1. Introduction to Machine Learning

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INDIAN INSTITUTE OF TECHNOLOGY PALAKKAD

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Artificial Intelligence (AI)

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- autonomous vehicles, playing games, search engines, online assistants, image recognition in photographs, spam filtering

Machine Learning

study of computer algorithms that improve automatically through experience

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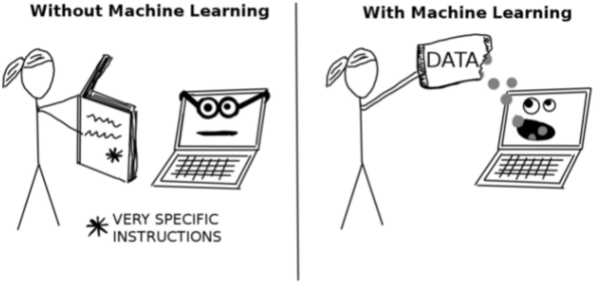

Machine Learning

- "A computer program is said to **learn** from experience `E` with respect to some class of tasks `T` and performance measure `P`, if its performance at tasks in `T`, as measured by `P`, improves with experience `E` " - `Tom Mitchell`

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  - `T` - predict whether an email is spam or not
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  - `P` - (i): *accuracy of prediction* - percentage of correct predictions

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  Here,
  - `T` - predict whether an email is spam or not
  - `E` - collection of spam and non-spam mails
  - `P` - (i): *accuracy of prediction* - percentage of correct predictions
    (ii): *precision* - proportion of true spam mails among those classified as spam

Datasets for machine learning

Attributes

sepal_length	sepal_width	petal_length	petal_width	Iris_class
5	2	3.5	1	versicolor
6	2.2	4	1	versicolor
6.2	2.2	4.5	1.5	versicolor
6	2.2	5	1.5	virginica
4.5	2.3	1.3	0.3	setosa
5.5	2.3	4	1.3	versicolor
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Data point /example

Numerical value

Categorical value

Dataset

Datasets for machine learning

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- table with the data from which a machine learns

Datasets for machine learning

Attributes

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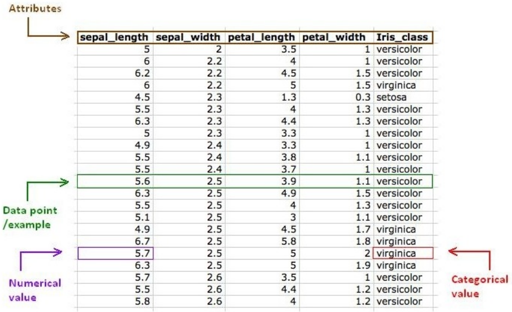
Dataset

- table with the data from which a machine learns
- contains features (columns) and observations (rows)

Datasets for machine learning

Features/Attributes



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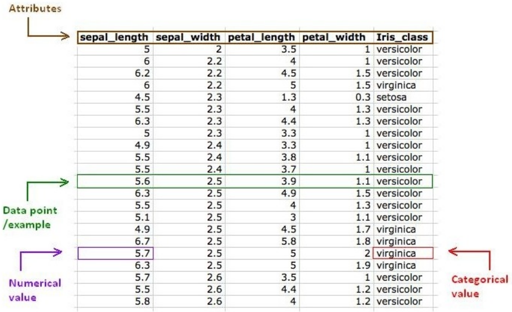

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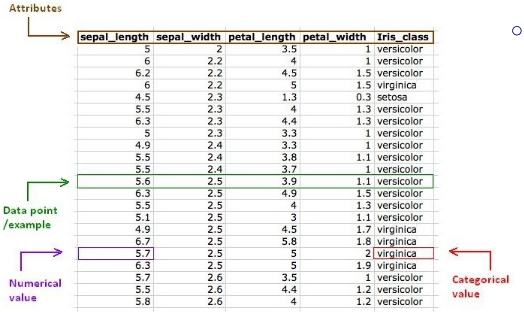
Features/Attributes

- columns in the dataset

Datasets for machine learning



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Datasets for machine learning

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Data point /example

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- gender of a person, grades obtained in a test, etc. are qualitative

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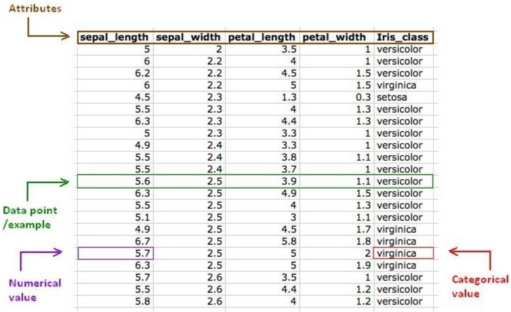

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- height, weight, temperature, etc. are quantitative

Datasets for machine learning

Data points/Observations

Attributes

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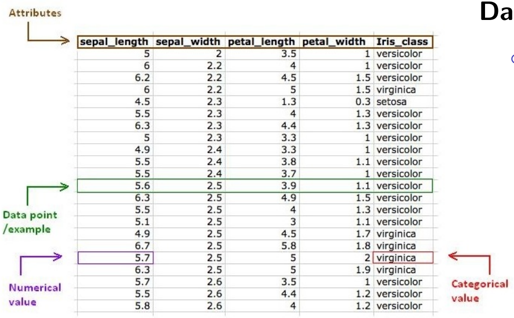
Data point /example

Numerical value

Categorical value

Datasets for machine learning



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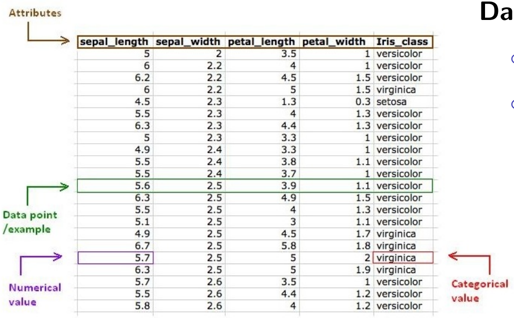
Data points/Observations

- rows in the dataset

Datasets for machine learning



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Data points/Observations

- rows in the dataset
- also called instance or example

Datasets for machine learning

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Data point /example

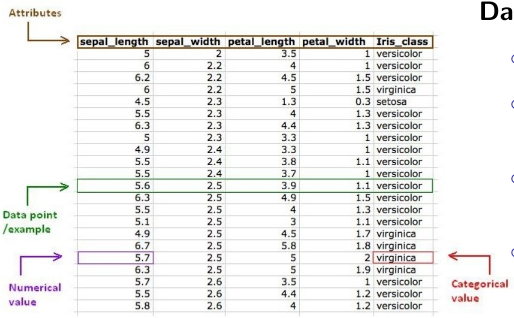
Numerical value

Categorical value

Data points/Observations

- rows in the dataset
- also called instance or example
- describes a single entity or observation

Datasets for machine learning



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5.5	2.4	3.8	1.1	versicolor
5.5	2.4	3.7	1	versicolor
5.6	2.5	3.9	1.1	versicolor
6.3	2.5	4.9	1.5	versicolor
5.5	2.5	4	1.3	versicolor
5.1	2.5	3	1.1	versicolor
4.9	2.5	4.5	1.7	virginica
6.7	2.5	5.8	1.8	virginica
5.7	2.5	5	2	virginica
6.3	2.5	5	1.9	virginica
5.7	2.6	3.5	1	versicolor
5.5	2.6	4.4	1.2	versicolor
5.8	2.6	4	1.2	versicolor

Data points/Observations

- rows in the dataset
- also called instance or example
- describes a single entity or observation
- features describe properties about that observation

Some basic terminology

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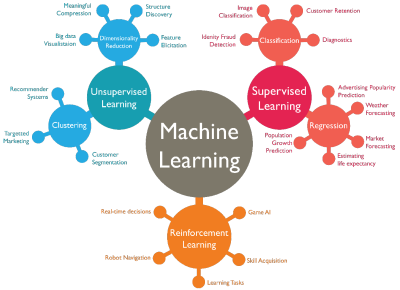
Target or Label

- the value predicted by a machine learning model

Types of machine learning algorithms



Supervised learning

- work on data sets that include its desired outputs (or labels)

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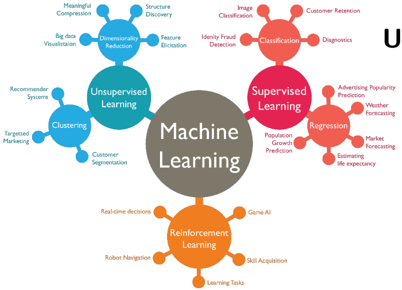

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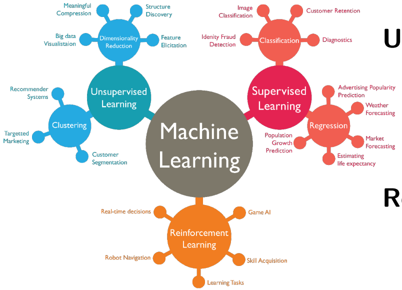

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Reinforcement learning

- algorithms attempt to learn actions that would maximize the reward by continuously interacting with the environment

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Supervised learning problems are categorized into:

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- regression
- classification

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Target value is continuous
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- *Multi-class classification* - three or more classes
  eg:- recognition of handwritten characters, object detection, etc.

Categorize these learning problems!

1. Given a picture of a male/female, predict his/her age based on given picture

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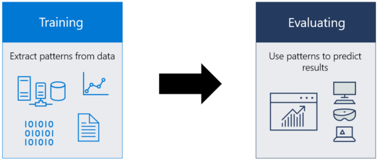

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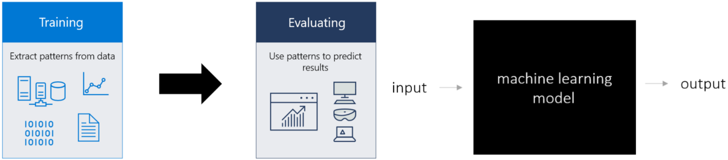

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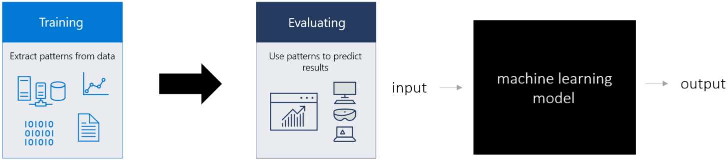

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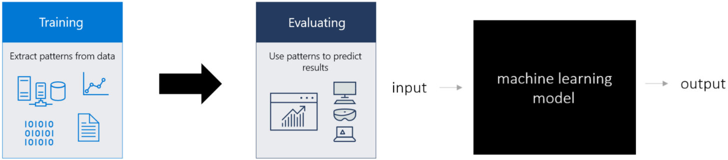

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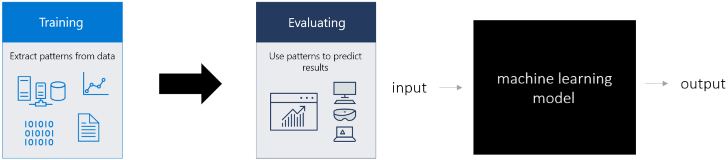

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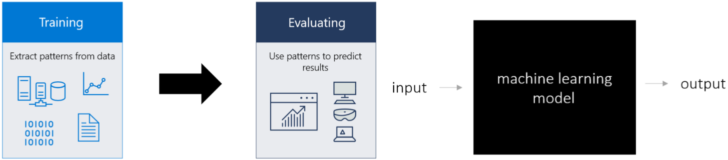

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- for each set of parameter values, we get a different function

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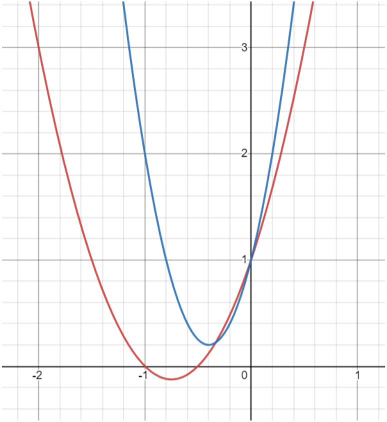

Figure: Plotting the functions $2x^2 + 3x + 1$(red) and $5x^2 + 4x + 1$(blue)

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- The more the data we have, the better the approximation of the target function

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- e is is called irreducible error because no matter how good we get at estimating the target function (f), we cannot reduce this error
- Approximating the target function could also become difficult due to the presence of noisy features

Training and Test datasets

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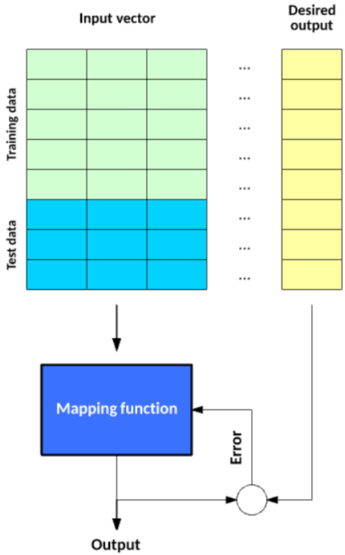

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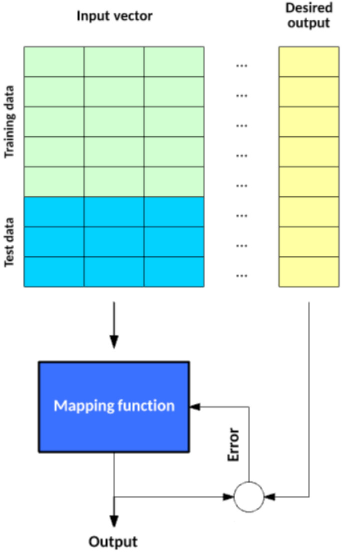

Dataset is segmented into two types of samples:

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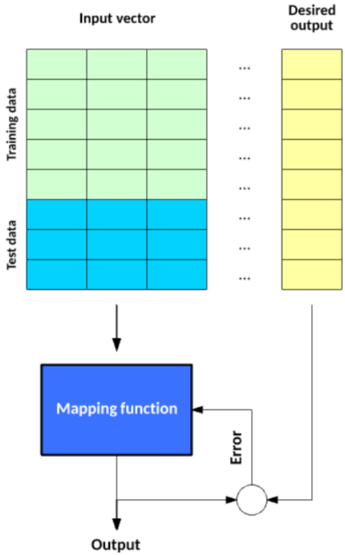

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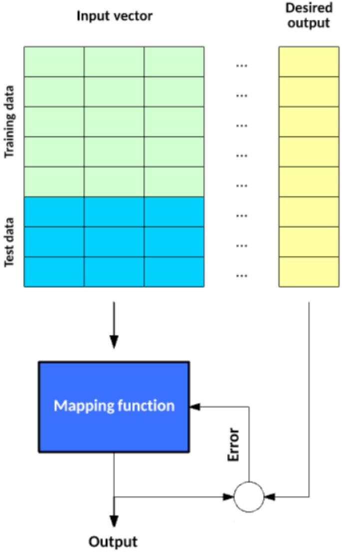

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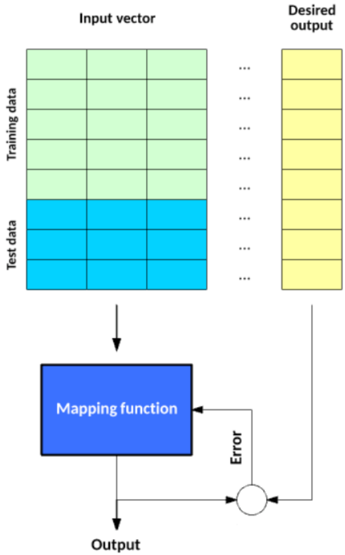

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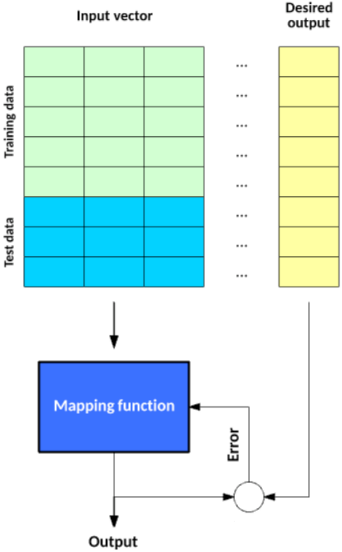

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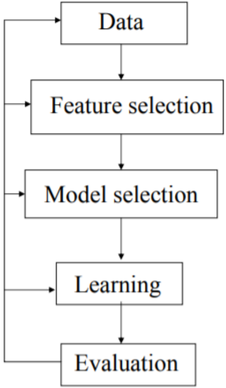
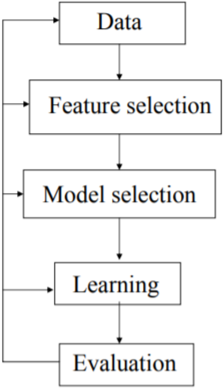
Performance on test data provides a good measure of how well the learned model generalizes to unseen data

Designing a machine learning system



Collecting Data

Designing a machine learning system



Collecting Data

- data can be
  - `structured` - data stored in rows and columns, such as spreadsheets

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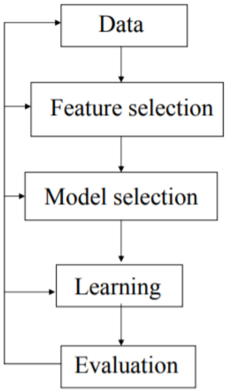

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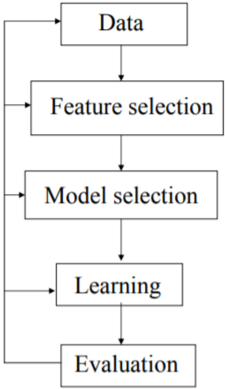

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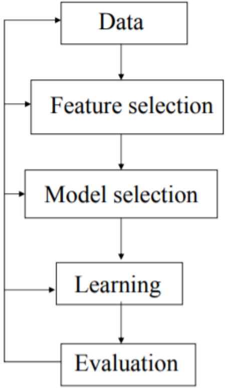

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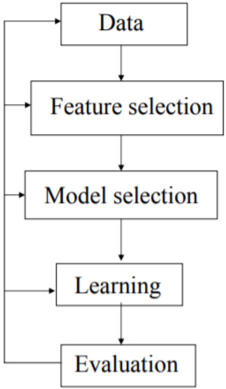

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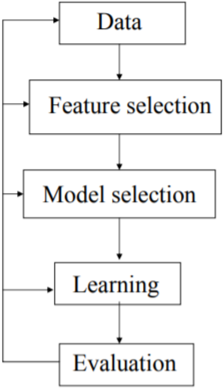

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  - `preprocessing` - rescaling, discretization, etc.

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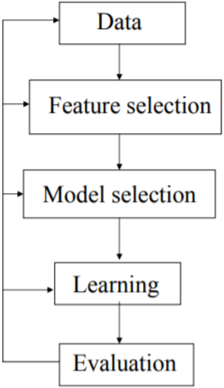
Features



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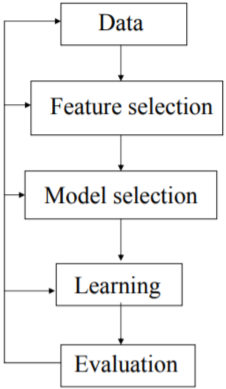

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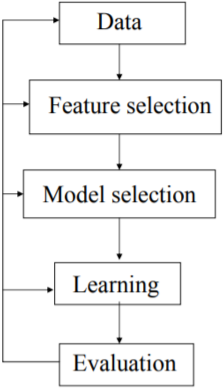

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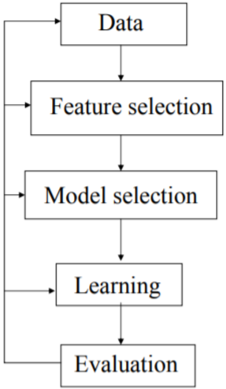
- quality of features have a major impact on model performance

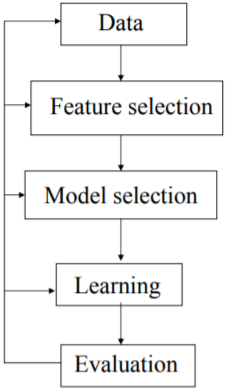
Designing a machine learning system



Features

- also called attributes or variables
  - measurable pieces of data used for analysis
  - appear as columns in structured data sets
- quality of features have a major impact on model performance
- `feature engineering` - generate new features from existing ones (eg:- BMI from height and weight)

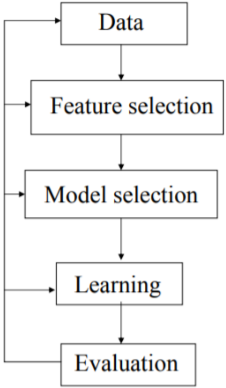
Designing a machine learning system



Features

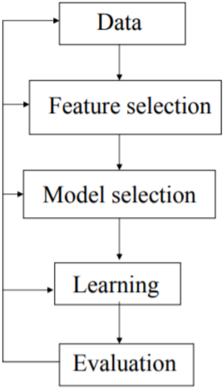
- also called attributes or variables
  - measurable pieces of data used for analysis
  - appear as columns in structured data sets
- quality of features have a major impact on model performance
- `feature engineering` - generate new features from existing ones (eg:- BMI from height and weight)
- `feature selection` - choose features contributing the most to model performance

Designing a machine learning system



Model Selection

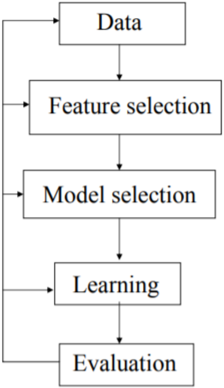
Designing a machine learning system



Model Selection

- selecting the best model from among a collection of candidate machine learning models for the task at hand

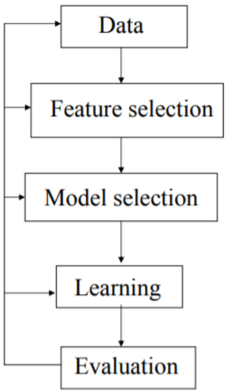
Designing a machine learning system



Model Selection

- selecting the best model from among a collection of candidate machine learning models for the task at hand
- need to select a model that generalizes well on unseen test data points

Designing a machine learning system



Model Selection

- selecting the best model from among a collection of candidate machine learning models for the task at hand
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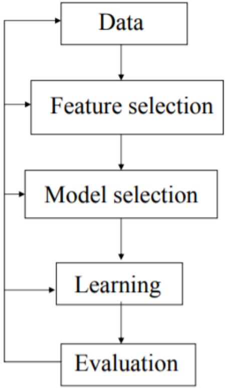
Learning

- using the data to *train* the model

Designing a machine learning system



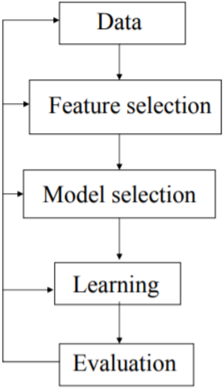
Model Selection

- selecting the best model from among a collection of candidate machine learning models for the task at hand
- need to select a model that generalizes well on unseen test data points

Learning

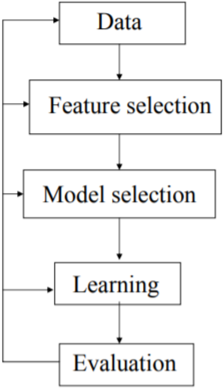
- using the data to *train* the model
- in other words, learning the model parameters from the dataset

Designing a machine learning system



Evaluation

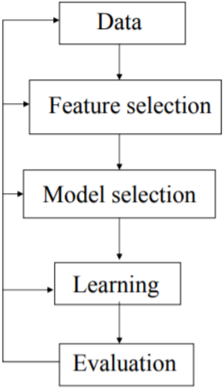
Designing a machine learning system



Evaluation

- measure the performance of the model

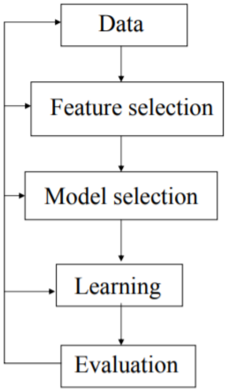
Designing a machine learning system



Evaluation

- measure the performance of the model
- models can be evaluated on multiple metrics
  - eg:- accuracy, precision, etc.

Designing a machine learning system



Evaluation

- measure the performance of the model
- models can be evaluated on multiple metrics
  - eg:- accuracy, precision, etc.
- right choice of an evaluation metric is crucial and often depends upon the problem being solved

References

1. https://en.wikipedia.org/wiki/Artificial_intelligence
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Thanks Google for the pictures!