

Introduction to Machine Learning

Hello! Instructor Introduction

- Instructor: **Anshu Pandey**
 - Microsoft Certified Trainer
 - Data Scientist
 - Microsoft Certified Azure AI Associate & Data Scientist
-
- A Data Scientist and AI Architect having 8+ years of experience of working with organizations to develop Data Science and AI Applications and helping them with AI Transformation.



Artificial Intelligence





What is Artificial Intelligence?

“The capability of a machine to imitate intelligent human behavior”

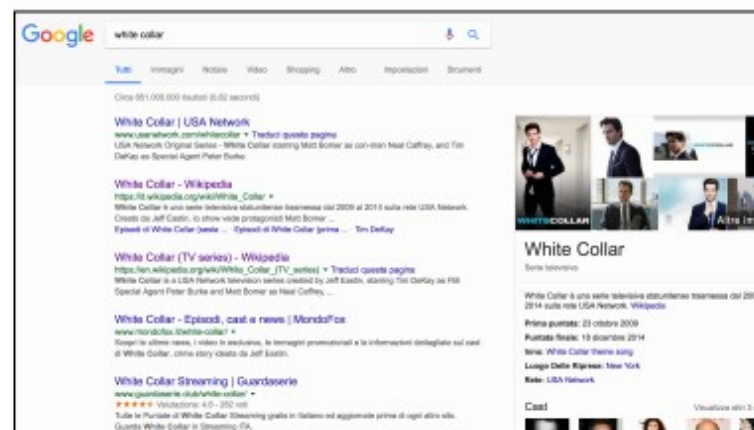
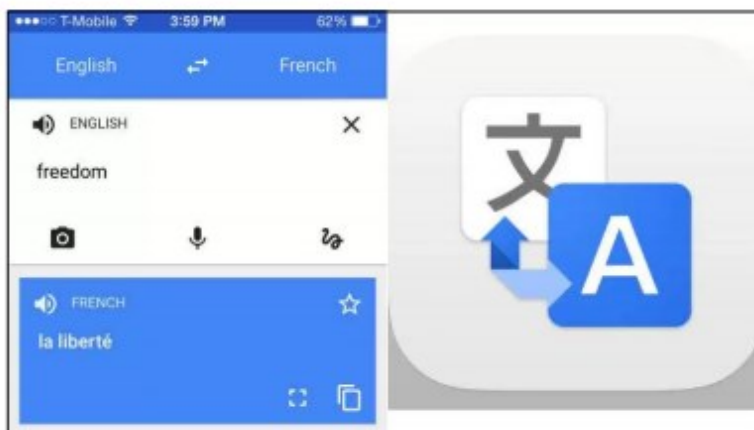
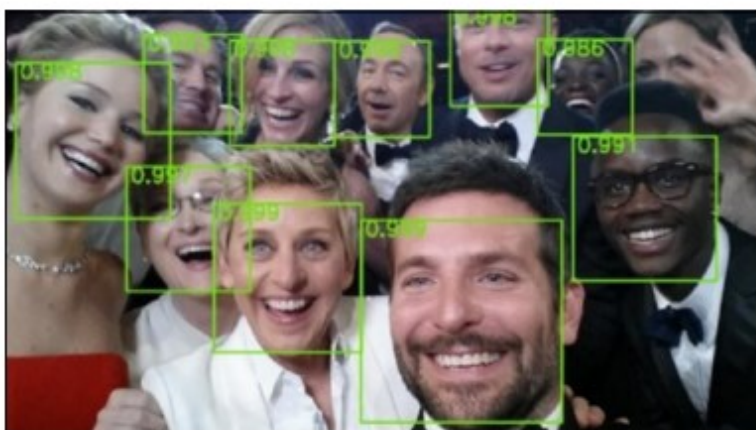
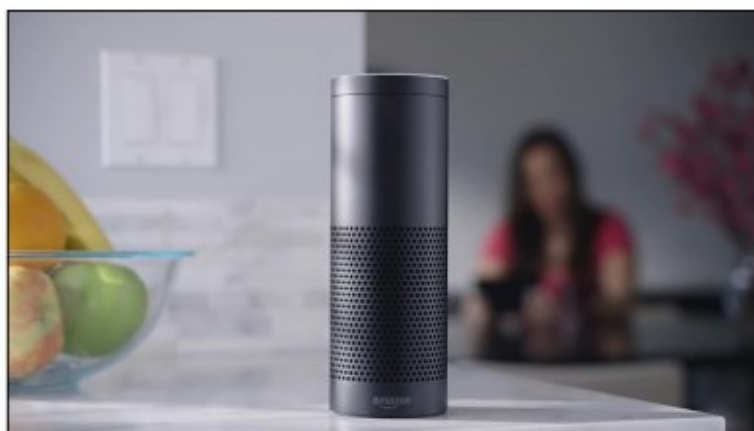
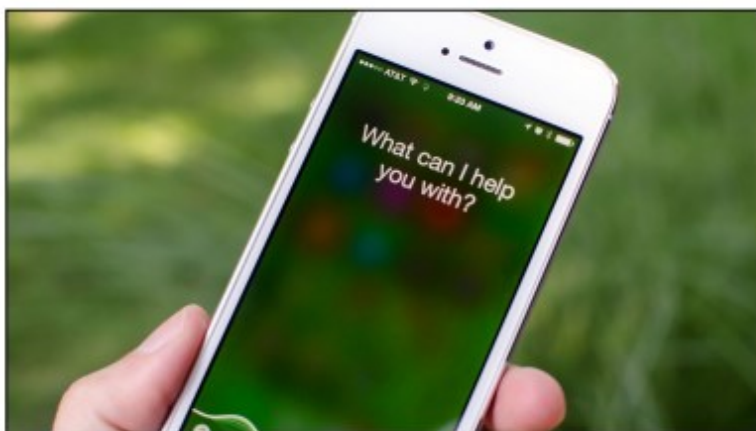
What is Artificial Intelligence?



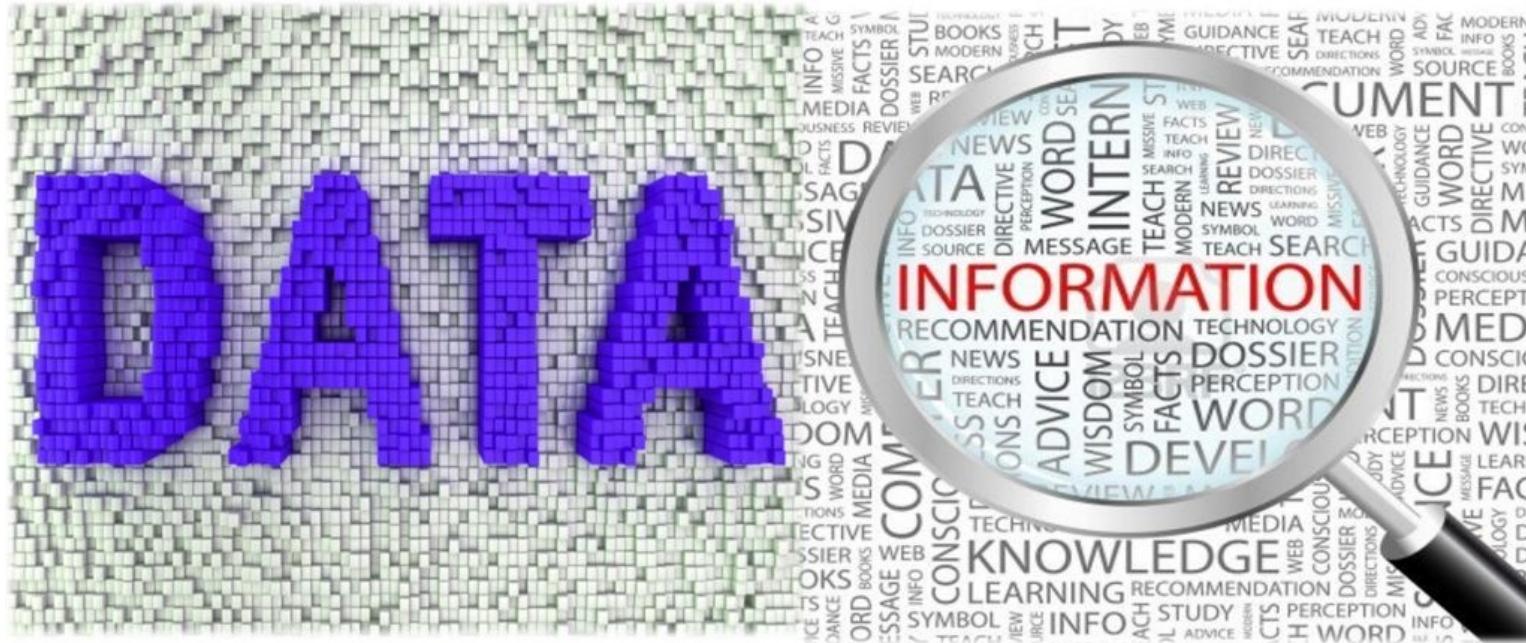
What is Artificial Intelligence?



Artificial Intelligence in everyday products



What is Data?

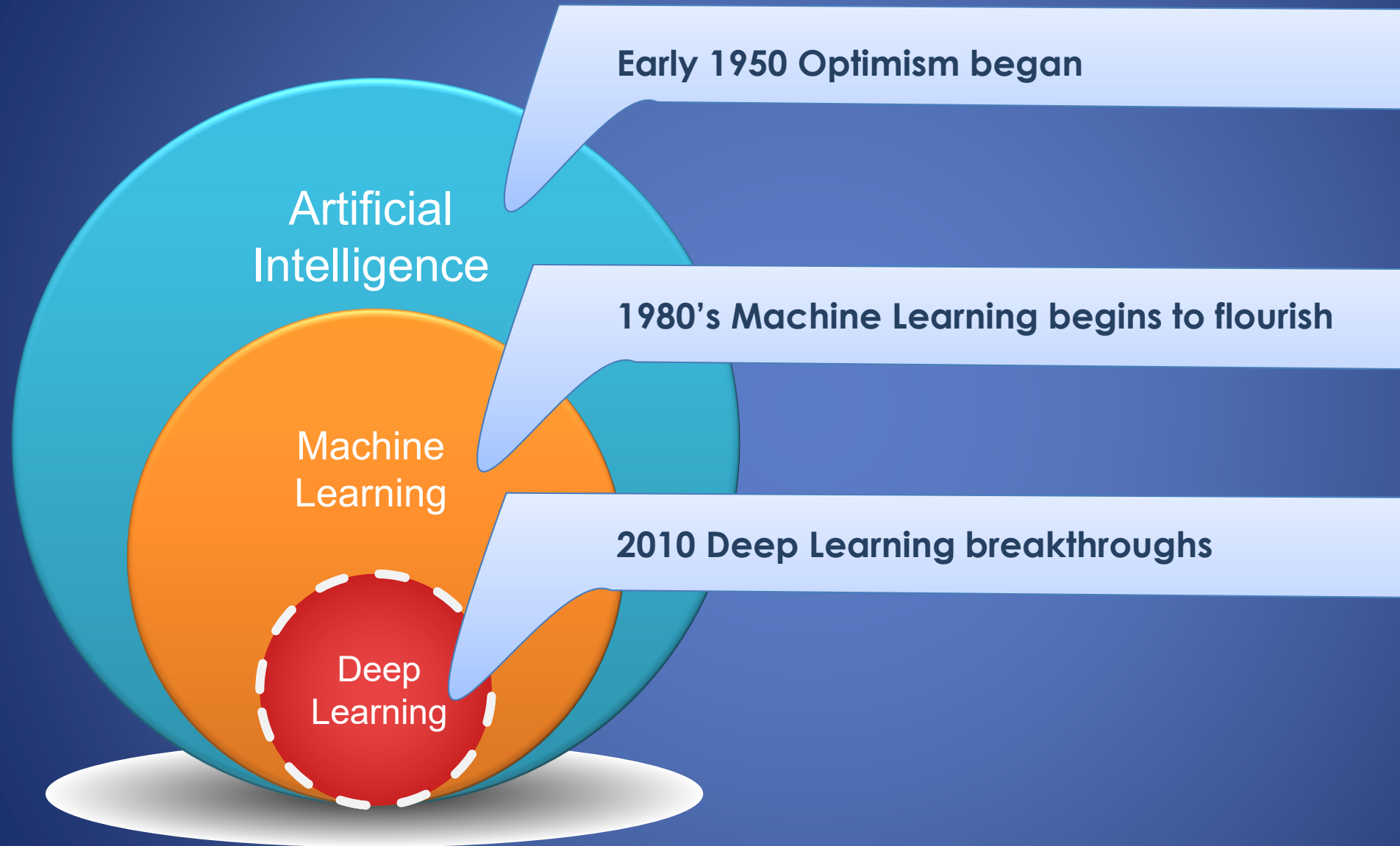


Structured

- Business Data, Excel, CSV

Unstructured

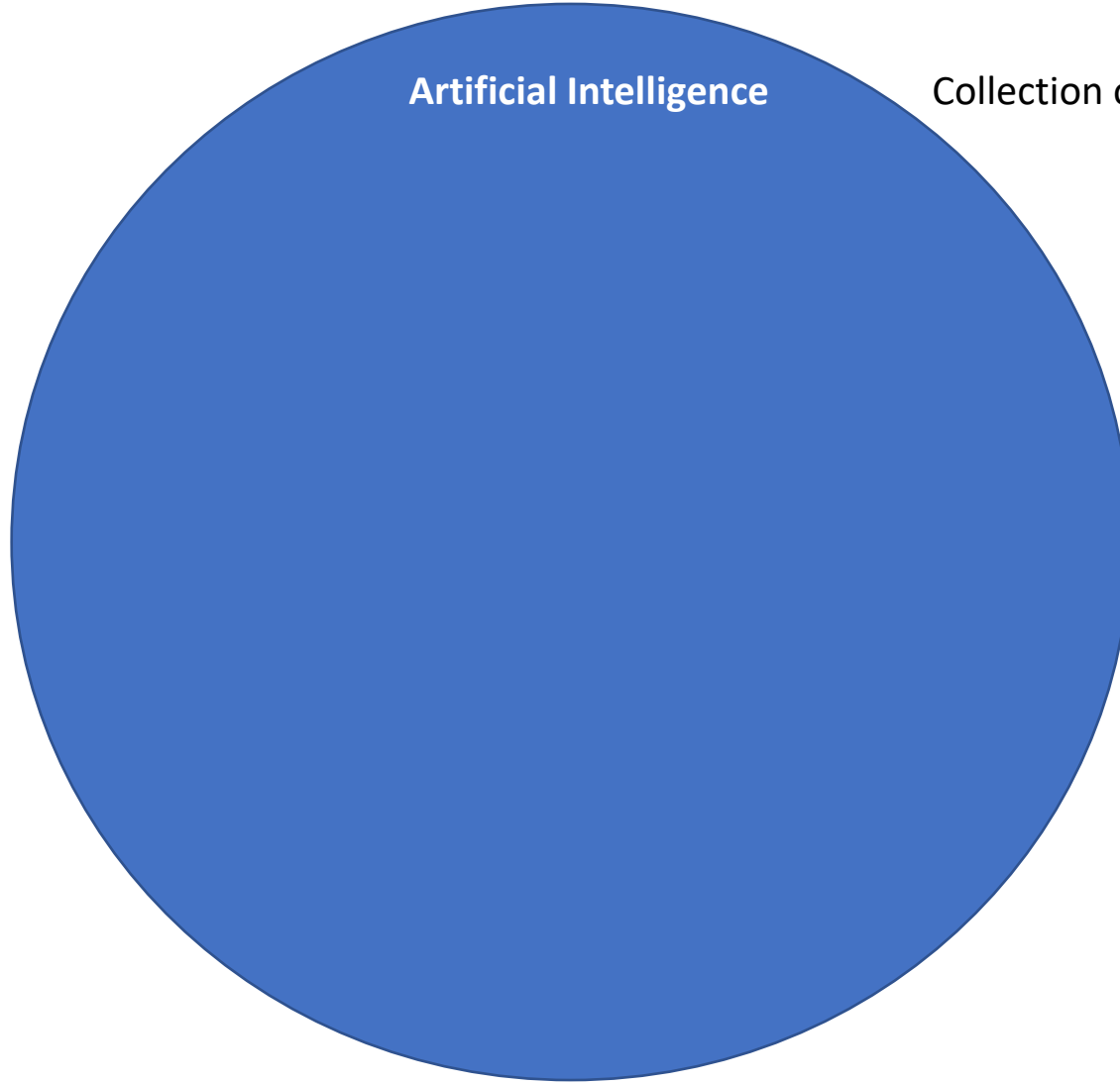
- Text, Images and Speech



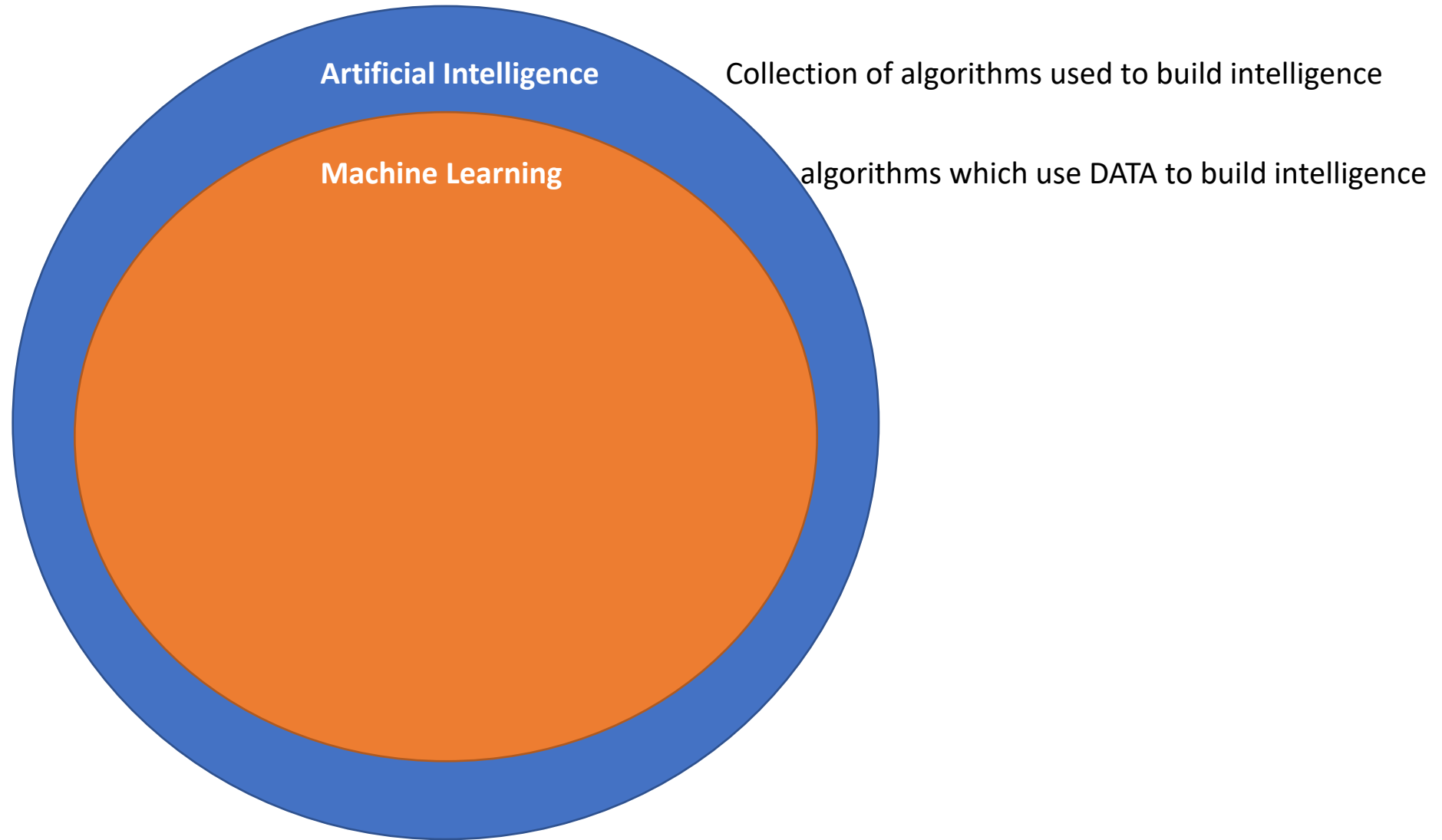
AI Landscape

Artificial Intelligence

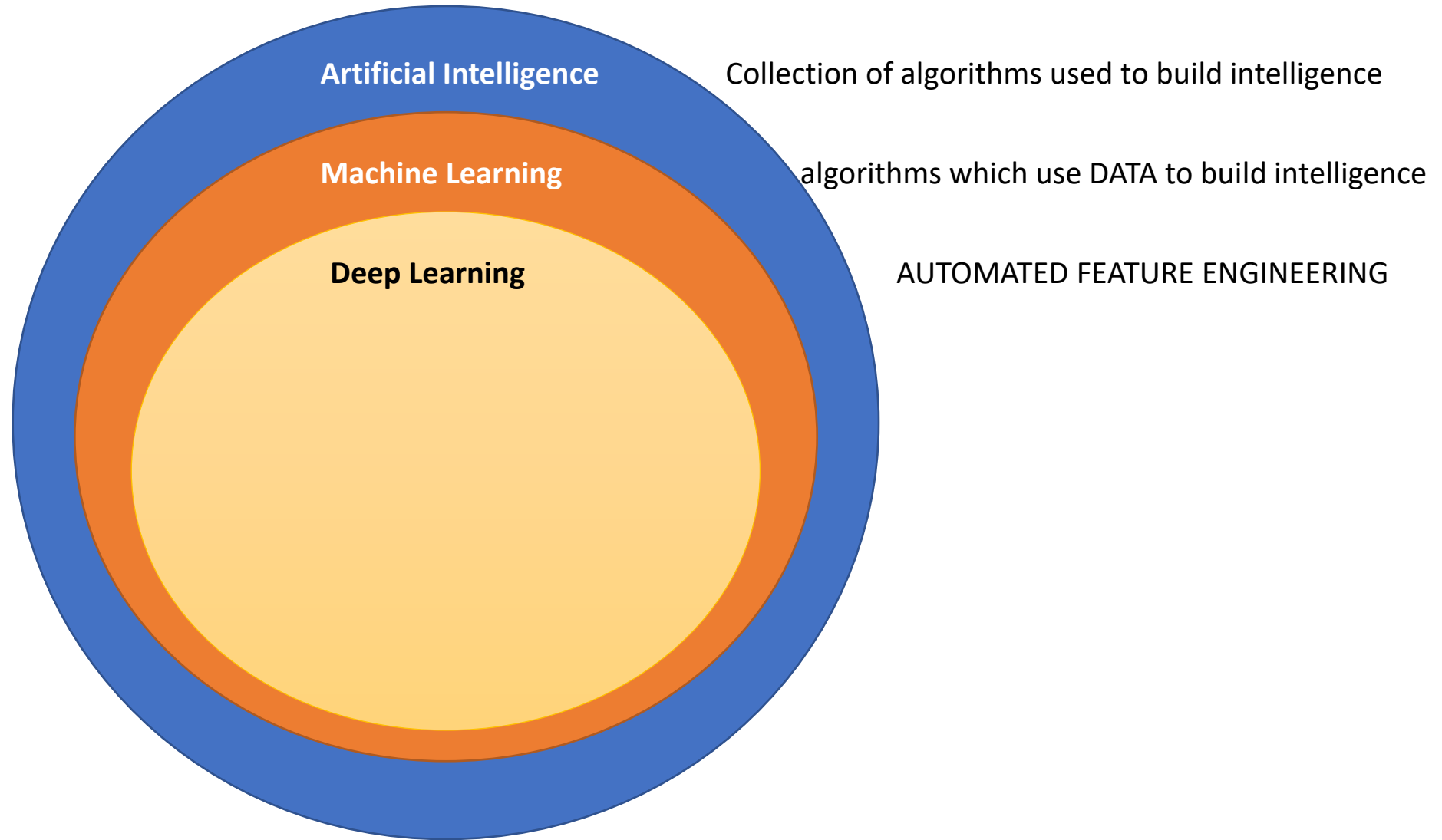
Collection of algorithms used to build intelligence



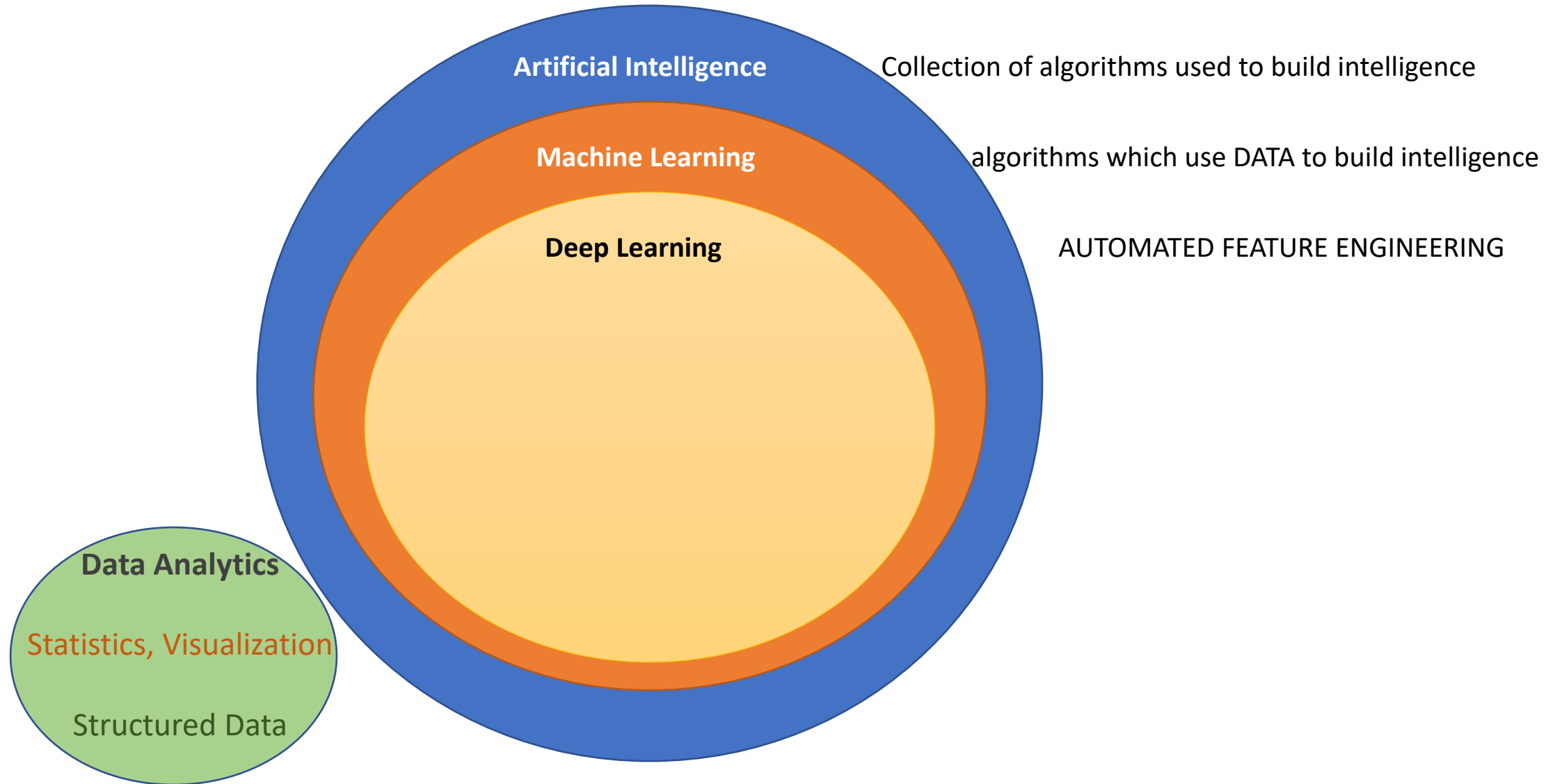
AI Landscape



AI Landscape

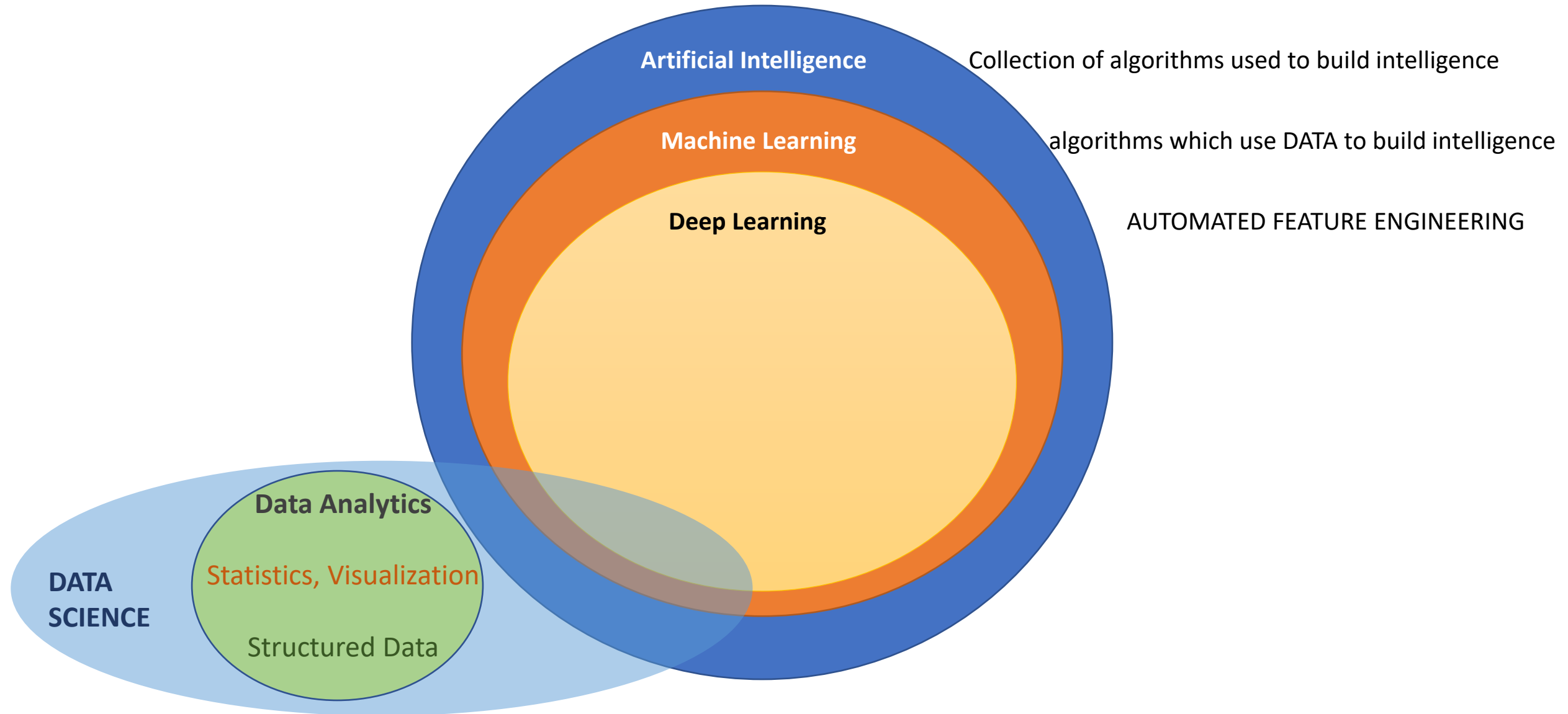


AI Landscape

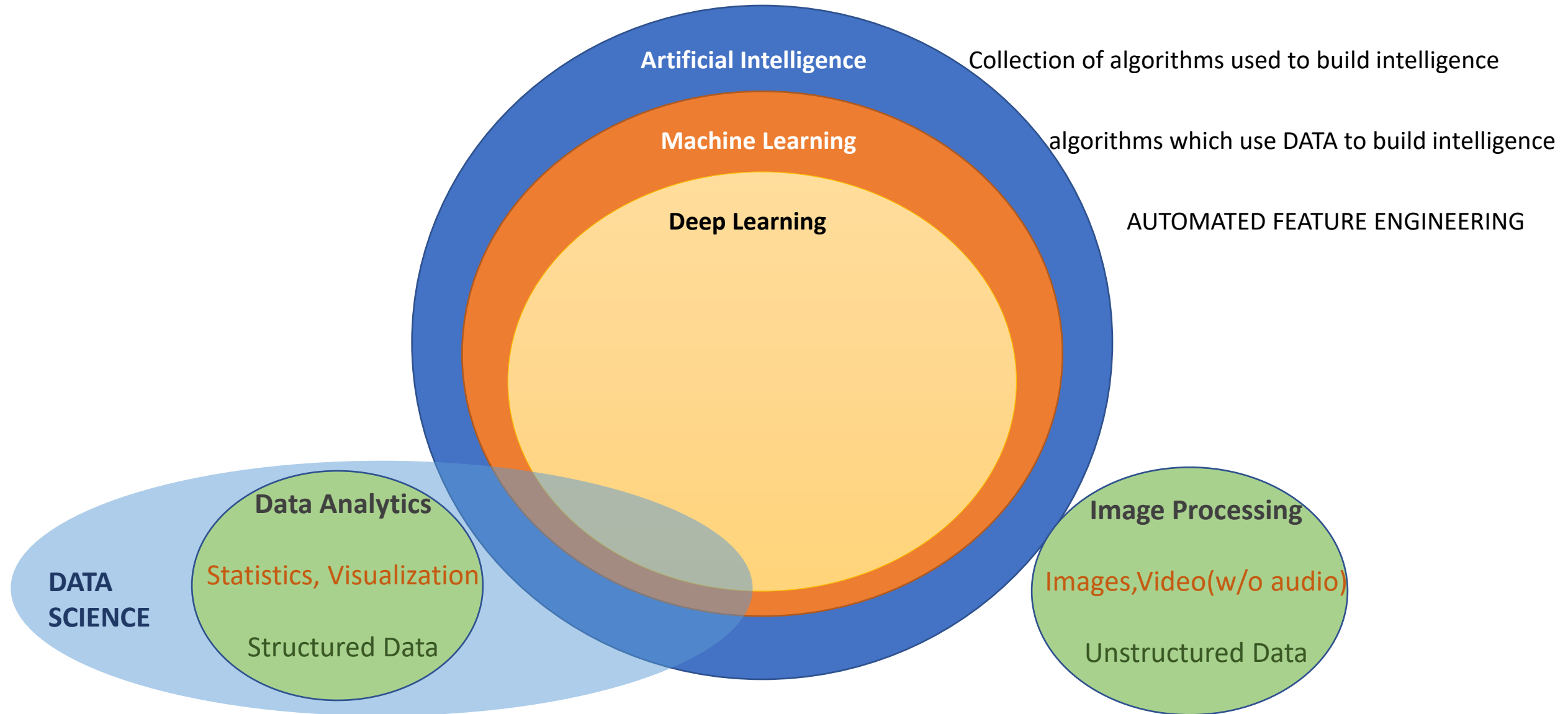


| | A | B | C | D | E | F | G | H | I | J | K | L | M | N |
|----|-----------|------------|---------------|-------------|-----------|--------|-----|--------|-----------|---------------|-----------|----------------|-----------------|--------|
| 1 | RowNumber | CustomerId | Surname | CreditScore | Geography | Gender | Age | Tenure | Balance | NumOfProducts | HasCrCard | IsActiveMember | EstimatedSalary | Exited |
| 2 | 1 | 15634602 | Hargrave | 619 | France | Female | 42 | 2 | 0 | 1 | 1 | 1 | 101348.88 | 1 |
| 3 | 2 | 15647311 | Hill | 608 | Spain | Female | 41 | 1 | 83807.86 | 1 | 0 | 1 | 112542.58 | 0 |
| 4 | 3 | 15619304 | Onio | 502 | France | Female | 42 | 8 | 159660.8 | 3 | 1 | 0 | 113931.57 | 1 |
| 5 | 4 | 15701354 | Boni | 699 | France | Female | 39 | 1 | 0 | 2 | 0 | 0 | 93826.63 | 0 |
| 6 | 5 | 15737888 | Mitchell | 850 | Spain | Female | 43 | 2 | 125510.82 | 1 | 1 | 1 | 79084.1 | 0 |
| 7 | 6 | 15574012 | Chu | 645 | Spain | Male | 44 | 8 | 113755.78 | 2 | 1 | 0 | 149756.71 | 1 |
| 8 | 7 | 15592531 | Bartlett | 822 | France | Male | 50 | 7 | 0 | 2 | 1 | 1 | 10062.8 | 0 |
| 9 | 8 | 15656148 | Obinna | 376 | Germany | Female | 29 | 4 | 115046.74 | 4 | 1 | 0 | 119346.88 | 1 |
| 10 | 9 | 15792365 | He | 501 | France | Male | 44 | 4 | 142051.07 | 2 | 0 | 1 | 74940.5 | 0 |
| 11 | 10 | 15592389 | H? | 684 | France | Male | 27 | 2 | 134603.88 | 1 | 1 | 1 | 71725.73 | 0 |
| 12 | 11 | 15767821 | Bearce | 528 | France | Male | 31 | 6 | 102016.72 | 2 | 0 | 0 | 80181.12 | 0 |
| 13 | 12 | 15737173 | Andrews | 497 | Spain | Male | 24 | 3 | 0 | 2 | 1 | 0 | 76390.01 | 0 |
| 14 | 13 | 15632264 | Kay | 476 | France | Female | 34 | 10 | 0 | 2 | 1 | 0 | 26260.98 | 0 |
| 15 | 14 | 15691483 | Chin | 549 | France | Female | 25 | 5 | 0 | 2 | 0 | 0 | 190857.79 | 0 |
| 16 | 15 | 15600882 | Scott | 635 | Spain | Female | 35 | 7 | 0 | 2 | 1 | 1 | 65951.65 | 0 |
| 17 | 16 | 15643966 | Goforth | 616 | Germany | Male | 45 | 3 | 143129.41 | 2 | 0 | 1 | 64327.26 | 0 |
| 18 | 17 | 15737452 | Romeo | 653 | Germany | Male | 58 | 1 | 132602.88 | 1 | 1 | 0 | 5097.67 | 1 |
| 19 | 18 | 15788218 | Henderson | 549 | Spain | Female | 24 | 9 | 0 | 2 | 1 | 1 | 14406.41 | 0 |
| 20 | 19 | 15661507 | Muldrow | 587 | Spain | Male | 45 | 6 | 0 | 1 | 0 | 0 | 158684.81 | 0 |
| 21 | 20 | 15568982 | Hao | 726 | France | Female | 24 | 6 | 0 | 2 | 1 | 1 | 54724.03 | 0 |
| 22 | 21 | 15577657 | McDonald | 732 | France | Male | 41 | 8 | 0 | 2 | 1 | 1 | 170886.17 | 0 |
| 23 | 22 | 15597945 | Dellucci | 636 | Spain | Female | 32 | 8 | 0 | 2 | 1 | 0 | 138555.46 | 0 |
| 24 | 23 | 15699309 | Gerasimov | 510 | Spain | Female | 38 | 4 | 0 | 1 | 1 | 0 | 118913.53 | 1 |
| 25 | 24 | 15725737 | Mosman | 669 | France | Male | 46 | 3 | 0 | 2 | 0 | 1 | 8487.75 | 0 |
| 26 | 25 | 15625047 | Yen | 846 | France | Female | 38 | 5 | 0 | 1 | 1 | 1 | 187616.16 | 0 |
| 27 | 26 | 15738191 | Maclean | 577 | France | Male | 25 | 3 | 0 | 2 | 0 | 1 | 124508.29 | 0 |
| 28 | 27 | 15736816 | Young | 756 | Germany | Male | 36 | 2 | 136815.64 | 1 | 1 | 1 | 170041.95 | 0 |
| 29 | 28 | 15700772 | Nebechi | 571 | France | Male | 44 | 9 | 0 | 2 | 0 | 0 | 38433.35 | 0 |
| 30 | 29 | 15728693 | McWilliams | 574 | Germany | Female | 43 | 3 | 141349.43 | 1 | 1 | 1 | 100187.43 | 0 |
| 31 | 30 | 15656300 | Lucciano | 411 | France | Male | 29 | 0 | 59697.17 | 2 | 1 | 1 | 53483.21 | 0 |
| 32 | 31 | 15589475 | Azikiwe | 591 | Spain | Female | 39 | 3 | 0 | 3 | 1 | 0 | 140469.38 | 1 |
| 33 | 32 | 15706552 | Odinakachukwu | 533 | France | Male | 36 | 7 | 85311.7 | 1 | 0 | 1 | 156731.91 | 0 |
| 34 | 33 | 15750181 | Sanderson | 553 | Germany | Male | 41 | 9 | 110112.54 | 2 | 0 | 0 | 81898.81 | 0 |
| 35 | 34 | 15659428 | Maggard | 520 | Spain | Female | 42 | 6 | 0 | 2 | 1 | 1 | 34410.55 | 0 |
| 36 | 35 | 15732963 | Clements | 722 | Spain | Female | 29 | 9 | 0 | 2 | 1 | 1 | 142033.07 | 0 |
| 37 | 36 | 15704171 | Lombardo | 475 | France | Female | 45 | 0 | 134364.04 | 1 | 1 | 0 | 27022.00 | 1 |

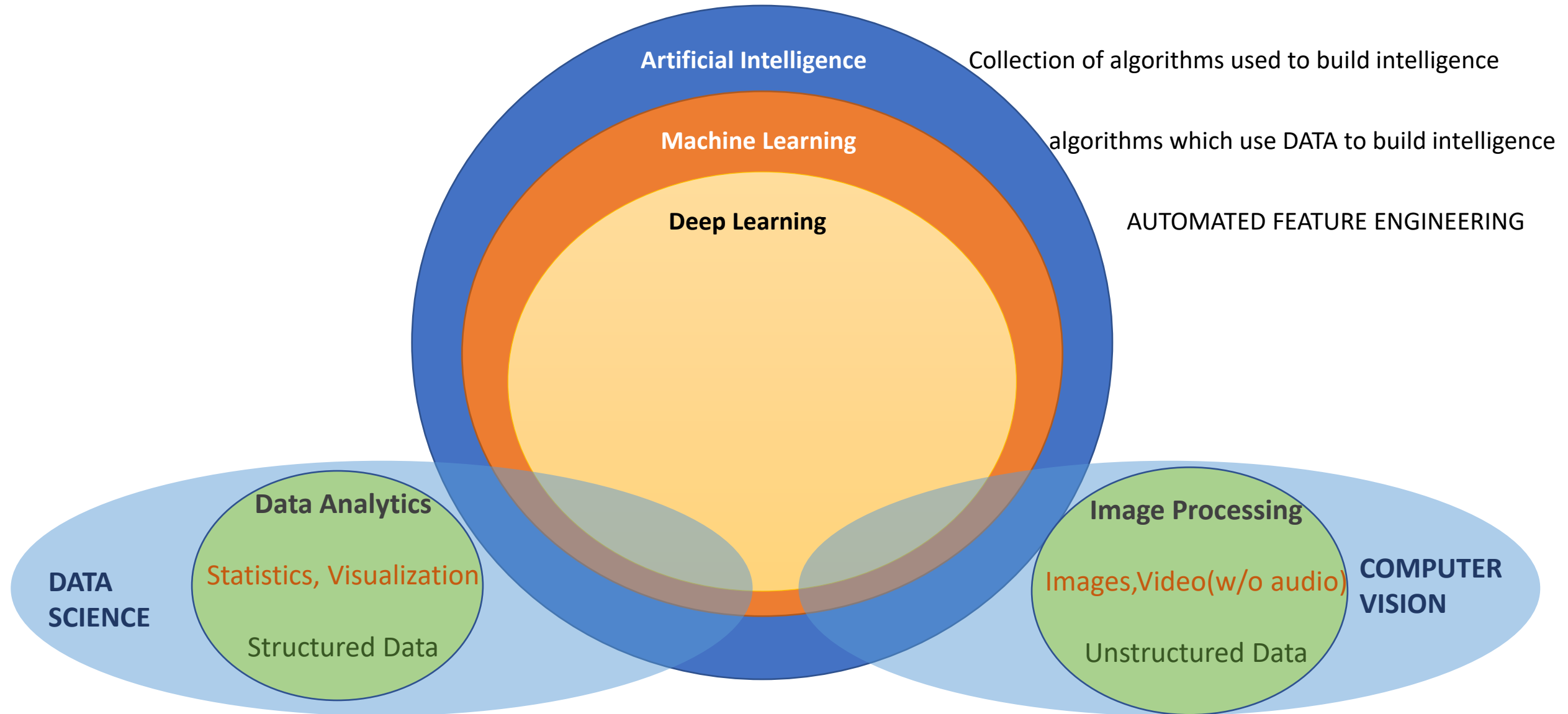
AI Landscape



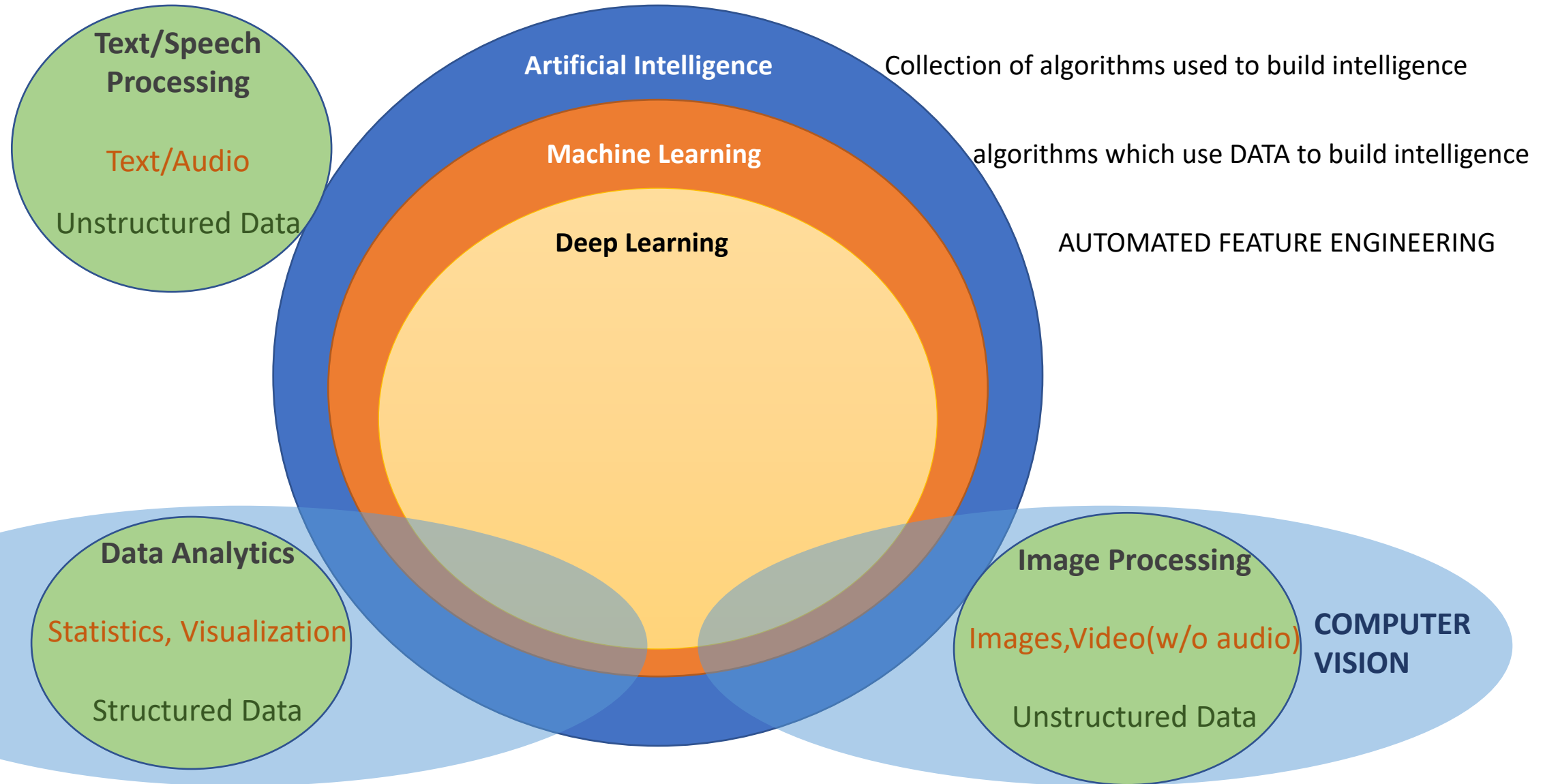
AI Landscape



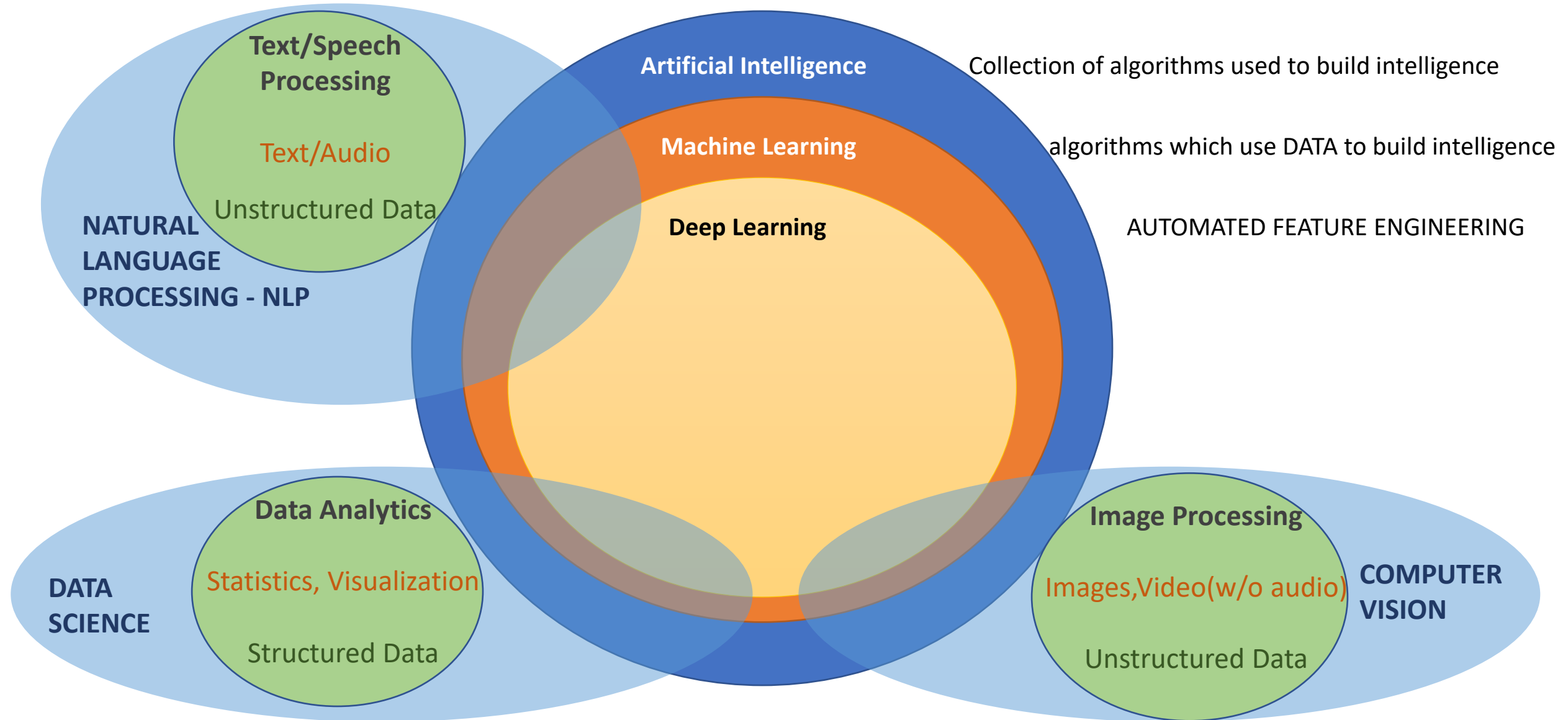
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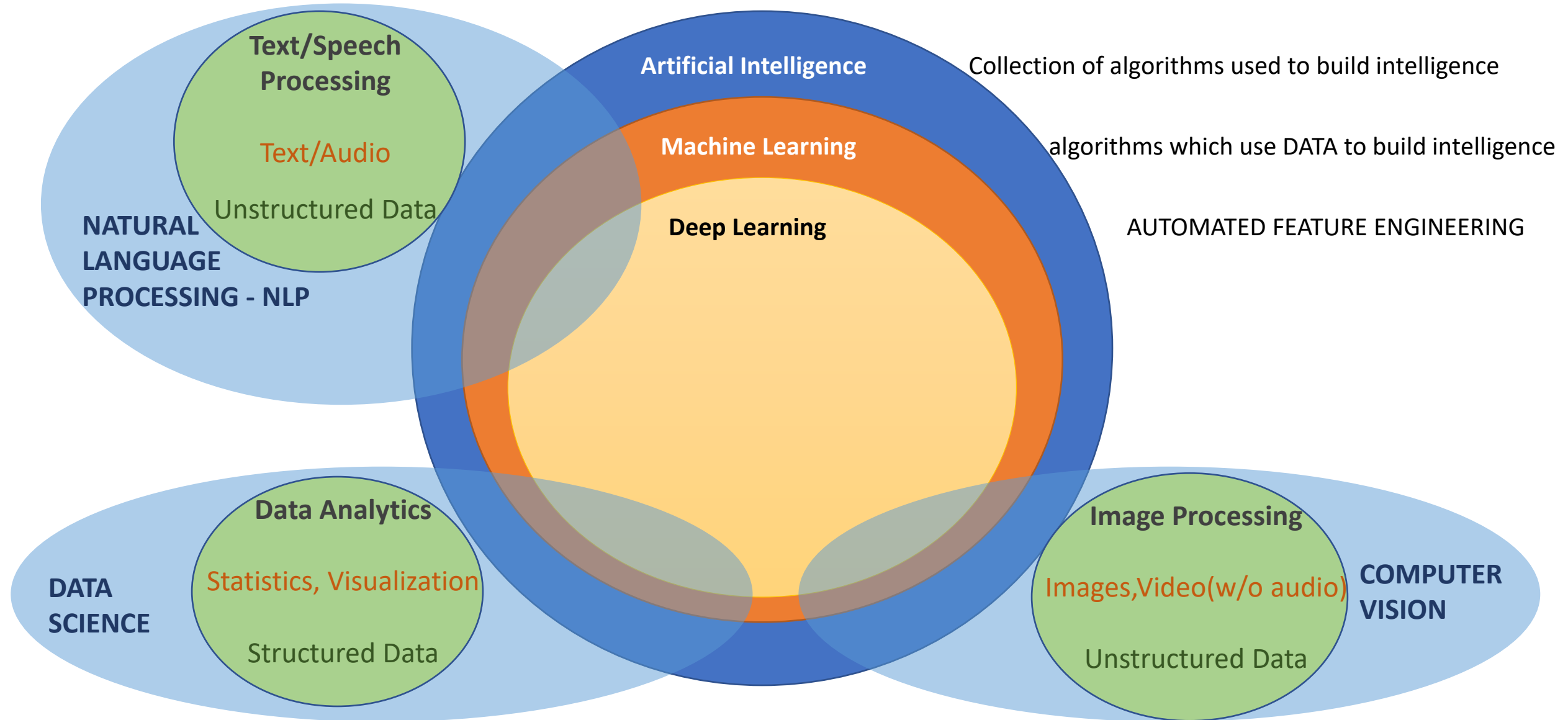
AI Landscape



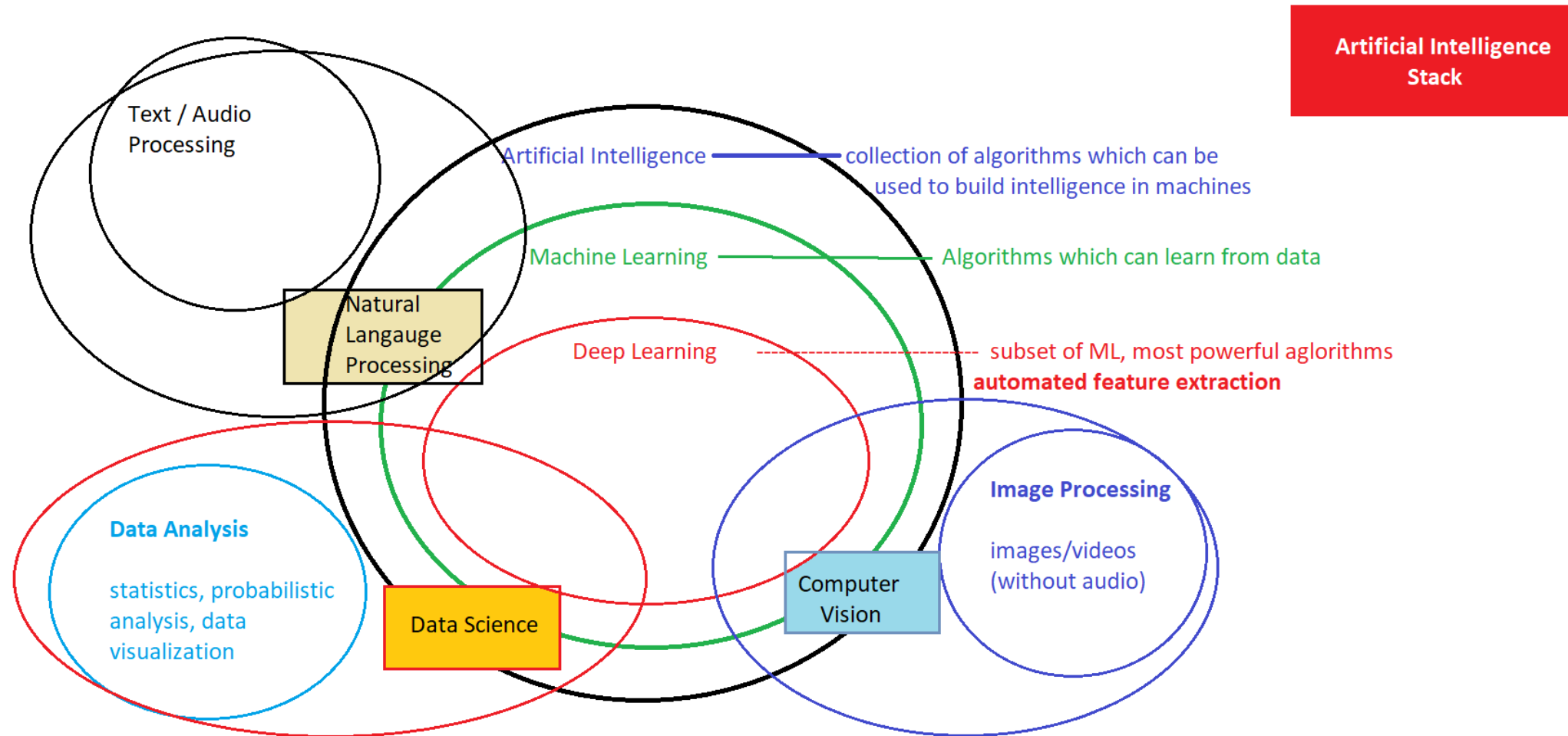
AI Landscape



AI Landscape



AI Stack



Artificial Intelligence

Data Science

Computer Vision

Natural Language
Processing

Artificial Intelligence

Data Science

- Predicting Stock prices, housing prices or any other item prices based on historical data
- Predicting whether customer will buy a product or not, customer will churn or not
- Classifying the customers in different known groups
- Risk predictions for financial transactions.
- Fraud Detection from transactional data
- Segmentation of customers, stocks and server logs
- Predicting patient readmission into hospital
- Detecting anomalies in access management, data control
- Building product recommendation systems

Computer Vision

Natural Language Processing

Artificial Intelligence

Data Science

Computer Vision

Natural Language
Processing

- Face Recognition, Emotion Recognition
- Optical Character Recognition
- Document verification, authentication
- Object Detection and Classification from images
- Identifying forgery in the images
- Vehicle number plate, type recognition
- Self Driving Cars – lane detection, traffic sign classification, Behavioural Cloning
- Motion Detection from videos
- Image restoration, colouring and pattern transfer
- Action Prediction

Artificial Intelligence

Data Science

Computer Vision

Natural Language
Processing

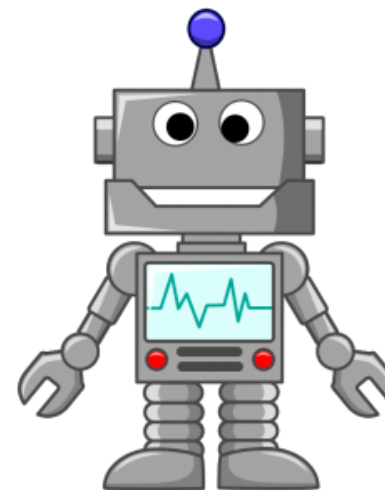
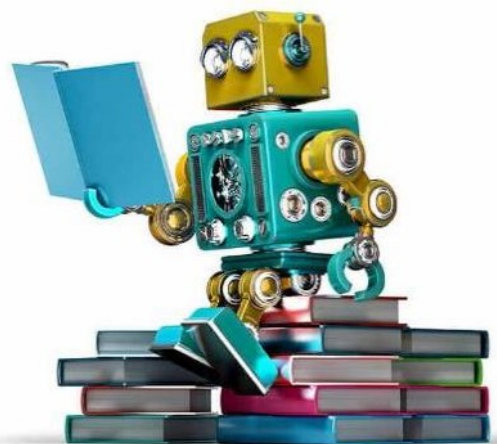
- Text/document classification
- Social Media Text mining and Analysis
- Speech to Text and Text to Speech conversion
- Caption generation
- Machine Translation
- Sentiment analysis from text
- Chatbots
- Speaker recognition
- Personal Assistant, Sentence Correction
- Text Generation, Similarity Matching, Topic Modelling

AN INTRODUCTION TO MACHINE LEARNING



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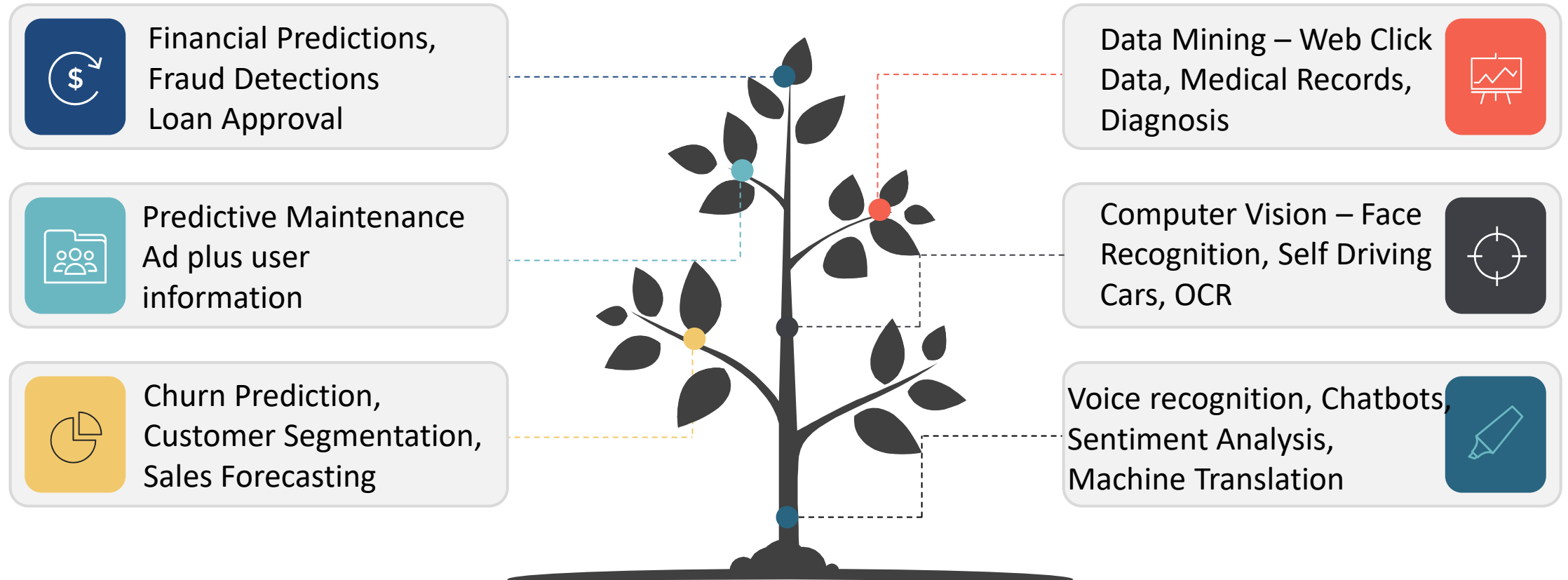




Machine learning is a field of computer science that gives computers the ability to learn without being explicitly programmed.

—Arthur Samuel, 1959

Applications of Machine Learning



What Machine Learning Can Do

A simple way to think about supervised learning.

| INPUT A | RESPONSE B | APPLICATION |
|--|------------------------------------|------------------------|
| Picture | Are there human faces? (0 or 1) | Photo tagging |
| Loan application | Will they repay the loan? (0 or 1) | Loan approvals |
| Ad plus user information | Will user click on ad? (0 or 1) | Targeted online ads |
| Audio clip | Transcript of audio clip | Speech recognition |
| English sentence | French sentence | Language translation |
| Sensors from hard disk, plane engine, etc. | Is it about to fail? | Preventive maintenance |
| Car camera and other sensors | Position of other cars | Self-driving cars |

Source – ANDREW NG



Point your camera at the menu during your next trip to Taiwan and the restaurant's selections will magically appear in English via the Google Translate app.

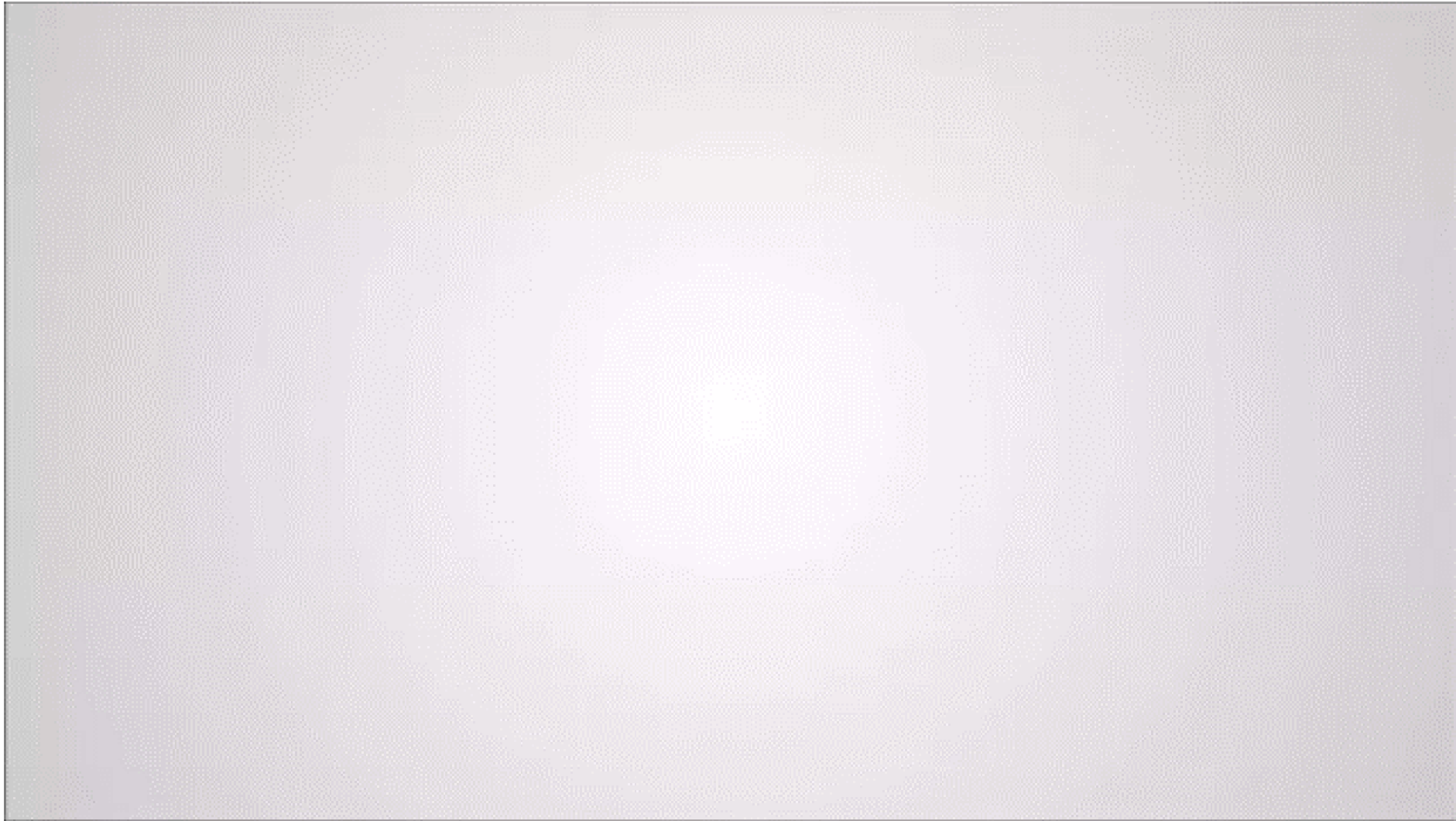
Google Translate overlaying English translations on a drink menu in real time using convolutional neural networks.



| Manufacturing | Retail | Financial Services |
|--|--|---|
| Predictive maintenance or condition monitoring Warranty reserve estimation Propensity to buy Demand forecasting Process optimization Telematics | Predictive inventory planning Recommendation engines Upsell and cross-channel marketing Market segmentation and targeting Customer ROI and lifetime value | Risk Analytics and Regulations Customer Segmentation Cross-selling and up-selling Sales and marketing campaign management Credit worthiness evaluation |
| Travel and Hospitality | Health Care and Life Sciences | Energy, Feedstock and Utility |
| Aircraft scheduling Dynamic pricing Social media — consumer feedback and interaction analysis Customer complaint resolution Traffic patterns and congestion management | Alerts and diagnostics from real-time patient data Disease identification and risk stratification Patient triage optimization Proactive health management Healthcare provider sentiment analysis | Power usage analytics Seismic data processing Carbon emissions and trading Customer-specific pricing Smart grid management Energy demand and supply optimization |

Netradyne

Netradyne's Driveri, a powerful camera that analyses driving patterns and can help determine the cause of an accident. The soap-bar-sized device is attached to a vehicle's rear-view mirror and rests on the inside of the windscreen, pointing towards the road.



Programming Languages -

Python

R

Machine Learning Cloud Platforms -

Microsoft Azure ML Studio

<https://azure.microsoft.com/en-us/services/machine-learning-studio/>

Amazon Machine Learning

<https://aws.amazon.com/ml/>

SAP Leonardo Machine Learning

<https://www.sap.com/india/products/leonardo/machine-learning.html>

Google ML Platform

<https://cloud.google.com/products/machine-learning/>

IBM Machine Learning

<https://www.ibm.com/analytics/data-science/machine-learning>



What to learn in machine Learning?

Programming and Tools

Python/R, spark etc.

30%

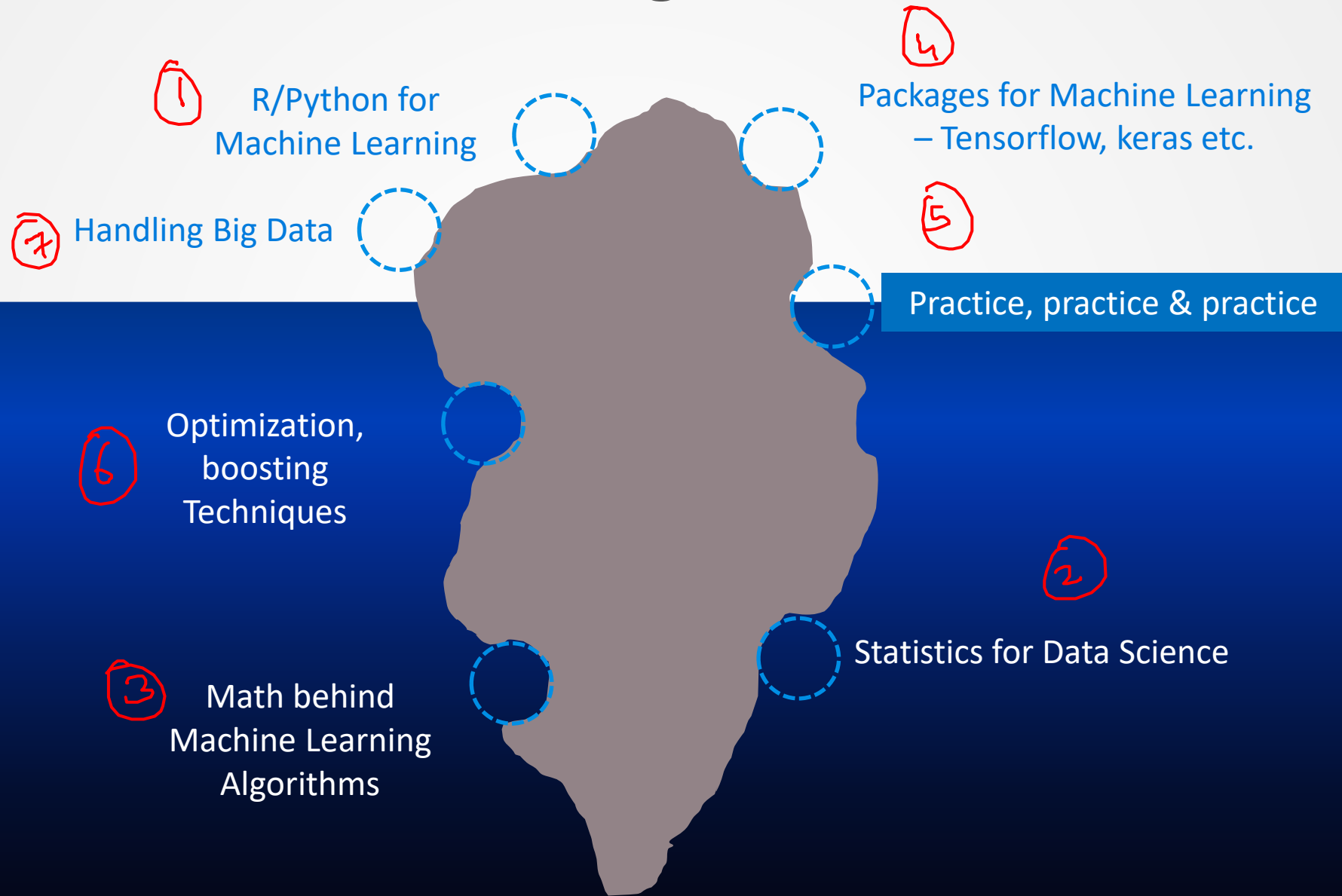
The Math behind Machine Learning

Probabilistic
Theory, Statistics
and Linear Algebra

70%



What to learn in Machine Learning?



Machine Learning Techniques

Supervised Learning

Learning with a labeled training set.
Email spam detector with training set of already labeled emails.

Unsupervised Learning

Discovering patterns in unlabeled data.
Cluster similar documents based on the text content.

Reinforcement Learning

Learning based on feedback or reward.
Learn to play chess by winning or losing.

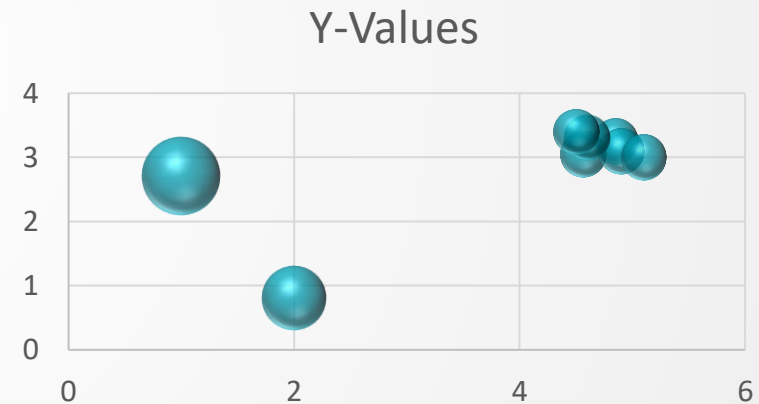
Supervised Learning

- We know what we are trying to predict. We use some examples that we (and the model) know the answer to, to “train” our model. It can then generate predictions to examples we don’t know the answer to.
- Examples: Predict the price a house will sell at. Identify the gender of someone based on a photograph.

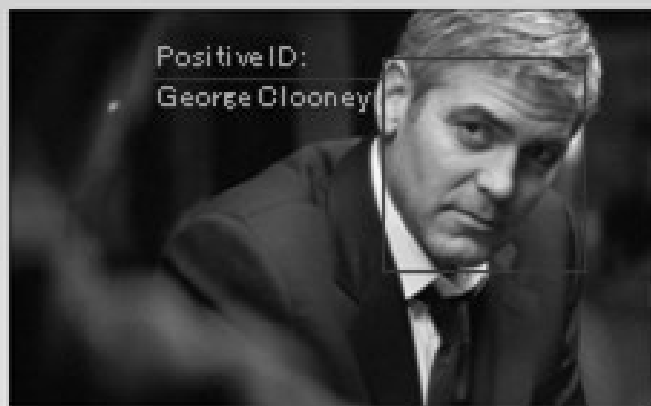


Unsupervised Learning

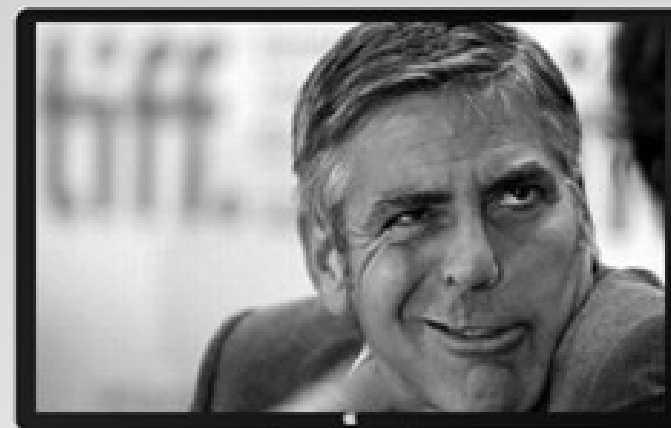
- We don't know what we are trying to predict. We are trying to identify some naturally occurring patterns in the data which may be informative.
- Examples: Try to identify “clusters” of customers based on data we have on them



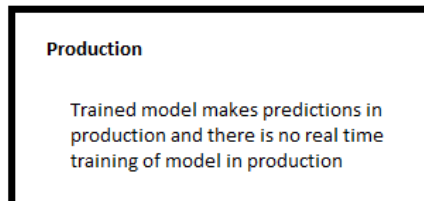
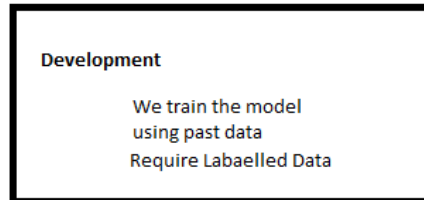
Supervised Learning



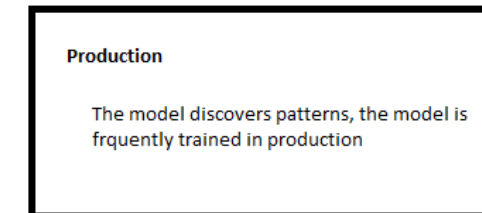
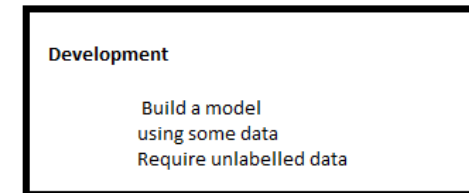
Unsupervised Learning



Supervised and Unsupervised Learning



**Supervised
Learning**



**Unsupervised
Learning**

Supervised Learning

Bank Churn Prediction

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Two class classification problem

New Customer $\begin{cases} 0 - \text{Not Leave the bank} \\ 1 - \text{leave the bank} \end{cases}$

Oct 2019 - accuracy = 95%

oct 2020 - accuracy = 70%

```
graph TD; Development --> Deployment; Deployment -- Pull Back --> Development; Deployment --> Redeployment;
```

Recognizing digits on vehicle number plates



0
1
2
3
.
.
.
8
9

2019 - Accuracy - 95%

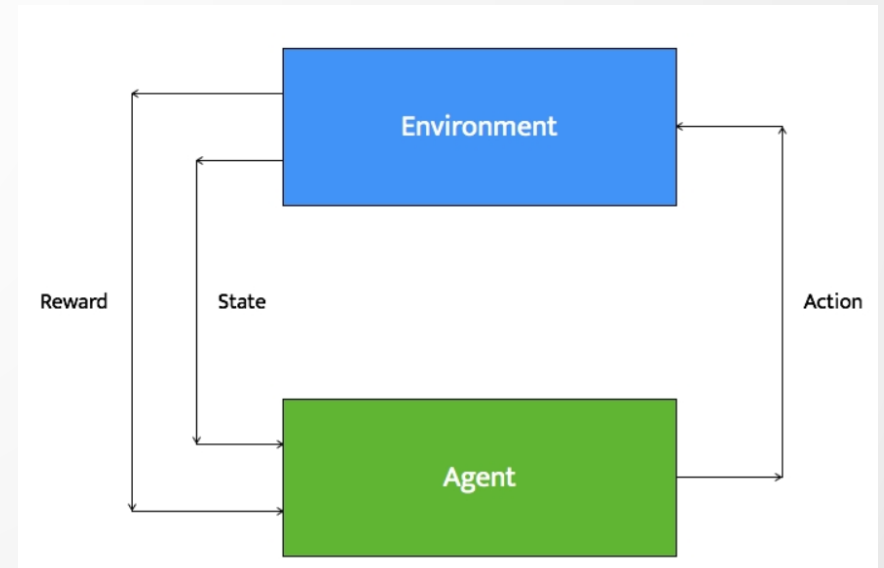
2025 - Accuracy - 95%

Development
↓
Deployment
↓
Forget

Supervised Learning models learn from labelled data, a trained model is deployed in production, but based on the dynamicness of business case, the trained model needs to be pulled back from production, retrained and redeployed.

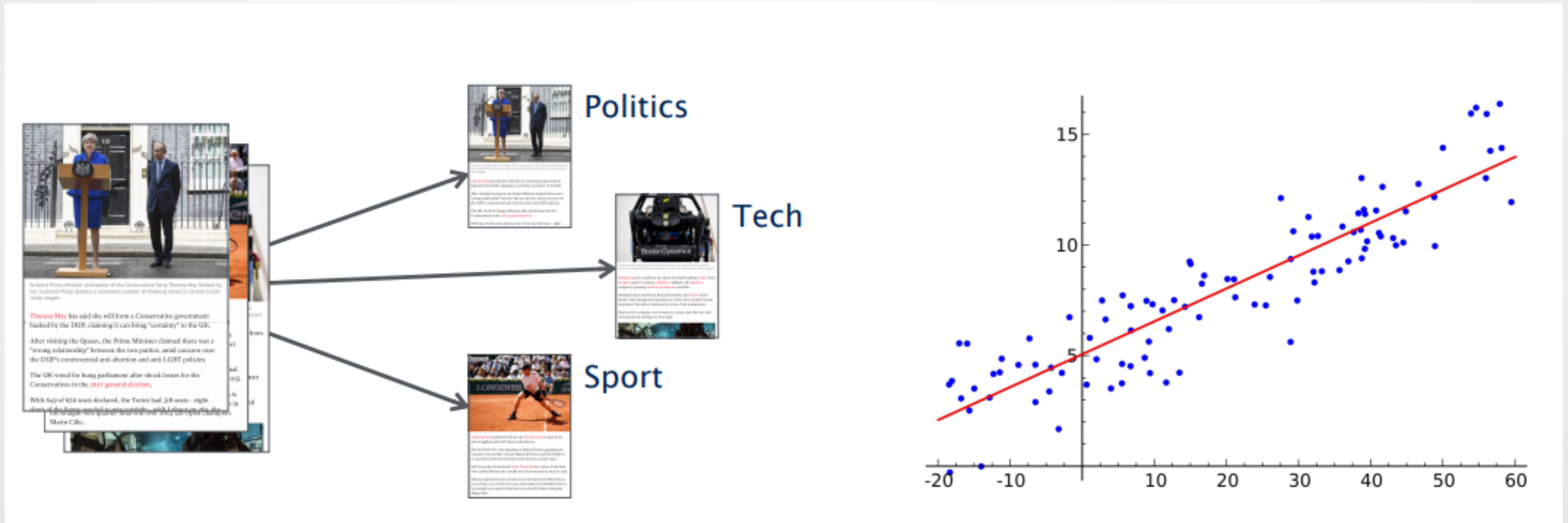
Reinforcement Learning

- Reinforcement learning systems can do multiple things simultaneously -- learn by performing a trial and error search, learn the model of the environment it is in, and then use that model to plan the next steps.
- Example: Let's consider a robot whose job is to explore a new building. It has to make sure it has enough power left to come back to the base station. This robot has to decide if it should make decisions by considering the trade off between the amount of information collected and the ability to reach back to base station safely.



Types of Problems in Machine Learning

Types of Problems in Supervised Machine Learning -



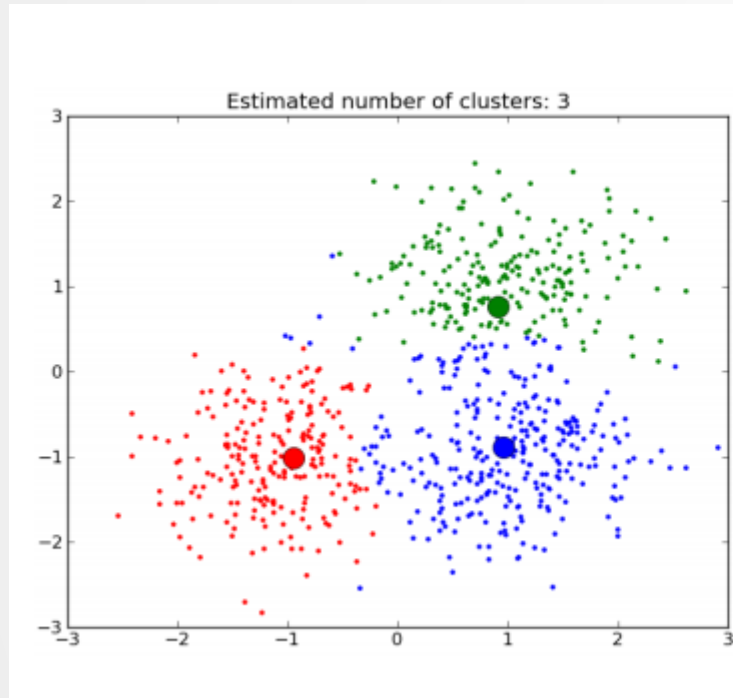
Classification

(discrete set of possible outcomes)

Regression

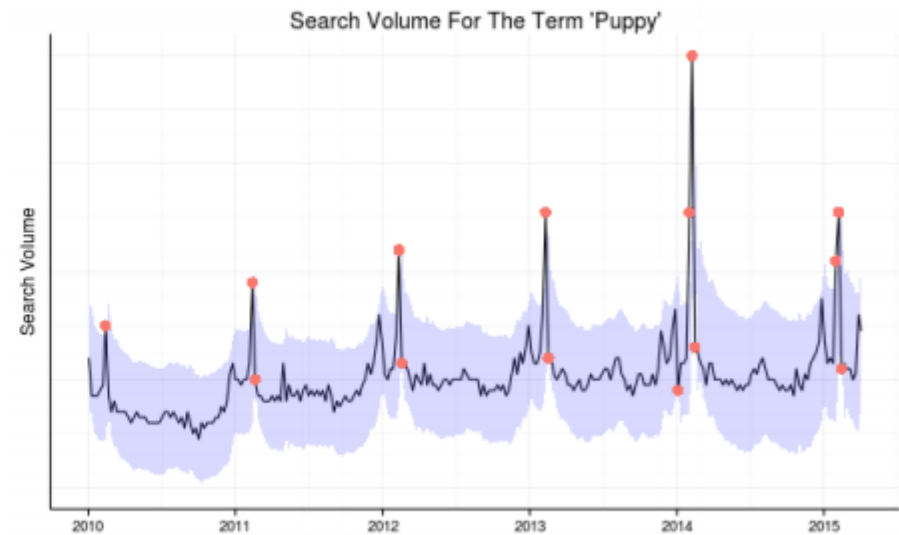
(possible outcome can be any numerical value within a particular continuous range)

Types of Problems in Unsupervised Machine Learning -



Clustering

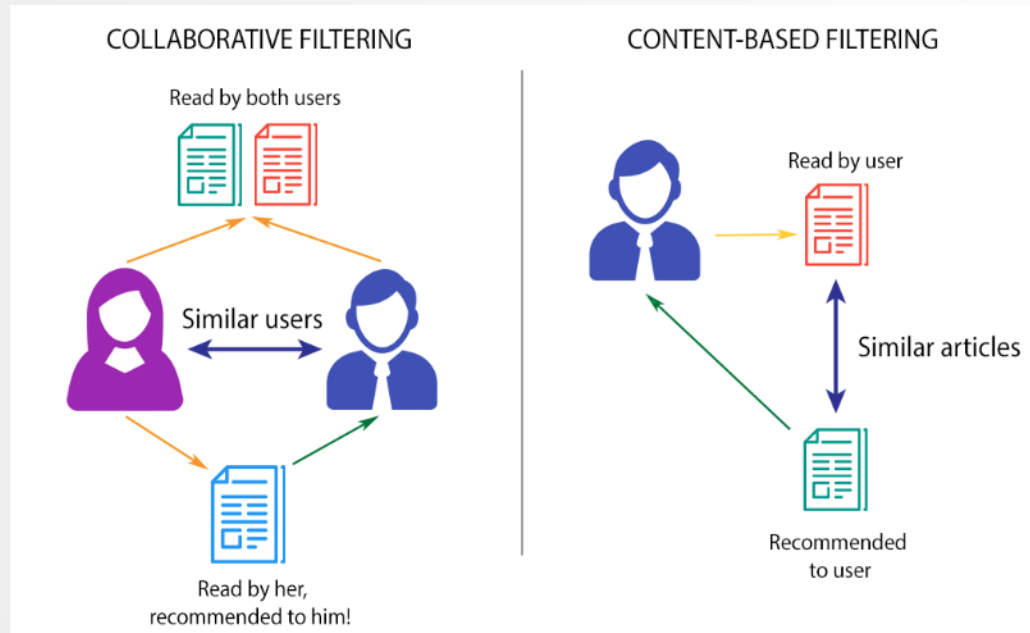
(categorization of samples based on similarity in features)



Anomaly Detection

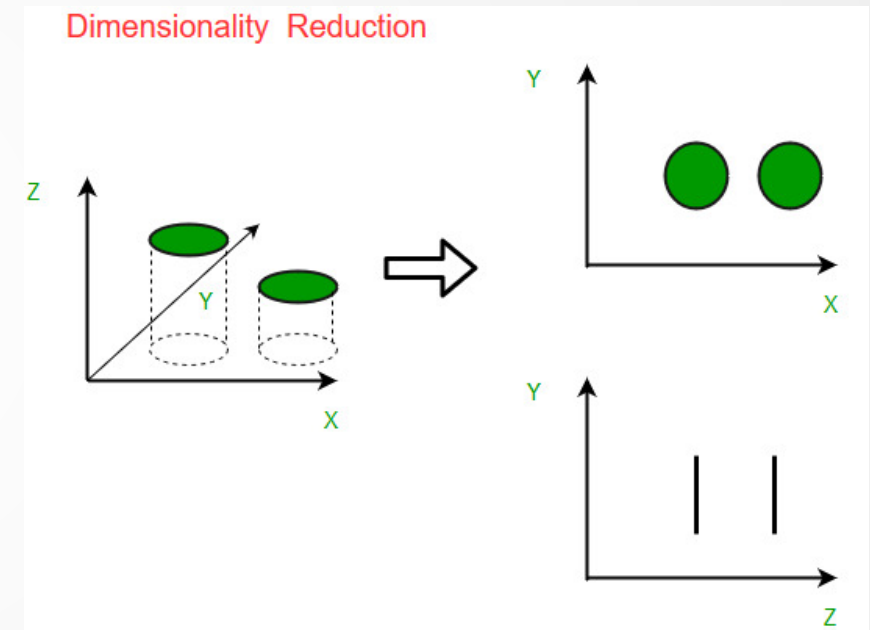
(detecting an anomaly in a general pattern)

Types of Problems in Unsupervised Machine Learning -



Recommendation Systems

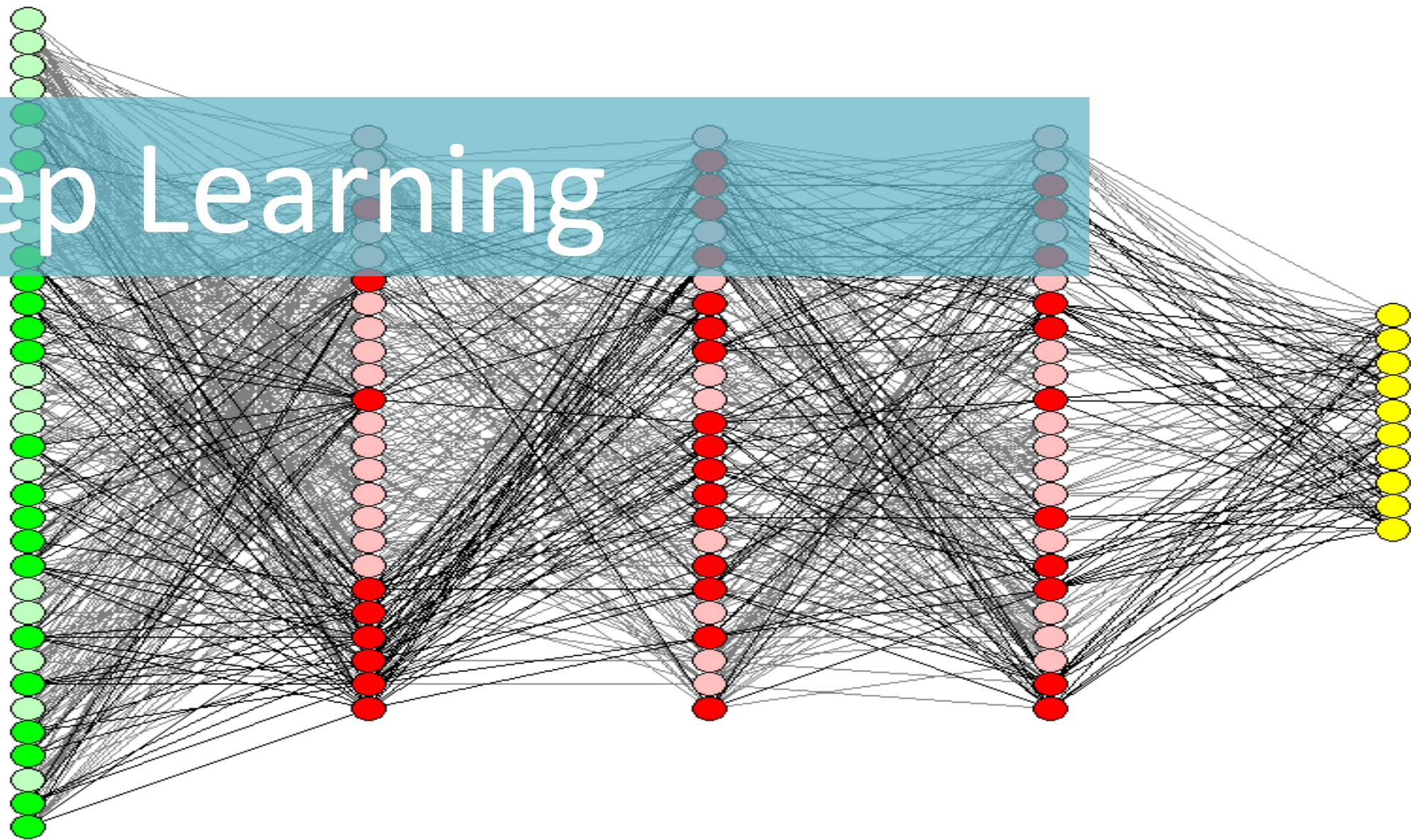
(profiling of users and items and recommending relevant items to user)



Dimensionality Reduction

(Reducing dimensionality/size of data)

Deep Learning



Deep Learning

Deep Learning is part of the machine learning field of learning representations of data. Exceptional effective at learning patterns.

Deep Learning in one slide

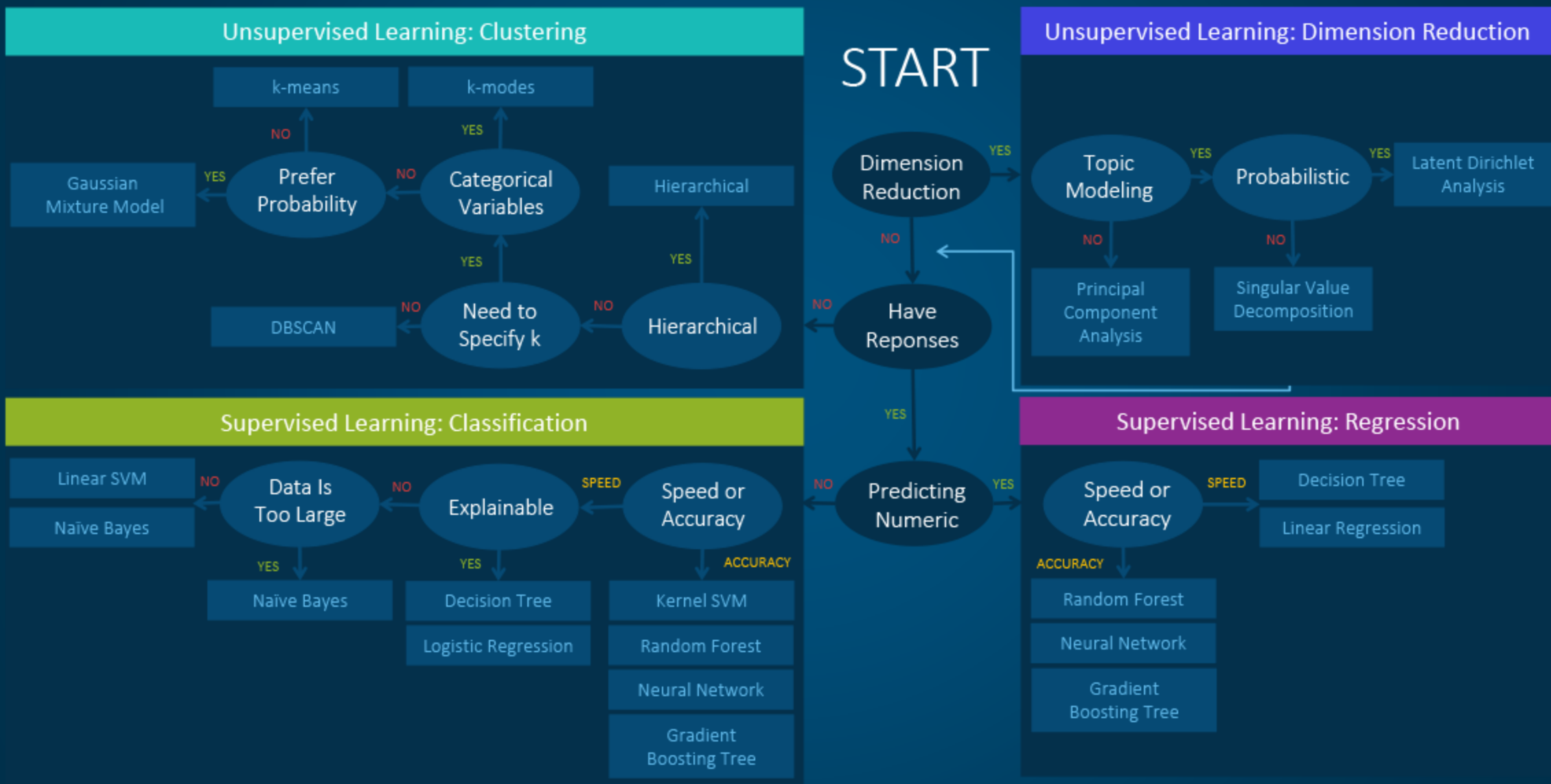
- **What is it:**
Extract useful patterns from data.
- **How:**
Neural network + optimization
- **How (Practical):**
Python + TensorFlow & friends
- **Hard Part:**
Good Questions + Good Data
- **Why now:**
Data, hardware, community, tools, investment
- **Where do we stand?**
Most big questions of intelligence have not been answered nor properly formulated
- **Exciting progress:**
 - Face recognition
 - Image classification
 - Speech recognition
 - Text to speech generation
 - Handwriting transcription
 - Machine translation
 - Medical diagnosis
 - Cars: drivable area, lane keeping
 - Digital assistants
 - Ads, search, social recommendations
 - Game playing with deep RL

What we can't do with Deep Learning?

- Mirrors
- Sparse information
- 3D Structure
- Physics
- What's on peoples' minds?
- What happens next?
- Humor



Machine Learning Algorithms Cheat Sheet





Happy Learning!

Stay Tuned for next exciting sessions on diving deeper into
Supervised Learning
