REVA UNIVERSITY
Bengaluru, India
Established as per the section 2(f) of the UGC Act, 1956,
Approved by AICTE, New Delhi

REVA Academy for Corporate Excellence (RACE)

Explainable Recommender Systems

Yashaswini Viswanath
SRN: R20MTA12

Date: 27/08/2022

Mentor: Dr. J. B. Simha

M.Tech in Artificial Intelligence

Capstone Project Presentation
Year: II

race.reva.edu.in

REVA UNIVERSITY
Bengaluru, India
Established as per the section 2(f) of the UGC Act, 1956,
Approved by AICTE, New Delhi

Agenda

01 Introduction
Background | Current status | Why this study

02 Literature Review
Seminal works | Summary | Research Gap

03 Problem Statement
Technical/Functional Problem

04 Project Objectives
Primary & Secondary Objectives | Expected Outcome

05 Project Methodology
Conceptual Framework | Research Design

06 Resources Specification
Software | Hardware

07 Software Design
High Level | Low Level Design Diagrams

08 Implementation
Demo | Application | Use cases

09 Testing and Validation
Test Results | Learnings

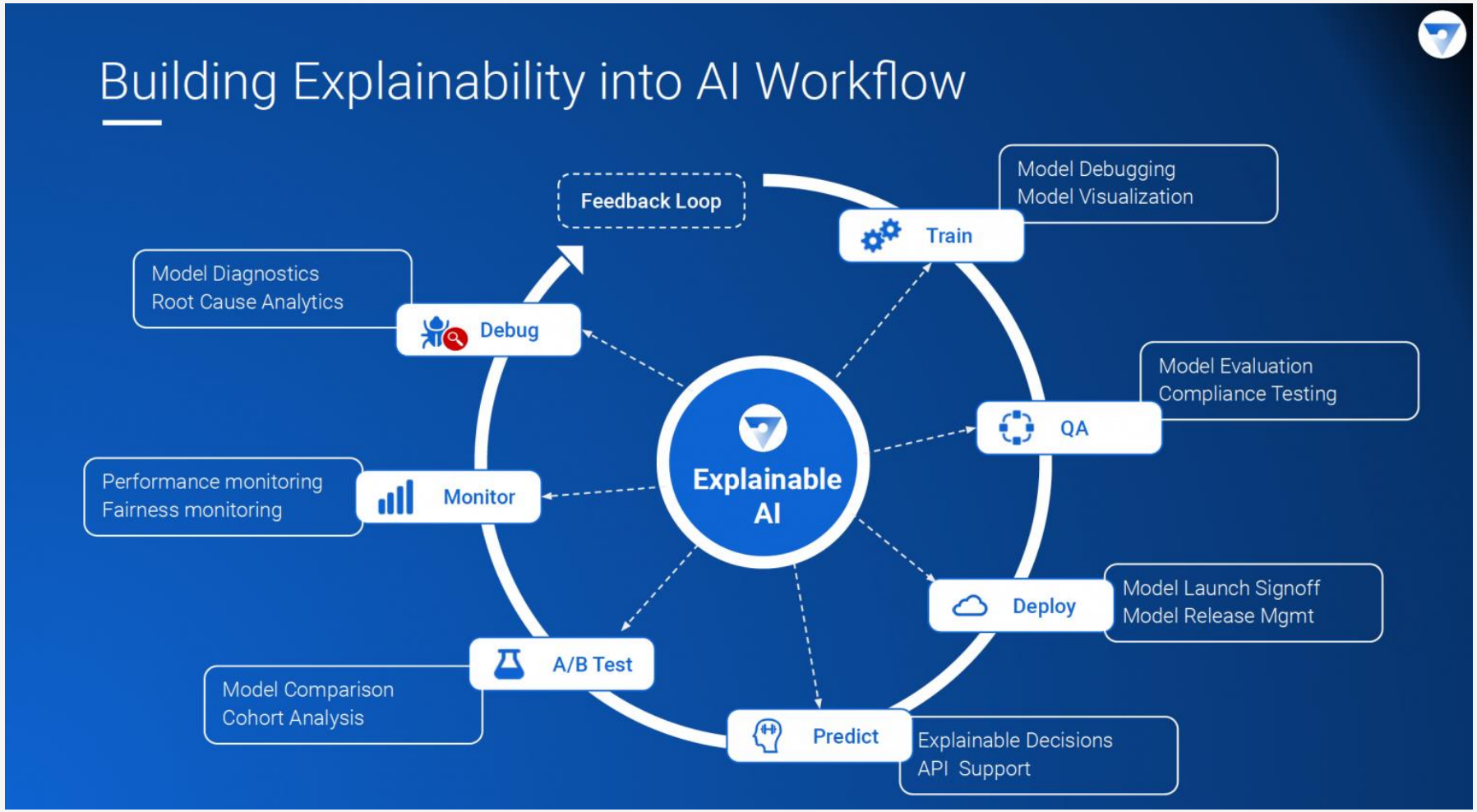
10 Analysis and Results
Key Findings | Insights

12 Suggestions and Conclusion
Insights | Next Step | Future Scope

13 Annexure
References | Publications | Plagiarism Score

Introduction

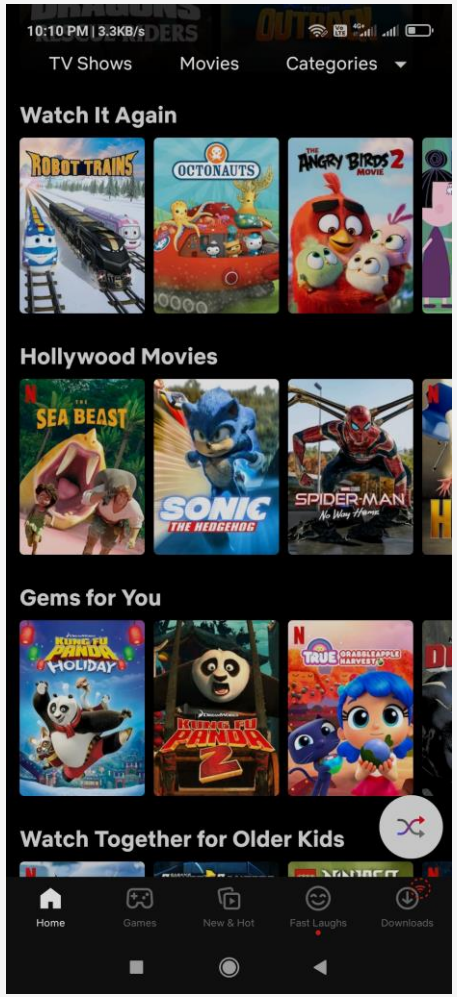
Background | Current status | Why this topic

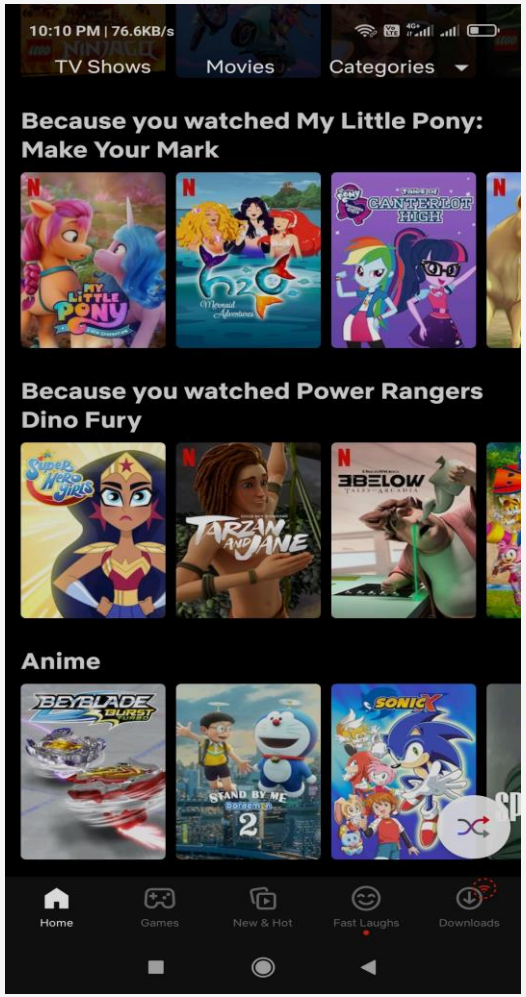


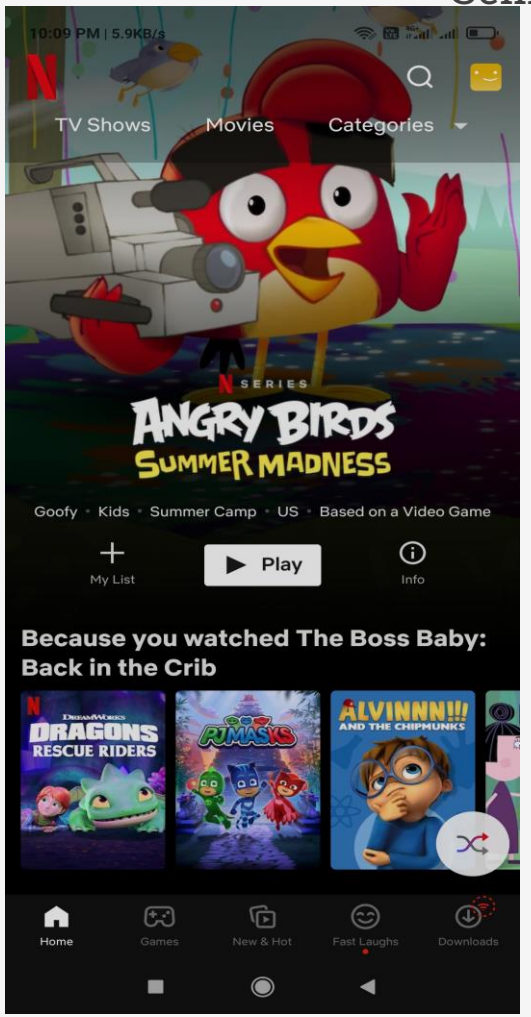
REVA UNIVERSITY
Bengaluru, India
Established as per the section 2(f) of the UGC Act, 1956,
Approved by AICTE, New Delhi

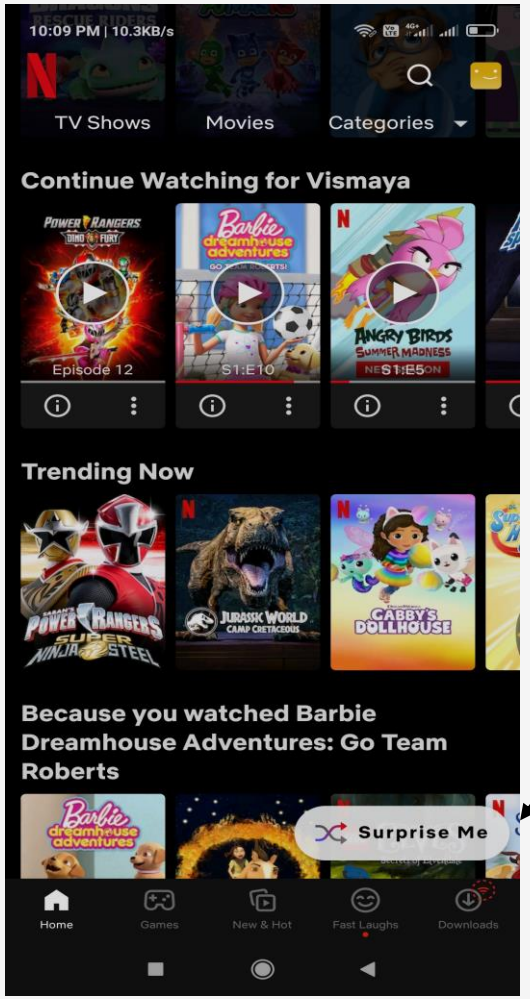
Literature Review

Seminal works | Summary | Research Gap



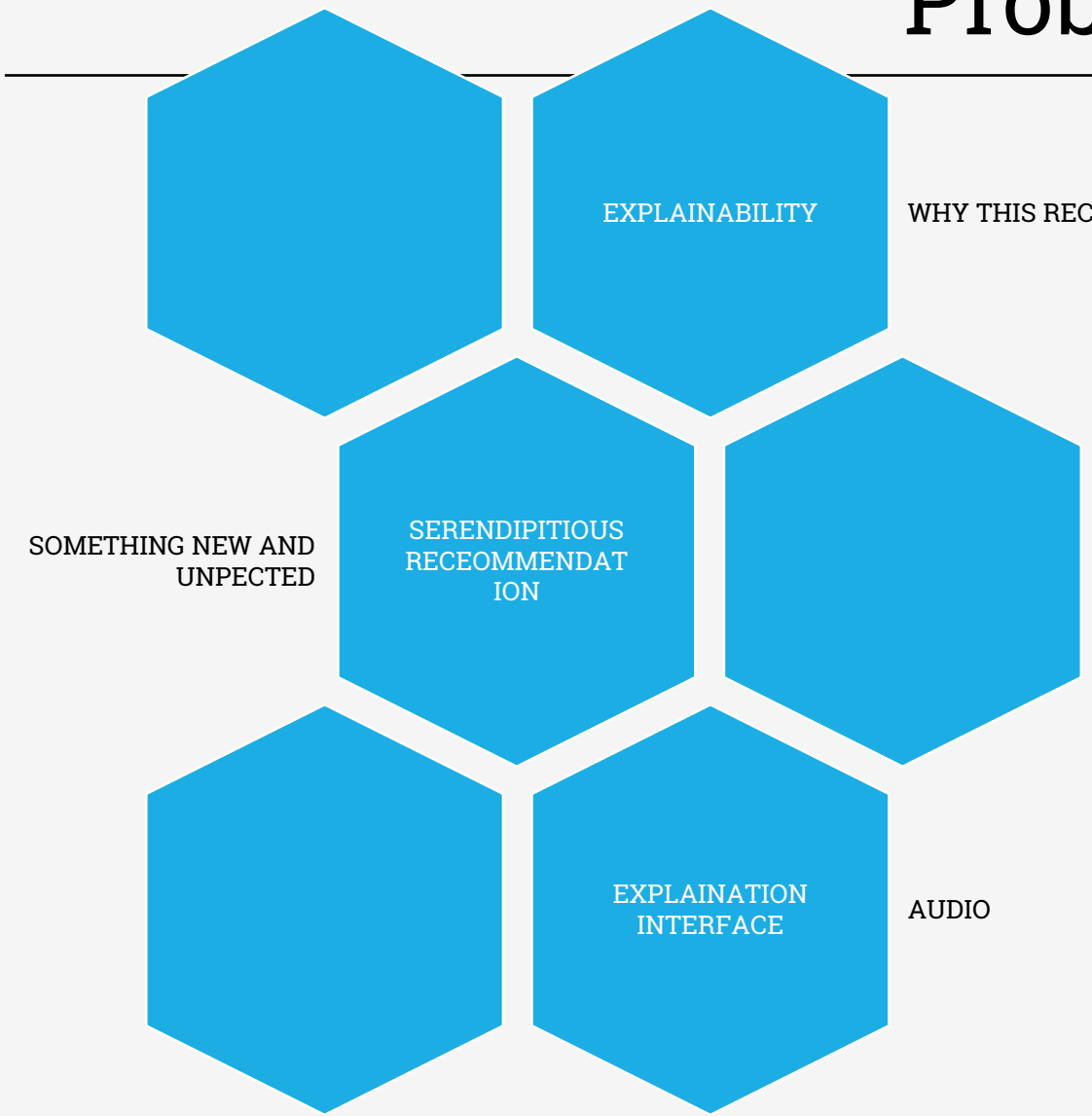






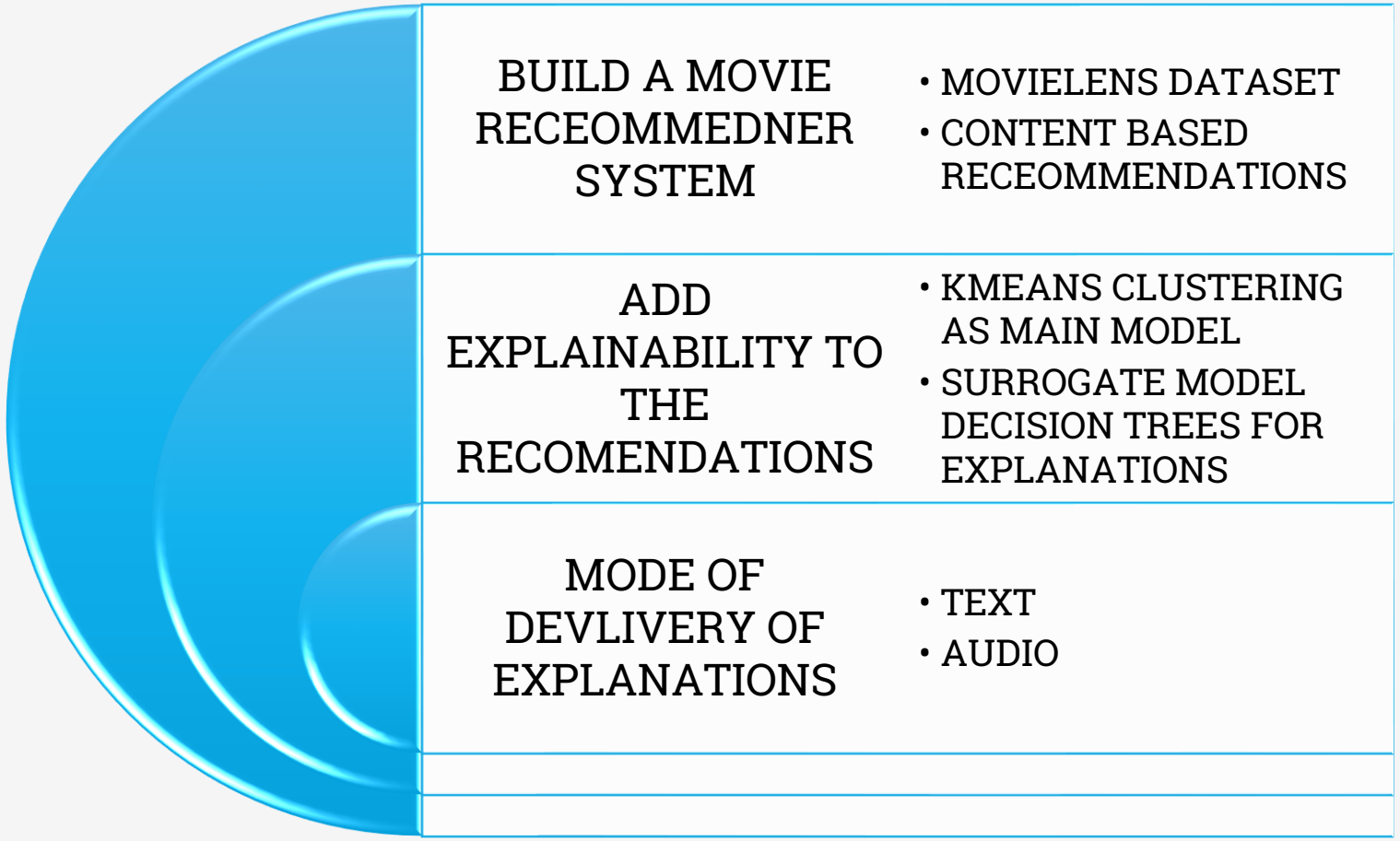
Problem Statement

Technical | Functional



Project Objectives

Primary & Secondary Objectives | Expected Outcome



Project Methodology

Conceptual Framework | Research Design

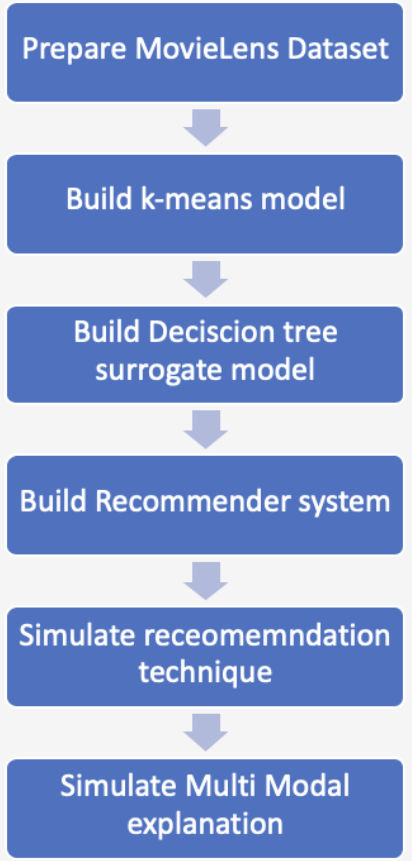
The *MovieLens* dataset needs to be prepared for usage in this project.

Processing the dataset such that the models can find patterns is a crucial step in the project methodology. Exploratory data analysis is to be conducted to understand the *MovieLens* dataset where the features of the dataset are the predictor variables.

Once the data is ready, k-means model needs to be built and cluster assignment is to be performed.

The important step is to build a decision tree classifier with cluster segments as labels. The so created decision tree classifier will provide explanations where the leaf nodes are the clusters and the non-leaf nodes are the features and their ranges.

The accuracy of the decision tree is the percentage of explainability. Watching movies on the Recommender System and Exploration of movie by the recommender system are simulated using audio.



grouplens about datasets publications blog

MovieLens

GroupLens Research has collected and made available rating data sets from the MovieLens web site (https://movielens.org). The data sets were collected over various periods of time, depending on the size of the set. Before using these data sets, please review their README files for the usage licenses and other details.

Seeking permission? If you are interested in obtaining permission to use MovieLens datasets, please first read the terms of use that are included in the README file. Then, please fill out this form to request use. We typically do not permit public redistribution (see Kaggle for an alternative download location if you are concerned about availability).

recommended for new research

MovieLens 25M Dataset

MovieLens 25M movie ratings. Stable benchmark dataset. 25 million ratings and one million tag applications applied to 62,000 movies by 162,000 users. Includes tag genome data with 15 million relevance scores across 1,129 tags. Released 12/2019

- README.txt
- ml-25m.zip (size: 250 MB, checksum)

Permalink: https://grouplens.org/datasets/movielens/25m/

MovieLens Tag Genome Dataset 2021

10.5 million computed tag-movie relevance scores from a pool of 1,084 tags applied to 9,734 movies. Released 12/2021. This dataset also contains input necessary to generate the tag genome using both the original process (Vig et al. 2012) and a more recent improvement (Kotkov et al. 2021)

- genome_2021_readme.txt
- genome_2021.zip (size: 1.8GB)

Permalink: https://grouplens.org/datasets/movielens/tag-genome-2021

recommended for education and development

Resource Specifications

Software | Hardware | Others

```
movies_data.genres.value_counts()
```

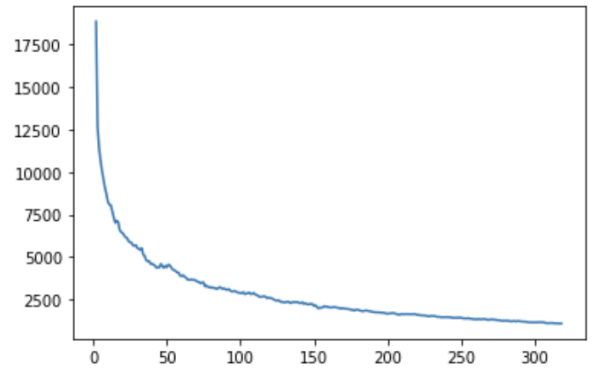
```
Drama                                          1053
Comedy                                          946
Comedy|Drama                                    435
Comedy|Romance                                  363
Drama|Romance                                   349
                                               ...
Action|Crime|Horror|Mystery|Thriller              1
Adventure|Animation|Children|Comedy|Musical|Romance  1
Action|Adventure|Animation|Comedy|Crime|Mystery   1
Children|Comedy|Fantasy|Sci-Fi                    1
Action|Animation|Comedy|Fantasy                   1
Name: genres, Length: 951, dtype: int64
```

Implementation

Demo | Application | Use cases

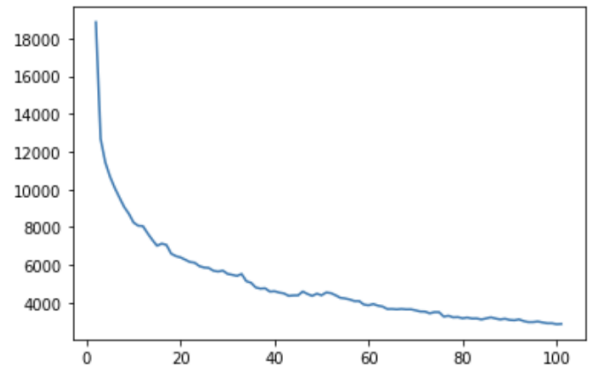
```
plt.plot(X,interia )
```

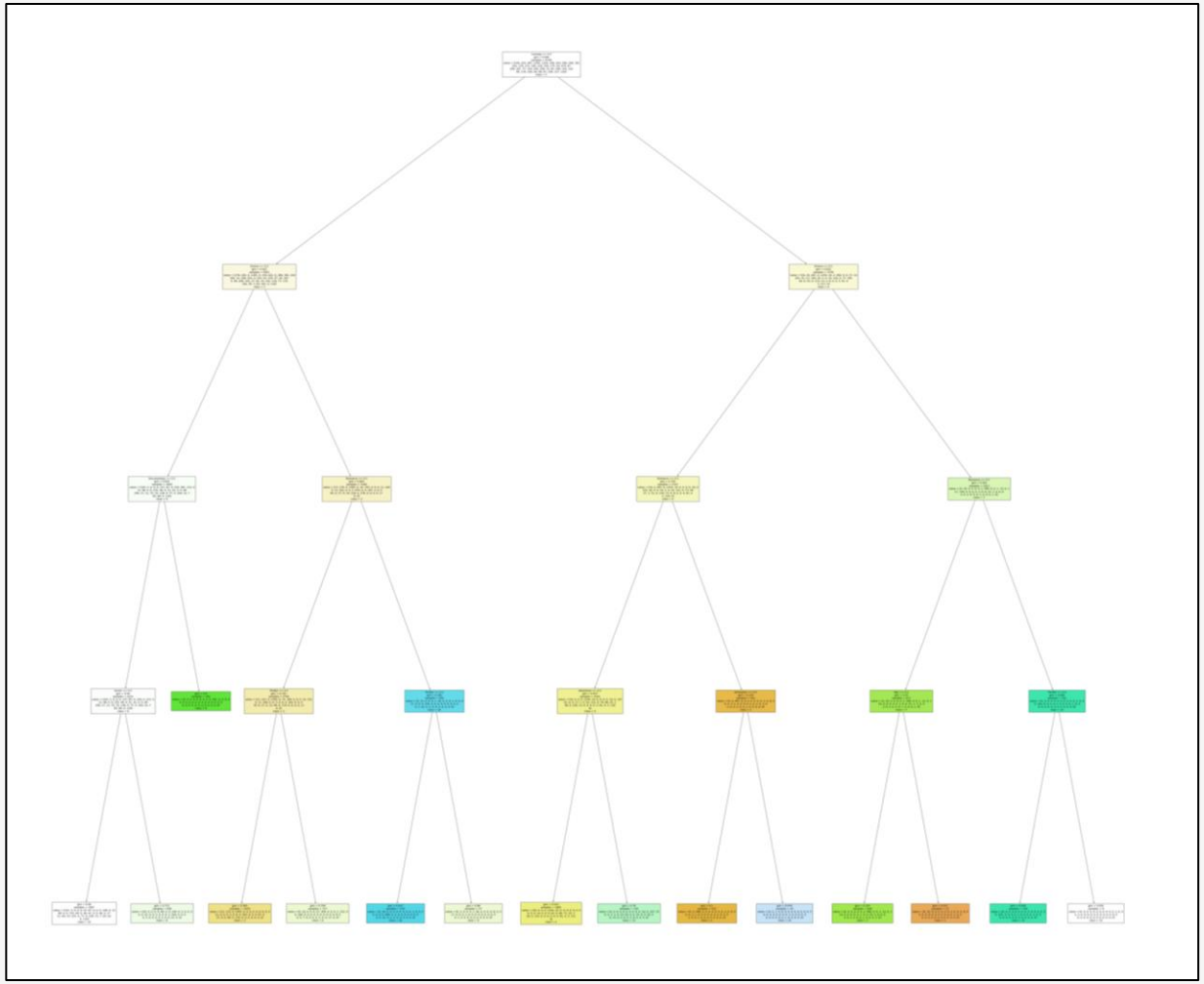
```
[<matplotlib.lines.Line2D at 0x7f5385b54610>]
```




```
plt.plot(X[:100],interia[:100] )
```

```
[<matplotlib.lines.Line2D at 0x7f5385ab4f50>]
```





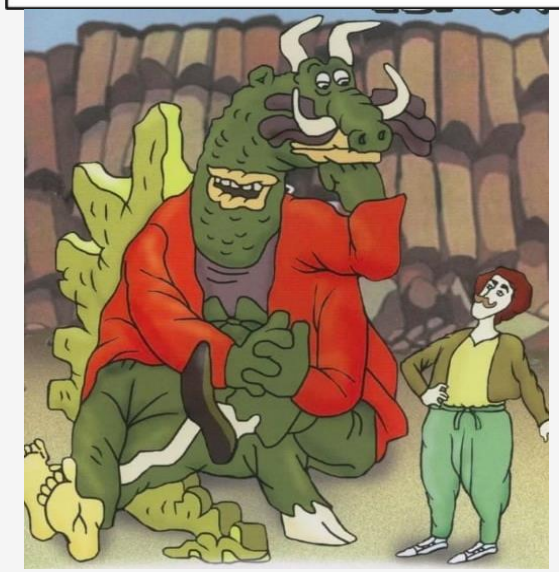
Results

Key Findings | Insights

```
1.  Stripes (1981)
2.  Parasite (1982)
3.  Robin Hood: Prince of Thieves (1991)
4.  Helvetica (2007)
5.  Cabaret (1972)
6.  Wow! A Talking Fish! (1983)
7.  Dunston Checks In (1996)
8.  Sabrina (1954)
9.  Little Boxes (2017)
10.  Our Town (1940)

sel_mov = input("Select any movie: ")

Select any movie: 6
```



0	Cruise, The (1998)	['Documentary']	['Comedy', 'Drama', 'Musical']
1	Mortdecai (2015)	['Comedy', 'Romance']	['Drama', 'Action']
2	I Am Trying to Break Your Heart (2002)	['Documentary']	['Comedy', 'Drama', 'Musical']
3	GLOW: The Story of the Gorgeous Ladies of Wres	['Documentary']	['Comedy', 'Drama', 'Musical']
4	Hoop Dreams (1994)	['Documentary']	['Comedy', 'Drama', 'Musical']
5	Kid Stays in the Picture, The (2002)	['Documentary']	['Comedy', 'Drama', 'Musical']
6	28 Up (1985)	['Documentary']	['Comedy', 'Drama', 'Musical']
7	My Architect: A Son's Journey (2003)	['Documentary']	['Comedy', 'Drama', 'Musical']
8	Last Days, The (1998)	['Documentary']	['Comedy', 'Drama', 'Musical']
9	When We First Met (2018)	['Comedy']	['Drama', 'Romance', 'Action']
10	Rock School (2005)	['Documentary']	['Comedy', 'Drama', 'Musical']
11	Night and Fog (Nuit et brouillard) (1955)	['Documentary']	['Comedy', 'Drama', 'Musical']
12	Blackfish (2013)	['Documentary']	['Comedy', 'Drama', 'Musical']
13	49 Up (2005)	['Documentary']	['Comedy', 'Drama', 'Musical']
14	Wild Parrots of Telegraph Hill, The (2003)	['Documentary']	['Comedy', 'Drama', 'Musical']
15	Human Planet (2011)	['Documentary']	['Comedy', 'Drama', 'Musical']
16	Iron Man (1931)	['Drama']	['Comedy', 'Romance', 'Thriller']
17	Eyes of Tammy Faye, The (2000)	['Documentary']	['Comedy', 'Drama', 'Musical']
18	The Thinning (2016)	[]	['Comedy', 'Drama', 'Documentary', 'Horror']
19	Life and Debt (2001)	['Documentary']	['Comedy', 'Drama', 'Musical']

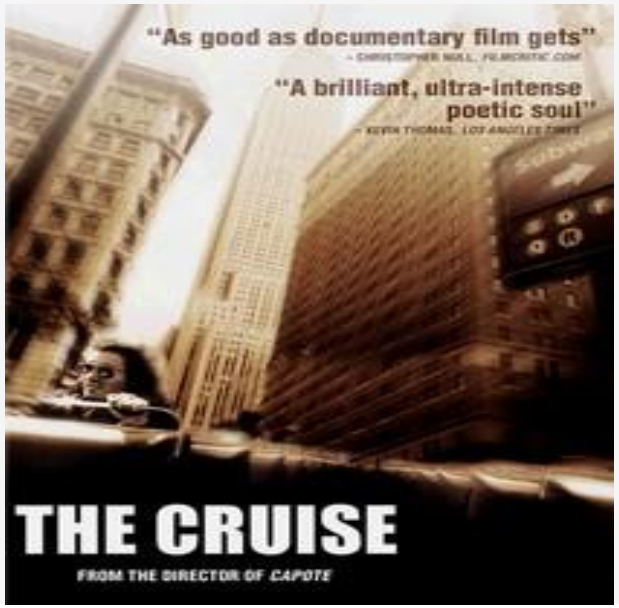
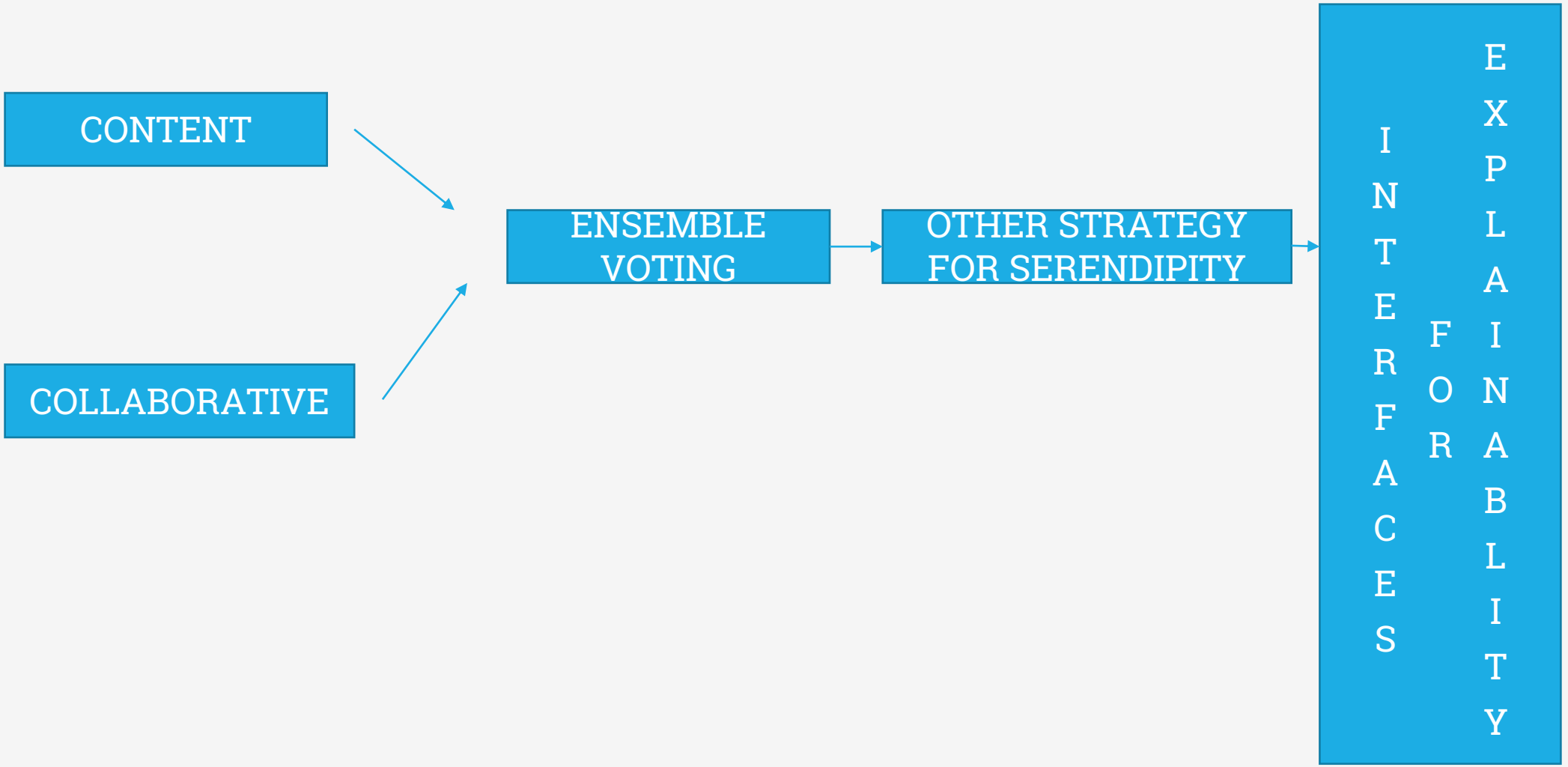


Figure No. 8.7: Movies that were recommended

Suggestions and Conclusion

Insights | Next Step | Future Scope



References

Bibliography | Webliography

1. Harper, F. M., & Konstan, J. A. (2015). The MovieLens datasets: History and context. Acm transactions on interactive intelligent systems (tiis), 5(4), 1-19.
2. Ahuja, R., Solanki, A., & Nayyar, A. (2019, January). Movie recommender system using K-Means clustering and K-Nearest Neighbor. In 2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 263-268). IEEE.
3. Rahul, M., Pal, P., Yadav, V., Dellwar, D. K., & Singh, S. (2021). Impact of similarity measures in K-means clustering method used in movie recommender systems. In IOP Conference Series: Materials Science and Engineering (Vol. 1022, No. 1, p. 012101). IOP Publishing.
4. Zarzour, H., Maazouzi, F., Al–Zinati, M., Jararweh, Y., & Baker, T. (2021, December). An Efficient Recommender System Based on Collaborative Filtering Recommendation and Cluster Ensemble. In 2021 Eighth International Conference on Social Network Analysis, Management and Security (SNAMS) (pp. 01-06). IEEE.
5. Wikipedia contributors. (2022, June 26). Netflix Prize. In Wikipedia, The Free Encyclopedia. Retrieved 09:30, July 2, 2022, from https://en.wikipedia.org/w/index.php?title=Netflix_Prize&oldid=1095044995
6. Tintarev, N., & Masthoff, J. (2007, April). A survey of explanations in recommender systems. In 2007 IEEE 23rd international conference on data engineering workshop (pp. 801-810). IEEE.

References

Bibliography | Webliography

7. Tintarev, N., & Masthoff, J. (2011). Designing and evaluating explanations for recommender systems. In Recommender systems handbook (pp. 479-510). Springer, Boston, MA.
8. Tintarev, N., & Masthoff, J. (2015). Explaining recommendations: Design and evaluation. In Recommender systems handbook (pp. 353-382). Springer, Boston, MA.
9. Dasgupta, S., Frost, N., Moshkovitz, M., & Rashtchian, C. (2020). Explainable k-means and k-medians clustering. arXiv preprint arXiv:2002.12538.
10. Resnick, P., & Varian, H. R. (1997). Recommender systems. Communications of the ACM, 40(3), 56-58.
11. Melville, P., & Sindhwani, V. (2010). Recommender systems. Encyclopedia of machine learning, 1, 829-838.
12. Iaquinta, L., De Gemmis, M., Lops, P., Semeraro, G., Filannino, M., & Molino, P. (2008, September). Introducing serendipity in a content-based recommender system. In 2008 eighth international conference on hybrid intelligent systems (pp. 168-173). IEEE.
13. Onuma, K., Tong, H., & Faloutsos, C. (2009, June). Tangent: a novel,'surprise me', recommendation algorithm. In Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 657-666).
14. Kotkov, D., Veijalainen, J., & Wang, S. (2020). How does serendipity affect diversity in recommender systems? A serendipity-oriented greedy algorithm. Computing, 102(2), 393-411.
15. Gedikli, F., Jannach, D., & Ge, M. (2014). How should I explain? A comparison of different explanation types for recommender systems. International Journal of Human-Computer Studies, 72(4), 367-382.

References

Bibliography | Webliography

16. Ko SK. et al. (2011) A Smart Movie Recommendation System. In: Smith M.J., Salvendy G. (eds) Human Interface and the Management of Information. Interacting with Information. Human Interface 2011. Lecture Notes in Computer Science, vol 6771. Springer, Berlin, Heidelberg
17. Ko, S. K., Choi, S. M., Eom, H. S., Cha, J. W., Cho, H., Kim, L., & Han, Y. S. (2011, July). A smart movie recommendation system. In Symposium on Human Interface (pp. 558-566). Springer, Berlin, Heidelberg.
18. Kużelewska, Urszula. (2014). Clustering Algorithms in Hybrid Recommender System on MovieLens Data. Studies in Logic, Grammar and Rhetoric. 37. 10.2478/slgr-2014-0021.
19. Molnar, C. Interpretable Machine Learning. Lulu. com, 2019. https://christoph m.github.io/interpretable-ml-book/.
20. W. J. Murdoch, C. Singh, K. Kumbier, R. Abbasi-Asl, και B. Yu, 'Definitions, methods, and applications in interpretable machine learning', Proceedings of the National Academy of Sciences, τ. 116, τχ. 44, σσ. 22071–22080, Οκτωβρίου 2019.
21. Dash, A., Chakraborty, A., Ghosh, S., Mukherjee, A., & Gummadi, K. P. (2022, April). Alexa, in you, I trust! Fairness and Interpretability Issues in E-commerce Search through Smart Speakers. In *Proceedings of the ACM Web Conference 2022* (pp. 3695-3705).

References

Bibliography | Webliography

22. "MovieLens," *MovieLens*. https://MovieLens.org/ (accessed Aug. 23, 2022).
23. Leysen, J., Michiels, L., Goethals, B., & Smets, A. (2022). What Are Filter Bubbles Really? A Review of the Conceptual and Empirical Work. In *Adjunct Proceedings of the 30th ACM Conference on User Modeling, Adaptation and Personalization*.
24. Cookson, J. A., Engelberg, J., & Mullins, W. (2022). Echo chambers. *Available at SSRN 3603107*.
25. Barraza-Urbina, A. (2017, August). The exploration-exploitation trade-off in interactive recommender systems. In *Proceedings of the Eleventh ACM Conference on Recommender Systems* (pp. 431-435).
26. Asanov, D. (2011). Algorithms and methods in recommender systems. *Berlin Institute of Technology, Berlin, Germany*.
27. Vasile, F., Smirnova, E., & Conneau, A. (2016, September). Meta-prod2vec: Product embeddings using side-information for recommendation. In *Proceedings of the 10th ACM conference on recommender systems* (pp. 225-232).
28. "KDD 2020 Tutorial: Advances in Recommender Systems," *KDD 2020 Tutorial: Advances in Recommender Systems*. https://sites.google.com/view/kdd20-marketplace-autorecsys/ (accessed Aug. 24, 2022).

References

Bibliography | Webliography

29. "Content-based Filtering Advantages & Disadvantages | Machine Learning | Google Developers," *Google Developers*. https://developers.google.com/machine-learning/recommendation/content-based/summary (accessed Aug. 24, 2022).
30. Lops, P., Jannach, D., Musto, C., Bogers, T., & Koolen, M. (2019). Trends in content-based recommendation. *User Modeling and User-Adapted Interaction*, *29*(2), 239-249.
31. Zhang, Y., & Chen, X. (2020). Explainable recommendation: A survey and new perspectives. *Foundations and Trends® in Information Retrieval*, *14*(1), 1-101.

Annexure

Additional Information | Plagiarism score

Explaining Clustering using Decision Trees

ORIGINALITY REPORT

5%	5%	2%	3%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	ukcatalogue.oup.com Internet Source	2%
2	onezero.blog Internet Source	1%
3	Submitted to Asia Pacific University College of Technology and Innovation (UCTI) Student Paper	<1%
4	Y. Brandman, A. Orlitsky, J. Hennessy. "A spectral lower bound technique for the size of decision trees and two-level AND/OR circuits", IEEE Transactions on Computers, 1990 Publication	<1%
5	www.ccis2k.org Internet Source	<1%
6	www.coursehero.com Internet Source	<1%
7	www.traumacenters.org Internet Source	<1%

REVA
UNIVERSITY

Bengaluru, India

Established as per the section 2(f) of the UGC Act, 1956,
Approved by AICTE, New Delhi

Thank You!