RepEval: Effective Text Evaluation with LLM Representation

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Abstract

Automatic evaluation metrics for generated texts play an important role in the NLG field, especially with the rapid growth of LLMs. However, existing metrics are often limited to specific scenarios, making it challenging to meet the evaluation requirements of expanding LLM applications. Therefore, there is a demand for new, flexible, and effective metrics. In this study, we introduce RepEval, the first metric leveraging the projection of LLM representations for evaluation. RepEval requires minimal sample pairs for training, and through simple prompt modifications, it can easily transition to various tasks. Results on ten datasets from three tasks demonstrate the high effectiveness of our method, which exhibits stronger correlations with human judgments compared to previous metrics, even outperforming GPT-4. Our work underscores the richness of information regarding text quality embedded within LLM representations, offering insights for the development of new metrics.

1 Introduction

Automatic evaluation metrics play an important role in the assessment of generated text. However, with the rapid development of Large Language Models (LLM), application scenarios of Natural Language Generation (NLG) tasks have expanded rapidly, introducing new challenges to the evaluation task. Consequently, Previous metrics struggle to meet evolving evaluation requirements. The most commonly used metrics are referencebased, necessitating human-written reference texts as input (Papineni et al., 2002; Zhang et al., 2019; Banerjee and Lavie, 2005), and requiring great human effort in reference creation. Reference-free metrics are proposed as a supplementary solution but are largely confined to specific application scenarios or evaluation criteria, e.g. consistency in

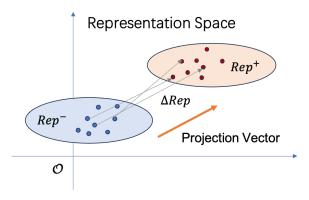


Figure 1: Utilizing representations for evaluation.

summarization, hindering their effective extension to new tasks (Ke et al., 2022; Zhong et al., 2022; Fu et al., 2023).

Applying LLM to evaluation tasks is an emerging trend in developing metrics, utilizing a zeroshot method to generate evaluation results (Chiang and Lee; Gao et al., 2023). However, employing LLM with more parameters is costly, while the outputs are often unsatisfactory (Shen et al., 2023). Fortunately, even when models struggle to generate appropriate responses, valuable information can still be obtained from LLM's representations with linear models (Zou et al., 2023). This implies that we can adopt models with fewer parameters, avoiding the excessive consumption of computational resources for better performance. The above discovery leads us to wonder: Do representations of LLM also encapsulate information relevant to text quality? How can we effectively extract and apply this information to evaluation tasks?

In this study, we introduce RepEval, a metric utilizing the projection of LLM representation(Rep) for evaluation. Our intuition is that Reps of high-quality and low-quality text exhibit distinct distributions. We validate that, in vector space, their projection in a specific direction characterizes the degree of variation in textual properties, as depicted in Figure 1. Experiments on three criteria with ten

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datasets from three tasks show that our method has better correlations with human judgments than previous metrics, which is flexible and easy to extend to other tasks or criteria. In summary, the key contributions of this work are:

- We introduced the evaluation metric RepEval, surpassing previous metrics on nearly all tasks, even outperforming GPT-4.
- RepEval is easily adaptable to new evaluation scenarios and requires only a few samples for training.
- RepEval offers insights for the introduction of new metrics, demonstrating that LLM representations contain valuable information about text quality.

2 Preliminary

2.1 Standard Evaluation

Denote the text to be evaluated as hyp, the source text used to generate hyp as src, and the reference as ref. For instance, in the summarization task, src is the original article, hyp is the summary generated by a language model, and ref is the reference answer written by human experts.

Consider an automatic metric NLG evaluation, which we denote as M, the evaluation result of hyp is generally in the form of a score, which can be described as Equation 1.

$$score = M(hyp, src, ref)$$
 (1)

Here, src and ref are optional inputs for metric M. Metrics can be classified into two types based on whether ref is required for the evaluation: Refbased and Ref-free. All Ref-free baselines used in this study require src as input, except for UniEval in fluency evaluation. RepEval and LLM-based metrics require hyp as input only, except for consistency, which also needs src as inputs.

2.2 Meta-Evaluation

The most common standard to measure the effectiveness of metric M is the correlation between human judgments and scores generated by M. The calculation is shown in 2.

$$correlation = \rho([s_1, s_2, \dots, s_N], [h_1, h_2, \dots, h_N]),$$
 (2)

where s_i is the metric score of the i-th sample in a certain dataset, h_i is the relative human judgment,

and ρ is the correlation function. In this study, we use Spearman Correlation (Spearman, 1987).

3 Methodology

3.1 Collecting Representation

As defined in Section 2.1, to collect the representation rep, we can simply apply hyp as input. However, this is agnostic to the evaluation scenarios, and constructing task-related prompt templates will help improve the performance.

In the evaluation of fluency and coherence, we apply the following prompt template.

Is the following sentence {criterion}?
Sentence: {hyp}
The sentence is:

Here, the "{criterion}" could be fluent or coherent, while "{hyp}" is filled by hyp to be evaluated. We also add a control group without the prompt template, using only hyp as inputs.

On evaluating consistency, as we need to measure the consistency between src and hyp, both hyp and src should be included in the inputs. Therefore, we use the following template.

Is the following hyp consistent with the src?

Src: {src}

Hyp: {hyp}

The hyp is:

Suppose we employ the LLM with l layers to transform the prompt p into a high-dimensional embedding, whose hidden state dimension is d. By inputting p into LLM, we can obtain $n \times l$ representation vectors \mathbf{rep} in the shape of $1 \times d$.

The next challenge is the selection of token positions and layer positions. Since we are using a decoder-only model, we only consider the few tokens (Zou et al., 2023). During training, we test the performance of different tokens across all layers and select the setting with the best performance, i.e. with the highest human correlations, on the validation set, and apply it to the test set.

3.2 Projection

Denote the representations of good text and bad text as rep^+ and rep^- , respectively. In the experiment, we categorize the quality of texts based on the ratings given by human evaluators. For each pair of (rep^+, rep^-) , their difference satisfies

 $\Delta rep = rep^+ - rep^-$. Suppose that we have collected n pairs of text pairs, and the relevant n Δrep s form a matrix R. According to Figure 1, the projection vector v_d indicates the direction of text quality variations, and the main component of R is closely related to v_d .

We therefore adopt Principal Component Analysis (PCA) to obtain the principal components of matrix R. Assuming that k main component vectors v are collected with PCA, as well as their importance score w, we can obtain v_d following Equation 3:

$$\boldsymbol{v_d} = \sum_{i=1}^k w_i \boldsymbol{v_i} \tag{3}$$

Here, k is also a parameter determined by experiment performance on the validation set, similar to the selection of token and layer, as described in Section 3.1. Finally, we can calculate the evaluation score of each hyp following Equation 4:

$$score = rep^T v_d, \tag{4}$$

where rep is the representation of the hyp.

3.3 **SVM**

We also add experiments with the Support Vector Machine (SVM) for comparison. With representation rep as inputs, the SVM method involves training a binary classifier on good-bad text pairs, and we use the probability of a text belonging to good text as the score result. To be specific, consider a specific text, denote the predicted probability of being good text as p_1 , the predicted probability of being bad text as p_0 , and the score satisfies:

$$score = p_1/(p_0 + p_1)$$
 (5)

4 Experiments

4.1 Datasets and Baselines

We focus on three evaluation criteria: fluency, consistency, and coherence, which are widely applied in NLG tasks. We utilize datasets from four tasks: Asset (Alva-Manchego et al., 2020) for simplification, SummEval (Fabbri et al., 2021) and Newsroom (Grusky et al., 2018) for summarization, WebNLG (Shimorina et al., 2019), SFRES, and SFHOT (Wen et al., 2015) for data-to-text, and USR-Persona (USR-P) and USR-Topic (USR-T) for dialogue (Mehri and Eskenazi, 2020). All texts in datasets are written in English.

On the selection of baseline metrics, we utilize three reference-based metrics: BLEU (Papineni et al., 2002), Meteor (Banerjee and Lavie, 2005), and BertScore (Zhang et al., 2019), along with three reference-free metrics: GPTScore (Fu et al., 2023), BARTScore (Yuan et al., 2021), and UniEval (Zhong et al., 2022). Additionally, we employ the Mistral-7b model and the ChatGPT API (gpt-3.5-turbo and gpt-4) provided by OpenAI to establish baselines by prompting large language models (LLMs) for evaluation, following the approach by Shen et al. (2023). Please refer to Appendix C for more details about datasets and metrics.

4.2 Training Set Construction

During the construction of the training set, we utilized Asset and GCDC. The reason for choosing them is that Asset belongs to the simplification task, which is unrelated to other datasets in this work. GCDC is a real-world text dataset specifically created for coherence evaluation. Creating the training set based on them minimizes bias introduced by tasks, ensuring that the construction of the projection vector is derived from variations in the quality of criteria.

We then need to set up the standard of classification of good text and bad text. The score range of human judgment on datasets Asset and GCDC is the same, between 1 and 3. We define hyp with a score of 3 as high quality and hyp with a score of 1 as low quality. For each pair, we randomly select one from the good text and another from the bad text.

4.2.1 Experiment Settings

When evaluating fluency and consistency, we construct the training dataset using Asset. For coherence evaluation, we utilize GCDC. During the training of the PCA model, the number of training pairs is set to 5 and 20. Additionally, we employ the SVM model for comparison with the PCA method, using 100 pairs for SVM training. As SVM needs more training data, during construction, we ensure the distinctiveness of each pair, though some pairs may contain the same good or bad text. No repeated data is contained in the training set of PCA.

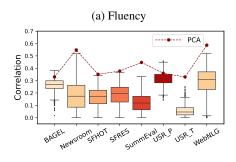
We collected representations with Mistral-7b following the process described in Section 3.1. We employ the Sklearn implementation of PCA and

 $^{^{1}} https://hugging face.co/lvkaokao/mistral-7b-fine tuned-orca-dpo-v2 \\$

		RepEval				Baselines								
		Prompt		Hyp-only		LLM		Ref-free				Ref-based		
		PCA(20)	PCA(5)	SVM	PCA(20)	GPT-4	GPT-3.5	Mistral-7b	GPTScore	BARTScore	UniEval	BLEU	Meteor	BertScore
FLU	BAGEL	0.330	0.236	0.358	0.060	0.325	0.222	0.156	0.152	0.241	0.309	0.193	0.109	0.247
	Newsroom	0.548	0.565	0.515	0.478	0.297	0.218	0.411	0.565	0.596	0.443	-0.163	0.157	0.182
	SFHOT	0.351	0.345	0.368	0.108	0.305	0.178	0.238	0.135	0.164	0.312	-0.054	0.015	0.164
	SFRES	0.377	0.370	0.391	0.021	0.352	0.289	0.272	0.229	0.226	0.332	0.100	0.143	0.183
	SummEval	0.447	0.424	0.419	0.324	0.245	0.120	0.285	0.288	0.285	0.451	-0.015	0.090	0.194
	USR-P	0.360	0.404	0.363	0.306	0.391	0.310	0.288	-0.030	0.034	0.239	-0.124	0.073	0.322
	USR-T	0.329	0.368	0.336	0.402	0.324	0.203	0.309	0.087	0.027	0.302	-0.093	0.200	0.292
	WebNLG	0.587	0.534	0.633	0.268	0.503	0.409	0.401	0.072	0.330	0.521	0.318	0.332	0.499
CON	QAGS-CNN	0.541	0.561	0.453	NA	0.505	0.295	0.380	0.583	0.680	0.618	0.082	0.326	0.507
	QAGS-XSUM	0.497	0.550	0.524	NA	0.457	0.315	0.185	0.081	0.159	0.387	-0.164	-0.015	-0.057
	SummEval	0.426	0.421	0.342	NA	0.436	0.269	0.210	0.355	0.334	0.435	0.048	0.152	0.200
сон	Newsroom	0.444	0.392	0.273	0.373	0.274	0.207	0.421	0.595	0.623	0.458	-0.201	0.198	0.221
СОН	SummEval	0.534	0.516	0.418	0.263	0.347	0.247	0.262	0.412	0.408	0.592	0.125	0.134	0.333

Table 1: Each row represents the **Spearman's correlations** of a metric with human judgments on different datasets. The **bold** scores represent the top two highest correlation results for each task on each criterion. Coherence, consistency, and fluency are written in abbreviations COH, CON, and FLU respectively.

SVM. For SVM, the kernel is set as Radial Basis Function (RBF), gamma = 1/d, and the regularization parameter C=1. We utilized Mistral-7b to generate representations using a single NVIDIA GeForce RTX 3090. The training of PCA and SVM models was performed on a CPU. More experiment details can be found in Appendix C.



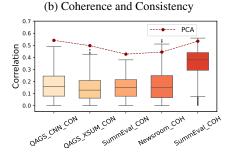


Figure 2: Box-plot of random test.

4.3 Correlation with Human Judgment

Following the description in previous sections, the correlations between human judgments and scores generated by each metric are presented in Table 1.

We observe that RepEval outperforms existing metrics on almost all datasets, even surpassing the performance of GPT-4. With just five text pairs, the PCA method surpasses previous metrics on half of the datasets, and with 20 pairs, it achieves a toptwo performance on seven datasets, similar to the results obtained by SVM, while significantly reducing the training cost. The Hyp-only experiment's outcome indicates that even without the addition of a prompt template, the embeddings in LLM contain information related to evaluation criteria such as fluency and coherence. Another notable point is that RepEval's performance is evidently better than directly prompting Mistral-7b for evaluation, indicating that even when LLM struggles to generate a satisfying response, their representations can still convey valuable information.

In summary, the projection of representations can efficiently extract information related to the quality of hyp with a few samples. Therefore, in most cases, there's no need to employ more complex models like SVM. Another advantage is that RepEval only requires hyp as input, whereas traditional metrics depend on src or ref. Compared with directly prompting LLMs like GPT-4, it exhibits better performance while maintaining a relatively low computational and time cost.

4.4 A Good Projection or Not?

Previous experiments show that PCA works effectively in identifying a suitable projection vector, surpassing other non-linear methods such as SVM. However, it remains uncertain whether PCA identifies the "best" projection. To address this question, we conduct the following random experiments.

We randomly generated 2000 vectors v_r with the same shape as the vector v_d obtained by PCA. We then collected hypothesis scores using the process outlined in Section 3.1, replacing v_d with v_r . The selection of token and layer positions followed the

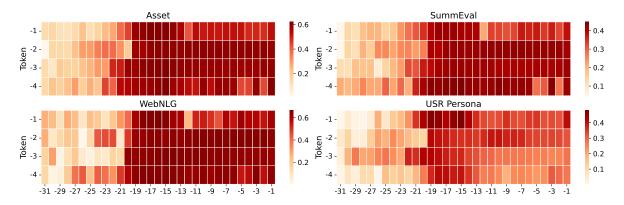


Figure 3: Correlation results for the evaluation of fluency using RepEval with different token and position selections. Layer and token counts are in reverse order, measuring the distance from the output. For instance, layer=-1 represents the last layer closest to the output.

settings of PCA (20 pairs) outlined in Section 3. The distribution of correlation scores is visualized through a box plot, as shown in Figure 2.

We observe that when employing linear projection for evaluation, v_d obtained through PCA is a relatively optimal result, achieving correlation scores nearly the highest possible when compared to random vectors. To further enhance evaluation effectiveness, additional research should be conducted on aspects such as layer and token selection.

4.5 What Influences the Information Stored in Representation?

To better utilize RepEval, in this section, we explore the performance of RepEval with different layers and token selections. Limited by space, we take fluency as an example and select four datasets from four tasks. All experiments follow the settings described in Section 4. The results are in Figure 3.

The results show that, surprisingly, the last token is not always the best one. Another observation is that the correlation scores increase sharply in the middle layers and achieve the best result. A possible explanation could be that the next token prediction is conducted based on this token, and it contains more information about the next token rather than the semantic features of the current sentence. A similar statement may be suitable for the change in layers, indicating that the closer a layer is to the output, the more information about the output is encoded in the representation.

This provides us with the following suggestions for improving RepEval. Firstly, we can opt for the token in the last second or third position, instead of the last one token. Secondly, choose embeddings from the second half of the layers. The layer should be far enough from the input to ensure that

sufficient information is encoded.

5 Conclusion

We introduced RepEval, an evaluation metric utilizing the projection of LLM representations to obtain evaluation results, which exhibits a stronger correlation with human judgments than previous metrics. RepEval is flexible and is easy to transfer to other evaluation scenarios, requiring only a few sample pairs for training, while avoiding the usage of LLMs with high parameters such as GPT-4. We also provide suggestions on the proper application of RepEval, such as the selection of tokens and layers. Our work provides insights into the development of new metrics.

Limitations

The experiments conducted in this study are limited to three specific tasks due to constraints in the dataset, and the language used is restricted to English. Further research is necessary to validate the identified performance across a broader spectrum of tasks and languages.

The analysis in this study is experimentally driven, we acknowledge the absence of a more comprehensive mathematical analysis explaining the underlying mechanisms of RepEval. Additionally, our evaluation relies solely on correlation as the measurement index. We leave a more detailed analysis for future work.

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A Evaluation Criteria

Coherence In accordance with Dang (2005), coherence evaluates whether models generate a well-structured and organized text body that aligns with the given task, steering clear of a mere compilation of related information.

Consistency Consistency, as per Honovich et al. (2022), assesses whether all factual information in the output text corresponds with the content provided in the input.

Fluency Fluency, as defined by Kann et al. (2018), gauges the natural perception of a sentence by humans. In certain instances, fluency is also referred to as naturalness, grammaticality, or readability.

B Related Work

B.1 Reference-based Metrics

Reference-based metrics measure the similarity between *hyp* and one or multiple *refs*, and a *hyp* more similar to *ref* is considered to be better (Gehrmann et al., 2023). Reference-based metrics can be classified into two types: n-gram-based and embedding-based. Popular n-gram-based metrics include BLEU (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005). Embedding-based metrics include BERTScore (Zhang et al., 2019) and MoverScore (Zhao et al., 2019). However, the requirement of human-written references limits their applications, as the creation of references is always a serious problem.

B.2 Reference-free Metrics

Reference-free Metrics require src and hyp, or hyp only for evaluation, and are widely used in the evaluation process when ref is not available. For example, BARTSCORE views the evaluation process as a generation problem, measuring how likely a target text can be generated based on the given inputs (Yuan et al., 2021). UNIEVAL views the evaluation task as a Boolean Question, providing a unified framework for multi-dimensional evaluation (Zhong et al., 2022). GPTScore uses conditional probability to evaluate the quality of given text (Fu et al., 2023), where each token is treated equally and a prompt is added to assist the evaluation process.

C Experiments

C.1 Datasets

ASSET ASSET is a dataset created for the tuning and evaluation of sentence simplification models (Alva-Manchego et al., 2020). In this research, we use the human rating corpus, which contains 100 pairs of original sentences and system simplification as well as the human evaluation results for the system output. For each pair, the rating is done by 15 crowd-sourced workers from 3 aspects: fluency, adequacy, and simplicity.

BAGEL BAGEL features annotations on data-to-text tasks gathered from a dialogue system, with human annotations covering informativeness and naturalness, according to Mairesse et al. (2010). In this context, informativeness is compared with the gold standard, differing from our defined usage. However, for our purposes, we solely utilize the judgment results related to naturalness.

GCDC is created with real-world texts, which is designed for the development of discourse coherence algorithms (Lai and Tetreault, 2018). Each sample in GCDC contains three evaluation scores of coherence on a 3-point scale from 1 (low coherence) to 3 (high coherence).

NEWSROOM NEWSROOM gathers 60 articles along with summarization outcomes from 7 models, featuring human-written summaries as references, as documented by Grusky et al. (2018). The evaluation encompasses coherence, fluency, relevance, and informativeness.

QAGS QAGS encompasses reference texts and annotation results focused on consistency in the context of the summarization task, as outlined by Wang et al. (2020). The approach involves collecting three annotations for each sentence in a generated summary, utilizing a majority vote strategy to determine a consistency score. The final score is obtained by calculating the mean value across all sentences.

SFHOT and SFRES SFHOT and SFRES deliver evaluation results for the data-to-text task, incorporating annotations of naturalness and informativeness, as detailed by Wen et al. (2015). In this context, informativeness gauges the consistent degree between sources and hypotheses. This dataset is utilized for analyzing consistency, while naturalness serves as a proxy for fluency.

SummEval SummEval offers a compilation of summarization outcomes produced by language models, as detailed by Fabbri et al. (2021). These models undergo training on the CNN/DailyMail datasets, as described by Hermann et al. (2015), along with their corresponding reference texts. Each generated summary in the dataset includes score results from both expert annotators and crowd-workers, covering four dimensions: coherence, consistency, fluency, and informativeness.

USR The USR dataset offers evaluation results for the dialogue task across five aspects: fluency, coherence, engagingness, groundedness, and understandability. In alignment with the rephrasing strategy outlined by Zhong et al. (2022), the original aspects "maintains context" and "natural" is renamed as "coherence" and "fluency," respectively.

WebNLG WebNLG includes human evaluation results from the 2017 WebNLG Challenge, which focuses on the data-to-text task, as described by Shimorina et al. (2019). The candidate text undergoes evaluation based on three aspects: fluency, grammar, and semantics. In this context, fluency assesses whether a text is smooth and natural, and the fluency score is employed for experimentation purposes.

The resources of all datasets we used are listed as follows.

- Newsroom, SummEval, QAGS_cnn, QAGS_XSUM, SFHOT, SFRES are downloaded from source provided by Yuan et al. (2021). The related URL is https://github.com/neulab/BARTScore.
- Asset and WebNLG is downloaded from source provided by Scialom and Hill (2021).
 The related URL is https://github.com/ ThomasScialom/BEAMetrics. We delete empty reference sentences before applying.
- USR_Topical and USR_Persona are created by Mehri and Eskenazi (2020). The related URL is https://github.com/shikib/usr.
- GCDC is created by Lai and Tetreault (2018), and the URL is https://github.com/aylai/GCDC-corpus.

Features contained in each dataset are listed in Table 2. With the exception of GCDC, all datasets include src.

	СОН	CON	FLU	REF
summarization				
-Newsroom	\checkmark		\checkmark	\checkmark
-QAGS		\checkmark		\checkmark
-SummEval	✓	✓	✓	✓
data-to-text				
-BAGEL			\checkmark	\checkmark
-SFHOT		\checkmark	\checkmark	\checkmark
-SFRES		\checkmark	\checkmark	\checkmark
-WebNLG			\checkmark	\checkmark
dialogue				
-USR-Persona	\checkmark		\checkmark	\checkmark
-USR-Topical	\checkmark		\checkmark	\checkmark
simplication				
-Asset			✓	
other				
-GCDC	\checkmark			

Table 2: Datasets and available features.

C.2 Implement of Baselines

- BARTScore is downloaded from https://github.com/neulab/BARTScore. We use the faithfulness-based variant based on "facebook/bart-large-cnn"² checkpoint (Lewis et al., 2020).
- BERTScore is downloaded from https://github.com/Tiiiger/bert_score. We use the F1 score calculated based on checkpoint "deberta-xlarge-mnli" (He et al., 2021).
- GPTScore is downloaded from https://github.com/jinlanfu/GPTScore and we use the checkpoint "gpt2-large" (Radford et al., 2019).
- UniEval is downloaded from https://github.com/maszhongming/UniEval. We use the "summarization" variant developed based on checkpoint "MingZhong/unieval-sum" (Zhong et al., 2022).
- For metric BLEU and Meteor, we use the implementation provided by the python package NLTK (Bird et al., 2009).

C.3 Selection of Token and Layer

Here we present the optimal layer and token selections for different RepEval settings and the SVM

²https://huggingface.co/facebook/ bart-large-cnn

³https://huggingface.co/microsoft/ deberta-xlarge-mnli

⁴https://huggingface.co/gpt2-large

⁵https://huggingface.co/MingZhong/unieval-sum

method, where k represents the number of components of PCA.

criterion	model	pairs	prompt	k	layer	token
	PCA	20	yes	4	-15	-4
FLU	PCA	5	yes	4	-15	-2
FLU	PCA	20	no	3	-21	-1
	SVM	100	yes	-	-2	-2
	PCA	20	yes	3	-16	-2
CON	PCA	5	yes	3	-15	-2
CON	SVM	100	yes	-	-2	-1
	PCA	20	yes	4	-9	-2
СОН	PCA	5	yes	2	-1	-2
СОП	PCA	20	no	3	-1	-2
	SVM	100	yes	-	-1	-3

Table 3: Selection of token and layer. Where k is the number of main components when using PCA.

C.4 Prompt of LLM

In this study, we use the gpt-3.5-turbo, gpt-4 API, and mistral-7b for zero-shot baseline. Following the designs of Shen et al. (2023) the prompts we utilized for each criteria are listed as follows:

C.4.1 Fluency

Score the following sentence with respect to fluency with one to five stars, where one star means "disfluency" and five stars means "perfect fluency". Note that fluency measures the quality of individual sentences, are they well-written and grammatically correct. Consider the quality of individual sentences.

Summary: hyp

Stars:

C.4.2 Coherence

Score the following text with respect to coherence with one to five stars, where one star means "incoherence" and five stars means "perfect coherence". Note that coherence measures the quality of all sentences collectively, to the fit together and sound naturally. Consider the quality of the sentences as a whole and just output an overall score and no more other.

Summary: hyp

Stars:

C.4.3 Consistency

Score the following summarization given the corresponding article with respect to consistency with one to five stars, where one star means "inconsistency" and five stars means "perfect consistency". Note that consistency measures whether the facts in the summary are consistent with the facts in the original article. Consider whether the summary does reproduce all facts accurately and does not make up untrue information.

Article: src Summary: hyp

Stars: