Smarter Sampling for LLM Judges: Reliable Evaluation on a Budget

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Abstract

Large language models (LLMs) are increasingly employed as judges for scalable evaluation of AI systems, where an LLM is prompted to assess the outputs of another model. This approach is particularly valuable for tasks with non-verifiable answers, but its reliability ultimately depends on alignment with human judgments. Because human annotations are expensive and time-consuming, especially in domains that demand expert knowledge such as clinical text generation, it is essential to reduce annotation effort while maintaining accurate estimates of judge reliability. In this work, we study the problem of estimating the intraclass correlation coefficient (ICC) between LLM judges and humans under limited annotation budgets. We derive Chernoff bounds on the estimation error, providing theoretical guarantees on sample requirements and reducing sample size requirements by an average of 18% compared to the baseline. Building on this, we propose and evaluate 6 sampling strategies designed to identify the most informative examples for annotation. Experiments on 4 diverse real-world datasets demonstrate that our methods yield narrower confidence intervals and achieve relative improvements of 5.5%–31% in ICC precision over random sampling baselines.

1 Introduction

Large language models (LLMs) are increasingly used for text generation tasks, but their rapid adoption has outpaced our ability to evaluate them at scale [Thirunavukarasu et al., 2023, Meyer et al., 2023, Yuan et al., 2021, Celikyilmaz et al., 2021]. Human evaluation remains the gold standard but is slow and expensive, particularly in domains like healthcare. To address these limitations, the *LLM-as-a-judge* framework, in which one LLM evaluates the outputs of another model, has emerged as a promising alternative [Gu et al., 2025]. Recent work has explored this direction through human-labeled benchmarks [Dubois et al., 2024] and reference-free evaluation methods [Tan et al., 2025]. However, the effectiveness of an LLM judge ultimately depends on alignment with human judgments.

Human-annotated scores are typically treated as the gold standard when evaluating a target LLM. However, human evaluation pipelines are slow and expensive, particularly in domains requiring

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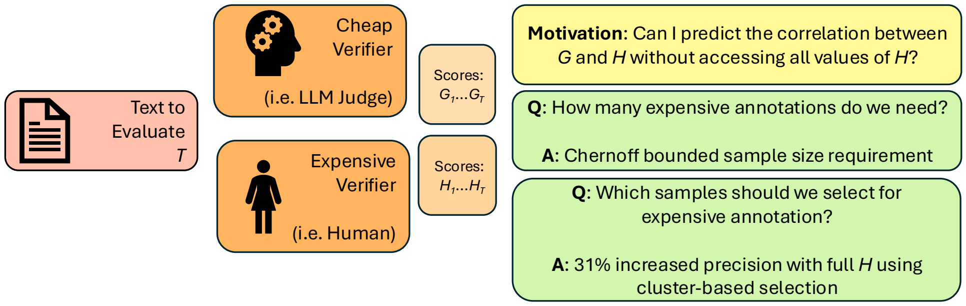


Figure 1: **Overview of the LLM judge evaluation framework and our approach.** Given text samples T to evaluate, we obtain inexpensive scores G from an LLM judge and expensive scores H from human annotators. Our work addresses two key questions: (i) *How many human annotations are needed to reliably estimate agreement between G and H?* We derive a Chernoff bound-based sample size requirement (2.2). (ii) *Which samples should be selected for human annotation?* We propose and evaluate 6 sampling strategies, with cluster-based selection achieving up to 31% relative improvement in ICC estimation precision compared to random sampling under limited annotation budgets (4).

expert annotations such as healthcare [Liang et al., 2022, Kiela et al., 2021, Arndt et al., 2017]. This creates a bottleneck for scalable evaluation: the cost of human labels directly limits the feasibility of benchmarking and alignment studies. To quantify judge reliability, we follow prior work [Bedi et al., 2025, Li et al., 2024, Croxford et al., 2025] and adopt the intra-class correlation coefficient (ICC) as a measure of agreement between LLM judges and humans. This leads to two central questions: *(i) How many human annotations are needed to accurately estimate ICC? (ii) How can we choose the most informative samples to minimize annotation cost?*

To address the first question, we derive a concentration inequality for ICC estimation using the classical Chernoff bound [Chernoff, 1952] on an asymptotic normal approximation of the ICC distribution. This yields a lower bound on the number of annotations required to guarantee with high probability that the empirical ICC is within ε of the population ICC.

For the second question, we empirically study how annotation efficiency can be improved through principled sample selection. We frame subset selection for human annotation as a core-set selection problem, assuming access to a fully LLM-annotated dataset. Building on ideas from statistical sampling [Cochran, 1977], clustering [Lloyd, 1982], and active learning [Settles and Craven, 2008], we compare several sampling strategies against random selection and evaluate their impact on ICC estimation under limited annotation budgets.

Given the pressing need to evaluate LLM judges under limited annotation budgets, we propose a theoretical framework for ICC estimation and principled sampling strategies. **Our contributions:**

1. We derive a Chernoff bound–based concentration inequality for ICC estimation, providing theoretical guarantees on the number of annotations required for reliable LLM judge evaluation.
2. We conduct a systematic empirical study of sampling strategies for annotation efficiency across 4 diverse real-world datasets spanning 15 axes of assessment.
3. We show that principled selection consistently outperforms random sampling under tight budgets ($\leq 5\%$ of data), with relative gains ranging from 5.5% to 31% in ICC estimation precision.

2 Theoretical Foundations

2.1 Background on Intra-class Correlation Coefficient

Intra-class Correlation Coefficient (ICC) was originally proposed by Fisher [1925] as an extension to *interclass* correlation coefficient (Pearson's correlation coefficient (PCC)), and measures the extent to which the total variance in observed data is due to differences between groups, rather than within groups. In this perspective, the ICC is understood within the analysis of variance (ANOVA) framework. As opposed to PCC, the data are pooled in the mean calculation.

In the generic version of our use case, ICC is considered a measure that quantifies inter-rater reliability between k raters on n subjects, first introduced as an application of the metric in Shrout and Fleiss [1979]. ICC measures reliability by decomposing the total variance in human evaluations into between-subjects variance and within-subjects error variance. The ICC determines the reliability of ratings by comparing the variability of different ratings of the same individuals to the total variation across all ratings and all individuals. As we only consider two raters, the human and the LLM, we consider the case $k = 2$.

Analogously, modern ICC estimators derive ICC through the random effects model framework. In the random effects model, X_{ij}, rating j on subject i, $i \in [n], j \in [k]$, is modeled as

$$X_{ij} = \mu + \alpha_i + c_j + \varepsilon_{ij}$$

such that μ is an unobserved overall mean, α_i is an unobserved random effect shared by all ratings on subject i, c_j is an unobserved random effect shared by all subject ratings by rater j, and ε_{ij} is an unobserved noise term. Each class of terms is assumed to be respectively identically distributed with expected value 0, and the terms are assumed to be uncorrelated. For certain random effects models, either α_i or c_j is neglected or considered fixed. We refer to Liljequist et al. [2019] for a comprehensive overview of ICC definitions and derivations relating classical estimators to the random effects model. See table in appendix A.1 for reproduced formulas.

In our specific use case, we use a two-way consistency average, i.e. $\mathrm{ICC}(3, k)$ as this formulation treats *raters* as fixed effects, (i.e. c_j is fixed), meaning the same evaluation panel assesses all LLM outputs, and estimates reliability for the average rating across k evaluators rather than individual rater consistency. The numerator $(MS_R - MS_E)$ captures the true variance between different LLM responses after removing measurement error, while the denominator represents the total variance in averaged ratings, making $\mathrm{ICC}(3, k)$ particularly sensitive to systematic differences in how evaluators rate different model outputs while accounting for random measurement error within the evaluation process. With random effects model for $\mathrm{ICC}(3, k)$, the population ICC

$$\rho = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\varepsilon^2 / k}$$

We utilize the associated formula as the ICC metric for our experiments due to the appropriateness of the setting, random effects model, and use in previous empirical work [Bedi et al., 2025, Croxford et al., 2025, Li et al., 2024]. In our theoretical analysis, we provide bounds with $\mathrm{ICC}(3, 1)$, as the expression resembles Fisher's original proposal for ICC and follows previous theoretical work [Zou, 2012, Bonett, 2002, Giraudeau and Mary, 2001]. Under $\mathrm{ICC}(3, 1)$, the associated random effects model dictates that the population ICC

$$\rho = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\varepsilon^2}$$

This is additionally the more commonly stated population ICC. Note that $\mathrm{ICC}(3, k)$ measures the reliability of the measurement as the average of k raters, whereas $\mathrm{ICC}(3, 1)$ measures the reliability of each single measurement. In the case where $k = 2$, these do not differ greatly. As previously stated, we consider $k = 2$ only in both our empirical and theoretical results.

2.1.1 Previous Work on Bounds for ICC

Previous work in bounding error in ICC estimation focuses on bounding the half-width of a confidence interval [Zou, 2012, Bonett, 2002, Giraudeau and Mary, 2001]. In the more recent of these works, used empirically [Bedi et al., 2025], Zou [2012] aims to determine the required sample size for estimating the intraclass correlation coefficient (ICC) with a desired $(1 - \alpha)100\%$ two-sided confidence interval half-width, ω and pre-specified assurance probability, $1 - \beta$. Thus, Zou [2012] sets

$$1 - \beta = \Pr\left[z_{\alpha/2} \sqrt{\mathrm{Var}(\hat{\rho})} \leq \omega \right]$$

to obtain a minimum bound on the required sample size such that the half-width of the confidence interval remains within the desired width with probability $1-\beta$, where $\hat{\rho}_n$ denotes the sample $\mathrm{ICC}(3,1)$ on n samples. Similarly, the variance Var here is assumed to be the sample variance as opposed to population variance, so $\sqrt{\mathrm{Var}(\hat{\rho})}$ is simply the sample standard deviation $\hat{\sigma}_{\hat{\rho}}$, where the $(1-\alpha)100\%$ two-sided confidence (Wald) interval is given by $\hat{\rho} \pm z_{\alpha/2}\hat{\sigma}_{\hat{\rho}}$, thus clearly the half-width of the confidence interval is $z_{\alpha/2}\hat{\sigma}_{\hat{\rho}}$.

Following this, Zou [2012] shows that for $\mathrm{ICC}(3,1)$ with two raters (human and LLM), the required sample size is:

$$
\begin{aligned}
n &= 1 + \left[\frac{A z_{\alpha/2} + \sqrt{A^2 z_{\alpha/2}^2 + 4\omega z_{\alpha/2} z_\beta A|B|}}{\omega\sqrt{2k(k-1)}} \right]^2 \\
&= 1 + \left[\frac{(1-\rho^2) z_{\alpha/2} + \sqrt{(1-\rho^2)^2 z_{\alpha/2}^2 + 8\omega z_{\alpha/2} z_\beta (1-\rho^2)|\rho|}}{2\omega} \right]^2
\end{aligned}
$$

where the latter line comes from plugging in $k=2$, $A=(1-\rho)[1+(k-1)\rho]=1-\rho^2$, $B=k-2+2\rho-2k\rho=-2\rho$ (thus $|B|=2|\rho|$), ω is the desired half-width, and z_γ denotes the upper γ quantile of the standard normal distribution.

In the next section, we translate the question of bounding the half-width of the confidence interval with high probability to that of bounding the difference between sample and population ICC with high probability – a concentration inequality framework. The two frameworks are translatable, but our concentration inequality framework is ideal for *directly* bounding the error with high probability, and requires fewer assumptions than those present in the calculation of, for instance, a Wald interval, as used in Zou [2012].

2.2 An Approximate Chernoff bound for Intra-class Correlation Coefficient

Here, we derive a straightforward concentration inequality for the intra-class correlation coefficient (ICC). Given annotation distributions, H and G, for human and LLM-generated, respectively, we assume a bivariate normal joint distribution, such that $H_i, G_i \sim \mathcal{N}(\mu, \mathbf{\Sigma})$ independently and identically distributed (i.i.d.), and $i \in \{1,\ldots,n\}$, where n number of samples. Denote the population ICC between H and G as ρ and the observed (sample) ICC at n samples, $\hat{\rho}_n$.

Fisher [1925] showed that given sufficient sample size n, and ρ not too close to its boundary $[-1,1]$, the distribution of $\hat{\rho}_n$ approaches normal asymptotically. In particular, the distribution of $\hat{\rho}_n$ approaches a Gaussian distribution with variance $\frac{(1-\rho^2)^2}{n-1}$. Therefore, we can use the Chernoff bound technique to derive a simple concentration inequality for the intra-class correlation coefficient.

We therefore obtain the following lemma.

Lemma 1 (Chernoff bound for approximate ICC) *Let H, G be two random variables of interest, and assume independently and identically distributed samples $H_i, G_i \sim \mathcal{N}(\mu, \mathbf{\Sigma})$ sampled from a bivariate normal distribution. Let ρ denote the population ICC, and $\hat{\rho}_n$ denote the sample ICC, as defined in Section 2.1. Given desired bound parameter $\varepsilon > 0$, n sufficiently large such that CLT holds, and $|\rho|$ not close to 1,*

$$
\Pr[|\hat{\rho}_n - \rho| \geq \varepsilon] 2\exp\left(-\frac{(n-1)\varepsilon^2}{2(1-\rho^2)^2} \right)
$$

Therefore, given $\delta > 0$, with probability $1-\delta$, the sample and population ICC are guaranteed to be ε-close if

$$
n 1 + \frac{2(1-\rho^2)^2}{\varepsilon^2} \log\left(\frac{2}{\delta}\right)
$$

See proof in Appendix A.2

We provide a comparison between our Chernoff bound and the bound from Zou [2012] in Table 1. As the bound frameworks technically bound two different events, we must translate between the relevant parameters. See Appendix A.3 for more details. Effectively, $\varepsilon = \omega$ and $\delta = 1 - (1 - \alpha) \cdot (1 - \beta)$. As shown in Table 1, the proposed Chernoff bound is more sample efficient, providing relative gains over the current baseline of up to 25.0% for $\rho = 0.8$ and an average of 18.3% over all ρ values*.

	Confidence Interval Parameters				Chernoff Bound Parameters		
ρ	α	ω, half width	β	Zou [2012] N	ε	δ	(Ours) N
0.6	0.05	0.1	0.5	158	0.1	0.525	**111**
0.6	0.05	0.15	0.5	71	0.15	0.525	**50**
0.6	0.05	0.2	0.5	40	0.2	0.525	**28**
0.6	0.05	0.1	0.2	183	0.1	0.240	**175**
0.6	0.05	0.15	0.2	87	0.15	0.240	**78**
0.6	0.05	0.2	0.2	52	0.2	0.240	**44**
0.6	0.05	0.1	0.1	**195**	0.1	0.145	216
0.6	0.05	0.15	0.1	**95**	0.15	0.145	97
0.6	0.05	0.2	0.1	58	0.2	0.145	**55**
0.7	0.05	0.1	0.5	101	0.1	0.525	**71**
0.7	0.05	0.15	0.5	45	0.15	0.525	**32**
0.7	0.05	0.2	0.5	26	0.2	0.525	**18**
0.7	0.05	0.1	0.2	123	0.1	0.240	**111**
0.7	0.05	0.15	0.2	60	0.15	0.240	**50**
0.7	0.05	0.2	0.2	37	0.2	0.240	**29**
0.7	0.05	0.1	0.1	**134**	0.1	0.145	138
0.7	0.05	0.15	0.1	67	0.15	0.145	**62**
0.7	0.05	0.2	0.1	42	0.2	0.145	**35**
0.8	0.05	0.1	0.5	51	0.1	0.525	**36**
0.8	0.05	0.15	0.5	23	0.15	0.525	**16**
0.8	0.05	0.2	0.5	13	0.2	0.525	**10**
0.8	0.05	0.1	0.2	68	0.1	0.240	**56**
0.8	0.05	0.15	0.2	35	0.15	0.240	**25**
0.8	0.05	0.2	0.2	22	0.2	0.240	**15**
0.8	0.05	0.1	0.1	77	0.1	0.145	**69**
0.8	0.05	0.15	0.1	40	0.15	0.145	**31**
0.8	0.05	0.2	0.1	26	0.2	0.145	**18**

Table 1: **The proposed Chernoff bound tighter in the required number of human annotations.** Relative to the interval-based bound of Zou [2012], our Chernoff bound achieves tighter bound by 18.3% in required sample size, with a median reduction of 21.6%. The gains are more pronounced at higher correlations: average improvements are 12.4% for $\rho = 0.6$, 17.6% for $\rho = 0.7$, and 25.0% for $\rho = 0.8$. The bold entries in the table indicate the lower sample complexity between the two bounds.

3 Methods

3.1 Problem Formulation

We study the problem of evaluating LLM judges under limited annotation budgets. Assume we have a set of items $\mathcal{X} = \{x_1, \ldots, x_n\}$ for evaluation, with associated inexpensive labels $G = \{g_i\}$ from an LLM judge. Similarly, there exists a set of gold labels $H = \{h_i\}$ from humans of which we are only able to collect some subset of size b. Reliability is measured using the Intraclass Correlation Coefficient (ICC$(3, k)$), which captures absolute agreement. Further information regarding the calculation of ICC scores can be found in Appendix A.1.

Given a budget $b < n$, we seek a subset $S^* \subseteq \mathcal{X}$ of size b such that the ICC $\hat{\rho}_b$ computed on (H_{S^*}, G_{S^*}) closely approximates the ICC $\hat{\rho}_n$ on the full dataset (H, G):

$$S^* = \arg \min_{S \subseteq \mathcal{X}, |S|=b} |\hat{\rho}_b(H_S, G_S) - \hat{\rho}_n(H, G)| .$$

We assume access to $\mathcal{X}$ and G, and a single-batch labeling regime (rather than an *active* iterative setting) such that labels in H_S are obtained all at once for a chosen S. Thus, our subset selection must rely solely on the items $\mathcal{X}$ and the inexpensive labels G.†

*Note that cases where the derived sample size is below 30, this violates the assumptions required for both bounds (that n is sufficiently large according to CLT).

†As LLM-annotated data is inexpensive, we assume that n is large, and $\hat{\rho}_n$ effectively acts as a stand-in for the population ICC ρ on the joint distribution $(H|\mathcal{X}, G|\mathcal{X})$, since we cannot access ρ in our evaluation. Similarly, we allow some abuse of notation such that $H = \{h_i\}_{i=1}^n$ and $G = \{g_i\}_{i=1}^n$ are assumed to capture label distributions $H|\mathcal{X}$ and $G|\mathcal{X}$, respectively.

3.2 Data Preparation

We provide empirical evaluations on 4 diverse real-world datasets: MSLR [Wang et al., 2023], HANNA [Chhun et al., 2024], MedVAL [Aali et al., 2025], and SummEval [Fabbri et al., 2021]. Each dataset is annotated along multiple axes (e.g., faithfulness, accuracy, creativity) with a total of 15 sets of human annotations by which to evaluate sampling performance, as shown in Table 2. All datasets contain samples that are annotated by more than one human, creating a distribution of continuous scores that requires the use of ICC over alternative ordinal or categorical agreement metrics. We take the average score of a subject between total raters as the true score and compare to the LLM judge score. All datasets use Likert scaling with a range of 1–5 [Joshi et al., 2015]. The evaluation axes span from more objective to more subjective scores, capturing a broad spectrum of evaluation types. We truncate each dataset to contain 300 human-labeled samples and perform evaluations on subsets of this annotation set. We perform the evaluations over 100 rollouts, each with its own random seed to account for variance in the predicted ICC value from the random components of the selection mechanisms (i.e., random selection, cluster initialization, etc.).

Table 2: Datasets, evaluation axes, and number of raters per datapoint.

Dataset	Axes of Evaluation	Raters per datapoint
SummEval	Coherence, Consistency, Fluency, Relevance	8
HANNA	Relevance, Coherence, Empathy, Surprise, Engagement, Complexity	3
MedVAL	Safety	1–3
MSLR	Fluency, Population, Intervention, Outcome	1–2

3.3 Sampling Methods

We compare 6 strategies for selecting S^* as shown in Table 3 against random sampling. Additional information regarding each algorithm is present in Appendix A.4

Table 3: Selection strategies for choosing k items from cheap ratings G.

Method	Description	Formula
Random	Uniformly sample k items without replacement	$S_{\text{rand}} = \text{UniformSample}(\mathcal{N}, k)$
Stratified	Partition ratings into k quantile strata; sample one per stratum	$S_{\text{strat}} = \bigcup_{j=1}^{k} \text{UniformSample}(\text{Stratum}_j, 1)$
QBC	Select items with largest inter-rater difference	$S_{\text{QBC}} = \arg\max_{\|S\|=k} \sum_{i \in S} \|g_i^{(1)} - g_i^{(2)}\|$
Stratified QBC	Combine stratified ($k/2$) and QBC ($k/2$)	$S_{\text{sQBC}} = S_{\text{strat}}^{(k/2)} \cup S_{\text{QBC}}^{(k/2)}$
Cluster	Choose item nearest to each K-means centroid	$S_{\text{clust}} = \{\arg\min_{i \in C_j} \|g_i - c_j\|\}_{j=1}^{k}$
Maximum-Variation	Iteratively add items maximizing variance	$S_{t+1} = S_t \cup \{\arg\max_{i \notin S_t} \dots\}$
Density-Based	Balance typical (high density) and outliers (low density)	$S_{\text{dens}} = S_{\text{high}} \cup S_{\text{low}}$

4 Results

4.1 Estimation Error By Selection Method

As shown in Figure 2, the **cluster** method consistently achieves a lower estimation error than random selection. Across all datasets and tasks, cluster-based selection consistently provides more sample-efficient ICC estimation with $n_{expensive} \leq 30$, with up to 31% relative improvement over random sampling in settings with $\leq 5\%$ of annotation budget available as shown in Table 4. We see saturation of gains from cluster-based selection as the data budget ($n_{expensive}$) increases, as random sampling is better able to capture the true distribution of samples with increased data points. While some relative improvements are negative at larger $n_{expensive}$, the difference between estimation error from cluster-based selection and random selection decreases as $n_{expensive}$ increases, so these negative values represent small differences (absolute differences are present in Appendix Table 5). However, in data-scarce settings, cluster selection consistently allows for lower estimation error between predicted and true ICC values.

In addition to minimizing the estimation error between true and predicted ICC values, cluster-based selections are also more stable and have a demonstrably smaller confidence interval than equivalent random selection, as shown in Table 4. For datasets HANNA, MedVAL, and SummEval, the improvement in confidence interval width is larger than with the MSLR dataset. Similarly, the MSLR dataset also shows the smallest improvement against random in estimation error as well as confidence interval width. We attribute this to the true ICC for all samples in this dataset against the judge model. The ICC of MSLR is 0.346, while the ICC of HANNA, MedVAL, and SummEval, respectively, are $0.655, 0.716, 0.627$. This indicates that clustering selection provides the most benefit under the assumption of a minimum ICC and concordance between the judge model and human scoring. When the raters are dissimilar, the clustering method converges to perform similarly to random selection.

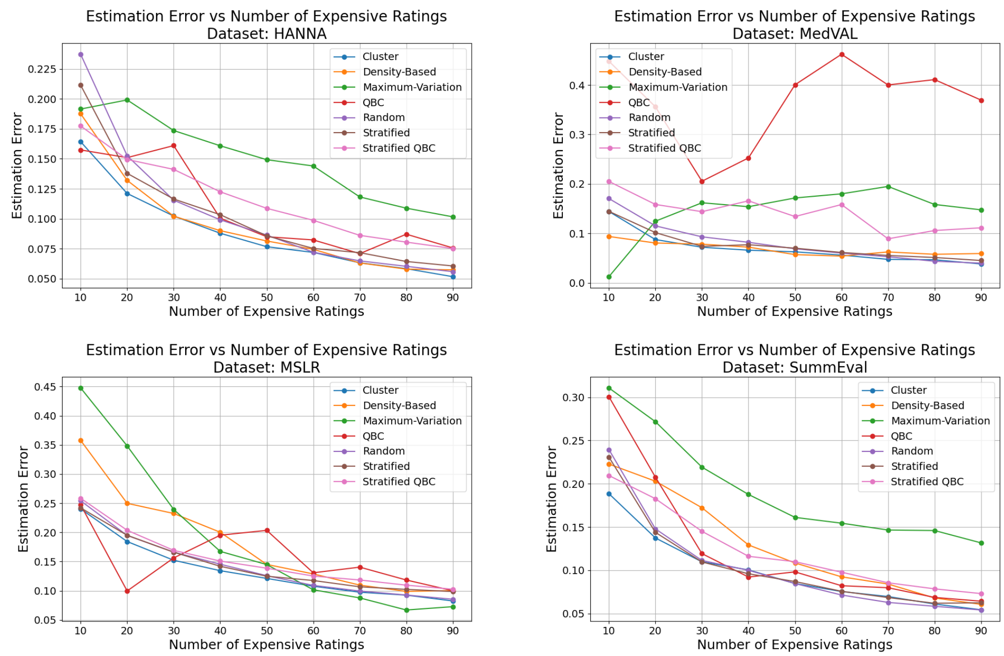


Figure 2: **Cluster-based sample selection for annotation leads to consistently lower estimation error.** We compare 6 methods of sample selection against a random baseline, showing that cluster-based approaches consistently perform at or above the precision level of random selection, providing improved estimations of true ICC values.

4.2 Coverage Perspective on Clustering

As discussed in Section 3.1, we frame our task as selecting a subset of samples such that the empirical intra-class correlation coefficient (ICC) on b annotated items, $\hat{\rho}_b$, closely approximates the ICC on the full dataset, $\hat{\rho}_n$. Since human labels are not available a priori, we cannot sample based on them directly. An optimal subset (H_S, G_S) should preserve the distributional properties of the full set (H, G), specifically the variance structure that determines ICC. While the human-label variance components are inaccessible, the inexpensive labels provide a coarse but useful proxy. Thus, our goal is to select a subset G_S whose distribution approximates that of G, effectively minimizing regret with respect to set coverage.

$n_{\text{expensive}}$	Mean ICC Improvement over Random (%)				CI Width Improvement of Cluster over Random (%)			
	HANNA	MedVAL	MSLR	SummEval	HANNA	MedVAL	MSLR	SummEval
10	31.0%	15.0%	5.5%	21.0%	6.4%	32.4%	−0.9%	24.1%
20	21.0%	24.0%	5.4%	7.1%	7.8%	18.3%	0.1%	21.9%
30	11.0%	23.0%	8.4%	1.4%	7.1%	13.9%	−2.4%	18.4%
40	11.0%	20.0%	7.6%	0.0%	2.6%	9.7%	−1.0%	14.6%
50	11.0%	9.0%	3.7%	0.0%	4.9%	9.4%	−0.7%	14.0%
60	0.0%	6.8%	1.3%	−5.6%	2.9%	2.1%	0.0%	11.3%
70	2.5%	10.0%	2.0%	−11.0%	3.5%	8.0%	−0.4%	9.1%
80	3.2%	−7.1%	0.0%	−4.4%	1.5%	5.9%	0.0%	7.8%
90	7.5%	4.2%	3.4%	0.0%	1.8%	4.5%	−1.3%	6.2%

Table 4: **Cluster-based sampling can decrease estimation error and improve confidence intervals in low data settings.** Relative improvement (%) of Cluster over Random for both average ICC (left block) and confidence interval width (right block). Negative values indicate cases where Cluster underperforms Random.

This motivates the use of clustering approaches to adequately capture set variance. A known problem in the context of set coverage is the k-Centers problem. Given a metric space $(\mathcal{X}, d)$, the objective of the k-Centers problem [Hakimi, 1964] is to find k centers $\mathcal{C}^* = \{c_1, \ldots, c_k\} \subseteq \mathcal{X}$ such that

$$\mathcal{C}^* = \arg \min_{C \subseteq \mathcal{X}, |C|=k} \max_{x \in \mathcal{X}} \min_{c \in C} d(c, x)$$

Although this problem is NP-hard, approximate solutions yield strong coverage guarantees [Lim et al., 2005]. While k-means clustering optimizes a different criterion (minimizing within-cluster variance rather than worst-case distance), it also provides effective coverage of the space [Wolf, 2011]. By covering the inexpensive label space, k-means ensures that the selected subset spans the diversity of the dataset, which in turn helps recover the variance structure and ICC of the full population. Prior work has similarly leveraged clustering for diverse sampling in related contexts [Sener and Savarese, 2018].

5 Discussion

As LLMs become central in various workflows, the ability to evaluate their outputs at scale becomes increasingly critical. LLM Judges emerge as the current state-of-the-art for scalable, non-verifiable evaluation, but these methods are only as good as they are aligned with human preferences. One way to quantify their correlation with human ratings is through the intra-class correlation coefficient (ICC). LLM judge outputs can be compared to gold-standard human outputs with ICC, but human outputs are expensive and time-intensive to obtain. We explore methods to reduce the human annotation burden.

We introduce a Chernoff bound that allows practitioners to derive an approximate bound on the minimum number of human annotations necessary to ascertain performance given a desired tolerance ε and probabilistic guarantee δ. This bound improves upon current baseline methods of sample size calculation by an average of 18.3% across parameter combinations. Additionally, we show that cluster-based selection consistently provides the most sample-efficient estimation of the true ICC value across a large range of potential "budget" ratios. The greatest improvements occur in low-budget settings, with relative improvement of 5.5% to 31% compared to random in settings where annotation budget is $\leq 5\%$ of total samples. This allows model practitioners to iterate on their LLM judge methodology with higher fidelity without wasting annotation budget. We compare the confidence interval size between randomly selected samples and samples selected using a cluster-based approach. We see that the cluster-based approach provides tighter confidence intervals in addition to the empirical results of more precise ICC estimates. This supports that in limited annotation settings, cluster-based selection of points to receive human annotation decreases ICC estimation error as well as produces narrower confidence intervals for the ICC estimate.

Future work can explore extensions beyond cluster-based methods to further reduce expensive annotation requirements. The utilization of the subject text as a part of the selection process could further act as a signal of diversity and coverage, thus allowing for improved sampling at lower budgets and exploring associated bounds with specific data selection mechanisms. Currently, the cluster method is most impactful under the key assumption that the LLM judge ratings are a reasonable proxy for human ratings. Further exploration should provide means to evaluate this assumption a priori, such that practitioners have a base understanding of what the alignment may be and whether these assumptions hold.

References

Asad Aali, Vasiliki Bikia, Maya Varma, Nicole Chiou, Sophie Ostmeier, Arnav Singhvi, Magdalini Paschali, Ashwin Kumar, Andrew Johnston, Karimar Amador-Martinez, Eduardo Juan Perez Guerrero, Paola Naovi Cruz Rivera, Sergios Gatidis, Christian Bluethgen, Eduardo Pontes Reis, Eddy D. Zandee van Rilland, Poonam Laxmappa Hosamani, Kevin R Keet, Minjoung Go, Evelyn Ling, David B. Larson, Curtis Langlotz, Roxana Daneshjou, Jason Hom, Sanmi Koyejo, Emily Alsentzer, and Akshay S. Chaudhari. Medval: Toward expert-level medical text validation with language models, 2025.

Brian G Arndt, John W Beasley, Michelle D Watkinson, Jonathan L Temte, Wen-Jan Tuan, Christine A Sinsky, and Valerie J Gilchrist. Tethered to the ehr: primary care physician workload assessment using ehr event log data and time-motion observations. *The Annals of Family Medicine*, 15(5): 419–426, 2017.

Suhana Bedi, Hejie Cui, Miguel Fuentes, Alyssa Unell, Michael Wornow, Juan M. Banda, Nikesh Kotecha, Timothy Keyes, Yifan Mai, Mert Oez, Hao Qiu, Shrey Jain, Leonardo Schettini, Mehr Kashyap, Jason Alan Fries, Akshay Swaminathan, Philip Chung, Fateme Nateghi, Asad Aali, Ashwin Nayak, Shivam Vedak, Sneha S. Jain, Birju Patel, Oluseyi Fayanju, Shreya Shah, Ethan Goh, Dong han Yao, Brian Soetikno, Eduardo Reis, Sergios Gatidis, Vasu Divi, Robson Capasso, Rachna Saralkar, Chia-Chun Chiang, Jenelle Jindal, Tho Pham, Faraz Ghoddusi, Steven Lin, Albert S. Chiou, Christy Hong, Mohana Roy, Michael F. Gensheimer, Hinesh Patel, Kevin Schulman, Dev Dash, Danton Char, Lance Downing, Francois Grolleau, Kameron Black, Bethel Mieso, Aydin Zahedivash, Wen wai Yim, Harshita Sharma, Tony Lee, Hannah Kirsch, Jennifer Lee, Nerissa Ambers, Carlene Lugtu, Aditya Sharma, Bilal Mawji, Alex Alekseyev, Vicky Zhou, Vikas Kakkar, Jarrod Helzer, Anurang Revri, Yair Bannett, Roxana Daneshjou, Jonathan Chen, Emily Alsentzer, Keith Morse, Nirmal Ravi, Nima Aghaeepour, Vanessa Kennedy, Akshay Chaudhari, Thomas Wang, Sanmi Koyejo, Matthew P. Lungren, Eric Horvitz, Percy Liang, Mike Pfeffer, and Nigam H. Shah. Medhelm: Holistic evaluation of large language models for medical tasks, 2025. URL `https://arxiv.org/abs/2505.23802`.

Douglas G. Bonett. Sample size requirements for estimating intraclass correlations with desired precision. *Statistics in Medicine*, 21(9):1331–1335, 2002.

Asli Celikyilmaz, Elizabeth Clark, and Jianfeng Gao. Evaluation of text generation: A survey, 2021. URL `https://arxiv.org/abs/2006.14799`.

Herman Chernoff. A measure of asymptotic efficiency for tests of a hypothesis based on the sum of observations. *The Annals of Mathematical Statistics*, 23(4):493–507, 1952. doi: 10.1214/aoms/1177729330.

Cyril Chhun, Fabian M. Suchanek, and Chloé Clavel. Do language models enjoy their own stories? Prompting large language models for automatic story evaluation. *Transactions of the Association for Computational Linguistics*, 12:1122–1142, 2024. ISSN 2307-387X. doi: 10.1162/tacl_a_00689. URL `https://doi.org/10.1162/tacl_a_00689`.

William G. Cochran. *Sampling Techniques*. John Wiley & Sons, 3 edition, 1977.

E. Croxford, Y. Gao, N. Pellegrino, K. Wong, G. Wills, E. First, M. Schnier, K. Burton, C. Ebby, J. Gorski, M. Kalscheur, S. Khalil, M. Pisani, T. Rubeor, P. Stetson, F. Liao, C. Goswami, B. Patterson, and M. Afshar. Development and validation of the provider documentation summarization quality instrument for large language models. *Journal of the American Medical Informatics Association*, 32(6):1050–1060, June 2025. doi: 10.1093/jamia/ocaf068.

Yann Dubois et al. Alpacaeval 2.0: Automatic evaluation of instruction-following models. *arXiv preprint arXiv:2401.04088*, 2024.

Alexander R. Fabbri, Wojciech Kryściński, Bryan McCann, Caiming Xiong, Richard Socher, and Dragomir Radev. Summeval: Re-evaluating summarization evaluation, 2021. URL https://arxiv.org/abs/2007.12626.

Ronald A. Fisher. Statistical methods for research workers. 1925.

Bruno Giraudeau and Jean-Yves Mary. Planning a reproducibility study: how many subjects and how many replicates per subject for an expected width of the 95 per cent confidence interval of the intraclass correlation coefficient. *Statistics in Medicine*, 20:3205–3214, 2001. doi: 10.1002/sim.935.abs.

Jiawei Gu, Xuhui Jiang, Zhichao Shi, Hexiang Tan, Xuehao Zhai, Chengjin Xu, Wei Li, Yinghan Shen, Shengjie Ma, Honghao Liu, Saizhuo Wang, Kun Zhang, Yuanzhuo Wang, Wen Gao, Lionel Ni, and Jian Guo. A survey on llm-as-a-judge, 2025. URL https://arxiv.org/abs/2411.15594.

S. L. Hakimi. Optimum locations of switching centers and the absolute centers and medians of a graph. *Operations Research*, 12(3):450–459, 1964. doi: 10.1287/opre.12.3.450.

Ankur Joshi, Saket Kale, Satish Chandel, and D Kumar Pal. Likert scale: Explored and explained. *British journal of applied science & technology*, 7(4):396, 2015.

Douwe Kiela, Max Bartolo, et al. Dynabench: Rethinking benchmarking in nlp. In *NAACL*, 2021.

Haitao Li, Qian Dong, Junjie Chen, Huixue Su, Yujia Zhou, Qingyao Ai, Ziyi Ye, and Yiqun Liu. Llms-as-judges: A comprehensive survey on llm-based evaluation methods, 2024.

Percy Liang, Rishi Bommasani, et al. Holistic evaluation of language models. In *NeurIPS*, 2022.

David Liljequist, Britt Elfving, and Kirsti Skavberg Roaldsen. Intraclass correlation – a discussion and demonstration of basic features. *PLOS ONE*, 14:1–35, 07 2019. doi: 10.1371/journal.pone.0219854. URL https://doi.org/10.1371/journal.pone.0219854.

Andrew Lim, Brian Rodrigues, Fan Wang, and Zhou Xu. k-center problems with minimum coverage. *Theoretical Computer Science*, 332(1):1–17, 2005. ISSN 0304-3975. doi: https://doi.org/10.1016/j.tcs.2004.08.010. URL https://www.sciencedirect.com/science/article/pii/S0304397504005717.

Stuart P. Lloyd. Least squares quantization in pcm. *IEEE Transactions on Information Theory*, 28(2):129–137, 1982.

Jayson G. Meyer, Ryan J. Urbanowicz, Pedro C. N. Martin, et al. Chatgpt and large language models in academia: opportunities and challenges. *BioData Mining*, 16(1):20, 2023. doi: 10.1186/s13040-023-00339-9.

Ozan Sener and Silvio Savarese. Active learning for convolutional neural networks: A core-set approach. In *Proceedings of the 5th International Conference on Learning Representations*, 2018.

Burr Settles and Mark Craven. An analysis of active learning strategies for sequence labeling tasks. In *Conference on Empirical Methods in Natural Language Processing*, pages 1070–1079, 2008.

Patrick E. Shrout and Joseph L. Fleiss. Intraclass correlations: uses in assessing rater reliability. *Psychological Bulletin*, 86(2):420–428, 1979. doi: 10.1037/0033-2909.86.2.420.

Sijun Tan, Siyuan Zhuang, Kyle Montgomery, William Y. Tang, Alejandro Cuadron, Chenguang Wang, Raluca Ada Popa, and Ion Stoica. Judgebench: A benchmark for evaluating llm-based judges, 2025. URL https://arxiv.org/abs/2410.12784.

Anuraj J. Thirunavukarasu, Daniel S. W. Ting, Kishore Elangovan, et al. Large language models in medicine. *Nature Medicine*, 29(9):1930–1940, 2023. doi: 10.1038/s41591-023-02448-8.

Lucy Lu Wang, Yulia Otmakhova, Jay DeYoung, Thinh Hung Truong, Bailey E Kuehl, Erin Bransom, and Byron C Wallace. Automated metrics for medical multi-document summarization disagree with human evaluations. In *Proceedings of the 61th Annual Meeting of the Association for Computational Linguistics (Long Papers)*, Toronto, Canada, 2023. Association for Computational Linguistics.

Gert W. Wolf. Facility location: concepts, models, algorithms and case studies. series: Contributions to management science. *Int. J. Geogr. Inf. Sci.*, 25(2):331–333, February 2011. ISSN 1365-8816. doi: 10.1080/13658816.2010.528422. URL https://doi.org/10.1080/13658816.2010.528422.

Weizhe Yuan, Graham Neubig, and Pengfei Liu. Bartscore: Evaluating generated text as text generation. In M. Ranzato, A. Beygelzimer, Y. Dauphin, P.S. Liang, and J. Wortman Vaughan, editors, *Advances in Neural Information Processing Systems*, volume 34, pages 27263–27277. Curran Associates, Inc., 2021. URL https://proceedings.neurips.cc/paper_files/paper/2021/file/e4d2b6e6fdeca3e60e0f1a62fee3d9dd-Paper.pdf.

G.Y. Zou. Sample size formulas for estimating intraclass correlation coefficients with precision and assurance. *Statistics in medicine*, 31(29):3972—3981, December 2012. ISSN 0277-6715. doi: 10.1002/sim.5466. URL https://doi.org/10.1002/sim.5466.

A Appendix

A.1 Intra-class Correlation Coefficient Definitions

See table below for reproduced formulas [Liljequist et al., 2019].

Name	Notation	Rater Model	Use Case	Formula
One-way single	ICC(1,1)	Random	Agreement of 1 random rater	$\frac{\mathrm{MS_R} - \mathrm{MS_E}}{\mathrm{MS_R} + (k-1)\mathrm{MS_E}}$
One-way average	ICC(1,k)	Random	Agreement of average random raters	$\frac{\mathrm{MS_R} - \mathrm{MS_E}}{\mathrm{MS_R}}$
Two-way absolute single	ICC(2,1)	Random	Absolute agreement of 1 random rater	$\frac{\mathrm{MS_R} - \mathrm{MS_E}}{\mathrm{MS_R} + (k-1)\mathrm{MS_E} + \frac{k}{n}(\mathrm{MS_C} - \mathrm{MS_E})}$
Two-way absolute average	ICC(2,k)	Random	Absolute agreement of average raters	$\frac{\mathrm{MS_R} - \mathrm{MS_E}}{\mathrm{MS_R} + \frac{1}{n}(\mathrm{MS_C} - \mathrm{MS_E})}$
Two-way consistency single	ICC(3,1)	Fixed	Consistency of 1 fixed rater	$\frac{\mathrm{MS_R} - \mathrm{MS_E}}{\mathrm{MS_R} + (k-1)\mathrm{MS_E}}$
Two-way consistency average	ICC(3,k)	Fixed	Consistency of average fixed raters	$\frac{\mathrm{MS_R} - \mathrm{MS_E}}{\mathrm{MS_R}}$
Pearson correlation	r	N/A	Correlation only (not agreement)	$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}}$

Notation:

- $\mathrm{MS_R}$: Mean square between targets (rows)
- $\mathrm{MS_C}$: Mean square between raters (columns)
- $\mathrm{MS_E}$: Residual mean square (error)
- n: Number of targets
- k: Number of raters

Formulas:

$$\mathrm{MS_R} = \frac{k}{n-1}\sum_{i=1}^{n}(S_i - \overline{X}_{\mathrm{tot}})^2$$

$$\mathrm{MS_C} = \frac{n}{k-1}\sum_{j=1}^{k}(M_j - \overline{X}_{\mathrm{tot}})^2$$

$$\mathrm{MS_E} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{k}(x_{ij} - M_j)^2 - k\sum_{i=1}^{n}(S_i - \overline{X}_{\mathrm{tot}})^2}{(n-1)(k-1)}$$

$$S_i = \frac{1}{k}\sum_{j=1}^{k} x_{ij}$$

$$M_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij}$$

$$\overline{X}_{\mathrm{tot}} = \frac{1}{k\cdot n}\sum_{i=1}^{n}\sum_{j=1}^{k} x_{ij}$$

A.2 Chernoff Bound on Intra-class Correlation Coefficient

Given the population ICC stated in the previous section, we denote the sample ICC of n samples as $\hat{\rho}_n$ and calculate as the formula listed in our table for $\mathrm{ICC}(3,1)$. In Fisher [1925], Fisher demonstrates that with the assumption of sufficiently large number of samples, and given that $\hat{\rho}_n$ is not close to -1 nor 1, the distribution of $\hat{\rho}_n$ on bivariate Gaussian random variables asymptotically approaches Gaussian with parameters $\mathbb{E}[\hat{\rho}_n] = \rho$ and $\mathrm{Var}(\hat{\rho}_n) = \frac{(1-\rho^2)^2}{n-1}$. As earlier work on sample bounds for ICC leverage this approximation and associated assumptions [Zou, 2012], we consider these assumptions and approximations reasonable. As stated in Section 2.2, we assume a bivariate normal distribution for LLM-annotated and human annotated samples.

Thus, we only require a few additional (already extant) propositions to derive an approximate Chernoff bound.

Proposition 2 *[Chernoff, 1952] For any random variable X, the Chernoff bound dictates that*

$$\Pr(X \geq \varepsilon) \leq \inf_{\lambda \geq 0} \varphi_X(\lambda) e^{-\lambda\varepsilon}$$

where $\varphi_X(\lambda)$ is the moment generating function for X.

For a Gaussian random variable $X \sim \mathcal{N}(\mu, \sigma^2)$, the moment generating function $\varphi_X(\lambda) = \exp(\mu\lambda + \sigma^2\lambda^2/2)$. Due to linearity of the Gaussian distribution, $X - \mu \sim \mathcal{N}(0, \sigma^2)$, and the moment generating function is $\varphi_X(\lambda) = \exp(\sigma^2\lambda^2/2)$. Thus, the Chernoff bound for a Gaussian random variable is

$$\Pr(X - \mu \geq \varepsilon) \leq \exp\left(-\frac{\varepsilon^2}{2\sigma^2}\right)$$

Analogously,

$$\Pr(\mu - X \geq \varepsilon) \leq \exp\left(-\frac{\varepsilon^2}{2\sigma^2}\right)$$

Therefore, as the events $X - \mu \geq \varepsilon$ and $\mu - X \geq \varepsilon$ are mutually exclusive and constitute the event $|X - \mu|$,

$$\Pr(|X - \mu| \geq \varepsilon) \leq 2\exp\left(-\frac{\varepsilon^2}{2\sigma^2}\right)$$

Combining this with the fact that $\hat{\rho_n}$ approaches Gaussian asymptotically with variance $\frac{(1-\rho^2)^2}{n-1}$, we obtain our desired approximate bound

$$\Pr[|\hat{\rho}_n - \rho| \geq \varepsilon] 2 \exp\left(- \frac{(n-1)\varepsilon^2}{2(1-\rho^2)^2} \right)$$

As standard with concentration inequalities, we can derive the necessary n such that $|\hat{\rho}_n - \rho| \geq \varepsilon$ with at most probability δ by setting δ equal to our bound and solving for n.

$$\begin{aligned}
\delta &= 2 \exp\left(- \frac{(n-1)\varepsilon^2}{2(1-\rho^2)^2} \right) \\
\log\left(\frac{2}{\delta}\right) &= \frac{(n-1)\varepsilon^2}{2(1-\rho^2)^2} \\
\frac{2(1-\rho^2)^2}{\varepsilon^2} \log\left(\frac{2}{\delta}\right) &= (n-1) \\
1 + \frac{2(1-\rho^2)^2}{\varepsilon^2} \log\left(\frac{2}{\delta}\right) &= n
\end{aligned}$$

A.3 Comparison between Confidence Interval and Concentration Inequality Bounds

In the context of the bound on a $(1-\alpha)100\%$ confidence interval, as detailed in Section **??**, the derived bound is technically on the confidence interval itself, in the case of [Zou, 2012], a Wald interval, i.e. $z_{\alpha/2}\hat{\sigma}_{\hat{\rho}_n}$. The $(1-\alpha)100\%$ two-sided confidence interval itself is already set such that $\Pr[|\hat{\rho}_n - \rho|] = 1-\alpha$. Thus, probability of the event $|\hat{\rho}_n - \rho| \geq \varepsilon$ must be decomposed as:

$$\begin{aligned}
\Pr[|\hat{\rho}_n - \rho| \geq \omega] &= \Pr[|\hat{\rho}_n - \rho| \geq z_{\alpha/2}\hat{\sigma}_{\hat{\rho}_n} \wedge z_{\alpha/2}\hat{\sigma}_{\hat{\rho}_n} \geq \omega] \\
&= \Pr[|\hat{\rho}_n - \rho| \geq z_{\alpha/2}\hat{\sigma}_{\hat{\rho}_n}] \cdot \Pr[z_{\alpha/2}\hat{\sigma}_{\hat{\rho}_n} \geq \omega] \\
&= (1-\alpha) \cdot \Pr[z_{\alpha/2}\hat{\sigma}_{\hat{\rho}_n} \geq \omega]
\end{aligned}$$

where indeed the latter term is the component bounded in Zou [2012] (and set to $1-\beta$, with β the pre-specified assurance probability). Thus, to translate between the frameworks, $\varepsilon = \omega$ and $\delta = 1 - (1-\alpha) \cdot (1-\beta)$. Note that their analysis involves multiple parameters (α, β) for our single δ, and thus is not directly translatable in the opposite direction, as many choices for α and β suffice. However, $\alpha = 0.05$ can be assumed to be effectively constant, as this is common practice in applied statistics.

A.4 Selection Methods

A.4.1 Random Selection

The baseline random selection strategy serves as our control method:

$$S_{\text{random}} = \text{UniformSample}(\mathcal{N}, k)$$

where items are selected uniformly at random from the full set $\mathcal{N}$ without replacement.

A.4.2 Stratified Selection

Stratified selection partitions the cheap ratings into k quantile-based strata and selects one representative from each stratum:

$$Q_j = \text{Quantile}(G, \frac{j}{k}) \quad \text{for } j = 0, 1, \ldots, k$$

$$\text{Stratum}_j = \{i \in \mathcal{N} : Q_{j-1} \leq g_i \leq Q_j\}$$

$$S_{\text{stratified}} = \bigcup_{j=1}^{k} \text{UniformSample}(\text{Stratum}_j, 1)$$

A.4.3 Query-by-committe (QBC)

This strategy prioritizes items where multiple cheap raters exhibit maximum disagreement, under the hypothesis that such items are most informative:

$$d_i = |g_i^{(1)} - g_i^{(2)}| \quad \text{for } i \in \mathcal{N}$$

$$S_{\text{QBC}} = \underset{|S|=k}{\arg\max} \sum_{i \in S} d_i$$

where $g_i^{(1)}$ and $g_i^{(2)}$ represent ratings from two different cheap judges.

A.4.4 Stratified QBC Selection

The hybrid approach combines stratified and disagreement-based selection:

$$S_{\text{sQBC}} = S_{\text{sQBC}}^{(k/2)} \cup S_{\text{QBC}}^{(k/2)}$$

where $S_{\text{strat}}^{(k/2)}$ contains $k/2$ items selected via stratification and $S_{\text{QBC}}^{(k/2)}$ contains the remaining items selected by disagreement, excluding those already chosen.

A.4.5 Cluster-Based Selection

This method applies K-means clustering to identify k clusters in the cheap rating space and selects the item closest to each cluster centroid:

$$\{\mathbf{c}_1, \mathbf{c}_2, \ldots, \mathbf{c}_z\} = \text{KMeans}(G, z)$$

$$S_{\text{cluster}} = \left\{ \underset{i \in C_j}{\arg\min} |g_i - c_j| : j = 1, 2, \ldots, k \right\}$$

where C_j represents the set of items assigned to cluster j and c_j is the corresponding cluster center.

A.4.6 Maximize-Variation Selection

Maximize-Variation selection aims to preserve the between-item variance crucial for ICC computation by iteratively selecting items that maximize subset variance:

$$S_0 = \left\{ \underset{i \in \mathcal{N}}{\arg\min} \, \big| g_i - \text{Median}(G) \big| \right\}$$

$$S_{t+1} = S_t \cup \left\{ \underset{i \in \mathcal{N} \setminus S_t}{\arg\max} \, \text{Var}\big(G_{S_t \cup \{i\}}\big) \right\}$$

A.4.7 Density-Based Selection

Density-based selection balances representation between high-density regions (typical cases) and low-density regions (outliers) using kernel density estimation:

$$\rho_i = \text{KDE}(g_i | G) \quad \text{for } i \in \mathcal{N}$$

$$S_{\text{high}} = \text{Sample}\left(\underset{|T|=k}{\arg\max} \sum_{i \in T} \rho_i, k/2 \right)$$

$$S_{\text{low}} = \text{Sample}\left(\underset{|T|=k, T \cap S_{\text{high}} = \emptyset}{\arg\min} \sum_{i \in T} \rho_i, k/2 \right)$$

$$S_{\text{density}} = S_{\text{high}} \cup S_{\text{low}}$$

where $\text{KDE}(g_i|G)$ represents the kernel density estimate of rating g_i given the distribution of all cheap ratings G.

A.5 Judge Model Information

We use GPT-4o-mini with API version 2023-05-15 as our primary model judge for this setting due to the balance of accuracy and cost. We use a temperature score of 0.2. For QBC based selection methods, we use Claude-3.5-Sonnet as an additional committee member. Future work should involve exploring generalizability of claims across additional judge model architectures and families.

A.6 Absolute Improvement Between Clustering and Random

We include absolute improvement between clustering selection and random selection to further ground the relative improvement results present above. We see from these results that occasions where random selection outperforms cluster-based selection are outperforming by relatively small margins compared to larger gains when $n_{expensive} \leq 20$.

$n_{\text{expensive}}$	HANNA	MedVAL	MSLR	SummEval
10	0.073	0.026	0.014	0.051
20	0.031	0.028	0.010	0.010
30	0.013	0.021	0.014	0.002
40	0.011	0.016	0.011	0.000
50	0.010	0.006	0.005	0.000
60	0.000	0.004	0.001	-0.004
70	0.002	0.005	0.002	-0.007
80	0.002	-0.003	0.000	-0.003
90	0.004	0.002	0.003	0.000

Table 5: Absolute Improvement Results across datasets for varying $n_{\text{expensive}}$.

A.7 Confidence Interval Visualization

We report the confidence interval width on the returned estimated subset ICC value from cluster-based sampling and random sampling. We use Fisher's Z transformation to derive the 95% confidence interval width, and report the standard deviation of this width across $k = 100$ iterations.

A.8 Ablation: Different judge model

We flip the main and QBC models to assess the reliance of our results on the specific judge model, such that our main model becomes Claude-3.5-Sonnet and our QBC model becomes GPT-4o-mini. We see that while the exact estimation error varies as a result of the judge, the benefit of cluster-based sampling over random sampling remains consistent.

A.9 Ablation: Different annotation budget ratio

We see with our full dataset of 300 samples that clustering outperforms random selection uniformly until our data budget is $n_{expensive} = 40$, which is 13% of the dataset. We run an ablation with the full dataset equal to 150 samples such that we can observe whether the trends correspond to the magnitude of the budget or the proportion of the budget in relation to the total dataset size. Similarly, with this subsample, we see that the first instance of random outperforming cluster selection is on the MSLR dataset at N=20, which is 13% of the data. This supports the claim that these methods are best suited for data scarce settings and that data scarcity can be defined in relation to the total data available.

A.10 Large Language Model Usage

We used large language models during the brainstorming and writing phases of our project. For writing, we used primarily for polishing grammar and improving flow between topics. We additionally used LLMs to recommend citations that may be relevant to our particular work.

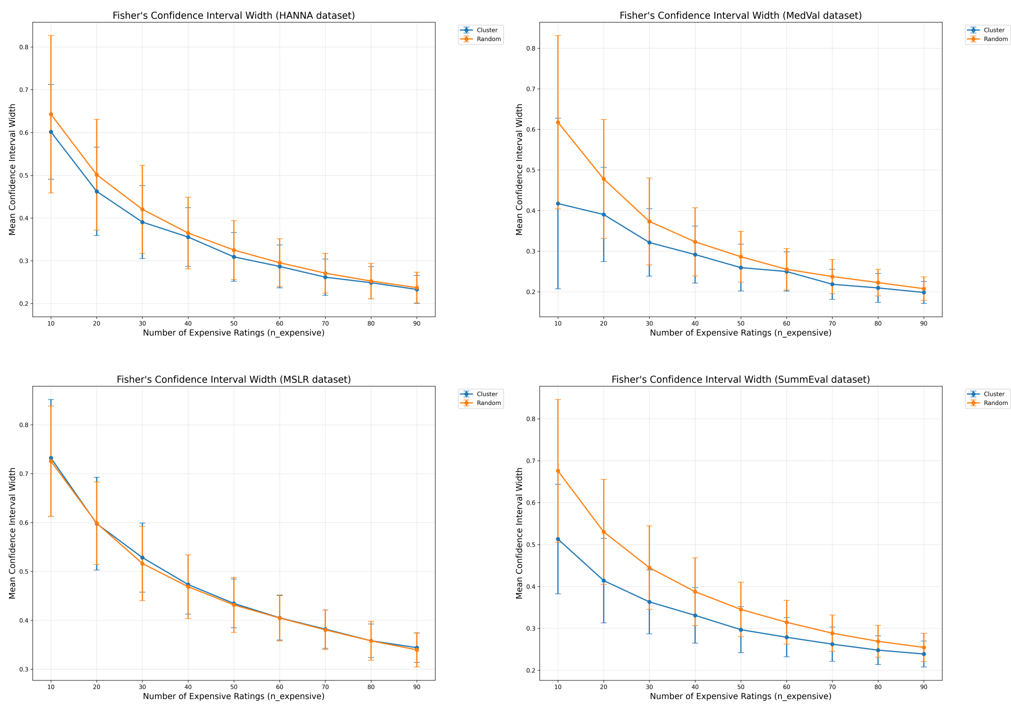
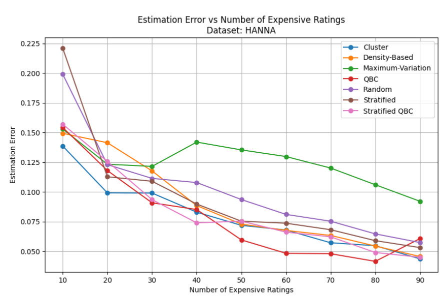
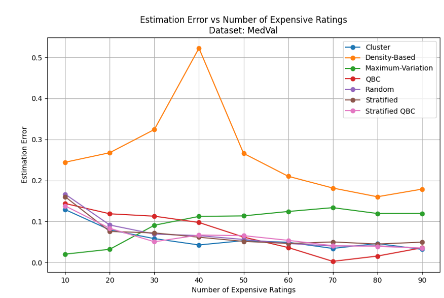


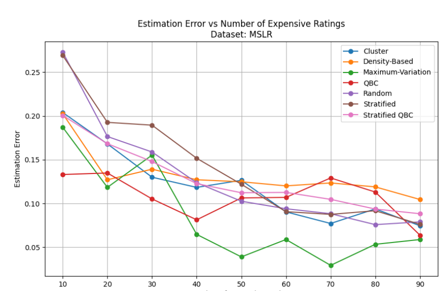
Figure 3: **Cluster selection yields more narrow confidence intervals than random selection.** 95% confidence intervals for intraclass correlation coefficients (ICC) estimated using the Fisher Z transformation.



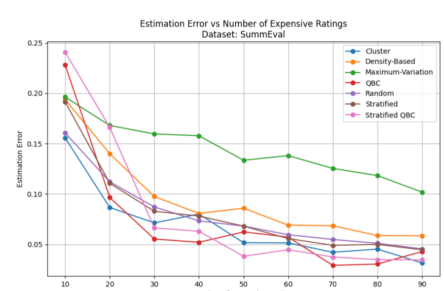
(a) Dataset: HANNA



(b) Dataset: MedVAL

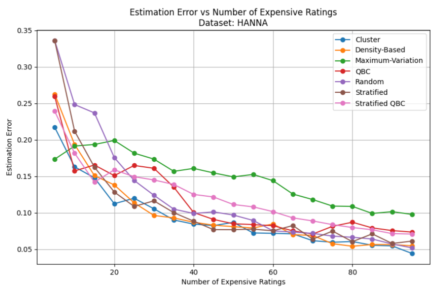


(c) Dataset: MSLR

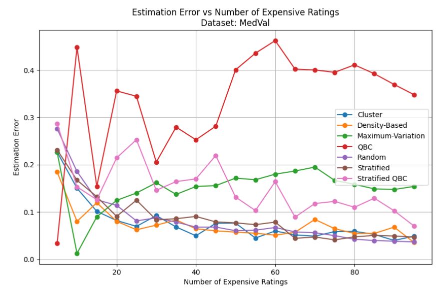


(d) Dataset: SummEval

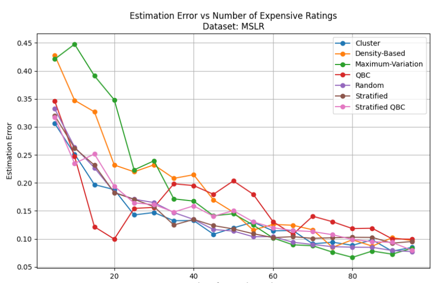
Figure 4: **Cluster based sample selection for annotation leads to lower estimation error across models.** We perform a complementary analysis of all selection methods with Claude-3.5-Sonnet as the judge model and observe consistency in trends, with cluster based selection still being a consistent method for improving performance over random.



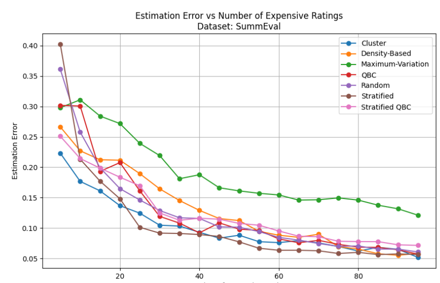
(a) Dataset: HANNA



(b) Dataset: MedVAL



(c) Dataset: MSLR



(d) Dataset: SummEval

Figure 5: **Cluster based selection advantages scale with dataset size.** We evaluate our selection strategies with N=150 such that all $n_{expensive}$ represent a larger fraction of the sample population and observe that general trends hold as with N=300, specifically that cluster selection leads to monotonic improvement until 13% of data is sampled and then improvement starts to converge with random performance.