

DQI: A Guide to Benchmark Evaluation

Swaroop Mishra¹ Anjana Arunkumar¹ Bhavdeep Sachdeva¹ Chris Bryan¹ Chitta Baral¹

Abstract

A ‘state of the art’ model A surpasses humans in a benchmark B , but fails on similar benchmarks C , D , and E . What does B have that the other benchmarks do not? Recent research provides the answer: spurious bias. However, developing A to solve benchmarks B through E does not guarantee that it will solve future benchmarks. To progress towards a model that ‘truly learns’ an underlying task, we need to quantify the differences between successive benchmarks, as opposed to existing binary and black-box approaches. We propose a novel approach to solve this underexplored task of quantifying benchmark quality by debuting a data quality metric: DQI.

1. Introduction

We evaluate progress in various AI domains such as NLP and Vision by building and solving increasingly harder benchmarks (and hence developing new models and architectures). Since this involves heavy investment in resources (time, money, hardware, etc.), it is reasonable to ask: *Can we rely on these benchmarks?* A growing number of recent works (Gururangan et al., 2018; Schwartz et al., 2017; Polliak et al., 2018; Kaushik and Lipton, 2018; Le Bras et al., 2020) reveal that models exploit spurious biases (unintended correlations between input and output (Torralba and Efros, 2011)) instead of the actual underlying features to solve many popular benchmarks. This begs a new question: *How do we mitigate spurious biases in benchmarks?*

Recently proposed approaches that address this include dataset pruning (Sakaguchi et al., 2019; Li and Vasconcelos, 2019; Li et al., 2018; Wang et al., 2018), residual learning (Clark et al., 2019; He et al., 2019; Mahabadi and Henderson, 2019), adversarial dataset creation (Zellers et al., 2018; Nie et al., 2019), and counterfactual data augmentation (Kaushik et al., 2019; Gardner et al., 2020). Each focuses on a specific part of the data-model loop, as illus-

trated in Figure 1, but all are limited by binary evaluation: (i) accepting or rejecting a data sample created by a crowd-worker (Nie et al., 2019), (ii) retaining or removing data with adversarial filtering (Sakaguchi et al., 2019; Li and Vasconcelos, 2019; Li et al., 2018), (iii) augmenting only counterfactual data (Kaushik et al., 2019; Gardner et al., 2020), and/or (iv) including data only if it can fool the model (Zellers et al., 2018; Nie et al., 2019).

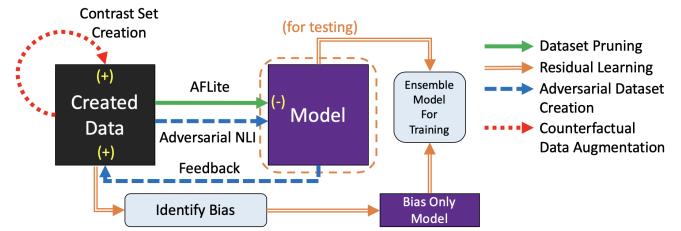


Figure 1. Existing approaches to eliminate bias

Binary evaluation is restrictive as it only allows inclusion or deletion of data, and further appends an overhead on human evaluators as there is uncertainty in class distinction. These approaches can also introduce new kinds of bias, and overfit to a specific model or task (Liu et al., 2019). Other limitations include: (i) wastage of resources invested in creating initial ‘biased’ data, (ii) a dataset creator does not learn what constitutes biased data, and is likely to repeat mistakes, (iii) important aspects of bias, like its dependency on a train-test split, are ignored, (iv) model training on each iteration increases time complexity, and (v) the absence of a suitable and illustrative feedback channel. A metric *quantifying benchmark quality* could address these issues, but remains underexplored.

As a solution, we propose a novel metric: Data Quality Index (DQI), building on a recent work (Mishra et al., 2020b) which identifies potential bias parameters based on a broad survey of AI literature. We construct an empirical formula for DQI based on these parameters with seven components and a varying number of sub-components and terms (e.g., NLI has 20 sub-components and 133 terms). In our study, lower bias and higher generalizability imply higher DQI.

DQI also captures a broad range of biases, unlike existing binary and black-box approaches (which only consider a specific set of biases). Specifically, we evaluate DQI against

¹Department of Computer Science, Arizona State University. Correspondence to: Swaroop Mishra <srmishr1@asu.edu>.

AFLite, a recent successful adversarial filtering approach, over NLI, QA, and RC datasets. In this paper, we focus on DQI for NLP, though our approach can be extended to other domains such as vision and speech.

DQI is inspired by successful quality indices in domains such as power (Bollen, 2000), air (Jones, 1999), food (Grunert, 2005) and water (Organization, 1993). On a related note, Data Shapley (Ghorbani and Zou, 2019) has been proposed as a metric to quantify the value of each training datum to the predictor performance, but follows a model and task-dependent approach and might fail when biases favor the predictor. So, we focus on building a generic DQI with minimal dependency on models and tasks.

2. DQI

DQI utilizes a generic parameter set (Mishra et al., 2020b) that captures bias properties—including origins, types and impact on performance, generalization, and robustness—for a hierarchy of datasets ranging from NLI to Text Summarization. We abstract this set and use appropriate mathematical transformations to algorithmically compute DQI. Our intuition is simple: a data quality metric should discourage biased samples and encourage samples with higher generalization capability (Mishra et al., 2020a). DQI has seven components corresponding to seven properties that cover various possible inter/intra-sample interactions in an NLP dataset, isolating those which lead to bias¹.

Formalization: Let X represent a dataset with size as its number of samples. X has vocabulary v , over a set of sentences S , with s denoting sentence lengths across S . Let the set of granularities across X be referenced as $i \in \{\text{Words}, \text{Verbs}, \text{Adjectives}, \text{Nouns}, \text{Adverbs}, \text{Bigram}, \text{Trigram}, \text{Sentences}\}$, with ν representing their respective frequencies, and c and d hyperparameters constraining ν . Let l span S , and Sim_{lm} represent sentence similarity between the l^{th} sentence and m^{th} sentence of S , where m spans $S - \{l\}$. SIM is a hyperparameter that is a lower bound for Sim_{lm} . e is a hyperparameter that depends on size , which is the minimum threshold for the number of sentences spanned by m where $\text{Sim}_{lm} > SIM$, and \max_{me} represents the similarity values for the top e sentences, for every $l \in S$. Let $WSim_{uv}$ stands for word similarity between the u^{th} word and the v^{th} word where u spans every word in a sentence $s' \in S$, and v spans $s' - \{u\}$, $WSIM$ is a hyperparameter dependent on size that represents the minimum threshold for $WSim_{uv}$. Let p represent sentences from one side and h represent sentences from the other side, such as premise and hypothesis respectively in NLI. $ISIM$ is a hyperparameter that represents the lower

¹More details about components and the intuition behind them are in supplemental materials

bound for Sim_{ph} , which is the similarity between p and h , with s_p and s_h representing premise and hypothesis lengths respectively. u_w represents unique words in p and h , q spans the sample, and q_p and q_h span the premise and hypothesis respectively. Let g be the upper limit for respective $i \in \{\text{Words}, \text{Verbs}, \text{Adjectives}, \text{Nouns}, \text{Adverbs}, \text{Bigram}, \text{Trigram}, \text{Sentences}\}$ across any individual label. Count_{label} is a vector of size labels , where labels represents the number of labels, which represents how many times each element of each i granularity has been assigned each of the labels, $label$. Let X_{train} and X_{test} represent the train and test splits respectively of X . $\text{Sim}_{train-test}$ stands for similarity between the train and test data and $SSIM$ is a hyperparameter that represents the optimal value of $\text{Sim}_{train-test}$. Let sgn represent the signum function. DQI_C represents DQI components as follows:

Vocabulary:

$$DQI_{c1} = \frac{v(X)}{\text{size}(X)} + \sigma(s(X)) * \frac{\sum_i \text{sgn}((s-a)(b-s))}{\text{size}(S)} \quad (1)$$

Inter-Sample N-gram Frequency and Relation:

$$DQI_{c2} = \sum_i \left(\frac{1}{\sigma(\frac{i(\nu)}{\text{size}(i)})} * \frac{\sum_i ((\nu_i - c)(d - \nu_i))}{\text{size}(i)} \right) \quad (2)$$

Inter-Sample STS:

$$DQI_{c3} = \frac{\sum_{\forall l \nu} \frac{\text{size}(S)}{\text{sgn}(\frac{|Sim_{lm} - SIM| - (Sim_{lm} - SIM)}{2}) + 1}}{(\sum_l \sum_e \max_{me} (|Sim_{lm} - SIM| - (Sim_{lm} - SIM))) + 1} + \frac{2 * \text{size}(S)}{(\sum_l \sum_e \max_{me} (|Sim_{lm} - SIM| - (Sim_{lm} - SIM))) + 1} \quad (3)$$

Intra-Sample Word Similarity:

$$DQI_{c4} = \frac{\text{size}(S)}{\sum_s (\forall l | \frac{\sum_m WSim_{uv}}{\text{length}(s')} - WSIM |) + 1} \quad (4)$$

Intra-Sample STS:

$$DQI_{c5} = \frac{\text{size}(X)}{\sum_X |\forall_p \forall_h \text{Sim}_{ph} - ISIM| + 1} + \frac{\text{size}(X)}{\sum_X |(s_p - s_h)| + 1} + \frac{\sigma(|(s_p - s_h)|)}{\text{size}(X)} + \frac{\sigma(\forall_p \forall_h \text{Sim}_{ph})}{\text{size}(X)} + \frac{\sum_X (\frac{s_p + s_h}{\forall_u w \sum_q \text{sgn}(2 - \nu_q)})}{\text{size}(X)} + \frac{\sum_X (\frac{1}{\forall_u w \sum_{eq_h} \max_{v \in q} WSim_{uv}})}{\text{size}(X)} \quad (5)$$

N-Gram Frequency per Label:

$$DQI_{c6} = \frac{\sum_{\text{labels}} (\sum_i \frac{1}{\sigma(\frac{i(\nu)}{\text{size}(i)})} * \frac{\sum_i ((g - \nu_i))}{\text{size}(i)})}{(\sum_{X_{label}} (|(s_p - s_h)|) + 1)} + \frac{\sigma(|(s_p - s_h)|)}{\text{size}(X_{label})} + \frac{\sum_i \frac{\text{size}(i(X))}{(\sum_{i(X)} \sigma(\forall_X \frac{(|1 - Count_{label}| - (1 - Count_{label}))}{2})) + 1}}{\text{size}(X_{label})} \quad (6)$$

Inter-Split STS:

$$DQI_{c7} = \frac{\text{size}(X_{test})}{(\sum_{test} \left| \max_{X_{train}} Sim_{train-test} - SSIM \right|) + 1} \quad (7)$$

We propose the empirical formula of DQI as a function of all components.

$$DQI = f(DQI_1, DQI_2, DQI_3, DQI_4, DQI_5, DQI_6, DQI_7) \quad (8)$$

Since f depends on both task and dataset, it needs to be experimentally tuned.

3. Comparing Performance Against AFLite

We apply DQI to compare its performance to that of AFLite on four datasets: SNLI (Bowman et al., 2015), MNLI (Williams et al., 2017), SQuAD 2.0 (Rajpurkar et al., 2018), and Story CLOZE Task (Mostafazadeh et al., 2016). AFLite divides samples into *good* and *bad* splits, i.e. samples retained and removed on filtering. Mishra et al. (Mishra et al., 2020b) show that SNLI contains a large number of artifacts, and that the Story CLOZE Task also has a significant number of artifacts. MNLI and SQuAD 2.0 are shown to have a relatively smaller number of artifacts, thus ensuring an adversarial evaluation of DQI. We tune hyperparameters on 0.01% of data manually in a supervised manner, mimicking how humans learn quickly from a few samples.² We perform two types of evaluation: (i) overall analysis of 133 terms, and 7 components to ascertain AFLite intricacies, and (ii) individual sample analysis across the most sensitive sub-components.

3.1. Overall Analysis:

By applying DQI to AFLite³, we can analyze where AFLite fails and succeeds at sample splitting.

AFLite Failures: We specifically examine language features that AFLite fails to appropriately consider as artifacts. The DQI formulas are constructed such that the *good* split is expected to have higher sub-component values than the *bad* split.

Sentence length: We expect variation of sentence lengths to be high, as length has been found to be an important parameter related to bias in SNLI (Mishra et al., 2020b). We find that even though the second and third sub-components of the *Vocabulary* component are higher for the good split, the difference is less than expected. Sentence length variation follows a similar pattern for each split. This is confirmed by calculating the percentage differences of sentence lengths between the splits. The takeaway is that AFLite likely does

²Detailed tuning results with various hyperparameters are in supplemental materials.

³Detailed analysis of each DQI sub-component and experimental results for all datasets are in Supplemental Materials.

not appropriately consider data with sentence length associated bias, as we would otherwise expect to see sentences with outlier length values mainly placed in the *bad* split. This is further supported by sub-component three (fails for neutral and contradiction labels) and sub-component four (fails for contradiction label) of the *N-gram Frequency per Label* component—responsible for ensuring that models do not overfit towards a fixed-length difference.

Sentence Similarity: For the *Inter-sample STS* component, sub-component one dictates that the number of sentences that cross the threshold set for spurious bias should have lower variance: if the distributions of similarity for all sentences are skewed, this leads to spurious bias. We find that the *bad* split outperforms the *good* split, which indicates that AFLite might not be considering imbalance due to sentence similarity.

Premise-Hypothesis Similarity The *Intra-sample STS* component quantifies: (i) how far premise- hypothesis pairs are from a particular similarity threshold, (ii) how much the length variation, word overlap, and maximum word similarity between premise and hypothesis are, and (iii) how much is the variation in similarities across all pairs in the dataset. We expect significant⁴ differences for sub-components between the *good* and *bad* splits. However, both sub-component and overall component values do not show a significant difference across splits. This is surprising, as this component captures several major bias-related parameters (Mishra et al., 2020b). This indicates AFLite might not be accurately filtering data with high premise-hypothesis similarity and length difference.

Bigrams, Trigrams: We expect a non-skewed distribution of granularities both within and across labels. We find that the first sub-component for *N-gram Frequency per Label* fails for bigrams, and trigrams. AFLite is likely not handling these granularities appropriately. For bigrams and trigrams, the fifth sub-component again has a lower value for the *good* split, indicating AFLite is not effectively identifying artifacts for bigrams and trigrams.

Neutral Category: For the *N-gram Frequency per Label* component, the second sub-component fails in the neutral label for the sentence, adjective, adverb, verb, bigram, and trigram granularities. This indicates that AFLite is potentially not filtering appropriately for neutral category samples.

Train-Test Split: For the *Inter-Split STS* component, we find no significant difference in train-test similarity between the *good* and *bad* splits, though it is expected that the *bad* split will show much higher similarity, as inter-split similarity has been identified as an important source of bias in SNLI (Mishra et al., 2020b). This indicates AFLite is poten-

⁴Significance is defined as values of order greater than e-03 for this component.

| Components | DQI-C1 | | | DQI-C2 | | DQI-C3 | | DQI-C4 | | DQI-C5 | | | | | | DQI-C6 | | | | | DQI-C7 |
|----------------|--------|------|------|--------|------|--------|------|--------|------|--------|-------|-------|-------|-------|-------|--------|-------|-------|-------|-------|--------|
| Sub Components | SC-1 | SC-2 | SC-3 | SC-4 | SC-5 | SC-6 | SC-7 | SC-8 | SC-9 | SC-10 | SC-11 | SC-12 | SC-13 | SC-14 | SC-15 | SC-16 | SC-17 | SC-18 | SC-19 | SC-20 | |
| SNLI | | | | | | | | | | | | | | | | | | | | | |
| MNLI | | | | | | | | | | | | | | | | | | | | | |
| SQuAD 2.0 | | | | | | | | | | | | | | | | | | | | | |
| Story CLOZE | | | | | | | | | | | | | | | | | | | | N/A | |

Figure 2. Summarized results for SNLI, MNLI, SQuAD 2.0, and Story CLOZE Task. Green indicates that the sub-component, SC, has a higher value for the *good* split, and red for the *bad* split. Yellow indicates that a tie is seen between the *good* and *bad* splits. Inter-Split Similarity is not evaluated in Story CLOZE Task due to the absence of training data.

tially not properly incorporating artifacts related to the train-test split, such as data leakage.

AFLite Pass Cases: For the *Vocabulary* component, the *good* split has a higher overall value than the *bad* split. Of the three sub-components in this component, the first shows the most significant difference. The granularity variation in the *Inter-Sample N-Gram Frequency and Relation* component passes for all granularities except sentences, which we attribute to lower repetition of sentences compared to the other granularities. We also calculate this sub-component without normalization and find that it holds for sentences without normalization; the second sub-component passes in all cases. The second sub-component for *Inter-Sample STS* also passes. We also observe that the *Intra-Sample Word Similarity* component passes, indicating that AFLite captures *Word Noise* in SNLI. We note that contradiction samples seem more prone to spurious bias, due to a high ratio between the *bad* and *good* split sample counts in comparison to the entailment and neutral labels.

Other Datasets: Figure 2 summarizes results for SNLI, MNLI, SQuAD 2.0, and Story CLOZE Task.⁵ The number of sub-components for which the *good* split has higher DQI values than the *bad* split reduces as we move in order between SNLI, Story CLOZE Task, MNLI, and SQuAD 2.0. This is likely due to the decrease in the number of artifacts.

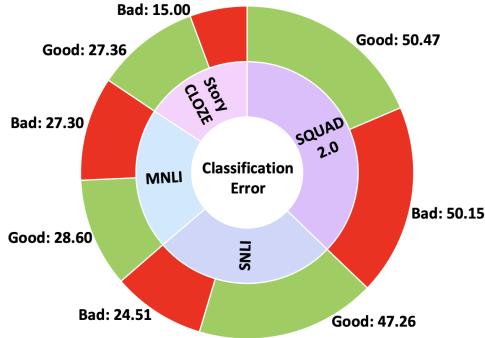


Figure 3. Misclassification percentages of AFLite, post evaluation using word overlap, word similarity and sentence length.

3.2. Sample-Wise Analysis

⁵Detailed results are in supplemental materials

We individually evaluate a subset of samples to quantify inconsistencies in AFLite. We set a minimum threshold value for DQI components to bin samples in the *good* split, by following the same steps as that of hyperparameter tuning (mentioned at the top of this section). Next, we calculate the DQI of samples in the *good* and *bad* splits and look for inconsistencies. Figure 3 summarizes the results, showing that 47.26% and 24.51% of SNLI samples are misclassified in the *good* and *bad* splits. The percentages for the other datasets are MNLI 28.60%/27.30%, SQuAD 2.0 50.47%/50.15%, and Story CLOZE Task 27.36%/15.00%.

4. Discussion: Towards a Paradigm Shift in Benchmarks and Models

DQI’s ability to quantify data quality can: (i) be leveraged to repair biased legacy datasets, (ii) provide realtime feedback to crowdworkers when creating samples for benchmarks, (iii) provide flexibility in controlling the ‘hardness’ of a benchmark by tuning relevant sub-components out of the 133 terms, (iv) help better utilize the investment of resources in creating datasets, as it does not require the deletion of biased data at a later stage, and (v) help understand which language properties are important to solve a dataset.

5. Conclusion

We introduce a novel metric Data Quality Index (DQI) to evaluate the quality of data in benchmarks. We build upon existing studies on bias and propose a formula for generic DQI. In contrast to existing binary and black-box approaches that only cover a specific set of biases, DQI captures a broad range of biases. DQI can serve as an automated mechanism to provide continuous feedback, neither overloading humans nor risking the possibility of bias associated with human validation. We use DQI to evaluate AFLite, a state of the art approach for adversarial filtering of NLP benchmarks. Our results show that DQI captures varieties of biases that AFLite does not capture. We show the efficacy of DQI in datasets spanning NLI, QA, and RC tasks. DQI already empowers the novel benchmarking paradigms in a series of recent works, and can further serve to inspire and validate the next generation of datasets and models.

Acknowledgements

We thank the anonymous reviewers for their thoughtful feedback. We also thank Jason Yalim and ASU HPC for their consistent support. The support of DARPA SAIL-ON program (W911NF2020006) is gratefully acknowledged.

References

- M. H. Bollen. Understanding power quality problems. In *Voltage sags and Interruptions*. IEEE press, 2000.
- S. R. Bowman, G. Angeli, C. Potts, and C. D. Manning. A large annotated corpus for learning natural language inference. *arXiv preprint arXiv:1508.05326*, 2015.
- C. Clark, M. Yatskar, and L. Zettlemoyer. Don’t take the easy way out: Ensemble based methods for avoiding known dataset biases. *arXiv preprint arXiv:1909.03683*, 2019.
- M. Gardner, Y. Artzi, V. Basmova, J. Berant, B. Bogin, S. Chen, P. Dasigi, D. Dua, Y. Elazar, A. Gottumukkala, et al. Evaluating nlp models via contrast sets. *arXiv preprint arXiv:2004.02709*, 2020.
- A. Ghorbani and J. Zou. Data shapley: Equitable valuation of data for machine learning. *arXiv preprint arXiv:1904.02868*, 2019.
- K. G. Grunert. Food quality and safety: consumer perception and demand. *European review of agricultural economics*, 32(3):369–391, 2005.
- S. Gururangan, S. Swayamdipta, O. Levy, R. Schwartz, S. R. Bowman, and N. A. Smith. Annotation artifacts in natural language inference data. *arXiv preprint arXiv:1803.02324*, 2018.
- H. He, S. Zha, and H. Wang. Unlearn dataset bias in natural language inference by fitting the residual. *arXiv preprint arXiv:1908.10763*, 2019.
- A. P. Jones. Indoor air quality and health. *Atmospheric environment*, 33(28):4535–4564, 1999.
- D. Kaushik and Z. C. Lipton. How much reading does reading comprehension require? a critical investigation of popular benchmarks. *arXiv preprint arXiv:1808.04926*, 2018.
- D. Kaushik, E. Hovy, and Z. C. Lipton. Learning the difference that makes a difference with counterfactually-augmented data. *arXiv preprint arXiv:1909.12434*, 2019.
- R. Le Bras, S. Swayamdipta, C. Bhagavatula, R. Zellers, M. E. Peters, A. Sabharwal, and Y. Choi. Adversarial filters of dataset biases. *arXiv*, pages arXiv–2002, 2020.
- Y. Li and N. Vasconcelos. Repair: Removing representation bias by dataset resampling. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 9572–9581, 2019.
- Y. Li, Y. Li, and N. Vasconcelos. Resound: Towards action recognition without representation bias. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 513–528, 2018.
- N. F. Liu, R. Schwartz, and N. A. Smith. Inoculation by fine-tuning: A method for analyzing challenge datasets. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 2171–2179, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1225. URL <https://www.aclweb.org/anthology/N19-1225>.
- R. K. Mahabadi and J. Henderson. simple but effective techniques to reduce biases. *arXiv preprint arXiv:1909.06321*, 2019.
- S. Mishra, A. Arunkumar, C. Bryan, and C. Baral. Our evaluation metric needs an update to encourage generalization. *arXiv preprint arXiv:2007.06898*, 2020a.
- S. Mishra, A. Arunkumar, B. Sachdeva, C. Bryan, and C. Baral. Dqi: Measuring data quality in nlp. *arXiv preprint arXiv:2005.00816*, 2020b.
- N. Mostafazadeh, N. Chambers, X. He, D. Parikh, D. Batra, L. Vanderwende, P. Kohli, and J. Allen. A corpus and evaluation framework for deeper understanding of commonsense stories. *arXiv preprint arXiv:1604.01696*, 2016.
- Y. Nie, A. Williams, E. Dinan, M. Bansal, J. Weston, and D. Kiela. Adversarial nli: A new benchmark for natural language understanding. *arXiv preprint arXiv:1910.14599*, 2019.
- W. H. Organization. *Guidelines for drinking-water quality*. World Health Organization, 1993.
- A. Poliak, J. Naradowsky, A. Haldar, R. Rudinger, and B. Van Durme. Hypothesis only baselines in natural language inference. *arXiv preprint arXiv:1805.01042*, 2018.
- P. Rajpurkar, R. Jia, and P. Liang. Know what you don’t know: Unanswerable questions for squad. *arXiv preprint arXiv:1806.03822*, 2018.
- K. Sakaguchi, R. L. Bras, C. Bhagavatula, and Y. Choi. Winogrande: An adversarial winograd schema challenge at scale. *arXiv preprint arXiv:1907.10641*, 2019.

R. Schwartz, M. Sap, I. Konstas, L. Zilles, Y. Choi, and N. A. Smith. The effect of different writing tasks on linguistic style: A case study of the roc story cloze task. *arXiv preprint arXiv:1702.01841*, 2017.

A. Torralba and A. A. Efros. Unbiased look at dataset bias. In *CVPR 2011*, pages 1521–1528. IEEE, 2011.

T. Wang, J.-Y. Zhu, A. Torralba, and A. A. Efros. Dataset distillation. *arXiv preprint arXiv:1811.10959*, 2018.

A. Williams, N. Nangia, and S. R. Bowman. A broad-coverage challenge corpus for sentence understanding through inference. *arXiv preprint arXiv:1704.05426*, 2017.

R. Zellers, Y. Bisk, R. Schwartz, and Y. Choi. Swag: A large-scale adversarial dataset for grounded commonsense inference. *arXiv preprint arXiv:1808.05326*, 2018.

6. Supplementary

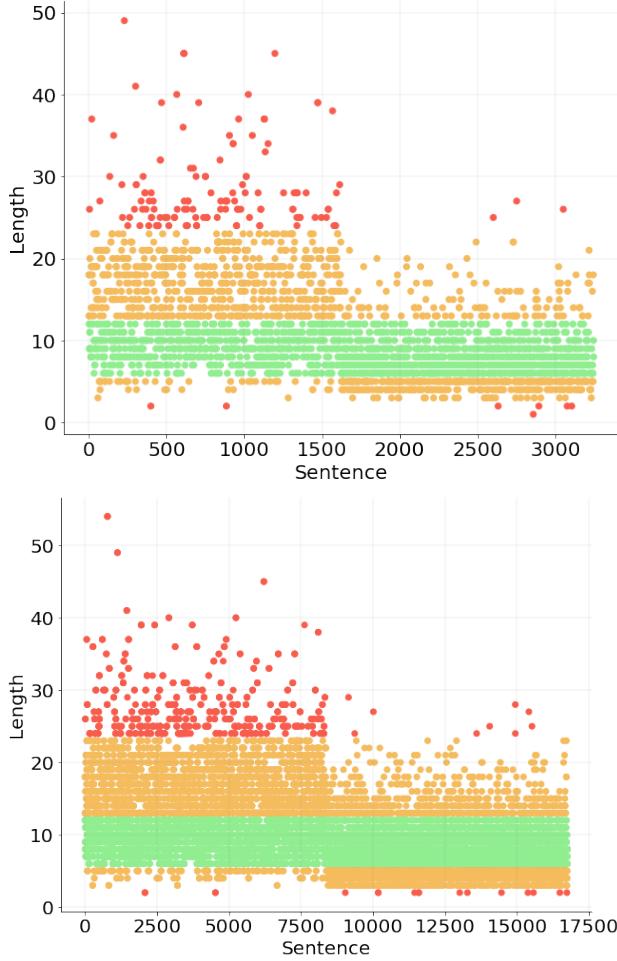


Figure 4. Sentences in SNLI visualized according to whether AFLite puts it in the *good* or *bad* split respectively. Each sentence is one dot; its vertical position denotes its length, and color indicates its DQI rating based on its Vocabulary component (green = good, orange = acceptable, red = bad).

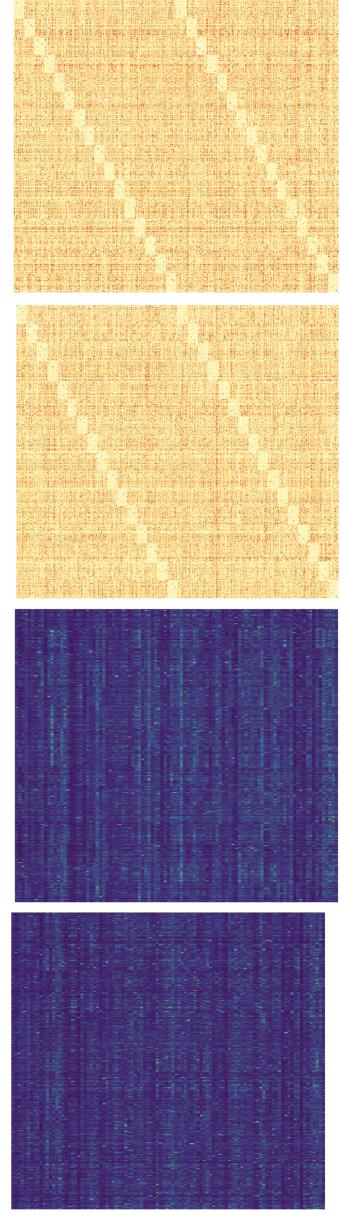


Figure 5. Semantic Textual Similarity plots where both row and column span all sentences in the dataset for C3 and rows represent train split and columns represent test split for C7. Color represents the similarity value. For C3 in the top two figures for the *good* and *bad* splits respectively, yellow represents zero similarity, and as the color moves towards red, the similarity increases. For C7 in the bottom two figures for the *good* and *bad* splits respectively, blue represents zero similarity, and as the color moves towards yellow, the similarity increases.

Vocabulary:

| Term | T1 | T2 | T3 | DQI C1 |
|------|--------|--------|--------|--------|
| Good | 1.8996 | 6.0409 | 0.9532 | 7.6578 |
| Bad | 0.6416 | 5.8135 | 0.9494 | 6.1609 |

Table 1. SNLI Sub-Component and Overall Values for DQI_{C1}

| Term | T1 | T2 | T3 | DQI C1 |
|------|---------------|-----------------|---------------|----------------|
| Good | 1.6177 | 104.6542 | 0.7550 | 80.6316 |
| Bad | 7.4100 | 14.1068 | 0.6020 | 15.9023 |

 Table 2. MNLI Sub-Component and Overall Values for DQI_{c1}

| Term | T1 | T2 | T3 | DQI C1 |
|------|----------------|----------------|---------------|----------------|
| Good | 1.7715 | 71.3947 | -0.0023 | 1.6073 |
| Bad | 11.1550 | 73.3092 | -0.001 | 11.1476 |

 Table 3. SQuAD 2.0 Sub-Component and Overall Values for DQI_{c1}

| Term | T1 | T2 | T3 | DQI C1 |
|------|---------------|----------------|---------------|---------------|
| Good | 3.3010 | 13.4569 | 0.2772 | 7.0313 |
| Bad | 4.7675 | 13.4895 | 0.2839 | 8.5972 |

 Table 4. Story-CLOZE Sub-Component and Overall Values for DQI_{c1}

Inter-Sample N-Gram Frequency and Relation:

| Granularity | Split | T1 | T2 | Contribution |
|------------------|-------|-------------------|---------------|------------------|
| Words | Good | 121.9512 | 0.7269 | 88.6463 |
| | Bad | 52.3560 | 0.6500 | 34.0314 |
| Adjectives | Good | 31.7460 | 0.2966 | 9.4159 |
| | Bad | 16.9205 | 0.3590 | 6.0745 |
| Adverbs | Good | 21.0970 | 0.1847 | 3.8966 |
| | Bad | 10.7875 | 0.1732 | 1.8684 |
| Verbs | Good | 43.6681 | 0.2349 | 10.2576 |
| | Bad | 16.5289 | 0.1893 | 3.1289 |
| Nouns | Good | 49.2611 | 0.4351 | 21.4335 |
| | Bad | 21.0084 | 0.3685 | 7.7416 |
| Bigrams | Good | 1296.3443 | 0.9374 | 1215.1931 |
| | Bad | 873.2862 | 0.9355 | 816.9592 |
| Trigrams | Good | 7686.3951 | 0.9546 | 7337.4328 |
| | Bad | 6119.9510 | 0.9422 | 5766.2178 |
| Sentences | Good | 9070.7819 | 0.6607 | 5993.0656 |
| | Bad | 14537.0541 | 0.2705 | 3932.2731 |
| Sentences | Good | 3.0656 | 0.6607 | 3.7263 |
| (Not Normalized) | Bad | 1.2655 | 0.2705 | 1.0607 |
| DQIC2 | Good | - | - | 8668.3012 |
| | Bad | - | - | 6636.3641 |

 Table 5. SNLI Sub-Component and Overall Values for DQI_{c2}

| Granularity | Split | T1 | T2 | Contribution |
|------------------|-------|-------------------|---------------|--------------------|
| Words | Good | 299.2489 | 0.9223 | 275.9972 |
| | Bad | 1026.2828 | 1.0000 | 1026.2828 |
| Adjectives | Good | 147.7382 | 1.0000 | 147.7382 |
| | Bad | 333.8001 | 1.0000 | 333.8001 |
| Adverbs | Good | 14.9467 | 0.5166 | 7.7214 |
| | Bad | 54.2488 | 0.7318 | 39.6992 |
| Verbs | Good | 76.0906 | 0.6893 | 52.4492 |
| | Bad | 182.7695 | 0.7130 | 130.3146 |
| Nouns | Good | 225.1162 | 0.9726 | 218.9480 |
| | Bad | 477.5051 | 0.9704 | 463.3709 |
| Bigrams | Good | 4394.8945 | 1.0000 | 4394.8945 |
| | Bad | 5615.4581 | 1.0000 | 5615.4581 |
| Trigrams | Good | 16628.8816 | 0.9907 | 16474.2330 |
| | Bad | 35285.2261 | 0.9735 | 34350.1676 |
| Sentences | Good | 15197.5684 | 0.0049 | 74.4680 |
| | Bad | 11085.6756 | 0.9680 | 10730.9339 |
| Sentences | Good | 1.2314 | 0.0049 | 0.0060 |
| (Not Normalized) | Bad | 11.1732 | 0.9680 | 10.8156 |
| DQIC2 | Good | - | - | 21646.4558 |
| | Bad | - | - | 52700.84312 |

 Table 6. MNLI Sub-Component and Overall Values for DQI_{c2}

| Granularity | Split | T1 | T2 | Contribution |
|------------------|-------|-------------------|---------------|--------------------|
| Words | Good | 138.6878 | 0.6744 | 93.5310 |
| | Bad | 615.0626 | 0.6224 | 382.8149 |
| Adjectives | Good | 37.0775 | 1.0000 | 37.0775 |
| | Bad | 161.0191 | 1.0000 | 161.0191 |
| Adverbs | Good | 4.0080 | 0.7473 | 2.9951 |
| | Bad | 18.7378 | 0.7610 | 14.2594 |
| Verbs | Good | 30.1469 | 0.9051 | 27.2859 |
| | Bad | 152.9500 | 0.9372 | 143.3447 |
| Nouns | Good | 58.5576 | 1.0000 | 58.5576 |
| | Bad | 255.8677 | 1.0000 | 255.8677 |
| Bigrams | Good | 1665.8142 | 0.9763 | 1626.3344 |
| | Bad | 4563.8191 | 0.9755 | 4452.0055 |
| Trigrams | Good | 20526.6346 | 1.0000 | 20526.6346 |
| | Bad | 39155.8925 | 0.9821 | 38455.0020 |
| Sentences | Good | 4811.1347 | -0.0013 | -6.2544 |
| | Bad | 1996.9248 | 0.2460 | 491.2435 |
| Sentences | Good | 0.3991 | -0.0013 | -0.0005 |
| (Not Normalized) | Bad | 1.3043 | 0.2460 | 0.3208 |
| DQIC2 | Good | - | - | 22366.1613 |
| | Bad | - | - | 44355.87788 |

 Table 7. SQuAD 2.0 Sub-Component and Overall Values for DQI_{c2}

| Granularity | Split | T1 | T2 | Contribution |
|------------------|-------|-------------------|---------------|--------------------|
| Words | Good | 396.9190 | 0.3661 | 145.3120 |
| | Bad | 52.3560 | 0.3239 | 16.9581 |
| Adjectives | Good | 77.3987 | 0.8307 | 64.2951 |
| | Bad | 70.2610 | 0.8020 | 56.3493 |
| Adverbs | Good | 17.3230 | 0.4292 | 7.4350 |
| | Bad | 27.8482 | 0.6178 | 17.2046 |
| Verbs | Good | 59.4638 | 0.5936 | 35.2977 |
| | Bad | 63.3871 | 0.5511 | 34.9326 |
| Nouns | Good | 270.8688 | 0.8953 | 242.5088 |
| | Bad | 250.9358 | 0.9289 | 233.0942 |
| Bigrams | Good | 4116.6448 | 1.0000 | 4116.6448 |
| | Bad | 2991.6306 | 1.0000 | 2991.6306 |
| Trigrams | Good | 30424.4890 | 1.0000 | 30424.4890 |
| | Bad | 17757.2356 | 0.9383 | 16661.6141 |
| Sentences | Good | 8161.7926 | -0.0015 | -12.2426 |
| | Bad | 2544.5235 | 0.0000 | 0.0000 |
| Sentences | Good | 2.1199 | -0.0015 | -0.0031 |
| (Not Normalized) | Bad | 2.1204 | 0.0000 | 0.0000 |
| DQIC2 | Good | - | - | 35023.73666 |
| | Bad | - | - | 20011.78371 |

 Table 8. Story CLOZE Sub-Component and Overall Values for DQI_{c2}

Inter-Sample STS:

| Split | SIML=0.3 | SIML=0.35 | SIML=0.4 |
|-------|----------------|----------------|----------------|
| Good | 9.1320 | 11.3955 | 14.3267 |
| Bad | 10.3842 | 13.1062 | 16.6390 |

 Table 9. SNLI Term 1 for DQI_{c3}

| Split | e=0.25 | e=0.33 | e=0.5 |
|-------|---------------|---------------|---------------|
| Good | 0.0468 | 0.0244 | 0.0103 |
| Bad | 0.0404 | 0.0216 | 0.0094 |

 Table 10. SNLI Term 2 for DQI_{c3} , with SIML=0.4

| Sample Set | DQI C3 (e=0.5) | DQI C3 (e=0.6) | DQI C3 (e=0.7) |
|------------|----------------|----------------|----------------|
| Good | 9.4123 | 11.4508 | 14.3370 |
| Bad | 10.3936 | 13.1156 | 16.7024 |

 Table 11. SNLI DQI_{C3}

| Split | SIML=0.3 | SIML=0.35 | SIML=0.4 |
|-------|----------|-----------|-----------|
| Good | 334.2154 | 695.0772 | 1040.5142 |
| Bad | 312.4684 | 643.3308 | 953.5445 |

 Table 12. MNLI Term 1 for DQI_{c3}

| Split | e=0.25 | e=0.33 | e=0.5 |
|-------|--------|--------|--------|
| Good | 0.0148 | 0.0108 | 0.0067 |
| Bad | 0.0111 | 0.0084 | 0.0056 |

 Table 13. MNLI Term 2 for DQI_{c3} , with SIML=0.4

| Sample Set | DQI C3 (e=0.5) | | |
|------------|----------------|----------|-----------|
| | SIM=0.5 | SIM=0.6 | SIM=0.7 |
| Good | 334.2221 | 695.0839 | 1040.5209 |
| Bad | 312.474 | 643.3364 | 953.5501 |

 Table 14. MNLI DQI_{C3}

| Split | SIML=0.3 | SIML=0.35 | SIML=0.4 |
|-------|----------|-----------|----------|
| Good | 129.8631 | 171.7117 | 228.9109 |
| Bad | 88.9812 | 110.6097 | 141.2737 |

 Table 15. SQuAD 2.0 Term 1 for DQI_{c3}

| Split | e=0.25 | e=0.33 | e=0.5 |
|-------|--------|--------|--------|
| Good | 0.0051 | 0.0039 | 0.0026 |
| Bad | 0.0055 | 0.0042 | 0.0094 |

 Table 16. SQuAD 2.0 Term 2 for DQI_{c3} , with SIML=0.4

| Sample Set | DQI C3 (e=0.5) | | |
|------------|----------------|----------|----------|
| | SIM=0.5 | SIM=0.6 | SIM=0.7 |
| Good | 129.8657 | 171.7143 | 228.9135 |
| Bad | 88.984 | 110.6125 | 141.2765 |

 Table 17. SQuAD 2.0 DQI_{C3}

| Split | SIML=0.3 | SIML=0.35 | SIML=0.4 |
|-------|----------|-----------|----------|
| Good | 285.1348 | 513.1720 | 820.2516 |
| Bad | 209.0823 | 368.5646 | 594.0969 |

 Table 18. Story CLOZE Term 1 for DQI_{c3}

| Split | e=0.25 | e=0.33 | e=0.5 |
|-------|--------|--------|--------|
| Good | 0.0069 | 0.0053 | 0.0036 |
| Bad | 0.0069 | 0.0053 | 0.0036 |

 Table 19. Story CLOZE Term 2 for DQI_{c3} , with SIML=0.4

| Sample Set | DQI C3 (e=0.5) | | |
|------------|----------------|----------|----------|
| | SIM=0.5 | SIM=0.6 | SIM=0.7 |
| Good | 285.1384 | 513.1756 | 820.2552 |
| Bad | 209.0859 | 368.5682 | 594.1005 |

 Table 20. Story CLOZE DQI_{C3}

Intra-Sample Word Similarity:

| Split | DQIC4 |
|-------|--------|
| Good | 0.0004 |
| Bad | 0.0001 |

 Table 21. SNLI DQI_{c4}

| Split | DQIC4 |
|-------|--------|
| Good | 0.0197 |
| Bad | 0.0011 |

 Table 22. MNLI DQI_{c4}

| Split | DQIC4 |
|-------|--------|
| Good | 5.2208 |
| Bad | 0.4577 |

 Table 23. SQuAD 2.0 DQI_{c4}

| Split | DQIC4 |
|-------|--------|
| Good | 0.0025 |
| Bad | 0.0008 |

 Table 24. Story CLOZE DQI_{c4}

Intra-Sample STS:

| Split | ISIM=0.3 | ISIM=0.4 | ISIM=0.5 | ISIM=0.6 |
|-------|----------|----------|----------|----------|
| Good | 2.2349 | 2.8763 | 4.0125 | 6.3065 |
| Bad | 2.2215 | 2.8558 | 3.9784 | 6.2237 |

 Table 25. SNLI Term 1 for DQI_{c5}

| Split | T2 | T3 | T4 | T5 | T6 |
|-------|--------|--------|------------|---------|--------|
| Good | 0.1439 | 0.0038 | 6.4064e-05 | 20.3518 | 0.0903 |
| Bad | 0.1430 | 0.0007 | 1.2711e-05 | 19.9288 | 0.0900 |

 Table 26. SNLI Terms 2,3,4,5,6 for DQI_{c5}

| Split | DQI C5 |
|-------|---------|
| Good | 24.6024 |
| Bad | 24.1409 |

 Table 27. SNLI DQI_{c5} , with ISIM=0.5

| Split | ISIM=0.3 | ISIM=0.4 | ISIM=0.5 | ISIM=0.6 |
|-------|----------|----------|----------|----------|
| Good | 2.2233 | 2.8585 | 3.9884 | 6.3364 |
| Bad | 2.1256 | 2.6986 | 3.6843 | 5.5845 |

 Table 28. MNLI Term 1 for DQI_{c5}

| Split | T2 | T3 | T4 | T5 | T6 |
|-------|--------|--------|-------------|---------|---------|
| Good | 0.0791 | 0.0162 | 1.1073E-05 | 15.3835 | 14.7547 |
| Bad | 0.0741 | 0.0307 | 20.9407E-05 | 12.3932 | 17.6181 |

 Table 29. MNLI Terms 2,3,4,5,6 for DQI_{c5}

| Split | DQI C5 |
|-------|---------|
| Good | 34.2219 |
| Bad | 33.8006 |

 Table 30. MNLI DQI_{c5} , with ISIM=0.5

| Split | ISIM=0.3 | ISIM=0.4 | ISIM=0.5 | ISIM=0.6 |
|-------|----------|----------|----------|----------|
| Good | 2.5073 | 3.3460 | 5.0031 | 9.1300 |
| Bad | 2.5379 | 3.4012 | 5.1352 | 9.6189 |

 Table 31. SQuAD 2.0 Term 1 for DQI_{c5}

| Split | T2 | T3 | T4 | T5 | T6 |
|-------|--------|--------|------------|---------|----------|
| Good | 0.0085 | 0.0052 | 7.3081E-06 | 22.9314 | 102.9990 |
| Bad | 0.0079 | 0.0524 | 7.4403E-05 | 27.0966 | 88.8872 |

 Table 32. SQuAD 2.0 Terms 2,3,4,5,6 for DQI_{c5}

| Split | DQI C5 |
|-------|----------|
| Good | 130.9472 |
| Bad | 121.1793 |

 Table 33. SQuAD 2.0 DQI_{c5} , with ISIM=0.5

| Split | ISIM=0.3 | ISIM=0.4 | ISIM=0.5 | ISIM=0.6 |
|-------|----------|----------|----------|----------|
| Good | 3.1103 | 4.5013 | 7.7337 | 14.4898 |
| Bad | 3.0639 | 4.4163 | 7.5943 | 14.7772 |

 Table 34. Story CLOZE Term 1 for DQI_{c5}

| Split | T2 | T3 | T4 | T5 | T6 |
|-------|--------|--------|------------|--------|------------|
| Good | 0.0400 | 0.0027 | 3.1939E-05 | 0.0400 | 2.6196e-06 |
| Bad | 0.0398 | 0.0084 | 9.7664E-05 | 0.0398 | 7.6306e-06 |

 Table 35. Story CLOZE Terms 2,3,4,5,6 for DQI_{c5}

| Split | DQI C5 |
|-------|--------|
| Good | 7.8164 |
| Bad | 7.6824 |

 Table 36. Story CLOZE DQI_{c5} , with ISIM=0.5

N-Gram Frequency Per Label

| Split/Label | Entailment | Neutral | Contradiction |
|-------------|------------|---------|---------------|
| Good | 1110 | 1430 | 708 |
| Bad | 5626 | 5008 | 6118 |

Table 37. SNLI Sample counts for Splits across Labels

DQI: A Guide to Benchmark Evaluation

| Split-Label | T1 | T2 |
|--------------------|-------------------|---------------|
| Good-Entailment | 8829.2425 | 0.9387 |
| Bad-Entailment | 21655.2868 | 0.8571 |
| Good-Neutral | 7467.5349 | 0.8699 |
| Bad-Neutral | 31616.2545 | 0.9141 |
| Good-Contradiction | 4932.7421 | 0.9210 |
| Bad-Contradiction | 29145.0957 | 0.8783 |

Table 38. SNLI Terms 1 and 2 for DQI_{c6} , Sentence Granularity

| Split-Label | T1 | T2 |
|--------------------|-----------------|---------------|
| Good-Entailment | 142.8571 | 0.7277 |
| Bad-Entailment | 81.9672 | 0.6110 |
| Good-Neutral | 153.8462 | 0.9118 |
| Bad-Neutral | 117.6471 | 0.7071 |
| Good-Contradiction | 163.9344 | 0.6764 |
| Bad-Contradiction | 101.0101 | 0.6088 |

Table 39. SNLI Terms 1 and 2 for DQI_{c6} , Word Granularity

| Split-Label | T1 | T2 |
|--------------------|----------------|----------------|
| Good-Entailment | 42.1230 | 0.34114 |
| Bad-Entailment | 26.4201 | 0.30551 |
| Good-Neutral | 48.8998 | 0.46865 |
| Bad-Neutral | 38.1534 | 0.47497 |
| Good-Contradiction | 43.1593 | 0.31019 |
| Bad-Contradiction | 29.2826 | 0.32385 |

Table 40. SNLI Terms 1 and 2 for DQI_{c6} , Adjective Granularity

| Split-Label | T1 | T2 |
|--------------------|----------------|----------------|
| Good-Entailment | 18.4128 | 0.056911 |
| Bad-Entailment | 11.0963 | 0.05816 |
| Good-Neutral | 8.6798 | 0.09709 |
| Bad-Neutral | 14.6135 | 0.43124 |
| Good-Contradiction | 37.9795 | 0.34286 |
| Bad-Contradiction | 23.7192 | 0.21583 |

Table 41. SNLI Terms 1 and 2 for DQI_{c6} , Adverb Granularity

| Split-Label | T1 | T2 |
|--------------------|----------------|----------------|
| Good-Entailment | 41.7885 | 0.16091 |
| Bad-Entailment | 22.9410 | 0.05348 |
| Good-Neutral | 48.9476 | 0.17946 |
| Bad-Neutral | 38.9105 | 0.20192 |
| Good-Contradiction | 53.5045 | 0.20000 |
| Bad-Contradiction | 34.6380 | 0.13589 |

Table 42. SNLI Terms 1 and 2 for DQI_{c6} , Verb Granularity

| Split-Label | T1 | T2 |
|--------------------|----------------|----------------|
| Good-Entailment | 59.2768 | 0.49650 |
| Bad-Entailment | 34.3643 | 0.38238 |
| Good-Neutral | 62.7353 | 0.44534 |
| Bad-Neutral | 46.4253 | 0.40586 |
| Good-Contradiction | 66.3570 | 0.45653 |
| Bad-Contradiction | 39.9202 | 0.37431 |

Table 43. SNLI Terms 1 and 2 for DQI_{c6} , Noun Granularity

| Split-Label | T1 | T2 |
|--------------------|------------------|----------------|
| Good-Entailment | 1131.7133 | 0.93307 |
| Bad-Entailment | 1173.5409 | 0.93206 |
| Good-Neutral | 1261.2663 | 0.93783 |
| Bad-Neutral | 1598.1514 | 0.94117 |
| Good-Contradiction | 1100.8597 | 0.94325 |
| Bad-Contradiction | 1369.0528 | 0.93387 |

Table 44. SNLI Terms 1 and 2 for DQI_{c6} , Bigram Granularity

| Split-Label | T1 | T2 |
|--------------------|-------------------|----------------|
| Good-Entailment | 5921.2942 | 0.94672 |
| Bad-Entailment | 7757.5306 | 0.93496 |
| Good-Neutral | 6414.8208 | 0.94517 |
| Bad-Neutral | 10229.7186 | 0.95015 |
| Good-Contradiction | 5478.1014 | 0.95359 |
| Bad-Contradiction | 8984.3224 | 0.94430 |

Table 45. SNLI Terms 1 and 2 for DQI_{c6} , Trigram Granularity

| Split-Repetition | 1 | 2 | 3 | 4 | 5 | 6 |
|--------------------|--------|--------|----------|---|--------|--------|
| Good-Entailment | 0.9844 | 0.0155 | 0 | 0 | 0 | 0 |
| Bad-Entailment | 0.9659 | 0.0308 | 0.001849 | 0 | 0.0007 | 0.0005 |
| Good-Neutral | 0.9667 | 0.0325 | 0.0007 | 0 | 0 | 0 |
| Bad-Neutral | 0.9785 | 0.0204 | 0.0010 | 0 | 0 | 0 |
| Good-Contradiction | 0.9798 | 0.0201 | 0 | 0 | 0 | 0 |
| Bad-Contradiction | 0.9785 | 0.0204 | 0.0010 | 0 | 0 | 0 |

Table 46. SNLI Sentence Granularity Repetitions

| Split-Label | T3 |
|--------------------|---------------|
| Good-Entailment | 0.1457 |
| Bad-Entailment | 0.1330 |
| Good-Neutral | 0.1496 |
| Bad-Neutral | 0.1571 |
| Good-Contradiction | 0.1313 |
| Bad-Contradiction | 0.1434 |

Table 47. SNLI T3 for DQI_{c6}

| Split-Label | T4 |
|--------------------|---------------|
| Good-Entailment | 0.0100 |
| Bad-Entailment | 0.0021 |
| Good-Neutral | 0.0084 |
| Bad-Neutral | 0.0022 |
| Good-Contradiction | 0.0197 |
| Bad-Contradiction | 0.0020 |

Table 48. SNLI T4 for DQI_{c6}

| Granularity/Split | Good | Bad |
|-------------------|----------------|---------------|
| Sentences | 15.3475 | 11.6614 |
| Words | 0.9313 | 0.6596 |
| Adjectives | 1.2190 | 0.9185 |
| Adverbs | 1.5708 | 1.1850 |
| Verbs | 0.9667 | 0.7001 |
| Nouns | 1.0623 | 0.7358 |
| Bigrams | 0.3646 | 0.4893 |
| Trigrams | 0.1860 | 0.2760 |

Table 49. SNLI T5 for DQI_{c6}

| Split-Label | DQI C6 |
|-------------|-----------------|
| Good | 556.6914 |
| Bad | 320.2893 |

Table 50. SNLI DQI_{c6}

| Split/Label | Entailment | Neutral | Contradiction |
|-------------|------------|---------|---------------|
| Good | 6150 | 6098 | 6082 |
| Bad | 700 | 60 | 240 |

Table 51. MNLI Sample counts for Splits across Labels

| Split-Label | T1 | T2 |
|--------------------|----------|--------|
| Good-Entailment | 2.69E+04 | 0.8133 |
| Bad-Entailment | 6.47E+03 | 0.9542 |
| Good-Neutral | 2.78E+04 | 0.8465 |
| Bad-Neutral | 4.76E+16 | 1.0000 |
| Good-Contradiction | 4.62E+04 | 0.9378 |
| Bad-Contradiction | 1.05E+17 | 1.0000 |

Table 52. MNLI Terms 1 and 2 for DQI_{c6} , Sentence Granularity

| Split-Label | T1 | T2 |
|--------------------|----------|-------------|
| Good-Entailment | 5.67E+02 | 0.970607701 |
| Bad-Entailment | 9.48E+02 | 0.957116548 |
| Good-Neutral | 8.70E+02 | 0.488048002 |
| Bad-Neutral | 6.74E+02 | 0.794573643 |
| Good-Contradiction | 9.40E+02 | 0.965482191 |
| Bad-Contradiction | 7.01E+02 | 0.885763001 |

Table 53. MNLI Terms 1 and 2 for DQI_{c6} , Word Granularity

| Split-Label | T1 | T2 |
|--------------------|----------|--------|
| Good-Entailment | 1.16E+02 | 0.7834 |
| Bad-Entailment | 2.83E+02 | 1.0000 |
| Good-Neutral | 2.86E+02 | 1.0000 |
| Bad-Neutral | 1.92E+02 | 0.8771 |
| Good-Contradiction | 3.47E+02 | 1.0000 |
| Bad-Contradiction | 2.67E+02 | 1.0000 |

Table 54. MNLI Terms 1 and 2 for DQI_{c6} , Adjective Granularity

| Split-Label | T1 | T2 |
|--------------------|----------|--------|
| Good-Entailment | 2.56E+01 | 0.4803 |
| Bad-Entailment | 5.20E+01 | 0.6531 |
| Good-Neutral | 3.61E+01 | 0.6091 |
| Bad-Neutral | 7.15E+01 | 0.6521 |
| Good-Contradiction | 3.43E+01 | 0.5017 |
| Bad-Contradiction | 5.19E+01 | 0.3939 |

Table 55. MNLI Terms 1 and 2 for DQI_{c6} , Adverb Granularity

| Split-Label | T1 | T2 |
|--------------------|----------|--------|
| Good-Entailment | 1.71E+02 | 0.7901 |
| Bad-Entailment | 1.61E+02 | 0.6620 |
| Good-Neutral | 1.43E+02 | 0.5911 |
| Bad-Neutral | 1.69E+02 | 0.3061 |
| Good-Contradiction | 1.79E+02 | 0.7271 |
| Bad-Contradiction | 1.30E+02 | 0.5636 |

Table 56. MNLI Terms 1 and 2 for DQI_{c6} , Verb Granularity

| Split-Label | T1 | T2 |
|--------------------|----------|--------|
| Good-Entailment | 2.61E+02 | 0.8994 |
| Bad-Entailment | 4.52E+02 | 0.9447 |
| Good-Neutral | 4.68E+02 | 1.0000 |
| Bad-Neutral | 2.61E+02 | 0.7235 |
| Good-Contradiction | 4.84E+02 | 1.0000 |
| Bad-Contradiction | 2.80E+02 | 0.9287 |

Table 57. MNLI Terms 1 and 2 for DQI_{c6} , Noun Granularity

| Split-Label | T1 | T2 |
|--------------------|----------|--------|
| Good-Entailment | 3.38E+03 | 0.9361 |
| Bad-Entailment | 4.83E+03 | 1.0000 |
| Good-Neutral | 9.21E+03 | 1.0000 |
| Bad-Neutral | 1.91E+03 | 1.0000 |
| Good-Contradiction | 1.04E+04 | 1.0000 |
| Bad-Contradiction | 2.97E+03 | 1.0000 |

Table 58. MNLI Terms 1 and 2 for DQI_{c6} , Bigram Granularity

| Split-Label | T1 | T2 |
|--------------------|----------|--------|
| Good-Entailment | 9.27E+03 | 0.9573 |
| Bad-Entailment | 2.93E+04 | 1.0000 |
| Good-Neutral | 4.54E+04 | 0.9913 |
| Bad-Neutral | 4.61E+03 | 0.8822 |
| Good-Contradiction | 1.04E+05 | 1.0000 |
| Bad-Contradiction | 6.96E+03 | 0.9937 |

Table 59. MNLI Terms 1 and 2 for DQI_{c6} , Trigram Granularity

| Split-Repetition | 1 | 2 | 3 |
|--------------------|--------|--------|--------|
| Good-Entailment | 0.9512 | 0.0484 | 0.0003 |
| Bad-Entailment | 0.9884 | 0.0115 | 0.0000 |
| Good-Neutral | 0.9612 | 0.0363 | 0.0024 |
| Bad-Neutral | 1.0000 | 0.0000 | 0.0000 |
| Good-Contradiction | 0.9844 | 0.0150 | 0.0005 |
| Bad-Contradiction | 1.0000 | 0.0000 | 0.0000 |

Table 60. MNLI Sentence Granularity Repetitions

| Split-Label | T3 |
|--------------------|--------|
| Good-Entailment | 0.0647 |
| Bad-Entailment | 0.0860 |
| Good-Neutral | 0.0926 |
| Bad-Neutral | 0.0590 |
| Good-Contradiction | 0.1000 |
| Bad-Contradiction | 0.2290 |

Table 61. MNLI T3 for DQI_{c6}

| Split-Label | T4 |
|--------------------|--------|
| Good-Entailment | 0.0803 |
| Bad-Entailment | 0.0202 |
| Good-Neutral | 0.0041 |
| Bad-Neutral | 0.0484 |
| Good-Contradiction | 0.2018 |
| Bad-Contradiction | 0.0326 |

Table 62. MNLI T4 for DQI_{c6}

| Split-Label | DQI C6 |
|-------------|----------|
| Good | 2.74E+05 |
| Bad | 1.53E+17 |

Table 63. MNLI DQI_{c6}

| Granularity/Split | Good | Bad |
|-------------------|---------|---------|
| Sentences | 14.6049 | 72.1687 |
| Words | 1.2571 | 0.8533 |
| Adjectives | 1.4557 | 1.7959 |
| Adverbs | 0.7319 | 0.9429 |
| Verbs | 1.0382 | 1.0345 |
| Nouns | 1.7755 | 1.5836 |
| Bigrams | 0.4008 | 0.3561 |
| Trigrams | 0.6547 | 0.9724 |

Table 64. MNLI T5 for DQI_{c6}

| Split/Label | True | False |
|-------------|-------|-------|
| Good | 10946 | 10770 |
| Bad | 914 | 1086 |

Table 65. SQuAD 2.0 Sample counts for Splits across Labels

| Split-Label | T1 | T2 |
|-------------|-----------|--------|
| Good-True | 4431.2159 | 0.0007 |
| Bad-True | 1921.2260 | 0.5448 |
| Good-False | 4412.2037 | 0.0014 |
| Bad-False | 1853.6963 | 0.5009 |

Table 66. SQuAD 2.0 Terms 1 and 2 for DQI_{c6} , Sentence Granularity

| Split-Label | T1 | T2 |
|-------------|----------|--------|
| Good-True | 263.6776 | 1.0000 |
| Bad-True | 954.5225 | 1.0000 |
| Good-False | 259.3381 | 0.3105 |
| Bad-False | 776.2031 | 1.0000 |

Table 67. SQuAD 2.0 Terms 1 and 2 for DQI_{c6} , Word Granularity

| Split-Label | T1 | T2 |
|-------------|----------|--------|
| Good-True | 75.3820 | 1.0000 |
| Bad-True | 244.8719 | 1.0000 |
| Good-False | 70.8210 | 1.0000 |
| Bad-False | 222.5754 | 1.0000 |

Table 68. SQuAD 2.0 Terms 1 and 2 for DQI_{c6} , Adjective Granularity

| Split-Label | T1 | T2 |
|-------------|---------|--------|
| Good-True | 6.31677 | 0.6666 |
| Bad-True | 27.6740 | 0.6494 |
| Good-False | 6.4805 | 0.6632 |
| Bad-False | 24.6482 | 0.6878 |

Table 69. SQuAD 2.0 Terms 1 and 2 for DQI_{c6} , Adverb Granularity

| Split-Label | T1 | T2 |
|-------------|----------|--------|
| Good-True | 58.2850 | 0.8789 |
| Bad-True | 219.8726 | 0.8851 |
| Good-False | 59.0344 | 0.9066 |
| Bad-False | 208.3846 | 0.9113 |

Table 70. SQuAD 2.0 Terms 1 and 2 for DQI_{c6} , Verb Granularity

| Split-Label | T1 | T2 |
|-------------|----------|--------|
| Good-True | 110.8118 | 1.0000 |
| Bad-True | 415.9473 | 1.0000 |
| Good-False | 109.7139 | 1.0000 |
| Bad-False | 307.1137 | 1.0000 |

Table 71. SQuAD 2.0 Terms 1 and 2 for DQI_{c6} , Noun Granularity

| Split-Label | T1 | T2 |
|-------------|-----------|--------|
| Good-True | 2923.9305 | 0.9768 |
| Bad-True | 5800.9793 | 0.9762 |
| Good-False | 2834.7978 | 0.9758 |
| Bad-False | 5157.4516 | 0.9749 |

Table 72. SQuAD 2.0 Terms 1 and 2 for DQI_{c6} , Bigram Granularity

| Split-Label | T1 | T2 |
|-------------|------------|--------|
| Good-True | 35363.3144 | 1.0000 |
| Bad-True | 49074.7258 | 1.0000 |
| Good-False | 34076.1381 | 1.0000 |
| Bad-False | 40854.1931 | 1.0000 |

Table 73. SQuAD 2.0 Terms 1 and 2 for DQI_{c6} , Trigram Granularity

| Split-Label | T3 |
|--------------------|-----------|
| Good-True | 0.0085 |
| Bad-True | 0.00852 |
| Good-False | 0.0079 |
| Bad-False | 0.0078 |

Table 74. SQuAD 2.0 T3 for DQI_{c6}

| Split-Label | T4 |
|--------------------|-----------|
| Good-True | 0.0104 |
| Bad-True | 0.0106 |
| Good-False | 0.1165 |
| Bad-False | 0.0954 |

Table 75. SQuAD 2.0 T4 for DQI_{c6}

| Granularity/Split | Good | Bad |
|--------------------------|-------------|------------|
| Sentences | 20.5287 | 9.6533 |
| Words | 0.0711 | 0.0682 |
| Adjectives | 0.6497 | 1.1487 |
| Adverbs | 0.4012 | 0.6832 |
| Verbs | 0.4918 | 0.8153 |
| Nouns | 0.5183 | 0.9957 |
| Bigrams | 0.1262 | 0.05600 |
| Trigrams | 0.1366 | 0.09422 |

Table 76. SQuAD 2.0 T5 for DQI_{c6}

| Split-Label | DQI C6 |
|--------------------|---------------|
| Good | 75918.2760 |
| Bad | 105949.3404 |

Table 77. SQuAD 2.0 DQI_{c6}

| Split/Label | True | False |
|--------------------|-------------|--------------|
| Good | 2568 | 2568 |
| Bad | 800 | 800 |

Table 78. Story CLOZE Sample counts for Splits across Labels

| Split-Label | T1 | T2 |
|--------------------|-----------|-----------|
| Good-True | 1.30E+05 | 0.9984 |
| Bad-True | 5.06E+16 | 1.0000 |
| Good-False | 1.30E+05 | 0.9984 |
| Bad-False | 5.06E+16 | 1.0000 |

Table 79. Story CLOZE Terms 1 and 2 for DQI_{c6} , Sentence Granularity

| Split-Label | T1 | T2 |
|--------------------|-----------|-----------|
| Good-True | 5.47E+05 | 0.9792 |
| Bad-True | 5.22E+05 | 0.8618 |
| Good-False | 5.47E+05 | 0.5316 |
| Bad-False | 4.96E+05 | 0.8537 |

Table 80. Story CLOZE Terms 1 and 2 for DQI_{c6} , Word Granularity

| Split-Label | T1 | T2 |
|--------------------|-----------|-----------|
| Good-True | 129.1883 | 0.7800 |
| Bad-True | 133.5904 | 0.7711 |
| Good-False | 121.0435 | 0.7459 |
| Bad-False | 128.3632 | 0.8014 |

Table 81. Story CLOZE Terms 1 and 2 for DQI_{c6} , Adjective Granularity

| Split-Label | T1 | T2 |
|--------------------|-----------|-----------|
| Good-True | 41.1600 | 0.5959 |
| Bad-True | 49.9482 | 0.5368 |
| Good-False | 36.9653 | 0.6145 |
| Bad-False | 54.7544 | 0.6194 |

Table 82. Story CLOZE Terms 1 and 2 for DQI_{c6} , Adverb Granularity

| Split-Label | T1 | T2 |
|--------------------|-----------|-----------|
| Good-True | 103.8261 | 0.5285 |
| Bad-True | 115.6968 | 0.5828 |
| Good-False | 112.3307 | 0.5946 |
| Bad-False | 113.4481 | 0.5155 |

Table 83. Story CLOZE Terms 1 and 2 for DQI_{c6} , Verb Granularity

| Split-Label | DQI C6 |
|--------------------|---------------|
| Good | 1.01E+17 |
| Bad | 1.01E+17 |

Table 90. Story CLOZE DQI_{c6}

| Split-Label | T1 | T2 |
|--------------------|-----------|-----------|
| Good-True | 551.3272 | 0.8898 |
| Bad-True | 458.9138 | 0.8862 |
| Good-False | 520.3204 | 0.9047 |
| Bad-False | 462.2876 | 0.9252 |

Table 84. Story CLOZE Terms 1 and 2 for DQI_{c6} , Noun Granularity

| Split-Label | T1 | T2 |
|--------------------|------------|-----------|
| Good-True | 7139.05776 | 1.0000 |
| Bad-True | 518.2473 | 1.0000 |
| Good-False | 6941.1989 | 1.0000 |
| Bad-False | 5006.1656 | 1.0000 |

Table 85. Story CLOZE Terms 1 and 2 for DQI_{c6} , Bigram Granularity

| Split-Label | T1 | T2 |
|--------------------|------------|-----------|
| Good-True | 54497.5504 | 1.0000 |
| Bad-True | 33876.9502 | 1.0000 |
| Good-False | 50906.0915 | 1.0000 |
| Bad-False | 33618.6103 | 1.0000 |

Table 86. Story CLOZE Terms 1 and 2 for DQI_{c6} , Trigram Granularity

| Split-Label | T3 |
|--------------------|-----------|
| Good-True | 0.0085 |
| Bad-True | 0.0079 |
| Good-False | 0.0085 |
| Bad-False | 0.0078 |

Table 87. Story CLOZE 2.0 T3 for DQI_{c6}

| Split-Label | T4 |
|--------------------|-----------|
| Good-True | 0.0104 |
| Bad-True | 0.1165 |
| Good-False | 0.0106 |
| Bad-False | 0.0954 |

Table 88. Story CLOZE 2.0 T4 for DQI_{c6}

| Granularity/Split | Good | Bad |
|--------------------------|-------------|------------|
| Sentences | 382.2842 | 2262.7417 |
| Words | 1.0447 | 1.0192 |
| Adjectives | 3.9910 | 5.0527 |
| Adverbs | 1.7714 | 3.1284 |
| Verbs | 2.2377 | 3.5188 |
| Nouns | 5.8841 | 7.3696 |
| Bigrams | 1.6522 | 1.9489 |
| Trigrams | 4.9660 | 6.8154 |

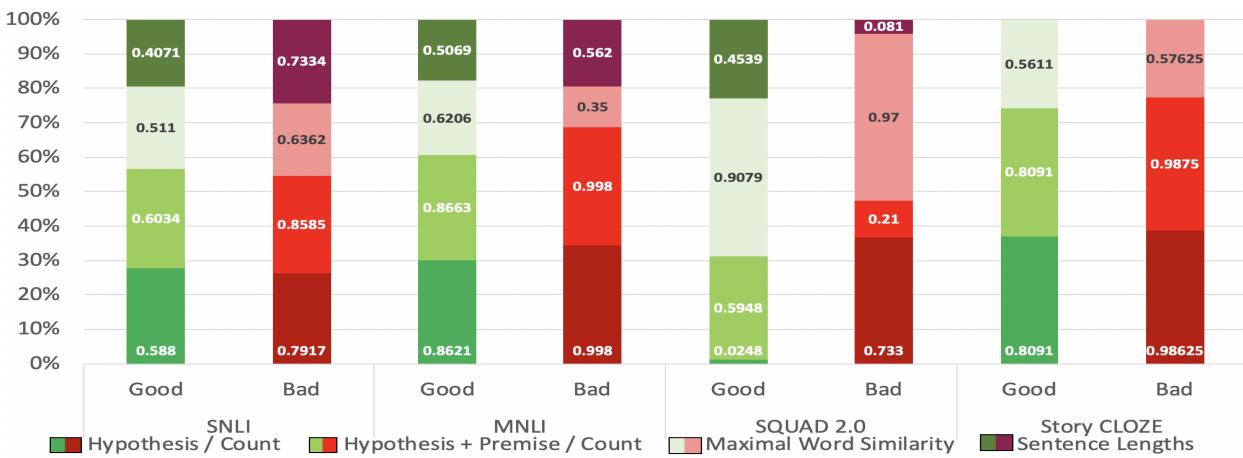
Table 89. Story CLOZE T5 for DQI_{c6}

| Split | SSMIL=0.2 | SSMIL=0.3 | SSMIL=0.4 |
|--------------|------------------|------------------|------------------|
| Good | 0.0004 | 0.0005 | 0.0002 |
| Bad | 0.0009 | 0.0011 | 0.0005 |

Table 92. MNLI DQI_{c7}

| Component | Sub-Component | Effect on Quality (Q) | Explanation |
|--|---|-----------------------|---|
| Vocabulary | Vocabulary Magnitude | $\propto Q$ | Low vocabulary provides lesser options to express thoughts, and may result in high repetition, leading to misunderstanding and potential bias |
| | Variation in Sentence Length | $\propto Q$ | Lack of variation in sentence length may act as a cue for a model to overfit |
| | Anomalies in Sentence Length | $\propto 1/Q$ | Longer sentences go to neutral, and shorter ones to entailment, so they may not contribute towards the total variation in sentence length |
| Inter-Sample N-Gram Frequency and Relation | Variation in Granularities | $\propto 1/Q$ | For Words, POS Tags, Bigrams, Trigrams, and Sentences, skewed distributions may allow overfitting |
| | Anomalies in Granularity Distribution | $\propto 1/Q$ | Both too much repetition and lack of usage may result in spurious bias. |
| Inter-Sample Semantic Textual Similarity (STS) | Variation of Degree of Isolation of a Sentence | $\propto 1/Q$ | Higher variation in the number of dissimilar sentences for each sentence may produce bias |
| | Characterization of Sentence Neighborhood | $\propto 1/Q$ | Absence of some minimum number of similar sentences may result in insufficient inductive bias to understand the sentence |
| Intra-Sample Word Similarity | Degree of Word Noise | $\propto 1/Q$ | This prevents adversarial attacks; a noisy sentence may be formed by repeating similar words many times, or by using very different words |
| Intra-Sample STS | Balancing Difficulty | $\propto 1/Q$ | Too similar or dissimilar a premise and hypothesis pair might reveal the label as either entailment or neutral, respectively |
| | Balancing Length Variation | $\propto 1/Q$ | If hypothesis length is too low or too high in comparison to the premise length , it can be an artifact |
| | Variation in Length Mismatch | $\propto Q$ | If length mismatch across the dataset does not vary significantly, a model can use it as a cue |
| | Variation in Difficulty | $\propto Q$ | Lesser variation in premise-hypothesis sentence similarity across a dataset may produce bias |
| | Word Overlap | $\propto 1/Q$ | Higher word overlap between the premise and hypothesis leads to bias |
| N-Gram Frequency Per Label | Word Similarity | $\propto 1/Q$ | Similar words in the premise and hypothesis in NLI allows a model to overfit |
| | Variation in Granularities Across Labels | $\propto 1/Q$ | A distribution skewed towards a specific label allows a model to exploit it as bias |
| | Anomalies in Granularity Distribution Across Labels | $\propto 1/Q$ | A highly frequent granularity element associated with a label may give rise to artifacts |
| | Balancing Length Variation Across Labels | $\propto Q$ | Frequent occurrence of premise-hypothesis length variation within a label leads to artifacts |
| | Variation in Length Mismatch Across Labels | $\propto 1/Q$ | A pattern in premise-hypothesis length variation for a label can cause bias |
| Inter-Split STS | Attachment with Label | $\propto 1/Q$ | A word or n-gram of any granularity becomes an artifact if it is associated with a specific label |
| | Balancing Splits | $\propto 1/Q$ | Data leakage happens if a test sample is very similar to the train sample; if they are too dissimilar there is a lack of necessary inductive bias |

Table 93. Intuitions behind DQI components and sub-components.


 Figure 6. Each bar shows the relative contribution amounts of four features: *word overlap* (hypothesis only, and hypothesis+premise), *maximal word similarity*, and *sentence lengths*, for *good* and *bad* split samples. Each bar stacks the four features, which are sized by their relative impact percent (raw contribution values are numbers inside each feature bar).