Chap1: Machine Learning in Security: An Overview #2

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Chap 1: An Overview of Machine Learning in Security: Topics

- Introduction to the Course Contents, Review of the Basic Machine Learning Concepts. Foundations of Machine Learning for Security: Artificial Intelligence and Machine Learning.
  Review of the ML techniques. Machine Learning problems viz. Classification, Regression, Clustering, Association rule learning, Structured output, Ranking. Linear Regression. Logistics Regression and Bayesian Classification. Support Vector Machines, Decision Tree and Random Forest, Neural Networks, DNNs , Ensemble learning. Principal Components Analysis. Un-supervised learning algorithms: K-means for clustering problems, K-NN (k nearest neighbours). Apriori algorithm for association rule learning problems. Generative vs Discriminative learning. [4 hours]

An Overview of ML tasks

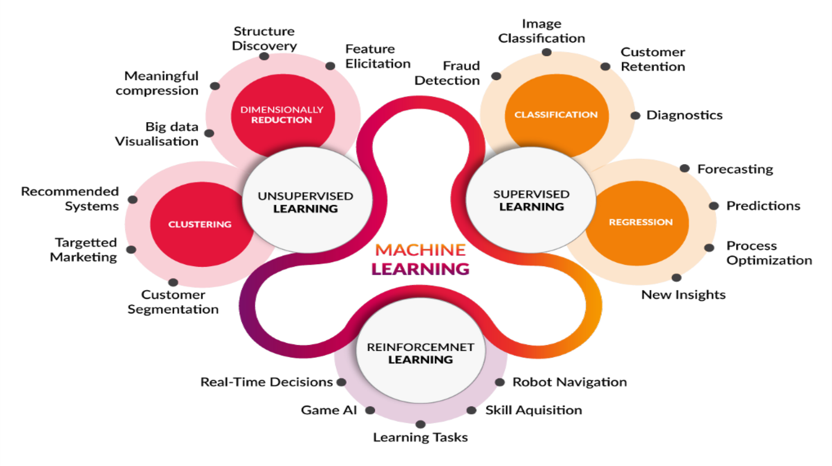
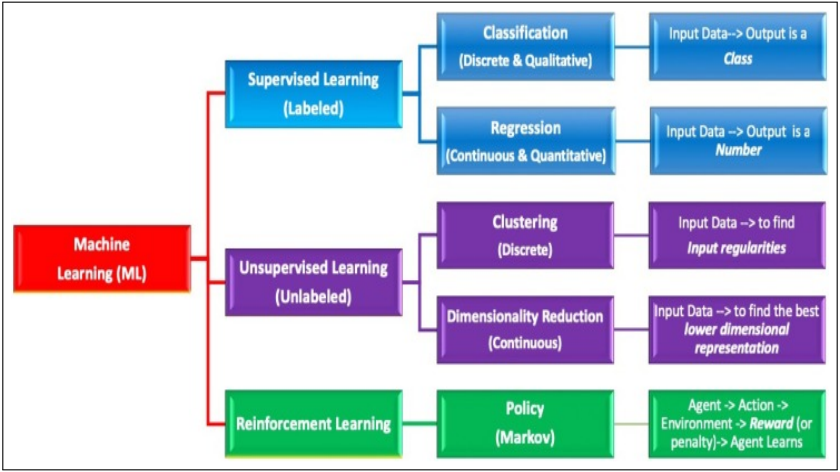


Figure: Machine Learning

Machine Learning...



1 Figure: Machine Learning Techniques w r to input and output

[1] Hooman Rashidi: Academic Pathology, Sept 2019

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- Thus, a classification task results in the model which, given a new individual, determines which class that individual belongs to.

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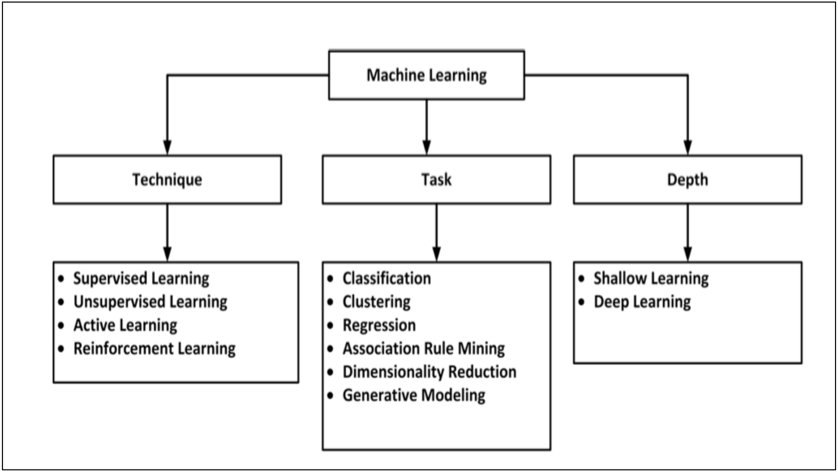

Figure: Machine Learning - Tasks, Techniques & Depth

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[1] Olakunle Ibitoye et al

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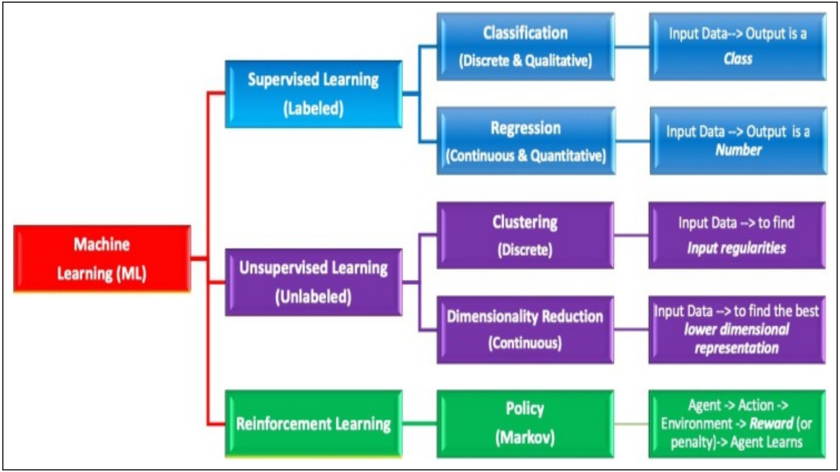
Machine Learning Tasks Dimensions... reviewed again



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    - e.g. determine the impact of gold prices, prices of crude oil etc on the inflation. Similarly, the analysis in sectors like insurance, agriculture, finance, investing.

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- Then, the ML can use the equation $y = a + bx$. (with known values of a and b) to make predictions.

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- Assignment: With the help of an example, explain the differences between similarity matching, classification, co-occurrence grouping and multi variate querying

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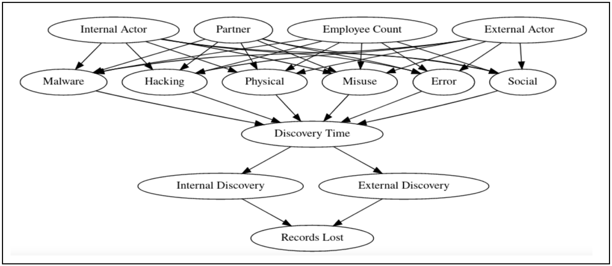
  - Causal Inference. is the process of drawing a conclusion about a causal connection based on the conditions of the occurrence of an effect

Causal modeling in Cyber Security

- in this research attempt[1], the characteristics of the VERIS Community Database (VCDB) were studied



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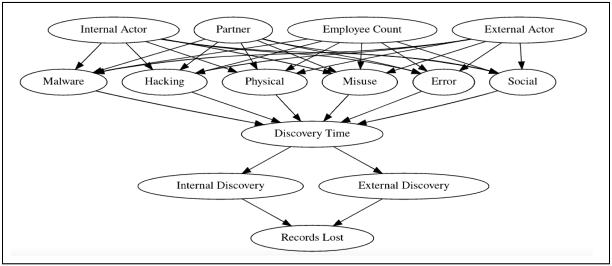

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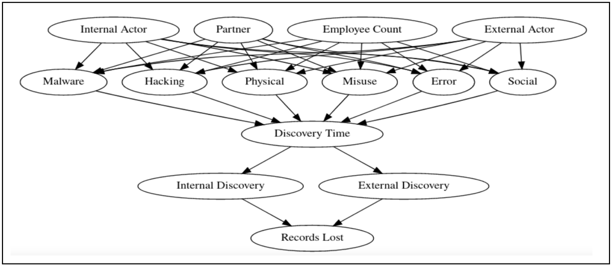

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- research is done with dimensionality reduction analysis (DRA) to cyber security where relevant features for threat detection are ranked and identified - reduced to improve the response time.

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- For example, if we have a dataset of images of animals, we can use synthesis to generate new images of animals that are similar to the ones in the dataset.

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- For example, if we have a dataset of images of animals, we can use synthesis to generate new images of animals that are similar to the ones in the dataset.

Sampling can be used

- to select a subset of data that is representative of the entire dataset.
- For example, if we have a dataset of images of animals, we can use sampling to select a subset of images that represents all the different animal types in the dataset.

An Overview of ML tasks: Anomaly detection

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- can be performed using a variety of ML models, such as density-based methods, cluster-based methods, and rule-based methods. Therefore, it is is important to select the right model for the particular application

An Overview of development phases in ML models

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   - one can check if the dataset contains missing data and the ways to handle those.

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   - For instance, we can plot scatter plots to investigate the relationships between the features and the target variable.

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3. after building the models, one needs to evaluate models using different metrics
4. select the best-performing model for deployment.

An Overview ML models development phases: Data Gathering

- Any ML problem requires a lot of data for training/testing purposes.
- Identifying the right data sources and gathering data from these data sources is the first step in ML development cycle
- Data could be found from databases, external agencies, the internet, etc.

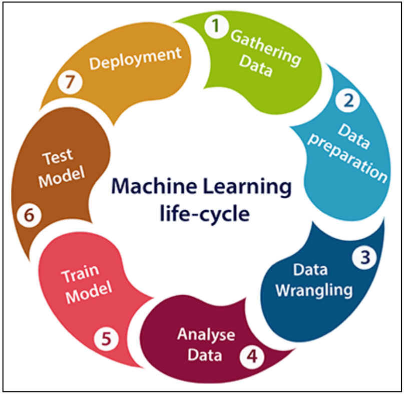


Figure: ML Development Life Cycle

- Before starting training the models, it is of utmost importance to prepare data appropriately.
- As part of data preprocessing, some of the following tasks may be required
  - Data cleaning requires one to identify attributes having not enough data or attributes which are not have variance. These data (rows and columns) need to be removed from the training data set.
  - Missing data imputation using data imputation techniques such as replacing missing data with mean, median, or mode.

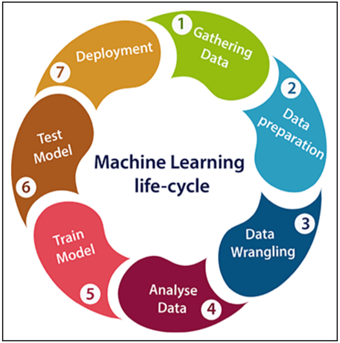


Figure: ML Development Life Cycle

An Overview ML models development phases: Exploratory Data Analysis (EDA)

- Once data is preprocessed, the next step is to perform exploratory data analysis.
- this is done to understand data distribution and relationships between/within the data.
- Some of the following are performed as part of EDA:
  - Correlation analysis
  - Multicollinearity analysis
  - Data distribution analysis

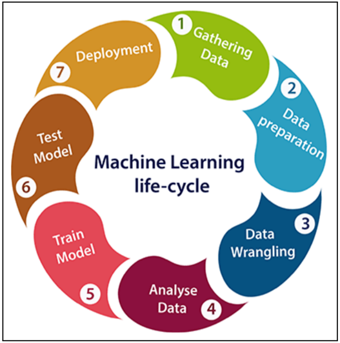


Figure: ML Development Life Cycle

- is one of the most critical tasks when building machine learning models
- this is so because not only would it help build models of higher accuracy but also help achieve objectives related to building simpler models, reducing overfitting etc.
- includes tasks such as
  - deriving features from raw features,
  - identifying important features,
  - feature extraction and feature selection.
- some of the techniques used for feature selection are enlisted on the next slide.

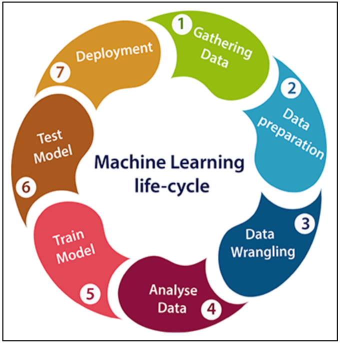


Figure: ML Development Life Cycle

An Overview ML models development phases: Feature Engineering...

The following are some of the statistical tests used in feature engineering:

- Pearson's correlation
- Linear discriminant analysis (LDA)
- Analysis of Variance (ANOVA)
- Chi-square tests
- Wrapper methods that use a subset of features.

The following are some of the algorithms used for Wrapper methods that help in feature selection by using a subset of features

- Forward selection
- Backward elimination
- Recursive feature elimination

The following are some of the algorithms used for Regularization techniques that penalize one or more features appropriately to come up with most important features.

- Regularization with classification algorithms such as Logistic regression, SVM, etc.
- Elastic net regularization
- LASSO (L1) regularization
- Ridge (L2) regularization

An Overview ML models development phases: Training Models

- is the step to be followed once the features are determined.
- one of the methods followed is as follows: start with random initial parameter values and then gradually update them by taking small steps until we reach an optimal solution.
- the iterative process helps us reduce error rates over time and ultimately provide better predictions for our target variable.

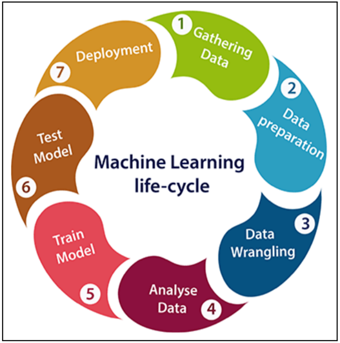


Figure: ML Development Life Cycle

- often, there are multiple models trained using different algorithms.
- hence, it is an important task is to select the most optimal models for deploying them in production.
- Hyperparameter tuning is the most common task performed as part of model selection.
- Also, if there are two models trained using different algorithms which have similar performance, then one also needs to perform algorithm selection.

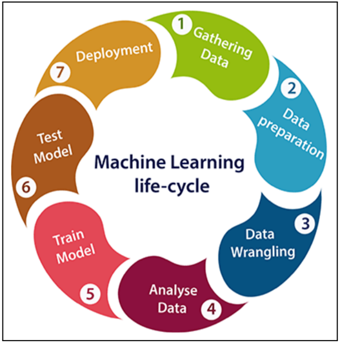


Figure: ML Development Life Cycle

An Overview ML models development phases: Testing and matching

- Testing and matching tasks relate to comparing data sets.
- Following are some of the methods that could be used for such kinds of problems:
    - Minimum spanning tree
    - Bipartite cross-matching
    - N-point correlation

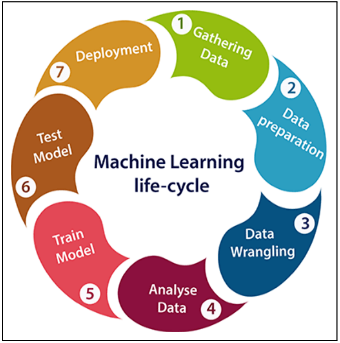


Figure: ML Development Life Cycle

An Overview ML models development phases: Model monitoring

- Once the models are trained and deployed, they require to be monitored at regular intervals.
- Monitoring models require the processing actual values and predicted values and measuring the model performance based on appropriate metrics.

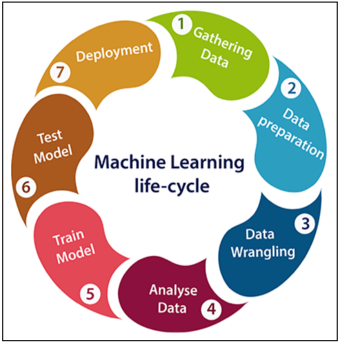
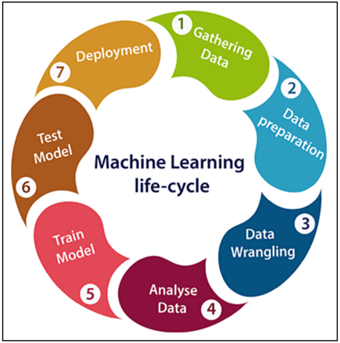


Figure: ML Development Life Cycle

- This is to be applied in case, the model performance degrades,
- the models subsequently required to be retrained.
- The following gets done as part of model retraining:
  - New features get determined
  - New algorithms can be used
  - Hyperparameters can get tuned
  - Model ensembles may get deployed



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Neural network

- is a more general term for this type of layered statistical learning architecture that might or might not be *deep* (i.e., have many layers).

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