Machine Listening for Music and Sound Analysis

Lecture 2 – Machine Learning

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https://machinelistening.github.io

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Learning Objectives

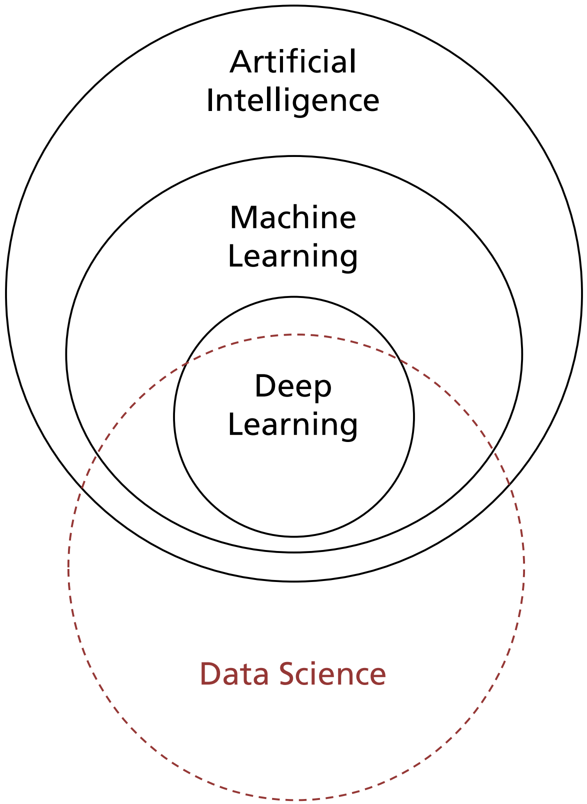
- Introduction
- Learning paradigms
- Machine learning (ML) project pipeline
- Deep learning

Introduction

- Goals
  - "...give computers the ability to learn without being explicitly programmed" [Samuels, 1959]
  - Learning structures in given (un)labeled data to make predictions on new / unseen data
- Paradigm change
  - <u>Now</u>: joint representation learning (features) & data modeling (classification)
  - <u>Before</u>: manually designed / general-purpose features
- Related disciplines
  - Statistics, data science, optimization

Introduction
Terminology

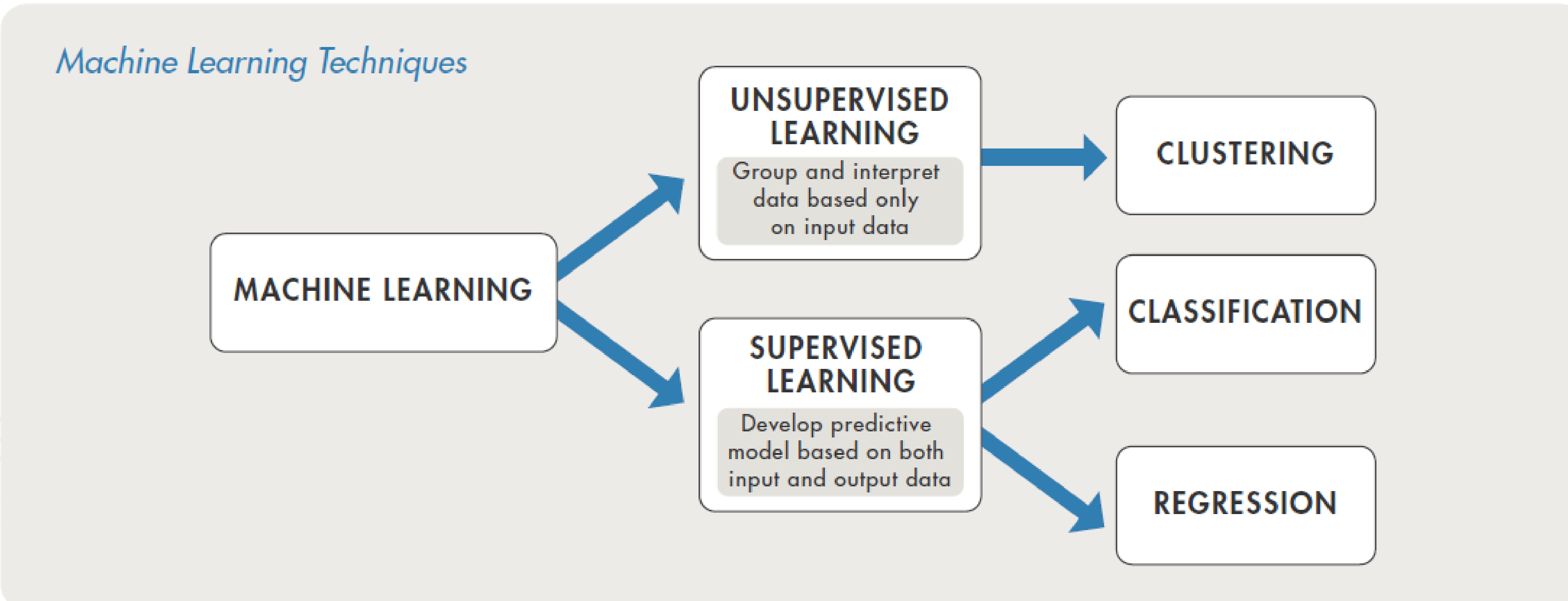
- Artificial Intelligence (AI)
    - „an agent‘s ability to achieve goals in a wide range of environments“ [Legg & Hutter, 2007]
- Machine Learning (ML)
    - Pattern recognition, data modeling, learning, prediction
- Deep Learning (DL)
    - (Brain-inspired) artificial neural networks (ANN)
- Data Science
    - Knowledge extraction from data



Introduction
Application Scenarios

- Computational finance (credit scoring, algorithmic trading)
- Computer vision (face & object recognition, motion detection)
- Computational biology (tumor detection, drug discovery, DNA sequencing)
- Energy (price & load forecasting)
- Predictive Maintenance (automotive, aerospace, manufacturing)
- Natural language processing (sentiment classification, text search, translation)
- Machine Listening (music transcription, instrument recognition, sound event detection, acoustic scene classification)

Learning Paradigms



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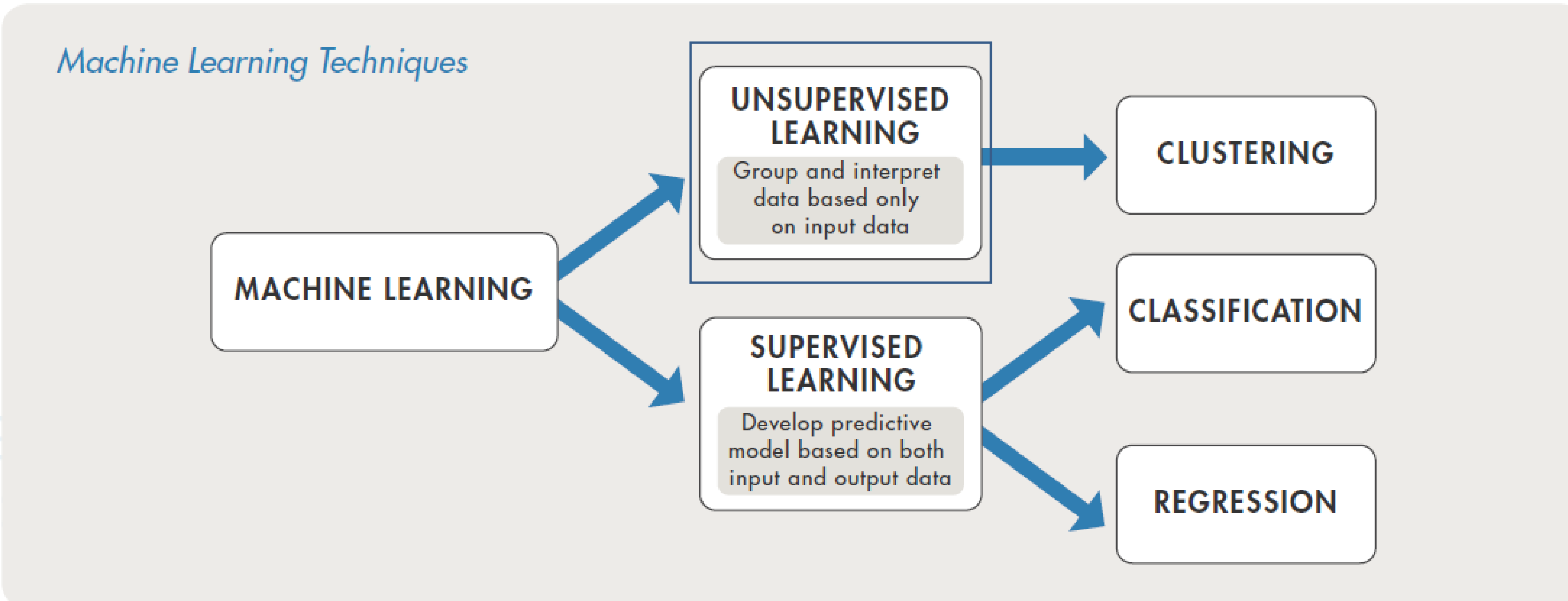
Learning Paradigms



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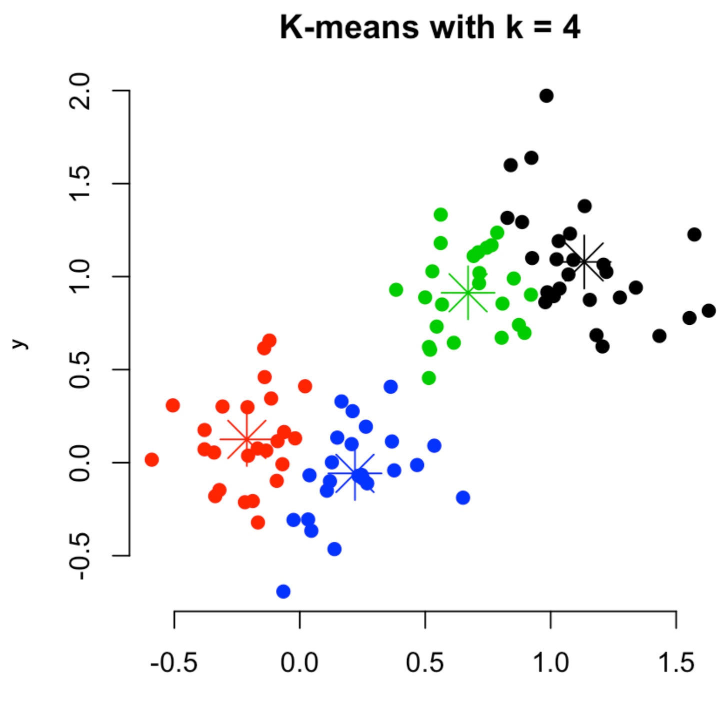
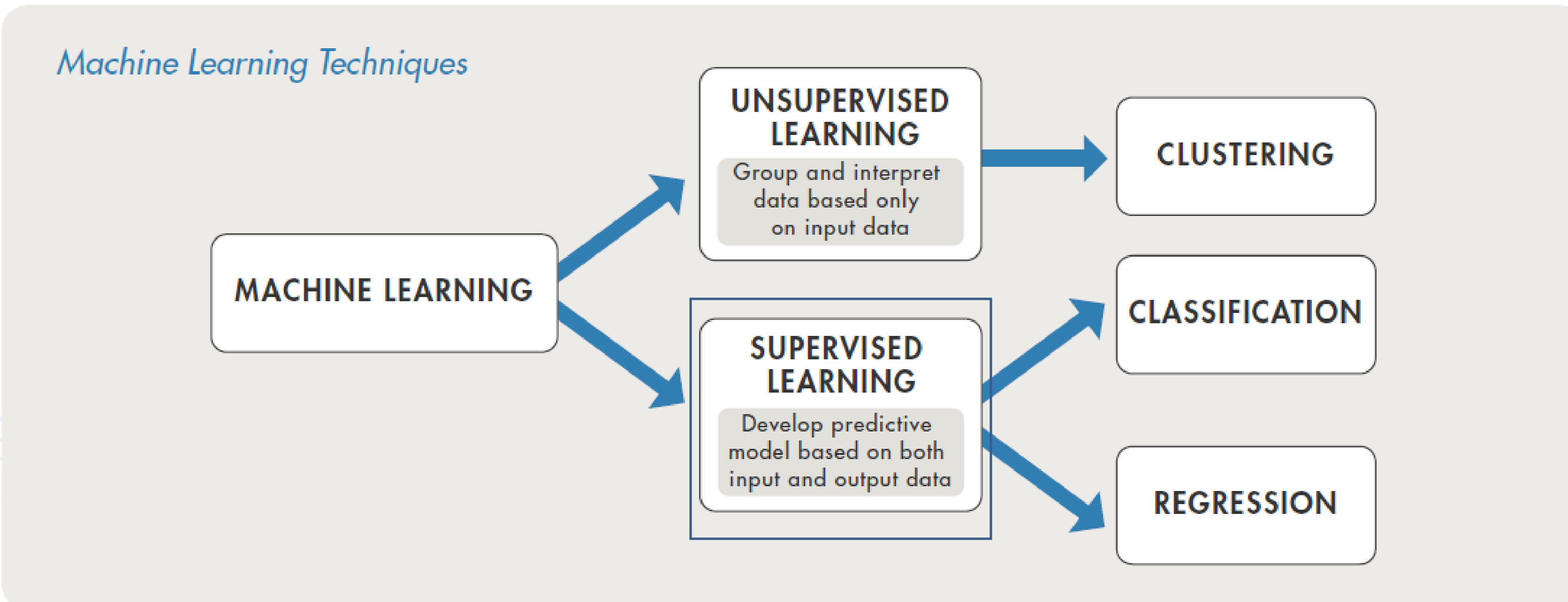
Learning Paradigms
Unsupervised Learning

- Goal
  - Model hidden structure in data
  - Density estimation
- Example
  - K-means clustering
    - Data partitioning into K clusters
    - Minimize within-cluster variance



Learning Paradigms
Supervised Learning



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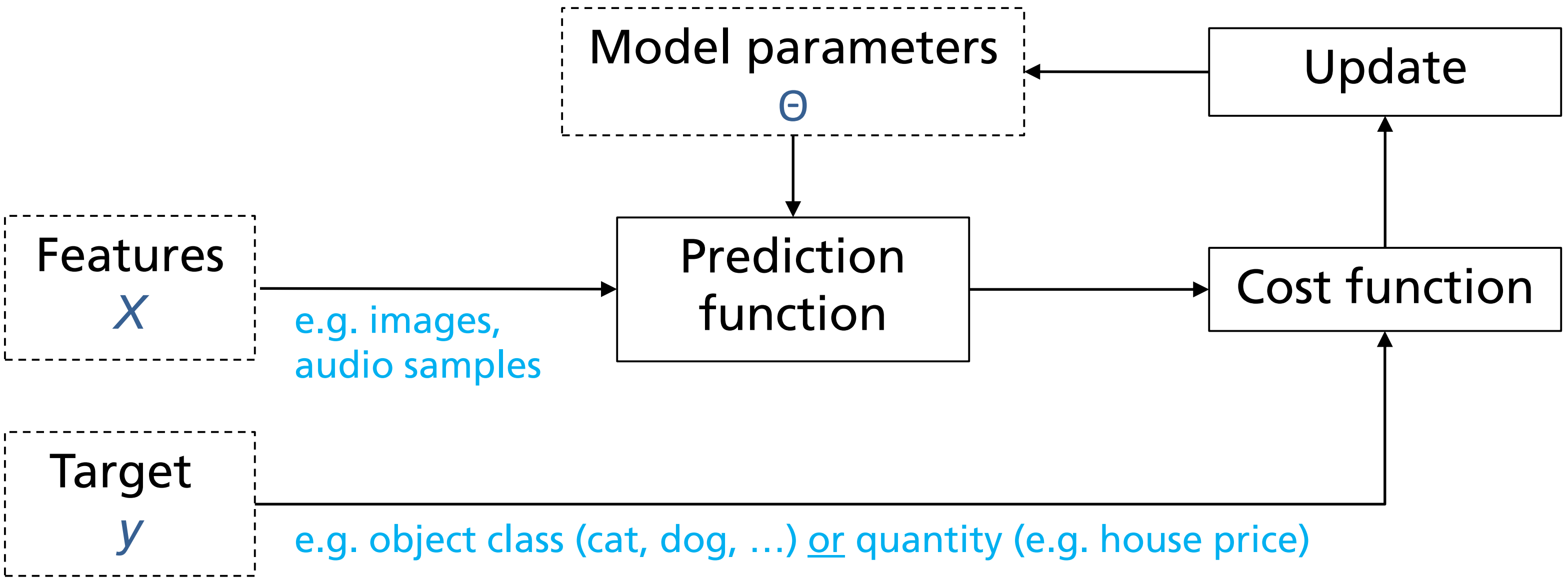
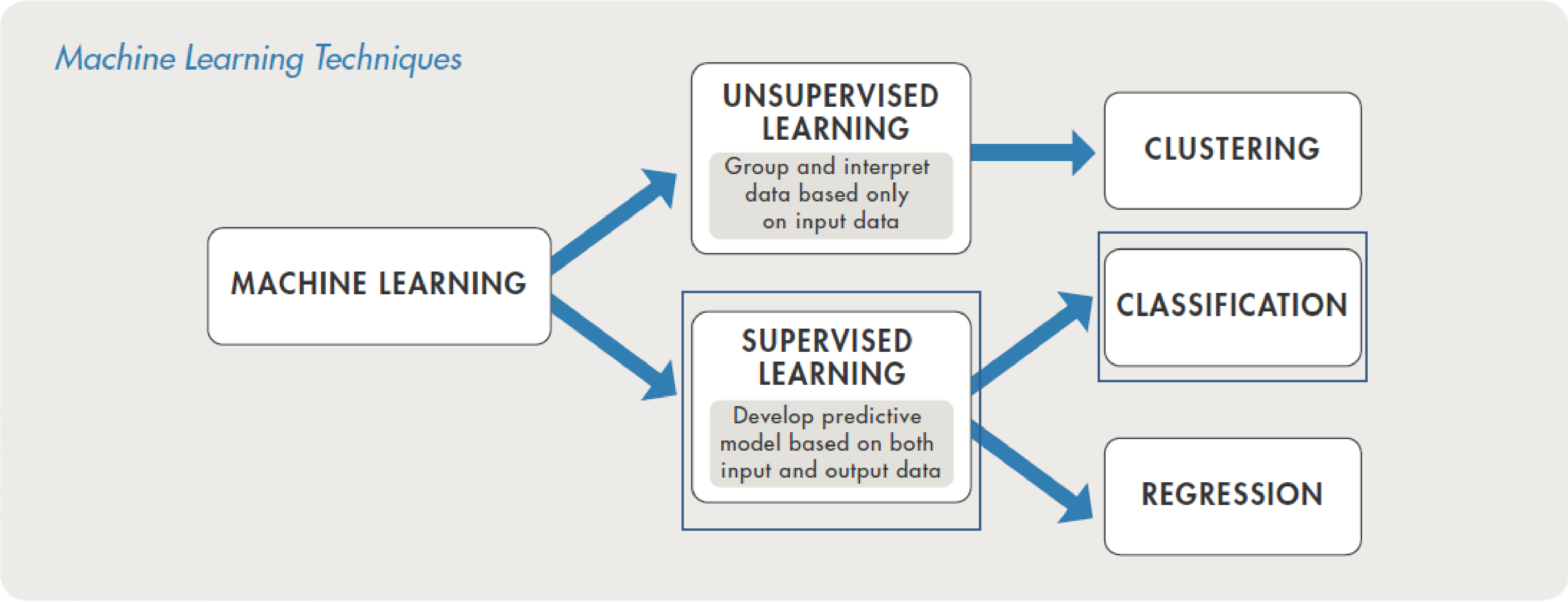
Learning Paradigms
Supervised Learning



Learning Paradigms
Supervised Learning - Classification



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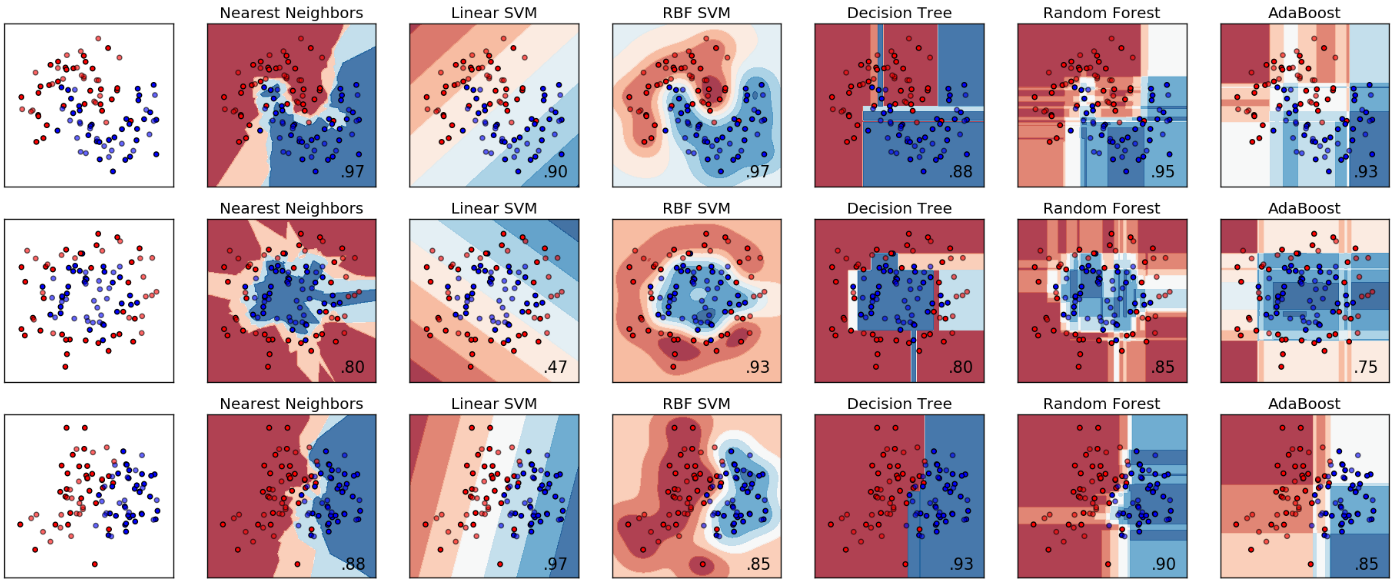
Learning Paradigms
Supervised Learning - Classification

- Predict one / multiple categorical label from features
    - Examples → music genre, instrument(s), key
- Feature space modeling (Example: 2 classes)



https://scikit-learn.org/stable/auto_examples/classification/plot_classifier_comparison.html
https://i.stack.imgur.com/hsilO.png

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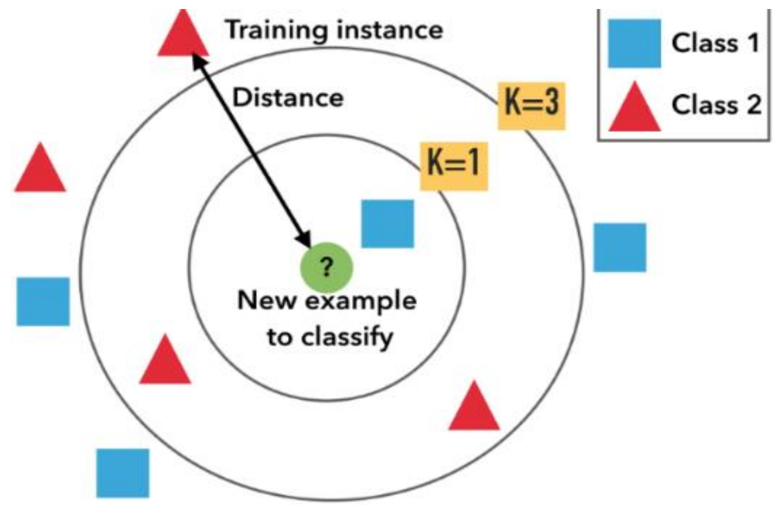
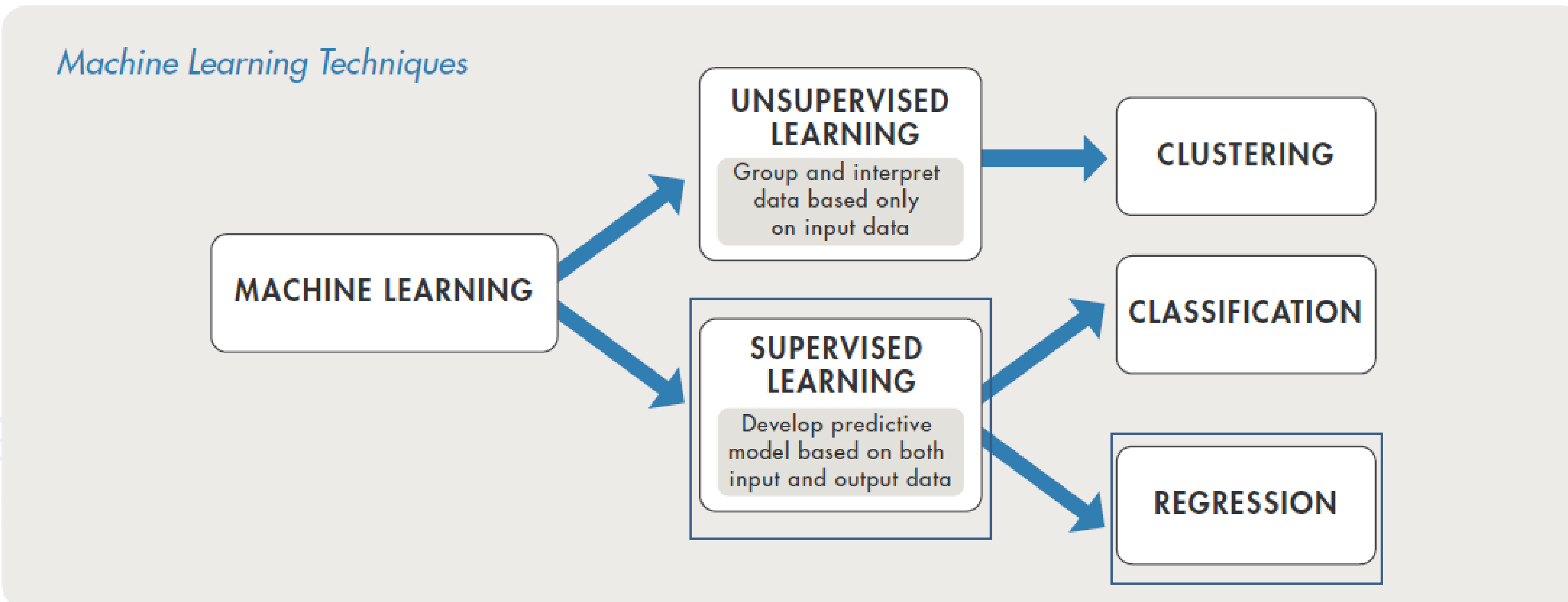
Learning Paradigms
Supervised Learning - Classification

- Example: K-Nearest Neighbors
  - Training → store all examples
  - Development → find best K
  - Test → assign test item to dominant class label of the K closest training data items
- Distance measures
  - Euclidean distance, manhattan distance, cosine distance, …



Machine Learning



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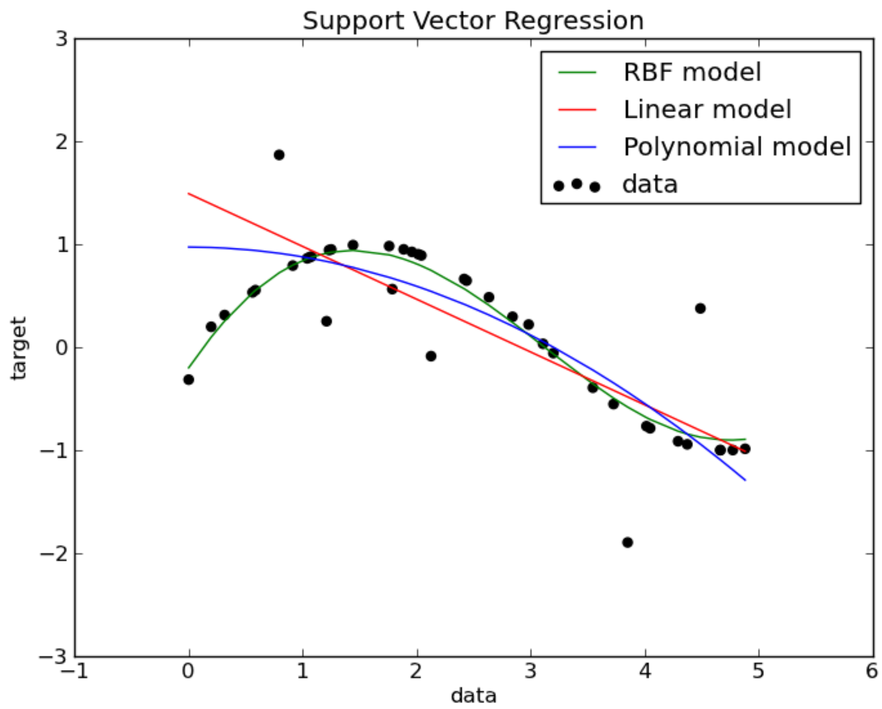
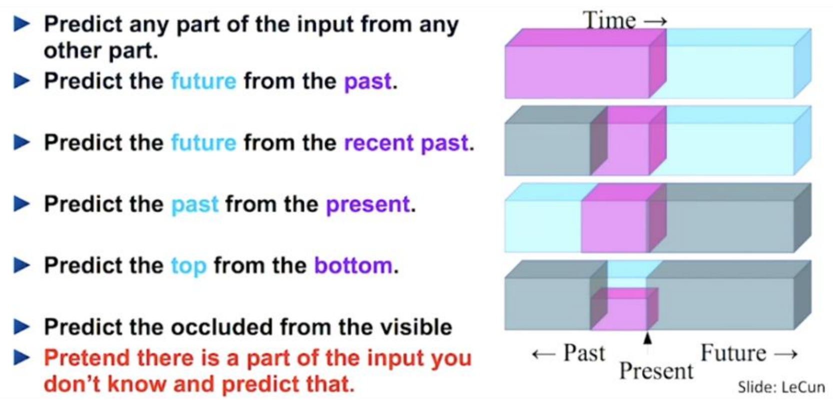
Learning Paradigms
Supervised Learning - Regression

- Predicting a continuous quantity from features
- Examples
  - House price prediction



Learning Paradigms
Self-supervised Learning

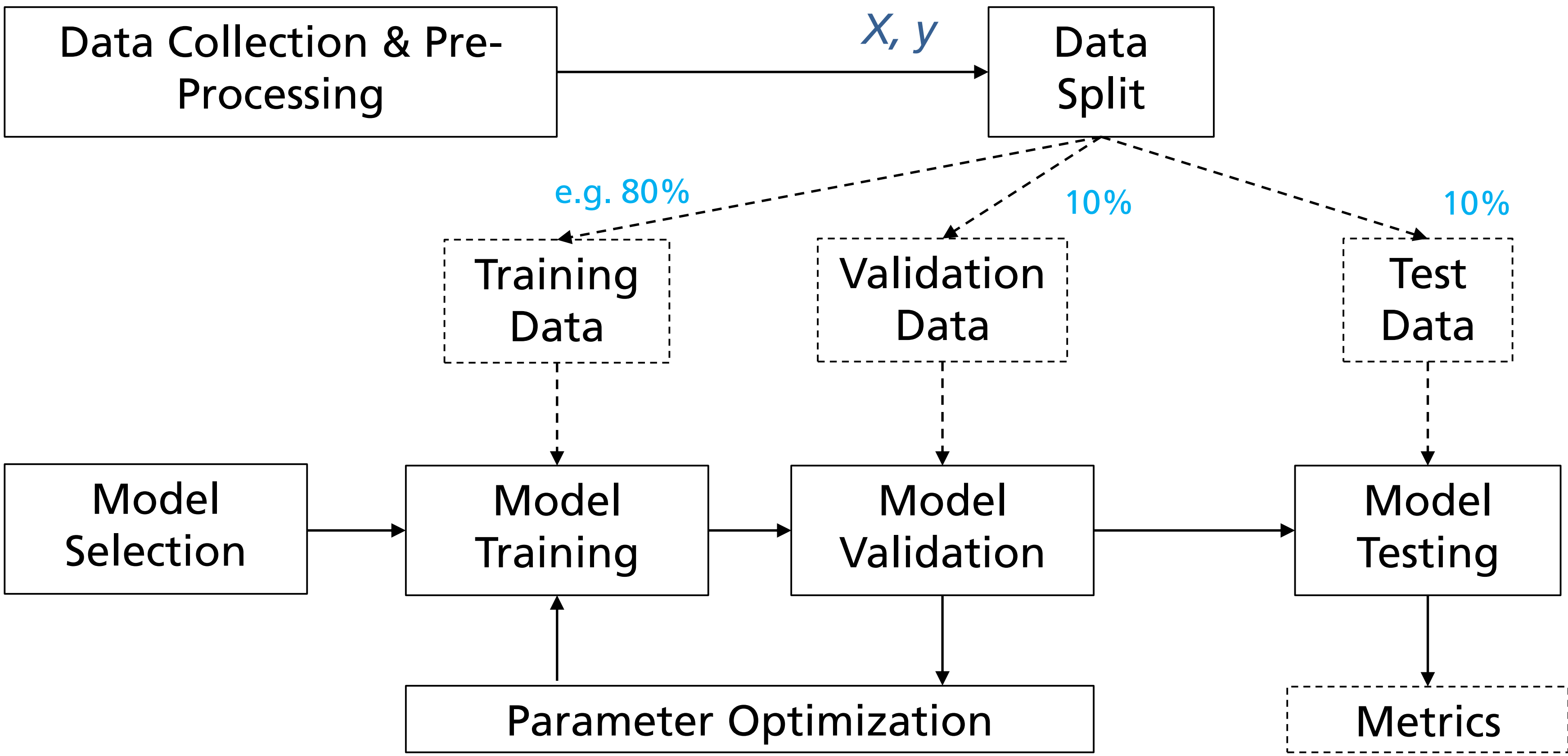
- Problem:
  - Supervised learning requires a lot of (annotated) data → expensive!
- Solution:
  - Train model on related (proxy) task (derive labels from the data!)



  - Transfer learning → Train model with fewer data on target task (e.g. sentiment classification in text)

https://lilianweng.github.io/lil-log/assets/images/self-sup-lecun.png

ML Project Pipeline

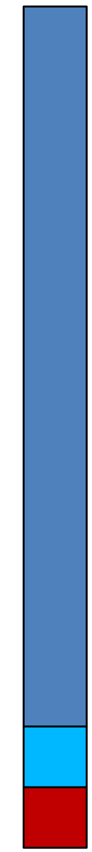


ML Project Pipeline
Data Collection & Pre-Processing

- Data collection
  - Check for available data resources for given (or related) task
  - Collect / record / annotate new data
  - Ensure data variability
    - Example (acoustic condition monitoring) → include different motor engine types & conditions, recording locations, microphones, …
- Data pre-processing
  - Cleanup remove errors, silence, empty files, …
  - Balance dataset (proportion among class examples)
  - Normalize (depends on the model)

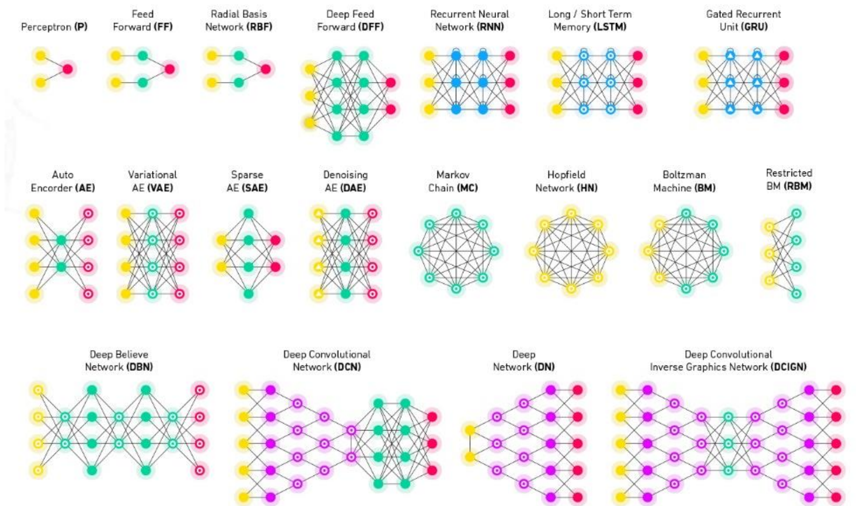
ML Project Pipeline
Data Split

- Training Set
  - Model learns from this data
- Validation Set (a.k.a development / dev set)
  - Used to fine-tune the model (hyper)parameters
  - Model occasionally sees but does not learn from this data
- Test set
  - Only used once after the model training & tuning is completed
  - Should reflect the targeted real-world use case for the model
- Common split ratios
  - 80% - 10% - 10% or even 98% - 1% - 1% (for bigger datasets)



ML Project Pipeline
Model Selection

- Many models and approaches exist
  - Types (SVM, GMM, logistic regression, DNNs)
  - Hyperparameters (SVM kernel functions, DNN layer types)
- Often constrained by the use-case / task
  - Model complexity (memory, training time, training data amount)
- Different models require different feature pre-processing
- Use simple models for simple tasks



https://docs.paperspace.com/machine-learning/wiki/machine-learning-models-explained

ML Project Pipeline
Model Training

- Iterative process
    - Use (batches) of training data to iteratively improve model predictions (optimization)
        - Learn from examples
    - Update model parameters according to loss function
- Often start with random parameter initialization

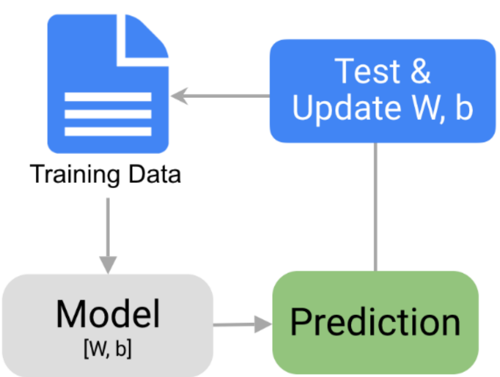
ML Project Pipeline
Model Training

- Example: linear regression

$$y = W \cdot x + b$$

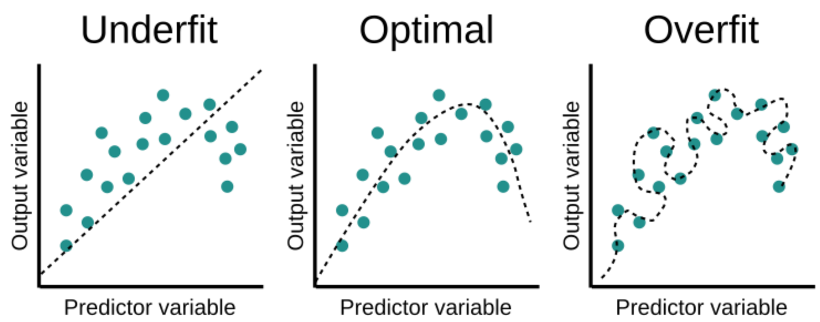
y	$\rightarrow$ target (output)
x	$\rightarrow$ features (input)
W	$\rightarrow$ weights
b	$\rightarrow$ bias

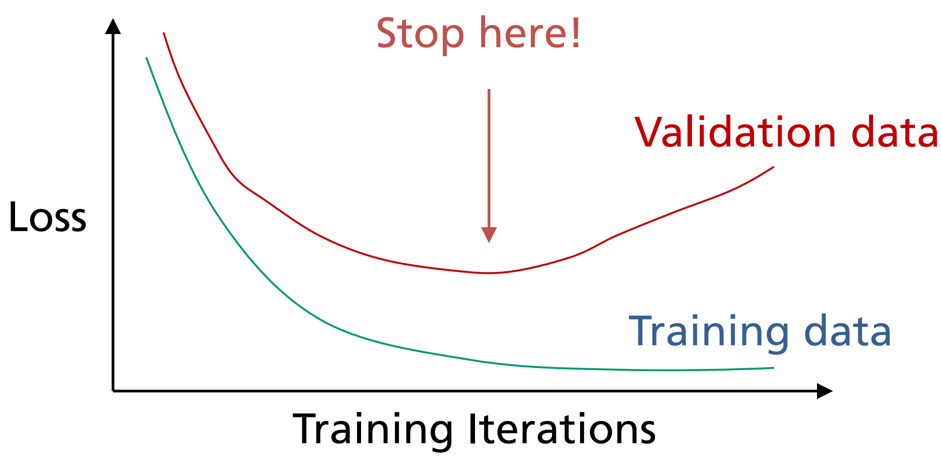
- Training loop



ML Project Pipeline
Model Validation

- Unbiased evaluation of the model after each training iteration
- Helps to
  - optimize model (hyper)parameters
  - detect overfitting on training data
  - stop the training





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ML Project Pipeline
Model Testing

- Final model evaluation
- Test set should reflect final application scenario (same data distribution)
- Evaluation metrics (binary classification)
    - Accuracy – % of correct classifications
    - Recall - % of actual positive examples were classified as positive
    - Precision - % of positive predictions are actually positive
    - F-Score – geometric mean of precision and recall

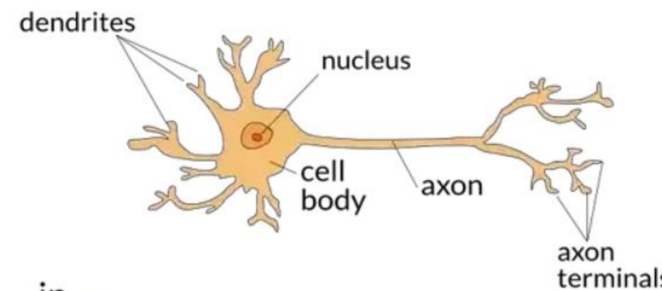
Actual Values

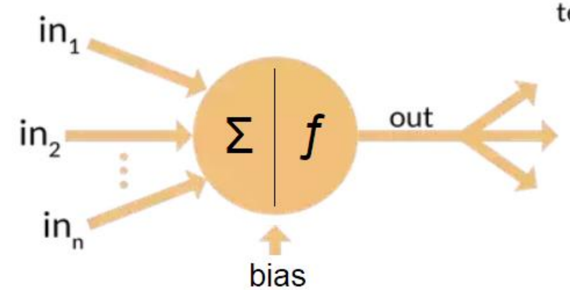
Predicted Values	Positive (1)	Negative (0)
Positive (1)	TP	FP
Negative (0)	FN	TN

https://miro.medium.com/max/534/1*Z54JgbS4DUwWSknhDCvNTQ.png

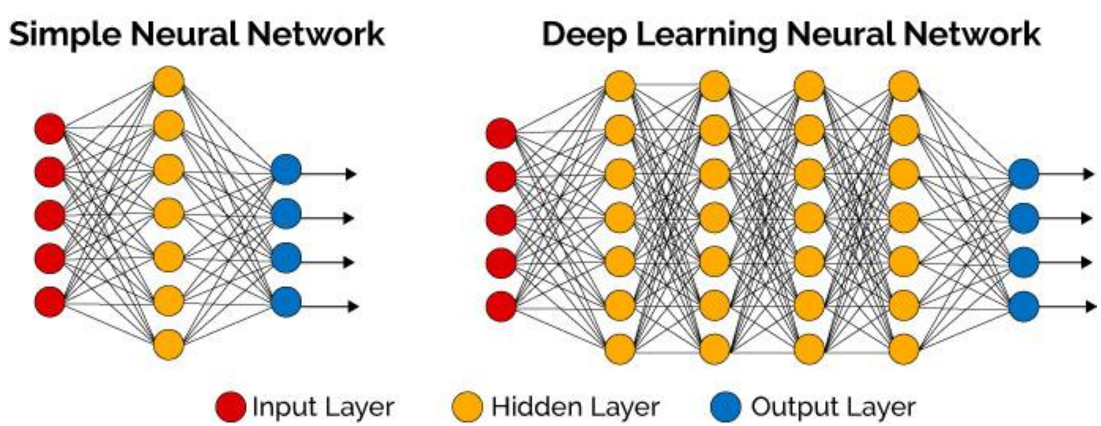
Deep Learning
Introduction

- Artificial neural networks → mimic brain processing
  - Connected neurons (weighted input summation & non-linear processing)





- Deep neural networks → multiple layers



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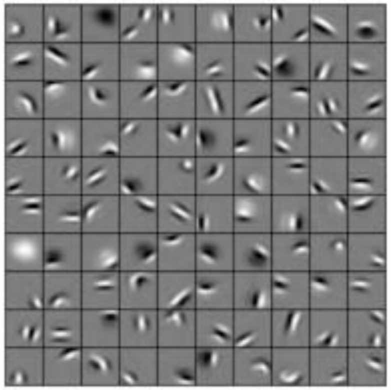
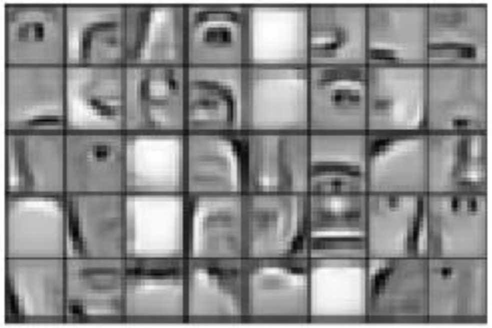
https://www.skampakis.com/wp-content/uploads/2018/03/simple_neural_network_vs_deep_learning.jpg

Deep Learning
Introduction

- Hierarchical feature learning
  - Example (face recognition)



Edges, curves



Shapes, object parts

Objects (faces)

First layers → Final layers

https://pic4.zhimg.com/80/v2-057b248288a8af2f01272a956f862873_1440w.png

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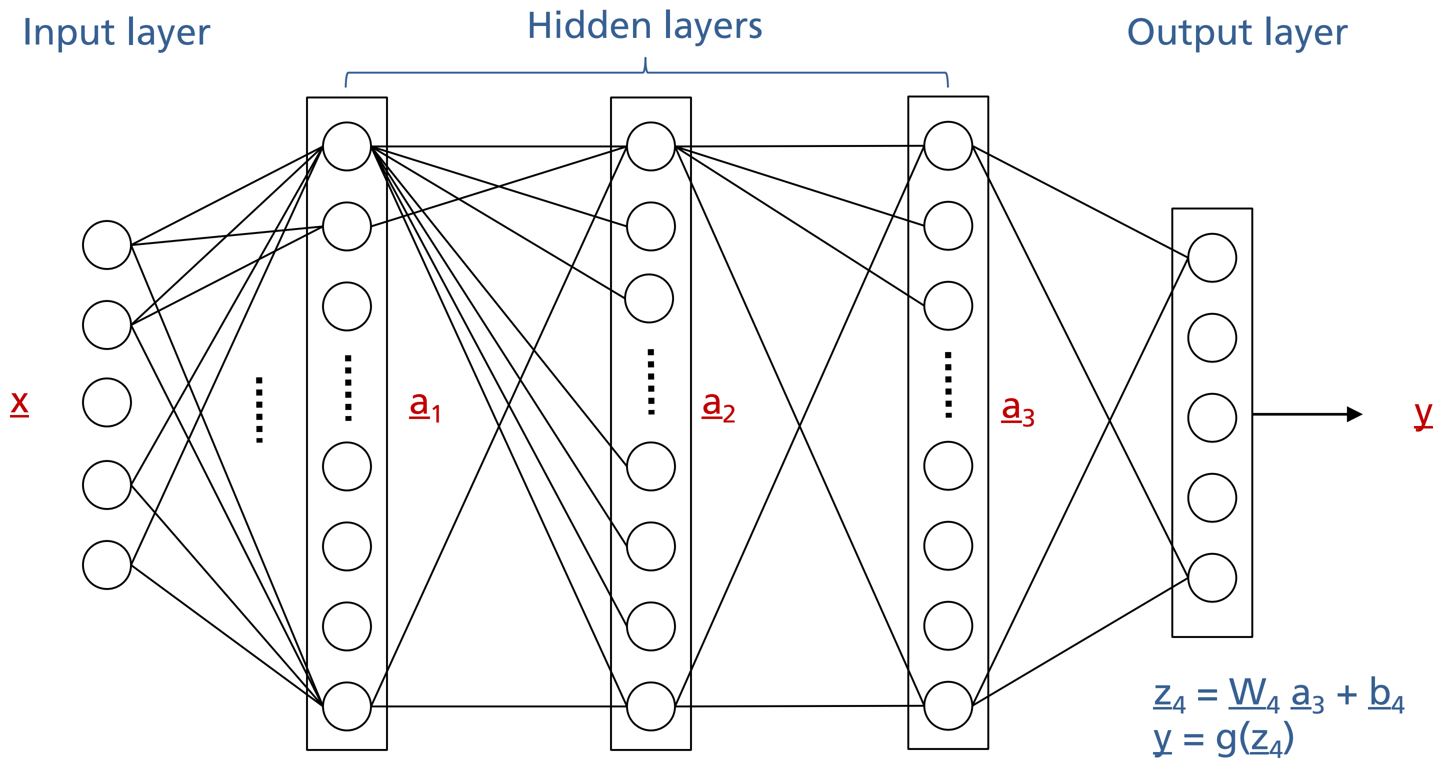
Deep Learning
Deep Neural Networks



1) Weights w & bias b
2) Non-linear activation function g(z)

$\underline{W}_1$, $\underline{b}_1$

$\underline{z}_1 = \underline{W}_1\ \underline{x} + \underline{b}_1$
$\underline{a}_1 = g(\underline{z}_1)$

$\underline{W}_2$, $\underline{b}_2$

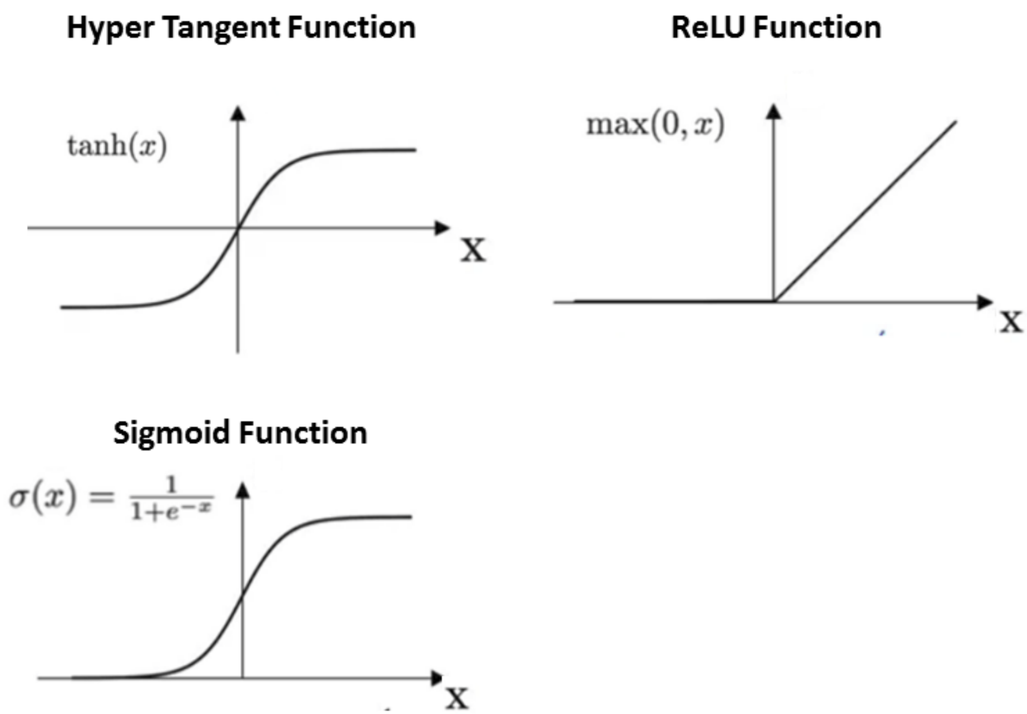
$\underline{z}_2 = \underline{W}_2\ \underline{a}_1 + \underline{b}_2$
$\underline{a}_2 = g(\underline{z}_2)$

$\underline{W}_3$, $\underline{b}_3$

$\underline{z}_3 = \underline{W}_3\ \underline{a}_2 + \underline{b}_3$
$\underline{a}_3 = g(\underline{z}_3)$

Deep Learning
Activation Functions

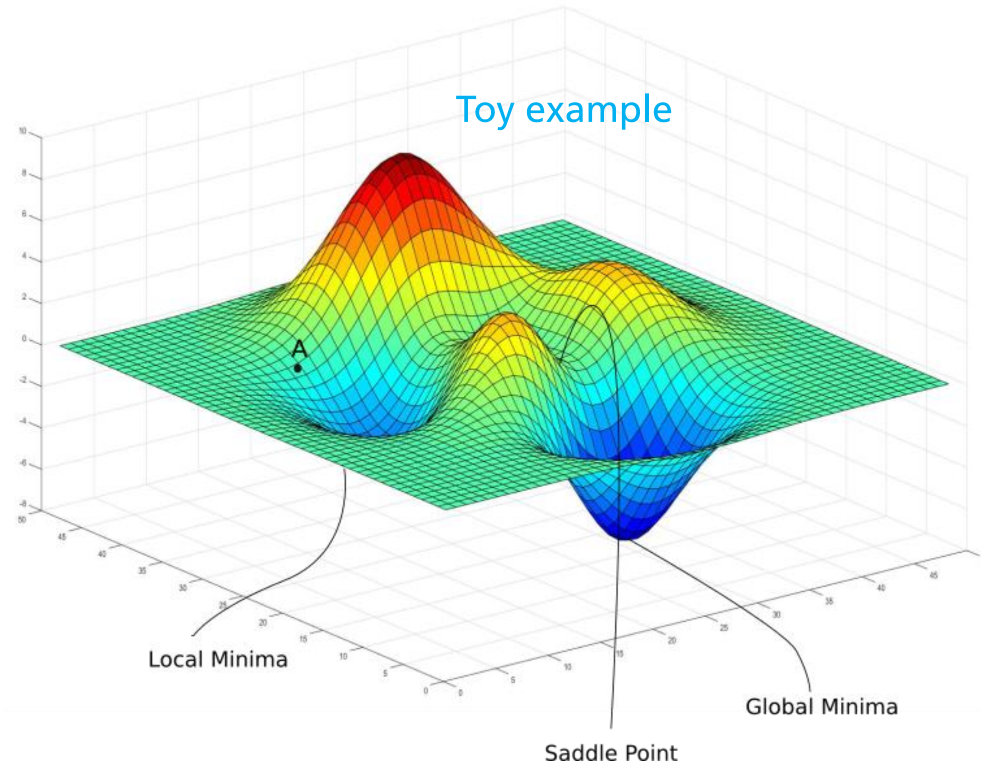
- Activation functions add non-linearity
- Make networks more powerful in (complex) pattern recognition
- Examples:



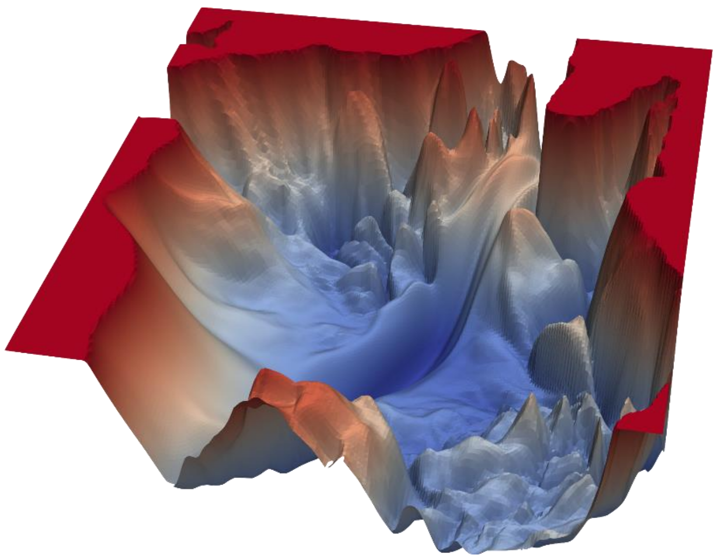
Deep Learning
Training

- Loss contour
  - Goal → find global minima

Toy example



Complex DNN



https://blog.paperspace.com/content/images/2018/05/challenges-1.png
https://www.cs.umd.edu/~tomg/img/landscapes/noshort.png

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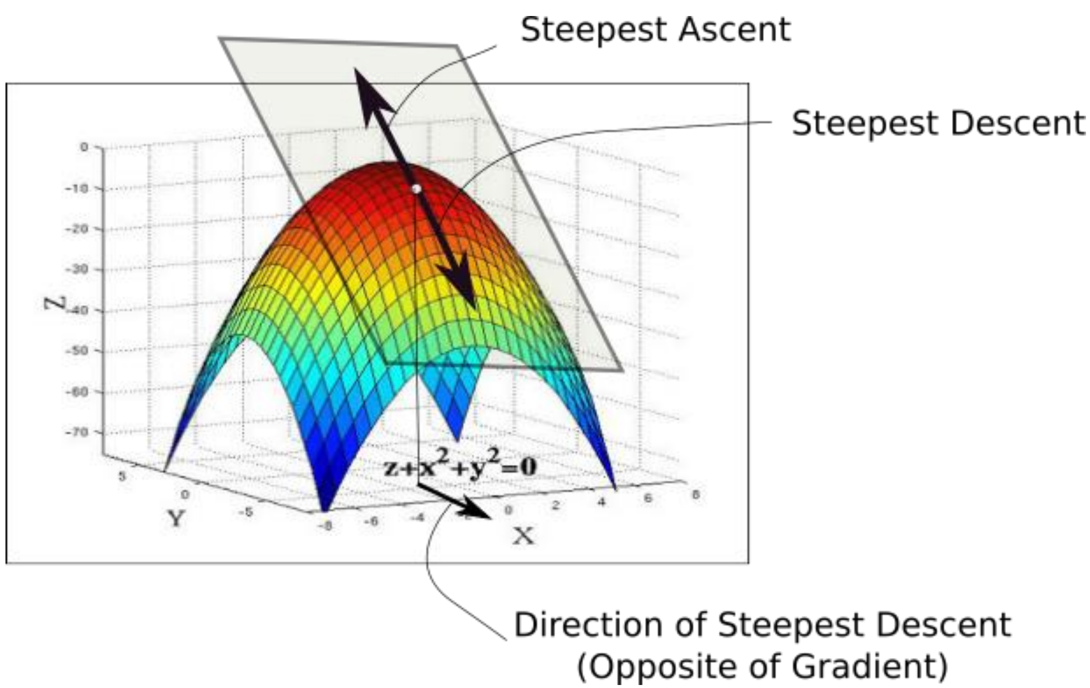
Deep Learning
Training

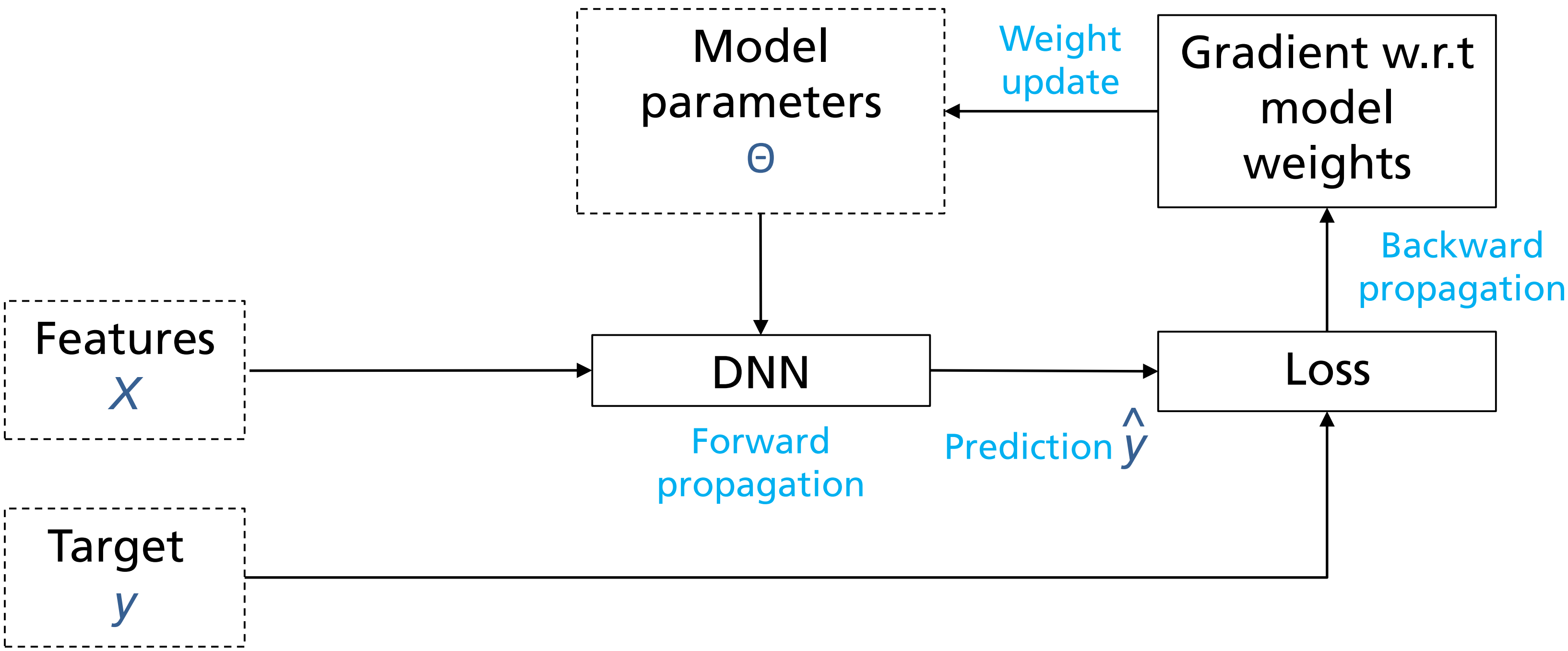
- Gradient descend
    - Move into opposite direction of gradient
    - Learning rate effects step size



https://blog.paperspace.com/content/images/2018/05/grad.png

Deep Learning
Training

- Back propagation

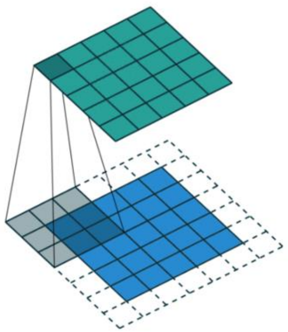


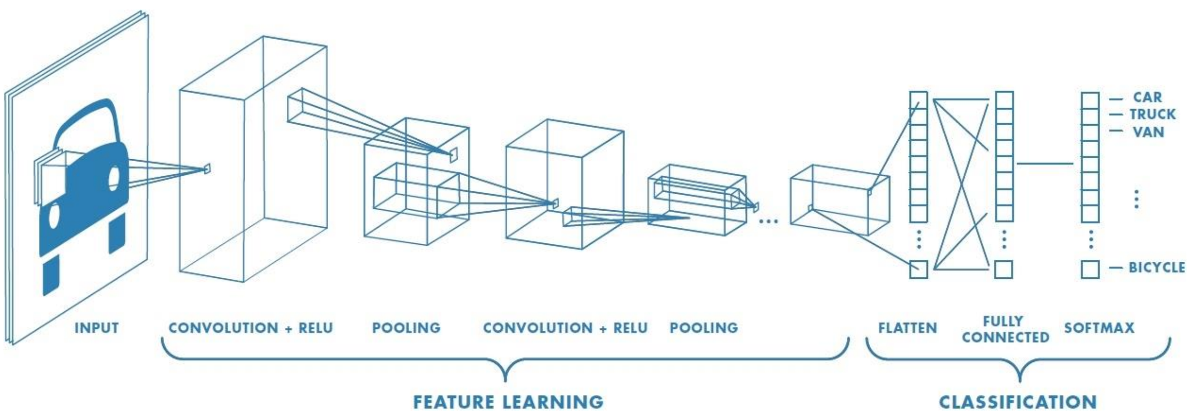
Deep Learning
Playground

- A neural network playground!
    - https://playground.tensorflow.org

Deep Learning
Convolutional Neural Networks (CNN)

- Convolutional layers
  - Local connectivity → receptive field
  - Shared weights
  - Translation Equivariance → translation of input = translation of activations
- Pooling → local aggregation

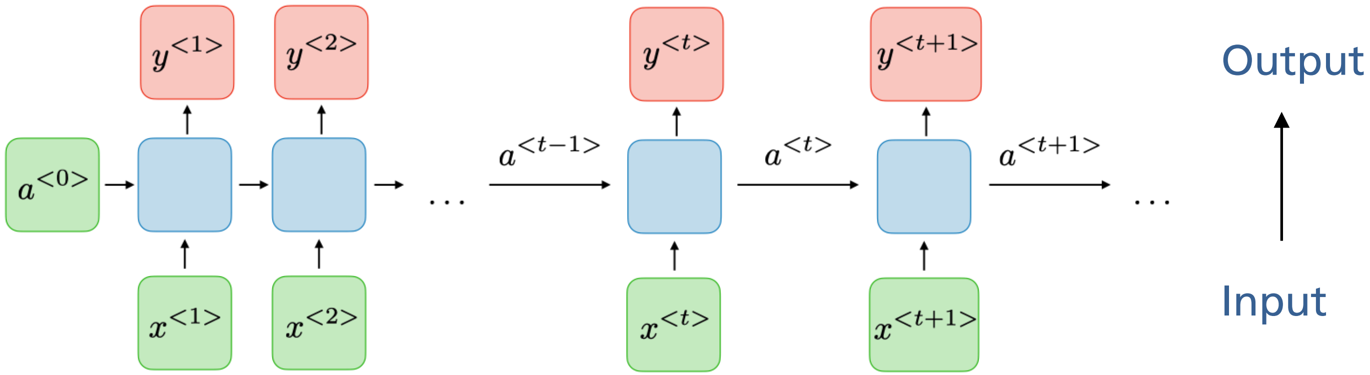




https://www.wandb.com/articles/intro-to-cnns-with-wandb
https://www.freecodecamp.org/news/an-intuitive-guide-to-convolutional-neural-networks-260c2de0a050/

Deep Learning
Recurrent Neural Networks (RNN)

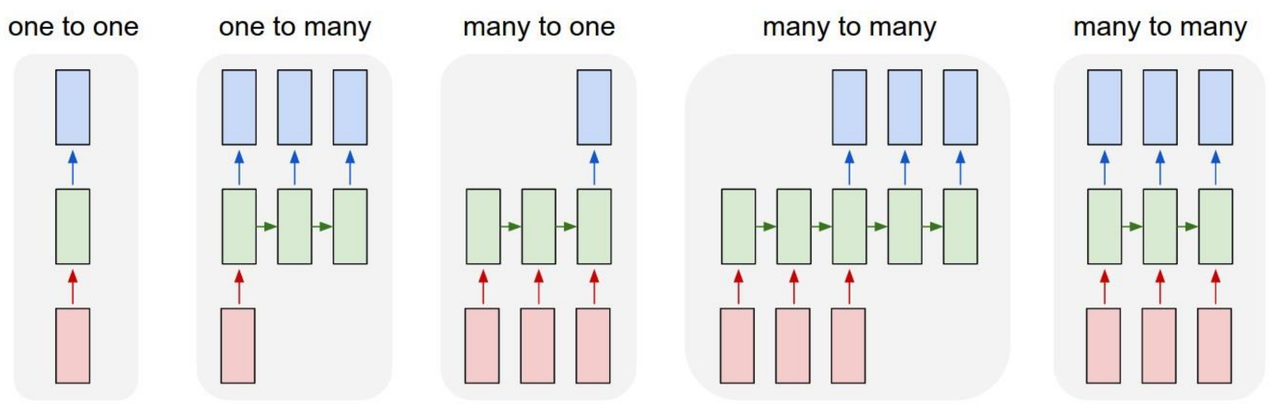
- Recurrent layers
  - Model sequential data → model dynamic temporal behaviour
  - Internal memory state(s) → memorize previous data for future predictions
- Vanishing gradient problem
  - Gating mechanisms (Gated Recurrent Units (GRU), Long Short-term Memory (LSTM)



https://wiki.tum.de/download/attachments/22578349/RNN1.png

Deep Learning
Recurrent Neural Networks (RNN)

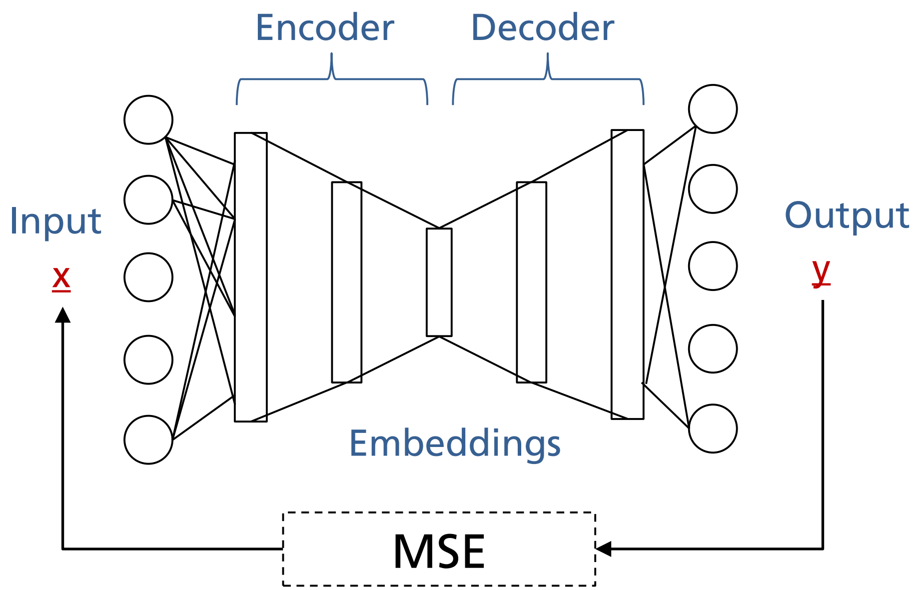
- Application Examples
  - One-to-many: sequential music generation (given a starting note)
  - Many-to-one: sentiment classification (positive vs. negative)
  - Many-to-many: machine translation (e.g. Spanish to German)



https://stanford.edu/~shervine/teaching/cs-230/illustrations/architecture-rnn-ltr.png

Deep Learning
Autoencoders

- Symmetric architecture (decoder & encoder)
- Objective: minimize reconstruction error (e.g. mean squared error)
- Compression of input (embedding)
- Prioritize on important information → learn useful representations



Summary

- Introduction
  - Terminology, application scenarios
- Learning Paradigms
  - Unsupervised, supervised, self-supervised learning
- ML project pipeline
  - Data collection, pre-processing, split
  - Model selection, validation, training, testing
- Deep Learning
  - DNN, CNN, RNN, Autoencoders

References

- S. Legg, M. Hutter (2007). Universal Intelligence: A Definition of Machine Intelligence. Minds & Machines. 17 (4): 391-444.
- A. L. Samuel (1959). Some studies in machine learning using the game of checkers. IBM Journal of research and development. 3(3), 210-229.