Investigating Language Preference of Multilingual RAG Systems

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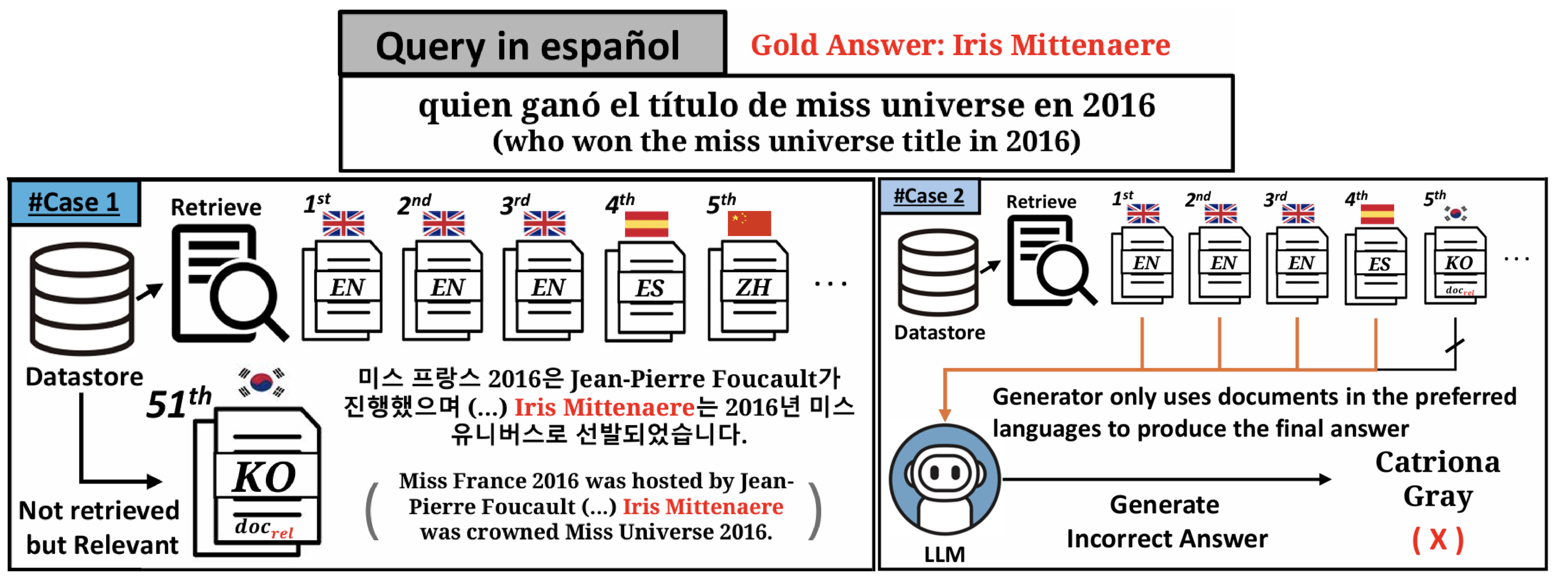
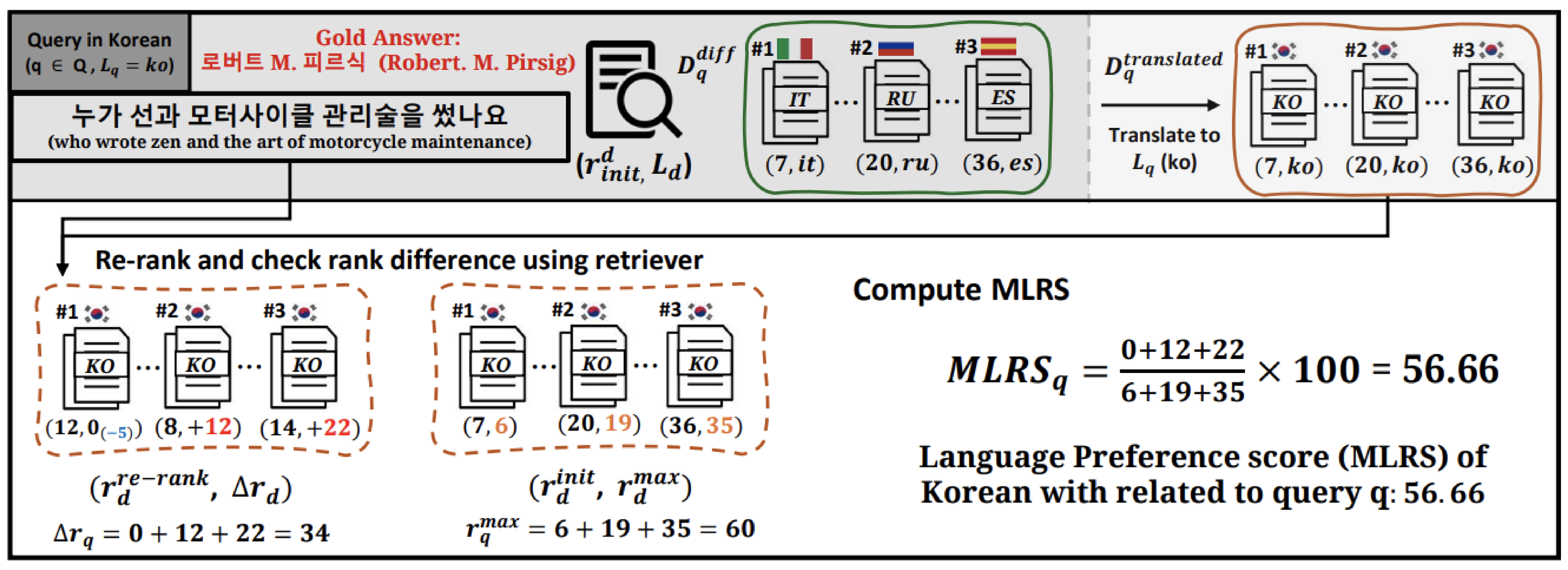
Motivation & Research Questions



- Multilingual Retrieval-Augmented Generation (mRAG) systems enhance language models by integrating external multilingual information to produce context-aware responses.
- However, because **mRAG systems favor certain languages**, the retriever often pulls in irrelevant contexts and this language preference present in both the retriever and the generator ultimately **degrades the system's generation quality**.
- We systematically investigate **language preferences in both retrieval and generation of mRAG** and propose a simple mRAG framework to mitigate language preference problem.
- These observations lead to three guiding questions:
  - ➢ ***RQ1. Which languages does the retriever prefer?***
  - ➢ ***RQ2. Which languages does the generator prefer, and how do these preferences correlate with mRAG performance?***
  - ➢ ***RQ3. How can we mitigate language preference in mRAG?***

Experimental Setting



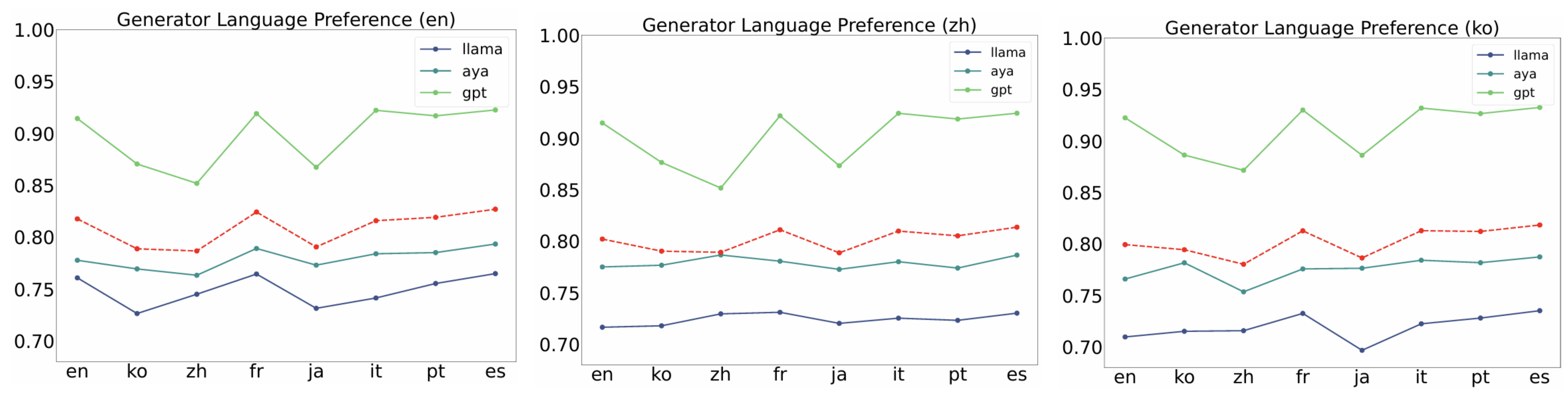
- We propose **MultiLingualRankShift (MLRS)**, an evaluation metric that **quantifies language preference of retrievers** by computing ranking improvement after translating non query language documents into query language.
- We use **MLRS** for measuring language preference of retrievers, and **answer consistency in different languages** for generators.

Language Preference of Retrievers

Query Lang.	Encoder	$L_q = L_d$	en	ko	zh	fr	ja	it	pt	es
			$L_q \neq L_d$							
en	bge-m3	**56.03**	–	33.02 (-23.01)	33.10 (-22.93)	36.61 (-19.42)	33.36 (-22.67)	35.89 (-20.14)	35.86 (-20.17)	<u>36.62</u> (-19.41)
	p-mMiniLM	**56.85**	–	34.34 (-22.51)	34.61 (-22.24)	<u>38.17</u> (-18.68)	34.52 (-22.33)	37.15 (-19.70)	36.73 (-20.12)	37.96 (-18.89)
	p-mMpNet	**57.49**	–	34.45 (-23.04)	34.27 (-23.22)	<u>37.94</u> (-19.55)	34.67 (-22.82)	37.34 (-20.15)	37.02 (-20.47)	37.90 (-19.59)
ko	bge-m3	<u>41.15</u>	**43.49** (+2.34)	–	34.42 (-6.73)	36.42 (-4.73)	37.18 (-3.97)	35.72 (-5.43)	35.30 (-5.85)	35.93 (-5.22)
	p-mMiniLM	<u>42.95</u>	**44.62** (+1.67)	–	36.04 (-6.91)	37.08 (-5.87)	38.47 (-4.48)	36.07 (-6.88)	36.18 (-6.77)	36.45 (-6.50)
	p-mMpNet	<u>42.53</u>	**44.98** (+2.45)	–	35.85 (-6.68)	37.20 (-5.33)	39.01 (-3.52)	36.21 (-6.32)	35.65 (-6.88)	36.34 (-6.19)
zh	bge-m3	<u>44.98</u>	**45.26** (+0.28)	34.52 (-10.46)	–	36.34 (-8.64)	36.05 (-8.93)	35.86 (-9.12)	35.73 (-9.25)	36.45 (-8.53)
	p-mMiniLM	**46.18**	<u>45.39</u> (-0.79)	35.46 (-10.72)	–	36.98 (-9.20)	36.77 (-9.41)	36.38 (-9.80)	36.05 (-10.13)	36.85 (-9.33)
	p-mMpNet	**46.27**	<u>45.41</u> (-0.86)	35.21 (-11.06)	–	36.87 (-9.40)	36.71 (-9.56)	36.28 (-9.99)	35.94 (-10.33)	36.78 (-9.49)
fr	bge-m3	<u>43.18</u>	**47.23** (+4.05)	33.29 (-9.89)	33.58 (-9.60)	–	34.07 (-9.11)	36.70 (-6.48)	36.30 (-6.88)	37.25 (-5.93)
	p-mMiniLM	<u>44.09</u>	**48.15** (+4.06)	34.54 (-9.55)	34.52 (-9.57)	–	34.83 (-9.26)	37.65 (-6.44)	37.05 (-7.04)	38.03 (-6.06)
	p-mMpNet	<u>43.96</u>	**48.14** (+4.18)	34.25 (-9.71)	34.37 (-9.59)	–	34.61 (-9.35)	37.59 (-6.37)	36.93 (-7.03)	38.01 (-5.95)
ja	bge-m3	<u>45.03</u>	**45.18** (+0.15)	35.45 (-9.58)	34.86 (-10.17)	36.71 (-8.32)	–	36.11 (-8.92)	35.88 (-9.15)	36.56 (-8.47)
	p-mMiniLM	**45.80**	<u>45.54</u> (-0.26)	35.90 (-9.90)	35.57 (-10.23)	37.18 (-8.62)	–	36.53 (-9.27)	36.25 (-9.55)	36.91 (-8.89)
	p-mMpNet	**45.67**	<u>45.39</u> (-0.28)	35.73 (-9.94)	35.30 (-10.37)	36.94 (-8.73)	–	36.24 (-9.43)	35.98 (-9.69)	36.62 (-9.05)
it	bge-m3	<u>41.06</u>	**46.63** (+5.57)	33.30 (-7.76)	33.47 (-7.59)	37.92 (-3.14)	33.86 (-7.20)	–	36.44 (-4.62)	37.68 (-3.38)
	p-mMiniLM	<u>42.11</u>	**47.69** (+5.58)	34.57 (-7.54)	34.59 (-7.52)	39.07 (-3.04)	34.80 (-7.31)	–	37.55 (-4.56)	38.83 (-3.28)
	p-mMpNet	<u>41.98</u>	**47.59** (+5.61)	34.48 (-7.50)	34.68 (-7.30)	38.94 (-3.04)	34.67 (-7.31)	–	37.27 (-4.71)	38.67 (-3.31)
pt	bge-m3	<u>39.19</u>	**46.64** (+7.45)	33.37 (-5.82)	33.46 (-5.73)	37.83 (-1.36)	34.02 (-5.17)	37.13 (-2.06)	–	38.61 (-0.58)
	p-mMiniLM	<u>40.17</u>	**47.75** (+7.58)	34.67 (-5.50)	34.91 (-5.26)	39.02 (-1.15)	35.03 (-5.14)	38.25 (-1.92)	–	39.68 (-0.49)
	p-mMpNet	<u>39.91</u>	**47.30** (+7.39)	34.68 (-5.23)	34.50 (-5.41)	38.70 (-1.21)	34.72 (-5.19)	38.01 (-1.90)	–	39.35 (-0.56)
es	bge-m3	<u>40.76</u>	**46.93** (+6.17)	33.36 (-7.40)	33.42 (-7.34)	37.73 (-3.03)	33.87 (-6.89)	37.22 (-3.54)	36.88 (-3.88)	–
	p-mMiniLM	<u>41.81</u>	**47.90** (+6.09)	34.63 (-7.18)	34.52 (-7.29)	38.86 (-2.95)	34.76 (-7.05)	38.33 (-3.48)	37.84 (-3.97)	–
	p-mMpNet	<u>41.33</u>	**47.34** (+6.01)	34.39 (-6.94)	34.19 (-7.14)	38.34 (-2.99)	34.39 (-6.94)	37.73 (-3.60)	37.25 (-4.08)	–

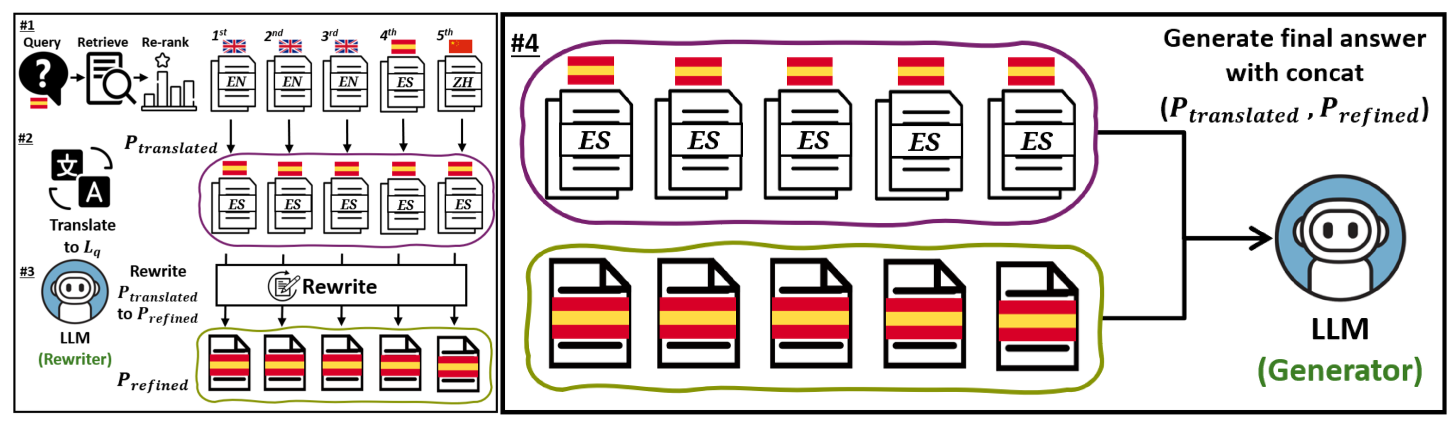
- Retrievers prefer **high-resource languages (en), Latin-script languages, and query language.**

Language Preference of Generators



- We measure language preference of generators by computing **multilingual embedding similarity of answers** for each language.
- Generators prefer Latin-script languages, slightly for query language.

How to Mitigate Language preference?



- To mitigate language preference problem in mRAG system, we propose **Dual Knowledge Multilingual RAG (DKM-RAG), a simple yet effective mRAG framework**.
- DKM-RAG leverages both **external translated passages** and passage refinement through **LLM's internal knowledge**.

Experimental Results

	all	en	zh	ko	fr	ja	it	pt	es	DKM-RAG	w/o P_{refined}	w/o $P_{\text{translated}}$
L_q = **en**												
aya-expanse-8b	<u>80.09</u>	79.34	63.08	64.46	76.13	61.20	75.47	75.65	76.32	**82.60**	79.34	81.10
Phi-4	<u>79.69</u>	78.89	63.06	52.30	74.43	48.86	74.02	74.39	75.32	**82.59**	78.89	81.08
Qwen2.5-7B-Inst.	<u>80.15</u>	79.11	50.31	64.90	76.28	62.62	75.47	75.97	76.54	**82.60**	79.11	81.06
Llama3.1-8B-Inst.	<u>80.25</u>	79.28	61.99	65.81	76.40	62.58	75.89	76.09	76.47	**82.57**	79.28	81.19
L_q = **zh**												
aya-expanse-8b	32.55	25.62	<u>38.31</u>	26.64	24.00	25.27	23.63	23.63	23.79	**44.57**	38.31	39.44
Phi-4	16.75	17.57	<u>36.76</u>	17.50	18.15	17.56	18.19	17.89	18.44	**44.56**	36.76	38.95
Qwen2.5-7B-Inst.	34.28	27.33	<u>38.31</u>	27.91	25.15	27.78	25.90	25.37	25.30	**44.70**	38.31	39.78
Llama3.1-8B-Inst.	28.50	24.36	<u>38.48</u>	23.84	22.48	23.78	23.18	23.32	23.02	**44.51**	38.48	39.35
L_q = **ko**												
aya-expanse-8b	40.60	38.08	26.01	<u>49.66</u>	25.37	26.82	24.98	25.26	25.51	**55.01**	49.66	46.15
Phi-4	26.80	20.24	17.54	<u>49.25</u>	19.03	17.91	18.93	19.19	19.19	**54.82**	49.25	45.24
Qwen2.5-7B-Inst.	36.50	22.87	20.08	<u>49.44</u>	21.79	20.94	21.65	21.44	21.52	**54.85**	49.44	45.32
Llama3.1-8B-Inst.	37.18	26.48	22.88	<u>49.87</u>	24.46	24.86	25.23	24.87	25.22	**54.99**	49.87	45.55
MLRS (Preference)	–	**47.70**	35.90	35.47	37.94	37.59	37.66	37.15	37.97	–	–	–

- We find a **strong correlation** between language preference and mRAG performance **for English queries**, but this relationship **weakens for non-English queries**. Although the mRAG system generally favors English, it performs best when the retrieved passages are in the **same language as the query**.
- DKM-RAG outperforms other document-based generator settings, highlighting **the importance of integrating translated and refined knowledge.**
- Ablation study confirms that removing any component from DKM-RAG decreases performance, highlighting that **every part is crucial** to its effectiveness.

Conclusion

- We show that mRAG systems prefer **high-resource** languages and **query** language.
- We **propose MLRS, a metric** that measures the **language preference of retrievers** by checking the rank difference between the translated passage and the original one.
- We propose **DKM-RAG, effective mRAG framework** which integrates translated passages with internal knowledge. Empirical results show that DKM-RAG consistently **enhances mRAG performance** across diverse languages.