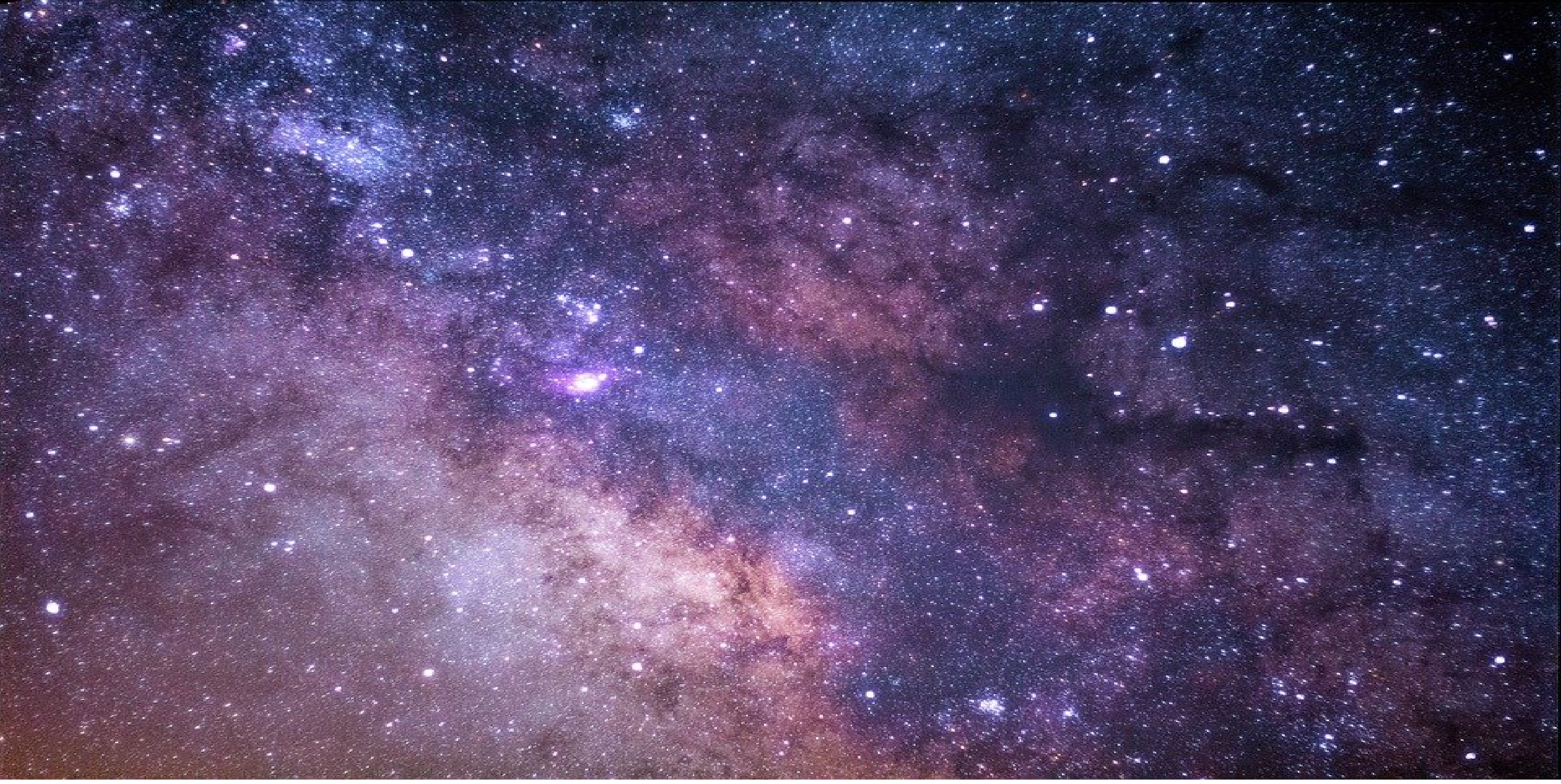

A simple explanation of how our Universe was formed

Development of a predictive model

Anders Andersen, Alfred Alfredsen, Anne Annesen

Energy Technology, TEPE4-1005, 2020-06

Master's Project

STUDENT REPORT

AALBORG UNIVERSITY

A study on the Universe

Development of a predictive model

Anders Andersen, Alfred Alfredsen, Anne Annesen
Energy Technology, TEPE4-1005, 2018-06

Master's Project

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Title:
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Theme:
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Project Period:
Fall Semester 2020

Project Group:
XXX

Participant(s):
Daniel Moesgaard Andersen
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Andreas Stenshøj

Supervisor(s):
Peter Dolog
Manfred Jaeger

Copies: 1

Page Numbers: 19

Date of Completion:
October 28, 2020

Abstract:

Here is the abstract

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Vejleder(e):
Peter Dolog
Manfred Jaeger

Oplagstal: 1

Sidetal: 19

Afleveringsdato:
28. oktober 2020

Abstract:

Her er resuméet

Contents

Todo list

Preface

Here is the preface. You should put your signatures at the end of the preface.

Aalborg University, October 28, 2020

Author 1
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Author 2
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Chapter 1

Introduction

Here is the introduction. The next chapter is chapter 3.

a new paragraph

1.1 Examples

You can also have examples in your document such as in example 1.1.

Example 1.1 (An Example of an Example)
Here is an example with some math

$$0 = \exp(i\pi) + 1 \ . \tag{1.1}$$

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1.2 How Does Sections, Subsections, and Subsections Look?

Well, like this

1.2.1 This is a Subsection

and this

This is a Subsubsection

and this.

A Paragraph You can also use paragraph titles which look like this.

A Subparagraph Moreover, you can also use subparagraph titles which look like this. They have a small indentation as opposed to the paragraph titles.

Is it possible to add a subsubparagraph?

I think that a summary of this exciting chapter should be added.

Chapter 2

Preliminary Investigation

2.1 Investigating results in context-aware recommender systems

Context-aware recommender systems consider various types of contextual information such as time, location, and social information when generating recommendations. They have generally been observed to greatly improve the effectiveness of recommendation processes [3]. To establish the usefulness of adding context to recommender systems we will conduct an investigation into recent papers relating to the topic examining the experimental results of different proposed methods. We will investigate the kinds of context data used in existing papers, how this context data was used, and how it was evaluated. Table 2.1 shows an overview of different papers relating to the topic of context-aware recommendations and the datasets used for evaluation. In the following subsections we will discuss the specific datasets and how they were used.

2.1.1 LDOS-CoMoDa

The LDOS-CoMoDa dataset is a context rich movie recommender dataset[12]. At the time of access, the dataset contains 121 users, 1232 unique movies, and 2296 ratings. Most context variables are expressed for each rating. The dataset contains the following context variables and their conditions:

- Time
  - Morning, Afternoon, Evening, Night
- Daytype
  - Working day, Weekend, Holiday

- Season
  - Spring, Summer, Autumn, Winter
- Location
  - Home, Public place, Friend's house
- Weather
  - Sunny / clear, Rainy, Stormy, Snowy, Cloudy
- Social
  - Alone, My partner, Friends, Colleagues, Parents, Public, My family
- EndEmo
  - Sad, Happy, Scared, Surprised, Angry, Disgusted, Neutral
- DominantEmo
  - Sad, Happy, Scared, Surprised, Angry, Disgusted, Neutral
- Mood
  - Positive, Neutral, Negative
- Physical
  - Healthy, Ill
- Decision
  - User decided which movie to watch, User was given a movie
- Interaction
  - First interaction with a movie, N-th interaction with a movie

EndEmo and *DominantEmo* relate to the emotional state of the user during the consumption stage. *DominantEmo* defines the emotional state that was dominant during the consumption of the movie, whereas *EndEmo* defines the emotional state of the user at the end of the movie[14]. [14] indicates that, on other datasets where the only context that could be derived were based on timestamps, many users would leave these ratings in a relatively short period of time, making them not representative of the contextual situation of the user at the time of consumption. The paper thus proposes the LDOS-CoMoDa dataset containing potential contextual information from the consumption stage, gathered through ratings and an accompanying questionnaire.

[14] employed a relevant-context-detection procedure to determine which of these contextual variables were in fact relevant. This was done through statistical hypothesis testing with a power analysis, where independence was tested between each contextual variable and the ratings. The null hypothesis of the test stated that the two variables were independent, whereas the alternative hypothesis stated that they were dependent. If the null hypothesis was rejected, a conclusion was drawn that the contextual variable and the rating were dependent and thus the contextual information was relevant. They employed a significance level of $\alpha = 0.05$ for the test.

The testing determined that six of the variables proved to be relevant, making them contextual - *EndEmo, DominantEmo, Mood, Physical, Decision* and *Interaction*. *Location* and *Daytype* could not be declared irrelevant, and *Time, Season, Weather* and *Social* were rejected as irrelevant contextual information. Generally, the paper finds that the variables detected as relevant perform better than the irrelevant ones, apart from the *Mood* variable, which performed worse than a variable deemed irrelevant. This means that, with the exception of the variable *Mood*, the paper finds that the contextual variables detected as relevant tend to perform better than the uncontextualized models, while the contextual variables detected as irrelevant tend to perform worse than the uncontextualized models, if there are enough ratings per each context variable value during training. The anomaly regarding *Mood* can be explained by an insolated case of high sparsity in the negative condition for the dataset.

A little discussion of how papers use it

2.1.2 MovieLens

The MovieLens datasets are datasets provided by GroupLens research from the MovieLens web site. These datasets were collected over various periods of time, and are available in different sizes[13]. The papers that were investigated made use of both the 1M dataset and the 100K stable benchmark datasets. The 1M dataset contains 1,000,209 ratings of 3706 movies made by 6040 users with a density of 4.47%, representing the percentage of cells in the full user-item matrix that contain rating values[9]. The 100K Dataset contains 100,000 ratings of 1682 movies made by 943 users with a density of 6.30%[9]. Each user in both datasets has rated at least 20 movies. The datasets do not contain specific contextual information, but it is possibly to derive a time context dimension from the timestamps provided along the ratings.

2.1.3 Frappé

Frappé is a mobile app recommender providing context-aware mobile app recommendations by means of a tensor factorization approach based on implicit feedback data[4]. Frappé was deployed on Android, leading to a context-aware app usage data set. Frappé collected implicit data on the following relevant context dimensions: time of day, weekday, whether or not it is weekend, at home or at work, weather, country, cost and city. The dataset consists of 96203 entries by 957 users for 4082 apps.

2.1.4 InCarMusic

InCarMusic is a mobile Android application offering music recommendations for the passengers of cars. In order to provide these recommendations, [5] collected the user's assessment of the effect of context on their music preferences, as well as had them enter ratings for tracks assuming certain contextual conditions held. [5] identified the following contextual variables as potentially relevant: driving style, road type, landscape, sleepiness, traffic conditions, mood, weather, natural phenomena. The data collection was carried out in two phases: one with an aim of determining the contextual factors that are more influential in changing the propensity of the user to listen to music of different genres, and another interested in individual tracks and their ratings, examining the case without considering any contextual conditions, and the case under the assumption that a certain contextual condition holds. Ultimately, this resulted in a dataset consisting of 4012 ratings, given by 42 different users on 139 songs. An issue with this dataset is that each entry only has data on one contextual dimension, and the rest are unknown.

2.1.5 DePaul

The *DePaulMovie* dataset is another alternative. This dataset has 5,029 ratings from 1-5, given by 97 users on 79 movies within three different context dimensions: *time, location* and *companion*[21]. The contextual dimensions distinguish between weekday or weekend, whether or not the movie was watched at home or at the cinema, and finally if it was watched alone, with family or with partner.

2.2 How the papers used the datasets

2.3 Evaluation protocols

When evaluating recommender systems the relevant properties must be determined. [18] defines a set of properties for recommender systems: *user preference, prediction accuracy, coverage, confidence, trust, novelty, serendipity, diversity, utility, risk,*

	LDOS-CoMoDa	MovieLens	Frappe	InCarMusic	DePaul
[10]	x	x	x	x	
[2]	x			x	
[1]	x				
[20]	x		x		
[22]	x				
[19]	x				
[8]	x				
[7]	x			x	
[15]	x				
[23]	x				
[6]		x		x	
[16]		x		x	x
[11]		x			
[17]		x			

Table 2.1: Context-Aware papers and the datasets used.

robustness, privacy, adaptivity and *scalability*. Each property is suited to certain types of tests, and different metrics are used for evaluating these properties. Some, such as user preference and trust are more suitable for testing through user studies. Properties relating to algorithmic effectiveness such as prediction accuracy, coverage and confidence are more suitable for offline experiments, while properties that relate to active use of the recommender system, such as serendipity, are suitable for online studies where real users interact with the system. **??** shows the metrics used for evaluation for the different examined papers, as well as the percentage of papers employing that metric for evaluation. It is evident that most of these papers focus on offline evaluation, investigating metrics related to algorithmic precision and efficiency, such as root-mean-square error(RMSE), mean absolute error(MAE) and F1-measure. These metrics are useful for two important problems associated with recommender systems: rating prediction and top-N recommendation[18]. The rating prediction problem concerns itself with predicting the rating that a user u will give an unrated item i, which is often defined as learning a function $f : U \times I \to S$, that predicts the rating $f(u,i)$ of a user u for a new item i, where U the set of users, I is the set of items, and S is the set of possible values for a rating. The top-N recommendation problem is the task of recommending a list $L(u_a)$ to an active user u_a containing N items to likely be of interest. Generally, the papers examined in **??** employ cross validation across a number of folds, across a range of 3-10 folds.

Særning om at de evaluerer vha crossfold validation, giv en range på størrelsen af deres forskellige sæt.

	Evaluation Metrics	Evaluation Protocol
[10]	RMSE, MSE, MAE, Precision, Recall, F-measure	5-fold, 4 training and 1 test
[2]	RMSE, MAE, Recall@N, DCG@N	50% training, 30% testing, 20% validation, averaged results
[1]	Recall@N, DCG@N	20% training,, 30% testing, 50% test and train from learning
[20]	RMSE, MAE	10 subsets, each subset split into 80% training, 10% testing, 10% validation
[22]	MAE, NDCG@N, Precision	5-fold, 4 training and 1 test
[19]	MAE, Coverage	50% training, 20% test
[8]	MAE, RMSE	5-fold
[7]	MAE, RMSE, Precision, Recall, F1-measure	3-fold, 2 training and 1 test
[15]	RMSE	2:1 proportion of training to test, averaged over 20 iterations
[23]	RMSE, MAE	Unspecified
[6]	RMSE, MAE, Precision@N, Recall@N, F1-measure	3 random partitions, 2 for training and 1 for testing, average over 5 iterations
[16]	Precision@N, MAP@N	10-fold, average over 10 iterations
[11]	MAE, Precision@N, Recall@N,	Unspecified
[17]	Recall@N, Precision@N, F1@N, NDCG	First 80% of each user’s history for training, remaining 20% for test

	LDOS-CoMoDa	MovieLens	Frappe	InCarMusic	DePaul	Evaluation Metrics	Evaluation Protocol
[10]	x	x	x	x		RMSE, MSE, MAE, Precision, Recall, F-measure	5-fold, 4 training and 1 test
[2]	x			x		RMSE, MAE, Recall@N, DCG@N	50% training, 30% testing, 20% validation, averaged results
[1]	x					Recall@N, DCG@N	20% training,, 30% testing, 50% test and train from learning
[20]	x		x			RMSE, MAE	10 subsets, each subset split into 80% training, 10% testing, 10% validation
[22]	x					MAE, NDCG@N, Precision	5-fold, 4 training and 1 test
[19]	x					MAE, Coverage	50% training, 20% test
[8]	x					MAE, RMSE	5-fold
[7]	x			x		MAE, RMSE, Precision, Recall, F1-measure	3-fold, 2 training and 1 test
[15]	x					RMSE	2:1 proportion of training to test, averaged over 20 iterations
[23]	x					RMSE, MAE	Unspecified
[6]		x		x		RMSE, MAE, Precision@N, Recall@N, F1-measure	3 random partitions, 2 for training and 1 for testing, average over 5 iterations
[16]		x		x	x	Precision@N, MAP@N	10-fold, average over 10 iterations
[11]		x				MAE, Precision@N, Recall@N,	Unspecified
[17]		x				Recall@N, Precision@N, F1@N, NDCG	First 80% of each user's history for training, remaining 20% for test

Table 2.2: Context-Aware papers and the datasets used.

	#Number	Percentage
RMSE	8	57.14
MAE	10	71.43
MSE	1	7.14
Precision	7	50
Recall	7	50
DCG	4	28.57
NDCG	2	14.29
F1-measure	3	21.43

Table 2.3: Total number of papers using a given metric.

	#Ratings	#Items	#Users	#Context variables
LDOS-CoMoDa	2296	1232	121	12
MovieLens 1M	1,000,209	3706	6040	1
MovieLens 100K	100,000	1682	943	1
Frappé	96203	957	4082	8
InCarMusic	4012	139	42	8
DePaulMovie	5029	79	97	3

Table 2.4: A final summary of the datasets.

Chapter 3

Chapter 2 name

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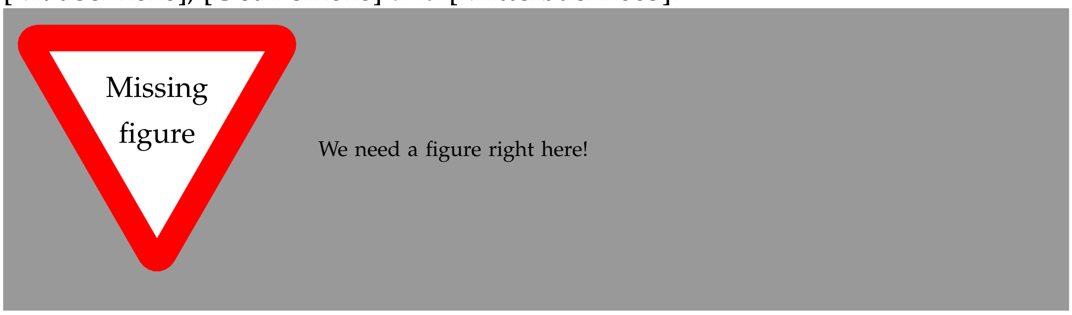

Chapter 4

Conclusion

In case you have questions, comments, suggestions or have found a bug, please do not hesitate to contact me. You can find my contact details below.

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Appendix A

Appendix A name

Here is the first appendix