An intelligent mechanism for adaptive peer user modeling in web-based environments


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Collaborative web based environments

- Have met rapid growth in recent years
- Users collaborate to improve the quality of their work
- There is a need for efficient assessment of user contributions
- However, the participation of large numbers of users makes efficient and timely assessment difficult


Peer assessment

- Enables users to evaluate and comment on each other’s work.
- Designed to maximize collective knowledge and experience
- Users benefit from the knowledge and experience of their peers, to improve the quality of their work.

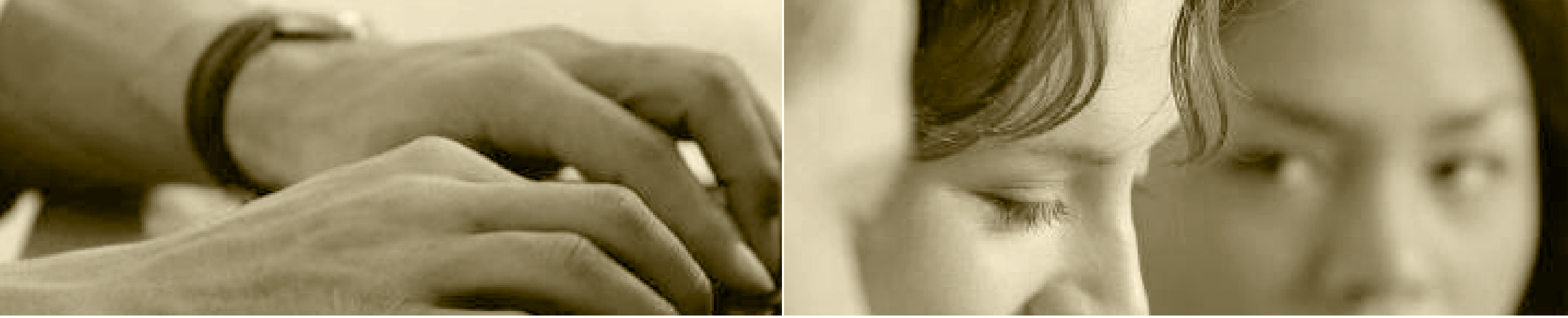
Peer matching problem

- The problem: How to assign the best reviewer for each author so that each user will receive the most useful comments?
- Current situation: A supervising expert selects the author-reviewer pairs, based on his personal knowledge of their profiles and their field of expertise.
- Disadvantages:
  - Need for personal knowledge of individual peer characteristics
  - Requires large amount of time from the supervisor
  - Difficulty in optimally matching large numbers of users

An intelligent mechanism for optimal peer matching

- This study proposes an adaptive peer matching algorithm based on:
  - Feed forward neural networks and
  - User profiles

  to match an author with the optimal reviewer who will provide good quality reviews.
- Aims at:
  - Providing optimal peer matching, adaptive to the changes in user profiles
  - Improving the quality of the author's work
  - Facilitating the supervisor in matching large numbers of users



Feed-forward neural networks

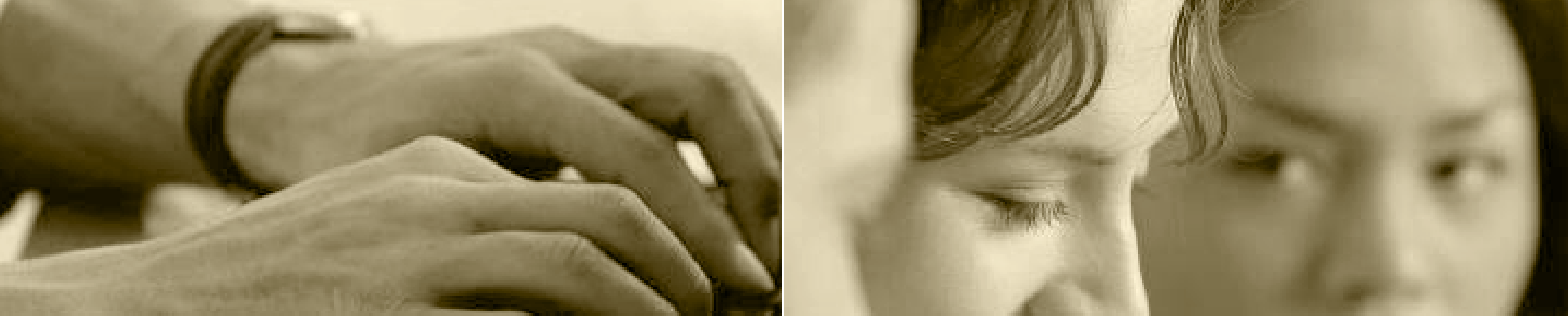
- Feed forward neural networks:
  - Are among the most popular forms of artificial neural networks
  - Can estimate any arbitrary function
  - Have been successfully applied to a variety of real-world problems


The proposed method (a)

- Two distinct profiles are constructed for each user:
- Reviewer profile:
  - Expertise/proficiency
  - Average level of strictness
  - Average rate of usefulness that the reviewer comments have received
  - Average acceptance ratio
- Author profile:
  - Expertise/proficiency
  - Average reviewer grading received.

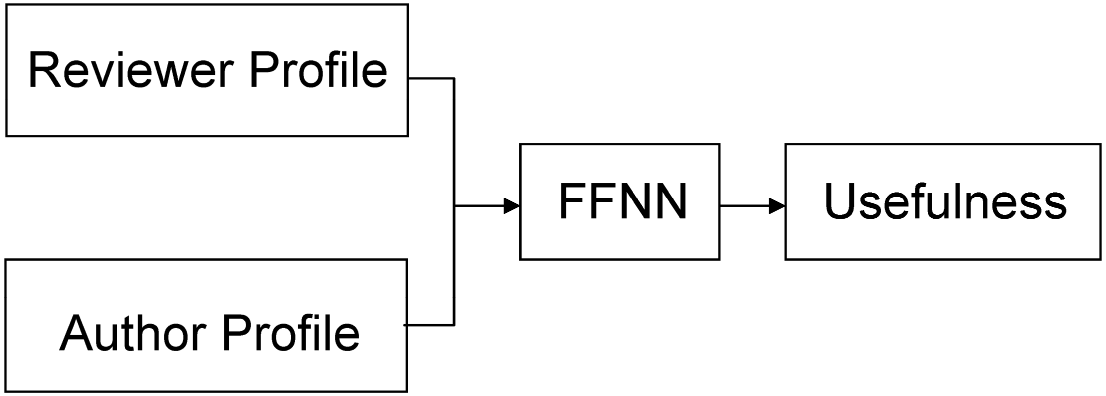

The proposed method (b)

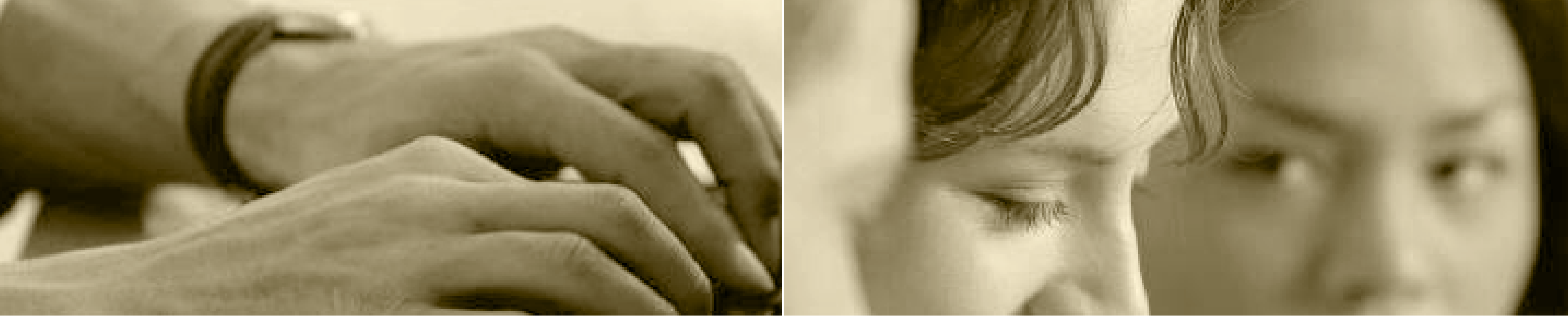
- During the peer assessment procedure, the reviewers make their comments and the authors rate their usefulness
- The algorithm uses a trained FFNN to estimate:
  - The expected usefulness rating that a specific author would give to each possible reviewer, based on user profiles.
- Then, for each author, the candidate reviewers are arranged in descending order.



The proposed method (c)

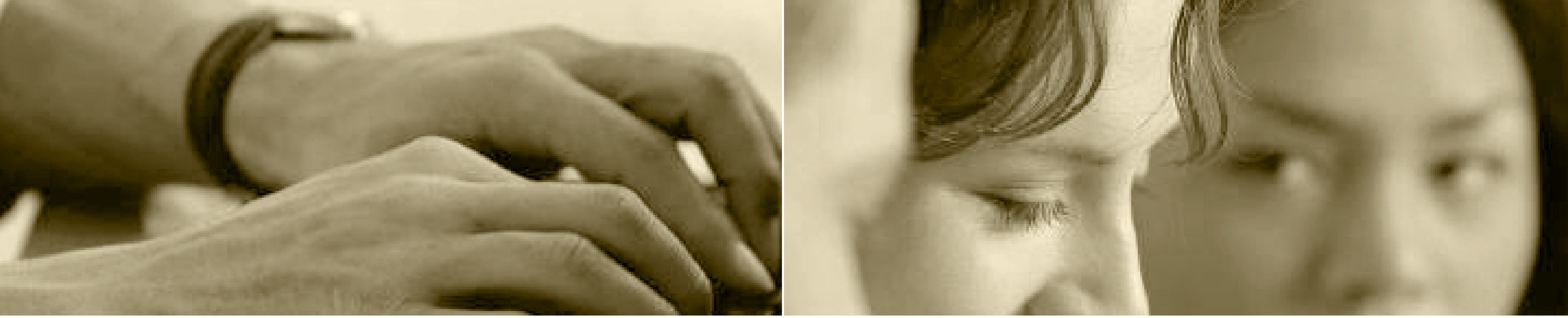
- The algorithm assigns reviewers to authors, taking into account the reviewer availability and the aforementioned order.
- In each peer assessment step, the algorithm adapts itself to calculate the optimal pairs based on the changing user profiles.





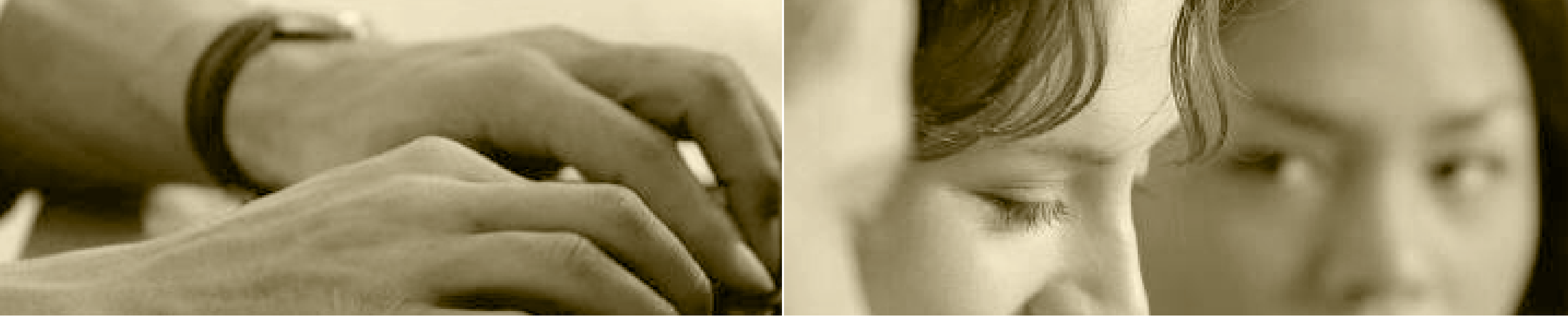
Algorithm implementation on e-learning data

- The efficiency of the algorithm was examined through its implementation on e-learning data
- E-learning course on: "Web Design", Spring semester 2008
- Students assess and review each other's projects
- Reviews refer to:
  - Project design
  - Technical soundness
  - Functionality
  - Overall impression



Algorithm implementation on e-learning data

- Student profiles which are fed into the FFNNs:
- Reviewer profile:
  - Reviewer proficiency: Average grade received in course (instructor + peer grades)
  - Average level of strictness: Average comment grades
  - Average rate of usefulness that the reviewer comments have received
  - Acceptance ratio
- Author profile:
  - Student expertise/proficiency
  - Average reviewer grading received



Method Results (a)

- Dataset used:
  - 152 reviews
  - 16 students
- Strategies to examine the network efficiency:
  - k-fold repeated random sub-sampling
  - For each student, comparison among students preferred and estimated reviewer order


K-fold repeated random sub-sampling

- Network trained and tested k=1000 times.
- Validation set (15%) randomly extracted from the dataset
- Network accuracy: 0.7682 (average mean absolute error)
- This means that the network estimations of an author’s perceived usefulness over a reviewer’s comment do not exceed 1 usefulness level in a scale of 5.


Optimal reviewer order estimation

- Data regarding a specific student were used as the test set
- The rest were used as train and validation sets
- Network estimations were used to determine the 1, 2, 3, 4 and 5 optimal reviewers and compared against the respective actual optimal reviewer order
- The overall algorithm accuracy results were 49%, 54%, 72%, 75% and 76% for the five criteria respectively
- Thus, these preliminary results indicate that the algorithm can help to select the optimal 3, 4 and 5 reviewers


Conclusion

- This study proposes a method that uses feed forward neural networks to determine the optimal reviewers for a specific author, during a peer assessment procedure


Thank you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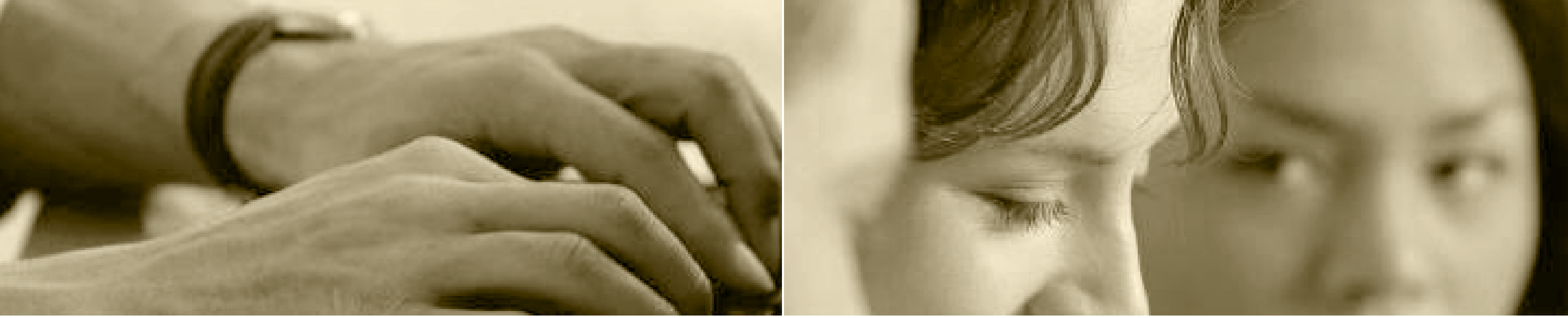

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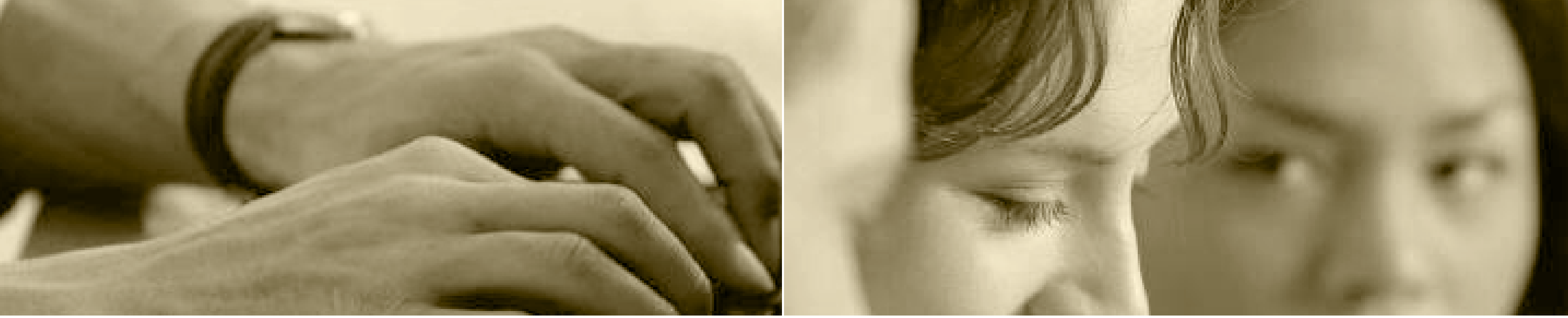

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