Recommender Systems

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Recommender Systems

Technical Report and Literature Review

This technical report is reviewing the literature and explaining the concepts behind Recommender Systems. A recommender system is a system performing information filtering to bring information items such as movies, music, books, news, images, web pages, tools to a user. This information is filtered so that it is likely to interest the user. This review is intended as an integral part of my research at the IDEAS research institute, Robert Gordon University, Aberdeen. Please feel free to comment, correct and contribute.

Contents

1. What is a Recommender System?

A recommender system is a system performing information filtering to bring information items such as movies, music, books, news, images, web pages, tools to a user. This information is filtered so that it is likely to interest the user. The aim of a recommender system is often to "help consumers learn about new products and desirable ones among myriad of choices" [1] [2].

Information filtering systems, more broadly, aim at removing redundant or unwanted information from an information base. They aims at presenting relevant information and reducing the information overload while improving the signal-to-noise ratio at the semantic level.

According to Ujjin's [3] review of some literature in 2001, "it seems that the definition of 'recommender system' varies depending on the author. Some researchers use the concepts 'recommender system', 'collaborative filtering' and 'social filtering' interchangeably [4] [5]". He also adds that "others regard ' recommender system' as a generic descriptor that represent various recommendation/ prediction techniques including collaborative, social and content based filtering, Bayesian networks and association rules. [6]" Ujjin concludes this discussion by stating that he will assume the second definition in the rest of its publication. This seems to be the current assumption nowadays in the field and it is also the definition chosen by Herlocker et al. [7].

1.1 Approach

Information of many types can be collected. "A simplified taxonomy separates recommender [systems] into content-based versus collaborative-filtering-based systems" [1]:

- Content based approach: the characteristics originate form the information item
- Collaborative filtering approach: the characteristics originate form the user environment (social, user preferences, patterns, etc.)

One of the main issues for with both approaches is the cold-start problem. New users have to interact with the system before to have a profile built-up and the system becomes efficient for their needs. [8] Hybrid approach is often considered, by combining features from collaborative and content-filtering methods, to prevent such limitations.

1.1.1 Content-based approach

The content based approach consists in analysing the content of the items being recommended. Each user is treated individually. There is no assumption of group or community [3]. The system works mainly by analysing items and the proximity of the selected items to others selected by the user. Then these items are selected to be recommended as they might interest the user.

This approach is heavily based on which items are being considered and on the user environment. There was no extended material found on general discussion of the subject.

1.1.2 Collaborative Information Filtering

Collaborative filtering "mimics word-of-mouth recommendations" [1]. Herlocker et al. [7] states that "one of the most successful technologies for recommender systems [is] called collaborative filtering". Collaborative filtering systems come from the earlier information filtering systems. Those systems were developed in order to bring only relevant information to the user by observing previous behaviours and thus, building a user profile. This system is based on the collection of taste information from many users. A sense of community is underlying. [3] It assumes that a group of users will have a similar appreciation to items then aims to "predict the unobserved preferences of an active user based on a linear weighted combination of other people's preference" [1].

Active filtering is separated from passive filtering because using active filtering require the user to dedicate some time in order to rate the information items when, using passive filtering, users automatically provide data by only accessing the item. Another approach is the item based approach.

Active filtering (or explicit data collection)

Active filtering is a method for collaborative filtering because of its peer-to-peer matching approach. Various profiles from peers are matched to extract similar interests. This approach is based on the facts that peers exchange information such are ratings and appreciation of specific items. It mimics the natural approach of peers recommending shops to each other. This type of filtering is particularly effective in cases where people are not knowledgeable about the mass of information available to them.

One of the main advantages of active filtering is that the information rating is provided by an actual person who has viewed the item with interest. Another advantage in heavily social-oriented systems is that it gives the opportunity for willing people to be heard and provide highly relevant information.

The main disadvantage is that this system requires some action by the user and thus makes the data more expensive to obtain and rarer. Another incidence of having an action required is that the feedbacks provided might be biased, for example towards a negative or positive experience, depending on the target customer. Another issue of those content filtering systems comes from the averaging effect occurring in some specific situations. Over a range of similar items, the system will not know the differentiating characteristics between items. This ultimately often causes the most popular items to be recommended more often as they will have more ratings. The First-Rater problem occurs for new items with no previous rating and the Cold start problem occurs for new users with no previous preferences.

Passive filtering (or implicit data collection)

Passive filtering is user to collect information implicitly. Some examples are:

- purchasing an item
- using, saving printing, modifying, commenting repeatedly on an item
- Referring or linking to a site (in another context than only rating, for example social media)
- Number of times an item is queried
- Time measurements to determine if the user is scanning, reading or working with a document.

The main advantage of passive filtering is that it broadens the population of user providing feedbacks. In effect, only some populations of users come back to the system to rate items whereas all connect to the system to access the item. Their behaviour during that phase is most likely able to provide information about their interest.

Item based filtering

In that filtering approach, items are rated and used as parameters for the matching instead of users. The items are grouped together and proposed to users. Users can then compare and rate them. User preferences are collected explicitly. Those preferences allows to group users by interest. The items are then selected using the ratings of a similar user.

1.2 Advantages and Inconvenient of Recommender Systems

1.2.1 Commercial viability

There are a large number of recommender systems currently available on the Internet. Many commercial websites develop tailored solution to help their user find items and increase sales. MovieLens, LIBRA and Dooyoo are 3 representative real-world systems often cited in the academic publications reviewed by Ujjin [3]. MacManus [9] reviews a few other and adds a statement by Iskold [10] [11] that there is "4 main approaches to recommendations:

- Personalized recommendation – recommend things based on the individual's past behaviour
- Social recommendation – recommend things based on the past behaviour of similar users
- Item recommendation – recommend things based on the item itself
- A combination of the three approaches above."

The following table describes special features of a few commercial systems:

System	Features	Particular Advantages/Issues
MovieLens [3]	• Collaborative filtering • Builds a profile by asking the user to rate movies • Searches for similar profiles • Stochastic and heuristic models to improve profile	• Common issue to collaborative filtering systems: explaining how recommendations are populated. • Herlocker et al. [12] introduces "explanation facilities for recommender systems in order to increase users' faith in the suggestions" [3]

1.2.2 Issues of Recommender Systems

Recently, MacManus published a series of articles in a social technologies related online publication. In one of them he highlights the current issues of

	matching	
LIBRA [3]	• Combines content-based approach and machine Learning • Uses Bayesian text-categorisation machine learning techniques to build models of user preferences relative to a specific item	• Explanations can easily be produced • Inappropriate to non-textual items (images, video, music clips)
Dooyoo [3]	• Gather qualitative opinions from users • Displays results in a similar way to search engines • Evaluates "usefulness" • Social approach: Creates groups of users with similar opinions.	• Easy to explain recommendations by using textual review • Not a fully automated system • Requires users to review and rate each individual item
Pandora [10] [9]	• Deep item analysis (Music Genome Project theory [13]) • User preference represented in term of a collection of items	• Low cost of entry for the user (pick one artist or song, refine later). Music starts instantly.
Amazon [9] [10]	• Combined approach (personalised, social and item based) • Recommendation based on matching of: actual items, related items, items other user purchased, new release, related items to new release	• Pure commercial approach. Aims at making users add more items to their shopping cart. • Their algorithm apparently overcomes the new item problem. (Cold start) • Based on a decade of data and system improvement and refinements.
Google [9]	• Customise search results based on location and recent search activity ("when possible") • Customise results based on account history • Uses pages link structures (social recommendation) • Recommendation to closest match (Did you mean feature)	• Although their system is initially a search engine, some recommender systems features are integrated to improve the user experience and deliver "personalised recommendations". [9]
Del.icio.us [10]	• Tag based indexing (similar approach to Pandora's genes [10]) • Tries to match multiple tags • Heuristic based	• Self-organising classification of items [10]

Recommender systems. [14]

The first issue exposed by MacManus is the lack of data. As recommender systems base their recommendation on previous behaviours, they need a lot of data on those as well as on the items being recommended. [14] Often, the quality of recommendations is linked to the amount of user, user data and items data available to the system. This is related to the problem of Cold-starting [8]. This is when a new user or a new item arrives in the system. A profile has to be generated at first to be able to match other data and obtain recommendation/be recommended. The amount of data required is not only referring to the number of item and number of users but also the number of variables extracted. [14] In some cases, user profiles contain many attributes and many of them will have incomplete or sparse data. [12] This makes finding matching profiles a difficult task. This is some times overcome using stochastic or heuristic approaches. Another approach is to user evolutionary algorithm. [3] Ujjin claims that "most current systems use standard nearest neighbour algorithms that consider only 'voting information' as a feature on which comparison between two profiles is made [4]". The system he proposes [3] is an hybrid system (content and collaboration) considering multiple features such as the user's age, gender and movie genre and then uses evolutionary algorithms to select and weight of the features.

The Data in the recommender systems are most often continuously changing. Edmunds, in [14] stated that systems are usually "biased towards the old and have difficulty showing new". New items will simply be less recommended because more data will be available on the old ones. In pure collaborative filtering systems, the system relies only on preference values (ratings). The performance of penetration of each item is then dependent on other user's rating. This some times induce an averaging effect. Overall most popular items will be recommended more often, increasing then their visibility and thus consumption. This induces more ratings for the item and worsens the averaging effect on recommendations. Another issue, linked with the previous one is the changing intention of users. One day a user might be searching for a specific item and another day for another unrelated item, perhaps for a friend. [14]

Some odd items are also difficult to categorise or associate. MacManus refers to it as "Unpredictable Items". This is linked to the fact that human tastes varies from one situation to another as well as over time. Herlocker et al. [7] points that "many researchers find that their newest algorithms yield a mean error of around 0.73/5 on movie rating datasets." They speculate that there is a "magic barrier" where the natural variability of user preference prevents more accuracy. They cite for support Hill et al. which have shown that "users provide inconsistent ratings when asked to rate the same movie at different times". Hill et al. [15] suggest that it is not possible for an algorithm to be more accurate than the natural variance in the user's ratings.

An issue more relevant to the algorithmic perspective is the scalability issue. Soboroff [16] explains that those issues were first identified around 1994, along with other questions (sparse ratings, handling of implicit ratings, content-collaboration hybrid approach, and commercial viability). In 1992, when the concept of Recommender Systems emerged, "expectations were fairly low […] 10,000 users and 100 predictions per second was a good performance and 'better than random' was effective" [16]. This issue is confirmed by Konstan and Riedl[17] when stating than "conducting an experiment to test a hypothesis relating to recommender systems requires too much experimental set-up and too much lag time" and denotes a lack of "technology, tools, testbeds and data sets needed to efficiently carry out research." In [7], Herlocker et al. find that "many collaborative filtering algorithms have been designed specifically for data sets where there are many more users than items. Such algorithms may be entirely inappropriate in a domain where there are many more items than users."

2. Working principles

2.1 Trends

The basic approach is to compare user's profiles to existing reference characteristics and attempt to predict the satisfaction of a user toward a specific item recommended. Various implicit and explicit data collection can be made in different ways (examples):

Explicit	Implicit
Rate Rank Choose between 2 items Select items in a list	Item browsed Viewing times Item purchased Items used Social Network analysis

The collected data is compared to similar data from other users. Then a list of recommended items is created for the user.

Various approach to comparing proximity appeared over the recent years. One of the most common approaches in commercial systems remains the Nearest Neighbourhood approach [18] [19]. Using a Pearson Correlation on the user preference data of the top-N neighbours, a particular preference can be found. An adaptation of this method based on evolution has been proposed by Ujjin [3]. This is an hybrid system (content and collaboration) considering multiple features such as the user's age, gender, movie genre, etc. It then uses evolutionary algorithms to select and weight of the features important for the comparison. It helps the system to produce tailored solution to each user as it adapts the weight of each parameter necessary for the correlation. The dynamic combination of variable seems to appear in various other work. In [16] it is stated that Delgado "presented a prediction algorithm which combines the correlation prediction with a weighted-majority voting scheme". It is also mentioned that a similar technique could be used to weight communities rather tan users. Claypool, in [16] is reported to present an algorithm using a combination of average of content and collaborative prediction weighted at a user level. Content was reported to be performing better initially but over time collaboration was weighted more importantly as the system learns.

Oh [1] also reports the use of neighbourhood-based methods such as the Pearson correlation coefficient as popular and traditional technique amongst early systems.

Alternative methods have since been developed such as the Bayesian preference model approach described by Ansari et al. [20]. This approach shows the following benefits: user heterogeneity, integration of expert and user information sources, explicability, using the regression model [1] (Markov chain Monte Carlo [20]). Condliff, as reported in [16] presented a "Bayesian model which integrates content and collaborative information". The model uses a naïve Bayesian classifier for each user based on item features. Then the classifiers are combined using a regression model in order to approximate maximum covariance. Using other techniques, Mooney is reported in [16] to have presented a book recommender system using "text categorization methods on the item information and reviews". This was a semi-structured “bag of word" model. In [4], Breese et al. proposed an alternative weighting method [1] using information retrieval techniques. In [21] Demir et al. proposes a Multiobjective Evolutionary Algorithm for Web Recommender System. They make use of research made on clustering using Evolutionary Algorithms [22]. Demir et al. [21] considers that "the clustering problem with automatic determination of the number of clusters is better approached with multiple objectives". They aim then at improving the fit of this clustering algorithm to use it as an off-line modeller for their recommender system.

Another area of focus is on the optimisation of the computation required for recommender systems. Goldberg is reported [16] to have presented a "technique to reduce the time needed to compute predictions" by computing only the principal components of a ratings matrix off-line instead of computing a full correlation matrix at the time of prediction. Herlocker, in [16] is said to have presented an application of clustering and partitioning algorithms to the rating matrix with mixed results on prediction accuracy. The approach is said to be potentially "suitable for parallelizing the problem without harming [the] accuracy and coverage too much". Demir et al. [21] states that "all web recommendation systems are composed of two components: an off-line component and an on-line component.” They add that usage patterns are extracted off-line and that the performance of the recommender system will "depend on how well the patterns are extracted from usage data" [21]. The scalability of recommender systems is also in focus. In [23], Herlocker et al. considered that some "highly correlated users do not perform well in predicting the preference ratings of the active user" [1].

Adomavicius et al. [24] suggests conceptual extensions to traditional recommender systems. For example, it could be possible to extend the traditional memory-based collaborative-filtering approach so that information such as the time, location, social interactions are taken into account (for example, who is going to see the film to be recommended with the user). "Several business applications are [...] more complex than [the standard] movie recommender system and would require recommendation systems to take many more factors into consideration."[1]

2.2 User acceptance

Oh [1] reviews various literature on the acceptance of a recommendation by a user. He quotes Felder and Hosanagar [25] which assumes that the probability of consumers' accepting a recommendation is a constant stochastic process. Oh [1] tampers this statement by adding: "while this assumption of invariance simplifies the analytical and simulation models, in recurring choices, decision makers update their trust toward the advisor based on the feedback of the quality of prior advice" [26].

One of the commonly identified issue across the recommender system literature is the lack of explicability [1]. Herlocker et al. [12] suggested that the black-box feature of most systems prevent those systems to be applied to higher risk domains. A well crafted recommender system can also be a strategic commercial advantage and disclosing the details behind the recommendations is often regarded as a commercially sensitive action. Sinah and Swearingen [27] show that the likeness of users toward a recommender system is significantly higher for transparent than for non-transparent recommendations. Helocker et al. [7] confirms that adding explanation improves the acceptance of collaborative-filtering systems and more generally of expert systems. This is also confirmed by Wang and Benbasat [28], Buchana and Shortliffe [29], Ye and Johnson[30] and Yaniv [31].

Senecal and Nantel [32] publish that consumers have a tendency to be more influenced by recommendation for experience products such as movies, music, food, than for search products such as camera, computer, etc. One explanation they provide is that experience products are more related to taste and common features searched by similar users when goods recommendations are more related to facts. A 'standard' product review will then be as applicable to a good product as a recommendation.

2.3 Evaluation of Recommender Systems

Herlocker et al. [7] states that "Recommender systems have been evaluated in many, often incomparable ways." One of the most common way to evaluate a recommender system is to seek user feedback on the recommendation (rating).[3] However, this is an expensive process and cannot always be performed as it requires the user to connect back into the system for that specific purpose. This can be simulated using multi-fold testing on the available dataset.

Recommender systems by nature have many possible objectives such as: finding good items, finding all good items, contextual annotations, sequence recommendation, browsing, help users, influence users, etc. This makes the task to compare and evaluate different systems difficult [7]. Most "standard" evaluation will not be suitable for new systems. The common domain features defined by Herlocker et al. [7] are:

- Content topic and associated context,
- User tasks supported,
- Novelty need and quality needs,
- Cost/benefit ratio of false/true positive negative,
- Granularity of true user preference.

Some of the most popular metrics used over time are: [7]

- Predictive accuracy metrics: how close the recommender system's predicted ratings are to the real user ratings. For example the mean absolute error which is the average absolute deviation between a predicted rating and the user's true rating.
- Classification Accuracy Metrics: frequency with which a recommender system makes correct or incorrect decision. This can be in the form of Precision and Recall, inspired from information retrieval techniques, which measure the occurrence of relevant and non-relevant items. Recall is said to be "almost always impractical" by [7].
- Ranks Accuracy Metrics: measure of the ability of a recommender system to produce an ordering of items that matches how the user would have ordered the same items.
- Prediction-Rating correlation: measures the correlation between the variance of the system's result and the variance of what the user would have chosen.
- Normalised Distance-based Performance Measure: developed by Yao [33] and can be used to compare two different weakly ordered rankings.

However, Herlocker et al. [7]states that there is an "emerging understanding that good recommendation alone does not give users of recommender systems an effective and satisfying experience". They add that not only accuracy, but usefulness should be provided by the recommender system. Usefulness could be measured using coverage ("measure of the domain of items in the system over which the system can form predictions or make recommendations" [7]). Other measures [7] are based on the learning rate (in the case of a system based on learning algorithm), Novelty and Serendipity (not recommending obvious items that all users would pickup anyway), Confidence (User confidence in the recommendation), User evaluation (implicit or explicit).

Additional resources can be found in: [34][35][36][37]

References

1. Oh,H., Litterature review on advisor selection
2. Resnick, P., Varian, H. R., Recommender Systems, Communications of ACM, Vol. 40, No.3, 1997, pp. 56-58
3. Ujjin, S.,Bentley,P.J., Building a Lifestyle Recommender System, Poster Proceedings of the 10th International World, 2001
4. Breese, J.S., Heckerman, D. and Kadie, C. 1998. Empirical analysis of predictive algorithms for collaborative filtering. In Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence, pp. 43-52.
5. Goldberg, K., Roeder, T., Gupta, D. and Perkins, C. August 2000. Eigentaste: A Constant Time Collaborative Filtering Algorithm. UCB ERL Technical Report M00/41
6. Terveen, L. and Hill, W. 2001. Beyond Recommender Systems: Helping People Help Each Other. In HCI In The New Millenium, Carroll, J. ed. Addison-Wesley
7. Herlocker, J. L.; Konstan, J. A.; Terveen, L. G.; Riedl, J. T. (January 2004), "Evaluating collaborative filtering recommender systems", ACM Trans. Inf. Syst. 22 (1): 5–53, doi:10.1145/963770.963772.
8. Adomavicius, G.; Tuzhilin, A. (June 2005), "Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions", IEEE Transactions on Knowledge and Data Engineering 17 (6): 734–749, doi:10.1109/TKDE.2005.99.
9. MacManus, R., A guide to Recommender Systems, http://www.readwriteweb.com/archives/recommendation_systems_where_we_need_to_go.php , 26 january 2009
A guide to Recommender Systems
10. Iskold, A., Rethinking Recommendation Engines, http://alexiskold.wordpress.com/2008/02/25/rethinking-recommendation-engines/ , 25 February 2008
Rethinking Recommendation Engines
11. Iskold, A., The Art, Science and Business of Recommendation Engines, http://www.readwriteweb.com/archives/recommendation_engines.php , 16 January 2007
The Art, Science and Business of Recommendation Engines
12. Herlocker, J.L., Konstan, J. A. and Riedl, J. 2000. Explaining Collaborative Filtering Recommendations. Proceedings of the ACM 2000 Conference on Computer Supported Cooperative Work
13. Westergren, T., The Music Genome Project®, http://www.pandora.com/mgp.shtml, 2000
The Music Genome Project®
14. MacManus, R., 5 problems of recommender systems, http://www.readwriteweb.com/archives/5_problems_of_recommender_systems.php, 28 January 2009
5 problems of recommender systems
15. HILL, W., STEAD, L., ROSENSTEIN, M., AND FURNAS, G. W. 1995. Recommending and evaluating choices in a virtual community of use. In Proceedings of ACM CHI'95 Conference on Human Factors in Computing Systems. ACM, New York, 194–201.
16. Soborof, I., Nicholas, C., Pazzani, M., Workshop on Recommender Systems: Algorithms and Evaluation, ACM SIGIR'99, 1999
17. Konstan, J.A., Riedl, J., Research resources for recommender systems. In CHI'99 Workshop Interacting with Recommender Systems, 1999.
18. Sarwar, B.; Karypis, G.; Konstan, J.; Riedl, J. (2000), Application of Dimensionality Reduction in Recommender System A Case Study.
19. Bell, R., Koren, Y., Volinsky, C."The BellKor solution to the Netflix Prize", 2007
20. Ansari, A., Essegaier, S., Kohli, R., Internet recommendation systems, Journal of Marketing Research, Vol. 37, No .3, 2000, pp 363-375
21. Demir, G., N., Uyar, A.,S., Oguducu, S., Graph-based sequence Clustering through Multiobjective Evolutionary Algorithms for Web Recommender Systems, GECCO'07, July 7-11, 2007, ACM: London
22. Handl, J., Knowles, J., An evolutionary approach to multiobjective clustering. IEEE Transactions on Evolutionary Computation, 11(1):56-76, 2007
23. Herlocker, J. L., konstan, J.A., Riedl, J., An algorithm framework for performing collaborative filtering, Proceedings of ACM SIGIR, 1999, pp. 230-237
24. Adomavicius, G., Sankaranarayanan, R., Sen, S., Tuzhilin, A., Incorporating contextual information in recommender systems using a multinational approach, ACM Transactions on Information Systems, Vol. 23, No. 1, January 2005, pp. 103-145
25. Felder,D., Hosanagar, K., Blockbuster culture's next rise of fall: The impact of recommender systems on sales diversity, Working Paper, The Wharton School, University of Pennsylvania, 2008
26. Yaniv, I., Kleinberger, E. Advice taking in decision making: Egocentric discounting and reputation formation, Organizational Behavior and Human Decision Processes, Vol. 83, No. 2, 2000, pp. 260-281
27. Sinha, R., Swearingern, K., The Role of Transparency in Recommender Systems, Proceeding of the ACM Conference on Human Factors in Computing Systems (CHI'02), pp. 830-831, Minneapolis, MN:ACM Press, 2002
28. Wang, W., Benbazat, I. Recommender Agents for electronic commerce: Effects of explanation facilities on trusting belief, Journal of Management Information Systems, Vol. 23, No. 4, 2007, pp. 217-246
29. Buchana, B., Shortliffe, E., Rule-based expert systems: The MYCUN experiments of the Stanford heuristic programming project, 1984, Addison-Wesley, reading, MA
30. Ye, L.R., Johnson, P.E. The impact of explanation facilities on user acceptance of expert systems advice, MIS Quarterly, Vol. 19, No. 2, 1995, 99.157-172.
31. Yaniv, I., receiving ither people's advice: Influence and benefit, Organizational Behavior and Human Decision Processes, Vol. 83, No.2, 2004, pp.1-13
32. Senecal, S., Nantel, j., The influence of online product recommendations on consumers' online choices, Journal of retailing, Vol. 80, 2004, pp.159-169
33. YAO, Y. Y. Measuring retrieval effectiveness based on user preference of documents. J. ASIS. 46, 133–145., 1995
34. Schafer, J.B., Konstan, J. and Riedl, J. 1999. Recommender Systems in E-Commerce. Proceedings of the ACM 1999 Conference on Electronic Commerce
35. Ujjin, S. 2001. An Adaptive Lifestyle Recommender System Using a Genetic Algorithm. Submitted to the Graduate Student Workshop, Genetic and Evolutionary Computation Conference 2001 (GECCO 2001).
36. Schafer, J.B., Konstan, J. A. and Riedl, J. January 2001. E-Commerce Recommendation Applications. Journal of Data Mining and Knowledge Discovery
37. mapat. recommendation system [Internet]. Version 2. Knol. 2008 Jul 27.
http://knol.google.com/k/peter-marosan/recommendation-system/3pz9q8d1vf2wg/18