

Data Science

for the automotive industry





Algeciras

2011
Aerospace
Engineering

Internship
Image Processing

Internship
Mechanical
testing

2013
M. Sc. in
Electronics, signal
Treatment and
Communications

R&D Engineer in
Material and
Processes

Reverse Engineering
Consultant

2018
PhD in Structural
Health Monitoring

2018
Telemetry systems
specialist

Data Scientist



What about you?

Name , Google e-mail and brief description of background.

Groups creation

Course roadmap

1) Data Science (1d)

What

Who

Why

When

How

2) Practical sessions with Python (3d)

Machine Learning

Deep Learning

Reinforcement Learning

3) Hackaton Python (1d)

1st day -> Creation of groups

3rd day -> Unveiling the topic

4th-5th -> Hackaton

Data Science

**Pre-
definitions**

What

Who

Why

When

How

**Pre-
definitions**

Data Science

What

Who

Why

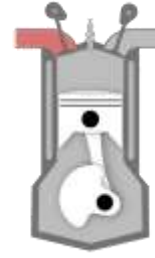
When

How

Low vs High level

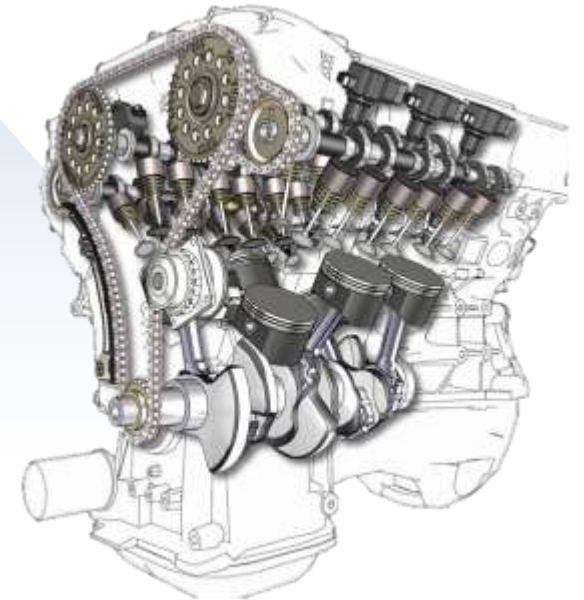
High Level

*Petrol
Engine*

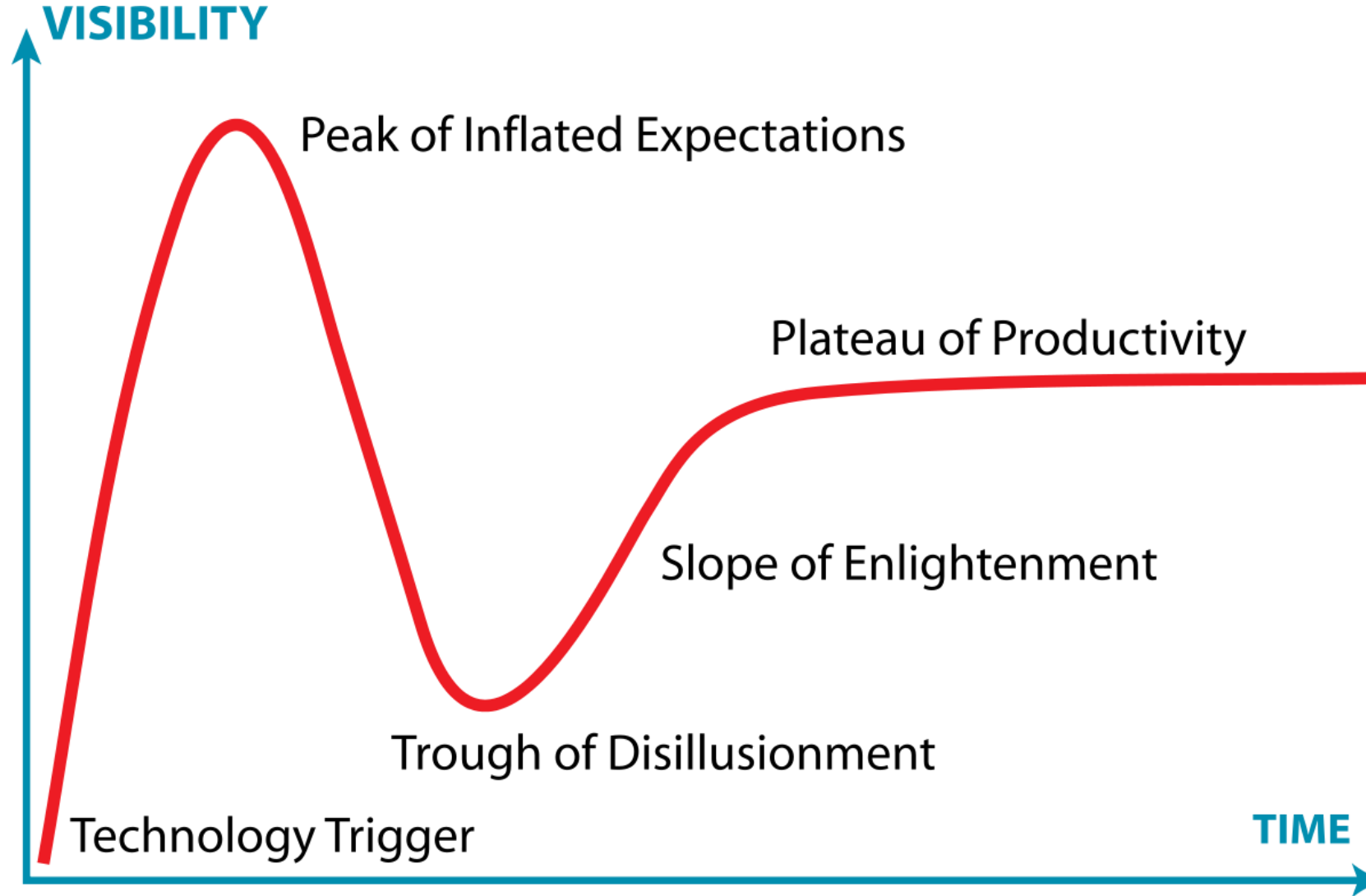


1. Intake
2. Compression
3. Power
4. Exhaust

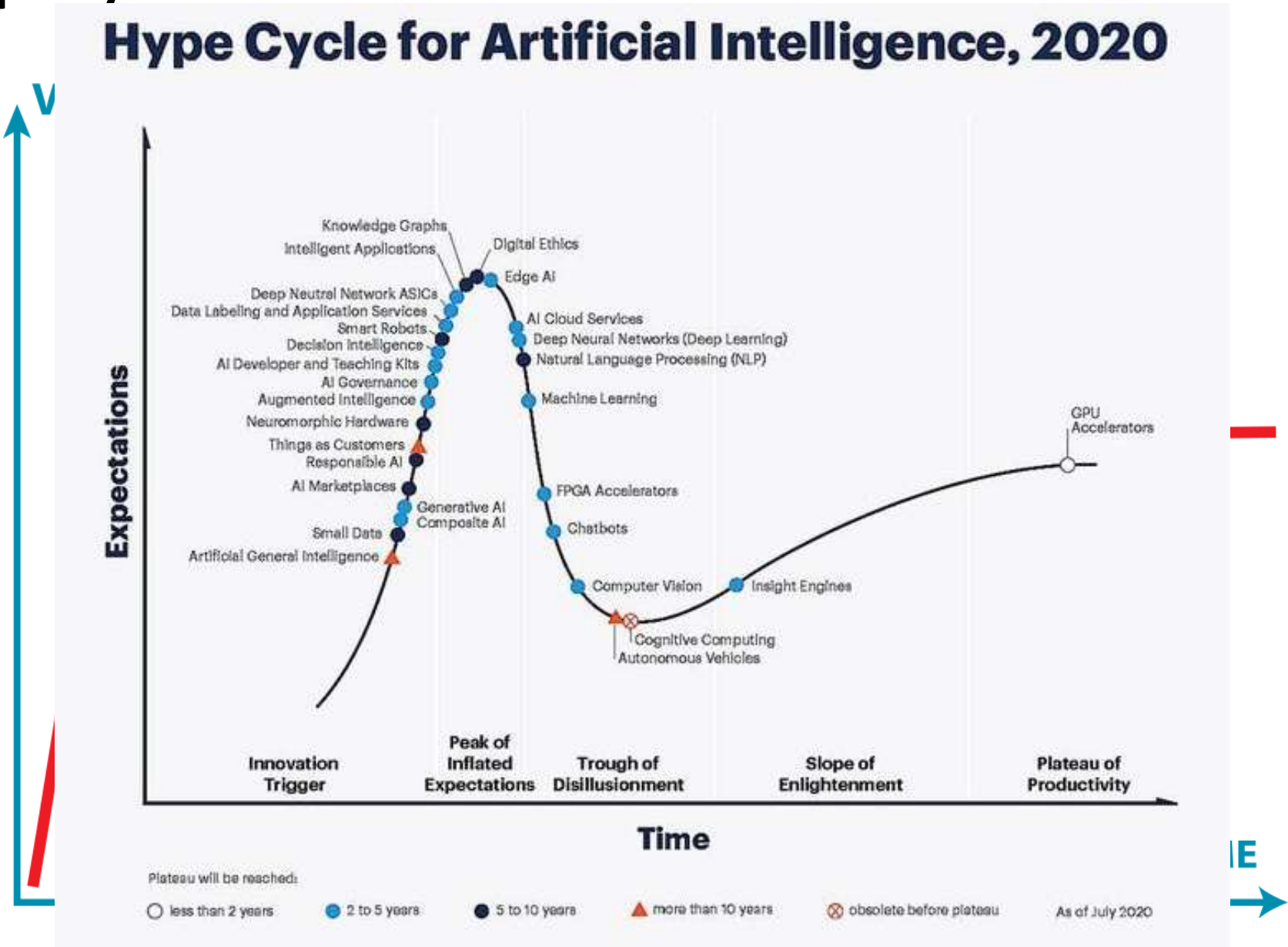
Low Level



Gartner Hype Cycle

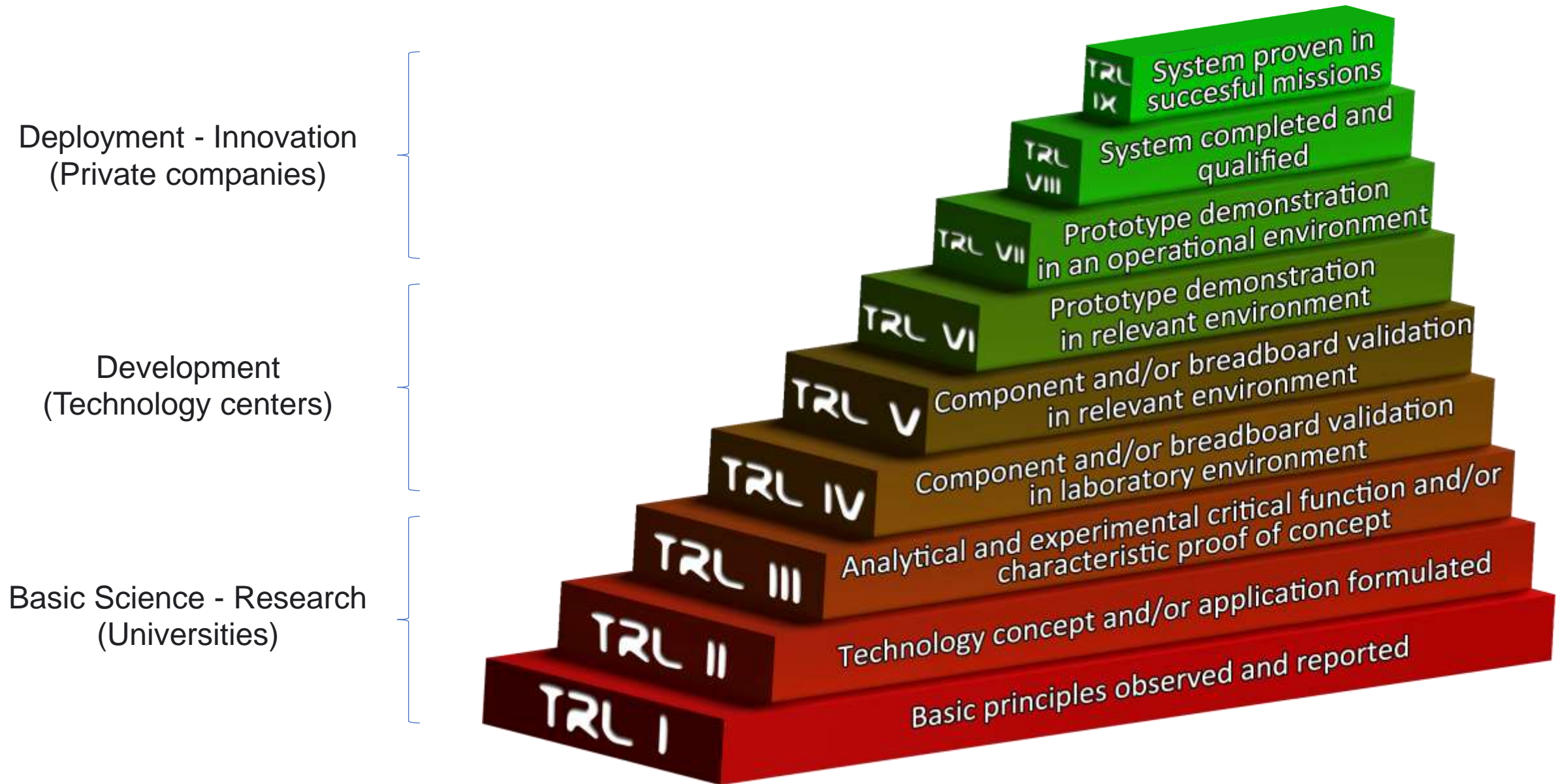


Gartner Hype Cycle



* <https://www.forbes.com/sites/louiscolumnbus/2020/10/04/whats-new-in-gartners-hype-cycle-for-ai-2020/>

Technology Readiness Level



Technology Readiness Level

Deployment - Innovation
(Private companies)

Development
(Technology centers)

Basic Science - Research
(Universities)

Technology Readiness Level (TRL) Process

NASA's quest to make jet engines quieter led to the development of chevrons, which moved relatively quickly through the TRL process to be deployed into the commercial marketplace.



TRL 8-9 (2005-now)

- Certification by the Federal Aviation Administration
- Deployed into market



TRL 7 (2001-2005)

- Validation of concept in flight
- Flight tests, final design



TRL 6 (1998-2000)

- Full scale tests for acoustics and aerodynamics
- Static engine tests

TRL 4-5 (1995-1997)

- Model tests for acoustics and aerodynamics
- Sub-scale model tests



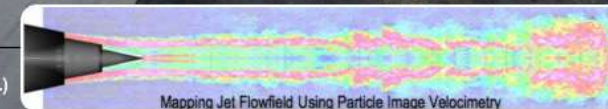
TRL 3 (Early 1990s)

- Applications to small nozzles and airfoils
- Lab tests, concept on paper

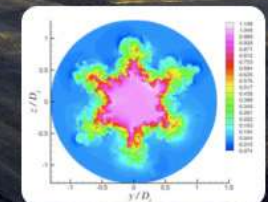


TRL 1-2 (1980s)

- Fundamental investigations of air-mixing devices (tabs, chevrons, etc.)
- No specific application, basic research in fluid physics



Mapping Jet Flowfield Using Particle Image Velocimetry



Data Science

**Pre-
definitions**

What

Who

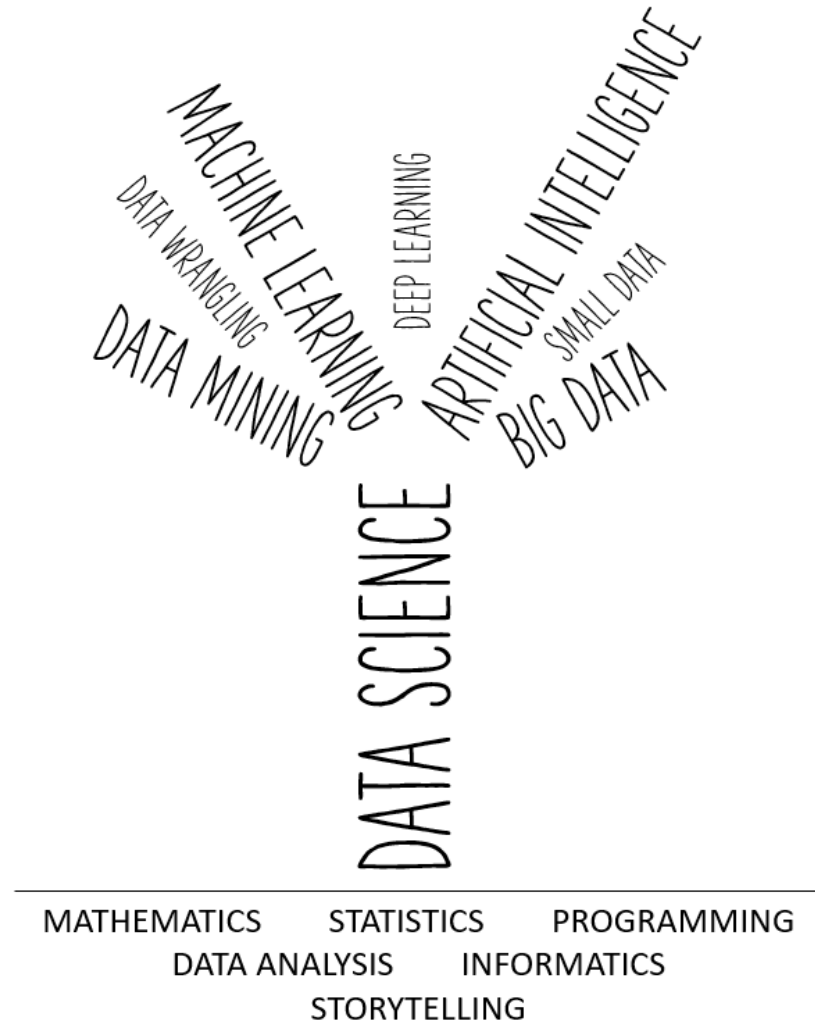
Why

When

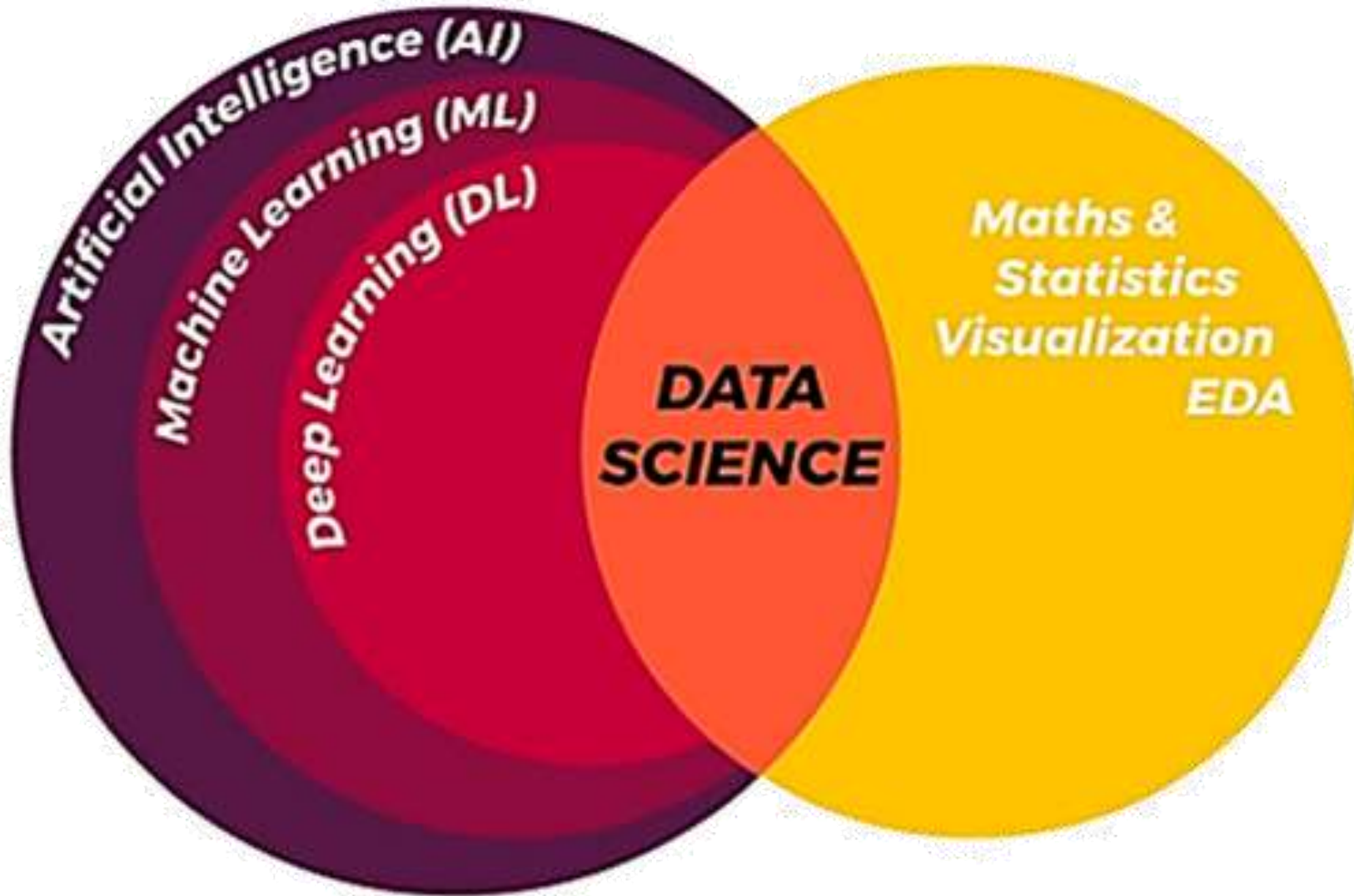
How

What is Data Science?

Interdisciplinary field focused on **extracting knowledge and insights** buried in **data** and **develop advanced tasks**.



What is Data Science?

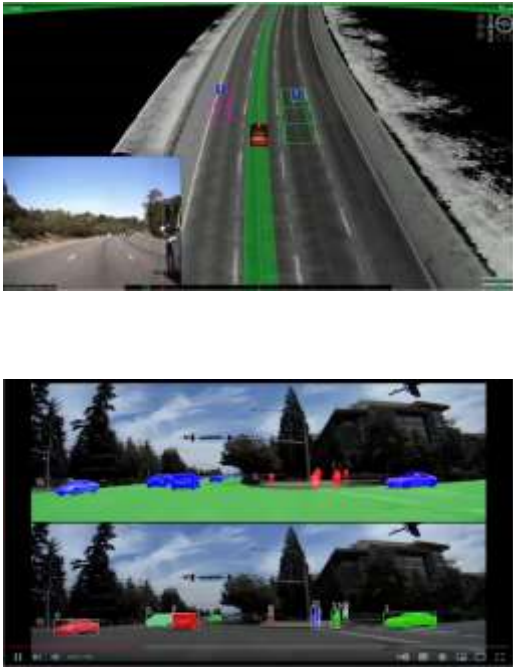


Examples

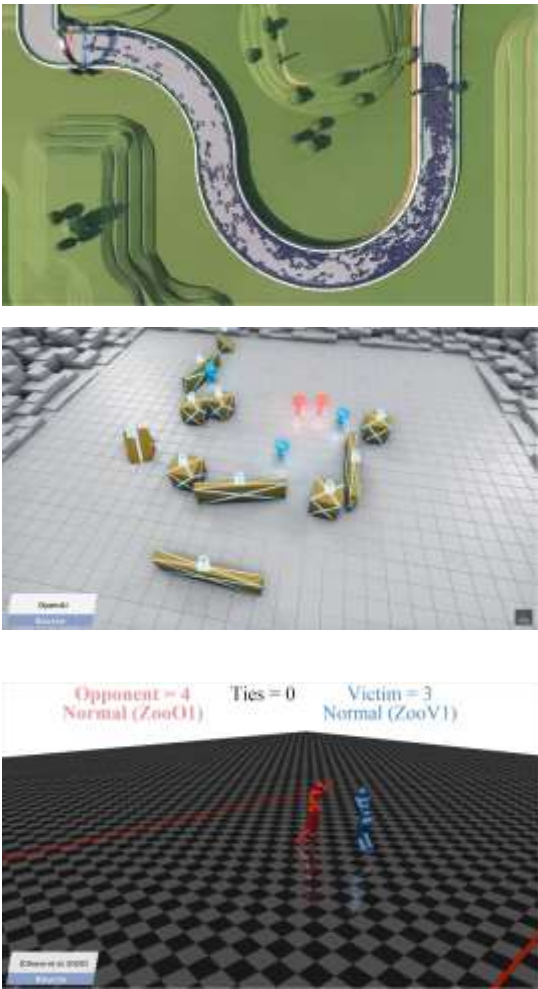
Deep fake



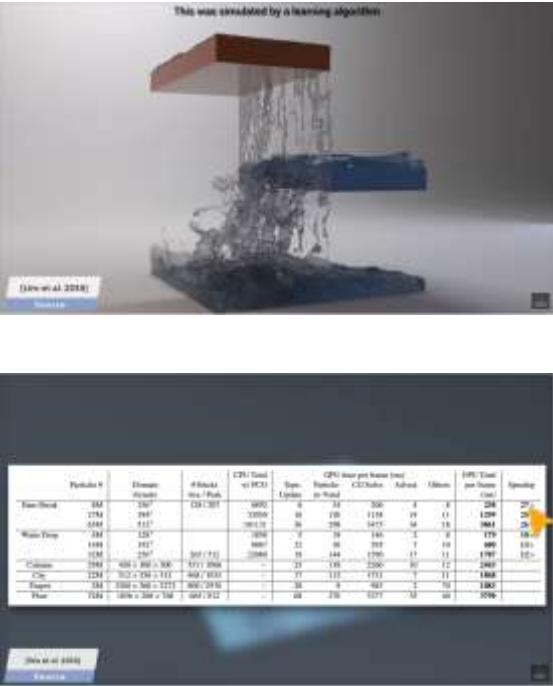
Autonomous driving



Reinforcement Learning



Physics Simulation



SOPHY in GT

The diagram illustrates the components of Data Science. It features a central horizontal bar labeled "Data Science". To the left of this bar is a vertical box labeled "Pre-definitions". Below the "Data Science" bar are five boxes labeled "What", "Who", "Why", "When", and "How". The "Who" box is highlighted in a darker blue, while the others are in lighter shades of blue.

Data Science

**Pre-
definitions**

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Who

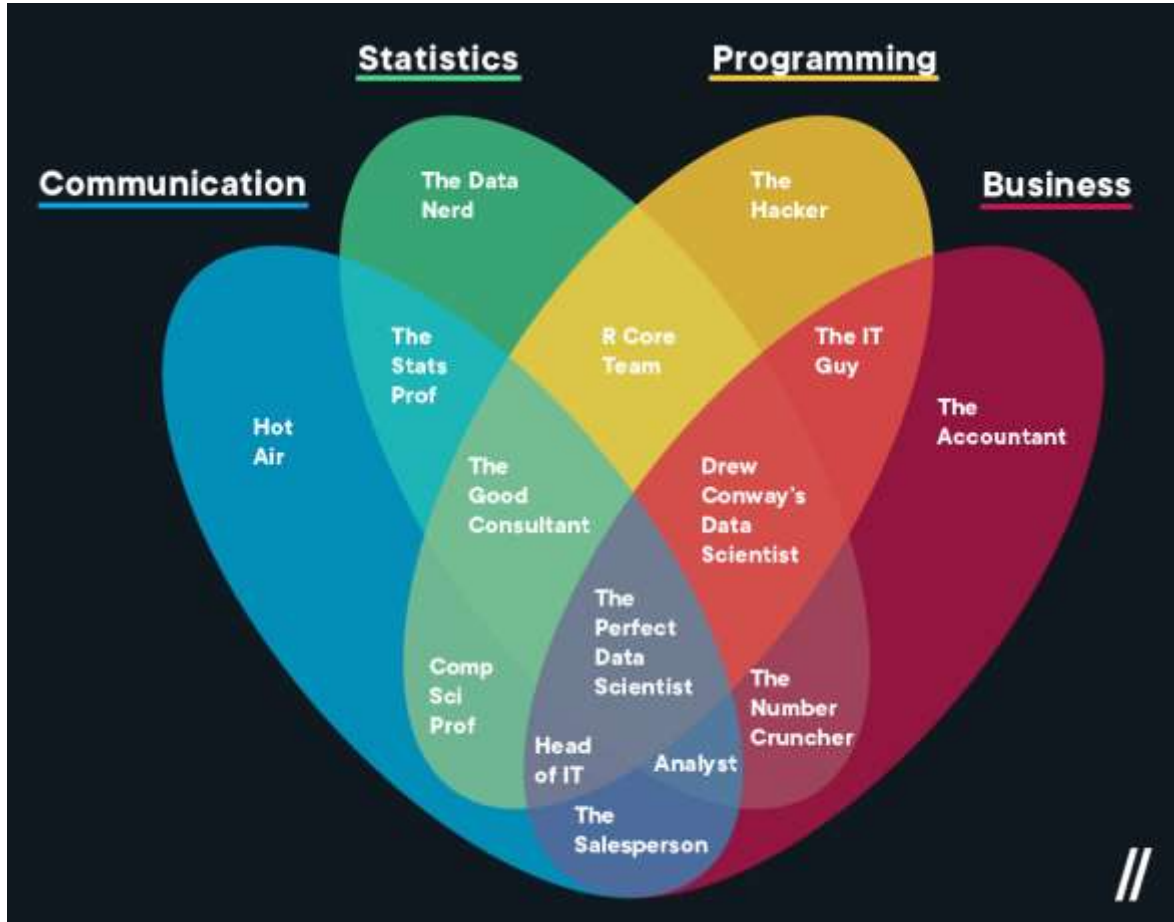
Why

When

How

What is a Data Scientist?

Data scientists **analyse, process, and model data** to find trends and uncover solutions.
Then they communicate the results.



Hard Skills

Maths
Statistics
Programming

Soft Skills

Curiosity
Story telling
Teamwork
Humbleness

Field knowledge
New technologies
Avid learner

What is a Data Scientist?

Data Science is not owned by Data Scientists!

Data Science is a very big and diverse field.

Humbleness is a must in Data Science as many people may know more than you in specific methods.

What is a Data Scientist?

Data Scientists create *data models*

What is a Data Scientist?

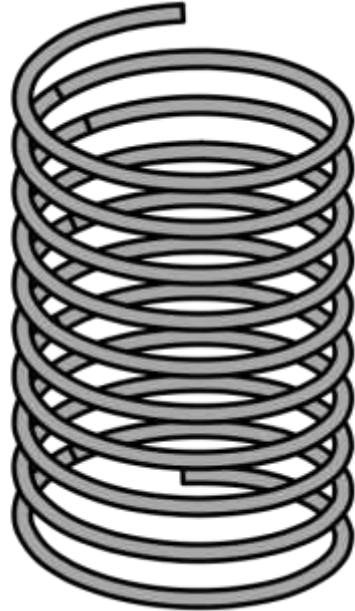
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A model is a virtual representation of the behaviour of a system in a subdomain of the variables space. It maps inputs and outputs.

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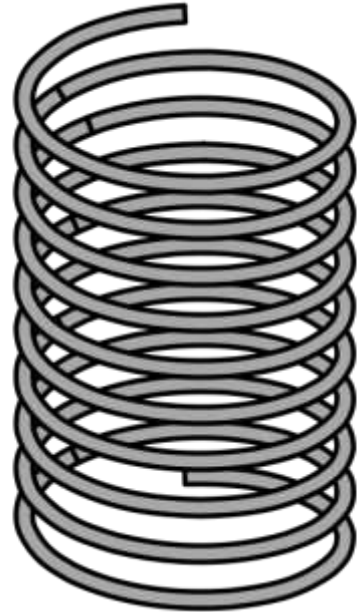
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Hooke Law

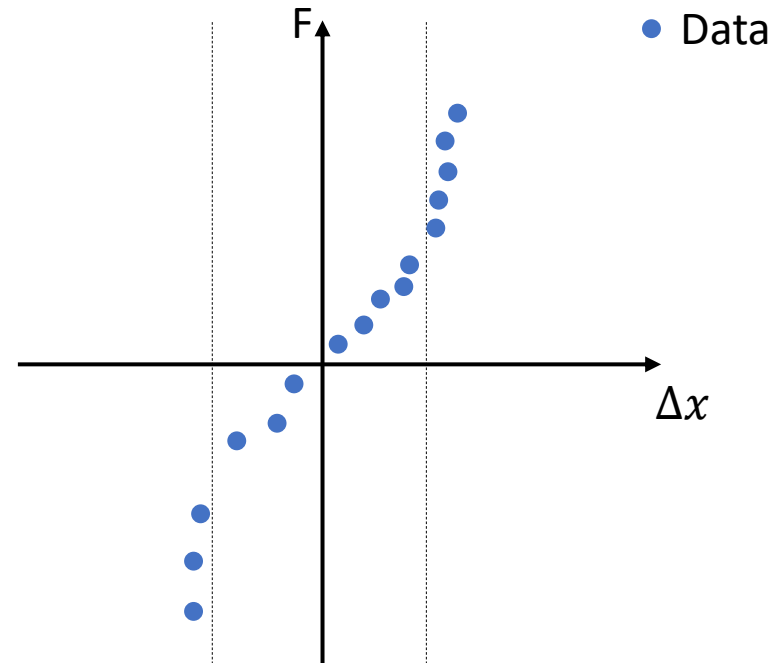
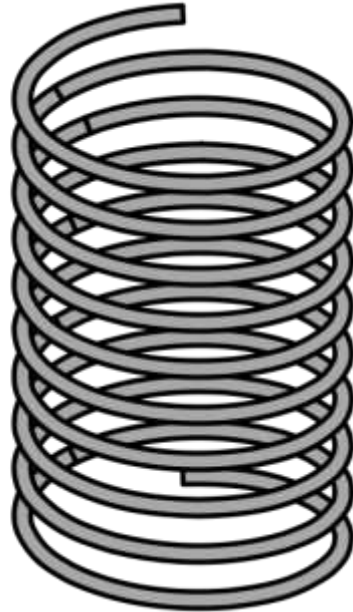
$$F = k\Delta x$$

(in the linear range)

What is a Data Scientist?

Data Scientists create data models

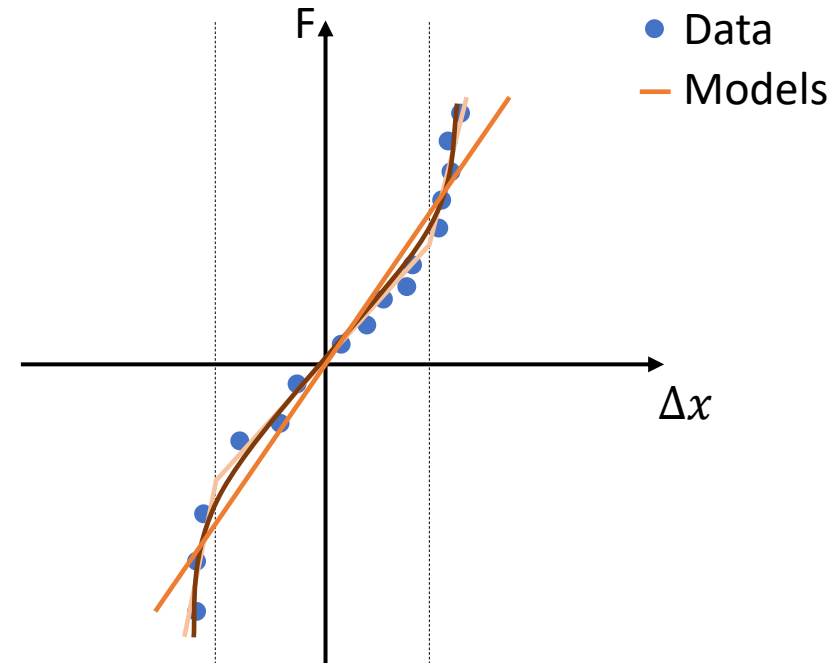
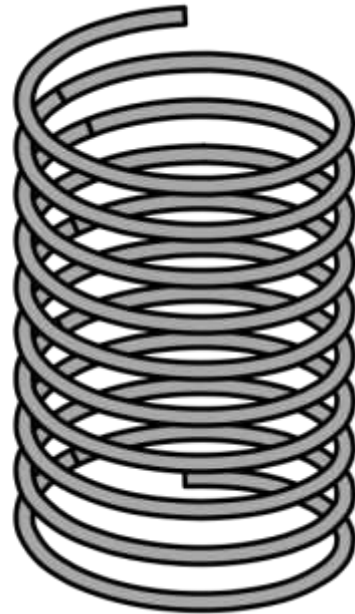
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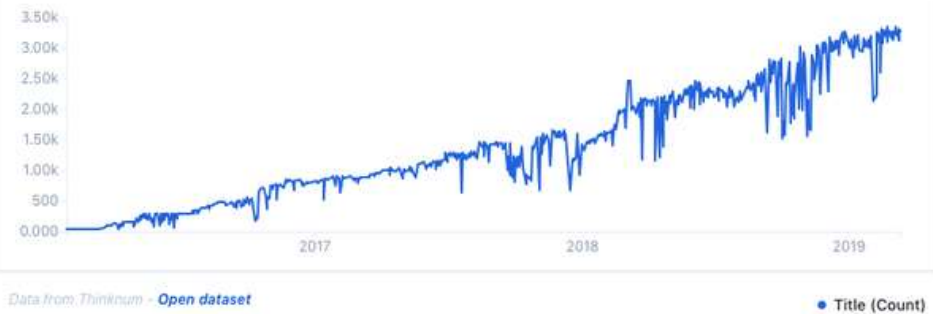
Analytics And Data Science

Data Scientist: The Sexiest Job of the 21st Century

Meet the people who can coax treasure out of messy, unstructured data. by Thomas H. Davenport and D.J. Patil

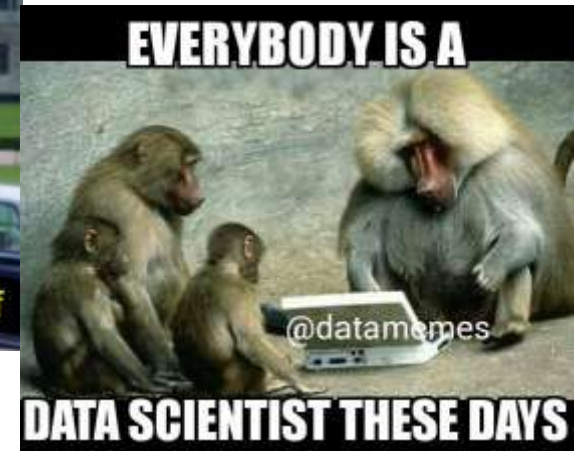
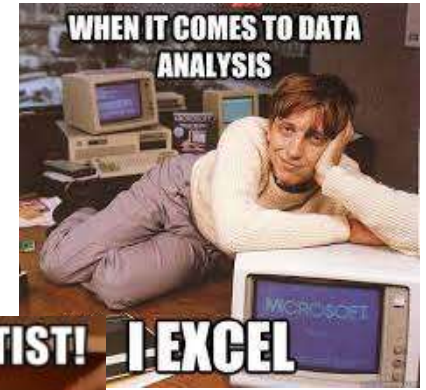
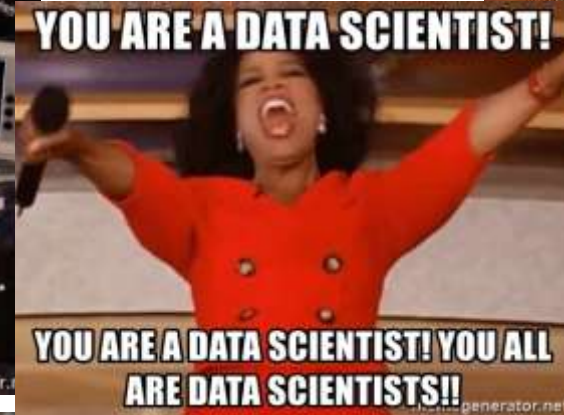
From the Magazine (October 2012)

Data Scientist job openings at the world's top companies



Job Trends from Indeed.com

— "Data Scientist"



The diagram consists of several rounded rectangular boxes. On the left is a vertical box labeled 'Pre-definitions'. To its right is a horizontal bar labeled 'Data Science'. Below the 'Data Science' bar are five boxes labeled 'What', 'Who', 'Why', 'When', and 'How'. The 'Why' box is highlighted with a darker blue color, while the others are lighter shades of blue.

Data Science

**Pre-
definitions**

What

Who

Why

When

How

Why data, Why now?

Sensors are everywhere

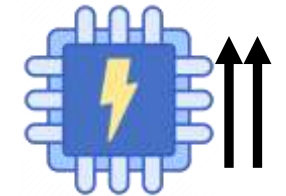
(Volume of data doubles every three years)



Data storage and computing power has increased,
cost has plummeted



Algorithms are advancing



Data Paradigm

**Classic
models**

Inputs

System rules

Outputs?

**Data
models**

Inputs

Outputs

System rules



Data Paradigm

**Classic
models**

Inputs

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Outputs?

**Data
models**

Inputs

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The diagram consists of a central horizontal bar labeled "Data Science". To the left of this bar is a vertical box labeled "Pre-definitions". Below the "Data Science" bar are five boxes labeled "What", "Who", "Why", "When", and "How". The "When" box is highlighted in a darker blue, while the others are in lighter shades of blue.

Data Science

**Pre-
definitions**

What

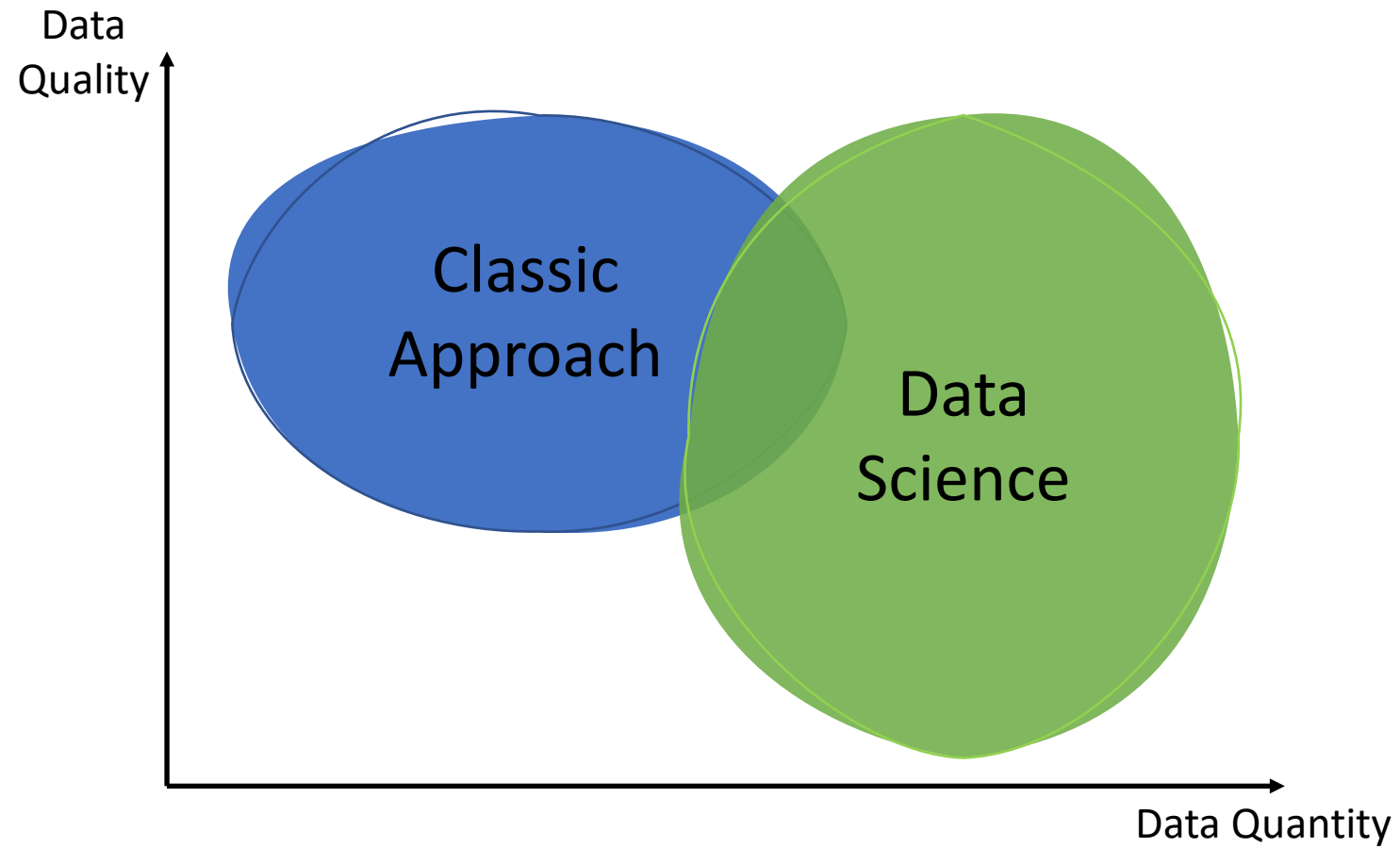
Who

Why

When

How

When Data Science?



Rules of ML (by Google)

| | |
|------------------------|--|
| Before ML | Rule 01: Go for simple heuristics first. |
| | Rule 02: Design and implement metrics. |
| | Rule 03: Choose ML over complex heuristics. |
| First Pipeline | Rule 04: Keep the first model simple and get the infrastructure right. |
| | Rule 07: Turn heuristics into features. |
| | Rule 13: Choose a simple metric for your first objective |
| Feature Engineering | Rule 16: Plan to launch and iterate. |
| | Rule 19: Use very specific features when you can. |
| | Rule 23: You are not a typical end user. |
| Growth | Rule 24: Measure the delta between models. |
| | Rule 43: ... |

Data Science

Pre-
definitions

What

Who

Why

When

How

Context

Toolkit

Project

Data in F1

Programming

Data Science

Pre-
definitions

What

Who

Why

When

How

Context

Toolkit

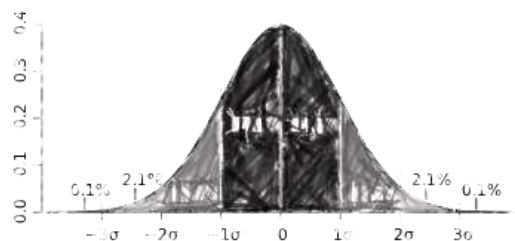
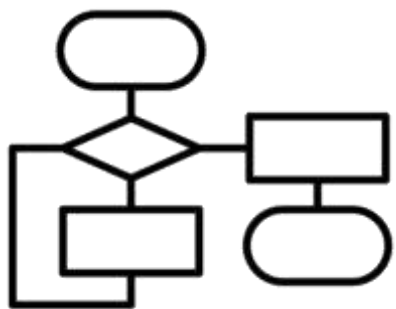
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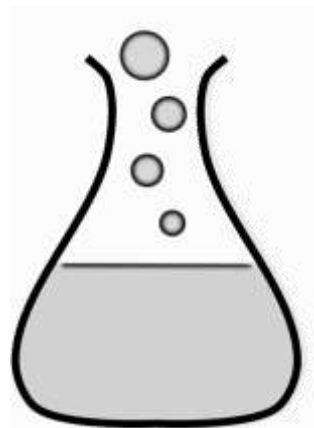
Data Analyst

Overview/pre-analysis



Data Scientist

Algorithms/models



$$\begin{aligned} Q &= mc\Delta t \quad R = \frac{\rho L}{A} \quad k = \frac{1}{\frac{1}{k_1} + \frac{1}{k_2} + \dots + \frac{1}{k_n}} \quad \oint \vec{B} \cdot d\vec{l} = \mu_0 \sum I_i \\ \beta &= \frac{\Delta I_c}{\Delta I_B} \quad E = \frac{1}{2} \hbar \omega \quad \omega = 2\pi f \quad C = \frac{Q}{V} \quad \vec{p} = \hbar \vec{k} \quad \phi = \frac{2\pi}{\lambda} \quad v = \frac{c}{\lambda} \\ f_0 &= \frac{1}{2\pi R L} \quad \vec{S} = \frac{1}{\mu_0} (\vec{E} \times \vec{B}) \quad \vec{A} = \frac{1}{4\pi} \oint \vec{B} \cdot d\vec{l} \quad \lambda^* T = b \quad H_A = \frac{\partial M_A}{\partial \lambda} \\ R_p &= \frac{F}{S} \quad F_v = \frac{F_n}{R} \quad E = mc^2 \quad f_0 = \frac{1}{2\pi} \frac{v}{L} \quad E = \hbar \omega \quad \lambda_n = \frac{c}{f_n} \\ v &= \frac{f \lambda}{n} \quad \sigma = \frac{Q}{S} \quad M_0 = \frac{4\pi}{3} r^3 \rho \quad I_n = \frac{1}{2} I_0 \left[\left(\frac{1}{k_1} + \frac{1}{k_2} + \dots + \frac{1}{k_n} \right)^2 \right] \quad F_g = \frac{m_1 m_2}{r^2} \\ M &= F d \cos \alpha \quad T = \frac{4\pi m_1 m_2}{(m_1 + m_2)^2} \quad 1 \text{ pc} = \frac{1 \text{ AU}}{r} \quad E = \frac{\hbar^2 k^2}{2m} \quad v = \frac{\partial \phi}{\partial t} \\ \oint \vec{D} \cdot d\vec{s} &= Q \quad F_x = \frac{1}{2} C_D \rho v^2 \quad F_h = S h p g \quad F_x = \frac{m_1}{r_1} + \frac{m_2}{r_2} = \frac{m_1 + m_2}{r} \quad \frac{\sin \theta}{\lambda} = \frac{m_1}{\lambda_1} + \frac{m_2}{\lambda_2} \end{aligned}$$

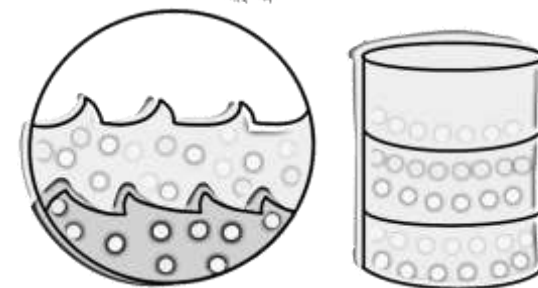
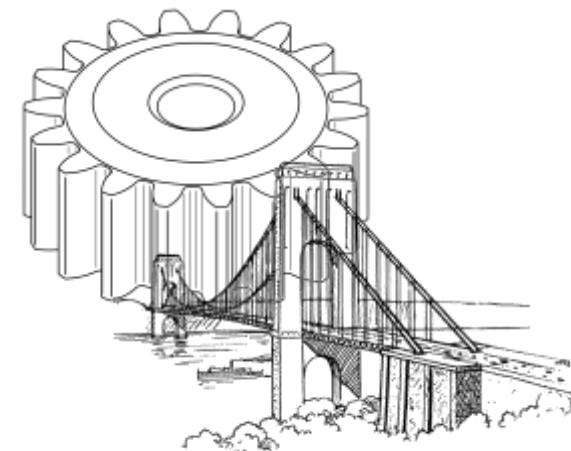
ML Engineer

Implementation



Data Engineer

Infrastructure



Technology stack

Data Analyst

Overview/pre-analysis

Data Scientist

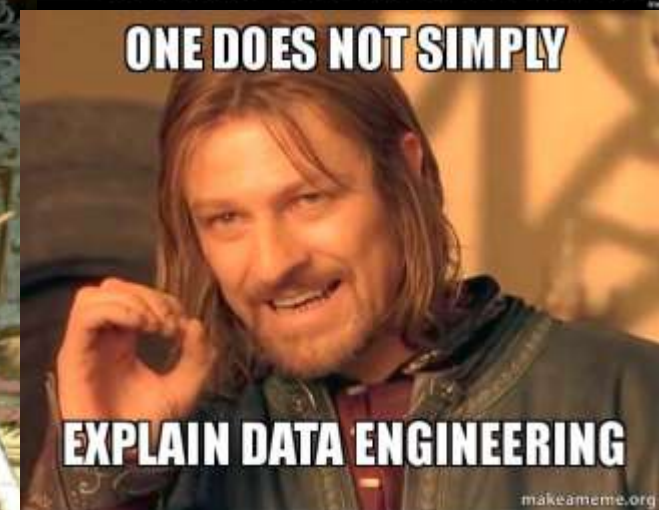
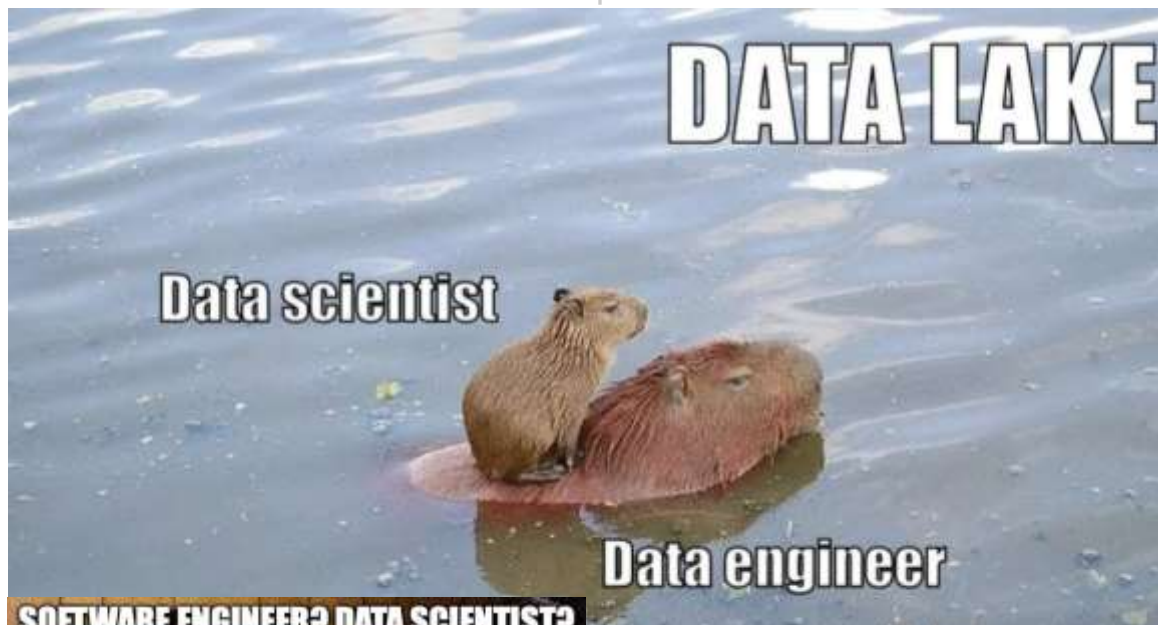
Algorithms/models

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Implementation

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Infrastructure



Structure



Storage



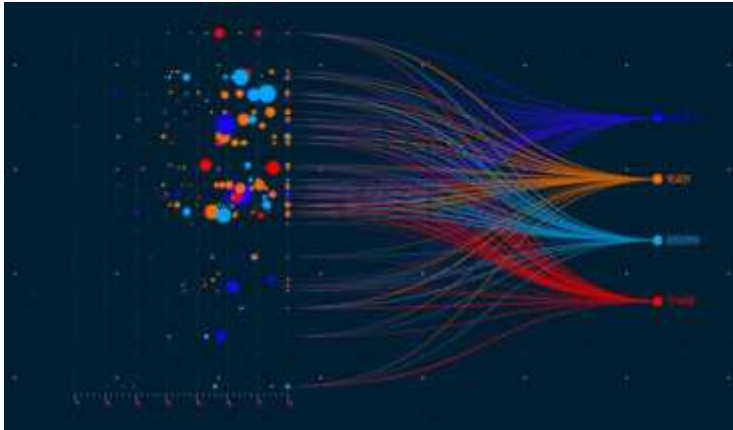
Size

BIG DATA

SMALL DATA

Data Science Work Flow

DATA



Data Science Work Flow

DATA

Structured

Databases (SQL, non SQL ...)

CSV, JSON files

Proprietary file formats

Unstructured

Websites

Videos, pictures, audio...



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Data Mining



Data Science Work Flow

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Data Mining

Exploratory
Data
Analysis



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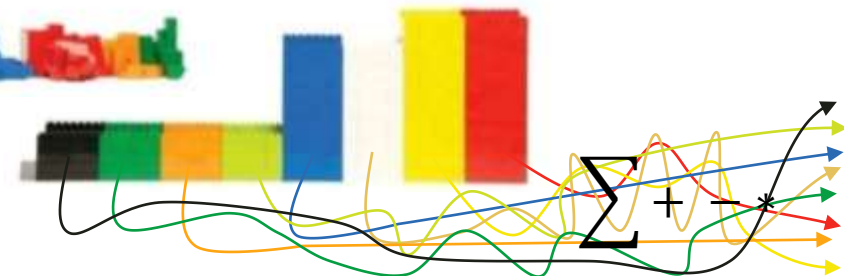
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Engineering

Modelling

Deploying



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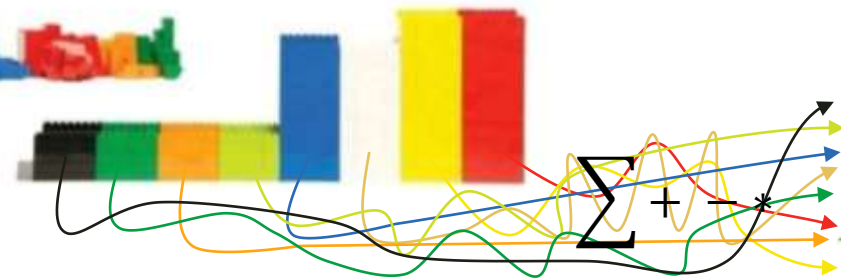
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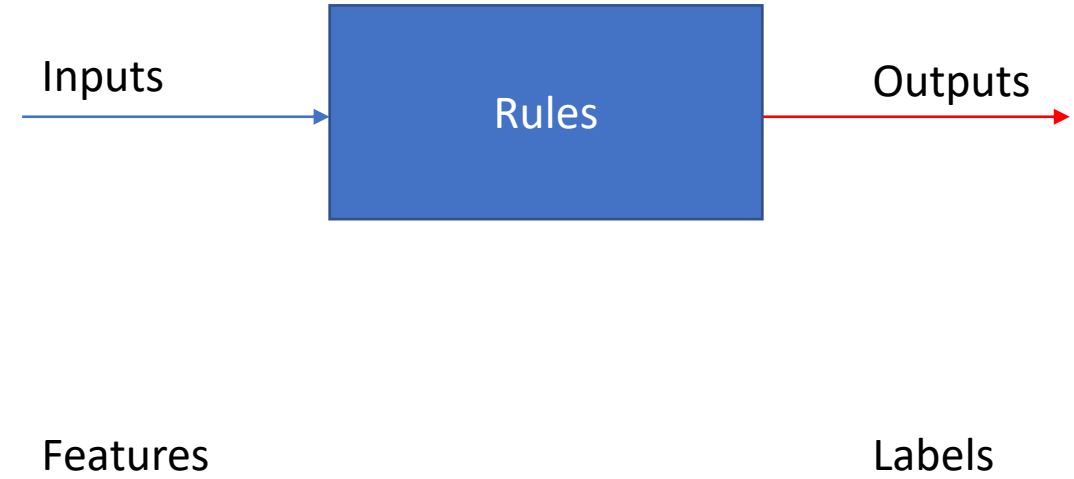
Toolkit

Project

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Programming

Modelling Toolkit



Modelling Toolkit



Supervised

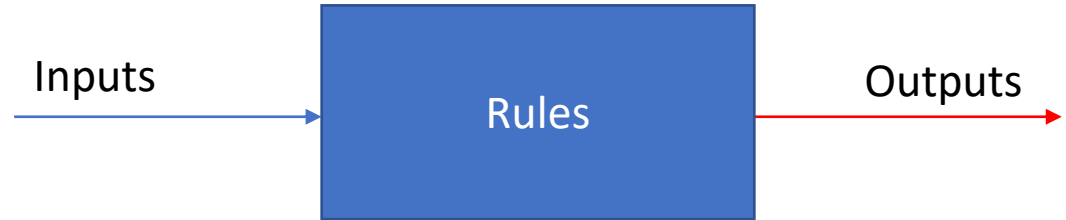
Features

Labels

Un-Supervised

Features

~~Labels~~



Modelling Toolkit

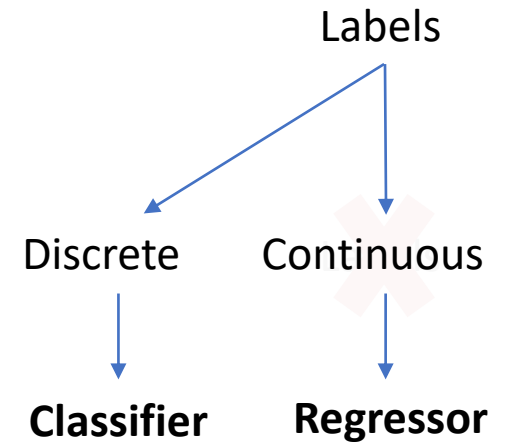


Supervised

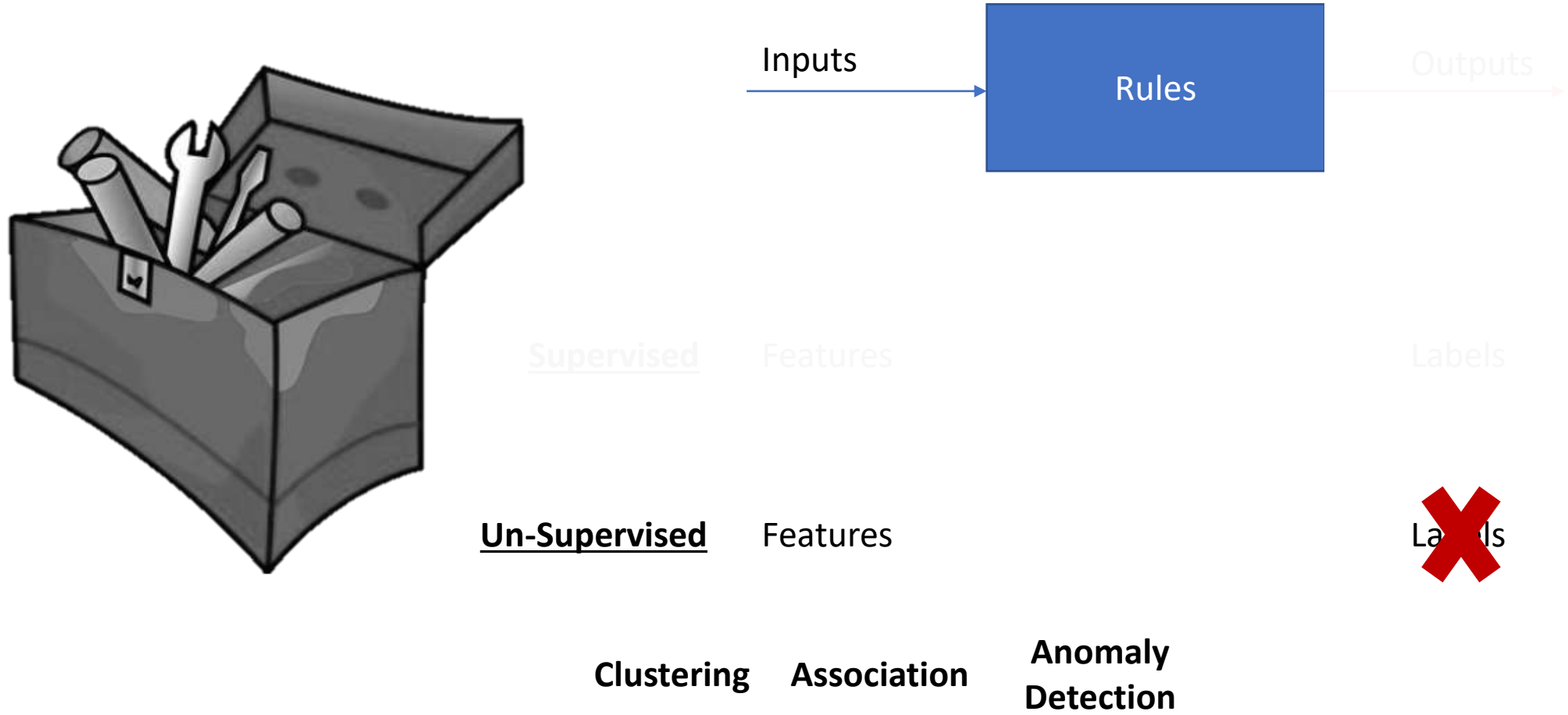
Features

Un-Supervised

Features



Modelling Toolkit



MACHINE LEARNING

SUPERVISED LEARNING

REGRESSION

LINEAR

RIDGE/
LASSO

SVR

MULTI

POLY

DECISION
TREE

...

CLASSIFICATION

LOGISTIC
REGRESSION

DECISION TREE

NAÏVE BAYES

SVM

...

...

UNSUPERVISED LEARNING

CLUSTERING

K-MEANS

HIERERCHICAL

...

ASSOCIATION

APRIORI

ECLAT

...

ANOMALY DETECTION

DENSITY-
BASED

CLUSTERING

SVM

SVM

...

...

REINFORCEMENT LEARNING

MARKOV DECISION
PROCESS

UPPER BOUND
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○ Course

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...

...

...



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```
graph TD; A[System to study] --> B[Sensors study]; B --> C[Installation of sensors]; C --> D[Interface]; D --> E[Storing the data]; E --> F[Data Science Project];
```

System to study

Sensors study

Installation of
sensors

Interface

Storing the data

Data Science
Project

System to study

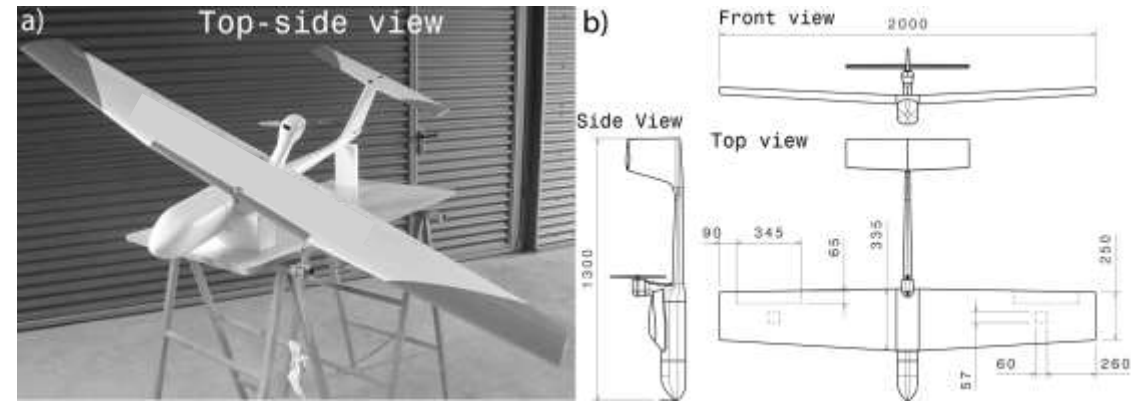
Sensors study

Installation of
sensors

Interface

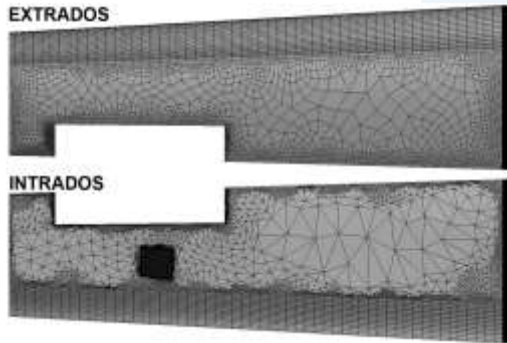
Storing the data

Data Science
Project



System to study

Sensors study

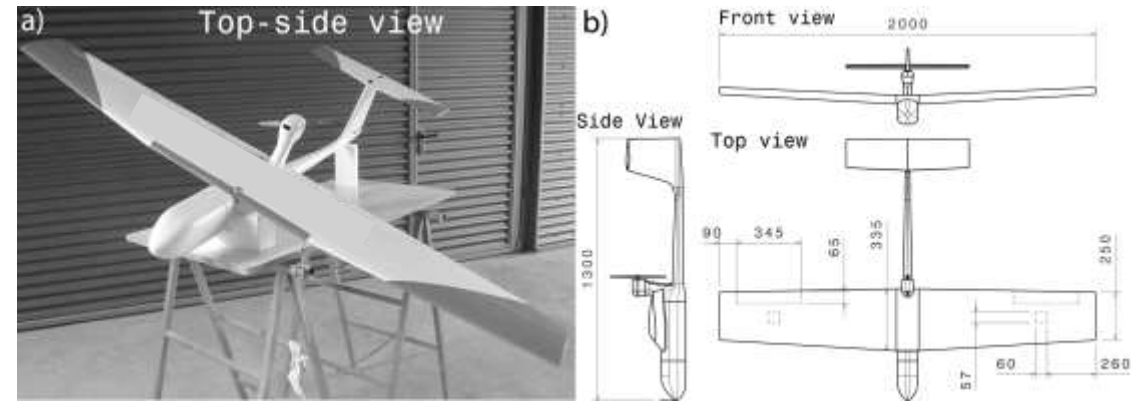


Installation of
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Interface

Storing the data

Data Science
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System to study

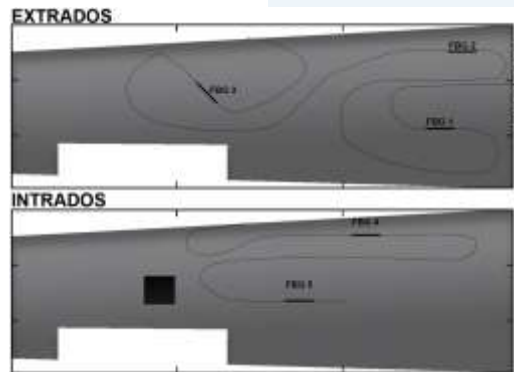
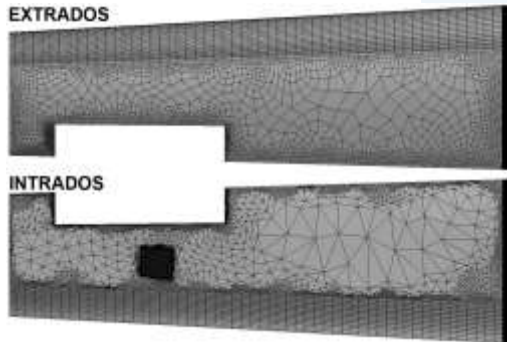
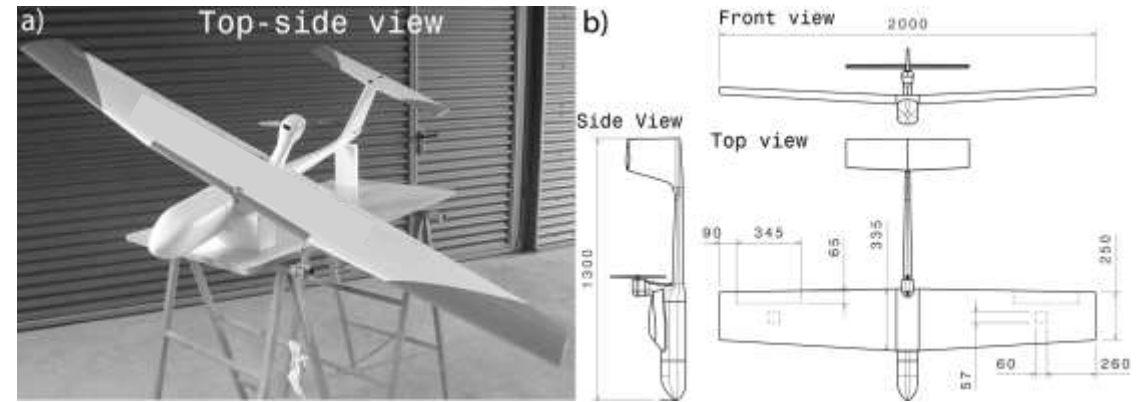
Sensors study

Installation of
sensors

Interface

Storing the data

Data Science
Project



Load cell

System to study

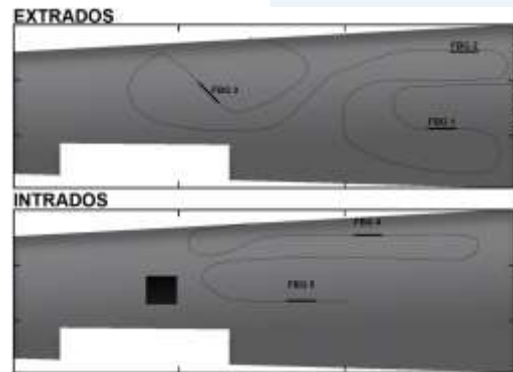
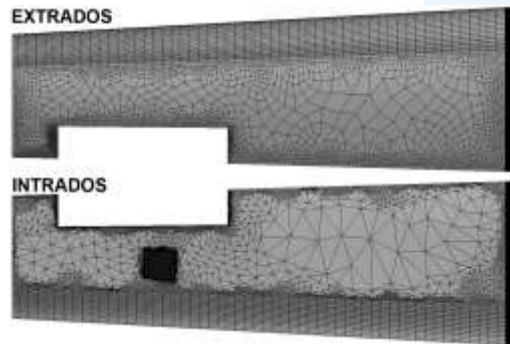
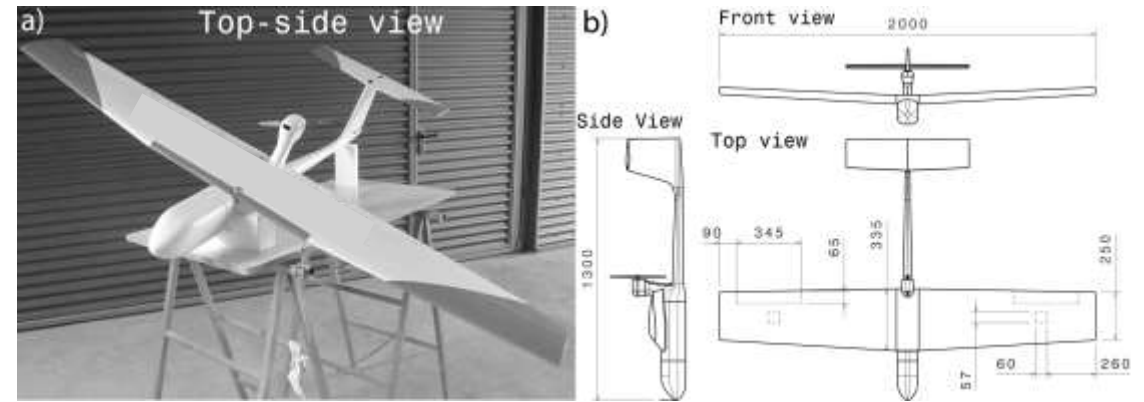
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Project



Load cell





DATA IS THE NEW OIL

ROB CROOKE

Senior Vice President and General Manager,
Non-Volatile Memory (NVM) Solutions Group



Standard
Tape 33\$ TB
Disk 45\$ TB

Storing the data

Data Science
Project

ARQUITECTURE

Business
Understanding

State of Art

Analytic
Approach

Data
Requirements

DEPLOYMENT & MAINTENANCE

Retrospective

Feedback

Deployment

Evaluation

IMPLEMENTATION

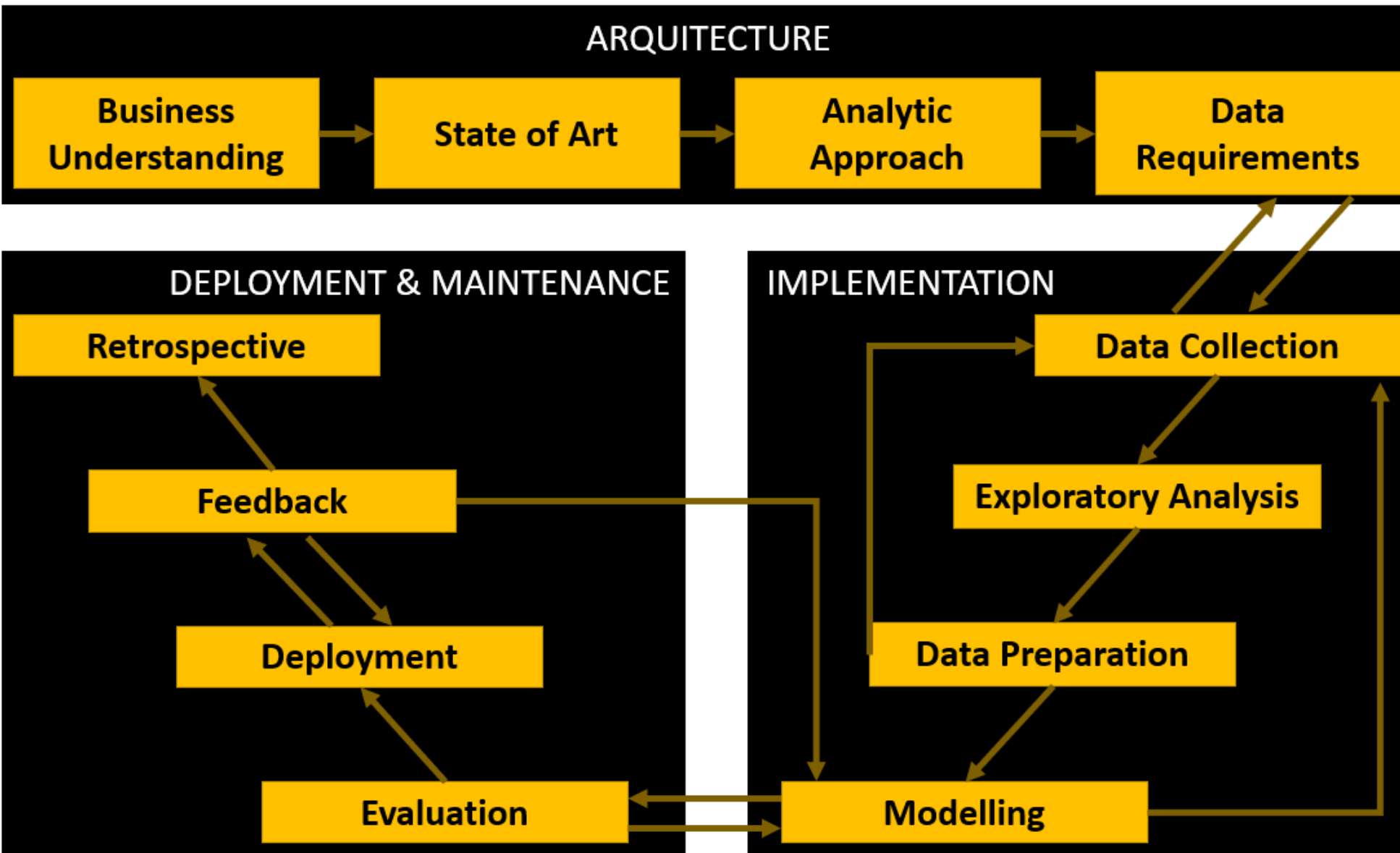
Data Collection

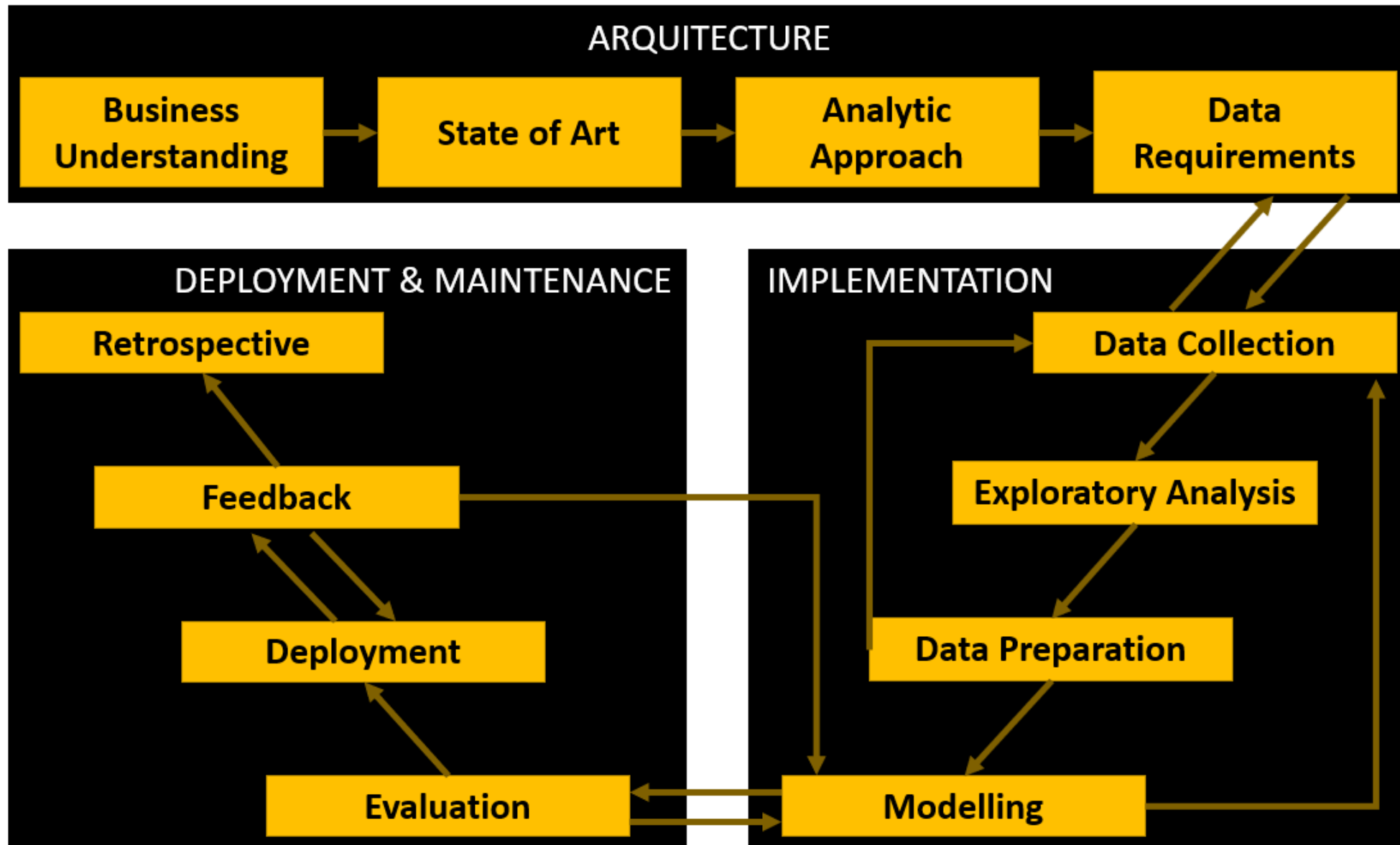
Exploratory Analysis

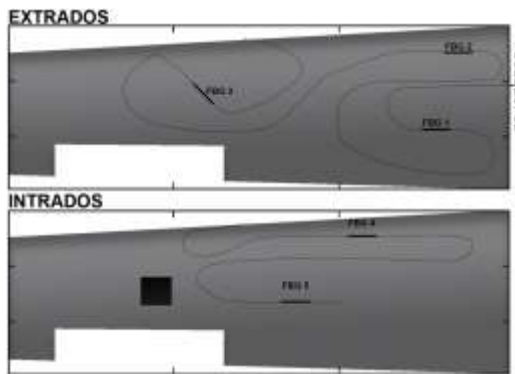
Data Preparation

Modelling

Data Science
Project







Storing the data



Load cell

- Alarms (thresholds) for load and strains
- Fatigue analysis
- Impact detection
- Dynamic analysis (aeroelasticity?)
- Distribution of the loads

- Regression models load-strain.
- Clustering of maneuvers.
- Patterns repeated in time.
- Anomaly detection (Sensor error or dangerous maneuvers)
- Classification of structural state.
- ...

Improvement of the product



Refinement of design and calculation,
reduce of costs and improvement of
performances

Data Science

Pre-
definitions

What

Who

Why

When

How

Context

Toolkit

Project

Data in F1

Programming

Data in F1



$\approx (O) 100$ sensors

$\approx (O) 10\text{Gb}$ per weekend

Data in F1



$\approx (O) 100$ sensors

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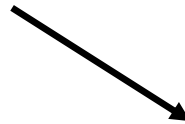
Data in F1



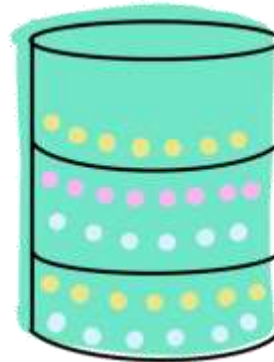
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**Trackside
engineers**



Design, calculation and manufacturing



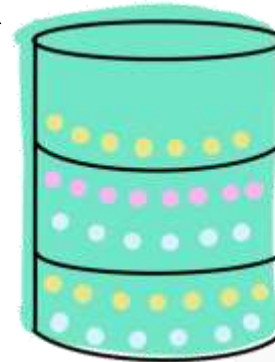
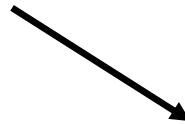
Data in F1



$\approx (O) 100$ sensors
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**Trackside
engineers**



Design, calculation and manufacturing

Vehicle Performance Group
Control Systems Modelling Group

Design Office

Aero

IT

...

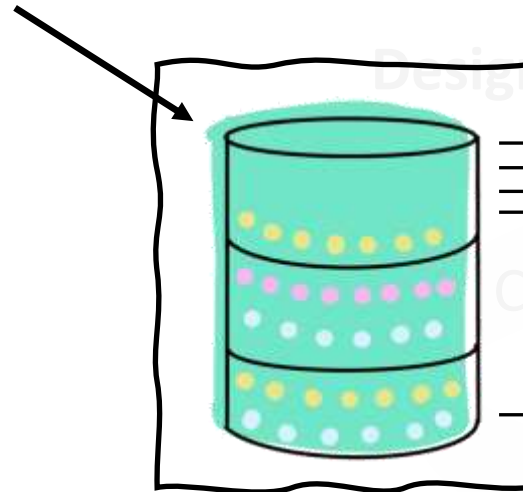
Data in F1



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Trackside
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Classic Models

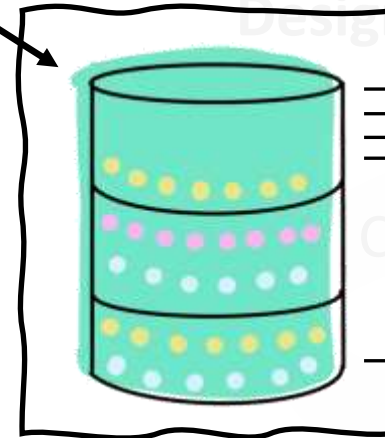
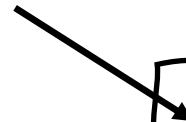
Data Models

Design, calculation and manufacturing
Virtual modelling
Control Systems Modelling Group
Design Office
Aero
IT
...

Data in F1



Trackside
engineers



Classic Models



Data Models

$\approx (O) 100$ sensors
 $\approx (O) 10\text{Gb}$ per weekend

**Data Science is exploding in F1,
stay tuned if you are
interested!!**

Data Science

Pre-
definitions

What

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How

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Project

Data in F1

Programming

Coding for Data Science

Data Science requires a support, a tool that allows quick and easy interaction with data.

Additionally the “bigger” the data, the “higher” the computational demands.

Coding for Data Science



Top 6 Data Science Programming Languages 2021 [Hand-Picked]

1. Python
2. JavaScript
3. Scala
4. R
5. SQL
6. Julia



9 Top Programming Languages for Data Science

1. Python
2. R
3. SQL
4. Scala
5. Julia
6. JavaScript
7. Java
8. C/C++
9. Matlab



The 10 Best Data Science Programming Languages to Learn in 2021

1. Python
2. JavaScript
3. Java
4. R
5. C/C++
6. SQL
7. Matlab
8. Scala
9. Julia
10. SAS



Top 8 programming languages every data scientist should master in 2019

1. Python
2. R
3. Java
4. SQL
5. Julia
6. Scala
7. Matlab
8. (Tensorflow)

Coding for Data Science



Top 6 Data Science Programming Languages 2021 [Hand-Picked]



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Why Python?

High level language

Easy to read, learn and write

Great community support

Famous and gaining more popularity

Interpreted

Free and open source

Great for Data Science

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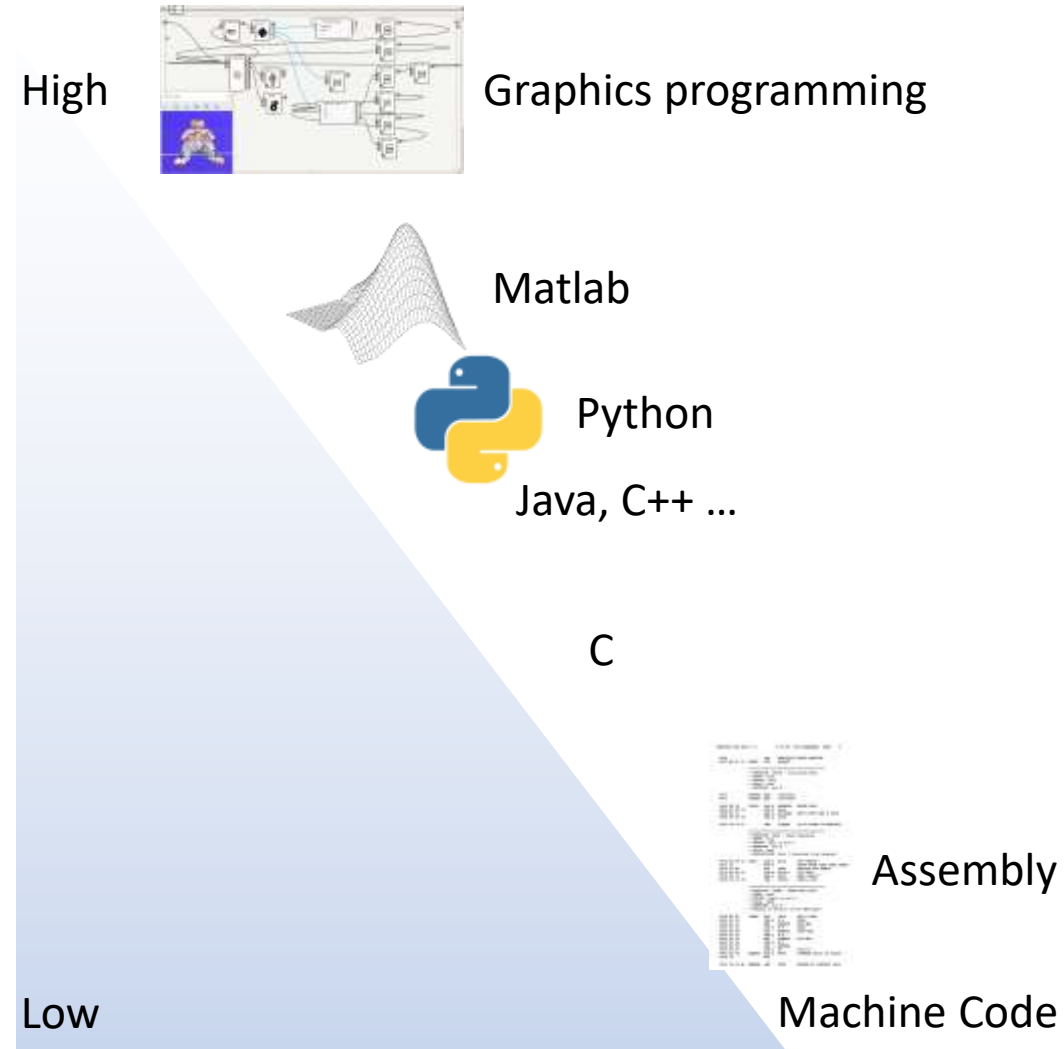
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Clean syntax and indentation structure

```
# Python 3: Simple output (with Unicode)
>>> print("Hello, I'm Python!")
Hello, I'm Python!

# Input, assignment
>>> name = input('What is your name?\n')
>>> print('Hi, %s.' % name)
What is your name?
Python
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```

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*Study by SlashData

The size of programming language communities in Q3 2020 is as follows:

1. JavaScript

Active developers: 12.4 million

Most popular in: Web, Cloud

Least popular in: Data Science, Machine Learning, AR/VR

2. Python

Active developers: 9 million

Most popular in: Data Science, Machine Learning, IoT

Least popular in: Mobile, Web

3. Java

Active developers: 8.2 million

Most popular in: Mobile, Cloud

Least popular in: Data Science, Machine Learning, Web

4. C/C++

Active developers: 6.3 million

Most popular in: IoT, AR/VR

Least popular in: Web, Cloud, Mobile

5. PHP

Active developers: 6.1 million

Most popular in: Web, Cloud

Least popular in: Data Science, Machine Learning, Mobile

6. C#

Active developers: 6.0 million

Most popular in: Games, AR/VR, Desktop

Least popular in: Data Science, Machine Learning, Mobile

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TIOBE Index

| Aug 2021 ▲ | Aug 2020 ◆ | Change ◆ | Programming language ◆ | Ratings ◆ | Change ◆ |
|------------|------------|----------|------------------------|-----------|----------|
| 1 | 1 | | C | 12.57% | -4.41% |
| 2 | 3 | ↑ | Python | 11.86% | +2.17% |
| 3 | 2 | ↓ | Java | 10.43% | -4.00% |
| 4 | 4 | | C++ | 7.36% | +0.52% |
| 5 | 5 | | C# | 5.14% | +0.46% |
| 6 | 6 | | Visual Basic | 4.67% | +0.01% |
| 7 | 7 | | JavaScript | 2.95% | +0.07% |
| 8 | 9 | ↑ | PHP | 2.19% | -0.05% |
| 9 | 14 | ↑↑ | Assembly language | 2.03% | +0.99% |
| 10 | 10 | | SQL | 1.47% | +0.02% |
| 11 | 18 | ↑↑ | Groovy | 1.36% | +0.59% |
| 12 | 17 | ↑↑ | Classic Visual Basic | 1.23% | +0.41% |
| 13 | 42 | ↑↑ | Fortran | 1.14% | +0.83% |
| 14 | 8 | ↓↓ | R | 1.05% | -1.75% |
| 15 | 15 | | Ruby | 1.01% | -0.03% |
| 16 | 12 | ↓↓ | Swift | 0.98% | -0.44% |
| 17 | 16 | ↓ | MATLAB | 0.98% | +0.11% |
| 18 | 11 | ↓↓ | Go | 0.90% | -0.52% |
| 19 | 36 | ↑↑ | Prolog | 0.80% | +0.41% |
| 20 | 13 | ↓↓ | Perl | 0.78% | -0.33% |

PYPL Index (Worldwide)

| Aug 2021 ▲ | Change ◆ | Programming language ◆ | Share ◆ | Trends ◆ |
|------------|----------|------------------------|---------|----------|
| 1 | | Python | 29.93 % | -2.2 % |
| 2 | | Java | 17.78 % | +1.2 % |
| 3 | | JavaScript | 8.79 % | +0.6 % |
| 4 | | C# | 6.73 % | +0.2 % |
| 5 | ↑ | C/C++ | 6.45 % | +0.7 % |
| 6 | ↓ | PHP | 5.76 % | -0.0 % |
| 7 | | R | 3.92 % | -0.1 % |
| 8 | | Objective-C | 2.26 % | -0.3 % |
| 9 | ↑ | TypeScript | 2.11 % | +0.2 % |
| 10 | ↓ | Swift | 1.96 % | -0.3 % |
| 11 | ↑ | Kotlin | 1.81 % | +0.3 % |
| 12 | ↓ | Matlab | 1.48 % | -0.4 % |
| 13 | | Go | 1.29 % | -0.2 % |
| 14 | ↑↑ | Rust | 1.21 % | +0.2 % |
| 15 | ↓ | VBA | 1.16 % | -0.1 % |
| 16 | ↓ | Ruby | 1.02 % | -0.1 % |
| 17 | | Scala | 0.79 % | -0.1 % |
| 18 | ↑ | Ada | 0.77 % | +0.2 % |
| 19 | ↓ | Visual Basic | 0.75 % | +0.0 % |
| 20 | | Dart | 0.68 % | +0.2 % |
| 21 | | Lua | 0.58 % | +0.1 % |
| 22 | ↑↑ | Cobol | 0.51 % | +0.1 % |
| 23 | | Groovy | 0.51 % | +0.1 % |
| 24 | ↓↓ | Abap | 0.46 % | -0.0 % |
| 25 | ↑ | Perl | 0.45 % | +0.1 % |
| 26 | ↓ | Julia | 0.39 % | -0.0 % |
| 27 | ↑ | Haskell | 0.24 % | -0.0 % |
| 28 | ↓ | Delphi/Pascal | 0.2 % | -0.1 % |

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>>> print('Hi, %s.' % name)
What is your name?
Python
Hi, Python.
```

VS

Compiled



```
public void InitAnimations()
{
    viewportSizeY = GetViewportRect().Size.y;
    spawnY = viewportSizeY / 2.0f + 16f;

    // Player Anim
    Animation anim = GetNode<AnimationPlayer>("FlyInAnim").GetAnimation("FlyIn");
    anim.TrackSetKeyValue(0, 0, new Vector2(0, -viewportSizeY / 2.0f + -80f));
    anim.TrackSetKeyValue(0, 1, new Vector2(0, (-viewportSizeY / 2.0f) + viewportSizeY / 1.0f));
    player.Position = new Vector2(0, -viewportSizeY / 2.0f + -80f);

    anim = GetNode<AnimationPlayer>("BgChangeAnim").GetAnimation("BgChangeAnim");
    anim.TrackSetKeyValue(1, 0, new Vector2(0, 0));
    anim.TrackSetKeyValue(1, 1, new Vector2(0, -viewportSizeY / 2.0f + 200.0f));

    GetNode<Sprite>("SpaceBGOverlay").Position = new Vector2(0, 0);

    anim = GetNode<AnimationPlayer>("BackgroundAnim").GetAnimation("BackgroundAnim");
    GetNode<AnimatedSprite>("BackgroundSprite").Frame = random.RandomRange(0, 1);
    anim.TrackSetKeyValue(0, 0, new Vector2(0, -viewportSizeY / 2.0f + 225.0f));
    anim.TrackSetKeyValue(0, 1, new Vector2(0, +viewportSizeY / 2.0f - 225.0f));
    GetNode<AnimatedSprite>("BackgroundSprite").Position = new Vector2(0, -viewportSizeY / 2.0f + 225.0f);

    GetNode<Sprite>("PratotypLogo").Position = new Vector2(0, 32f); // new Vector2(0, viewportSizeY/2.0f-(viewportSizeY/3.0f));
}
```


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No royalties or licenses

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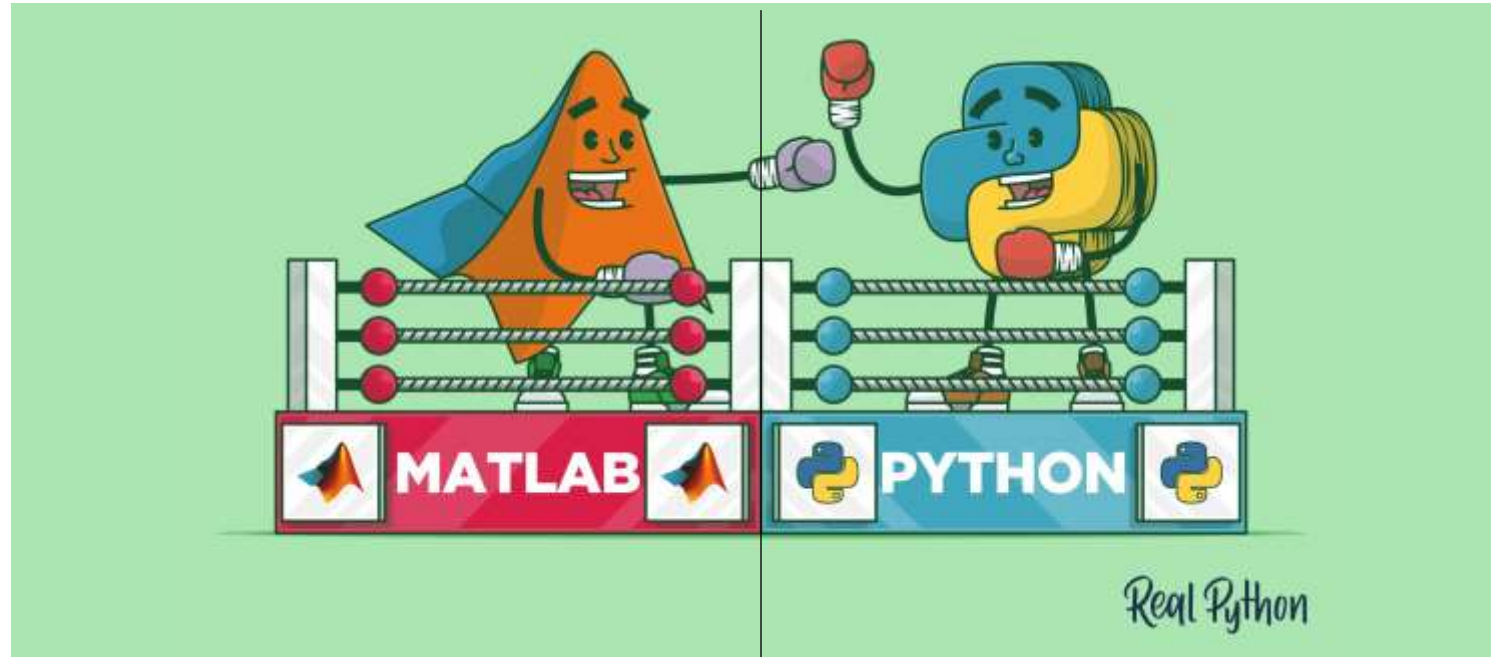
Great for Data Science



...

Python vs Matlab

Interpreted
High level and easy to use



Slightly higher performing (out of the box)
Proprietary (Pricey!)
Closed source
Poor deployment options
Integration with Simulink
King of simulation
Single IDE, Toolboxes agreed with MathWorks
Amazing help developed by MathWorks

Free
Open Source
Good deployment options
Integration with a huge amount of packages
King of Data Science
Multiple IDEs and packages
Huge community support (and growing!)

Starting with Python for Data Science

Bare Python



Python from python.org

Select an IDE

Link the IDE to the Python interpreter



Great for Data Science

GUI for environments

Easy import-export of env

Easy integration with IDEs

It can be used for Jupyter as well



Nice interface to program and share.

Need Python first (Or docker)

Virtual environments



Python from python.org

pipx

pipenv

→ Env per project_1

→ Env per project_2

→ Env per project_3

QUESTIONS?

