Reducing the Sparsity of Contextual Information for Recommendation

Dušan Zeleník*
Institute of Informatics and Software Engineering
Faculty of Informatics and Information Technologies
Slovak University of Technology in Bratislava
Ilkovičova 2, 842 16 Bratislava, Slovakia
zelenik@fiit.stuba.sk

Abstract
In order to make recommendation more precise in various systems we focus on contextual information as another aspect of information space. A context could be used for estimation of item relevance which are subject to further recommendation. However, it is often not trivial to obtain information on context. Users are not willing to share this information (socio-demographic, location) or we simply have no possibilities to collect it (mental condition or physical health). We proposed a method of context inference by analyzing information which is available for individual users. We use techniques of machine learning and evaluate results in real environment with information gathered by monitoring real users in several domains (news reading, social network, movie ratings).

Categories and Subject Descriptors
H.3 [**Information Storage and Retrieval**]: Clustering Information and Filtering; H.2 [**Database Applications**]: Data mining

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context, behavioral analysis, movies, ratings

1. Introduction
Personalization received much attention last years. Our possibilities to adapt and personalize has increased since people became part of the Web. Personalization itself mostly involves data mining techniques as proposed in the chapter on data mining for web personalization by [12]. Besides preprocessing and integrating data sources, they mainly discuss patterns discovery based on clustering, association rules mining or sequential pattern mining. Similarly [18] proposed their approach to analyze users and discover their behavioral patterns. Authors in [2] denoted that user profiling is no longer about answering questions or filling forms. It is about gathering and analyzing sequential data such as clickstreams and queries.

Current evolution of mobile devices indicates our need to be equipped by something smart all the time and everywhere. Smart devices are becoming our accompanies what also brings advantages we had never thought about. These devices are learning and adapting using advanced methods. They know who we are, what we do, where we are and even what we need. Everything should be understood as profitable for the user. Mobile devices could be used as a tool for observation. Even more, talking about pervasive computing, we are able to use every surrounding device to observe the user and his activities. Starting with surveillance cameras through credit cards and ending with Web browsers we are monitored and our actions could be stored. And this is only beginning of what we can do nowadays. Step by step, new an new technological inventions surround us and more options to observe users emerge.

Even if we use advanced techniques to observe user and put him into context of the situation we are not capable to capture all aspects of the particular moment. These aspects could be very useful (e.g. in information retrieval or recommendation). Thus seeking for other options to cover this missing space is important research problem.

To cover missing information on user behavior which we are not able to acquire in common manner (by direct user observation), we need to bring in implicit information acquisition.

In our work we focus on information associated with a user which describes the user and the state of his environment. Basically we recognize two sets of aspects which affect user behavior:

- user attributes (e.g. gender, age, religion, skills),
- environment attributes (e.g. location, time, weather).

Our goal is to acquire these attributes. In general, user attributes are explicitly expressed by users. Users are

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usually asked to complete forms where this information is required. Acquired attributes have usually long-term nature. For instance, date of birth never changes, so does not gender. Other attributes such as weight or height are changing rarely or in long periods.

We focus on the context as a combination of user attributes and environment attributes. We analyze trends and research which has been done in the area of user modeling, information retrieval, recommendation or adaptive systems. This led us to recognition of the potential research interest in this field. We show state-of-art approaches and link them with modern approaches, trends and perspectives [1] stated during panel discussion on context and context-awareness. This emerged in the particular goals which we are focused on.

We state our goals as an effort to improve current state-of-art approaches to recommending. Our intention is to apply our ideas emerged from the observations of user behavior in various systems. We observed preferences and their change in different conditions. User behavior is therefore our main topic in this thesis.

Our goals are as follows:

- *Enrich users' behavior records by context of their actions.* Even explicit communication with a user does not reveal the reason of his actions. User behavior therefore seems to be random in case we miss the context. Our goal is to gather as much information on context as possible. This could be done by explicit and implicit feedback. Our goal here is to reveal those contexts which could not be revealed directly.

- *Understand relation among context and user behavior.* User preferences or needs change over time. It is normal to have different tastes in different conditions. Our goal is to discover patterns in user behavior to reveal the reason of user actions. These patterns should explain the temporal nature of user needs. Explaining user needs and their origin is a contribution to any form of personalization, therefore even in our scope of recommender systems.

- *Use the potential of discovered context in recommendation.* Context became very popular in recommender systems. However, we know that context-aware systems are not yet successful enough to outperform other approaches [8]. Our goal is to contribute in the area of context-aware recommending in form of identifying and fixing problems that usually suppress the potential of the context. Context and its potential showed to be promising in the area of knowledge-based recommender systems [14], where the recommendation is generated using rules consisting of context and interest. We also aim to incorporate behavioral patterns of individuals into recommendation process. Besides post- and pre-filtering we search for natural usage of context in recommendation process.

2. Related Work

Acquiring context could be generally divided into explicit and implicit. Where implicit acquisition is combination of inference using user activities and other contextual information. Following is our division of the approaches into three categories by the concept of their acquirement:

- *Explicitly by direct user confrontation.* Acquiring is focused on the user. Methods use explicit approach to gather information about current situation of the user. We are directly questioning the user and answers are processed to discover contexts. This approach is logically suitable only for contexts related to the user. However, the user is often not willing to answer and provide information about himself. The user treats the system as bothering. In some cases, we need to explicitly acquire context because some *hidden contexts* cannot be discovered implicitly. In work by [17] questions are used to gather contexts collaboratively to make this bothering process easier for individual users. At first are users asked to answer questions. Later, other users benefit from the information which was already gathered. An example could be the user who leaves the house regularly in the morning on weekdays because of work. The user is asked to explain the task what would explain similar behavior of other users.

- *Implicit using user activities.* In many cases, we acquire context implicitly by mining the data of user activity records. This particular process of the user modeling requires no direct interaction with the user [4]. It could be even done collaboratively by simple game playing as described by [6], or monitoring masses in WikiPop project [5]. One of the disadvantages of such an approach is inability to discover hidden contexts. Using these complex methods is not necessary if we want to find out how the user feels. On the other hand, this approach does not bother the user, because no user attention is required.

- *Implicit using other contextual information.* In some cases we need acquire context which could be derived from existing contextual information. For example, two users share the same computer. Records of the Web usage are stored, but we cannot determine who exactly was browsing the Web, what is the age of the user or gender. One option is to associate actions with already known contextual information such as time. Using patterns in time enables us to split actions into different context of the time what could be used to infer attributes of the user. The same happens with TV, because we cannot determine which family member is watching TV at the moment without complex context and user modeling.

We split our options of contexts acquirement into three groups. Actually, there could be also intersection of these three approaches. There is always a good reason to include the user as the best source of knowledge even if the process of contexts acquiring is bothering. The explicit form produces less information but these are in fact more precise, thus valuable. On the other hand, implicit form gives us many information but with higher noise. Value of the information gained by explicit questioning brings us to the problem of the customization of the human-computer interaction. There is, again, no generic solution since users are different and their attitude differs. We only presume that the process of explicit context acquirement should be attractive particularly for users which would transfer the knowledge with greatest efficiency. In work by [15] authors dedicate their effort to evaluate such explicit form of knowledge acquirement with implicit form. Their work was on feedback, but the outputs are the same - even small group of good and explicit contributors would substitute the mass of implicitly monitored individuals.

There are many context types that are considered in the existing context-aware systems. Sometimes there is no need to model all contexts in specific domains but if we want to create generic and robust systems we should define context at least by its structure or scheme. Context types could be defined by five categories:

- *Personal context.* Personal context could be divided into physiological and mental contexts. Physiological context are user's age, sex, height etc. Mental context are more temporal and also more difficult to acquire. Mental contexts are modeled as long-term interests, experiences, skills or knowledge. By personal context we also understand mood or emotions [10, 3].
- *Environment context.* User is always in some environment with surrounding entities. This environment has its attributes such as luminance, humidity, temperature, or noise which could be captured by low level sensors [7]. User is also surrounded by things and other people. These surrounding entities are also parts of the environment context.
- *Social context.* Similarly to the environment context, social context includes people. However, the aspect of observing these people is different. Here we work with relations to the other persons such as partnership, friendship, family, co-worker etc. Social context also defines a role in the society.
- *Task context.* Current agenda of a user should be interpreted as task context. These are current actions, activities, but also plans or goals of the user as e.g., intention to transport to the work which [17] tries to identify by asking explicitly, supported by prediction over collaborative approach. Another example is our previous work [19] where we anticipated upcoming event and notified user in appropriate time to transport from current location to location of anticipated event on time.
- *Spatio-temporal context.* Location over time is the simplest way how to describe this context. However, we could include also movement speed or direction. Time is a sub-context of spatio-temporal context. Time could be interpreted not only as precise moments but also by intervals (Monday, evening, winter. Spatio-temporal context of the user is nowadays the most popular. This context is used in many systems such in the COMPASS [16] to achieve location-based recommendation of tourist places. Another example is approach of [11] to social matching. They tried to acquire the context using mobile device with GPS support.

3. Method for Context Inference

Every human has different habits and his behavior is influenced by different aspects. Different tastes lead to user profiling. Authors in [13] proposed a method for analyzing conversations to detect a topic of the electronic communication. Authors observe communication to extract interests of individuals. This short term observation showed to be promising also for long term user profiling. Using Wikipedia as a source of keywords also enabled them to work with relations among these topics or interests. Authors can observe the user and his preferences over time what means they are able to differ which interests are long term and which is short term. We can imagine that classification of behavior by [9] could be applied here to recognize the weight of the interest. Because one time topic discussion or decreasing amount of discussion on topic might suggest its further irrelevance.

Human needs have to be respected if we want to recommend items based on user preferences. We observed that user needs and behavior itself are influenced by long term user attributes such as gender or age, or mostly short term environment attributes such as location, time or weather. This information is often missing or is not complete.

We identified three topics which we discuss here:

- User behavior and context of user actions correlate.
- Similar users have similar habits.
- More information on user characteristics increases the precision of predicting behavior.

In this chapter we summarize our analysis of current state within user behavior. Here we sum up our findings and conclude our discovery which we are going to use later for method design.

3.1 Users and their Similar Habits

We have recognized, that user has habits and rituals. Actually, we can not extract knowledge from individual user and presume that this knowledge is also valid for other users. Every user could have different rituals, however, some users have some similar habits. We can observe that group of users are doing the same actions and their behavior correlates. We can identify which users are similar by comparing conditions which were valid during similar actions.

We presume that there are users whose behavior is similar. These users could be clustered into groups of similar users. Each cluster forms a stereotype of user behavior. In such a group are users who are potentially interested in the same items.

We do not have to focus on similar users and their global behavior. We presume that conditions in association with actions are more relevant than global behavior itself. Thus, clustering users by actions and searching for behavioral similarity we do not consider to be the best way. This leads to long term observation, thus ignoring relevant short term contextual information. We have to incorporate context to work with conditions and find groups of similar users. Condition in form of contextual information is better to reflect real user rituals or habits. It means, that one user's ritual is associated with some condition. Clustering users by these rituals should form groups of users whose behavior is similar and their interests and needs should be similar too.

We observed that some information is missing for specific users and some is not (e.g. demographics). We presume that by discovering similar users we are able to propagate information to reduce missing information. We identified tasks we face:

- *Discover similar users using rituals.* Users' behavior is not random. Everyone has some stereotypes and we can find rituals in this behavior. These rituals or habits are sometimes similar among users. Each user could have more habits which are similar to other users. It is useful to discover these similarities. We could use this information for building user models in higher abstraction and later for propagating information among them. This behavioral similarity is usually calculated using only items as joins. However, we use context to find context-aware similarities among users.
- *Propagate contextual information.* Contextual information is usually connected with user action. These actions happens in some situations. It means that contextual information covers these situations. For some actions is, however, difficult or impossible to acquire this information directly. But if we knew that this situation could be similar to the situation of different action with contextual information, we could propagate this information.
- *Infer missing information with associated confidence.* Missing information on context could be inferred by the aforementioned propagation. However, we can not be sure about our inference. One eventuality is to use values representing the confidence of inferred information. Since we infer these information, we can naturally compute the confidence. The confidence is a real number associated with inferred contextual information. This number should be greater in case we have more original information which is used for context inference.

These three tasks led us to approach for context inference which is inspired by collaborative filtering. Our aim is to infer new contextual information, in the meaning of adding new value. Therefore we are not going to simply extrapolate existing data, but discovering new information to fill gaps in dataset of user actions.

3.2 Working with User Behavior

Our method for method for context inference takes users' behavior as input. This is a set of actions with identified user, item and conditions. Input could be sparse considering contextual information on user's action. We use sets of conditions associated with actions to reveal patterns. Pattern consists of set of context values which are co-occurring with items. We discover many patterns which have both higher and lower frequencies. Items which are associated with actions are now associated with patterns. Each pattern could have more items. These patterns are grouped into stereotypes (ignoring item). Stereotype is a set of patterns.

Context inference itself needs user and his behavior as input. User behavior is mapped onto stereotypes. Every action of the user could be associated with the stereotype using intersecting conditions (context). Via these actions is the user assigned to a stereotype. It means we have stereotypes which are more relevant for the user. Important part is that these stereotypes include patterns with context which might be missing for the user. Missing context is then inferred using particular patterns in stereotype.

We understand that user behavior could be influenced by various attributes called generally context. The reason we showed the correlation among user behavior and context is that we need to understand human behavior before we predict what he would like. Since every user is somehow different than others we need to understand if there are any similarities which would possibly reduce the complexity of human nature. We had a presumption that some of the influences are more general than others. It means that user is acting like a mass in some cases. But we have to mind the deviance of the individuals.

Observations which we presented led us to stop understanding a user himself as the reason of deviation in human behavior. We now understand that every user composed of more personalities which are changing over time. These personalities are plausibly combined in some form of constellation for each moment we take. This discovery means that we should use partial personalities to provide some recommendations. From now on, we refer to these personalities as stereotypes since these partial personalities are usually repeating in the set of users.

3.3 Propagation of Contextual Information

We propose a method for context inference which enriches logs of user activity with information which could be relevant. Our aim is not to acquire available information but to estimate context components which are not available directly. We reduce the sparsity of information which leads to better recommendations or even other information retrieval processes. We work with visible and hidden user information. We also consider the availability for specific user.

We recognized that besides easily acquired contextual information (time, location) we need to acquire more complex information on context. The difficulty differs from domain to domain. It means that we can not define exact information type to be visible or hidden but we can split information types by the way they occur in specific domains. We split contextual information into two basic types:

- *Visible contextual information.* Available user information which is easily acquired in particular domains. For instance, time is contextual information which we can easily acquire almost in every domain. Other example could be gender of the user, which is often public information in social networks.
- *Hidden contextual information.* Present but not available. This type of contextual information is not easily acquired. It actually exists and has impact on the user behavior but we can not obtain this information directly. For example, it could be dwelling time. It definitely affects our needs when we are at home, but system has no direct information on such context. This is therefore a subject for further inference. Other example could be age of the particular user. This information is often private or at least it is private for majority users. However, for many

types, we do not need exact age of the user, we can infer this information to only categorize user into young, adult or elder. An estimation of age interval is in most cases sufficient and actually very interesting information considering recommender systems.

We focus on hidden user characteristics and infer context which could not be directly acquired. If context is hidden for specific user it does not necessarily mean that it is hidden for other users. From this point of view we can split contextual information which is hidden for specific user into two types:

- *Known contextual information.* Visible for other users but hidden for the specific user until inferred. For example, when the user reads mostly local news and we can not acquire his location we could infer this contextual information. We can do this through other users with visible context of location who are interested in the same news. We actually presume that this could be done for any other user attribute such as age or gender.
- *Unknown contextual information.* Not visible for anyone. This could be inferred as the constellation of visible information or its components. Actually we can not recognize this type of information as rigid information. We can only work with the set of other information components which describe this type of hidden information. As we mentioned before, knowledge-based recommender systems would hinder by these unknown information. However, by enlarging the set of users and connecting more domains we could achieve reduction in such a set of unknown information.

Our method for context inference is based on user behavior and context which has impact on this behavior. To complete missing information on context we analyze users and their actions. We reveal *hidden* context by gathering visible context and propagation. The main idea is in propagation of the context using groups of similar users. The similarity is calculated using visible context and patterns which we observe in users' behavior.

However, not every rule discovered by observation is valid for some group of similar users. Some of them are appropriate only for individuals, some of them are mainstream patterns. Thus we respect different natures of behavioral patterns.

We define three different groups of patterns:

- *Psychology of the Crowd.* Crowd or the mass and its behavior is easily observed. When we watch decision of more users we notice that there are patterns of activity which could be applied to everyone or majority of the users. For example, in the domain of movie watching we observed that users are more interest in movies which had bigger budget. Explanation is simple, they are affected by promotions and advertisement which movie producers afford. The opposite scenario is observable when a user does not select movie in different language probably because it is not comfortable for him to watch the movie with subtitles. These two logical examples only proves that user often takes actions which are observable for the masses. This holds in majority of the cases. However, behavior of the crowd does not necessarily mean that every user is affected by these conditions. We have to focus on groups of users whose interaction with the system is slightly different.
- *Psychology of the Individual.* Every user has some of his own preferences which differ from the mainstream. However, these rare reactions to context have very low impact when enriching user behavior by context. Such a behavior is only minor in comparison to other actions user takes. Although this behavior has almost no relevancy in the recognition of behavioral patterns we do apply these rare influences to support the process of enriching contextual information on user behavior. We only work with users who are identified as very rare considering their behavior and their actions does not fit to mainstream actions or actions of identified community.
- *Psychology of Similar Users.* Behavior of the crowd and psychology of individuals affected by mainstream behavior could be applied to majority of people. However, some people are different and they behave like a community or group of similar users. We do not try to recognize this group, we only try to recognize groups of similar users who are interested in specific items in specific conditions. The behavior of the group of people should be considered in order to recognize stereotypes of people and their behavioral patterns.

4. Evaluating Sparsity Reduction

We present evaluation of our method on several datasets. We work with news reading from `SME.sk`, social network `azet.sk` and dataset with movie ratings CoMoDa.

We presume that the inferred information correctly enriches existing data. We proved this presumption by the inference of *visible* context. We compared inferred and real contextual information and calculated relative error, precision and recall.

We presume that inferred information improves the prediction of user activity. We repeat the same prediction with and without inferred context and compare the results of both predictions.

Our intention was to present context inference as positive contribution to the quality of the data used for further personalization. We experimented with the domain of news, social network and movie ratings.

We discovered that the domain itself is not that important in case of precision. What is more important is the quality of the data before we apply our method for context inference and secondly the context types for particular domains.

In other words, it means that very sparse data is less likely to be enriched with correct information. Our method for context inference is basically based on the extrapolation of original information. Very sparse datasets have very poor information on user behavior and since our method is based on user behavior, the quality lowers with dataset sparsity.

Second observation is that we could not say which context could be inferred with higher precision because it changes from domain to domain. It eventually means that particular context type could have different influence on user behavior in different domains. On the other hand, we are able to say what is the influence of a particular context for specific domain when necessary data is provided.

Regarding the recommendation itself we worked with simple recommendation based on predicting user interest based on the user history. Our added value, which we demonstrated in experiment is in aforementioned context inference. It basically means, that we are able to improve the quality of the dataset used for recommendation. We also showed that using context could be almost transparent for the recommendation technique. We are able to incorporate context directly to the user model thus recommendation could work with context as effective as with content (tags associated with user in the user model).

5. Future Work

We focused on one of the problems which makes the context-aware recommendation less successful than it could be. We recognized that missing values in contextual information lead to lower precision in predicting user behavior. There are many different problems related to context-aware recommending regarding its precision.

Beyond our current scope we identify that complexity of recommender systems using context is very high. We consider every aspect of the future action of the user. To do this we have to incorporate many dimensions of the user behavior what makes the representation too complex. Working with multidimensional space of user actions will lead us to use some type of factorization or complexity reduction. This could be done by identifying most relevant contextual information regarding user behviour, thus reducing its complexity. However, this approach should be covered also in the model representing user behavior and conditions. We should not use simple matrix but probably a graph. Then it is a question of graph algorithms which should make the recommendation possible even if original complexity is too high. Graph representation actually outperforms relation databases when the complexity and variety of entities is high. In the case of graph representation we could employ algorithms like activation spread or search for distances.

Another direction which should be followed is evaluation of the context-aware recommender systems. Evaluation itself is very time consuming since we need to cover most of the situations which could occur in the system. For instance, considering the season of the year would take at least one year to cover all cases. Moreover, if we want to evaluate some sort of periodicity regarding season of the year we should watch users for much longer than year. We expect, that this will be solved using hypothetical situations and simulation of these unreachable situations to cover as much situations as possible. In such a approach we could ask user to imagine some situation and respond to question or rate some recommendation accordingly. We should be able to cover most of the situation in this manner. On the other hand, we should ensure that user is given a hypothetical situation which he probably already experienced or experienced very similar situation. For instance, we should not ask male to imagine that he is a female.

Context-aware recommending needs to be transformed into context-based recommending. Context-aware recommending is usually done by one of the well-known approaches such as collaborative filtering or content-based. Context has a role of filter. But we expect that recommender system will be actually based on the context in the future. Context is highly related to user behavior, so there is potential to predict user action very precisely.

Future research and trends in the field of reducing the sparsity of contextual information leads to several new approaches. We expect that using mobile devices for facing this particular problem will be very intense since there is great power to acquire context. On the other hand, privacy issues will be always an issue.

Another direction would be in connecting many systems which acquire user context. Connecting these systems will create a united environment holding almost complete contextual information capable of inter-system context inference. More contextual information we will have, more accurate will the context inference be. There are already approaches focusing on the unification of these systems.

6. Conclusions

We analyzed user behavior and influence of contextual information in meaning of user and environment attributes. We have found out that user behavior is observable and it seems to repeat in a pattern. We focused on these patterns with intention to improve recommendation process and its outputs. Our idea is in completing missing information on context thus reducing the sparsity of dataset which is used to recommend items. Our main hypothesis which we confirmed was formed as:

> *Information on the user behavior could be enhanced implicitly by analyzing known patterns in users' behavior.*

We decomposed our hypothesis into smaller assumptions which we used for our method proposal. We worked with these three assumptions:

- User behavior and context of user actions correlate.
- Similar users have similar habits.
- More information on user behavior increases the precision of predicting behavior.

We proposed our method for context inference which follows these tasks. Our method is a contribution in the field of recommender systems. Our method reduces the sparsity in context-based user model for recommender system. We proved that predicting behavior considerably improves information retrieval or recommendation since behavior has profound effects on the information need. We also proved that our approach where we used inferred information outperformed the same recommender system which suffered by missing information, since user model was very sparse. We showed that our method and its precision changes with the domain and context type.

Our approach combines more techniques available in data mining with intention to infer context which is not directly available. We decided not to use standard association rules mining because it seriously suffers from discretized values. We work with continuous values instead of nominal or discretized. We showed how this approach is designed and what is the precision in the domain of news to contribute to the field of context-based recommender systems.

Another interesting fact about our method for context inference is that it uses rules which are assigned to incomplete user models respecting that our behavior is either mainstream, individual or stereotyped.

Our effort and results are summed up in the Chapter 4 where we experiment with two strategies in three different domains. In aforementioned chapter we present experiments which reveal abilities but also negative aspects of our method for context inference. We showed that user behavior could be used to infer the context, thus both user behavior and context of user actions correlate. Actually, context affects the user behavior, but could be backward reconstructed with high accuracy, depending on the amount of contextual information which we know.

Finally, we discuss our contribution as the accomplishment of previously stated goals:

- *Enriching users' behavior records by context of their actions.* We experimented with user activity logs which we artificially blurred. We removed some information on users' behavior and tried to infer the missing information. This technique helped us to empirically prove, that our method for context inference is able to enrich existing information on user behaviour. Thus we are able to improve the quality of datasets. Even more, we showed that we are able to determine user attributes like demographics. On the other hand, the precision of our approach for context inference lowers with very high sparsity in information.
- *Understanding relation among context and user behavior.* We analyzed user behavior to recognize what is the role of the context. We only presumed that context has real impact on user behavior. In our thesis we empirically showed that user behavior is directly affected by the context. It means that we could understand a user as a set of personalities which are changing over time due to current situation. We also discovered that these personalities could be mixed is some form of constellation.
- *Using the potential of discovered context in recommendation.* We experimented with recommendation which was boosted by inferred context. We used only simulations of user interest using real datasets of user actions. We showed that context could be directly incorporated into the process of interest prediction. In these simulations we empirically prove that we could improve the precision of the prediction model. Although the improvement is very mild, we primarily showed that context should be used when recommendation is designed.

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