# Computational model of behavior in gambling with betting

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**Abstract** We aim to find if there is a way of betting that is somehow specific for each person. We created a simple card game with betting, and volunteers were asked to play it while the evolution of each game was recorded. The data collected was processed using decision trees. The performance obtained by the classifiers suggests the existence of a playing style for each participant, which can be modelled by means of a decision tree.

**Key words**: computational model, computer game, gambling behavior, decision tree

## 1 Introduction

According to Henri Laborit [8,9,10] all animals have four basic forms of behavior:

- *struggle*, or even aggression, required for example to hunt prey, dominate a territory or to protect the chicks;
- *consumption*, which can manifest itself for example when eating or at the time of mating, as well as in the human sense to buy goods;
- *trail*, whose most obvious example is to escape from a predator or a stronger opponent;
- *inhibition*, poor conduct of every action and in the simplest case is represented by an animal that pretends to be dead faced with the inability to fight or flee.

According to Laborit, the above classification can also be applied to humans, because the four basic behaviors are governed by the oldest layers of the central nervous system. He stated that the newer strata of the human brain function as adapters in the manifestation of those behaviors. Thus, life in society restricts the expression of behaviors, eg in the case of aggression, criminal conduct is socially reprehensible, but a wide range of aggressive behaviors that point to the rise in the hierarchy within a large company are considered acceptable. To Laborit, for the most part, our super-valued neocortex must cope with the task of generating a discourse that justifies aggressive behavior or absurd consumption before our fellow men. Finally, Laborit states that only by recognizing the purely animal nature which governs the basis of most of our behavior will be possible to seek a way less harmful than the tendency of humans to engage in wars.

In this paper, we conjecture that in conditions with little variation humans, as animals, tend to express complex behaviors-for example, their attitude in the workplace on a typical day, with a stable proportion of the 4 basic behaviors.

Using this premise as a starting point, the study aims to develop a computational tool based on a card game, which under controlled conditions evokes the appearance of a fixed repertoire of behavior-the actions of the game. Thus, the composition of the repertoire would be representative of the proportion of four basic behaviors characteristic of each individual. However, it is important to note that is not the purpose of the work to characterize computationally the behavior of a playing person with an accuracy that allows the identification of that individual. In any case, we believe possible to find a limited variety of styles of play. In the extreme case, the styles of play would be indicators of more complex concepts as the structure of personality. However, it is totally outside the scope of this paper give a psychological interpretation of the results obtained, or identify the alleged general styles of play. The goal is to investigate the feasibility of building a computational tool that captures faithfully the acceptable standard of play of an individual, and thus even realize the existence of differences between individuals.

There is no intention to build the map that establishes the correspondence between the actions allowed by the rules of the game with four basic behaviors suggested by Laborit. However, according to the conjecture presented above, we assume that this correspondence is stable in the sense that for a given individual it does not change significantly with neither the time nor the circumstances.

Gambling games are often the object of study for a variety of behavior research fields. For example, there are many studies investigating the misconduct behind the compulsive tendency to bet. According to the DSM-IV [2] such diversions are a subgroup of the class of anxiety disorders [4,15,17]. Other studies [1,14,5] investigate the efficacy of introducing changes in the operation of slot machines to attenuate the compulsion to play. Some psychological approaches [13,7,6] explores the motivational component of the person with deviant behavior. Note however that neither the methodology nor the models obtained with a tool developed here aim to have applications related to the diagnosis or treatment of dependence on gambling.

Another approach to gambling is the mathematical modeling of the problem of choosing the best strategy to win. Whether using the Theory of Games or using statistical tools, are designed studies that point to optimize some cost function [18,11,19]. In this study the outcome of the game has no direct relevance to the study. The fact of winning or losing is integrated by the player who will adapt his/her strategy according to his/her own style. So the outcome of a game is a shot in the arm to which the player must answer guided by their tendency to express a combination of four basic behaviors.

## 2 Material and methods

### 2.1 Cacilda Card Game

The goal of the card game is to favor the appearance of a fixed repertoire of behavior under controlled conditions. The repertoire consists of the actions allowed by the rules of the game. As was indicated in the previous section, the purpose of the information collected is to find a pattern in the player's action choices. There is no intention to evaluate the performance of the human, not to force the success or failure of it. For this reason, in the designing of the card game was given priority to the simplicity of the rules, and we developed an intuitive and user friendly graphical interface (see Figure 1). The name given to the virtual player that represents the computer-and by extension, the name of the game - is Cacilda.

In general, the rules of the game chosen are inclined to a dynamic that requires little use of reasoning, ie developing strategies or requiring the learning of "shortcuts" in the rules. With this we seek to facilitate player interaction based on intuition or hunch.

The implementation of the game was fully developed using the Python language.


**Figure 1.** Screenshot of the game on a play where the hand is the human player.

## 2.2 Game's Rules[1]

In the Cacilda game, a human player is confronted with a virtual one (Cacilda, for short) in a card game with bets. At any time the human player can choose to end the game. Each play consists of one or more *betting rounds*, where the turn to *open* is randomly given to the human player or to Cacilda by the *dealer* (the program itself). In each betting round, a player can at most have two turns to act: he can open and consequently, he can *call* the *raise* made by the other player. Alternatively, the opening player may *check,* thus closing the betting round (in this situation, the opponent gets no turn to act).

The deck consists of cards with values one, two or three; cards with value *one* lose for cards with the other values, while cards with value *three* win from all the others.

The deck is composed of fifteen cards with value *one*, fifteen with value *two* and fifteen with value *three*, totalizing 45 cards. At the beginning of each game the deck is shuffled and each player receives a hand of fifteen cards drawn randomly. The remaining fifteen cards form the *muck*. Neither player knows the composition of his hand. At the beginning of each round, each player can see only the value of the top card of his packet (this value is unknown to the opponent, of course). After the *showdown*, both cards go to the muck.

Depending on the turn of the player, he can choose one of the following:

first turn: *to fold* and ask the dealer for a new hand[2], *to check*, to bet or to finish the game;
second turn: to check, to bet, to raise or to finish the game;
third turn: to check, to bet or to finish the game.

The consequences of each action are detailed in the following. At the beginning of each game, the human player and Cacilda receive a *stack* of 50 credits, which are used to make bets, to deposit the *ante* or to pay the cost of folding and asking for a new hand. At the beginning of each round each player brings two credits as ante to the pot. The composition of the pot is always showed, detailing the credits provided by Cacilda and by the human player.

At any turn, a player that checks implies the end of the round, and both cards go back to the muck unseen; the pot is transfered to the stack of the other player.

When a player folds and asks for a new hand, the muck is shuffled with the player's cards, and he receives a new hand with the same amount of cards he brings. The player who folds must submit 4 additional credits in the pot. After the release of the new hand, the round is closed and the pot is transfered to the stack of the other player.

Bets have a fixed value of 10 credits. After the player in the first turn open the round, is the turn to the other player to decide his action. The player on the second turn has the option of raise, bringing to the pot a fixed value of 20

[1] The terms used to describe the game were adapted from the poker's protocol.
[2] The player receives the same amount of cards he folds.

credits. If this is the case, the turn goes to the first player who has to choose between to call the raise or to check; this turn closes the round.

The showdown comes after the last player active call the bet. Both players see the cards considered in the round. After the dealer's arbitration, both cards go to the muck and the winner of the round accumulate the pot onto his stack. In the case where both cards have the same value, the pot is equally distributed between the players.

At anytime a player does not have enough credits to feed the pot, the game is over resulting in the other player as winner of the game.

### 2.3 Cacilda's Strategy

Virtual player Cacilda choose its actions in a probabilistic way, taking into account the value of its active card and the amount of its stack.

In the present stage of research, Cacilda's strategy is always the same in all games, regardless of the human opponent.

### 2.4 Data collected

The system records every action performed by both players and stores the data in corresponding files, each game is associated to a separate file which states the date and time of the game as well as an identifier of the player.

As already indicated, the study aims to detect a pattern of play, based on the actions chosen by players over several games. Therefore, it is interesting to consider those variables evaluated by a player in deciding their next action. The simplicity of the game, as well as the relative independence between the hands, suggest what kind of attributes are relevant to the decision of the player. These attributes (with the exception of two, we will explain later on) represent the information presented on the screen of the game in each turn. Therefore, in each turn were stored the following attributes for both opponents: the turn, the value of the card seen, the available credits for the human, the available credits for Cacilda, the number of cards seen with value one in the last 7 rounds and the amount cards seen with value three in the last 7 rounds; each move is labeled with the action chosen by the player.

Note that the attributes *credits available for human* and *credits available for Cacilda*, are not independent since at the beginning of the game were assigned 50 to each. However, for the human player is a subjective difference between the two attributes, and this perception could influence the choice of action.

The human player does not opt for fold and change his hand based solely on the values of variables presented at a given moment in the game. To "fold and change" is perceived as convenient when several successive rounds the value of the card seen is low. Therefore, the system has a record of the amount of cards with value one and value three in the seven most recent rounds. The values of these two attributes are not displayed on the screen of the game but are stored as a way to capture the subjective perception of the quality of the hand that the human might have. The last seven hands are chosen to calculate the frequency of the values of the cards based on the results of psychometric studies referred to working memory [3]. These studies indicate that the human cognitive system can maintain under his attention about five to nine different pieces of information.

## 3 Results

### 3.1 Tests done

The game was presented separately to three volunteers who played a minimum of 30 games each in one or more sessions. We did not used any criteria for the selection of participants, since our purpose is the evaluation of the tool in development. The profiles of volunteers appear summarized in Table 1. In the presentation of the game to each player, the rules were explained, and were completed two sets of learning games, which were not considered in further processing.

As was explained at the beginning of Section 2.4, each set is stored in a separate file, and the amount of moves per game varies. The data of all files generated for a player were unified in a global file, in which the ranking of the moves is random. Thus, the influence of possible biased effects (for example, the player's attention at the beginning of a game session, confidence with the dynamics of the game) is minimized.

Table 2 presents the sizes of the sets of samples collected for each player.

**Table 1.** Volunteer Information

| | Age | Genre | Education |
|---|---|---|---|
| Volunteer 1 | 35 | M | Master |
| Volunteer 2 | 25 | F | Bachelor |
| Volunteer 3 | 28 | F | PhD |

**Table 2.** Size of the sets of examples and error rate of classifiers chosen.

| | Training | Test | Error |
|---|---|---|---|
| Cacilda | 1802 | 200 | 0,5% |
| Volunteer 1 | 781 | 87 | 1,1 % |
| Volunteer 2 | 675 | 75 | 2,7 % |
| Volunteer 3 | 991 | 110 | 0,9 % |

### 3.2 Supervised Learning Algorithm

The inductive learning algorithm, decision trees was chosen to build classifiers that capture the style of play of an individual. Decision trees are especially appropriate when the function to be approximated has a co-domain discrete and finite[12]; in the particular case of the game, the decision tree of a specific player must predict the action he will choose, based on the value of other attributes. In this study we used the implementation of the algorithm C4.5 Ross Quinlan[16]. The comprehensive set of each player, including Cacilda, was the source of data used in combination with the technique of cross validation (ten-folds cross validation), to generate multiple classifiers.

For each player, was chosen the tree pruned with less error when evaluated on the test set. A particularly simple example of these trees is the one corresponding to the Volunteer 2 (see Figure 2). The list of errors of the trees chosen for each player appears in Table 2. The values found correspond to a high accuracy of their respective classifiers, a fact that allows us to conclude that the decision trees along with the attributes chosen for the storage, capture adequately the playing style of an individual.

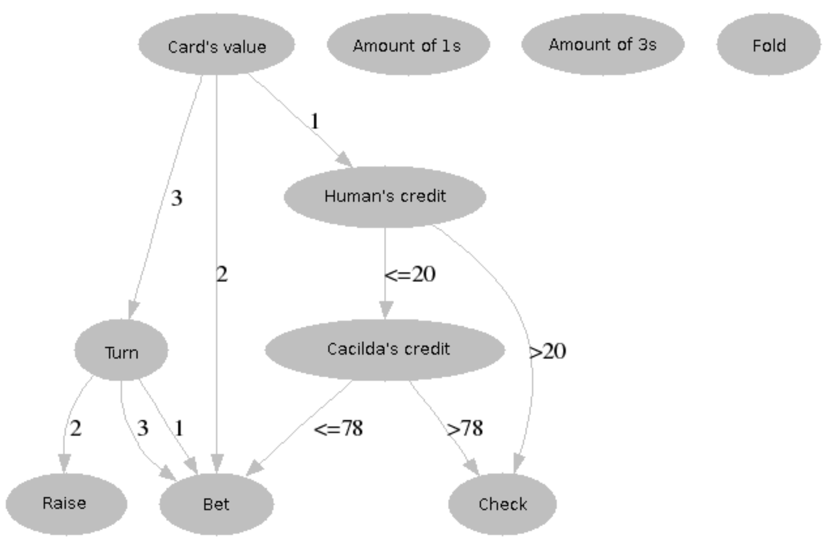


**Figure 2.** Decision tree for Volunteer 2

To assess the specificity of the classifiers selected, the overall set of each volunteer was used as the test set for the trees of the other players. Table3 the columns correspond to the classifiers associated with each player, while the lines are associated with the origin of the data sets used as test. In the case of the diagonal cells, the value corresponds to the error of the classifier on the same test set used in Table 2; in other cells, the test set coincides with the global set of each player. Thus, the classifiers are always being evaluated on examples not used for training and therefore the trends in calculated errors are minimized. Since the lowest error values are shown in diagonal, it can be concluded that each classifier has a specificity for the corresponding player. Note also that the differences that specificity can be explained by the similarity of style of play for two participants. In this sense, the chosen set of volunteers is a relatively homogeneous sample of people, considering the variables shown in Table 1. In later stages of research, we aim to evaluate the hypothesis of groupings in the styles of play, taking as representatives of the classifiers generated with the methodology described so far.

**Table 3.** Error of the classifiers when applied to data from another volunteer (the columns represent the classifiers).

| | Cacilda | Volunteer 1 | Volunteer 2 | Volunteer 3 |
|---|---|---|---|---|
| Cacilda | 0,5% | 11,7% | 15,8% | 7,6% |
| Volunteer1 | 2,5% | 1,1% | 9,4% | 4,3% |
| Volunteer 2 | 3,6% | 4,7% | 2,7% | 4,7% |
| Volunteer 3 | 0,9% | 3,1% | 8,0% | 0,9% |

## 4 Conclusion and Future Works

The main goal of this work was to design a simple card game with betting with the aim to investigate whether it is possible to detect differences in the playing style of each volunteer. The behavior of each player was learned by means of a supervised learning algorithm. In this stage, decision trees were chosen because they are easy to interpret. Nevertheless, the results show that, even if decision trees are not the best suitable algorithm for this application, it is possible to grant enough sensitivity to distinguish among volunteers. In later stages of our work, other algorithms will be tested seeking for the one that better captures styles of playing.

The simplicity of the game's rules allows to consider all the different configurations that a player could be confronted along a play (there are about 4 millions of different configurations). Since a classifier is a reasonable approximation to the way a player acts, the action that a player will choose in each configuration can be predicted. Then, the expected probability for each possible action can be calculated for each player. Once a player can choose one out of only four possible actions, the tuple formed by the four probabilities can be represented by a point in the $\mathcal{I}^4$ subspace, with $\mathcal{I} = [0, 1)$. Further works can perform multivariate analysis relating attributes of players with the distribution of points in the subspace. It is worth to investigate the existence of clusters whose members share the same values for a subset of the attributes. Later, styles of playing can be related, for example, with the expected success of integration of a specific person to a pre-existent team.

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