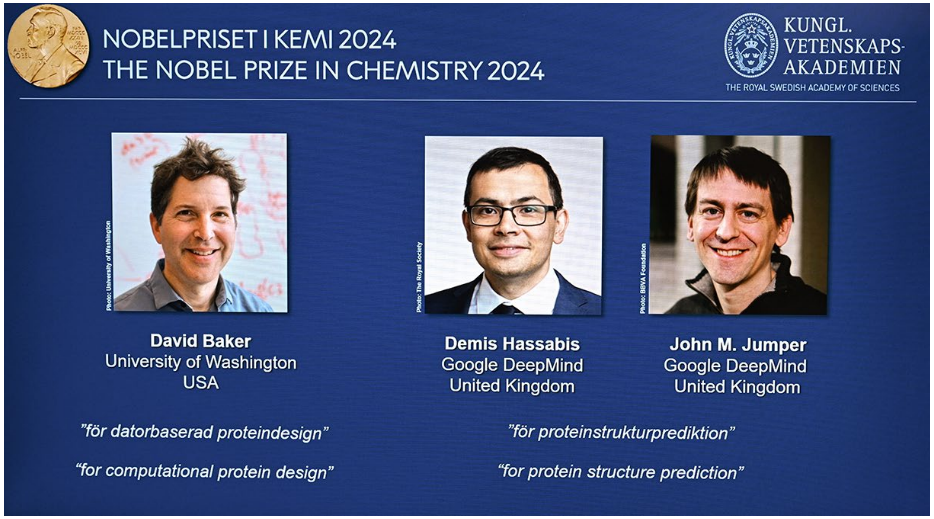
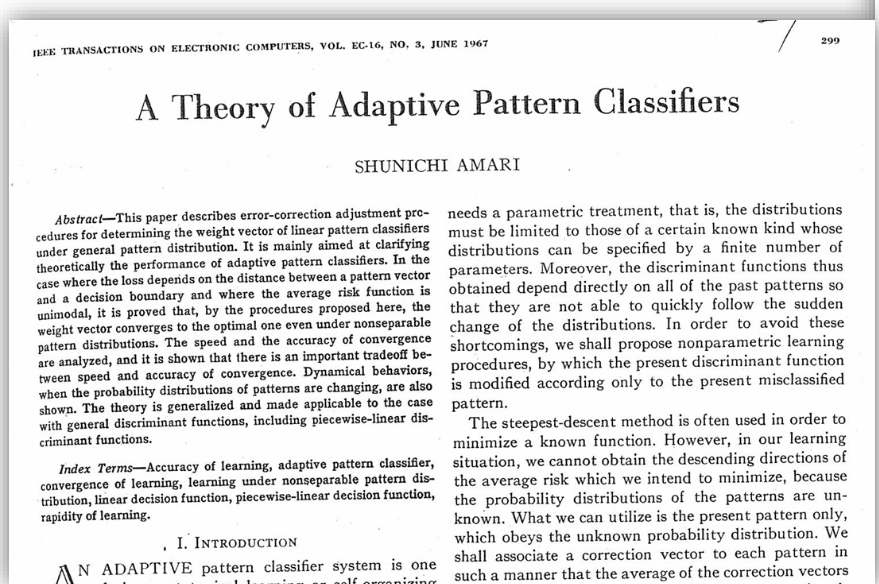
# 機械学習基礎第６章補足図表

赤穂昭太郎

# Nobel Prize to AI

# Shun-ichi Amari



IEEE TRANSACTIONS ON ELECTRONIC COMPUTERS, VOL. EC-16, NO. 3, JUNE 1967 299

## A Theory of Adaptive Pattern Classifiers

SHUNICHI AMARI

*Abstract*—This paper describes error-correction adjustment procedures for determining the weight vector of linear pattern classifiers under general pattern distribution. It is mainly aimed at clarifying theoretically the performance of adaptive pattern classifiers. In the case where the loss depends on the distance between a pattern vector and a decision boundary and where the average risk function is unimodal, it is proved that, by the procedures proposed here, the weight vector converges to the optimal one even under nonseparable pattern distributions. The speed and the accuracy of convergence are analyzed, and it is shown that there is an important tradeoff between speed and accuracy of convergence. Dynamical behaviors, when the probability distributions of patterns are changing, are also shown. The theory is generalized and made applicable to the case with general discriminant functions, including piecewise-linear discriminant functions.

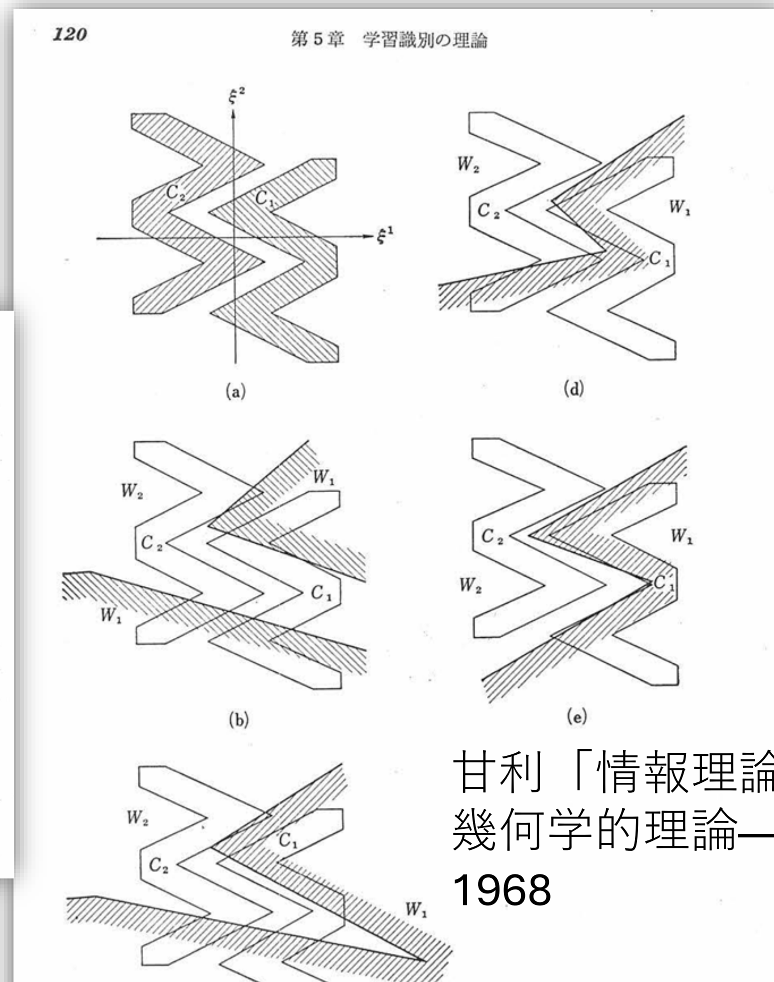
*Index Terms*—Accuracy of learning, adaptive pattern classifier, convergence of learning, learning under nonseparable pattern distribution, linear decision function, piecewise-linear decision function, rapidity of learning.

I. Introduction

AN ADAPTIVE pattern classifier system is one of the most typical learning or self-organizing

needs a parametric treatment, that is, the distributions must be limited to those of a certain known kind whose distributions can be specified by a finite number of parameters. Moreover, the discriminant functions thus obtained depend directly on all of the past patterns so that they are not able to quickly follow the sudden change of the distributions. In order to avoid these shortcomings, we shall propose nonparametric learning procedures, by which the present discriminant function is modified according only to the present misclassified pattern.

The steepest-descent method is often used in order to minimize a known function. However, in our learning situation, we cannot obtain the descending directions of the average risk which we intend to minimize, because the probability distributions of the patterns are unknown. What we can utilize is the present pattern only, which obeys the unknown probability distribution. We shall associate a correction vector to each pattern in such a manner that the average of the correction vectors




甘利「情報理論II—情報の幾何学的理論—」共立出版 1968

FDIG 2025 https://sites.google.com/view/fdig2025/

# RAAG Memoirs

めくるめく数理の世界（甘利）

近藤先生は，学会などはボス教授の巣食うところであり，ここでは真の学問はできない，学会は権力と腐敗の源であるからそこには参加するな，真の学問は我々がするのじゃ，と弟子どもに仰せつけた．そして，RAAG での活動が国際的にも本格化し，10 年間でいずれも 600 ページを超える 4 巻の分厚い英文の論文集を刊行し，成果を世界に問うた．これが論文集 RAAG Memoirs である．

RAAG MEMOIRS
Vol. 4, 1968

I-III

## Theory of Learning Decision Systems*

By
Shun-ichi AMARI**

〔Received February 1967〕

### INTRODUCTION

IN Divisions F and I of these Memoirs, infor-

only a finite number of parameters specifying the distribution can be estimated. Moreover, the parametric method cannot be applied, if the pat-

# Associative memory

Proc. Natl. Acad. Sci. USA
Vol. 79, pp. 2554–2558, April 1982
Biophysics

## Neural networks and physical systems with emergent collective computational abilities

(associative memory/parallel processing/categorization/content-addressable memory/fail-soft devices)

J. J. Hopfield

Division of Chemistry and Biology, California Institute of Technology, Pasadena, California 91125; and Bell Laboratories, Murray Hill, New Jersey 07974

*Contributed by John J. Hopfield, January 15, 1982*

**ABSTRACT** Computational properties of use to biological organisms or to the construction of computers can emerge as collective properties of systems having a large number of simple equivalent components (or neurons). The physical meaning of content-addressable memory is described by an appropriate phase space flow of the state of a system. A model of such a system is given, based on aspects of neurobiology but readily adapted to integrated circuits. The collective properties of this model produce a content-addressable memory which correctly yields an entire memory from any subpart of sufficient size. The algorithm for the time evolution of the state of the system is based on asynchronous parallel processing. Additional emergent collective properties in-
cl... calized content-addressable memory or categorizer using extensive asynchronous parallel processing.

**The general content-addressable memory of a physical system**

Suppose that an item stored in memory is "H. A. Kramers & G. H. Wannier *Phys. Rev.* **60**, 252 (1941)." A general content-addressable memory would be capable of retrieving this entire memory item on the basis of sufficient partial information. The input "& Wannier, (1941)" might suffice. An ideal memory could deal with errors and retrieve this reference even from the input "Vannier, (1941)". In computers, only relatively simple

Biol. Cybernetics 26, 175—185 (1977)

Biological Cybernetics


## Neural Theory of Association and Concept-Formation

S.-I. Amari*

University of Tokyo, Tokyo, Japan; Center for Systems Neuroscience, University of Massachusetts, Amherst, MA, USA

**Abstract.** The present paper looks for possible neural mechanism underlying such high-level brain functioning as association and concept-formation. Primitive neural models of association and concept-formation are presented, which will elucidate the distributed and multiply superposed manner of retaining knowledge in the brain. The models are subject to two rules of self-organization of synaptic weights, orthogonal and covariance learning. The convergence of self-organiza- long as the essential features are not missed. This is a common attitude of the author's neural researches (Amari, 1971; 1972a, b; 1974a, b; 1975; 1977a, b).

We consider the following association net. The net, learning from $k$ pairs of stimulus patterns $(x_1, z_1), \ldots, (x_k, z_k)$, self-organizes in such a manner that, when the net receives a key pattern $x_\alpha (\alpha = 1, \ldots, k)$, it correctly outputs the associated partner $z_\alpha$. The self-organization is carried into effect through modification of the

## LEARNING PROCESS IN A MODEL OF ASSOCIATIVE MEMORY

Kaoru NaKano

University of Tokyo

Tokyo, Japan

SUMMARY

The excellent information processing in a human brain is considered to depend upon its association mechanisms. To simulate this function, we propose in this paper a model of the neural network named "Associatron" which operates like a human brain in some points. Associatron stores many entities at the same place of its structure, and recalls the whole of any entity from a part of it. From that mechanism some properties are derived, which are expected to be utilized for human-like information processing. After the properties of the model have been analyzed, an Associatron with 180 neurons is simulated by a computer and is applied to simple examples of concept formation and game playing. Hardware realization of an Associatron with 25 neurons and thinking process by the sequence of associations are mentioned, too.

INTRODUCTION

The purpose of this paper is to outline the work of simulating the association mechanism of a human brain and of applying it to human-like information processing.

The first aspect of this work is to design an associative memory device that is considered to be reasonable as a model for association mechanisms in the human brain. Association was studied mainly in the field of psychology, and some semantic models for association were presented in the last few years. On the other hand, biological studies have gradually revealed the structure of the nervous system. Although knowledge about it is still not enough

172

K. S. Fu (ed.), *Pattern Recognition and Machine Learning*

Biol. Cybernetics 36, 193–202 (1980)

# Neocognitron

Biological Cybernetics


## Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position

Kunihiko Fukushima

NHK Broadcasting Science Research Laboratories, Kinuta, Setagaya, Tokyo, Japan

**Abstract.** A neural network model for a mechanism of
visual pattern recognition i
The network is self-organiz
teacher", and acquires an ab
patterns based on the geom
of their shapes without affec
network is given a nickna
completion of self-organiza
structure similar to the hier
nervous system proposed b
network consists of an in
array) followed by a cascade
modular structures, each of
layers of cells connected in a
each module consists of "S-

reveal it only by conventional physiological experi-

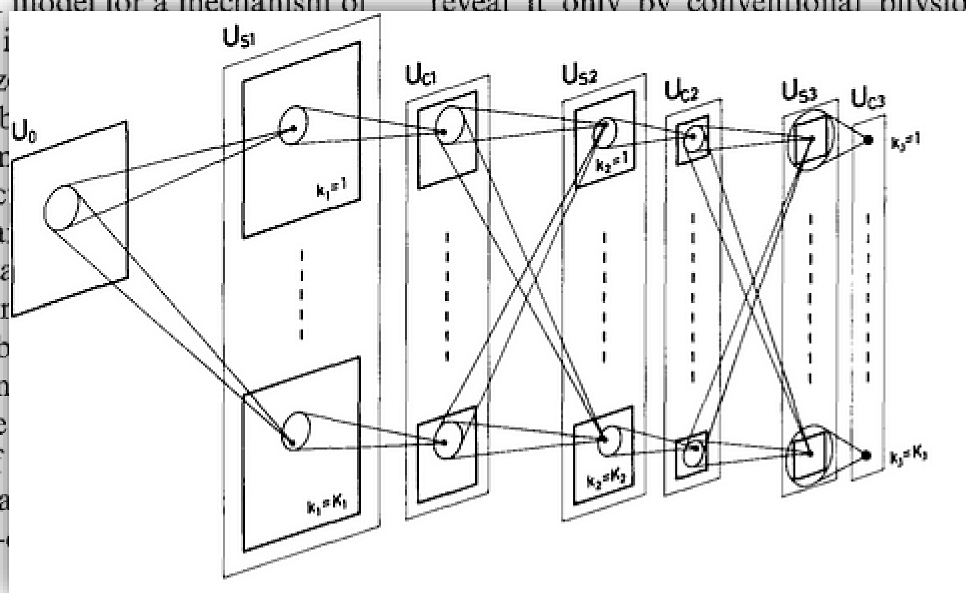
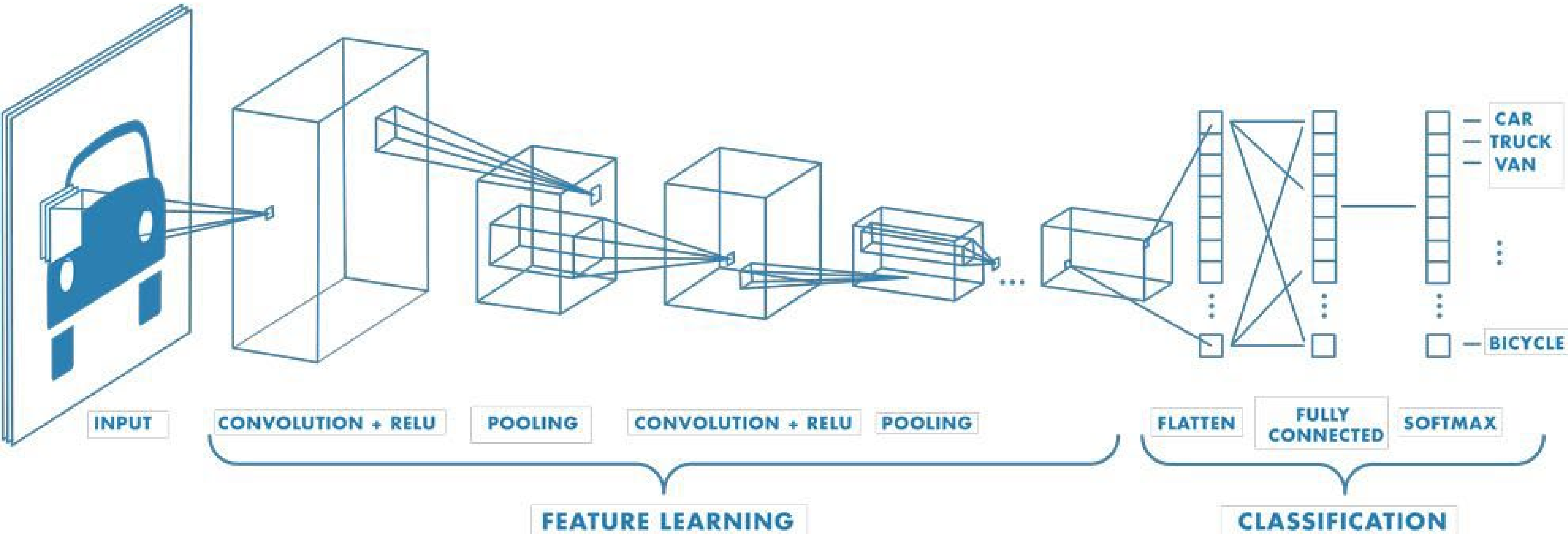


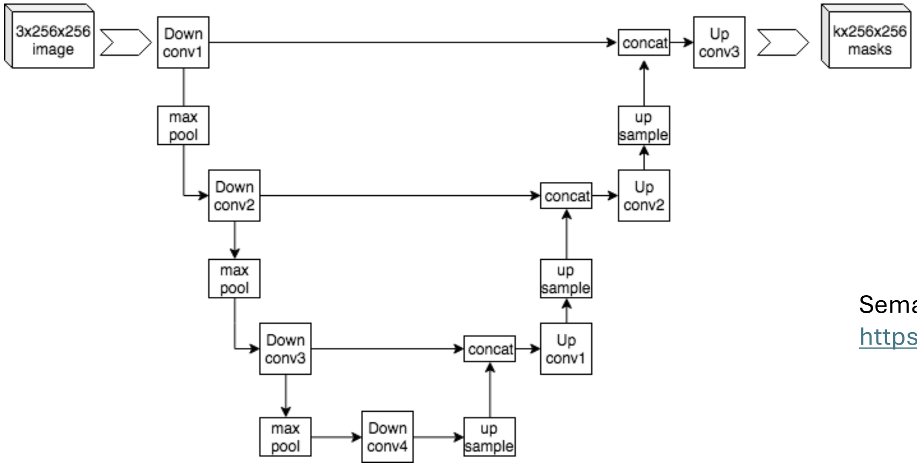

**Fig. 2.** Schematic diagram illustrating the interconnections between layers in the neocognitron

# CNN

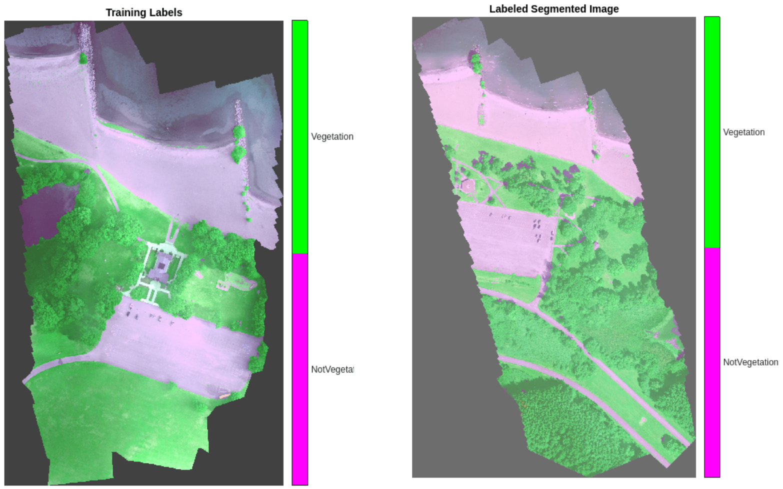



https://jp.mathworks.com/discovery/convolutional-neural-network.html

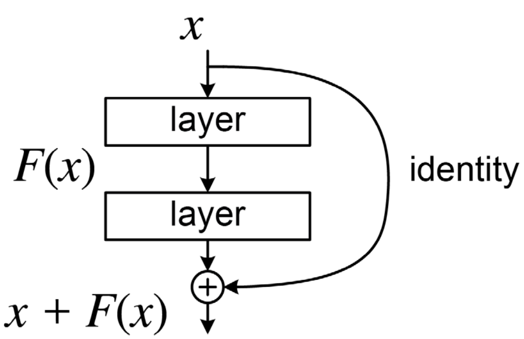
# CNN families




U-net ©Wikipedia

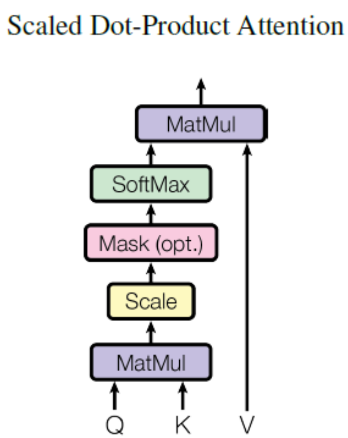


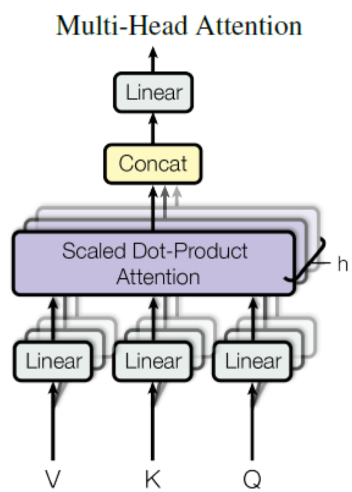

Semantic segmentation using U-net
https://jp.mathworks.com/help/images/multispectral-semantic-segmentation-using-de

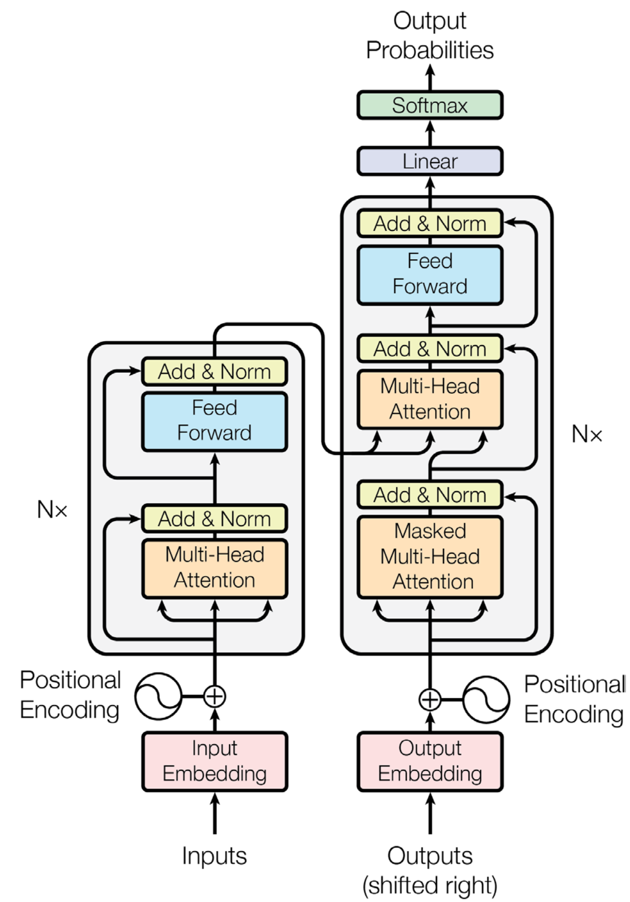



ResNet ©Wikipedia

# Transformer (attention)

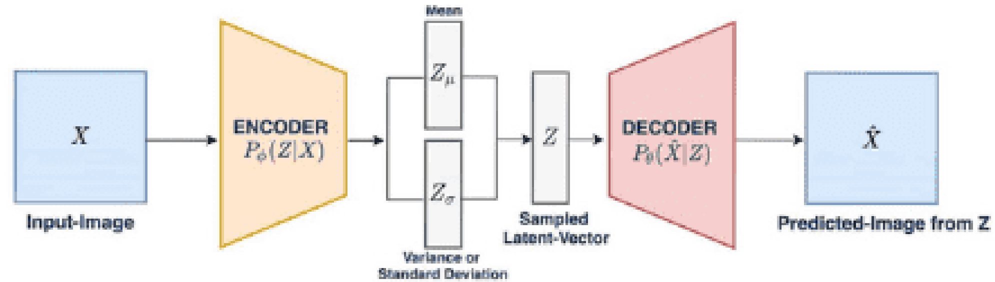


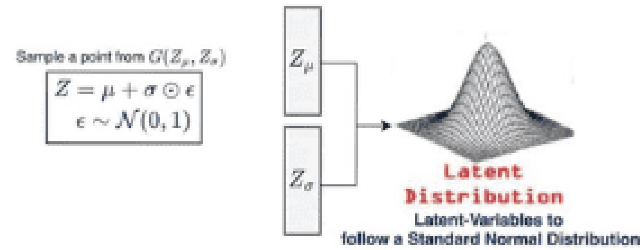



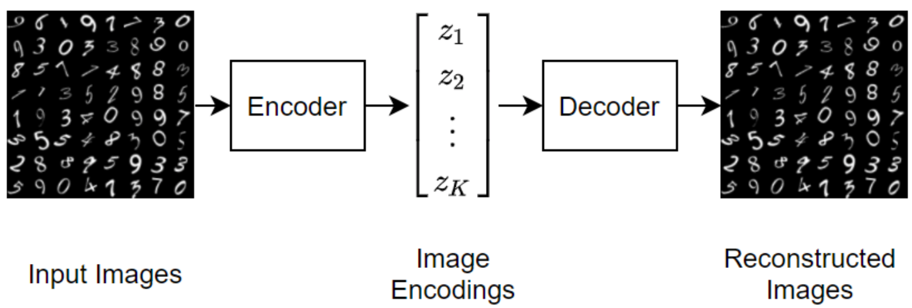

https://arxiv.org/abs/1706.03762

# VAE

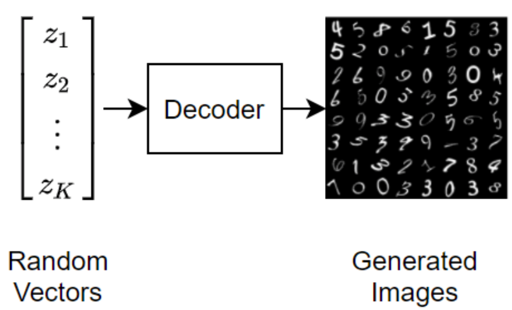



https://pyimagesearch.com/2023/10/02/a-deep-dive-into-variational-autoencoders-with-pytorch/



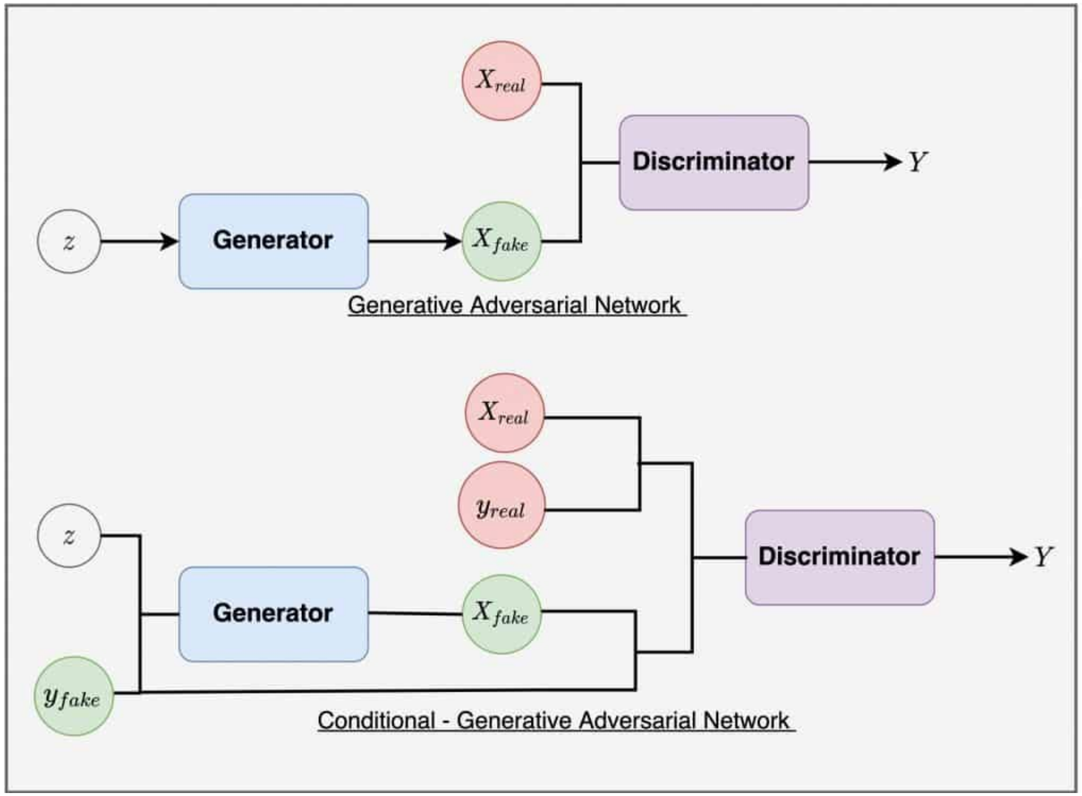



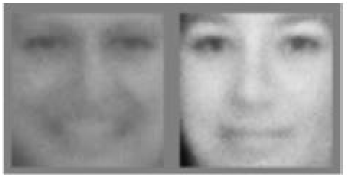

変分自己符号化器を使用して新しいイメージを生成するには、ランダム ベクトルを復号化器に入力します。



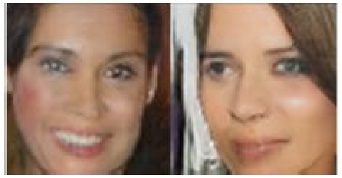

https://jp.mathworks.com/help/deeplearning/ug/train-a-variational-autoencoder-vae-to-generate-images.html

# GAN

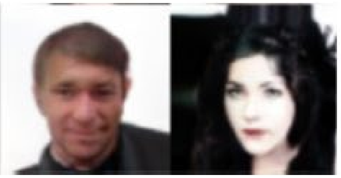


[Goodfellow et al., 2014]
University of Montreal



[Radford et al., 2015]
Facebook AI Research

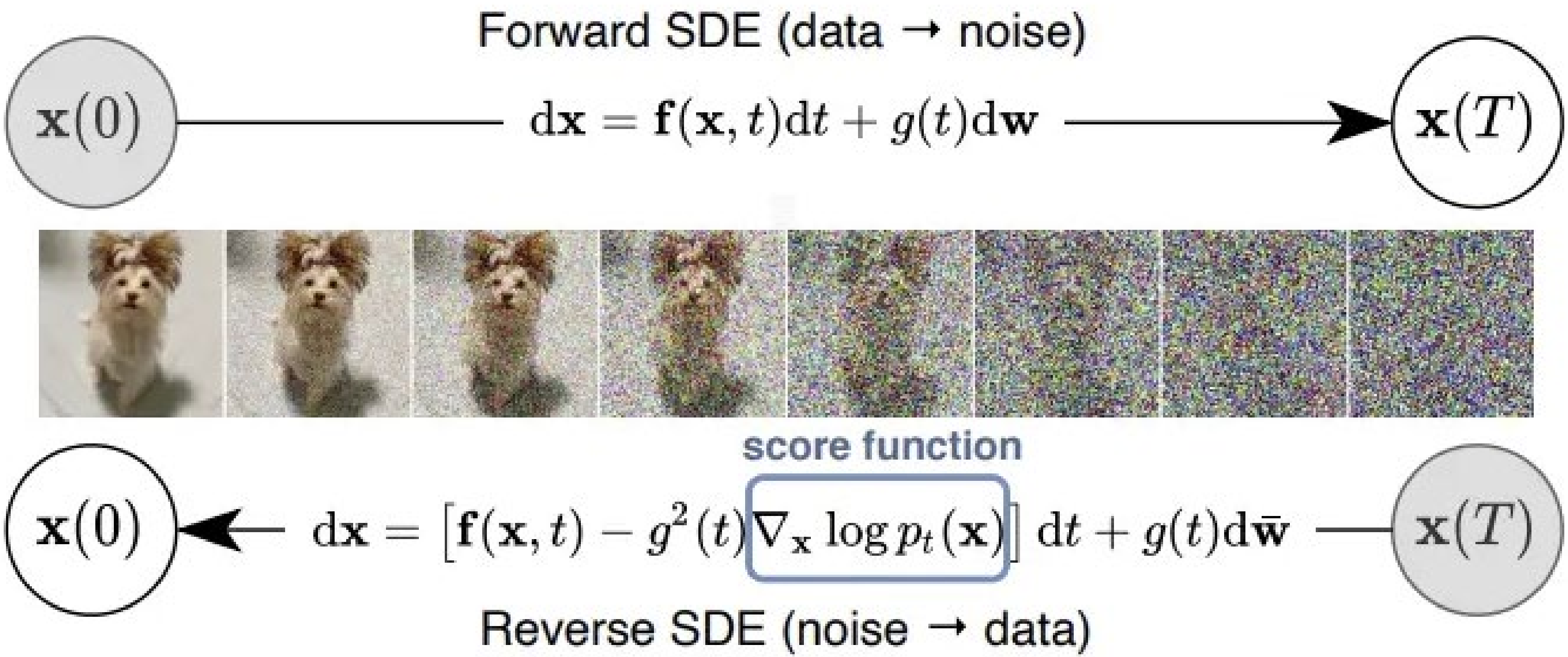


[Roth et al., 2017]
Microsoft and ETHZ

[Karras et al., 2018]
NVIDIA

https://ieeexplore.ieee.org/abstract/document/9625798

# Diffusion model




https://www.superannotate.com/blog/diffusion-models

# CLIP

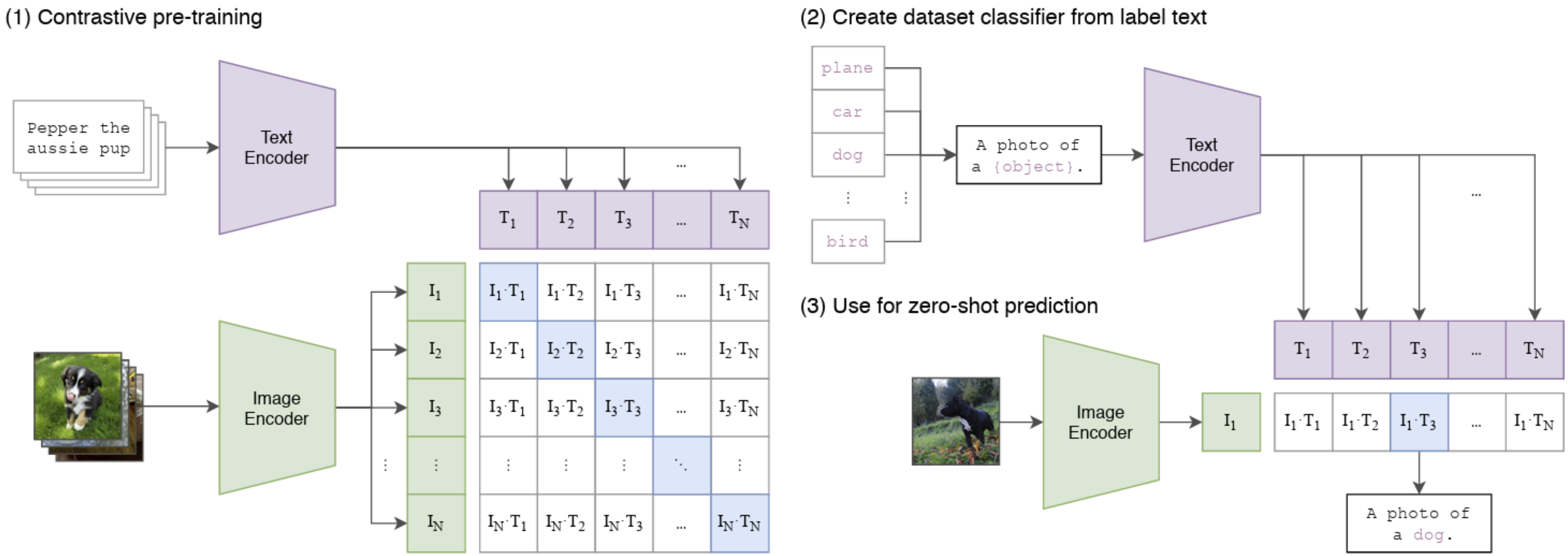
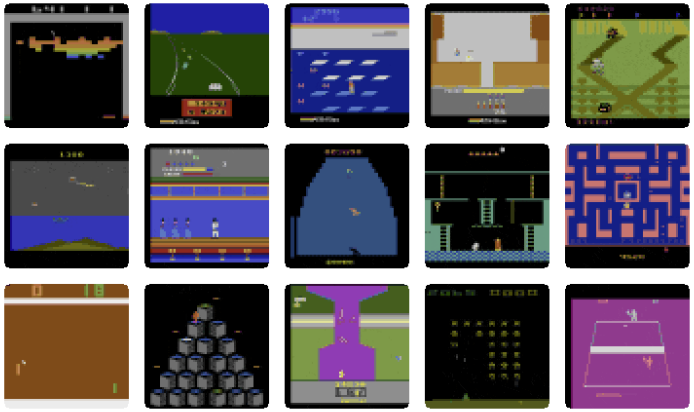


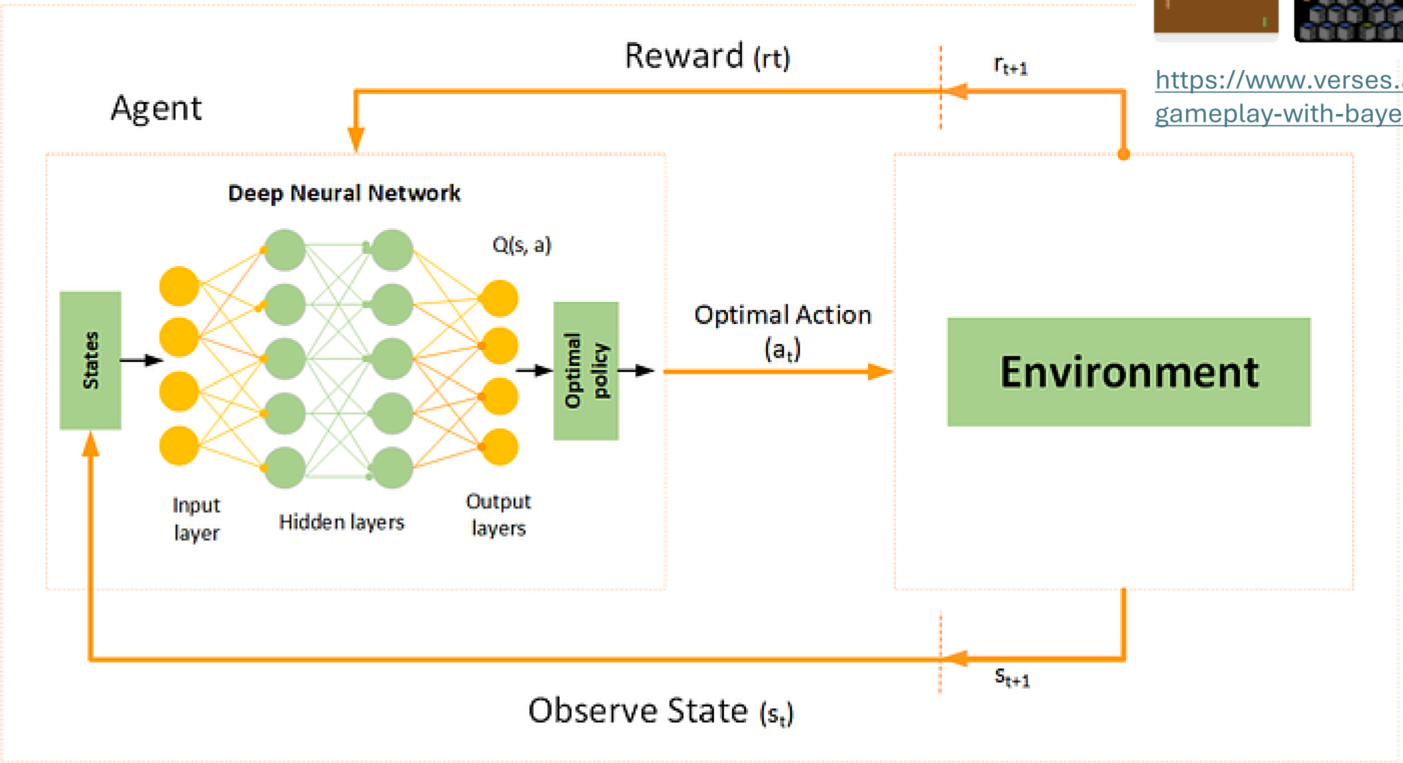

*Figure 1.* Summary of our approach. While standard image models jointly train an image feature extractor and a linear classifier to predict some label, CLIP jointly trains an image encoder and a text encoder to predict the correct pairings of a batch of (image, text) training examples. At test time the learned text encoder synthesizes a zero-shot linear classifier by embedding the names or descriptions of the target dataset's classes.

https://arxiv.org/abs/2103.00020

# Deep Q Network



https://www.verses.ai/research-blog/achieving-human-lev
gameplay-with-bayesian-object-priors-and-active-inferenc




https://medium.com/@samina.amin/deep-q-learning-dqn-71c109586bae

# AlphaFold2

**Article**

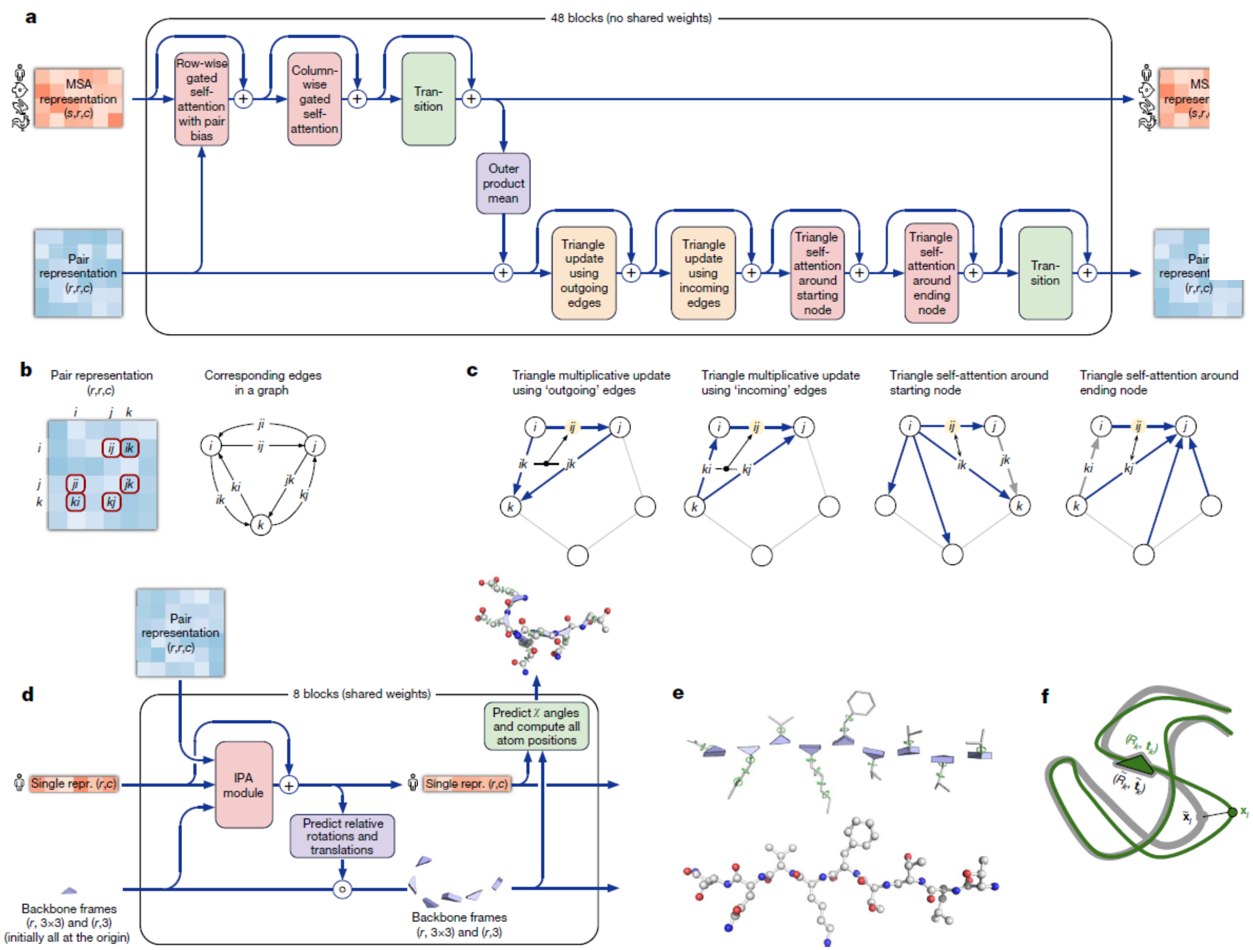
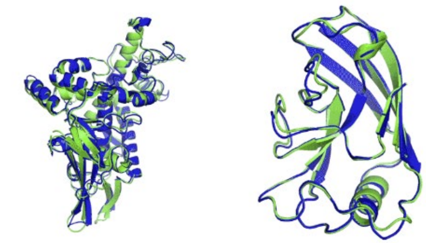



**Fig. 3 | Architectural details. a,** Evoformer block. Arrows show the information flow. The shape of the arrays is shown in parentheses. **b,** The pair representation interpreted as directed edges in a graph. **c,** Triangle multiplicative update and triangle self-attention. The circles represent residues. Entries in the pair representation are illustrated as directed edges and in each diagram, the edge being updated is *ij*. **d,** Structure module including Invariant point attention (IPA) module. The single representation is a copy of the first row of the MSA representation. **e,** Residue gas: a representation of each residue as one free-floating rigid body for the backbone (blue triangles) and χ angles for the side chains (green circles). The corresponding atomic structure is shown below. **f,** Frame aligned point error (FAPE). Green, predicted structure; grey, true structure; $(R_k, \mathbf{t}_k)$, frames; $\mathbf{x}_i$, atom positions.



**T1037 / 6vr4**
90.7 GDT
(RNA polymerase domain)

**T1049 / 6y4f**
93.3 GDT
(adhesin tip)

● Experimental result
● Computational prediction

https://nesi.github.io/alphafold2-on-mahuika/

https://www.nature.com/articles/s41586-021-03819-2

# Grad-CAM

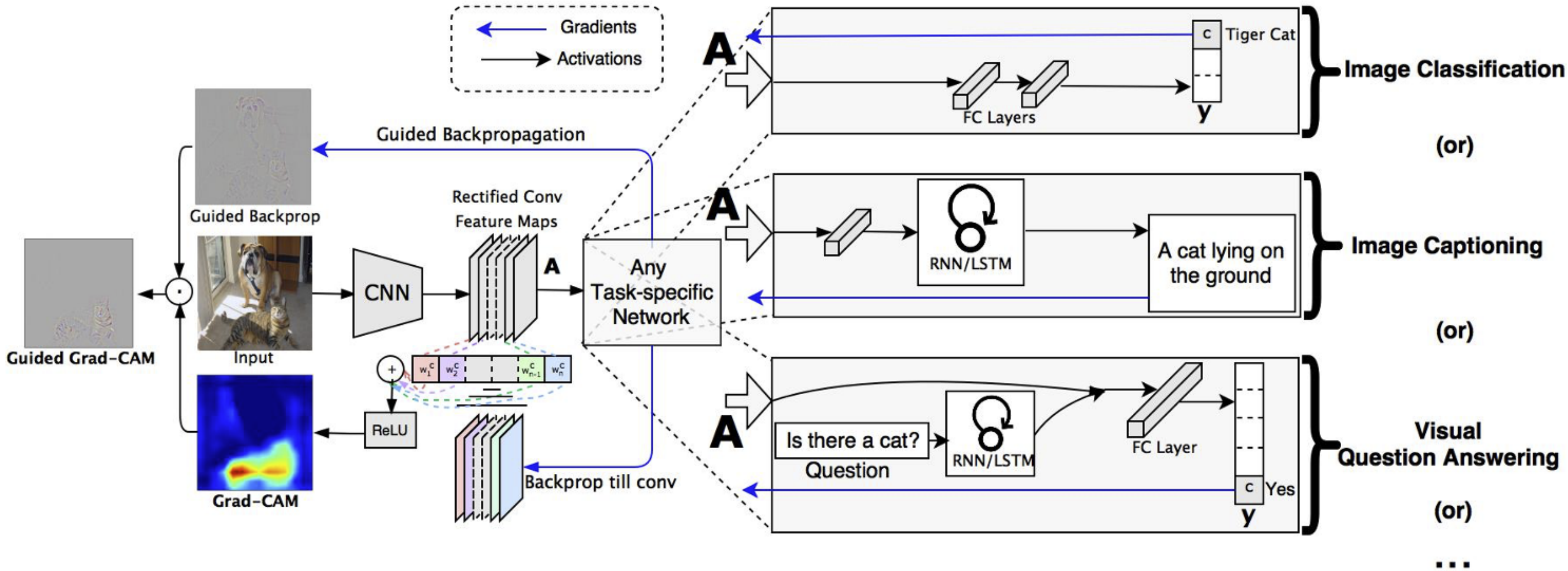
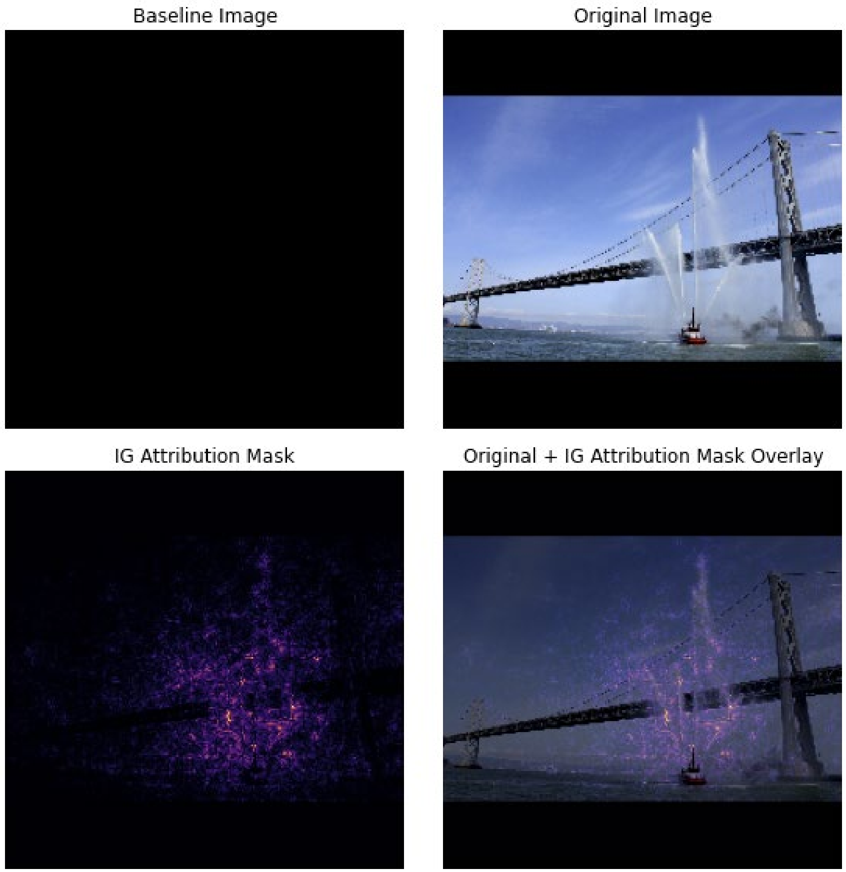



Fig. 2: Grad-CAM overview: Given an image and a class of interest (*e.g.*, 'tiger cat' or any other type of differentiable output) as input, we forward propagate the image through the CNN part of the model and then through task-specific computations to obtain a raw score for the category. The gradients are set to zero for all classes except the desired class (tiger cat), which is set to 1. This signal is then backpropagated to the rectified convolutional feature maps of interest, which we combine to compute the coarse Grad-CAM localization (blue heatmap) which represents where the model has to look to make the particular decision. Finally, we pointwise multiply the heatmap with guided backpropagation to get Guided Grad-CAM visualizations which are both high-resolution and concept-specific.

https://arxiv.org/abs/1610.02391

# Integrated-Gradient




https://www.tensorflow.org/tutorials/interpretability/integrated_gradients?hl=ja