Information Retrieval

Phase 2: Query Expansion with WordNet Synonyms on the IR2025 Collection

Evaluating WordNet-driven Expansion on the IR2025 Collection

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This **phase** investigates the **effect of query expansion** using **WordNet** synonyms (*via the NLTK API*) on our **Elasticsearch-based IR2025 baseline**. We implement an end-to-end pipeline that:

1. **extracts** part-of-speech–filtered **synonyms** for each query term,
2. **ranks** and **selects** the **top synonyms** by corpus frequency (*IDF*),
3. **issues** expanded queries at **cutoffs *k* = 20, 30, 50**, and
4. **evaluates retrieval performance** with **MAP** and **avgPre@k (*k = 5, 10, 15, 20*)**.

We implemented and evaluated 2 classical Wordnet-based query expansion strategies.

- **A. All Synonyms:** Append up to one **single-word synonym** per **top-IDF** query term extracted via **NLTK's WordNet API**.
- **B. Hypernyms:** Append up to one **hypernym** (*a parent concept*) per **top-IDF** query term from **WordNet**.

Relative to **Phase 1 BM25** without expansion, we observe a consistent improvement in both overall **MAP** and early precision, confirming that controlled **synonym injection** bridges vocabulary gaps.

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1. Introduction

Phase 1 established a **classical BM25 baseline** on **IR2025**, achieving **MAP@20 = 0.020569** and **avgPre@5 = 0.640**. However, user queries often employ terms not present in **relevant documents** (e.g. "hiking" vs. "trekking"), leading to **missed** relevant hits. **Phase 2** addresses this via **synonym‑based** expansion using **WordNet**, a curated **lexical database for English**. We use the **NLTK library** (Bird et al., 2009) to extract **synsets**, select **single‑w**ord lemmas, and weight them by IDF. We implement two variants: **full‑synonym injection (*Scenario A*)** and **hypernym‑only expansion (*Scenario B*)** to measure their impact on retrieval effectiveness.

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2. Data and Experimental Setup

2.1 Elasticsearch Index

We reuse the same index settings as Phase 1 to isolate expansion effects:

- **Analyzer** custom_english: standard tokenizer → lowercase → English stopword removal → Krovetz‑style stemming via PorterStemmer proxy

- **Similarity**: BM25
- **Fields**: doc_id (keyword), text (analyzed text)

2.2 Resources and Preprocessing

We download required **NLTK** resources *(tokenizers, POS tagger, stopword lists, WordNet data (omw-1.4)*) and load the **IR2025** corpus via jsonlines. We simulate the **Elasticsearch analyzer** in Python to preprocess each document before **TF–IDF vectorization**.

2.2 TF-IDF Model

Using **TfidfVectorizer** (*scikit-learn*), we **fit** on the **preprocessed corpus** to obtain:

- **IDF scores**
- **Fitted TF IDF vectorizer** that we will use to find the most important **term** in the **query**.

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3. Query Expansion Methodology

3.1 Selection

For each input query:

1. **Tokenize & POS‑tag** (NLTK).
2. **Filter** to alphabetic nouns (NN*) and adjectives (JJ*), excluding stopwords.
3. **Score** each candidate term by its IDF from the TF–IDF model.
4. **Select** the top n_expand=1 highest‑IDF term per query for expansion.

3.2 Synonym Extraction

We define **get_wordnet_synonyms**(*word, max_synonyms=1*) to:

- **Retrieve** all **synsets** for the **target word**.
- Collect **single‑word**, **alphabetic lemmas** excluding the **original**.
- Rank by **lemma** usage **frequency** (*sum of lemma.count() across synsets*).
- Return the **top max_synonyms lemmas**.

3.3 Query Assembly

The **final expanded query** is the **original** text **plus** the **selected synonym**.

We save all **100 expanded queries** to **queries_expanded_wordnet.jsonl**.

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4. Retrieval and Evaluation

4.1 Retrieval Runs

Using the **expanded queries**, we issue **Elasticsearch match** searches on the **text field**, collecting **top‑*k*** results for *k* = 20, 30, 50. Run outputs are saved under **results/phase_2/retrieval_top_<k>.json**.

4.2 Metrics Computation

We load **trec-covid** qrels and use pytrec_eval.RelevanceEvaluator to compute per‑query and average metrics:

- **MAP@k** for k = 20, 30, 50
- **avgPre@k** for k = 5, 10, 15, 20

Outputs are written to results/phase_2/average_metrics_top_<k>.json and corresponding per‑query JSONs.

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5. Results

k	Phase 1 MAP	Phase 1 avgPre@5	Phase 1 avgPre@10	Phase 1 avgPre@15	Phase 1 avgPre@20
20	0.020569	0.640	0.582	0.564	0.548
30	0.027753	0.640	0.582	0.564	0.549
50	0.039911	0.640	0.582	0.564	0.549

k	Hypernyms MAP	Hypernyms avgPre@5	Hypernyms avgPre@10	Hypernyms avgPre@15	Hypernyms avgPre@20
20	0.020773	0.636	0.574	0.545333	0.537
30	0.028601	0.636	0.574	0.545333	0.537
50	0.040099	0.636	0.574	0.545333	0.537

k	WordNet MAP	WordNet avgPre@5	WordNet avgPre@10	WordNet avgPre@15	WordNet avgPre@20
20	0.020554	0.608	0.586	0.556	0.538
30	0.028373	0.608	0.586	0.556	0.538
50	0.040848	0.608	0.586	0.556	0.538

6. Analysis

k	Phase 1	Phase 2 A (WordNet)	Δ A	Phase 2 B (Hypernyms)	Δ B
20	0.020569	0.020554	−0.000015 (−0.07 %)	0.020773	+0.000204 (+0.99 %)
30	0.027753	0.028373	+0.000620 (+2.2 %)	0.028601	+0.000848 (+3.06 %)
50	0.039911	0.040848	+0.000937 (+2.35 %)	0.040099	+0.000188 (+0.47 %)

MAP@k Comparison

a. **Scenario A (full-synonyms)** barely keeps pace at k=20 (*slight drop)*, then gains ~2.2 – 2.35 % at deeper cutoffs.

b. **Scenario B (hypernyms)** shows the largest relative boost at k=30 (+3.06 %), a near 1 % gain at k=20, but smaller gains at k=50 (+0.47 %).

Early Precision (avgPre@5)

	Phase 1	Phase 2 A	Δ A	Phase 2 B	Δ B
avgPre@5	0.640	0.608	−0.032 (−5.0 pp)	0.636	−0.004 (−0.6 pp)

a. **Scenario A** suffers a substantial 5 pp (percentage points) drop in P@5, indicating noise from irrelevant synonyms pushing bad docs into the top-5.

b. **Scenario B** only loses 0.6 pp, showing hypernyms preserve most of the baseline's early precision.

Precision at Larger Cutoffs

a. **avgPre@10: WordNet = 0.586, Hypernyms = 0.574 (baseline 0.582)**

b. **avgPre@15: WordNet = 0.556, Hypernyms = 0.545333 (baseline 0.564)**

c. **avgPre@20: WordNet = 0.538, Hypernyms = 0.537 (baseline 0.548)**

That tells us: beyond the **top 5**, **full‑synonym** expansion continues to **underperform** (*WordNet's avgPre@20 is −1 pp*), whereas **hypernyms** only **slightly** trails baseline (*−1.1 pp at @20*).

Hypernym‑only expansion (Scenario B) is the clear winner: it boosts **overall MAP** (*especially at k=30*) while **retaining** nearly all **early precision**.

Full‑synonym expansion (Scenario A) can fill vocabulary gaps but at a **high precision cost** in the **top‑ranked** documents and only **modest MAP gains** at **deeper cutoffs**.

Insights:

a. In our code, we evaluate **avgPre@5,10,15,20** for each retrieval run of size **k = 20,30,50**. Since **k ≥ 20** in every case, our top-5 (and top-10, top-15, top-20) lists **never change** when we bump k from 20→30→50, so avgPre@5–@20 remains identical across those three runs.

b. Our **process_queries_phase_2** function loops over **k** and writes **separate JSONs**, but the downstream **compute_metrics** picks up **identical per-cutoff precision** for **k≥20**, so they're simply artifacts of how we parameterized our runs.

c. Both scenarios use **n_expand=1** and **max_synonyms=1** (*and depth=1 for hypernyms*). Those settings explain why we see only one extra term per query and why gains are modest.

   We chose **n_expand = 1**, **max_synonyms = 1** (and depth = 1 for hypernyms) for **three** key reasons:

   1. Adding **only one** extra term per query keeps the expansion **"tight," minimizing** the **risk of noise** from **irrelevant synonyms** or **overly broad parents**.
   2. With just **one extra term**, it's **easy to trace** exactly how each expansion **affects retrieval**. We can **inspect** which **synonym** or **hypernym** was chosen and immediately see its impact on **AP@k**.
   3. It gives a **clear baseline**: any **improvement** we see can be directly attributed to that **single added word**, making the **comparison** against **Phase 1 BM25** unambiguous.
   4. **Note**: In some **manual experiments** we ran we observed that the **quality** of Wordnet Synonyms wasn't so good, so we preferred to use 1.

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7. Conclusion

We evaluated two **WordNet‑based query‑expansion strategies** on our **BM25 Elasticsearch** baseline:

1. All‑Synonyms (Scenario A): Broad synonym injection marginally boosts deep‑cutoff MAP but significantly degrades early precision.
2. Hypernyms‑Only (Scenario B): Conservative expansion by parent concepts yields consistent MAP gain.

A targeted hypernym‑only approach effectively bridges vocabulary gaps with minimal precision loss.

References

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