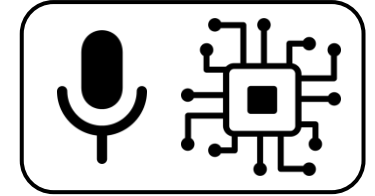

Computational Analysis of Sound and Music

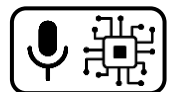


Machine Learning

Dr.-Ing. Jakob Abeßer

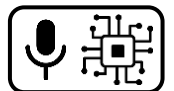
Fraunhofer IDMT

jakob.abesser@idmt.fraunhofer.de



Outline

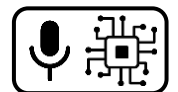
- **Machine Learning**
 - Introduction
 - Application Scenarios
 - Learning Paradigms
- Machine Learning Pipeline



Machine Learning

Introduction

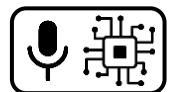
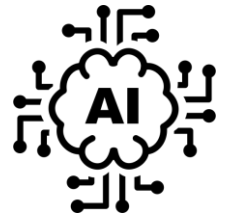
- Human intelligence
 - “mental quality that consists of the abilities to **learn** from experience, **adapt** to new situations, **understand** and handle abstract concepts, and use knowledge to **manipulate** one’s environment.” [1]
- Human learning
 - “Learning is the process of acquiring new **understanding, knowledge, behaviors, skills, values, attitudes, and preferences.**”



Machine Learning

Introduction

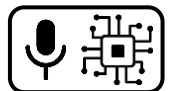
- Artificial Intelligence
 - Agent (machine)
 - **Perceive** and **react** to environments
 - Performs **actions** to achieve **goals** [2]
- Levels of AI
 - **Narrow/weak AI** (single task, limited context)
 - Examples: Voice assistants, self-driving cars, chat bots
 - **Artificial general intelligence (AGI)**
 - Multiple task
 - Knowledge generalization across tasks



Machine Learning

Introduction

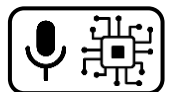
- Machine Learning (ML)
 - Sub-field of AI
 - “...give computers the ability to learn **without being explicitly programmed**” [3]
 - Learning structures in given (un)labeled data to make predictions on new / unseen data
- Paradigm change
 - Before: Use **domain knowledge** to design (general-purpose) features
 - Now: **Learn** suitable **representations** (features) & **models** (classification) **jointly** by analyzing (annotated) **data**



Machine Learning

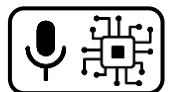
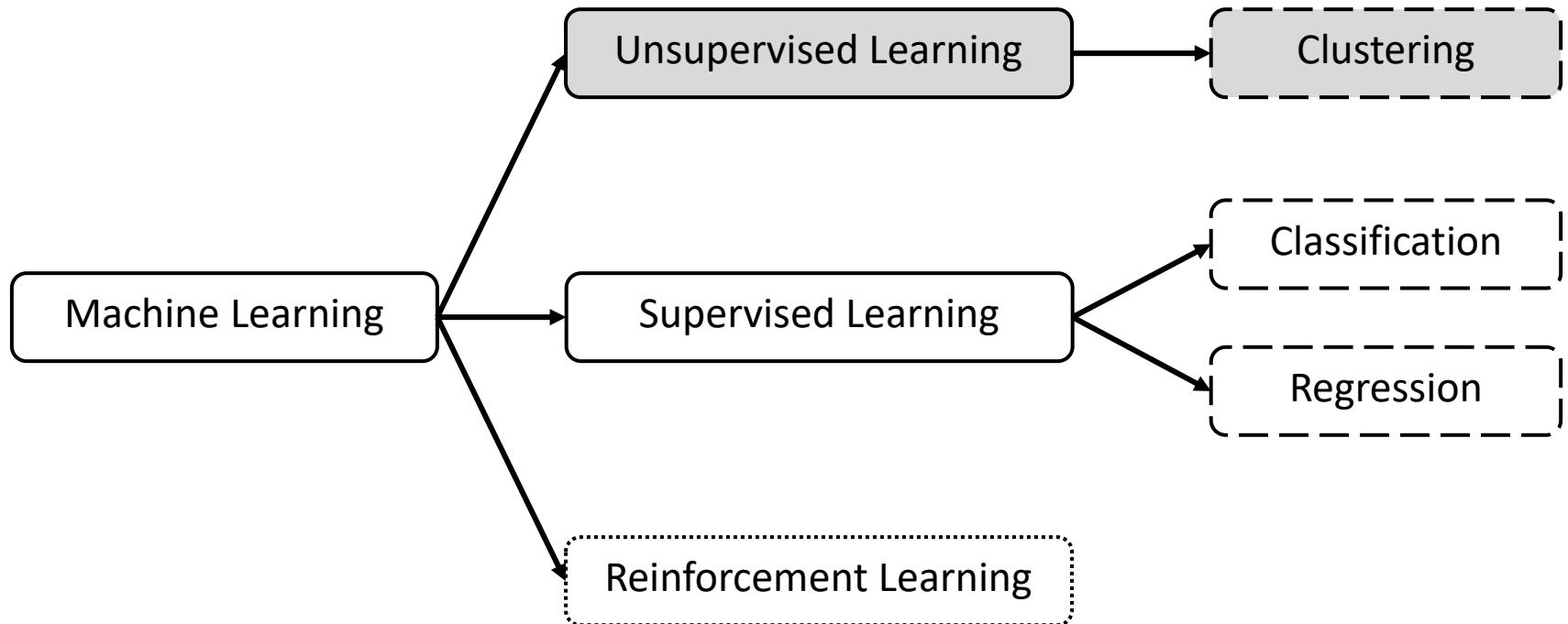
Application Scenarios

- 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)



Machine Learning

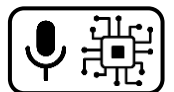
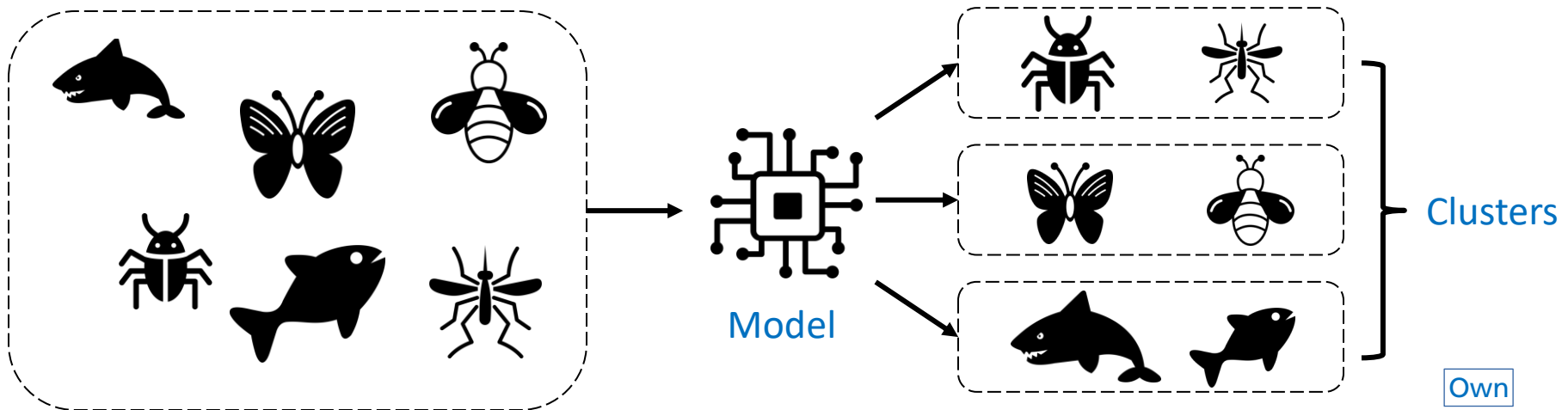
Learning Paradigms



Machine Learning

Unsupervised Learning

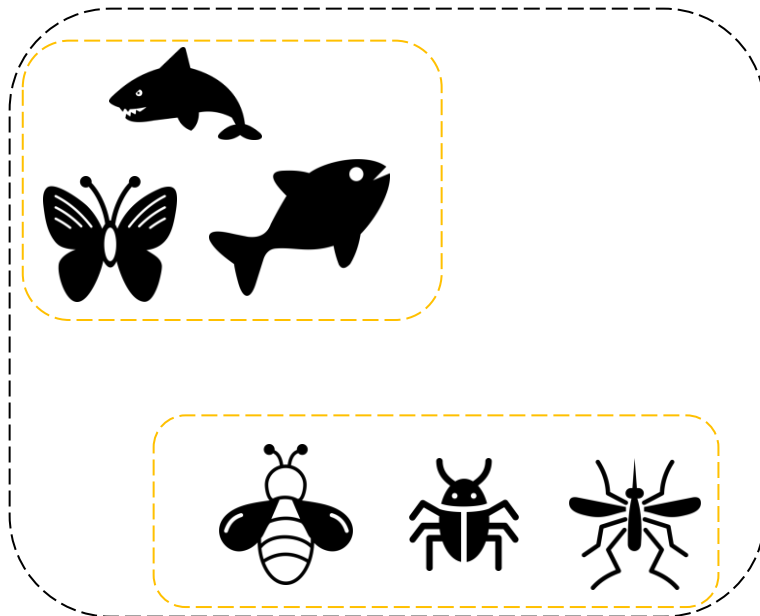
- Goal
 - Find hidden **structure** and **patterns** in data
 - **No annotations** available
- Clustering
 - **Grouping of similar data instances**



Machine Learning

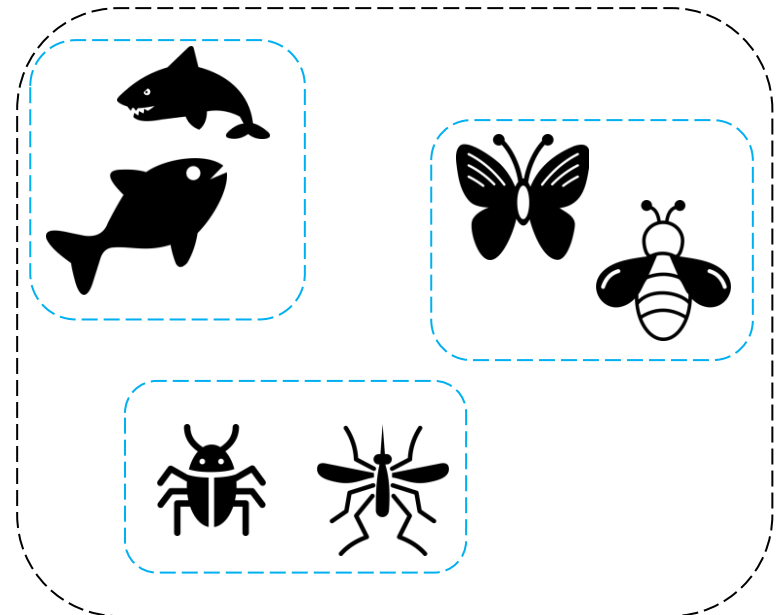
Unsupervised Learning

- Challenges
 - What is the **optimal number of clusters**?



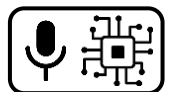
2 clusters

?



3 clusters

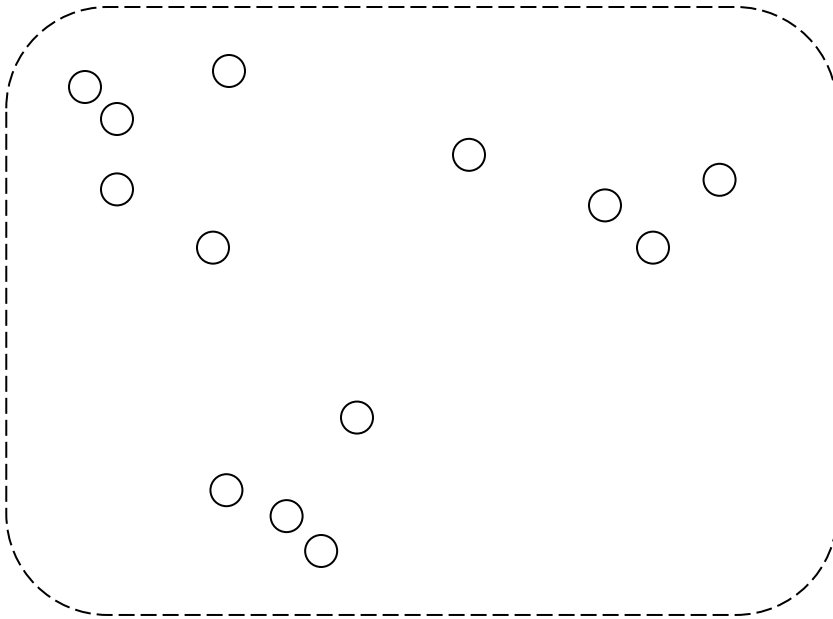
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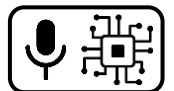
Machine Learning

Unsupervised Learning

- k -means clustering



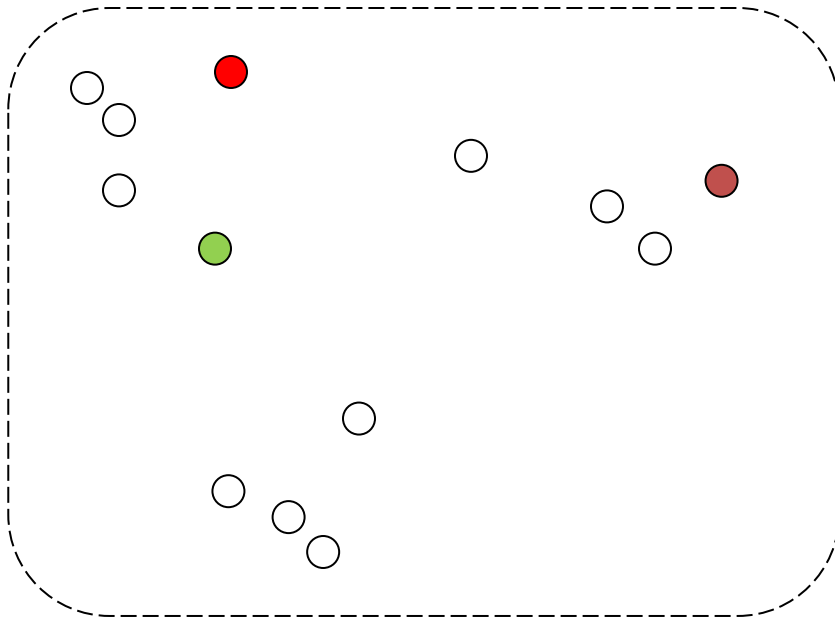
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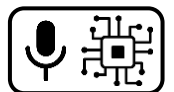
Machine Learning

Unsupervised Learning

- k -means clustering
 - Initialize k randomly (here: $k = 3$) → number of clusters



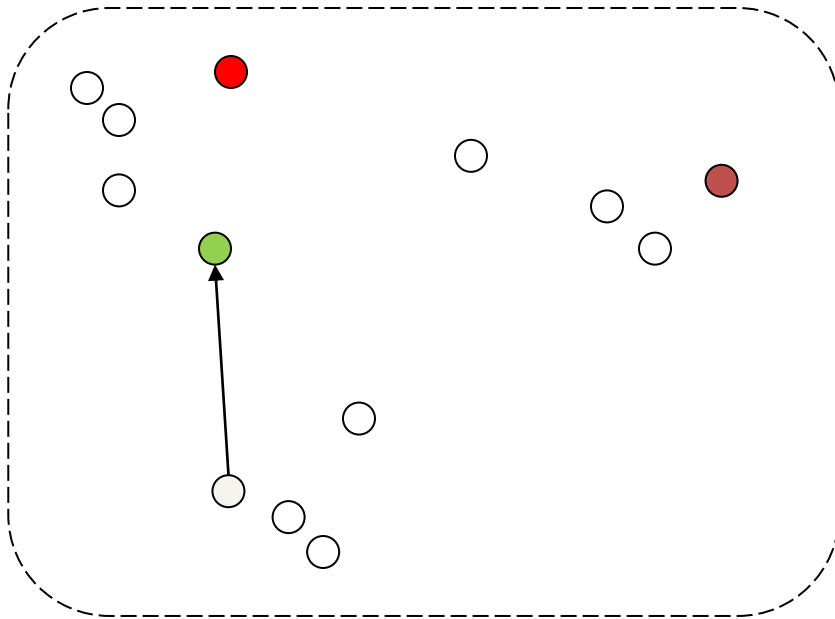
Own



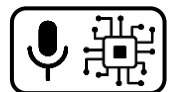
Machine Learning

Unsupervised Learning

- k -means clustering
 - Assignment: assign each data point to its closest mean



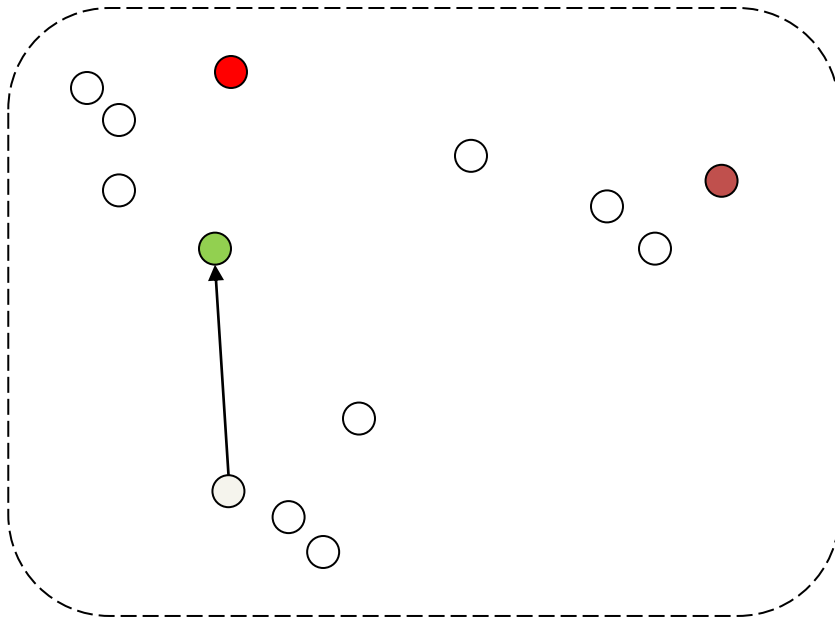
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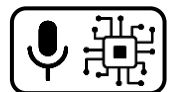
Machine Learning

Unsupervised Learning

- k -means clustering
 - Assignment: assign each data point to its closest mean



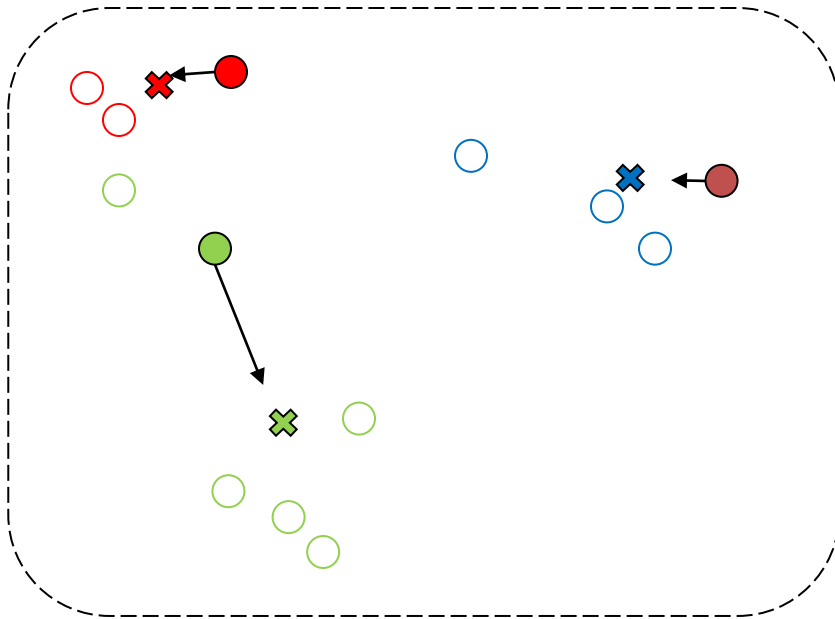
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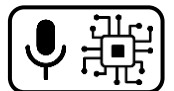
Machine Learning

Unsupervised Learning

- k -means clustering
 - Update: update mean by average over all assigned data points



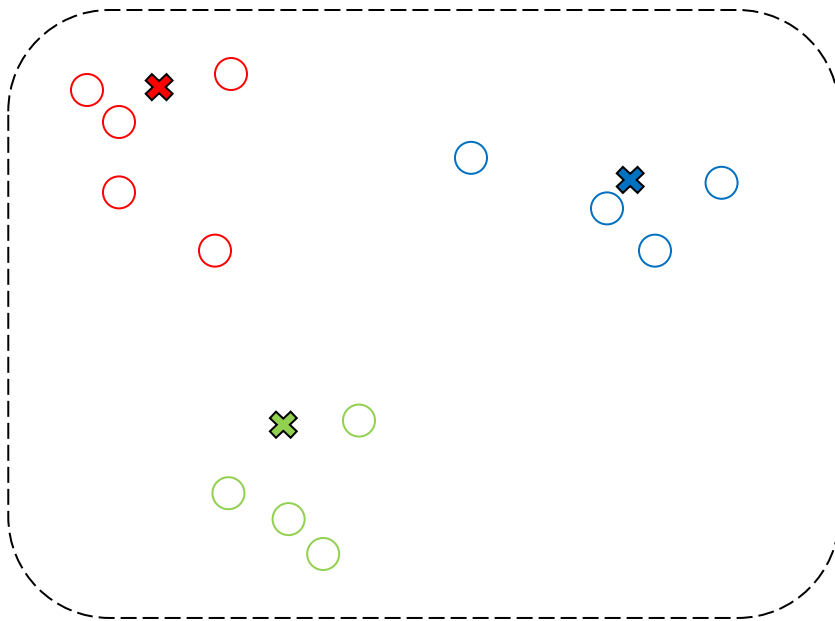
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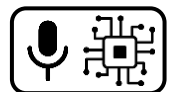
Machine Learning

Unsupervised Learning

- k -means clustering
 - Assignment: re-assign data points to closest mean



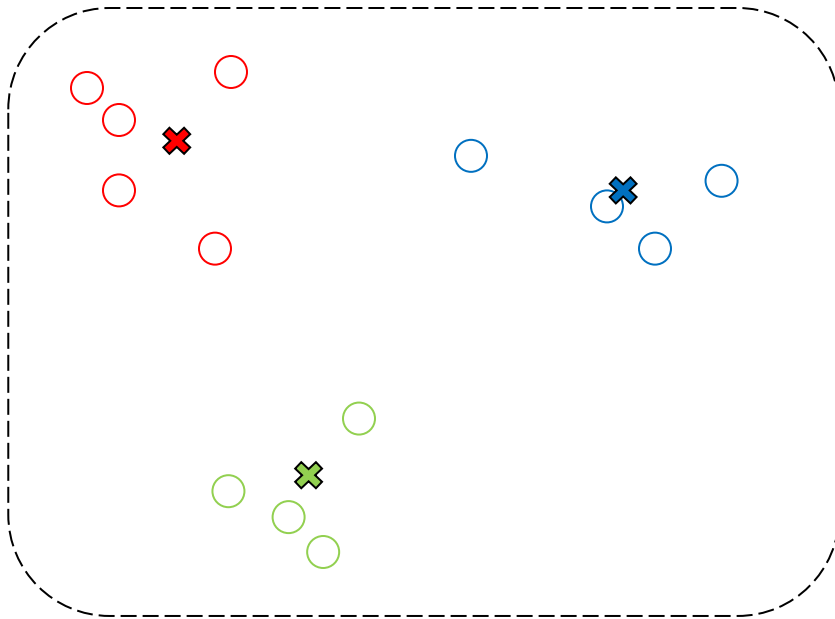
Own



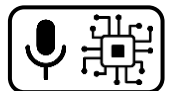
Machine Learning

Unsupervised Learning

- k -means clustering
 - Repeat until convergence

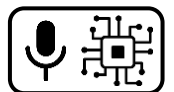
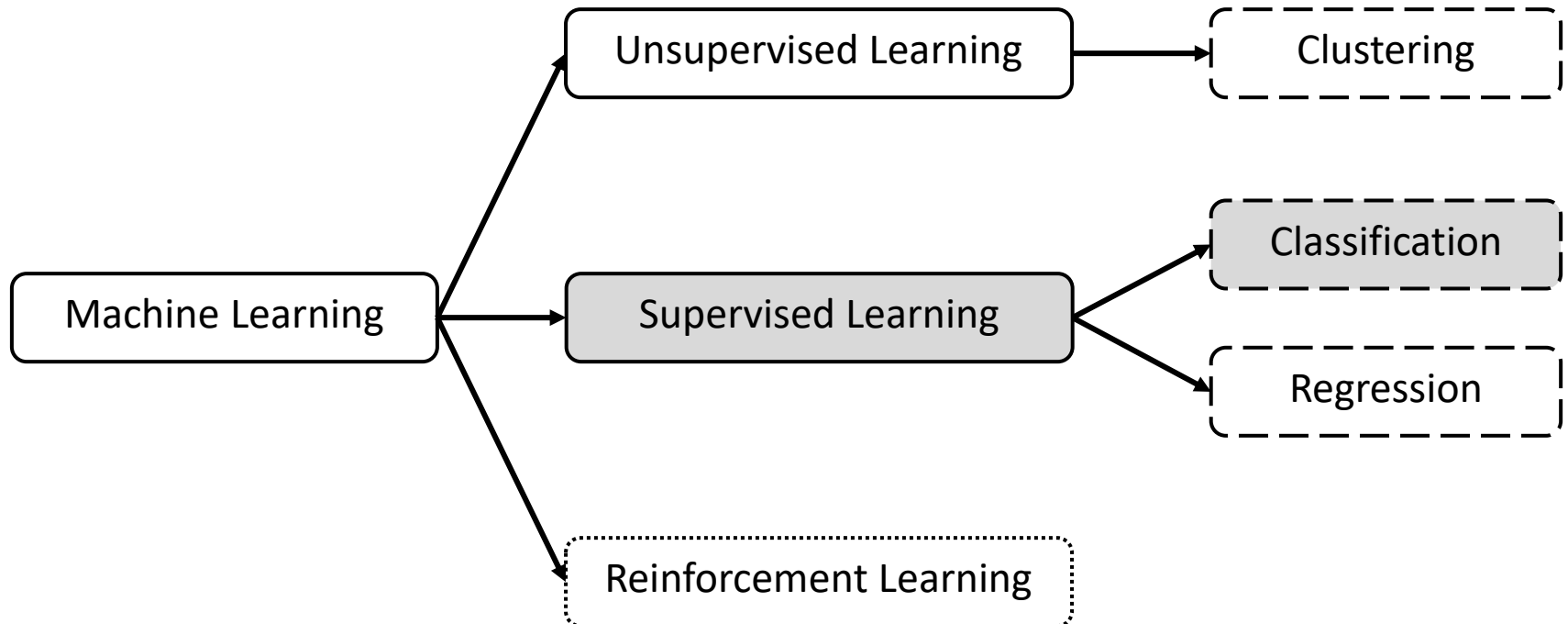


Own



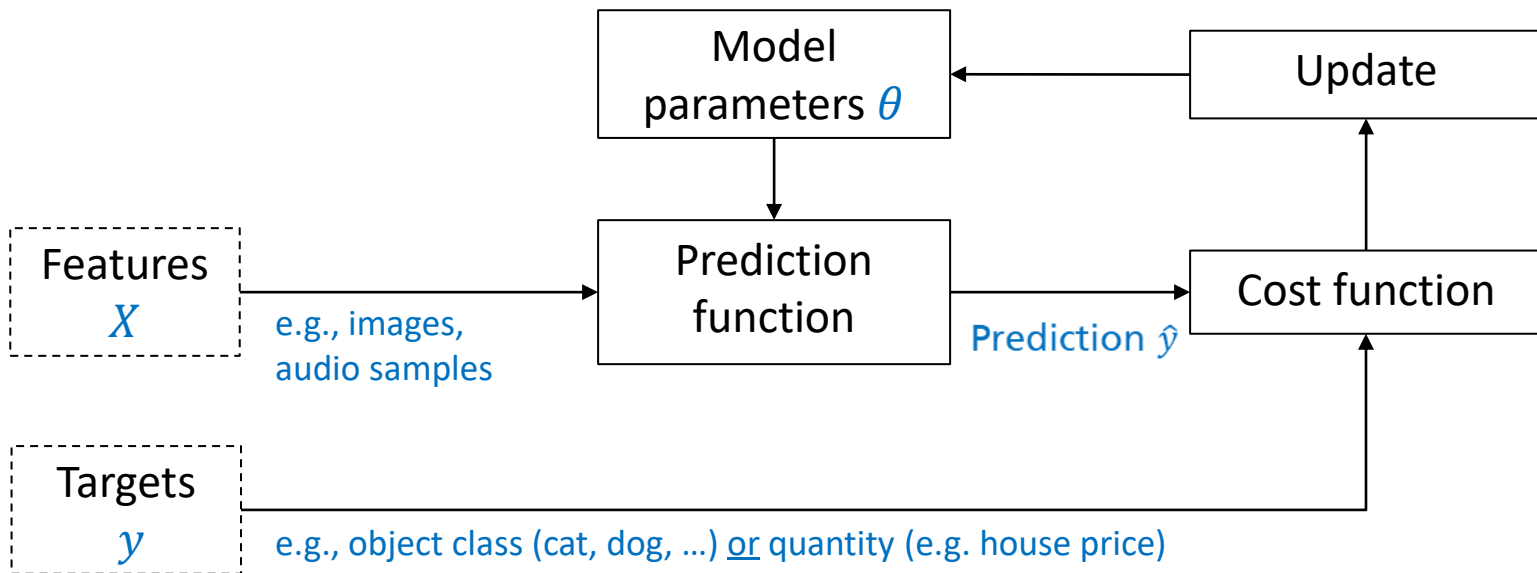
Machine Learning

Learning Paradigms

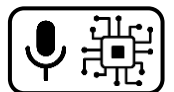


Machine Learning

Supervised Learning



Own



Machine Learning

Supervised Learning (Classification)

- Predict one or multiple **categorical** labels from features
 - Examples → music genre, instrument(s), key
- **Feature space** (Example: 2 classes)

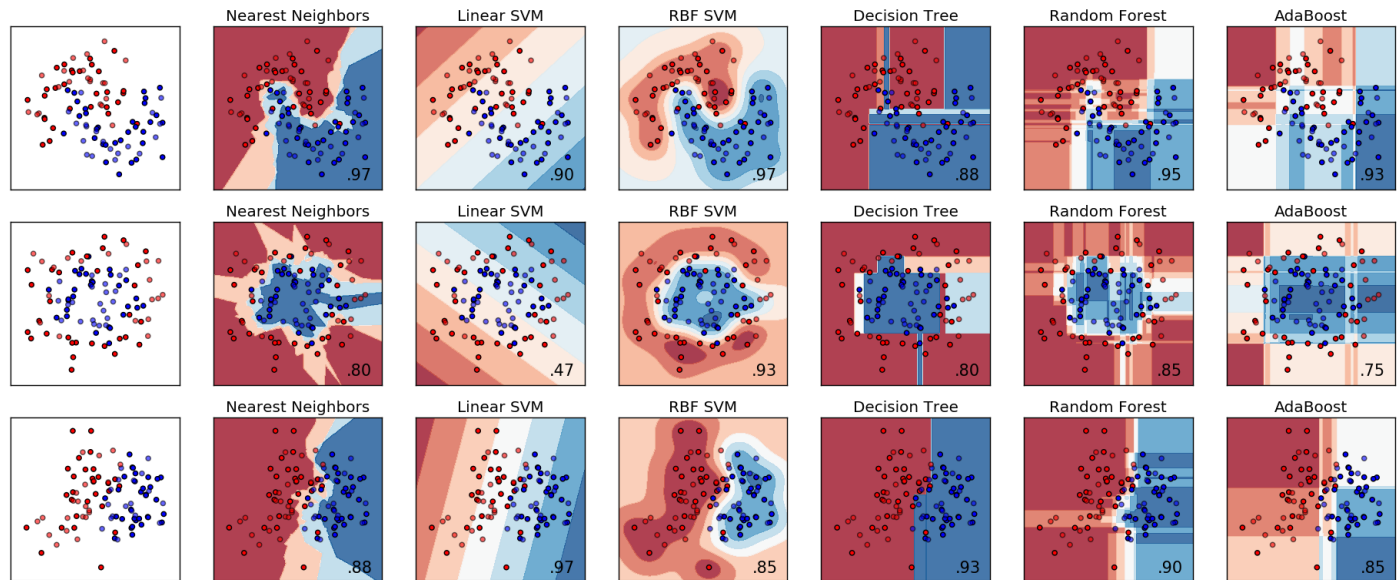
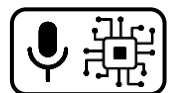


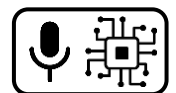
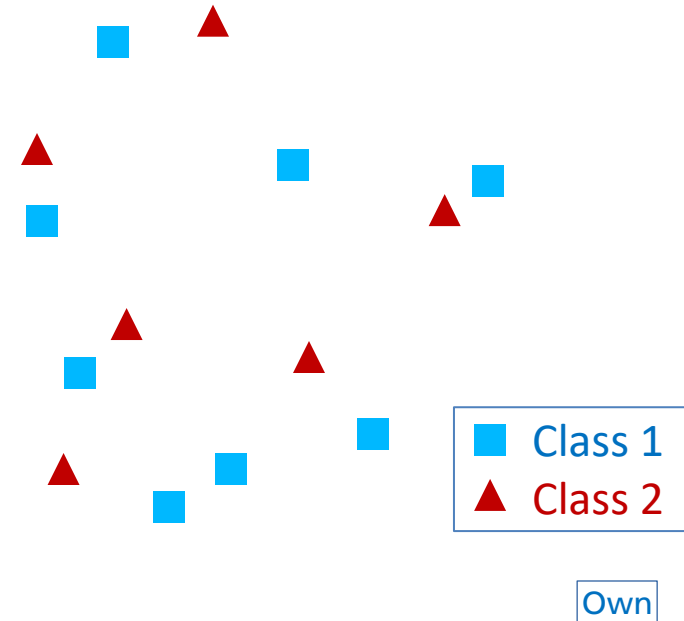
Fig-D1-1



Machine Learning

Supervised Learning (Classification)

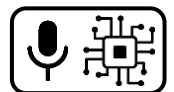
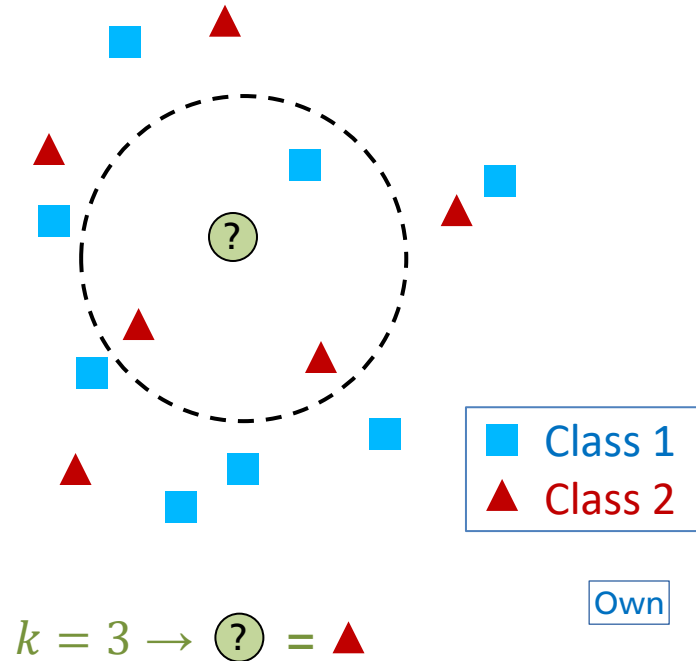
- k -nearest neighbors classifier
 - Training → Store all examples



Machine Learning

Supervised Learning (Classification)

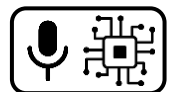
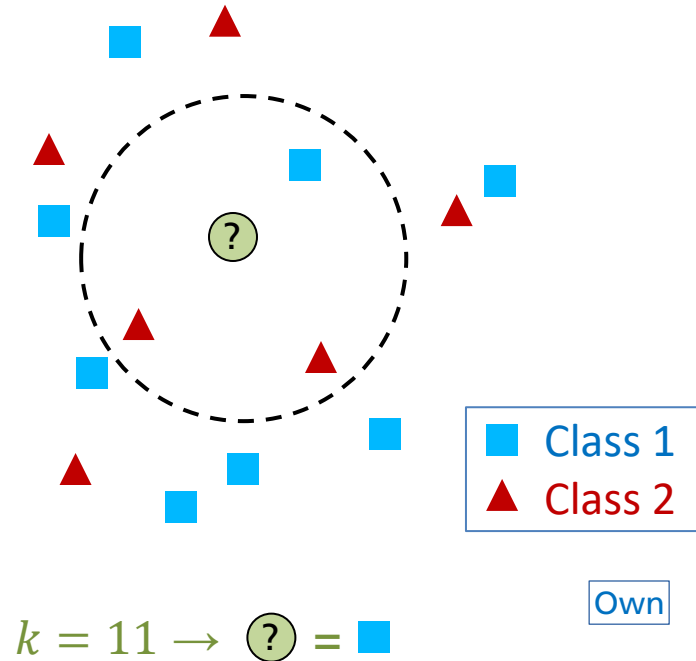
- k -nearest neighbors classifier
 - Training → Store all examples
 - Test → Assign test item to dominant class label of the k closest training data items



Machine Learning

Supervised Learning (Classification)

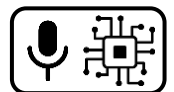
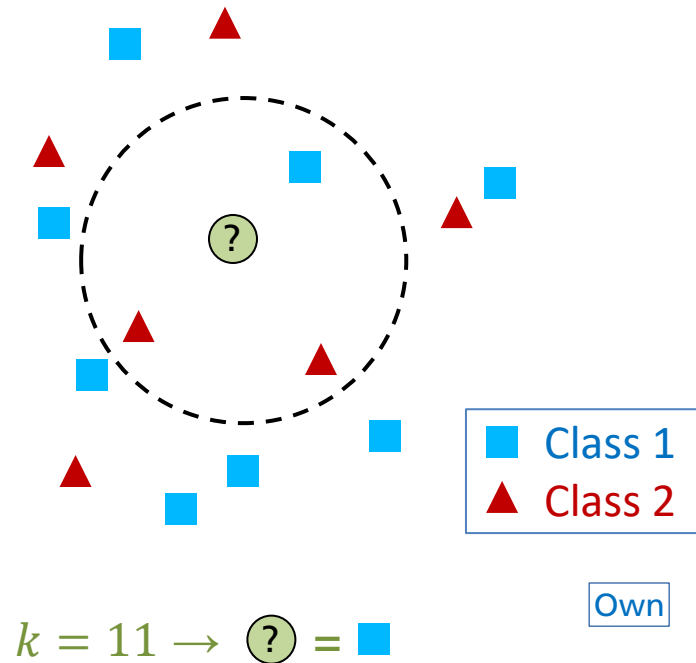
- k -nearest neighbors classifier
 - Training → Store all examples
 - Test → Assign test item to dominant class label of the k closest training data items



Machine Learning

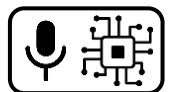
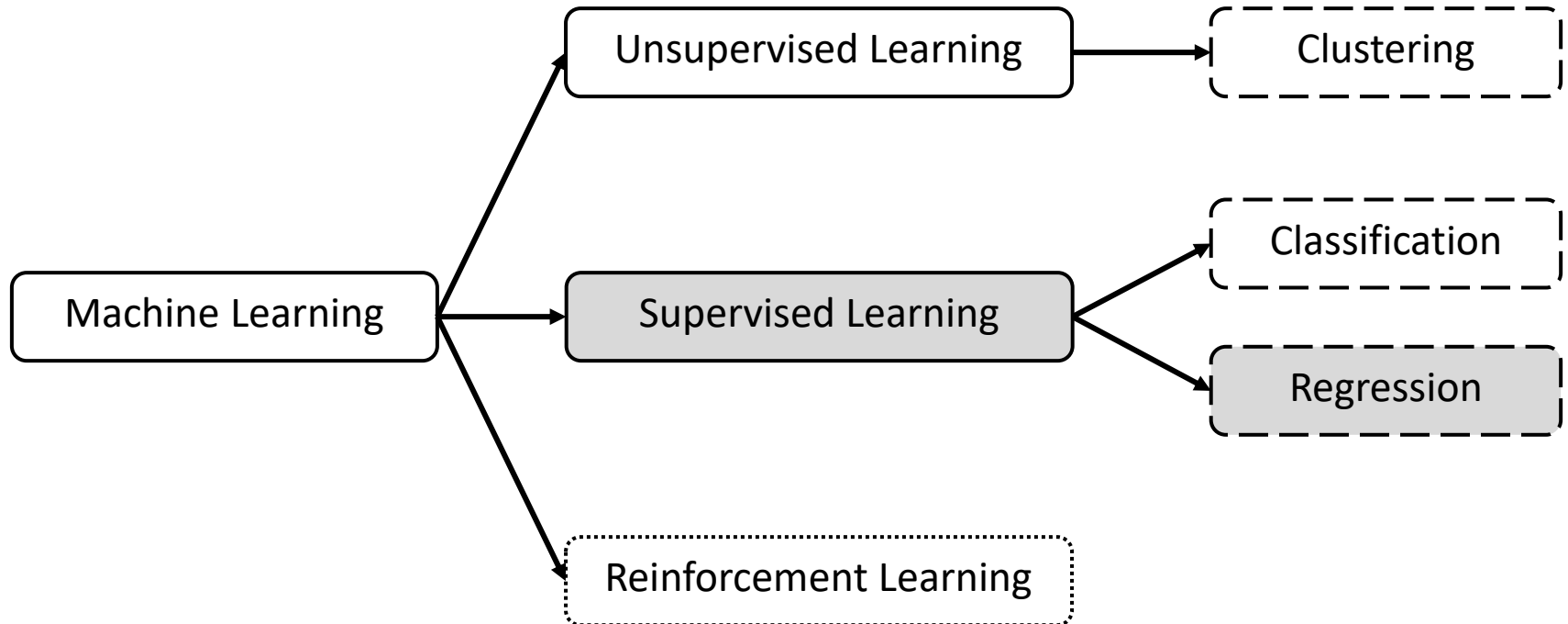
Supervised Learning (Classification)

- k -nearest neighbors classifier
 - Training → Store all examples
 - Test → Assign test item to dominant class label of the k closest training data items
 - Distance measures
 - Euclidean distance
 - Cosine distance, ...



Machine Learning

Learning Paradigms



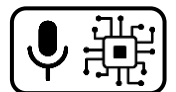
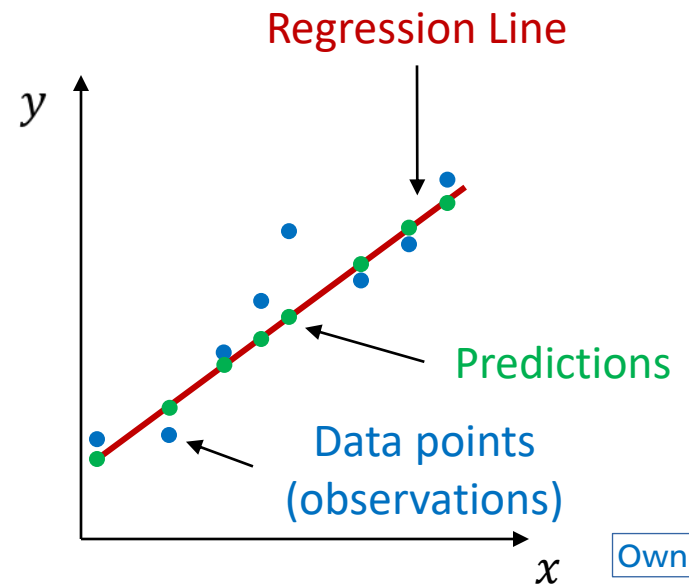
Machine Learning

Supervised Learning (Regression)

- Goal
 - Predict a **dependent** (response) **variable** given one or multiple **independent variables** (features)
 - **Continuous** quantities
- Examples
 - Univariate (linear) regression

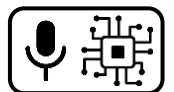
$$y \sim \beta_0 + \beta_1 \cdot x$$

- β_0 (bias)
- β_1 (weight)



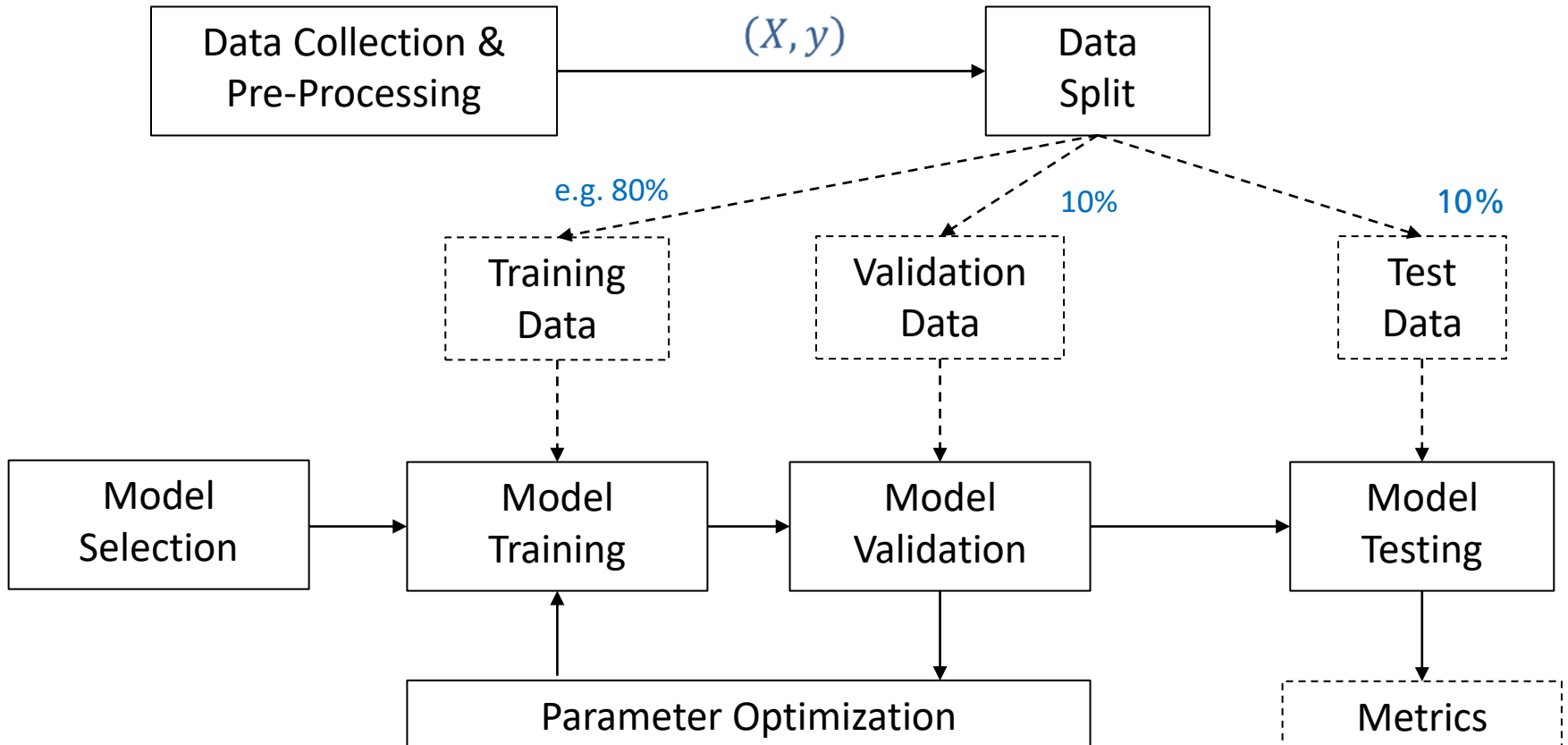
Outline

- Machine Learning
 - Introduction
 - Application Scenarios
 - Learning Paradigms
- **Machine Learning Pipeline**

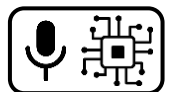


Machine Learning

Machine Learning Pipeline




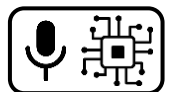
Own



Machine Learning



Machine Learning Pipeline (Data Split)

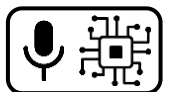
- Training Set 
 - Model learns from this data



Machine Learning




Machine Learning Pipeline (Data Split)

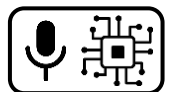
- Training Set 
 - Model learns from this data
- Validation / Development Set 
 - Used to fine-tune the model (hyper)parameters
 - Model occasionally sees but does not learn from this data



Machine Learning

Machine Learning Pipeline (Data Split)

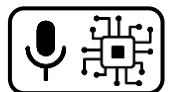
- Training Set 
 - Model learns from this data
- Validation / Development Set 
 - Used to fine-tune the model (hyper)parameters
 - Model occasionally sees but does not learn from this data
- Test set 
 - Only used once after the model training & tuning is completed
 - Should reflect the targeted real-world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



Machine Learning

Machine Learning 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 (from acoustic condition monitoring) → include different motor engine types & conditions, recording locations, microphones, ...
- Data cleanup / pre-processing
 - Remove errors, silence, empty files, ...
 - **Balance** dataset (proportions among class examples)
 - **Normalize** (depends on the model)



Machine Learning

Machine Learning 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)
- Feature pre-processing depends on model type
- Use simple models for simple tasks

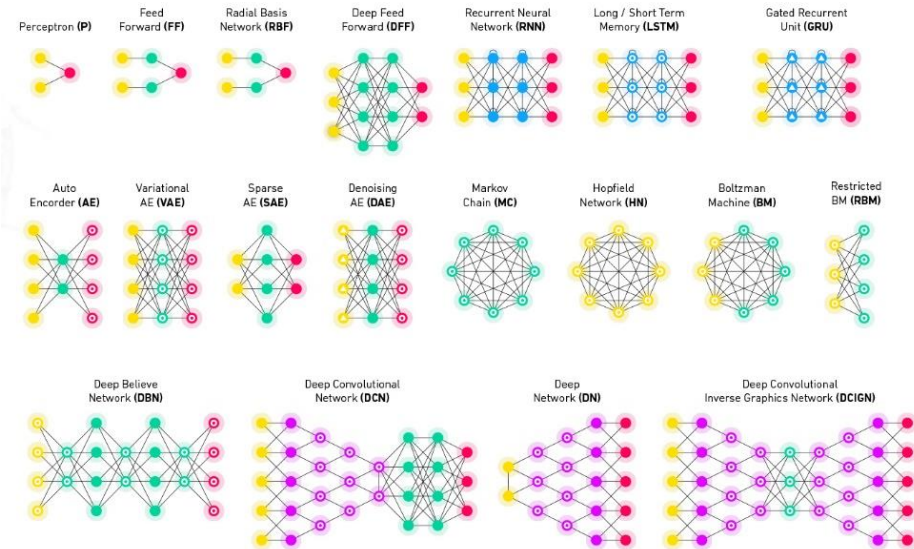
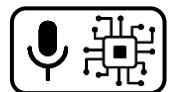


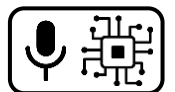
Fig-D1-2



Machine Learning

Machine Learning Pipeline (Model Training)

- Iterative process
 - (Random) parameter initialization
 - Use (**batches** of) training data to iteratively improve model predictions (optimization)
 - Learn from examples
 - Update model parameters according to loss function
 - Monitor improved performance
 - Repeat until convergence



Machine Learning

Machine Learning Pipeline (Model Validation)

- Regular model evaluation each or multiple training iteration
 - Optimize model (hyper)parameters
 - Detect overfitting on training data
 - Stop the training

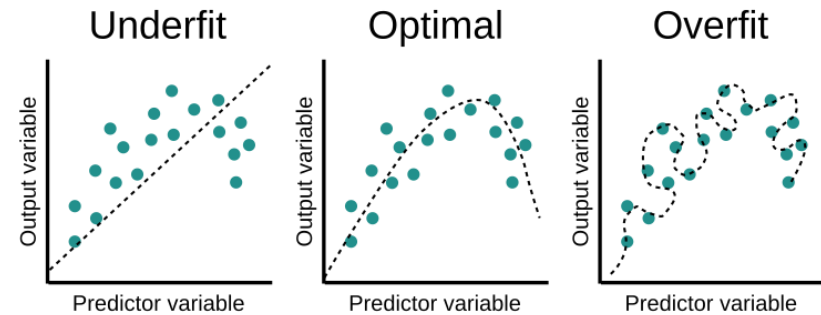
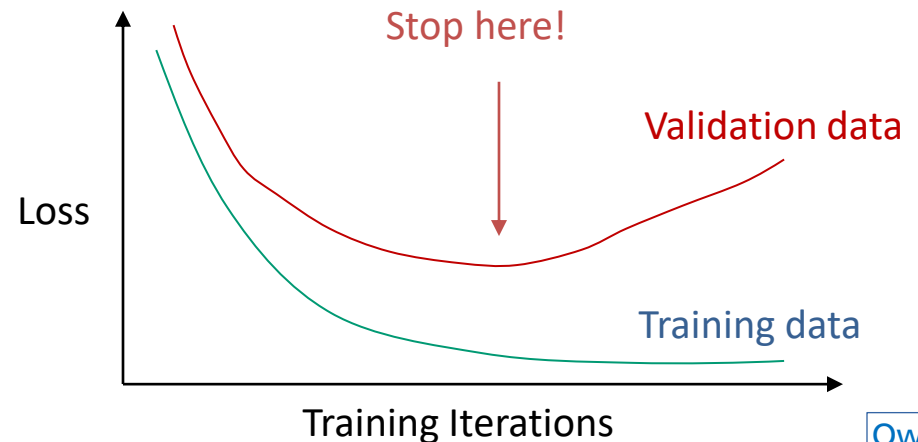
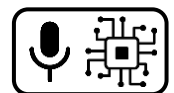


Fig-D1-3



Own



Machine Learning

Machine Learning Pipeline (Model Testing)

- Example: Binary classification evaluation
 - True/false positives (TP/FP)
 - True/false negatives (TN/FN)
 - Metrics
 - Precision
 - Recall
 - Accuracy
 - F-score

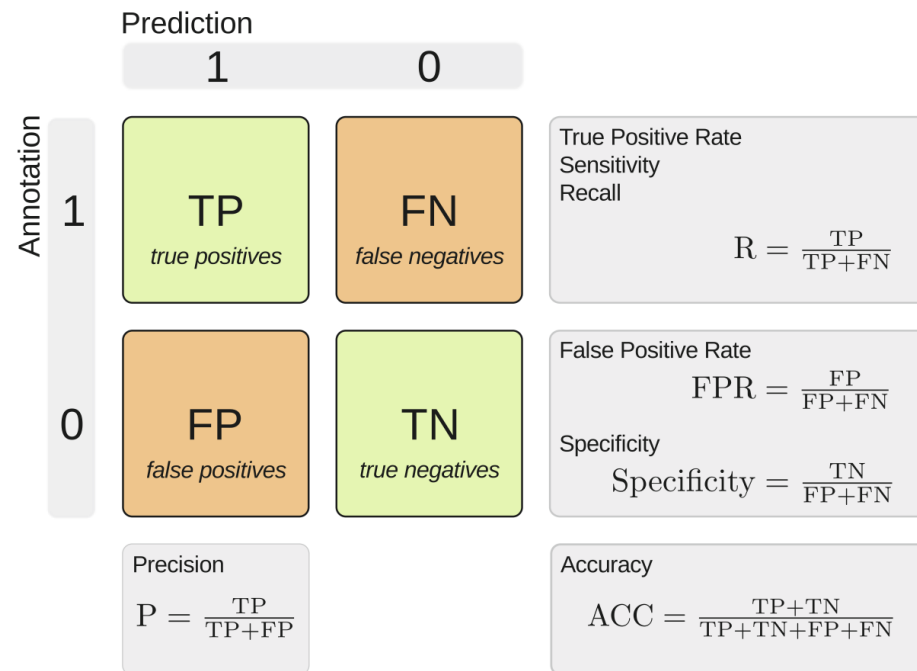
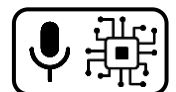


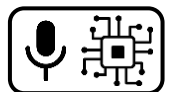
Fig-D1-4



Programming session



Fig-A2-13



References

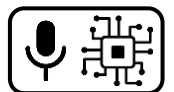
Images

Fig-D1-1: <https://i.stack.imgur.com/hsiIO.png> (https://scikit-learn.org/stable/auto_examples/classification/plot_classifier_comparison.html)

Fig-D1-2: Neural Network Zoo (<https://www.asimovinstitute.org/wp-content/uploads/2019/04/NeuralNetworkZoo20042019.png>)

Fig-D1-3: <https://www.educative.io/api/edpresso/shot/6668977167138816/image/5033807687188480>

Fig-D1-4: Virtanen, T., Plumbley, M. D., & Ellis, D. (Eds.). (2018). Computational Analysis of Sound Scenes and Events. Cham, Switzerland: Springer International Publishing, p. 170, Fig. 6.7



References

References

[1] Introducing Machine Learning. (2016). Retrieved from https://www.mathworks.com/content/dam/mathworks/tag-team/Objects/i/88174_92991v00_machine_learning_section1_ebook.pdf

[2] S. Legg, M. Hutter (2007). Universal Intelligence: A Definition of Machine Intelligence. *Minds & Machines*. 17 (4): 391-444.

[3] L. Samuel (1959). Some studies in machine learning using the game of checkers. *IBM Journal of research and development*. 3(3), 210-229

