

Introduction





How words change meaning over time:

"Baseline" (in NLP)

1998: random choice

2005: majority class

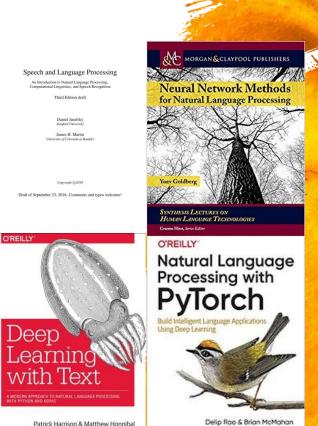
2012: bag of words

2019: LSTM with attention & pre-trained

embeddings

2:45 PM - 11 May 2019





New Frameworks

- × PyTorch is where it's at!
- × Pythia
 - a PyTorch framework for bridging the gap
 - DL for Text and Computer Vision
 - great for VQA challenges
 - https://github.com/facebookresearch/pythia
- × transfer-NLP
 - Transfer code and Transfer Learning
 - Based on PyTorch and Delip Rao book
 - https://github.com/feedly/transfer-nlp



- Williams

Large-scale data sets

- DL needs large data sets
 - 10k to 1M examples or more
- × DecaNLP MTL as QA
- × GLUE MTL benchmark for NLU
- × SquAD 2.0 Stanford QA
- × **SWAG** Situations with Adversarial Generation
- × VGR Visual Commonsense Reasoning
- × Gab.ai Social Media posts
- NarrativeQA Reading Comprehension

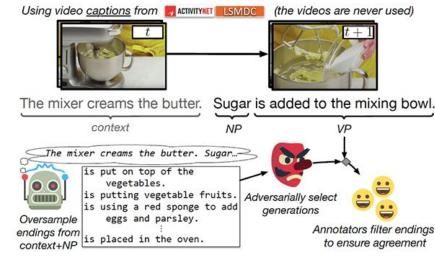


Figure 1: Overview of the data collection process.



Bias

- Gender and representation bias
- × Unconscious bias
- × Aim for balanced gender
- × IBM's Al Fairness 360
 - 10 fairness SoA algorithms
- × Relational Inductive biases in Graphs
 - Bias is in the networks
 - https://arxiv.org/pdf/1806.01261.pdf
- × Gender and Resource Co-reference Bias
 - https://arxiv.org/pdf/1804.06876.pdf

Type 1

The physician hired the secretary because he was overwhelmed with clients.

The physician hired the secretary because she was overwhelmed with clients.

The physician hired the secretary because she was highly recommended.

The physician hired the secretary because he was highly recommended.

Type 2

The secretary called the physician and told him about a new patient.

The secretary called the physician and told her about a new patient.

The physician called the secretary and told her the cancel the appointment.

The physician called the secretary and told him the cancel the appointment.



BERT and Friends

1 - Semi-supervised training on large amounts of text (books, wikipedia..etc).

The model is trained on a certain task that enables it to grasp patterns in language. By the end of the training process, BERT has language-processing abilities capable of empowering many models we later need to build and train in a supervised way.

Semi-supervised Learning Step

Model:

BERT

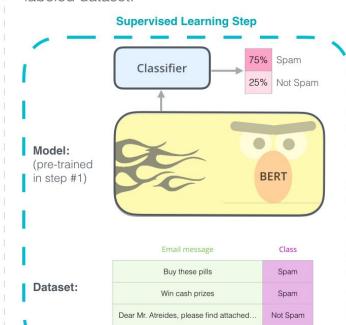
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Predict the masked word

(langauge modeling)

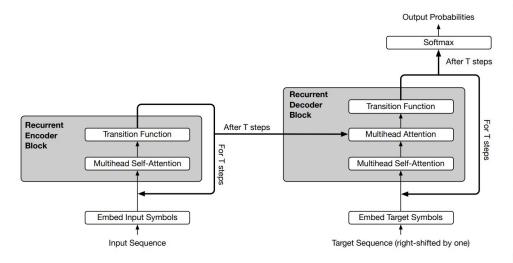
Objective:

2 - Supervised training on a specific task with a labeled dataset.



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Universal Transformers



• Step#1

John went to the hallway. John went to the hallway. John went back to the bathroom John went back to the bathroom . John grabbed the milk there. John grabbed the milk there . Sandra went back to the office . Sandra went back to the office . Sandra journeyed to the kitchen . Sandra journeyed to the kitchen . Sandra got the apple there . Sandra got the apple there Sandra dropped the apple there Sandra dropped the apple there . John dropped the milk . John dropped the milk . Where is the milk? Where is the milk?

Step#2

John went to the hallway. John went to the hallway. John went back to the bathroom. John went back to the bathroom . John grabbed the milk there. John grabbed the milk there . Sandra went back to the office . Sandra went back to the office . Sandra journeyed to the kitchen . Sandra journeyed to the kitchen. Sandra got the apple there . Sandra got the apple there . Sandra dropped the apple there . Sandra dropped the apple there . John dropped the milk . John dropped the milk . Where is the milk? Where is the milk?

Step#3

John went to the hallway .

John went back to the bathroom .

John grabbed the milk there .

Sandra went back to the office .

Sandra journeyed to the kitchen .

Sandra got the apple there .

Sandra dropped the apple there .

John dropped the milk .

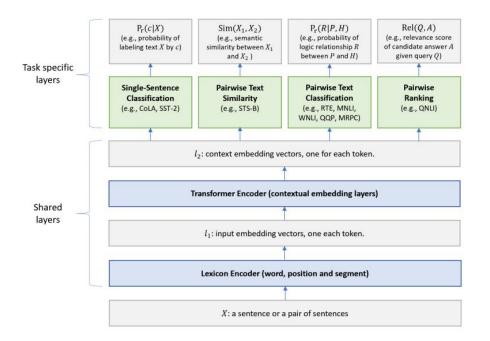
Where is the milk?

John went to the hallway .
John went back to the bathroom .
John grabbed the milk there .
Sandra went back to the office .
Sandra journeyed to the kitchen .
Sandra got the apple there .
Sandra dropped the apple there .
John dropped the milk .
Where is the milk?

Step#4

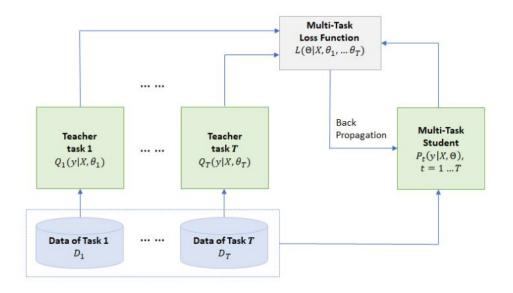
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Microsoft MT-DNN





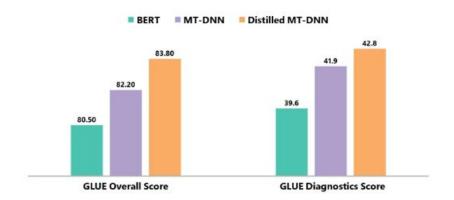
Knowledge Distillation



Improving Multi-Task Deep Neural Networks via Knowledge Distillation for Natural Language Understanding, https://www.microsoft.com/en-us/research/publication/improving-multi-task-deep-neural-networks-via-knowledge-distillation-for-natural-language-understanding/

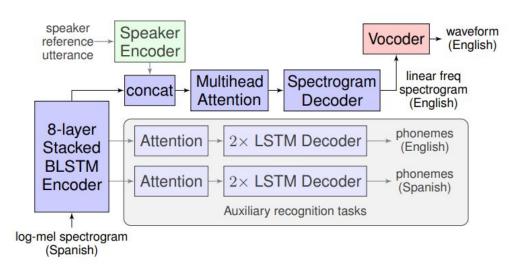
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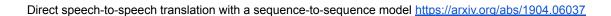
Knowledge Distillation





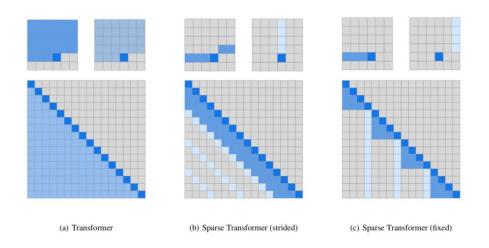
Google Al 'Translatotron'





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OpenAl Sparse Transformers



Generative Modeling with Sparse Transformers https://openai.com/blog/sparse-transformer/ Generating Long Sequences with Sparse Transformers https://arxiv.org/abs/1904.10509



OpenAl

Multi-task learning (MTL) has led to successes in many applications of machine learning, from natural language processing and speech recognition to computer vision and drug discovery. This article aims to give a general overview of MTL, particularly in deep neural networks. It introduces the two most common methods for MTL in Deep Learning, gives an overview of the literature, and discusses recent advances. The article then briefly considers the advantages and challenges of using MTL in combination with regularization and classification. Finally, a brief overview of the various approaches to MTL is provided, before examining more technical questions that arise from the use of MTL.



