



# Introduction to Machine Learning

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# Machine learning definition

**Machine Learning (ML)** is the field of data science interested in the development of computer **algorithms** to transform data into insights and action.

Machine learning is teaching computers how to use data to solve a problem.

**ML driving force:** Growth in **data** necessitated additional **computing power**, which in turn spurred the development of **statistical methods** to analyse large datasets.

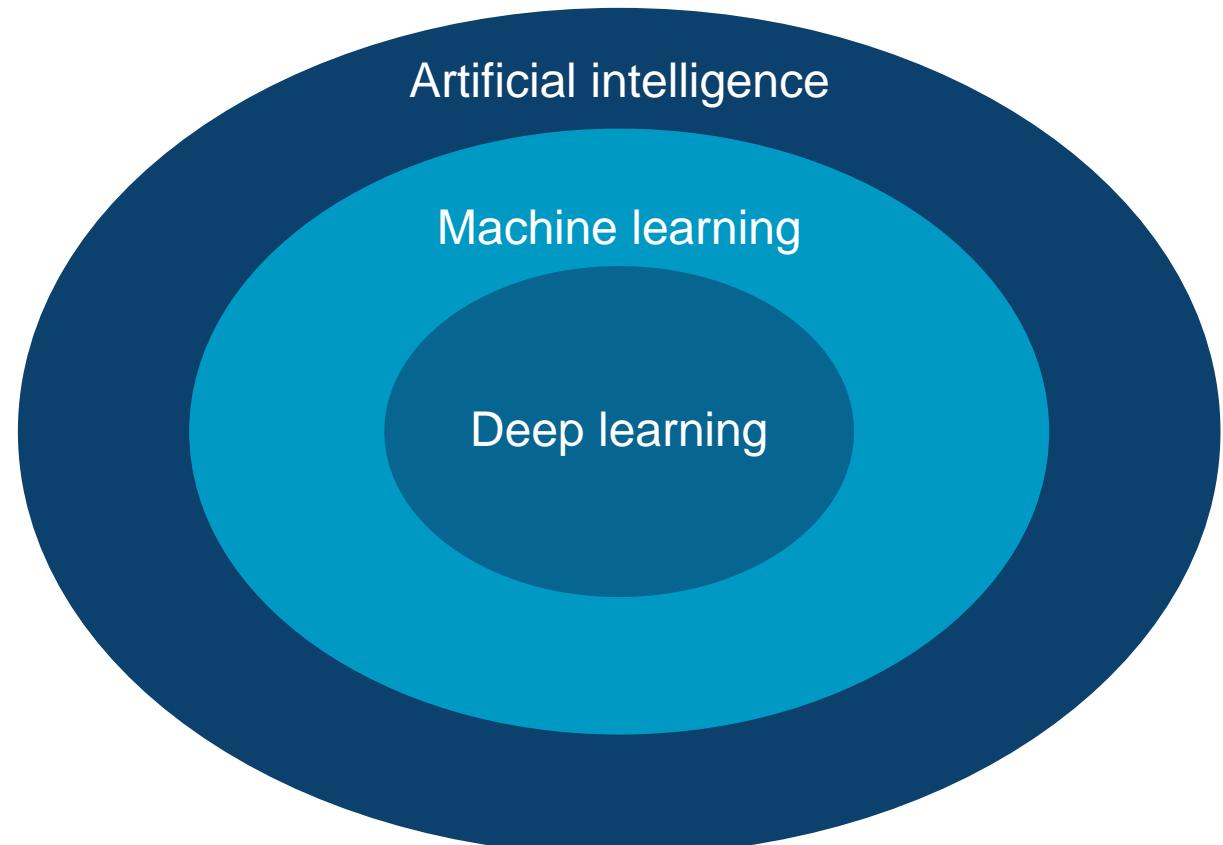




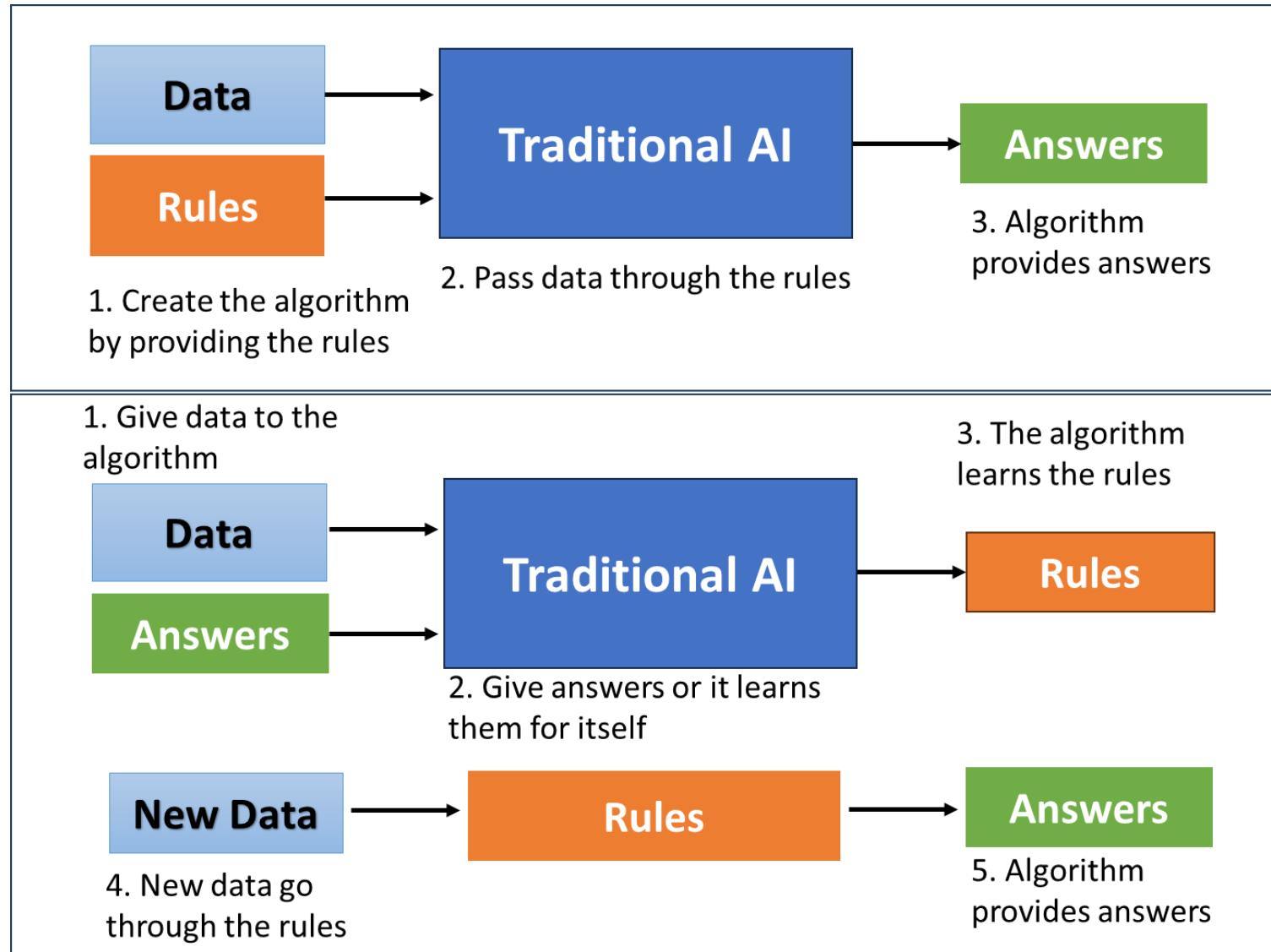
# Machine learning definition

**Machine Learning is a sub-field of artificial intelligence (AI).**

- The term ML was first used in 1959 to describe a form of AI that involved training an algorithm to **learn** to play the game of checkers.
- Traditional AI is programmatic.
- ML trains a computer to learn relationships in data to identify meaningful patterns or make predictions.



# Traditional AI vs ML





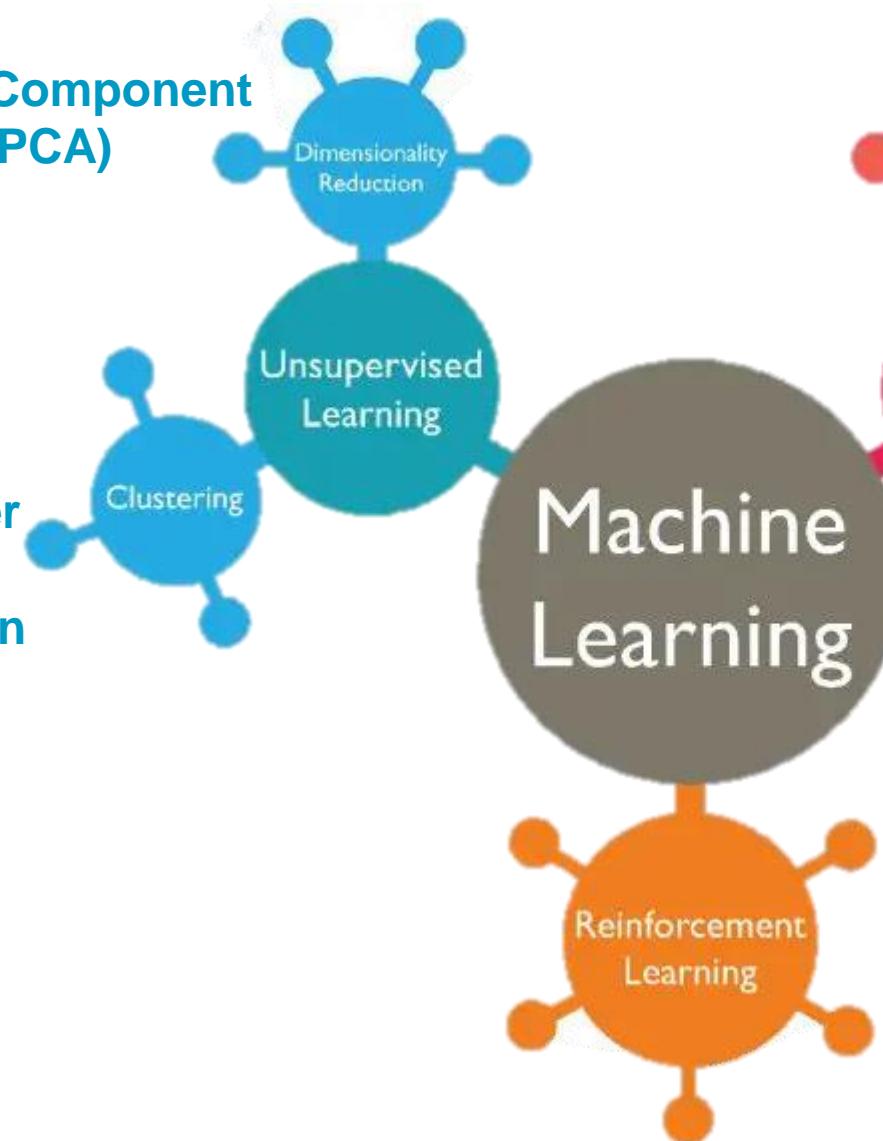
# ML applications



# Types of Machine Learning

## Principal Component Analysis (PCA)

- K-means
- Hierarchical Cluster Analysis (HCA)
- Fuzzy Classification



- K-Nearest Neighbours (kNN)
- Decision Trees
- Neural Networks
- Support Vector Machine (SVM)
- Naïve Bayes

- Generalised Linear Models
- Ridge Regression
- Elastic Net
- Partial Least Square (PLS)

- Deep Q-Networks (DQN)
- Double and Dueling DQN (DD-DQN)

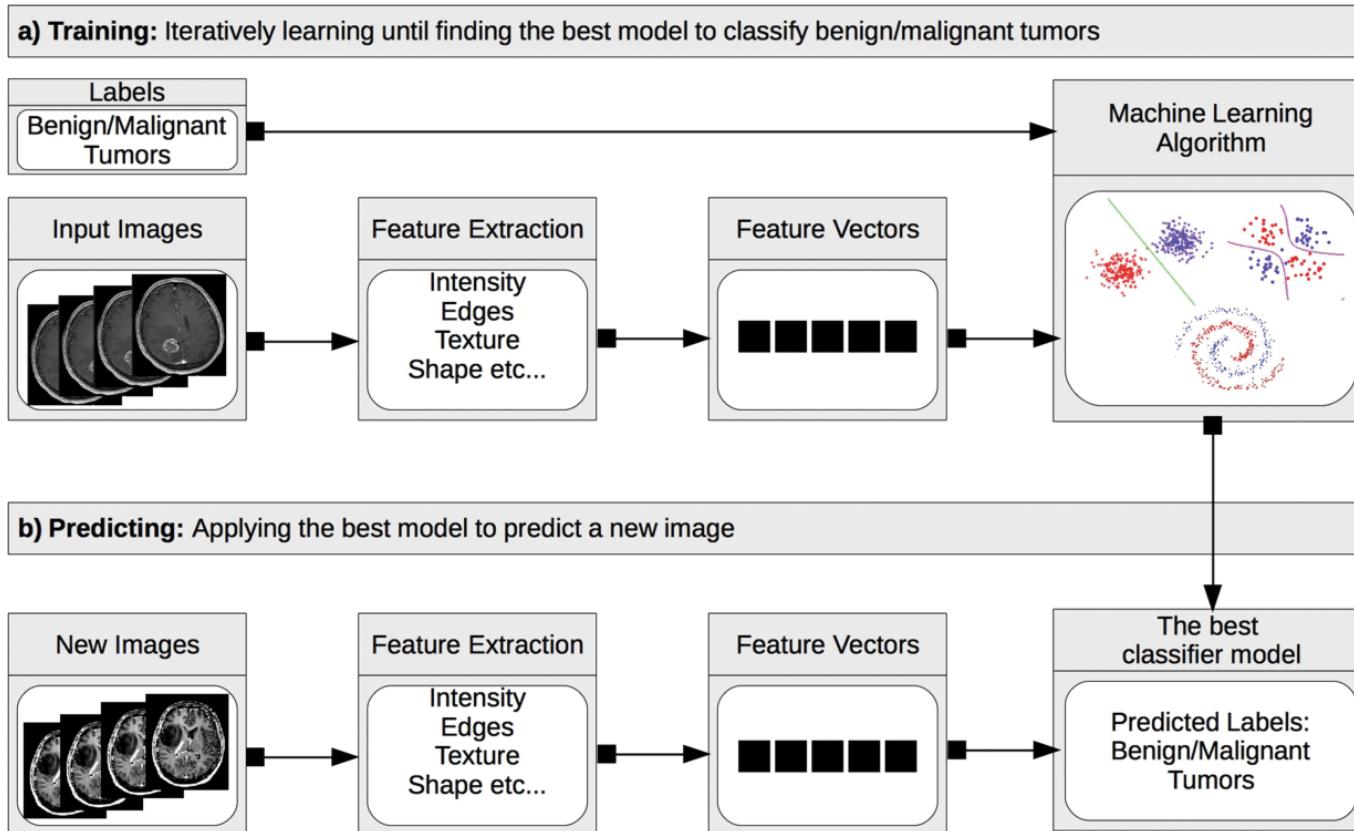


# ML in healthcare



## ML: a game-changer in healthcare

- Early disease identification and diagnosis:
  - Rapid cancer detection;
  - Heart disease;
  - Mental health disorders;
  - Genetic mutations.
- Personalised treatment.
- New drugs discovery.
- Predict health epidemics.



Erickson et al., 2017, *RadioGraphics*

# ML applications in bioinformatics

## Machine and deep learning integration with bioinformatics

### Molecular evolution

#### Phylogenetic inference

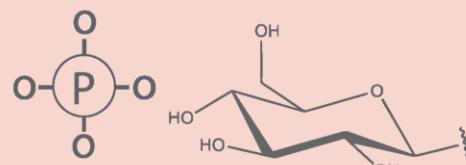


#### Alignment-free sequence classification

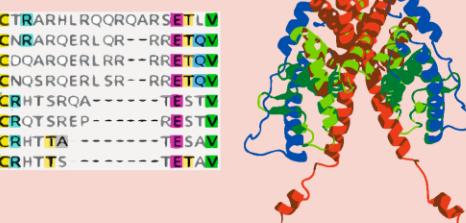


### Protein structure Analysis

#### Post translational modification

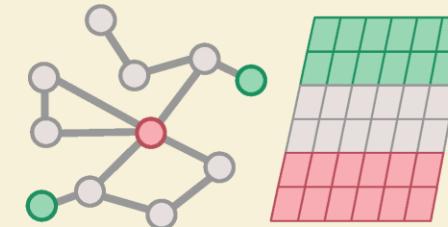


#### Folding and structure

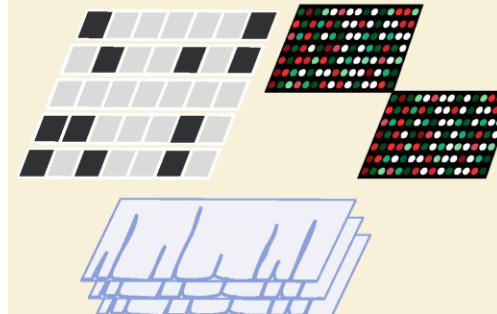


### Systems biology

#### Biological Networks

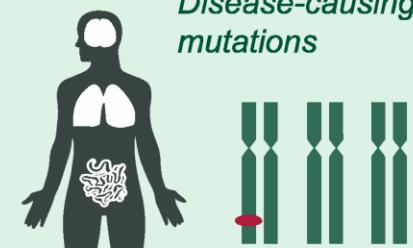


#### Multi-Omics integration

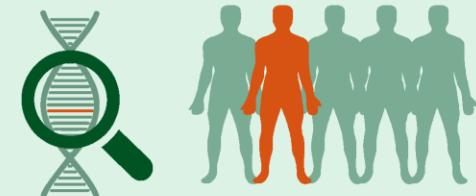


### Genomics for Disease Research

#### Disease-causing mutations



#### Biomarkers discovery



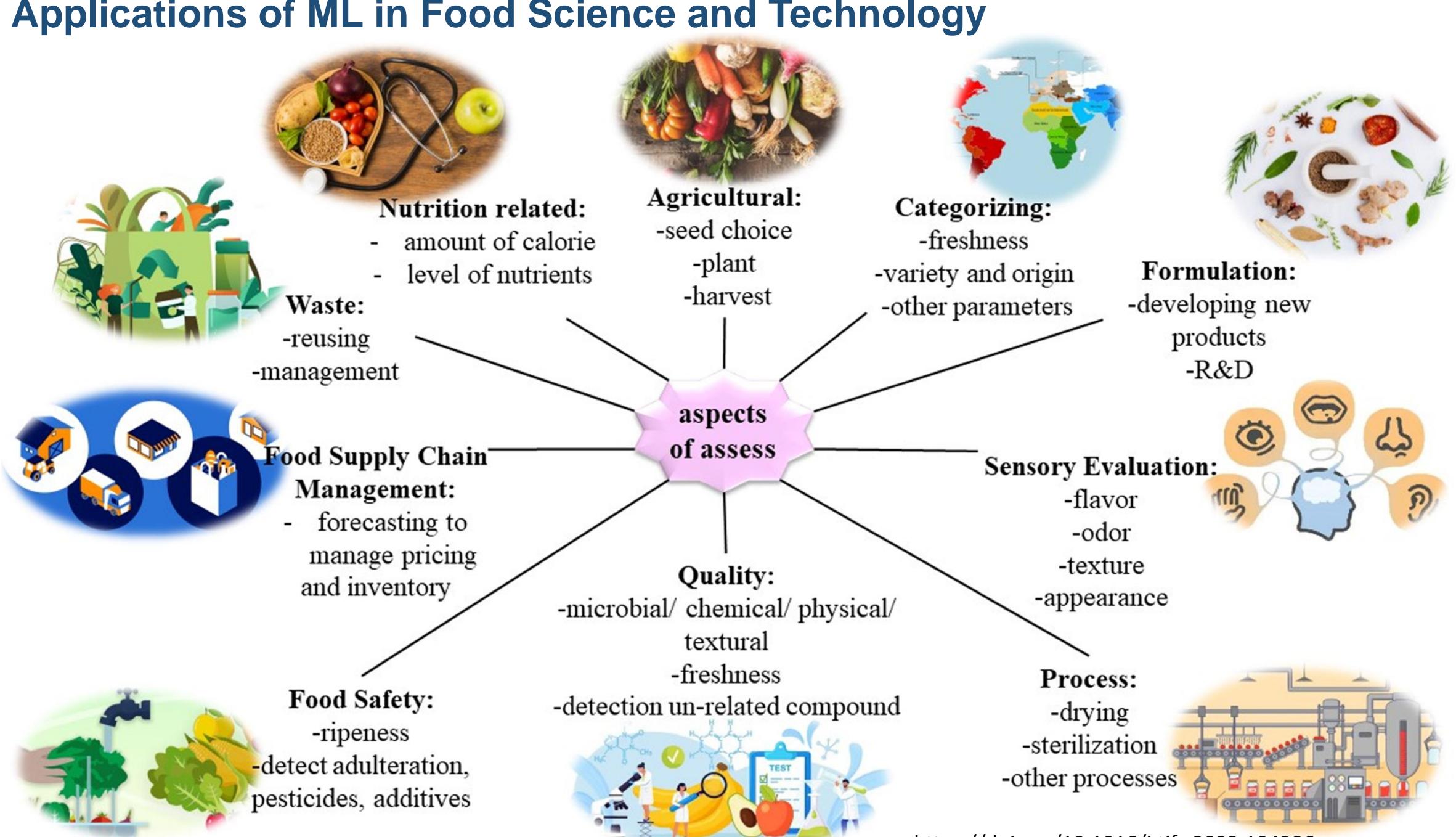
- Inference of tree topology
- Sequence classification
- Viral sequence identification
- functional annotation

- Phosphorylation site prediction
- Protein glycosylation prediction
- Protein contact maps prediction
- Structural homology prediction

- Biological networks construction
- Biological interactions prediction
- Pathway dynamics prediction
- Platform integration frameworks

- Disease associated genes and mutations
- Biomarkers
- Precision medicine applications

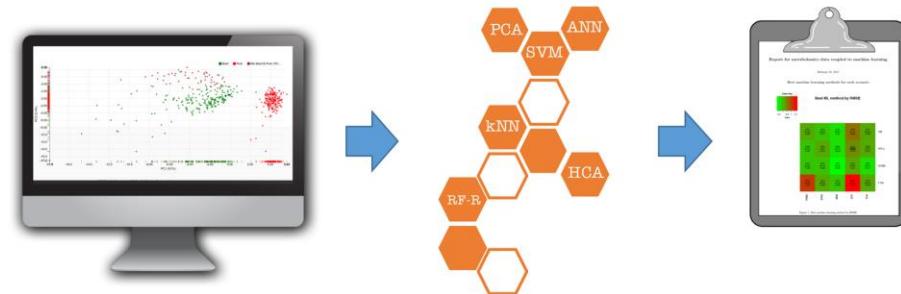
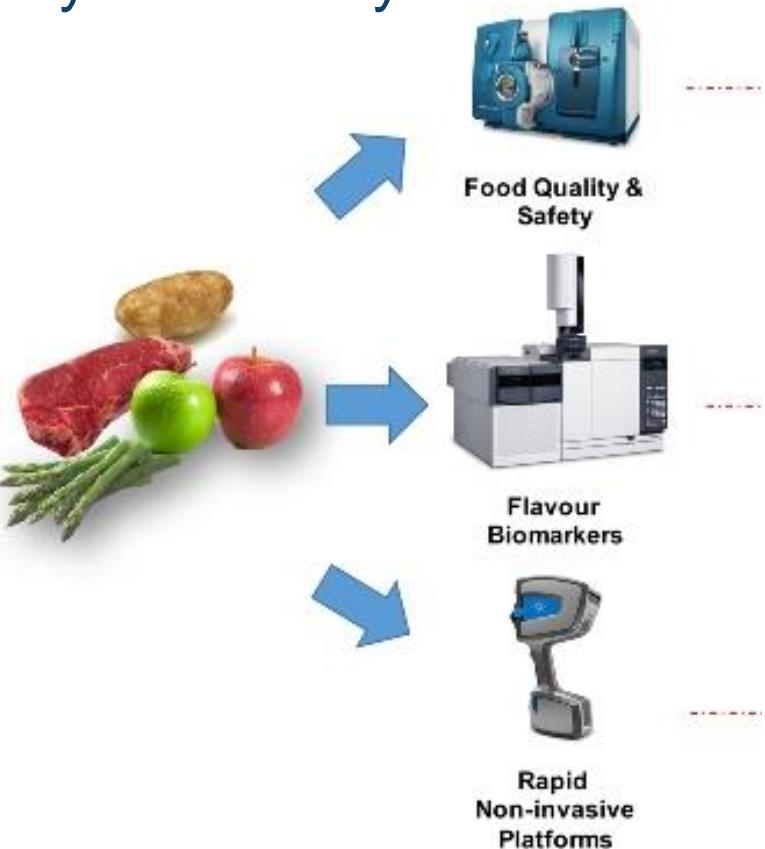
# Applications of ML in Food Science and Technology





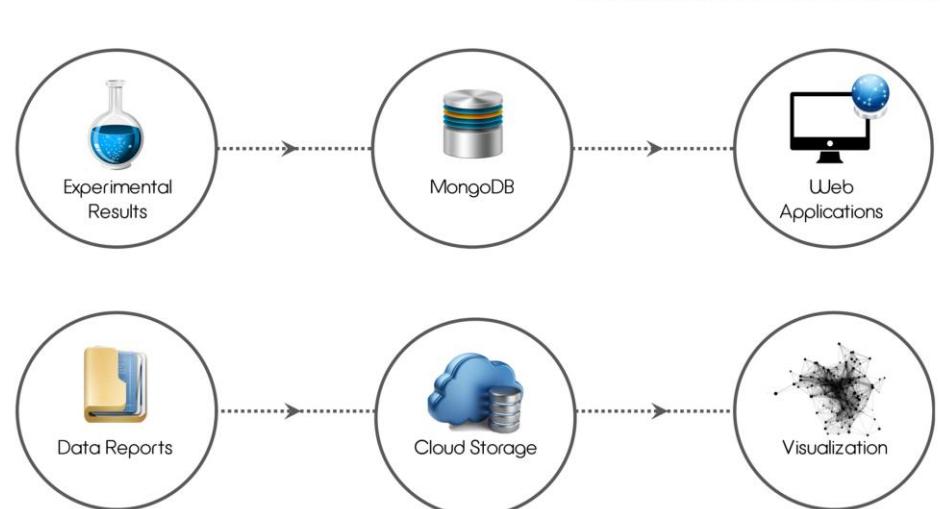
# Bioinformatics Team ML applications

Applications in Food  
Diagnostics for monitoring of  
food quality and safety.



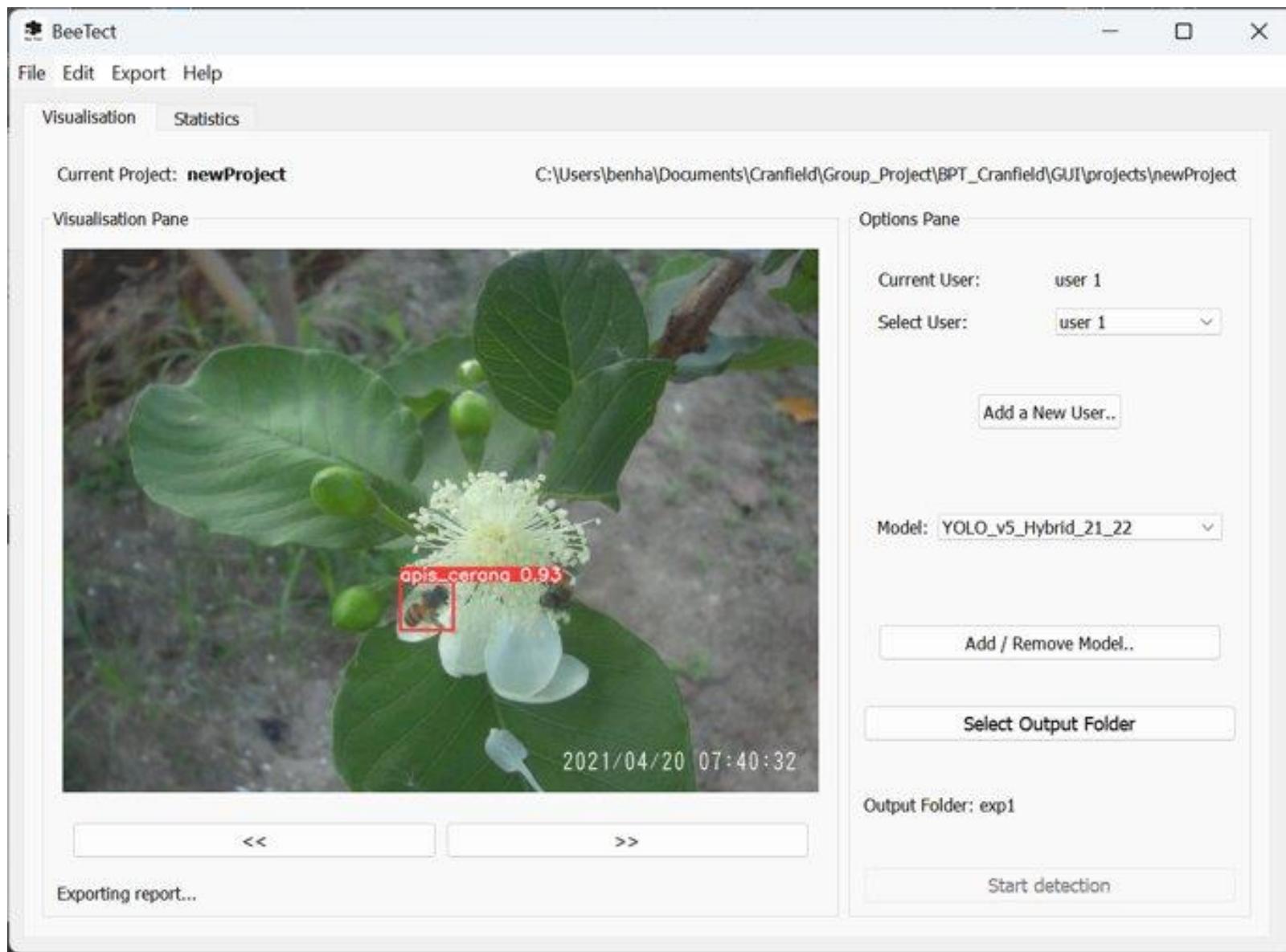
## SorfML

The machine learning classification  
& regression analysis ranking system



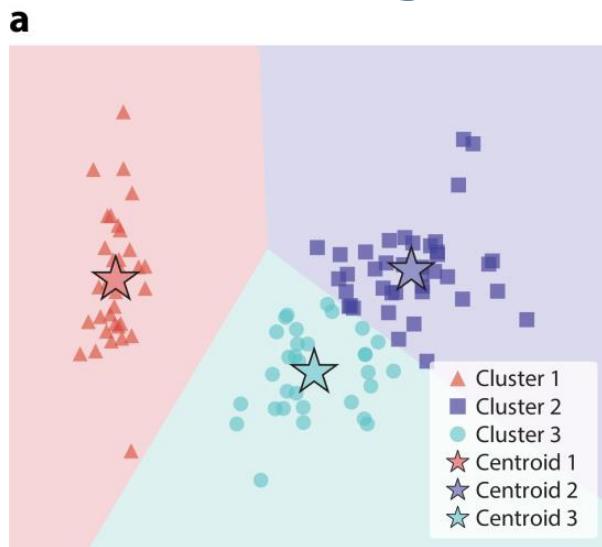


# Bioinformatics Team ML applications

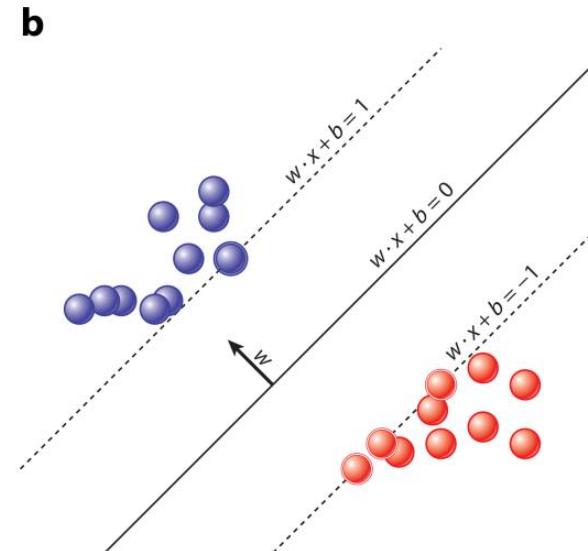
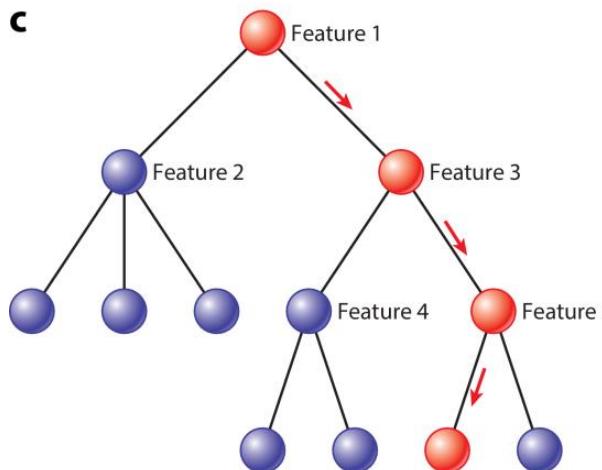


# Examples of ML algorithms

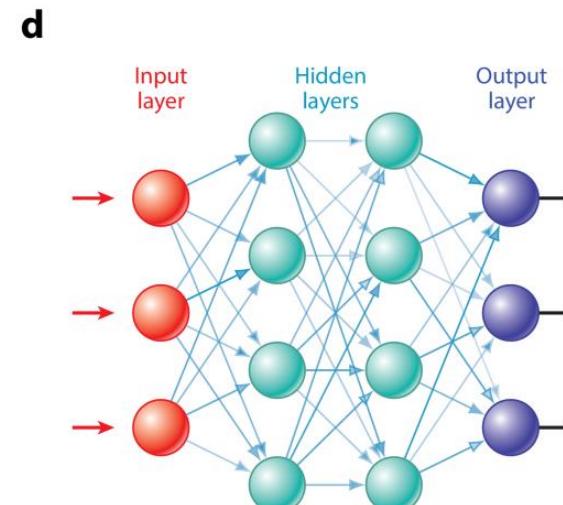
k-means clustering



Decision trees



Support vector machine



Neural Networks



## ML limitations

- Machine learning is not in any way a substitute for a human brain.....(yet).
- Machine learning is only as good as the data it learns from.
- A computer still needs a human to motivate the analysis and turn the result into meaningful action.
- It has very little flexibility to extrapolate outside of the strict parameters it learned and knows no common sense.
- Machine learning is most successful when it augments rather than replaces the specialised knowledge of a subject-matter expert.

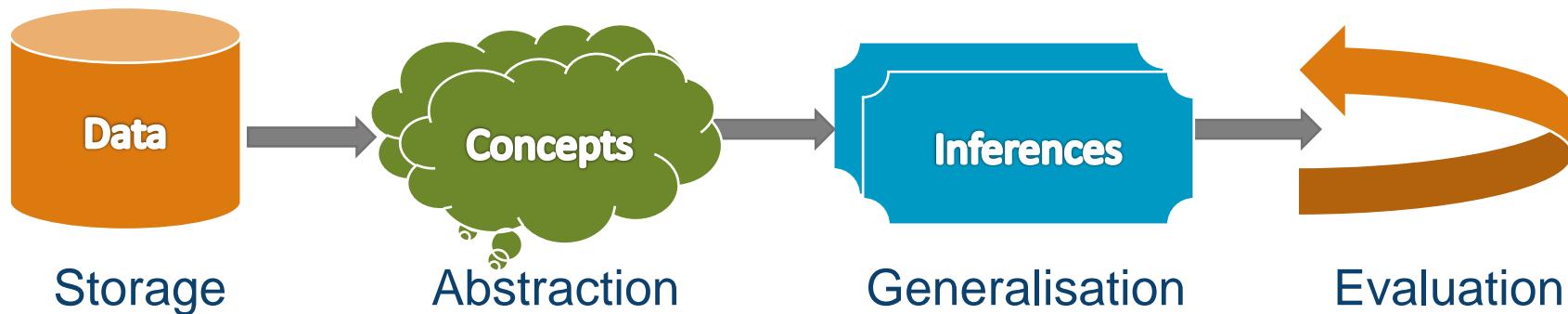


The boy is holding a baseball bat.

# How machines learn

## Learning Process:

1. **Data collection/storage:** all learning must begin with data.
2. **Abstraction:** translates data into broader representations and concepts.
3. **Generalisation:** uses abstracted data to create knowledge and inferences that drive action in new contexts.
4. **Evaluation:** provides a feedback mechanism to measure the utility of learned knowledge and inform potential improvements.



# Data abstraction

A computer summarises stored raw data using a **model**.

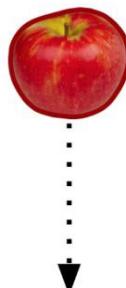
**Model fitting = Model training = Data abstraction**

## Some model types

- Mathematical equations;
- Relational diagrams such as graphs;
- Logical if / else rules;
- Groupings of data known as clusters.

A model can be useful for the discovery of previously unseen relationships among data.

Observations → Data → Model



Distance	Time
4.9m	1s
19.6m	2s
44.1m	3s
78.5m	4s

**Gravitational force**  
 $g = 9.8\text{m/s}^2$

$$t=\sqrt{(2d/g)}$$

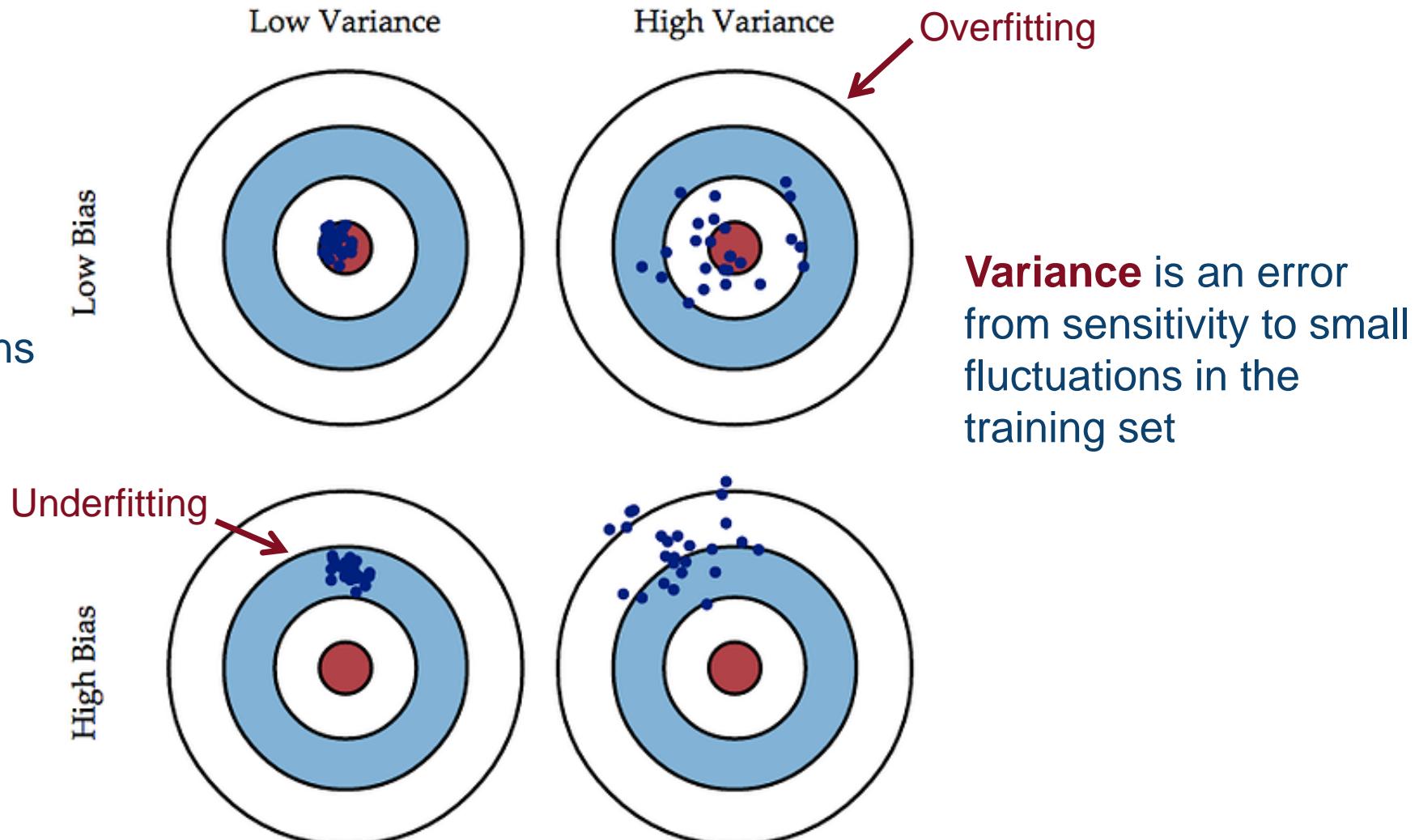


## Generalisation

- In generalisation, the learner tries to limit the patterns it discovers to only those most relevant to its future tasks.
- Machine learning algorithms generally employ shortcuts that reduce the search space more quickly.
- the algorithm employs **heuristics**, which are educated guesses about where to find the most useful inferences.
- The heuristics employed by machine learning algorithms can introduce a bias.

# Generalisation: Bias vs Variance

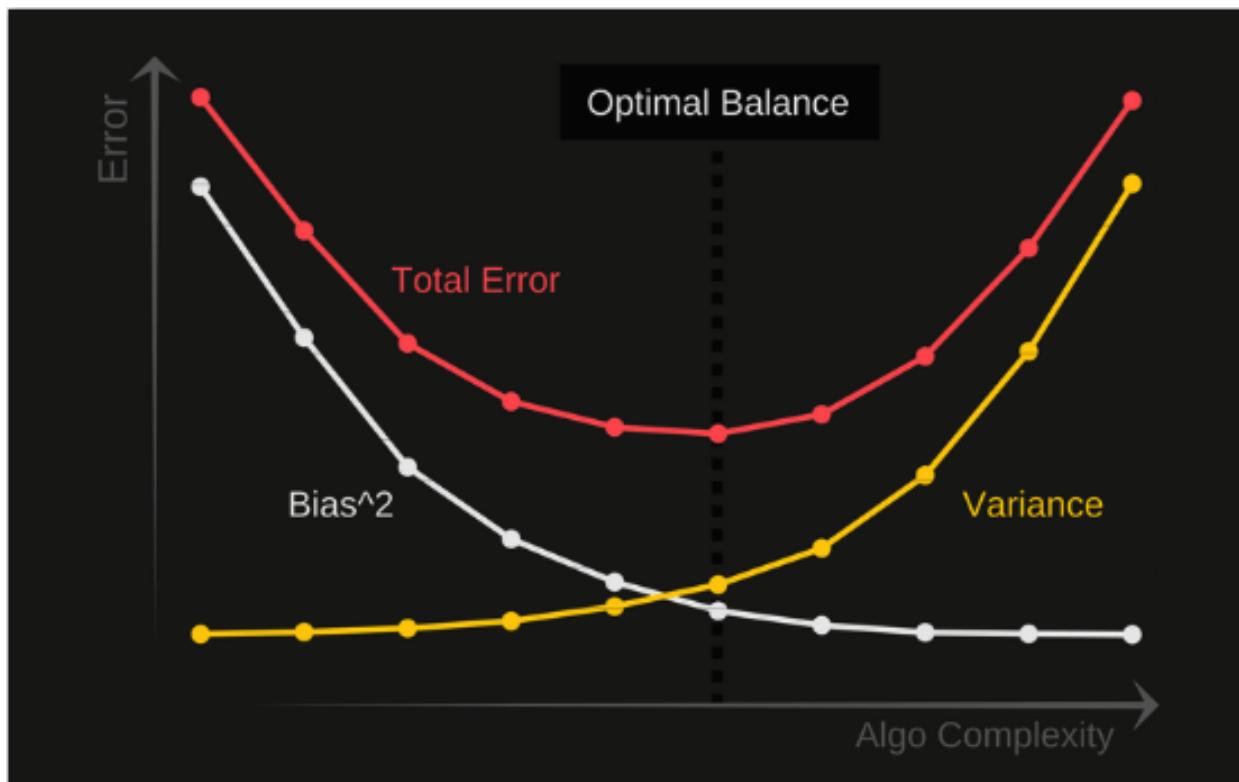
**Bias** is an error from erroneous assumptions in the algorithm.



# Generalisation: Bias vs Variance

A good model minimizes the total error by finding a balance between bias and variance.

$$\text{Total Error} = \text{Bias}^2 + \text{Variance} + \text{noise}$$

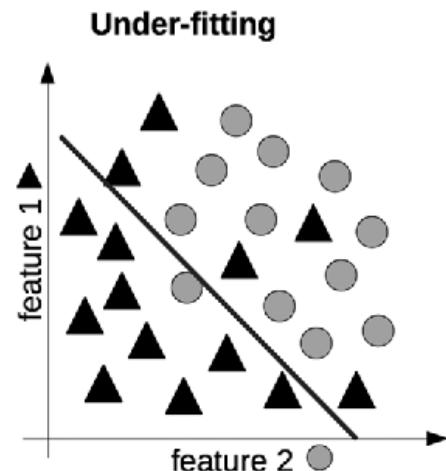


# Evaluation

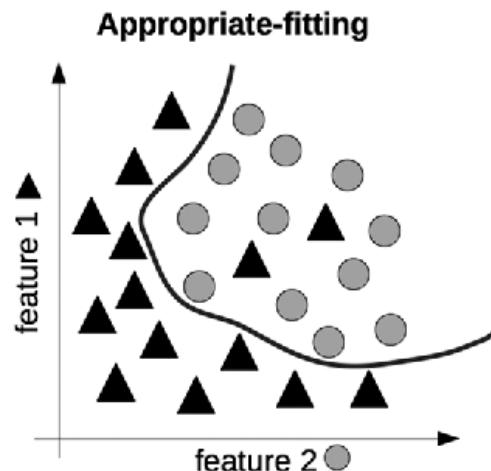
**Evaluation:** occurs after a model has been trained on an initial training dataset. Then, the model is evaluated on a new test dataset in order to judge how well its characterisation of the training data generalises to new, unseen data.

In parts, models fail to perfectly generalise due to the problem of **noise**.

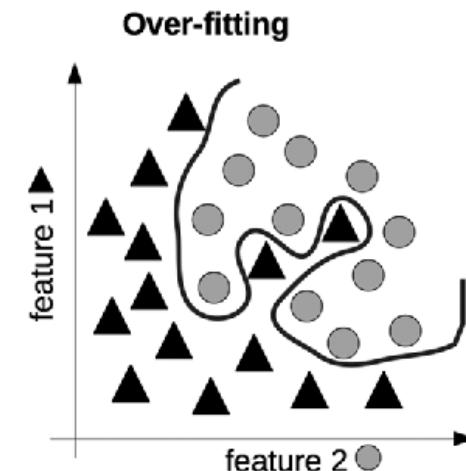
Trying to model noise causes **overfitting**.



High bias



High Variance





# Typical ML Workflow

1. Data pre-processing



2. Feature Selection



3. Model Selection



4. Model Optimisation



5. Model Testing

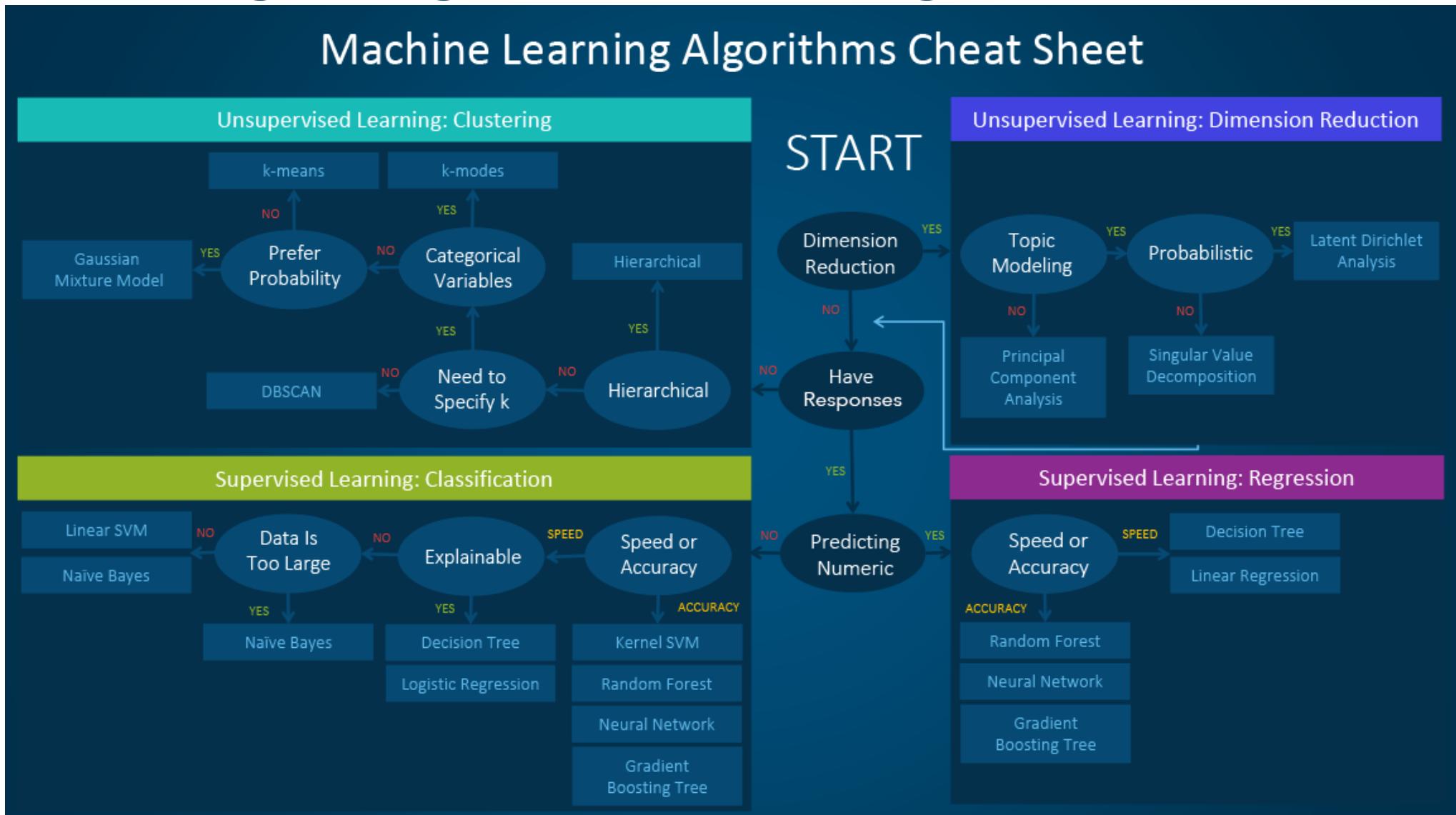


# Applications of ML algorithms

- a) Predictive models:** discover and model the relationship between the target feature and the other features → **supervised learning**.
- b) Descriptive models:** aiming at gaining insights from summarising data in new and interesting ways → **unsupervised learning**.
- c) Meta-learning analysis:** algorithms focused on how to learn more effectively.

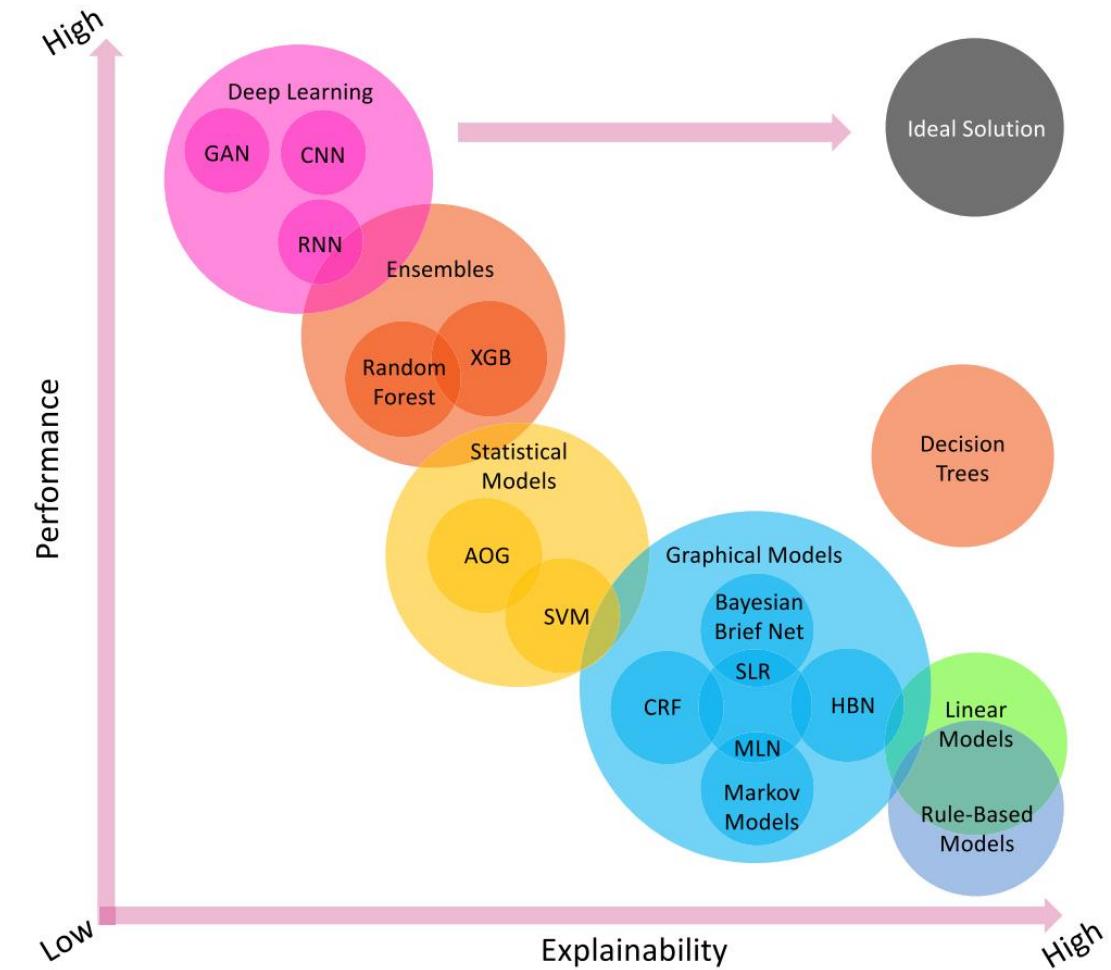
Meta-learners use the result of some learning to inform additional learning.

# Matching ML algorithms to learning tasks



# Matching ML algorithms to learning tasks

	Frequently used algorithms for biomedical research	Example usage (data type)
Supervised learning	<b>Machine learning</b>	<ul style="list-style-type: none"> <li>SVM</li> <li>KNN</li> <li>Regression</li> <li>Random forest</li> </ul>
	CNN	<ul style="list-style-type: none"> <li>Cancer vs healthy classification (gene expression)</li> </ul>
	RNN	<ul style="list-style-type: none"> <li>Multiclass tissue classification (gene expression)</li> <li>Genome-wide association analysis (SNP)</li> </ul>
		<ul style="list-style-type: none"> <li>Pathway-based classification (gene expression, SNP)</li> </ul>
Unsupervised learning	<b>Deep learning</b>	<ul style="list-style-type: none"> <li>Protein secondary structure prediction (amino acid sequence)</li> <li>Sequence similarity prediction (nucleotide sequence)</li> </ul>
	Hierarchical	<ul style="list-style-type: none"> <li>Protein family clustering (amino acid sequence)</li> </ul>
	K-means	<ul style="list-style-type: none"> <li>Clustering genes by chromosomes (gene expression)</li> </ul>
	PCA	<ul style="list-style-type: none"> <li>Classification of outliers (gene expression)</li> <li>Data visualization (single cell RNA-sequencing)</li> </ul>
dimensionality reduction	tSNE	<ul style="list-style-type: none"> <li>Clustering gene expression profiles (gene expression)</li> </ul>
	NMF	





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