This is a list of resources to help new-comers to get started with Machine Learning. We divide it into various sections depending on amount of knowledge one has.

Pre-requisites

- **Calculus** : Basic Course for Calculus required for Machine Learning.
- **Linear Algebra**:
  - Khan Academy : Basic concepts of Linear Algebra.
  - 3Blue-1Brown : Good resource to "visualise" Linear Algebra.
- **Probability & Statistics**:
  - Khan Academy : Basic Probability & Statistics Concept.
  - Machine Learning Mastery : Probability from a Machine Leaning prospective.
- **Python** :
  - Theory : Udemy
  - Coding Practice: Hackerrank
  - Anaconda Setup:
    - Windows Setup : Facilitates virtual environments to keep the libraries in one place
    - Ubuntu Setup : For Ubuntu (make sure your version matches), else google for the same.
  - Cheat Sheet
- **Python Libraries & Tools** :
  - **NumPy** : NumPy proficiency is a must for writing as well as understanding ML codes.
    - Documentation
    - Tutorial
    - Practice (Coding)
  - **Pandas** : It is a software library for data analysis and manipulation.
    - Documentation
    - Tutorial - Things you would wish you knew earlier.
    - Practice (Coding)
  - **Matplotlib** : Being able to plot and visualise things is a must in ML, so be sure to master it!
    - Documentation
    - Tutorial
    - Cheat sheet

Some Blogs to Follow

These are some informative blogs in ML & AI, which you can refer to understand any particular concept or topic:

1. Medium
2. Towards Data Science
3. Machine Learning Mastery
4. Paperspace Blogs : This is really an active site with really good & latest tutorials and concepts.
5. Distill - This is a bit advanced blog, but understandable once you complete Intermediate Section. But rest assured, this blog is a treasure who are inclined towards development & research!
6. Christopher Olah's Blog - A really nice & well explained blog.
7. Andrej Karpathy Blog
8. The Batch - deeplearning.ai's Weekly magazine on advancements in Machine Learning & AI.
9. DeepMind's blog: Follow for research coming out of DeepMind.
10. OpenAI's blog: Follow for research coming out of OpenAI.
11. paperswithcode.com:Highlights trends on AI research, along with code implementations of papers, and more.

Books

There are tremendous number of books available on internet, but we have shortlisted those which are **sufficient** to understand any topic:

1. Deep Learning by Yoshua Bengio, Ian Goodfellow and Aaron Courville.

2. Machine Learning - A Probabilistic Perspective by Kevin Murphy (takes you from very basics of Probability to Modern State of Art methods in ML).
3. Pattern Recognition And Machine Learning by Christopher M. Bishop.
4. Statistical Inference, Casella and Berger: Grad level statistics reference, prepares you for a rigorous machine learning journey.
5. Information Theory, Inference, and Learning Algorithms by David J.C. MacKay (gives essence of Bayesian Inference and how it connects with Neural Networks).
6. Deep Learning Methods and Applications Li Deng and Dong Yu.
7. Dive into Deep Learning(d2l.ai): VERY comprehensive, along with implementations in PyTorch, Tensorflow, and MXnet(NumPy).

Beginner

- What is machine learning?
- Try this out and wonder how could this work!
- What's a neural network?
- Play with this and try developing some intuition.
- Basic Machine Learning :
    - This is Andrew Ng's famous course on Machine Learning, where he covers mostly the Classical ML and also touches a bit of Deep Learning.
    - Unfortunately, the assignments in this course are made in Octave, find the same assignments in **python** here.

Remember the best way to make sure that you master something is to do it in unfavourable circumstances.

- Stat-Quest : This is another nice channel where you can look at good explanations of many basic concepts .
- Sci-Kit Learn Implementation : Sci-Kit Learn is an essential python library to implement classical ML Algorithms, it contains almost all the needed algorithms, so make sure to get used to it!

Multi-Layer Perceptron - Acquainted with regression? Now dive in to find what a Multi Layer Perceptron can do that a simple perceptron (logistic regression) cannot!

Neural Network Playground - Just play with this framework. It is very helpful for visualising and building simple neural networks on the go and seeing the results. It will also give you a "feel" of how Neural Network learns and what is the effect of different parameters on its training.

- *Use this link as a guide to various terminologies used in deep learning at length*
- Going deeper into the neural networks**!** *(Chap 1 and 2 have basics, 3, 4, 5 and 6 are for those who have good grip on basics)*

- **Deep Learning** :
  - Deep Learning Specialisation : This is the first course out of 5 in series of Deep Learning Specialisation available on Coursera. It contains basic Deep Learning Theory & Implementation. This is a must do course if you are interested in Deep Learning, do all the assignments (don't skip it) they are very essential to understand the roots of DL.
  - Hyper-Parameter Tuning : This is a bit implementation based short course, one should do if interested in real time implementation and better understanding of how Hyper-parameters play an important role in performance of a Neural Network. You can manage to implement DL even without this course (it's up to you :)).
  - 3Blue-1Brown : A very good series of videos to give intuition of what Neural Networks are and how they work.
- **Implementation** : One should choose between Tensorflow and Pytorch to implement their Deep Learning models. The thumb rule according to many resources is that - If you are into product deployment, real-time implementation, Go with Tensorflow. If you are into Research and want to try different models, Go with Pytorch.
  - **Tensorflow** : A free and open source software library for dataflow and differential programming
    - Udacity Course : Course on Tensorflow.
    - Tensorflow Specialisation : It contains 4 courses, we prefer to take the basic one so that you are familiar with the basics, then apply it according to your need. If you stumble across any problem, you can always refer to Stackoverflow and similar websites for solutions. If you are working in a particular area though (eg. Computer Vision, NLP or Time Series

Prediction) then it would be useful to take one of the other specialised courses.
        - Tensorflow Deployment : It contains 4 courses, all of these courses are deployment based, i.e, made for someone who is looking to deploy his/her model in real-time, say on an app or a website. It is very essential for developers, or someone who is looking to clear GSoC in Deep Learning.
        - Tensorflow Roadmap : A Book with all the topic wise tutorials of Tensorflow. One can use it as a shorthand resource if needed to refer to something.
    - **Pytorch** :
        - Udacity : Course on Pytorch.
        - Tutorials : Official Pytorch tutorials.
- **Keras :**
    - Introduction
    - Documentation
    - Cheat sheet
- **keras Vs tf.keras**

It's completely fine if you don't understand it the very first time;) So, don't worry!

Intermediate

Suit yourselves!

The following courses are optional, but we encourage you to go through the descriptions and choose according to your taste:)

- Statistical Machine Learning : This is course based on pure Statistical Machine Learning. It is quite different from Deep Learning! Beauty of statistical ML is nothing is black-box here! Everything is in-front of you. Mathematics Enthusiasts (specially those who love Probability & Statistics) should try this out.
- Stanford's CS229: This is one of the MOST FAMOUS courses on Machine Learning, taught for many years now at Stanford, by the famous Andrew Ng.

- In-depth Deep Learning : This is a bit in-depth course for Deep Learning given by pioneers of DL, this is preferred for someone interested in the research sphere in DL. It also contains few research based tutorials.
- Fast.ai Practical Deep Learning for Coders : If you are looking for a course which explains all the theory with equal emphasis on the implementation, then this is a perfect course for you. In fact you can consider this as an Implementation course, with theory. Reason to add this course is that the lecturer here explains everything with subtle clarity.

Convolutional Neural Networks, here you go!

Before proceeding further, make sure you have completed the Classical Machine Learning course by Andrew Ng at least till week 5 and the Neural networks and deep learning course or its equivalent!

- Prior to diving into one of the most enthusiastic fields of machine learning i.e. Computer vision, having a sound knowledge about optimizers and regularization methods is extremely important. So if you haven't yet come across the Improving Deep Neural Networks course, follow the given link.
- Convolutional Neural Networks : This is a must do course if you are interested in CNNs, Image processing or Computer Vision (this is one of the really fascinating courses, where you will learn to do some "cool" stuff too!).
- Didn't get how the backpropagation worked? Follow this link for better understanding!
- For those willing to know the much deeper theory, go be an expert! For those preferring videos, click here.

Some important topics/blogs

- Stanford's CS231n : This video has various computer vision tasks for instance object detection, semantic segmentation, etc.
- Object detection overview
- YOLO
- Deep Learning for Computer Vision: j

Now you would have got an overview of some advanced models like VGG and RESNET. If you are comfortable with the above topics you may start with :

- Sequence Models : Course on Sequence Models (Recurrent Neural Networks (RNNs), LSTMs, GRUs, etc). Initially this course was said to be essential for Natural Language Processing (NLP), but nowadays sequential models have found there role in every field of DL, be it images or 1D predictive data.
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Natural Language Processing

- Cs224n : Stanford's course on the topic of Natural Language Processing(NLP).

  Check video lectures here.
- Coursera: Deeplearning.AI's course on NLP, covers a wide range of topics in short depth.
- Multilingual NLP: taught at Carnegie Mellon, Fall 2020.
- NPTEL(2017): coordinated by IITKGP
- NPTEL(2012): coordinated by IITB, taught by the former director of IIT Patna. *Check for outdated concepts*
- NPTEL(2019): coordinated by IIT Madras, most up to date with the state of the art.
- Dan Jurafsky's lecture series(Stanford): Taught by Dan Jurafsky, winner of IBM Watson question answering challenge.

Reinforcement Learning:

- Stanford's course cs234n:
- CS 294 Deep Reinforcement Learning, Fall 2017: Offered by UC Berkeley, taught by famed Sergey Levine.
- Dived Silver's course: taught in 2014 at UCL by David Silver, co-founder of DeepMind
- Deep Reinforcement Learning: DeepMind(RL + DL) lecture series.
- NPTEL Reinforcement Learning, IITM
- coursera specialization: by Alberta Machine Intelligence Institute.
- Sutton & Barto:Classic RL textbook.
- Simon's Institute RL bootcamp: VERY Advanced RL topics, dive in only after covering the basics first.

Also check out:
Stanford CS224w: Machine learning for graphs.
Probabilistic Machine Learning: by Philipp Henning
NYU Deep Learning
Applied Machine Learning(Cornell)