ProMal: Precise Window Transition Graphs for Android via Synergy of Program Analysis and Machine Learning

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ABSTRACT

Mobile apps have been an integral part in our daily life. As these apps become more complex, it is critical to provide automated analysis techniques to ensure the correctness, security, and performance of these apps. A key component for these automated analysis techniques is to create a graphical user interface (GUI) model of an app, i.e., a window transition graph (WTG), that models windows and transitions among the windows. While existing work has provided both static and dynamic analysis to build the WTG for an app, the constructed WTG misses many transitions or contains many infeasible transitions due to the coverage issues of dynamic analysis and over-approximation of the static analysis. We propose ProMal, a "tribrid" analysis that synergistically combines static analysis, dynamic analysis, and machine learning to construct a precise WTG. Specifically, ProMal first applies static analysis to build a static WTG, and then applies dynamic analysis to verify the transitions in the static WTG. For the unverified transitions, ProMal further provides machine learning techniques that leverage runtime information (i.e., screenshots, UI layouts, and text information) to predict whether they are feasible transitions. Our evaluations on 40 real-world apps demonstrate the superiority of ProMal in building WTGs over static analysis, dynamic analysis, and machine learning techniques when they are applied separately.

CCS CONCEPTS

• **Theory of computation → Program analysis**; • **Software and its engineering → Software testing and debugging**; • **Computing methodologies → Machine learning**.

KEYWORDS

mobile apps; window transition graph; static analysis; deep learning

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1 INTRODUCTION

Mobile applications (i.e., apps) have become an integral part of our daily life, from entertainment, travel, education, and even to business [12, 53]. Thus, it is critical to improve the quality and reliability of these apps by developing automated analysis techniques to ensure the correctness, security, and performance of these apps [19, 26, 41, 47, 47, 54, 69, 70]. As a key component for these automated analysis techniques, we focus on creating a graphical user interface (GUI) model of an app, i.e., a window transition graph (WTG). In WTG, nodes represent windows and edges represent transitions between windows, triggered by callbacks executed in the GUI thread. For example, clicking a button in the GUI will result in the execution of a callback that changes the screen to display another window. WTG can be directly used for understanding, testing, and exploring apps' behaviors [7, 26, 54]. It can also assist static analyses, such as detecting security-sensitive behaviors and other non-functional properties like energy efficiency [9, 10, 63, 65].

While considerable research efforts have been spent to construct WTGs [26, 41, 47, 54, 70] via either static analysis techniques or dynamic analysis techniques, it is still challenging to obtain an accurate WTG. On one hand, dynamic analysis such as dynamic exploration [26, 41, 54] is precise in identifying transitions between windows, but this type of techniques suffer from the notorious coverage problem as other dynamic analysis techniques [14, 64, 66]. On the other hand, while static analysis that models the GUI objects, events, and callbacks [47, 69, 70] shows promising results in constructing a more comprehensive WTG, the imprecision in reference analysis and over-approximation in computing data flows often result in infeasible transitions. For example, if the imprecision of the reference analysis causes several buttons to be aliases with each other, then a transition triggered by one button will also result in the model to include incorrect transitions from the other buttons. Such incorrect transitions will further cause the imprecision for the downstream analysis such as control and data flow analysis [47, 69].

To address these challenges, we propose **a novel "tribrid analysis" approach**, ProMal, that **synergistically combines static/-dynamic program analysis and machine learning techniques to construct a WTG for an app**. In particular, ProMal aims to benefit from the precise analysis from dynamic analysis, and at the

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same time mitigate the low coverage of dynamic analysis and the imprecision caused by the static analysis. ① Specifically, ProMal first *combines static analysis and dynamic analysis: ProMal applies static analysis to construct a WTG, and then runs dynamic analysis to verify the detected transitions.* Due to the coverage issues of dynamic analysis and over-approximation of the static analysis, it is expected that a substantial amount of transitions cannot be verified by the dynamic analysis. ② Instead of including all these unverified transitions in the WTG, which potentially will generate many infeasible transitions, ProMal further *uses a machine learning technique, window transition prediction, that leverages the features for the unverified transitions (e.g., screenshots and text) to predict which transition to include.* **Our novel techniques (① for verifying static WTGs using dynamic WTGs and ② for predicting unverified transitions) allowing ProMal to construct a more precise WTG that can benefit downstream analysis techniques**.

Existing static analysis techniques [47, 69, 70] are effective in detecting transitions among windows, but are limited in detecting transitions among dialogs. ProMal improves the existing static analysis by modeling the dialog builder APIs and detects transitions buried in the callbacks of dialogs to identify the transitions from dialogs to other windows and dialogs. As dynamic analysis [26, 41, 54] typically models the window transitions differently from the static analysis, ProMal instruments the app under analysis, which will record the information that can be used to align the dynamic WTG with the static WTG. This includes the identifiers of GUI widgets (i.e., *XPath*) and interaction events. Moreover, the instrumentation will collect the runtime information, including screenshots of the windows, the view tree[1] [23], and the text shown in the windows. The runtime information is later used by the machine learning techniques to predict unverified transitions. For the windows found by static analysis but dynamic analysis cannot reach due to coverage issues, ProMal uses static UI rendering based on ADT (Android Developer Tools) [3, 32] to render the UI layouts for obtaining the screenshots and the view tree, and applies static analysis on the UI layout file to obtain the text.

To predict whether unverified transitions should be included in the WTG, we construct a model of window transition prediction based on machine learning techniques. Given a GUI widget in a window and another window, the model first extracts features of them to learn their low-dimensional representations, which are then fed into a link predictor to estimate the likelihood of whether these exists a transition between the widget and window. However, due to the large amount of parameters in the prediction model, it is difficult to directly train the model since obtaining a large amount of manually labelled WTGs is infeasible. To address this issue, we adopt a two-phase training models: (1) pre-training on the dynamic WTGs collected by dynamic program analysis from a large amount of apps, and (2) fine-tuning on the manually labelled WTGs from a small set of apps. The essence of the design lies in getting a model general enough to accurately predict window transitions.

We implement ProMal upon Gator [47, 69, 70] and Paladin [41], and evaluate ProMal on a diversified set of real apps (40 apps with $\sim$ 2.5 million LOC). These apps have non-trivial WTGs of different sizes (# of edges ranging from 5 to 538). We apply Paladin to construct WTGs for these apps, and compare the WTGs with the groundtruth WTGs. We pre-train our prediction model on 1,625 apps explored by Paladin, and fine-tune the model using 90% of the apps in our evaluation dataset. We perform 10-fold validation to predict the transitions for each app. The results show that ProMal effectively identifies the feasible transitions among the windows in constructing WTGs, achieving a precision of 90.18%, a recall of 79.69%, and a F_1-score of 82.82% on average. Moreover, the WTGs built by ProMal achieves a significantly better F_1-score than the WTGs built by Gator (46.24%) and the combined WTGs built by Gator and Paladin (61.93%). These results reveal the limitations of static analysis in modeling windows/callbacks for diversified real apps, and demonstrate the effectiveness of ProMal in using a synergy approach of program analysis and machine learning.

This paper makes the following main contributions:

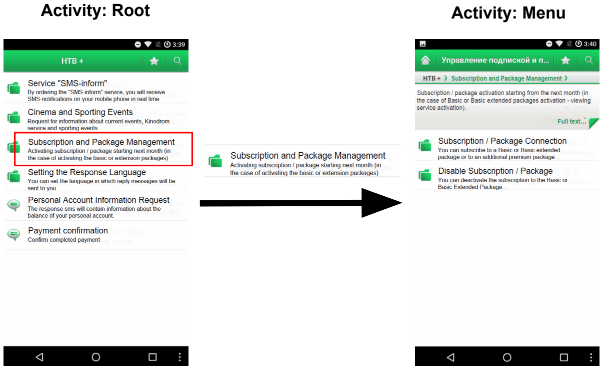
- A novel approach, ProMal, that synergistically combines static/-dynamic analysis and machine learning to construct WTGs for Android apps.
- A novel static analysis technique that builds static WTGs with transitions among windows and dialogs.
- A novel dynamic analysis technique that instruments apps under analysis and leverages app exploration techniques to build dynamic WTGs and collect runtime information for window transition prediction.
- A machine-learning model to predict window transitions, which can be pre-trained on apps explored by dynamic analysis and fine-tuned using labelled WTGs to improve the performance.
- An evaluation on a diversified set of Android apps to demonstrate the effectiveness of ProMal. The tool and the results are available at the project website [4].

2 BACKGROUND

In an Android app, an activity provides a window to draw the GUI [23]. A GUI consists of GUI widgets (e.g., buttons and text boxes) and layout models (e.g., linear layout) that describe how to arrange UI widgets. Each GUI widget can respond to several events, where each event triggers a sequence of callbacks. For example, the click event in a button corresponds to clicking the button, and it triggers the event handler callback that is registered to the click event, such as `onClick`. A callback can open a new window. For example, this can be done via calling the API `startActivity`. When a new window is opened, it causes a window transition. Besides widget event callbacks, hardware events (e.g., pressing BACK or HOME button) can also trigger callbacks to cause window transitions. In particular, Android maintains a back stack that stores the order of the opened window, so that it can be used to decide which window to return to when the BACK button is pressed.

Window transition graph (WTG) is a type of GUI model that represents window transitions. Existing work [47, 69, 70] defines a WTG as a directed graph, where nodes represent windows and edges represent transitions. The edges in WTG are annotated with three types of labels (i.e., ϵ, δ, σ), where ϵ represents the event to trigger the transition, δ represents a sequence of window stack

[1] A tree structure shows that hierarchy of the GUI widgets and the layout containers (e.g., `LinearLayout` and `RelativeLayout`).



3:39

HTB +

Service "SMS-inform"
By ordering the "SMS-inform" service, you will receive SMS-notifications on your mobile phone in real time.

Cinema and Sporting Events
Request for information about current events, Kinodrom service and sporting events...

Subscription and Package Management
Activating subscription / package starting next month (in the case of activating the basic or extension packages).

Setting the Response Language
You can set the language in which reply messages will be sent to you.

Personal Account Information Request
The response sms will contain information about the balance of your personal account.

Payment confirmation
Confirm completed payment

Subscription and Package Management
Activating subscription / package starting next month (in the case of activating the basic or extension packages).

3:40

Управление подпиской и п...

HTB + › Subscription and Package Management ›

Subscription / package activation starting from the next month (in the case of Basic or Basic extended packages activation - viewing service activation).

Full text...

Subscription / Package Connection
You can subscribe to a Basic or Basic extended package or to an additional premium package...

Disable Subscription / Package
You can deactivate the subscription to the Basic or Basic Extended Package...

Figure 1: Example UIs of "Subscriber Assistant Application" and a window transition

operations that push or pop the window to the window stack[2], and σ represents the sequence of callbacks for the transition. Besides widget events such as click events, the model further supports five *default events* that corresponds to pressing the BACK, HOME, POWER, MENU buttons and rotating the phone. A series of static analysis techniques are then developed to identify GUI widgets, associate their callbacks, and build a static WTG. While dynamic analysis such as app exploration [26, 40, 41, 54] usually does not explicitly build a WTG, they provide their own models to represent UI states, which can be considered as another type of WTGs with different representations for windows and their transitions.

Applications of WTGs. WTGs can be used to improve various types of software analysis, such as testing, security vetting, and performance profiling [11, 56, 60, 62, 63, 68]. Wu et al. [62] generates GUI tests based on the paths in the WTGs and analyzes the UI callbacks and activity life cycle methods to examine sensors that are not properly released. Yang et al. [68] uses a WTG to determine which activities can reach more other activities to prioritize test exploration. Another GUI testing tool [11] uses a statically computed WTG to guide which widget to trigger when the other exploration rules fail. Besides testing, WTGs are also used for performance profiling and security vetting. Wang et al. [60] profile potential resource demanding tasks in the UI thread by using WTGs to identify callbacks that trigger "janky" operations and the window transition sequences that trigger such callbacks. Tang et al. [56] build a UI-oriented program dependence graph, which is essentially a WTG, to discover link hijacking vulnerabilities. All these applications rely on WTGs built explicitly or implicitly, and thus it is crucial to improve the precision of the built WTGs for improving the effectiveness of these applications.

3 MOTIVATION EXAMPLE

Figure 1 shows the UI (after translation) of an example window transition of the app "Subscriber Assistant Application"[3], which allows users to subscribe various services in Russia. When the highlighted button is clicked, the UI transits from the activity `Root` to the activity `Menu`, resulting in a window transition. We can construct

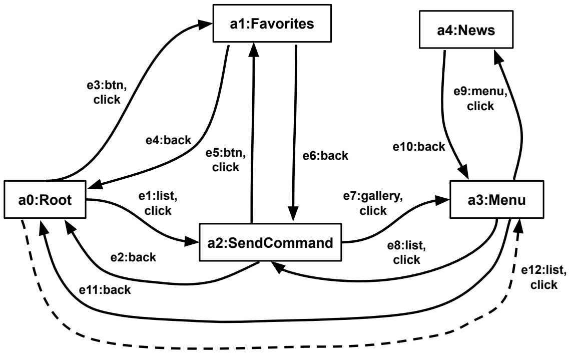


Figure 2: Partial WTG of "Subscriber Assistant Application"

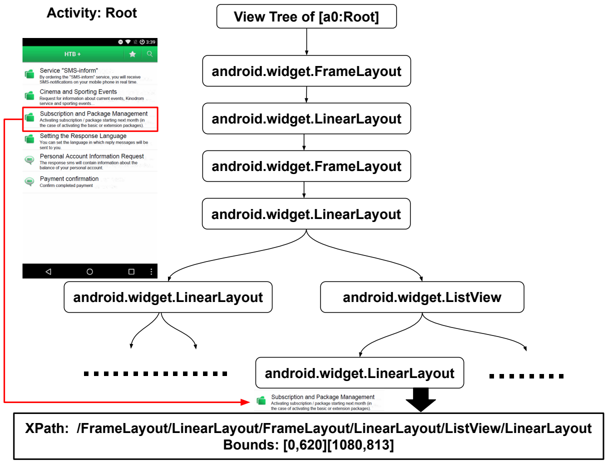

Activity: Root
View Tree of [a0:Root]
android.widget.FrameLayout
android.widget.LinearLayout
android.widget.FrameLayout
android.widget.LinearLayout
android.widget.LinearLayout
android.widget.ListView
android.widget.LinearLayout
XPath: /FrameLayout/LinearLayout/FrameLayout/LinearLayout/ListView/LinearLayout
Bounds: [0,620][1080,813]

Figure 3: Example view tree of Root window

a WTG for this app to model these transitions, where 8 nodes are used to represent the activities and 125 edges are used to represent the transitions among them. Due to space limit, Figure 2 shows the partial WTG of the app. There are 5 nodes and 12 edges in the WTG. The nodes show the name of the activity (e.g., `a0: Root` and `a1: Favorite`). The labels on the edges represent the events to trigger the transition (e.g., `e3: btn, click` means that after clicking the button, the active window of app will transit from the activity `Root` to the activity `Favorite`).

To obtain this WTG, ProMal first applies both static and dynamic WTG analysis to obtain the static WTG and the dynamic WTG, respectively. Then, ProMal aligns the static WTG and the dynamic WTG to form a single WTG. As shown in Figure 2, the solid edges represent matching edges between the static WTG and the dynamic WTG, i.e., , verified edges. Due to the over-approximation of static WTG analysis and the coverage issue of the dynamic WTG analysis, there always will be some edges in the static WTG that cannot be verified by the dynamic WTG. The one dashed edge in Figure 2 represents such kind of unverified edge. To address this problem, ProMal further uses window transition prediction to predict whether the unverified edges are likely to be transitions or not. To do so, ProMal collects the screenshots and the text information

[2] Window stack is a generalization of Android back stack that includes more types of windows (dialogs and menus) and models the changes of the stack.
[3] Package name of the app is "com.olsoft.sa.ntvplus".

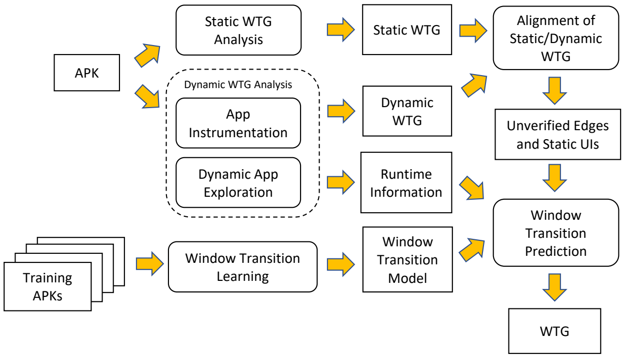


Figure 4: Workflow of ProMal

of the activities (as shown in Figure 1) and also the structural information of the UI layout, i.e., the view tree. Figure 3 shows the partial view tree of the activity `Root`. As we can see, the view tree shows the hierarchy of the UI widgets (e.g., `ListView`) and the layout container (e.g., `LinearLayout`), and also the boundary of each UI widget (i.e., represented using screen coordinates). Since Android uses XML layout files to build view trees at runtime, XPath [1] can be used to locate the UI widget and the layout container. For example, the XPath shown at the bottom of Figure 3 points to a `LinearLayout` that can be clicked, and the "Bounds" shows its boundary in the UI using screen coordinates. With the screenshots and the text information of the activities and the view tree as input, the window transition prediction correctly predicts the transition from the activity `Root` to the activity `Menu`) in Figure 1, enhancing the WTG constructed by the static and dynamic WTG analysis.

4 OVERVIEW

Figure 4 shows the workflow of ProMal. ProMal consists of three major components: static WTG analysis, dynamic WTG analysis, and window transition prediction. ProMal accepts an Android app APK file as input and applies both static and dynamic WTG analysis to obtain the static and dynamic WTGs, respectively. The static WTG analysis performs static analysis on the GUI layout files and the code of the APK file and outputs a static WTG. The dynamic WTG analysis consists of two steps: it firsts performs app instrumentation, which adds the code component into the APK file to collect runtime information, and then applies dynamic app exploration to explore apps' behaviors for building the dynamic WTG. ProMal then aligns the static and dynamic WTGs to obtain the edges (i.e., window transitions) that are verified by the dynamic WTG analysis (i.e., *verified edges*). For the unverified edges, ProMal uses the window transition prediction to predict whether the unverified edges are likely to be feasible transitions. The window transition prediction trains its model on a set of training APK files, and uses the runtime information (i.e., screenshots, text information, and UI layouts) to predict window transitions. As unverified edges are not explored by the dynamic analysis, ProMal statically renders the GUIs involved in the unverified edges for obtaining the information required for the prediction. The output WTG contains only the verified edges and the edges predicted to be feasible edges.

5 DESIGN OF PROMAL

In this section, we first provide the formal definition of window transition graph (WTG), and then describe the three major components of ProMal: *static WTG analysis*, *dynamic WTG analysis*, and *window transition prediction*.

5.1 Definition of WTG

We represent a WTG as a directed graph $G = (Win, E, \epsilon)$, where Win represents a set of nodes where each node represents a *window* of an app, $E \subseteq (Win \times Win)$ is the set of edges that represent transitions among windows, and $\epsilon : E \longrightarrow Evt$ represents the edge labels that describe the events Evt that cause the transitions.

Window. We consider 3 categories of windows that users can interact with as a node in a WTG: *activities*, *menus*, and *dialogs*. An activity is often presented to the users as a full-screen window, serving as the build block of an app's GUI. Menus include *OptionsMenu* which is associated with activities and *ContextMenu* which is associated with GUI widgets. Dialogs are short-lived windows that often need user actions to proceed to the next window.

Edge (Transition). An edge $e = (win_s, win_t)$ represents a transition from a source window win_s to a target window win_t, and the labels on the edges describe the events that cause the transition, such as a button click. Without loss of generality, we treat back edges as the other edges but with a special "back" label, which makes it easier to match the back edges identified in the static WTG with the dynamically observed ones. Moreover, we exclude loops in E. A loop is an edge $e_l = (win_s, win_t)$ that points to itself, i.e., $win_s = win_t$. For example, when the user clicks a button representing numbers in a calculator app, which does not result in a window transition but stays at the same window, resulting in a loop. As GUI widgets that do not cause inter-window transitions will result in loops, these edges are of a large amount. Thus, adding loops to E only complicates a WTG without providing more useful information.

Event. An event $evt = (w, t)$ is a label associated with an edge $e = (win_s, win_t)$, where w represents a GUI widget in w_s and t is the type of this event (e.g., w is a button and t is "long_click"). We model two types of events: *widget events* and *default events*. Widget events correspond to the interactions with a GUI widget (e.g., clicking a button), which are categorized into two groups: (1) click events, including *touch*, *select*, *click*, *item_click*, and *item_selected*, and (2) long click events, including *long_click* and *item_long_click*. We exclude several widget events because they mainly cause loops, such as *scroll*, *drag*, *focus_changed*, and *enter_text*. In fact, in our evaluation dataset, all 181 edges corresponding to these events are loops. *Default events* correspond to the interactions with the physical buttons or rotating the device. We focus on the events caused by pressing the back button and the menu button, and exclude events caused by rotating the phone and pressing the home button and the power buttons since these excluded default events only cause loops and app switches. In our dataset, 1,116 out of 1,430 edges related to these events are loops, and the remaining 314 edges represent app switches. For example, when an app shows a menu or a dialog and the user presses the home button, the phone exits the app and shows the home screen; when the user goes back to the app, the app shows the parent activity of the menu or the dialog.

While it seems like a "transition" from the menu or the dialog back to the activity, it is in fact an app switch, which is generally not interesting in app explorations or testing [26, 41, 54, 72].

Our model currently does not include *System events* since they usually do not trigger window transitions but rather changing the states of a window. System events correspond to changes of system states, such as receiving new messages and volume adjustment [5, 17, 42, 45, 54, 59]. These events are of a huge amount and can significantly damper the performance of the testing tool, and thus they are randomly injected during testing [45, 54].

5.2 Dynamic WTG Analysis

Dynamic WTG analysis instruments apps and leverages app exploration techniques to automatically explore apps' behaviors and collect the runtime information for building dynamic WTGs and predicting window transitions. We next describe the app instrumentation and runtime information collection.

App Instrumentation. ProMal instruments an app to record widget interactions and window transitions. Specifically, based on our WTG definition, ProMal monitors two major types of interaction events:

- *Widget Events*: ProMal records the click events, the click coordinates, and the GUI widgets.
- *Default Events*: ProMal records the default events for pressing the BACK and the MENU buttons.

To correctly identify window transitions, the instrumentation records the foreground activity before each interaction, and leverages the changes of the foreground activity to identify the source window and the target window when a transition happens. During the exploration, we collect the attributes of the visited windows (e.g., titles and texts), the call stacks of their parent methods, and the screenshots of dialogs and menus.

Since some GUI widgets may not possess widget IDs, ProMal further uses coordinates and XPath to identify GUI widgets in a window, as illustrated in Figure 3. ProMal hooks the `dispatchTouchEvent` API to obtain the screen coordinates for each interaction (e.g., clicking a button), and leverages UIAutomator [25] to obtain the information of the GUI state after the interaction, which includes a view tree and a screenshot. As Android's GUI is rendered based on an XML layout file, the rendered GUI state can be represented as a view tree, where the root element is a layout container such as `LinearLayout`. Based on this view tree, we can use XPath to describe the path from the root element to the XML element of the clicked GUI widget. Besides, a view tree provides the boundaries of each GUI widget, which enables ProMal to locate the GUI widgets in the view tree using the screen coordinates of an interaction, and then generate the XPath of the clicked widget accordingly. To ensure the interaction event is fully executed when we capture the GUI state, the dynamic exploration adds a waiting period of two seconds between two interaction commands.

Building Dynamic WTG. To build a dynamic WTG, ProMal first identifies windows from the data collected during app exploration. ProMal leverages two types of information to uniquely identify a window: (1) *window type* (i.e., "Activity","Dialog","Menu") and (2) *resource name*. For an activity, the resource name is the resource id of the activity. For a menu, the resource name is the resource id of the activity that owns the menu. For a dialog, the resource name is the resource id of the activity that owns the dialog (i.e., host activity) plus the method calls that create the dialog, which can distinguish different dialogs opened from the same activity. Then, ProMal leverages the source window, the target window, the class of the GUI widget, the widget ID, and the coordinates of the interaction as the attributes to uniquely identify edges among the windows. These identified edges and windows are then used to build the dynamic WTGs.

5.3 Static WTG Analysis

Static WTG analysis applies static analysis to identify windows, GUI widgets, and the transitions among the windows. Based on our definition, three types of windows are considered: activities, dialogs, and menus. Note that we consider both the classes "ContextMenu" and "OptionsMenu" as menus. ProMal first applies the existing static analysis technique (i.e., Gator) [47, 70] to identify edges among windows as we defined in 5.1. It performs a constraint graph based reference analysis to model Android GUI related objects (e.g., Activities, Views, and callback listeners) and their association relationship. It then builds a WTG based on the analysis of the GUI event callbacks and the window lifecycle callbacks. Besides modeling GUI related objects, ProMal extracts GUI widget information (i.e., title and text) from the view tree, which is later used for matching the dynamic WTGs. For events that trigger transitions, our static analysis focuses on widget events (i.e., "Click" and "Long Click" events) and default events (i.e., pressing the back and the menu buttons).

Dialog Transitions. Existing static analysis [47, 69] mainly identifies transitions from activity window to dialogs, but fails to identify transitions from the dialogs to other windows. The major reason is that these transitions are often buried in the callbacks of dialogs, which are defined using specific APIs in dialog builders (e.g., the `setItems` API of `AlertDialog.Builder`). To identify these transitions, we extend the static analysis techniques to identify these APIs, and associate the callbacks built through these APIs to the dialog constructed by the dialog builders. Specifically, our extended static analysis techniques identify the following dialog transitions:

- *To Other Dialogs*: the analysis examines whether a known dialog allocation API call is found in the associated callbacks.
- *To Host Activities*: executing APIs such as `dismiss` or `cancel` and registering a `null` or `nop` handler will trigger a transition to the host activity of the dialog. To detect such transitions, our analysis first leverages the dynamic runtime information collected in Section 5.2 to identify the host activities for all the dialogs; if a dialog is not covered during dynamic exploration, our analysis uses the callback registration sites identified by the static analysis techniques to infer the activity.
- *To Other Activities*: the analysis examines the activity transition calls (e.g., `startActivity()` and `startActivityForResult`) and the values of their `Intent` arguments to identify the other activities.
- *To Previous Activities*: calling APIs like `Activity.finish` will cause transitions to the previous activity. These transitions are inferred based on the collected dynamic exploration traces.

5.4 Alignment of Static and Dynamic WTG

After obtaining the static WTG and the Dynamic WTG of an app, ProMal aligns them by matching each edge in the static WTG to an edge in the dynamic WTG. We next describe the detailed steps.

Matching Windows. ProMal matches windows using different attributes based on their types: (1) for activities, ProMal checks their activity names; (2) for menus, ProMal checks the names of the activities that create the menus; (3) for dialogues, ProMal checks the call stack of the functions that creates the dialogs.

Matching Events and GUI Widgets. To match the event on an edge, we first check if the event types are identical. For widget events that associate with a certain GUI widget, ProMal tries to obtain the widget ID in both the static WTG and the dynamic WTG to match the widgets. However, the edges in the static WTGs do not always possess a widget ID. Sometimes they can only provide a class name of the GUI widgets or even provide nothing to infer the associated widgets. This imprecision of static analysis makes it impossible for users to pinpoint the widgets, and hence they are regarded as unmatched.

The edges in the static WTGs that cannot be matched will be subject to further machine learning prediction.

5.5 Window Transition Prediction

The window transition model is used to predict the unverified edges in the static WTGs. As shown in the example of Figure 5, the window transition model consists of the embedding models (the widget embedding model and the window embedding model) and the link predictor. Given a pair of a GUI widget and a window, ProMal first extracts the features from them, such as screen snapshot and text, and then feeds these features into the embedding models to obtain the embedding vectors of the GUI widget and the window. The link predictor then uses the two embedding vectors to tell how likely there is a link between the widget and the window. We next describe the embedding models and the link predictor in detail.

Window Embedding Model. The window embedding model uses the features of a window (i.e., screen snapshot, text information, and GUI tree) to generate a low-dimensional embedding vector. We next describe the features of a window:

- *Screenshot*: The screenshot of a window displays all visible fragments of an app activity in one image. Following the recent success in using CNN for modeling images [22, 29, 37], we adopt a block of DenseNet [31] to retrieve useful information from the screenshots.
- *Text*: Users can easily understand the window's purpose and functionality from the texts in GUIs. To utilize these texts, ProMal segments the texts and uses a pre-trained Word2Vec [43] model to generate the representations of each word. Then, ProMal computes the average word embedding as the feature vector for the window. Figure 5 shows how the window embedding model computes the embedding of all the text in the target window.
- *GUI Tree*: A GUI tree contains all the GUI widgets in a window. A GUI widget can be an instance of a system widget class (e.g., buttons and checkboxes) or a customized widget class extending the class `android.view.View`. Thus, the name of a GUI widget class's superclass, which we regard as the GUI widget's "tag", contains the information about the basic functionality of this widget, and one-hot embedding is used to represent the tag. Besides the tags, the positions and sizes of the GUI widgets may also be used to infer the functionality of widgets. To encode all the GUI widgets in a window, ProMal traverses the GUI tree via in-order tree traversal to generate a *widget sequence*, and adapts LSTM [22, 29, 30] to learn the representation of the widget sequence. Figure 5 shows how the tags and other information in a GUI tree are unrolled to a sequence.

The representations of these three features are then concatenated and fed to a fully connected layer (FC) to generate the window embedding vector.

Widget Embedding Model. To generate an embedding vector for a GUI widget, besides the features of the source window, the widget embedding model also extracts the features of a GUI widget, including the widget screenshot, the text, and the GUI properties. The feature extraction for the source window adopts the same approach as the window embedding model. We next describe the other three features:

- *Widget Screenshot*: The widget embedding model uses a block of DenseNet for modeling the screenshot of the source window, and another block of DenseNet for modeling the screenshot of the GUI widget, as shown in the red frame in Figure 5.
- *Text*: The widget embedding model segments both the texts in the source window and the GUI widget and feed both sequences of words to the Word2Vec model to generate two vectors. As shown in Figure 5, the widget embedding model computes the word representation of the text "Does not repeat" in the GUI widget as well as the average embedding of every word in the source window.
- *GUI Property*: The widget embedding model encodes the GUI tree using a similar approach as the window embedding model. Apart from the widget sequence of the source window, it also extracts the tag, the size, and the position of the GUI widget, and feeds these features to a fully connected layer to generate a vector, as shown in Figure 5.

The feature vectors of the source window and the GUI widget are concatenated and fed into a fully connected layer to generate the widget embedding vector.

Link Predictor. The widget embedding and window embedding generated by the embedding models will be fed to the link predictor to infer whether there is a link between the widget-window pair. The link predictor is designed by leveraging the neural tensor network (NTN) [52], which relates the two inputs (i.e., the widget embedding and window embedding vectors) multiplicatively instead of only implicitly through the non-linearity as with the standard neural networks where the entity vectors are simply concatenated. Thus, it provides a more powerful way to infer the relationship between entities than a standard neural network layer.

Let w represent a GUI widget and a represent a window of an app activity. ϕ_w is the widget embedding model and ϕ_a is the window embedding model. The link predictor computes a score of how likely there is a link between them, which is represented by $\Psi(\phi_w(w), \phi_a(a))$. The score is computed by using the following

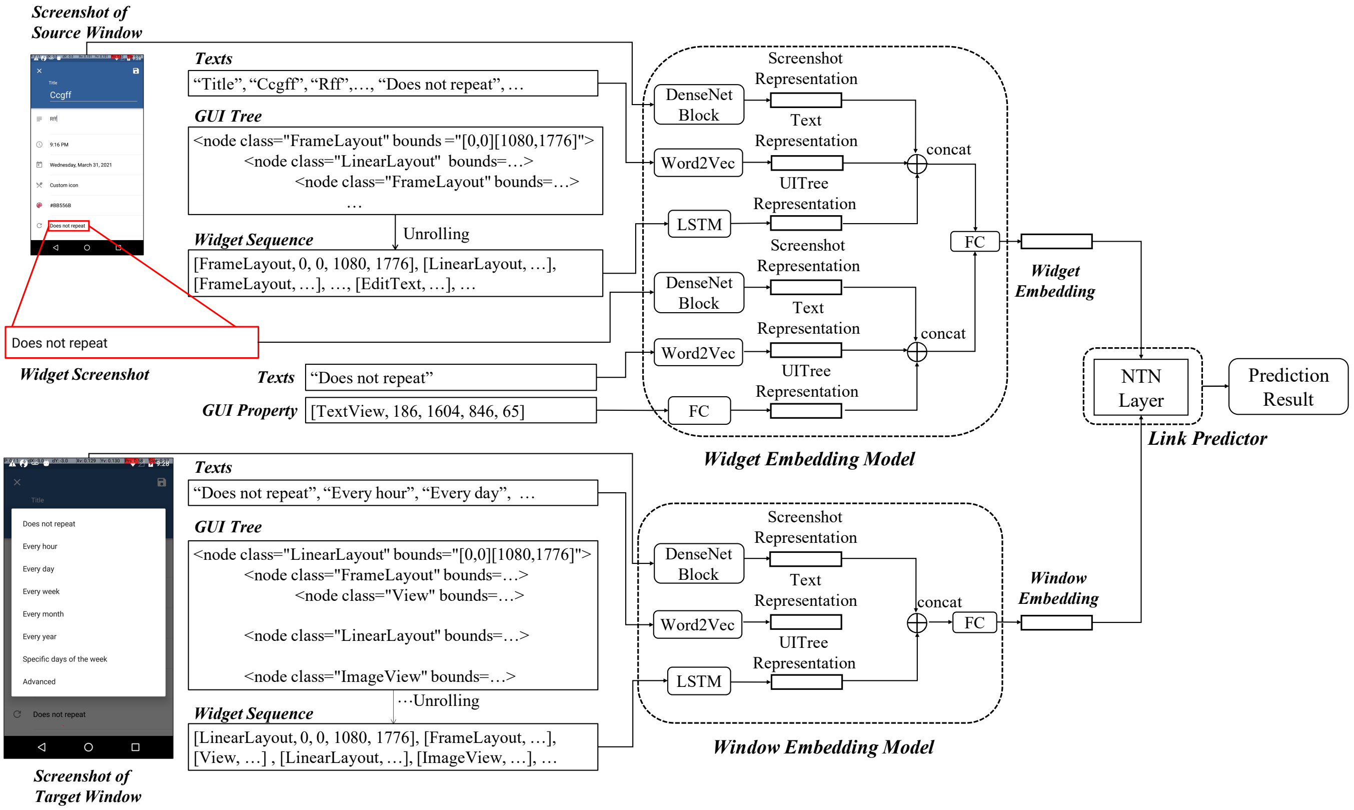

Screenshot of Source Window
Texts
"Title", "Ccgff", "Rff",…, "Does not repeat", …
GUI Tree
<node class="FrameLayout" bounds ="[0,0][1080,1776]">
<node class="LinearLayout" bounds=…>
<node class="FrameLayout" bounds=…>
…
Unrolling
Widget Sequence
[FrameLayout, 0, 0, 1080, 1776], [LinearLayout, …], [FrameLayout, …], …, [EditText, …], …
Does not repeat
Widget Screenshot
Texts
"Does not repeat"
GUI Property
[TextView, 186, 1604, 846, 65]
Screenshot Representation
DenseNet Block
Text Representation
Word2Vec
UITree Representation
LSTM
concat
FC
Screenshot Representation
DenseNet Block
Text Representation
Word2Vec
concat
UITree Representation
FC
Widget Embedding Model
Widget Embedding
NTN Layer
Prediction Result
Link Predictor
Texts
"Does not repeat", "Every hour", "Every day", …
GUI Tree
<node class="LinearLayout" bounds="[0,0][1080,1776]">
<node class="FrameLayout" bounds=…>
<node class="View" bounds=…>
<node class="LinearLayout" bounds=…>
<node class="ImageView" bounds=…>
…Unrolling
Widget Sequence
[LinearLayout, 0, 0, 1080, 1776], [FrameLayout, …], [View, …] , [LinearLayout, …], [ImageView, …], …
Screenshot of Target Window
Screenshot Representation
DenseNet Block
Text Representation
Word2Vec
concat
FC
UITree Representation
LSTM
Window Embedding
Window Embedding Model
Does not repeat
Every hour
Every day
Every week
Every month
Every year
Specific days of the week
Advanced

Figure 5: Illustration of how the window transition model predicts whether interacting with a GUI widget in a source window causes a transition to a target window. The figure shows part of the extracted features for the GUI widget, the source window, and the target window, and illustrates how they are processed in the embedding models to produce the embedding vectors, which are used by the link predictor to make the prediction.

function:

$$\Psi(\phi_w(w), \phi_a(a)) = u_R^T f(\phi_w(w)^T W_R^{[1:k]} \phi_a(a) + V_R \begin{bmatrix} \phi_w(w) \\ \phi_a(a) \end{bmatrix} + b_R) \quad (1)$$

where $f = tanh$ is a standard non-linearity applied element-wise and $W_R^{[1:k]} \in \mathbb{R}^{d \times d \times k}$ is a tensor. $\phi_w(w)^T W_R^{[1:k]} \phi_a(a)$ is a bilinear tensor product and results in a vector $d \in R^k$, where each entry is computed by one slice $m = 1, \ldots, k$ of the tensor: $\phi_w(w)^T W_R^{[m]} \phi_a(a)$. The other parameters for relation R are the standard form of a neural network: $V_R \in \mathbb{R}^{k \times 2d}$ and $U \in \mathbb{R}^k$, $\mathrm{b}_R \in \mathbb{R}^k$ [52].

Two-Phase Training. Due to the large amount of parameters in the model, we have to use a correspondingly large amount of widget-window pairs as the training data, which are infeasible to be manually labeled. To address this challenge, we adopt a two-phase training process. We first apply dynamic app exploration techniques [26, 41, 54] to automatically explore a large number of apps dynamically and pre-train the model based on the dynamically observed transitions. The variety of apps makes the embedding models general enough. As these transitions bias towards the transitions that can be easily found by dynamic analysis, we further fine tune the pre-trained model based on the manually identified window transitions from a smaller set of apps. In the fine tuning process, the parameters of the embedding models are frozen (i.e., weights and biases), meaning that these parameters do not change, while the parameters of the link predictor are set trainable to adapt the patterns related to window transitions.

6 EVALUATION

In this section, we seek to evaluate the effectiveness of ProMal to construct window transition graphs for real-world Android apps. We implement ProMal in Java. ProMal uses Gator [47, 69, 70], a state-of-the-art static Android GUI analysis tool, to build static WTGs, and uses Paladin [41], a state-of-the-art app exploration tool, to build dynamic WTGs. ProMal also uses Xposed [2] to instrument apps for collecting window transitions and other runtime information. The window transition prediction is implemented using Keras[13]. Specifically, we aim to answer the following research questions:

- **RQ1:** How effectively can ProMal build the WTGs?
- **RQ2:** How effectively can ProMal improve over Gator and Paladin?
- **RQ3:** How effectively can the NTN model and the two-phase training improve ProMal's window transition prediction?

Table 1: 40 apps used in our evaluations. The 35 real apps are sorted by their densities and divided evenly in 7 groups. F-Droid is the last group.

Group	Density	LOC	# Nodes	# Edges
Group 1	1.5–3.25	33,048	28	61
Group 2	3.3–4.8	46,508	28	59
Group 3	5.2–7.8	78,217	32	83
Group 4	8.8–12.7	344,144	40	136
Group 5	14.0–23.6	389,586	72	186
Group 6	25.5–37.4	823,086	76	246
Group 7	37.6–155.6	55,259	43	122
F-droid	1.5–35.8	714,044	50	178
Total	–	2,483,892	369	1,071

6.1 Subjects and Evaluation Setup

We use a diversified set of apps from Google Play [24] as our evaluation subjects. These apps are from 14 categories, such as Game, Entertainment, and Education. We also include popular open-sourced apps from F-Droid [20] in our evaluation subjects. Once we downloaded an app, we applied Gator to build static WTGs and excluded the apps with less than 3 windows, since their WTGs are fairly simple and will not be proper subjects for assessing the effectiveness of ProMal. In total, we examined 4,326 apps and got 2,216 apps with at least 3 windows. As shown in Figure 2, a node (window) may have multiple edges (transitions) to another node in WTGs, making the WTGs more complex than the WTGs that have one or two transitions among windows. Thus, we use *density* to represent the complexity of WTGs, where the density is computed using the number of edges divided by the number of nodes in static WTGs. Note that the edges in static WTGs may be infeasible, but they can still form a reasonable estimation of the actual WTG. Based on the density, we divided the apps into 7 groups equally, and randomly sample a subset from each group to evaluate ProMal on the WTGs of different complexities. As there is no publicly available groundtruth WTG for these apps, we need to construct the groundtruth WTGs by manually exploring the apps and inspecting their source code. Because the number of edges grows drastically as the complexity of the App grows, collecting the groundtruth requires a non-trivial effort. Within our affordable efforts, we randomly chose 5 apps from each group as our evaluation subjects. Together with the 5 apps chosen from F-Droid, we have 40 apps in 8 density groups. These apps also belong to different popular categories (e.g., sports, game, tools). The total LOC of these apps is ~ 2.5 million. The summary of the apps is shown in Table 1, and more details can be found on our website [4].

We then applied Paladin and ProMal on these 40 apps to build dynamic WTGs and performed window transition predictions to build the optimized WTGs. Paladin is a dynamic app exploration tool that models view trees as UI states to avoid visiting the same UI states during the exploration. It triggers actionable widgets in a Depth-First-Search manner to exercise as many behaviors as possible. Among all the apps analyzed by Paladin, the minimum running time is 1.35 minutes, and the maximum time is around 97 minutes. The average running time for all the apps is about 15.8 minutes per app.

Obtaining Groundtruth WTGs. We installed these apps on an Android phone, and manually explored the apps by interacting with each GUI widget to construct the groundtruth WTGs. We then matched the manually explored edges to the static WTGs, and then manually verify the unmatched edges in the static WTGs. As described in the studies [69, 70], due to the deficiencies in window/widget modeling [47] and event handler analysis [69], Gator will incorrectly include infeasible edges and also miss some feasible edges in the built WTGs. Thus, we further manually inspected the decompiled source code using Jadx [51] in the real apps and the source code in open source apps. We analyzed all the method calls of `startActivity` and all the callbacks of GUI widgets to identify the windows and transitions that we cannot observe in the static WTGs. The statistics of the groundtruth WTGs are shown in Table 1.

Training Prediction Model. To train the prediction model, we collect the most popular 30 apps (indicated by the downloading times) from each category of two app marketplaces, i.e., Google Play and Wandoujia [58] (a leading Android app marketplace in China). Then we use Paladin to perform dynamic analysis on each of the collected apps, and finally get dynamic WTGs from 1,625 apps. In the pre-training process, the model learns the parameters for the embedding model using these dynamic WTGs. In the fine-tuning process, the model learns to explore the relationship between an app widget and an app window. The model is evaluated using 10-fold cross validation, which is repeated 10 times. For the model parameters, we set the max word sequence length to 512, the word embedding size to 100, the LSTM state size to 72, the fully connected layer (FC) units of both the embedding models to 64, and the output size of NTN layer to 16. We take a batch size of 32 in both the pre-training and fine-tuning processes. Since there are far more negative samples (i.e., widget-window pairs without edges) than the positive samples (i.e., widget-window pairs with edges) in the dataset, we apply the method of negative sampling, by which we sample negative samples randomly for training. The final number of the negative samples is four times of the number of positive samples, so the class weights for the negative samples and the positive samples are set to 1 and 4, respectively.

Metrics. To measure the effectiveness of ProMal, we measure the nodes and edges of the WTGs built by ProMal, Gator, and Paladin, and compare these WTGs with the groundtruth WTGs to compute the precision, recall, and F_1-score for the detected edges. An edge (i.e., a window transition) in a WTG is considered as a true positive (TP) only if the nodes (i.e., windows) of the edge and the edge both match the corresponding nodes and edge in the groundtruth WTG; otherwise, it is considered as a false positive (FP). If a WTG misses an edge in the groundtruth WTG, we consider the missing edge as a false negative (FN); otherwise, it is a true negative (TN). Based on these values, we compute the precision as $prec = \frac{TP}{TP+FP}$, recall as $rec = \frac{TP}{TP+FN}$, and $F_1 = 2 \cdot \frac{prec \cdot rec}{prec + rec}$.

6.2 RQ1: Overall Effectiveness

Table 2 shows the details of the WTGs built by ProMal for each app. Column "# Nodes" shows the number of nodes in the WTG. Column "# Edges" shows the number of edges in the WTG. Column "Prec. (Edges)" and Column "Recall (Edges)" shows the precision and the recall of the detected edges. As we can see, on average,

Table 2: Details of the WTGs built by ProMal

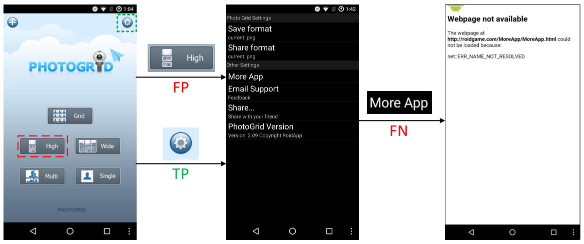
App Group	# Nodes	# Edges	Prec. (Edges)*	Recall (Edges)*
Group 1	26	56	89.00%	92.86%
Group 2	24	54	100.00%	92.95%
Group 3	28	63	97.33%	75.40%
Group 4	34	122	81.29%	71.08%
Group 5	52	148	83.98%	73.59%
Group 6	51	155	82.36%	59.34%
Group 7	36	107	90.37%	80.47%
F-Droid	27	154	97.09%	91.84%
Total	275	859	90.18%	79.69%

* Prec. and Recall are average values.

ProMal achieves a precision of 90.18%, a recall of 79.69%, and a F_1-score of 82.82%. In particular, ProMal achieves 97 + % precision in Groups 2 and 3, and 92 + % recall for Groups 1 and 2. It also achieves 91 + % precision and recall for the F-droid group. These results show that *ProMal is highly effective in identifying feasible edges in building WTGs.*

Combination of Gator and Paladin. We compare the WTGs built by ProMal and the combination of Gator and Paladin. The results show that the WTGs built by combining the WTGs of Gator and Paladin achieve a precision of 53.95%, a recall of 88.47%, and a F_1-score of 61.93% on average. Since all the edges produced by Paladin are feasible edges, the low precision is caused by a huge number of infeasible edges introduced by Gator. For the 40 apps in our dataset, Gator yields 3, 236 edges in total, while only 12.2% can be found in the WTGs built by Paladin. Thus, the majority of edges in Gator are further analyzed by the window transition prediction. For the 2, 841 unverified edges, 47.1% (1, 337) contains incomplete information (e.g., missing UI layout information or unable to locate the widget based on Gator's widget information). Our model hence regards these edges as infeasible edges and predicts the remaining 1, 504 edges. It is also noteworthy that 245 of the remaining edges from Gator are not specified with a widget ID. Instead, the widgets of these edges are often assigned to a whole window or an anonymous `MenuItem`, or a certain type of class name. To address such imprecision of Gator, ProMal considers all the clickable widgets that fit the widget information provided by Gator in the source window of these edges as the edges' source widgets, and predicts whether the edges are feasible. For edges with back events, we consider them as feasible if a non-back edge from the target window to the source window can be found in the predicted WTG. Only the edges that are predicted to be feasible edges are kept in the final WTGs. With the window transition prediction, the precision of the built WTGs is significantly improved (from 53.95% to 90.18%), which results in a significant improvement of F_1-score (from 61.93% to 82.82%). These results clearly demonstrate *the effectiveness of ProMal in using a synergy approach of program analysis and machine learning.*

FPs and FNs. Due to the *FP*s and the *FN*s, ProMal achieves a relatively low precision in Groups 4, 5, 6 and a relatively low recall in Group 6 (i.e., more than 5% lower). Figure 6 illustrates how ProMal produces an *FP* and an *FN*. The window on the left is from the activity `MainPage`. ProMal correctly identifies a transition from `MainPage` to the activity `Preference`, resulted from clicking the "info" button (highlighted in green). However, ProMal also incorrectly identifies another transition to the activity `Preference`, resulted from clicking the "High" button (highlighted in red). This *FP* is caused by the patterns learned by the machine learning model. Figure 6 also includes a *FN* produced by ProMal. In the `Preference` activity, if the "More App" button is clicked, the app will transit to the `More` activity, which serves as a built-in browser and displays a website to users. Due to the drastic changes of the UI states, the window transition prediction model cannot infer any close relationship between the source window and the target window from their UI layouts and screen snapshots, and thus produces a *FN*.



Webpage not available

The webpage at **http://roidgame.com/MoreApp/MoreApp.html** could not be loaded because:

net::ERR_NAME_NOT_RESOLVED

Figure 6: Example *FP* and *FN* produced by ProMal

Table 3: Details of the static WTGs built by Gator

App Group	# Nodes	# Edges	Prec. (Edges)*	Recall (Edges)*
Group 1	20	36	62.64%	46.22%
Group 2	23	48	62.36%	48.54%
Group 3	32	120	64.87%	77.00%
Group 4	44	212	48.99%	71.92%
Group 5	79	552	28.49%	77.02%
Group 6	117	832	28.47%	56.51%
Group 7	48	1219	22.75%	69.48%
F-Droid	29	217	50.00%	32.44%
Total	392	3,236	46.07%	59.89%

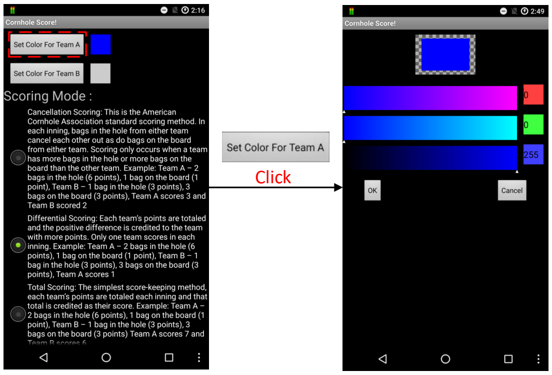
* Prec. and Recall are average values.

Furthermore, the limitations of Gator's model hinders the performance of ProMal. First, gator have trouble distinguishing widgets without widget IDs and will associate them with all possible handlers declared in the same method. This type of overapproximation makes ProMal generate extra edges. Second, a large number of false negatives are caused by Gator failing to identify dialog instances. Thus ProMal cannot detect transitions from these dialogs.

6.3 RQ2: Comparison with Paladin and Gator

Comparison with Gator Table 3 shows the details of the WTGs built by Gator for each app. As indicated by the results, many of the edges found by Gator are infeasible edges, i.e., *FP*s. These results show that the WTG built by Gator for each app is rather inaccurate, achieving a precision of 46.07%, a recall of 59.89%, and a F_1-score of 46.24%.

Upon further investigations, we find that Gator performs poorly on both precision and recall for two main reasons. The first reason is due to the imprecision of Gator. We empirically find out that Gator often yields multiple transitions with different target windows from the same UI widget, while most of them turn out to be infeasible. Figure 7 shows an example transition from the game app "com.twobitinc.cornholescore". The left window is from the activity `OptionsActivity`, which shows 5 buttons for users to customize certain game parameters such as the color of the team and the scoring

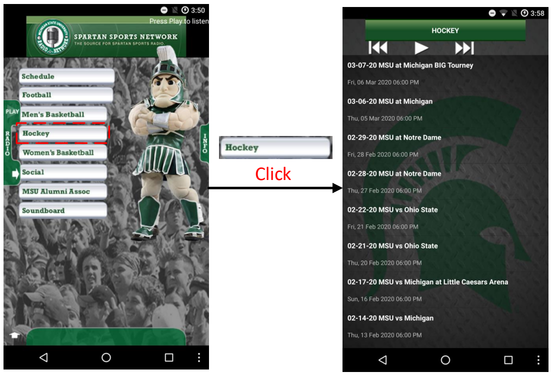


Cancellation Scoring: This is the American Cornhole Association standard scoring method. In each inning, bags in the hole from either team cancel each other out as do bags on the board from either team. Scoring only occurs when a team has more bags in the hole or more bags on the board than the other team. Example: Team A – 2 bags in the hole (6 points), 1 bag on the board (1 point), Team B – 1 bag in the hole (3 points), 3 bags on the board (3 points), Team A scores 3 and Team B scored 2

Differential Scoring: Each team's points are totaled and the positive difference is credited to the team with more points. Only one team scores in each inning. Example: Team A – 2 bags in the hole (6 points), 1 bag on the board (1 point), Team B – 1 bag in the hole (3 points), 3 bags on the board (3 points), Team A scores 1

Total Scoring: The simplest score-keeping method, each team's points are totaled each inning and that total is credited as their score. Example: Team A – 2 bags in the hole (6 points), 1 bag on the board (1 point), Team B – 1 bag in the hole (3 points), 3 bags on the board (3 points) Team A scores 7 and Team B scores 6

Figure 7: Example *FP* produced by Gator



03-07-20 MSU at Michigan BIG Tourney
Fri, 06 Mar 2020 06:00 PM
03-06-20 MSU at Michigan
Thu, 05 Mar 2020 06:00 PM
02-29-20 MSU at Notre Dame
Fri, 28 Feb 2020 06:00 PM
02-28-20 MSU at Notre Dame
Thu, 27 Feb 2020 06:00 PM
02-22-20 MSU vs Ohio State
Fri, 21 Feb 2020 06:00 PM
02-21-20 MSU vs Ohio State
Thu, 20 Feb 2020 06:00 PM
02-17-20 MSU vs Michigan at Little Caesars Arena
Sun, 16 Feb 2020 06:00 PM
02-14-20 MSU vs Michigan
Thu, 13 Feb 2020 06:00 PM

Figure 8: Example *FN* produced by Gator

mode. When the "Set Color" button is clicked, the UI transits to the activity **`RgbPickActivity`**. However, due to the imprecision in associating widget IDs and event handler methods, Gator infers that clicking any of the button will transit to 3 different activities. In this way, Gator infers 2 infeasible edges for each of the 5 buttons, and results in 10 *FP* edges for a single activity, which significantly reduces Gator's precision.

Second, Gator often fails to identify transitions between activities due to the limitation in modeling certain transitions. Figure 8 shows an example transition for the app "com.jacobsmedia.sparts". Upon clicking the "hockey" button, the app transits from the activity **`Main`** to another activity **`XmlPage`**. But Gator fails to infer this edge. Actually, the built WTG for this app indicates that the activity **`XmlPage`**, along with two other activities, have only transitions to themselves. However, there are in fact 9 edges among the three activities in the groundtruth WTGs, which cause 9 *FN*s for Gator.

Compared to Gator, ProMal significantly improves both the precision and the recall in building WTGs, with the help of dynamic analysis and window transition prediction. The predictions on the unverified edges in total rule out $2,351$ out of $2,399$ *FP* edges, hence significantly improving the precision of ProMal by 95.02%, from 46.24% to 90.18%. By adding the 708 edges detected by Paladin and the 63 edges from Gator's WTGs, the recall of the WTG built by ProMal is improved from 59.89% to 79.69%.

Comparison with Paladin. Table 4 shows the details of the WTGs built by Paladin. As Paladin adopts dynamic analysis, the precision in finding feasible edges is always 100%. On average, the WTGs built by Paladin achieve an average recall of 71.25% in finding feasible edges. We can observe that ProMal improves the built WTGs with the help of static analysis and window transition prediction. On average, ProMal improves the recall of Paladin by 8.44% and in turn improves the F_1-score by 2.35%. In particular, ProMal improves the recall significantly for Group 2 (from 76.36% to 92.95%) and Group 7 (from 68.23% to 80.47%). *The increased recall will enable testing to cover more behaviors with tolerable extra efforts on the reported infeasible transitions, with the precision still being* $90+\%$.

Table 4: Details of the dynamic WTGs built by Paladin

App Group	# Nodes	# Edges	Prec. (Edges)*	Recall (Edges)*
Group 1	26	55	100.00%	91.04%
Group 2	24	44	100.00%	76.36%
Group 3	26	54	100.00%	65.91%
Group 4	33	104	100.00%	67.68%
Group 5	51	122	100.00%	64.31%
Group 6	45	107	100.00%	46.61%
Group 7	35	82	100.00%	68.23%
F-Droid	45	140	100.00%	89.87%
Total	285	708	100.00%	71.25%

* Prec. and Recall are average values.

6.4 RQ3: Window Transition Prediction

We first compare the performance of the alternative models for the link predictor, and then measure the improvement brought by the two-phase training.

Comparison of Link Predictor Models. We compare our NTN model with the bilinear model [33, 55], which is also an effective way to model the relationships between entities. We train both models using the window transitions collected from the dataset of 1,625 apps, which are automatically explored by Paladin. The results show that NTN achieves a precision of 96.97%, a recall of 95.26% and a F_1-score of 95.73%, while the bilinear model only achieves a precision of 83.64%, a recall of 75.40% and a F_1-score of 73.98%. Thus, NTN is a better choice for the link predictor.

Effectiveness of Two-Phase Training. By performing our two-phase training, the prediction model achieves a precision of 50.00%, a recall 73.91%, and a F_1-score of 59.65%. However, if we directly use 90% of the groundtruth WTGs to train the model, the prediction model achieves a precision of 33.82%, a recall of 67.65%, and a F_1-score of 45.10%. This clearly demonstrates the improvement brought by the two-phase training. Moreover, even though the two-phase training improves the performance of the prediction, the overall performance of prediction is still not satisfactory. The reason is that for these unverified edges, ProMal uses static GUI rendering [3, 32] to render the layout files to obtain the view trees and screenshots, which are not as accurate as dynamic analysis. Even so, when it is applied on only the unverified edges, ProMal can achieve further improvement by combining the prediction results of the unverified edges with the verified edges, improving the F_1-score to 82.82%. If we use the model without pre-training in ProMal, the precision drops to 61.12%, the recall becomes 78.31%, and the F_1-score is only 65.33%, indicating the importance of two-phase training.

7 DISCUSSION

Static Analysis. ProMal builds the static analysis upon Gator [47, 69, 69], and extends the static analysis to detect dialog transitions buried in the callbacks of dialogs. While Gator provides a comprehensive model of Android environment (e.g., back stacks, events, and callbacks), it adopts an over-approximation algorithm that applies only weak updates when associating the widget IDs and event handler callbacks. Such problems can be mitigated by applying more expensive but precise analysis such as path-sensitive analysis like FlowDroid [6] and symbolic execution [21, 34, 36, 44, 49].

Dynamic Analysis. Dynamic app exploration [26, 27, 40, 41, 54] has been used to generate GUI tests, discover app behaviors, and detect violations ad fraud. ProMal leverages dynamic app exploration to build the dynamic WTG for an app. While these approaches can automatically trigger both UI widget events and hardware events (e.g., pressing BACK button), they still suffer from coverage issues due to various environment dependencies. This issue can be mitigated by using developer-provided test cases as seeds [8, 71] to improve app exploration.

Window Transition Prediction. Due to the functionality and design differences between different apps, many transition features are quite unique. Therefore, the prediction model has a rather good performance in apps similar to its training set and performs poorly in other apps. In future work, we plan to extract more features such as whether the widget is clickable or not to improve the prediction.

Threats to Validity Our evaluation subjects may not be representative of the entire market. To mitigate the issue, we choose apps that have WTGs of different complexities, and the subjects used for pre-training (1,625 apps) also alleviate the issue. We plan to address this limitation by including more diversified market apps to further reduce the threats. Also, we discard apps that cannot be analyzed by either Paladin or Gator, which are mainly caused by the compatibility problem of the libraries and SDK versions. This can be mitigated by upgrading the libraries and adding support for later SDK versions. Inaccuracies in the manual code inspection are inevitable due to the lack of the ground truth WTGs. In addition, there may be human errors in collecting statistics and studying the evaluation results. These threats are mitigated by double-checking all manual work and ensuring that the results were agreed upon by at least two authors.

8 RELATED WORK

Android UI Modelling. Rountev et al.'s Gator [47, 69, 70] is among the first to provide a static analysis framework for modeling Android apps' UIs. Gator models GUI-related Android objects, their flow through the application, and their interactions with each other via the abstractions defined by the Android platform [47], and provides a context-sensitive static analysis of callback methods to link callback methods to GUI objects [69]. Built upon this static analysis, Gator further generalizes the analysis with explicit modeling of the window stack to generate a static WTG [70]. Besides static analysis, dynamic analysis builds a UI model that represents different states for windows, which can be considered as a finer grained WTG [26, 40, 41, 54]. These UI states are used to guide the dynamic exploration to either discover more behaviors or identify certain violations (e.g., ad frauds). ProMal's WTG analysis is built upon these static and dynamic analysis techniques, where the dynamic analysis is used to verify the results of the static analysis.

Hybrid Program Analysis. Hybrid program analysis has been used to improve the precision of various static analysis. Check 'n' crash [15, 16] takes the error conditions inferred using theorem proving techniques by a static checker and produces test cases to determine whether an error truly exists. This technique has shown advantages over both static checking and automatic testing individually. Blended analysis [18, 61] combines dynamic and static analysis by first applying dynamic analysis to capture runtime information and then performing static analysis on each dynamic trace to identify solutions, which has been shown to achieve promising results in performance understanding and taint analysis. Another important line of hybrid analysis is concolic testing [21, 49, 57, 66, 67], where dynamic analysis is used to collect constraints along the executed program paths and static symbolic analysis and constraint solver are used to derive new inputs to explore more program paths. ProMal's "tribrid analysis" is inspired by the idea of hybrid program analysis, where machine learning techniques are used to address the limitations of both static and dynamic analysis.

Machine-Learning Based Link Prediction. Link prediction is a fundamental problem in link mining that attempts to predict the existence of a link between two nodes based on observed links and the attributes of nodes[50]. Link prediction and recommendation problem was first proposed by Liben-nowell et. al [39]. Traditionally, there are two ways of making link predictions: one way to make this prediction is based on structural properties of the network [39], another way is to make use of attribute information for link prediction [46]. Recently, a lot of methods based on machine learning techniques are proposed [35, 38, 48]. The first to study the link prediction problem as a supervised learning problem is Hasan et. al. [28], where the existing and non-existing social links are treated as the positive and negative instances respectively. ProMal is related to link prediction but focuses on predicting transitions among windows using app-specific UI information.

9 CONCLUSION

We have proposed ProMal, a synergistic analysis that combines static analysis, dynamic analysis, and machine learning to construct a precise WTG. ProMal applies static analysis and dynamic analysis to build the static WTG and the dynamic WTG for an app, and identifies the verified edges by matching the edges in these two WTGs. ProMal then leverages machine learning techniques to predict the unverified edges in the WTG to determine whether they are feasible transitions. Our evaluations on 40 real-world apps demonstrate the superiority of ProMal in building WTGs over static analysis and dynamic analysis when they are applied separately.

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REFERENCES

[1] 1999. XML Path Language (XPath). https://www.w3.org/TR/1999/REC-xpath-19991116/.

[2] 2017. Xposed. http://repo.xposed.info/module/de.robv.android.xposed.installer

[3] 2019. Android Development Tools (ADT). https://marketplace.eclipse.org/content/android-development-tools-eclipse.

[4] 2021. Promal Project Website. https://github.com/promal-android/Promal.

[5] 2021. UI/Application Exerciser Monkey. https://developer.android.com/studio/test/monkey. Accessed: 2021-01-30.

[6] Steven Arzt, Siegfried Rasthofer, Christian Fritz, Eric Bodden, Alexandre Bartel, Jacques Klein, Yves Le Traon, Damien Octeau, and Patrick McDaniel. 2014. FlowDroid: Precise context, flow, field, object-sensitive and lifecycle-aware taint analysis for Android apps. In *Proceedings of the ACM Conference on Programming Language Design and Implementation (PLDI)*.

[7] Tanzirul Azim and Iulian Neamtiu. 2013. Targeted and depth-first exploration for systematic testing of Android apps. In *Proceedings of the ACM International Conference on Object Oriented Programming Systems Languages & Applications (OOPSLA)*.

[8] Domagoj Babić, Lorenzo Martignoni, Stephen McCamant, and Dawn Song. 2011. Statically-directed dynamic automated test generation. In *Proceedings of the International Symposium on Software Testing and Analysis (ISSTA)*.

[9] Abhijeet Banerjee, Lee Kee Chong, Clément Ballabriga, and Abhik Roychoudhury. 2018. EnergyPatch: Repairing resource leaks to improve energy-efficiency of Android apps. *IEEE Transactions on Software Engineering (TSE)* 44, 5 (2018), 470–490.

[10] Abhijeet Banerjee, Lee Kee Chong, Sudipta Chattopadhyay, and Abhik Roychoudhury. 2014. Detecting energy bugs and hotspots in mobile apps. In *Proceedings of the ACM International Symposium on Foundations of Software Engineering (FSE)*.

[11] Farnaz Behrang and Alessandro Orso. 2019. Test migration between mobile apps with similar functionality. In *Proceedings of the IEEE/ACM International Conference on Automated Software Engineering (ASE)*.

[12] buildfire. 2020. Mobile App Download and Usage Statistics (2020). https://buildfire.com/app-statistics/. Accessed: 2021-01-30.

[13] François Chollet et al. 2015. Keras. https://keras.io.

[14] Shauvik Roy Choudhary, Alessandra Gorla, and Alessandro Orso. 2015. Automated test input generation for Android: Are we there yet?. In *Proceedings of IEEE/ACM International Conference on Automated Software Engineering (ASE)*.

[15] Christoph Csallner and Yannis Smaragdakis. 2005. Check 'N' Crash: Combining static checking and testing. In *Proceedings of the International Conference on Software Engineering (ICSE)*.

[16] Christoph Csallner, Yannis Smaragdakis, and Tao Xie. 2008. DSD-Crasher: A hybrid analysis tool for bug finding. *ACM Transactions on Software Engineering and Methodology (TOSEM)* 17, 2 (2008), 8:1–8:37.

[17] Zhen Dong, Marcel Böhme, Lucia Cojocaru, and Abhik Roychoudhury. 2020. Time-travel testing of Android apps. In *Proceedings of the ACM/IEEE International Conference on Software Engineering (ICSE)*.

[18] Bruno Dufour, Barbara G. Ryder, and Gary Sevitsky. 2007. Blended analysis for performance understanding of framework-based applications. In *Proceedings of the ACM International Symposium on Software Testing and Analysis (ISSTA)*.

[19] Michael D. Ernst, René Just, Suzanne Millstein, Werner Dietl, Stuart Pernsteiner, Franziska Roesner, Karl Koscher, Paulo Barros, Ravi Bhoraskar, Seungyeop Han, Paul Vines, and Edward XueJun Wu. 2014. Collaborative verification of information flow for a high-assurance app store. In *Proceedings of the ACM Conference on Computer and Communications Security (CCS)*.

[20] F-Droid. 2021. FOSS Apps for Android. https://f-droid.org/

[21] Patrice Godefroid, Nils Klarlund, and Koushik Sen. 2005. DART: Directed automated random testing. In *Proceedings of the ACM Conference on Programming Language Design and Implementation (PLDI)*.

[22] Ian J. Goodfellow, Yoshua Bengio, and Aaron C. Courville. 2016. *Deep Learning*. MIT Press. http://www.deeplearningbook.org/

[23] Google. 2017. Android View System. https://developer.android.com/guide/topics/ui/declaring-layout.html.

[24] Google. 2017. Google Play Store. https://play.google.com/store?hl=en.

[25] Google. 2020. UI Automator. https://developer.android.com/training/testing/ui-automator.

[26] Tianxiao Gu, Chengnian Sun, Xiaoxing Ma, Chun Cao, Chang Xu, Yuan Yao, Qirun Zhang, Jian Lu, and Zhendong Su. 2019. Practical GUI testing of Android applications via model abstraction and refinement. In *Proceedings of the International Conference on Software Engineering (ICSE)*.

[27] Shuai Hao, Bin Liu, Suman Nath, William G. J. Halfond, and Ramesh Govindan. 2014. PUMA: Programmable UI-automation for large-scale dynamic analysis of mobile apps. In *Proceedings of the Annual International Conference on Mobile Systems, Applications, and Services (MobiSys)*.

[28] Mohammad Al Hasan, Vineet Chaoji, Saeed Salem, and Mohammed Zaki. 2006. Link prediction using supervised learning. In *Proceedings of SDM workshop on Link Analysis, Counterterrorism and Security*.

[29] Geoffrey E. Hinton, Simon Osindero, and Yee-Whye Teh. 2006. A fast learning algorithm for deep belief nets. *Neural Computing* 18, 7 (2006), 1527–1554.

[30] Geoffrey E Hinton and Ruslan R Salakhutdinov. 2006. Reducing the dimensionality of data with neural networks. *Science* 313, 5786 (2006), 504–507.

[31] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. 2017. Densely connected convolutional networks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

[32] Jianjun Huang, Zhichun Li, Xusheng Xiao, Zhenyu Wu, Kangjie Lu, Xiangyu Zhang, and Guofei Jiang. 2015. SUPOR: Precise and scalable sensitive user input detection for Android apps. In *Proceedings of the USENIX Security Symposium (USENIX Security)*.

[33] Rodolphe Jenatton, Nicolas Le Roux, Antoine Bordes, and Guillaume Obozinski. 2012. A latent factor model for highly multi-relational data. In *Proceedings of the Advances in Neural Information Processing Systems (NIPS)*.

[34] Jinseong Jeon, Kristopher K. Micinski, and Jeffrey S. Foster. 2012. *SymDroid: Symbolic execution for dalvik bytecode*. Technical Report. CS-TR-5022, Department of Computer Science, University of Maryland, College Park.

[35] Mohammad Mehdi Keikha, Maseud Rahgozar, and Masoud Asadpour. 2021. DeepLink: A novel link prediction framework based on deep learning. *Journal of Information Science* 47, 5 (2021), 642–657.

[36] James C. King. 1976. Symbolic execution and program testing. *Communications of ACM (CACM)* 19, 7 (1976), 385–394.

[37] Yann LeCun, Yoshua Bengio, et al. 1995. Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks* 3361, 10 (1995), 1995.

[38] Xin Li and Hsinchun Chen. 2009. Recommendation as link prediction in bipartite graphs: A graph kernel-based machine learning approach. *Decision Support Systems* 54, 2 (2009), 213–216.

[39] David Liben-nowell and Jon Kleinberg. 2010. The link prediction problem for social networks. *Journal of the American Society for Information Science and Technology (JASIST)* 58, 7 (2010), 1019–1031.

[40] Bin Liu, Suman Nath, Ramesh Govindan, and Jie Liu. 2014. DECAF: Detecting and characterizing Ad fraud in mobile apps. In *Proceedings of the USENIX Symposium on Networked Systems Design and Implementation (NSDI)*.

[41] Yun Ma, Yangyang Huang, Ziniu Hu, Xusheng Xiao, and Xuanzhe Liu. 2019. Paladin: Automated generation of reproducible test cases for Android apps. In *Proceedings of the International Workshop on Mobile Computing Systems and Applications (HotMobile)*.

[42] Ke Mao, Mark Harman, and Yue Jia. 2016. Sapienz: Multi-objective automated testing for android applications. In *Proceedings of the International Symposium on Software Testing and Analysis (ISSTA)*.

[43] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781* (2013).

[44] Nariman Mirzaei, Sam Malek, Corina S. Pasareanu, Naeem Esfahani, and Riyadh Mahmood. 2012. Testing Android apps through symbolic execution. *ACM Software Engineering Notes (SEN)* 37, 6 (2012), 1–5.

[45] Minxue Pan, An Huang, Guoxin Wang, Tian Zhang, and Xuandong Li. 2020. Reinforcement learning based curiosity-driven testing of Android applications. In *Proceedings of the ACM International Symposium on Software Testing and Analysis (ISSTA)*.

[46] A Popescul. 2003. Statistical relational learning for link prediction. In *Proceedings of the IJCAI Workshop on Learning Statistical MODELS From Relational Data*.

[47] Atanas Rountev and Dacong Yan. 2014. Static reference analysis for GUI objects in Android software. In *Proceedings of Annual IEEE/ACM International Symposium on Code Generation and Optimization (CGO)*.

[48] Salvatore Scellato, Anastasios Noulas, and Cecilia Mascolo. 2011. Exploiting place features in link prediction on location-based social networks. In *Proceedings of the ACM International Conference on Knowledge Discovery and Data Mining (KDD)*.

[49] Koushik Sen, Darko Marinov, and Gul Agha. 2005. CUTE: A concolic unit testing engine for C. In *Proceedings of the ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE)*.

[50] Chuan Shi, Yitong Li, Jiawei Zhang, Yizhou Sun, and Philip S. Yu. 2016. A survey of heterogeneous information network analysis. *IEEE Transactions on Knowledge and Data Engineering (TKDE)* 29, 1 (2016), 17–37.

[51] skylot. 2020. JADX - Dex to Java decompiler. https://github.com/skylot/jadx.

[52] R. Socher, D. Chen, C. D. Manning, and A. Y. Ng. 2013. Reasoning with neural tensor networks for knowledge base completion. In *Proceedings of the International Conference on Neural Information Processing Systems (NIPS)*.

[53] Statista. 2020. Global mobile OS market share. https://www.statista.com/statistics/266136/global-market-share-held-by-smartphone-operating-systems/.

[54] Ting Su, Guozhu Meng, Yuting Chen, Ke Wu, Weiming Yang, Yao Yao, Geguang Pu, Yang Liu, and Zhendong Su. 2017. Guided, stochastic model-based GUI testing of Android apps. In *Proceedings of the ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE)*.

[55] Ilya Sutskever, Joshua Tenenbaum, and Russ R Salakhutdinov. 2009. Modelling relational data using bayesian clustered tensor factorization. *Advances in neural information processing systems* 22 (2009).

[56] Yutian Tang, Yulei Sui, Haoyu Wang, Xiapu Luo, Hao Zhou, and Zhou Xu. 2020. All your app links are belong to us: understanding the threats of instant apps

based attacks. In *Proceedings of the ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE)*.

[57] Nikolai Tillmann and Jonathan de Halleux. 2008. Pex - White box test generation for .NET. In *Proceedings of the International Conference on Tests and Proofs (TAP)*.

[58] wandoujia. 2017. WanDouJia App Store. http://www.wandoujia.com/apps. Accessed: 2021-01-30.

[59] Jue Wang, Yanyan Jiang, Chang Xu, Chun Cao, Xiaoxing Ma, and Jian Lu. 2020. ComboDroid: generating high-quality test inputs for Android apps via use case combinations. In *Proceedings of the ACM/IEEE International Conference on Software Engineering (ICSE)*.

[60] Yan Wang and Atanas Rountev. 2016. Profiling the responsiveness of android applications via automated resource amplification. In *Proceedings of the IEEE/ACM International Conference on Mobile Software Engineering and Systems (MOBILESoft)*.

[61] Shiyi Wei and Barbara G. Ryder. 2013. Practical blended taint analysis for JavaScript. In *Proceedings of the International Symposium on Software Testing and Analysis (ISSTA)*.

[62] Haowei Wu, Yan Wang, and Atanas Rountev. 2018. Sentinel: generating GUI tests for Android sensor leaks. In *Proceedings of the IEEE/ACM International Workshop on Automation of Software Test (AST)*.

[63] Shengqu Xi, Shao Yang, Xusheng Xiao, Yuan Yao, Yayuan Xiong, Fengyuan Xu, Haoyu Wang, Peng Gao, Zhuotao Liu, Feng Xu, , and Jian Lu. 2019. DeepIntent : Deep icon-behavior learning for detecting intention-behavior discrepancy in mobile apps. In *Proceedings of the ACM Conference on Computer and Communications Security (CCS)*.

[64] Xusheng Xiao, Sihan Li, Tao Xie, and Nikolai Tillmann. 2013. Characteristic studies of loop problems for structural test generation via symbolic execution. In *Proceedings of the International Conference on Automated Software Engineering (ASE)*.

[65] Xusheng Xiao, Xiaoyin Wang, Zhihao Cao, Hanlin Wang, and Peng Gao. 2019. IconIntent: Automatic identification of sensitive UI widgets based on icon classification for Android apps. In *Proceedings of the International Conference on Software Engineering (ICSE)*.

[66] Xusheng Xiao, Tao Xie, Nikolai Tillmann, and Jonathan de Halleux. 2011. Precise identification of problems for structural test generation. In *Proceedings of the International Conference on Software Engineering (ICSE)*.

[67] Tao Xie, Nikolai Tillmann, Peli de Halleux, and Wolfram Schulte. 2009. Fitness-guided path exploration in dynamic symbolic execution. In *Proceedings of the IEEE/IFIP International Conference on Dependable Systems and Networks (DSN)*.

[68] Jiwei Yan, Hao Liu, Linjie Pan, Jun Yan, Jian Zhang, and Bin Liang. 2020. Multiple-entry testing of android applications by constructing activity launching contexts. In *Proceedings of the IEEE/ACM International Conference on Software Engineering (ICSE)*.

[69] Shengqian Yang, Dacong Yan, Haowei Wu, Yan Wang, and Atanas Rountev. 2015. Static control-flow analysis of user-driven callbacks in Android applications. In *Proceedings of the International Conference on Software Engineering (ICSE)*.

[70] Shengqian Yang, Hailong Zhang, Haowei Wu, Yan Wang, Dacong Yan, and Atanas Rountev. 2015. Static window transition graphs for Android. In *Proceedings of the IEEE/ACM International Conference on Automated Software Engineering (ASE)*.

[71] X. Yuan and A. M. Memon. 2007. Using GUI run-time state as feedback to generate test cases. In *Proceedings of the International Conference on Software Engineering (ICSE)*.

[72] Yujie Yuan, Lihua Xu, Xusheng Xiao, Andy Podgurski, and Huibiao Zhu. 2017. RunDroid: recovering execution call graphs for Android applications. In *Proceedings of the ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE)*.