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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) [14] [2] [6], *Seq2Seq* Model [3], *Screen2Vec* Model [11], *Intention2Text* [17], *Html2Vec* [16]), 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 [12] or complete test sequences via Rico [4] or ERICA [5].

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 [9]
- elimination of technical expertise on individual features that would be required to manually compare user sessions [8]
- 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) [15]

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

Contents

1	Introduction	17
1.1	Necessarity of Vectors for Android UI	17
2	Related Work	19
2.1	UI Tree and Datasets	19
2.1.1	ERICA	19
2.1.2	RICO / RicoSCA	19
2.1.3	Mobile UI CLAY Dataset	21
2.2	Vector models	21
2.2.1	Doc2Vec and Word2Vec	21
2.2.2	Screen2Vec	21
2.2.3	Screen2Words	21
2.2.4	Intention2Text	21
2.2.5	Html2Vec	21
2.2.6	Tree2Vec	21
2.2.7	Activity2Vec	21
2.3	Time Series / Sequence models	21
2.3.1	Seq2Seq Model	21
3	Theoretical Framework	23
3.1	Android UI Data	23
3.1.1	Data tree structure	23
3.1.2	Retrieval of UI data via Android Accessibility Service	23
3.2	Machine Learning	24
3.2.1	Preprocessing	25
3.2.1.1	Feature selection	25
3.2.1.2	Missing data	25
3.2.1.3	Normalization and Standardization	25
3.2.1.4	Padding	26
3.2.1.5	Categorical Variables	26
3.2.2	Supervised vs Unsupervised vs Semisupervised	26
3.2.2.1	Supervised Learning	26
3.2.2.2	Unsupervised Learning	26
3.2.3	Under and Overfitting	26
3.2.4	Evaluation Metrics	26
3.3	Artificial Neural Nets	26
3.3.1	Classes of Neural Nets	27
3.3.1.1	Deep Neural Nets	27
3.3.1.2	Convolutional Neural Nets	27

3.3.1.3	Recurrent Neural Networks and LSTMs / GRU	27
3.3.1.4	Autoencoders	27
3.3.2	Tensorflow and Keras	27
3.4	Evaluation and Metrics	27
3.4.1	Mean Squared Error	27
3.4.2	F1 Score	27
4	Methodology	29
4.1	Data Aquisition	29
4.2	Methodological variety	29
4.3	Methodological choices	30
4.4	Research Biases	30
5	Results	31
5.1	Datasets	31
5.1.1	Rico	31
5.2	Preprocessing Android UI tree data	31
5.2.1	Filtering privacy invasive details	31
5.2.2	Normalization, Feature selection	31
5.3	Model	31
5.4	Evaluation	32
5.4.1	Mean Squared Error	32
5.4.2	F1 Score	32
5.5	Limitations	32
6	Application of Android UI tree vectors	33
6.1	Automation and testing of Android apps	33
6.2	UI design similarities	33
6.3	Action prediction models, User behavior modeling	33
6.4	Behavioral analyses for smartphone usage patterns	33
7	Conclusion and Future Work	35

List of Figures

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 improvde through the users feedback.	4
2	Schedule as a Gantt Chart	5
3.1	https://developer.android.com/studio/debug/layout-inspector , https://github.com/mimuc/app-ins-gruene	23
5.1	Model loss vs validation loss	32

List of Tables

2.1 Values of Rico Node 20

Glossary

Big Data Extremely large and complex data sets which can only be processed with modern computing soft- and hardware. 24

Acronyms

Machine Learning (ML) Scientific approach to form statistical models without the need to explicitly program it. 24, 25

1 Introduction

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

1.1 Necessarity of Vectors for Android UI

Motivation for transforming Android UI tree data to vectors

[TODO]: P1.1. What is the large scope of the problem?

[TODO]: P1.2. What is the specific problem?

[TODO]: P2.1. The second paragraph should be about what have others been doing

[TODO]: P2.2. Why is the problem important? Why was this work carried out?

[TODO]: P3.1. What have you done?

[TODO]: P3.2. What is new about your work?

[TODO]: P4.1. What did you find out? What are the concrete results?

[TODO]: 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.

2.1 UI Tree and Datasets

2.1.1 ERICA

ERICA is a design and interaction mining application, which allows gathering *interaction traces* by capturing the users activity on Android apps [5]. This is accomplished through a web-based interaction layer in contrast to the other common approach of using *accessibility services* directly. They justify that approach by the lack of need to install additional applications, as only a browser is required. A further reason is the response latency of the commonly used *UiAutomator*, which cannot collect the data in time. Also they argue that capturing and simultaneously interacting with the apps may overload the user device and challenges the user experience. Therefore the much more powerful servers take the task of capturing the UI trees. The apps are hosted on multiple physical devices with a modified Android OS directly connected with the server. ERICA captures UI screens and user flows by tracking UI changes. They then used this data to form k-mean clusters from the UI elements (visual and textual features) and the interactive elements (icons and buttons). Based on the clusters they then build classifiers and trained an ?? to determine the flows from the test dataset. The authors worked out 23 common user flows (from over a thousand popular Android apps) which aim to provide complementary, promising or new design patterns and trends.

2.1.2 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."

Use web interface to gain tree and interaction traces

See [4]

Key	Type	Shape	Description
Per Trace			
activity_name	string	(1, None)	Name of the activity: “com.my_app.AppName.MainActivity”
is_keyboard_deployed	bool	(1)	Indicates if the keyboard is shown
request_id	int	(1)	<div>[TODO]: TODO</div>

Per Node			
abs-pos	bool	(1)	Indicates if position in bounds is relative to the parent or absolute to the screen boundaries
adapter-view	bool	(1)	Indicates that children are loaded via an adapter, see https://developer.android.com/reference/android/widget/AdapterView
ancestors	bool	(1)	<div>[TODO]: TODO</div>
bounds	bool	(1)	<div>[TODO]: TODO</div>
children	[node]	(1)	<div>[TODO]: TODO</div>
class	bool	(1)	<div>[TODO]: TODO</div>
clickable	bool	(1)	User can interact by press / click
content-desc	bool	(1)	<div>[TODO]: TODO</div>
draw	bool	(1)	<div>[TODO]: TODO</div>
enabled	bool	(1)	<div>[TODO]: TODO</div>
focusable	bool	(1)	<div>[TODO]: TODO</div>
focused	bool	(1)	<div>[TODO]: TODO</div>
font-family	bool	(1)	<div>[TODO]: TODO</div>
long-clickable	bool	(1)	<div>[TODO]: TODO</div>

2.1.3 Mobile UI CLAY Dataset

Learning to Denoise Raw Mobile UI Layouts for Improving Datasets at Scale

- Provides a so-called *CLAY* pipeline which denoises mobile UI layouts from incorrect nodes or adding semantics to it.
- better than heuristic approach
- results are dynamic and out of sync, invisible objects, misaligned, in the background (greyed out)
- aim: “large scale high quality layout dataset”
- 37.4 % of the screens contain invalid objects

See [10] <https://github.com/google-research/google-research/tree/master/clay>

2.2 Vector models

2.2.1 Doc2Vec and Word2Vec

2.2.2 Screen2Vec

2.2.3 Screen2Words

2.2.4 Intention2Text

2.2.5 Html2Vec

2.2.6 Tree2Vec

2.2.7 Activity2Vec

2.3 Time Series / Sequence models

2.3.1 Seq2Seq Model

3 Theoretical Framework

3.1 Android UI Data

3.1.1 Data tree structure

3.1.2 Retrieval of UI data via Android Accessibility Service

Semantics tree: <https://developer.android.com/jetpack/compose/semantics> <https://android.googlesource.com/platform/frameworks/support/+/androidx-main:compose/ui/uiautomator/library/src/com/android/uiautomator/core/AccessibilityNodeInfoDumper.java>
<https://github.com/Gustl22/android-accessibility/blob/c158808533d6fc017455184a7317555d3e6946f6/GlobalActionBar>

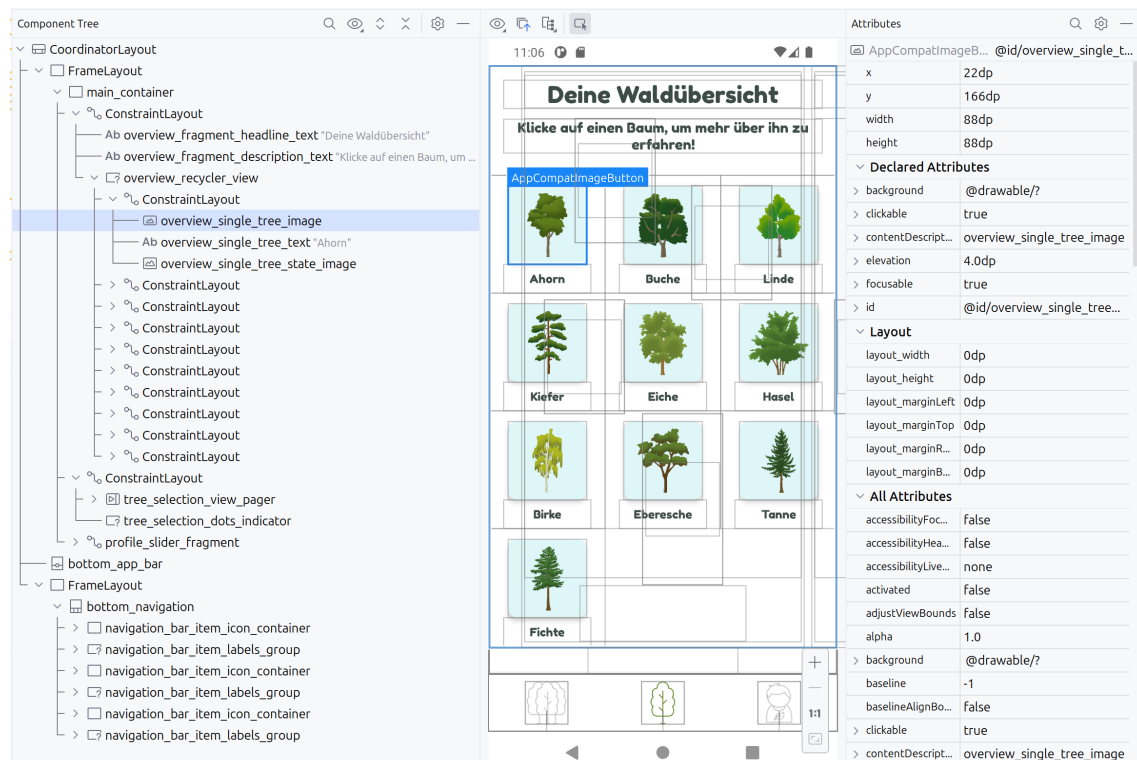


Figure 3.1: <https://developer.android.com/studio/debug/layout-inspector>,
<https://github.com/mimuc/app-ins-gruene>

```
<?xml version='1.0' encoding='UTF-8' standalone='yes' ?>
<hierarchy>
  <node index="0" text="" resource-id="" class="android.view.ViewGroup"
    package="de.lmu.treeapp" content-desc="" checkable="false"
    checked="false" clickable="false" enabled="true" focusable="false"
    focused="false" scrollable="false" long-clickable="false"
    password="false" selected="false" visible-to-user="true"
    bounds="[0,137][1440,2923]">
    <node index="0" text="" resource-id=""
      class="androidx.viewpager.widget.ViewPager" package="de.lmu.treeapp"
      content-desc="" checkable="false" checked="false" clickable="false"
      enabled="true" focusable="true" focused="false" scrollable="true"
      long-clickable="false" password="false" selected="false"
      visible-to-user="true" bounds="[4,141][1436,2707]">
      <node index="22" text="Eiche" resource-id=""
        class="android.widget.TextView" package="de.lmu.treeapp"
        content-desc="" checkable="false" checked="false"
        clickable="false" enabled="true" focusable="false"
        focused="false" scrollable="false" long-clickable="false"
        password="false" selected="false" visible-to-user="true"
        bounds="[116,182][1324,315]" />
      </node>
    <node index="1" text="" resource-id="" class="android.view.ViewGroup" ...>
      <node NAF="true" index="0" text="" resource-id=""
        class="android.widget.FrameLayout" package="de.lmu.treeapp" ... />
    </node>
  </node>
</hierarchy>
```

Listing 3.1: Android Accessibility Node in XML.

3.2 Machine Learning

Machine Learning (ML), a term spread by Arthur Lee Samuel, is a method of data analysis, more precisely a scientific approach to form statistical models without the need to explicitly program it [13]. It uses algorithms to iteratively learn how data is structured. In contrast to statistical inference or manually crafted statistical models respectively, ML can solve tasks by automation of model building. Its advantages lie in finding hidden relations and patterns from the context, without having any or only a small pre knowledge of the data, thus it is a strong tool for generalization or abstraction of large datasets, also known as Big Data. ML can be applied to the following fields among others: email and spam filtering, fraud detection, cybersecurity, web search engines, recommender systems (like known from Netflix or Amazon), advertising, translators and text generation, pattern and image recognition. The data driven approach also comes with some drawbacks: the outcome heavily depends on the provided data. It can include biases and therefore may acquire forms of discrimination or unfair treatment. Nonetheless ML has a lot of potential to uncover hidden connections in large datasets.

3.2.1 Preprocessing

Preprocessing describes the step after one acquired their data, but before training the ML model. This step is not to be underestimated. A ML model can perform significantly better when certain preprocessing steps are applied [1].

To be able to preprocess the data, we have to know with what kind of data we handle with. Data can occur in different forms, but we can break them down in three main types:

- **Categorical values:** a value is always assigned to a class with fixed pool of predetermined classes. E.g. letters, words, brands, animals, chemical elements
- **Continuous values:** the value can be fractional and may lie in between a lower and an upper bound. E.g. temperature, velocity, geographic position
- **Integer values:** the value is a whole number and may also lie in between a lower and an upper bound. E.g. revolutions per minute, product number, annual sales

For discrete and continuous values, we have a wide variety of options to prepare them to be able to be processed by a ML model [7].

[TODO]: Tensors, Datasets

3.2.1.1 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

3.2.1.2 Missing data

Some data entries may be missing. Therefore, you have two approaches to get around these missing values. One can drop these values by removing the column or row. This is only recommended if you are not relying on this data entry, or this the whole feature is not expected to be important enough to bring any value to the model's performance. Further you can fill the data with a default value like zero or calculate a reasonable value from the surrounding data entries by taking their "mean, median, or interpolation" [7]. The second approach can only be applied to numerical data.

3.2.1.3 Normalization and Standardization

This is only applicable for numerical data. Many ML models work better or exclusively with normalized data. This means that the values have to be in a certain range, most commonly are from 0 to 1 or from -1 to 1. This can be achieved by dividing all values with the difference of the minimum and maximum value and shift the output accordingly [7].

3 Theoretical Framework

Sometimes this is not enough, e.g. if having a few extreme values, and an approach is desired which better reflects the average data. Here the standardization, also called z-score normalization, comes into play. This method scales the values so that the mean value is placed at **0** and the standard deviation is placed at **1**.

3.2.1.4 Padding

3.2.1.5 Categorical Variables

[TODO]: categorical

According to [1] these steps can be removal of emoticons, elimination of stopwords and stemming for text based models.

Category Embedding before LSTM

- Embedding layer Dimension near the actual average length of features (?)

3.2.2 Supervised vs Unsupervised vs Semisupervised

3.2.2.1 Supervised Learning

Supervised: Classification and regression Uses **labeled** examples: Input and output is known

Learns by comparison of the output it is provided with the output the model *predicts*.

Steps: - Data acquisition - Data cleaning / Preprocessing (Panadas) - Split into Training Data, Validation data, and Test data (cannot adapt the model after using the test data) - Train the model with the train data - Evaluate the model with the test data, then can adapt the model by the developer - Last deploy the model to production

3.2.2.2 Unsupervised Learning

Clustering Reinforcement learning

3.2.3 Under and Overfitting

3.2.4 Evaluation Metrics

3.3 Artificial Neural Nets

- Uses biological neuron systems as paradigm to generate mathematical models - can solve tasks by abstraction or generalization of data relations

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

3.3.1 Classes of Neural Nets

3.3.1.1 Deep Neural Nets

Neural Net with more than one layer - Dense Layer

3.3.1.2 Convolutional Neural Nets

3.3.1.3 Recurrent Neural Networks and LSTMs / GRU

LSTM 4 dimensional

Limitations to only 3 dimensions, needs flattening

Sample dimension (X -> y) Time (Step) Dimension Feature Dimension Data, Quantity dimension, such as Image dimensions, or multiple nodes

TimeDistributedLayer

3.3.1.4 Autoencoders

Encoder, Decoder

3.3.2 Tensorflow and Keras

Layers FlattenLayer

Positive Integer to Dense Vectors of fixed size

3.4 Evaluation and Metrics

3.4.1 Mean Squared Error

3.4.2 F1 Score

4 Methodology

[TODO]: Describe methodology

Start with your overall approach to the research. What research problem or question did you investigate? What type of data did you need to answer it? Quantitative, qualitative, or mixed? Primary or secondary? Experimental or descriptive?

4.1 Data Aquisition

How you collected and analyzed your data Describe the specific methods you used for data collection and analysis. How did you collect and analyze your data? What tools or materials did you use? How did you ensure the quality and accuracy of your data?

- Why RICO, rather use a dataset with accessibility service. - ERICA employs a human-powered approach over an automated one: - More realistic results - required user input, which cannot emulated, Google Captcha, real data - humans detect the completion of UI updates [5] - erica is quite outdated

Any tools or materials you used in the research. The type of research you conducted

E.g. Google Scholar, Google Research, Tensorflow, Keras, Udemy, Open Source, Reproducible

4.2 Methodological variety

Explain why you chose these methods over others. How do they relate to your research question and literature review? How do they address the limitations or gaps in existing research? How do they suit your research design and objectives?

- No similar approach - No dataset present with consecutive sequential app usages - Many different approaches to solve this problem: - Encoder, Decoder, etc... - A Study can follow

4.3 Methodological choices

Evaluate and justify your methodological choices. Why you chose these methods How did they affect the outcome of your research? What challenges or difficulties did you encounter and how did you overcome them? How can you ensure the credibility and generalizability of your findings?

[TODO]: overall goal is more than just interaction traces

Goal: Make the algorithm as independent of the data as possible. Find general rules to feed the data. Applicable to other research fields, not just UI traces. Use LSTM, so predict something unseen, in contrast to RICO or ERICA, which only categorize the current context

4.4 Research Biases

How you mitigated or avoided research biases

How this thesis is working? Apparatus, Procedure, Utilities

5 Results

5.1 Datasets

- Problem with sequential data sets

5.1.1 Rico

- Too less frames.
- No transition between apps.

5.2 Preprocessing Android UI tree data

5.2.1 Filtering privacy invasive details

5.2.2 Normalization, Feature selection

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

5.3 Model

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.

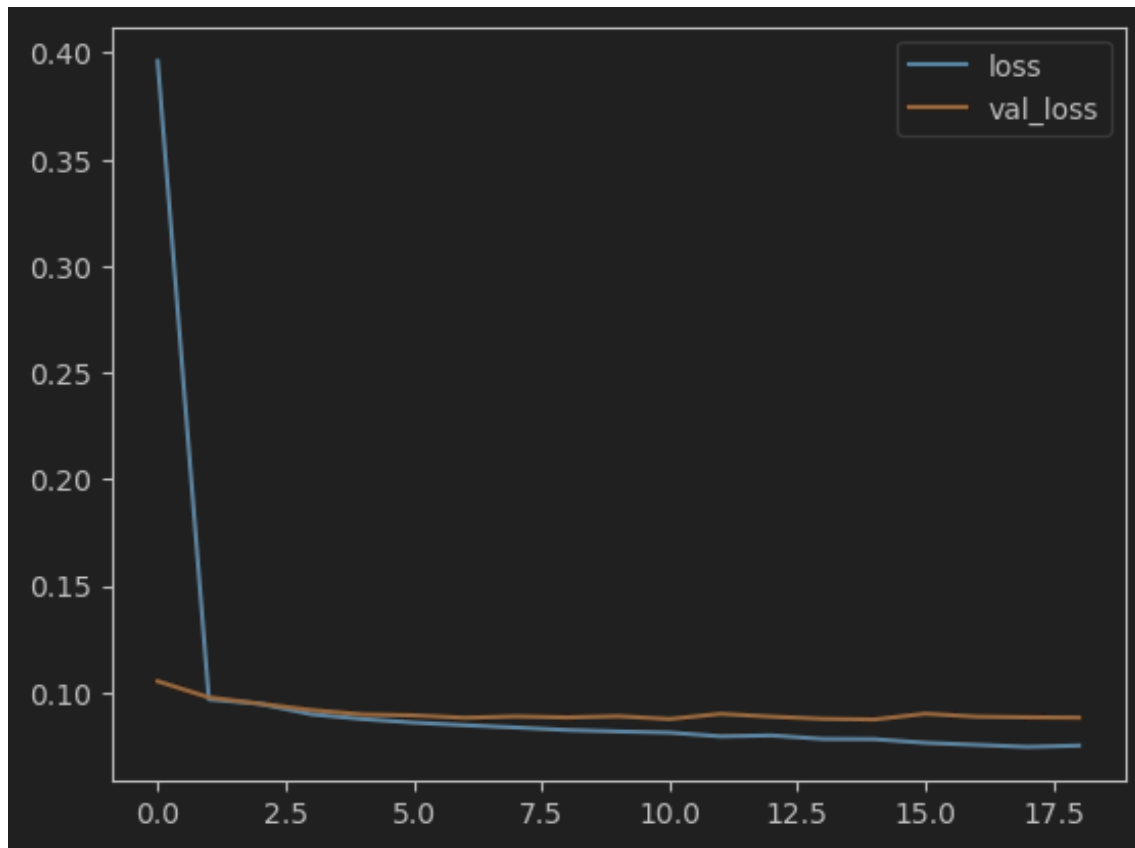


Figure 5.1: Model loss vs validation loss

5.4 Evaluation

5.4.1 Mean Squared Error

5.4.2 F1 Score

5.5 Limitations

Dataset Dataset is not through different apps, only in one app. Dataset is not detailed enough in the time steps, or not containing all data Dataset is not long enough Dataset has no paid apps or apps with login, which most services require Dataset has wrong data see [10]

Preprocessing Need more time to validate what are the core parameters to predict the next user intent

Model needs more investigation on what data is needed How many neurons are required to achieve this Play around with different layers, also Convolutional and pretrained embeddings

6 Application of Android UI tree vectors

6.1 Automation and testing of Android apps

6.2 UI design similarities

6.3 Action prediction models, User behavior modeling

6.4 Behavioral analyses for smartphone usage patterns

7 Conclusion and Future Work

Summary

Outlook

Future directions for research in this area

ChatGPT – Image Recognition – Limitation als Ausblick

Generate Dataset which overcomes the limitations

Make a study with actual feedback on a prediction system, visualization -> Learn faster and directly, Reinforced learning

Work out user flows, like in ERICA, but without the need to separate it from the interaction tree

Take in visual and textual context (semantics).

Make dataset with app overlapping traces.

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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.

place, date, signature