

CS6109 - Compiler Design

Project Documentation

Predicting and Classifying Interests of Users Based on Direct Interactions

Team - 3

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Introduction:

The basis of our project is to provide a textual analysis of the interactions between multiple users, and predict their interests, as well as categorize them.

This is an important function of recommendation systems, that is, to offer a personalized experience for each user, by understanding their preferences.

Direct interactions between users will be subject to lexical, syntax and semantic analysis, from which we will obtain their preferences to items, as well as actions and hobbies.

List of Modules:

We will employ the standard principles of compiler design, up to intermediate code generation. Lexical, syntax and semantic analysis will be used in the following order to analyse the input text:

- 1. Identify tokens (cricket, leather bag, smart phone) and verbs in the continuous sense (e.g. eating, playing) and such, using lexical analysis.
- 2. Obtain the sentiment of the users to find out whether they like the item or not, and show the dependency trees for each dialogue.
- 3. Getting a long, unorganized list of possible recommendations based on the users' interests, without sentiment considerations.
- 4. Recommending the products to the users with respect to sentiment, and recommending alternatives based on the interests of friends to users with negative sentiments.

The result will be an organized collection of information obtained from the interaction, showing the preferences and their respective categories.

Literature Survey:

No	Publication	Author, Year	Methodology	Advantages	Limitations
1.	Short systematic review on e-learning recommender systems	W.M.Chugtai, A.B.Selama, Imran Ghani (2013)	Content-Based Filtering, Hybrid-Based Filtering, Knowledge-Based Filtering	Useful insight on the cold- start issue in e-learning recommender systems.	Limited to four types of filtering approaches.
2.	A systematic review of scholar context- aware recommender systems	Z.D.Champiri, S.R.Shahamirib, S.S.B.Salima (2015)	Kitchenham Systematic Review Methodology	Categorises recommendations into user's context, document context and env. context.	Requires tracking and analyzing previous students' interactions.
3.	Recommender Systems: Review	Akshita.J, Smita.A (2013)	Content-Based Filtering	Discusses various techniques.	Requires combination with hybrid recommenders.
4.	A literature review and classifications of recommender systems research	D.H.Park, H.K.Kim, I.Y.Choi, J.K.Kim (2012)	Data Mining Techniques (K- Means, Link Analysis, etc.)	Provides insight about future trends in the field of recommender systems.	Limited to eight types of data mining techniques.
5.	The use of machine learning algorithms in recommender systems	Ivens Portugal, Paulo Alencar, Donald Cowan (2015)	Bayesian and Decision Tree Algorithms	Identifies research opportunities for software engineering research.	Nowadays, DL algorithms surpass ML algorithms in speed and power.

Problem Statement:

We can understand that we now have pre-trained deep learning models to work with, over machine learning models.

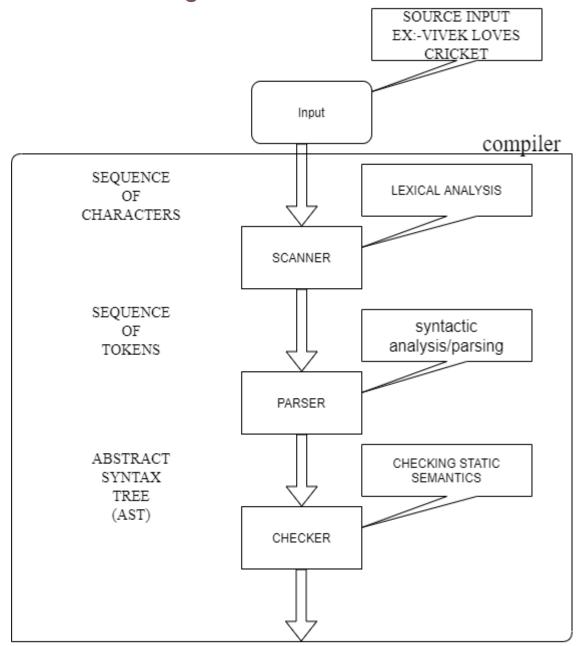
We will try to separate the tokens and tag them, whilst filtering out useless words.

The sentiment of the user's statement also needs to be considered while recommending.

To obtain the raw recommendations, we need to check for correlations between the tokens and the product names.

Organizing the recommendations and allocating them to each user will give us our final set of recommendations.

Architecture Diagram:



TARGET OUTPUT (FINAL RECOMMENDATION)

Pseudocode:

Module - I:

```
For each dialogue in conversation:
     Split dialogue in tokens and store them
     doc = nlp(dialogue)
     For each token in token_list:
           if tag == 'NOUN', add to noun_list
           else if tag == 'VERB' add to verb_list
     End for loop...
     #Using Spacy's functions, we can identify entities.
     For entity in doc.ents:
           Append entity to users
           Append entity_lab to user_types
     End for loop...
End for loop....
#Remove any leftover stop words in the nouns list
nouns = [word for word in nouns if not word in stopwords.words()]
Store all tokens in a data frame, and return the data frame
```

Module - II:

```
#Obtain sentiments using the NLTK Vader Sentiment Analyzer
Create a data frame to store sentiment values
sid = SentimentIntensityAnalyzer()
For each dialogue in conversation:
     Calculate polarity scores for each dialogue
     Append values to sentiments data frame corresponding
     to each sentiment
     Return the sentiment values data frame
End for loop....
#Displaying the dependency trees....
For each dialogue in conversation:
     #Use loaded dictionary of English words from Spacy library
     nlp = spacy.load('en_core_web_md')
     doc = nlp(dialogue)
     #Displacy is a visualization library for NLP
     displacy.render(doc, style = 'dep')
End for loop...
```

Module - III:

```
For each noun in noun_list:
     For each item in complete_list:
     If lower(noun) is present in lower(item name):
     Append item name to temp_list
     End for loop...
     Append temp_list to init_rec
End for loop...
Return the list init rec
Module - IV:
For index in the range of length of init_rec:
     If sentiment for user[index] is positive:
     Append random items to final_rec[index]
     If sentiment for user[index] is negative:
           Choose random items from other user interests
           Append those to final_rec[index]
     #We have chosen to recommend 5 items per user
     If sentiment for user[index] is neutral:
           Append random items to final_rec[index]
End for loop...
Return the list of lists final rec
```

List of Modules (in detail):

Module - 1:

The main focus of lexical analysis is to obtain tokens from the given text input.

We need to differentiate between entities (users, organizations, religion, etc.) and interests (garments, tech, etc.).

The technique we are going to employ is called POS tagging. (POS -> Part of Speech)

POS tagging algorithms allocate tags to each token, such as "NOUN", "VERB", "ADJ", etc., based on the similarity to their respective tagged categories.

We will be using the Spacy library, which contains pre-trained NLP models and a huge dictionary of words.

The input is parsed sentence by sentence, from which nouns, verbs, users, and user types are obtained. The respective information is summarized in a pandas data frame.

Keep in mind the input is made to understand short conversations - especially one-liners. Basically, we separate the text blob by the '\n', or newline symbol. This is done by using the splitlines() function.

If any respective dialogue consists of two lines, the parser will be confused and allocate an extra user to the extra line.

This is done with consideration to social messaging applications, as users frequently communicate with short dialogues.

Module - II:

The main point of understanding the syntax of the sentence is to check the order by which tokens are parsed.

For example, seeing a "not" before a verb, say "enjoying", can imply a negative sentiment.

Sentiment analysis is an important tool in recommendation - it helps recommend products to those who want it.

People who express negative sentiment towards a product will not recieve recommendations on it.

Instead, they will get recommendations based on what their friends like.

The NTLK Vader Sentiment Analyzer is an excellent tool for quickly analyzing the sentiment of a sentence.

We will obtain the polarity scores in each sentiment category, i.e "Positive", "Negative", "Neutral", and "Compound", for each user.

The Spacy library consists of one more feature - the ability to show dependency trees. Dependency trees are useful in understanding the parsing process, in pursuit of finding the sentiments.

The arrows infer dependencies between words. If an arrow points from 'a' to 'b', then it can be understood that 'a' depends on 'b'.

This is useful in seeing how the tokens are tagged, and how the sentence is syntactically analyzed.

Finally, from experimentation, we have concluded that 0 is a suitable threshold to determine whether the said user should be recommended any products or not. The main reason is that, if the compound sentiment is zero or more, then the user is neutral or positive of the product, however if it is less than zero, the user does not like the product. Based on this logic, we recommend the products.

Module - III:

We will check the list of nouns from our summary of tokens to see what the interests of the users are.

If the particular noun is present in any product name, we will store that product name in a new list.

This new list is considered as our initial set of recommendations.

Now, our initial recommendations are quite a large number.

We will pick five products at random, to recommend to each user.

Of course, we do not want to get the same products again in our random selection.

This is easily achieved by using random.sample(list, k), where k is the number of items selected. This function also ensures that there is no repetition in the selection of items.

Module - IV:

This is the final recommendation.

You can see the user's names followed by a list of recommendations based on their interests.

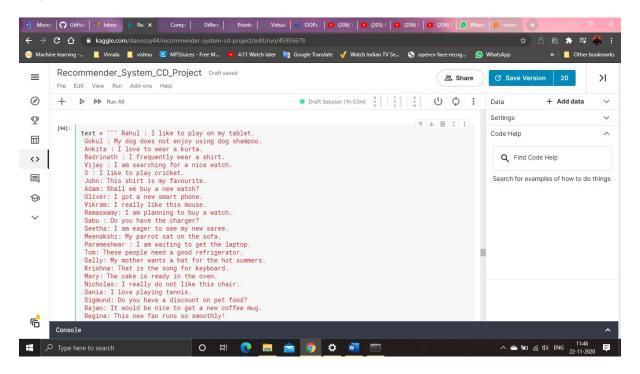
Keep in mind that for the most part the recommendations are accurate, but you may chance upon some outliers, due to the random nature of product selection.

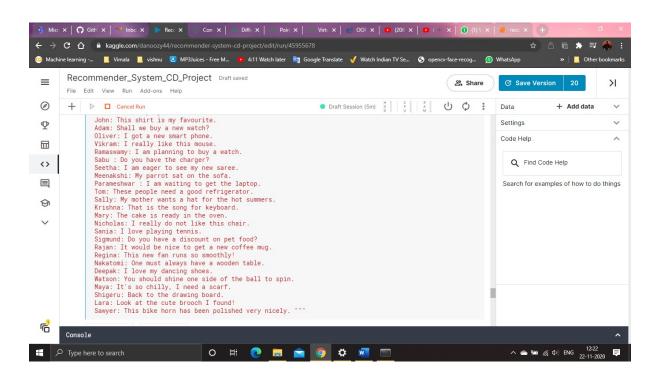
As stated before, the sentiment of the user is considered as a factor in the recommendation process. The compounded polarity score is considered here.

If a user's sentiment is negative, then we pick a random recommendation based on the interests of that user's friends.

Otherwise, if it is positive or neutral, we can directly recommend based on their individual interest.

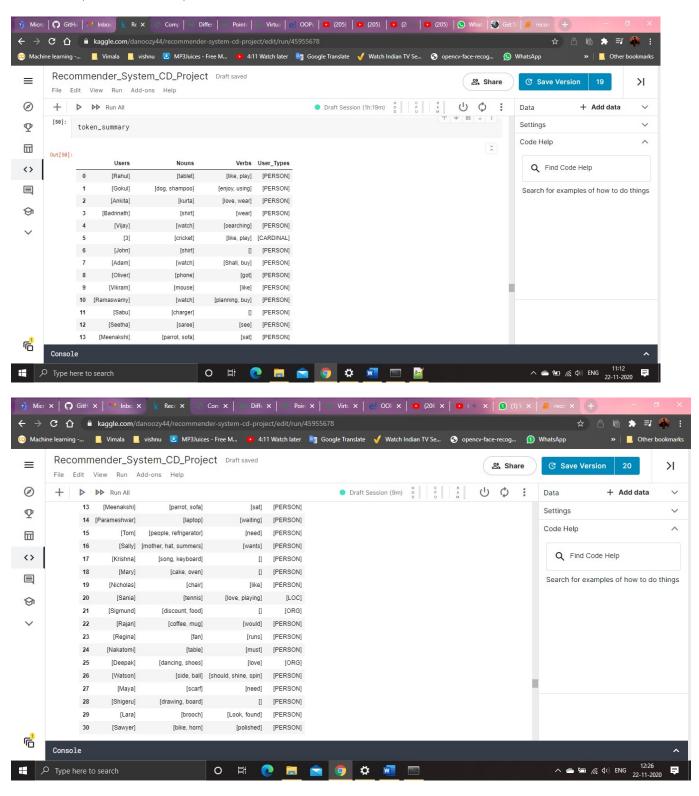
Input:



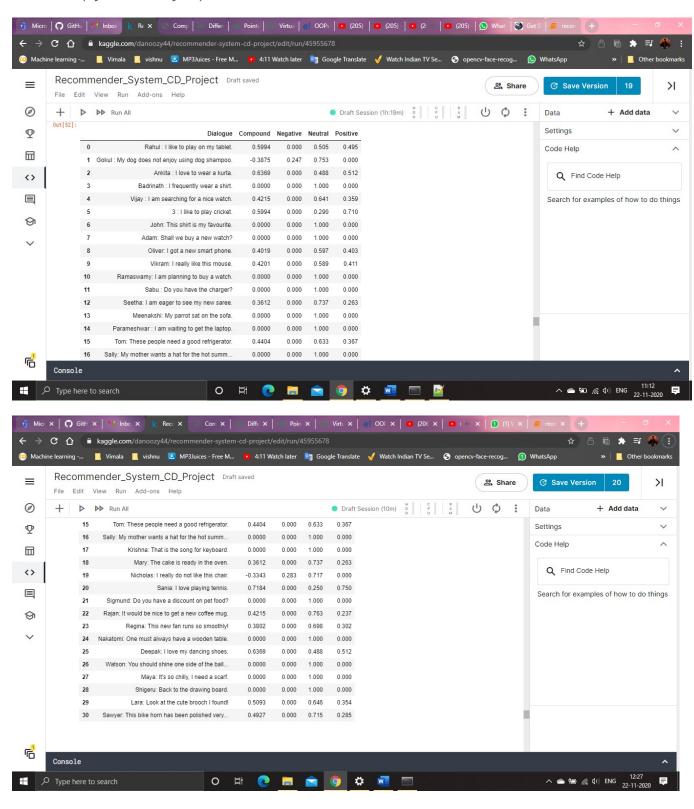


Output:

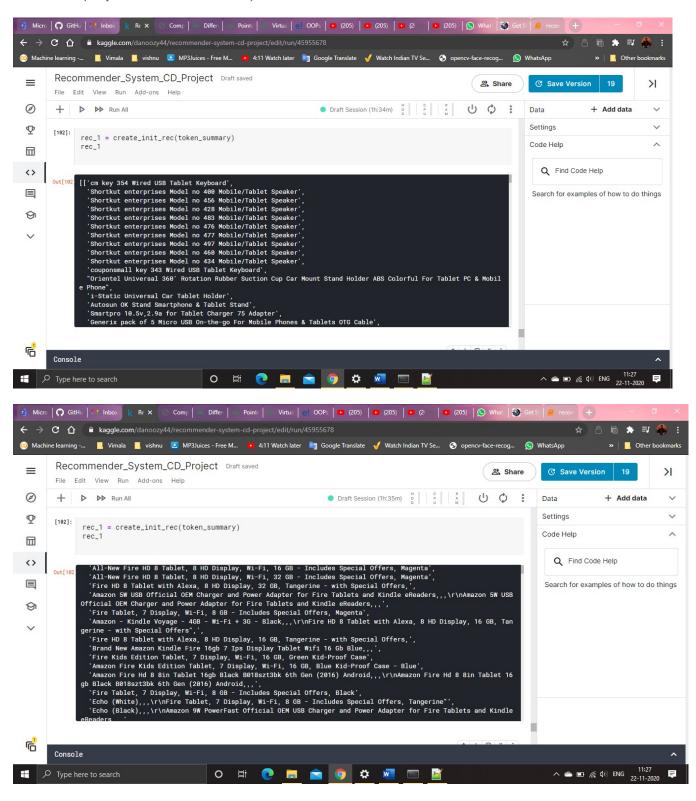
Module 1(Tokenization):

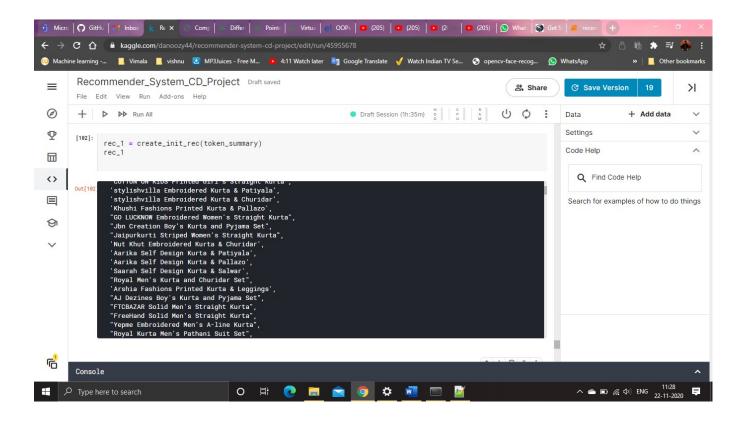


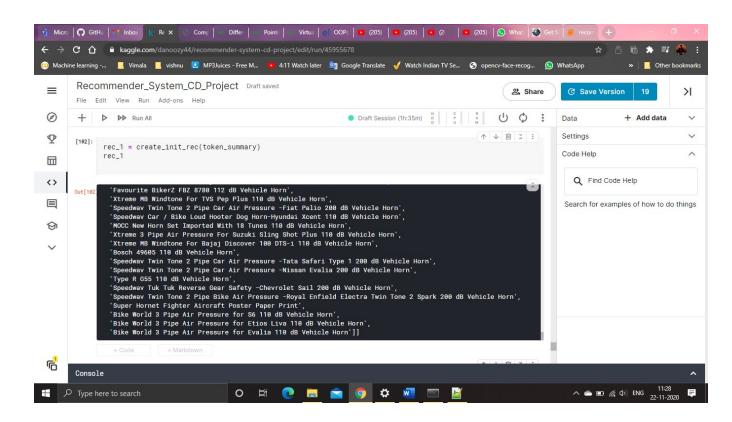
Module 2(Syntax analysis):



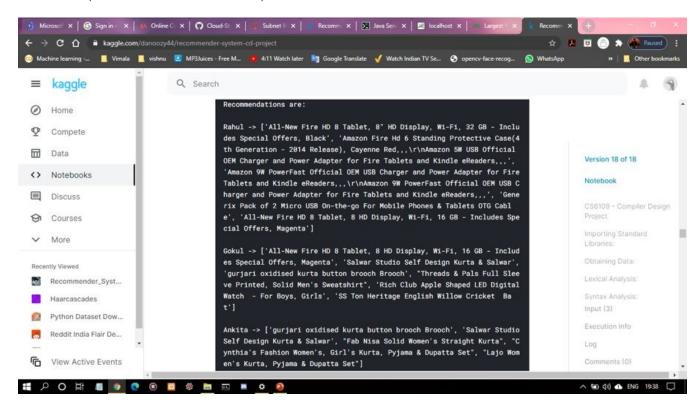
Module 3(Top Recommendation):

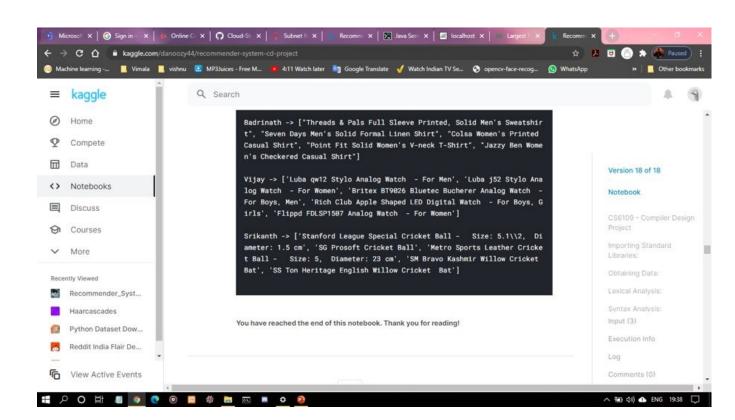






Module 4(Final recommendation):





Results Discussion:

Since we've checked for subsequences of the occurring string, the nouns, inside product names, of course we cannot guarantee an accuracy of 100%.

Regardless, the recommendation system seems to works fairly well - it recommends what the users want based on their interests.

For users with negative sentiment - it doesn't recommend the products associated with the user. Rather, it recommends products associated with the user's friends.

We also ensure any product recommendation is not repeated for the same user.

The end result is fairly straight-forward. It works for most cases, with some exceptions, a rare case.

Module 1(Tokenization):

token_summary			

	Users	Nouns	Verbs	User_Types
0	[Rahul]	[tablet]	[like, play]	[PERSON]
1	[Gokul]	[dog, shampoo]	[enjoy, using]	[PERSON]
2	[Ankita]	[kurta]	[love, wear]	[PERSON]
3	[Badrinath]	[shirt]	[wear]	[PERSON]
4	[Vijay]	[watch]	[searching]	[PERSON]
5	[3]	[cricket]	[like, play]	[CARDINAL]
6	[John]	[shirt]	0	[PERSON]
7	[Adam]	[watch]	[Shall, buy]	[PERSON]
8	[Oliver]	[phone]	[got]	[PERSON]
9	[Vikram]	[mouse]	[like]	[PERSON]
10	[Ramaswamy]	[watch]	[planning, buy]	[PERSON]
11	[Sabu]	[charger]	0	[PERSON]
12	[Seetha]	[saree]	[see]	[PERSON]
13	[Meenakshi]	[parrot, sofa]	[sat]	[PERSON]
14	[Parameshwar]	[laptop]	[waiting]	[PERSON]
15	[Tom]	[people, refrigerator]	[need]	[PERSON]
16	[Sally]	[mother, hat, summers]	[wants]	[PERSON]
17	[Krishna]	[song, keyboard]	D	[PERSON]

18	[Mary]	[cake, oven]	O	[PERSON]
19	[Nicholas]	[chair]	[like]	[PERSON]
20	[Sania]	[tennis]	[love, playing]	[LOC]
21	[Sigmund]	[discount, food]	0	[ORG]
22	[Rajan]	[coffee, mug]	[would]	[PERSON]
23	[Regina]	[fan]	[runs]	[PERSON]
24	[Nakatomi]	[table]	[must]	[PERSON]
25	[Deepak]	[dancing, shoes]	[love]	[ORG]
26	[Watson]	[side, ball]	[should, shine, spin]	[PERSON]
27	[Maya]	[scarf]	[need]	[PERSON]
28	[Shigeru]	[drawing, board]	0	[PERSON]
29	[Lara]	[brooch]	[Look, found]	[PERSON]
30	[Sawyer]	[bike, horn]	[polished]	[PERSON]

Module 2(Syntax analysis):

sentiments

	Dialogue	Compound	Negative	Neutral	Positive
0	Rahul : I like to play on my tablet.	0.5994	0.000	0.505	0.495
1	Gokul: My dog does not enjoy using dog shampoo.	-0.3875	0.247	0.753	0.000
2	Ankita: I love to wear a kurta.	0.6369	0.000	0.488	0.512
3	Badrinath: I frequently wear a shirt.	0.0000	0.000	1.000	0.000
4	Vijay : I am searching for a nice watch.	0.4215	0.000	0.641	0.359
5	3 : I like to play cricket.	0.5994	0.000	0.290	0.710
6	John: This shirt is my favourite.	0.0000	0.000	1.000	0.000
7	Adam: Shall we buy a new watch?	0.0000	0.000	1.000	0.000
8	Oliver: I got a new smart phone.	0.4019	0.000	0.597	0.403
9	Vikram: I really like this mouse.	0.4201	0.000	0.589	0.411
10	Ramaswamy: I am planning to buy a watch.	0.0000	0.000	1.000	0.000
11	Sabu : Do you have the charger?	0.0000	0.000	1.000	0.000
12	Seetha: I am eager to see my new saree.	0.3612	0.000	0.737	0.263
13	Meenakshi: My parrot sat on the sofa.	0.0000	0.000	1.000	0.000
14	Parameshwar: I am waiting to get the laptop.	0.0000	0.000	1.000	0.000
15	Tom: These people need a good refrigerator.	0.4404	0.000	0.633	0.367
16	Sally: My mother wants a hat for the hot summ	0.0000	0.000	1.000	0.000
17	Krishna: That is the song for keyboard.	0.0000	0.000	1.000	0.000

18	Mary: The cake is ready in the oven.	0.3612	0.000	0.737	0.263
19	Nicholas: I really do not like this chair.	-0.3343	0.283	0.717	0.000
20	Sania: I love playing tennis.	0.7184	0.000	0.250	0.750
21	Sigmund: Do you have a discount on pet food?	0.0000	0.000	1.000	0.000
22	Rajan: It would be nice to get a new coffee mug.	0.4215	0.000	0.763	0.237
23	Regina: This new fan runs so smoothly!	0.3802	0.000	0.698	0.302
24	Nakatomi: One must always have a wooden table.	0.0000	0.000	1.000	0.000
25	Deepak: I love my dancing shoes.	0.6369	0.000	0.488	0.512
26	Watson: You should shine one side of the ball	0.0000	0.000	1.000	0.000
27	Maya: It's so chilly, I need a scarf.	0.0000	0.000	1.000	0.000
28	Shigeru: Back to the drawing board.	0.0000	0.000	1.000	0.000
29	Lara: Look at the cute brooch I found!	0.5093	0.000	0.646	0.354
30	Sawyer: This bike horn has been polished very	0.4927	0.000	0.715	0.285

Module 3(Top Recommendation):

```
'cm key 354 Wired USB Tablet Keyboard',
  'Shortkut enterprises Model no 400 Mobile/Tablet Speaker',
  'Shortkut enterprises Model no 456 Mobile/Tablet Speaker',
  'Shortkut enterprises Model no 428 Mobile/Tablet Speaker',
  'Shortkut enterprises Model no 483 Mobile/Tablet Speaker',
  'Shortkut enterprises Model no 476 Mobile/Tablet Speaker',
  'Shortkut enterprises Model no 477 Mobile/Tablet Speaker',
  'Shortkut enterprises Model no 497 Mobile/Tablet Speaker',
  'Shortkut enterprises Model no 460 Mobile/Tablet Speaker',
  'Shortkut enterprises Model no 434 Mobile/Tablet Speaker',
  'couponsmall key 343 Wired USB Tablet Keyboard',
  "Orientel Universal 360' Rotation Rubber Suction Cup Car Mount
Stand Holder ABS Colorful For Tablet PC & Mobile Phone",
  'i-Static Universal Car Tablet Holder',
  "RETAIL SHOP INDIA Printed Girl's Straight Kurta",
  "Love More Printed Women's Flared Kurta",
  'Saarah Self Design Kurta & Churidar',
  'Salwar Studio Geometric Print, Paisley Kurta & Salwar',
  'Salwar Studio Self Design Kurta & Salwar',
  'F-Loop Self Design Kurta & Churidar',
  "Aarika Girl's Kurta and Pallazo Set",
  "Swag India Girl's Kurta and Pallazo Set",
  "Retaaz Girl's Kurta and Leggings Set",
  "NIPPY Boy's Kurta, Waistcoat and Breeches Set",
  'JDK NOVELTY Brocade, Art Silk, Organza Floral Print Multi-purpose
Fabric,
  Kurti Fabric, Blouse Material,
  Kurta Fabric, Dress/Top Material, Jacket Fabric, Kurta & Pallazo
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Material, Sherwani Fabric, Kurta & Churidar Material, Lace, Salwar
Suit Material, Kurta & Patiyala Material, Lehenga Choli Material',
  'JDK NOVELTY Brocade, Art Silk, Organza Self Design Multi-purpose
Fabric, Kurti Fabric, Blouse Material, Kurta Fabric, Dress/Top
Material, Jacket Fabric, Kurta & Pallazo Material, Sherwani Fabric,
Kurta & Churidar Material, Lace, Salwar Suit Material, Kurta &
Patiyala Material, Lehenga Choli Material',
  'JDK NOVELTY Brocade, Art Silk, Organza Floral Print Multi-purpose
Fabric, Kurti Fabric, Blouse Material, Kurta Fabric, Dress/Top
Material, Jacket Fabric, Lehenga Choli Material, Kurta & Patiyala
Material, Salwar Suit Material, Lace, Kurta & Churidar Material,
Sherwani Fabric, Kurta & Pallazo Material',
  "TSG Breeze Printed Women's Round Neck Multicolor T-Shirt",
 "Starsy Printed Women's Round Neck Green T-Shirt",
  "Clovia Women's T-Shirt Bra",
  "run of luck Solid Women's Round Neck Dark Blue T-Shirt",
  "Starsy Solid Women's Round Neck Green T-Shirt",
  "Attitude Printed Women's Round Neck Black T-Shirt",
  "The Cotton Company Solid Women's Polo Neck Pink T-Shirt",
  'Adimani Mustuw Scarf Fabric Necklace',
  'Adimani Felimq Scarf Fabric Necklace',
1
```

Module 4(Final Recommendation):

USERS	RECOMMENDED PRODUCTS
Rahul	'Brand New Amazon Kindle Fire 16gb 7 Ips Display Tablet Wifi 16 Gb Blue,,,', 'Amazon 9W PowerFast Official OEM USB Charger and Power Adapter for Fire Tablets and Kindle eReaders,,,\r\nAmazon 9W PowerFast Official OEM USB Charger and Power Adapter for Fire Tablets and Kindle eReaders,,,', 'All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi, 32 GB - Includes Special Offers, Black', 'Echo (White),,,\ r\nFire Tablet, 7 Display, Wi-Fi, 8 GB - Includes Special Offers, Tangerine"', 'All-New Fire HD 8 Tablet, 8 HD Display, Wi-Fi, 16 GB - Includes Special Offers, Blue'
Gokul	'Brand New Amazon Kindle Fire 16gb 7 Ips Display Tablet Wifi 16 Gb Blue,,,', "Gulmohar Jaipur Embroidered Women's Straight Kurta", 'Aarika Self Design Kurta & Pallazo', "ShowTime Women's Full Coverage, T-Shirt Bra", 'HMT S3648

Analog Watch - For Men', 'Spick Cricket Shoes', "Mast & Harbour Women's Printed Casual Shirt", 'Gift Island SW13390E Fashionin Digital Watch - For Men', 'AdroitZ Premium Phone Socket Holder For Nokia N9', 'Ekku Mickey Mouse - 15 inch', 'Disney DW100405 Digital Watch - For Boys', 'Hako 85W Magsafe Laptop Charger For APPLE MacBook Pro 17 MA897LLA 85 Adapter', 'AMY Karena Kapoor in Green Saree A5 Notebook Spiral Bound', 'Adaa Terracotta -Reclining Ganesha on Sofa - Pink Showpiece - 11.9 cm', 'PRINT SHAPES Best green ball Laptop Skin with Mouse pad Combo Set', "People Women's Checkered Formal Shirt", 'AKUP happy-mothers-day Ceramic Mug', 'Saco Karbonn Smart Ta Fone A37 Hd Tablet Wired USB Tablet Keyboard', 'MasterweaverIndia Cotton Woven Blouse Material', 'RoyalOak Metal Outdoor Chair', 'Dunlop Fort Tennis Ball - Size: 0, Diameter: 2.5 cm', 'Royal Canin Maxi Starter 1kg Vegetable Dog Food', 'Prithish Wild And Free Ceramic Mug', 'JRB 1019 Smallest Mobile Powered By OTG Enabled Android Smart Phone Portable 1019 USB Fan', 'Craft And Curtain Multicolor 178 cm Table Runner', 'N Five Running Shoes', 'Uniball Kurutoga Round Shaped Pencils', 'Dimpy Stuff Bear W/Scarf in Sitting 50Cm - 50 cm', 'Satzuma UCH100 USB Clapper Board', 'B-Fashionable Combo of Drop & Round Bead Kilangi Brooch', 'Cm Treder cm h4 light 145 Motorbike LED Bulb' "Gulmohar Jaipur Embroidered Women's Straight Kurta", "Jeet Boy's Kurta and Pyjama Set", "Gulmohar Jaipur Printed Women's Straight Kurta", 'Aarika Self Design Kurta & Pallazo', "Swag India Girl's Kurta and Pallazo Set."

Ankita

Badrinath

"J Marks Men's Striped Formal

	Shirt", "ShowTime Women's Full Coverage, T-Shirt Bra", "Penny Pro Women's T-Shirt Bra", "Concepts Women's Printed Casual Shirt", "Omtex Solid Men's Polo Neck T- Shirt"
Vijay	'Now B170-SLL09 Now Analog Watch - For Girls', 'Cartier W6701005 Analog Watch - For Boys, Men', 'Zoop C4040PP03 Digital Watch - For Boys, Girls', 'Alfajr WQ18 Qibla Compass Digital Watch - For Men, Boys, Girls', 'HMT S3648 Analog Watch - For Men'

Conclusion:

The information obtained from direct interactions can be a valuable tool, as we can create recommendation systems on the basis of user-user interactions, such as comments on a forum, rather than user-site interactions.

Previous systems understand and provide recommendations based on similarities between users, which might lead to a bias evaluation for user preferences. This provides a solution for this issue by integrating direct interactions into recommendation systems.

However, there is still much left to improve, and a full accuracy of such systems is never guaranteed, but this approach will definitely up the bar in extending further recommendation systems.

References:

1. C.Li, F.Xiong, "Social Recommendations with Multiple Influence from Direct User Interactions", Aug. 2017.

- 2. C. Pan, W. Li, Research paper recommendation with topic analysis in Computer Design and Applications IEEE, 4 (2010), pp. V4-264
- 3. J.A. Konstan, J. Riedl, Recommender Systems: From Algorithms to User Experience, User Model User-Adapt Interact, 22 (2012), pp. 101-123