Continuity of Semantic Operators and Their Approximation by Artificial Neural Networks

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We want to represent operators associated with Logic Programs by Artificial Neural Networks.

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Idea

- Logic Programs and Neural Networks are very different paradigms.
- Neural Networks can uniformly approximate continuous real operators.
- We study this kind of continuity for Logic Programs
- and use it for obtaining approximation results.

The approach builds on work by Hölldobler, Kalinke and Störr 199x.

We thank Howard A. **Blair** (Syracuse), Steffen **Hölldobler**, and Hans-Peter **Störr** (Dresden) for helpful discussions on the subject matter.

Logic Programs

A logic program P is a finite set of clauses

$$\forall(A \leftarrow L_1 \wedge \cdots \wedge L_n)$$

from first order logic, usually written as

$$A \leftarrow L_1, \ldots, L_n,$$

where A an atom, L_i a literal, $n \geq 0$.
B_P: Herbrand base (all ground atoms).
$I_P = 2^{B_P}$: set of all Herbrand interpretations.
ground(P): set of all ground instances
of clauses of P.

Define (non-monotonic) operator $T_P : I_P \to I_P$ by
$T_P(I)$ is set of all $A \in B_P$
for which there is a clause $A \leftarrow L_1 \wedge \cdots \wedge L_n$
in ground(P) s.t. $I \models L_1 \wedge \cdots \wedge L_n$.

I is a *supported model* iff $T_P(I) = I$.

T_P operator in 2-valued logic.
Many-valued logic has also been studied.

Many-valued Interpretations

Truth values $\mathcal{T} = \{t_1, \ldots, t_n\}$.

Interpretations are functions $I : B_P \to \mathcal{T}$.

$I_{P,n} (= I_P)$ set of all interpretations.

$A \in B_P$ then $\mathcal{B}_A$ set of all atoms in clauses of ground(P) with head A.

$T : I_P \to I_P$ *consequence operator* for P
if for all $I \in I_P$ and for all $A \leftarrow \texttt{body}$ in P,
where $T(I)(A) = t_i$ and $I(\texttt{body}) = t_j$, say,
$t_i \leftarrow t_j$ is true via truth table.

Consequence operator T is *local* if for all $A \in B_P$ and all $I, K \in I_P$ which agree on all atoms in $\mathcal{B}_A$, we have $T(I)(A) = T(K)(A)$.

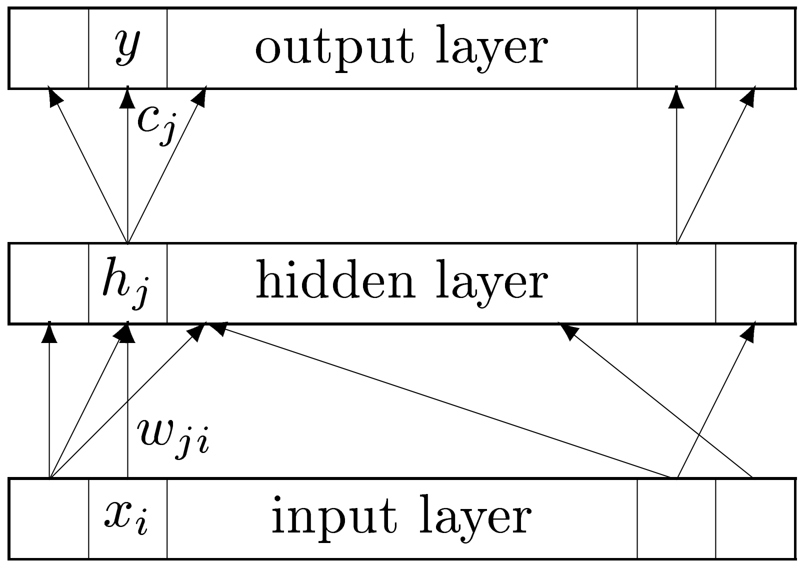
T_P is a local consequence operator.

Other examples: Operators due to Fitting (1985, 199x), in 3- and 4-valued logic.

Artificial Neural Networks I

A *3-layer feedforward network* (3ffn) consists of

- finitely many computational units
- organized in three layers:
  - input layer, hidden layer, output layer
- weighted connections between units
  - from input to hidden layer and
  - from hidden to output layer.



x_i	inputs
w_{ji}, c_j	connection weights
y	output

Artificial Neural Networks II

The input-output function $f : \mathbb{R}^n \to \mathbb{R}$ is

$$y = f(x_1, \ldots, x_r) = \sum_j c_j \phi \left(\sum_i w_{ji} x_i - \theta_j \right)$$

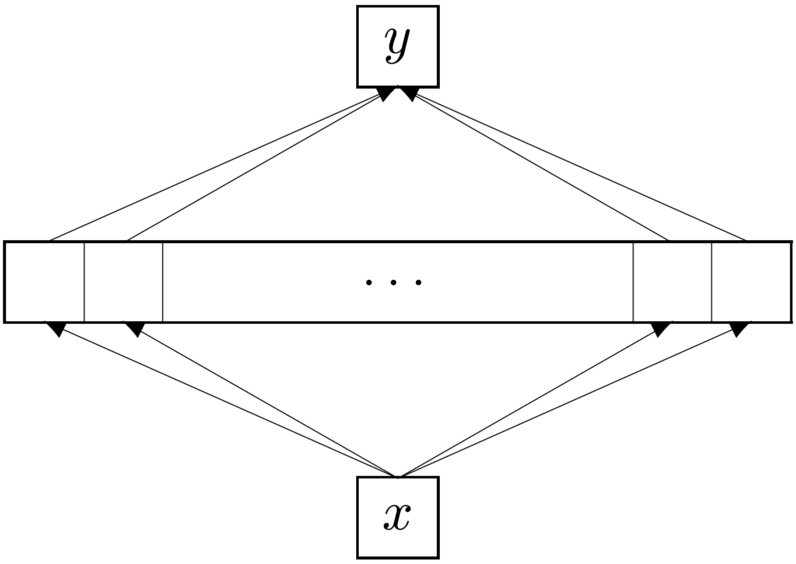
with *thresholds* $\theta_j \in \mathbb{R}$ and *squashing function* ϕ.

$\phi : \mathbb{R} \to \mathbb{R}$ is the same for each unit and usually

- non-constant, bounded, monotonic increasing,
- sometimes continuous.

The following architecture will suffice:

- one input unit x
- one output unit y



LPs versus ANNs

Neural Networks:

- approximates ("interpolates") functions
- hardly any knowledge about the fct^n needed
- trained using incomplete data
- declarative semantics not available
- recursive networks hardly understood
- symbolic data difficult to represent

Logic Programming:

- direct implementation of relations
- explicit expert knowledge required
- highly recursive structure
- well understood declarative semantics
- symbolic data easy to represent

Seek the best of both paradigms!

Approximation of LPs by ANNs

Theorem (Funahashi 1989, simplified version):

ϕ non-constant, bounded, monotone increasing, continuous.

$K \subseteq \mathbb{R}$ compact,

$f : K \to \mathbb{R}$ continuous,

$\varepsilon > 0$.

Then exists a 3ffn with squashing fct$^{\mathrm{n}}$ ϕ and input-output function $\bar{f} : K \to \mathbb{R}$ with

$$\max_{x \in K} \left\{ d\left(f(x), \bar{f}(x)\right) \right\} < \varepsilon;$$

d metric which induces natural top. on $\mathbb{R}$.

- "Each continuous function $f : K \to \mathbb{R}$ can be uniformly approximated by input-output functions of 3ffns."

The approach in [HKS]

Let P be a logic program which is *acyclic*, i.e. there exists a *level mapping* $l : B_P \to \mathbb{N}$ such that for each $A \leftarrow L_1, \dots, L_n$ in ground(P) we have $l(A) > l(L_i)$ for all $i = 1, \dots, n$.

We can define a complete metric d_l on I_P by $d_l(J, K) = 2^{-n}$, where $n \in \mathbb{N}$ is least s.t. J and K differ on an atom of level n.

For P acyclic, T_P is a contraction wrt. d_l.

- Banach contraction mapping theorem applies.
- T_P has unique fixed point M.
- M can be obtained as limit (in d_l) of the sequence $(T_P^n(K))_{n\in\mathbb{N}}$ for any $K \in I_P$.
- T_P is continuous wrt. d_l.

For injective l and acyclic P, [HKS] gave imbedding $\iota : I_P \to \mathbb{R}$ s.t. $\iota(T_P)$ was contraction on $\mathbb{R}$.

Generalized Atomic Topology $\mathcal{Q}$

Extends atomic topology (Seda 1995) and query topology (Batharek and Subrahmanian 1989).

Given P we define $\mathcal{Q}$ on I_P to be the product topology on $\mathcal{T}^{B_P}$, where $\mathcal{T} = \{t_1, \ldots, t_n\}$ is endowed with the discrete topology.

$\mathcal{Q}$ second countable totally disconnected compact Hausdorff topology which is dense in itself.

$\mathcal{Q}$ is metrizable and homeomorphic to the Cantor topology on the unit interval of the real line. (Note B_P is countable.)

Cantor Space $\mathcal{C}$ with subspace topology from $\mathbb{R}$ carries Cantor topology.

$\mathcal{C}$ compact subset of $\mathbb{R}$.

Continuity in $\mathcal{Q}$

Consequence operator T on I_P is *finitely local* if for all $A \in B_P$ and all $I \in I_P$ there exists a finite subset $S \subseteq \mathcal{B}_A$ such that $T(J)(A) = T(I)(A)$ for all $J \in I_P$ which agree with I on S.

Theorem

> A local consequence operator is finitely local if and only if it is continuous in $\mathcal{Q}$.

Conditions which imply that T is finitely local:

- P has no local variables.
- There exists injective *level mapping* $l : B_P \to \mathbb{N}$ such that for each $A \in B_P$ there exists $n_A \in \mathbb{N}$ such that $l(B) < n_A$ for all $B \in \mathcal{B}_A$. (Communicated by H.A. Blair.)

Main Theorem

Theorem

Let P be a logic program and T a consequence operator which is finitely local, and let ι be a homeomorphism from $(I_{P,n}, \mathcal{Q})$ to $\mathcal{C}$.
Then T (more precisely $\iota(T)$) can be uniformly approximated by input-output mappings of 3-layer feedforward networks.

Measurability I

Theorem (Hornik, Stinchcombe, White 1989, simplified version)

$\phi : \mathbb{R} \to (0,1)$ monotone increasing, surjective.
$f : \mathbb{R} \to \mathbb{R}$ Borel-measurable,
μ probability Borel-measure on $\mathbb{R}$,
$\varepsilon > 0$.

Then exists 3ffn with squashing fct$^{\mathrm{n}}$ ϕ and input-output function $\bar{f} : \mathbb{R} \to \mathbb{R}$ with
$\varrho_\mu(f, \bar{f}) =$

$$\inf \left\{ \delta > 0 : \mu \left\{ x : \left| f(x) - \bar{f}(x) \right| > \delta \right\} < \delta \right\} < \varepsilon.$$

- "The class of functions computed by 3ffns is dense in the set of all Borel measurable functions $f : \mathbb{R} \to \mathbb{R}$ rel. to the metric ϱ_μ."

Measurability II

Theorem

Local consequence operators are always measurable with respect to $\sigma(\mathcal{Q})$.

Approximation is only *almost everywhere*
i.e. except a set of measure 0.

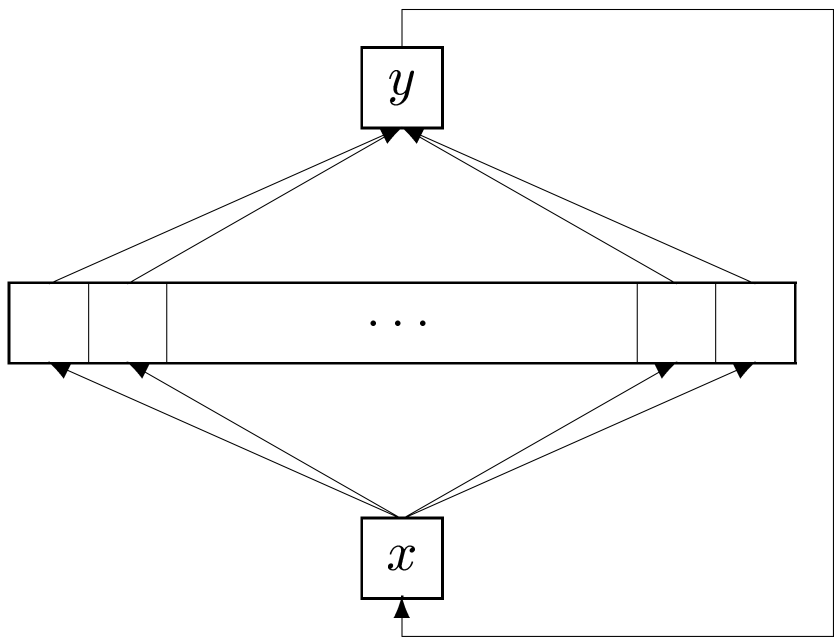
$\iota(I_P) = \mathcal{C}$ is set of measure 0.

Possible approach: "Blowing up" of Cantor set in order to give it positive measure.

Recurrent Architecture I

- Approximation results give no way of constructing the network.
- Is the obtained approximation sufficient?

[HKS] use the following recurrent architecture:



- Network iterates consequence operator.

Recurrent Architecture II

T locally finite local consequence operator.
f I/O function of approximating network.

For any $I \in I_P$ and any $n \in \mathbb{N}$ we have

$$|f^n(\iota(I)) - \iota(T^n(I))| \leq \varepsilon \frac{1-\lambda^n}{1-\lambda}.$$

λ Lipschitz constant of F which is the extension of $\iota(T)$ onto $[0,1]$.
ε error of the network.

If F is a contraction on $[0,1]$,
then $\left(F^k(\iota(I))\right)$ converges for every I to the unique fixed point x of F and there exists $m \in \mathbb{N}$ such that for all $n \geq m$ we have

$$|f^n(\iota(I)) - x| \leq \varepsilon \frac{1}{1-\lambda}.$$

If F is a contraction on $[0,1]$, then T is a contraction on the complete subspace $\mathcal{C}$, and also has a fixed point M, and $\iota(M) = x$.

Recurrent Architecture III

If for some $I \in I_P$, $T^n(I)$ converges in $\mathcal{Q}$ to a fixed point M of T, then for every $\delta > 0$ there exists a network with input-output function f, and some $n \in \mathbb{N}$ such that $|f^n(\iota(I)) - \iota(M)| < \delta$.

A logic program P is called *acyclic* if there exists a mapping $l : B_P \to \mathbb{N}$, called a *level mapping*, such that for each clause $A \leftarrow L_1, \ldots, L_n$ in ground(P) we have $l(A) > l(L_i)$ for all $i = 1, \ldots, n$.

Define $d : I_P \times I_P \to \mathbb{R}$ by $d(I, J) = 2^{-n}$, where n is least such that I and J differ on some atom A with $l(A) = n$.
d is a complete metric on I_P.

T is a contraction with respect to d if P is acyclic. Banach contraction theorem applies.

Let P be an acyclic program and T be a local consequence operator for P. Then for any $I \in I_P$ we have that $T^n(I)$ converges in $\mathcal{Q}$ to the unique fixed point M of T.

Conclusions

Proposed the study of nonmonotonic semantic operators in multi-valued logic. This extends the tools available for studying declarative semantics of logic programs.

Obtained theoretical results concerning the representation of first order logic programs by neural networks.

Questions:

Constructing the networks?

How to circumvent the measurability problem?