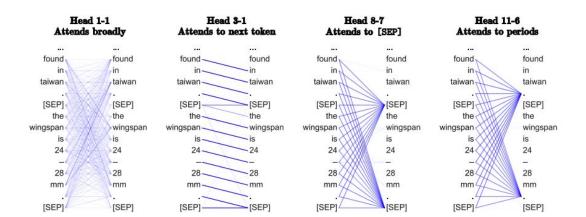
Towards Interpreting BERT for Reading Comprehension Based QA EMNLP 2020

Sahana Ramnath, Preksha Nema, Deep Sahni, Mitesh M. Khapra Robert Bosch Centre for Data Science and AI (RBC-DSAI) Indian Institute of Technology Madras, Chennai, India Towards Interpreting BERT for Reading Comprehension Based QA

Recent Works

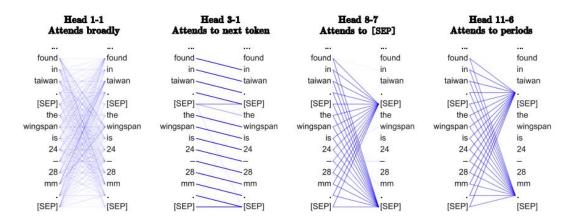
- Syntactic and semantic roles played by BERT's layers [Tenney et al.,2019], [Peters et al.,2018]
- Linguistic phenomena in BERT's attention heads
 [Clark et al., 2019]



Recent Works

- Syntactic and semantic roles played by BERT's layers [Tenney et al.,2019], [Peters et al.,2018]
- Linguistic phenomena in BERT's attention heads et al..2019





Interpreting BERT has not been much explored for Complex tasks like QA.

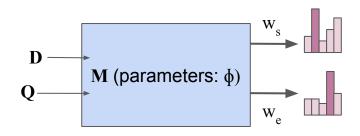


Towards Interpreting BERT for Reading Comprehension Based QA

RCQA Task

Document (D): The Panthers finished the regular season with a 15-1 record ... The Broncos finished the regular season with a 12-4 record.... They joined the Patriots, Dallas Cowboys, and Pittsburgh Steelers as one of <u>four teams</u> that have made eight appearances in the Super Bowl.

RCQA Task



$$p(w_s, w_e) = argmax M(w_s, w_e | \mathbf{D}, \mathbf{Q}, \phi)$$

Document (D): The Panthers finished the regular season with a 15-1 record ... The Broncos finished the regular season with a 12-4 record.... They joined the Patriots, Dallas Cowboys,

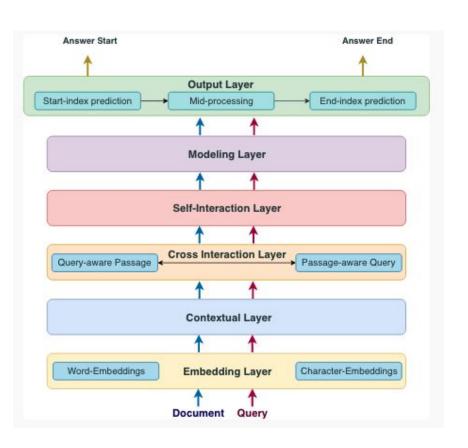


and Pittsburgh Steelers as one of <u>four teams</u> that have made eight appearances in the Super Bowl

Pre-BERT RCQA Models

Pre-BERT models intuitively modeled layers based on how an answer should be arrived at : BiDAF or DCN

[Seo et al., 2016].[Xiong et al., 2016]



Pre-BERT RCQA Models

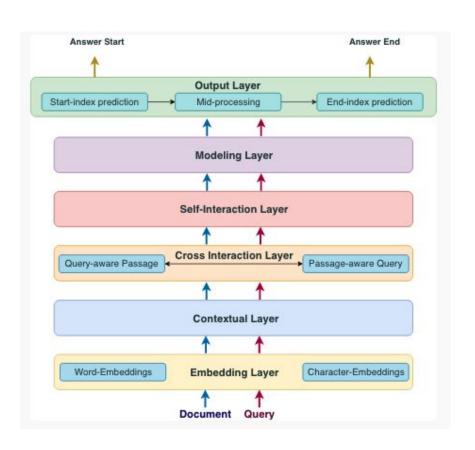
Contextual Layer: Learns
contextual representations for the
passage and the question
independently.

Cross-Interaction Layer: Attends to information in the passage specific to the question.

Self-Interaction/Modelling Layer:

Refines the passage word representations.

Output Layer: Predicts the answer

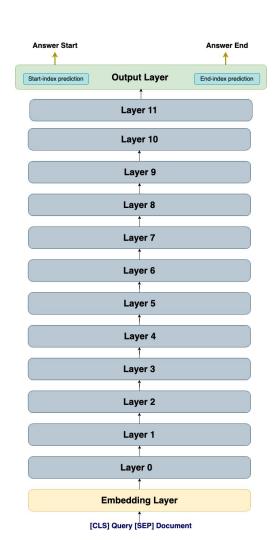


BERT based RCQA Models

BERT is a large 12/24 layer model, with all layers implementing the same transformer block function.

No pre-defined roles for layers in BERT

This combined with BERT's high non-linearity and number of parameters makes it *challenging* to analyse BERT for the task of RCQA.



Towards Interpreting BERT for Reading Comprehension Based QA

This Work

We analyze each of **BERT's layers as one unit**, for RCQA.

 We first explicitly define mathematical functionalities for layers using the attribution method Integrated Gradients.

 We then analyze each layer's functionality with respect to the pre-defined roles modeled in earlier RCQA systems.

Experimental Setup: Datasets

SQuAD 1.1

- 90K/10K train/dev samples
- 100-300 words passage
- Natural language question
- Answer span in passage itself

DuoRC - SelfRC dataset

- 60K/13K train/dev samples
- 500 words on average passage
- Natural language question
- Answer span in passage itself

Layer Level Functionality - Importance Scores

We use the layer functionality to obtain a **distribution across passage words** that represents how important these words are for the answer prediction at that layer.

 0.001	0.01	0.0	0.001	0.003	0.005	 0.61	0.31	
 They	joined	the	Patriots	Dallas	Cowboys	 four	teams	

Layer-11

 0.1	0.2	0.0	0.07	0.10	0.15	 0.33	0.33	
 They	joined	the	Patriots	Dallas	Cowboys	 four	teams	

Layer-k

Obtaining importance scores:

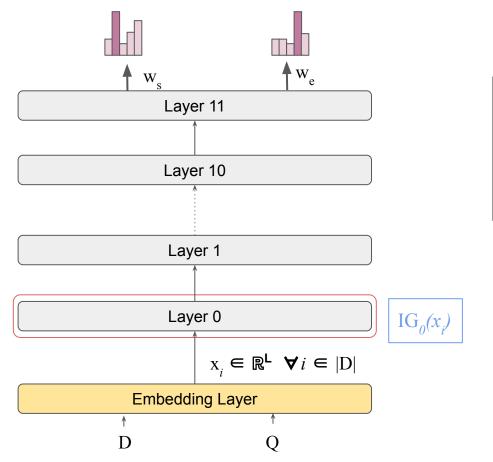
Many techniques to attribute a deep network's predictions to its input features - LIME, **Integrated Gradients**, DeepLift, LRP,etc.

The Integrated Gradients for a passage word w_i , represented as $x_i \in \mathbb{R}^L$ is computed as follows:

If a word w gets a **higher IG** score, it means that it is **more important** to the final prediction with respect to that layer.

$$IG(x_i) = \int_{\alpha=0}^{1} \frac{\partial M(\tilde{x} + \alpha(x_i - x_{baseline}))}{\partial x_i} d\alpha$$

Obtaining importance scores for each Layer:

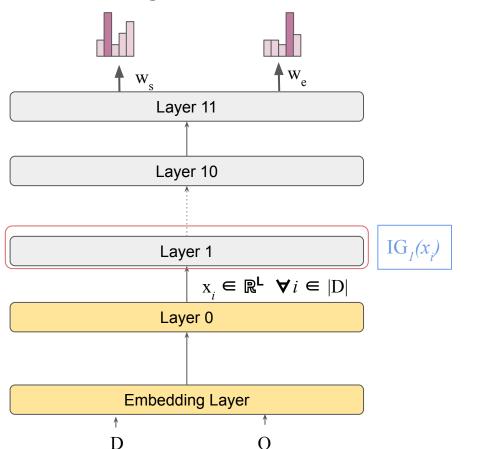


The Integrated Gradient for a passage word w_i , represented as $x_i \in \mathbb{R}^L$ is computed as follows:

A **higher IG scor**e highlights **the importance** of word w_i in the final prediction.

$$IG(x_i) = \int_{\alpha=0}^{1} \frac{\partial M(\tilde{x} + \alpha(x_i - x_{baseline}))}{\partial x_i} d\alpha$$

Obtaining importance scores across Layers:



The Integrated Gradient for a passage word w_i , represented as $x_i \in \mathbb{R}^L$ is computed as follows:

A **higher IG scor**e highlights **the importance** of word w_i in the final prediction.

$$IG(x_i) = \int_{\alpha=0}^{1} \frac{\partial M(\tilde{x} + \alpha(x_i - x_{baseline}))}{\partial x_i} d\alpha$$

Importance Distribution - Qualitative Example

Question: Why was Polonia relegated from the country's top flight in 2013?

Answer: <u>disastrous financial situation</u>

Initial Layers					
Layer 0	Polonia was relegated from the country's top flight in 2013 because of their disastrous financial situation. They are now playing in the 4th league				
Layer 1	Polonia was relegated from the country's top flight in 2013 because of their disastrous financial situation. They are now playing in the 4th league				

	Final Layers					
Layer 10	Polonia was relegated from the country's top flight in 2013 because of their disastrous financial situation. They are now playing in the 4th league					
Layer 11	Polonia was relegated from the country's top flight in 2013 because of their disastrous financial situation. They are now playing in the 4th league					

What makes a layer unique?

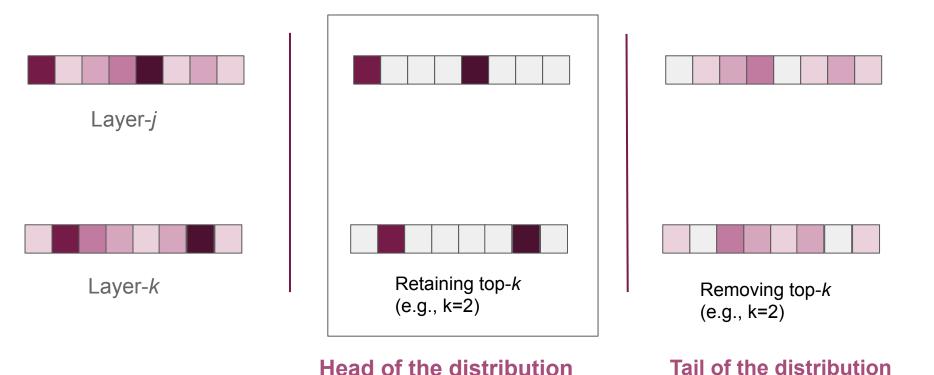
We compare the head and tail of each layer's distribution using **Jensen-Shannon Divergence**, to understand what makes each layer unique.

 0.001	0.01	0.0	0.001	0.003	0.005	 0.61	0.31	
 They	joined	the	Patriots	Dallas	Cowboys	 four	teams	

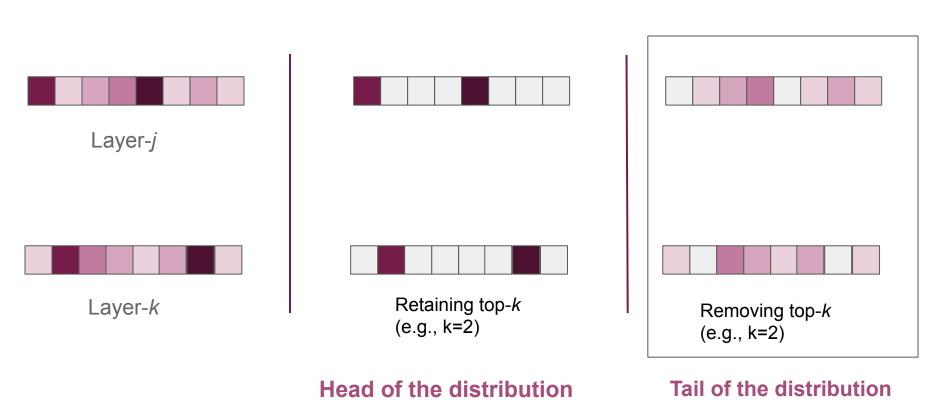
JSD

0.1	0.2	0.0	0.07	0.10	0.15	 0.33	0.33	
They	ioined	the	Patriots	Dallae	Cowhovs	four	toame	

Comparison between distributions of two layers:

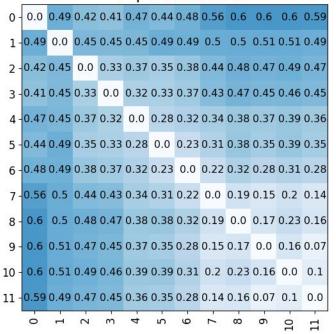


Comparison between distributions of two layers:



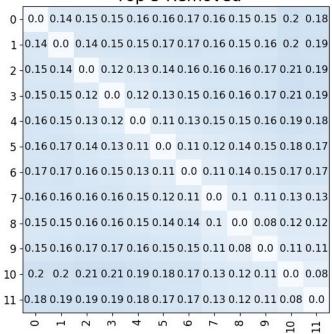
Comparison between distributions across two layers

BERT - SQuAD Integrated Gradients JSD Top 5 Retained



Higher values when top-5 words are retained (min 0.07/max 0.6)

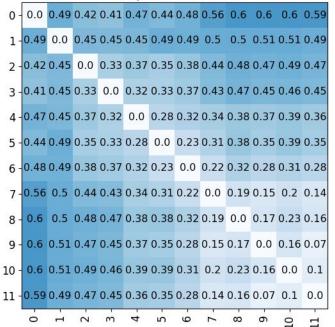
BERT - SQuAD Integrated Gradients JSD Top 5 Removed



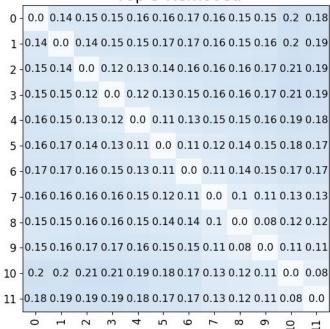
Lower values when top-5 words are removed (min 0.09/max 0.21)

Comparison between distributions across two layers





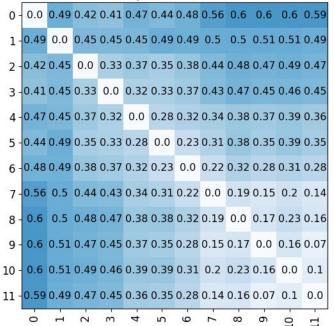
BERT - SQuAD Integrated Gradients JSD
Top 5 Removed



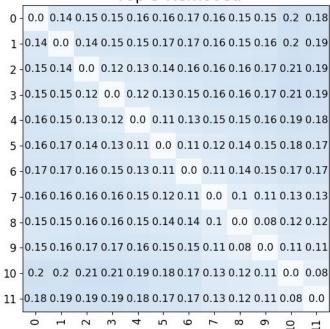
A layer's functionality is reflected by the head (top-k important words).

Comparison between distributions across two layers





BERT - SQuAD Integrated Gradients JSD
Top 5 Removed



Hence, for semantic analysis, we take the **top-5** words highlighted by a layer to **represent** that layer.

Results and Discussions

We analyze the top-5 important words of each layer, to see which of them focus on the question, the context around the answer and the answer span.

Document (D): The Panthers finished the regular season with a 15-1 record ... The Broncos finished the regular season with a 12-4 record.... They joined the Patriots, Dallas Cowboys, and Pittsburgh Steelers as one of <u>four teams</u> that have made eight appearances in the Super Bowl

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Answer Words

Words in the answer span in the passage

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Answer Words

Words in the answer span in the passage

Query Words

Words in the question that appear in the passage (except stopwords)

Document (D): The Panthers finished the regular season with a 15-1 record ... The Broncos finished the regular season with a 12-4 record.... They joined the Patriots, Dallas Cowboys, and Pittsburgh Steelers as one of <u>four teams</u> that have made <u>eight</u> appearances in the <u>Super Bowl</u>.

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Answer Words

Words in the answer span in the passage

Query Words

Words in the question that appear in the passage (except stopwords)

Supporting Words

Words surrounding the answer within a window size of 5

Document (D): The Panthers finished the regular season with a 15-1 record ... The Broncos finished the regular season with a 12-4 record.... They joined the Patriots, Dallas Cowboys, and *Pittsburgh Steelers as one of* four teams *that have made eight appearances* in the Super Bowl.

Layer	% answer span	% Q-words	% Support Words
L0	26.99		
L1	26.09		
L2	29.9		
L3	30.44		
L4	30.06		
L5	30.75		
L6	31.25		
L7	32.37		
L8	30.78		
L9	34.58		
L10	34.31		
L11	34.63		

Observations

 Later layers focus on enhancing and verifying the model's prediction.

Layer	% answer span	% Q-words	% Support Words
LO	26.99	22.94	
L1	26.09	24.35	
L2	29.9	22.41	
L3	30.44	19.55	
L4	30.06	18.33	
L5	30.75	14.71	
L6	31.25	15.33	
L7	32.37	12.29	
L8	30.78	18.91	
L9	34.58	10.21	
L10	34.31	10.56	
L11	34.63	12.0	

Observations

- Later layers focus on enhancing and verifying the model's prediction.
- Initial layers focus on connecting the query and passage.

Layer	% answer span	% Q-words	% Support Words
L0	26.99	22.94	9.45
L1	26.09	24.35	9.43
L2	29.9	22.41	11.65
L3	30.44	19.55	11.13
L4	30.06	18.33	11.23
L5	30.75	14.71	11.57
L6	31.25	15.33	11.94
L7	32.37	12.29	12.32
L8	30.78	18.91	12.07
L9	34.58	10.21	13.41
L10	34.31	10.56	13.39
L11	34.63	12.0	13.74

Observations

- Later layers focus on enhancing and verifying the model's prediction.
- Initial layers focus on connecting the query and passage.
- Contextual role increases from the initial to the final layers.

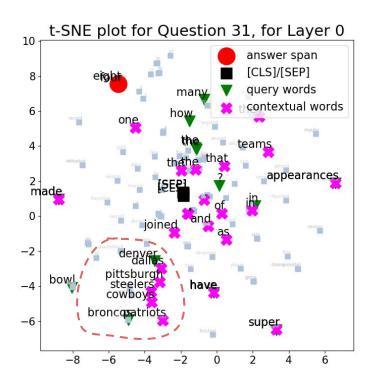
Document (D): The Panthers finished the regular season with a 15-1 record ... The Broncos finished the regular season with a 12-4 record.... They joined the Patriots, Dallas Cowboys, and Pittsburgh Steelers as one of four teams that have made eight appearances in the Super Bowl

Question (Q): How many appearances have the Broncos made in the super bowl?

We perform qualitative analysis of word embeddings using t-SNE plots.

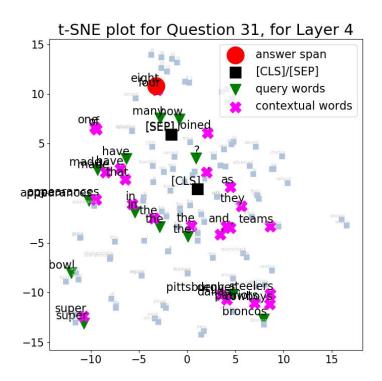
Layer 0:

Similar words (e.g., team names, stop words) are close to each other.



Intermediate Layers: such as Layer 4

All the contextual, answer and question words intermingle.

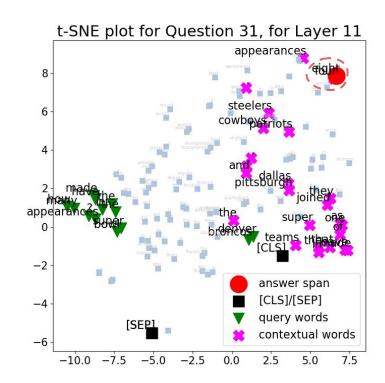


Later Layers: Layer (9-11)

The answer **eight** segregates from other words.

The question words separate from the answer and the supporting words

However, numerical entity **four**, is very close to the answer, across all 12 layers.



Question Type

- How much?
- How many?

Confusing Words

- Many numerical entities in the passage
- Could lead to the model getting confused

Document (D): The Panthers finished the regular season with a <u>15-1</u> record ... The Broncos finished the regular season with a <u>12-4</u> record.... They joined the Patriots, Dallas Cowboys, and Pittsburgh Steelers as one of <u>four</u> teams that have made <u>eight</u> appearances in the Super Bowl.

Question (Q): How many appearances have the Broncos made in the super bowl?

Answer (A): eight

We measure the ratio of confusing words (N_q) marked important by each layer.

ratio =
$$\frac{\text{card}(N_q \text{ in top-5})}{\text{card}(N_q \text{ in passage})}$$

Interestingly, we observe that this ratio <u>increases</u> as we go from layers 0 to 11.

BERT, in its later layers, distributes its importance over potentially confusing words

Layer	SQuAD	DuoRC
Layer 0	5.6%	12.9%
Layer 10	17.7%	21.6%
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However, BERT still predicts the correct answer for such questions with a high confidence of ~85%

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However, BERT still predicts the correct answer for such questions with a high confidence of ~85%

(87.35% accuracy for such questions for SQuAD, and 53.5% in DuoRC)

Open-ended questions

- If the focus on confusing words increases from the initial to later layers, how does BERT still have a high accuracy?
- 2. Why do the question word representations move away from contextual and answer representation in later layers?

We hope that our work will help the research community interpret BERT for other complex tasks and explore the above open-ended questions.

THANK YOU