Learning in Intelligent Systems

Artificial Intelligence @ Allegheny College

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Overview of Learning

Learning in Humans

- The act / process of acquiring, modify or reinforcing knowledge or skills through synthesizing different types of new or existed information.

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- Progress over time tends to follow learning curves (relatively permanent).

Learning in Computing Systems

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- Experience – data driven task.
- Computer science – involves learning algorithms, analysis of complexity, and theoretical guarantees.

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Artificial intelligence | Machine learning

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- Computer program(s) with adaptive mechanisms that enable computer / machine to learn from experience /example / analogy / rewards.

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Artificial intelligence | Machine learning

- Computer program(s) with adaptive mechanisms that enable computer / machine to learn from experience /example / analogy / rewards.
- It improves the performance of an intelligent system over time (e.g, reducing error rate, improving rewards).

Why Learning in Computing Systems?

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- Fill in skeletal or incomplete knowledge / expert specifications about a domain.

Applications of Learning

Mainly in decision making / pattern recognition / intelligent systems.

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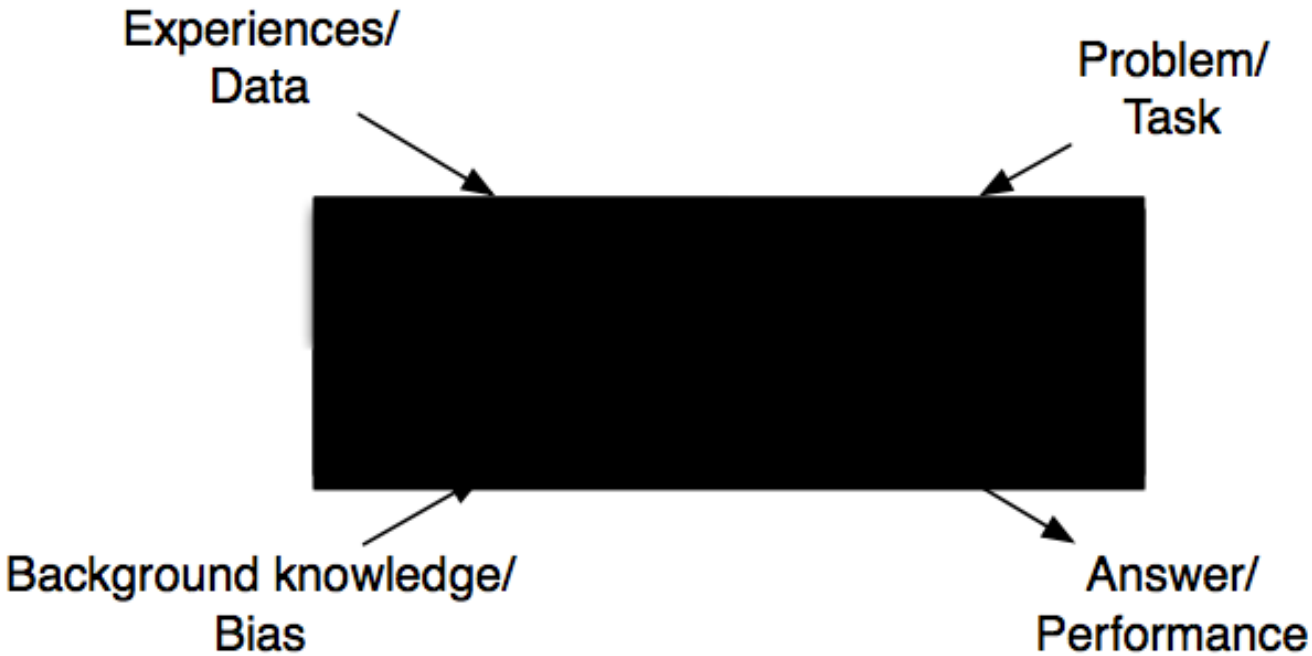
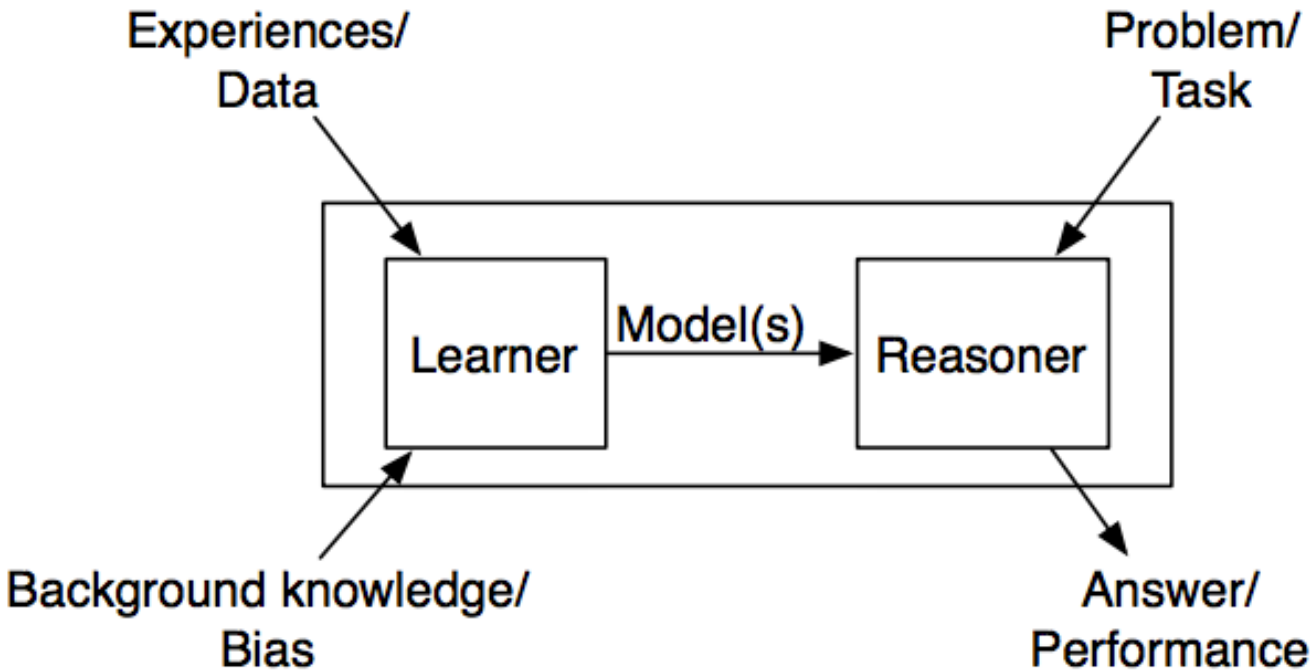
- Robot navigation.
- Automatic speech recognition (Siri in iPhone, Google speech-to-text search).
- Search and recommendation (Google, Amazon, eBay).
- Financial prediction, fraud detection, medical diagnosis.
- Video games, data visualization.

Black-box Learning



Learning Architecture



Learning Paradigms

- **Supervised learning**
  - input-output relationships

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  - relationship among inputs
- **Reinforcement learning**
  - input-action relates to rewards / punishment

Supervised Learning

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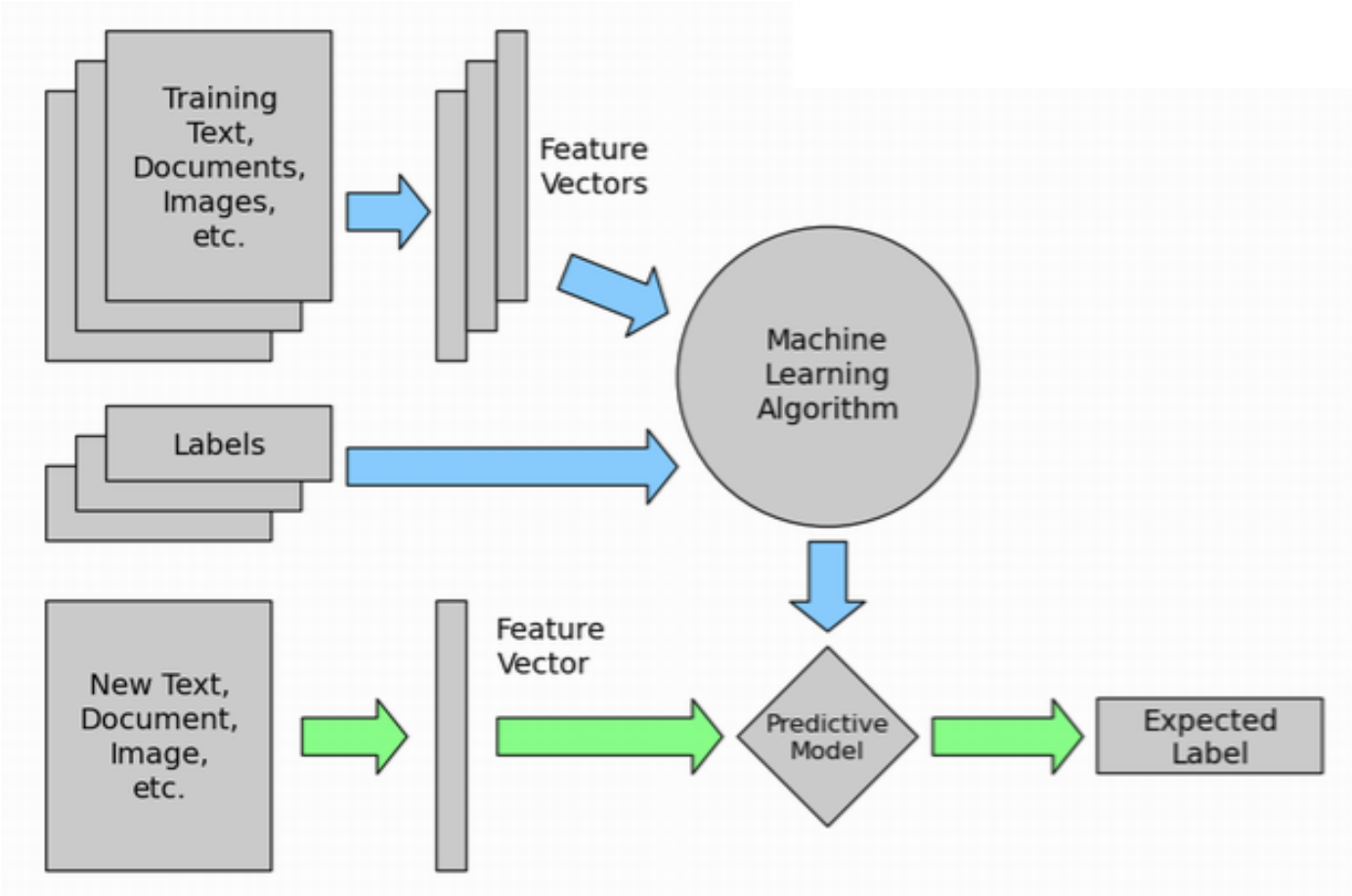
Tasks:

- Classification (categorizing output: correct class)
- Regression (continuous output to predict output based for new inputs)
- Prediction (classify / regression on new input sequences)

Supervised Learning



Unsupervised Learning

Given only inputs and automatically discover representations, features, structure etc.

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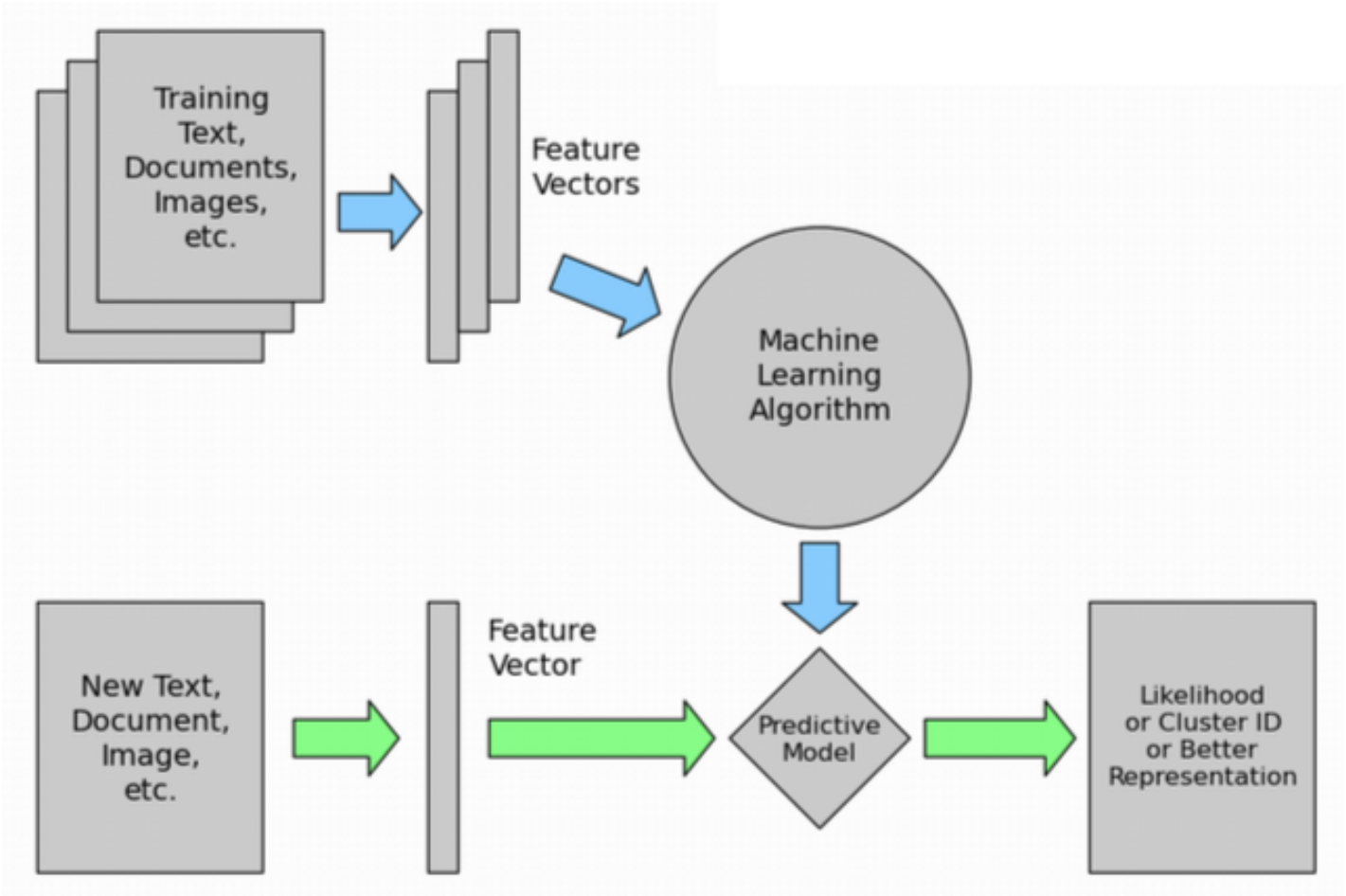
Tasks:

- Clustering (to group similar data into a finite number of clusters / groups)
- Vector Quantization (compress / decode dataset into a new representation but maintaining internal information)
- Outlier Detection (select highly unusual cases/sequences)

Unsupervised Learning



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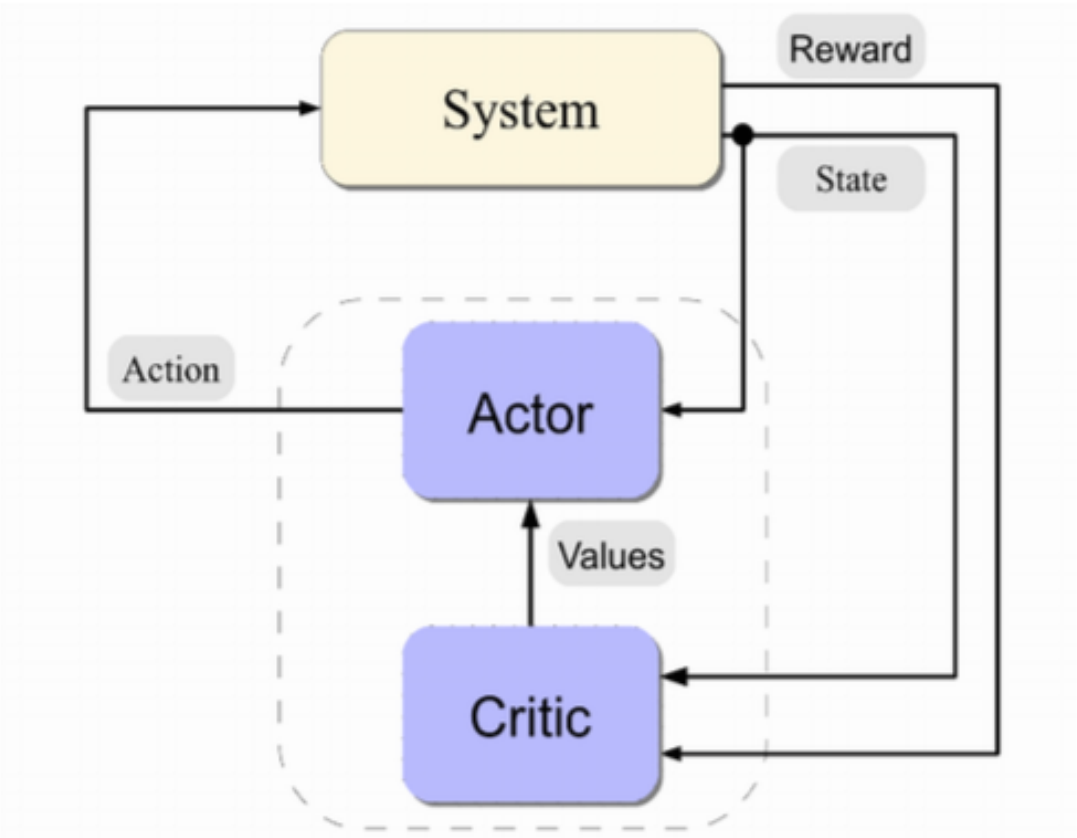
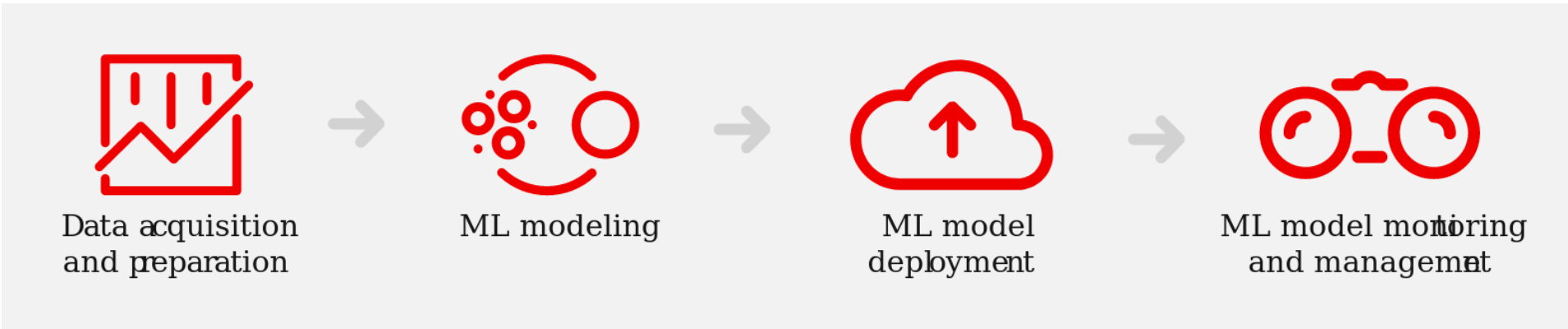
- Consider teaching a domestic animal. We cannot tell it what to do, but we can reward / punish if it does the right/ wrong thing.
- Process to determine what it did that made it get the reward / punishment – "credit assignment problem."

Reinforcement Learning



Learning Lifecycle



https://www.openshift.com/

Activity 5: Algorithmic Bias

Google Search

Supervised Learning

Supervised Learning: Performance Measures

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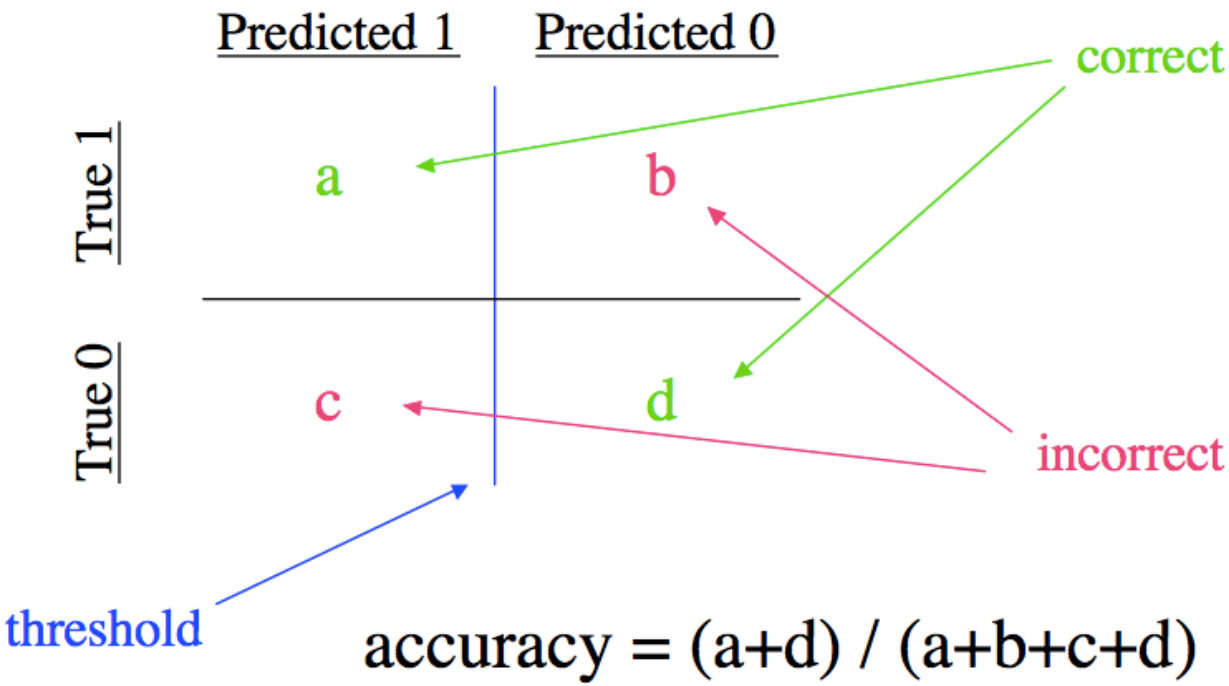
- **Discrimination** attempts to separate distinct sets of objects.
- **Classification** attempts to allocate new objects to predefined groups.

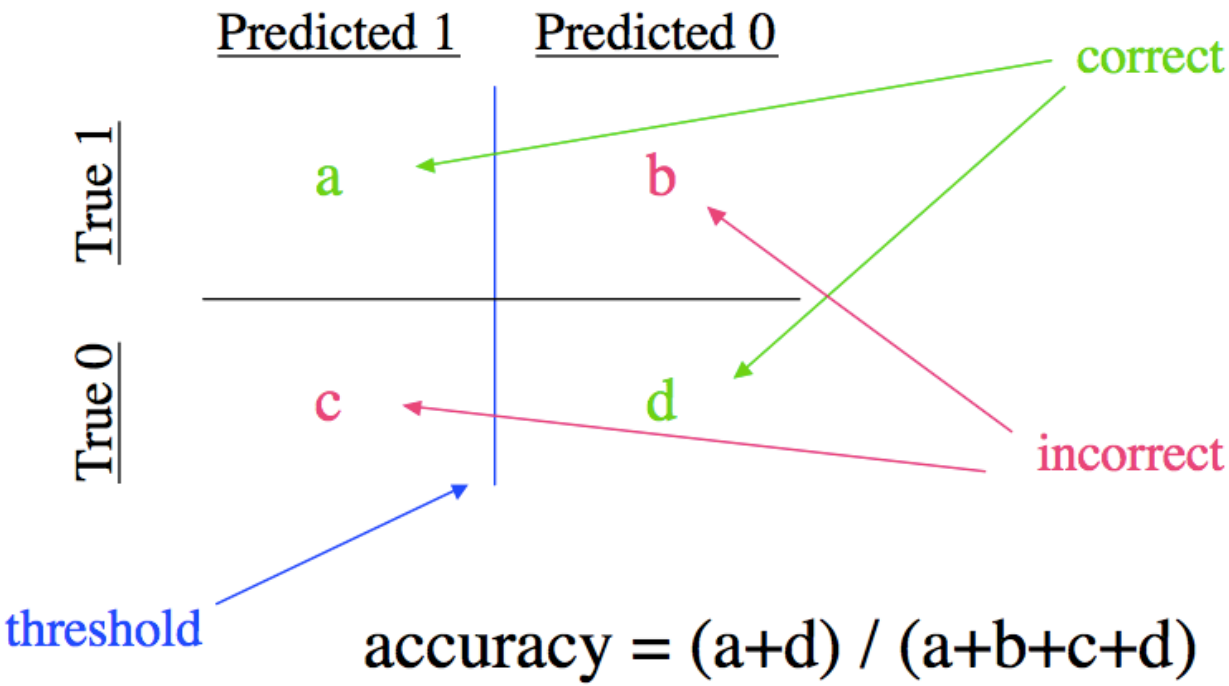
Performance Measures

- **Cost ratio** is a ratio of *false positives* (given condition is present when it is not) to *false negatives* (given condition is not present when it actually is).
- **Confusion matrix** (error matrix): a table to visualize the performance of an algorithm with rows/columns representing instances of predictions and columns/rows representing instances of actual class.

Confusion Matrix



Confusion Matrix



- a is a *true positive (TP)*.
- d is a *true negative (FN)*.
- c is a *false positive (FP)*.
- b is a *false negative (FN)*.

Classification Accuracy

Number of correctly classified examples divided by the total number of examples.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

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$$Error = 1 - Accuracy \tag{2}$$

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Higher the recall the better class is correctly recognized (small number of FN).

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$$Precision = \frac{TP}{TP + FP} \tag{4}$$

Higher the precision the better indication of an example labeled as positive being indeed positive (small number of FP).

Performance Measures

- High recall, low precision: Most of the positive examples are correctly recognized (low FN) but there are a lot of false positives.
- Low recall, high precision: Miss a lot of positive examples (high FN) but those we predict as positive are indeed positive (low FP).

Performance Measures

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$$F1 = 2\frac{Precision * Recall}{Precision + Recall} \tag{5}$$

F1 Score is used to find a balance between Precision and Recall.

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- ROC Curves summarize the trade-off between the true positive rate and false positive rate for a predictive model using different probability thresholds.
- Precision-Recall curves summarize the trade-off between the true positive rate and the positive predictive value for a predictive model using different probability thresholds.
- ROC curves are appropriate when the observations are balanced between each class, whereas precision-recall curves are appropriate for imbalanced datasets.

What-If Tool

Smile Detection Demo

https://pair-code.github.io/what-if-tool/