

Aspects of practical application of ANN

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SICS

Neural Networks

Neural
Networks

Neural
Networks

Logical
Inference

Case-
based

Statistical
Methods

Machine Learning methods

Typical machine learning tasks:

- Classification / Diagnosis
- Prediction / Prognosis
- Clustering / Categorization

Different domain characteristics:

- Logical / Discrete / Continuous
- Few or many attributes
- Few or many classes
- Deterministic / Noisy

Machine Learning methods

Neural Networks

- Multi-layer Perceptrons
- Self-Organizing Maps
- Hopfield Networks
- Boltzmann machines

Logical Inference

- Decision Rules
- Decision Trees
- Rule based systems

Case-based methods

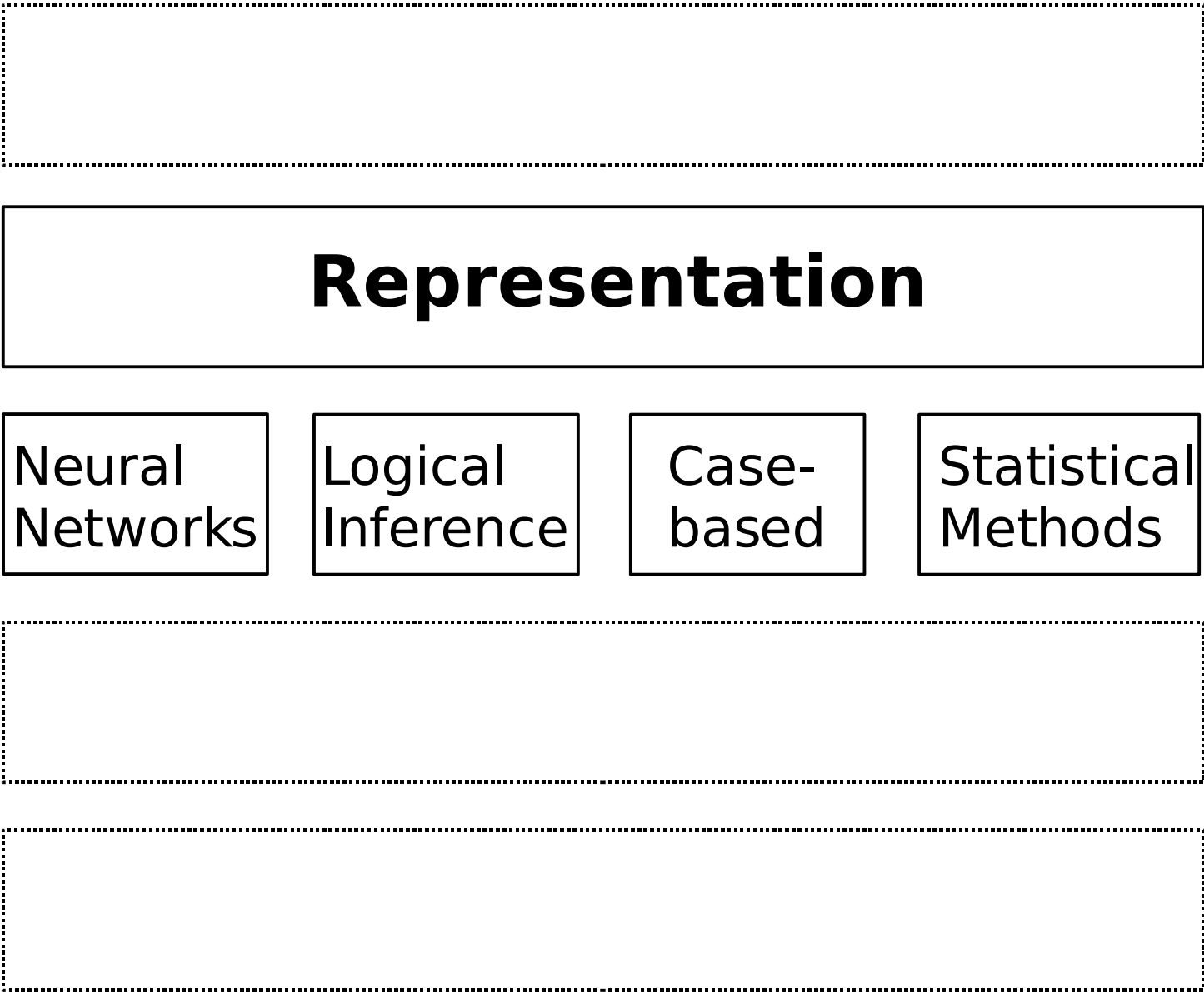
- Table-lookup
- Nearest Neighbour
- k-Nearest Neighbour

Statistical methods

- Regression
- Naïve Bayes
- Mixture Models
- Graph Models
- MCMC

Machine Learning methods

- The exact choice of method is usually not critical
- The choice of problem representation *is* critical!
- This requires domain understanding



The diagram consists of a central box labeled 'Representation'. Above and below this box are two large, empty rectangular boxes with dotted borders. To the left and right of the central box are four smaller boxes, each containing a method name: 'Neural Networks', 'Logical Inference', 'Case-based', and 'Statistical Methods'. These four boxes are arranged in a row, flanking the central 'Representation' box.

Representation

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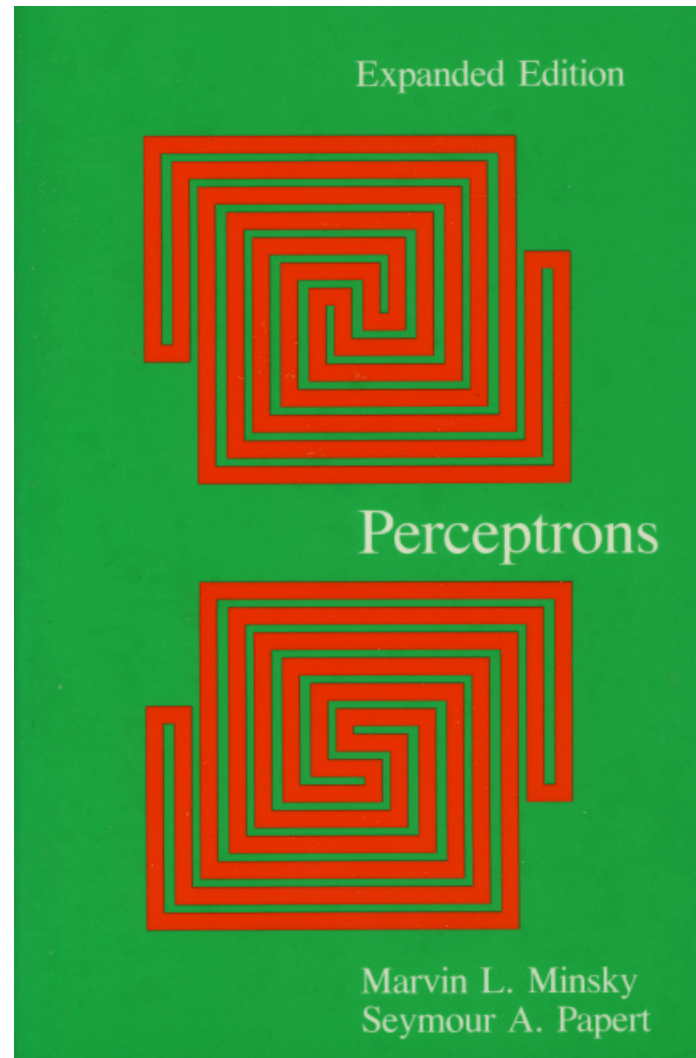
Case-
based

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Representation

- With the wrong representation *no* method will succeed
- Once you have found a good representation, almost *any* method will do
- Once preprocessing has turned data into something reasonable, a simple model may be sufficient
- With limited amount of independent data, the number of parameters must be kept low

Neural Network book, 1969



Representation

- Many types of real data, e.g. images, sounds, time series, free text, binary register dumps, etc, require special pre-processing to pick out whats relevant
- Look out for invariances

Data cleaning

Representation

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Data cleaning

Real data is not clean:

- Missing data
- Out of sync fields
- Misspellings
- Special values (temperature -9999)
- Spikes (10e+14)
- Dirty or drifting sensors (0.3 – 100.3 %)
- Data from different sources (old / new), with slightly different meaning

Data cleaning

Attr 1	Attr 2	Attr3	Attr 4	Attr 5
12.2827	2002080612220500	10.47	5.2	Kyln. på
12.2826	2002080612220622	15.39	4.7	Valsbyte
12.2825	2002080612220743	12.66	5.9	hasp temp 680
12.2824	2002080612220886	-999.0	22.8	Hasp-temp
1.22823	2002080612221012	-999.0	Overflow	kyln
12.2819	2002080612221136	-999.0	Overflow	Kylning
12.2815	1858111700000000	13.49	Error	karkylning på
122821	1858111700000000	25.85	Error	valsb.
12.2823	2002080612221631	22.98	0.6	ej i dragläge
...	...	...	...	...

Data cleaning

One even earlier step: Getting data

- Not so easy, often takes time
- Data samples are always too few!
- Even when they claim there are huge amounts of data, the relevant part may be very small
- A large amount of input attributes is no guarantee for successful modelling. The relevant attributes may still not be included.
- An iterative process to get the right data

Mid-time conclusions

- Pre-processing (understanding the domain and the problem, getting relevant data, cleaning the data, and finding a good representation) takes more than 90% of the time of a project
- No black box method - domain knowledge is critical for success

Data cleaning

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Validation



Validation

- “Validation” is used to estimate the performance on new data, i.e. how it would perform when actually used
- To get good generalization you must avoid overtraining the network
- There are unimaginably many ways that makes the result look better in the laboratory than in the real life
- However hard you try to avoid it, you will *always* get too optimistic validation results!

Validation

Some ways to guarantee overtraining:

- Too few data samples
- Too complicated model
- Too similar training, test and validation samples
- Fine-tuning your parameters
- Evaluating several models with the same validation set

Data cleaning

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Deployment

Deployment

- The method is on its own
- Keep it simple and robust
- Must the network be regularly retrained?
Can the “ground truth” be trusted?
Can stability and performance be guaranteed?
- Did your pre-study test the right thing?
Distinction between prediction and control
Distinction between prediction and causation
- Be prepared to go all over the process again

Conclusions

- Thoroughly understand the problem you are working on and try to understand the process that generated the data
- Take extreme care with validation
- Test the application on as much real-world data as you can
- Keep it as simple as possible

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Commercial applications of ANN

FossTecator:

ANN modelling of NIR data - a tool for managing local and global commercial transactions in grain trading.

CellaVision:

Provide systems for the health-care sector for automatic digital cell morphology. DiffMaster - Blood cell classification using neural networks.

Pharma Vision Systems AB:

Automatic microscopy of particle shape and size.

Malcolm - ANN for graphic art quality control.
(Halmstad University)