

AI Fostering Group Collaboration

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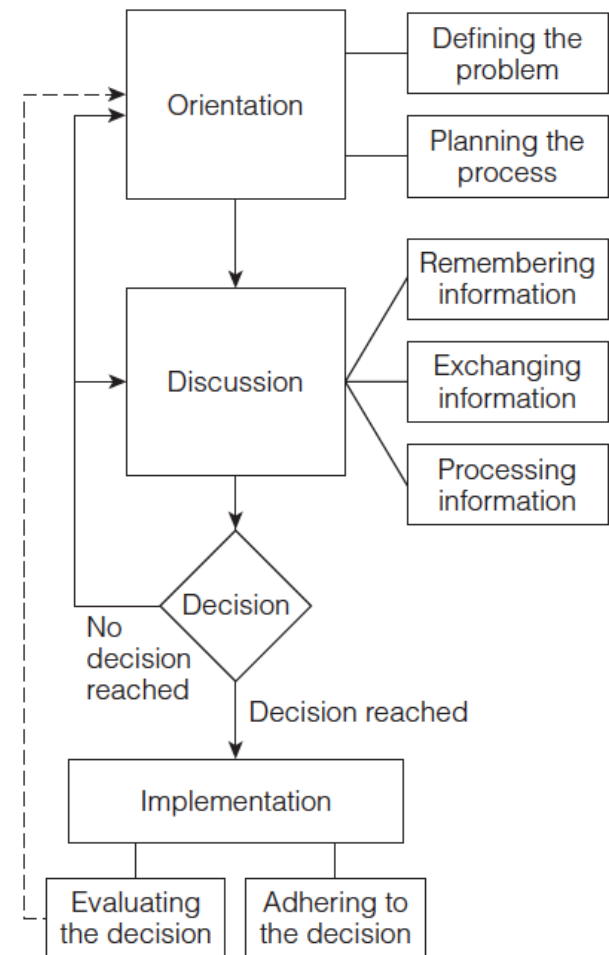
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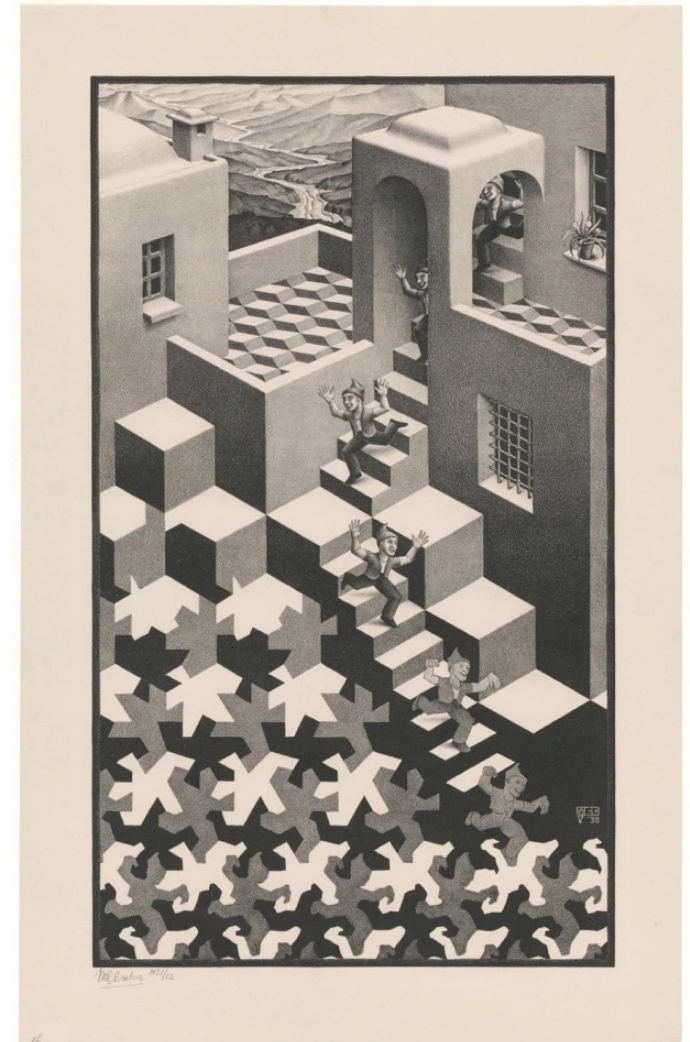
User's Tasks

- **Decision making** is the **last step**
- Groups must also:
 - **Decide how** the group should decide (orientation)
 - **Follow** the planned decision-making process
 - **Discuss alternatives** and **exchange information** and opinions.



Why using AI is hard

- **Coordination** of the actors: group members and the AI agent
- Providing various types of **information**, about the process and the options: how much, when, how
- Achieving **fairness**: no single best way for preference aggregation
- Variation of **contextual** conditions: available time, personalities (conflict resolution styles), value of the options...



Group Recommender Systems

- Major focus on **recommending** fair options, given the knowledge of the individuals' preferences
- Slow growth of the subject: hard to compare offline alternative **algorithms** (compared to individual RSs)
- Complexity of supporting a **realistic scenario**: multiple users, synchronous/asynchronous interaction, integration of item-related data.



1 Introduction

Most work on recommender systems to date focuses on recommending items to individual users. For instance, they may select a book for a particular user to read based on a model of that user's preferences in the past. Here, preferences are considered to be either implicit (e.g., clicks, purchase, viewing time, etc.), or explicit (e.g., likes, ratings, rankings, etc.) [1]. The challenge recommender system designers traditionally faced is how to decide what would be optimal for an individual user. A lot of progress has been made on this, as evidenced by other chapters in this handbook (e.g., [2–4]).

In this chapter, we go one-step further. There are many situations when it would be good if we could recommend to a group of users rather than to an individual. For instance, a recommender system may select television programmes for a group to view or a sequence of songs to listen to, based on individual preferences of all group members. Recommending to groups is more complicated than recommending to individuals. Assuming that we know perfectly what is good for individual users, the issue arises how to define and find what is also good for a group composed by the same individuals. The usual approach to solve this issue usually revolves around combining individual user preferences into a group preference model, or recommendations tailored for individuals into group recommendations. Methods or algorithms that combine individual user preferences or recommendations are called preference aggregation strategies. In this chapter, we will discuss how group

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Where GRSs use AI

- **Dynamic** updating of users' and group **profiles**: constraint satisfaction and optimization (representation)
- **Learning** to replicate observed choice behaviour: DNN for rating prediction – with various types of assumptions about “group rating” (learning)
- **Aggregation** of group members' preferences: social choice (reasoning)
- **Conversational** approaches: critiquing, negotiation, mediator.



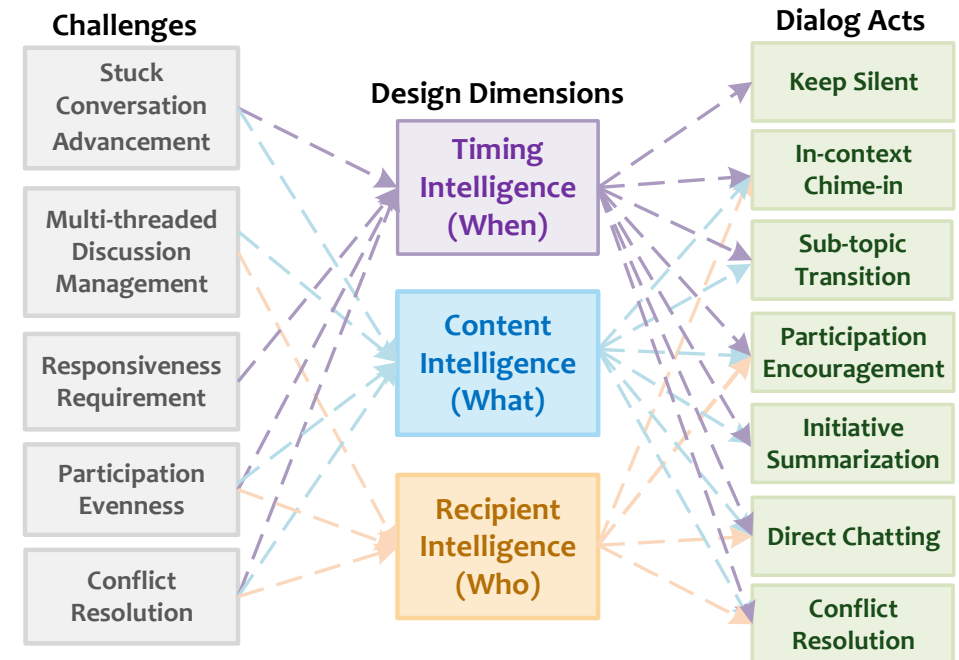
Vision - CAJO

- AI as a **Coach**: informs and trains the group on how to set and achieve members' goals
- AI as an **Arbiter**: intervenes to keep the process fair and target oriented
- AI as a **Judge**: suggests decisions having weighted the group members' actions during the process
- AI as an **Oracle**: tells the truth about the process and the options.



Some results

- **CHARM**: instant message chat augmented with a light **judge**
- **MUCA**: multi user chat assistant (**arbiter**)
- Group **choice prediction** based on Social Decision Scheme (**oracle**)



- A. Delic, H. Emamgholizadeh, T. N. Nguyen, F. Ricci: CHARM: a Group Decision Making Support Chatbot. IUI Companion 2024: 7-10
- M. Mao, P. Ting, Y. Xiang, M. Xu, J. Chen, J. Lin, Multi-User Chat Assistant (MUCA): a Framework Using LLMs to Facilitate Group Conversations. CoRR abs/2401.04883 (2024)
- H. Emamgholizadeh, A. Delic, F. Ricci: Predicting Group Choices from Group Profiles. ACM Trans. Interact. Intell. Syst. 14(1): 7:1-7:27 (2024)

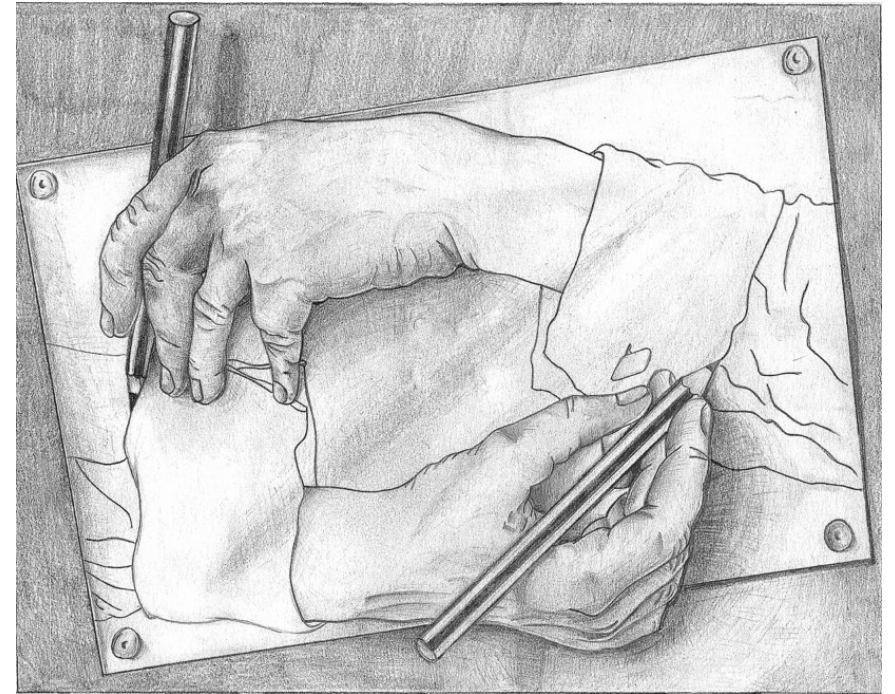
User Modeling

- Design a proper user **modelling language** (portability, cross systems) – *by using nlp?*
- Creating a model of **what users know about what the other users know** (beliefs about other group members' beliefs)
- Making the user model highly **dynamic** and **contextual**
- ***Understanding*** what users really mean and want to achieve.



Interacting with Users

- Using a **proper language** for each group
- Dealing with 1-to-1 and 1-to-n **communication channels**
- **Persuading** users to follow the coach and respect the judge
- Dealing with **information overload**
- Enhancing **process transparency**, without overloading and focusing on choice value rather than on fairness.



Functionality

- Offering a wide range of **information**: group members (opinions, personalities), decision process and options (**oracle**)
- Integrating a wide range of **knowledge sources** (**oracle**)
- **Manipulating** group members' beliefs to optimise a given metric, while being seen as a **coach**
- **Suggesting** *valuable options* that will be accepted (**judge**) – *fairness is not the primary goal*
- Giving the *tempo* to the conversation (**arbiter**).

Technologies

- **LLM** based conversational agents
- Negotiation agents based on proved **negotiation** strategies
- **Context aware recommender systems** trained on observed dialogues
- **User modelling** with textual based descriptions (LLM digestible).





Discussion

Discussion/Research topics

- Text based user modeling for groups – modeling beliefs about beliefs
- Persuasion strategies in groups – applying Cialdini's principles
- Generating context aware group recommendations – are the three basic CARS approaches still viable?
- Generative recommendations for groups
 - Repurposing items for groups
 - Bundling or sequencing for group satisfaction
- Group interaction data acquisition
 - Observational studies
 - Generating synthetic data (with LLMs)
 - Simulation (feedback and choice modeling)