

### Machine Learning

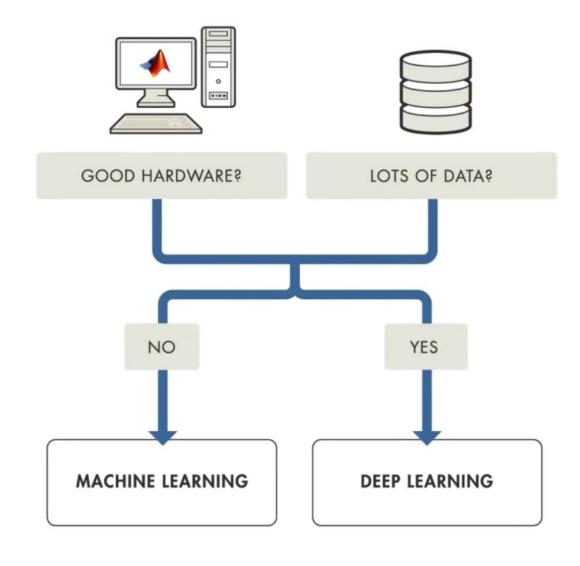
# MACHINE LEARNING VS. DEEP LEARNING RECAP

Cigdem Beyan

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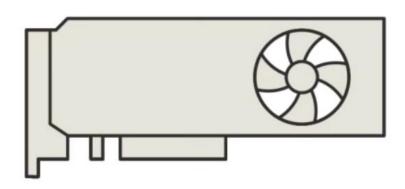
### ML VS DL





### ML VS DL

# High-Performance Computing



Big Data





# ML VS DL (IN A NUTSHELL)

	Machine Learning	Deep Learning
Training dataset	Small	Large
Choose your own features	Yes	No
# of classifiers available	Many	Few
Training time	Short	Long



#### Data Dependency

- ML: Performs well with smaller datasets (100s to 1000s).
- **DL:** Requires larger datasets (tens of thousands to millions of samples) due to high complexity and vast number of parameters

#### Feature engineering

- **ML:** Relies on manual feature extraction and selection. When there is the ability to craft meaningful features using domain knowledge.
- **DL:** Automatically performs feature extraction vis hidden layers in neural networks, with no need for manual feature engineering. Better in complex data such as images, videos or audio.



#### Computational resources

- ML: Less computational intensive. Can run efficiently on CPUs
- **DL**: Highly resource-intensive, requires GPUs

#### Model Interpretability

- **ML:** Often interpretable such as decision trees, linear regression, or logistic regression.
- **DL:** Often Black box. Requires other techniques like LIME, and SHAP to perform interpretability.

#### Training time

- **ML:** Faster to train
- **DL:** Slower to train.



#### Problem Complexity

- **ML:** To be used for problems that do not require complex representations.
- **DL:** Good for complex data structures where hierarchical or abstract feature representation is necessary

#### Flexibilitiy

- **ML:** more flexible across a wider range of tasks. With a minor adjustment, the same algorithm can be applied to regression, and classification.
- **DL:** Specialized in specific architectures tailored to the task at hand. E.g., CNNs for image data, RNNs or Transformers for sequential data.



#### Scalability

- **ML:** Struggle with scalability. When the data size grows significantly, training time may increase disproportionately
- **DL:** The performance of deep models improves significantly with more data



# RECAP



### WHAT HAVE WE SEEN?

- A structured presentation (not in the order of our course schedule)
- **Basics:** Definition of machine learning, types of machine learning (supervised, unsupervised), applications, error function, regularization, overfitting/underfitting
- **Data cleaning:** Categorical data to numeric data, missing values, data cleaning, outlier removal, feature normalization, dimensionality reduction (e.g., PCA), feature selection (regression-based, forward feature selection)
- **Model evaluation:** Train/validation/test split, cross-validation, metrics for regression, classification, clustering, grid search for parameter selection



### WHAT HAVE WE SEEN?

- Supervised Learning (Linear Models): linear regression, L1/L2 regression, logistic regression, linear SVM, perceptron, etc.
- **Supervised Learning (Instance-based):** K-NN, distance metrics, and their impact on performance
- Supervised Learning (Decision trees) and Ensemble Learning: CART algorithm, pruning, entropy, information gain, random forest, bagging, boosting, AdaBoost
- **Support Vector Machines:** Large Margin classifiers, SVM for binary classification, kernel trick for non-linear classification, regularization, and the role of C parameter



### WHAT HAVE WE SEEN?

- **Unsupervised Learning Clustering:** K-means, hierarchical clustering, DBSCAN, etc. evaluation metrics (silhouette score, Davies-Bouldin index...)
- **Unsupervised Learning Dimensionality Reduction:** PCA, Fisher Discriminant, t-SNE
- **Probabilities Models:** Naïve Bayes, Gaussian Mixture Models, Hidden Markov Models

