Multicriteria Recommender System for Life Insurance Plans based on Utility Theory

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Abstract

Background/Objectives: This paper proposes a recommender system for life insurance. Insurance is a way of managing risks and has been used as financial instrument for a long time. The remarkable increase in competition within the insurance sector of the India has resulted in an overwhelming number of insurance products being available in the market. **Methods:** Utility theory is applied to recommend most suitable policy to users. Grey Relation Analysis (GRA) is utilized in intuitionistic fuzzy environment to determine users' preference over alternatives. **Results/Findings:** The proposed recommender system has been tested with approximately 600 potential customers of different region of Chhattisgarh (INDIA). The accuracy of the recommender system is 92.6%. Also, our recommendation system has been tested with different levels (Branch Manager, Insurance Advisor, Development officers). They also found the results significantly accurate. **Improvement:** Most existing recommender system are based on collaborative filtering technique or content based system, which mainly focuses on finding relations between products and between customers through machine learning techniques. They recommend products without concerning the users' personalized requirement. Our recommender system takes users' current need in account and recommends most suitable policy to them. **Application:** The proposed recommendation technique has worked efficiently with the life insurance products and electronic home appliances.

Keywords: Grey Relational Analysis, Intuitionistic Fuzzy Sets, Life Insurance, Multi Criteria Recommender System, Utility based System

1. Introduction

In order to make good decisions, it is necessary to possess ample amount of information. However, there are several examples showing that too much information is as bad as inadequate information; it is called information overload problem^{1,2}. Recommender System has been introduced to solve this problem. It is very popular and useful concept in current digital era. It is an information filtering system that suggests products and services most relevant to the User.

Recommender System has been used widely for the products and services, intended for entertainment like music, books, and movies, online games, restaurants and completely based on user ratings. Some other applications are Personalized B2B E-Services³, Critique-Based Mobile Recommendation⁴, Intelligent Fashion Recommender System⁵, and Academic Paper Recommendation⁶. These products are routine products and users keep trying new products very frequently; hence if some recommendations fail to please some of their users, it is just a trivial issue and does not affect users' living. Consider a product that serves an essential purpose, intended to succor the users in future contingency, can be acquired only few in a life time and every user has specific preference about the product that cannot be generalized. Accurate recommendations of such products require users' contextual opinion on it. Since, traditional recommender systems are merely based on similarities between products and between users, they do not perform efficiently with aforementioned products. Life Insurance is such kind of product. The liberalization of the insurance market in India has resulted into a number of insurance companies, and increasing competition among companies resulted in huge range of insurance products. Insurance policies have complex terminology and numerous features. Also, terms and conditions of insurance policies are not effortlessly comprehensible to customers. Therefore a recommendation system has been required for a long time that hides complexities and recommends best polices to its users.

This paper proposes a Utility Based Multi Criteria Recommender System, which recommends best insurance policies to users as per their preferences. User's preference is elicited using Intuitionistic Fuzzy Sets (IFS's)⁷ and utility of policy to user is estimated using Grey Relational Analysis (GRA)⁸. The system predicts policies that are most preferable to users according to their contextual requirements. Proposed system prevents users to get into complex terms, condition and calculations of insurance. It also provides a simple way to opt life insurance policies.

The rest of the paper is organized as follows: section 2 describes the fundamental knowledge of techniques used in our research. Section 3 describes framework and methodology of proposed system. In section 4, step by step procedure of proposed system is given. A numerical example is given in section 5 for demonstration purpose. Section 6 concludes the paper.

2. Preliminaries

2.1 Recommender System

Recommendation system has been proved significant method of solving the information overload problem. It saves precious time of consumers while searching for products and services of their interest. It is the criteria of 'personalized' and 'interesting and useful' that makes distinction between recommender system and information retrieval systems. Recommendation technique is the core of the recommendation system. Main components of the recommendation system are background data, input data and the algorithm. Background data refers to information which is required by the system before the recommendation is made. Input data refers to information which is provided by users in order to generate a recommendation. The algorithm is a process that combines background data and input data for arriving at suggestion⁹. In his paper Burke⁹ categorized Recommender system as:

- *Content based:* Content based recommender system suggests products based on the text information of the item. It recommends items to user, similar to the ones which are preferred in the past. The similarity between items can be calculated by the Pearson's correlation method or Cosine based method.
- *Collaborative filtering:* Collaborative filtering based recommender system has similarity with content based recommender system; the difference is that it calculates similarity between users instead of items. Users who exhibit similarity with the target user are called neighbors. The neighborhood-based collaborative filtering recommendation technique recommends items to target user that is pursued by his neighbors.
- *Demographic:* Recommendation system categorizes users or items, based on personal attribute of the user, and make suggestion upon demographic categorizations.
- *Utility based:* Recommendation is based on utility of product to the user; product with the maximum utility is suggested. Utility of each item is calculated for a user, for that a utility function has to be stored.
- *Knowledge based:* The recommendation relies on domain knowledge, which can be extracted by domain expert or extensive literature survey. Knowledge based system can be considered as combination of expert system and content based filters.
- *Hybrid:* It is a combination between two or more recommendation techniques to overcome the limitations in each algorithm.

The Recommender Systems use several data analysis methods to predict items that are interesting and relevant to the users. Multi Criteria Recommender System (MCRS) is an extension of Recommender System, which employs MCDM methods and techniques from MCDM discipline. MCRS is the primary interest of our paper.

2.2 Recommendation as Multi Criteria Decision Making Problem

Multi Criteria Decision Making (MCDM) is a cognitive process of modeling and solving decision problems involving multiple criteria or attributes. Objective of MCDM is to support a decision maker in selection of the best alternatives when multiple conflicting criteria, are involved. Traditional recommender system uses data mining techniques for collaborative filtering and Content based recommendations using single criteria (often ratings). Systems that use multiple criteria to support recommendation are referred to as Multi Criteria Recommender System (MCRS).

In order to introduce multiple criteria in fundamental recommendation problem, one of the classic MCDM methodologies can be followed^{10,11}, one of the pioneers in MCDM proposed a methodology for generic modeling of decision making problems. Roy's methodology¹¹ includes four steps when analyzing a decision making problem:

- *Defining the object of decision*, the object of the decision is alternative that has to chosen from the set of all candidate alternatives. Alternatives can be items or some course of action, upon which the decision has to be made.
- *Defining a consistent family of criteria*, The performance of alternatives is evaluated upon a set of criteria. This step involves identification of all criteria that influence objective of the decision. These should cover all the attributed affecting the decision and be exhaustive and non-redundant.
- *Global Preference Model*, In this step aggregator function is defined, that determine global preference of the decision maker about each item by synthesizing the partial preferences upon each criteria.
- *Decision support process*, this step involves designing and development of procedures or software systems that will assist decision maker in making final decision (in accordance to results of previous steps) for a given MCDM problem.

2.3 Intuitionistic fuzzy sets

The notion of intuitionistic fuzzy sets (IFS) is given by⁷. The concept of IFS is a generalization of classis fuzzy sets introduced by¹². IFS can also deals with non-participation or hesitancy in decision makers' judgments. Let X be universe of discourse, an IFS A in X can be defined as:

$$A = \{ (x, \mu_A(x), \nu_A(x)) \mid x \in X \}$$
(1)

Where the functions $\mu_A(\mathbf{x}): \mathbf{X} \to [0, 1]$ and $\nu_A(\mathbf{x}): \mathbf{X} \to [0, 1]$ satisfy the condition $0 \le \mu_A(\mathbf{x}) + \mathbf{v}_A(\mathbf{x}) \le 1$ for all $\mathbf{x} \in \mathbf{X} \cdot \mu_A(\mathbf{x})$ denotes the degree of membership and and $\nu_A(\mathbf{x})$ denotes degree of non-membership of the element $\mathbf{x} \in \mathbf{X}$ to the set A. In addition and $\pi_A(\mathbf{x}) = 1 - \mu_A(\mathbf{x}) - \mathbf{v}_A(\mathbf{x})$ is called degree of hesitancy or degree of indeterminacy, which represent abstention in decision makers' judgment. In case of $\pi_{\mathbf{A}}(\mathbf{x}) = \mathbf{0}$, the IFS functions as normal fuzzy set.

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For convenience, we call $\alpha = (\mu_{\alpha}, \nu_{\alpha}, \pi_{\alpha})$ an intuitionistic fuzzy value, where $\mu_{\alpha} \in [0,1], \nu_{\alpha} \in [0,1], \mu_{\alpha} + \nu_{\alpha} \leq 1$ and $\pi_{\alpha} = 1 - \mu_{\alpha} - \nu_{\alpha}$.

3. Proposed Recommender System

The recommendation is considered as multi criteria decision problem; the recommendations are based on performance of products upon certain criteria and user preferences. The objective of the system is to propose most promising policies to the users.

3.1 Definition and Terminology

Let C be the set of users and S be the set of all possible products that can be recommended. We defined a utility function $U^{c}(s)$ that calculates utility of product $s \in S$ for user $c \in C$. System recommends product with the maximum utility to the user,

Recommended product
$$\rightarrow \max_{s\in S} (U^c(s))$$
 (2)

The proposed system utilizes GRA as utility function, which estimates utilities of policies to user. The detailed description on working of the system is given in next section.

3.2 System Framework

The proposed system consists of three phases. In first phase a knowledge repository is built, that contains background information required by system before recommendation process starts. Second phase obtains certain inputs from user; and third phase is recommendation phase, which makes inference by combining background information and user inputs. Working of the system is depicted in Figure 1.

3.2.1 Domain Modeling

In this phase information regarding each product in Policy set S is fed to the system; a policy $s \in S$ contains two subsets: a set of constraint set a customer should satisfy, which defines the target customers and a set of features which describes the benefits offered by product to customers.

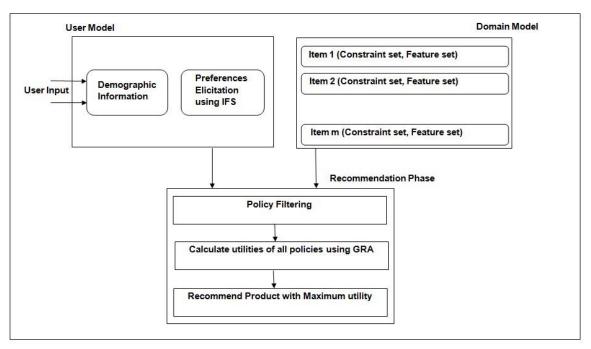


Figure 1. System Frame work.

Constraints Set

We identified four inherent constrains of an insurance policy from our study, which must be matched with user's demographic specifications:

- Entry Age, A customer's age must be between minentry age and max-entry age. It influences amount of premium; younger the age, less the premium.
- Sum-Assured, Sum-assured is the minimum amount that has to be paid by insurance company in case of death of the policy holder. Every policy has minimum and maximum sum assured, which makes a range, from which customers can choose one amount. Most of policies have "No Limit" for maximum sumassured. It also influences amount of premium; more the sum-assured, more the premium.
- **Term,** Term is the time period, a policy is valid for. Every policy has minimum and maximum term, which makes a range, from which customers can choose one time period. It also influences amount of premium; longer the term, less the premium.
- Maturity- Age, Maturity-age is the age of customer on which the policy gets "matured". Often polices have maximum maturity-age, but few polices (often designed for children) also have minimum maturityage. Sum of customer's age and term must be less than or equal to maturity-age.

Our proposed recommendation system matches these constraints with user's demographic specifications and filters only those policies whose constraints are satisfied by user information.

Features Set

Dutta¹³ identified 9 key parameters of Life Insurance Policies:

- 1. Low premium
- 2. Flexibility in payment structure
- 3. Tax benefits in insurance plan
- 4. Benefits on death
- 5. Benefits on survival
- 6. Good customer service:
- Online payment,
- Renegotiation of term/insured amount
 - 7. Bonus
 - 8. Add-ons& Special Schemes:
- Loan against policy,
- Group schemes

9. Availability of riders enabling customization of insurance plan:

- Accident and disability benefit,
- Critical illness benefit

Our proposed recommendation system considers these features as evaluating criteria of insurance policies

and calculates utility of each feature for determining overall utility.

3.2.2 Domain Modeling

A Recommender System suggests its user to "which movie to watch", "which item to purchase", "which song to listen" and so forth. An accurate Recommender System is expected to be able to make suggestions that satisfy the user's requirement. To achieve this accuracy, Recommender system must gain knowledge of user's preferences and decision procedures¹⁴.

In this phase our proposed system extract information about user $\mathbf{u} \in \mathbf{U}$ to accurately suggest products targeted to that user. This phase has two parts: first obtains demographic information (age, income, term and sumassured) from the user and second performs preferences modeling of the user using intuitionistic fuzzy set.

Obtaining Demographic Information

Our system requires following information from user to proceed:

- Age, Required to match Entry age, and influences premium and maximum Sum Assured.
- **Income,** Required to determining maximum Sum Assured.
- **Term,** Required to estimate payable premium amount and benefits.
- **Sum-assured**, Required to estimating payable premium amount and benefits.

Preferences Modeling

Proposed recommender system employs intuitionistic fuzzy sets to determine user's preferences for different features of insurance policies. These features are considered as evaluating criteria for an insurance policy. These preferences exhibit user's individualized requirements and expectations from the policy.

User expresses his/her preference for some feature using linguistic variables defined in Table 1 and the proposed recommender system quantifies users' preferences using Eq. (3) ¹⁵. The weight of j^{th} feature can be obtained as:

$$\lambda_{j} = \frac{\left(\mu_{j} + \pi_{j}\left(\frac{\mu_{j}}{\mu_{j} + \nu_{j}}\right)\right)}{\sum_{j=1}^{n} \left(\mu_{j} + \pi_{j}\left(\frac{\mu_{j}}{\mu_{j} + \nu_{j}}\right)\right)} \text{ for all } j = 1, 2, ..., n$$
(3)

In Eq. (3), λ_j is weight of **j**th feature. Symbols μ_j , v_j , and π_j denote degree of membership, degree of non-membership and degree of hesitancy respectively.

Table 1.
Table 1.

Linguistic variables	IFNs
Very Important	(0.90,0.05,0.05)
Important	(0.75,0.20,0.05)
Medium	(0.50,0.40,0.10)
Unimportant	(0.25,0.60,0.15)
Very unimportant	(0.10,0.80,0.10)

3.2.3 Recommendation Phase

In this phase proposed system combines background data (domain knowledge) and input data (user information), retrieved from domain model phase and user model phase to arrive at recommendation.

4. Policy Filtering

The proposed system filters policies whose constraints are satisfied by user information before performing utility calculations. As we have stated earlier that a life insurance policy has some inherent properties or constraints and listed them. Those constraints are:

- Entry Age
- Term
- Sum Assured
- Maturity Age

Minimum user interaction is an essential requirement in design of a good recommender system. Our proposed recommender system obtains *age* and *income* as user input for matching *entry-age* and *maturity-age*; since *age* and *income* are user specific facts and cannot be chosen explicitly(a 17 year old do not have option to opt his age and buy a policy with constraint of 18 year as min-entry age), the system needs to obtain these information from user. On the other hand *term* and *sum-assured* are flexible properties that are opted by user from a range (min, max) and hence the most suitable values can be either opted by users or suggested by the system.

A person does not have liberty to buy life insurance policies beyond a certain limit specified by IRDA¹.The sum of all policies of the customers must be less than or equal to this limit. Underwriting² process determines that to which extent a customer can purchase policy by assessing customer's age, income and risk preferences. Proposed system assumes that users of the system do not have any prior policies. Most of the policies have "No Limit" for maximum sum-assured; hence the system calculates the maximum worth of insurance that the users can buy and consider it as maximum sum-assured to create a range(min sum-assured, max sum-assured). Rules for calculating maximum sum assured are depicted in Table 2.

Table 2.Rules of Maximum Sum-AssuredCalculation

Age	Maximum Sum Assured
Age < = 30	22 🗙 Annual Income
31 < = age < = 40	17 🗙 Annual Income
41 < = age < = 50	12 🗙 Annual Income
51 < = age	10 🗙 Annual Income

Estimating utilities of policies to the user using GRA

Step 1. For a multi criteria recommendation problem, if there are *m* alternatives(policies) and *n* attributes (features), the *i*th alternative can be expressed as $Yi = (y_{i1}, y_{i2}, ..., y_{in})$, where y_{ij} is the performance value of alternative *i* over feature *j*. The term Y_i can be translated into the comparability sequence $X_i = (x_{i1}, x_{i1}, ..., x_{in})$ by using Eq. (4)¹⁶.

$$x_{ij} = \frac{y_{ij} - \min\{y_{ij}, i = 1, 2, ..., m\}}{\max\{y_{ij}, i = 1, 2, ..., m\} - \min\{y_{ij}, i = 1, 2, ..., m\}},$$
 (4)

For i=1, 2,..., m and j=1,2,....n.

Step 2. After the grey relational generating using Eq. (4), all performance scores will be ranged into [0, 1]. For an attribute j of alternative i, if the value x_{ij} is equal to 1, or nearer to 1 than the value for any other alternative, that imply that the performance of alternative i is the best one for the attribute j. However, this kind of alternative does not usually exist and hence a reference sequence X_0 needs to be defined as $(x_{01}, x_{02}, ..., x_{0n}) = (1, 1, ..., 1)$. The reference sequence is considered as hypothetical optimal alternative and is used to compare other alternatives' performance.

Step 3. In this step, grey relational coefficients are calculated. It determines how close x_{ij} is to x_{0j} . The larger the grey relation coefficient, the closer x_{ij} and x_{0j} are. The grey relational coefficient can be calculated by using Eq. (5).

$$\gamma_{ij} = \gamma \left(x_{0j}, x_{ij} \right) = \frac{\Delta_{\min} + \rho \Delta_{\max}}{\Delta_{ij} + \rho \Delta_{\max}}$$
(5)

In Eq. (5), γ_{ij} is the grey relational coefficient between x_{0j} and x_{ij} . Δ_{ii} is distance between x_{0j} and x_{ij} , $\Delta_{\min} \Box_{and} \Delta_{\max} \Box$ are minimum and maximum value of Δ_{ij} respectively. ρ is user controlled distinguishing coefficient, $\rho \in [0,1]$. The purpose of distinguishing coefficient is to expand or compress the range of grey relational coefficients.

Step 4. In the final step, grey relational grade is calculated using Eq.(6)

$$\xi_i = \sum_{j=1}^n w_j \gamma_{ij}, \quad for \ i = 1, 2, \dots, m$$
 (6)

Where ξ_i denotes grey relational grade of i^{th} policy, which reflects aggregated score of i^{th} policy. w_j denotes weight of j^{th} feature and γ_{ij} is grey relational coefficient of i^{th} policy over j^{th} feature.

5. Utility Based Multi Criteria Recommender System

In this section, we give the procedure of Utility Based Multi Criteria Recommender System, which is as follows:

Step 1. Obtain age, income, term and sum-assured from user.

Step 2. User expresses his/her preference towards different criteria of insurance policy using Table1.

Step 3. Determine importance of criteria to user by utilizing Eq. (3).

Step 4. Proposed system filter policies that matches user profile.

Step 5. Performance of each policy over each feature is evaluated.

Step 6. Calculate grey relational co-efficient of each policy over each criteria using Eq. (5).

Step 7. Estimate overall utility to the user as grey relation grade of each policy utilizing Eq. (6).

Step 8. Recommend the policy with maximum utility to the user.

6. Numerical Example

In this section of the paper we present a numerical example that demonstrates that how proposed system works. For sake of simplicity we have taken only 8 policies say, **P1.P2, P3.P4.P5.P6.P7.P8**. These 8 policies belong to different types (e.g. term plans, endowment plan, money-back Plan, children's Plan) in policy set.

Example 1: Suppose a user login to proposed recommender system. User input is given in Table 3 and Table 4.

Proposed system calculates quantitative equivalence of user's preference given in Table 6 using Eq. (3) as:

$$\lambda_{1} = \frac{\left(0.9 + 0.05 \left(\frac{0.9}{0.9 + 0.05}\right)\right)}{5.284} = 0.179$$

Similarly, we can calculate weights for all features. The result is shown in Table 5.

After eliciting user preferences on features, the proposed recommender system filters policies that match user's demographic information. Then, it evaluates remaining alternative policies' performances over all features. Table 6 shows evaluation of all policies over all features.

Since these performance scores are already ranged into [0, 100], we can omit the grey relational generating step and calculate grey relational coefficient using Eq. (5). The reference sequence will be as $X_0 = (100,100 \dots 100)$ and we set the value of distinguishing coefficient $\rho = 0.1$.

Then we calculate grey relation grade using Eq. (6) as overall utility of policies to user and normalize them. The final ranking is shown in Table 7.

Evidently, The Recommender System recommends policy P7 to user.

Table 3.User input on demographicinformation

User Information	Input Values
Age	25
Income	2 5,00,000
Term	20
Sum-assured	2 15,00,000

Features	Importance in linguistic terms
Low premium	Very Important
Flexibility in payment structure	Unimportant
Tax benefits in insurance plan	Medium
Benefits on death	Very Important
Benefits on survival	Important
Good customer service	Unimportant
Bonus	Important
Add-ons & Special Schemes	Very unimportant
Availability of riders enabling customization of insurance plan	Medium

Lable 5. Importance of realures to user	Table 5.	Importance of features to user	
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Features	Importance
Low premium	0.179
Flexibility in payment structure	0.056
Tax benefits in insurance plan	0.105
Benefits on death	0.179
Benefits on survival	0.149
Good customer service	0.056
Bonus	0.149
Add-ons & Special Schemes	0.021
Availability of riders enabling	0.105
customization of insurance plan	

Table 6.Performances of alternative policies over allfeatures

Features	P1	P2	P4	P6	P 7
Low premium	100	80	72	92	86
Flexibility in payment structure	0	100	0	75	50
Tax benefits in insurance plan	60	80	86	64	70
Benefits on death	66	85	86	70	74
Benefits on survival	64	90	88	74	80
Good customer service	80	80	80	80	80
Bonus	80	100	90	90	100
Add-ons & Special Schemes	60	60	80	0	0
Availability of riders enabling	100	0	0	100	100
customization of insurance plan					

Table 7.	Final Scores and Ranking
of alterna	tive policies

Policy	Final Score	Rank
P1	0.208	3
P2	0.218	2
P4	0.159	5
P6	0.194	4
P7	0.221	1

7. Conclusion

We proposed an original perception based utility recommender system for supporting insurance policy related decision making. Unlike existing recommender system, which mainly focuses on relations between products and between customers, proposed system's recommendations are based on user's contextual requirement. The proposed system filters insurance policies that match user's demographic information, determines utility of them according to user preferences and recommend spolicies with maximum utility to the users. Insurance is very important need in today's uncertain life but understanding features, terms and conditions of each product is very tedious and time taking process and always influenced by insurance agent's biases. Our recommendation system has been tested with approximately 600 potential insurance buyers with different age and income group. The hit-rate of the proposed system was about 92.6%. The recommendation technique is also validated by domain experts. They found the results significantly accurate.

We compared our proposed system with other existing recommender systems and decision support systems for insurance, presented in literature. Other systems mainly use fuzzy logic and data mining tools for recommending policies or policy segments, but do not extract user's preference. Insurance is a context based product; even same customer can buy different policies in different situations, therefore user's preference plays significant role in accuracy of recommendations. Our recommender system elicits user's preferences for evaluating criteria using user inputs; hence provides more individualized recommendation.

In our future research work, we will work on simplifying user preference elicitation process. We hope to develop an improved algorithm that requires less amount of user interaction but will have all the merits of current system. Our future studies will also focus to develop an insurance recommender system based on demographic information. Since, insurance is a product purchased to support family in case of contingency; we hope to develop a recommender system that obtains demographic information about the users and their families and predicts their current and future needs. The system will also recommend a set of policies that accomplish them.

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