APPLICATION OF DECISION TREE LEARNING IN MILITARY DECISION MAKING PROCESS

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Abstract: *Supremacy in the 21st century will be the result of positioning in the artificial intelligence (AI) competition, a competition not always fair, but justified primarily by the advantages offered in terms of power: the winner dictates the rules in all domains. AI has the ability to create new forms of military conflicts, one of the directions being the optimization of the decision-making process. At the same time, human-AI synergy represents one of the challenges of authority and trust for moving to the implementation stage. The purpose of this article is to highlight the impact that AI has on the interpretation of certain courses of action related to a given scenario. Through the analysis based on the decision tree learning, a frequently used form of machine learning, both optimal decisions and those that do not correspond to the desired final state will be highlighted. Thus, the requirements for improving the performance of the military decision-making process for new and/or changing future situations are answered.*

Keywords: *military decision making; decision tree learning; targeting; course of action; unmanned aerial system*

1. INTRODUCTION

The AI revolution is not a strategic surprise at the level of global actors (NSCAI, 2021), but by opening new opportunities to state and non-state actors, new and unpredictable security challenges can be activated. We are currently in the stage where, by reporting on the transition curve, AI validates expectations, but at the same time, by capitalizing on technological opportunities, it potentiates vulnerability at a strategic level.

From the multitude of definitions of AI, some common elements can be identified: IT systems [capable of performing], functions [intelligent behavior], [for] improving performance [in the environment in which it operates] (USGAO, 2022; HLEG, 2019).

The effects produced in military affairs lead to a possible algorithm versus algorithm confrontation, which follows the cycle: data collection; data analysis; connectivity; strike system. The applicability of AI in the military field represents a redefinition and activation of "next generation" capabilities: innovative operational concepts (doctrines); adapted organizational structures (organization); technical education, training environments through simulation (training, leadership and education); autonomous AI systems (hardware); development of digital teams (personnel); digital ecosystem (facilities); integration in allied context (interoperability).

The military superiority generated by the implementation of AI becomes quantifiable both at the decision-making level (faster, more relevant, more substantiated decisions) and at the action level (more efficient weapon systems). The more advanced the position on the Revolution in Military Affairs (RMA) scale, the more difficult is the change/adaptation generated by the AI revolution.

Information technology (IT) and AI will penetrate deeper and deeper into the military organization, radically transforming the way missions are carried out both in peace, but especially in crisis and war. The development and implementation of AI elements in the military decision-making process (MDMP) must comply with the requirement that low performances are not accepted (Cerri *et al.*, 2018). Thus, a series of threats and associated possible consequences were identified, the management of which reduces the speed of innovation propagation (Table 1).

Tab. 1 AI militarization

Threat	Consequence
Authorizing the deployment of AI to strategic weapons	The emergence of unintentional nuclear conflicts

The unregulated proliferation of AI-based AWS	Possibility of use by terrorists/ non-state actors
Misunderstanding of the doctrine/ principles of use in battle	Accidental escalation of conflicts/ crises
Lack of a consensus regarding the responsible use of AI in the military field	The impossibility of establishing concrete measures on which to build mutual trust
Inability to fully understand technology	Adopting unfounded decisions
Difficulties in monitoring performance	Unsafe systems and irresponsible use

The human factor - AI cooperation in the military plan is realized in the optimization of processes, the substantial reduction or even the reduction of the risk of errors, the avoidance of overloading the human factor, the identification of a much more varied range of action possibilities and the considerable improvement of the reaction speed.

The integration of AI actively and with an established level of autonomy in the military decision-making process (MDMP) and its related activities would actually optimize all the internal mechanisms of the activities carried out at all levels: strategic, operational and tactical (Alon, 2013). The available MDMP database can be exploited by transforming it into training data for an automatic learning model. In this way, the computer system is allowed to learn to program itself through experience to predict specific results (MITSSM, 2021).

The aim of the paper is to optimize a decision-tree-learning based on the training data from the created hypothesis, which assumes the existence of several attributes. Correct prediction on new training data becomes a classification problem specific to supervised learning: destruction/ combat or failure. Moreover, being an inductive type tool, the decision tree will fold on the operational requirements of the scenario, its completion providing the finality of each direction and significantly diminishing the weight of specifically human analyses that would require extending the necessary time or omitting some details of major importance. The paper is innovative and can be considered relevant for the research field of MDMP for the following reasons: the introduction of supervised learning as a solution in line with technological progress to improve MDMP, as well as the development of a decision tree study with learning for an application of TGTG. The paper is organized as follows. Section 2 presents the supervised learning method in the context of MDMP. Section 3 puts forth the proposed decision tree learning and its TGTG application are described. The last section outlines the conclusions and summarizes the main results obtained during the research.

2. SUPERVISED LEARNING IN MDMP

The quantity and quality of data related t_0 the characteristics of the operational environment have grown directly proportional to the proliferation of disruptive technologies against the backdrop of technological progress. These data are somewhat predetermined (do not undergo major changes from one environment to another) or are in permanent change (derived from diversity, unpredictability and perpetual fluctuations) (Stoffler, 2019). Thus, data about the operational environment can be divided into three subclasses: the set of data that will be readily available, the set of data that requires thorough research or simulation, and the set of data on which collection is resumed. From the point of view of the target management process, the data associated with the three specific vectors (the target, the weapon and the operational environment) can be distributed in two categories: observation data and result data.

The applicability of the learning problem derives from the operating principle: set of training data (input-output pairs) – learning function – prediction of outputs for new input data (Figure 1) (Russell and Norvig, 2016).

A viable automatic learning model must fulfill at time t0 the function for which it was designed at the initially established performance level, and at time t_1 the performance evaluation should highlight an improvement.

There are several ways to train an automatic learning model: supervised learning (the training data is also associated with the desired output); unsupervised (the training data does not contain the desired output, clusters and associations are identified without the need for human intervention); reinforcement learning (learns based on the feedback received after a decision is made) (Mironica and Ionescu, 2018).

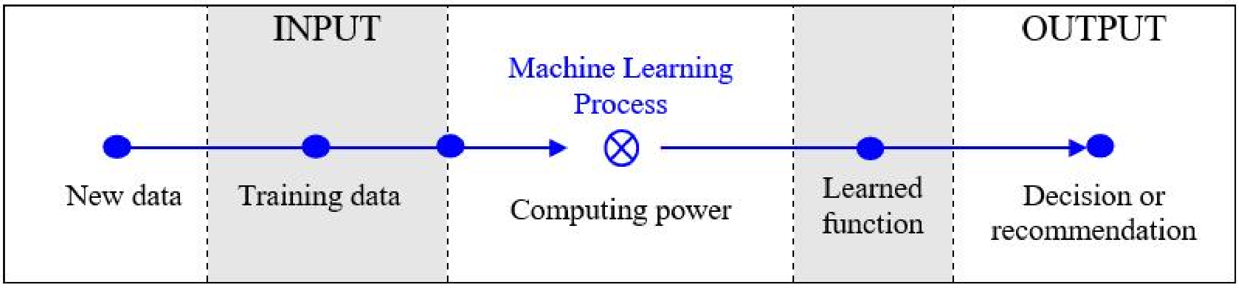

Fig. 1 Machine learning model

The decision tree is one of the algorithms specific to supervised learning that is applied with very good results in classification and regression problems. In the field of targeting (TGTG), a regression problem can take the form of predicting effects and collateral damage, and a classification problem could be the recognition and prioritization of targets. The decision tree, algorithm specific to supervised learning, allows the separation of a data set into smaller subsets and, at the same time, is developed on the levels of the tree on decision and hazard nodes, until reaching the result nodes, which are terminal nodes.

3. DECISION TREE LEARNING APPLICATION

The hypothesis created through the prism of a TGTG scenario assumes the existence of the following attributes: the location and mobility of the target, the moment of receiving the mission, the weather conditions, the action within the target range and the type of weaponry used. The integrated analysis of the six considered attributes results in the existence of three possible generated effects - results: destruction, combat and failure.

In order to facilitate an overview of the possibilities that military decision makers must analyze, a training data set consisting of ten concrete examples, formulated on the basis of experience and correlated with the present scenario, was developed (Table 2).

Decision makers must analyze each variable separately and assign, depending on the situation at hand, importance and priority coefficients, so that the considered COA represents the most desirable outcome.

For the inductive construction of the decision tree, the ID3 algorithm is used. It is based on the selection of the most important attribute, using entropy (E). Entropy shows the level of "disorder" of the data set (Squire, 2004) and is defined by the symbiosis of variants with positive (p) and negative (n) results (equation 1).

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$$E = \left[-\frac{p}{p+n}\cdot log_2\left(\frac{p}{p+n}\right)\right] - \left[\frac{n}{p+n}\cdot log_2\left(\frac{n}{p+n}\right)\right] \quad (1)$$

For the training data set considered, *p* (destruction of 4, and *E* is 0.971. The algorithm for determining the root node proceeds by determining *E* for each attribute individually. Since each possibility of the attribute variables is interpreted in terms of *p* and *n*, it is necessary to determine the mean *E* (E_{medie}) for both circumstances (equation 2), where *t* represents the total number of action possibilities valid at the time of the calculation.

$$E_{medie} = \left(\frac{p+n}{t}\right)\cdot E \quad (2)$$

Once the distinct values of the specific E_{medie} are determined, the average information entropy (Average Information Entropy - *I*) is calculated, where *i* represents the number of characteristics of the considered attribute (equation 3).

$$I = \sum_{i=1}^{n} E_{medie\ i} \quad (3)$$

To determine the measure of the degree of efficiency in the selection of attributes, the informational gain (Gain - *G*) is used. It is defined according to the E_{medie} and *I* associated with attribute *k* (equation 4).

$$G_k = E_{medie\_k} - I_k \quad (4)$$

Tab. 2 The training data set

Location of the target	Mobility of the target	Time of receiving the mission	Weather conditions	Action within the range of the target	Type of weaponry used	Final result
Input attribute values						*Output attribute values*
isolated	fixed	at takeoff	stable atmosphere, no significant changes	immediate launch, no hesitation	AGM-176	destruction
isolated	mobile	in flight	stable atmosphere, no significant changes	immediate launch, no hesitation	AGM-114	combat
isolated	fixed	in flight	partial cloudiness and light wind	delayed launch	GBU-12	failure
isolated	mobile	at takeoff	high cloudiness and strong	delayed launch	AGM-176	combat
isolated	mobile	in flight	partial cloudiness and light wind	delayed launch	AGM-114	combat
crowded environment	fixed	at takeoff	high cloudiness and strong	abandonment	no weapon	failure
crowded environment	mobile	at takeoff	partial cloudiness and light wind	delayed launch	GBU-12	combat
crowded environment	fixed	in flight	stable atmosphere, no significant changes	immediate launch, no hesitation	AGM-176	destruction
crowded environment	fixed	at takeoff	partial cloudiness and light wind	abandonment	no weapon	failure
crowded environment	mobile	in flight	stable atmosphere, no significant changes	immediate launch, no hesitation	AGM-114	failure

Since no possibility of firing on the target has been ruled out until now, the total number of action possibilities is equivalent to that of the initial phase. So, having $t = 10$ as a reference point and substituting the values related to each individual situation in the previously mentioned expressions, the results are contained in table 3.

The attribute variable with the highest value G_k represents the root node, being highlighted by positioning the *Type of weapon used* as the main attribute, with future tree splits configured according to the type of missile used.

Passing through the filter of the *type of weapon used* attribute all the ten distinct situations in the data set, the existence of two possibilities is highlighted which, for reasons related to failure as the final result, will constitute a leaf node.

In order to outline the following ramifications constituted according to the root node, it is necessary to analyze the main attribute from a triple perspective: AGM-176, AGM-114 and GBU-12. The analysis of the AGM-176 characteristic reveals three positive results (p), thus resulting in the second leaf node corresponding to *success*. The analysis of the AGM-114 characteristic reveals two positive results (p) and one negative result (n).

The decision-making component of AGM-114 will be interpreted from a multi-criteria perspective derived, in turn, from the investigation of the remaining attributes: *the location and mobility of the target, the moment of receiving the mission, the weather conditions, the action in the range of the target*. Thus, for each individual attribute, the p, n, E, E_{medie}, I and G_k, values are centralized and calculated, according to equations (1-4) (Table 4).

Since the comparative analysis of all G_k values highlights the maximum result as the one for *the target location* attribute, it will represent the next node of the decision tree. By interpreting the final states, it is possible to notice both the isolated target-combat correlation and the crowded environment-failure correlation, corresponding to two other leaf nodes.

The analysis of the GBU-12 characteristic reveals a positive result (p) and a negative result (n).

Tab. 3 Informational gains associated with attributes

Attributes (k)	Characteristics (i)	E_{medie}	I	G_k
Target location	*isolated*	0,361	0,846	0,125
	crowded environment	0,485		
Target mobility	*fixed*	0,485	0,552	0,419
	mobile	0,067		
The moment of receiving the mission	*at takeoff*	0,485	0,971	0
	during the flight	0,485		
Weather conditions	*stable atmosphere without significant changes*	0,325	0,925	0,046
	partly cloudy and light wind	0,4		
	high cloudiness and strong wind	0,2		
Action within target range	*immediate launch without hesitation*	0,325	0,649	0,322
	delayed release	0,325		
	abandonment	0		
Type of weapon used	*AGM-176*	0	0,475	**0,496 (max)**
	AGM-114	0,275		
	GBU-12	0,2		
	no weapon	0		

Tab. 4 The informational gains associated with the remaining attributes

Attributes (k)	Characteristics (i)	E_{medie}	I	G_k
Target location	*isolated*	0	0	**0,918 (max)**
	crowded enviroement	0		
Mobility of the target	*mobile*	0,344	0,344	0,574
The moment of receiving the mission	*during flight*	0,344	0,344	0,574
Weather conditions	*stable atmosphere without significant changes*	0,25	0,25	0,668
	partly cloudy and light wind	0		
Action within target range	*immediate launch without hesitation*	0,25	0,25	0,668
	delayed release	0		

Thus, the process is repeated as in the case of AGM-114, resulting in three equal maximum G_k values, corresponding to the following three distinct attributes: *target location, target mobility and the moment of receiving the mission*.

In such situations, it is up to the decision-makers to choose the most important attribute. In our case, the attribute mobility of the target was chosen, the results showing that both fixed and mobile targets lead to singular effects, combat, respectively failure, a fact that substantially diminishes the scope of the subsequent development of the tree. Moreover, the fixed-combat and mobile-failure correlations are unique, which is why further division would be unnecessary. The centralization of all the data used throughout the algorithm converges towards the design of the final decision tree (Figure 2).

Starting from a set of 10 training data, the decision tree considerably narrows the analysis which, in the absence of such an approach, would mainly require the involvement of a relatively larger number of resources and an extended time interval.

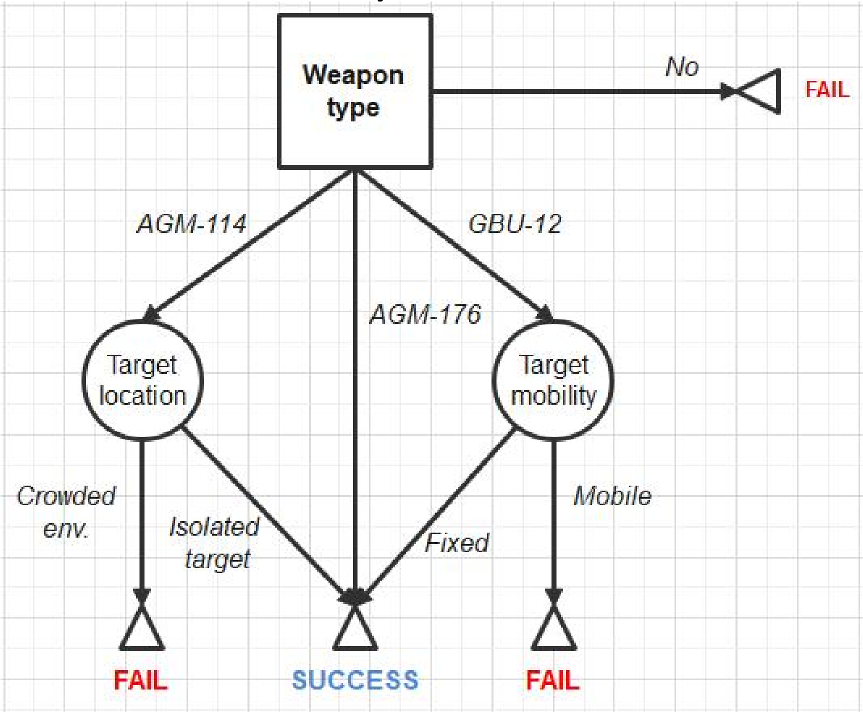

Fig. 2 The optimised decision tree

In Matlab, programming and computing platform, it is possible to implement the ID3 algorithm for decision tree learning, where the tree is built recursively based on attribute selection using information gain and entropy calculations.

The "DECISION_TREE_LEARNING" function takes three input arguments: "examples", "attributes", and "parent_examples". It returns a decision tree represented as a structure. The "PLURALITY_VALUE" function returns the mode (most frequent value) of the input labels and the "IMPORTANCE" function calculates the importance of each attribute based on the information gain.

```
function tree = DECISION_TREE_LEARNING(examples, attributes, parent_examples)
  if isempty(examples)
    tree = struct('class', PLURALITY_VALUE(parent_examples), 'children', {});
    return;
  elseif all(examples(:, end) == examples(1, end))
    tree = struct('class', examples(1, end), 'children', {});
    return;
  elseif isempty(attributes)
    tree = struct('class', PLURALITY_VALUE(examples(:, end)), 'children', {});
    return;
  else
    best_attribute = IMPORTANCE(examples(:, 1:end-1), examples(:, end));
    tree = struct('attribute', attributes{best_attribute}, 'children', {});

    attribute_values = unique(examples(:, best_attribute));
```

The first condition checks if the "examples" matrix is empty. If it is, it means we have reached a leaf node, and we create a leaf node with the majority class from "parent_examples" using the "PLURALITY_VALUE" function. The decision tree structure is returned with an empty children field. The second condition checks if all the examples have the same classification. If they do, we create a leaf node with the common classification and return the decision tree structure. The third condition checks if there are no remaining attributes to split on. If so, we create a leaf node with the majority class from the current examples.

If none of the above conditions are met, we proceed with the recursive part of the algorithm. First, we determine the best attribute to split on using the "IMPORTANCE" function. The decision tree structure is created with the selected attribute as the root node and an empty children field. We obtain the unique values of the selected attribute from the examples and iterate over them. For each attribute value, we filter the examples to obtain the subset that matches the value.

```
for i = 1:length(attribute_values)
        value = attribute_values(i);
        exs = examples(examples(:, best_attribute) == value, :);

        subtree = DECISION_TREE_LEARNING(exs, attributes([1:best_attribute-1 best_attribute 1:end]), examples);

        tree.children{i} = struct('attribute_value', value, 'subtree', subtree);
end
```

We recursively call the "DECISION_TREE_LEARNING" function on the subset of examples, excluding the selected attribute. The resulting subtree is assigned to the current attribute value in the children field of the decision tree structure. After iterating over all attribute values, the decision tree structure is returned.

The "calculate_entropy" function calculates the entropy of the input labels using the formula for entropy. It iterates over unique labels, calculates the proportion of each label, and accumulates the entropy.

```
function entropy = calculate_entropy(labels)
  unique_labels = unique(labels);
  entropy = 0;

  for i = 1:length(unique_labels)
    label = unique_labels(i);
    proportion = sum(labels == label) / numel(labels);
    entropy = entropy - proportion * log2(proportion);
  end

  entropy(isnan(entropy)) = 0;
end
```

The use of the Matlab programming language for the implementation of the decision tree learning represents a viable solution to reduce the time and prediction pressures that act as stress factors for the targeting specialist.

4. CONCLUSIONS

The use of AI in the military field has become a necessary, but not yet sufficient, condition for ensuring success. The applications in MDMP converge towards assigning the technological component, in a weighted measure, to procedural tasks, increasing the speed of reaction, reducing the risk for the human factor, optimizing the decisions adopted, avoiding major errors, integrating and analyzing multiple and diversified information from sensors, analyzing through the lens of several filters the considered problem and increasing the efficiency exponentially.

The decision tree algorithm with learning is based on the strategy of testing the most important attribute. This method leads to the division of a complex problem into several sub problems, which can be solved in a recursive manner. The evolutionary architecture of a decision tree, for which it was necessary to filter the data according to certain considered parameters, highlighted, in an easy and much better time-anchored manner, both desirable and less effective decisions than the expected result since the assignment of the mission. The decision tree has managed to considerably narrow down the analysis which, in the absence of such an approach, would require more resources which, in turn, would be able to manage the situation in question, analyze huge volumes of information and make the right decision in a very short time.

The good results obtained by integrating machine learning in simple TGTG scenarios are encouraging for adaptation and testing in the case of complex decision-making situations: multiple decision variables, incomplete or possibly contradictory information, rapid changes in the operational environment.

Further research will be focused on increasing the training data set, developing validation and test sets, and evaluating prediction error and generalization ability.

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