Emergent Conversational Recommendations: 
A Dialogue Behavior Approach*

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Abstract
This paper presents and evaluates a behavior-based approach to dialogue management, where a system’s complete dialogue strategy is viewed as the result of running several dialogue behaviors in parallel leading to an emergent coherent and flexible dialogue behavior. The conducted overhearer evaluation of the behavior-based conversational recommender system CORESONG indicates that the approach can give rise to informative and coherent dialogue; and that a complete dialogue strategy can be modeled as an emergent phenomenon in terms of lower-level autonomous behaviors for the studied class of recommendation dialogue interaction.

1 Introduction
The purpose of a recommender system is to produce personalized recommendations of potentially useful items from a large space of possible options that is hard to manually browse or search. Conversational Recommender Systems (CRSs) approach user preference acquisition from a dialogue point of view, where preferences are captured and put to use in the course of on-going natural language dialogue. The approach is motivated by its aim to make interaction efficient and natural (Burke et al., 1997; Thompson et al., 2004), to acquire preferences from the user in a context when she is motivated to give them (Carenini et al., 2003), as well as to facilitate exploration of the domain and the development of the user’s preferences (Wärnestål, 2005). A CRS’s dialogue strategy to achieve these aspects of the interaction is thus crucial for its performance and usability. In particular, we are interested in exploring robust and emergent factual and preferential dialogue with recommendation capabilities.

This paper presents our behavior-based approach to dialogue management and reports on an evaluation of the CRS CORESONG’s dialogue behaviors.

2 Dialogue Behaviors in Recommendation Dialogues
By a dialogue behavior of a dialogue agent, we understand a conceptual and computational functionality in the agent’s dialogue strategy. Computationally, a dialogue behavior is coded into a Dialogue Behavior Diagram (DBD), that describes a state automaton where each state contains (one or more) commands and transitions with optional conditions. The DBD automaton is similar to the UML activity diagram.

DBDs invoke, and use, results from other software modules, denoted jointly as external resources (e.g. databases and recommender engines).

Four DBDs constitute the complete recommendation dialogue model: Conventional, Direct Delivery, Indirect Delivery, and Interview. A more detailed account of each of these behaviors are found in (Wärnestål et al., 2007).

Delivery Behaviors On a fundamental level, the goal for CORESONG (or any recommender system)
is to provide the user with a delivery, such as an explicitly requested piece of information from a database resource, or a recommendation from a recommender engine. The **direct** delivery typically uses a database that the user can query. In cases where a successful database call has been made (that is, a non-empty result set not larger than a predefined size limit is returned as response to a user’s request), a delivery is written to the out stream. In order to support domain exploration and to drive the dialogue forward (Wärnestål, 2005), positive preference statements trigger the system to fetch information related to the preference from an external database resource (e.g. utterances S3a, S4a and S5a in Figure 1).

While the direct delivery behavior is functional for information-providing dialogue, and can cater for basic recommendations, it has been found that human-like recommendations occur in a slightly different fashion (Wärnestål et al., 2007). Therefore, the **indirect** delivery behavior has been designed (Wärnestål et al., 2007). It provides a motivation before presenting the actual recommendation (as exemplified by utterances S5b/S5c in Figure 1). Since the system cannot know whether the suggestion is previously familiar to the user, it delivers the recommendations in the form of questions (S5c).

**Interview Behavior** The purpose of the interview behavior is to collect relevant information about domain entity types (e.g. genres, artists or albums in the music domain) or items. This is a useful dialogue behavior in cases where deliveries cannot be completed due to e.g. ambiguous or incomplete user requests. It is also useful in preferential interviews used for recommendations, where the system acquires user preferences to be used by a recommender engine resource. A particular system may thus employ several interview DBD instances, connected to different external resources.

### 2.1 Emergent Dialogue

We view the dialogue system’s complete behavior as emerging from the different DBDs. By **emergent** functionality in a system, we understand components that operate simultaneously in order to achieve a desired behavior. This is contrasted to hierarchical systems, where sub-functions are invoked from a central component or representation.

Our approach to dialogue system design is inspired by the layered subsumption architecture (Brooks, 1991) where layers correspond to behaviors that are organized hierarchically, and where higher-level behaviors can subsume lower-level layers by inhibition or modification.

A dialogue agent’s complete strategy is described by a set of DBD instances that run as a DBD strata machine. The DBD strata machine streams input and merges each behavior’s output (see Figure 2). There is no central representation of the complete dialogue, and the individual behaviors do not model each other since each DBD processes the incoming token stream autonomously. Therefore, the outputs from the DBDs need to be integrated (and typically reduced) into a coherent system turn, and is managed by two constructs in the Output Weaver: behavior priority and an order heuristic.

**Behavior Priority** DBDs are indexed with a priority and order the out statements accordingly (ascending order). The request with highest priority will be chosen. This hinders the occurrence of two requests back to the user which obviously could be confusing. The order of CORESONG’s DBDs are (lowest to highest priority): Conventional, Direct Delivery,
Indirect Delivery, and Interview (Figure 2). DBD instances connected to the recommender engine have higher priority than those of the music database.

**Order Heuristic** Due to the behavior priority, there is only one request action available each turn. The order heuristic places this request at the end of the output, so that informing system action statements are guaranteed to precede the request. This guarantees that the constrain request (S2c) in the first system utterance in Figure 1 always occur after the direct delivery (S2a) even though their statements origin from different DBD instances.

## 3 Experiment

To validate the behavior based approach to dialogue management we conducted an “overhearer” experiment (Whittaker and Walker, 2004) by using four different behavior configurations of the CORESONG system (see Table 1). The reason for using the overhearer model is to avoid natural language interpretation problems (since the coverage of grammar and lexicon is not our focus), and letting personal music preferences that may not be covered by our recommender engine and database affect the subjects’ experience of dialogue interaction. The experiment was run with 30 subjects.

### 3.1 CoreSong

Configuration of dialogue behaviors and attached external resources is easily done in CORESONG by switching DBD instances on or off. The two external resources used by the DBD instances are (a) a music information database and (b) a content-based recommender engine (Burke, 2002).

A DBD instance implementation consists of defining LookUp calls, and the surface realization of the action statements in the DBDs.

The Input Streamer (IS) feeds the interpretations of user input to each of the DBD instances in the DBD strata machine. Each DBD instance processes the input and writes to an out stream using the command out. The Output Weaver module (OW) then weaves together each DBD instance’s output as outlined in Section 2.1.

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1 Note that interview and delivery behaviors of the same external resource are naturally designed to be mutually exclusive.

### Table 1: Experiment configurations. DD = Direct Delivery, IW = Interview, ID = Indirect Delivery, Db = Database, R = Recommender Engine.

| Config. | DD(Db) | IW(Db) | DD(R) | ID(R) | IW(R) |
|---------|--------|--------|--------|--------|--------|
| Q-A     | X      | X      |        |        |        |
| BLUNT   | X      | X      | X      | X      | X      |
| PRYING  |        | X      |        | X      | X      |
| REC     | X      | X      |        | X      | X      |

Four different DBD instance configurations were used to generate the test dialogues, as shown in Table 1. The different configurations effectively modify CORESONG’s complete dialogue strategy. Q-A, for example, with only the database resource, results in a question-answer system without recommendation capabilities, whereas the PRYING configuration supports a preference interview but with no power to deliver answers to factual requests. The BLUNT configuration has the power to deliver both database results and recommendations; but the recommendations are not delivered with motivations and follow-up questions as the indirect delivery (RECOMMENDER configuration) is designed to do.

Figures 1 (RECOMMENDER) and 3 (BLUNT) exemplify the differences.

### 3.2 Procedure

Each subject was presented with the four test dialogues, one at a time, displayed in a web browser. For each of the dialogues they were asked to fill...
The results show that BCORN’s non-centralized approach that views dialogue strategy modeling as an emergent phenomenon is feasible, and encourages future development of the approach. They also imply that natural and coherent recommendation dialogue can be explained in terms of the suggested dialogue behaviors.

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