REVIEW ON ZIEGLER’S
Towards Decentralized Recommender Systems

by Richard Kwo
richardkwo@gmail.com
About Me

郭方健 (Richard Kwo)

• 2006~2009 Chengdu No.7 High School
• 2009~present Yingcai Experimental School, UESTC

Interests

• Science
• Reading
• Music, including rock, folk etc.
• Using, playing & programming GNU Linux/open-source stuff etc.
• Graphic design & Typography

Contact me

• richardkwo@gmail.com
• 13882042045
About Cai-Nicolas Ziegler

IEEE Computer Society *Best Paper Award* for

*Spreading Activation Models for Trust Propagation*

- 2003~2005: PhD student at Albert-Ludwigs-University Freiburg, Germany
- 2005~2007: Consultant with Siemens AG
- 2008~2010: Consultant with BCG
  while postdoc with Albert-Ludwigs-University Freiburg
Overview of Ziegler’s work

- Taxonomy-driven filtering
  - Topic diversification
- Trust propagation model
Overview of Ziegler’s work
About Decentralization

- Centralized (traditional)

Data Storage ➔ Server ➔ Download Result ➔ User’s PC

Computation ➔ Server
About Decentralization

- Decentralized

Data Storage → Network Nodes

Computation → User’s PC

Download Data
Taxonomy-driven Filtering

- Intuition
  1. Profiling

![Diagram showing agents and products with relationships](image-url)
Taxonomy-driven Filtering

- **Intuition**

2. Proximity computation and Neighborhood formation

![Diagram showing relationships between agents and products with correlation and proximity measures](image)
Taxonomy-driven Filtering

- **Intuition**

3. Rating prediction and Recommendation generation
Problem — **Sparsity (low profile overlapping)**

- **Taxonomy:**
  - Multiple
  - Hierarchical

Human: History: Ming Dynasty

Ancient: Ming Dynasty

- **a**₁
- **a**₂
- **a**₃
Taxonomy-driven Filtering

- Mathematical Model
  - Tree-structural Taxonomy Set

\[ D = \{d_1, d_2, d_3, \ldots, d_l\} \]
Taxonomy-driven Filtering

- Mathematical Model
  - Taxonomy-based (topic-based) profile
    \[ \tilde{v}_i = (v_{i,1}, v_{i,2}, \cdots, v_{i,l}) \]
  
- Normalization
  (we only care user’s interest distribution among all topics)

\[ \sum_{k=1}^{l} v_{i,k} = s \]
Taxonomy-driven Filtering

Mathematical Model

Generating profile from *implicit ratings*

- Assumption: implicit ratings are expressed in *binary form* (discuss it later)

For each user $a_i$

\[ B = \{b_1, b_2, b_3, \ldots, b_m\} \]

\[ R_i \subseteq B \]

- Rated (positively)

\[ B / R_i \]

- Unrated
Taxonomy-driven Filtering

- **Mathematical Model**
  - Generating profile from *implicit ratings*
    - Step 1: Distribute total score *evenly* among topics that rated products belong to

\[
sc(d_{ke}) = \frac{s}{|R_i||f(b_k)|}
\]

![Diagram showing a graph with topics and products](attachment:image.png)
Taxonomy-driven Filtering

Mathematical Model

Generating profile from *implicit ratings*

- **Step 2:** Redistribute the score to all topics with two assumptions
  - Conservation along hierarchical path (to ensure normalization)
    \[ \sum_{m=0}^{q} sco(p_m) = sc(d_{ke}) \]
  - Redistribute each topic score along hierarchical path to its super-topics with semantic decays
Generating profile from *implicit ratings*

- Step 2: Redistribute the score to all topics with two assumptions
  - Conservation (normalization)
  - Redistribute each topic score along hierarchical path to its super-topics with semantic decays

\[
sco(d_m) = k \frac{sco(d_{m+1})}{sib(d_{m+1}) + 1}
\]

(Recursive redistribution)
Taxonomy-driven Filtering

- **Mathematical Model**
  - Generating profile from *implicit ratings*
  - Measuring proximity and forming neighborhood
    - Proximity measurement: *Pearson Correlation*
      
      \[
      c(a_i, a_j) = \frac{\sum_{k=1}^{|D|} (\hat{v}_{i,k} - \bar{v}_i)(\hat{v}_{j,k} - \bar{v}_j)}{\sqrt{\sum_{k=1}^{|D|} (\hat{v}_{i,k} - \bar{v}_i)^2} \sqrt{\sum_{k=1}^{|D|} (\hat{v}_{j,k} - \bar{v}_j)^2}}
      \]

    - Neighbors Selection: *Top-M*
Taxonomy-driven Filtering

- Mathematical Model
  - Generating profile from *implicit ratings*
  - Measuring proximity and forming neighborhood
  - Forming recommendation list
    - Two-fold relevance (*user-proximity & product-proximity*)
      - User-proximity: Pearson
      - Product-proximity: "dummy user trick"

\[
\text{dummy user } \quad a_\theta \text{ with } R_\theta = \{b_k\}
\]

\[
c_b(a_i, b_k) \triangleq c(a_i, a_\theta)
\]
Taxonomy-driven Filtering

- **Mathematical Model**
  - Generating profile from *implicit ratings*
  - Measuring proximity and forming neighborhood
  - Forming recommendation list
    - Two-fold relevance (*user-proximity & product-proximity*)

\[
w_i(b_k) = \frac{qc_b(a_i, b_k) \cdot \sum_{a_j \in A_i(b_k)} c(a_i, a_j)}{|A_i(b_k)| + \gamma_R}
\]

*For fine-tune*
Taxonomy-driven Filtering

- Mathematical Model
  - Generating profile from *implicit ratings*
  - Measuring proximity and forming neighborhood
  - Forming recommendation list
    - Two-fold relevance (*user-proximity & product-proximity*)
    - *Topic Diversification Technique*
      - For alleviating “Winners Take All” problem
Taxonomy-driven Filtering

- Topic Diversification

\[ \text{OriginalRank}(b) + \theta_F \text{DissimilarRank}(b) \]

Sort

Recommendation List
Taxonomy-driven Filtering

- **Mathematical Model**

- **Evaluation**
  - How to evaluate the utility of a recommender
    - Precision
    - Recall
    - Breese Score

  *the expected utility of a recommendation list is simply the probability of viewing a recommended product that is actually relevant*

  *Assumption: each successive item in the recommendation list is less likely to be viewed with exponential decay*
Taxonomy-driven Filtering

- Mathematical Model
- Evaluation
  - How to evaluate the utility of a recommender
  - Comparison: with random recommender and two other CF’s
  - Two sets of empirical data
    - All Consuming book community (sparse)
    - MovieLens movie community (dense)
- Result
  - Work better than counterparts in comparison
  - Larger advantage gap in sparser community
Taxonomy-driven Filtering

- Random
- Pure CF
- Hybrid
- Taxonomic

Breese, Half-Life = 5

Minimum Required Ratings / User
My Review on Taxonomy-driven Filtering

- Effectiveness of Taxonomy
  - Structuralize user-rating network

Form neighborhoods

Agents

\[a_1, a_2, a_3, a_4, a_5, a_6\]

Rate

Products

\[b_1, b_2, b_3, b_4\]

Categorize with taxonomy
My Review on Taxonomy-driven Filtering

- Recommendation *beyond the dimension of accuracy*?
  - Topic Diversification
    - Positive-feedback of recommendation list? *(initial-value sensitive?)*
  - How would recommendation be *adaptive in response to user’s behavior/attitude*?
    - What can I do if I’m not satisfied with recommendation?
My Review on Taxonomy-driven Filtering

- **Explicit** rating vs. **Implicit** rating

(Mr. Ziegler made his recommender based on *implicit*)

- Is explicit rating *necessarily a burden* upon users?
- Can implicit rating really *supersede* explicit rating?
- Is implicit rating necessarily *binary*?

\[ a_i \rightarrow R_i = \{\text{rated products}\} \]

- Observation *diversity*
  - Viewing/purchase, browsing behavior, listened/watched, comment etc.

- *Insufficient input information*?

  \[ \text{unrated} \neq \text{dislike} \]
My Review on Taxonomy-driven Filtering

- What do we *rely on* when *designing* a recommender?
  - What *knowledge* do we have about *users’ behavior*?
  - Are *statistical distributions* *useful*?

- What do we *rely on* when *evaluating* a recommender?
  - Can *one set of data* justify the performance for *all data*?
  - *Is simulation completely unreliable/impossible*?

- *How to fine-tune parameters?*
Trust Propagation Model

- Computational trust in three dimensions
  - Network perspective
    - **Global trust** *(public reputation)*
    - **Local trust** *(one’s personal trust towards another)*
Trust Propagation Model

- Computational trust in three dimensions
  - Computation Locus
    - *Centralized computation*
  - *Decentralized computation*
  - Link Evaluation

```
All graph info                          All trust info
  "a_2" → 3.5 → "a_3" → 2.1 → "a_1"
  "a_2" → 1.5 → "a_3" → 4.9 → "a_1"

Trust-info share issue
 Relevant info
Trust info that I concern
```
Trust Propagation Model

- Appleseed trust model (**energy-propagation**)
  - Trust assertions
    \[
    A = \{a_1, a_2, \ldots, a_n\}
    \]
  - Agent i’s trust assertions
    \[
    W_i: A \rightarrow [0,1]^\perp
    \]

Diagram:

- Node $a_i$
- Node $a_j$
- Edge $W_i(a_j)$
Trust Propagation Model

- Appleseed trust model (energy-propagation)
  - Trust assertions
  - Trust propagation (energize)

Spreading factor

(Recursive Energization)

(Energy Conservation)
Trust Propagation Model

- Appleseed trust model (*energy-propagation*)
  - Trust assertions
  - Trust propagation (*energize*)
    - Problems
Trust Propagation Model

- Appleseed trust model (energy-propagation)
  - Trust assertions
  - Trust propagation (energize)
    - Problems
    - Solution — Backward trust propagation to trust source

Every node blindly trusts the source
Trust Propagation Model

- Appleseed trust model (*energy-propagation*)
  - Trust assertions
  - Trust propagation (*energize*)
- Computation
  - Only *relevant data* are acquired for local computation
  - Terminate recursion when reaching threshold
  - Convergence

\[
\sum_{x \in A} trust_i(x) \leq InitialEnergy
\]
Trust Propagation Model

- Appleseed trust model (*energy-propagation*)
  - Trust assertions
  - Trust propagation (*energize*)
  - Computation
- Analysis
  - Attack-resistance

“Bad node’s trust assignment cannot affect trust value.”
- Incorporate *distrust* into this model?

```
<table>
<thead>
<tr>
<th>Distrust</th>
<th>Trust</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1</td>
<td>0</td>
</tr>
</tbody>
</table>
```
Trust Propagation Model

- Appleseed trust model (*energy-propagation*)
  - Incorporate *distrust* into this model?

\[
e_{x \rightarrow y} = \begin{cases} 
  d \cdot \text{in}(x) \cdot \frac{|W(x, y)|}{\sum_{(x,s) \in E} |W(x, s)|}, & \text{in}(x) > 0 \\
  0, & \text{in}(x) \leq 0
\end{cases}
\]
Further investigation into trust/distrust interaction?

- What does trust/distrust mean?

\[
\text{distrust} \neq \text{lack of trust info}
\]

- How do trust and distrust propagate and interact?
My Review on Trust Propagation Model

- The implication of introducing a super-node connecting all other nodes?
  - also applied in “Leaders in Social Networks”
Thanks!

Questions and Discussion …