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Master Thesis

# Intent Prediction with Vectorized Sequential UI Tree Data

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## **Kurzfassung**

<Short summary of the thesis>

## Abstract

The interaction of a user with an end device such as a smartphone or a computer is very diverse and difficult to predict. Nevertheless, user-specific (personalized) as well as global (collaborative) patterns can possibly be worked out with the help of preceding user interactions. These could be used to predict the intention of a user or a group of users. It is interesting to know to what level of detail these predictions can be made reliably. By making use of the continuous on-device data an attempt can be made to gain more insights in the user behavior or even forecast their next actions.

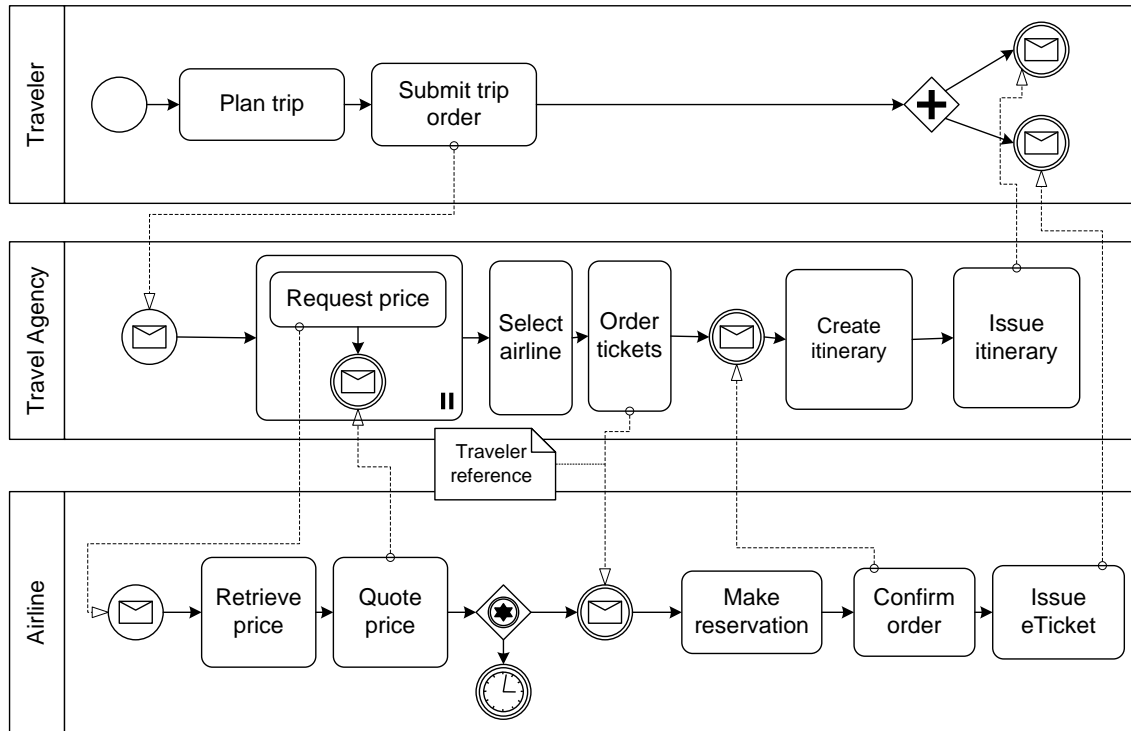
It suggests itself to implement this with the help of user interactions in sessions on Android devices. For this purpose, the Sequential UI Tree data of the device could be tracked, filtered and labeled and then trained with a machine learning model to find similar interaction sequences and then make predictions. These can then be very coarse, such as predicting the next app. Or they can be very detailed, e.g., determining the next user action, such as filling out a form field.

A concept will be developed on how a model for predicting user intent could be built and how it could be applied to the user session. To this end, possibilities for collecting and vectorizing sequential UI trees (e.g., from the Android Accessibility Service) will be discussed (e.g., via Recurrent Neural Network (*RNN*) [10] [1] [5], *Seq2Seq* Model [2], *Screen2Vec* Model [8], *Intention2Text* [13], *Html2Vec* [12]), which are designed to predict the user intent. Here, privacy and feature pre-filtering in UI data plays an important role. After that, personalized as well as collaborative data can be used in a hybrid approach. This model should then be made available to the user in an Android app service and, depending on the level of detail, suggest upcoming apps or actions to the user at a suitable time. It should also be considered whether the user can contribute to the learning process and improve suggested actions through feedback (labeling). The performance of the model can be measured, for example, by indicators such as the amount of training data and time spent on the learning process. The effectiveness can be evaluated by accuracy metrics in predicting, for example, app categories [9] or complete test sequences via Rico [3] or ERICA [4].

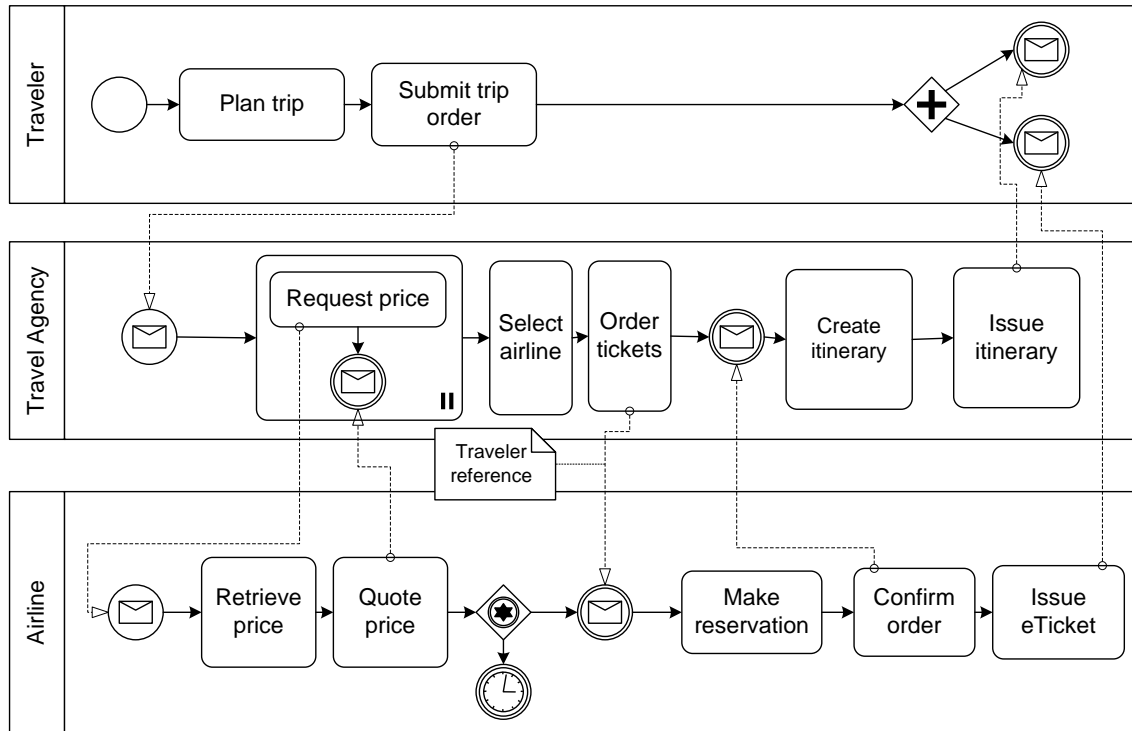
Furthermore, the machine learning model could provide the following benefits in addition to intent prediction:

- reduction of the complexity and size of the UI tree
- creation of user groups that have similar behavior when using digital UI systems [7]
- elimination of technical expertise on individual features that would be required to manually compare user sessions [6]
- consideration of a user's history over time (sequential)
- comparison of user interactions without providing privacy invasive information
- supporting app developers to improve their app design and usability
- application in psychology and market research
- pre-loading of processes on devices (energy savings) [11]

As listed above, many fields of application can profit by elaborating such a system. It would be exciting to know, how the concrete concept would look like and if it can be implemented successfully e.g. to improve the user experience on end-user devices.



**Figure 1:** Possible procedure using a Machine-Learning algorithm to predict the next intent from a beginning user session: The input (1) can be a sequence of Android tree data. With help of a Machine-Learning-Model (2) (e.g. RNN) a vector representation can be trained and then predict the most probable action or screen (3) from a given starting sequence, but also can be improve through the users feedback.



**Figure 2:** Schedule as a Gantt Chart



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# 1 Introduction

This is a typical human-computer interaction thesis structure for an introduction which is structured in four paragraphs as follows:

## 1.1 Motivation for transforming Android UI tree data to vectors

P1.1. What is the large scope of the problem?

P1.2. What is the specific problem?

P2.1. The second paragraph should be about what have others been doing

P2.2. Why is the problem important? Why was this work carried out?

P3.1. What have you done?

P3.2. What is new about your work?

P4.1. What did you find out? What are the concrete results?

P4.2. What are the implications? What does this mean for the bigger picture?



## 2 Related Work

Describe relevant scientific literature related to your work.

a) Doc2Vec and Word2Vec b) Tree2Vec c) Html2Vec d) Activity2Vec

### 2.1 Vector models

#### 2.1.1 Seq2Seq Model

### 2.2 Time Series / Sequence models

#### 2.2.1 RICO / RicoSCA

"Rico is a public UI corpus with 72K Android UI screens mined from 9.7K Android apps. [...] We manually removed screens whose view hierarchies do not match their screenshots by asking annotators to visually verify whether the bounding boxes of view hierarchy leaves match each UI object on the corresponding screenshot image. This filtering results in 25K unique screens."

#### 2.2.2 Screen2Vec

#### 2.2.3 Screen2Words

#### 2.2.4 Intention2Text

#### 2.2.5 Html2Vec





## **3 Methodology**

### **3.1 Android UI Data**

#### **3.1.1 Data tree structure**

#### **3.1.2 Retrieval of UI data via Android Accessibility Service**

### **3.2 Machine Learning**

#### **3.2.1 Preprocessing**

##### **3.2.1.1 Normalization, Feature selection**

Such as Filtering privacy invasive details

Parameterizing the vectorization process a) Vector length b) Weighting of features c) Manipulating individual parameters of model

##### **3.2.2 Supervised vs Unsupervised vs Semisupervised**

##### **3.2.3 Under and Overfitting**

##### **3.2.4 Evaluation Metrics**

##### **3.2.5 Neuronal Nets**

Activation Functions Cost function Gradient - Regression: Continuous Values - Classification: Multiple class - One Class

Tensors

LSTM 4 dimensional

Embedding before LSTM

TimeDistributedLayer

### **3.2.5.1 Deep Neuronal Nets**

### **3.2.5.2 Convolutional Neuronal Nets**

### **3.2.5.3 Recurrent Neuronal Networks and LSTMs / GRU**

### **3.2.6 Layers**

- Embedding layer Dimension near the actual average length of features - Dense Layer

Positive Integer to Dense Vectors of fixed size

#### **3.2.6.1 Autoencoders**

## 4 Results

### 4.1 Datasets

- Problem with sequential data sets

#### 4.1.1 Rico

- Too less frames.
- No transition between apps.

### 4.2 Preprocessing Android UI tree data

#### 4.2.1 Filtering privacy invasive details

#### 4.2.2 Normalization, Feature selection

Dealing with variable length data `tf.io.VarLenFeature()`

### 4.3 Evaluation

Multiple approaches

AutoEncoder:

- Encoder -> Decoder -> LSTM -> Decoder - Encoder -> LSTM -> Decoder - LSTM -> Encoder -> Decoder (AutoEncoder)

Decoder can either only decode to x and y or to whole UI tree.

#### 4.3.1 Mean Squared Error

#### 4.3.2 F1 Score



## **5 Application of Android UI tree vectors**

**5.1 Automation and testing of Android apps**

**5.2 UI design similarities**

**5.3 Action prediction models, User behavior modeling**

**5.4 Behavioral analyses for smartphone usage patterns**



## **6 Conclusion and Future Work**

### **Summary**

### **Outlook**

Future directions for research in this area

ChatGPT – Image Recognition – Limitation als Ausblick

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### **Declaration**

I hereby declare that the work presented in this thesis is entirely my own and that I did not use any other sources and references than the listed ones. I have marked all direct or indirect statements from other sources contained therein as quotations. Neither this work nor significant parts of it were part of another examination procedure. I have not published this work in whole or in part before. The electronic copy is consistent with all submitted copies.

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