Human-LLM Hybrid Text Answer Aggregation for Crowd Annotations

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Abstract

The quality is a crucial issue for crowd annotations. Answer aggregation is an important type of solution. The aggregated answers estimated from multiple crowd answers to the same instance are the eventually collected annotations, rather than the individual crowd answers themselves. Recently, the capability of Large Language Models (LLMs) on data annotation tasks has attracted interest from researchers. Most of the existing studies mainly focus on the average performance of individual crowd workers; several recent works studied the scenarios of aggregation on categorical labels and LLMs used as label creators. However, the scenario of aggregation on text answers and the role of LLMs as aggregators are not yet well-studied. In this paper, we investigate the capability of LLMs as aggregators in the scenario of close-ended crowd text answer aggregation. We propose a human-LLM hybrid text answer aggregation method with a Creator-Aggregator Multi-Stage (CAMS) crowdsourcing framework. We make the experiments based on public crowdsourcing datasets. The results show the effectiveness of our approach based on the collaboration of crowd workers and LLMs.

1 Introduction

Because of the ability or diligence of the workers, the quality of crowdsourced annotations is a crucial issue. One solution of quality control is collecting redundant annotations by assigning multiple crowd workers to one instance and aggregating the multiple answers to this instance into an estimated answer which has high reliability.

There are many existing works in the crowdsourcing area on answer aggregation for various types of annotations. For example, for the classification tasks, crowd workers provide categorical labels to the instances (Snow et al., 2008; Whitehill et al., 2009; Venanzi et al., 2014). For some ranking tasks, workers provide pairwise preference labels, i.e., whether an instance is preferred to the other instance (Chen et al., 2013; Chen and Joachims, 2016a; Jin et al., 2020). In this paper, we mainly focus on the tasks with text answers, which can be the translations of given sentences (Li and Fukumoto, 2019), free-text rationales for explaining NLP models (Hartmann and Sonntag, 2022; Wiegreffe and Marasovic, 2021), and so on. We mainly consider the close-ended text answer annotations, i.e., the target answers are determined to some extent and can be considered as the golden standards, while the aggregation methods estimate these golden standards based on multiple crowd answers. Table 1 shows examples of categorical label aggregation and text answer aggregation. We denote these answer aggregation methods as model aggregators.

Table 1: Examples of aggregation tasks for crowd annotations. a_i^j represents the crowd answer to an instance q_i by a crowd worker w_j. $\hat{z}_i$ represents the estimated answer by an aggregation method. To aid in understanding the crowd text answer aggregation task in this study, we also provide an example of the crowd categorical label aggregation task in other studies.

I: Categorical Answer (Label) Aggregation Task

		a_1^1	a_1^2	a_1^3	a_1^4	a_1^5	a_1^j	$\hat{z}_1$
q_1		leopard	jaguar	cheetah	leopard	jaguar	...	leopard

II: Text Answer Aggregation Task (this study focuses this task)

q_1: 私には車椅子なんか全く必要が無い (Translate into English)	a_1^1: For me it is not necessary to have a wheelchair at all.	$\hat{z}_1$: I don't need a wheelchair at all.
	a_1^2: A wheelchair is not necessary for me at all.	
	a_1^3: The wheelchair is totally unnecessary for me.	
	a_1^4: There is no need for me to have such a wheelchair.	
	a_1^5: I never need wheelchair.	
	a_1^j:	

Recently, the capability of Large Language Models (LLMs) on data annotation tasks has attracted interest from researchers. Because LLMs are cheaper than crowd workers for annotating the instances (e.g., Gilardi et al. (2023) reported that ChatGPT is about twenty times cheaper than MTurk in their experiments), whether LLMs can outperform crowdsourcing is one of the issues con-

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cerned. Veselovsky et al. (2023) found that the crowd workers on MTurk have been recently using LLMs to complete the crowdsourcing tasks. Some works verified this issue with the average performance of individual crowd workers and LLMs on some specific tasks by collecting new datasets for their target tasks (Zhu et al., 2023; Gilardi et al., 2023; Törnberg, 2023; Cegin et al., 2023; He et al., 2024a). These LLM studies mainly concentrate on the average performance of individual crowd workers. However, the aggregated answers are the eventually collected annotations, rather than the crowd answers themselves. Therefore, the scenarios involving crowd answer aggregation need further study.

Several recent works (Li, 2024; He et al., 2024b) studied the scenario of answer aggregation on the crowd categorical labels in the classification tasks and LLMs are used as creators of the labels. The scenario of aggregation on other types of crowd annotations such as text answers and other types of LLM roles such as aggregators are not yet well-studied. We focus on investigating the capability of LLMs as aggregators on crowd text answer aggregation. LLMs can naturally utilize multiple text answers as the input, aggregate them, and generate the estimated answer. In other words, we can utilize a LLM as a LLM aggregator.

In crowdsourcing area, because single-stage frameworks only collect all annotations by crowd workers at once, which is limited for the requesters to flexibly set diverse additional mechanisms for improving the data quality, multi-stage frameworks are proposed, e.g., Creation-Review two stages (Baba and Kashima, 2013) for image description and logo design, Find-Fix-Verify three stages (Bernstein et al., 2015) for shortening long texts, and so on. Wu et al. (2023) utilized LLMs in some multi-stage crowdsourcing frameworks.

In this paper, we propose a human-LLM hybrid text answer aggregation method based on a Creator-Aggregator Multi-Stage (CAMS) crowdsourcing framework. In the first stage, crowd workers (Crowd Creators) provide the raw text answers. In the next stage, we ask crowd workers (Crowd Aggregators) and LLMs (LLM Aggregators) to aggregate the raw crowd answers to each instance. In the final stage, we utilize the model aggregators on the combinations of three resources of answers with the workers, including raw crowd answers, the estimated answers by crowd aggregators, and the estimated answers by LLM aggregators, to estimate the true answers. We construct experiments with public crowdsourcing datasets. The contributions are as follows.

- We investigate the capability of LLMs as aggregators in the scenario of crowd text answer aggregation for the quality control of crowdsourced close-ended text answer annotations tasks.
- We propose a human-LLM hybrid text answer aggregation method with a Creator-Aggregator Multi-Stage (CAMS) crowdsourcing framework which is a solution based on the collaboration of crowd workers and LLMs.
- We conducted experiments using public crowdsourcing datasets for crowd creators and additional data for crowd aggregators. The results show that both crowd aggregators and LLM aggregators can produce higher-quality estimated answers compared to raw crowd answers from crowd creators. Our CAMS approach with model aggregators can further improve the answer quality based on the combinations of three resources of workers and answers.

2 Related Work

There are many existing works in the crowdsourcing area on answer aggregation for various types of annotations. For the categorical labels, some approaches jointly estimate worker ability and true answers using the maximum entropy principle (Zhou et al., 2012), and Bayesian inference (Venanzi et al., 2014). More sophisticated models incorporate task difficulty (Whitehill et al., 2009) and their Bayesian treatments (Wauthier and Jordan, 2011; Bachrach et al., 2012). There are also other methods based on diverse techniques such as autoencoders (Yin et al., 2017), graph mining (Kawase et al., 2019), and so on (Li and Kashima, 2017; Li et al., 2018a, 2020). Besides answer aggregation approaches, There is another type of approach that directly trains the classification models with the noisy crowd labels (Li et al., 2022). In addition, some approaches consider reducing the budget while preserving the utility of the aggregated labels (Li, 2019).

For pairwise preference comparison labels (Cattelan, 2012), a typical solution is the Bradley-Terry model and its various extensions or generalizations to diverse settings (Causeur and Husson, 2005; Chen and Joachims, 2016a,b; Chen et al., 2013;

Raman and Joachims, 2014; Li et al., 2018b; Jin et al., 2020; Zuo et al., 2020; Li, 2022; Zhang et al., 2022). There are also other types of methods, e.g., matrix completion (Yi et al., 2013; Oh et al., 2015).

There are also methods for pairwise similarity labels (Hinton and Roweis, 2002; van der Maaten and Hinton, 2008; Gomes et al., 2011; Yi et al., 2012), triplet similarity labels (van der Maaten and Weinberger, 2012; Li et al., 2021; Lu et al., 2023), numerical data (Li et al., 2014) and text data (Li and Fukumoto, 2019; Li, 2020). We share our crowdsourcing datasets, including various data types, which can be utilized for research on topics such as answer aggregation for crowd annotations at `https://github.com/garfieldpigljy/ljycrowd`. In this paper, we mainly consider the close-ended text answer annotations.

In crowdsourcing area, because single-stage frameworks only collect all annotations by crowd workers at once, which is limited for the requesters to flexibly set diverse additional mechanisms for improving the data quality, multi-stage frameworks are proposed, e.g., Partition-Map-Reduce (Kittur et al., 2011) for writing essays, Price-Divide-Solve (Kulkarni et al., 2012) for writing essays, Creation-Review (Baba and Kashima, 2013) for image description and logo design, Find-Fix-Verify (Bernstein et al., 2015) for shortening long texts, Pair-Compare-Sort (Cheng et al., 2015) for sorting, and so on. Wu et al. (2023) utilized LLMs in some multi-stage crowdsourcing frameworks, e.g., the Find-Fix-Verify framework. Furthermore, Wu et al. (2022) compared the similarities and differences between LLM chains and multi-stage crowdsourcing frameworks. In this paper, we propose a specialized creator-aggregator multi-stage crowdsourcing framework for crowd text answer aggregation tasks.

3 Preliminary

3.1 Problem Setting of Answer Aggregation

We formulate the general problem setting of crowd text answer aggregation for quality control in close-ended text answer annotations. We define the instance set $\mathcal{Q} = \{q_i\}_i$, worker set $\mathcal{W} = \{w_j\}_j$, answer set $\mathcal{A} = \{a_i^j\}_{i,j}$, where a_i^j represents the answer to question q_i by worker w_j, true answer set $\mathcal{Z} = \{z_i\}_i$ and estimated answer set $\hat{\mathcal{Z}} = \{\hat{z}_i\}_i$. The answer set of an instance q_i is $\mathcal{A}_i$; the answer set of a worker w_j is $\mathcal{A}^j$. Because the number of instances can be large, a worker is not necessary to annotate all instances.

In the setting of the crowd answer aggregation, ground truths cannot be used by model aggregators because the purpose of data annotation tasks is collecting and estimating the ground truth. Therefore, abstractive aggregation methods, such as abstractive text summarization, which require ground truth for training, are not easily adaptable for use as model aggregators. Existing model aggregators for crowd text answer aggregation (e.g., (Kobayashi, 2018; Li and Fukumoto, 2019)) are mainly extractive aggregation methods and select the potential optimal one from multiple crowd answers. Given the instance set $\mathcal{Q}$, worker set $\mathcal{W}$ and answer set $\mathcal{A}$, a model aggregator estimates the true answer $\hat{\mathcal{Z}}$ by selecting one optimal answer $\hat{z}_i$ from $\mathcal{A}_i$ for each instance q_i, i.e., the answer aggregation can be defined as $\hat{\mathcal{Z}} = \text{Agg}(\mathcal{Q}, \mathcal{W}, \mathcal{A})$. Note that, in this study, only model aggregators are extractive aggregators. Crowd aggregators and LLM aggregators are abstractive aggregators because they read the raw crowd answers and generate aggregated answers in their own words.

3.2 Model Aggregators

We utilize several aggregation approaches from existing works as the model aggregators. These approaches utilize an encoder $e(\cdot)$ to convert the text into embeddings.

Sequence Majority Voting (SMV): It is a naïve but typical answer aggregation approach that is adapted from majority voting. For each instance, it estimates the embeddings of the true answers by $\hat{e}_i = mean(e(\mathcal{A}_i))$, and selects the worker answer $\hat{z}_i = \arg\max_{a_i^j} sim(e(a_i^j), \hat{e}_i)$.

Sequence Maximum Similarity (SMS): For each instance, SMS (Kobayashi, 2018) selects the worker answer which has the largest sum of similarity with other answers to this question. It can be regarded as creating a kernel density estimator and selecting the maximum density answer. The kernel function uses the cosine similarity. The formulation is $\hat{z}_i = \arg\max_{a_i^{j_1}} \sum_{j_1 \neq j_2} sim(e(a_i^{j_1}), e(a_i^{j_2}))$.

Reliability Aware Sequence Aggregation (RASA): RASA (Li and Fukumoto, 2019) models the worker reliability θ to strengthen the influences of answers provided by the workers with higher estimated reliability. It first estimates the embeddings of the true answers considering worker reliability. It iteratively estimates θ and $\hat{e}_i$ until convergence, $\theta_j = \frac{\chi^2_{(\alpha/2, |\mathcal{A}^j|)}}{\sum_i ||e(a_i^j) - \hat{e}_i||^2}, \hat{e}_i = \frac{\sum_j \theta_j e(a_i^j)}{\sum_j \theta_j}$, where χ^2 is

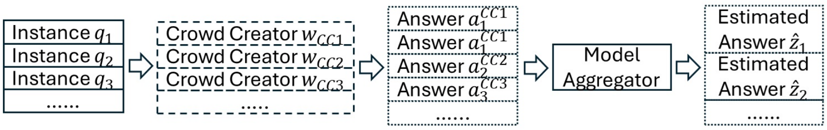


Figure 1: Existing Single-Stage framework for crowdsourced text answer aggregation.

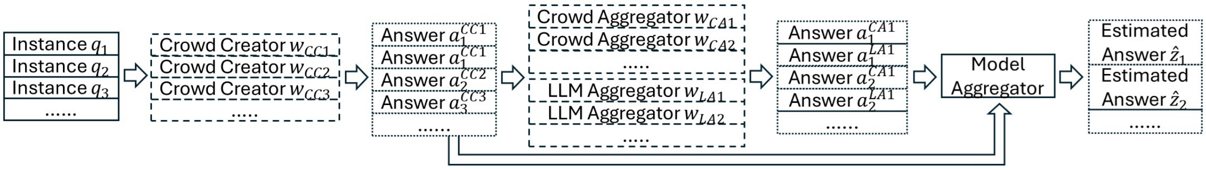


Figure 2: Our Creator-Aggregator Multi-Stage (CAMS) framework for crowdsourced text answer aggregation.

Table 2: Statistics of the datasets, $|\cdot|$ is the size of the sets. The answers $\mathcal{A}_{C.C.}$ by crowd creators $\mathcal{W}_{C.C.}$ is from CrowdWSA; the answers $\mathcal{A}_{C.A.}$ by crowd aggregators $\mathcal{W}_{C.A.}$ are collected by this work.

Data	$\|\mathcal{Q}\|$	$\|\mathcal{W}_{C.C.}\|$	$\|\mathcal{A}_{C.C.}\|$	$\|\mathcal{W}_{C.A.}\|$	$\|\mathcal{A}_{C.A.}\|$
J1	250	70	2,490	106	1250
T1	100	42	1,000	69	500
T2	100	43	1,000	71	500

the chi-squared distribution and the significance level α is set as 0.05 empirically. $\hat{e}_i$ can be initialized by using the SMV method. After that, it selects a worker answer that is most similar to the embeddings of the estimated true answer $\hat{e}_i$.

SMV and SMS are instance-wise aggregators that utilize the answers of an instance as the input. RASA is a dataset-wise aggregator that leverages the potential relations among workers and instances to estimate the answers for all instances. From this viewpoint, the crowd aggregators and LLM aggregators are instance-wise aggregators.

4 Human-LLM Hybrid Aggregation

Most of the existing work on crowdsourced annotation is based on the single-stage framework, i.e., all crowd answers are collected from crowd creators at once and the model aggregator estimates the true answers on these raw crowd answers directly. Figure 1 shows an example of a single-stage framework for crowdsourced text answer annotation. Single-stage frameworks are limited for the requesters to flexibly set diverse additional mechanisms for improving the data quality. Multi-stage frameworks are candidate solutions to improve flexibility and quality.

Because the crowd answers in this study are text, it is intuitive to ask LLMs to read the multiple crowd text answers to a given instance, and generate the estimated text answer. LLMs can be used as LLM aggregators. Similarly, crowd workers can be asked to provide the estimated answer by reading the raw crowd answers of an instance, and be used as crowd aggregators. We regard the Crowd Creator (C.C.), Crowd Aggregator (C.A.), and LLM Aggregator (L.A.) as three different types of workers. To distinguish these three resources of workers and answers, we define crowd creator workers and their answers as $\mathcal{W}_{C.C.}$ and $\mathcal{A}_{C.C.}$, crowd aggregator workers and their answers as $\mathcal{W}_{C.A.}$ and $\mathcal{A}_{C.A.}$, and LLM aggregator workers and their answers as $\mathcal{W}_{L.A.}$ and $\mathcal{A}_{L.A.}$. Note that crowd creators $\mathcal{W}_{C.C.}$ and crowd aggregators $\mathcal{W}_{C.A.}$ are allowed to have overlaps; they are not necessary to be the same or completely different. This is a tractable setting for requesters in practice, because $\mathcal{A}_{C.C.}$ and $\mathcal{A}_{C.A.}$ are collected in separate stages.

To effectively leverage these three resources of workers and answers in one crowdsourcing framework, we propose a Creator-Aggregator Multi-Stage (CAMS) framework. Figure 2 shows the proposed CAMS framework. In the first stage, crowd creators provide the raw crowd answers. In the next stage, we ask crowd aggregators and/or LLM aggregators to aggregate the raw crowd answers into estimated answers in their own words. In the final stage, we utilize the model aggregators on the combinations of three resources of workers and answers to generate the estimated true answers.

There are different versions of our approach. We can combine two or three resources of workers and answers to create the merged sets, which are then used as input for the model aggregator to estimate the true answers. We provide an example based on a version that utilizes all three resources of workers and answers. Given the instance set $\mathcal{Q}$, we can construct the worker set $\mathcal{W}$ by merging three worker sets with $\mathcal{W}$ = $\mathcal{W}_{C.C.}$+$\mathcal{W}_{C.A.}$+$\mathcal{W}_{L.A.}$, and the answer set $\mathcal{A}$ by merging three answer sets with $\mathcal{A}$ = $\mathcal{A}_{C.C.}$+$\mathcal{A}_{C.A.}$+$\mathcal{A}_{L.A.}$. We use the symbol '+' rather than the symbol '$\cup$' for $\mathcal{W}$ and $\mathcal{A}$. Because the answer creation and answer aggregation are different tasks, if the same crowd worker provides answers as both crowd creator and crowd aggregator, he/she may have different behaviors and reliabilities in these two roles. We thus treat such a worker as different workers when merging the worker and answer resources. We can then utilize the model aggregators on these $\mathcal{Q}$, $\mathcal{W}$, and $\mathcal{A}$ to estimate the true answers, i.e., $\hat{\mathcal{Z}} = \text{Agg}(\mathcal{Q}, \mathcal{W}, \mathcal{A})$ where Agg is one of SMV, SMS or RASA.

5 Experiments

5.1 Datasets

To investigate our study, we need datasets that contain multiple crowd text answers for each instance as well as the golden answers. We thus utilize the real datasets J1, T1, and T2 in CrowdWSA (Li and Fukumoto, 2019) which involve the translated sentences of the target language by multiple crowd workers for the sentences of the source language as well as the golden translations. Table 2 lists the statistics of the three datasets. The crowd workers in these datasets are regarded as the crowd creators (C.C.) in our CAMS framework. Each crowd creator provides answers for a subset of all instances.

5.2 Experimental Settings

5.2.1 Crowd Aggregators

For crowd aggregators (C.A.), we utilize a commercial crowdsourcing platform Lancers[1] to collect the estimated answers. Each instance is assigned to five crowd aggregators. Each crowd aggregator provides estimated answers for a subset of all instances. The following instructions and task descriptions are shown to the crowd aggregators when deploying the micro crowdsourcing tasks:

Instructions: *The data is collected for use in academic research. The collected data will be used for research on natural language processing and machine learning. The workers' nicknames will not be disclosed to any third party other than the person requesting this task.*

Descriptions: *The ten English short sentences below were written by ten non-native English speakers who translated the same one Japanese short sentence from Japanese. Read each of the English short sentences below, infer the meaning of the original Japanese text, and based on your understanding, create what you consider to be one appropriate short sentence each in Japanese and English.*

The original text instructions and task descriptions used at Lancers are in Japanese. Table 2 lists the statistics of the answers $\mathcal{A}_{C.A.}$ by crowd aggregators $\mathcal{W}_{C.A.}$ collected by this work.

5.2.2 LLM Aggregators

For LLM aggregators (L.A.), we utilize GPT-4[2] and Gemini[3]. L.A.(O) uses GPT-4 and L.A.(G) uses Gemini. Because Gemini results are almost always worse than GPT-4 results, we only put GPT-4 results in the main manuscript and put Gemini results in the Appendix Section. We utilize different temperature values to construct multiple LLM aggregators. The main results are based on five LLM aggregators with temperatures [0,0.25,0.5,0.75,1], with one trial conducted for each temperature. Each LLM aggregator provides answers for all instances. The following prompt is presented to the LLMs:

Prompt: *The following ten short English sentences were written by ten non-native English speakers who translated the same Japanese short text from Japanese to English. Please read each English sentence and infer the meaning of the original Japanese text, and based on your understanding, provide the appropriate Japanese original text and its English translation. Only output the text without showing "Japanese original text" and "English translation". \n\n <1. sentence 1>\n<2. sentence 2>\n......<10. sentence 10>\n. Output format separated by " and <tab>: "Japanese original text. " <tab> "its English translation. " \n\n*

Regarding the budget cost associated with crowd aggregators and LLM aggregators, LLMs are generally cheaper than crowd workers for annotating instances. For example, Gilardi et al. (2023) reported that ChatGPT is about twenty times cheaper than MTurk in their experiments. In our experiments, LLM aggregators cost less than 0.01 dollars per instance, while crowd aggregators cost around 0.36 dollars per instance, indicating a cost difference of more than thirtyfold.

[1] https://www.lancers.co.jp/

[2] The version is gpt-4-0125-preview.

[3] The version is gemini-1.5-pro-latest in May 9-14th 2024.

Table 3: Quality of individual answers by Crowd Creators (C.C.), Crowd Aggregators (C.A.) and LLM Aggregators (L.A., GPT-4 (O)) on GLEU, METEOR, and embedding similarity.

(a) GLEU

	MIN			MEAN			MAX			STD			TIAA		
Data	C.C.	C.A.	L.A.(O)	C.C.	C.A.	L.A.(O)	C.C.	C.A.	L.A.(O)	C.C.	C.A.	L.A.(O)	C.C.	C.A.	L.A.(O)
J1	0.0724	0.0000	**0.2706**	0.1868	0.2124	**0.2729**	0.5948	**1.0000**	0.2756	0.0915	0.1399	0.0018	0.1798	0.2746	0.7438
T1	0.0669	0.0217	**0.2144**	0.1764	0.1874	**0.2184**	0.5534	**0.7895**	0.2283	0.0818	0.1297	0.0051	0.2533	0.3473	0.7809
T2	0.0503	0.0000	**0.2025**	0.1716	0.1817	**0.2136**	0.4540	**0.6842**	0.2244	0.0838	0.1190	0.0083	0.2377	0.3371	0.7589

(b) METEOR

Data	MIN			MEAN			MAX			STD			TIAA		
	C.C.	C.A.	L.A.(O)	C.C.	C.A.	L.A.(O)	C.C.	C.A.	L.A.(O)	C.C.	C.A.	L.A.(O)	C.C.	C.A.	L.A.(O)
J1	0.2041	0.0490	**0.4987**	0.3762	0.4156	**0.5049**	0.7464	**0.9985**	0.5103	0.1037	0.1569	0.0039	0.3791	0.4910	0.8683
T1	0.1781	0.0394	**0.4247**	0.3771	0.3909	**0.4294**	0.7163	**0.9170**	0.4392	0.0987	0.1666	0.0051	0.4763	0.5670	0.8918
T2	0.1523	0.0476	**0.4102**	0.3630	0.3840	**0.4278**	0.6473	**0.8288**	0.4407	0.1010	0.1619	0.0103	0.4402	0.5492	0.8696

(c) Embedding Similarity

Data	MIN			MEAN			MAX			STD			TIAA		
	C.C.	C.A.	L.A.(O)	C.C.	C.A.	L.A.(O)	C.C.	C.A.	L.A.(O)	C.C.	C.A.	L.A.(O)	C.C.	C.A.	L.A.(O)
J1	0.4233	0.2243	**0.7216**	0.6620	0.6857	**0.7313**	0.8795	**1.0000**	0.7379	0.0687	0.1135	0.0053	0.6583	0.7286	0.9322
T1	0.5827	0.1282	**0.7758**	0.7260	0.7336	**0.7786**	0.9043	**1.0000**	0.7824	0.0687	0.1511	0.0029	0.7252	0.7850	0.9532
T2	0.4726	0.2700	**0.7602**	0.7077	0.7215	**0.7651**	0.8958	**1.0000**	0.7679	0.0861	0.1250	0.0031	0.7060	0.7752	0.9343

5.2.3 Model Aggregators

For the model aggregators, following CrowdWSA, we use the answer aggregation approaches SMV, SMS, and RASA, and utilize universal sentence encoder[4](Cer et al., 2018) as the text encoder.

5.2.4 Evaluation Metrics

We also use three evaluation metrics to verify the proposal. Two of them are GLEU[5] and METEOR[6]. We compute the average scores between estimated answers and true answers. The other one is the average cosine similarity between the encoder embeddings of the estimated answers and the true answers. We utilize the original target sentences in the Japanese-English parallel corpus used by CrowdWSA as the ground truth.

5.3 Q1: Quality of Individual Answers by Crowd workers and LLMs

We investigate the individual performance of crowd creators, crowd aggregators, and LLM aggregators from the viewpoint of the quality of answers they provide or generate. Table 3 lists the results. First, the results in the columns of "Mean" show that both crowd aggregators and LLM aggregators can generate estimated answers with higher quality than raw crowd answers from crowd creators.

Second, the results in the columns of "MIN", "MEAN", and "MAX" show that LLMs outperform bad and average crowd workers, but are worse than good crowd workers. Considering that model aggregators can amplify the influence of good workers when estimating true answers, a human-LLM hybrid aggregation with merged answer sets and model aggregators in the final stage has the potential to achieve better performance than aggregation results only based on crowd workers or LLMs.

Furthermore, an observation is that the standard deviations ("STD" column) of LLM aggregators are much smaller than those of crowd creators and crowd aggregators. In such close-ended text answers, multiple LLM aggregators constructed using the same LLM with various temperature values (including relatively high values) have lower diversity than crowd creators and crowd aggregators. A potential disadvantage of low diversity is if the answer to an instance is not good, the LLM may not generate a good answer by re-generation or using diverse temperature values. High diversity in the answers is not bad for answer aggregation, because it provides a broader exploration of candidate answers and aggregation methods are proposed to estimate good workers and answers from raw answers.

We also investigate the Inter-Annotator Agreement (IAA) among different types of workers. Because Cohen's Kappa for IAA is a statistical measure used to quantify the level of agreement between two raters who classify items into categories, while our annotations are text answers, we

[4] https://tfhub.dev/google/universal-sentence-encoder/4. This version is newer than the one used in the public implementation of CrowdWSA, thus the results of model aggregators on the answers of only crowd creators are different from those reported in CrowdWSA.

[5] We use NLTK package: nltk.translate.gleu_score

[6] We use NLTK package: nltk.translate.meteor_score

Table 4: Performance of different aggregators, C.A., L.A. (GPT-4 (O)), and Model Aggregator on the raw crowd answers $\mathcal{A}_{C.C.}$.

Data	C.A.	L.A. (O)	Model Aggregator SMV	SMS	RASA
(a) GLEU					
J1	0.2124	**0.2729**	0.1930	0.2489	0.2537
T1	0.1874	0.2184	0.1740	0.2310	**0.2376**
T2	0.1817	0.2136	0.1616	0.2189	**0.2340**
(b) METEOR					
J1	0.4156	**0.5049**	0.3861	0.4666	0.4745
T1	0.3909	0.4294	0.3786	0.4548	**0.4718**
T2	0.3840	0.4278	0.3604	0.4426	**0.4653**
(c) Embedding Similarity					
J1	0.6857	0.7313	0.6732	**0.7426**	0.7414
T1	0.7336	0.7786	0.7245	0.7935	**0.8020**
T2	0.7215	0.7651	0.7105	0.7860	**0.7935**

Table 5: Results of text answer aggregation: GLEU; LLM aggregator (GPT-4 (O)).

	Answers $\mathcal{A}_{C.C.}$	$\mathcal{A}_{C.A.}$	$\mathcal{A}_{L.A.}$	Model Aggregator SMV	SMS	RASA
J1						
I	○			0.1930	0.2489	0.2537
II		○		0.2260	0.2740	0.2444
			○(O)	**0.2729**	0.2770	0.2740
III	○	○		0.2040	0.2873	0.2708
IV	○		○(O)	0.2196	0.2846	0.2742
		○	○(O)	0.2494	0.2962	0.2732
	○	○	○(O)	0.2212	**0.3003**	**0.2812**
T1						
I	○			0.1740	0.2310	**0.2376**
II		○		0.1819	0.2074	0.2007
			○(O)	**0.2184**	0.2238	0.2170
III	○	○		0.1767	0.2257	0.2307
IV	○		○(O)	0.1888	**0.2334**	0.2218
		○	○(O)	0.2001	0.2249	0.2218
	○	○	○(O)	0.1871	0.2329	0.2307
T2						
I	○			0.1616	0.2189	0.2340
II		○		0.1769	0.2087	0.1952
			○(O)	**0.2136**	0.2122	0.2095
III	○	○		0.1667	**0.2369**	0.2341
IV	○		○(O)	0.1789	0.2293	0.2194
		○	○(O)	0.1953	0.2253	0.2252
	○	○	○(O)	0.1784	0.2309	**0.2372**

define a Text-Inter-Annotator Agreement (TIAA) for text answers by computing the scores between two answers to the same instance, $\kappa_{text} = \frac{1}{|\mathcal{Q}|}\sum_i \frac{1}{N_{j_1,j_2}}\sum_{j_1,j_2}\mathcal{G}(a_i^{j_1}, a_i^{j_2})$. $\mathcal{G}$ can be GLEU, METEOR, and Embedding Similarity. Higher TIAA means lower diversity in the answers. The results in the "TIAA" columns are based on GLEU and also show the lower diversity of LLM aggregators than crowd creators and crowd aggregators. We address this issue and candidate solution in the limitation section.

5.4 Q2: Performance of Different Aggregators

We also compare different types of aggregators on the raw crowd answers. We use the mean results of crowd aggregators and LLM aggregators in Table 3 and add the results of the model aggregators to list them in Table 4. The dataset-wise model aggregator RASA that models worker reliability performs best in many cases, and performs better than instance-wise model aggregators SMV and SMS. LLM aggregators sometimes perform best because they not only select answers from the raw answers but also infer answers through their language understanding and reasoning ability.

5.5 Q3: Results on Text Answer Aggregation

Table 5 shows the results of text answer aggregation on the evaluation metric GLEU. $\mathcal{A}_{L.A.}$ with (O) uses GPT-4. To facilitate the discussions, the results are organized into four groups. Group I represents the existing work with only crowd creators and the single-stage framework; Group II is the performance of our CAMS framework with only crowd aggregators or LLM aggregators; Group III and Group IV are answer aggregations with our CAMS framework with more than two answer resources; Group IV includes the human-LLM hybrid combinations with LLM aggregators. *Groups II, III and IV are our proposals*. We address the major observations as follows.

First, comparing the results among three columns, SMV performs worst in all three model aggregators. It shows that utilizing a strong model aggregator rather than a majority-based naïve aggregator is important for answer aggregation. Although the L.A.-only version of our approach performs best in all three datasets when using SMV, the performance is always lower than those using SMS and RASA. The following discussions will only focus on the results based on SMS and RASA.

Second, comparing the SMS (RASA) results between the L.A.-only version in Group II and Group IV, the versions in Group IV that utilize human-LLM hybrid aggregation outperform the version in Group II that only utilizes the answers of the LLM aggregators in most of the cases. In addition, the versions in Group IV also always outperform the results of LLM aggregators without model aggregators. They show that, although LLM aggregators perform better than the average of crowd workers in Table 3, the answers provided by crowd workers contain valuable information for model aggregators to generate good answers. One purpose of answer aggregation methods is to estimate good workers and good answers from the raw crowd answers (looking for the needle in a haystack). Following the observation in Table 3 that there are

Table 6: Results of text answer aggregation: METEOR; LLM aggregator (GPT-4 (O)).

	Answers			Model Aggregator		
	$\mathcal{A}_{C.C.}$	$\mathcal{A}_{C.A.}$	$\mathcal{A}_{L.A.}$	SMV	SMS	RASA
			J1			
I	○			0.3861	0.4666	0.4745
II		○		0.4397	0.4912	0.4524
			○(O)	**0.5049**	0.5110	0.5070
III	○	○		0.4040	0.5092	0.4946
IV	○		○(O)	0.4258	0.5166	0.5076
		○	○(O)	0.4723	**0.5248**	0.5064
	○	○	○(O)	0.4293	0.5240	**0.5147**
			T1			
I	○			0.3786	0.4548	**0.4718**
II		○		0.3927	0.4330	0.4272
			○(O)	**0.4294**	0.4351	0.4275
III	○	○		0.3833	0.4528	0.4564
IV	○		○(O)	0.3955	0.4538	0.4378
		○	○(O)	0.4110	0.4406	0.4366
	○	○	○(O)	0.3948	**0.4609**	0.4495
			T2			
I	○			0.3604	0.4426	**0.4653**
II		○		0.3746	0.4238	0.4083
			○(O)	**0.4278**	0.4330	0.4287
III	○	○		0.3651	0.4507	0.4551
IV	○		○(O)	0.3829	0.4523	0.4402
		○	○(O)	0.4012	0.4423	0.4482
	○	○	○(O)	0.3808	**0.4606**	0.4626

Table 7: Results of text answer aggregation: Embedding Similarity; LLM aggregator (GPT-4 (O)).

	Answers			Model Aggregator		
	$\mathcal{A}_{C.C.}$	$\mathcal{A}_{C.A.}$	$\mathcal{A}_{L.A.}$	SMV	SMS	RASA
			J1			
I	○			0.6732	0.7426	0.7414
II		○		0.6983	0.7360	0.7188
			○(O)	**0.7313**	0.7332	0.7317
III	○	○		0.6815	**0.7516**	**0.7459**
IV	○		○(O)	0.6926	0.7427	0.7356
		○	○(O)	0.7148	0.7413	0.7336
	○	○	○(O)	0.6940	0.7484	0.7410
			T1			
I	○			0.7245	0.7935	**0.8020**
II		○		0.7430	0.7851	0.7758
			○(O)	**0.7786**	0.7807	0.7762
III	○	○		0.7306	0.7965	0.7976
IV	○		○(O)	0.7425	0.7894	0.7793
		○	○(O)	0.7608	0.7854	0.7807
	○	○	○(O)	0.7426	**0.7993**	0.7890
			T2			
I	○			0.7105	0.7860	**0.7935**
II		○		0.7282	0.7681	0.7468
			○(O)	**0.7651**	0.7725	0.7673
III	○	○		0.7164	**0.7885**	0.7822
IV	○		○(O)	0.7287	0.7856	0.7744
		○	○(O)	0.7467	0.7712	0.7728
	○	○	○(O)	0.7286	0.7851	0.7824

still good crowd workers (creators and aggregators) who perform better than LLMs (aggregators), a strong model aggregator can target such good workers and answers. In contrast to replacing crowd workers by only using LLMs, human-LLM hybrid solutions potentially have advantages.

Third, Table 6 and 7 list the results on the evaluation metrics METEOR and Embedding Similarity. They reach similar observations with the evaluation metric GLEU.

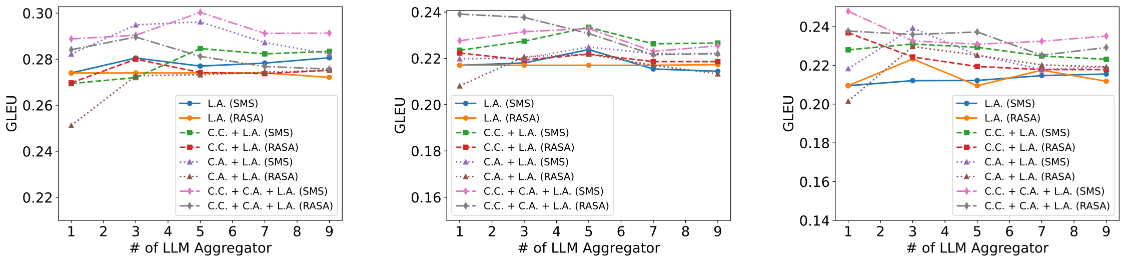
Fourth, regarding the performance of different components (ablations) of the proposed method within the CAMS framework, (1) the results of columns C.A. or L.A. in Table 4 represent components that include only crowd aggregators or LLM aggregators, without the use of model aggregators; (2) Group I represents components with only crowd creators and the single-stage framework. Comparing these results with those of Groups II, III and Group IV in Tables 5, 6 and 7 illustrates the effectiveness of our human-LLM hybrid aggregation approach and CAMS framework.

Fifth, in the main results, we utilize the same number of LLM aggregators with crowd aggregators, we thus also investigate the influences of different numbers of LLM aggregators on the performance. Figures 3, 4 and 5 show the results on the evaluation metrics GLEU, METEOR and Embedding Similarity by GPT-4 LLM aggregators based on model aggregators SMS and RASA. The results by Gemini LLM aggregators are in the Appendix. No consistent patterns were observed across different datasets; sometimes, more LLM aggregators are better; sometimes, fewer LLM aggregators are better; it depends on the datasets; we cannot know which case it is in practical crowd annotations. In all cases of the J1 dataset and some cases of the T1 and T2 datasets, the results of only using one LLM aggregator are bad; using multiple LLM aggregators is recommended to avoid risk.

Finally, the approach we propose in this work has several versions (six combinations of worker and answer resources in Groups II, III, and IV). The best version depends on the specific application. If there is no prior knowledge of the target task or dataset, we recommend using all workers and answers (i.e., crowd creators, crowd aggregators, and LLM aggregators) together with a reliable model aggregator (e.g., SMS or RASA).

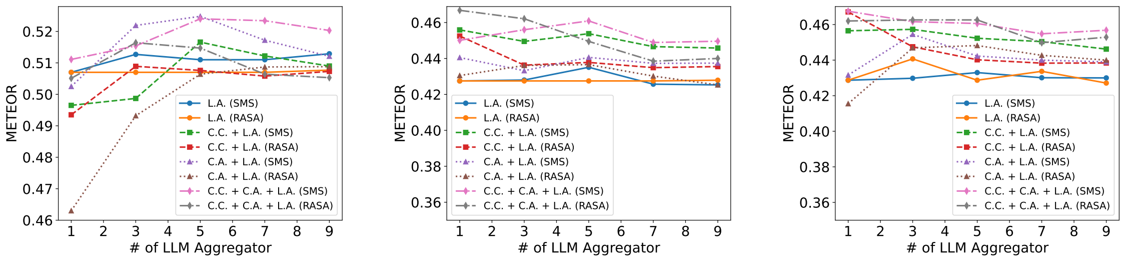
6 Conclusion

In this paper, we investigate the capability of LLMs as aggregators in the scenario of crowd text answer aggregation for the quality control of crowdsourced close-ended text answer annotation tasks. We propose a human-LLM hybrid text answer aggregation method with a Creator-Aggregator Multi-Stage (CAMS) crowdsourcing framework. The experimental results show both crowd aggregators and LLM aggregators can generate estimated answers with higher quality than raw crowd answers provided by crowd creators. Our CAMS approach with model



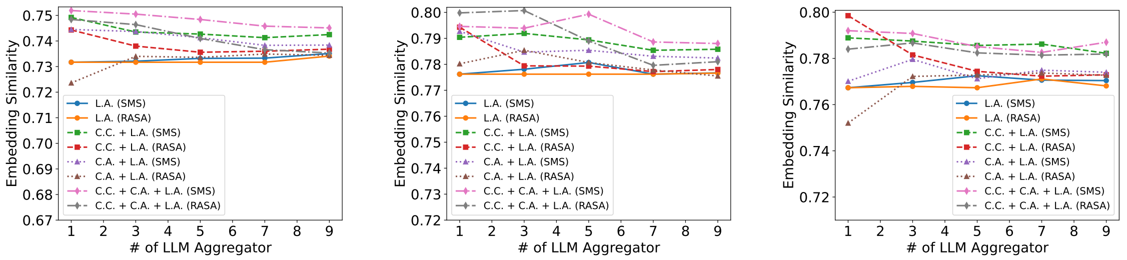
(a) J1 (b) T1 (c) T2

Figure 3: GLEU Results by different number of L.A. (GPT-4 (O)) based on SMS and RASA.



(a) J1 (b) T1 (c) T2

Figure 4: METEOR Results by different number of L.A. (GPT-4 (O)) based on SMS and RASA.



(a) J1 (b) T1 (c) T2

Figure 5: Embedding Similarity Results by different number of L.A. (GPT-4 (O)) based on SMS and RASA.

aggregators can further improve the answer quality based on the combinations of three resources of workers and answers. This work presents a solution based on human-AI collaboration for a specific task. Humans can leverage AI to enhance the quality and efficiency of tasks like data annotation. We share the datasets and source codes at https://github.com/garfieldpigljy/HumanLLMHybridAggregation.

Limitations

In this work, we only verify two popular commercial LLMs, i.e., GPT-4 and Gemini-1.5-Pro. We think that GPT-4 and Gemini-1.5-Pro can represent the performance that LLMs can currently achieve, and they are enough for the empirical experiments. On the other hand, the performance of other LLMs (e.g., some open-source LLM models) is also an interesting issue for investigation. In the future work, we will verify other LLMs.

For the purpose of investigating the results with one LLM, people usually select a single LLM provider to complete the tasks. In the experiments, we used different LLMs (GPT-4 or Gemini) separately. Different LLM aggregators are constructed by using different temperature parameters. As shown in the experimental results in Section 5.3, the answers generated by multiple LLM aggregators constructed by the same LLM have relatively low diversity. In future work, a candidate solution is using different LLMs and different temperatures to construct many LLM aggregators.

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Ethic Statement

No personal information is used in this study, and therefore no demographic or geographic characteristics of the annotators are included or utilized in the data. The crowd workers have obtained sufficient wages by local standards.

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Table 8: Performance of different aggregators, C.A., L.A. (Gemini (G)), and Model Aggregator on the raw crowd answers $\mathcal{A}_{C.C.}$.

Data	C.A.	L.A.	Model Aggregator		
		(G)	SMV	SMS	RASA
			(a) GLEU		
J1	0.2124	**0.2633**	0.1930	0.2489	0.2537
T1	0.1874	0.2015	0.1740	0.2310	**0.2376**
T2	0.1817	0.1751	0.1616	0.2189	**0.2340**
			(b) METEOR		
J1	0.4156	**0.4926**	0.3861	0.4666	0.4745
T1	0.3909	0.4218	0.3786	0.4548	**0.4718**
T2	0.3840	0.3833	0.3604	0.4426	**0.4653**
			(c) Embedding Similarity		
J1	0.6857	0.7310	0.6732	**0.7426**	0.7414
T1	0.7336	0.7635	0.7245	0.7935	**0.8020**
T2	0.7215	0.7540	0.7105	0.7860	**0.7935**

Table 9: Results of text answer aggregation: GLEU; LLM aggregator (Gemini (G)).

	Answers			Model Aggregator		
	$\mathcal{A}_{C.C.}$	$\mathcal{A}_{C.A.}$	$\mathcal{A}_{L.A.}$	SMV	SMS	RASA
			J1			
I	○			0.1930	0.2489	0.2537
II		○		0.2260	0.2740	0.2444
			○(G)	**0.2661**	0.2623	0.2626
III	○	○		0.2040	0.2873	0.2708
	○		○(G)	0.2174	0.2856	0.2620
IV		○	○(G)	0.2460	0.2746	0.2564
	○	○	○(G)	0.2195	**0.2920**	**0.2723**
			T1			
I	○			0.1740	0.2310	**0.2376**
II		○		0.1819	0.2074	0.2007
			○(G)	**0.2082**	0.2136	0.2126
III	○	○		0.1767	0.2257	0.2307
	○		○(G)	0.1854	**0.2337**	0.2138
IV		○	○(G)	0.1950	0.2204	0.2169
	○	○	○(G)	0.1845	0.2274	0.2274
			T2			
I	○			0.1616	0.2189	0.2340
II		○		0.1769	0.2087	0.1952
			○(G)	**0.1837**	0.1853	0.1707
III	○	○		0.1667	**0.2369**	**0.2341**
	○		○(G)	0.1690	0.2174	0.2032
IV		○	○(G)	0.1803	0.2061	0.2191
	○	○	○(G)	0.1710	0.2202	0.2277

A Appendix

B Additional Results By Gemini

Because the Gemini results are almost always worse than GPT-4 results, we only put the GPT-4 results in the main manuscript and put the Gemini results in the Appendix Section.

Table 12 lists the results of the individual performance of crowd creators, crowd aggregators, and Gemini LLM aggregators from the viewpoint of the quality of answers they provide or generate.

We also make a comparison among different types of aggregators on the raw crowd answers. We use the mean results of crowd aggregators and LLM aggregators in Table 12 and add the results of the model aggregator to list them in Table 8.

Table 10: Results of text answer aggregation: METEOR; LLM aggregator (Gemini (G)).

	Answers			Model Aggregator		
	$\mathcal{A}_{C.C.}$	$\mathcal{A}_{C.A.}$	$\mathcal{A}_{L.A.}$	SMV	SMS	RASA
			J1			
I	○			0.3861	0.4666	0.4745
II		○		0.4397	0.4912	0.4524
			○(G)	**0.4954**	0.4925	0.4885
III	○	○		0.4040	0.5092	0.4946
	○		○(G)	0.4226	0.5142	0.4911
IV		○	○(G)	0.4675	0.5084	0.4878
	○	○	○(G)	0.4269	**0.5204**	**0.5037**
			T1			
I	○			0.3786	0.4548	**0.4718**
II		○		0.3927	0.4330	0.4272
			○(G)	**0.4258**	0.4364	0.4392
III	○	○		0.3833	0.4528	0.4564
	○		○(G)	0.3943	**0.4630**	0.4447
IV		○	○(G)	0.4092	0.4395	0.4379
	○	○	○(G)	0.3939	0.4584	0.4514
			T2			
I	○			0.3604	0.4426	**0.4653**
II		○		0.3746	0.4238	0.4083
			○(G)	**0.3956**	0.3999	0.3754
III	○	○		0.3651	**0.4507**	0.4551
	○		○(G)	0.3721	0.4426	0.4179
IV		○	○(G)	0.3851	0.4200	0.4324
	○	○	○(G)	0.3727	0.4384	0.4469

Table 11: Results of text answer aggregation: Embedding Similarity; LLM aggregator (Gemini (G)).

	Answers			Model Aggregator		
	$\mathcal{A}_{C.C.}$	$\mathcal{A}_{C.A.}$	$\mathcal{A}_{L.A.}$	SMV	SMS	RASA
			J1			
I	○			0.6732	0.7426	0.7414
II		○		0.6983	0.7360	0.7188
			○(G)	**0.7310**	0.7313	0.7311
III	○	○		0.6815	0.7516	**0.7459**
	○		○(G)	0.6925	0.7463	0.7311
IV		○	○(G)	0.7147	0.7391	0.7315
	○	○	○(G)	0.6939	**0.7521**	0.7423
			T1			
I	○			0.7245	0.7935	**0.8020**
II		○		0.7430	0.7851	0.7758
			○(G)	**0.7635**	0.7698	0.7701
III	○	○		0.7306	0.7965	0.7976
	○		○(G)	0.7375	**0.7978**	0.7762
IV		○	○(G)	0.7532	0.7803	0.7803
	○	○	○(G)	0.7389	0.7963	0.7953
			T2			
I	○			0.7105	0.7860	**0.7935**
II		○		0.7282	0.7681	0.7468
			○(G)	**0.7540**	0.7579	0.7468
III	○	○		0.7164	**0.7885**	0.7822
	○		○(G)	0.7250	0.7856	0.7744
IV		○	○(G)	0.7411	0.7679	0.7724
	○	○	○(G)	0.7258	0.7833	0.7831

Table 9 shows the results on text answer aggregation on the evaluation metric GLEU. $\mathcal{A}_{L.A.}$ with (G) uses Gemini. Table 10 and 11 list the results on the evaluation metrics METEOR and Embedding Similarity. They reach similar observations with the evaluation metric GLEU.

Figure 6, 7 and 8 shows the results on GLEU, METEOR and Embedding Similarity by Gemini LLM aggregators based on model aggregators SMS and RASA. They reach similar observations with the evaluations GPT-4 LLM aggregators in the main manuscript.

Table 12: Quality of individual answers by Crowd Creators (C.C.), Crowd Aggregators (C.A.) and LLM Aggregators (L.A., Gemini (G)) on GLEU, METEOR and embedding similarity.

(a) GLEU

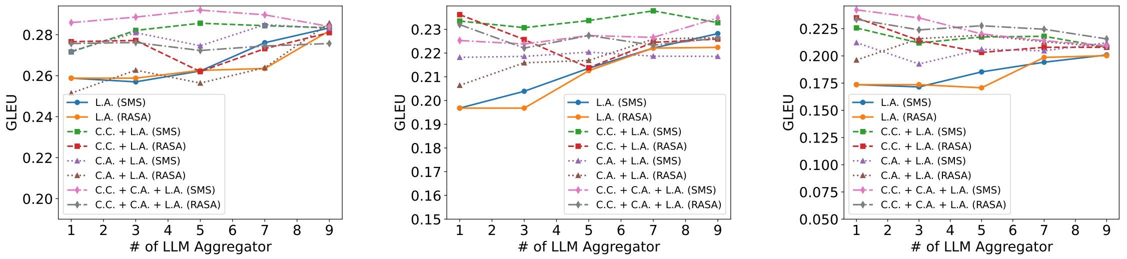
	MIN			MEAN			MAX			STD			TIAA		
Data	C.C.	C.A.	L.A.(G)	C.C.	C.A.	L.A.(G)	C.C.	C.A.	L.A.(G)	C.C.	C.A.	L.A.(G)	C.C.	C.A.	L.A.(G)
J1	0.0724	0.0000	**0.2588**	0.1868	0.2124	**0.2633**	0.5948	**1.0000**	0.2714	0.0915	0.1399	0.0057	0.1798	0.2746	0.7749
T1	0.0669	0.0217	**0.1968**	0.1764	0.1874	**0.2015**	0.5534	**0.7895**	0.2064	0.0818	0.1297	0.0039	0.2533	0.3473	0.8028
T2	0.0503	0.0000	**0.1707**	0.1716	**0.1817**	0.1751	0.4540	**0.6842**	0.1810	0.0838	0.1190	0.0043	0.2377	0.3371	0.7854

(b) METEOR

Data	MIN			MEAN			MAX			STD			TIAA		
	C.C.	C.A.	L.A.(G)	C.C.	C.A.	L.A.(G)	C.C.	C.A.	L.A.(G)	C.C.	C.A.	L.A.(G)	C.C.	C.A.	L.A.(G)
J1	0.2041	0.0490	**0.4869**	0.3762	0.4156	**0.4926**	0.7464	**0.9985**	0.4993	0.1037	0.1569	0.0051	0.3791	0.4910	0.8792
T1	0.1781	0.0394	**0.4165**	0.3771	0.3909	**0.4218**	0.7163	**0.9170**	0.4310	0.0987	0.1666	0.0065	0.4763	0.5670	0.8830
T2	0.1523	0.0476	**0.3754**	0.3630	**0.3840**	0.3833	0.6473	**0.8288**	0.3941	0.1010	0.1619	0.0078	0.4402	0.5492	0.8728

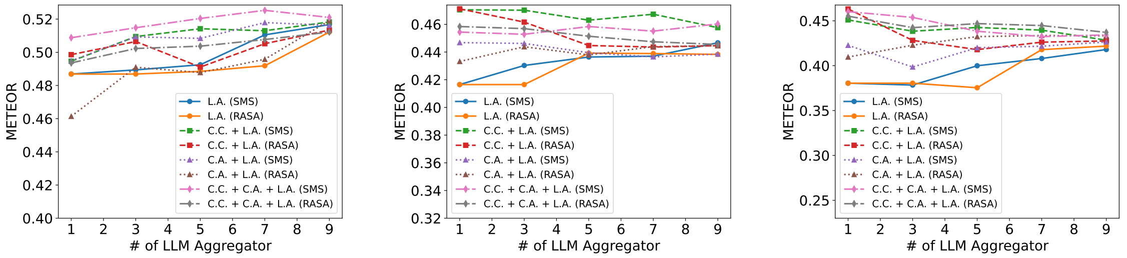
(c) Embedding Similarity

Data	MIN			MEAN			MAX			STD			TIAA		
	C.C.	C.A.	L.A.(G)	C.C.	C.A.	L.A.(G)	C.C.	C.A.	L.A.(G)	C.C.	C.A.	L.A.(G)	C.C.	C.A.	L.A.(G)
J1	0.4233	0.2243	**0.7265**	0.6620	0.6857	**0.7310**	0.8795	**1.0000**	0.7373	0.0687	0.1135	0.0036	0.6583	0.7286	0.9373
T1	0.5827	0.1282	**0.7566**	0.7260	0.7336	**0.7635**	0.9043	**1.0000**	0.7719	0.0687	0.1511	0.0058	0.7252	0.7850	0.9502
T2	0.4726	0.2700	**0.7458**	0.7077	0.7215	**0.7540**	0.8958	**1.0000**	0.7684	0.0861	0.1250	0.0086	0.7060	0.7752	0.9360



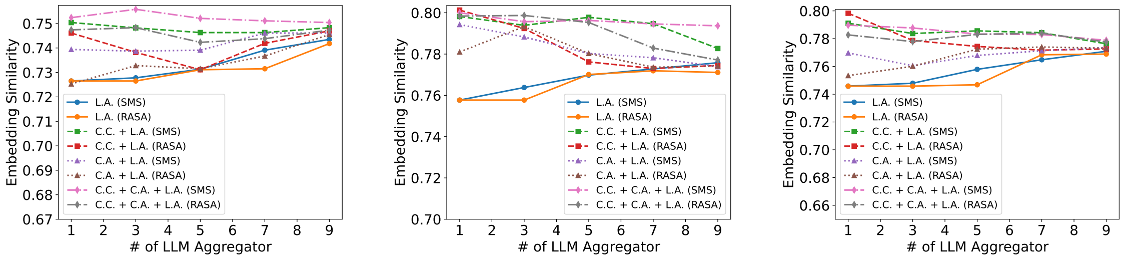
(a) J1 (b) T1 (c) T2

Figure 6: GLEU Results by different number of L.A. (Gemini) based on SMS and RASA.



(a) J1 (b) T1 (c) T2

Figure 7: METEOR Results by different number of L.A. (Gemini) based on SMS and RASA.



(a) J1 (b) T1 (c) T2

Figure 8: Embedding Similarity Results by different number of L.A. (Gemini) based on SMS and RASA.