

An Isabelle Formalization of the Expressiveness of Deep Learning

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Motivation

- ▶ Case study of proof assistance in the field of machine learning
- ▶ Development of general-purpose libraries
- ▶ Study of the mathematics behind deep learning

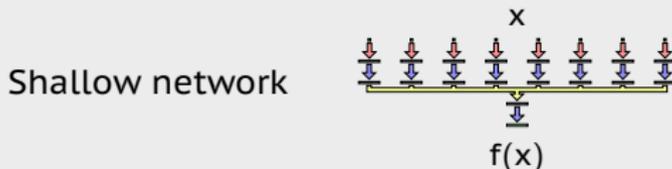
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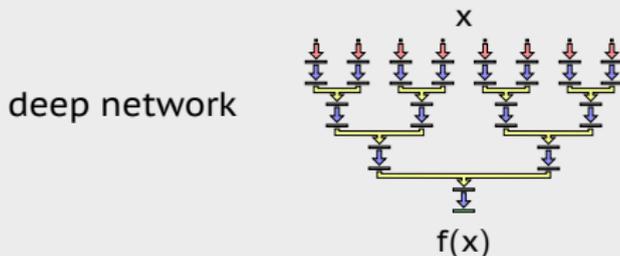
Just wanted to formalize something!

Fundamental Theorem of Network Capacity

(Cohen, Sharir & Shashua, 2015)



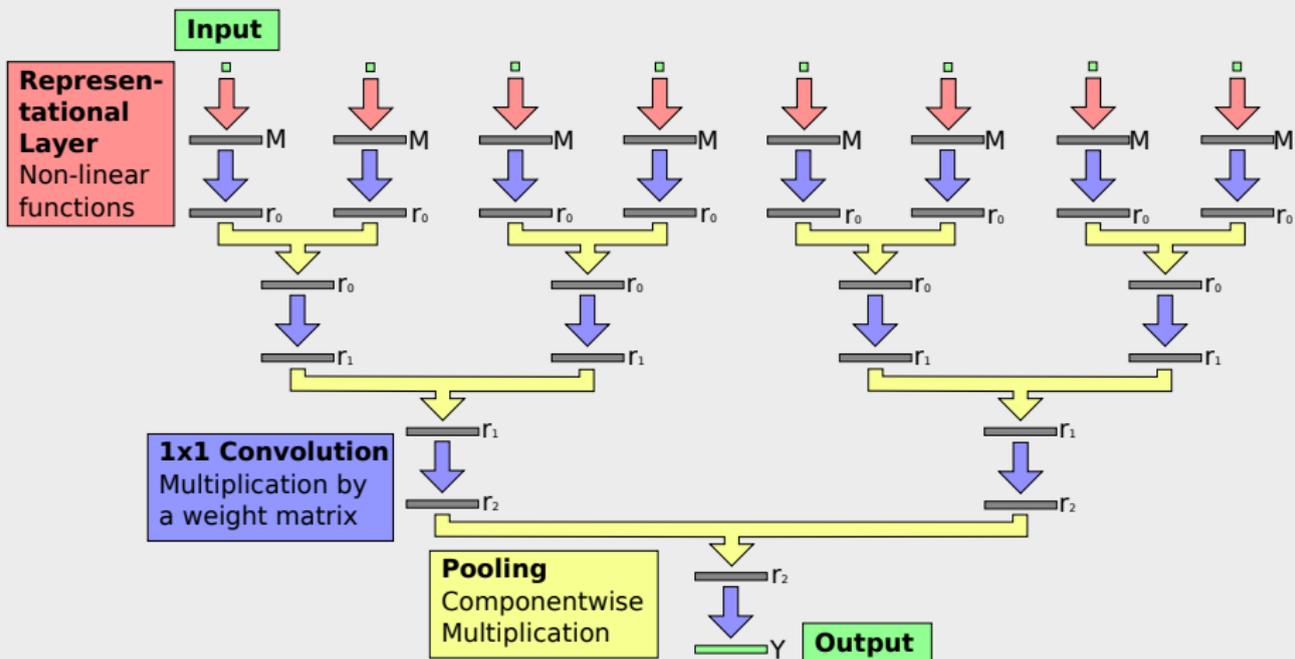
needs exponentially more nodes to express the same function as



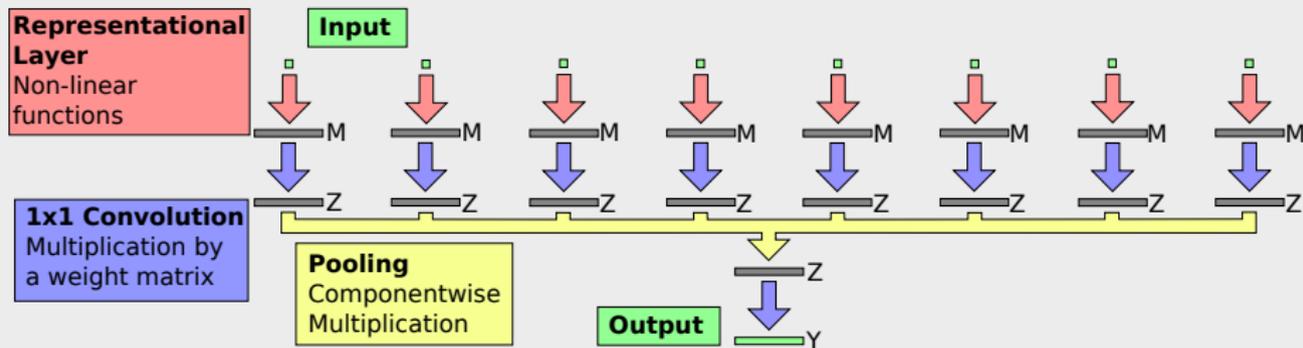
for the vast majority of functions*

* except for a Lebesgue null set

Deep convolutional arithmetic circuit



Shallow convolutional arithmetic circuit



Lebesgue measure

definition `lborel` :: (α :: euclidean_space) measure

 Isabelle's standard probability library

vs.

 My new definition

definition `lborelf` :: nat \Rightarrow (nat \Rightarrow real) measure
where `lborelf n` =
 $\prod_M \mathbf{b} \in \{.. < n\}$. (`lborel` :: real measure)

Matrices

- ▶ Isabelle's multivariate analysis library
- ▶ Sternagel & Thiemann's matrix library
(Archive of Formal Proofs, 2010)
- ▶ Thiemann & Yamada's matrix library
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I added definitions and lemmas for

- ▶ matrix rank
- ▶ submatrices

Multivariate polynomials

Lochbihler & Haftmann's polynomial library

I added various definitions, lemmas, and the theorem

- ▶ "Zero sets of polynomials $\neq 0$ are Lebesgue null sets."

theorem:

fixes $p :: \text{real mpoly}$

assumes $p \neq 0$ **and** $\text{vars } p \subseteq \{.. < n\}$

shows $\{x \in \text{space } (\text{lborel}_f \ n). \text{insertion } x \ p = 0\}$
 $\in \text{null_sets } (\text{lborel}_f \ n)$

My tensor library

typedef α tensor =

{(ds :: nat list, as :: α list). length as = prod_list ds}

- ▶ addition, multiplication by scalars, tensor product, matricization, CP-rank
- ▶ Powerful induction principle uses subtensors:
 - ▶ Slices a $d_1 \times d_2 \times \cdots \times d_N$ tensor into d_1 subtensors of dimension $d_2 \times \cdots \times d_N$

definition subtensor :: α tensor \Rightarrow nat \Rightarrow α tensor

The proof on one slide

Def1 Define a tensor $\mathcal{A}(w)$ that describes the function expressed by the deep network with weights w

Lem1 The CP-rank of $\mathcal{A}(w)$ indicates how many nodes the shallow network needs to express the same function

Def2 Define a polynomial p with the deep network weights w as variables

Lem2 If $p(w) \neq 0$, then $\mathcal{A}(w)$ has a high CP-rank

Lem3 $p(w) \neq 0$ almost everywhere

Restructuring the proof

Before

Def1	Tensors
Lem1	Tensors, shallow network
Induction over the deep network	
Lem2	Polynomials, Matrices
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Lem3a	Matrices, Tensors
Lem3b	Measures, Polynomials

After

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* except for a zero set of a polynomial

Type for convolutional arithmetic circuits

datatype α cac =

Input nat

Conv α (α cac)

Pool (α cac) (α cac)

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$(\text{nat} \times \text{nat}) \text{ cac} \Rightarrow (\text{nat} \Rightarrow \text{real}) \Rightarrow \text{real mat cac}$
network without weights weights network with weights

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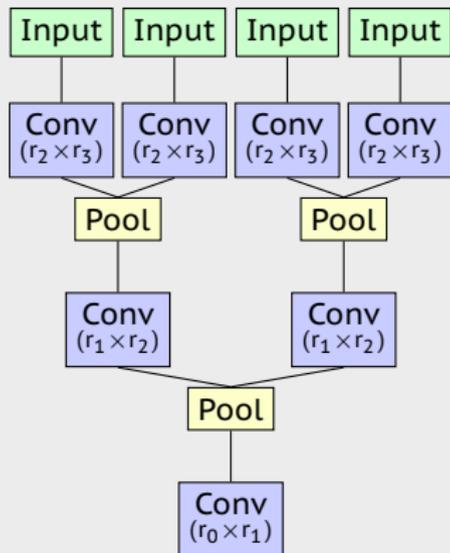
fun evaluate_net :: $\text{real mat cac} \Rightarrow \text{real vec list} \Rightarrow \text{real vec}$
network input output

Deep network parameters

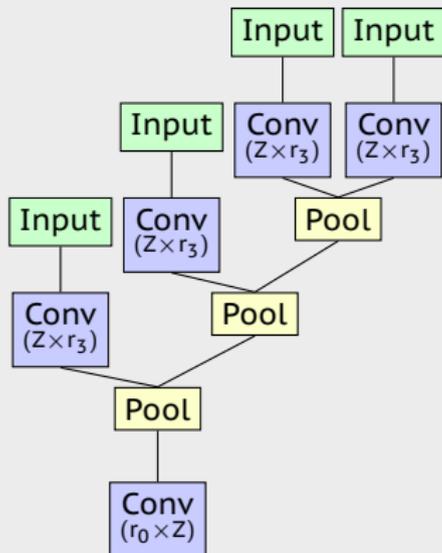
```
locale deep_net_params =  
  fixes rs :: nat list  
  assumes deep: length rs  $\geq$  3  
  and no_zeros:  $\bigwedge r. r \in \text{set } rs \implies 0 < r$ 
```

Deep and shallow networks

deep_net =



shallow_net Z =



Def1 Define a tensor $\mathcal{A}(w)$ that describes the function expressed by the deep network with weights w

definition $\mathcal{A} :: (\text{nat} \Rightarrow \text{real}) \Rightarrow \text{real tensor}$
where $\mathcal{A} w = \text{tensor_from_net} (\text{insert_weights deep_net } w)$

The function `tensor_from_net` represents networks by tensors:

fun `tensor_from_net` :: `real mat cac` \Rightarrow `real tensor`

If two networks express the same function, the representing tensors are the same

Lem1 The CP-rank of $\mathcal{A}(w)$ indicates how many nodes the shallow network needs to express the same function

lemma `cprank_shallow_model`:
shows `cprank (tensor_from_net
 (insert_weights w (shallow_net Z))) ≤ Z`

- ▶ Can be proved by definition of the CP-rank

Def2 Define a polynomial p with the deep network weights w as variables

Easy to define as a function:

definition $p_{\text{func}} :: (\text{nat} \Rightarrow \text{real}) \Rightarrow \text{real}$ **where**

$$p_{\text{func}} w = \det (\text{submatrix } [A_i w] \text{ rows_with_1 rows_with_1})$$

But we must prove that p_{func} is a polynomial function

Lem2 If $p(w) \neq 0$, then $\mathcal{A}(w)$ has a high CP-rank

lemma

assumes $p_{\text{func}} w \neq 0$

shows $r^{\text{N_half}} \leq \text{cprank}(\mathcal{A} w)$

- ▶ Follows directly from definition of p using properties of matricization and of matrix rank

Lem3 $p(w) \neq 0$ almost everywhere

Zero sets of polynomials $\neq 0$ are Lebesgue null sets

\implies It suffices to show that $p \neq 0$

We need a weight configuration w with $p(w) \neq 0$

Final theorem

theorem

$\forall_{ae} w_d$ w.r.t. $lborel_f$ $weight_space_dim.$ $\#w_s Z.$

$Z < r^{N_half} \wedge$

$\forall is. input_correct\ is \rightarrow$

$evaluate_net\ (insert_weights\ deep_net\ w_d)\ is =$

$evaluate_net\ (insert_weights\ (shallow_net\ Z)\ w_s)\ is$

Conclusion

Outcome

- ▶ First formalization on deep learning
Substantial development (~ 7000 lines including developed libraries)
- ▶ Development of libraries
New tensor library and extension of other libraries
- ▶ Generalization of the theorem
Proof restructuring led to a more precise result

More information:

<http://matryoshka.gforge.inria.fr/#Publications>

AITP abstract

Archive of Formal Proofs entry

ITP paper draft (coming soon)

M.Sc. thesis