

**<>** Google Developer Student Clubs

# ML Study Jams

Session #3 - Classification



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### Classification

Essence

Categorise a set of data into a set of classes.

Learn the classification rules from labelled input data

### Where do you think classification is used?

Hint: There are many 🌚



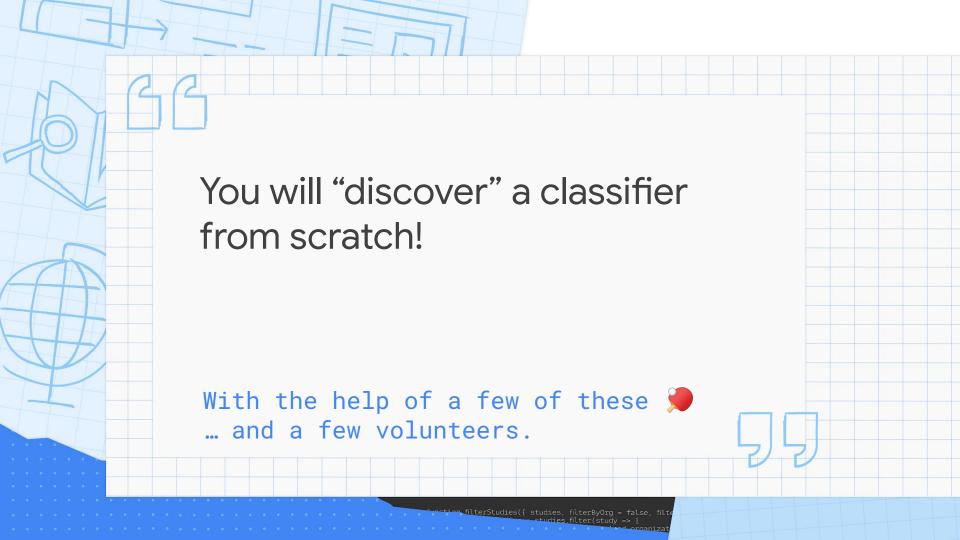
Go to slido.com and use the code **3597601** 

### slido



### Use cases of classification

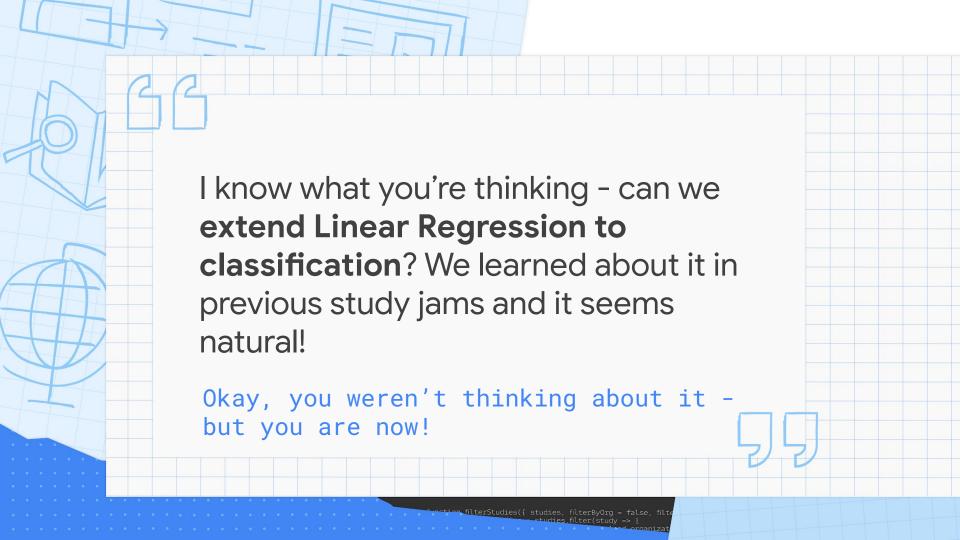
① Start presenting to display the poll results on this slide.



# K - Nearest Neighbours

One of the simplest classifiers

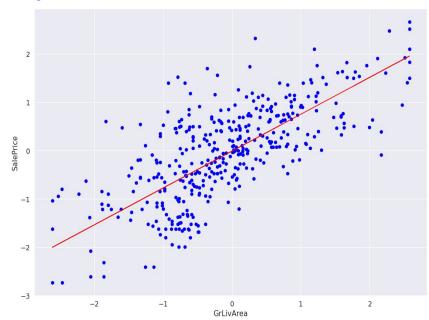
- Find the k nearest neighbours of the target point given the input data
- Assign the target point based on the majority class of the nearest neighbours
- Tie-breakers based on nearest distance





## Linear Regression - the big picture

Credits: ML Study Jams - sessions 1 and 2





### Linear Regression for everyone!

#### a.k.a Gentle Introduction

- We estimate a target variable by representing it as a linear sum of input features
- The parameters of the linear sum (weights) are learned through the rinse-repeat cycle of changing them based on a *Loss function*
- At the end of training, we have a **function** that takes features' data and gives a **real number** that bears some resemblance to what the target variable would be for the same inputs.

### Linear Regression - equations

Credits: ML study Jams - sessions 1 and 2

$$J(\theta) = \sum_{i=1}^{N} (y_i - x_i^T \theta)^2 \qquad \text{Loss function -} \\ \text{we just saw this!} \qquad J(\theta) = ||Y - X\theta||^2$$

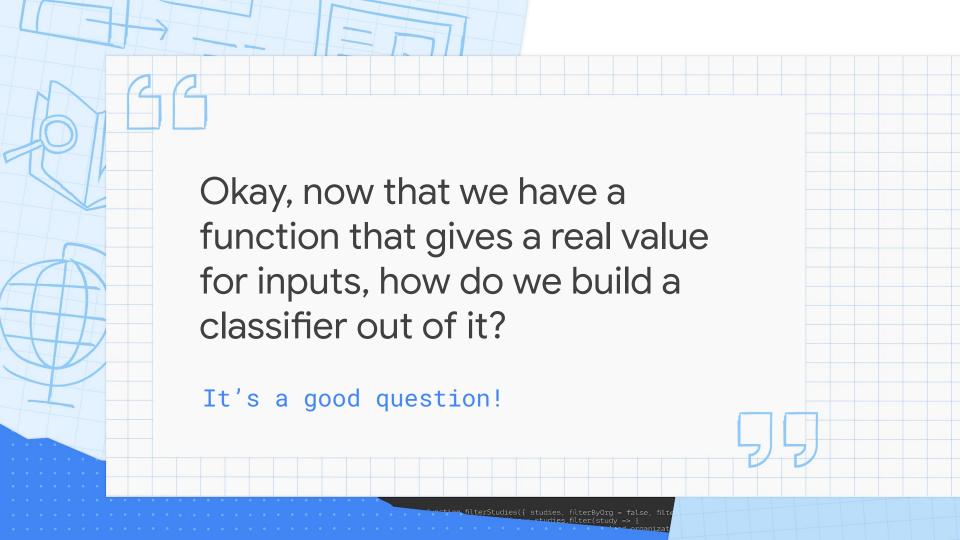
$$\frac{\partial J}{\partial \theta} = 2(X^T X \theta - X^T Y)$$

Remember Gradient descent?

Updating the parameters (theta) by progressing against the gradient







Thresholding 3 Assume binary classification 11 11 11 4 def condition(y): pass # What will you fill here? 6 11 11 11 Find class 10 Based on the "linear sum" output, decide which class 11 11 11 11 def find\_class\_0\_1(X, theta): 12 13 y = theta.T \* X # For exampleif condition(y): 14 return 0 15 16 else: 17 return 1

```
Thresholding
 3
            Assume binary classification
    11 11 11
 4
    def condition(y):
        pass # What will you fill here?
6
    11 11 11
        Find class
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            Based on the "linear sum" output, decide which class
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    11 11 11
    def find_class_0_1(X, theta):
12
13
        y = theta.T * X # For example
        if condition(y):
14
            return 0
15
16
        else:
17
            return 1
```



## What is your intuition?

Vote now on your phones!

### Stepping stones from LR to Classification

There are no right or wrong answers here, we're all learning :)



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Our current loss function is Mean Squared Error. Do you think that should change for Binary Classification?

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Do you think it's easier to work with (threshold) any value in R or a smaller range say [0,1]?

① Start presenting to display the poll results on this slide.



### First, let's look at the questions again

#### Remember Slido?



- Keeping the thresholding range as **R** might come with a major unintended consequence - outliers would play a much bigger scale.
- Arithmetic errors might come into the picture, too.



## Logistic Regression

#### The essence of the approach

- Much like Linear Regression, we learn a line.
- We feed this line into some function to get a value between 0 and 1.
- We then threshold this value to a particular class (0 or 1).



### About the Loss Function

This is where things get interesting.

While RMSE is definitely valid, there's a far more effective Loss function for Binary Classification: The Log-Loss function

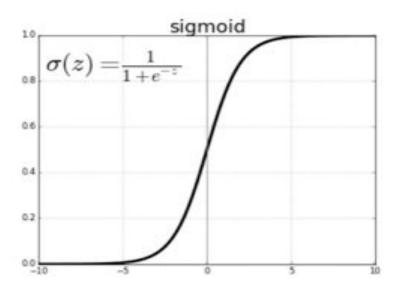
$$J = -\sum_{i=1}^N y_i \log(h_{ heta}(x_i)) + (1-y_i) \log(1-h_{ heta}(x_i))$$

h is the thresholded value based on theta

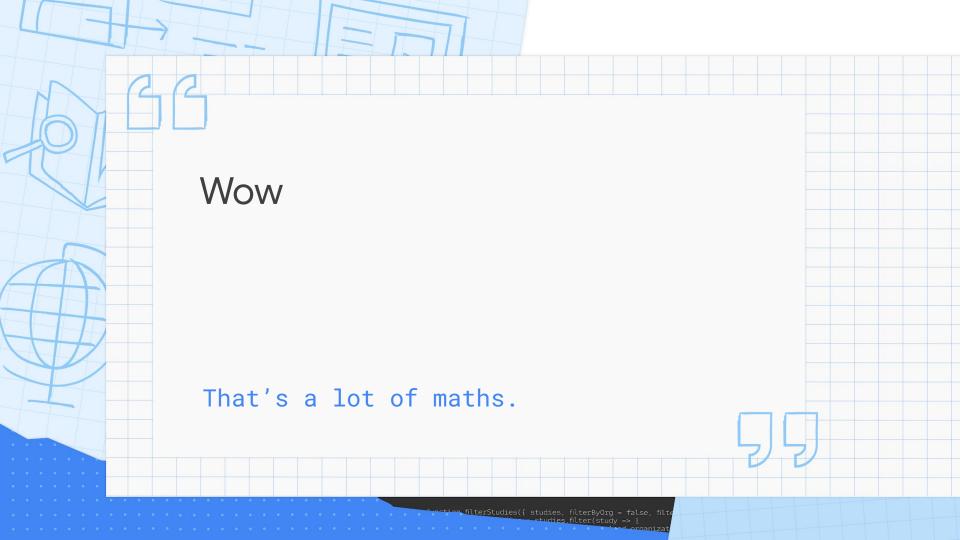


## How do we generate $h(\theta)$ though?

How does one convert a real number into a range from [0,1]?







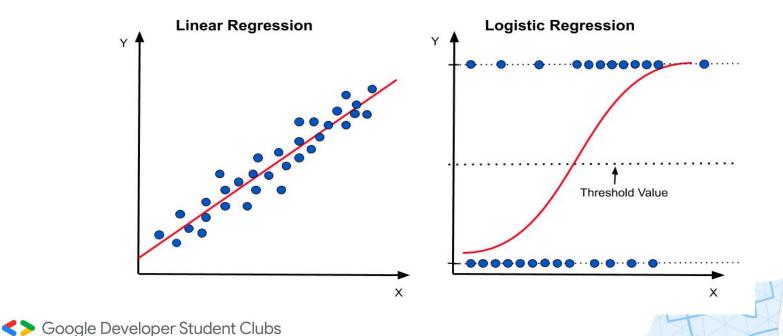
### Logistic Regression - Summary

a.k.a "What just happened for the last 15 minutes?"

- We learn a line and threshold it using the Sigmoid function
- After every iteration, the loss corresponding to the current parameters are calculated through **Log loss**.
- The parameters of the line are learnt through a variation of Gradient Descent similar to Linear Regression, but the gradients will change owing to the new loss function.
- At the end of training, the output of the function will be 0/1 a discrete class label!
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## Logistic Regression - Summary

Comparison with Linear Regression



# Let's build a simple LogReg Classifier!

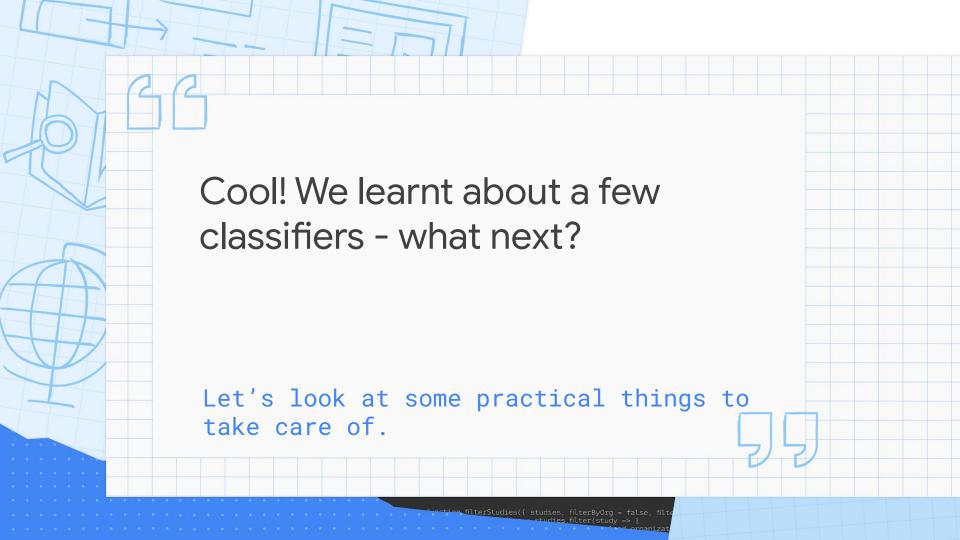
Please make a copy of the ipynb file and let's get started!

https://colab.research.google.com/drive/1FpeoFaWKUcq7Oeacjylq5nJdVuLBo6v

m?usp=sharing







### **PSA**

From now on, consider your classifier to be a "black box".

### Dealing with multiple classes

#### More than just 0/1

- One vs All method
  - Make k classifiers one for each class
  - Most confident class
- Some classifiers have support for multiple classes
  - More complex loss functions and prediction functions
  - Look into Multinomial Log Loss

### Dealing with Class Imbalance

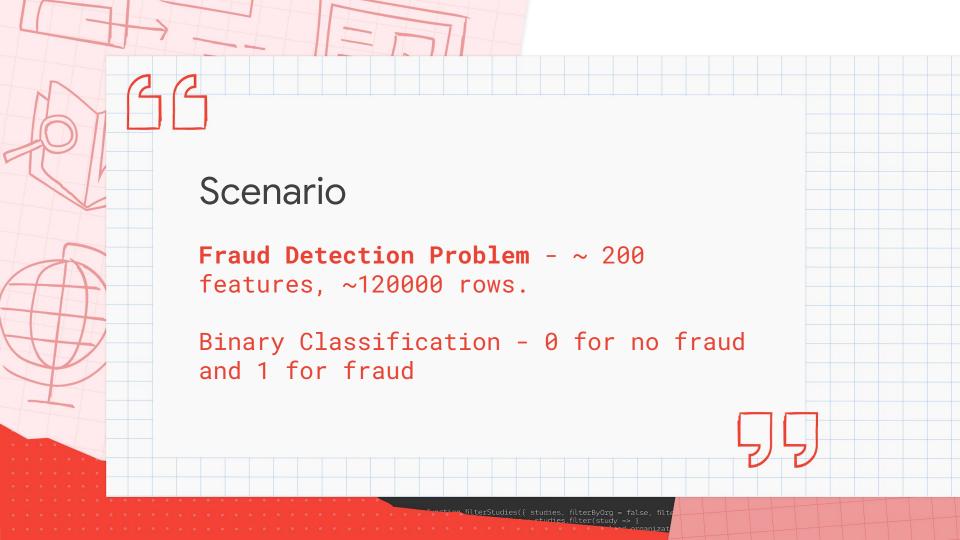
#### Relative frequency of data points

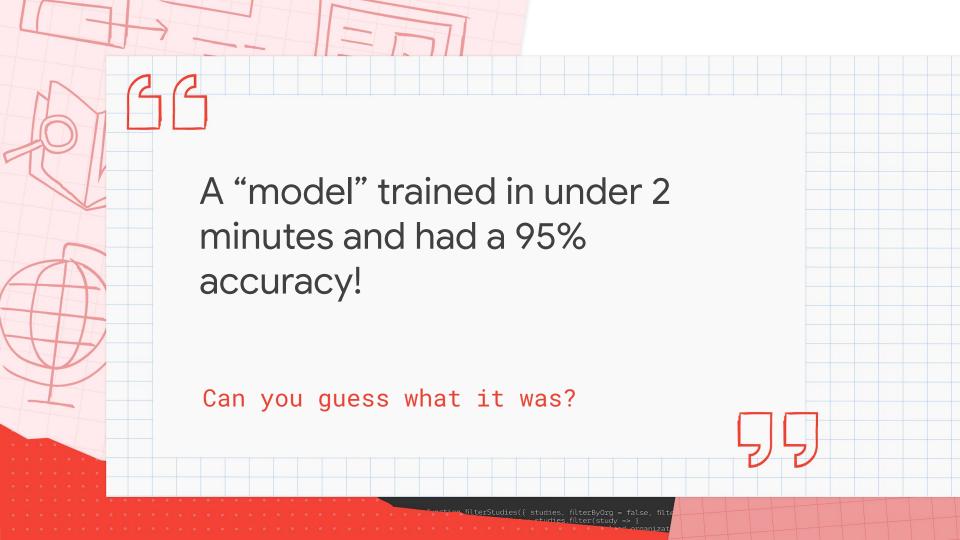
- Oversampling minority class
  - o Example: SMOTE
- Undersampling majority class
- Passing class\_weights as a parameter to the model

### Dealing with Class Imbalance

How about testing the predictions?

This is a loaded question.





```
1 """
2   Crazy Model
3          Trained under 2 minutes and gave 95% accuracy
4 """
5   def get_predictions(X_test):
6         # What do you think goes here?
```

```
1 """
2   Crazy Model
3     Trained under 2 minutes and gave 95% accuracy
4 """
5  def get_predictions(X_test):
6   return [0] * len(X_test)
```

It just returned "Not fraud" for all samples!



## Dealing with Class Imbalance

Sometimes, accuracy is not enough

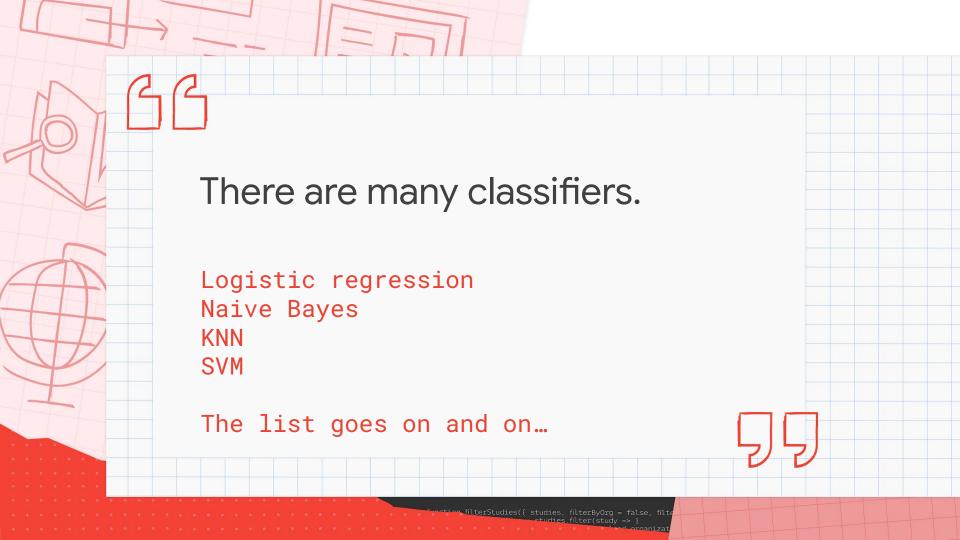
We need to account for class frequencies too. A good tester is the **F1 score** metric that weights false positives and false negatives too!

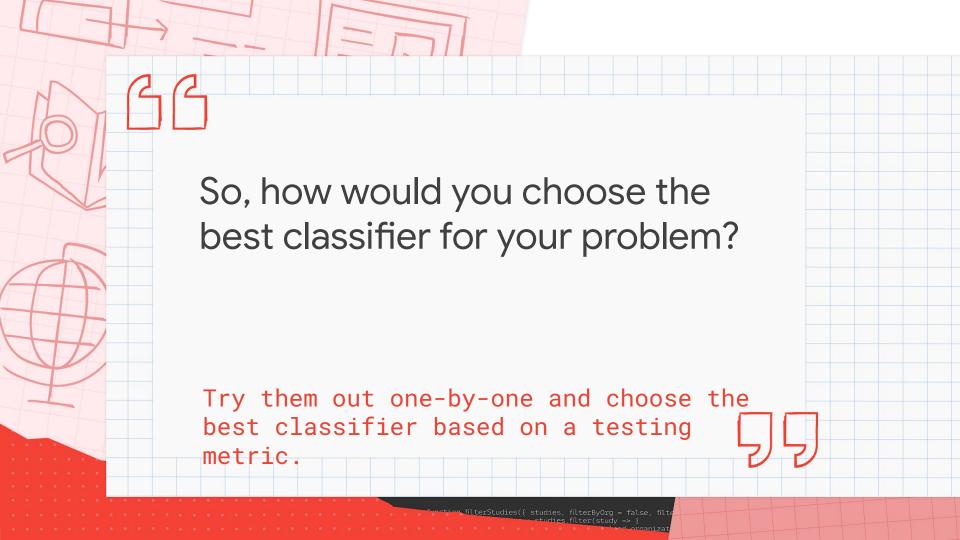


# Dealing with underfitting and overfitting

a.k.a "nah m8 not happening" and "suffering from success"

- Underfitting
  - Increasing training time
  - Making the hypothesis more complex
  - Making the data more streamlined
- Overfitting
  - Validation sets and validation testing
    - Cross-validation





### Can we do better?

The PTSD associated with this statement...

Should we only stick to **one** model?

What if we can combine models? Won't that be good?

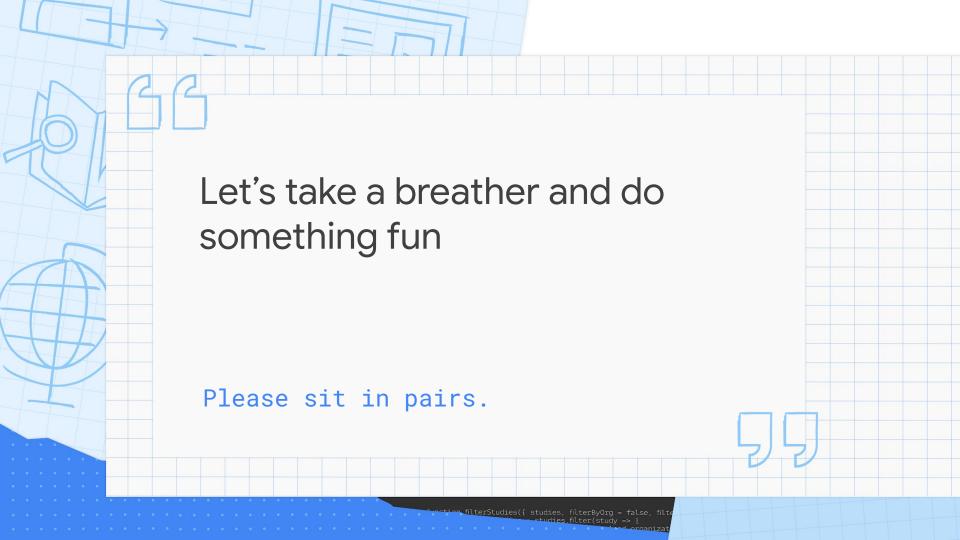
### **Ensemble Methods**

#### Combining multiple models

- Bagging
  - Take m models
  - Find out the predictions of each model
  - Take the most frequent prediction
  - Does this sound familiar?

 There's also boosting and stacking, which is left as an exercise to the reader





#### Teachable Machine

Note: You need to enable your webcams for this.



https://teachablemachine.withgoogle.com/train/image

#### Teachable Machine

#### How do they do it?

- Very complex neural networks!
- Transfer learning



## Does that sound interesting to you?

Please say yes :)

Find out more about these topics in our next session!

Session #4: Big-brain time with neural networks



## Thank you!

If you'd like to post about the event, please tag @gdsc\_iiitb





# Any questions?

