Toward Intelligent Meeting Agents

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Groupware—computer aids designed for collaborative work—has produced measurable productivity gains for major corporations in recent years. Agent software enhances productivity even more by helping groupware perform convergent tasks, thus freeing users for more creative work. The result is a significant time savings over groupware without agents.

Agents represent a fundamental shift in the human-computer interaction paradigm, however. Broadly defined, an agent is a program that performs unique tasks without direct human supervision. As such, it transforms the user from a worker into a manager who delegates tasks to that agent. Agents must be able to engage and help all types of end users—whether that is to act as "spiders" on the Internet searching for relevant information, schedule meetings based on an executive's constraints, or filter articles based on learned user profiles.1

In this article, we describe an experiment to validate the performance of an intelligent agent. An intelligent agent differs from an agent in part because of its ability to reason about a task and learn from task performance. The sidebar "What makes an agent intelligent?" describes the differences in more detail. Our intelligent agent supports the GroupSystems electronic meeting system developed by the University of Arizona. The agent organizes ideas from brainstorming sessions into category lists for further discussion, a task often difficult for human meeting facilitators.

The goal of our experiment was to verify the agent's performance against that of human meeting facilitators. The experiment addresses a weakness in intelligent agent research: Many projects involving intelligent agents have rarely experimentally or empirically tested or verified performance against humans.1 In our experiment, we used 12 human facilitators and four sessions of varying sizes. We were able to verify that the agent performed as well as experienced human facilitators in identifying important meeting concepts—and it took a fifth of the time. The agent was less effective in generating precise and relevant concepts. However, since identifying concepts is a much more time-consuming task for meeting facilitators, the agent is still extremely practical. The experiment facilitators have used it in many actual sessions to create a strawman category list, which they then refine to be more precise.

An experiment with an AI-based software agent shows that it can help users organize and consolidate ideas from electronic brainstorming. The agent recalled concepts as effectively as experienced human meeting facilitators and in a fifth of the time.

CONSOLIDATING IDEAS

Electronically supported meetings can help reduce the time required for managers to complete complex projects by 90 percent, according to Fortune.2 Electronic meeting systems can improve meeting quality by permitting
anonymous comments, by providing instant access to information, by offering a structure for making decisions and evaluating alternatives, and by encouraging equal participation.

An electronic meeting has several stages. One is idea generation. During this stage, the group feels energized as it realizes the positive contribution to the question posed. Group members' overall satisfaction increases. The idea organization stage condenses all the comments into a manageable list of categories. As group members perceive that categorizing ideas is going to be difficult and time-consuming, satisfaction begins to decline. When the group senses they have reached a manageable list of categories (typically 10 to 15 items), satisfaction starts to increase again. As the group settles on a set of consensus categories, satisfaction continues to increase and the group proceeds to complete its task.

A major advantage of electronic meetings is that members can brainstorm in parallel. Indeed, electronic meeting systems are generally very effective during idea generation. A major disadvantage is that all the ideas from brainstorming—typically several hundred comments—must be organized. For this stage, the meeting system often requires additional tools. Idea-organizing tools let participants identify and consolidate ideas, typically by separately suggesting categories that merit further consideration.

The process of identifying crucial ideas embedded in meeting comments and generating a category list is a convergent task that must meet several challenges:

- Information overload. Idea generation tends to produce many ideas, which results in information overload. In a typical meeting of 10 to 20 participants, several hundred brainstorming comments can be generated in less than an hour, making it extremely difficult for participants to browse and consolidate comments. The participants are often impressed with the number of ideas generated but become overwhelmed with the task of organizing them into categories.
- Lack of a collaborative vocabulary. During electronic brainstorming, the goal is to generate creative, uncensored ideas. A natural consequence is that different participants use different vocabularies to convey those ideas. In fact, research shows that in a spontaneous word choice for objects in five domains, the probability that two people would use the same term is less than 20 percent. During idea organization, these vocabulary differences can cause problems, and there is little system support to alleviate them. Human meeting facilitators often try to address the vocabulary problem, but the overwhelming demand to monitor group dynamics and operate in a complex meeting environment makes this task difficult, especially when they are not familiar with the subject.
- Pressure to synthesize tasks. To be useful, ideas from electronic brainstorming must be consolidated and organized in a short time. Participants may take up to an hour to browse and understand the ideas generated, judge their merits, merge similar ideas, eliminate redundant or irrelevant ideas, consult other members, and so on. Many comments are raw or unpolished and often require special synthesizing. This process can be frustrating and ineffective, causing group satisfaction levels and productivity to diminish significantly. Some unique ideas may also be lost during this cognitively demanding process.
- Sensitive topics and lack of trust. Sensitive topics may emerge during idea organization. Participants may be reluctant to suggest such topics as categories because they are afraid to cause disagreements. An idea-organizing tool must address this reluctance by letting participants comment anonymously.

<table>
<thead>
<tr>
<th>What makes an agent intelligent?</th>
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</thead>
<tbody>
<tr>
<td><strong>Expressive.</strong> The agent must accept requests in different modalities.</td>
</tr>
<tr>
<td><strong>Goal-oriented.</strong> The agent must determine how and when to achieve a goal.</td>
</tr>
<tr>
<td><strong>Cooperative.</strong> The agent must collaborate with the user.</td>
</tr>
<tr>
<td><strong>Customized.</strong> The agent must adapt to different users.</td>
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In summary, an intelligent agent must be capable of autonomous goal-oriented behavior in some environment that acts as a personal assistant to the user (such as an electronic meeting software). Our meeting agent is able to satisfy these criteria, and so is truly "intelligent."

Reference
MEETING AGENT

Figure 1 shows some output from a typical electronic brainstorming session. The constraints of meeting time and variations in participants' typing skills often make the comments quite "noisy." Typos and incomplete or ungrammatical sentences are common. Comments may vary from a few words to multiple paragraphs.

After a one-hour brainstorming session, meeting participants typically take a break of 10 to 15 minutes before moving to idea organization. Thus, an agent must analyze and classify comments within this brief time using the electronic meeting system's platform. It must also accommodate the general-purpose, domain independent nature of the meeting software, which is designed to support any kind of meeting, task, participant, and institution.

In our experiments we used the GroupSystems electronic meeting system, which is now at 500 sites, including business, government, and universities. In our implementation, GroupSystems runs on a 486 66-MHz PC with Microsoft Windows 3.1. The agent uses files from electronic brainstorming sessions extracted directly from GroupSystems as input.

The GroupSystems configuration we used required that we develop the agent in Borland C++. We added two graphical user interfaces, one for generating concepts and one for analyzing comments. We describe these in more detail later. Basically, a meeting facilitator can invoke the agent at any time to produce a category list of ideas. Each category is linked to specific comments, which users can browse. Figure 2 shows our agent's category list for the entire session excerpted in Figure 1, for example.

Algorithms

Several natural language parsing techniques that are domain dependent and based on AI concepts work extremely well in narrow topics with well-defined vocabularies. However, the noisy data, diversity of vocabularies, and jargon in meetings make it infeasible to use these techniques for organizing the ideas generated in electronic brainstorming. The agent uses three techniques to produce the list, all of which are described in detail elsewhere:

- **Automatic indexing.** The agent's first task is to identify the content of each comment. Automatic indexing is domain-independent and computationally efficient. The technique identifies subject descriptors in each comment and computes the number of times each descriptor occurs in the entire session. A descriptor can be a one-, two- or three-word phrase; a document is one comment. The user can remove incidental or noisy descriptors from consideration by selecting a term-frequency threshold (typically two or three occurrences of a term) for a document.

- **Cluster analysis.** The importance of each descriptor in representing the content of the entire document (comment) varies. Using term frequency and inverse document frequency, cluster analysis assigns weights to each term in a document to represent the term's level of importance. Term frequency measures how often a particular term occurs in the entire collection. Inverse document frequency indicates the specificity of the term and allows terms to get higher weights during cluster analysis. Cluster analysis then converts raw data (indexes and weights) into a matrix that shows similarities and dissimilarities among terms. Using an asymmetric cluster function, we generated a network-like concept space of terms and their weighted relationships.

- **Hopfield net classification.** The Hopfield net is a neural net that groups similar term pairs as we chose the Hopfield net over others because it has a content-addressable memory and has been successfully used in other AI applications. The net stores information in single-layer, interconnected neurons (nodes) and weighted synapses (links). In applying the net to idea organization, we treated each term as a neuron and the asymmetric weight between any
two terms as the unidirectional, weighted connection between neurons. Using each term as an individual input pattern, the Hopfield algorithm activates neighbors, combines weights from all associated neighbors, and repeats this process until convergence occurs. The resulting output reveals all concepts semantically relevant to the input term. By repeating this process for all the terms according to their occurrence (most frequent to least frequent), we identified the underlying clusters of ideas in the EBS comments.

User interaction
When meeting participants invoke the agent, they see the screen in Figure 3. The first thing they do is select the electronic brainstorming session they want the agent to organize. They are most often interested in the session at hand, but they may want to use the agent to analyze previous sessions in the meeting (a meeting can have multiple brainstorming sessions) to compare and refine the category lists. The meeting participant in Figure 3 is looking at a large session (30-60 Kbytes). The agent can also handle small and medium sessions.

The participant has set the document frequency to 4. This means that if a term or phrase appears less than four times, the agent does not consider it a category descriptor. The facilitator can set the threshold from 1 to 5. If no threshold is set, the agent will default to a value appropriate to the session size. The facilitator can also set a threshold for the co-occurrence weight. If the relationship between two terms is below the threshold, the agent will not pair the terms into a phrase. The higher the weight, the stronger the relationship must be. Again, if the facilitator does not set a threshold, the agent will default to the session size.

The four buttons beneath co-occurrence weight give the facilitator the option of starting the concept generator, analyzing topics (which calls up another screen), setting defaults, or exiting the agent. The facilitator in Figure 3 has selected Generate Topics, and the list appears below. If the facilitator wants to analyze the topic list, he selects Analyze Topics and sees the screen in Figure 4. He can then highlight a topic for review or editing. He can also add or delete entire topics. The facilitator has highlighted Product/Design/Support. The agent displays all the comments related to that topic. The summary shows the distribution of topic terms in the comments. The agent saves whatever topics the facilitator deletes in an uncategorized

Figure 3. Invoking the agent. The user can start the concept generator or move on to the next screen to analyze comments.

Figure 4. Analyzing the topic list.
Table 1. Results by individual subject and session.

<table>
<thead>
<tr>
<th>Session 1: Large session</th>
<th>Experienced</th>
<th>Inexperienced</th>
<th>Session</th>
<th>Agent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lists</td>
<td>A1 A3 A6</td>
<td>A2 A4 A5</td>
<td>A7 A8</td>
<td></td>
</tr>
<tr>
<td>Recall</td>
<td>.54 .60 .89</td>
<td>.85 .80 .79</td>
<td>.87</td>
<td>.67</td>
</tr>
<tr>
<td>Precision</td>
<td>.94** .72**</td>
<td>.96** .71</td>
<td>.93**</td>
<td>.49</td>
</tr>
</tbody>
</table>

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<thead>
<tr>
<th>Session 2: Small session</th>
<th>Experienced</th>
<th>Inexperienced</th>
<th>Session</th>
<th>Agent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lists</td>
<td>A1 A3 A6</td>
<td>A2 A4 A5</td>
<td>A7 A8</td>
<td></td>
</tr>
<tr>
<td>Recall</td>
<td>.73 .59 .83</td>
<td>.74 .90 .74</td>
<td>.80</td>
<td>.72</td>
</tr>
<tr>
<td>Precision</td>
<td>.98** .89**</td>
<td>.92** .76*</td>
<td>.73*</td>
<td>.51</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Session 3: Large session</th>
<th>Experienced</th>
<th>Inexperienced</th>
<th>Session</th>
<th>Agent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lists</td>
<td>B1 B2 B5</td>
<td>B3 B4 .86</td>
<td>B7 B8</td>
<td></td>
</tr>
<tr>
<td>Recall</td>
<td>.83 .86 .96</td>
<td>.86 .86 .94</td>
<td>.88</td>
<td>.83</td>
</tr>
<tr>
<td>Precision</td>
<td>.83** .91**</td>
<td>.94** .82*</td>
<td>.97**</td>
<td>.61</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Session 4: Small session</th>
<th>Experienced</th>
<th>Inexperienced</th>
<th>Session</th>
<th>Agent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lists</td>
<td>B1 B2 B5</td>
<td>B3 B4 .86</td>
<td>B7 B8</td>
<td></td>
</tr>
<tr>
<td>Recall</td>
<td>.78 .84 .94</td>
<td>.61 .79 .90</td>
<td>.85</td>
<td>.77</td>
</tr>
<tr>
<td>Precision</td>
<td>.88** .91**</td>
<td>.83* .73</td>
<td>.82*</td>
<td>.58</td>
</tr>
</tbody>
</table>

where ** indicates that P < 0.05 and * indicates that 0.05 < P < 0.1 (vs. agent)

comment bin (not shown). When the facilitator is ready to exit the agent, he has a choice of saving or not saving changes to the topic list. He may decide not to save changes and have the agent regenerate a topic list using different co-occurrence weights, for example.

THE EXPERIMENT

Experienced facilitators were able to consistently achieve about 80 percent concept recall and concept precision. We wanted to see how well our agent compared with these figures.

Parameters and procedure

We chose four GroupSystems electronic brainstorming sessions from the files at the University of Arizona. Two of the sessions were small (less than 250 comments) and two were large (more than 400 comments). We omitted medium sessions in the experiment because it would make the parameters unnecessarily complex. Each session had to meet two criteria:

- The category list generated by the meeting participants was available.
- Domain knowledge was not required to adequately categorize the session.

We grouped the four sessions into two sets, each of which contained one large and one small session. We selected 12 facilitators from the university's Center for the Management of Information and from Ventana Corp., a spin-off company that develops GroupSystems technology. We classified the facilitators according to their years of experience and the facilitator to evaluate both sessions in the assigned session set and generate a category list for each session. At the same time, we ran the agent for that session. We recorded the time it took for all facilitators and the agent to generate each category list. The agent took three minutes for the small sessions and five minutes for the large sessions. The facilitators took from five to 81 minutes. The average times for large sessions were 25.8 and 42 minutes (two sets); for the small session, they were 20.5 and 25.7.

LIST EVALUATION. We next asked each facilitator to evaluate and modify eight category lists for each categorized session. The facilitators could not tell which category list was from the agent because the experimenters used the same font for all the lists. The eight lists consisted of

- three lists generated by experienced facilitators,
- three lists generated by inexperienced facilitators,
- one list generated by the meeting participants during the session, and
- one list generated by the agent.

We used the list generated by the meeting participants as a basis for comparison. We asked the facilitators to modify each list until it captured all relevant categories and eliminated all nonrelevant ones. We also asked them to rank each list according to how well it represented the session.

CODING AND ANALYSIS. In the final phase, two experimenters coded the results generated in phase 2. The experimenters independently categorized the facilitator's modifications to each list according to seven variables.
They also calculated intercoder reliability as one of the measures, using a well-known formula to ensure coding consistency. Intercoder reliability for the two experimenters in four sessions was 93.8, 96.5, 94.5, and 93 percent, all exceeding the 80 percent significance threshold adopted in past research.

**Results**

We used three measures—identified, target, and relevant—to calculate concept recall and concept precision. Identified represents the items on the original list. Target represents the total items on the list after all additions, deletions, and merges, and so represents the categories the facilitator felt should be on each list. Differences between lists were commonly due to variations in the terms used and the granularity of ideas. Relevant, the intersection of the other two measures, indicates the items on the identified list that were also on the target list.

We calculated concept recall and concept precision using a variation of the document recall and precision measures popular in information science applications. Concept recall—the relevant items divided by the target items—represents the percentage of relevant meeting ideas that were correctly captured in the original list. Concept precision—relevant items divided by identified items—represents the percentage of concepts on the original list that the facilitators deemed relevant to the meeting topics (taken from phase 2). Values for these two measures were between 0 and 1, with 1 being the most desirable.

**BY FACILITATOR AND SESSION.** Table 1 summarizes the experimental results by session (within sets A and B) and list generator—experienced facilitators, inexperienced facilitators, original session, and agent. Within a given session, we compared each facilitator-generated list with the agent’s list using a two-sample t-test. The statistically significant results (10 percent level) are marked with * in the table; the very significant results (five percent level) are marked with **.

In 26 of the 28 cases (the four cases with the original session are not counted), the agent’s mean concept recall was not significantly different from any of the individual lists generated by the facilitators, although the scores for the agent’s lists were generally poorer. Overall, the agent was able to produce 75 percent concept recall.

As Table 1 shows, however, the agent performed poorly in concept precision, with a mean of 55 percent. In only four cases, the agent’s precision level was not significantly different from that of a facilitator-generated list. In all the other cases, the agent lists were significantly worse. Facilitators also consistently ranked the agent’s lists lower than all other lists, probably as a result of this poor performance.

**BY FACILITATOR EXPERIENCE.** Figures 5 and 6 are comparisons of concept recall and concept precision, respectively, grouped by facilitator experience. We had 23 list

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**Figure 5. Concept recall comparison by facilitator experience.**

**Figure 6. Concept precision comparison by facilitator experience.**
evaluations each for the session output and agent output (we had to eliminate one set of evaluations because a facilitator left the company toward the end of the experiment) and 69 evaluations for the facilitators’ lists (again because a facilitator departed, we lost three evaluations). We used the Minitab statistical software to perform a one-way analysis of variance on each grouping. Concept recall’s F-ratio indicated that the results were not significant, so we did not pursue further analysis. However, concept precision’s F-ratio indicated that the results were significant, so we also performed pairwise, two-sample t-tests on the data.

The results confirmed our earlier observations for individual facilitator and session lists. For concept recall, the differences between the agent list and the facilitator lists were statistically insignificant. There was no statistical difference between any of the three kinds of facilitator lists and the agent’s lists for concept recall. However, the agent lists were significantly inferior when compared with facilitator lists on concept precision.

We also noted that the performance of experienced and inexperienced facilitators was indistinguishable, both in concept recall and concept precision. This suggests that facilitator experience is not necessarily a good predictor of the ability to categorize ideas.

**For all Facilitators.** Figures 7 and 8 summarize the performance of all facilitators in concept recall and concept precision, respectively. Once again, the agent’s lists were comparable to facilitators’ lists in concept recall, but significantly inferior in concept precision. Facilitators were able to achieve 80 percent concept recall (versus the agent’s 76 percent) and 86 percent concept precision (versus the agent’s 55 percent).

**Interpretation.** These results bear closer examination.

**Facilitation Experience.** There are two possible reasons inexperienced facilitators performed as well as experienced facilitators. First, analytical skills and training can influence a person’s ability to organize ideas. Second, the four sessions might have been so generic that the idea organization became trivial and did not depend on experience.

**List Generation Time.** The agent generated categories in a fifth of the time a facilitator took. This time savings could be even more significant because the facilitators generated their category lists under ideal conditions—no distractions and no responsibility to manage or facilitate a live meeting. Many subjects commented that they would welcome such a tool in an actual electronic meeting environment. With the agent providing a strawman category list, meeting facilitators and participants could focus on the more productive and satisfying tasks of generating creative ideas and engaging in group decision making.

**Quality of the System List.** One recurring criticism of the agent’s lists was that there were too many general terms that did not contain enough context (meaning) to be considered relevant. Sometimes the categories were too general to be useful and sometimes they were too specific to be considered summaries. The facilitators generally deleted such categories, lowering the agent’s concept precision scores. One solution to this problem might be to decrease the length of the agent list, which the user can set at runtime. At present the default is 20 items. Generating a list of 10 to 15 items might improve

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**Figure 7. Concept recall comparison for all facilitators.**

**Figure 8. Concept precision comparison for all facilitators.**

Computer
precision. On the other hand, recall might suffer. We plan
to do more experimentation to determine the effects of sys-
tem list size.

RECALL VERSUS PRECISION. Although the agent did rela-
tively poorly in concept precision, we do not view this as
a major weakness. The reason is that it is easier to refine a
list than to generate additional topics for a list that is too
short. Concept recall is a far harder and more time-con-
suming task than concept precision. If we focus on short-
ening that phase of the meeting, the facilitator and
participants can work together to prune and refine the raw
list as part of the consensus-building phase of the meet-
ing. The agent’s comment analyzer (Figure 4) helps in that
work. The facilitators have also indicated that they prefer
to have the agent generate long straw-man lists with high
recall (but lower precision) as opposed to shorter lists with
high precision (but lower recall).

The agent was well-received by facilitators both in our
experiments and in subsequent live sessions. In the live
sessions, facilitators used the agent to generate a straw-
man category list, which the group then inspected, eval-
uated, and modified. For the most part, the feedback from
these sessions has been positive.

We believe the agent addresses all the problems inher-
ent in idea organization:

- Information overload. The agent effectively handles
large amounts of data, rapidly segmenting the data into
smaller, more manageable chunks.
- Lack of a collaborative vocabulary. The agent exam-
ined participants’ vocabularies and was able to pro-
duce a consolidated list. The primary problem in
arriving at a collaborative vocabulary is time. The
agent was able to do in minutes what experienced
facilitators generally take hours to do.
- Pressure to synthesize tasks. The agent produced categ-
yories in a fifth of the time it took human facilitators.
- Sensitive topics and lack of trust. For better or worse,
the agent surfaces any category discussed during the
meeting. Participants may also view the agent as an
unbiased party. In fact, some participants favored the
agent’s suggestions over the facilitator’s suggestions
because of this perception.

Other advantages of the agent are that it is not domain
specific and, perhaps most important, that it reduces the
mental load of organizing ideas. An interesting, unan-
ticipated application of the agent was a modified version
of data mining. The client wanted to combine and cate-
gorize several months of electronic meeting data to dis-
cover ongoing or recurring issues. The agent was able to
generate a satisfactory list in just minutes. The facilitators
involved had estimated that it would take several hours to
accomplish the task.

The agent also has some weaknesses. The three most
often given and our suggested improvements are

- Many categories are too general. We can give meeting
participants access to the stop-word file. This file con-
tains commonly occurring but semantically mean-

ingless words (“a,” “or”), which the agent ignores
when indexing documents.
- Single-word descriptors lack content. We could add
another parameter to the agent’s program during
automatic indexing that would favor multiple-word
descriptors over single words.
- The agent cannot generalize. We could add access to a
domain-specific thesaurus during cluster analysis.

Our immediate work involves designing a graphical,
two-dimensional concept clustering agent based on a self-
orGANizing feature map. The agent will analyze meeting
output and produce a graphical summary map that users
can browse. The system should be more intuitive and thus
more suitable for categorizing meeting output. We are also
experimenting with applying these techniques to other
groupware applications and are examining the use of
agent techniques to analyze documents such as Lotus
Notes discussions and online newsgroup items.

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