A Formal Proof of the Expressiveness of Deep Learning

Alexander Bentkamp Vrije Universiteit Amsterdam

Jasmin Blanchette Vrije Universiteit Amsterdam

Dietrich Klakow Universität des Saarlandes

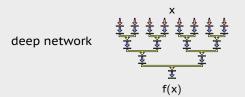
Motivation

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

Fundamental Theorem of Network Capacity

(Cohen, Sharir & Shashua, 2015)

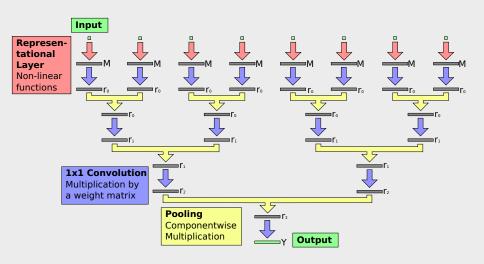
needs exponentially more nodes to express the same function as



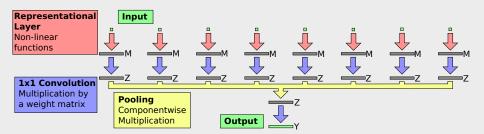
for the vast majority of functions*

^{*} except for a Lebesque null set of functions

Deep convolutional arithmetic circuit



Shallow convolutional arithmetic circuit



Convolutional arithmetic circuits \neq CNNs

CACs are not quite the standard architecture

But:

- Easier to analyze
- Allow to prove similar results for CNNs
- Perform better than CNNs when computational resources are limited

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 $\mathcal{A}(w)$ tells 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 A(w) has a high CP-rank
- Lem3 $p(w) \neq 0$ almost everywhere

Restructuring the proof

Before

Def1 Tensors	
Lem1 Tensors, shall	ow network
Induction over the deep network	
Lem2 Polynomials,	Matrices
Def2 Polynomials,	Tensors
Lem3a Matrices, Ten	sors
Lem3b Measures, Po	lynomials

After

Def1	Tensors
Lem1	Tensors, shallow network
	on over the deep network Polynomials, Tensors
Lem2	Polynomials, Matrices
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Restructuring the proof

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Def1	Tensors	
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Lem2	Polynomials, Matrices	
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Lem3b	Measures, Polynomials	

^{*} except for a Lebesgue null set

^{*} except for a zero set of a polynomial

Lebesgue measure

definition lborel :: (α :: euclidean_space) measure

Isabelle's standard probability library

Lebesgue measure

- Isabelle's multivariate analysis library
- Sternagel & Thiemann's matrix library (Archive of Formal Proofs, 2010)
- Thiemann & Yamada's matrix library (Archive of Formal Proofs, 2015)

matrix dimension fixed by the type

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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 ≠ 0 are Lebesgue null sets."

theorem

```
\begin{split} & \text{fixes } p :: \text{real mpoly} \\ & \text{assumes } p \neq 0 \text{ and } \text{vars } p \subseteq \{.. < n\} \\ & \text{shows } \{x \in \text{space (lborel}_f n). \text{ insertion } x \mid p = 0\} \\ & \in \text{null\_sets (lborel}_f n) \end{split}
```

My tensor library

```
typedef \alpha tensor = {(ds :: nat list, as :: \alpha list). |as| = \prod ds}
```

- addition, multiplication by scalars, tensor product, matricization, CP-rank
- Powerful induction principle uses subtensors:
 - Slices a d₁ × d₂ × · · · × d_N tensor into d₁ subtensors of dimension d₂ × · · · × d_N

Type for convolutional arithmetic circuits

```
\begin{array}{c|c} \textbf{datatype} \ \alpha \ \mathsf{cac} = \\ \hline \text{Input nat} \ | \ \hline \textbf{Conv} \ \alpha \ (\alpha \ \mathsf{cac}) \ | \ \hline \textbf{Pool} \ (\alpha \ \mathsf{cac}) \ (\alpha \ \mathsf{cac}) \end{array}
```

Type for convolutional arithmetic circuits

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```

```
fun insert_weights :: \underbrace{(\text{nat} \times \text{nat}) \text{ cac}}_{\text{network without weights}} \underbrace{(\text{nat} \Rightarrow \text{real})}_{\text{network without weights}} \Rightarrow \underbrace{\text{real mat cac}}_{\text{network with weights}}
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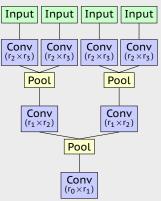
fun evaluate_net ::
$$\underbrace{\text{real mat cac}}_{\text{network}} \Rightarrow \underbrace{\text{real vec list}}_{\text{input}} \Rightarrow \underbrace{\text{real vec}}_{\text{output}}$$

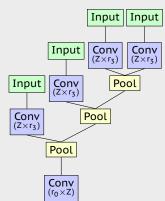
Deep network parameters

```
locale deep_net_params = fixes rs :: nat list assumes length rs \geq 3 and \forallr \in set rs. 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

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The function tensor_from_net represents networks by tensors:

fun tensor_from_net :: real mat cac ⇒ real tensor

Def1 Define a tensor A(w) that describes the function expressed by the deep network with weights w

```
definition A :: (nat \Rightarrow real) \Rightarrow real tensor where 
 <math>A w = tensor\_from\_net (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 $\mathcal{A}(w)$ tells how many nodes the shallow network needs to express the same function

lemma

```
\label{eq:continuous} \begin{array}{c} cprank \; (tensor\_from\_net \\ & (insert\_weights \; w \; (shallow\_net \; Z))) \leq Z \end{array}
```

by definition of CP-rank

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

Easy to define as a function:

But:

We must prove that p_{func} corresponds to a polynomial

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

lemma assumes p_{func} $w \neq 0$ shows $r^{N_half} \leq cprank (A w)$

 Follows directly from definition of p_{func} using properties of matricization and of matrix rank Lem3 $p(w) \neq 0$ almost everywhere

Theorem:

Zero sets of polynomials $\not\equiv 0$ are Lebesgue null sets

Hence it suffices to show that $p \not\equiv 0$

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

Final theorem

theorem

```
\begin{array}{l} \forall_{\rm ae}\,w_{\rm d}\,\,{\rm w.r.t.}\ \ \mbox{lborel}_{\rm f}\,\,\mbox{weight\_space\_dim.}\,\, \mbox{\mbox{$\frac{1}{2}$}} w_{\rm s}\,\,\mbox{Z}.\\ \mbox{$Z< r^{N\_half}}\,\,\, \wedge\\ \mbox{$\forall$is. input\_correct is} \longrightarrow\\ \mbox{evaluate\_net (insert\_weights deep\_net}\,\,w_{\rm d})\,\,\mbox{is} =\\ \mbox{evaluate\_net (insert\_weights (shallow\_net}\,\,\mbox{Z})}\,\,w_{\rm s})\,\,\mbox{is} \end{array}
```

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

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More information:

