Intelligent Code Completion with Bayesian Networks

SEBASTIAN PROKSCH, JOHANNES LERCH, and MIRA MEZINI,
Technische Universität Darmstadt

Code completion is an integral part of modern *Integrated Development Environments* (IDEs). Developers often use it to explore *Application Programming Interfaces* (APIs). It is also useful to reduce the required amount of typing and to help avoid typos. Traditional code completion systems propose all type-correct methods to the developer. Such a list is often very long with many irrelevant items. More intelligent code completion systems have been proposed in prior work to reduce the list of proposed methods to relevant items.

This work extends one of these existing approaches, the *Best Matching Neighbor* (BMN) algorithm. We introduce Bayesian networks as an alternative underlying model, use additional context information for more precise recommendations, and apply clustering techniques to improve model sizes. We compare our new approach, *Pattern-based Bayesian Networks* (PBN), to the existing BMN algorithm. We extend previously used evaluation methodologies and, in addition to prediction quality, we also evaluate model size and inference speed.

Our results show that the additional context information we collect improves prediction quality, especially for queries that do not contain method calls. We also show that PBN can obtain comparable prediction quality to BMN, while model size and inference speed scale better with large input sizes.

Categories and Subject Descriptors: D.2.6 [**Software Engineering**]: Programming Environments—*Integrated environments*; I.2.6 [**Artificial Intelligence**]: Learning—*Knowledge acquisition*; K.6.3 [**Management of Computing and Information Systems**]: Software Management—*Software development*

General Terms: Algorithms, Experimentation, Measurement, Performance

Additional Key Words and Phrases: Content assist, code completion, integrated development environments, machine learning, evaluation, code recommender, productivity

ACM Reference Format:
Sebastian Proksch, Johannes Lerch, and Mira Mezini. 2015. Intelligent code completion with Bayesian networks. ACM Trans. Softw. Eng. Methodol. 25, 1, Article 3 (November 2015), 31 pages.
DOI: http://dx.doi.org/10.1145/2744200

1. INTRODUCTION

Code completion systems are an integral part of modern *Integrated Development Environments* (IDEs). They reduce the amount of typing required, thus accelerating coding, and are often used by developers as a quick reference for the *Application Programming Interface* (API) because they show which fields and methods can be used in a certain context. Typically, the context is determined by the static type of the variable on which the developer triggers the completion. However, using the static type of the variable as the only criterion for determining the developers's context may produce spurious

The work presented in this article was partially funded by the German Federal Ministry of Education and Research (BMBF) within the Software Campus project KaVE, grant no. 01IS12054, as well as within EC SPRIDE. The authors assume responsibility for the content.
Authors' addresses: S. Proksch (corresponding author), J. Lerch, and M. Mezini, Technische Universität Darmstadt, Karolinenpl. 5, 64289 Darmstadt, Germany; email: proksch@st.informatik.tu-darmstadt.de.

DOI: http://dx.doi.org/10.1145/2744200

```
class MyDialog extends Dialog {
  private Text text;
  @Override
  void createDialogArea(Composite parent) {
    text = new Text(parent);
    text.
  }
}
```

Cursor position, i.e., code completion invoked here

Identifier	Type	Definition	Call Site	Kind
parent	Composite	Parameter	Text.<init>(Composite)	Parameter
text	Text	New	Text.<init>(Composite)	Receiver

Fig. 1. Example of a code completion and extracted information.

recommendations, thus diminishing the effectiveness of the completion system [Bruch et al. 2009]: Showing the developer hundreds of recommendations (e.g., the type Text in the SWT framework of Eclipse[1] lists 168 methods and field declarations) may be as ineffective as showing none. Many IDEs support prefix filtering to reduce the number of irrelevant recommendations. If completion is triggered on a prefix (e.g., toS|), then only proposals that start with that prefix (e.g., toString) will be shown. This effectively assists developers that know what they are looking for, but is of little help for developers that are unfamiliar with the API.

Intelligent code completions better target the needs of developers that are unfamiliar with an API. The FrUiT tool [Bruch et al. 2006] and its successor using the *Best-Matching Neighbor* (BMN) algorithm [Bruch et al. 2009], which resulted in Eclipse Code Recommenders[2], are examples of intelligent code completion systems. They use code repositories containing clients of an API to build a knowledge base that contains common usages for different types of that API. On a completion event, the models learned from the repositories are used to show relevant proposals. Besides the static type of the variable on which code completion is triggered, these systems also consider some structural context of the code being developed to select the models from which to extract the recommendations. The method within which the completion system was triggered is an example of such a structural context.

The usefulness of considering some form of structural context is illustrated in Figure 1. Here, the developer triggers code completion on the variable `text`. Like a standard code completion, an intelligent code completion system can determine that the static type of the variable is `Text`. But, additionally, it can consider the following structural context features: (a) it was triggered inside the method `createDialogArea`, an overridden method originally declared in the type `Dialog`; and (b) the variable was assigned the result of the call to the constructor of `Text`. By considering typical usages, an intelligent code completion system may infer that the text widget is being initialized in the current situation, as indicated by both the enclosing method and the constructor call. Therefore it proposes method calls known to appear in such contexts frequently, such as `setText` or `addListener`. Method calls that are unlikely in the given context (e.g., `getText`) appear at the end of completion proposals or are omitted altogether.

Bruch et al. [2009] show that, by applying the best-matching neighbor algorithm and some context information to filter relevant usage patterns, intelligent code completions clearly outperform standard code completion systems with regard to prediction

[1]http://www.eclipse.org/swt/.
[2]http://www.eclipse.org/recommenders/.

quality. Two metrics are used for judging prediction quality: precision and recall, which both need to be maximized. High precision means that a high percentage of proposals are relevant; high recall means that as few relevant proposals are missing in the recommended list as possible. Also, relevant method calls must be proposed before any irrelevant completions.

However, the work presented in Bruch et al. [2009] represents only a first and partial step in investigating the design space of intelligent code completions. First, it lacks a comprehensive analysis of the kind of context to be considered and its effect on prediction quality. The structural context information used by this approach consists of the type of the receiver object, the set of already performed calls on the receiver, and the enclosing method definition. The effect of using additional context information (e.g., the enclosing class of the object, methods to which it was passed as an actual parameter, or information about its definition) on prediction quality is not considered. Second, the approach does not at all investigate two further important quality dimensions that need to be considered for code completion engines to effectively support developers: *inference speed* and *model size*.

First, it is of paramount importance that predictions are computed quickly, in order not to disturb the workflow of the developer. Based on prior research that analyzed the impact of user interface delays on users [Nielsen 1994], we derive two timing constraints: (1) a code completion should provide information in less than 100 milliseconds to avoid any noticeable delay in the workflow of the developer; (2) it must answer in less than a second because the current thought of the developer is interrupted, otherwise. Given these constraints, it is infeasible to search for typical usages in large code repositories on-the-fly; typical usages must rather be extracted beforehand and provided in a model that allows efficient inference of potential completions. These models are provided for arbitrary framework types and are typically distributed over a network.

Second, we also need to take the model size into account when evaluating an intelligent code completion system. It is preferable to have smaller models. As already mentioned, the models are usually distributed over a network and the distribution of small models is easier. Further, the models need to be loaded into the IDE of the developer and model size effectively affects the number of models that can be loaded simultaneously and the time necessary to read and deserialize them from the hard drive.

The three quality dimensions—prediction quality, prediction speed, and model sizes—are not orthogonal and the mutual effect they have on each other must be considered. The hypothesis is that prediction quality is increased by considering more features of the structural context. However, this will presumably increase the model size and negatively affect prediction speed. We need code completion engines that provide a good trade-off between these quality dimensions or are even configurable along them.

This article contributes towards tackling these problems. We will extract and use more context information than originally proposed and will show that this indeed improves prediction quality by up to 3% at the cost of significantly increased model sizes by factor 2 and more. We propose *Pattern-Based Bayesian Networks* (PBN) to tackle the issue of significantly increased model sizes, a new technique to infer intelligent code completions that enables to reduce model sizes via clustering.

Like BMN, PBN learns typical usage patterns of frameworks from data, which is extracted by statically analyzing source-code repositories. Unlike BMN that uses a table of binary values to represent usages of different framework types in client code, PBN encodes the same information as a Bayesian network. A major technical difference is that PBN internally stores floating-point values in multiple conditioned nodes, whereas BMN stores binary values in a table. A key consequence is that PBN allows to merge different patterns and to denote probabilities (instead of boolean existence) for all context information. We introduced a clustering approach for PBN that leverages this property

and enables to trade off model size for prediction quality. It is not clear how such a clustering could be adopted for BMN, because its binary representations do not allow for representing clustered results. While the approach is applicable to all object-oriented languages, our PBN implementation and evaluation are focussed on Java.

We perform comprehensive experiments to investigate the correlation between prediction quality and different model sizes. We show that, by exploiting clustering, PBN can indeed decrease the model size by as much as 90% with only minor decrease of prediction quality. We also perform a comprehensive analysis of the effect of input data size on prediction quality, speed, and model size. Our experiments show that prediction quality increases with increased input data and that both the model size and prediction speed scale better with the input data size for PBN compared to BMN. With PBN, proposals can be inferred without noticeable delay even if thousands of examples are used as input.

To summarize, this work presents the following contributions:

—a description of (previously unpublished) implementation details of the existing static analysis of BMN to facilitate future replications;
—a novel extension of the static analysis that extracts the features required for machine learning to support extended contexts;
—an extensible inference engine for intelligent code completion systems, called *Pattern-Based Bayesian Network* (PBN);
—a novel approach for model training that uses the extended context information;
—a clustering approach for model learning that scales to large input sizes; and
—an extensive evaluation of the resulting intelligent code completion system.

We have released downloadable artifacts to allow replication of our results.[3] The released artifacts include all object usages used in this article and the complete source code (i.e., all intelligent code completion engines and the evaluations). This should encourage other researches to compare their results based on the same dataset.

The remainder of the article is organized as follows. We start with a detailed description of our static analysis in Section 2. A detailed introduction of the intelligent code completion systems that we consider follows in Section 3. We continue with the evaluation in Section 4, threats to validity in Section 5, and related work in Section 6. The article ends with an outlook to future work in Section 7 and a conclusion in Section 8.

2. STATIC ANALYSIS OF REPOSITORIES

To learn how specific types of an API are typically used, we implemented a static analysis that extracts *object usages* from source code. The term "object usage" refers to an abstract representation of how an instance of an API type is used in example code and consists of two pieces of information: (1) all methods that are invoked on that instance and (2) the *context* in which the object usage was observed. The first captures the method calls that should be later proposed in the intelligent code completion. The second captures all information about the surrounding source code, that is, the enclosing method and class. This idea is based on prior work [Bruch et al. 2009], but was not clearly described in the resulting publication. Our work contains a detailed description of the static analysis to allow other researchers to build their own implementations. Additionally, we extract more information than the original publication.

Re-usable Context Information. The goal of the static analysis is to extract as much *re-usable* context information from the source code as possible. In object-oriented programming languages, there are two ways to make functionality re-usable and to

[3]http://www.st.informatik.tu-darmstadt.de/artifacts/pbn/.

distribute it to others: *libraries* and *frameworks*. Libraries provide useful helpers that can be re-used anywhere in your code. For example, the *Java Database Connectivity* (JDBC) API is an example of a library API. In such a context, an intelligent code completion engine can learn API protocols or which methods are usually invoked together. However, the surrounding source code usually refers to user specifics, that is, the names are unique and will never be re-used by other developers. This does not provide any information relevant for intelligent code completion. Contrary, a framework (e.g., Swing, the Java UI widget toolkit) is an example of the *inversion of control principle* [Martin 2003]. The framework authors decided for well-designed extension points and provide base classes and interfaces as the mean for extension. Custom functionality is added by extending or implementing these. Inside this custom functionality, other building bricks of the framework are used. Because of that, the extensions of a framework contain useful pointers to overridden methods that can also be observed in source code of other developers. While intelligent code completion systems can also be provided for libraries, we focus on frameworks because the surrounding code contains more context information and the intelligent code completion can provide more specific proposals.

Consider the example from Figure 1: the user-specific subclass `MyDialog` extends the framework class `Dialog`. Learning how objects are usually used in a context referencing `MyDialog` does not provide shareable knowledge because other developers will name their user-specific subclass differently than `MyDialog`, most likely. The extension point that was intended by the author of the framework was `Dialog` so we would reference this as the enclosing type. The enclosing method is even more concrete and follows the same pattern. Instead of pointing to `MyDialog.createDialogArea`, the analysis extracts `Dialog.createDialog` as the enclosing method. By going up in the class hierarchy as much as possible, we increase the likelihood that others use the same classes. This is valid because, according to the *Liskov subsitution principle* (LSP), the contract of all subclasses must not break the contract of the superclass [Martin 2003].

In addition to the information about the enclosing method, we further extend the notion of a *context* in this work and extract more information than in the original publication. We also capture the enclosing type context, all method invocations to which an object usage was passed to as parameter, and information about the definition of an object.

Entry Points and Tracking. We assume that the typical usage of a type is context dependent, therefore we collect object usages separately for each context. Thereby, each public or protected method is considered as a single context and is used as an entry point for the analysis. Private methods do not form a context on their own because they were created by the author of the concrete class, do not belong to the abstraction expressed in the base class or interface, and do not carry any re-usable information. A call graph is computed for each entry point method p_{entry}, in which all method invocations are pruned that leave the enclosing class. Additionally, all exception handling edges are pruned from the intra-procedural control-flow graph.

An object usage is created for every distinct object instance used in the scope of p_{entry}. We use the call graph to track the object instances inter-procedurally in the class. The tracking stops on calls leaving the current class (e.g., calls to methods of other classes) or on calls in the current class that are either entry points or defined in a superclass. In case we find a call to a private method, we step down in this method and *track* all objects of the current scope in the private method.

Example. We illustrate our static analysis in Figure 2. When starting at method `A.entry1()`, the analysis stores the method calls `B.m1()` and `B.m2()` on field `b` as well as the call to method `C.entry2(B)`, for which `b` is used as an actual parameter. The call to method `B.m2()` is stored because the private method `A.helper()` is called from within

```
public class A extends S {

  private B b = new B();

  @Override
  public void entry1() {
    b.m1();
    helper();
    C c = fromS();
    c.entry2(b);
  }

  private void helper() {
    b.m2();
  }
}
```

```
public class C {

  public void entry2(B b) {
    b.m3();
    entry3();
  }

  protected void entry3() {
    D d = new D();
    try {
      d.m4();
    } catch(Exception e) {
      d.m5();
    }
  }
}
```

Entry Point	Type	Class Context	Method Context	Definition	Call Site	Call Site Kind
`A.entry1`	`B`	`S`	`S.entry1`	Field	`B.m1()`	Receiver
					`B.m2()`	Receiver
					`C.entry2(B)`	Parameter
`A.entry1`	`C`	`S`	`S.entry1`	Return	`C.entry2(B)`	Receiver
`A.entry1`	`S`	`S`	`S.entry1`	This	`S.fromS()`	Receiver
`C.entry2`	`B`	`Object`	`C.entry2`	Parameter	`B.m3()`	Receiver
`C.entry3`	`D`	`Object`	`C.entry3`	New	`D.m4()`	Receiver

Fig. 2. Object usages extracted from three entry points.

the entry point `entry1()` and `b` is tracked in it. `b` is not tracked in method `C.entry2(B)` (i.e., `B.m3()` is not stored)—even though it is called from within `A.entry1()`—because it is declared in a class other than p_{entry}. Instead of tracking `b` to this method, the static analysis stores the information that `b` is passed as an actual parameter to it. `C.entry2(B)` is another entry point for the static analysis. A separate object usage is created that extracts information about the usage of type `B` in the context `C.entry2(B)`.

The interpretation of method invocations on `this` depends on the place of definition of the target method. Consider the call to `A.helper` in `A.entry()`. It is defined in the same class and is no entry point, so the analysis steps down into the method and tracks all objects in it. In contrast to that, the call to `S.fromS()` is not tracked because it is defined in another class. Objects are never tracked into calls to other entry points independently of the defining class (same class or other class).

Data Structure. The following list describes all properties that are collected for an *object usage*. The properties *Parameter Call Sites*, *Class Context*, and *Definitions* are introduced in this work. All other properties were previously used and are just included to complete the description.

—*Type.* Type is the type name of a variable or, if discernible, the more specific type of an object instance. For example, if a `String` is assigned to a variable of type `Object` then `String` is stored as the type of this variable, if this is always the case.
—*Call Sites.* Call sites are all call sites connected with the instance. These can be of two kinds:
  —*Receiver Call Sites* are method calls invoked on the object instance. The statically linked method is stored. In the example in Figure 2, these are the methods `m1()` and `m2()` for variable `b` starting from entry point `entry1()`.

—*Parameter Call Sites* are stored if the object instance is passed as the actual parameter to another method. The invoked method is looked up in the type hierarchy and the first declaration is stored, which can be an interface or an abstract base class to store the most re-usable context reference. In the enclosing method `entry1()`, the method call `entry2(B)` is an example of a parameter call site for variable `b`. The argument index at which the object was passed is stored as well (omitted for brevity in the example).

—*Class Context.* Class context is the direct supertype of the class enclosing p_{entry}. In the example, the class context is type `X` for `entry1()`, and `Object` for `entry2(B)` and `entry3()`.

—*Method Context.* Method context is the first declaration of p_{entry} in the type hierarchy, that is, the method declaration of a supertype that is overridden by p_{entry} or the method declaration in an interface that is implemented by p_{entry}. In the example, `A.entry1()` overrides `X.entry1()`, therefore `X.entry1()` is used as method context. If no method is overridden then the method itself is used as the context.

—*Definition.* Definition is information about how the object instance became available in p_{entry}. We distinguish five different definition kinds, each carrying specific information.

  —*New.* The instance is created by calling a constructor[4]; the specific constructor is stored for this kind of definition. In the example, the object usage extracted for variable `d` in `entry3()` is defined by a call to a constructor. Note that field `b` of class `A` is not recognized as having a new definition because the constructor is not called as part of the considered entry point.

  —*Parameter.* The instance is a formal parameter of p_{entry}; the parameter index is stored. In the example, the object usage extracted for `b` in `entry2(B)` is defined by a parameter.

  —*Return.* The instance is returned by a method call; the name of the invoked method is stored. In the example, the object usage extracted for `c` is returned by a method call.

  —*Field.* This definition kind denotes that the reference to the object was received by accessing a class field. We store the fully qualified name of this field. In the example, the variable `b` used in `entry1()` is recognized as field. If the field is initialized in p_{entry}, for example, assigned by a constructor call, then we refer to this definition instead, assuming it to be more precise.

  —*This.* This denotes that the object usage was the receiver of the call to p_{entry}. The same rules as for the enclosing methods apply here: only calls to methods defined in any supertype are collected. `S.fromS()` is an example of this definition in `A.entry1()`. However, the method `A.helper()` is not included because it is defined in the same class as the entry point.

The static analysis always captures *fully qualified* references to types, fields, and methods. A fully qualified reference to a type includes the package name and the type name. A fully qualified field name includes the fully qualified declaring type, as well as the name and the fully qualified type of the field. For a method it is the fully qualified type of the declaring type, the method name, the fully qualified return type, and fully qualified types of parameters.

Implementation. We implemented the described algorithm to analyze arbitrary Java bytecode. Some context information are extracted from the class hierarchies so all types

[4]In Bruch et al. [2009] constructor calls were treated as method calls. With the introduction of definition kinds as part of context information, in this work this is changed.

in the example code need to be fully resolvable. Our implementation is based on WALA,[5] the static analysis toolkit for Java bytecode of IBM. We use the 1-CFA [Shiveas 1988, 1991a, 1991b] implementation that is available in WALA for the points-to analysis to track object instances inter-procedurally. Note that the order of call sites cannot be retained because the 1-CFA implementation is flow insensitive. This is not an issue in our case since we already store call sites as unordered sets.

The work on the analysis was done in a cooperation with an external company; the source code of the analysis is proprietary and cannot be made public. However, as already mentioned in the Introduction, we have released enough artifacts to make the results of the article replicable even without the static analysis code.

3. MODELS FOR INTELLIGENT CODE COMPLETION

The object usages collected by the static analysis are the input data used to generate models for an intelligent code completion system. This article compares two approaches to the design of such models. The first approach is the *best-matching neighbor* algorithm (BMN) [Bruch et al. 2009]. The second approach, called *pattern-based Bayesian network* (PBN), is a novel contribution of this article.

We implemented both BMN and PBN to support the context information described in Section 2. Unfortunately, neither the original implementation of the BMN algorithms nor the evaluation pipeline was publicly available, so we had to rebuild it. Both approaches have the same interface to the outside and take exactly the same input. This makes it very easy to replace the former implementation with the new one; both can be used interchangeably. In fact, the Eclipse Code Recommenders[6] project adapted the PBN approach for their intelligent call completion in the meantime.

Both BMN and PBN can be queried with an incomplete *object usage* for a list of missing method calls. The proposed methods are ordered by the frequency of their occurrence in matching situations. Both BMN and PBN can be integrated into existing *code completion systems* of modern IDEs. Once the code completion is triggered, the query is generated automatically by analyzing the surrounding source code. The completions proposed by the models are integrated into the default code completion popup offered by the IDE. To propose a method, the equivalent non-recommended entry is looked up in the list of proposals given by the static type system. A newly created entry decorates the original proposal, includes the calculated confidence in its label, and is added to the top of the proposal list. A selection event is passed to the decorated proposal, so no additional source code needs to be synthesized.

3.1. Best-Matching Neighbor

The BMN algorithm [Bruch et al. 2009] is inspired by the *k-Nearest-Neighbor* (kNN) algorithm [Cover and Hart 2006] and leverages domain knowledge specific to object usages. BMN represents each object usage as a binary vector in which each dimension represents an observed *method context* or a *receiver call site*. In detail, each binary vector representing an object usage contains a "1" for each context information and call site that applies for the object usage at the corresponding dimension, and "0" otherwise. The model for each object type is a matrix that consists of multiple object usages, that is, binary vectors. Each column in the matrix represents a context information or a call site. Each row represents an object usage found by the static analysis. For illustration, the matrix for the imaginary type `Text` is shown in the upper part of Figure 3. *Usage 1* is equivalent to the object usage of the `Text` widget listed in Figure 1.

[5]T.J. Watson Libraries for Analysis (WALA), http://wala.sf.net/.
[6]http://eclipse.org/recommenders/.

	Dialog. createDialogArea	ModifyListener. modifyText	<init>	setText	getText
Usage 1	1	0	1	0	0
Usage 2	1	0	1	1	0
Usage 3	0	1	0	1	1
Query	1	0	1	?	?
Proposal				50%	0%

Fig. 3. Proposal inference for BMN.

Queries are partial object usages and treated similarly. A query is represented as a vector with the same dimensions as the vectors of object usages in the model. Each observed context information and all call sites already connected to the variable for which the completion is invoked are marked with a "1" in that vector. Context information that does not match is marked with a "0". All receiver call sites which are not contained in the query are potential method proposals; this is illustrated by marking them with "?". If a developer triggers code completion at the position illustrated in Figure 1, the query shown in the lower part of Figure 3 is generated.

The nearest neighbors are determined by calculating the distance between the object usages and the query. The Euclidean distance is used as distance measure, whereby only dimensions containing a "1" or "0" in the query vector are considered. However, receiver call sites that do not exist in the query are not included in the calculation because it cannot be decided whether they are missing on purpose or if they should be proposed. The *nearest neighbors* are those object usages with the smallest distance to the query. Unlike kNN, all neighbors that share the smallest distance to the query are selected, not only the k-nearest neighbors. In our example, *Usage 1* and *Usage 2* both have distance 0 and *Usage 3* has distance $\sqrt{3}$, thus the former two are nearest neighbors.

The nearest neighbors are considered for the second step of computing proposals. For each potential method proposal, the frequency of this method is determined in the set of nearest neighbors. The probability is computed by dividing it by the total number of nearest neighbors. In the running example in Figure 3, the call to `setText` is contained in one out of the two nearest neighbors of the query. Therefore the call is recommended with a probability of 50%. The call `getText` is not contained in any nearest neighbor, so the probability is 0%. The call sites are passed to the completion system as proposals for the developer, ordered by probability.

BMN was re-implemented for this work to be usable in the evaluation. We optimized it for inference speed of proposals and for model size. For example, we introduced an additional `counter` column in the matrix. Instead of inserting multiple occurrences of the same row, we increase the counter. In addition, we extended the model by more context information, represented as additional columns in the model matrix. Originally, only the method context and receiver call sites were included and we added support for the class context, definition, and parameter call sites to obtain a fair comparison of BMN and PBN. The inclusion in the table is configurable for all context information. We use this to evaluate whether the extra context makes a difference.

3.2. Pattern-Based Bayesian Network

This article introduces a novel approach for intelligent code completion called PBN. Bayesian networks are directed acyclic graphs that consist of *nodes* and *edges*. A node represents a random variable that has at least two *states*, which again have probabilities. The states are complete for each random variable and the sum of their probabilities

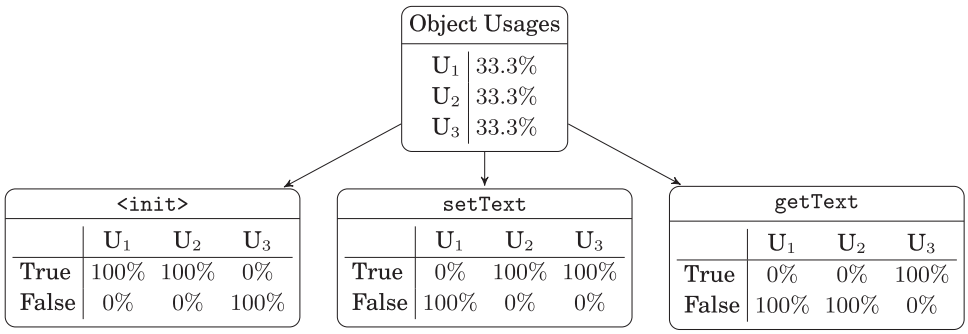


Fig. 4. Conditional probabilities in a Bayesian network.

is always 1.0. Nodes can be connected by directed edges that indicate that the probabilities of the target node are conditioned by the state of the source node. A Bayesian network can be used to answer probabilistic queries about the modeled random variables. If the state of one variable is observed, this knowledge can be used to infer the updated probabilities of other variables. This has already been used in other areas, for example, to rank Web searches [Chapelle and Zhang 2009] or for recommendations in social networks [Yang et al. 2011].

Using Bayesian Networks as Code Completion Models. PBN uses a Bayesian network to identify how likely are specific method calls, given that context information, and potentially even other method calls, have already been observed. The idea is to describe the probability of a method call conditioned by a specific object usage. We apply Bayes' theorem to answer the reverse question: how likely is a specific object usage, given that a method call is already present in the current code? This information can then be used to infer how likely other yet not present method calls.

Figure 4 shows the Bayesian network for the example from Figure 3. The *Object Usages* node has the states U_1, U_2, and U_3, representing *Usage 1* to *3* of Figure 3. We have observed three object usages and each of them exactly once, thus each has a probability of 33%. The remaining three nodes represent the method calls `<init>`, `setText`, and `getText`. The edge from the *Object Usages* node to the method call nodes indicates that the probabilities of the calls are conditioned by the object usage. The states of each method call node are *True* and *False*, which represents whether the method call appears in an object usage or not. For example, the call `<init>` is present in *Usage 1*, but neither are `setText` nor `getText`. Therefore the conditional probabilities for the different methods are

$$P(\texttt{<init>}|U_1) = 100\%, \qquad P(\texttt{setText}|U_1) = 0\%, \qquad P(\texttt{getText}|U_1) = 0\%.$$

Please note that the correct notation is $P(\texttt{<init>} = \textit{true}|U_1)$, but the check for the state is omitted for brevity. Although this kind of data is easily extractable from example object usages, we want to answer a different kind of question in the use-case of code completion. It can be observed, for example, that the constructor `<init>` is called on an instance of type `Text`. The developer wants to know which method call is missing. Therefore, the probabilities of all method calls are calculated in such a case and method calls with a high probability are proposed as missing. Hence, if the method `setText` is one of the possible calls, we want to calculate the probability $P(\texttt{setText}|\texttt{<init>})$.

For the following equations which show the calculations to answer the previous question, we will need the probability of $P(\texttt{<init>})$. It is defined as the sum of the joint

probabilities of <init> and each usage U_i:

$$\begin{aligned} P(\texttt{<init>}) &= \sum_{i=1}^{3} P(\texttt{<init>}, U_i) \\ &= 0.333 + 0.333 + 0 \\ &= 0.667. \end{aligned}$$

The probability of the method call setText, given that <init> was called before is

$$P(\texttt{setText}|\texttt{<init>}) = \sum_{i=1}^{3} P(\texttt{setText}, U_i|\texttt{<init>}).$$

Assuming the independence of all methods, Bayes' theorem can be applied to calculate the probability:[7]

$$\begin{aligned} P(\texttt{setText}, U_1|\texttt{<init>}) &= P(\texttt{setText}|U_1) \cdot P(U_1|\texttt{<init>}) \\ &= \frac{P(\texttt{setText}|U_1) \cdot P(\texttt{<init>}|U_1) \cdot P(U_1)}{P(\texttt{<init>})} \\ &= \frac{0 \cdot 1 \cdot 0.333}{0.667} = 0. \end{aligned}$$

The calculations of $P(\texttt{setText}, U_2|\texttt{<init>})$ and $P(\texttt{setText}, U_3|\texttt{<init>})$ are similar:

$$\begin{aligned} P(\texttt{setText}, U_2|\texttt{<init>}) &= \frac{P(\texttt{setText}|U_2) \cdot P(\texttt{<init>}|U_2) \cdot P(U_2)}{P(\texttt{<init>})} \\ &= \frac{1 \cdot 1 \cdot 0.333}{0.667} = 0.5 \end{aligned}$$

$$\begin{aligned} P(\texttt{setText}, U_3|\texttt{<init>}) &= \frac{P(\texttt{setText}|U_3) \cdot P(\texttt{<init>}|U_3) \cdot P(U_3)}{P(\texttt{<init>})} \\ &= \frac{1 \cdot 0 \cdot 0.333}{0.667} = 0. \end{aligned}$$

By combining the intermediate results, $P(\texttt{setText}|\texttt{<init>})$ can be calculated as

$$\begin{aligned} P(\texttt{setText}|\texttt{<init>}) &= \sum_{i=1}^{3} P(\texttt{setText}, U_i|\texttt{<init>}) \\ &= 0 + 0.5 + 0 \\ &= 0.5. \end{aligned}$$

The interpretation of this result is that, if <init> is observed for an object instance, a call to the method setText has a probability of 50%. The same calculations can be done to reason over getText. Generally, all states of context information and all calls present in the query are used as evidence in the Bayesian network. Accordingly, the probabilities of all remaining receiver calls are inferred with respect to these observations. These calls are collected in a proposal list that is ordered by probability.

If the query contains a combination of features never observed in the training data, proposals might be incomputable. To avoid such cases, we implemented *add-delta*

[7]Even though the methods might not be independent, previous work has shown that no direct correlation exists between the accuracy and the degree of feature dependencies [Rish 2001]. We will show in our experiments that the accuracy is comparable to existing techniques.

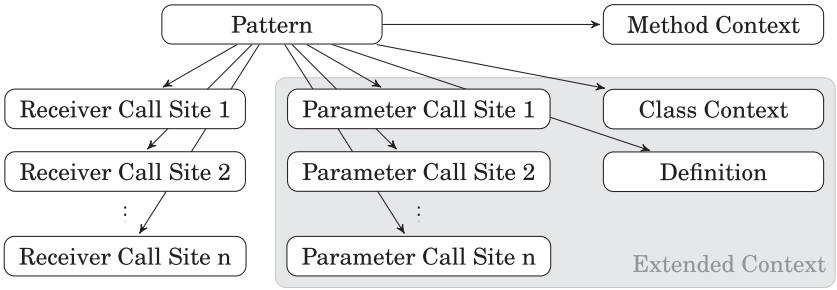


Fig. 5. Structural representation of the Bayesian network used in PBN.

smoothing in our learning algorithm [Chen and Goodman 1996]. A small delta of 0.000001 is added to all probabilities and their sum is normalized to 1.0 afterwards.

Adding Context Information to the Network Structure. So far, the Bayesian network presented in the preceding example does not include context information. To add the context information, the model is extended by adding more nodes that are conditioned by the object usage node. For example, the method context is modeled by a node that contains one state per observed method context. In contrast to call site nodes that only have two states, *True* and *False*, a state in the method context node corresponds to a method name and the number of states is not limited. Assume that the node contains M method contexts and, as it is conditioned by the pattern node with N patterns, the probability table of this node contains $M \times N$ values. Each value describes how the corresponding method was observed, given a specific pattern. Other context information nodes are added in the same way.

The complete Bayesian network that will be used in experiments is illustrated in Figure 5. All nodes for call sites contain only two states—namely the nodes of the method context and the class context—and the definitions contain multiple states. Note the distinction between *receiver* call sites and *parameter* call sites.

Additionally, we changed the name of the root node from *Object Usages* to the more generic name *Pattern*, because the states of this node do not necessarily map exactly to observed object usages. In fact, we collapse all object usages that have the same receiver call sites into a single *pattern* state. Therefore, context information previously having conditional probabilities of 0% or 100% will now be represented by their frequency in the set of collapsed object usages. For example, consider the case of two object usages for which both the method calls `m1()` and `m2()` were invoked. Additionally, assume that one usage was observed in method context `C1`, the other in `C2`. Both will be represented in a single state P of the pattern node because they refer to the same combination of method calls. As the context was different for both, both method contexts `m1()` and `m2()` each have a probability of 50% given the pattern P. The probability of all states in the pattern node is calculated by normalizing their frequency.

Introducing Clustering for Improved Learning. The number of detected patterns has a major impact on the size of the resulting model. Each detected pattern creates a new state in the pattern node so its size grows accordingly. Additionally, the number of stored values in all other nodes also depends on the number of patterns, because all nodes are conditioned by the pattern node. Each conditioned node needs to store an amount of values equal to the product of its own states and patterns. Therefore reducing the number of states in the pattern node has a huge positive impact on the model size. We propose to use a clustering technique to reduce the number of detected

patterns. Information may be lost in this process because multiple *similar* object usages are merged and the quality of recommendations could be affected. On the other hand, clustering ensures the scalability of our approach. It is necessary to find a reasonable trade-off between model size and proposal quality.

We implemented a learning algorithm that is inspired by Canopy Clustering [McCallum et al. 2000] to detect patterns for the PBN model. Similar to Canopy, a random object usage is chosen from the set of all object usages found for a specific type. This object usage becomes a cluster center. Each object usage that has a smaller distance to this cluster center than a specific threshold is assigned to the cluster and removed from the set of object usages still to be assigned to clusters. The algorithm proceeds until all object usages are assigned to clusters. Each cluster becomes a state of the pattern node in the resulting Bayesian network. The probability of the pattern state is the number of object usages in that cluster, divided by the total amount of object usages. Each value, that is, call site or context that was set in any object usage belonging to the cluster, gets a conditioned probability reflecting the frequency of the respective value in the cluster.

To determine the distance between two object usages, the cosine similarity [Strehl et al. 2000] is used, which is also a common choice in the research area of information retrieval. There, vector representations have similar characteristics as in the context of representing object usages: they are typically sparse and high dimensional. Cosine similarity can deal with such vector characteristics well [Schultz and Liberman 1999]. It is defined as the angle between two *vectors* v_1 and v_2:

$$d_{cosine} = 1 - \frac{v_1 \cdot v_2}{|v_1| \cdot |v_2|}.$$

It has a helpful property for distance calculation between object usages: If vectors differ, their distance gets smaller with the number of (set) dimensions they have in common. For example, the distance between two vectors that differ by one call without having another call in common is bigger than the distance between two vectors that differ by one call but that have one or more calls in common. Note that 1.0 is the maximum distance calculated by cosine similarity. A geometrical interpretation of this distance is that two vectors are orthogonal and no dimension is set for both.

Although this clustering approach is very simple, our experiments show reasonable results. The algorithm is fast and can handle huge amounts of data. Also, it implicitly solves the question of how many patterns are to be found, which for many clustering algorithms must be defined upfront. Additionally, the distance threshold can directly control the trade-off between prediction quality and model size. For example, the minimum threshold 0.0 results in practically no clustering at all. The higher the value chosen, the more information will be lost and the smaller the size of the model will become. In the following sections, we will encode the concrete threshold used for a PBN instance in the name, for instance, a PBN_{10} instance uses a distance threshold of 0.10. By using a threshold of PBN_{100}, all usages are merged into a single pattern. In that case, the model degenerates to a simple call-frequency-based model in which context information no longer has no influence on the proposals.

4. EVALUATION

Two different recommender engines have been discussed in the last section. Both approaches can be used interchangeably: they work on the same input data generated by the same static analysis, have the same interface to the outside, and create the same kind of proposals. Differences between them will studied by a comprehensive evaluation in this section.

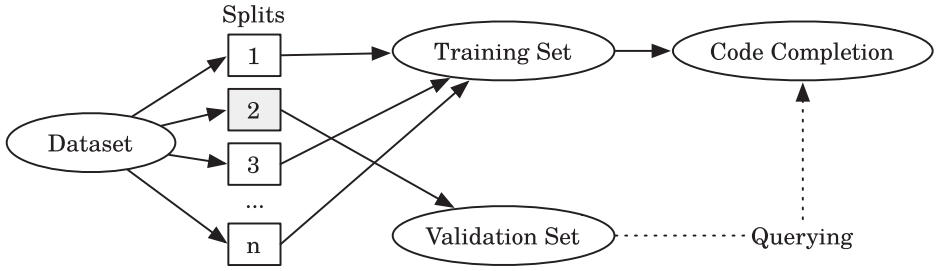


Fig. 6. One iteration of an n-fold cross-validation.

4.1. Methodology

The evaluation of previous recommender systems is usually focused on comparing prediction quality of different algorithms, while performance or mode sizes are only mentioned as a side note.[8] While we also thoroughly evaluate prediction quality, we also focus on additional criteria. Since recommender systems are supposed to be used by humans on typical developer machines with limited resources, we believe that an (empirical) evaluation of recommender systems should take two additional properties into consideration: (1) time needed to compute proposals and (2) size of the models that are used to make the proposals.

Evaluating the Prediction Quality. We evaluate each type in an API under investigation separately with a tenfold cross-validation. We split all available object usages for a single type that have been extracted from the static analysis into 10 different splits, as shown in Figure 6. Ten folds are built out of these splits, whereby each fold consists of one split used as *validation set* and the union of the remaining nine splits as *training set*. For each fold, models are learned from the training set and the validation set is used to query these models. Accordingly, it is guaranteed that no object usage is used for training and validation at the same time.

Our experiments have shown that intra-project comparisons introduce a positive bias to prediction quality. We want to avoid this kind of bias to better reflect development reality, that is, the intelligent code completion engine is used in a code base that was not used to learn the models. Therefore we ensure that all object usages generated from the same project are assigned to the same split. This means that the set of projects used to create queries is disjoint from that used to built the model. As a result, we can only include types in the evaluation that are used in at least 10 different projects and the sizes of the splits differ slightly, especially if the total number of object usages is small for a specific type.

Each usage from the *validation set* is used to query the model and to measure the results. This approach is illustrated in Figure 7. A *query* is created by removing information from a complete *usage*. The resulting incomplete usage is used as a *query*, and the removed information constitutes the *expectation*. When a completion is requested by passing a query, the recommender engine returns a list of *proposals* in descending order of the proposals' confidence value. We follow previous work and filter all proposals with a confidence value lower than 30% [Bruch et al. 2009]. The proposals are compared to the expectation and the F_1 measure is calculated to quantify the quality of a given proposal. F_1 is the harmonic mean of the two measures *precision* and *recall*:

$$precision = \frac{\#hits}{\#proposed}, \qquad recall = \frac{\#hits}{\#expected}, \qquad F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}.$$

[8]For example, in Li and Zhou [2005], Bruch et al. [2009], and Zhang et al. [2012].

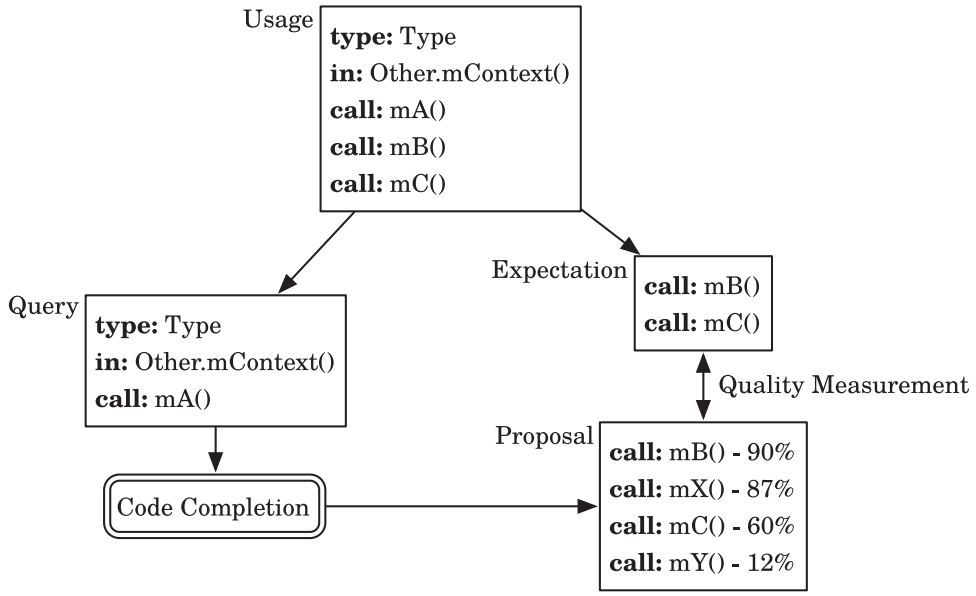


Fig. 7. Conceptual illustration of the evaluation of a single proposal.

Call sites are stored in an *unordered set*, so no information is available on the order in which the calls happen. We use different strategies of removing both receiver and parameter call sites to create queries. Other context information (e.g., the enclosing method) is not removed because we think they always exist in the context of a framework.

We make use of two different strategies to remove call sites from the set. The *No-Calls* strategy removes all call sites and therefore creates exactly one query for each usage. This mimics a developer that starts to work in a new method and triggers code completion to get a first impression of what to do. The resulting queries are denoted as 0|M queries, where M is the number of receiver calls contained in the original object usage (i.e., a 0|3 query contains no calls from the three calls that are contained in the original object usage). The *Partial-Calls* strategy removes about half of the call sites (i.e., 0|1, 1|2, 1|3, 2|4, ...). The resulting queries are denoted as N|M queries, where N is the number of calls contained in the query, and M the number of calls in the original object usage. Both N and M refer to a number of receiver call sites. This strategy simulates developers who started to do some work in a specific context, but came to a point where they did not know how to continue and trigger code completion for help. There are $\binom{M}{N}$ possibilities to remove calls from the set. Because this number gets impractically large with a growing number of calls in the set, only 3 random N|M queries are taken. We calculate the average result of these queries to merge the separate results into a single result value and store it as the quality for the originating object usage. Parameter call sites are removed separately with the same strategy, however, they are not part of the notation as they are only context information and not proposed by the completion system. If not stated otherwise, the *Partial-Calls* strategy is used in all experiments of this article.

Evaluating the Model Size. The model size can be determined empirically by measuring the memory representation in the *Java runtime environment* (JRE). However, the result of this approach depends on implementation details of the model, the used JRE,

and characteristics of the garbage collection, which might induce considerable noise. We decided to use a more simple approach of calculating the theoretical model size of the raw information that is contained. For BMN, the size is calculated by multiplying the number of rows in the table by the size of each row. For PBN, the total number of stored float values in the Bayesian network is calculated. We calculate the size in Byte for both approaches to create comparable values.

Evaluating the Inference Speed. All computations that depend on context information can be made efficient by precomputing as much as possible and storing this information in the model. The precomputation does not need to be fast because it can happen offline on a powerful server. However, using intelligent code completion requires several steps which are complex to compute whenever code completion is activated:

(1) analysis of the working context in which the completion was triggered;
(2) building a query;
(3) loading of the appropriate model, used to answer the query;
(4) inference of relevant method calls; and
(5) rendering of the code completion popup.

The perceived duration of the completion task for the user is the sum of all of these steps, but not all of them are evaluated in this article: the static analysis of the working context is the same for BMN and PBN. Therefore, step 1 is not considered. All models are precomputed and stored in a serialized form. To be usable, they need to be deserialized again and loaded into memory. Nevertheless, by using caches this loading time can be avoided in most cases. Additionally, I/O increases noise in performance measurements and the loading time itself mostly depends on the framework used for serialization. Therefore we ignore step 3 as well. The two steps (2 and 5) are trivial compared to other phases and can safely be ignored. Step 4 is of relevance for this article. First, it depends on the size of represented data in a model and is critical for scalability. Second, the inference process differs between the models.

The precision of timing information that can be read from the system timer is milliseconds.[9] To increase the precision of the results, we: (1) measured the total computation time for all proposals and divided this time by the number of queries and (2) ensured that at least 3,000 proposals are requested per type. The second point mainly addresses the evaluation for types with only a few object usages, because here the typical answer times are smaller than a millisecond. We repeated all experiments that include timing three times and calculated the average to overcome slight deviations caused by potential interfering processes.

Our experiments showed that the just-in-time compilation of modern runtime environments has a significant impact on the performance of the inference. The steady state is reached after thousands of queries for each model. Although this might be unrealistic for a practical usage of the completion system, we decided to repeat all experiments that evaluated inference speed multiple times, until the resulting values were stable to create comparable and repeatable results.

Experimental Setup. To speed-up the experiments, we implemented a map-reduce-like computation in the evaluation framework and distributed the computation to multiple worker threads running on different machines. All machines were running Oracle Java 8 SE.[10] Experiments that include measurement of timings were run locally on an Intel Core i7 machine.[11] We designed the evaluation such that the results are

[9]http://www.ibm.com/developerworks/java/library/j-benchmark1/.
[10]Java(TM) SE Runtime Environment (build 1.8.0_25-b17) with heap settings -Xmx3g.
[11]Intel Core i7 with 2.8GHZ and 16GB of RAM with a clock speed of 1600MHZ.

not influenced by disc I/O (e.g., loading all necessary data into memory before starting the evaluation), hence further information about the storage system is omitted.

Dataset. The SWT framework,[12] the open-source UI toolkit used in the Eclipse development environment, is used to evaluate the code completion engines presented in the previous section. For both approaches, we learn from and test against SWT example code. We chose a snapshot of the Eclipse Kepler update site[13]—the main source of plugins for all Eclipse developers—as the code base. We assume that the API usage reached a stable state because the source code is already released and no longer under development. Changes to it are only due to bugs being fixed. Our static analysis identified about 190,000 object usages for different SWT widget types within the 3,186 contained plugins. The type `org.eclipse.swt.widgets.Button` is by far the type with the most usage data, with more than 47,000 object usages.

4.2. Analyzing Impact of Additional Context Information

Section 2 presented the context information that we collect per object usage. Three kinds of context information—the type of the receiver, the receiver call sites, and the enclosing method definition—were previously used for code completion recommendations. The other three kinds—parameter call sites ($\square_{+P}$), class context ($\square_{+C}$), and definitions ($\square_{+D}$)—are introduced in this work.

In this section, we investigate whether the new context information can be used to improve the quality of the intelligent code completion. The baseline for this experiment are models that do not use the new context information. We compare this to models that are created with the new context information and exhaustively evaluate all combinations of enabled information classes. First, we activate all information classes separately, then we activate pairs ($\square_{+DP}$, $\square_{+CP}$, $\square_{+CD}$), and in the end, we activate all together ($\square_{+ALL}$). We are especially interested in first insights about the trade-off between increased model size and prediction quality gain.

We use all available object usages in this experiment that were extracted for types that belong to the `org.eclipse.swt.widgets` package. We average the prediction quality over all queries and average the model size over all models generated for different types. However, it is necessary to be cautious with the interpretation of the model size in this plot, for two reasons: First, a simple average puts an emphasis on types with only few object usages in that the available input is not equally distributed among the types, rather the majority of object usages are extracted for a minority of types. Therefore, the resulting model sizes shown in the plot are biased towards small input sizes. Second, it is not possible to directly compare model sizes for BMN and PBN in this plot. As we will see in a later section, their implementation makes them scale differently for types with only a few object usages. All the same, we decided to include the model size. Even though it is necessary to read it with caution, it is a first indicator of the impact of a specific information class on the resulting model size. The exact impact of the amount of available input on model sizes is analyzed in a later section.

Figure 8 shows the experiment results. The horizontal axis of the plot shows different configurations of context; the legend under the plot shows which context information is used in each configuration. The vertical axis is organized in two dimensions: the prediction quality (on the left) is depicted with black bars and the average model size (on the right right) is depicted with smaller white bars. The plot contains results for different BMN and (unclustered) PBN_0 models.

[12]http://www.eclipse.org/swt/.

[13]http://download.eclipse.org/releases/kepler/, accessed September 30, 2013.

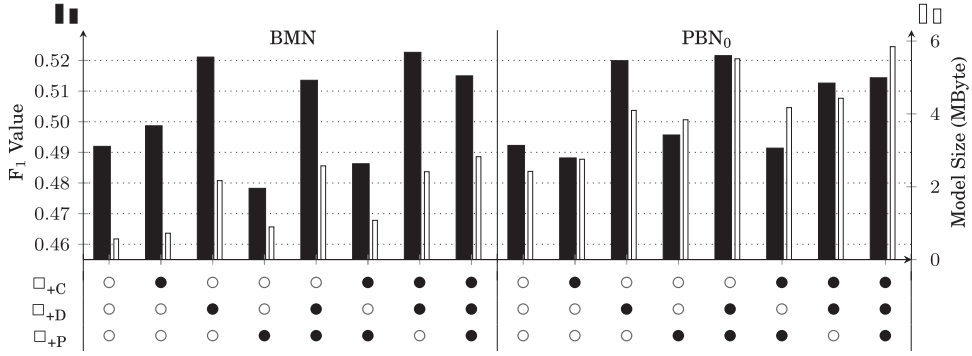


Fig. 8. Comparison of context information (all SWT widgets).

When comparing the configurations with activations of each context information kind in isolation, $\square_{+D}$ is the context information with the biggest impact (third bars in the plots of both BMN and PBN). Compared to baseline, this configuration increases the F_1 value by 0.03, which represents an improvement of 6% for both BMN_{+D} and PBN_{+D}. However, this comes at the cost of a model size that is three times bigger for BMN_{+D} and 1.7 times bigger for PBN_{+D}. The results are indecisive for both $\square_{+C}$ and $\square_{+P}$: In case of BMN, the prediction quality is slightly increased for BMN_{+C} and decreased for BMN_{+P}, but it is the other way around for PBN_0. We consider both deltas irrelevant for the results as they are small (i.e., 0.01). While $\square_{+C}$ has only a minor effect on the model size, $\square_{+P}$ significantly increases it.

▌ $\square_{+D}$ is the dominating context information; the others seem to be negligible.

The results are similar when multiple context information kinds are activated together. We can ignore $\square_{+CP}$ because the prediction quality gain is low. In case of BMN_{+CP}, it is even lower than the baseline. Both $\square_{+CD}$ and $\square_{+DP}$ show a comparable prediction quality to $\square_{+D}$. However, the introduction of both information classes increases the model size. We conclude that adding them is unnecessary, since they do not increase the prediction quality. For both BMN and PBN the $\square_{+ALL}$ configuration leads to worse results. Presumably, the reason for this is that queries become too specific, that is, different object usages become more similar because they share irrelevant features. However, we did not further analyze this result.

Given the results, in the remaining experiments, we focus on the evaluation of $\square_{+D}$ approaches only. Next, we investigate ways of reducing the model size of PBN via clustering and analyze the effect of so doing on the prediction quality. The model size cannot be reduced for BMN, so BMN_{+D} and PBN_0 will be our reference points regarding prediction quality.

4.3. Distance Thresholds of the Clustering for PBN

In Section 3.2 we introduced a clustering technique to reduce the size of learned models. Now, we compare BMN to several instances of the PBN approach that all have different thresholds for the clustering. The distance threshold is used to control how much information is dropped during the clustering. Recall that the threshold is encoded in the name, for example, a PBN_{15} configuration clusters all data points with a mutual distance of less than 0.15. PBN_0 is the unclustered instance. We conduct this experiment to identify distance thresholds that provide useful trade-offs between prediction quality and model size.

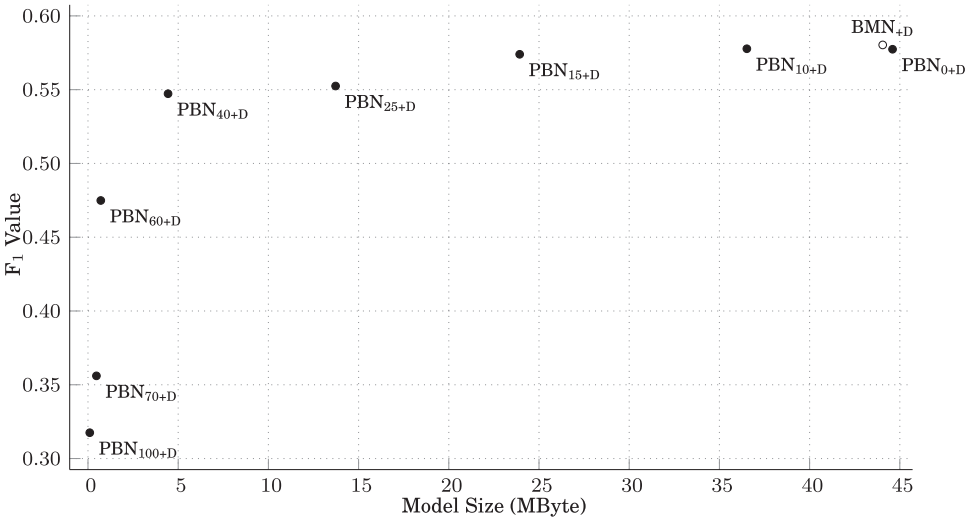


Fig. 9. Quality and size of different recommenders (about 47,000 usages for button).

Model sizes will not only depend on the chosen threshold, but also on the number of available usages for a type. Therefore, this section has a focus on `org.eclipse.swt.widgets.Button`. With about 47,000 usages, this is the type for which we have extracted the most object usages.

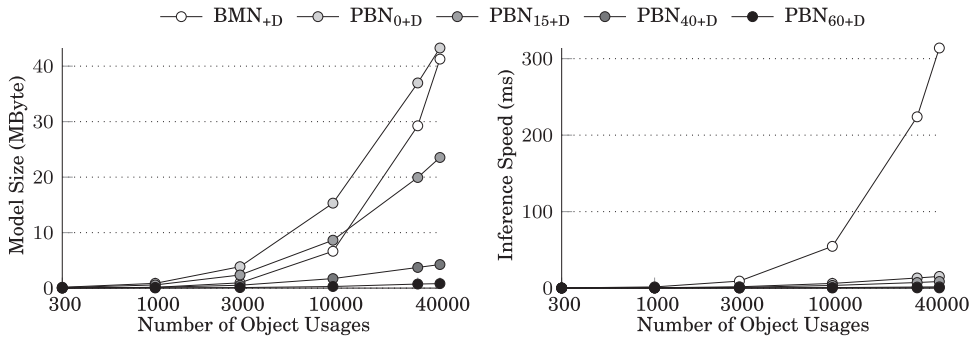
The results of this experiment are illustrated in the scatter plot in Figure 9. The plot contains data points for BMN_{+D} and for several PBN_{+D} variants with different distance thresholds. All points are positioned according to their respective model size in Megabytes and prediction quality is denoted by the F_1 measure.

The plot shows that the data points for BMN_{+D} and for the unclustered PBN_{0+D} are very close. This means that they exhibit similar model sizes and prediction quality. The model size can be reduced through clustering by setting the distance threshold. Even with a conservative distance threshold of PBN_{15+D}, it is already possible to significantly reduce the model size with virtually no effect on the prediction quality. If the threshold is further increased, a small decrease in quality can be measured while the model size constantly decreases. The imaginary curve that connects all PBN instances in the plot has an inflection point at PBN_{40+D}. This inflection point seems to be a moderate clustering that leads to a good trade-off between prediction quality and model size.

▌PBN_{40+D} saves 90% of the model size with an F_1 decrease of only 0.03.

If the threshold is even further increased, the clustering generates fewer and fewer patterns because all object usages are aggressively merged. This leads to a very fast decrease in prediction quality. The prediction quality of PBN_{60+D} decreases by 0.08 when compared to PBN_{40+D}. However, the model size is comparable to the minimal model size of the PBN_{100+D} approach. The prediction quality drops significantly if the threshold is increased beyond 0.60. These cases can be ignored, as the model size is already negligible for PBN_{60+D}.

In summary, the distance threshold can be used to control the trade-off between model size and prediction quality depending on the use-case. The maximum prediction quality is provided by BMN_{+D} or from the unclustered PBN_{0+D} instance (there is no measurable difference between them); however, both come with large model sizes. If a



(a) on model size (b) on inference speed

Fig. 10. Effects of increasing number of object usages (button).

small model size is important, then the aggressive clustering of PBN_{60+D} still provides a reasonable prediction quality. For use-cases where both model size and prediction quality are important, PBN_{15+D} or PBN_{40+D} seem to provide good trade-offs. We use these three thresholds in the remaining experiments to create clustered instances, in addition to the two unclustered variants.

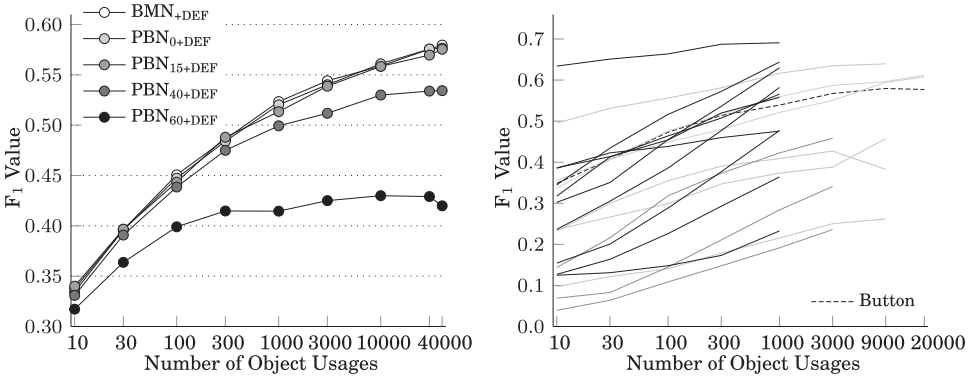
The PBN distance threshold can be used to control the trade-off between model size and prediction quality.

4.4. Scale to Large Input Sizes

We now look at the effect of increasing the number of object usages on the prediction quality, model size, and inference speed. We wanted to investigate two different questions: (1) How do different approaches scale from smaller to bigger input sizes? (2) Is it possible to further increase prediction quality by using bigger datasets? We wanted to extrapolate the results to predict saturation effects, that is, when providing more usages will not increase prediction quality.

The experiment is limited to `org.eclipse.swt.widgets.Button` because it is the only type for which we have more than 40,000 object usages available. A random subset of all available object usages was used to conduct a cross-fold validation. We started with a minimal set of object usages and exponentially increased the input size in all experiments of this section. To get stable results, we ran three iterations for each input size and stored their average result. The previously chosen representative PBN instances and BMN are used in this experiment, all including $\square_{+D}$ context information.

Model Size. The impact that scaling the input size has on the model size is shown in Figure 10(a). The input size is shown on the logarithmic horizontal axis and the resulting model size in Megabytes on the vertical axis. The plot shows that the model size for PBN_{0+D} is generally bigger than BMN_{+D}. However, the model size grows faster with an increasing input size for BMN_{+D}. At an input size of 40,000, both have a comparable model size. We could not evaluate larger input sizes, but the plot shows that the model size of BMN_{+D} grows faster. A non-logarithmic plot of the same values, which we omit for space reasons, shows a linear increase for BMN_{+D} and a logarithmic increase for all PBN instances. If we extrapolate the results to more object usages, we expect that BMN_{+D} has bigger models than PBN_{0+D}. This is even more obvious for clustered instances: the break-even for PBN_{15+D} is reached at ~10,000 usages, and at even less than 3,000 usages for PBN_{40+D} and PBN_{60+D}.



(a) button only (b) types with most object usages (PBN_{0+D})

Fig. 11. Prediction quality for increasing amounts of object usages per type.

▌The model size of PBN scales better than BMN with the input size.

Inference Speed. The impact of the scaled input size on the inference speed is shown in Figure 10(b). The input size is shown on the logarithmic horizontal axis and the resulting inference speed in milliseconds is shown on the vertical axis. The plot shows that inference speed is irrelevant for input sizes less than 10,000. However, starting from 3,000, the slope of the BMN_{+D} plot is much higher. A non-logarithmic plot, which we omit for space reasons, shows a linear increase for BMN and a logarithmic increase for PBN.

▌Inference speed is significantly higher with PBN and scales better than with BMN.

Section 4 introduced time limits for the proposal for inference. The imperceivable delay of 100 milliseconds is hit by BMN_{+D} at about 15,000 usages. If the input size is larger than that, a delay is perceivable in the code completion. By extrapolating the results beyond 40,000 object usages, it becomes obvious that a further increased input size soon exceeds the limit of a second. This would interrupt the developer's thought process and present a disturbance in the workflow.

The inference computation of PBN is significantly faster than this limit. Even the unclustered PBN_{0+D} takes only 15ms to compute the proposals with 40,000 object usages. The inference speed is even higher for the clustered PBN instances. By extrapolating the results, it is obvious that the input size can be significantly increased before any time limit is reached.

▌Input size can be significantly increased before inference speed is an issue for PBN.

Prediction Quality. The last property to analyze was the impact of the scaled input size on the prediction quality. The results are shown in Figure 11. In both plots, the input size is shown on the logarithmic horizontal axis, and the prediction quality denoted by the F_1 measure is shown on the vertical axis.

Figure 11(a) was created with input of `Button` only to compare the results of different approaches. Unsurprisingly, the plot shows that increasing the input size has a positive impact on prediction quality. BMN_{+D} and PBN_{0+D} show equal prediction quality and no difference in scaling behavior: the plot flattens for larger input sizes, even though

it has a logarithmic scale. The interpretation is twofold: First, it is possible to see saturation effects starting at about 1,000 object usages, that is, every tripling of the input size leads to a smaller increase in prediction quality. This is a promising result because for most types there is not so much input available. Second, even though the gain in prediction quality constantly decreases, it is still possible to further increase it by using more input. By extrapolating the results for larger input sizes, it seems that the boundary for `Button` is an F_1 value of 0.6–0.65.

First saturation effects can be observed with an input of 1,000 object usages, and use more input to maximize prediction quality.

The plot also contains the results of the three clustered PBN instances. Even though we have seen in the previous experiments that PBN_{15+D} scales significantly better with input size than the unclustered PBN_{0+D}, the prediction quality is exactly the same. If the clustering is more relaxed, a negative impact on the prediction quality can be seen. For PBN_{40+D}, there seems to be a gap in prediction quality if more than 300 usages are used. For PBN_{60+D}, the prediction quality seems to saturate between 300–1,000 usages. Both results suggest that there might be potential to improve the clustering approach, which we want to address in future work.

Using PBN_{15+D} for large input sizes preserves a reasonable prediction speed and model size, without negative effect on prediction quality.

We further analyzed whether these results for `Button` also hold for other types. Therefore, we conducted the same experiment for all types of SWT for which we could extract at least 1,000 object usages. We used PBN_{0+D} for the comparison. The results are shown in Figure 11(b). The result for `Button`, which has already been shown in previous figures, is shown as the dashed line. Lines that are not continued to the end of the plot belong to types for which we do not have enough object usages. The plot is not meant to present quantitative results of how well models for these types work, but to qualitatively illustrate general trends of saturation effects. The plot shows that recommender systems do not work equally well for all types: Some already start on a high F_1 level, others barely reach an F_1 level of 0.2 with models learned from 3,000 usages. However, all plots roughly point in the same direction, which means that their scaling with the input size is comparable and that the previous findings are also valid for all of them.

Lessons Learned. The experiments have shown that it is possible to increase the prediction quality even further by using more than 40,000 usages as input. However, the number of input values that lead to further improvement grows exponentially. Such large input datasets make the evaluation very time consuming, though, because with an n-fold cross-validation every usage is used as a query once. In total, we had an input dataset of over 190,000 usages. Even for fast code completion configurations which infer the proposals in less than 100ms, computing all queries takes about 5.5 hours. All experiments exercised more than one configuration, including very slow ones that need more than a second for inferring proposals, therefore a complete evaluation run took more than 7 days for some experiments.

We have shown that, for our dataset, the prediction quality is already very close to the expected maximum with an input size of 10,000 to 30,000 usages. Even though we used all available input in our experiments, we postulate that it is enough to use only a subset to get reasonable evaluation results, as long as this subset is large enough. For future evaluations, a faster yet nevertheless valid approach may be to run experiments

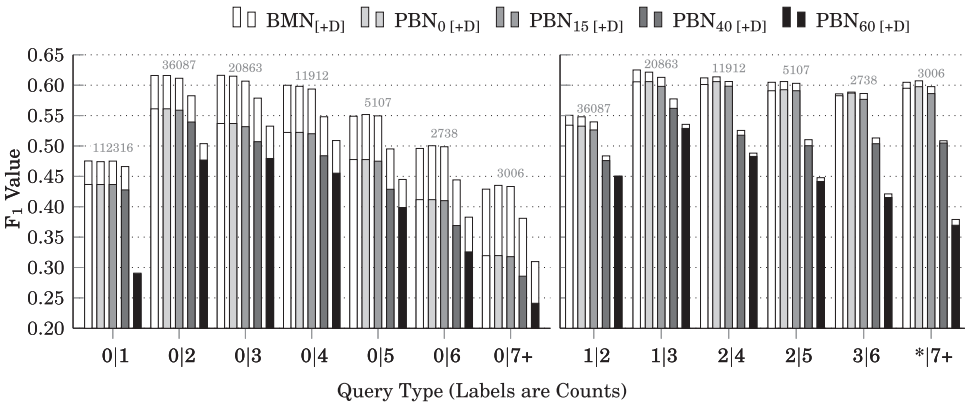


Fig. 12. F_1 values for 0|M and N|M queries (all SWT widgets).

multiple times with randomly selected subsets and to average the results. This would speed-up the experiments significantly without invalidating the results.

4.5. Closer Look at the Prediction Quality

All experiments in prior sections were focussed on very general questions regarding configuration and scaling. We are also interested in a better understanding of the prediction quality of the recommender. This last series of experiments analyzes the impact of the new context information in different scenarios. We identify scenarios that greatly benefit from the added context information, but we also point to examples in which the added context information does not make a difference.

Different Query Types. We compare the results for different types of queries. We use two kinds of queries for the experiment: *No-Calls* queries that do not contain any calls (i.e., 0|M) and *Partial-Calls* queries that preserve about half of the calls from the original usage (i.e., N|M). As motivated in the description of the methodology in Section 4.1, these query types represent two different use-cases.

The plot in Figure 12 shows the results for different recommender instances. The filled bars represent the result for instances that do not consider the additional context information. All bars have a white extension on top that represents the increase in prediction quality gained by considering $\square_{+D}$. The rightmost category in both parts of the plot contains the aggregated results of all queries that contained 7 or more method calls and therefore did not fit into another category (i.e., 0|7+ contains 0|7, 0|8,...; *|7+ contains 3|7, 4|8, 4|9,...). The small grey number over the bar groups denotes the amount of queries that fall into this category.

Let us first consider only the filled bars of the approaches without additional context information. We find that 0|1 seems to be a special type of query for two reasons. First, it occurs about three times as often as 0|2 but the prediction quality is lower. Second, compared to the other query types and to PBN_0, the impact of the clustering on prediction quality is notably different for PBN_{60} (i.e., 0.15 versus ~0.08). All approaches show similar characteristics: they have a jump in prediction quality from 0|1 to 0|2, but the prediction quality constantly decreases for 0|2+ queries. However, the decrease is uniform for all approaches.

Prediction quality stays roughly on the same level across all N|M categories. Only PBN_{60+D} exhibits a decreasing F_1 value for increasing M values. Both plots suggest that calls seem to be a very important piece of context information. Additionally, calls

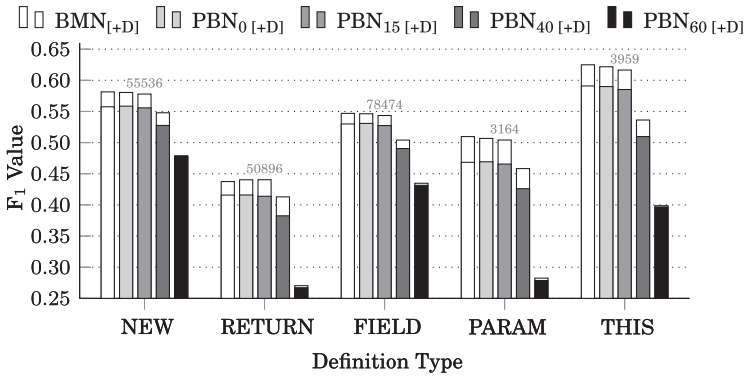


Fig. 13. Results for different definition sites (all SWT widgets).

seem hard to predict when no other calls are given already, and the F_1 value of 0|M is lower across all approaches.

▌Patterns that contain many calls are hard to predict if queries contain no calls.

Now, let us consider the white bar on top of all results, which represents the delta in prediction quality introduced by considering $\square_{+D}$. The plot shows that the additional context information leads to a general increment of prediction quality. However, the increment is so small for some combinations that the white box is invisible.

A special case is the 0|M queries, which show a big delta. Apparently, the additional context information is especially helpful in situations where no calls are included. The delta seems comparable between all other query types and between all approaches, and the differences seem negligible. It only seems to be a bit bigger for 0|7+ queries. The benefit of the additional context information for N|M queries is smaller, but present.

▌The greatest benefit of using $\square_{+D}$ is gained for queries that do not contain any calls.

Different Definitions. To get a better understanding about scenarios in which the recommender systems perform well, we conducted an experiment that separately evaluated the different kinds of definition information discussed in Section 2. We generated queries with the *Partial-Calls* strategy for the available object usages of all SWT types. The resulting F_1 value is the average over all queries.

The results of this experiment are shown in Figure 13. Each bar group in the plot represents a definition kind, denoted in the horizontal axis. Each single bar reflects the results for a specific approach. The filled part of the bar is the result if no additional context information is used, while the white part on top represents the delta introduced by $\square_{+D}$. The small numbers attached to the bars denote how many queries are available for this kind of definition; please note the large differences in these numbers. Compared to the other definitions, there are only few usages available for PARAM and THIS. The vertical axis shows the prediction quality as F_1 value.

In general, it is interesting to see that the prediction quality is very different for the various kinds of definition. The best results are observed for queries on object usages with THIS definition, but the number of queries might not be big enough to decide that. Many queries exist on object usages with NEW and FIELD definitions and both show comparable results, even though queries on object usages with NEW definition perform with higher prediction quality. The prediction quality for queries on object usages with

PARAM definition is slightly lower than this but, again, there is only a small number of usages available for this definition. The worst results are achieved for queries on object usages with RETURN definition, where the prediction quality is ∼0.15 lower than for NEW definition.

All recommenders in this experiment gained similar improvements from additional context information over all definitions. The only exception is the excessively clustered PBN_{60+D} instance, for which the gain was so small that it is not visible in some bars of the plot.

▌The additional context information is equally valuable for all definition kinds.

5. THREATS TO VALIDITY

In the following, we outline some risks and threats to validity that we identified, alongside a discussion of our countermeasures to mitigate them.

The selection of the data used in this work may not generalize. One decision that may be challenged is the use of framework SWT for which to learn the typical usages. It is questionable whether the findings generalize for other frameworks. However, SWT was already used in prior research [Bruch et al. 2009; Zhang et al. 2012] and, by using the same dataset, the results are made comparable. In addition, we analyzed a newer Eclipse version with a bigger code base and observed a significantly higher number of object usages compared to those previous works. The second decision to justify is using the main Eclipse update site as the input source. We claim that this is the best source for SWT usages one can find for the following reasons: Eclipse is a major application that uses SWT and contains a variety of plugins implemented by different developers. Further, the code quality is very high: all code is released and actively used inside the Eclipse IDE, there is no unfinished code, and unmaintained or dead projects are removed from the official update site.

Another threat to the validity of the results is induced by the static analysis, the basis for all object usages used for learning and the evaluation. Potential errors propagate through both phases and would influence the results. To mitigate this issue, we created an extensive test suite for the static analysis. Currently, it consists of 67 automated unit tests that contain code snippets, and we check the analysis results for validity. Several assumptions and design decisions are taken for the analysis (e.g., to take the first appearance of a method in the type hierarchy to define the method context, instead of, for example, using the supermethod). Another decision was to prune exception handling edges from the call graph and therefore ignore all method calls inside catch blocks. These assumptions and decisions influence the results and should be further analyzed in the future. However, the only consequence is that the recommendations are potentially suboptimal. The assumptions do not introduce an unfair bias in the experiment results, so are not a threat in a strict sense.

The evaluation methodology may also pose a threat. As it is based on complete source code, it is unclear in which order calls to methods were originally introduced by the developer. The sequence of method calls, as they appear in the finished source code, might not be the same as the order in which they were added. Not knowing this, it is unclear in N|M experiments which N method calls must be provided as known to be already called. The mitigation technique used is to randomly choose the method calls and generate three random queries for each object usage that should be used for validation. Another mitigation strategy could be to preserve the ordering of the method calls as they were found in the analyzed code, but we think the former is the more conservative assumption. The only real solution would be to use real user data for the validation instead of an artificial evaluation, which is outside of the scope of this article.

6. RELATED WORK

Robillard et al. [2013] provide a comprehensive survey of research on inferring API properties in the last decade (i.e., 2000–2011). We will discuss work closely related to our approach and refer the reader to the survey for a broader view.

The first paper in the area of learning re-use patterns is from Michail [2000] who uses association rule mining to document typical API usage. Li and Zhou [2005] also use association rule mining for PR-Miner. They learn the rules on item-sets of program elements to automatically extract general programming rules. Potential bugs are identified by finding code that violates the learned rules.

DynaMine [Livshits and Zimmermann 2005] uses check-ins extracted from the revision history of a project to learn about calls that are introduced together. Similar to the approach discussed before, the rules are used to detect potential bugs. However, in this case, the rules are checked at runtime instead of in a purely static analysis.

Monperrus et al. [2010] propose an approach to learn from object usages which methods are typically called on a type in specific contexts. On the learned data, they define a strangeness function to score user code. The higher the strangeness score, the more likely the code misses a method call, which might be a bug and should be investigated further. Their strangeness function seems to be a reverse of our distance measure, but it is calculated differently (i.e., by relating the number of exact matches of an object usage to the number of almost exact matches). They evaluate their approach by artificially degrading real code and detecting the created bugs. Additionally, they manually investigate the 19 highest-confidence warnings reported for the user interface part of the Eclipse IDE and report them as potential bugs. Out of these, 8 were already fixed at the time they submitted their approach.

FrUiT is a Framework Understanding Tool integrated into Eclipse [Bruch et al. 2006] that applies association rule mining on the class level. The authors use three kinds of properties to learn the rules for an example class: all method calls existing in that class, the list of extended classes, and the list of overridden methods. The approach is evaluated using three case studies with rules learned for the SWT framework from code shipped together with the Eclipse IDE. The results are promising, but even the authors stated that the algorithm does not scale to large input sizes. Their more recent work, the Best-Matching Neighbor algorithm [Bruch et al. 2009], which learns from existing example code to improve code completion systems, was discussed in detail in Section 3.1. We propose an alternative model, show potential extensions, and compare both models in our experiments. A position paper by the same authors proposes the idea to use graphical models as documentation for typical usage patterns [Bruch and Mezini 2008]. However, the structure of the models was in an early stage and the focus was primarily on documentation instead of code completion.

Zhang et al. [2012] develop the tool Precise to recommend actual parameters to specific calls. They adapt the kNN algorithm [Cover and Hart 2006] to find usages similar to the current context. The parameter call sites we extract could also be used to build a similar parameter recommender. It is also very likely that their approach would benefit from the context information introduced in this article.

Gvero at al. [2013] propose the code completion tool InSynth. In contrast to our approach, it does not require a receiver object as input, but instead the expected type of an expression which should be completed. Knowing the expected type, they search for possible expressions like constructor calls and method calls in reachable APIs and fit available locals as required arguments. They use weights to guide their search but potentially propose all possible solutions, whereas our approach proposes only typical usages which are considered helpful in the current context.

Besides the prior approaches for unordered usage patterns, several approaches infer *ordered* usage patterns. Obviously, capturing sequences in which calls appear in

code requires more sophisticated data structures. Therefore most approaches introduce graph-based structures.

Zhong et al. [2008] propose *Program Rules Graphs* (PRGs). PRGs are directed graphs where vertices denote methods and edges the relationships between those. In their tool, Java Rule Finder, they use an iterative rule inference approach to extract PRGs from API source code, that is, contrary to other approaches they do not require any client code of the API. Similarly, Nguyen et al. [2009] use a graph-based object usage model (Groum) for their tool GrouMiner. However, their graph additionally contains data and temporal dependencies between method calls as well as control structures. GrouMiner is used to automatically document specific protocols of interplay between multiple objects. In a follow-up work, they introduce GraPacc [Nguyen et al. 2012] to use Groums extracted by GrouMiner for code completion.

Buse and Weimer [2012] use dataflow analysis to extract single type usages. They assume that a single type may have multiple common use-cases. They apply clustering to discover and merge related single-object usage patterns and generate human-readable documentations of these patterns.

Other work by Hindle et al. [2012] shows that source code contains regular and predictable utterances, similar to natural languages. They apply n-gram-based techniques on program tokens to learn statistical models of programs. Their experiments prove it is possible to predict potential tokens. Compared to our approach, they are not limited to code completion of method calls. However, this generalization results in a lower prediction quality.

The system proposed by Heinemann et al. [2012] recommends methods to a developer that are relevant in the class currently under development. This is achieved by identifying the loopback of n preceding identifiers that occur in front of a method call. Queries to the system contain the preceding identifiers in front of the cursor. The recommendations are then inferred by matching them against the model. The intentions and knowledge of the developer, expressed in the identifiers, are used to learn the models in this approach, instead of using structural information.

7. FUTURE WORK

This article evaluated different types of context information (i.e., receiver call sites, definition sites, etc.). However, there is other information that could also be used (e.g., the current package name, identifiers of variables, comments inside the analyzed code, etc.). Future work should include more information and analyze the effect on model size, inference speed, and prediction quality.

This article showed that parameter call sites and the enclosing class context do not contribute much to prediction quality. However, this information could be crucial to find the right proposals for some types. Consider a method that takes two parameters of the same type and that copies contents from the one object to the other. In order to distinguish both objects, it is necessary to have the parameter information. It seems that a general decision about which context information are in- or excluded for learning is too coarse grained. Instead, future work should improve the feature selection process and analyze whether it is possible to answer this question on a lower level. As a first step, the importance of all context information should be evaluated per object type. The next step could be selecting the most helpful context information only, for instance, include only some parameter sites and exclude the rest.

Although parameter call site information is not very effective in terms of increasing prediction quality, it could be used to provide a new engine to recommend parameters to method calls. Such an engine was already proposed [Zhang et al. 2012]. Future work could compare both approaches and analyze whether the previous approach could benefit from extended contexts as proposed in this article.

This article introduced a clustering approach for PBN. However, the clustering approach could be replaced by more sophisticated machine learning techniques. For example, the machine learning algorithm could detect and remove outliers in the dataset to further improve prediction quality. Future work could also leverage the fact that there are high correlations between some information to further reduce the model size. For example, if two method calls are always observed together, it is not necessary to include them separately in the model. Merging or removing these correlating information will most likely have a beneficial effect on the prediction quality, because this simplification also removes noise from the data.

The different scenarios and configurations (e.g., clustering thresholds) evaluated in this article provided an overview of the average quality for all SWT widgets. However, the selection of the appropriate thresholds was only based on experiments with a single type because we assumed that it is the same for all types. Future work should analyze this assumption because it might be beneficial to select the threshold per type instead of defining it globally.

Both BMN and PBN assume that the developer can decide in which order completed methods have to be used. Therefore both do not consider the ordering information. We think that this information is important and we want to consider it in future work. However, we feel that the information cannot be meaningfully integrated in a simple call completion recommender because it cannot be considered in separation from control structures. Instead, it seems more promising to extend works on snippet completion to support ordering, like GrouMiner [Nguyen et al. 2009].

The state-of-the-art evaluation methodology for code completion systems uses artificially generated queries. This automatic method is much better than approaches that qualitatively evaluate a small number of manually selected completion scenarios. There is no empirical evidence which shows that artificially generated queries faithfully mimic real code completion events. Ideally, the evaluation should use implicit feedback of developers as ground truth that is collected during real usages of a code completion. An evaluation would then compare the collected data with the proposals of the code completion system. The results can be used to validate the evaluation methodology (i.e., evaluation with artificial queries) or to propose a valid alternative. However, major effort is necessary to collect such a dataset.

All evaluations of this work were based on code completion for the SWT framework. However, the proposed algorithm is applicable to other frameworks, too. By analyzing new frameworks as subjects for the experiments, future work could identify cases in which the approach could be further improved. Additionally, other work already pointed out the necessity of diversity in software engineering research [Nagappan et al. 2013]. We already sketched how this finding could be adopted to recommender systems in software engineering [Proksch et al. 2014]. Future work should validate the representativeness of the results of this work for different datasets.

We have already discussed limitations of the static analysis, such as pruning of exception handling edges. Future work can reduce these limitations and increase the precision of the static analysis. Context information could be extracted that is currently ignored to distinguish usage scenarios that are currently indistinguishable.

8. CONCLUSIONS

This work presented advances in the state of the art in intelligent code completion systems in three ways: (1) We extended the static analysis of the *best-matching neighbor* approach (BMN) and extracted more context information; (2) we introduced a new approach for intelligent code completion called *Pattern-Based Bayesian Network* (PBN), which uses extended context information; and (3) we extended the state-of-the-art methodology for evaluating code completion systems.

The summary of technical contributions in comparison to BMN is as follows. Both BMN and PBN approaches learn typical usage patterns of frameworks from data which is extracted by statically analyzing source-code repositories. Unlike BMN that uses a table of binary values to represent usages of different framework types in client code, PBN encodes the same information as a Bayesian network. A major technical difference is that PBN internally stores floating-point values in multiple conditioned nodes, whereas BMN stores binary values in a table. A key consequence of this difference is that PBN allows to merge different patterns and to denote probabilities—instead of boolean existence—for all context information and method calls. Therefore, a direct mapping between extracted usages and created patterns is no longer necessary. We introduced a clustering approach for PBN that leverages this property and enables to trade off model size for prediction quality. It is not clear how such a clustering could be adopted for BMN because its binary representations do not allow for representing clustered results.

This article makes important contributions to the evaluation methodology of intelligent code completion engines. We argued that, in addition to prediction quality, two other criteria ought to be considered: memory needs for storing extracted models and the inference speed. To get meaningful results, it is also necessary to evaluate how well the results scale with an increasing input size. In the article, we presented an extensive evaluation that uses all the aforesaid criteria to compare both approaches.

We used the additional context information and evaluated the impact. Our results have shown that not all contribute equally to the prediction quality; the definition is the most valuable context information, with an increase in prediction quality of about 0.03. But at the same time, definitions significantly increase the model size. We found that using parameter call sites and the class context does not pay off in terms of model size. The prediction quality increases marginally, but this is disproportionate to the increased model sizes.

We have shown that BMN_{+D} and (unclustered) PBN_{0+D} exhibit very similar prediction quality in all experiments, but each approach has its own advantages and disadvantages. Their model sizes scale differently: the BMN tables are small for small input sizes and the network structure of PBN creates an overhead. However, model sizes of PBN scale better with the input size (logarithmic scaling for PBN, and linear scaling for BMN). For input sizes of less than $\sim$15,000 usages, speed is not an issue for both approaches, even though PBN is already significantly faster than BMN. If the input size gets larger, PBN excels with a very high inference speed. With an input size of 40,000 usages, both approaches have similar model size and prediction quality, but PBN is 10 times faster than BMN. In the code base used for our experiments, we did not observe that many object usages for most of the types. However, these scaling properties might be of relevance for future work when more data is available—and when therefore more object usages are extracted—or when more context information is used.

We have shown that both the model size and inference speed improved significantly for the clustered instances of PBN. It is possible to control the trade-off between model size and prediction quality by configuring the threshold of the clustering. Conservative clustering (PBN_{15+D}) can save $\sim$50% of the model size with negligible impact on the prediction quality. A moderate clustering (PBN_{40+D}) saves $\sim$90% model size with a loss of prediction quality of $\sim$0.03. An aggressive clustering (PBN_{60+D}) comes close to the minimal model size of a purely statistical model, but also exhibits a decreased prediction quality of $\sim$0.1.

In the end, we would like to emphasize that PBN is not bound to a specific machine learning approach. It is an extensible inference engine for intelligent code completion systems. In the future, we hope to see other researchers using it, extending it, or creating networks for it with more sophisticated machine learning techniques.

ACKNOWLEDGMENTS

Special thanks to Andreas Sewe and Sarah Nadi for valuable feedback on this paper.

REFERENCES

Marcel Bruch and Mira Mezini. 2008. Improving code recommender systems using Boolean factor analysis and graphical models. In *Proceedings of the International Workshop on Recommendation Systems for Software Engineering (RSSE'08)*. ACM Press, New York.

Marcel Bruch, Martin Monperrus, and Mira Mezini. 2009. Learning from examples to improve code completion systems. In *Proceedings of the 7th Joint Meeting of the European Software Engineering Conference and the ACM SIGSOFT Symposium on The Foundations of Software Engineering (ESEC/FSE'09)*. ACM Press, New York, 213–222.

Marcel Bruch, Thorsten Schafer, and Mira Mezini. 2006. FrUiT: IDE support for framework understanding. In *Proceedings of the OOPSLA Workshop on Eclipse Technology eXchange (Eclipse'06)*. ACM Press, New York, 55–59.

Raymond P. L. Buse and Westley Weimer. 2012. Synthesizing API usage examples. In *Proceedings of the International Conference on Software Engineering (ICSE'12)*. IEEE Press, 782–792.

Olivier Chapelle and Ya Zhang. 2009. A dynamic Bayesian network click model for Web search ranking. In *Proceedings of the 18th International Conference on World Wide Web (WWW'09)*. ACM Press, New York, 1–10.

Stanley F. Chen and Joshua Goodman. 1996. An empirical study of smoothing techniques for language modeling. In *Proceedings of the 34th Annual Meeting on Association for Computational Linguistics (ACL'96)*. Association for Computational Linguistics, 310–318.

Thomas Cover and Peter Hart. 2006. Nearest neighbor pattern classification. *IEEE Trans. Inf. Theory* 13, 1, 21–27.

Tihomir Gvero, Viktor Kuncak, Ivan Kuraj, and Ruzica Piskac. 2013. Complete completion using types and weights. In *Proceedings of the 34th Conference on Programming Language Design and Implementation (PLDI'13)*. ACM Press, New York, 27–38.

Lars Heinemann, Veronika Bauer, Markus Herrmannsdoerfer, and Benjamin Hummel. 2012. Identifier-based context-dependent API method recommendation. In *Proceedings of the 16th European Conference on Software Maintenance and Reengineering (CSMR'12)*. IEEE, 31–40.

Abram Hindle, Earl T. Barr, Zhendong Su, Mark Gabel, and Premkumar Devanbu. 2012. On the naturalness of software. In *Proceedings of the International Conference on Software Engineering (ICSE'12)*. IEEE Press, 837–847.

Zhenmin Li and Yuanyuan Zhou. 2005. PR-Miner: Automatically extracting implicit programming rules and detecting violations in large software code. In *Proceedings of the 10th European Software Engineering Conference Held Jointly with the 13th International Symposium on The Foundations of Software Engineering (ESEC/FSE'05)*. ACM Press, New York, 306–315.

Benjamin Livshits and Thomas Zimmermann. 2005. DynaMine: Finding common error patterns by mining software revision histories. In *Proceedings of the 10th European Software Engineering Conference Held Jointly with the 13th International Symposium on The Foundations of Software Engineering (ESEC/FSE'05)*. ACM Press, New York, 296–305.

Robert Cecil Martin. 2003. *Agile Software Development: Principles, Patterns, and Practices*. Prentice Hall, PTR, Upper Saddle River, NJ.

Andrew Mccallum, Kamal Nigam, and Lyle H. Ungar. 2000. Efficient clustering of high-dimensional data sets with application to reference matching. In *Proceedings of the 6th International Conference on Knowledge Discovery and Data Mining (KDD'00)*. ACM Press, New York, 169–178.

Amir Michail. 2000. Data mining library reuse patterns using generalized association rules. In *Proceedings of the 22nd International Conference on Software Engineering (ICSE'00)*. ACM Press, New York, 167–176.

Martin Monperrus, Marcel Bruch, and Mira Mezini. 2010. Detecting missing method calls in object-oriented software. In *Proceedings of the 24th European Conference on Object-Oriented Programming (ECOOP'10)*. 2–25.

Meiyappan Nagappan, Thomas Zimmermann, and Christian Bird. 2013. Diversity in software engineering research. In *Proceedings of the 9th Joint Meeting of the European Software Engineering Conference and the Symposium on The Foundations of Software Engineering (ESEC/FSE'13)*. ACM Press, New York, 466–476.

Anh Tuan Nguyen, Tung Thanh Nguyen, Hoan Anh Nguyen, Ahmed Tamrawi, Hung Viet Nguyen, Jafar Al-Kofahi, and Tien N. Nguyen. 2012. Graph-based pattern-oriented, context-sensitive source code

completion. In *Proceedings of the International Conference on Software Engineering (ICSE'12)*. IEEE Press, 69–79.

Tung Thanh Nguyen, Hoan Anh Nguyen, Nam H. Pham, Jafar M. Al-Kofahi, and Tien N. Nguyen. 2009. Graph-based mining of multiple object usage patterns. In *Proceedings of the 7th Joint Meeting of the European Software Engineering Conference and the Symposium on The Foundations of Software Engineering (ESEC/FSE'09)*. ACM Press, New York, 383–392.

Jakob Nielsen. 1994. *Usability Engineering*. Elsevier, Amsterdam.

Sebastian Proksch, Sven Amann, and Mira Mezini. 2014. Towards standardized evaluation of developer-assistance tools. In *Proceedings of the 4th International Workshop on Recommendation Systems for Software Engineering (RSSE'14)*. ACM Press, New York, 14–18.

Irina Rish. 2001. An empirical study of the naive Bayes classifier. In *Proceedings of the Workshop on Empirical Methods in Artificial Intelligence (IJCAI'01)*. IBM, New York, 41–46.

Martin P. Robillard, Eric Bodden, David Kawrykow, Mira Mezini, and Tristan Ratchford. 2013. Automated API property inference techniques. *IEEE Trans. Softw. Engin.* 39, 5, 613–637.

J. Michael Schultz and Mark Liberman. 1999. Topic detection and tracking using idf-weighted cosine coefficient. In *Proceedings of the DARPA Broadcast News Workshop*. Morgan Kaufmann Publishers, 189–192.

Olin Shivers. 1988. Control flow analysis in scheme. In *Proceedings of the Conference on Programming Language Design and Implementation (PLDI'88)*. ACM Press, New York, 164–174.

Olin Shivers. 1991a. Data-flow analysis and type recovery in scheme. In *Topics in Advanced Language Implementation*. The MIT Press, Cambridge, MA.

Olin Shivers. 1991b. The semantics of scheme control-flow analysis. In *Proceedings of the ACM SIGPLAN Symposium on Partial Evaluation and Semantics-Based Program Manipulation (PEPM'91)*. ACM Press, New York, 190–198.

Alexander Strehl, Joydeep Ghosh, and Raymond Mooney. 2000. Impact of similarity measures on web-page clustering. In *Proceedings of the Workshop on Artificial Intelligence for Web Search (AAAI'00)*. 58–64.

Xiwang Yang, Yang Guo, and Yong Liu. 2011. Bayesian-inference based recommendation in online social networks. In *Proceedings of the INFOCOM Conference (INFOCOM'11)*. 551–555.

Cheng Zhang, Juyuan Yang, Yi Zhang, Jing Fan, Xin Zhang, Jianjun Zhao, and Peizhao Ou. 2012. Automatic parameter recommendation for practical API usage. In *Proceedings of the International Conference on Software Engineering (ICSE'12)*. IEEE Press, 826–836.

Hao Zhong, Lu Zhang, and Hong Mei. 2008. Inferring specifications of object oriented APIs from API source code. In *Proceedings of the 15th Asia-Pacific Software Engineering Conference (APSEC'08)*. IEEE Computer Society, 221–228.

Received February 2014; revised January 2015; accepted March 2015