Recommender Systems and Learning Analytics in TEL

Hendrik Drachsler
Open University of the Netherlands
Hendrik Drachsler

• **Assistant professor** at the Centre for Learning Sciences and Technologies (CELSTECh)

• Track record in **TEL projects** such as TENCompetence, SC4L, LTfLL, Handover, dataTEL.

• Main research focus:
  – **Personalization** of learning with information retrieval technologies, recommender systems and educational datasets
  – **Visualization** of educational data, data **mash-up** environments, supporting **context-awareness** by data mining
  – **Social and ethical implications** of data mining in education

• Leader of the **dataTEL Theme Team** of the STELLAR network of excellence (join the SIG on TELeurope.eu)

• Just recently: new **alterEGO project** granted by the Netherlands Laboratory for Lifelong Learning (on limitations of learning analytics in formal and informal learning)
Recommender Systems and Learning Analytics in TEL

23.07.2011 MUP/PLE lecture series,
Knowledge Media Institute, Open University UK

Hendrik Drachsler
Centre for Learning Sciences and Technology
Open University of the Netherlands
Goals of the lecture

1. Crash course Recommender Systems (RecSys)
2. Overview of RecSys in TEL
3. Open research issues for RecSys in TEL
4. TEL RecSys and Learning Analytics
Introduction into Recommender Systems

Introduction
Objectives
Technologies
Evaluation
Introduction:: Application areas

Application areas

• E-commerce websites (Amazon)
• Video, Music websites (Netflix, last.fm)
• Content websites (CNN, Google News)
• Information Support Systems

Major claims

• Highly application-oriented research area, every domain and task needs a specific RecSys
• Always build around content or products they never exist as on their own
Introduction:: Definition

Using the opinions of a community of users to help individuals in that community to identify more effectively content of interest from a potentially overwhelming set of choices.

Introduction::Definition

Using the **opinions of a community** of users to help **individuals** in that community to identify more effectively **content of interest** from a potentially overwhelming set of choices.


Any system that produces **personalized recommendations** as output or has the effect of guiding the user in a personalized way to **interesting** or **useful** objects in a large space of possible options.

Introduction:: Example
Introduction:: Example

8
Introduction::Example
Introduction::Example
Introduction:: Example

1. **iRobot 560 Roomba Vacuuming Robot, Black and Silver**
   by iRobot

   Your tags: [Add] (What’s this?)

   Rate this item: ★★★★★
   I own it

**1.** Use the search box above to find your favorite books, movies, albums, artists, authors and brands.

**2.** Tell us what you think of the items we return for your search by rating the item or telling us you already own them.

**3.** Repeat until the Recommendations you find in Your Amazon.com reflect your tastes and interests.
Introduction::Example
Introduction::Example
Introduction:: Example

What did we learn from the small exercise?

• There are different kinds of recommendations
  a. People who bought X also bought Y
  b. there are more advanced personalized recommendations

• When registering, we have to tell the RecSys what we like (and what not). Thus, it requires information to offer suitable recommendations and it learns our preferences.
Introduction:: The Long Tail

“We are leaving the age of information and entering the age of recommendation”.

Introduction: Age of RecSys?

...10 minutes on Google.
Introduction:: Age of RecSys?

...10 minutes on Google.
Introduction:: Age of RecSys?

... another 10 minutes, research on RecSys is becoming main stream.

Some examples:
– ACM RecSys conference
– ICWSM: Weblog and Social Media
– WebKDD: Web Knowledge Discovery and Data Mining
– WWW: The original WWW conference
– SIGIR: Information Retrieval
– ACM KDD: Knowledge Discovery and Data Mining
– LAK: Learning Analytics and Knowledge
– Educational data mining conference
– ICML: Machine Learning
– ...

... and various workshops, books, and journals.
Objectives of RecSys

The idea is to pick from my previous list 20-50 movies that share similar audience with "Taken," then how much I will like this movie depend on how much I liked those early movies. In short: I tend to watch this movie because I have watched those movies… or People who have watched those movies also liked this movie (Amazon style).
Objectives:: Aims

- Converting Browsers into Buyers
- Increasing Cross-sales
- Building Loyalty


Foto by [markhillary](https://www.flickr.com/photos/markhillary/)

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Using RecSys to:

- Convert users (Browsers) into buyers
- Increase cross-sales
- Build loyalty

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– People who have watched those movies also liked this movie (Amazon style)

probabilistic combination of

– Item-based method
– User-based method
– Matrix Factorization
– (May be) content-based method

Find good items
presenting a ranked list of recommendations.

Find all good items
user wants to identify all items that might be interesting, e.g. medical or legal cases

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Find good items presenting a ranked list of recommendations.

Find all good items user wants to identify all items that might be interesting, e.g. medical or legal cases.

Receive sequence of items sequence of related items is recommended to the user, e.g. music recommender

Annotation in context predicted usefulness of an item that the user is currently viewing, e.g. links within a website

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RecSys Technologies

1. Predict how much a user may like a certain product

2. Create a list of Top-N best items

3. Adjust its prediction based on feedback of the target user and like-minded users

RecSys Technologies

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Just some examples there are more technologies available.

Technologies:: Collaborative filtering

User-based filtering (GroupLens, 1994)

Take about **20-50** people who share **similar taste** with you, afterwards predict how much you might like an item depended on how much the others liked it.

You may like it because your “friends” liked it.
User-based filtering
(Grouplens, 1994)

Take about **20-50** people who share **similar taste** with you, afterwards predict how much you might like an item depended on how much the others liked it.

You may like it because your “friends” liked it.

Item-based filtering
(Amazon, 2001)

Pick from your previous list **20-50** items that share **similar people** with “the target item”, how much you will like the target item depends on how much the others liked those earlier items.

You tend to like that item because you have liked those items.
Information needs of user and characteristics of items are represented in *keywords*, *attributes*, *tags* that describe past selections, e.g., TF-IDF.
The idea is to pick from my previous list 20-50 movies that share similar audience with "Taken", then how much I will like depends on how much I liked those early movies – In short: I tend to watch this movie because I have watched those movies … or – People who have watched those movies also liked this movie (Amazon style)

Technologies:: Hybrid RecSys

Combination of techniques to overcome disadvantages and advantages of single techniques.

**Advantages**
- No content analysis
- Quality improves
- No cold-start problem
- No new user / item problem

**Disadvantages**
- Cold-start problem
- Over-fitting
- New user / item problem
- Sparsity
Technologies:: **Hybrid RecSys**

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Just some examples there are more (dis)advantages available.
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probabilistic combination of

– Item-based method
– User-based method
– Matrix Factorization
– (May be) content-based method
Evaluation:: General idea

Most of the time based on performance measures ("How good are your recommendations?")

For example:

- Predict what rating will a user give an item?
- Will the user select an item?
- What is the order of usefulness of items to a user?

Evaluation:: Reference datasets

... and various commercial datasets.
Evaluation Approaches

1. Simulation
   - User preference
   - Prediction accuracy
   - Coverage
   - Confidence
   - Trust
   - Novelty
   - Serendipity
   - Diversity
   - Utility
   - Risk
   - Robustness
   - Privacy
   - Adaptivity
   - Scalability

2. User study

+
Evaluation::Metrics

**Precision** – The portion of recommendations that were successful. (Selected by the algorithm and by the user)

**Recall** – The portion of relevant items selected by algorithm compared to a total number of relevant items available.

**F1** - Measure balances Precision and Recall into a single measurement.

**Evaluation Metrics**

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<td>True-positive</td>
<td>False-negative</td>
</tr>
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<table>
<thead>
<tr>
<th>Measures</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precision (p)</td>
<td>TP / (TP + FP)</td>
</tr>
<tr>
<td>Recall (tpr)</td>
<td>TP / (TP + FN)</td>
</tr>
<tr>
<td>F1-Measure</td>
<td>(2 * tpr * p) / (tpr + p)</td>
</tr>
</tbody>
</table>

Evaluation::Metrics

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Just some examples there are more metrics available like MAE, RSME.

Conclusion:
Pearson is better than Cosine, because less errors in predicting TOP-N items.

**Evaluation::Metrics**

**Conclusion:**
Pearson is better than Cosine, because less errors in predicting TOP-N items.

**Conclusion:**
Cosine better than Pearson, because of higher precision and recall value on TOP-N items.

RecSys:: TimeToThink

What do you expect that a RecSys in a MUP/PLE should do with respect to ...

• Aims
• Tasks
• Technology
• Evaluation

Blackmore’s custom-built LSD Drive
http://www.flickr.com/photos/rootoftwo/
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2. Overview of RecSys in TEL
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Recommender Systems for TEL

Introduction  Objectives  Technologies  Evaluation
TEL RecSys::Definition

Using the experiences of a community of learners to help individual learners in that community to identify more effectively learning content from a potentially overwhelming set of choices.

TEL RecSys:: Learning spectrum

Formal
You go where the bus goes.

Informal
You go where you choose.

The Long Tail

Short Head
- Blockbusters
- Top 40
- Widely popular
- Short-lived
- Narrow scope

Long Tail
- Blockbusters in a niche
- Narrowly popular
- Popular in the past
- Good, but not great content
- D-list content

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

TEL RecSys:: Technologies

- OpenScout
- STELLAR
- ReMashed
- Organic.Edunet
- aposdle
- VOAAR
- TEN Competence
- MAVSEL
- ROLE

Minining, analysis and visualization based on social aspects of e-learning

funded by the Spanish Ministry of Science & Innovation, Reference TIN2010-21715-C02-01
# TEL RecSys:: Technologies

<table>
<thead>
<tr>
<th>Delicious username:</th>
<th>It is mandatory to specify at least one Web 2.0 service.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flickr username:</td>
<td>If you specify more than one Web 2.0 service we can predict better recommendations for you.</td>
</tr>
<tr>
<td>Blog Rss feed of blog:</td>
<td></td>
</tr>
<tr>
<td>Slideshare username:</td>
<td></td>
</tr>
<tr>
<td>Youtube username:</td>
<td></td>
</tr>
<tr>
<td>Twitter username:</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Interest A:</th>
<th>Please specify three main interests and your knowledge level in the particular interest.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technology enhanced learning</td>
<td></td>
</tr>
<tr>
<td>Knowledge Level A:</td>
<td>0 = Beginner 5 = Expert</td>
</tr>
<tr>
<td>0 1 2 3 4 5</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Interest B:</th>
</tr>
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<tbody>
<tr>
<td>Language learning</td>
</tr>
<tr>
<td>Knowledge Level B:</td>
</tr>
<tr>
<td>0 1 2 3 4 5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Interest C:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knowledge Level C:</td>
</tr>
<tr>
<td>0 1 2 3 4 5</td>
</tr>
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</table>
RecSys Task:
Find good items

Hybrid RecSys:
• Content-based on interests
• Collaborative filtering

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Find good items
e.g. relevant items for a learning task or a learning goal

Receive sequence of items
e.g. recommend a learning path to achieve a certain competence

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e.g. recommend a learning path to achieve a certain competence

Annotation in context
e.g. take into account location, time, noise level, prior knowledge, peers around

Evaluation of TEL RecSys
### 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 [81, 82, 92, 104]</td>
<td>Full system</td>
<td>Interface, Algorithm, System usage</td>
<td>Human users</td>
</tr>
<tr>
<td>RACOFH [2, 64]</td>
<td>Prototype</td>
<td>Algorithm</td>
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</tr>
<tr>
<td>OSAI [78, 79]</td>
<td>Full system</td>
<td>---</td>
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<tr>
<td>CYCLADES [4]</td>
<td>Full system</td>
<td>Algorithm</td>
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<td>CoLiNd [29, 50]</td>
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<tr>
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<td>iES - Hybrid Personalised Recommender System [23]</td>
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<tr>
<td>Learning Object Recommendation Model [85]</td>
<td>Design</td>
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<td>Simulation environment [72]</td>
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<td>Prototype</td>
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<td>APOSEL Recommendation Service [1]</td>
<td>Prototype</td>
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<td>A2M Recommending System [86]</td>
<td>Prototype</td>
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<td>Moodle Recommender System [44]</td>
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<td>Prototype</td>
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Conclusions:

Half of the systems (11/20) still at design or prototyping stage
only 8 systems evaluated through trials with human users.

Thus...

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

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

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

• Validity
• Verification
• Compare results
## TEL RecSys::Evaluation/datasets

<table>
<thead>
<tr>
<th></th>
<th>Mendeley</th>
<th>APOSDEL</th>
<th>ReMash</th>
<th>Organic</th>
<th>Mace</th>
<th>Melt</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Collection period</strong></td>
<td>1 year</td>
<td>3 months</td>
<td>2 years</td>
<td>9 months</td>
<td>3 years</td>
<td>6 months</td>
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<tr>
<td><strong>Users</strong></td>
<td>200,000</td>
<td>6</td>
<td>140</td>
<td>1,000</td>
<td>1.148</td>
<td>98</td>
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<tr>
<td><strong>Items</strong></td>
<td>1,857,912</td>
<td>163</td>
<td>96,000</td>
<td>11,000</td>
<td>12,000</td>
<td>1,923</td>
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<tr>
<td><strong>Activities</strong></td>
<td>4,848,725</td>
<td>1,500</td>
<td>23,264</td>
<td>920</td>
<td>461,982</td>
<td>16,353</td>
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<td><strong>reads</strong></td>
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<td><strong>downloads</strong></td>
<td>+</td>
<td>+</td>
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<tr>
<td><strong>search</strong></td>
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<tr>
<td><strong>tasks/goals</strong></td>
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<tr>
<td><strong>sequence</strong></td>
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<tr>
<td><strong>competence</strong></td>
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<table>
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<tr>
<th></th>
<th>Mendeley</th>
<th>APOSDELE</th>
<th>ReMashed</th>
<th>Organic.edunet</th>
<th>Mace</th>
<th>Melt</th>
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<tbody>
<tr>
<td><strong>Collection period</strong></td>
<td>1 year</td>
<td>3 months</td>
<td>2 years</td>
<td>9 months</td>
<td>3 years</td>
<td>6 months</td>
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<td><strong>Users</strong></td>
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<td>6</td>
<td>140</td>
<td>1,000</td>
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<tr>
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<td>96,000</td>
<td>11,000</td>
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<td>+</td>
<td>(+)</td>
<td>+</td>
<td>+</td>
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<tr>
<td><strong>ratings</strong></td>
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<tr>
<td><strong>downloads</strong></td>
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</table>
Evaluation:: Metrics

**MAE – Mean Absolute Error:** Deviation of recommendations from the user-specified ratings. The lower the MAE, the more accurately the RecSys predicts user ratings.

Evaluation:: Metrics

**MAE – Mean Absolute Error:** Deviation of recommendations from the user-specified ratings. The lower the MAE, the more accurately the RecSys predicts user ratings.

Outcomes:
Tanimoto similarity + item-based CF was the most accurate.

Evaluation:: Metrics

Outcomes:

• User-based CF Algorithm that predicts the top 10 most relevant items for a user has a F1 score of almost 30%.

• Implicit ratings like download rates, bookmarks can successfully used in TEL.

MAE – Mean Absolute Error: Deviation of recommendations from the user-specified ratings. The lower the MAE, the more accurately the RecSys predicts user ratings.

TEL RecSys::Evaluation

Combined approach by

Drachsler et al. 2008

Kirkpatrick model by

Manouselis et al. 2010
TEL RecSys:: Evaluation

1. Accuracy
2. Coverage
3. Precision

Combined approach by Drachsler et al. 2008

Kirkpatrick model by Manouselis et al. 2010
TEL RecSys::Evaluation

1. Accuracy
2. Coverage
3. Precision

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

Combined approach by *Drachsler et al. 2008*

Kirkpatrick model by *Manouselis et al. 2010*
### TEL RecSys::Evaluation

<table>
<thead>
<tr>
<th>Accuracy</th>
<th>Kirkpatrick model by Manousselis et al. 2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coverage</td>
<td></td>
</tr>
<tr>
<td>Precision</td>
<td></td>
</tr>
</tbody>
</table>

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

Combined approach by Drachsler et al. 2008

Kirkpatrick model by Manousselis et al. 2010
Goals of the lecture

1. Crash course Recommender Systems (RecSys)
2. Overview of RecSys in TEL
3. Open research issues for RecSys in TEL
4. TEL RecSys and Learning Analytics
TEL RecSys::Open issues

1. Evaluation of TEL RecSys
2. Publicly available datasets
3. Comparable experiments
4. Body of knowledge
5. Privacy and data protection
6. Design learning driven RecSys
Goals of the lecture

1. Crash course Recommender Systems (RecSys)
2. Overview of RecSys in TEL
3. Open research issues for RecSys in TEL
4. TEL RecSys and Learning Analytics
Learning Analytics

Greller, W., & Drachsler, H., 2011.
Learning Analytics

EDM
RecSys
Statistical Analysis

Greller, W., & Drachsler, H., 2011.
Greller, W., & Drachsler, H., 2011.
Greller, W., & Drachsler, H., 2011.
Greller, W., & Drachsler, H., 2011.
Learning Analytics

Greller, W., & Drachsler, H., 2011.
Learning Analytics

Stakeholders: Institutions, Teachers, Learners, Parents

Competencies: Critical thinking, Interpretation

Constraints: Privacy, Ethics

Technologies: EDM, RecSys, Statistical Analysis

Reflection, Prediction, Open, Protected

Objectives, Educational Data

Greller, W., & Drachsler, H., 2011.
Learning Analytics::TimeToThink

- Consider the Learning Analytics framework and imagine some great TEL RecSys that could support you in your stakeholder role

  alternatively

- Name a learning task where a TEL RecSys would be useful for.
Thank you for attending this lecture!

This slide is available at:
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Twittering at: http://twitter.com/HDrachsler