Towards an Understanding of Ideas by Machines

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Presentation Outline

Multisets

Informal definition

A **multiset** is a collection of objects, such that elements of this collection may occur multiple times in the collection.

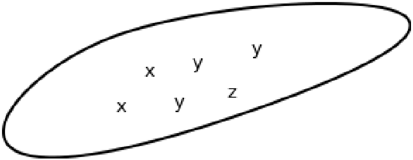


Figure: An Euler diagram of a multiset $\{x, x, y, y, y, z\}$.

Multisets

- The number of times an element occurs in a multiset is called a **multiplicity** and belongs to the set of all natural numbers.
- Multisets may be considered as a generalization of sets.
- A formal (axiomatic) theory of multisets has been given by W. D. Blizard [1].

Axiomatic generalizations of multiset theories

- Multiplicities of elements belong to the set of all positive and negative integers (what implies a possibility of negative membership) [3].
- Multiplicities belong to the set of all positive real numbers [2].
- Multiplicities belong to the set of all positive and negative real numbers [4].

Additive union of generalized multisets

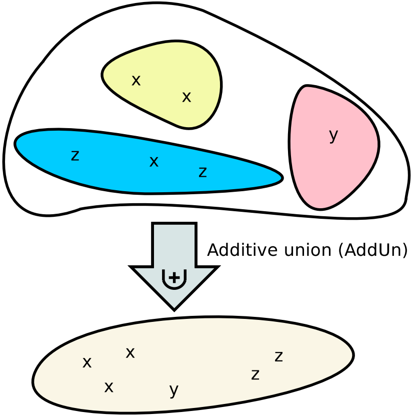


Figure: An Euler diagram of the additive union of a generalized multiset $\{\{x, x\}, \{z, x, z\}, \{y\}\}$.

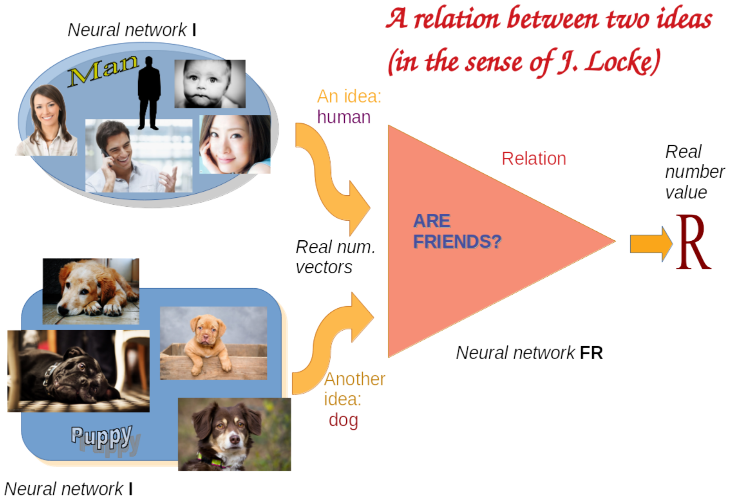
Conjectures

1. Simple ideas[1] can be produced by neural networks.
2. Neural networks can evaluate relations among ideas[2].
3. Understanding of a new, percepted sensation, *i.e.* sensory input, is a process of finding a similarity relation between the percepted sensation and one or more of previously experienced sensations or ideas.

[1] In the sense of John Locke.

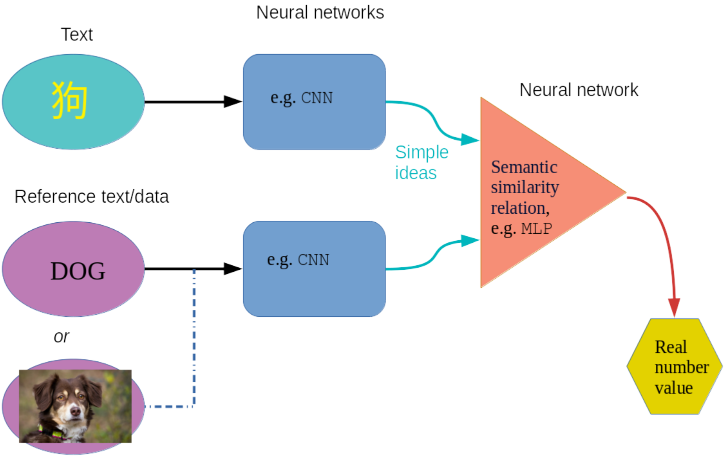
[2] Thus we can construct complex ideas in the sense of John Locke.

A general example



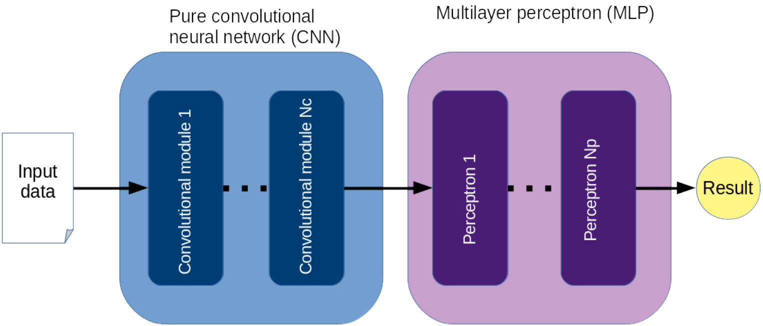
Semantic relationship

A more specific example: semantic comparator

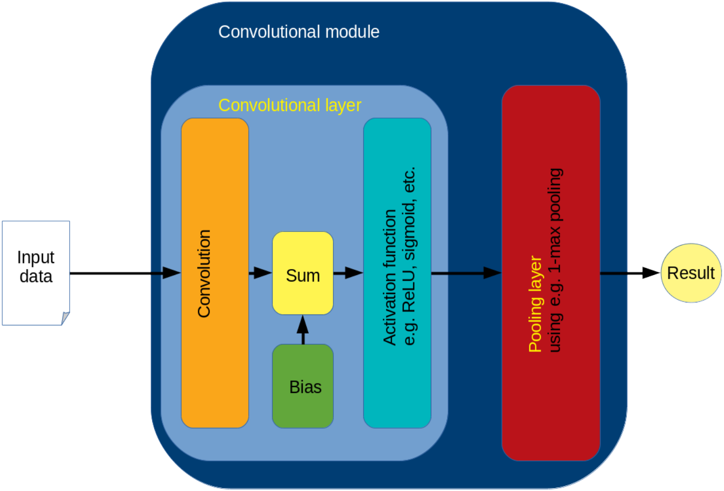


Core architecture

A hybrid of CNN and MLP



Convolutional modules



Perceptrons

Training rule

Steepest descent algorithm

$$P_{new} = P_{old} - \alpha \frac{\partial E}{\partial P} \tag{1}$$

where:

P - a network parameter, *e.g.* a weight, a bias or an element of a convolutional filter, $P \in \mathbb{R}$,

E - squared error between desired and actual output, $E \in \mathbb{R}$,

α - learning rate, $\alpha \in \mathbb{R}$, $\alpha > 0$.

The *Empiria* training method
Algorithm

Suppose that we have a set $\{P_1, P_2, \ldots, P_n\}$ of network parameters, E is measured for a single training pair and $\Delta > 0$. Then:

1. Set i to 1.
2. Measure $E(P_i)$.
3. Measure $E(P_i + \Delta)$.
4. Estimate $\frac{\partial E}{\partial P_i}$ as $\frac{E(P_i+\Delta)-E(P_i)}{\Delta}$.
5. Apply the training rule (1) to obtain a new value of P_i.
6. If $i < n$, then increment i by 1 and go to the step 2; otherwise finish.

The *Empiria* training method

Benefits

1. The algorithm is conceptualy much simpler than backpropagation and thus easier to implement.
2. The simplicity and generality of the algorithm allows for easy modification of the network architecture without significant change of the training algorithm.
3. The algorithm does not require a differentiable activation function.

Drawbacks

1. Tests showed that training using the Empiria training algorithm is slower than training using backpropagation.

Scientific questions

1. To which degree the conjectures are true? Firstly, is that question answerable?
2. Can a machine understand a text by evaluation of semantic similarity relation with respect to another text or data?
3. An universe of philosophical questions; *e.g.* does our AI machine actually perceive the world (as humans do)? If not, then – according to George Berkeley – our machine does not exist – since it is only an idea in the minds of perceivers; then may an idea exist in the machine, *viz.* can an idea exist inside an idea?

Research plan

Development of semantic comparator prototype

1. Development of:
   - convolutional layers,
   - pooling layers,
   - multilayer perceptron,
   - network training algorithms,
   - a system for pre-processing of input data, *e.g.* it would include file reading programs, word embedding, *etc.*,
   - a graphical user interface,
2. parallelization of calculations,
3. preparation of a set of training examples,
4. training of the network,
5. evaluation of the network performance,
6. manual adjustment of the network hyperparameters.

Research plan

Improvements and extension to arbitrary relations

1. Experiments involving relations between ideas derived from text and ideas derived from other sources, such as pictures or speech (heterogenous sensations),
2. an application of genetic algorithms for the training problem, as long as such an approach is in its infancy [6],
3. application of the dropout method to prevent an overfitting,
4. an introduction of the technology of capsules of neurons [5],
5. an additional CNN for recognition of words and symbols in source texts, what may facilitate exploitation of text graphical features and enable to avoid the need for word embedding.

Research plan

Automatic optimization of hyperparameters

Development of a genetic algorithm for automatic optimization of hyperparameters. This would involve:

- design of:
  1. a data structure for representation of network hyperparameters,
  2. a method for creation of new generations of solutions, using elitism, selection, crossover and mutation,
  3. a fitness function,
  4. a method for adaptive tuning of genetic algorithm parameters (probabilities of mutation and crossover), this step may be optional,
- implementation and evaluation of the genetic algorithm.

Summary

1. Scientific questions concerning cognitive problems has been formulated.
2. A research plan, induced by a will to answer the questions, has been proposed.
3. The research plan is partially realised.
4. The first interesting result of the endeavor is development and preliminary evaluation of a non-classical training algorithm.

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