Artificial Intelligence (in Pharmacology)

Workshop 04 March 2022 Mathematical Modelling for Pharmacology University of Reading

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Workshop Questions?

Artificial Intelligence

- 1. What is it?
- 2. How is it done?
- 3. What has revolutionised it?
- 4. How to know it is working well?
- 5. Where is it in Pharmacology?

PART 1

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> What is it? 12:25 PM

Artificial Intelligence (AI)

to create intelligent machine that think (react) and act (work) like human beings

Alan Turing

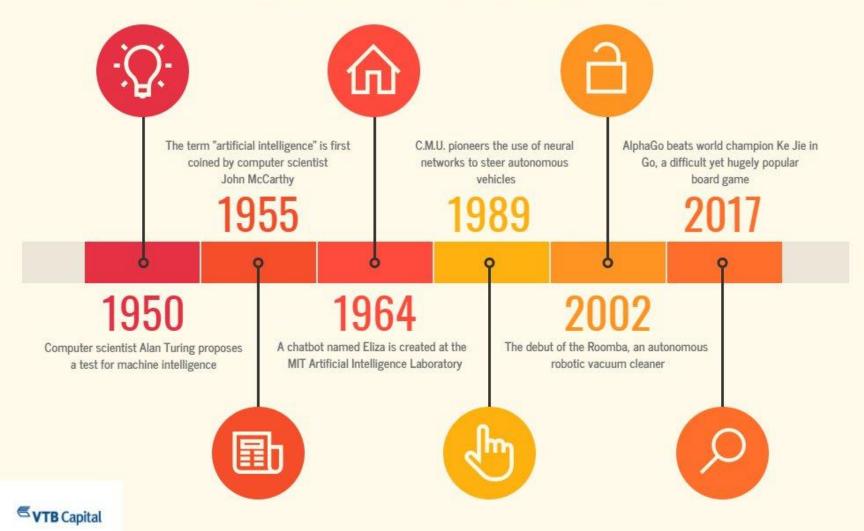
23 June 1912 – 7 June 1954

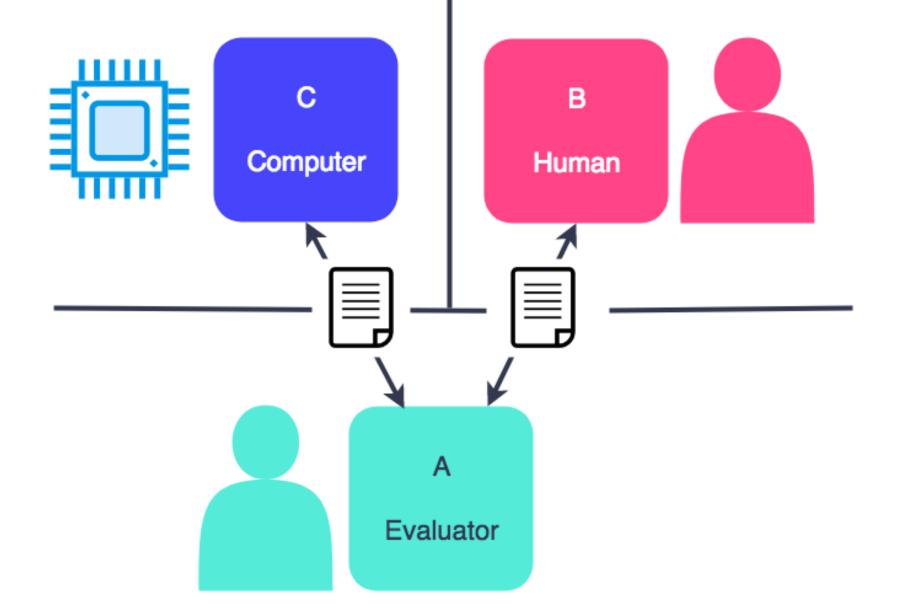
Consider as the Father of Computer Science and Artificial Intelligence



7 Decades of Artificial Intelligence History

Artificial Intelligence, or Al, is revolutionizing industries. Business executives, managers, and analysts worldwide see it as strategic priority in an ever shifting Information Age. Here is a timeline of six of Al's big moments.



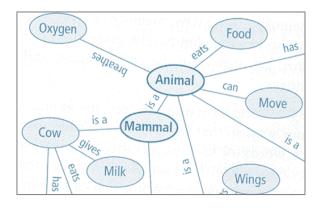


The **Turing test**

Al need to have:

natural language processing knowledge representation automated reasoning machine learning computer vision robotics logic

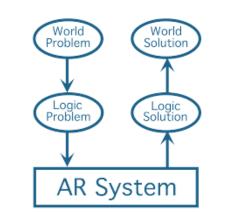
What Does AI Really Do?



Knowledge Representation



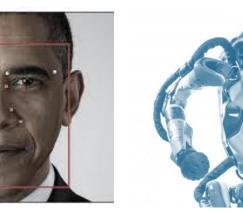
Natural language understanding





Planning

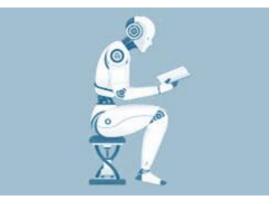
Automated reasoning



Machine vision

Robotics

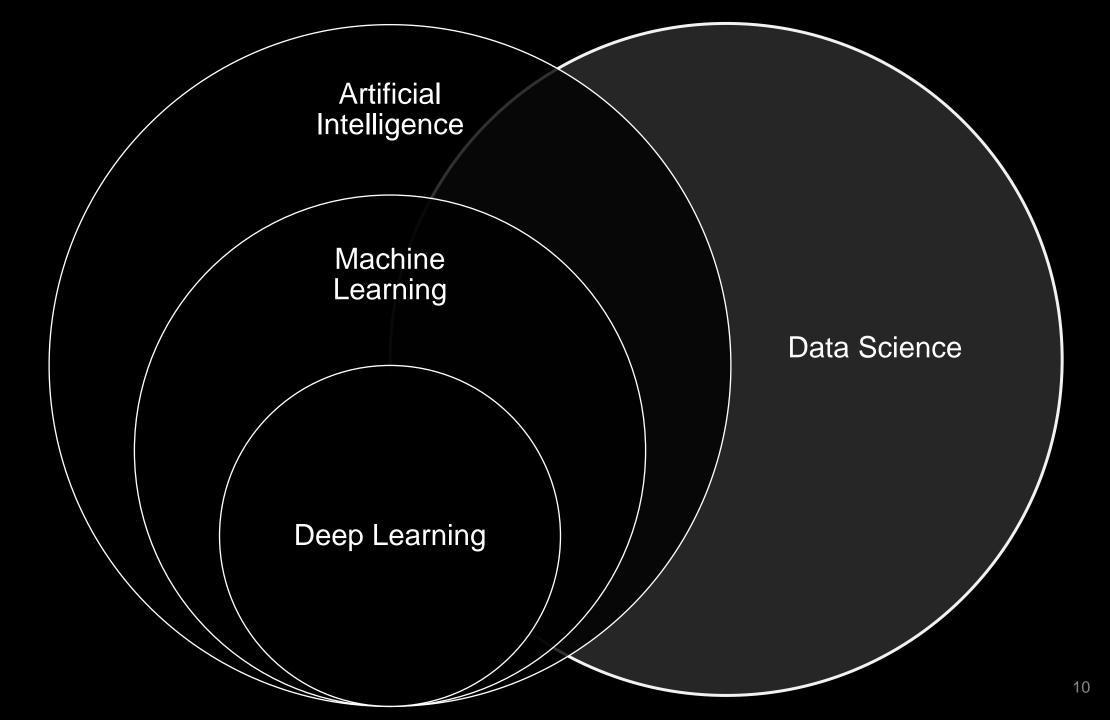
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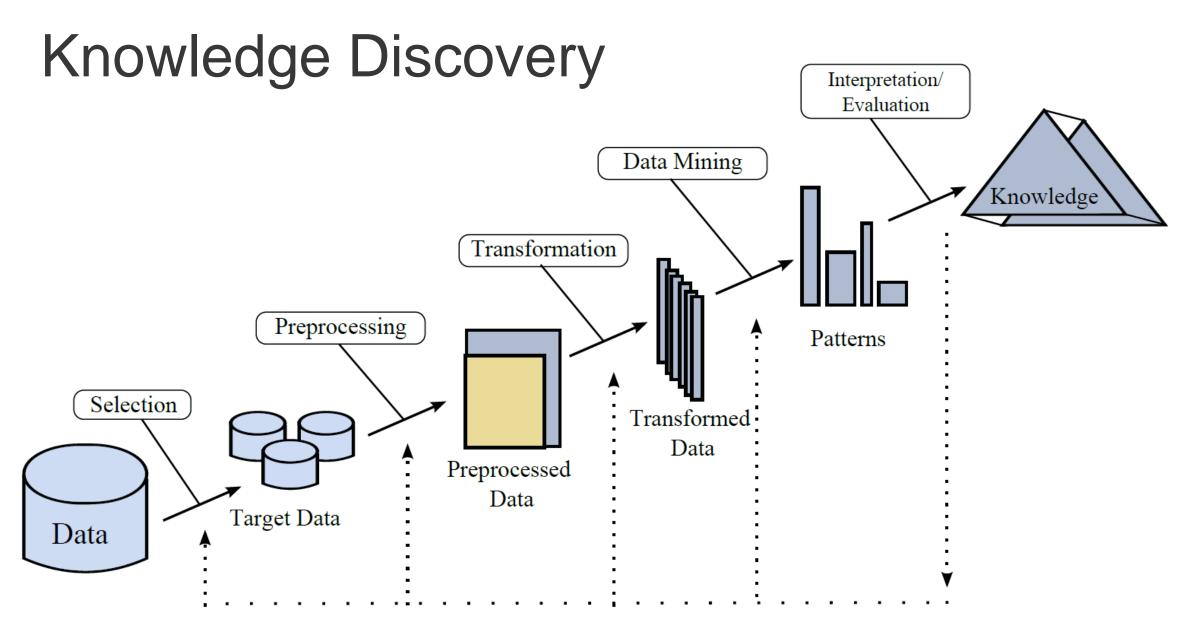


Machine Learning

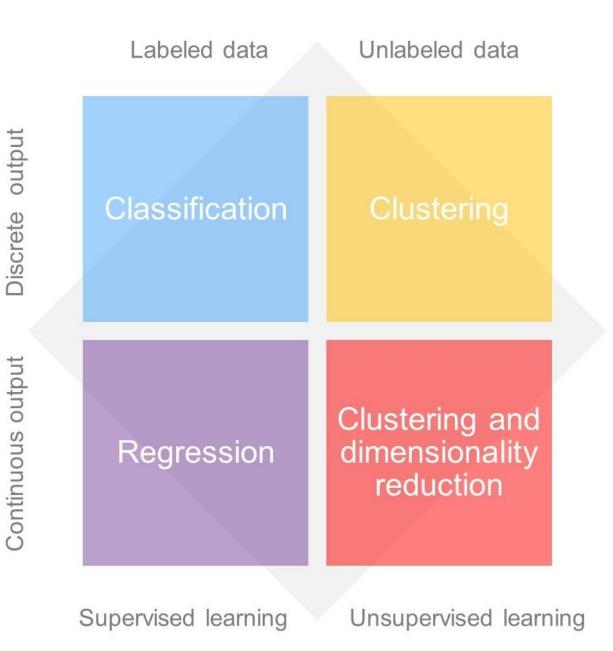
Google

Web Search



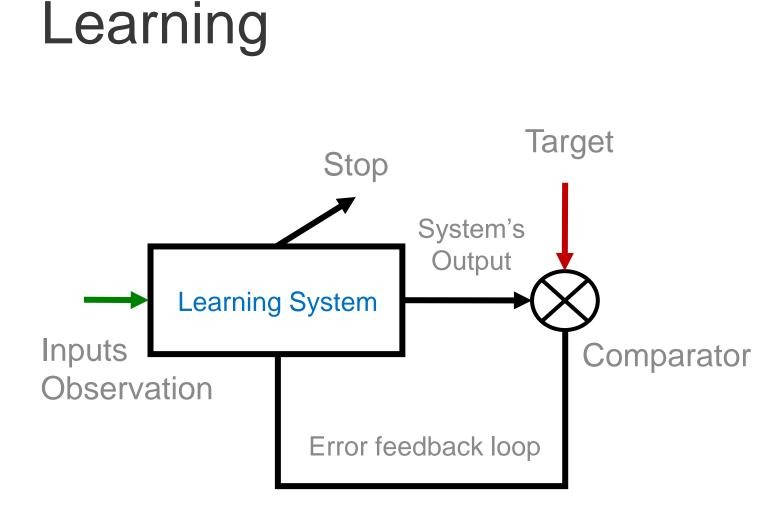


Paradigms of extracting Knowledge from data



Continuous output

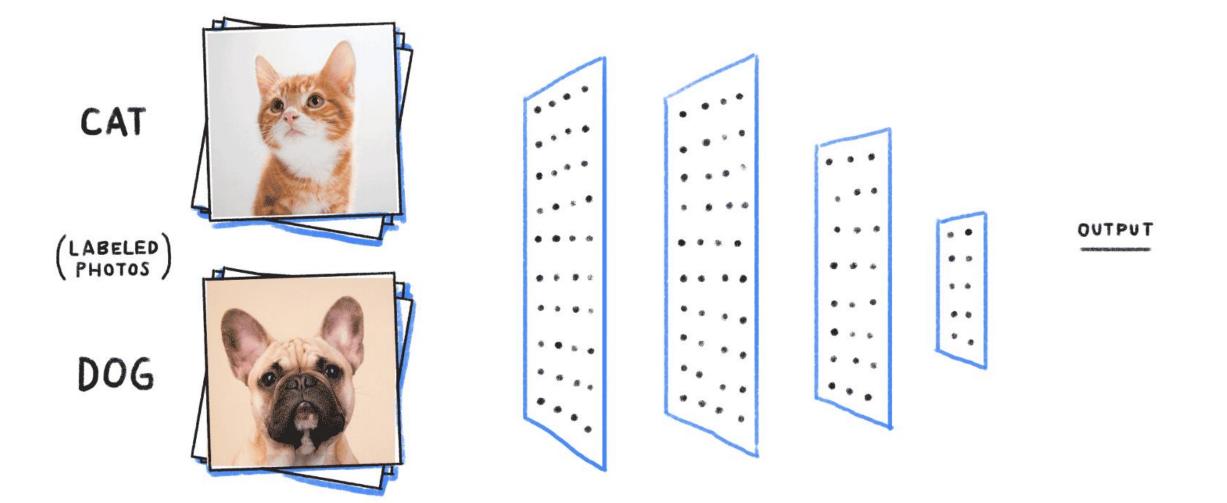
output



Learning Cycle:
Input (Continuous input)
Target (Known output)
Output (System's output)
Feedback Loop (Training
iteration)
Learning System (Model)
Stop (When to stop learning)

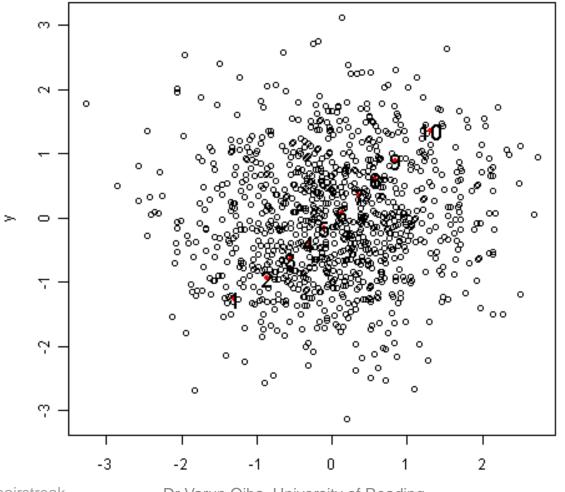
Supervised Learning

Source: https://becominghuman.ai/building-an-image-classifier-using-deep-learning-in-python-totally-from-a-beginners-perspective-be8dbaf22dd8



Unsupervised Learning

k-means cluster animation



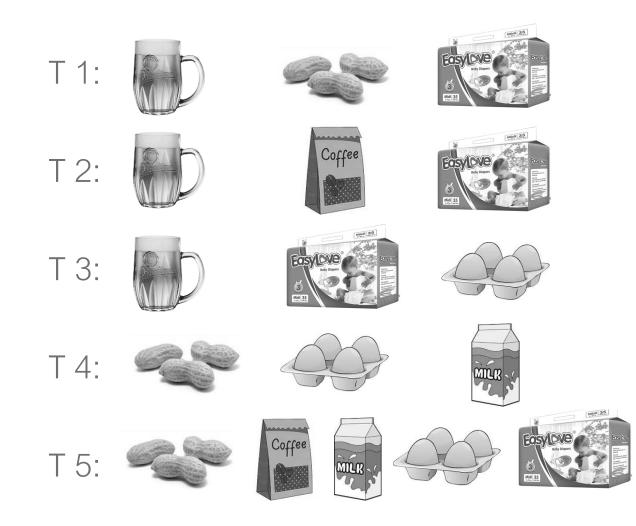
Source: https://gfycat.com/basicenchantinghairstreak

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initial

15

Product recommendation



Associated Rule Mining: to find frequent pattern (rule) in dataset. (The Impossible Correlation - 1992)

- **IF** someone buy an item X **THEN** what is the possibility that the person will by the item Y
 - So compute $X \rightarrow Y$ (Support, Confidence)
 - Support: The probability that transaction contain both X and Y
 - Confidence: The conditional probability that the transaction containing X also contain Y.
 - $\bullet \qquad \text{Beer} \rightarrow \text{Diapers (60\%, 100\%)}$
 - Diapers \rightarrow Beer (60%, 75%)

Fraud Detection

Detect unusual transaction

1234 56 9012 3456 CARDHIER 6/15 NAME

Image source: https://goo.gl/images/kUzUho

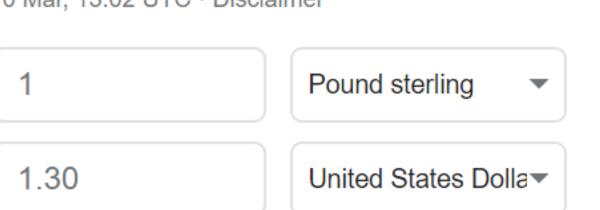
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Trend/ Forecast

1 Pound sterling equals

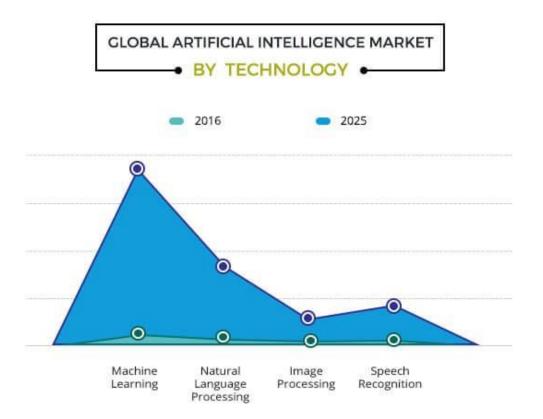
1.30 United States Dollar

10 Mar, 13:02 UTC · Disclaimer





Which AI will be used most



MACHINE LEARNING is projected as one of the most lucrative segments.

Source: https://www.alliedmarketresearch.com/artificial-intelligence-market

PART 2 Artificial Intelligence (in Pharmacology)

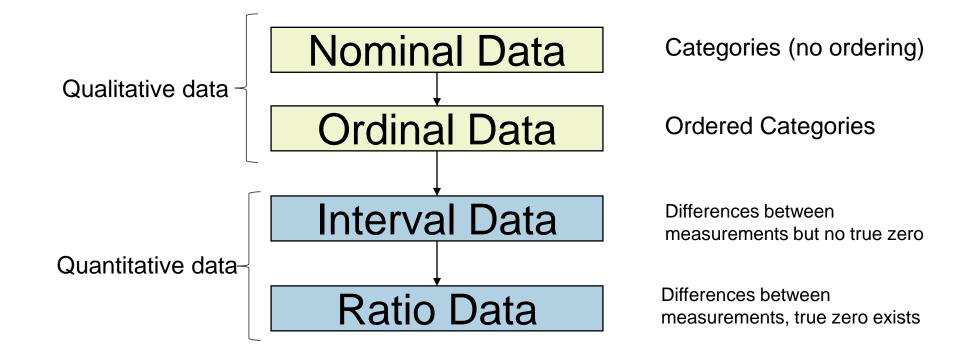
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Data-Driven Artificial Intelligence

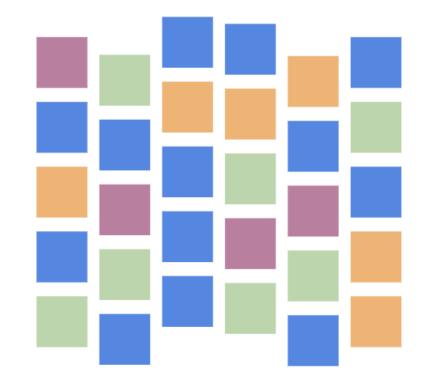
Types of Data



Structured data

Data stored in databases and tables Images, text, audio, video, documents

Unstructured data



Data Quality

Noise

Outliers

Missing values

100100 101010 001001 01010

Feature Subset Selection (Techniques)

M

Score 50'l

- Brute-force approach:
 - Try all possible feature subsets
- Filter approaches:
 - Features are selected before the run -
- Wrapper approaches:
 - Use the data mining algorithm as a black box to find the best subset

M

Score 901

XX AB

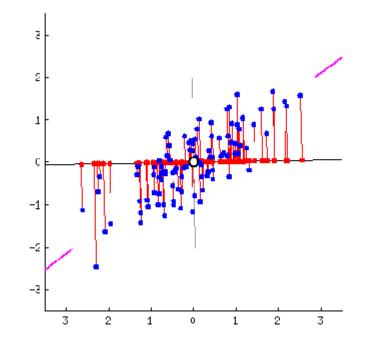
N

Score 60/

Dimensionality Reduction with PCA

• Principle Component Analysis (PCA):

• Goal is to find a projection that captures the largest amount of variation in data



Supervised Learning (Classification)

Training Data ML Algorithm Model **Prediction** Apple Orange **Class: Apple** Unseen and

unlabeled data





Regression and Classification

Class/Traget attribute

| | # | Inputs Attributes (Independent) | | Target/Class/Output Attributes (Dependent) | Regression Continuous |
|---------|-------|------------------------------------|-----------------|--|--------------------------|
| | | A1 | A2 | A3 | 🖌 (Numerical) |
| - | Ex. 0 | A1 ₀ | A2 ₀ | A3 ₀ | labeled data |
| | Ex. 1 | A1 ₁ | A2 ₁ | A3 ₁ | |
| | Ex. 2 | A1 ₂ | A2 ₂ | A3 ₂ | Target (Class) |
| | Ex. 3 | A1 ₃ | A2 ₃ | A3 ₃ | Attributes (A3) |
| Records | Ex. 4 | A1 ₄ | A2 ₄ | A3 ₄ | Classification |
| Records | Ex. 5 | A1 ₅ | A2 ₅ | A3 ₅ | |
| | Ex. 6 | A1 ₆ | A2 ₆ | A3 ₆ | Discrete |
| | Ex. 7 | A1 ₇ | A2 ₇ | A3 ₇ | (Categorical) |
| | Ex. 8 | A1 ₈ | A2 ₈ | A3 ₈ | labeled data |
| | Ex. 9 | A1 ₉ | A2 ₉ | A3 ₉ | labeled data |





Continuous labeled data

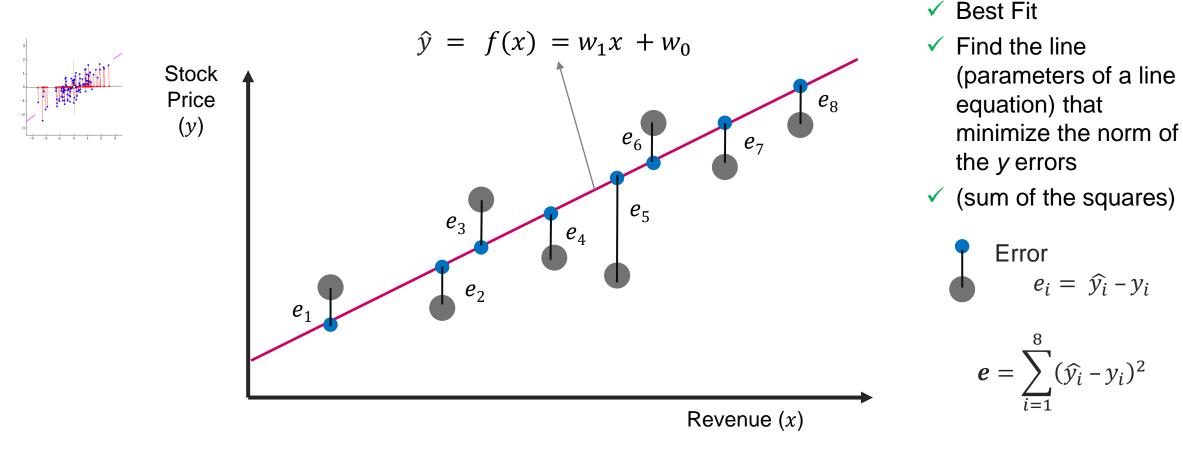
| | Inp | outs (X) | Target (Y) | |
|-------|------------------------|----------------|-------------|--|
| # | Area (m ²) | Distance(mile) | Price (£Bn) | |
| Ex. 0 | 76.85 | 17.27 | 0.15 | |
| Ex. 1 | 76.97 | 19.54 | 0.5 | |
| Ex. 2 | 77.10 | 18.51 | 0.76 | |
| Ex. 3 | 85.28 | 46.09 | 0.23 | |
| Ex. 4 | 85.42 | 35.83 | 0.6 | |
| Ex. 5 | 88.02 | 2.59 | 0.67 | |
| Ex. 6 | 77.25 | 6.34 | 0.89 | |
| Ex. 7 | 77.49 | 6.98 | 0.2 | |
| Ex. 8 | 85.81 | 12.18 | 0.55 | |
| Ex. 9 | 98.81 | 2.18 | 9.45 | |

Discrete labeled data

| | Inpu | ts (X) | Class (Y) | |
|-------|-------------|-------------|-----------|--|
| # | Length (cm) | Weight (kg) | Sales | |
| Ex. 0 | 23.2 | 3.2 | Good | |
| Ex. 1 | 70.9 | 19.5 | Bad | |
| Ex. 2 | 60.5 | 18.51 | Bad | |
| Ex. 3 | 24.5 | 4.6 | Good | |
| Ex. 4 | 110.0 | 35.83 | Bad | |
| Ex. 5 | 23.8 | 3.7 | Good | |
| Ex. 6 | 25.8 | 4.5 | Good | |
| Ex. 7 | 24.7 | 4.9 | Good | |
| Ex. 8 | 85.8 | 25.6 | Bad | |
| Ex. 9 | 78.8 | 20.33 | Bad | |

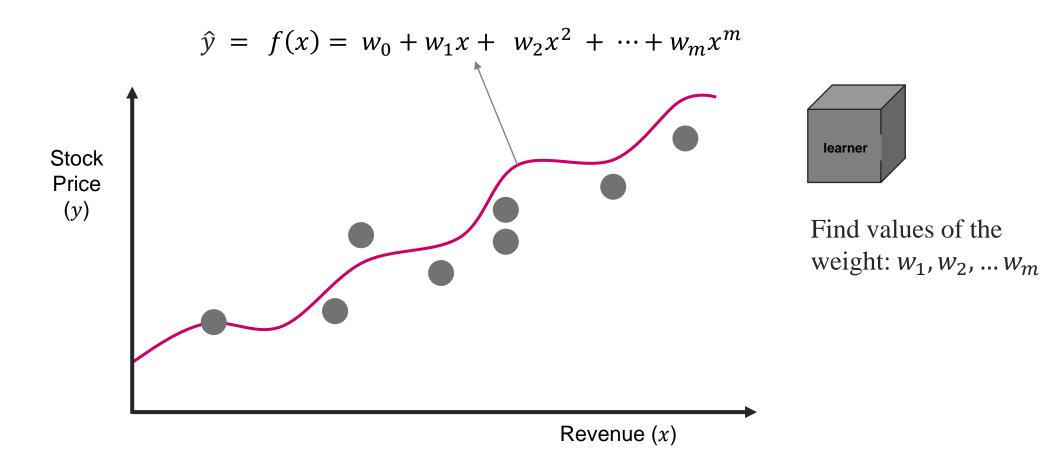


Regression: Linear function



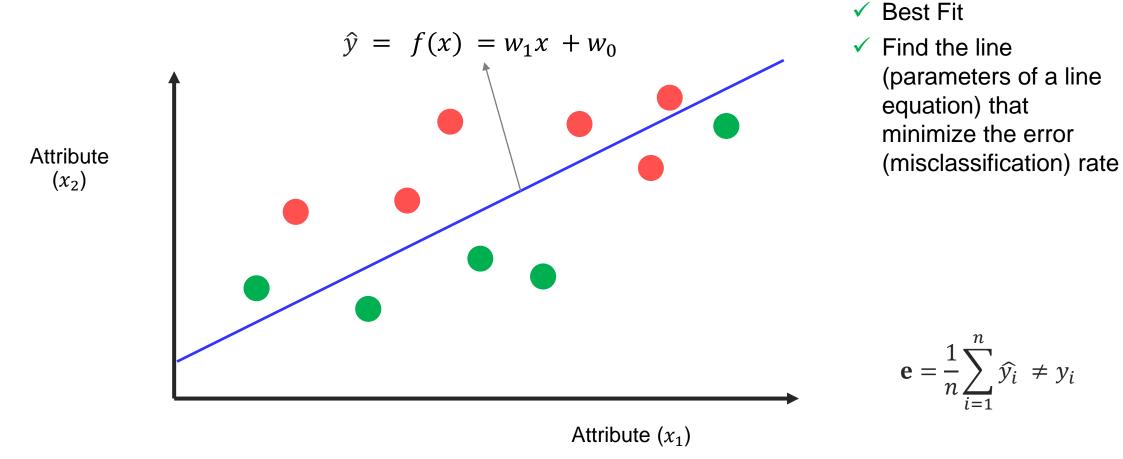


Regression: Non-Linear function



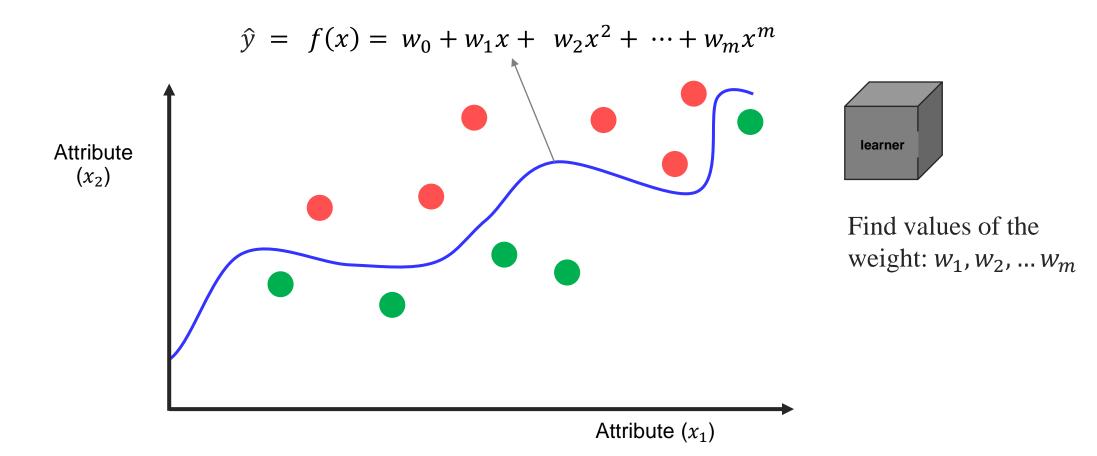


Classification: Linear function





Classification: Non-Linear function



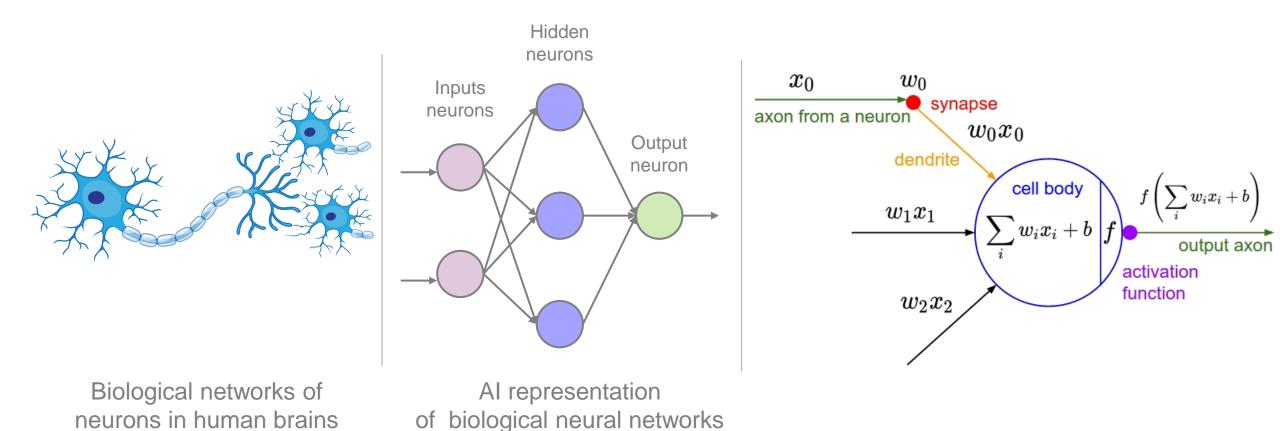
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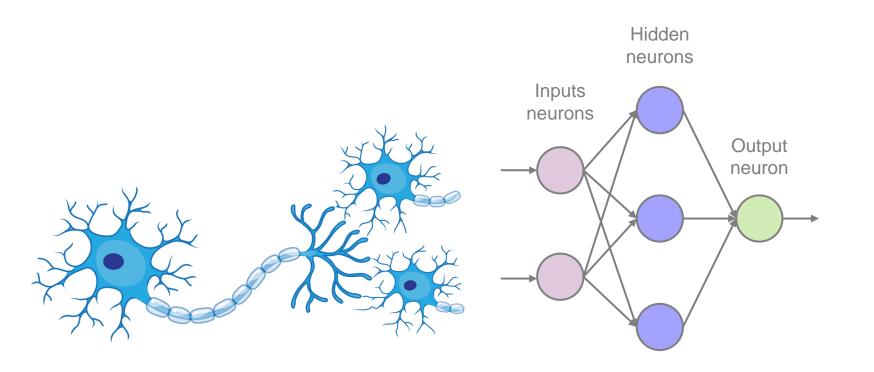
What has revolutionised it?

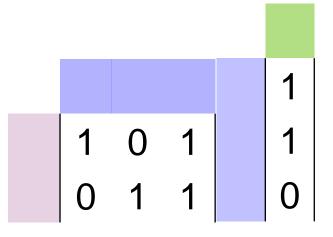
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Learning Systems: Neural Networks



Learning Systems: Neural Networks

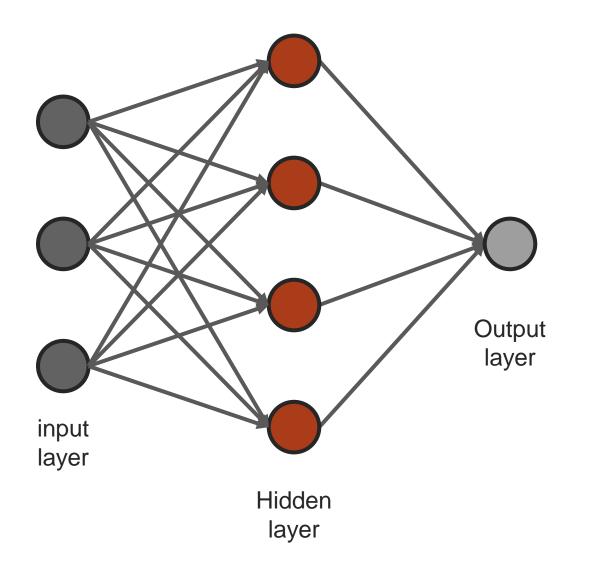


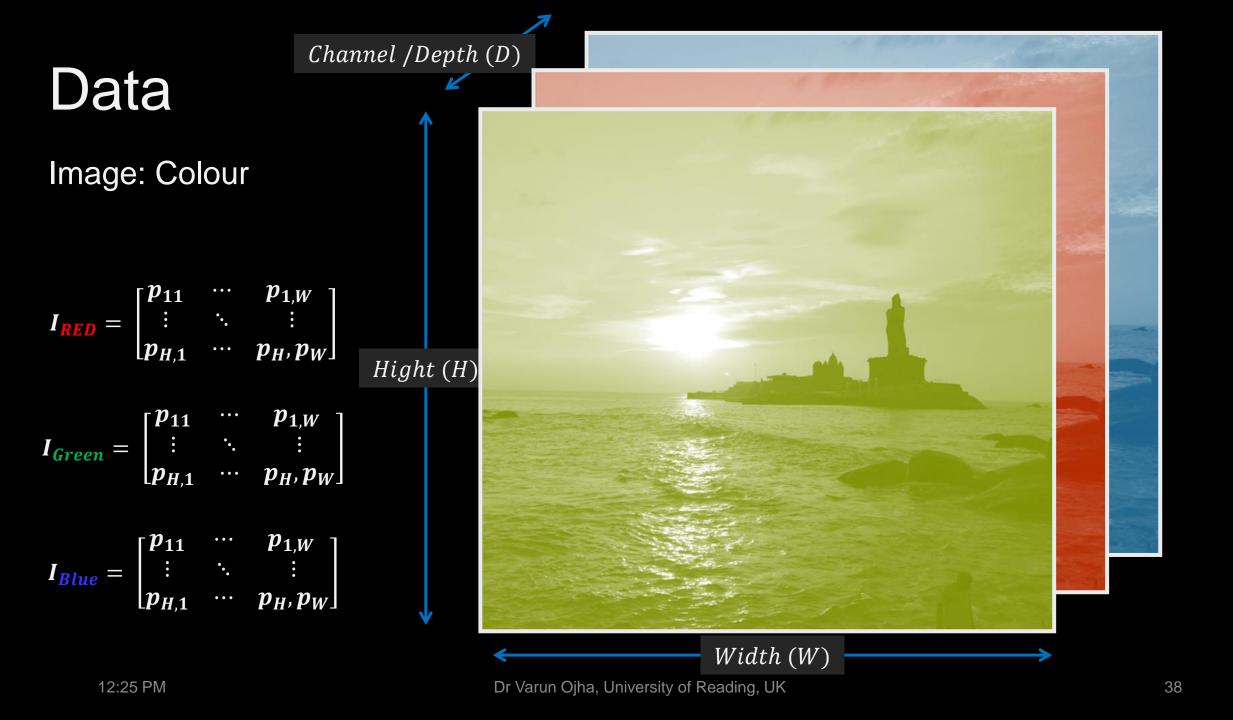


Biological networks of neurons in human brains **2** Al representation of biological neural networks Mathematical representation of the neural networks

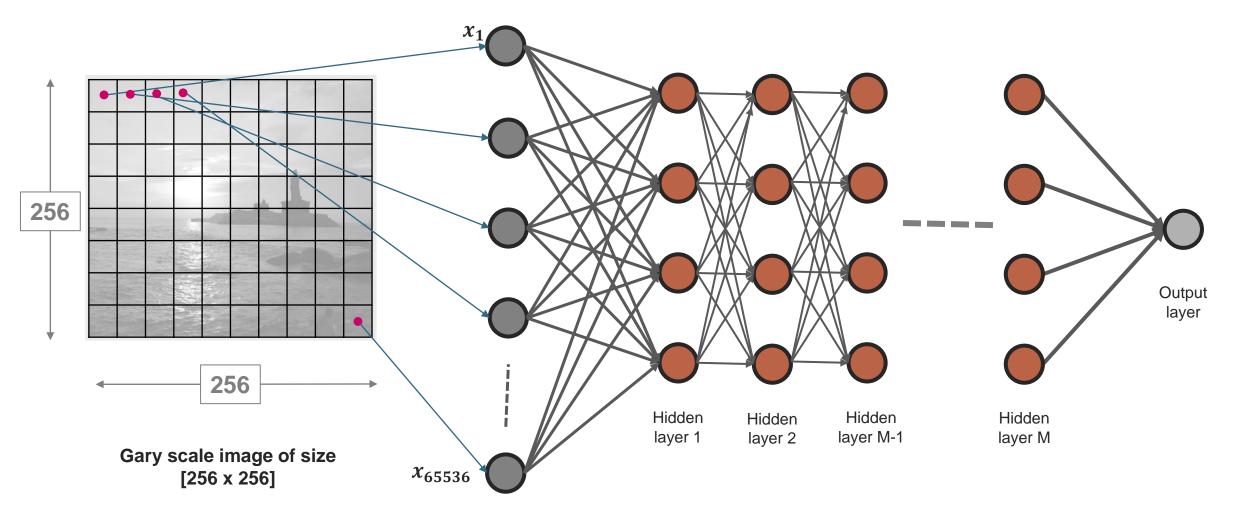
NEURAL NETWORK

Architecture





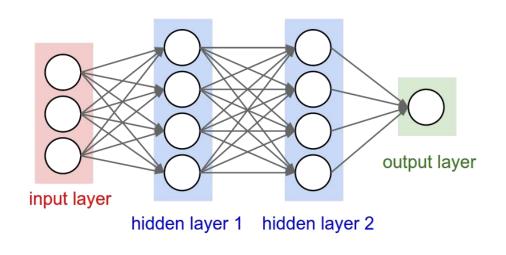
Deep Learning

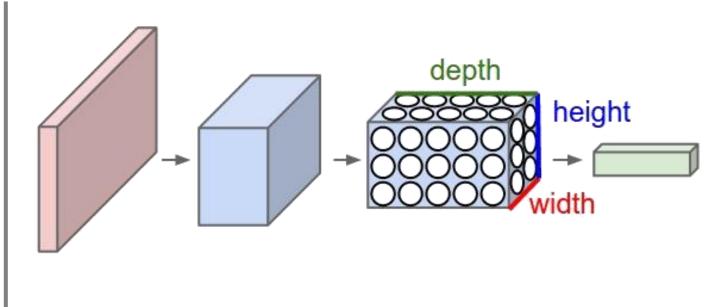


input layer

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Convolutional Neural Network (CNN)





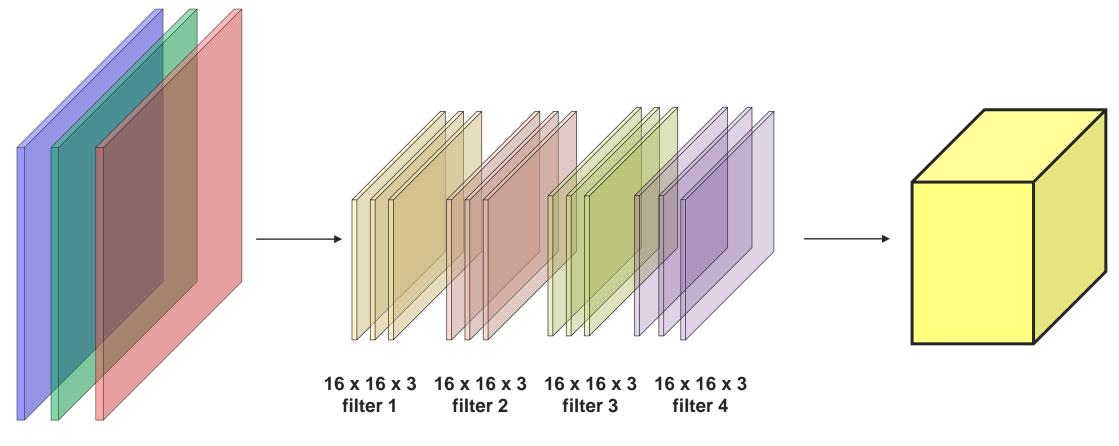
A regular Deep Neural Network

Convolutional Neural Network

A very good source: http://cs231n.github.io/convolutional-networks/

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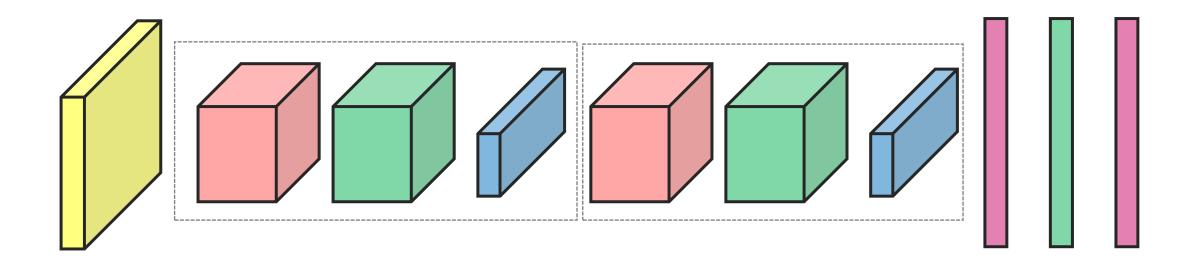
Convolution



16 x 16 x 4

Convolutional Net Architecture

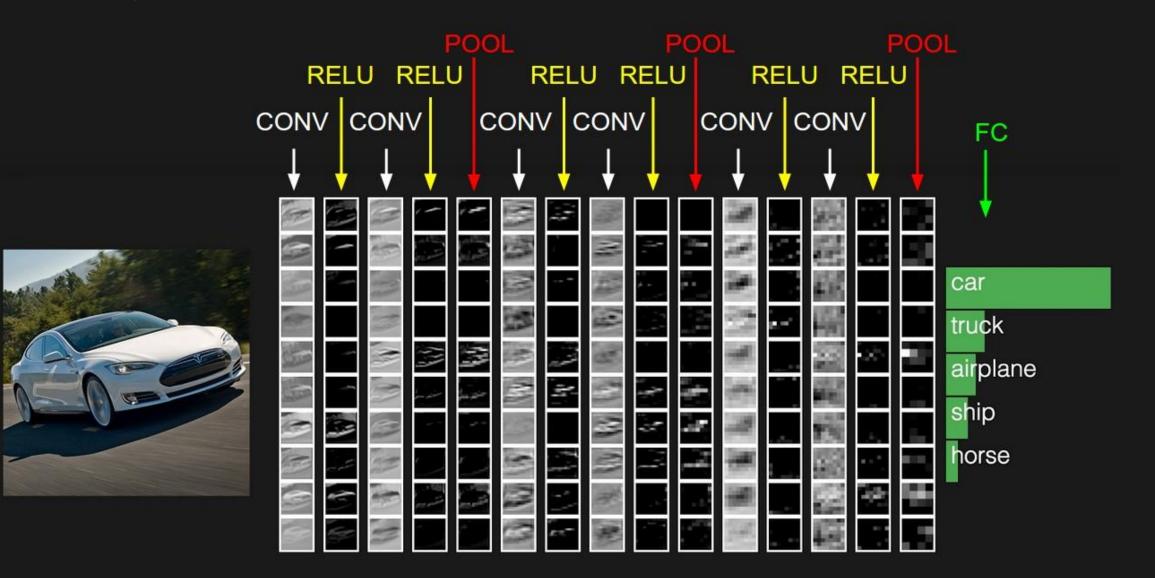
 $INPUT \rightarrow [CONV \rightarrow RELU \rightarrow POOL] * 2 \rightarrow FC \rightarrow RELU \rightarrow FC$



A very good source: http://cs231n.github.io/convolutional-networks/

ConvNet/ CNN: A Simple Example

Live demo http://cs231n.stanford.edu/



PART 4 Artificial Intelligence (in Pharmacology)

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How to know it is working well?

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Loss function: Mean Squared Error, E

$$E = \frac{1}{n} \sum_{i=1}^{n} (\widehat{y}_i - y_i)^2$$

 \hat{y}_i - predicted output

 y_i - target output

n - number of examples in training/test set

Loss function: Mean Absolute Error, E

$$\boldsymbol{E} = \frac{1}{n} \sum_{i=1}^{n} |\widehat{y_i} - y_i|$$

 \hat{y}_i - predicted output

 y_i - target output

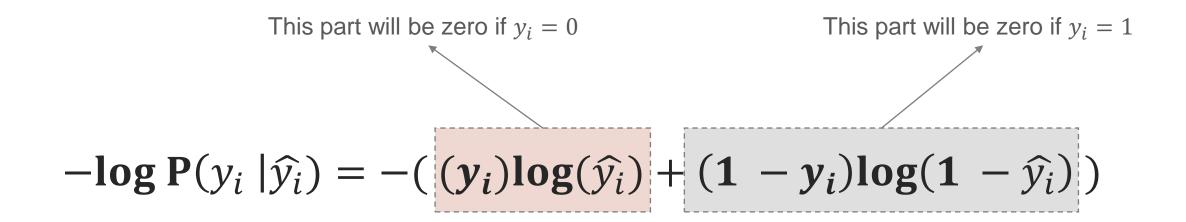
n - number of examples in training/test set

Loss function: Misclassification rate, E

$$\boldsymbol{E} = \frac{1}{n} \sum_{i=1}^{n} (\widehat{y}_i \neq y_i)$$

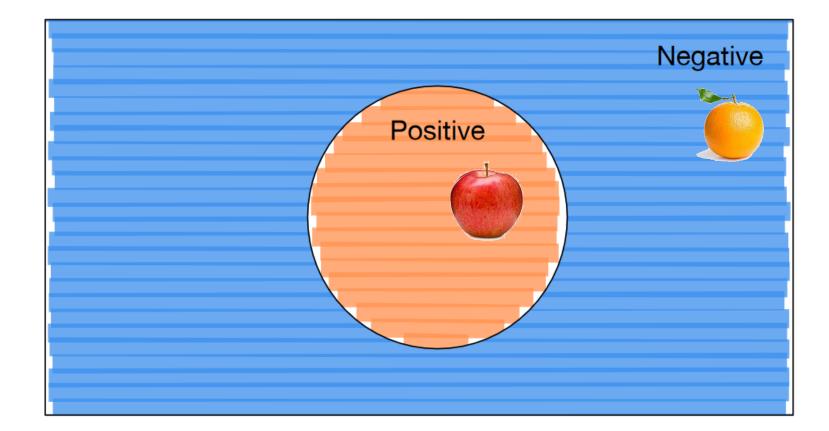
- \hat{y}_i predicted output
- y_i target output
- n number of examples in training/test set

Loss function: Log loss

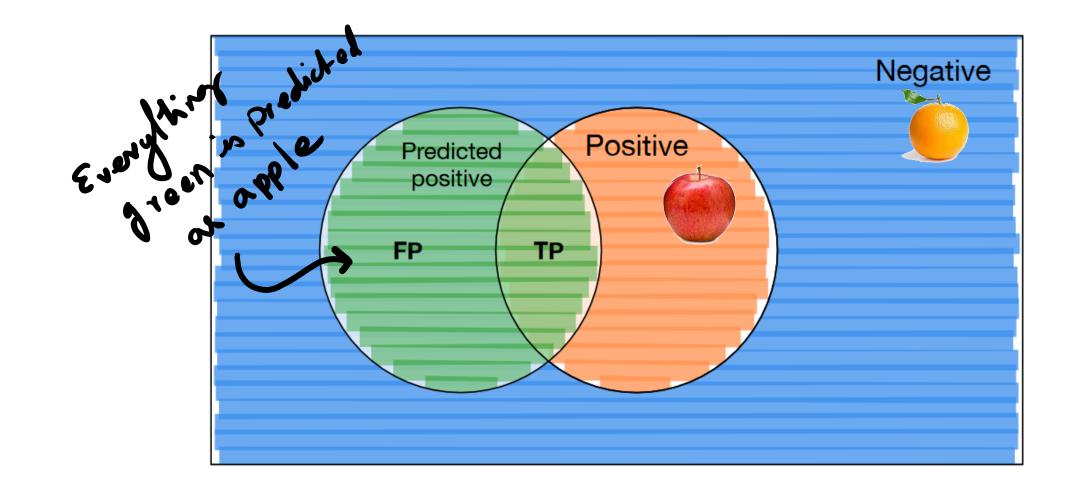


- \hat{y}_i predicted output
- y_i target output
- n number of examples in training/test set

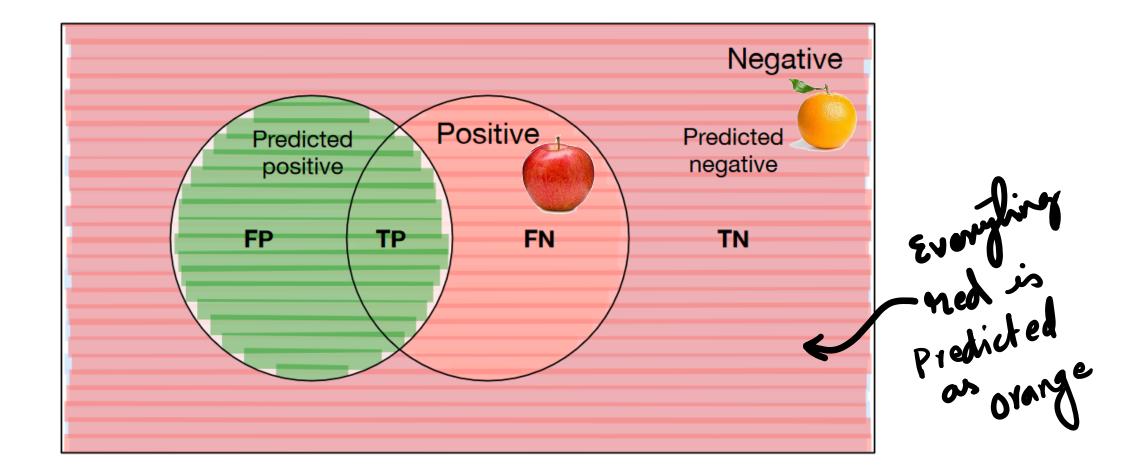
A Binary Classification Problem



False Positives and True Positives

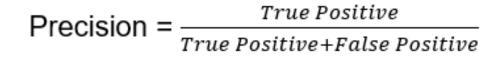


False Negatives and True Negatives



Evaluation Metrics: Precision

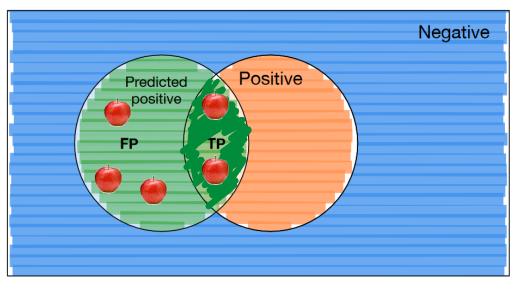
• Precision is the fraction of positive predictions for the respective class that is correct: *How well you guess*





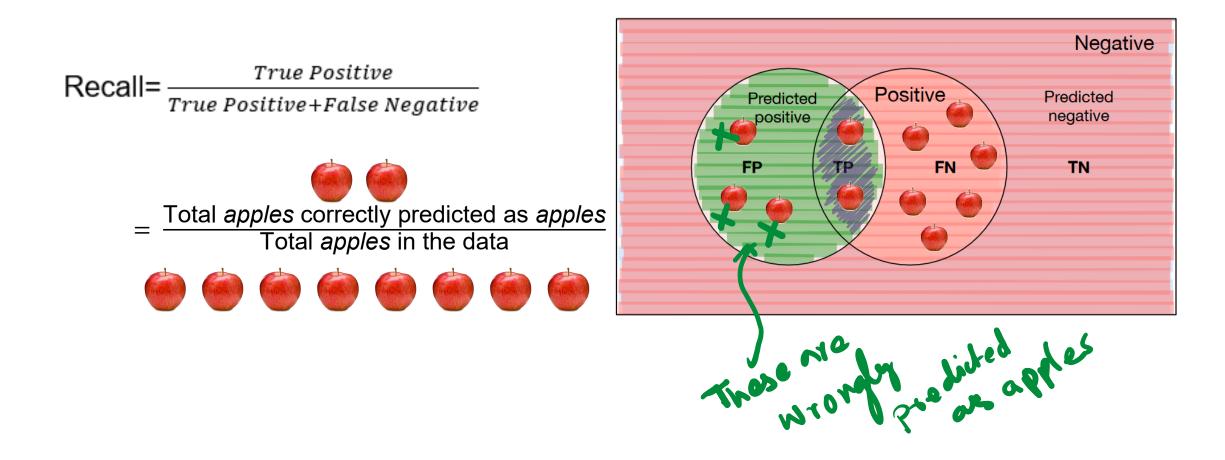
 $= \frac{\text{Total apples correctly predicted as apples}}{\text{Total number of postive prediction in the data}}$





Evaluation Metrics: Recall

Recall is the fraction of positive values in the data that we correctly predict: *How complete is the prediction?*



PART 4 Artificial Intelligence (in Pharmacology)

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Where is it in Pharmacology?

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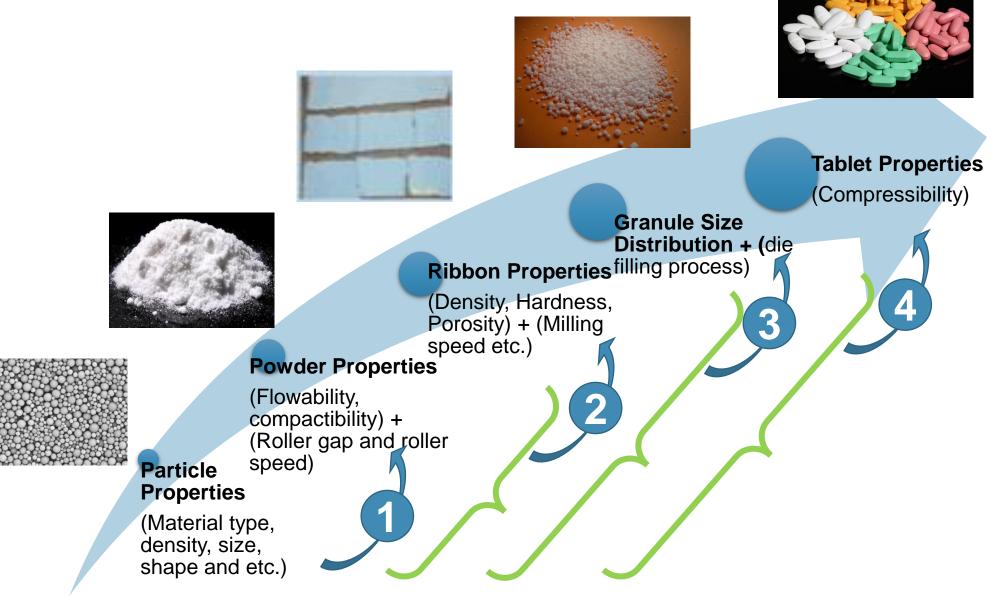
Pharmaceutical (Drugs Production)





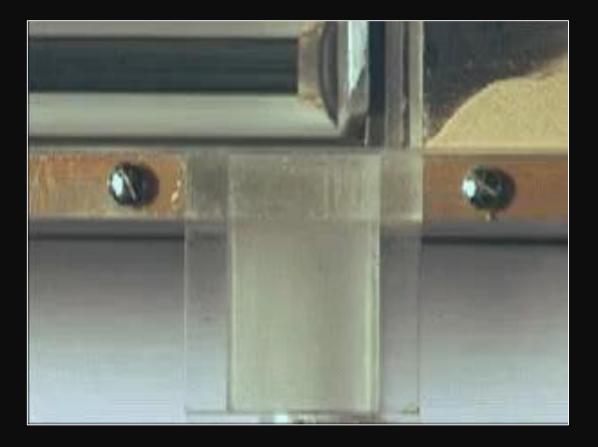
| | | 1 | | | | | | |
|--|----|---|--|--|--|--|----------------------|----|
| | | | | | | | | |
| | | | | | | | | |
| | | | | | | | | |
| | | | | | | | | |
| | | | | | | | | |
| | 94 | | | | | | | |
| | | | | | | | in the second second | 56 |

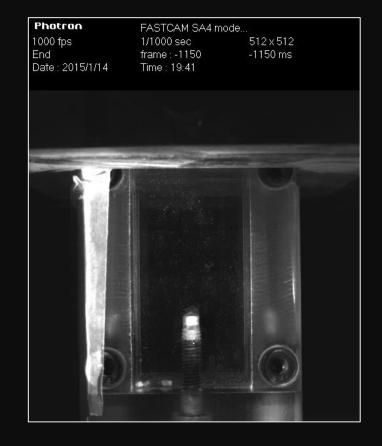
The Process and Variables



Computational intelligence modelling of pharmaceutical industrial processes

Die Filling





Ojha VK et al. (2017) Neural Computing and Applications

Data Collection for Modelling Die Filling

| | Samples | | In | put | | Output |
|-----|------------|--------------|----------------|---------------|--------------|----------|
| # | Name | True density | d50 (μ m) | Granules size | Shoe speed | Mass (g) |
| | | Feature #1 | Feature $#2$ | Feature $#3$ | Feature $#4$ | - |
| 1 | MCC PH 101 | 1581 | 59.83 | 90 | 10 | 12.81 |
| 2 | MCC PH 101 | 1581 | 59.83 | 90 | 10 | 12.78 |
| : | : | : | : | : | : | : |
| 5 | MCC PH 101 | 1581 | 59.83 | 90 | 20 | 12.3 |
| 6 | MCC PH 101 | 1581 | 59.83 | 90 | 30 | 9.55 |
| : | : | : | : | : | : | : |
| 135 | MCC PH 102 | 1570.3 | 94.7 | 250 | 50 | 13.45 |
| 136 | MCC PH 102 | 1570.3 | 94.7 | 250 | 60 | 13.5 |
| : | : | : | : | : | : | : |
| 388 | MCC DG | 1785.6 | 52.33 | 2360 | 400 | 9.51 |
| 389 | MCC DG | 1785.6 | 52.33 | 2360 | 400 | 9.3 |

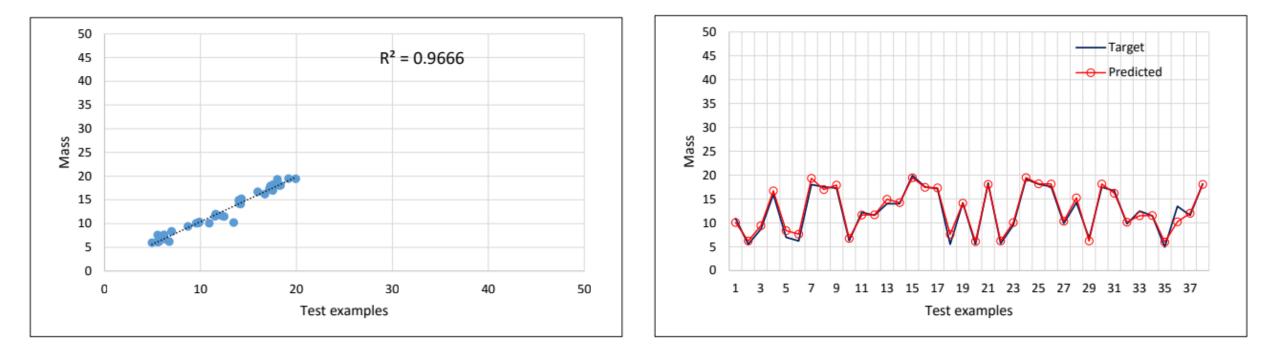
Ojha VK et al. (2017) Neural Computing and Applications

Performance of Algorithms on Prediction and Feature Selection

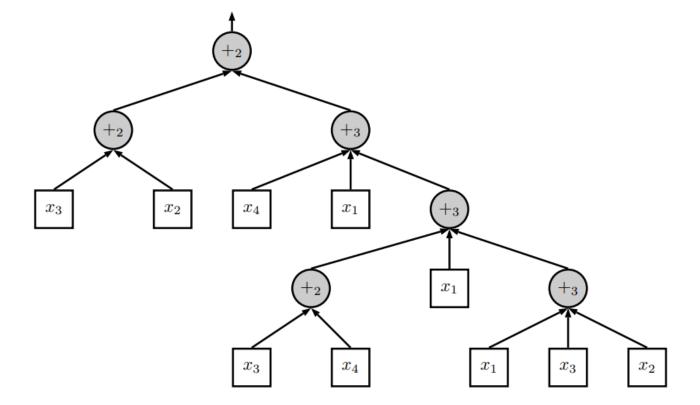
| Model | Model | Mean of | RMSEs | Mean | of r | Std c | over r | Model | Selected |
|----------|-----------------|---------|--------|-------|--------|--------|----------|----------------|-----------------------|
| No. | Type | Train | Test | Train | Test | Train | Test | $Complexity^1$ | $\mathrm{Features}^2$ |
| 1 | FNT | 2.0206 | 2.0571 | 0.93 | 0.95 | 0.0087 | 0.0383 | 43 | 1,2,3,4 |
| 2 | | 2.3891 | 2.3934 | 0.91 | 0.91 | 0.0083 | 0.0617 | 34 | 2, 3, 4 |
| 3 | | 2.5491 | 2.2618 | 0.88 | 0.91 | 0.0078 | 0.0563 | 32 | 3, 4 |
| 4 | REP-Tree | 2.5751 | 3.1637 | 0.88 | 0.82 | - | - | 99 | 1,2,3,4 |
| 5 | GPR | 2.9632 | 3.4023 | 0.86 | 0.79 | - | - | - | 1,2,3,4 |
| 6 | MLP | 3.3687 | 3.4427 | 0.81 | 0.79 | - | - | - | 1,2,3,4 |

Note: ¹Complexity is the sum of total nodes in the created tree-model. ²Features Nos are assigned in Table 1

Assessing Performance Visually



Neural Tree Model for Future Use



Quality of each Feature

| # | Input Features set | Selection Rate (R) | Predictability Score (P) |
|---|-----------------------------|----------------------|----------------------------|
| 1 | A_1 = True density | 0.55173 | 0.541356 |
| 2 | $A_2 = d50$ | 0.62069 | 0.586262 |
| 3 | $A_3 = \text{Granule size}$ | 1 | 1 |
| 4 | A_4 = Shoe speed | 0.86207 | 0.92563 |

Quality of the Subset

| # | Input Feature set | Selection Rate (R) | Predictability Score (P) |
|----------|---|----------------------|----------------------------|
| 1 | A_1 = True density, d50, Granule size, Shoe speed | 0.31035 | 0.969497 |
| 2 | $A_2 = d50$, Granule size, Shoe Speed | 0.17242 | 0.941601 |
| 3 | A_3 = True density, Granule size, Shoe speed | 0.13793 | 1 |
| 4 | A_4 = Granule size, Shoe speed | 0.24138 | 0.979663 |
| 5 | A_5 = True density, d50, Granule size | 0.10345 | 0.493741 |
| 6 | $A_6 = d50$, Granule size | 0.03448 | 0.470451 |

Drug Dissolution

Ojha VK et al. (2015) International Journal of Nanomedicine





The PLGA dataset description

PLGA: poly(lactic-co-glycolic acid)

| SI No | Group name | No of features | Importance |
|-------|-----------------------------|----------------|---|
| I | Protein descriptors | 85 | Describes the type of molecules and proteins used |
| 2 | Formulation characteristics | 17 | Describe the molecular properties such as molecular weight, particle size, etc |
| 3 | Plasticizer | 98 | Describe the properties such as fluidity of the material used |
| 4 | Emulsifier | 99 | Describe the properties of stabilizing/increase the pharmaceutical product life |
| 5 | Time in days | I. | Time taken to dissolve |
| 6 | % of molecules dissolved | I. | Output |

Abbreviations: PLGA, poly(lactic-co-glycolic acid); SI, serial; No, number.

Ojha VK et al. (2015) International Journal of Nanomedicine

Prediction of Dissolution Rate

| Selection method | Selected features | GPReg | LReg | MLP | REP | SMOReg |
|----------------------|-------------------|-------|-------|-------|-------|--------|
| No selection | 300 | 16.81 | 17.07 | 18.57 | 13.05 | 17.95 |
| BFE | I. | 27.47 | 26.61 | 28.33 | 24.37 | 26.97 |
| BFE | 5 | 17.11 | 23.45 | 23.11 | 14.23 | 23.38 |
| CFS | 5 | 20.80 | 25.08 | 22.41 | 18.31 | 25.42 |
| Class-MLP-greedy | 7 | 17.96 | 25.03 | 22.26 | 14.96 | 25.35 |
| BFE | 10 | 15.93 | 19.98 | 21.00 | 13.19 | 19.53 |
| Class-MLP-BFS | 15 | 15.88 | 22.90 | 16.83 | 13.91 | 24.23 |
| Wrapper-GPReg-greedy | 15 | 14.88 | 20.22 | 15.20 | 13.34 | 20.86 |
| Class-GPReg-BFS | 16 | 18.46 | 23.07 | 19.71 | 14.19 | 23.69 |
| Class-GPReg-greedy | 19 | 15.06 | 19.05 | 15.61 | 14.03 | 19.68 |
| Wrapper-MLP-greedy | 19 | 16.44 | 24.01 | 20.42 | 14.26 | 24.85 |
| Wrapper-LReg-greedy | 24 | 15.91 | 17.46 | 17.03 | 13.54 | 18.02 |
| BFE | Optimal* | 15.71 | 17.85 | 17.82 | 13.90 | 17.88 |
| Class-LReg-BFS | 31 | 15.95 | 16.92 | 15.63 | 14.00 | 17.58 |
| Class-LReg-greedy | 37 | 16.31 | 17.14 | 16.27 | 14.02 | 17.69 |

Notes: Values are the average of ten RMSE. *Optimal set of attributes for the GPReg, LReg, MLP, REP and SMOReg regression models are 18, 32, 31, 31, and 30, respectively.

Abbreviations: 10-CV, ten-fold cross-validation; GPReg, Gaussian process regression; LReg, linear regression; MLP, multilayer perception; REP, reduced error pruning; SMOReg, sequential minimal optimization; No, number; BFE, backward feature elimination; CFS, correlation-based feature selection; BFS, best fit search; wrapper, wrapper feature selection; greedy, greedy search; class, classifier-based feature selection.

Performance of Algorithms on Prediction and Feature Selection

| Algorithm | RMSE E_t | No. of features |
|---------------------------|-------------------|-----------------|
| MLP | 14.3 | 17 |
| HFIT | 13.2 | 15 |
| REP Tree | 13.3 | 15 |
| GPR | 14.9 | 15 |
| MLP | 15.2 | 15 |
| MLP | 15.4 | 11 |
| T1HFIT ^M | 18.6 | 7 |
| T2HFIT^M | 15.2 | 4 |

Fuzzy Tree Model for Future Use (Type 1 T1HFIT^M and Type 2 T2HFIT^M)

