Personalised Product Recommendations on E-Commerce Websites with the use of Social Media

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Abstract

In e-commerce businesses, it is common nowadays to showcase products to the users on the basis of analytics which can turn those products into potential purchases. However, mostly e-commerce websites recommend only similar set of products on the basis of recent search history and not a curated set of products with higher confidence level of likeability. Rather than focusing just on a recent search history, if we can utilize social media data with this, it can open up a huge pool of data about a user and with this information, we will be able to provide well suited recommendations. Our objective in this paper is to develop an algorithm to provide very effective recommendations using the social media data of a user. This can help increase the efficiency of existing recommendation systems. Algorithm introduced in this paper follows a Fuzzy Logic technique to find relevant keywords emanated from Keywords Derivation algorithm which is a necessary algorithm for final result. It also makes use of Google Cloud Natural Language API to classify keywords in their respective categories. This algorithm is befitting to any products/services as long as the information about products and user's social media data are available.

Keywords: E-commerce, Analytics, Social Media, Product recommendation, Algorithm

1. Introduction

1.1. Internet Usage

In our daily life, internet usage is increasing day by day along with social media usage with increasing infrastructure and ample available bandwidth. As per report from "We are Social" and "Hootsuite" of 2018, out of total population of 7.593 Billion in the world, 4.021 Billion are internet users and out of which 3.196 Billion are active social media users. Numbers of internet users are increasing 7% year on year and number of social media users are increasing 13% year on year as per 2018 report.

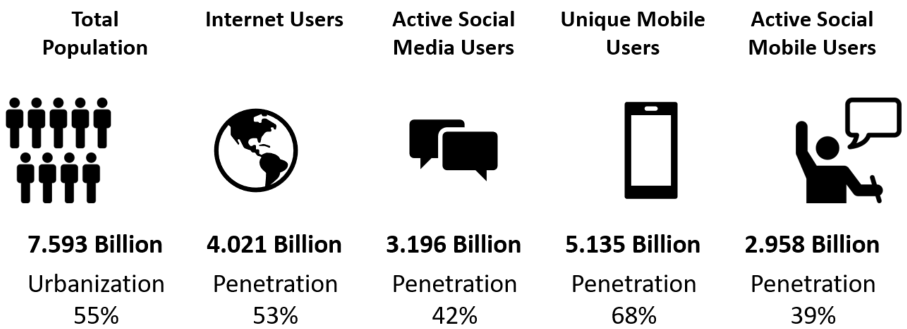

Figure 1. Key statistical indicators for the world's internet, mobile and social media users

Average internet users spend approximately 6 hours daily on an average on internet enabled devices and services which is approximately 33% of their daily day time.

1.2. Social Media Usage

Globally, number of people using social media is increased by 13% in last 1 year. We can infer that heavy usage of internet, increased usage of social media, availability of personal mobile devices and infrastructure on availability of internet gives users' information on individual basis and more personalization can be done provided users provide their social media data access to companies where it would be beneficial to company and users both in return.

Filipinos spent highest of their daily time on social media as per the report. Indians, on an average spend around 2 hours and 25 minutes on social media out of daily time they spend on the internet which is 7 hours and 25 minutes. The age group of 18-24 and 25-34 shows highest number of users of Facebook as per the report. There is a significant increase of 5% in teenagers and 20% of increase in number of users aged 65 and above in last year.

15% of users are increasing year on year on Facebook's platform which itself shows sign of dominance in social media. From around most important 25 social media platforms, Facebook is having most number of monthly active users followed by YouTube, WhatsApp, and FB Messenger after Facebook, which again envisage the social media usage and Facebook's continuous work towards attracting users and hold them to use their platform (Kemp,2018).

1.3. E-commerce growth

Latest report from Statista website shows that total value of e-commerce market for consumer goods grew by 16% over 2016. Worldwide, the number of people using e-commerce platforms to buy consumer goods increased by 8%. Such reports strengthen our argument that social media and e-commerce are used heavily worldwide and there is a continuous increase in the usage of them.

As per the report from EMarketer, retail e-commerce sales worldwide will reach USD 2.842 Trillion in 2018 increasing 23.3% since 2017. In 2017, e-retail sale accounted for 10.2% of all retail sales worldwide.

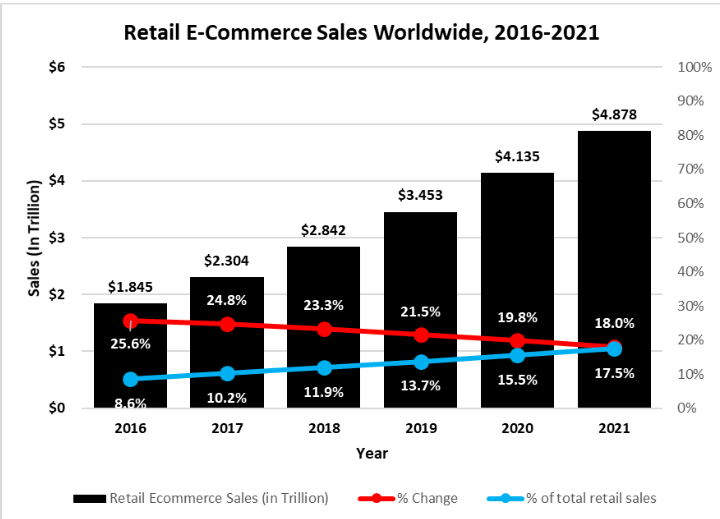

Figure 2. Retail e-commerce sales worldwide (2016-21)

Based on the reports and graphs, we can envisage that e-commerce sales would increase gradually along with usage of internet and social media worldwide.

1.4. Concepts of Recommendation Engine

To start with, let's understand the basic terminologies and methods that we will explore in this paper that are important to understand the algorithm that we propose. The terms are: personalization, recommendation engine, collaborative filtering, content-based filtering, hybrid recommendations, and how recommendation engine works with various processes like collecting data, storing data, analysing data and filtering data. This will give us idea about basic techniques which are already in use in the industry and various software systems that exist to suggest products and services to users.

1.4.1. Personalization

Personalization is possible in e-commerce with the use of online marketing and digital service innovation. Different types of personalization methods are available where based on users' product purchase history, usage history, access history or cookie based, product recommendations are suggested. In recommender system, marketing content is selected for individual customers with the goal of increasing specific business outcomes which should be the solution where everyone benefits.(Kaptein& Parvinen ,2015)

1.4.2. What is a Recommendation Engine?

Recommendation Engine is nothing but a software algorithm which finds products from the catalogue which may be of interest to the users. It is essentially a data filtering tool which analyses the data given, makes use of its core algorithm & produces output in terms of recommended products (D,2016,Shaikh et al,2017,Hendrick et al.2018) .

There are fundamentally three different types of recommendation engines, based on the method used, as explained below:

1.4.2.1. Collaborative Filtering

This method is based on the liking of similar users in the system and not specifically based on what a user likes. A principal advantage of using this method is that it is not dependent on machine analysing capability and thus it is very proficient in recommending complex items such as movies (D,2016,Shaikh et al,2017,Hendrick et al.2018) .To cite an example of the mentioned technique, if user A likes 1,2,3 & user B likes 2,3,4, a conclusion can be derived on the similarity of their preferences and thus user A will like 4 & user B will like 1.

1.4.2.2. Content Based Filtering

This method is based on the description of the item and the likings of the user. More often, items are associated with a variety of tags and user's likings, based on his/her history in terms of tags, are then compared to them. Output of this activity will yield likeable products for the user. This is essentially digging out the history of the user, extract the information on liked items and provide similar items as recommendations (D,2016).

1.4.2.3. Hybrid Recommendation Systems

This method is not an independent one but a blend of the two methods illustrated above. Hybrid method can be implemented with predictions made with content and collaborative methods separately and combining them with another set of algorithms. Research2 has proven that hybrid method leads to more effectiveness (Hendrick et al.2018)

1.4.3. How does this Recommendation Engine work?

An archetypal recommendation engine goes through four phases before giving its output namely collection, storing, analysing, and filtering. First step in any recommendation engine is collection of data. Explicit data can be collected through user's activities such as comments, reviews. Implicit data can be derived through user's history of orders, return history, cart products etc. Behavioural data on the other hand is collected through the logging of every activity a user does on the web applications. Data generated through the first phase is stored in database simultaneously. Then data is analysed to extract the information from data.

The final filtering phase involves activities that have already been mentioned above as content-based, clustering, and collaborative filtering. This phase helps us suggesting new products or services based on previous data of user, groups, and similar profile users.

1.5. Research Objective

Main objective of this paper is to introduce an algorithm which blends finely between social media and e-commerce. Data suggests that as rate of internet adoption increases, more and more people are adopting social media. When so much information is available about consumers online, we think, it's in the best interest to both businesses and consumers to leverage that to its maximum use.

Benefit that this algorithm proposes is that it can introduce wide range of personalised products to individual consumers which otherwise would have rarely come in browsing. At the same time, for businesses, it will be a solution to their long tail problem. With the use of this algorithm, we are trying to fill a gap between what businesses highlight and what consumers actually want.

2. Literature Review

With overload of information available on the e-commerce websites, it's getting difficult for consumers to search for products and they must spend more and more time on internet. One possible solution to this problem is to provide them the information before they start searching through personalised recommendations. It not only benefits consumers but helps organizations manage their business efficiently.(Renjie Zhou, et al.2010) concluded in their paper titled *The Impact of YouTube Recommendation System on Video Views* that about 30% video views are from the recommendations and there is an existence of a strong correlation between the view count of a video and average view count of its top referral video (Zhou et al. 2010).

Significant relation between social median information and online purchase have been found. Users express strong personal interest on social media and are highly focused when they purchase online (Zhang and Pennacchiotti, 2013).Understanding the customers would help reaching next steps of sales process easily (Andzulis et al., 2012).Prediction can be done for future events by using agent-based markets where computer-based agents will embody human-user sentiments and their knowledge, beliefs and assessments which will help in knowing wisdom of crowd (Zeng et al.2010).

3. Research Methodology

3.1. Proposed Framework

In this section, an intelligent online recommendation system for personalized shopping is proposed which uses data mining through social media, fuzzy logic & classification techniques in beneficial to provide products which can turn into potential purchases. As this system uses data from the public social media of users, there aren't any specific interest forms which consumers are expected to fill periodically to show their interests. Data is fetched from their social media accounts on first time login and is refreshed every 3 months. Data once gathered is stored in a very secure environment and analytics tools are run to come up with solid information which can relate to the products available. Based on the current system, information regarding consumers' wants can be transferred into feasible set of products.

The implementation goes through the following steps which are covered in this study:

1. Gather data from user's social media account upon login. This data includes his/her public information regarding places one has been to, activities one has indulged in, and interests one has followed etc.
2. Apply a set of algorithms to the data we have gathered and derive information that is represented by a set of keywords.
3. Fuzzy logic is set up here between the information and the products.
4. Algorithms are applied to rank the products according to the fuzzy logic geometric distance.

3.1.1. Algorithm

Based on the proposed system, product features can be associated with the analysis made on the social data gathered using which recommendations are given. In this approach, we are going to use fuzzy logic, classification & clustering technique in order to establish proper relation between products and consumer interests.

Fuzzy logic is derived here with the use of a keyword based algorithm. Data when fetched from social media accounts are processed & information regarding the data is derived with available public API from Google which is Cloud Natural Language. Each set of data is then tagged with a number of associated keywords found from the use of API. These keywords play an essential role in deriving the fuzzy number. Fuzzy logic here is specific to the product category while choosing product category is achieved via classification technique.

Our method assumes that every piece of information regarding each product is available with us. When user visits a website and we are unsure about choice of products, classification & clustering techniques are used to pick the product category first. Post which, fuzzy logic technique is used to segregate his/her choice of products within the category.

Flowchart

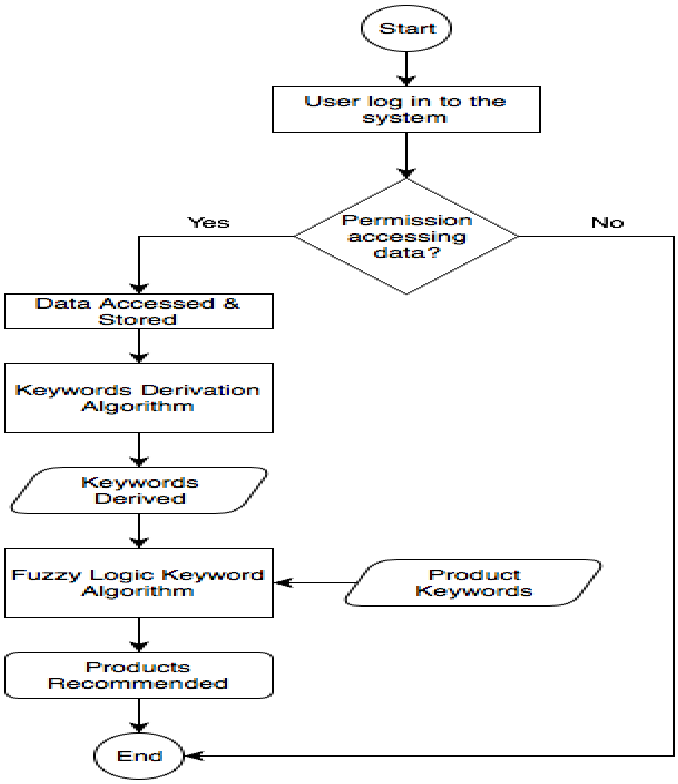

Figure 3. Process Flowchart of the proposed algorithm

3.1.2. Keywords Derivation Algorithm

There are generally three set of ways users put substantial information on Facebook (we have considered Facebook out of all social media platforms for its extensive user network).

I. Status updates – These are plain text sentences updated by users to share their views and information. These can also be accompanied by any of the below mentioned ways.
II. Check-ins – These are location based tagging events where users mentioned about their visit to various places.
III. Activities – Users mention about the activities that they are currently undergoing. These include watching a match, eating food, travelling to places, reading books, attending seminars etc.
IV. Pages – Users follow their interests via pages, a platform for users to interact with a community of users and perhaps organisation directly.

We will use Check-ins, Activities and Pages to derive specific set of keywords associated with users' profiles. We will go through each method to derive keywords.

1. Check-Ins
   Check-ins are usually updated for places people visit that include food joints, tourist places etc.
   When a person visits a place, information regarding the same is gathered from Facebook. If it's a tourist place and visit duration is not so long ago, we will add a keyword associated with the place to his/her keyword database. If it's a food joint and we find repetitive interactions with similar kind of places such as pizza place, we will add a keyword to the database. We will also use state of the art Google Cloud Natural Language API to classify our objects into meaningful keywords. Following flow chart explains the process:

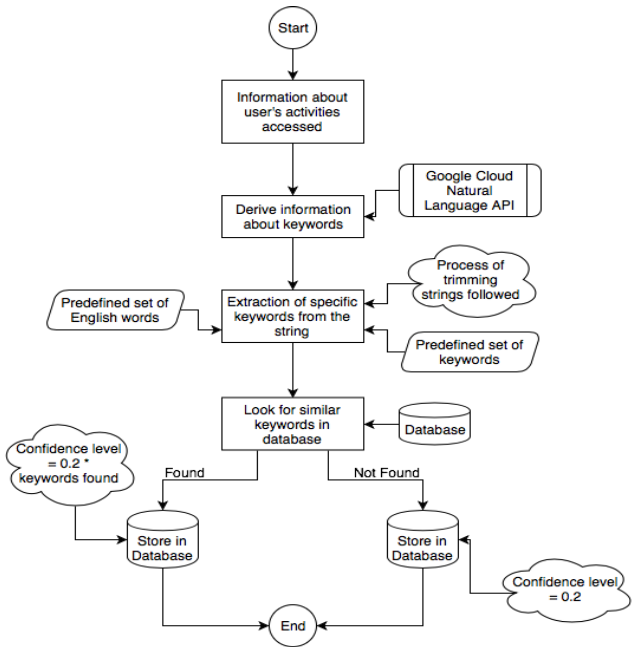

Figure 4. Flowchart of the steps with activities.

Step 1: Input:Where, W_{ij} is a set of words, S_i is sentence

$$\begin{cases} W_{1a}, W_{2a} \ldots W_{na} = S_a \\ W_{1b}, W_{2b} \ldots W_{nb} = S_b \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ W_{1z}, W_{2z} \ldots W_{nz} = S_n \end{cases}$$

Step 2: Use Google Cloud Natural Language API to classify the keywords

$$\begin{cases} W_{1a}, W_{2a} \ldots W_{na}, X_{1a}, X_{4a} \ldots X_{na} = O_a \\ W_{1b}, W_{2b} \ldots W_{nb}, X_{3b}, X_{9b} \ldots X_{nb} = O_b \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ W_{1z}, W_{2z} \ldots W_{nz}, X_{2z}, X_{7z} \ldots X_{nz} = O_n \end{cases}$$

Where Oi is output with more keywords assigned to existing set of keywords

Step 3: Trim Function is applied on input to retrieve useful set of keywords

$$Output = english\_keyword\_function\ (trim\_function(input)\ )$$

trim_function removes unnecessary characters, punctuations and it gives a substring occurring after a certain conjunction such as *at, in*

*english_keyword_function*removes very common predefined English words as it will be unnecessary for our analysis

Output:

$$\begin{cases} W_{1a}, W_{5a} \ldots W_{na} = O_a \\ W_{4b}, W_{9b} \ldots W_{nb} = O_b \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \end{cases}$$

$W_{3z}, W_{6z} \ldots W_{nz} = O_n$

Where, W_{ij} is a set of useful keywords retrieved
O_i is output assigned

Step 4: Look for similar keywords existing in database
If yes
*Assign a confidence score of 0.2*number of keywords found*
If no
Assign a confidence score of 0.2

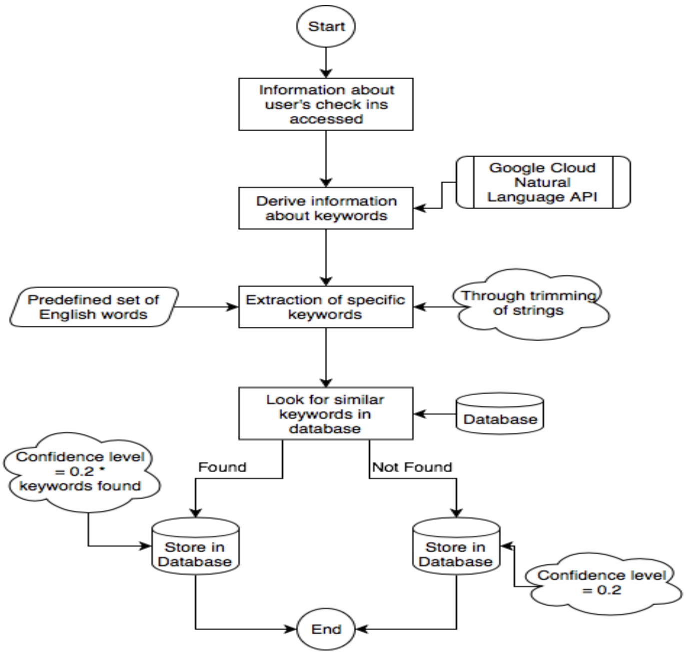

Figure 5.Flowchart of the steps with check in details.

2. Activities

Four major activities that users update on Facebook are watching, listening, playing and reading, activities which say a lot about users' interests. When user is indulged in any of the activities mentioned above, we store the information in keyword form chronologically. Let's take an example of a user watching a match between Manchester United and Arsenal. It cannot be decided which team user supports on singular activity, however with repetitive interactions of one team, we can say, with some probability, that user likes one of the other team and subsequently information about the same is added to the database. Also, using Google Cloud Natural Language API, we can process the sentiment analysis on the status updated along with the activity and try to find out about the team user supports. This however will work only with the status updated with the activity.

Following flowchart explains the process followed here:

Step 1: Input:

$$\begin{cases} W_{1a}, W_{2a} \ldots W_{na} = S_a \\ W_{1b}, W_{2b} \ldots W_{nb} = S_b \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ W_{1z}, W_{2z} \ldots W_{nz} = S_n \end{cases}$$

Where, W_{ij} is a set of words
S_i is sentence

Step 2: Use Google Cloud Natural Language API to classify the keywords

$$\begin{cases} W_{1a},W_{2a}\ldots W_{na,}X_{1a},X_{4a}\ldots X_{na} = O_a \\ W_{1b},W_{2b}\ldots W_{nb},X_{3b},X_{9b}\ldots X_{nb} = O_b \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ W_{1z},W_{2z}\ldots W_{nz},X_{2z},X_{7z}\ldots X_{nz}= O_n \end{cases}$$

Where O_i is output with more keywords assigned to existing set of keywords

Step 3: Trim Function is applied on input to retrieve useful set of keywords

$$output = keyword\_function(\ english\_keyword\_function\ (trim\_function(input)\ )\ )$$

trim_function removes unnecessary characters, punctuations and it gives a substring occurring after a certain conjunction such as *at, in*

*english_keyword_function*removes very common predefined English words as it will be unnecessary for our analysis

keyword_function look for specific keywords occurring after predefined set of keywords such as *watching, reading, travelling etc.*

Output:

$$\begin{cases} W_{1a},W_{5a}\ldots W_{na} = O_a \\ W_{4b},W_{9b}\ldots W_{nb} = O_b \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ W_{3z},W_{6z}\ldots W_{nz} = O_n \end{cases}$$

Where, W_{ij} is a set of useful keywords retrieved
O_i is output assigned

Step 4: Look for similar keywords existing in database
If yes
*Assign a confidence score of 0.2*number of keywords found*
If no
Assign a confidence score of 0.2

3. Pages
Pages are created by companies, sponsors or users themselves.
When a user likes a page, we can fairly assume that his/her interest lies there. With subsequent interactions, we can build up our confidence level.

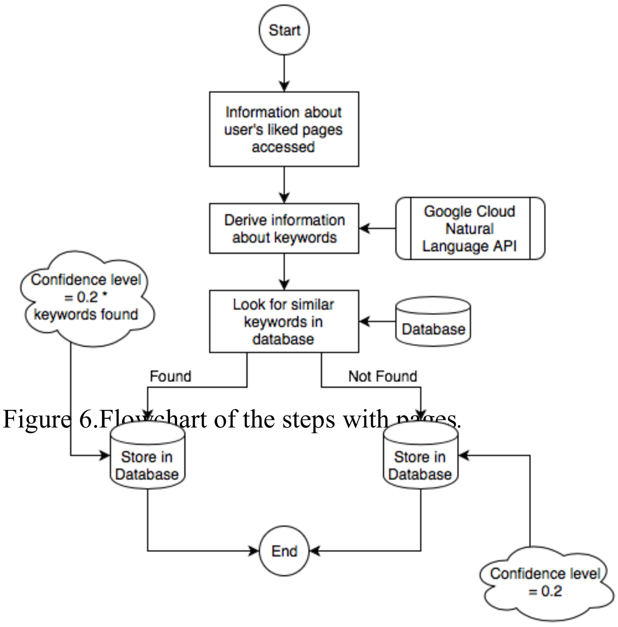

Figure 6.Flowchart of the steps with pages.

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Step 1: Input:

$$\begin{cases} W_{1a}, W_{2a} \ldots W_{na} = S_a \\ W_{1b}, W_{2b} \ldots W_{nb} = S_b \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ W_{1z}, W_{2z} \ldots W_{nz} = S_n \end{cases}$$

Where, W_{ij} is a set of words
S_i is sentence

Step 2: Use Google Cloud Natural Language API to classify the keywords
(Since Pages provide us with direct keywords, there is no necessity to use other functions)

$$\begin{cases} W_{1a}, W_{5a} \ldots W_{na}, X_{1a}, X_{4a} \ldots X_{na} = O_a \\ W_{4b}, W_{9b} \ldots W_{nb}, X_{3b}, X_{9b} \ldots X_{nb} = O_b \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ W_{3z}, W_{6z} \ldots W_{nz}, X_{2z}, X_{7z} \ldots X_{nz} = O_n \end{cases}$$

Where O_i is output with more keywords assigned to existing set of keywords

Step 3: Look for similar keywords existing in database
If yes
*Assign a confidence score of 0.2*number of keywords found*
If no
Assign a confidence score of 0.2

These three activities mentioned above work seamlessly with one another. For our previous example, if a user has already liked a page of Manchester United, we can say with higher level of confidence, that a user is a fan of Manchester United and not the other team. We can add a keyword there itself without further waiting for more interactions.

Fuzzy Logic Keyword Algorithm

For each matching keyword with product information, a score of 0.1*confidence score is assigned with a maximum cumulative score of 1. It is assumed that a total of 10 keywords would suffice to find a perfect correlation between a product and consumer's choice.

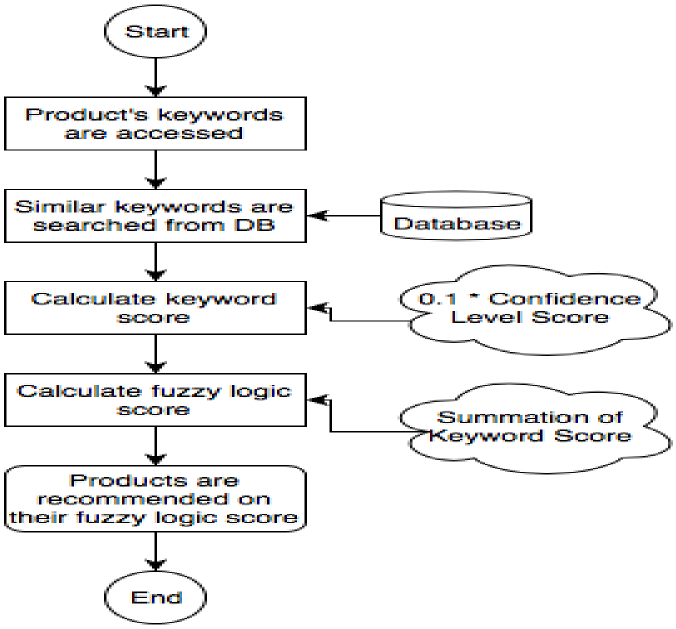

Figure 7. Flowchart of the keyword algorithm.

Step 1: Input

$\{P_1,P_2 \ldots P_{10} = P_i$ Where $P_1,P_2\ldots$ are product keywords

Step 2: Search similar keywords in database with highest confidence level score

Step 3: Calculate keyword score for each keyword

$$KeywordScore_i = 0.1 * ConfidenceLevelScore_i$$

Step 4: Calculate Fuzzy Logic Score

$$FuzzyLogicScore = \sum_{i=1}^{10} KeywordScore_i$$

With Fuzzy Logic Score between 0 and 1, products are recommended in their descending score. This score represents consumer's possible likeability towards particular product as we have associated it with a number of keywords that we have derived from his/her social media activities.

4. Discussion

4.1 Limitations

Crux of this algorithm is in user's data and it well hinges in the air if we do not get permission to access the data from a user. The biggest limitation of this algorithm is thus getting the data of a user.

Second limitation of this algorithm is that it doesn't go with all sort of products and generally aim to personalized products only. Example may include that of electronic products which highly depend on their specification and generally don't collide with user's personality. However, related products such as protection covers, bags etc. very well go with personalization.

4.2 Scope

Algorithm proposed in this paper can be useful for any e-commerce firms eyeing over attracting their users to the range of products which are hard to discover. With the use of this algorithm, consumers are very likely to find the set of products which are suited to their likeability. An empirical research with users connected with Facebook, Linked-in etc. can be carried out to validate the model with large sample size.

Even though this paper is aimed towards e-commerce mainly, scope of this algorithm can be extended to any internet businesses where preferences of users are inevitable in suggesting their services.

4.3 Conclusion

A primary research carried out on 228 users suggests that nearly 50% of people are either neutral or unsatisfied with the current system of recommendations provided. With the use of the social media data of users, the algorithm that we have introduced in this paper will be very useful in finding personalized products for the users. Analytics being used on social media data can give us insights about users' interests which are crucial in finding the products aligned with their likeability. Concerns shown by the users during our survey were majorly on privacy issues related to sharing their profiles which, if can be handled properly, this method will be very useful.

References

KEMP, S., Digital in 2018: World's internet users pass the 4 billion mark. Retrieved April 25, 2018, from https://wearesocial.com/uk/blog/2018/01/global-digital-report-2018.

Kaptein, M., & Parvinen, P. Advancing E-Commerce Personalization: Process Framework and Case Study, *International Journal of Electronic Commerce*, 19(3), pp.7-33, 2015.

Dataconomy, *An Introduction to Recommendation Engines.* May 30, 2016. Retrieved April 25, 2018, from http://dataconomy.com/2015/03/an-introduction-to-recommendation-engines/

Shaikh, S., Rathi, S., & Janrao, P. *Recommendation System in E-Commerce Websites: A Graph Based Approached.* 2017 *IEEE 7th International Advance Computing Conference (IACC), pp.*931-934, 2017.

Hendrick, D., Lanphear, D., Mahfoud, R., & Megraw, R., U.S. Patent No. US9922360B2. Washington, DC: U.S. Patent and Trademark Office, 2018.

Using Machine Learning on Compute Engine to Make Product Recommendations | Solutions | Google Cloud. (n.d.). Retrieved April 25, 2018, from https://cloud.google.com/solutions/recommendations-using-machine-learning-on-compute-engine.

Zhou, R., Khemmarat, S., & Gao, L. The impact of YouTube recommendation system on video views*, Proceedings of the 10th Annual Conference on Internet Measurement* - IMC 10. 2010.

Andzulis, J., Panagopoulos, N. G., & Rapp, A. A Review of Social Media and Implications for the Sales Process, *Journal of Personal Selling & Sales Management*,32(3), pp. 305-316, 2012.

Zhang, Y., & Pennacchiotti, M. Predicting purchase behaviors from social media, Proceedings *of the 22nd International Conference on World Wide Web* - WWW 13, 2013.

Zeng, D., Chen, H., Lusch, R., & Li, S. Social Media Analytics and Intelligence. *IEEE Intelligent Systems*, 25(6), pp. 13-16, 2010.

Biographies

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