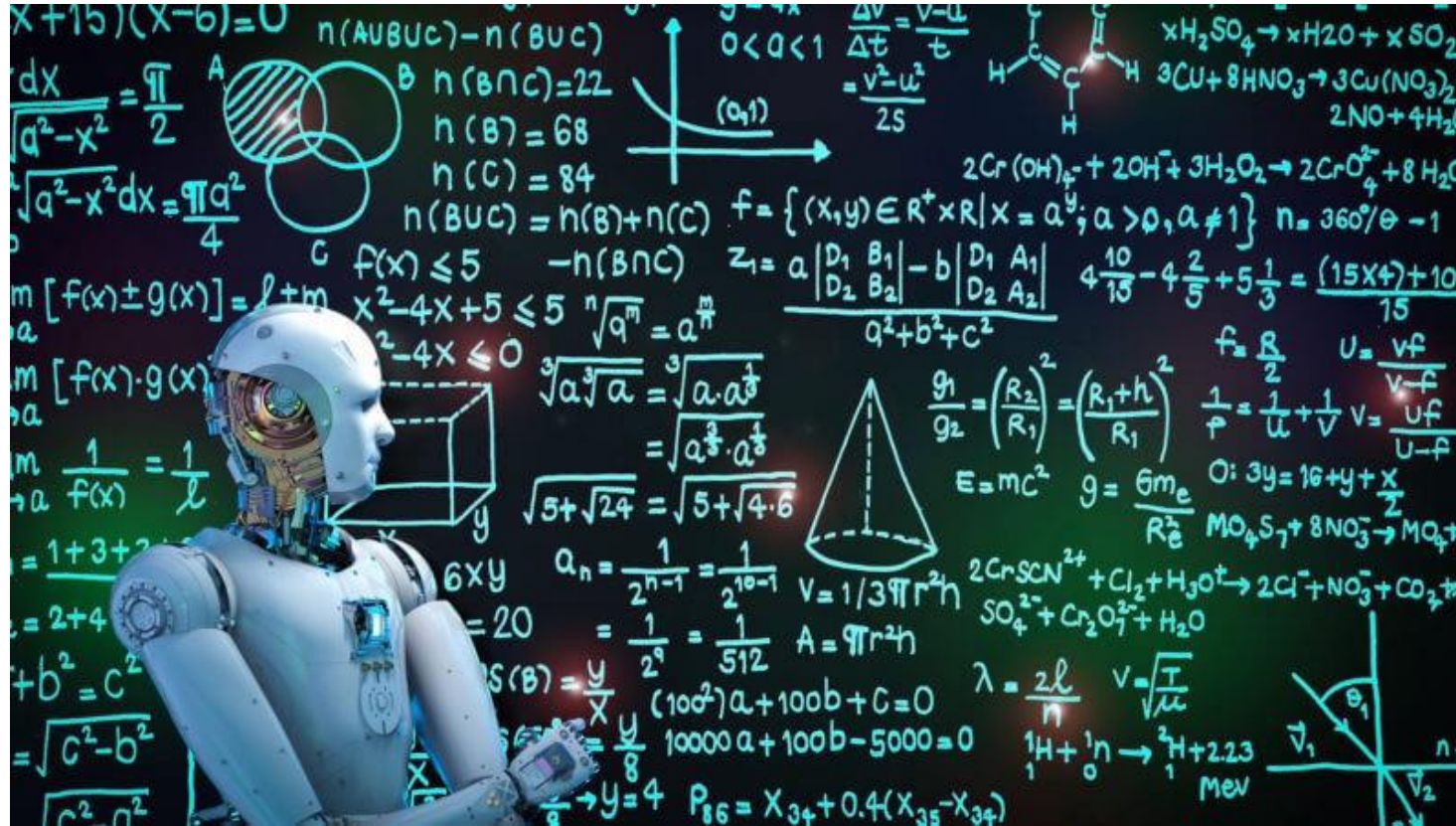


# Linear Algebra for Machine Learning – An Introduction

Bhavathy Kathirgamanathan  
University College Dublin



# What is Machine Learning?

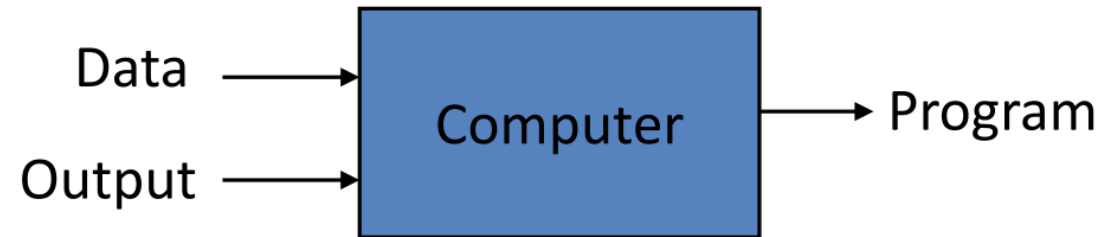
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*“Field of study that gives computers the ability to learn without being explicitly programmed” - Arthur Samuel (1959)*

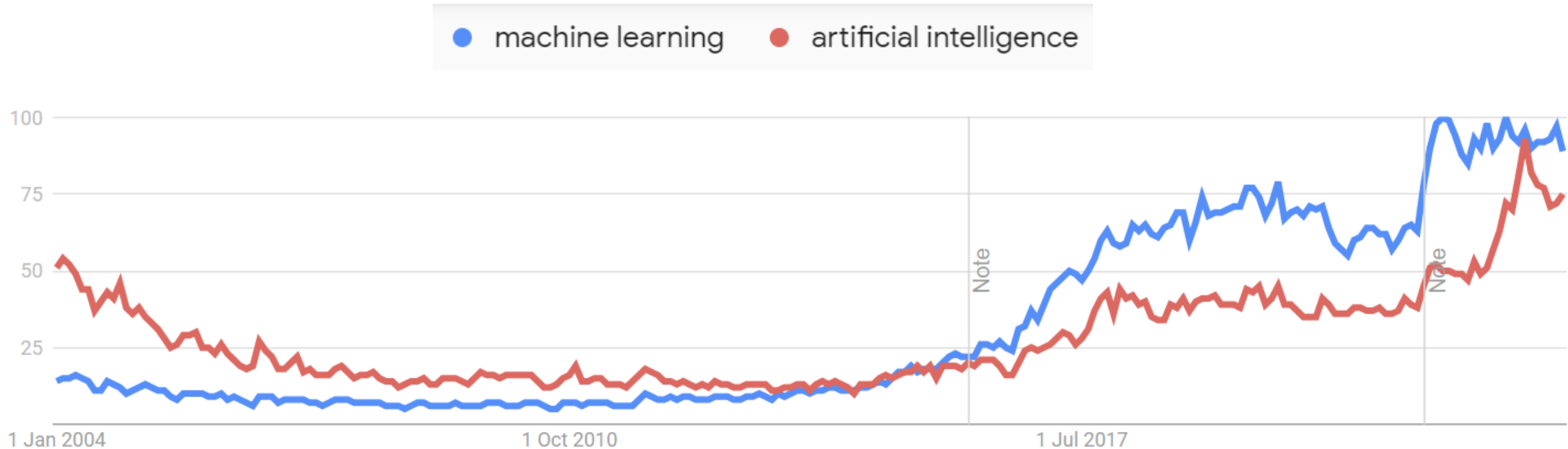
## Traditional Programming



## Machine Learning



# Machine Learning and Artificial Intelligence



Generated using Google trends

<https://trends.google.com/trends/explore?date=all&q=machine%20learning,artificial%20intelligence&hl=en-GB>

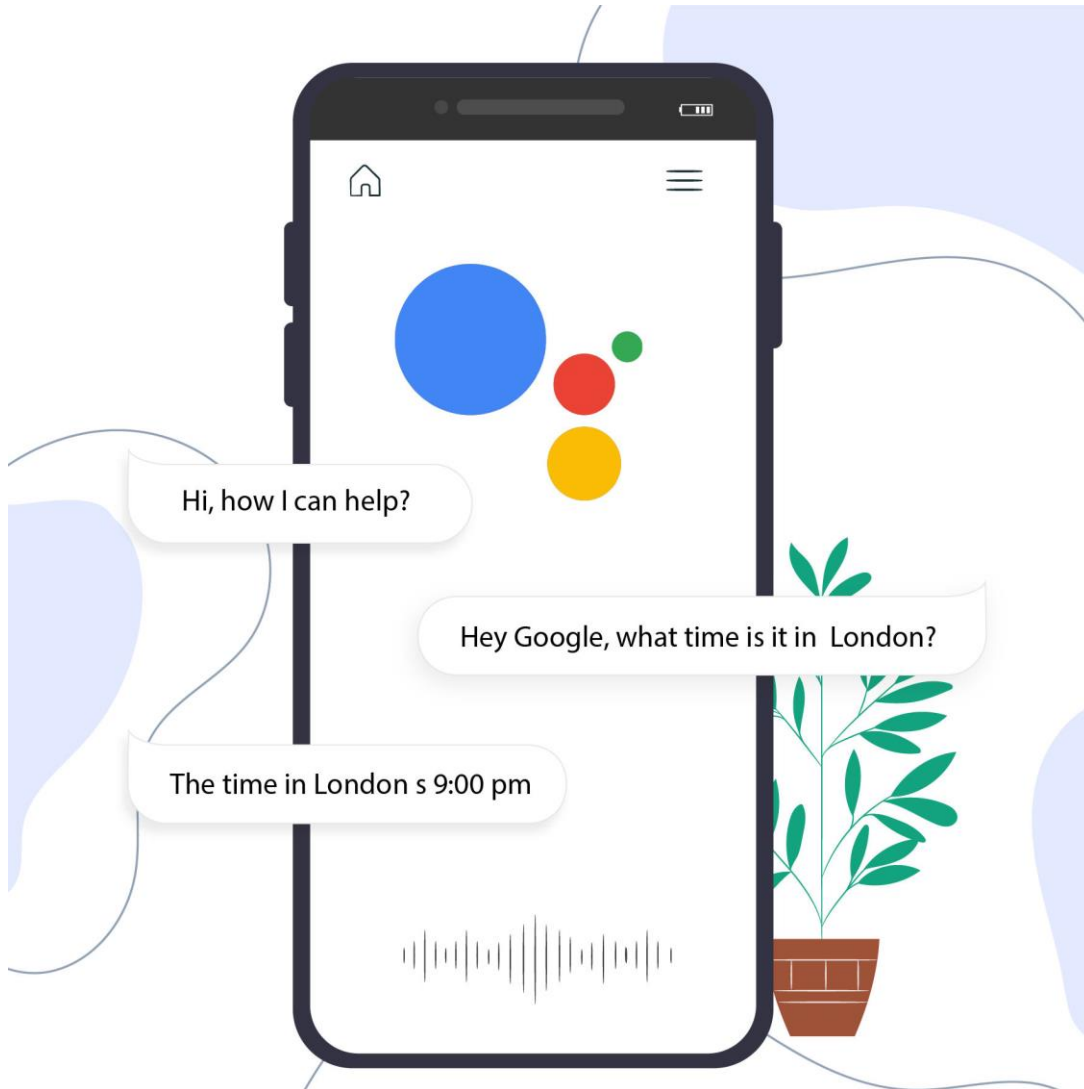
# Application: Spam Classification

The screenshot shows a Gmail interface with the search bar set to "in:spam". The left sidebar lists various email categories with their counts: Inbox (2,082), Starred, Snoozed, Important, Sent, Drafts (22), Categories (Social: 1,432, Updates: 2,566, Forums: 5, Promotions: 2,679), Less, and Chats. The main content area displays a list of spam messages. A notification at the top states: "Messages that have been in Spam more than 30 days will be automatically deleted. [Delete all spam messages now](#)". The message list includes:

From	Subject	Date
UCD Students' Union	Your Students' Union Update - UCDSU Update- 21.11.23 The days are growing sho...	Nov 22
ICCEAD2024	Please Join the Technical Program Committee of International Conference on...	Nov 18
Gipsyy	🚗🎉 BLACKFRIDAY GIPSY 🎉🚗 - 🚗🎉 Hoje é o dia! Nossa #BlackFriday come...	Nov 12
UCD Students' Union	Your Students' Union Update - (Optional) UCDSU November Newsletter. 🍁 Welc...	Nov 7
Celine Lee	Reminder: [No APC] Dear Dr. Kathirgamanathan---Dr. Nicusor V. Iftimia invite...	Nov 7
Gipsyy	A tua opinião é muito importante* ;Tu opinión es muy importante! * Your opin...	Nov 1
ACDSA 2024	Seychelles Conference with IEEE publication chance - Deadline extended - In...	Nov 1
Celine Lee	Reminder: [No APC] Dear Dr. Kathirgamanathan---Dr. Nicusor V. Iftimia invite...	Oct 31

# Application: Chatbots

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"Alexa, let's chat."



"What's on your mind?"




# Application: Machine Translation

English - Detected English Spanish French

welcome to this lecture







23 / 5,000



↔ Sinhala Tamil English



இந்த விரிவுரைக்கு வரவேற்கிறோம்

Inta virivuraikku varavēṟkiṛōm




English - Detected English Spanish French

welcome to this lecture







23 / 5,000



↔ Sinhala Tamil English

මෙම දේශනයට සාදරයෙන් පිළිගනිමු

mema dēśanayaṭa sādārayen piḷiganimu





# Application: Self-Driving Cars



# Supervised vs Unsupervised learning

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## Supervised Learning:

An algorithm that learns a function from examples of inputs and outputs. This type of learning required manually labelled data in a training set which is then used to train a model to predict on “unseen” data.

i.e: Classification, Regression

## Unsupervised Learning:

An algorithm that finds structure in unlabelled data. These algorithms are more focused on data exploration and knowledge discovery.

i.e: Clustering



# Typical Supervised Learning Process

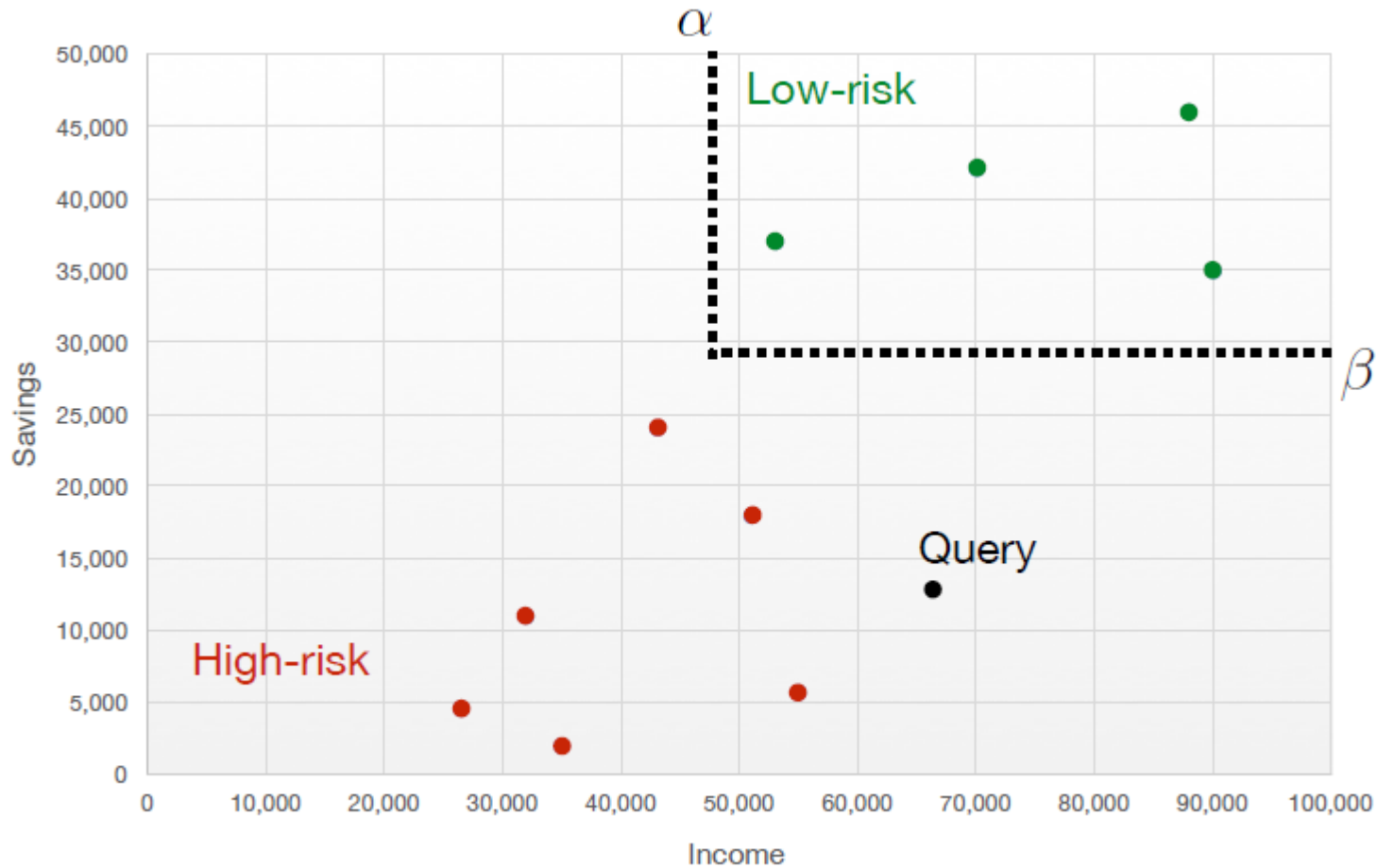
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**A Decision Process:** Based on the input data, the algorithm produces an estimate of the pattern in the data

**An Error Function:** A method which evaluates how good the prediction made is

**A Model Optimisation Procedure:** Model is adjusted to try to fit the data better and the error is re-evaluated. This step is repeated until the threshold accuracy is met.

# Typical Classification Task



Aim: Can we train an algorithm to learn how to classify a new customer as high risk or low risk?

i.e: Can we learn  $\alpha$  and  $\beta$  – the decision boundaries

# Typical Classification Task

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<i>Example</i>	<i>Income</i>	<i>Savings</i>	<i>Married</i>	<i>Gender</i>	<i>Age</i>	<i>Class</i>
1	35,000	2,000	Y	M	32	High-risk
2	51,000	18,000	N	M	34	High-risk
3	70,000	42,000	Y	F	41	Low-risk
4	26,500	4,500	N	M	22	High-risk
5	32,000	11,000	N	F	25	High-risk
6	53,000	37,000	N	F	39	Low-risk
7	88,000	46,000	Y	M	48	Low-risk
8	55,000	5,700	N	M	55	High-risk
9	90,000	35,000	Y	F	61	Low-risk
10	43,000	24,000	Y	M	33	High-risk

<i>Example</i>	<i>Income</i>	<i>Savings</i>	<i>Married</i>	<i>Gender</i>	<i>Age</i>	<i>Class</i>
X	66,000	13,000	Y	M	44	???

# Classification Algorithms

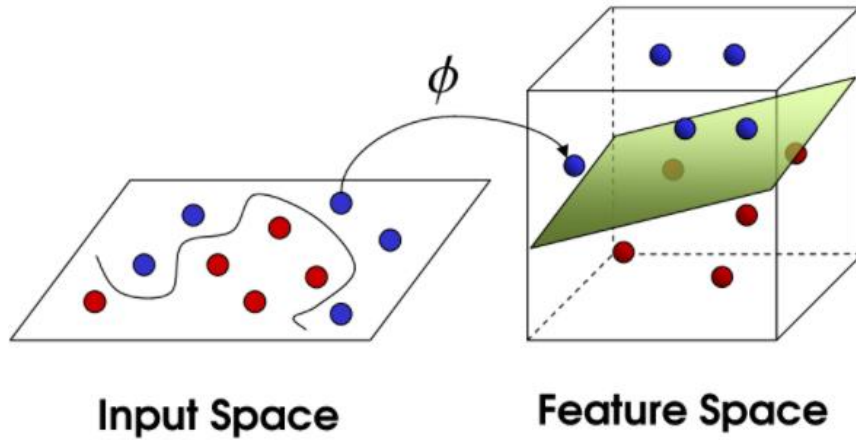
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- There are many different learning algorithms for classification
- Popular algorithms include: k-Nearest Neighbour, Decision Trees, Neural Network, Support Vector Machine)
- The choice of classification algorithm depends on the data. There is no one model that performs best for every dataset

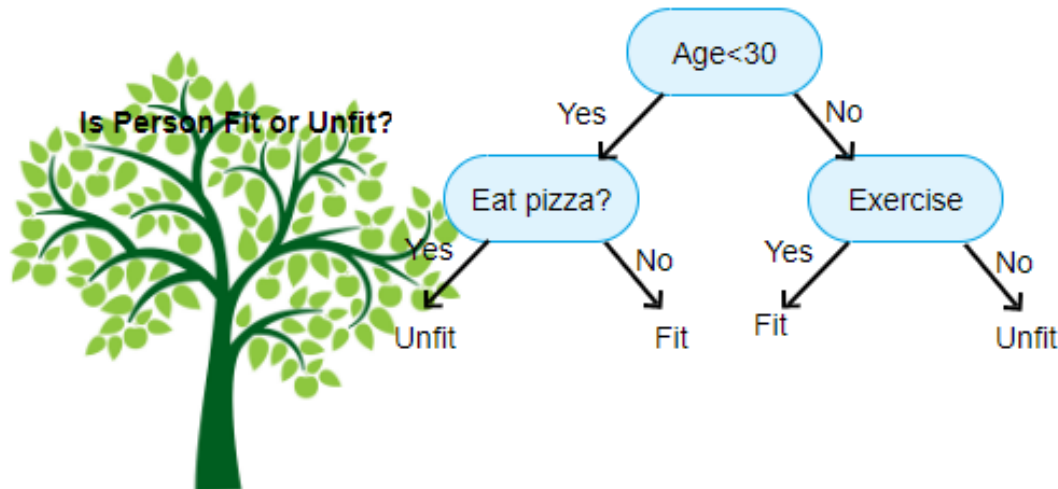
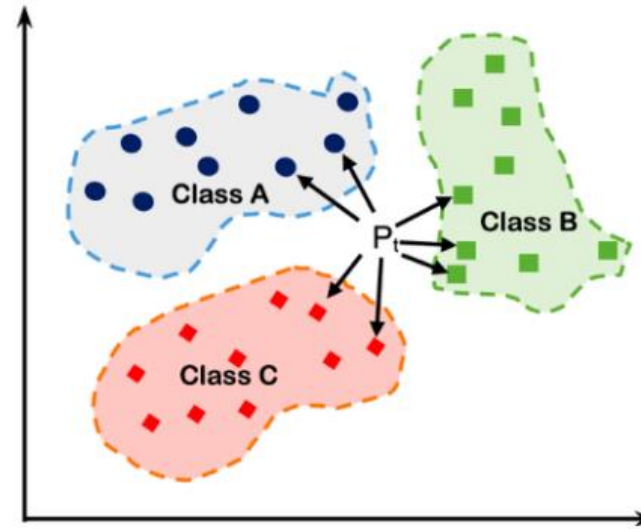


# Classification Algorithms

## Support Vector Machines



## K-Nearest Neighbour

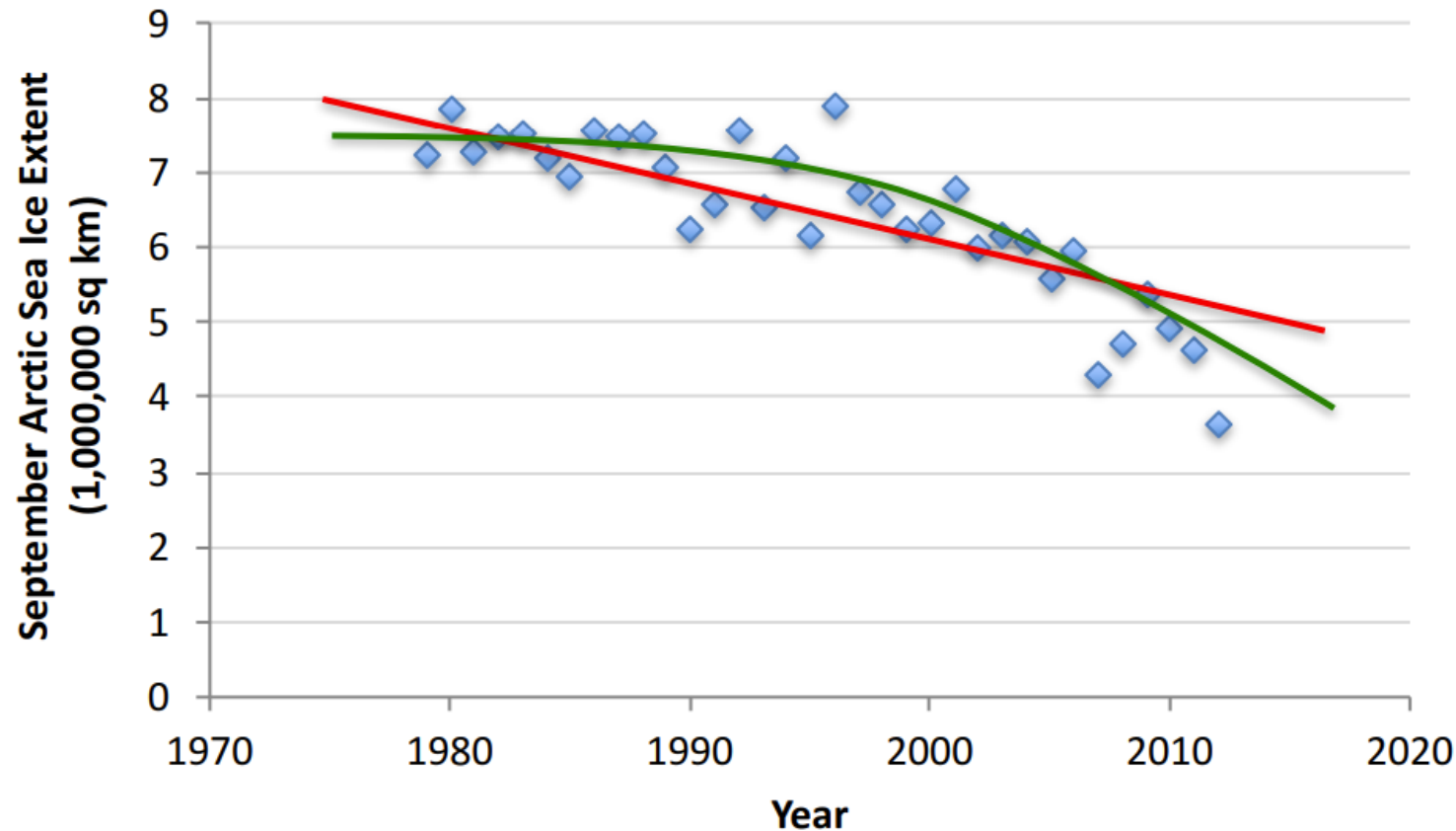


## Decision Tree

# Typical Regression Task

Given  $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ , can we learn a function  $f(x)$  to predict  $y$  given  $x$ ?

If  $y$  is real-valued, the task is regression



# Linear algebra and Machine Learning

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- Linear algebra is the **mathematics of arrays**...

Many tasks in Machine Learning are performed using arrays:

- Representing data (inputs and outputs)
- Some models are represented using arrays
- Some internal computations use arrays

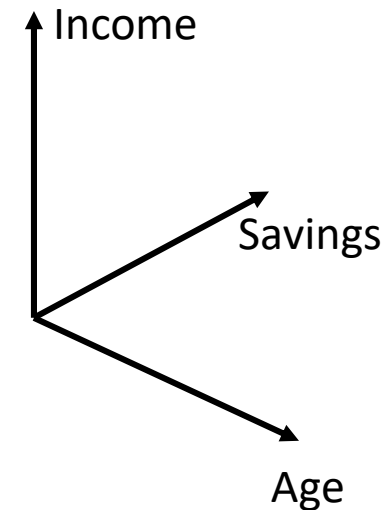
# Representing data as vectors...

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A feature vector is a vector containing the “features” of some instance

$$C = \begin{bmatrix} 35,000 \\ 2000 \\ 32 \end{bmatrix} \begin{matrix} \textit{Income} \\ \textit{Savings} \\ \textit{Age} \end{matrix}$$

Where C represents the feature space for the credit risk for one person



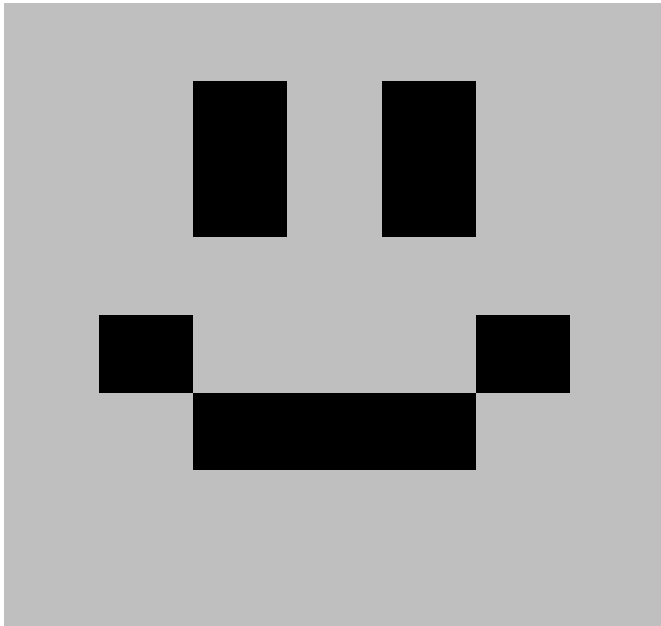
In Machine Learning, this vector space is called the **feature space**



# Representing data as vectors...

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## Images


$$\begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 & 1 & 0 & 1 \\ 1 & 1 & 0 & 0 & 0 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 0 \\ 1 \\ 0 \\ \vdots \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

# Representing data as arrays...

---

## Words and Documents

Given a collection of Wikipedia articles, create a vector for every word where the  $i^{th}$  entry is the number of times that word appears in the  $i^{th}$  document.

**Has potential to end up as a very large vector space**

$$\text{Dog} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 10 \\ 0 \\ 0 \\ 0 \\ 1 \\ 0 \\ 55 \\ 0 \\ 0 \\ 1 \end{bmatrix} \begin{array}{l} \textit{Wiki doc 1} \\ \textit{Wiki doc 2} \\ \textit{Wiki doc 3} \\ \textit{Wiki doc 4} \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \vdots \\ \textit{Wiki doc 11} \\ \textit{Wiki doc 12} \\ \textit{Wiki doc 13} \end{array}$$

# Representing data as arrays...

---

How about non-numerical data (e.g. words)

## One hot encoding

One hot encoding means, each object (or each word) is assigned a vector with a single one and zeros elsewhere. As an example if we have a dictionary with four words.

$$\text{Apple} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$\text{Mango} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

$$\text{Orange} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

$$\text{Banana} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

# Challenges in representing data as vectors...

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- Data can be very large – hence large vectors/matrices
- Vectors can be very **sparse** meaning a lot of zeros.



# Singular Value Decomposition (SVD)

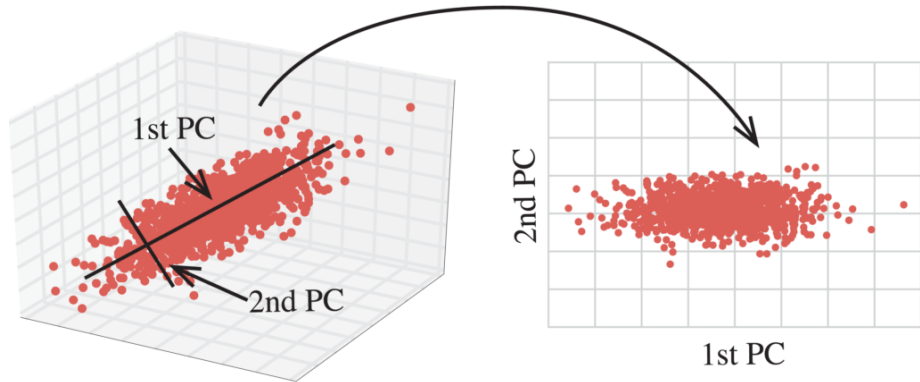
- SVD of a matrix means the factorization of that matrix into three smaller matrices

Columns are Orthonormal      Diagonal Matrix      Rows are Orthonormal

$$\begin{bmatrix} \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \end{bmatrix} = \begin{bmatrix} \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \end{bmatrix} \begin{bmatrix} \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet \end{bmatrix} \begin{bmatrix} \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \end{bmatrix}$$

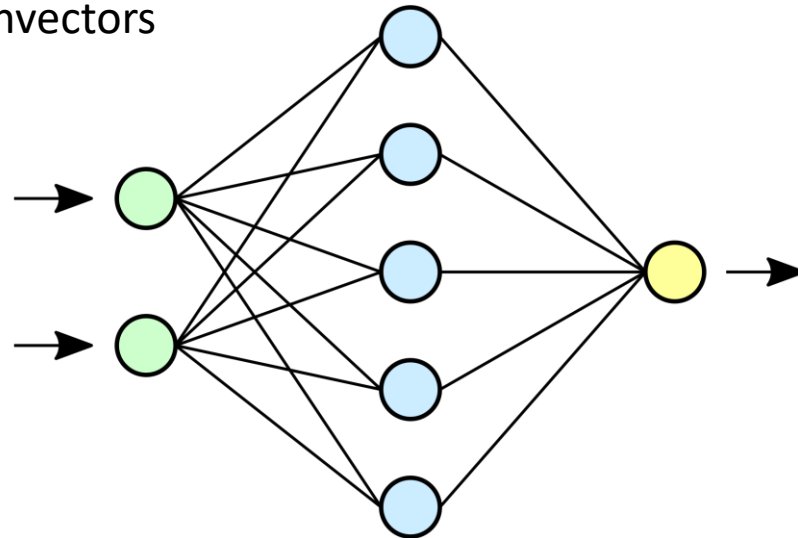
$M$        $U$        $D$        $V$   
 $n \times m$        $n \times k$        $k \times k$        $k \times m$   
 $k = \text{rank of } M$

# There is much more...



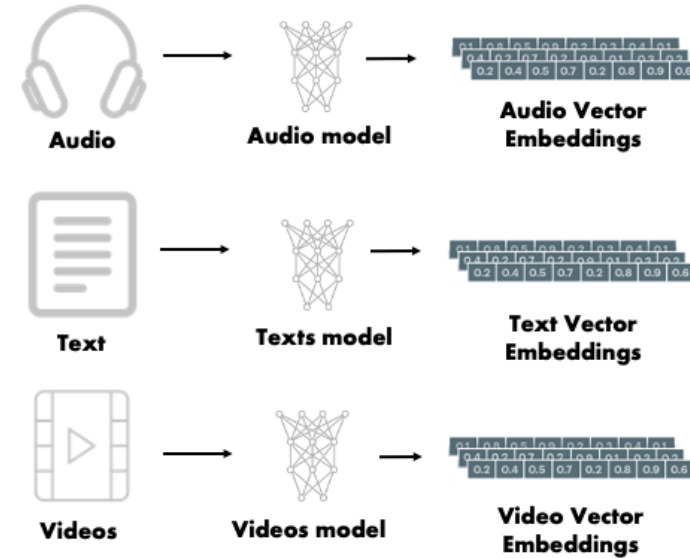
## Dimensionality Reduction

Reduce large dimensional data using linear maps and their eigenvalues and eigenvectors



## Math inside ML Models

Much of the math inside machine learning models involve linear algebra techniques



## Vector Embeddings

Convert data into meaningful embeddings

# What do I do?

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Understand Performance

Diagnose Injury

Monitor Recovery

- PhD Researcher at University College Dublin in Ireland
- Applying Machine Learning methods to Sports Analytics applications
- Particularly, using time series techniques on wearable sensor data

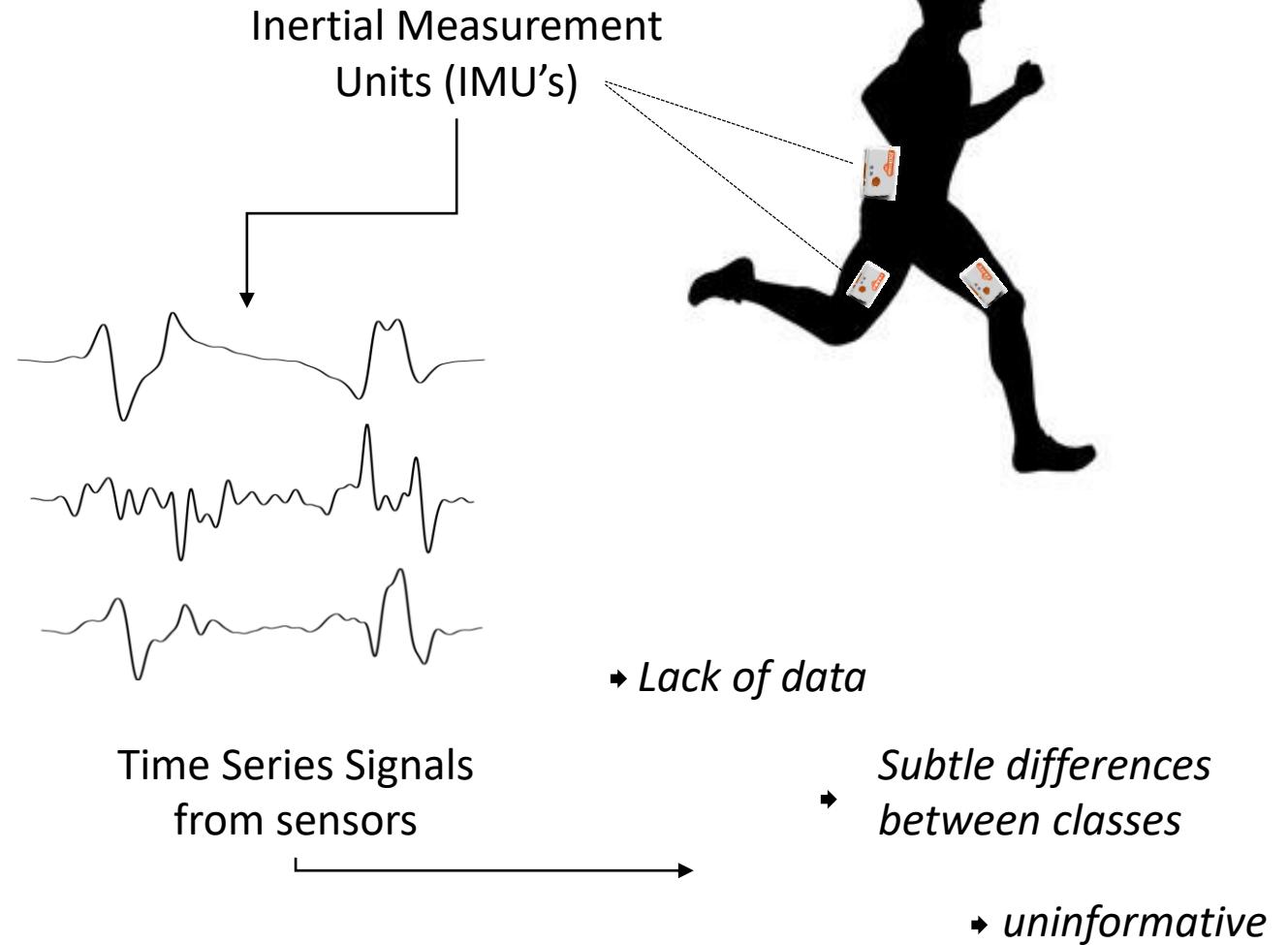
# My Research



Fatigue 

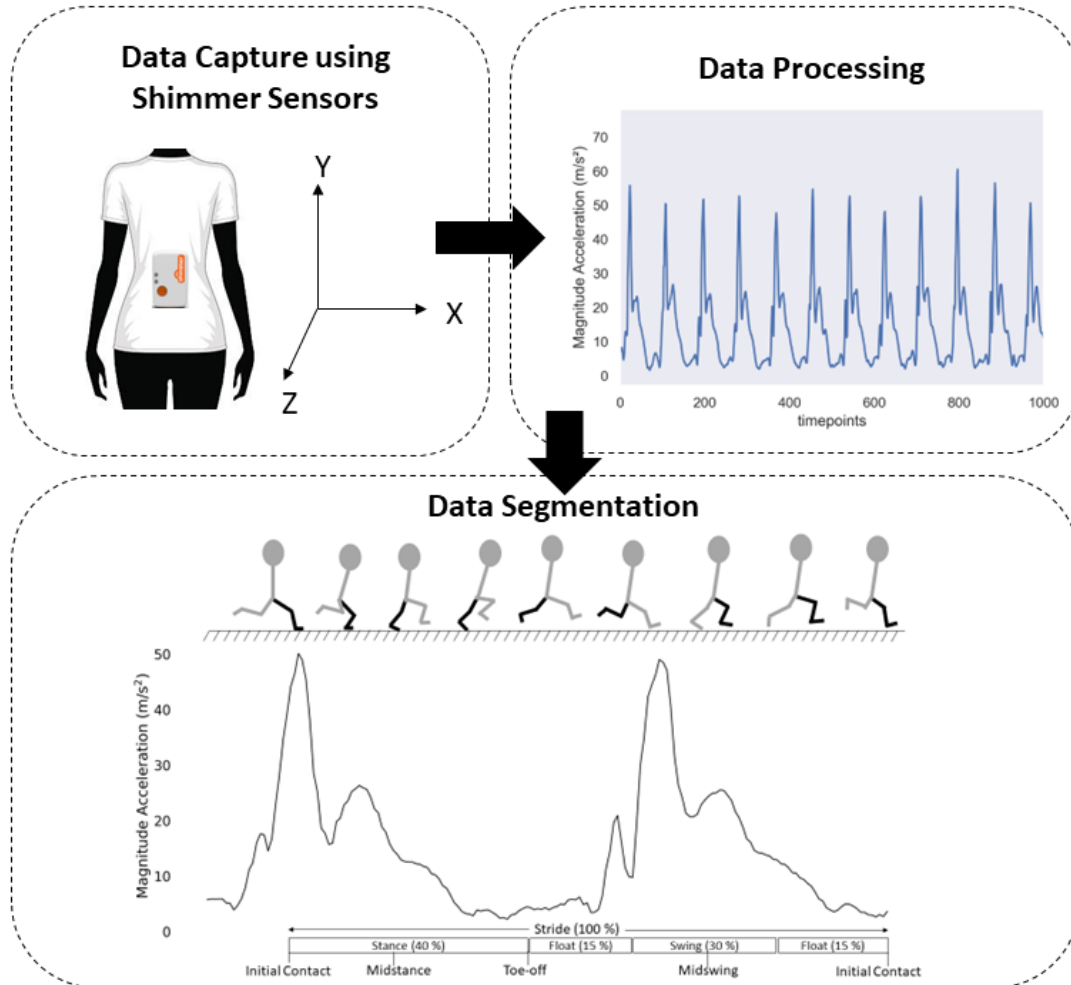


Risk of Injury 





# My Research

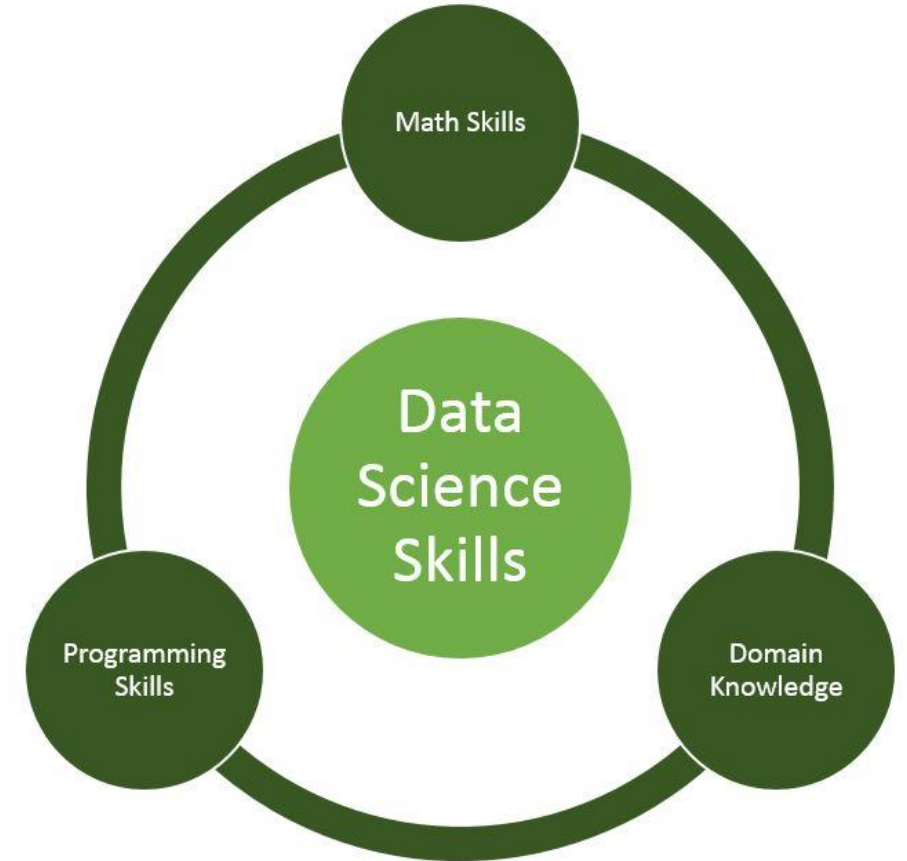


- Data is in a time series format.
- Features are represented as feature matrices instead of feature vectors
- 3D representation -> number of instances x number of timepoints x number of variable
- Hence a lot of matrix manipulation is required

# Thinking of a career in Machine Learning?

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- Applications of ML exists in every field
- Maths and Programming are essential
- Often a postgraduate degree is required
- Job Market = Excellent!!!



# References and Resources used

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TensorFlow – A friendly introduction to linear algebra for ML  
(<https://www.youtube.com/watch?v=LIKAna21fLE>)

# Questions??

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## Linear Algebra for Machine Learning – An Introduction

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