SEMINAR REPORT ON CHATBOTS IN BANKING

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2021-2022

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ACKNOWLEDGEMENT

I would like to extend my sincere gratitude to my seminar guide, Mrs. Sarika Joglekar for her valuable guidance, suggestions and timely help in completion of my seminar report. I would also like to thank her for helping and supporting me throughout the completion of the seminar.

I am grateful to Dr Supriya Kelkar, Head of Department for Computer Engineering and all staff members of Computer Engineering department for their support and guidance.

Ms Prajakta Deokule

ABSTRACT

Banks play a very important role in the economic development of a country. The pandemic has changed the expectations of the customers from the banks. Customers now expect a personalized, speedy and easy medium of interaction with the banks for performing various financial operations. This has led to increase in the popularity of chatbots and other assistants which help in improving the customer experience.

Today chatbots are used by many financial organizations all over the world and still a lot of growth in their usage is expected. These assistants help the banks in automating a lot of repetitive and time consuming jobs which are performed by customer support teams. They also act as a listening channel for the banks. This helps banks in understanding user habits, predict customer actions and deliver personalized offers and services. There are mainly three different kinds of chatbots available-1.Rule based chatbots, 2. AI based chatbots and 3.hybrid chatbots (that use NLP but are less sophisticated than AI chatbots). The architecture of all these types has been discussed in detail with their examples.

There are many benefits of chatbots both for the customers and for the banks. Some existing banking chatbots are mentioned along with the future scope of chatbots in banking.

Keywords: chatbot, AI, NLP, NLG, NLU, AIML

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Chapter 1. INTRODUCTION



Fig 1.1.1. A chatbot in banking

1.1 Digital Banking Moves Forward

Digital transformation has affected all the industries. Organisation are trying to get a competitive edge and fulfill the today's customer demands. The banking industry had also recognised the enormous effect, artificial intelligence would have and optimised their online and mobile banking models with customer interaction platforms.

Covid 19 accelerated the digital banking momentum. In spite of rise in online banking, banks had not anticipated not having face to face contact with people for an extended time or not having employees physically present in offices. Banks are attempting to meet these challenges and guarantee business continuity irrespective of any crisis. Social distancing altered how people work and communicate and banks had to reduce their dependence on humans. Banks must invest in improving their contact points with customers beyond physical branches and outsourced call centres. Today customers expect flawless, immediate and personalized interactions with banks.

The new wave of digital banking is all about customer experience. Banks must improve their customer service and provide scalable 24/7 customer support on multiple languages and channels. To achieve this objective robust platforms are required that can provide immediate assistance to customers for transferring money, checking account balances and other requests. Banks need intelligent platforms which will interact with customers and understand their needs. They require intelligent chatbots.

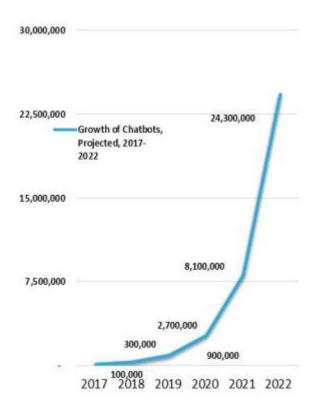


Fig 1.1.1 Projected Growth of chatbots from 2017 to 2022

1.2 What are Chatbots?

The bot in chatbot derives from robot. A bot means a software that will perform automatic tasks.

A chatbot is an agent that communicates with customers in their language. A chatbot can help customers. This reduces the work for a customer service agent who can now focus on more complex issues which the chatbot is not able to solve.

Chatbots are used across many businesses and have had proven success.

- They have been used in customer service for answering questions and queries, for booking tickets for shows, for finding and recommending products and building a remarkable customer experience.
- Chatbots are employed in sales to automate sales and in marketing. Chatbots can create exceptional conversational experiences for a company's website visitors. These interested customers are then directed to the proper sales representative for closing sales immediately or for booking an appointment.
- Chatbots increase the user participation on company's websites and social media due to their presence. They communicate with customers through live chat platforms like Facebook messenger. They help in improving customer service and help users to perform transactions.
- Chatbots can confirm orders and track shipping. Zalando, a European fashion brand incorporates a chatbot use case of providing immediate order tracking for its customers

just after they have purchased an item. Hence customer support team can focus on more complex issues.

- Chatbots are being employed to streamline personal services. These services include: health, fitness, diet, and other daily activities. Daily Fitbot is a chatbot that works on Facebook messenger app. It specializes in high intensity interval training workouts. It has instructional videos and also provides various lifestyle related articles.
- Food industry has benefited by chatbots. Domino's is the first pizza brand that launched a chatbot on Facebook Messenger and it has helped it in increasing its revenue.
- Airlines are using chatbots to answer common questions which are asked by the users and displays basic information about flights. Aero Mexico, a flight service has launched its chatbot and has improved its customer service.

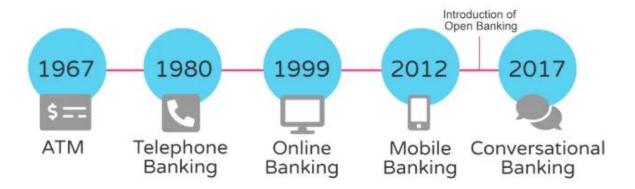


Fig 1.2.2. Evolution of digitalized banking

1.3 Introduction to Conversational Banking

Digital banking allowed users to do many tasks on their phone app. However the shift from offline to online has caused users to miss the personalization in the experience. Users need to connect with banks for resolving their queries. Offline banks help in this but it is not convenient.

Conversational banking involves digital banking through text messaging, voice and visually interactive tools.

It includes the use of all mediums-websites, mobile apps, messaging apps etc. to interact with users.

In conversational banking, customers interact with voice assistants, with chatbots and with human agents via live chat, mobile apps to get specific advice other than visiting the bank branch.

Conversational banking involves IVR systems and chatbots.

Chapter 2. CHATBOTS IN BANKING



Fig 2.1.1.Use cases of chatbots in banking

2.1 Chatbots use cases in Banking

The customers' demand for online and digital access to banks has caused chatbots to become a necessity in customer service.

Towards the end of 2020, the number of financial institutions using chatbots had tripled (from 4% in the previous year to 12%) with 16% of additional banks intending to invest in the technology (Izraylevych, 2021).

Following are some of the uses of chatbots in the financial sector-

1. Reviewing Account Information

With chatbots, users can check their balance and adjust account settings comfortably from their homes. They can also apply for different products and services, update security information and review loan details. This saves a lot of customers' time as they don't need to waste time on making phone calls and waiting for a customer service agent to respond to them. With advancements in chatbot architecture, users will also receive individual guidance for digital services like money transfers, paying bills and purchasing other services.

2. Creating Personalized Alerts

Chatbots are also used to remind bank consumers of their upcoming bill payments and expected transactions. They can also notify users of changes to accounts, or any suspicious activity. Chatbots can also send alerts and warnings to users about late or missed payments or large money transfers.

3. Handling Customer Service Complaints

Chatbots provide immediate 24/7 customer support globally. They can solve noncomplex but urgent problems. This saves a user from wasting time over a simple issue which would have caused a lot of frustration. Further a banking chatbot could engage unhappy clients with easy to respond feedback forms. The personalized messaging, convenience and privacy offered by a chatbot can encourage involvement.

3. Responsive Q& A

A chatbot can use its computing power to answer common and location specific questions. By using its data a chat bot can answer most questions asked by the user in a personalized manner. This will give an efficient, speedy and personalized user to the user.

2.2 Advantages of banking chatbots

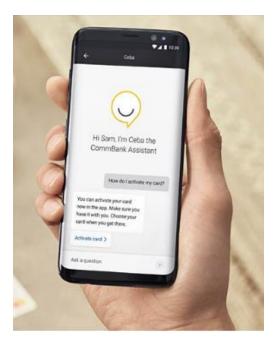


Fig 2.2.1 Ceba chatbot of Commonwealth Bank

2.2.1 For customers:

- **Simplicity and ease in usage** Chatbots can be easily used with other platforms like various messaging platforms, company websites and mobile apps. Hence these banking operations can be performed on all these platforms which provides a lot of flexibility to the user.
- **24/7 support**: These assistants can help users instantaneously. Customers don't have to keep waiting for the available customer representative. Connecting with bank representatives for trivial issues may sometimes be a very time consuming and frustrating experience for users.

• **Increase in user engagement**: Banks regularly have new campaigns and services to offer along with personalized financial plans (Dilmegani, 2022). Chatbots can make it easier for a user to choose the appropriate products for them and obtain information about the services relevant to them (Dilmegani, 2022).

2.2.2 For banks:

- **Reduced costs**: Instead of hiring and managing multiple employees for customer service, launching a chatbot is much easier, faster and cheaper. A chatbot platform can serve numerous customers and they serve 24/7 without any leave.
- **Fraud reduction**: Credit card users frequently face fraud and other security issues in online banking. Chatbots can inform the user if they find any of suspicious transactions and try to prevent frauds.

Chapter 3. TYPES OF CHATBOTS

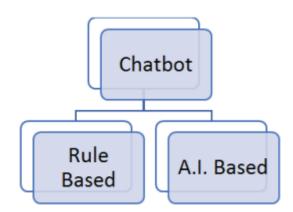


Fig 3.1.1. Types of Chatbots

Chatbot is a software which is used to interact with humans in different languages through different mobile apps, websites, messages, etc.

The chatbots have been known for some time but they have gained such popularity only in the recent years. However over the past few years, chatbots have attracted many industries. First set up in the 1960s, chatbots have come a long way from their initial development (Suhel, Shukla, Vyas, & Mishra, 2020).

3.1 Different types of chatbots

- Rule based bots consist of simple systems and have limited responses. The program scans and decides keywords and responds with the appropriate command type the user input (Suhel, Shukla, Vyas, & Mishra, 2020).
 Rule-based chatbots do not respond when they encounter unfamiliar commands and unrecognized phrases.
- Artificial intelligence based Chatbots
 - These chatbots use natural language processing tools for artificial intelligence (Suhel, Shukla, Vyas, & Mishra, 2020). Computers are configured in this framework for reading, processing and analyzing large amounts of natural language information (Suhel, Shukla, Vyas, & Mishra, 2020). ML algorithms are also used in AI bots. These bots keep expanding their database by learning from people's conversations and interactions.
- **Hybrid chatbots**: Hybrid chatbots rely both on rules and NLP to understand users and generate responses (Dilmegani, 2022). Databases of these chatbots are easier to tweak but have limited conversational capabilities compared to AI-based chatbots (Dilmegani, 2022).

3.2 Rule based Chatbots

Example of rule-based or pattern-based approach is ALICE that uses AIML as the language for defining patterns for queries and its answers (Shah, Shetty, Shah, & Pamnani, 2017).

However large numbers of rules are required for ensuring proper working of the assistant (Shah, Shetty, Shah, & Pamnani, 2017). Some examples of assistants using this approach are, ALICE, Chatterbot, Jabberwacky, etc (Shah, Shetty, Shah, & Pamnani, 2017). If combined with machine learning, this approach can significantly improve the efficiency of the assistant (Shah, Shetty, Shah, & Pamnani, 2017).

3.2.1 Artificial Intelligence Markup Language (AIML) (Suhel, Shukla, Vyas, & Mishra, 2020)

There are three basic elements of AIML

• AIML's building block is the **category**.

Each category contains a question-answer or input-response pair

The set of all categories makes the chatbot Knowledge Base (Shah, Shetty, Shah, & Pamnani, 2017)

Categories are made up of patterns and templates (Suhel, Shukla, Vyas, & Mishra, 2020).

- The **pattern** tag defines a possible **user input**, and (Shah, Shetty, Shah, & Pamnani, 2017)
- The **template** tag sets the **chatbot response** for a certain user input (Shah, Shetty, Shah, & Pamnani, 2017).
- Types of AIML Categories (Suhel, Shukla, Vyas, & Mishra, 2020)

Atomic categories: Don't have wildcard symbols like _ and * (Suhel, Shukla, Vyas, & Mishra, 2020)

Default categories: Have wildcard signs such as * or .

Recursive categories: These are the ones that apply to the laws of recursive reduction with templates and tags (Suhel, Shukla, Vyas, & Mishra, 2020).

3.3.2 The Alice Chat Bot System

The Artificial Linguistic Internet Computer Enterprise was developed by Richard Wallace. It uses AIML language.

AIML is a subset of the Markup language (XML) (Suhel, Shukla, Vyas, & Mishra, 2020). AIML is case-insensitive.

AIML comprises of data items called AIML objects that contain structures:-topics and categories (Suhel, Shukla, Vyas, & Mishra, 2020).

The principle of matching pattern strategy is based on finding the shortest, best match between patterns (Suhel, Shukla, Vyas, & Mishra, 2020). This is used to produce the answer to the chatbot of ALICE (Suhel, Shukla, Vyas, & Mishra, 2020).

<aiml> tag marks the start and end of a AIML document (AIML-Quick Guide, n.d.).

The **topic** is an additional item at the top level and has a name attribute and a **collection of similar categories** (Suhel, Shukla, Vyas, & Mishra, 2020).

```
<aiml>
<topic name= "topic" >
<category>
 <pattern> ...(Your question)
  <template> (Answer to the question)</template>
</category> (Shah, Shetty, Shah, & Pamnani, 2017)
</topic>
</aiml> (Shah, Shetty, Shah, & Pamnani, 2017)
<that> stores last response
<category>
 <pattern> What about the rate of interest ?</pattern>
  <template>Do you like increase in rate of interest? </template>
</category>
<category>
  <pattern>YES</pattern>
  <template>Do you like increase in rate of interest? (Shah, Shetty, Shah, & Pamnani,
2017) </template>
  <that>What about increase in rate of interest?</that>
   <template> Even I prefer increase in the rate of interest (Shah, Shetty, Shah, &
Pamnani, 2017). Good for customers right?!</template>
</category>
```

<random> gives random responses from a list of templates can be used

```
</random>
</template>
</category>
```

Some other tags are <srai> multipurpose tag that enables AIML to define the different targets for the same template **<srai>** pattern **</srai>** (AIML-Quick Guide, n.d.)

<star> is used to match wild card * character(s) in <pattern> Tag.

<think> is used to store a variable without notifying the user (AIML-Quick Guide, n.d.).

<condition> is similar to switch statements in programming language (AIML-Quick Guide, n.d.). It helps ALICE to respond to the matching input (Gupta, Hathwar, & Vijayakumar, 2020).

3.3 Architecture of Rule Based chatbots

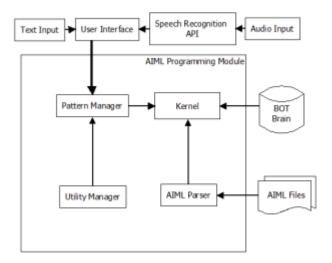


Fig 3.3.1. Architecture of Rule based chatbots

The user enters his/her query on the chatbot interface (Gupta, Hathwar, & Vijayakumar, 2020).

The user's query is processed to match with the predefined format template (Gupta, Hathwar, & Vijayakumar, 2020). Pattern matching is done between the knowledge base that stores the predefined template and the user's query in order to arrive at a solution (Gupta, Hathwar, & Vijayakumar, 2020). Finally, the pattern-oriented answer is presented to the user (Gupta, Hathwar, & Vijayakumar, 2020).

3.4 AI Based Chatbots

These bot are equipped with an artificial brain. They are trained using machine-learning algorithms and can understand open-ended queries.

They comprehend orders and also understands the language. These bots improve as they learn from the interactions they have with users

Here different NLP techniques are applied for processing the text submitted by the customer. Then the grammar is checked and information is extracted out of it. This information that has been extracted is analysed and an appropriate response is generated for the query.

An example of NLP based assistant is IBM's Watson. (Shah, Shetty, Shah, & Pamnani, 2017)

One limitation of this approach is that this approach is slower if the architectures are not parallelized. (Shah, Shetty, Shah, & Pamnani, 2017)

3.4.1 AI Based chatbot Components

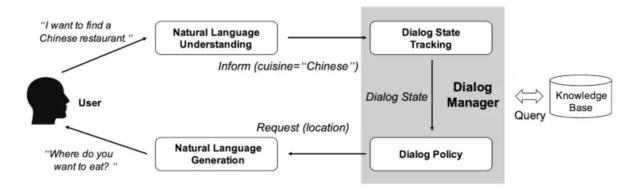


Fig 3.4.1. AI chatbot components

AI chatbots are made up of:

Natural Language Processing

There are two parts of an NLP system: NLU and NLG. When a text is entered into an NLP engine, what the user intends to say is deciphered by the NLU and NLG generates the response to be given to the user.

This equation denotes how NLP, NLU, and NLG are related:

NLP = NLU + NLG

Process flow:

User Text -> Chatbot -> NLU -> Meaning deciphered -> NLG -> Response Generated

Natural language understanding (NLU): Is the subfield of NLP. It is based on understanding the meaning of human speech by recognizing patterns in unstructured speech input (Dilmegani, 2022).

NLU helps chatbots classify customer's intents and generate a response based on training data (Dilmegani, 2022).

Components:-

- Natural Language Inference (NLI) and paraphrasing It determines if a statement is true, false or neutral. This is achieved by setting a 'premise' for the system in the form of a training database.
- o <u>Dialogue agent</u> This Manager keep track of the current state of conversations
- Semantic parsing It converts natural language text into a form that can be understood by machine
- o Question answering To automatically answer in a natural language
- Sentiment analysis It focusses on deciphering feelings and emotions of the user. It also analyses the user's intentions and interest levels.
- Summarization —involves shortening the message and emphasizing the major points (intent/entity).

An intent captures the general meaning of sentence. The chatbot is trained to be able to distinguish sentences from sentences with other meanings. The *dataset* containing different intents is created. Here the central idea is that the words are represented with vectors. The vectors are compared and a small distance between them indicates words having similar meaning. Entity refers to the additional information that is not captured by an intent.

Natural Language Generation- It is the conversion of machine produced structured data into text that is readable by the user (Dilmegani, 2022).

Natural Language Generation has these steps-

- o Content Determination-Knowledge base is filtered to choose the response.
- o Data interpretation-Data is interpreted, patterns are identified and put into context.
- o Document structuring- Narrative structure chosen based on the type of data.
- Sentence aggregation-Relevant sentences or phrases are combined to summarize the topic
- o <u>Grammatical structuring</u>-Program deduces syntactical structure of sentence and then rewrites sentence in grammatically correct manner.
- <u>Language Presentation</u>-Final output is generated based on the template chosen by the user

Data Storage: The conversations held by the chatbot with the customers are stored for further training and testing of the chatbot. They are stored in structured form on cloud or physically.

Knowledge Base: It is the information that the chatbot relies on to respond to users. Different businesses require different kinds of knowledge base. Here the knowledge base will contain all the customers' financial information and information about the bank that the chatbot will display to the answers asked by the customers.

User Interface: The front-end of a chatbot which is used for conversing with the user. The chatbots can be integrated into different messaging platforms, such as WhatsApp, Slack, and Facebook Messenger etc. (Dilmegani, 2022).

3.5 Design and Architecture of NLP based Banking chatbot

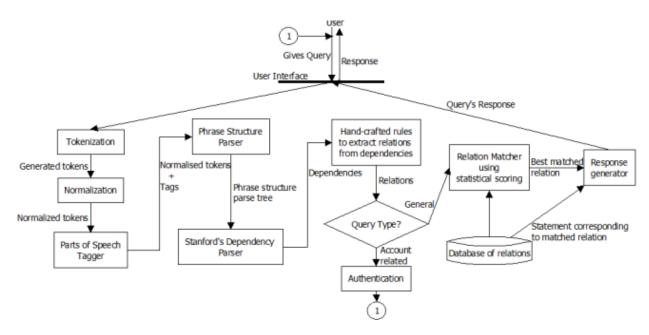


Fig 3.5.1. Architecture of Banking assistant using NLP

In the architecture for banking assistant several modules are involved.

- <u>User interface:</u> Here the user enters his / her query and submits it to the banking chatbot for processing (Shah, Shetty, Shah, & Pamnani, 2017).
- After submitting the query the Tokenizer is involved. The tokenizer splits the query using delimiters and generates useful tokens. The delimiters include space, or comma or semi-colon, etc (Shah, Shetty, Shah, & Pamnani, 2017).
- The tokens thus generated are sent to the Normalizer (Shah, Shetty, Shah, & Pamnani, 2017). Here pre-processing is done on the tokens which involves
 - 1. **correcting the spelling of words** (using Damerau-Levenshtein distance)

[the **Damerau–Levenshtein distance** is a string metric used for measuring the <u>edit</u> <u>distance</u> between two sequences (S Y Yuliani, 2019).

Damerau–Levenshtein distance between two words is the minimum number of operations (insertions, deletions or substitutions of a single character, or transposition of two adjacent characters)this required for changing one word into the other. (S Y Yuliani, 2019)]

- 2. **expanding of acronyms and abbreviations** (by looking into a database of common acronyms and abbreviations) (Shah, Shetty, Shah, & Pamnani, 2017)and
- 3. conversion of tokens to standard format (e.g. all characters in lowercase) (Shah, Shetty, Shah, & Pamnani, 2017).
 - The normalized words are sent to a <u>Parts of Speech (POS) Tagger</u> (Shah, Shetty, Shah, & Pamnani, 2017).**Here meaningful labels will be assigned to these words.**

Let us understand this with an example.

Suppose the sentence is: "The bank provides 8% interest on fixed deposit." (Shah, Shetty, Shah, & Pamnani, 2017)

Here output from POS Tagger is

"The/DT bank/NN provides/VBZ 8/CD %/NN interest/NN on/IN fixed/VBN deposit/NN ./." (Shah, Shetty, Shah, & Pamnani, 2017)

[Here DT=determinant/article, NN=noun(singular) VBZ=Verb third person singular CD=cardinal digit IN=preposition VBN=verb past participle]

In corpus linguistics, part-of-speech tagging, also called grammatical tagging is the process of marking up a word in a text as corresponding to a particular part of speech, based on both its definition and its context.

A Part-Of-Speech Tagger (POS Tagger) is a piece of software that reads text in some language and assigns parts of speech to each word (and other token), such as noun, verb, adjective, etc., although generally computational applications use more fine-grained POS tags like 'noun-plural'.

POS Tagger can be implemented using Hidden Markov Models using Viterbi's algorithm (Shah, Shetty, Shah, & Pamnani, 2017). Stanford Log Linear part of speech tagger is also available

(Hidden Markov Model is probabilistic model for machine learning. It is mostly used in speech recognition, to some extent it is also applied for classification task. HMM provides solution of three problems: evaluation, decoding and learning to find most likelihood classification (Chapter 3 Hidden Markov Model). Viterbi algorithm is the most common decoding algorithms for HMMs. the Viterbi algorithm has a dynamic programming approach)

The output is given to a **Phrase Structure PCFG Parser** (Shah, Shetty, Shah, & Pamnani, 2017).

A parser is used to check whether a language follows a pre-defined syntax (Shah, Shetty, Shah, & Pamnani, 2017). Parser takes input in the form of sequence of tokens and produces output in the form of parse tree.

In case of natural language, it's very difficult to define a standard grammar as there will be large number of syntactic rules (Shah, Shetty, Shah, & Pamnani, 2017). Thus, **some limited number of rules will be used and probability will be used as a measure to determine the best parse for a sentence** (Shah, Shetty, Shah, & Pamnani, 2017).

Thus, the grammar must be a Probabilistic Context-free Grammar (PCFG) (Shah, Shetty, Shah, & Pamnani, 2017).

A probabilistic context-free grammar G can be defined by the quintuple,

G = (M, T, R, S, P) where

M is the set of non-terminal symbols (like NP, VP, NN, etc.),

T is the set of terminal symbols,

R is the set of production rules,

S is the start symbol and

P is the set of probabilities on production rules (Shah, Shetty, Shah, & Pamnani, 2017).

The probabilistic version of Cocke-Younger-Kasami (PCYK) algorithm is well suited for the parser (Shah, Shetty, Shah, & Pamnani, 2017). The output of the parser will be a parse tree.

(A parse tree or derivation tree is an ordered, rooted tree that represents the syntactic structure of a string according to some context-free grammar)

From the example that we used for POS Tagger, the parse tree obtained will be (Shah, Shetty, Shah, & Pamnani, 2017):

```
(ROOT
(S
(NP (DT The) (NN bank))
(VP (VBZ provides)
(NP
(ADJP (CD 8) (NN %))
(NN interest))
(PP (IN on)
(NP (VBN fixed) (NN deposit))))
(. . .)))
```

Fig 3.5.2 Parse Tree obtained from POS Tagger

• The parse tree obtained from parser is then given to a <u>dependency parser</u> which will convert the phrase structure rules into dependencies (Shah, Shetty, Shah, & Pamnani, 2017).

Dependency Parsing

It is the process to analyze the grammatical structure in a sentence and find out related words as well as the type of the relationship between them (Jaiswal, 2021).

Each relationship has one **head** and a **dependent** that modifies the **head** (Jaiswal, 2021).

And each relationship is labelled according to the nature of the dependency between the **head** and the **dependent** (Jaiswal, 2021). These labels can be found at Universal Dependency Relations (Jaiswal, 2021).

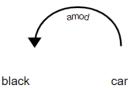


Fig 3.5.3 Example showing Dependency Parsing

In this diagram, there is a relationship between car and black because black modifies the meaning of car (Jaiswal, 2021).

Here, car acts as the **head** and black is a **dependent** of the head (Jaiswal, 2021). The nature of the relationship here is **amod** which stands for (Jaiswal, 2021)"Adjectival Modifier". It is an adjective or an adjective phrase that modifies a noun (Jaiswal, 2021).

The Dependency Parser from Stanford's API is preferred for (Shah, Shetty, Shah, & Pamnani, 2017) this purpose.

[Stanford parser_is a Java-based pure language parser. Stanford CoreNLP parser is used to perform dependency parsing. The parser supports a number of languages, including English, Chinese, German, and Arabic.]

The output will be the dependencies between various words in the sentence (Shah, Shetty, Shah, & Pamnani, 2017). Considering the example from before

```
det(bank-2, The-1)
nsubj(provides-3, bank-2)
root(ROOT-0, provides-3)
compound(%-5, 8-4)
amod(interest-6, %-5)
dobj(provides-3, interest-6)
case(deposit-9, on-7)
amod(deposit-9, fixed-8)
nmod(provides-3, deposit-9)
```

Fig 3.5.4. Dependencies between words in the given example

here det(bank-2, The-1) indicates "bank" is dependent on "The" by the relation "det" i.e. determiner and so on (Shah, Shetty, Shah, & Pamnani, 2017).

• These dependencies help in relation extraction by following some hand-written rules for extracting useful relational information from the dependencies (Shah, Shetty, Shah, & Pamnani, 2017).

Some typical examples of such relations are

- o quantity (which gives quantity of something; usually obtained from dependency nummod),
- o characteristics (like color; obtained from dependency amod),
- o main subject in the sentence (obtained from dependency nsubj), etc (Shah, Shetty, Shah, & Pamnani, 2017).

From the given example sentence, we can find the following relations from input dependencies

subject is bank, object is interest, characteristic is fixed deposit

action is provides and quantity is 8% interest

• After obtaining the relations, analysis is made **to categorize the obtained query** in the form of relations into an appropriate type (Shah, Shetty, Shah, & Pamnani, 2017).

The types are **Account related** and **General queries** (Shah, Shetty, Shah, & Pamnani, 2017).

This is essential as Account related information should be confidential. To ensure this, two authentication is done so that only the legitimate users can access such information.

• Then the relations are sent to a **Relation Matcher** (Shah, Shetty, Shah, & Pamnani, 2017). It tries to **match the query relation with the relations in a database to find any matching answers** (Shah, Shetty, Shah, & Pamnani, 2017). The database consists of relations mapped to their respective natural language sentences (Shah, Shetty, Shah, & Pamnani, 2017) (Jaiswal, 2021).

This matching is done using relation scoring as shown in Algorithm 1 (Shah, Shetty, Shah, & Pamnani, 2017).

```
Algorithm 1: Relation matching
    Let \langle A_i, R_i, B_i \rangle be a set of relations for i = 1 to k in
     the database.

 Let < P<sub>i</sub>, S<sub>i</sub>, Q<sub>i</sub> > be a set of input query relations for

     j = 1 \text{ to } m
Initialize score = 0
4. for i = 1 to k
             for j = 1 to m
                if A_i = P_i and R_i = S_i and B_i = Q_i, then
                  Add 10 to score
                else if A_i = P_i and R_i = S_i, then
                  Add 5 to score
                else if R_i = S_i and B_i = Q_i, then
                  Add 10 to score
                else if A_i = P_i or B_i = Q_i, then
                  Add 2 to score
              endfor
          endfor
return score
     end
```

Fig 3.5.5.Relation matching algorithm used

The matcher's output will be the sentence that references to a relation with highest score (Shah, Shetty, Shah, & Pamnani, 2017).

• The relation output will determine the natural language sentence that will be given as output to the user as a response (Shah, Shetty, Shah, & Pamnani, 2017).

Example of AI Based Bot

LV= is a company in the banking sector in UK. Its Broker division provides various commercial and personal line products for third-party brokers. The chatbot **alVin was** built and trained with information about LV= Broker's products. It offers live chat service to customers. It also helps with transactional tasks and is also used to connect to customer service representatives in case of complex scenarios. alVin helps automate support process for direct queries.

Chapter 4. CURRENTLY AVAILABLE BANKING CHATBOTS

4.1 Examples of Chatbots in Banks



Fig 4.1.1.Erica chatbot

6.3 12.2 105.6 12.2 Q1 2019 Q1 2020 Q1 2021 Erica Users Erica Interactions

Total Erica Users and Interactions (MM)

Fig 4.1.2 Growth in Erica's users from 2019 to 2021

1. Erica from Bank of America

The financial assistant of Bank of America is Erica. It has seen an exponential growth in its usage from 2019 to 2022. The pandemic led to an unprecedented growth in Erica's popularity. Erica is available on the Bank's mobile app and uses advanced analytics and cognitive messaging. Some features of Erica are allowing a user to view balances across all accounts, locate past transactions across a consumer's accounts, monitor recurring charges, receive bill reminders when payments are scheduled to be made and review weekly updates on monthly spending.

Erica has been able to answer more than 250 million queries since it was launched. The conversations held with Erica are secured by leading privacy and security features same that were used in online banking.

2. Ally Assist from Ally Bank: Ally Assist was one of the oldest chatbots that was launched in 2015 by the Ally Bank. Today Ally Bank's virtual assistant almost talks in customer's language. Ally Bank's assistant can talk to customers both via text and speech. The customer can log into the mobile app of the bank and click on Ally icon to chat with the assistant. Ally assist helps a user understand a transaction in detail

and it provides a wide range of services to the customer. Providing a highly personalized experience Ally Assist is also available on iPads and tablets and has surveyed that one third of the bank's customers are using mobile banking regularly.

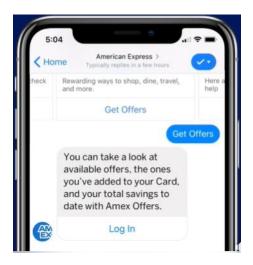


Fig 4.1.3.Amex chatbot on Facebook Messenger

3. Amex bot from American Express

The 'Amex bot' works on the bank's app and Facebook Messenger. Now American Express is adding a contextual and predictive search capability inside its app. Contextual search is gaining popularity in the field of NLP. Apart from all the basic features available in chatbots, this searching ability would be added to the bot. This search feature will try to understand scenarios and predict what a customer needs before he/she types anything on the basis of real time location and scenario tracking or in case a user opens a search after noticing duplicate transactions, it can determine they're mostly interested in claiming a credit card transaction.

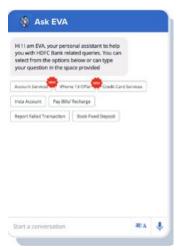


Fig.4.1.4 Eva chatbot

4. HDFC'S EVA

HDFC Bank's EVA has been the first AI banking bot in India. EVA was launched in 2017. It has answered more than five million queries from customers. Customers can get a personalized digital banking experience with EVA. EVA was built by Senseforth AI Research Private Limited, startup working on research in conversational banking. It uses NLP and AI for its working. A customer can apply for various loans, credit card and many more products through Eva.



Fig 4.1.5. iPal Chatbot from ICICI Bank

5. iPal bot from ICICI Bank.

The bot helps with general banking queries, transactions, navigation within app/website, showing personalised offers to customers and finding nearest branch and ATM. Now iPal also has been integrated with Amazon Alexa and Google Assistant for providing voice assistance features to the user for improving the customer banking experience. For using the voice banking service, Alexa or Google Assistant has to be linked with customer's ICICI bank account through a two factor authentication. Then just by speaking to Alexa or Google Assistant they will be able to view their balance, credit card details and last 5 transactions. They will also get personalized assistance regarding the bank's products and services through iPal.

6. PAi: National Payment Corporation of India (NPCI) launched the chatbot PAi to improve the online banking scenario in India.

The chatbot works 24/7 to help customers with correct information on NPCI products like FASTag, RuPay, UPI, and AePS. It was built by CoRover.

PAi was built to assist in rise of the adoption of digital payments among Indian citizens.

Chapter 5.

FUTURE OF CHATBOTS IN BANKING

Conversational banking has come a long way, but a lot remains to be achieved. Today most banks have chatbots which are able to perform the basic operations related to giving information about various products and services offered by the bank and perform simple transactions and operations. Very few chatbots are currently able to provide advanced artificial intelligence to offer predictive insights. Also chatbots in banking have still not become very task oriented and a lot of banking tasks could still be automated. Security and privacy of these banking transactions remains a major cause in not being able to automate a lot of tasks by using chatbots.

Most chatbots are unable to engage in complex conversations with users and solve complicated customer queries. There is a lot of scope for research in the field of architecture of chatbots used in banking. But with emerging trends in AI and NLP, there are predictions that chatbots will be much more commonly used. In future, chatbots will be predict human behaviour with higher accuracy and use this for self-learning. Voice bots are also gaining popularity these days and expect a lot of growth in their usage.

APPENDIX

a) PLAGIARISM REPORT

1 turnitin

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b) FREQUENTLY ASKED QUESTIONS

1. Why are chatbots used in banking?

Chatbots give the user a personalized assistance in online banking. They help the customer in getting 24/7 assistance for small banking functions and queries that earlier used to be solved by support agents. At the bank's side they reduce the burden of customer service agents and help in automating a lot of repetitive tasks. Banks are also able to collect a lot of customer's information for providing customized services. They also help in predictive analytics about a customer and help in detecting frauds in online banking.

2. Other than chatbots what is included in conversational banking? Apart from chatbots, conversational banking also includes live, in app chat with a customer support agent for solving complex queries of the customer. It also includes a video call with a customer support agent, financial advisor or banker. Other than live scheduled appointments, videos can also include pre-recorded instructional videos.

3. What are the components of AI based chatbots?

AI based chatbots include a user interface, a natural language understanding unit (NLU) that helps the chatbot classify customer's intents, knowledge base that is used for generating an appropriate response to the query, a natural language generation unit (NLG) which is used for generating a human understandable response from the machine response and a data storage unit that stores the conversations of the user with the chatbot for training and testing purposes.

4. How do rule based chatbots differ from AI based chatbots?

Rule based chatbots perform direct pattern matching of queries and responses using AIML language (which is a form of XML language). This reduces the functionality of rule based chatbots. AI based chatbots perform natural language processing on the queries entered by the user and extract the intent and meaning from the text entered by the user and hence can work with a large number of questions with less training data. AI based chatbots have higher value and are used for solving complex queries than rule based chatbots. However rule based chatbots are still preferred for smaller specific industries.

5. What is dependency parsing?

Dependency parsing is analyzing the grammar and assigning relationships between the words. In each relationship there is one word which is the head as the other is the dependent word that modifies the head.

6. Give example of rule based chatbot.

ALICE chatbot is a main example of rule based chatbot. Chatterbot is another example.

7. Name some chatbots that are currently used in banks.

Some chatbots currently used in banks are EVA (used by HSBC), Erica (used by Bank of America), Amex chatbot (used by American Express), iPal(used by ICICI Bank), Keya(used in Kotak Bank).

GLOSSARY

Chatbot: Chatbots allow customers to manage requests swiftly and efficiently while acting as a listening channel so that banks can better understand user habits, anticipate customer actions and deliver personalized offers and services.

AI: Artificial intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions.

NLP: Natural language processing (NLP) refers to the branch of computer science—and more specifically, the branch of **artificial intelligence or AI**—concerned with giving computers the ability to understand text and spoken words in much the same way human beings can.

NLG: Natural language generation (NLG) is the use of artificial intelligence (AI) provided programming to produce written or spoken narratives from a dataset.

NLU: NLU is understanding the meaning of the user's input. Primarily focused on machine reading comprehension, NLU gets the chatbot to comprehend what a body of text means. NLU is nothing but an understanding of the text given and classifying it into proper intents.

AIML: AIML stands for Artificial Intelligence Modelling Language. AIML is an XML based Markup language meant to create artificial intelligent applications.

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