Automated Mobile App Test Script Intent Generation via Image and Code Understanding

Shengcheng Yu, Chunrong Fang∗, Tongyu Li, Mingzhe Du, Xuan Li, Jing Zhang, Yexiao Yun, Xu Wang, Zhenyu Chen
State Key Laboratory for Novel Software Technology, Nanjing University, Nanjing, China
fangchunrong@nju.edu.cn

ABSTRACT
Testing is the most direct and effective technique to ensure software quality. However, it is a burden for developers to understand the poorly-commented tests, which are common in industry environment projects. Mobile applications (app) are GUI-intensive and event-driven, so test scripts focusing on GUI interactions play a more important role in mobile app testing besides the test cases for the source code. Therefore, more attention should be paid to the user interactions and the corresponding user event responses. However, test scripts are loosely linked to apps under test (AUT) based on widget selectors, making it hard to map the operations to the functionality code of AUT. In such a situation, code understanding (i.e., comment generation, code summarization) algorithms may lose efficacy if directly applied to mobile app test scripts.

In this paper, we present a novel approach, namely TestIntent, to infer the intent of mobile app test scripts, and TestIntent combines the GUI image understanding technologies and code understanding technologies. The test script is transferred into an operation sequence model. For each operation of the operation sequence, TestIntent extracts the operated widget selector1 and link the selector to the UI layout structure, which stores the detailed information of the widgets, including coordinates, type, etc. With code understanding technologies, TestIntent can locate the response methods in the app source code. Afterwards, NLP algorithms are adopted to understand the code and generate natural language descriptions. Also, TestIntent can locate widgets on the app GUI images. Then, TestIntent can understand the widget intent with an encoder-decoder model. With the combination of the results from GUI and code understanding, TestIntent generates the test intents in natural language format. We also conduct an empirical experiment, and the results prove the outstanding performance of TestIntent. A user study also declares that TestIntent can save developers’ time to understand test scripts.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

Conference 2021, 2021,
© 2021 Association for Computing Machinery.
ACM ISBN 978-x-xxxx-xxxx-x/YY/MM . . $15.00
https://doi.org/10.1145/nnnnnnn.nnmm

CCS CONCEPTS
• Software and its engineering → Software testing and debugging.

KEYWORDS
Mobile App Testing, GUI Understanding, Code Understanding

ACM Reference Format:
Shengcheng Yu, Chunrong Fang∗, Tongyu Li, Mingzhe Du, Xuan Li, Jing Zhang, Yexiao Yun, Xu Wang, Zhenyu Chen. 2021. Automated Mobile App Test Script Intent Generation via Image and Code Understanding. In Conference 2021. ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/nnnnnnn.nnmm

1 INTRODUCTION
With the rapid development of mobile internet and smart devices, mobile apps have had a pivotal position on a large number of aspects of the whole society and common people’s daily lives. Therefore, app quality assurance has become an important topic for both academia and industry. During the development, testing is the most widely-used and most effective way for app quality assurance [1]. For most software artifacts, developers write unit test cases to test the software functionality. However, mobile apps are GUI-intensive and event-driven. Test cases cannot fully explore the AUT or traverse all the functionalities, so developing GUI test scripts based on automated frameworks or techniques, i.e., Appium, is a more practical approach for the mobile app testing scenario. Test scripts can faithfully simulate human user events, and are reusable in regression testing. Developers do not have to develop brand new test scripts after app version iteration for the original functionalities.

However, during mobile app maintenance, developers spend a large amount of time understanding the test scripts on the target functionality of the specific AUT. According to Xia et al. [2], 59% time are spent on programming comprehension activities. Study of Sridhara et al. [3] shows that good comments can greatly improve comprehension efficiency with the aid of natural language information. However, despite the significance of code comments, most existing or under-developing test scripts are poorly commented. It is difficult to require developers to write easy-to-understand comments manually, and it is even harder work to write appropriate comments for large-scale existing test scripts. It is especially difficult for successors to fully understand what functionalities are tested in the test scripts with the iteration of the developers who are in command of the test scripts.

1http://appium.io/docs/en/commands/element/find-elements/index.html#selector-strategies
Therefore, it is important to have automated approaches to assist understand the target functionalities and test goals of test scripts, which we refer to as test script intents.

Considering the GUI-intensive and event-driven features of mobile apps, we propose a novel approach, TestIntent, to infer the test script intents and generate natural language descriptions. Targeted at the GUI-intensive feature, we dump the dynamic UI layout structure and extract the target widget screenshot. Then we feed the widget screenshot into a pre-trained encoder-decoder model, consisting of a convolutional neural network (CNN) and a recurrent neural network (RNN), which is used to infer the widget intent. Focused on the event-driven feature, we use code understanding technologies to extract the response method of the operated widget in the test script, and then we use an RNN model to learn code features and obtain the code functionality intent. With the combination of the results from GUI image and code understanding, TestIntent can generate the test intent descriptions in natural language, which can address the missing comment problem and help app developers better understand test script intents.

Specifically, TestIntent is composed of two parts, GUIIntent and CodeIntent. For each test script, we model it as an operation sequence, which is linked to some specific intent, e.g., business logic, functionality traversal, etc. Each operation sequence is composed of a sequence of operations, including clicking actions, test input actions, long-press actions, and so on. In TestIntent, we gather the test intents of each operation separately to acquire the operation intents. Afterwards, we aggregate the test intents of all the operations and get the intent of the whole test script.

GUIIntent includes the image understanding and widget analysis. With the development of computer vision (CV) technologies, much research has been done to analyze the app screenshot. Mobile apps are GUI-intensive software, so much information can be obtained from the GUI images. Based on such a concept, we record the screenshot of each operation. As proposed in [4], the GUI screenshots should not be considered simple images but rich information collections of widgets. Therefore, we use CV algorithms to extract all the widgets from the screenshots, and with the help of the UI layout files, we can find abundant information about the target widget of the operation. With the widget image of the operation, we can infer the widget intents by a pre-trained DL model, which is trained by a large-scale self-constructed widget image dataset.

CodeIntent contains the response method localization and slicing, semantics inferring, and code intent generation. With the widget identifier (ID), we can locate the response method snippets from the source code by template matching. With such one or several response code snippets, we feed them into a pre-trained RNN model, which can extract code features and generate the code intent descriptions in natural language format for each operation.

With the results from GUIIntent and CodeIntent, TestIntent merges them and make some post-processing, including text deduplication. Till then, TestIntent can effectively generate test intent descriptions for the given mobile app test scripts. We also design and implement a tool to evaluate the effectiveness of TestIntent. Results show that TestIntent can effectively generate test script intents for the reference of app developers and can significantly save their time to review and understand the test script intents.

In this paper, we declare the following contributions:

- A novel tool, TestIntent, utilizing GUI image and code understanding, is introduced to fully explore and infer the code, textual, and image information, and then generate test script intent descriptions in natural language.
- A novel algorithm combining GUI image and code understanding is proposed to map operations in test scripts to the corresponding response methods in source code.
- The results of an experiment attached with a user study show the effectiveness of TestIntent and the capability to alleviate developers’ burden to understand test scripts.

The rest of this paper is organized as follows. In Section 2, we present the existing challenges. Section 3 illustrates the framework and technologies of TestIntent in detail. We have also conducted an empirical experiment on the proposed TestIntent to evaluate the effectiveness in Section 4. Some related work of this paper is introduced in Section 5. Finally, we make a conclusion in Section 6. A supplementary package can be seen on https://sites.google.com/view/testintent.

2 CHALLENGE

2.1 Script Intent Understanding

As described in many researches that are designed to automatically generate code comments for source code, developers hardly write complete and generally comprehensible code comments [5] [6] [7] [8] [9] [10]. The above research may behave well on code comment generation tasks as shown in the corresponding papers, but situations are different for GUI test scripts of mobile apps. For common projects, the business logic is self-harmonious, while for mobile app test scripts, the business logic heavily depends on the AUT. To fully and appropriately infer and generate test script intents, it is necessary to find the link between operations and the corresponding response information.

We conduct a preliminary study on such a situation. We define a metric named “comment-code ratio”, which is the ratio of line of comments and line of code, and can be expressed as ratio = LOC_comments / LOC_code. If ratio is higher than 0.3, we hold that the test is well commented. If ratio is over 0, we hold that the test is commented.

We investigate the apps from an open dataset AndroZooOpen2. From the dataset, we randomly choose 100 projects with tests and review the test part. The results show that only 1% of tests are well commented. For the rest, 33% have some fragmentary comments showing the test intents. That is to say, most (66%) of the tests have no comments, leading to an obstacle for test understanding. This survey and the judgment of the completeness of test code is conducted and verified by two senior software testing experts. The results show that a large majority of app developers are not used to writing comments for the test part of the project.

To further illustrate the severity of such a problem, we have also investigated the comment situation of mobile app test scripts. We collect a dataset of 100 test scripts for 5 different mobile apps from a real-life industrial mobile app testing platform. The test scripts are developed by 81 different testers. The testers are skillful test engineers with at least 2 years of mobile app testing experience.

2http://knowledgezoo.xyz/AndroZooOpen/
3Some of the testers write more than one test script on different apps, and none of the testers writes more than one test script for the same app.
With the collected test scripts, we require the 2 recruited mobile app testing experts to estimate the comprehensibility of the test scripts according to the code comment amount and completeness. The results show that 64% of the test scripts have no comments to illustrate the test script intents or operation intents. 24% of the test scripts have few comments that simply help the test script developers themselves to understand the intents, while the comments are hard for other people to understand. Only 12% of the test scripts are with complete comments.

Thus, understanding test script intent is a challenging task for different app developers. Specifically, for the scripts supported by the most widely used framework, Appium\(^1\), widgets are located by IDs or XPaths, so during the understanding of test scripts, developers have to locate the business logic methods with such selectors manually. It is a hard and time-consuming task to locate the business logic methods one by one and assemble the intents of the whole test scripts.

Faced with such a tough situation, we try to simulate and automate the manual process to understand the test script intents. For each operation in the operation sequence, we locate the business logic methods, or response methods, with the selectors, i.e., IDs or XPaths. Afterwards, TestIntent slices code snippets and use deep learning (DL) models to analyze code snippet descriptions in natural language.

### 2.2 Code Snippet Localization and Analysis

The accurate and complete localization is another spiny problem. According to our investigation, all the widgets in the test scripts are located by a unique selector, which is an ID or an XPath. For widgets located by IDs, the response methods can be located because the methods are bound to the widgets explicitly with the ID. However, for widgets located by the XPath, the response method localization is more complicated. Due to the event-driven feature, some widgets are dynamically generated, and the response methods are also dynamically bound to the widgets. Therefore, some implicit underlying mechanisms of the Android platform helps the binding, and it is hardly possible to manually locate the corresponding response methods.

According to our study on the test scripts, we find that due to not strictly following the coding criteria, more than 50% widgets are located by XPath in the test scripts, lacking the ID labeled. Among the widgets located by XPath, about 77% are located with the hierarchy, and the rest are located with the XML attribute content-desc, which shows the visible texts of the widgets.

One vivid example of implicit response method binding is the Adapter: the example is shown in Code Snippet 1. This operation is from an app named iWeather. Users click on the search box and input the city name, and the app will post a request and return the data. The returned data is adapted with the CityAdapter. The recyclerview utilizes the adapter to render the data to the GUI. Such a process is dynamic, and the list items are dynamically generated, so it is hard to bind the response method statically.

**Code Snippet 1: Example for Implicit Response Method Binding**

```
1mAdapter = new CityAdapter(this, mList);
2mAdapter.setOnItemClickListener(new CityAdapter.OnItemClickListener() {
3    @Override
4    public void onItemClick(View v, ImageView favo, int position) {
5        LocationEntity entity = mList.get(position);
6        final FavoriteEntity favoriteEntity = new FavoriteEntity(entity.getId(),
7            entity.getName(), entity.getPath());
8        mViewModel.insertFavorite(favoriteEntity);
9        entity.setFavorite(true);
10        favo setSelected(true);
11    }
12});
13recyclerView.setLayoutManager(new LinearLayoutManager(this));
14recyclerView.setAdapter(mAdapter);
```

### 3 APPROACH

In this section, we illustrate the general framework of TestIntent. TestIntent is composed of 2 parts, the GUIIntent and the CodeIntent. The results from the 2 parts are merged to get the final test script intents. Figure 1 presents the general framework of TestIntent. One thing to mention is that the illustrations in the following 2 subsections (Section 3.2 and Section 3.3) are describing the processing of each operation.

#### 3.1 Operation Sequence Model

TestIntent is targeted at mobile app test scripts based on Appium. Therefore, each operation (Op) in the operation sequence are driven by the AppiumDriver. the driver object invokes the findViewByIdById method or the findElementByXPath method. Therefore, we use string matching to extract all the operations and form the operation sequence model. The operation sequence model (OpSeq) is as follows:

\[
\text{OpSeq} = \{O_{p1}, O_{p2}, O_{p3},...,O_{pn}\}
\]

where the \(O_{pi}\) is a 4-dimension tuple:

\[
O_{pi} = \{\text{type}, \text{selector}, \text{operation}, \text{content}\}
\]

The type determines whether the widget is located by ID or by XPath. The selector is the concrete locating selectors of the widget, i.e., “com.app.calendar:id/switcher_layout”, “/hierarchy/LinearLayout[2]/Button[2]”. The operation refers to the concrete operation, i.e., click(), sendKeys(). The operation are not applicable for all types of operations, and only some of the operations should be assigned with some contents. For example, the sendKeys() method should be assigned with a string, like for the username field, the method should be invoked as sendKeys(“admin”).

#### 3.2 GUI Intent

GUIIntent is mainly targeted at the widgets located by XPath. As described in Section 2.2, it is hardly possible to find the binding response methods for widgets located by XPath. However, XPaths are formed by the hierarchy structure, so it is easy to locate the widget from the UI layout files. Furthermore, the UI layout files would

\(^1\)http://appium.io/
contain rich information about the widget intent. Besides, mobile apps are GUI-intensive, so we can infer the widget intents from the widget screenshots with image understanding technologies. So, GUIIntent is composed of Textual Information Retrieval and Widget Image Understanding.

3.2.1 Textual Information Retrieval. For current mobile apps, textual information extracted from the graphical user interface (GUI) is rich, and such textual information can provide accurate information of the widget intents. Typical examples are easy to find like the “Submit” button, “Cancel” button, “Username” text box, “Password” text box, etc. Therefore, we hold that such textual information is valuable for us to infer the test script intents. However, as discussed above, the textual information of some widgets cannot be obtained from the original UI layout files because some widgets are dynamically generated. Therefore, TestIntent has to dump the UI layout files at runtime. With the help of UIAutomator, we can manually dump the runtime UI layout files easily. However, such a process is hard to automate. To solve the problem, we design a driver wrapper for the AppiumDriver and add the functionality to dump useful information, including:

- **App Screenshot.** App screenshots can be used to extract existing textual information from the GUI level.
- **Widget Screenshot.** Widget screenshots may have implied information about the widgets.
- **Activity UI Layout File.** Activity UI layout files can be used to extract textual information that is not shown on the GUI level (i.e., widget name, content description, etc.), which can also help infer and generate the widget intents.

With the designed driver wrapper for the AppiumDriver, TestIntent realizes the automated dump of the required files for each operation during runtime.

The process of App Screenshot and the Widget Screenshot will be presented in detail in Section 3.2.2. The Activity UI Layout File is used in the combination of XPaths to locate the target widgets and obtain the textual information. Widgets located by XPaths are divided into 2 categories. The first category is in the format of Formula 3. For such a type, we only need to use regular expression match to match the widgetType field and the content-desc field.

\[
\text{//<widgetType>[@content-desc="<text>"]} \quad (3)
\]

\[
\text{/hierarchy/<viewType>/.../}
\text{<viewType>[i]/.../<viewType>} \quad (4)
\]

The second type of widgets located by XPath is on the basis of XML hierarchy structure. Such XPaths are in the format of Formula 4. TestIntent split the XPath by slashes. Widgets without index indicate that such a widget type can be uniquely determined under the former widget. Widgets with index indicate that such widgets cannot be uniquely determined by type, so the numerical order is needed.

The widget elements have many different attributes. After the target widget is determined, we extract the intent-related attributes, including text and content-desc. However, there are some textual information that cannot be acquired from the runtime UI layout files. Therefore, we utilize CV technologies to further process the app screenshots. The specific technology we adopt is optical character recognition (OCR) technologies, which can not only recognize the texts on the screenshot but also is capable of locating the text coordinates. From the runtime UI layout files, we can also acquire the location of the target widget. We match the OCR results and the widget coordinates from the runtime UI layout files and obtain the GUI-level textual information. Finally, we combine the textual information both from runtime UI layout files and GUI level recognition results to generate the intents of the target widgets.

3.2.2 Widget Image Understanding. Some widgets attached with explicit textual information can be easily processed with UI layout files and OCR technologies on app screenshots as illustrated in Section 3.2.1. However, some widgets are not attached with explicit textual information. For example, a magnifier icon always refers to the “search” functionality, three points refer to the “more” menu, etc. To understand the widgets without textual information and generate captions for the input images, we construct an “Encoder-Decoder” structure deep learning model. Our model is developed on the basis of [12], and the general model framework is shown in Figure 2.

The encoder part encodes the image input and the caption texts, respectively, which is the widget feature extractor and the sequence feature processor.
The widget feature extractor is designed to extract the visual features from the input widget images. We use a convolutional neural network (CNN) to extract the image features, which is widely used to process images and extract features. The CNN model contains 2 different types of layers to extract the image features, the convolutional layer, and the pooling layer. For a common CNN model used to execute a classification task, the output is a vector of probabilities that the image belongs to each preset type. However, our goal is to extract the image feature for further processing, so we cut the last layer and directly output the feature vector, which is a 256-dimension vector for each input widget image.

For the text input, we use a sequence feature processor to extract the features. The initial sequence is a start token, <STARTSEQ>. The sequence is fed into an embedding layer to encode the natural language into vectors. The advantages of embedding over one-hot encoding are that 1) one-hot encoding is quite sparse for a large corpus, which is a waste of computation resources; 2) embedding considers the semantics of the texts. Then, the embedded words are fed into an LSTM model [13] to parse the embedded tests into a 256-dimension vector.

After obtaining the 2 feature vectors of widgets images and current sequences, we concatenate the vectors and get a 512-dimension feature vector. The feature vector is fed into the fully connected layer to further decode the feature. The intermediate result vector is fed into a SoftMax layer to predict the next word of the widget image caption. The output of the SoftMax layer is an output probability vector and can be mapped to a single word in the corpus, which is the current result in Figure 2. The current result will be concatenated to the previous result sequence, and the prediction process will be repeated. The end flag is the <ENDSEQ>.

The model is trained on the basis of a large-scale widget image dataset we construct. The dataset contains 2,000 different widget images attached with intent captions. Some examples can be seen in Figure 3. The dataset is divided according to the conventional ratio, 7:2:1, into the training set, the validation set, and the test set.

### 3.3 Code Intent

For the widgets located by ID, we can find the binding response methods and infer the corresponding intents. With the ID obtained from the test scripts, we find the corresponding response methods, and we feed the code snippets into an RNN model to acquire the test intents in the form of natural language. **CODEINTENT** is composed of **Response Method Localization and Slicing** and **Code Intent Generation**.

#### 3.3.1 Response Method Localization and Slicing

The response method localization and slicing is a significant part of **TestIntent**. For operations located by ID, **TestIntent** has a global search and matching for the target IDs. After obtaining the source code files containing the target IDs, **TestIntent** uses the template matching to execute the localization of the response method. According to our study on the Android API, we have summarized 5 different templates that can cover the overwhelming majority of response methods in real-world Android apps.

**Code Snippet 2: Example for Switch Statement Template**

```java
1 case R.id.action_pin_recipe_to_widget:
2     pinRecipeToAppWidget();
3     return true;
```

The first template is in the form of the switch statements. An example is in Code Snippet 2. In such a template, the ID is used as the condition to trigger different response methods.

**Code Snippet 3: Example for If-Else Statement Template**

```java
1 if(item.getItemId() == R.id.action_settings) {
2     startActivity(new Intent(this, SettingsActivity.class));
3 }
```

The second template is in the form of if-else statements (Code Snippet 3). Similar to the first one, the ID is used as the judging condition to trigger different response methods.

**Code Snippet 4: Example for ID Binding Template**
AST is a 6-dimension tuple:

1. The third template is in the form of ID binding (Code Snippet 4). Specifically, the ID is bound to a widget object. There are 2 sub-types. For the first sub-type, the ID acts as a parameter of the findViewById() method, and for the second sub-type, the ID acts as a parameter of a @BindView annotation label, and is assigned to a member variable.

Code Snippet 5: Example for @OnClick Annotation Template

```java
@OnClick(R.id.fab_search)
void fabSearch()
```

2. The fourth template is in the form of @OnClick annotation (Code Snippet 5). The ID is a parameter for the @OnClick label, and the annotation label is assigned to a response method, which corresponds to the widget.

Code Snippet 6: Example for Layout File Attribute Declaration Template

```xml
<Button
    android:id="@+id/nextButton"
    android:onClick="onNext"
    android:text="@string/next"
/>
```

3. The last template is in the form of the layout file attribute declaration (Code Snippet 6). This template is the only one that is matched by the UI layout files. In the attributes of the widget, the android:onClick attribute explicitly shows the response methods.

For the aforementioned 5 templates, we rank them according to their priority, and the priority is determined by their appearing frequency according to our survey mentioned in Section 2.2. Such a priority helps reduce the time required for the response method search and template matching. For example, as is shown in Code Snippet 7 for the app named iWeather, the response method can be located both by template ➍ and by template ❼. However, if we use template ➍, we need a further process to eliminate the influence of another ID. If we use template ❼, another ID will not be considered.

Code Snippet 7: Code Template Prioritization

```java
@OnClick((R.id.fab_search, R.id.fab_region))
public void onClick(View view){
    fab.collapse();
    if (view.getId() == R.id.fab_search) {
        Intent intent = new Intent(this,
            SearchActivity.class);
        startActivity(intent);
    } else if (view.getId() == R.id.fab_region) {
        Intent intent = new Intent(this,
            RegionActivity.class);
        startActivity(intent);
    }
}
```

After TestIntent obtains the response, code intent generation may still encounter problems. For example, in Code Snippet 2, the widget ID is bound to an encapsulated method. This can lead to information insufficiency and invalidate the code intent generation algorithm. Therefore, we introduce a nested search to complement the information. Specifically, we locate the method body and replace the method name with the located method body.

3.3.2 Code Intent Generation. With the code snippets of the response methods, we use another ‘Encoder-Decoder’ structure deep learning model to understand the code snippet and generate the code intention. Our model is based on the code2seq model proposed by Alon et al. [14]. In natural language processing tasks, the input of the model is the natural language fragments. However, for code snippet input, texts cannot be directly processed due to the special semantics and syntax. As used in many program understanding models like [15] [14], code snippets are transferred into abstract syntax trees (AST). Then, the AST paths are fed into the encoder-decoder models to generate code intents.

**AST Extraction.** AST is a 6-dimension tuple:

\[
AST = \langle N, T, X, s, \delta, v \rangle
\]

where the \(N\) is the non-leaf node set; \(T\) is the leaf node set; \(X\) is the leaf node value set; \(s\) is the root node; \(\delta\) is the map from \(N\) to \(N \cup T\), which means the relationship of father nodes and the corresponding son nodes, and \(v\) is the map from \(T\) to \(X\), which binds each leaf node with the specific value.

A set of AST paths can be extracted from one AST. The first and the last node of each AST path are terminals, and the values are tokens in the code. According to [16] and [17], we split the two nodes into subtokens.

**Code Intent Generation Model.** The AST Extraction process is a processing of the code snippet transferring. Afterwards, the AST paths are fed into the code intent generation model. First, the paths are encoded with a bi-directional LSTM model to a 128-vector. Several path vectors are merged with an average calculation. Then, the vector is fed into the decoder. We add an attention mechanism [18] to the decoder. The decoder decodes the extracted AST path vector into a result sequence, representing the code snippet intent.

3.4 Intent Aggregation

With the intent of each operation of the operation sequence is acquired, we aggregate them to get the final test intent of the whole operation sequence. The output is a highly comprehensible report that presents the test intent of the whole operation sequence and each operation.

We also formally describe the workflow of TestIntent generation process in 1.?? The input is the Appium based mobile app test script, and the output is a report presenting the test intents. The first step is to formalize the test script into an operation sequence (Line 1), consisting of a series of operations, and then the following steps are processed on each operation. If the operation is located by XPath, we invoke the GUITest (Line 4-9) including Textual Information Retrieval (Line 7) and Widget Image Understanding (Line 5-6). If the operation is located by ID (Line
3.5 Implementation

TestIntent involves 2 deep learning models, and in this section, we give a detailed explanation of the concrete implementation of the models.

3.5.1 Widget Image Understanding Model. The widget image understanding model is composed of two encoders and a decoder. The encoder for widget images we use is the VGG-16 model [19]. The input image size is (244, 244, 3). The model is composed of a series of convolutional layers, pooling layers, and fully-connected layers. The last layer of the original model is cut, and the last but one layer is taken as the output layer.

3.5.2 Code Intent Generation Model. The code intent generation model is also in the form of the “encoder-decoder” structure. For the model, we use sparse_softmax_cross_entropy as the loss function. The optimization method is the Nesterov momentum method. We train the model for 3,000 epochs, and the batch size is 512. The corpus size for generating code snippet intent is 27,000. The AST paths need a threshold to limit the number, and we set the threshold as 9, which means one AST path contains no more than 9 nodes. The original code2seq model is trained with 9,500 java projects. In order to better fit our scenario, we add 100 more mobile app projects from the AndroZooOpen dataset. The original model is a console application, and we encapsulate the model into a callable method that returns the result string. The model loading process is invoked in parallel.

4 EXPERIMENT

In this section, we present the empirical evaluation of TestIntent and the corresponding user study.

4.1 Experimental Setup

4.1.1 Research Questions. We set 3 research questions (RQ), respectively evaluate the mapping effectiveness, the intent generation effectiveness, and the user experience.

- **RQ1: (TestIntent Effectiveness)** How effective can TestIntent generate natural language test intents?
- **RQ2: (Mapping Effectiveness)** How effective can TestIntent map the operations of the operation sequence to the response code or GUI information?
- **RQ3: (User Experience)** How much can TestIntent improve the developers’ efficiency to understand scripts?

4.1.2 Data Preparation. In this experiment, we randomly select 20 mobile apps (in Table 1) from open dataset AndroZooOpen [11]. The advantage of this dataset is that the apps are open-sourced, and we can obtain the source code for code understanding and then infer the test intents. The apps are of different app store categories, which can prove the generalizability of TestIntent. We have the following selecting criteria:

1. The apps should be developed by pure Java language without Kotlin language. Because Kotlin code has different syntax rules, which are not fit to TestIntent.
2. The activities of the app should not be video games. Because the computer vision technologies we adopt focuses on the table-like layout.

We recruit 3 graduate students to develop 5 scripts for each AUT. The students are with at least 3 years of mobile app testing. They are familiar with Appium and Appium scripts for mobile app testing. Each script has an unambiguous test intent (ground truth).
1. Mobile Apps in the Experiment

| App Name                   | Category   | LOC   | Project Size |
|----------------------------|------------|-------|--------------|
| AgendaOnce                 | Productivity | 485   | 175 KB       |
| AppIconLoader              | Tool       | 1,519 | 923 KB       |
| Baking                     | Education  | 1,723 | 5.1 MB       |
| CallBlocker                | Communi.   | 1,136 | 433 KB       |
| ContactManager             | Business   | 810   | 3.1 MB       |
| CourseAssist               | Education  | 2,844 | 10.3 MB      |
| Covid19-Tracker            | Tools      | 1,643 | 2.6 MB       |
| Covid19-Tracker-kenya      | Tools      | 590   | 12 MB        |
| ES-FileExplorer-3          | Tools      | 1,095,985 | 54.2 MB |
| Eyewitness                 | Communi.   | 3,257 | 3 MB         |
| FastLib                    | Productivity | 16,373 | 49.6 MB   |
| iWeather                   | Weather    | 4,109 | 12.6 MB      |
| Kassenschnitt              | Finance    | 1,165 | 250 KB       |
| NeverTooManyBooks          | Books      | 116,919 | 10.1 MB |
| PopularMovies              | Entertainment | 2,545 | 4.6 MB      |
| ProgressNote               | Productivity | 4,091 | 17.6 MB    |
| SakuraAnime                | Entertainment | 9,801 | 9.1 MB     |
| TEPAPTracker               | Tools      | 1,068 | 506 KB       |
| Untertestival               | Sports     | 4,679 | 8.8 MB       |
| VocabableTrainer           | Education  | 15,312 | 2.5 MB     |

Different test scripts of the same app are of different intents. The intents are linked to the business logic of the mobile app. The test scripts are recorded on a HUAWEI P30 mobile phone.

The length of operations contained in the test scripts ranges from 1 to 16. The 100 test scripts have an average of 4.24 operations. The standard deviation is 3.06.

4.1.3 Evaluation Metric. The whole framework of TestIntent can be considered a sequence-to-sequence model. Therefore, we adopt the widely used evaluation metrics, BLEU [20], CIDEr [21], METEOR [22] and ROUGE [23].

BLEU (Bilingual Evaluation Understudy) is a metric used in evaluating machine translation models. It is calculated as the product of $n$-gram precision and brevity penalty, where the $n$ can take any real number. For the reason that most test script intents are short so we take $n$ equaling to 1, 2, 3, and 4, and denote them as BLEU@1, BLEU@2, BLEU@3, and BLEU@4.

CIDEr (Consensus-Based Image Description Evaluation) mainly adopt the TF-IDF (Term Frequency Inverse Document Frequency) to calculate the weights of $n$-grams in different reference sentences. The basis consensus is that the less the $n$-grams appear, the more information it may contain.

METEOR (Metric for Evaluation of Translation with Explicit Order) is also widely used for sequence to sequence model evaluation. Compared with BLEU, METEOR takes the synonyms and recall ratio into consideration.

ROUGE (Recall-Oriented Understudy for Gisting Evaluation) refers to a set of metrics on the basis of recall ratio. We use a variant of ROUGE, ROUGE-L, which calculates the similarity between candidate sentences generated by TestIntent and reference sentences based on the longest common subsequence (LCS).

The range of all the adopted metrics is $[0, 1]$. The higher the score is, the closer the TestIntent generated intents is to the ground truth. We complete the ground truth intents manually with 3 experts who have experience of over 3 years of mobile app testing. They develop and cross-validate the ground truth intents of the mobile app test scripts.

4.2 RQ1: TestIntent Effectiveness

To evaluate the effectiveness of TestIntent to generate test intents, we compare TestIntent with 3 baselines.

- **code2seq**: code2seq is a state-of-the-art approach for code comment generation, which has been proved effective for Java source code summarization.
- **GUIIntent**: GUIIntent is part of TestIntent, which can extract textual or image information from the UI layout files and GUI images.
- **CodeIntent**: CodeIntent is part of TestIntent, which can map operations to the response methods and then generate natural language descriptions to the test script with a sequence-to-sequence model.

Table 2 shows the experimental results. Independently, the average BLEU score ($n=1, 2, 3, 4$) of TestIntent is 14.4886. The scores decrease with $n$ increasing. The reason is that for the operation sequence, a few words can summarize the test intent, so the ground truth sentences are short. If $n$ is large, the score would definitely decrease. For another 3 metrics, the CIDEr score is 10.7632, the METEOR score is 25.8949, and the ROUGE score is 25.8470.

By comparison, TestIntent behaves much better than code2seq. One reason is that in test scripts, there is no complex logic, and the scripts only contain the operation sequences where app widgets are located by IDs and XPaths. Therefore, code2seq model cannot extract valuable information from the test scripts. So, TestIntent maps each operation to the response method or the GUI image information, which helps take the business logic information into consideration and effectively help the intent generation.

Further, we analyze the generated intent from the step granularity. 100 test scripts contain 424 steps, and the average BLEU score ($n=1, 2, 3, 4$) is 18.5832, 28.3% higher than the integrated result. The CIDEr score is 17.4291, 61.9329% higher than the integrated result. The METEOR score is 28.5689, 10.3265% higher than the integrated result. The ROUGE score is 14.4886, 10.3265% higher than the integrated result. The LOCS is 1.4886, 10.3265% higher than the integrated result. The ROUGE score is 13.3502. The step granularity ROUGE is lower than the integrated result because that the calculation of ROUGE involves the LCS calculation, while the step granularity limits the common subsequence length.

4.3 RQ2: Mapping Effectiveness

This research question is set to verify the effectiveness of TestIntent to map operation to corresponding information, including response method and GUI information. This research question is studied on the step granularity. For in total 424 steps, 246 steps are successfully mapped to the expected information and generate the corresponding test intents (Figure 5).

Among the successful mapping operations, intents of about 90% operations are generated by GUIIntent module. The main reason is that few IDs are available during the test script development. The usage of IDs heavily depends on the app developers’ developing habits on whether they label the widgets with an ID. Second, the Android mechanism allows developers to use repetitive IDs,
Table 2: Experimental Results and Comparison

|        | BLEU@1 (%) | BLEU@2 (%) | BLEU@3 (%) | BLEU@4 (%) | CIDEr (%) | METEOR (%) | ROUGE (%) |
|--------|------------|------------|------------|------------|-----------|------------|-----------|
| code2seq [14] | 2.0065     | 0.3162     | 0          | 0          | 0.4588    | 1.4308     | 4.7500    |
| GUIIntent   | 21.2117    | 16.0883    | 9.4319     | 5.4919     | 9.1843    | 22.9903    | 21.8708   |
| CodeIntent  | 6.2133     | 5.0000     | 2.0000     | 0          | 3.0669    | 5.3207     | 3.2262    |
| TestIntent  | 23.2544    | 17.7681    | 11.4319    | 5.4919     | 10.7632   | 25.8949    | 25.8470   |
| TestIntent (step) | 34.7299 | 21.4805 | 11.2463 | 6.8760 | 17.4291 | 28.5689 | 15.3502 |

Figure 5: Result of Mapping Effectiveness

which prevents TestIntent from mapping the operation to the appropriate response methods. On such a condition, GUIIntent is especially critical, which is a prominent contribution of this work.

Among the failing mapping operations, according to our in-depth observation, we find that most operations that fail to be mapped are transition operations. In other words, such operations do not have concrete test intents, and they just play the role of transiting from the former operation to the next operation. Therefore, it is hard to infer the corresponding test intents for transition operations even for testing experts.

4.4 RQ3: A User Study on User Experience

To better illustrate the effectiveness of TestIntent, we also conduct a user study. We randomly choose 15 test scripts out of our test script dataset for three recruited users. The users are familiar with mobile app testing and Appium scripts, and TestIntent is transparent to them. A significance test on the users’ capability to understand the test scripts is conducted, and the significance value is smaller than 0.05. Based on the 15 test scripts, we construct 2 test script sets. SetA is the initial test scripts without comments. SetB is the test scripts attached with TestIntent generated test intents. The test scripts are labeled from A1 to A15, and B1 to B15. The 30 test script items are randomly distributed to three users, and we make sure no one gets the two versions of the same script.

The results can be seen from Figure 6. The average understanding time for SetA is 76.33s, and the average understanding time for SetB is 22.27. With the assistance of TestIntent, users can save 70.83% of the time to understand test scripts, which improves the test script development efficiency.

Figure 6: Result of User Study

4.5 Threats to Validity

Some factors may pose threats to the validity of the experiment, while some settings can help relieve the influence.

The apps we use in the experiment are limited. We collect 20 apps in this experiment, which seems inadequate. However, the apps cover different categories, including tools, productivity, finance, entertainment, etc. Moreover, the only restrictions we can find have been claimed in Section 4.1.2. Therefore, we hold that the apps are representative and can well prove the generalizability of TestIntent.

The test scenarios we set in the experiment are limited. For each app, we require the graduate students to set 5 different test scripts, which represent 5 different test scenarios. The test scripts do not cover all the source code, and do not fully explore the functionality space. However, during the development of the test scripts, the students are required to refer to the apps’ documents and follow the dominating business logic paths to set the test scenarios, which are representative.

The manual efforts involved in this experiment are graduate students. During the experiment and the preliminary survey (Section 2.1), we recruit senior software engineering majored students to design the test scenarios and develop test scripts. This may be a threat. However, Salman et al. propose that senior students are sufficient developer proxies in well-controlled experiments [24].
5 RELATED WORK

5.1 Code Comment Generation

Code comment generation, also known as code summarization, has been a long-lasting and important topic in the program analysis field. Main-stream code summarization approaches include three major categories, manual template, information retrieval (IR), and learning based approaches.

As a representative work of manual template approach, Sridhara et al. propose a method for automatically generate descriptive comments for Java methods with the analysis on the AST and call flow graph (CFG) [3]. Another work of Sridhara et al. focuses on the high-level actions [25]. The approach analyzes the statement blocks and generates comments for each high-level action. Rui et al. conclude 26 different “nano-patterns” [26], which are used as templates to generate code comments. Moreno et al. introduce a class-level heuristic code summarization approach [27], focusing on the class content and responsibilities. Malhotra et al. also generate code comments from class level [28]. They analyze the dependency relationship and analyze the change proneness. Nazar et al. recruit students to label the collected projects based on 21 different features and construct a classifier to generate code comments [29].

IR models are also widely used in code comment generation models. Haiduc et al. first extract the words from code files and link them with the most related words in the corpus and generate code comments [30]. Haiduc et al. also propose a method to generate code comments based on code lexical information and structure information [31]. Interestingly, Rodeghero et al. identify the statements and keywords developers focus based on eye-tracking technologies [32] [33]. Then, based on the information acquired, they can generate higher quality code comments. Some techniques focus on software repository mining. Wong et al. utilize the crawling technology to obtain a large amount of code snippets and corresponding descriptions [10], and construct the “code-description” mappings as the corpus and use code similarity to infer the code comments. Alon et al. propose Code2Seq and Code2Vec [14] [15], considering the semantic similarity among methods, to generate code comments.

Taking advantage of the development of DL technology, code comment generation also has a breakthrough. Iyer et al. propose CODE-NN [34], which combines LSTM and Attention mechanism to encode and decode the code snippets. Zheng introduces a novel attention mechanism, code attention et al. [35], to use domain features (i.e., symbol, identifier) to understand the code structure. Hu et al. transfer code snippets into AST to analyze the structure and semantic information [6]. Leclair et al. propose ast-attendgru [36], which combines code text and AST representation as neural network input to generate code comments.

5.2 GUI Image Analysis

With the development of computer vision and deep learning, GUI image analysis has been advanced.

Some work analyzes the GUI images and uses the information to reconstruct the editable GUI files. Chen et al. present a neural network machine translator that combines recent advances in computer vision and machine translation and translates UI images into GUI skeletons [37]. Pix2Code [38] is a method presented by Beltramelli. It applies an end-to-end image captioning model to predict a description of the GUI layout. Chen et al. introduce a novel approach that automates cross-platform GUI code generation with the detection and extraction of GUI widgets [39].

Some work focuses on the UI widget understanding and the automation of the GUI testing. Chang et al. present a new approach that using CV technologies to automate GUI testing and execute GUI actions [40]. Nguyen et al. firstly introduce an approach, namely REMAUI [41], to use input images to identify UI elements such as texts, images, and containers, using computer vision and optical character recognition (OCR) techniques. Chen et al. propose an approach that combines traditional CV technologies and DL based object detection models to identify the widgets in the GUI screenshots [42]. Moran et al. propose a machine learning model to construct prototypes of GUIs for mobile apps [43].

Some novel papers are related to the usage of GUI widget intent understanding. Xiao et al. propose IconIntent [44], a tool used to understand the intents of GUI widgets to identify sensitivity. IconIntent analyzes the meta files of GUI and extracts textual information, and widget images. Also, Xi et al. present DeepIntent [45], which is developed to focus on the UI widgets and examine whether the intentions reflected in their UIs justify their actual permission uses. Zhang et al. propose a technique that creates accessibility metadata with an understanding of app GUI screenshots [46]. Chen et al. present an approach to automatically add labels to UI components using deep learning models [12].

6 CONCLUSION

Program understanding has long been a hot topic in the software engineering community, while most of the work focuses on source code. Few or even no work has been done to help understand the test part (i.e., test scripts) of an AUT. However, the intents of test scripts are closely related to the source code of AUTs, so existing technologies may lose effect when applied on test scripts. It is important to map the test operations to the corresponding source code or GUI elements. Therefore, with the GUI-intensive and event-driven feature of mobile apps, we design a novel approach, TestIntent, to analyze, infer and generate test script intents.

TestIntent is composed of GUIIntent and CodeIntent. GUIIntent is used to process the GUI information of the operation, including the textual information and widget image intents. CodeIntent is designed to explore the response methods of the operations and to have an in-depth understanding of the response method intents.

We also provide an operation sequence model that formally represents the test scripts. For each operation in the operation sequence, we apply GUIIntent and/or CodeIntent to generate the intents, and finally, we aggregate the intents of all the operations as the test script intent.

To evaluate the effectiveness of the proposed approach, TestIntent, we design an experiment attached with a user study. The results show that TestIntent can effectively assist app developers to understand test scripts and save their time.

In conclusion, TestIntent is the first approach that helps understand mobile app test script intents and starts the automated assistance targeted at mobile app testing.
REFERENCES

[1] M. Harman, A. Al-Subaibin, Y. Ju, W. Martin, F. Sarro, and Y. Zhang, “Mobile app and app store analysis, testing and optimisation,” in Proceedings of the International Conference on Mobile Software Engineering and Systems, 2016, pp. 243–244.

[2] X. Xia, L. Bao, D. Lo, Z. Xing, A. E. Hassan, and S. Li, “Measuring program comprehension: A large-scale field study with professionals,” IEEE Transactions on Software Engineering, vol. 44, no. 10, pp. 952–976, 2017.

[3] G. Sridhara, E. Hill, D. Muppaneni, L. Pollock, and K. Vijay-Shanker, “Towards automatically generating summary comments for java methods,” inProceedings of the IEEE/ACM International Conference on Automated software engineering, 2010, pp. 43–52.

[4] S. Yu, C. Fang, Y. Yun, and Y. Peng, "Layout and image recognition driving cross-platform automated mobile testing (accepted)," in Proceedings of the IEEE/ACM international conference on software engineering, 2021.

[5] T. Haibe-Kains, M. Pineau, G. Van den Berghe, and L. Heuer, "Automatic comment generation using a neural translation model," Inf. Softw. Technol., vol. 55, no. 3, pp. 258–268, 2016.

[6] X. Hu, G. Li, X. Xia, D. Lo, and Z. Jin, "Deep code comment generation," in 2018 IEEE/ACM 26th International Conference on Program Comprehension (ICPC). IEEE, 2018, pp. 200–2010.

[7] ——, “Deep code comment generation with hybrid lexical and syntactical information,” Empirical Software Engineering, vol. 25, no. 3, pp. 2179–2217, 2020.

[8] Y. Liang and K. Zhu, "Automatic generation of test descriptive comments for code blocks," in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 32, no. 1, 2018.

[9] X. Song, H. Sun, X. Wang, and J. Yan, “A survey of automatic generation of source code comments: Algorithms and techniques,” IEEE Access, vol. 7, pp. 111 411–111 428, 2019.

[10] E. Wong, J. Yang, and L. Tan, "AutoComment: Mining question and answer sites for automatic comment generation," in 2013 28th IEEE/ACM International Conference on Automated Software Engineering, 2013, pp. 562–567.

[11] P. Liu, L. Li, Y. Zhao, X. Sun, and J. Grundy, "Androzooopen: Collecting large-scale open source android apps for the research community," in Proceedings of the 17th International Conference on Mining Software Repositories, 2020, pp. 548–552.

[12] J. Chen, C. Chen, Z. Xing, X. Xu, L. Zhu, G. Li, and J. Wang, "Unblind your apps: Predicting natural-language labels for mobile gui components by deep learning," Association for Computing Machinery, 2020, p. 322–334.

[13] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[14] U. Alon, S. Brody, O. Levy, and E. Yahav, "code2seq: Generating sequences from structured representations of code," in International Conference on Learning Representations, 2019.

[15] U. Alon, M. Zilberstein, O. Levy, and E. Yahav, "code2vec: Learning distributed representations of code," inProceedings of the ACM on Programming Languages, vol. 3, no. POPL, pp. 1–29, 2019.

[16] M. Alamanis, E. T. Barr, C. Bird, and C. Sutton, "Suggesting accurate method and class names," inProceedings of the 2015 19th Joint Meeting on Foundations of Software Engineering, 2015, pp. 38–49.

[17] M. Alamanis, H. Peng, and C. Sutton, "A convolutional attention network for extreme summarization of source code," inInternational conference on machine learning, 2016, pp. 2091–2100.

[18] D. Bahdanau, K. Cho, and Y. Bengio, "Neural machine translation by jointly learning to align and translate," arXiv preprint arXiv:1409.0473, 2014.

[19] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” arXiv preprint arXiv:1409.1556, 2014.

[20] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu, "Bleu: a method for automatic evaluation of machine translation," inProceedings of the 40th annual meeting of the Association for Computational Linguistics, 2002, pp. 311–318.

[21] R. Vedantam, C. Lawrence Zitnick, and D. Parikh, "Cider: Consensus-based image description evaluation," inProceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 4566–4575.

[22] S. Banerjee and A. Lavie, "Meteor: An automatic metric for mt evaluation with improved correlation with human judgments," inProceedings of the acl workshop on intrinsic and extrinsic evaluation measures for machine translation and/or summarization, 2005, pp. 65–72.

[23] C.-Y. Lin and E. Hovy, "Automatic evaluation of summaries using n-gram co-occurrence statistics," inProceedings of the 2003 Human Language Technology Conference of the North American Chapter of the Association for Computational Linguistics, 2003, pp. 150–157.

[24] I. Salman, A. T. Misirli, and N. Juristo, “Are students representatives of professionals in software engineering experiments?” inProceedings of the 37th IEEE International Conference on Software Engineering. IEEE, 2015, pp. 666–676.

[25] G. Sridhara, L. Pollock, and K. Vijay-Shanker, “Automatically detecting and describing high level actions within methods,” inProceedings of the 33rd International Conference on Software Engineering (ICSE). IEEE, 2011, pp. 101–110.