# Reproducibility Report
# Towards Interpreting BERT for Reading Comprehension QA

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## Reproducibility Summary

In the paper, the authors attempt to understand BERT's near-perfect performance for RCQA tasks by defining each Self-Attention Layer's role using Integrated Gradients for SQuAD v1.1 and DuoRC SelfRC datasets. After this, they follow through with experiments and analysis to infer how each layer works to predict the answer based on the context and question.

### Scope of Reproducibility

Ramnath et al. suggest that the initial layers focus on query-passage interaction, while the later layers focus more on contextual understanding and enhancing answer prediction. In our reproducibility plan, we aim at validating this claim and other related claims, by completely replicating the authors' experiments to analyze BERT layers in order to understand their RCQA-specific role and their behavior on potentially confusing Quantifier Questions.

### Methodology

Since the official code for this paper is not available, we prepare our own scripts and modules for processing the data and re-implement the approach as described in the paper. We refer to the original research paper to cross-check our results with their reporting. For fine-tuning the model and calculating the Integrated Gradients, we use Google Colab's free GPU for 35-40 hours. Rest of the experiments can be performed on a CPU within 10-15 hours.

### Results

Our reproduced results for all experiments support the central claim made in the paper. All of our statistics and plots agree with those in the original paper within a good margin. We have also analyzed some results beyond the paper and find that the scope of the original paper is transferable and generalizable.

### What was easy

Using HuggingFace Transformers and Datasets for the SQuAD v1.1 was easy as we could adapt the author's ideas to our code experiments and verify their central claim without much effort. There are also libraries readily available for Jensen-Shannon Divergence and t-SNE and could be used easily.

### What was difficult

Re-implementing the paper was more difficult than we expected as there were ambiguities and conflicts in our approaches for Integrated Gradients calculation, as well as DuoRC pre-processing and post-processing. There were differences in our methods of implementation and multiple iterations had to be performed to decide upon the case to be used, which took up a lot of computational power unnecessarily.

### Communication with original authors

We had frequent interaction with the first author via email for clarification and discussion.

Submitted to ML Reproducibility Challenge 2020. Do not distribute.

# 1 Introduction

Previous research on interpreting BERT [1] and its derivatives on several Natural Language tasks has focused on issues such as analyzing syntactic and layer-wise semantic roles[2, 3] and understanding BERT's attention heads for syntactic and linguistic phenomena[4]. However, there has been no popular work on understanding BERT for complex tasks like Reading Comprehension based Question Answering (RCQA). Ramnath et al. [5] attempt to interpret BERT for RCQA by defining each layer's role using Integrated Gradients (IG)[6] for SQuAD v1.1 [7] and DuoRC SelfRC [8] datasets. Following this, they perform analysis across all Self-Attention Layers to understand how the model predicts the answers accurately.

As a part of the ML Reproducibility Challenge 2020, we replicate the experiments from scratch and analyze if their observations and claims hold true for our implementation.

# 2 Scope of Reproducibility

An analysis of how BERT predicts answers during RCQA task is challenging due to the lack of pre-defined layer roles and its large number of parameters. The authors address the former by defining the roles of each layer using IG to get word importance scores across individual layers. Then, they use analysis techniques such as Jensen-Shannon Divergence (JSD), t-SNE plots, Part-of-Speech tagging etc. to understand how each layer learns to predict the correct answer. **The central claim of the paper is that the initial layers focus on query-passage interaction, while the later layers focus on contextual understanding and answer prediction**. Following are the claims that can be extracted from the paper and that we validate through our experiments -

1. The top-K important tokens show more divergence across layers than the rest of the tokens. We explore this by analyzing JSD Heatmaps in Section 4.1.2 and 4.2.2.
2. The importance scores of Contextual Words[1] and Answer Words increase from initial to final layers, while the importance scores of Query Words decrease. This is verified in Section 4.1.3 using semantic statistics.
3. The initial layers find Query Words[2] more important, while the final layers focus on the Answer Words. This is verified using visualization in Section 4.1.4.
4. The initial layers represent similar words together. As the layers progress, the Query Words and Answer Words come closer to each other. Eventually, all Query Words are separated from Answer and Contextual Spans[3]. We plot t-SNE representation in Section 4.1.5 to validate this claim.
5. Numerical Words stay close to each other in representation throughout the layers. The t-SNE plot in Section 4.1.5 checks this claim as well.
6. For Quantifier Questions, importance of Numerical Words increases from initial to the final layers, meaning that the confusing words are more important to the model towards the end. Section 4.1.6 discusses the relevant scores and statistics.
7. BERT has higher confidence score on Quantifier Questions with more than one numerical entity in passage vs. Non-Quantifier Questions. Section 4.1.6 discusses the relevant scores.

# 3 Methodology

The authors use the official BERT fine-tuning script for SQuAD[4]. Since there is no official code for the paper yet, we implement the authors' approaches from scratch in PyTorch. We use HuggingFace's (HF) Datasets[9] and Transformers[10] for fine-tuning BERT, and Captum for Integrated Gradients.

## 3.1 Fine-tuning and Integrated Gradients

**Fine-tuning** - We use HF's BertForQuestionAnswering model and load the pre-trained checkpoint - *bert-base-uncased*. The BERT model has 12 layers, 768 hidden units per token, 12 attention heads per layer and 110M parameters. It is pre-trained on lower-case English text.

[1] Contextual Words are words close to the Answer Words within a window.

[2] Query Words are those question words which are present in the passage.

[3] Contextual Spans are those words which appear in the same sentence as the Answer Words.

[4] Official Fine-tuning Script: `https://github.com/google-research/bert/blob/master/run_squad.py`

**Attributions** - We use Captum's implementation of Integrated Gradients. IG is based on the fine-tuned BERT model. **Note that our $(n+1)^{th}$ layer corresponds to the $n^{th}$ layer of the authors' notation as we take the Embedding Layer to be Layer 0. We perform experiments on all Self-Attention Layers and the Embedding Layer**.

## 3.2 Datasets

### 3.2.1 SQuAD v1.1 (SQuAD)

We use the SQuAD v1.1[5] dataset available on HF's Datasets[6] library for its simplicity. The train/dev splits contain 87599/10570 question-answer pairs for various passages, with start position and answer text specifying the answer. Each example breaks into tokenized features[7] using a max-overlap stride of 128, and a max sequence length of 384. We don't use a max query length of 64, unlike the official fine-tuning script. We use HF Transformers's BertTokenizerFast with the pre-trained checkpoint - *bert-base-uncased*. In cases where the ground truth is absent in the context due to splitting, we mark '[CLS]' to be the answer. Our final train/development sets have 88524/10784 features.

### 3.2.2 DuoRC SelfRC (DuoRC)

We use the original DuoRC SelfRC[8] train/dev splits which have 60721/12961 question-answer pairs based on 4800/984 different movie plots. Additionally, a question can have multiple answers - which may or may not exist in the plot. No start positions are provided for the answers. Training BERT on a Question Answering task requires start and end positions of the answer. Hence, we first convert DuoRC dataset to SQuAD format.We find the answers using exact matching in the plot. We consider the following four cases for train and dev sets -

1. **No Answer exists** - We keep the example with an empty answer. There are 627/116 questions in train/dev.
2. **Single Answer** - We include single answers found in the plot using first matching index.
3. **Multiple Answers** - We take the first answer found and store first index in the train set. In dev set, we store all the answers and corresponding first indices.
4. **Answer exists, but not found in plot** - We drop such examples in train, but keep them with empty answers in dev. There are 26596/5768 such examples.

The exact details for processing DuoRC are not provided in the paper, but we assume that this process is similar to choosing a sample for fine-tuning and prediction. The authors' claims should hold true, irrespective of the sample chosen. After this first step of pre-processing, we get 34166/12961 examples in the train/dev sets, which are then processed similarly as SQuAD to get 118676/44831 tokenized features.

## 3.3 Hyperparameters

### 3.3.1 Fine-tuning

We use hyperparameters similar to the original BERT script while fine-tuning our model. The train/eval batch sizes are 6/8. Optimizer AdamW is used with a learning rate of $3 \times 10^{-5}$, a weight decay of 0.01 and an epsilon of $1 \times 10^{-6}$. The training is done for 2 epochs. A polynomial learning rate scheduler with 10% of total training steps as warmup steps is used. The other default hyperparameters in HF Transformer's TrainingArguments are not changed.

### 3.3.2 Integrated Gradients

Although calculation of attributions using IG is performed after training, the choices made can significantly affect the importance distributions based on these attributions. Hence, we provide a brief description of the same.

We calculate attributions on the softmax outputs of start and end logits from the BERT model. The targets positions chosen are those where start and end logits have the maximum value. Only those features which give the best answer for an example during the predictions are chosen, based on our discussion with the authors. Reimann Right numerical approximation is used for calculating the integral value. The number of steps chosen is 25, and an internal batch size of 4 is used. We perform IG on only 1000 examples from the dev sets due to computational restrictions.

[5] SQuAD v1.1 dataset : https://github.com/rajpurkar/SQuAD-explorer/tree/master/dataset

[6] HuggingFace's SQuAD dataset: https://huggingface.co/datasets/squad#dataset-description

[7] We use "features" to denote multiple question-context pairs per example due to the max sequence length.

[8] DuoRC SelfRC dataset: https://github.com/duorc/duorc/tree/master/dataset.

### 3.4 Experimental Setup and Code

#### 3.4.1 Fine-tuning BERT

We fine-tune BERT using HF Transformer's Trainer with the hyperparameters mentioned in Section 3.3.1. We use the tokenized features for training and validation. Post-training, the predictions for each feature are processed. We choose the best valid feature per example based on the best score (start logit + end logit) for top 20 start and top 20 end logits. We discard spans greater than length 30. We store the respective input token IDs, attention masks, predicted text, ground start/end positions, predicted start/end positions for the best feature for all examples in a JSON file. We use SQuAD v1.1[9] and SQuAD v2[10] evaluation scripts for SQuAD and DuoRC, respectively. This is done as DuoRC predictions/ground truth may contain no answers. We consider exact match (EM) and $F_1$ scores from these evaluations.

#### 3.4.2 Integrated Gradients

Taking the predictions from our JSON file to load the best features, we use respective input token IDs, attention masks to calculate IG. This eliminates the possibility of using multiple features per example, improving our sample distribution.

We calculate start and end attributions using Captum's IntegratedGradients on 1000 randomly chosen examples. For the same, we create a method to find the start and end logits given the layer index and the corresponding hidden states. We add the start and end attributions and take Euclidean norm for each token in the sequence, which is then normalized to get a probability/importance distribution for that sequence. This is repeated for all 13 layers. The token-wise importance scores are stored for each layer and sample. Note that this process is similar to the algorithm described in the paper, except that they do not calculate attributions on Embedding Layer outputs.

We change the token-wise distributions to word-wise distributions by ignoring the special tokens - *[CLS]*, *[SEP]*, *[PAD]* - and adding importance scores for multiple tokens per word. The concatenation of the tokens and the addition of importance scores is done by using the fact that subsequent tokens for a word start with ##. The offset mapping for each token is used to get the exact word in the passage/question. The combined scores are re-normalized to get an importance distribution for the words. Along with this, the word-wise categories - answer, question, context - are stored for each sample based on the predicted answer spans.

#### 3.4.3 Jensen-Shannon Divergence

For JSD heatmaps, we use pair-wise JSD of all 13 layers (Embedding Layer + Self-Attention Layers). This gives us a $13 \times 13$ heatmap for each example, which is then averaged over the 1000 examples we chose during IG calculation. This helps us understand how the layer outputs are different from each other in terms of their attributions. We use the same *dit*[11] library as the authors to calculate JSD. Index 0 in our heatmaps represents the Embedding Layer.

The authors create two heatmaps for each of the datasets - one with top-K token importance scores retained and the rest zeroed out, and the other with top-K token importance scores zeroed out. They chose K=2 for their experiments. We create similar heatmaps based on the token-wise importance scores generated in Section 3.4.2 using Seaborn[12] and vary the K values in - 2,5,10.

#### 3.4.4 QA and POS Functionality Tables

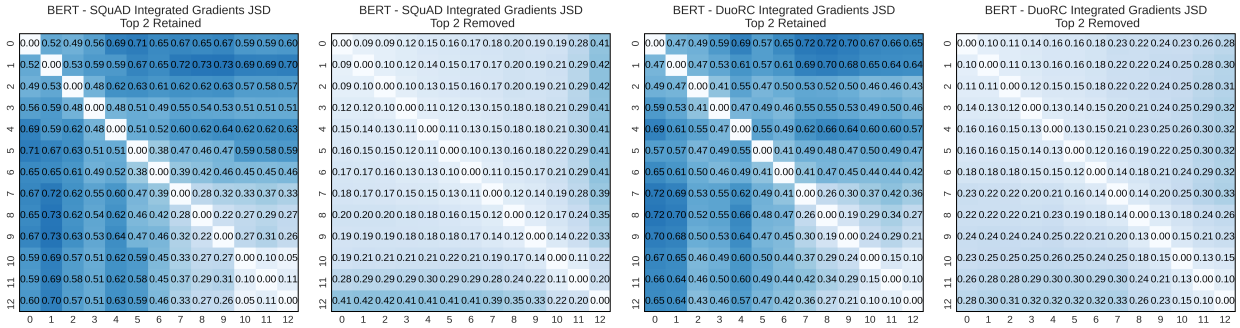
We calculate the percentage of predicted Answer Words, Query Words, and Contextual Words (within window size=5 of the Answer Spans) in the top-5 words for the 1000 examples we chose for IG. We represent show the average values in Tables 1 and 2. The Query Words are selected using lower-case exact matching in the passage. Only words in the passage are considered. Similarly, based on the paper's Appendix, we also calculate Part-of-Speech ratios in top-5 words using NLTK's Part-of-Speech Tagger.

#### 3.4.5 t-SNE Representation

We plot t-SNE representations for tokens across multiple layers based on the Query Tokens, the Answer Tokens, and the Contextual Spans. The predicted Answer Tokens are used, and all the tokens from the sentence containing the Answer Tokens (between two periods (.)) are chosen as the Supporting/Contextual Spans. *[PAD]* tokens are dropped, and only the context tokens are considered for plotting. The categories finally used are - query words, answer spans, contextual words, [CLS]/[SEP] and background. We use sklearn's t-SNE[13] with PCA initialization and 1000 iterations to represent the hidden states in 2 dimensions and plot them using Matplotlib[14].

[9] Link to the HuggingFace metrics - SQuAD v1.1https://huggingface.co/metrics/squad

[10] Link to the HuggingFace metrics - SQuAD v2https://huggingface.co/metrics/squad_v2




(a) (b) (c) (d)

Figure 1: Jensen-Shannon Divergence Heatmaps for K=2

#### 3.4.6 Quantifier Questions

We search Quantifier Questions using 'how man' and 'how much'. We use 'man' instead of 'many' because of typographical error in some questions. There are 799 such examples in SQuAD and 310 in DuoRC dev-splits. We use IG on our predicted features for these examples to get the importance distributions. Then, using the word-wise importance scores, we find out the percentage of numerical words which are tagged as "Cardinal"(CD) by NLTK's Part-of-Speech Tagger[15]. Additionally, we also include phrases like "thousands", "hundreds" and "two thousand and three" using the word2number library. We calculate the percentages of Numerical Words in top-5 words out of Total Numerical Words in the passage and average the values. For EM calculations on Quantifier Question, we use the respective evaluation scripts. For calculation of the confidence, we take the maximum of sum of softmax start and end scores. Then, we average these values across the samples to get the average confidence per category.

### 3.5 Computational Requirements

We use the free NVIDIA K80/T4 GPU provided by Google Colab for training the BERT model and calculating Integrated Gradients. All other experiments are performed on an Intel i5-6200U quad-core CPU. For each dataset - fine-tuning the BERT model takes ~5-7 hours on the GPU; prediction takes ~10-20 GPU minutes; and processing of predictions takes ~4-5 CPU hours; Integrated Gradients step takes ~5-6 GPU hours per 1000 examples; JSD Heatmap generation takes ~2-3 CPU hours for 1000 examples; while the tables are generated in negligible CPU time. For Integrated Gradients on Quantifier Question on dev splits, SQuAD takes ~4 GPU hours, and DuoRC takes ~1.5 GPU hours. The calculation of confidence on Quantifier/Non-Quantifier Questions takes ~10-20 GPU minutes per dataset.

## 4 Results

### 4.1 Results reproducing original paper

#### 4.1.1 Fine-tuning

The authors achieved $F_1$ scores of 88.73 and 54.80 on SQuAD and DuoRC dev-splits. Our fine-tuned BERT model achieves 88.51 and 50.73 on our tokenized dev-splits of SQuAD and DuoRC. ( 3.2).

#### 4.1.2 Jensen-Shannon Divergence Heatmaps

We plot heatmaps for the JSD values, with top-2 scores in the token-wise distribution retained and removed for both SQuAD and DuoRC (Figure 1). We see a similar pattern on the heatmap as the paper - the top-2 retained JSD heatmaps have a higher range for both SQuAD(0.05-0.73), and DuoRC(0.10-0.70) across the Self-Attention layers. The top-2 removed JSD heatmaps have lower ranges for SQuAD (0.10-0.42) and DuoRC (0.10-0.32). The ranges are slightly different from the paper which can be attributed to sampling. Regardless, the ranges imply that the top-2 words which the layers focus on are more *different* than the rest of the words across the layers. Claim 1 is justified and verified by our experiments. We repeat this experiment for other values of K - 5, 10 and analyze it in Section 4.2.2.

| Layer Name | Answer Words% | Contextual Words% | Q-Words% |
|---|---|---|---|
| Embedding | 38.10 | 32.96 | 22.46 |
| Layer 1 | 37.58 | 33.04 | 22.20 |
| Layer 2 | 37.10 | 33.58 | 24.08 |
| Layer 3 | 41.00 | 33.10 | 19.62 |
| Layer 4 | 40.42 | 36.40 | 16.34 |
| Layer 5 | 40.82 | 34.68 | 18.58 |
| Layer 6 | 40.74 | 36.46 | 15.62 |
| Layer 7 | 40.06 | 35.76 | 14.12 |
| Layer 8 | 41.90 | 34.94 | 11.38 |
| Layer 9 | 41.18 | 36.12 | 11.66 |
| Layer 10 | 43.36 | 35.40 | 9.74 |
| Layer 11 | 42.52 | 32.14 | 10.30 |
| Layer 12 | 42.94 | 34.02 | 10.42 |

Table 1: Semantic statistics of top-5 words - SQuAD

| Layer Name | Answer Words% | Contextual Words% | Q-Words% |
|---|---|---|---|
| Embedding | 11.78 | 9.36 | 24.00 |
| Layer 1 | 11.70 | 12.00 | 19.20 |
| Layer 2 | 12.60 | 11.84 | 17.54 |
| Layer 3 | 13.36 | 11.96 | 16.18 |
| Layer 4 | 13.16 | 12.64 | 20.30 |
| Layer 5 | 12.68 | 11.24 | 22.02 |
| Layer 6 | 12.96 | 11.72 | 15.72 |
| Layer 7 | 12.68 | 11.90 | 12.86 |
| Layer 8 | 13.36 | 12.22 | 8.24 |
| Layer 9 | 12.66 | 12.78 | 5.50 |
| Layer 10 | 12.90 | 11.12 | 6.74 |
| Layer 11 | 13.06 | 11.86 | 7.52 |
| Layer 12 | 12.94 | 11.78 | 8.68 |

Table 2: Semantic statistics of top-5 words - DuoRC

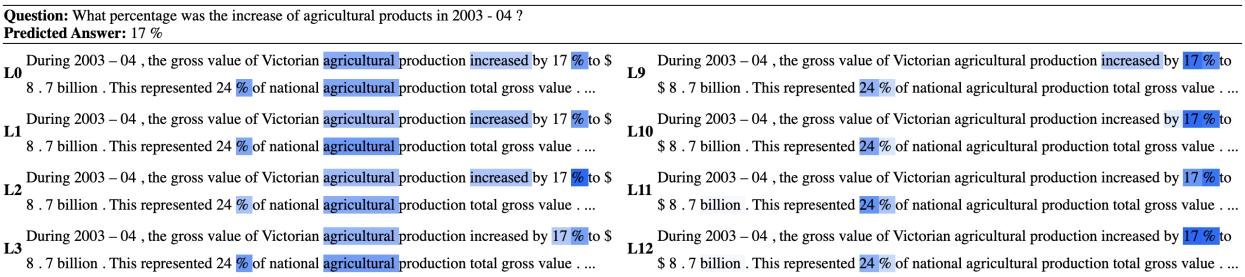



Figure 2: Qualitative Visualization of top-5 words - SQuAD

#### 4.1.3 QA Functionality

We calculate the semantic statistics of the top-5 words for SQuAD and DuoRC as described in Section 3.4.4. Table 1 for 1000 examples of SQuAD follows this trend for Answer Words (37.58%(L1) - 42.94%(L12)), Contextual Words (33.04%(L1) - 34.02%(L12)), as well as Query Words (22.20%(L1) - 10.42%(L12)). The numbers, however, are slightly different from the paper. The reasons behind this could be smaller sampling size and differences in the way of counting Query and Contextual Words. For DuoRC, Table 2 shows the average statistics for the 1000 examples. While the Answer Words (11.70%(L1) - 12.94%(L12)) and Query Words(19.20%(L1) - 8.68%(L12)) follow the expected trend, the percentage of Contextual Words remains between 11-12% for the BERT Self-Attention Layers. In the paper, Contextual Words do not follow an increasing trend for DuoRC and vary between 15-33%. For DuoRC, our percentage of Answer Words is low (11-13%) compared to the paper (33-44%). In addition to the factors stated for SQuAD, DuoRC results can also deviate because of possible differences in how predictions are processed. Since our results broadly align with the paper, Claim 2 holds true.

#### 4.1.4 Visualization

Claim 3 says that the focus is more on query-passage interaction in the initial layers, while in the final layers more importance is given to the answer and contextual spans. From the visualized example in Figure 2, we can see that the Query Words - (*percentage/%*, *increase/increased*, *agriculture*) - are given more importance in Embedding Layer(L0), Layers 1, 2, and 3. While the Answer Words - *17* - and Contextual Words - *%* - receive more importance in the later layers. This agrees with the example shown in the original paper, and validates Claim 3.

#### 4.1.5 t-SNE Representation

We plot t-SNE representations in Figure 3 which verify that Claims 4 and 5 hold true. We observe that in the initial layers similar words like *california, francisco, santa, clara* are close to each other. In the later layers, the Answer Words and Query Words separate out. The Layer 12 plot shows that the model has successfully recognised and separated Answer and Query Words. Additionally, BERT representations of confusing words are closer to each other in the later layers. On careful observation, we see that Numerical Words like *50*, *2015* and *50th* are close to the representation of the Answer Word *2016*. This is similar to what has been observed by the authors.

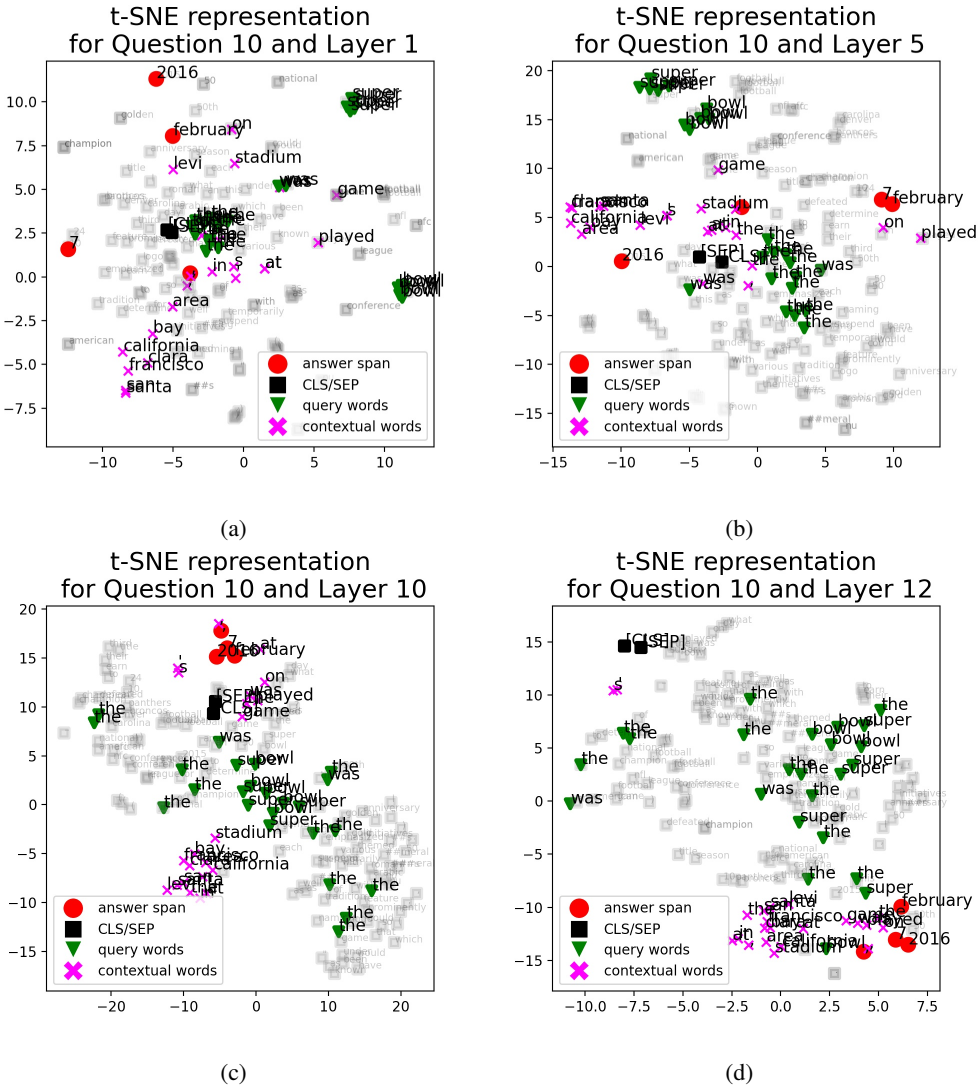



Figure 3: t-SNE Plots for Layers 1, 5, 10, 12 on a SQuAD Example

#### 4.1.6 Quantifier Questions

For Quantifier Questions, there are two claims - 6 and 7. For the first claim, we perform experiments mentioned in Section 3.4.6 to find out the percentages of Numerical Words in top-5 words out of all Numerical Words in the passage. We observe that this ratio increases as we go higher up (SQuAD - L1-6.83%, L11-9.44%, L12-9.93%; DuoRC - L1-36.21%, L11-51.98%, L12-53.04%). The ranges of numbers are different from the original paper, but the suggested trend is followed. A reason for this difference can be that our counting of Numerical Words could be slightly different from the authors. The author mentioned that they only used cardinal (CD) Parts-of-Speech during our discussion. But, a lot of Quantifier Questions do not have cardinal (CD) words in them.

The confidence scores for Non-Quantifier Questions (SQuAD - 79.04% ; DuoRC - 86.33%), are significantly lower than for Quantifier Questions with more than one Numerical Word (SQuAD - 85.24% ; DuoRC - 91.20%). Our EM scores on Quantifier Questions are 86.73% for SQuAD , and 54.65% for DuoRC. Our results thus validate Claims 6, 7.

### 4.2 Results beyond the paper

#### 4.2.1 An alternative way of using Integrated Gradients

Before a thorough discussion with the authors, we performed Integrated Gradients in a different manner - we used the ground truth positions as targets for attribution calculation, and the logit outputs (instead of softmax outputs). Note

that this would make all the Layer 12 output attributions zero except for two tokens (which have the ground truth start and end positions). When using softmax outputs, the token hidden states affect each other in Layer 12 because of the the normalization term used in softmax, and hence all tokens get some attributions. The categories for the words were also chosen based on the ground truth answers. Multiple features could be sampled from a single answer as the best features per example were not used. Surprisingly, the results observed were similar to the paper and can be referred to in Appendix B. This means that the claims 1 and 2 hold true for SQuAD for both the ways that we calculate IG.

#### 4.2.2 JSD Heatmaps for multiple K values

We plot JSD heatmaps for different values of K (Appendix C). We see that as we increase K, the range of the values on the heatmaps reduce. This means that layers tend to focus on similar words after the first few values of K. For K=5, our top-5 retained heatmap has a range of 0.06-0.60 for SQuAD, and 0.06-0.59 for DuoRC. When K is increased to 10, the top-10 retained heatmap has a range of 0.06-0.56 for SQuAD, and 0.07-0.57 for DuoRC. We expect these ranges to reduce further as we increase the value of K as the words/tokens will get progressively more similar. Thus, limiting K to 5 seems like a good decision on behalf of the authors.

## 5 Discussion

Due to lack of computational resources and time constraints, we were unable to perform IG on all dev samples, and thus chose 1000 random samples per dataset. This can affect the results and statistics significantly. Additionally, the results for DuoRC do not match very well with the authors due to several factors which have been mentioned throughout the report. At the same time, we also show that the authors' claims hold true even for a fraction of the dev set for most cases, which strengthens their claims. Through our code, we also provide a system where researchers can extend this analysis to other datasets by just defining a dataset class similar to ours, specifically a method which converts the dataset into SQuAD format. We also experimented with an alternative way of performing Integrated Gradients described in Section 4.2.1. The results based on the same align with those of the authors and further strengthen their claim.

### 5.1 What was easy

The authors describe the IG algorithm in their paper, and also provide the link to the code they used to fine-tune BERT. This helped us to prepare the fine-tuning code easily, and find the correct hyperparameters accordingly. Using HuggingFace Datasets and Transformers reduced our workload significantly. Also, many popular articles and tutorials exist for fine-tuning BERT on SQuAD for both frameworks PyTorch and TensorFlow, which can be referred to for any help required with implementation. The calculation of JSD across the layers was very simple and pair-wise JSD can be calculated using dit[11] in just three lines of code. The plotting of heatmaps, qualitative visualization, and t-SNE scatter plots was also easy because of very-well documented libraries - Seaborn and Matplotlib.

### 5.2 What was difficult

Since the authors do not provide the original code at this time of writing, the conversion from DuoRC to SQuAD format was difficult. DuoRC contains examples which have no answers and multiple answers which may or may not exist in the original span. SQuAD, on the other hand has single answers in the training set with a start index provided. This part took us a lot of time and used up a lot of computational resources unnecessarily. IG has also not been described in the paper in great detail, despite the mention of the algorithm. We had a lot of queries while implementing IG. One can use ground truth, max softmax logits, or the predicted positions for target positions. Similarly, the output considered can be the logits or softmax output of the logits which would change the attribution values significantly. This was only clarified through back-and-forth communication with the authors. Finally, the exact details of how the numerical words are counted, what is done when a word is both contextual and a query words are also not mentioned in the paper, and we had to make our own choices after discussing with the authors.

### 5.3 Communication with original authors

We communicated with the author - Sahana Ramnath - very frequently for over two weeks. We list all the significant questions we asked on our GitHub repository.

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# Appendix A

## Part-of-Speech Functionality

Our Part-of-Speech Tables - Table 3 for SQuAD and Table 4 for DuoRC are shown. We observe that all layers are majorly focused on entity based words with Nouns being 50%-60% of the top-5 words in SQuAD and 60%-70% in DuoRC. However, in comparison with the authors, we observe slightly higher importance to stop words and slightly lower importance to adjectives in the top-5 words. The importance on punctuation marks is also higher.

| Layer Name | % nouns | % verbs | % stop words | % adverbs | % adjectives | % punct marks | % words in answer span |
|---|---|---|---|---|---|---|---|
| Embedding | 58.88 | 8.96 | 12.02 | 2.12 | 6.78 | 7.34 | 38.10 |
| Layer 1 | 55.94 | 8.28 | 12.54 | 1.96 | 7.18 | 9.98 | 37.58 |
| Layer 2 | 57.10 | 10.12 | 13.08 | 2.44 | 6.78 | 7.20 | 37.10 |
| Layer 3 | 55.58 | 9.18 | 14.40 | 2.42 | 6.74 | 7.48 | 41.00 |
| Layer 4 | 51.22 | 8.66 | 17.54 | 2.00 | 6.14 | 10.52 | 40.42 |
| Layer 5 | 51.60 | 8.58 | 19.36 | 2.30 | 7.00 | 6.56 | 40.82 |
| Layer 6 | 48.04 | 8.90 | 20.30 | 2.18 | 6.26 | 9.70 | 40.74 |
| Layer 7 | 48.80 | 8.18 | 18.26 | 1.84 | 5.90 | 11.98 | 40.06 |
| Layer 8 | 52.72 | 7.74 | 18.02 | 2.00 | 6.06 | 7.78 | 41.90 |
| Layer 9 | 50.42 | 6.24 | 17.44 | 1.96 | 5.98 | 11.74 | 41.18 |
| Layer 10 | 53.00 | 5.98 | 18.20 | 1.88 | 5.90 | 10.08 | 43.36 |
| Layer 11 | 57.90 | 3.78 | 15.06 | 1.76 | 6.30 | 8.26 | 42.52 |
| Layer 12 | 54.86 | 3.68 | 15.14 | 1.74 | 5.90 | 12.12 | 42.94 |

Table 3: Part-of-Speech statistics of top-5 words - SQuAD

| Layer Name | % nouns | % verbs | % stop words | % adverbs | % adjectives | % punct marks | % words in answer span |
|---|---|---|---|---|---|---|---|
| Embedding | 72.72 | 7.40 | 8.26 | 1.36 | 4.02 | 6.28 | 11.78 |
| Layer 1 | 66.56 | 7.48 | 11.62 | 1.32 | 3.68 | 9.54 | 11.70 |
| Layer 2 | 67.16 | 6.64 | 9.12 | 1.34 | 3.68 | 11.58 | 12.60 |
| Layer 3 | 67.20 | 6.92 | 11.70 | 1.46 | 3.98 | 8.86 | 13.36 |
| Layer 4 | 68.38 | 7.04 | 13.34 | 1.34 | 3.56 | 6.74 | 13.16 |
| Layer 5 | 67.52 | 7.16 | 14.08 | 1.44 | 3.72 | 6.36 | 12.68 |
| Layer 6 | 62.64 | 8.28 | 15.48 | 1.08 | 3.26 | 10.40 | 12.96 |
| Layer 7 | 61.24 | 6.30 | 14.26 | 1.12 | 2.86 | 15.02 | 12.68 |
| Layer 8 | 69.86 | 4.14 | 10.78 | 1.24 | 3.56 | 9.58 | 13.36 |
| Layer 9 | 74.72 | 2.34 | 6.40 | 1.18 | 2.72 | 11.60 | 12.66 |
| Layer 10 | 69.66 | 2.58 | 8.04 | 1.18 | 3.26 | 14.88 | 12.90 |
| Layer 11 | 66.38 | 2.38 | 10.10 | 1.24 | 3.66 | 15.74 | 13.06 |
| Layer 12 | 72.08 | 2.80 | 11.10 | 1.36 | 3.86 | 8.36 | 12.94 |

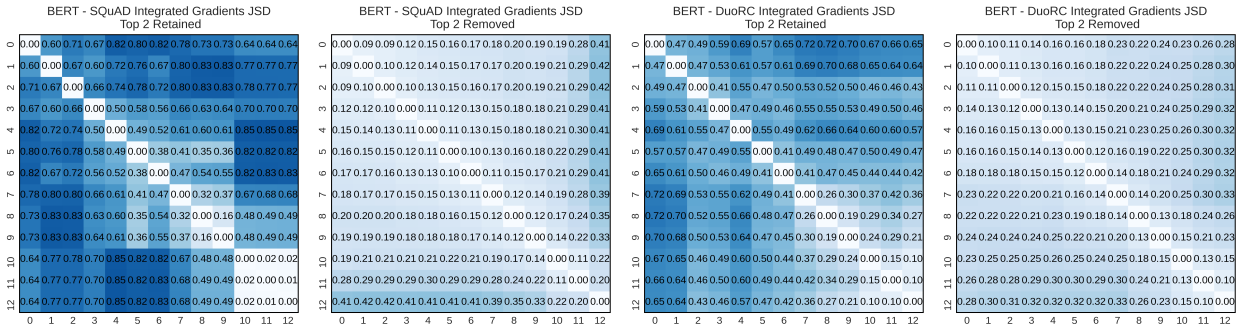
Table 4: Part-of-Speech statistics of top-5 words - DuoRC

# Appendix B

## Old Integrated Gradients Results

This appendix reports the results we observed for Section 4.2.1 -

1. **JSD Heatmaps** - A range of 0.02-0.85 for SQuAD and 0.03-0.91 for DuoRC in the case where top-2 scores were retained. For the case where top-2 scores were removed, the ranges were 0.04-0.23 and 0.04-0.24 for SQuAD and DuoRC.




(a) (b) (c) (d)

Figure 4: Old Jensen-Shannon Divergence Heatmaps for K=2

2. **QA Functionality** - For SQuAD, we observed similar trends in the percentages of Answer Words(L1-30.50%, L11 - 38.18%, L12 - 27.84%). The Query Words (24.58%(L1) - 4.62%(L12)) and Contextual Words (32.66%(L1) - 34.24%(L12)) also followed the trends. For DuoRC, however, only the query words (18.66% (L1) - 3.70% (L12) followed a decreasing trend. Contextual (7.36%(L1) - 6.66%(L12))and Answer Words (4.38%(L1) - 3.26%(L12)) in DuoRC remain more or less constant across the layers. Refer Tables 5 and 6.

| Layer Name | Answer Words% | Contextual Words% | Q-Words% |
|---|---|---|---|
| Embedding | 32.06 | 33.10 | 25.50 |
| Layer 1 | 30.50 | 32.66 | 24.58 |
| Layer 2 | 31.84 | 32.72 | 26.40 |
| Layer 3 | 34.18 | 34.06 | 23.64 |
| Layer 4 | 33.98 | 36.24 | 20.66 |
| Layer 5 | 33.68 | 36.00 | 22.70 |
| Layer 6 | 32.08 | 39.50 | 18.50 |
| Layer 7 | 31.70 | 41.68 | 15.54 |
| Layer 8 | 35.00 | 40.80 | 13.68 |
| Layer 9 | 35.20 | 42.06 | 10.12 |
| Layer 10 | 37.72 | 40.76 | 9.10 |
| Layer 11 | 38.18 | 37.54 | 9.14 |
| Layer 12 | 27.84 | 34.24 | 4.62 |

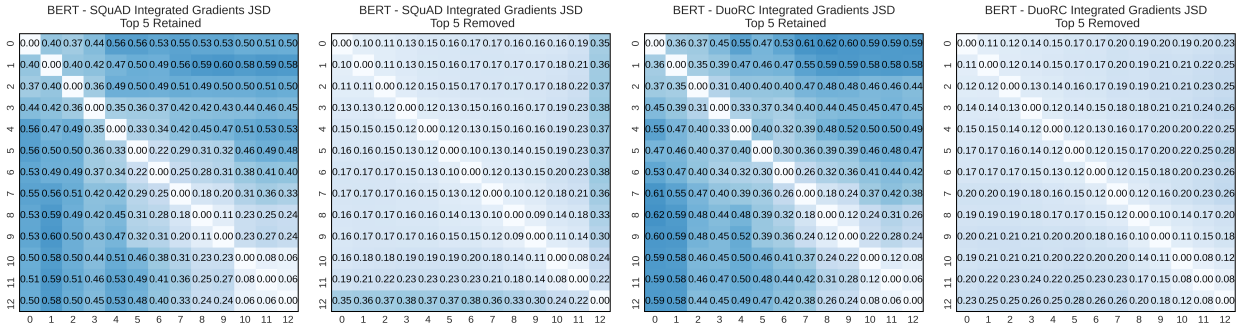
Table 5: Old Semantic statistics of top-5 words - SQuAD

| Layer Name | Answer Words% | Contextual Words% | Q-Words% |
|---|---|---|---|
| Embedding | 4.40 | 6.88 | 20.72 |
| Layer 1 | 4.38 | 7.36 | 18.66 |
| Layer 2 | 4.50 | 7.16 | 18.00 |
| Layer 3 | 4.70 | 7.62 | 19.36 |
| Layer 4 | 4.54 | 7.52 | 23.10 |
| Layer 5 | 4.58 | 7.22 | 20.08 |
| Layer 6 | 4.44 | 7.48 | 16.12 |
| Layer 7 | 4.34 | 7.02 | 12.80 |
| Layer 8 | 4.88 | 7.50 | 10.58 |
| Layer 9 | 4.50 | 7.00 | 5.80 |
| Layer 10 | 4.32 | 6.70 | 4.48 |
| Layer 11 | 4.40 | 6.80 | 4.06 |
| Layer 12 | 3.26 | 6.66 | 3.70 |

Table 6: Old Semantic statistics of top-5 words - DuoRC

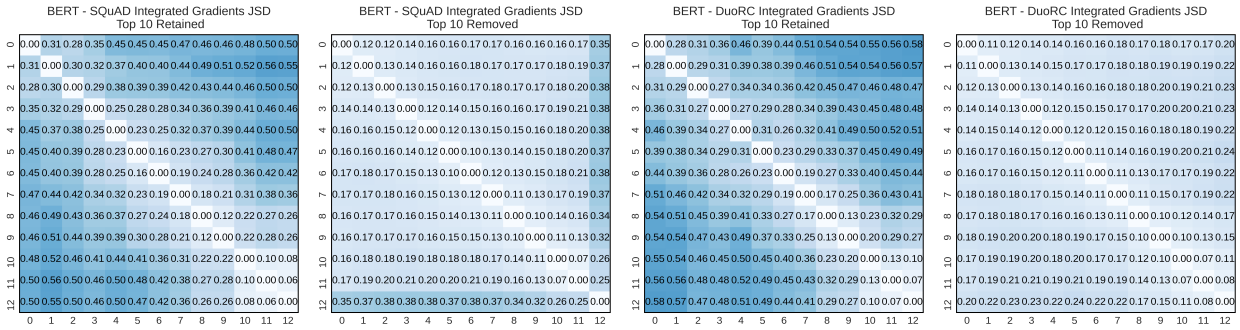
# Appendix C

## JSD Heatmaps with K=5,10




(a) (b) (c) (d)

Figure 5: Jensen-Shannon Divergence Heatmaps for K=5




(a) (b) (c) (d)

Figure 6: Jensen-Shannon Divergence Heatmaps for K=10

# Appendix D

## Qualitative Visualization for DuoRC

We visualize an interesting example for DuoRC in Figure 7. DuoRC examples contains long passages, which are broken into several features when we use a maximum length of 384 tokens. Also, since we allow examples to have no answers, we store the first feature (since there is no best feature) in the predictions in case of no answers. In Figure 7, although the original example had no predicted answer, the BERT model is still giving importance to the actual answer *"Chi-Chi"* for the question provided. This means that there was another feature which predicted *"no answer"* with a higher score than this feature which predicted *"Chi-Chi"*. However, there is a good chance that the other feature didn't have access to this portion of the context tokens and thus predicted *"no answer"*. This implies that we need to re-think the way we post-process the predicted answers for each example, as some features might predict correct answers despite having a lower overall score. We will explore this further in the future.

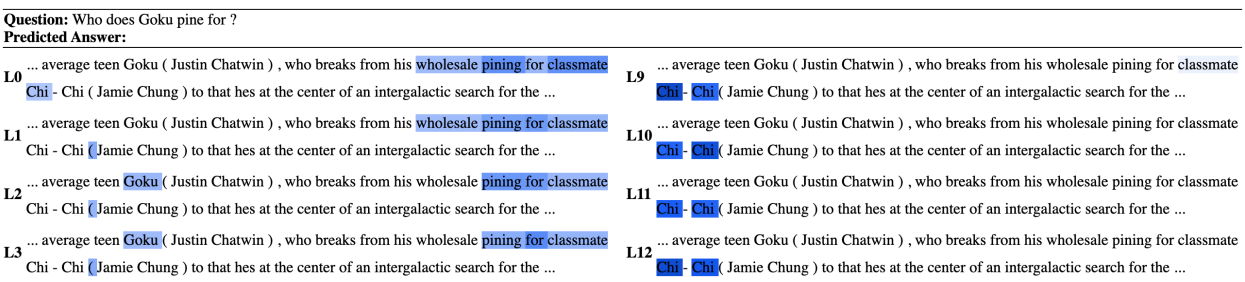



Figure 7: Qualitative Visualization of top-5 words - DuoRC