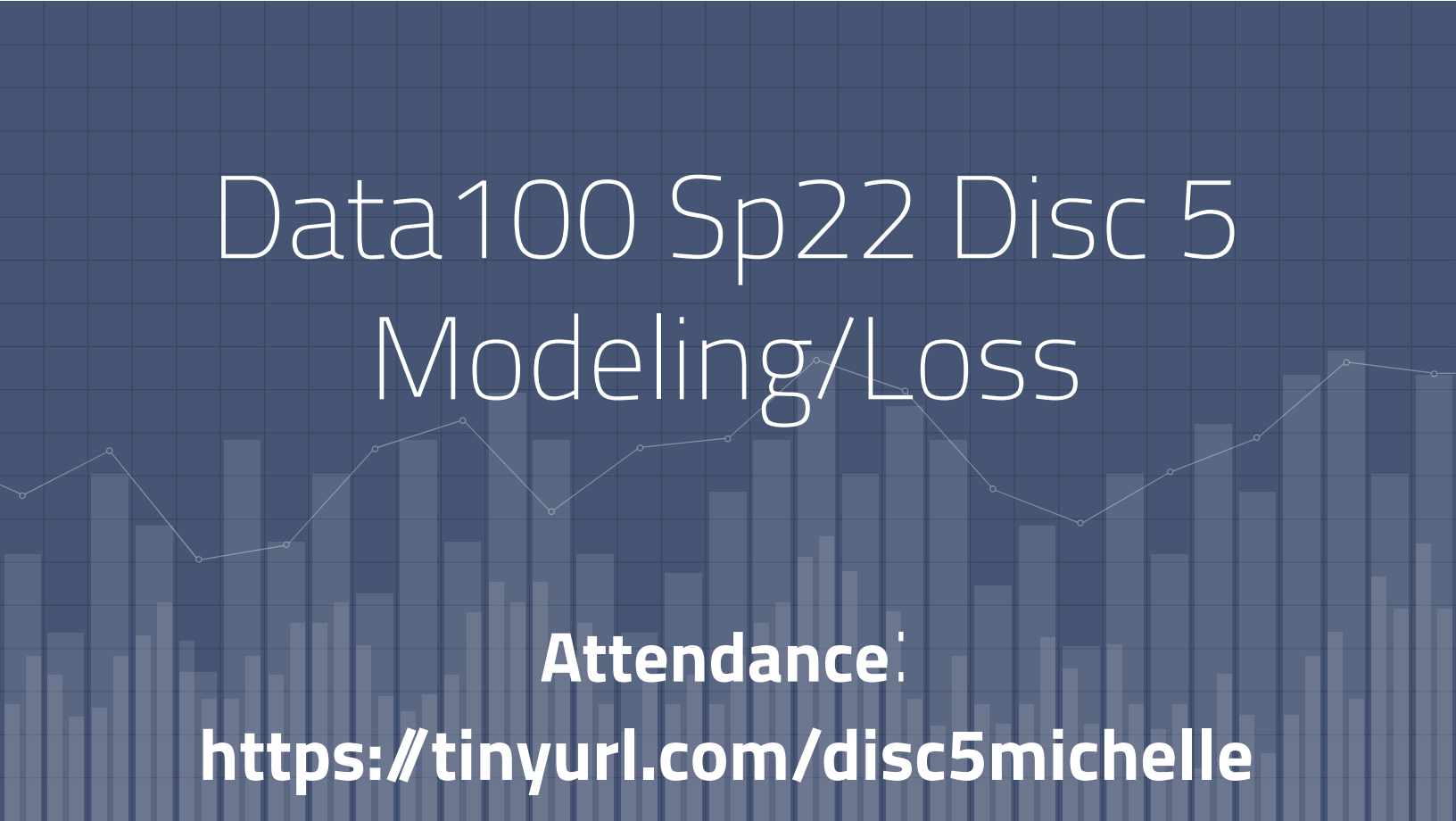


# Data100 Sp22 Disc 5

## Modeling/Loss



**Attendance:**

**<https://tinyurl.com/disc5michelle>**

# Announcements

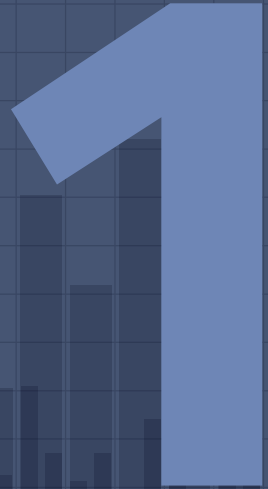
## Due Dates

- Homework 5 due March 3 (start early)
- Lab 4 due Feb 22
- Weekly Check 5 due Feb 28

## Other

- Review session Feb19 (tomorrow lol) 1-4pm
- \* I'll be teaching visualizations :D \*

# Transformations



# Motivation

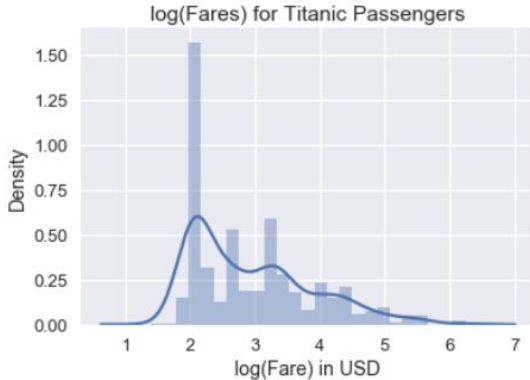
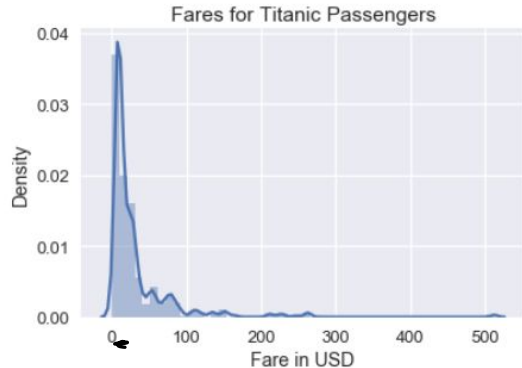
## 1. Transformations can help 'normalize' skewed data

- Normal curve has several nice properties (e.g 68-95-99.7 rule)
- Left Skew -> Square or Cube Data
- Right Skew -> Square Root or Log Data

# Motivation

## 1. Transformations can help 'normalize' skewed data

- Normal curve has several nice properties (e.g 68-95-99.7 rule)
- Left Skew -> Square or Cube x-axis
- Right Skew -> Square Root or Log x-axis



# Motivation

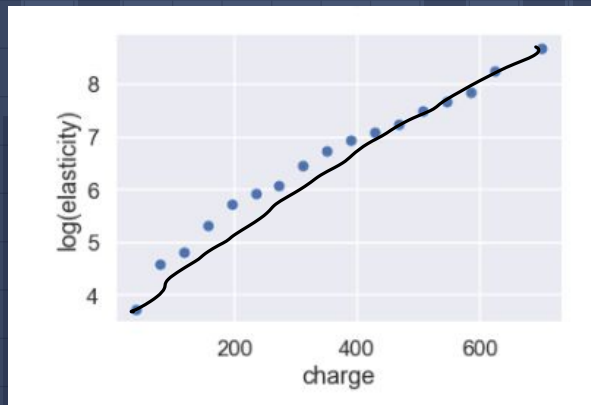
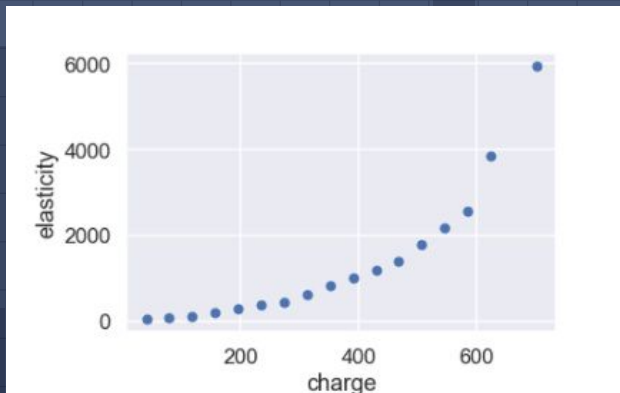
## 2. Extract hidden linear relationships

- Often difficult to visualize relationships when our data is non-linear
- Transforming data can reveal hidden linear relationships!
- We like linear relationships because they are easy to model!

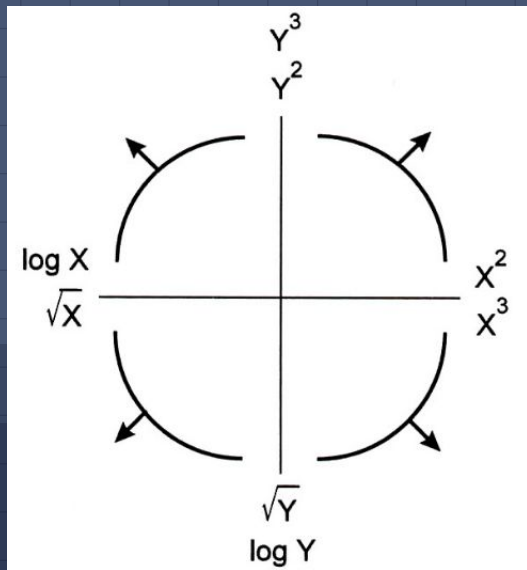
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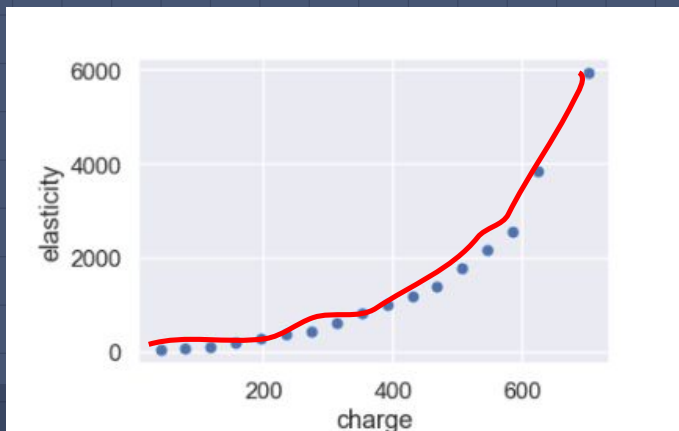
# What transformation do I use?



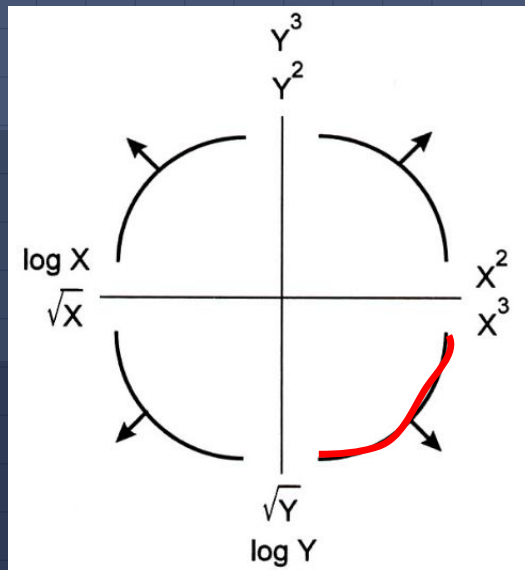
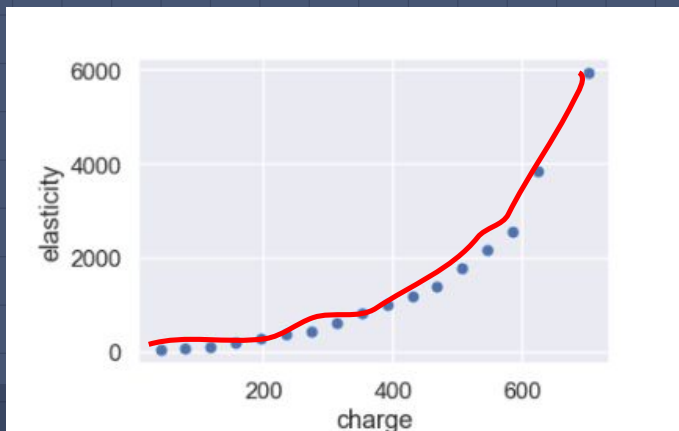
Pls  
save  
this!!



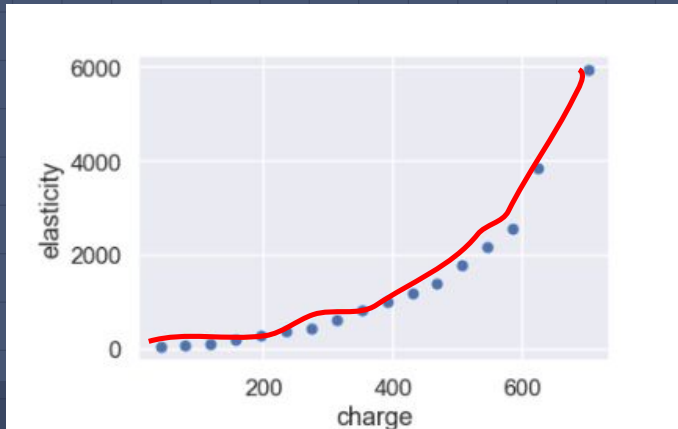
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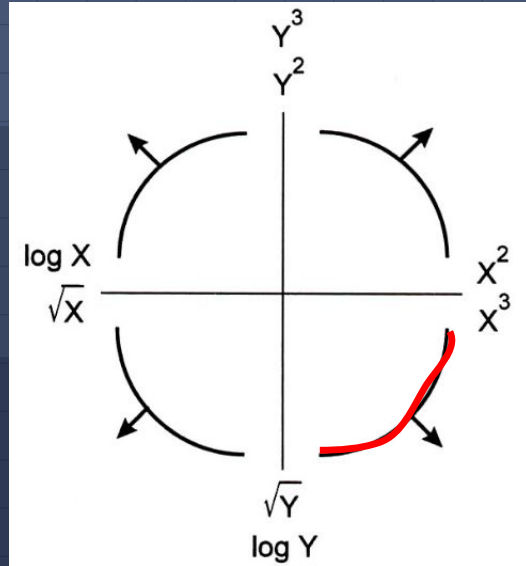
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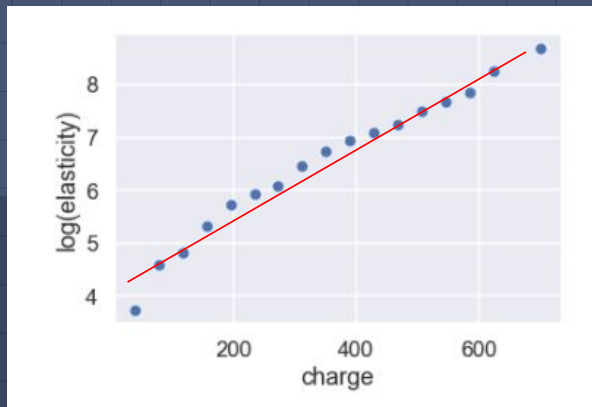
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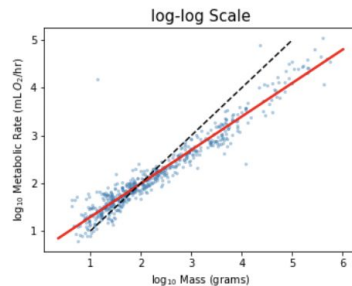
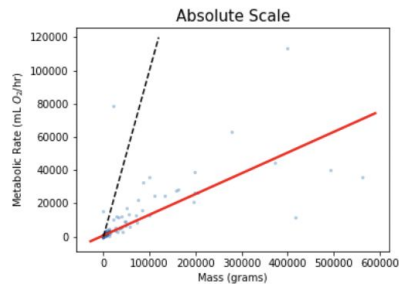
- Use  $\log(Y) = \log(\text{elasticity})$  or  $X^2 = \text{charge}^2$



# What transformation do I use?



- Use  $\log(Y) = \log(\text{elasticity})$  or  $X^2 = \text{charge}^2$



$$\log_{10} y = a + k \log_{10} x$$

$\begin{matrix} \text{y-int} & \text{slope} \end{matrix}$

$$\log_{10} 10^a = a + k \log_{10} 10$$

$$a = a + k$$

$$y = 10^a \cdot 10^{k \log_{10} x}$$

$$= C (10^{\log_{10} x})^k$$

$$y = C x^k$$

$$C = 10^a$$

- (a) Let  $C$  and  $k$  be some constants and  $x$  and  $y$  represent mass and metabolic rate, respectively. Based on the plots, which of the following best describe the pattern seen in the data? Reminder:  $\log(ab) = \log(a) + \log(b)$ .

○ A.  $y = C + kx$     ○ B.  $y = C \times 10^{kx}$     ○ C.  $y = C + k \log_{10}(x)$     ☒ D.  $y = Cx^k$

- (b) What parts of the plots could you use to make initial guesses on  $C$  and  $k$ ?

$C = 10^a \Rightarrow a$  is y-int of log-log graph  
 $k =$  slope of log-log graph

- (c) Your friend points to the solid line on the log-log plot and says “since this line is going up and to the right, we can say that, in general, the bigger a mammal is, the greater its metabolic rate”. Is this a reasonable interpretation of the plot?

Yes. slope  $> 0$

KDE

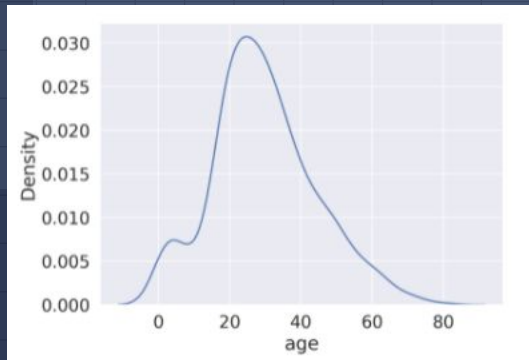
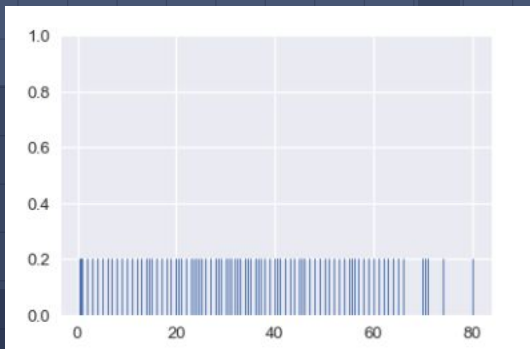
2

# What is KDE?

- Kernel Density Estimation allows us to estimate **density curve** (probability density function)
  - Total area under curve must sum to 1

# Why use KDE?

- Why do this?
  - 'Smoothing' 1-dimensional data





# Why KDE over histogram?

- Can vary the alpha to make things more interpretable using KDE
- KDE gives us a better sense of the underlying structure (density curve) of the data -> better analysis

# Three Steps to Create a KDE

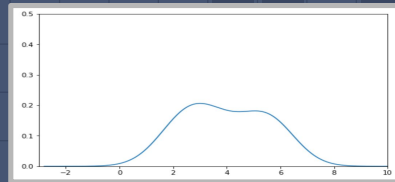
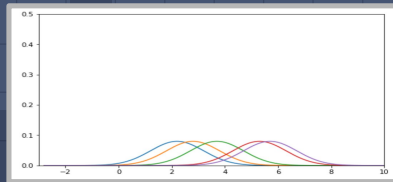
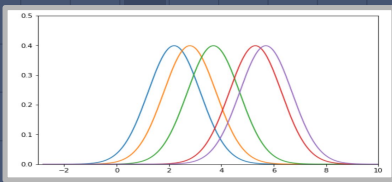
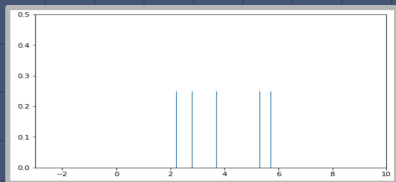
- Place a kernel at each data point
  - E.g. Gaussian Kernel w bandwidth  $\alpha=1$  (creates tiny normals)
  - Can pick other kernels too!
- Normalize (scale) kernels
  - Total area must be one!
- Sum kernels

# Three Steps to Create a KDE

Step 1 - Placing Kernel

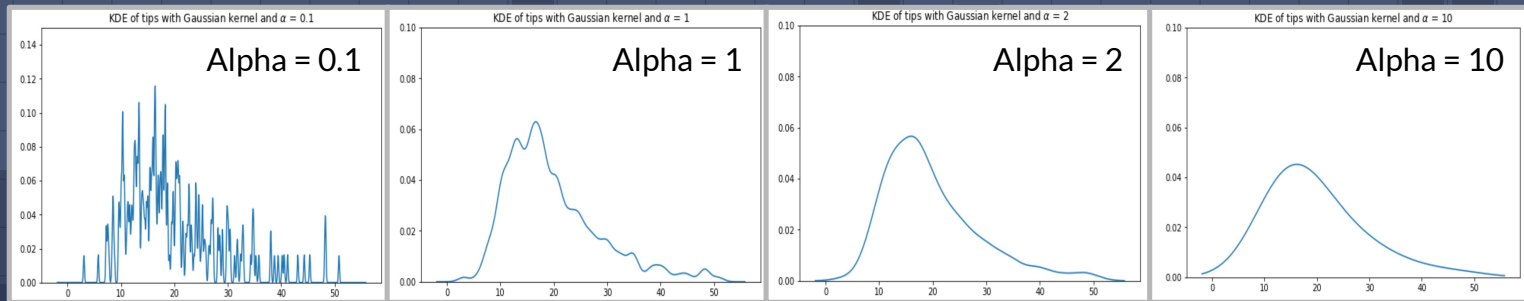
Step 2 - Normalizing

Step 3 - Summing



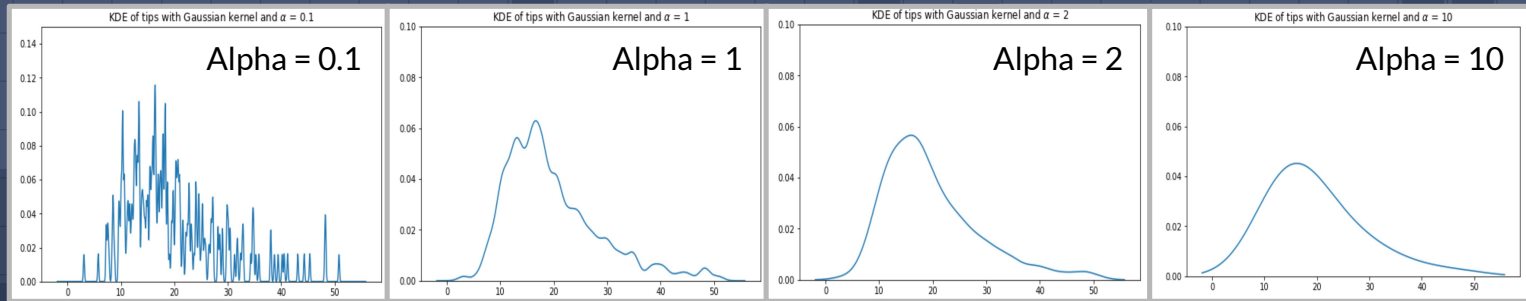
# Alpha

- Alpha is bandwidth parameter, aka. Smoothness
  - Higher alpha = more smooth....but be careful of TOO smooth
  - Losing structure present in data



# Alpha (Bandwidth)

- Alpha is bandwidth parameter, aka. Smoothness
  - Higher alpha = more smooth....but be careful of TOO smooth
  - Losing structure present in data



# Types of Kernels

Gaussian

$$K_{\alpha}(x, x_i) = \frac{1}{\sqrt{2\pi\alpha^2}} e^{-\frac{(x-x_i)^2}{2\alpha^2}}$$

Boxcar

$$K_{\alpha}(x, x_i) = \begin{cases} \frac{1}{\alpha}, & |x - x_i| \leq \frac{\alpha}{2} \\ 0, & \text{else} \end{cases}$$

Loss

3

# Modeling and Loss Functions

-Why do we use models?

- Modeling is a way we represent the world, can help us understand data and make predictions
- Examples: Constant model, SLR (simple linear regression)

-How do we evaluate models?

- Loss functions!



# L2 loss

**MSE (Average Squared Loss)**

$$\rightarrow R(\theta) = \frac{1}{n} \sum_{i=1}^n (y_i - \theta)^2$$

Minimized with **sample mean**:

$$\hat{\theta} = \underline{\text{mean}(y)}$$

# L1 Loss

**MAE (Average Absolute Loss)**

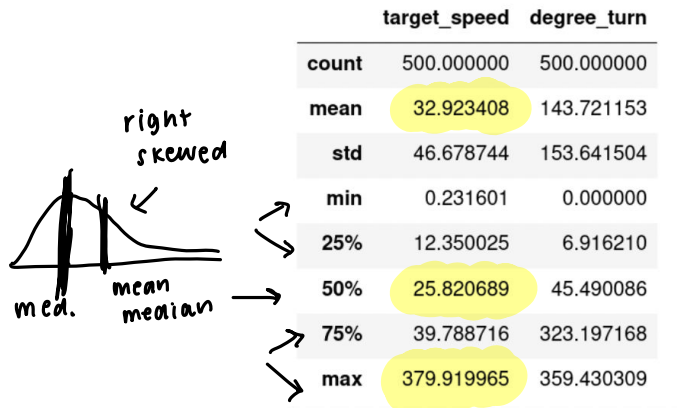
$$\rightarrow R(\theta) = \frac{1}{n} \sum_{i=1}^n |y_i - \theta|$$

Minimized with **sample median**:

$$\hat{\theta} = \underline{\text{median}(y)}$$

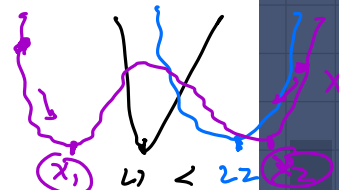
# Choosing a loss function

- L1 loss is more robust, not affected by outliers as much
- Will compare L1 and L2 more later!



$L_1$  loss  $\rightarrow$   
median

$L_2$  loss  $\rightarrow$   
mean



- (a) Suppose the first part of the model predicts the target speed of the car. Using constant models trained on the speeds on the collected data shown above with  $L_1$  and  $L_2$  loss functions, which of the following is true?
- ☒ A. The model trained with the  $L_1$  loss will always drive slower than the model trained with  $L_2$  loss.
  - ☐ B. The model trained with the  $L_2$  loss will always drive slower than the model trained with  $L_1$  loss.
  - ☐ C. The model trained with the  $L_1$  loss will sometimes drive slower than the model trained with  $L_2$  loss.
  - ☐ D. The model trained with the  $L_2$  loss will sometimes drive slower than the model trained with  $L_1$  loss.

(b) Finding that the model trained with the  $L_2$  loss drives too slowly, Adam changes the loss function for the constant model where the loss is penalized **more** if the speed is higher.

That way, the model wants to optimize more for the case where we wish to drive faster since the loss is higher, accomplishing his goal.

Find the optimal  $\hat{\theta}$  for the constant model using the new loss function below:

differentiate  
between  
constants  
& variables

minimize this

$$\text{Loss} \rightarrow L(\theta) = \frac{1}{n} \sum_i y_i (y_i - \theta)^2$$

$$\frac{dL}{d\theta} = \frac{1}{n} \sum_i \frac{d}{d\theta} y_i (y_i - \theta)^2$$

$$\Rightarrow \frac{1}{n} \sum_i -2y_i (y_i - \theta)$$

$$\Rightarrow -\frac{2}{n} \sum_i y_i^2 - y_i \theta$$

$$-\frac{2}{n} \sum_i y_i^2 - y_i \theta = 0$$

$$\sum_i y_i^2 = \sum_i \theta y_i$$

$$\sum_i y_i^2 = \theta \sum_i y_i$$

$$\hat{\theta} = \frac{\sum_i y_i^2}{\sum_i y_i}$$

- (c) Suppose he is working on a model that predicts the degree of turning at a particular time between 0 and 359 degrees using the data in the `degree_turn` column. Explain why a constant model is likely inappropriate in this use case.

*Extra:* If you've studied some physics, you may recognize the behaviour of our constant model!

(d) Suppose we finally expand our modeling framework to use simple linear regression (i.e.  $f_{\theta}(x) = \theta_{w,0} + \theta_{w,1}x$ ). For our first simple linear regression model, we predict the turn angle ( $y$ ) using target speed ( $x$ ). Our optimal parameters are:  $\hat{\theta}_{w,0} = 0.019$  and  $\hat{\theta}_{w,1} = 143.1$ .

However, we realize that we actually want a model that predicts target speed (our new  $y$ ) using turn angle, our new  $x$  (instead of the other way around)! What are our new optimal parameters for this new model?