

# Deep Learning

## Network Application Diagnostics

### B2M32DSAA

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Prague CZ

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## 1 Artificial Intelligence

- AI in a Broad Sense

## 2 Machine Learning

- Learning Principles
- Classification Evaluation
- Deep Learning

## 3 Natural Language Processing (NLP)

- Embeddings and Neural Network Architectures

# Outline

## 1 Artificial Intelligence

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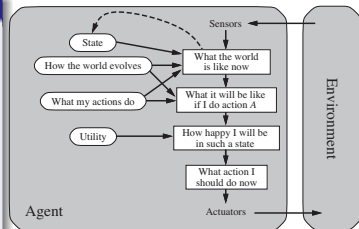
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- Embeddings and Neural Network Architectures

# Intelligence in General <sup>[RN10]</sup>

## Studies of intelligence in general:

- How do we **perceive** the world?
- How do we **understand** the world?
- How do we **reason** about the world?
- How do we **predict** the consequences of our actions?
- How do we act to **influence** the world?

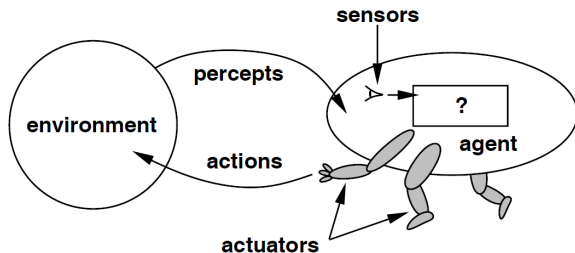


Artificial Intelligence (AI) not only wants to understand the “intelligence”, but also wants to

- create an intelligent entity (agent, robot)
- imitating or improving
- the human behavior and effects in the outer world, and/or
- the inner human mind processes and reasoning.



# What is AI for us? [RN10]



## ● Acting rationally:

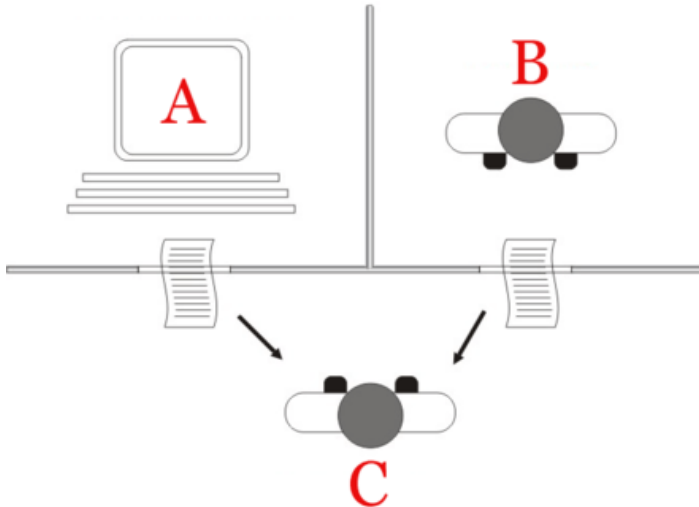
- Care only about what they do and if they achieve their goals optimally.
- Goals are described in terms of the utility of the outcomes.
- **Maximize the expected utility of the outcomes of their decisions.**

## ● Good decisions:

- Take into account similar situations that happened in the past.  
**Machine learning.**
- Simulations using a model of the world. Be aware of the consequences of your actions and plan ahead. **Inference, planning.**

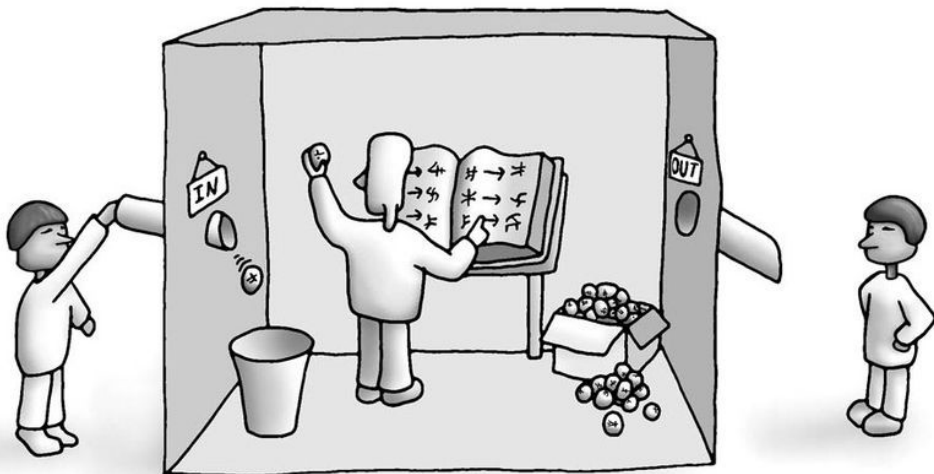


# Turing Test



[https://en.wikipedia.org/wiki/Turing\\_test](https://en.wikipedia.org/wiki/Turing_test)

# Chinesse Room



<http://america.pink/>

# Superintelligence? (NO)



However, even **narrow AI** might be abused by people against people!



# AI Science Disciplines <sup>[RN10]</sup>

- **Knowledge representation:**

- how to store the model of the world, the relations between the entities in the world, the rules that are valid in the world, ...

- **Automated reasoning:**

- how to infer some conclusions from what is known or answer some questions

- **Planning:**

- how to find an action sequence that puts the world in the desired state

- **Pattern recognition:**

- how to decide about the state of the world based on observations

- **Machine learning:**

- how to create/adapt the model of the world using new observations

- **Multiagent systems:**

- how to coordinate and cooperate in a group of agents to reach the desired goal

- **Natural language processing:**

- how to understand what people say and how to say something to them

- **Computer vision:**

- how to understand the observed scene, what is going on in a sequence of pictures

- **Robotics:**

- how to move, how to manipulate with objects, how to localize and navigate



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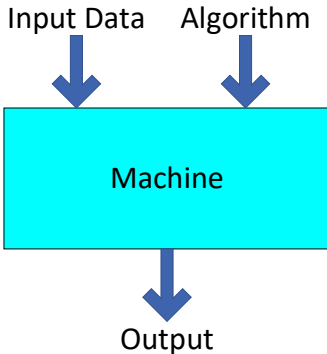
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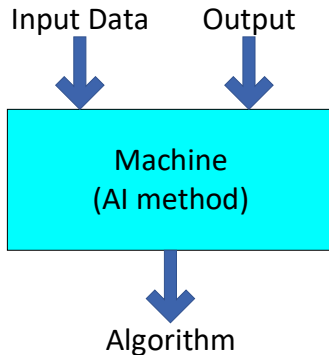


# AI Machine Learning Principle <sup>[RN10]</sup>

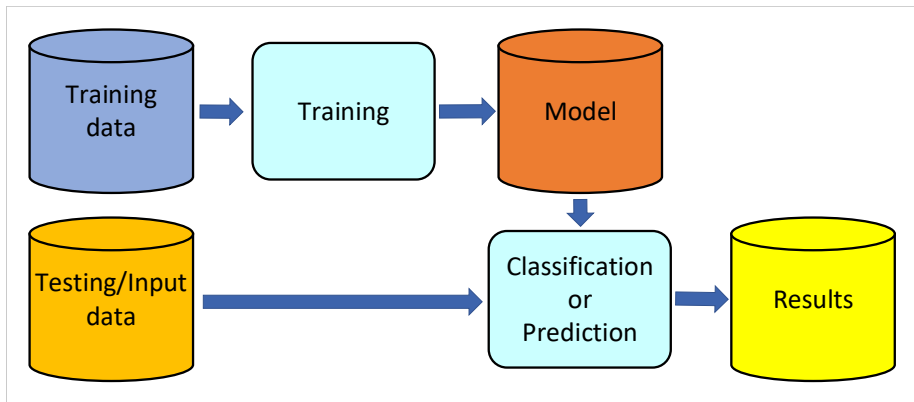
## Traditional Programming



## Machine Learning



# AI Machine Learning Workflow <sup>[RN10]</sup>





# The Universal Approximation Theorem

- Any neural network architecture aims at finding any mathematical function  $y = f(x)$  that can map attributes  $x$  to output  $y$ .
- The function  $f(x)$  can be arbitrarily complex.
- The Universal Approximation Theorem tells us that Neural Networks has a kind of **universality** i.e. no matter what  $f(x)$  is, there is a network that can approximate the result.

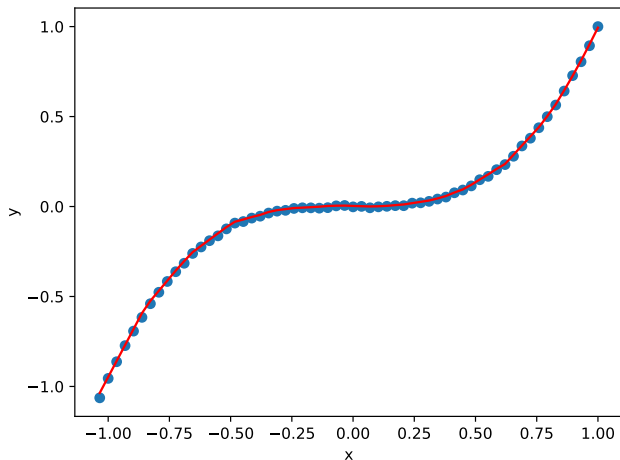
<https://towardsdatascience.com/>

neural-networks-and-the-universal-approximation-theorem-8a389a33d30a

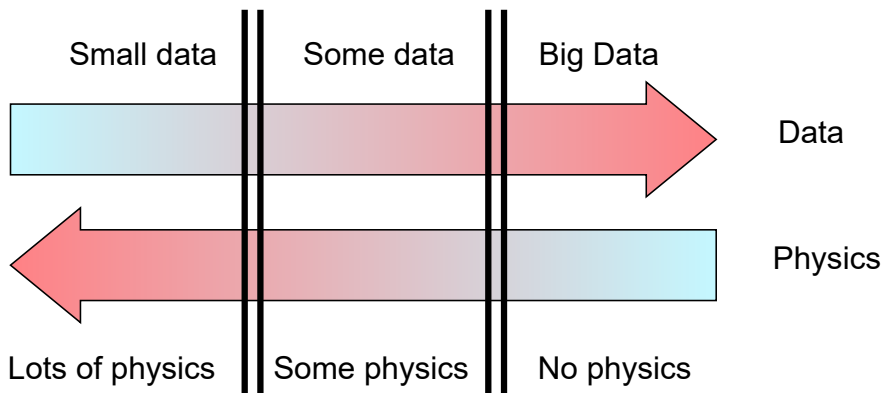


# Cubic Function - Deep NN

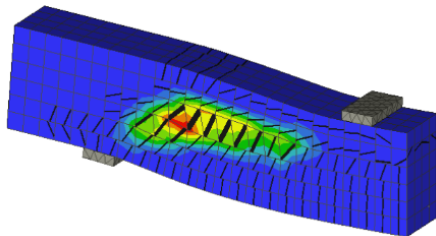
Input( $x$ ), Dense(200), Dense(50), Dense(10), Dense(1)



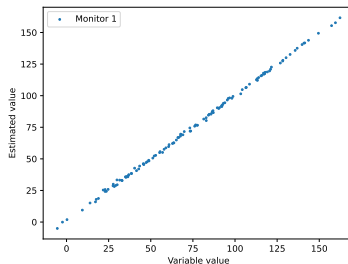
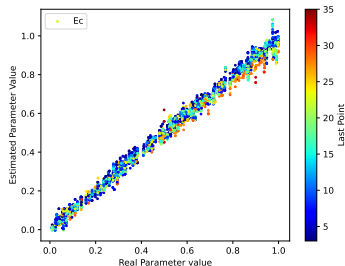
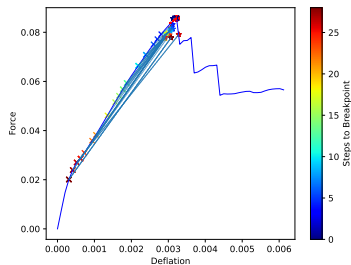
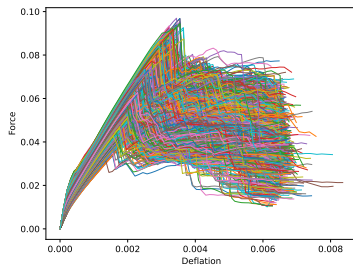
# Physics versus Data



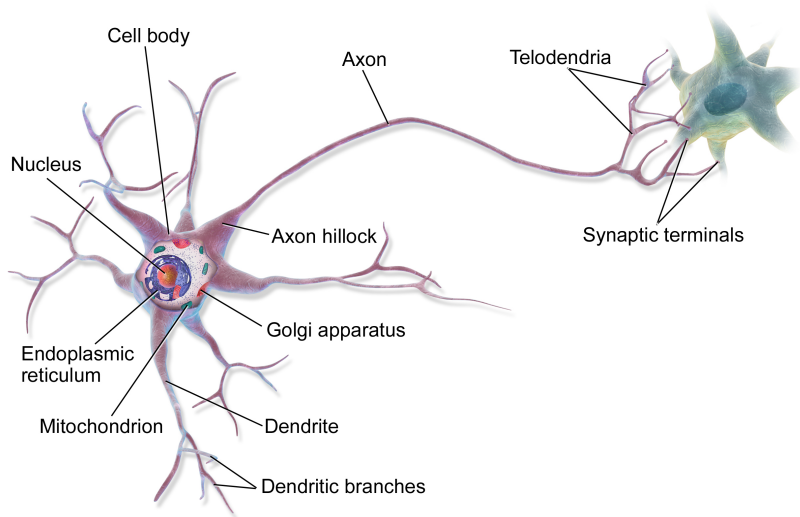
# Concrete Bridge Twin (Project TAČR CK03000023 2022-2024)



# TwinBridge Results



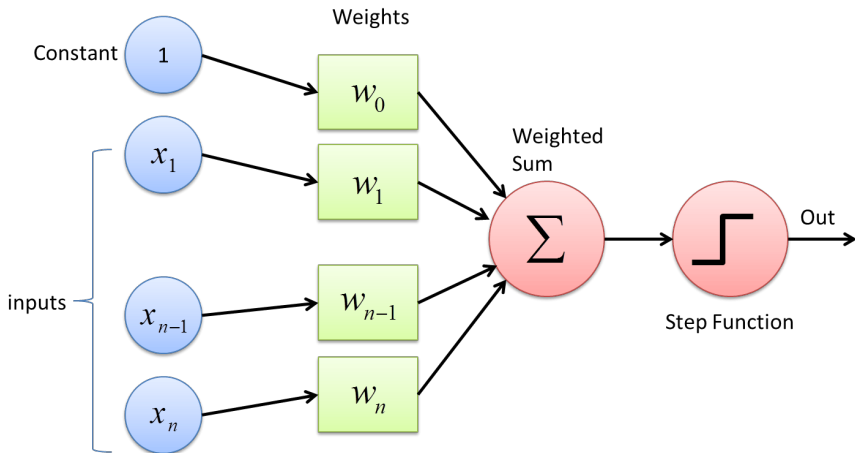
# Neuron



[https://en.wikipedia.org/wiki/Multipolar\\_neuron](https://en.wikipedia.org/wiki/Multipolar_neuron)



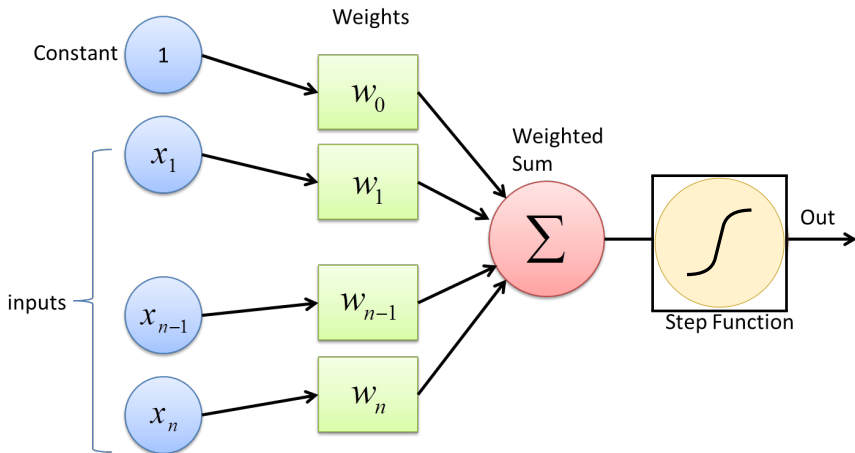
# Perceptron <sup>[Ros58]</sup>



<https://towardsdatascience.com/what-the-hell-is-perceptron-626217814f53>



# Perceptron <sup>[Ros58]</sup>



<https://towardsdatascience.com/what-the-hell-is-perceptron-626217814f53>





# Binary Classification Task (dichotomy)

**Training dataset**  $T = \{(\mathbf{x}^{(1)}, y^{(1)}), \dots, (\mathbf{x}^{(|T|)}, y^{(|T|)})\}$ :

- each sample described by a vector  $\mathbf{x} = (x_1, \dots, x_D)$ ,
- labeled with the correct class  $y \in \{+1, -1\}$ .

**Discriminant function**  $f(\mathbf{x})$ :

- Used to create a **decision rule** which assigns a class to an observation:

$$f(\mathbf{x}) > 0 \iff \hat{y} = +1, \text{ and}$$

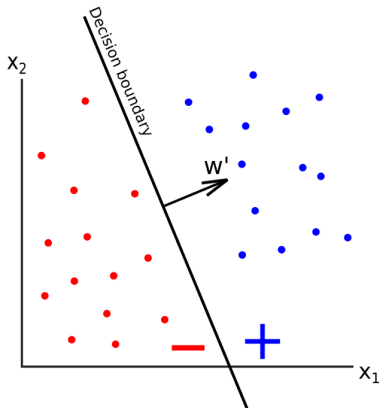
$$f(\mathbf{x}) < 0 \iff \hat{y} = -1$$

$$\text{i.e. } \hat{y} = \text{sign}(f(\mathbf{x}))$$

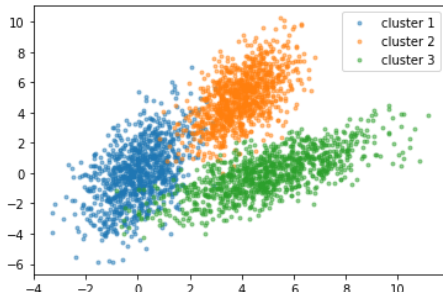
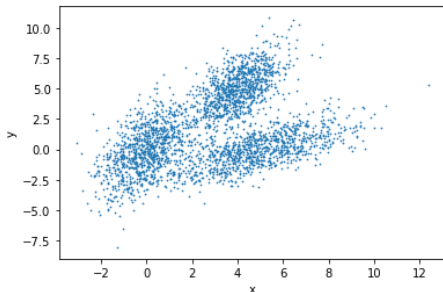
**Decision boundary:**  $\{\mathbf{x} | f(\mathbf{x}) = 0\}$

**Linear classification:** the decision boundaries must be linear.

**Learning:** searching (suitable parameters of) function  $f$ .



# Clustering



- **Unsupervised learning** ... to discover hidden patterns in any unlabeled data.
- **A cluster** ... a group containing data points with high similarity and low similarity with data points in other groups.
- **Clustering** ... to divide a set of data points in such a way that similar items fall into the same cluster, whereas dissimilar data points fall in different clusters.

[https://training.galaxyproject.org/training-material/topics/statistics/tutorials/clustering\\_](https://training.galaxyproject.org/training-material/topics/statistics/tutorials/clustering_)



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# Classification Predictions <sup>[Wik19a]</sup>

- **The expectation:** the terms *positive* and *negative* refer to the classifier's prediction.
- **The observation:** the terms *true* and *false* refer to whether that prediction corresponds to the external judgment.
- The confusion matrix (CZ kontingenční tabulka)

		Predicted / Classified	
		Negative	Positive
Actual	Negative	True Negative	False Positive
	Positive	False Negative	True Positive

## • TN / True Negative

- the real case is negative
- and predicted negative

## • FP / False Positive

- the real case is negative
- but predicted positive
- Type I error

## • TP / True Positive

- the real case is positive
- and predicted as positive

## • FN / False Negative

- the real case is positive
- but predicted negative
- Type II error



# Precision and Recall [Wik19a, ?]

## • Precision

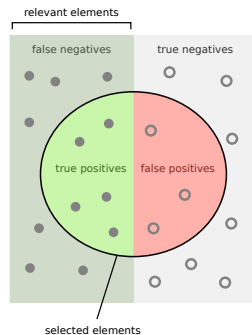
- the probability that a (randomly selected) retrieved document is relevant.
- the probability that a (randomly selected) object is correctly classified.

$$\text{Precision} = \frac{TP}{TP + FP}$$

## • Recall

- the probability that a (randomly selected) relevant document is retrieved in a search.
- the probability that a (randomly selected) class object is correctly classified.

$$\text{Recall} = \frac{TP}{TP + FN}$$



How many selected items are relevant?

$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

How many relevant items are selected?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

# Accuracy and F1-Measure <sup>[Wik19a, ?]</sup>

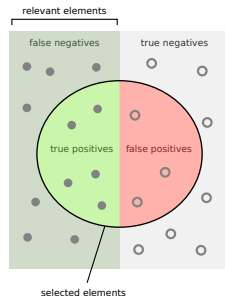
## • Accuracy

- the proportion of true results (both true positives and true negatives) among the total number of cases examined.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

## • F1-Measure

- the harmonic mean of precision and recall.
- an  $F1$  score reaches its best value at 1 (perfect precision and recall) and worst at 0.



How many selected items are relevant?



How many relevant items are selected?

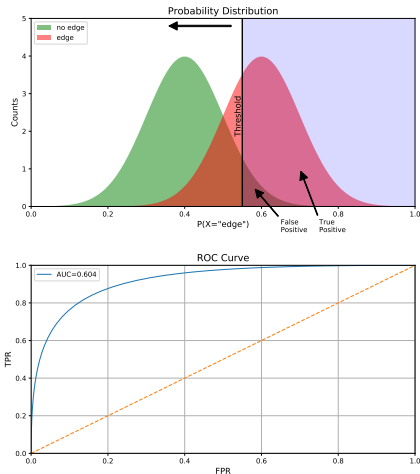


$$F1 = \left( \frac{\text{Precision}^{-1} + \text{Recall}^{-1}}{2} \right)^{-1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$



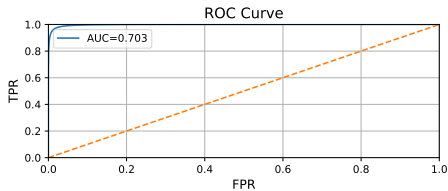
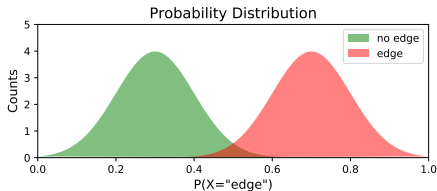
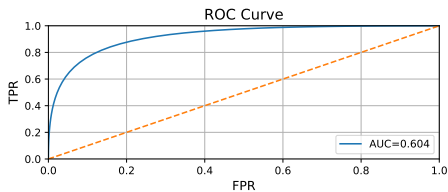
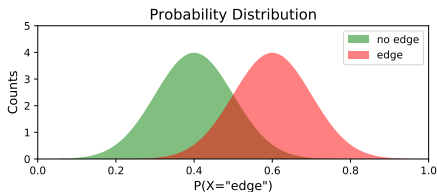
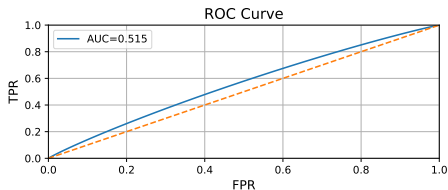
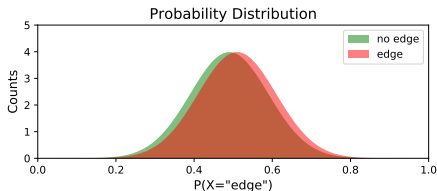
# ROC (Receiver Operating Characteristic) Curves <sup>[Wik19b]</sup>

- Plotting the true positive rate (TPR) against the false positive rate (FPR).
- Dealing with heavy class imbalance.
- The model performance is measured by the area under the ROC curve (AUC).
- The best possible AUC is 1.
- The worst AUC is 0.5 (the 45 degrees random line).
- If the AUC is below 0.5, do the exact opposite of what the model recommends.



$$TPR = \frac{TP}{TP + FN}, \quad FPR = \frac{FP}{FP + TN}$$

# ROC Performance Assessment [Wik19b]





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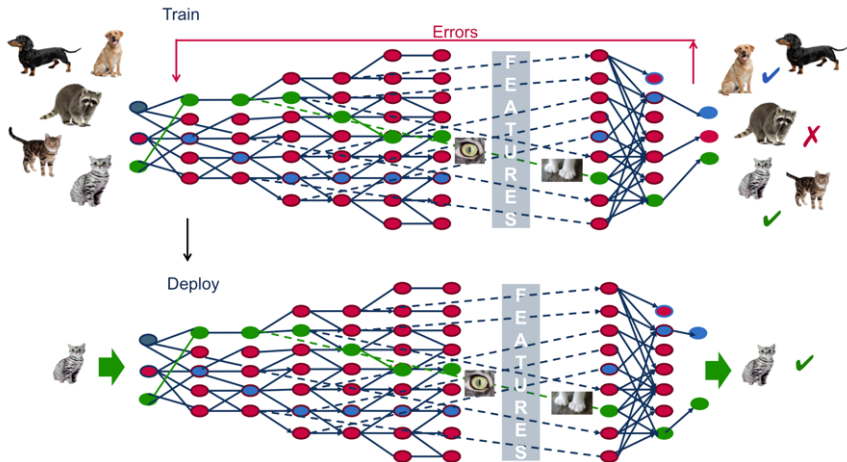
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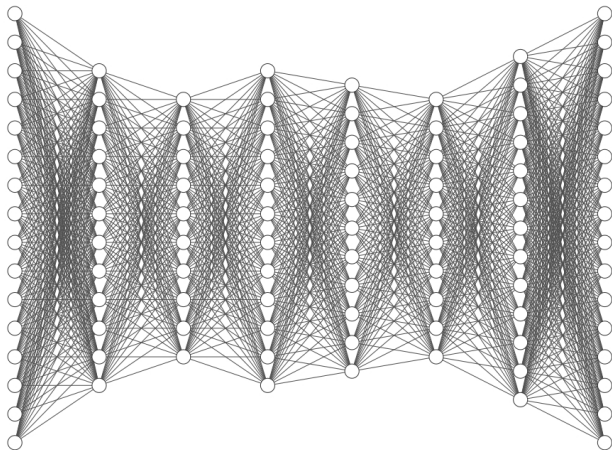
# Deep learning (2006)



<https://mapr.com/blog/demystifying-ai-ml-dl/>



# Multilayer perceptron (MLP)



Fully connected. Used in speech recognition and machine translation.

<https://alexlenail.me/NN-SVG/index.html>



# MLP Structure

- Each neuron is characterized by its **weight**, **bias**, and **activation function**.
- **The input layer** takes raw input from the domain. No computation is performed at this layer. Nodes here just pass on the information (features) to the hidden layer.
- **The hidden layers** perform all kinds of computation on the features entered through the input layer and transfers the result to the output layer.
- **The output layer** brings the information learned through the hidden layer and delivers the final value as a result.

<https://www.v7labs.com/blog/neural-networks-activation-functions>



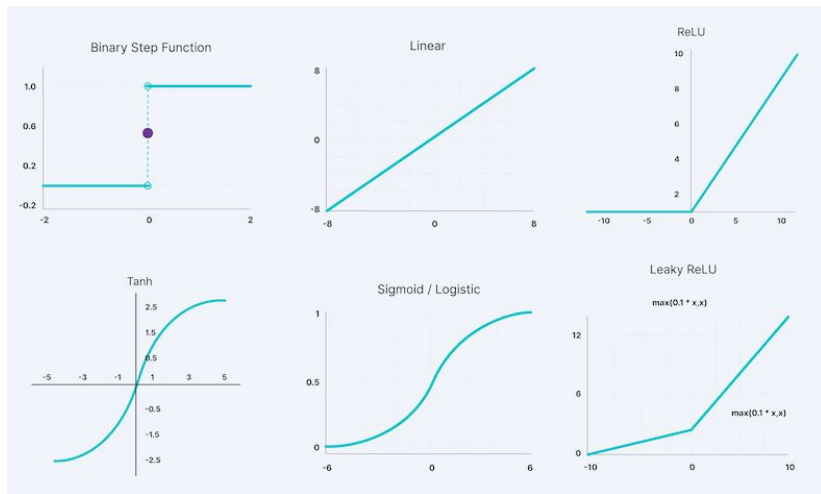
# Feedforward vs. Backpropagation

- **Feedforward Propagation** - the flow of information occurs in the forward direction. The input is used to calculate some intermediate function in the hidden layer, which is then used to calculate an output.
- **Backpropagation** - the weights of the network connections are repeatedly adjusted to minimize the difference between the actual output vector of the net and the desired output vector.
  - Backpropagation aims to minimize the cost function by adjusting the network's weights and biases.
  - The cost function gradients determine the level of adjustment with respect to parameters like activation function, weights, bias, etc.
- **Training** = Feedforward Propagation and Backpropagation
- **Testing** = Feedforward Propagation

<https://www.v7labs.com/blog/neural-networks-activation-functions>



# Activation Functions



<https://www.v7labs.com/blog/neural-networks-activation-functions>



# Loss/Cost Functions - Regression

- **Regression** - model needs to predict a continuous number
  - *Mean Squared Error (MSE) Loss*

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

- *Mean Absolute Error (MAE) Loss*

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

<https://www.geeksforgeeks.org/deep-learning/loss-functions-in-deep-learning/>



# Loss/Cost Functions - Classification

- **Classification** - classification loss functions are used to evaluate how well a classification model's predictions match the actual class labels.
  - *Binary Cross-Entropy Loss (Log Loss)*. It is used for binary classification problems. It measures the performance of a classification model whose output is a probability value between 0 and 1.

$$\text{Binary Cross-Entropy} = -\frac{1}{n} \sum_{i=1}^n [y_i \log(\hat{y}_i) + [(1 - y_i) \log(1 - \hat{y}_i)]]$$

- *Categorical Cross-Entropy Loss* - is used for multiclass classification problems. It measures the performance of a classification model whose output is a probability distribution over multiple classes.

$$\text{Categorical Cross-Entropy} = - \sum_{i=1}^n \sum_{j=1}^k y_{ij} \log(\hat{y}_{ij})$$

where data point  $i$ ,  $k$  is the number of classes,  $\hat{y}_{ij}$  is the predicted probability for class  $j$ .





# Regularization Functions

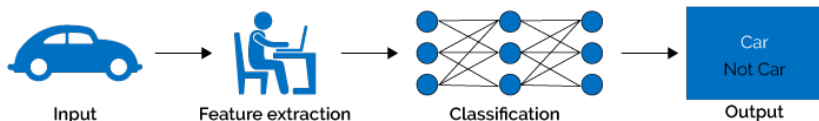
- *Regularization* is a technique used in machine learning to prevent overfitting and improve the generalization performance of a model on unseen data.
- *Overfitting* occurs when a model learns to perform well on the training data but fails to generalize to new, unseen data.
- **Dropout** - In Dropout, a random subset of neurons is temporarily excluded or “dropped out” during each iteration.
- *Batch Normalization* involves normalizing the inputs of each layer in a mini-batch by subtracting the mean and dividing by the standard deviation.
- *Adaptive Average Pool* is a pooling layer that automatically calculates the right kernel size, stride, and padding to produce a specific output size, regardless of the input's height and width.

[https://medium.com/@datasciencejourney100\\_83560/regularization-techniques-in-deep-learning-3de958b14fba](https://medium.com/@datasciencejourney100_83560/regularization-techniques-in-deep-learning-3de958b14fba)

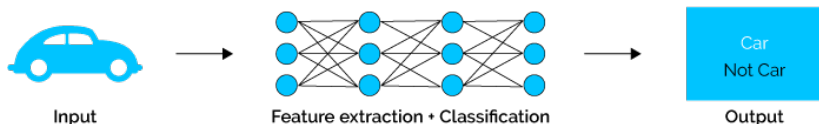


# Machine Learning vs. Deep Learning

## Machine Learning



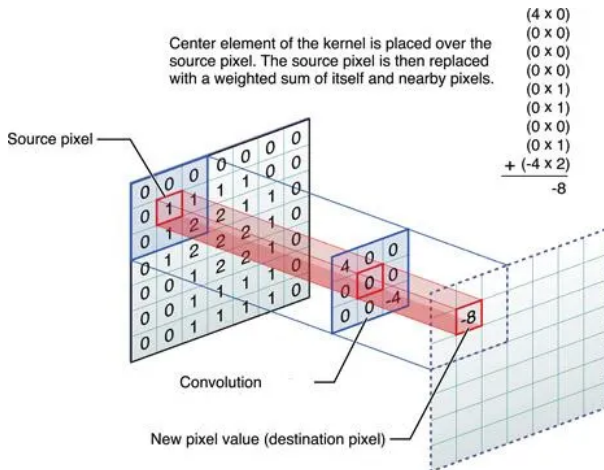
## Deep Learning



<https://www.thecrazyprogrammer.com/2018/03/difference-deep-learning-machine-learning.html>



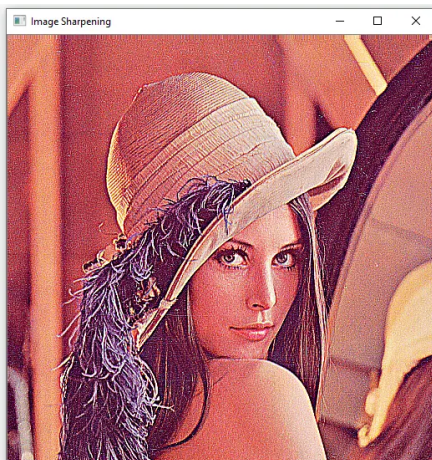
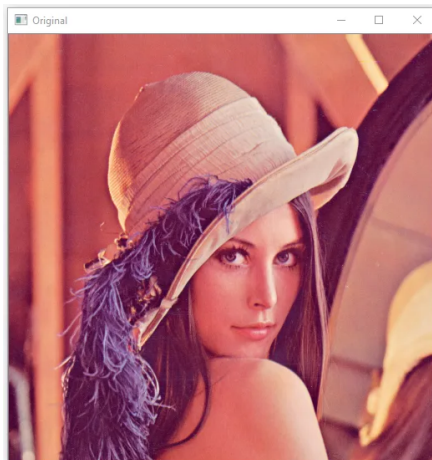
# Convolution Operation



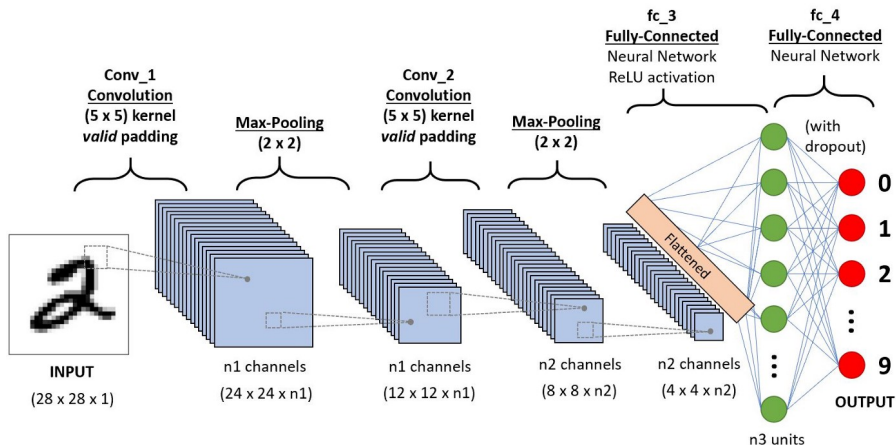
<https://medium.com/@bdhuma/6-basic-things-to-know-about-convolution-daef5e1bc411>



# Feature Enhancement


$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$


# Convolutional Neural Network (ConvNet/CNN)

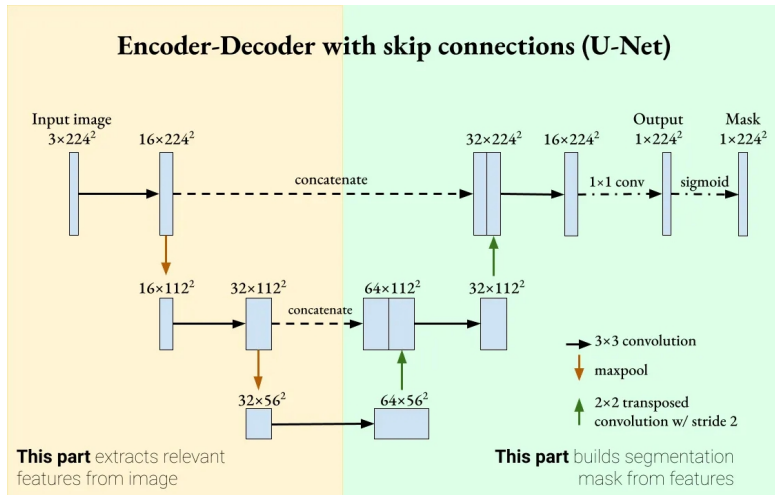


Used in computer vision to generate features.

https:

<https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53>

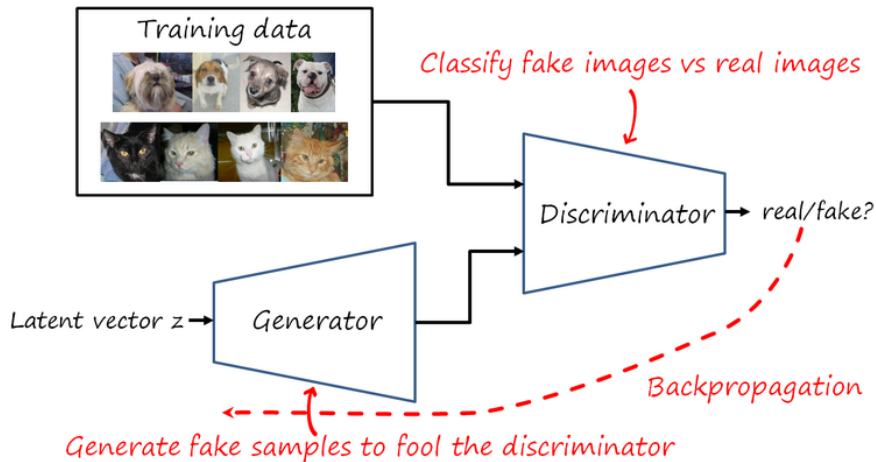
# UNet Neural Network (CRAFT<sup>[BLH<sup>+</sup>19]</sup>)



Used in computer vision in segmentation.

<https://towardsdatascience.com/understanding-u-net-61276b10f360>

# Generative adversarial networks (GANs) (2014)



## Wasserstein GAN (2017)

<http://www.lherranz.org/2018/08/07/imagetranslation/>



# Fake Image Generation (2018)



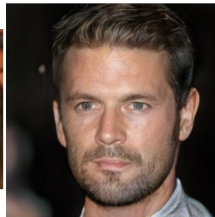
2014



2015



2016



2017



2018





# Image Style Conversion - CycleGAN (2017) <sup>[ZPIE17]</sup>

Monet ↔ Photos



Monet → photo



photo → Monet

Summer ↔ Winter



summer → winter



winter → summer



# Image Style Conversion Failures (2017) <sup>[ZPIE17]</sup>



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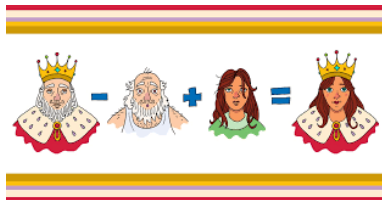
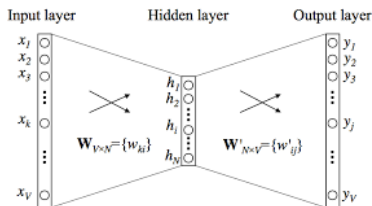
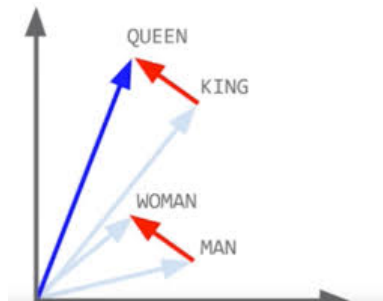
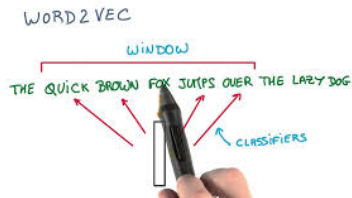
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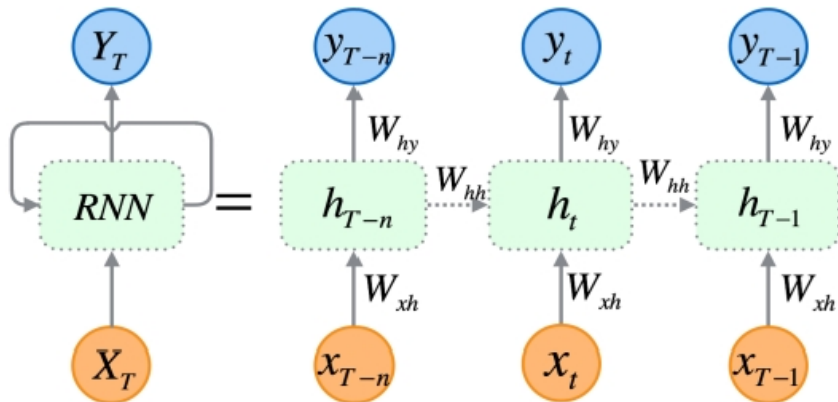
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# Embeddings - Word2vec Word Representation (Skipgram)



# Recurrent Neural Network (RNN)

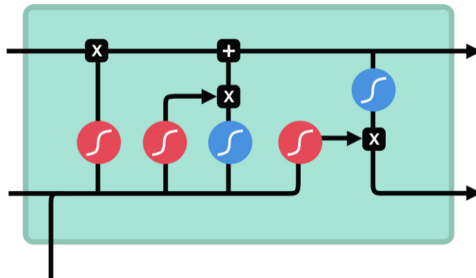


Used in natural language processing.

<https://www.i2tutorials.com/what-is-the-difference-between-bidirectional-rnn-and-rnn/>



# Long Short-Term Memory (LSTM) Network <sup>[HS97]</sup>



sigmoid

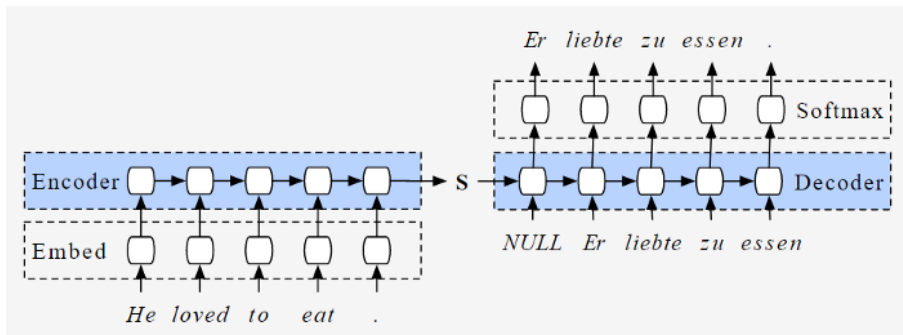


tanh

pointwise  
multiplicationpointwise  
additionvector  
concatenation

Used in natural language processing.

# Sequence2Sequence Network <sup>[SVL14]</sup>



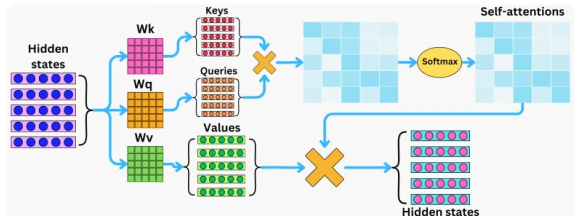
Used in natural language processing.

<https://www.analyticsvidhya.com/blog/2020/08/a-simple-introduction-to-sequence-to-sequence-models/>

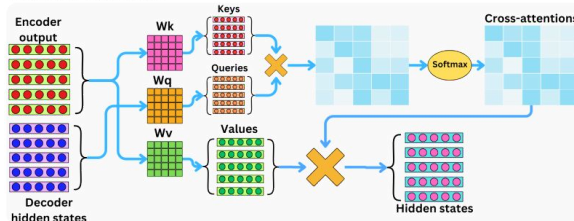


# Self and Cross Attention <sup>[BCB16]</sup>

## The Self-Attentions



## The Cross-Attentions



Used in natural language processing and computer vision.

[https://www.linkedin.com/posts/damienbenveniste\\_](https://www.linkedin.com/posts/damienbenveniste_)

what-is-the-difference-between-self-attention-activity-7211029906166624257-m0Wn/





# Transformer Network <sup>[VSP<sup>+</sup>17]</sup>

- Used in natural language processing.
- Self-Attention. . . attention applied to a single sequence (position dependencies)
- Multi-head Attention . . . several subspaces of attention
- Language models
  - ELMo . . . March 2018,
  - GPT . . . June 2018, 117Mi pars
  - BERT . . . May 2019, BERTlarge 340M pars,
    - ALBERT(base:12M, xxlarge: 235M), RoBERTa (160GB of text), DistillBERT (66 mil.), DeBERTa (2021.01, 1.5B)
  - GPT2 . . . November 2019, 1.5Bi pars, 8 milion web pages (40GB)
  - XLNet . . . January 2020, Large: 340M pars
  - GPT3 . . . July 2020, 175Bi pars
  - GPT4 . . . March 2023, ≈1.7 trillion pars

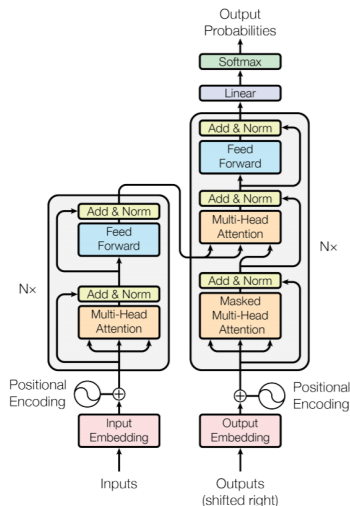


Figure 1: The Transformer - model architecture.

<https://towardsdatascience.com/transformer-neural-network-step-by-step-breakdown-of-the-beast-b3e096dc857f>

# Gardiner Code to Transliteration Translation

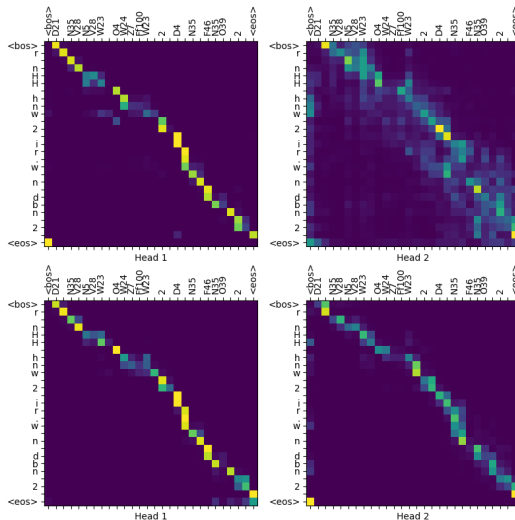


*ḥtp-dj-nsw ʾsjr nb ḏdw nṯr ʿ3 nb ʾbdw*

Htp-dj-nsw Asjr nb Ddw nTr aA nb AbDw

An offering which the king gives (to) Osiris,  
lord of Djedu, great god, lord of Abydos

# Model 7 Cross Attention Visualization (2H/1B+2H/2B)

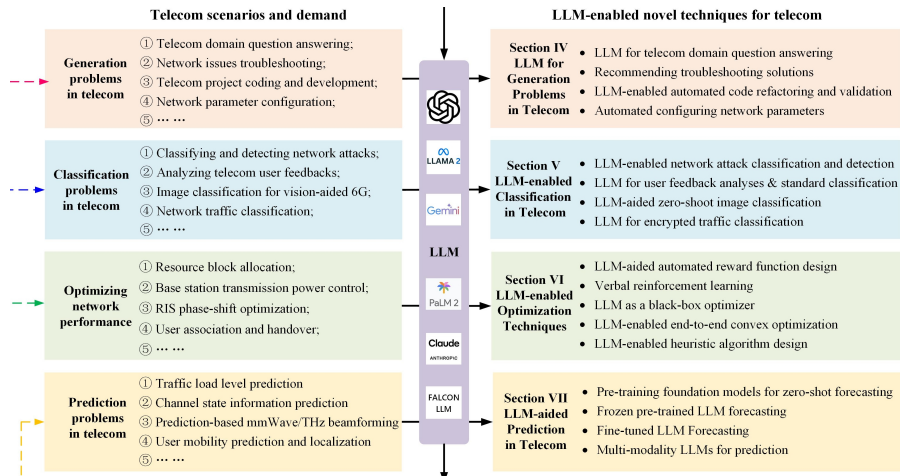


# LLM in Telecommunications - Survey

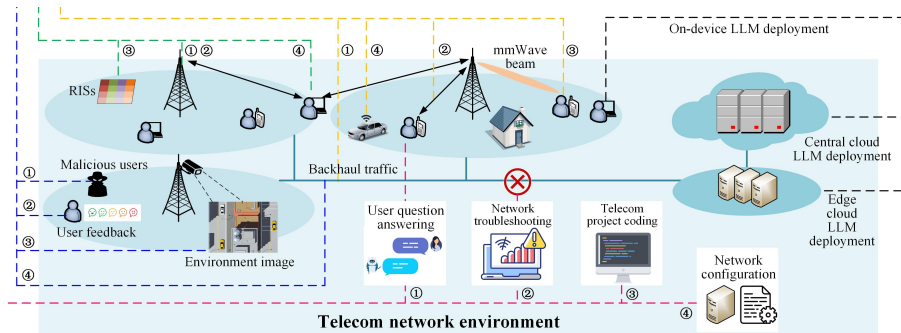
<b>Section I Introduction</b>	<ul style="list-style-type: none"> <li>• Background</li> <li>• Motivations</li> </ul>	<ul style="list-style-type: none"> <li>• Contributions</li> </ul>	<b>Section II Related Surveys</b> <ul style="list-style-type: none"> <li>• Comparison with existing studies</li> <li>• Main differences</li> </ul>
<b>Section III LLM Fundamentals</b>	<ul style="list-style-type: none"> <li>• Model architecture</li> <li>• Pre-training</li> <li>• Fine-tuning</li> </ul>	<ul style="list-style-type: none"> <li>• Inference and utilization</li> <li>• Evaluation of LLM performance</li> </ul>	<ul style="list-style-type: none"> <li>• Deploying LLMs in telecom networks ← - - -</li> <li>• Analyses of LLM fundamentals in the telecom domain</li> </ul>
<b>Section VIII Challenges and Future Directions of LLM-empowered Telecom</b>		<ul style="list-style-type: none"> <li>• Challenges of applying LLMs to telecom</li> <li>• Future directions</li> </ul>	



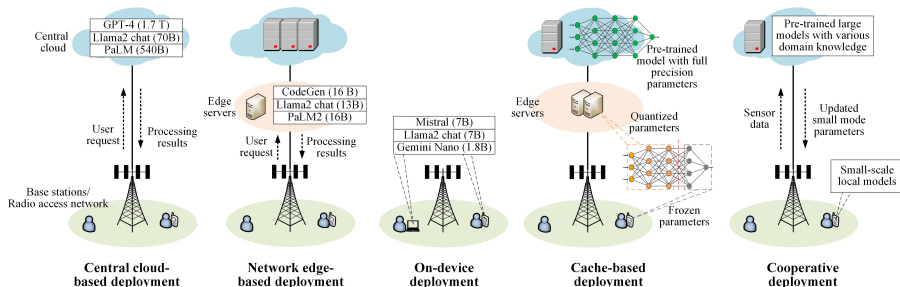
# LLM in Telecommunications- Use Cases



# LLM in Telecommunications - Environment



# LLM in Telecommunications - Deployment





# THANK YOU

THANK YOU



# References I

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