Sentence-Based Model Agnostic NLP Interpretability

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Abstract

Today, interpretability of Black-Box Natural Language Processing (NLP) models based on surrogates, like LIME or SHAP, uses word-based sampling to build the explanations. In this paper we explore the use of sentences to tackle NLP interpretability. While this choice may seem straightforward, we show that, when using complex classifiers like BERT, the word-based approach raises issues not only of computational complexity, but also of an out of distribution sampling, eventually leading to non founded explanations. By using sentences, the altered text remains in-distribution and the dimensionality of the problem is reduced for better fidelity to the black-box at comparable computational complexity.

1 Introduction

With the introduction of the transformer architecture (Vaswani et al., 2017) and its variants in recent years, we have seen a rise of complex NLP models, capable of solving more and more difficult tasks, in some cases even with superhuman capabilities (Nangia and Bowman, 2019).

The growth in complexity of the NLP models gives rise to the question of interpretability. Even if some argue that neural network architectures can be interpreted by white box approaches, which have access to model internals like gradients and activations (Arras et al., 2016; Dimopoulos et al., 1995), in practice, NLP pipelines between the input and the output of the overall model are often complex including various preprocessing methods. The final model is therefore a combination of programmatic rules and a learned classifier. In this case, a model agnostic approach which does not need access to model internals nor specific developments or continuous gradient flow is often more suitable to draw interpretable insights.

Models like LIME (Ribeiro et al., 2016) and SHAP (Lundberg and Lee, 2017) are examples of black-box interpreters which can be applied to texts. They create an interpretation for a text sample, called local interpretation. To this end, a dataset of similar texts is sampled by repeatedly removing words from the original text and observing the change in output, called the neighborhood. The local behaviour of the model is then approximated using a weighted regression on the presence of words.

In this work, we explore the limits of this approach of using words when it comes to complex language models like BERT (Devlin et al., 2019). Our main contributions are the identification of the segmentation step as a crucial, often overlooked stage in black-box NLP interpretability. In addition to displaying the problems arising from this negligence, we show that our interpreter using sentences as elementary units does not face the same problems. Finally, we achieve substantially higher performance in the benchmark problem used for assessing fidelity to the underlying classifier.

2 The Case Against Word-Based Black-Box Interpretability

While the approach of removing words is suitable for Bag-Of-Words (BOW) models without n-grams, the use of models like BERT (Devlin et al., 2019), which try to model word interactions using the attention mechanism, raises the question of knowing if this is the appropriate sampling mechanism for BERT-like models: Removing random words from a text can sometimes make it unreadable for humans, since key interactions, like verb-subject, are broken. Is this also observed with BERT? What are other consequences of word-based sampling? We compare the commonly used word based sampling to sentence-based sampling, which we argue is a
more natural choice for interpretability, since sentences represent syntactically closed units and can greatly reduce the number of samples needed for explanation.

2.1 Distributional Shift

Detecting if a language model is confused by an input text is difficult. We can however compare the distributions of the text embedding for normal text and for altered text from the neighborhood generated by model-agnostic interpretability approaches. A different distribution signifies that the altered texts are not normal, but also raises questions on the accuracy of the language models on those texts: For neural networks, it is well studied that the Out-Of-Distribution (OOD, different distribution than training distribution) performance can be significantly worse than In-Distribution (ID, same distribution as training data) performance (Nguyen et al., 2015; Amodei et al., 2016; Hendrycks and Gimpel, 2016; Liang et al., 2017; Moosavi-Dezfooli et al., 2017), with sometimes dramatic errors known as adversarial attacks. In order for the explanation, which is based on the altered texts, to be truthful, classifier accuracy must be maintained for those samples. This can only be guaranteed if remain ID after alteration, which we will show is not the case with word-based sampling.

Inspired by Lee et al. (2018) where hidden activations were used to detect OOD samples for images, we designed the two following experiments. For both of them, we use the last embedding of the classification token as text embedding.

2.1.1 Visualizing Distributional Shift with t-SNE

In the first experiment, we compare the distribution of the embeddings of the original text, after removing a random sentence and after randomly removing the same number of words. We compute the embeddings for 10,000 randomly selected Wikipedia snippets from the SQuAD dataset (Rajpurkar et al., 2016) using BERT (Devlin et al., 2019). The distributions of the embeddings (original text, sentence removed, words removed) are compared using t-SNE visualisation. Further, we report the 1-Wasserstein distance ($W_1$), which is often referred to as "earth mover distance", since it measures the minimum cost (probability mass multiplied by distance moved) to turn one probability distribution into another. The results are displayed in Figure 1. One can observe that the distribution obtained by removing words (orange) is significantly different from the original one (blue), while no big difference is observed with removing sentences (green). This is confirmed by a significant decrease in Wasserstein Distance from 8.6 to 4.1 when using sentences. This observation implies that removing random words from the text results in a strongly different embedding distribution than for normal texts, while this effect is much reduced when removing a sentence. Since the classifier is trained on normal texts, its OOD accuracy on the texts obtained by word-sampling, such as used by current state of the art model-agnostic interpretability methods, is questionable, while sentence sampling produces ID texts, for which normal accuracy can be expected.

2.1.2 Evaluating Distributional Shift with Classifier Accuracy

One may wonder if the observed effect is only because a relatively high number of words was removed, reflecting a strong alteration of the text. This is why we perform a second experiment, removing less than 1 word per sentence on average. We frame the detection of distributional shift as a classification problem. If no distributional shift was present, a classifier would not be able to distinguish between the two distributions, resulting in low accuracy.

We compare the embeddings of the original texts, with 5 words removed and with 1 sentence removed. In order to further study if the distributional shift effect is present across different pretraining schemes and prevails after distillation, we use a range of language models other than BERT (Devlin et al., 2019), namely DistilBERT (Sanh et al., 2019), ROBERTA (Liu et al., 2019) and ELECTRA (Clark et al., 2020), where DistilBERT is a distilled version of BERT, while ROBERTA and ELECTRA use different pretraining tasks, notably...
loosing next sentence prediction. Further, we employ a variety of different text domains by using context from SQuAD 2.0 (Rajpurkar et al., 2018) and SQuADShifts (Miller et al., 2020). For each binary classification (Original-Word and Original-Sentence), we train a Random Forest Classifier on the embeddings and observe its performance on a held-out test set. The results are given in Figure 2. Since the binary classifications are balanced, random predictions would yield a classification accuracy of 0.5. We observe that for all datasets and Language Models, the classification accuracy for sentence-removal is much lower compared to word-removal, almost down to random prediction. This suggests that the distributional shift with sentence-removal is much lower, confirming the results from Section 2.1.1 and suggesting that distributional shift is a problem across text domains and transformer-based Language Models. Further, using sentences seems to successfully address the issue for most language models except ROBERTA, where the altered text seems to still be OOD, although much improved. While this behaviour of the different language models is an interesting property, we leave its analysis for further works, since for the arguments presented here it suffices to note that sentence-based interpretability shows preferable distributional properties.

2.2 Computational Complexity

In addition to distributional shift, computational complexity is an important problem when using language models, which often require substantial computation power for inference. Removing words or sentences as atomic units can be seen as sampling a binary vector encoding the presence/absence of words or sentences. The dimension of this binary vector is the number of atomic units. The neighborhood from which points for explanation are sampled is thus of size $2^n_{units}$. Obviously, the number of units $n_{units}$ is much smaller for sentences than for words, since sentences are comprised of multiple words. Take for example the contexts from the SQuAD 2.0 (Rajpurkar et al., 2018) dataset: They contain on average 137.7 words in 5.1 sentences. The number of elements in the neighborhood are thus $2^{127.7} = 2.8 \times 10^{41}$ and $2^{5.1} = 34.3$ for word-based and sentence-based alteration respectively. Since the number of samples are limited by the available computation power, the smaller sentence based neighborhood can be much better explored, resulting in a better estimation of the model’s decision surface.

In the next section, we use sentence-based sampling, which we showed to be less affected by the problems of distributional shift and computational complexity, to propose the GUTEK framework for NLP interpretability.

3 GUTEK

Traditional post-hoc model agnostic black-box interpretability follows the same scheme, independent of input data type: For a sample to explain, we create a dataset of the local neighborhood by repeatedly perturbing parts of the input. Based on the insights from Section 2, we choose sentences as atomic units for explanations. In addition to sentence-based alteration, we employ a different methodology to select which parts to alter. For tabular data, Laugel et al. (2018) conclude that defining locality is a crucial issue for local black-box interpretability. We think that the same holds for text classification: Texts should be sampled such that small changes are more frequent than large changes. This is why we enumerate the most local neighborhood possible, that is the neighborhood with the fewest sentences removed. Since the dataset of the neighborhood reflects a truly local behaviour, sample weighting in the regression is not necessary.

We thus formulate the GUTEK\(^1\) framework as a three stage approach:

1. **Segmentation**: Split the input text into sentences.

2. **Local Sampling/Dataset Generation**: Repeatedly remove some sentences in order to

\(^1\)GUTEK stands for **G**enerating **U**nderstandable **T**ext **E**xplanations based on **K**ey segments. It is also a diminutive for “Gutenberg” in Polish.
create a dataset reflecting the local neighborhood.

3. Modelling for Explanation: Fit a linear regression to the dataset created in Step 2.

We will evaluate if the theoretical advancements of sentence-based sampling materialize in better explanations in the next section.

4 Experiments and Analysis

In Section 2 we point out the main reasons for proposing sentence-based interpretability: computational complexity and distributional shift. While we give theoretical arguments why these are important drawbacks of word-based methods to address, we ultimately want to give better explanations. Defining what a good explanation constitutes is still an open question in interpretability research, but we identify 2 main properties a good explanation should possess: Firstly, we want high fidelity. This means that the given explanation well reflects the reasoning of the underlying classifier. Secondly, we want the explanations to be understandable to humans. The explanation should be simple in order for humans to understand and reason based on.

4.1 Fidelity Evaluation with QUACKIE

In order to assess if GUTEK correctly explains the classifier’s reasoning, we test if it is able to detect which parts of the text were important for the prediction. We use QUACKIE (Rychener et al., 2020), which uses a specific classification task for which interpretability ground-truths arise directly without additional human annotation. We compare our approach to LIME, which represents the current best-performing Black-Box method in the benchmark. We use LIME with sum aggregation, since it outperforms max aggregation in the primary metrics IoU and HPD, representing performance of correctly identifying the important sentence and highly ranking the important sentence respectively. We report the results for the SQuAD 2.0 dataset in Table 1, other results are given in Appendix D but show the same behaviour. We outperform the previous method by a substantial margin in both IoU and HPD for both classifiers. Notably in IoU, our approaches scores are more than double LIME’s scores with the same number of samples, which implies that we find the most important sentence twice as often as the word-based approach. Only in the SNR metric, representing selectiveness, LIME is outperforming GUTEK. When allowing LIME 10 times as many samples as our approach (100 samples vs. 10 samples for GUTEK) it gets closer our performance without matching it. Obviously, drawing 10 times as many samples also results in a 10 fold increase in required computation power and thus a roughly 10 fold increase in computation time. Using 100 samples with the sentence-based approach results in a minor improvement of about 3 percentage points in the primary metrics IoU and HPD, suggesting that the neighborhood is already sufficiently well explored with 10 samples. Overall, the explanations from the sentence-based approach thus better represent the model’s reasoning.

4.2 Qualitative Evaluation of Understandability

We resort to a simple qualitative evaluation by the authors to assess the understandability of the results. It suggests that sentence-based explanations are easier to understand, as they include context. It seems that the provided context in the sentence allows for reasoning based on the explanation. For example, by giving the whole sentence in a movie review, we know what was the worst (the villain), what the movie needed much more of (energy and spunk) and which role was poorly played out (phantom). The explanations can be used beyond debugging and troubleshooting for reasoning and understanding. The specific Example is given in Figure 3 in Appendix C, which also contains further examples.

5 Related Work and Discussion

Our post-hoc interpretability approach allows to explain any existing classifier. This is contrasted by the numerous developments in inherently interpretable classification models based on rationale extraction, for example by Lei et al. (2016), Jain et al. (2020) and Chang et al. (2019), which work in two steps: Extract a Rationale and Make the prediction based on the Rationale. While this approach can be argued to be inherently interpretable (the classifier only has access to the rationale), we
are not aware of this method being applicable to all possible, potentially pretrained classifiers, while the black-box approach allows to use any classifier, thus potentially harnessing the most powerful classifiers for prediction.

Compared to other, word-based black-box post-hoc NLP interpretability methods like LIME (Ribeiro et al., 2016) and SHAP (Lundberg and Lee, 2017), we have a much smaller search space (Section 2.2). Further, our experiments suggest that no distributional shift occurs when removing sentences (Section 2.1). We hypothesize that these are the two reasons contributing to improved fidelity at comparable computational complexity (Section 4.1) compared to LIME and SHAP.

In addition to better fidelity, the explanations are easier to understand (Section 4.2). The context provided with the explanation further opens the door for knowledge discovery, for example by comparing the topics of positive and negative sentences in reviews.

6 Conclusion

In this work, we illustrated limits of current state of the art model-agnostic interpretability methods based on word sampling (e.g. LIME, SHAP) when it comes to more complex classifiers like BERT. We showed that using sentences as elementary units can address the problems arising with computational complexity and distributional shift, resulting in better fidelity and human understandability. One could also imagine using other, more sophisticated methods to extract atomic units for explanation. We leave this analysis into segmentation methods for interpretability for further work. Further, we hope that this work sparks attention to the importance of the perturbation and sampling of any agnostic post-hoc interpretability method.

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To ensure reproducibility, we give the implementation details of our experiments. Direct implementations can also be found directly on our Github\footnote{https://github.com/axa-rev-research/gutek}.

\subsection{The Case Against Word-Based Black-Box Interpretability}

\subsubsection{Distributional Shift}

We use the last embedding of the classification token as representation of the whole text. We use base uncased BERT (Devlin et al., 2019). For the visualisation experiment, we directly use this embedding to calculate Wasserstein distance. To visualize, we use t-SNE on the combined dataset (word removed + sentence removed + original) with PCA initialisation and a perplexity of 100. The algorithm is given a maximum of 5000 iterations, for other parameters we used SKLearn (Pedregosa et al., 2011) defaults.

For evaluating distributional shift with classifier accuracy, we use base uncased BERT (Devlin et al., 2019), base RoBERTa (Liu et al., 2019), base uncased DistilBERT (Sanh et al., 2019) and the small ELECTRA (Clark et al., 2020) discriminator. The text embeddings are pairwise used to create a classification problem, which uses a random 75-25 train test split. We train a Random Forest Classifier using default SKLearn parameters, controlling for complexity using the maximum depth with options 2, 5, 7, 10, 15 and 20. The best choice is selected using out-of-bag accuracy. Results in Figure 2 and Table 2 represents performance on the test-set.

\subsubsection{Computational Complexity}

In order to have normal flowing text, we use text from Wikipedia, notably contexts from SQuAD 2.0 (Rajpurkar et al., 2018). We compare the number of sentences and the number of words, obtained using NLTK (Bird et al., 2009) \texttt{sent} and \texttt{word} respectively.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|}
\hline
\textbf{Sentence} & \textbf{Word} & \textbf{Data} \\
\hline
\hline
\end{tabular}
\caption{Comparison of text size between different datasets.}
\end{table}
| DATASET   | LM       | WORD | SENTENCE |
|-----------|----------|------|----------|
| WIKIPEDIA | BERT 0.81| 0.57 |          |
|           | DISTILBERT 0.79 | 0.56 |          |
|           | ROBERTA 0.86 | 0.70 |          |
|           | ELECTRA 0.92 | 0.60 |          |
| AMAZON    | BERT 0.81 | 0.59 |          |
|           | DISTILBERT 0.79 | 0.56 |          |
|           | ROBERTA 0.87 | 0.76 |          |
|           | ELECTRA 0.91 | 0.61 |          |
| NYT       | BERT 0.79 | 0.59 |          |
|           | DISTILBERT 0.78 | 0.57 |          |
|           | ROBERTA 0.86 | 0.76 |          |
|           | ELECTRA 0.92 | 0.60 |          |
| REDDIT    | BERT 0.79 | 0.59 |          |
|           | DISTILBERT 0.78 | 0.56 |          |
|           | ROBERTA 0.86 | 0.76 |          |
|           | ELECTRA 0.92 | 0.60 |          |

Table 2: OOD Classification Results in Tabular Form

A.2 Experiments and Analysis

A.2.1 Fidelity Evaluation with QUACKIE

We use code provided with QUACKIE (Rychener et al., 2020) to test GUTEK. In our implementation of GUTEK, we use NLTK `sent_tokenize` to split the text into sentences and use the SKLearn implementation of the Linear Regression as surrogate. The coefficients of the linear regression are used as sentence scores.

A.2.2 Human Understandability

As underlying classifier, we use a combination of TF-IDF and Random Forest Classifier. For TF-IDF, we use English stopwords, an n-gram range from 1 to 3, no maximum number of features, maximum document frequency of 0.8, minimum token occurrence of 4, using L1 normalization and sublinear term-frequency. Random Forest uses default parameters. Both implementations are by SKLearn. We use the standard LIME (Ribeiro et al., 2016) package and our implementation of GUTEK described in Appendix A.2.1. For both interpreters, probability outputs are used.

B Tabular Results for OOD Classification

In addition to plotting, we give the results from Figure 2 in Table 2.

C Further Examples for Qualitative Evaluation

In addition to the example from Figure 3, we provide further examples for qualitative evaluation in Figures 4, 5 and 6. Note that we manually tweaked the text size and figure size in order for the text to not overlap in visualisation. Also, no post-processing (like filtering important parts only) was done after GUTEK.

D Complete QUACKIE results

We also give results for all datasets in QUACKIE and report the scores for all other methods currently in QUACKIE in Tables 3, 4 and 5.
Treat Williams, looking like Rhett Butler but sounding like Mickey Mouse, is one of the worst villains I have ever seen in a movie. Oh yeah, the Phantom also has a secret identity but this is so poorly played out you won’t even care.

She has energy and spunk, which the movie needed much more of. Wincer displays absolutely no skill in setting up an exciting action sequence.

Only Catherine Zeta Jones, as one of Williams’ cohorts, turns in a good performance. Kristy Swanson is given very little to do, and does very little with it.

Billy Zane is wooden as the hero.

This is not a good movie. However, if you’re looking for a fun family movie, go watch the underrated Flipper.
The problem is that the writers, James Cameron and Jay Cocks, were too ambitious, aiming for a film with social relevance, thrills, and drama.

This film features good performances, impressive film-making technique and breath-taking crowd scenes.

Director Kathryn Bigelow knows her stuff and does not hesitate to use it.

As the locals gear up for the new millennium, Lenny Nero (Ralph Fiennes) goes about his business of peddling erotic memory clips.

But as a whole, this is an unsatisfying movie.

The film just ends up preachy, unexciting and uninvolving.

He pines for his ex-girlfriend, Faith (Juliette Lewis), not noticing that another friend, Mace (Angela Bassett) really cares for him.

Not that ambitious film-making should be discouraged; just that when it fails to achieve its goals, it fails badly and obviously.
The answer is quite simple—I don't want to waste any more of my time writing or thinking about this movie than absolutely necessary.

You might be asking yourself why this is such a short review.

Note to Reese: you were great in Fear, what happened this time?

Bottom line—I'm still shaking my head.

Freeway is giving me second thoughts.

Note to both: don't worry about it too much, no one saw this movie anyway.

Don't waste your time on this turkey.

After seeing the end result, undoubtedly they are both asking themselves the same question.

If you want to see a great Kiefer Sutherland movie, go rent Flatliners or Young Guns.

Because you keep making movies like this.

Only in the nineties, little red riding hood is a foul-mouthed juvenile delinquent played by Reese Witherspoon, and the big bad wolf is a serial killer (Kiefer Sutherland).

So what are they doing in this movie?

Do yourself a favor and rent one of these movies—but stay as far away from Freeway as you possibly can.

Freeway is a modern retelling of little red riding hood.

Reese Witherspoon's abundant acting talents are used to their full potential in Fear, a great thriller.

Kiefer Sutherland is one of Hollywood's most talented, yet underrated actors, and Reese Witherspoon is exceptionally talented and will most likely become a major star.

Note to Kiefer: you wonder why you aren't a bigger star in Hollywood?

To top that pathetic premise off—Reese goes to visit Granny and you'll never guess who's waiting under the cover's in Granny's bed.

I wasted enough of my time just sitting through it.
After watching the film again, I am convinced that it is simply one of the finest works of cinematic genius to ever illuminate the big screen. Using stunning cinematography, costuming, and direction, shot in the most uninhabitable location on the face of the earth, I can only imagine what it must have been like to sit in a theater in 1962 and watch this story unfold before my eyes. Lawrence quickly sees just how caring and great these desert dwelling people can be and ends up rallying the various tribes together to fight the Turks and help the British turn the tide of World War I.

After watching the film, the first thing that came to my mind was, "I've got to do a remake of this film!" But then I thought about trying to pitch the idea to a modern-day movie executive: "Okay, it's going to be almost 3.5 hours long. And we are going to need to blow up a full-size train because computer-generated effects probably won't do it justice. And we are not going to use any big stars, and we won't have any female actors since there's no love story.

But at least we still have the proof to show all would-be producers and directors out there just how good a film can be.

After all, it's considered by just about everyone to be the masterpiece epic of director David Lean, who also directed Bridge on the River Kwai, and Doctor Zhivago. But then I thought about trying to pitch the idea to a modern-day movie executive: 'Okay, it's going to be almost four hours long and shot over three months on location in the Sahara desert.'

Yes, my friends, the velvet curtain fell on the golden-era of Hollywood a long time ago. I was initially skeptical that something made almost 40 years ago would be able to keep my attention for the butt-numbing 3.5 hours of its duration. But now I fully understand why this has become the film that other epic films are judged against — the winner of seven Academy Awards in 1963 for best picture, director, editing, cinematography, art direction, music, and sound.

David Lean put his reputation on the line to get this film completed, and the fact that it was even greenlit in the first place says something about the ideology of the motion picture industry at the time, a far cry from its pathetic, uncreative existence today. And we are not going to use any big stars, and won't have any female actors since there's no love story.

But at least we still have the proof to show all would-be producers and directors out there just how good a film can be.

Figure 6: Comparison of Explanations for TFIDF movie sentiment classifier, GUTEK (left) vs LIME (right) (sample id 70)
| Interpreter | Aggregation | Samples | SQuAD Classif | SQuAD QA | New Wiki Classif | New Wiki QA | NYT Classif | NYT QA | Reddit Classif | Reddit QA | Amazon Classif | Amazon QA |
|-------------|-------------|---------|---------------|----------|-----------------|-----------|-------------|--------|----------------|----------|--------------|----------|
| **GUTEK**   | -           | 10      | 88.55 90.53   | 87.7 89.54 | 87.66 88.04     | 71.62 76.86 | 79.09 78.95 |        |                |          |              |          |
|             |             | 100     | 91.38 90.53   | 90.83 90.55 | 91.56 91.84     | 80.62 86.98 | 84.77 86.14 |        |                |          |              |          |
| **LIME**    | sum         | 10      | 37.70 38.47   | 40.72 41.40 | 40.22 41.98     | 31.35 35.34 | 32.69 35.27 |        |                |          |              |          |
|             |             | 100     | 58.04 69.90   | 60.74 70.82 | 62.02 73.50     | 50.33 69.02 | 53.57 67.58 |        |                |          |              |          |
|             | max         | 100     | 34.06 35.36   | 36.98 37.77 | 36.19 36.43     | 26.52 28.89 | 29.80 32.12 |        |                |          |              |          |
|             |             | 50      | 57.86 68.30   | 59.65 68.43 | 61.57 72.00     | 48.22 65.23 | 53.09 66.24 |        |                |          |              |          |
| **SHAP**    | sum         | 10      | 30.48 32.90   | 31.66 32.84 | 29.26 31.03     | 23.13 23.75 | 24.59 25.43 |        |                |          |              |          |
|             |             | 100     | 54.85 65.92   | 57.53 65.79 | 56.38 67.70     | 49.35 65.02 | 54.03 67.68 |        |                |          |              |          |
|             | max         | 100     | 29.69 30.81   | 30.72 31.68 | 28.32 30.00     | 21.17 22.58 | 22.72 23.84 |        |                |          |              |          |
|             |             | 50      | 52.45 62.34   | 54.56 63.18 | 53.19 64.78     | 45.79 60.03 | 49.54 63.35 |        |                |          |              |          |

| Interpreter | Aggregation | Samples | Saliency sum | Integrated Gradients | SmoothGrad | Random |
|-------------|-------------|---------|--------------|----------------------|------------|--------|
| **Saliency** | -           | 10      | 74.7 91.12   | 68.87 84.46         | 57.57 85.26 | 64.82 85.91 |
|             |             | 100     | 66.27 80.79  | 58.95 76.07         | 48.41 77.33 | 59.52 79.70 |
| **Integrated Gradients** | sum         | 50      | 67.63 85.93  | 65.44 85.20         | 51.62 79.73 | 51.96 78.21 |
|             |             | 50      | 62.73 87.05  | 61.63 85.92         | 50.24 82.35 | 49.09 82.45 |
| **SmoothGrad** | sum         | 5       | 60.98 91.28  | 60.25 88.29         | 50.32 84.51 | 52.34 84.40 |
|             |             | 5       | 59.48 82.16  | 56.93 78.35         | 45.95 77.72 | 53.03 78.26 |

| Interpreter | Aggregation | Samples | Saliency sum | Integrated Gradients | SmoothGrad | Random |
|-------------|-------------|---------|--------------|----------------------|------------|--------|
| **Saliency** | -           | 10      | 79.1 93.01   | 74.9 90.71          | 63.05 87.21 | 69.96 88.01 |
|             |             | 100     | 72.99 84.83  | 66.86 80.94         | 55.10 80.32 | 65.31 82.74 |
| **Integrated Gradients** | sum         | 50      | 73.52 88.85  | 71.99 88.00         | 57.84 82.46 | 58.93 81.56 |
|             |             | 50      | 70.15 89.67  | 68.73 88.52         | 56.51 84.70 | 56.35 85.10 |
| **SmoothGrad** | sum         | 5       | 69.03 93.08  | 68.05 90.52         | 56.77 86.38 | 59.36 86.72 |
|             |             | 5       | 67.83 85.77  | 65.32 82.65         | 53.00 80.64 | 59.84 81.43 |

| Interpreter | Aggregation | Samples | Saliency sum | Integrated Gradients | SmoothGrad | Random |
|-------------|-------------|---------|--------------|----------------------|------------|--------|
| **Saliency** | -           | 10      | 40.28 40.71  | 42.66 42.92         | 27.41 27.17 | 30.79 31.34 |
|             |             | 100     | 39.48 37.37  | 32.21 30.68         | 19.12 17.89 | 26.11 22.72 |

| Interpreter | Aggregation | Samples | Saliency sum | Integrated Gradients | SmoothGrad | Random |
|-------------|-------------|---------|--------------|----------------------|------------|--------|
| **Saliency** | -           | 10      | 39.23 38.20  | 41.82 40.66         | 25.89 22.84 | 27.87 27.08 |
|             |             | 100     | 39.30 40.91  | 42.30 43.96         | 32.90 46.71 | 27.42 32.52 |
| **Integrated Gradients** | sum         | 50      | 99.16 102.31 | 97.10 92.66         | 130.98 127.01 | 99.87 102.16 |
|             |             | 50      | 107.51 137.72 | 102.01 123.57     | 135.62 207.62 | 115.62 207.62 |

| Interpreter | Aggregation | Samples | Saliency sum | Integrated Gradients | SmoothGrad | Random |
|-------------|-------------|---------|--------------|----------------------|------------|--------|
| **Saliency** | -           | 10      | 37.29 39.92  | 40.88 40.14         | 19.10 19.77 | 22.90 23.34 |
|             |             | 100     | 35.58 38.20  | 39.75 39.81         | 19.15 20.04 | 22.17 23.78 |
| **Integrated Gradients** | sum         | 50      | 37.28 37.32  | 39.16 40.19         | 18.96 20.60 | 22.50 24.60 |
|             |             | 50      | 35.71 34.99  | 38.74 38.09         | 32.55 32.80 | 21.80 23.69 |
| **SmoothGrad** | sum         | 5       | 38.13 37.22  | 41.29 40.15         | 35.16 33.04 | 23.34 23.11 |
|             |             | 5       | 37.55 36.61  | 40.29 40.04         | 34.85 35.98 | 22.45 22.69 |

| Interpreter | Aggregation | Samples | Saliency sum | Integrated Gradients | SmoothGrad | Random |
|-------------|-------------|---------|--------------|----------------------|------------|--------|
| **Random**  | -           | 10      | 37.70 37.34  | 40.63 40.52         | 19.24 19.79 | 23.21 23.70 |

Table 5: SNR Results (Examples for which noise cannot be estimated are omitted)