Instituto Infnet

MIT - Data Science, Data Analytics & Machine Learning

Como recomendar filmes com base em classificações?

Final Assignment

Abordagem híbrida para sistema de recomendação

Renan Rocha e Thiago de Carvalho

problem_statement

É possível que um sistema de recomendação de filmes que sugira itens propensos a serem classificados (favoráveis e fora da bolha) a fim de reduzir organicamente a esparsidade dos dados a longo prazo?

print(sincere)

Desenvolver um sistema colaborativo de recomendação de filmes, baseado em classificações que sugiram para os usuários 4 segmentos de filmes:

Tipos de filmes vistos frequentemente

TRUE LOVE
(zona de conforto)

AFFAIR
(quando o amor vacila)

ONE NIGHT STAND
(por que não tentar a sorte?)

DRUNK FLERT
(cara, eu não me reconheço!)

Tipos de filmes vistos raramente

print(scope, len(movielens_dataset_ml-25m))

ESCOPO

Desenvolver um sistema colaborativo de recomendação de filmes filtrados com base em classificações.

- abordagem híbrida, aplicando pelo menos 3 algoritmos,
- para tratar de questões de esparsidade (sparsity) de dados

FORA DO ESCOPO

- Outros problemas clássicos (Scalability, Cold Start)
- Conta compartilhada: Múltiplos usuários/utilização de telas
- Heavy users/ bots

25MM ratings

162K users

62K movies

95% sparsity

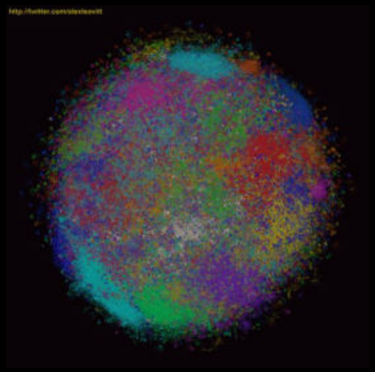
concepts.restore(memory_cards)

Sparsity index

Índice que varia de 1 a 0, quanto mais alto o índice, mais o esparso (com poucas avaliações / total de possíveis avaliações) o item ou usuário é..

$$sparsity = 1 - \frac{count\_nonzero(A)}{total\_elements\_of\_A}$$

Fuzzy clustering



Uma forma de agrupamento em que cada ponto de dados pode pertencer a mais de um grupo.

NPS - Net promoter score

Métrica que mostra a probabilidade de os usuários recomendarem uma empresa, produto ou serviço a um amigo ou colega - desenvolvida por Fred Reichheld.

SVD

Algoritmo de fatoração matricial, popularizado por Simon Funk durante o Prêmio Netflix, que é equivalente à fatoraçao Matricial Probabilística quando as linhas de base não são utilizadas.

Para o Sincere, o hiperparametro de fatores latentes foi definido para 75 vizinhos. Isso significa, extrair características e correlação da matriz de 75 itens de usuário mais próximos.

Benchmarks and references

- Najafabadi et Al. - An Effective Collaborative User Model Using Hybrid Clustering Recommendation Methods
- Mohammed Fadhel Aljunid, Manjaiah DH - An Efficient Deep Learning Approach for Collaborative Filtering Recommender System
- Nicholas Becker - https://beckernick.github.io/

pip update recommender_systems (a)

Aplicação sequencial de dois métodos distintos de agrupamento:

1º (hard clustering) os itens são agrupados por k means para reduzir a disparidade

2º (soft clustering) agrupamento de usuários usando fuzzy c means.

[!] O output do k means é usado como input do fuzzy, quantidade de filmes de cada cluster vistos por usuário atributo diferencia-los quanto ao uso.

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An Effective Collaborative User Model Using Hybrid Clustering Recommendation Methods

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Keywords:
recommendation system, fuzzy clustering, collaborative filtering, sparsity

ABSTRACT

Collaborative Filtering (CF) has been known as the most successful recommendation technique in which recommendations are made based on the past rating records from like-minded users. Significant growth of users and items have negatively affected the efficiency of CF and pose key issues related to computational aspects and the quality of recommendation such as high dimensionality and data sparsity. In this study, a hybrid method was proposed and was capable to solve the mentioned problems using a neighborhood selection process for each user through two clustering algorithms which were item-based k-means clustering and user-based Fuzzy Clustering. Item-based k-means clustering was applied because of its advantages in computational time and hence it is able to address the high dimensionality issues. To create user groups and find the correlation between users, we employed the user-based Fuzzy Clustering and it has not yet been used in user-based CF clustering. This clustering can calculate the degree of membership among users into set of clustered items. Furthermore, a new similarity metric was designed to compute the similarity value among users with affecting the output of user-based Fuzzy Clustering. This metric is an alternative to the basic similarity metrics in CF and it has been proven to provide high-quality recommendations and a noticeable improvement on the accuracy of recommendations to the users. The proposed method has been evaluated using two benchmark datasets, MovieLens and LastFM in order to make a comparison with the existing recommendation methods.

1. INTRODUCTION

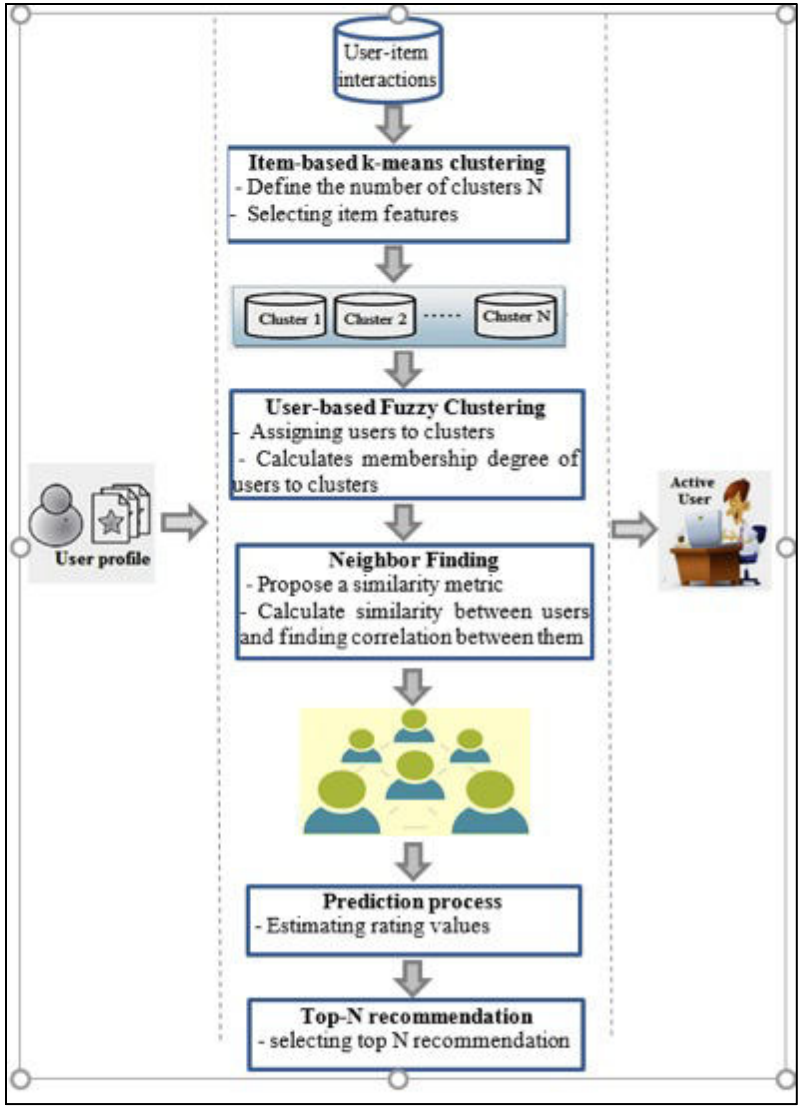
A recommender system provides a personalized set of recommendations by incorporating users' needs into a user model and applying suitable recommendation algorithms in mapping the user model into targeted item recommendations [1-3]. Due to the advancement in Internet technology, the development of recommender systems in e-commerce sites for product purchase advice is becoming more significant. This is due to its ability to save users' time and effort in searching for items [4-6].

Recent works have showed that to provide high-quality recommendations, the similarity metrics design have to be innovative and artificial learning machine and artificial intelligence ought to be employed [7, 8]. The major challenge is to accurately discover users' interests through creating a proper user model. In doing this, it is significant to identify the computation times which is necessary for defining the relations among users or items that can be regarded as performance issue of the recommender systems due to the large numbers of items or users. Moreover, there are drawbacks of CF recommendation systems that need to be addressed in increasing the quality of recommendation and accuracy of the predicted rated. These drawbacks are high dimensionality, data sparsity, and cold-start [9-12]. Most of the proposed recommender systems in solving drawbacks of CF failed to take action based on both sides of similarity (similarity among users and items) and it was discovered that the amount of time spent in calculating similarity among users or items to produce recommendations was extended. With the goal of reducing the execution of time with the number of bit processing, this study proposes a hybrid recommender system with a new similarity measurement method that combines the calculation of similarity between items and users in predicting the score of active users on unseen items.

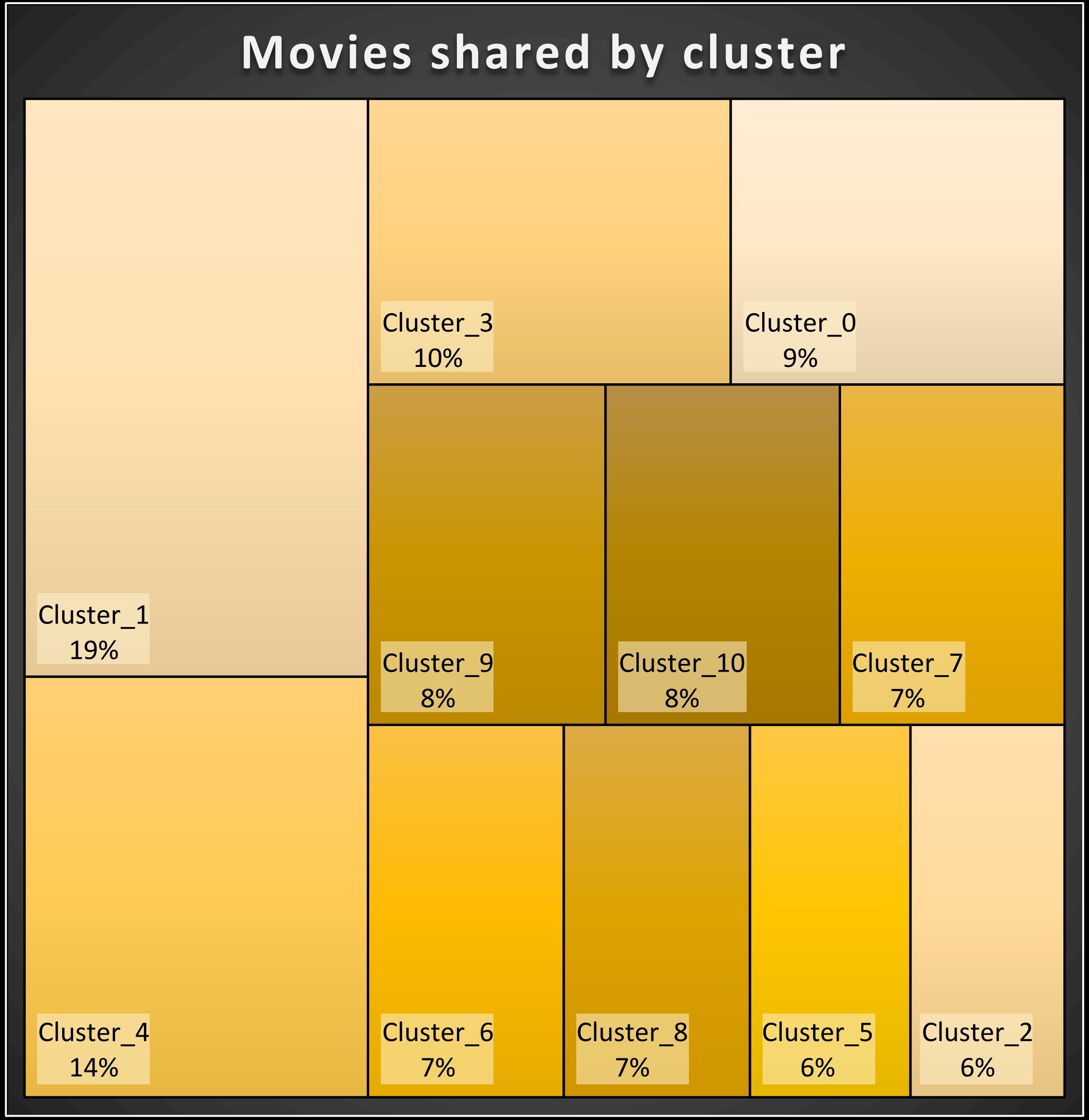
The motivation and contribution of this study will be presented in sub-section 1.1. This paper is organized into the following sections: Section 2 briefly provides reviews on previous works on recommender systems and the clustering techniques. Section 3 presents the research methodology used in this study. The proposed recommendation method and experiment methodology will be described in the following subsections (3.1 and 3.2). Section 4 describes results of the experiment conducted. Section 5 outlines the conclusions and future direction of this work.

1.1 Motivation

One of the most successful clustering techniques to overcome the issues of CF is fuzzy c-means. In fact, there are research methodologies developed to increase the quality of recommendations that apply fuzzy C-means clustering in CF. However, these research methodologies have not yet been applied in user's modeling for making recommendations and none of those concentrate on execution time that is required to calculate the similarity of active users among the existing users



print(movie_clustering_results)



	Movie_cluster_0	Movie_cluster_1	Movie_cluster_2	Movie_cluster_3
movie age	-	-	old	youth
popularity ML	very rated	few ratings	very rated	few ratings
popularity IMDB	-	awarded	-	higher rates
NPS ML	-	higher satisfaction	-	high satisfaction
Genres	Crime	Biography	Animation	Biography
	Film-Noir	Sport	Family	Documentary
	Mystery	War	Fantasy	Music
	Thriller	Drama	Musical	News
	-	-	Short	Sport

	Movie_cluster_4	Movie_cluster_5	Movie_cluster_6	Movie_cluster_7
movie age	old	youth	-	-
popularity ML	-	-	-	-
popularity IMDB	-	-	-	lower rating
NPS ML	-	-	low satisfaction	low satisfaction
Genres	Comedy	Mystery	Comedy	Adult
	Musical	Thriller	-	Horror
	Reality-TV	-	-	Sci-Fi
	Talk-Show	-	-	-
	Western	-	-	-

	Movie_cluster_8	Movie_cluster_9	Movie_cluster_10
movie age	-	old	-
popularity ML	lots of ratings	-	-
popularity IMDB	-	awarded	-
NPS ML	lower satisfaction	-	low satisfaction
Genres	Action	Romance	Romance
	Adventure	-	Musical
	Sci-Fi	-	-
	-	-	-
	-	-	-

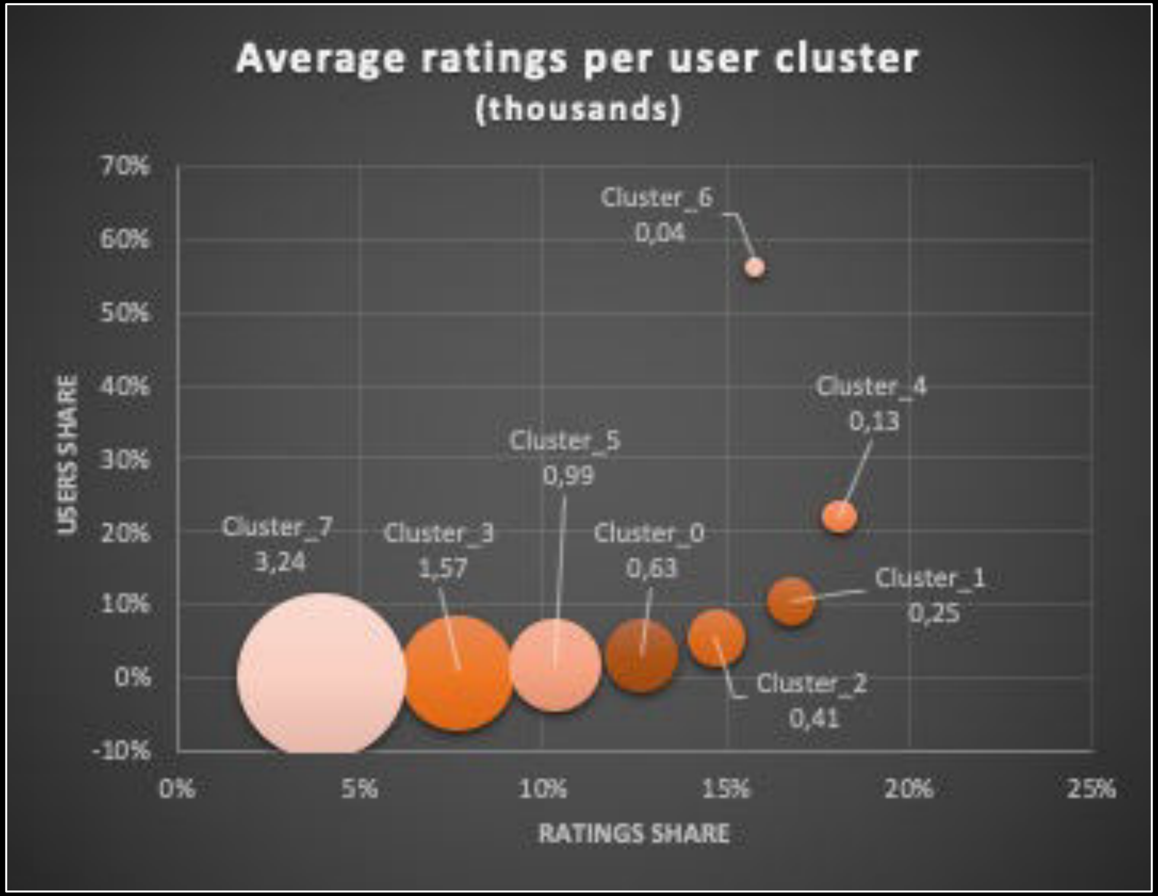
Clustering metrics used to define k=11: Elbow, Silhouette, David Boudin and Dendrogram

Fuzzy C-means

	movie_cluster_0.0	movie_cluster_1.0	movie_cluster_2.0	movie_cluster_3.0	movie_cluster_4.0	movie_cluster_5.0	movie_cluster_6.0	movie_cluster_7.0	movie_cluster_8.0	movie_cluster_9.0	movie_cluster_10.0
0	6.0	21.0	2.0	1.0	7.0	3.0	8.0	0.0	2.0	13.0	7.0
1	16.0	47.0	21.0	0.0	16.0	9.0	8.0	1.0	43.0	9.0	14.0
2	92.0	63.0	49.0	1.0	62.0	61.0	22.0	22.0	237.0	16.0	31.0
3	18.0	15.0	31.0	5.0	35.0	17.0	1.0	4.0	110.0	1.0	5.0
4	14.0	18.0	10.0	0.0	16.0	4.0	11.0	1.0	12.0	6.0	9.0
...	...	...	...	...	...	...	...	...	...	...	...
162536	6.0	11.0	8.0	0.0	17.0	4.0	10.0	2.0	9.0	10.0	24.0
162537	6.0	14.0	14.0	0.0	21.0	7.0	11.0	2.0	14.0	30.0	35.0
162538	3.0	10.0	2.0	0.0	3.0	4.0	4.0	0.0	12.0	7.0	2.0
162539	5.0	10.0	20.0	0.0	2.0	7.0	3.0	6.0	17.0	8.0	10.0
162540	15.0	26.0	17.0	1.0	31.0	6.0	14.0	4.0	40.0	14.0	14.0

Fuzzy Matrix		User Fuzzy C Means Clustering							
		0	1	2	3	4	5	6	7
User_cluster_Label	0	45%	9%	22%	2%	5%	12%	4%	0%
	1	2%	51%	14%	0%	22%	0%	9%	0%
	2	14%	22%	47%	0%	9%	2%	5%	0%
	3	9%	4%	6%	49%	3%	21%	3%	5%
	4	0%	13%	2%	0%	61%	0%	23%	0%
	5	20%	6%	9%	12%	4%	46%	3%	0%
	6	0%	1%	0%	0%	10%	0%	89%	0%
	7	6%	5%	5%	17%	4%	9%	4%	50%

print(user_clustering_results)

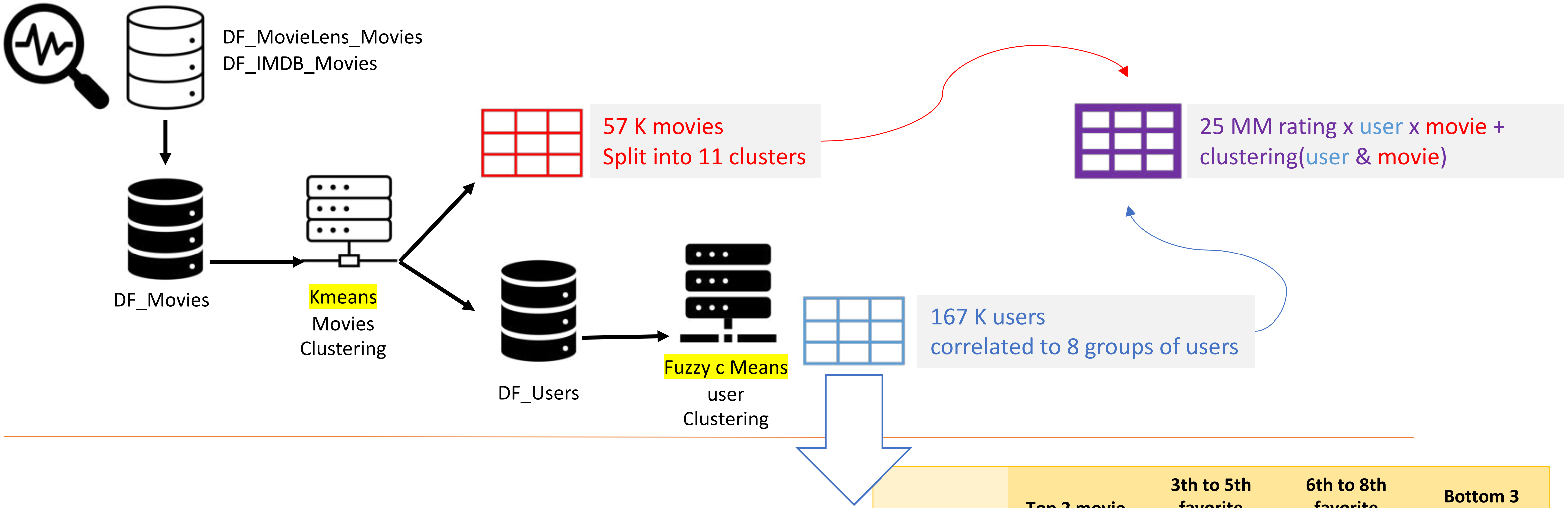


		User_cluster_0	User_cluster_1	User_cluster_2	User_cluster_3
	Favorite day	Monday Wednesday	Saturday Monday	Saturday Monday	Tuesday -
	Favorite time	afternoon	morning	morning	evening
	Voter profile	neutral mid voter	neutral mid voter	neutral mid voter	detractor heavy voter
Movie Clusters	True love movie clusters	8, 0	8, 4	0, 1	8, 1
	Affair movie clusters	2, 1, 9	1, 0, 10	8, 4, 10	0, 5, 7
	1 night stand movie clusters	4, 10, 5	2, 7, 6	5, 6, 2	2, 4, 9
	Drunk flert movie clusters	6, 7, 3	5, 9, 3	9, 7, 3	10, 6, 3

		User_cluster_4	User_cluster_5	User_cluster_6	User_cluster_7
	Favorite day	not Monday -	Wednesday -	Thursday Friday	Saturday Wednesday
	Favorite time	afternoon	morning	night	evening
	Voter profile	promoter lower voter	detractor mid voter	promoter lower voter	neutral heavy voter
Movie Clusters	True love movie clusters	0, 8	8, 1	8, 4	0, 1
	Affair movie clusters	1, 10, 2	10, 2, 4	0, 1, 2	8, 4, 10
	1 night stand movie clusters	4, 5, 9	9, 0, 5	10, 6, 5	5, 6, 9
	Drunk flert movie clusters	6, 7, 3	6, 7, 3	7, 3, 9	3, 2, 7

plt.sincere_setup.show()

Setup



Output

User Cluster	Top 2 movie clusters	3th to 5th favorite movie clusters	6th to 8th favorite movie clusters	Bottom 3 movie clusters
1	1, 2	4,5,6	7,8,9	3,10,11
2	2,5	1,3,9	4,8,10	6, 7,11
…	…	…	…	…
n	6,9	7,8,10	2,3,11	1,4,5

pip update recommender_systems (b)

Um sistema híbrido de recomendação que é estabelecido com base em de fatoração de matrizes (...) que trabalha sobre os feedbacks implícitos dos usuários e também informações auxiliares tanto dos usuários quanto dos itens.

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An Efficient Deep Learning Approach for Collaborative Filtering Recommender System

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Abstract

Owing to the enormous growth in information over the past few decades, the world has become a global village. The recommendation system remains the most widely used type of commercial websites. The personalized recommender system is of paramount importance in modeling user's preference on items based on their past interactions (e.g., ratings and clicks), known as collaborative filtering (CF) technique. Although CF is very important among the algorithms used in recommendation systems, it suffers some setbacks such as the sparsity of matrix ratings, scalability, and integrals nature of data. Several research studies have shown that the above-mentioned obstacle could be tackled with the help of matrix factorization (MF) techniques. In spite of the fact that the technique is likely to suffer from lack of some meaningful signals by using a low ranked approximation as well as lack of sparsity in times of denser singular vectors. Recently, deep learning techniques have proven to learn good representation in natural language processing, image classification, and so on. In this work, we propose a deep learning method of collaborative recommender systems (DLCRS). We have made a comparative study of the proposed method and existing methods. Experimental results demonstrate that our approach gives improved results compared to already existing methods. We empirically evaluate DLCRS on two famous datasets: 100K and 1M Movielens.

Keywords: Recommender System , Collaborative Filtering , Matrix Factorization , Deep Learning , Movielens Datasets;

1. Introduction

The advancement of artificial intelligence and machine learning technologies has brought intelligent products that are essential in providing access to various endeavors of peoples' day-to-day life. Effective and useful information

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10.1016/j.procs.2020.04.090

plt.sincere_schema.show()

32 MATRIZES FATORADAS VIA SVD

8 CLUSTERS DE USUÁRIOS
*
4 SEGMENTOS
- TRUE LOVE
- AFFAIR
- 1 NIGHT STAND
- DRUNK FLERT

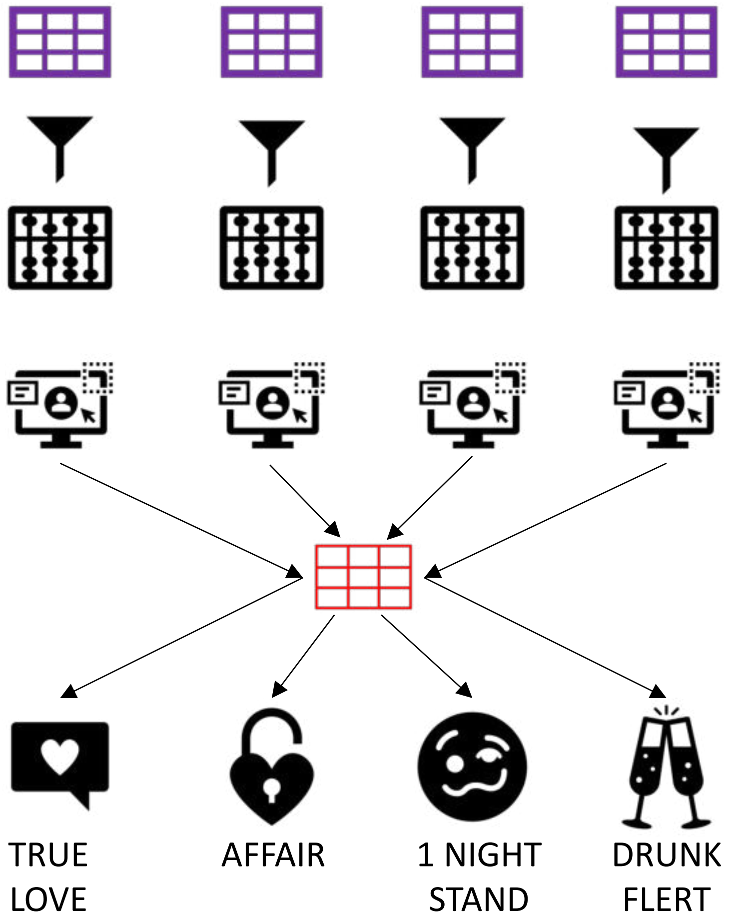
User Cluster	Top 2 movie clusters	3th to 5th favorite movie clusters	6th to 8th favorite movie clusters	Bottom 3 movie clusters
2	2,5	1,3,9	4,8,10	6,7,11

Filter 25 MM ratings database by user cluster and movie cluster

Factorization Matrix via (SVD)

Making Predictions from the Decomposed Matrices

Making Movie Recommendations



print(sincere)

Sincere recommendations

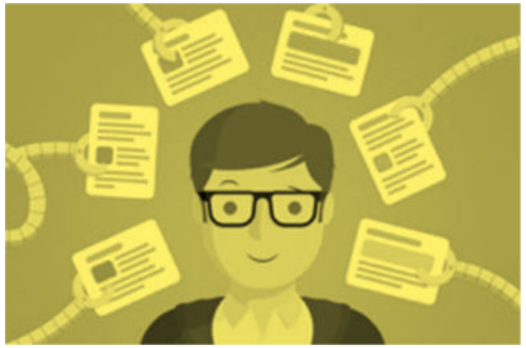
recommending and checking results

tests.describe( )

Sampling

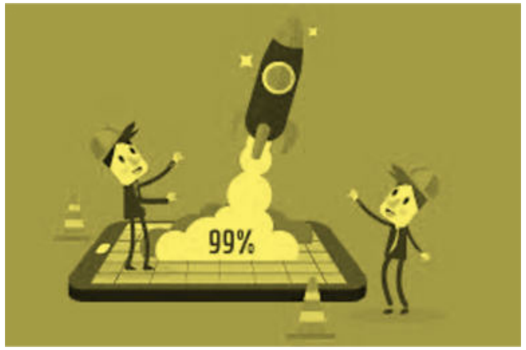
1 Amostra de 80 usuários. 10 de cada cluster com índice fuzzy alto.

Recommending



Recomendação de 20 filmes (5 para cada segmento de afinidade) usando Sincere.

Checking results



Analisar a similaridade e esparsidade das recomendações

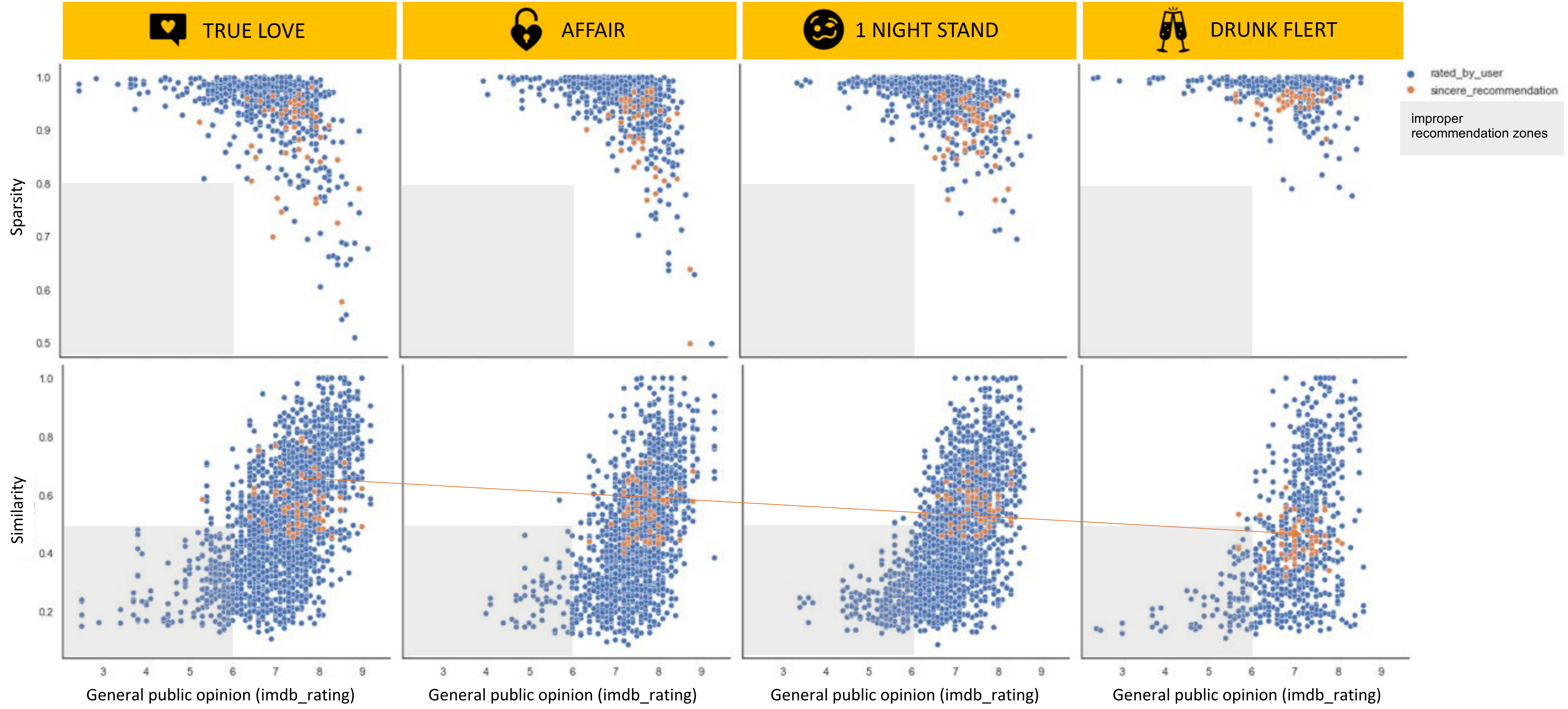
Target

Sincere recomendou filmes com avaliações esparsas?

Os filmes recomendados foram relevantes para o público em geral?

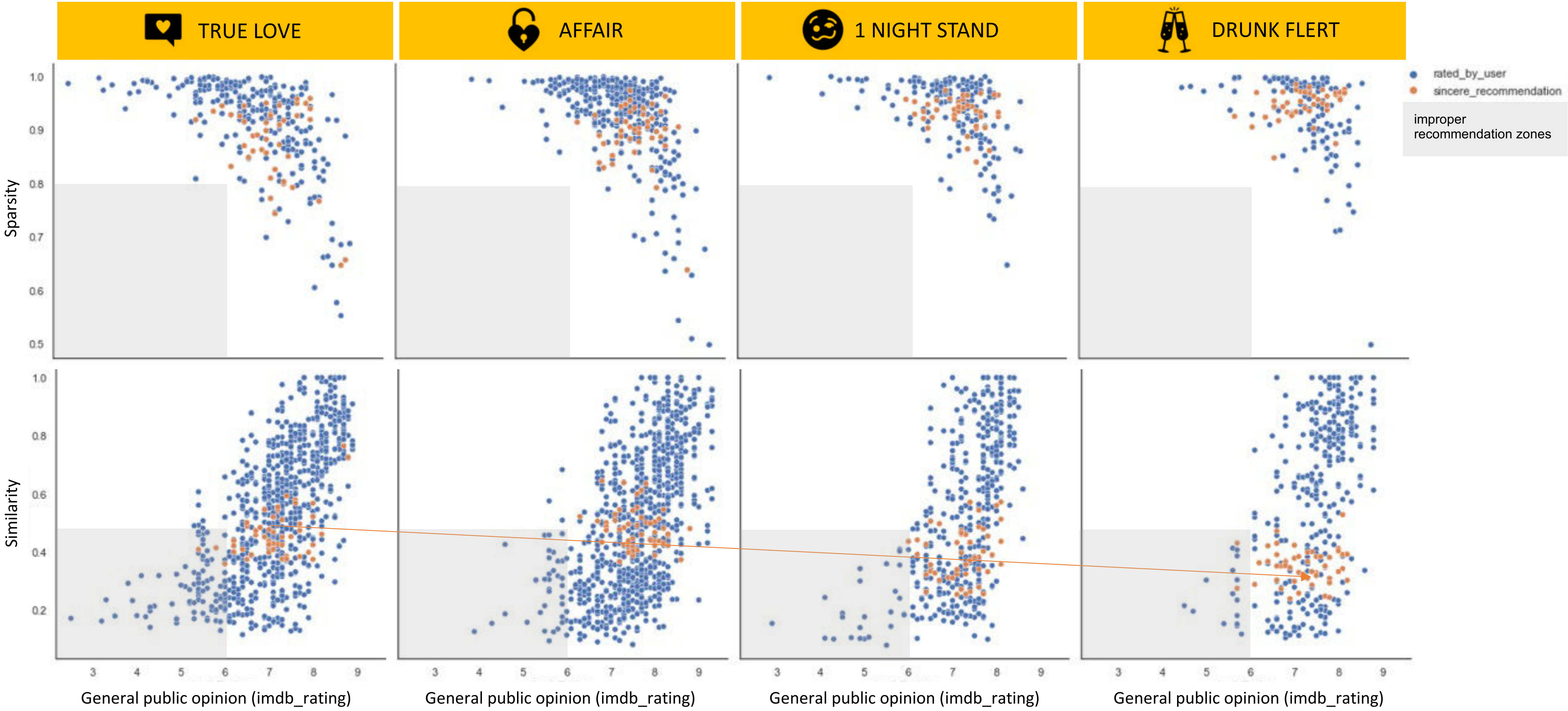
plt.sincere_results(Cluster_0)

Para os grupos de usuários mais densos (0, 1, 2, 3, 5 e 7), Sincere recomendou filmes com alta esparsidade e com classificação geral (IMDB) superior a 6. A semelhança relativa com o interesse comum do usuário está diminuindo de acordo com o segmento de recomendação, como esperado..



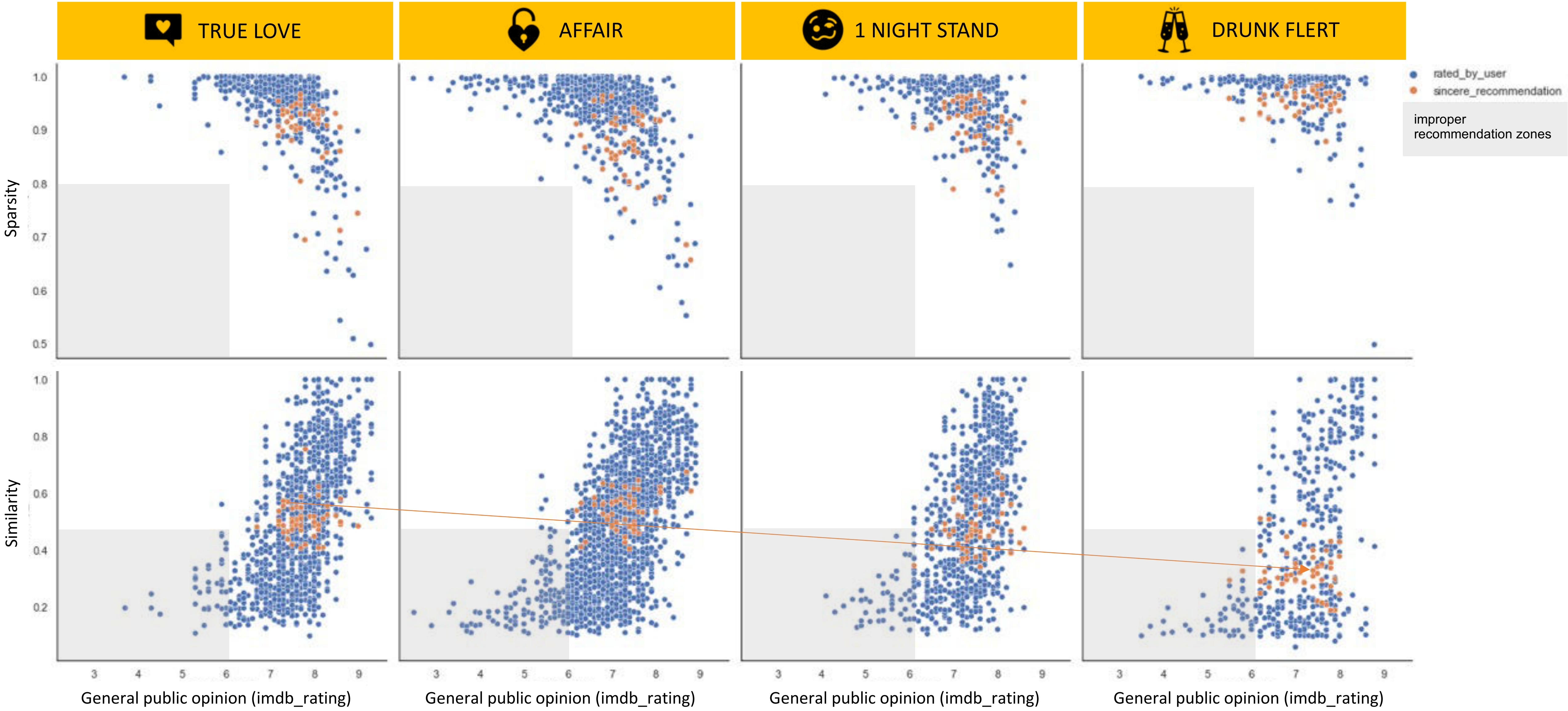
plt.sincere_results(Cluster_1)

Para os grupos de usuários mais densos (0, 1, 2, 3, 5 e 7), Sincere recomendou filmes com alta esparsidade e com classificação geral (IMDB) superior a 6. A semelhança relativa com o interesse comum do usuário está diminuindo de acordo com o segmento de recomendação, como esperado..



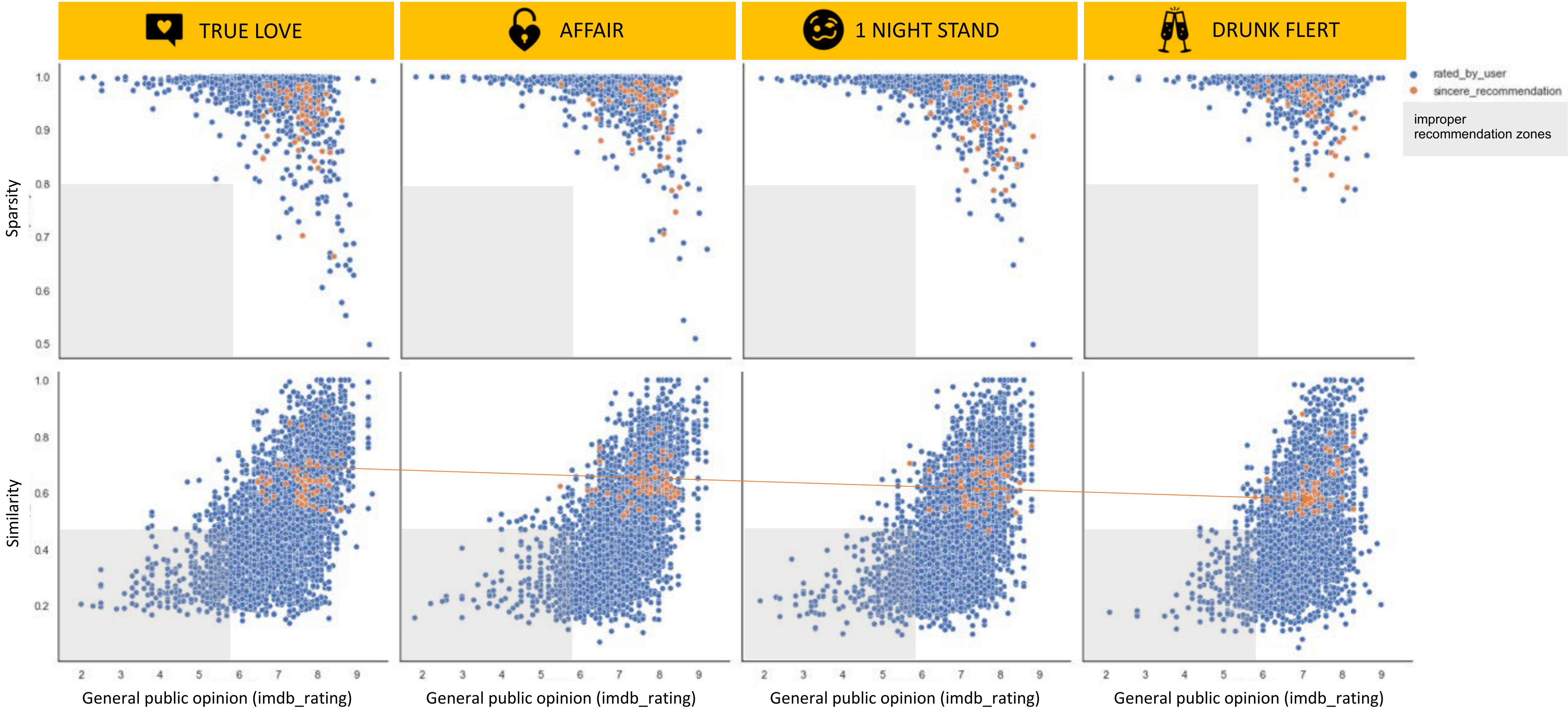
plt.sincere_results(Cluster_2)

Para os grupos de usuários mais densos (0, 1, 2, 3, 5 e 7), Sincere recomendou filmes com alta esparsidade e com classificação geral (IMDB) superior a 6. A semelhança relativa com o interesse comum do usuário está diminuindo de acordo com o segmento de recomendação, como esperado..



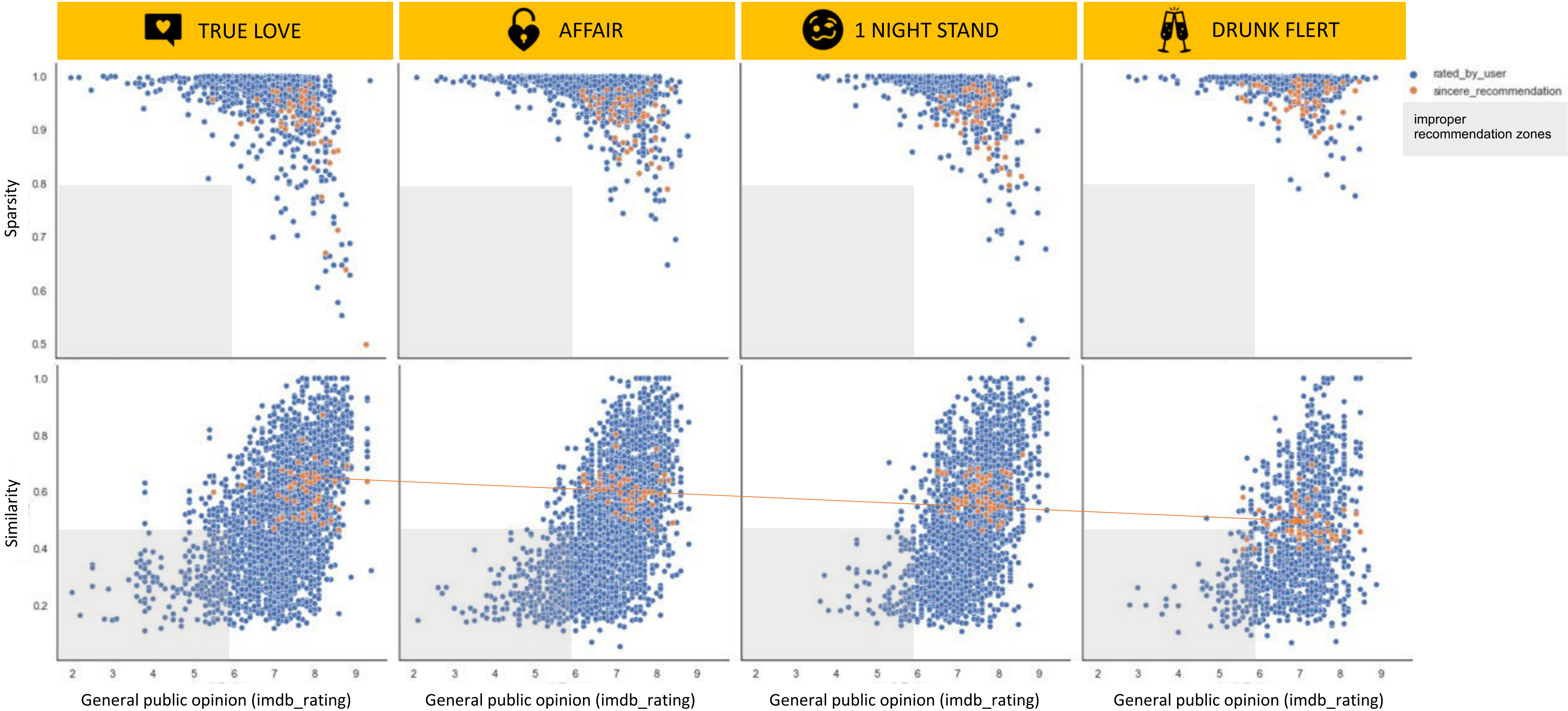
plt.sincere_results(Cluster_3)

Para os grupos de usuários mais densos (0, 1, 2, 3, 5 e 7), Sincere recomendou filmes com alta esparsidade e com classificação geral (IMDB) superior a 6. A semelhança relativa com o interesse comum do usuário está diminuindo de acordo com o segmento de recomendação, como esperado..



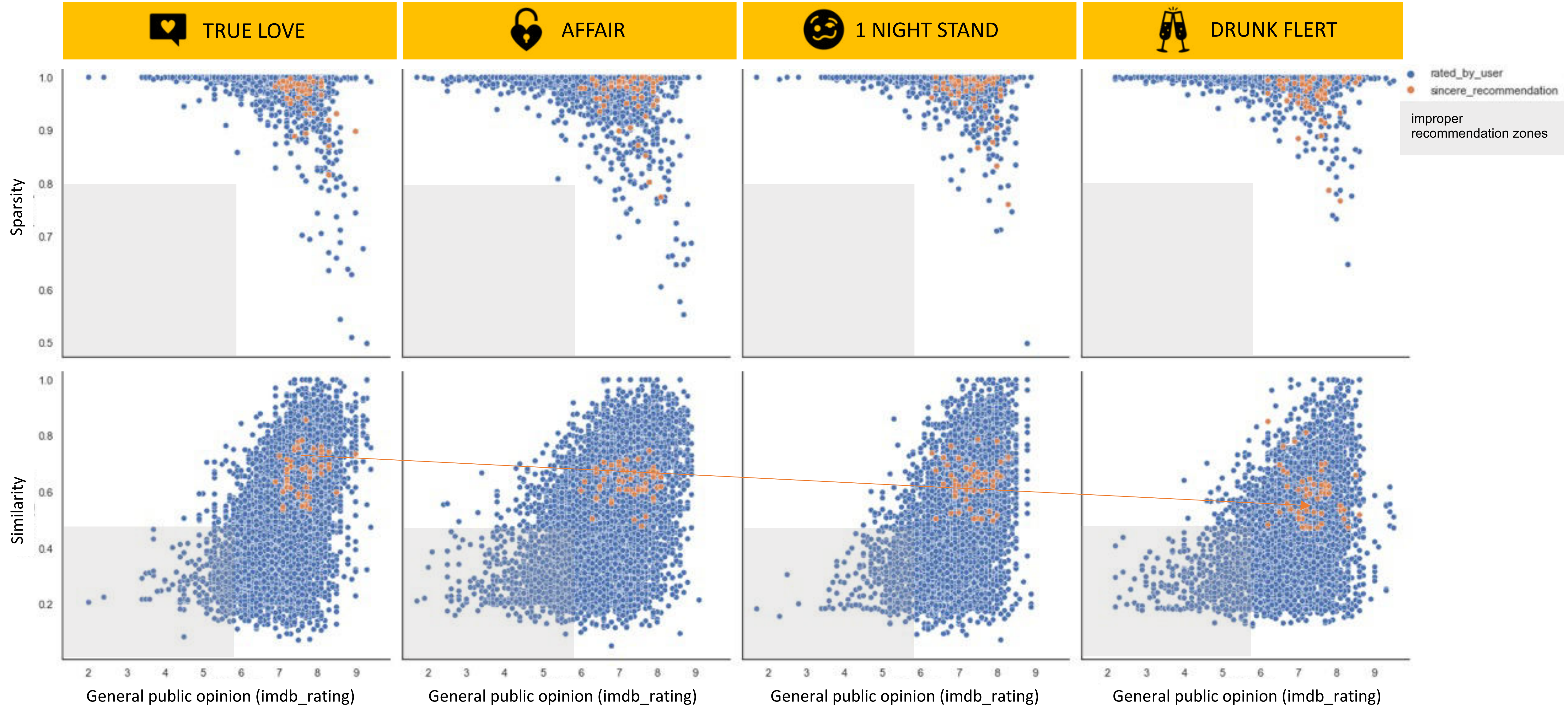
plt.sincere_results(Cluster_5)

Para os grupos de usuários mais densos (0, 1, 2, 3, 5 e 7), Sincere recomendou filmes com alta esparsidade e com classificação geral (IMDB) superior a 6. A semelhança relativa com o interesse comum do usuário está diminuindo de acordo com o segmento de recomendação, como esperado..



plt.sincere_results(Cluster_7)

Para os grupos de usuários mais densos (0, 1, 2, 3, 5 e 7), Sincere recomendou filmes com alta esparsidade e com classificação geral (IMDB) superior a 6. A semelhança relativa com o interesse comum do usuário está diminuindo de acordo com o segmento de recomendação, como esperado..



Example.({userId:130311,cluster:0})

	TRUE LOVE	AFFAIR	1 NIGHT STAND	DRUNK FLERT

Rated by user

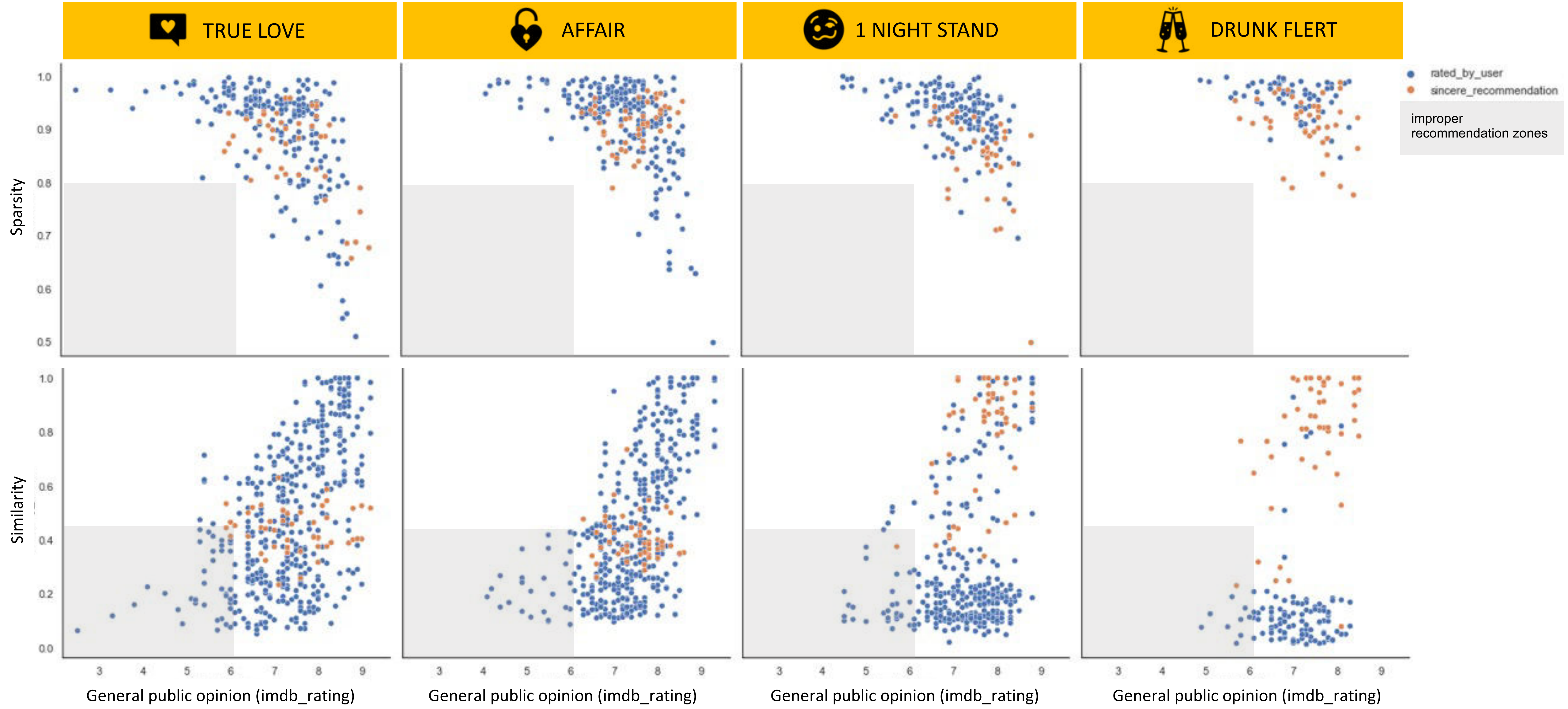
	TRUE LOVE	AFFAIR	1 NIGHT STAND	DRUNK FLERT
Imdb	9.0	9.3	8.6	8.4
Sparsity	0.99	0.99	0.99	0.99

Sincere

	TRUE LOVE	AFFAIR	1 NIGHT STAND	DRUNK FLERT
Imdb	8.1	7.3	8.3	7.7
Sparsity	0.96	0.94	0.91	0.97
Similarity	0.61	0.43	0.56	0.55

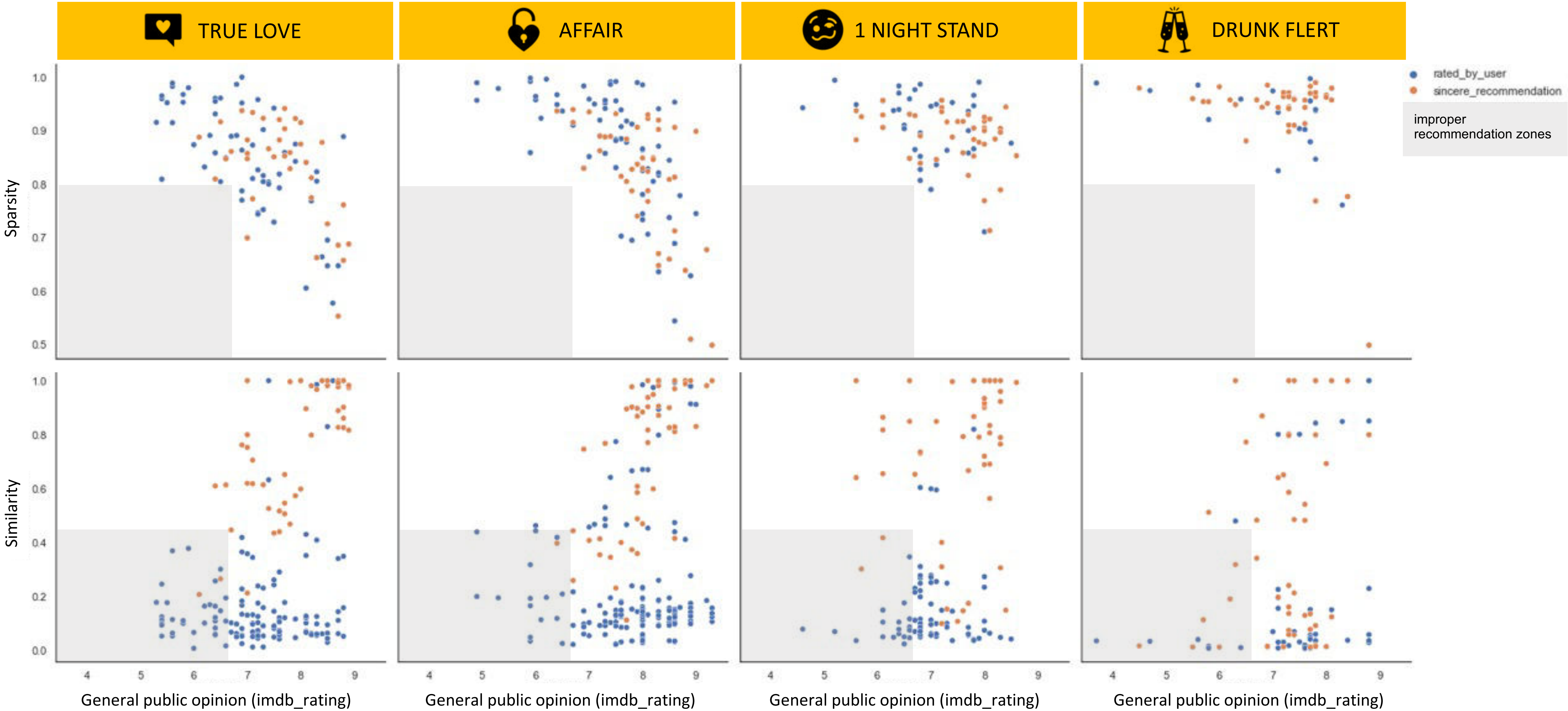
plt.sincere_results(Cluster_4)

Com o aumento da sparsity (clusters de usuários 4 e 6), nosso modelo tentou para recomendar adequadamente filmes seguindo nossas diretrizes de remoção da sparsity, escolhendo opções com melhor classificação geral (IMDB) e relativa similaridade com o interesse comum do usuário.



plt.sincere_results(Cluster_6)

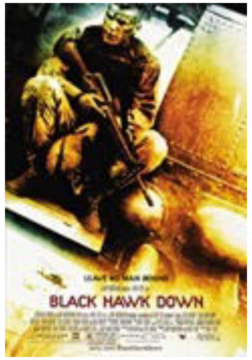
Com o aumento da sparsity (clusters de usuários 4 e 6), nosso modelo tentou recomendar adequadamente filmes seguindo nossas diretrizes de remoção da sparsity, escolhendo opções com melhor classificação geral (IMDB) e relativa similaridade com o interesse comum do usuário.

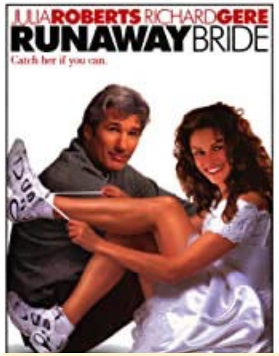


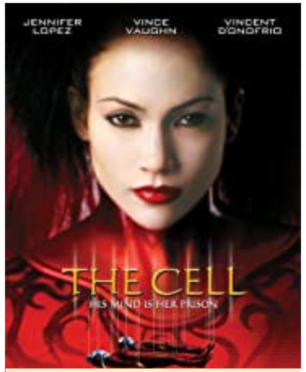
Example.({userId:135548,cluster:6})

	TRUE LOVE	AFFAIR	1 NIGHT STAND	DRUNK FLERT

Rated by user

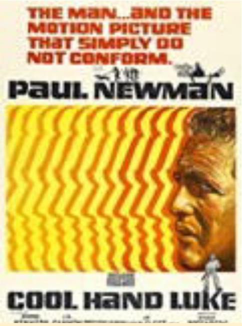


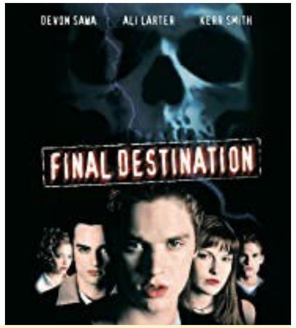




	TRUE LOVE	AFFAIR	1 NIGHT STAND	DRUNK FLERT
Imdb	8.7	8.8	7.8	8.7
Sparsity	0.96	0.96	0.95	0.95
Similarity	0.16	0.66	0.58	0.84

Sincere

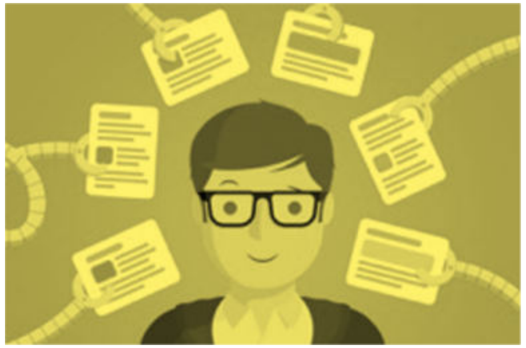



	TRUE LOVE	AFFAIR	1 NIGHT STAND	DRUNK FLERT
Imdb	8.1	8.0	8.3	7.7
Sparsity	0.96	0.97	0.91	0.97
Similarity	1	1	1	1

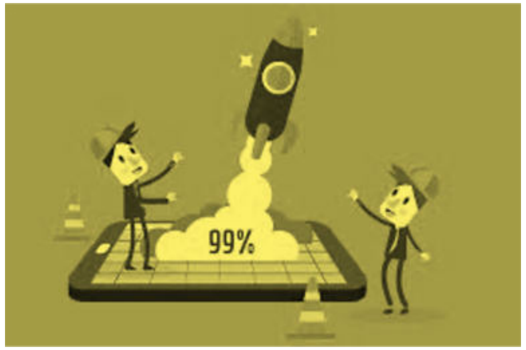
tests.describe( )

Sampling

Recommending



Checking results



Target

1

Amostra de 80 usuários. 10 de cada cluster com índice fuzzy alto.

Recomendação de 20 filmes (5 para cada segmento de afinidade) usando Sincere.

Analisar a similaridade e esparsidade das recomendações

2

Dividir o banco de dados para identificar os 10% de usuários com índice fuzzy mais alto. (Com os 80 da amostra usada no teste 1 incluídos).

Recomendação de 20 filmes para os mesmos 80 usuários com o sistema de recomendação tradicional.

Verificar se os resultados sinceros em comparação com o sistema de recomendação comum.

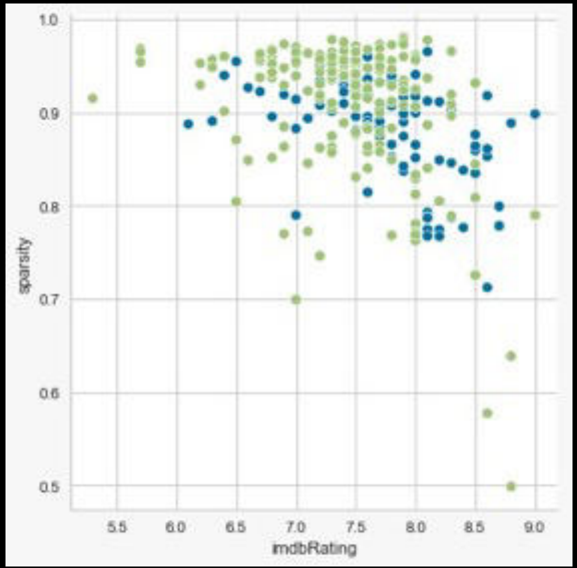
Sincere recomendou filmes com avaliações esparsas?

Os filmes recomendados foram relevantes para o público em geral?

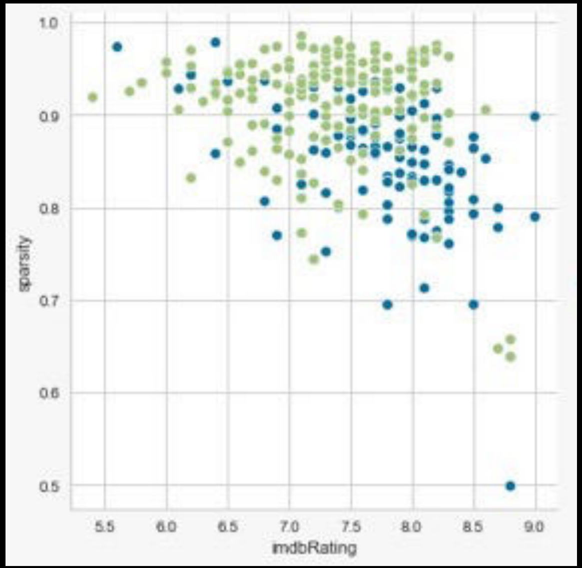
sparsity_vs_rating.compare()

- ordinary recommendations
- sincere recommendations

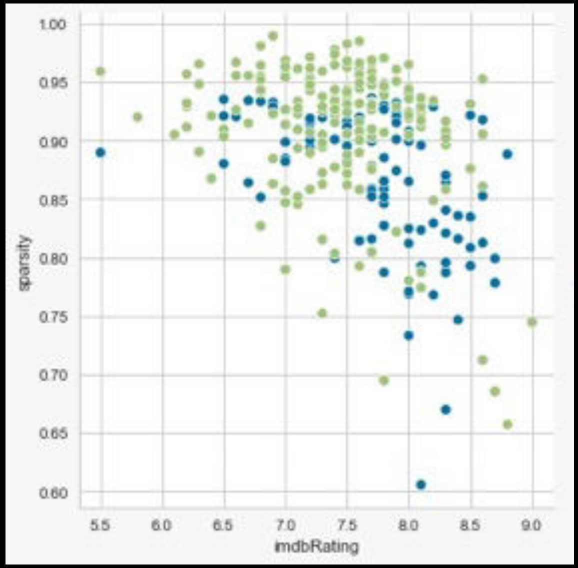
Cluster 0



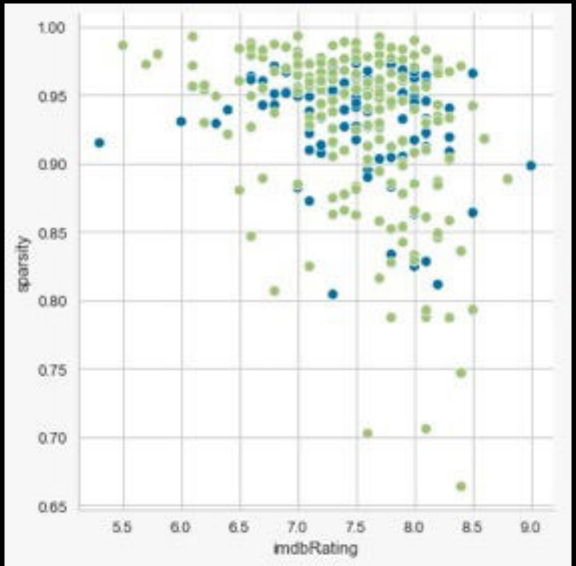
Cluster 1



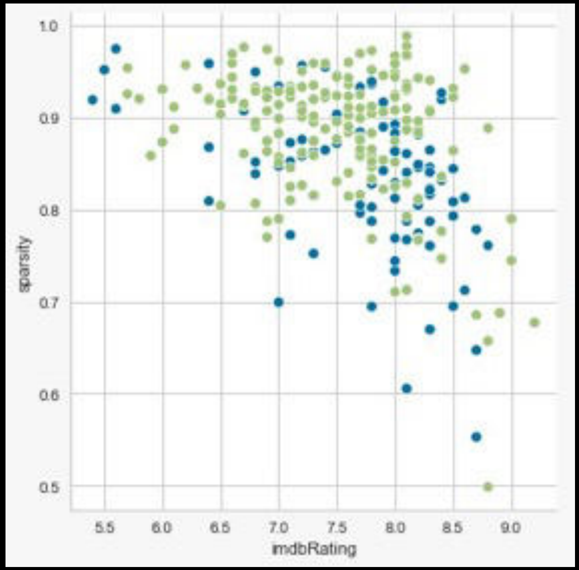
Cluster 2



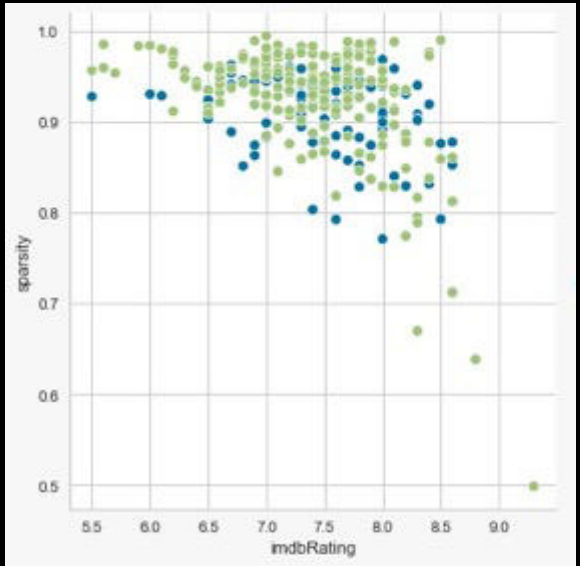
Cluster 3



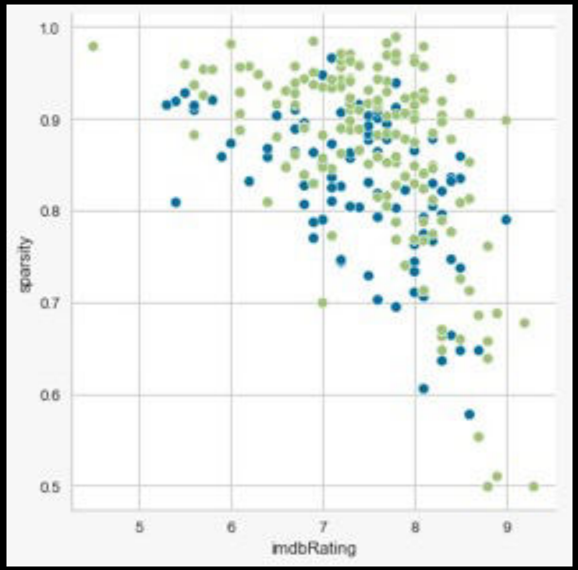
Cluster 4



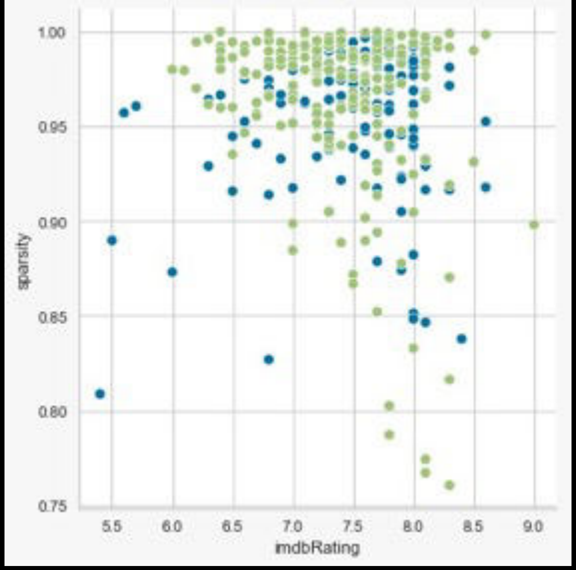
Cluster 5



Cluster 6



Cluster 7



print(sincere_key_findings)

print(f'conclusion: {conclusion}')

O experimento SINCERE, com os seus resultados preliminares sugere que:

- É possível implantar mecanismos de recomendação que reduzem esparsidade sem afetar a satisfação do usuário.
- Não há bala de prata para recomendar corretamente para todos os usuários, é conveniente misturar técnicas.
- Os sistemas de recomendação também podem ser uma arma para estourar a bolha da segregação cultural nas redes.
- A divisão do conjunto de dados por 4 segmentos de filmes similares também superou algumas limitações computacionais.

- Enriquecer o modelo com dados dos usuários
- Revisar a clusterização de usuários especialmente para clusters 6 e 4, a fim de maximizando os benefícios do fuzzy.
- Testar outros métodos de fatoração: PMF, SVD++, NMF
- Aplicar outros modelos tradicionais de recomendação e comparar com os resultados do Sincere.
- Colocar o modelo em produção, aceitando input de novos usuários e itens

Evoluções do trabalho

- Análise do perfil de votação pode gerar mais engajamento e satisfação ao notificar usuários.
- Campanha promocional para voters pode estimular bons resultados contra esparsidade [exemplo: convites para premiéres exclusivas]

Business insights

Sincerely, Yours

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