

Efficient SPARQL Autocompletion via SPARQL

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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 in the sense that they lead to a non-empty result and are 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, which we call *autocompletion queries*. For existing SPARQL engines, these queries are impractically slow on large knowledge bases. We present various algorithmic and engineering improvements of an existing SPARQL engine such that these autocompletion queries are executed efficiently. We provide an extensive evaluation of a variety of suggestion methods on three large knowledge bases, including Wikidata (6.9B triples). We explore the trade-off between the relevance of the suggestions and the processing time of the autocompletion queries. We compare our results with two widely used SPARQL engines, Virtuoso and Blazegraph. On Wikidata, we achieve fully sensitive suggestions with sub-second response times for over 90% of a large and diverse set of thousands of autocompletion queries.

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1 INTRODUCTION

Knowledge bases play an increasingly important role in modern retrieval systems. 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

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an *International Resource Identifier* (IRI), enclosed in angle brackets, or a so-called *literal*, enclosed in quotes. For example:

<Meryl_Streep>	<is_a>	<Person>
<Meryl_Streep>	<gender>	<Female>
<Meryl_Streep>	<award_won>	<Oscar_Best_Actress>
<Meryl_Streep>	<birth_date>	"1949-06-22"
<Ang_Lee>	<award_won>	<Oscar_Best_Director>
<Oscar_Best_Actress>	<is_a>	<Oscar>
<Oscar_Best_Director>	<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 .  
  ?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 seven 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* (6.9B triples, as of 07-01-2020) [19]. *Fbeasy* has human-readable IRIs for all entities. In *Wikidata*, almost all IRIs are alpha-numeric and human-readable names can be obtained via dedicated predicates; see the example query below. *Freebase* uses a mix of human-readable and alpha-numeric IRIs. We consider all three knowledge bases in this paper; see Section 5.2 for details.

SPARQL is conceptually easy, because queries can be formulated as lists of triples, just like the data. However, finding the IRIs relevant for a query is often hard in practice. This is true even for human-readable IRIs when there are very many of them. It becomes extremely hard when IRIs are alpha-numeric. For example, consider the seemingly simple request: the Oscars of Meryl Streep and the movies she won them for. The correct SPARQL query on *Wikidata* is quite complex (an explanation follows below the query).

```
SELECT ?award ?film WHERE {  
  wd:Q873 p:P166 ?m .  
  ?m pq:P1686 ?film_id .  
  ?m ps:P166 ?award_id .
```

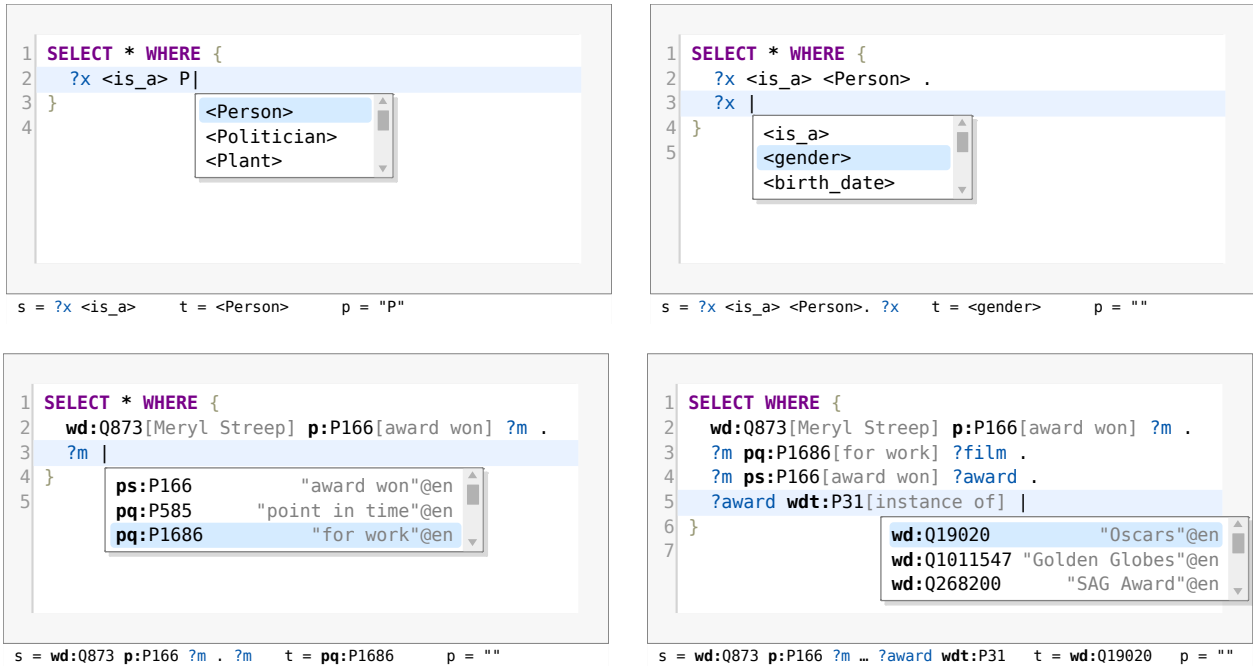


Figure 1: Four screenshots of our autocompletion in action, with three suggestions each. Top-left and top-right: Examples 1 and 2 from Section 1.1, for a query on Fbeasy, where IRIs are understandable for a human. Bottom-left and bottom-right: Example 3 from Section 1.1 and a continuation not described in the text, for a query on Wikidata, where IRIs are alpha-numeric. The assignment below each screenshot show the values of the variables from our problem definition: s (the part of the SPARQL query already typed), t (the desired token), and p (a prefix of a name or alias of that token).

```
?award_id wdt:P31 wd:Q19020 .
?award_id rdfs:label ?award .
?film_id rdfs:label ?film }
```

The wd -, wdt -, etc. are IRI prefixes. We have omitted their definition here to save space; see <https://en.wikibooks.org/wiki/SPARQL/Prefixes>. The IRIs $wd:Q873$ and $wd:Q19020$ denote *Meryl Streep* and the *Academy Awards*, respectively. The IRIs $p:P166$ and $ps:P166$ both represent the predicate *award received*. In Wikidata, a predicate with prefix p : connects a subject to a statement node, which can then be connected to several objects, thus representing an n -ary relation between the subject and the objects. The predicate with prefix ps : connects the subject to the “main object” of the relation; the IRI of the award in this case. Predicates with prefix pq : connect the subject to so-called “qualifying” information; the IRI of the film in this case (there is also a pq : predicate for the point in time). The IRI $wdt:P31$ stands for the *instance of* relation. The $rdfs:label$ predicate connects entities to their human-readable names.

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 at any point in the query. 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 three examples.

Definition. Imagine a valid SPARQL query typed until a certain point, called the *cursor position*. Let s be the part of the body of the

SPARQL query until that point. Let t be the complete token (subject, predicate, or object) 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:

1. 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 how likely that entity is at the cursor position).
2. The rows of the table are sorted in descending order of $?score$.
3. One of the rows contains t in the $?entity$ column.

There are two objectives:

Relevance: Each suggestion should be *context-sensitive*¹ 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. The row with the desired t should be as high up in the table as possible.

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

We next illustrate this definition by three examples, which are also depicted in Figure 1. We also discuss running times for various SPARQL engines. These engine are described in Section 4.1, and our experimental setup is described in Section 5.1.

¹In the following, we often just call such suggestions *sensitive*.

Example 1 Assume 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 all objects *?entity* and their 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*.

```
SELECT ?entity ?name (COUNT(?x) AS ?score) WHERE {
  ?x <is_a> ?entity .
  BIND (STR(?entity) AS ?name) .
  FILTER REGEX(?name, "^P")
} GROUP BY ?entity ?name 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).

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

Let us discuss the objectives from our definition for this AC query.

Relevance: Perfect, because the desired token *t* appears in the first row of the table, and, by construction, all suggested entities lead to a non-empty result.

Efficiency: Most query engines, including our competitors Virtuoso and Blazegraph, process this query as follows: First materialize a table *?x ?entity ?name* with all subjects and objects of the `<is_a>` predicate and the name of these objects. On Fbeasy, this table has 130M rows. Then check for each row whether the name matches the regular expression. This is slow: it takes 20s on Virtuoso and 48s on Blazegraph. Our engine works with internal IDs for the strings, which are pre-ordered in lexicographical order of the strings. That way, we can maximally delay a materialization of the strings and perform prefix matches via binary search. This is a major performance factor, not only for AC queries. In particular, the AC query above takes only 0.3s. More details in Section 4.

Example 2 Now assume that we have typed the SPARQL query a little bit further. The following is now our *s* and 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.²

```
SELECT ?entity ?name (COUNT(DISTINCT ?x) AS ?score) WHERE {
  ?x <is_a> <Person> .
  ?x ?entity [].
  BIND (STR(?entity) AS ?name) .
} GROUP BY ?entity ?name ORDER BY DESC(?score)
```

²If a person has several triples with the same predicate, we only count the predicate once, hence the *DISTINCT*. This is explained in more detail in Section 3.

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

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

Relevance: 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. In Section 5, we will also evaluate so-called *agnostic* AC queries. An agnostic AC query computes a list of *all* predicates, ordered by frequency, but independent of the rest of the query. Such a query would have bad relevance here: `<gender>` would not be among the top suggestions, and there would be many suggestions that are not meaningful for a person, for example `<release>` (of a musical recording).

Efficiency: Most query engines, including our competitors Virtuoso and Blazegraph, process this AC query as follows. The two triples from the query body are joined into a large table, with one row for each triple of each person. In Fbeasy this table has 37M rows. Producing a table of that size is slow and so is determining the predicate counts from that table. Without the *BIND* and the *DISTINCT*, Virtuoso takes 2.4s and Blazegraph takes 35s.³ For the corresponding AC query on Wikidata, the table has 196M rows. Virtuoso can process it in 5.8s, while Blazegraph aborts with an out-of-memory error after 85s. Our query engine avoids iterating over all the triples for each person. Instead, our engine makes use of a query-independent pre-processing that identifies groups of entities with the exact same set of predicates (called a *pattern*). This trick is described in Section 4.2. It enables a query time of below 0.1s for the AC query above on Fbeasy, and 0.6s for its counterpart on Wikidata.

Example 3 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 3.1.

```
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)
```

³Neither Virtuoso nor Blazegraph can handle the query with the *DISTINCT*, apparently because that would require a full sort of the table. However, suggestions are also reasonable (though not quite as good) without the *DISTINCT*.

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

<i>ps:P166</i>	"award received"	"33"
<i>pq:P585</i>	"point in time"	"23"
<i>pq:P1686</i>	"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 3.3, 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 planning⁴ and the *rdfs:label* triples in main memory, Blazegraph processes the query in around 100ms, Virtuoso takes 10ms, and our engine takes 1ms.

1.2 Scope and limits of our definition

Our AC queries provide suggestions for the IRIs and literals in a SPARQL query. A 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. These suggestions are not particularly challenging with respect to relevance or efficiency. However, our AC queries do have to deal properly with these constructs, when they occur in the query; see Section 3.5.

Our definition assumes that queries are typed from top to bottom and that each triple is entered from left to right (subject, predicate, object). It would be straightforward to drop those constraints using variants of our AC queries. However, it’s not strictly necessary for the incremental construction of a SPARQL query and it would significantly complicate our definition and explanations in this paper. We therefore omitted this use case from our definition.

1.3 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. See Sections 2 and 3.
- We extend an existing query engine, called *QLever*, such that these AC queries can be processed efficiently. The extension is technically challenging and comprises both algorithmic ideas and algorithm engineering. See Section 4.
- We provide an extensive evaluation on three large knowledge bases, including Wikidata (6.9B triples). We explore a variety of AC queries in depth, in particular, their relevance and efficiency and the trade-off between these two objectives. We compare our results

⁴When 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.

with two widely used SPARQL engines, Virtuoso and Blazegraph, which we outperform by a large margin. On Wikidata, we achieve fully sensitive suggestions with sub-second response times for over 90% of a large and diverse set of thousands of autocompletion queries. See Section 5.

- We provide materials for full reproducibility: code, queries, indexes, result files, and a web application that allows an interactive exploration of all the details of our experimental results. In particular, the web application provides the \LaTeX code for Table 1 with a single click. These materials are available under <http://vldb2021-1807.hopto.org>.

2 RELATED WORK

We first discuss related work on SPARQL autocompletion via queries in (variants of) SPARQL. We then provide a brief overview of other approaches assisting users to formulate their query.

2.1 SPARQL autocompletion via SPARQL

Campinas et al. [10] 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 pattern trick in Section 4.2 but with the important difference, that our implementation does not affect relevance; we come back to this in Section 4.2. In a follow-up paper, Campinas [9] 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 briefly discuss the two objectives from our definition in Section 1.1 for these papers.

Relevance: The AC queries of *Gosparqled* are similar to those from Section 1.1, but with a LIMIT (of 10, 100 or 500). Hence all suggestions are meaningful continuations of the part of the query already typed. In the evaluation, the suggestions are compared to suggestions without this LIMIT. The average Jaccard similarity varies between 11% and 62%, depending on the complexity of the query and the LIMIT. With the graph summary, the Jaccard similarity does not decrease significantly. Our sensitive AC queries impose no LIMIT and, by definition, achieve a similarity of 100%.

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 reduces the average run time further 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 [13] 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 make the same suggestion for each predicate, 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 correct 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 provide autocompletion also for that and efficiently so. 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 [12] 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 on the results 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 4.4).

2.2 Other assisted formulation systems

There is a wide literature on other approaches to assist the user in creating SPARQL queries or get results from a knowledge base. We provide an overview by briefly describing a representative system for each approach.

Arenas et al. [1] present *SemFacet*, a faceted search system for RDF data, reminiscent of Broccoli above. The user starts with a keyword query (e.g. “person”), from which the system computes a list of matching entities. For each predicate, users can narrow down the results by choosing specific objects (e.g. `<Actor>`). The suggested predicates and objects are not ranked, for efficiency reasons. The underlying queries are SPARQL queries, restricted to trees. One of the first systems of this kind is *BrowseRDF* by Oren et al. [16]. *BrowseRDF* shows entities for the root variable, while in *SemFacet* any variable can be selected. *BrowseRDF* also suggests inverse predicates and negation.

Rafes et al. [17] introduce a log-based system called *SPARQLets-Finder*, which takes a basic graph pattern (essentially: a part of a SPARQL query) and suggests a ranked lists of graph patterns to extend the query. The suggestions are based on a hierarchical clustering of the graph patterns in the given query log, using a metric introduced in the paper. The evaluation compares the recommendations with those made by a related tool.

Khoussainova et al. [14] present *SnipSuggest*, a log-based auto-completion tool for SQL. The user starts with a simple query. The system then suggests additional *features* to the user, for example, a

table in the FROM clause or a condition in the WHERE clause. *SnipSuggest* achieves this by transforming the partially written query into a set of such features, and then computing the most popular additional features according to the query log. Alternatively, the suggestions are optimized for diversity. The evaluation shows that the suggestions are useful and better than from naive approaches, which recommend the overall most popular features.

Bast et al. [6] present *Aqqu*, a state-of-the-art system for *semantic parsing*. The task is to translate a given question in natural language into an equivalent SPARQL query. The translation is learned only from question-answer pairs (no ground truth SPARQL queries are needed). There is a wide literature on this setting.

Arkoudas and Yahya [2] also present a system that translates questions in natural language to structured queries (SPARQL or SQL). The system is interactive: as the user types the question, the system suggests possible continuations. Three different suggestion algorithms are combined: Two of these algorithms are *log-based* (one returns suggestions when everything typed so far matches, the other also supports partial matches). The third is based on templates. That way, the system makes effective use of a query log but also covers queries unseen so far.

Lehmann and Bühmann [15] present *AutoSPARQL*, which suggests whole SPARQL queries (restricted to trees) in a back-and-forth with the user. The user starts by formulating a simple query that contains at least one result of the target query. *AutoSPARQL* then asks whether certain results should be contained in the target query or not. Based on the user feedback, new SPARQL queries are suggested and new feedback is asked. This is repeated until the desired query is found or no tree query exists. In the evaluation, on average 5 iterations were needed to find the target query or conclude that no matching query exists.

Fan et al. [11] present *QLSUGG*, which uses keyword search to suggest entire queries to the user. Keywords may refer to either table values, the meta-data (e.g. names of relation tables or attributes), or aggregate functions (e.g. the function COUNT). To get suggestions, they use templates and rank them based on the keywords typed.

3 AC QUERY TEMPLATES

In this section, we describe the templates of the various AC queries mentioned in Section 1 and used in our evaluation in Section 5. In Section 5.3, we will derive actual AC queries from these templates.

In Section 3.1, we first specify two easy-to-understand queries `%entities%` and `%predicates%`. In Sections 3.2 - 3.4, we will use them as building blocks to construct our actual AC query templates. For the sake of explanation, we first assume SPARQL queries, where the body consists only of triples. In Section 3.5, we then explain how to extend this to more complex SPARQL queries.

3.1 Building blocks for Wikidata

The building block `%entities%` computes for each entity its name and aliases and a score. Here is the query for Wikidata:

```
1. SELECT ?entity ?name (COUNT(?x) AS ?score) WHERE {
2.   ?entity rdfs:label|skos:altLabel ?name .
3.   ?entity ^ schema:about ?x .
4. } GROUP BY ?entity ?name
```

For the score, we use the number of Wikipedia articles about an entity (line 3). For Freebase, the predicates in lines 2 and 3 are replaced by `fb:type.object.name|fb:common.topic.alias` and `fb:type.object.type`, respectively. For Fbeasy, line 2 is replaced by `BIND(STR(?entity) AS ?name)` and the predicate in line 3 is replaced by `<is_a>`. That is, for Fbeasy and Freebase we use the number of types to rank entities. As we will see in the next section, these scores are only needed for sensitive AC queries for subjects or for agnostic AC queries.

The building block `%predicates%` computes a name and a score for each predicate. Here is the query for Wikidata:

```
1. SELECT ?entity ?name ?score WHERE {
2.   { SELECT ?entity (COUNT(DISTINCT ?x) AS ?score) WHERE {
3.     ?x ?entity []
4.   } GROUP BY ?entity }
5.   ?entity (^(<>|<>)(/rdfs:label|skos:altLabel))? ?name
6. }
```

As score for each predicate, we take the number of distinct subjects of that predicate. The name of a predicate is obtained via a special (predicate-dependent) property. From the subject of that property, we then obtain the name via the usual predicates. The `^(<>|<>)` in line 5 is just a SPARQL shorthand of saying: follow any predicate in reverse direction. Some predicates, like `rdf:type` have no explicit name at all, in which case we take the IRI as the name, hence the `(...)?` around the predicate path. For Freebase, we replace line 5 by `?entity fb:type.object.name ?name`. For Fbeasy, all IRIs are human-readable and we replace line 5 by `BIND(STR(?entity) AS ?name)`.

3.2 Sensitive AC queries

According to our definition in Section 1.1, to construct an AC query, we can make use of the part `s` of the SPARQL query body already typed. It is important that we only use that part of `s` that is actually “connected” to the triple at the current cursor position.⁵ We call this part the `%context%` and next explain how it is computed.

Let T be the partial triple that is currently being typed. Let S be the set of all complete 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.⁶ Then `%context%` is `s` without T and without all nodes in S that are not reachable from T . It can be easily computed with, for example, a breadth-first search starting from T .

Here is the AC query template for a subject with a non-empty `%prefix%` (the `p` from our definition).

```
1. SELECT ?entity (SAMPLE(?name) AS ?name)
2.   (SAMPLE(?score) AS ?score) WHERE {
3.   { %entities% } FILTER REGEX(?name, "^%prefix%")
4. } GROUP BY ?entity ORDER BY DESC (?score)
```

Here is the AC query template for a predicate for given `%prefix%`, `%context%`, and `%subject%` (the subject of the triple at the current cursor position). If `%context%` is empty, lines 3-5 are (redundant

⁵In SPARQL, the result of two disconnected graph patterns is the cross product, which can become huge very easily and is usually not what one wants.

⁶We also take care of scoping and variable renaming introduced by subqueries.

and) omitted and `?score_2` in line 2 is replaced by `?score`. If `%subject%` is a variable, `%x%` is `DISTINCT %subject%`, otherwise `?object`.

```
1. SELECT ?entity (SAMPLE(?name) AS ?name)
2.   (SAMPLE(?score_2) AS ?score) WHERE {
3.   { SELECT ?entity (COUNT(%x%) AS ?score_2) WHERE {
4.     %context% %subject% ?entity ?object
5.   } GROUP BY ?entity }
6.   { %predicates% } FILTER REGEX(?name, "^%prefix%")
7. } GROUP BY ?entity ORDER BY DESC (?score)
```

Here is the AC query template for an object for given `%prefix%`, `%context%`, `%subject%`, and `%predicate%` (the predicate of the triple at the current cursor position).

```
1. SELECT ?entity (SAMPLE(?name) AS ?name)
2.   (SAMPLE(?score_2) AS ?score) WHERE {
3.   { SELECT ?entity (COUNT(?entity) AS ?score_2) WHERE {
4.     %context% %subject% %predicate% ?entity
5.   } GROUP BY ?entity }
6.   { %entities% } FILTER REGEX(?name, "^%prefix%")
7. } GROUP BY ?entity ORDER BY DESC (?score)
```

3.3 Agnostic and Unranked AC queries

We first define the agnostic AC queries. For a subject and a predicate, the agnostic AC query is like the respective sensitive queries, but with empty `%context%`. The agnostic AC query for an object is identical to the agnostic AC query for a subject.

The result for an agnostic AC query is then exactly the result of the precomputed `%entities%` or `%predicates%`, filtered by `%prefix%`. In Section 5, we will see that QLever can always process these queries in time below one second. Note that some work is required at query time if `%prefix%` is non-empty: we then need to filter out the results matching the prefix (from a table sorted by entity name), which can be many if the prefix is short or common. Also note that, in principle, we could compute the results for these queries with a special-purpose data structure, outside of the SPARQL engine.⁷ However, it is convenient if we don’t need such a data structure and can just use the engine that we have in place anyway.

The unranked AC queries are just like the agnostic AC queries, but without the final ORDER BY. They have no practical relevance, but we include them in our evaluation in Section 5 as a baseline, to show how important ranking of suggestions (neglected in several previous works for efficiency reasons, see Section 2) is.

3.4 Mixed AC queries

The suggestions of sensitive AC queries are clearly preferable, but as we will see in our evaluation in Section 5, some of them are very hard to compute, especially on a large knowledge base like Wikidata. In contrast, agnostic AC queries are always fast, at the price of a much lower relevance.

We therefore also consider a *mixed* mode, where we simultaneously issue an agnostic and a sensitive query. If the sensitive query finishes within a given timeout, we take that result. Otherwise,

⁷In fact, Blazegraph uses such a special-purpose data structure to compute names for entities to avoid the expensive join with the huge `rdfs:label` predicate.

we take the result from the agnostic query. We pick a timeout of 1s, since users are rarely willing to wait longer for an interactive suggestion. Since we can answer all agnostic queries in time 1s, we then always get suggestions within 1s, though not always sensitive. Mixed AC queries are thus a compromise between relevance and efficiency. The faster the engine, the better the compromise. More about this in Section 5.

3.5 AC queries for complex SPARQL constructs

In our definition of `%context%` in Section 3.2, we have assumed that the triple T at the current cursor position is not inside of an OPTIONAL, UNION, MINUS, or a sub-query and does not contain a property path. We handle these cases as follows.

1. If T is inside of an OPTIONAL clause, we treat it as if it were outside of the OPTIONAL clause. This means that we only get suggestions that lead to at least one result (without NULL values).
2. If T is inside a UNION clause, we also treat it as if it were they were outside of the clause. Additionally, triples from the other “branch” of the same UNION are excluded from the context. That way we ensure that each branch contributes at least one result to the query.
3. If T is inside a MINUS clause, we ignore the MINUS and give suggestions as if the triple was added and not subtracted. As a consequence, we rank those suggestions highest, that would *remove* the highest number of results when added to the query using MINUS.
4. If T is inside a sub-query (SPARQL queries nested inside the body of another SPARQL query), the surrounding query is ignored. We could also incorporate the surrounding query into the `%context%`, but found this to have negligible benefit in our evaluation.
5. A triple with a property path like `wdt:P31/wdt:P279*` (*instance of*, followed by any number of *subclass of*) is equivalently transformed into two triples with a single predicate each. We then launch an AC query for each of these predicates (one after the other).

Note that by handling OPTIONAL, UNION and MINUS this way, we achieve more than the relevance objective from our definition in Section 1.1 requires. Namely, we achieve that all our suggestions actually make a difference for the SPARQL query.

4 EFFICIENT AC QUERIES

This section describes our main techniques to make AC queries efficient. In our evaluation in Section 5, 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.

4.1 Basic architecture of QLever, Virtuoso, and Blazegraph

We implement the extensions described in the following subsections as extensions to QLever. In our evaluation in Section 5, we compare this to Virtuoso and Blazegraph.

QLever [5] is an open-source query 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 [18] 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 columns⁸ (subject, predicate, object) in column-layout with indexes PSO, POS, SP, and OP. Blazegraph [7] is the query engine behind the official SPARQL endpoint of the Wikidata Query Service [20]. 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 (subject, predicate, object) is assigned a unique integer ID, stored as an 8-byte integer. There are three types of tokens: IRIs, numerical literals, other literals. For each type, the order of the IDs corresponds to the canonical (lexicographical or numerical) order of the tokens of that type. The IDs form a contiguous interval starting from 0 and the map from each ID to its token is stored in one large array. Each permutation is stored on disk in a large array using $24n$ bytes, where n is the number of triples; metadata is stored in memory. SPARQL update operations are not supported, but building the index from scratch is very fast (30 minutes for Fbeasy, 2.5 hours for Freebase, less than 24 hours for Wikidata, on a single machine, as described in Section 5.1). At query time, each token from the query is translated to its ID using binary search on the above-mentioned map. 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 are the IDs converted to IRIs or literals again. For the AC queries, there is always a LIMIT k for a small value of k , so that the last step takes negligible time.

In contrast, Virtuoso and Blazegraph are able to produce results “one row at a time”, without always having to fully materialize all intermediate results. 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.

4.2 AC Queries for Predicates Using Patterns

Our predicate AC queries use subqueries of the following kind.

```
SELECT ?entity (COUNT(DISTINCT ?x) AS ?score) WHERE {
  %context% ?x ?entity [].
} GROUP BY ?entity ORDER BY DESC(?score)
```

As explained in Section 1.1, existing SPARQL engines materialize a table with one row for each triple of every $?x$. For a `%context%` that constrains $?x$ little or not at all, this takes a (very) long time to compute. To answer this kind of query efficiently, we make the following preprocessing:

1. Let \mathcal{S} be the set of all distinct subjects in the knowledge base. For each $x \in \mathcal{S}$, 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. This is easily done by a pass over the above-mentioned SPO index (which our evaluation does not need anymore after that).
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 $|\mathcal{S}|$.

The following table provides statistics of this pre-processing for our

⁸There is another column for the “graph name”, but in our evaluation, we only use one “graph” (knowledge base) per Virtuoso instance

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	60M	0.3M	3M	0.3GB
Freebase	476M	3.1M	95M	2.5GB
Wikidata	2068M	4.4M	160M	9.0GB

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 $S \subseteq \mathcal{S}$ be the set of subjects $?x$ from `%context%` or $S = \mathcal{S}$ 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 predicates 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 37M triples. They have only $|\mathcal{P}_S| = 115K$ distinct patterns with $\sum_{P \in \mathcal{P}_S} |P| = 1.4M$ predicates. With QLever extended by the pattern trick, the query can be solved in under 0.1s. With the standard query processing, QLever takes 6.6s, comprising 1.6s for sorting 37M elements.

We remark that Virtuoso has a dedicated SP index, which maps each subject to its distinct predicates. In theory, this index could be used to optimize the execution of the predicate AC queries. However, despite our best efforts, we could not find a way to make Virtuoso use this index for queries like the above.

We briefly comment on how our patterns compare to the graph summary of Campinas et al. [10] mentioned in Section 2.1. For the graph summary, entities that have the same set of types are grouped together. For each group and each predicate, it is then precomputed how many entities of that group have that predicate. For example, on Fbeasy, out of 3 970 825 entities of type `<Person>`, 103 488 have the predicate `<award_won>`. This can be used for sensitive AC queries for predicates when the `%context%` is exactly one triple that specifies the type. Our preprocessing is more general and works for an arbitrary `%context%`.

4.3 Efficient names + prefix filtering

Here is a variant of Example 1 from Section 1.1 on Wikidata:

```
SELECT ?entity ?name (COUNT(?x) AS ?score) WHERE {
  ?x wdt:P31 ?entity .
  ?entity rdfs:label ?name .
  FILTER (LANG(?name) = "en")
  FILTER REGEX(?name, "^P")
} GROUP BY ?entity ?name ORDER BY DESC(?score)
```

A straightforward processing of this query has two problems.

1. The `rdfs:label` predicate has 359M triples on Wikidata. Materializing this table and then joining and filtering it is very slow.
2. The result of the first three rows of the WHERE clause is a table with 3 columns and 72M rows. Materializing all `?name` strings and applying a regex to each of them would be very slow.

@1: Blazegraph’s Wikidata setup circumvents this problem by providing a so-called *label service* via the SPARQL SERVICE keyword. This label service provides labels in the desired languages via a separate process dedicated to only this task. In QLever, we deal with this problem as follows: duplicate all predicates with language literals during index building, and split the duplicate into one predicate per language. For the query above, then the predicate `@en@rdfs:label` is used, which has 60M rows. The join with the first triple is then indeed materialized, but in ID space.

@2: Virtuoso and Blazegraph do exactly this and are correspondingly slow. In QLever, we make use of the fact that literals also have IDs, where the order of the IDs is the lexicographical order of the literals. A FILTER with a prefix regex like in the query above can then be realized with two binary searches.

4.4 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 (which in SPARQL are always tables, too). 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.

For example, assume we have typed the body of the first query from the introduction (female oscar winners) until this point:

```
?subject <is_a> <Person> .
?subject <gender> <Female> .
?subject -
```

After the AC query for this predicate, the result for the first two triples (all female persons) are in the cache. Now assume that we have typed one triple further:

```
?subject <is_a> <Person> .
?subject <gender> <Female> .
?subject <won award> ?award .
?subject -
```

To compute the result from the first three triples, the best query plan is then to take the result from the first two triples from the cache and join it with the result for the third triple.

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 result of

the two building blocks **%entities%** and **%predicates%**, described in Section 3.1, from which all our AC queries are built. We store the results in two orders: *ORDER BY ?entity* (for fast *GROUP BY* on *?entity*) and *ORDER BY ?name* (for fast prefix search). The memory consumption of these results is a small fraction of the index size (for Wikidata: 6.7 GB for all pinned results).

5 EVALUATION

In this section, we describe how we evaluated our approach, and then present and discuss the results of this evaluation.

5.1 SPARQL Engines and Hardware

We evaluate our own extension of QLever, described in Section 4, against Virtuoso and Blazegraph, the basic architecture of which is described in Section 4.1.

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). We also ran our experiments on HDD storage (Raid 5), and found little difference.⁹

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 4.4. Before each experiment, the query cache was cleared and the results of the queries **%entities%** and **%predicates%** were pinned, as explained in Section 4.4. 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.¹⁰ 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.

We took great care to configure and use each engine optimally for the evaluation. This comprises slight (equivalent) reformulations of the AC queries, in order to avoid bad query plans; this is described in Section 5.3.

5.2 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-readable vs. alpha-numeric IRIs.

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

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

Wikidata [19]: 6.9B triples, 1.2B subjects, 32K predicates (complete dump from 01/2020). Almost all IDs are alpha-numeric (e.g. *wd:Q873* for Meryl Streep and *wdt:P21* for gender). To help Virtuoso and Blazegraph, we removed all non-English literals and all triples involving Wikimedia sitelinks. The latter are only needed for the agnostic AC queries, which are executed solely by QLever; see Section 5.3. In QLever, we load the complete data (11.3B triples). By

⁹However, indexing on HDD is much slower for Virtuoso and Blazegraph, but that is not the focus of this paper.

¹⁰When scaling this preset up to 128GB we found no significantly different results, but frequently ran into problems with the out-of-memory killer.

the design of QLever, this does not slow down queries (and doesn’t make them faster either); see Section 4.3.

5.3 Autocompletion (AC) queries

The basis for our evaluation are the 334 example queries from the Wikidata Query Service [20]. 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:

Wikidata (301 queries): We excluded all 9 “Lexeme” queries because the respective triples are not part of the core Wikidata. We excluded another 14 queries because they involve the SERVICE keyword as a crucial part of the query and we did not want to make querying a remote SPARQL endpoint part of our evaluation. We further excluded 10 queries involving distance computations or other mathematical expressions because those features are not implemented in QLever and the queries became meaningless or impossible to compute without these computations. In several other queries we could remove these expressions but were able to keep the queries. 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 (6.9B triples vs. 1.9B triples, not counting literals in other languages 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. Note that Fbeasy contains no *n*-ary information (for example: an award, the awardee, the work awarded, and the date). Instead, it retains only the binary “core” of each such tuple (for example: award and awardee).

We consider all four modes of AC queries presented in Section 3: unranked, agnostic, sensitive, and mixed. For a given mode and a given SPARQL query, we generate AC queries as follows:

1. Consider each token (subject, predicate, or object) in the query that is either an IRI or a literal. We 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.¹¹

For each such token do the following:

2. Compute **%context%** as described in Section 3 (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 result of the **%entities%** query (canonical name and aliases) for that token uniformly at random.

¹¹In the 301 Wikidata queries, there are 408 triples of the form *?x rdfs:label ?label* (similarly for Freebase). For entities with an *rdfs:label*, that predicate is always among the most frequent suggestions. There is only one *rdfs:label* triple with a literal, namely *?author rdfs:label "Ernest Hemingway"@en*. The reason is that in SPARQL, one would directly use the entity (*wd:Q23434*) rather than specifying it indirectly via its name. With autocompletion, we easily find such an entity via (a prefix of) its name.

Fbeasy (314 tokens)		$\leq 0.2s$	$\leq 1.0s$	Max	Sens	MRR₇			KS₇
Unranked	Qlever	100%	100%	444ms	0%	0: 0%	3: 33%	7: 72%	8.04
Agnostic	Qlever	100%	100%	470ms	0%	0: 25%	3: 86%	7: 96%	3.75
Sensitive	Blazegraph	26%	42%	45% > 5s	55%	0: 38%	3: 53%	7: 53%	5.74
Sensitive	Virtuoso	37%	61%	25% > 5s	75%	0: 58%	3: 65%	7: 65%	3.79
Sensitive	Qlever	91%	97%	1% > 5s	99%	0: 67%	3: 96%	7: 97%	1.77
Mixed	Blazegraph	26%	97%	1234ms	45%	0: 50%	3: 94%	7: 97%	2.52
Mixed	Virtuoso	47%	100%	1000ms	72%	0: 57%	3: 96%	7: 91%	2.07
Mixed	Qlever	90%	100%	1000ms	98%	0: 66%	3: 96%	7: 98%	1.75

Freebase (478 tokens)		$\leq 0.2s$	$\leq 1.0s$	Max	Sens	MRR₇			KS₇
Unranked	Qlever	100%	100%	645ms	0%	0: 0%	3: 24%	7: 55%	9.05
Agnostic	Qlever	100%	100%	621ms	0%	0: 12%	3: 83%	7: 94%	4.52
Sensitive	Blazegraph	29%	46%	41% > 5s	59%	0: 39%	3: 57%	7: 58%	5.32
Sensitive	Virtuoso	41%	59%	19% > 5s	81%	0: 43%	3: 79%	7: 80%	3.79
Sensitive	Qlever	87%	97%	0.5% > 5s	100%	0: 60%	3: 97%	7: 99%	2.06
Mixed	Blazegraph	28%	100%	1041ms	49%	0: 42%	3: 93%	7: 98%	2.68
Mixed	Virtuoso	42%	100%	1000ms	62%	0: 43%	3: 97%	7: 99%	2.42
Mixed	Qlever	73%	100%	1000ms	82%	0: 59%	3: 96%	7: 99%	2.15

Wikidata (1258 tokens)		$\leq 0.2s$	$\leq 1.0s$	Max	Sens	MRR₇			KS₇
Unranked	Qlever	100%	100%	635ms	0%	0: 0%	3: 8%	7: 53%	10.87
Agnostic	Qlever	100%	100%	696ms	0%	0: 6%	3: 64%	7: 92%	5.88
Sensitive	Blazegraph	3%	27%	59% > 5s	41%	0: 26%	3: 36%	7: 37%	7.93
Sensitive	Virtuoso	35%	53%	24% > 5s	76%	0: 38%	3: 67%	7: 67%	5.26
Sensitive	Qlever	71%	90%	6% > 5s	94%	0: 50%	3: 92%	7: 95%	2.91
Mixed	Blazegraph	0%	98%	1066ms	25%	0: 22%	3: 71%	7: 94%	4.71
Mixed	Virtuoso	35%	100%	1002ms	59%	0: 36%	3: 76%	7: 91%	4.22
Mixed	Qlever	68%	100%	1000ms	88%	0: 47%	3: 93%	7: 98%	2.76

Table 1: Query processing times and suggestion relevance for our three knowledge bases, four completion modes, and three SPARQL engines. For each to-be-completed token, three AC queries were issued, for prefix lengths 0, 3, and 7. The column for the MRR₇ shows average results per AC query, and hence per prefix length. The percentages in the “Max” column indicate the fraction of AC queries that timed out after 5s. For the 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. Column “Sens” shows the percentage of sensitive AC queries that did not time out. See Sections 5.2 - 5.4 for more details, and Section 5.5 for a discussion.

4. From that name, compute three prefixes for `%prefix%`: of length 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 3 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 `%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.

The agnostic and the unranked AC queries only filter precomputed ranked lists of entities and their names by the typed `%prefix%`. As explained in Section 3.3, this could be done with a special-purpose data structure. In our evaluation, we evaluate them with Qlever, which turns out to be sufficiently fast; see Table 1.

We set the timeout for all AC queries (for all knowledge bases and all engines) to 5s. In mixed mode, we launch a sensitive query and an agnostic query in parallel. If the sensitive query does not finish within 1s, we take the result from the agnostic query. That way, in mixed mode, we always obtain a result fast, it might just not be sensitive.

In our evaluation, we took great care to get the best query times for each engine, given its capabilities. We found that for some of the AC queries, some engines produced suboptimal query plans,

leading to overly large processing times. To remedy this, we used slightly different (but all equivalent) formulations of the AC queries for each engine. The only exception: in the predicate AC queries, we dropped the DISTINCT for Virtuoso and Blazegraph because almost all of their queries failed otherwise; see the running times and explanations for Example 2 in Section 1.1.

The reader may wonder, why we did not evaluate AC queries after each keystroke. We did this on purpose, 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.

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

Relevance: We report the percentage of sensitive queries that did not time out. For these queries, *all* suggestions are sensitive in the sense of our definition from Section 1.1. Note that also an agnostic or unranked query can contain some sensitive suggestions. However, this is of limited value to a user if they don't know which suggestions are sensitive and which are not. What is important is the rank of the desired token, which we evaluate 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.

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.

5.5 Main results and discussion

Table 1 summarizes our main results. It contains a lot of information, which we tried to arrange as clearly as possible. The main takeaways are as follows. The table shows only results for those AC queries, for which the result is not already fully precomputed; these are discussed separately at the end of this section.

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. 50%. 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. In Section 1.1, Example 3 showed a typical situation, where it is very hard to guess even the first few letters of the desired token. 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.

Sensitive AC queries are feasible with QLever, but often fail with Virtuoso and Blazegraph. Even on the very large Wikidata, QLever can provide 90% of the sensitive suggestions in under a second, and 71% under 200ms. Only few AC queries time out after 5s on Wikidata, and hardly any on the smaller knowledge bases. On Wikidata, two thirds of the timed out AC queries are object queries involving predicate paths with huge intermediate results. The most frequently occurring is *wdt:P31/wdt:P279** (“instance of” followed by one or more “subclass of”), which matches 1.5B triples. In Section 6, we discuss an ad-hoc fix for this problem. For our evaluation, we explicitly wanted an approach with minimal configuration and no ad-hoc adjustments.

For Virtuoso, a quarter of the AC queries time out. For Blazegraph, over half of the AC queries time out and hardly any are fast. For the smaller knowledge bases, QLever has practically no timeouts, but Virtuoso and Blazegraph still have many. Note that 5s is a rather generous timeout: users hardly want to wait that long for a suggestion in an interactive scenario. In our own experience, usage becomes annoying if you have to wait beyond 1s.

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. This is not surprising, since the results are essentially precomputed. The only non-trivial work to do at query time is to filter the precomputed results by the prefix typed. As explained in Section 3.3, this could also be achieved with a special-purpose data structure. But it is nice that we don't need such a data structure, but can just use our SPARQL engine for it.

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 discussion and running time in Example 1 in Section 1.1 and in Section 4.3.

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. Mixed is therefore a perfect solution with respect to efficiency.

The MRR₇ of Mixed for the important prefix-length-0 case comes very close to the MRR₇ for Sensitive. For prefix length 3 and 7, Mixed is even better, the difference being larger for Virtuoso and Blazegraph. The reason is that when the sensitive AC query times out, the reciprocal rank (RR) for Sensitive is 0 because we don't have any suggestions. With Agnostic, we get at least some suggestions. As discussed for Agnostic above, these suggestions are not very good for prefix length 0, but quite good for prefix lengths 3 and 7. For prefix length 0, the MRR₇ of Mixed is worse than that of Sensitive because of the smaller timeout (1s instead of 5s).

A downside of Mixed is that for the agnostic suggestions, even when they are good, the user does not know if they are good. A user interface could indicate this fact by showing suggestions from agnostic queries in a different color or with some other visual marker. On Wikidata using QLever, 88% of the mixed AC queries are sensitive. Note that the number is smaller than in the Sensitive row because of the smaller timeout.

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 = 6%). For a prefix length of 7, the MRR₇ rises to 53%, but it's still much worse than the 92% of Agnostic. Note that ranking for sensitive autocompletion is mainly an efficiency problem: often very large of suggestions have to be computed and sorted. In some of the previous work we discussed, ranking was omitted due to this reason; see Section 2.

Results for AC queries without context. Table 1 does not include predicate AC queries with a variable `%subject%` and empty `%context%` or for subject AC queries. The reason is that the suggestions for these queries are exactly the results of our building blocks `%predicates%` and `%entities%`, which we precompute once and then pin to the cache. These queries can hence be processed just as fast as the agnostic AC queries.

There are 112 such tokens for Fbeasy, 132 for Freebase, and 363 for Wikidata; so about one fourth of all tokens for Fbeasy and Freebase, and one fifth for Wikidata (each token corresponds to three AC queries, one for each prefix length). The average MRR₇ per prefix length (0-3-7) for these AC queries are: 59%-95%-99% for Fbeasy, 52%-97%-99% for Freebase, and 21%-78%-95% for Wikidata. The KS₇ results are: 1.94 for Fbeasy, 1.90 for Freebase, 5.00 for Wikidata.

These MRR₇ and KS₇ results (without context) are significantly better than for the agnostic queries in Table 1 (with context). There are two reasons for this. First, most of the AC queries without context are predicate suggestions, and there are much fewer predicates than entities, so that it is easier to have a desired predicate highly ranked. Second, the predicates in a SPARQL query that have no context are often frequent predicates, like `<is_a>` on Fbeasy or `wdt:P31` (instance of) on Wikidata.

6 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 two ways out. First, we showed how to extend an existing open-source SPARQL engine to deal with most of these hard queries efficiently. Second, we introduced a mixed mode that sacrifices context-sensitivity for efficiency. Here are some interesting directions for future work:

1. An obvious next step is to implement a user interface based on the autocompletion mechanism described in this paper. Such a user interface would also have to implement various syntactic suggestions; see Section 1.2. While this is straightforward algorithmically, it poses various challenge from a UX perspective.
2. Our pattern preprocessing, described in Section 4.2, goes a long way towards providing predicate suggestions in interactive time. There is still room for improvement, however. Especially on Wikidata, there are large groups of entities, which have very similar but not exactly equal patterns. If we could identify these groups, we would have even fewer patterns and could store for each entity the common pattern and its small difference to that pattern. This has the potential to speed up predicate suggestions further.
3. Our autocompletion is a fantastic help for finding the individual IRIs in a SPARQL query. However, for some SPARQL queries, it can be hard to know in advance which information is represented as a predicate and which information is represented as an object in the knowledge base. For example, when looking for US presidents in Wikidata, the right predicate is `wd:P39` (position held) and the right object is `wd:Q11696` (President of the US). But the predicate might as well have been `wdt:P31` (instance of) or the information about the job title could have been split over two triples (being president and of which country). A more intelligent autocompletion might provide suggestions for both predicates and objects and figure out automatically where to place them in the query.
4. Among the remaining very hard AC queries in our evaluation are queries involving predicate paths like `wdt:P31/wdt:P279*` (instance of, subclass of). A simple ad-hoc fix for this problem is as follows: Identify all predicates in the knowledge base, which can meaningfully form such chains. Wikidata even provides a dedicated predicate (`wdt:P6609`, named "value hierarchy property") for this (for example, it connects `wdt:P31` with `wdt:P279`, and `wdt:P279` with itself). For each of these paths, precompute the objects ordered by frequency. These queries are hard to compute, but result size is on the same order as for our `%entities%` query. For the corresponding AC query, then show the precomputed result. This is not fully sensitive, but close to it: for example, in the case of `wdt:P31/wdt:P279*`, only "types" are suggested, instead of entities that obviously make no sense as objects of this predicate path.

REFERENCES

- [1] Marcelo Arenas, Bernardo Cuenca Grau, Evgeny Kharlamov, Sarunas Marciuska, and Dmitriy Zheleznyakov. 2016. Faceted search over RDF-based knowledge graphs. *J. Web Semant.* 37-38 (2016), 55–74.
- [2] Konstantine Arkoudas and Mohamed Yahya. 2019. Semantically Driven Auto-completion. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management, CIKM 2019, Beijing, China, November 3-7, 2019*. ACM, 2693–2701. <https://doi.org/10.1145/3357384.3357811>
- [3] Hannah Bast, Florian Baurle, Björn Buchhold, and Elmar Haussmann. 2012. Broccoli: Semantic full-text search at your fingertips. *arXiv preprint arXiv:1207.2615* (2012).
- [4] Hannah Bast, Florian Baurle, Björn Buchhold, and Elmar Haussmann. 2014. Easy access to the Freebase dataset. In *WWW (Companion Volume)*. ACM, 95–98.
- [5] Hannah Bast and Björn Buchhold. 2017. QLever: A Query Engine for Efficient SPARQL+Text Search. In *CIKM*. ACM, 647–656.
- [6] Hannah Bast and Elmar Haussmann. 2015. More accurate question answering on freebase. In *Proceedings of the 24th ACM International on Conference on Information and Knowledge Management*. 1431–1440.
- [7] Blazegraph [n.d.]. Blazegraph. https://blazegraph.com/docs/bigdata_architecture_whitepaper.pdf, retrieved 30.01.2021. Wikidata setup: https://www.mediawiki.org/wiki/Wikidata_Query_Service/User_Manual.
- [8] Kurt D. Bollacker, Colin Evans, Praveen Paritosh, Tim Sturge, and Jamie Taylor. 2008. Freebase: a collaboratively created graph database for structuring human knowledge. In *SIGMOD Conference*. ACM, 1247–1250.
- [9] Stéphane Campinas. 2014. Live SPARQL Auto-Completion. In *ISWC Posters & Demos (CEUR Workshop Proceedings)*, Vol. 1272. 477–480. <https://pdfs.semanticscholar.org/2628/15d156def72810bad221d1f2db1799f12daf.pdf>
- [10] Stéphane Campinas, Thomas Perry, Diego Ceccarelli, Renaud Delbru, and Giovanni Tummarello. 2012. Introducing RDF Graph Summary with Application to Assisted SPARQL Formulation. In *DEXA Workshops*. IEEE Computer Society, 261–266. <http://www.renaud.delbru.fr/doc/pub/webs2012-sparql.pdf>
- [11] Ju Fan, Guoliang Li, and Lizhu Zhou. 2011. Interactive SQL query suggestion: Making databases user-friendly. In *Proceedings of the 27th International Conference on Data Engineering, ICDE 2011, April 11-16, 2011, Hannover, Germany*. IEEE Computer Society, 351–362. <https://doi.org/10.1109/ICDE.2011.5767843>
- [12] Sébastien Ferré. 2017. Sparklis: An expressive query builder for SPARQL endpoints with guidance in natural language. *Semantic Web* 8, 3 (2017), 405–418.
- [13] Mustafa Jarrar and Marios D. Dikaiakos. 2012. A Query Formulation Language for the Data Web. *IEEE Trans. Knowl. Data Eng.* 24, 5 (2012), 783–798. <http://linc.ucy.ac.cy/publications/pdfs/2012-TKDE-mashQL.pdf>
- [14] Nodira Khoussainova, YongChul Kwon, Magdalena Balazinska, and Dan Suciu. 2010. SnipSuggest: Context-Aware Autocompletion for SQL. *Proc. VLDB Endow.* 4, 1 (2010), 22–33. <https://doi.org/10.14778/1880172.1880175>
- [15] Jens Lehmann and Lorenz Bühmann. 2011. AutoSPARQL: Let Users Query Your Knowledge Base. In *The Semantic Web: Research and Applications - 8th Extended Semantic Web Conference, ESWC 2011, Heraklion, Crete, Greece, May 29-June 2, 2011, Proceedings, Part I (Lecture Notes in Computer Science)*, Vol. 6643. Springer, 63–79. https://doi.org/10.1007/978-3-642-21034-1_5
- [16] Eyal Oren, Renaud Delbru, and Stefan Decker. 2006. Extending Faceted Navigation for RDF Data. In *International Semantic Web Conference (Lecture Notes in Computer Science)*, Vol. 4273. Springer, 559–572.
- [17] Karima Rafes, Serge Abiteboul, Sarah Cohen Boulakia, and Bastien Rance. 2018. Designing Scientific SPARQL Queries Using Autocompletion by Snippets. In *eScience*. IEEE Computer Society, 234–244.
- [18] Virtuoso [n.d.]. OpenLink Virtuoso. <http://docs.openlinksw.com>, retrieved 30.01.2021. RDF Index Scheme: <http://docs.openlinksw.com/virtuoso/rdferfrdfscheme>.
- [19] Denny Vrandečić and Markus Krötzsch. 2014. Wikidata: a free collaborative knowledgebase. *Commun. ACM* 57, 10 (2014), 78–85.
- [20] Wikimedia [n.d.]. Wikidata Query Service (WDQS). <https://query.wikidata.org>. Example queries retrieved on 23.10.2020.