

# ZusammenQA:

## Data Augmentation with Specialized Models for Cross-lingual Open-retrieval Question Answering System

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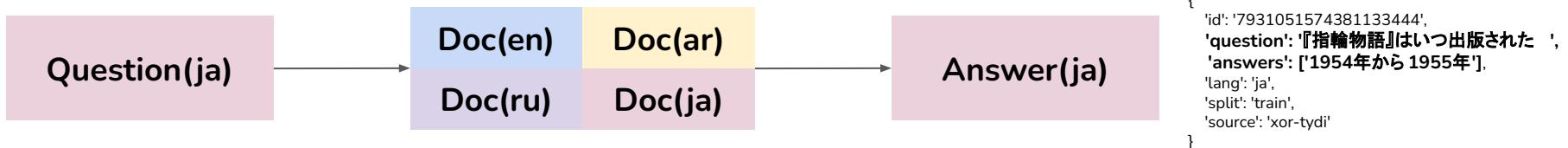
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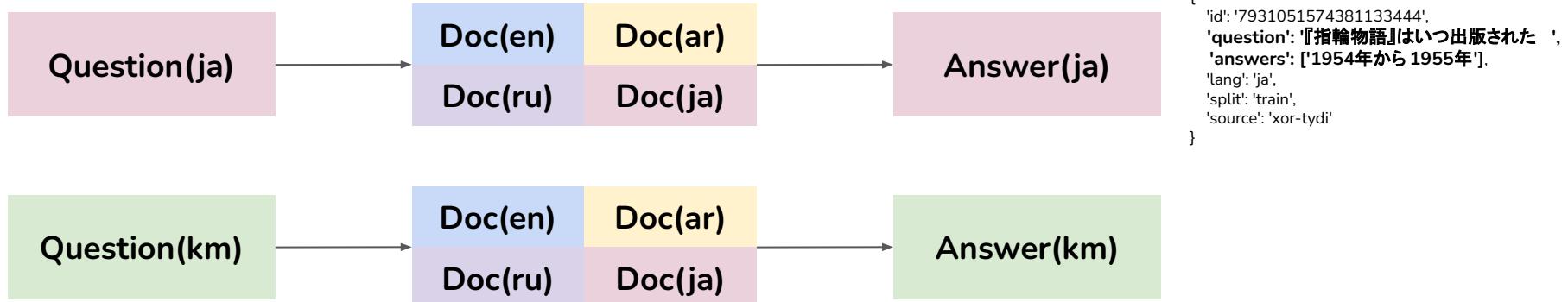
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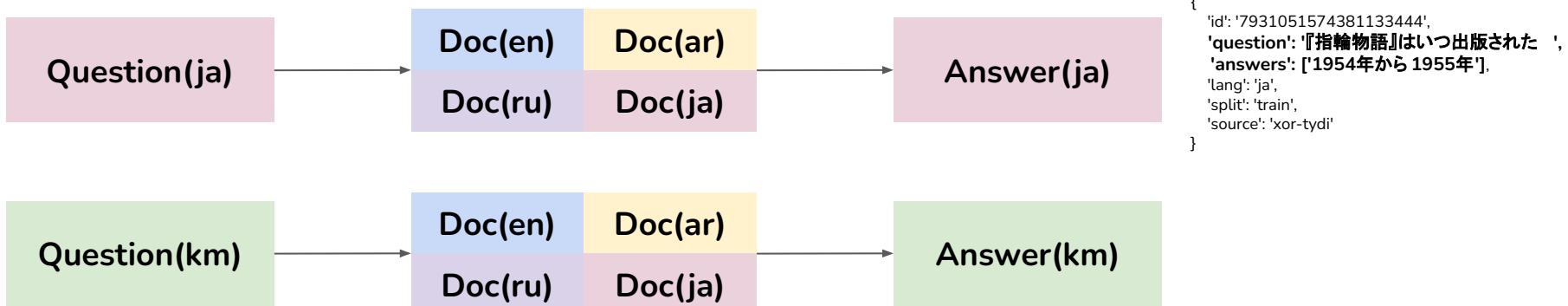
# Cross-lingual Open-retrieval Question Answering (COQA)



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## MIA-Shared Task: Constrained Track

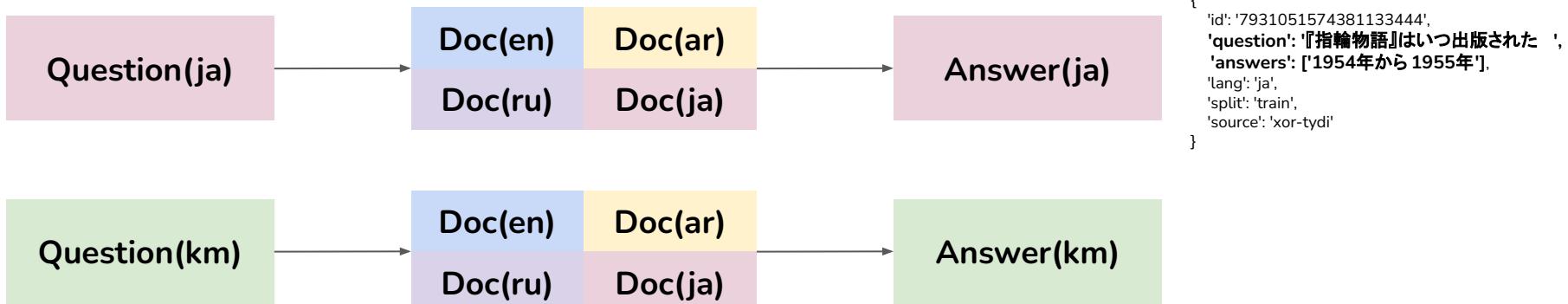
- Train: Natural Questions [Kwiatkowski et al., 2019], XOR-TyDi QA [Asai et al., 2021]
- Dev / Test: XOR-TyDi QA, MKQA [Longpre et al., 2020], Surprise Languages
- Preprocessed Wikipedia Passages
- Unlabeled data

with training data	without training data
Arabic (ar), Bengali (bn), English (en), Finnish (fi), Japanese (ja), Korean (ko), Russian (ru), Telugu (te)	Spanish (es), Khmer (km), Malay (ms), Swedish (sv), Turkish (tr), Chinese (zh-cn), Tamil (ta)*, Tagalog (tl)*

Table 1: languages for the shared task datasets

\*surprise languages

# Cross-lingual Open-retrieval Question Answering (COQA)



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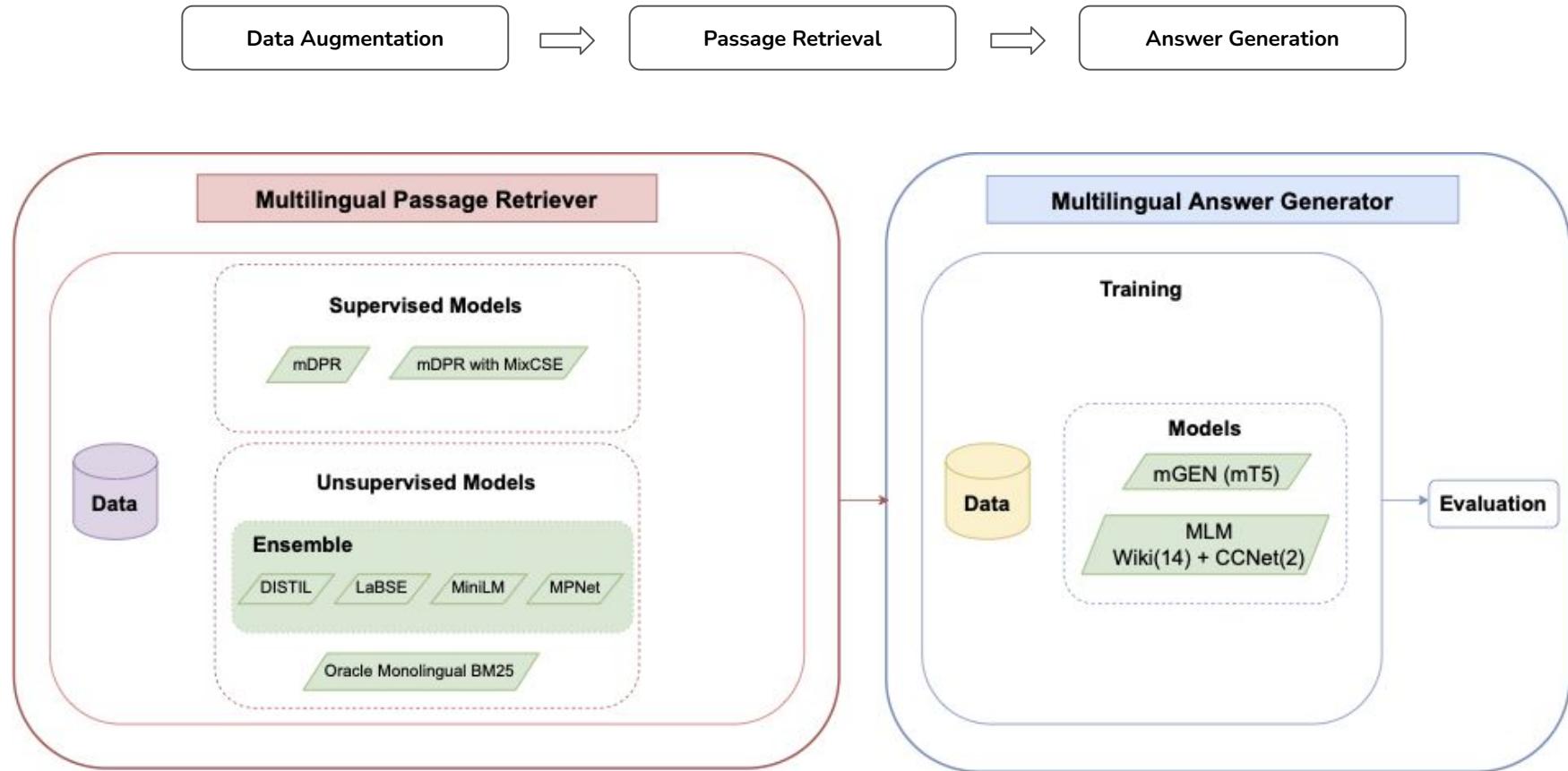
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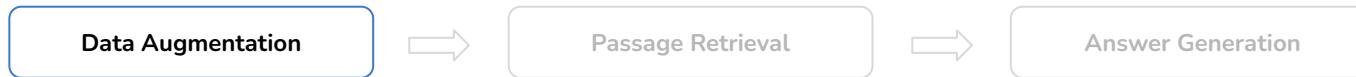
Table 1: languages for the shared task datasets

\*surprise languages

Will data augmentation help to improve the unseen languages performance?  
Will language- and domain-specialization help to improve the COQA performance?

# ZusammenQA: Data Augmentation with Specialized Models for COQA System





## QA generation

The Lego Group began manufacturing the interlocking toy bricks in 1949. Movies, games, competitions, and six Legoland amusement [...]



**QA-generator  
(T5)**



**Question:** Who funded LEGO?  
**Answer:** Ole Krik Christiansen

Further, we translated QA pairs and run heuristics rule-based filtering.



- **Supervised Models (mDPR variants)**

- mDPR [Asai et al., 2021] with MixCSE loss [Zhang et al., 2022]
  - Contrastive learning can help to alleviate the *anisotropy problem*
  - As training goes by, the influence of the negatives fades
  - **Mixed negatives** can help in keeping a strong gradient

$$\mathcal{L}_{\text{mdpr}} = -\log \frac{\langle \mathbf{e}_{q_i}, \mathbf{e}_{p_i^+} \rangle}{\langle \mathbf{e}_{q_i}, \mathbf{e}_{p_i^+} \rangle + \sum_{j=1}^n \langle \mathbf{e}_{q_i}, \mathbf{e}_{p_{i,j}^-} \rangle}$$

$\tilde{\mathbf{e}}_i = \frac{\lambda \mathbf{e}_{p_i^+} + (1 - \lambda) \mathbf{e}_{p_{i,j}^-}}{\|\lambda \mathbf{e}_{p_i^+} + (1 - \lambda) \mathbf{e}_{p_{i,j}^-}\|_2}$

- mDPR trained with augmented data



- **Unsupervised Models**

- Dense Retrieval
  - Rank ensembling with sentence encoders
    - DISTIL [Reimers and Gurevych, 2020]
    - LaBSE [Feng et al. 2022]
    - MiniLM [Wang et al., 2020]
    - MPNet [Song et al., 2020]
- Term-based Retrieval
  - Monolingual oracle BM25
    - We create **monolingual** indexes using BM25 representations
    - Language identification of the question
    - Querying of the indexes using the answer (*oracle*)



## Sequence to Sequence

Question

レゴグループを設立したのは誰ですか?<sup>1</sup>

Retrieved Passages



Generator  
(mT5)

Answer

オレ・カーク・クリスチャンセン<sup>2</sup>

<sup>1</sup> Who funded the LEGO group? <sup>2</sup> Ole Kirk Christiansen

# ZusammenQA: Data Augmentation with Specialized Models for COQA System



Input Document

レゴグループは  
1949年に運動  
おもちゃのレン  
ガの製造を開始しまし  
た。<X>、ゲーム、競  
技会、および6つのレ  
ゴランド遊園地がこの  
ブランドで <Y> されま  
した。2015年7月 現  
在、[...]

## Model Specialization

Generator  
(mT5)

## Masked Tokens Prediction

<X> 映画 <Y> 開発

Additional masked language modeling on documents for domain / language specialization.

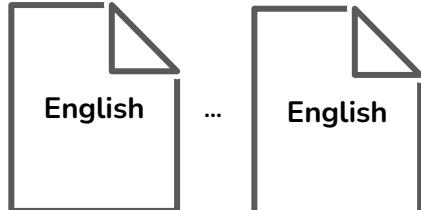


## Sequence to Sequence with Augmented Data - AUG-QA

Question

レゴグループを設立したのは誰ですか?<sup>1</sup>

Retrieved Passages



Generator  
(mT5)

Answer

オレ・カーク・クリスチャンセン<sup>2</sup>

Translate only augmented question and answer

<sup>1</sup> Who funded the LEGO group? <sup>2</sup> Ole Kirk Christiansen

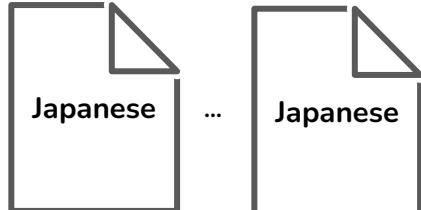


## Two types of Augmented Data - AUG-QAP

Question

レゴグループを設立したのは誰ですか?<sup>1</sup>

Retrieved Passages



Generator  
(mT5)

Answer

オレ・カーク・クリスチャンセン<sup>2</sup>

Translate only augmented question, answer and passages

<sup>1</sup> Who funded the LEGO group? <sup>2</sup> Ole Kirk Christiansen

# Evaluation: Overall Performance

Models	XOR-TyDi QA								Avg.
	ar	bn	fi	ja	ko	ru	te		
mDPR + mGEN (baseline 1)	49.66	33.99	<b>39.54</b>	39.72	<b>25.59</b>	<b>40.98</b>	36.16		<b>37.949</b>
<b>Unsupervised Retrieval</b>									
OracleBM25 + MLM-14	0.34	0.49	0.52	2.56	0.19	0.57	5.16		1.404
EnsembleRank + MLM-14	0.34	0.49	1.33	2.56	0.38	6.27	16.21		3.161
<b>Supervised Retrieval</b>									
mDPR(AUG) with MixCSE + MLM-14	20.94	7.18	15.27	23.16	10.25	19.23	10.53		15.223
mDPR(AUG) + MLM-14	24.99	15.19	20.33	22.31	10.68	18.82	11.97		17.754
mDPR + MLM-14	<b>51.66</b>	31.96	38.68	40.89	25.35	39.87	<b>37.26</b>		<b>37.951</b>
mDPR + MLM-14(XORQA & AUG-QA)	49.41	32.90	37.95	<b>40.97</b>	24.22	39.29	35.76		37.213
mDPR + MLM-14(XORQA & AUG-QAP)	48.79	33.73	38.33	39.87	25.26	39.11	37.94		37.577
mDPR + MLM-16	49.92	31.16	37.20	39.92	24.63	38.78	34.30		36.558
mDPR + MLM-16(XORQA & AUG-QA)	49.45	31.59	38.33	40.44	23.83	38.67	35.92		36.889
mDPR + MLM-16(XORQA & AUG-QAP)	48.21	<b>34.20</b>	38.78	40.76	24.81	39.49	34.37		37.231

Table 2: Evaluation results on XOR-TyDi QA test data with F1 and macro-average F1 scores

Models	Avg.
mDPR + mGEN (baseline1)	<b>27.55</b>
<b>Unsupervised Retrieval</b>	
OracleBM25 + MLM-14	2.75
EnsembleRank + MLM-wiki14	7.94
<b>Supervised Retrieval</b>	
mDPR(AUG) with MixCSE + MLM-14	11.91
mDPR(AUG) + MLM-14	14.27
mDPR + MLM-14	27.00
mDPR + MLM-14(XORQA & AUG-QA)	26.56
mDPR + MLM-14(XORQA & AUG-QAP)	26.83
mDPR + MLM-16	26.00
mDPR + MLM-16(XORQA & AUG-QA)	26.47
mDPR + MLM-16(XORQA & AUG-QAP)	26.57

Table 4: Results of macro-average F1 for all QA datasets

Models	MKQA													Surprise	Avg.
	ar	en	es	fi	ja	km	ko	ms	ru	sv	tr	zh-cn	ta	tl	
mDPR + mGEN (baseline1)	<b>9.52</b>	<b>36.34</b>	<b>27.23</b>	<b>22.70</b>	<b>15.89</b>	6.00	<b>7.68</b>	<b>25.11</b>	<b>14.60</b>	<b>26.69</b>	<b>21.66</b>	13.78	0.00	12.78	<b>17.141</b>
<b>Unsupervised Retrieval</b>															
OracleBM25 + MLM-14	2.80	10.81	3.70	3.29	5.89	1.53	1.51	5.49	1.85	7.42	2.94	1.81	0.00	8.23	4.090
EnsembleRank + MLM-14	6.43	31.66	20.02	17.38	10.68	<b>6.24</b>	4.38	21.03	6.27	21.09	17.13	7.22	0.00	8.39	12.709
<b>Supervised Retrieval</b>															
mDPR(AUG) with MixCSE + MLM-14	4.71	28.06	12.78	8.22	7.92	5.44	2.74	12.90	4.65	13.86	8.38	3.99	0.00	6.72	8.599
mDPR(AUG) + MLM-14	5.64	29.23	17.27	15.51	7.81	5.83	3.38	16.57	6.80	17.21	13.10	4.53	0.00	8.09	10.785
mDPR + MLM-14	8.73	35.32	25.54	20.42	14.27	6.06	6.78	24.10	12.01	25.97	20.27	13.95	0.00	11.14	16.040
mDPR + MLM-14(XORQA & AUG-QA)	8.46	35.12	24.74	19.50	14.38	5.62	7.22	23.24	11.46	24.49	19.67	<b>15.79</b>	<b>0.86</b>	12.18	15.909
mDPR + MLM-14(XORQA & AUG-QAP)	8.48	34.73	25.46	20.09	14.61	5.00	7.42	24.16	12.04	25.61	19.62	15.60	0.00	12.41	16.089
mDPR + MLM-16	8.15	34.14	24.85	19.38	13.73	5.93	6.51	22.21	11.46	24.91	18.82	13.62	0.00	12.59	15.451
mDPR + MLM-16(XORQA & AUG-QA)	8.21	34.06	25.65	20.14	14.22	5.80	6.70	24.40	11.82	25.71	19.92	15.42	0.40	12.36	16.057
mDPR + MLM-16(XORQA & AUG-QAP)	8.08	33.89	24.94	20.50	14.11	5.15	7.15	22.95	12.95	24.93	19.68	15.27	0.14	<b>13.07</b>	15.915

Table 3: Evaluation results on MKQA test dataset and two surprise languages with F1 and macro-average F1 scores

# Conclusions

- Data augmentation with language- and domain-specialized additional training helps to improve resource-lean languages
- Unsupervised vs Supervised retrieval models
- Batch-size for Dense Passage Retrieval methods

