

Deep learning: Challenges in learning and generalization

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What is generalization?

Memorization

- to remember all training examples (Universal Approximator)
- $2 + 3 = 5$, $3 + 2 = 5$, ...

Generalization

- to infer novel conclusions
- $123 + 234 = 357$, ...

How much do deep neural networks generalize?

- Often less than we would expect (or hope)
- It is easy to make wrong conclusions when using deep networks without understanding how they work
- In this talk: examples of limits of learning in recurrent neural networks

Language Modeling for strong AI

- Language models assign probability to sentences
- $P(\text{"Capital city of Czech is Prague"}) > P(\text{"Capital city of Czech is Barcelona"})$

AI-complete problem:

- *A bit of progress in language modeling*, Joshua Goodman 2001
- Hutter prize compression challenge

AI-completeness of language modeling

We could build intelligent question answering systems and chatbots using perfect language models:

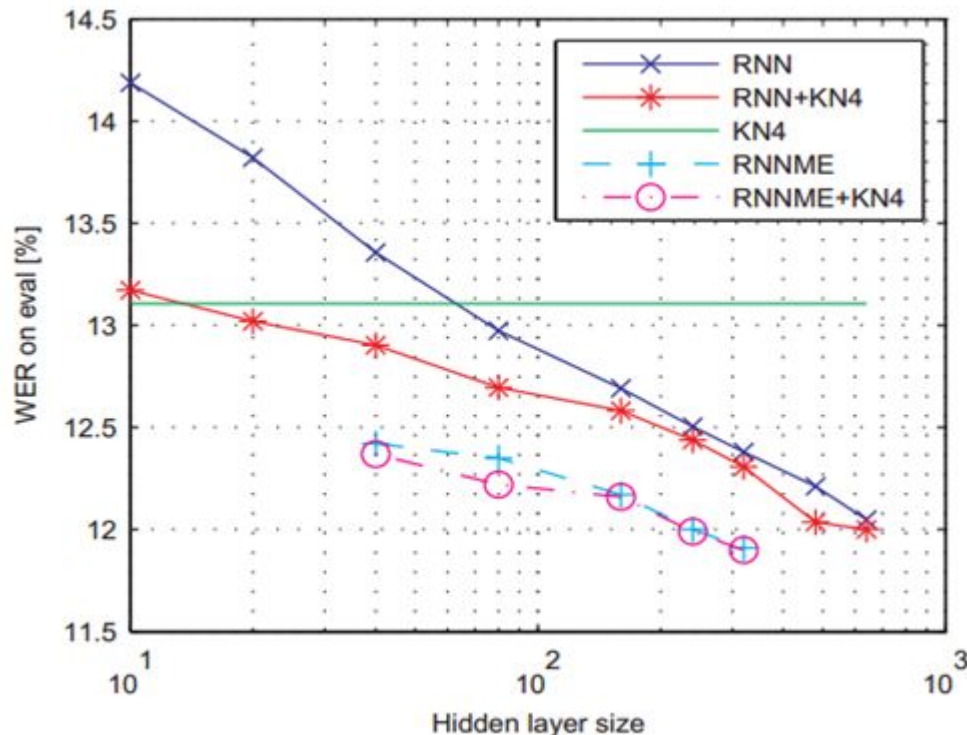
- $P(\text{"Is the value of of Pi larger than 3.14? Yes."}) > P(\text{"Is the value of of Pi larger than 3.14? No."})$

Language models can generate novel text:

- better language models generate significantly better text (RNNLM, 2010)

Recurrent neural language models

- Breakthrough after 30 years of dominance of n-grams
- The bigger, the better!
 - This continues to be the mainstream even today
- Can this lead to AGI?



Strategies for training large scale neural network language models, Mikolov et al, 2011

End-to-end Machine Translation with RNNLM (2012)

Simple idea - create a training set from pairs of sentences in different languages:

1. Today it is Sunday. Hoy es domingo.
It was sunny yesterday. Ayer estaba soleado.
...
2. Train RNNLM
3. Generate continuation of text given only the English sentence: translation!

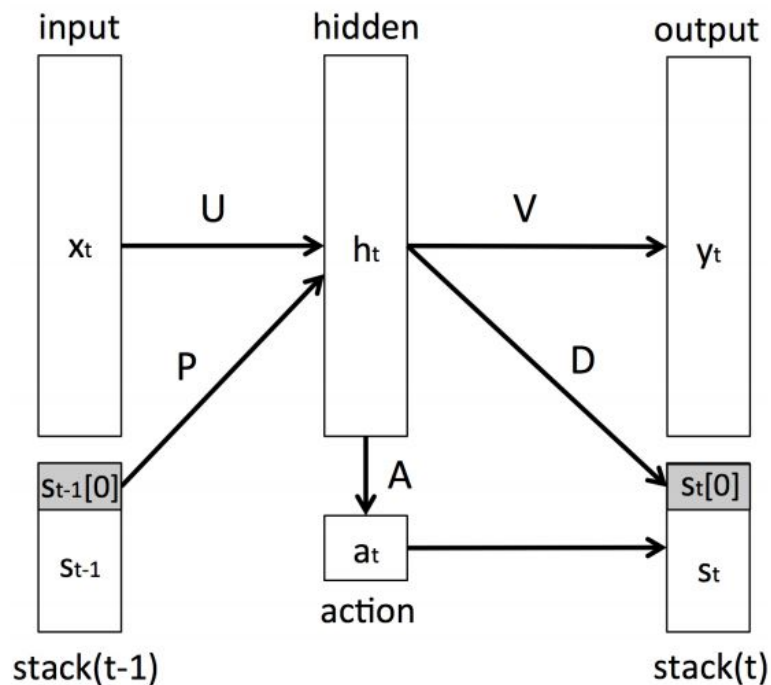
End-to-end Machine Translation with RNNLM (2012)

- Problem: the performance drops for long sentences
- Even worse: cannot **learn** identity!
 - Today it is Sunday. Today it is Sunday.
It was sunny yesterday. It was sunny yesterday.
...
 - Can perfectly memorize training examples, but fails when test data contain longer sequences

Towards RNNs that learn algorithms

- RNNs trained with stochastic gradient descent usually do not learn algorithms
 - just memorize training examples
 - does not matter how many hidden layers we use, and how big the hidden layers are
- This does not have to be a serious problem for applied machine learning
 - memorization is often just fine
- A critical issue for achieving strong AI / AGI

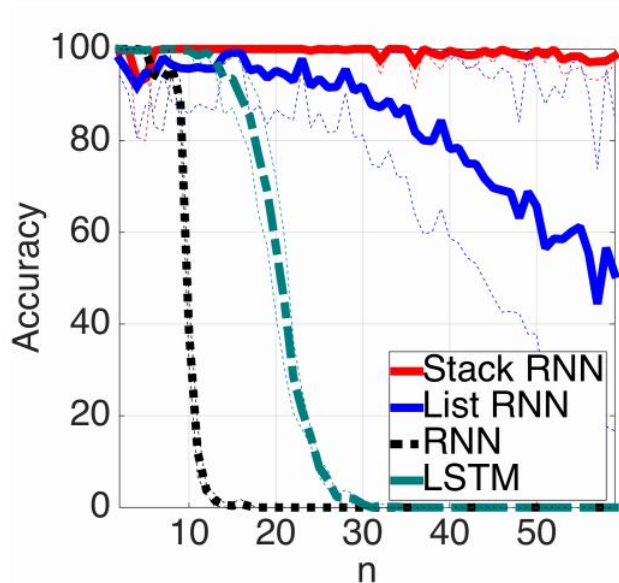
Stack-augmented RNN



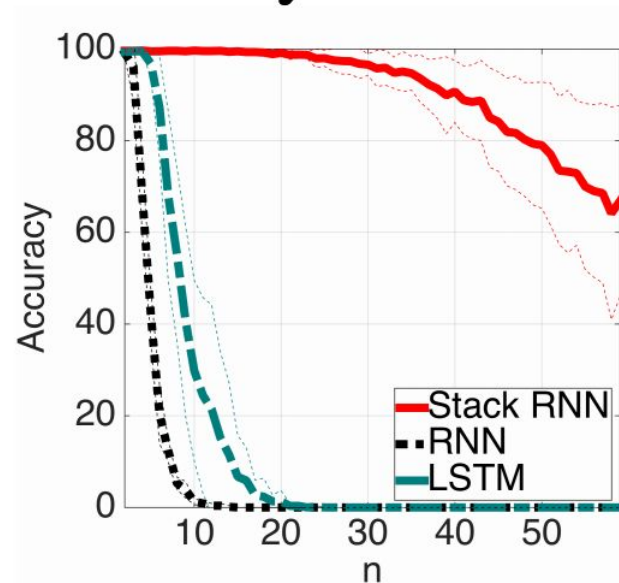
Inferring algorithmic patterns with stack-augmented recurrent nets, Joulin & Mikolov, 2015

Generalization in RNNs

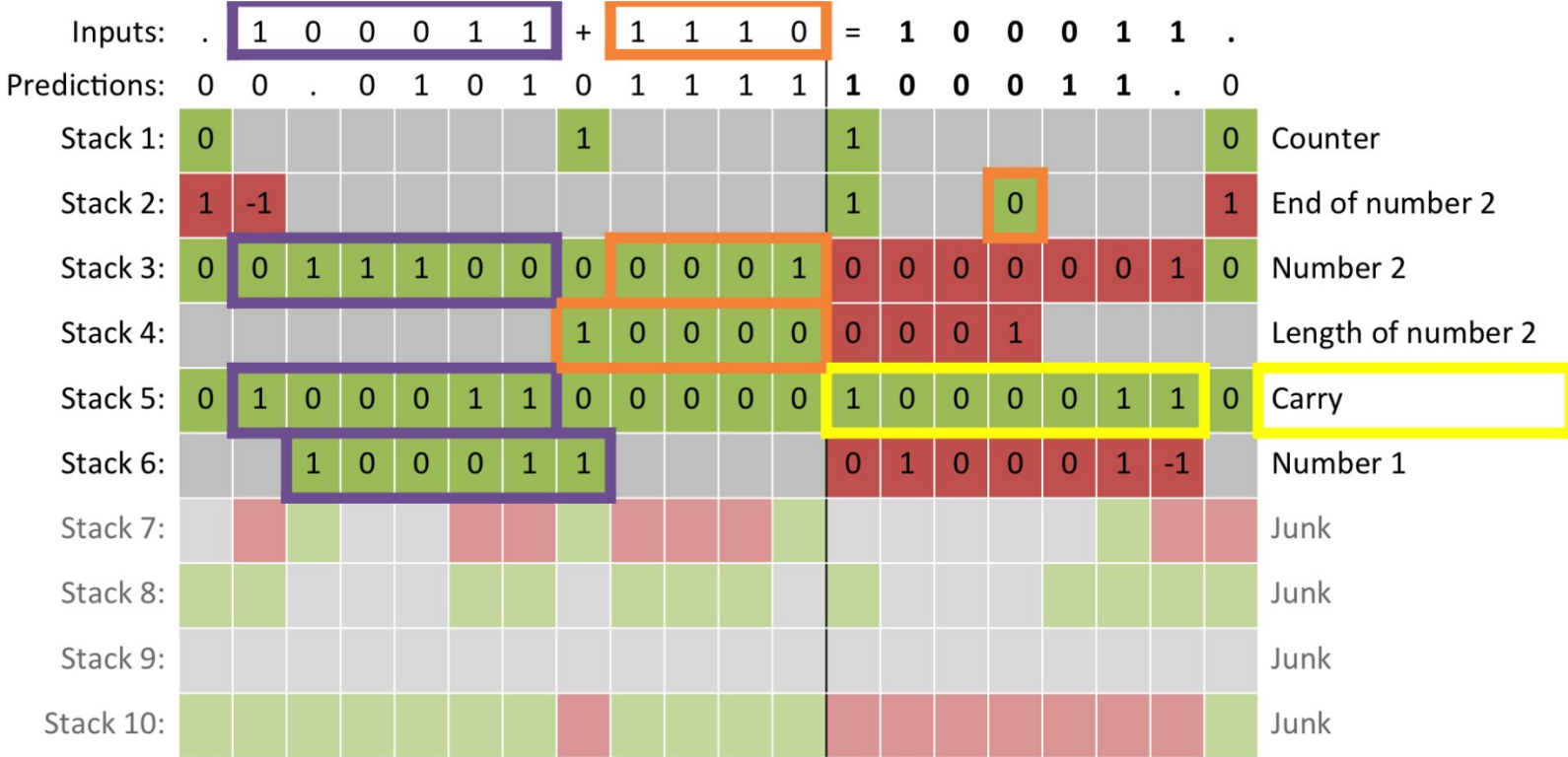
Memorization



Binary addition



Binary addition learned with no supervision



Future research - algorithmic transfer learning

- current machine learning models are usually bad at high-level transfer learning
- the “solution” that is learned is often closer to look up table than minimum description length solution
- teaching an RNN to solve a slightly more complex version of already solved task thus mostly fails

A roadmap towards machine intelligence, Mikolov et al, 2015

Future research - different approach to learning

- we need much less supervision
- probably no SGD, no convergence (learning never ends)
- maybe more fundamental (basic) model than RNN?
 - are memory, learning, tasks, rewards etc. just emergent properties in a more general system?