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CHATBOT FOR KNOWLEDGE – BASED MUSEUM RECOMMENDER SYSTEM (CASE STUDY: MUSEUM IN JAKARTA)

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ABSTRAK

Sistem pemberi rekomendasi yang umum digunakan untuk merekomendasi museum adalah content-based filtering dan collaborative filtering. Tetapi, sistem pemberi rekomendasi tersebut mengalami permasalahan seperti cold start dan data sparsity, karena beberapa museum masih memiliki rating dan feedback yang rendah. Untuk mengatasi masalah tersebut, knowledge-based recommender system dapat digunakan untuk memberikan rekomendasi museum berdasarkan preferensi pengguna, sehingga sistem tidak perlu menggunakan rating dan feedback. Preferensi pengguna bisa didapatkan menggunakan conversational recommender system dengan memanfaatkan percakapan dua arah antara pengguna dengan sistem. Chatbot merupakan salah satu bentuk conversational recommender system yang umum digunakan. Penelitian ini mengembangkan sebuah chatbot untuk merekomendasikan museum di Jakarta menggunakan knowledge-based recommender system. Sistem yang dikembangkan menggunakan Rasa framework untuk membangun chatbot yang mampu melakukan percakapan dengan pengguna. Knowledge graph dan k-nearest neighbor digunakan untuk merekomendasikan museum berdasarkan preferensi pengguna. Berdasarkan evaluasi yang telah dilakukan, sistem yang dikembangkan dapat memahami pesan pengguna dan memberikan rekomendasi museum berdasarkan preferensi pengguna. Tetapi, performa sistem masih dapat dikembangkan supaya sistem dapat diandalkan pada skenario dunia nyata.

Kata Kunci: *knowledge graph, recommender system, chatbot, cultural heritage*

ABSTRACT

Recommender systems that are generally used to recommend museums are content-based filtering and collaborative filtering. However, those recommender system have problems such as cold start and data sparsity because some museums still have a low rating and feedback. To handle those problems, knowledge-based recommender system can be used to give museum recommendation based on the user preferences, so that the system does not need to use rating and feedback. User preferences can be obtained using conversational recommender system by utilizing two-way conversation between the user and the system. Chatbot is one of the forms of conversational recommender system that is generally used. In this paper, a chatbot for recommending museum in Jakarta using knowledge-based recommender system has been developed. The developed system uses Rasa Framework to develop a chatbot that can hold a conversation with the user. Knowledge graph and k-nearest neighbor are used to give museum recommendation based on the user preferences. Based on the evaluation that has been done, the developed system can understand user messages and give museum recommendations based on the user preferences. However, the system performance can still be improved so that it is reliable in a real-world scenario.

Keywords: *knowledge graph, recommender system, chatbot, cultural heritage*

I. INTRODUCTION

In general, museum recommender systems use content-based filtering and collaborative filtering [1][2][3]. However, museum recommender systems that use content – based filtering and collaborative filtering have problems such as cold start and data sparsity, because some museums still have a low rating and feedback [4]. These problems can be handled by using knowledge-based recommender system [5].

Ontology is one of the knowledge representations that is often used in the development of knowledge-based recommender system [6]. Center for Intercultural Documentation Conceptual Reference Model (CIDOC CRM) is an ontology that is often used for cultural heritage domain such as museum, because it is the standard ontology for cultural heritage domain [7].

Knowledge-based recommender system does not depend on the amount of user rating or user feedback. However, the recommendation is done based on user preferences [8]. Meanwhile, conversational recommender system is one of the forms of knowledge-based recommender system, where user preferences is obtained via a conversation [9]. Conversational recommender system also has many kinds of forms, one of the forms that is often used is chatbot

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[10].

Capuano et al., [2] developed CATReS (Context-Aware Recommender System) using content-based filtering and collaborative filtering to recommend museum visit path based on contextual information (e.g., weather, transportation) and user preferences using chatbot. Contextual information that are used is obtained from the user smartphone. However, there are still problems that is often faced by the recommender system that is used by the system such as cold start and data sparsity. Lee et al., [11] developed an ontology-based tourism recommendation system using semantic web technology such as Protégé and SPARQL query language. The method that is used can handle the cold start and data sparsity problem that is faced by content-based filtering and collaborative filtering, but this system needs to be implemented to a website first with jQuery before it can be used.

This research developed a chatbot using Rasa framework, an open-source framework to build a chatbot. The chatbot utilizes museum ontology. We developed the museum ontology by using TypeDB, a tool to develop a knowledge graph that represents an ontology in the form of entity relationship diagram [12]. The differences between *TypeDB* and semantic web standards technology (i.e., Protégé) [13] is that TypeDB is not as complex as semantic web standards, TypeDB works better with a more complex data, Protégé is made for the web, whereas TypeDB is made for a closed system [14].

The purpose of this research focused on developing a system that can recommend museums in Jakarta using TypeDB's knowledge graph based on the preferences that is given by the user via chatbot. K-nearest neighbor is also used to recommend museums that has attributes with high similarity [15]. Museum information that are used in the system is taken from the book "Katalog Museum Indonesia Jilid 1" that is published in the year 2018 by "Kementrian Pendidikan dan Kebudayaan Idonesia."

II. RESEARCH METHOD

A. System Design

The system development stage that we have done for this research is shown in fig. 1. Our system uses a chatbot that is developed using Rasa components to understand the user messages and an interface that can be accessed via a browser. The chatbot also uses custom actions (functions) to send and receive data from the knowledge graph and k-nearest neighbor. The knowledge graph and k-nearest neighbor gives a list of 15 museums recommendation and are shown by the chatbot interface. The workflow of the system that we developed is shown in fig. 2.

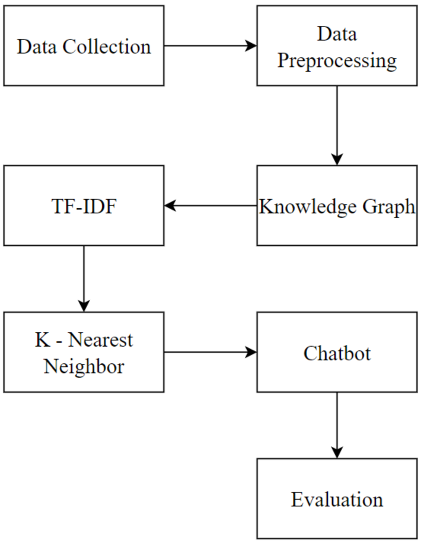

Fig. 1. System development stages

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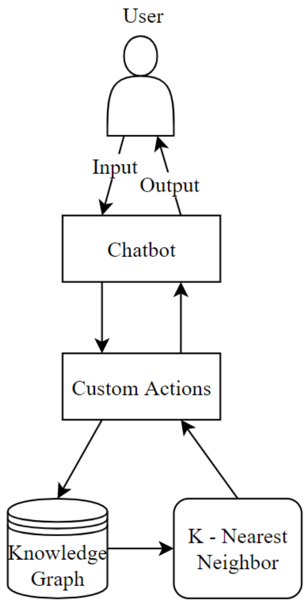

Fig. 2. The system workflow

B. *Data Collection*

The museum data are taken from the book “Katalog Museum Indonesia Jilid 1.” This book has information about museum from several cities in Indonesia. Our system utilizes museum information located in Jakarta city. The numbers of museum located in Jakarta are 61 museums. The data from the book are information that can be used by museum visitors. Data example from the book is shown in table 1.

TABLE I
DATA EXAMPLE FROM THE BOOK “KATALOG MUSEUM INDONESIA JILID 1”

Attribute Name	**Attribute Value**
Museum Name	Art: 1 New Museum
City	Jakarta Pusat
Category	Seni
Description	Art: 1 New Museum merupakan museum khusus …
Visit Time	Selasa – Sabtu 10:00 – 18:00
Entry Ticket Price	Umum Rp100.000,00, ... , Pelajar Rp75.000,00
Facebook	Art: 1 New Museum
Twitter	@art1_newmuseum
Instagram	@art1newmuseum
Phone	(021) 64700168
Email	info@mondecor.com
Website	http://www.mondecor.com
Address	Jl. Rajawali Selatan Raya No 3, Jakarta Pusat
Coordinate	6°08’48.9”LS 106°50’24.4”BT
Distance to Museum	Dari Stasiun Rajawali 750 m, …, Dari Stasiun Sawah Besar 3,2 km

Before we use the data in table 1, we separate “Distance to Museum” into “Public Transportation” and “Distance from Public Transportation,” “Visit Time” into “Schedule,” “Open,” and “Closed.” For “Coordinate,” we change it to latitude and longitude. Table 2 shows data example that the system uses.

TABLE II
DATA EXAMPLE THAT THE SYSTEM USES

Attribute Name	**Attribute Value**
Museum Name	Art: 1 New Museum
City	Jakarta Pusat
Category	Seni
Description	Art: 1 New Museum merupakan museum khusus …
Schedule	Selasa, Rabu, …, Sabtu

Open	10:00
Closed	18:00
Ticket Category	Umum, ..., Pelajar
Ticket Price	Rp100.000,00, Rp75.000,00, …
Facebook	Art: 1 New Museum
Twitter	@art1_newmuseum
Instagram	@art1newmuseum
Phone	(021) 64700168
Email	info@mondecor.com
Website	http://www.mondecor.com
Address	Jl. Rajawali Selatan Raya No 3, Jakarta Pusat
Latitude	-6,146950173
Longitude	106,8402895
Public Transportation	Stasiun Rajawali, …, Stasiun Sawah Besar
Public Transportation Distance to Museum	750 m, …, 3.2 km,

C. Data Preprocessing

We do data preprocessing so that the data does not have a null value, unsuitable data format and an attribute that is not required for the recommendation process. The data preprocessing covers data cleansing, data wrangling, data transformation and normalization. We also remove stop words, punctuation, numbers, converts all words to lower case and do lemmatization to all words for description attribute.

Data cleansing is a process to remove null value and remove attributes that is not required for the recommendation process. Table 3 shows museum attributes after the data cleansing process.

TABLE III
MUSEUM ATTRIBUTES THAT THE SYSTEM USES

Attribute Name	**Attribute Value**
Museum Name	Art: 1 New Museum
City	Jakarta Pusat
Category	Seni
Description	Art: 1 New Museum merupakan museum khusus …
Schedule	Selasa, Rabu, …, Sabtu
Open	10:00
Closed	18:00
Ticket Category	Umum, Pelajar, ...
Ticket Price	Rp100.000,00, Rp75.000,00, …
Public Transportation	Stasiun Rajawali, Stasiun Sawah Besar, …

Data wrangling is a process to change data shape for an attribute so that it can be processed by other processes. Value in “Ticket Price” has rupiah symbol and a separator such as full stop symbol and a comma that is not needed, therefore “Rp100.000,00” and “Rp75.000,00” are changed to “100000” and “75000.”

Data transformation is a process to format data type in an attribute that has data type such as object, string to numerical. For attribute that has categorical type such as “City,” “Category,” “Schedule,” “Ticket Category,” and “Public Transportation” is formatted to binary using one hot encoding. Whereas for “Open” and “Closed” are formatted to seconds, thus becoming numerical by using (1), with $t(h,m)$ is a function to convert time to seconds, h is unit of hour, m is minutes.

$$t(h,m) = (h \times 3600) + (m \times 60) \qquad (1)$$

Normalization is a process to change the numerical data in a set of data to use a generalized scale. The attribute “Ticket Price,” “Open,” and “Closed” are going to be normalized with min – max normalization using (2), with x is the value of an attribute that will be normalized, x' is value of x after normalized, min (x) is minimum value in an attribute, max (x) is maximum value in an attribute.

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$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{2}$$

D. Knowledge Graph

We use knowledge graph as a knowledge representation for the chatbot. Knowledge graph has an ability to do automatic reasoning by using some rules, so that they can get an implicit information from explicit data [12]. We developed the knowledge graph using CIDOC CRM ontology. CIDOC CRM provides Class (E) and Property (P) definition to transform museum information that we use into an ontology [16]. Ontology that we developed is shown in fig. 3.

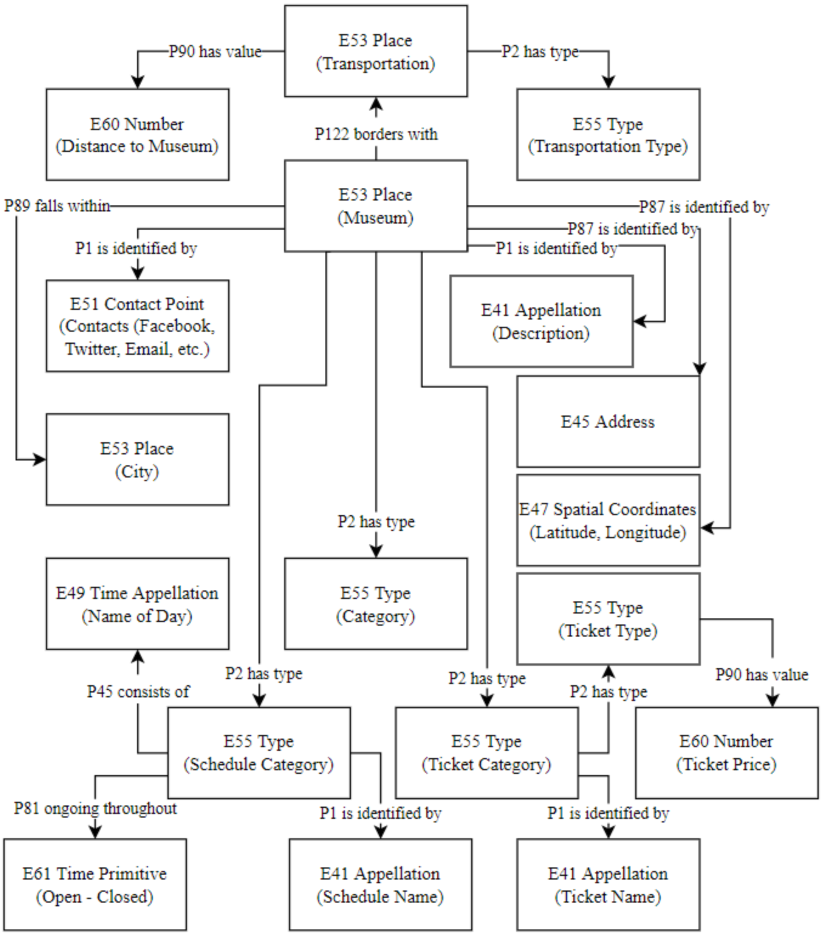

Fig. 3. Museum ontology using CIDOC CRM

Our knowledge graph has some rules for recommending museums. Table 4 shows the rules that we use. Our knowledge graph gives 5 museums recommendation using the rules in table 4. Ontology and rules are implemented using TypeDB. TypeDB can show the visualization of the knowledge graph that has been developed (fig. 4).

TABLE IV
RULES FOR THE SYSTEM'S KNOWLEDGE GRAPH

Rule Name	Rule Condition
Nearby museums	If museum A and museum B can be accessed with the same public transportation, with distance less than 10 km, then museum A and museum B is nearby to each other.
Museum has ticket price “paling murah”	If user ask for ticket price “paling murah”, then give museum that has ticket price less than Rp4.000.
Museum has ticket price “murah”	If user ask for ticket price “murah”, then give museum that has ticket price greater than or equal to Rp4.000, and less than Rp15.000.

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Museum has ticket price “mahal”	If user ask for ticket price “mahal”, then give museum that has ticket price greater than or equal to Rp15.000, and less than Rp50.000.
Museum has ticket price “paling mahal”	If user ask for ticket price “paling mahal”, the give museum that has ticket price greater than Rp50.000.

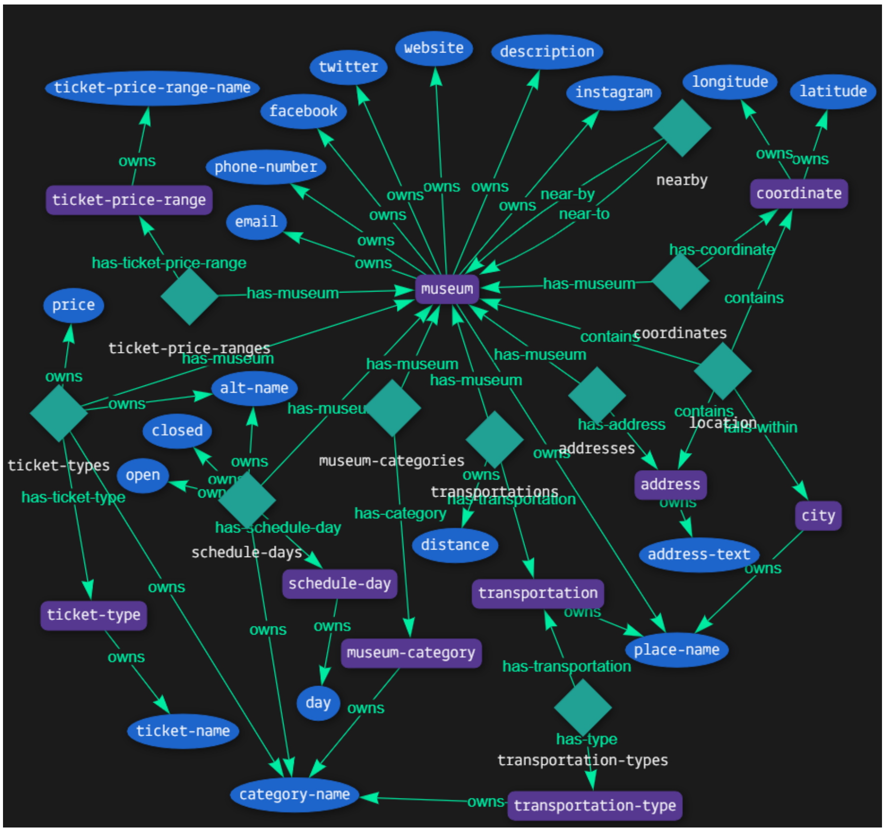

Fig. 4. Visualization of the system knowledge graph using TypeDB

E. TF-IDF

Term Frequency Inverse Document Frequency (TF-IDF) is an algorithm to get the weight value of all words in a document. TF-IDF is used to get the weight value of all words in a museum description, then those weight value are used to get the similarity value between museums. Weight value of a word is obtained by using TF-IDF Vectorizer, that will make a vector that contains weight value of every word in a museum description.

F. K-Nearest Neighbor

We use k-nearest neighbor (KNN) to add more recommendation based on the first museum obtained from knowledge graph. KNN recommends museums with the same characteristic [15]. KNN obtains the recommended museum by comparing museum attributes using a distance metric [17] to get the similarity distance between museums. We use (3) for the distance metric in our KNN implementation.

$$d(x,y) = 1 - \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2}\sqrt{\sum_{i=1}^{n} y_i^2}} \quad (3)$$

with $d(x,y)$ is cosine distance function, x is attribute from museum x, y is attribute from museum y, n is total attribute from museum x and y. The museum is recommended based on the distance close to 0 between museum x with other museums. KNN in our system will recommend 10 museums.

G. Chatbot

Chatbot acts as an agent that will help to give user museums recommendation. Chatbot uses variable name to store data such as chatbot messages to reply to user messages or the user responses. Our chatbot uses questions to obtain the user preferences. Some questions that we use is shown in table 5.

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TABLE V
QUESTIONS TO OBTAIN USER PREFERENCES

Variable Name	Questions
ask use public transport	Apakah kamu akan menggunakan kendaraan umum, kendaraan pribadi atau tidak pakai kendaraan?
ask schedule day	Di hari apa saja kamu bisa mengunjungi museum?
ask ticket price	pilih salah satu kategori harga tiket yang kamu mau: - paling murah - murah - mahal - paling mahal

The chatbot that we developed uses Rasa framework. We need training data, stories, rules, and actions to use Rasa. Training data is a set of data that are used to train the chatbot. Training data has an intent name and example of sentences and words as data set to train the chatbot along with several entities. Entities in training data are words that are used as a value for the user preference for an intent. Some training data that we use are shown in table 6.

TABLE VI
TRAINING DATA SAMPLE TO TRAIN THE CHATBOT

Intent Name	Training Data
greet	halo, hello, hey, hi, hai
goodbye	terima kasih, selamat tinggal, sampai jumpa
use public transport	kendaraan pribadi, tidak pakai kendaraan, pakai kendaraan umum
schedule day	Saya berangkat di hari senin, selasa, rabu, di hari Jumat, Sabtu, Minggu
ticket price	Yang murah, paling mahal, saya mau yang termurah, saya pilih yang mahal

An example of entities in Table 6, can be found in the intent "schedule day", the entities are "senin," "selasa," and "rabu," because those days will be used as a value for the user preference for the question "ask schedule day" in table 5.

Actions give the chatbot some functions to do a certain action. The actions that we give to the chatbot are functions for querying the knowledge graph, return museums recommendation and give museum information.

Stories are the conversation flow that will be carried out between the chatbot and the user. A story has a name and the steps for the conversation flow. Chatbot can have more than one story, and a story can lead to a fulfilling (Happy path) or unfulfilling (Unhappy path) conversation. Table 7 shows stories example that we use in our system.

TABLE VII
STORY EXAMPLES

Story Name	Story Path
Happy path	- ask use public transport - intent use public transport - ask schedule day - intent schedule day - ask ticket price - intent ticket price - action submit answers - action get recommendation - found recommendations - send list of recommendations
Unhappy path	- ask use public transport - intent use public transport - ask schedule day - intent schedule day - ask ticket price - intent ticket price

	- action submit answers - action get recommendation - recommendation not found - send recommendation empty message

The difference between the story “Happy path” and “Unhappy path” in table 7 is that “Happy path” ends with the chatbot able to give a list of museum recommendation, while “Unhappy path” ends with the chatbot unable to give a list of museum recommendation to the user.

Rules are instructions for the chatbot to follow according to the order of intent and action in the rule. Without a rule, a conversation between chatbot and user can lead to an undesired conversation flow or the chatbot uses the wrong action.

H. Evaluation

We evaluate the system based on user satisfaction using a survey. The survey has 7 questions that covers the chatbot and the recommender system. The survey questions are categorized into Recommendation (R), Conversation (C), Informative (I), Usability (U), Future Developments (F), to evaluate the system. Users can choose between Totally Agree (TA), Agree (A), Neutral (N), Disagree (D), Totally Disagree (TD), according to the survey statements. The survey that we gave to the users uses these statements shown in table 8.

TABLE VIII
SURVEY STATEMENTS FOR SYSTEM EVALUATION

No	Category	Statements
Q1	R	Recommendations given by the chatbot fulfill the user needs based on the preferences that are given by the user.
Q2	C	The conversation with the chatbot went smoothly without any wrong responds from the chatbot.
Q3	C	The chatbot can understand the intent / respond from the user.
Q4	I	The provided museum information is informative and helpful.
Q5	I	The provided museum information is presented appropriately.
Q6	U	The time needed for the chatbot to respond is relatively fast.
Q7	F	It would be better if the chatbot is implemented on a chat platform like WhatsApp / Telegram.

III. RESULT AND DISCUSSION

A. Implementation

The chatbot that we developed uses the interface provided by the Rasa Framework. The chatbot interface is accessible via a web browser. The interface that we use is shown in fig. 5. The interface has a chat window to show the conversation and an input text with a send button to send a message. The conversation can be started with a greeting. The recommendation process started after the user replies to the greeting from the chatbot.

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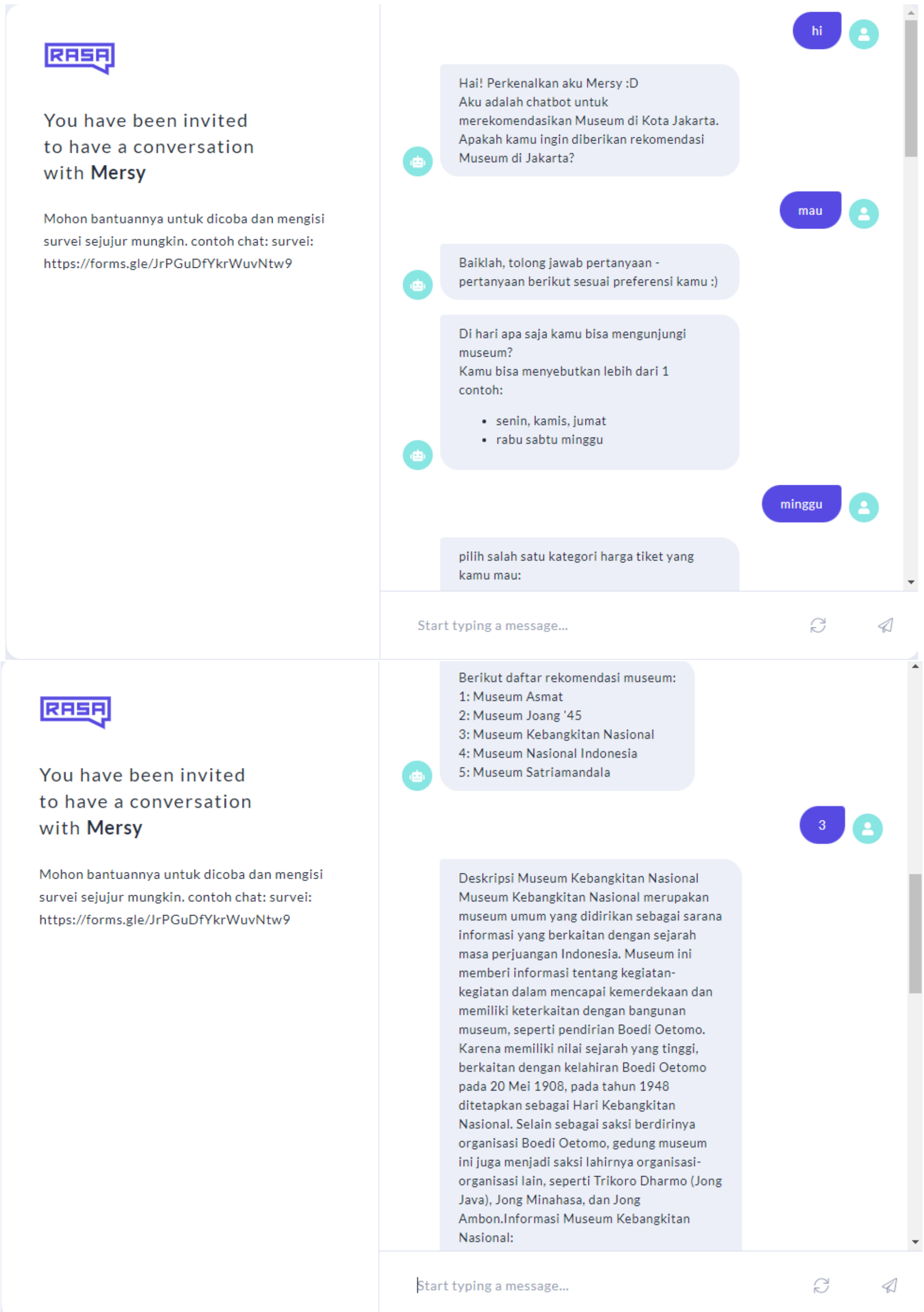

Fig. 5. Some screenshots of the chatbot interface

B. Survey Result

The survey is given to users after they have tried using the chatbot that we developed, so that users can give their answers objectively. A total of 40 college students with the age of 18-22 years old tried to use the chatbot and answers the survey. The survey result is shown in table 9.

TABLE IX
NUMBER OF SURVEY ANSWERS BY CATEGORY

Kategori	Jawaban				
	TA	A	N	D	TD
R	25%	67,5%	7,5%	0	0
C	22,5%	58,75%	13,75%	5%	0
I	37,5%	46,25%	11,25%	5%	0
U	12,5%	52,5%	25%	10%	0
F	55%	42,5%	2,5%	0	0

Usability (U) has the highest negative feedback. Some users feel that time needed for the chatbot to reply is not fast enough. This can happen largely due to bad performance when the chatbot and the recommender system are processing the data. This suggests that we need to improve the chatbot performance when processing and sending messages. We also need to improve the system performance in the recommendation process.

Recommendation (R) and Future Developments (F) have the highest positive feedback. This suggests that the system can fulfill the user needs, by giving recommendations based on user preferences, and most users wants the chatbot to be accessible via chat applications such as WhatsApp and Telegram.

IV. CONCLUSION

This research has developed a chatbot for recommending museums in Jakarta using knowledge-based recommender system. According to the survey, the developed chatbot using Rasa framework can understand the messages sent by the user and respond correctly to the user. The system can also give museum recommendations based on the user preferences using TypeDB's knowledge graph and k-nearest neighbor. However, the system has slow performance when it's looking for recommendations and responding to the user. The system performance needs to be improved so that the system can be used and relied upon in real-world scenario.

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