Lecture 18: Neural Networks – Overview and example applications

COMP90049

Semester 1, 2023

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Roadmap

So far ...

The theory and practice of deep learning

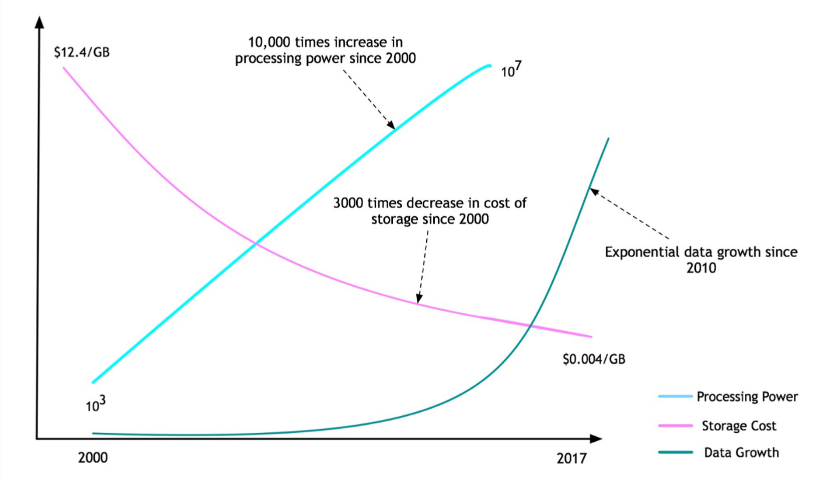
1. Logistic regression and the perceptron
2. Stacking processing units into neural networks (MLPs)
3. Representation learning and on-linear classification
4. Designing neural networks
5. Learning neural network parameters

Today...

- Deep learning: recap and wrap-up
- Example use cases
- A glimpse into large language models and open questions

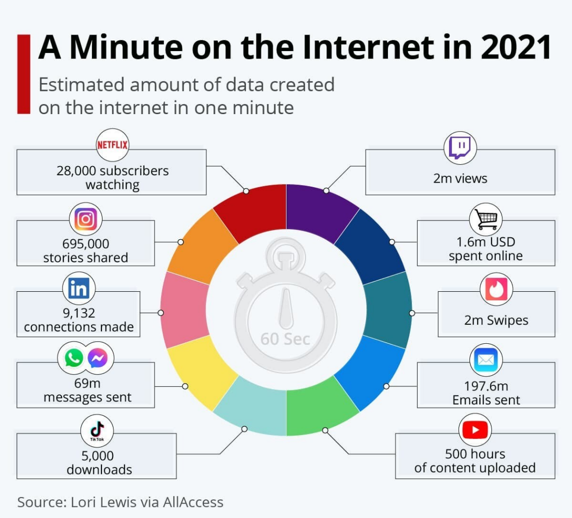
Introduction

Reasons for Success I: Storage & Compute



Source: `https://rpradeepmenon.medium.com/an-executive-primer-to-deep-learning-80c1ece69b34`

Reasons for Success II: Big data

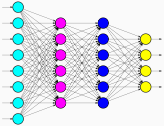


Source:

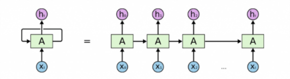
https://www.weforum.org/agenda/2021/08/one-minute-internet-web-social-media-technology-online/

Flavors of Deep Learning

Feed Forward Neural Networks

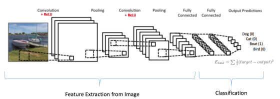


Recurrent neural networks

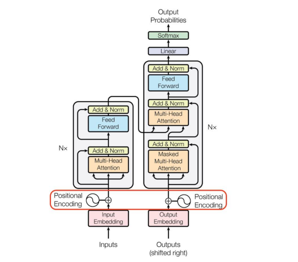


An unrolled recurrent neural network.

Convolutional neural networks



Transformers and large language models



Traditional vs. Deep Learning

Features

- “Traditional” (non neural) ML: feature engineering and/or feature selection
- Deep learning: the model “learns” its own representations from raw intput

Advantage of more training data

- Traditional models at some point do not benefit from more data. why?
- Large neural networks can benefit from ever growing data sets. why?

Can you think of **advantages** of traditional approaches?

Case Study 1:
Deep learning for Medical Image Recognition

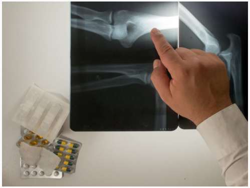
Motivation and impact

Medical doctors...

- improve with *experience*
- are not universally available (rural, remote areas)
- are limited by speed
- get tired

Medical data

- Electronic health records becoming the de-facto standard
- Images are a large part of the record
- (Small) repositories of “doctor-**labelled** images”
- Lots of **unlabeled** medical images/scans ← **“big data”**



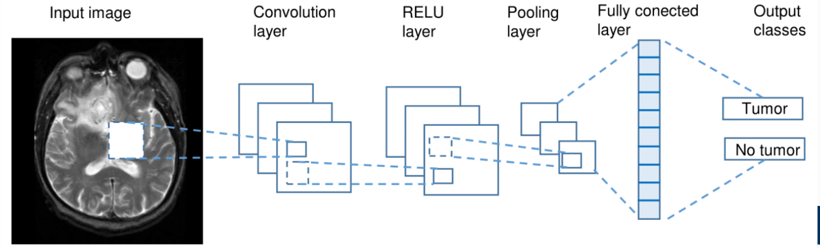
AI to promote reliable and universally accessible health care.

Medical Image Analysis Tasks

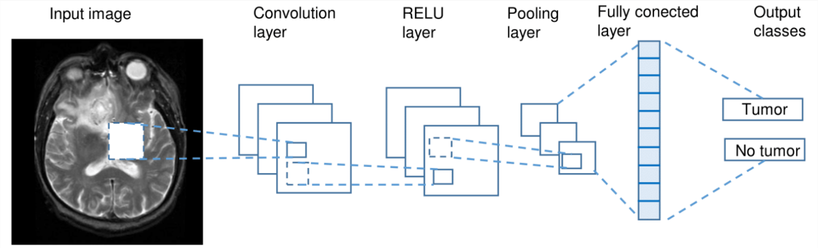
- Detection (“Is the disease present?”)
- Localization (“Where is the kidney in this image?”)
- Segmentation (“Where are the boundaries of the lung tumor?”)

Brief history of medical AI

- Rule-based systems (1970s)
- Manual **feature extraction** and supervised learning (early 2000s-2015)
- Supervised neural networks (2015–)
  - “Automatic” feature extraction
  - Take as input **raw, labeled** images



Convolutional Neural Networks



Intuition

- Input: raw pixels
- Analyze local patches of the image (**convolution layer**)
- Preserve local structure
- Generate more and more high-level shapes / features
- Eventually: predict class from final representation

Medical Image Analysis Tasks

- Detection (“Is the disease present?”)
- Localization (“Where is the kidney in this image?”)
- Segmentation (“Where are the boundaries of the lung tumor?”)

Formalize these tasks as machine learning tasks (or: concepts).

Experiments and Performance

(Very!) generally,

- Increasingly, human doctors (e.g. dermatologists and radiologists) are outperformed by machine learning algorithms [Ker et al., 2017] (*But be careful: evaluation error! Are the test sets representative?*)
- That is, despite training on often small, **supervised** data sets (see e.g., [Ker et al., 2017, Shen et al., 2017] for details if interested)

> *"Cho et al. [...] ascertained the accuracy of a CNN [...] in classifying individual axial CT images into one of 6 body regions: brain, neck, shoulder, chest, abdomen, pelvis. With 200 training images, accuracies of 88-98% were achieved on a test set of 6000 images."* [Ker et al., 2017]

Discuss the trade-off between **model bias** and **evaluation bias** in the context of medical applications and the quote above.

Medical image analysis: Outlook

Research challenges

- Leveraging unlabeled images
- Class imbalance in the training data
  - Most patients are healthy
  - Few images for rare diseases
- Patients' perception/trust of an “AI doctor”
- Legal and moral responsibility if “things go wrong”

More medical ML problems

- Medical/surgical robotics
- Text and vision tasks: medical report summarization or retrieval
- Generating images with (neural) generative models

An expert's outlook: `https://www.youtube.com/watch?v=G1IsZeFR_Rk`

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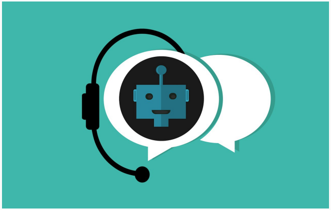
Case Study 2: Chatbots!

What?

"A computer program designed to simulate conversation with human users, especially over the Internet"

[Adamopoulou and Moussiades, 2020]



Why?

- Language as the most natural way to interact with electronic devices
- FAQ vs chatbot vs human advice
- Business/e-commerce: scale customer service
- Health, age care: improve access
- Entertainment: Alexa, Siri, ...

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A chatbot's tasks

Message analysis

- Natural language understanding
- Making sense of the human's language
- Possibly follow a multi-human conversation

Dialogue management

- Plan the content to contribute next ("turn")
- The turn type must make sense in context (e.g., ask a clarification question if unsure; provide an answer if human asked a question; ...)
- Often: abstract content, logic

Response generation

- Natural language generation
- Translate the turn/content into natural language

Brief history of chatbots

From pattern matching to machine learning

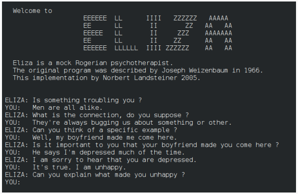
1950s : The Turing test

1960s : ELIZA. simulated Psychotherapist (patterns and templates)

2000s : SmarterChild. AOL/Microsoft messenger, to check news, weather etc (access to knowledge base)

2010s- : “Smart” personal voice assistants (Alexa, Siri, Cortana, ...). Diverse, extensible, adaptable, access personal and public data.

2022- : Large language models with human feedback (ChatGPT and variants)



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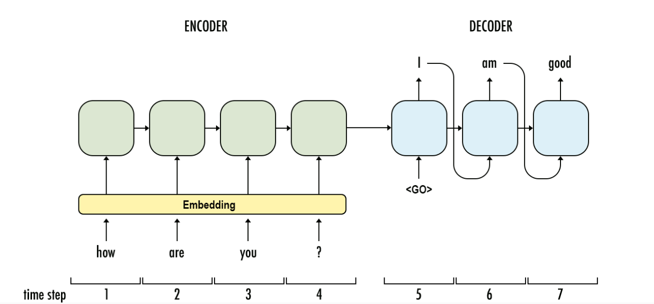
Sequence-to-sequence neural networks

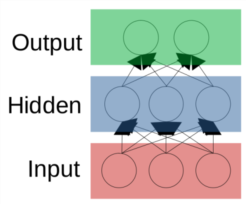


The **encoder** passes an input through a neural network and generates a hidden, vector representation. The **decoder** takes this vector and generates a natural language response.

An **end-to-end model**, rather than a collection of task-specific modules.

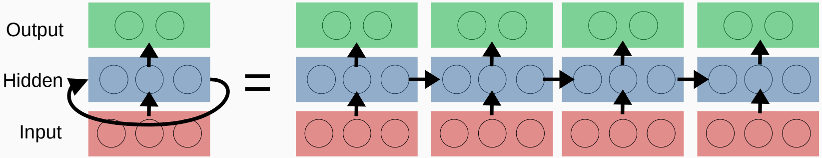
Feed Forward Neural Network

- Many, connected perceptron units
- Information flows from input (bottom) to output (top)



Recurrent Neural Network for Language Generation

- Information also flows from left-to-right
- Time step N receives as input the **hidden state** of time step $N - 1$
- Time step N receives as input the **output** of time step $N - 1$



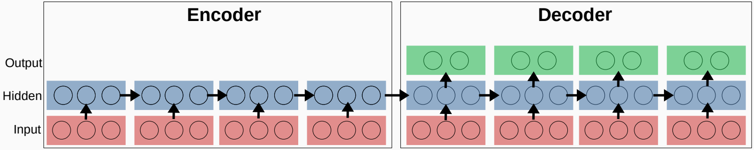
Deep learning for Chatbots

Encoder network

- reads in the input (user utterance)
- passes its last hidden state to the initial hidden state of the decoder

Decoder RNN

- generates the output (system response)



Training a chatbot model

Typical training data sets [Shao et al., 2017, Vinyals and Le, 2015]

- Reddit conversations (221 million conversations)
- Movie subtitles (0.5 million conversations)
- IT Helpdesk Troubleshooting conversations (

Tasks

- The tasks of understanding, planning, generation are not necessarily separated any longer
- With more data/bigger models, more dialogue history can be considered

Does it work?

Describe your problem: i forgot my password
Machine: *hi , this is <NAME> from helpdesk connect , what can i help you with today ?*
Human: *hi , i forgot my password*

Machine: *ok great*
Human: *can you tell me how i can recover it ?*
Machine: *i ' ll need to verify who it is at that machine*
Machine: *can we do a hangout*
Machine: *?*
Human: *yes*
Machine: *<anonymized hangout instructions and verifications>*
Human: *cool , i am good now*
Machine: *how ' s this looking good ?*
Machine: *i ' ll go ahead and close this chat .*
Machine: *take care . :)*
Human: *bye*
Machine: *bye .*

[Vinyals and Le, 2015]

Which of the evaluation metrics covered in this subject can be used to evaluate a dialogue system? Discyss & justify your answer.

Does it work?

Challenges: Generally short answers (not diverse), and a trade-off between length and coherence:

- incoherent (“The sun is in the center of the sun.”),
- redundancy (“i like cake and cake”),
- contradiction (“I don’t own a gun, but I do own a gun.”)

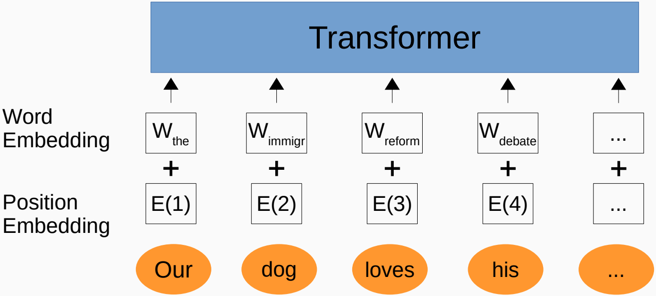
Human: *what is your job ?*
Machine: *i ’m a lawyer .*
Human: *what do you do ?*
Machine: *i ’m a doctor .*

Which of the evaluation metrics covered in this subject can be used to evaluate a dialogue system? Discyss & justify your answer.

The idea

- Train a **base language model** on general **language understanding**
- Teaching it to do a specific task (e.g. sentiment classification) can be done with very little extra effort (**Few-shot learning**)
- This works well if the base language model is **very large**.

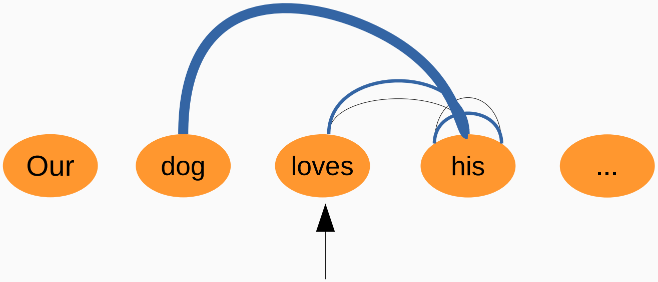
→ Trick 1: No more recurrence with **position embeddings**



The Transformer

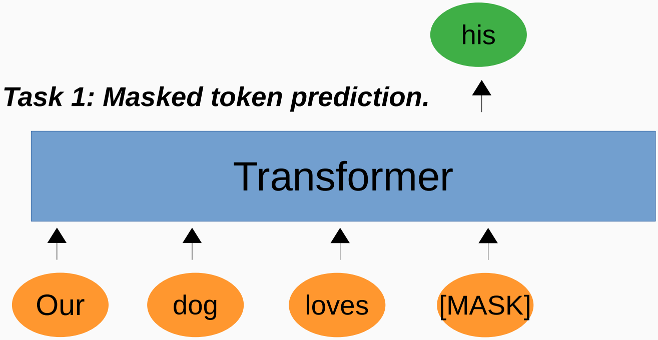
→ Trick 2: **Attention**

- Long-range dependencies
- Each word: selectively incorporates its relevant context to re-weigh its representation
- Repeat with different attention parameters (=‘multi-head’)



→ Trick 3: **Self-supervision**

- Cheap training at **massive** scale
- Many different variants and tasks (here: GPT-style)



Why does it work so well?

Task: predict the next word given the previous context

- Trained massive, cleaned data sets from the internet
- It sees a LOT of diverse examples
- GPT models have the **capacity** to store this knowledge, and generalize from it.
- GPT-3 has 175 Billion parameters
- **Regularization** to prevent **overfitting**
  - Dropout: randomly ‘remove’ certain weight connections during training
  - Weight decay: restrict parameter values to be (relatively) small

Zero-shot and few-shot learning

We can train GPT models to solve a task by instructing it in natural language + examples (few-shot)

"Translate English to German			$\leftarrow$ *task description*
the house	$\rightarrow$	Das Haus	
a girl	$\rightarrow$	Ein Maedchen	$\leftarrow$ *three examples*
five bananas	$\rightarrow$	Fuenf Bananen	
three women	$\rightarrow$	___"	$\leftarrow$ *prompt*

Or without any examples at all (zero shot)

"Translate English to German			$\leftarrow$ *task description*
three women	$\rightarrow$	___"	$\leftarrow$ *prompt*

ChatGPT = GPT-3 + Dialoue + Human feedback (+X)

Supervised fine-tuning for dialogue

- Very high-quality, natural human dialogues
- Teach ChaptGPT to respone appropriately to questions, comments, . . .

Reinforcement learning from human feedback

- There are many different ways to respond to a question or coment (or prompt)
- Humans provide feedback on GPT output (e.g., *Output A is better than Output B*). This feedback is used to further fine-tune the model.
- Learning from feedback (reinfocement learning) is different from learning from supervision (supervised learning). We'll gloss over the many, complex details.

Other factors of ChatGPT's success

- Yet more data
- A user interface!

Open Questions

- How do we understand what the models contain?
- Memorization vs. producing novel content?
- Are there theoretical bounds on what can (not) be learned with a fairly simple masked language model training?
- What biases are encoded in these models (more in 2 weeks!)
- Training and using these models requires vast amounts of energy and creates a large CO_2 footprint

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Summary

Today

- The impact of deep learning on AI in everyday life
- Medical image analysis
- Chatbots
- Of course, there's lots more: assisted driving, machine translation, ...

Next

- Inner workings of (feed forward) neural networks
- Neural network training with backpropagation

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