Cornelia Ilin, Ph.D. UC Berkeley School of Information May 10, 2023

⁶⁶ ChatGPT could threaten 300 million jobs ⁹⁹

⁶⁶ ChatGPT is the hottest in-demand job skill ⁹⁹

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Powered by the Transformer architecture

Learning Objectives: Transformers

History

• Architecture

• Application (with a deep-dive into electronic medical records)

Conclusions













Attention is All You Need

Vaswani et al., 2017

Issue with RNN/LSTMs

Proposed solution

Cannot parallelize due to recurrency, i.e., very long training times

Remove recurrency and rely on positional encodings and self-attention only

> Transformer architecture

Transformer (High Level View)

- Vaswani et al., 2017 considered the task of machine translation
- Encoder encodes source sentence (source token embeddings)
- Decoder predicts target sentence, one token at a time





Architecture walkthrough (model training)



the black cat

Architecture walkthrough (model training)



the black cat

E[<s>]

Architecture walkthrough (model training)



the black cat

Architecture walkthrough (model training)



the black cat

Architecture walkthrough (model training)



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Architecture walkthrough (model training)



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Architecture walkthrough (model training)



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the black cat



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Architecture walkthrough (inference)



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Architecture walkthrough (inference)



Architecture walkthrough (inference)






















the black cat

noir







Q 1: What was the "model of choice" before Transformers?

Q 2: What was the main issue Vaswani et al. 2017, wanted to address with the new Transformer architecture?

Q 2: Do you need both, an encoder and decoder?















Devlin et al., 2018

Task 1: pre-train the model on large self-labeled data



Devlin et al., 2018

Task 1: pre-train the model on large self-labeled data





Devlin et al., 2018



Devlin et al., 2018



Devlin et al., 2018



Devlin et al., 2018



Devlin et al., 2018



Devlin et al., 2018



Q 4: What is the difference between pre-training and fine-tuning?

Ped-BERT: Early Detection of Disease for Pediatric Care



• Literature review







- recurrent fevers
- progressive fat loss
- swollen eyelids
- first seizure



- recurrent fevers
- progressive fat loss
- swollen eyelids
- first seizure





- recurrent fevers
- progressive fat loss
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- first seizure



- recurrent fevers
- progressive fat loss
- swollen eyelids
- first seizure



clinician alone



- recurrent fevers
- progressive fat loss
- swollen eyelids
- first seizure



clinician alone



Can we augment clinical decision making with ML?

- recurrent fevers
- progressive fat loss
- swollen eyelids
- first seizure





- recurrent fevers
- progressive fat loss
- swollen eyelids
- first seizure




- recurrent fevers
- progressive fat loss
- swollen eyelids
- first seizure





Even more relevant for pediatric patients



	Our study	Previous studies
Age	Pediatrics	Adults (mostly)



	Our study	Previous studies
Age	Pediatrics	Adults (mostly)
Data	US (+7000 hospitals in California)	UK (mostly)



	Our study	Previous studies
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Rare diseases	Yes	No



	Our study	Previous studies
Age	Pediatrics	Adults (mostly)
Data	US (+7000 hospitals in California)	UK (mostly)
Rare diseases	Yes	No
Modeling	Ped-BERT (incl., zip location)	Logistic, RNN/LSTM, BERT

Ped-BERT Data

Restricted-access data vitals stats and mother pre- and post-partum health status



Ped-BERT Data

Restricted-access data vitals stats and mother pre- and post-partum health status



(diagnosis codes)

Ped-BERT Data



keep only Birth IDs with a SSN

keep records with SSN in Birth IDs

Ped-BERT Data



keep records with \geq 3 ER/PD visits

Ped-BERT Data



Ped-BERT Data





Ped-BERT Data

Task 1: pre-train the model on large self-labeled data Task 2: fine-tune to specific task, diagnosis code prediction



Ped-BERT Data

Task 1: pre-train the model on large self-labeled data Task 2: fine-tune to specific task, diagnosis code prediction



Ped-BERT Data

Task 1: pre-train the model on large self-labeled data

Task 2: fine-tune to specific task, diagnosis code prediction



Ped-BERT Architecture















Ped-BERT Pre-training Fully connected + Softmax P_{MASK}={..,D2,...} layer Encoder Add & normalize Fully connected network 6 × Add & E[zip1] E[zip2] E[zip1] E[zip3] E[zip3] normalize Multi-head E[age1] E[age1] E[age2] attention E[age3] E[age3] age and zip Positional E[1] E[2] E[3] E[0] E[4] 4 embeddings encoding Embedding E[D1] E[MASK] E[<s>] E[D3] E[<e>] -Source sequence ▲ [D1, MASK, D3]

visit 1 visit 2 visit 3

Is it hard to code the Encoder block?



ENCODER ##

encoder_output = embeddings for i in range(config.NUM_LAYERS): # only 1 layer

Multi-Head self-attention

query = encoder_output key = encoder output value = encoder output

add multihead attention layer

attention_output = layers.MultiHeadAttention(num_heads=config.NUM_HEAD, # implement 8 attention layers key_dim=config.EMBED_DIM // config.NUM_HEAD, name="encoder_{}/att".format(i),)(query, key, value)

add droput layer

attention_output = layers.Dropout(0.1, name="encoder_{}/att_dropout".format(i))(attention output)

add normalization layer

attention_output = layers.LayerNormalization(epsilon=1e-6, name="encoder {}/att layernormalization".format(i))(query + attention output)

Feed Forward Layer

fully connected layer ffn = keras.Sequential(

[layers.Dense(config.FF_DIM, activation="relu"), layers.Dense(config.EMBED_DIM)], name="encoder_{}/ffn".format(i),

)

ffn output = ffn(attention output) # add dropout layer ffn_output = layers.Dropout(

config.RATE, name="encoder_{}/ffn_dropout".format(i))(ffn output

add normalization layer

sequence output = layers.LayerNormalization(epsilon=1e-6, name="encoder_{}/ffn_layernormalization".format(i))(attention_output + ffn_output)

encoder output = sequence output



Did we learn useful embeddings?

Let's project embeddings in 2D space...



E2

I-SN











T-SNE1

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I-SN

International Classification of Diseases (ICD Codes)

- 001-139 Infectious and Parasitic Diseases 140-239 Neoplasms 240-279 Endocrine, Nutritional and Metabolic Diseases, And Immunity Disorders 280-289 Diseases Of The Blood And Blood-Forming Organs 290-319 Mental Disorders Diseases Of the Nervous System and Sense Organs 320-389 **390-459** Diseases Of The Circulatory System Diseases of the Respiratory System 460-519 **Diseases Of The Digestive System** 520-579 **Diseases Of The Genitourinary System** 580-629 Complications Of Pregnancy, Childbirth, And The Puerperium Diseases Of The Skin and Subcutaneous Tissue Diseases Of The Musculoskeletal System And Connective Tissue **Congenital Anomalies** Certain Conditions Originating In The Perinatal Period Symptoms, Signs, And Ill-Defined Conditions
 - 00-999 Injury And Poisoning



T-SNE1

E2

I-SN

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-999 Injury And Poisoning

Ped-BERT Fine-tuning

next medical diagnosis



Ped-BERT Fine-tuning



Ped-BERT Results



Sample-average ROC AUC curve: 0.911

Ped-BERT Results


Ped-BERT Results



Least 4 diagnosis predictions by ROC AUC

Persons With Potential Health Hazards Related to Personal And Family History (AUC = 0.433)

Zoonotic Bacterial Diseases (AUC = 0.188)

Malignant Neoplasm of Respiratory And Intrathoracic Organs (AUC = 0.107)

Subclinical Iodine-Deficiency Hyperthyroidism (AUC = 0.084)

QUIZ

Q 5: What other model performance questions are important to look at?



Less stable ROC AUC results across mother place of birth



Less stable ROC AUC results for older patients



Less stable ROC AUC results for patients with higher level of zip-code pollution exposure



Stable ROC AUC results across these dimensions



Stable ROC AUC results across these dimensions

QUIZ

Q 6: Given the data and the results presented, can you think of other areas of exploration?

- recurrent fevers
- progressive fat loss
- swollen eyelids
- first seizure



- recurrent fevers
- progressive fat loss
- swollen eyelids
- first seizure



after 12 (!) hospital visits...

CANDLE syndrome, a rare, usually genetic, autoinflammatory condition

- recurrent fevers
- progressive fat loss
- swollen eyelids
- first seizure



after 12 (!) hospital visits...

CANDLE syndrome, a rare, usually genetic, autoinflammatory condition

80% of rare diseases, usually genetic, onset during the first years of life (pediatric patients)

- recurrent fevers
- progressive fat loss
- swollen eyelids
- first seizure



Can we use Ped-BERT to detect rare diseases earlier?

80% of rare diseases, usually genetic, onset during the first years of life (pediatric patients) after 12 (!) hospital visits...

CANDLE syndrome, a rare, usually genetic, autoinflammatory condition

Conclusions

Transformers: history and architecture

• BERT (Transformer-encoder): architecture

• Application: predict diagnosis outcomes for pediatric patients using Ped-BERT

THANKS