Introduction: History + Overview

LING 574 Deep Learning for NLP

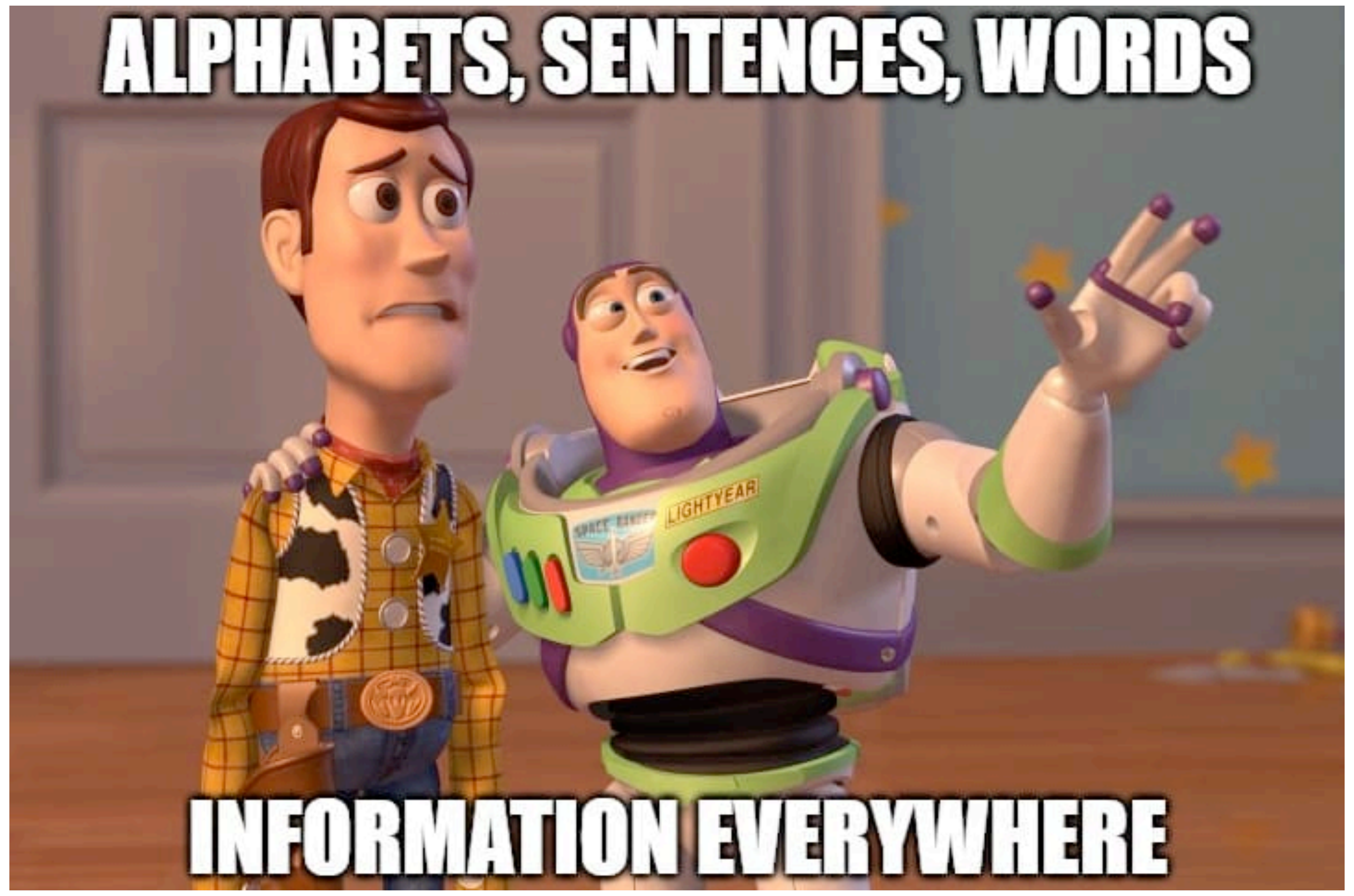
Shane Steinert-Threlkeld

Today's Plan

- Brief general introduction
- Potted History of Deep Learning
- Potted History of Models in NLP
- Course information / logistics

What is deep learning for NLP?

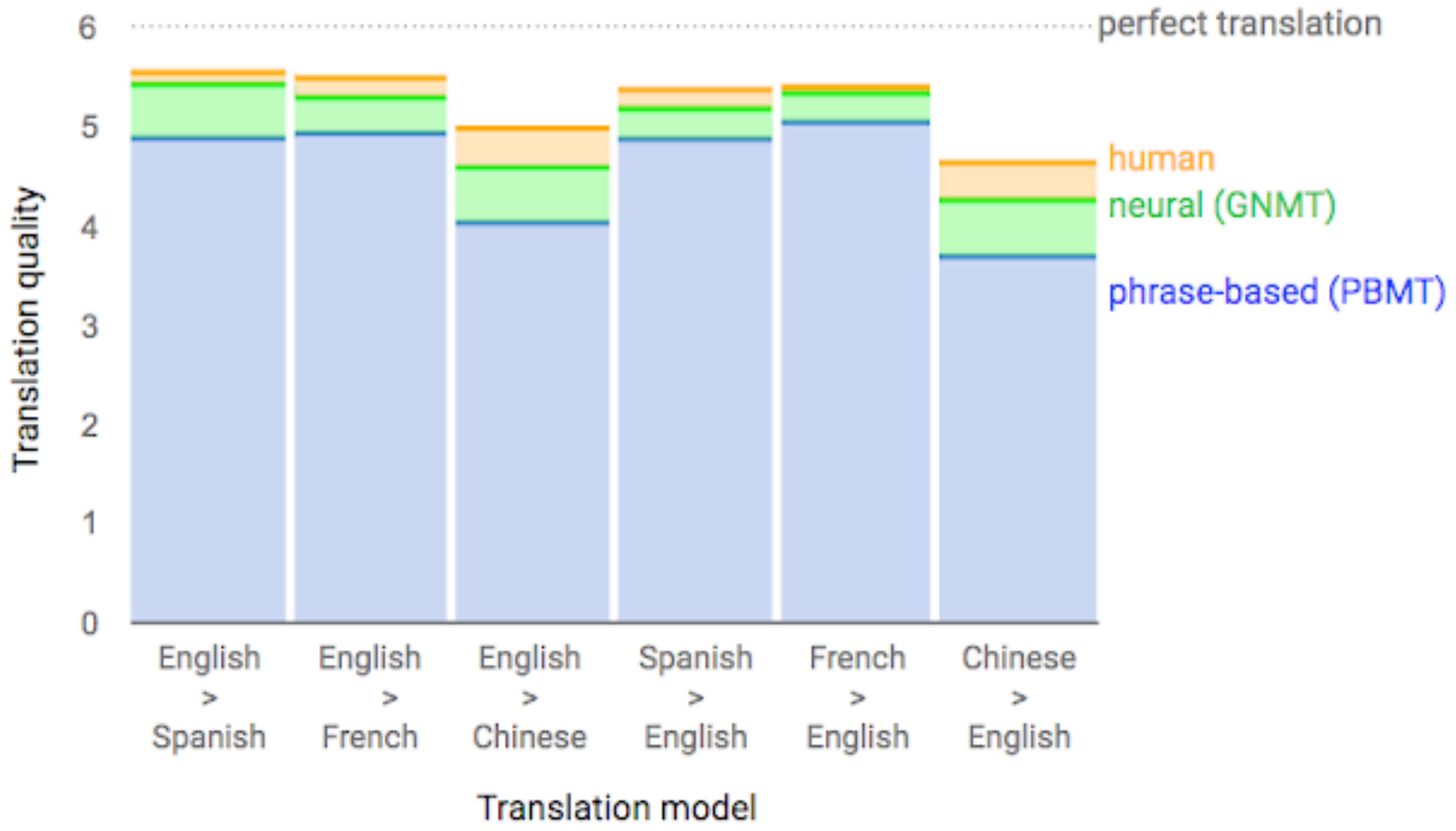
- Language is an amazingly flexible system for communicating complex information.
  - Novel expressions
  - Arbitrarily complex
  - Systematic generalization
- Prime example of a *symbolic system*
- How do we enable computers to understand and process language?
  - Traditional approach: by manipulating symbols

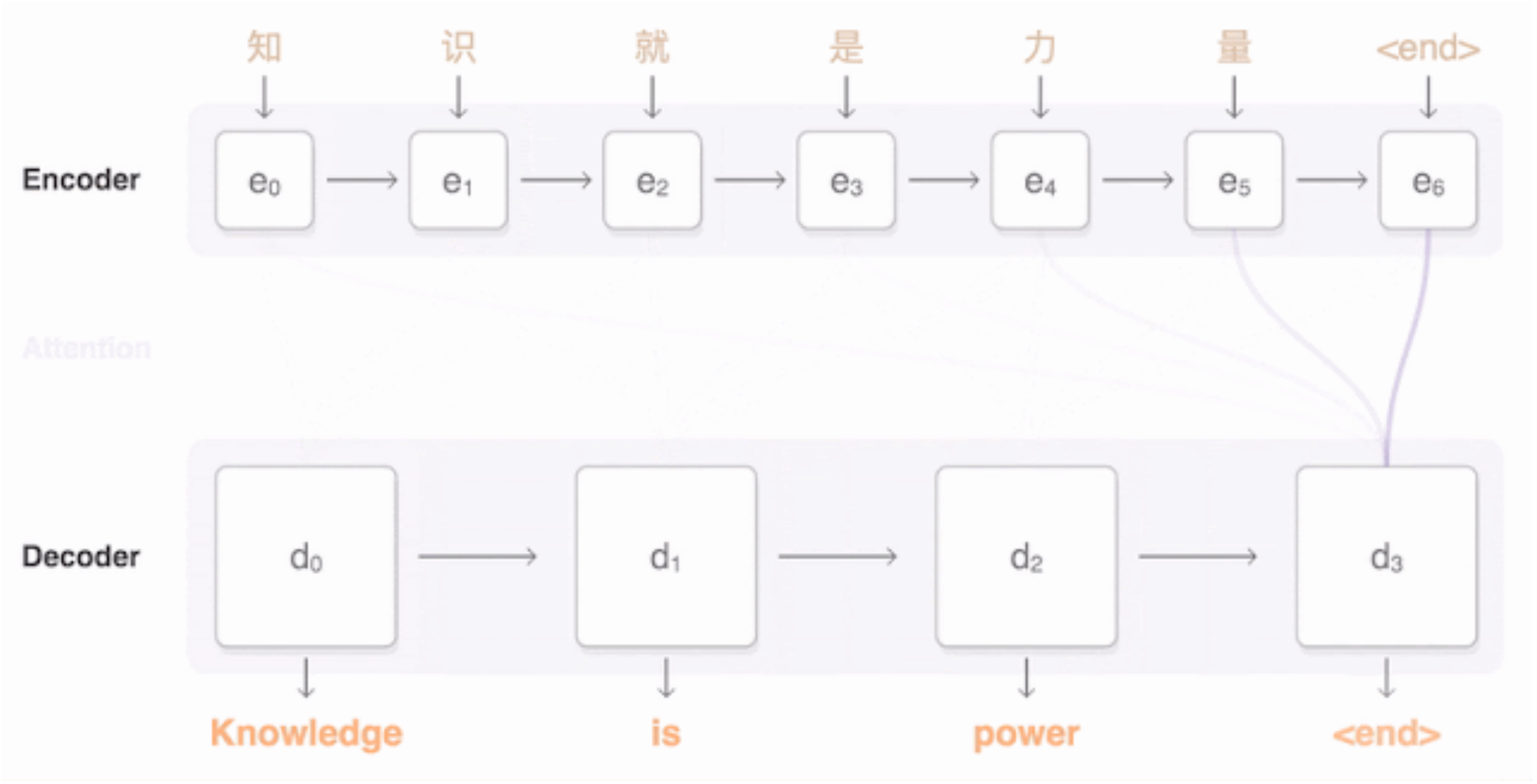


What is deep learning for NLP?

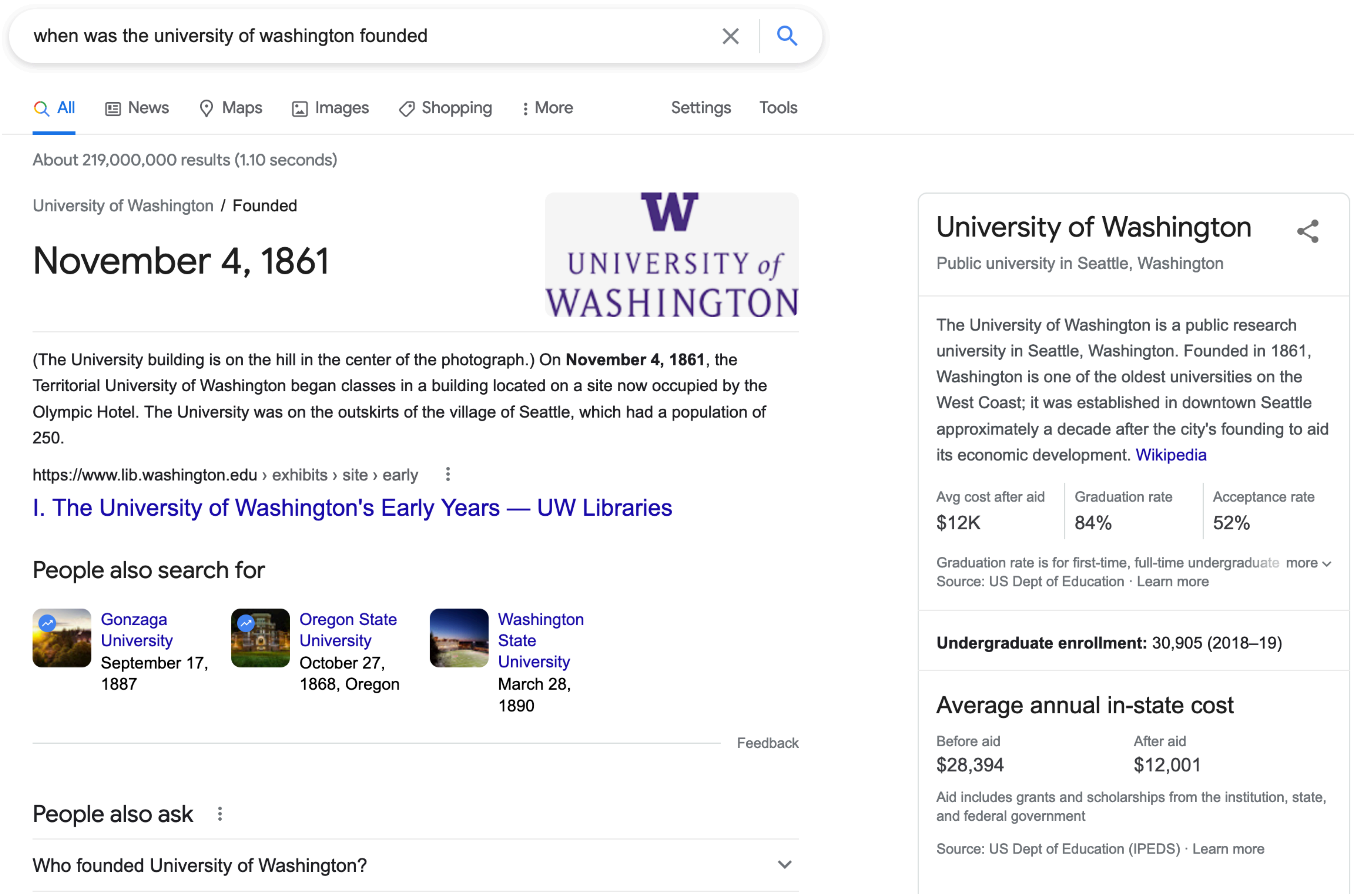
- Application of neural networks specifically to language data and tasks
- Discrete symbols are replaced by *continuous vectors*
  - Large models build “deep” (hopefully hierarchically structured) representations of text
- But: can they successfully mimic human language understanding?

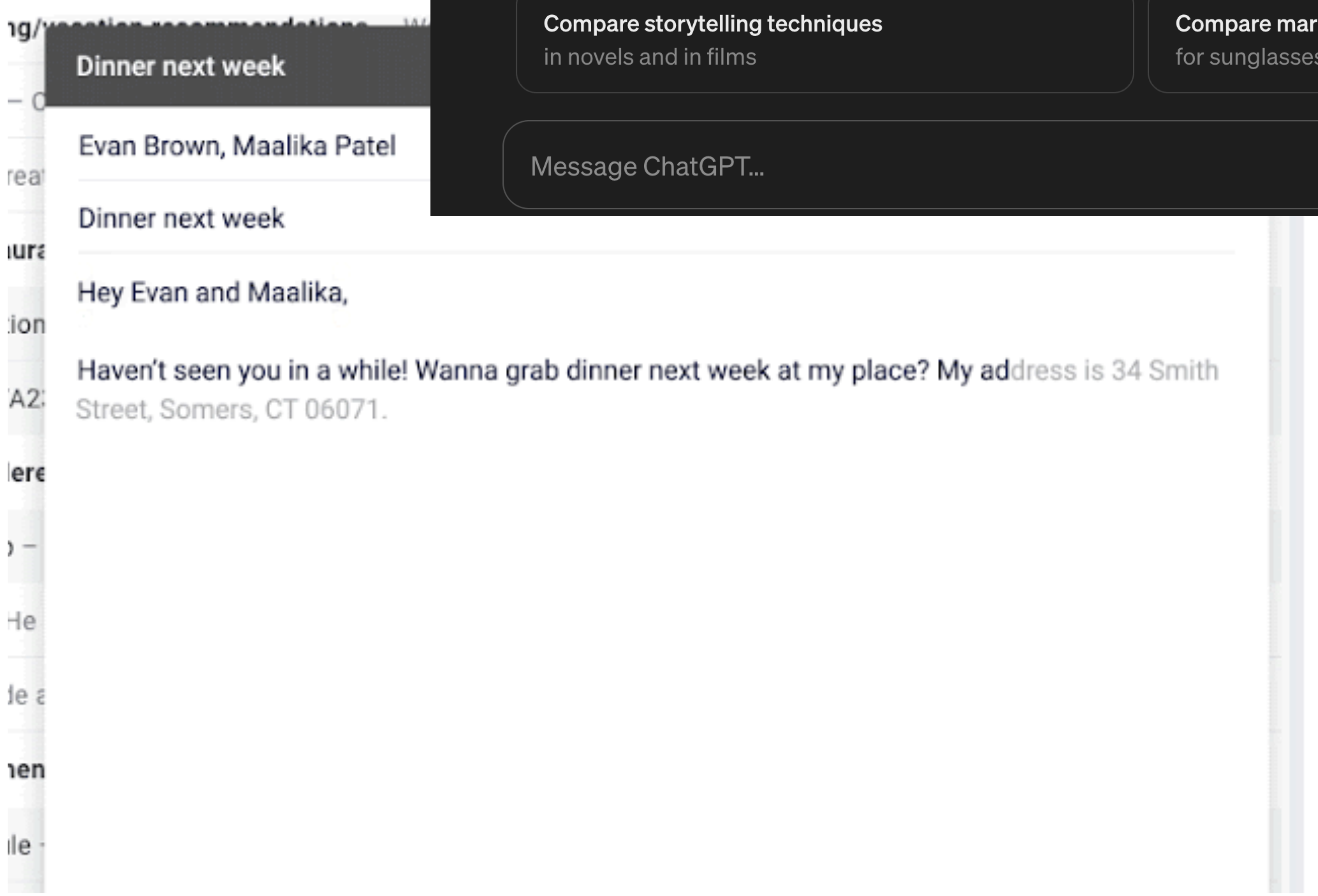
“Early” Success: Neural Machine Translation

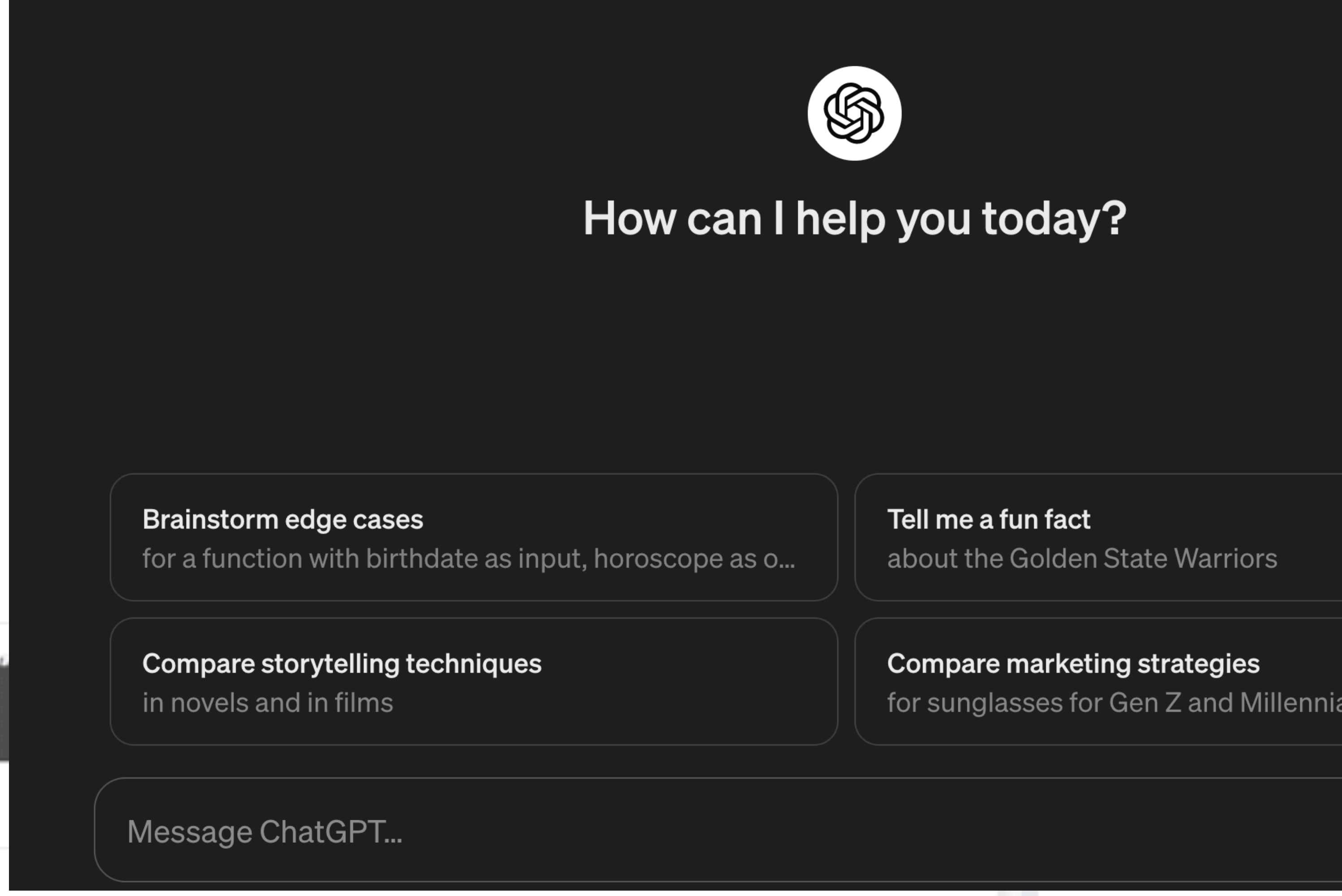


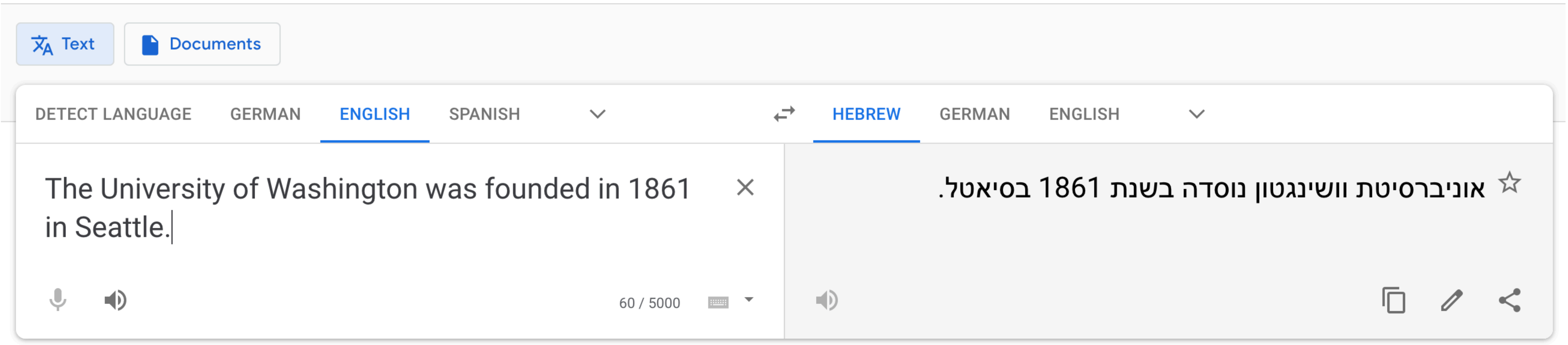


https://ai.googleblog.com/2016/09/a-neural-network-for-machine.html


when was the university of washington founded
All News Maps Images Shopping More Settings Tools
About 219,000,000 results (1.10 seconds)
University of Washington / Founded
November 4, 1861
W UNIVERSITY of WASHINGTON
(The University building is on the hill in the center of the photograph.) On November 4, 1861, the Territorial University of Washington began classes in a building located on a site now occupied by the Olympic Hotel. The University was on the outskirts of the village of Seattle, which had a population of 250.
https://www.lib.washington.edu › exhibits › site › early
I. The University of Washington's Early Years — UW Libraries
People also search for
Gonzaga University September 17, 1887
Oregon State University October 27, 1868, Oregon
Washington State University March 28, 1890
Feedback
People also ask
Who founded University of Washington?
University of Washington
Public university in Seattle, Washington
The University of Washington is a public research university in Seattle, Washington. Founded in 1861, Washington is one of the oldest universities on the West Coast; it was established in downtown Seattle approximately a decade after the city's founding to aid its economic development. Wikipedia
Avg cost after aid $12K
Graduation rate 84%
Acceptance rate 52%
Graduation rate is for first-time, full-time undergraduate more
Source: US Dept of Education · Learn more
Undergraduate enrollment: 30,905 (2018–19)
Average annual in-state cost
Before aid $28,394
After aid $12,001
Aid includes grants and scholarships from the institution, state, and federal government
Source: US Dept of Education (IPEDS) · Learn more


Dinner next week
Evan Brown, Maalika Patel
Dinner next week
Hey Evan and Maalika,
Haven't seen you in a while! Wanna grab dinner next week at my place? My address is 34 Smith Street, Somers, CT 06071.


How can I help you today?
Brainstorm edge cases
for a function with birthdate as input, horoscope as o...
Tell me a fun fact
about the Golden State Warriors
Compare storytelling techniques
in novels and in films
Compare marketing strategies
for sunglasses for Gen Z and Millenni
Message ChatGPT...


Text
Documents
DETECT LANGUAGE GERMAN ENGLISH SPANISH
HEBREW GERMAN ENGLISH
The University of Washington was founded in 1861 in Seattle.
אוניברסיטת וושינגטון נוסדה בשנת 1861 בסיאטל.
60 / 5000
Send feedback

What This Course Is and Is Not

- Provide a firm theoretical understanding of how to apply deep learning methods to natural language tasks
- From the ground up, progressing in complexity
- We will apply different kinds of models to interesting linguistic tasks, but this course is not simply:
    - How to use the latest libraries (though we will)
    - Full end-to-end application development
- By understanding the theory behind and building blocks of progressively complex systems, you will be able to:
    - Process new developments, diagnose / debug perplexing errors, understand why things work the way they do (in the good and the bad case)

A Potted History of NNs

The first artificial neural network: 1943

BULLETIN OF
MATHEMATICAL BIOPHYSICS
VOLUME 5, 1943

A LOGICAL CALCULUS OF THE
IDEAS IMMANENT IN NERVOUS ACTIVITY

WARREN S. MCCULLOCH AND WALTER PITTS

FROM THE UNIVERSITY OF ILLINOIS, COLLEGE OF MEDICINE,
DEPARTMENT OF PSYCHIATRY AT THE ILLINOIS NEUROPSYCHIATRIC INSTITUTE,
AND THE UNIVERSITY OF CHICAGO

Turing Award: 2018

MORE ACM AWARDS

A.M. TURING AWARD

A.M. TURING AWARD WINNERS BY...

ALPHABETICAL LISTING | YEAR OF THE AWARD | RESEARCH SUBJECT

Yoshua Bengio

Geoffrey E Hinton

Yann LeCun

GEOFFREY HINTON AND YANN LECUN TO DELIVER TURING LECTURE AT FCRC 2019

June 23, 5:15 - 6:30 P.M., Symphony Hall

We are pleased to announce that Geoffrey Hinton and Yann LeCun will deliver the Turing Lecture at FCRC 2019. Hinton's talk, "The Deep Learning Revolution," and LeCun's talk, "The Deep Learning Revolution: The Sequel," will be presented June 23rd from 5:15-6:30pm in Symphony Hall, Phoenix, Arizona.

No registration or tickets necessary to attend.

View the Livestream

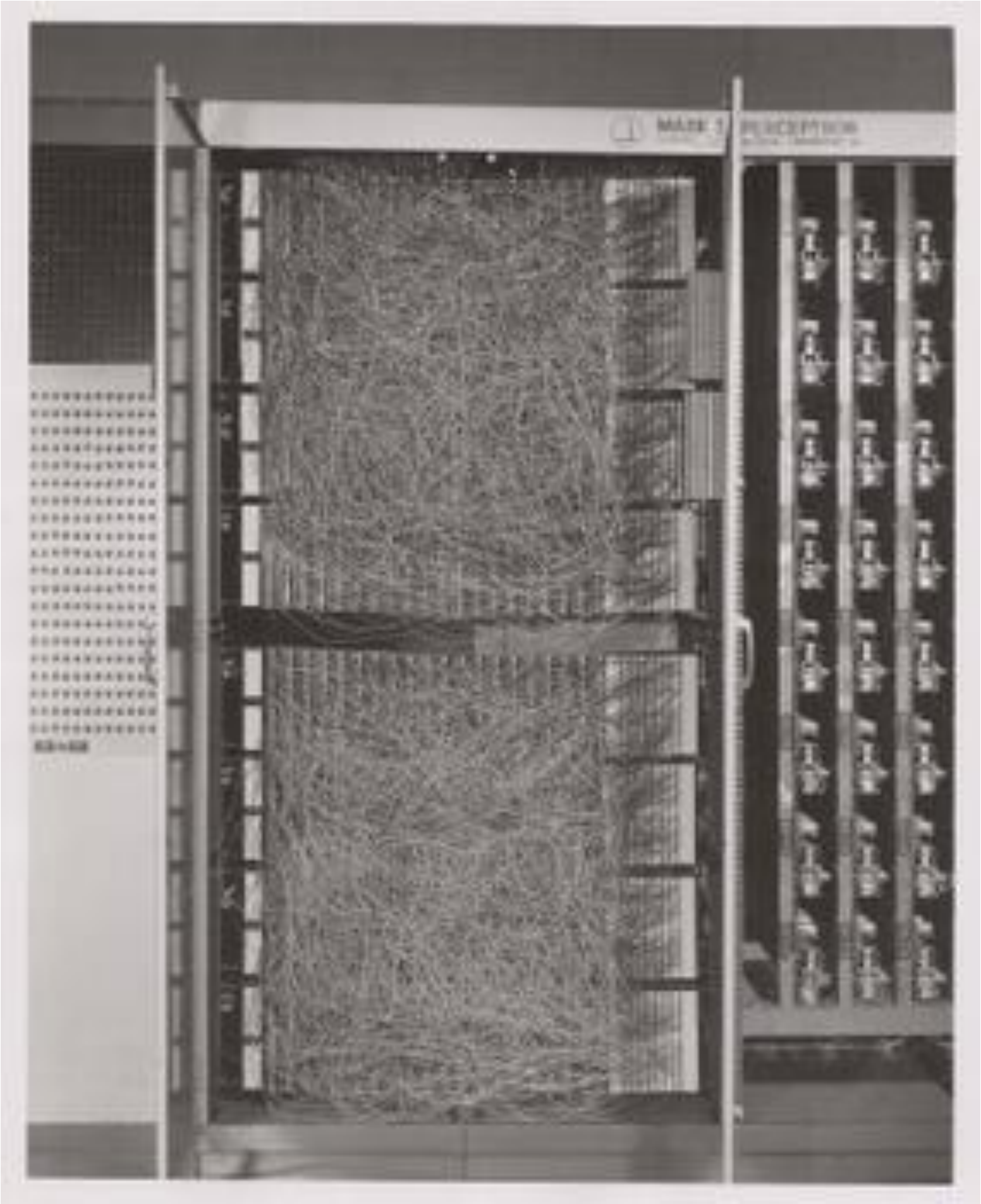
FATHERS OF THE DEEP LEARNING REVOLUTION RECEIVE ACM A.M. TURING AWARD

Bengio, Hinton, and LeCun Ushered in Major Breakthroughs in Artificial Intelligence

ACM named Yoshua Bengio, Geoffrey Hinton, and Yann LeCun recipients of the 2018 ACM A.M. Turing Award for conceptual and engineering breakthroughs that have made deep neural networks a critical component of computing. Bengio is Professor at the University of Montreal and Scientific Director at Mila, Quebec's Artificial Intelligence Institute; Hinton is VP and Engineering Fellow of Google, Chief Scientific Adviser of The Vector Institute, and University Professor Emeritus at the University of Toronto; and LeCun is Professor at New York University and VP and Chief AI Scientist at Facebook.

Working independently and together, Hinton, LeCun and Bengio developed conceptual foundations for the field, identified surprising phenomena through experiments, and contributed engineering advances that demonstrated the practical advantages of deep neural networks. In recent years, deep learning methods have been

Perceptron (1958)



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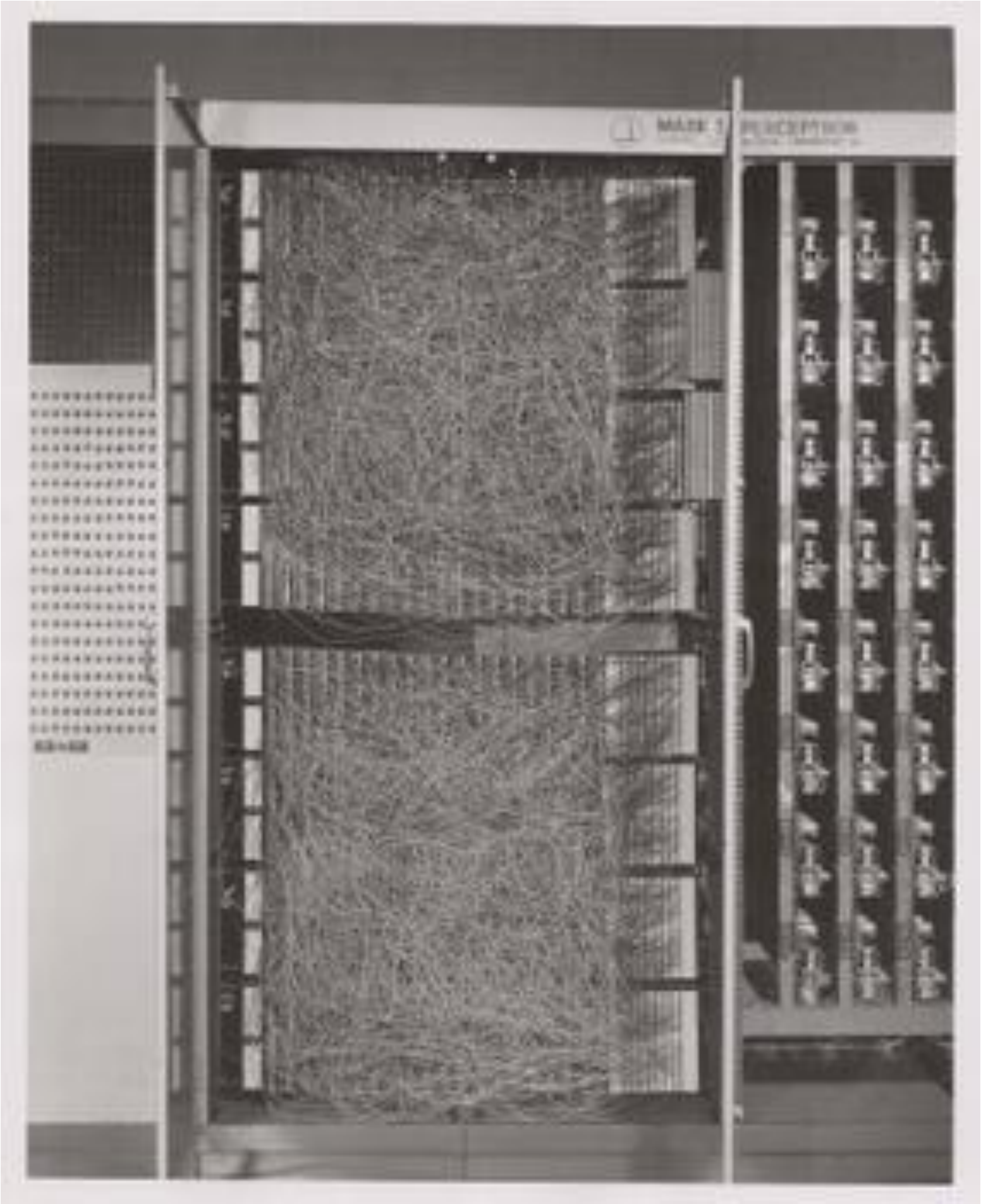
Perceptron (1958)



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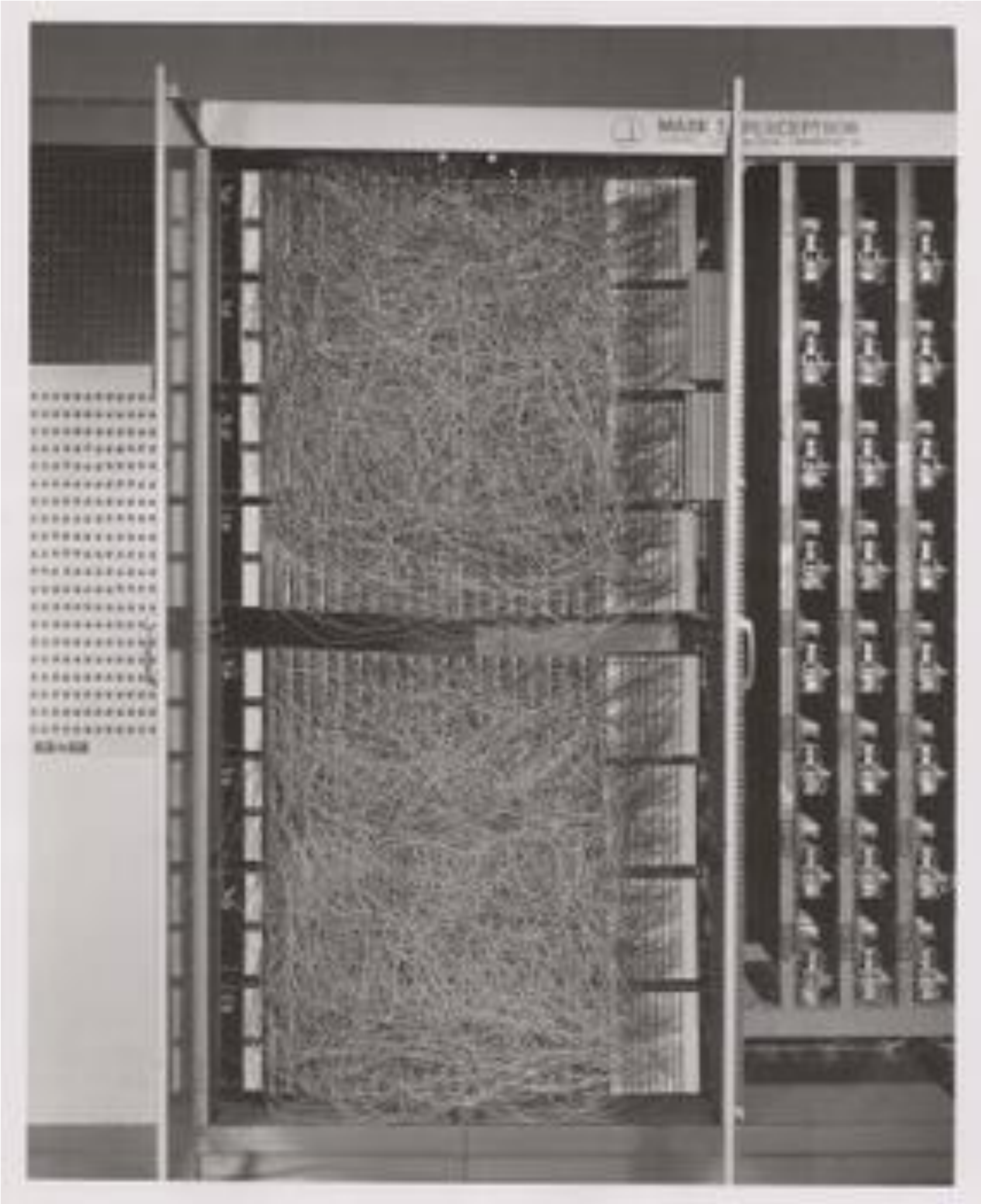
$$f(\mathbf{x}) = \begin{cases} 1 & \mathbf{w} \cdot \mathbf{x} + b > 0 \\ 0 & \text{otherwise} \end{cases}$$

Perceptron (1958)

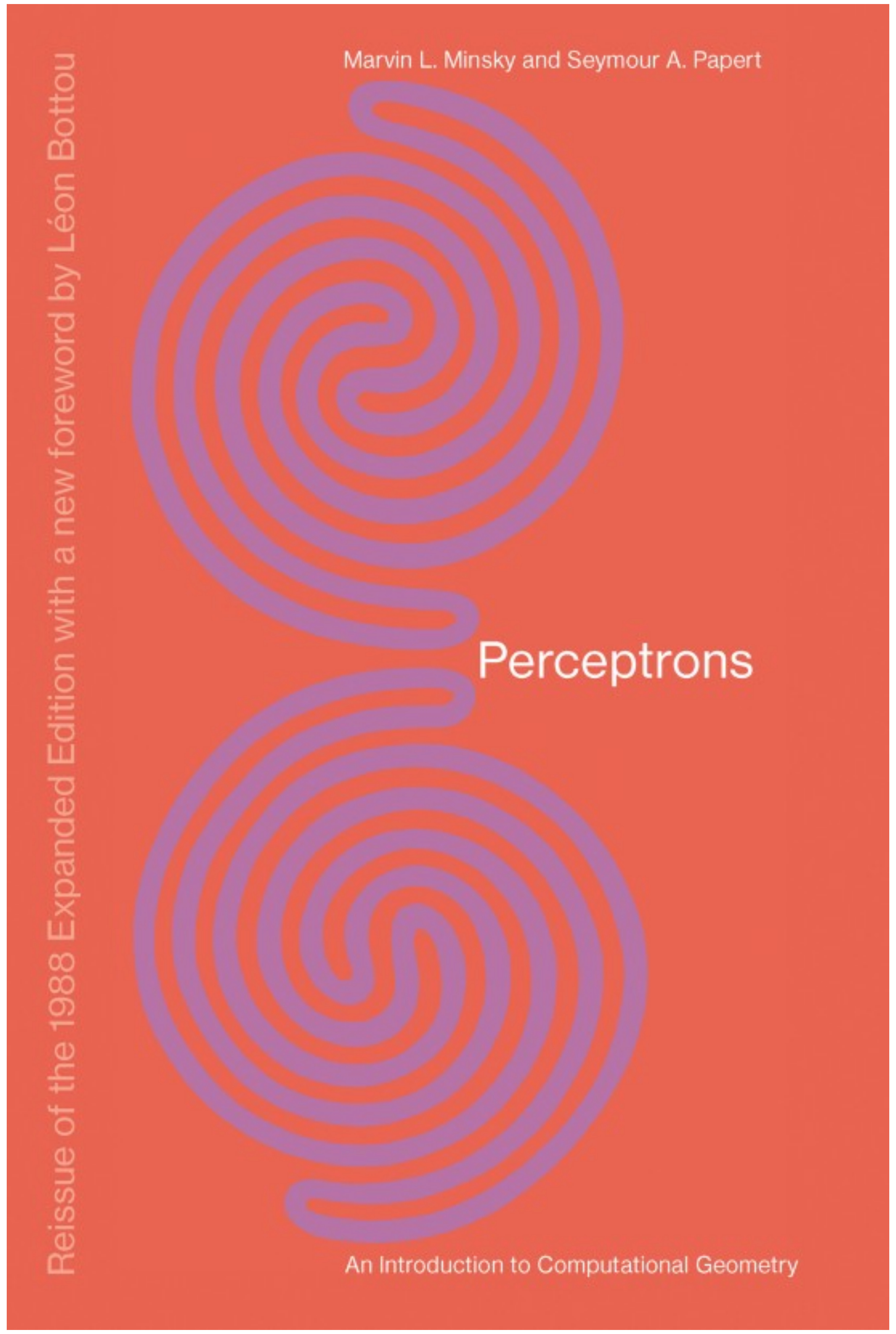


source

$$f(\mathbf{x}) = \begin{cases} 1 & \mathbf{w} \cdot \mathbf{x} + b > 0 \\ 0 & \text{otherwise} \end{cases}$$

"the embryo of an electronic computer that [the Navy] expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence."
—New York Times

Perceptrons (1969)



- Limitative results on functions computable by the basic perceptron
- Famous example (we'll return to it later):
  - Exclusive disjunction (XOR) is not computable
- Other examples that are uncomputable assuming *local connectivity*

AI Winter

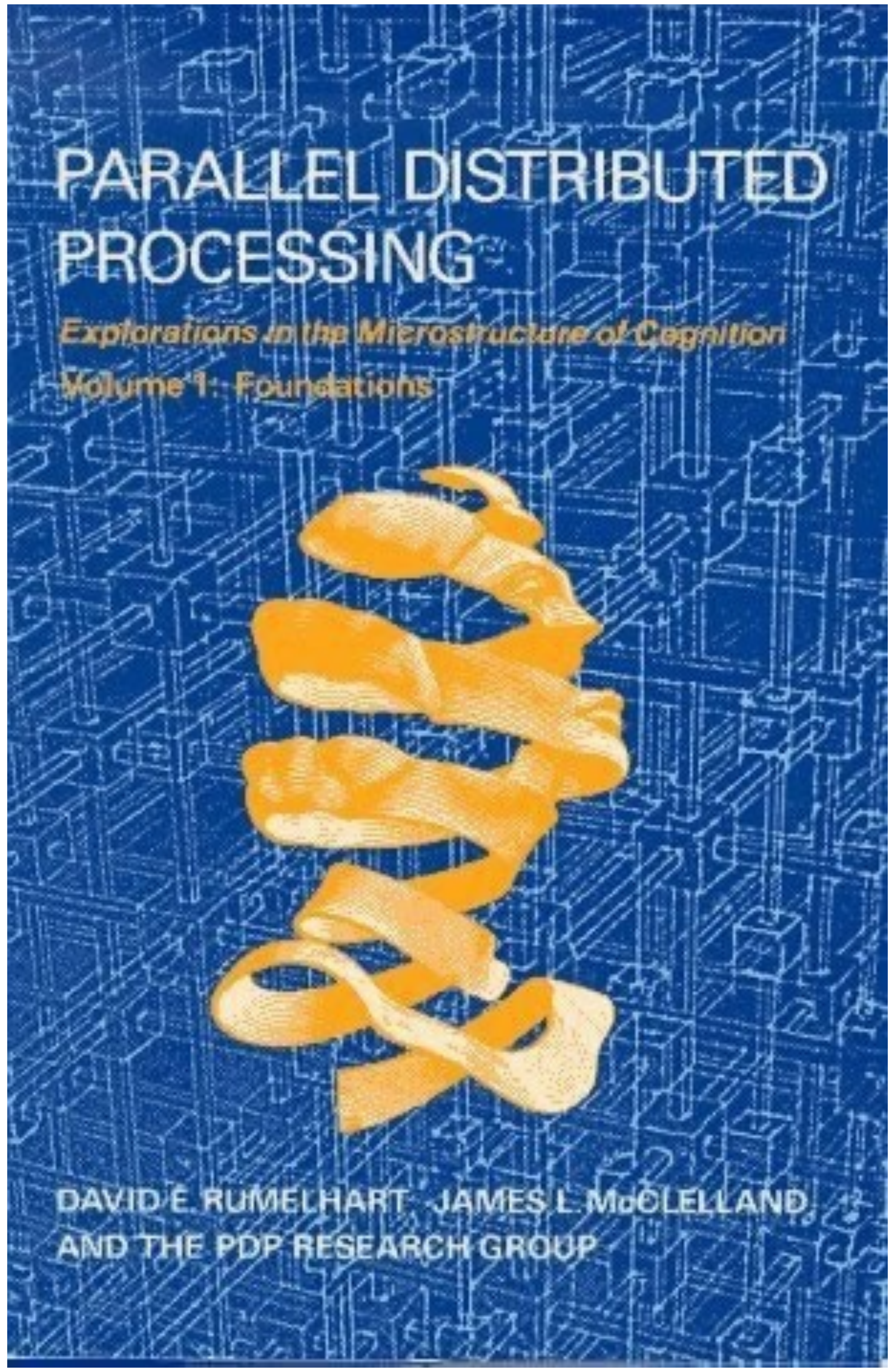
AI Winter

- Reaction to the results:
  - The approach of learning perceptrons for data cannot deliver on the promises
  - Funding from e.g. government agencies dried up significantly
  - Community lost interest in the approach

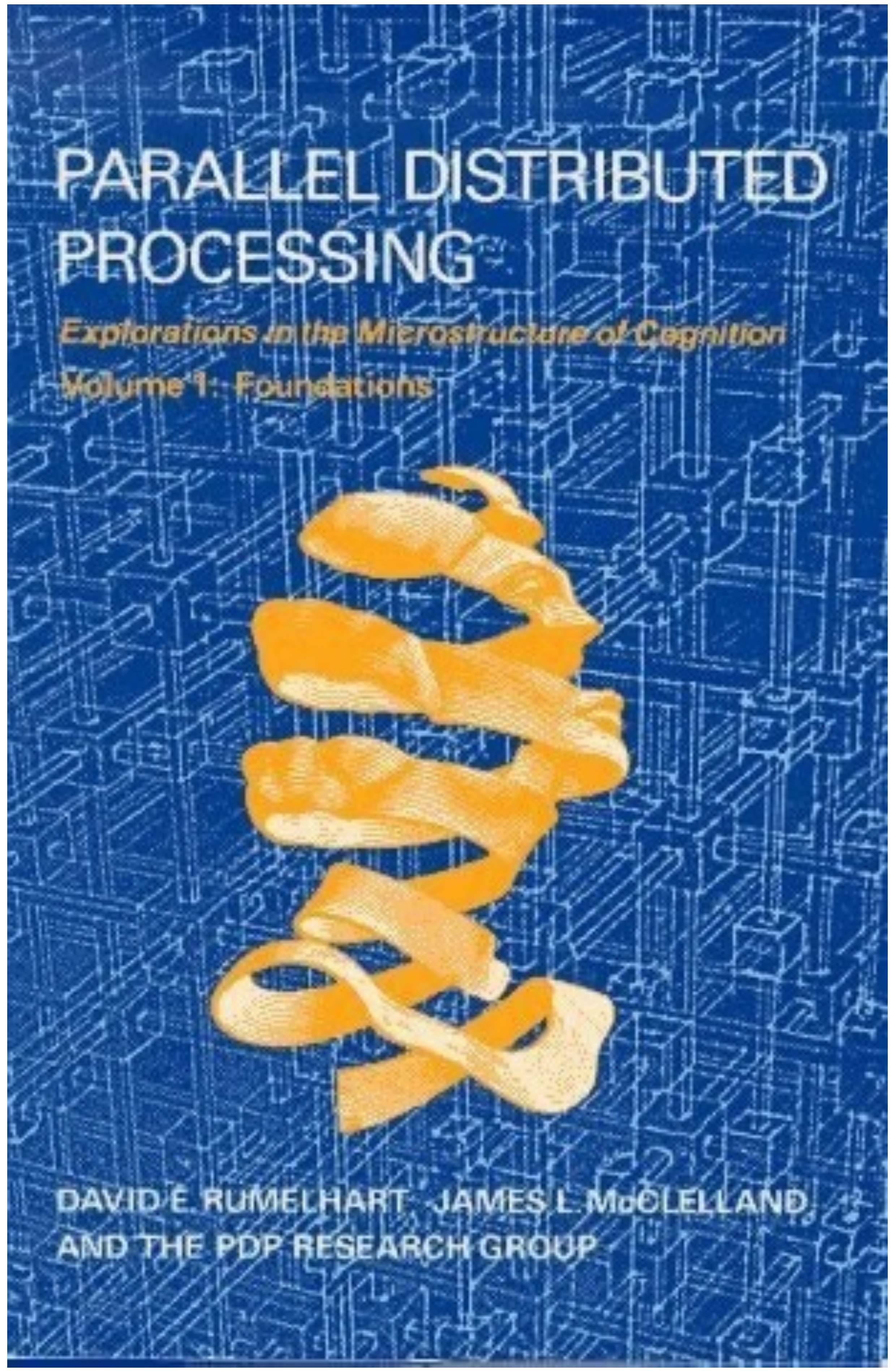
AI Winter

- Reaction to the results:
  - The approach of learning perceptrons for data cannot deliver on the promises
  - Funding from e.g. government agencies dried up significantly
  - Community lost interest in the approach
- Very unfortunate:
  - Already known from McCulloch and Pitts that any boolean function can be computed by "deeper" networks of perceptrons
  - Negative consequences of the results were significantly over-blown

Deeper Backpropagation (1986)

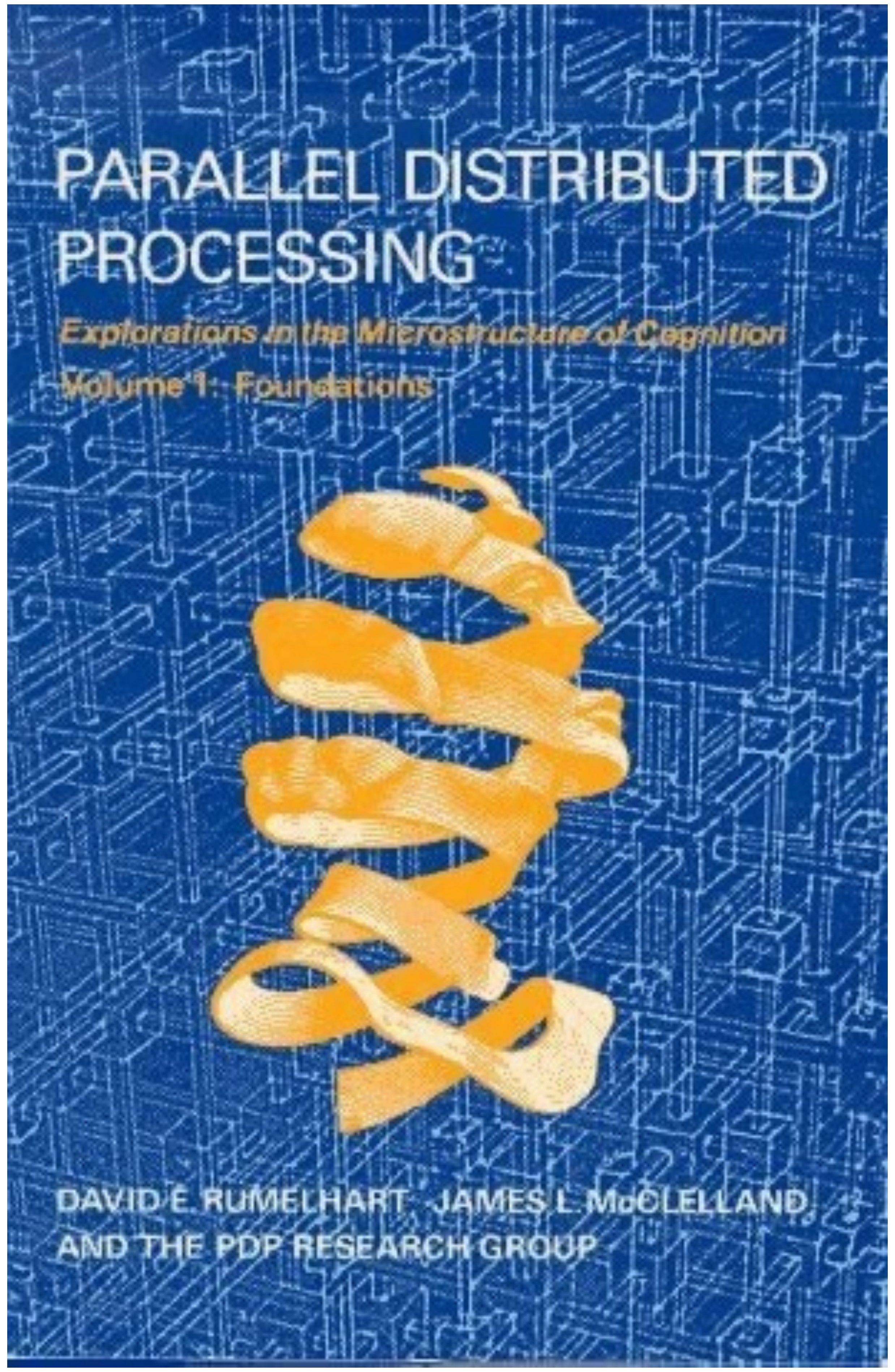


Deeper Backpropagation (1986)



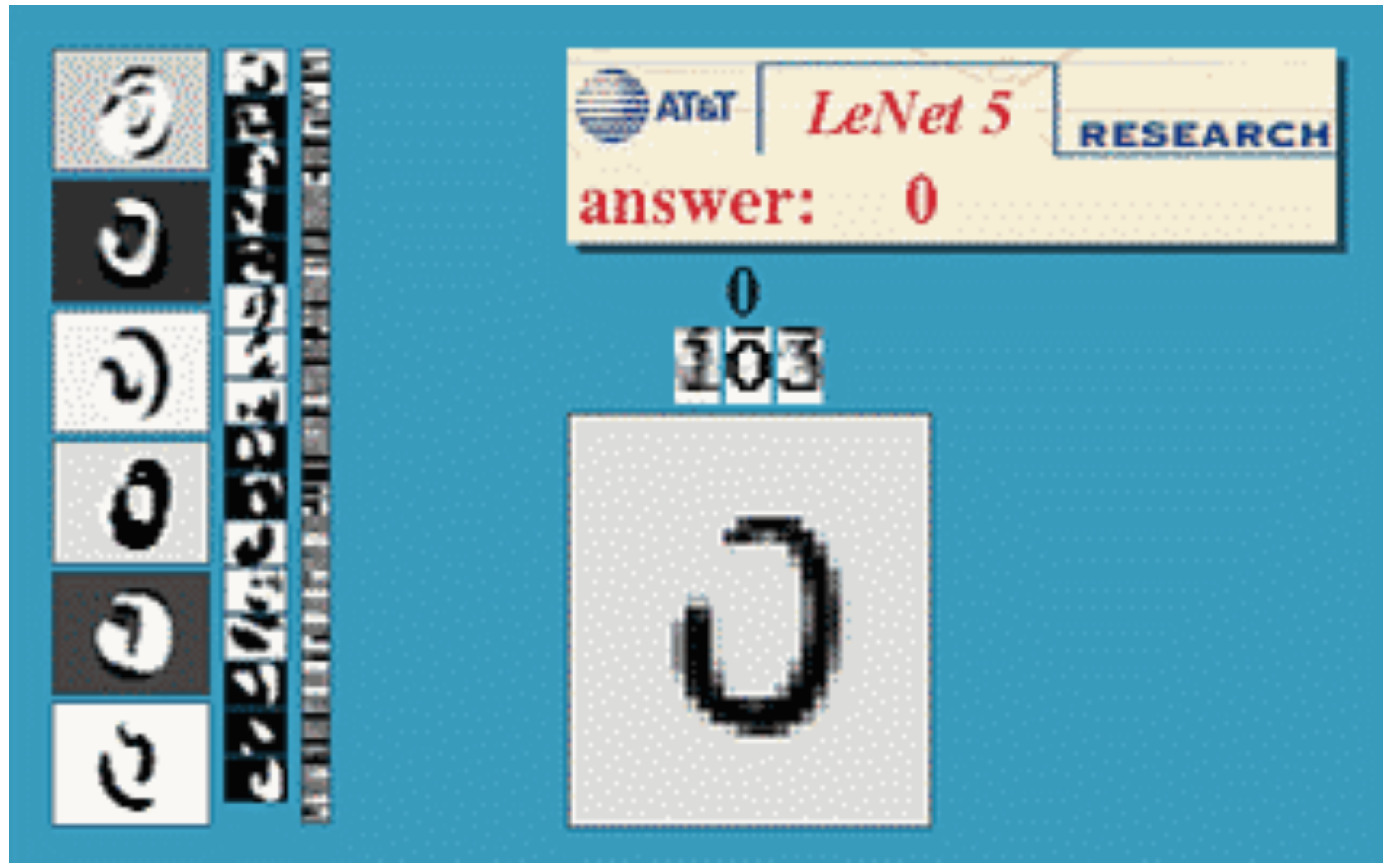
- Multi-layer networks, trained by backpropagation, applied to cognitive tasks

Deeper Backpropagation (1986)



- Multi-layer networks, trained by backpropagation, applied to cognitive tasks
- "Efficient applications of the chain rule based on dynamic programming began to appear in the 1960s and 1970s, mostly for control applications (Kelley, 1960; Bryson and Denham, 1961; Dreyfus, 1962; Bryson and Ho, 1969; Dreyfus, 1973) …. The idea was finally developed in practice after being independently rediscovered in different ways (LeCun, 1985; Parker, 1985; Rumelhart et al., 1986a). The book *Parallel Distributed Processing* presented the results of some of the first successful experiments with back-propagation in a chapter (Rumelhart et al., 1986b) that contributed greatly to the popularization of back-propagation and initiated a very active period of research in multilayer neural networks."

Successful Engineering Application (1989)



original website

- *Convolutional* networks ("LeNet", after Yann LeCun) applied to recognizing hand-written digits
  - MNIST dataset
  - Still useful for setting up pipelines, testing simple baselines, etc.
- Deployed for automatic reading of mailing addresses, check amounts, etc.

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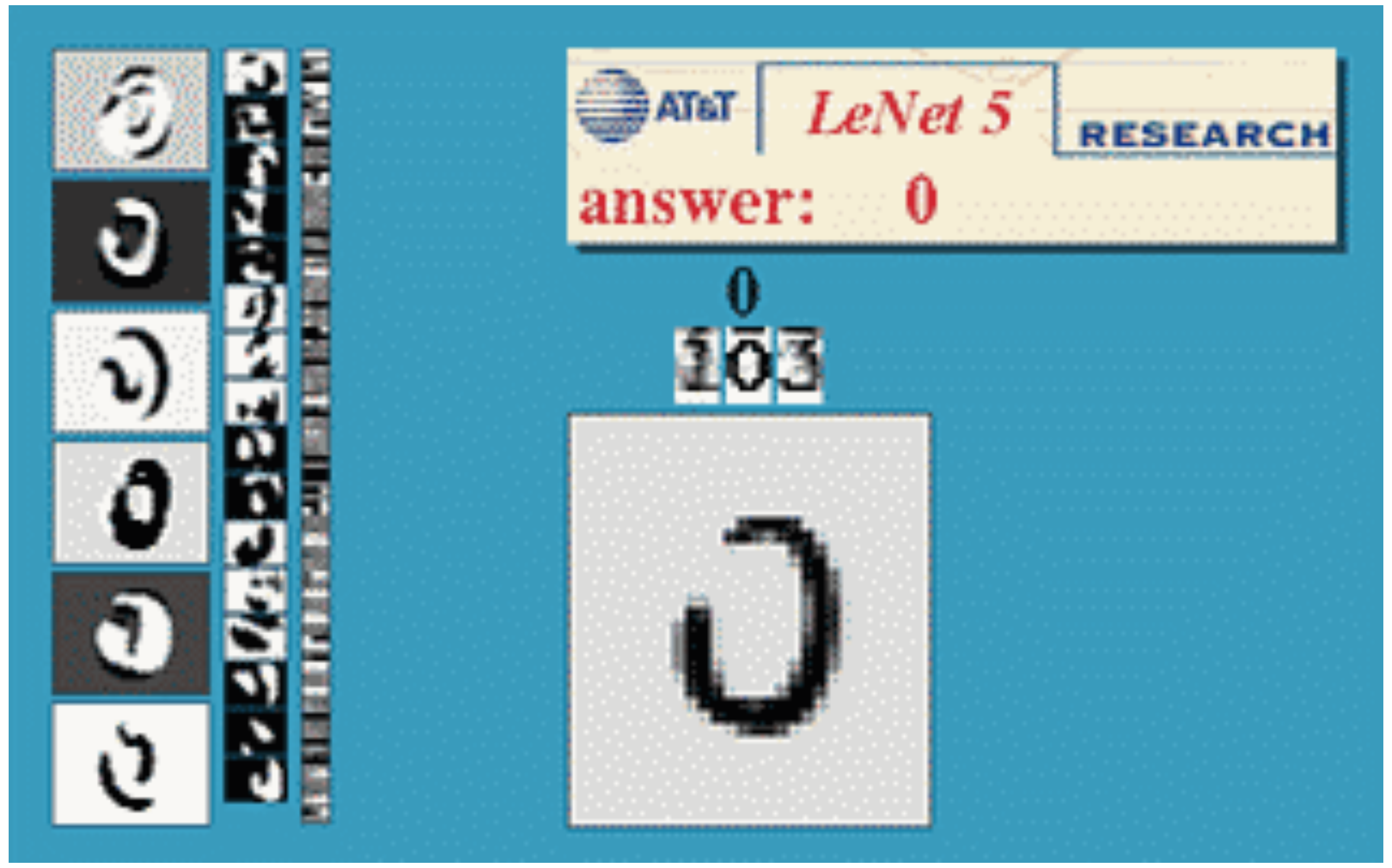

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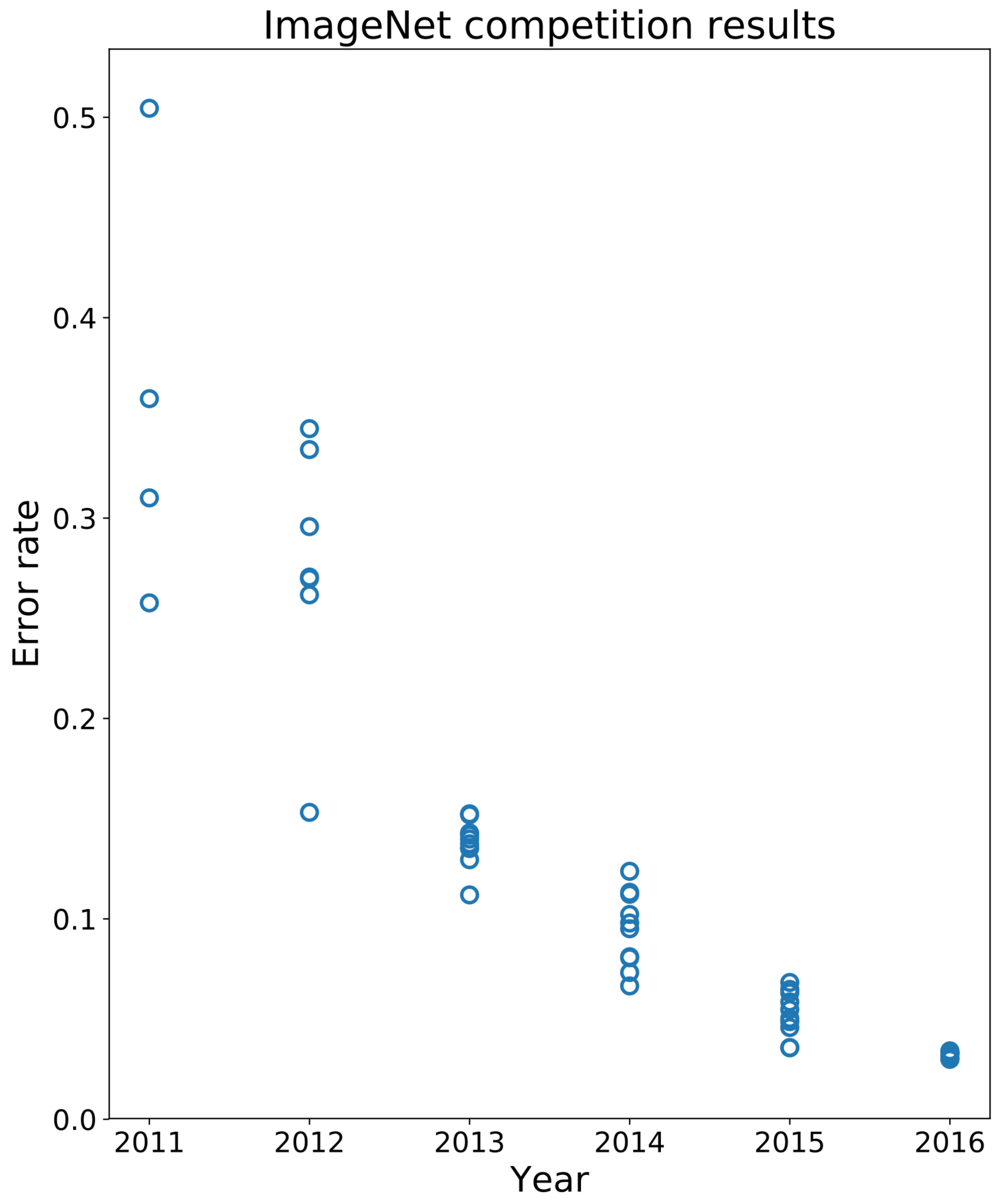
ImageNet (ILSVRC) results (2012)



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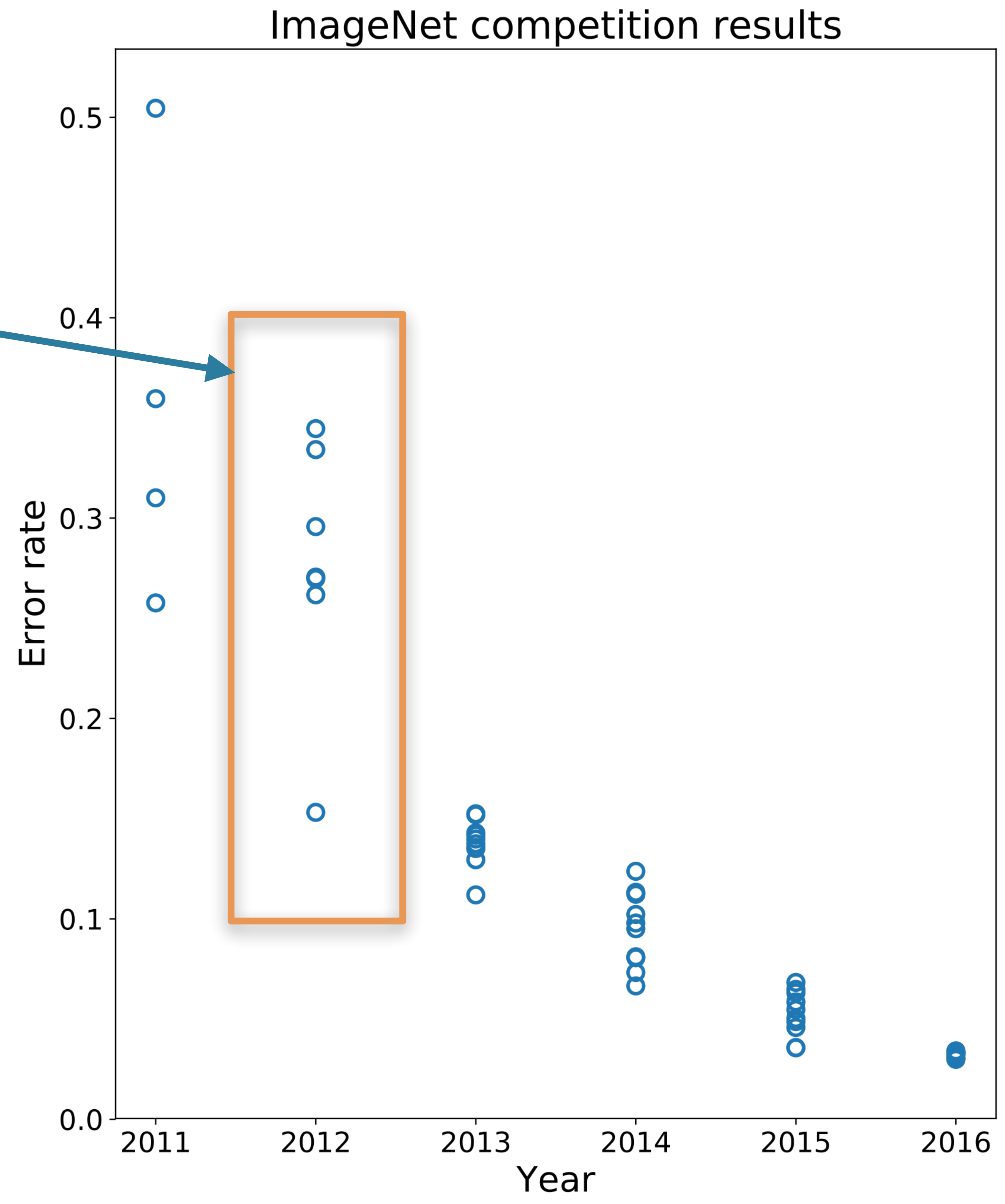
ImageNet (ILSVRC) results (2012)

What happened in 2012?



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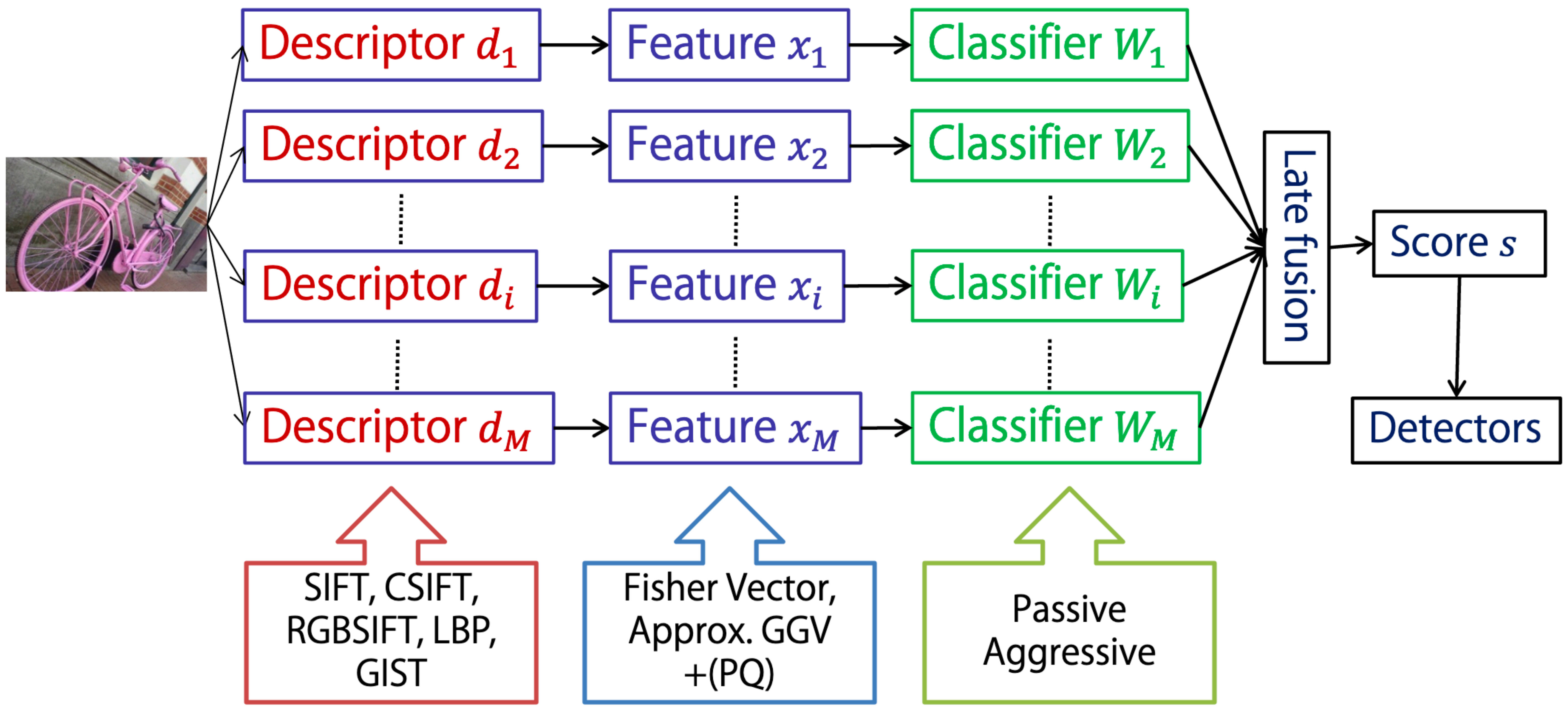
ILSVRC 2012: runner-up

Fisher based features + Multi class linear classifiers



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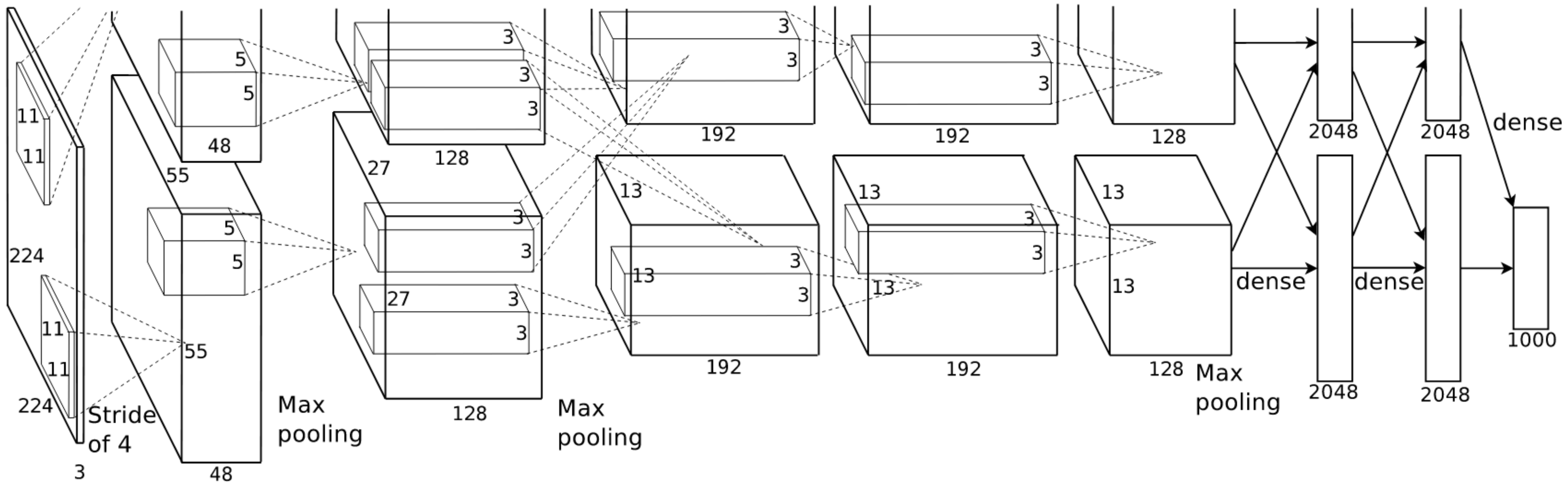
ILSVRC 2012: winner



ImageNet Classification with Deep Convolutional Neural Networks

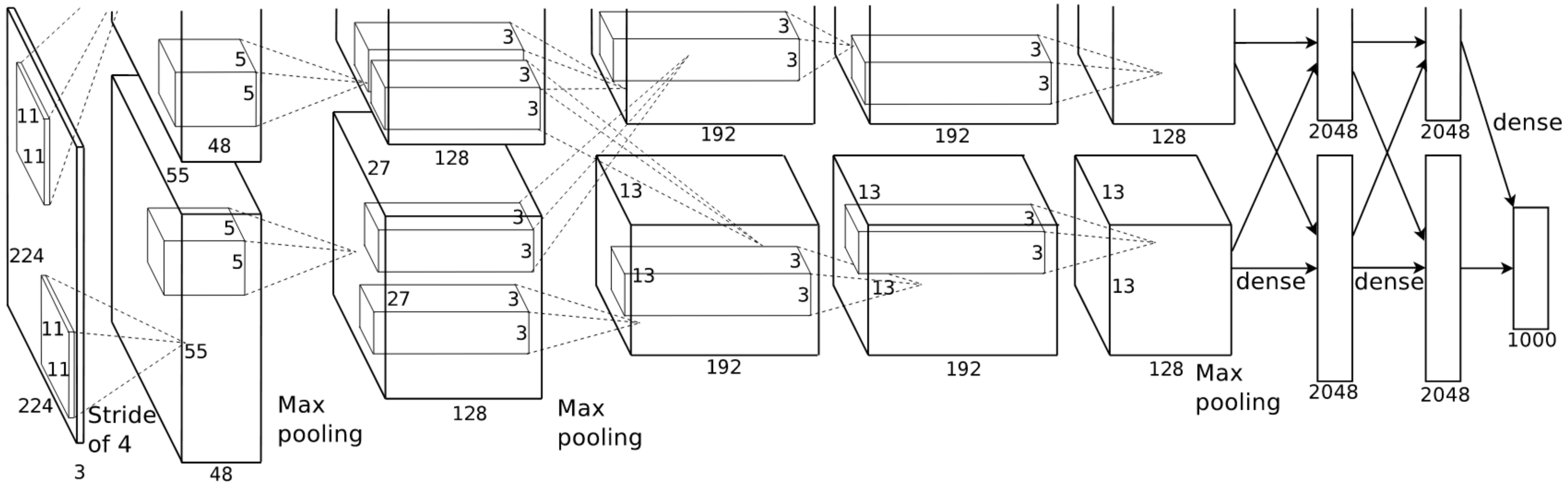
Alex Krizhevsky
University of Toronto
kriz@cs.utoronto.ca

Ilya Sutskever
University of Toronto
ilya@cs.utoronto.ca

Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca

NeurIPS 2012 paper

ILSVRC 2012: winner



"AlexNet"

ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
University of Toronto
kriz@cs.utoronto.ca

Ilya Sutskever
University of Toronto
ilya@cs.utoronto.ca

Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca

NeurIPS 2012 paper

2012-now

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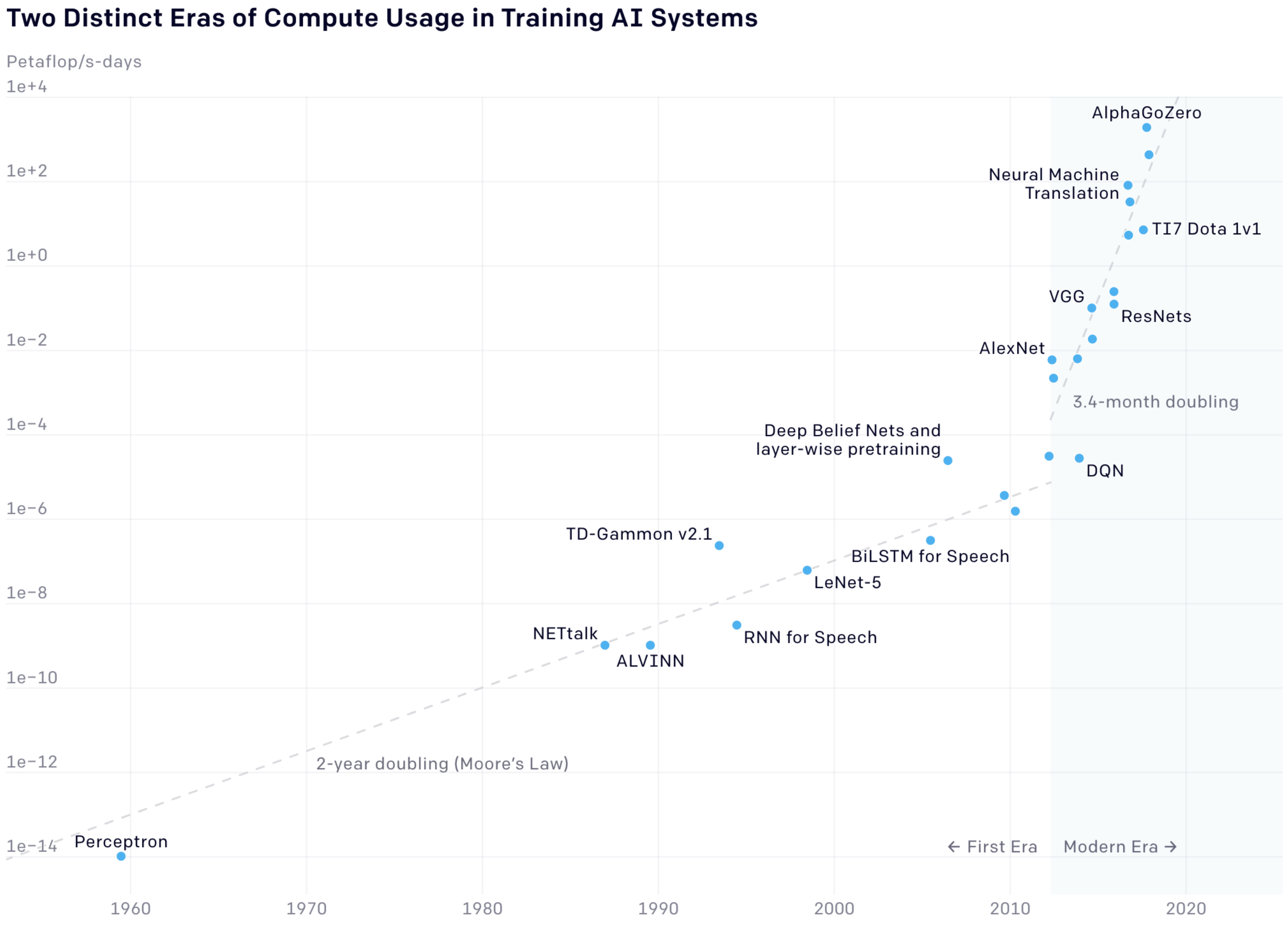
- Widespread adoption of deep neural networks across a range of domains / tasks
  - Image processing of various kinds
  - Reinforcement learning (e.g. AlphaGo/AlphaZero, …)
  - NLP!

2012-now

- Widespread adoption of deep neural networks across a range of domains / tasks
  - Image processing of various kinds
  - Reinforcement learning (e.g. AlphaGo/AlphaZero, …)
  - NLP!
- What happened?
  - Better learning algorithms / training regimes
  - Larger and larger, standardized datasets
  - Compute! GPUs, now dedicated hardware (TPUs)

Compute in Deep Learning



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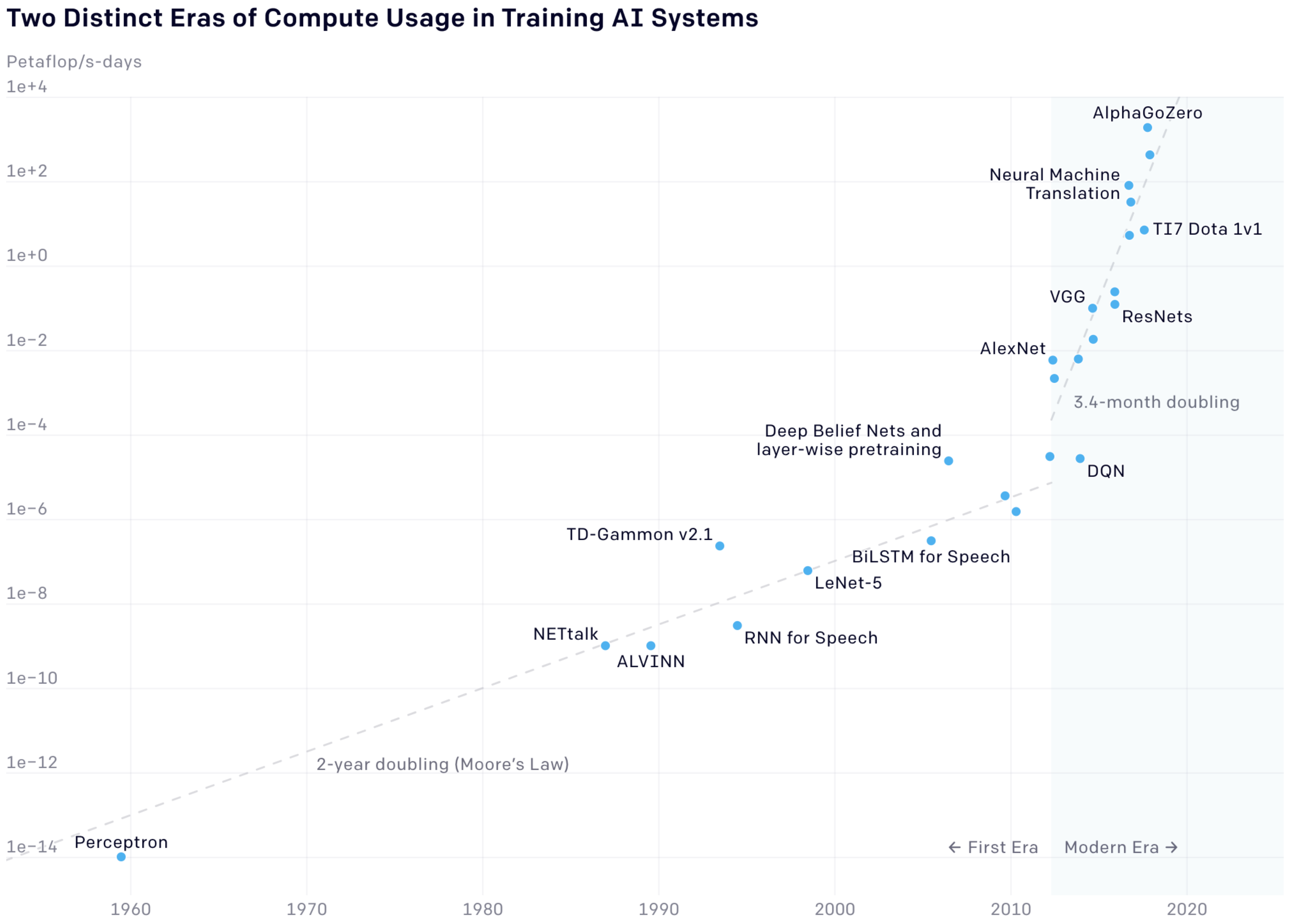
Compute in Deep Learning

log-scale!!



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Caveat Emptor

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- Hugely expensive
  - Carbon emissions
  - Monetarily
    - Inequitable access

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Energy and Policy Considerations for Deep Learning in NLP

Emma Strubell **Ananya Ganesh** **Andrew McCallum**
College of Information and Computer Sciences
University of Massachusetts Amherst
{strubell, aganesh, mccallum}@cs.umass.edu

Abstract

Recent progress in hardware and methodology for training neural networks has ushered in a new generation of large networks trained on abundant data. These models have obtained notable gains in accuracy across many NLP tasks. However, these accuracy improvements depend on the availability of exceptionally large computational resources that necessitate similarly substantial energy consumption. As a result these models are costly to train and develop, both financially, due to the cost of hardware and electricity or cloud compute time, and environmentally, due to the carbon footprint required to fuel modern tensor

Consumption	CO_2e (lbs)
Air travel, 1 person, NY↔SF	1984
Human life, avg, 1 year	11,023
American life, avg, 1 year	36,156
Car, avg incl. fuel, 1 lifetime	126,000
Training one model (GPU)	
NLP pipeline (parsing, SRL)	39
w/ tuning & experiments	78,468
Transformer (big)	192
w/ neural arch. search	626,155

Table 1: Estimated CO_2 emissions from training common NLP models, compared to familiar consumption.[1]

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Energy and Policy Considerations for Deep Learning in NLP

Emma Strubell **Ananya Ganesh** **Andrew McCallum**
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Green AI

Roy Schwartz* ◊ Jesse Dodge*◊♣ Noah A. Smith◊♡ Oren Etzioni◊

◊Allen Institute for AI, Seattle, Washington, USA
♣ Carnegie Mellon University, Pittsburgh, Pennsylvania, USA
♡ University of Washington, Seattle, Washington, USA

July 2019

Abstract

The computations required for deep learning research have been doubling every few months, resulting in an estimated 300,000x increase from 2012 to 2018 [2]. These computations have a surprisingly large carbon footprint [40]. Ironically, deep learning was inspired by the human brain, which is remarkably energy efficient. Moreover, the financial cost of the computations can make it difficult for academics, students, and researchers, in particular those from emerging economies, to engage in deep learning research.

This position paper advocates a practical solution by making **efficiency** an evaluation criterion for research alongside accuracy and related measures. In addition, we propose reporting the financial cost or “price tag” of developing, training, and running models to provide baselines for the investigation of increasingly efficient methods. Our goal is to make AI both greener and more inclusive—enabling any inspired undergraduate with a laptop to write high-quality research papers. Green AI is an emerging focus at the Allen Institute for AI.

Potted History of Models in NLP

Four Broad “Eras”

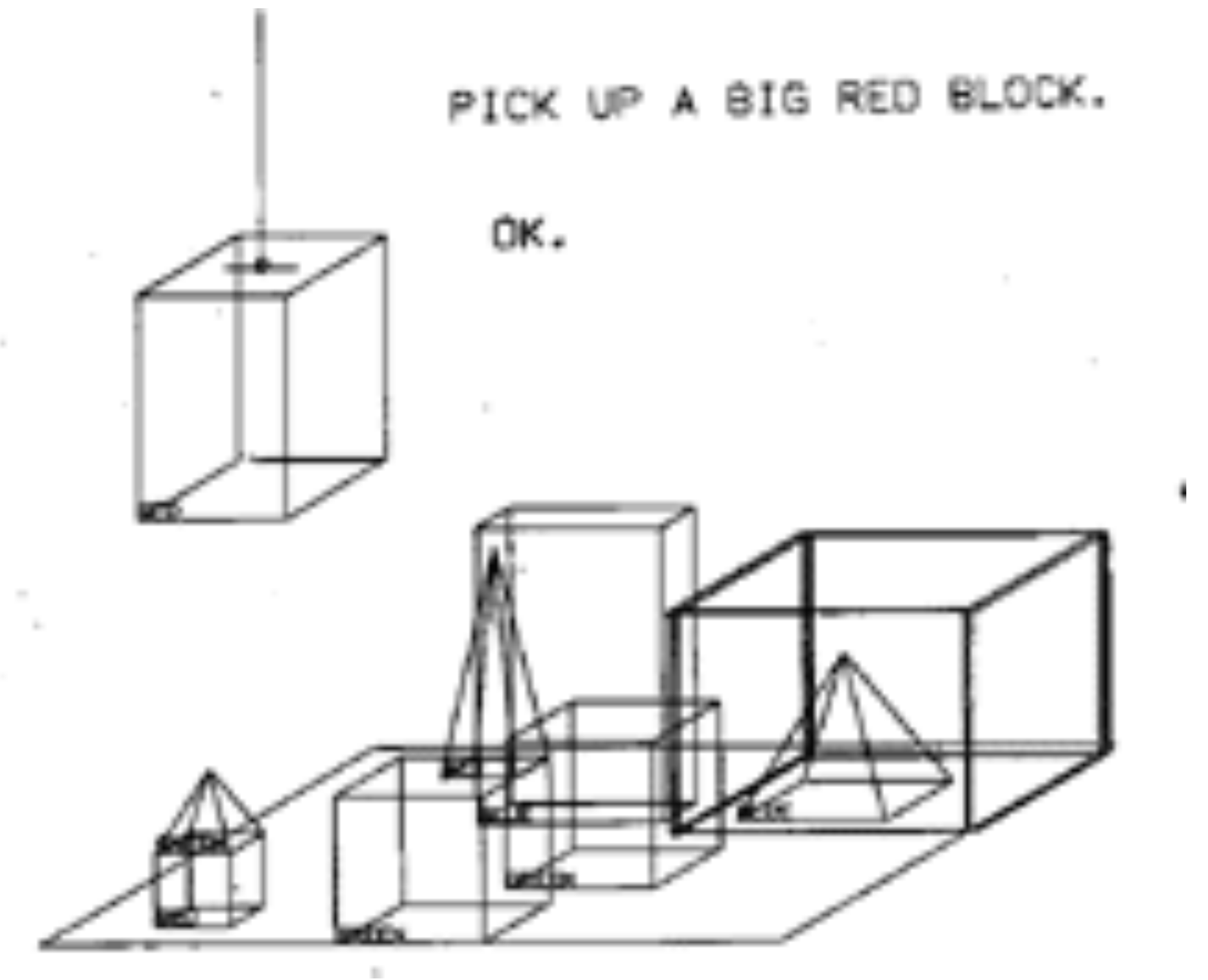
- Four very general phases in types of models dominant in NLP:
  - 100% rule-based systems [1960s -]
  - Machine learning, I [mid-80s - mid-90s]
    - Decision trees, naive bayes, etc
  - Log-linear (i.e. maxent) models [mid-90s - mid-2010s]
  - Neural networks [2013 - now]

- NB: _all_ of these are still used in applications in every area!
  - They all have different strengths and weaknesses

Early NLP Systems (1960s-1990s)

- SHRDLU, e.g.:

```
Person: Pick up a big red block.
Computer: OK.
Person: Grasp the pyramid.
Computer: I DON'T UNDERSTAND WHICH PYRAMID YOU MEAN.
Person (changing their mind): Find a block which is
taller than the one you are holding and put it into the
box.
Computer: BY "IT", I ASSUME YOU MEAN THE BLOCK WHICH IS
TALLER THAN THE ONE I AM HOLDING.
Computer: OK.
Person: What does the box contain?
Computer: THE BLUE PYRAMID AND THE BLUE BLOCK.
Person: What is the pyramid supported by?
Computer: THE BOX.
```



Early NLP Systems (1960s-1990s)

- 100% rule-based, hand-written algorithms
- Lots of energy in ontology development / knowledge representation
- Exhibit many core features of human linguistic competence:
  - Compositional generalization
  - Abstract representations of meaning
- Fully “interpretable”, because fully engineered
- But:
  - Brittle, no graceful degradation, domain-specific

ML I (80s-90s)

- Increase in compute power, availability of larger corpora for parameter estimation
- Generally, *generative models* (i.e. models of joint distribution $P(x, y)$)
  - N-grams, Naive Bayes, HMMs, PCFGs, …
- Parameter estimation via counting = very simple training
- Generally relies on heavy use of feature engineering
- Still work surprisingly well! Always try them first.

Log-linear models

- Aka maximum entropy (maxent), multinomial classifiers, softmax, …
- *Discriminative* models (i.e. of $P(y \mid x)$)

$$P(y \mid x) \propto e^{\sum_j w_j f_j(x,y)}$$

Log-linear models

- Learnable using standard optimization methods
- Interpretable: can see feature importance
  - e.g. Klein et al 2003 on Named Entity Recognition:
    - Weight for class PER for feature CURWORD:Grace: 0.03
    - Weight for class PER for prefix “<G”: 0.45
- Feature engineering:
  - Expensive
  - Incomplete
  - Sparse [= wasted compute as well]

	O	LOC	MISC	ORG	PER
WORDS					
PWORD:at	-0.18	0.94	-0.31	0.28	-0.73
CWORD:Grace	-0.01	0	0	-0.02	0.03
NWORD:Road	0.02	0.27	-0.01	-0.25	-0.03
PWORD-CWORD:at-Grace	0	0	0	0	1 0
CWORD-NWORD:Grace-Road	0	0	0	0	0
NGRAMS (prefix/suffix only here)					
⟨G	-0.57	-0.04	0.26	-0.04	0.45
⟨Gr	0.27	-0.06	0.12	-0.17	-0.16
⟨Gra	-0.01	-0.37	0.19	-0.09	0.28
⟨Grac	-0.01	0	0	-0.02	0.03
⟨Grace	-0.01	0	0	-0.02	0.03
⟨Grace⟩	-0.01	0	0	-0.02	0.03
Grace⟩	-0.01	0	0	-0.02	0.03
race⟩	0	0	0	-0.02	0.03
ace⟩	0.08	0.24	0.07	-0.30	-0.10
ce⟩	0.44	0.31	-0.34	-0.02	-0.38
e⟩	0.38	-0.14	-0.18	-0.06	0
TAGS					
PTAG:IN	-0.40	0.24	0.16	0.08	-0.08
CTAG:NNP	-1.09	0.45	-0.26	0.43	0.47
NTAG:NNP	0.05	-0.19	0.18	-0.12	0.08
PTAG-CTAG:IN-NNP	0	0.14	-0.03	-0.01	-0.10
CTAG-NTAG:NNP-NNP	-0.11	-0.05	0	-0.38	-0.54
TYPES					
PTYPE:x:2	-0.07	-0.15	0.35	0.18	-0.31
CTYPE:Xx	-2.02	0.46	0.19	0.57	0.80
NTYPE:Xx	-0.22	-0.42	-0.19	0.29	0.54
PTYPE-CTYPE:x:2-Xx	-0.20	0.08	0.10	0.10	-0.09
CTYPE-NTYPE:Xx-Xx	0.55	-0.13	-0.55	-0.13	0.26
PTYPE-CTYPE-NTYPE:x:2-Xx-Xx	0.10	0.37	0.10	0.12	-0.69
WORDS/TYPES					
PWORD-CTYPE:at-Xx	-0.21	0.57	-0.21	0.41	-0.56
CTYPE-NWORD:Xx-Road	-0.01	0.27	-0.01	-0.23	-0.03
STATES					
PSTATE:O	2.91	-0.92	-0.72	-0.58	-0.70
PPSTATE-PSTATE:O-O	1.14	-0.60	-0.08	-0.43	-0.04
WORDS/STATES					
PSTATE-CWORD:O-Grace	-0.01	0	0	-0.02	0.03
TAGS/STATES					
PSTATE-PTAG-CTAG:O-IN-NNP	0.12	0.59	-0.29	-0.28	-0.14
PPSTATE-PPTAG-PSTATE-PTAG-CTAG:O-NN-O-IN-NNP	0.01	-0.03	-0.31	0.31	0.01
TYPES/STATES					
PSTATE-CTYPE:O-Xx	-1.13	0.37	-0.12	0.20	0.68
PSTATE-NTYPE:O-Xx	-0.69	-0.3	0.29	0.39	0.30
PSTATE-PTYPE-CTYPE:O-x:2-Xx	-0.28	0.82	-0.10	-0.26	-0.20
PPSTATE-PPTYPE-PSTATE-PTYPE-CTYPE:O-x-O-x:2-Xx	-0.22	-0.04	-0.04	-0.06	0.22
Total:	-1.40	2.68	-1.74	-0.19	-0.58

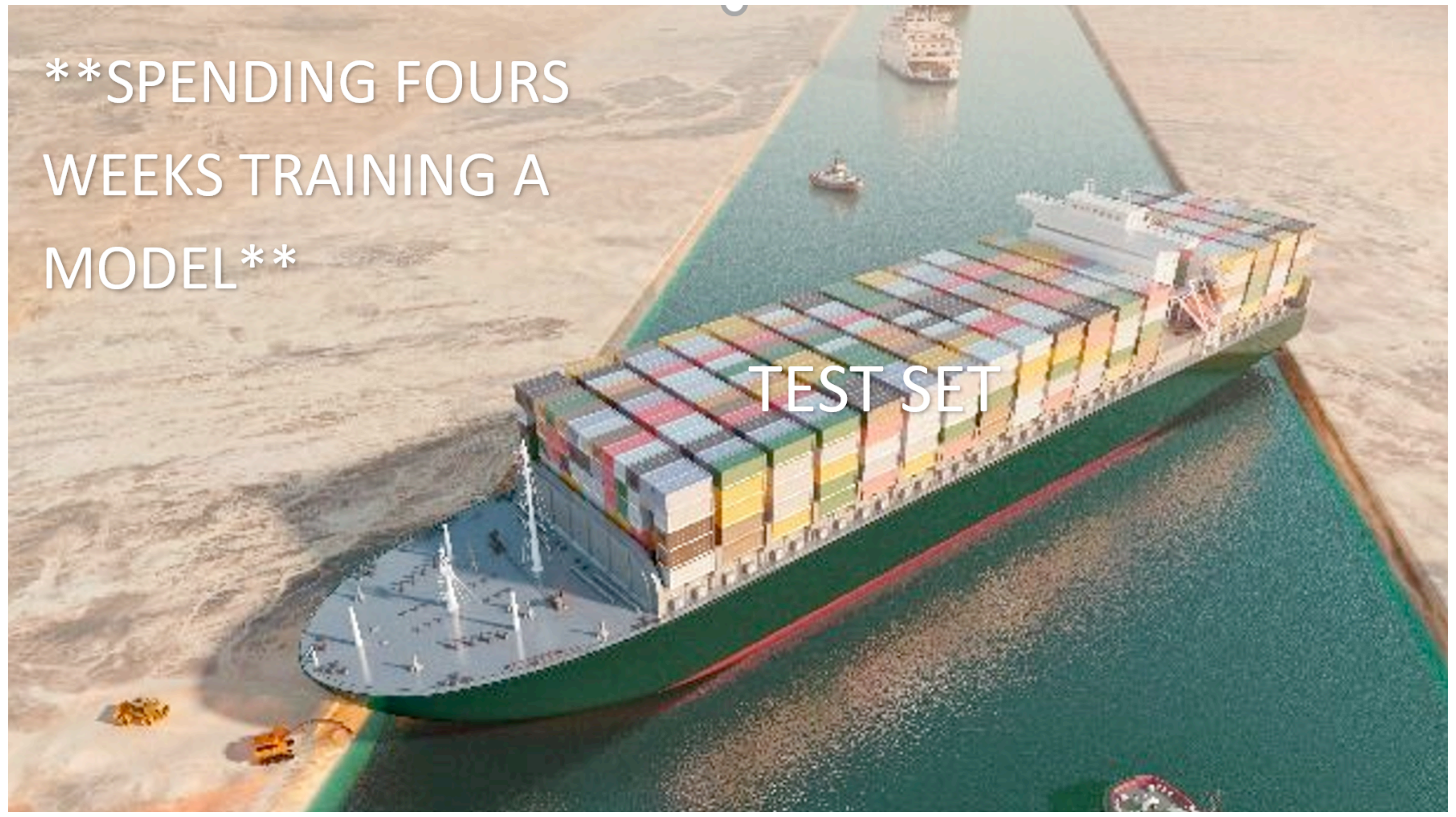
Neural Networks

- Key idea:
  - No feature engineering
  - Have a larger model *learn which features are useful*
    - [but can be combined with feature extraction as well]
- “End-to-end” learning paradigm:

raw text → learned non-linear model → output

Neural Networks

- Cons [to recur throughout course]:
  - "Black box":
    - How do we know *what* the model has learned?
    - How can we trust it in deployment?
    - Often learns to solve a dataset, not a task; may be very different from our linguistic competence
  - Larger and larger compute needs [equity, environmental costs]
  - Larger and larger data needs
    - Documentation debt
    - Privacy concerns
    - Amplifying biases



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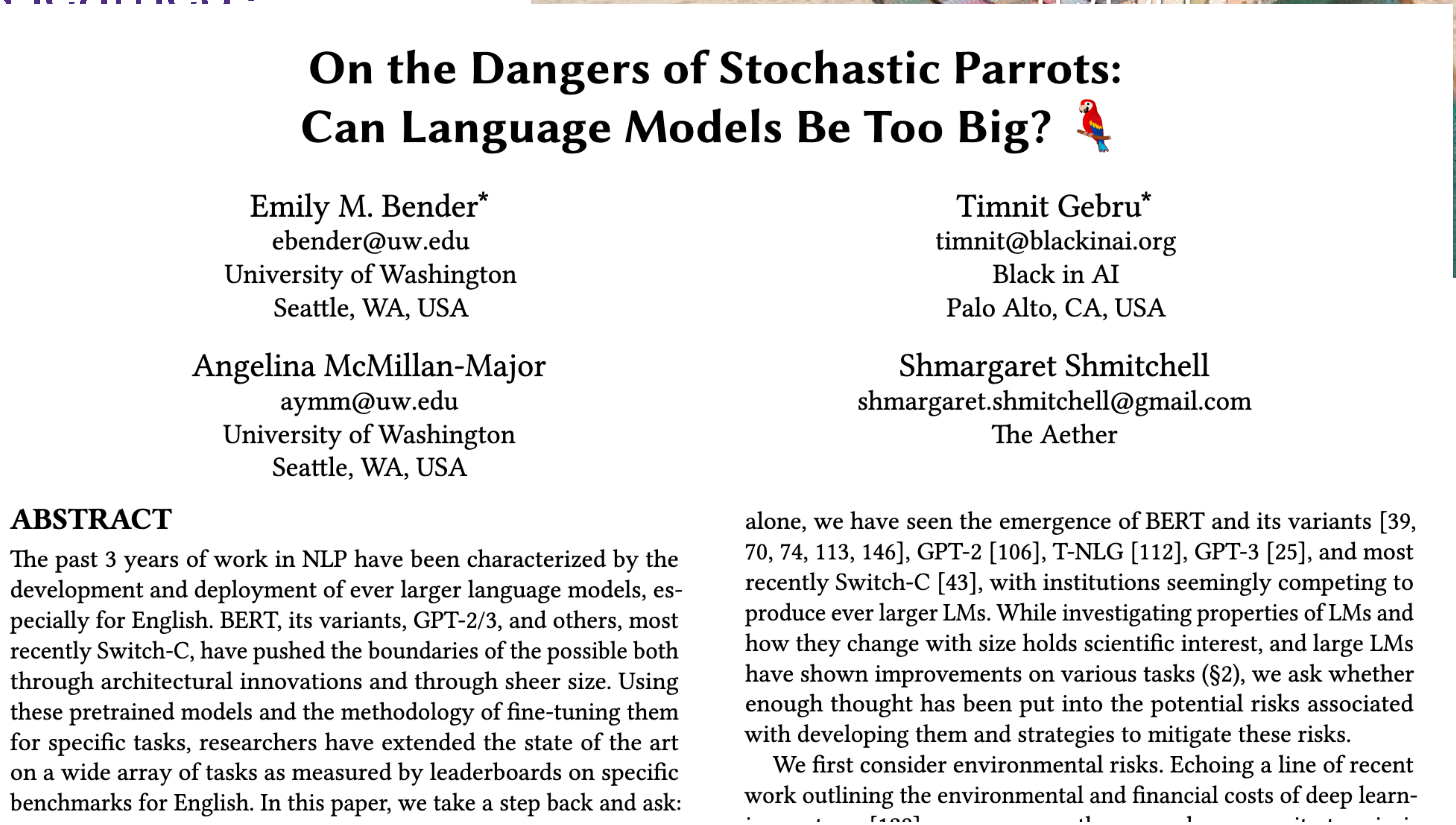

On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? 🦜

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ABSTRACT

The past 3 years of work in NLP have been characterized by the development and deployment of ever larger language models, especially for English. BERT, its variants, GPT-2/3, and others, most recently Switch-C, have pushed the boundaries of the possible both through architectural innovations and through sheer size. Using these pretrained models and the methodology of fine-tuning them for specific tasks, researchers have extended the state of the art on a wide array of tasks as measured by leaderboards on specific benchmarks for English. In this paper, we take a step back and ask:

alone, we have seen the emergence of BERT and its variants [39, 70, 74, 113, 146], GPT-2 [106], T-NLG [112], GPT-3 [25], and most recently Switch-C [43], with institutions seemingly competing to produce ever larger LMs. While investigating properties of LMs and how they change with size holds scientific interest, and large LMs have shown improvements on various tasks (§2), we ask whether enough thought has been put into the potential risks associated with developing them and strategies to mitigate these risks.

We first consider environmental risks. Echoing a line of recent work outlining the environmental and financial costs of deep learn-

Course Information / Overview

Learning Objectives

- Provide hands-on experience with building neural networks and using them for NLP tasks
- Theoretical understanding of building blocks
  - Computation graphs + gradient descent
  - Forward/backward API
    - Chain rule for computing gradients [backpropagation]
  - Various network architectures; their structure and biases

Content

- Model architectures [in computation graph paradigm]:
  - Feed-forward networks
  - Recurrent networks
  - Transformers
- Primary tasks:
  - Language modeling
  - Text classification [sentiment analysis in particular]
  - Translation
- Pre-training + fine-tuning, interpretability/analysis

Content, cont.

- Special topics:
  - Low-resource / multilingual NLP [C.M. Downey]
  - Ethics / societal impacts [Angelina McMillan-Major]
  - Efficiency [Tim Dettmers]
  - Future directions

Course web page

- Course page: https://www.shane.st/teaching/574/spr24/
- Canvas: https://canvas.uw.edu/courses/1720014
  - Lecture recording
  - Assignment submission / grading
  - Discussion!

Communication

Communication

- Contacting teaching staff:
  - If you prefer, you can use your Canvas inbox for all course-related emails:
  - If you do send email, please include LING574 in your subject line of email to us.
  - We will respond within 24 hours, but only during “business hours” during the week.

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  - All content and logistics questions
  - If you have the question, someone else does too. Someone else besides the teaching staff might also have the answer.
  - Many non-CLMS students here in the class.

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  - Many non-CLMS students here in the class.
- We will use Canvas:Announcement for important messages and reminders.

Office hours

Office hours

- Shane:
  - Email: shanest@uw.edu

  - Office hours:
    - Wednesday 3-5pm
      - GUG 415K
      - https://washington.zoom.us/my/shanest

TA office hours

- Say Karamali
  - Email: karamali@uw.edu
  - Office hours:
    - TBD

Homework assignments

Homework assignments

- Due date: every Thurs at 11pm unless specified otherwise.
- The submission area closes two days after the due date.
- Late penalty:
  - 1% for the 1st hour
  - 10% for the 1st 24 hours
  - 20% for the 1st 48 hours
- Your code must run, and will be tested, on patas.

Homework Submission

- For each assignment, submit two files through Canvas:
  - A note file: readme.txt or readme.pdf
  - A gzipped tar file that includes everything: hwX.tar.gz

```
cd hwX/          # suppose hwX is your dir that includes all the files
tar -czvf hw.tar.gz *
```

- Before submitting, run check_hwX.sh to check the tar file: e.g.,

```
/dropbox/23-24/574/hw1/check_hw1.sh hw1.tar.gz
```

- check_hwX.sh checks only the existence of files, not the format or content of the files.

- For each shell script submitted, you also need to submit the source code and binary code: see 574/hwX/submit-file-list

Rubric

- Standard portion: 25 points
  - 2 points: hw.tar.gz submitted
  - 2 points: readme.[txt|pdf] submitted
  - 6 points: all files and folders are present in the expected locations
  - 10 points: program runs to completion
  - 5 points: output of program on patas matches submitted output

- Assignment-specific portion: 75 points

Regrading requests

- You can request regrading for:
  - wrong submission or missing files: show the timestamp
  - crashed code that can be easily fixed (e.g., wrong version of compiler)
  - output files that are not produced on patas
- At most two requests for the course.
- 10% penalty for the part that is being regraded.
- For regrading and any other grade-related issues: you must contact the TA within a week after the grade is posted.

Final grade

- Grade:
  - Assignments: 100% (lowest score is removed)
  - Bonus for participation: up to 2%
  - The percentage is then mapped to final grade.
- No midterm or final exams
- Grades in Canvas:Grades
- TA feedback returned through Canvas:Assignments

Assignment Overview

- Assignments 1-5: FFNNs for LM/classification from the ground up
  - Implemented in edugrad
  - Minimal Implementation of PyTorch API
- 6-7: RNNs for LM + classification
- Attention and NMT
- Transformers / pre-training

Next Time

- WTF is a word vector?
- How do we train them?
  - Crash course in gradient descent
- Establishing notation for the rest of the course

Thanks! Looking forward to a great quarter!