

On a Chatbot Conducting a Virtual Dialogue in Financial Domain

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Abstract

We demo a chatbot in a personal finance domain that delivers content in the form of virtual dialogues automatically produced from plain texts extracted and selected from documents. Given an initial query, this chatbot finds documents, extracts topics from them, organizes these topics in clusters according to conflicting viewpoints, receives from the user clarification on which cluster is most relevant to her opinion, and provides the content for this cluster. This content is provided in the form of a virtual dialogue where the answers are derived from the found and selected documents and its split results, and questions are automatically generated for these answers.

1 A Virtual Dialogue

Presentation of knowledge in dialogue format is a popular way to communicate information effectively. Usability studies have shown that for information acquirers, dialogues often communicate information more effectively and persuade stronger than monologue most of the times [Cox et al., 1999].

A virtual dialogue is defined as a multi-turn dialogue, possibly with adversarial argumentation, between imaginary agents obtained as a result of content transformation [Piwek et al., 2007].

Dialogue construction from the text is based on the Rhetorical Structure Theory (RST, [Mann and Thompson., 1988]). To obtain a sequence of answers from a text, we automatically split it into elementary discourse units (EDUs) and then form a discourse tree where these units are labels for the leaves of this tree. Satellite EDUs are then selected as answers to the questions that are derived from these EDUs by means of generalization. Nucleus EDUs will follow the satellite EDUs in dialogue answers to maintain its cohesiveness [Barzilay and Lapata, 2008; Galitsky et al., 2015]. Discourse tree is constructed with the RST-parser [Surdeanu et al., 2015].

An example of converting a text into a virtual dialogue is shown in the form of a discourse tree below. Answers are obtained by splitting text into EDUs, and questions are inserted in text before satellite EDUs. Generated questions are shown in angle brackets and bolded.

For the text “*Lower risk investments, such as government bonds, offer lower but more stable returns and less chance of losing the money you invest. But, lower returns may mean that inflation reduces the value of your investments*” we have the following discourse tree with inserted questions:

elaboration (LeftToRight)

contrast (RightToLeft)

same-unit

TEXT: Lower risk investments such as government bonds

elaboration (LeftToRight)

<what kind of return it can give?>

TEXT: offer lower but more stable returns, less chance

elaboration (LeftToRight)

TEXT: of losing the money

TEXT: you invest .

attribution (RightToLeft)

TEXT: But, lower returns may mean

<What can inflation do with my investment?>

TEXT: that inflation reduces the value of investments.

2 A Session with a Virtual Dialogue Chatbot

We present an exploratory session that combines information delivery in the form of traditional textual answers (conventional dialogue) and in a form of a virtual dialogue. The dialogue starts from the user question, ‘*pros and cons of investment in annuity*’ (Fig. 1).

Bot>ask a new question

User> **pros and cons of investment in annuity**

Bot> exploring <https://www.bankrate.com/retirement/5-pros-andcons-of-investing-in-annuities/>

I believe these are the main topics of your query: is that what you meant? Please select

[1] 'establish your own salary from an annuity'

[2] 'an insurance or investment company in exchange'

[3] 'predictable retirement income'

User> **predictable retirement income**

Bot> If you are thinking of investing for retirement years,

there are many options for you to choose from...
*Are you OK with this answer? yes/more/no/specify
 [different topic] // virtual dialogue*

User > **virtual dialogue**

Bot> This is what other people chat about your topic:

Bot>An advantage of an annuity is the reliable income that it produces, according to annuity-pros-cons.com .
 User>**What will my own salary be?**
 Bot>The annuity establishes a known schedule for when you will receive your money. This allows you to establish your own salary from an annuity
 User>**What if I find a better investment?**
 Bot> While an annuity pays you a known amount for a specific amount of time, it cannot be changed. You cannot pull your money out of the annuity.

User> **What category of people has the highest financial anxiety?**

Bot>This has been answered to users with similar questions:

Bot> Having a predictable retirement income can help you feel happier
 User>**Where is the strongest financial anxiety?**
 Bot> Conversely, the researchers discovered that retirees who must withdraw money from investments to pay for retirement expenses had the highest financial anxiety.

Figure 1: Chatbot session with conventional and virtual dialogue.

The chatbot consults the sources and extracts the content from each page (or document) expected to be relevant for the query. The chatbot forms the list of topics extracted from these search results so that the user might select the one of her interest. The user selects his topic of interest and requests a specific answer. Once the answer is read, there are multiple options:

- accept the answer and conclude the session;
- navigate to the next/specific answer from the chatbot list;
- attempt to reformulate the query;
- reduce search to a specified web domain;
- proceed to more search results in the form of a virtual dialogue.

The user selects the last option and the chatbot builds a virtual dialogue. It is a conversation between imaginary people where the conversation topic is retained, matching the original query. Virtual dialogues are shown in frames.

Chatbot demo videos (please, check *10 min video*) and instructions on how to use it are available at our [GitHub](#) in the “**What is new?**” section.

3 Evaluation of Effectiveness

Evaluating the effectiveness of information delivery via virtual dialogues, we compare the conventional chatbot sessions where users were given plain-text answers, and the ones where users were given a content via virtual dialogues.

Table 1. Evaluation of comparative effectiveness of conventional and virtual dialogues

| | Conventional dialogues | | | Virtual dialogues | | |
|----------------------------------|----------------------------|----------------------------|---------------------------------------|----------------------------|----------------------------|---------------------------------------|
| | # of iterations till found | # iterations till decision | Coverage of exploration # of entities | # of iterations till found | # iterations till decision | Coverage of exploration # of entities |
| Conventional only | 4.6 | 6.3 | 10.8 | - | - | - |
| Virtual only | - | - | - | 4.1 | 6.0 | 13.7 |
| Conventional followed by virtual | 4.0 | 5.7 | 7.6 | 6.1 | 11.3 | 15.1 |
| Virtual followed by conventional | 5.6 | 7.1 | 12.3 | 3.7 | 7.0 | 11.5 |

We assess dialogues with respect to following usability properties.

The speed of arriving to a decision to commit a transaction such as purchase or product selection. A user is expected to accumulate sufficient information, and this information should be convincing enough for making such decision;

We also measure **how many entities** (in linguistic sense) were explored during a session with the chatbot. We are interested in how thorough and comprehensive the chatbot session is. This assessment is sometimes opposite to the above two measures but nevertheless is important for understanding the overall usability of various conversational modes.

We do not compare precision and recall of search sessions with either dialogue mode since the same information is delivered, but in distinct modes.

In the first and second rows, we assess the stand-alone systems. Virtual dialogues take less iteration on average for information access and about the same number of iterations for decisions as conventional dialogues do.

In the bottom two rows, we observe the usability of the hybrid system. When a conventional dialogue is followed by a virtual one, a lower portion of users is satisfied by the first step in comparison to the inverse architecture, where virtual is followed by conventional.

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