THE UNIVERSITY OF QUEENSLAND
AUSTRALIA

CREATE CHANGE

AI Hype or Revolution

ITEE Summer of AI

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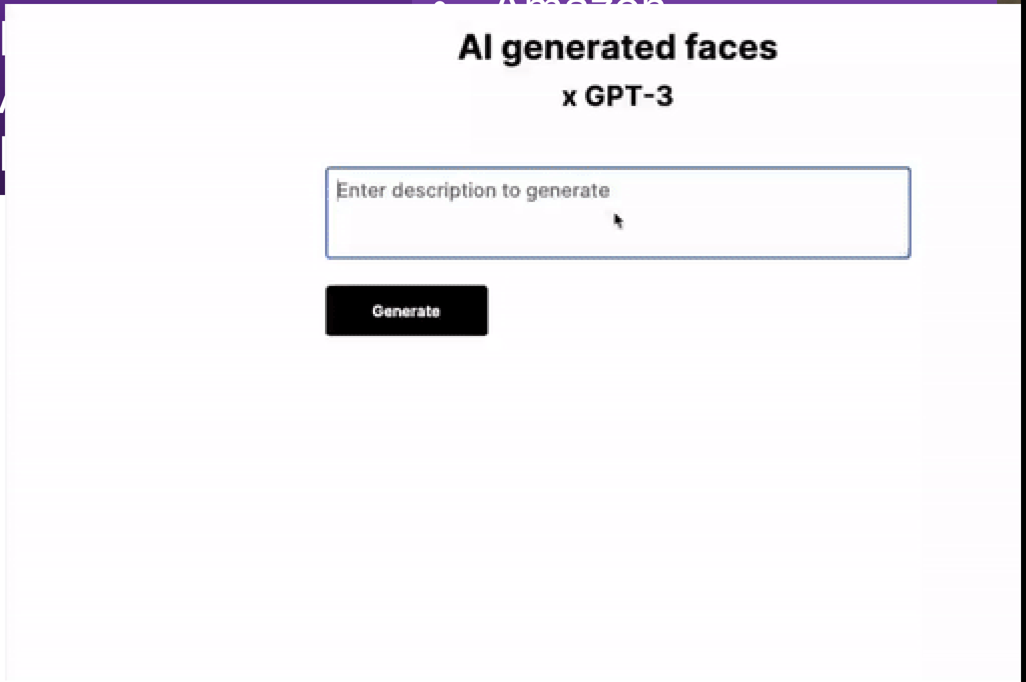
Why Summer of AI!

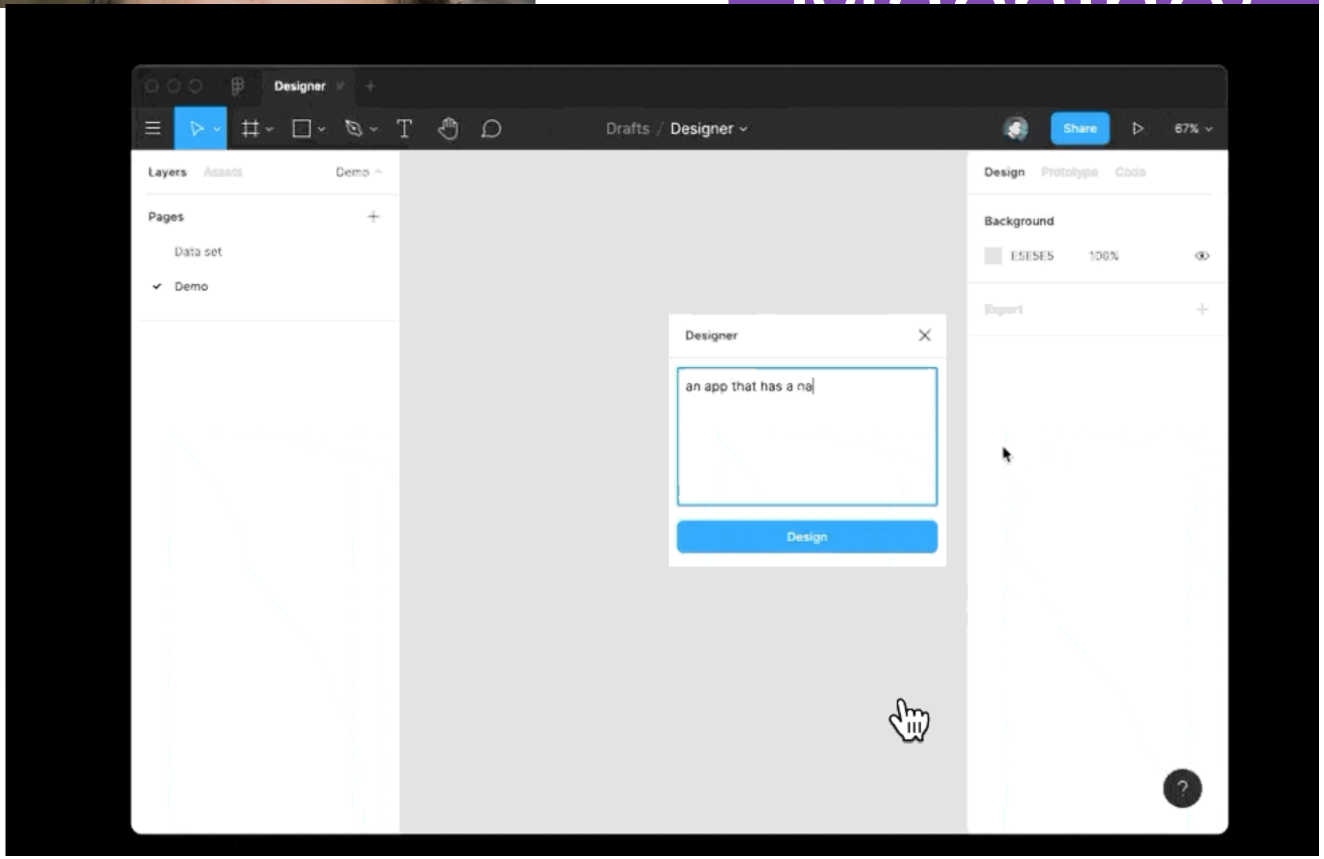
- Live transcribing
- Digital assistants
- Recommendations

- Google
- Microsoft
- Amazon

https://thispersondoesnotexist.com/

Machine/

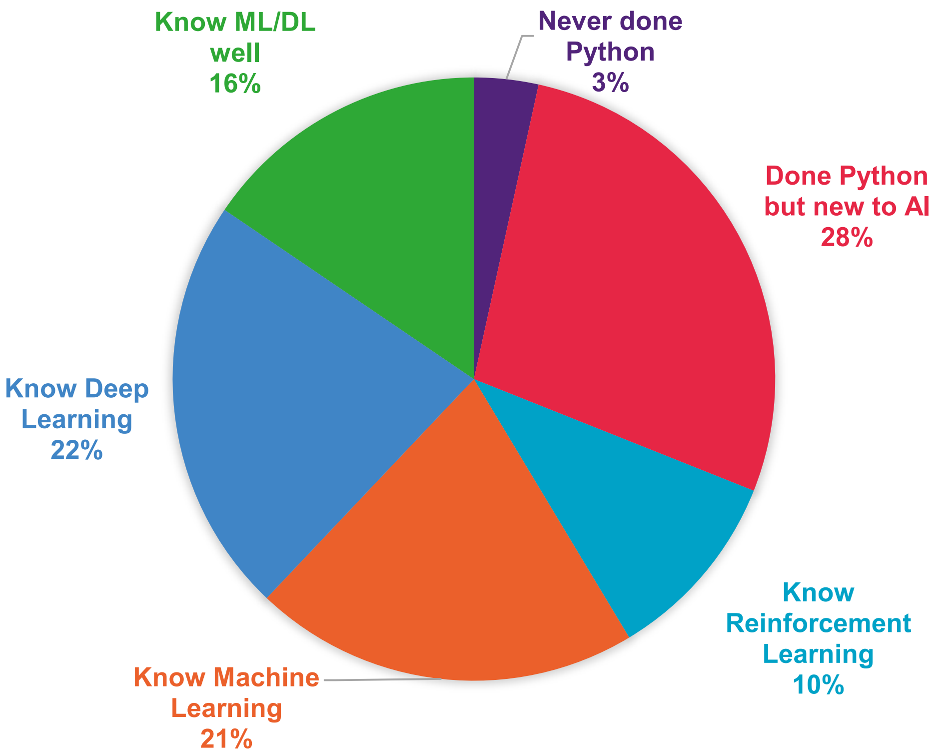


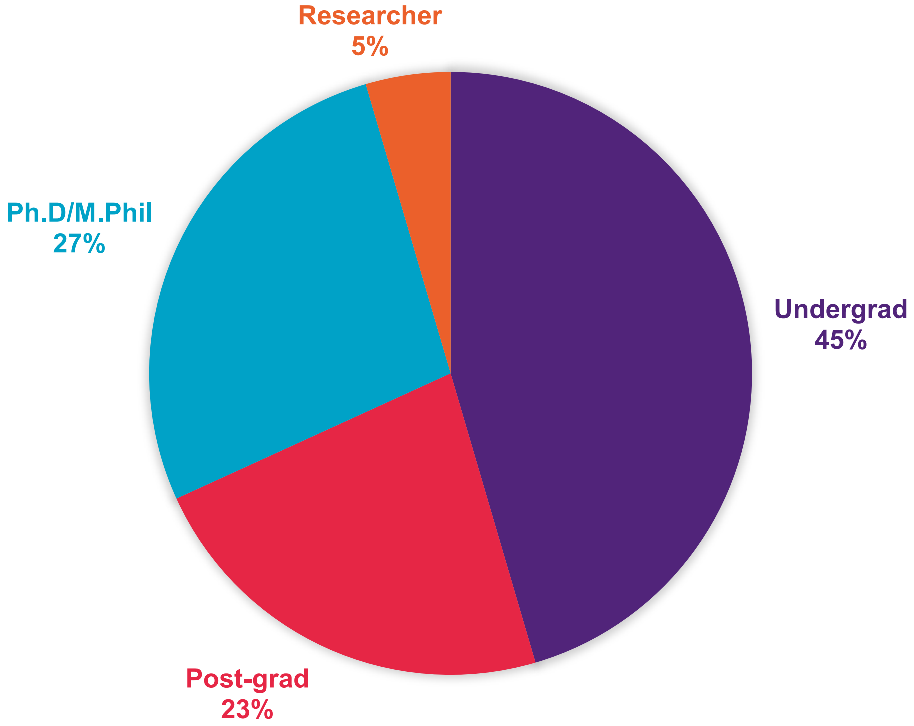


Why Summer of AI

- So many opportunities – AI has developed so much in so little time that there are many opportunities in nearly every area of science and engineering
- Professional development – a chance for you to grow!
- Open source – Nearly all of the AI algorithms are available open source making it easier to learn and use for any project
- Disseminate knowledge – So much is being developed, let’s work together to share the knowledge
- Employment opportunities – There is a high demand for AI skilled workers and here at UQ we want to help create the best of them…. You!
- Help researchers – because there are many opportunities, we want to help researchers achieve their AI inspired goals
- Our benefit? Perhaps we can find some budding and promising new researchers of our own through UQ’s Ph.D programs.

Survey Results





120+ participants so far!

What is causing the surge in AI?

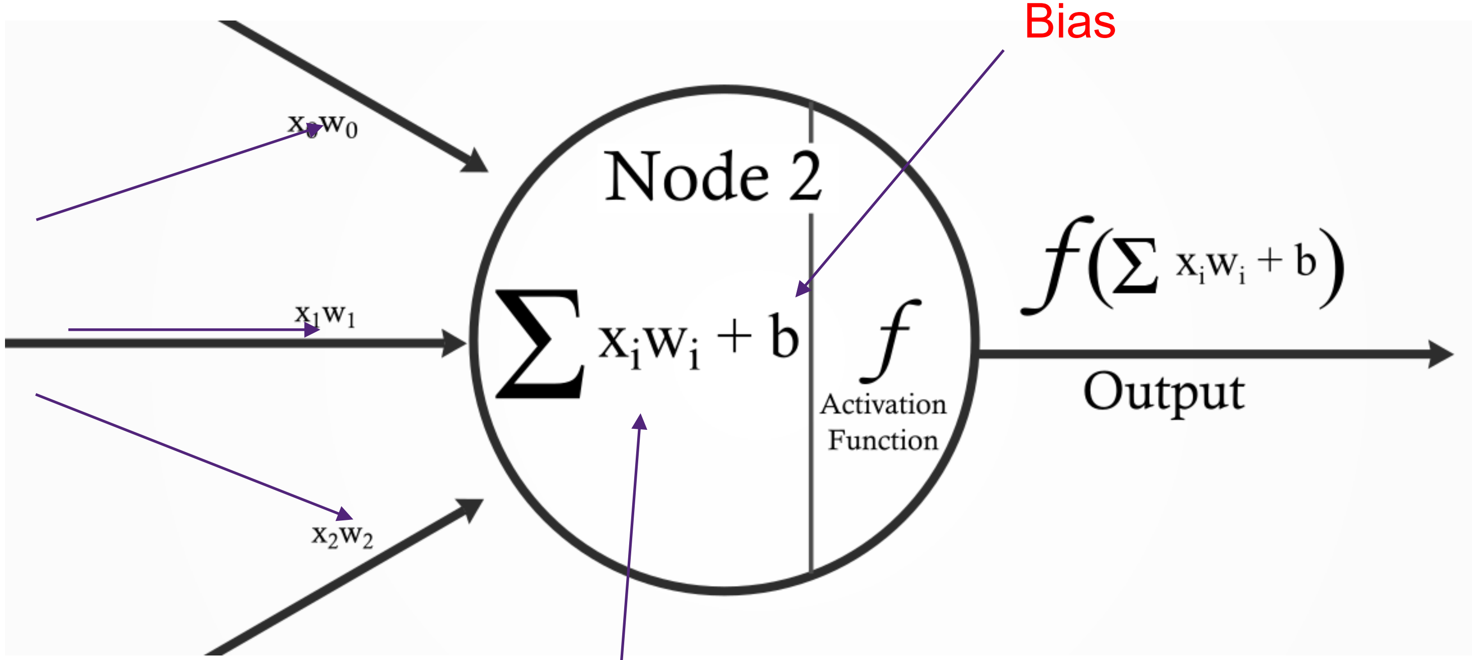
- We can now compute many fundamental operations such as linear algebra in parallel via Graphical Processing Units (GPUs)
- Big tech companies are releasing their software frameworks open source making it freely available for anyone to use
- Mobile hardware is now nearly as powerful and affordable as their desktop variants
- High speed Internet connectivity is now commonplace
- Internet now provides a wealth of freely available and open datasets that can be used to build models
- Society in general is more tech savvy than its ever been
- Artificial Neural Networks (ANNs) is one of the major drivers
- Many different types of NNs including convolutional, generative and more!
- A key results and roadblocks in AI have only recently been broken through (backpropagation, ReLU, Adam, Residual Connections etc.)

Neuron

- Given an arbitrary number of input connections, each weighted by corresponding set of weights, activate only according to an activation function if weighted summation > threshold.

Bias

Weights



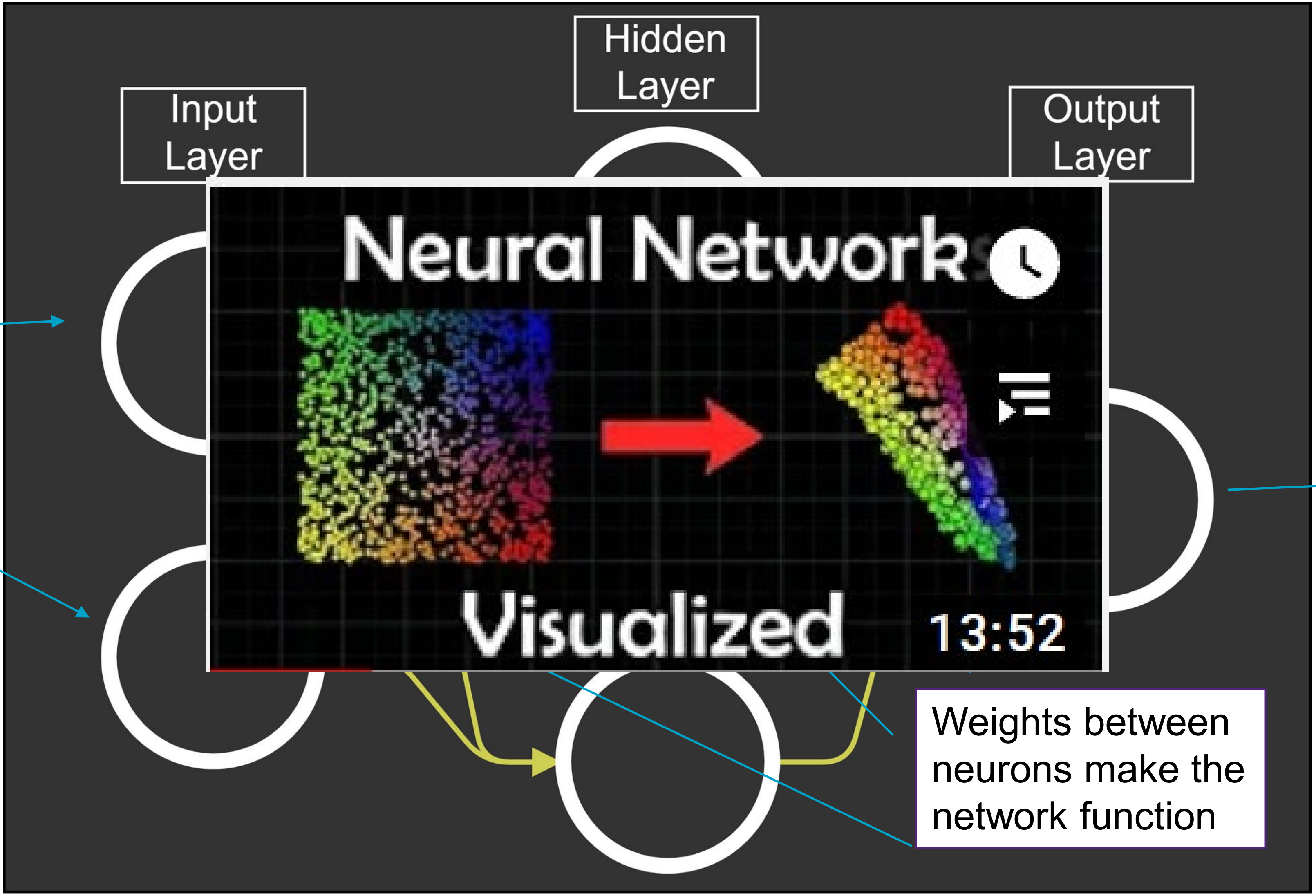
Linear Algebra

https://theffork.com/activation-functions-in-neural-networks/

Neural Network

https://mlfromscratch.com/neural-networks-explained/#/

Data goes here,
One value at a time



Result comes out, Usually needs Training, so in training stage we have the answer or label

Weights between neurons make the network function

Convolutional Neural Networks

Image by NVIDIA

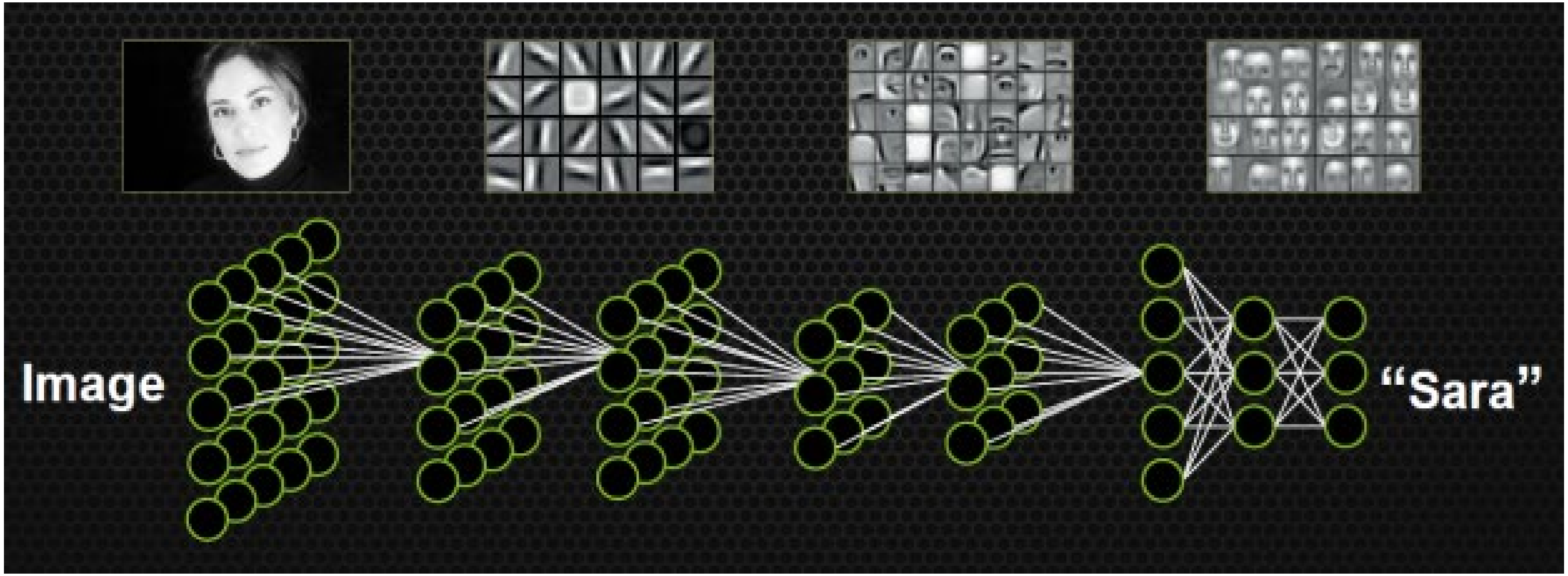
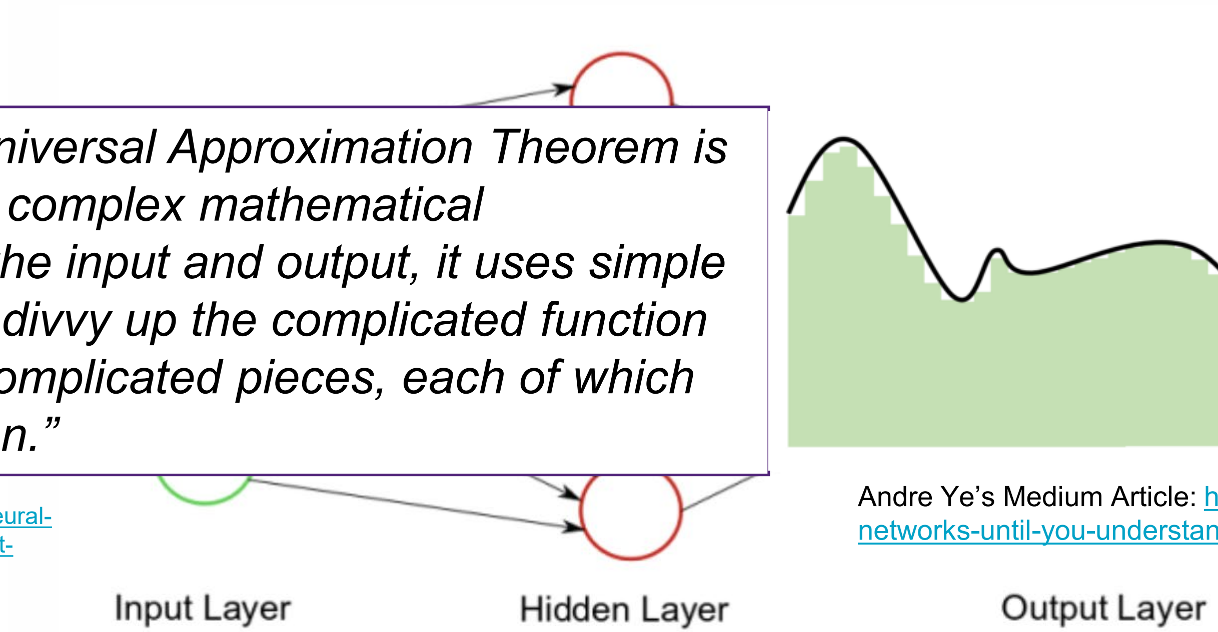


Figure 1: A convolutional neural network (CNN) learning the underlying features of faces to recognise "Sara". Each 'layer' of the network learns features at different scales in a hierarchical fashion to gain some understanding of faces and their properties. These features are learnt by the network in a data-driven way without any supervision or intervention from the user via the optimization of network parameters.

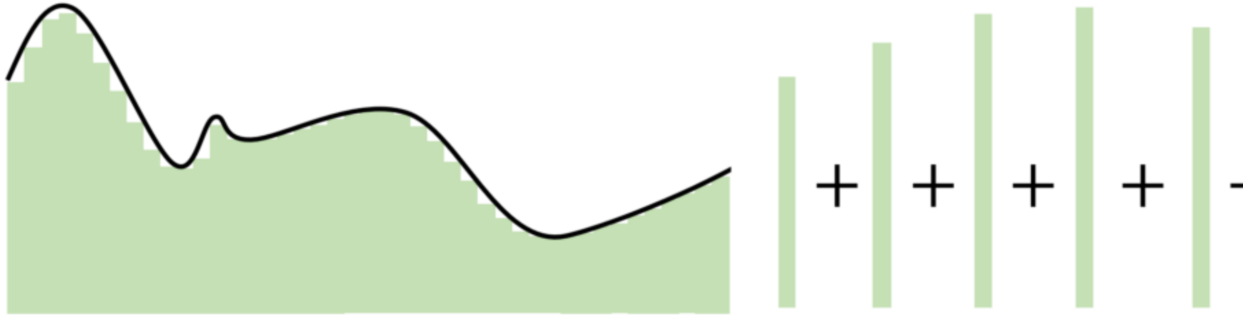
Powerful function approximator - arbitrarily accurate

Universal Approximation Theorem

A neural network can approximate ANY continuous function with arbitrary precision with only a single hidden layer [1, 2]



“The key point in the Universal Approximation Theorem is that instead of creating complex mathematical relationships between the input and output, it uses simple linear manipulations to divvy up the complicated function into many small, less complicated pieces, each of which are taken by one neuron.”

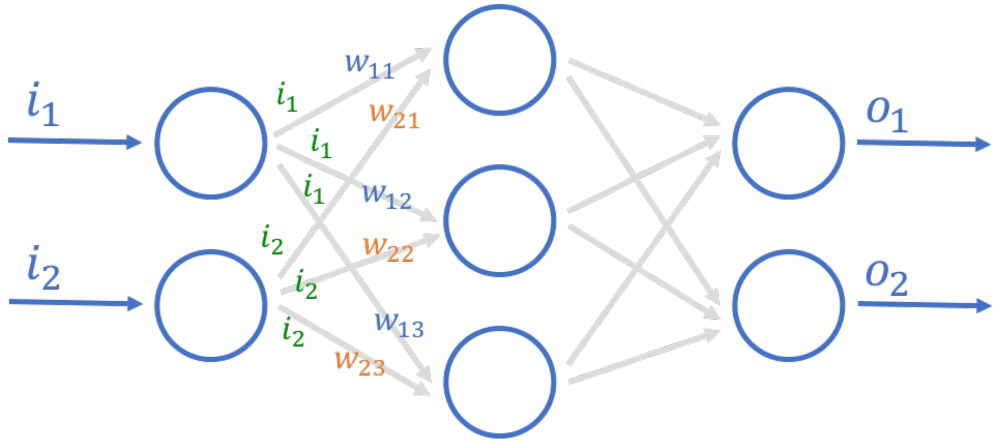


https://www.kdnuggets.com/2017/10/neural-network-foundations-explained-gradient-descent.html

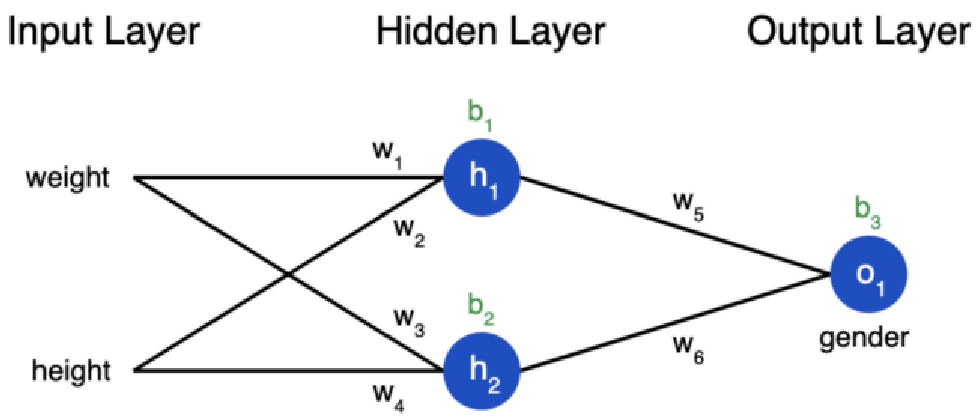
Andre Ye’s Medium Article: https://medium.com/analytics-vidhya/you-dont-understand-neural-networks-until-you-understand-the-universal-approximation-theorem-85b3e7677126

[1] K. Hornik, M. Stinchcombe, and H. White, ‘Multilayer feedforward networks are universal approximators’, *Neural Networks*, vol. 2, no. 5, pp. 359–366, Jan. 1989, doi: 10.1016/0893-6080(89)90020-8.
[2] G. Cybenko, ‘Approximation by superpositions of a sigmoidal function’, *Math. Control Signal Systems*, vol. 2, no. 4, pp. 303–314, Dec. 1989, doi: 10.1007/BF02551274.

Network data structure – fast inference



https://sausheong.github.io/posts/how-to-build-a-simple-artificial-neural-network-with-go/



https://victorzhou.com/blog/intro-to-neural-networks/

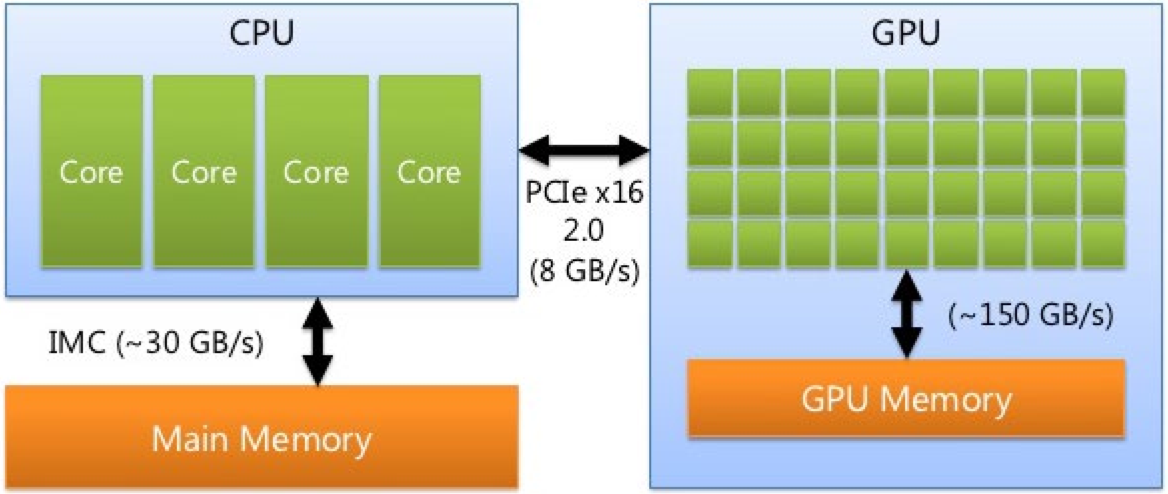
$$\begin{bmatrix} w_{11} & w_{21} \\ w_{12} & w_{22} \\ w_{13} & w_{23} \end{bmatrix} \cdot \begin{bmatrix} i_1 \\ i_2 \end{bmatrix} = \begin{bmatrix} (w_{11} \times i_1) + (w_{21} \times i_2) \\ (w_{12} \times i_1) + (w_{22} \times i_2) \\ (w_{13} \times i_1) + (w_{23} \times i_2) \end{bmatrix}$$

Graphical Processing Units (GPUs) – 10 TeraFLOPS

Highly parallelisable – GPUs

Graphical Processing Units (GPUs) – 10 TeraFLOPS
~ $1000 – $10000 AUD

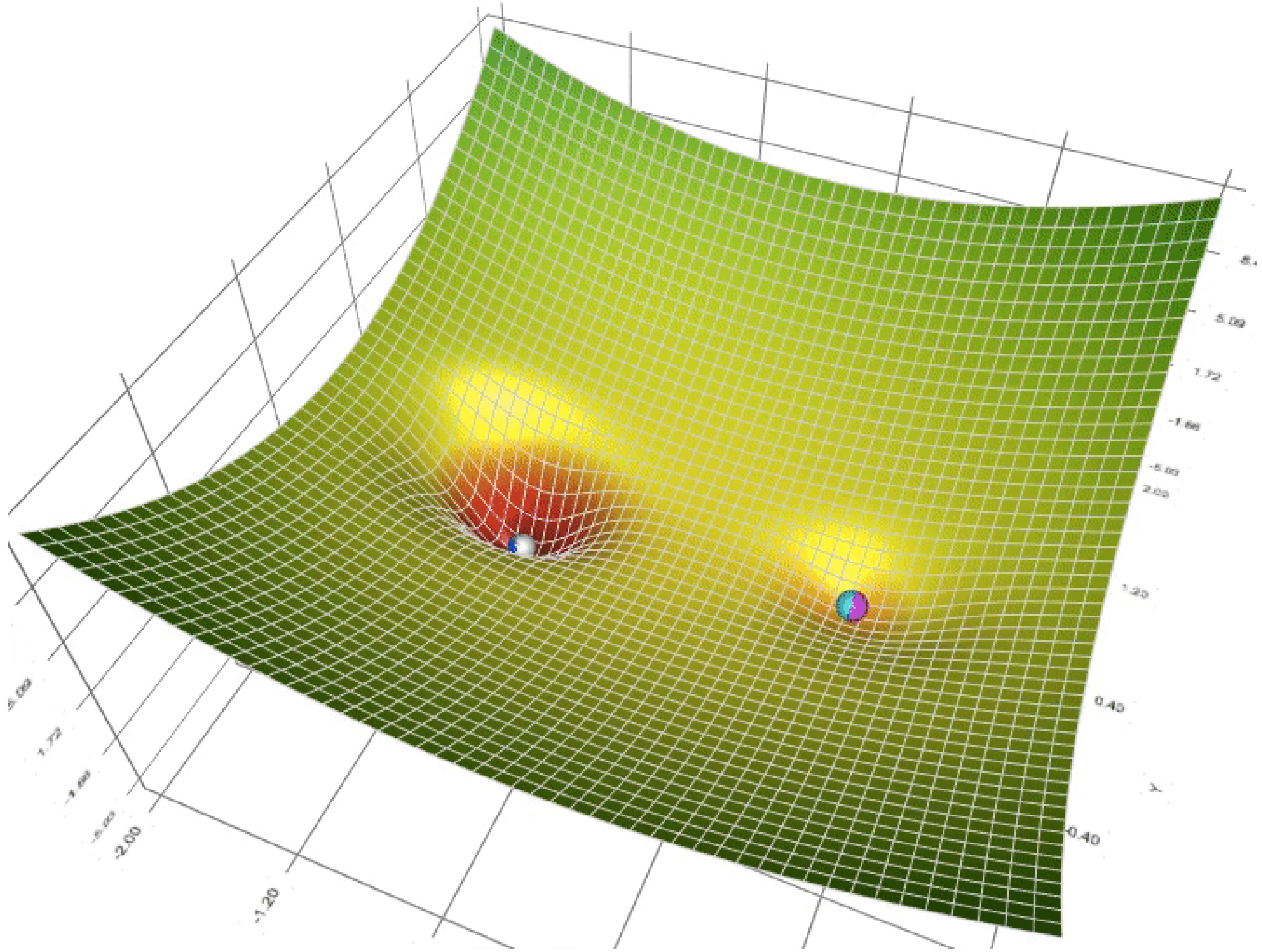
Highly Parallel

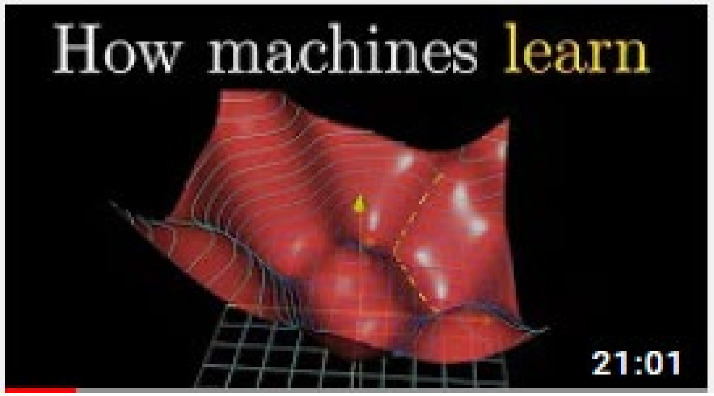


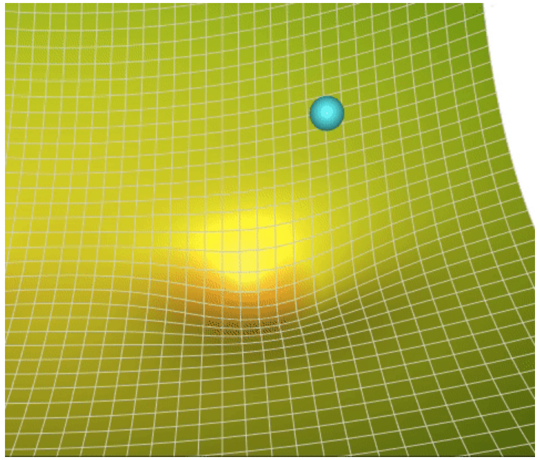
https://people.duke.edu/~ccc14/sta-663/GPUsAndCUDAC.html https://theffork.com/activation-functions-in-neural-networks/

Non-linear mappings – activations

Map any optimization problem - solve it with gradient descent

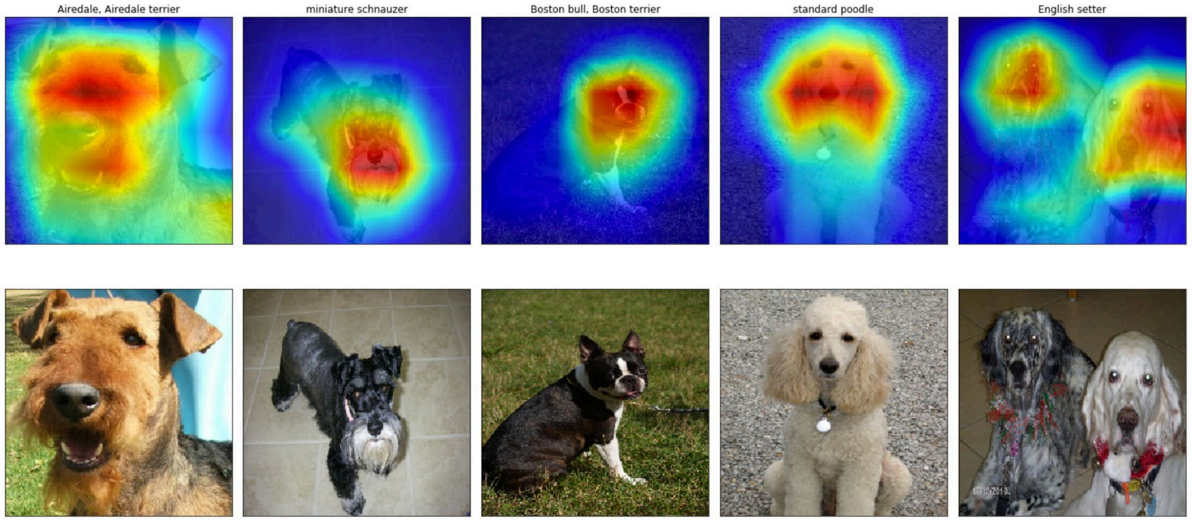


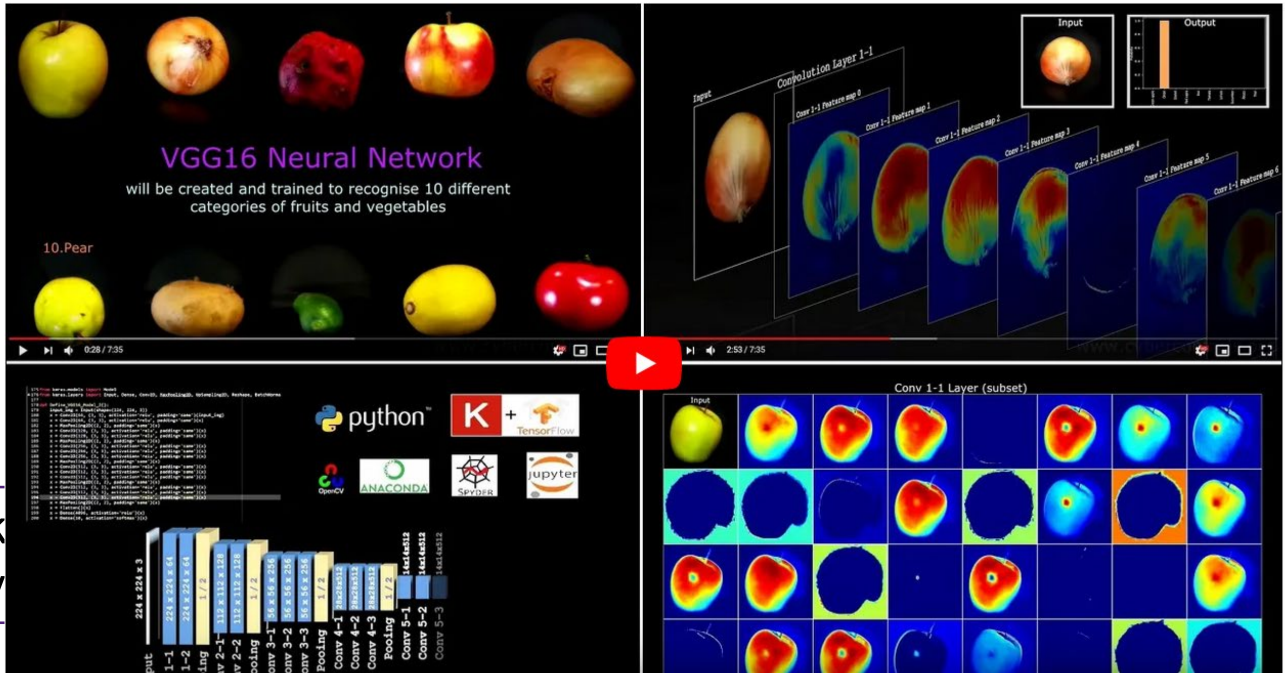




https://towardsdatascience.com/a-visual-explanation-of-gradient-descent-methods-momentum-adagrad-rmsprop-adam-f898b102325c

Data-driven - automation

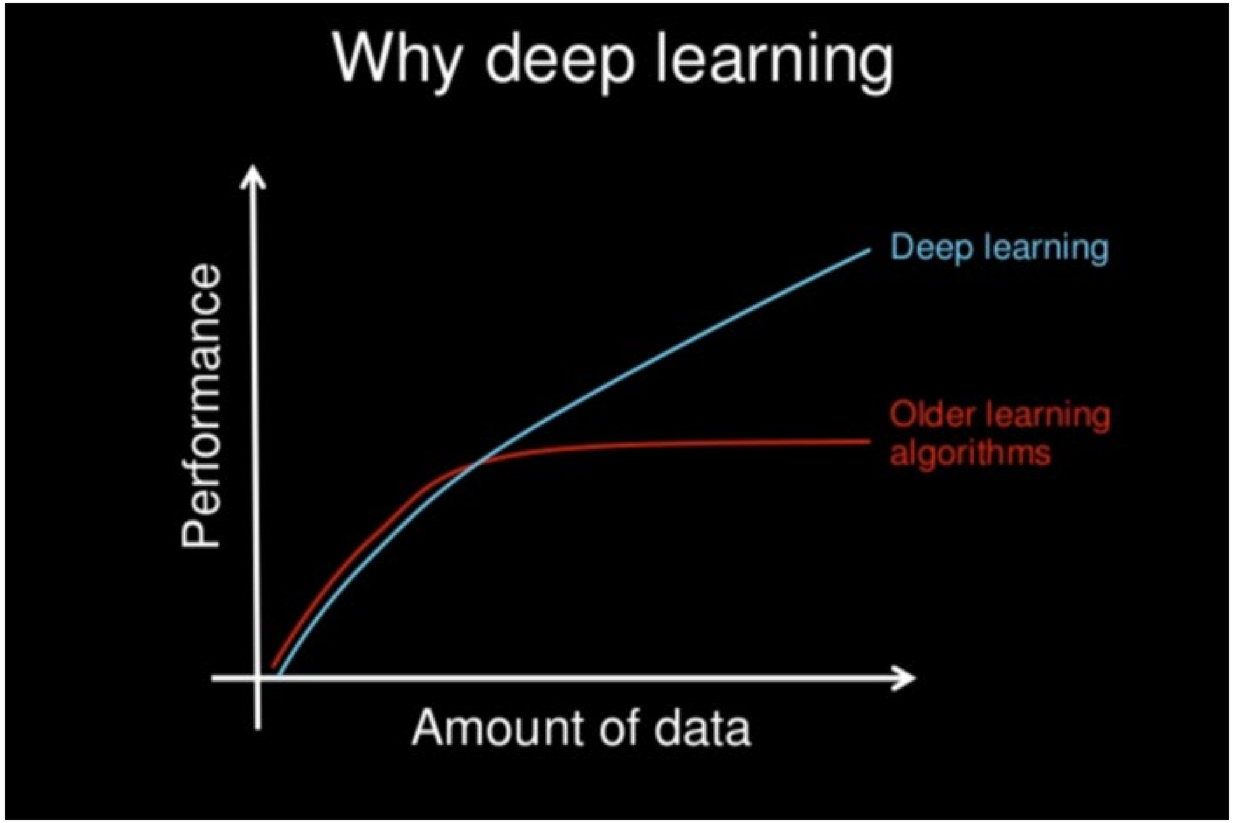




https://alexisbcook.github.io/2017/global-average-pooling-layers-for-object-localization/

Improves with more data - Big data support

- Contrary to traditional statistical and machine learning methods, performance of deep learning models do not plateau, but grow according to a power law [3]
- This is because deep learning models typically consist of millions of parameters and under normal data considerations, would require millions of samples
- However, these models perform and converge remarkably well even with order of magnitude less data than theoretically predicted, reasons for which are not yet fully understood
- Thus, the standard practice in conventional imaging is usually to obtain as much data as possible.



https://machinelearningmastery.com/what-is-deep-learning/

[3] C. Sun, A. Shrivastava, S. Singh, and A. Gupta, 'Revisiting Unreasonable Effectiveness of Data in Deep Learning Era', 2017, pp. 843–852, Accessed: Jul. 08, 2020. [Online]. Available: https://openaccess.thecvf.com/content_iccv_2017/html/Sun_Revisiting_Unreasonable_Effectiveness_ICCV_2017_paper.html.

Direction solution – state-of-the-art performance

- No need to use a mechanism such as pre-processing or registration or some other surrogate measure or algorithm to solve your problem
- Neural networks can be designed to solve the problem directly – input to output
- Same algorithm in deep learning runs at least 20-30 (sometimes 1000) times faster
- 15-20% more accurate/performance because it is direct
- Completely data-driven, no need to have an expert of the data

The Problem – Imaging in Medicine

We now live in an age where there is too much data for humans to process in meaningful time.

Results in hard decisions about treatment and care, as well as hindering our understanding

- for example, each MRI scan consists of a series of (order of a few hundred) 2D images
- usually takes expert several hours to process a single clinical scan accurately for treatment (and that's only after extensive practice & experience)
- each patient can have several scans (repeated yearly, let's say 7) across at least a few visits (let's say 3)
- latest studies now have 1000s of patients
- **it would take an expert** 1000 x 3 x 7 = 21,000 images with 21,000 x 3 hrs = 63,000 hours to process, **that's roughly 7.2 years!**
- a deep learning model can process an image in **3 seconds at a time with the same accuracy**, it would take 21,000 x 3 secs = 63,000 seconds, **which is less than a day!**
- in addition, we can have **another network that can actually look at ALL of the data at once and learn the entire domain** (see [4])!

[4] B. Zhu, J. Z. Liu, S. F. Cauley, B. R. Rosen, and M. S. Rosen, "Image reconstruction by domain-transform manifold learning," *Nature*, vol. 555, no. 7697, pp. 487–492, Mar. 2018, doi: 10.1038/nature25988.

Now Back Down to Earth

- ANNs are computationally complex and therefore not suitable for ‘small’ problems
- Training can take hours/days and more complicated generative models can take weeks
- It is well known that they reach equivalent performance as other traditional machine learning methods with the data size is small (< 120-150 samples or so)
- Classification and regression tasks for small datasets can achieved just as well by the random forest, while not requiring GPUs
- ANNs can do linear regression, but don’t expect it to be any better than usual methods
- Use of ANNs and Deep Learning usually needs to be justified carefully for small problems

Summer of AI – What’s in it for Me?

- Special workshops and master class for those new to AI, ANNs and Deep Learning
- Advanced workshops for those familiar with machine learning and deep learning
- A chance to work on cutting edge research projects with experts in the field
- Researchers may find new and energetic students to join their cause
- Students get a chance to learn new skills before joining the workforce
- Learning about new and recent work in AI to keep up with the vast and rapidly growing research area
- Create new knowledge and open-source software
- A chance to share and develop ideas with others with like-mindedness
- A chance to take-part in the AI ‘culture’ of competitions and challenges
- Let’s work and maybe even publish together over the summer!

Slack Workspace: https://app.slack.com/client/TL80HC93L/CLKCD4K0Q

Conclusion

- Neural networks and their variants are driving the AI revolution
- It is possible to create an algorithm that out-performs convention algorithm by 10-15%, runs near real-time, can handle non-linearity, is not limited by large data, while being solved by gradient descent.
- New opportunities exist in nearly every research area
- AI skills are in high demand
- Summer of AI will hopefully help get you to where you want to be!

Thank you

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