



Eidgenössische Technische Hochschule Zürich  
Swiss Federal Institute of Technology Zurich

# Applying the GAN Framework to Recommender Systems

Master Thesis

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### **Abstract**

This example thesis briefly shows the main features of our thesis style, and how to use it for your purposes.



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## Chapter 1

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# Introduction

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- Recommender System are a field in machine learning that get more and more attention
- In principle the goal of a recommender system is to recommend items (in the case of an e-commerce system products) to users
- The idea is that the system helps the user navigate the mass of products available and to show the user what is relevant
- A recomender system can be tuned to optimize for different metrics such as click through rate, conversion rate etc.
- In the past there have been mainly two approaches to recommender systems user based and item based
- In the last years there have been more and more proposals for session based approaches (refer to paper that does the survey)
- Specifically GRU4Rec has gained attention as a RNN based approach to solving this problem
- In a session based setting we try to model the sequence of events a user makes when he browses the product catalog instead of items or users themselves.
- This has the following advantages: Usually we have a lot of users that only visit the site once or twice a year, these users are very difficult to model. The same goes for products, there are a lot of products that have limited attention from the userbase, therefore it is difficult to get a useful representation for products like this.
- In a session based setting we model the sequence of events, which is more useful since there is a lot more data, and sessions are comparable even if we do not know which user is online.

## 1. INTRODUCTION

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- Session based approaches work in both settings where we don't know the user and where we know the user
- Item based are for unknown users and user based for known users
- The goal of the thesis is twofold:
  - First we want to explore the capabilities of such a system in a production setting with real world data. Are we really better than simple approaches like "often bought together"?
  - Also we want to compare it to a more sophisticated system that is a blackbox and consumed as a service provided by Google.
  - Third, since this is an RNN approach we want to find out if we can improve the system by applying the GAN framework in form of professor forcing
  - Fourth, the system inherently produces embeddings for products and users, we want to find out if we can improve the overall performance if we use a pretrained product embedding which captures the semantic similarity of products



## Background

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### 2.1 Recommendation Systems

#### 2.1.1 Problem Statement

- The general form of a recommendation system is that we assign scores to items.
- A personalized recommendation system uses the context of the user to produce scores dependant of the active user.
- Write out a function that describes a general recommendation system

#### 2.1.2 Variants

- User Based
- Item Based
- Session Based

#### 2.1.3 Well-Known Systems

- Describe a classical user based approach
- Describe a classical item based approach

### 2.2 Concepts

#### 2.2.1 Recurrent Neural Networks

- Explain the concept of neural Networks

- What are the problems (vanishing gradients etc)
- Explain what a GRU is and why does it handle vanishing gradient better than simple RNN cells?
- How does a layered RNN work?

### 2.2.2 Generative Adversarial Network Framework

- Explain the way GANs work
- Loss function is learnable
- The discriminator is part of the loss function
- Especially good if we want generate stuff

### 2.2.3 Teacher Forcing

- RNN have two modes: Teacher forced and Free running
- When training we always use the ground truth as input
- This generates two different distributions of hidden states, which in turn generates two different distributions for the output
- This is a problem since this makes RNNs in production less predictable

## 2.3 Previous Work

### 2.3.1 Professor Forcing

- Here we want to mitigate the teacher forcing problem, by applying the gan framework
- Add graphic showing how it should work
- Describe the model as we did in the slides, show the loss function

[1]

### 2.3.2 Meta-Prod2Vec

- This is a model that allows us to capture the semantic similarity between products
- Explain how it works by relating to word2vec (refer to word2vec paper)

[3]

### **2.3.3 Hierarchical RNNs for personalized Recommendations**

- This is the starting point for the thesis
- Which components does the system have?
- Show the graphic from the paper

[2]

## **2.4 KPIs**

### **2.4.1 Click-Through-Rate**

### **2.4.2 Conversion Rate**

- Describe different KPIs
- What do they measure, how to optimize for it



## Chapter 3

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# Dataset

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### 3.1 Data Collection

#### 3.1.1 Data Generation Mechanism

- Each click the user makes on the site is tracked
- An event is generated containing the information and context of the click of the user
- This event is sent to a message queue
- From the message queue there is a subscriber that archives this event in Google BigQuery
- The most important fields tracked are: UserId, SessionId, ProductId, Timestamp, LastLoggedInUserId
- Google BigQuery is a Data Warehousing solution consisting of append-only tables

#### 3.1.2 Data Storage

- Data is stored in BigQuery in a denormalized form
- One row describes one event

### 3.2 Data Extraction

- First we extract the events on ProductDetail Pages from BigQuery
- This is done in shards, where each shard approximately corresponds to one day of events

- We only use the data where we know which user produced the event
- The events are filtered first by removing all events generated by known bot user agents
- In a second step we merge the fields `UserId` and `LastLoggedInUserId`, if the latter is set we know that the user "passively" logged out of the shop (long time without a session)
- Then the events are grouped by sessions
- Then the sessions are grouped by users
- After that we filter out users that have too few sessions
- Then we filter products that have too few events
- After that we have a dataset that contains all users with enough sessions and all events on products with enough events
- Show the structure of one user in the json

### 3.3 User Parallel Batches

- Show how the user parallel batches should look like
- Explain how we transform the json dataset to these user parallel batches

## System Overview

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### 4.1 Model Architecture

- Describe Model Architecture
- Describe different Components of Model Architecture
- Describe different variants of the model (with/without pf, with/without embeddings)

### 4.2 Implementation

- Describe Class Diagram
- Describe Code Structure
- Describe Deployment
- Describe prediction mode/training mode





## Chapter 5

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# Experiments

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For each of the model variants evaluate the experiments offline and online.

### 5.1 Offline

#### 5.1.1 Experiment Setup

- Describe the last session out split (test and eval)
- Describe how we train the model and how we evaluate it

#### 5.1.2 Measurements

- Here we want to confirm a few things: user rnn helps, embeddings helps, profforcing helps
- The evaluation set is always the same
- Show the relevant KPIs (described in the chapter before)

### 5.2 Online/Production Experiment Setup

#### 5.2.1 Experiment Setup

- Describe the online shop
- Where do we have recommendations, general description
- Explain SOFI
- Where do we put our recommendation system? Against what does it compete?

### 5.2.2 Measurements

- Show results for AutoML, Often Bought Together and our system in the different variants
- Show the relevant KPIs

## Chapter 6

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# Results

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- bring everything together
- compare best performing model to automl from google



## Appendix A

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# Dummy Appendix

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You can defer lengthy calculations that would otherwise only interrupt the flow of your thesis to an appendix.



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