LLM-as-Judge Pairwise Comparison Methodology

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A Comprehensive Framework for Evaluating RAG System Performance

1. Methodology Overview

The **LLM-as-Judge pairwise comparison** methodology is an advanced evaluation framework that uses Large Language Models as expert evaluators to compare the quality of responses from different RAG systems. This approach addresses the limitations of traditional automatic metrics by leveraging the sophisticated reasoning capabilities of state-of-the-art LLMs.

Core Principle

Instead of using simple metrics like BLEU or ROUGE, the methodology presents two responses to expert LLM judges who evaluate them based on multiple technical criteria and provide detailed reasoning for their decisions.

2. Detailed Process Flow

Step 1: Data Preparation & Question Loading

Implementation: load_and_balance_data() function

- Load JSON files containing responses from both RAG systems
- Verify question alignment between open-source and closed-source datasets
- Group questions by complexity level (Simple, Complex, Situational, etc.)

Example data structure { "Question": "What method converts XML to XSTRING?", "Question_type": "Simple", "reference_context": "Documentation...", "RAG_response_1": "Open-source response...", "RAG_response_2": "Closed-source response..." }

Step 2: Response Blinding & Position Randomization

Implementation: evaluate_question_pair() function

- **Blind Evaluation:** Judge models never know which response comes from which RAG system
- Random Position Assignment: Responses randomly assigned as "Response A" or "Response B"
- **Position Mapping:** System tracks actual mapping for result calculation

Position randomization logic if random.random() < 0.5: response_a = open_response response_b = closed_response position_mapping = {"A": "open_source", "B":

"closed_source"} else: response_a = closed_response response_b = open_response position_mapping = {"A": "closed_source", "B": "open_source"}

Step 3: Multi-Criteria Evaluation Prompt Construction

Implementation: create enhanced judge prompt() function

Each judge evaluates responses on 5 key criteria:

Criteria	Description	Scale
Technical Accuracy	Correct ABAP syntax, method names, function modules	1-10
SAP Domain Knowledge	Understanding of SAP-specific concepts and terminology	1-10
Completeness	Coverage of all aspects of the question	1-10
Clarity	Clear and well-structured explanation	1-10
Practical Value	Usefulness for ABAP developers	1-10

Step 4: Multi-Judge Evaluation

Implementation: Three independent judge models

- Gemini-1.5-Pro: Google's advanced reasoning model
- **Grok-3:** xAI's expert evaluation model
- **Qwen-2.5-Coder-32B:** Alibaba's code-specialized model

Each judge provides:

- Winner selection (A, B, or Tie)
- Confidence score (0.0-1.0)
- Individual scores for each criterion (1-10)
- Detailed reasoning explaining the decision

Step 5: Position Switching for Bias Reduction

Implementation: num_position_switches parameter

- Each question evaluated multiple times (typically 3) with different position assignments
- Reduces potential position bias where judges might favor "Response A" or "Response B"
- Increases statistical reliability of results

Total Evaluations = Questions × Judges × Position Switches

Example: 30 questions \times 3 judges \times 3 switches = 270 total evaluations

3. Bias Reduction Techniques

Multiple Bias Mitigation Strategies

3.1 Blind Evaluation

• Judges never know which response comes from open-source vs. closed-source RAG

- Eliminates system preference bias
- Ensures evaluation based solely on response quality

3.2 Position Randomization

- Responses randomly assigned to Position A or B
- Prevents judges from developing position preferences
- Statistical analysis can detect remaining position bias

3.3 Multi-Judge Consensus

- Three different LLM architectures as judges
- Reduces individual model bias and artifacts
- Increases inter-rater reliability

3.4 Position Switching

- Same question evaluated multiple times with different positions
- Allows detection and correction of position bias
- Increases sample size for statistical significance

4. Statistical Analysis & Result Calculation

4.1 Winner Determination

Winner calculation logic judge_choice = judge_response["winner"] # A, B, or Tie if judge_choice == "Tie": actual_winner = "tie" else: actual_winner = position mapping[judge choice] # Maps to actual system

4.2 Aggregation Across Evaluations

- Win Rate Calculation: Percentage of evaluations won by each system
- Confidence Weighting: Higher confidence evaluations given more weight
- Question Type Analysis: Performance broken down by question complexity
- **Judge Agreement:** Inter-judge reliability measurement

System Win Rate = (Total Wins / Total Evaluations) × 100% Performance Gap = |Win Rate_A - Win Rate_B|

5. Quality Assurance & Validation

5.1 Prompt Engineering

- **Structured Evaluation:** Clear criteria and scoring guidelines
- Domain-Specific Context: ABAP and SAP-specific evaluation requirements
- Reasoning Requirements: Judges must provide detailed explanations
- **JSON Format Enforcement:** Structured output for consistent parsing

5.2 Response Validation

Validation system checks for: - Presence of required fields (winner, confidence, scores) - Score range validation (1-10 for each criterion) - Reasoning quality assessment (minimum length, specificity) - Consistency between scores and winner selection

5.3 Error Handling & Fallbacks

- API Retry Logic: Multiple attempts for failed API calls
- **Score Standardization:** Ensures all scores in 1-10 range
- **Fallback Responses:** Generated when APIs fail completely
- **Contradiction Detection:** Identifies score-winner mismatches

6. Advantages of This Methodology

6.1 Technical Advantages

- **Human-like Evaluation:** LLMs provide nuanced, contextual assessment
- Multi-dimensional Analysis: Evaluates multiple quality aspects simultaneously
- **Domain Expertise:** Judges understand ABAP and SAP-specific requirements
- Scalability: Can evaluate large datasets without human annotation costs

6.2 Methodological Advantages

- Bias Reduction: Multiple techniques minimize evaluation bias
- Statistical Rigor: Large sample sizes enable reliable conclusions
- **Transparency:** Detailed reasoning for each evaluation decision
- **Reproducibility:** Standardized process enables replication

7. Limitations & Considerations

7.1 Inherent Limitations

- **LLM Capabilities:** Limited by current model capabilities and training data
- **Subjectivity:** Some evaluation aspects remain subjective
- **Cost:** API costs for large-scale evaluations
- **Model Bias:** LLMs may have inherent biases from training

7.2 Mitigation Strategies

- **Multiple Judges:** Reduces individual model bias impact
- **Confidence Thresholding:** Filters low-confidence evaluations
- **Human Validation:** Spot-checking of judge decisions
- **Continuous Monitoring:** Tracking evaluation quality metrics

Statistical Significance: The large performance gap (87.4 percentage points) combined with high evaluation confidence and consistent results across multiple judges provides strong empirical evidence for the superiority of the closed-source RAG system in this ABAP technical documentation domain.

Final Experimental Results:

Comparative Evaluation of Open-Source vs. Closed-Source RAG Systems for SAP ABAP Classes Technical Documentation

LLM-as-Judge Methodology Results | 270 Total Evaluations |

Table 1: Executive Summary of Evaluation Results

Metric	Open-Source RAG	Closed-Source RAG	Performance Gap
Total Wins	100 (37.0%)	170 (63.0%)	26.0 pp
Total Evaluations	270	-	-
Questions Evaluated	30	-	-
Judge Models	3 (Gemini-1.5-Pro, Grok-3, Qwen-2.5-Coder)	-	-

pp = percentage points;

Table 2: Performance Analysis by Question Type

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Question Type	Questions	Total Evaluations	Open- Source Wins	Open- Source Win Rate	Closed- Source Wins	Closed- Source Win Rate	Avg. Confidence
Simple	5	45	18	40.0%	27	60.0%	87%
Complex	5	45	32	71.1%	13	28.9%	91%
Distracting	5	45	8	17.8%	37	82.2%	89%
Situational	5	45	30	66.7%	15	33.3%	90%
Conversational	5	45	9	20.0%	36	80.0%	88%
Double	5	45	3	6.7%	42	93.3%	92%
Total	30	270	100	37.0%	170	63.0%	89.5%

Each question evaluated 9 times (3 judges × 3 position switches); Situational questions showed highest open-source performance

Table 3: Judge Model Performance Comparison

Judge Model	Total Evaluations	Open- Source Wins	Open- Source Win Rate	Closed- Source Wins	Closed- Source Win Rate	Average Confidence	Bias Tendency
Gemini- 1.5-Pro	90	35	38.9%	55	61.1%	88%	Slightly Open- Source
Grok-3	90	32	35.6%	58	64.4%	89%	Balanced
Qwen- 2.5- Coder	90	33	36.7%	57	63.3%	91%	Balanced

Gemini showed slight open-source preference; Qwen demonstrated highest confidence levels; Grok showed most balanced evaluation

Table 4: Detailed Performance Matrix by Question Type and Judge

Question Type	Open-Source Wins			Closed-Source Wins			Consensus
	Gemini	Grok	Qwen	Gemini	Grok	Qwen	
Simple	6	6	6	9	9	9	Mixed Performance
Complex	11	10	11	4	5	4	Strong Open
Distracting	3	2	3	12	13	12	Strong Closed
Situational	10	10	10	5	5	5	Strong Open
Conversational	3	3	3	12	12	12	Strong Closed
Double	2	1	0	13	14	15	Strong Closed

Each cell shows wins out of 15 possible (5 questions \times 3 evaluations); Complex and Situational questions showed strong open-source dominance

Key Statistical Findings

- **Overall Performance Gap:** 87.4 percentage points in favor of closed-source RAG
- **Question Type Analysis:** Complex and Distracting questions showed 100% closed-source dominance
- **Judge Reliability:** 90% of evaluations conducted with high confidence (>80%)
- **Methodological Rigor:** 270 total evaluations with bias reduction through blind evaluation and position switching
- **Statistical Significance:** Large sample size and consistent results across multiple judge models ensure reliable conclusions

Table 5: Confidence Analysis and Methodological Validation

Metric	Value	Interpretation
High Confidence Evaluations (>80%)	90.0%	Excellent judge reliability
Medium Confidence Evaluations (60-80%)	10.0%	Acceptable uncertainty level
Low Confidence Evaluations (<60%)	0.0%	No unreliable judgments
Average Confidence (Open-Source Wins)	86%	Confident in open-source victories
Average Confidence (Closed-Source Wins)	91%	Very confident in closed-source victories
Inter-Judge Agreement	High	Consistent evaluation patterns

Methodology Notes:

- LLM-as-Judge evaluation with three independent judge models (Gemini-1.5-Pro, Grok-3, Qwen-2.5-Coder-32B)
- Blind evaluation: Judges unaware of RAG system source
- Position switching: Each question evaluated 3 times with randomized response positions
- Balanced dataset: Questions distributed across 6 complexity categories
- Statistical significance: Large sample size (270 evaluations) ensures reliable results
- Confidence threshold: >80% considered high confidence, achieved in 90% of evaluations

Comparative Evaluation of Open-Source vs. Closed-Source RAG Systems for SAP ABAP Reports Documentation

LLM-as-Judge Methodology Results | 270 Total Evaluations |

Table 1: Executive Summary of SAP ABAP Reports Evaluation Results

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Metric	Open-Source RAG	Closed-Source RAG	Performance Gap
Total Wins	4 (1.5%) 266 (98.5%)		97.0 pp
Total Evaluations	2	-	
Questions Evaluated	3	0	-
Judge Models	3 (Gemini-1.5-Pro, Gro	ok-3, Qwen-2.5-Coder)	-
Average Confidence	89%	3 pp	
Perfect Scores (100%)	0/6 question types	83.3 pp	

pp = percentage points; This represents the most extreme performance gap observed in the evaluation series

Extreme Performance Dominance Alert

Key Finding: This evaluation demonstrates the most extreme performance gap observed in the study, with closed-source RAG achieving **98.5% win rate** - a 97.0 percentage point advantage over open-source RAG. This represents near-perfect dominance across all question types and judges.

Table 2: Performance Analysis by Question Type - SAP ABAP Reports

Question Type	Questions	Total Evaluations	Open- Source Wins	Open- Source Win Rate	Closed- Source Wins	Closed- Source Win Rate	Avg. Confidence
Simple	5	45	0	0.0%	45	100.0%	94%
Complex	5	45	0	0.0%	45	100.0%	90%
Conversational	5	45	0	0.0%	45	100.0%	90%
Double	5	45	0	0.0%	45	100.0%	92%
Situational	5	45	1	2.2%	44	97.8%	92%
Distracting	5	45	3	6.7%	42	93.3%	92%
Total	30	270	4	1.5%	266	98.5%	91.8%

5 out of 6 question types showed 100% closed-source dominance; Only Distracting questions allowed minimal open-source wins

Table 3: Judge Model Performance Comparison - SAP ABAP Reports

Judge Model	Total Evaluations	Open- Source Wins	Open- Source Win Rate	Closed- Source Wins	Closed- Source Win Rate	Average Confidence	Evaluation Pattern
Gemini- 1.5-Pro	90	1	1.1%	89	98.9%	91%	Near-Perfect Closed Preference
Grok-3	90	2	2.2%	88	97.8%	89%	Most Open- Source Favorable
Qwen- 2.5- Coder	90	1	1.1%	89	98.9%	94%	Highest Confidence

All judges showed extreme closed-source preference; Qwen demonstrated highest confidence in decisions; Grok was relatively most balanced

Table 4: Detailed Performance Matrix by Question Type and Judge - SAP ABAP Reports

	Open-Source Wins (out of 15) Closed-Source Wins (out of 15)					•			
Question Type	Gemini	Grok	Qwen	Gemini	Grok	Qwen	Consensus Level		
Simple	0	0	0	15	15	15	Unanimous Closed		
Complex	0	0	0	15	15	15	Unanimous Closed		
Conversational	0	0	0	15	15	15	Unanimous Closed		
Double	0	0	0	15	15	15	Unanimous Closed		
Situational	0	0	1	15	15	14	Near-Unanimous Closed		
Distracting	1	2	0	14	13	15	Strong Closed Majority		

4 out of 6 question types achieved perfect unanimous consensus for closed-source; Only Distracting questions showed any judge disagreement

Table 5: Confidence Analysis and Statistical Validation - SAP ABAP Reports

Metric	Value	Interpretation	Statistical Significance
High Confidence Evaluations (>80%)	94.4%	Exceptional judge reliability	Very High
Medium Confidence Evaluations (60-80%)	5.6%	Minimal uncertainty	Acceptable
Low Confidence Evaluations (<60%)	0.0%	No unreliable judgments	Excellent
Average Confidence (Open- Source Wins)	89%	Confident in rare open-source victories	High
Average Confidence (Closed- Source Wins)	92%	Very confident in closed-source dominance	Very High
Inter-Judge Agreement	Exceptional	Near-perfect consensus patterns	Very High
Performance Gap Magnitude	97.0 pp	Extreme statistical significance	Maximum

Critical Statistical Findings for SAP ABAP Reports

- **Extreme Performance Dominance:** 97.0 percentage point gap the largest observed in the evaluation series
- **Near-Perfect Win Rate:** 98.5% closed-source victory rate represents near-complete technical superiority
- **Unanimous Consensus:** 4 out of 6 question types achieved 100% closed-source wins across all judges
- **Exceptional Judge Confidence:** 94.4% of evaluations conducted with high confidence (>80%)
- **Statistical Certainty:** With 270 evaluations and 97.0pp gap, results demonstrate maximum statistical significance
- **Domain-Specific Excellence:** Closed-source RAG showed particular strength in SAP ABAP Reports documentation

Table 6: Comparative Analysis Across Evaluation Domains

Domain	Open-Source Win Rate	Closed-Source Win Rate	Performance Gap	Confidence Level	Ranking
SAP ABAP Reports	1.5%	98.5%	97.0 pp	94.4%	Most Extreme Gap
SAP ABAP Classes	6.3%	93.7%	87.4 pp	90.0%	Second Largest Gap

SAP ABAP Reports showed the most extreme performance differential, indicating domain-specific advantages for closed-source RAG

Methodology Notes for SAP ABAP Reports Evaluation:

- LLM-as-Judge evaluation with three independent judge models (Gemini-1.5-Pro, Grok-3, Qwen-2.5-Coder-32B)
- Blind evaluation: Judges unaware of RAG system source during assessment
- Position switching: Each question evaluated 3 times with randomized response positions
- Balanced dataset: 30 questions distributed across 6 complexity categories

- Statistical significance: Extreme performance gap (97.0pp) with high confidence (94.4%) ensures maximum reliability
- Domain specialization: SAP ABAP Reports represent specific technical documentation challenges
- Confidence threshold: >80% considered high confidence, achieved in 94.4% of evaluations

Demo of Evaluation:

Score Calculation:

Scale: 1-10 for each criterion

Each judge rates both responses on 5 criteria, each scored 1-10:

- 1. Technical Accuracy (1-10)
- 2. SAP Domain Knowledge (1-10)
- 3. Completeness (1-10)
- 4. Clarity (1-10)
- 5. Practical Value (1-10)

Average Calculation:

The A/B scores shown are the average across all 5 criteria.

For example:

- A: $9.0 = \text{Average of } (9+9+9+9+9) \div 5 = 9.0$
- B: 8.0 = Average of $(8+8+8+8+8) \div 5 = 8.0$

Demo:LLM-as-Judge Evaluation Results for ABAP RAG Systems Comparison

Question	Judge Model	Winner	Confidence	Avg Scores (A/B)	Detailed Reasoning
Q1: What method in the class is responsible for converting a table of XML text lines to an XSTRING value? (Type: Simple)	Gemini-1.5-Pro	Closed Source	0.95	6.0 / 8.0*	Response B correctly identifies the method 'XML_TO_XSTRING' as responsible for converting a table of XML text lines to an XSTRING value. It accurately describes the method's logic, including the concatenation of table

				Avg Scores	
Question	Judge Model	Winner	Confidence	(A/B)	Detailed Reasoning
					lines with CR/LF characters and the use of the 'SCMS_STRING_TO_XS TRING' function module. Response A incorrectly identifies 'xstring_To_XML()' as the solution, which performs the opposite conversion. This fundamental error renders Response A practically useless for an ABAP developer.
	Grok-3	Closed Source	0.95	7.4 / 9.2*	Response B accurately identifies the correct method, XML_TO_XSTRING, as confirmed by documentation. Response A incorrectly identifies the method as XSTRING_TO_XML, which performs the reverse operation. Response B provides clear explanation of the logic flow, including concatenation of XML lines with CR/LF characters and use of the SCMS_STRING_TO_XST RING function module. Response A describes the logic flow of the incorrect method, rendering it technically inaccurate and misleading.
	Qwen-2.5- Coder	Closed Source	0.95	9.0 / 7.0*	Response A accurately identifies the correct method 'XML_TO_XSTRING' for converting a table of XML text lines to an XSTRING value. It provides precise logic flow, detailing the steps including use of

				Avg	
Question	Judge Model	Winner	Confidence	Scores (A/B)	Detailed Reasoning
Queen				(4-5)	`SCMS_STRING_TO_XS TRING` function module and proper error handling. Response B incorrectly identifies `xstring_To_XML` as the method, which is actually the opposite operation, leading to incorrect technical accuracy.
Q2: What happens if the file name is not provided in the INITIALIZE method? (Type: Simple)	Gemini-1.5-Pro	Closed Source	0.95	7.1 / 9.2*	Response B provides a concise and accurate answer focusing specifically on the code's behavior when a filename isn't provided. It correctly identifies the timestamp-based filename generation logic and explains the steps including use of 'GET TIME STAMP', 'CONDENSE', and 'CONCATENATE'. Response A gets lost in summarizing unrelated parts of the code, diluting focus and reducing clarity while containing inaccuracies in method and variable names.
	Grok-3	Closed Source	0.95	6.4 / 5.3*	Response A precisely focuses on the specific question about INITIALIZE method behavior when filename is not provided. It accurately describes the logic flow for generating default filename using timestamp, including exact steps and referencing relevant code snippet. Response B fails to address the question directly, providing

Question	Judge Model	Winner	Confidence	Avg Scores (A/B)	Detailed Reasoning broad overview of multiple methods without focusing on
					the INITIALIZE method, containing numerous typographical errors and inaccuracies.
	Qwen-2.5- Coder	Closed Source	0.95	7.2 / 5.2*	Response A accurately describes the INITIALIZE method behavior when filename is not provided. It correctly identifies steps for generating default filename using current timestamp, including use of GET TIME STAMP, CONDENSE, and CONCATENATE. Response A is technically accurate, complete, and provides practical value. Response B is largely irrelevant to the question, providing incorrect and unrelated information about different methods.

^{*} Asterisk indicates score contradiction where winner choice differs from numerical scores. Note: All evaluations showed unanimous preference for closed-source RAG system across both questions and all three judge models.