Smart Broker Agent Learning How to Reach Appropriate Goal by Making Appropriate Compromises

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Abstract: In this paper a new Smart Broker Learning Agent (SBLA) has been proposed, which trains to find the most acceptable solution to a given problem, according to the individual requirements and emotions of a particular user. For this purpose, a new structure of the agent has been proposed and reinforcement-learning algorithm has been used. When the scenarios and criteria under consideration are complex, and when mixed emotions arise, it may be necessary to compromise on certain criteria in order to achieve the goal. Then knowledge of the preferences and emotions of the particular user is needed. In these cases, the SBLA does not allow compromises that are unacceptable to this user. The structure and the way of acting of the agent have been considered. The knowledge that the SBLA must have and the process of its formation have been described. The scenarios for solving a specific task and the conducted experiments have been presented. Some contributions, arising from the use of the proposed agent's architecture have been discussed, such as: the opportunity for the agent to explain decisions; to offer the most appropriate solution for each specific user; to avoid unacceptable compromises, to have empathy, and the greater approval of the offered solutions.

1 INTRODUCTION

In many tasks, the requirements for choosing a goal and finding a way to achieve it are too complex and often contradictory. Sometimes they are strictly individual and personalized and correspond to the understandings and habits of the particular user, whose problem is being solved. Negotiating and modeling empathy, gift giving, smart shopping for example require an understanding of consumer needs, understandings and preferences as well (Gehghani et. all, 2012, Johnson et.all, 2019, Paiva et. all, 2017, Budakova and Dakovski, 2019).

Reinforcement learning algorithms are useful for solving such problems (Sutton and Barto, 2014.). Yet it is possible to improve them even more by very many ways (Gosavi, 2009, Torrado et. all, 2018). The Imitation learning, for example, is a way for their optimization (Argall, 2009, Amor et. all, 2013, Takahashi, 2017). In (Moffaert, 2016, Moffaert and Nowé, 2014, Natarajan, Tadepalli, 2005) multiple objectives problems with conflict of interests are considered. In this case multi-objective reinforcement learning algorithms can provide one or more Pareto optimal balances of the original objectives. The single-policy techniques can be employed to guide the search toward a particular compromise solution, when the decision maker's preferences are known a priori. It might be appropriate to provide a set of Pareto optimal compromise solutions to the decision maker, each compromising a different balance of objectives (Moffaert, 2016, Cho et. all, 2017) when the preference is unclear before the optimization process starts. The advanced idea is the simultaneous learning of a set of compromise solutions. Multiple objectives modeling and performance optimizations are described in (Cho et. all, 2017).

When a goal cannot be achieved according to the set requirements, compromises have to be made (Gunantara, 2018, Vachhani et. all, 2015). One solution is for the agent to reach the goal by making as few compromises as possible with the required

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criteria (Budakova et. all, 2019). This solution may recommend compromises that are unacceptable to a user. Users are reluctant to take actions that are unacceptable to them and reject the proposed by the system way to reach the goal.

The SBLA, proposed in this paper, chooses ways to reach the goal by making only acceptable compromises. To achieve this, knowledge of the individual understandings and emotional attitudes of each individual user about the possible ways to reach the goal is needed. Knowledge of public attitudes and understandings of these possibilities is also needed. The SBLA can then choose whether or not an action is acceptable to a user. For this purpose, a new structure of the agent has been proposed and reinforcement-learning algorithm has been used.

The rest of the paper is structured as it follows: the SBLA structure is explained in section 2; the experimental setting is given in section 3; the conducted experiments are presented in sections 4 and 5; and in the 6-th section a number of conclusions are drawn.

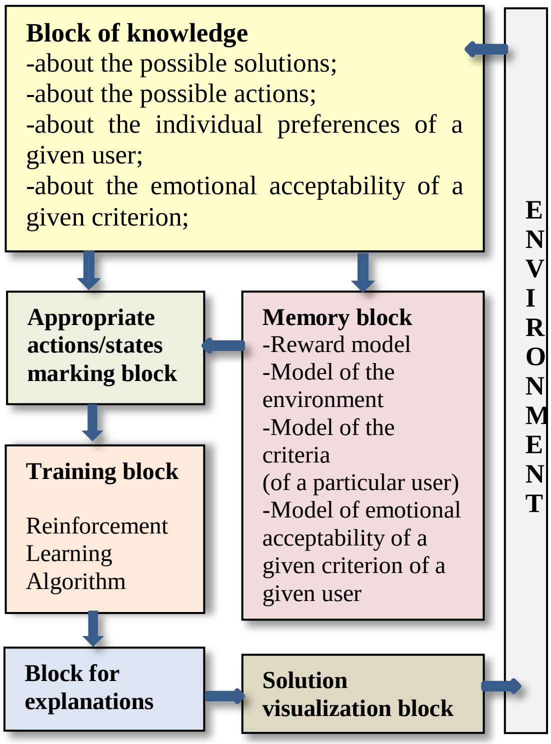

Figure 1: SBLA structure.

2 SMART BROKER LEARNING AGENT STRUCTURE

A new SBLA has been proposed, which trains to find the most acceptable solution to a given problem, according to the individual requirements and emotions of a particular user.

To this end, the agent is trained to offer the most appropriate goal and the best way to achieve it. For this purpose, a new structure of the agent has been proposed, (Figure 1) which includes a memory block (criteria-based model, model of rewards, model of the environment), block of knowledge (of the possible solutions, the individual requirements and emotions of a user, as well as of the possible scenarios), appropriate actions/states marking block, training block, containing a Reinforcement learning algorithm, explanation block, solution visualization block.

When the scenarios and criteria under consideration are complex, and when mixed emotions arise, it may be necessary to compromise on certain criteria in order to achieve the goal. Then knowledge of the preferences and emotions of the particular user is needed.

In order to make the reinforcement agent find the appropriate path to the suitable goal by meeting complex criteria, a critera-based model, model represented as an additional agent memory matrix is introduced. This model shows how the user perceives and evaluates the potential goals and the options for their achievement. The criteria-based model is similar to the reward model of the Q-learning algorithm. For the sake of convenience it will be further called the Broker Matrix. The criteria-based model maintains a specific value for each existing edge in the graph. It is a measure value for each edge and node, i.e., an estimate of the choice to move from one state to another using a given edge. When working on an algorithm, the transition from one state to another is sought by selecting edges and states only with a specific estimate. If such edges or states are missing, only those with acceptable measure values are selected.

On the one hand, the Pareto front can provide a set of optimal compromise solutions. On the other hand, the proposed SBLA and reinforcement learning algorithm can provide a way of achieving the goal by means of the most acceptable compromises.

3 EXPERIMENTAL SETTING

In the considered example the goal is the purchase of a small property of 20-30 square meters built area in a big industrial city, where the user is about to start working. The property can be a residential one or an office with a possibility to be used as a hotel room, or a place where one can spend a night occasionally. The user prefers new construction. However, the possibility of buying a well-preserved old property with a larger area at an equivalent price is also under consideration. The focus is on small property types because the user does not have funds. He/she has to save, but saving takes years of patience. He/she can sell a property he/she already possesses, but a sold property is a loss for him/her. He/she can take a loan, but taking loans is risky. Therefore, according to the Pareto front, a small property is the compromised balanced option, suitable for this particular person.

Figure 2 presents a graph, which shows the possible states (the nodes in the graph) for solving the problem of buying the most appropriate residential property in the most suitable for a particular user way. The existing sequences of these states are presented by means of the oriented edges in the given graph.

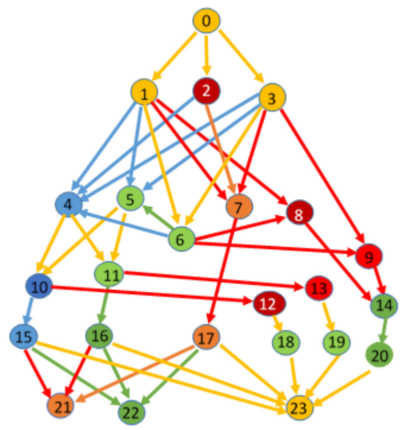

Figure 2: Oriented graph, which presents the states in solving the problem of buying a property and their sequence. The colours show how the user perceives them emotionally.

Table 1 gives a description of these states and the trade-offs required in the process of their selection. The colors show the emotions provoked by the given states and by undertaking actions for their achievement on the side of the user. The correspondence between the colors and the emotions they reveal is given in Tables 2 and 3.

The SBLA will suggest ways to reach each of the three most appropriate targets from the Pareto front. They are marked by the following nodes: node 21 – an old but preserved property with a living area of 35 square meters; node 22 - a small property suitable for an office and a hotel room with a built-up area of 20 sq. m. and node 23 - a small property in a new building with a built-up area of 30 sq. m.

The initial state is indicated by node 0 and yellow color. It starts the process of considering the problem. The user moves to a large industrial city to take a job position there and has no property to live in. As this is a dream job for him/her, this node is marked as a state in which the emotion is joy and enthusiasm. Consequently, it is unacceptable for him/her to give up the offered job. From here, things get trickier. It is possible that the user has another (and only) residential property - node 1; he/she may have no property at all - node 2; and it is also possible that he/she possesses other properties in other places - node 3. As it can be seen from Figure 1, the state graph for solving this problem (albeit simplified) allows many different modes of action. Actions and situations, evoking joy and enthusiasm in the user, are marked in yellow; the non-risky ones are marked in green; the extremely unacceptable are red; the more acceptable ones are orange; and the blue color marks the actions and situations which are not very comfortable, not risk-free and not very desirable, but still hopeful.

Thus, even at first glance, Figure 2 shows that from the initial node 0 to any of the three targets, defined as acceptable and represented by nodes 21, 22 and 23, there is no path in the graph that includes only states and actions, evoking enjoyment and excitement in the user; nor is there a path that includes only risk-free states and actions, and so on. In other words, whichever path is chosen, compromises and choices will have to be made.

Table 1: Description of the states, presented in the graph in Figure 2 and the compromises they require.

N	Description; Compromises/Advantages.
0	The user works in a big city. To move somewhere else is an unacceptable compromise for him/her.
1	The user owns a residential property. This makes him/her feel secure.
2	The user does not own a residential property. This is risky. Not having a property is an unacceptable compromise for him/her.
3	The user owns more than one residential property. This gives him/her great safety.

4	The user rents a property and saves to buy a residential property of his/her own; It takes years of patience, but it’s risk-free.
5	The user commutes to his/her workplace every day or on a schedule and saves on the purchase of a residential property. It takes years of patience, but it's not risky.
6	The user renovates and improves the properties possessed by him/her. The period for raising funds for the purchase of a new property is extended. Safety is provided. Acceptable compromise.
7	The user gets a mortgage credit amounting at 60% of the price of the new property, but he/she has no other savings. A consumer credit is required for the remaining amount of money needed. There is a great risk for all his/her property. Living with two loans would mean great restrictions. A difficult to accept compromise.
8	The user sells his/her only property. Loss of property. Risk of running out of property. Unacceptable compromise.
9	Sells one of his/her properties. Loss of property. Difficult compromise to accept.
10	20% of the price collected. Enough to get a mortgage. Acceptable compromise. Brings safety.
11	40% of the property price available - enough to get a mortgage. Acceptable compromise. Safety.
12	He/she sells his/her only property, but only after he/she has collected 20% of the necessary funds. Loss of property. Unacceptable compromise.
13	Sells one of his residential properties, but after he has got 40% of the necessary funds ready. Loss of property. Acceptable compromise.
14	50% of the necessary funds available after the sale. Loss of property and risk of funds shortage. Acceptable compromise.
15	Takes a mortgage credit 80% of the value of the new property and has the remaining funds available. Acceptable risk. Acceptable compromise.
16	He/she takes a mortgage on 60% of the new property and has the remaining funds. Acceptable risk. Acceptable compromise.
17	Takes a consumer credit to cover the mortgage up to 100%. Risk for all property. Must live in limitations and deprivation. Difficult compromise to accept.
18	Takes a 30% mortgage credit and has the remaining funds available. This is risk-free and no compromise is required.
19	Takes a 10% mortgage credit and has the remaining funds available. This is a great level of security. No compromises required.
20	Takes a mortgage credit 50% of the price of the property and has the remaining funds available. There is some risk. Acceptable compromise.
21	Buys an old but larger residential property. Though the property is old, the compromise is acceptable.
22	Buys a very small office in order to use it both as a hotel room and as an office. It is not a residential property and the expenses for taxes, electricity and water are higher. Safety. Acceptable compromise.
23	Buys a new very small residential property in the city where he works. No compromise needed. This is the dream home.

Table 2: Meaning of the colors of the nodes and edges in the graph, given in Figure 2.

Colour	Description
Green	The state leads to security
Dark red	The state requires a highly unacceptable compromise.
Red	The state requires an unacceptable compromise
Orange	The state requires a poorly acceptable compromise.
Yellow	Achieving this state is highly desirable.
Blue	It means an acceptable state in which there is no risk, but a poorly acceptable compromise is required to be made.

Table 3: Description of the emotion represented by the colors of the nodes and edges in the graph, given in Figure 2.

Color	Emotion
Green	Security.
Red	Panic, anxiety, dissatisfaction.
Yellow	Joy and enthusiasm.
Blue	Calm and hope.

For example, the user will have to decide whether to sell the properties he/she already possesses and buy the desired property or not to sell but instead repair and improve them. In the second case he/she will have to rent a room/house for several years and at the same time to save money until he collects part or all of the required sum. He/she has to decide whether to take a mortgage loan or not and for what part of the property price. All these decisions will change the buyer's life both in the short and in the long run. They all have their advantages and disadvantages. The purpose of a SBLA is to understand the user's way of thinking and to offer solutions regarding the ways to realize the most appropriate option.

What sequence of actions should the user follow in order to feel happiest on the way to achieving the goal?

What sequence of actions should he/she follow in order to feel most secure on his way to the goal of having his home in the big industrial city in which he/she works?

Is there a sequence of actions making the user feel excited and happy all the way to the goal? It turns out that such a sequence of actions on the way to the goal does not exist and compromises are required. So what are the most acceptable compromises? Are there actions that guarantee greater security, but not so much elan and enthusiasm in the user and what are the most acceptable compromises? It is precisely this type of actions, which can be considered to be the most acceptable compromises. Also, are there actions that require more time, are less safe, cause some inconvenience, and are still acceptable? The aim is to avoid the unacceptable actions. It can be seen from Figure 2 that the sale of the properties he/she owns is an unacceptable action for the person under consideration.

4 FIRST EXPERIMENT

A buyer, who does not own any property is considered. After starting a secure job in a large industrial city, he/she wants to buy a place to live. The system offers the fastest way to achieve this goal, namely, to take a mortgage loan from the bank up to 80% and to cover the remaining 20% with a consumer loan (Figure 3).

A dotted black line shows the sequence of states until a solution is reached. The system offers this solution if the modification of the reinforcement learning algorithm is not used. In this case, there will be a great risk over the years until the consumer loan is repaid. After that moment only the mortgage will remain. The amount of loan installments will be drastically reduced and the user could feel calmer and lead a normal life.

When the criteria-based model, presented by the Broker Matrix is used, it is established that the consumer considers taking such loans to be highly risky (orange states 7 and 17). Taking a mortgage loan of up to 80% of the sum is relatively promising for him/her. However, it is not acceptable to take a consumer loan in parallel in order to fully cover the price of the property. This action makes the user anxious.

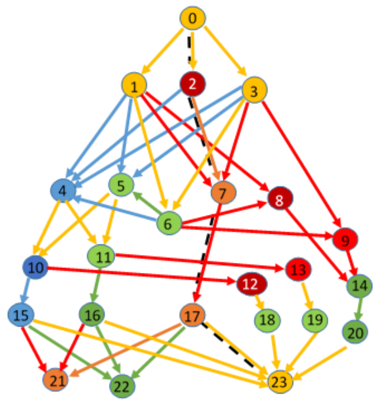

Figure 3: A dotted black line shows a sequence of states for buying a property by a person, who does not have any residential properties. The system offers this sequence only if the newly introduced criteria-based model, presented by the Broker Matrix, is not used.

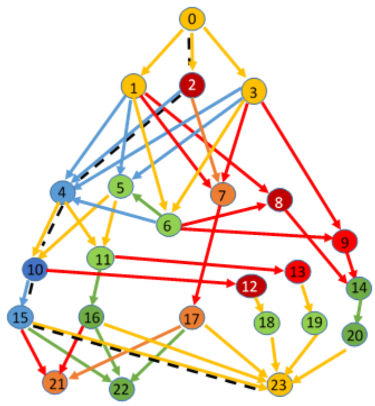

Figure 4: A dotted black line shows a sequence of states for buying a property by a person, who does not have any residential properties. It is proposed by the system when using the newly introduced criteria-based model, presented by the Broker Matrix.

A condition is set therefore - to offer the buyer only actions, acceptable to him/her, i.e., actions, perceived by him/her as reliable and secure and/or which he/she would undertake with joy and readiness or with mixed feelings between joy and hope, but without panic and stress. This leads to the option shown in Figure 4. According to it, the buyer could live for several years in a rented apartment and save money until the accumulation of at least 20% of the price of the property he/she wishes to buy, having in mind that he/she will then be able to buy the property only against a mortgage loan. This option turns out to be acceptable for the buyer. Depending on the years he/she could spend on fundraising and the size of his/her salary, he/she will have to decide which of the proposed housing options to buy. Only appropriate compromises were made and a suitable property was chosen.

5 SECOND EXPERIMENT

This time a buyer, who starts his dream job in a large industrial city but owns properties in another smaller provincial town is considered. He/she wants to buy a property near his/her workplace. A survey, conducted with the potential buyer reveals that he/she prefers security and does not like to take risks. He/she is reluctant to sell real estate and this thought strains and repulses him. On the contrary, he/she loves to travel and would like to regularly invest small sums to maintain and improve the properties he/she owns. He/she loves travelling and although it takes time, he/she would gladly travel for several years. He wants to speed up the deal as much as possible and therefore prefers to buy a home as soon as he collects 20% of the sum. It is known that the bank could give him a mortgage up to 80% of the value of the property.

The system is looking for a way in which the user can buy the most suitable home in the best possible way. A sequence of actions should be proposed that will allow him/her to feel as happy and confident as possible.

5.1 Result of a Survey Conducted With the Buyer, Aiming at Clarifying His/her Way of Thinking

A survey with a specific buyer on his/her opinion and the emotions he/she feels about the different ways of buying a property are presented in Figure 2. Here are the more important considerations of the buyer.

A small newly built office - smaller than the area of the homes under construction - is a compromise option, as it is a cheaper property, smaller, but sufficient for both residential needs and business solution. The minimalist lifestyle is acceptable to him/her. The required amount of money will be collected in a shorter time. The risk is lower. This is the most secure solution and is therefore marked in green.

A residential property that is not newly-built and is in need of renovation allows a few more squares for the same price as the new but smaller home. This is an unacceptable compromise for the user in question. However, it is marked in orange because it can still be considered as an affordable compromise.

On the one hand, raising more funds requires more time. On the other hand, in case of availability of a larger percentage from the price of the purchased property, the user will feel more secure. That is why the saved 20% of the price of the property are marked in blue color, as not very secure but time-saving. An available saved sum of up to 40% of the price of the property is marked in green as a secure enough state.

The available 50% of the price of the property coming from the sale of another property is also marked in green as an amount that provides security.

Taking a mortgage loan of 50% - 60% is considered a risk-free step to the goal. Mortgage loan in the range of 10% - 30%, if the remaining funds are available, gives not only security but also joy and enthusiasm to the buyer. That is why it is marked in yellow.

The maintenance and improvement of the properties the buyer owns brings joy, satisfaction and security to him/her, on the one hand. However, these actions require investment and allocation of funds. This, in turn, extends the period for collecting savings to buy the dream home. Leaving the care of the owned property causes panic, indignation and anger in the buyer and would be unacceptable. The maintenance and improvement of the properties he/she owns are marked in yellow - the color of joy and satisfaction.

Commuting to work and back is tiring and a waste of time, but it is acceptable for the user and gives him/her security and comfort. Therefore, it is considered a preferred action and is marked in green - the color of security.

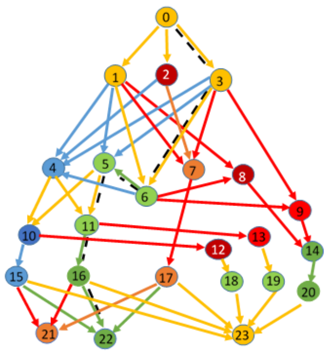

Figure 5: A sequence of the most secure possible conditions for buying a property by a person, who has properties in a location other than where he wants to buy a property. The innovative criteria-based model presented by the Broker Matrix is used.

Renting is acceptable for the buyer if the rent is not high. This means that the conditions of living will be only limited to the most basic ones and that his/her life will be minimalistic for years, but full of hope. Therefore, this action is marked in blue - the color of hope.

5.2 Solutions, Proposed By the System

Figure 5 shows the sequence of states for buying a residential property by a person, who already has another property in a settlement other than the place where he/she wants to buy one. This sequence is offered by the system when using the newly introduced criteria-based model presented by the Broker Matrix. The goal is to choose a course of action that is as secure as possible for the buyer. It can be seen that the proposed path covers nodes 5, 6, 11, 16 and 22, which are secure. Nodes 0 and 3 are yellow, i.e., they make the person happy. It means that the buyer cannot give up his job and cannot sell the properties he possesses. The system does not suggest these unacceptable options to him/her.

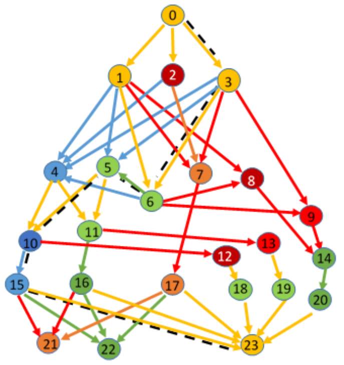

Figure 6: A sequence of states that will make the user as happy and enthusiastic as possible when buying a property though he/she will have to compromise on security. The user owns properties in a location other than the one he/she wants to buy the new property in. The innovative criteria-based model presented by the Broker Matrix is used.

Figure 6 suggests another option that would be acceptable to this user. This is the sequence of actions that would make our user as happy as possible at every step, but in which the risk is greater. It can be seen that in this case not all actions are in yellow, i.e., the user will have to make compromises though acceptable ones. They are colored blue and are related to security. The user, on the one hand, saves time and speeds up the purchase of the property by collecting only 20% of its price. On the other hand, he focuses on buying a more expensive new residential property, instead of a small and cheaper office. However, the risk in this case is higher. He/she takes a bigger mortgage and will pay it off for a longer time.

6 CONCLUSIONS

This paper proposes a new SBLA that includes a memory block (criteria-based model, model of rewards, model of the environment), block of knowledge (of the possible solutions, the individual requirements and emotions of a user, as well as of the possible scenarios), appropriate actions/states marking block, training block, containing a Reinforcement learning algorithm, explanation block, solution visualization block. The aim is to empower the learning agent to propose an appropriate way of reaching a suitable goal. The use of the criteria-based model represented as an additional agent memory matrix is important. This model shows how the user perceives and evaluates the potential goals and the possibilities for their realization. This means that knowledge of the user's habits and understandings is required.

The agents can make a compromise by not following a given criterion. The criteria are arranged by their level of emotional acceptability for the user. That is way the agent can choose the most acceptable compromises. The learning agent can solve problems by not allowing unacceptable compromises to be made. On the one hand, the Pareto front can provide a set of optimal compromise solutions. On the other hand, the proposed SBLA and reinforcement learning algorithm can provide a way of achieving the goal by means of the most acceptable compromises.

The introduced criteria-based model, represented by the Broker Matrix is not a probabilistic one. It reflects the user's opinion on the considered problem. This is useful when solving problems, not common in a user's life and when there is no statistics on user actions. An example of such a problem is the purchase of a residential property. And it is possible that the user buys a property for the first and last time in his life.

Also, the development and use of criteria-based models allows to avoid the use of penalties in the work of the reinforcement learning algorithm. Instead, the choice of actions can be explained. If emotional, motivational and other models are built, then the learning agent will be able to give explanations for each action from a different point of view.

The proposed SBLA is also suitable for negotiating and modeling empathy. These activities require an understanding of consumer needs, understandings and preferences as well (Gehghani et. all, 2012, Johnson et. all, 2019, Paiva et. all, 2017, Maslow, 1998).

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