

Data Driven Chatbots: a New Approach to Conversational Applications

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Abstract. Chatbots and conversational interfaces are becoming ubiquitous and a new HCI paradigm to access applications and information. This paper proposes a novel approach and an innovative technology (iCHAT) for the development of “data-driven chatbots”. Key ingredients are “meta-conversation”, “conversation tables” (controlling the interface), and a “conversation engine”.

Several advantages are envisioned: (i) lower effort for developing new conversational applications; (ii) easiness of maintenance and update, and therefore improved quality; (iii) possibility for content experts of developing conversational applications, without the need of ICT experts. The approach of iCHAT is quite general and it can be applied to all domains. It is being tested by developing a conversational tutor, supporting adaptive learning, for two MOOCs developed at Politecnico di Milano (Italy) in the frame of an EIT program. This paper describes the overall architecture of iCHAT and analyzes its most original aspects: the conversation engine and the conversation tables.

Keywords: Chatbots, Data-driven application development, Educational framework.

1 Introduction and Background

A new paradigm for interfaces is becoming ubiquitous: **conversational interfaces** [1]. Conversations, today, are available via different technologies¹ and different software solutions. Users, especially youngsters, are getting ever more used to conversations as a way to interact with applications. Conversations can be supported by several devices: π computers, phones, home devices (e.g. “Echo”), etc. They can be delivered via text interfaces or audio interfaces (using speech-to-text and/or text-to-speech technologies). The baseline is <the-user-speaks-to-the-chatbot and the chatbot-

¹ See for example www.pega.com/chatbot-revolution

speaks-to-the-user>. Current technologies, such as WATSON by IBM, support quite well the development of specific conversations, by designing a conversation flows.

This paper introduces a new paradigm for designing conversational interfaces, based on two core ideas: A) designing and implementing **chatbots as “data-driven”, i.e. controlled via Data Bases and tables**; B) using chatbots as interfaces for **adaptive information intensive applications**. These application allow users to access organized streams of information items.

Conversational interfaces may offer: (i) easiness of use, especially for the younger ones; (ii) lower level of attention required, letting the user focus upon content; (iii) empathic (if not entertaining) interaction, thus improving the user satisfaction; (iv) encouragement to the users to express themselves; (v) possibility to collect “non-functional feedback” (e.g. emotions or feelings) as the interaction process evolves; (vi) possibility to react to unforeseen situations (e.g. to a perceived distress by the learner), etc.

Some important research questions arise: **A) which functionalities** should be supported? **B) how should the production process** be organized? **C) which technology** should be used to support “A” and “B”?

Question **A** is about **Adaptativity**: what does it mean, from a user point of view, to access adaptively a set of information items? We started investigating Adaptativity in the domain of Education, striving for an adaptive use of material offered by a MOOC. Our approach is exemplified (in the realm of education) by iMOOC, i.e. a methodology for developing and organizing online courses [2]. iMOOC is based upon the assumption that there is a “body of knowledge” represented by a **(large or very large) set of content items**. Items should be properly **tagged and enriched with metadata** (e.g. level of difficulty, time available, type of proffered content, ...), in order to make it possible adaptivity. Items are offered to a user arranged into “**learning paths**”, i.e. predefined topologies used for traversing the “corpus” of content. Each learning path corresponds to an “**adaptive answer**” to a **learning need** (according to various criteria, as it will be explained next). Politecnico di Milano has used iMOOC in order to develop two online courses “Recommender Systems Basic” and “Recommender Systems Advanced.”, that will be available on Coursera by Summer 2019. They are part of a master of the European Institute of Technology (EIT). The first course consists of 43 items, for a total of 110 minutes of videos; the second course consists 31 items, for a total of 106 minutes of videos.

Question B is about **feasibility and sustainability** of adaptive conversational applications. The production process must be reasonably efficient, both from an author and a publisher point of view. If the development of a chatbot requires excessive effort by the author, it will not be afforded. We are discussing with major publishers about this issue, but in this paper we only address it indirectly, while describing the technology.

Question C is about **technology**, but it has a clear impact on “A” (what the chatbot does), and “B” (how the chatbot is designed, implemented and maintained). To address this question, at Politecnico di Milano (in cooperation with IBM Research Italy) we are developing iCHAT [3]. In this paper we are specifically concerned with

a portion of the technology: **how to make conversations data-driven**, instead of being explicitly modelled for each application.

In Section 2 we briefly discuss the functionalities of chatbots (for the domain of education) and the overall architecture of iCHAT. In Section 3, we discuss the main theme of this paper: how to use a data-driven approach to design and implement a conversational chatbot. In Section 4 we discuss the state of art. In Section 5 we draw conclusions and sketch future work.

2 iCHAT Architecture for Educational Chatbots

The overall conceptual architecture of iCHAT is shown in Figure 1.

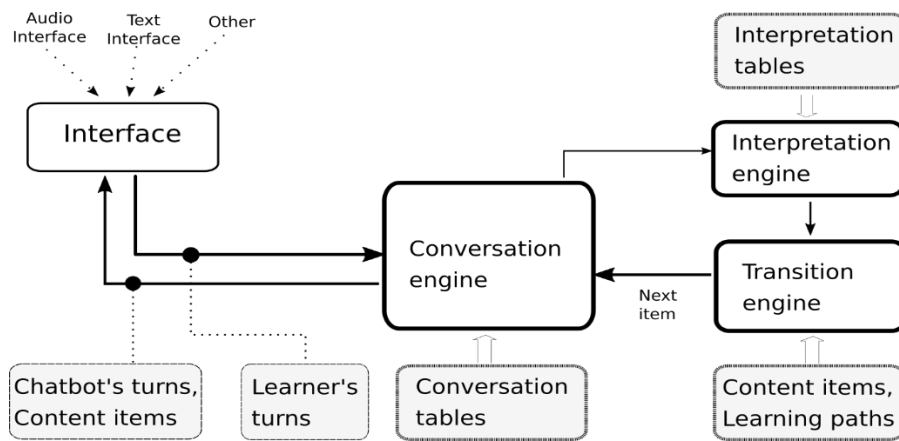


Figure 1: The conceptual architecture of iCHAT

iCHAT entails three main engines: the **conversation engine**, the **interpretation engine**, and the **transition engine**. Since the conversation is the main subject of this paper, for the sake of completeness, we briefly here the other two engines.

The role of the **transition engine** is to control the progress on a learning path (or a pathway of content items in general). When a proper request is received, the transition engine selects the next content item for the user. The transition engine is driven via the “content DB”, consisting of the content items (with their tags and metadata) and the pathways (again with their tags and metadata).

The role of the **interpretation engine** is to decide, using the session-variables collected up to a certain moment, how the conversation should move on. A conversation could be “**completed**” (the pathway has been fully covered), “**paused**” (for a later resumption), “**halted**” (with no resumption possible) or “**continued**”. In the latter case, a proper request is formulated to the transition engine. The interpretation engine is controlled via a set of rules called “interpretation tables”.

The role of the **conversation engine** is to keep effective and efficient the conversation between the user and the chatbot. Users have their turns, and the chatbot has its turns. The most important **turns of the chatbot**, (at least from a learning point of view) are those in which **content items are offered** for “consumption”. In our approach, the **chatbot is not an answering machine** but rather a **proactive tutor**. The chatbot has a pathway of content² to cover, and a successful conversation is the one leading the user to the completion of the pathway. This is why the chatbot has to be “empathic” and “persuasive”: **the appropriateness of its turns and the quality of the wording are very important**.

The chatbot is **not an expert of a domain**, though it may seem to be to the user. The chatbot, in fact, knows about the content items (title, abstract, metadata, tags, ...), knows about the pathways (content, topology, metadata, ...), knows what the user has done up to a certain point and what still needs to be covered, but it does not actually understand the domain³. We can say that the chatbot knows a specific “corpus of content” but not the subject of the course.

Adaptativity of the learning experience comes in two fashions. **Content Adaptativity**: only suitable content items are offered to the user, and with a suitable organization. This can be very important, for example, for MOOCs [2, 3] or professional training on the job, where there is a large variety of learners, with different learning goals, different backgrounds, different degrees of possible efforts, etc. **Conversation Adaptativity**: the conversation is tuned to the user profile and the specific needs. Different elements can be “adapted”: the number of the turns of the chatbot, the subject of those turns, the length of these turns, the wording used by the chatbots, etc. In the next section we focus upon the issue of controlling the Adaptativity of the chatbot.

3 Controlling the conversation of a chatbot: a data-driven approach

In this paper, we mainly examine a **data-driven approach**, in order to control the conversation of a chatbot speaks. Figure 2 shows a sample of a conversation (from the course “Recommender Systems Basic”).

Most chatbots, currently, could be considered as “glorified answering machines”: the user takes the lead and formulates requests, the chatbot answers in a conversational fashion (that may take several turns).

For iCHAT, instead, the approach is quite different, since the chatbot is somehow leading the conversation. A conversation goes on as a sequence of “turns” by the chatbot and the user. The turns are not necessarily alternated: the chatbot and the user can take some turns in a sequence⁴. Both for the user and the chatbot there are **solicited turns** (replying to a request) and **unsolicited turns** (autonomous moves). In line 3, for example, the user is replying to a request by the chatbot; in line 7 the user makes an unsolicited comment. In line 10 the chatbot replies to a request by the user [4].

² The selection of the proper pathway (among a set of possible pathways on the same content) is not part of the chatbot and it falls outside of the scope of this paper.

³ And this is different from other approaches aiming at building “smart chatbots”.

⁴ This creates the problem of avoiding overlapping turns, that we can’t discuss here.

1 <i>Chatbot</i> : so far you have covered 6 items, for a total of 13 minutes.
2 <i>Chatbot</i> : can we move on or do you feel tired?
3 <i>User</i> : please, go on
4 <i>Chatbot</i> : next item is of medium difficulty and it is recommended by the teacher. The title is URM matrix and it takes 2.5 minutes.
5 <i>Chatbot</i> : would you like an abstract of it?
6 <i>User</i> : no, move on
... <content consumption of video items>
7 <i>User</i> : I found it relatively easy
8 <i>Chatbot</i> : so far you are doing well; congratulations....
9 <i>User</i> : how much do we have to cover still to complete this learning path?
10 <i>Chatbot</i> : there are 9 items, for a total of 17 minutes. 4 items are advanced
....

Figure 2: fragment of a possible conversation for the course “Recommender Systems, Basic”

These are the main elements of our approach

- **The chatbot has an “agenda”** driven by content. In this example, the agenda is a learning path to be covered [3]; in another application (being developed at Politecnico di Milano) [4] the agenda could be a set of activities to be performed by children with special needs.
- The agenda implies that **the chatbot helps the user to go through a set of content items** (arranged in a possibly complex topology). The purpose of the chatbot is therefore to **“persuade”** the user to access (flexibly and adaptively) the maximum number of items (keeping following the indications of the author) and also to **“support”** this consumption of content.
- As a consequence of the above, **the chatbot is quite proactive**. It takes the lead supporting the user in an adaptive course, and also listening to possible specific requests.
- **The user may “interrupt” the chatbot** for different reasons: making comments or expressing feelings (e.g. line 7), requesting additional info (e.g. line 9) or requesting (directly or indirectly) to “suspend” the conversation or to “stop it”.
- The fact that the **user can express her feeling** suggests a number of interesting developments: (i) data may suggest another course of action (e.g. accelerating or using a different conversation style); (ii) “non-functional data analytics” (i.e. how the user reacts to interactions with the chatbot) can be harvested and used later to improve content and its organization⁵; (iii) data may suggest ways to improve the conversation styles of the chatbot.

3.1 Chatbots are “data driven”

The most outstanding feature of iCHAT chatbots is the way they are modelled and implemented, justifying the overall label of “data driven”.

⁵ This would be a sharp improvement over what Learning Management Systems do: they log the actions of the user, but they do not know why the user is performing those actions.

Chatbot technology is currently mainly based upon conversation modelling. Using, for example, WATSON conversation features [5], or a similar platform, the main task is to identify possible inquiries by the user (called “user intents”): they are the possible subjects of the conversation. For each subject, possible continuations of the conversation are identified. The result, overall, is a tree-structure⁶ representing the possible evolution of the conversation⁷. It is therefore clear that modelling an application consists into modelling a conversation: data are accessed when needed by the conversation. A negative effect is that for each different problem the conversation must be modeled and implemented: specialists are needed; time is required; costs are high; maintenance is difficult. The goal of iCHAT is to make **chatbot production sustainable**, lowering costs and not requiring extensive intervention by ICT specialists. If a new conversation is needed, the authors or conversation specialists should be able to generate it, without modelling it explicitly, which is a job for ICT specialists. This is the essence, as far as conversation is concerned, of what we call being “**data driven**”. The approach of iCHAT is drastically different from the above described conversation modeling.

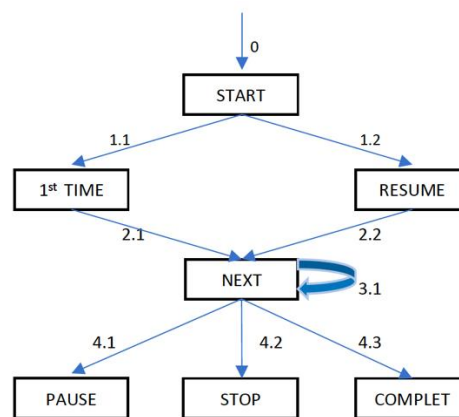


Figure 3 A simplified conceptual representation of the meta-conversation controlling the turns of the chatbot

These are the main features of iCHAT for controlling the chatbot:

- a) There is a unique “meta-conversation” model, a simplified version of which is shown in Figure 3. The meta-conversation is content independent and therefore can be used for various applications.
- b) Different arcs of the meta conversation corresponds to different states of a “conversation machine”. For each “arc” we have defined the possible turns of the chatbot, creating “conversation tables”

⁶ Additional mechanism (like “activation rules” or “context variables”) allow to deliver conversations that do not appear hierarchical to the user.

⁷ More sophisticated, but in essence not dissimilar from hierarchical menu of call-answering software.

- c) The turns are purely conversational, and they are totally unrelated to the subject of the conversation. If reference to a specific “corpus of content” is needed⁸, this is obtained by using general variables and accessing the content DB.
- d) The turns of the chatbot may belong to one out of 11 different categories. Considering the conversation of the example of Figure 2 we use categories like “summary” (line 1), “preview” (lines 4), “proactivity” (lines 2, 5), “reinforcement” (line 8), “forecast” (line 10). For each category we specify: (i) What the chatbot may say (i) The “rule”: under which condition it will say it.
- e) Users are assigned a “conversational profile”. Using a number of variables (as time available, level of background, ...), each user falls into a “stereotype”. With stereotype 1, for example, the chatbot keeps the conversation to a minimum (less turns, fewer categories, short formulations). With stereotype 3, the chatbot formulates an extended conversation. Stereotype 2 falls in between.
- f) In addition to the “standard” formulation there are alternative formulations for each possible turn, which used to make the chatbot more “human”. E.g. line 2 of Figure 2, could be formulated like this: “Now we can move to the next item”.
- g) Whether a chatbot, in a given situation, will say “x” depends on 3 factors: (i) is “x” appropriate in this situation? (ii) is “x” appropriate for the user profile? (iii) is the current turn “far enough” from the last turn when “x” was uttered? Let us consider, for example. line 8 of Figure 2; it is a reinforcement message, it would sound unnatural (and boring) to repeat it every time that the user gets a content item.
- h) In order to make the chatbot “content aware”, the turns of the chatbot may embed “templates” and “variables”. A turn, for example could be (as in line 4 of Figure 2) “Next item is <short item description>”. The template “Short item description” is defined in a separate table, as a pattern of words incorporating a number of variable values. Another example is shown at line 10 of Figure 2: the chatbot can speak about what is coming next. Example of variables are: *item_title*, *item_abstract*, *item_length*, etc.
- i) Technically speaking, the meta-conversation is content independent, but users may have a different perception. From their point of view, in fact, the chatbot knows the material being covered; (i) the overall organization of the material; (ii) the title and the description of chapters and sections; (iii) the title and the description of each item (including length, level of difficulty, relevance, ...).

Figure 4 shows a simplified sample of “setting” for Arc 3.1, the most important one. (there more than 60 settings for this arc, in reality).

Conversation tables, such as the one shown in Fig. 4, allow relevant results:

- Creating and delivering a chatbot tutor for **a different course**, would require only to create a different content Database.
- Changing the **“wording”** of the various turns, would require only modifying tables like the one shown in Figure 4, without the support of ICT experts.
- Modifying **the turns of the chatbot**, again needs to modify the conversation table, without modelling the conversation again.

⁸ E.g. the title of an Item or its description.

- Changing **discipline** (e.g. a course in Humanities) would imply also a (possibly minor) revision of the conversation tables, with no need of ICT experts.

CATEGORY ASSESSMENT	<i>Basic formulation</i>	<i>Alternative 1</i>	<i>Alternative 2</i>
<i>Stereotype 1: every M turns</i>	What do you think of this learning session, so far?	How is this learning session going?	What is your opinion on the this learning session?
<i>Stereotype 3: every N turns</i>	<USER name>, could you rate the learning session that you have followed so far? What do you think of it?	<USER name>, are you happy with what you are learning, so far?	<USER name>, I'd like, again, to know your opinion on this learning session. Does it seem useful to you?

Figure 4a A simplified representation of some turns for assessment for ARC3.1

CATEGORY PREVIEW	<i>Basic formulation</i>	<i>Alternative 1</i>	<i>Alternative 2</i>
<i>Before proposing next content-item</i> <i>Stereotype 1: always</i>	Next item is <ITEM title>.	Next item is going to be <ITEM title>	Let's move on to the next item: <ITEM title>.
<i>Before proposing next content-item</i> <i>Stereotype 3: always</i>	Next item is <ITEM description long>.	Next item: <ITEM description long>.	Let's move on to the next item: <ITEM description long>.

Figure 4b A simplified representation of some turns for preview for ARC3.1

CATEGORY REINFORCEMENT	Basic formulation	Alternative 1	Alternative 2
Stereotype 1: never Stereotype 2: every M turns	<USER name>, you are progressing well. Good job!	You are doing great!	It seems that you are doing well, congratulations!
Stereotype 3: every N (turns)	<USER id>, you are progressing well. Good job!	You are doing great!	It seems that you are doing well, congratulations!

Figure 4c A simplified representation of some turns for reinforcement for ARC3.1 of Fig. 3

In the next section we briefly analyze the relevant state of art, while in section 5 we sketch the future direction of research.

4 State of the art

Various market technologies are available for the creation of chatbots, almost all sharing a similar approach to the design. Most of the technologies that used in the chatbots are pattern matching techniques and language tricks [6]. IBM Watson Assistants, for example, allows the creation of customized chatbots⁹ modeling the conversation as a tree of dialogue nodes, where each node associates a request by the user with a set of replies by the chatbot. The use of “context variables” and of “rules” (governing when a reply is appropriate or not) makes the chatbot quite flexible and powerful. Still, two main drawbacks remain.

The first drawback is that chatbots are conceived (and perceived) as “answering machines” [7]. The emphasis is on understanding the user’s input, by classifying the user’s will in a series of “intents”. An intent is defined by several messages’ examples. Thus, the most common use cases for this kind of technologies are question/answering and the automation of business tasks. The purpose of the work presented in this paper is instead to build chatbots that can use conversations as a way to support the learning process, as already Carbonell, in 1970 [8], meant to do when he created a Socratic tutor using a semantic network technique. Since the seventies, a number of different efforts have been made in this direction and Pedagogical agents, Educational agents, Learning companions, Virtual Teaching Assistants, Intelligent Tutoring Systems have been designed and deployed. Though not all can be called “chatbots” in strict sense, they all show how the dream of supporting interactive learning has been persistent and resilient [9, 10].

Pedagogical agents (PAs), or Educational Agents, are “lifelike characters in virtual environments that help facilitate learning through social interactions and the virtual real relationships with the learners” [11, 12]. They can be seen as “computer-simulated character, which presents users with human-like characteristics, such as domain competence, emotions, and other personal characteristics” [13]; they can go from making a presentation engaging to interacting on a topic [14]. In contrast to PAs, chatbots provide an interacting interface in a synchronous way with learners to react on individual intents [15]. Learning companions can be seen as “animated digital characters functioning to simulate human-peer-like interaction—might provide an opportunity to simulate such social interaction in computer-based learning” [13, 16]. Virtual Teaching Assistants support teacher in delivering courses (e.g. a programming course: Chou et al [17]). Intelligent Tutoring Systems (ITSs) are “virtual teachers” that can be used for one-to-one tutoring [18-20]. Technology-mediated learning (TML) is an environment to provide learning materials in an interactive way for students [21]. In TML during the learning process students impacted by structural factors such as learning methods [22]. Nowadays chatbots, which are rising a new wave of interest [1, 23-25], are in the same stream.

The second drawback, more relevant for this paper, is that current approaches use conversations explicitly modelled as such; this means that taking up a different application would require to re-do the modeling. Our approach, instead, is totally different: there is a meta-conversation, basically fitting if not all, a quite large number of use

⁹ <https://console.bluemix.net/docs/services/assistant/dialog-overview.html#dialog-overview>

cases and each new case requires only to provide a new set of data (mainly a content DB, as described in this paper). The novelty brought about by the iCHAT approach lies mainly in the separation between educational content in strict sense (learning objects, videos, texts...) and conversation: the chatbot engages in a conversation with the user leading it like a teacher would do, allowing the user to express all (and only) the intents (“I’m frustrated, I’ve understood, this is not clear...”) that are relevant for the bot to decide what to show next, following a smart strategy the instructional designer has integrated in the content organization.

5 Conclusions and future work

In this paper we have described a technology for designing and deploying data-driven chatbots. Politecnico di Milano is developing iCHAT, leveraging on WATSON technology, in cooperation with IBM-Research-Italy.

We are striving for a generalized solution, that could be applied for various applications. The current chatbot fully supports two courses (MOOCs) developed by Politecnico di Milano. Learning pathways, currently, are defined taking into account the following criteria: what part of the course needs to be covered; the level of difficulty of the wished items; the relevance of the items (as defined by the teacher). The conversation is profiled according to two criteria: time available and learner’s background.

As far as **education** is concerned, these are the most relevant aspects: **conversational interfaces can help into making the learning processes** more effective. Effectiveness should come (i) from **the possibility of better enforcing adaptive learning**, (ii) from the possibility of fostering **longer learning sessions** and also (iii) from the increased **“empathy”** of the interaction, fostering a better mood for the learner. In addition, conversational interaction allows **to collect a number of crucial “non-functional information”** about the learner: how she feels, what she thinks, her cognitive/emotional situation, ... This may lead to a very interesting development of **a new generation of learning analytics**, focusing not so much on the “mechanics” of learning (still available, in any case), but rather on the learner reaction to learning.

As for as **technology** is concerned, the most important contribution of iCHAT is the idea that instead of modelling and implementing conversations, chatbots should be **driven by data. Conversation tables**, in fact, allow to control the turns of conversation by the chatbot: a) when to speak, when to use a given “category” of what is being said; b) how to use it; c) the specific “message”; d) the specific wording, etc. Conversation tables are used in order to drive a **meta-conversation. Pathways** are another aspect of “data-driven” chatbots: they provide the “agenda” for the conversation.

Another part of the effort, not discussed in this paper, is a set of tables used to understand what the user says (“intents”). In all cases our chatbot does not allow a general conversation; only turns of conversations focused on the learning process (e.g. “I like it”, “it was difficult”, “I’m tired”, ...) are recognized. It is clear that only empirical validation with users for an extended period (at least 6 months) will allow to tune the various tables, making the conversations fluid and effective from the user point of view.

Several **technological improvements are planned**, the most important being: (i) improving the ability to understand what the user says; (ii) creation of a friendly authoring environment for conversation tables; (iii) enhancing the transition engine, in order to handle more complex topologies for pathways; (iv) expanding and refining the meta-conversation model, etc.

In terms of applications, IBM and Politecnico are considering to enlarge the scope of iCHAT technology, considering a more general purpose idea: **adaptive streams of information items delivered via adaptive conversational interfaces**. Applications are being investigated for domains like eCulture, eTourism and eFood.

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