On the Transferability of Minimal Prediction Preserving Inputs in Question Answering

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Abstract

Recent work (Feng et al., 2018) establishes the presence of short, uninterpretable input fragments that yield high confidence and accuracy in neural models. We refer to these as Minimal Prediction Preserving Inputs (MPPIs). In the context of question answering, we investigate competing hypotheses for the existence of MPPIs, including poor posterior calibration of neural models, lack of pretraining, and “dataset bias” (where a model learns to attend to spurious, non-generalizable cues in the training data). We discover a perplexing invariance of MPPIs to random training seed, model architecture, pretraining, and training domain. MPPIs demonstrate remarkable transferability across domains — closing half the gap between models performance on comparably short queries and original queries. Additionally, penalizing over-confidence on MPPIs fails to improve either generalization or adversarial robustness. These results suggest the interpetability of MPPIs is insufficient to characterize generalization capacity of these models. We hope this focused investigation encourages a more systematic analysis of model behavior outside of the human interpretable distribution of examples.

1 Introduction

Feng et al. (2018) establish the presence of shortened input sequences that yield high confidence and accuracy for non pretrained neural models. These Minimal Prediction Preserving Inputs (MPPIs) are constructed by iteratively removing the least important word from the query to obtain the shortest sequence for which the model’s prediction remains unchanged.1 Humans are unable to make either confident or accurate predictions on these inputs. This work and others (Kaushik and Lipton, 2018) have raised the concern whether question answering models are properly learning the task. Accordingly, we investigate the properties of MPPIs in question answering (QA) and how their existence relates to “dataset bias”, out-of-domain generalization, and adversarial robustness.

First we examine the hypothesis that MPPIs are a symptom of poor neural calibration. Feng et al. (2018) propose we can “attribute [these neural] pathologies primarily to the lack of accurate uncertainty estimates in neural models trained with maximum likelihood. This idea stems from the observation that neural models tend to overfit the log-likelihood objective by predicting low-entropy distributions (Guo et al., 2017), and this can manifest in over-confidence on gibberish examples outside of the training distribution (Goodfellow et al., 2014). We test this hypothesis using pretrained models, shown to have better posterior calibration and out-of-distribution robustness (Hendrycks et al., 2020; Desai and Durrett, 2020). Contrary to expectations, we find large-scale pretraining does not produce more human interpretable MPPIs.

Second we examine the hypothesis that MPPIs are the symptom of “dataset bias” — where a flawed annotation procedure results in hidden linguistic cues or “annotation artifacts” (Gururangan et al., 2018; Niven and Kao, 2019). Models trained on such data distribution can rely on simple heuristics rather than learning the task. As such, input fragments or “partial inputs” are often sufficient for a model to achieve strong performance on flawed datasets. This explanation has been considered for both Natural Language Inference tasks (the “hypothesis-only” input for Poliak et al. (2018); Gururangan et al. (2018)) and for Visual Question Answering (the “question-only” model for Goyal et al. (2017)). We expect models which rely on

1For question answering we construct MPPIs by only removing words from the query. Modifying the context paragraph is poorly defined in MPPI generation as it perturbs the output space, rendering an answer impossible or trivial.
these spurious cues would fail to generalize well to other “domains” (datasets with different collection and annotation procedures). We discover even models trained in different domains perform nearly as well on MPPIs as on full inputs, contradicting this hypothesis. Further, we test their transferability across a number of other factors, including random training seed, model size, and pretraining strategy, and confirm their invariance to each of these.

Third we examine the hypothesis that MPPIs inhibit generalization. This intuition is based on MPPI’s poor human interpretability, which could suggest models should not attend to these signals. To test this hypothesis, we regularize this phenomenon directly to promote more human understandable MPPIs, and measure the impact on out-domain generalization and adversarial robustness. Interestingly, out-domain generalization and robustness on Adversarial SQuAD (Jia and Liang, 2017) vary significantly by domain, with both declining slightly on average due to regularization.

In conjunction, these results suggest MPPIs may represent an unique phenomenon from what previous work has observed and analyzed. The performance of these inputs is not well explained by domain-specific biases, or posterior overconfidence on out-domain inputs. Instead, this behavior may correspond to relevant signals as the impact of their partial mitigation suggests. We hope these results encourage a more systematic analysis of hypotheses regarding model behavior outside of the human interpretable distribution of examples.

2 Experimental Methodology

All models trained, including DRQA (Chen et al., 2017), BERT (Devlin et al., 2019), and XLNET (Yang et al., 2019), employ parameter choices tuned from Longpre et al. (2019). We generate MPPIs by iteratively removing the least important word from the question, while keeping the original prediction unchanged. The least important word is given as that for which the model’s confidence in its prediction remains highest in its absence. To examine how MPPIs transfer across Question Answering domains we employ 6 diverse QA training sets and 12 evaluation sets. The datasets were

2For DRQA, we borrowed the hyper-parameters from hitvoice (https://github.com/hitvoice/DrQA)

3Details of model training and examples of MPPI generation are described in Appendix A.

4Refer to Appendix A.3 for details, or the MRQA 2019 workshop: https://mrqa.github.io/shared. As a simplifying assumption, these datasets have been normalized

3 Experiments

3.1 Invariance of MPPIs

Feng et al. (2018) establish the “human-insufficiency” property of MPPIs for non-pretrained, LSTM and attention-based models, including DRQA, and BitMPM (Wang et al., 2017). We extend this investigation for modern Transformers, and assess the “invariance” of MPPIs: measuring whether they are random, or are affected by model architecture, pretraining strategy, or training dataset (domain).

Random Seed: First, we investigate whether MPPIs are “random”, or influenced by weight initialization and training data order. We compare pairs of SQuAD-trained BERT models with different random seeds, measuring the Exact Match and Jaccard Similarity between their MPPI token sequences on the 2k evaluation set. Averaging over this evaluation set we observe $\text{EM}_{\text{MPPI}} = 33.6\% \pm 6\%$ into purely extractive format (Fisch et al., 2019).

| Dataset | ORIGINAL | BERT-B | XLNET-L |
|---------|----------|--------|---------|
| SQUAD (Rajpurkar et al., 2016) | 11.54 | 2.32 | 2.65 |
| HOTPOTQA (Yang et al., 2018) | 18.96 | 2.07 | 2.55 |
|NewsQA (Trischler et al., 2016) | 7.59 | 2.08 | 1.80 |
| NATURAL_Q (Kwiatkowski et al., 2019) | 9.17 | 1.22 | 1.26 |
| TRIVIAQA (Joshi et al., 2017) | 15.68 | 2.33 | 1.80 |
| SEARCHQA (Dunn et al., 2017) | 17.43 | 1.81 | 1.05 |

Table 1: Number of MPPI query tokens, for different datasets and models.

|        | DRQA     | BERT-B   | XLNET-L   |
|--------|----------|----------|-----------|
| BERT-B | 32.1 / 9.9 | - / - | 29.8 / 9.9 |
| XLNET-L| 26.0 / 7.2 | 29.8 / 9.9 | - / -   |

Table 2: The mean similarity, measured in Jaccard Similarity / Exact Match (%), between the MPPIs from different model types and the random baseline.
we might expect models that are better calibrated expect them to be relatively domain specific, as dif-
培克等，2018）, its impact on generalization or robustness has not yet been examined. While penalizing over-confidence on MPPI s has improved generalization, or adversarial robustness. MPPI s are highly transferable across domains. We would like to measure MPPI transferability even when they differ between models. If QA models perform well on MPPI s generated from a range of domains then this would suggest they are not a product of bias in the training data. Instead, they may retain information important to question answering, rather than annotation artifacts. To better measure the extent of MPPI transferability, we (a) train one model on SQuAD (Train Dataset), and another on NewsQA (Reduction Dataset), (b) use the NewsQA-model to generate $2k$ MPPI s on the NewsQA evaluation set, and (c) measure the F1 performance of the SQuAD-model evaluated on both the original NewsQA evaluation set and the MPPI queries as generated in part (b).

Table 3: The Jaccard Similarity (%) between BERT generated MPPIs, across domains. In parentheses are the Jaccard Similarity scores between the Random MPPI baseline and Train Dataset MPPIs.

| Train Dataset | Reduction Dataset | SQuAD | HotPotQA | NewsQA | NATURALQ |
|---------------|-------------------|-------|----------|--------|----------|
| SQuAD         | (-)               | 31.4  | (8.8)    | 41.0   | (21.6)   | 29.2     | (12.5)   |
| HotPotQA      | 39.7 (12.8)       | (-)   | 39.6 (18.8) | 33.8 (13.5) |
| NewsQA        | 41.1 (13.0)       | 31.6 (7.2) | (-)   | 39.5 (12.5) |
| NATURALQ      | 37.5 (12.7)       | 28.7 (7.1) | 40.2 (17.9) | (-) |
| Average       | 39.4 (12.8)       | 30.6 (7.7) | 40.3 (19.4) | 32.7 (12.8) |

Table 3: The Jaccard Similarity (%) between BERT generated MPPIs, across domains. In parentheses are the Jaccard Similarity scores between the Random MPPI baseline and Train Dataset MPPIs.

1.3, and $JS_{MPPI} = 57.1\% \pm 1.2$, as compared to $EM_R = 0.9\% \pm 0.3$, and $JS_R = 13.8\% \pm 0.8$ on the Random MPPI baseline. This suggests MPPIs are not simply the side-effect of randomness in the training procedure.

Pretraining and Architecture: One hypothesis is that traditional LSTM-based models, such as DRQA and BiMPM, do not have sufficient pretraining or “world knowledge” to rely on the entire sequence, and overfit to subsets of the input. If this were the primary source of MPPIs, we might expect models that are better calibrated and more robust to out-of-distribution examples to have longer and more interpretable MPPIs. Accordingly, we test this hypothesis with large pretrained transformers, which recent work demonstrates have better posterior calibration and robustness to out-of-distribution inputs (Hendrycks et al., 2020; Desai and Durrett, 2020). In Table 1 we show MPPIs remain incomprehensibly short for all 6 domains and even for pretrained transformer models (DRQA produces MPPIs on SQuAD of mean length 2.04). In Table 2 we show MPPIs produced by different model architectures and pretraining strategies are similar, significantly exceeding the Jaccard Similarity of the Random MPPI baseline ($JS_R = 13.8\%$). We also verify with manual grading tasks that the MPPIs for BERT and XLNet are no more interpretable to humans than DrQAs MPPIs (details in Appendix C). This suggests that short, uninterpretable MPPIs are ubiquitous in modern neural question answering models and unmitigated by large scale pretraining, or improved out-of-distribution robustness.

Cross-Domain Similarity: Next, we investigate the extent to which MPPIs are domain-specific. We do this by measuring their similarity when produced by models trained in different domains. If MPPIs are the product of bias in the training data, such as annotation artifacts, we would expect them to be relatively domain specific, as dif-
ferent datasets carry different biases. In Table 3 a model trained from each domain (Train Dataset) generates MPPIs for each other domain (Reduction Dataset). For each Reduction Dataset, we measure the mean Jaccard Similarity between MPPIs produced by the Train Dataset model and MPPIs produced by the Reduction Dataset (in-domain) model. In parentheses we show the mean Jaccard Similarity between the Random MPPIs and the Train Dataset MPPIs. In all cases, MPPIs demonstrate higher similarity than the random baseline, indicating that they are not domain specific.

3.2 Cross-Domain Transferability of MPPIs
The percentage of shared MPPIs between models is a lower bound on how well they transfer between domains. We would like to measure MPPI transferability even when they differ between models. If QA models perform well on MPPIs generated from a range of domains then this would suggest they are not a product of bias in the training data. Instead, they may retain information important to question answering, rather than annotation artifacts. To better measure the extent of MPPI transferability, we (a) train one model on SQuAD (Train Dataset), and another on NewsQA (Reduction Dataset), (b) use the NewsQA-model to generate $2k$ MPPIs on the NewsQA evaluation set, and (c) measure the F1 performance of the SQuAD-model evaluated on both the original NewsQA evaluation set and the MPPI queries as generated in part (b).

Figure 1 shows performance on out-domain MPPIs are 46.6% closer to original performance than on Random MPPIs. This evidence suggests MPPIs are highly transferable across domains. Consequently, MPPIs may relate to generalization, despite their poor human interpretability.

3.3 Human-Sufficient MPPIs do not Improve Generalization
Even though MPPIs are highly transferable between domains, their presence may be associated with poor generalization. To evaluate this possibility, we examine whether the penalization of MPPIs improves generalization, or adversarial robustness. While penalizing over-confidence on MPPIs has been shown to maintain equivalent in-domain performance, and yield subsequently longer and more human interpretable MPPI queries (Feng et al., 2018), its impact on generalization or robustness has not yet been examined.

We employ a simplified version of the MPPI
Train Dataset | SearchQA | HotpotQA | NewsQA | NaturalQ | TriviaQA | SQuAD
---|---|---|---|---|---|---
SQuAD | 52.9 | 52.9 | 52.9 | 52.9 | 52.9 | 52.9
HotpotQA | 48.5 | 48.5 | 48.5 | 48.5 | 48.5 | 48.5
NewsQA | 53.0 | 53.0 | 53.0 | 53.0 | 53.0 | 53.0
NaturalQ | 51.6 | 51.6 | 51.6 | 51.6 | 51.6 | 51.6
TriviaQA | 42.3 | 42.3 | 42.3 | 42.3 | 42.3 | 42.3
SearchQA | 38.0 | 38.0 | 38.0 | 38.0 | 38.0 | 38.0

Table 4: The impact of MPPI regularization on in-domain (ID) performance, macro-average out-domain (OD) generalization over 12 evaluation datasets, and adversarial robustness (AR) on Adversarial SQUAD. △X = F1 of MPPI regularized model minus F1 of regular model on target X (any of ID, OD, or AR).

penalization used by Feng et al. (2018), training a model with equal quantities of regular and MPPI examples — maintaining normal QA loss terms for the regular examples, and applying an entropy penalty to MPPI examples. When penalizing over-confidence on MPPIs, we confirm the new MPPI length is significantly longer, and more human interpretable (Appendix sections B and C).

In Table 4 we show the difference in F1 scores (∆) between the regularized and original models. Results demonstrate that in-domain F1 (ID), macro-average out-domain F1 over 12 datasets (OD), and adversarial robustness F1 on Adversarial SQUAD (AR) all decline slightly on average with MPPI regularization — by 0.2%, 2.7%, and 0.6% respectively. These results suggest a model’s ability to make predictions on MPPIs is not strongly correlated with either generalization or robustness across 13 total QA datasets. However, the relative stability of in-domain performance as compared to out-domain performance suggests mitigating MPPIs is more harmful when crossing domain boundaries.

Certain train datasets exhibit greater sensitivity to MPPI regularization than others. For instance SearchQA is drastically affected in all measures, HotpotQA hardly at all, and SQuAD actually improves by 3.1% in adversarial robustness. Additionally, Table 4 shows the 95% confidence intervals for out-domain generalization are often as large as the mean change in performance. Empirically, this demonstrates the effect of MPPI regularization is not consistent, having both positive and negative impacts on performance, depending on which of the 12 out-domain datasets is in question.  

4 Discussion

We find no evidence that MPPIs are explained by poorly calibrated neural models, lack of pretraining knowledge, or dataset-specific bias. Alternatively they may relate, at least in part, to useful and transferable signals. This observation closely relates to prior work in computer vision suggesting human uninterpretable, adversarial examples can be the result of “features” as opposed to “bugs”, in which Ilyas et al. (2019) observe “a misalignment between the (human-specified) notion of robustness and the inherent geometry of the data.”

Out-domain generalization and adversarial robustness appear to be uncorrelated with the impact of MPPI regularization. This observation underscores the importance for ML practitioners to tailor their mitigation methods to the undesired model behaviour, and to rigorously evaluate the intended effect on robustness and generalization.

5 Conclusion

We empirically verify the surprising invariance of MPPIs to random seed, model architecture, and pretraining, as well as their wide transferability across domains. These results suggest that MPPIs may not be best explained by poorly calibrated neural estimates of confidence or dataset-specific bias. Examining their relationship to generalization and adversarial robustness, we highlight the ability to maintain in-domain performance but significantly alter out-domain performance and robustness. We hope our results encourage a more systematic analysis of hypotheses regarding model behavior outside the human interpretable distribution of examples.

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^5See Appendix section A.4 for details.

^6See Figure 9 in Appendix A.4 for details.
6 Acknowledgments

We would like to acknowledge Eric Wallace, Shi Feng, Jordan Boyd-Graber, Christopher Clark, Drew Frank, Kanit Wongsuphasawat, Ni Lao, and Charlie Maalouf for their guiding insights and helpful discussion.

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Appendices

A Reproducibility

A.1 Question Answering Models

For reproducibility, we share our hyper-parameter selection in Table 5. We borrow our hyper-parameters from Longpre et al. (2019) for training all Question Answering (QA) models. Their parameters are tuned for the same datasets in the MRQA Shared Task. We found these choices to provide stable and strong results across all datasets.

Our BERT and XLNet question answering modules build upon the standard PyTorch (Paszke et al., 2019) implementations from HuggingFace, and are trained on 8 NVIDIA Tesla V100 GPUs. For DrQA, by Chen et al. (2017), we borrowed the implementation and hyper-parameters from hitvoice (https://github.com/hitvoice/DrQA) and train on 1 NVIDIA Tesla V100 GPU.

A.2 Dataset

We employ 6 diverse QA training sets and 12 evaluation sets from the MRQA 2019 workshop (https://github.com/mrqa/MRQA-Shared-Task-2019) (Fisch et al., 2019). These datasets have been normalized into purely extractive format and all questions are answerable. The 6 training datasets are SQuAD (Rajpurkar et al., 2016), NewsQA (Trischler et al., 2016), TriviaQA (Joshi et al., 2017), SearchQA (Dunn et al., 2017), HotpotQA (Yang et al., 2018), and NaturalQuestion (Kwiatkowski et al., 2019). Six other evaluation datasets are included: BioASQ (Tsatsaronis et al., 2012), DROP (Dua et al., 2019), DuoRC (Saha et al., 2018), RACE (Lai et al., 2017), RelationsExtraction (Levy et al., 2017), and TextbookQA (Kembhavi et al., 2017). Table 6 shows their statistics.

We use the hyperparameters described in Table 5 for training on each dataset. We use all the training data provided for each by MRQA.

A.3 Generating MPPIs

The process for generating MPPIs closely follows the procedure described by Feng et al. (2018). We operate with a beam size of \( k = 3 \), finding that larger beam sizes exhibit diminishing returns, and rarely produce different results. The procedure involves iteratively removing the token which is “least important” to the model. The least important token is defined as the one that when removed provides the smallest decrease in confidence in the originally predicted span. Note that in some cases confidence in the originally predicted span can even increase with the removal of a token. In any case, the least important token is always designated by the lowest confidence in the original prediction. The stop condition is when removing any additional token would change the model’s prediction.

Note that we follow previous work in only removing words from the query in extractive question answering. The reason for this is the MPPI can be poorly defined when context tokens are removed. Since the output predictions are over the context tokens for extractive question answering, its possible to warp the answer space, or remove the answer
altogether. Additionally, if we do not permit any alterations to the original prediction tokens, then there exists a trivial solution: remove all tokens except for the predicted answer. In this case an extractive question answering model is forced to predict that answer, with no alternative options. Consequently, MPPIs that allow modifications to the context, or output space, can be poorly defined. Since in question answering the query is an essential input to provide confident answers, we believe this is the most reasonable setup for the task.

\[ p_{ij} = \max(\text{softmax}(S_i + E_j)) \]  

(1)

For completeness, we describe our method of computing span confidence for question answering, given that there are many variations. Let \( S \in \mathbb{R}^N \) be the vector of start logits and \( E \in \mathbb{R}^N \) be the vector of end logits, both of sequence length \( N \). For every combination of \( i, j \in [0, N] \) where \( j \geq i \leq \min(j+C, N) \), and \( C = 30 \) is the maximum answer span length, we compute the confidence for that span of answer text as the sum of their respective logits \( S_i + E_j \). The final confidence probability \( p_{ij} \) for a given span is as shown in Equation 1.

Figure 2 shows an MPPI example generated from SQuAD by a BERT model. On average, the reduced question (or “MPPI”) is not sufficient for a human to make an informed prediction (Feng et al., 2018). The model, on the other hand, can still make the same prediction as it did on the full input, and with a similar degree of confidence.

A.4 Regularizing MPPIs

There are a couple differences between the MPPI entropy-regularization strategy employed in this work and in Feng et al. (2018). While Feng et al. (2018) fine-tune an already trained model for the question answering task, we regularize MPPIs in the initial fine-tuning stage (starting from BERT and XLNet’s pre-trained weights). Secondly, they alternate updates between two optimizers, one batch of maximum likelihood, two for MPPI entropy maximization, whereas we use the same optimizer and shuffle together equal numbers of MPPI and regular inputs. We find our method (without rigorous comparison) to be slightly more effective on BERT at mitigating the MPPI phenomenon (measured by subsequent MPPI length). We suspect, if there is an advantage, it is due to the regularization beginning with the start of fine-tuning.
rather than on a subsequent stage of fine-tuning.

\[ \mathcal{L}_{MPPI} = C - \lambda \sum_{\tilde{x} \in \mathcal{X}} \mathbb{H}(f(y|\tilde{x})) \]  \hspace{1cm} (2)

\[ \mathcal{L} = \mathcal{L}_{QA} + \mathcal{L}_{MPPI} \]  \hspace{1cm} (3)

For completeness, we provide our entropy regularization loss term in Equation 2. Let \( \mathcal{X} \) denote the set of inputs that have been reduced to their MPPI, \( \mathbb{H}(\cdot) \) denote the entropy and \( f(y|x) \) denote the predicted confidence for \( y \) given \( x \). We then represent the loss term for MPPIs as \( \mathcal{L}_{MPPI} \), where the constant \( C = 10 \) is chosen such that maximizing the entropy will minimize the loss. We use \( \lambda = 0.1 \) as the most effective choice in our limited set of trials. The full loss term, for all inter-mixed regular question answering, and MPPI examples is the sum of standard QA loss \( \mathcal{L}_{QA} \), and the MPPI loss term \( \mathcal{L}_{MPPI} \), as shown in Equation 3.

In Figure 3 we display the full comparison between the performances of the MPPI regularized models and the regular models on 13 QA datasets, including Adversarial SQuAD (Jia and Liang, 2017).

B How do MPPI Lengths Compare?

In the main paper we describe the differences in length distributions between original and MPPI queries. To provide more detail into the length distributions we plot histograms of the query word lengths, for the original queries, MPPI queries, and MPPI queries after the MPPI regularization procedure. These lengths are plotted below for SQuAD (Figure 4), HotpotQA (Figure 5), NewsQA (Figure 6), Natural Questions (Figure 7), TriviaQA (Figure 8), and SearchQA (Figure 9).
Figure 3: The generalization and robustness of BERT models evaluated on 12 datasets, as well as Adversarial SQuAD. The “(*)” indicates MPPI-regularization during training.

The query length distributions show that MPPIs are significantly shorter than original queries, with the MPPIs of regularized models somewhere in between. These length distributions may be sufficient to explain why humans find the non-regularized MPPIs completely uninterpretable, and the regularized MPPIs somewhat more interpretable.

C Are MPPIs Human Insufficient?

In the main paper we define the “human insufficiency” property as the inability for humans to make accurate or confident predictions on most MPPIs. This can be roughly measured in F1 or Exact Match as the human performance on the question answering task, using MPPI queries. Feng et al. (2018) began benchmarking this measure of human interpretability with DrQA on SQuAD. They found human annotators achieved an Exact Match of 31.7%, significantly lower than the 82.3% on the original, well-formed input, and much lower than the neural model could achieve. (They also show that humans do not prefer MPPI queries over a random sub-sequence of words dervied from the original query, in order to predict the answer.)

We conducted the same annotation task for BERT and XLNet models on SQuAD to examine if significant pre-training, and superior performance affects the human interpretability of MPPIs. The results are shown in Table 7. We also provide the random baseline for comparison, comprising of randomly selected tokens from the query, to match the length distribution of BERT’s MPPI queries.

In Table 7 we see the same behavior for BERT and XLNet. Compared to the “Original” human performance on SQuAD, their MPPIs are far worse for humans to make accurate predictions. Instead, there appears to be no significant human interpretability difference between the MPPIs generated by large pre-trained models and those generated by non-pretrained models. Additionally, we observe human performance on these MPPIs are slightly better than “Randomly” shortened queries, and MPPI regularization significantly improves interpretability.

D Are MPPIs Invariant to Random Seed?

One of the preliminary questions in our investigation was whether changing the random training seed significantly altered the MPPI produced by a model. If it were the case that this had a drastic effect, we might suspect MPPIs were some-
Table 8: Observing the Jaccard Similarity and Exact Match between MPPIs on the SQuAD 2k evaluation set, we see significant token overlap despite seed differences. In contrast, the randomly generated sequences, preserving the length distribution of MPPIs, produces far less similar token sequences.

| Seed A | Seed B | JS / EM |
|--------|--------|---------|
| 0      | 1      | 55.0 / 31.7 |
| 2      | 3      | 56.8 / 33.2 |
| 4      | 5      | 58.3 / 34.7 |
| 6      | 7      | 57.4 / 33.2 |
| 8      | 9      | 58.1 / 35.2 |

Overall 57.1 / 33.6

Rand-A Rand-B 13.8 / 0.9

Their similarity metrics far exceed those of Rand-A, and Rand-B, which are akin to a “random” simulation of MPPIs. As with our previous random baselines these are generated by randomly sampling tokens from the original query, preserving word order, and ensuring that the length distribution matches that of the actual MPPIs to which they are being compared.

**E Are MPPIs Invariant to Training Domain?**

We discussed the invariance of MPPIs to training domain at length in the paper for BERT. For completeness, we provide the raw results. The cross-domain generalization of BERT and XLNet models on MPPIs sourced from different training domains is available in Table 9 and Table 10 respectively. Figure 10 visualizes how well XLNet generalizes to different MPPI domains.

F Do QA Models Generalize to different MPPI Domains?

Expanding on the MPPI generalization analysis in Section 3.2, we provide the raw results. The cross-domain generalization of BERT and XLNet models on MPPIs sourced from different training domains is available in Table 11 and Table 12 respectively. Figure 10 visualizes how well XLNet generalizes to different MPPI domains.

\[
GJS(X, Y) = \frac{\sum_{i=1}^{n} \min(X_i, Y_i)}{\sum_{i=1}^{n} \max(X_i, Y_i)} \tag{4}
\]

Their similarity metrics far exceed those of Rand-A, and Rand-B, which are akin to a “random” simulation of MPPIs. As with our previous random baselines these are generated by randomly sampling tokens from the original query, preserving word order, and ensuring that the length distribution matches that of the actual MPPIs to which they are being compared.

Figure 10: XLNet performance with different training sets (y-axis), and evaluation sets (x-axis). Bars measure the F1 score on the 2k evaluation set, colored by input type.
### Table 9: The Jaccard Similarity (%) between BERT generated MPPIs, across domains. The Random baseline MPPIs are in parentheses.

| Train Dataset | SQUAD | HotPotQA | NEWSQA | NATRUALQ | TRIVIAQA | SEARCHQA |
|---------------|-------|----------|--------|----------|----------|----------|
| SQUAD Original | 87.74 | 56.31 | 48.81 | 21.53 | 56.74 | 52.62 |
| SQUAD MPPI | 87.74 | 28.84 | 31.68 | 13.52 | 43.02 | 30.93 |
| SQUAD Random MPPI | 26.42 | 16.19 | 19.69 | 9.55 | 13.01 | 17.46 |
| TriviaQA Original | 54.64 | 71.04 | 42.27 | 38.9 | 75.09 | 34.45 |
| TriviaQA MPPI | 34.25 | 71.04 | 24.67 | 32.28 | 33.85 | 18.91 |
| TriviaQA Random MPPI | 15.21 | 32.23 | 15.92 | 25.49 | 14.12 | 12.67 |
| NaturalQ Original | 75.28 | 58.18 | 77.78 | 37.84 | 54.08 | 51.16 |
| NaturalQ MPPI | 55.15 | 40.43 | 77.78 | 24.32 | 44.52 | 34.25 |
| NaturalQ Random MPPI | 23.28 | 23.94 | 38.43 | 18.39 | 16.32 | 17.34 |
| SearchQA Original | 40.25 | 59.44 | 32.58 | 78.11 | 35.93 | 20.61 |
| SearchQA MPPI | 24.84 | 41.67 | 21.24 | 78.11 | 24.96 | 15.9 |
| SearchQA Random MPPI | 11.92 | 24.69 | 14.73 | 45.7 | 12.34 | 9.7 |
| HotpotQA Original | 71.52 | 53.4 | 32.51 | 38.9 | 75.09 | 34.45 |
| HotpotQA MPPI | 49.52 | 34.56 | 37.23 | 20.66 | 75.09 | 30.38 |
| HotpotQA Random MPPI | 21.09 | 19.28 | 24.92 | 15.2 | 17.76 | 17.88 |
| NewsQA Original | 78.16 | 60.91 | 59.94 | 33.79 | 56.53 | 68.19 |
| NewsQA MPPI | 61.32 | 39.17 | 42.48 | 19.44 | 48.58 | 68.19 |
| NewsQA Random MPPI | 22.78 | 20.4 | 22.74 | 15.05 | 14.49 | 24.83 |

### Table 10: The Jaccard Similarity (%) between XLNET generated MPPIs, across domains. The Random baseline MPPIs are in parentheses.

| Train Dataset | SQUAD | HotPotQA | NEWSQA | NATRUALQ | TRIVIAQA | SEARCHQA |
|---------------|-------|----------|--------|----------|----------|----------|
| SQUAD Original | 25.8 (9.0) | 37.7 (19.7) | 30.9 (11.1) | 18.1 (10.5) | 22.7 (26.3) |
| SQUAD MPPI | 28.4 (15.3) | 31.2 (17.6) | 31.5 (12.4) | 17.8 (12.0) | 27.1 (25.5) |
| SQUAD Random MPPI | 31.8 (13.1) | 25.3 (8.2) | 36.6 (11.9) | 20.6 (9.0) | 13.3 (11.7) |
| TriviaQA Original | 29.9 (12.9) | 42.4 (8.4) | 40.2 (16.8) | 22.3 (11.0) | 19.2 (16.3) |
| TriviaQA MPPI | 25.6 (14.8) | 19.0 (8.0) | 29.8 (17.4) | 29.2 (13.7) | 31.2 (20.6) |
| TriviaQA Random MPPI | 21.6 (13.8) | 15.5 (7.7) | 25.2 (15.1) | 24.6 (14.1) | 28.3 (13.4) |
| Average | 27.5 (14.0) | 22.0 (8.3) | 32.8 (17.3) | 30.6 (12.6) | 21.4 (11.2) | 22.7 (20.1) |

### Table 11: Cross-Domain Generalization of BERT Base models on different types of inputs. Values correspond to F1 scores on the question answering 2k evaluation set specified by the column.

| Train Dataset | Query Type | SQUAD | HotpotQA | NewsQA | NaturalQ | TriviaQA | SearchQA |
|---------------|------------|-------|----------|--------|----------|----------|----------|
| SQUAD Original | 87.74 | 56.31 | 48.81 | 21.53 | 56.74 | 52.62 |
| SQUAD MPPI | 87.74 | 28.84 | 31.68 | 13.52 | 43.02 | 30.93 |
| SQUAD Random MPPI | 26.42 | 16.19 | 19.69 | 9.55 | 13.01 | 17.46 |
| TriviaQA Original | 34.64 | 71.04 | 42.27 | 47.53 | 51.85 | 34.45 |
| TriviaQA MPPI | 34.25 | 71.04 | 24.67 | 32.28 | 33.85 | 18.91 |
| TriviaQA Random MPPI | 15.21 | 32.23 | 15.92 | 25.49 | 14.12 | 12.67 |
| NaturalQ Original | 75.28 | 58.18 | 77.78 | 37.84 | 54.08 | 51.16 |
| NaturalQ MPPI | 55.15 | 40.43 | 77.78 | 24.32 | 44.52 | 34.25 |
| NaturalQ Random MPPI | 23.28 | 23.94 | 38.43 | 18.39 | 16.32 | 17.34 |
| SearchQA Original | 40.25 | 59.44 | 32.58 | 78.11 | 35.93 | 20.61 |
| SearchQA MPPI | 24.84 | 41.67 | 21.24 | 78.11 | 24.96 | 15.9 |
| SearchQA Random MPPI | 11.92 | 24.69 | 14.73 | 45.7 | 12.34 | 9.7 |
| HotpotQA Original | 71.52 | 53.34 | 32.51 | 38.9 | 75.09 | 47.03 |
| HotpotQA MPPI | 49.52 | 34.56 | 37.23 | 20.66 | 75.09 | 30.38 |
| HotpotQA Random MPPI | 21.09 | 19.28 | 24.92 | 15.2 | 17.76 | 17.88 |
| NewsQA Original | 78.16 | 60.91 | 59.94 | 33.79 | 56.53 | 68.19 |
| NewsQA MPPI | 61.32 | 39.17 | 42.48 | 19.44 | 48.58 | 68.19 |
| NewsQA Random MPPI | 22.78 | 20.4 | 22.74 | 15.05 | 14.49 | 24.83 |
| Train Dataset | Query Type | SQuAD | HotpotQA | NewsQA | NaturalQ | TriviaQA | SearchQA |
|---------------|------------|-------|----------|--------|----------|----------|----------|
| SQuAD         | Original   | 93.92 | 64.97    | 66.62  | 15.13    | 70.51    | 65.06    |
| SQuAD         | MPPI       | 93.95 | 17.75    | 39.95  | 6.37     | 41.36    | 35.27    |
| SQuAD         | Random MPPI| 31.0  | 12.86    | 21.12  | 7.3      | 16.19    | 17.85    |
| TriviaQA      | Original   | 67.55 | 78.15    | 51.7   | 67.69    | 57.85    | 44.97    |
| TriviaQA      | MPPI       | 31.77 | 78.18    | 27.8   | 43.63    | 32.34    | 22.24    |
| TriviaQA      | Random MPPI| 17.01 | 34.03    | 16.03  | 33.18    | 14.54    | 13.27    |
| NaturalQ      | Original   | 85.61 | 67.84    | 82.06  | 42.92    | 67.43    | 60.82    |
| NaturalQ      | MPPI       | 63.02 | 35.73    | 82.06  | 20.44    | 46.19    | 42.95    |
| NaturalQ      | Random MPPI| 31.74 | 23.31    | 36.07  | 18.05    | 19.98    | 22.45    |
| SearchQA      | Original   | 55.23 | 74.37    | 43.43  | 84.08    | 45.33    | 32.82    |
| SearchQA      | MPPI       | 25.6  | 47.5     | 26.33  | 84.08    | 29.41    | 18.57    |
| SearchQA      | Random MPPI| 15.92 | 33.29    | 16.81  | 53.58    | 15.57    | 12.13    |
| HotpotQA      | Original   | 82.85 | 61.03    | 61.93  | 23.98    | 80.28    | 54.19    |
| HotpotQA      | MPPI       | 51.11 | 14.57    | 40.95  | 9.08     | 80.3     | 23.66    |
| HotpotQA      | Random MPPI| 27.83 | 14.0     | 23.89  | 14.03    | 21.33    | 15.25    |
| NewsQA        | Original   | 88.56 | 69.32    | 67.61  | 30.74    | 69.14    | 73.17    |
| NewsQA        | MPPI       | 65.64 | 29.66    | 48.56  | 11.0     | 45.15    | 73.12    |
| NewsQA        | Random MPPI| 30.47 | 16.29    | 20.27  | 6.64     | 15.71    | 25.35    |

Table 12: Cross-Domain Generalization of XLNET. Large models on different types of inputs. Values correspond to F1 scores on the question answering task evaluation set specified by the column.