

# Presentació del Curs

Machine Learning | Enginyeria Informàtica

Santi Seguí | 2022-2023

# **1. Objectius del curs**

## **Objectius del curs**

- Introducció descriptiva a un conjunt de tècniques i mètodes basats amb l'aprenentatge automàtic (Machine Learning).
- Coneixement dels principis en que es basen algunes d'aquestes tècniques.
- Coneixement dels principis d'avaluació dels mètodes d'aprenentatge automàtic.
- Contacte pràctic amb exemples representatius amb diversitat de dades

## 2. Prerequisites

## Prerequisites

- Conceptes dels cursos de Càlcul i Àlgebra
- Algunes idees generals del curs de Probabilitat i Estadística
- Curiositat per la **Intel·ligència Artificial**

# 3. Organització

## **Coordinador:**

• **Santi Seguí**

Email: [santi.segui@ub.edu](mailto:santi.segui@ub.edu)

## **Teoria** (Dijous 17.00-19.00h)

• **Santi Seguí**

Email: [santi.segui@ub.edu](mailto:santi.segui@ub.edu)

## **Laboratoris** (Dimarts 15h-17h)

• **Josep Fortiana**

Email: [fortiana@ub.edu](mailto:fortiana@ub.edu)

## Com s'organitza l'assignatura?

- L'assignatura s'imparteix en classes teòriques i pràctiques. L'assignatura es coordinarà mitjançat el:
  - Campus Virtual. A través d'aquest entorn tindreu: anuncis, apunts, notes, fòrum, calendari, enllaços a la bibliografia, etc.
    - <https://campusvirtual.ub.edu/>
  - Github del curs:  
[https://github.com/ssegui/ml\\_ub](https://github.com/ssegui/ml_ub)
- **Com seran les classes teòriques? (2 hora a la setmana)**
  - Introduirem els conceptes teòric
- **Com seran les classes pràctiques? (2 hores a la setmana)**
  - Les pràctiques es realitzen de forma individual o amb parelles.

## Llenguatge de programació?

- Python & R

## Programació de l'oferta docent del Primer semestre

Activitat							
Grup	Dies	Horari	Professorat	Aula	Llengua		
<b>Teoria [Presencial]</b>							
T1	dl. dt. dc. dj. dv.	1r sem.	17.00-19.00	<a href="#">Segui Mesquida, Santiago</a>	<a href="#">Aula B7</a>	Català	
<b>Pràctiques de laboratori d'ordinadors [Presencial]</b>							
a00	dl. dt. dc. dj. dv.	1r sem.	15.00-17.00	<a href="#">Fortiana Gregori, Jose</a>	<a href="#">Aula IG</a>	Català	
<b>Exàmens : 1r parcial [Presencial]</b>							
G1	8 de novembre de 2022.		18.00-21.00	<a href="#">Fortiana Gregori, Jose</a> <a href="#">Segui Mesquida, Santiago</a>		-	
<b>Exàmens : Final [Presencial]</b>							
G1	12 de gener de 2023.		15.00-20.00	<a href="#">Fortiana Gregori, Jose</a> <a href="#">Segui Mesquida, Santiago</a>		-	
<b>Exàmens : Revaluació [Presencial]</b>							
G1	27 de gener de 2023.		15.00-20.00	<a href="#">Fortiana Gregori, Jose</a> <a href="#">Segui Mesquida, Santiago</a>		-	

	Laboratori (Dimarts - 13h-15h)		Teoria (Dijous (17h - 19h)
13-Set	No Class	15-Set	Introduction
20-Set	Lab0	22-Set	A typical Machine Learning project
27-Set	Lab1	29-Set	Regression
4-Oct	Lab2	6-Oct	Classification
11-Oct	Lab3	13-Oct	Training Models
18-Oct	Lab4	20-Oct	Support Vector Machines
25-Oct	Lab5	27-Oct	Tree Based Models
1-Nov	FESTIU	3-Nov	Boosting - Bagging - Ensembles
8-Nov	Exam - NO EXAM!!!	10-Nov	Exam - NO EXAM!!!
15-Nov	Lab7	17-Nov	Neural Networks
22-Nov	Lab8	24-Nov	Convolutional Neural Networks
29-Nov	Lab9	1-Dec	Convolutional Neural Networks
6-Dec	Festiu	8-Dec	Festiu
13-Dec	Lab10	15-Dec	Unsupervised Learning
19-Dec	Lab11	22-Dec	Free Class

# 4. Avaluació

**Avaluació Continuada**

# **Avaluació basada en projectes**

# Avaluació Continuada

## Basada en Projectes

### Com s'avaluarà l'assignatura?

- **participació i entrega dels projectes**
- **Iliurament de pràctiques**

### Proves presencials:

- Durant el curs es presentaran diversos projectes ( $>=3$ ).
- Cadascun d'aquests projectes tindrà una puntuació associada.
- La nota mínima final obtinguda ha de ser de 4 punts
- La nota màxima final que podrà obtenir l'alumne es de 10 punts

### Lliurament de pràctiques:

- Lliurament de pràctiques: Cada un dels lliuraments de pràctiques serà avaluat pel professor amb una nota que pot anar de 0 (nota mínima) a 10 (nota màxima). Si l'estudiant no lliura les pràctiques dins del període assenyalat, obtindrà un 0.
- La nota final (NP) de la part de pràctiques és la mitjana de tots els lliuraments (3 en total).

**IMPORTANT:** La nota final de teoria (**NT**) i la nota final de pràctiques (**NP**) han de tenir una nota mínima de 4.5 per fer mitja.

## Avaluació Única

- L'estudiant que es vulgui acollir a l'avaluació única ho ha de sol·licitar a la Secretaria de la Facultat dins del termini establert en cada curs acadèmic.
- Hi ha un examen final de teoria i un examen final de pràctiques de laboratori. Anomenem **NT** i **NP**, respectivament, les notes obtingudes en aquests exàmens.
- Es requereix la presentació oral i escrita d'un treball de curs, prèviament acordat amb el professor. Anomenem **NPTC** la qualificació d'aquest treball.
- La nota final de l'assignatura (Nota\_Final) es calcula mitjançant la fórmula següent:  $\text{Nota\_Final} = 0,5 * \text{NPTC} + 0,2 * \text{NT} + 0,3 * \text{NP}$ .
- Per poder calcular la nota final és imprescindible una puntuació igual o superior a 3 en tots tres components.

# **5. Recursos**

## GITHUB / Campus Virtual

[https://github.com/ssegui/ml\\_ub](https://github.com/ssegui/ml_ub)

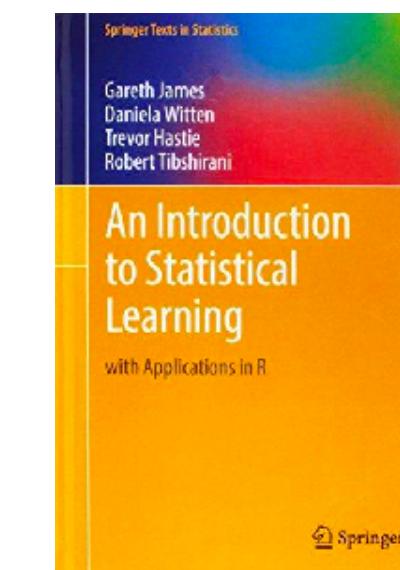
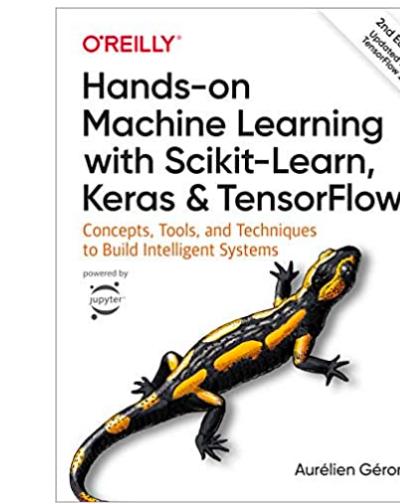
- Làmines de les sessions de l'aula
- Guions de les pràctiques
- Entregues
- Documentació i informació complementària

## Programari

- Python & R

## Bibliografia

- Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems. [Aurelien Geron](#)
- An Introduction to Statistical Learning: with Applications in R  
PDF Online Gratuit: <http://faculty.marshall.usc.edu/gareth-james/>





## **6. Delimitar els continguts de l'assignatura**

# What is Machine Learning:

**Machine Learning is the science (and art) of programming computers so they can learn from data.**

A more general definition: *Machine Learning is the field of study that gives computers the ability to learn without being explicitly programmed.*

— Arthur Samuel, 1959

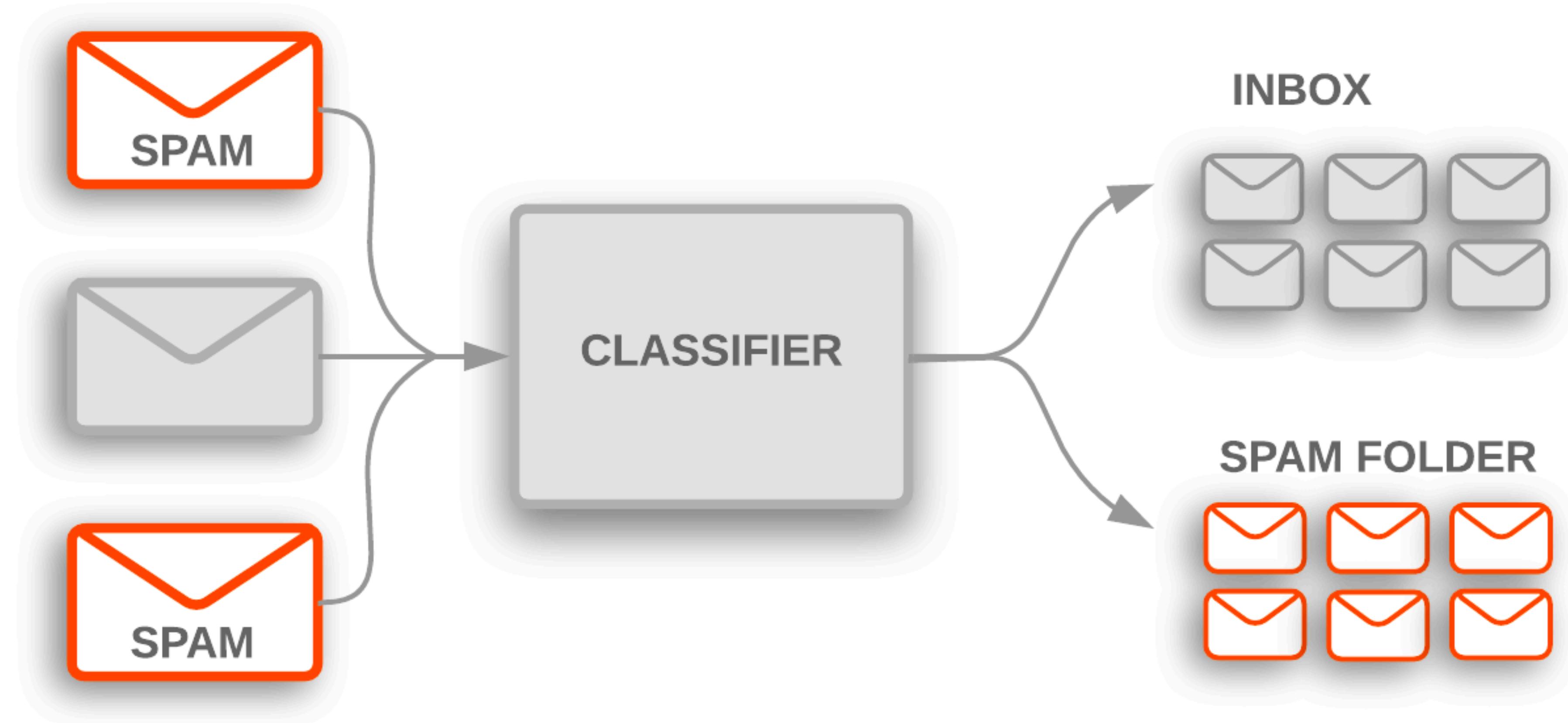
# What is Machine Learning:

Study of algorithms that:

- improve their performance P
- at some task T
- with experience E

Well-defined learning task: <P,T,E>

— Tom Michell, 1997



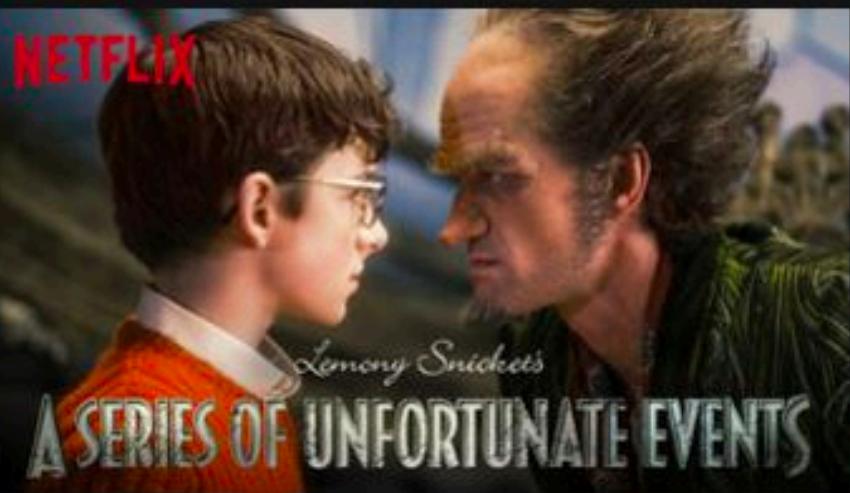


Browse ▾

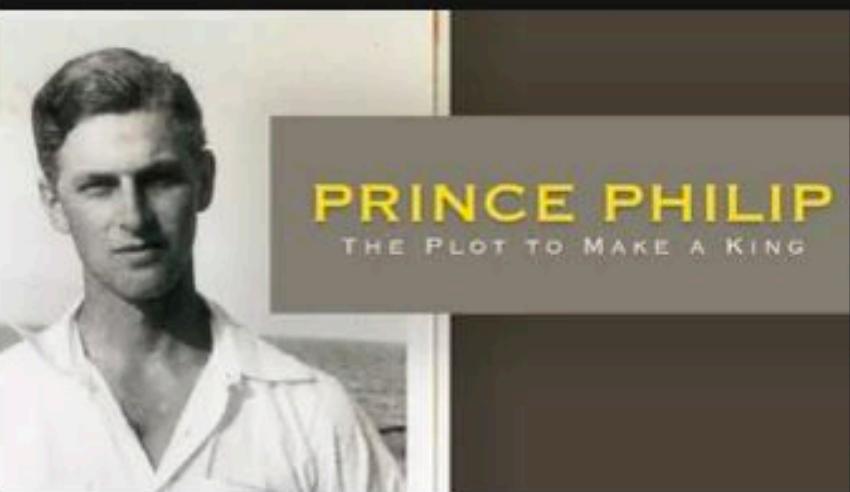
DVD

SEARCH

Because you watched Stranger Things

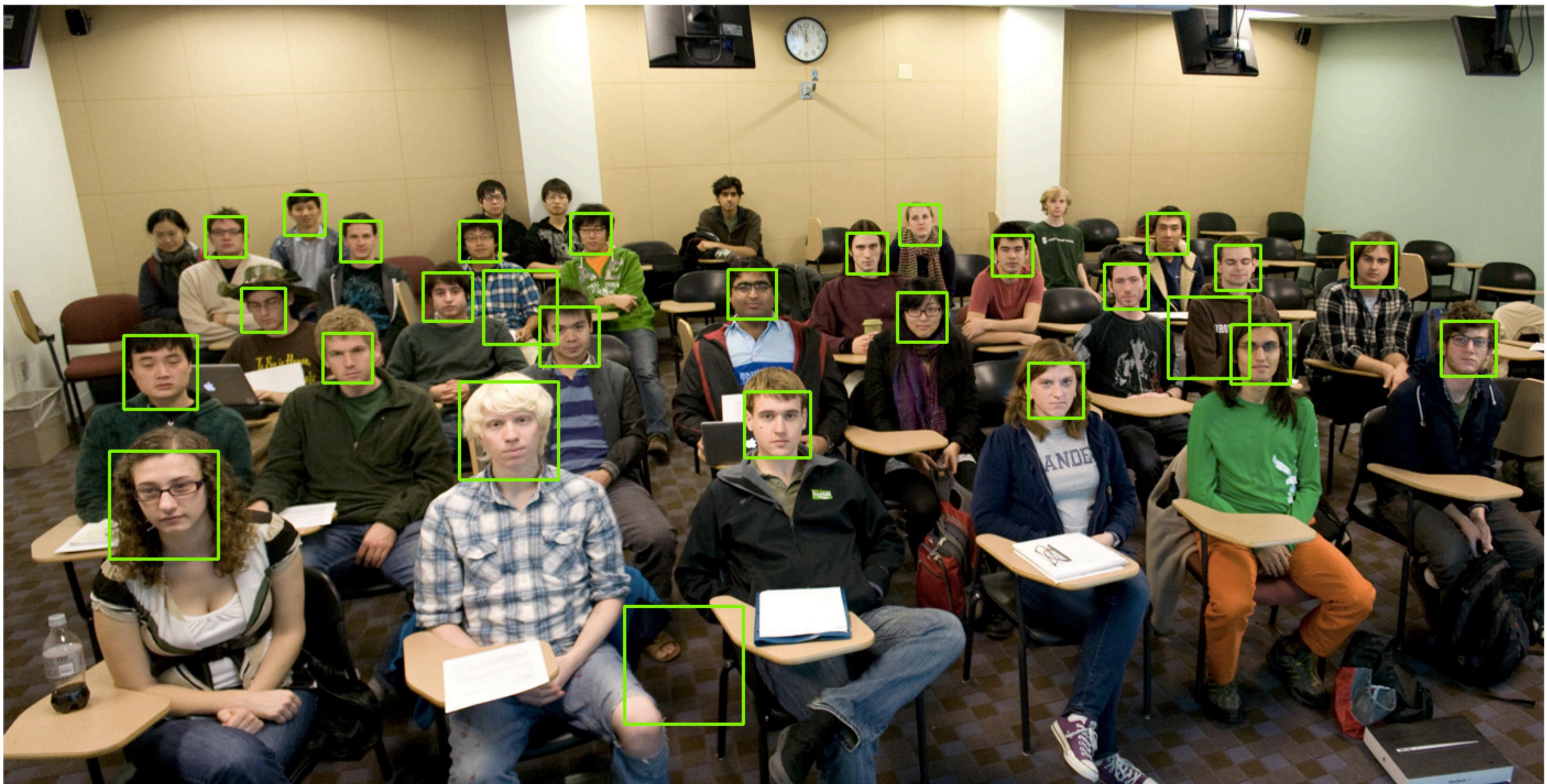


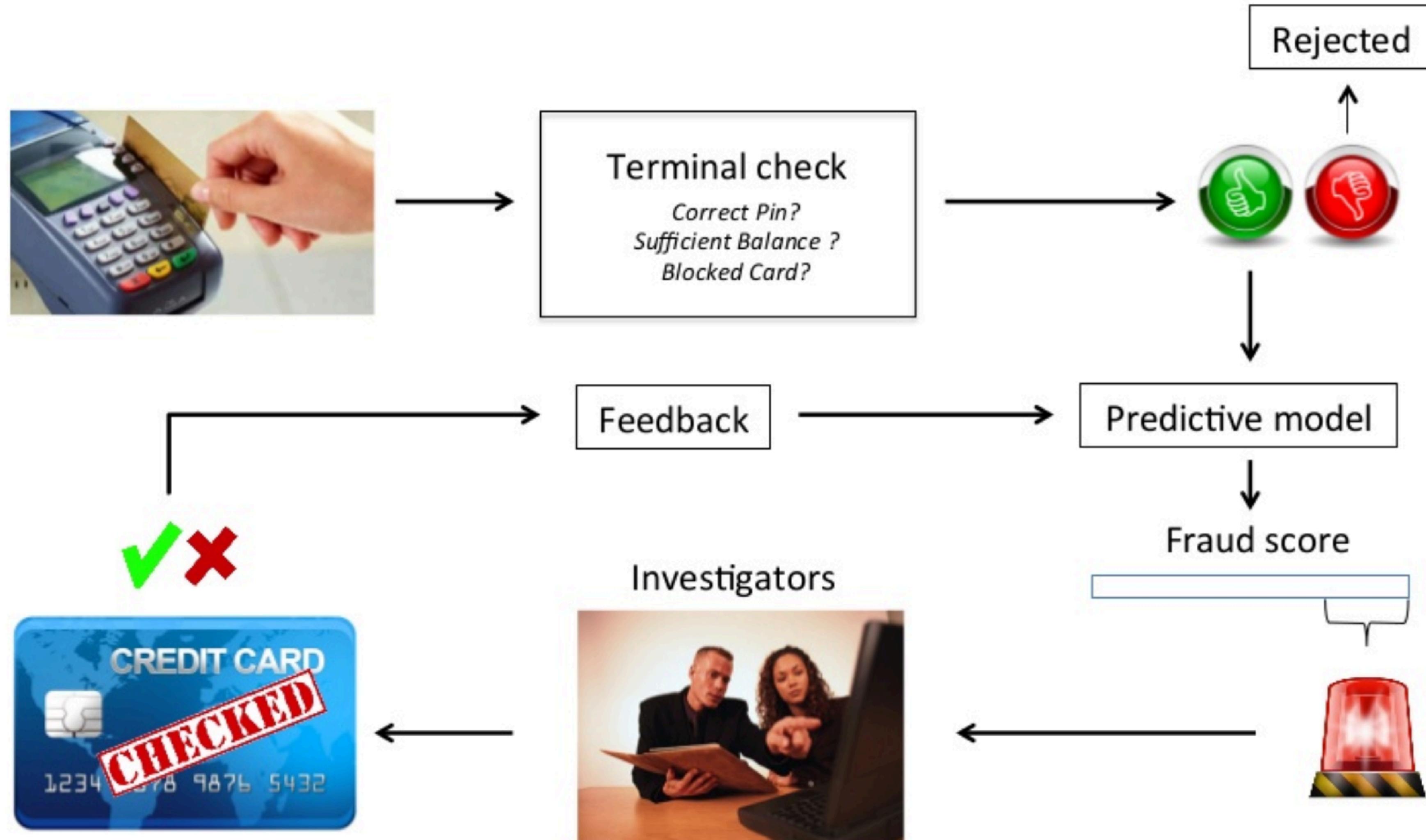
Because you watched The Crown



Because you watched American Crime Story: The People v. O.J. Simpson





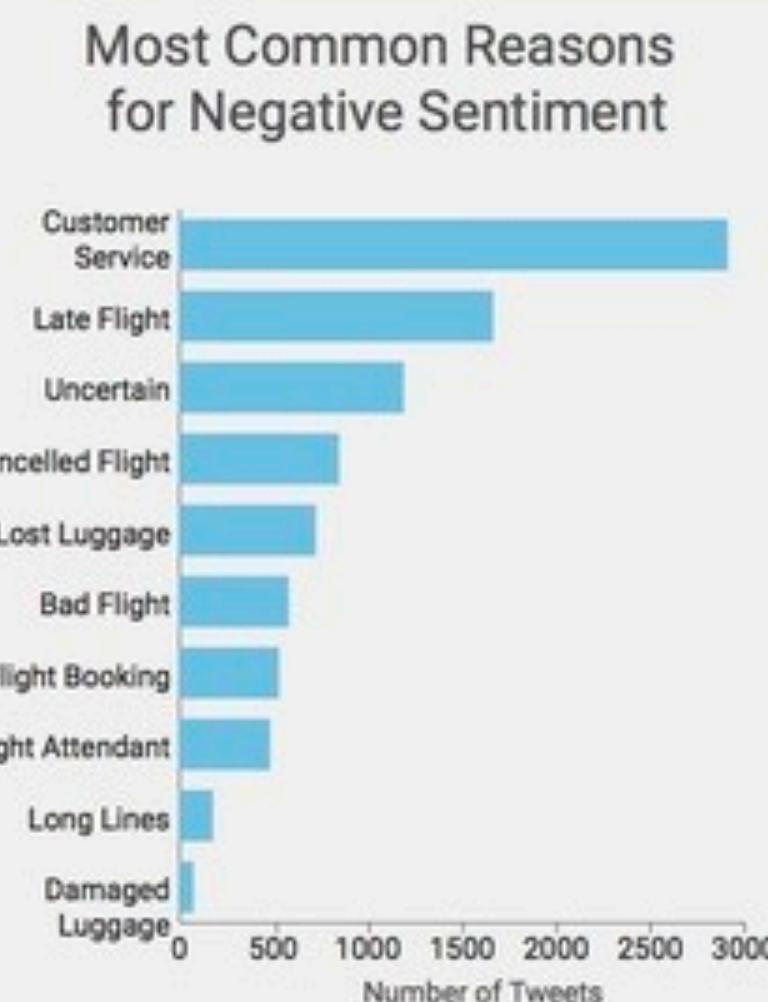
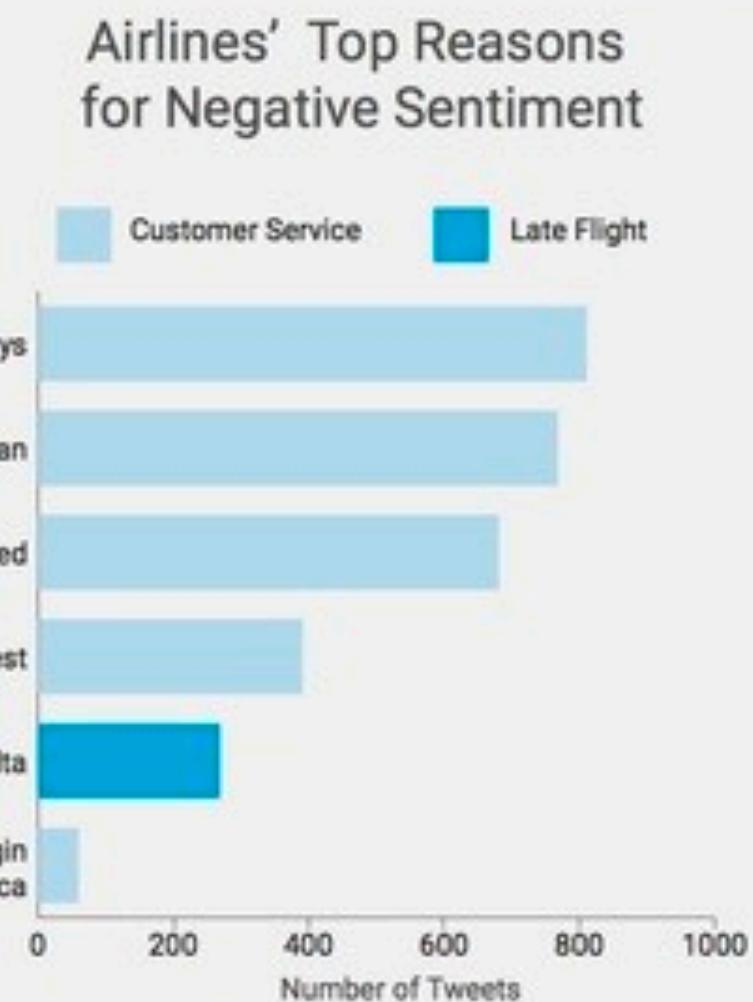
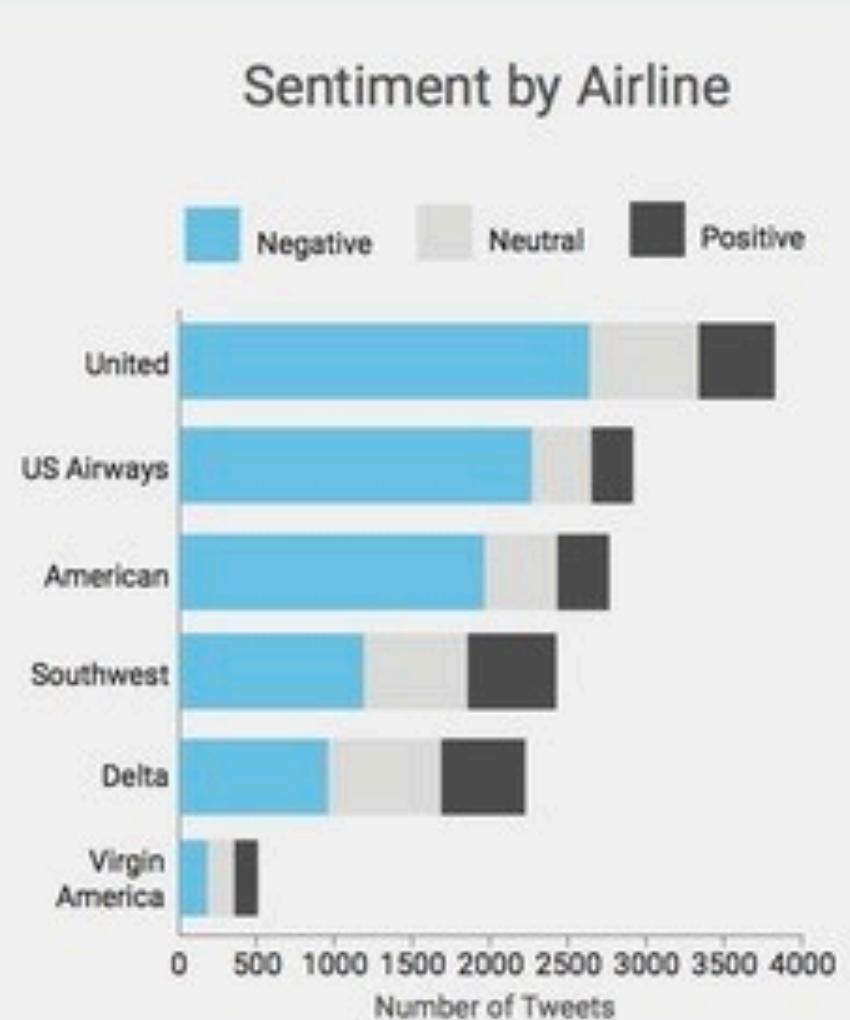




# U.S. Airline Twitter Sentiment

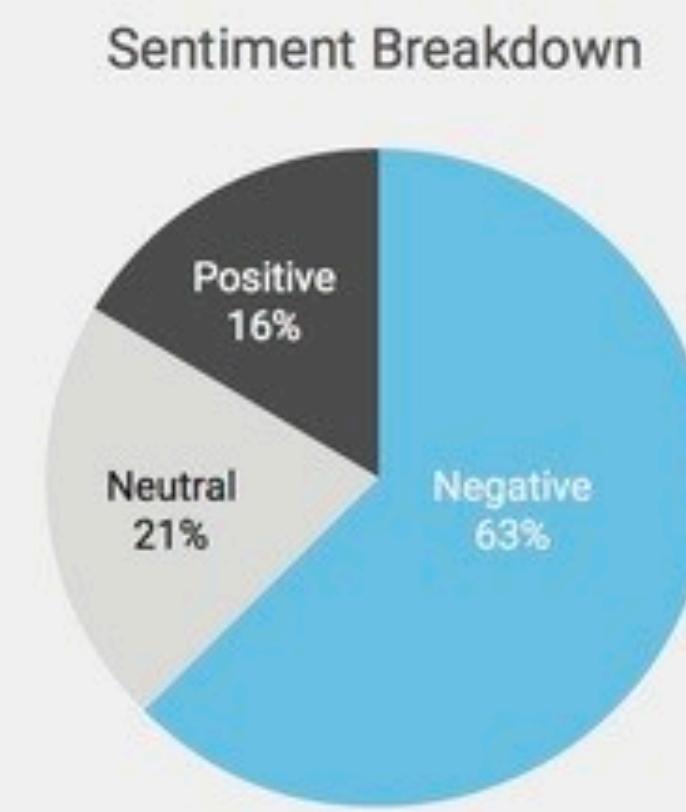
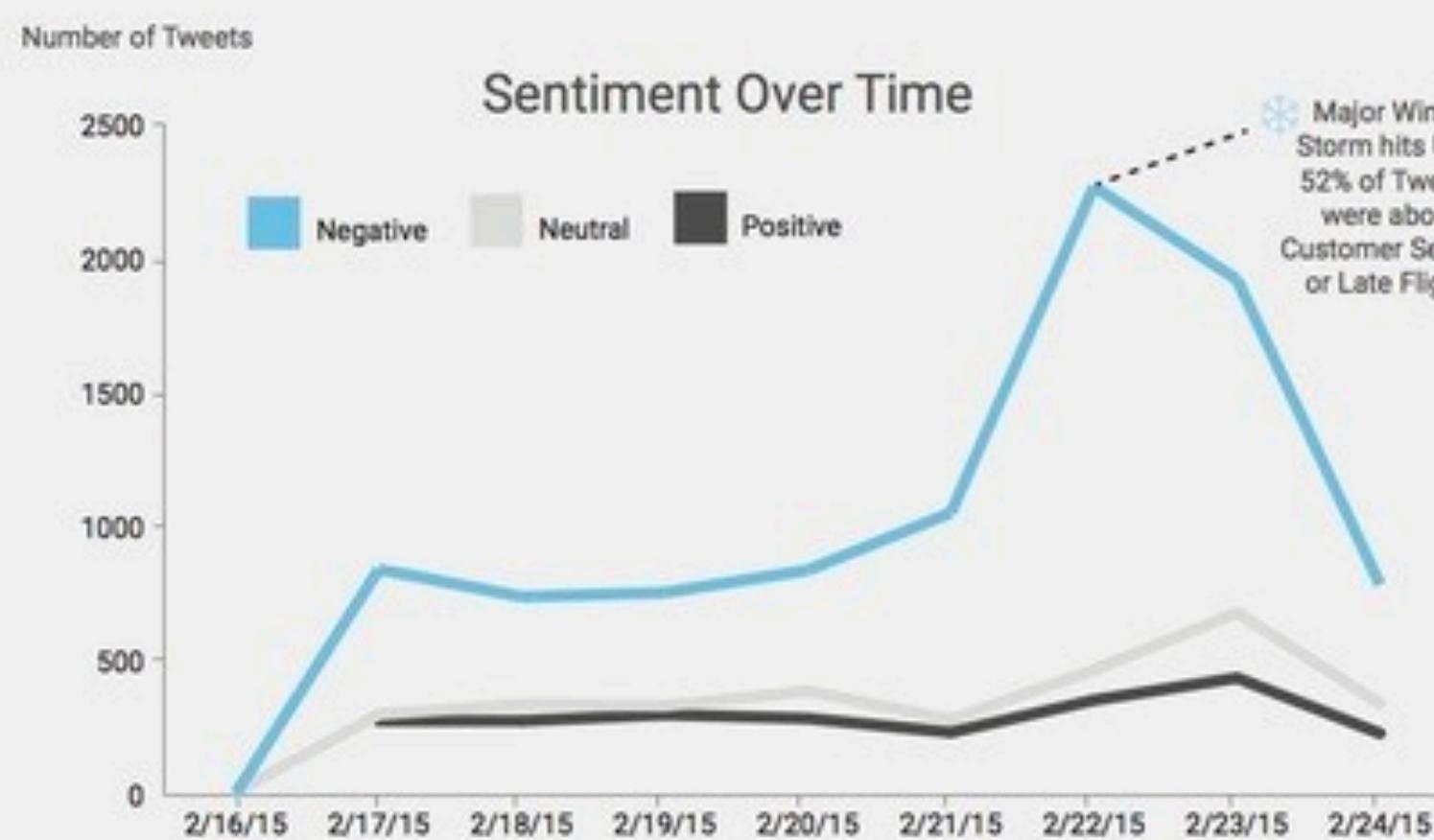
Analysis of traveler's Tweets from a week in February 2015

Cathy Liewen, Heidi Slojewski  
HCI 512 | Winter 2016





## Most Retweeted Negative Sentiments

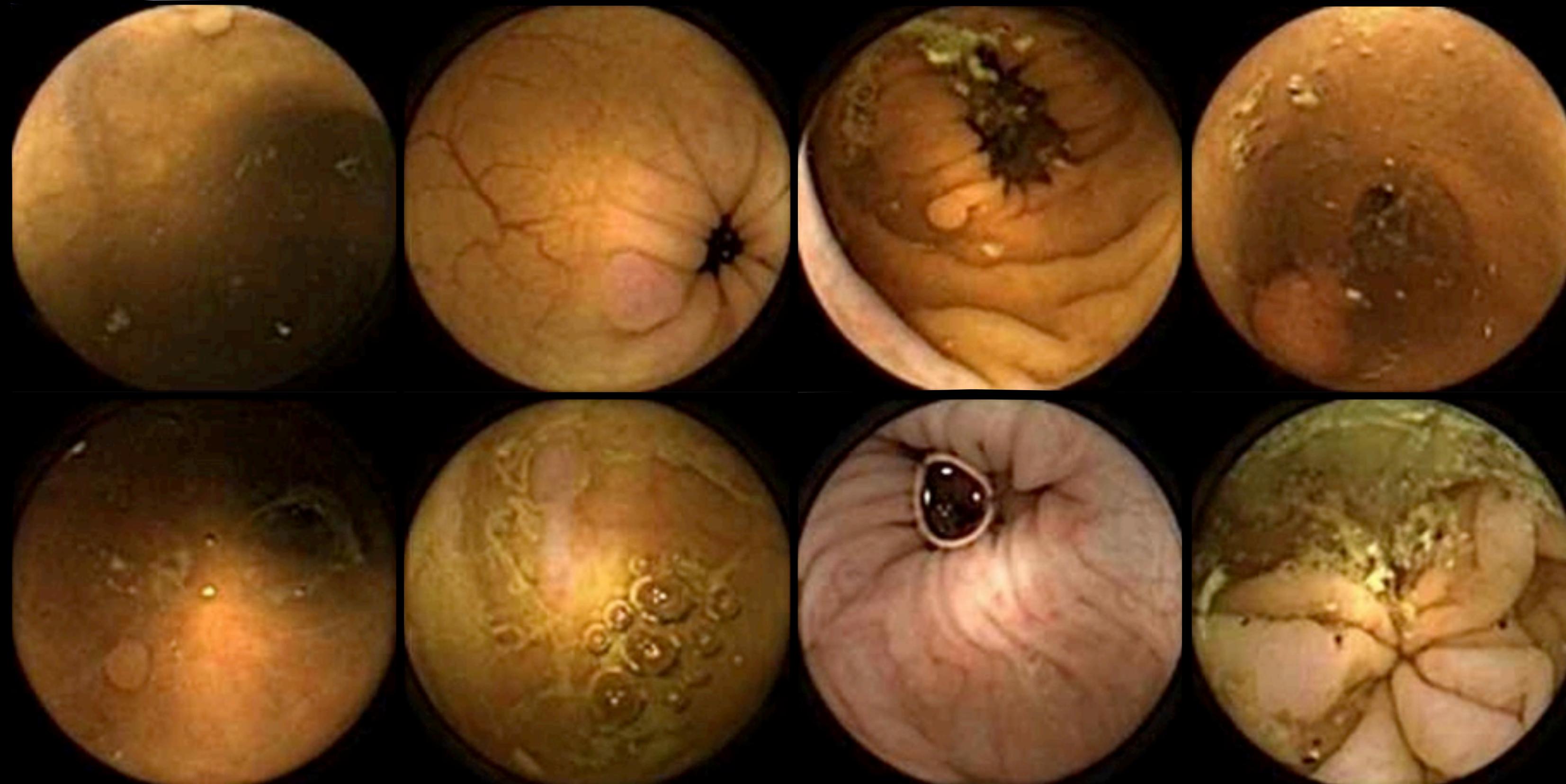


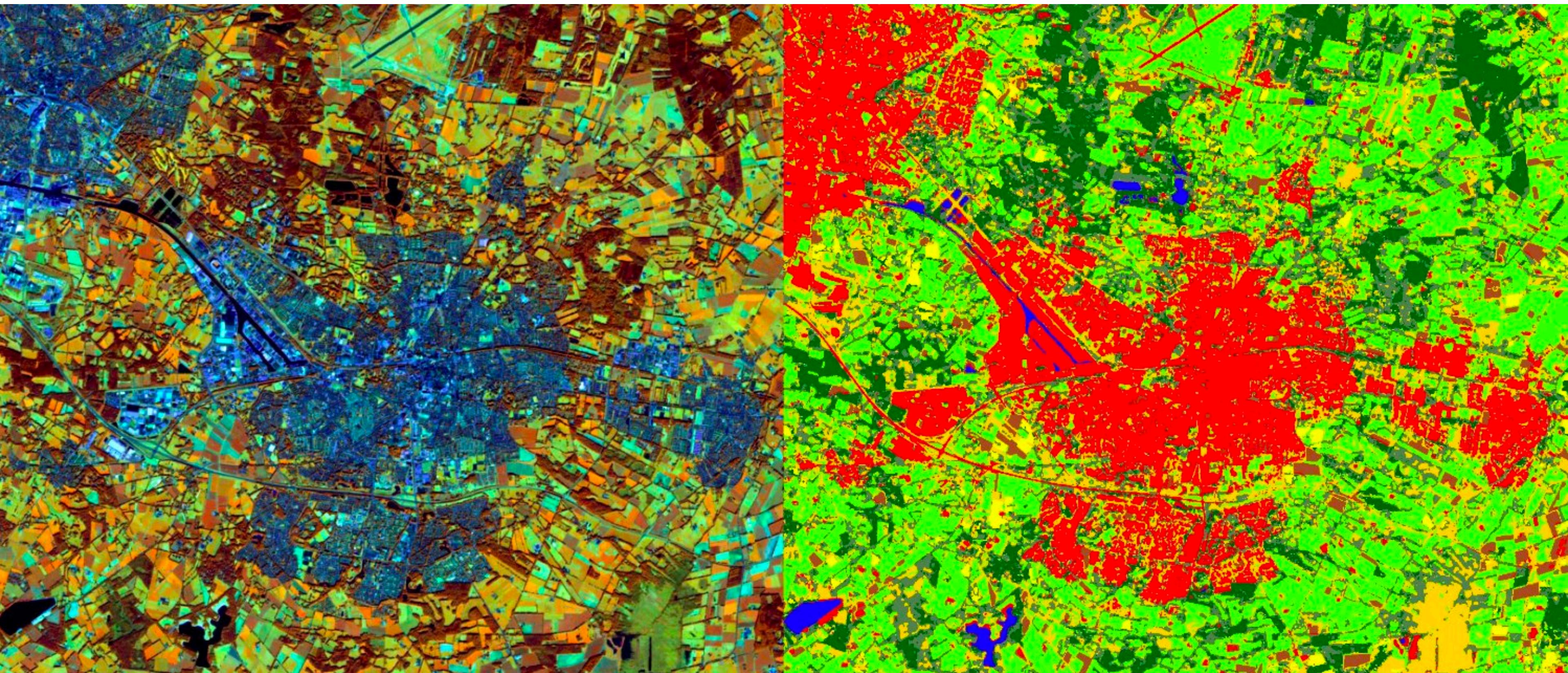
## Most Common Words from Negative Tweets

Image Source: <https://www.bloomberg.com/news/articles/2016-12-20/the-tesla-advantage-1-3-billion-miles-of-data>

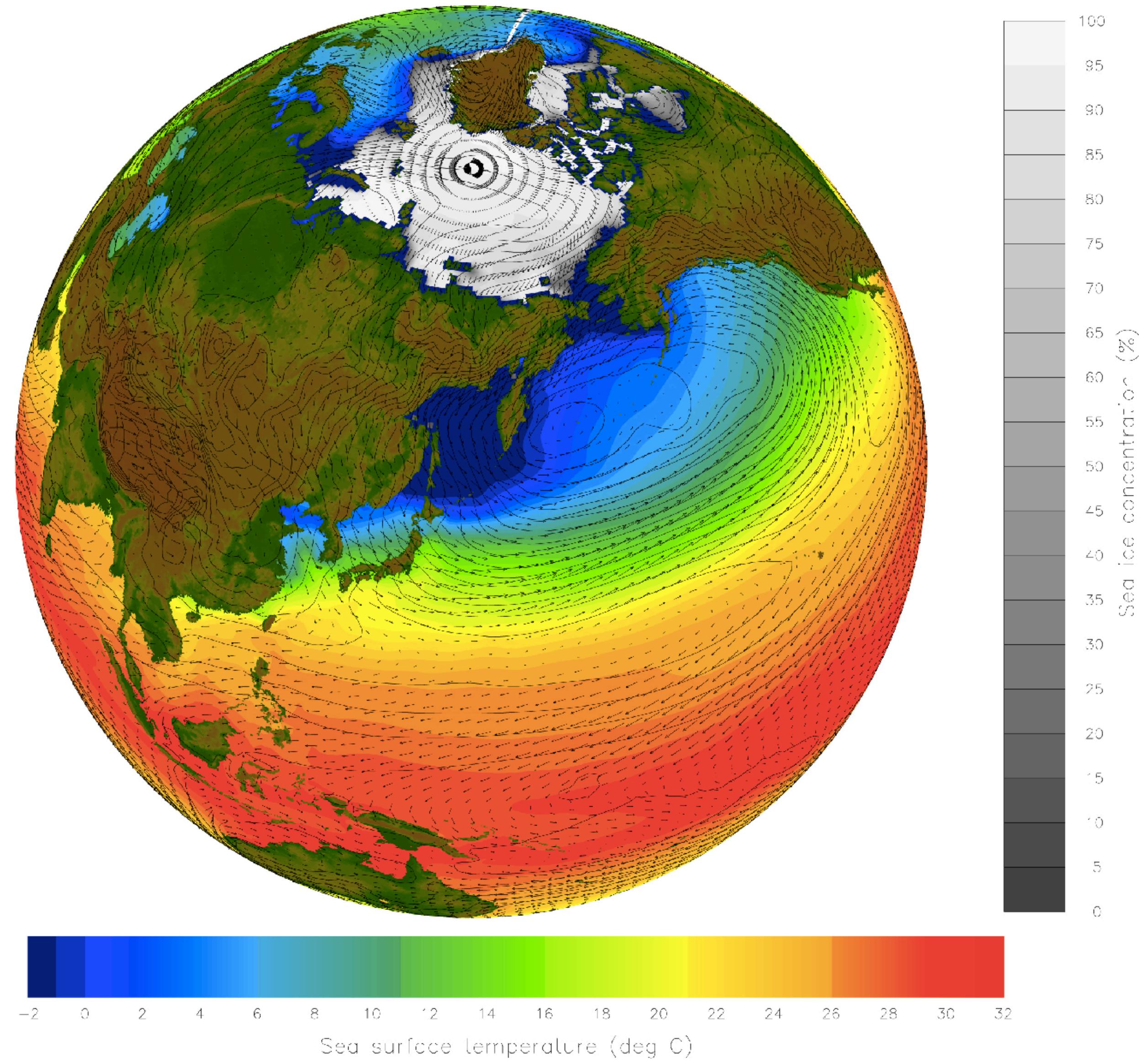






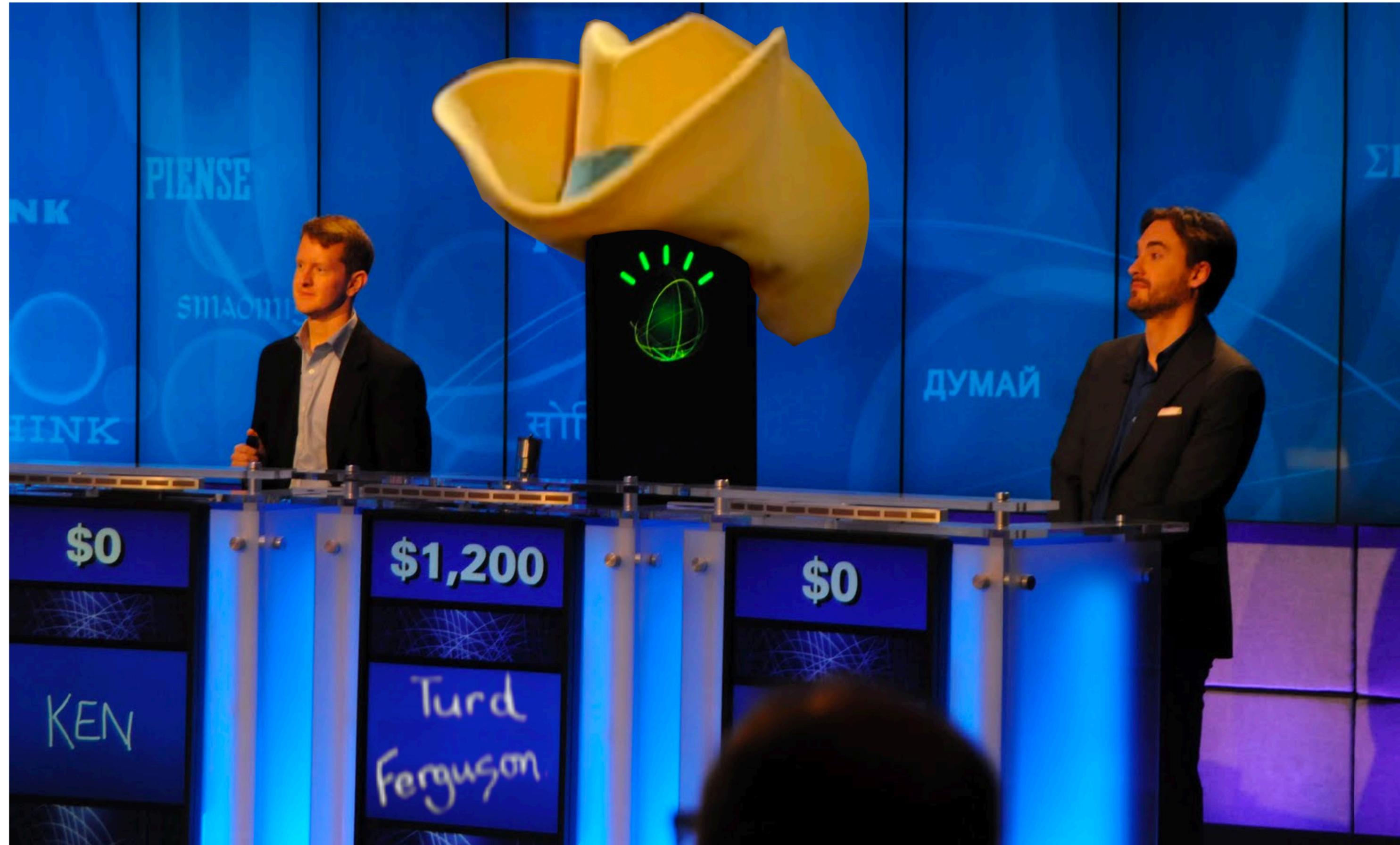


# Climate change

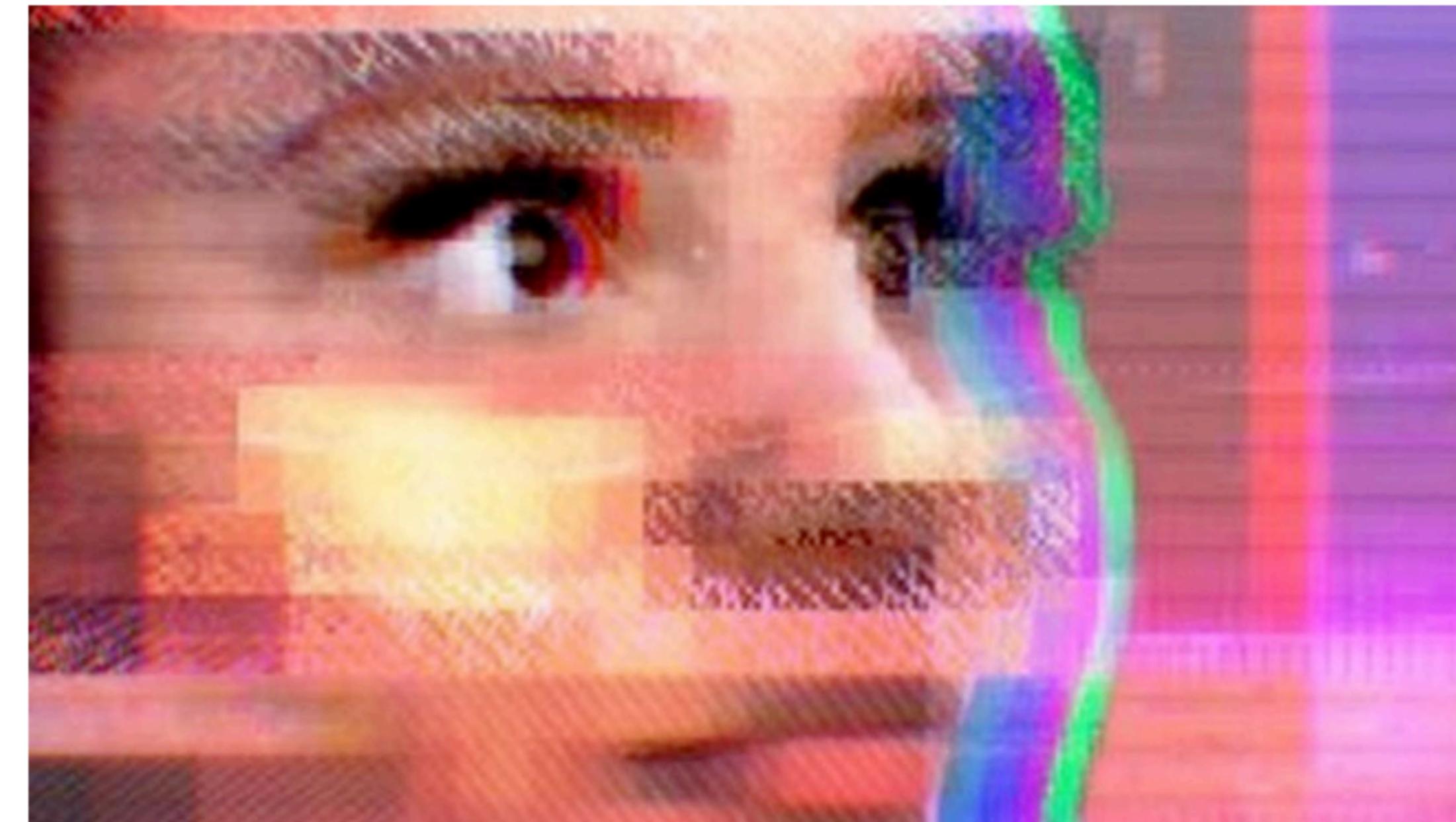
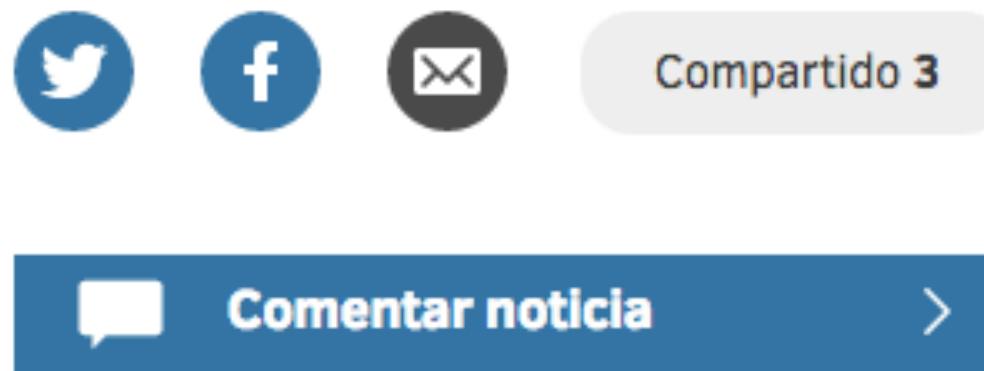




How IBM build Watson, its Jeopardy-playing supercomputer (2011).

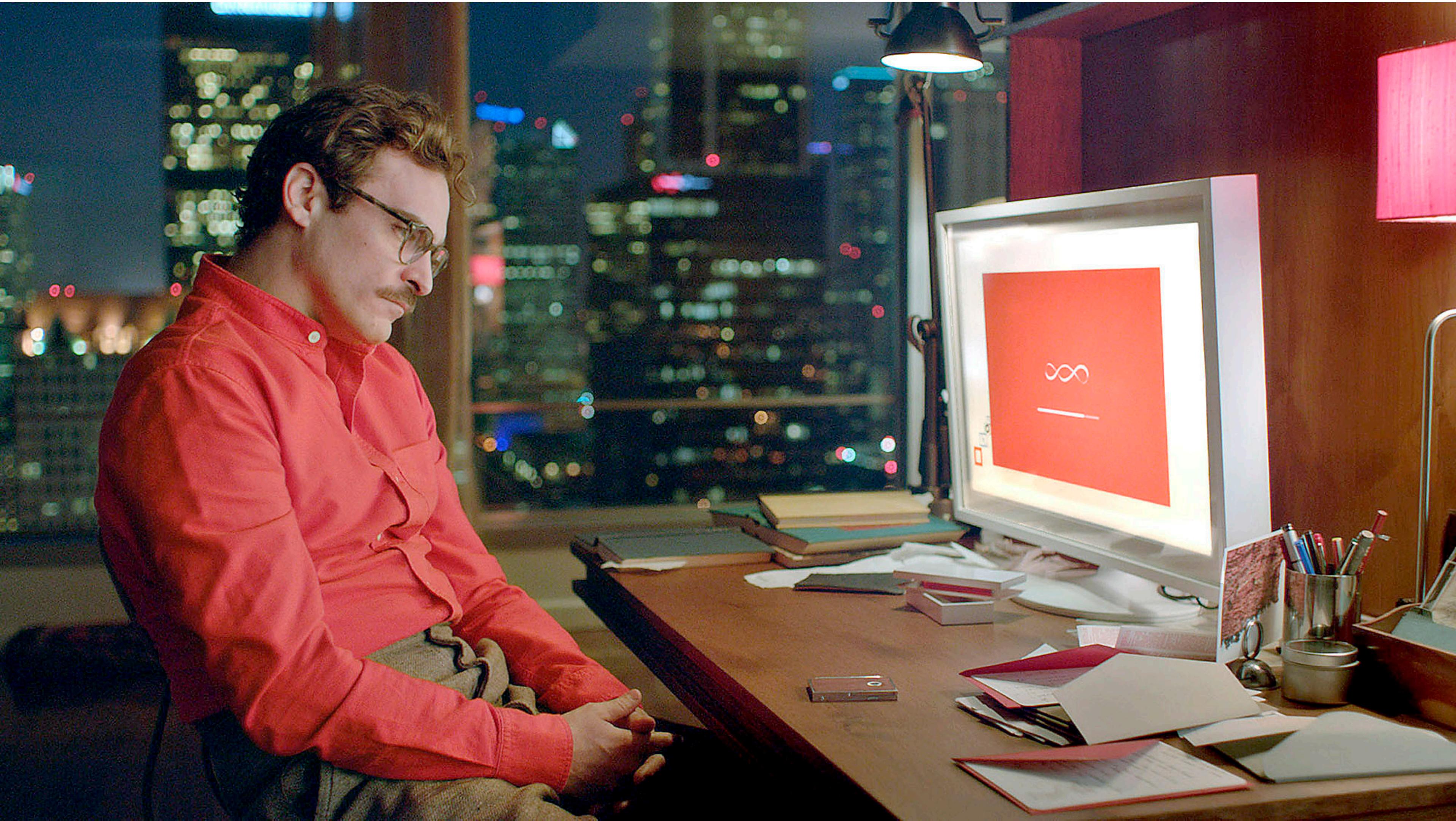


# Una inteligencia artificial se vuelve racista, antisemita y homófoba en menos de un día en Twitter



- En algunos de sus 'tweets', dijo que Hitler tenía razón. También deseó que las feministas ardieran en el infierno.

# Science Fiction or Future?

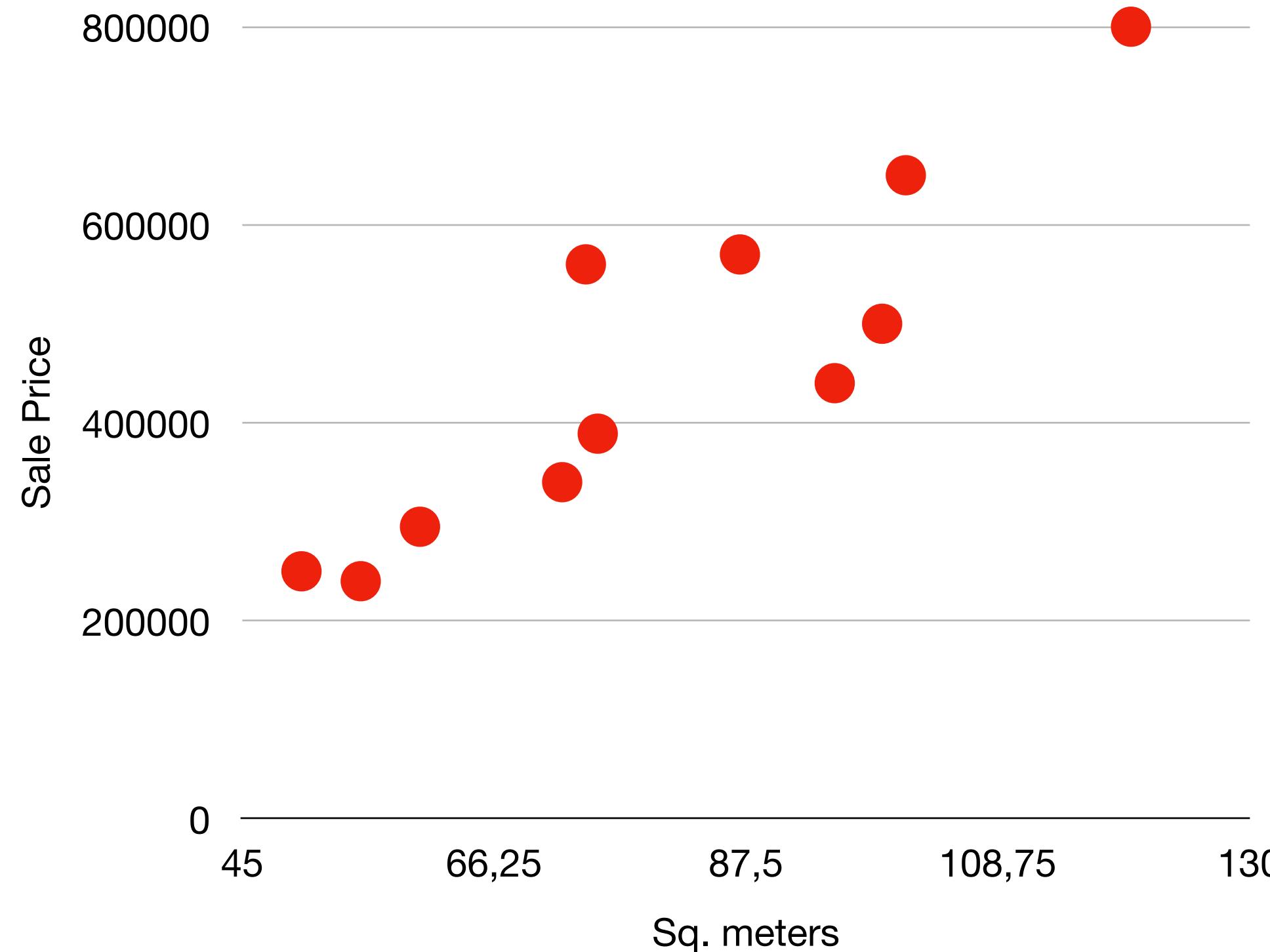


$$\hat{Y} = bX + a$$

# Example of Machine Learning

Task: Predict sale price

Square meters	Sale Price
50	250.000
75	389.000
72	340.000
60	295.000
95	440.000
55	240.000
120	800.000
87	570.000



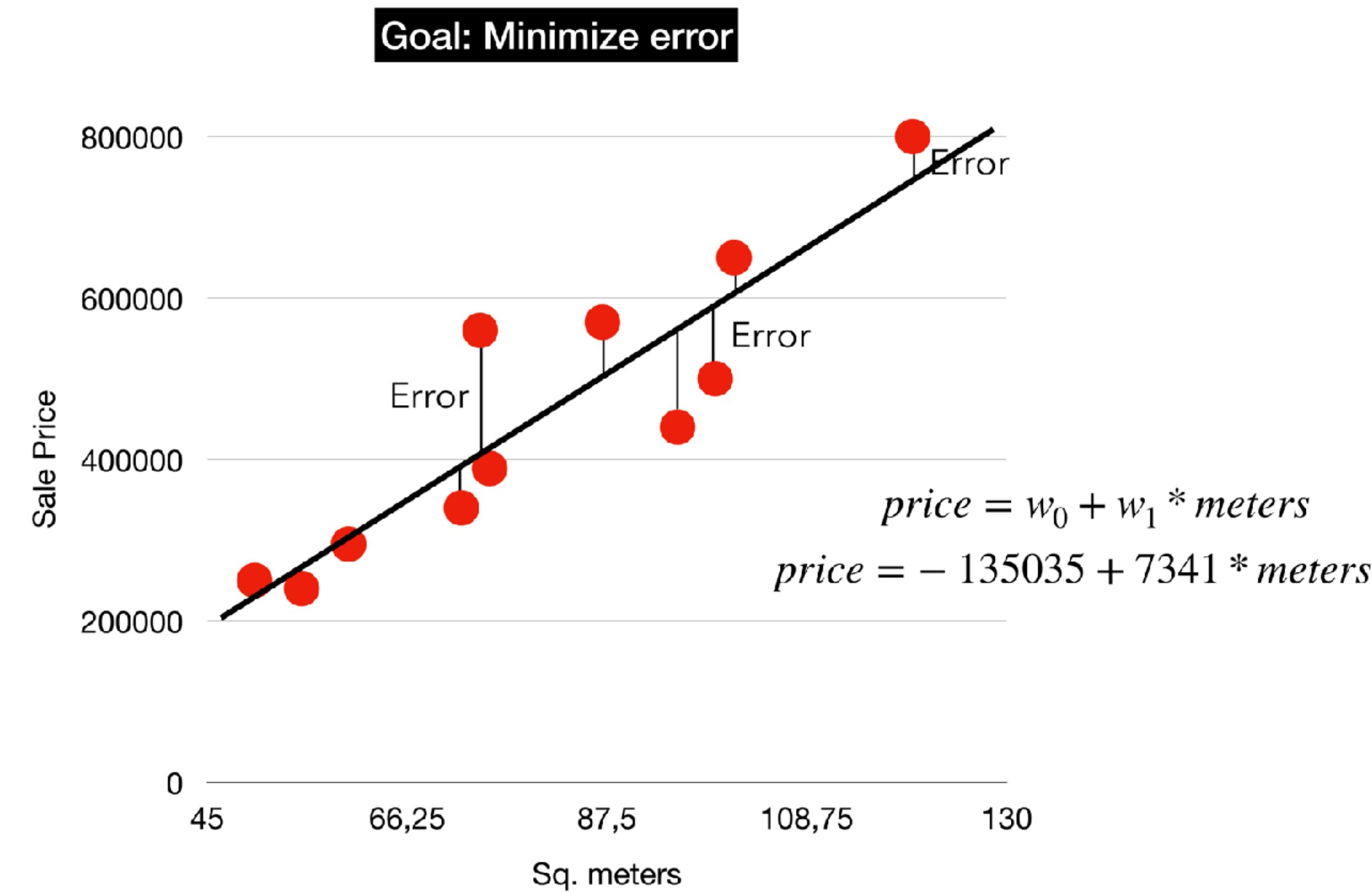
# Example of Machine Learning

Sq. meters	Sale Price
50	250.000
75	389.000
72	340.000
60	295.000
95	440.000
55	240.000
120	800.000
87	570.000



# Example of Machine Learning

Sq. meters	Sale Price	Prediction
50	250.000	232.015
75	389.000	415.540
72	340.000	393.517
60	295.000	305.425
95	440.000	562.360
55	240.000	268.720
120	800.000	745.885
87	570.000	503.632

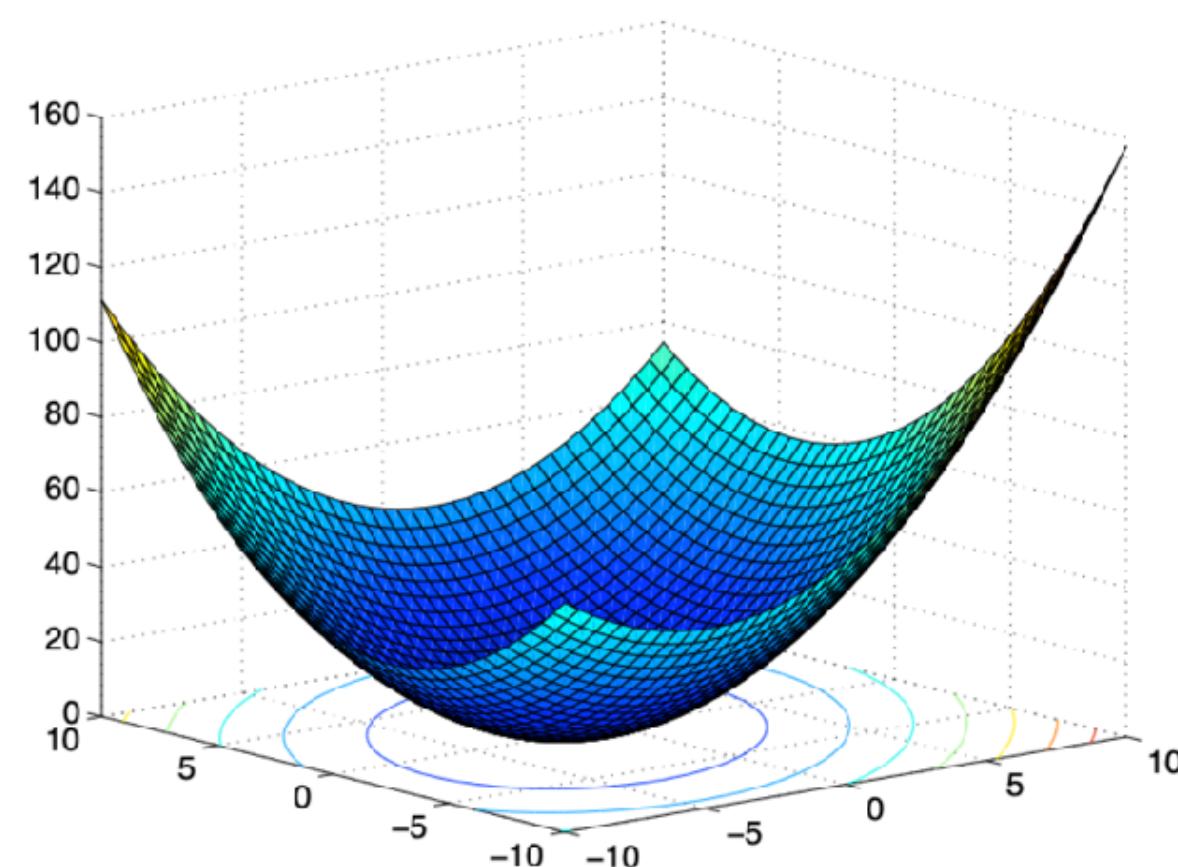


# Optimization

We will have to define a cost function, as for instance:

$$cost = \frac{\sum_i^N (y_i - \hat{y}_i)^2}{N}$$

and minimize it using the training data



# Type of Machine Learning

**Unsupervised  
Learning**

Clustering

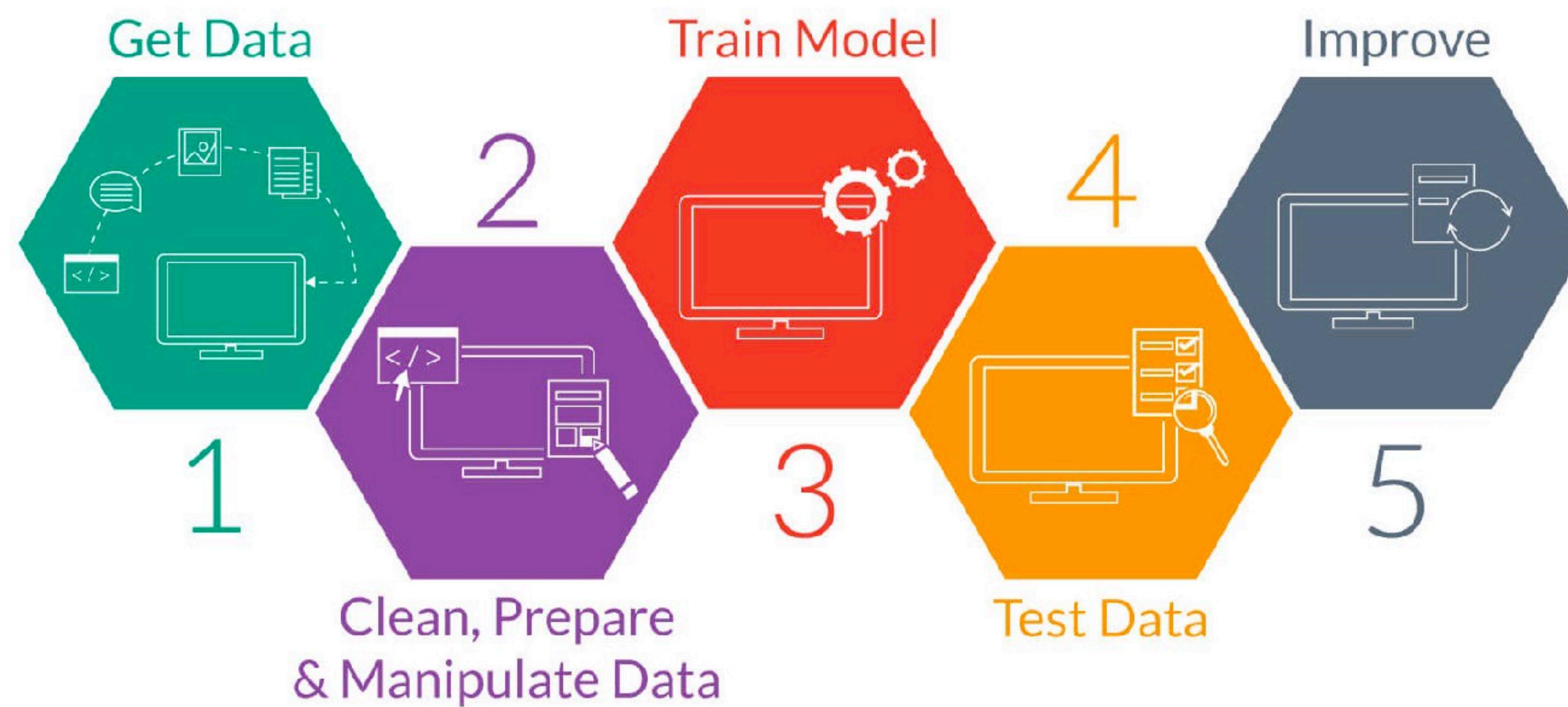
**Supervised  
Learning**

Classification  
Regression

**Reinforcement  
Learning**

Learn from mistakes

## The core steps of typical machine learning workflow



*Dirty Data*

# BIG DATA Data Science

**Fat Data**

Data Mining

Clustering

**Artificial Intelligence**

# Machine Learning

Reinforcement Learning

Deep Learning

# Machine Learning vs Artificial Intelligence



# Machine Learning Artificial Intelligence

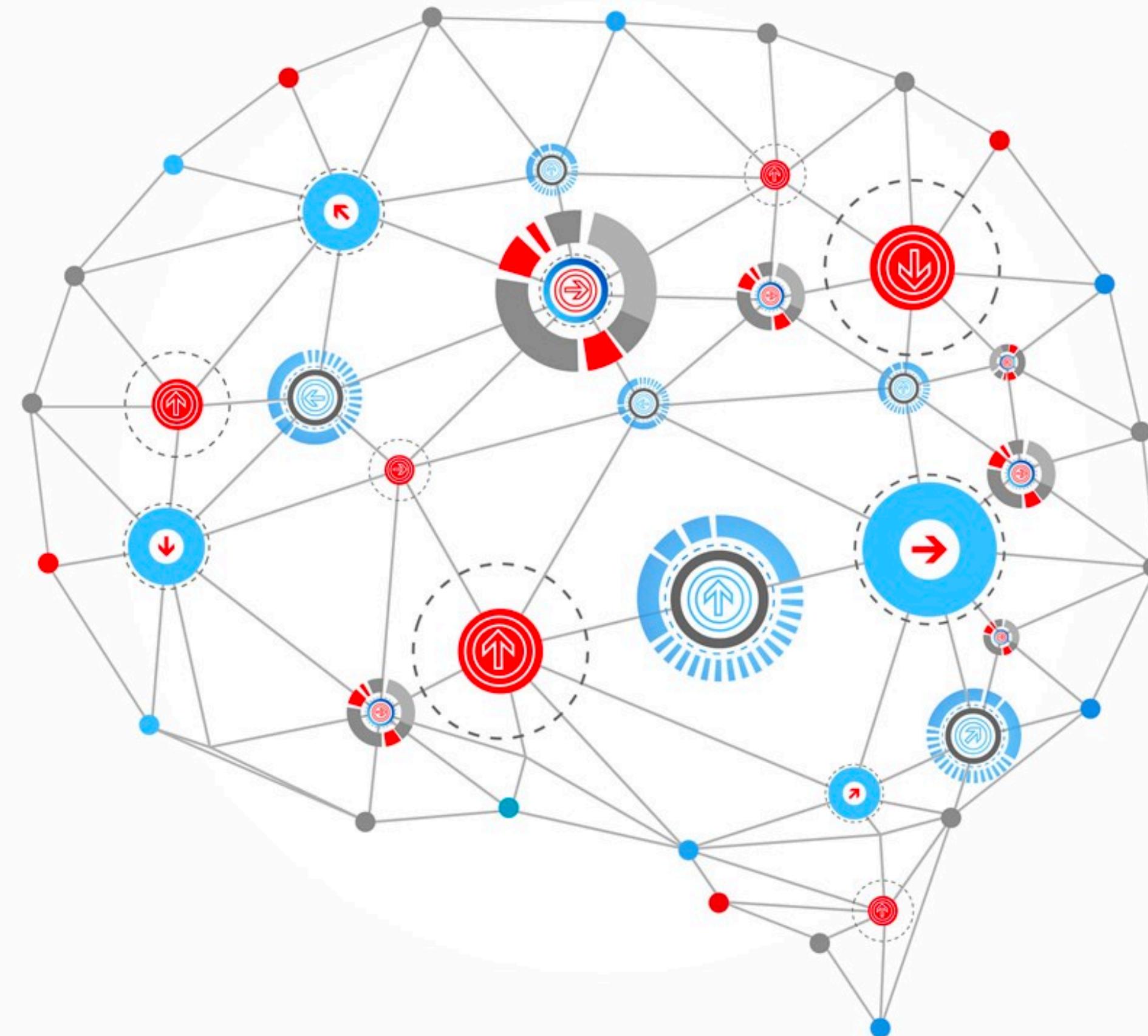
**Artificial Intelligence** is an academic discipline devoted to the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, language recognition, decision-making, planning, reasoning, etc.

Artificial Intelligence is classified into two parts, **General AI** and **Narrow AI**. General AI refers to making intelligent in a wide array of activities that involve thinking and reasoning. Narrow AI, on the other hand, involves the use of artificial intelligence for a very specific task.

**Machine learning** is a subset of artificial intelligence that uses algorithms to learn from data (inductive behavior).

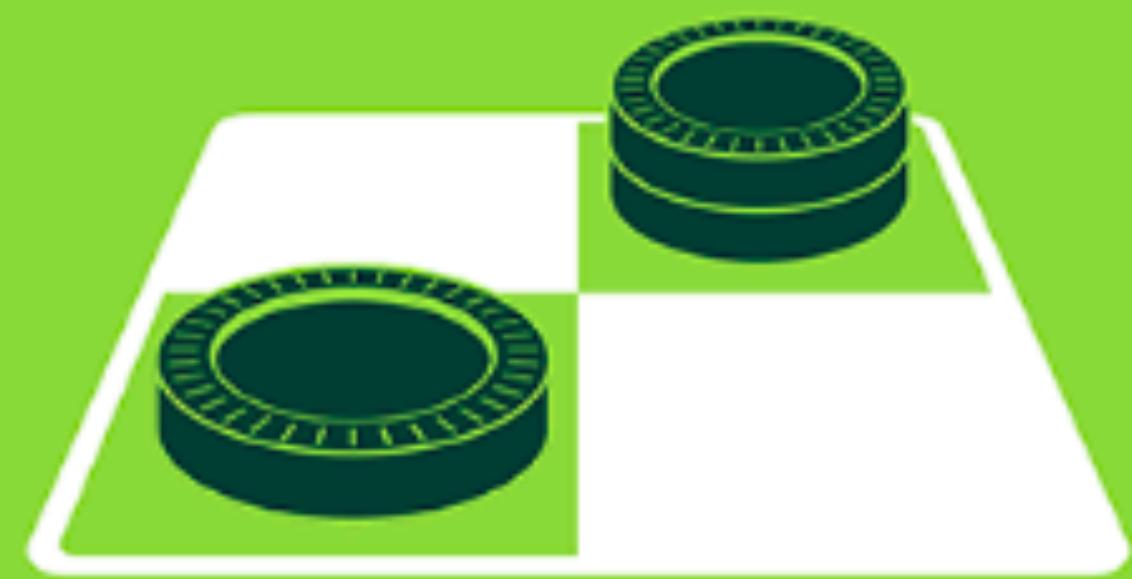
**“Machine learning** is a subset of  
**artificial intelligence**  
that uses algorithms to **learn from data**  
and enables machines to improve with  
**experience”**

**Deep learning (DL) is ML that uses a particular class of algorithms  
(neural networks)**



## ARTIFICIAL INTELLIGENCE

Early artificial intelligence stirs excitement.



1950's

1960's

1970's

1980's

1990's

2000's

2010's

## MACHINE LEARNING

Machine learning begins to flourish.



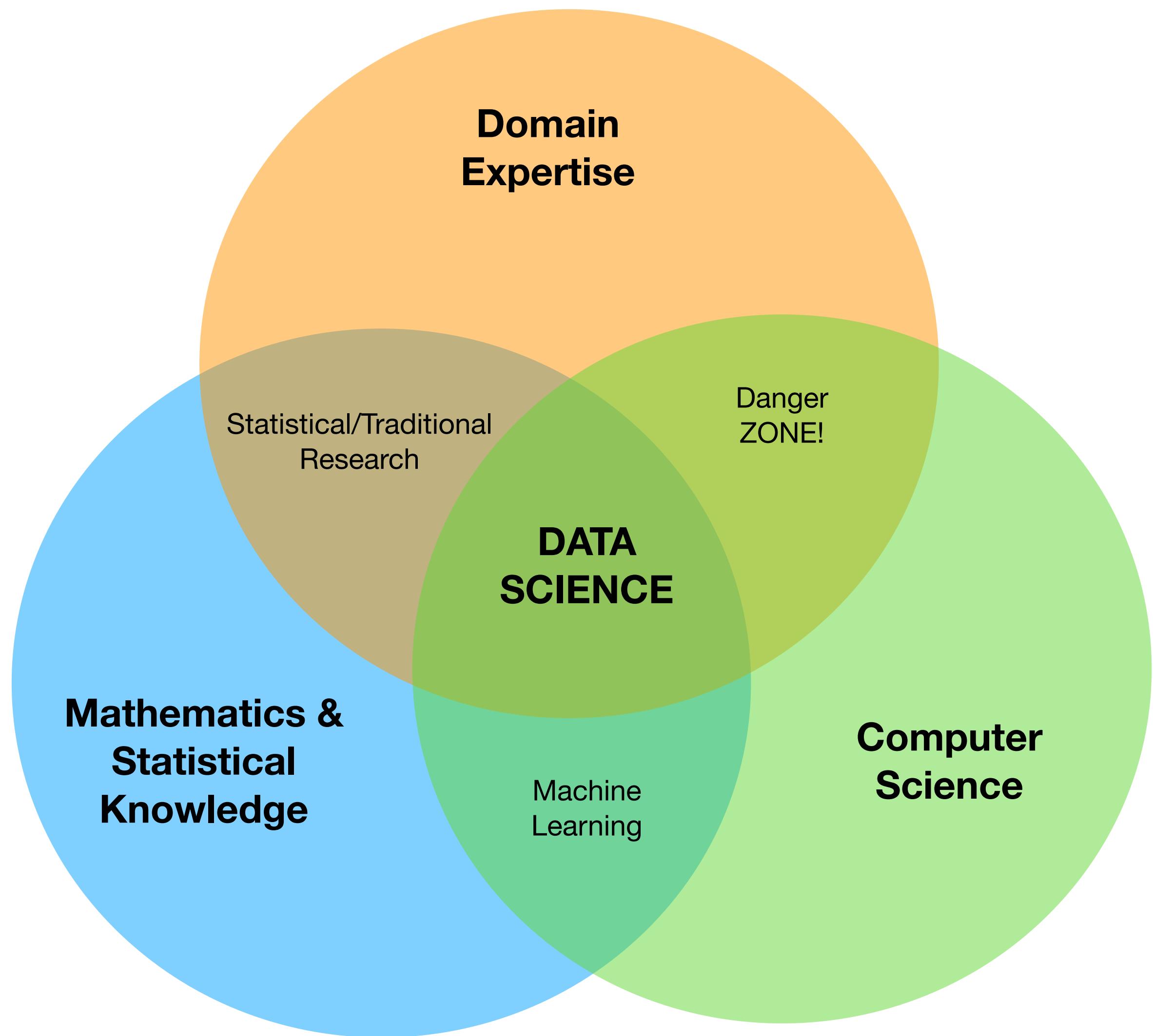
## DEEP LEARNING

Deep learning breakthroughs drive AI boom.



# Data Science

is a **multidisciplinary methodology**  
to help to define what we want to do with  
data, how to evaluate our algorithms, what  
decisions can be grounded on data, how do  
we combine evidences from several  
sources, etc..



**Drew Conway's Data Science Venn Diagram**



DATA

# Data Scientist: The Sexiest Job of the 21st Century

by Thomas H. Davenport and D.J. Patil

FROM THE OCTOBER 2012 ISSUE

# THE DATA SCIENCE **HIERARCHY OF NEEDS**

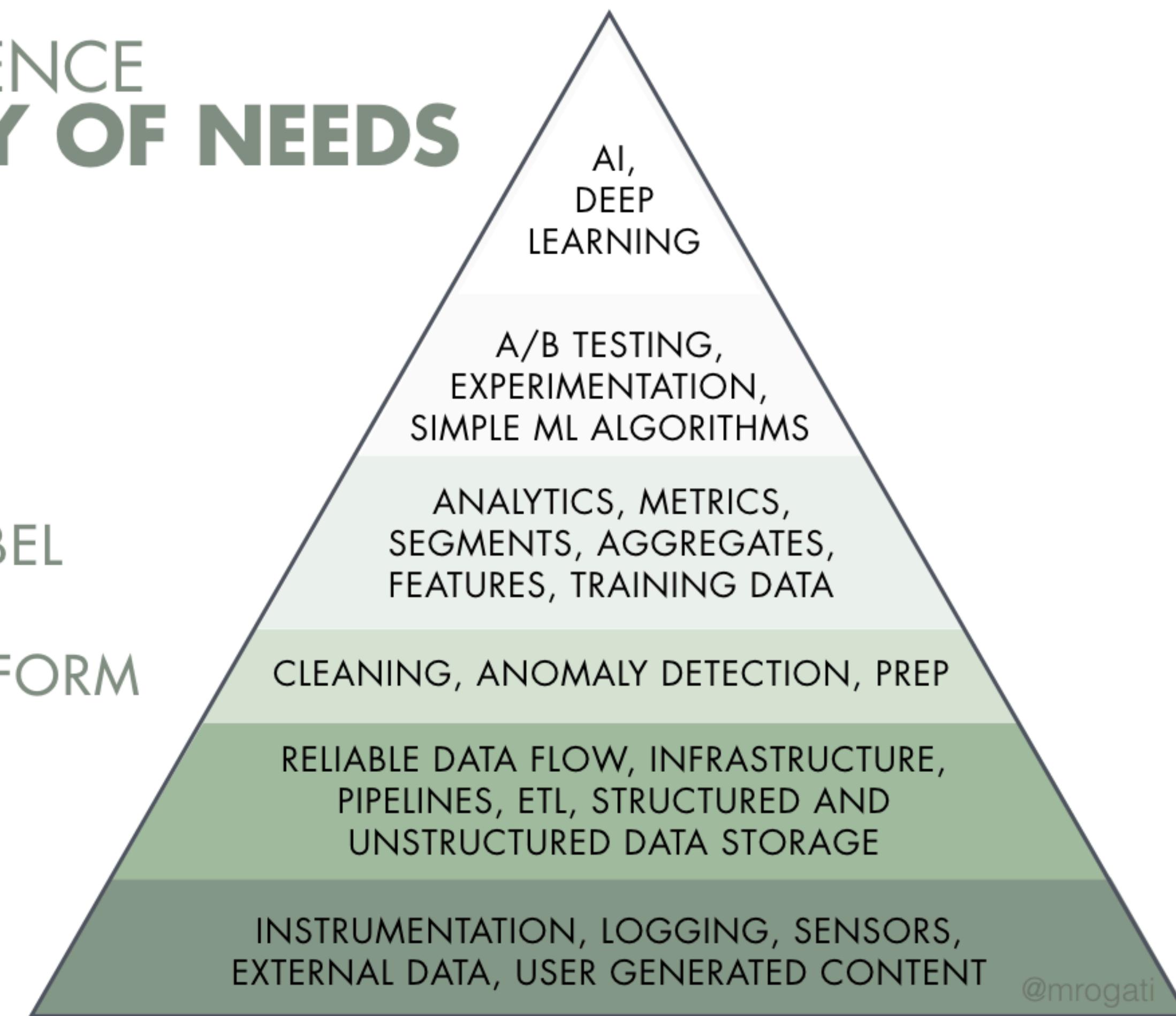
LEARN/OPTIMIZE

AGGREGATE/LABEL

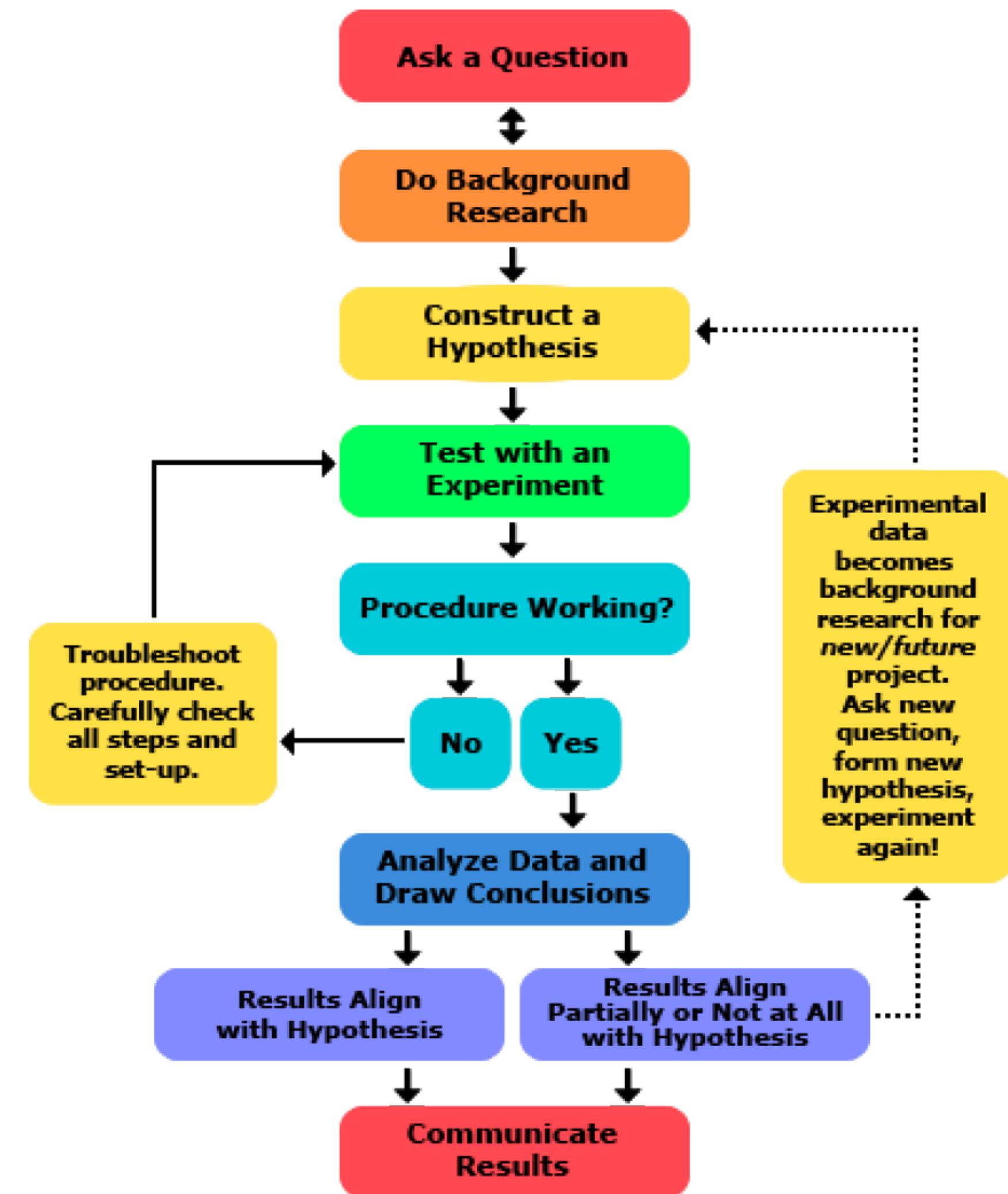
EXPLORE/TRANSFORM

MOVE/STORE

COLLECT







# Data Science Path

What do I want?  
Does it have sense?

What are my data  
sources? How reliable  
are they?

How do I develop an  
understanding of the  
content of my data?

What are the key  
relationships in my  
data?

How do I develop an  
understanding of the  
content of my data?

What are the likely  
future outcomes?

Are my expectations  
fulfilled?

## Question

## Acquire

## Describe

## Discover

## Analyze

## Predict

## Evaluate

# Main Challenges of Machine learning

Insufficient Quantity of Data

Non representative Training Data

Poor-Quality Data

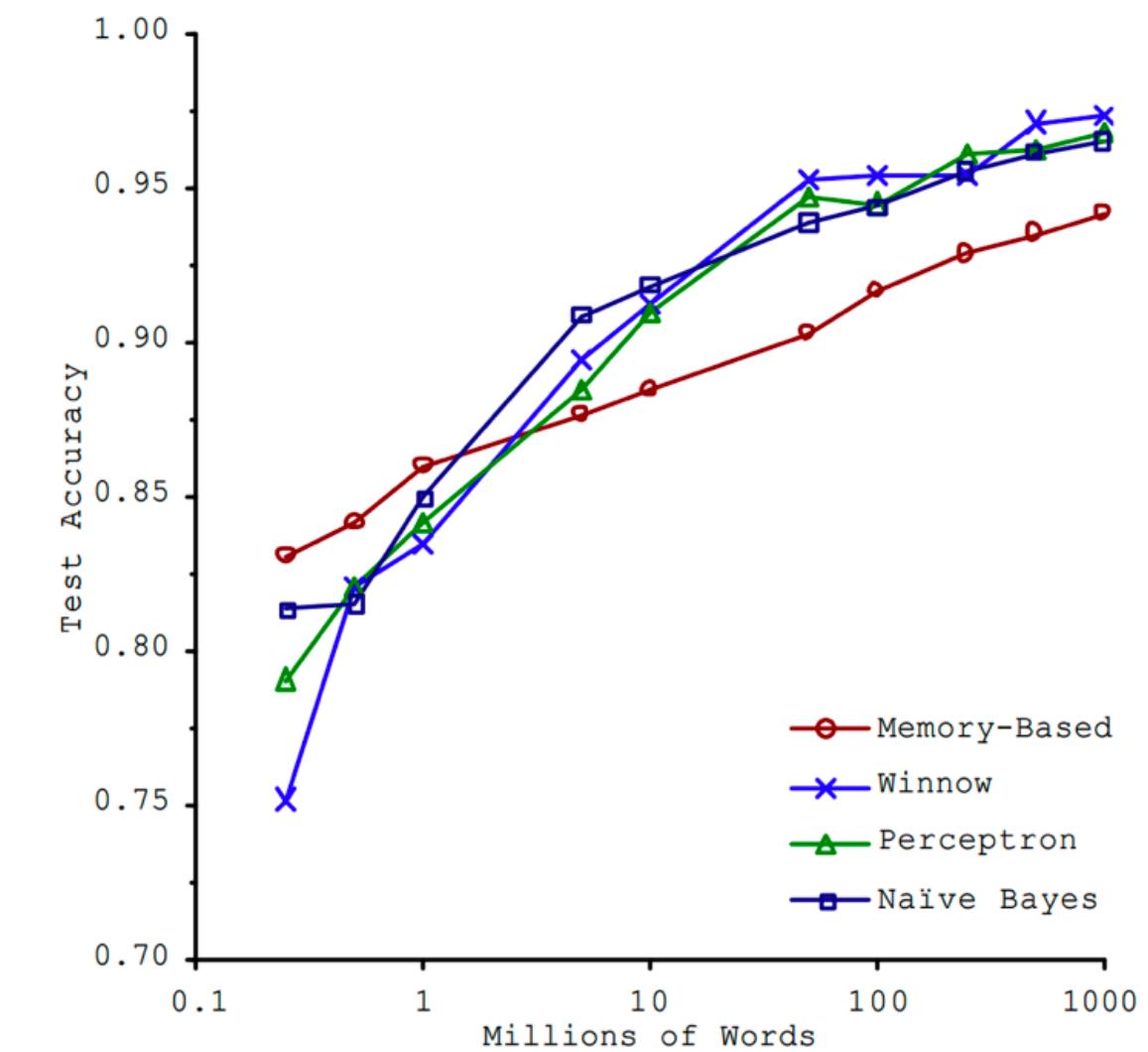
Irrelevant Features

Overfitting the Training Data

Underfitting the Training Data

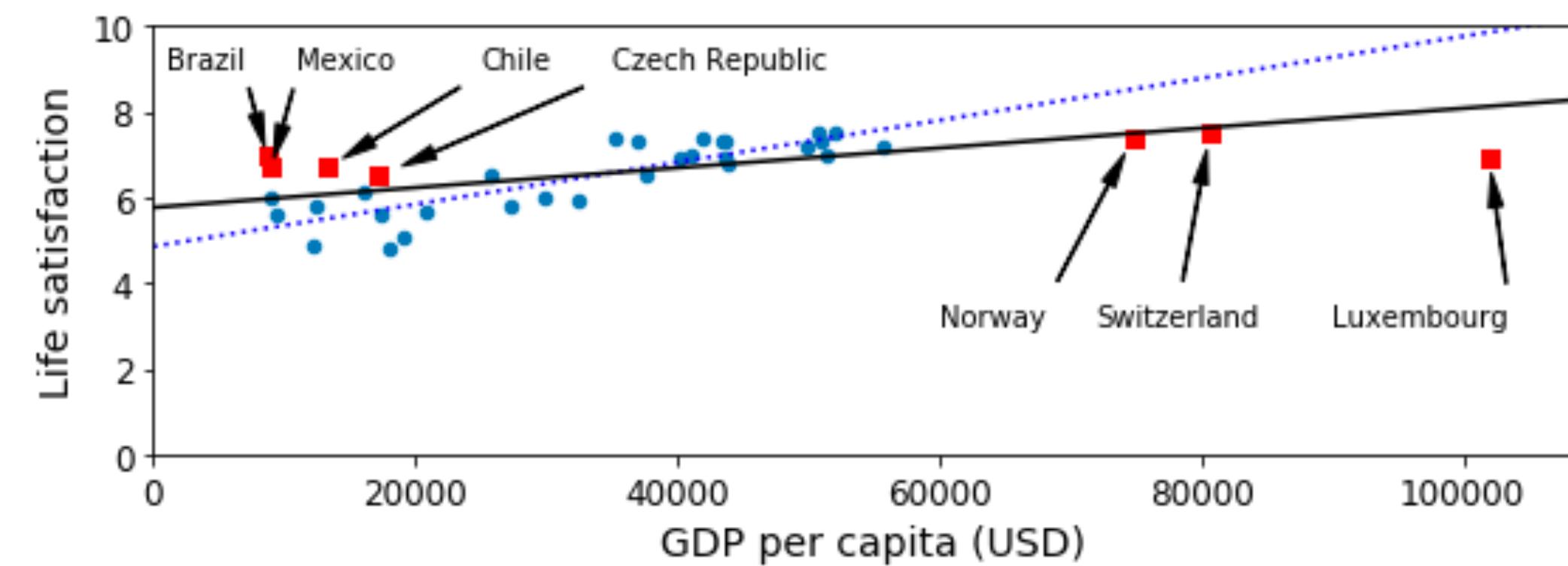
# Insufficient Quantity of Data

- The importance of data versus algorithms
- What is best? more data or a better model?
  - Several studies shows that very different algorithms, perform almost identically when enough data is provided
- Peter Norvig in his paper titled “The Unreasonable Effectiveness of data” popularized the idea that data matters more than algorithms.
  - However, small- and medium -sized datasets are still very common.  
In many cases data is really expensive



# Non representative Training Data

- In order to generalize well, it is crucial that your training data be representative of the new cases you want to generalize to.



**Careful about the sampling BIAS**

# Poor-Quality of data

- Our training data can be full of errors, outliers, and noise.
  - If there are outliers in the training set perhaps we should simply discard them.
  - Missing features from some instances. **What we can do?**
    - Remove those instances
    - Remove those features
    - Impute those features to those instances

# Irrelevant Features

- Your system will be only capable to learn if the training data contains **enough relevant** features and **not too many irrelevant ones**.
- The process called *feature* engineering aims to come up with a good set of features to train with. The process involves the following steps:
  - Feature Selection
  - Feature Extraction
  - Creating new features by gathering new data

# Overfitting/Underfitting the Training Data

