Recent R&D on Recommender Systems in TEL

18.01.2011 Learning Network Seminar on Recommender Systems in TEL

Hendrik Drachsler
Centre for Learning Sciences and Technology
@ Open University of the Netherlands
What is dataTEL

- dataTEL is a Theme Team funded by the STELLAR network of excellence.
- It address 2 STELLAR Grand Challenges
  1. Connecting Learner
  2. Contextualisation
dataTEL::Objectives

Standardize research on recommender systems in TEL

Five core questions:

1. How can data sets be shared according to privacy and legal protection rights?
2. How to development a policy to use and share data sets?
3. How to pre-process data sets to make them suitable for other researchers?
4. How to define common evaluation criteria for TEL recommender systems?
5. How to develop overview methods to monitor the performance of TEL recommender systems on data sets?
Recommender in TEL

OpenScout

Organic.Edunet

VADR

STELLAR

TEN Competence

aposdle

learn @ work
The TEL recommender are a bit like this...
The TEL recommender are a bit like this...

We need to select for each application an appropriate RecSys that fits its needs.
But...

“The performance results of different research efforts in recommender systems are hardly comparable.”

(Manouselis et al., 2010)
But...

The TEL recommender experiments lack transparency. They need to be repeatable to test:

• Validity
• Verification
• Compare results
## Survey on TEL Recommender

### Table 12.3: Implemented TEL recommender systems reported in literature

<table>
<thead>
<tr>
<th>System</th>
<th>Status</th>
<th>Evaluator focus</th>
<th>Evaluation roles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Altered Vista [101, 102, 102, 104]</td>
<td>Full system</td>
<td>Interface, Algorithm, System usage</td>
<td>Human users</td>
</tr>
<tr>
<td>RACOTI [2, 63]</td>
<td>Prototype</td>
<td>Algorithm</td>
<td>System designers</td>
</tr>
<tr>
<td>QSAI [73, 79]</td>
<td>Full system</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>CYCLADES [4]</td>
<td>Full system</td>
<td>Algorithm</td>
<td>System designers</td>
</tr>
<tr>
<td>CoFiind [29, 30]</td>
<td>Prototype</td>
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</tr>
<tr>
<td>Learning object sequencing [88]</td>
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</tr>
<tr>
<td>Evolving e-learning system [90, 91, 92, 95]</td>
<td>Full system</td>
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<td>Simulated users, Human users</td>
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<tr>
<td>DDS - Hybrid Personalised Recommender Systems [28]</td>
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<td>System designers</td>
</tr>
<tr>
<td>Learning Object Recommendation Model [85]</td>
<td>Design</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>RecoSearch [32]</td>
<td>Design</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Simulation environment [72]</td>
<td>Full system</td>
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<tr>
<td>CBR Recommender Interface [33]</td>
<td>Prototype</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>APOSIDE Recommendation Service [1]</td>
<td>Prototype</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>A2M Recommending System [86]</td>
<td>Prototype</td>
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<td>Human users</td>
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The continuation of small-scale experiments with a limited amount of learners that rate the relevance of suggested resources only adds little contributions to a evidence driven knowledge base on recommender systems in TEL.

How others compare their recommenders

Netflix

movielens
helping you find the right movies

bookcrossing.com

Sandbox from Yahoo! Research
What kind of data set we can expect in TEL

Spectrum of Learning

Formal
You go where the bus goes.

Informal
You go where you choose.

Graphic by J. Cross, Informal learning, Pfeifer (2006)
The Long Tail

The Long Tail of Learning

The Long Tail of Learning

Formal
- Planned
- Scheduled and assigned
- Common knowledge
- “Top down” and codified
- Semi-permanent
- Expert-created
- Expensive
- Pushed

Informal
- Ad Hoc
- Time of need, in the “flow”
- Specialized knowledge
- Emergent and collaborative
- Temporary or semi-permanent
- Crowd-sourced
- Low cost
- Pulled

## dataTEL::Collection

Table 1. Overview data sets

<table>
<thead>
<tr>
<th>Feature</th>
<th>Mendeley</th>
<th>APOSDELE</th>
<th>Mace</th>
<th>Travel well</th>
</tr>
</thead>
<tbody>
<tr>
<td>Collection period</td>
<td>1 year</td>
<td>3 months</td>
<td>3 years</td>
<td>6 months</td>
</tr>
<tr>
<td>Number of users</td>
<td>200,000</td>
<td>6</td>
<td>1.148</td>
<td>87</td>
</tr>
<tr>
<td>Number of items</td>
<td>1,857,912</td>
<td>163</td>
<td>12,000</td>
<td>1,791</td>
</tr>
<tr>
<td>Number of activities</td>
<td>4,848,725</td>
<td>1,500</td>
<td>461,982</td>
<td>13,922</td>
</tr>
<tr>
<td>reads</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>tags</td>
<td>+</td>
<td>(+)</td>
<td>+</td>
<td>+</td>
</tr>
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<td>-</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
<td>download or add to collection</td>
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<td>+</td>
<td>+</td>
<td>+</td>
</tr>
<tr>
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<td>-</td>
<td>+</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
<td>collaborations</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>learning goal/task</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>learning sequence</td>
<td>-</td>
<td>+</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>competencies/ experience level</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>-</td>
</tr>
<tr>
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The task of a CF algorithm is to find item likeliness of two forms:

**Prediction** – a numerical value, expressing the predicted likeliness of an item the user hasn’t expressed his/her opinion about.

**Recommendation** – a list of N items the active user will like the most (Top-N recommendations).
Collaborative Filtering

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- **Prediction** – a numerical value, expressing the predicted likeliness of an item the user hasn’t expressed his/her opinion about.
- **Recommendation** – a list of N items the active user will like the most (Top-N recommendations).
MAE – Mean Absolute Error: deviation of recommendations from their true user-specified values in the data. The lower the MAE, the more accurately the recommendation engine predicts user ratings.

F1 - Measure balances Precision and Recall into a single measurement. Recall is defined as the ratio of relevant items by the recommender to a total number of relevant items available.
Evaluation criteria

**MAE** – Mean Absolute Error: deviation of recommendations from their true user-specified values in the data. The lower the MAE, the more accurately the recommendation engine predicts user ratings.

**F1** - Measure balances Precision and Recall into a single measurement. Recall is defined as the ratio of relevant items by the recommender to a total number of relevant items available.
Fig. 2. MAE of user-based, item-based and slope-one collaborative filtering
Fig. 2. MAE of user-based, item-

Fig. 3. F1 of user-based collaborative filtering with increasing number of neighbors
Fig. 2. MAE of user-based, item-
The main research question remains: *How can generic algorithms be modified to support learners or teachers?*

To give an example: *Form a pure learning perspective the most valuable resources contain different opinions or facts that challenge the learners to disagree, agree and redefine their mental model.*
Target: Knowledge Environment

Formal

Datasets

Informal

Data A

Data B

Data C

Algorithms:
- Algorithm A
- Algorithm B
- Algorithm C

Models:
- Learner Model A
- Learner Model B

Measured attributes:
- Attribute A
- Attribute B
- Attribute C

Algorithms:
- Algorithm D
- Algorithm E
- Algorithm C

Models:
- Learner Model C
- Learner Model D

Measured attributes:
- Attribute A
- Attribute B
- Attribute C

Algorithms:
- Algorithm B
- Algorithm D

Models:
- Learner Model A
- Learner Model C

Measured attributes:
- Attribute A
- Attribute B
- Attribute C
Challenges to deal with for the Knowledge Environment
1. Protection Rights
1. Protection Rights

**Recent Empty Homes**

- **@wgirarde** left home and checked in less than a minute ago:

- **@TennesseeTimHill** left home and checked in less than a minute ago:
  Feeding my addiction (@ Starbucks') [http://4sq.com/72m9vj](http://4sq.com/72m9vj)
1. Protection Rights

OVERSHARING
1. Protection Rights

Oversharing

Were the founders of PleaseRobMe.com actually allowed to grab the data from the web and present it in that way?
I. Protection Rights

OVERSHARING

Were the founders of PleaseRobMe.com actually allowed to grab the data from the web and present it in that way?

Are we allowed to use data from social handles and reuse it for research purposes?
I. Protection Rights

OVERSHARING

Were the founders of PleaseRobMe.com actually allowed to grab the data from the web and present it in that way?

Are we allowed to use data from social handles and reuse it for research purposes?

and there is more company protection rights!
2. Policies to use Data
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2. Policies to use Data

Thank you for requesting Yahoo! WebScope data. Here are the steps to take to receive the data.

1. Read the data sharing agreement below and if you agree, click "agree"
2. You must also obtain your department chair approval to receive this data.
3. Your department chair that you provided will receive an email and link to the data sharing agreement. They will need to "agree" to the data sharing agreement before we can provide the data. If you have any questions please contact us at research-data-requests@yahoo-inc.com

Agreement for Datasets:
R5. Yahoo! Delicious Popular URLs and Tags, version 1.0,
L9. Yahoo! Answers Question Types Sample of 1000, version 1.0

YAHOO WEBSCOPE™ DATA LICENSE AGREEMENT
INTERNATIONAL

This data license agreement ("Agreement") is between you and Yahoo! Inc. ("Yahoo!") regarding your access to and use of the Yahoo! WebScope™ data that you wish to use and download from the Yahoo! website located at http://webscope.sandbox.yahoo.com ("Data"). Your access to and use of the Data is subject to the terms and conditions of this Agreement.

BY CLICKING THE "I AGREE" BUTTON, DOWNLOADING OR USING THE DATA, YOU AGREE THAT THAT YOU HAVE READ AND UNDERSTAND THE TERMS OF THIS AGREEMENT, AND THAT YOU AGREE TO BE BOUND AND TO ABIDE BY THIS AGREEMENT AND YAHOO'S TERMS OF USE. IF YOU DO NOT UNDERSTAND THIS AGREEMENT, DO NOT DOWNLOAD, ACCESS OR USE THE DATA.

1. SCOPE OF AGREEMENT
1.1 The Data is valuable and confidential information of Yahoo!. You agree to use the Data only in accordance with this Agreement, and to hold the Data in strict confidence. You will not perform any analysis, reverse engineering or processing...
2. Policies to use Data

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Next Steps:

- Yahoo! will review your request
- Your department chair will be contacted for their approval
- Upon approval of the data sharing agreement, Yahoo! will send an e-mail notification with access information.
- For those datasets that are not available via download we will ship those to the mailing address provided on your request.
- Data must be destroyed after 2 years.

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3. Pre-Process Data Sets

For informal data sets:

1. Collect data
2. Process data
3. Share data

For formal data sets from LMS:

1. Data storing scripts
2. Anonymisation scripts
4. Evaluation Criteria

Combine approach by
Drachsl er et al. 2008

Kirkpatrick model by
Manouselis et al. 2010
4. Evaluation Criteria

1. Accuracy
2. Coverage
3. Precision

Combine approach by Drachsler et al. 2008

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1. Accuracy
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1. Effectiveness of learning
2. Efficiency of learning
3. Drop out rate
4. Satisfaction

Combine approach by Drachsler et al. 2008
Kirkpatrick model by Manouselis et al. 2010
4. Evaluation Criteria

1. Accuracy
2. Coverage
3. Precision
1. Effectiveness of learning
2. Efficiency of learning
3. Drop out rate
4. Satisfaction

1. Reaction of learner
2. Learning improved
3. Behaviour
4. Results

Combine approach by Drachsler et al. 2008
Kirkpatrick model by Manouselis et al. 2010
3 take away message

1. In order to create evidence driven knowledge about the effect of recommender systems on learners and personalized learning more standardized experiments are needed.

2. The continuation of additional small-scale experiments with a limited amount of learners that rate the relevance of suggested resources only adds little contributions to a evidence driven knowledge base on recommender systems in TEL.

3. The key question remains how generic algorithms need to be modified in order to support learners or teachers
Join us for a Coffee ...

http://www.teleurope.eu/pg/groups/9405/datatel/
Upcoming event ...

Workshop: dataTEL- Data Sets for Technology Enhanced Learning

Date: March 30th to March 31st, 2011

Location: Ski resort La Clusaz in the French Alps, Massif des Aravis

Funding: Food and lodging for 3 nights for 10 selected participants

Submissions: For being funded, please send extended abstracts to http://www.easychair.org/conferences/?conf=datatel2011

Deadline for submissions: October 25th, 2010

CfP: http://www.teleurope.eu/pg/pages/view/46082/
Many thanks for your interests

This slide is available at:
http://www.slideshare.com/Drachsler

Email: hendrik.drachsler@ou.nl

Skype: celstec-hendrik.drachsler

Blogging at: http://www.drachsler.de

Twittering at: http://twitter.com/HDrachsler