CS5805 : Machine Learning I
Lecture #1

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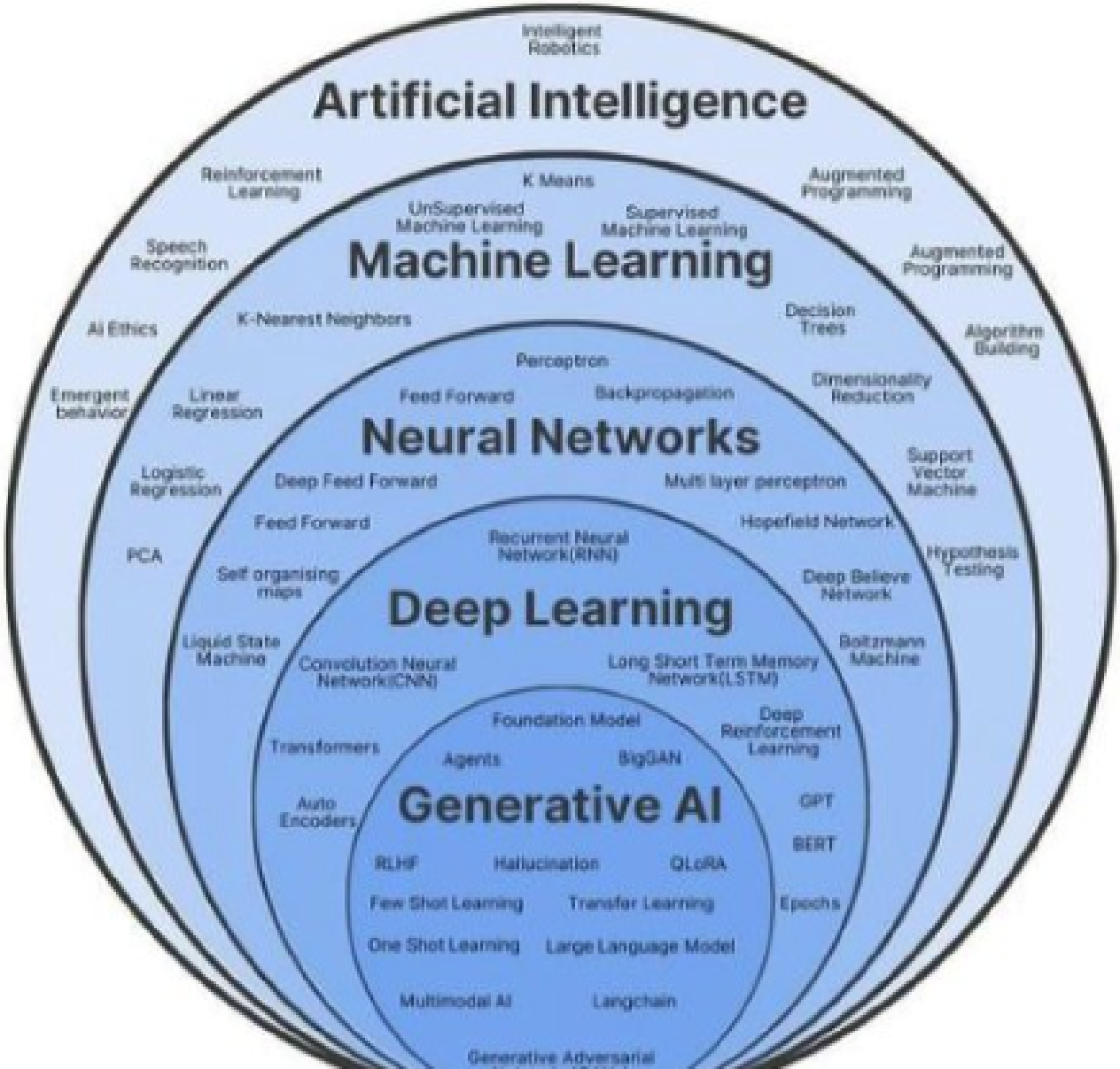
World of Artificial Intelligence



Can you read this?

http://www.mrc-cbu.cam.ac.uk/~mattd/Cmabrigde/ (January 2008)

Aoccdrnig to a rscheearch at Cmabrigde Uinervtisy, it deosn't mttaer in waht oredr the ltteers in a wrod are, the olny iprmoetnt tihng is taht the frist and lsat ltteer be at the rghit pclae. The rset can be a toatl mses and you can sitll raed it wouthit porbelm. Tihs is bcuseae the huamn mnid deos not raed ervey lteter by istlef, but the wrod as a wlohe.

Machine Learning

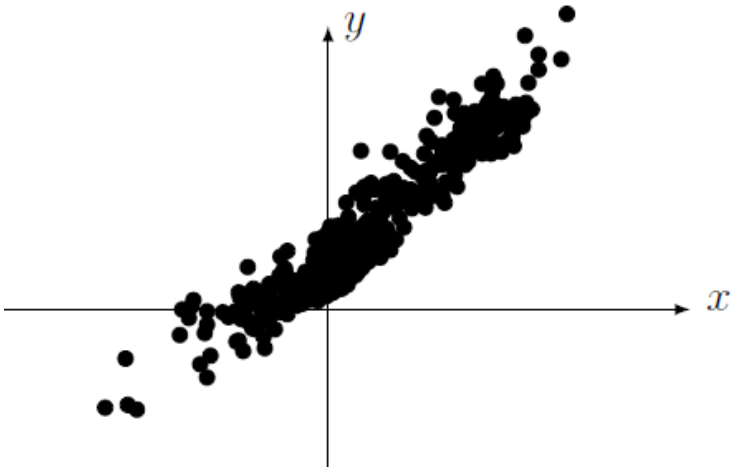
- Imagine looking outside of the window during the morning of a winter day in Finland.
- We can down load the recordings of minimum and maximum daytime temperature for most days

$$\mathbb{D} = \{\mathbf{z}^{(1)}, ..., \mathbf{z}^{(m)}\}$$

Machine Learning

- Each data point $\mathbf{z}^{(i)} = (x^{(i)}, y^{(i)})$ for $i = 1, ..., n$ represents some previous day min and max daytime temperature $x^{(i)}$ and $y^{(i)}$.
- Machine Learning learn a hypothesis $h(x)$ reads min temperature and delivers a prediction $\hat{y} = h(x)$.
- Every practical ML method uses a particular hypothesis space out of which the hypothesis h is chosen.

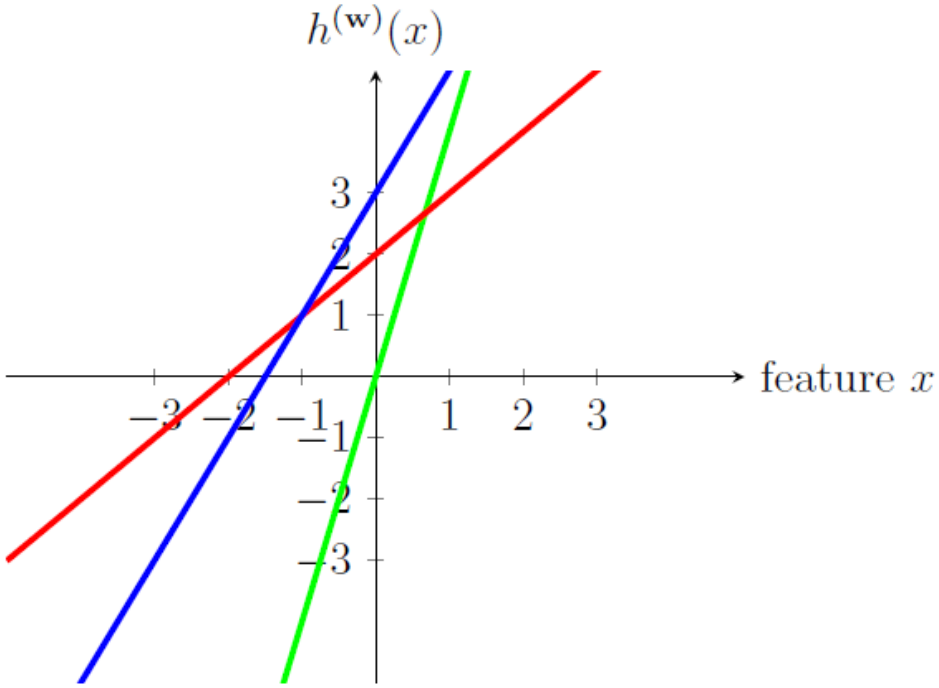
$$\boxed{h(x) := w_1 x + w_0}, w_1 \in \mathbb{R}_+, w_0 \in \mathbb{R}$$



Loss function

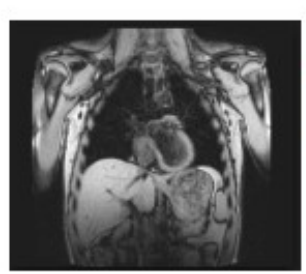
- The loss function quantify the difference between actual data and predicted data.
- Or Mean of Squared of Errors[MSE]

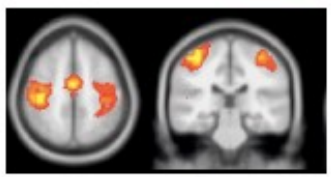
$$(1/n)\sum_{i=1}^{n}(y^{(i)} - h(x^{(i)}))^2$$

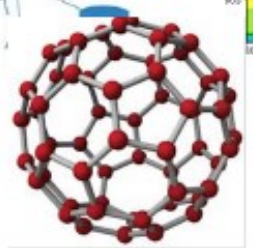


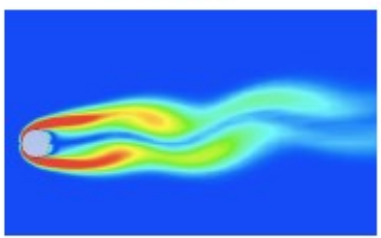
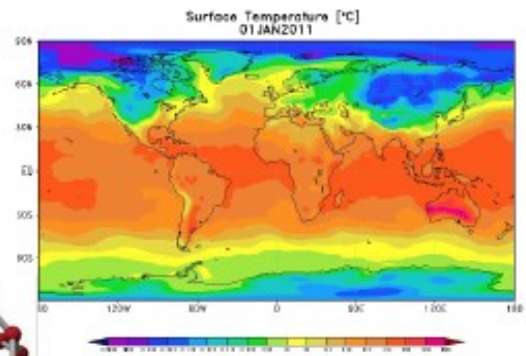
Large-scale Data is Everywhere!

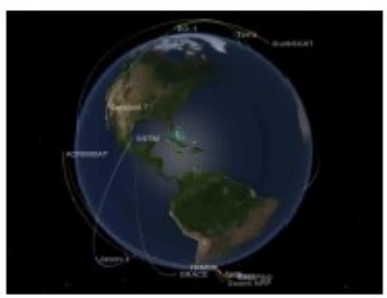
- There has been enormous growth of data in both commercial and scientific arena due to advances in data generation, storage and retrieval technologies.









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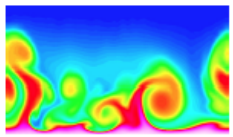
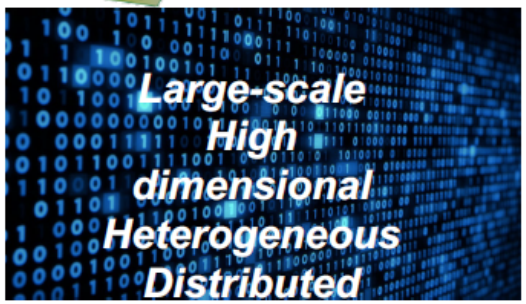
- Every day, $\approx$ 2.5 quintillion($\times 10^{18}$) bytes of data is created.

Golden Age of Data Science

Data → ***Data Science*** → **Knowledge**





Machine Learning
Artificial Intelligence
Pattern Recognition
Data Mining / Data Analytics

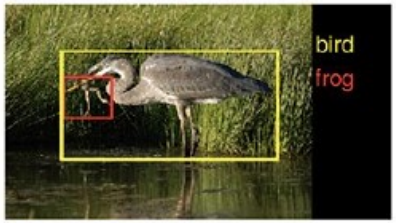
- **Patterns**
- **Models**
- **Relationships**

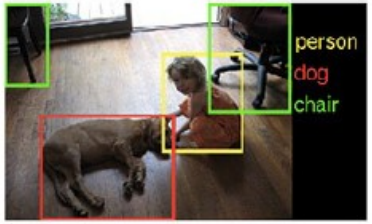
Automated tools for knowledge extraction from large volumes of data

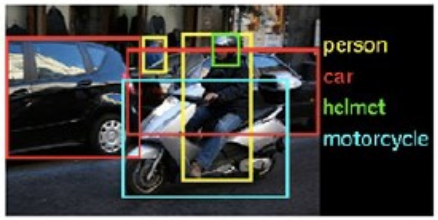
Why Data Mining? Commercial Viewpoint

- Lots of data is being collected and warehoused.
- Competitive pressure is strong.

IMAGENET







DeepMind

NETFLIX

WATSON VS HUMANS: THE JEOPARDY FINALE LIVE

facebook

Google AI algorithm masters ancient game of Go

Google Ads

Why Data Mining? Scientific Viewpoint

- Data collected and stored at enormous speeds.

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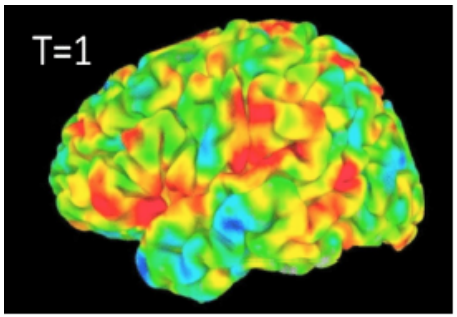
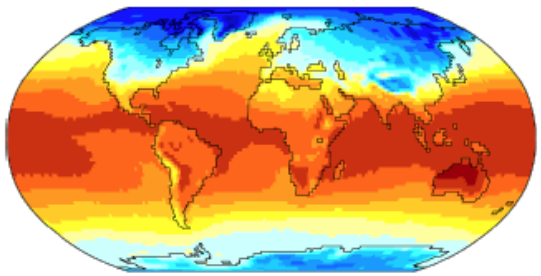
- Data mining helps scientists:



fMRI Data from Brain


Sky Survey Data


Surface Temperature of Earth

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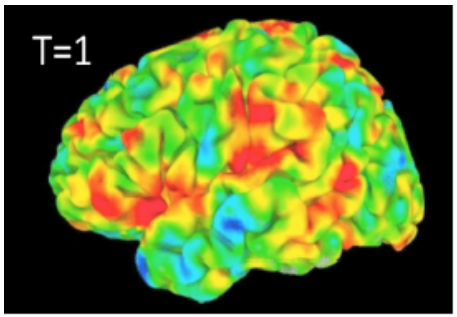

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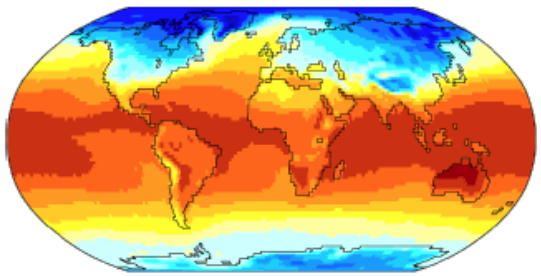
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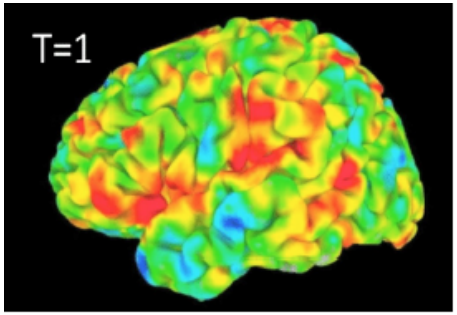
  - In hypothesis formation.



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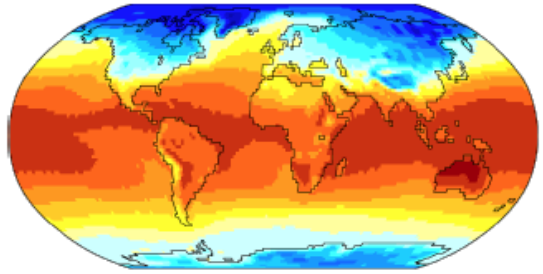
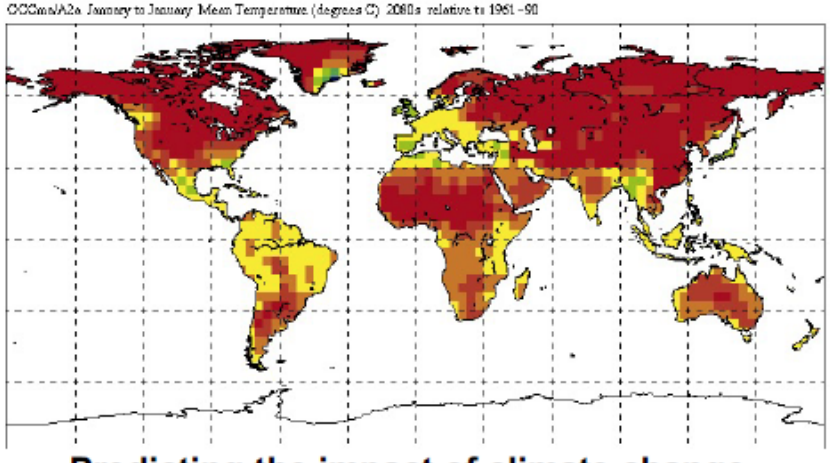

Surface Temperature of Earth

Great Opportunities to Solve Society's Major Problems

Improving health care and reducing costs



Predicting the impact of climate change

Finding alternative/ green energy sources

Reducing hunger and poverty by increasing agriculture production

What is Not Data Mining?

- What is not Data Mining?
  - Look up phone number in phone directory

- What is 'Data Mining?

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  - Credit card application [Approval/Denial]
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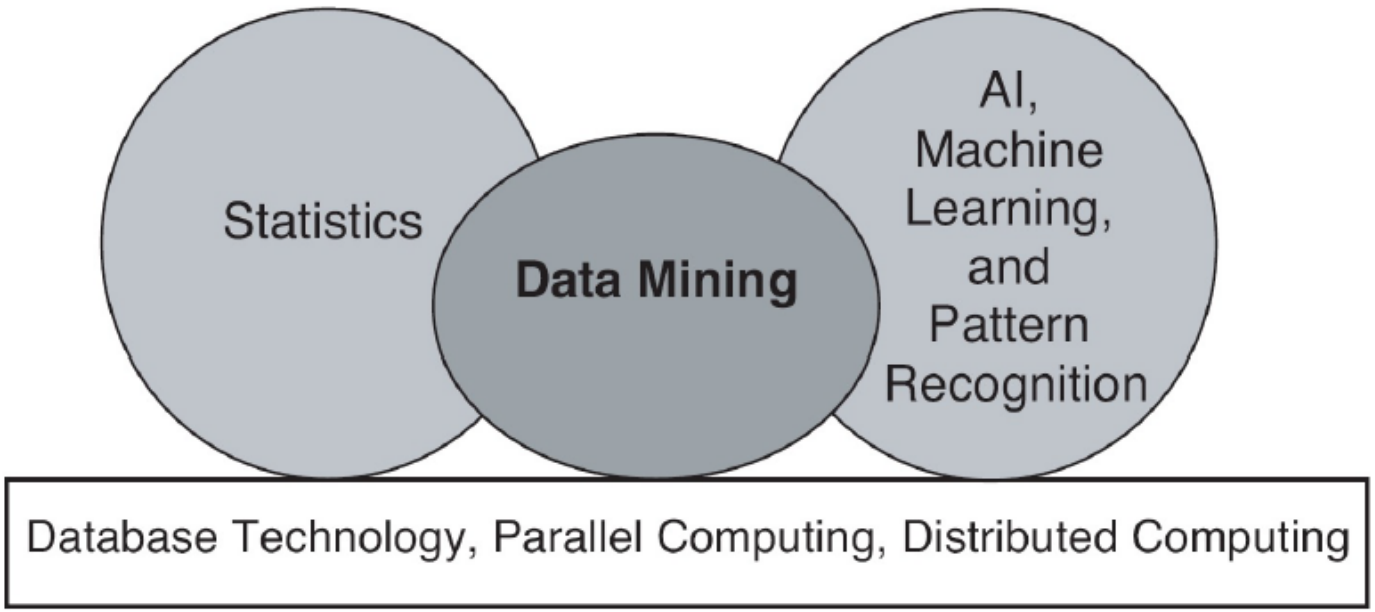
  - Playing tennis based on the weather features.
  - Diabetes classification based on patient information

Origin of Data Mining

- Draws ideas from machine learning/AI, pattern recognition, statistics, and database systems.



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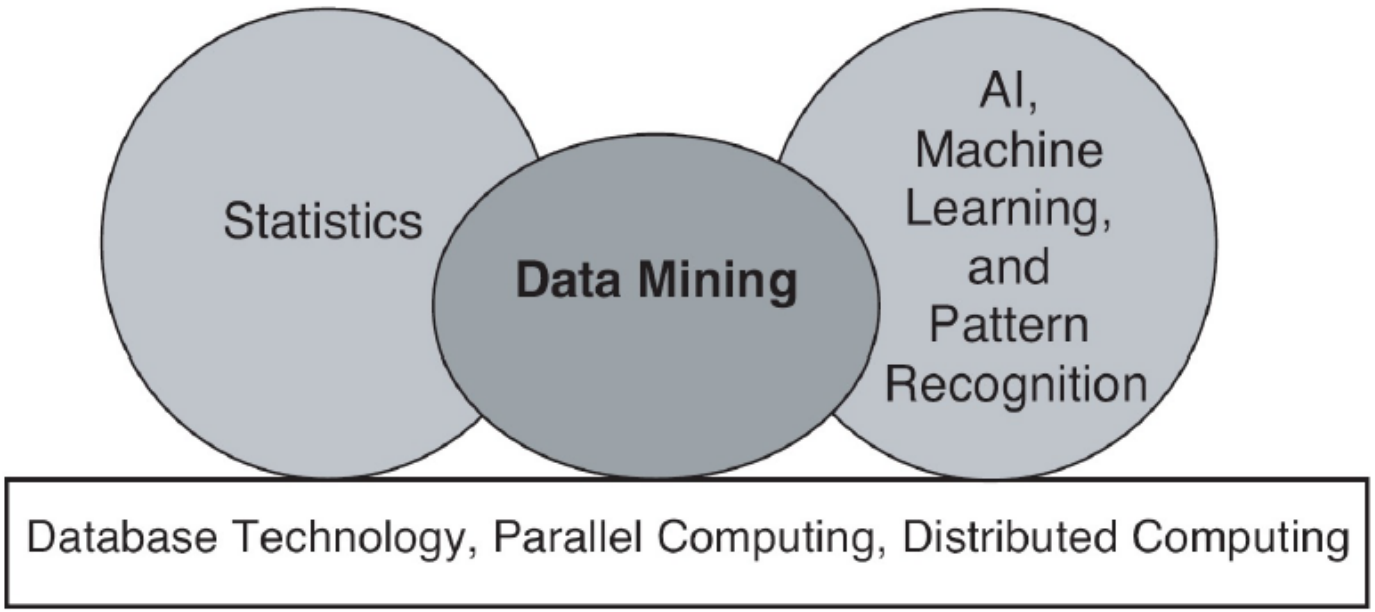

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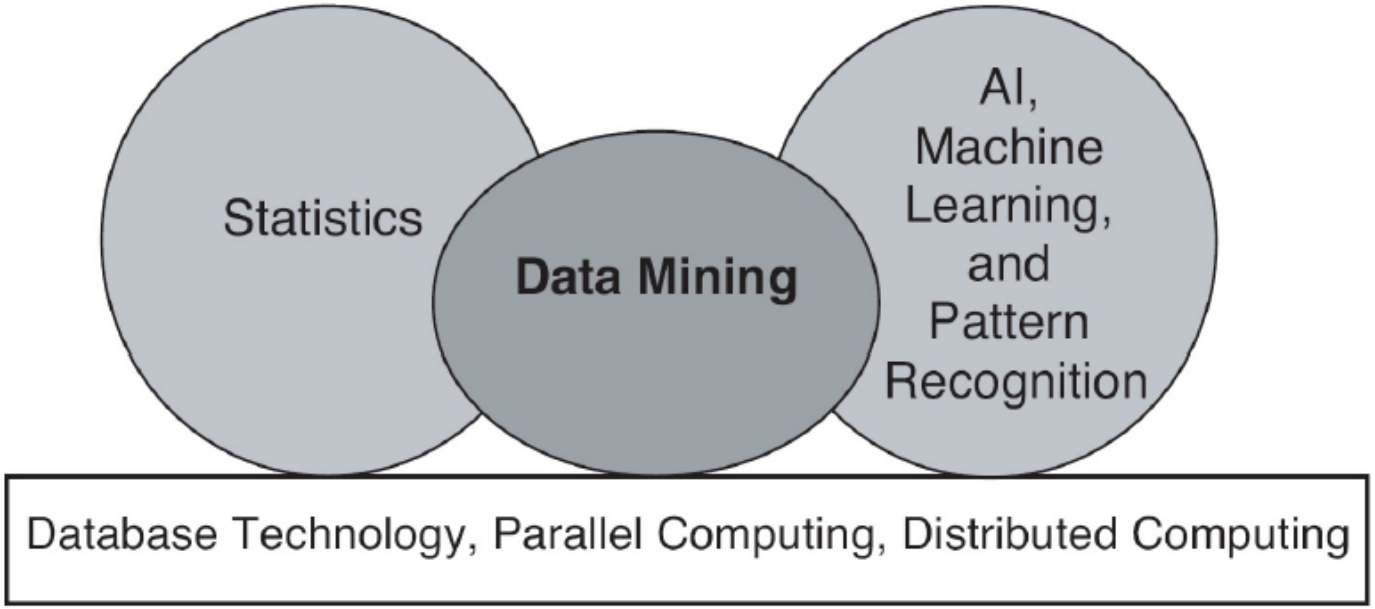
- Draws ideas from machine learning/AI, pattern recognition, statistics, and database systems.
- Traditional techniques may be unsuitable due to data that is
  - Large-scale



Origin of Data Mining

- Draws ideas from machine learning/AI, pattern recognition, statistics, and database systems.
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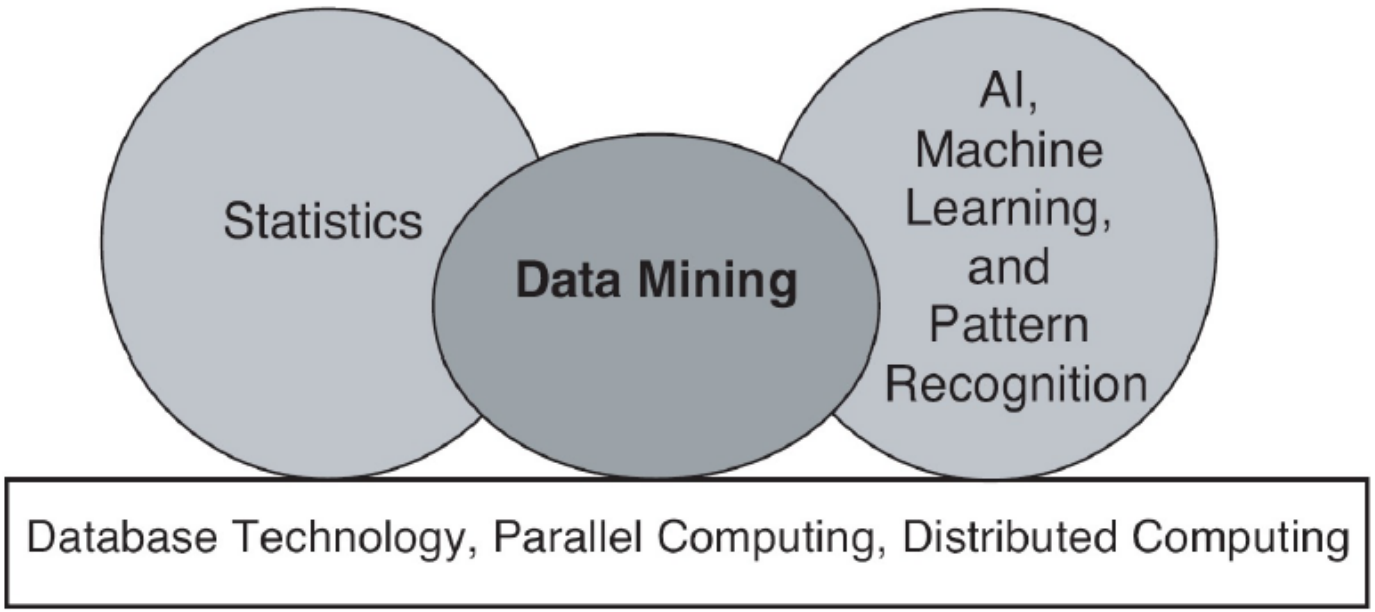
  - Large-scale
  - High dimensional



Origin of Data Mining

- Draws ideas from machine learning/AI, pattern recognition, statistics, and database systems.
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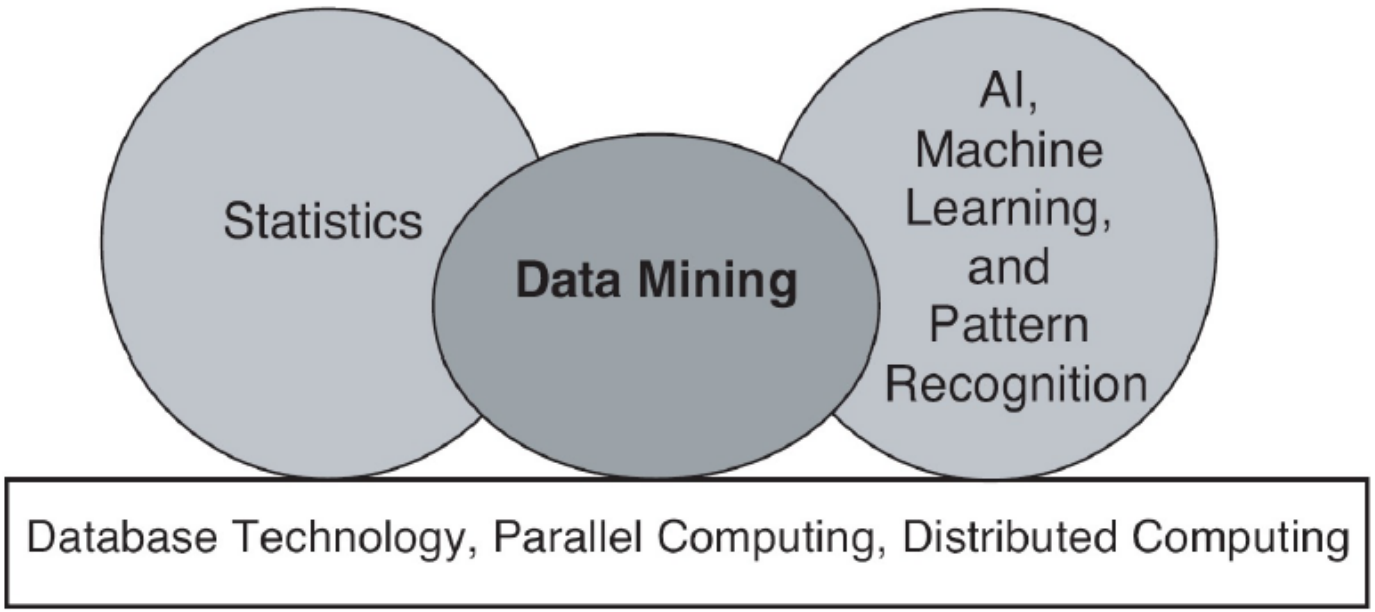

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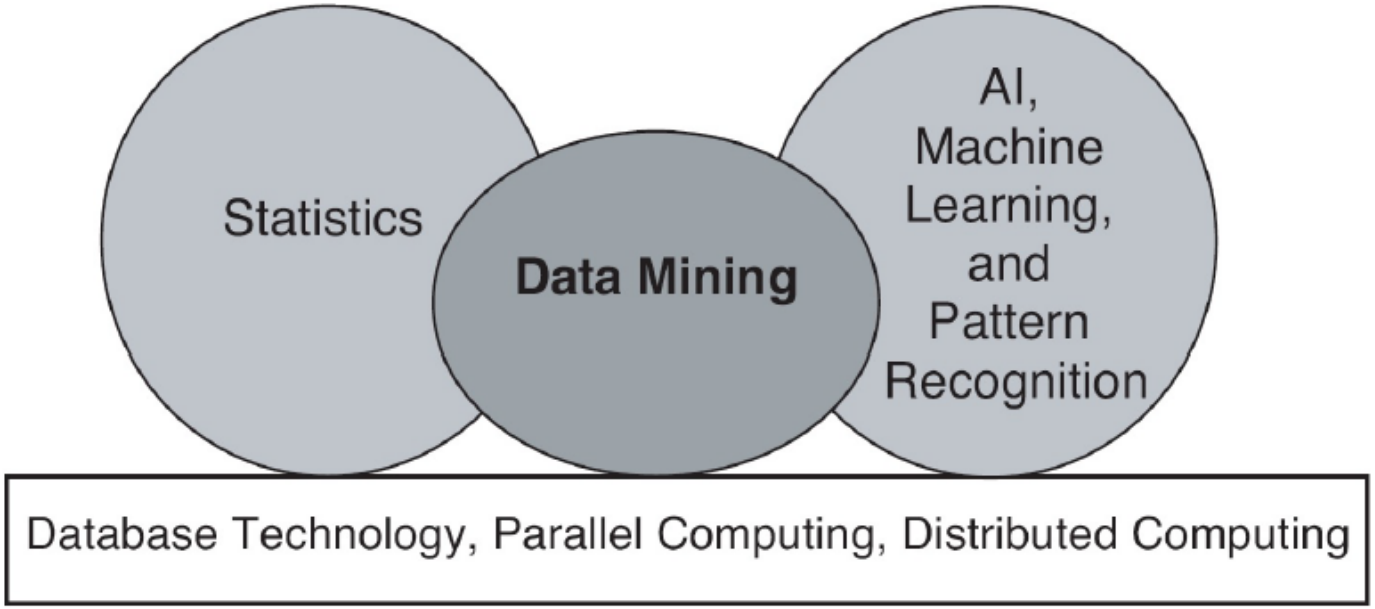

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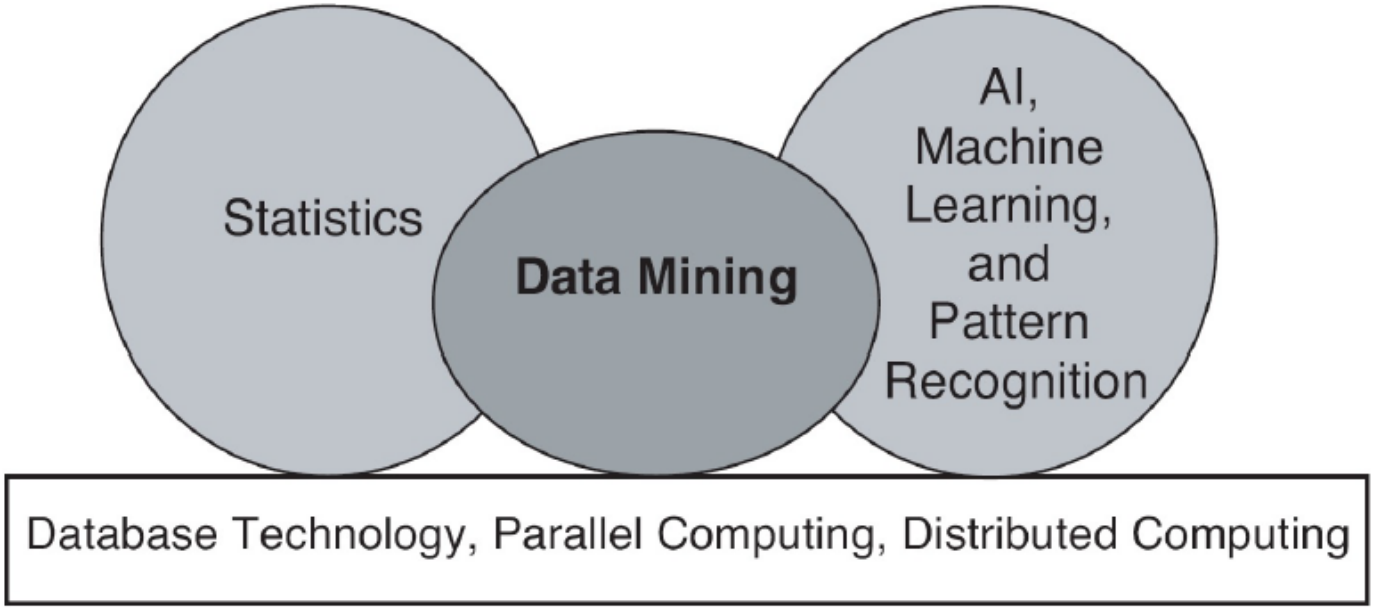
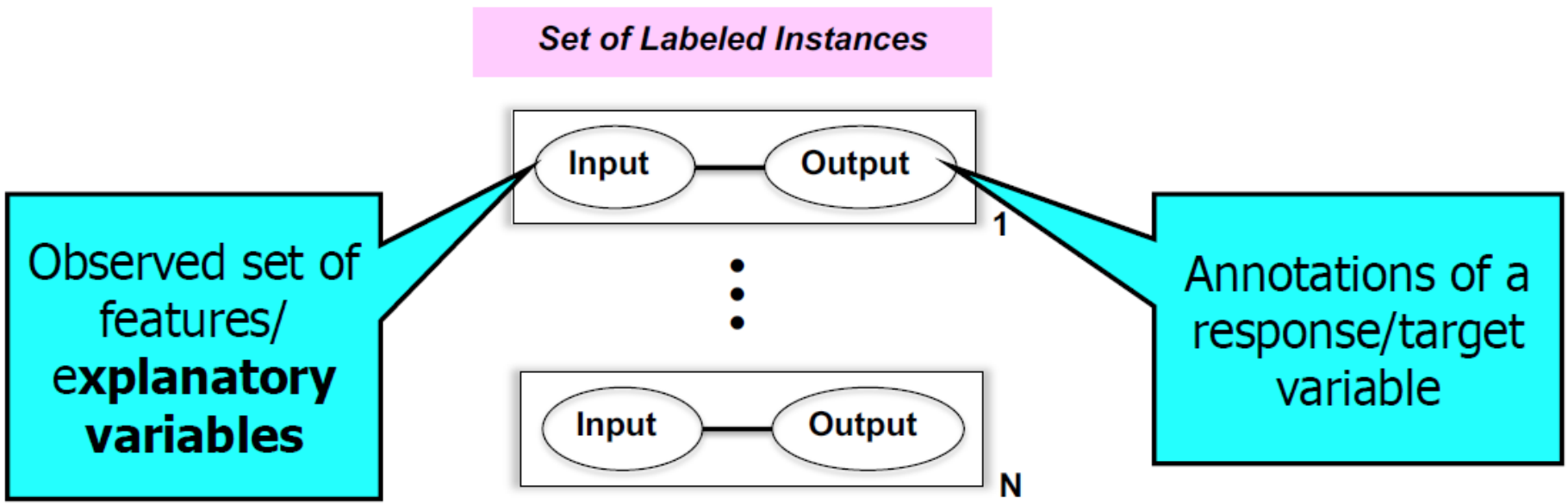


Key Areas of Data Mining

- Predictive Modeling / Supervised Learning

Big Goal

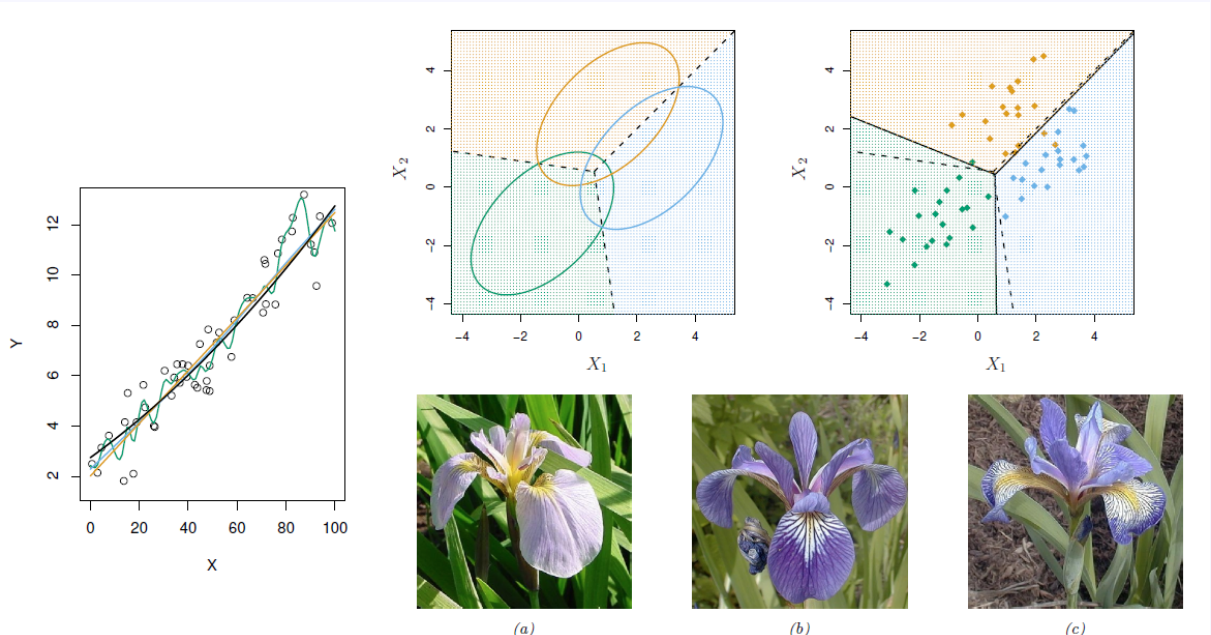
Model relationship between input and output variables to predict the output on unseen (new) instances



Key Areas of Data Mining

1- Predictive Modeling

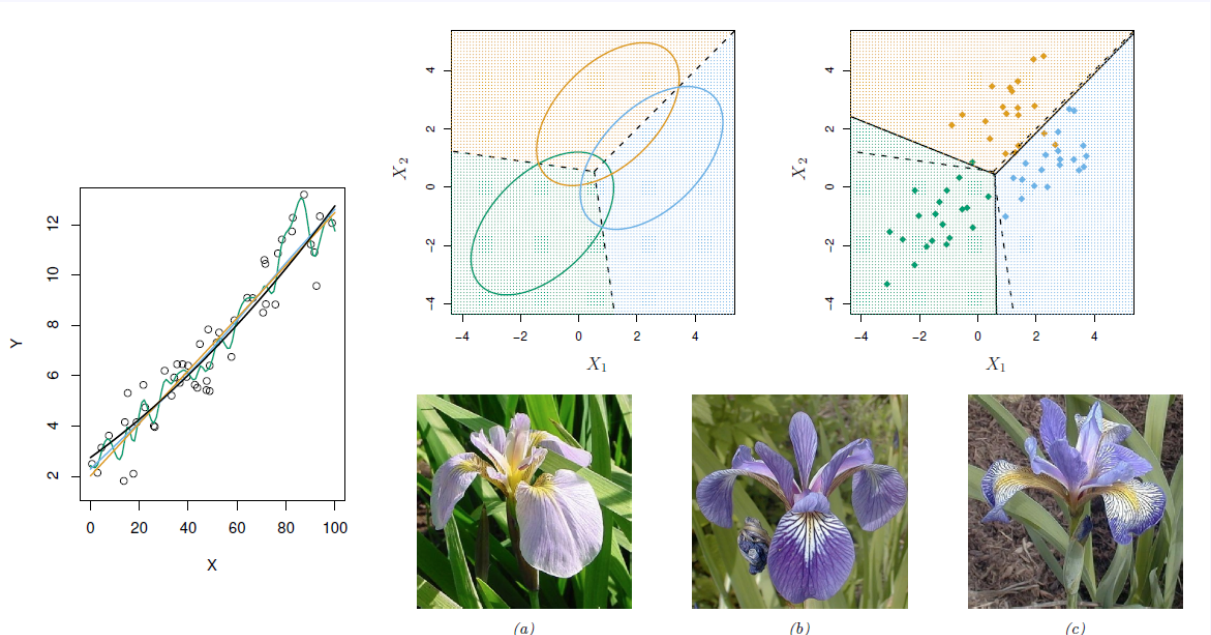
- Regression



Key Areas of Data Mining

1- Predictive Modeling

- Regression
  - Target takes continuous values



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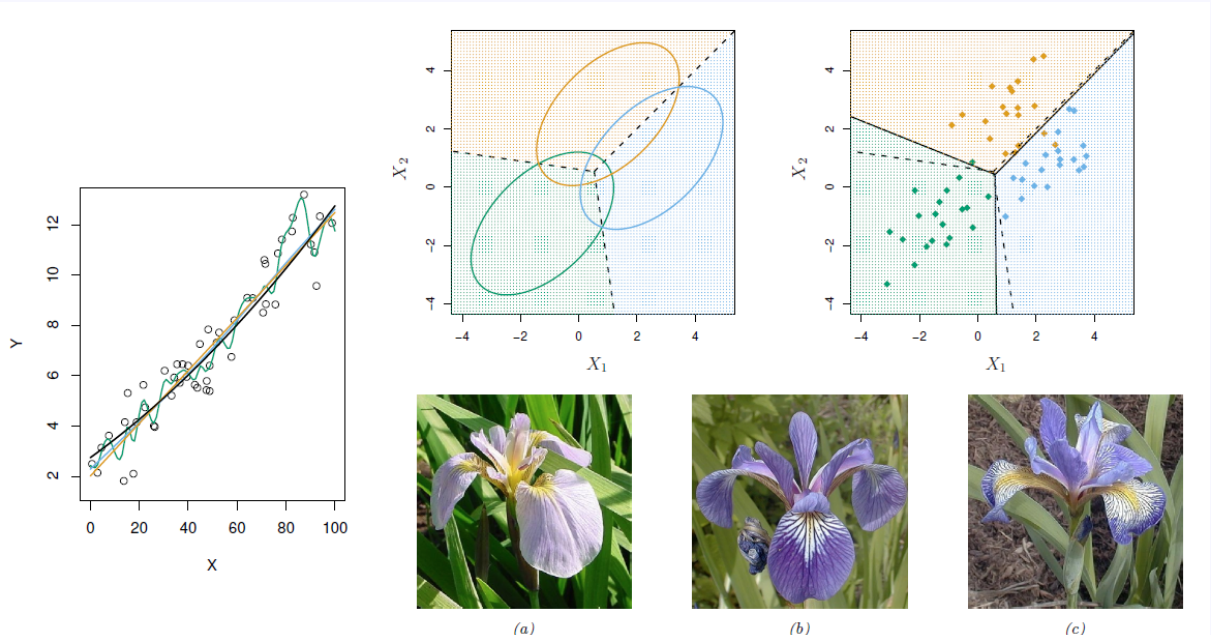
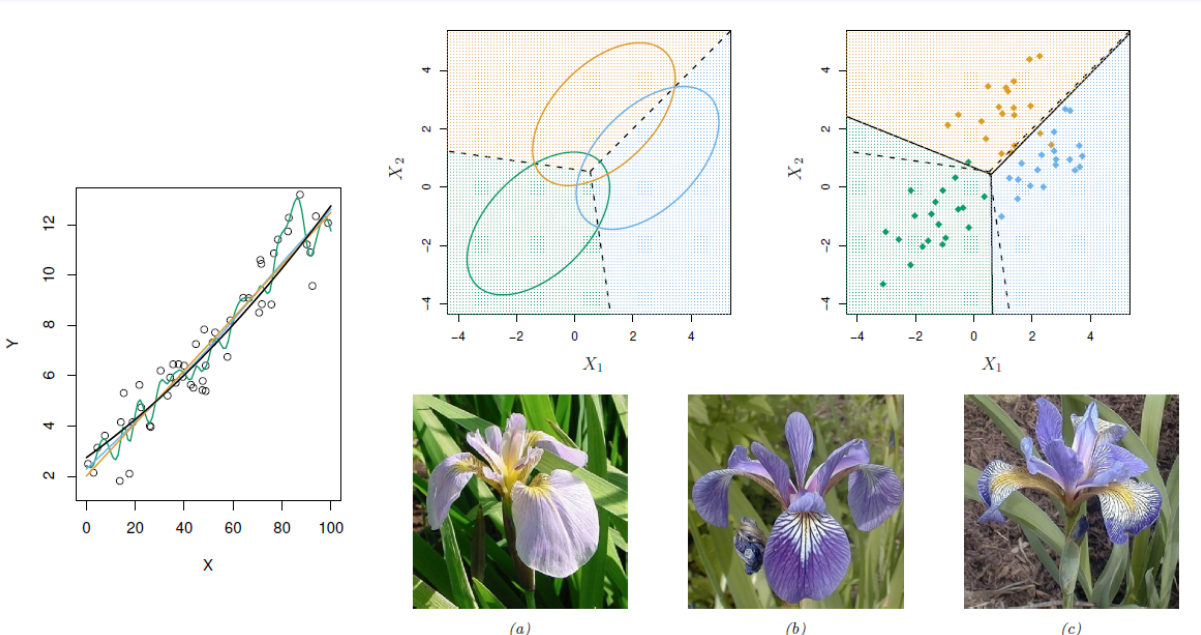
- Classification



Key Areas of Data Mining

1- Predictive Modeling

- Regression
  - Target takes continuous values
- Classification
  - Target takes discrete values/label : $\{setosa, versicolor, virginica\}$

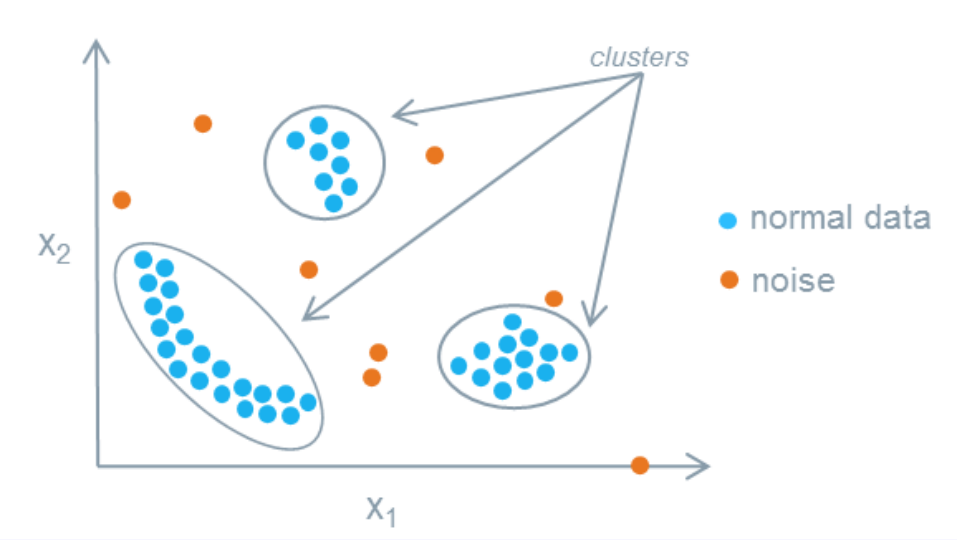


Key Areas of Data Mining

2- Descriptive Modeling/ Unsupervised Learning

Find human-interpretable patterns from "unlabeled" data

- Clustering

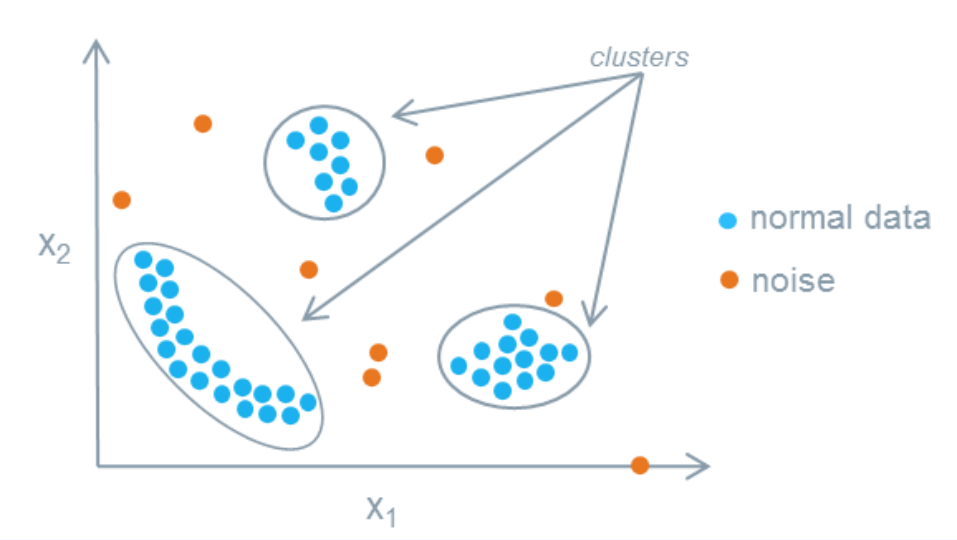


Key Areas of Data Mining

2- Descriptive Modeling/ Unsupervised Learning

Find human-interpretable patterns from "unlabeled" data

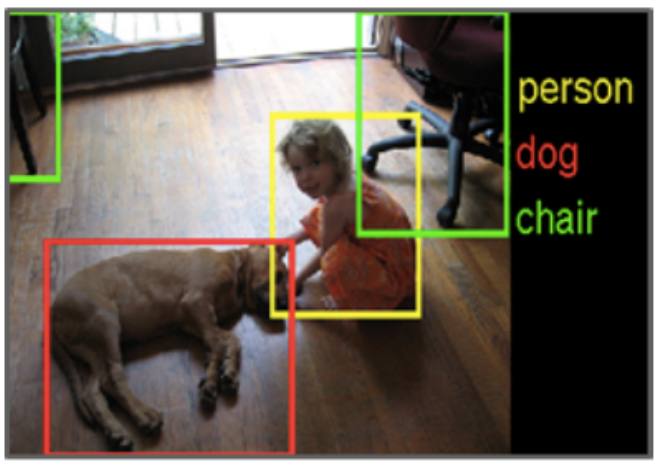
- Clustering
  - Find groups with similar properties
- Anomaly Detection
  - Find unusual instances

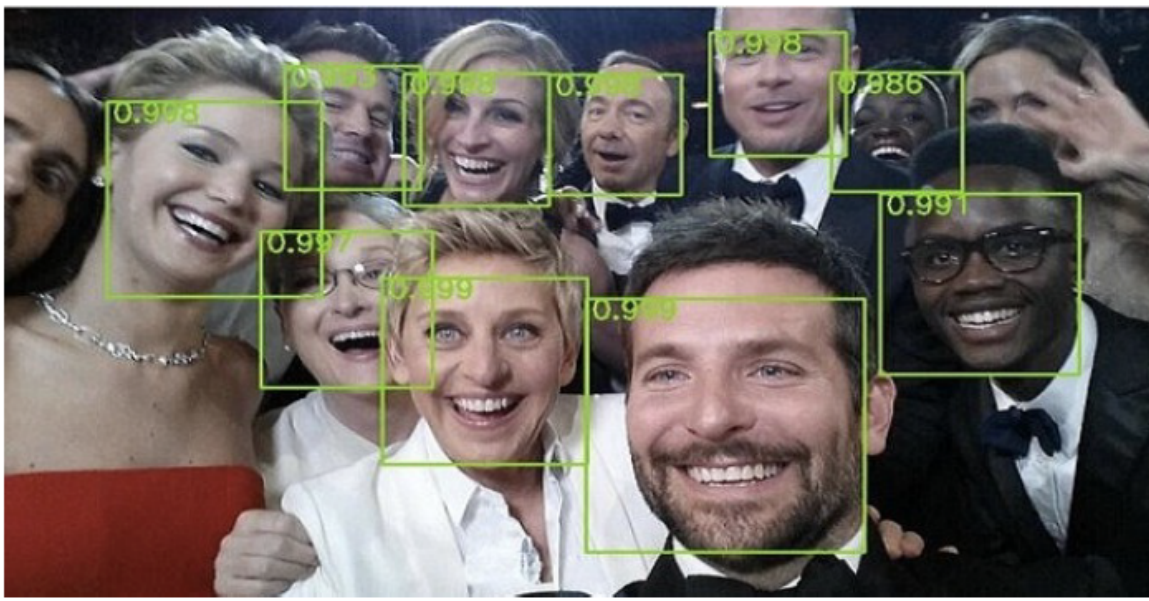


Classification: Illustrative Examples

Image Recognition

Given the pixel values of an image region (features), identify the type of object (class)





Classification: Illustrative Examples

Spam Filtering

Given the message header and content of an email (features), classify spam or no spam (class)

Land Cover Mapping

Given the multi-spectral values (features), classify land cover: water, vegetation, urban, etc. (class)

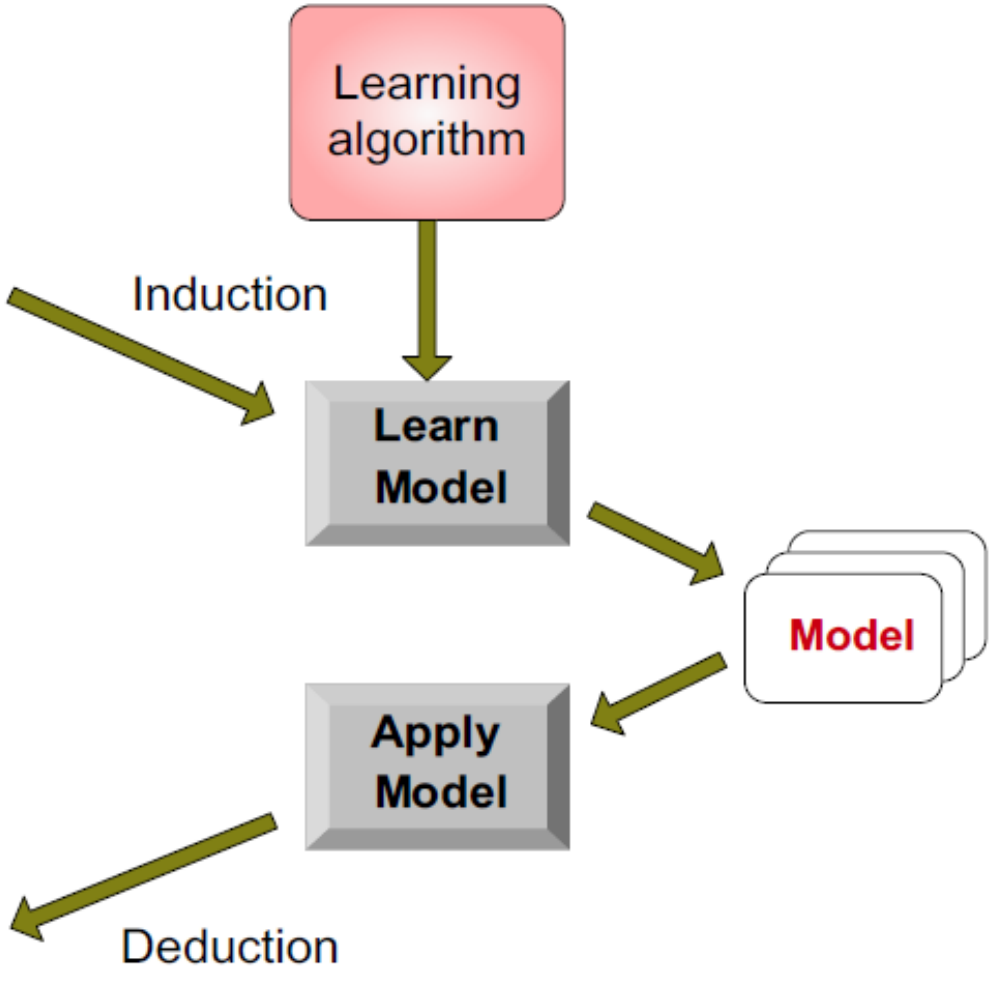
Predictive Modeling: General Approach

Tid	Attrib1	Attrib2	Attrib3	Class
1	Yes	Large	125K	No
2	No	Medium	100K	No
3	No	Small	70K	No
4	Yes	Medium	120K	No
5	No	Large	95K	Yes
6	No	Medium	60K	No
7	Yes	Large	220K	No
8	No	Small	85K	Yes
9	No	Medium	75K	No
10	No	Small	90K	Yes

Training Set

Tid	Attrib1	Attrib2	Attrib3	Class
11	No	Small	55K	?
12	Yes	Medium	80K	?
13	Yes	Large	110K	?
14	No	Small	95K	?
15	No	Large	67K	?

Test Set



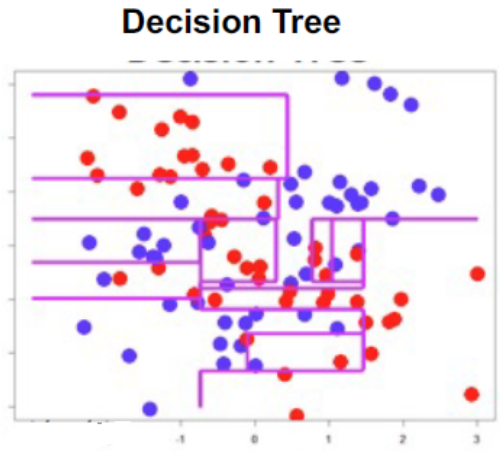
Classification Models

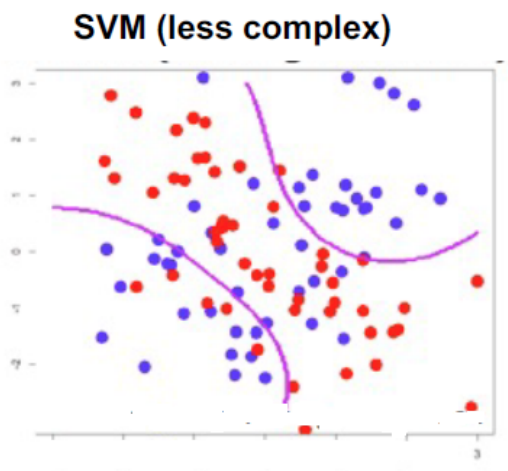
Decision Trees

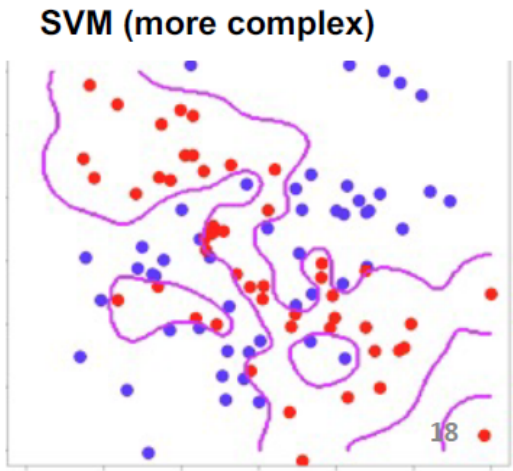
Nearest-neighbor Classifier

Naïve Bayes and Probabilistic Graphical Models

Artificial Neural Networks

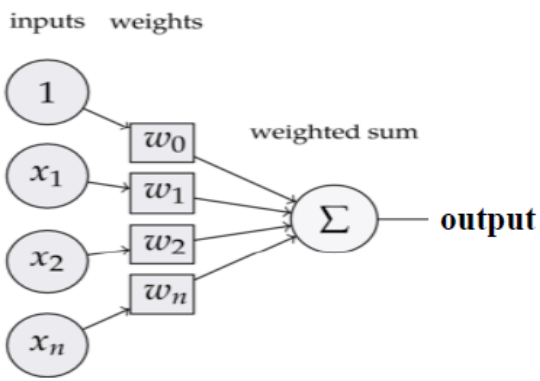


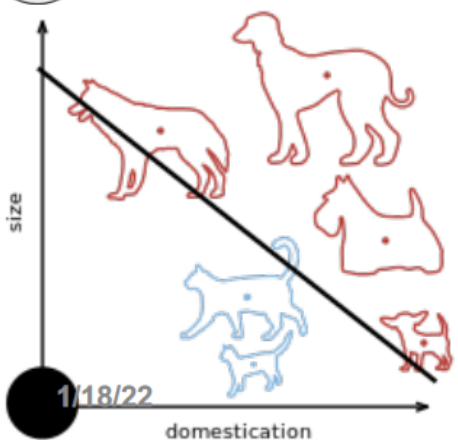




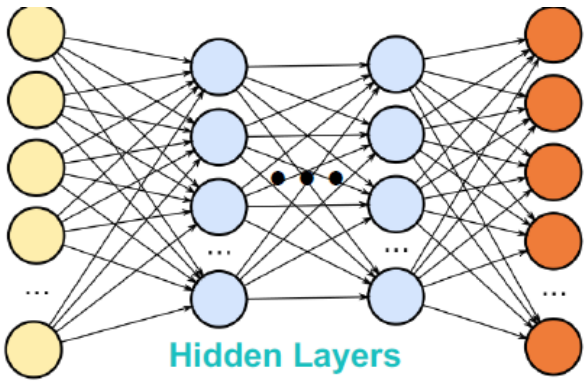
Example of Classification Model: Deep Learning

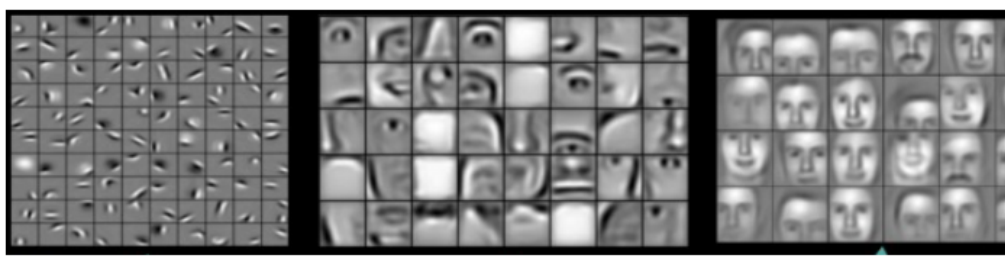
- Perceptron 1970's





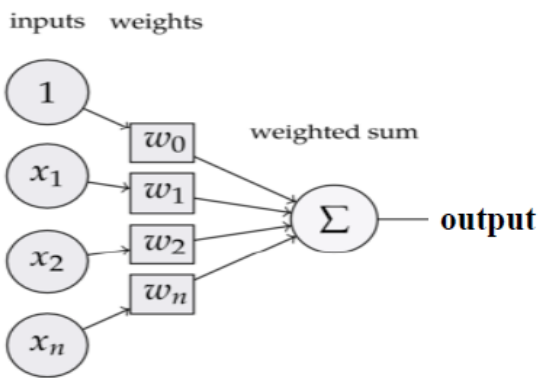
- Perceptron ~2010+

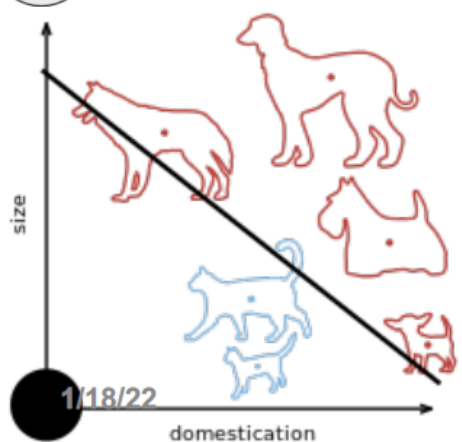




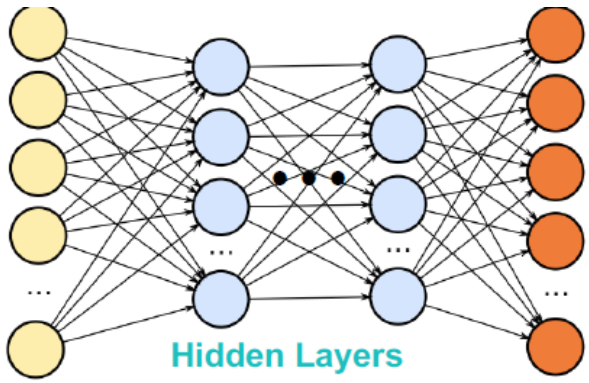
Example of Classification Model: Deep Learning

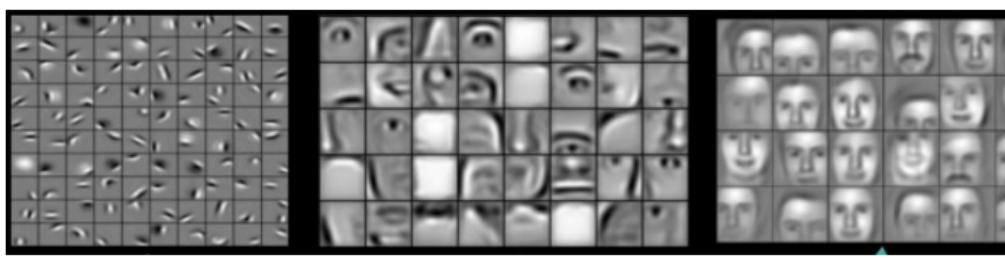
- Perceptron 1970's
- Single processing unit





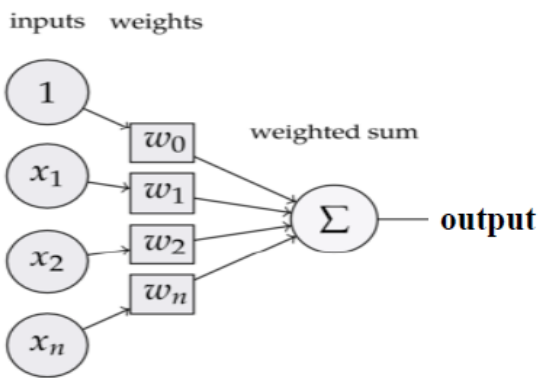
- Perceptron ~2010+
- Composition of a large number of processing units

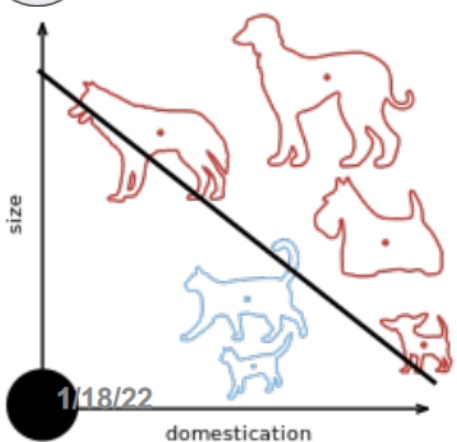




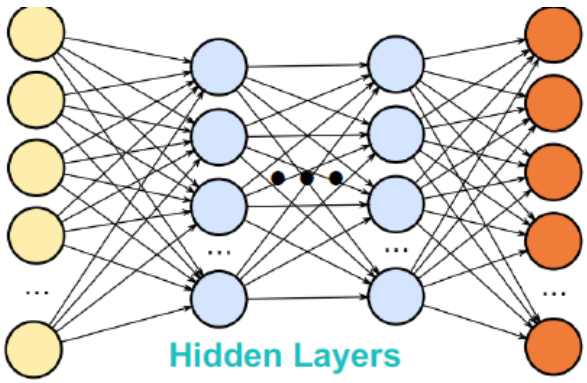
Example of Classification Model: Deep Learning

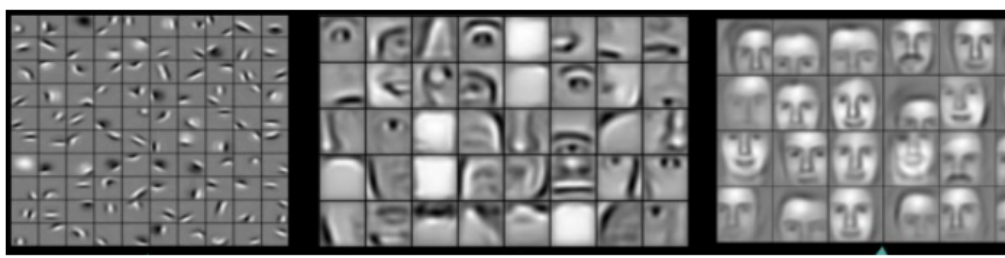
- Perceptron 1970's
- Single processing unit
- Can only learn linear decision





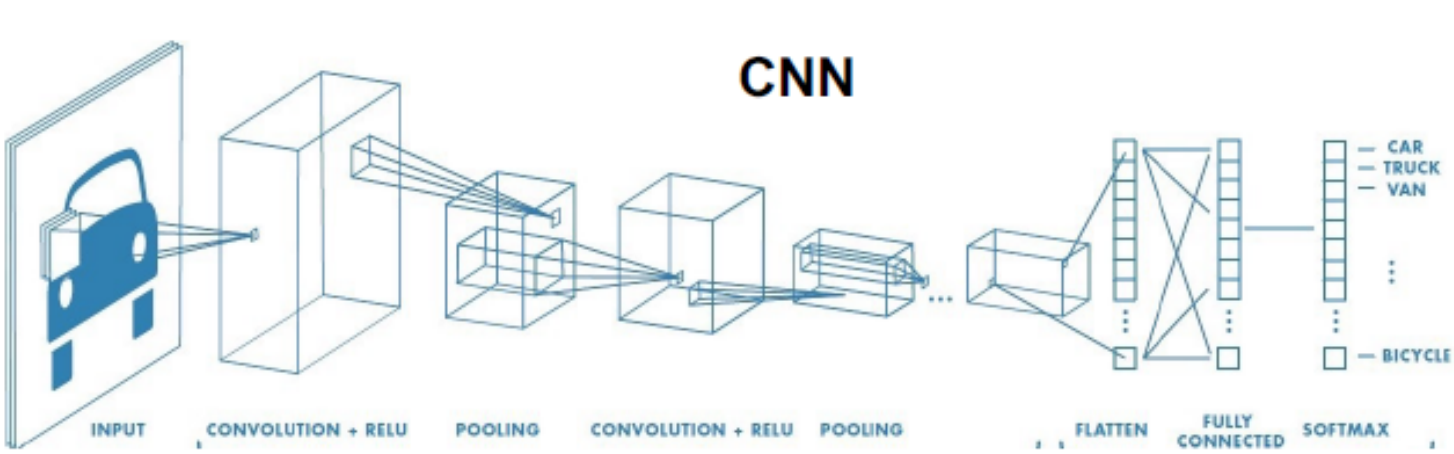
- Perceptron ~2010+
- Composition of a large number of processing units
- Can learn highly complex decision boundaries

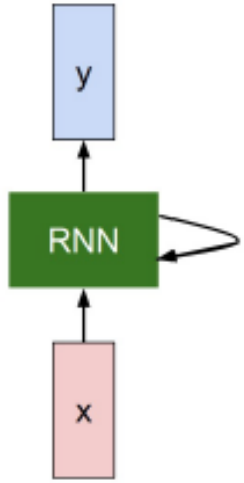




Deep Learning Topics

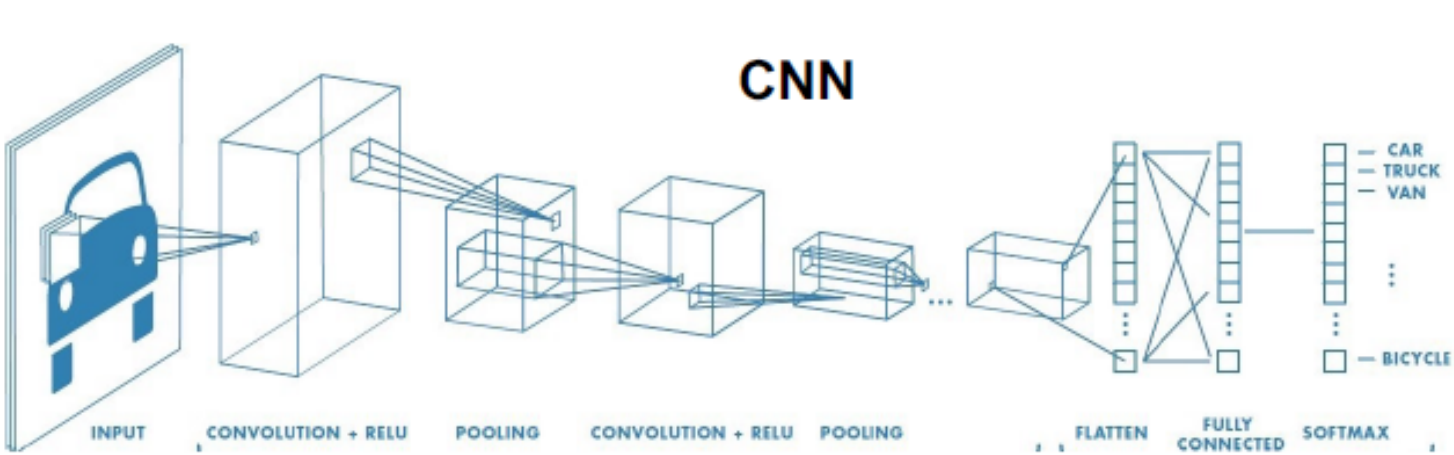
- Deep Learning architectures

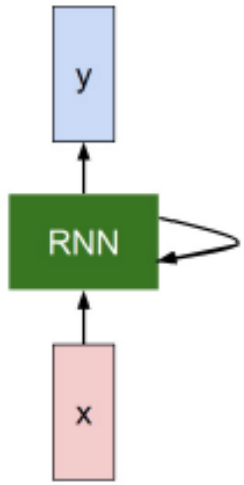




Deep Learning Topics

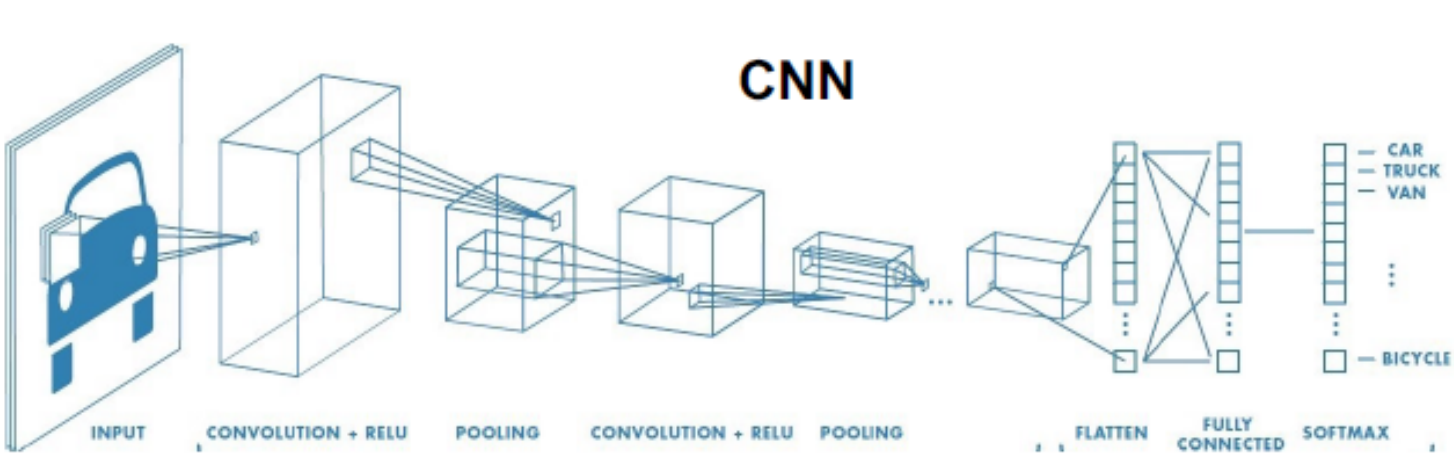
- Deep Learning architectures
  - Multilayer Perceptron (MLP)

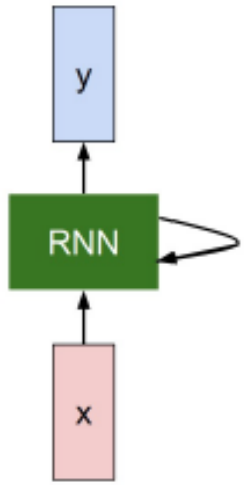




Deep Learning Topics

- Deep Learning architectures
  - Multilayer Perceptron (MLP)
  - Convolutional neural networks (CNNs)





Deep Learning Topics

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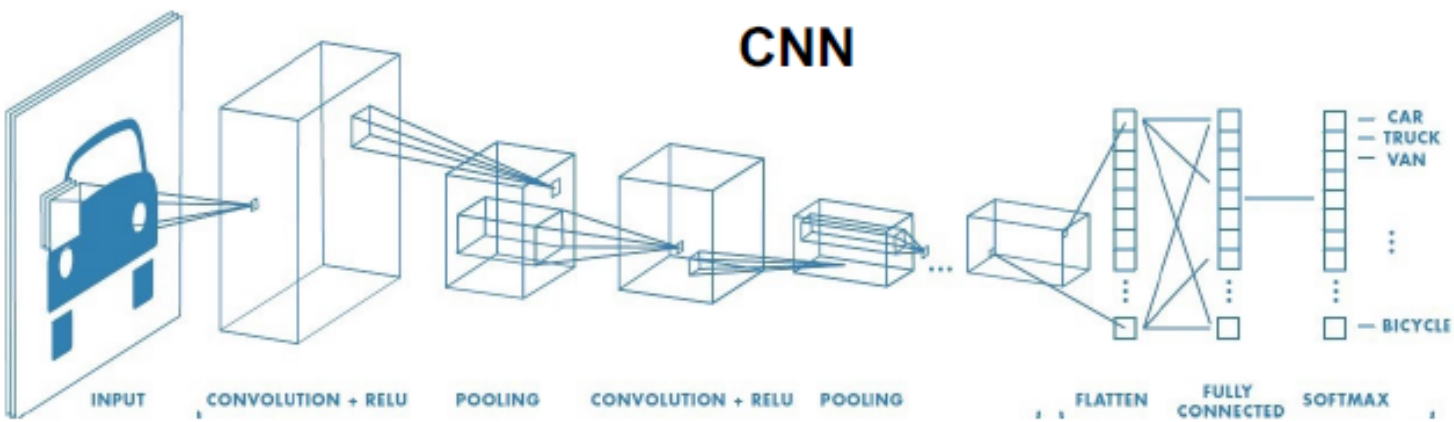
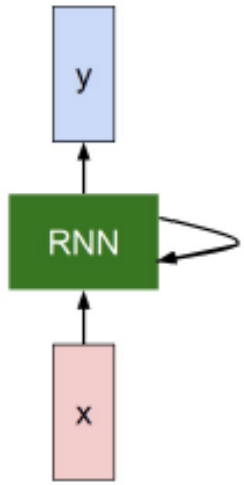
  - Convolutional neural networks (CNNs)
  - Recurrent neural networks (RNNs)





Deep Learning Topics

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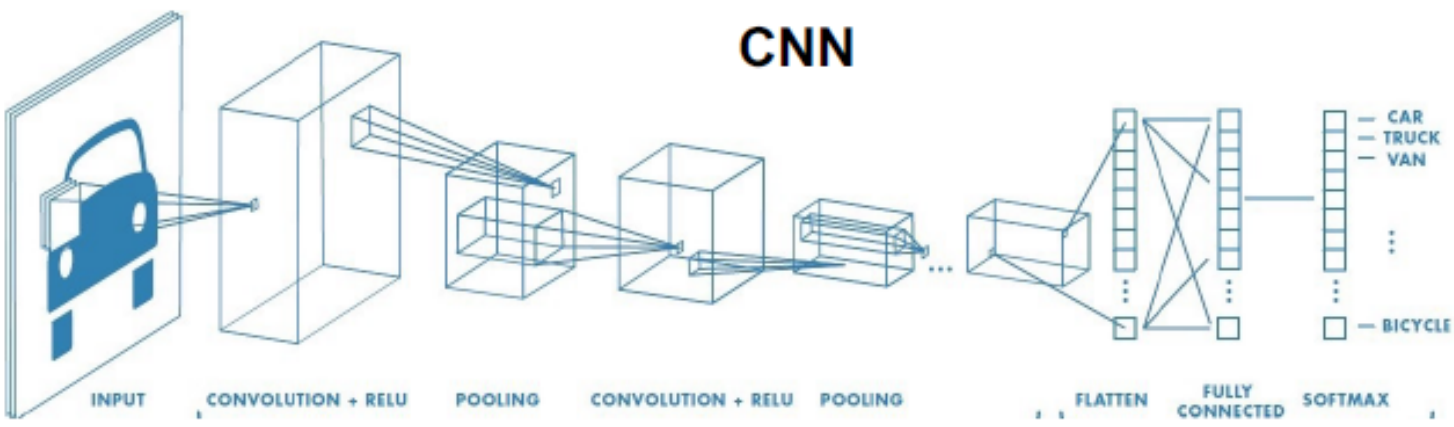
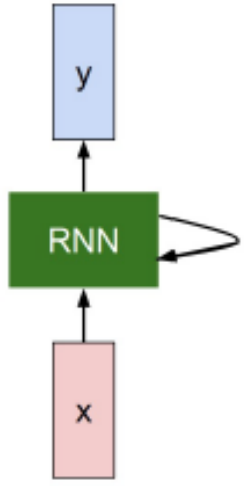
  - Recurrent neural networks (RNNs)
  - Long short-term memory (LSTM)





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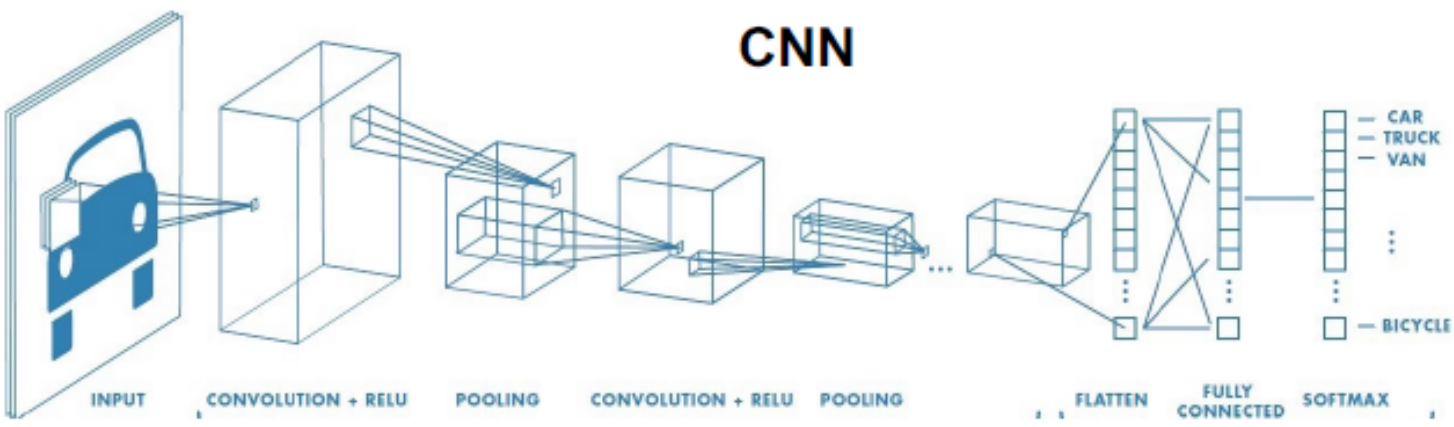
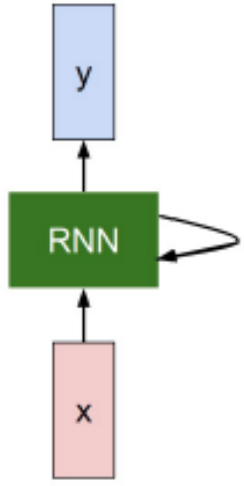
  - Generative adversarial networks (GANs)





Additional Topics: Association Analysis

- Given a set of records each of which contain some number of items from a given collection

TID	Items
1	Bread, Coke, Milk
2	Beer, Bread
3	Beer, Coke, Diaper, Milk
4	Beer, Bread, Diaper, Milk
5	Coke, Diaper, Milk

Rules Discovered:

{Milk} --> {Coke}

{Diaper, Milk} --> {Beer}

Additional Topics: Association Analysis

- Given a set of records each of which contain some number of items from a given collection
  - Find patterns of co-occurrence of items

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  - Medical Informatics: Rules are used to find combination of patient symptoms and test results associated with certain diseases

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Required Software

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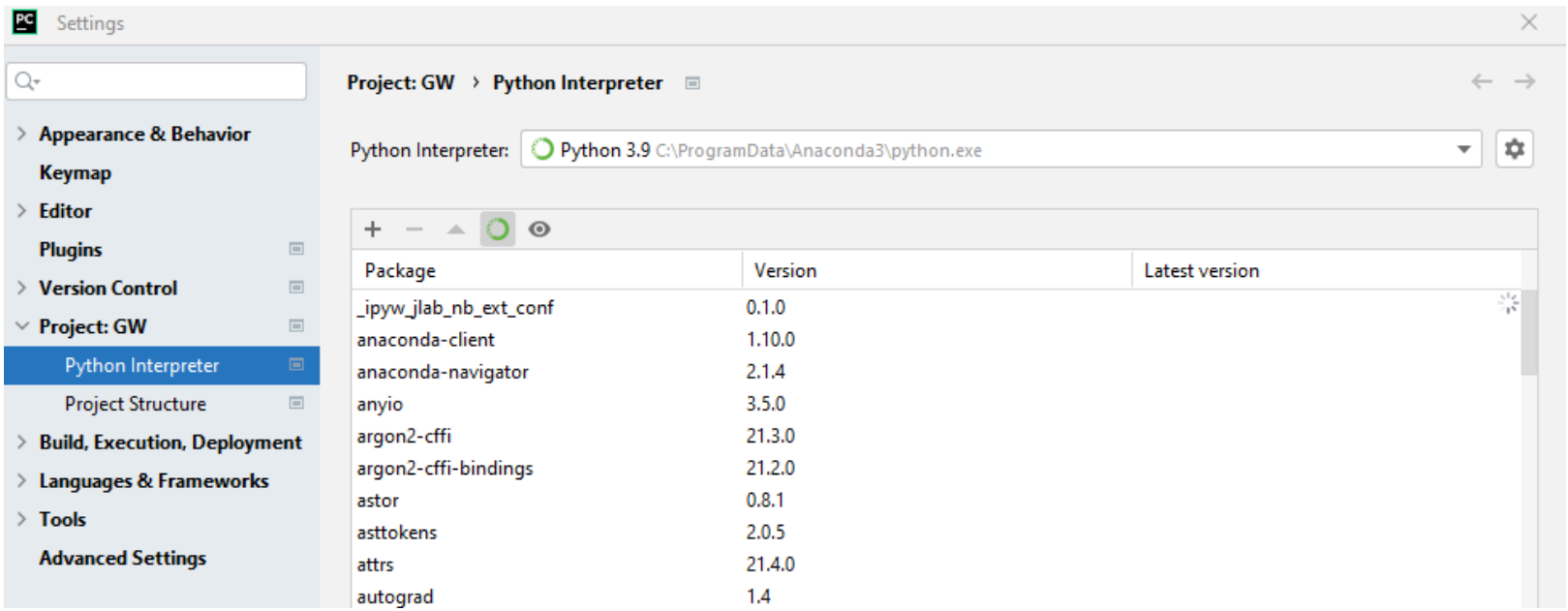

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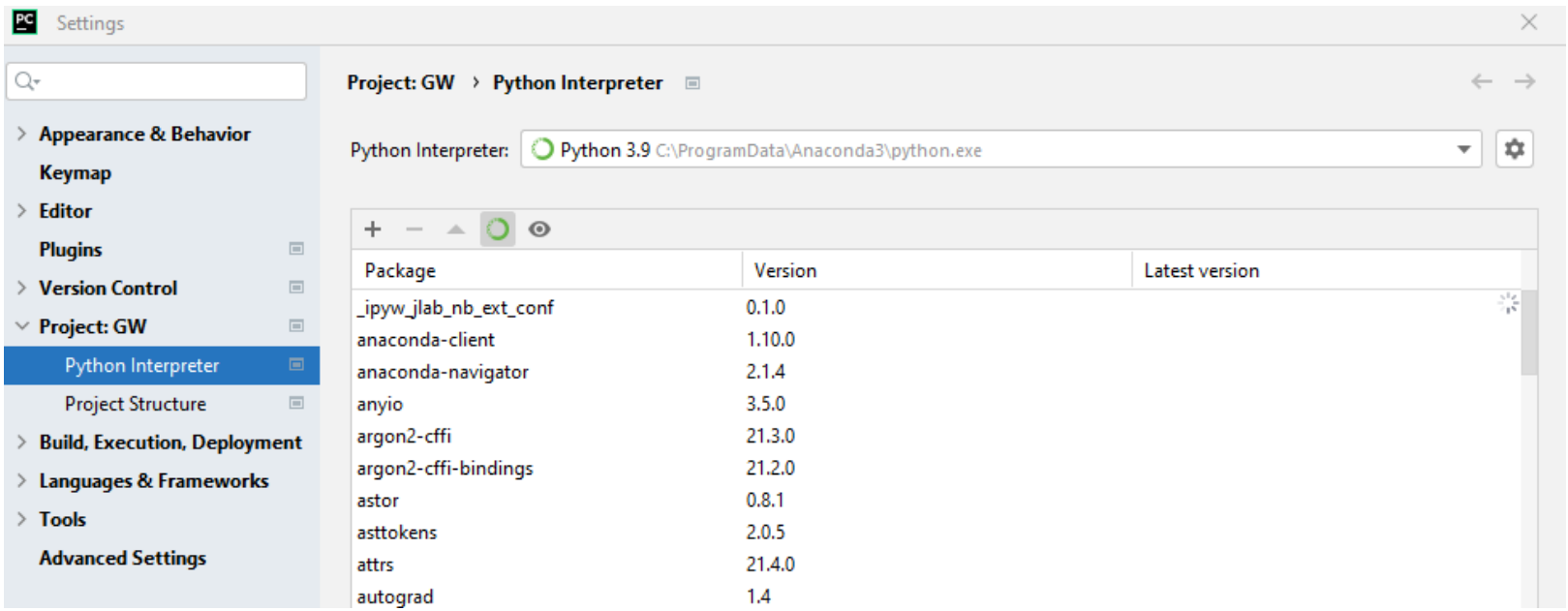

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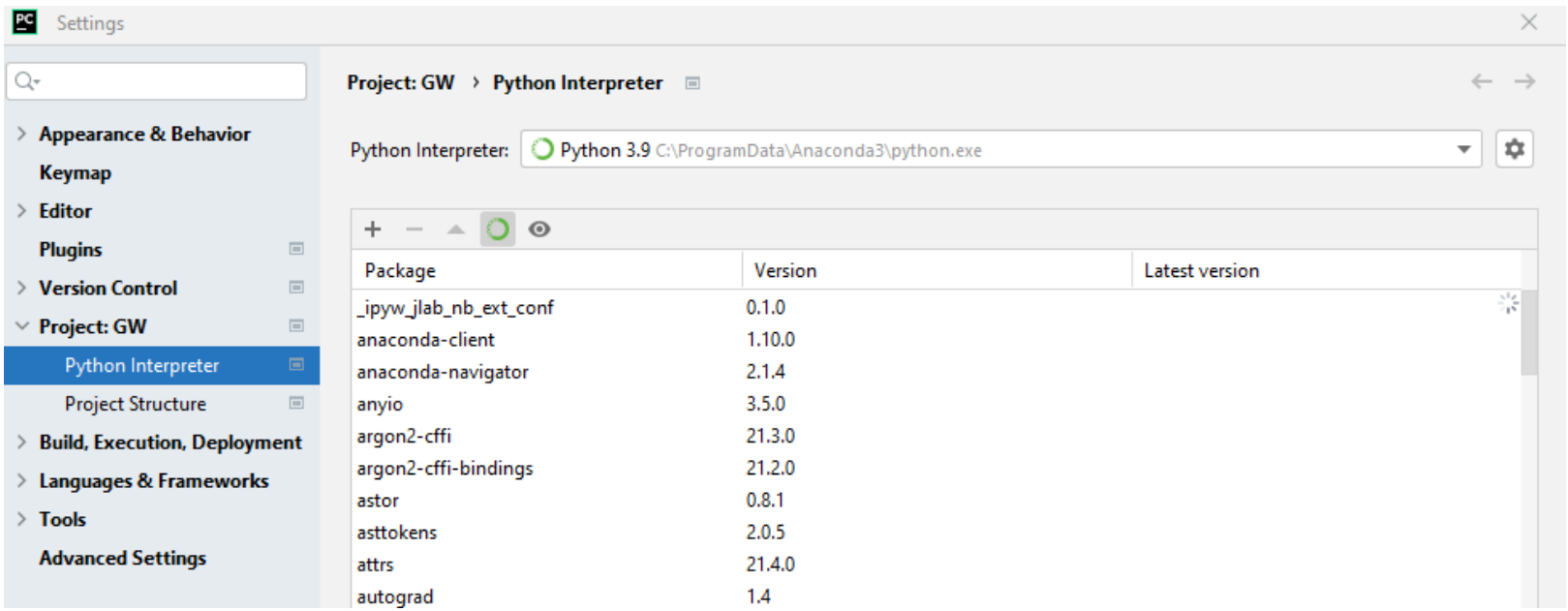

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- It is highly recommended to install Anaconda[Link] and set the pycharm interpreter as the pyhton 3.9+ using Anaconda.