

# Data science for kids!

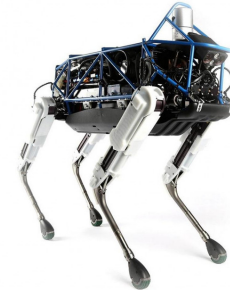
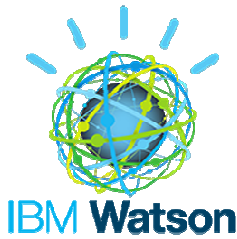
**Shashank Srikant**

**Varun Aggarwal**

**And other members from Aspiring Minds Research  
who made this a success**

# Data science

**Interesting  
applications**



**NETFLIX**



**Voted the sexiest job  
of the 21<sup>st</sup> century**

**Among the highest paying  
job profiles today**

**\$50B industry**



**amazon**

# Data science

**50% gap** in the supply of data  
scientists versus demand

McKinsey&Company

# Data science

**50% gap** in the supply of data scientists versus demand

McKinsey&Company

## Market reaction

**Being introduced in undergraduate courses**

**Specialized graduate-level courses and doctoral programs**

**Lots of online material and sandboxes for learning and practice**



# But what about school curricula?

- ❑ We have realized the importance of writing code
- ❑ Increasing outreach effort at the high school level



SCRATCH

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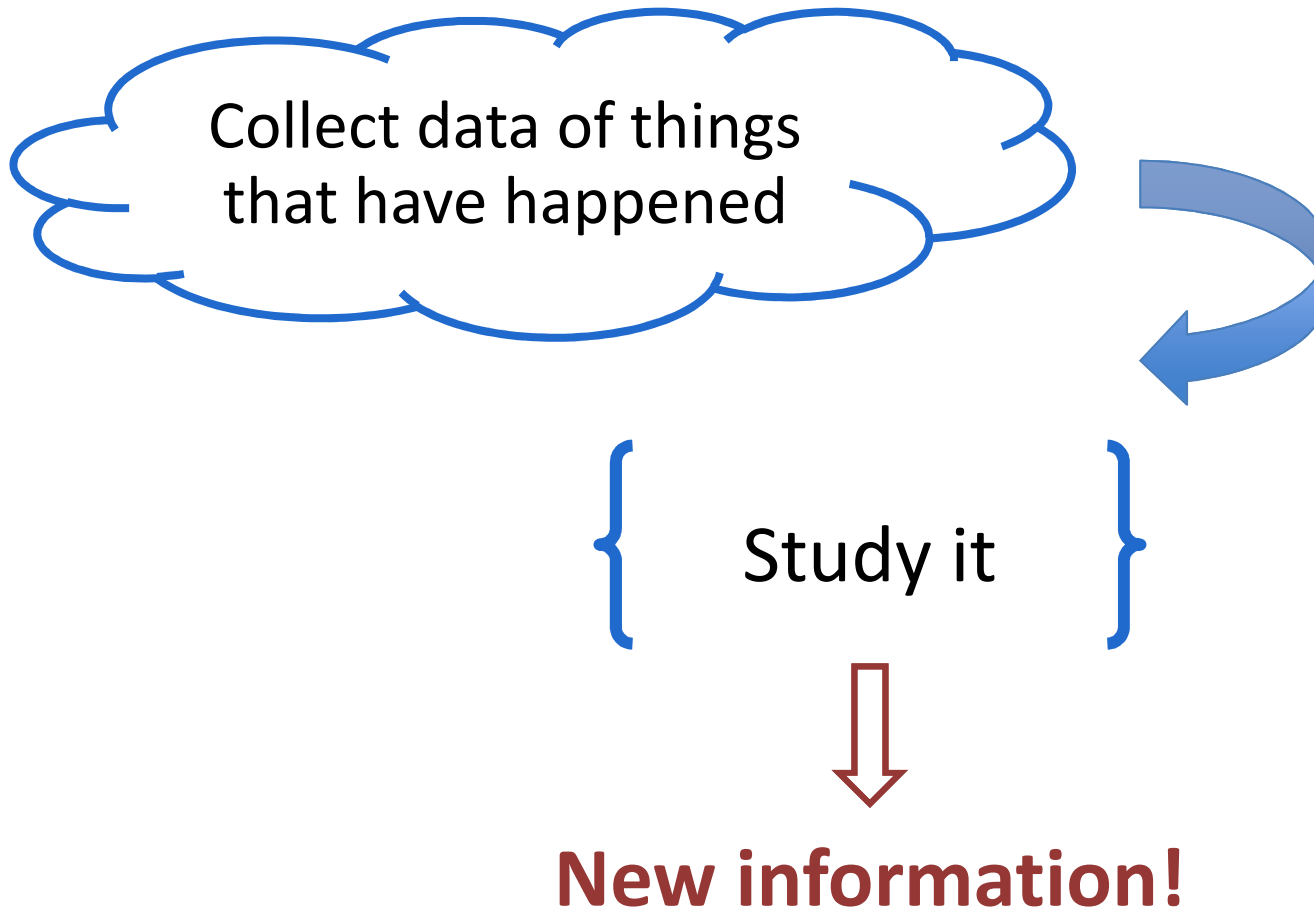
SCRATCH

## What about data science?

# Our aim

- ❑ Develop a framework to teach the foundations of data science to a school audience
- ❑ Lay out the design principles for such a curriculum
- ❑ Ensure that it is pedagogically **experiential learning** and **problem-based learning** than being simply lecture content plans
- ❑ Demonstrate its utility by implementing it
- ❑ Keep the material very accessible. Make it easy for the community to *replicate*.

# What is data science?





# Predictive data science

**Supervised  
learning**

**Unsupervised  
learning**

# Predictive data science

We know what we want to predict

We have concrete values of some outputs.

We then see what can signal such values

## Supervised learning

**input:** What we believe helps predict the desired output

**output:** What we want to predict

We're trying to learn a function  $f$  such that

$$f(\text{input}) = \text{output}$$

# Predictive data science

	Age	Sport	....	Height	Is sick?
S1	5 years	football		160 cm	Yes
S2	15 years	baseball		164 cm	No
S3	15 years	football	....	128 cm	No
S4	5 years	swimming		149 cm	Yes

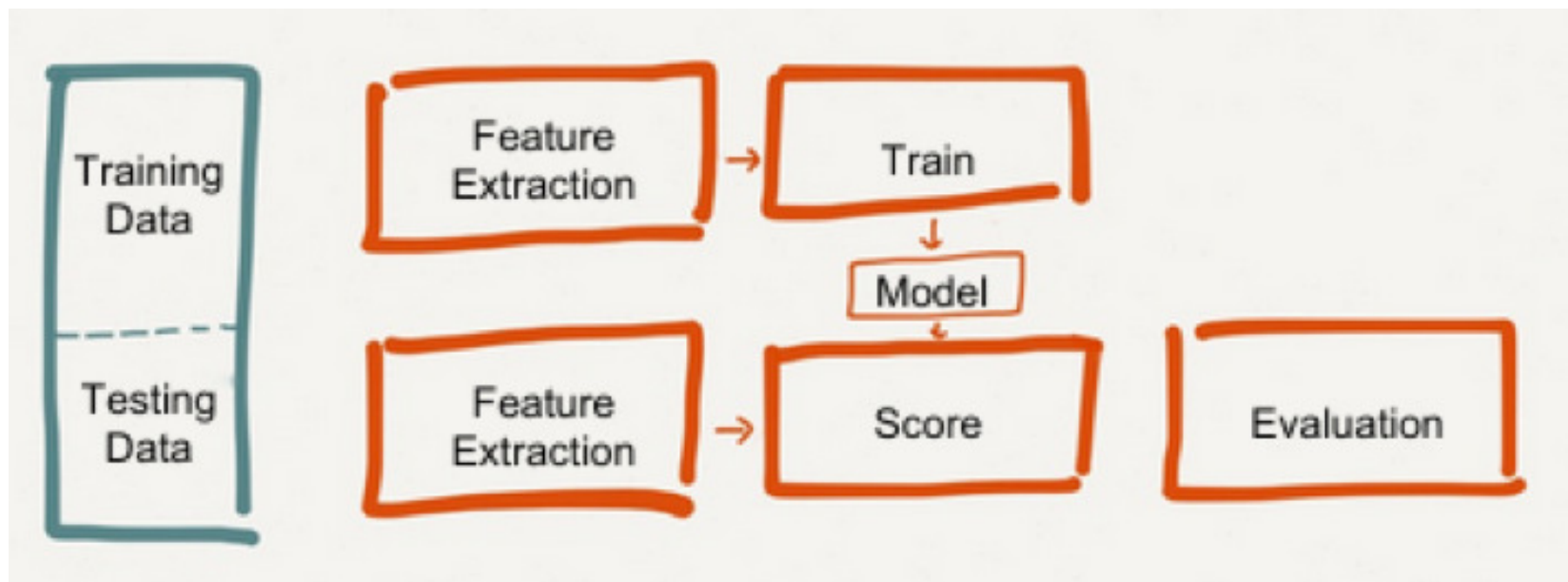
# Predictive data science

$$f(\text{Age} \text{ Sport} \dots \text{Height}) = \text{Is sick?}$$

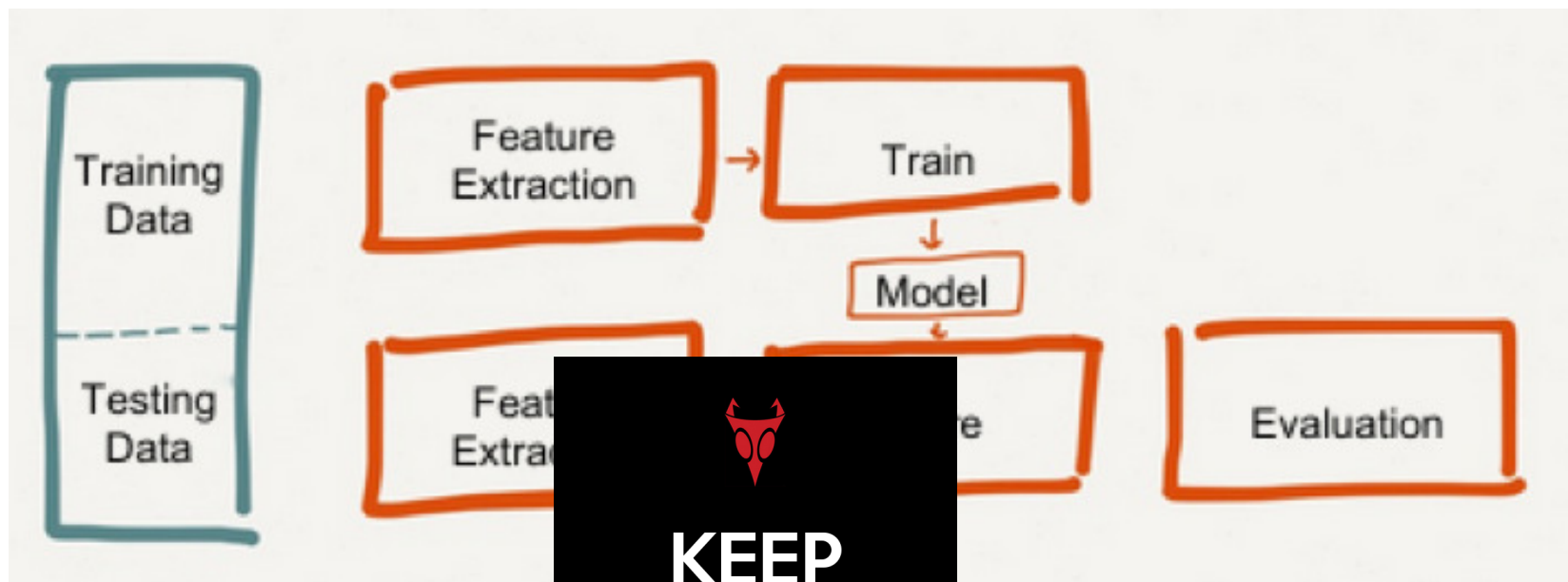


$$a(\text{Age}) + b(\text{Sport}) + \dots = \text{Is sick?}$$

# Overview – Supervised learning



# Our aim



  
**KEEP  
CALM  
AND  
CONQUER  
ALL**

# The exercise that we designed



We get them to build a **friend predictor**

Can we predict whom you will befriend  
based on friends you've just made?



# They first rate a bunch of flash cards

Surendra



likes  
sketching

Seeta



likes  
to sing

Aaryan



likes  
playing badminton

Vaamika



likes  
gardening

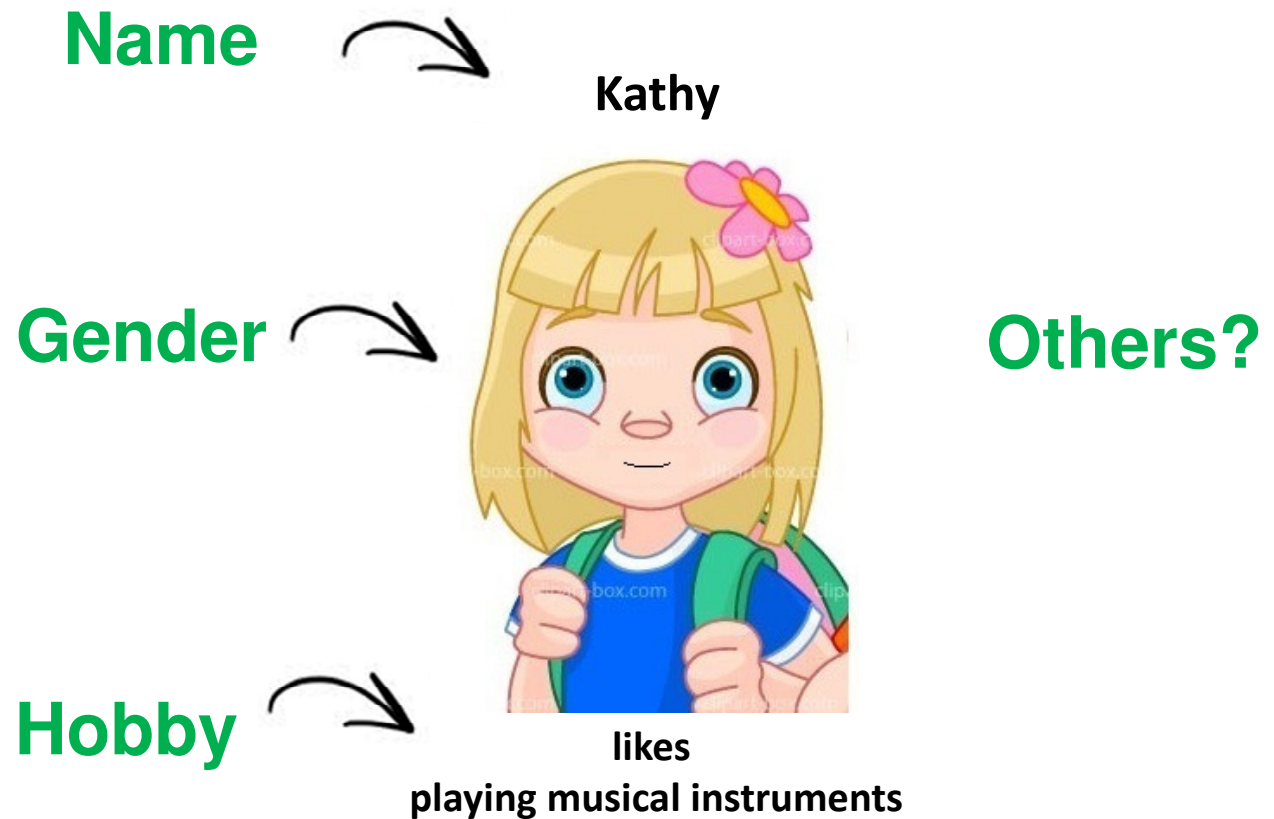
Students tell us whether they would befriend kids we show them on flash cards

These are kids with their names and hobbies described

Students grade them on a scale of 1-5: 1 – least likely to befriend

56 such samples rated

## We then discuss possible features

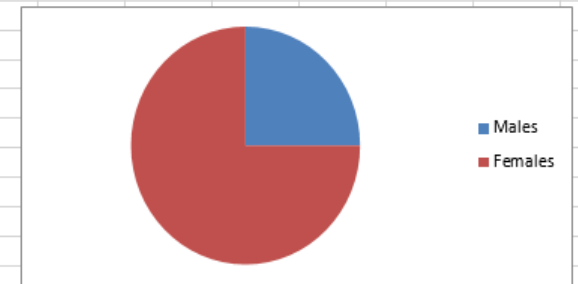


# Get them to add this information on a spreadsheet

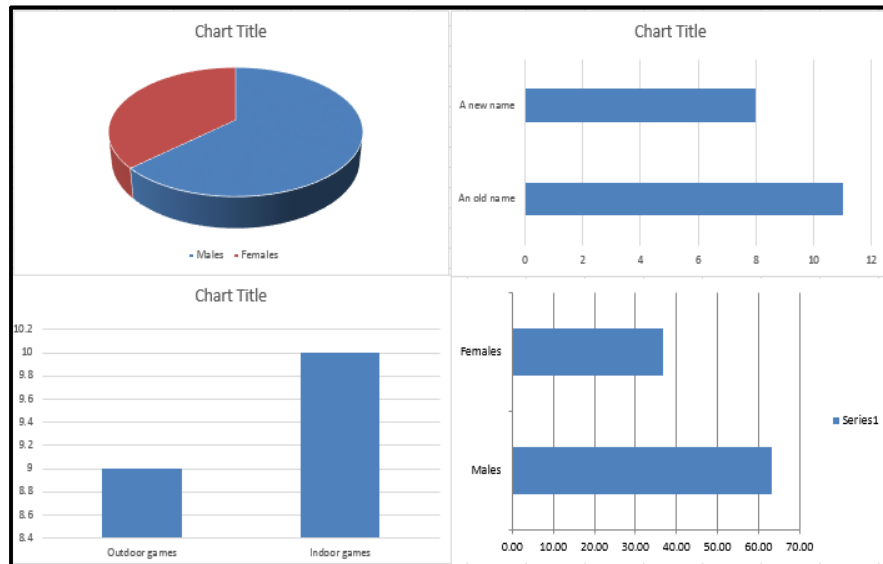
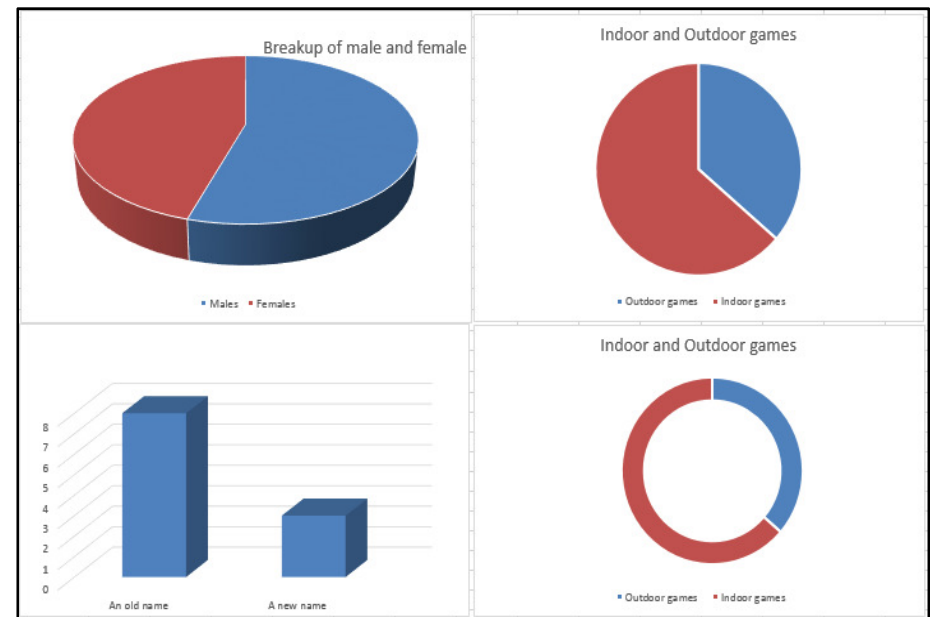
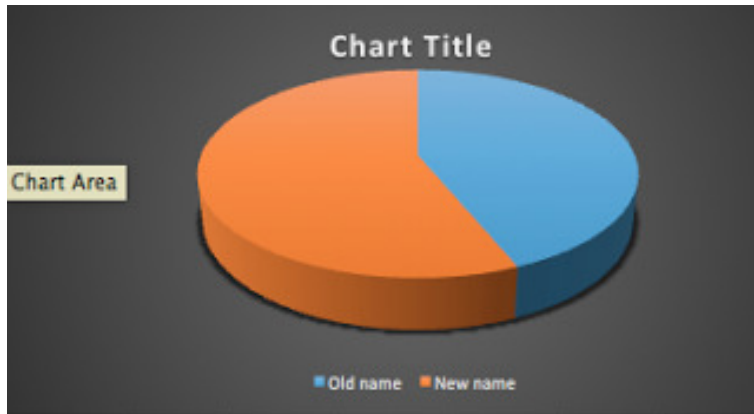
	A	B	C	D	E	F	G	H	I
1		Student fills these					Calculated results		
2	ID	Name	Gender	Hobby	Extra feat	Rating	Friends?	Predictor	Accuracy
3	1	Old	Male	Indoor		3	1	1	accurate
4	2	Old	Female	Indoor		2	0	1	inaccurate
5	3	New	Male	Outdoor		1	0	0	accurate
6	4	New	Male	Outdoor		4	1	0	inaccurate
7	5	New	Female	Indoor		5	1	1	accurate
8	6	New	Female	Indoor		5	1	1	accurate
9	7	Old	Female	Outdoor		2	0	1	inaccurate
10	8								
11	9								
12	10								

# Visualize this information

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
1																		
2	Output Visualization			Counts		Filtered Visualization				For plotting								
3	Wants to really friend					How many friends are			percentages									
4	yes, mostly a friend					Males	5	25.00		Males	25.00							
5	May friend					Females	15	75.00		Females	75.00							
6	May not friend						20											
7	Doesn't want to friend at all																	
8				0														
9						How many friends have												
10	Input variables					An old name		0.00		An old name	0							
11	Males					A new name		0.00		A new name	0							
12	Females						0											
13		32																
14						How many friends like												
15						Outdoor games		0.00		Outdoor games	0							
16						Indoor games		0.00		Indoor games	0							
17							0											
18																		



# Visualize this information



# Build a predictor

Use a simple IF-clause and a combination of AND, OR conditions

SUM

✕ ✓ *fx*

=IF(OR(B3="Old",D3="Indoor"),1,0)

	A	B	C	D	E	F	G	H	I	J
1		Student fills these					Calculated results			
2	ID	Name	Gender	Hobby	Extra feat	Rating	Friends?	Predictor	Accuracy	
3	1	Old	Male	Indoor		3	1	=IF(OR(B3="Old",D3="Indoor"),1,0)	accurate	
4	2	Old	Female	Indoor		2	0	1	inaccurate	
5	3	New	Male	Outdoor		1	0	0	accurate	

# Validate predictor on unseen data



**Validate the models on the unseen ratings which were held out**

**Each student builds models of other students**

**Create an air of suspense to see whether the model does indeed generalize on unseen data**

# Data consent



**Explain importance of  
anonymity and privacy  
of data**

**Get them to participate  
in providing consent  
to share their ratings**



# Crowd source mentors



# Some design choices

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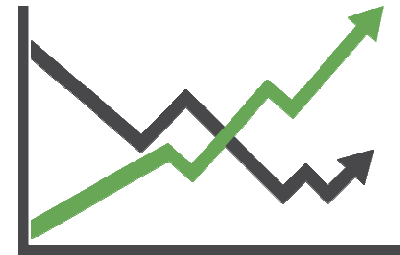
## Picking a problem statement

# Picking a problem statement

Should not be an obvious exercise in prediction



Should not be too unrelatable



# Some design choices

## Data collection

# Data collection

**No to pre-built datasets**



**Engage students by getting them to  
upload/play around with the data**

# Some design choices

## Features

# Features

**Not more than 2-3 features:** It gets harder to demonstrate their interaction for anything more

**Discrete features:** easy to understand and intuitive to handle at the modeling stage



# Some design choices

## Output

# Output

**Discrete output:** easy to understand and intuitive to handle at the modeling stage

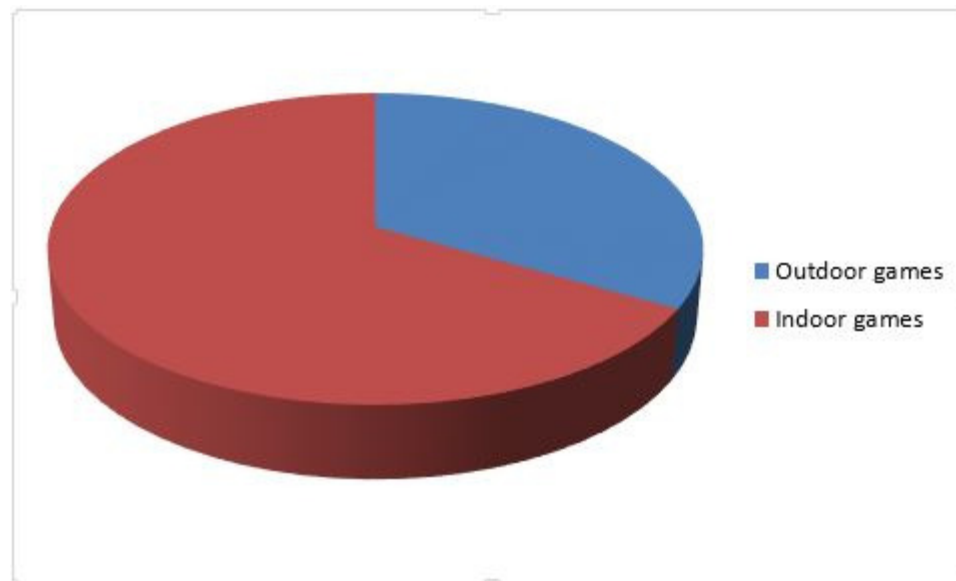
**Binary output:** easy to understand and visualize

# Some design choices

**Balanced datasets (inputs)**

# Balanced datasets (important)

**Look at both classes:** Importance of looking at the *Friend* class and the *Not Friend* class both



# Some design choices

**Simple arithmetic, easy tech**

# Simple arithmetic, easy tech

- ❑ Doesn't require anything more than addition, multiplication, division and taking ratios/percentages
- ❑ The tool to implement this idea is any commonly available spreadsheet software. Very flat learning curve
- ❑ Can always go manual if formulas are not comprehensible

# Did students enjoy and learn?

- ❑ Conducted this tutorial in 4 cities so far – New Delhi, Pune, Bangalore, UC (Illinois)
- ❑ Each cohort had ~18 students in the age group of 10-15 (median age: 13)
- ❑ Each session was 3 hours long
- ❑ Each of them was given a survey at the end of the tutorial

# Did the students enjoy and learn?

Statement	Strongly disagree	Disagree	Agree	Strongly agree
I could understand what the tutor was explaining	0%	1%	32%	67%
I understood how data science is applied to problems	0%	0%	3%	97%
The tutorial was interactive	0%	0%	21%	79%
The tutorial was boring	79%	21%	0%	0%
The tutorial was theoretical	97%	3%	0%	0%
The tutorial was difficult	79%	19%	1%	1%
The tutorial was fast for me	65%	34%	1%	0%
I learned new concepts	0%	0%	2%	98%



# Did the students enjoy and learn?

## Student prompts

- ❑ **Want to monitor my pocket money and expenses**
- ❑ **Want to figure out where a criminal resides by clustering the areas of crime**
- ❑ **One of them developed the intuition for overfitting and underfitting while at the tutorial and raised questions about splitting train and test sets**

# Did the students enjoy and learn?

## Features that were brainstormed

- **Artsy vs. Non-artsy hobbies**
- **Happy vs. Grumpy looking faces**
- **“Weird” vs. “Common” name**
- **Hobbies involving hand held tools vs. otherwise**

# Future work

## Reduce TAs

## A Scratch equivalent for DS

# Key learning

- ❑ It is possible to pick up data science and provide a higher level intuition to a young audience without boring them
- ❑ Design choices have to be made carefully to ensure students are not burdened with too many new concepts in one session
- ❑ Easy to implement and involves a sizeable do-it-yourself component

# Data science for kids!

It's more than a hype or a career choice. It's a way of problem solving and thinking which can be used in everyday life. Stories and learnings behind organizing the first ever data camp for kids.

[Home](#)[Why data science?](#)[Kids speak](#)[Mentor learnings](#)[Organizing your own camp](#)[Gallery](#)[About AM Research](#)

## Data science for kids!

Two weeks back, we decided to experiment teaching data science to grade 6<sup>th</sup>.9<sup>th</sup> kids! We think it is important to introduce students to thinking in a data-driven way early on in their lives; also kids are way more fun than higher-ed students, so it was an easier choice for us to make!

We sent out a [form](#) asking kids to apply to our cool Kids Data Camp - the first in the world?! We thought kids in 5<sup>th</sup> grade would have

## What's new?

🔴 We are on GitHub!

🔴 Our pedagogy will be published at SIGCSE 2017!

# datasciencekids.org

## All our material is on it for you to replicate

## We're also on GitHub now

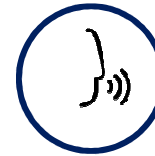
# Research at Aspiring Minds

- ❑ Define product vision. Research and develop prototypes which demonstrate application of state of the art computer science technology in assessment products
- ❑ Publish at the very best conferences and venues
- ❑ Multiple outreach programs to popularize data science and machine learning
  - ❑ Data science for kids
  - ❑ ML-India
  - ❑ ASSESS – Annual workshop on data science for assessments
  - ❑ AMEO 2015



## CoDS 2016

Release AMEO-2016, public dataset on employability outcomes, based on AMCAT data



## ACL 2015

Work on machine learning and crowdsourcing in speech evaluation



## ICML 2015

Work on learning models for job selection



## KDD 2014

Work on using machine learning in programming evaluation

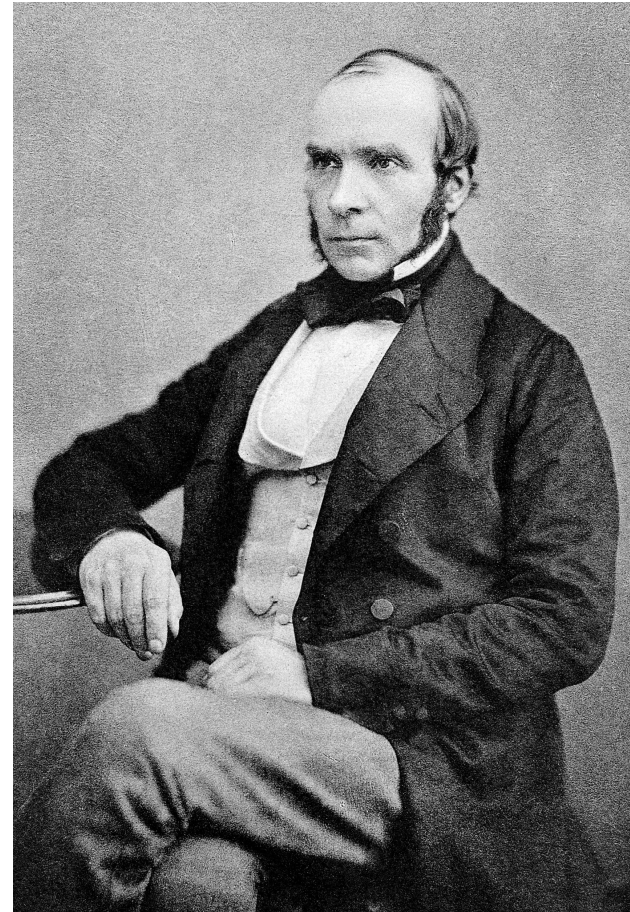
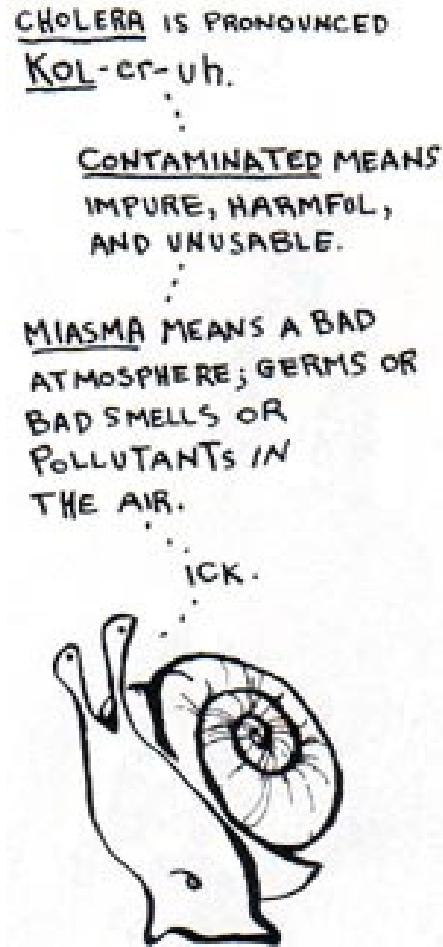


## NIPS 2013

Framework for using machine learning in assessments



## Introduce the broader idea through an example



*John Snow*