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What are the best systems? New perspectives on NLP Benchmarking

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Abstract

In Machine Learning, a benchmark refers to an ensemble of datasets associated with one or multiple metrics together with a way to aggregate different systems performances. They are instrumental in *(i)* assessing the progress of new methods along different axes and *(ii)* selecting the best systems for practical use. This is particularly the case for NLP with the development of large pre-trained models (*e.g.* GPT, BERT) that are expected to generalize well on a variety of tasks. While the community mainly focused on developing new datasets and metrics, there has been little interest in the aggregation procedure, which is often reduced to a simple average over various performance measures. However, this procedure can be problematic when the metrics are on a different scale, which may lead to spurious conclusions. This paper proposes a new procedure to rank systems based on their performance across different tasks. Motivated by the social choice theory, the final system ordering is obtained through aggregating the rankings induced by each task and is theoretically grounded. We conduct extensive numerical experiments (on over 270k scores) to assess the soundness of our approach both on synthetic and real scores (*e.g.* GLUE, EXTREM, SEVAL, TAC, FLICKR). In particular, we show that our method yields different conclusions on state-of-the-art systems than the mean-aggregation procedure while being both more reliable and robust.

1 Introduction

This paper is about improving current practices regarding benchmarks of NLP systems. As pointed out by [83], benchmarks are made of datasets, metrics, and a way to aggregate performance. Our point is that, if the bulk of the NLP community efforts on this domain is about collecting new datasets and introducing new metrics, little work is concerned with the third part, namely *how to aggregate various performances*.

Why are benchmarks vital? Research advances in Machine Learning (ML) are crucially fueled by reliable evaluation procedures [34, 78]. The latter are indeed mandatory to fairly compare new methods and systems. Usually, one relies on a well-chosen metric that reflects the ability to perform on a task – *e.g.* accuracy for classification, mean-squared error for regression.

The multi-tasks evaluation setting. If single-tasks problems are quite common, to best understand weakness and model in real-world scenario, the community is heading towards more complex

evaluations involving fine-grained evaluation [61] across several metrics (or criteria [46, 103]) and several tasks [36, 47, 63, 89, 91, 108]. This is due to the increasing performance of deep neural networks, which are nowadays designed to generalize in a great variety of situations and to solve complex tasks [86]. One is typically seeking for models with good *transfer learning* properties, meaning an ability to generalize well under distribution shift and/or task shift [51].

How to aggregate performances? The multi-tasks setting has been investigated in recent works that provide benchmark of state-of-the-art models across a great variety of tasks [28, 62, 80, 90, 108], sometimes with more than fifty [2, 84, 85, 94]. These papers provide tables of scores across the considered tasks, but the only non-qualitative way to compare systems consists in averaging the performances across tasks and then ranking systems according to their mean score values. This is, for instance, done with the GLUE benchmark [91] and its derivatives [92]. However, taking the mean is seriously flawed since the different metrics are usually not on the same scales and can even be unbounded [23, 102]. Even a pre-processing renormalization scheme would fail to capture the intrinsic difficulty of the tasks.

Contribution 1. Our first contribution is to provide a reliable tool to rank systems in a multi-tasks setting. We rely on a ranking aggregation procedure which, from a set of rankings induced by each criterion, returns a single ranking that somehow aggregates the former. This procedure, called the *Kemeny consensus* [52], can be seen as a voting rule and stems from the social choice theory [66].

Aggregation when instance-level information is available. As illustrated by Ruder [83], Zhong et al. [109], a fine-grained understanding of the model performance should include instance-level scores. If taking the mean is quite natural in the classification setting, this is not always the case, as recently pointed out by [73] in the NLG setting. In this article, the authors investigate pairwise comparison of NLG systems for a single metric (*e.g.* BLEU [71], ROUGE [59], METEOR [5, 35, 49], CHRF [76, 77], BertScore [105]). They prove that a comparison based on the mean or the median of the scores across test utterances can be highly flawed. They rather advise to rely on the Bradley-Terry [10] pairwise comparison method, which consists, for two systems A and B, in computing the proportion of utterances on which A achieves a better score than B. Their work is a significant advance but remains limited to pairwise comparisons.

Contribution 2. Our second contribution consists in going one step further than [73] by applying our ranking procedure to an arbitrarily large set of NLG systems with respect to a group of fixed criterion. Our evaluation methodology can be seen as a natural extension of [73] since it coincides with the latter in the particular case of pairwise comparison. In a more realistic multi-criteria scenario, we combine our two contributions and develop a *two-stages ranking aggregation procedure* which first aggregates along utterances and then along criteria.

Experiments. Our two contributions rely on our aggregation procedure which is proved to be effective through several experiments.

1. We explain on a simple synthetic example the superiority of our approach compared to the mean-aggregation procedure and the pairwise-aggregation procedure, both in terms of consistency and robustness.
2. We use our ranking procedure on 10 multi-tasks / multi-criteria benchmarks and observe it leads to different conclusions than mean- and pairwise-aggregation procedures.
3. We argue our procedure is more robust by investigating its stability with respect to the addition of criteria and with respect to the addition of systems.

Our code and the collected data will be released to accelerate the adoption of what we think is a reliable evaluation method for multi-tasks and multi-criteria benchmarks.

2 Problem Formulation and limitations of existing methods

2.1 General Considerations

When comparing systems performances, two settings can be distinguished depending on the information granularity at our disposal and on the way one wishes to use this information. In general, each system is scored on each instance of a test set with respect to a given metric. The final (single) score of the system with respect to this metric is obtained through an aggregation procedure we

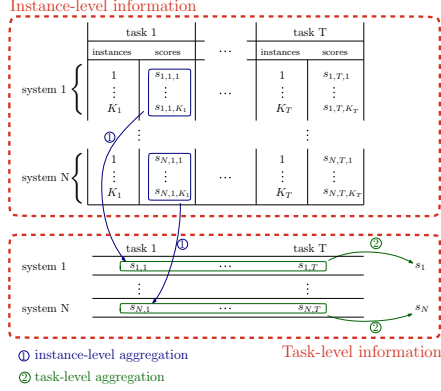


Figure 1: Illustration of the two considered frameworks relying on different information granularity: task-level information (below) or instance-level information (above). From the latter, one can derive the former relying on what we call an instance-level aggregation. A task-level aggregation can then be performed to synthesize a system performance.

will call *instance-level aggregation*, and which has to be chosen by the practitioner (usually, the mean of the instances-scores). Then, the final benchmark score of the system is obtained through an aggregation we call *task-level aggregation* of the scores of this system for each metric of the considered benchmark. See Fig. 1 for an illustration.

Notations. Suppose we are given $N \geq 1$ systems evaluated on $T \geq 1$ tasks, each task $t \in \{1, \dots, T\}$ being associated with a metric and a test set made of $K_t \geq 1$ instances. For every $n \in \{1, \dots, N\}$, $t \in \{1, \dots, T\}$ and $k \in \{1, \dots, K_t\}$, we denote by $s_{n,t,k} \in \mathbb{R}$ the score of system n on the instance k of task t .

Instance-level aggregation. The performance of system n on task t is an aggregation of its scores $(s_{n,t,k})_{1 \leq k \leq K_t}$ on each instances. This aggregation is chosen by the practitioner and is usually the *mean-aggregation* defined by $s_{n,t}^{\text{mean}} := \frac{1}{K_t} \sum_{1 \leq k \leq K_t} s_{n,t,k}$.

Task-level aggregation. Sometimes, one only has access to the aggregated scores of each system on each task, that is, for every $n \in \{1, \dots, N\}$ and $t \in \{1, \dots, T\}$, to a score $s_{n,t} \in \mathbb{R}$ which corresponds to an instance-level aggregation for system n on the instances of task t . From these quantities, one can then compute, for each system, a synthetic score reflecting the overall performance of this system across every considered task. Again, the usually-taken synthetic score of system n is the mean-aggregation: $s_n^{\text{mean}} := \frac{1}{T} \sum_{1 \leq t \leq T} s_{n,t}$.

2.2 Problem Formulation

Ranking objective. When benchmarking systems, the goal is to output a ranking of each systems according to some objective criterion. Formally, we need to introduce the symmetric group on N elements, denoted by \mathfrak{S}_N , which elements are the $N!$ permutations of $\{1, \dots, N\}$. Equipped with this notation, our goal is to output a permutation

$$\sigma^* = [\sigma_1^*, \dots, \sigma_N^*] \in \mathfrak{S}_N,$$

corresponding to the rankings of the systems. For instance, one reads “system i is the σ_i -th best system”. Depending on the granularity of the information at our disposal, we distinguish two problems.

Ranking Systems from Task Level Information. *Given a set of scores $(s_{n,t}, 1 \leq n \leq N, 1 \leq t \leq T)$ of N systems on T tasks, find a proper aggregation procedure.*

Ranking Systems from Instance Level Information. *Given a set of scores $(s_{n,t,k}, 1 \leq n \leq N, 1 \leq t \leq T, 1 \leq k \leq K_t)$ of N systems on the different instances of T tasks, find a proper aggregation procedure.*

2.3 Limitation of Existing Methods

Mean-aggregation procedure. The mean-aggregation procedure consists in taking the permutation σ_n^{mean} that would rank the aggregated means $s_n^{\text{mean}}, 1 \leq n \leq N$. This procedure suffers from several flaws. First, it is not well-suited when the metrics associated with the considered tasks are not on the same scale. Consider, for instance, the situation where one of the tasks (say task t_0) is associated with a metric that is at a significantly larger scale than the others. In that case, the ranking obtained through mean-aggregation would probably correspond to the ranking induced by task t_0 . One could argue that a remedy would first normalize each metric so that everything is on the same scale. However, the

	Task1	Task2	Task3	Task4	Task5	Task6	SUM
A	0.3 (3)	5 (3)	10 (1)	0.02 (2)	1.0 (1)	0.4 (3)	16.72 (13)
B	0.1 (2)	4 (2)	13 (2)	0.01 (1)	2.2 (3)	0.3 (2)	19.61 (12)
C	0.0 (1)	3 (1)	15 (3)	0.03 (3)	2.0 (2)	0.2 (1)	20.23 (11)

Table 1: Example of where pairwise rankings can be paradoxical. Mean aggregation outputs $A > B > C$ while pairwise ranking considered in [73] fails to rank the systems and produce $B > A, C > B, A = C$. Our method does not have this flaw and outputs $C > B > A$.

resulting aggregation would still fail to capture each task’s intrinsic difficulty. Worse, this procedure is impractical in cases where some metrics are unbounded – for instance, this is the case of the BARTScore [102]. Finally, another weakness of the mean-aggregation ranking procedure is that the score of a system is computed irrespective of its relative performance with respect to the others. This simple observation has been pointed out by [73] who advises, in the special case of two systems and one metric, to compute the number of times a system is better than the other on the instances.

Pairwise ranking. To be a bit more formal, the pairwise ranking aggregation proposed by [73] to rank two systems A and B , which scores on a given task are given by s_1^A, \dots, s_K^A and s_1^B, \dots, s_K^B , consists in computing

$$\lambda_A := \sum_{k=1}^K \mathbf{1}_{s_k^A \geq s_k^B} \quad \text{and} \quad \lambda_B = K - \lambda_A.$$

Then, A is better than B if and only if $\lambda_A > \lambda_B$. As explained by the authors, this method is more relevant than the mean-aggregation in the context of NLG evaluation. However, it is limited to the evaluation of two systems and does not apply for a general number $N \geq 3$ of systems. A solution would be to give a rank for each pair of systems and then aggregate these pairwise rankings. However, this would lead to a prohibitive $\binom{N}{2}$ computational factor for the complexity. Moreover, the conclusion of these pairwise rankings can be paradoxical. Tab. 1 below provides a toy example where three systems A , B , and C are evaluated on 6 tasks, and where the pairwise comparisons give the paradoxical conclusion $B > A, C > B$ and $A = C$.

3 Ranking via Kemeny consensus

We now turn to the description of our methodology to rank an arbitrary number of systems on multi-tasks / multi-criteria benchmarks.

3.1 Kemeny Consensus

Let us consider the problem of ranking N systems on T tasks based on the information of the scores $s_{n,t}$ of each system n on each task t . We believe a robust approach to this problem consist in relying on the relative performance between systems on each task. More precisely, for each task $t \in \{1, \dots, T\}$, we consider

$$\sigma^t = [\sigma_1^t, \dots, \sigma_N^t] \in \mathfrak{S}_N,$$

where σ_n^t corresponds to the rank of system n on task t , in decreasing order. Then, we would like to find an appropriate procedure that aggregates the T rankings $\sigma^1, \dots, \sigma^T$. More formally, we would like to define a function

$$f : \underbrace{\mathfrak{S}_N \times \dots \times \mathfrak{S}_N}_{T \text{ times}} \rightarrow \mathfrak{S}_N.$$

This function, from a set of T permutations corresponding to rankings, should return a final permutation that summarizes them. One difficulty is that the mean procedure makes no sense on the symmetric group, which is not a vector space. It turns out that a very natural choice consists in taking f as the so-called *Kemeny consensus* [52] aggregation procedure, which somehow corresponds to compute a barycenter.

Kemeny consensus. Let d be the Kendall distance on the symmetric group, defined for every $\eta, \tau \in \mathfrak{S}_N$ by $d(\eta, \tau) := \sum_{1 \leq i, j \leq N} \mathbf{1}_{(\eta_i - \eta_j)(\tau_i - \tau_j) < 0}$. A *Kemeny consensus* σ^* of $\sigma^1, \dots, \sigma^T$ is a solution of the following minimization problem $\min_{\sigma \in \mathfrak{S}_N} \sum_{1 \leq t \leq T} d(\sigma^t, \sigma)$.

Why is Kemeny consensus natural? As proved by Young and Levenglick [100], the Kemeny consensus aggregation procedure is the only rule that satisfies three natural properties: *neutrality*,

meaning that it does not depend on the order of the tasks; *consistency*, meaning that if the tasks are split in two subsets and that the aggregation in the two subsets rank system i above system j then $\sigma_i^* > \sigma_j^*$; and *the Condorcet criterion* [27], meaning that an item winning all its pairwise comparison is ranked first. Moreover, the Kemeny consensus is also the maximum likelihood of the widely-used Mallows statistical on the symmetric group [99].

3.2 Borda’s count approximation

If the Kemeny consensus is the ideal objective one would like to obtain, its computation is, in general, an NP-hard problem [6, 40] – although some regularity assumptions, rarely satisfied in practice, can speed up the computation, see for instance [8] and [11]. Fortunately, there exist many ways to get satisfying approximations of the latter: see for example [1] for a comprehensive empirical study. For our experiments, we choose the so-called Borda’s count procedure, defined hereafter for the instance-level and/or task-level aggregation.

Borda’s count. *The Borda’s count consists, from a set of permutations $\eta^1, \dots, \eta^L \in \mathfrak{N}$ corresponding to the ranking of N systems across $L \geq 1$ tasks or instances, to sum the ranks of each system and then to rank the obtained sums. Formally, it*

1. Compute $\text{sum}_n := \sum_{l=1}^L \eta_n^l$ for every $1 \leq n \leq N$,
2. Output $\eta := \text{Borda}(\eta^1, \dots, \eta^L) \in \mathfrak{S}_N$ that ranks the sums, sum_n ($\text{argsort}(\text{argsort}(\text{sum}_1, \dots, \text{sum}_T))$).

There are at least four explanations for choosing Borda’s count procedure. First, it coincides with the pairwise ranking procedure in the case of two systems, making it a natural generalization. Second, there exists a theoretical result assessing it is a 5-approximation of the Kemeny consensus [30] with respect to the Kendall distance [42]. Third, it is an unbiased estimator of the Kemeny consensus with low sample complexity for data distributed according to standard rankings models such as Mallows [13, 44]. Fourth, from a practical perspective, [1] observe it is efficient, accurate, and actually 10 times faster than the other approximation algorithms. Fourth, We are now in a position to give our answers to the initial ranking problems from Task Level Information and from Instance Level Information.

3.3 Our Ranking Procedures

How to rank Systems from Task Level Information. Let $\sigma^t \in \mathfrak{S}_N$ be permutation that ranks the scores $s_{1,t}, \dots, s_{N,t}$. Our aggregation procedure (σ^*) output is $\sigma^* := \text{Borda}(\sigma^1, \dots, \sigma^T)$.

How to rank Systems from Instance Level Information. We actually give two different procedures. For every task $t \in \{1, \dots, T\}$ and every instance $k \in \{1, \dots, K_t\}$ of that task, let $\sigma^{t,k}$ be the permutation that ranks the scores $s_{1,t,k}, \dots, s_{N,t,k}$. See Figure 2 for an illustration.

Two-level aggregation (σ^{2l}). This procedure

1. Compute $\sigma^t := \text{Borda}(\sigma^{t,k}, 1 \leq k \leq K_t)$ for each task $t \in \{1, \dots, T\}$,
2. Output $\sigma^{2l} := \text{Borda}(\sigma^t, 1 \leq t \leq T)$.

One-level aggregation (σ^l). This procedure outputs $\sigma^l := \text{Borda}(\sigma^{t,k}, 1 \leq t \leq T, 1 \leq k \leq K_t)$.

3.4 How to compare rankings

The rest of the paper is dedicated to synthetic and empirical experiments, on which we demonstrate the soundness of our approach. In order to obtain a quantitative result, one needs to be able to compare different rankings quantitatively. Two measures can be used for that purpose: (1) the Kendall

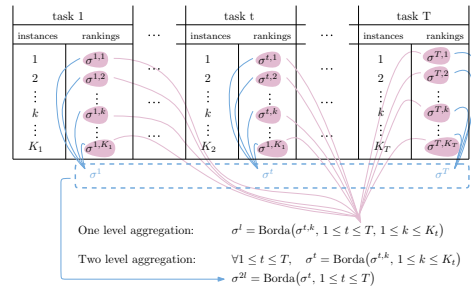


Figure 2: Illustration of our two aggregation procedures to rank systems from instance-level information.

distance and (2) the Kendall correlation (τ) [53, 54]. The Kendall distance computes the number of inversions between two permutations and is therefore adapted for our purpose of ranking systems. The values of τ range from $[-1, 1]$ where the value of 1 corresponds to a strong agreement, and close to -1 indicates strong disagreement.

4 Synthetic Experiments

In this section, we validate on simulated data the performance of our method on two criteria: robustness to manipulation and robustness to scaling.

4.1 Data Generation

The toy experiment analysis is carried out on synthetic scores over $N = 20$ systems, $T = 20$ tasks and $K = 20$ instances. For each $n \in \{1, \dots, N\}$, we model the performance of system n by a Gumbel r.v. G_n centered at $\phi * n$ at scale $\beta = 1$, where $\phi \in [0, 1]$ is a dispersion parameter. The scores of system n , $(s_{n,t,k})_{t,k}$, are i.i.d. samples of G_n centered at $\phi * n$ with scale $\beta = 1$, where $\phi \in [0, 1]$ is a dispersion parameter. Moreover, the scores of different systems are sampled independently. Since $G_{n+1} - G_n$ follows a logistic distribution with mean ϕ at scale 1, this imply that $\mathbb{P}(G_{n+1} - G_n > 0) > 0.5$, the probability that system $n + 1$ performs better than system n is at least 0.5. Therefore, for all k, t , the rankings of systems is a realization of the *ground-truth ranking* $[1, \dots, N]$, with a noise term controlled by the ‘dispersion’ parameter ϕ .

Extreme scenarii correspond to the choices $\phi = 0$ and $\phi = 1$. More precisely, $\phi = 0$ implies that all scores $s_{n,t,k}$ have the same distribution, whereas $\phi = 1$ induces a strong consensus, *i.e.*, a clear system ranking emerges.

Remark 1. *Sampling $s_{n,t,k}$ according to the described procedure is equivalent to sampling the ranking of the systems from the well-know Plackett-Luce distribution [39, 75] with weights $w_i = \phi * n$. Interestingly, this distribution over ranking can be seen both from the utilitarian perspective in which the scores $s_{n,t,k}$ are real numbers and from a ranking-model perspective in which the ranking of systems have known distribution.*

4.2 Robustness to manipulation

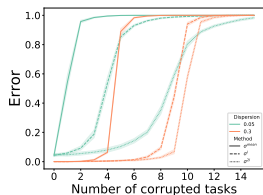
Setting. To test the robustness of our ranking procedure, we analyze its stability with respect to perturbations of the scores. More precisely, our way to corrupt scores of a given task t consists in sampling $(s_{n,t,k})_{n,k}$ as i.i.d. samples following Gumbel distribution centered at $-n$. This implies that, for that task t , the underlying ranking is $[N, \dots, 1]$, namely the exact opposite of the ground truth $[1, \dots, N]$. The robustness to manipulation analysis shows how the error on the final ranking of systems increases as the scores of some t tasks are ‘corrupted’. Here, the error is computed relying on the normalized Kendall distance between the ground-truth ranking $[1, \dots, N]$ and the ranking of systems obtained relying on the corrupted scores.

Results: For each of the considered methods, σ^{mean} , σ^l and σ^{2l} we report in Fig. 3 the results of the robustness analysis when ϕ and the number of corrupted task varies. The results of the robustness analysis show that σ^{2l} outperforms σ^l which at the same time consistently outperforms σ^{mean} . Overall, for the same number of corrupted tasks and dispersion, the error of σ^{2l} is always the smallest. Moreover, the score-based method σ^{mean} gets an error larger than .75 when just 2, 3, and 5 out of the total of $T = 20$ tasks have been corrupted, while for σ^l the same error is achieved with 5, 7 and 10 corrupted tasks. The most robust method is the two-level σ^{2l} for which 10, 11 and 11 out of $T = 20$ tasks have to be corrupted to get the same error of 0.75.

Takeaways: We conclude that the ranking-based methods are more robust than σ^{mean} . In particular, the 2-level aggregation σ^{2l} is the most robust aggregation procedure.

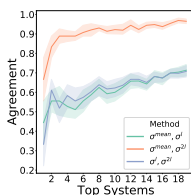
4.3 Robustness to scaling

To further compare the ranking, we corrupt the scores of a given task by re-scaling them by a factor of $x > 0$. Whereas it does not affect our ranking procedure (every ranking induced by a task-instance pair remains the same), it increasingly perturbs the mean aggregation procedure as x increases. Re-scaling the scores by a factor of 2 produces an error larger than 90%. For larger ϕ , re-scaling the

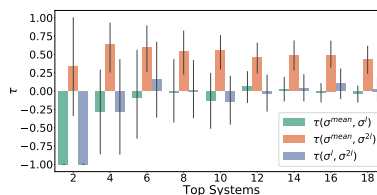


(a) Synthetic Scores

Figure 3: Robustness on synthetic scores.



(a) Agreement Analysis



(b) Correlation Analysis

Figure 4: Global Analysis of Instance Level Raning

scores by a factor of 7 produces the same error (see Fig. 7 for detailed results).

Takeaways: Re-scaling one task’s score with an arbitrarily large number will always produce an arbitrarily large error for mean aggregation while not affecting ranking based aggregation.

5 Empirical Experiments

In this section, we present our results on real evaluation scores. Our large scale experiments relies on real evaluation scores (over 270k scores) which are described in Ssec. 5.1. In Ssec. 5.2 we gather experimental results for *Ranking Systems from Task Level Information*, while Ssec. 5.3 is dedicated to the problem of *Ranking Systems from Instance Level Information*.

5.1 Data Collection

Datasets with Task Level Information We collect the results of GLUE [91], SGLUE [92]¹ and XTREME [50]. For GLUE the dataset is composed of $N = 105$ systems that are evaluated on 9 different tasks: CoLA [93], SST-2 [87], MRPC [38], STS-B [14], QQP, MNLI [96], QNLI [80], RTE [7, 31, 48] and WNLI [57]. For SGLUE, the final dataset gathers scores from $N = 24$ systems that are evaluated on 10 different tasks: BoolQ [17], CB [33], COPA [82], MultiRC [55], ReCoRD [104], RTE, WiC [74], WSC and its derivatives AX-b AX-g [57]. XTREM benchmark is composed of $N = 15$ systems and include tasks such as sentence classification (using XNLI [29, 95] and PAXS-X [98, 106]), structured prediction (relying on Universal Dependencies v2.5 [68] and Wikiann [70, 79]), sentence retrieval (with BUCC [110, 111] and Tatoeba [3]) and question answering (via XQuAD [4, 80], MLQA [58], TyDiQA-GoldP [18]). For all benchmarks, various types of metrics with various scales are reported (*i.e* accuracy, f1, correlation).

Datasets with Instance-level information In this setting we focus on NLG evaluation as these scores are among the easiest to be collected. We focus on five different tasks: summary evaluation, image description, dialogue and translation. For *summary evaluation*, we use TAC08 [32], TAC10, TAC11 [69], RSUM [9] and SEVAL [41]. For *sentence-based image description* we rely on FLICKR [101] and for *dialogue* we use PersonaChat (PC) and TopicalChat (TC) [64]. Finally for *machine translation*, we rely on the multilingual quality estimation (MLQE) introduced in Ranasinghe et al. [81]. For all datasets except MLQE, we consider automatic metric based on S3 (both variant pyr/resp) [72], ROUGE [59] (including 5 of its variants [67]), JS [1-2] [60], ChrFpp [77], BLEU, BERTScore [105], MoverScore [107]. For MLQE we solely consider several version of BERTScore, MoverScore and ContrastScore. We also add human evaluation which is specific to each dataset. All details corresponding to these dataset can be found in Appendix A.

5.2 Task-level Aggregation Experiments

In this section, we address the aggregation problem when task-level information is available. We first study the final ranking obtained by different methods on GLUE, SGLUE, and XTREM. Then, we assess the robustness of σ^* when removing tasks.

Comparison with mean-aggregation To compare the rankings σ^{mean} and σ^* , we compute (i) the

¹Results can be found at <https://super.gluebenchmark.com/>

Dataset	Top 1	Top 3	Top 5	Top 10
XT.	1	0.66	0.8	0.9
GLUE	1	1	0.8	0.8
SGLUE	1	1	0.8	0.9
Dataset	Last 3	Last 5	Last 10	τ
EXT.	1	0.8	0.9	0.82
GLUE	1	0.8	0.7	0.92
SGLUE	1	1	1	0.91

Table 2: Agreement count between Top N/Last N systems on the Ranking when Task Level Information is available. τ is computed on the total ranking.

GLUE			XTREM		
σ^*	Team	σ^{mean}	σ^*	Team	σ^{mean}
0 (1430)	Ms Alex	0 (88.6)	0 (55)	ULR	0 (83.2)
1 (1405)	ERNIE	1 (88.0)	1 (50)	CoFe	1 (82.6)
2 (1397)	DEBERTA	2 (87.9)	2 (44)	InfoLXL	3 (80.6)
3 (1391)	AliceMind	3 (87.8)	3 (42)	VECO	4 (80.3)
4 (1375)	PING-AH	5 (87.6)	4 (35)	Unicoder	5 (79.4)
5 (1362)	HFL	4 (87.7)	5 (34)	PolyGlot	2 (80.6)
6 (1361)	T5	6 (87.5)	6 (31)	ULR-v2	6 (79.4)
7 (1358)	DIRL	10 (86.7)	7 (29)	HiCTL	8 (79.1)
8 (1331)	Zihan	7 (87.6)	8 (29)	Ernie	7 (79.1)
9 (1316)	ELECTRA	11 (86.7)	9 (21)	Anony	10 (78.3)

Table 3: Qualitative analysis between ranking obtained with σ^* or σ^{mean} . Results in parenthesis report the score of the considered aggregation procedure.

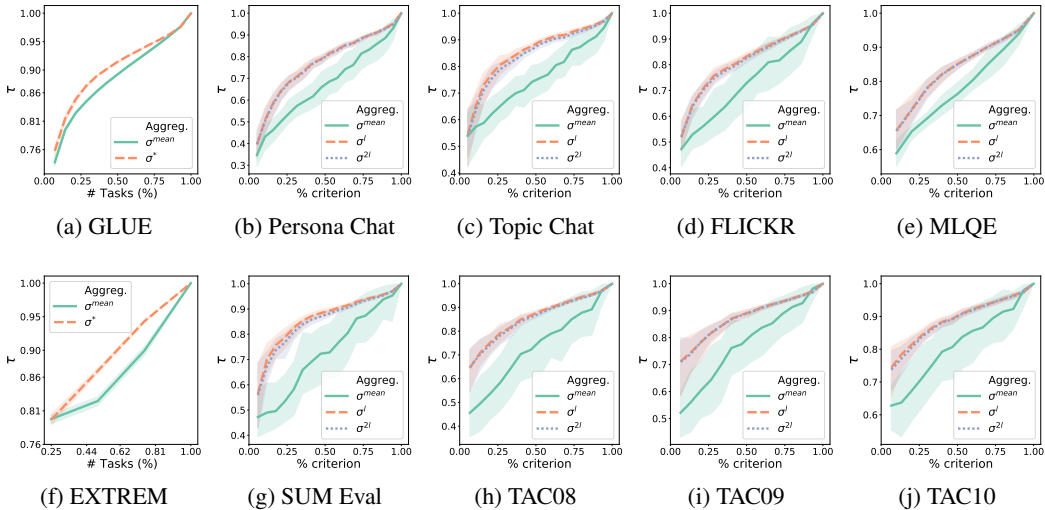


Figure 5: Impact of adding/removing metrics/tasks. The first column refers to ranking obtained with task-level information, while others columns refer to ranking obtained with instance-level information.

agreement rate (in %) which is the proportion of common top-ranked systems between σ^{mean} and σ^* , and (ii) the Kendall Tau correlation (τ) between the rankings.

Results. In Tab. 2, we compare the rankings of aforementioned methods for Top K systems (strongest systems) and Last K systems (weakest systems). For the three benchmarks, we observe a high correlation between the final rankings (*i.e.* correlation values are in the range [0.80, 1]). To a finer degree, we also observe that methods tend to agree on which are the best/worst systems. Although σ^{mean} and σ^* agree on the best/worst systems, they do not rank them in the same order (see Tab. 3). For instance, on XTREM, the third-best system according to σ^{mean} (rank 2) is actually the sixth-best system according to σ^* .

Takeaways. When changing the aggregation function, the response to our initial question "what are the best systems?" varies.

How does the addition/removal of new tasks/metrics affect the ranking? When building a benchmark, practitioners can always add new tasks to refine the model performance assessment (it boils down to adding a new column in Tab. 1). In this experiment, we analyze how adding and removing tasks affect the rankings of the aggregation procedures.

Setting. We compare the rankings obtained when considering a subset of the tasks and the one obtained using all the tasks. Formally, for a given number of tasks $t \leq T$, we randomly sample t tasks, compute the rankings obtain by our procedure and by the mean procedure, $\sigma^{*,t}$ and $\sigma^{mean,t}$, on these t tasks, and finally compute the Kendall correlation between $\sigma^{*,t}$ (resp. $\sigma^{mean,t}$) and the "ground truth" σ^* (resp. σ^{mean}). We repeat this random sampling 100 times to obtain a mean/variance plot of the correlations in the function of the number of sub-tasks.

Results. We report in Fig. 5(a,f) the obtained results for varying size of subsets. Interestingly we

observe that correlation between the $\sigma^{*,t}$ and σ^* is consistently higher than the one between $\sigma^{mean,t}$ and σ^{mean} . This difference is particularly visible in the range [0.25% – 0.75%]. We observe a similar behavior when considering SGLUE (see Fig. 8)

Takeaways. The ranking from σ^* is more robust to task addition/drop than the one from σ^{mean} .

5.3 Instance-level Aggregation Experiments

For instance level aggregation, we conduct experiments on the 9 aforementioned data-sets. We study both the final ranking obtained for each aggregation (*i.e.* σ^l , σ^{2l} and σ^{mean}) as well as the effect of task addition/removal.

Global analysis When conducting our experiments, we observe that the three different aggregation procedures lead to three different state-of-the-art in 8 datasets out of 9. Furthermore, they never agree on the top 3 systems. In what follows, we compare σ^l , σ^{2l} and σ^{mean} .

Setting. We compare the obtained ranking by (1) comparing the Kendall correlation (see Fig. 6), (2) comparing the number of agreements between the top N systems, (3) computing the Kendall correlation between them.

Results. When considering the agreement analysis of Fig. 4(a), we observe that σ^{2l} and σ^{mean} select a high number of common top systems. However, the correlation of the rankings induced by σ^{2l} and σ^{mean} on these top-systems is low (see Fig. 4(b)). This is also the case for the correlation of the entire rankings (see Fig. 4). In short σ^{2l} and σ^{mean} select similar systems but rank them differently. Similar analysis shows that σ^l disagrees from σ^{2l} and σ^{mean} both on top systems and on their orders.

Takeaways. σ^{2l} exhibits a more similar behavior than σ^l with respect to σ^{mean} .

What is the impact of removing/adding tasks? In NLG, different metrics (*i.e.* task) assess the quality of a generated sentence along a different axis. As adding a new metric may affect the final ranking, we investigate the impact of task addition/removal on the final system ordering.

Setting. Similarly to ??, we study the evolution between the correlation between the ranking computed on a subset of tasks and the ground truth ranking (computed on all tasks) for each of the three procedures.

Results. We observe that for all datasets both σ^{2l} , σ^l obtain higher correlation and lower variance compared to σ^{mean} when adding/removing tasks. Results for RSUM reports a similar trends (see Fig. 9).

Takeaways. The ranking obtained with either σ^l or σ^{2l} are more robust to task addition/drop than the one from σ^{mean} .

	PC	TC	FLI	MLQE
$\tau(\sigma^l, \sigma^{2l})$	-0.08	-0.01	0	-0.03
$\tau(\sigma^{mean}, \sigma^{2l})$	0.32	0.27	0.29	0.01
$\tau(\sigma^{mean}, \sigma^l)$	-0.10	-0.15	-0.04	0.00
RSUM	SEVAL	TAC08	TAC09	TAC11
0.04	0.14	0.28	0.06	-0.06
0.07	0.52	0.32	0.37	0.37
0	0.10	0.23	0.19	0.07

Figure 6: τ on global instance-level rankings.

6 Conclusion and Future Works

In this paper, we introduced new aggregation procedures to rank systems when either task level scores or instance level scores are available. Our methods, which are theoretically grounded and rely on Kemeny ranking consensus, address fundamental flaws of the widely used arithmetic mean.

We conducted extensive numerical experiments, which show that our methods are both more reliable and more robust than the mean aggregation while leading to different conclusions on which are the best systems. Overall, when task-level (resp. instance-level) information is available, we would recommend using the aggregation procedure σ^* (resp. σ^{2l}) rather than the σ^{mean} (resp. σ^{mean} and σ^l).

Although we focused on NLP benchmarks, our methodology could be applied in other modalities (*e.g.* Computer Vision, Audio). Another interesting avenue would be to consider a weighted version of the Kemeny consensus where weight could reflect task-specific criteria (*e.g.* fairness, robustness, complexity).

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References

- [1] Alnur Ali and Marina Meilă. Experiments with kemeny ranking: What works when? *Mathematical Social Sciences*, 64(1):28–40, 2012.
- [2] Vamsi Aribandi, Yi Tay, Tal Schuster, Jinfeng Rao, Huaixiu Steven Zheng, Sanket Vaibhav Mehta, Honglei Zhuang, Vinh Q Tran, Dara Bahri, Jianmo Ni, et al. Ext5: Towards extreme multi-task scaling for transfer learning. *arXiv preprint arXiv:2111.10952*, 2021.
- [3] Mikel Artetxe and Holger Schwenk. Massively multilingual sentence embeddings for zero-shot cross-lingual transfer and beyond. *Transactions of the Association for Computational Linguistics*, 7:597–610, 2019.
- [4] Mikel Artetxe, Sebastian Ruder, and Dani Yogatama. On the cross-lingual transferability of monolingual representations. *arXiv preprint arXiv:1910.11856*, 2019.
- [5] Satanjeev Banerjee and Alon Lavie. Meteor: An automatic metric for mt evaluation with improved correlation with human judgments. In *Proceedings of the acl workshop on intrinsic and extrinsic evaluation measures for machine translation and/or summarization*, pages 65–72, 2005.
- [6] John J Bartholdi, Craig A Tovey, and Michael A Trick. The computational difficulty of manipulating an election. *Social Choice and Welfare*, 6(3):227–241, 1989.
- [7] Luisa Bentivogli, Peter Clark, Ido Dagan, and Danilo Giampiccolo. The fifth pascal recognizing textual entailment challenge. In *TAC*, 2009.
- [8] Nadja Betzler, Michael R Fellows, Jiong Guo, Rolf Niedermeier, and Frances A Rosamond. How similarity helps to efficiently compute kemeny rankings. In *Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems-Volume 1*, pages 657–664, 2009.
- [9] Manik Bhandari, Pranav Gour, Atabak Ashfaq, Pengfei Liu, and Graham Neubig. Re-evaluating evaluation in text summarization. *arXiv preprint arXiv:2010.07100*, 2020.
- [10] Ralph Allan Bradley and Milton E Terry. Rank analysis of incomplete block designs: I. the method of paired comparisons. *Biometrika*, 39(3/4):324–345, 1952.
- [11] Felix Brandt, Markus Brill, Edith Hemaspaandra, and Lane A Hemaspaandra. Bypassing combinatorial protections: Polynomial-time algorithms for single-peaked electorates. In *Twenty-Fourth AAAI Conference on Artificial Intelligence*, 2010.
- [12] Róbert Busa-Fekete, Dimitris Fotakis, and Emmanouil Zampetakis. Private and non-private uniformity testing for ranking data. *Advances in Neural Information Processing Systems*, 34, 2021.
- [13] Ioannis Caragiannis, Ariel D Procaccia, and Nisarg Shah. When Do Noisy Votes Reveal the Truth? In *Proceedings of the Fourteenth ACM Conference on Electronic Commerce, EC ’13*, pages 143–160. ACM, 2013. ISBN 978-1-4503-1962-1. doi: 10.1145/2482540.2482570. URL <http://doi.acm.org/10.1145/2482540.2482570>.
- [14] Daniel Cer, Mona Diab, Eneko Agirre, Inigo Lopez-Gazpio, and Lucia Specia. Semeval-2017 task 1: Semantic textual similarity-multilingual and cross-lingual focused evaluation. *arXiv preprint arXiv:1708.00055*, 2017.
- [15] Emile Chapuis, Pierre Colombo, Matteo Manica, Matthieu Labeau, and Chloe Clavel. Hierarchical pre-training for sequence labelling in spoken dialog. *arXiv preprint arXiv:2009.11152*, 2020.
- [16] Emile Chapuis, Pierre Colombo, Matthieu Labeau, and Chloe Clavel. Code-switched inspired losses for generic spoken dialog representations. *arXiv preprint arXiv:2108.12465*, 2021.
- [17] Christopher Clark, Kenton Lee, Ming-Wei Chang, Tom Kwiatkowski, Michael Collins, and Kristina Toutanova. Boolq: Exploring the surprising difficulty of natural yes/no questions. *arXiv preprint arXiv:1905.10044*, 2019.

- [18] Jonathan H Clark, Eunsol Choi, Michael Collins, Dan Garrette, Tom Kwiatkowski, Vitaly Nikolaev, and Jennimaria Palomaki. Tydi qa: A benchmark for information-seeking question answering in typologically diverse languages. *Transactions of the Association for Computational Linguistics*, 8:454–470, 2020.
- [19] Pierre Colombo. *Learning to represent and generate text using information measures*. PhD thesis, Institut polytechnique de Paris, 2021.
- [20] Pierre Colombo, Wojciech Witon, Ashutosh Modi, James Kennedy, and Mubbasir Kapadia. Affect-driven dialog generation. *arXiv preprint arXiv:1904.02793*, 2019.
- [21] Pierre Colombo, Emile Chapuis, Matteo Manica, Emmanuel Vignon, Giovanna Varni, and Chloe Clavel. Guiding attention in sequence-to-sequence models for dialogue act prediction. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 7594–7601, 2020.
- [22] Pierre Colombo, Emile Chapuis, Matthieu Labeau, and Chloe Clavel. Improving multimodal fusion via mutual dependency maximisation. *arXiv preprint arXiv:2109.00922*, 2021.
- [23] Pierre Colombo, Chloe Clavel, and Pablo Piantanida. Infomn: A new metric to evaluate summarization & data2text generation. *arXiv preprint arXiv:2112.01589*, 2021.
- [24] Pierre Colombo, Chloe Clavel, and Pablo Piantanida. A novel estimator of mutual information for learning to disentangle textual representations. *arXiv preprint arXiv:2105.02685*, 2021.
- [25] Pierre Colombo, Guillaume Staerman, Chloe Clavel, and Pablo Piantanida. Automatic text evaluation through the lens of wasserstein barycenters. *arXiv preprint arXiv:2108.12463*, 2021.
- [26] Pierre Colombo, Chouchang Yang, Giovanna Varni, and Chloé Clavel. Beam search with bidirectional strategies for neural response generation. *arXiv preprint arXiv:2110.03389*, 2021.
- [27] N. Condorcet. *Essai sur l'application de l'analyse à la probabilité des décisions rendues à la pluralité des voix*. de l'Imprimerie Royale, 1785.
- [28] Alexis Conneau, German Kruszewski, Guillaume Lample, Loïc Barrault, and Marco Baroni. What you can cram into a single vector: Probing sentence embeddings for linguistic properties. *arXiv preprint arXiv:1805.01070*, 2018.
- [29] Alexis Conneau, Guillaume Lample, Ruty Rinott, Adina Williams, Samuel R Bowman, Holger Schwenk, and Veselin Stoyanov. Xnli: Evaluating cross-lingual sentence representations. *arXiv preprint arXiv:1809.05053*, 2018.
- [30] Don Coppersmith, Lisa Fleischer, and Atri Rudra. Ordering by weighted number of wins gives a good ranking for weighted tournaments. In *Proceedings of the seventeenth annual ACM-SIAM symposium on Discrete algorithm*, pages 776–782, 2006.
- [31] Ido Dagan, Oren Glickman, and Bernardo Magnini. The pascal recognising textual entailment challenge. In *Machine Learning Challenges Workshop*, pages 177–190. Springer, 2005.
- [32] Hoa Trang Dang, Karolina Owczarzak, et al. Overview of the tac 2008 update summarization task. In *TAC*, 2008.
- [33] Marie-Catherine De Marneffe, Mandy Simons, and Judith Tonhauser. The commitmentbank: Investigating projection in naturally occurring discourse. In *proceedings of Sinn und Bedeutung*, volume 23, pages 107–124, 2019.
- [34] Mostafa Dehghani, Yi Tay, Alexey A Gritsenko, Zhe Zhao, Neil Houlsby, Fernando Diaz, Donald Metzler, and Oriol Vinyals. The benchmark lottery. *arXiv preprint arXiv:2107.07002*, 2021.
- [35] Michael Denkowski and Alon Lavie. Meteor universal: Language specific translation evaluation for any target language. In *Proceedings of the ninth workshop on statistical machine translation*, pages 376–380, 2014.

- [36] Kaustubh D Dhole, Varun Gangal, Sebastian Gehrmann, Aadesh Gupta, Zhenhao Li, Saad Mahamood, Abinaya Mahendiran, Simon Mille, Ashish Srivastava, Samson Tan, et al. NI-augmenter: A framework for task-sensitive natural language augmentation. *arXiv preprint arXiv:2112.02721*, 2021.
- [37] Tanvi Dinkar, Pierre Colombo, Matthieu Labeau, and Chloé Clavel. The importance of fillers for text representations of speech transcripts. *arXiv preprint arXiv:2009.11340*, 2020.
- [38] William B Dolan and Chris Brockett. Automatically constructing a corpus of sentential paraphrases. In *Proceedings of the Third International Workshop on Paraphrasing (IWP2005)*, 2005.
- [39] Luce R Duncan. Individual choice behavior: A theoretical analysis, 1959.
- [40] Cynthia Dwork, Ravi Kumar, Moni Naor, and Dandapani Sivakumar. Rank aggregation methods for the web. In *Proceedings of the 10th international conference on World Wide Web*, pages 613–622, 2001.
- [41] Alexander R Fabbri, Wojciech Kryściński, Bryan McCann, Caiming Xiong, Richard Socher, and Dragomir Radev. Summeval: Re-evaluating summarization evaluation. *Transactions of the Association for Computational Linguistics*, 9:391–409, 2021.
- [42] Ronald Fagin, Ravi Kumar, and Dakshinamurthi Sivakumar. Comparing top k lists. *SIAM Journal on discrete mathematics*, 17(1):134–160, 2003.
- [43] Michael A Fligner and Joseph S Verducci. Distance based ranking models. *Journal of the Royal Statistical Society*, 48(3):359–369, 1986.
- [44] Michael A Fligner and Joseph S Verducci. Multistage Ranking Models. *Journal of the American Statistical Association*, 83(403):892–901, 1988. ISSN 01621459. doi: 10.2307/2289322. URL <http://www.jstor.org/stable/2289322?origin=crossref>.
- [45] Alexandre Garcia, Pierre Colombo, Slim Essid, Florence d’Alché Buc, and Chloé Clavel. From the token to the review: A hierarchical multimodal approach to opinion mining. *arXiv preprint arXiv:1908.11216*, 2019.
- [46] Claire Gardent, Anastasia Shimorina, Shashi Narayan, and Laura Perez-Beltrachini. Creating training corpora for nlg micro-planning. In *55th annual meeting of the Association for Computational Linguistics (ACL)*, 2017.
- [47] Sebastian Gehrmann, Tosin Adewumi, Karmanya Aggarwal, Pawan Sasanka Ammanamanchi, Anuoluwapo Aremu, Antoine Bosselut, Khyathi Raghavi Chandu, Miruna-Adriana Clinciu, Dipanjan Das, Kaustubh Dhole, Wanyu Du, Esin Durmus, Ondřej Dušek, Chris Chinenye Emezue, Varun Gangal, Cristina Garbacea, Tatsunori Hashimoto, Yufang Hou, Yacine Jernite, Harsh Jhamtani, Yangfeng Ji, Shailza Jolly, Mihir Kale, Dhruv Kumar, Faisal Ladhak, Aman Madaan, Mounica Maddela, Khyati Mahajan, Saad Mahamood, Bodhisattwa Prasad Majumder, Pedro Henrique Martins, Angelina McMillan-Major, Simon Mille, Emiel van Miltenburg, Moin Nadeem, Shashi Narayan, Vitaly Nikolaev, Andre Niyongabo Rubungo, Salomey Osei, Ankur Parikh, Laura Perez-Beltrachini, Niranjan Ramesh Rao, Vikas Raunak, Juan Diego Rodriguez, Sashank Santhanam, João Sedoc, Thibault Sellam, Samira Shaikh, Anastasia Shimorina, Marco Antonio Sobrevilla Cabezudo, Hendrik Strobelt, Nishant Subramani, Wei Xu, Diyi Yang, Akhila Yerukola, and Jiawei Zhou. The GEM benchmark: Natural language generation, its evaluation and metrics. In *Proceedings of the 1st Workshop on Natural Language Generation, Evaluation, and Metrics (GEM 2021)*, pages 96–120, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.gem-1.10. URL <https://aclanthology.org/2021.gem-1.10>.
- [48] Danilo Giampiccolo, Bernardo Magnini, Ido Dagan, and William B Dolan. The third pascal recognizing textual entailment challenge. In *Proceedings of the ACL-PASCAL workshop on textual entailment and paraphrasing*, pages 1–9, 2007.

- [49] Yinuo Guo and Junfeng Hu. Meteor++ 2.0: Adopt syntactic level paraphrase knowledge into machine translation evaluation. In *Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1)*, pages 501–506, Florence, Italy, August 2019. Association for Computational Linguistics. doi: 10.18653/v1/W19-5357. URL <https://www.aclweb.org/anthology/W19-5357>.
- [50] Junjie Hu, Sebastian Ruder, Aditya Siddhant, Graham Neubig, Orhan Firat, and Melvin Johnson. Xtreme: A massively multilingual multi-task benchmark for evaluating cross-lingual generalisation. In *International Conference on Machine Learning*, pages 4411–4421. PMLR, 2020.
- [51] Kenji Kawaguchi, Leslie Pack Kaelbling, and Yoshua Bengio. Generalization in deep learning. *arXiv preprint arXiv:1710.05468*, 2017.
- [52] John G Kemeny. Mathematics without numbers. *Daedalus*, 88(4):577–591, 1959.
- [53] Maurice G Kendall. A new measure of rank correlation. *Biometrika*, 30(1/2):81–93, 1938.
- [54] Maurice G Kendall. The treatment of ties in ranking problems. *Biometrika*, 33(3):239–251, 1945.
- [55] Daniel Khashabi, Snigdha Chaturvedi, Michael Roth, Shyam Upadhyay, and Dan Roth. Looking beyond the surface: A challenge set for reading comprehension over multiple sentences. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 252–262, 2018.
- [56] Anna Korba, Stephan Cl  men  on, and Eric Sibony. A learning theory of ranking aggregation. In *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics, AISTATS 2017*, 2017.
- [57] Hector Levesque, Ernest Davis, and Leora Morgenstern. The winograd schema challenge. In *Thirteenth International Conference on the Principles of Knowledge Representation and Reasoning*, 2012.
- [58] Patrick Lewis, Barlas O  uz, Ruty Rinott, Sebastian Riedel, and Holger Schwenk. Mlqa: Evaluating cross-lingual extractive question answering. *arXiv preprint arXiv:1910.07475*, 2019.
- [59] Chin-Yew Lin. Rouge: A package for automatic evaluation of summaries. In *Text summarization branches out*, pages 74–81, 2004.
- [60] Chin-Yew Lin, Guihong Cao, Jianfeng Gao, and Jian-Yun Nie. An information-theoretic approach to automatic evaluation of summaries. In *Proceedings of the Human Language Technology Conference of the NAACL, Main Conference*, pages 463–470, 2006.
- [61] Pengfei Liu, Jinlan Fu, Yang Xiao, Weizhe Yuan, Shuaicheng Chang, Junqi Dai, Yixin Liu, Zihuiwen Ye, Zi-Yi Dou, and Graham Neubig. Explainaboard: An explainable leaderboard for nlp. *arXiv preprint arXiv:2104.06387*, 2021.
- [62] Bryan McCann, Nitish Shirish Keskar, Caiming Xiong, and Richard Socher. The natural language decathlon: Multitask learning as question answering. *arXiv preprint arXiv:1806.08730*, 2018.
- [63] Angelina McMillan-Major, Salomey Osei, Juan Diego Rodriguez, Pawan Sasanka Ammanamanchi, Sebastian Gehrmann, and Yacine Jernite. Reusable templates and guides for documenting datasets and models for natural language processing and generation: A case study of the HuggingFace and GEM data and model cards. In *Proceedings of the 1st Workshop on Natural Language Generation, Evaluation, and Metrics (GEM 2021)*, pages 121–135, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.gem-1.11. URL <https://aclanthology.org/2021.gem-1.11>.
- [64] Shikib Mehri and Maxine Eskenazi. Usr: An unsupervised and reference free evaluation metric for dialog generation. *arXiv preprint arXiv:2005.00456*, 2020.

- [65] Volodymyr Mnih, Csaba Szepesvári, and Jean-Yves Audibert. Empirical bernstein stopping. In *Proceedings of the 25th international conference on Machine learning*, pages 672–679, 2008.
- [66] Roger B Myerson. Fundamentals of social choice theory. Technical report, Discussion Paper, 1996.
- [67] Jun-Ping Ng and Viktoria Abrecht. Better summarization evaluation with word embeddings for rouge. *arXiv preprint arXiv:1508.06034*, 2015.
- [68] Joakim Nivre, Mitchell Abrams, Zeljko Agic, Lars Ahrenberg, Lene Antonsen, et al. Universal dependencies 2.2 (2018). URL <http://hdl.handle.net/11234/1-1983xxx>. LINDAT/CLARIN digital library at the Institute of Formal and Applied Linguistics, Charles University, Prague, <http://hdl.handle.net/11234/1-1983xxx>.
- [69] Karolina Owczarzak and Hoa Trang Dang. Overview of the tac 2011 summarization track: Guided task and aesop task. In *Proceedings of the Text Analysis Conference (TAC 2011)*, Gaithersburg, Maryland, USA, November, 2011.
- [70] Xiaoman Pan, Boliang Zhang, Jonathan May, Joel Nothman, Kevin Knight, and Heng Ji. Cross-lingual name tagging and linking for 282 languages. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1946–1958, 2017.
- [71] Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting of the Association for Computational Linguistics*, pages 311–318, 2002.
- [72] Maxime Peyrard, Teresa Botschen, and Iryna Gurevych. Learning to score system summaries for better content selection evaluation. In *Proceedings of the Workshop on New Frontiers in Summarization*, pages 74–84, 2017.
- [73] Maxime Peyrard, Wei Zhao, Steffen Eger, and Robert West. Better than average: Paired evaluation of nlp systems. *arXiv preprint arXiv:2110.10746*, 2021.
- [74] Mohammad Taher Pilehvar and Jose Camacho-Collados. Wic: the word-in-context dataset for evaluating context-sensitive meaning representations. *arXiv preprint arXiv:1808.09121*, 2018.
- [75] Robin L Plackett. The analysis of permutations. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 24(2):193–202, 1975.
- [76] Maja Popović. chrF: character n-gram f-score for automatic mt evaluation. In *Proceedings of the Tenth Workshop on Statistical Machine Translation*, pages 392–395, 2015.
- [77] Maja Popović. chrF++: words helping character n-grams. In *Proceedings of the second conference on machine translation*, pages 612–618, 2017.
- [78] Matt Post. A call for clarity in reporting BLEU scores. In *Proceedings of the Third Conference on Machine Translation: Research Papers*, pages 186–191, Belgium, Brussels, October 2018. Association for Computational Linguistics. URL <https://www.aclweb.org/anthology/W18-6319>.
- [79] Afshin Rahimi, Yuan Li, and Trevor Cohn. Massively multilingual transfer for ner. *arXiv preprint arXiv:1902.00193*, 2019.
- [80] Pranav Rajpurkar, Jian Zhang, Konstantin Lopyrev, and Percy Liang. Squad: 100,000+ questions for machine comprehension of text. *arXiv preprint arXiv:1606.05250*, 2016.
- [81] Tharindu Ranasinghe, Constantin Orasan, and Ruslan Mitkov. An exploratory analysis of multilingual word-level quality estimation with cross-lingual transformers. *arXiv preprint arXiv:2106.00143*, 2021.
- [82] Melissa Roemmele, Cosmin Adrian Bejan, and Andrew S Gordon. Choice of plausible alternatives: An evaluation of commonsense causal reasoning. In *2011 AAAI Spring Symposium Series*, 2011.

- [83] Sebastian Ruder. Challenges and Opportunities in NLP Benchmarking. <http://ruder.io/nlp-benchmarking>, 2021.
- [84] Victor Sanh, Albert Webson, Colin Raffel, Stephen H Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Teven Le Scao, Arun Raja, et al. Multitask prompted training enables zero-shot task generalization. *arXiv preprint arXiv:2110.08207*, 2021.
- [85] Aditya Siddhant, Junjie Hu, Melvin Johnson, Orhan Firat, and Sebastian Ruder. Xtreme: A massively multilingual multi-task benchmark for evaluating cross-lingual generalization. 2020.
- [86] David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. *nature*, 529(7587): 484–489, 2016.
- [87] Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D Manning, Andrew Y Ng, and Christopher Potts. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 conference on empirical methods in natural language processing*, pages 1631–1642, 2013.
- [88] Guillaume Staerman, Pavlo Mozharovskiy, Stéphan Cléménçon, and Florence d’Alché Buc. Depth-based pseudo-metrics between probability distributions. *arXiv e-prints*, pages arXiv–2103, 2021.
- [89] Yi Tay, Mostafa Dehghani, Samira Abnar, Yikang Shen, Dara Bahri, Philip Pham, Jinfeng Rao, Liu Yang, Sebastian Ruder, and Donald Metzler. Long range arena: A benchmark for efficient transformers. *arXiv preprint arXiv:2011.04006*, 2020.
- [90] Yi Tay, Donovan Ong, Jie Fu, Alvin Chan, Nancy Chen, Anh Tuan Luu, and Christopher Pal. Would you rather? a new benchmark for learning machine alignment with cultural values and social preferences. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5369–5373, 2020.
- [91] Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. Glue: A multi-task benchmark and analysis platform for natural language understanding. *arXiv preprint arXiv:1804.07461*, 2018.
- [92] Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. Superglue: A stickier benchmark for general-purpose language understanding systems. *arXiv preprint arXiv:1905.00537*, 2019.
- [93] Alex Warstadt, Amanpreet Singh, and Samuel R Bowman. Neural network acceptability judgments. *Transactions of the Association for Computational Linguistics*, 7:625–641, 2019.
- [94] Jason Wei, Maarten Bosma, Vincent Y Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. Finetuned language models are zero-shot learners. *arXiv preprint arXiv:2109.01652*, 2021.
- [95] Adina Williams, Nikita Nangia, and Samuel R Bowman. A broad-coverage challenge corpus for sentence understanding through inference. *arXiv preprint arXiv:1704.05426*, 2017.
- [96] Adina Williams, Nikita Nangia, and Samuel R Bowman. A broad-coverage challenge corpus for sentence understanding through inference. *arXiv preprint arXiv:1704.05426*, 2017.
- [97] Wojciech Witon, Pierre Colombo, Ashutosh Modi, and Mubbasir Kapadia. Disney at iest 2018: Predicting emotions using an ensemble. In *Proceedings of the 9th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*, pages 248–253, 2018.
- [98] Yinfei Yang, Yuan Zhang, Chris Tar, and Jason Baldridge. Paws-x: A cross-lingual adversarial dataset for paraphrase identification. *arXiv preprint arXiv:1908.11828*, 2019.
- [99] H Peyton Young. Condorcet’s theory of voting. *American Political science review*, 82(4): 1231–1244, 1988.

- [100] H Peyton Young and Arthur Levenglick. A consistent extension of condorcet’s election principle. *SIAM Journal on applied Mathematics*, 35(2):285–300, 1978.
- [101] Peter Young, Alice Lai, Micah Hodosh, and Julia Hockenmaier. From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. *Transactions of the Association for Computational Linguistics*, 2:67–78, 2014.
- [102] Weizhe Yuan, Graham Neubig, and Pengfei Liu. Bartscore: Evaluating generated text as text generation. *arXiv preprint arXiv:2106.11520*, 2021.
- [103] Xiaoyong Yuan, Pan He, Qile Zhu, and Xiaolin Li. Adversarial examples: Attacks and defenses for deep learning. *IEEE transactions on neural networks and learning systems*, 30(9):2805–2824, 2019.
- [104] Sheng Zhang, Xiaodong Liu, Jingjing Liu, Jianfeng Gao, Kevin Duh, and Benjamin Van Durme. Record: Bridging the gap between human and machine commonsense reading comprehension. *arXiv preprint arXiv:1810.12885*, 2018.
- [105] Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q Weinberger, and Yoav Artzi. Bertscore: Evaluating text generation with bert. *arXiv preprint arXiv:1904.09675*, 2019.
- [106] Yuan Zhang, Jason Baldridge, and Luheng He. Paws: Paraphrase adversaries from word scrambling. *arXiv preprint arXiv:1904.01130*, 2019.
- [107] Wei Zhao, Maxime Peyrard, Fei Liu, Yang Gao, Christian M Meyer, and Steffen Eger. Moverscore: Text generation evaluating with contextualized embeddings and earth mover distance. *arXiv preprint arXiv:1909.02622*, 2019.
- [108] Yanan Zheng, Jing Zhou, Yujie Qian, Ming Ding, Jian Li, Ruslan Salakhutdinov, Jie Tang, Sebastian Ruder, and Zhilin Yang. Fewnlu: Benchmarking state-of-the-art methods for few-shot natural language understanding. *arXiv preprint arXiv:2109.12742*, 2021.
- [109] Ruiqi Zhong, Dhruva Ghosh, Dan Klein, and Jacob Steinhardt. Are larger pretrained language models uniformly better? comparing performance at the instance level. *arXiv preprint arXiv:2105.06020*, 2021.
- [110] Pierre Zweigenbaum, Serge Sharoff, and Reinhard Rapp. Overview of the second bucc shared task: Spotting parallel sentences in comparable corpora. In *Proceedings of the 10th Workshop on Building and Using Comparable Corpora*, pages 60–67, 2017.
- [111] Pierre Zweigenbaum, Serge Sharoff, and Reinhard Rapp. Overview of the third bucc shared task: Spotting parallel sentences in comparable corpora. In *Proceedings of 11th Workshop on Building and Using Comparable Corpora*, pages 39–42, 2018.

Checklist

The checklist follows the references. Please read the checklist guidelines carefully for information on how to answer these questions. For each question, change the default **[TODO]** to **[Yes]**, **[No]**, or **[N/A]**. You are strongly encouraged to include a **justification to your answer**, either by referencing the appropriate section of your paper or providing a brief inline description. For example:

- Did you include the license to the code and datasets? **[Yes]**
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1. For all authors...

- (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
 - (b) Did you describe the limitations of your work? [Yes]
 - (c) Did you discuss any potential negative societal impacts of your work? [N/A] Our works aim at developing safe ai systems.
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3. If you ran experiments...
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 - (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A]