IIAI Open Conference Publication Series
IIAI Letters on Informatics and Interdisciplinary Research
Vol.006, LIIR326
DOI: https://doi.org/10.52731/liir.v006.326

An Automatic Bottom-up Idea Grouping Method based on LLMs

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Abstract

This paper presents a novel automatic Bottom-up idea grouping method leveraging Large Language Models (LLMs) to facilitate the organization of ideas and concepts. Traditional methods of idea grouping, such as the KJ method, require significant manual effort to group and synthesize information effectively. Our approach utilizes the contextual understanding and grouping capabilities of LLMs to automate this process, aiming to reduce cognitive load and improve efficiency. By performing unsupervised grouping based on the insight of each idea, the model automatically generates cohesive idea groups from diverse sets of inputs in the bottom-up way. We evaluate the effectiveness of our method on qualitative datasets, comparing it with top-down categorizing method. Results indicate that the proposed bottom-up method not only aligns well with human clustering but also demonstrates a high level of interpretability and accuracy in grouping similar ideas. This study highlights the potential of LLMs in transforming qualitative analysis by offering a scalable and intuitive solution for idea grouping.

Keywords: AI-based Discussion Support, LLM-based Grouping, KJ Method

1 Introduction

In the modern landscape of problem-solving and innovation, methods such as Design Thinking and the KJ Method[7] have gained prominence for their structured yet flexible approaches to organizing and synthesizing ideas. These methodologies are widely used in design, research, and business to manage complex datasets, explore user needs, and uncover actionable insights. However, as data grows exponentially and collaboration becomes increasingly virtual, traditional methods like the KJ Method face limitations in scalability, consistency, and efficiency. To address these challenges, we propose a Large Language Model (LLM)-based approach for automatic bottom-up idea grouping, aiming to streamline and enhance the idea organization process.

The KJ Method, developed by Japanese anthropologist Jiro Kawakita, is a bottom-up technique that facilitates emergent grouping of ideas. Participants gather data, such as ideas

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or user feedback, and organize them into clusters based on perceived relationships, allowing categories and patterns to emerge organically. This process encourages a holistic view of complex information, uncovering hidden connections and driving collective understanding. Similarly, Design Thinking relies on phases of divergence and convergence to explore broad possibilities before refining ideas into practical solutions. Divergent thinking supports the generation of diverse insights, while convergent thinking helps synthesize these insights into coherent themes and directions.

Despite their strengths, these methods have notable drawbacks. The traditional KJ Method is labor-intensive and time-consuming, requiring substantial manual effort to group, label, and interpret clusters, especially when dealing with large datasets. Additionally, the subjective nature of manual grouping introduces variability, as different facilitators or teams may produce different results based on their interpretations. Design Thinking faces similar challenges in the divergence and convergence phases. While these phases foster creativity and inclusivity, they also risk overwhelming participants when the volume of data is too high. The reliance on human-led clustering can lead to inconsistencies, as participants may interpret and prioritize data differently, leading to biases and inefficiencies.

To overcome these limitations, we propose an automatic bottom-up idea grouping method using LLMs. Large Language Models, with their advanced natural language processing capabilities, offer a promising solution for automating the grouping process by analyzing semantic relationships between ideas. By applying LLMs in a bottom-up fashion, we can replicate the emergent clustering of the KJ Method and the divergent-convergent balance of Design Thinking while reducing manual effort, increasing scalability, and ensuring greater consistency. Our approach leverages the language model's contextual understanding to identify patterns and group similar ideas, making it especially suitable for large datasets or remote collaborative settings where traditional methods may falter.

In this paper, we outline the design and implementation of our LLM-based grouping method, evaluate its effectiveness in comparison to manual grouping techniques, and discuss its potential applications in fields that rely heavily on qualitative analysis and collaborative ideation. Through this automated approach, we aim to enhance the efficiency and reliability of bottom-up idea grouping, enabling teams to focus more on insight generation and decision-making, and less on the logistical burdens of manual data synthesis.

This paper is organized as follows. Section 2 provides the related work. Section 3 provides the proposed bottom-up grouping method. One-shot method and top-down method are also described. Section 4 presents the experimental results and discussions, and finally we summarize this paper in Section 5.

2 Related Work

2.1 KJ Method

The KJ Method[7], also known as Affinity Diagramming, is a collaborative approach for organizing ideas or data based on natural relationships. Developed by Japanese anthropologist Jiro Kawakita in the 1960s, the method allows teams to synthesize large amounts of information, revealing patterns and insights that support problem-solving, brainstorming, and qualitative research. It's widely used in fields like design thinking, market research, and project planning, where organizing complex or unstructured data is essential.

The KJ Method involves several steps. First, participants collect data or generate ideas, usually writing each one on a sticky note or card. These notes are then grouped based on perceived similarities without pre-defined categories, allowing themes to emerge organically. Once grouped, each cluster is labeled to capture its main idea, and groups can be further organized into broader themes if needed. The process concludes with a discussion to analyze the grouped data and derive actionable insights or directions.

The method has several advantages, such as encouraging teamwork, uncovering hidden patterns, and simplifying large data sets, which fosters creativity and helps teams make sense of complex information. However, it can also be time-consuming and subjective, as grouping depends on participants' perspectives. Additionally, it may not scale well with very large datasets, where automated tools are increasingly applied. Recent advances in language models, like those using machine learning, are being explored to replicate and scale the KJ Method, enabling faster and more consistent results across large datasets.

2.2 Design Process and Design Thinking

In design thinking[1], the divergence and convergence process is a fundamental approach used to explore and refine ideas when solving complex problems. These two complementary phases – divergence and convergence – help teams and individuals move fluidly between expansive, creative thinking and focused, evaluative thinking. Together, they create a balanced approach that encourages creativity while ensuring that solutions are practical and actionable.

The divergence phase is an exploratory phase where the aim is to generate as many ideas, insights, or perspectives as possible. During this phase, designers are encouraged to think freely, challenge assumptions, and look at the problem from various angles. Divergent thinking is often used in early stages, such as during user research, brainstorming, or ideation sessions, where quantity and breadth of ideas are prioritized over immediate feasibility. Techniques like brainstorming, mind mapping, and empathy mapping are commonly employed to expand the range of possible solutions.

This phase is crucial for uncovering unexpected or innovative insights that may not emerge in a purely linear or constrained approach. Divergence also emphasizes inclusivity, encouraging all participants to share their ideas without fear of criticism. This freedom helps capture diverse perspectives, which can lead to breakthrough ideas that would otherwise be overlooked in a more restrictive process.

Once a broad set of ideas has been generated, the convergence phase begins. Convergence focuses on narrowing down options, evaluating ideas, and selecting the most feasible and impactful solutions. During this phase, designers assess ideas based on criteria such as feasibility, relevance, and alignment with user needs or business goals. Techniques like affinity mapping, clustering, and prioritization matrices are used to synthesize and organize ideas, making it easier to identify the most promising directions for further development.

The convergence process requires critical thinking and often involves collaboration to ensure that decisions are informed by a range of perspectives. While the divergence phase is expansive, convergence is more selective, aiming to distill complex ideas into actionable, concrete solutions. This step is essential for moving from abstract or high-level ideas to practical and achievable outcomes that can be implemented.

The interplay between divergence and convergence is central to the iterative nature of design thinking. Divergence allows teams to explore a wide range of possibilities, which can lead to more creative and user-centered solutions, while convergence provides a structured approach for refining those ideas into viable solutions. Designers may move through these phases multiple times, iteratively expanding and refining ideas as they develop and test prototypes.

By alternating between these two processes, design teams can effectively balance creativity with practicality, maximizing the potential for innovative solutions that are grounded in user needs and real-world feasibility. The divergence and convergence process, therefore, serves as a powerful framework for navigating the complexities of problem-solving in design.

2.3 LLM-based Discussion Support Approaches

D-AGREE: AI-BASED DISCUSSION SUPPORT SYSTEM D-Agree[6, 2] is an innovative platform that supports democratic discussions through AI-driven facilitation. Developed as a web-based forum by Agreebit, Inc., a Japanese startup, D-Agree aims to enhance the efficiency and quality of conversations among participants. The platform's AI agent actively guides discussions, helping users focus on structured, meaningful dialogue and ensuring discussions remain productive. Agreebit has worked with local governments, businesses, and other organizations in Japan to implement D-Agree in various contexts where effective, structured conversation is essential.

Central to D-Agree is its AI agent, which follows the IBIS (Issue-Based Information System) model to frame discussions around key issues, ideas, and arguments. By using IBIS, the agent helps keep conversations organized and focused, making it easier for participants to reach well-structured conclusions. The AI agent prevents discussions from becoming fragmented or unproductive, instead aligning them with the goals of the conversation, thus creating a more cohesive and goal-oriented dialogue.

D-Agree's practical applications are evident in Afghanistan[4, 9, 3, 11, 5, 10] and multiple Japanese cities, including Kobe, Nagoya, Musashino, and Sapporo, where it has been used to gather public opinion for policy-making. By incorporating D-Agree, these municipalities have been able to better engage citizens in democratic discourse, giving voice to a broad range of perspectives. This platform provides local governments with valuable insights into public sentiment, supporting more informed, community-driven decision-making based on the collective views of their residents.

MULTIPLE AIS THAT SUPPORT IBIS-STYLE BRAINSTORMING Brainstorming is essential for encouraging creative idea generation and remains widely used today. Group brainstorming, in particular, benefits from the diversity of perspectives, as it incorporates ideas that may not emerge in individual sessions. However, group brainstorming can suffer from reduced productivity due to "free riding/social loafing" and "social inhibition". This study[8] addresses these issues by introducing a brainstorming support system that assigns agent-based roles, simulating group dynamics .

AI MEDIATED DISCUSSION An AI system called Herbermas Machine aims to help people find common ground in group discussions[12]. Traditional group deliberation faces several challenges: it's often slow, hard to manage with large groups, and risks missing some people's input. The researchers developed an AI mediator that listens to everyone's views and criticisms, then works to create statements that capture the group's collective understanding on contested topics. They tested this with over 5,700 participants, who found the AI's summaries more balanced and easier to understand than those written by human mediators. After discussions mediated by the AI, many participants shifted their views toward a shared middle ground. Analysis showed successful group statements managed to both acknowledge minority viewpoints while reflecting majority opinions. The researchers confirmed these results through a test case - a virtual citizens' assembly with participants chosen to represent different demographics across the UK.

3 Automatic Bottom-up Grouping Method based on LLM

3.1 The Problem: Idea Grouping

Idea grouping addresses the challenge of grouping large numbers of ideas (including opinions, posts, etc.) into meaningful groups based on their underlying insights. There are two primary approaches to grouping: top-down and bottom-up.

The top-down approach is commonly used in real-world settings, where categories are defined in advance, and ideas are then assigned to one of these predefined categories. While practical, this approach limits creativity, as it relies heavily on established classifications, which can introduce bias and restrict innovative thinking. In contrast, the KJ Method avoids top-down grouping for this reason; predefined categories can lead people to overlook novel insights embedded in the original ideas.

Instead, the KJ Method emphasizes the importance of a bottom-up approach, where ideas are grouped based on their inherent insights rather than fitting into pre-existing categories. This requires a careful understanding of each idea's essence and encourages finding natural groupings among ideas with similar insights. In this paper, we propose LLM-based approaches for both top-down and bottom-up automatic idea grouping. The LLM-based method significantly reduces the time required to organize ideas, particularly for the bottom-up approach, which demands deep consideration of each idea's insight and is highly time-consuming. By leveraging LLMs, we can achieve a more sophisticated and efficient bottom-up grouping, enhancing the overall process.

3.2 Methods

In this paper, we present 3 different methods for idea grouping methods with a LLM: one-shot categorizing, top-down categorizing, and bottom-up grouping. We describe the details of each method below:

ONE-SHOT CATEGORIZING (BASELINE): In order to have the baseline of the performance of grouping, we propose one-shot categorizing, in which we just give the prompts with the dataset to the LLM once (Figure 1). The prompt consists of 2 parts: the 1st prompt is the instruction to generate the adequate categories/labels from the entire set of idea data. Then, the 2nd prompt is to assign the ideas to each category. These 2 parts are described as one prompt.

It is simple and also it works at the certain level when we use GPT4o and similar models. However, the categories generated tend to be general, and also assignments are rather top-down and not correct enough.

TOP-DOWN CATEGORIZING: Because the one-shot categorizing fails to categorise ideas to categories correctly, we propose the top-down categorizing method. Top-down categorizing consists of the following 2 steps: (1) Generating the categories from the whole set of the ideas(opinons) by using LLM. (2) Measuring the fitness for each idea by using LLM, and allocating each idea to one of the categories based on the measured fitness.

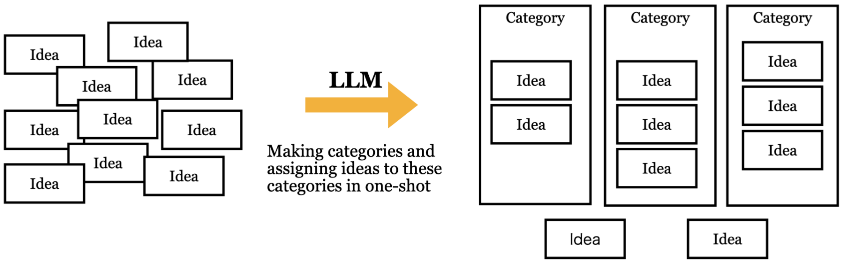

Figure 1: One-shot categorizing

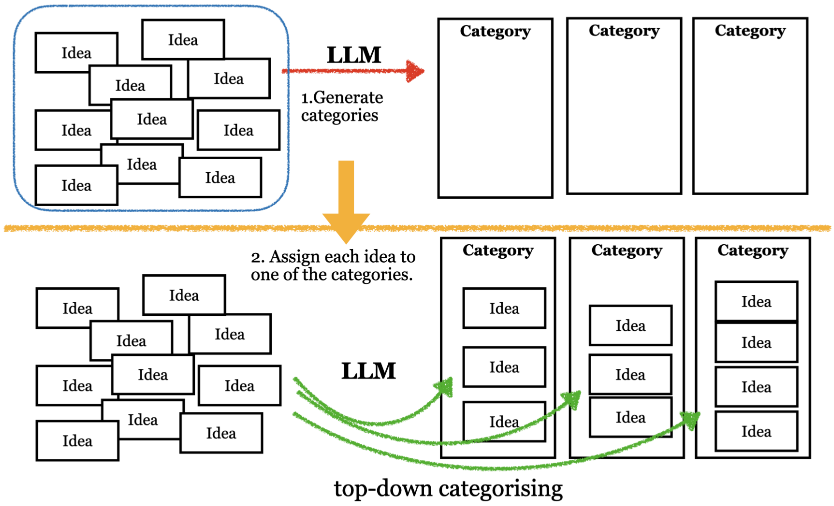

Figure 2: Top-down categorizing

BOTTOM-UP GROUPING: As we mentioned, one of the important sprits of the KJ method is ”bottom-up” thinking. Firstly, the insight of each idea must be extracted. Then, based on those insights, ideas should be grouped. It is not good to forcibly allocate an unallocated idea into a certain group. Such an idea can be seen as a distinguished and an exceptional idea. Then, finally, for each group, a label that represents the main insight of that group must be carefully generated. In order to realize this process, firstly, we ask the LLM to group ideas based on the insights by the prompt. Then, for each group, by using the LLM, we generate a label for that group.

4 Experiments and Evaluations

4.1 Experimental Setup

In the experiments, we employ the OpenAI’s GPT4o model as the LLM. GTP4o is the state of the art on LLMs at the November 2024. Our proposed methods are general enough to use the more advanced GPTs in the near future.

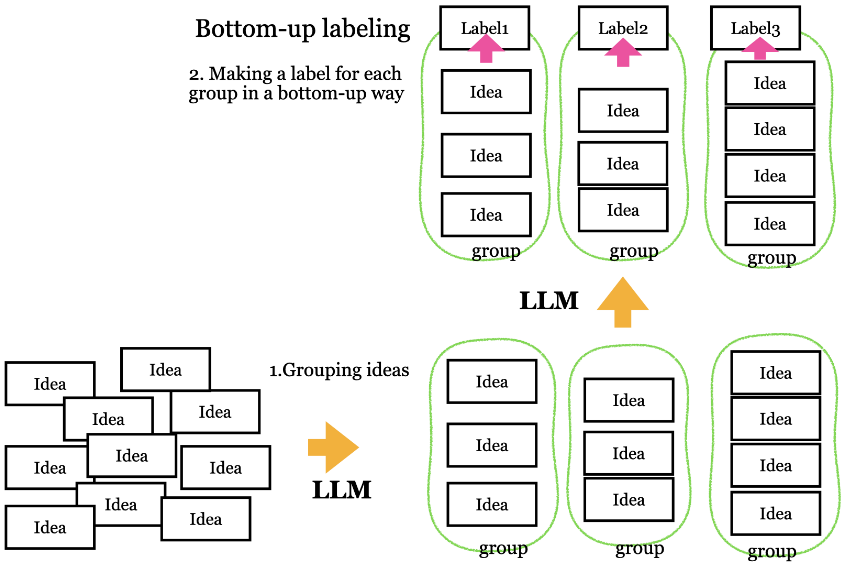

Figure 3: Bottom-up Grouping

THE DATASET FROM THE D-AGREE SOCIETAL EXPERIMENT IN NAGOYA-CITY 2018: For the experiments, we used dataset from a societal experiment conducted in Nagoya City via the D-agree platform, aiming to gather public input on the city's Next-Generation Comprehensive Plan. Held from November 1 to December 7, 2018, the experiment attracted 798 visitors, 157 registered participants, and generated 432 submitted opinions across five themes regarding Nagoya's development. These discussions received over 15,000 page views, and the insights collected were included in a comprehensive booklet that contributed to policy discussions in the municipal assembly, impacting future administrative actions.

The plan covered five key themes: (1) Human rights and diversity, (2) Secure childcare, (3) Disaster prevention, (4) City environment, and (5) Attractiveness for industry and the world. Discussions on Themes 1 and 2 were facilitated by human experts using specialized techniques, including the IBIS method, while Themes 3 and 4 were managed solely by automated agents. Theme 5 was co-facilitated by human facilitators and agents, combining AI and human support to foster an inclusive discussion environment.

The experiment had two phases: a 30-day open discussion phase on D-agree, followed by a 7-day voting phase. In the initial phase, citizens could register and participate anonymously, with user data securely managed. The second phase involved summarizing the discussions into concrete ideas, which participants then voted on. Promotion efforts included Google Ads, Nagoya's official website, local meetings, and social media, ensuring broad community engagement.

4.2 Experimental Results

By using the proposed methods, we conducted the experiments by using the sataset described above. As describe in the previous section, it is practical because the dataset has been gathered in the realworld. The following shows the result of categorizing and grouping by using the proposed methods:

ONE-SHOT CATEGORIZING (BASELINE): The following is a part of the one-shot categorizing result:

- Multicultural Conviviality and Diversity
  ”In order to create a town where everyone can live and work with vitality, we first need to deepen our mutual understanding. I think it’s easier to understand other people when you think about things from their perspective. ”, etc.
- Inclusive Society
  ”In a world where there is an increasing diversity of families, including DINKs, single mothers, single fathers, and de facto marriages, I think it will become essential in the future to create cities where it is easy to raise children and spend time with family, regardless of your circumstances. I think that as rules are relaxed and systems are put in place, society will naturally become more tolerant. ”, etc.
- Community and Place-making
  ”I see - if it’s a fun event, there will probably be a lot of people who take part. I wonder what kind of event would be fun? I like eating, so food is essential...“, etc.
- Language Support
  “Thank you for your comment. So, the first thing to do is to start with languages! It might be necessary to display information in languages other than English. Announcements on the subway are made in three languages (or was it?), aren’t they? Were there any announcements in English?“, etc.
- Gender Equality and Reverse Discrimination
  “I think it’s great that women are asserting their rights, but it’s sad that the voices of those who make excessive criticisms are so loud that good feminists feel like they can’t speak up. Is there anything that can be done about this?”, etc.
- Citizens’ Awareness and Participation
  ”Citizens don’t have the knowledge to comment on the city government, so they can’t express their opinions at town meetings about the interim plan. ‘, etc.
- Uncategorized
  ”Everyone, please feel free to post your thoughts and ideas about things you feel are restrictive in your daily life, or things you think would make living here more comfortable. ”, etc.

TOP-DOWN CATEGORIZING: The following is a part of the top-down categorizing result:

- Diversity and Multicultural Conviviality
  “In order to create a town where everyone can live and play an active role, we first need to deepen our understanding of each other. I think it’s easier to understand other people if you think about things from their perspective.”, etc.
- Social systems and legal development
  ”In a world where there is an increasing diversity of families, including DINKs, single mothers, single fathers, and de facto marriages, I think it will become essential in the future to develop cities that are easy to live in and raise children in, regardless of your circumstances. I think that as rules are relaxed and systems are put in place, society will naturally become more tolerant. ”, etc.
- Support for the Disabled and the Elderly
  ”Nagoya Castle’s wooden reconstruction: Nagoya City Mayor Takashi Kawamura has stated that he will not install an elevator. However, disabled people from all over the country have been voicing their criticism of this decision, which impedes access to public facilities for the disabled and elderly. Nevertheless, Mayor Kawamura has continued to respond in good faith, repeating unrealistic phrases such as “using a drone to lift them up” and “lifting them up with a ladder truck”. ”, etc.

- Social characteristics of Nagoya
  "HAMAgree, starting today! I'm Kome, the human facilitator. The other facilitator (who will be posting later) will be in charge. Thank you for your cooperation. The theme here is "a city where human rights are respected, where everyone can live and play an active role". It's a bit of a difficult theme, but I'd like to think about what kind of city Nagoya is that makes it easy for us to live in . Please feel free to share your thoughts and opinions. ", etc.
- Language and Communication
  "Thank you for your comment. So, we should start with language, right? It might be necessary to display not only English but also other languages. Announcements on the subway are made in three languages (or was it?), right? Did you hear any announcements in English?", etc.
- Gender equality and reverse discrimination
  "I think it's great that women are asserting their rights, but it's sad that the voices of those who make excessive criticisms are so loud that good feminists feel like they can't speak up. Is there anything that can be done about this?", etc.
- Social Participation and the Role of Government
  "Hello, everyone. I'm Kometto, a human facilitator. I'm joined by another human facilitator, Kame-san. Let's all talk about the kind of town we want to achieve in the future. ", etc.
- Personal experience and complaints
  "I see - if it's a fun event, there will probably be a lot of people who take part. I wonder what kind of event would be fun? I like eating, so food is essential...", etc.

BOTTOM-UP GROUPING:

- The importance of understanding diversity from different perspectives
  "In order to create a town where everyone can live and play an active role, we first need to deepen our understanding of each other.", etc.
- The need to improve systems to meet the needs of diverse family structures
  "you're right. I also feel that family structures are becoming more diverse. However, do you feel that there are still systems that need to be put in place in order to accept this diversity? In a world where there are more diverse families, single mothers, single fathers, and common-law marriages, I think it will become essential to create cities where it is easy to raise children and spend time with your family in any legal situation. I think that as rules are relaxed and systems are put in place, society will naturally become more tolerant.", etc.
- The importance of diversity and promoting it
  "I think that measures to promote essential diversity are important. I think it is important for people with different ways of thinking to come together and cooperate in a positive way.", etc.
- Strengthening information sharing and support systems in the community
  "I hope that places where no one is left behind will continue to spread. If you know of any, I would be grateful if you could share the information. In situations like this, do you have any organizations in mind that you can consult with? However, I think we can discuss measures here to reduce the number of people who feel this way. This is a place where we can receive and consolidate everyone's various thoughts and suggestions. Perhaps, if there is a one-stop consultation service, or if there is already one, and if there are many staff members, will that be a clue to a solution?", etc.
- A culture of suppressing the potential of individuals by striking out
  "Japan is a country that sings of equality but strikes down those who stand out, and this prevents people from reaching their full potential. I think that recognizing people's abilities and allowing them to play an active role in a variety of settings will lead to a more vibrant

way of life. This will block people's abilities and potential. I think that recognizing people's abilities and allowing them to play an active role in various fields will lead to a lively life.", etc.

4.3 Discussions

We observed that the proposed three methods differ in their approaches to grouping opinions, resulting in distinct categories and labels across each method. Notably, the bottom-up grouping method produces higher quality and more concrete labels that effectively capture the insights within each opinion group.

The cost of using LLMs is a significant factor in this type of application. The one-shot method calls the LLM only once, the top-down method requires as many calls as there are ideas, and the bottom-up method calls the LLM twice per grouping step.

There is a trade-off between minimizing LLM costs and maximizing grouping quality. Our proposed bottom-up method effectively addresses this balance, achieving both cost efficiency and enhanced grouping quality.

Further comparison across these methods with different datasets is necessary for comprehensive evaluation. However, we anticipate that the categorization and grouping patterns observed here will remain consistent.

5 Conclusions and Future Work

In this study, we introduced and evaluated three methods for automatic idea grouping using Large Language Models (LLMs): one-shot categorizing, top-down categorizing, and bottom-up grouping. Our findings reveal that each method approaches grouping differently, leading to unique category structures and labeling outcomes. Notably, the bottom-up grouping method demonstrated superior quality and specificity in label generation, capturing the insights within each opinion group more effectively.

Cost is a significant consideration in LLM applications, as each method varies in the number of LLM calls required. While the one-shot method is the most cost-effective with a single LLM call, it is limited in accuracy. The top-down approach improves categorization by allowing one call per idea, but the bottom-up method, which calls the LLM twice per grouping step, strikes a better balance between cost and grouping quality. This method is especially effective for high-quality, nuanced clustering that reflects underlying insights.

Future work should explore these methods across a variety of datasets to further validate our results and assess consistency in categorization patterns. Our findings indicate that the bottom-up approach holds considerable promise for applications requiring both cost-efficiency and precise, insight-driven grouping.

Acknowledgments

This work was supported partially by JSPS KAKENHI Grant Number JP22H00533, JST Strategic International Collaborative Research Program (SICORP), Grant Number JPMJSC2307, and JST CREST Grant Number JPMJCR20D1 , Japan.

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