# The Machine Learning Landscape

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  For example, Task (T): Flag spam for new emails, Experience (E): Training data of example spam and non-spam emails & Performance (P): Accuracy of spam detection.

# Why Use Machine Learning?

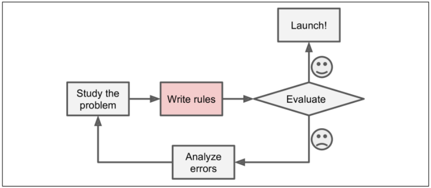


*Figure 1-1. The traditional approach*

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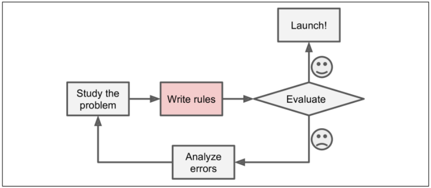


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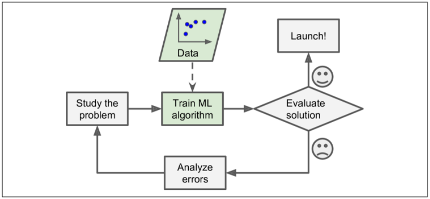


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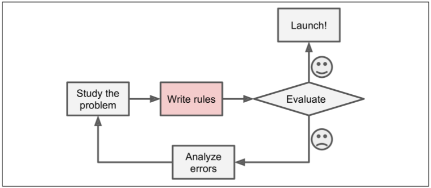


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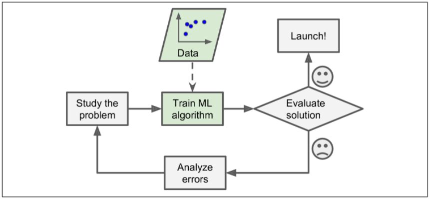


*Figure 1-2. Machine Learning approach*

## ML is Great For:

- Problems requiring lots of hand-tuning or long lists of rules.
- Complex problems with no traditional solution.
- Fluctuating environments (ML systems can adapt).
- Getting insights from large amounts of data (Data Mining).

# Types of Machine Learning Systems

ML systems can be classified based on:

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    - Unsupervised
    - Semisupervised
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   - Online Learning
3. **Generalization Strategy:** Whether they work by simply comparing new data points to known data points, or instead detect patterns in the training data and build a predictive model, much like scientists do.
   - Instance-Based Learning
   - Model-Based Learning

# 1. Human Supervision: Supervised Learning

## Core Concept

The training data fed to the algorithm includes the desired solutions, called **labels**. The system learns from a "teacher."

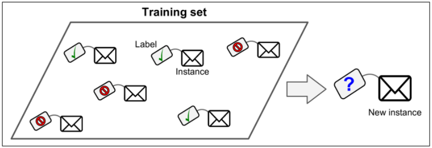


*Figure 1-5. A labeled training set for supervised learning (e.g., spam classification)*

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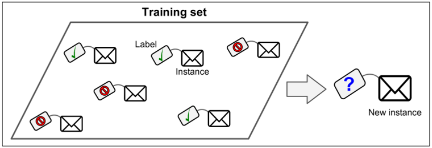


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*Figure 1-6. Regression*

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- Predicts a class or category.
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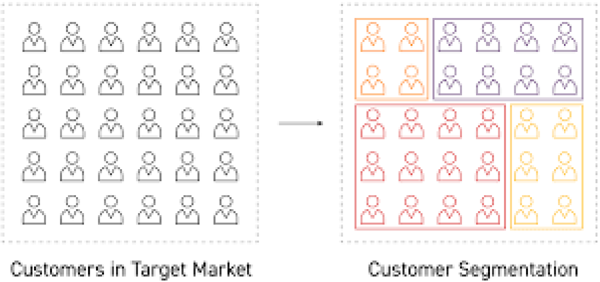
### Common Algorithms

k-Nearest Neighbors, Linear Regression, Support Vector Machines (SVMs), Decision Trees & Random Forests, Neural Networks.

# 1. Human Supervision: Unsupervised Learning



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- **Dimensionality Reduction:** Simplify data by merging correlated features.
  - *Example:* Combining a car's age and mileage into a "wear and tear" feature.
- **Association Rule Learning:** Discover interesting relations between attributes.
  - *Example:* Discovering that customers who buy barbecue sauce also tend to buy steak.

# 1. Human Supervision: Other Methods

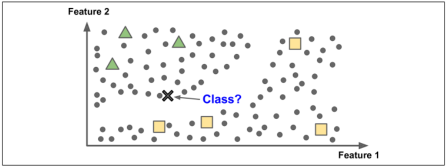

*Figure 1-11. Semisupervised learning*

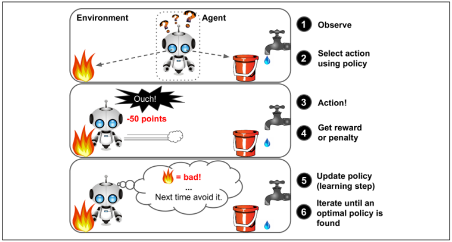

*Figure 1-12. Reinforcement Learning*

# 1. Human Supervision: Other Methods

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Deals with partially labeled data: mostly unlabeled data with a small amount of labeled data.

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## Reinforcement Learning

An **agent** learns by performing actions and getting rewards or penalties. It learns the best strategy (**policy**) to maximize its reward over time.

- **Example:** A robot learning to walk, or DeepMind's AlphaGo learning to play Go.

# 2. Learning Method: Batch vs. Online

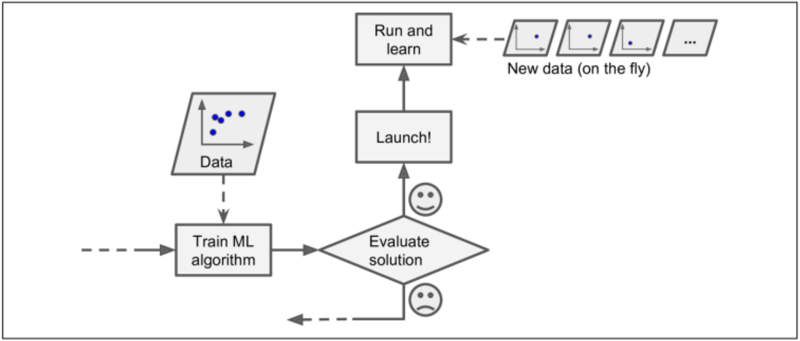


*Figure 1-13. Online learning*

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- Trains the system by feeding it data instances sequentially (or in mini-batches).
- Learns about new data on the fly.
- Great for systems with continuous data flow (e.g., stock prices).
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**Challenge with Online Learning**

Performance can decline if bad data is fed to the system.

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The true goal of ML is to perform well on **new instances** it has never seen before. This is called **generalization**.

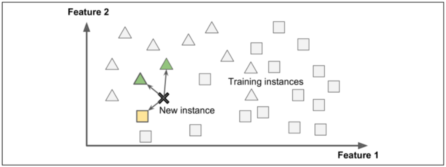


*Figure 1-15. Instance-based learning*

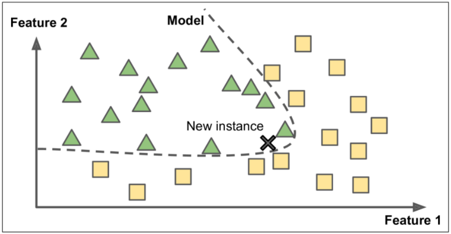


*Figure 1-16. Model-based learning*

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- Generalizes to new cases using a **similarity measure**.
- **Example:** k-Nearest Neighbors. To predict a new instance, it looks at the 'k' most similar instances in the training data.

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**Model-Based Learning**

- Builds a **model** from the training examples.
- Uses that model to make predictions.
- **Example:** Linear Regression. The algorithm finds the best-fit line (the model) to the data.

# Main Challenges in ML: Bad Data

Your main task is to select an algorithm and train it on data. The two things that can go wrong are "bad algorithm" and "bad data."

## Examples of Bad Data

- **Insufficient Quantity of Training Data:** Most ML algorithms need thousands of examples to work properly.

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- **Irrelevant Features:** "Garbage in, garbage out." The success of an ML project depends on **feature engineering** (selecting, extracting, and creating good features).

# Main Challenges in ML: Bad Algorithm

## Overfitting the Training Data

The model performs well on the training data, but it does not generalize well to new instances.

- **Cause:** The model is too complex relative to the amount and noisiness of the data. It detects patterns in the noise itself.
- **Solutions:**
  - Simplify the model (fewer parameters).
  - Gather more training data.
  - Reduce noise in the data.
  - Constrain the model (**Regularization**).

# Main Challenges in ML: Bad Algorithm

## Underfitting the Training Data

The opposite of overfitting. The model is too simple to learn the underlying structure of the data.

- **Solutions:**
  - Select a more powerful model (more parameters).
  - Feed better features to the algorithm (feature engineering).
  - Reduce the constraints on the model (e.g., reduce regularization).

# Testing and Validating

How do you know how well a model will generalize to new cases?

## Splitting Your Data

Split your data into two (or three) sets:

- **Training Set:** Used to train the model.
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## The Hyperparameter Tuning Problem

If you measure the generalization error multiple times on the test set to find the best model hyperparameters, your model will be tuned for that specific test set and may not perform well on new data.

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## Solution: Validation Set

- Hold out a third set, the **validation set**.
- Train multiple models on the training set.
- Select the best model by comparing performance on the validation set.
- After you have your final model, you perform a single final test on the test set.
- **Cross-validation** is a common technique to avoid wasting too much training data in a single validation set. For example: 10-fold cross validation.

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- The model must find a balance between being too simple (**underfitting**) and too complex (**overfitting**).
- Always evaluate your model's ability to generalize using a holdout test set.

# Questions?

Thank You!