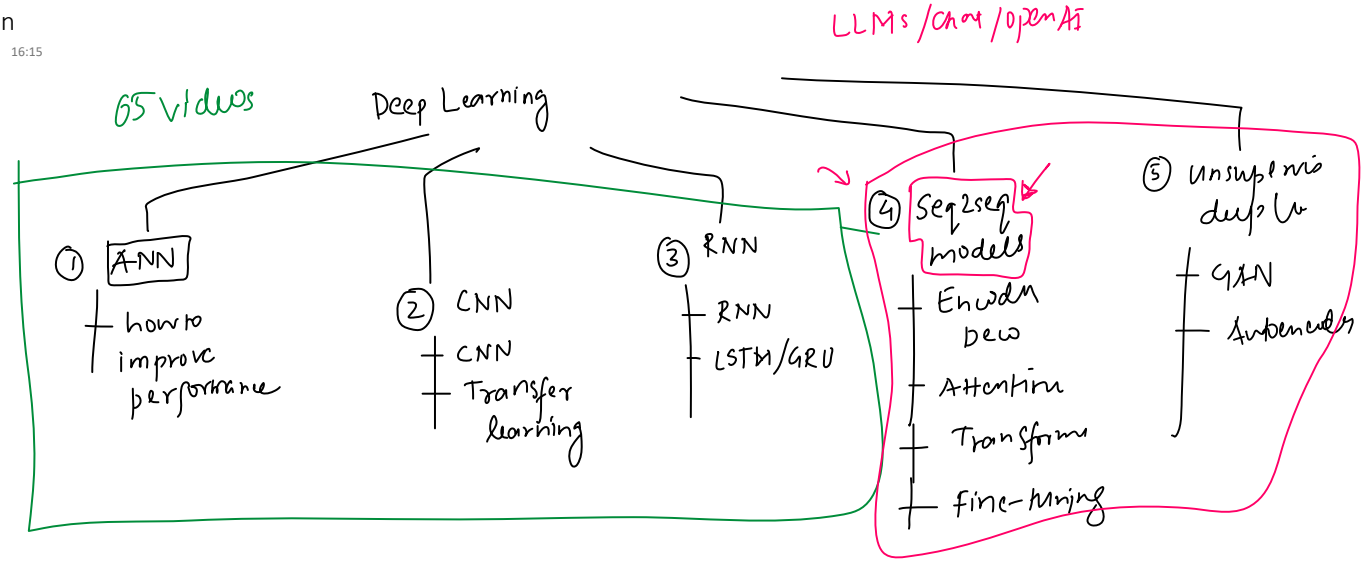
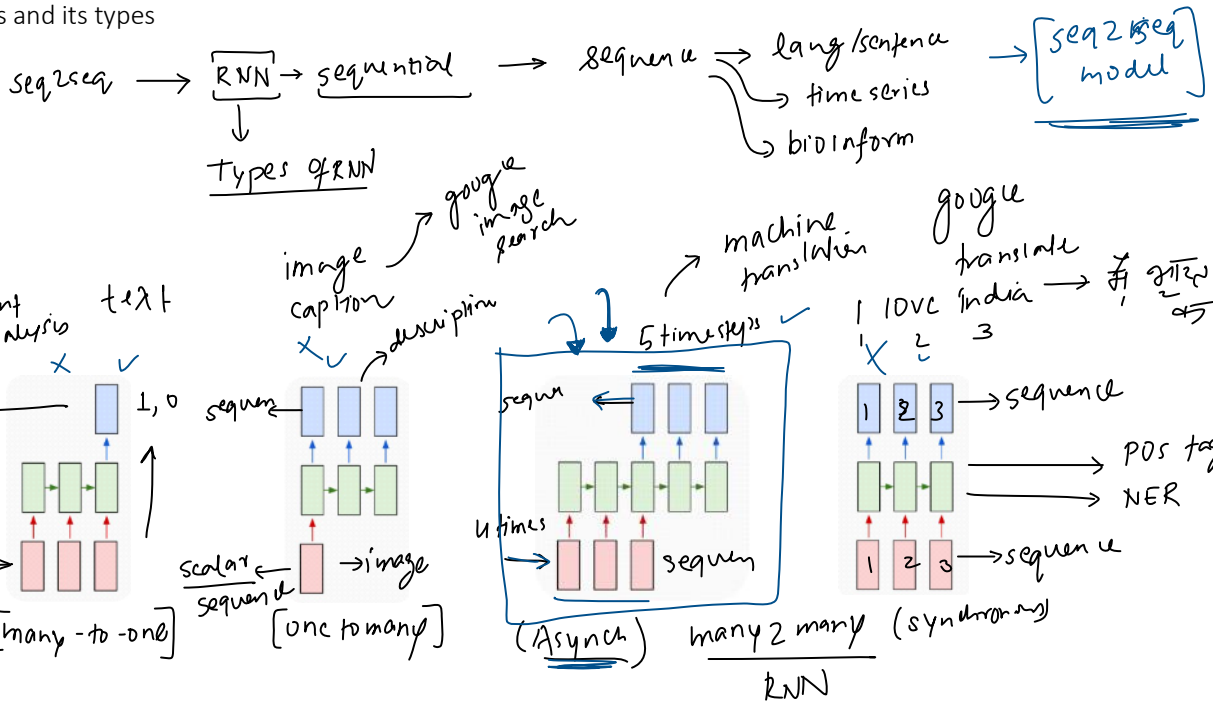
# Introduction

16 November 2023 16:15



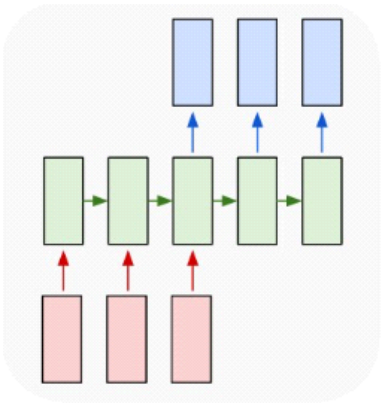
Sequence Tasks and its types

16 November 2023 16:16



# Seq2Seq Tasks

16 November 2023 16:16



NLP

Seq2seq → machine trans

1) text summari → seq → seq

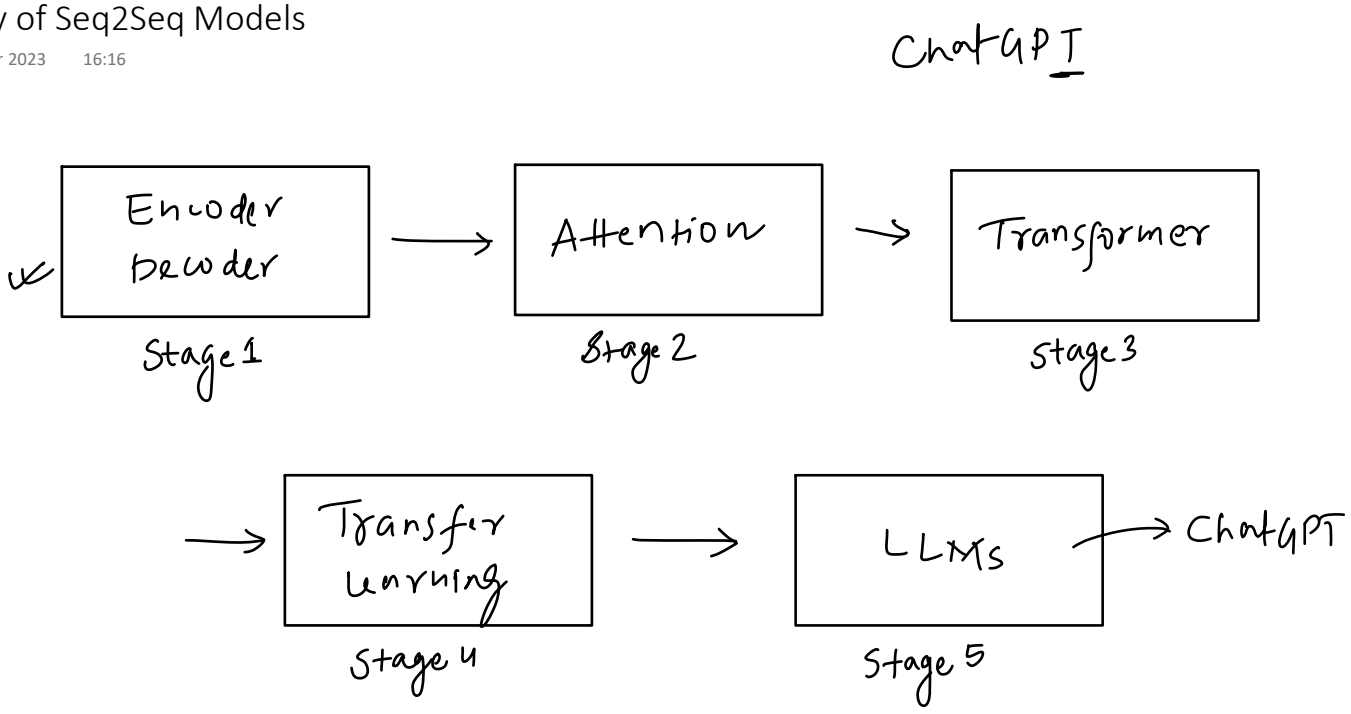
2) Question answer → seq → seq (knowledge base)

3) chatbot → input (text) → output (text)

4) speech-to-text → seq seq → seq2seq → chatgpt

# History of Seq2Seq Models

16 November 2023 16:16



# Stage 1 - Encoder Decoder Architecture

18 November 2023 16:16

2014 Seminal

## Sequence to Sequence Learning with Neural Networks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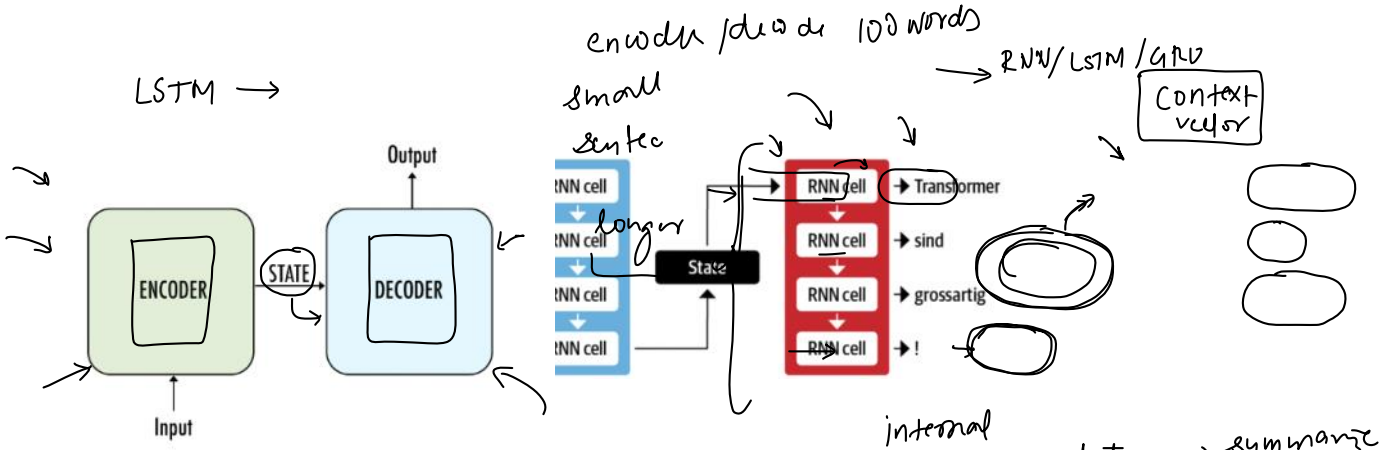
**Abstract**

Deep Neural Networks (DNNs) are powerful models that have achieved excellent performance on difficult learning tasks. Although DNNs work well whenever large labeled training sets are available, they cannot be used to map sequences to sequences. In this paper, we present a general end-to-end approach to sequence learning that makes minimal assumptions on the sequence structure. Our method uses a multilayered Long Short-Term Memory (LSTM) to map the input sequence to a vector of a fixed dimensionality, and then another deep LSTM to decode the target sequence from the vector. Our main result is that on an English to French translation task from the WMT'14 dataset, the translations produced by the LSTM achieve a BLEU score of 34.8 on the entire test set, where the LSTM's BLEU score was penalized on out-of-vocabulary words. Additionally, the LSTM did not have difficulty on long sentences. For comparison, a phrase-based SMT system achieves a BLEU score of 33.3 on the same dataset. When we used the LSTM to rerank the 1000 hypotheses produced by the aforementioned SMT system, its BLEU score increases to 36.5, which is close to the previous best result on this task. The LSTM also learned sensible phrase and sentence representations that are sensitive to word order and are relatively invariant to the active and the passive voice. Finally, we found that reversing the order of the words in all source sentences (but not target sentences) improved the LSTM's performance markedly, because doing so introduced many short term dependencies between the source and the target sentence which made the optimization problem easier.


Ilya Sutskever → cofounder OpenAI

seq2seq
↓
diff
↳ encoder decoder




seq2seq → input → output
machine translation
eng → hindi

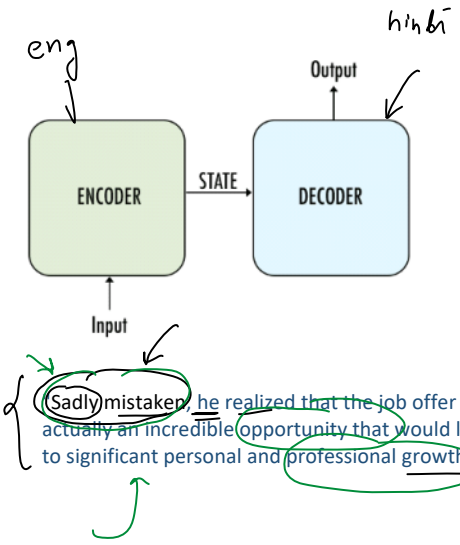
I love India → मैं भारत से प्यार करता हूँ

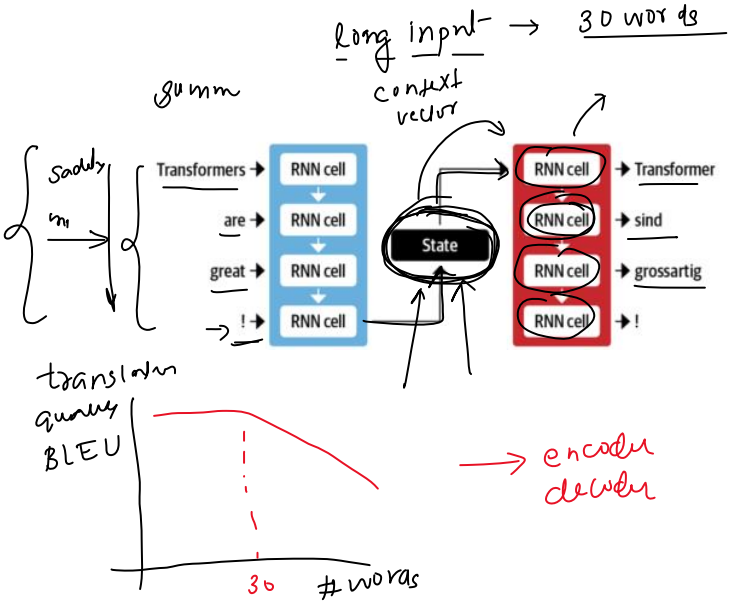
process word by word → compress

Attention mechanism

# Stage 2 - Attention Mechanism

20 November 2023 10:59



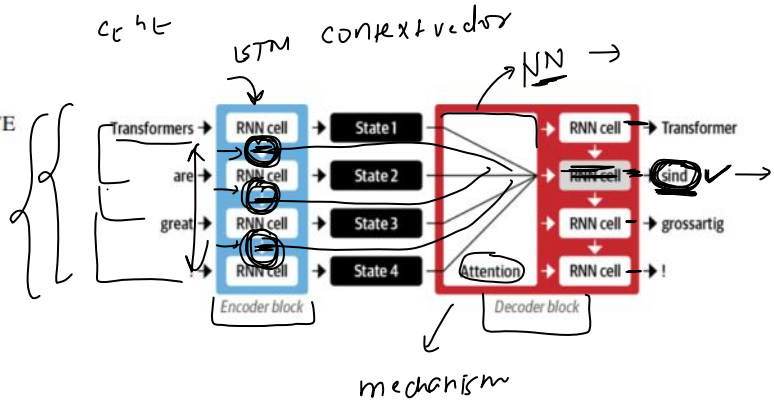




2015 Attention

## NEURAL MACHINE TRANSLATION BY JOINTLY LEARNING TO ALIGN AND TRANSLATE

**Dzmitry Bahdanau**
Jacobs University Bremen, Germany

**KyungHyun Cho** **Yoshua Bengio***
Université de Montréal




### ABSTRACT

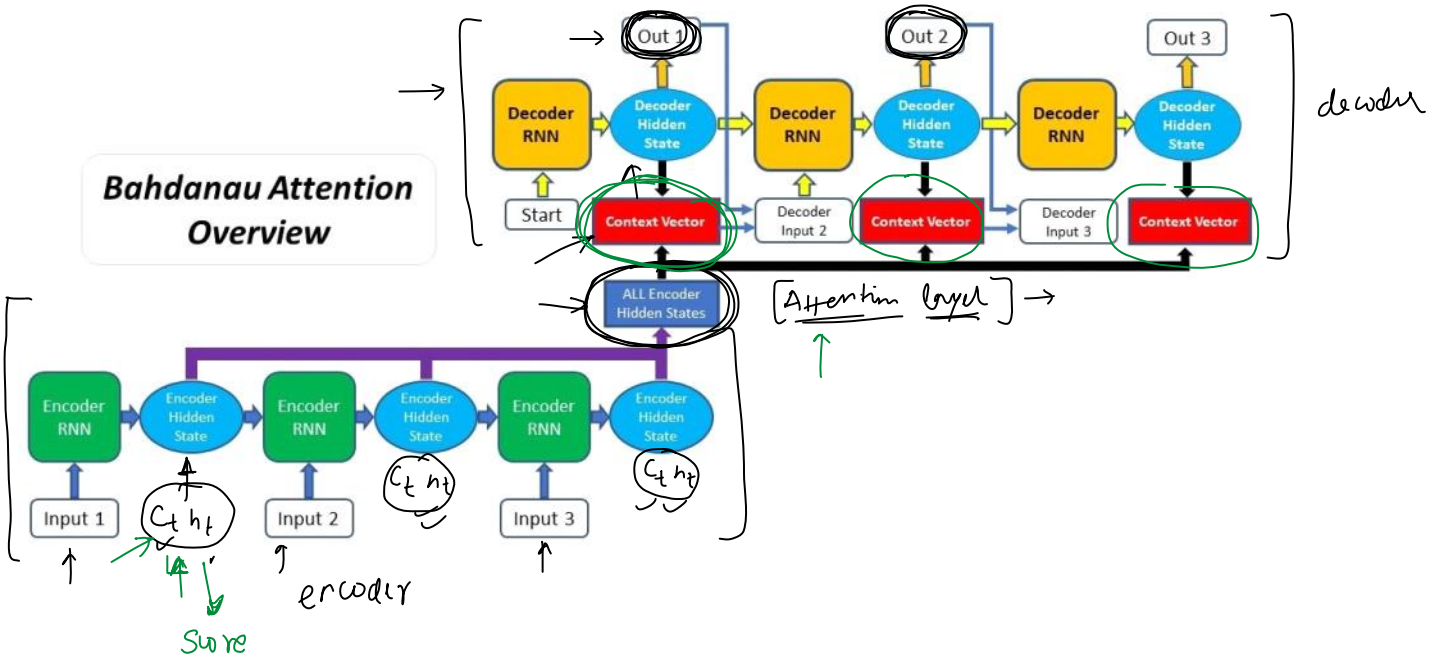
Neural machine translation is a recently proposed approach to machine translation. Unlike the traditional statistical machine translation, the neural machine translation aims at building a single neural network that can be jointly tuned to maximize the translation performance. The models proposed recently for neural machine translation often belong to a family of encoder–decoders and encode a source sentence into a fixed-length vector from which a decoder generates a translation. In this paper, we conjecture that the use of a fixed-length vector is a bottleneck in improving the performance of this basic encoder–decoder architecture, and propose to extend this by allowing a model to automatically (soft-)search for parts of a source sentence that are relevant to predicting a target word, without having to form these parts as a hard segment explicitly. With this new approach, we achieve a translation performance comparable to the existing state-of-the-art phrase-based system on the task of English-to-French translation. Furthermore, qualitative analysis reveals that the (soft-)alignments found by the model agree well with our intuition.

### 1 INTRODUCTION

*Neural machine translation* is a newly emerging approach to machine translation, recently proposed by Kalchbrenner and Blunsom (2013), Sutskever *et al.* (2014) and Cho *et al.* (2014b). Unlike the traditional phrase-based translation system (see, e.g., Koehn *et al.*, 2003) which consists of many small sub-components that are tuned separately, neural machine translation attempts to build and train a single, large neural network that reads a sentence and outputs a correct translation.

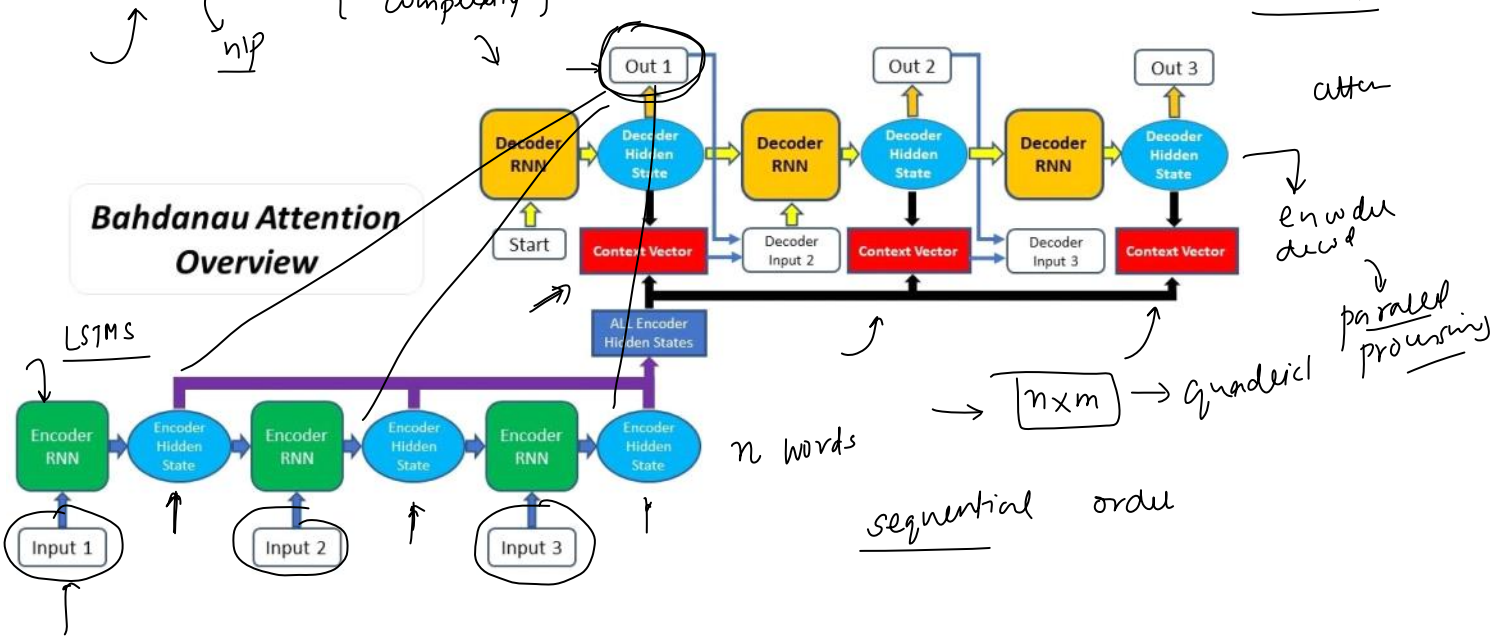
Most of the proposed neural machine translation models belong to a family of *encoder–decoders* (Sutskever *et al.*, 2014; Cho *et al.*, 2014a), with an encoder and a decoder for each language, or involve a language-specific encoder applied to each sentence whose outputs are then compared (Hermann and Blunsom, 2014). An encoder neural network reads and encodes a source sentence into a fixed-length vector. A decoder then outputs a translation from the encoded vector. The whole encoder–decoder system, which consists of the encoder and the decoder for a language pair, is jointly trained to maximize the probability of a correct translation given a source sentence.

A potential issue with this encoder–decoder approach is that a neural network needs to be able to compress all the necessary information of a source sentence into a fixed-length vector. This may make it difficult for the neural network to cope with long sentences, especially those that are longer than the sentences in the training corpus. Cho *et al.* (2014b) showed that indeed the performance of a basic encoder–decoder deteriorates rapidly as the length of an input sentence increases.


Bahdanau Attention Overview
Out 1
Out 2
Out 3
Decoder RNN
Decoder Hidden State
Start
Context Vector
Decoder Input 2
Decoder Input 3
ALL Encoder Hidden States
Encoder RNN
Encoder Hidden State
Input 1
Input 2
Input 3
decoder
Attention layer
encoder
Score

Stage 3 - Transformers

20 November 2023 12:18




**Attention Is All You Need**


**Ashish Vaswani*** Google Brain avaswani@google.com
**Noam Shazeer*** Google Brain noam@google.com
**Niki Parmar*** Google Research nikip@google.com
**Jakob Uszkoreit*** Google Research usz@google.com
**Llion Jones*** Google Research llion@google.com
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**Abstract**

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

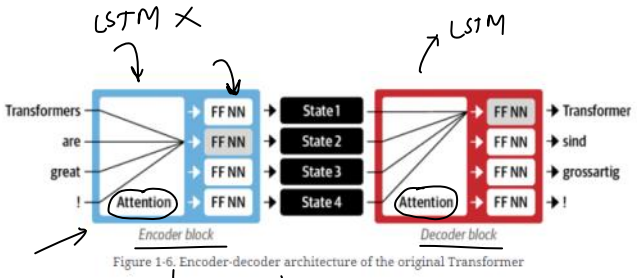




Figure 1-6. Encoder-decoder architecture of the original Transformer

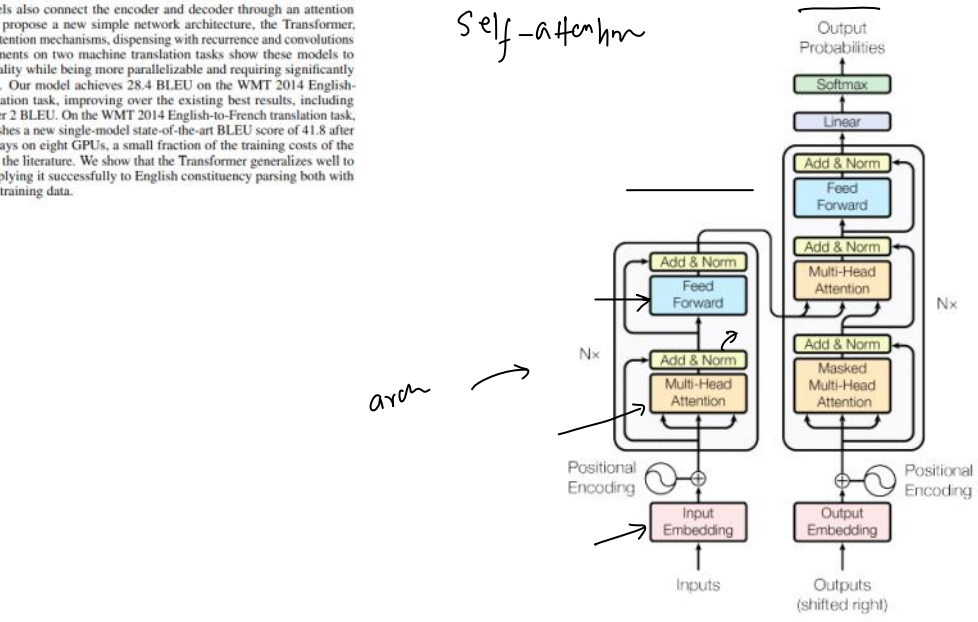
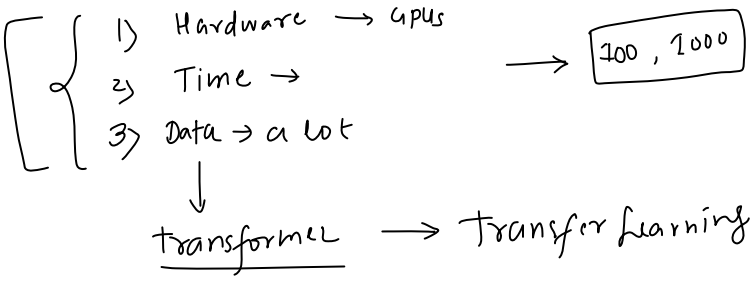



Figure 1: The Transformer - model architecture.

# Stage 4 - Transfer Learning

20 November 2023 15:39




ULMFiT

**Universal Language Model Fine-tuning for Text Classification**

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**Sebastian Ruder***
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Aylien Ltd., Dublin
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2018 → vision

transfer → NLP tasks

ULMFit

primary pretrain

**Abstract**

Inductive transfer learning has greatly impacted computer vision, but existing approaches in NLP still require task-specific modifications and training from scratch. We propose Universal Language Model Fine-tuning (ULMFiT), an effective transfer learning method that can be applied to any task in NLP, and introduce techniques that are key for fine-tuning a language model. Our method significantly outperforms the state-of-the-art on six text classification tasks, reducing the error by 18-24% on the majority of datasets. Furthermore, with only 100 labeled examples, it matches the performance of training from scratch on 100× more data. We open-source our pretrained models and code[1].

## 1 Introduction

Inductive transfer learning has had a large impact on computer vision (CV). Applied CV models (including object detection, classification, and segmentation) are rarely trained from scratch, but instead are fine-tuned from models that have been pretrained on ImageNet, MS-COCO, and other datasets (Sharif Razavian et al., 2014; Long et al., 2015a; He et al., 2016; Huang et al., 2017).

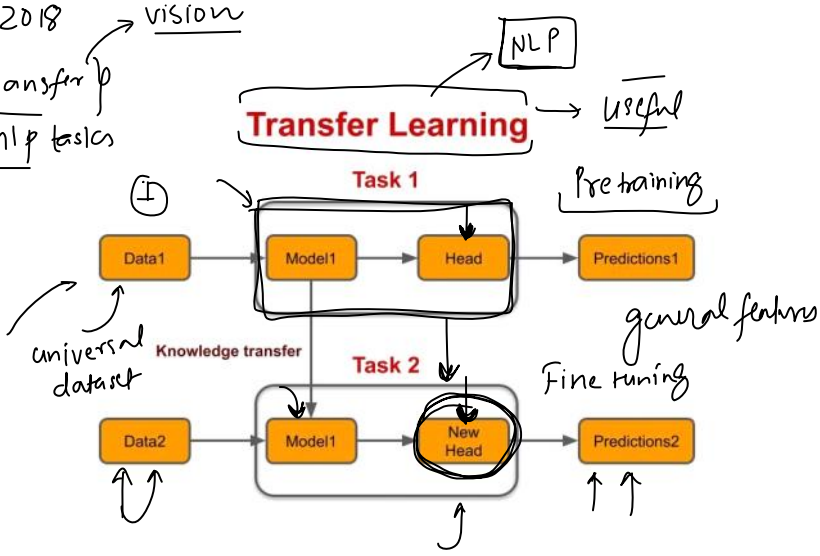
Text classification is a category of Natural Language Processing (NLP) tasks with real-world applications such as spam, fraud, and bot detection (Jindal and Liu, 2007; Ngai et al., 2011; Chu et al., 2012), emergency response (Caragea et al., 2011), and commercial document classification, such as for legal discovery (Roitblat et al., 2010).

While Deep Learning models have achieved state-of-the-art on many NLP tasks, these models are trained from scratch, requiring large datasets, and days to converge. Research in NLP focused mostly on *transductive* transfer (Blitzer et al., 2007). For *inductive* transfer, fine-tuning pretrained word embeddings (Mikolov et al., 2013), a simple transfer technique that only targets a model's first layer, has had a large impact in practice and is used in most state-of-the-art models. Recent approaches that concatenate embeddings derived from other tasks with the input at different layers (Peters et al., 2017; McCann et al., 2017; Peters et al., 2018) still train the main task model from scratch and treat pretrained embeddings as fixed parameters, limiting their usefulness.

In light of the benefits of pretraining (Erhan et al., 2010), we should be able to do better than *randomly initializing* the remaining parameters of our models. However, inductive transfer via fine-tuning has been unsuccessful for NLP (Mou et al., 2016). Dai and Le (2015) first proposed fine-tuning a language model (LM) but require millions of in-domain documents to achieve good performance, which severely limits its applicability.

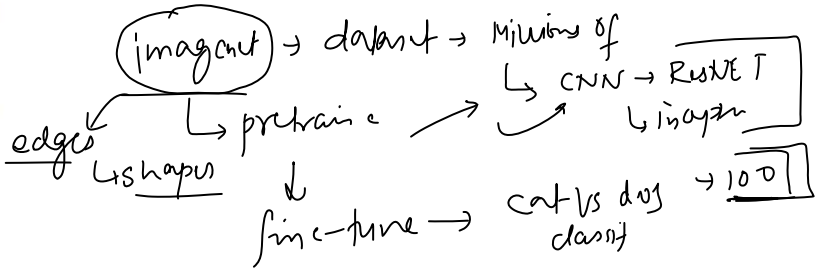
We show that not the idea of LM fine-tuning but our lack of knowledge of how to train them effectively has been hindering wider adoption. LMs overfit to small datasets and suffered catastrophic forgetting when fine-tuned with a classifier. Compared to CV, NLP models are typically more shallow and thus require different fine-tuning methods.

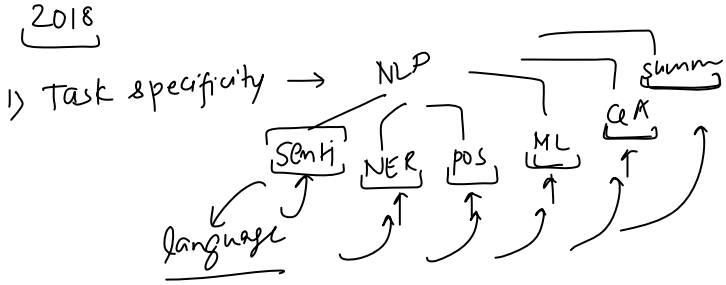
We propose a new method, Universal Language Model Fine-tuning (ULMFiT) that addresses these issues and enables robust inductive transfer learning for any NLP task, akin to fine-tuning ImageNet



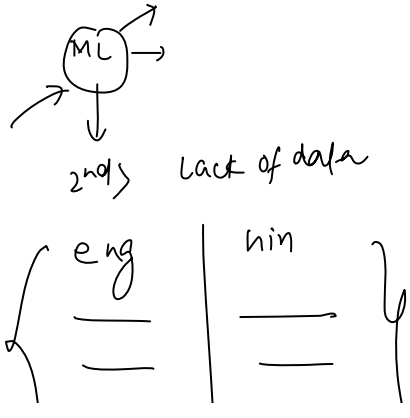

Transfer learning (TL) is a technique in which knowledge learned from a task is re-used in order to boost performance on a related task.

For example, for image classification, knowledge gained while learning to recognize cars could be applied when trying to recognize trucks.

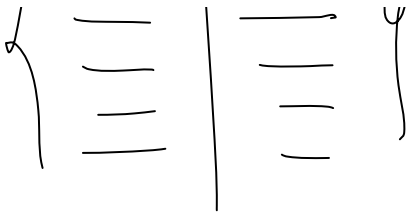



NLP → transfer learning



NLP → transfer learning



Pretraining → Machine transl X

→ language modelling → pretraining → sucessful → (2)

NLP task → NLP/DL model next word pred

I live in india. and the capital is New Delhi

Language modelling as a Pretraining task

→ unsupervised pretrain task

1) Rich feature learning

The hotel was exceptionally clean, yet the service was bad / pathetic

→ know trans

↓

text classi / quest. | textsumm | NER | pos

mt (labw → supervised labeled

eng | nin → unsupervised task

2) Huge avail of data

pdf → dataset labelling

[ULMFiT]

fine tuning

X transformer

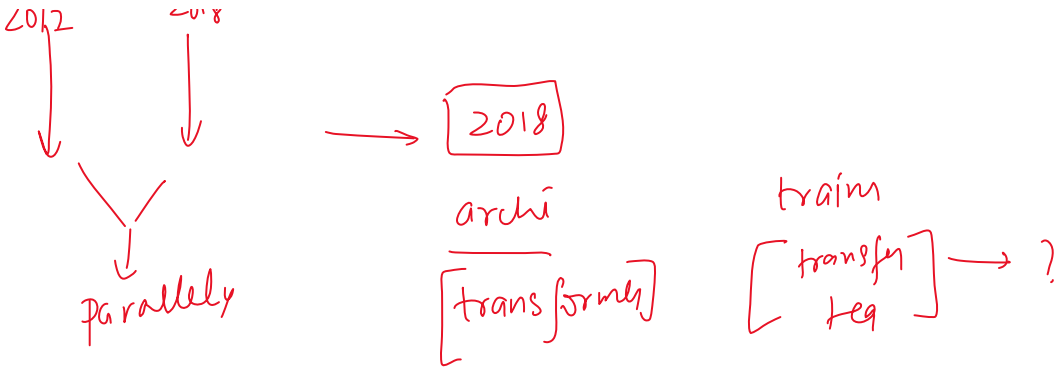
AWD LSTM → wikipedia → classifier → imdb / yelp / new data → model → test → State of the art

Unsupervised pretrain Language modelling

Scratch → 10000 rows

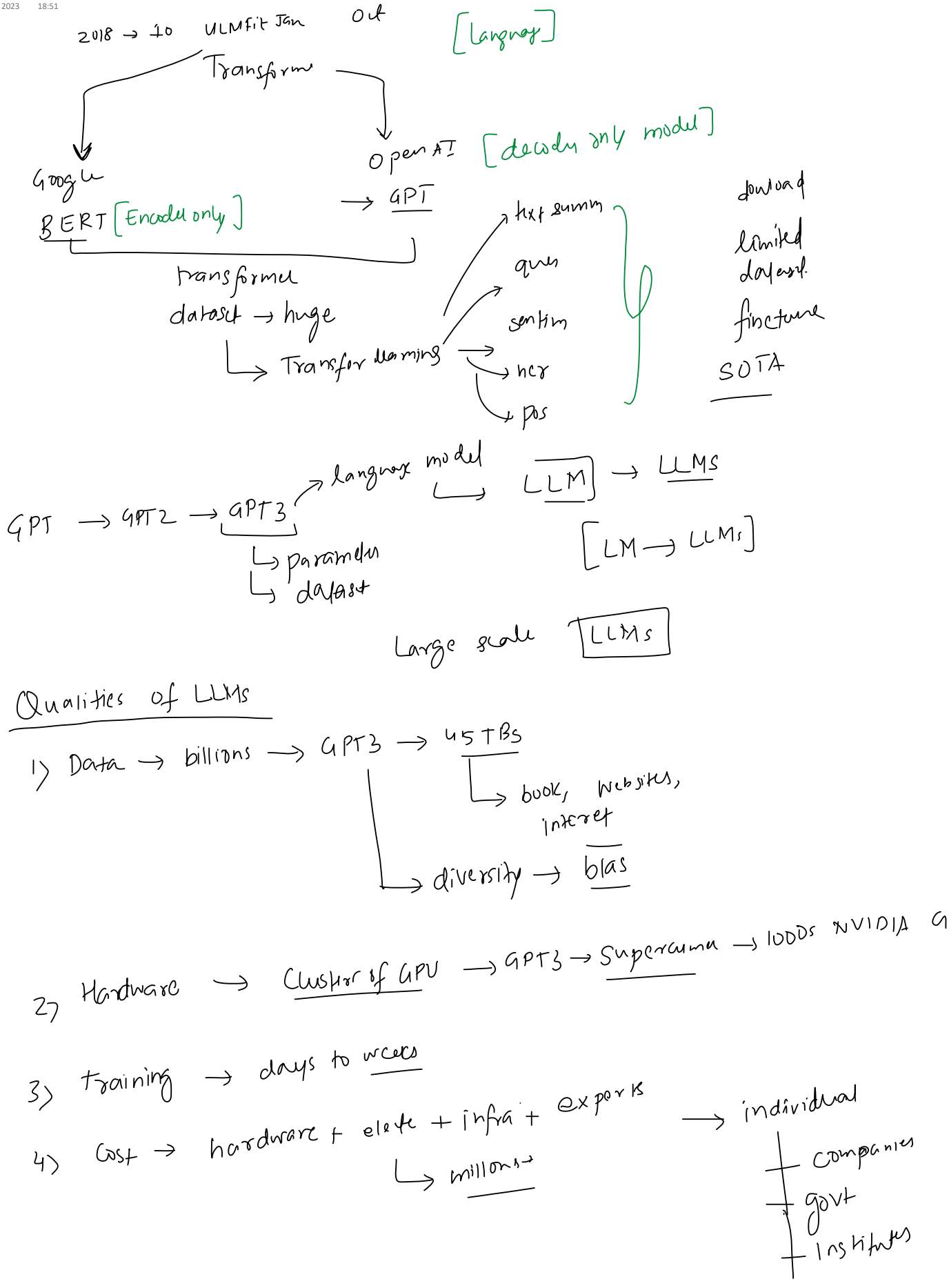
100 row → better →

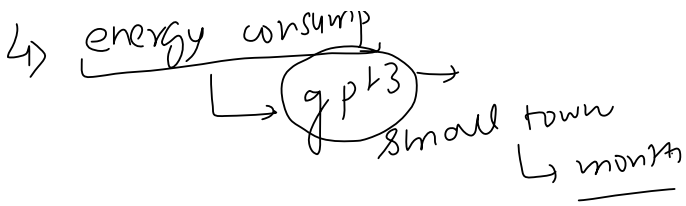
2012 2018


2012
2018
parallely
2018
archi
transformer
train
transfer
eq
?

Stage 5 - LLMs

20 November 2023 18:51




energy consump
gpt3
small town
month

# The Grand Finale - ChatGPT

22 November 2023 10:13

GPT3 → chatGPT

[diff]

GPT → model

[ChatGPT] → application

Chat-bot

NOV

hp → chatgpt → Bard, Jasper

intel → GPT

dell

ASW

GPT3 → [ChatGPT]

1) RLHF → Reinf lea from human feed

- 1 Supervised Fine tuning → dataset → labeled
- 2 Reinforce → prompt produces
  - responses
  - human → respone rank

2) Incorporate safety and ethical guideline

- minize biases

3) improvent in contextual point

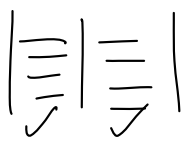
context retain → maintain context → dialogu Convrs

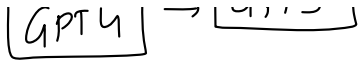
4) Dialogue specific training

- conversation
- better under → dialogue lang → patterns

5) ChatGPT continous imp → human feedback usu

train → refining → GPT4 → GPT3


train → gpt


GPT4