


Introduction to AI/ML



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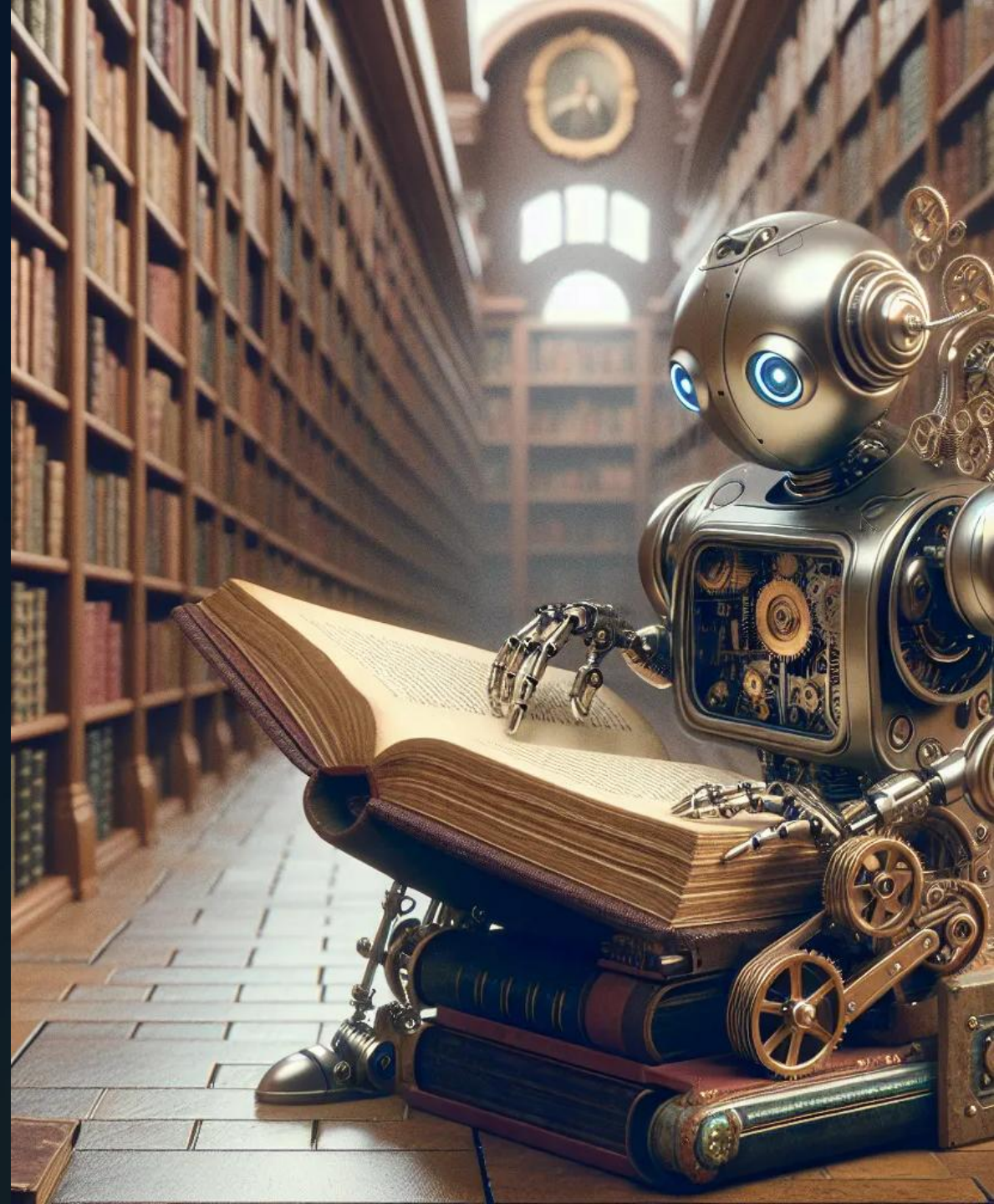
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Education

- Bachelor of Engineering in Mechatronics Engineering King Mongkut's University of Technology Thonburi (2019)
- Master of Science in Artificial Intelligence for Business Analytics King Mongkut's Institute of Technology Ladkrabang (2023)

Work Experience

- AI Engineer
STELLIGENCE Co., Ltd. (2024 – Present)
- AI&NLP Engineer
Omniscien Technologies (2023)

Certification

- Coursera IBM Data Science Professional Certificate - IBM
- DeepLearning.AI TensorFlow Developer Specialization - DeepLearning.AI
- Machine Learning Specialization By DeepLearning.AI & Stanford
- Google Data Analytics Professional Certificate - Google



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Education

- Bachelor's Degree, Robotics and Automation Engineer with First Class Honours
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Work Experience

- AI Engineer
STELLIGENCE Co., Ltd. (2024 – Present)
- AI Engineer
The Mather Co., Ltd. (2024)
- AI Engineer (Internship)
Bangkok Unitrade Co., Ltd. (2023)
- Teaching Assistant
Institute of field robotics, KMUTT (2022 – 2024)

Types of Machine Learning Algorithms

- Supervised Learning: Learning from labeled data (e.g., classification and regression tasks).
- Unsupervised Learning: Learning from unlabeled data (e.g., clustering, anomaly detection).
- Semi-Supervised Learning: A mix of labeled and unlabeled data for training.
- Reinforcement Learning: Learning by interacting with an environment and receiving feedback.
- Self-Supervised Learning: A type of unsupervised learning where the system generates its own labels for training.

Supervised Learning Algorithms

Definition: Learning from labeled data where the model is trained on input-output pairs.

Examples:

- Classification Algorithms:

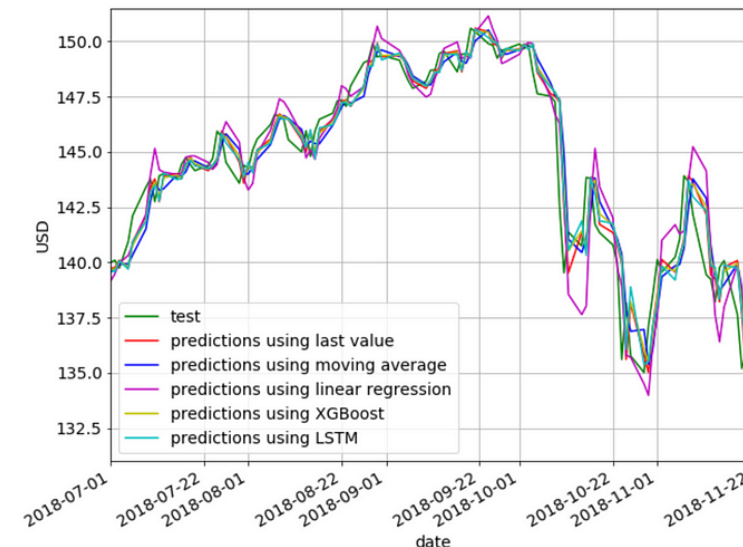
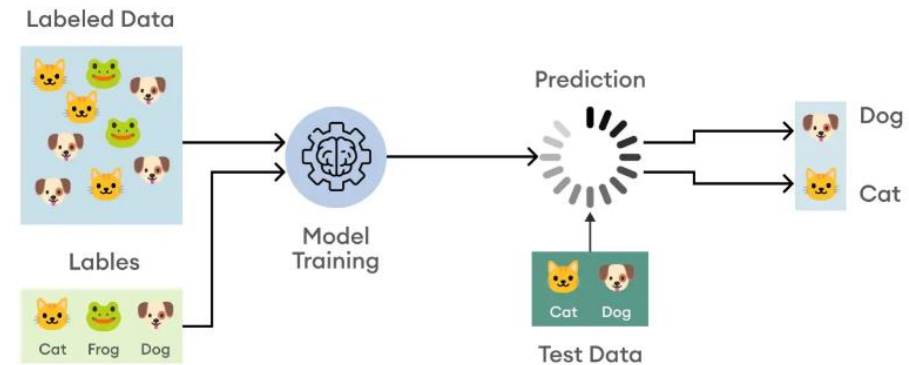
- Logistic Regression
- Decision Trees
- Random Forest
- Support Vector Machines (SVM)
- k-Nearest Neighbors (k-NN)

- Regression Algorithms:

- Linear Regression
- Lasso Regression
- Ridge Regression

- Time series forecasting

- ARIMA
- LSTM



Unsupervised Learning Algorithms

•Definition: Learning from unlabeled data where the algorithm tries to find hidden patterns or structure in the data.

Examples:

- Clustering Algorithms:
 - K-means
 - Hierarchical Clustering
- Dimensionality Reduction:
 - Principal Component Analysis (PCA)
 - t-Distributed Stochastic Neighbor Embedding (t-SNE)

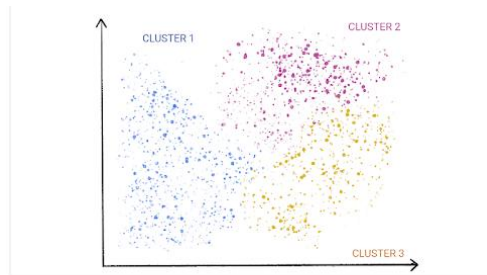


Figure 1. An ML model clustering similar data points.

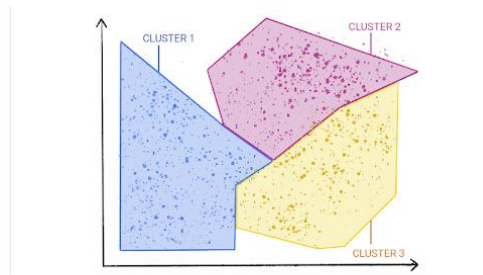
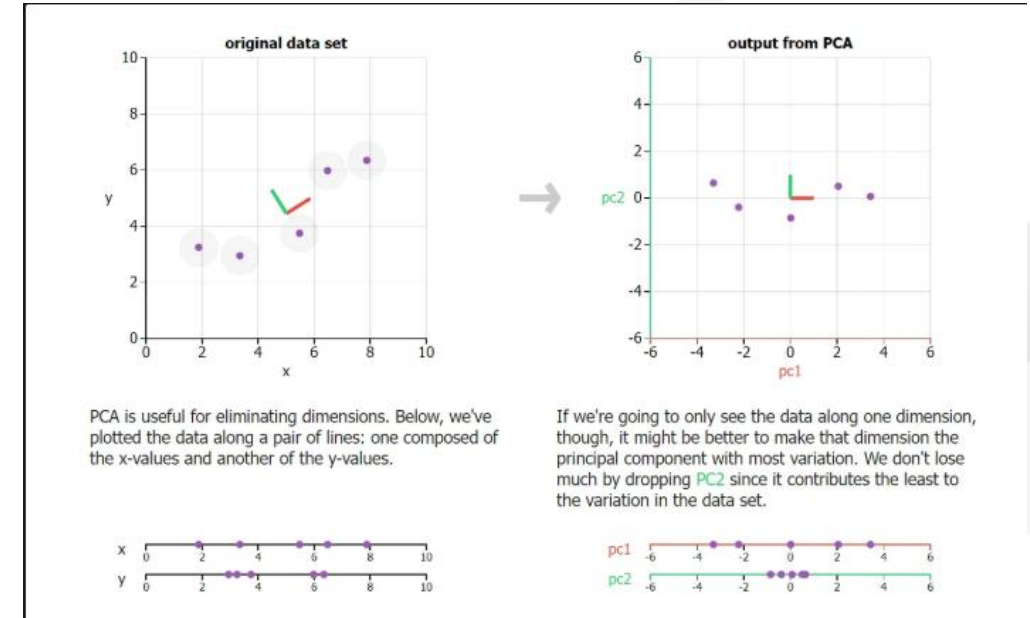


Figure 2. Groups of clusters with natural demarcations.

PCA: <https://setosa.io/ev/principal-component-analysis/>



Reinforcement Learning Algorithms

Definition: Learning by interacting with the environment and receiving rewards or penalties based on the actions.

Examples:

- Q-learning
- Deep Q Networks (DQN)
- Policy Gradient Methods
- Proximal Policy Optimization (PPO)



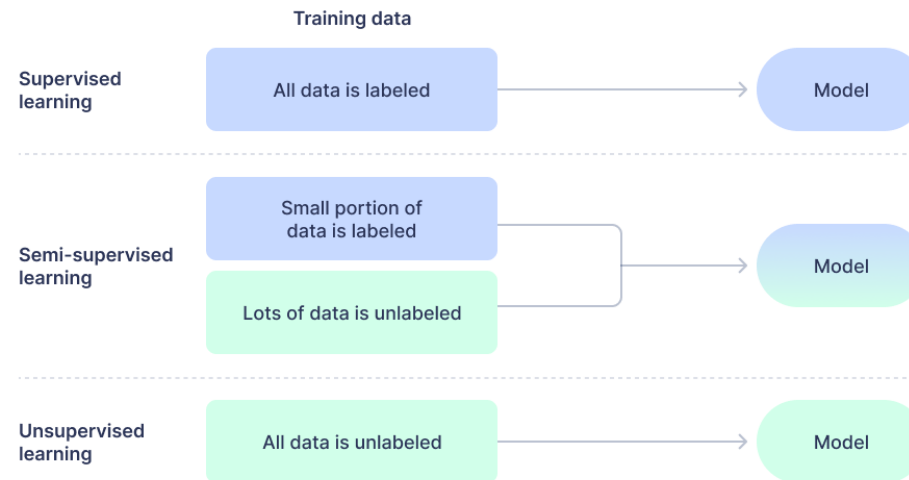
- <https://huggingface.co/spaces/ThomasSimonini/Huggy>

- <https://huggingface.co/learn/deep-rl-course/en/unitbonus1/how-huggy-works>

Semi-Supervised Learning Algorithms

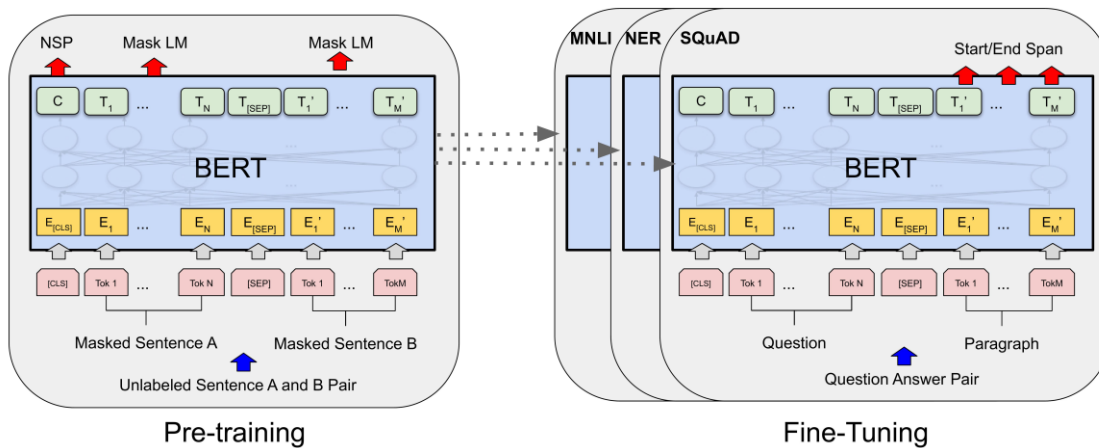
Definition: A hybrid of supervised and unsupervised learning where only a small amount of labeled data is used, and a large amount of unlabeled data is available.

Supervised learning vs Semi-supervised learning vs Unsupervised learning

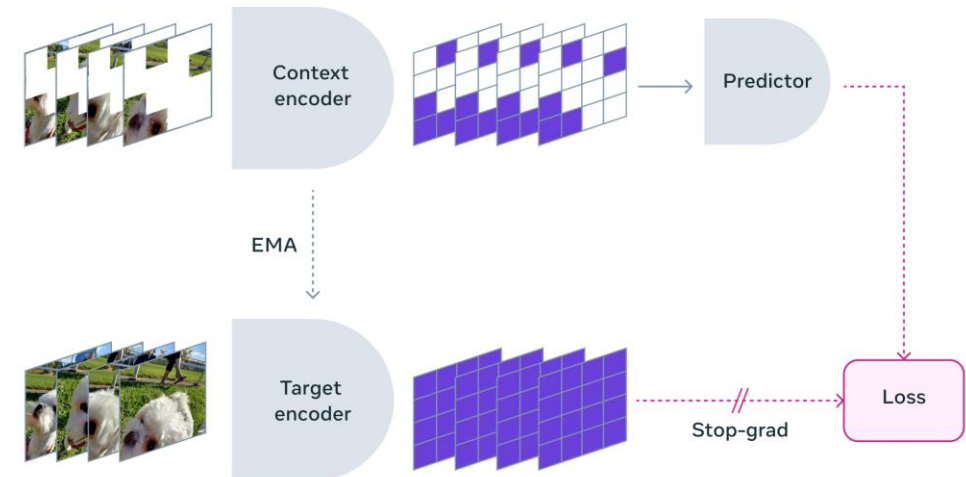


Self-Supervised Learning

Definition: A form of unsupervised learning where the system creates its own labels from the input data (often used for tasks like representation learning).



BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

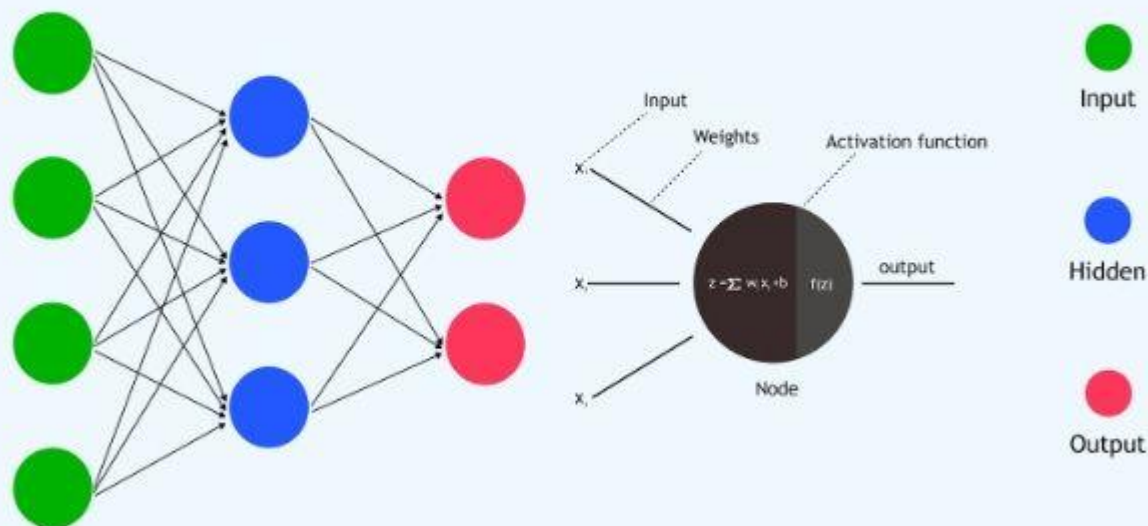


V-JEPA: The next step toward Yann LeCun's vision of advanced machine intelligence (AMI)

- BERT: <https://arxiv.org/pdf/1810.04805>
- SimCLR: <https://ai.meta.com/blog/v-jepa-yann-lecun-ai-model-video-joint-embedding-predictive-architecture/>

Neural network

Neural Network Architecture



```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
import numpy as np

np.random.seed(42)
tf.random.set_seed(42)

model = Sequential()
model.add(Dense(3, input_dim=4, activation='relu'))
model.add(Dense(2, activation='softmax'))

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

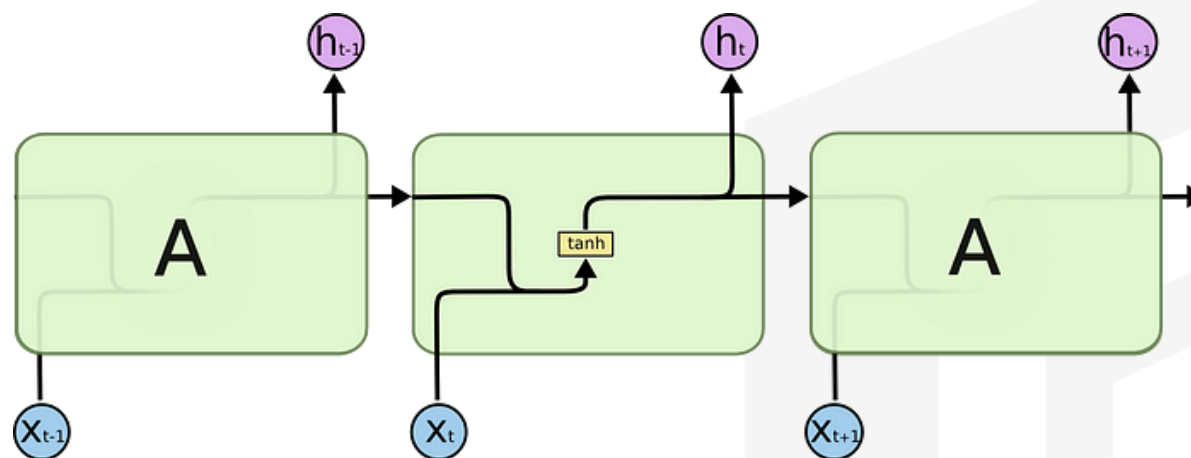
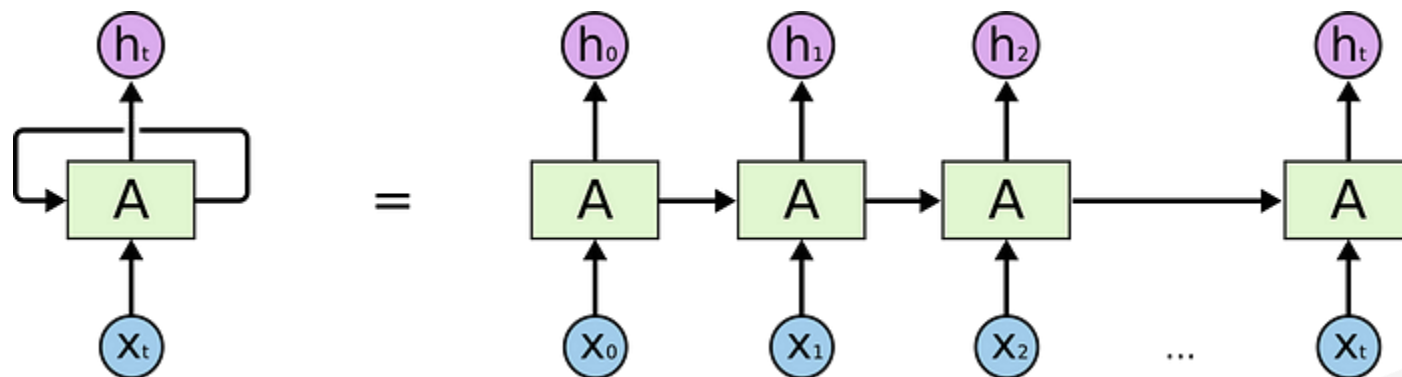
model.summary()

X_train = np.random.rand(10, 4)
y_train = np.random.randint(0, 2, size=(10, 2))

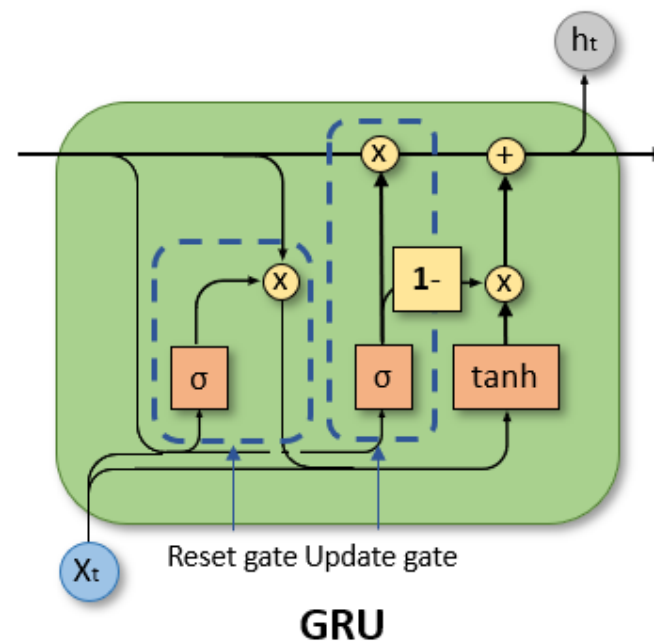
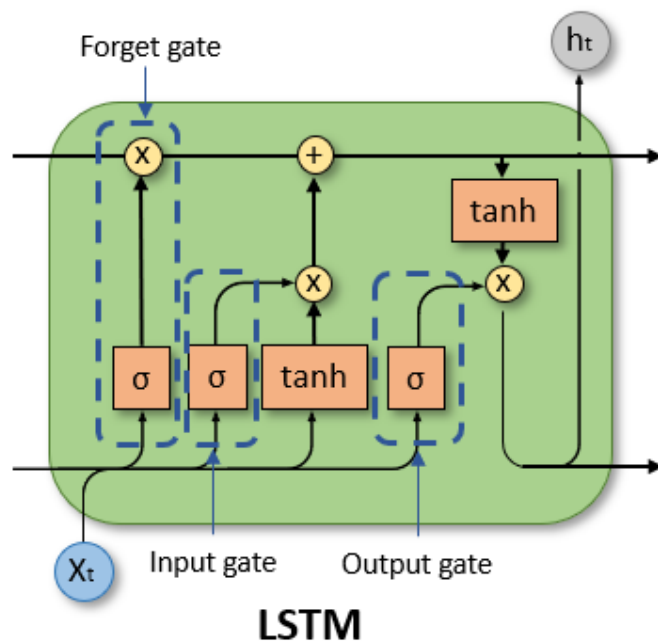
model.fit(X_train, y_train, epochs=10)
```

Neural network layer in NLP

RNN

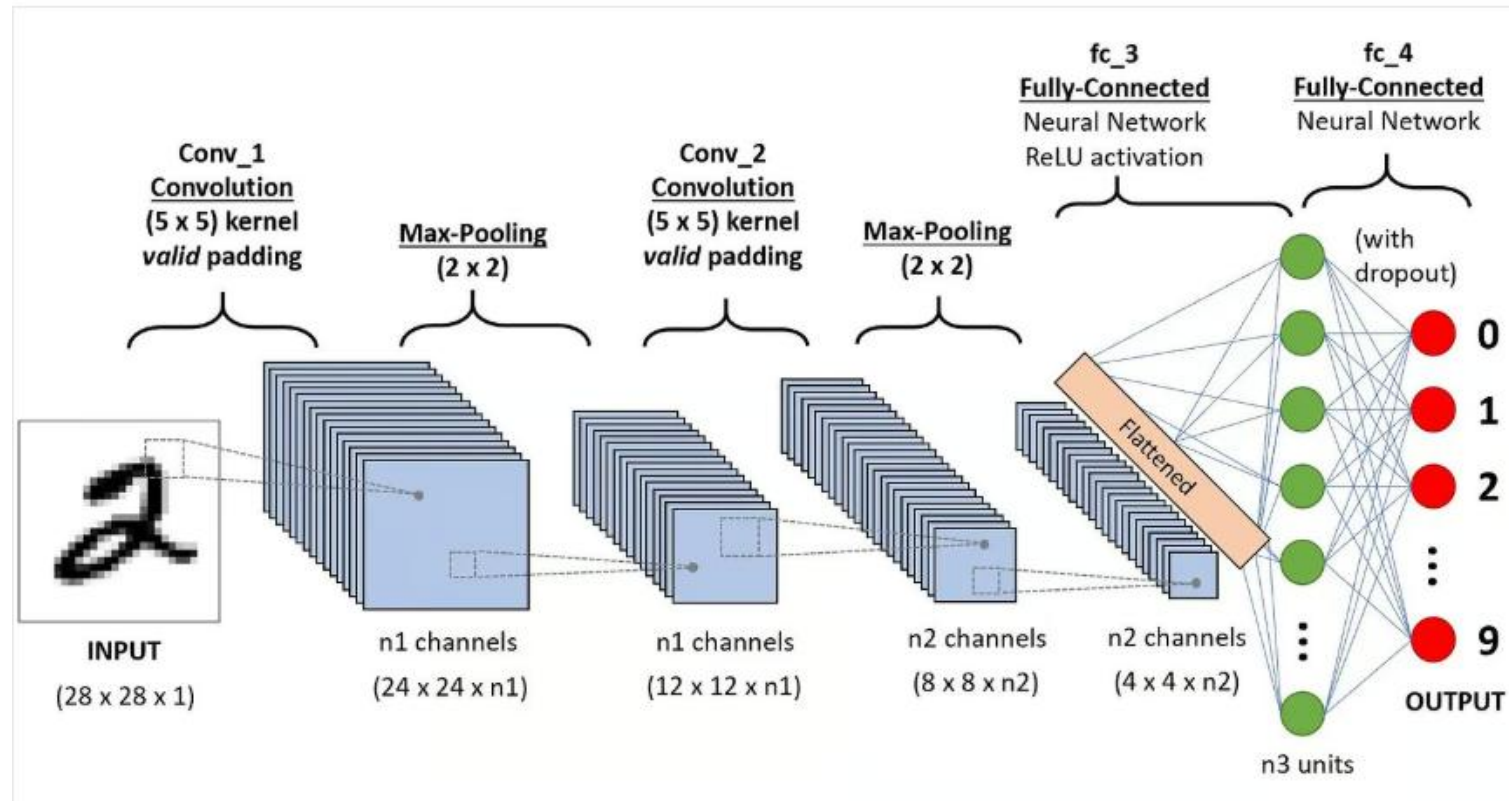


Neural network layer in NLP



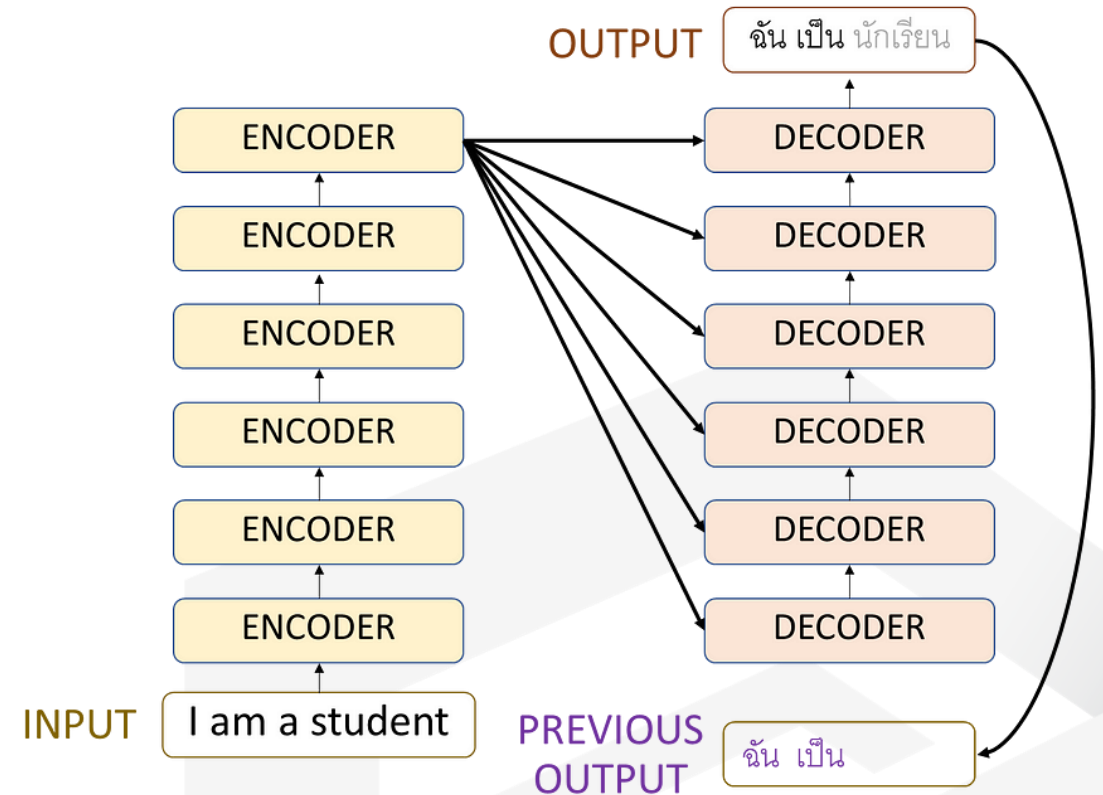
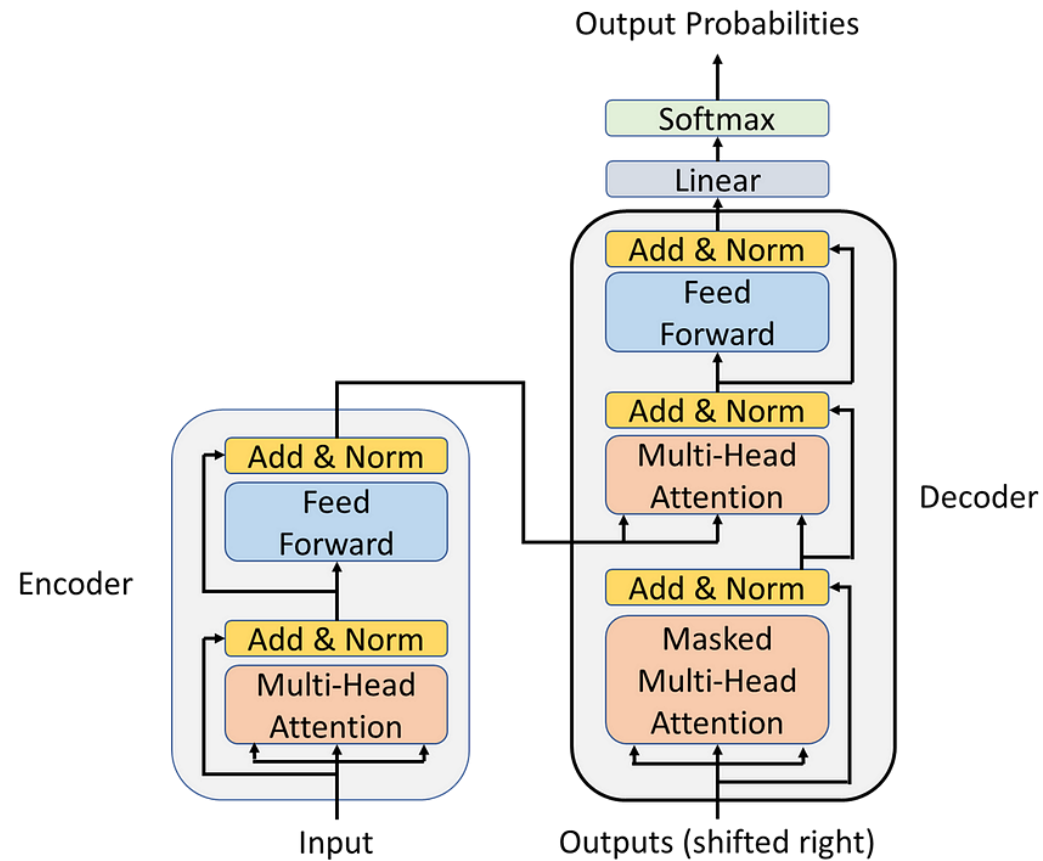
- <https://colah.github.io/posts/2015-08-Understanding-LSTMs>

Convolutional neural network

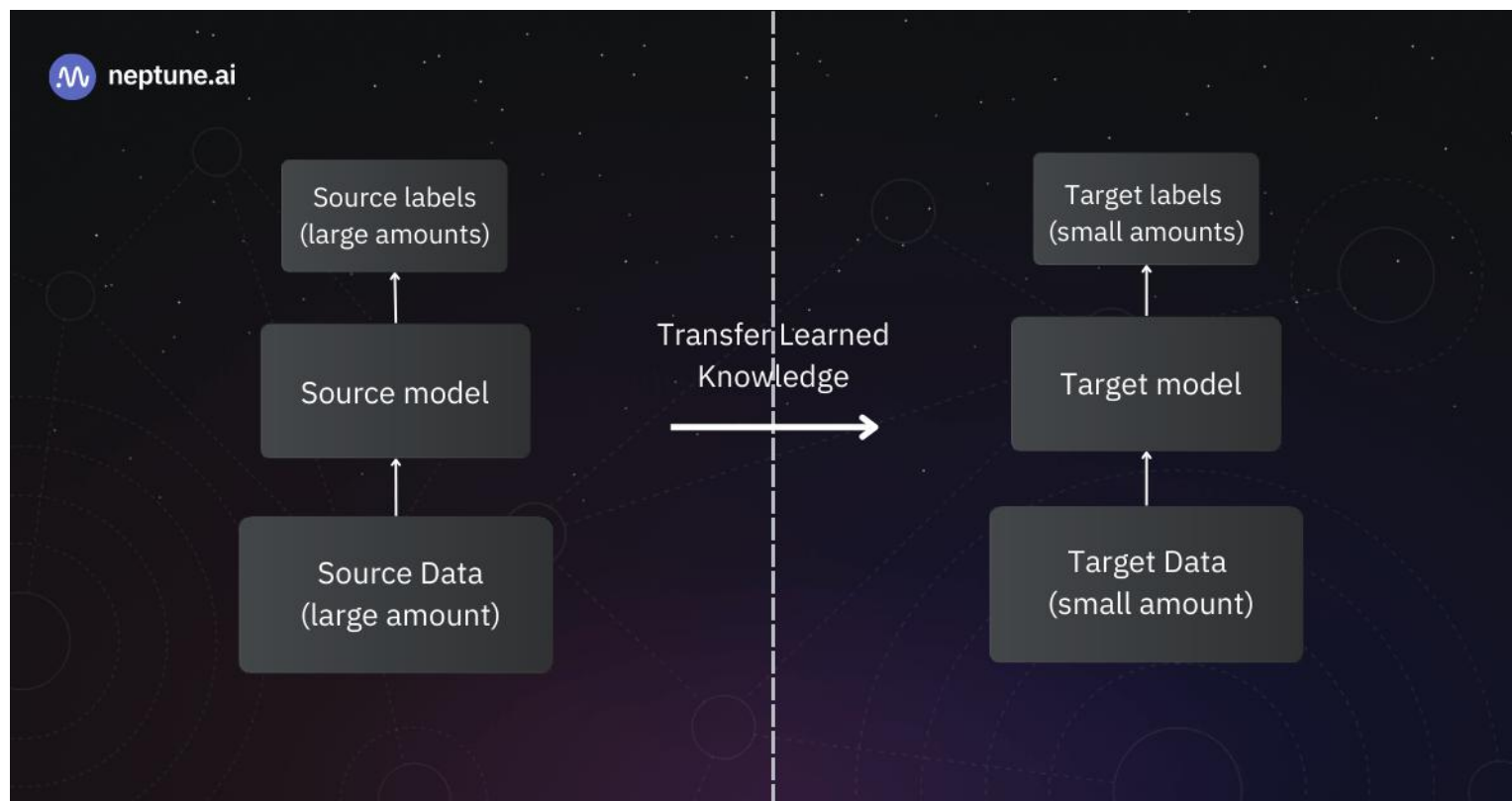


- https://adamharley.com/nn_vis/cnn/3d.html
- <https://medium.com/@muhammadshoaibali/flattening-cnn-layers-for-neural-network-694a232eda6a>

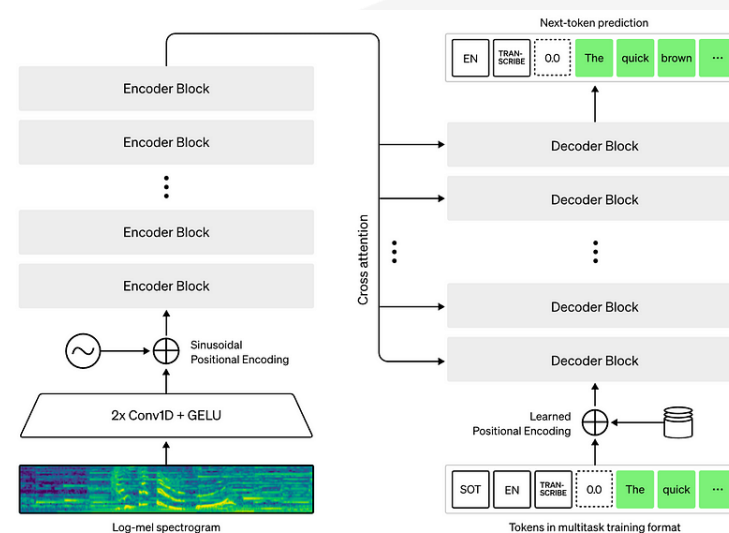
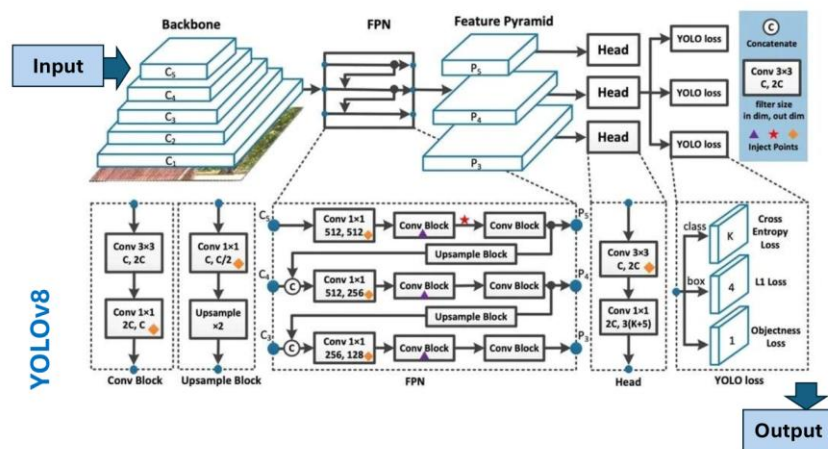
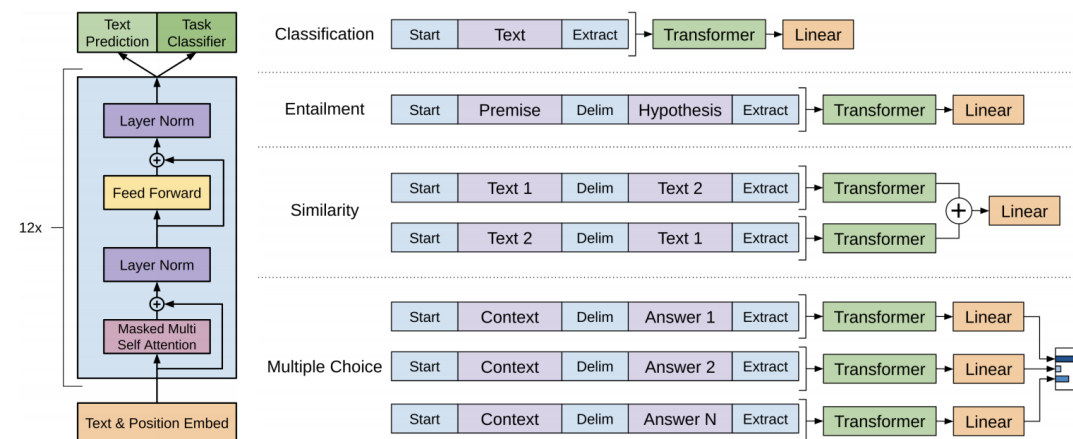
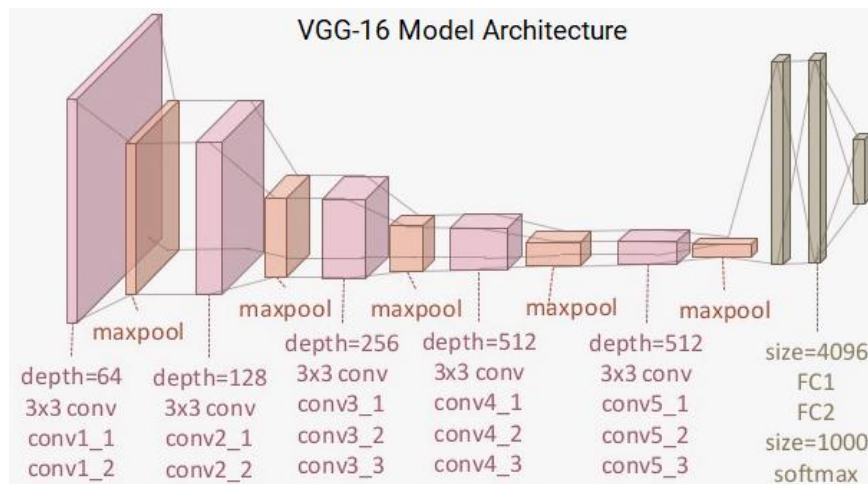
Attention Is All You Need



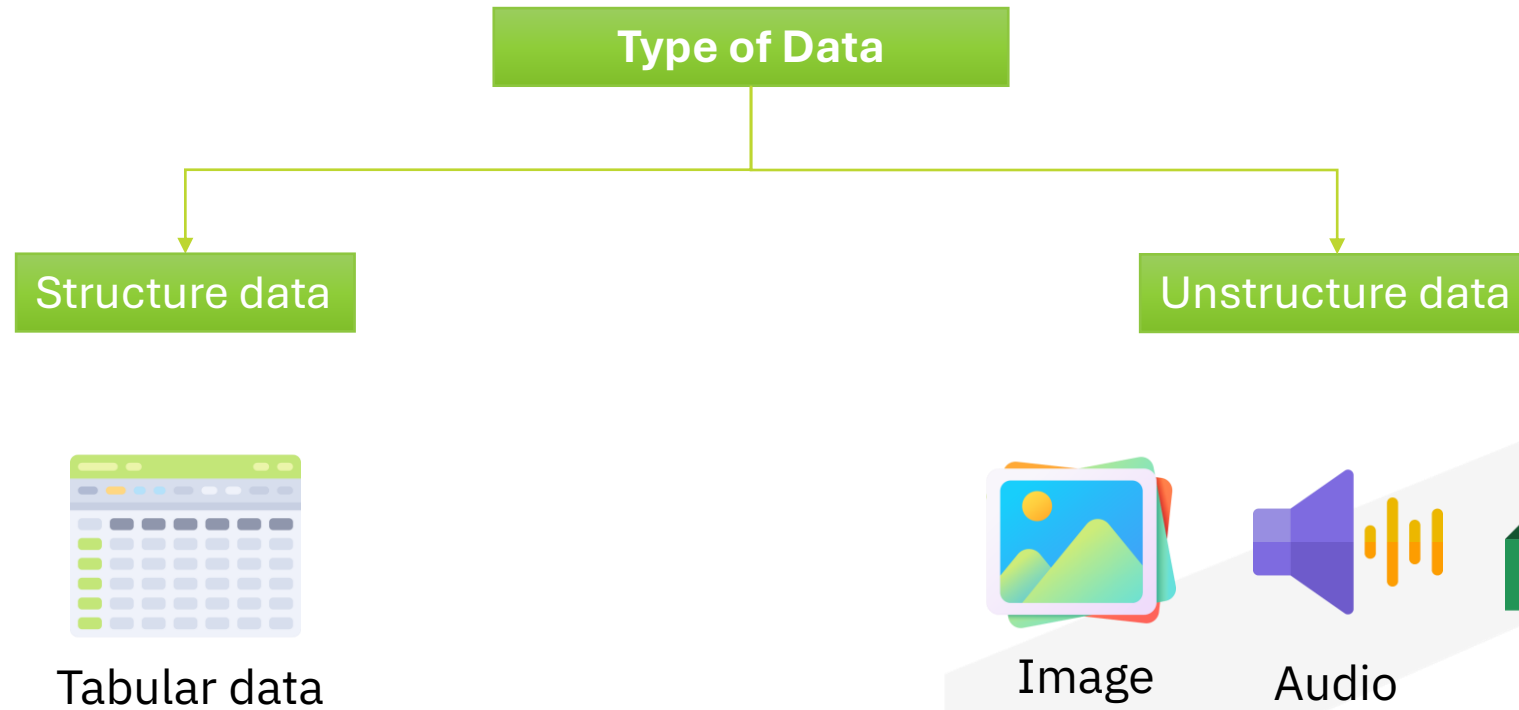
Transfer learning



Transfer learning

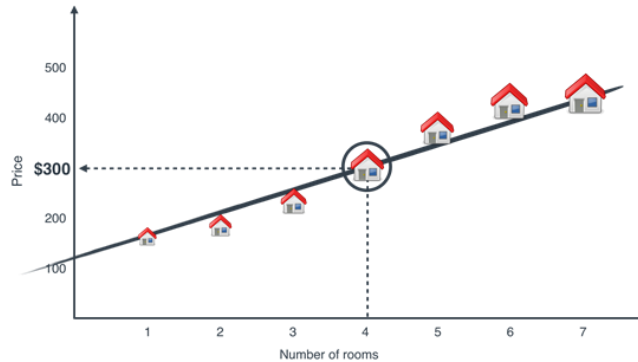


AI Applications Across Data Types

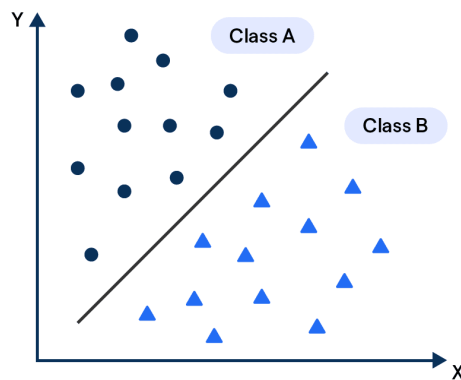


AI Applications Across Data Types

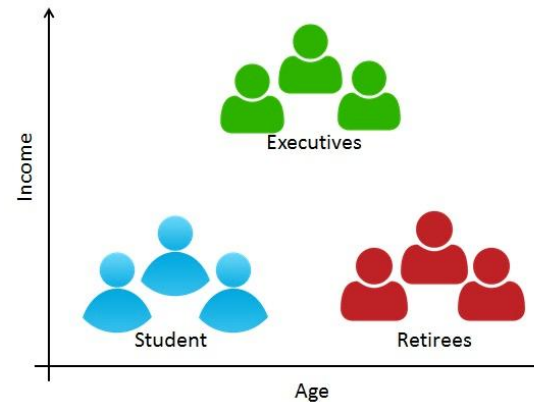
Structured Data (Tabular Data)



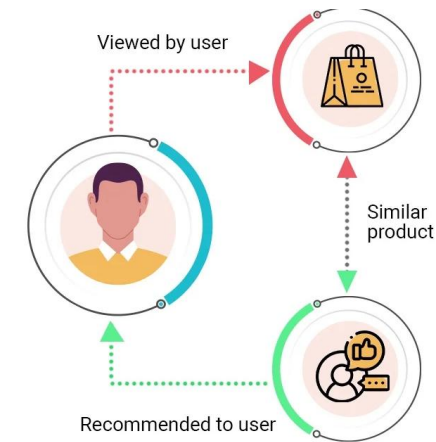
Predictive Modeling / Regression



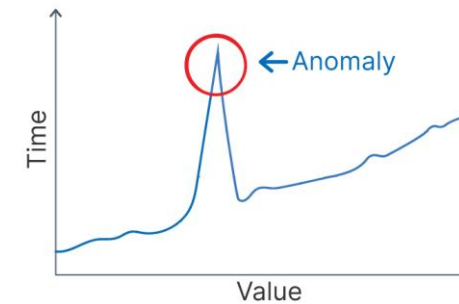
Classification



Clustering



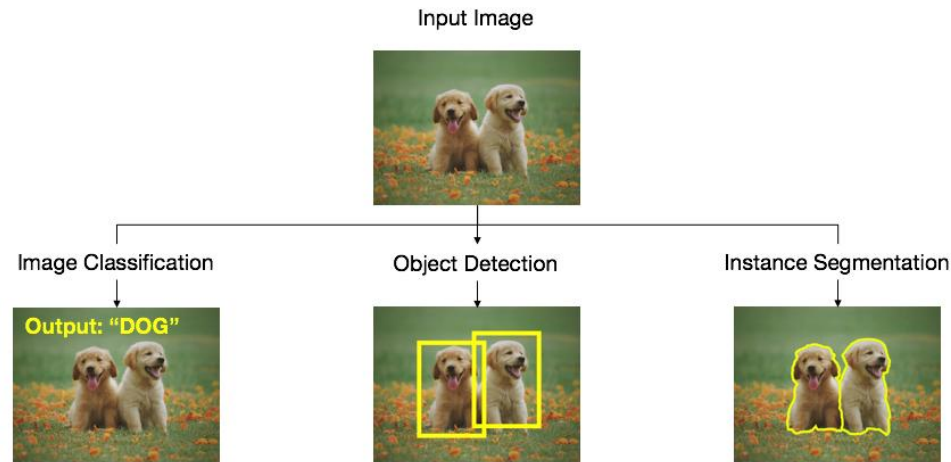
Recommendation **Systems**



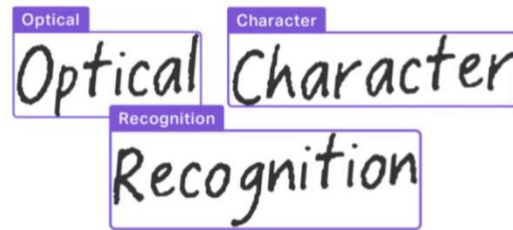
Anomaly Detection

AI Applications Across Data Types

Unstructured Data - Image Data



Pose landmark detection



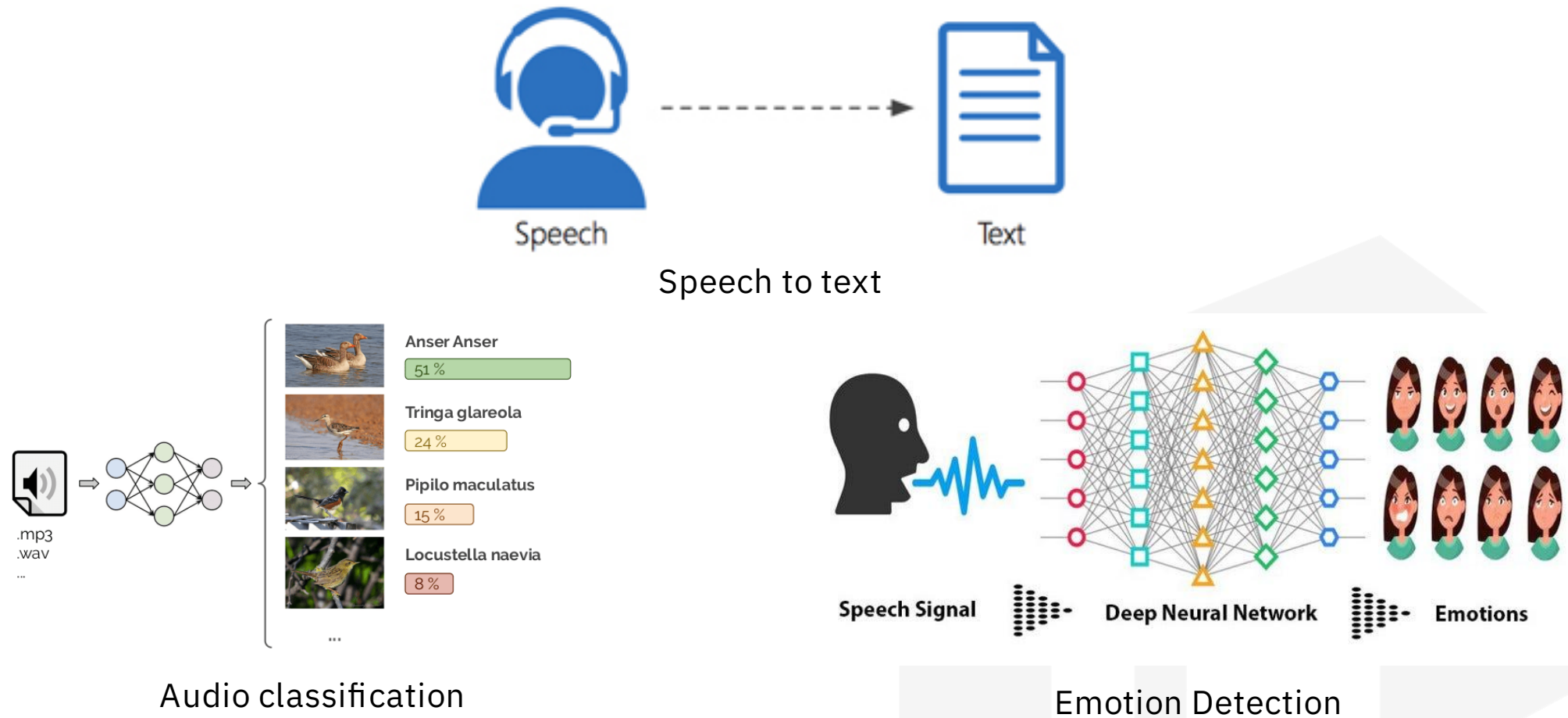
OCR



Facial recognition

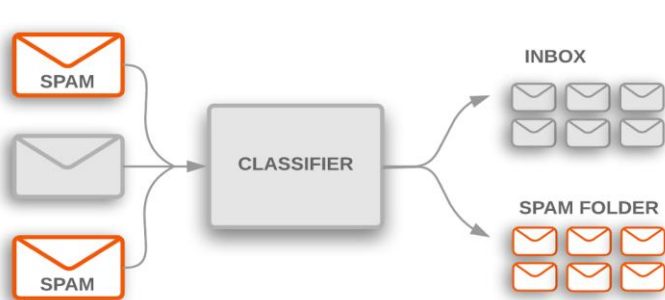
AI Applications Across Data Types

Unstructured Data - Audio Data

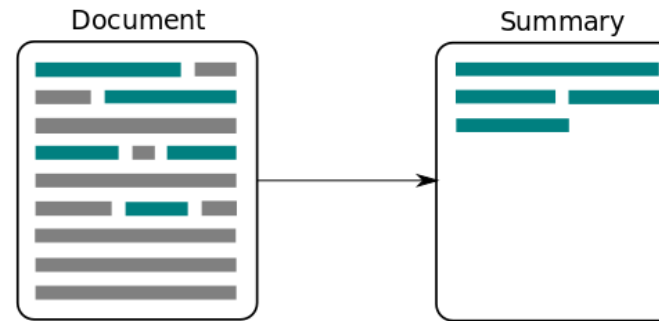


AI Applications Across Data Types

Unstructured Data - Text Data



Spam detection



Text summarization

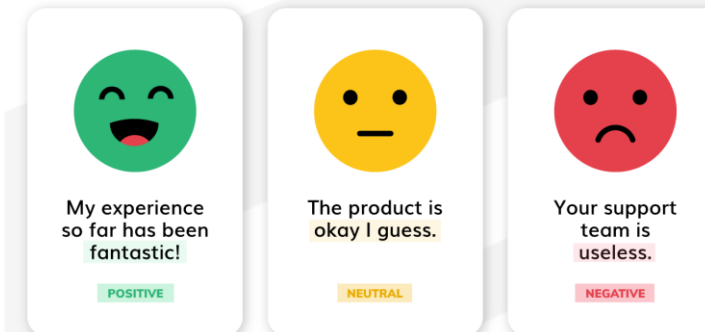


Chatbot

When **Sebastian Thrun** **PERSON** started at **Google** **ORG** in **2007** **DATE**, few people outside of the company took him seriously. "I can tell you very senior CEOs of major **American** **NORP** car companies would shake my hand and turn away because I wasn't worth talking to," said **Thrun** **PERSON**, now the co-founder and CEO of online higher education startup Udacity, in an interview with **Recode** **ORG** **earlier this week** **DATE**.

A little **less than a decade later** **DATE**, dozens of self-driving startups have cropped up while automakers around the world clamor, wallet in hand, to secure their place in the fast-moving world of fully automated transportation.

Entity recognition



Sentiment classification

Evaluate regression model

Mean squared error (MSE) is one of the most popular evaluation metrics. As shown in the following formula, MSE is closely related to the residual sum of squares. The difference is that you are now interested in the average error instead of the total error.

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

The formula to calculate mean absolute error (MAE) is similar to the MSE formula. Replace the square with the absolute value.

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

R-squared (R^2), also known as the coefficient of determination, represents the proportion of variance explained by a model. To be more precise, R^2 corresponds to the degree to which the variance in the dependent variable (the target) can be explained by the independent variables (features).

$$R^2 = 1 - \frac{RSS}{TSS} = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2}$$

Evaluate classification model

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

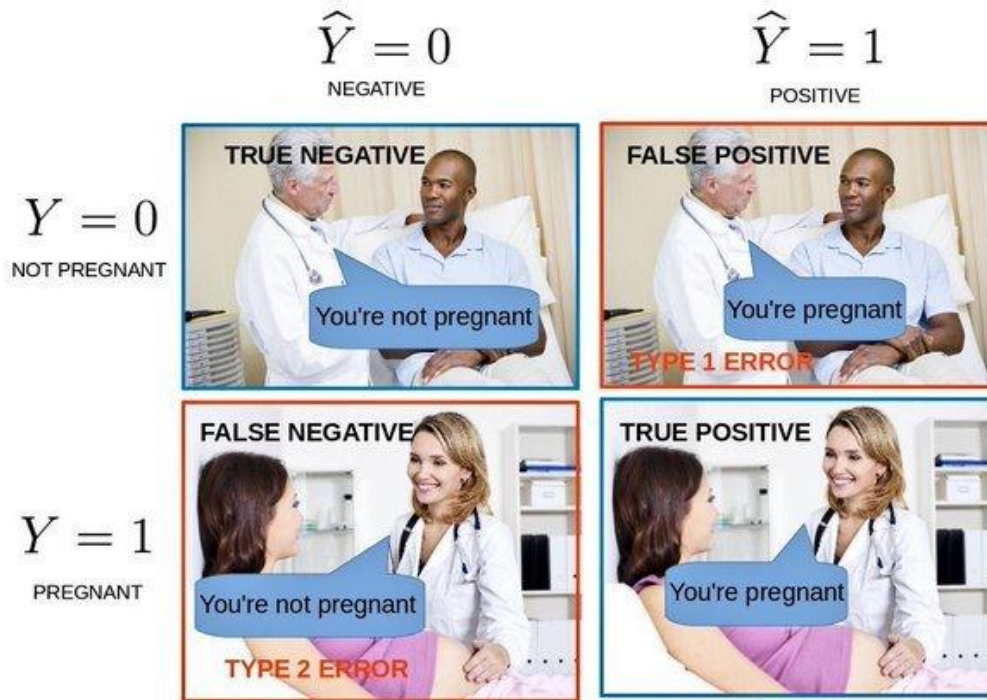
Accuracy is a metric that measures how often a machine learning model correctly predicts the outcome.

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}}$$

Precision is a metric that measures how often a machine learning model correctly predicts the positive class.

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}$$

Recall is a metric that measures how often a machine learning model correctly identifies positive instances (true positives) from all the actual positive samples in the dataset.



Evaluate classification model



STelligence

The F-Beta Score is a measure that assesses the accuracy of an output of a model from two aspects of precision and recall. Unlike in F1 Score that directed average percentage of recall and percent of precision, it allows to prioritize one of two using the β parameter.

$$F_{\beta} = (1 + \beta^2) \cdot \frac{\text{Precision} \cdot \text{Recall}}{(\beta^2 \cdot \text{Precision} + \text{Recall})}$$

Scenario: A binary classification model is applied to a dataset, resulting in the following confusion matrix:

	Predicted Positive	Predicted Negative
Actual Positive	TP = 40	FN = 10
Actual Negative	FP = 5	TN = 45

Step1: Calculate Precision

$$\text{Precision} = \frac{40}{40 + 5} = \frac{40}{45} \approx 0.8889$$

Step2: Calculate Recall

$$\text{Recall} = \frac{40}{40 + 10} = \frac{40}{50} = 0.8$$

Step3: Calculate F-Beta Score

For $\beta = 1$ (F1 Score):

$$F_1 = (1 + 1^2) \cdot \frac{0.8889 \cdot 0.8}{(1^2 \cdot 0.8889) + 0.8} = 2 \cdot \frac{0.7111}{1.6889} \approx 0.842$$

For $\beta = 2$ (F2 Score, recall-focused):

$$F_2 = (1 + 2^2) \cdot \frac{0.8889 \cdot 0.8}{(2^2 \cdot 0.8889) + 0.8} = 5 \cdot \frac{0.7111}{4.3556} \approx 0.817$$

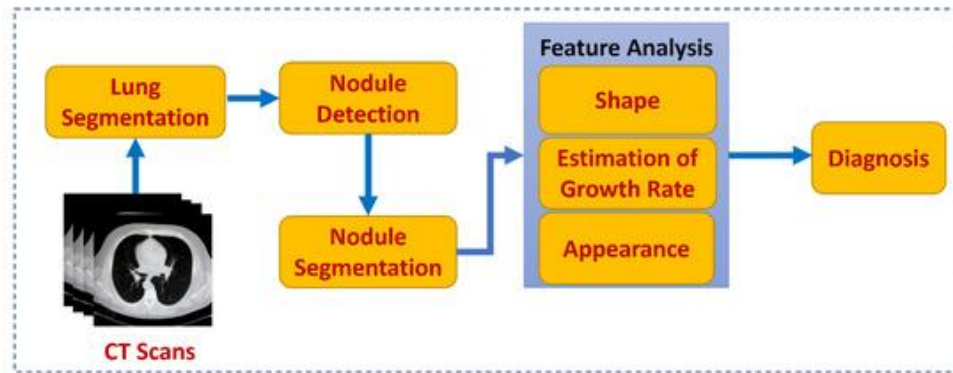
For $\beta = 0.5$ (F0.5 Score, precision-focused):

$$F_{0.5} = (1 + 0.5^2) \cdot \frac{0.8889 \cdot 0.8}{(0.5^2 \cdot 0.8889) + 0.8} = 1.25 \cdot \frac{0.7111}{0.4222 + 0.8} \approx 0.934$$

AI Solution in Health Care

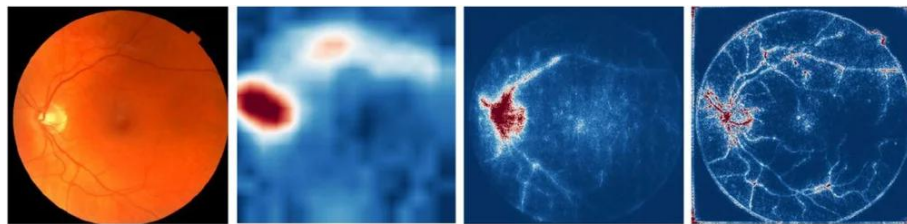
AI for Imaging and Diagnostics

AI is utilized to analyze medical images, such as X-rays, MRIs, CT scans, and other to assist in diagnosing conditions



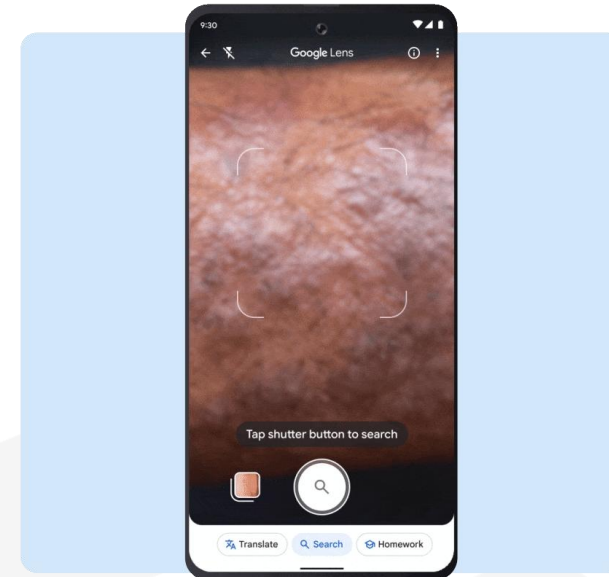
Diagnostic Dilemma of Pulmonary Nodules

<https://www.mdpi.com/2072-6694/14/7/1840>



Detecting hidden signs of anemia from the eye

<https://blog.google/technology/health/anemia-detection-retina/>



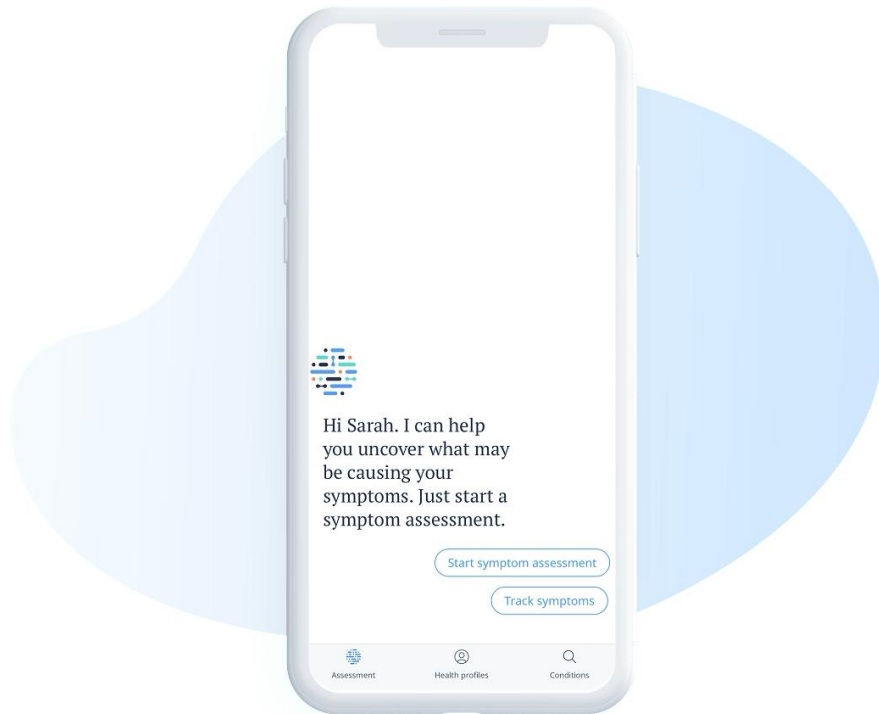
Deep learning system for diagnosis of skin diseases

<https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2779250>

AI Solution in Health Care

Diagnosis chat bot

Diagnosis chatbots use AI to interact with users, collect symptom information, and suggest possible diagnoses. By analyzing user input through natural language processing, they provide guidance on potential conditions and recommend next steps.



Symptom **Collection**



Analyzing Input



Diagnosis Algorithm

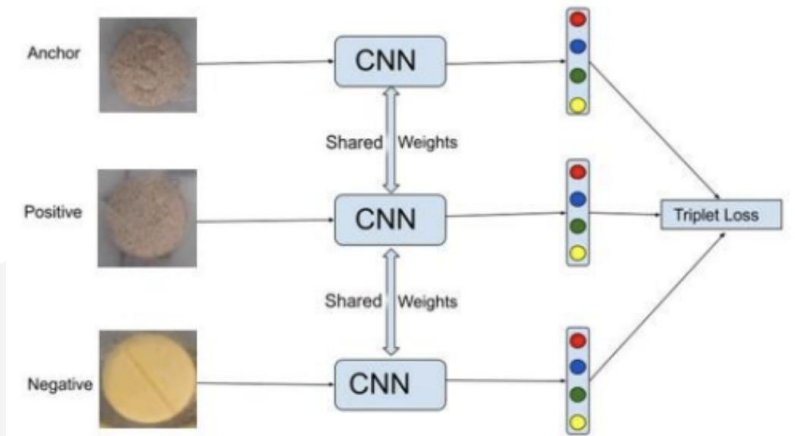
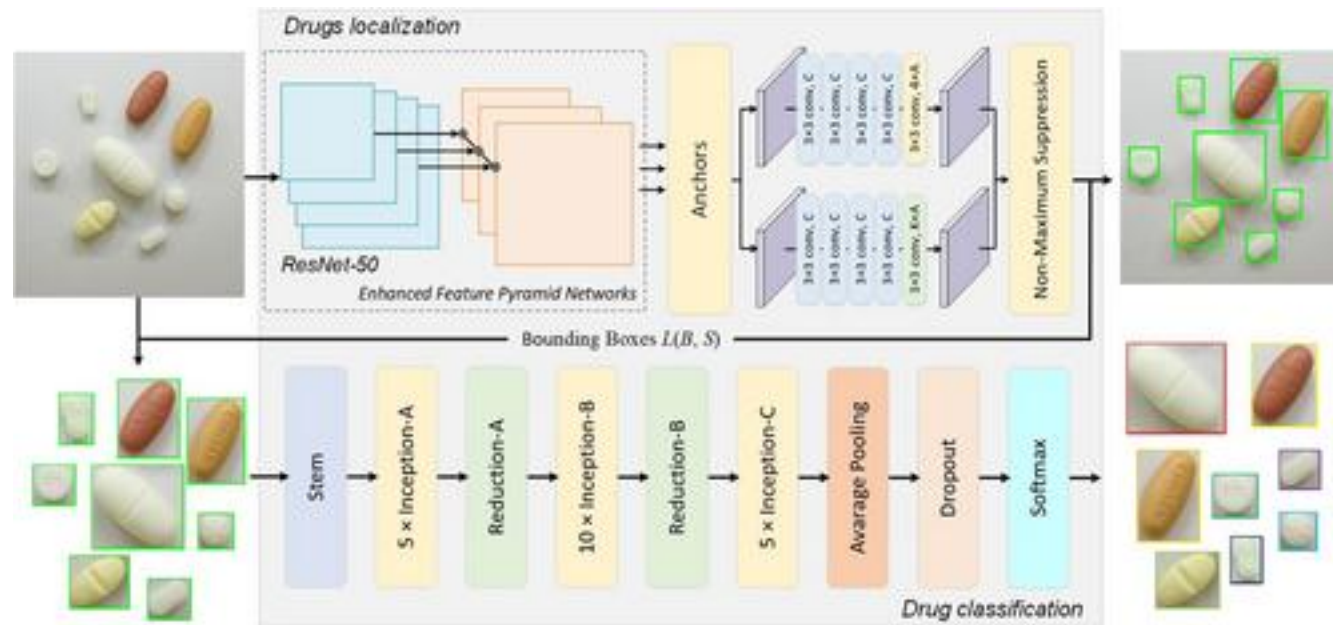


Diagnosis Suggestion

AI Solution in Health Care

AI for Pill Classification and Identification

AI is increasingly used for pill classification by analyzing images of tablets and capsules to identify their shape, color, and imprints. Using machine learning algorithms, AI can compare these visual features to large databases of known medications, helping to accurately classify pills and detect counterfeit drugs



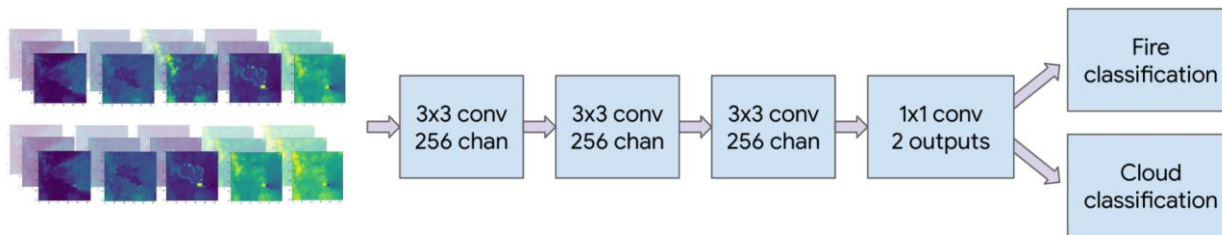
Siamese Network

<https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/iet-cvi.2019.0171>

AI Solution in Climate

Real-time tracking of wildfire boundaries using satellite imagery

Google applies machine learning to track and map wildfires in real time using satellite imagery from geostationary satellites like GOES-16, GOES-18, Himawari-9, and GK2A. Their model, a convolutional neural network (CNN), detects fire boundaries accurately every 10–15 minutes and integrates cloud detection to improve precision. This technology helps inform communities and authorities through Google Search and Google Maps, providing life-saving information in critical moments.

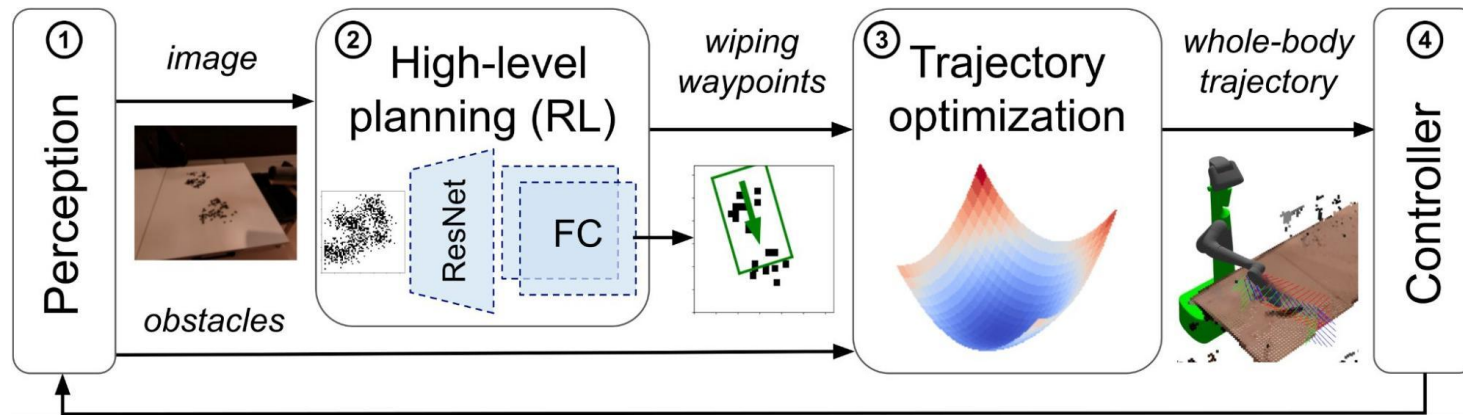


- <https://research.google/blog/real-time-tracking-of-wildfire-boundaries-using-satellite-imagery/>

AI Solution in Robotic

Towards ML-enabled cleaning robots

Google's table-wiping framework uses a vision-based RL policy to plan wipe actions, and a trajectory optimizer to convert those plans into whole-body robot motions, with perception and low-level control completing the loop.



Assignment (Score 30 points)

Text Classification

Task Requirement (15 points):

- Use the sentiment dataset to classify the text into Positive or Negative sentiment. Follow the instructions below:
 - You can build your models using statistical methods (e.g., TF-IDF, Bag of Words, Naive Bayes, Logistic Regression) or neural networks (e.g., RNN, LSTM, GRU) to classify the test set.
 - The provided dataset contains only the test set, so you are not allowed to use it for training. You must explore or create your own training dataset to perform the classification task.
 - (5 points) – Preprocess the data and generate a training dataset.
 - (5 points) – Model development: Build at least 3 models. You can earn extra points if you apply advanced techniques or demonstrate good performance.
 - (5 points) – Analyze and compare the results from each model. Present your findings clearly.

Provided Test Dataset:

- Contains 2 sentiment classes: Positive and Negative

Image Classification

Task Requirement (15 points):

- Using the provided test set dataset to build an image classification system to classify a multiclass dataset, Develop and evaluate 3 different approach
 - (3 points) Build and train a CNN without using any pre-trained weights. (you are not allowed to use test set for training.)
 - (3 points) Use pre-trained model (e.g., VGG, ResNet) without training
 - (3 points) Use a pre-trained model as a base and train the model using your training dataset (you are not allowed to use test set for training.)
 - You can use other additional approach to solve this problem
- (2 points) You are required to conduct at least three distinct experiments to evaluate how different techniques impact the performance of your model. These experiments can be: Difference pretrained model, Image preprocessing, Data augmentation, Model Parameter tuning or other technique.
- (2 points) Each experiment must include a detailed performance.
 - Training and validation accuracy/loss
 - Classification performance across each class
 - Visual examples of misclassified images
 - Other
- (2 points) Provide an analysis of all experiments, highlighting the impact of each technique on model performance and identify which combinations were most effective.

Provided Test Dataset:

- Contains 5 animal classes: dog, cat, elephant, lion , tiger.
- 20 images per class