LLM-BLENDER: Ensembling Large Language Models with Pairwise Ranking and Generative Fusion

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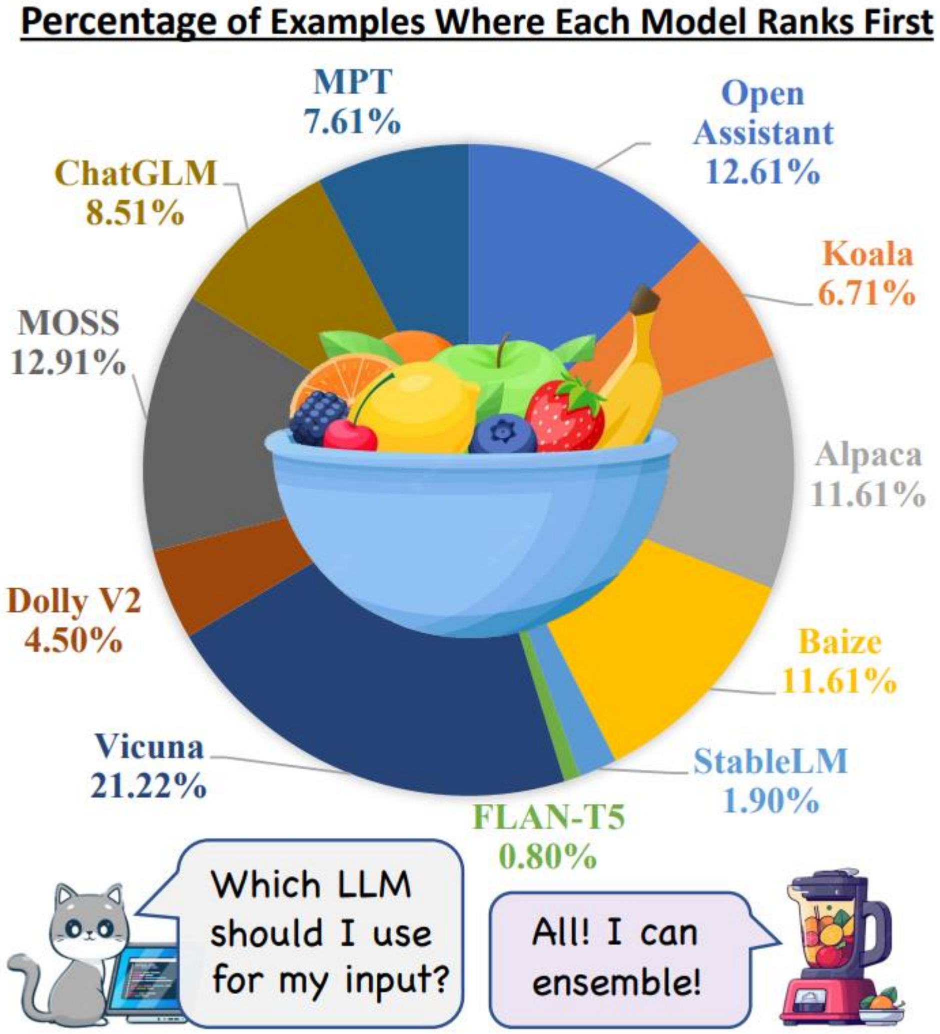
Introduction

• Motivation of ensembling LLMs



Open-source LLMs exhibit diverse strengths & weaknesses

- Optimal LLMs for different examples can significantly vary
- Variations in data, architectures, and hyperparameters

← **Pie Graph :** Distribution of best LLMs on 5,000 instructions that we collected

Combine unique contributions

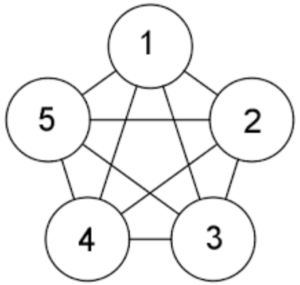
- Alleviate biases, errors, and uncertainties in individual LLMs
- Result in outputs better aligned with human preferences

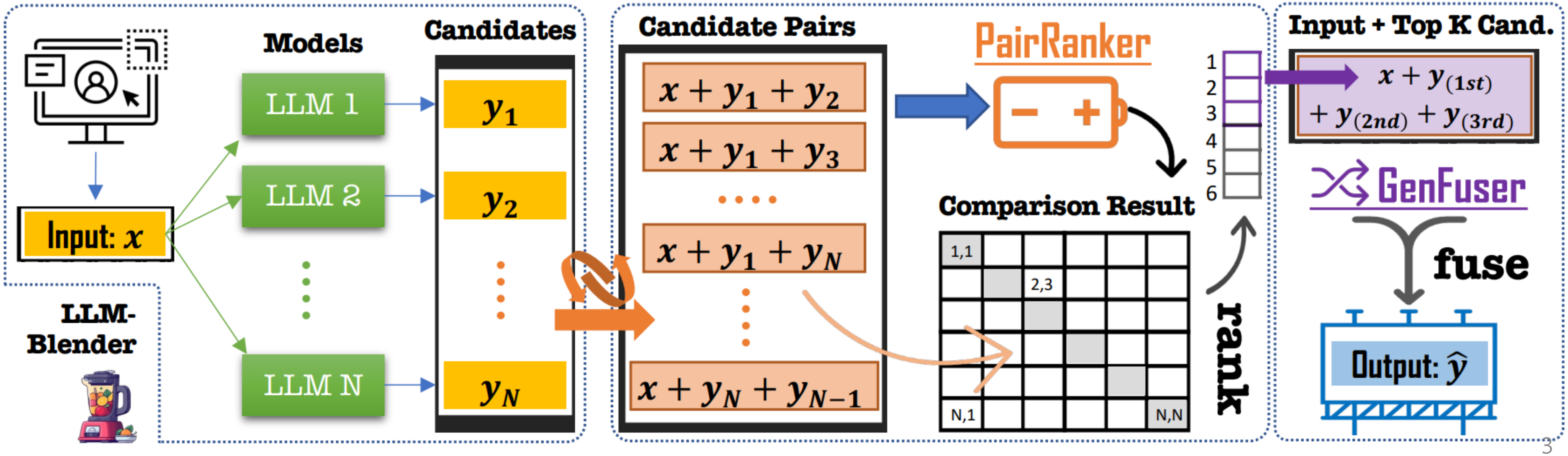
Introduction

- **LLM-BLENDER framework**
  - PairRanker
    - Create the $N(N-1)/2$ pairs of their outputs from N models
    - x and y as input for cross-attention encoder
  - GenFuser
    - Fuse the top K of the N ranked candidates and generate an improved output

e.g. Number of League Games

$N(N-1)/2$





Method

- **Problem Setup**
  - Model $\{\mathcal{M}_1, \ldots, \mathcal{M}_N\}$
  - Candidate output $\mathbb{Y} = \{y_1, \ldots, y_N\}$
  - Produces an output $\hat{y}$ for the input x, maximizing similarity $Q(\hat{y}, y; x)$
  - Maxmize similarity for test set $D_{\text{test}} = \{(x^{(i)}, y^{(i)})\}$

    $\sum_i Q(\hat{y}^{(i)}, y^{(i)}; x^{(i)})$
  - Primary approaches for ensembling LLMs
    - Selection-based method: PairRanker
    - Generation-based method: GenFuser

Method

• Benchmark Dataset: MixInstruct


```
[{"id":"unified_chip2\/69962",
  "instruction":"",
  "input":"I've always wondered what the difference is between a skeptic and a denier.",
  "output":"A skeptic is someone who questions the validity of something, …",
  "candidates":[
              {"decoding_method":"top_p_sampling",
               "model":"oasst-sft-4-pythia-12b-epoch-3.5",
              "text":"A skeptic is someone who doubts or expresses doubt …",
        "scores":{
            "logprobs":-0.0240402222,
            "rougeL":0.2321428571,
            "rouge2":0.1272727273,
            "rougeLsum":0.2321428571,
            "rouge1":0.2857142857,
            "bleu":5.6561527509,
            "bertscore":0.7549101114,
            "bleurt":0.0506142341,
            "bartscore":-2.887932539
            }, … ],
   "cmp_results": "{\"alpaca-native,chatglm-6b\": \"A is better\",
                   \"alpaca-native,moss-moon-003-sft\": \"Same good\",
                   \"koala-7B-HF,dolly-v2-12b\": \"Same bad\"
```


Open-Source LLMs

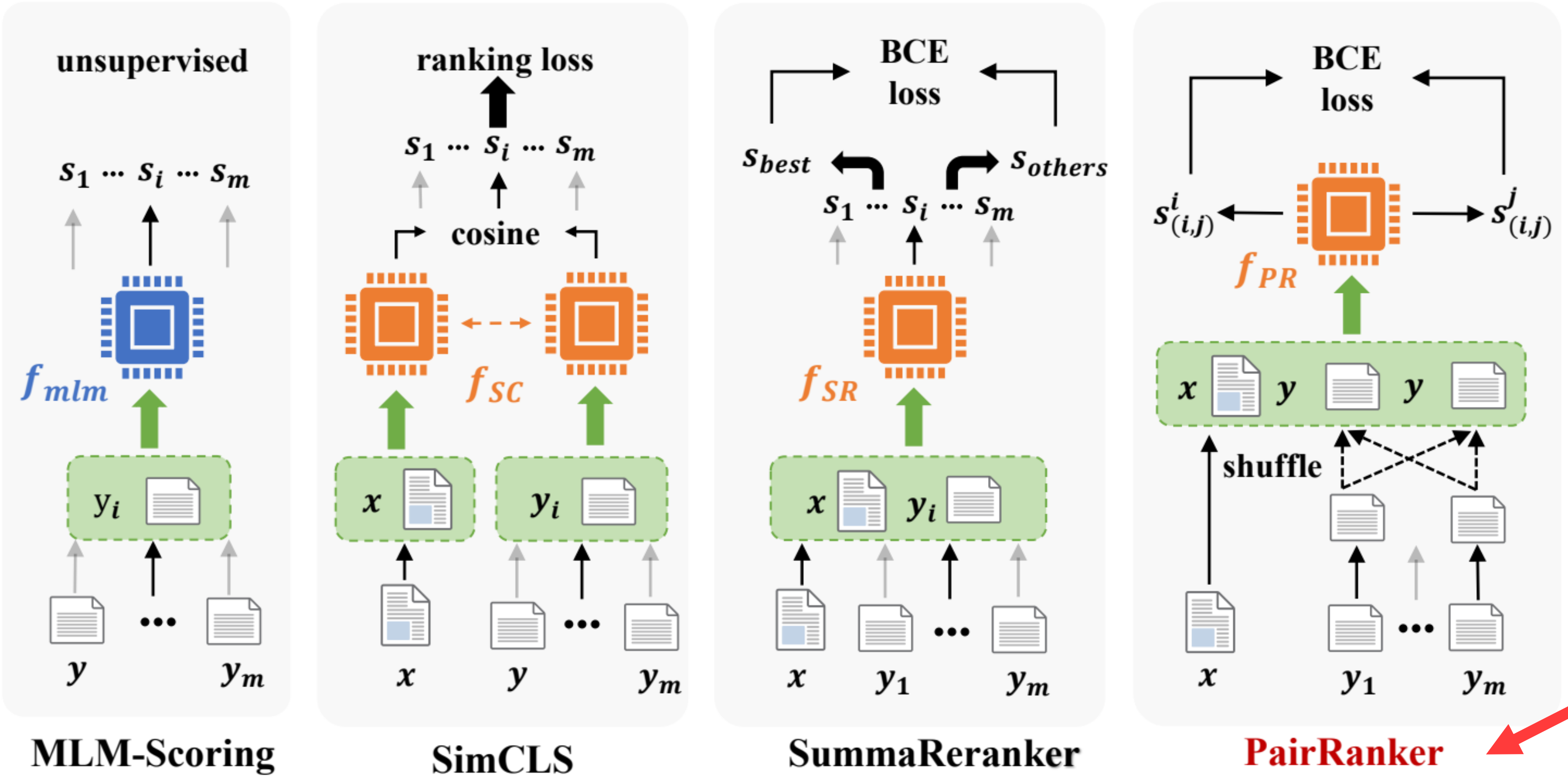
- Stanford Alpaca
- FastChat Vicuna
- Dolly V2, StableLM
- Open Assistant, Koala
- Baize, Flan-T5, ChatGLM
- MOSS, Moasic MPT

Data Source

Sources	#Examples	Source	I/O Tokens
Alpaca-GPT4	22,862	GPT-4	22 / 48
Dolly-15K	7,584	Human	24 / 53
GPT4All-LAION	76,552	ChatGPT	18 / 72
ShareGPT	3,002	ChatGPT	36 / 63
Total	110K	Mix	20 / 66

Method

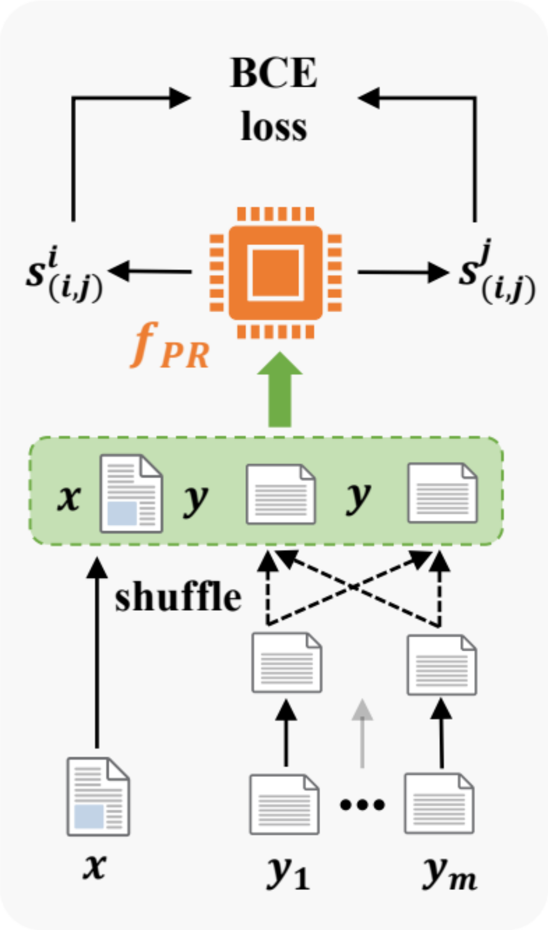
- **Individual Scoring (Pointwise Scoring)**
  - Insufficient for selection in the context of instruction-following tasks
  - Quality of outputs is generally high when LLMs are competitive
    (e.g, a few different words in shorter responses vary significantly in harmfulness)



Pairwise Scoring

Method

• Pairwise Scoring



PairRanker

PairRanker

- Create the $N(N-1)/2$ pairs of their outputs
- x and y as input for cross-attention encoder
- Model's confidence in thinking y_i is better than y_j $\quad s_{ij} = s^i_{(i,j)} - s^j_{(i,j)}$
- Sigmoid Function: σ $\quad \mathcal{L}_Q = -z_i \log \sigma(s^i_{(i,j)}) - (1 - z_j) \log \sigma(s^j_{(i,j)})$
- Multiple Q functions to optimize (e.g., BERTScore, BARTScore)

$$(z_i, z_j) = \begin{cases} (1,0), & Q(y_i, y) \geq Q(y_j, y) \\ (0,1), & Q(y_i, y) < Q(y_j, y) \end{cases}$$

- Take the average as the final multi-objective loss $\mathcal{L} = \sum \mathcal{L}_Q$

Method

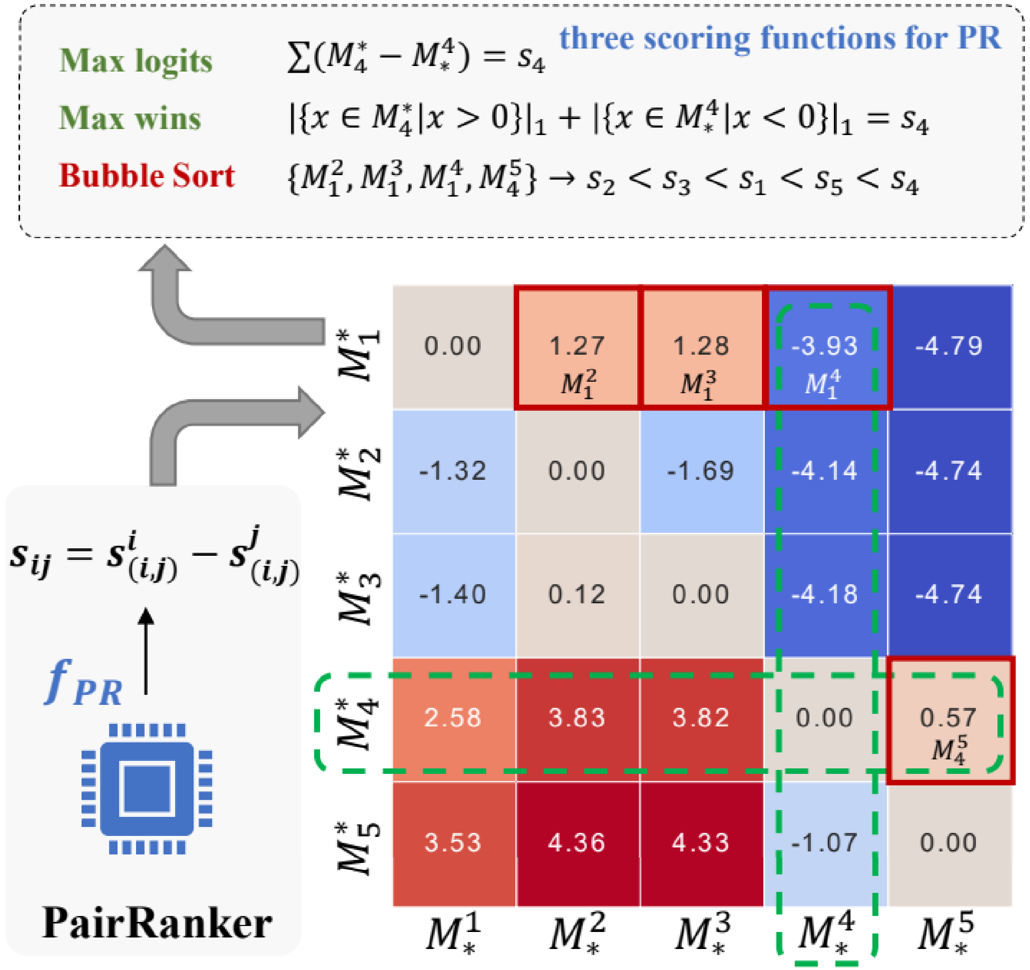
- **PairRanker Architecture: Embedding, Training**
  - Embedding
    - Concatenate segments sequentially with special tokens as separators

<s><source> x </s> <candidate1> yi </s> <candidate2> yj </s>

  - Training
    - Pass concatenated embeddings through a single-head layer
    - MLP with the final layer's each dimension represents a computed Q score
    - Instead of all the $N(N-1)/2$ pairs
      Randomly select some combinations from the candidate pool $\mathbb{Y}$
    - Shuffle the order of candidates within each training pair (x, y_i, y_j) and (x, y_j, y_i)

Method

• PairRanker Architecture: Inference



Scoring Function For Q Similiarty

- MaxLogits:
  Sum(Horizontal rectangle) - Sum(Vertical rectangle)
- MaxWins:
  Count(Positive in horizontal rectangle) –
  Count(Negative in vertical rectangle)

- MaxLogits yields the best performance
- MaxLogits as the default aggregator for PairRanker

Bubble Sort

- $O(N^2)$ iterations for N candidates can be burdensome
- $N-1$ Comparisons
- Reduce the inference time complexity from $O(N^2)$ to $O(N)$

Method

- **GENFUSER**
  - Effectiveness of PairRanker is constrained from the candidate pool
    - Merging multiple top-ranked candidates
    - Generate a superior response by combining advantages while mitigating shortcomings
  - Overcome complementary strengths and weaknesses
    - Fuse the top K of the N ranked candidates and generate an improved output
    - Use separator tokens, such as <extra_id_i>
    - Fine-tune a Flan-T5-XL model to learn to generate

Experiment

• Evaluation

- DeBERTa (400M) as backbone for PairRanker / GenFuser is based on Flan-T5-XL (3B)
- e.g., Koala approximately 40% of examples' quality is as good as both OA and Vic

Category	Methods	BERTScore↑	BARTScore↑	BLEURT↑	GPT-Rank↓	≥ Vic(%)↑	≥ OA(%)↑	Top-3(%)↑
LLMs	Open Assistant (LAION-AI, 2023)	**74.68**	-3.45	**-0.39**	**3.90**	**62.78**	N/A	51.98
	Vicuna (Chiang et al., 2023)	69.60	**-3.44**	-0.61	4.13	N/A	**64.77**	**52.88**
	Alpaca (Taori et al., 2023)	71.46	-3.57	-0.53	4.62	56.70	61.35	44.46
	Baize (Xu et al., 2023)	65.57	-3.53	-0.66	4.86	52.76	56.40	38.80
	MOSS (Sun and Qiu, 2023)	64.85	-3.65	-0.73	5.09	51.62	51.79	38.27
	ChatGLM (Du et al., 2022)	70.38	-3.52	-0.62	5.63	44.04	45.67	28.78
	Koala (Geng et al., 2023)	63.96	-3.85	-0.84	6.76	39.93	39.01	22.55
	Dolly V2 (Conover et al., 2023)	62.26	-3.83	-0.87	6.90	33.33	31.44	16.45
	Mosaic MPT (MosaicML, 2023)	63.21	-3.72	-0.82	7.19	30.87	30.16	16.24
	StableLM (Stability-AI, 2023)	62.47	-4.12	-0.98	8.71	21.55	19.87	7.96
	Flan-T5 (Chung et al., 2022)	64.92	-4.57	-1.23	8.81	23.89	19.93	5.32
Analysis	Oracle (BERTScore)	**77.67**	-3.17	-0.27	3.88	54.41	38.84	53.49
	Oracle (BLEURT)	75.02	-3.15	**-0.15**	3.77	55.61	45.80	55.36
	Oracle (BARTScore)	73.23	**-2.87**	-0.38	3.69	50.32	57.01	57.33
	Oracle (GPT-Rank)	70.32	-3.33	-0.51	**1.00**	**100.00**	**100.00**	**100.00**
Rankers	Random	66.36	-3.76	-0.77	6.14	37.75	36.91	29.05
	MLM-Scoring	64.77	-4.03	-0.88	7.00	33.87	30.39	21.46
	SimCLS	**73.14**	-3.22	-0.38	3.50	52.11	49.93	60.72
	SummaReranker	71.60	-3.25	-0.41	3.66	**55.63**	48.46	57.54
	PairRanker	72.97	**-3.14**	**-0.37**	**3.20**	54.76	**57.79**	**65.12**
LLM-BLENDER	**PR (K = 3) + GF**	**79.09**	**-3.02**	**-0.17**	**3.01**	**70.73**	**77.72**	**68.59**

Experiment

• Ranking correlation with GPT-Rank

Ranking Methods	Pearson Correlation ↑	Spearman's Correlation ↑	Spearman's Footrule ↓
Random	0.00	0.00	48.27
BLEU	28.70	26.92	33.57
Rouge2	29.17	27.77	32.96
BERTScore	32.25	30.33	33.34
BLEURT	34.14	32.31	32.17
BARTScore	**38.49**	**36.76**	**30.93**
MLM-Scoring	-0.02	-0.01	47.16
SimCLS	39.89	38.13	29.32
SummaReranker	41.13	39.10	29.69
PairRanker	**46.98**	**44.98**	**27.52**

Evaluation Metric

- Bartscore gets the highest correlation with GPT-Rank

Pointwise Ranking & Pairwise Ranking

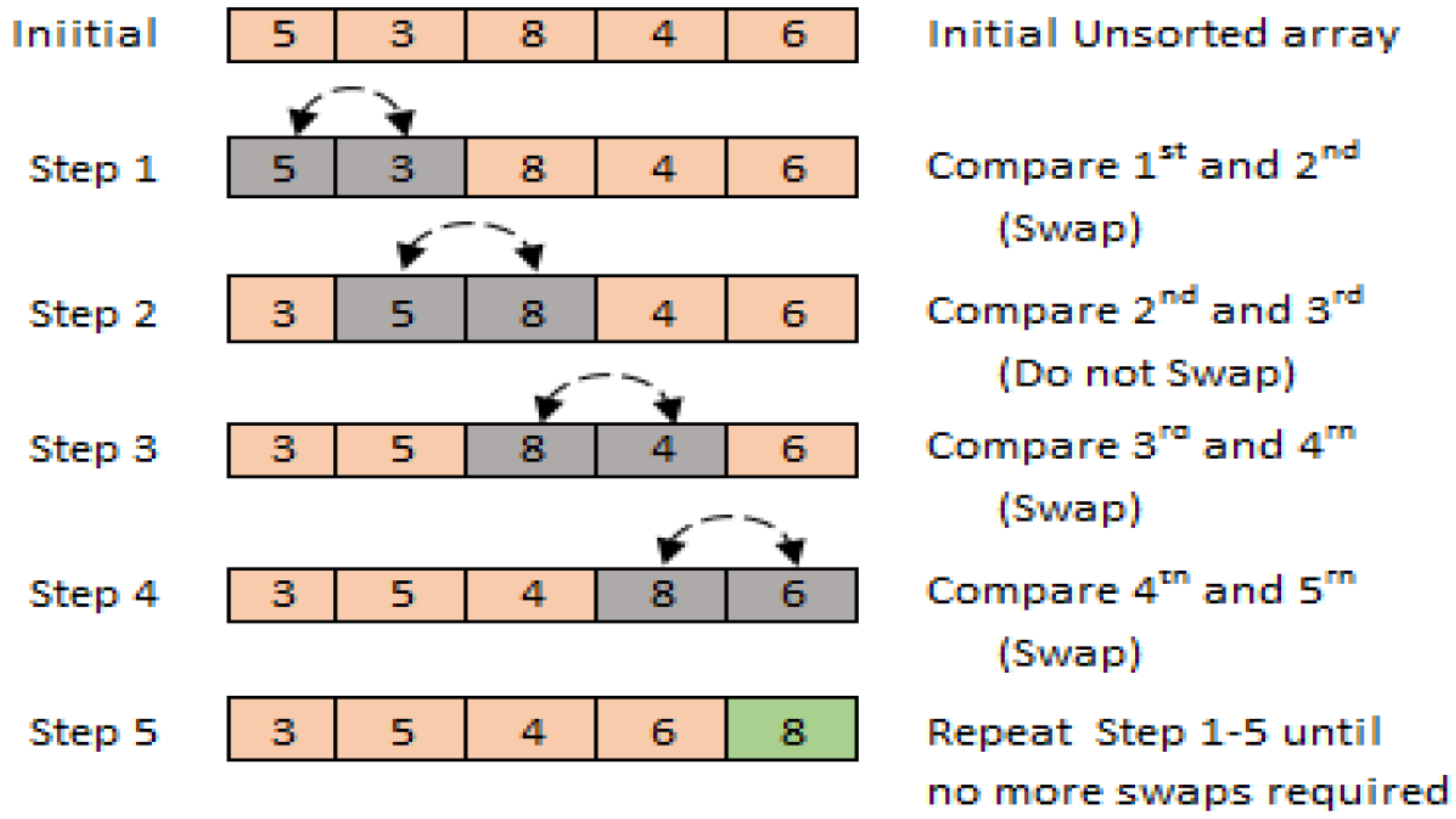
- MLM-Scoring still underperforms random permutations
- SummaReranker: Pearson Correlation (41.13), Spearman's Correlation (39.10)
- SimCLS: Spearman's Footrule distance (29.32)
- PairRanker achieves the highest correlation with GPT-Rank

Conclusion

- **Conclusion**
  - Post-hoc LLM ensemble learning method
    - PairRanker & GenFuser: Ranking and fusing the outputs from multiple LLMs:
    - Improve the overall results on various metrics
    - MixInstruct: Benchmark dataset for evaluating ensembling methods
  - Future directions
    - Investigating the transferability of our ensembling approach to other domains and tasks
- **Limitation**
  - Less Efficiency
    - To get the optimal performance from PAIRRANKER
    - One may need to call the model $O(N^2)$ times for getting the full matrix
  - Human evaluation VS ChatGPT evaluation
    - We cannot afford large-scale human evaluation
    - We argue that our use of ChatGPT for evaluation is a good alternative

Appendix

- **Bubble Sort**



Dipak Kandel. Bubble Sort Algorithm | Algorithm | Flowchart | Data Structures. Researchgate. 2018