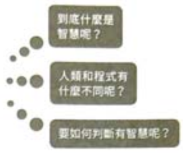
AI與醫藥健康(上)

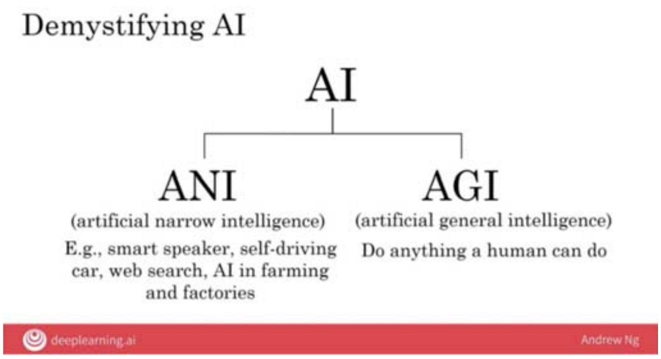
鄭喻仁

Line：@bid3398n

AI？

- Artificial Intelligence (AI)
- 人工智慧
- 定義？





莫拉維克悖論 (Moravec's Paradox)

要讓電腦如成人般下棋是相對容易的，但是要讓電腦有如一歲小孩般地感知和行動卻是相當困難甚至是不可能的。

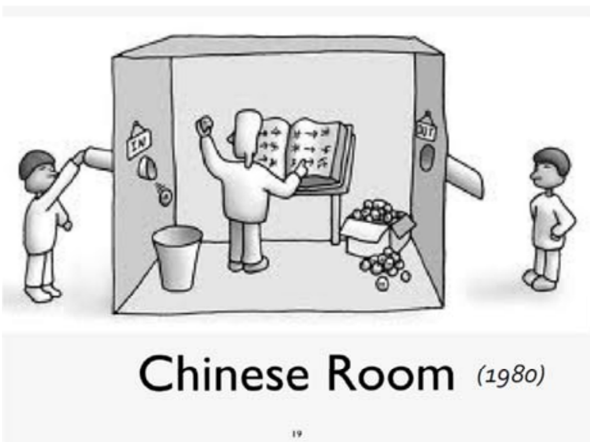
High cognitive processes	Low Cognitive processes
Conscious processes • Chesses, math, problem solving	Perception, action, fight/flight responses, social interactions
Difficult for humans	Easy for humans
Easy for computers	Difficult for computers

弱人工智慧 Vs. 強人工智慧

為什麼要再次複習這個概念？因為太多人關注人工智慧、談論人工智慧，還有不少人提出警告，說人工智慧即將取代多數人的工作。對於技術的不夠熟悉，再加上大眾媒體的推波助瀾，甚至還出現「人工智慧末日論」，好像人工智慧就快要統治人類了。

事實上，只要對於人工智慧技術稍微有點認識，就會知道這些擔心是多餘的，這幾年進展快速的是「弱人工智慧」，這一波人工智慧的主流是透過機器學習，從資料裡頭淬取規則，把某一個工作做到最好；真的會思考、會推理、自我學習，能跟人對答如流，甚至還有自我情緒的「強人工智慧」，連影子都還沒看見。最樂觀的預測是，電影中所出現的強人工智慧，也許會由下一世代的人工智慧實現，但不會是我們今天所談的人工智慧技術。

但即使是弱人工智慧，因為已證明在許多產業應用上的價值，讓許多企業趨之若鶩，不論本來談不談、做不做資料科學及大數據研發及導入的企業，今年都開始談人工智慧。他們可能說，我們已從大數據「進化」到人工智慧，比其他還在做大數據的公司更「先進」，這種有趣的說法，正好見證社會上有些人的不求甚解，經常在未真正瞭解一個詞彙之前就開始使用。



博藍尼悖論 (Polanyi's Paradox)

我們懂的事情，
比我們能表達出來的更多。

哲學家博藍尼在 1964 年說明了這個現象：

博藍尼悖論不只限制我們能告訴另一個人的事情，一直以來，也為我們賦予機器智慧的能力，設下根本的限制。長久以來，這限制了機器在經濟中能有效執行的活動。

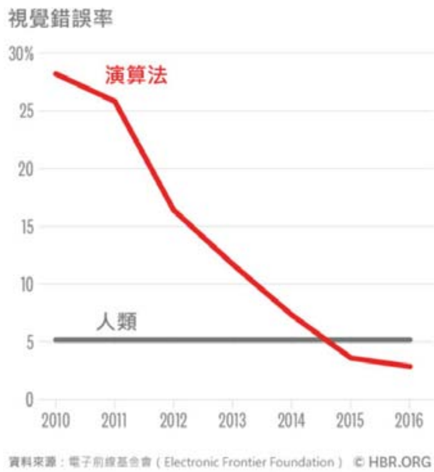
陳昇瑋 / 人工智慧在台灣

人工智慧定義

人工智慧的定義是，任何讓電腦能夠表現出類似人類智慧行為的技術。實現人工智慧的技術有許多種，目前這一波的人工智慧浪潮中，最主要用來實現人工智慧的技術叫做機器學習。

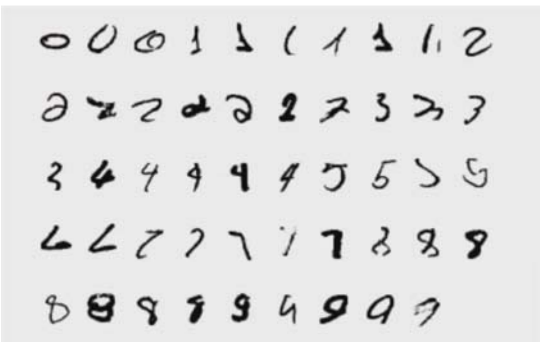
機器學習的定義是，能夠從資料裡頭學習到規則的演算法，之後我們就可以將這些規則實作在電腦系統中，讓電腦展現看起來有智慧的行為。依這個定義來看，機器學習需要有資料才能發揮功用，所以，是否有合適的可用資料也是實現人工智慧的關鍵之一。

因此，人工智慧、機器學習以及大數據這三個大家常見的名詞，事實上是息息相關的。今天的人工智慧系統，底層的引擎都是機器學習模型；而機器學習必須要基於大數據才能淬取出有用的規則。換句話說，我們可以將大數據想成原料，機器學習則是處理這些原料的方法，而產出的結果就是人工智慧。

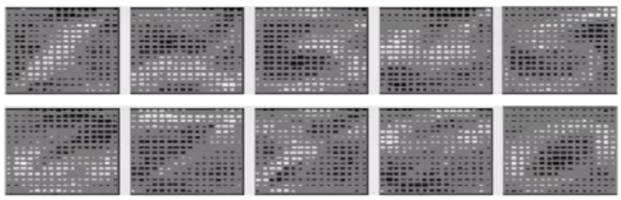


機器學習學到的規則跟你想的不太一樣

0、1、2、3、4、5、6、7、8、9



機器學習學到的規則跟你想的不太一樣



在醫療領域...

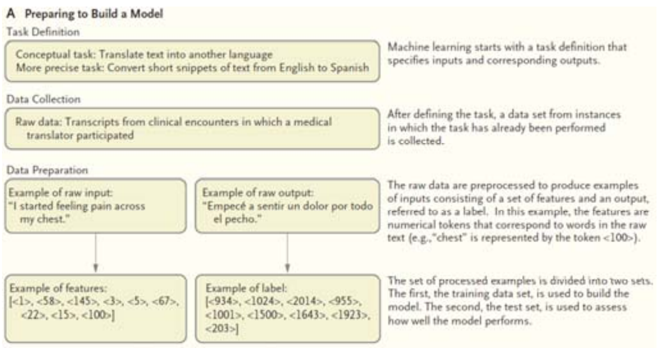
The NEW ENGLAND JOURNAL *of* MEDICINE
N ENGL J MED 380;14 NEJM.ORG APRIL 4, 2019

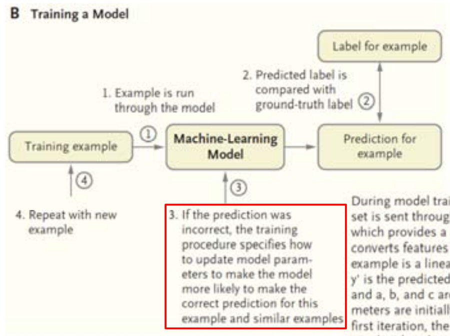
REVIEW ARTICLE

FRONTIERS IN MEDICINE

Machine Learning in Medicine

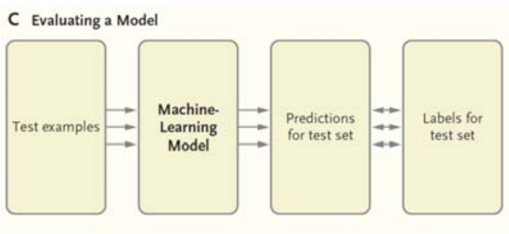
Figure 1. Conceptual Overview of Supervised Machine Learning.
As shown in Panel A, machine learning starts with a task definition that specifies an input that should be mapped to a corresponding output. The task in this example is to take a snippet of text from one language (input) and produce text of the same meaning but in a different language (output). There is no simple set of rules to perform this mapping well; for example, simply translating each word without examining the context does not lead to high-quality translations. As shown in Panel B, there are key steps in training machine-learning models. As shown in Panel C, models are evaluated with data that were not used to build them (i.e., the test set). This evaluation generally precedes formal testing to determine whether the models are effective in live clinical environments involving trial designs, such as randomized clinical trials.





During model training, an example from the training set is sent through a machine-learning system, which provides a mathematical function that converts features to a predicted label. A simple example is a linear function, $y' = ax_1 + bx_2 + c$, where y' is the predicted label, x_1 and x_2 are the features, and a, b, and c are parameters. The model parameters are initially randomly assigned, and in the first iteration, the predicted label y' is generally unrelated to the ground-truth label.

In the key step of machine learning (step 3), an algorithm determines how the parameters need to be modified to make the prediction more likely to match the ground truth. The system iterates through all the examples in the training data, potentially multiple times, to complete training.



The test set is then run through the final model. Statistics are computed, and the predictions of the test set are compared with the ground-truth labels.

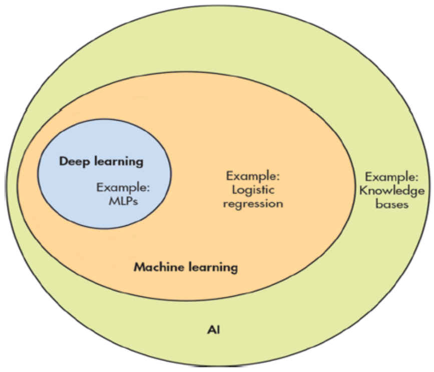
To apply the model, new input examples, which have not been previously labeled, can be run through the model. However, the model learns patterns from data only in the training set, so if new examples are sufficiently different from those in the training data, the model may not produce accurate predictions for them.

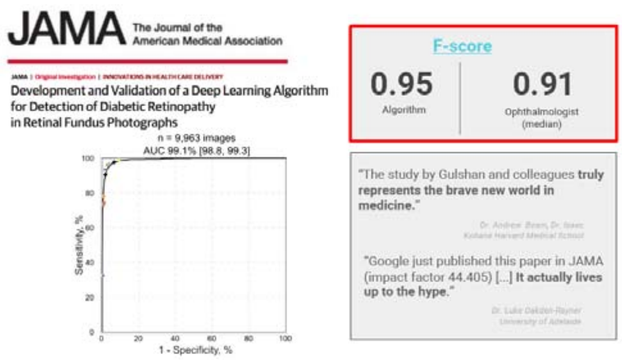
機器學習技術又包含傳統機器學習與深度學習，兩者的差別是，深度學習技術所計算出來的規則是有層次的，而傳統機器學習的產出皆是單一層次的規則。

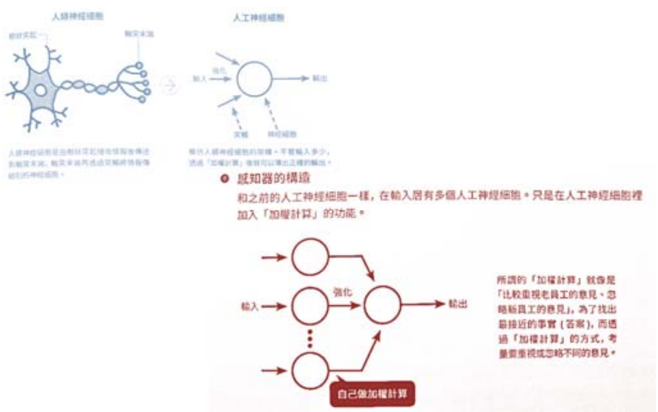
例如線性迴歸或決策樹就屬於傳統機器學習。相較於傳統機器學習，深度學習需要的資料量較大，運算量的需求也更為龐大，但好處是它可以處理高維度的問題，也就是具有上百、上千、甚至上萬個變數的問題。

生活中常見的問題多屬於此類，例如涉及文字、影像、聲音、影片等問題通常皆是高維度的問題，也因此若有足夠的資料量，深度學習通常可以提供比傳統機器學習更好的解答。也因此，深度學習是目前人工智慧的主流技術，舉凡我們最近所見的臉部辨識、語音辨識、無人車等等，幾乎都是深度學習技術的成果。

Deep Learning, Machine Learning, and AI







Article | Open Access | Published: 20 September 2019

Deep learning algorithm predicts diabetic retinopathy progression in individual patients

Filippo Arcadu, Fethallah Benmansour, Andreas Maunz, Jeff Willis, Zdenka Haskova & Marco Prunotto

npj Digital Medicine **2**, Article number: 92 (2019) | Cite this article

Deep learning algorithm predicts diabetic retinopathy progression in individual patients

Filippo Arcadu[1,2], Fethallah Benmansour[1,2], Andreas Maunz[1,2], Jeff Willis[3,4], Zdenka Haskova[3,4,7]* and Marco Prunotto[2,5,6,7]*

The global burden of diabetic retinopathy (DR) continues to worsen and DR remains a leading cause of vision loss worldwide. Here, we describe an algorithm to predict DR progression by means of deep learning (DL), using as input color fundus photographs (CFPs) acquired at a single visit from a patient with DR. The proposed DL models were designed to predict future DR progression, defined as 2-step worsening on the Early Treatment Diabetic Retinopathy Diabetic Retinopathy Severity Scale, and were trained against DR severity scores assessed after 6, 12, and 24 months from the baseline visit by masked, well-trained, human reading center graders. The performance of one of these models (prediction at month 12) resulted in an area under the curve equal to 0.79. Interestingly, our results highlight the importance of the predictive signal located in the peripheral retinal fields, not routinely collected for DR assessments, and the importance of microvascular abnormalities. Our findings show the feasibility of predicting future DR progression by leveraging CFPs of a patient acquired at a single visit. Upon further development on larger and more diverse datasets, such an algorithm could enable early diagnosis and referral to a retina specialist for more frequent monitoring and even consideration of early intervention. Moreover, it could also improve patient recruitment for clinical trials targeting DR.

npj Digital Medicine (2019)2:92 ; https://doi.org/10.1038/s41746-019-0172-3

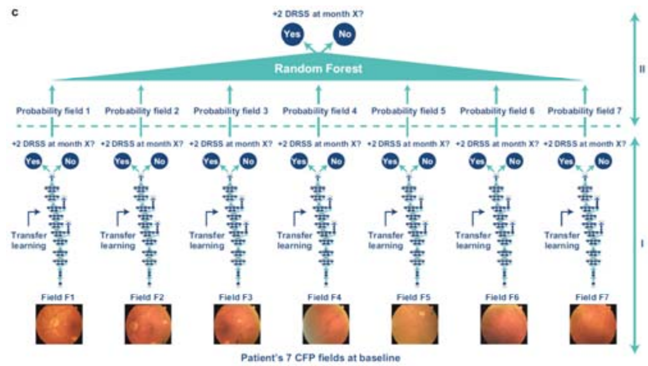


Fig. 1 An overview of retinal imaging features analyzed to assess diabetic retinopathy (DR) severity and a schematic of the study design. **a** Example of fovea-centered color fundus photographs (CFPs) of a patient without DR (left) and a patient with signs of DR (right). In the CFP of the patient with signs of DR (right), one example each of hemorrhage, exudate, and a microaneurysm are highlighted. Both examples have been selected from the Kaggle DR dataset.[47] **b** Schematic of the Diabetic Retinopathy Severity Scale (DRSS) established by the Early Treatment Diabetic Retinopathy Study (ETDRS) group to measure DR worsening over time. **c** Schematic of the two-phase modeling to detect two-step or more DRSS worsening over time. In phase I, field-specific Inception-v3 deep convolutional neural networks (DCNNs) called "field-specific DCNNs" or "pillars" are trained by means of transfer learning to predict whether the patient will progress two ETDRS DRSS steps. In phase II, the probabilities independently generated by the field-specific DCNNs are aggregated by means of random forest

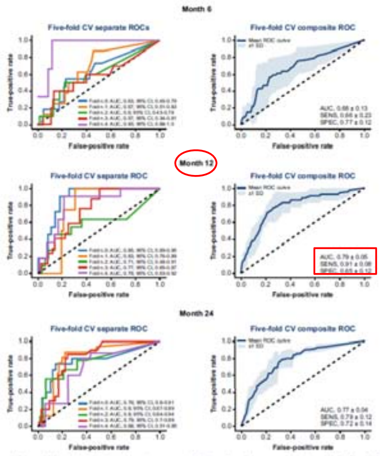


Fig. 2 Summary of the results for the prediction of two-step or more diabetic retinopathy progression at months 6, 12, and 24 using 7-field color fundus photographs of patients at baseline. AUC area under the curve, CI confidence interval, CV cross-validation, ROC receiver operating characteristic, SD standard deviation, SENS sensitivity, SPEC specificity

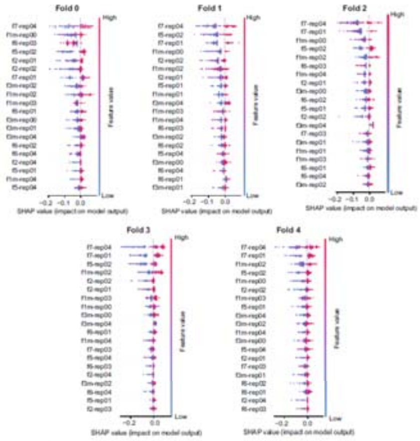


Fig. 3 SHAP plots summarizing the pointwise and average contribution of each deep convolutional neural network (DCNN) to the random forest aggregation. SHAP plots outlining the pointwise contribution of each DCNN. In this example, the SHAP analysis is related to the five folds used for the prediction of DR progression at month 24 is showed. The DCNNs are ordered in importance from top to bottom. The naming convention of the DCNNs highlights the field ('f1,' 'f2,' etc.) and repetition ('rep00,' 'rep01,' etc.)

thank you!

謝謝聆聽

THANK YOU FOR YOUR ATTENTION

鄭喻仁

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