

# Presentació Curs

Machine Learning | Enginyeria Informàtica

Santi Seguí | 2020-2021

# 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 Online** (Divendres 12.30-13.30h)

• **Santi Seguí**

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

## **Teoricopràctica** (Dijous 15-16.30h)

• **Santi Seguí**

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

## **Laboratoris** (Dimarts 18h-19h)

• **Josep Fortiana**

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

# Com s'organitza l'assignatura?

- L'assignatura s'imparteix en classes teòriques, pràctiques i teoricopràctiques. 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? (1 hora a la setmana)

- Contingut online acotat a una hora de dedicació

## Com seran les classes teòricopràctiques? (1.5 hores a la setmana)

- Classes presencials on es reforçaran conceptes i resoldran problemes

## • Com seran les classes pràctiques? (1 hores a la setmana)

- Sessió online. Les pràctiques es realitzen de forma individual o amb parelles.

# Llenguatge de programació?

- Python & R

## ENGINYERIA INFORMÀTICA

Curs: 2020-2021 Assignatures - Horaris

### APRENENTATGE AUTOMÀTIC

Codi: **365828**



Pla docent

Tipus	Impartició	Crèdits	Curs/Semestre	Unitat Acadèmica
Optativa del grau	Quadrimestral	6	4 /	Dept. Matemàtiques i Informàtica

#### Programació de l'oferta docent del Primer semestre

##### Activitat

Grup	Dies	Horari	Professorat	Aula	Idioma
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##### Teoria [No presencial]

M0	dl. dt. dc. dj. dv.	1r sem.	12.30-13.30	Segui Mesquida, Santiago	<a href="#">Aula virtual - Matemàtiques i Informàtica</a>	Català
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##### Teoricopràctica [Presencial]

MA	dl. dt. dc. dj. dv.	1r sem.	15.00-16.30	Segui Mesquida, Santiago	<a href="#">Aula B7</a>	
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##### Pràctiques de laboratori [No presencial]

Ma	dl. dt. dc. dj. dv.	1r sem.	18.00-19.00	Fortiana Gregori, Jose	<a href="#">Aula virtual - Matemàtiques I Informàtica</a>	Català
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##### Exàmens : 1r parcial [Presencial]

G1	
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##### Exàmens : Final [Presencial]

G1	
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##### Exàmens : Reavaluació [Presencial]

G1	
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	Theory (1 hora)	Presencial 1.5h	Pràctiques
1-Oct		Introduction	Introducció R
8-Oct	A typical Machine Learning project	Your first DS problem	Regression
15-Oct	Regression	A typical Machine Learning project	Regression
22-Oct	Classification	Regression	Regression
29-Oct	Training Models	Classification	Classification
5-Nov	Support Vector Machines	Training Models	Classification
12-Nov	Tree Based Methods	Examen Parcial	Classification
19-Nov	Boosting & Bagging - Ensembles	Support Vector Machines & Tree Based Methods	Unsupervised Learning
26-Nov	Dimensionality Reduction	Boosting & Bagging - Ensembles	Unsupervised Learning
3-Dec	Unsupervised Learning	Dimensionality Reduction	Unsupervised Learning
9-Dec	Neural Networks	Unsupervised Learning	NN
17-Dec	Neural Networks	Neural Networks	NN

# 4. Avaluació

# **Avaluació Continuada**

## **Dues modalitats:**

- Basada amb projectes
- Basada amb exàmens

# **Avaluació Continuada**

## **Basada amb 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
- L'alumne haurà de defensar el projecte i demostrar la seva autoria (a les sessions presencials o mitjançant sessions online específiques).

### **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 Continuada**

## **Basada amb Examens**

### **Com s'avaluarà l'assignatura?**

- L'assignatura seguirà un esquema d'avaluació continuada, amb dos elements principals:  
**proves presencials i Iliurament de pràctiques**

#### **Proves presencials:**

- Durant el curs, l'estudiant ha de fer 2 proves escrites sobre la teoria:
  - Parcial (NTP) + Final (NTF)
- **La nota final teoria NT = NTP/2 + NTF/2**

#### **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

6. Recursos

## GITHUB / Campus Virtual

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

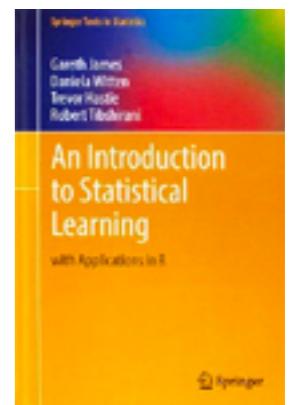
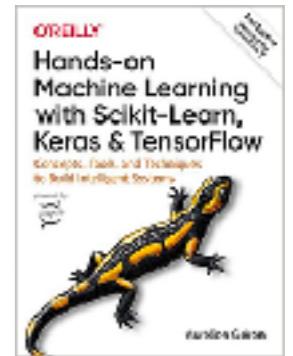
- Làmines de les sessions de l'aula
- Guions de les pràctiques
- Entregues
- Documentació i informació complementària

## 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/>



# Kahoot!

# 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:

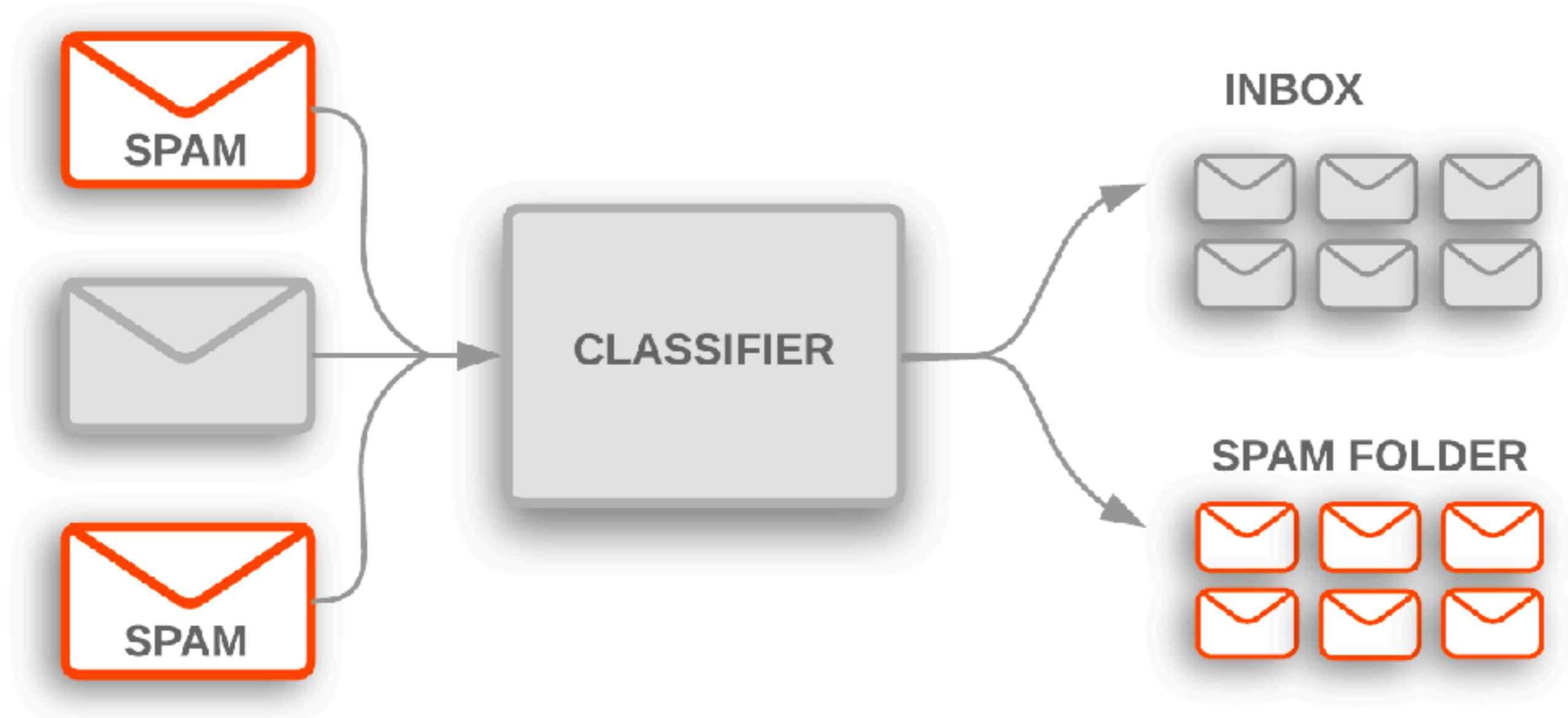
Study of algorithms that:

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

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

— Tom Michell, 1997

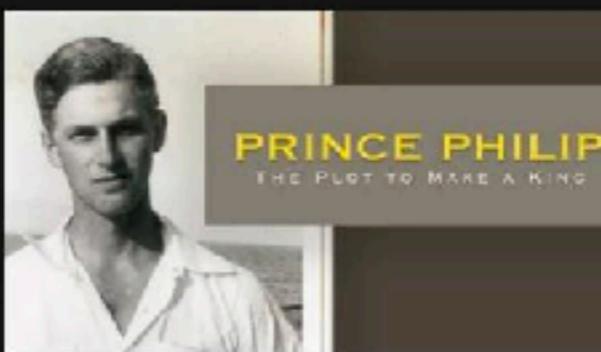
**Machine learning** is the “**best**” solution  
for tasks such as:



Because you watched **Stranger Things**

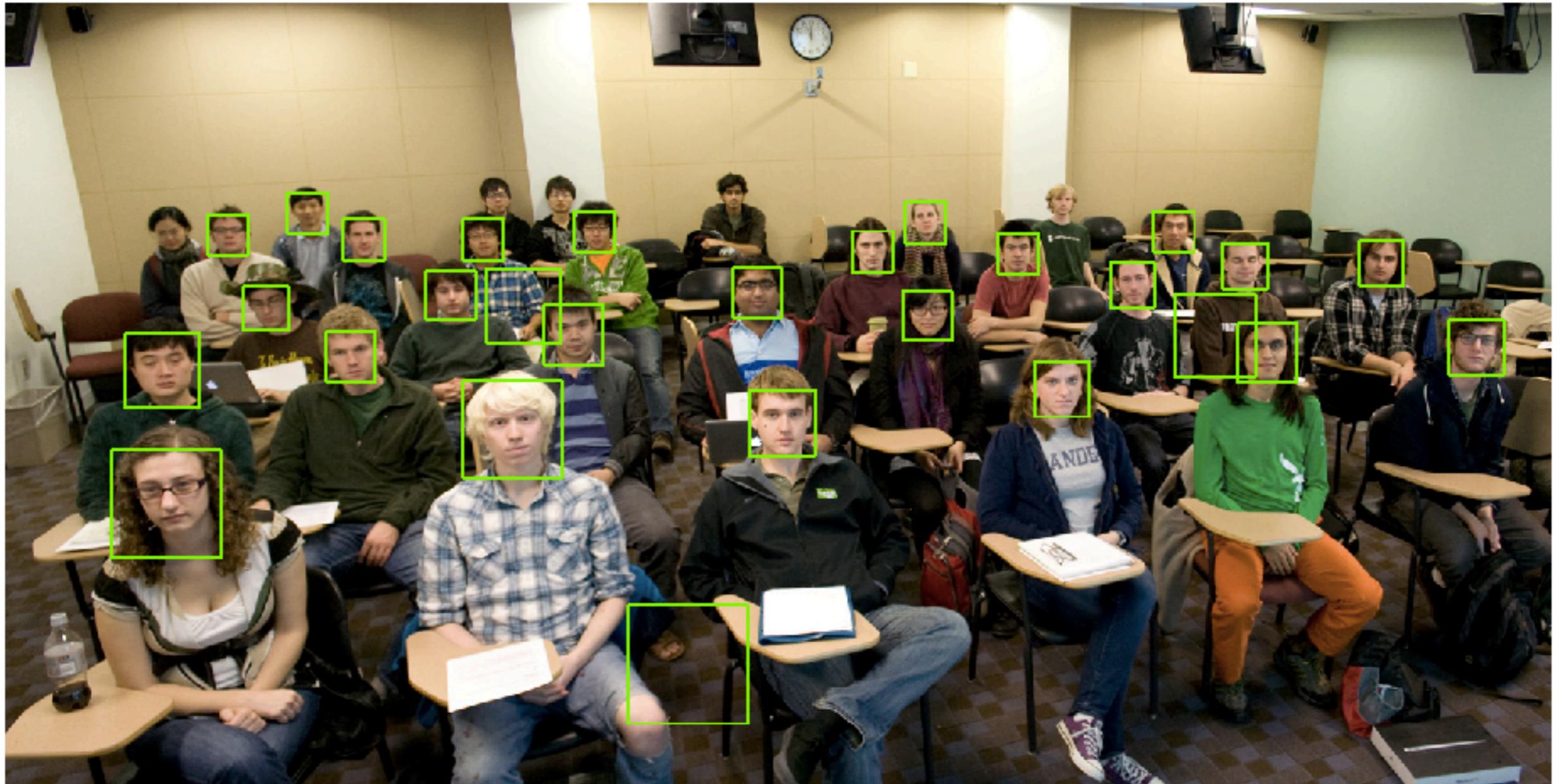


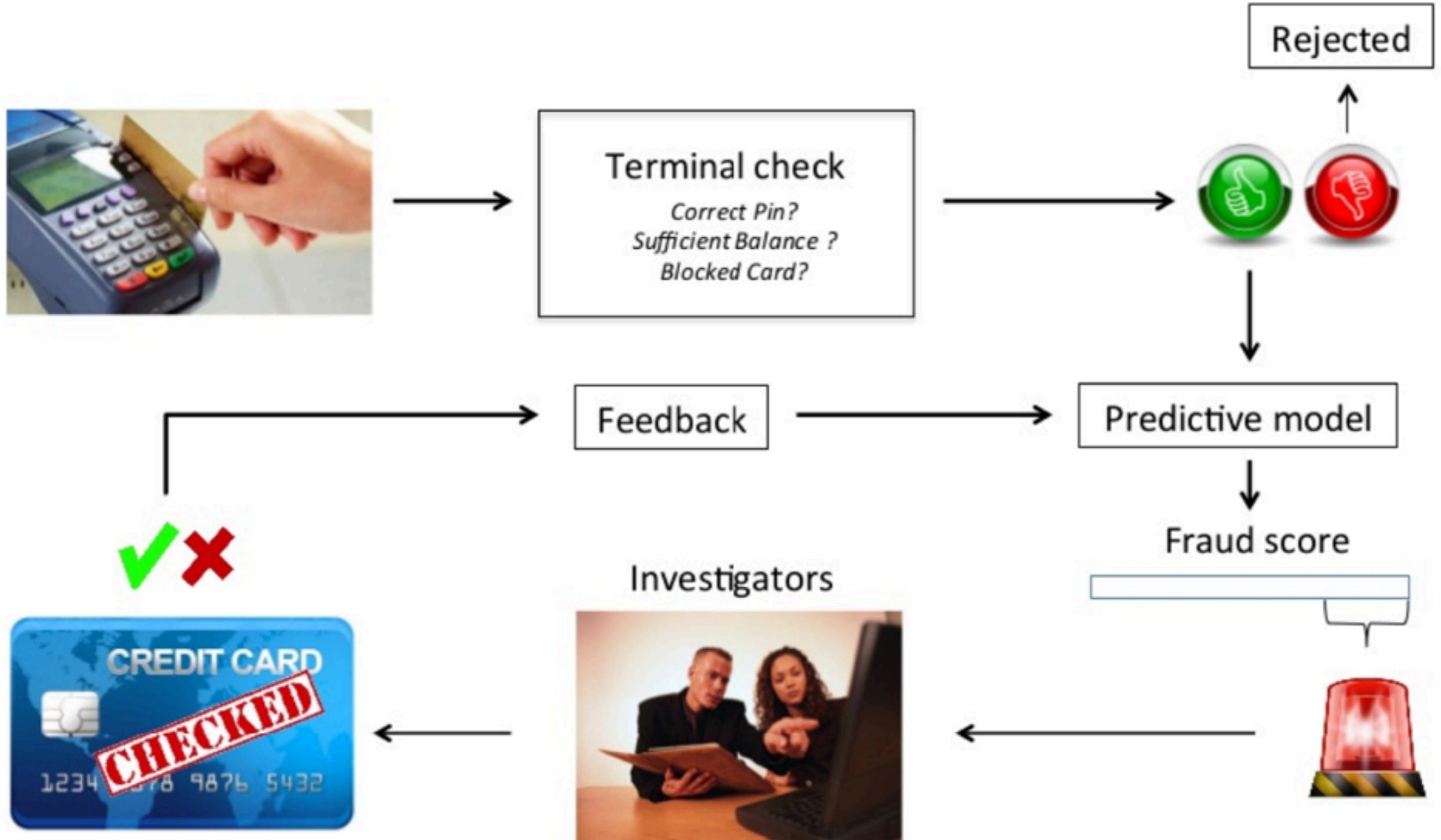
Because you watched **The Crown**



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







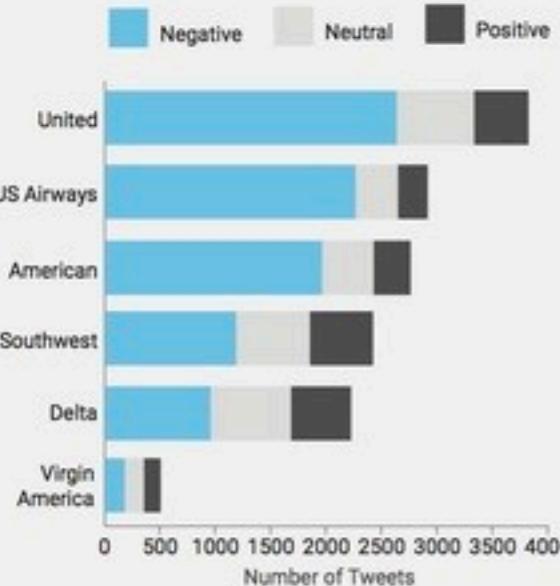


# U.S. Airline Twitter Sentiment

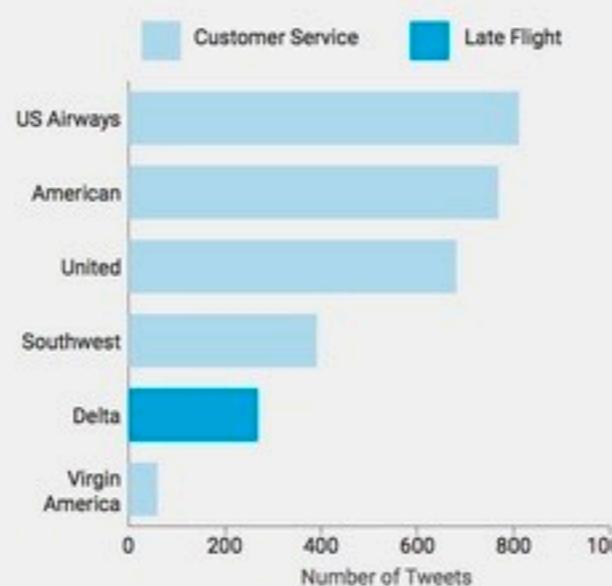
Analysis of traveler's Tweets from a week in February 2015

Cathy Liewen, Heidi Slojewski  
HCI 512 | Winter 2016

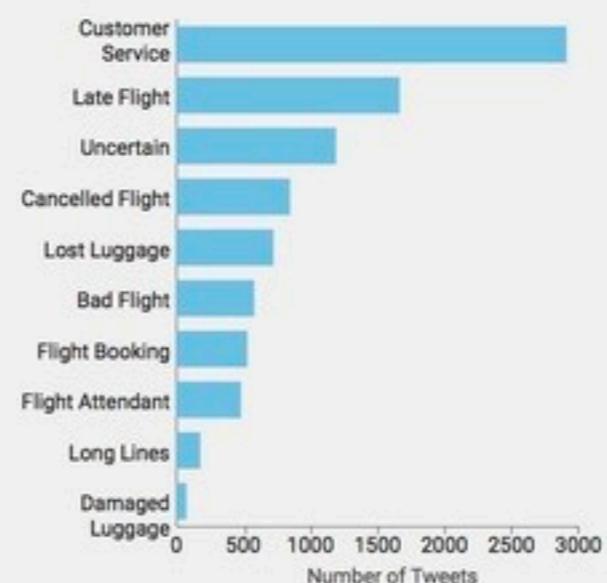
Sentiment by Airline



Airlines' Top Reasons for Negative Sentiment



Most Common Reasons for Negative Sentiment



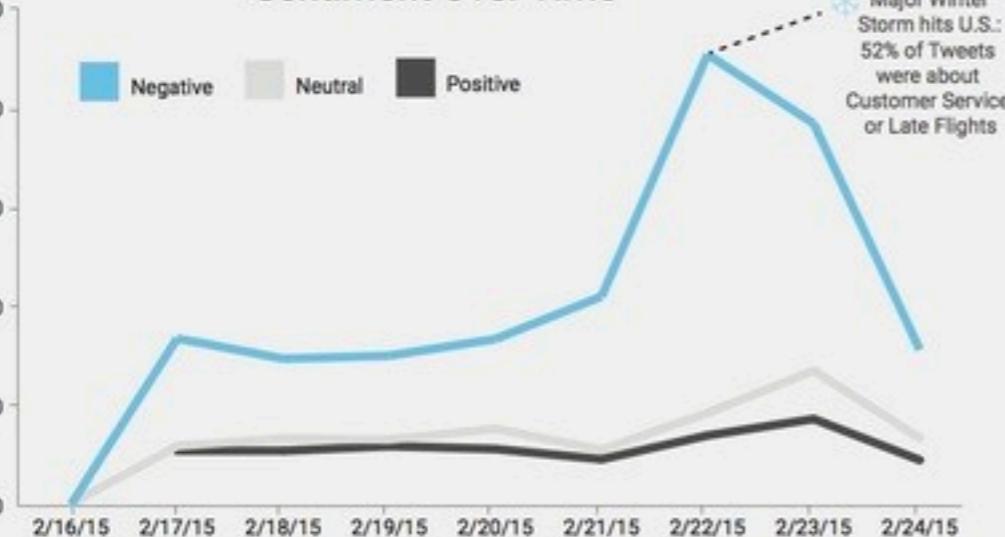
Most Retweeted Negative Sentiments

"@USAirways 5 hr flight delay and a delay when we land . Is that even real life ? Get me off this plane , I wanna go home" -OBJ\_3

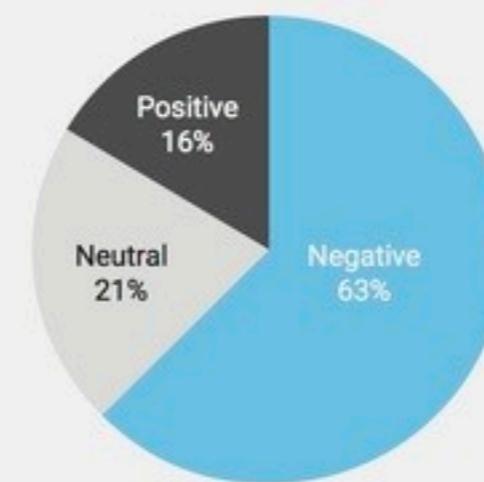
"@USAirways of course never again tho. Thanks for tweetin ur concern but not Doin anythin to fix what happened. I'll choose wiser next time" -OBJ\_3

Number of Tweets

Sentiment Over Time



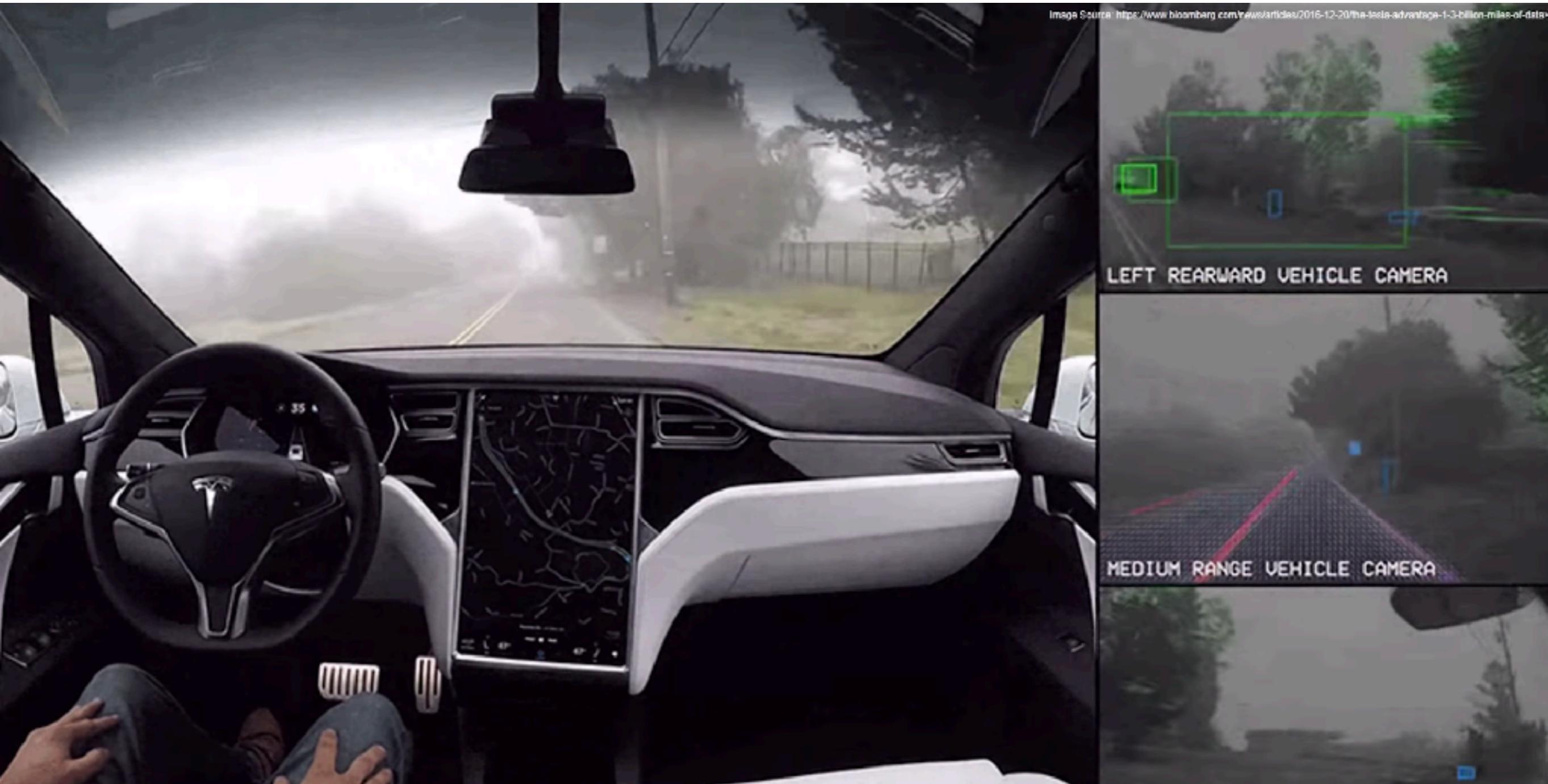
Sentiment Breakdown

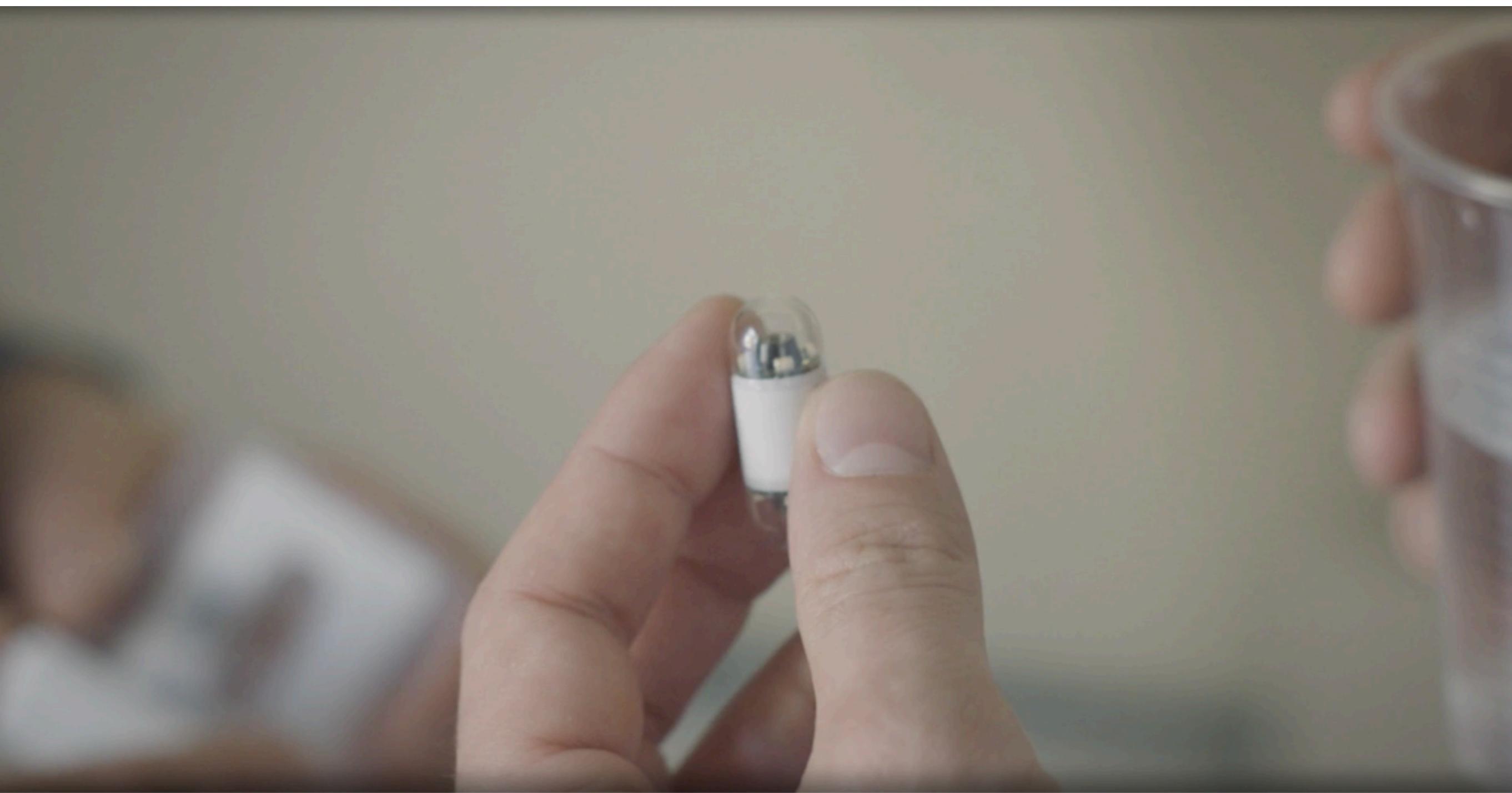


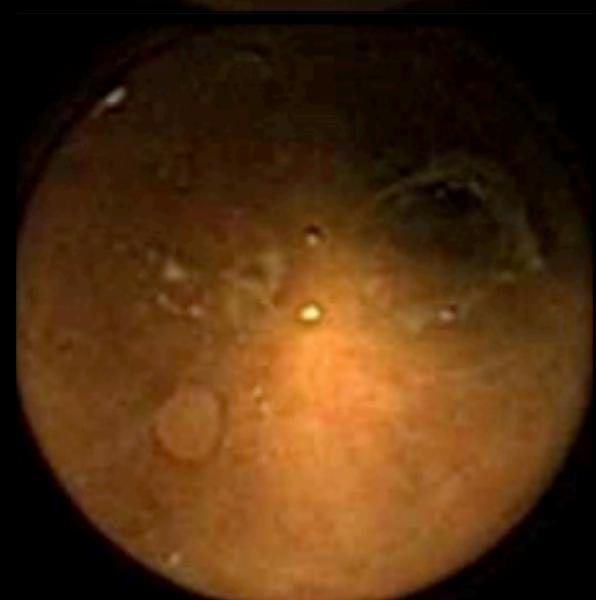
Most Common Words from Negative Tweets

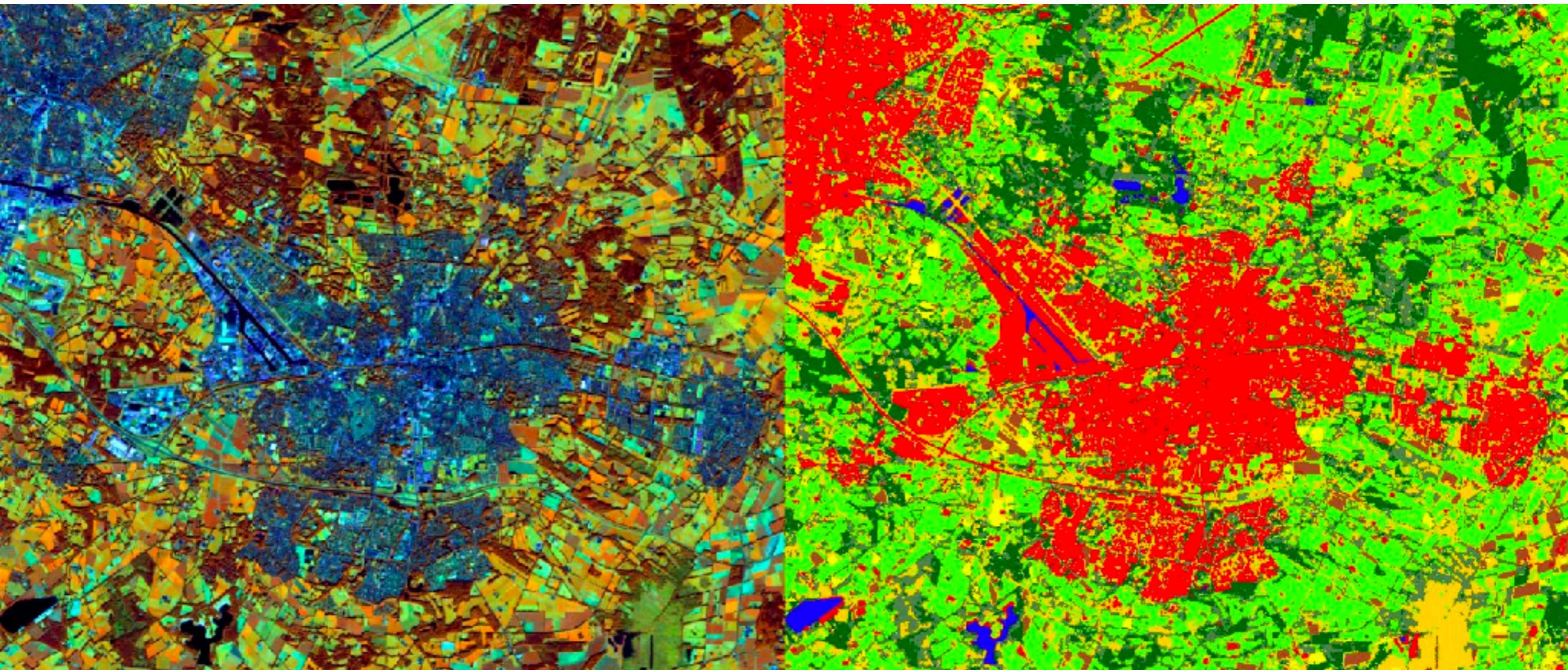
destination unacceptable guys connecting disconnected supervisor luggage info treated SUCKS boarded happens frustrated airlines changing flown voucher apology website options members inconvenience reschedule runway online automated min hope layover paying missed customers confirmation rebooked plans cancelled delayed traveling update agents wifi reservation scheduled

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

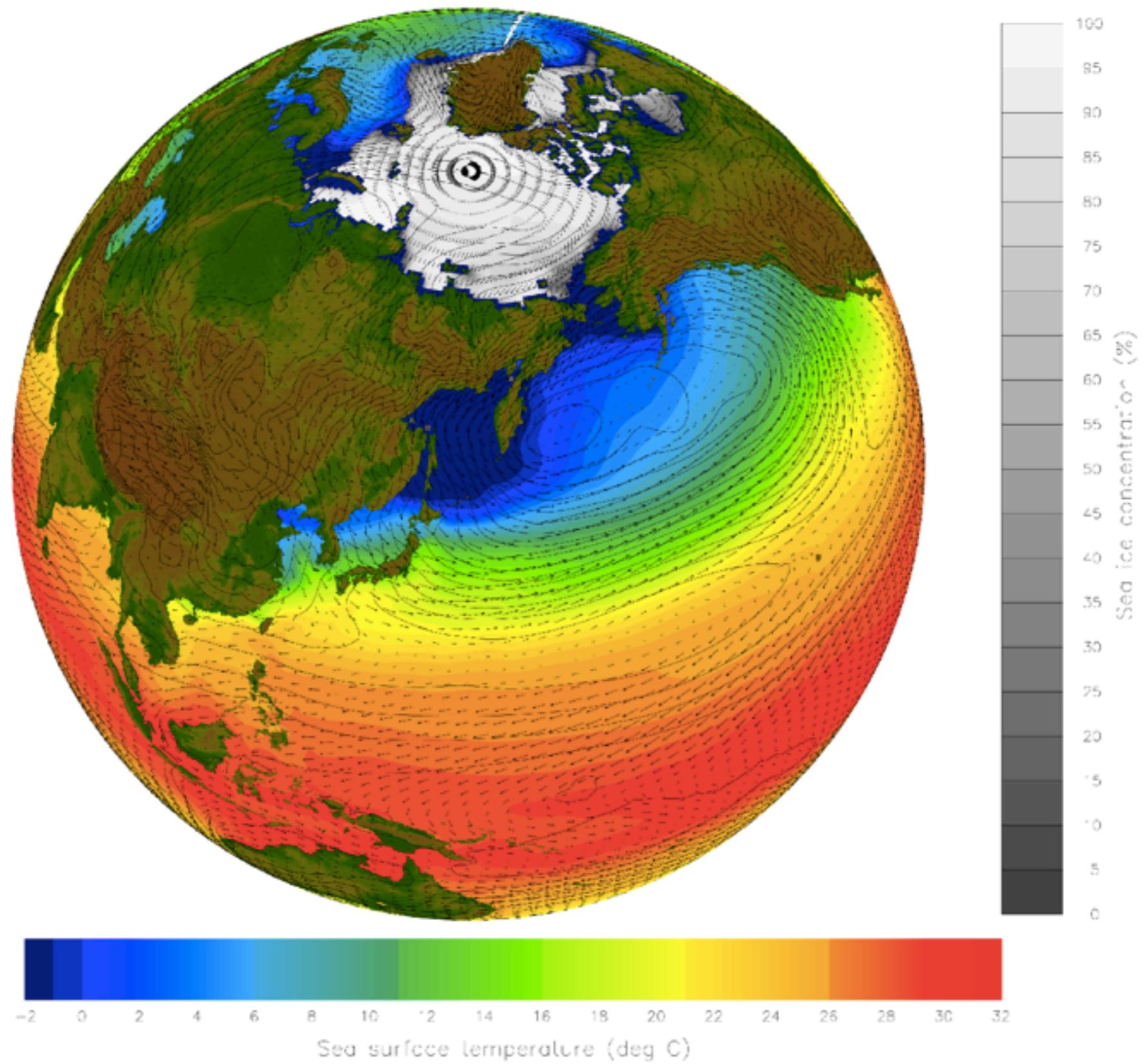






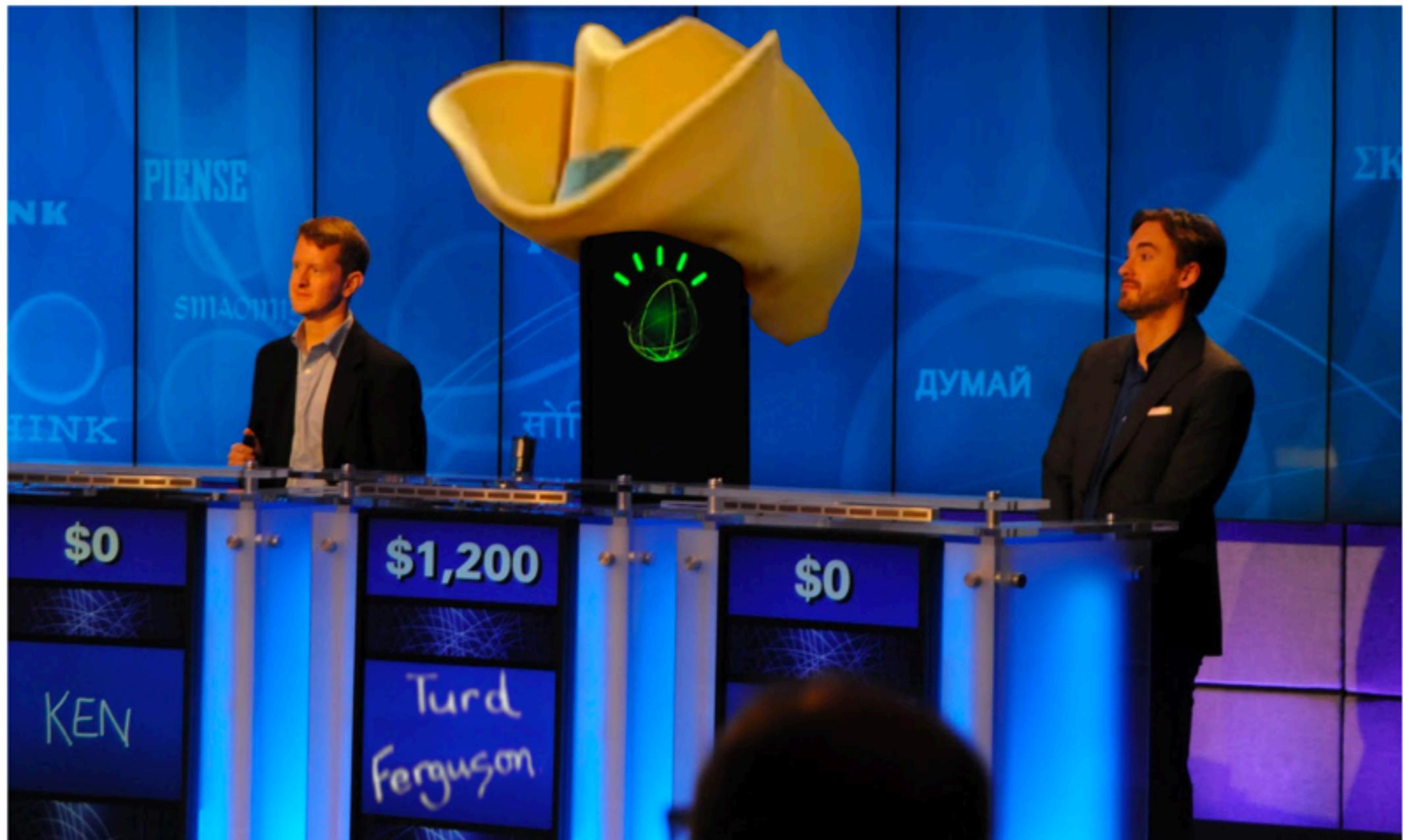


# Climate change





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



## **Machine learning is the “best” solution for tasks such as:**

- Voice Recognition
- Product recommendation
- Search engines
- Detection of fraudulent cards
- Biometric identification
- Character recognition
- Face recognition
- Medical diagnosis of some pathologies
- ...

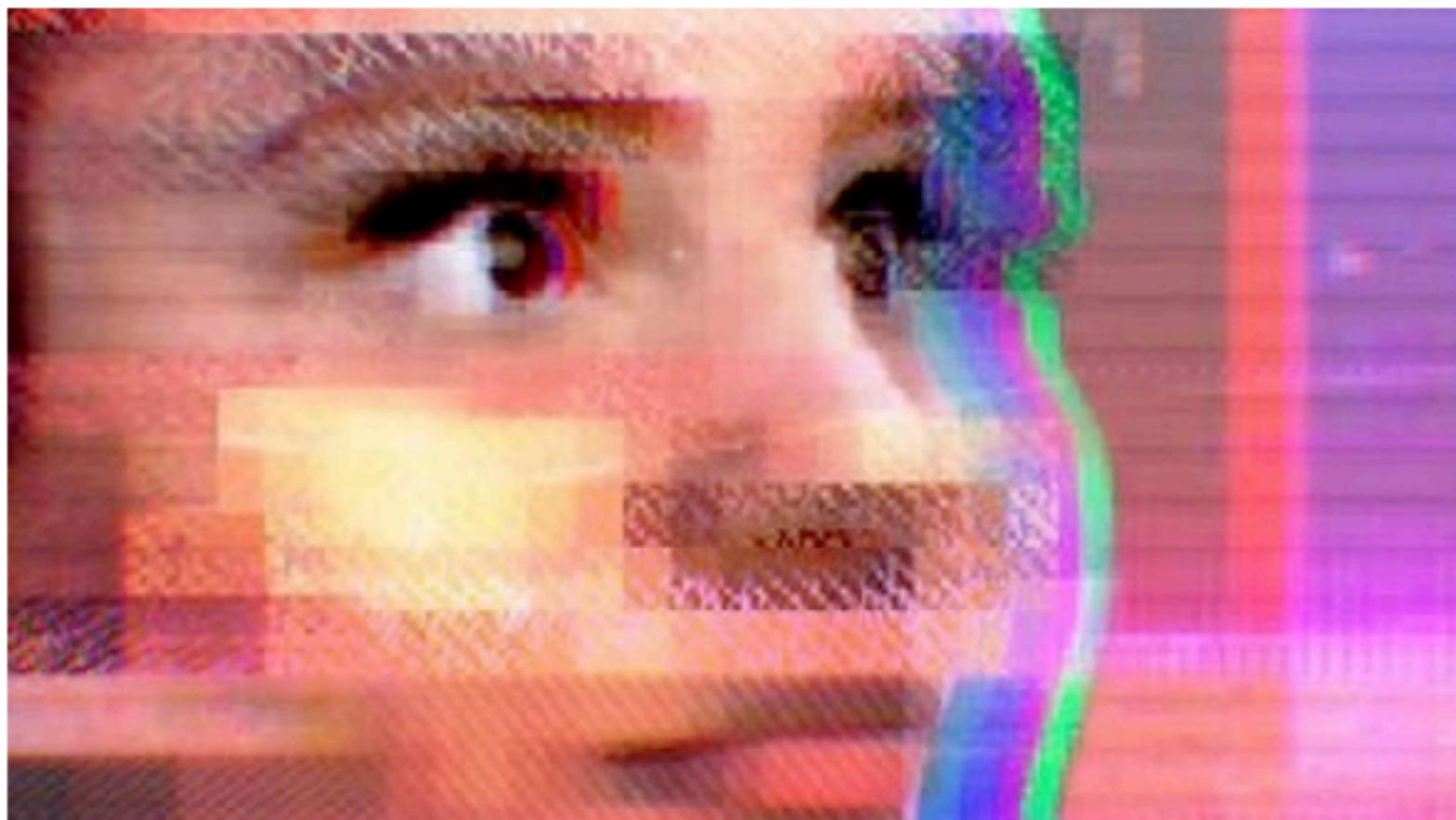
# Una inteligencia artificial se vuelve racista, antisemita y homófoba en menos de un día en Twitter



Compartido 3

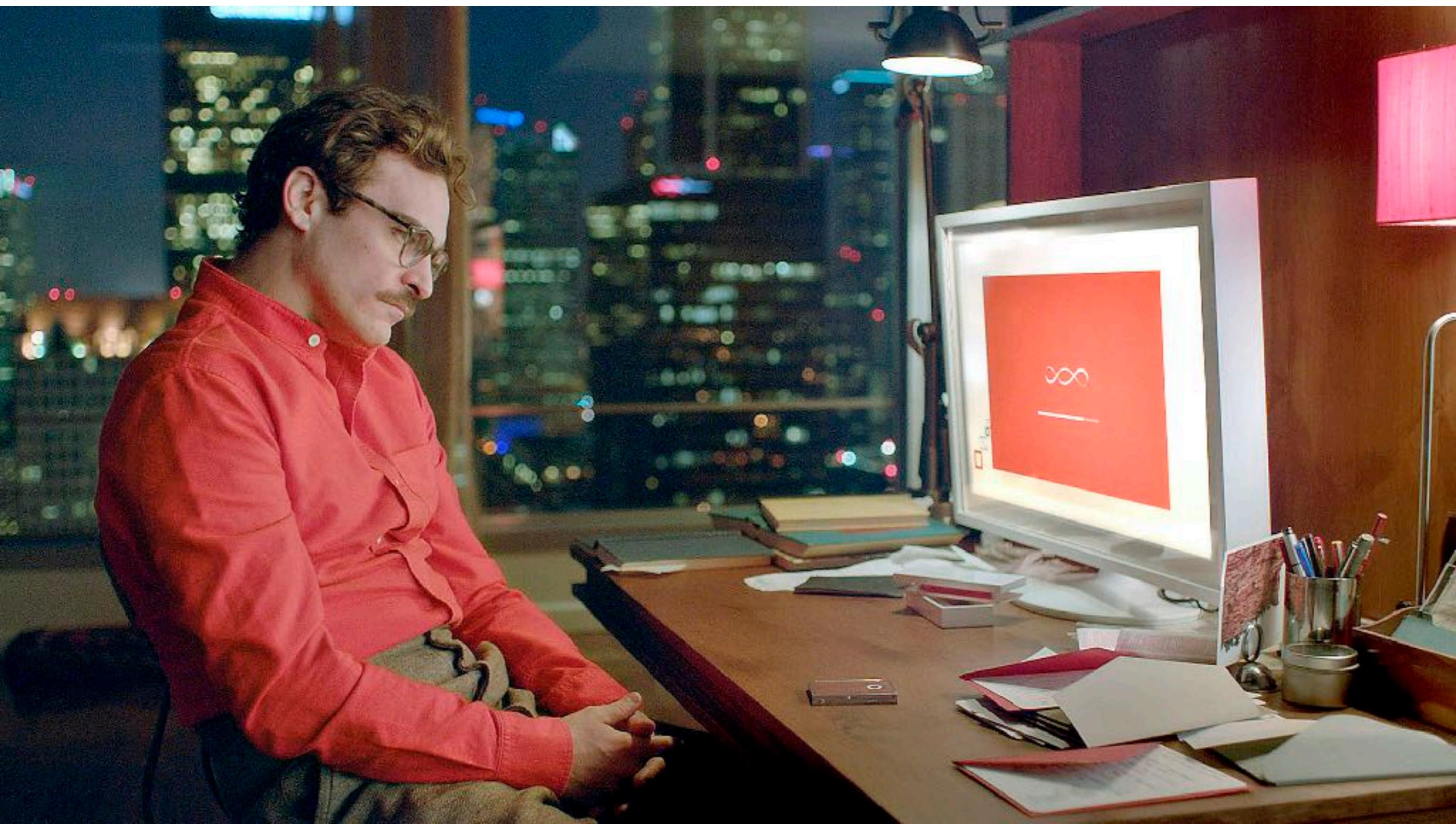


Comentar noticia



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

# Science Fiction or Future?

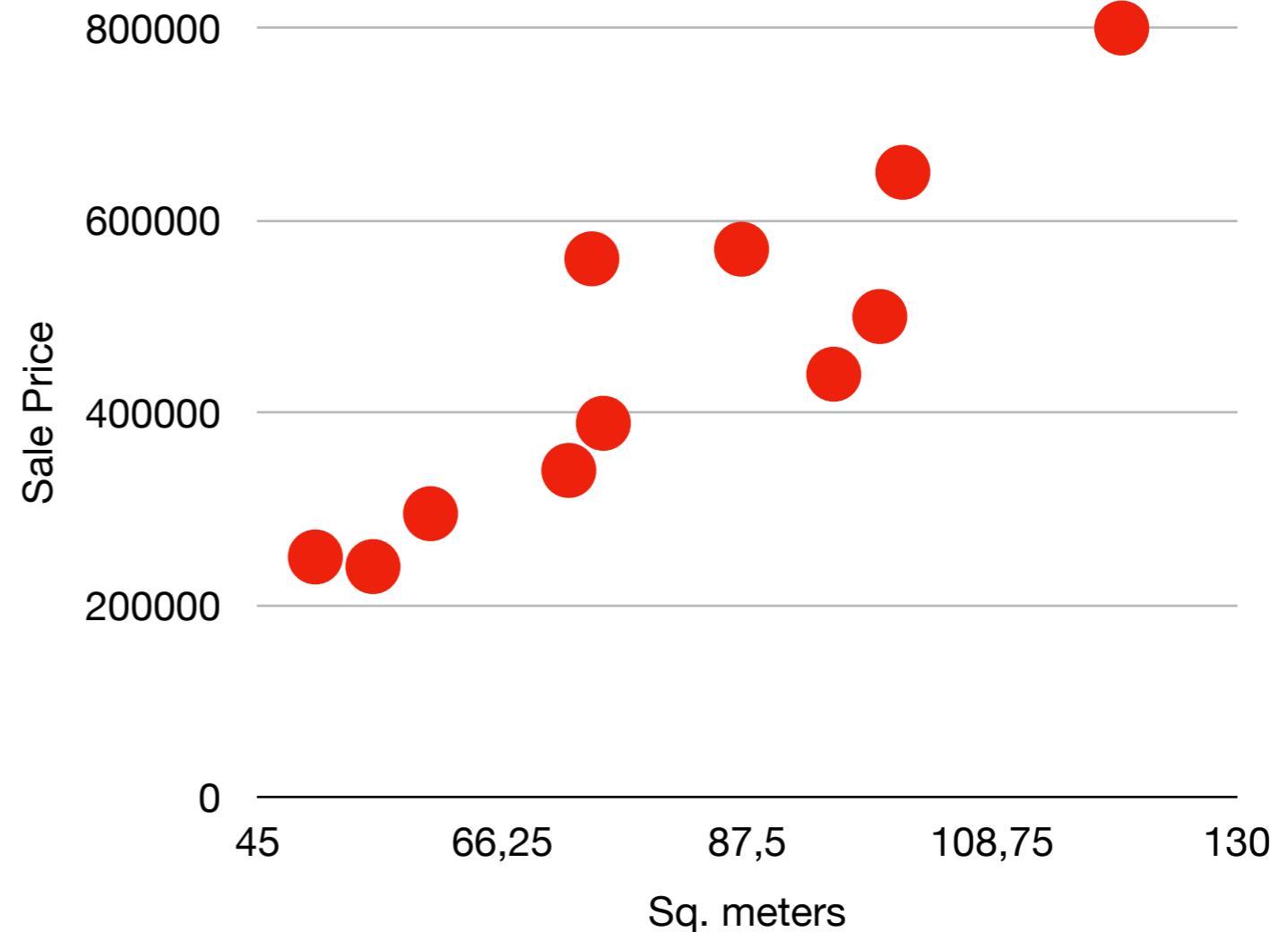


$$\hat{Y} = bX + a$$

# 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

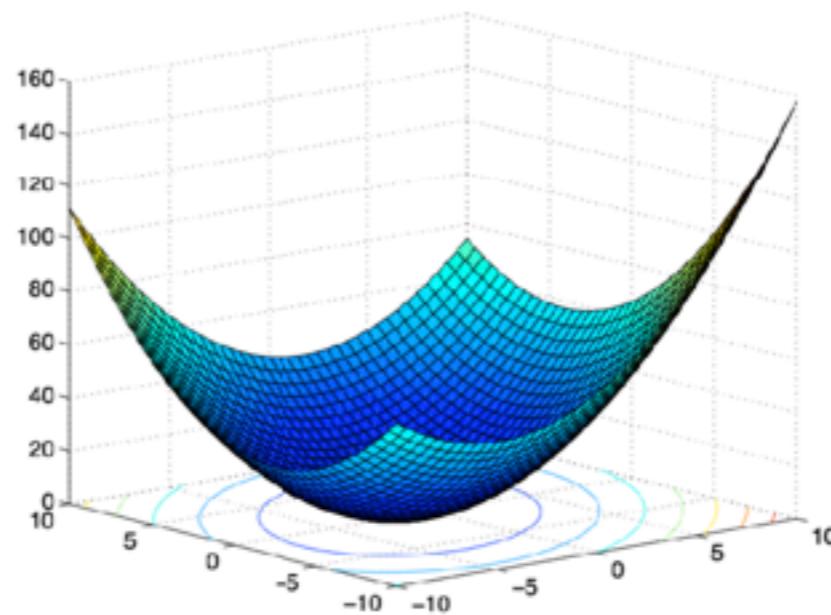


# Example of Machine Learning

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

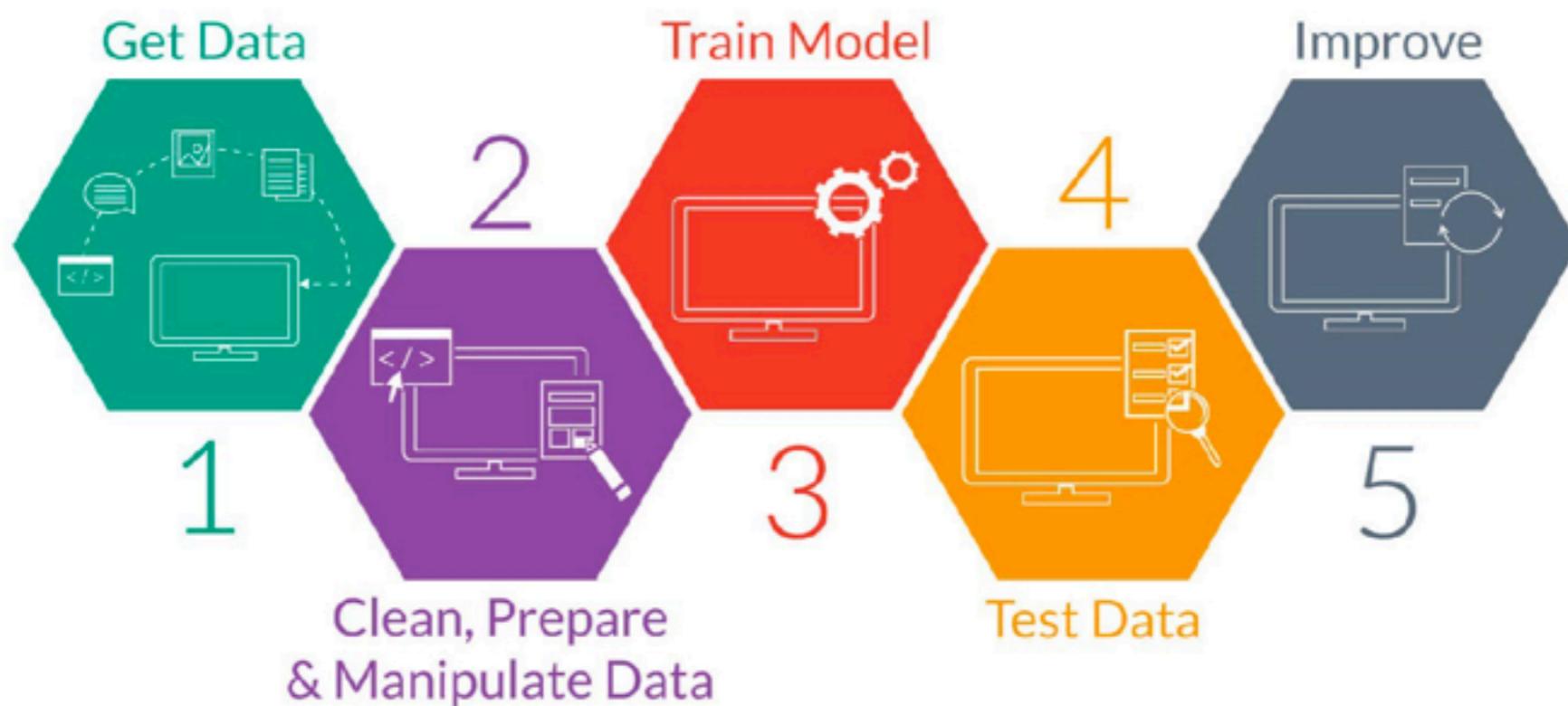
**Supervised  
Learning**

Classification  
Regression

**Reinforcement  
Learning**

Learn from mistakes

## The core steps of typical machine learning workflow



BIG DATA

Dirty Data

Fat Data

Data  
Science

Data Mining

Clustering

Artificial Intelligence

Machine Learning

Reinforcement Learning

Deep Learning

# Machine Learning vs Artificial Intelligence



# Machine Learning vs Artificial Intelligence

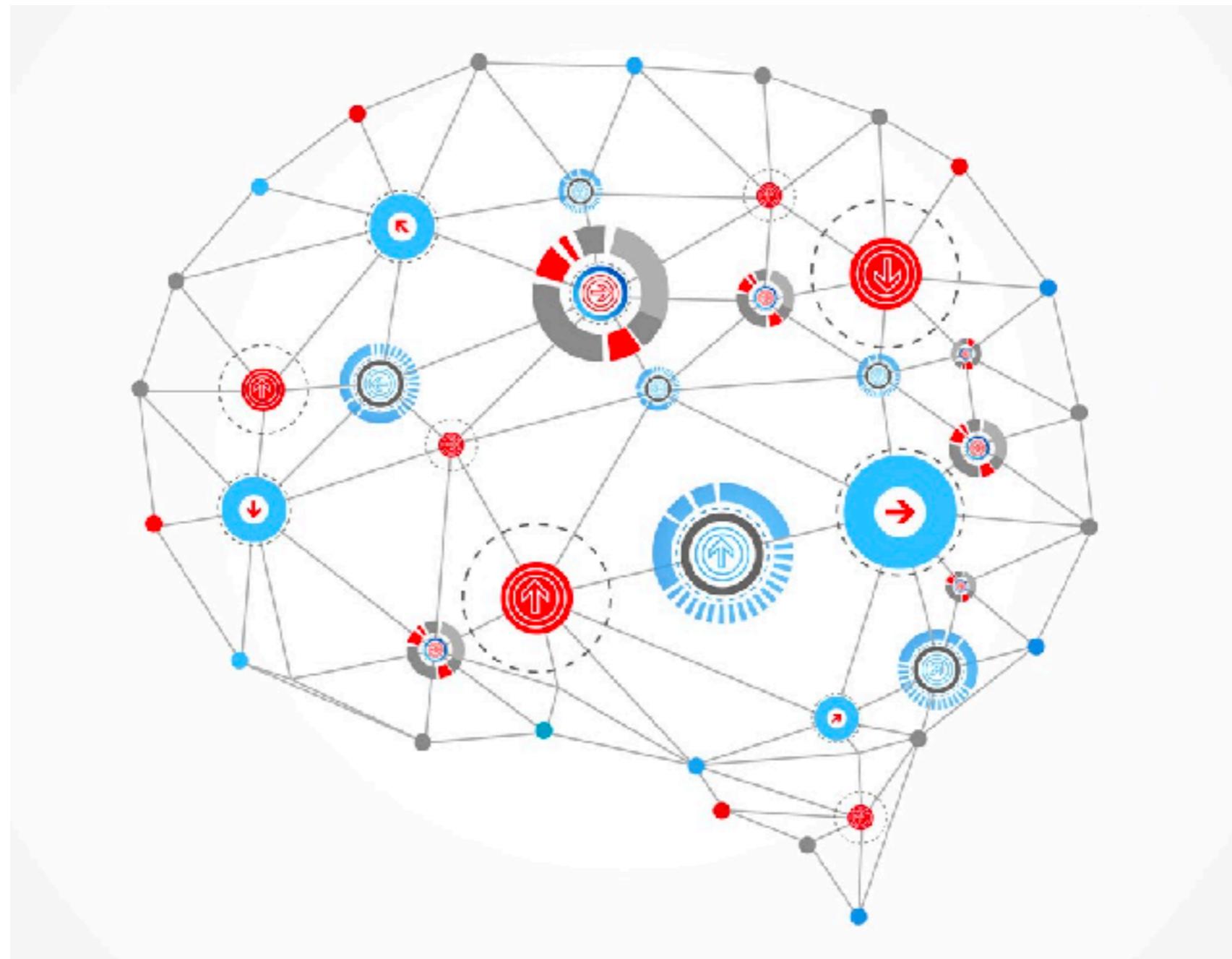
**Artificial Intelligence** is an academic discipline devoted to the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, language recognition, decision-making, planning, reasoning, etc.

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).

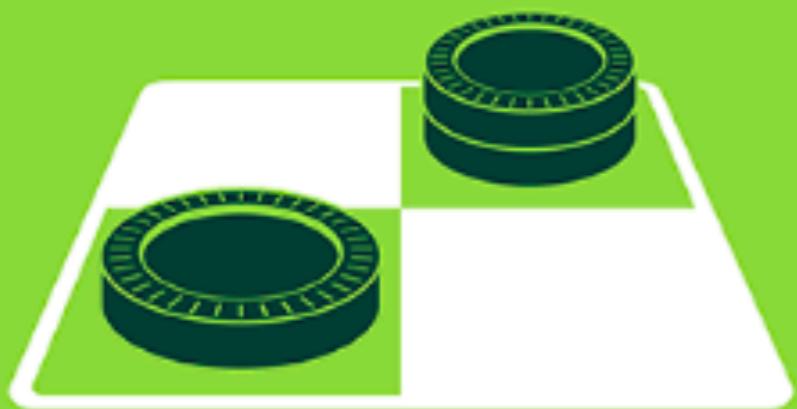
**“Machine learning** is a subset of  
**artificial intelligence**  
that uses algorithms to **learn from data**  
and enables machines to improve with  
**experience”**

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



# ARTIFICIAL INTELLIGENCE

Early artificial intelligence stirs excitement.



## MACHINE LEARNING

Machine learning begins to flourish.



## DEEP LEARNING

Deep learning breakthroughs drive AI boom.



1950's

1960's

1970's

1980's

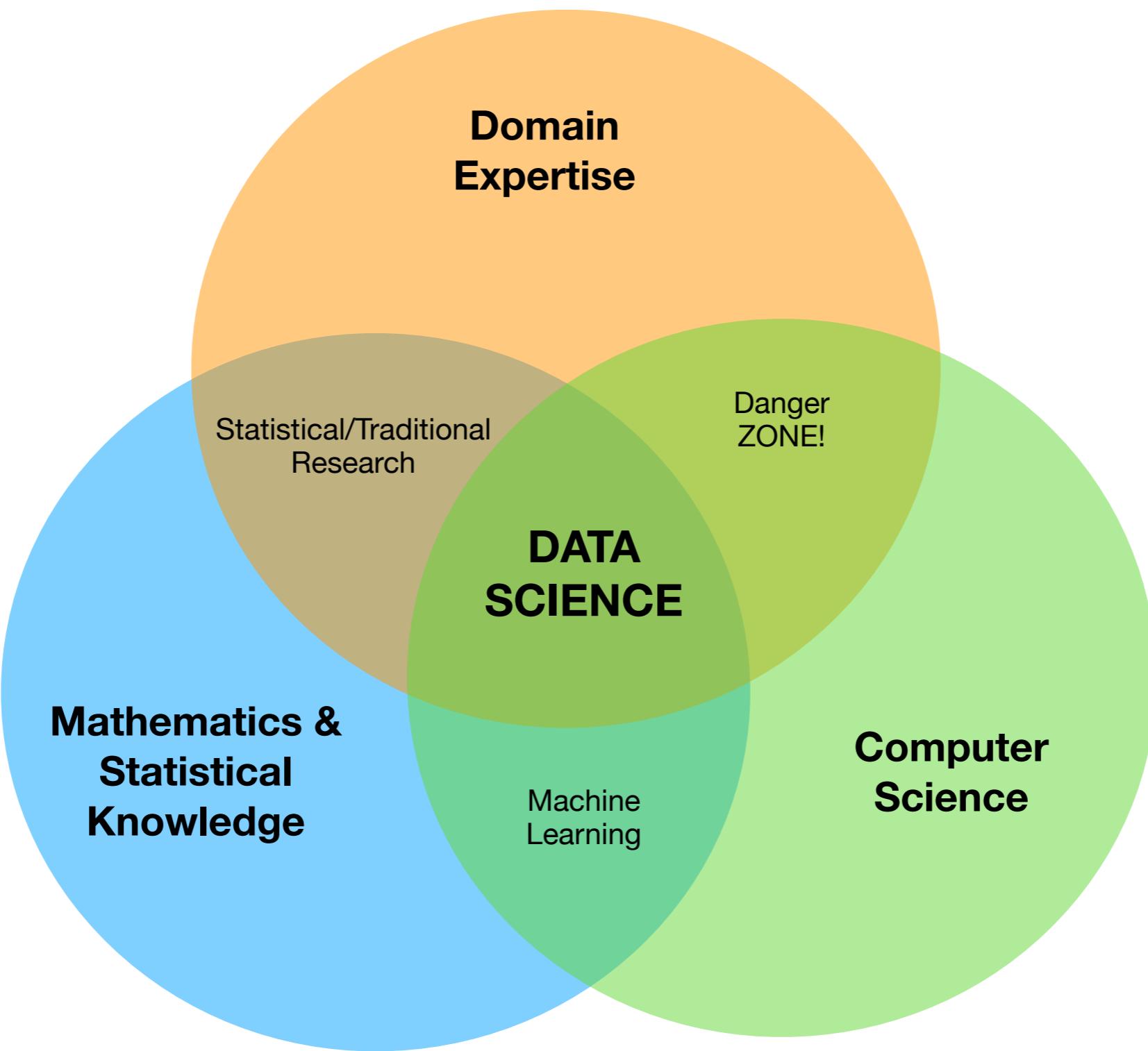
1990's

2000's

2010's

# 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**

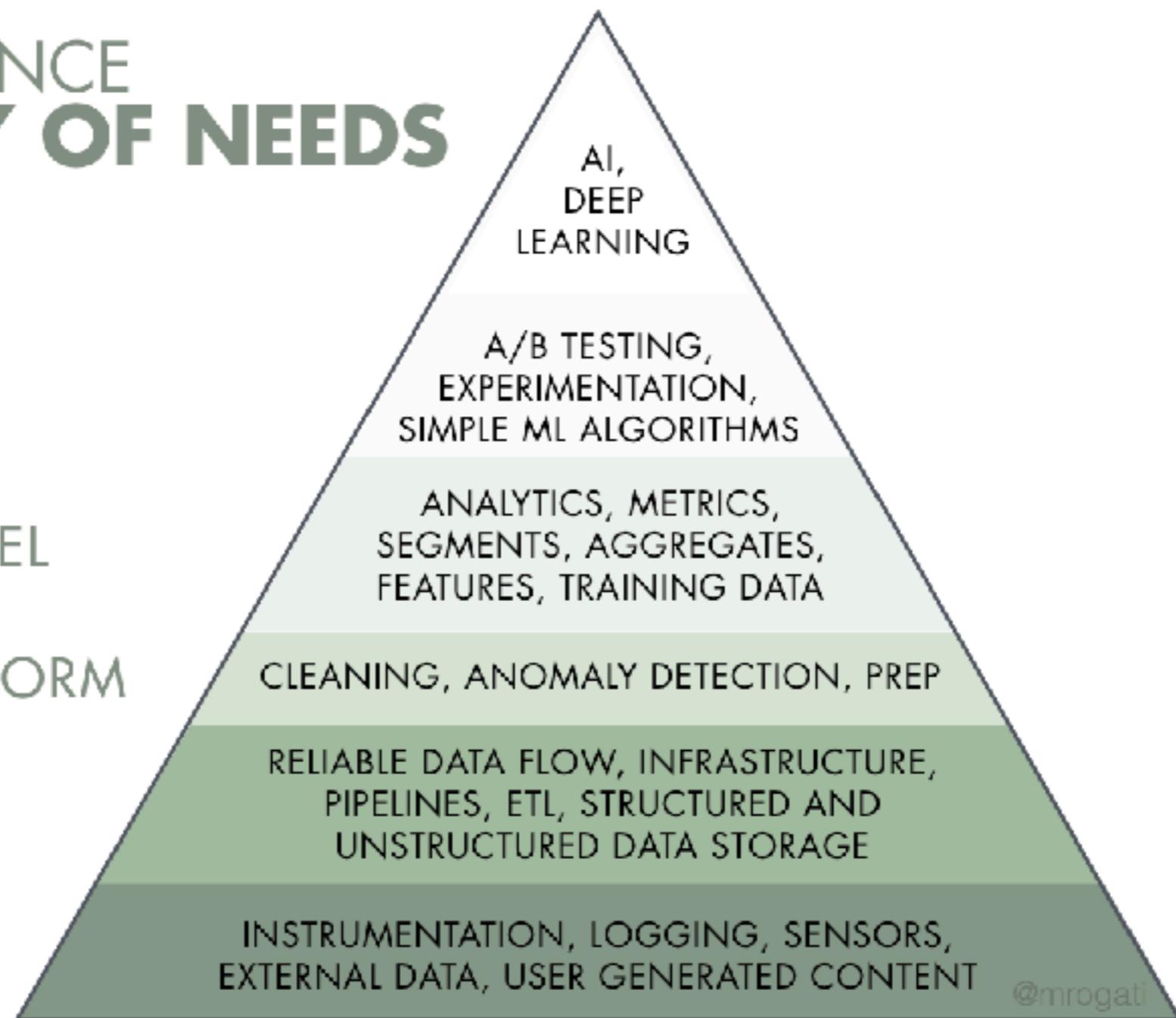
LEARN/OPTIMIZE

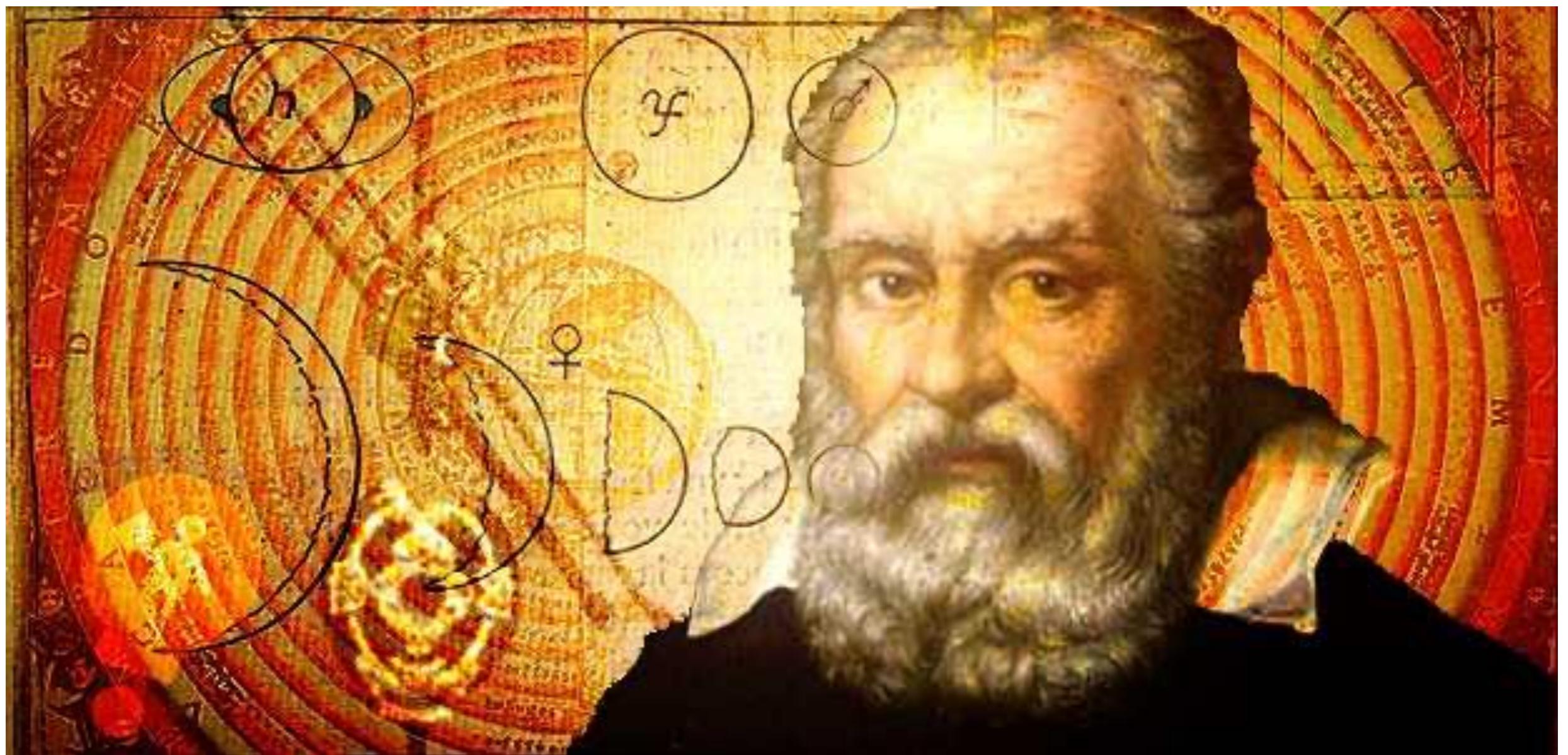
AGGREGATE/LABEL

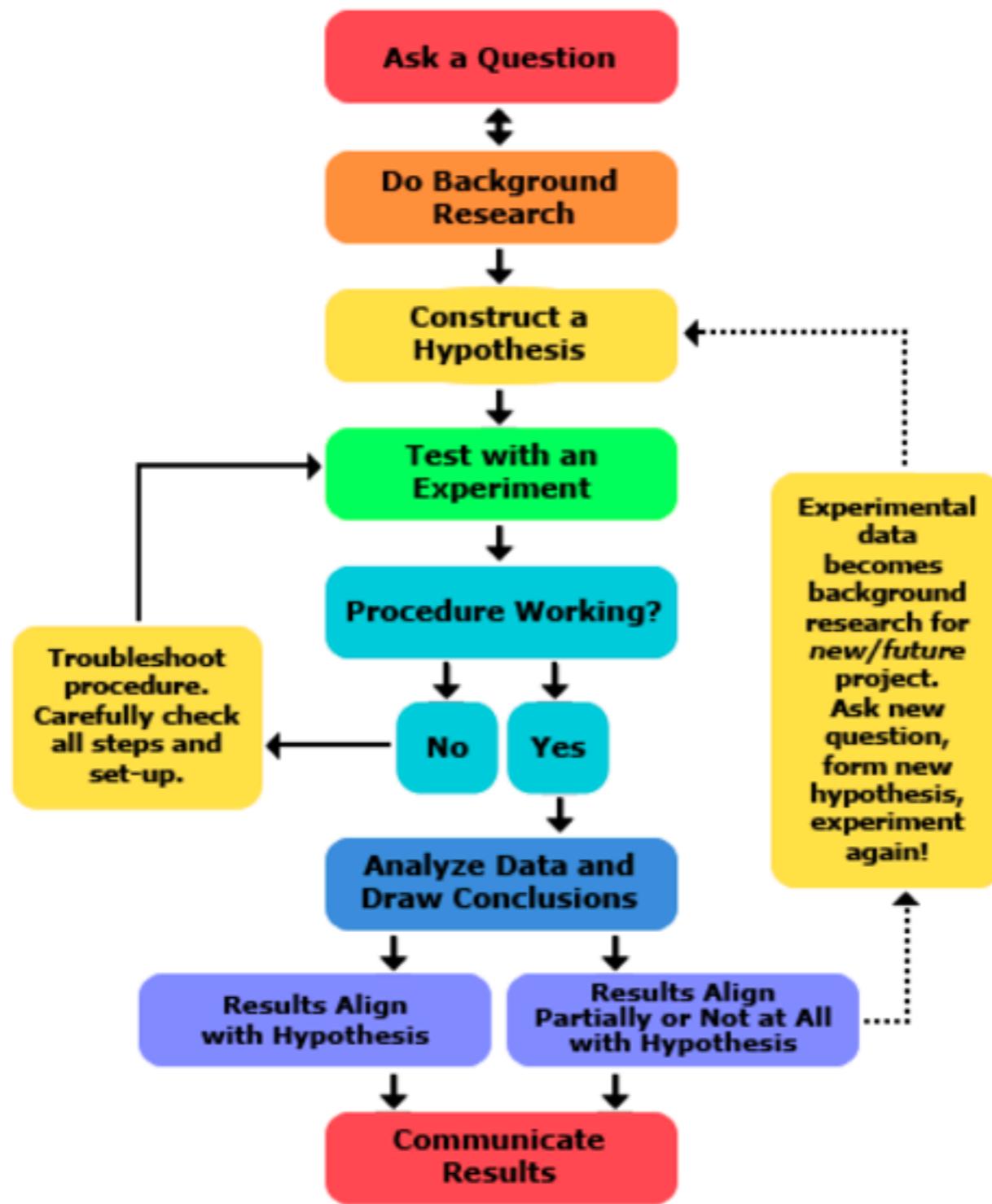
EXPLORE/TRANSFORM

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

Nonrepresentative Training Data

Poor-Quality Data

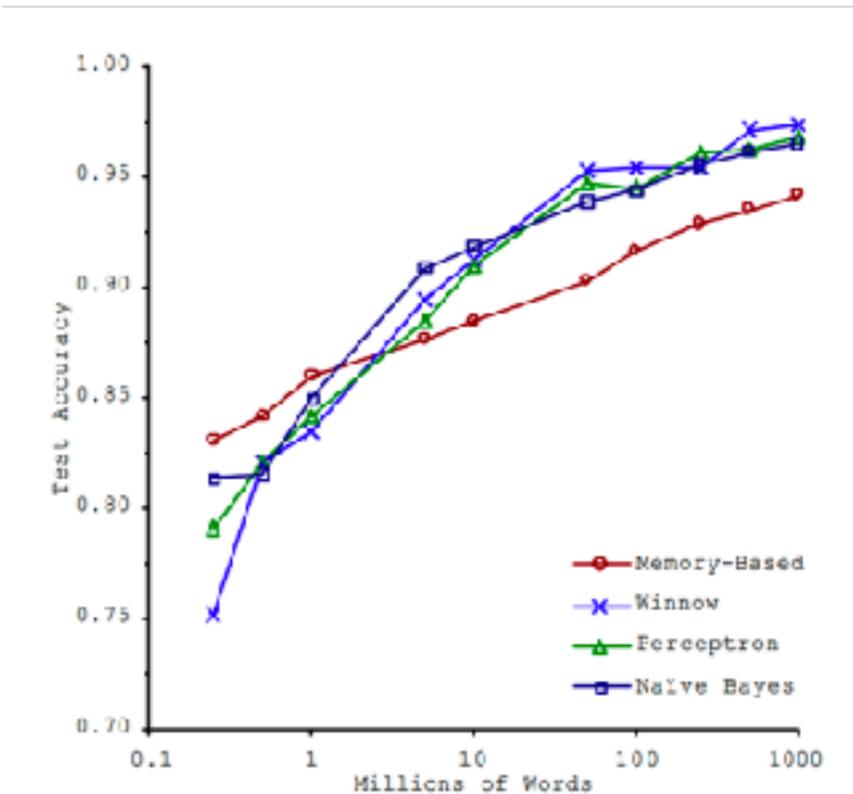
Irrelevant Features

Overfitting the Training Data

Underfitting the Training Data

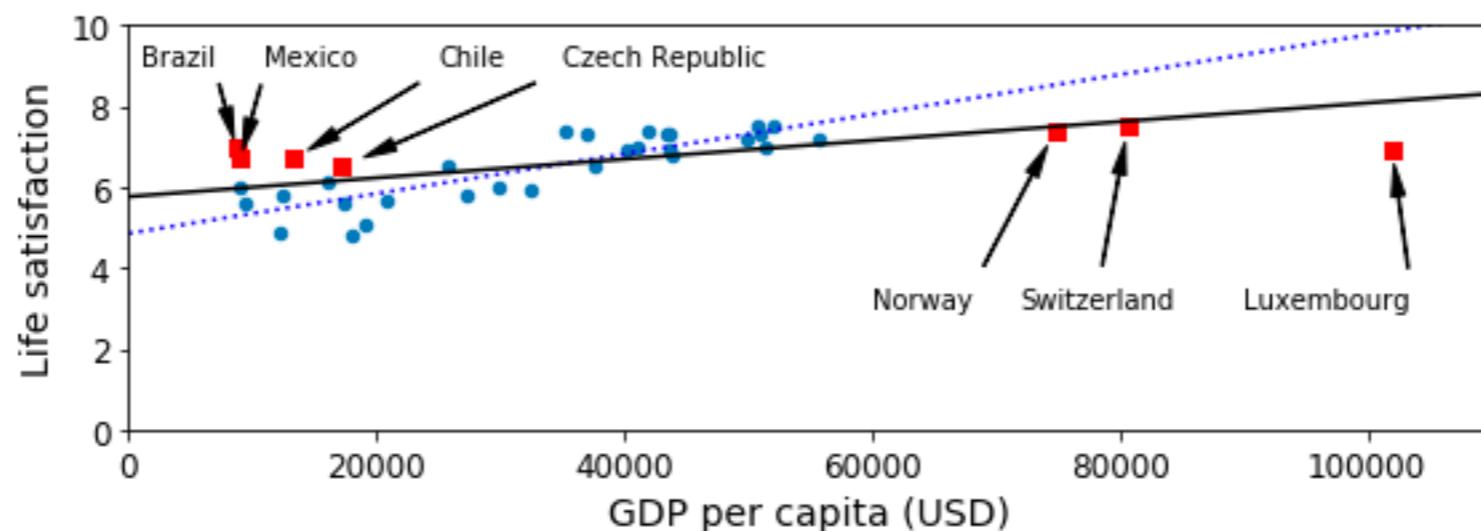
# Insufficient Quantity of Data

- The importance of data versus algorithms
- What is best? more data or a better model?
  - Several studies shows that very different algorithms, including fairly simples ones, 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



# Nonrepresentative 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**

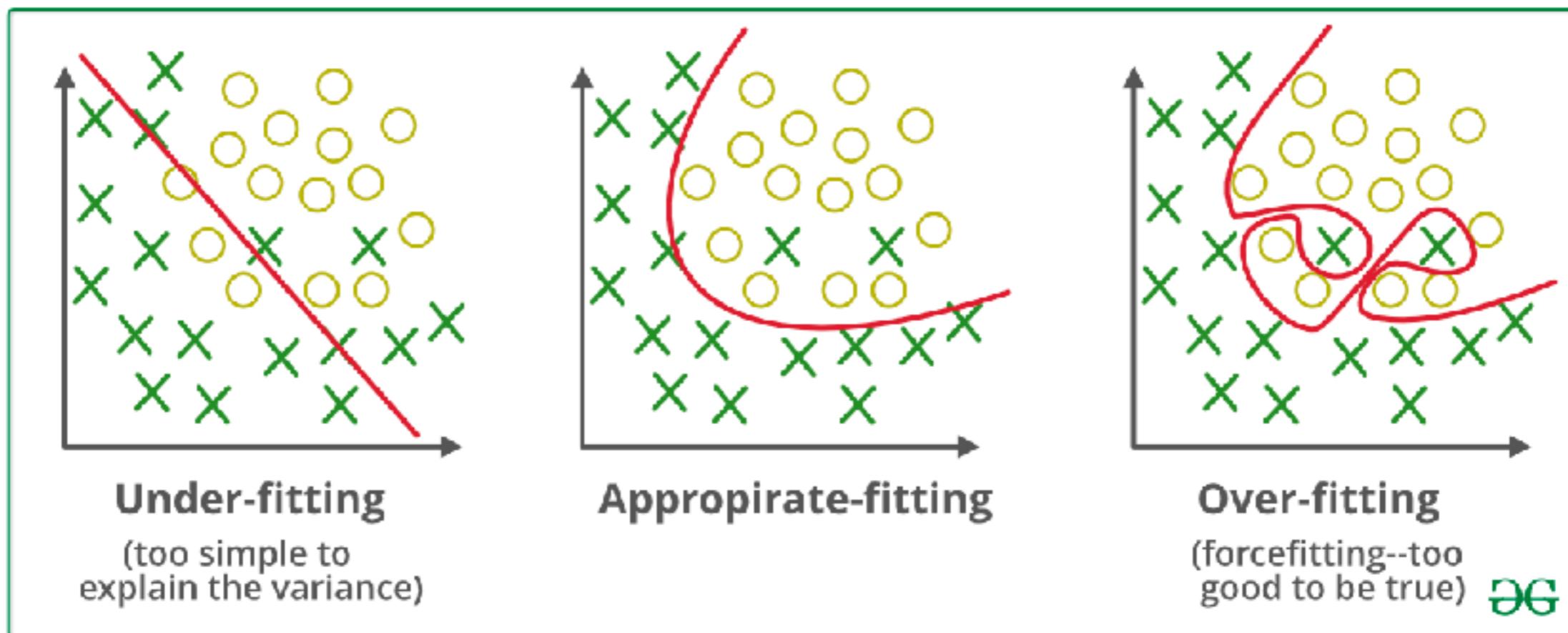
# Poor-Quality of data

- 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



## **Next Session**

<https://github.com/ssegui/ml-ub/tree/master/notebooks/Session1.ipynb>

### **First Project:**

<https://www.kaggle.com/t/afe495cd9e90462baa84b5ce320791dd>

### **Score:**

1 point + 0.25 for the winner

