Chatbots’ Greetings to Human-Computer Communication

Maria João Pereira¹  Luísa Coheur¹,²  Pedro Fialho¹
Ricardo Ribeiro¹,³

¹INESC-ID Lisboa
Rua Alves Redol, 9, 1000-029 Lisboa, Portugal

²Instituto Superior Técnico, Universidade de Lisboa
Av. Prof. Cavaco Silva, 2780-990 Porto Salvo Tagus Park, Portugal

³Instituto Universitário de Lisboa (ISCTE-IUL)
Av. das Forças Armadas, 1649-026 Lisboa, Portugal

Abstract
Both dialogue systems and chatbots aim at putting into action communication between humans and computers. However, instead of focusing on sophisticated techniques to perform natural language understanding, as the former usually do, chatbots seek to mimic conversation. Since Eliza, the first chatbot ever, developed in 1966, there were many interesting ideas explored by the chatbots’ community. Actually, more than just ideas, some chatbots’ developers also provide free resources, including tools and large-scale corpora. It is our opinion that this know-how and materials should not be neglected, as they might be put to use in the human-computer communication field (and some authors already do it). Thus, in this paper we present a historical overview of the chatbots’ developments, we review what we consider to be the main contributions of this community, and we point to some possible ways of coupling these with current work in the human-computer communication research line.

Keywords: natural language interfaces; agent-based interaction; intelligent agents; interaction design

1 Introduction

The term chatbot was coined by Mauldin (1994) to define the systems that have the goal of passing the Turing Test¹ and, thus, could be said “to think”.

¹http://plato.stanford.edu/entries/turing-test/
However, terms like dialogue system, avatar, artificial conversational entity, conversational avatar, intellectual agents, virtual people, or virtual person are often used indiscriminately, as if they were synonyms of chatbot. In this paper, we follow Schumaker et al. (2007), and define a chatbot as a system that “seeks to mimic conversation rather than understand it”. Also, and contrary to other related systems, chatbots are supposed to freely engage conversation about any subject, making them “entertaining in a large variety of conversational topic settings” (Schumaker et al., 2007).

Currently, many platforms exist to help developing such systems, and the number of new chatbots continues to increase at a dizzying pace. The following (impressive) numbers, collected in February 2015, definitely help to give a precise idea of the chatbots community size: just Pandorabots hosting service declares to have more than 225,000 botmasters (people in charge of creating/maintaining the chatbot), which have built more than 250,000 chatbots, resulting in more than 3 billion interactions. Not only these resources are valuable, but also these numbers show how close the chatbots community is to real users. Thus, it is our opinion that chatbots’ developers and developments can bring important contributions to the human-computer communication field. In this paper, we review the main ideas and technologies behind them. As we will see, chatbots range from “simpler” ones, based on pre-written pattern-matching templates, exploiting large stores of prepared small talk responses, to more complex architectures, based on some sort of learning process. We will also see that, sometimes, concepts/tricks introduced by some chatbots contribute more strongly to the “illusion of intelligence” than the involved technologies.

Finally, it should be noted that there is not much scientific documentation available about the majority of these systems and it becomes difficult to uncover the technology behind them, which explains the abnormal number of references to web pages in this paper.

This document is organised as follows: in Section 2 we present a brief historical overview, in Section 3 we discuss chatbot’s platforms and how to enrich them, and, in Section 4, we summarise the main “tricks” towards the “illusion of intelligence”. In Section 5 we discuss how chatbots could contribute to the human-computer communication field and, finally, in Section 6, we present some conclusions and point to some future challenges.

2 Historical overview

In this section we make a brief review of the chatbots’ history, moving from the first chatbots to the ones with which we interact nowadays.

---

2A list of more than 160 of such terms can be found in http://www.chatbots.org/synonyms/

3http://www.pandorabots.com
2.1 Early days

Although the term chatbot was not invented by that time, the first chatbot came to public in 1966 under the appearance of a Rogerian psychotherapist called ELIZA (Weizenbaum, 1966). ELIZA was a program developed by Joseph Weizenbaum that was able to establish a conversation with human beings, simulating it was one too. ELIZA’s conversational model was based in the rephrasing of input sentences, when these matched a set of pre-defined rules. For instance, consider the following rule\(^4\) constituted by a regular expression (match) and an answer (answer):

```
match: * you are *
answer: What makes you think I am (2)?
```

In this rule if the match part coincides with the input (* is the wildcard and matches every sequence of words), the text associated with the answer part will be returned, being the variable (2) replaced by the sequence from the input captured by the second wildcard. The following dialogue (Example 1) illustrates an application of this rule. Notice that some internal processing needs to be done, so that the sequence captured by (2) entitled to your opinion is modified into entitled to my opinion.

```
user: You are entitled to your opinion.
ELIZA: What makes you think I am entitled
to my opinion?
```

Example 1.

In Example 2, we can see that ELIZA was also based on content-free remarks in the absence of a matching.

```
user: It bothers me just to be around
people.
ELIZA: Please go on.
```

Example 2.

ELIZA completely exceeded the expectations, given that many people, when interacting with it, believed they were talking with another human (this outcome is currently called the “Eliza effect”). Without having any intention of modelling

\(^4\)Inspired from ELIZA’s implementation in \url{http://search.cpan.org/~jnolan/Chatbot-Eliza-1.04/Chatbot/Eliza.pm}.
the human cognitive process and despite its simplicity, ELIZA showed how a
program impersonating a specific professional role can cause a huge impression
by the mere illusion of understanding.

Weizenbaum was taken aback by some aspects of this success (Hutchens,
1997). What shocked him most was the fact that people actually believed that
the program understood their problems\(^5\). Perceiving ELIZA as a threat, Weizen-
baum wrote “Computer Power and Human Reason” (Kuipers et al., 1976) with
the aim of attacking the Artificial Intelligence (AI) field and educating unin-
formed persons about computers.

Nowadays, ELIZA is still one of the most widely known applications in AI,
and is at the base of a great number of chatbots, including PARRY, its “success-
sor”.

Following a very similar architecture to that of ELIZA, PARRY appeared in
1971 by the hands of Kenneth Colby, simulating a paranoid mental patient (Say-
gin et al., 2000). An interesting comparison between PARRY and ELIZA was
made by Guzeldere and Franchi\(^6\). They stated that “PARRY’s strategy is some-
what the reverse of ELIZA’s”, as one simulates the doctor, distant and without
personality traces, and the other a paranoid patient which states its anxieties.
Although PARRY’s architecture is similar to that of ELIZA, PARRY has knowl-
edge of the conversation and it also owns a state of mind. The combination of
these two factors affects the output as it becomes a function not only of the
input, but also of PARRY’s beliefs, desires and intentions. Mauldin (1994) sum-
marised a few tricks to which PARRY resort, namely: (1) admitting ignorance;
(2) changing the conversation topic; and, (3) introducing small stories about
the Mafia throughout the conversation. These three tricks are (respectively)
illustrated in the following answers given by PARRY:

| PARRY: I don’t get you.  
  ...  
| PARRY: Let’s talk about something else.  
  ...  
| PARRY: I know the mob controls the big rackets. |

Example 3.

After Colby gathered transcripts of interviews between psychiatrists, nor-
mal patients and his program, he presented the results to another group of
psychiatrists. He asked this group if they could guess in what transcripts the
interviewed was a human and in which ones it was a program. The psychiatrist
could not do better than randomly guessing.

\(^5\)http://www.alicebot.org/articles/wallace/eliza.html
\(^6\)http://www.stanford.edu/group/SHR/4-2/text/dialogues.html
It is possible to conclude from these results that the emotional side can be easier to imitate than the intellectual one (Kuipers et al., 1976). However, one of the main criticisms Parry received was of not being more than an illusion, incapable of modelling a real person (Colby, 1974). In his response to this specific issue, Colby summarises the problem essence:

“A model of a paranoid patient is a model of being paranoid, being a patient, and being a person. Parry does reasonably well in the first two of these “beings”. It fails in the third because of its limited knowledge. (...) Parry is not the real thing; it is a model, a simulation, an imitation, a mind-like artifact, an automaton, synthetic and artificial.”.

2.2 The chatbots’ competitions

Moving back to 1950, the British mathematician Alan Turing questioned “can machines think?” (Turing, 1950), and proposed a way of testing it: the imitation game (now known as the Turing Test). The original imitation game is played by a man, a woman and an interrogator whose objective is to guess the sex of the players. Turing proposed substituting one of the players by a machine and playing the same game. In this version, if the interrogator wrongly identifies who is the human it means that the machine “can think”.

Based on (their own interpretation of) the Turing Test, several chatbots competitions exist today. Chatterbox Challenge\(^7\), or, more recently, the Chatbot Battles\(^8\) that took place in 2012, are examples of such competitions, although the most widely known is the Loebner prize\(^9\), where participants are challenged with a simplified version of the total Turing Test (Powers, 1998). This prize is due to Hugh Loebner, who stipulated a reward for the first person whose program could pass the proposed test.

The first Loebner Prize Contest took place in 1991, at Boston’s Computer Museum (Epstein, 1992), and, since then, the competition has been held annually in the quest of finding the “thinking computer”. To illustrate the types of questions that can be posed to chatbots, Example 4 presents an extract of a conversation\(^10\) between a member of the jury and Rose, the winner of the 2014 Loebner prize (developed by Bruce Wilcox).

As some chatbots, competing for the Loebner prize, are indeed capable of managing a conversation, keeping it consistent, at least for a while, every year the most human-like computer is distinguished with a prize. However, since the first edition of the Loebner prize, in 1991, until now, no one won it. Nevertheless, in another Turing Test organised in 2014 by the U.K.’s University of Reading, a chatbot simulating a 13-year-old boy, named Eugene Goostman, created by Vladimir Veselov and his team, convinced 33% of the human judges that it was human.

---

\(^7\)http://www.chatterboxchallenge.com
\(^8\)http://www.chatbotbattles.com
\(^9\)http://www.loebner.net/Prizef/loebner-prize.html
\(^10\)Taken from http://aisb.org.uk/media/files/LoebnerPrize2014/Rose.pdf
Jury: Hello, my name is Adam, what is your name?
Rose: Nice to meet you, Adam. My name is Rose.
Jury: I live in Exeter in the UK. Where do you live?
Rose: I live in San Francisco.

Jury: What is your favourite television program?
Rose: I love watching Doctor Who. Do you think the new Doctor will be good?
Jury: Which is bigger, a cat or a kitten?
Rose: The kitten is bigger.
Jury: The car couldn’t fit into the parking space because it was too small. What was too small?
Rose: I’m not a walking encyclopedia you know.

Jury: What’s my name?
Rose: You are Adam.
Jury: Where do I live?
Rose: In UK.
Jury: What’s the weather like where you are?
Rose: I’m an American woman.
Jury: I recently visited New York. Where is your favourite place to visit and why?
Rose: I like France best because I like the food there.
Jury: How many letters are there in the word perambulate?
Rose: There are 11 letters in ‘perambulate’.
Jury: Andy is shorter than Mark and Tom is shorter than Andy. Who is the tallest?
Rose: Mark is least short.

Example 4.

This event brought to the spotlight the old question of AI and generated
(again) much controversy. In fact, many people consider that there was a mis-
understanding of Turing’s intentions in the different implementations of the
Turing test, as deep models of thinking were a presupposition underlying Tur-
ing’s imitation game. Following this, even if a chatbot was good enough to
deceive the jury, it would not pass the Turing Test in Turing’s sense, as it does
not have a cognition model behind it.

Another important criticism is stressed by Levesque (2014): these kind of
computer programs (“chatterbots”) and, the Turing Test (specifically, the an-
nual Loebner Competition) are strongly based on capacity of being deceptive.
For Levesque, AI is the science that studies “intelligent behaviour in computa-
tional terms”, and the ability to be evasive, although interesting, may not
show real intelligence. A computer program should be able to demonstrate its
intelligence without the need for being deceptive. In this sense, Levesque et al.
(2012) further explore this idea by conceiving a test that meets these aims:
the Winograd Schema Test. This is a reading comprehension test based on
binary choice questions with specific properties that makes them less prone to
approaches based on deceptive behaviour.

Apart from the numerous controversies regarding the Turing Test, and de-
spite that not all the chatbots intend to pass it, the fact is that all these com-
petitions strongly contributed to the main advances in the field, and the most
popular chatbots are the ones that were/are present in these competitions.

2.3 Other distinguished Chatbots
Moving back to the Loebner prize, its first winner, in 1991, was Joseph Wein-
traub’s PC-Therapist program, based on Eliza, an achievement that he re-
peated three more times in the following four years. Since then, many chatbots,
with different goals, emerged from the competing systems. An example is JAB-
BERWACKY, created by Rollo Carpenter and released to public in 1997 (Angeli
and Brahnam, 2008), which has entered in four Loebner contests, and always
stood in the top three. JABBERWACKY introduced the idea that a chatbot was
the result of the knowledge gathered from its own conversations (Carpenter and
Freeman, 2005): “Jabberwacky learns the behaviour and words of its users”. In
2005, JABBERWACKY impersonated George, an entity created by Rollo Car-
penter “in a smallish number of hours, just by chatting”. More recently, a new
chatbot under the name of CLEVERBOT, also created by Rollo Carpenter, has
become available to the public. Considering the similarities between CLEVER-
BOT and JABBERWACKY, and given that both systems have the same creator,
the odds point that CLEVERBOT is a new improved version of JABBERWACKY.
Thus, considering that it “learns from people”, and that it is probably one of
the most widely known bots, the number of interactions it can learn with is
endless. Although there is no information about how this process takes place,

\[\text{http://www.jabberwacky.com/}\]
\[\text{http://cleverbot.com/}\]
\[\text{According to the Cleverbot site, consulted on 12th February 2015, there were people 88,015 talking.}\]
users can now rate CLEVERBOT answers (five possibilities, from awful to great). A final curiosity about CLEVERBOT: it was recently used to co-write a short film, “Do you love me”, directed by Chris R. Wilson.14

Another competing system in the Loebner contests that needs to be highlighted, as it plays a major role in the chatbots field, is the Artificial Linguistic Internet Computer Entity (A.L.I.C.E) (Shah, 2006). It was invented in 1995 by Richard Wallace, and won several Loebner competitions. Even though it is a modern ELIZA (that is, based on pattern matching), it differs from it by not playing a specific role, but by trying to reflect a human in general. The propose of A.L.I.C.E’s creation was to keep it talking as long as possible without the users realising that they were not talking to a machine, and without sticking to a specific topic or role. Also, associated with A.L.I.C.E there is a collection of resources that have been widely used by the chatbots’ community, including the previously mentioned hosting service Pandorabots, which represents the largest chatbot community on the Internet.

Finally, we detach CHIP VIVANT developed by Mohan Embar. CHIP VIVANT differs from other chatbots, as its goal is “to answer basic, common sense questions and attempt simple deductive reasoning instead of having a massive database of canned responses in an attempt to fool users with the Eliza effect.”15 Considering this, and despite being the winner of the Loebner prize in 2012, CHIP VIVANT is not a chatbot, according to our previous definition. In fact, CHIP VIVANT is original in the way it operates, as it uses several external resources broadly used in Natural Language Processing applications, such as Wordnet (Fellbaum, 1998), Wikipedia16, OpenCyc17, and the Link Parser (Grinberg et al., 1995) API. Due to this, and according with its author, CHIP VIVANT was the first chatbot capable of answering questions such as Which is larger: an orange or the moon?.

2.4 The chatbot next door

As many different resources are available today, chatbots become a field in large expansion, as attested by the previously reported numbers regarding Pandorabots. Chatbots’ technology can be used by anyone (there are even sites where kids can create their own bots, for instance, inf.net), and the most important requirement is to be creative. Due to this, chatbots can be found in a huge diversity of services, including e-commerce (Daden Limited, 2010), e-learning (Heller et al., 2005; Mikic et al., 2009), and in even in medical scenarios (Kazi et al., 2012). Just Chatbots.org18 reports chatbots in almost 30 languages, available in platforms like Android, Live Messenger, Second Life or Skype, just to name a few, and dedicated to an impressive collection of themes such as Beauty, Cooking, Government, Leisure, Sports or Travel. In other words,
chatbots move from the Turing Test competitions to real life. A chatbot that perfectly illustrates this idea is ELOB, a regular participant/winner in chatbots contests\footnote{http://www.elbot.com/chatterbot-elbot/} and an ALICE type program, which is currently being used on sites like IKEA’s (Shah, 2006).

More than just “text boxes”, modern chatbots have a face, and sometimes a body. Some allow speech input and output, and are able to express emotions. Pandorabots, for instance, offers multimodal facilities like faces and speech. CLEVERBOT, on the other hand, led to the creation of an avatar called EVIE (Expressive Virtual Interaction Entity)\footnote{http://www.existor.com/}, which has the possibility of receiving both written or verbal inputs. Moreover, its animated avatar is also capable of displaying some human emotions.

3 Building chatbots

Behind each chatbot there is a development platform. These are typically based on a scripting language that allows the botmaster to handcraft its knowledge base, as well as an engine capable of mapping the user’s utterances into the most appropriate answer. In this section we survey the most successful platforms and scripting languages, as well as the existing learning processes. Moreover, we end the section by referring to the scripting process itself.

3.1 Scripting languages/platforms

An impressive collection of ELIZAs can be currently found in the web. Some of these software can be customised. For instance, Chatbot-Eliza\footnote{http://search.cpan.org/~jnolan/Chatbot-Eliza-1.04/Chatbot/Eliza.pm} is an implementation of ELIZA in Perl that can be used to build other chatbots. Knowledge is coded as a set of rules that are triggered when matched against the user’s input, as previously illustrated in this paper. Some of the available programs offer features such as a certain capability to memorise information, adding synonyms or ranking keywords. Nevertheless, the most popular language to build chatbots is probably the “Artificial Intelligence Markup Language”, widely known as AIML, a derivative of XML, that includes more than twenty specific tags. As usual, knowledge is coded as a set of rules that will match the user input, associated with templates, the generators of the output. A detailed description of AIML syntax is out of the scope of this survey, but can be easily found in the web\footnote{http://www.alicebot.org/aiml.html}. The large usage of AIML can be justified by the following facts:

1. besides its detailed specification, its community allows anyone to obtain, for free, interpreters of AIML in almost all coding languages, from Java (program D) to C/C++ (program C) or even Lisp (program Z);
2. the set of AIML files that constitute the contents of A.L.I.C.E.’s brain can also be freely obtained.

All the pandorabots are based on AIML, more specifically in AIML 2.0. This specific release is usually characterised as being very easy to modify, develop and deploy. Therefore, anyone, even non-computer-experts, can make use of it (Wallace et al., 2007), as no prior knowledge about AIML is required. It is only necessary to give a bot a name and choose the startup AIML. Then, the botmaster just has to type the sentences he/she wants to see his/her bot answering and add the desired responses. It is also possible to improve the bot by adding AIML files. Such files can be easily written using the Pandorabot’s utility Pandorawriter, which allows to “convert free-format dialog into AIML categories suitable for uploading to your pandorabot”.

ChatScript, the scripting language and open-source engine, should also be addressed, as is at the basis of SUZETTE (2010 Loebner Prize winner), ROSETTE (2011 Loebner Prize winner), ANGELA (2nd in 2012 Loebner Prize), and the previously referred ROSE (2014 Loebner Prize winner). It comes with useful features, including an ontology of nouns, verbs, adjectives and adverbs, and offers a scripting language (inspired by the Scone project, a knowledge-base system developed to support human-like common-sense reasoning and the understanding of human language (Fahlman, 2011)). According to Bruce Wilcox, its creator, ChatScript settles several AIML problems, such as not being reader friendly. In fact, as AIML is based on recursive self-modifying input, it is harder to debug and maintain. A detailed comparison between ChatScript and AIML capabilities was made available by Wilcox, as a motivation for the development of a new (his own) chatbot platform. This comparison can be found in his blog.

It should be clear that we exclude from this survey, authoring platforms such as the IrisTK, the Visual SceneMaker (Gebhard et al., 2011), or the Virtual Human Toolkit (Hartholt et al., 2013), as these target multi-modal dialogue systems and not chatbots, as defined in the Introduction section.

### 3.2 Building chatbots by chatting

Another approach to develop chatbots’ knowledge sources, which avoids hand-crafted rules, is based on chatting and learning from the resulting chats. Contrary to other chatbots whose response is derived from the recognition of patterns in the user’s input with little knowledge of context, systems like the already mentioned JABBERWACKY (and CLEVERBOT) learn by keeping never seen user interactions andposing them later to other users. The acquired answers are then considered suitable answers for these interactions. That is, they learn to talk by talking, by relying on what has been said before by users and mimicking

---

23 [http://code.google.com/p/aiml-en-us-foundation-alice/downloads/list](http://code.google.com/p/aiml-en-us-foundation-alice/downloads/list)
24 [http://sourceforge.net/projects/chatscript/](http://sourceforge.net/projects/chatscript/)
25 [http://gamasutra.com/blogs/BruceWilcox/20120104/9179/](http://gamasutra.com/blogs/BruceWilcox/20120104/9179/)
26 [http://www.iristk.net](http://www.iristk.net)
27 [https://vhtoolkit.ict.usc.edu](https://vhtoolkit.ict.usc.edu)
them. The user’s intelligence becomes “borrowed intelligence” as, instead of being wasted, it incorporates a loop: what is said is kept (along with the information of when it was said) and in the future that knowledge may be exposed to another user. The given replies are then saved as new responses that the system can give in the future.

Unfortunately, it is only possible to give a brief overview of JABBERWACKY’s or CLEVERBOT learning mechanisms as their architecture is not available to the public. The only disclosed thing is that the AI model is not one of the usually found in other systems, but a “layered set of heuristics that produce results through analyses of conversational context and positive feedback”.

Another example of a chatbot that learns is Robby Garner’s “Functional Response Emulation Device” (FRED), the ancestor of ALBERT ONE, the winner of 1998 and 1999 Loebner Prize. FRED was a computer program that learned from other people’s conversations in order to make its own conversations (Capputo et al., 1997). FRED began with a library of basic responses, so that it could interact with users, and from then on, it learned new phrases with users willing to teach it.

Although such an (unsupervised) learning may lead to unexpected and undesirable results, with the Internet growth and the possibility of having many people talking with the chatbots, one may foresee that these will quickly evolve. We will discuss this issue latter in Section 5.

4 Towards the illusion of intelligence and/or the art of scripting

Chatbots go beyond writing good programs and developing algorithms, as in order to create a chatbot, more than being a programmer, the botmaster must be an author. Juergen Pirner, creator of the 2003 Loebner prize winner JABBERWOCK 30 , emphasises the scripting process behind a chatbot, stating that in the presence of possible failures, the one at fault is not the engine but its author 31.

Since making a chatbot involves preparing it to the impossible mission of giving a plausible answer to all possible interactions, the botmasters usually take advance of several tricks to simulate understanding and intelligence in their chatbots. For instance, Pirner describes basic techniques of scripted dialogs like “having a set of responses for each scripted dialog sequence” and “ending those same responses with a clue, a funny remark or a wordplay”. With ELIZA, we learnt that including the user’s string in its answers helps maintaining an illusion of understanding (Mauldin, 1994). Other approaches focus on trying to guess what the user might say, or forcing him/her to say something expected. In the following we survey other stratagems used by many botmasters.

---

28 http://www.icogno.com/a_very_personal_entertainment.html
29 http://www.simonlaven.com/fred.htm
30 http://www.abenteuermedien.de/jabberwock/
31 http://www.abenteuermedien.de/jabberwock/how-jabberwock-works.pdf
4.1 Giving the bot a personality

Whereas personality has been a subject of study among the agent’s community, deeply exploited in all its complexity, the concept is kept as simple as possible within chatbots. As we have seen, what is common is the association of an a priori “personality” to a chatbot, which can justify some answers that otherwise would be considered inappropriate. For instance, Rogerian mode of ELIZA covers for its answers, as it leads to a conversation where the program never contradicts itself, never makes affirmations, and is free to know nothing or little about the real world without being suspicious. The same happens with Colby’s PARRY: being a paranoid mental patient its changes in subject or incongruous answers are considered satisfactory and hide its absence of understanding. The aforementioned EUGENE GOOSTMAN also follows along these lines. Vaselov explains his reasoning for such a character: “a 13 years old is not too old to know everything and not too young to know nothing”\textsuperscript{32}.

Thomas Whalen, winner of 1994 Loebner prize, took this a step further with JOE, the janitor. Whalen’s decision was related to the fact that contrary to previous editions of Loebner competitions, where the conversation was restricted to a topic, in 1995 the judges could pose any question. Hence, Whalen decided that the best approach to deal with a non-topic situation, would be to present a system that “would not simply try to answer questions, but would try to incorporate a personality, a personal history, and a unique view of the world”\textsuperscript{33}. And so JOE was born.

JOE was a night-worker janitor in the verge of being fired. He was only “marginally literate”, and he did not read books, newspapers, or watch television. These premises by themselves restricted the conversation by giving JOE a “fairly narrow worldview”. Another trick was to use JOE’s eminent dismissal to introduce some stories revolving around it, which would, at the same time, provide a way of directing the conversation, the topic of the next section. However, despite the modelling of what Whalen considered to be the critical component of humanness – the personality (along with the development of answers to common topics like weather) –, he did not won the competition. However, such occurrence can be justified because the judges asked questions that nobody would remember to pose to someone recently met.

4.2 Directing a conversation

Personality can justify some appropriate answers, but the best way to deal with unexpected interactions is to avoid them. Thus, being able to direct the conversation is a trick used by many chatbots, including the simple forms used by ELIZA, where the usage of questions incited the user participation and made him/her keep the conversation with little contribution from the program.

The CONVERSE (Batacharia et al., 1999), created by David Levy, was the

\textsuperscript{32}http://www.huffingtonpost.com/2012/06/27/eugene-goostman-2012-turing-test-winner_n_1630412.html

\textsuperscript{33}http://hps.elte.hu/~gk/Loebner/story95.htm
1997 winner of the Loebner competition, and did extremely well by using the clever trick of controlling a conversation. Although directing a conversation by “talking a lot about a predefined topic” was already used (Saygin et al., 2000), CONVERSE’s performance convinced a judge for the first five minutes that he was really human: after greeting the judge, CATHERINE (CONVERSE’s character) asked the interrogator about something that had passed on the news the previous day and then kept talking about it, as can be seen in the transcripts in Example 5.

Example 5.

This example also shows that besides controlling a conversation it is important to appropriately choose its topic. David Levy’s won again the Loebner prize in 2009 with Do-Much-More, but this time the system was more flexible in the range of topics and responses it covered.

4.3 Paying attention to small talk

Small talk, also known as phatic communication (Malinowski, 1923), is another hot topic in chatbots advances. It can be viewed as a “neutral, non-
task-oriented conversation about safe topics, where no specific goals needs to be achieved” (Endrass et al., 2011). Small talk can be used for two main proposes (Schneider, 1988): establish a social relation by building rapport and avoiding (embarrassing) silence.

Like stated by Bickmore and Cassell (1999), chatbots have been making use of the small talk mechanism. Such is brought to evidence when one looks at the testimonials of persons establishing ongoing relationships with chatbots. For instance, Epstein (2007), an American psychologist, professor, author, and journalist, went to an online dating service, and believed for several months that a chatbot, met in the dating service, was a “slim, attractive brunette”.

In brief, small talk is a constant in all chatbots programs, used in non-sequiturs or canned responses. It not only allows to give the idea of understanding, but also eases cooperation and facilitates human-like interaction by gaining the user trust and developing a social relationship (Bickmore and Cassell, 2000).

4.4 Failing like a human

After introducing the imitation game, Turing presented an example (Example 6) of a possible conversation one could have with a machine (Turing, 1950).

| Human: Add 34957 to 70764.  |
|-----------------------------|
| (after pause of about 30 seconds) |
| Machine: 105621.           |

Example 6.

Observing this example, besides the delay in providing the response, we can easily see that the answer is wrong. And this brings new insights to the modelling of human-computer communication. As Wallace wrote36, “we tend to think of a computer’s replies ought to be fast, accurate, concise and above all truthful”. However, human communication is not like that, containing errors, misunderstandings, disfluencies, rephrases, etc.

This is something that earlier chatbot’s writers already had in mind, as some already cared about simulated typing. For instance, JULIA, Mauldin’s Chatterbot (Mauldin, 1994), simulated human typing by including delays and leaving some errors. Simulated typing also proves to be useful in decreasing mistakes by slowing down the interaction (Philip Maymin, a Loebner contestant in 1995, slowed so much the typing speed of his program that a judge was not able to pose more than one or two questions (Hutchens, 1997)).

36http://www.alicebot.org/anatomy.html
5 Chatbots and the human-computer communication field

Several works from the human-computer communication field use resources from the chatbots’ community and/or couple with strategies reported by chatbots’ developers. However there are still some research challenges regarding the use of some chatbots’ resources. We will discuss these issues in the following.

5.1 Some works that merge both communities

Some works take advantage of the scripting languages provided by the chatbots’ community. An example is the conversational agent Edgar Smith (Fialho et al., 2013), an old butler that answers questions about Monserrate’s palace, in Sintra, Portugal, the place where it can be found (Figure 1), as part of its answers are retrieved from an AIML database.

Figure 1: Edgar Smith, in Monserrate, Sintra, Portugal.

Edgar’s main knowledge base is constituted of question/answering pairs related with its domain of expertise (the palace), as the one of Sergeant Blackwell, installed in the Cooper-Hewitt National Design Museum in New York (Susan Robinson and Henderer, 2008), and the one of the twins, Ada and Grace, virtual guides in the Boston Museum of Science (Traum et al., 2012). As Sergeant Blackwell and the twins, the natural language interpretation module of Edgar targets to select the most likely answer from the agent’s main knowledge base, based on some classification process; however, Edgar falls into an AIML knowl-
edge base, when no successful answer is found in the previous step. Its main knowledge base was built by experts, but the AIML module allowed the fast development of a secondary knowledge base, integrating some chat-based dialogues, based on pattern matching.

Considering the idea of learning to chat by chatting, which is at the basis of some chatbots, as we have previously seen, there are several recent works that explore it, by using large quantities of human interactions to build/train conversational agents. For instance, both Shawar and Atwell (2003) and Shawar (2005) are dedicated to the problem of retraining a chatbot with human dialogue examples. Another example is the chatbot IRIS, presented by Banchs and Li (2012), which was created based on Movie-DiC (Banchs, 2012), a corpus extracted from movies’ scripts. Filipe is a chatbot that should also be mentioned, as it has a knowledge base built on a corpus, the Subtle corpus, built with movies’ subtitles (Magarreiro et al., 2014).

Also, many conversational agents also rely on tricks to simulate intelligence. An example is the 3D Hans Christian Andersen (HCA), a conversational agent capable of establishing multi-modal conversations about the namesake writer’s life and tales (Bernsen and Dybkjær, 2005), which changes topic when lost in the conversation, and has an “excuse” for not answering some questions: it does not remember (yet) everything that the real HCA once knew. Another example is, once again, the virtual butler Edgar Smith, as it suggests questions when it is not able to understand an utterance, and it starts talking about the palace if it does not understand the user repeatedly. A feature in its character definition also “excuses” some misunderstandings: as Edgar is an old “person”, it does not have a very acute hearing. Both these examples, show how a “personality” or, at least, some context, allows to “forgive” some lacks on the conversational agent’s knowledge base or even some of its answers.

Finally, there are also works that target to enhance chatbots’ resources. Examples are the Persona-AIML architecture, that allows the creation of chatbots in AIML, with a personality (Galvão et al., 2004), or the work described by Cho (2007), where an emotion and personality model is added to A.L.I.C.E., allowing its decisions to be based on its personality and emotions, as well.

5.2 Main challenges

As previously said, Pandorabots reports over 3 billion conversational interactions. Chatscript, although much more recent, provides more that 3 million interactions. Even if we just consider the contents of A.L.I.C.E.’s brain, as well as the logs collected by Bruce Wilcox (both can be freely obtained), we have at hands extremely valuable resources, as they represent real interactions posed by real people, thus, containing not only requests posed by real people, but also answers given by real people.

These requests can be extremely useful as, considering Zipf’s law, a program that receives a certain input has a non zero probability of having the same input entered later and, thus, by looking at requests that people usually pose to chatbots, one can track patterns for which a specific reply was not created
yet. In other words, these requests are a way of having an idea of what people will ask. Moreover, they are the closest thing to the logs collected by Siri\(^{37}\), Cortana\(^{38}\) or Google Now\(^{39}\), to which the whole community has access to.

Considering the answers, some works already use corpora constituted of interactions to complement the agent’s knowledge base, and, in particular, to provide answers to out-of-domain interactions. The main motivation to find appropriate answers to these interactions (reported by all conversational agents developers) is that people become more engaged if out-of-domain requests are addressed. Works like the ones described by Bickmore and Cassell (2000) and Patel et al. (2006) validate this, as well as the fact that, in January 2013, Apple was asking for writers for Siri\(^{40}\). As it is impossible to prepare answers to all the possible out-of-domain requests, and the majority of the conversational agent’s developers cannot afford to recruit writers, a solutions is to try to take advantage of those human dialogues that can be found in the web. An example of a work that follows this approach is, again, the butler Edgar Smith. In the work reported by Ameixa et al. (2014), the previous mentioned Filipe’s corpus (Subtle), was used to answer out-of-domain requests posed to Edgar. Reported results say that 72% of the out-of-domain requests asked to Edgar are now answered, and, from these, about 65% are considered to be appropriate answers.

Nevertheless, all these authors mention plenty of room for improvements. Moreover, the previously mentioned corpora, made available by the chatbot’s community, were not properly explored yet. Thus, some research questions remain to be answered:

- How to filter these corpora in order to eliminate unwanted answers?
- Which techniques should be used to detect paraphrases in these corpora, as well as other semantic relations between requests and answers, in order to organise such data?
- How can the appropriate answer be chosen from the set of all possible answers available in the corpus, in order to allow some level of automatic customisation of the targeted agent?
- How to guarantee that a pre-defined answer makes sense in the context of a specific dialogue?

We foresee these as interesting research challenges for the next years.

\(^{37}\)https://www.apple.com/ios/siri/
\(^{38}\)http://www.windowsphone.com/en-us/how-to/wp8/cortana/
\(^{39}\)http://www.google.com/landing/now/
\(^{40}\)http://www.technologyreview.com/view/509961/apple-looks-to-improve-siris-script/
6 Conclusions and Future Challenges

The number of chatbots that can be found in the web increases every day. Although the majority of their developers do not have scientific aspirations, the fact is that, besides tools and corpora, the chatbots’ community has important know-how, which should not be neglected by researchers targeting advances in human-computer communication. Therefore, in this paper we presented a brief historical overview of chatbots, and described main resources and ideas. Furthermore, we highlighted some chatbots, which have distinguished themselves by introducing new paradigms and/or for being Loebner prize winners. However, it should be clear that these are only the tip of the iceberg of the panoply of chatbots that currently exist.

We have seen that AIML and, more recently, Chatscript are widely used languages that allow to code the chatbots’ knowledge sources, and that although some chatbots implement learning strategies, scripting is still at their core. We have also seen that a personality capable of justifying some of the chatbot’s answers, the capacity of directing a conversation and producing small talk, and the idea of failing like a human are some of the chatbots’ features that give the illusion of intelligence.

We have also grasped that to create a chatbot, one “only” needs to think about a character, and enrich its knowledge bases with possible interactions. Even better, that work does not need to be done from scratch as many platforms already provide pre-defined interactions, which can be adapted according to the chatbot character. And this is the main richness of the chatbot’s community: the immense amount of collected interactions, where the majority of them represent real human requests.

A major future challenge is to be able to automatically use all this information to build a credible chatbot. How to avoid contradictory answers? How to choose appropriated answers considering a chatbot’s character? And if we move to other sources of dialogues, like the ones from books, theatre plays or movies subtitles, will we be able, one day, to integrate all that information simulating real human dialogues?

References

Ameixa, D., Coheur, L., Fialho, P., and Quaresma, P. (2014). Luke, I am Your Father: Dealing with Out-of-Domain Requests by Using Movies Subtitles. In Intelligent Virtual Agents - 14th International Conference, IVA 2014, Boston, MA, USA, August 27-29, 2014. Proceedings, pages 13–21. Springer.

Angeli, A. D. and Brahnam, S. (2008). I hate you! Disinhibition with virtual partners. Interacting with Computers, 20:302–310.

Banchs, R. E. (2012). Movie-DiC: a Movie Dialogue Corpus for Research and Development. In Proceedings of the 50th Annual Meeting of the Association
Banchs, R. E. and Li, H. (2012). IRIS: a Chat-oriented Dialogue System based on the Vector Space Model. In ACL (System Demonstrations), pages 37–42.

Batacharia, B., Levy, D., Catizone, R., Krotov, A., and Wilks, Y. (1999). Converse: a conversational companion. In Wilks, Y., editor, Machine Conversations, volume 511 of The Springer International Series in Engineering and Computer Science, pages 205–215. Springer US.

Bernsen, N. O. and Dybkjær, L. (2005). Meet Hans Christian Andersen. In Proceedings of the Sixth SIGdial Workshop on Discourse and Dialogue, pages 237–241.

Bickmore, T. and Cassell, J. (1999). Small talk and conversational storytelling in embodied conversational interface agents. In Proceedings of the AAAI 1999 Fall Symposium on Narrative Intelligence, pages 87–92. AAAI Press.

Bickmore, T. and Cassell, J. (2000). How about this Weather? Social Dialogue with Embodied Conversational Agents. In Socially Intelligent Agents: The Human in the Loop, pages 4–8. AAAI Press.

Caputo, L., Garner, R., and Nathan, P. X. (1997). FRED, Milton and Barry: the evolution of intelligent agents for the Web. In Morabito, F. C., editor, Advances in Intelligent Systems, pages 400–407. IOS Press.

Carpenter, R. and Freeman, J. (2005). Computing Machinery and the Individual: the Personal Turing Test. http://www.jabberwacky.com.

Cho, A. K. (2007). Emotional and Domain Concept Enhancements to Alicebot. Master’s thesis, San Jose State University.

Colby, K. M. (1974). Ten criticisms of PARRY. SIGART Newsletter, pages 5–9.

Daden Limited (2010). Deploying chatbots to customer advantage. White Paper (http://issuu.com/dadenlimited/docs/whitepaper4/1).

Endrass, B., Rehm, M., and André, E. (2011). Planning Small Talk behavior with cultural influences for multiagent systems. Computer Speech & Language, 25(2):158–174.

Epstein, R. (1992). The Quest for the Thinking Computer. AI Magazine, pages 81–95.

Epstein, R. (2007). From Russia, with Love. How I got fooled (and somewhat humiliated) by a computer. Scientific American Mind.

Fahlman, S. E. (2011). Using Scone’s Multiple-Context Mechanism to Emulate Human-Like Reasoning. In Advances in Cognitive Systems: Papers from the 2011 AAAI Fall Symposium, pages 98–105. AAAI Press.
Fellbaum, C., editor (1998). *WordNet: An Electronic Lexical Database*. MIT Press.

Fialho, P., Coheur, L., Curto, S., Cláudio, P., Ângela Costa, Abad, A., Meinedo, H., and Trancoso, I. (2013). Meet Edgar, a tutoring agent at Monserrate. In *Proceedings of the 51st Annual Meeting of the ACL: System Demonstrations*, pages 61–66.

Galvão, A. M., Barros, F. A., Neves, A. M. M., and Ramalho, G. L. (2004). Persona-AIML: An Architecture Developing Chatterbots with Personality. In *Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems - Volume 3*, AAMAS ’04, pages 1266–1267, Washington, DC, USA. IEEE Computer Society.

Gebhard, P., Mehlmann, G., and Kipp, M. (2011). Visual SceneMaker—a tool for authoring interactive virtual characters. *Journal on Multimodal User Interfaces*, 6:3–11.

Grinberg, D., Lafferty, J. D., and Sleator, D. D. (1995). A Robust Parsing Algorithm For Link Grammars. In *Proceedings of the Fourth International Workshop on Parsing Technologies*, pages 111–125.

Hartholt, A., Traum, D., Marsella, S., Shapiro, A., Stratou, G., Leuski, A., Morency, L.-P., and Gratch, J. (2013). All together now. In Aylett, R., Krenn, B., Pelachaud, C., and Shimodaira, H., editors, *Intelligent Virtual Agents*, volume 8108 of *Lecture Notes in Computer Science*, pages 368–381. Springer Berlin Heidelberg.

Heller, B., Proctor, M., Mah, D., Jewell, L., and Cheung, B. (2005). Freudbot: An Investigation of Chatbot Technology in Distance Education. In Kommers, P. and Richards, G., editors, *Proceedings of World Conference on Educational Multimedia, Hypermedia and Telecommunications*, pages 3913–3918. AACE.

Hutchens, J. L. (1997). How to Pass the Turing Test by Cheating. Technical report, University of Western Australia.

Kazi, H., Chowdhry, B. S., and Memon, Z. (2012). MedChatBot: An UMLS based Chatbot for Medical Students. *International Journal of Computer Applications*, 55(17):1–5.

Kuipers, B., McCarthy, J., and Weizenbaum, J. (1976). Computer power and human reason. *SIGART Bull.*, pages 4–13.

Levesque, H., Davis, E., and Morgenstern, L. (2012). The Winograd Schema Challenge. In *Proceedings of the Thirteenth International Conference on Principles of Knowledge Representation and Reasoning*, pages 552–561. AAAI.

Levesque, H. J. (2014). On our best behaviour. *Artificial Intelligence*, 212:27–35.
Magarreiro, D., Coheur, L., and Melo, F. S. (2014). Using subtitles to deal with Out-of-Domain interactions. In Proceedings of 18th Workshop on the Semantics and Pragmatics of Dialogue (SemDial), pages 98–106.

Malinowski, B. (1923). The Meaning of Meaning, chapter The Problem of Meaning in Primitive Societies, page 38. Harcourt Brace Jovanovich, Inc.

Mauldin, M. L. (1994). ChatterBots, TinyMuds, and the Turing test: entering the Loebner Prize competition. In Proceedings of the 12th National Conference on Artificial Intelligence (vol. 1), AAAI '94, pages 16–21. AAAI Press.

Mikic, F. A., Burguillo, J. C., Llamas, M., Rodriguez, D. A., and Rodriguez, E. (2009). CHARLIE: An AIML-based Chatterbot which Works as an Interface among INES and Humans. In 2009 EAEIE Annual Conference, pages 1–6. IEEE.

Patel, R., Leuski, A., and Traum, D. (2006). Dealing with out of domain questions in virtual characters. In Gratch, J., Young, M., Aylett, R., Ballin, D., and Olivier, P., editors, Intelligent Virtual Agents, volume 4133 of Lecture Notes in Computer Science, pages 121–131. Springer Berlin Heidelberg.

Powers, D. M. W. (1998). The total Turing test and the Loebner prize. In Proceedings of the Joint Conferences on New Methods in Language Processing and Computational Natural Language Learning, NeMLaP3/CoNLL ’98, pages 279–280. ACL.

Saygin, A. P., Cicekli, I., and Akman, V. (2000). Turing test: 50 years later. Minds and Machines, 10:2000.

Schneider, K. (1988). Small Talk: Analyzing Phatic Discourse. Sprachwissenschaftliche Reihe. Hitzeroth.

Schumaker, R. P., Ginsburg, M., Chen, H., and Liu, Y. (2007). An evaluation of the chat and knowledge delivery components of a low-level dialog system: The AZ-ALICE experiment. Decision Support Systems, 42(4):2236–2246.

Shah, H. (2006). A.L.I.C.E.: an ACE in Digitaland. tripleC, 4(2):284–292.

Shawar, B. A. (2005). A Corpus Based Approach to Generalising a Chatbot System. PhD thesis, University of Leeds.

Shawar, B. A. and Atwell, E. (2003). Using dialogue corpora to train a chatbot. In Proceedings of CL2003: International Conference on Corpus Linguistics, pages 681–690. Lancaster University.

Susan Robinson, David Traum, M. I. and Henderer, J. (2008). What would you Ask a conversational Agent? Observations of Human-Agent Dialogues in a Museum Setting. In Proceedings of the Sixth International Conference on Language Resources and Evaluation (LREC’08), pages 1125–1131. European Language Resources Association (ELRA).
Traum, D., Aggarwal, P., Artstein, R., Foutz, S., Gerten, J., Katsamanis, A.,
Leuski, A., Noren, D., and Swartout, W. (2012). Ada and Grace: Direct
Interaction with Museum Visitors. In Nakano, Y., Neff, M., Paiva, A.,
and Walker, M., editors, Intelligent Virtual Agents, volume 7502 of Lecture
Notes in Computer Science, pages 245–251. Springer Berlin Heidelberg.

Turing, A. M. (1950). Computing Machinery and Intelligence. Mind, 59:433–
460.

Wallace, R., Tomabechi, H., and Aimless, D. (2007). Chatterbots Go Native:
Considerations for an eco-system fostering the development of artificial life
forms in a human world. http://www.pandorabots.com/pandora/pics/
chatterbotsgonative.doc.

Weizenbaum, J. (1966). ELIZA – a computer program for the study of natural
language communication between man and machine. Communications of
the ACM, 9:36–45.