Recommender system based on Psychographics similarity

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Agenda

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Abstract:

A recommender system has a job to predict the user preference by analyzing the past and current knowledge about the user.

The existing data-driven methodologies are highly dependent on a huge amount of past data.

Here we used Psychographics market segmentation Approach to build recommendation engine by finding the similarity score between the products

Introduction

Recommender system is used for estimating users' preferences and group the similar items they have not seen

It predicts the rating and rank of the product to the users

Types: 1) Content Based Recommendation (focused in Items Objects)

2) Collaborative filtering Recommendation (focused in relations)

Problems of Existing system

It works well, when it have a enough data to predict

Lack of information produce Cold start situation

Cold start happens when new users or new items arrive in to the system

Proposed system

Psychographics Market segmentation techniques along with ,Demographics Cognitive Attributes Collection, and Item to Item based collaborative filtering, makes the efficient recommendation system

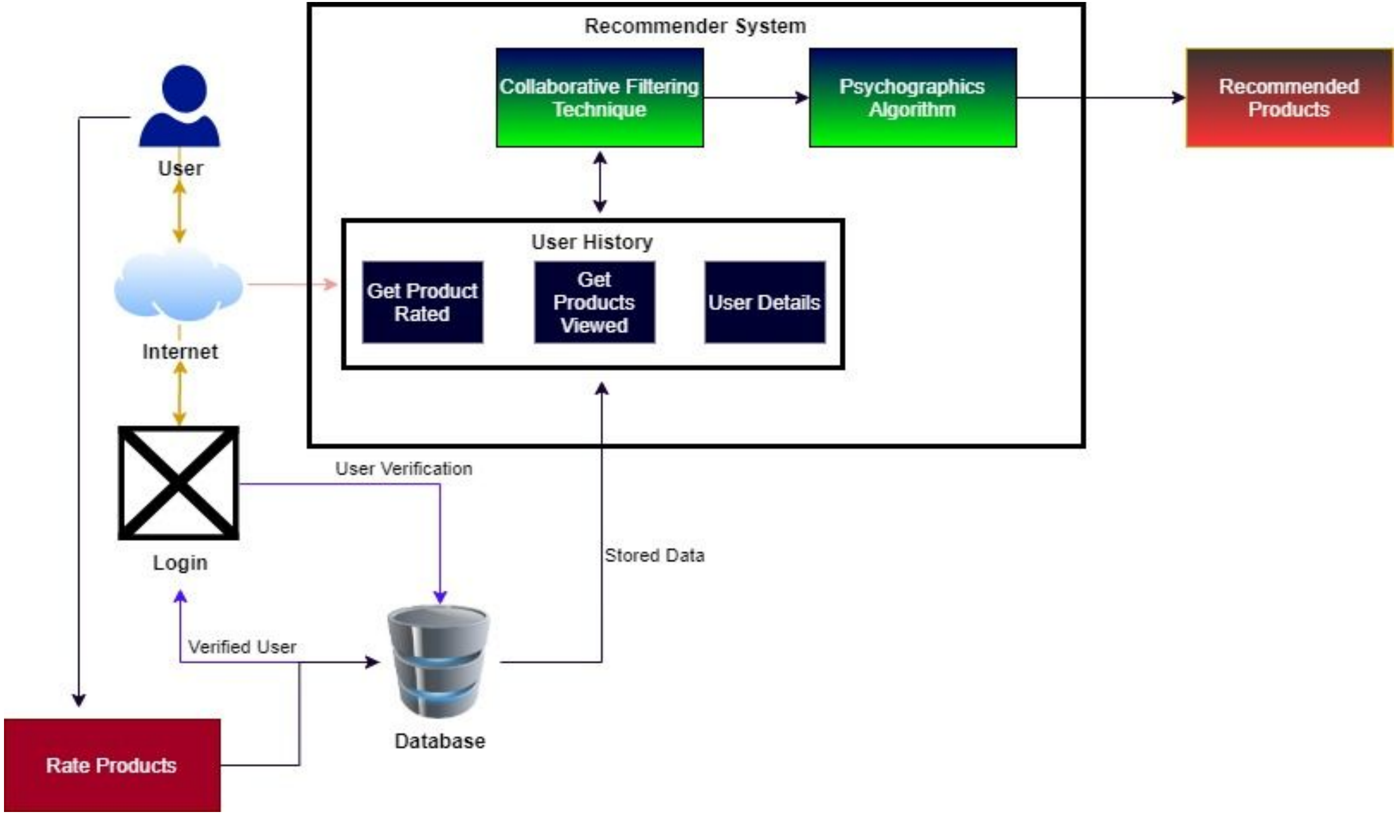
Literature Survey

Title	Advantages	Disadvantages
Content-based filtering for recommendation systems using multi attribute networks -JieunSon, Seoung BumKim -2017	Reliable results when fewer number of users and product	1.Requires a lot of domain knowledge 2.Model has limited ability to expand
Collaborative Filtering Recommendation Algorithm Based on Knowledge Graph - Ruihui Mu , Xiaoqin Zeng1 (2018)	Obtain the similarity model by using filtering the similar items, and grouping in together	1.Fully depends on user ratings and available data 2.Cold start

Literature Survey

Title	Advantages	Disadvantages
A Collaborative Recommendation System for Online Courses Recommendations-Raghad Obeidat ; Rehab Duwairi ; Ahmad Al-Aiad	recommends courses based on similarities of students' course history. The system employs data mining techniques to discover patterns	1.user’s past history and engagement score has been required 2.hard to scale
Recommendation System Using Semi-Supervised Learning-Sushmita Roy ; Mahendra Sharma ; Santosh Kumar Singh	Recommendation by using machine learning algorithms such as a content-based filtering approach, a collaborative-based filtering approach.	1 High computation required 2.Cold start problem,

Architecture diagram



Modules

1. Obtain and Optimize the dataset
2. Find the similarity matrix
3. Stored in reliable database
4. Recommend that item to user
5. Feedback

Calculate similarity

- Psychographics market segmentation

  Mainly focused on divides consumers into subgroups based on shared psychological characteristics

- Item to item based collaborative filtering

  similarity between items calculated using the rating users have given to items

Big Five personality traits -Psychographics

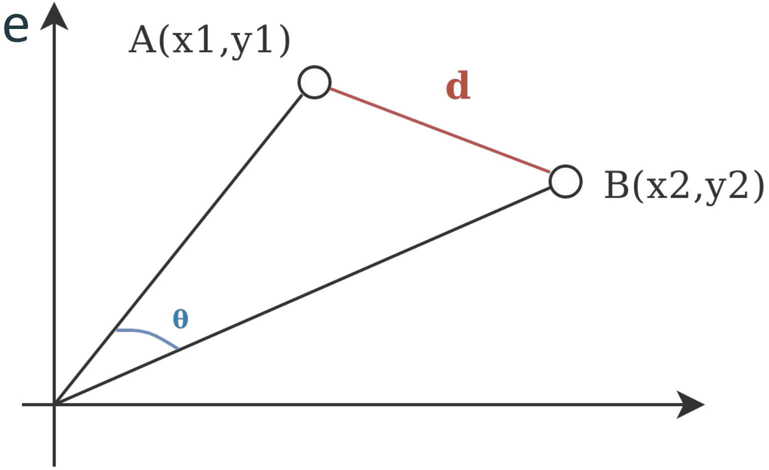
- Openness
- Consciousness
- Extraversion
- Agreeableness
- Neuroticism

Low score	Five personality traits	High score
Practical; conventional; prefers routine	Openness (O): Imagination; feelings; actions; ideas	Curious; wide range of interests; independent
Impulsive; careless; disorganized	Conscientiousness (C): Competence; self-discipline; thoughtfulness; goal-driven	Hardworking; dependable; organized
Quiet; reserved; withdrawn	Extraversion (E): Sociability; assertiveness; emotional expression	Outgoing; warm; seeks adventure
Critical; uncooperative; suspicious	Agreeableness (A): Cooperative; trustworthy; good-natured	Helpful; trusting; empathetic
Calm; even-tempered; secure	Neuroticism (N): Tendency toward unstable emotions	Anxious; prone to negative emotions

Psychographics Score Calculation

Compare the similarity, against to another product by using euclidean distance and take a mean value

$$d_{L2}(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$



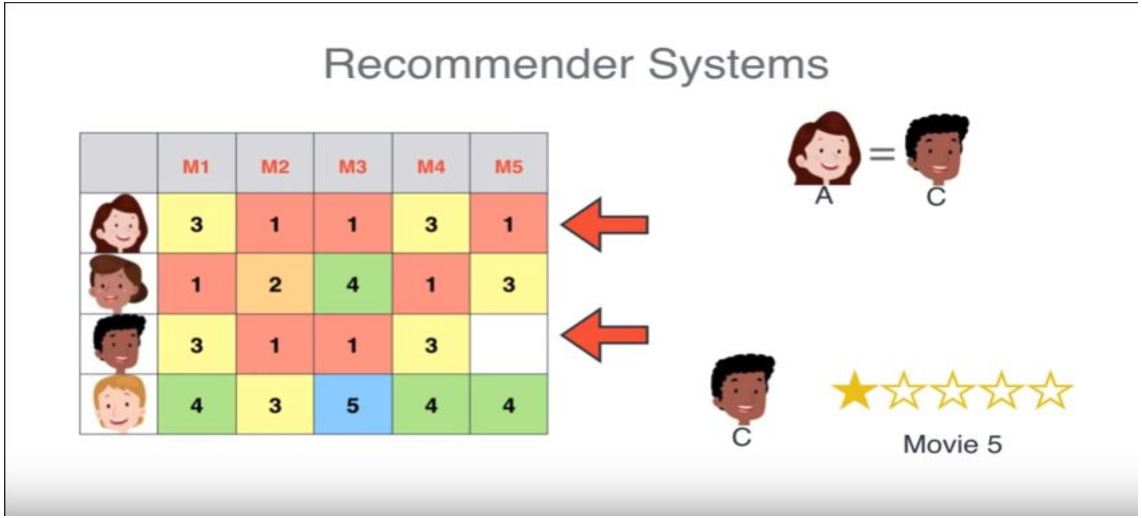
x = Product A vector

Y = Product B vector

D = Distance

Collaborative filtering Recommendation

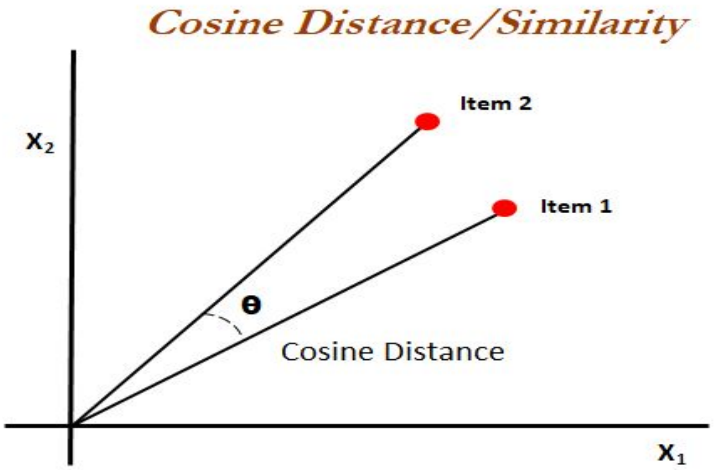
The key idea behind CF is that similar users share the same interest and that similar items are liked by a user



Score calculation in Collaborative filtering

Find the similarity between the items by using method like **cosine similarity** in two vectors

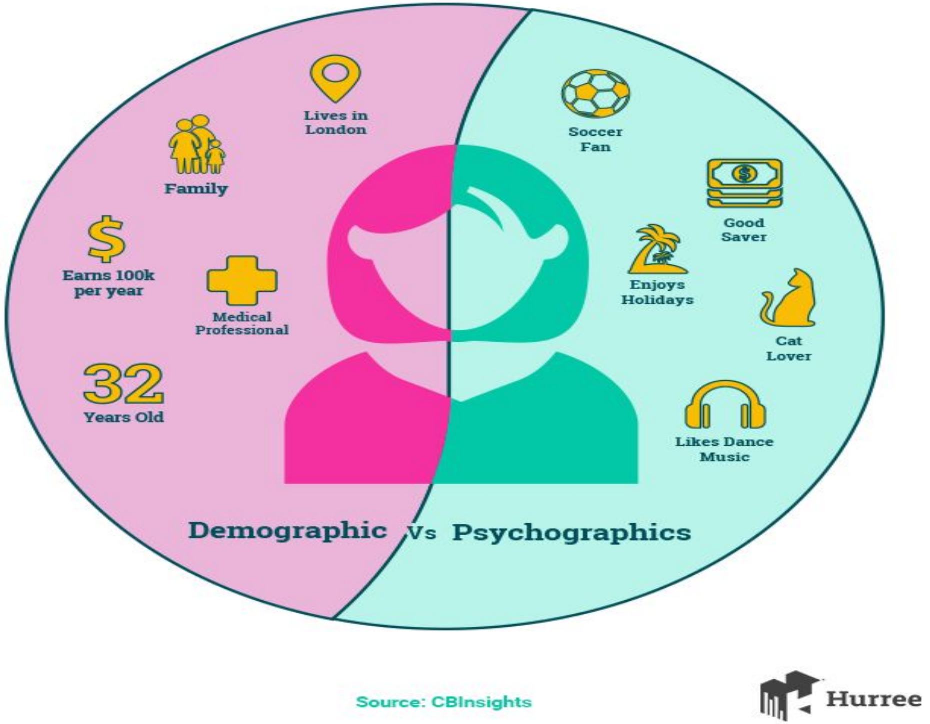
$$similarity(A,B) = \frac{A \cdot B}{\|A\| \times \|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}}$$



A = Product A vector
B = Product B vector

Combining with demographics

It includes: Age, race, ethnicity, gender, marital status, income, education, and employment.



Implementation

Psychographic dataset for the product was obtained from the series of **Brainstorming** session in each Cognitive attribute

Collaborative filtering was achieved by collection ratings

Application follows Microservice Architecture

Feedback

The feedback of recommendation has been collected and analyse the accuracy rate

It is responsible to tell performance of recommendation system

Its gives a opportunity to upgrade or recalculate the scores

Output

```
[ ] def get_similar(product_name,user_rating):
        similar_score = item_similarity_df[product_name]*(user_rating-2.5)
        similar_score = similar_score.sort_values(ascending=False)

        return similar_score

    print(get_similar("Product6",1))
```

```
Product1    1.371159
Product2    1.265061
Product3    1.203271
Product5   -0.590909
Product4   -1.085620
Product6   -1.500000
Name: Product6, dtype: float64
```

Collaborative approach

zero@alpha: ~/workspace/cognitive


```
{
  name: 'product0',
  similar: [
    { score: 0 },
    { score: 4.47213595499958 },
    { score: 9.219544457292887 },
    { score: 6.324555320336759 },
    { score: 0 },
    { score: 7.615773105863909 },
    { score: 4.47213595499958 },
    { score: 8.94427190999916 },
    { score: 0 },
    { score: 2.23606797749979 },
    { score: 5.0990195135927845 },
    { score: 1.4142135623730951 },
    { score: 0 },
    { score: 11.313708498984761 },
    { score: 5.656854249492381 },
    { score: 12.727922061357855 },
    { score: 0 },
    { score: 7.280109889280518 },
    { score: 7.615773105863909 },
    { score: 6.082762530298219 }
  ]
}
```


Psychographics score calculation

Conclusion

This System can provide a efficient recommendation with minimal computation requirement

Ability to scale and compatible to emerging application needs

Applications

Well suitable for efficient product matching and filtering

Deliver the results in the form of REST

Profound Decision making strategies by answering the question what? Why?

Further Enhancement

We are looking forward to implement that approach in neural networks to build a psychographic models on live

Implement the OSINT (Open source Intelligence) capabilities

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Thank You