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Motivation: Leaderboard for Retrieval Effectiveness on Robust04



- Bobust04: 249 test queries with dense judgments
 - Traditional setup with cross-validation

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Motivation: Leaderboard for Retrieval Effectiveness on Robust04



- Robust04: 249 test queries with dense judgments
 - Traditional setup with cross-validation
- MonoT5 (zero-shot)
 - Trained only on MS MARCO (> 10 million queries available)
 - There might be overlapping queries: Is this train-test leakage?



Overlapping Queries for Topic 441 of Robust04

MS MARCO

Robust04



Train on many queries

Title: lyme disease Description: How do you prevent and treat Lyme disease? Narrative: Documents that discuss current prevention and treatment techniques for Lyme disease are relevant. Reports of research on new treatments of the disease are also relevant. Query variants: Lyme disease treatments

lyme disease treatments prevent lyme disease

□ Test on 249 queries



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Is the evaluation of MonoT5 invalidated by overlapping queries?



Might MonoT5 Benefit From Overlapping Queries?

MonoT5

- □ 3 billion parameters sequence-to-sequence model
- \Box The query q and the document d are embedded in a input sequence:

Query: q Document: d Relevant:

Documents ranked by the probability that the next token is "true"



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WHEN YOU TRAIN PREDICTIVE MODELS ON INPUT FROM YOUR USERS, IT CAN



Candidates for Leaking Queries

- □ Nearest-neighbor search for overlapping queries
- □ Sentence-BERT embeddings for all MS MARCO and ORCAS queries
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| Union | 181 | 3,960 |



Verification of Candidates for Leaking Queries

- □ Manually review of the 5 most similar candidates per topic above threshold
- Identified query reformulation types:

| Туре | Queries |
|-----------------|---------|
| Identical | 187 |
| Generalization | 124 |
| Specialization | 228 |
| Reformulation | 182 |
| Different Topic | 106 |



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172 of 249 test queries from Robust04 occur in MS MARCO (69%)



Impact of Leaking Queries: Experimental Setup

- Models trained on dedicated datasets to assess train-test leakage
- □ Varying training set sizes: 1,000 to 128,000 instances
- Each model trained five times on each dataset
- **Training Datasets**
 - No Leakage
 - Random non-leaking queries
 - balanced between MS MARCO and ORCAS
 - MS MARCO Leakage
 - 500 random manually verified leaking queries from MS MARCO
 - supplemented by no-leakage queries
 - Test Leakage
 - 500 queries from the actual test data
 - supplemented by no-leakage queries
 - Meant as an "upper bound" for any train-test leakage effect



Effectiveness of Retrieval Models





Effectiveness of Retrieval Models

Multiple models in five-fold cross-validation setup

| Model | nDCG@10 on R04 | | |
|----------|----------------|---------------------------|---------------------------|
| | No Leakage | MS MARCO Leakage | Test Leakage |
| Duet | 0.201 | 0.198 | 0.224 [†] |
| KNRM | 0.194 | 0.214 [†] | 0.309 [†] |
| monoBERT | 0.394 | 0.373^{\dagger} | 0.396 |
| monoT5 | 0.461 | 0.457 | 0.478 [†] |
| PACRR | 0.382 | 0.364^{\dagger} | 0.391 |



Effectiveness of Retrieval Models

Increase in rank-offset between leaked relevant and non-relevant documents

| Model | MS MARCO Leakage | Test Leakage |
|----------|---|-------------------------------------|
| Duet | 6.378 ±32.15 | $0.809 \scriptstyle \pm 17.69$ |
| KNRM | 0.640 ± 19.22 | $1.335{\scriptstyle~\pm 11.75}$ |
| monoBERT | $0.692 \scriptstyle \pm 17.97$ | $\textbf{3.886} \pm \textbf{20.39}$ |
| monoT5 | $\textbf{0.443}_{\pm 8.60}$ | $\textbf{3.443} \pm \textbf{19.96}$ |
| PACRR | $\textbf{0.043} \scriptstyle \pm 19.30$ | 1.952 ± 17.71 |



Takeaways

- Possible train-test leakage for models trained on MS MARCO
 - Potential to invalidate experiments
 - Default in PyTerrier/Pyserini/PyGaggle often trained on MS MARCO
 - Only few training instances overlap: Impact measurable, but negligible
- □ Future work:
 - Effects on Dense Retrieval models
 - Practical consequences for real search engines



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Thank You!

