ABSTRACT
The availability of shared software models provides opportunities for reusing, adapting and learning from them. Public models are typically stored in a variety of locations, including model repositories, regular source code repositories, web pages, etc. To profit from them developers need effective search mechanisms to locate the models relevant for their tasks. However, to date, there has been little success in creating a generic and efficient search engine specially tailored to the modelling domain.

In this paper we present MAR, a search engine for models. MAR is generic in the sense that it can index any type of model if its meta-model is known. MAR uses a query-by-example approach, that is, it uses example models as queries. The search takes the model structure into account using the notion of bag of paths, which encodes the structure of a model using paths between model elements and is a representation amenable for indexing. MAR is built over HBase using a specific design to deal with large repositories. Our benchmarks show that the engine is efficient and has fast response times in most cases. We have also evaluated the precision of the search engine by creating model mutants which simulate user queries. A REST API is available to perform queries and an Eclipse plug-in allows end users to connect to the search engine from model editors. We have currently indexed more than 50,000 models of different kinds, including Ecore meta-models, BPMN diagrams and UML models. MAR is available at http://mar-search.org.

CCS CONCEPTS
- Software and its engineering → Model-driven software engineering; Unified Modeling Language (UML); Software libraries and repositories; - Information systems → Search engine architectures and scalability.

KEYWORDS
Search engine, Model repositories, Meta-model classification

1 INTRODUCTION
Model repositories are essential for the success of the MDE paradigm [17, 20], since they have the potential to foster communities of modellers, improve learning by letting newcomers explore existing models and provide high-quality models which can be reused. There are several model repositories available [20], some of which offer public models. For instance, the GenMyModel1 cloud modeling service features a public repository with thousands of available models. To profit from them advanced search mechanisms are needed [12].

In particular, a search engine has the potential to aggregate models from several sources, including model repositories (e.g., the AtlanMod Zoo2) and code repositories (e.g., GitHub [34]), thus boosting the user chances to retrieve the desired results easily. Despite some efforts [16, 23, 27] there are still open challenges, which includes indexing models efficiently for search and retrieval, taking the model structure into account in the search, and aggregating models of different types and from different sources under a single platform.

In this paper we present MAR, a search engine specifically designed for models. MAR is generic, in the sense that it can handle any EMF model [35] regardless of its meta-model. An important challenge is how to encode the structure of the model in a manner that can be stored in an inverted index [4] (a map from items to documents containing such item). To tackle this we encode a model by computing paths of maximum, configurable length $n$ between objects and attribute values of the model. At the user level, our system employs a query-by-example approach in which the user just needs to create model fragments using a regular modelling tool. The system extracts the paths of the query and access the inverted index to perform the scoring of the relevant models. We have evaluated the precision of MAR for finding relevant models by automatically deriving queries using mutation operators, obtaining good results. Moreover, we evaluate its performance obtaining results that show its practical applicability. We also discuss several applications of MAR beyond its main use case, that is, searching for models stored in repositories. Notably we have used MAR for meta-model classification showing that using a simple $k$-Nearest Neighbours approach can reach similar precision as state-of-the-art methods [30]. Finally, MAR has currently indexed more than 50,000 models from several sources, including Ecore meta-models, UML models and BPMN models. MAR is freely accessible at http://mar-search.org through a REST API, a web interface and an Eclipse plug-in.

Organization. Section 2 presents an overview of our approach and the running example. The formal model of the search process is presented in Sect. 3, whereas Sect. 4 describes the practical aspects in the design of our search engine. Section 5 introduces applications of a search engine, while Sect. 6 reports the results of the evaluation. Finally, Sect. 7 discusses the related work and Sect. 8 concludes.

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1https://www.genmymodel.com/
2https://web.imt-atlantique.fr/x-info/atlanmod/index.php?title=Zoos
The design of a search engine for models requires considering several aspects [27]. The search should be meta-model based in the sense that only models conforming to the meta-model of interest are retrieved. There exists search engines for specific modelling languages (e.g., UML [23] and WebML [16]), but the diversity of modelling approaches and the emergence of DSLs suggests that search engines should be generic. Moreover, the nature of the search process requires an algorithm to perform inexact matching because the user is interested in obtaining several search results, using some ranking mechanism to sort the results according to their relevance. A search engine requires an indexing mechanism for processing and storing the available models in a manner which is adequate for efficient look up. In addition, a good search engine should be able to handle large repositories of models while maintaining a good performance as well as search precision. Another aspect is how to present the results to the user. This requires considering the integration with existing tools and building dedicated web services.

Our design addresses these concerns by including the following features, which are depicted in Fig. 1.

- **Query by example.** The user interacts with the system using a query mechanism based on examples. The user creates an example model containing elements that describe the expected results. The system receives the model (and the name of its meta-model) to drive the search and to present a ranked list of results.
- **Frontend.** The functionality is exposed through a REST API which can be used directly or through some tool exposing its capabilities in a user friendly manner. In particular, we have implemented a web interface and an Eclipse plug-in which integrates the search engine with Ecore editors.
- **Indexing.** An inverted index is populated with models crawled from existing software repositories and datasets (e.g., Github, GenMyModel). Implementation-wise, it is an HBase database, which stores the information needed for the search.
- **Scoring algorithm.** The results are obtained by accessing the index to collect the relevant models among those available. They are ranked according to a scoring function and returned to the user. The IDE or the web frontend are responsible for presenting the results in a user-friendly manner.
- **Generic search.** The search is meta-model based because it takes into account the structure given by the meta-model, but the engine is generic, in the sense that it can index and search models conforming to any EMF meta-model.

**Running example.** Let us consider the task of searching for UML state machine models using a search engine, like MAR, which has indexed thousands of UML models. An excerpt of the UML meta-model for state machine diagrams is shown in Fig. 2. Let us suppose that MAR has indexed a state machine which represents making or receiving mobile phone calls, similar to the diagram shown in Fig. 3(left). A user interested in models representing phone calls may create a query like the one in Fig. 3(right). The query is different since it models only the reception of calls. The modelling style is also different because in the query the system waits for the incoming call in **Wait** and then transitions to **Waiting** to pick up, whereas in Fig. 3(left) the system automatically transitions to **Talking** when there is an incoming call. A search engine for models should be able to match attribute values (e.g., strings) and to detect which structures of the model match to which structures of the query, and provide a relevance score based on this.

## 3 RETRIEVING MODELS

Our approach is based on the conceptual model typically used to address text retrieval problems [33], but it is adapted to cover the specific case of model retrieval in which the structure of models plays an important role. In this section, we present our approach formally, and the next section describes the practical aspects.

**Model retrieval.** We define the model retrieval problem as follows: let $\mathcal{M} = \{m_1, \ldots, m_t\}$ be a set of models which conform to the same meta-model and a query $q$ made by a user (which in our case is a model conforming to the same meta-model as the models in $\mathcal{M}$). We are interested in computing $R(q) \subset \mathcal{M}$ the set of relevant models to the user who defined the query $q$. However, it is not realistic to find exactly that set, so typically an approximation $R'(q)$ is considered. In particular, using a ranking approach, we have:

$$R'(q) = \{m \in \mathcal{M} | r(q, m) \geq \theta\},$$

where $r(\cdot, \cdot)$ is called the ranking function and $\theta$ is a threshold. In practice, the user is given a list of models sorted decreasingly by
the scores of each model, and the threshold is implicitly defined by the user who browses the list in descending order until she or he considers appropriate. A good ranking function should rank all relevant documents on top of all non-relevant ones.

Our approach has two main ingredients, which are described in the rest of the section. First, encoding the set $M$ into a suitable type of document which represents the structure in a compact manner. We use the notion of graph paths to transform the repository into a set of bags of paths. Second, choosing a scoring function to rank the models in the repository with respect to the query.

### 3.1 Models as bags of paths

A key element in our approach is the ability to perform fast, approximate structural matching. As noted in [6], taking the structure of models into account is essential to precisely compare models in scenarios like search, clustering, clone detection, classification, etc.

**Graph construction.** Our approach is based on representing the structure of a model as a bag of paths. To this end, we first define the structure of the graph from which paths will be extracted.

**Definition 3.1.** A directed multigraph is a tuple $(V, E, f)$ where $V$ is a nonempty finite set whose elements are called vertices, $E$ is a finite set whose elements are called edges and $f : E \rightarrow V \times V$ is a function which defines the source and target vertex of an edge. The edges $e_1$ and $e_2$ are called multiple edges (or multi-edges) if and only if $f(e_1) = f(e_2)$.

**Definition 3.2.** A labeled directed multigraph is a tuple of the form $G = (V, E, f, M_V, M_E)$ where

- $(V, E, f)$ is a directed multigraph.
- $M_V = \{\mu_V : V \rightarrow L : 0 \leq |L| < \infty\}$ is a set of vertex labeling functions.
- $M_E = \{\mu_E : E \rightarrow L : 0 \leq |L| < \infty\}$ is a set of edge labeling functions.

In particular we are interested in a labeled directed multigraph $G = (V, E, f, \{\mu_V, \mu_E\}, \{\mu_E\})$ with three labeling functions:

- $\mu_V : V \rightarrow \text{(attribute, class)}$ which indicates if a vertex represents an attribute value or the class name of an object.
- $\mu_E : V \rightarrow L_V = L_A \cup L_C$ maps vertices to a finite vocabulary which has two components:
  - $L_A$ corresponds to the set of attribute values in the model.
  - Given $v \in V$, if $\mu_V(v) = \text{attribute}$ then $\mu_V(v) \in L_A$.
  - $L_C$ corresponds to the set of names of the different classes.
  - Given $v \in V$, if $\mu_V(v) = \text{class}$ then $\mu_V(v) \in L_C$.
- $\mu_E : E \rightarrow L_E = L_R \cup L_AR$ maps edges to a finite vocabulary which has two components:
  - $L_R$ corresponds to the set of names of the different references.
  - Given $e \in E$ where $f(e) = (v_1, w)$, if $\mu_E(e) = \text{class}$ and $\mu_E(e) = \text{class}$ then $\mu_E(e) \in L_R$.
  - $L_AR$ corresponds to the set of names of the different attributes.
  - Given $e \in E$ where $f(e) = (v_1, w)$, if $\mu_E(e) = \text{attribute}$ and $\mu_E(e) = \text{attribute}$ then $\mu_E(e) \in L_AR$.

As can be noted, we explicitly consider two types of nodes: attribute values and class names of individual objects (which will be referred to as “object class” nodes for brevity). The aim is to be able to construct paths between the model elements which carry the meaning of the model. For instance, the value \textit{Waiting} of the State\_name attribute would yield a node, and each object of type State would yield another node labeled as State. The construction of the graph is relatively straightforward, and we do not detail the algorithm for brevity. Fig. 4 shows an excerpt of the graph that is obtained for the query model shown in Fig. 3(right). There are explicit edges for both references and attributes. Nodes associated with objects classes are depicted as rounded rectangles, while nodes associated with attributes are depicted as ovals.

**Bag of paths.** In our approach a bag of paths (BoP) refers to the paths between each vertex of the multigraph to another one and the singleton paths with just one vertex. This is defined more formally in the following.

**Definition 3.3.** Let us have $G = (V, E, f, \{\mu_V, \mu_E\}, \{\mu_E\})$. A bag of paths for $G$ is a multiset BoP whose elements are of the form:

- $(\mu_V(v))$ where $v \in V$ or
- $(\mu_E(e_1), \mu_E(e_2), \ldots, \mu_E(e_n))$, $(\mu_E(e_n-1), \mu_E(e_n))$ where $n \geq 2$
- $(v_1, \ldots, v_n)$ a path of length $n-1$, i.e. a sequence of vertices where, for all $1 \leq j \leq n-1$, $f(e_j) = (v_j, v_{j+1})$.

This definition of BoP does not enforce which paths must be computed, but a criteria must be defined depending on the application domain. For instance, the criteria could be to select all paths of the graph of length 3. In this case, the following paths would be part of the BoP of Fig. 4: $(\text{answer call}, \text{name}, \text{Transition})$, $(\text{name}, \text{Transition}, \text{container}, \text{Region}, \text{transition}, \text{Transition})$, $(\text{source}, \text{State})$, etc. The concrete criteria that we use in the BoP extraction for our search engine is explained in Sect. 4.1.

A BoP has two main characteristics: it is a compact representation of the model structure and it can be used to reveal relevant models with respect to the query. For instance, the path $(\text{answer call}\_\text{name}, \text{Transition}, \text{target}, \text{State}, \text{name}, \text{Talking})$ extracted from the query graph encodes the fact that the user is interested models with a transition named answer call whose target state is named Talking.

\textit{To facilitate reading the paths we use ovals to denote attribute nodes, superscripted arrows to denote edges and rounded rectangles for class nodes.}
The same path exists in the repository model Fig. 3(Left), hence this model becomes relevant to the query.

### 3.2 Scoring and ranking models

Given a query \( q \), our goal is to determine the relevance of the models with respect to it. To achieve this, the models that belong to \( M \) are transformed into a set of graphs. For each graph, the paths are extracted generating a set of bags of paths, \( \text{BoPs} = \{ \text{BoP}_1, \ldots, \text{BoP}_t \} \), where \( t = |M| \). On the other hand, the query \( q \) is processed in a similar way generating the bag of paths \( \text{BoP}_q \).

We are interested in comparing \( \text{BoP}_q \) with each \( \text{BoP}_i \) in the repository. The comparison must take into account the number of paths that appear in both \( \text{BoP}_q \) and \( \text{BoP}_i \) (matching paths) and the relevance that each matching path has within each \( \text{BoP}_i \). To this end, we have chosen the ranking function Okapi BM25 [33, 39] which is computed using the matching paths between both \( \text{BoP}_q \) and \( \text{BoP}_i \), and taking into account the relevance of each match according to the size \( |\text{BoP}_i| \) in comparison to the sizes of the BoPs in the repository and the number of repetitions of each path in \( \text{BoP}_i \). Thus, \( r( \text{BoP}_q, \text{BoP}_i ) \) using our adapted version of Okapi BM25 is:

\[
\sum_{\omega \in \text{BoP}_q \cap \text{BoP}_i} \frac{c(\omega, \text{BoP}_q) (z+1)c(\omega, \text{BoP}_i)}{z \left( 1 - b + b \frac{|\text{BoP}_i|}{\text{avdl}} \right) \log \left( \frac{t+1}{df(\omega)} \right)}, \tag{1}
\]

where \( 1 \leq i \leq t \), \( c(\omega, \text{BoP}) \) is the number of times that a path \( \omega \) appears in a bag \( \text{BoP} \), \( df(\omega) \) is the number of bags in \( \text{BoP} \)s which have that path, \( \text{avdl} \) is the average of the number of paths in all the BoPs in the repository and \( z \in [0, +\infty) \), \( b \in [0, 1] \) are hyperparameters. The parameter \( b \) controls the penalization of models which have a large size and \( z \) controls how quickly an increase in the path occurrence frequency results in path frequency saturation.

If \( b \rightarrow 1 \), larger models have more penalization. In our current version we take \( b = 0.75 \) as default value. If \( z \rightarrow 0 \) the saturation is quicker and if \( z \rightarrow \infty \) the saturation is slower. We take \( z = 0.1 \) (quick saturation) because a lot of repetitions of a path in a model does not imply that this model has much more relevance than other model that has this path repeated less times.

Computing a ranking using this formula is straightforward, just by taking the query and all the models in the repository, computing \( r(\text{BoP}_q, \text{BoP}_i) \) for every model of the repository and sorting the models in decreasing order. However this approach is very inefficient since it has to visit all the models in the repository, performs the path extraction for each one and compute \( r \). Next section describes how to engineer the search engine to efficiently compute the ranking.

### 4 ENGINEERING A SEARCH ENGINE

In this section, we describe the practical aspects of our search engine. The architecture is depicted in Fig. 5. There are two main processes: offline and online. The offline process is in charge of gathering models from one or more model repositories using dedicated crawlers. The indexer takes these models, process them, and constructs an inverted index over Apache HBase using a specific encoding to make the search fast. For each model, a pipeline made of several components is applied: a model to graph transformation, a path extraction process to obtain a bag of paths of a given length from the graph (see Sect. 4.1), a normalization process in which some standard Natural Language Processing (NLP) techniques are applied to have a more semantic handling of string values (see Sect. 4.2), and the stop path removal process which filters out some irrelevant paths from the bag of paths.

On the other hand, given a query we apply the same pipeline. In this case, the resulting bag of paths is used by the scorer, which implements the scoring function in Equation 1 by accessing the index, and returns a ranked list of models according to their similarity.

In the following we describe the design and some implementation details of these components.

#### 4.1 Path extraction

Path extraction is an important element of our search engine, since it transforms the structural information of the model into a form suitable for indexing. In the previous section we define the multiset \( \text{BoP} \) by describing the form of the elements that belong to it in a generic way. In practice, we need to define a criteria to extract a relevant \( \text{BoP} \) from a model. To establish this criteria we follow this reasoning: increasing the length of the path is equivalent to increasing the requirements that a model of the repository has to satisfy in order to be relevant to the user query. For instance, for the graph in Fig. 4 we can extract these two paths:

\[
\begin{align*}
\text{answer call} \rightarrow \text{name} \rightarrow \text{Transition} \rightarrow \text{target} \rightarrow \text{State} \rightarrow \text{name} \rightarrow \text{StateMachine} \quad &\text{and} \quad \text{answer call} \rightarrow \text{name} \rightarrow \text{Transition} \rightarrow \text{target} \rightarrow \text{State} \rightarrow \text{name} \rightarrow \text{Talking}.
\end{align*}
\]

The first path (length one) is less restrictive in the sense that all models which have a transition called \( \text{answer call} \) will be relevant. The second path (length three) is more restrictive since it states that relevant models need to have a transition called \( \text{answer call} \) that has a target state of name \( \text{Talking} \). Therefore, we construct the \( \text{BoP} \) by considering all simple paths (no cycles) of length \( \text{less or equal} \) than a threshold (typically 4). On the other hand, even with a fixed length, considering all paths between all vertices will make a huge \( \text{BoP} \). Consequently, we consider the paths with the following forms:

- All singleton paths for objects with no attributes: \( \mu^1_v(\nu) \) where \( \nu \in V \), \( \mu^1_v(\nu) = \text{class} \) and \( \forall w \text{ accessible from } \nu \), \( \mu^1(\nu) = \text{class} \). Path \( \text{Region} \) is the only one in the example.
- All paths of length \( = 1 \) between attribute values and its associated object class: \( \mu^1_v(\nu), \mu^2(\nu), \mu^2(\eta) \) where \( \mu^1_v(\nu) \) = attribute. These encode object data. For instance, \( \text{initial} \rightarrow \text{kind} \rightarrow \text{PseudoState} \) and \( \text{Phone call} \rightarrow \text{name} \rightarrow \text{StateMachine} \).
\[ \forall \theta, \mu \in \mathbb{V}, V_\mu, \forall \nu \in \mathbb{V}, V_\nu, \forall w \in \mathbb{W}, V_w, \forall n \in \mathbb{N}, V_n, \forall v \in \mathbb{V}, V_v, \forall c \in \mathbb{C}, V_c, \forall e \in \mathbb{E}, V_e \]

\[ \begin{align*}
    \text{answer call} & \quad \text{name, Transition, kind, external} \\
    \text{Phone call} & \quad \text{name, StateMachine, region, Region} \\
    \text{Talking} & \quad \text{name, container, Region, subvertex, State, name, Phone call} \\
   \end{align*} \]

The rationale is to represent the data of an object (its internal state) with paths of \( \text{length} = 1 \), or with \( \text{length} = 0 \) if an object does not have attributes and we use the class name as a surrogate. We use paths of \( \text{length} > 1 \) to encode the model structure in terms of the relationships between the data of the objects (their attribute values). In practice, MAR is configurable to reduce the BoP size even more by filtering out classes, attributes or references which might not be of interest for specific meta-models.

### 4.2 Normalization

Once the BoP of a model has been computed, the next step is to normalize to increase the chances of having matching paths.

#### 4.2.1 Word normalization

Oftentimes attribute values are strings, which typically carry some meaning according to the model domain. However, small variations in the same word prevent matching similar words. Given an attribute of type string, we apply the following techniques typically used in Natural Language Processing (NLP):

- **Tokenization**: Given a character sequence, tokenization is the task of dividing it into pieces, called tokens. This process is customizable. In the running example we use a white space tokenizer and make characters lower case. The tokenization of \( \text{Waiting to pick up} \) results in \([\text{waiting}] [\text{to}] [\text{pick}] [\text{up}]\).

- **Stop words removal**: The term stop word refers to a word that appears very frequently when using a language. Thus, a typical process in NLP systems is to remove them. In our case, we remove tokens containing English stop words. In the previous example we would apply stop word removal as follows: \([\text{waiting}] [\text{to}] [\text{pick}] [\text{up}] \longrightarrow [\text{waiting}] [\text{pick}]\).

- **Stemming**: This is an NLP technique whose goal is to reduce inflectional forms and sometimes derivationally related forms of a word to a common base form. In particular we use the Porter Stemming Algorithm \([32]\). In the example, the application of stemming would produces: \([\text{stem(waiting)}] \rightarrow [\text{wait}] [\text{pick}]\).

At the end of this process we might end up with a single string value (e.g., "Waiting to pick up") split into zero or more tokens. If there are no tokens, the node is removed. If there are more than one token, the node is duplicated according to the split and all the paths including such node are duplicated accordingly. For instance, the path \( [\text{Transition}, \text{name}, \text{State}] \) is transformed in these two paths: \( [\text{wait}, \text{name}, \text{State}] \) and \( [\text{pick}, \text{name}, \text{State}] \).

#### 4.2.2 Stop paths removal

There exists some paths which do not provide any information about the model, in the sense of how similar or different is from other models. This happens for paths which appear in the majority of the models, which we call stop paths. For example, a path like \( ([\text{initial}, \text{kind}, \text{PseudoState}] \) is a stop path because most state machines have an initial state. Currently, we heuristically consider a path to be a stop path if it appears in the 70% of the models in the repository. This is calculated only once as a post-processing in the indexing.

### 4.3 Indexing models

In a search engine, the indexer is in charge of organising the documents in a way that enables a fast response to the queries. In our case, the documents indexed by the search engine are models obtained by crawling existing model repositories. We have created a number of scripts to semi-automate this process for GitHub, GenMyModel and the AtlanMod Zoo. The results are collections of XML files which are consumed by the indexer.

The main data structure used by the indexer is the inverted index \([4]\). It is a large array with one entry per word in the global vocabulary and each entry points to a list of documents that contains such word. In MAR, we index models, and therefore there is an entry per different path and, for each one, a pointer to the list of models which have this path. However, compared to text retrieval systems the size of the index is larger since there are much more paths than words and queries are bigger (in a text retrieval system the queries are keywords), that is, there are more accesses to the inverted index. For instance, in a repository of 17.000 models, we counted more than twenty million different paths and a small query could have hundreds of different paths.

We use Apache HBase \([22]\) to implement the inverted index. HBase is a sparse, distributed, persistent multidimensional sorted map database, inspired by Google’s BigTable \([18]\). HBase is prepared to provide random access over large amounts of information, and its horizontally scalable, meaning that it scales just by adding more machines into the pool of resources. In HBase each table has rows identified by row keys, each row has some columns (qualifiers) and each column belongs to a column family and has an associated value. A distinctive feature of HBase is that two rows can have different columns, and a row may have thousands of columns. HBase provides two read operations: scan and get. Scan is used to iterate over all rows that satisfy a given filter. Get is used for random access by key to a particular row.

Building an inverted index over HBase can be straightforward if each path is a row key and the models that contain this path are columns whose qualifier (i.e., the column name) is the model identifier and whose value is a pair containing the number of times the models have the path and the total number of paths of the model.
The main idea is to explode the lexicographic order in each petition (this information is pre-computed to calculate the score efficiently). However, this approach is not optimal because to implement the scoring function we need to perform as many get calls as paths in the query. This causes a performance bottleneck because each get is completely independent; that is, for each path in the query (e.g., a thousand paths) an independent look up is done just to recover the needed information about one and only one path. Another option is to use a scan with a prefix filter. However, this can return a lot of paths that we have to filter in the client side.

An alternative is to organize the table schema in a way that accommodates to the most common access pattern, so that the data that is read together is stored together. In HBase the data is stored following a lexicographic order of the concatenation of the row key and the column qualifier in a family column. Therefore, we propose a database schema similar to the one in Fig. 6. Each type of model has an inverted index (a table). Each path is split into two parts: the prefix and the rest, and the prefix is used as row key and the rest is a column qualifier. The split is different depending on whether it starts with a attribute node or an object class node.

**Path starts with attribute value.** The prefix is the first sub-path of length 1. For instance, the path \( (\text{hang}, \text{name}, \text{Transition}) \) is split into a row key: \( (\text{hang}, \text{name}, \text{Transition} \) and the column qualifier: \( , \text{source}, \text{Name}, \text{name}, \text{talk} \). The value associated to the column is a serialized map which associates the identifier of the models which have this path with the number of times the path appears in the models and the total number of paths of the models (these two numbers are necessary in the calculation of the score). In the figure, \( \text{sm1 [1, 1032]} \) means that the path appears in model \( \text{sm1} \) only once and 1032 is the number of paths that \( \text{sm1} \) has. For paths of length = 1 we use the symbol \( ) \) as a marker for the column qualifier, as in \( (\text{hang}, \text{name}, \text{Transition} \) .

**Path starts with object class.** For instance, an example could be \( (\text{Region}, \text{subvertex}, \text{Name}, \text{talk}) \). This path is split into \( (\text{Region} \) and \( , \text{subvertex}, \text{Name}, \text{name}, \text{talk} \). \( \text{Region} \) is going to be the row key and \( , \text{subvertex}, \text{Name}, \text{name}, \text{talk} \) will be the column qualifier. For paths of null length, for instance \( (\text{Region} \) we use \( ) \) as column name as before.

### 4.4 Scorer

Using this schema, the underlying idea to implement an optimized version of the scoring function is to gather information about more paths of null length, for instance \( (\text{Region} \) that we have to filter in the client side.

An alternative is to organize the table schema in a way that accommodates to the most common access pattern, so that the data that is read together is stored together. In HBase the data is stored following a lexicographic order of the concatenation of the row key and the column qualifier in a family column. Therefore, we propose a database schema similar to the one in Fig. 6. Each type of model has an inverted index (a table). Each path is split into two parts: the prefix and the rest, and the prefix is used as row key and the rest is a column qualifier. The split is different depending on whether it starts with a attribute node or an object class node.

**Path starts with attribute value.** The prefix is the first sub-path of length 1. For instance, the path \( (\text{hang}, \text{name}, \text{Transition}) \) is split into a row key: \( (\text{hang}, \text{name}, \text{Transition} \) and the column qualifier: \( , \text{source}, \text{Name}, \text{name}, \text{talk} \). The value associated to the column is a serialized map which associates the identifier of the models which have this path with the number of times the path appears in the models and the total number of paths of the models (these two numbers are necessary in the calculation of the score). In the figure, \( \text{sm1 [1, 1032]} \) means that the path appears in model \( \text{sm1} \) only once and 1032 is the number of paths that \( \text{sm1} \) has. For paths of length = 1 we use the symbol \( ) \) as a marker for the column qualifier, as in \( (\text{hang}, \text{name}, \text{Transition} \) .

**Path starts with object class.** For instance, an example could be \( (\text{Region}, \text{subvertex}, \text{Name}, \text{talk}) \). This path is split into \( (\text{Region} \) and \( , \text{subvertex}, \text{Name}, \text{name}, \text{talk} \). \( \text{Region} \) is going to be the row key and \( , \text{subvertex}, \text{Name}, \text{name}, \text{talk} \) will be the column qualifier. For paths of null length, for instance \( (\text{Region} \) we use \( ) \) as column name as before.

#### 4.4 Scorer

Using this schema, the underlying idea to implement an optimized version of the scoring function is to gather information about more than one path in each database get petition. Given a query, for each distinct prefix there is only one petition to HBase because it is possible add the columns that you want to retrieve in a single get. The main idea is to explode the lexicographic order in each petition returning the needed information about some paths that are stored together due to the fact that they have the same row key (i.e. the same prefix). The following algorithm shows how to implement the scoring function for HBase.

In this algorithm paths are split into prefix and rest as explained in Sect. 4.3, and elements \( w \), \( c \) and \( df \) were explained in Sect. 3.2. If a user introduces the query Fig. 3(right) in our search engine, it would return a ranked list in which the first result is the one shown in Fig. 3(left) with a score of 1520.15. Some of the paths that contribute to the score (i.e. that match) are \( (\text{wait}, \text{name}, \text{State}) \).

#### 5 APPLICATIONS

The main application of our search engine is obviously searching for models, but it can also be applied to other scenarios. For instance, it can be used as the basis to build a model recommender which searches in the background for relevant models and then extracts new features to suggest (e.g., a property for a class). It can also be used as a means to find reusable MDE components (e.g., transformations, editors, etc.) by indexing the meta-model footprint of each component. In this section we discuss two applications for which we have already used and experimented with our search engine: searching for models and meta-model classification, but we want to implement new applications in the future.
5.1 Model searching

The availability of model repositories has been regarded as an important element for the success of MDE, since they may foster the reuse and sharing of software models, thus increasing the visibility of the MDE paradigm. There are several model repositories (e.g., ReMoDD, AtlanMod Zoo, GenMyModel), but models are also stored in regular code repositories (e.g., as part of GitHub projects). This makes it difficult for users to retrieve relevant models, since it implies looking up in several locations. Moreover search tools in these repositories are not model-oriented or there might be no search tool at all [20]. MAR is able to aggregate models coming from several sources and provides an unified access to them. MAR is available at http://mar-search.org, in which updated statistics about the number and types of models can also be checked. We also provide access to MAR through a REST API and an Eclipse-plugin.

Access through a REST API. We have implemented a simple REST API to allow the integration of the search engine in tools of diverse nature, like a web-based interface, extensions of modelling environments, or simply to perform experiments.

The REST API has two main methods: search is a POST method which receives a file in XMI format, the type of model and an integer with the maximum number of results. It connects with the search engine and returns as a response a JSON document with the list of relevant document as pairs of (id, score). The GET method get_model retrieves the data associated to a given model.

Eclipse plug-in. As a prototype we have implemented an Eclipse plug-in to add search functionality to existing Eclipse model editors. Fig. 7 shows a screenshot. An Eclipse view connects to the active editor. The search button takes the contents of the current editor, serializes it and submits the query. The results can be inspected using a dedicated view or downloaded for further manipulation.

5.2 Meta-model classification

The automated classification of model repositories is regarded as an important activity to support reuse in large model repositories [30]. Automated methods could annotate models with fine-grained metadata to help developers make decisions about what to reuse.

Recent works have used supervised machine learning methods like neural networks [30] and unsupervised methods like clustering [7, 13] to classify meta-models into application domains automatically (e.g., state machines, class diagrams, etc.). An alternative and simpler method is to use a model search engine like ours to apply the k−Nearest Neighbors (k−NN) supervised learning algorithm to this task [39]. Let us suppose that we have a repository labeled with the domain of each meta-model. If we want to classify a new meta-model, we use it as a query for our search engine, we select the top k meta-models of the ranked list of results, and finally we assign to it the label of the majority.

To take advantage of the score provided by the search engine we use weighted k−NN, which is a modification of k−NN. Weighted k−NN is based on assigning weights to the votes of the test data’s neighbors. In our case, the weights will be the score of each result.

To evaluate the adequacy of this approach we replicate the experiment carried out in [30] and compare the results. We use the same dataset of 555 metamodels [5] retrieved from GitHub. In this dataset, each meta-model is labeled with its domain (9 domains were identified). We follow this procedure to estimate the performance of weighted k−NN using MAR.

Selecting k. Split the 555 metamodels into two sets: training set (70% of them) and test set (30% of them). We use the training set to select the k hyperparameter (i.e., number of neighbours) and estimate the performance. We do a 10−fold cross-validation and, as evaluation metric, we use the accuracy (i.e., the percentage of correctly classified models). After the 10−fold cross-validation, for each considered k = 2 . . . 10, we choose the k that maximizes the accuracy’s mean of validation sets. The best results are achieved with k = 2 with an accuracy of 93.23%.

Test. Once the k hyperparameter has been chosen, we can directly evaluate the test set. In particular, with k = 2 the accuracy of our method in the test set is 93.37%.

Assessment. The approach in [30] uses a neural network and estimate an accuracy of 95.45%, which is slightly better than ours (93.23%). Hence, it can be claimed that MAR can also be used for meta-model classification with results comparable to state-of-the-art techniques. It is also worth mentioning that neural networks are very powerful but they are black box, that is, you do not know the reason of its predictions. In this way, our approach is more transparent because the classification decision is determined easily by just looking at the models of the ranked list of results.

6 EVALUATION

This section reports the results of the evaluation of our search engine. First, we evaluate its search precision, that is, the ability of MAR to rank relevant models on top. Second, we show the performance results. The datasets and a replication package are available at http://mar-search.org/experiments/models20.

6.1 Search precision

The evaluation of the precision of a search engine requires some metric about the adequacy and relevance of the search results. A user-oriented study about the relevance of the search results would be an appropriate manner to evaluate the usefulness of our system. However, setting up this kind of study is out of the scope of the paper and it is left as future work. Instead, to have an initial evaluation of MAR we have devised an automated approach.

The underlying idea is to simulate a user who has in mind a concrete model and the query is automatically derived using mutation operators that generate a shrinked version of the model which
includes some structural and naming changes. Thus, for each generated query mutant there is only one relevant model, which known beforehand. This type of evaluation is called known item search [39].

As target for the search, we have used all the Ecore meta-models indexed by MAR (17975). We perform the evaluation twice, with two different sets of mutants. The first set comes from 281 meta-models obtained from the AtlanMod zoo (referred to as MutantsAtlanMod). The second set comes from 2000 meta-models randomly selected from all the indexed meta-models (referred to as MutantsAll). To ensure a certain degree of quality in the query mutants, we require that the meta-models have at least 20 classes and 40 elements (adding up EClass and EStructuralFeature elements). The aim is to filter out small meta-models which may result in queries very close to the original.

For each meta-model we apply in turn the mutation operators summarized in Table 1. First, we identify a potential root class for the meta-model and we keep all classes within a given “radius” (i.e., the number of reference or supertype/subtype relationships which needs to be traversed to reach a class from the root), and the rest are removed. All EPackage elements are renamed to avoid any naming bias. From this, we apply mutants to remove some elements (mutations 2–6). Next, mutation #7 is intended to make the query more general by removing elements whose name is very specific of this meta-model and it is almost never used in other meta-models (in text retrieval terms the element name has a low document frequency). Finally, to implement mutation #8 we have applied clustering (k-means), based on the names of the elements of the meta-models, in order to group meta-models that belong to the same domain. In this way, this mutant attempts to apply meaningful renamings by picking up names from other meta-models within the same cluster. We apply this process with different radius configurations (5, 6 and 7) and we discard mutants with less than 3 classes or with less references than \(|\text{classes}|/2\). Using this strategy we generate 128 queries for MutantsAtlanMod and 1595 queries for MutantsAll.

Given that we do not have access to any other model search engine, we have implemented a text-based model search engine on top of Whoosh [2] (a pure Python search engine library) as way to have a baseline to compare against. The full repository is translated to text documents which contain the names of each meta-model (i.e., property ENamedElement.name). These documents are indexed and we associate the original meta-model to the document. Similarly, we generate the text counterparts of the mutant queries.

The procedure to evaluate the precision of each search engine and query set is as follows. Each query has associated the meta-model from which it was derived. For each query we perform a search and we retrieve the ranked list of results. We look up the original meta-model in the list and take its position, \(r\). Then, we compute the reciprocal rank which is \(1/r\). To summarize all reciprocal ranks we take the average of them (Mean Reciprocal Rank, MRR). To compare the precision of MAR and Whoosh we use the parametric \(t\)-test for the two set of queries. In both cases, we have \(p-value < .001\) indicating that the difference in the mean reciprocal rank is significant. Table 2 shows the global results of the evaluation and Fig. 8 shows the proportion of queries which are ranked in the first, second up to the fifth position or more. MAR ranks more queries in the first position in both query sets. It is also interesting to observe that the proportion of queries ranked in positions equal or greater than 5 is smaller in MAR. In addition, the results for RepoAtlanMod are better than RepoAll in both MAR and Whoosh. The reason is that the AtlanMod meta-models are generally more complete (e.g., more classes, features, etc.), than the random sample taken from MAR’s index. Therefore the query mutants tend to be of better quality.

From these results we conclude that MAR has a good precision, and the precision seems to improve when we search for larger models using well defined queries. The fact that MAR is better in both query sets reinforces our hypothesis that MAR outperforms plain text search in general.

The main threat to validity of this experiment is that the obtained mutants might not represent the queries that an actual user would create. To minimise it we have tried several mutation operators and

| Mutant | Description |
|--------|-------------|
| 1 | Extract connected subset |
| 2 | Remove inheritance |
| 3 | Remove leaf classes |
| 4 | Remove references |
| 5 | Remove enumeration |
| 6 | Remove attributes |
| 7 | Remove low-df classes |
| 8 | Rename from cluster |

| Mutant | MAR – MRR | Whoosh – MRR | Differences in MRR | \(p-value\) |
|--------|-----------|--------------|-------------------|------------|
| MutantsAll | 0.752 | 0.988 | 0.036 | < .001 |
| MutantsAtlanMod | 0.668 | 0.894 | 0.026 | < .001 |

Figure 8: Precision evaluation results. Proportion of queries (y-axis), the position of the relevant document (x-axis) in the ranked list and engine/query set as colour of the bars.

Table 1: Mutations operators used to simulate queries.

Table 2: Results of search precision evaluation.

The first position in both query sets. It is also interesting to observe that the proportion of queries ranked in positions equal or greater than 5 is smaller in MAR. In addition, the results for RepoAtlanMod are better than RepoAll in both MAR and Whoosh. The reason is that the AtlanMod meta-models are generally more complete (e.g., more classes, features, etc.), than the random sample taken from MAR’s index. Therefore the query mutants tend to be of better quality.

From these results we conclude that MAR has a good precision, and the precision seems to improve when we search for larger models using well defined queries. The fact that MAR is better in both query sets reinforces our hypothesis that MAR outperforms plain text search in general.

The main threat to validity of this experiment is that the obtained mutants might not represent the queries that an actual user would create. To minimise it we have tried several mutation operators and
configurations and reviewed the mutants manually until we found reasonable results. Nevertheless, we expect to understand better the user behaviour as MAR is used by the community.

6.2 Performance evaluation
To evaluate the performance of MAR we have used all mutant queries extracted from Mutants840. We want to evaluate the effect of the index size in the response time. Thus, we have incrementally indexed batches of 1,000 meta-models (randomly selected), and for each new batch we measure the response time for each query mutant. Moreover, to evaluate the effect of the query size we count the number of packages, classes, structural features and enumerations and we classify the queries in three types: small (less than 20 elements), medium (between 20 and 70) and large (more than 70). Table 3 shows some details about the contents of the queries.

We run the experiments on a desktop machine with an i7-5820K CPU, with 6 cores at 3.30GHz and maximum heap 16GB. We use Docker to deploy HBase (which runs in a pseudo-distributed mode) and we access it locally since we are mainly interested in understanding the raw performance of our design of the inverted index, and not on potential network effects.

![Figure 9: Query response time depending on the index size.](image)

### Table 4: Results for an index with 17,000 meta-models.

|        | Small | Medium | Large |
|--------|-------|--------|-------|
| Paths  | Mean  | Max    | Mean  | Max    | Mean  | Max    |
| 0.07   | 1.07  | 0.01   | 0.17  | 0.06   | 0.79  | 1.38   |
| Get    | 0.31  | 0.78   | 2.85  | 1.38   | 4.63  |       |
| Score  | 0.22  | 0.45   | 0.97  | 0.61   | 1.39  |       |
| Total  | 0.55  | 1.49   | 1.24  | 3.99   | 2.06  | 6.27  |

Fig. 9 shows the relationship between index size and response time, and Table 4 summarizes the results for the largest index. As can be observed MAR scales smoothly as the size of the index increases and, as expected, larger queries take more time (except some outliers because of the garbage collector). On the other hand, small queries correspond to scenarios in which the user would develop a query in a fast manner, possibly with little details. In this case, the average response time is 0.53 seconds for the larger index. The average response time for medium and large queries is 1.24 and 2.06 seconds respectively, which is quite acceptable since there are queries with up to 193 classes. This would be useful in scenarios like model clone detection. In general, the computation of the bag of paths and the scoring are fast. The execution of get petitions to HBase consumes most of the execution time, and it is where we could improve more the overall performance. Nevertheless, this experiment shows that MAR is already an efficient search engine.

7 RELATED WORK
In this section we review works related to our proposal, organised in three categories: model encoding techniques which are relevant for model search and indexing, model repositories and search engines for models themselves.

**Model encoding techniques.** Code2Vec is an technique for representing snippets of code as continuous distributed vectors [3]. For each code snippet, a multiset of paths (named bag of path-contexts) is extracted from the AST and it is used as an input of a neural network. Our idea of BoP was inspired by the concept of bag of path-contexts. SAMOS is a platform for model analytics, which employs a technique to transform models into vectors in order to apply supervised learning, unsupervised learning, statistical analysis, etc. SAMOS is used in [6] for model clustering and meta-model clone detection is proposed in [9]. The notion of n-grams is used to represent paths of length n between nodes in a graph associated to a model. Models are transformed into a set of n-grams and then to a explicit vector whose dimension is determined by the number of distinct n-grams in the repository. This is similar to MAR, since we both use paths to encode the structure. However there are some key differences: our graph is different as we consider single attributes as independent nodes, and therefore the extracted paths are different. SAMOS considers paths of the same length, whereas our BoPs are formed by paths of length less or equal than a threshold. SAMOS is, in principle, not oriented to implement a search engine since it uses similarity metrics (to build the vectors) which are not thought to perform a fast search. In [28] locality sensitive hashing is applied to summarize EMF models as a hash. This has different applications including intellectual property protection and fast model comparison. This could be an alternative strategy to organize a search index. On the other hand, AURORA [30] extracts tokens from an Ecore model following an encoding schema (they propose three encoding schemes that try to reflect the model structure) and then, using these tokens, models are transformed to a vector in a vector space that will be an input of a neural network. In [19], the authors propose using graph kernels for clustering software modeling artifacts. The general idea is to transform a set of software models to a set of graphs and then use graph kernels to measure the distance between each other. For clone detection, Exas is a vector encoding of graph models to perform approximate matching of model fragments [29, 31], which has also been applied to detect model transformation clones [37]. In [24] both structural and syntactic metrics are used in order to compare two meta-models. Also, they used genetic algorithms for meta-model matching. However, their approach did not support indexing so the matching was not thought to be fast. The notion of domain-specific distance is discussed in [38], which could be incorporated to improve the precision of the search.
Model repositories. MDEForge is a collaborative modelling platform [11] intended to foster “modelling as a service” by providing facilities like model storage, search, clustering, workspaces, etc. It is based on a mega-model to keep track of the relationships between the stored modelling artefacts. GenMyModel is a cloud service which provides online editors to create different types of models and stores thousands of public models [1]. ReMoDD is a repository of MDE artifacts of different nature, which is available through a web-based interface [21]. Hawk provides an architecture to index models [10], typically for private projects and it can be queried with OCL. Regarding built-in search facilities in existing model repositories, the study in [20] shows that search is typically keyword-based, tag-based or simply there is no search facility.

Search engines. Several search engines for models have been proposed in the past years, but as far as we know none of them is widely used. Table 5 shows a summary of their characteristics. In [16], a search engine for WebML models is presented. It supports two query formats: keywords and example-based query. An index is supported only in the keyword query format so structured-based search could be slow if the repository is large. MOOGLE [26] is a generic search engine that only supports text queries in which the user can specify the type of the desired model element to be returned. MOOGLE uses the Apache Lucene query syntax and Apache SOLR as the backend search engine. In [14], a similar approach to MOOGLE is proposed with some new features like megamodel-awareness (consideration of relations among different kinds of artifacts). On the other hand, [23] focuses on the retrieval of UML models using the combination of WordNet and Case-Based Reasoning. MoScript is proposed in [25], a DSL for querying and manipulating model repositories. This approach is model-independent, but the user has to type complex OCL-like queries that only retrieve exact models, not a ranking list of models. Regarding our query-by-example approach, some graph transformation engines have been extended to support this feature. For instance, IncQUERY has been extended to derive a graph query from an example model [15], and VMQL (Visual Model Query Language) uses the concrete syntax of the source language as the query language [36].

Regarding the scale of the system in terms of the number of models handled, the closest system to MAR is SAMOS [9], which performs clustering of 22k meta-models. However, a clustering process is different from indexing, so the approaches are not really comparable. Nevertheless, clustering a huge model repository is computationally expensive. In particular, SAMOS is running over Apache Spark in [8] and takes 17 hours to process a repository of 7k meta-models. With respect to the size of the indexed models, our system increases in at least an order of magnitude existing proposals. For instance, MOOGLE [26] only indexes 146 models, [16] indexes 12 real-world WebML projects which consist on 342 models, and in [14] up to 3000 models are indexed.

8 CONCLUSIONS

In this work we have presented a novel search engine for models. The key idea is to use paths between attribute values to encode the model structure in an indexable manner. Our evaluation shows that MAR is both precise and efficient. Moreover, we have applied MAR to meta-model classification obtaining results comparable to state-of-the-art techniques. Regarding its practical usage, MAR is able to crawl models in several sources and it has currently indexed more than 50,000 models of different kind, including Ecore meta-models, BPMN diagrams and UML models. This makes it a unique system in the MDE ecosystem, that we hope it is useful for the community.

As future work we plan to improve our crawlers to reach more repositories. We also want to include information about the model quality in the ranking. Finally, as MAR is used in practice we aim at thoroughly evaluating it with an empirical study.

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