Modeling Trust for Recommender Systems using Similarity Metrics

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Recommender systems

- What they are: eBay, Epinions, Amazon
- Idea: CF, History of agreeing/Similarity, Virtual relationships, Predictions
- Problems: Sparcisty/Accuracy, Cold-start, Attacks
- Efficiency: Accuracy, Coverage.
- Metrics: Similarity *(Pearson)*

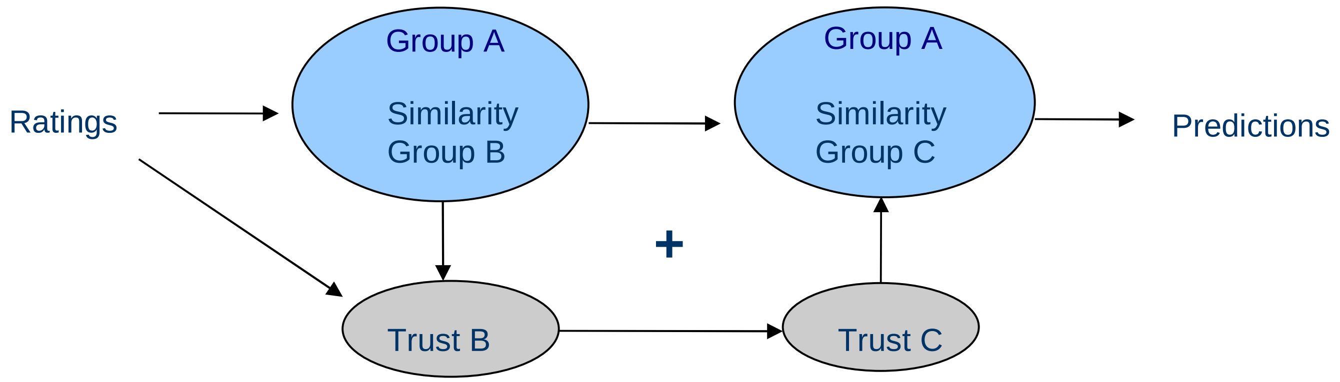
$$p_{a,i} = \bar{r}_a + \sum_{u=1}^{n} w_{a,u}(r_{u,i} - \bar{r}_u)$$

Potential of Trust

- Notion: Express integrity in relationships, Evidence.
- Characteristics: Transitive/propagation, Subjective
- Commonality with Similarity: relationship graph
- Potential aim: Extend neighbouring base, Extra correlations.
- Requirement: Transform similarity to trust and vice versa.
- Problems: Notion difficult to understand, User abilities,
- Solution: Mapping between Trust and Similarity.

The system architecture

High level view



The concept

- Distributed RS: As opposed to existing ones
- Benefits: Low cost (spread across users), Resistant to attacks (Data can be protected)
- Challenges: Accurate predictions, Keep the cost of computations low, Less sparse data sets, Scalable, Secure.
- Current work: Less sparce data, accurate predictions.

Existing modeling approach

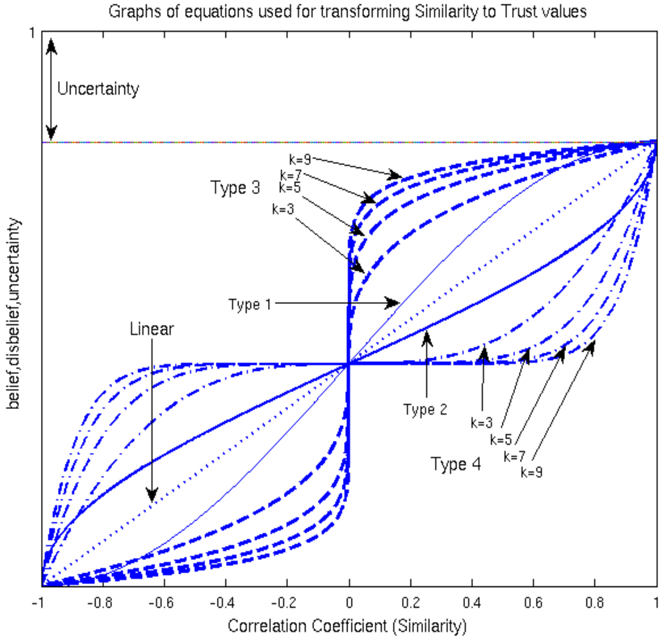
- **Basis:** Subjective logic, Useful characteristics, Uncertainty, Algebra, Transitivity.
- **Input:** Experiences (user ratings)
- **Output:** Direct Trust , Indirect trust derived, similarity
- **Logical reasoning:** for each property b,d,u
  - Uncertainty: $u=\frac{1}{k}\sum_{x=1}^{k}\frac{|p_x-r_x|}{m}$
    - Inability to make accurate predictions, Proportional to prediction error and dependent both on quantity of observations.
  - Belief. $b=\frac{(1-u)}{2}(1+CC)$ Max -> Correlation = 1
  - Disbelief. $d=\frac{(1-u)}{2}(1-CC)$ Max -> Correlation = -1

  No correlation means that *(1-u)* should be equally distributed to *b* and *d*.
- **Problems:** CPU intensive, High Complexity *O(n^2),* Not satisfactory accuracy.

New proposed model

- Motivation: complexity, expensive to compute.
- Basis: subjective logic, as before.
- Logical reasoning: $u = (n+1)^{-1}$
  - Uncertainty: based solely on quantitative criteria. Evidence, inverse proportional
  - Belief: is a function of similarity coefficient, various formulas tested.
  - Disbelief: Symmetrical to Belief: (1-u-b)
  - Same assumptions used as before.
- Advantages: Less complex *O(n)*, Higher accuracy

Graphs and formulas



$$b = \frac{1}{2}\left(\sin\left(CC \cdot \frac{\pi}{2}\right) + 1\right) \cdot (1-u)$$

$$b = \frac{1}{2} + \left(\frac{\arcsin(CC)}{\pi}\right) \cdot (1-u)$$

$$b = \frac{1}{2}(1-u)\left(1 + CC^{\frac{1}{K}}\right)$$

$$b = \frac{1}{2}(1-u)\left(1 + CC^{K}\right)$$

Evaluation

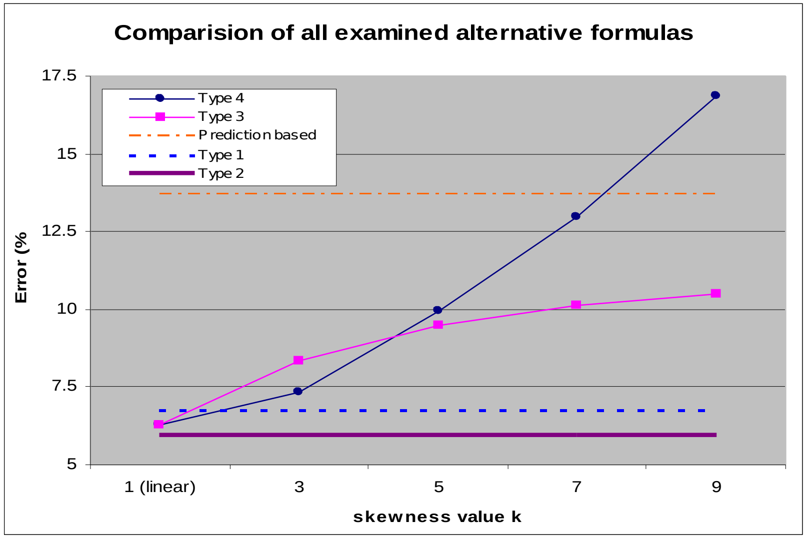
- Aim: Evaluate each equation, choose the best. Usage range
- Setup: Grouplens dataset, 10 sets of 100 users.(5K ratings)
- Plan: Compare Pearson similarity with Trust derived Similarity. Trust network used. All alternative paths of 2 hops distance checked and combined.
- Metrics: MAE for every user $$MAE = \frac{|S - S'|}{C_{\max} - C_{\min}}$$
- Assumptions: The accuracy of trust transitivity mechanism.

Results I

- Best candidate: Type 2

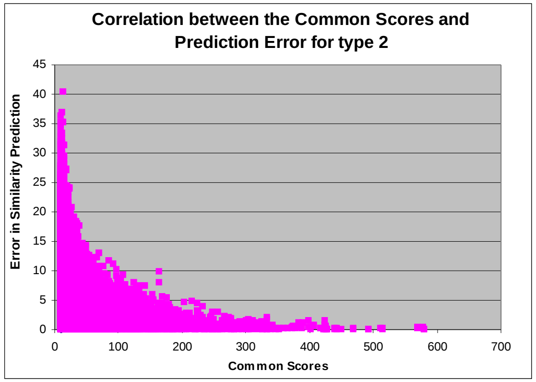
$$b=\frac{1}{2}+\left(\frac{\arcsin(CC)}{\pi}\right)\cdot(1-u)$$

- Average error less than 6% as opposed to 13% of the old approach
- Max error is half than of the old approach (very promising)
- Using a non-quantitative criteria for uncertainty is not good



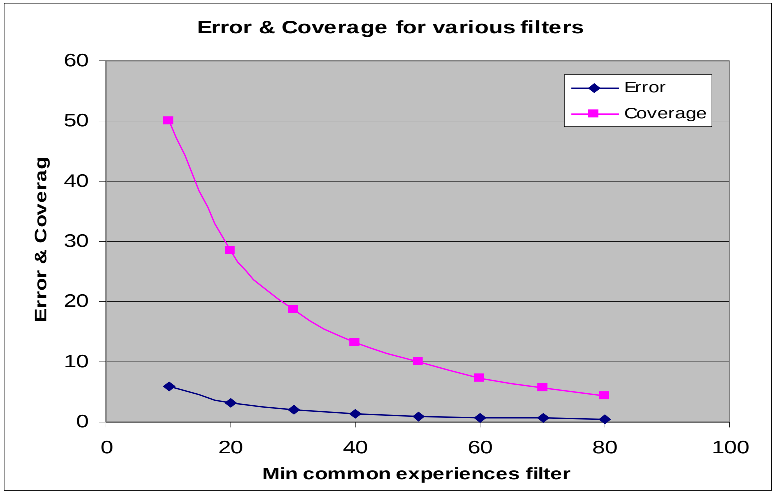
Results II

- Revealed correlation between error and common scores
- Practical use: Used as criterion for choosing the appropriate threshold for min common scores.
- Relationships based on poor data can be disclosed: Error is predictable
- Correlation declines as *k* (skewness) increases
- Error adapts best to non-linear approximation (R^2= -0.41)
- Error is higher when Similarity is in [-1..0] Predictions are easier when tastes agree. The formula not useful for disagreeing tastes. Using a unique mapping is not ideal.



Results III

- Examining relationships between Accuracy , Coverage and Number of observations
  - Analytical experiments showed that filtering relationships affects signsificantly the number or predictions that can be made
- Practical meaning:
  - Coverage is highly affected by the use of strong filters. Trade offs must be used.



Work in Progress

- Evaluation to a real recommender system
  - Test against the prediction error of a rating given to a certain item
  - First tests very encouraging for 2 hops distance.
  - Tests for 3 hops still in progress.

- Experimenting with evolution of Trust as the system develops
  - Examining if the cold start problem can be alleviated

Conclusions

- Empirical technique presented
- Shaferian type of trust
- Evaluation (against older approach)
- Beneficial complexity, accuracy, High potential
- Suitable when evidence are in form that only the user can understand