

Efficient SPARQL Autocompletion via SPARQL

ABSTRACT

We show how to achieve fast autocompletion for SPARQL queries on very large knowledge bases. At any position in the body of a SPARQL query, the autocompletion suggests matching subjects, predicates, or objects. The suggestions are context-sensitive and ranked by their relevance to the part of the query already typed. The suggestions can be narrowed down by prefix search on the names and aliases of the desired subject, predicate, or object. All suggestions are themselves obtained via SPARQL queries. For existing SPARQL engines, these queries are impractically slow on large knowledge bases. We present various algorithmic and engineering improvements of an open-source SPARQL engine such that these queries are executed efficiently. We provide an extensive evaluation of a variety of suggestion methods on three large knowledge bases, including the complete Wikidata (9.9B triples). We compare our results with two widely used SPARQL engines, Virtuoso and Blazegraph. Materials for full reproducibility and an interactive evaluation web app are available on <http://www2022-181.hopto.org>.

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1 INTRODUCTION

Knowledge bases play an increasingly important role in modern web search engines. The prevailing data model is the Resource Description Framework (RDF), where the data is stored as subject-predicate-object triples. Each subject, predicate, or object is either an *Internationalized Resource Identifier* (IRI), enclosed in angle brackets, or a so-called *literal*, enclosed in quotes. A toy example:

```
<Meryl_Streep>    <is_a>        <Person>
<Meryl_Streep>    <gender>       <Female>
<Meryl_Streep>    <award_won>  <Oscar_Best_Actress>
<Meryl_Streep>    <birth_date>  "1949-06-22"
<Oscar_Best_Actress> <is_a>        <Oscar>
```

RDF data allow queries with precise semantics. For example, the following query finds all women who won an Oscar. The query is formulated in SPARQL, the standard query language for RDF data.

```
SELECT ?entity ?award WHERE {
  ?entity <is_a>        <Person> .
  ?entity <gender>     <Female> .
  ?entity <award_won>  ?award .
```

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```
?award <is_a>        <Oscar>    }
```

The result for this query is a table with two columns, where each row contains the name of the person and the name of the award. For the tiny example knowledge base above, the result is:

```
<Meryl_Streep> <Oscar_Best_Actress>
```

The five example triples above come from *Fbeasy* (362M triples) [4], an easy-to-use subset of *Freebase* (1.9B triples) [8]. The largest general-purpose knowledge base to date is *Wikidata* (10B triples, as of 10-06-2021) [21]. *Fbeasy* has (human-)understandable IRIs for all entities. In *Wikidata*, almost all IRIs are abstract, whereas understandable names can be obtained via dedicated predicates; see the example query below. *Freebase* uses a mix of understandable and abstract IRIs. We consider all three knowledge bases in this paper; see Section 4.2 for details.

SPARQL is conceptually easy, but it is hard, even for experts, to find or guess the right IRIs to express what you are looking for. It becomes extremely hard when IRIs are abstract. For example, here is the correct SPARQL query on *Wikidata* to obtain the list of all Oscars of Meryl Streep and the movies she won them for:

```
SELECT ?award ?film WHERE {
  wd:Q873 p:P166 ?m .
  ?m pq:P1686 ?film_id .
  ?m ps:P166 ?award_id .
  ?award_id wdt:P31 wd:Q19020 .
  ?award_id rdfs:label ?award .
  ?film_id rdfs:label ?film }
```

The *wd:*, *wdt:*, *p:*, *pq:*, *ps:*, and *rdfs:* are IRI prefixes.¹ The IRI *wd:Q873* stands for *Meryl Streep* and *wd:Q19020* for the *Academy Awards*. The *p:P166* leads to a so-called statement node, representing a particular award. The *ps:P166* leads to the award entity and the *pq:P1686* leads to the awarded film. The *wdt:P31* stands for *instance of*.

1.1 Problem Definition and Three Examples

The goal of this paper is to assist the user in typing the body of a SPARQL query by providing suggestions for IRIs and literals at any point in the query.² The suggestions should be ranked by relevance to the part of the query already typed. We first provide a formal problem definition and then explain it at length via two examples in the text and four examples depicted in Figure 1.

Definition. Let *s* be the part of the body of a valid SPARQL query typed until a certain point, called the *cursor position*. Let *t* be the complete *token* (subject, predicate, or object) that is intended at the cursor position. Let *p* be a *prefix* of a name or alias of *t*, possibly empty. The *SPARQL Autocompletion via SPARQL* problem is: Given *s* and *p*, construct and process a SPARQL query, called *autocompletion query* or *AC query*, with the following properties:

¹Definitions omitted to save space; see <https://en.wikibooks.org/wiki/SPARQL/Prefixes>
²A typical user interface for SPARQL autocompletion also involves suggestions for variable names or SPARQL constructs like OPTIONAL, FILTER, UNION or GROUP BY at appropriate positions in the query. We omit this aspect here, as such suggestions are not particularly challenging with respect to relevance or efficiency.



Figure 1: Four screenshots of our autocomplete in action, with three suggestions each. Top-left and top-right: Examples 1 and 2 from Section 1.1. The assignments below each screenshot show the values of the variables from our problem definition.

The AC query returns a table with each row corresponding to a suggestion and the following three columns:

- ?entity* (an entity from the knowledge base),
- ?name* (a name or alias of that entity, starting with *p*),
- ?score* (an estimate of the relevance of this entity suggestion).

The rows are sorted in descending order of *?score*. One of the rows contains *t* in the *?entity* column. There are three objectives:

Relevance: The row with the desired *t* should be as high up in the table as possible.

Sensitivity: Each suggestion should be *context-sensitive* (or just *sensitive*) in the sense that it continues the SPARQL query in a meaningful way, that is, such that there exists a continuation with a non-empty result.

Efficiency: The query should be processed as quickly as possible.

Example 1 Assume that we have typed the body of the first SPARQL query from the introduction until before the first object; see below. This is the *s* from the definition. The *_* symbol marks the cursor position and the prefix *p* is "P". The token *t* we are looking for at this position is *<Person>*. The knowledge base is Fbeasy.

```
?x <is_a> P_
```

The following AC query computes a table containing each object *?entity* and its name *?name*, such that the name starts with *P* and the triple *?x <is_a> ?entity* exists. The table is sorted in descending order of the number of such triples for each *?entity*.

1. `SELECT ?entity ?name ?score WHERE {`
2. `{ SELECT ?entity (COUNT(?x) AS ?score) WHERE {`
3. `?x <is_a> ?entity`

4. `} GROUP BY ?entity }`
5. `BIND(STR(?entity) AS ?name) . FILTER REGEX(?name, "^P")`
6. `} ORDER BY DESC (?score)`

The first three result rows for that query look as follows. Note that for this knowledge base, the name of an entity is simply the IRI, interpreted as a string (that is what the *STR* function does).

<i><Person></i>	"Person"	3970825
<i><Politician></i>	"Politician"	127809
<i><Plant></i>	"Plant"	60459

Relevance: The desired token *t* is the first suggestion.

Sensitivity: By construction of the AC query, all suggested entities lead to a non-empty result.

Efficiency: Our competitors Virtuoso and Blazegraph (introduced later) require several seconds for this query. They materialize each matching *?name* string and check the regular expression for each of these strings. Our engine addresses this problem and can process the query above in 0.2s. This is explained in detail in Section 3.

Example 2 Now assume that we have typed the SPARQL query until the following *s*. The desired token *t* at the cursor position is *<gender>*. The prefix *p* is empty.

```
?x <is_a> <Person> .
?x _
```

The following AC query gives us a ranked list of *predicates* that lead to a non-empty result. The score for each predicate is the number of persons (that is, entities matching the first triple) that have a triple with that predicate. If a person has several triples with the same

predicate, we only count the predicate once, hence the DISTINCT; this is explained more below and in Section B.

```

1. SELECT ?entity ?name ?score WHERE {
2.   { SELECT ?entity (COUNT(DISTINCT ?x) AS ?score) WHERE {
3.     ?x <is_a> <Person> . ?x ?entity ?object
4.   } GROUP BY ?entity }
5.   BIND(STR(?entity) AS ?name)
6. } ORDER BY DESC (?score)

```

The first three result rows for this AC query are as follows:

<is_a>	"is_a"	3970825
<gender>	"gender"	2276146
<birth_date>	"birth_date"	1915167

Relevance and Sensitivity: The desired token t is second in this table and, again by construction, the AC query only returns predicates that lead to a hit. The suggestions are ranked by how often each of them occurs with the set of entities defined by the part of the query already typed. Because of this, we did not have to type a single letter here to get very good suggestions. It is important to note that without the first triple in the AC query above, <gender> would not be among the top suggestions. We call that approach *Agnostic* and will evaluate it in Section 4.

Efficiency: Most query engines process the AC query above as follows: The two triples from line 3 are joined into a large table (one row for each triple of each person, 37M for the query above), which is then grouped. This is expensive: Virtuoso and Blazgraph both time out for the query above. When removing the DISTINCT, they still require 2.4s and 35s, respectively.³ Our engine can solve such queries very fast (0.1s for the query above), using a general technique described in Section 3.1.

Figure 1 shows two more AC queries for the Wikidata knowledge base, where IRIs are abstract and we need to filter on the names of these IRIs, obtained via the *rdfs:label* predicate. For a detailed explanation of the first of these (bottom left in the figure), see Section A.

It is important to note that the construction of our AC queries is *generic* and can be generalized to arbitrary knowledge bases. More details are provided in our evaluation (Section 4) and Section B.

1.2 Our contributions

We consider the following as our main contributions:

- We develop the idea of providing SPARQL autocompletion via SPARQL queries. These *AC queries* can be processed by any (standard-conforming) SPARQL engine. The basic idea is already found in previous work, but in less generality, without an efficient solution, and without an extensive quality evaluation. See Section 2.
- We extend an existing SPARQL engine such that these AC queries can be processed efficiently. Our extensions are technically challenging, comprise algorithmic ideas and algorithm engineering, and are valuable also beyond autocompletion. See Section 3.
- We show how to realize AC queries with good (though not optimal) quality also for two existing and widely used SPARQL

³We therefore evaluate Virtuoso and Blazgraph without the DISTINCT for these queries; see Section 4.3. Suggestions are then still reasonable, though not quite as good.

engines (Virtuoso and Blazgraph), despite their less efficient query processing. Again, see Section 3.

- We provide an extensive evaluation of all three SPARQL engines on three large knowledge bases, including the complete Wikidata (9.9B triples). In particular, we explore the trade-offs between sensitivity, relevance and efficiency. See Section 4.
- We achieve strong results. For example, on Wikidata we can realize sub-second response times with an average relevance (MRR) of 43% per token without typing anything, and over 90% when typing only three characters.
- We provide materials for full reproducibility at <http://www2022-181.hopto.org> : code, queries, indexes, result files, and a web application for an interactive exploration of our experimental results.

2 RELATED WORK

Campinas et al. [11] present an autocompletion system that is able to recommend predicates and types (i.e. objects of a *type* predicate). This approach uses AC queries, but runs them on a smaller *graph summary* that only captures the structure of the data, which helps efficiency, but harms relevance. The idea behind the graph summary is similar to our technique for predicate AC queries, but with the important difference that our implementation does not affect relevance; this will be explained in detail in Section 3.1. In a follow-up paper, Campinas [10] presents a system called *Gosparqled* that uses AC queries similar to ours. However, suggestions are again only possible for predicates and types and the results are not ranked. We next discuss the three objectives from our definition in Section 1.1 for these papers:

Relevance and Sensitivity: The AC queries of *Gosparqled* are fully sensitive and similar to those from Section 1.1, but with a LIMIT (of 10, 100 or 500) on the matches for the triple(s) on line 4, to reduce the cost of the GROUP BY. We call this mode *Sensitive-Trunc* in our evaluation, and compare it to the mode, where AC queries are not truncated. In [10], the two modes are compared via the Jaccard similarity of the suggestions. We compare actual relevance.

Efficiency: *Gosparqled* achieves response time below 0.2s for 94% of the AC queries. The main reason is the mentioned LIMIT, which severely impacts relevance. The graph summary further reduces the average run time by about 35%. The knowledge base used for the evaluation consists of less than half the amount of triples than our smallest dataset, Fbeasy. The evaluation setup is also different in that for each suggestion, only the desired token is removed from the query. That way, the AC queries have very restricting contexts, which helps efficiency a lot. In contrast, we simulate typing the query from beginning to end, which results in many very hard AC queries that have to deal with huge intermediate results.

Jarrar and Dikaiakos [14] present autocompletion for *MashQL*, a variant of SPARQL with essentially the same functionality as SPARQL. They also use AC queries to suggest entities to the user. *MashQL*'s completions are only context-sensitive for *linear-shaped* queries. For example, if the user has already typed $?x1$ <place of birth> $?x2$. $?x2$ <country> $?x3$. $?x3$ _, *MashQL* will consider this context. But if the user has typed $?x$ <place of birth> <Berlin> . $?x$ <gender> <Female> . $?x$ _, *MashQL* will suggest predicates without taking the previous context into account. To be able to run the AC

queries more efficiently, they use two graph summaries. In one graph summary, entities with the same *outgoing* paths are grouped together and in the other one, entities with the same *incoming* paths are grouped together. These summaries only lead to context-sensitive results for the above mentioned *linear-shaped* queries.

Bast et al. [3] present a system called *Broccoli*, which provides context-sensitive suggestions for tree-shaped queries and depicts the queries as trees. The underlying query language is equivalent to SPARQL, restricted to trees and basic graph patterns. The focus of the paper is on extending the query language by a text-search component and on providing efficient auto-completion for this component as well. The user interface and the evaluation work with a knowledge base with human-readable IRIs (similar to Fbeasy, but only 26M triples) and do not support synonyms or aliases.

Ferré [13] presents a system called *SPARKLIS*, which suggests context-sensitive continuations for SPARQL queries. Queries are formulated in natural language (for instance “Give me every person whose gender is female and who won an award that is an Oscar”). It supports most of the functionality of SPARQL. Suggestions are obtained via AC queries similar to those from Section 1.1. In order to address efficiency issues, there is a LIMIT as described for Gosparql above, and results are not ranked. As the user types, results of the partially written query are computed and shown. These intermediate results are used to compute the suggestions faster (similar to our cache described in Section 3.3).

There is a wide literature on other approaches to assist the user in creating SPARQL queries (or get results from a knowledge base) by other means than token-based auto-completion. In particular: *SemFacet* [1], *BrowseRDF* [18], *SPARQLets-Finder* [19], *SnipSuggest* [15], *Aqqu* [6], *Question AC* [2], *AutoSPARQL* [17], *SQLSUGG* [12]. They are not directly relevant to our work in this paper, so we omit a detailed discussion due to the space restrictions.

3 EFFICIENT AC QUERIES

This section describes our main techniques to make AC queries efficient. In our evaluation in Section 4, we impose a timeout for each AC query (a user is only willing to wait so long for suggestions). Efficiency is therefore a prerequisite for quality.

We implement the extensions described in the following subsections as extensions of the open-source SPARQL engine QLever [5]. In our evaluation, we compare this to Virtuoso [20] and Blazegraph [7]. Virtuoso is one of the most widely used SPARQL engines and Blazegraph is the SPARQL engine behind the Wikidata Query Service at <https://query.wikidata.org>. The general architecture of all three engines is similar, a quick overview over the main principles is provided in Section D.

3.1 AC Queries for Predicates Using Patterns

Our predicate AC queries involve queries of the following kind, where `%context%` are the completed triples from the part `s` of the SPARQL query that has already been typed; see our definition in Section 1.1.

```
SELECT ?entity (COUNT(DISTINCT ?x) AS ?score) WHERE {
  %context% . ?x ?entity ?object
} GROUP BY ?entity
```

As explained for Example 2 of Section 1.1, existing SPARQL engines materialize all matches for `%context% . ?x ?entity ?object` before computing the GROUP BY. If `%context%` constrains `?x` little or not at all, this is very expensive to compute.

We want to stress that these queries do not just occur in the context of auto-completion. For example, users of the SPARQL endpoint for the huge UniProt knowledge base (91B triples) formulate many “discovery” or “statistics” queries that are of a similar form as our AC queries [9]. The rule miner from [16] is based on queries like the above, but has its own data structures to process them because existing SPARQL are too slow or time out.

To answer this kind of query efficiently, we make the following preprocessing:

1. Let S be the set of all distinct subjects in the knowledge base. For each $x \in S$, compute the set of the distinct predicates from all triples that have x as subject. This set is called the (predicate) *pattern* of x . From these sets, compute the set \mathcal{P} of distinct patterns.
2. Give consecutive IDs to the patterns from \mathcal{P} and store the map from IDs to patterns in an array of size $|\mathcal{P}|$.
3. Store the map from each subject to its pattern ID in an array of size $|S|$.

The following table provides statistics of this pre-processing for our three knowledge bases. The fourth column counts the total size of the patterns, where the size of a pattern is the number of predicates and each pattern is counted once. The fifth column specifies the total memory consumption of the result of the pre-processing.

	$ S $	$ \mathcal{P} $	$\sum_{P \in \mathcal{P}} P $	Mem
Fbeasy	60 M	0.3 M	3 M	0.3 GB
Freebase	476 M	3.1 M	95 M	2.5 GB
Wikidata	2068 M	4.4 M	160 M	9.0 GB

To process the above query, we make use of these precomputed patterns as follows, where steps 2 and 3 can be (and are) parallelized:

1. Let $S \subseteq S$ be the set of subjects `?x` from `%context%` or $S = S$ if `%context%` is empty.
2. Look up the pattern IDs from all $x \in S$ in the precomputed array and compute a map $c : \mathcal{P}_S \rightarrow \mathbb{N}$ that, for each pattern ID that occurs at least once, counts how many $x \in S$ have that pattern ID. This can be done in time linear in the size of S .
3. For each pattern $P \in \mathcal{P}_S$, retrieve the corresponding set of predicate IDs and for each p in that set, increase a counter (initially 0) by $c(P)$. This takes time linear in $\sum_{P \in \mathcal{P}_S} |P|$.
4. Sort the encountered p by the final counter values. This yields the result for the query above.

The worst case for this algorithm is that every subject has a different predicate pattern and exactly one triple for each predicate. Then $|\mathcal{P}_S| = |S|$, each $c(P)$ is 1, and Step 3 does exactly what the naive algorithm described in Section 1.1 would do. However, in realistic knowledge bases, many subjects share the exact same set of predicates, so that $|\mathcal{P}_S| < |S|$, and $\sum_{P \in \mathcal{P}_S} |P|$ is much smaller than the total number of triples of all $x \in S$.

For example, consider the AC query above for Fbeasy, with `%context% = ?x <is_a> <Person>`. In Fbeasy, there are 4.0M persons with a total of 37 M triples. They have only $|\mathcal{P}_S| = 115K$ distinct

patterns with $\sum_{P \in \mathcal{P}_S} |P| = 1.4\text{M}$ predicates. With QLever extended by the pattern trick, the query can be solved in under 0.1s. With the standard query processing, QLever would take 6.6s, of which 1.6s are spent on sorting 37M elements.

The graph summaries from [11] (see Section 2) realize the special case when the `%context%` is one triple that specifies the type.

3.2 Prefix filtering

Here is a variant of the AC query from Example 1 in Section 1.1, translated to Wikidata (`wdt:P50` relates written works to authors):

```
1. SELECT ?entity (SAMPLE(?name) AS ?name)
2.           (SAMPLE(?score) AS ?score) WHERE {
3.   { SELECT ?entity (COUNT(?entity) AS ?score) WHERE {
4.     ?x wdt:P50 ?entity
5.   } GROUP BY ?entity }
6.   ?entity rdfs:label|skos:altLabel ?name
7.   FILTER REGEX(STR(?name), "^[P]")
8. } GROUP BY ?entity ORDER BY DESC(?score)
```

Blazegraph and Virtuoso both time out on this query, for the following reason. They materialize all `?name` strings (2.3M in the example query, this depends on the query context in line 4) and then check the regular expression for each of them. Our extension of QLever makes use of the fact that in QLever, each IRI and literal has a unique internal ID (more about the internals of QLever in Section D). For the literals, we order the IDs such that the order by ID is exactly the same as the lexicographical order. A FILTER with a prefix regex can then be realized with two binary searches. The query above can then be processed in $\leq 0.4\text{s}$.

This trick also permits the following optimization for longer prefixes.⁴ For object AC queries, which all have the form above (what differs is the `%context%` of line 4 and the prefix in line 7 by which we filter), we simply swap line 5 with lines 6 and 7. The effect is that when the triples of line 4 yield a large intermediate result, this is now significantly reduced before the GROUP BY.

3.3 Caching and pinned results

We have extended QLever by a thread-safe least-recently-used (LRU) query cache with the following features, important for our AC queries. The cache stores not only final results of a query, but also results from the intermediate operations. The query planner is aware of results in the cache: the cost estimate for computing the result of a cached query is zero. This is crucial for the processing of sequences of similar SPARQL queries, as it naturally happens in our setting.

Our cache also allows *pinning* results. These results will not be removed by an LRU eviction (but there is a special command to clear the cache completely). In our evaluation, we pin the results of two queries: the query that provides the canonical name, score⁵, and aliases for each entity that can occur as subject or object, and the query that provides the same information for each entity that can occur as predicate. We pin the first result in two orders: by entity (for efficient joins with the `%context%`.) and by alias (for

⁴In our evaluation, we apply this when the prefix length is ≥ 3 .

⁵The score only matters for subject AC queries, which are rare, and for agnostic queries, which we use in our evaluation as a baseline (see Section 4.4).

efficient filtering by prefix). Even for the large Wikidata, the size of these pinned results is just 6.7 GB.

4 EVALUATION

In this section, we describe how we evaluated our approach, and then present and discuss the results of this evaluation. Reproducibility materials are available on <http://www2022-181.hopto.org>. In particular, a web app is provided that permits an interactive exploration of the details and performance of *all* our AC queries.

4.1 SPARQL Engines and Hardware

We evaluate our own extension of QLever, described in Section 3, against Virtuoso and Blazegraph; see Section D for a description of their basic architecture. All experiments were performed on a standard PC with an AMD Ryzen 7 3700X CPU (8 cores + SMT), 128 GB of DDR-4 RAM and 4 TB SSD storage (NVME, Raid 0).⁶

QLever was configured with a memory limit of 70 GB for query processing, of which 30 GB were available to the query cache; see Section 3.3. Before each experiment, the query cache was cleared and the results of the queries without context were pinned, as explained in Section 3.3. For Virtuoso, we use the latest release candidate of the open-source edition (7.2.6), configured using the largest memory preset for 64 GB of RAM.⁷ For Blazegraph, we used the latest stable release (2.1.5), configured according to Blazegraph's own recommendations for running Wikidata [7]. In particular, Blazegraph gets 16 GB for the JVM heap, while the rest of the RAM is used for disk caching by the operating system.

4.2 Knowledge Bases

We evaluate on the following three knowledge bases, already introduced in Section 1. We deliberately chose three knowledge bases with related content (general knowledge in this case), but different sizes and combinations of human-understandable vs. abstract IRIs.

Fbeasy [4]: 362M triples, 50M subjects, 2K predicates. All IRIs are simple and understandable (e.g. `<Meryl_Streep>` or `<gender>`).

Freebase [8]: 1.9B triples, 125M subjects, 785K predicates. Entity IRIs are abstract (e.g. `fb:m.05dfkg3` for Meryl Streep), but most predicate IRIs are understandable (e.g. `fb:people.person.gender`).

Wikidata [21]: 9.9B triples, 1.8B subjects, 41K predicates (dump from 10.06.2021). Almost all IDs are abstract (e.g. `wd:Q873` for Meryl Streep and `wdt:P21` for gender). We removed all non-English literals to help Virtuoso and Blazegraph, because these engines do not support efficient language filters.

4.3 Autocompletion (AC) queries

The basis for our evaluation are the 334 example queries from the Wikidata Query Service [22]. These queries cover a wide spectrum of SPARQL queries: they range from simple to complex, use SPARQL features like UNION, OPTIONAL, MINUS, predicate paths, subqueries, and cover the whole breadth of the content in the knowledge base. We had to exclude some queries for technical reasons:

⁶We also ran our experiments on HDD storage (Raid 5), and found little difference. However, indexing on HDD is much slower for Virtuoso and Blazegraph.

⁷When scaling this preset up to 128 GB we found no significantly different results, but frequently ran into problems with the out-of-memory killer.

Fbeasy (315 tokens)		$\leq 0.2s$	$\leq 1.0s$	Max	Sensitivity			MRR₇			KS₇
Unranked	Qlever	100%	100%	281ms	0: 3%	3: 24%	7: 61%	0: 0%	3: 39%	7: 69%	7.21
Agnostic	Qlever	100%	100%	362ms	0: 48%	3: 44%	7: 56%	0: 25%	3: 85%	7: 97%	3.58
Sensitive-Trunc	Blazegraph	24%	95%	3% > 5s	0: 100%	3: 100%	7: 100%	0: 50%	3: 69%	7: 82%	4.26
Sensitive-Trunc	Virtuoso	15%	38%	2% > 5s	0: 100%	3: 100%	7: 100%	0: 56%	3: 79%	7: 87%	3.14
Sensitive	Qlever	93%	99%	2605ms	0: 100%	3: 100%	7: 100%	0: 68%	3: 96%	7: 98%	1.69
Mixed-Trunc	Blazegraph	25%	98%	1000ms	0: 95%	3: 72%	7: 73%	0: 50%	3: 93%	7: 95%	2.49
Mixed-Trunc	Virtuoso	14%	100%	1000ms	0: 92%	3: 72%	7: 79%	0: 52%	3: 93%	7: 97%	2.35
Mixed	Qlever	93%	100%	1000ms	0: 99%	3: 100%	7: 100%	0: 67%	3: 96%	7: 98%	1.70

Freebase (479 tokens)		$\leq 0.2s$	$\leq 1.0s$	Max	Sensitivity			MRR₇			KS₇
Unranked	Qlever	100%	100%	355ms	0: 3%	3: 8%	7: 16%	0: 0%	3: 24%	7: 55%	8.93
Agnostic	Qlever	100%	100%	367ms	0: 42%	3: 25%	7: 25%	0: 12%	3: 83%	7: 94%	4.41
Sensitive-Trunc	Blazegraph	25%	92%	5% > 5s	0: 100%	3: 100%	7: 100%	0: 43%	3: 76%	7: 76%	3.73
Sensitive-Trunc	Virtuoso	35%	50%	13% > 5s	0: 100%	3: 100%	7: 100%	0: 44%	3: 76%	7: 77%	3.98
Sensitive	Qlever	91%	98%	3074ms	0: 100%	3: 100%	7: 100%	0: 60%	3: 98%	7: 99%	1.99
Mixed-Trunc	Blazegraph	23%	99%	1000ms	0: 78%	3: 69%	7: 65%	0: 43%	3: 94%	7: 97%	2.55
Mixed-Trunc	Virtuoso	29%	100%	1000ms	0: 87%	3: 73%	7: 73%	0: 47%	3: 96%	7: 98%	2.40
Mixed	Qlever	90%	100%	1000ms	0: 99%	3: 99%	7: 100%	0: 60%	3: 98%	7: 99%	2.00

Wikidata (1244 tokens)		$\leq 0.2s$	$\leq 1.0s$	Max	Sensitivity			MRR₇			KS₇
Unranked	Qlever	99%	100%	445ms	0: 0%	3: 3%	7: 23%	0: 0%	3: 9%	7: 52%	10.89
Agnostic	Qlever	99%	100%	476ms	0: 27%	3: 28%	7: 34%	0: 6%	3: 62%	7: 91%	6.02
Sensitive-Trunc	Blazegraph	18%	82%	13% > 5s	0: 100%	3: 100%	7: 100%	0: 44%	3: 71%	7: 67%	4.80
Sensitive-Trunc	Virtuoso	34%	52%	10% > 5s	0: 100%	3: 100%	7: 100%	0: 44%	3: 80%	7: 84%	3.92
Sensitive	Qlever	57%	85%	4% > 5s	0: 100%	3: 100%	7: 100%	0: 44%	3: 93%	7: 97%	2.93
Mixed-Trunc	Blazegraph	3%	98%	1000ms	0: 89%	3: 36%	7: 46%	0: 42%	3: 74%	7: 92%	3.94
Mixed-Trunc	Virtuoso	30%	100%	1000ms	0: 84%	3: 70%	7: 72%	0: 36%	3: 81%	7: 96%	3.63
Mixed	Qlever	55%	100%	1000ms	0: 90%	3: 94%	7: 96%	0: 43%	3: 93%	7: 98%	2.86

Table 1: Query times, sensitivity, and relevance for three knowledge bases, six completion modes, and three SPARQL engines. Section 4.4 explains the choice of combinations evaluated. For each token, three AC queries were issued, for prefix lengths 0, 3, and 7. The columns for Sensitivity and MRR₇ show average results per prefix length. The “Max” column shows the fraction of AC queries that timed out after 5s. For MRR₇ and KS₇ those queries are treated as if the desired token appeared at position ∞ and the number of keystrokes required is the length of the token name plus 1.

Wikidata (301 queries): We excluded the following queries: 9 “Lexeme” queries because the respective triples are not part of the core Wikidata, 14 queries involving the *SERVICE* keyword as a crucial part of the query, 10 queries involving distance computations or other mathematical expressions not implemented in Qlever. For 3 queries, the first triple of the SPARQL query was of the form $?x ?y ?z$, which is not a meaningful start in iterative query construction. We moved it to the end of those queries.

Freebase (115 queries): We manually translated those Wikidata queries, for which the contents are also contained in Freebase. The translation is as close to the original Wikidata query as possible. Note that Freebase became read-only in 2015 and Wikidata has much more contents by now (9.9B triples vs. 1.9B triples, not counting literals in languages other than English).

Fbeasy (99 queries): We manually translated all Freebase queries for which the contents are also contained in Fbeasy. Again, the

translation is as close to the original query as possible.

From these full SPARQL queries, we generate AC queries by conceptually “typing” the queries from left to right, top to bottom. For each token that is an IRI, we pick a random alias (the same for all methods we compare) and generate three AC queries: for the empty prefix, for prefix length 3, and for prefix length 7. If the name has less characters, we change the AC query such that it requires a full-word match. There is one template for subject AC queries, one for predicate AC queries, and one for object AC queries. See the example AC queries in Sections 1.1, 3.1, and 3.2. More details about these AC queries are provided in Section C.

We took great care to get the best query times for each engine, given its capabilities. To avoid bad query plans, we used slightly different formulations of the AC queries for each engine. As already discussed for Example 2 in Section 1.1, in the predicate AC queries,

we dropped the DISTINCT for Virtuoso and Blazegraph because almost all of their queries fail otherwise.

We deliberately did not evaluate AC queries after each keystroke, for the following reason: Ideally, a user does not have to type anything, and the desired token is suggested highly ranked already for prefix length 0. But if the suggestions for prefix length 0 are not good, the user needs an idea of what to type anyway and she might as well type a few letters instead of just one. We chose 7 as a representative for a prefix length that is not too long, yet should sufficiently narrow down the search for most tokens.

4.4 Modes

We evaluate the following modes. The exact AC queries for all these modes are available on <http://www2022-181.hopto.org>.

Sensitive: These are the AC queries explained in Section 1.1. They are ideal regarding sensitivity, but a challenge regarding efficiency. While our extension of QLever can handle these queries, Blazegraph and Virtuoso often time out. We therefore evaluate these engines on modified AC queries explained next.

Sensitive-Trunc: All our AC queries have the same structure: an “inner” part, enclosed by a SELECT ... WHERE with a GROUP BY, followed by a prefix filter; see Sections 1.1, 3.1, 3.2, and B. For Blazegraph, we truncate this inner part (before the GROUP BY is computed) by LIMIT 10.000 on Fbeasy and by LIMIT 100.000 on Freebase and Wikidata. The same approach was used in [10] for a less general class of AC queries; see Section 2. For Virtuoso, we use Virtuoso’s “Anytime” feature with a timeout of 5 seconds: It will then produce a subset of the full result approximately within that time frame. This feature, which is unique to Virtuoso, gives slightly better results than mere truncation.

Agnostic: Agnostic AC queries completely ignore the context of the token. They return all entities where a name matches the prefix, ordered by a precomputed score.⁸ These queries are always fast (see Section 3), but at the expense of sensitivity and relevance.

Unranked: Like Agnostic, but rank the suggestions alphabetically.

Mixed: Simultaneously issue an agnostic and a sensitive query. If the sensitive query finishes within 1s, take that result, otherwise take the result of the agnostic query.

Mixed-Trunc: Like mixed, but using Sensitive-Trunc instead of Sensitive for prefix length 0 (for reasons that will become clear in Section 4.6). We use this for Blazegraph and Virtuoso, for exactly the reasons explained for Sensitive-Trunc above.

We set the timeout for all sensitive AC queries (for all knowledge bases and all engines) to 5s. Note that the timeout for mixed mode is just 1s. We deliberately set this lower to also explore the effects of different timeouts on relevance. Also, 1s is more what a user would expect from an interactive experience.

4.5 Evaluation metrics

We evaluate both objectives from our definition in Section 1.1.

Efficiency: We report the percentage of AC queries that can be processed faster than 0.2s (this feels close to instantaneous) and faster than 1.0s (noticeable delay, but still acceptable). If no query

⁸The details of this scoring are provided in Section B. For example, we use the number of Wikimedia sitelinks as a score for subjects and objects on Wikidata.

times out, we also report the maximum query time; otherwise, we report the percentage of AC queries that timed out.

Sensitivity: For each AC query, we compute the percentage of suggestions that lead to a non-empty result; see Section 1.1. By definition, this is 100% for the sensitive and sensitive-trunc AC queries. But also agnostic or unranked AC queries can contain sensitive suggestions.

Relevance: Of utmost importance to a user is the rank of the desired token in the list of suggestions. We evaluate this as follows. We assume that suggestions are shown on “pages” of k suggestions each. Ideally, the desired token is on the first page (which is displayed after each keystroke). In our evaluation, we take $k = 7$. We use the following two metrics:

MRR_k (mean reciprocal rank): For each AC query, the reciprocal rank is $1/r$, when r is the index of the suggestion page on which the desired token occurs, that is, at a position in $(r - 1) \cdot k .. r \cdot k - 1$, with the first position being 0. We report the mean reciprocal rank of all AC queries with a particular prefix length (0, 3, and 7). The maximum value of MRR₇ is 100%; it is achieved when each token appears on the first page of suggestions.

Note that the reciprocal rank is a very natural measure in our setting: we only have one relevant item and the “gain” for the user indeed decreases sharply with the index of the page where the item occurs. A user would rather continue typing instead of scrolling down much further in the list of suggestions.

KS_k (number of keystrokes): For each token, the number of keystrokes is the minimal prefix length (out of 0, 3, and 7), for which the token appears on the first page of suggestions. If it is not on the first page even for prefix length 7, we take the number of keystrokes for that token as the length of the name of the token plus 1. This corresponds to typing the full name and indicating that it is not a prefix, but the full name.

4.6 Main results and discussion

Table 1 summarizes our main results on all AC queries with context.⁹ The main takeaways are as follows.

Sensitive AC queries help relevance a lot. Compare the MRR₇ of Agnostic and Sensitive using QLever on Wikidata. The values at prefix length 0 are 6% vs. 44%. This shows that without typing anything, the desired token is hardly ever on the first pages of suggestions with Agnostic, but frequently on the first or second page for Sensitive. This case is particularly important because if you have to type something, then you already need an idea what you are looking for; see Figure 1 on Page 2 (examples at the bottom). After typing three letters, the result is almost always on the first page for Sensitive, and Agnostic is also becoming better.

We also see a clear difference in the KS₇, that is, with Sensitive a user has to type considerably less to get the desired token on the first page of suggestions. However, we consider the MRR₇ broken down by prefix length to be the more important and insightful measure. The results on the smaller knowledge bases are similar, though the difference is less dramatic.

⁹Namely, not included are subject AC queries or predicate AC queries with variable subject and empty %context% because context-sensitivity plays no role for those queries and our methods (Agnostic, Sensitive, Mixed) all give the same results.

Sensitive AC queries are feasible with QLever, but require truncation for Virtuoso and Blazegraph. Even on the very large Wikidata, our extension of QLever can compute fully sensitive suggestions in ≤ 1 s for 85% of all AC queries. Only 4% of these AC queries time out after 5s on Wikidata, and none at all on the smaller knowledge bases.

Without truncation, many AC queries time out for Blazegraph and Virtuoso (47% and 25%, respectively, on Wikidata). These numbers are not reported in Table 1, but can be found on <http://www2022-181.hopto.org>.

With truncation, the results for Blazegraph and Virtuoso are on par with those of QLever for prefix length 0. The reason is that when relevance is high for an empty prefix, this usually means that there are few suggestions. If there are a lot of possible suggestions, the truncation regularly eliminates the desired token, which then is not suggested even when a longer prefix is typed. Also, unlike Blazegraph and Virtuoso, we can make use of longer prefixes for more efficient query processing, leading to less timeouts, see Section 3.2. The result is that the MRR on longer prefixes for Blazegraph and Virtuoso is significantly lower than for QLever.

Agnostic AC queries are always fast; relevance is bad for prefix length 0 but quite good for longer prefix lengths. All agnostic AC queries can be processed in well under one second because a large part of the results are pre-computed; see Section 3.3. The only non-trivial work to do at query time is to filter the precomputed results by the typed prefix.

For an agnostic AC query with prefix length 0, the desired token will be rarely among the top suggestions because of the complete lack of contextual information. But a prefix length of 3 or even 7 is often enough to restrict the suggestions sufficiently, even without **%context%**. This is important in order to understand the results for the mixed AC queries, discussed below.

Virtuoso and Blazegraph both perform very poorly for agnostic AC queries, which is why we do not report them in Table 1. The reason is that both engines handle prefix searches on large lists of strings very inefficiently. See the discussions in Section 1.1 (after Example 1) and in Section 3.2.

With agnostic suggestions, typing helps relevance more than sensitivity. When typing more letters, the sensitivity increases much less than the relevance. For example, when typing seven letters with Agnostic on Wikidata, the MRR₇ is 91% and almost as high as with Sensitive. But sensitivity is only 27%. That is, the desired token will often be on the first page of suggestions, but mixed with suggestions which do not lead to a non-empty result. In a best case, the non-sensitive suggestions are merely confusing because they have nothing to do with the part of the query already typed. In a worst case, there are multiple suggestions with the same name, and the user has no way to figure out which is the desired one. The latter is not unusual for very large knowledge bases.¹⁰

Mixed AC queries are a good compromise between sensitivity and performance. Mixed always produces a result within 1s and so never times out. The reason is that agnostic AC queries can always be processed in under 1s. The price is that some of the suggestions may not be context-sensitive. But note that a user

interface could indicate whether the suggestion came from the agnostic or from the sensitive AC query.

Our extension of QLever achieves essentially the same MRR₇ scores as in Sensitive mode, but faster (always within 1s) and with only a small sacrifice in sensitivity. The reason is that most of the suggestions actually come from sensitive AC queries, even with the 1s time limit.

Blazegraph and Virtuoso show an improved MRR₇ for long prefixes, but at the price of a significantly reduced sensitivity. Also note that since Blazegraph and Virtuoso cannot efficiently process agnostic queries by themselves (for our evaluation, these queries were computed via QLever), they cannot support mixed mode out of the box. Indeed, the Wikidata Query Service, which is realized using Blazegraph, uses a separate service (implemented via dedicated data structures) for its agnostic autocompletion.

Unranked AC queries perform very poorly on large knowledge bases. Recall that the suggestions of Unranked are the same as those of Agnostic, but without ranking them by score. We include this mode in our evaluation to show how important ranking is. On Wikidata, even for a prefix length of 3, the relevance of Unranked is very poor (MRR₇ = 9%). For a prefix length of 7, the MRR₇ rises to 52%, but it's still much worse than the 91% of Agnostic. Note that ranking for autocompletion is mainly an efficiency problem: often a very large number of suggestions has to be computed and sorted. In some of the previous work we discussed, ranking was omitted due to this reason; see Section 2.

5 CONCLUSIONS

We showed how to perform context-sensitive SPARQL autocompletion with very good relevance and efficiency, for a large variety of queries on three different knowledge bases. All suggestions were themselves provided via SPARQL queries, on the same knowledge base on which we want to construct SPARQL queries with the aid of autocompletion. That way, our scheme can be used with any (standard-conforming) SPARQL engine.

We showed that on very large knowledge bases (like Wikidata), many autocompletion queries are hard for existing SPARQL engines. We showed three ways out. First, we showed how to extend an existing open-source SPARQL engine to deal with most of these hard queries efficiently. Our extensions are useful also beyond autocompletion, since they speed up classes of SPARQL queries that occur frequently. Second, we introduced a mixed mode that sacrifices context-sensitivity for efficiency. Third, we showed how truncation helps slower engines.

Interesting directions for future work are: implement a fully-functional user interface based on the ideas presented in this paper, improve the pattern processing in Section 3.1 to also profit from patterns that are similar but not necessarily identical (this would further improve query times on Wikidata significantly), improve the running time of the sensitive AC queries that still time out (see Section 4.6), compute approximate scores via sampling in order to be able to handle queries with a very large context, and extend the autocompletion mechanism to suggest more than just individual tokens (for example, predicate paths or predicate and object at the same time).

¹⁰For example, Wikidata knows six entities with name *female*, but only one of them is used for *wdt:P21* (gender).

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SUPPLEMENTARY MATERIAL

The following sections contain supplementary material for our submission. They explain the gory details for how exactly our AC queries are constructed from generic templates. The contributions and results from our paper can be understood without these details. But to appreciate some finer points and to understand how exactly we have done it, these details are interesting.

The first section provides a third example for an AC query. The second section described our generic templates. The third section explains how exactly the AC queries for our evaluation are derived from these templates. The fourth section describes the general architecture of the SPARQL engines QLever, Virtuoso, and Blazegraph.

A A THIRD EXAMPLE AC QUERY

Our last example is based on Wikidata, where entities have alpha-numeric IRIs, and names and aliases are obtained via dedicated predicates *rdfs:name* and *skos:altLabel*. Assume that we have typed the body of our second SPARQL query from the introduction this far:

```
wd:Q873 p:P166 ?m .
?m _
```

This is our *s* and the prefix *p* is again empty. Recall that *wd:Q873* stands for *Meryl Streep* and *p:P166* connects this entity to all statement nodes *?m* pertaining to one of her awards. The desired token *t* is *pq:P1686*, which leads us to the awarded films. The following AC query gives us a list of predicates (and their names) that lead to results at this point. The score is analogous to that of the previous example. The predicate path `^(<>|<>)/rdfs:label` gives us the label of a predicate in Wikidata; see Section B.

```
SELECT ?entity ?name (COUNT(DISTINCT ?m) AS ?score) WHERE {
  wd:Q873 p:P166 ?m .
  ?m ?entity [].
  ?entity ^(<>|<>)/rdfs:label ?name
} GROUP BY ?entity ?name ORDER BY DESC(?score)
```

The first three result rows for this AC query look as follows:

```
ps:P166      "award received"   "33"
pq:P585      "point in time"     "23"
pq:P1686     "for work"         "10"
```

These rows tell us that Wikidata knows about 33 awards of Meryl Streep, the point in time for 23 of them, and for which work the award was given for 10 of them.

Relevance: Again perfect for this AC query. And note how helpful the suggestions are! Without these suggestions it would require extremely intimate knowledge of Wikidata to know that we need the predicate suffixes *P166* and *P1686* and the prefixes *ps:* (which stands for the main entity of a statement node) and *pq:* (which stands for additional properties of a statement node). Agnostic suggestions, as briefly mentioned in Example 2 and defined in Section 4.4, would not be of much help here.

Efficiency: The query is easy because there are only few bindings for *?m*, namely one for each of Meryl Streep's awards. With optimal query planning¹¹ and the *rdfs:label* triples in main memory,

¹¹When equivalently rewriting the query, such that the result from the first two triples are aggregated in a subquery (which corresponds to the best query plan), Blazegraph inexplicably takes forever.

Blazegraph processes the query in around 100ms, Virtuoso takes 10ms, and our engine takes 1ms.

B AC QUERY TEMPLATES

In Section 1.1, we have already seen AC queries for two concrete examples. In this section, we show how these can be generalized to arbitrary knowledge bases. All AC queries explained in this section are provided in full on <http://www2022-181.hopto.org>.

Our approach is completely generic. All we need for a given knowledge base is a predicate path `%name-path%`, used to obtain names and aliases from IRIs¹² and a predicate path `%ranking-path%`, used to obtain counts for ranking IRIs if no context is given¹³. The next subsection shows how these are used in concrete AC queries. Technically, there is no need to restrict them to predicate paths; this only serves to make our AC queries easier to display.

It is also important to note that the ranking with `%ranking-path%` is only needed for AC queries *without* context, in particular, for our *agnostic* baseline (see Section 4.4). There is a meaningful default setting for any knowledge base.⁶

Sensitive AC queries: We use the part *s* of the SPARQL query body already typed; see our definition in Section 1.1. We first need to compute the `%context%`, which is the part of *s* that is actually "connected" to the triple at the current cursor position.

Let *T* be the partial triple that is currently being typed. Let *S* be the set of all finished triples and FILTER clauses inside *s*. Note that *S* also includes triples and filters that appear inside SPARQL constructs like OPTIONAL, UNION, MINUS, and sub-queries. Construct an undirected graph with node set $S \cup \{T\}$ and an edge between two nodes if they share a variable.¹⁴ Then `%context%` is *s* without *T* and without all nodes in *S* that are not reachable from *T*. It can be computed with a breadth-first search starting from *T*. Further, let `%subject%` and `%predicate%` be the subject and predicate of the triple at the current cursor position (if they already exist) and let `%prefix%` be the prefix (possibly empty) typed by the user.

All our AC queries follow the same template: a subquery computing the suggested entities and their scores and a surrounding part adding the names and filtering by the given `%prefix%`. An entity can have multiple matching names, hence the outer *GROUP BY*.

1. `SELECT ?entity (SAMPLE(STR(?name)) AS ?name)`
2. `(SAMPLE(?score) AS ?score) WHERE {`
3. `%entity-score-subquery%`
4. `?entity %name-path% ?name .`
5. `FILTER REGEX(STR(?name), "%prefix%")`
6. `} GROUP BY ?entity ORDER BY DESC (?score)`

¹²Wikidata: `rdfs:label|skos:altLabel` to obtain names for subjects and objects, and `^(<>|<>)/(rdfs:label|skos:altLabel)` for predicates: the `^(<>|<>)` follows an arbitrary predicate in reverse direction; Freebase: `fb:type.object.name|fb:common.topic.alias` for all; Fbeasy: the identity predicate `!(<>|<>)?` for all, which plays the role of the `BIND(STR ...)` in the examples from Section 1.1.

¹³Wikidata: `^schema:about` (all Wikimedia links of an entity); Freebase: `fb:type.object.type` (all types of an entity); Fbeasy: `<is-a>` (dito). A meaningful default setting would be `<>|<>`, which matches any predicate.

¹⁴We also take care of scoping and variable renaming introduced by subqueries.

Here is **%entity-score-subquery%** for subject suggestions; for these, **%context%** is always empty; see its definition above.

```
3. { SELECT ?entity (COUNT(?r) AS ?score) WHERE {
4.   ?entity %ranking-path% ?r
5. } GROUP BY ?entity }
```

Here is **%entity-score-subquery%** for predicate suggestions. If **%subject%** is a variable, **%x%** is *DISTINCT %subject%*, otherwise *?object*. Together with the template above, this and the following subquery generalize Examples 1 and 2 from Section 1.1, which also provide an intuition for the score.

```
3. { SELECT ?entity (COUNT(%x%) AS ?score) WHERE {
4.   %context% . %subject% ?entity ?object
5. } GROUP BY ?entity }
```

Here is **%entity-score-subquery%** for object suggestions.

```
3. { SELECT ?entity (COUNT(?entity) AS ?score) WHERE {
4.   %context% . %subject% %predicate% ?entity
5. } GROUP BY ?entity }
```

Agnostic and Unranked AC queries: Agnostic queries trade off relevance for efficiency. For subject and object suggestions, the agnostic AC query is identical to the sensitive AC query for subject suggestions above (which never has context). For predicate suggestions, the agnostic AC query is like the respective sensitive query, but with empty **%context%**. In Section 4, we have seen that our engine can always process these queries in time below one second.

The unranked AC queries are just like the agnostic AC queries, but without the final ORDER BY.

C DETAILS OF AC QUERY CONSTRUCTION

For a given mode and a given SPARQL query, we generate AC queries from the templates described in Section B as follows:

1. Consider each token (subject, predicate, or object) in the query that is either an IRI or a literal.¹⁵ For each such token do the following:
2. Compute **%context%** as described in Section B (only needed for the sensitive AC queries), and depending on the position of the token, also determine **%subject%** and **%predicate%**.
3. Choose a name from the **%name-path%** predicate path (canonical name and aliases) for that token uniformly at random.
4. From that name, compute three prefixes for **%prefix%**, of lengths 0 (the empty word), 3, and 7. For prefix lengths 3 and 7, if the name has less characters, take **%prefix%** as the complete name with \$ appended, indicating a full-word match.
5. For each prefix length, pick the AC query template from Section B according to the position of the token (subject, predicate, object) and the mode (unranked, agnostic, sensitive, mixed). Plug in **%context%** and **%prefix%**, and depending on the position also

¹⁵We exclude the special name predicates (*fb:type.object.name* for Freebase, *rdfs:label* for Wikidata) because they occur in almost every query and are trivial to suggest and would only distort our results. In the 301 Wikidata queries, there are 408 triples of the form *?x rdfs:label ?label* (similarly for Freebase). After having typed the subject variable, *rdfs:label* is then always among the most frequent suggestions.

%subject% and **%predicate%**.

For our first example query from the introduction (female Oscar winners), this yields $7 \cdot 3 = 21$ AC queries per mode. For our second example query (Oscars of Meryl Streep and corresponding films), this yields $6 \cdot 3 = 18$ AC queries per mode.

D QLEVER, VIRTUOSO, AND BLAZEGRAPH

QLever [5] is an open-source SPARQL engine, which stores the knowledge base triples in up to six permutations: POS, PSO, SPO, SOP, OPS, OSP (where S = subject, P = predicate, O = object). The last four are optional and not needed for our evaluation. Virtuoso [20] is a widely used SPARQL engine in research. Virtuoso translates SPARQL queries to SQL queries, which are then executed by Virtuoso’s own DB engine. Triples are stored in one large table with three columns¹⁶ (subject, predicate, object) in column-layout with indexes PSO, POS, SP, and OP. Blazegraph [7] is the query engine behind the Wikidata Query Service [22]. Triples are stored in a B+ tree in three permutations: POS, SPO, and OSP. There is little difference between the three engines in this respect.

In QLever, each token is assigned a unique integer ID, stored as an 8-byte integer. Each permutation is stored on disk in an array using $24n$ bytes, where n is the number of triples; metadata is stored in memory. At query time, each token from the query is translated to its ID using binary search; the query execution then takes place entirely in the ID space. All intermediate results are fully materialized, as tables with fixed-size columns of size 8 bytes each. Only for the final result, the IDs are converted to IRIs or literals again.

In contrast, Virtuoso and Blazegraph produce results “one row at a time”. This can be an advantage for certain queries with a LIMIT, but is a disadvantage for queries, where full materialization is required. Most notably, this is typically required, when results are needed in a particular order.

¹⁶There is another column for the “graph name”, but in our evaluation, we only use one “graph” (knowledge base) per Virtuoso instance.