# Machine Learning & AI

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MCI

B.Sc - Machine Learning and Data Science II

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# Introduction

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# Introduction

- The goal of this lecture is to give you the fundamentals of ML and understanding of mathematical and programming principles.
- This lecture is a total of 2 SWS with a total of sixty (30) hours.
- There is a written exam at the end of the lecture series.
- There is one (1) assignment for this course.

  **1**$^{st}$ will be a pre-defined work which is individual based.

# Introduction

- The individual assignment focuses on understanding ML principles.
- The assignment is uploaded to SAKAI for you to work on along with what is required of you for submission.
  - The assignment contains questions where applications of ML will be needed.
- The deadline is the **last lecture before the examination**.

# Introduction

- The final exam will be done on the last session where questions covering the entire lecture will be asked.
- The duration of the exam will be ninety (90) and will be done written.
- You are able to bring a calculator to the exam but no personal reference sheets are allowed.
- Any reference documents (if needed) will be provided for you during the beginning of the exam.

| Assessment Type | Overall Points | Breakdown | % |
|---|---|---|---|
| Homework | 40 | | |
| | | Report | 20 |
| | | Solution(s) | 60 |
| | | Code Analysis | 20 |
| Final Examination | 60 | | |

**Table 1:** Assessment Grade breakdown for the lecture.

| Covered Topic | Appointment |
|---:|:---:|
| Machine Learning Landscape | 1 |
| End-to-End Machine Learning Project | 2 |
| Classification | 3 |
| Training Models | 4 |
| Support Vector Machines | 5 |
| Decision Trees | 5 |
| Ensemble Learning and Random Forests | 5 |
| Dimensional Reduction | 6 |
| Unsupervised Learning | 6 |
| Introduction to Artificial Neural Networks | 7 |

**Table 2:** Distribution of materials across the semester.

## Machine Learning Landscape

- Covers the methods used in ML
  - Example applications
  - Types of ML Systems
  - Challenges of ML
  - Testing and Validations

### End-to-End Machine Learning Project

- A ML project to work from beginning to end
  - Working with real data
  - Visualising the data
  - Select and train the data
  - Testing the model

## Classification

- Focusing on how to work with data
  - MNIST,
  - Performance Measures,
  - Error Analysis
  - Multi-label Classification

# Introduction

## Training Models

- Understanding how to get models to explain data
  - Linear Regression
  - Gradient Descent,
  - Polynomial Regression,
  - Logistic Regression.

## Support Vector Machines

- Focusing on Vector machines
  - Linear & non-linear SVM
  - SVM Regression

## Decision Trees

- Focus on building decision trees
  - Training a decision tree
  - Making predictions
  - Estimating probabilities

### Ensemble Learning and Random Forests

- Focusing on random forests
  - Voting Classifiers
  - Bagging and Pasting
  - Random Forests
  - Stacking

### Dimensional Reduction

- Focusing on how to work with high-dimension data
  - Approaches to reduce dimensions,
  - Manifold learning,
  - PCA,
  - Kernel PCA.

## Unsupervised Learning

- How to work with models with no clear training.
  - K-means,
  - DBSCAN,
  - Gaussian Mixtures.

## Introduction to Artificial Neural Networks

- A deep dive into artificial neural networks (ANNs)
  - The Perceptron,
  - Backpropagation,
  - Regression multi-layer Perceptrons,
  - Classification multi-layer perceptrons.

### Books

- Aggarwal S. "*Neural Networks and Deep Learning*" Springer, 2023.
- Raschka S., et. al "*Python Machine Learning*" Packt 2017.
- Geron A. "*Hands-on Machine Learning with Scikit-Learn, Keras & TensorFlow*" O'Reilly 2022.
- Albon C. "*Machine Learning with Python Cookbook*" O'Reilly 2018.

# Introduction

### Lecture Notes

- Ng A., et.al "*CS229 Lecture Notes*",
- Migel A., et.al "*Lecture Notes on Machine Learning*"

## Web Resources

- Scikit-learn documentation
- OpenCV documentation
- Pillow (fork of PIL) documentation

# Machine Learning Landscape

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## Learning Outcomes

(LO1) An Introduction to ML,

(LO2) Overview of Learning Methods,

(LO3) Application of ML Algorithms,

(LO4) General Problems of ML Training/Evaluations.

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# Machine Learning Landscape

- Spam filters are a great place to start showing use of ML.
- A spam filter is a ML program where, given examples of spam emails (flagged by users) and examples of regular emails (non-spam, also called `ham`), can learn to flag spam.
- Examples the system uses to learn are called the training set.
- Each training example is called a training instance (i.e., sample).
- Part of the ML system learning and making predictions is called a model.
  - Neural networks and random forests are examples of models.

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**Figure 1:** "Spam, Spam, Spam, Spam... Lovely Spam! Wonderful Spam!"

- Consider how you would write a spam filter using traditional method;

1. Define spam.
   - Some words or phrases (such as `4U`, `credit card`, `free`, `amazing`) tend to come up a lot in subject.
   - You also notice sender email also looks fishy.
2. Write an `if/else` statement for each case, and the program would flag emails as `spam` if a number of these patterns were detected.
3. Test program and release it to the public.
4. Profit!!

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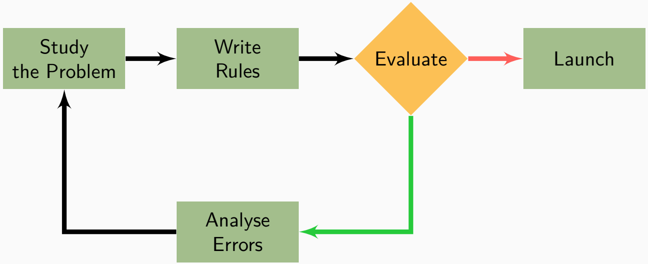


**Figure 2:** A block diagram on how to structure a spam filter using the traditional programming methods.

- As the problem is difficult, the traditional program will become a long list of complex rules.
  - This would be pretty hard to maintain.
- Whereas, a spam filter using ML automatically learns which words and phrases are good predictors of spam by detecting unusually frequent patterns of words in the spam examples compared to the ham examples [7].

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> The program is much shorter, easier to maintain, and most likely more accurate.

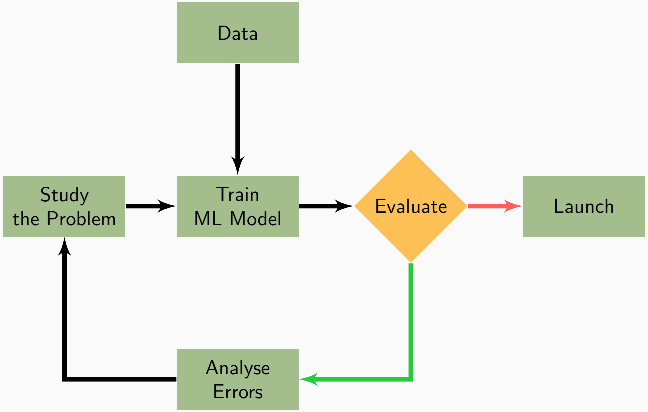


**Figure 3:** A block diagram on how to structure a spam filter using the ML approach.

- What if spammers notice that all their emails containing `4U` are blocked?
  - They might start writing `For U` instead.
- The traditional method needs to be updated to flag `For U` emails.
- If spammers keep working around your spam filter, you will need to keep writing new rules forever.

> A spam filter based on ML automatically notices that `For U` has become unusually frequent in spam flagged by users, and it starts flagging them without your intervention.

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ML works best for problems too complex for traditional approaches or have no known algorithm.

- Consider speech recognition [5]:
- Say you want to write a program capable of distinguishing the words `one` and `two`.
- You notice the word `two` starts with a high-pitch sound `T`.
- You could hard-code an algorithm measuring high-pitch sound intensity and use it to distinguish ones and twos.
  - This technique will not scale to thousands of words spoken by millions of very different people in noisy environments and in dozens of languages [2].
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- ML can also help humans learn.
- ML models can be inspected to see what they have learned.
  - Although for some models this can be tricky.
    - such as [illegible] models.
- i.e., once a spam filter has been trained on enough spam, it can easily be inspected to reveal the list of words and combinations of words that it believes are the best predictors of spam.
- Sometimes this will reveal unsuspected correlations or new trends, and thereby lead to a better understanding of the problem.
- Digging into large amounts of data to discover hidden patterns is called data mining, and ML excels at it [11].

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  - Fluctuating environments.
  - Getting insights about complex problems and large amounts of data.

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- Analysing images on production line items classify [9]:
  - Called image classification, performed using convolutional neural networks or sometimes transformers.
- Detecting tumours in scans [10]:
  - Called semantic image segmentation, where each pixel in the image is classified, to determine the exact location and shape of tumours, typically using CNNs or transformers.
- Automatically classifying news articles [1]:
  - Called natural language processing (NLP), more specifically text classification, tackled using recurrent neural networks (RNNs) and CNNs, but transformers work even better.

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- Automatically flagging offensive comments on discussion forums [6]
  - Called text classification, using the same NLP tools.
- Summarising long documents automatically [14]:
  - Called text summarising, a sub-field of NLP.
- Creating a chat-bot or a personal assistant [16, 3]
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- Summarising long documents automatically [14]:
  - Called text summarising, a sub-field of NLP.
- Creating a chat-bot or a personal assistant [16, 3]
  - Involves many NLP components, including:
    - Natural language understanding (NLU),
    - Question-Answering modules.

# Machine Learning Landscape

- Forecasting a company's revenue next year [20], based on many metrics.
  - Called regression using any regression model, such as:
    - linear regression,
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**Figure 4:** Deep Blue, computer chess-playing system designed by IBM in the early 1990s, playing against then current grand-master Garry Kasparov. It became the first computer winning against a world champion under tournament conditions [4].


**Figure 5:** AlphaGo was designed to play GO (a very complex game for computers to tackle) and was able to win a master which was deemed a milestone in ML.

# Machine Learning Landscape

- There types of ML useful to classify data in broad categories:
  - Supervision during training:
    - Supervised,
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    - Semi-supervised,
    - Self-supervised.
  - Whether or not they can learn incrementally on the fly:
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These criteria are not exclusive. It is possible to combine them. For example, a state-of-the-art spam filter may learn on the fly using a DNN model trained using human-provided examples of spam and ham; this makes it an online, model-based, supervised learning system.

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- ML can be classified based on the amount and type of supervision they get during training.
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## Supervised learning

- The fed training set includes the desired solutions, called labels.
- A typical supervised learning task is classification.
- The spam filter is a good example of this:
  - Trained with many example emails along with their class, and it must learn how to classify new emails.
- Another typical task is to predict a target numeric value, such as the price of a car, given a set of features.
  - Called regression and to train it you need many examples of cars, including both their features and their targets.

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> Some regression models can be used for classification as well, and vice versa. i.e., logistic regression is commonly used for classification [13], as it can output a value that corresponds to the probability of belonging to a given class (e.g., 20% chance of being spam).

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## Supervised learning

- Target and label are generally treated as synonyms in supervised learning.
- But target is more common in regression tasks and label is more common in classification tasks.
- Features are sometimes called predictors or attributes.
- These terms may refer to individual samples, i.e.,

  **individual** this car's mileage feature is equal to 15,000,

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- For example say you have a lot of data about your blog's visitors.
  - Run a clustering algorithm to try to detect groups of similar visitors.
  - At no point algorithm knows which group a visitor belongs to,
    - it finds those connections without your help.
  - i.e., it notices % of visitors are teenagers who love comic books and read your blog after school while % are adults who enjoy sci-fi and who visit during the weekends.
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- Training data is unlabelled where it tries to learn without a teacher.
- For example say you have a lot of data about your blog's visitors.
  - Run a clustering algorithm to try to detect groups of similar visitors.
  - At no point algorithm knows which group a visitor belongs to,
    - it finds those connections without your help.
  - i.e., it notices % of visitors are teenagers who love comic books and read your blog after school while % are adults who enjoy sci-fi and who visit during the weekends.
  - If you use a hierarchical clustering algorithm it may also subdivide each group into smaller groups.
  - This may help you target your posts for each group.

## Unsupervised learning

- Visualisation algorithms are also good examples.
- Feed them a lot of complex and unlabelled data and they output a 2D or 3D representation of your data that can easily be plotted.
- These algorithms try to preserve as much structure as they can.
  - Trying to keep separate clusters in the input space from overlapping in the visualisation.
- This would show how the data is organised and perhaps identify unsuspected patterns.

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## Unsupervised learning

- A related task is dimensionality reduction where the goal is to simplify the data without losing too much information.
- A way is to merge several correlated features into one.
- i.e., a car's mileage may be strongly correlated with its age so the dimensionality reduction algorithm will merge them into one feature that represents the car's wear and tear.
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It is a good idea to reduce the number of dimensions in your training data using a dimensionality reduction algorithm before feeding it to another ML algorithm (such as a supervised learning algorithm)

It will run much faster the data will take up less disk and memory space and in some cases it may also perform better [17].

## Unsupervised learning

- Another task is anomaly detection.
  - Detecting unusual credit card transactions to prevent fraud,
  - Catching manufacturing defects,
  - Automatically removing outliers before feeding to another ML.

  Shown normal instances during training so it can recognise.
  When it sees a new instance it can tell whether it looks like a normal one or whether it is likely an anomaly.
- Another task is novelty detection.
  - Aims to detect new instances looking different from all instances in the training set.

> This requires having a very clean training set devoid of any instance that you would like the algorithm to detect.

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- For example if you have thousands of pictures of dogs:
  - % of these pictures are Chihuahuas then novelty detection should not treat new pictures of Chihuahuas as novelties.
  - Whereas anomaly detection may consider these dogs as so rare and so different from other dogs and classify them as anomalies.
- Finally another common unsupervised task is association rule learning digging into big data and discover interesting relations between attributes.
- For example suppose you own a supermarket.
  - Running association rule on logs reveal people who purchase barbecue sauce and potato chips also tend to buy steak,
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## Semi-supervised Learning

- Labelling data is usually time consuming and costly.
  - Often have plenty of unlabelled and few labelled instances.
- Some algorithms can deal with data that's partially labelled.
  - This is called semi-supervised learning [18].
- Some photo-hosting services are good examples of this.
  - Once images are uploaded it recognises `person A` appears on many photos and will categories them as a class.
  - This is the unsupervised part of the algorithm (clustering).
  - All the system needs is for you to tell it who these people are.

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Most semi-supervised learning algorithms are combinations of unsupervised and supervised,

i.e., a clustering algorithm may be used to group similar instances together and then every unlabelled instance can be labelled with the most common label in its cluster,

Once the whole dataset is labelled it is possible to use any supervised learning algorithm.

## Self-Supervised Learning

- Involves actually generating a fully labelled dataset from a fully unlabelled one.
- Once the whole dataset is labelled any supervised learning algorithm can be used.
- i.e., if you have a large dataset of unlabelled images you can randomly mask a small part of each image and then train a model to recover the original image.

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## Self-Supervised Learning

- During training the masked images are used as the inputs to the model and the original images are used as the labels.
- The resulting model may be quite useful in itself.
  - i.e., to repair damaged images or to erase unwanted objects from pictures
- Generally a model trained using self-supervised learning is not the final goal,
- You'll usually want to tweak and fine-tune the model for a slightly different task.
  - One that you actually care about.

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## Self-Supervised Learning

- For example suppose you need a pet classification model.
    - Given a picture of a pet it will tell you what species it belongs.
- If you have a dataset of unlabelled photos you can start by training an image repairing model using self-supervised learning.
- Once performing, it should be able to distinguish different pet species.
    - Repairing masked cat image it must know not to add a dog.
- If model's architecture allows, it is possible to tweak the model so that it predicts pet species instead of repairing images.
- Final is to fine-tune the model on a labelled dataset,
    - Model already knows what cats and dogs look like.
    - Only needed so the model can learn the mapping between the species it already knows and the labels we expect from it.

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- If you have a dataset of unlabelled photos you can start by training

> Transferring knowledge from one task to another is called **transfer learning** and it's one of the most important techniques in machine learning today especially when using deep neural networks

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- Some consider self-supervised learning to be a part of unsupervised learning as it deals with fully unlabelled datasets,
- But self-supervised learning uses generated labels during training so it's closer to supervised learning.
- And the term unsupervised learning is generally used when dealing with tasks like clustering dimensionality reduction or anomaly detection.
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## Reinforcement learning

- Reinforcement learning is a very different problem
- The learning method called an agent in this context
  - can observe the environment,
  - select and perform actions,
  - get rewards in return,
    - or penalties in the form of negative rewards
- It must then learn by itself what is the best strategy called a policy to get the most reward over time

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- The system is incapable of learning incrementally.
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  - This phenomenon is often called model rot or data drift.
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- Finally replacing the old model with the new one.
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> Training using the full set of data can take many hours so you would typically train a new system only every few hours or even just weekly If your system needs to adapt to rapidly changing data then you need a more reactive solution.

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- Finally if your system needs to be able to learn autonomously and it has limited resources then carrying around large amounts of training data and taking up a lot of resources to train for hours every day is a showstopper.
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  - Either individually or in small groups called mini batches.
- Each learning step is fast and cheap so the system can learn about new data on the fly as it arrives.
- Useful for systems needing to adapt to change extremely rapidly.
  - such as patterns in the stock market.
- It is also a good option if you have limited computing resources.
  - i.e., if the model is trained on a mobile device.
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- A way to categorise ML systems is by how they generalise.
- Most ML tasks are about making predictions.
  - This means that given a number of training examples the system needs to be able to make good predictions for examples it has never seen before.
- Having a good performance measure on the training data is good but insufficient.
  - The true goal is to perform well on new instances.
- There are two (2) main approaches to generalisation:
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- A way to categorise ML systems is by how they generalise.
- Most ML tasks are about making predictions.
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- The system learns the examples by heart then generalises to new cases by using a similarity measure to compare them to the learned examples.
- For example, flagging emails that are identical to known spam emails very similar to known spam emails.
- This requires a measure of similarity between two emails.
- Similarity measure between two emails could be to count the number of words they have in common.

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- Generalise from a set of examples is to build a model of examples and then use that model to make predictions.

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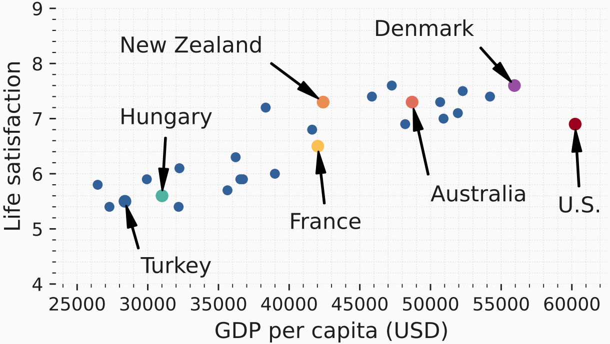
- Generalise from a set of examples is to build a model of examples and then use that model to make predictions.

- For example you want to know if money makes people happy.
- You look at the graph below.

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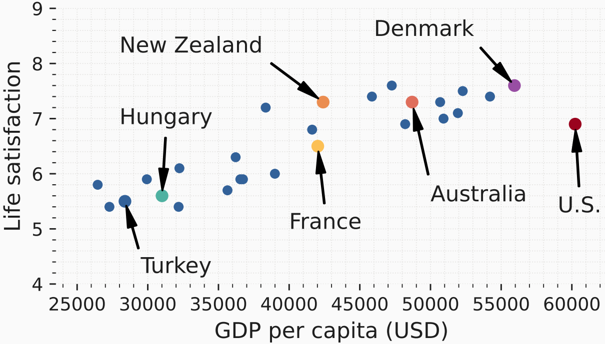


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# Machine Learning Landscape

- Looks like life satisfaction goes up more or less linearly as the country's GDP per capita.
- We can model life satisfaction as a linear function of GDP per capita.
- This step is called model selection you selected a linear model of life satisfaction with just one attribute, GDP per capita.

$$\text{Life Satisfaction} = \theta_0 + \theta_1 \text{GDP per Capita.}$$

- Before modelling, define the parameter values $\theta_0$, $\theta_1$.
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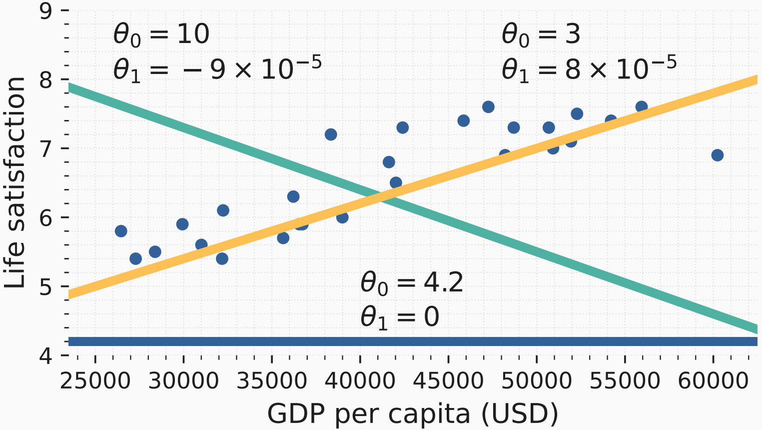


**Figure 7:** Possible linear models.

# Machine Learning Landscape

- To answer this question, specify a performance measure.
- Either define a utility function (or fitness function) measuring how good your model is or define a cost function measures how bad it is.
- For linear regression problems people typically use a cost function that measures the distance between the linear model's predictions and the training example.

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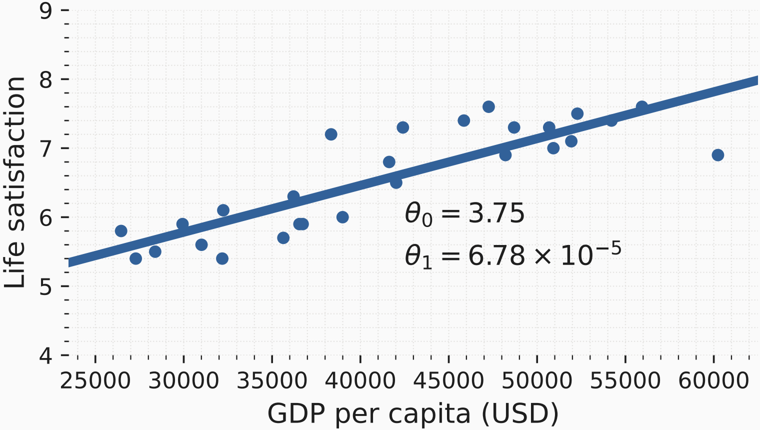


**Figure 8:** Best fit to the training set.

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- As the main task is to select a model and train it on some data the two (2) things that can go wrong are:
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- For a toddler to learn an apple all it takes is for you to point to an apple and say "apple".
- Now the child is able to recognise apples in all sorts of colours and shapes.
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- This is true whether you use instance-based learning or model-based learning
- For example the set of countries earlier for training the linear model was not perfectly representative.
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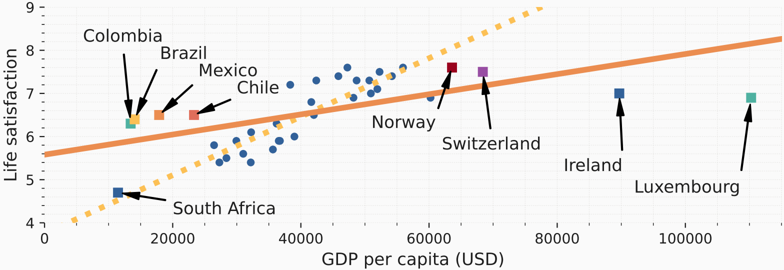


**Figure 9:** A more representative training sample.

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- If you train a linear model on this data you get the solid line,
- while the old model is represented by the dotted line.
- Adding missing countries significantly alter the model and shows a simple linear model would not work well.

> By using a non-representative training set you trained a model that is unlikely to make accurate predictions especially for very poor and very rich countries.

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- If your training data is full of errors outliers and noise, it will make it harder for the system to detect the underlying patterns.
- It is worth cleaning up the training data.
  - If some instances are clearly outliers it may help to simply discard them or try to fix the errors manually
  - If some instances are missing a few features decide whether to:
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- System will only be capable of learning if the training data contains enough relevant features and not too many irrelevant ones.
- A critical part of the success of a ML project is coming up with a good set of features to train on.
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- Say you are visiting a foreign country and the taxi driver rips you off.
- You might be tempted to say that all taxi drivers in that country are thieves.
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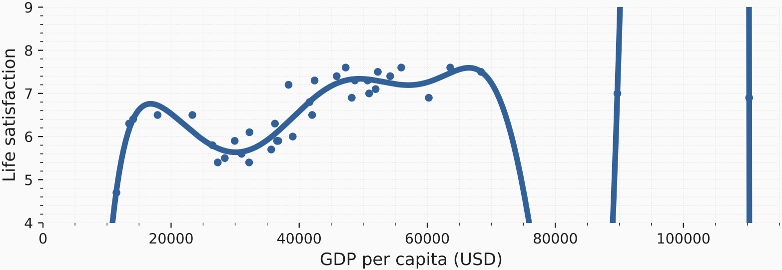


**Figure 10:** Overfitting the training data.

- The figure shows an example of a high-degree polynomial life satisfaction model that strongly over-fits the training data.
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  - If the training set is noisy or has sampling noise then the model is likely to detect patterns in the noise itself.
- Obviously these patterns will not generalise to new instances.
- For example feeding life satisfaction model with attributes.
  - including uninformative ones such as the country's name.
- A complex model may detect patterns like the fact that all countries in the training data with a w in their name have a life satisfaction greater than 7.
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- Obviously these patterns will not generalise to new instances.
- For example feeding life satisfaction model with attributes.
  - including uninformative ones such as the country's name.
- A complex model may detect patterns like the fact that all countries in the training data with a w in their name have a life satisfaction greater than 7.
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- Constraining a model to make it simpler and reduce the risk of over-fitting is called regularisation.
- For example, the linear model has two parameters $\theta_0$, $\theta_1$.
- This gives the learning algorithm two degrees of freedom.
  - Forcing $\theta_1 = 0$ make the model have a line that can only go up or down.
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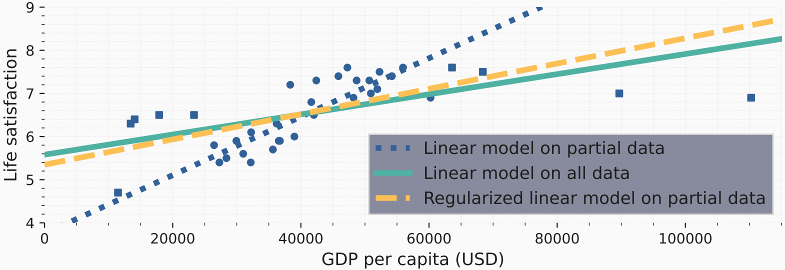


**Figure 11:** Regularisation reduces the risk of over-fitting.

- The amount of regularisation to apply during learning can be controlled by a hyper-parameter.
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  - Occurs when your model is too simple to learn the underlying structure of the data.
- For example a linear model of life satisfaction is prone to under-fit.
  - Reality is just more complex than the model so its predictions are bound to be inaccurate even on the training examples.
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  - Select a more powerful model with more parameters,
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- The problem is the generalisation error was measured multiple times on the test set and adapted the model and hyper-parameters to produce the best model for that particular set.
- This means the model is unlikely to perform as well on new data.
- A solution to this problem is called holdout validation.
- Simply hold out part of the training set to evaluate several candidate models and select the best one
- The new held-out set is called the validation set.
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- Having a large amount of data for training does not making better if the data does not represent the application.
- For example, a mobile app to take pictures of flowers and automatically determine their species.
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A black-box ML refers to machine learning models that give you a result or reach a decision without explaining or showing how they did so.

The internal processes used and the various weighted factors remain unknown. In other words, there is a lack of transparency in this technology.

# Appendix

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Data mining is the process of extracting and discovering patterns in large data sets involving methods at the intersection of machine learning, statistics, and database systems.

Data mining is an interdisciplinary subfield of computer science and statistics with an overall goal of extracting information (with intelligent methods) from a data set and transforming the information into a comprehensible structure for further use.

[1] Jeelani Ahmed and Muqeem Ahmed. "Online news classification using machine learning techniques". In: *IIUM Engineering Journal* 22.2 (2021), pp. 210–225.

[2] MA Anusuya and Shriniwas K Katti. "Speech recognition by machine, a review". In: *arXiv preprint arXiv:1001.2267* (2010).

[3] Soufyane Ayanouz, Boudhir Anouar Abdelhakim, and Mohammed Benhmed. "A smart chatbot architecture based NLP and machine learning for health care assistance". In: *Proceedings of the 3rd international conference on networking, information systems & security*. 2020, pp. 1–6.

[4] The Editors of Encyclopaedia. Britannica. *Deep Blue*. 2024. URL: `https://www.britannica.com/topic/Deep-Blue`.

[5] Santosh K Gaikwad, Bharti W Gawali, and Pravin Yannawar. "A review on speech recognition technique". In: *International Journal of Computer Applications* 10.3 (2010), pp. 16–24.

[6] Aditya Gaydhani et al. "Detecting hate speech and offensive language on twitter using machine learning: An n-gram and tfidf based approach". In: *arXiv preprint arXiv:1809.08651* (2018).

[7] MD Islam and Morshed Chowdhury. "Spam filtering using ML algorithms". In: (2005).

[8] H Jabbar and Rafiqul Zaman Khan. “Methods to avoid over-fitting and under-fitting in supervised machine learning (comparative study)”. In: *Computer Science, Communication and Instrumentation Devices* 70.10.3850 (2015), pp. 978–981.

[9] Ziqiu Kang, Cagatay Catal, and Bedir Tekinerdogan. “Machine learning applications in production lines: A systematic literature review”. In: *Computers & Industrial Engineering* 149 (2020), p. 106773.

[10] Ye-Jiao Mao et al. “Breast tumour classification using ultrasound elastography with machine learning: A systematic scoping review”. In: *Cancers* 14.2 (2022), p. 367.

[11] What Is Data Mining. *Introduction to data mining*. Springer, 2006.

[12] Patel Monil et al. “Customer segmentation using machine learning”. In: *International Journal for Research in Applied Science and Engineering Technology (IJRASET)* 8.6 (2020), pp. 2104–2108.

[13] Abdallah Bashir Musa. “Comparative study on classification performance between support vector machine and logistic regression”. In: *International Journal of Machine Learning and Cybernetics* 4 (2013), pp. 13–24.

[14] Joel Larocca Neto, Alex A Freitas, and Celso AA Kaestner. "Automatic text summarization using a machine learning approach". In: *Advances in Artificial Intelligence: 16th Brazilian Symposium on Artificial Intelligence, SBIA 2002 Porto de Galinhas/Recife, Brazil, November 11–14, 2002 Proceedings 16*. Springer. 2002, pp. 205–215.

[15] Jatin Sharma et al. "Product recommendation system a comprehensive review". In: *IOP conference series: materials science and engineering*. Vol. 1022. 1. IOP Publishing. 2021, p. 012021.

[16] Prissadang Suta et al. "An overview of machine learning in chatbots". In: *International Journal of Mechanical Engineering and Robotics Research* 9.4 (2020), pp. 502–510.

[17] Laurens Van Der Maaten, Eric Postma, Jaap Van den Herik, et al. "Dimensionality reduction: a comparative". In: *J Mach Learn Res* 10.66-71 (2009).

[18] Jesper E Van Engelen and Holger H Hoos. "A survey on semi-supervised learning". In: *Machine learning* 109.2 (2020), pp. 373–440.

[19] Jiajing Wang et al. "Predicting stock market trends using lstm networks: overcoming RNN limitations for improved financial forecasting". In: *Journal of Computer Science and Software Applications* 4.3 (2024), pp. 1–7.

[20] Helmut Wasserbacher and Martin Spindler. "Machine learning for financial forecasting, planning and analysis: recent developments and pitfalls". In: *Digital Finance* 4.1 (2022), pp. 63–88.