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DEVELOPMENT OF AN INTELLIGENT RECOMMENDER ASSISTANT USING THE TELEGRAM PLATFORM

Abstract: The article includes theoretical information about the types of recommender systems, stages of developing our own system of recommendations, mathematical information about the estimation formula for rating and the formula itself. And the article also explains the work of Telegram bot.

Key words: recommender systems, Telegram

Language: English

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Introduction

We live in the era of new technologies. And we guess it's better to say that now almost every man has smartphone, tablet or another equipment which allow him to surf the Internet. Everyday people use the metro, buses, taxis, and we see that they can't let their phones out of hands. They are reading electronic books, listening to music, surfing the Internet to know something interesting, writing messages, calling friends and relatives. Besides now the best way to send message is to send it online with the help of special messenger or by SMS, then send it by postal service.

This article is covered the theme of conversation between people and the theme of special programs which makes this conversation possible. One of the most modern developments are messengers where registration takes about few minutes and all you need is to enter your phone number and login.

Telegram is cloud-based instant messaging service found by the Russian entrepreneur Pavel Durov. Users can send messages and exchange photos, videos, stickers, audio and files of any type. Everyday about 600.000 people use Telegram for a lot of different things: they are writing messages, reading the news channels (now almost every site, online magazine or store has its own channel where it is telling people about its activity and other special news) [1][2].

But Telegram is known not only for its chats and channels, it is also known for bots - some kind of program which is fully automatic and can do a lot of things, it is an assistant like Siri or Alexa but exists in Telegram. For example, bot can send you everyday jokes or fun pictures, music or news, or may be if you want to receive weather announcements it can do it too.

So this is the best way to say that the theme of article is relevant and important because if thousands of people use this messenger, use a lot of different bots of its, so we guess they are really interested in in such built-in apps, which have some intelligence and people can spend really fun time while they are on the bus.

Therefore, it seemed to interesting to start developing such a mini-helper which will advise users what to drink depending on the products that users entered into the chat, so that bot will choose the most suitable of all drinks, because we hope you are not supposed to drink milk with cucumbers. Of course, it is obvious that every person is able to choose for its own but if he is totally not sure about what drinks is proper for red meat or oyster then the bot will easily make this choice.

In this case, the bot itself is interesting not only from the user's side but also from the developer's. In order to fully organize the work of an assistant program it is not enough to just write the code using one of the programming languages, you must also create a database, otherwise the bot would be quite



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primitive without a warehouse for keeping the important data and all the code should be push on the remote server for autonomous operation. And most importantly is to add some intelligence to bot, because first of all it should be like human - say «hello», ask about people's choice, ask to score drinks and other things to do and secondly it could with great believability and confidence offer the user the right drink.

The aim of the article

The aim of current work is to develop an intelligent advisory assistant which will be helpful and useful for a lot of people who use messenger for real lifetime. And before this aim, the following tasks were set: first, to analyze the area of bot working, then make the research about the types of recommendation algorithms and estimation systems, develop the bot module using Python language and create our own recommender system suitable for current project, develop a database using the PostgreSQL database management system, and as it was said before to push the ready-to-use application to the Heroku for autonomous work.

Stack of used technologies

The practical part of this article is to develop an intellectual program that is integrated into some messenger, followed by pushing out on the PaaS-platform for autonomous work.

Python programming language is used for developing [3], because firstly this language is the most used for writing bots, it is in the top five programming languages, it is brief and easy in syntax, it allows you to create complex code without spending a lot of time resources on it and the program itself looks more compact and readable.

In addition to writing a program in a programming language, the project being developed

has a different component - the database. It was decided to choose a DBMS like PostgreSQL, because it is free and available, meets all the requirements that must be implemented to develop the current database, and it is also well integrated with the Heroku service.

Heroku is a cloud-based PaaS platform. PaaS stands for Platform as a Service, that is, "platform as a service" - the user gets access to the use of various information platforms: operating systems, database management systems, development and testing tools, and so on. In this case, we put the developed program on Heroku, connect a special add-on (appendix) with the database and the bot then works off-line when accessing it via Telegram.

Content of database

The main purpose of the database is to store data for the proper operation of the bot.

It should contain organized tables for the rating system: a global rating for all users and a local rating for each user separately.

Each product has its own category, that is, cucumber - vegetable, cottage cheese - a dairy product.

And each drink has its own subcategory: juice - orange, apple, multifruit, etc. So, it is necessary to create two special tables for this purpose.

Also, in database should be created a table with contextual information: to which product the user chose which drink - it will help further to select drinks using content filtration.

Combinations of drinks and products

As it was said before, the developed bot will make offer to drink something based on the entered by user products. To analyze the compatibility of drinks and products various cookbooks, infographics and articles of culinary blogs were used [4][5].

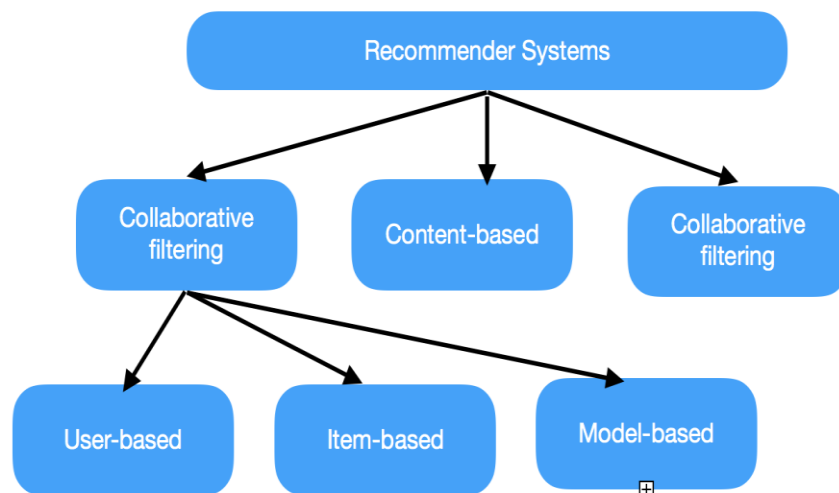


Fig. 1 The types of recommender systems

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From these sources different names of drinks were taken, also rules how to properly combine fish, meat, seafood, sweets and other categories of products with wines, juices, various types of tea, water and so on. Different infographics were useful too.

Types of recommendation

In order to understand the essence of present telegram-bot, it is necessary to introduce the definition of a recommender system - it is a program that tries to predict which objects (movies, music, announcements, new) will be interested to user based on its information in profile [6].

There are three main types of recommender systems (Figure 1):

1. Content-based filtration
2. Collaborative filtration
3. Hybrid approach

Let's discuss the first one - *content-based method*. This kind of recommender systems tries to recommend items similar to those a current user has liked in the past. The basic process consists in matching up the attributes of a user profile in which preferences and interest are stored, with the attributes of content object (item) in order to recommend to the user new interesting items.

The second is *collaborative filtration*. It is a method that instead of recommendation of similar past liked items tries to identify users which have the same interests as current and make recommendations based on the opinion of users group. The key idea is that the rating for a new and non-rated object of user A will be similar to the rating of this item belonging to user B, if A and B rated other items in the same way. Likewise, user A will probably score two items *i* and *j* in a similar way, if other users of the system gave the same ratings to these items.

Collaborative filtering has a great advantage over the content method: for example, for objects that do not have such additional information, it is still possible to predict the recommendations based on the assessments and feedback of other users using the collaborative method.

In addition, this kind of recommendations is based on the quality of items, for example, the film is specifically rated for its plot, genre, actors' game in general, and the context in this situation may not be useful, and even be a poor indicator of quality - not in all good movies are played by famous actors, in which case you cannot rely on additional information in the form of a list of people who have played in the movie.

There are three types of collaborative filtration:

1. User-based is looking for users who are similar to the current one (let's say user R) - to determine such neighbors different metrics of similarity are used (for example, the metric of the cosine or the Chebyshev distance) and based on estimates of the most similar neighbors with R,

estimates are calculated for objects not yet evaluated by the user.

2. Based on the similarity of objects (Item-based) - is to predict what kind of rating the user will give to the object O, using those products that are most similar to this one.

3. Based on the model (model-based) - in this method, a model of preferences of users, objects and their interrelations are first formed, and then recommendations based on this model are formed.

And the last one is *hybrid approach*. It is kind of recommendations that combines the previous methods of collaborative and content filtering. Due to this, it is possible to avoid some of the limitations that these systems possess. The advantages of this approach can be considered on a concrete example.

For example, one user appreciated the resource associated with Oracle databases, and another user choose a source about PostgreSQL for studying databases for himself. Using only collaborative filtering based on the neighborhood of users, will show nothing useful, but content filtering will show what databases users were interested in, and it is possible for each of them to recommend opposing databases, since they have common information. Thus, a combination of different methods makes it possible to obtain more extensive recommendations.

Selection the type of recommender system

Since we are creating such an assistant program that will recommend certain drinks to users, it is needed to come up with and develop a confident algorithm of recommendations, so that the person would be offered the most suitable set of drinks for the introduced products at the moment.

For this purpose, it was decided to choose hybrid method of making recommendations, namely, the collaborative filtering is combined on the basis of user evaluations (that is, item-based collaborative filtering, but searching for objects that were not similar to each other, but the most common ones) and the content filtering approach.

The main object for recommendations to a particular user A are the scores of the rest of the users of the system - the collaborative method, and the content filtration consists in selecting only those drinks that have been selected for to those products that user A entered. In addition, also at the last step before the conclusion of getting the final set, the opinion of the user himself (his previous ratings), if there are any.

To sum up, we select drinks based on the context, using user ratings, in order to kick out low-priced drinks, and take advantage of the person's opinion.

Steps of recommendations

In order to recommend drinks reasonably, a system of selection stages was developed. And let's



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discuss the steps of the system. For example, User has entered three different products - Product 1, Product 2 and Product 3 - and all items belong to different product categories.

First step is the step of usual selection. Each of the entered products is compared to its product category: a vegetable, a fruit or maybe it is a seafood. The database already has a table of comparability for each of the product categories and drinks, and the initial set of juices, waters and everything else that can be drunk along with specific products is collected. And also, when compiling a set, we count how many times a given drink has met, that is, it is suitable for one dish or can be for all entered. It can look like this: {Drink 1: 3, Drink 2: 3, Drink 3: 2, Drink 4: 1}.

Then we need to choose those drinks which are more suitable for all entered drinks. For this we:

1. Find the maximum number of occurrences for all drinks - Max

2. Then pass through all the elements of the initial set and find the ratio of the occurrence of a particular beverage (denote as CurrentValue) to the maximum value - Max, and call this relation Relate

3. Define Relate:

- 3.1. If the value of the Relate is 50% or upper, we can relate on this drink, it means that this drink is suitable for at least half of the products. And at the end of selection we will have new set of drinks which parameters of occurrence are in the range [CurrentValue; Max].

- 3.2. If the value of Relate is lower than 50%, this drink is not suitable for the set of entered products and add it to DrinksToCancel.

After the first step we have final set with appropriate drinks - DrinksToChoose and set DrinksToCancel which consists of the rejected drinks.

The second step is context selection. Here we create a new set based on context, that is, we select drinks that were selected by other users with the same entered products. From this set of new drinks, we choose only those drinks that are not in DrinksToCancel (if there are any) and add them to DrinksToChoose.

The third step is based on global rating of drinks. In system we have a special table - GlobalRate that includes score for each drink that were calculated based on user personal ratings.

We find all scores for all drinks from DrinksToChoose, then we are looking for a median of the number series, and those drinks which have rating above this median are considered as more popular and we add them to a new set Drinks.

And the last step is based on selection from Drinks set according to User personal preferences. We select score for each drink from a separate table. And if one of the drinks was rated too low, it means

that User does not like this drink and it will be wisely not to include it into final set for output.

At the end of this system of selection stages we get set of suitable drinks which will be outputted for user in chat.

Estimation formula

At one stage of the current recommender system, drinks are selected according to their global rating, which is calculated on the basis of the users' estimates that they entered when choosing this drink. Therefore, a specific question arises - how to calculate this global rating

Initially it was supposed, as the simplest variant, that it is possible to take the arithmetic average for all user estimates for one drink, but this method is not optimal and accurate. Why? Let's consider an example: suppose there is a very rare, specific drink X, which is not very popular with most people, and it is of interest only to a limited number of people. You can accurately say that this small circle, when you display such a drink on the screen, will choose it and give it a high mark.

There is also a drink Y, which is sold in every store, is constantly advertised and is in everybody's mind, and thanks to the same advertisement, people buy it and try it, which means that a large number of people will choose it in our bot (or it will be offered for post-evaluation) and will assess it. Thus, we get the following possible data, indicating that the average score for drink X will be higher than the average for Y, although the second estimated a much larger number of people interviewed.

Therefore, we can say that in fact the average is not an accurate, convincing proof of the quality of the product, and it is necessary to find another method for calculating the rating.

In the process of searching for such a method, it was decided to use one of the existing algorithms [7][8] for calculating the rating - (1).

$$W = \frac{R \cdot v + C \cdot m}{v + m} \quad (1)$$

Let us consider in more detail its components:

- W - calculated weighted rating
- R - average rating on a drink
- v - number of votes per drink
- C - the average value for all drinks in the system
- m - the number of votes in order for the estimate to be considered plausible.

This formula is used by many sites that are designed to make ratings of films, books, various institutions, users, and so on. The most famous of these sources are IMDB and Kinopoisk. They use current formula to calculate the Top-250 rating of the

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film. In their systems, they use constant values for the parameters m (the number of votes to hit the top 500 for Kinopoisk and 25,000 for IMDB) and C (the average for all movies is 7.1715 and 7, respectively), because they have a large number of users and they do not have a cold start problem.

The bot is also designed for an unlimited number of users, but at the time of first launch and further development may not have enough people to declare specific constant values for the necessary parameters. Proceeding from the above arguments, another question arises: how to choose the right parameters for the system that has not yet been formed, so that the rating can be reliably calculated even with a small number of users participating in the evaluation.

To calculate the average value for all drinks (C parameter), a completely logical solution suggests - after inputting an estimate by any user, recalculate the average, and if there are already a large number of people in the system, the average is normalized, and then it can already be taken as a constant value and not recalculated by adding each estimate, but with a significant increase in the number of users from the time when this constant value was calculated.

As for the parameter m (the number of votes for the evaluation to be considered plausible): it was decided to recalculate this parameter depending on the number of users using the formula for determining the sample size. Let us consider in detail the algorithm for calculating it.

First, we introduce some necessary concepts to understand next parameters [9].

Statistical (general) population is a group, about which we want to draw conclusions, in this case it is the total number of users in the system.

The sample is a group of people who appreciated the drink.

Margin of error - a parameter that shows how effective the user poll will be, the smaller the error, the more accurate the answer will be at a certain level of confidence.

Confidence level - a parameter that shows how reliable the results will be. The value of this parameter is set at 90%, 95% and 99%. When determining the sample size, the z-score (coefficient) of the confidence level is used, which is calculated using a special Z-table [10] depending on the level of confidence.

Percentage - the sample size requirements may vary depending on the percentage of the sample that gives a definite answer (for example, how many positive responses have been given). If in one of the polls it was found that 75% of people positively assess the drink, then if you transfer the system to a new messenger or take it to a separate application, then for new calculations you can use a new percentage value.

Now we give the necessary formula and write down its parameters - (2).

$$\frac{\frac{z^2 \cdot p \cdot (1-p)}{e^2}}{1 + \left(\frac{z^2 \cdot p \cdot (1-p)}{e^2 \cdot N}\right)} \quad (2)$$

Its components:

- p - percentage value, for the developed system it was decided to take the value 0.5, so we get an approximate sample size that will not be either too conservative or too free.
- e - margin of error (use the value of 5% - 0,05)
- z - z-score, as mentioned above, is a value that is taken from the table, depending on the level of confidence. Since the most commonly used is the confidence level of 95%, based on it we take the z-score of 1.96
- N - the size of the general population, the number of users in the system.

Example of conversation

So after all the theoretical work, we started to develop the real program using programming language Python and PostgreSQL to create database.

The bot was developed with all claimed technical requirements:

- Create database
- Create module of the bot and integrate it with Telegram
- Develop estimate formula for drinks
- Develop an intelligence for the bot, so that it can respond to human requests correctly
- Push the code of program to Heroku for autonomous work

The conversation between the bot and the person is that a person enters a command or a word and the bot react to it.

System has four commands:

- start - you begin to communicate with bot
- products - you need to enter different products divided by «,» or SPACE
- help - you need to type this command if you need some help and bot will explain what to do
- reset - this command is used when you do not want to communicate with bot anymore.

So, let's explain the process of communication with bot (Fig. 2).

First of all, you need to find it in search tab using bot's nickname. Then you press start and bot tell you what to do if you are a new user (there is no

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record about you and your choices in database). After that, you press «products» command and enter your products. And then you see result, you need to

choose what do you want to drink with these products and score them. You can do this step a lot of times while there are drinks in the field.

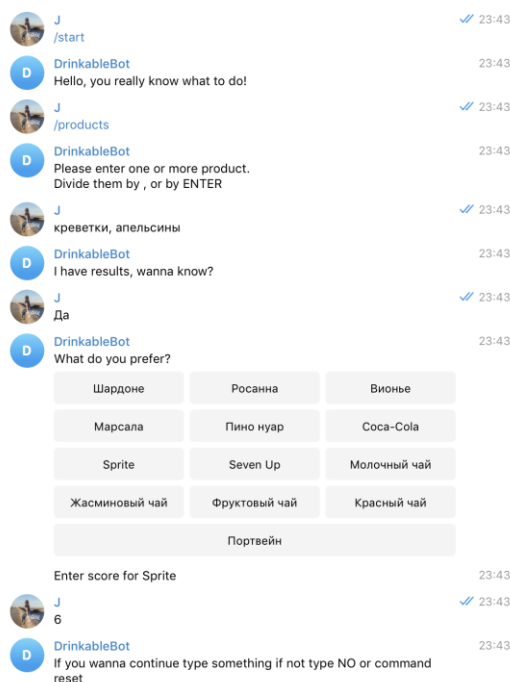


Figure 2 - conversation between user and bot

Then when you have chosen everything you wanted to choose, you can press «reset» and that's all. Next time just press «products» command and repeat actions.

Conclusion

A ready-to-use built-in Telegram app was created. This bot allows users to make proper choice

when they do not know what they want to drink with not usual but some extraordinary food.

In the future, it is planned to integrate current bot with new platforms like Slack, VKontakte or Facebook to expand the audience of users.

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