Agents Behavior and Preferences Characterization in Civilization IV

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Abstract

Player Modeling is becoming an important feature in Digital Games. It basically consists in understanding and modeling the player characteristics and behaviors during the game and has been mainly used to improve the games artificial intelligence, making games more adaptable to different players. In this paper, we try to characterize the preference of the players using a novel approach in games: we use mathematical regressions to characterize players behavior, looking for functions that best fit these behaviors. Using AI controlled players in *Civilization IV* as a testbed, this characterization is performed by extracting game data (score and resources, for example) at the end of each turn and generating functions that characterize the data evolution during the game. We were able to obtain models that distinguish the agents preferences showing the effectiveness of this approach.

Keywords:: Civilization IV, Player Modeling, Preference Modeling, Turn-based Strategy Game, Workload Characterization

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1 Introduction

The main goal of computer games is entertainment and one of the best ways to achieve it is generating challenging situations for each player. One way of doing this that is gradually receiving more attention from the scientific community is *player modeling* [Machado et al. 2011], *i.e.*, automatically adapting the game for each player. This modeling can be based on several characteristics such as knowledge, satisfaction or preferences.

Preference modeling consists in the observation of players with the objective of classifying them on a preference group. Among the several preference groups, we can try to classify the players by the way they play. Two works that have done this are [den Teuling 2010] and [Spronck and den Teuling 2010]. The authors used the game *Civilization IV* to try to learn with AI controlled agents of the game and use the learned models to classify human players. Unfortunately, the authors did not have much success on this goal.

We believe that a better understanding of artificial agents behavior is essential to make this type of classification. Our work is an extension of [den Teuling 2010] and [Spronck and den Teuling 2010] since we evaluate some of their assumptions and we propose a different approach for the problem of modeling player preferences in the game Civilization IV. We believe that the best way to model human players is trying to fit them in a predefined profile in the game. In this direction, Civilization IV is extremely interesting since it has a great amount of agents with distinct characteristics.

The game Civilization IV is turn based and after each turn we can collect information from its gameplay (from now on we call the end of each turn *state*). A state consists of several game *information* like the amount of gold a civilization has or the number of cities, for example. Besides the game states, we can also define the agents *preferences*, which are descriptions of the way the agents play, *i.e.* their main priorities during the game such as gold, culture or religion. These preferences are defined by the agents *attributes*, numbers attached to each agent description.

There are several paths to explore in player modeling, but the two main questions that we want to answer in this paper are:

- The information of intermediate states of the game do characterize distinct preferences of different agents?
- What available information distinguish the agents preferences? What is the relation between their predefined attributes and this information?

These questions are answered with an extensive characterization of the behavior of AI controlled agents, looking for relations between the agents predefined preferences and their behavior.

The main contribution of this work is the introduction of models that are able to distinguish the behavior of agents with different preferences. We also present evidences that data may be influenced by more than one preference. This reflects interactions between preferences, which directly influences in the gameplay and, sometimes, can be counterintuitive.

We start from the premise that the adversarial agent actions do not impact the state of the player we are analyzing and we characterized several of its behaviors and preferences. After this first phase, we relax this premise and we note that it is correct. Thus we can assume this independence with no further consequences.

This work is organized as follows: the next section presents works somehow related to this, while Section 3 deeply discuss the game platform used for tests, the agents preferences and the way they are modeled. Section 4 explains the used methodology for the agents behavior characterization. Finally, Section 5 presents the characterization of different agent preferences and the utility of separating data between matches that were won and that were lost. Section 6 concludes this paper with a final discussion and the presentation of several possible future works.

2 Related Work

A quantitative characterization (in other areas known as *workload characterization*) in games is not a common activity in the field and, when it is done, is generally related to game performance. A work that really characterized game data was [Roca et al. 2006] that evaluated system performance while executing different 3D games. Another interesting work is [Morillo et al. 2006] where the authors characterized movement patterns in a FPS game. As far as we know there are no works in the field that analyzed data (characterized it) obtained during a game, focusing on a better comprehension of its agents AI. Our work does this as a different approach for *player modeling*, an area that is gradually receiving more attention. A taxonomy for it, as well as a large revision about the main papers in the field, is presented in [Machado et al. 2011].

A related work that characterized its data focusing on *player modeling* is [Pedersen et al. 2010] that presented a very complete discussion about these data, mainly based on the search for correlations to maximize the players satisfaction through the automatic content creation.

As mentioned, our work is based on [den Teuling 2010] and [Spronck and den Teuling 2010]. Both works tried to model Civilization IV agents preferences. As previously discussed, we have the same objective but the authors of these works, after gathering the data just processed it with machine learning algorithms, without a deeper comprehension of them. We believe this comprehension can benefit the search for the problem solution. Other works that are also related to the preference modeling topic are [Rohs 2007] and [Pedersen et al. 2010].

Due to the small number of characterization works in the game field, mainly applied to some kind of classification, we also looked for papers from different areas that did data characterization that were later used by a classification algorithm based on *machine learning*. A work that met these requirements is [Mourão et al. 2008] where the authors characterized textual documents evolving through the time. They presented evidences of this evolution as metrics and experiments that confirmed it. Another work in this same subject was [Salles 2011] that redid the analysis presented in [Mourão et al. 2008] for an additional dataset. He also applied factorial projects techniques [Jain 1991] to identify the impact of variations in the classification algorithms.

During the text we present the main concepts that are necessary for understanding our work but a much deeper discussion about the main mathematical concepts used in our analysis is done by [Jain 1991].

3 Civilization IV, Agents and their Preferences

For a better understanding of this work, including the analysis performed, it is important to deeply discuss the game being characterized, *i.e.*, Civilization IV.

A high-level description of this game is nicely presented in [den Teuling 2010]: "In CIV4 *[Civilization IV]* a player begins with selecting an empire and an appropriate leader. There are eighteen different empires available and a total of 26 leaders. Once the empire and leader have been selected, the game starts in the year 4000 BC. From here on, the player has to compete with rival leaders, manage cities, develop infrastructure, encourage scientific and cultural progress, found religions, etcetera. An original characteristic of CIV4 *[Civilization IV]*, is that defeating the opponent is not the only way to be victorious. There are six conditions to be victorious as mentioned in [Games 2005]: (1) *Time Victory*, (2) *Conquest Victory*, (3) *Domination Victory*, (4) *Cultural Victory*, (5) *Space Race* and (6) *Diplomatic Victory*. Because of these six different victory conditions the relation between the player and the opponent is different from most strategy games. The main part of the game the player is at peace with his opponents. Therefore it is possible to interact, to negotiate, to trade, to threaten and to make deals with opponents. Only after declaring war or being declared war upon, a player is at war. Any player can declare war any time, unless that player is in an agreement with an opponent which specifically forbids war declaration." Some in-game screenshots are presented in Figure 1.

Once we presented an overview of the game, we can discuss some of its details: the turn based pace of the game is very useful for us since it clearly defines the data collection moment at the end of each turn. This collection was done in [den Teuling 2010] [Spronck and den Teuling 2010] as well. Our work characterizes the same data used in these works, which are the result of the collection of each turn of matches between non-human agents. The way this data was generated is discussed in the next section.

Each civilization in the game is represented by a specific agent (leader) and each agent has specific preferences as we previously discussed. They are discrete variables and their set of possible values is $\{0, 2, 5, 10\}$. This game is extremely complex and it consists on the management of a set of entities that are in the civilization, like military units, workers and cities. Each of these entities can receive different instructions at each turn and these instructions define the way a civilization evolves. Civilization IV has several scores for each civilization concern, like technology, military, growth and religion, and these scores are affected by the entities actions. We call these scores as *indicators* of agents tendencies, since it is much easier to collect and interpret them contrast to analyzing each agent single action. The way we did this is also discussed on the next section.

To illustrate last paragraph's discussion consider the following example: cities are responsible for creating buildings, units or spreading influence (among others) while military are responsible for defending these cities or attacking enemies. Workers are responsible for the evolution and harvesting of the lands around the cities. Each of these units in a turn may be ordered to act somehow: a city can be instructed to build a military unit while a worker can be ordered to build a road in the map. At the end of the turn, supposing that the city has already finished the military unit construction we may have different scores related to that civilization. The workers job hardly will be observed in the score in a short time since a road is a way to optimize other actions, but the construction of military units certainly will, since the army growth implies in a higher military score.

As previously said, Civilization IV has 26 different agents that are characterized by their attributes (*flavours*), that are identical to the preferences defined in [den Teuling 2010], [Spronck and den Teuling 2010]. These attributes define the way an agent plays. The players models are explicit implemented [Spronck 2005] by an editable XML among the game configuration files. This is the way we were able to obtain the agents attributes.

In the next section we present the methodology of our experiments, detailing the used data, the agents and preferences that were modeled.

4 Methodology

As previously discussed, our objective is to characterize the behavior of different agents and try to correlate them with their preferences. This is done by using game state indicators gathered in several matches between different AI agents. Our intuition was that we would be able to find different functions describing game data for different agents since they have different preferences.

We have worked with the same data [den Teuling 2010] and [Spronck and den Teuling 2010] used. They implemented an application called *AIAutoPlay* that allows computer controlled to play against each other without the need of a human player. Each game takes, at most, 460 turns and this dataset was built randomly selecting six different agents among all of them. Each agent plays against the other five (always in 1x1 games), generating five matches per agent. We repeated the experiments intending to generate more data with this replication: each one was repeated eight times generating 40 battles per agent.

In this paper we have used a subset of the data described above to study three agents preferences: *Culture*, *Gold* and *Growth*. This modeling was performed by observing games between two different agents and analyzing the data generated by these observations. We have carefully chosen these agents in a way that one of them has no interest in a certain preference and the other has high interest in this same preference (values 0 and 5 in the game, respectively). This was done to simplify the comparison between indicators that were supposed to indirectly represent preferences, *i.e.*, we expected a higher value for an agent indicator that has a high interest in the preference related to that indicator.

For example, the agent called *Mansa Musa* has a high interest in *Gold* while the agent *Louis XIV* has no interest in it. Based on this, we compared some indicators of both to model their growth, looking for different functions to each agent. In fact, we expect the *Louis XIV* indicators to be lower than *Mansa Musa* indicators since *Mansa Musa* has a higher preference.

We have used the agents in the examples above to analyze *Gold* preference. To analyze the *Growth* and *Culture* preferences we have used the agents *Alexander* and *Hatshepsut*. The *Growth* preference has a peculiarity: in our dataset there was no agent with a high interest on this preference, just an average interest. We used the agent *Alexander* as the one having interest on it while *Hatshepsut* was the one who has no interest. Seven attributes were chosen by[den Teuling 2010] and [Spronck and den Teuling 2010] to model each agent. The final attributes that define the agents in the dataset are: (1) *Aggression*, (2) *Culture*, (3) *Gold*, (4) *Growth*, (5) *Military*, (6) *Religion* and (7) *Science*. All of them, except *Aggression*, have values in the discrete set $F = \{0, 2, 5, 10\}$, that can be interpreted as *no interest, average interest, high interest* and *unique interest* [den Teuling 2010]. The preference values for Aggression are in the range $\{1, 2, 3, 4, 5\}$. In fact no attribute has value 10 in our dataset.

After the characterization of the three listed preferences we separated matches by their results: victory or defeat. We revisited every analysis now using two different sets to understand the game result impact in our characterization, allowing us to answer the question if the result influence the analyzed functions.

In all the analysis, we have characterized each preference comparing the agents states in each turn seeking for a function capable of representing this evolution. We did linear regressions of all the data and, when the data did not fit in this model, we applied transformations on it to be able to use a linear regression, since the mathematical analysis is simpler and it does not imply in a loss of generality. A liner regression generates functions in the form $y = b_0 + b_1x$. Our main concern is b_1 since it represents the evolution of the indicators in the game.

We have summarized the agents states calculating, for each turn and for each indicator, the average of 40 matches. At the end we have 460 points where each point p_i represents the mean of turn i for all agent matches.

In the next section we will discuss the characterization of each preference modeled in this paper. We also analyze the impact of separating games by their result.

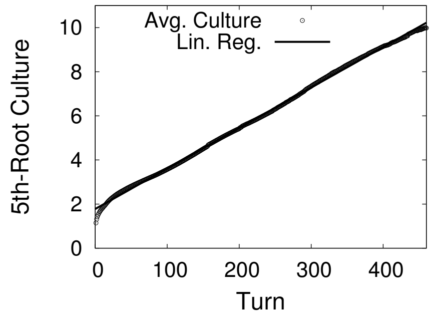
5 Agents Characterization

5.1 *Culture* Preference

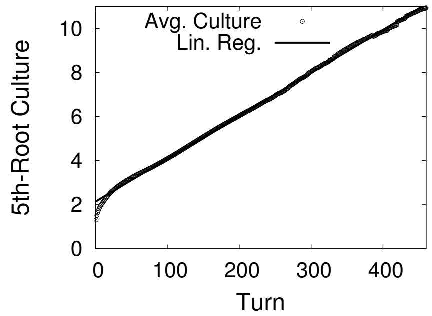
As the other characterizations in this paper, we have selected some indicators collected during gameplay under the premise that they would be relevant to analyze the preferences being studied. These indicators were selected intuitively based on our knowledge about the game. All the regression algorithms and evaluation metrics used in this paper are discussed in [Jain 1991]. We have selected two indicators for this preference: *Culture* and *CultureRate*. As previously discussed the characterization was done using the agents *Alexander* and *Hatshepsut*. The indicators are defined in [den Teuling 2010] as being the "Overall cultural score" and the "Amount of culture gained per turn", respectively.

We were able to characterize almost perfectly this preference with the two selected indicators. To do it we have modeled the *Culture* indicator as a polynomial of degree five and *CultureRate* as a polynomial of degree four. This was very satisfying since it is the order of the derivative of the polynomial that represents the *Culture* (as expected, we have tested regressions of these indicators to other functions, we decided to present only the best result). As we discussed in the previous section, a linear regression simplifies this analysis without loss of generality so we applied the fifth root to all values of *Culture* and the fourth root to all values of *CultureRate*.

As presented in Table 1 we obtained very high coefficients of determination[1] to the *Culture* (99.86% to *Alexander* and 99.85% to *Hatshepsut*) and *CultureRate* indicators (99.11% and 98.93% to *Alexander* and *Hatshepsut*, respectively), besides this, all obtained coefficients are significant with a confidence of 99%. The graphs with the regressions are in Figures 1 and 2.



(a) *Alexander*



(b) *Hatshepsut*

Figure 1: *Linear Regression of the* $\sqrt[5]{Culture}$ *indicator*

Beyond the regression quality is important to note that the coefficients b_0 e b_1 of *Hatshepsut* are bigger than those of *Alexander* with a confidence of 99%. This is what we expected in this situation since *Hatshepsut* has a higher *Culture* preference. This result confirms our hypothesis that the gameplay patterns are able to distinguish preferences of two different agents (at least some preferences).

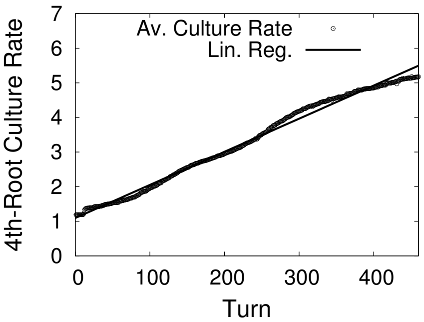
It is interesting to note that this preference has very few interactions in the game and maybe *Culture* is the most easily preference to be isolated since only buildings generate culture. Most of the buildings that generates culture do not exist at the beggining of the game and they become very present in the future, explaining why we obtained a polynomial of fifth degree. We believe that it should be represented by an exponential function but the limited turn number does not allow enough growing. Among the buildings that generate *Culture* are: palaces, educational and religious buildings and wonders.

5.2 *Growth* Preference

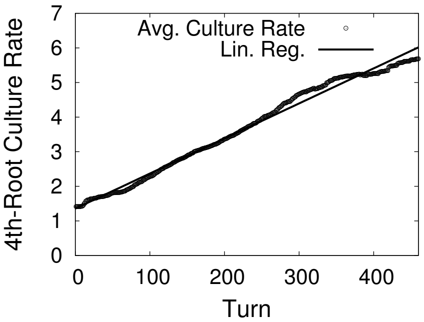
We have analyzed the *Growth* preference observing three different indicators: *Cities, Land* and *Plots*. The first one is defined as the "Number of cities", the second as "Amount of land tiles" and the third as "Amount of land and water tiles". All these definitions were presented in [den Teuling 2010].

The analysis of these three indicators presented to us a recurrent and expected situation: the existence of two distinct intervals in the dataset. Initially there is a period which the growth rate (of *Cities, Land* or *Plots*) is high. This *expansionist* period occurs when still exist unoccupied lands that are easily dominated. After this initial period we can observe a *maintenance* phase where there is almost an stabilization of these indicators since all the world has

[1]"The fraction of the variation that is explained determines the goodness of the regression and is called the coefficient of determination, R^2" [Jain 1991]

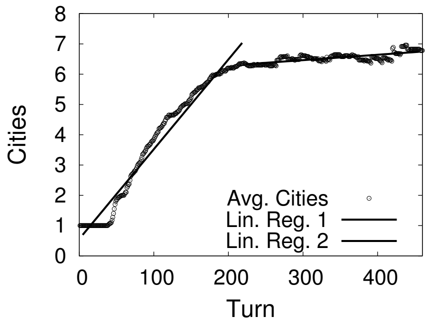


(a) *Alexander*

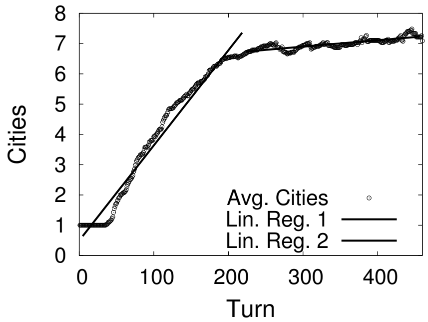


(b) *Hatshepsut*

Figure 2: *Linear Regression of the* $\sqrt[4]{CultureRate}$ *indicator*



(a) *Hatshepsut*



(b) *Alexander*

Figure 3: *Linear Regression of the Cities indicator*

already been "colonized" by some agent. The turn number we have chosen as turning point, as several other information related to the performed regressions are in Table 1.

We were able to model these preferences since we obtained functions to each indicator that characterize well the agents behavior during the game, mainly in the expansionist period. All these functions were modeled as lines (two for each indicator, as discussed in the last paragraph). The agents differentiation was also possible in some situations as we discuss in the following paragraphs.

Surprisingly, the best indicator for *Growth* characterization was *Cities*, that presents the lowest range. For this indicator, we were able to obtain a linear function representing the expansionist period with coefficients different from zero with a confidence of 99% and a coefficient of determination equals to 97.17% to *Alexander* and 96.80% to *Hatshepsut*. The second line segment, of the maintenance period, was not so successful in modeling the agents behavior. As in the first line segment all coefficients are different from zero with a confidence of 99% but we were able to achieve a coefficient of determination equals only to 71.39% to *Alexander* and 56.02% to *Hatshepsut*. The regression of these indicators are in Figure 3.

In the expansionist period we were able to show that the model coefficients are different between agents. As we said, using the model $y = b_0 + b_1 x$, the coefficient b_1, with a confidence of 99%, is bigger for *Alexander*. The equality of b_0 is also expected since all agents start with the same number of cities.

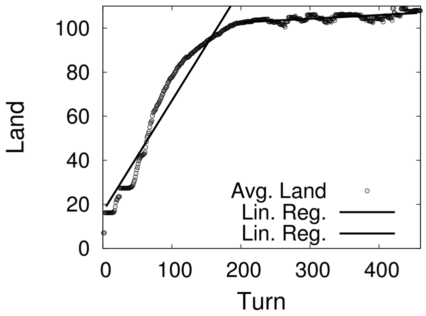
We were also able to show that the coefficients in the second line segment of *Alexander* are bigger than those of *Hatshepsut*. This result is not so important due to the coefficient of determination of these regressions, but is still interesting to note that these data corroborate the hypothesis that agents with a higher preference by *Growth* have bigger coefficients.

The *Land* indicator allowed us to characterize the expansionist period (coefficient of determination equals to 97.90% to *Alexander* and 93.76% to *Hatshepsut*), with a confidence of 95% that the coefficients are different from zero – we were able to achieve $b_1 \neq 0$ with a confidence of 99% but we were not able to distinguish the coefficients between agents. In the maintenance interval the regression did not explain the data nicely since the coefficient of determination (R^2) of *Alexander* in this interval was 23.90% and 50.04% to *Hatshepsut*. Even being able to show that the coefficients are different from zero with a confidence of 99% there is no sense evaluate the intersecction between these two agents. Figure 4 presents this regression and, as the others regressions, its coefficients are presented in Table 1 where the confidence intervals are presented with a confidence of 90% to show that relax the confidence interval still does not allow the coefficient separation.

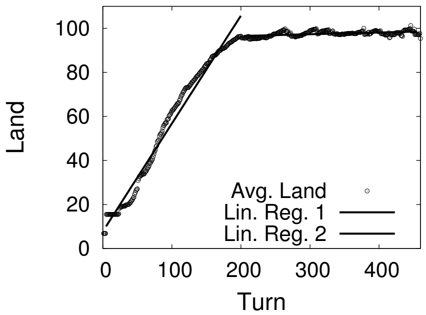
There is a reason to the *Land* indicator be descriptive but not discriminative. As the *Cities* indicator, initially there are too much to be conquered and this allow us to precisely describe the expansionist period but not the maintenance period since there is a natural unpredictability in the game after its stabilization, this is what generates entertainment. This unpredictability is smaller to the *Cities* indicator because is harder to have a decrease in its value since a whole city must be lost while, for the *Land* indicator, this variability is much higher since its borders change much more frequently. This alteration also depends on other preferences like *Culture*, that also makes it harder to be modeled.

We believe the inability to discriminate the generated model coefficients are due to the fact that *Land* can also grow with investment in *Culture*, not necessarily just building cities. An agent who privileges cities may evolve its territory just like an agent that does not but invest in culture, what raises its cities borders and maybe imply in a high *Land* value. The non-independent coefficient (b_1) is the growth rate of the agents borders, this implies that the cities creation generates peaks in some curve points but, in general, this is amortized since we generally have a maximum of 10 cities and 460 turns.

Finally, the last indicator we evaluated was *Plots*, that is *Land* summed with the water *tiles*. As *Land* we were able to nicely describe the expansionist period but we were not able to discern the two agents (*Alexander* coefficient of determination is 99.15% and *Hathshepsut* is 95.05%, with b_1 different from zero with a confidence of 99%). All the discussions previously done are also apliable here. The biggest difference between these two indicators was related to the second phase, the maintenance. We were able to achieve better models than those of *Land* indicator (R^2 equals to 78.73% to *Alexander* and 88.22% to *Hatshepsut* with coefficients different from zero with a confidence of 99%). The regression of these indicators is in Figure 5.

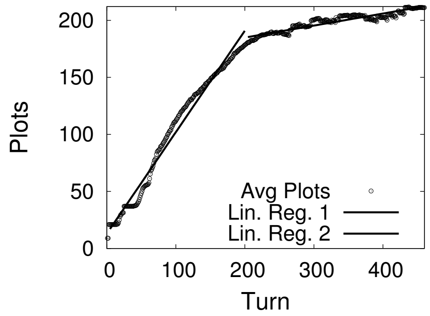


(a) *Hatshepsut*

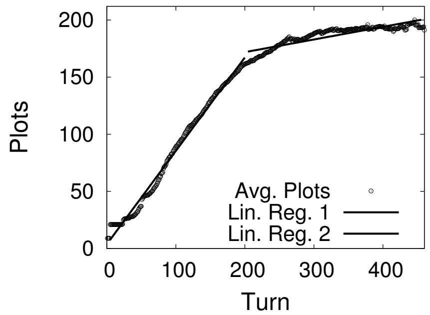


(b) *Alexander*

Figure 4: *Linear Regressions of the Land indicator*



(a) *Hatshepsut*



(b) *Alexander*

Figure 5: *Linear Regressions of the Plots indicator*

We believe this higher "stability" is explained just by the water *tiles* that are harder to be lost by reasons like *Culture*.

As the other indicator, its coefficients overlaps. Based on this the number of cities in each turn is the unique indicator that allow us to discern agents with different game preferences while all indicators successfully describe the agents behaviors. Is interesting to highlight that the chosen agent, as the one with higher preference, did not have this preference on its higher level, showing us that even intermediate levels are distinguishable.

Besides this we were able to observe that the characterization/differentiation sometimes is impaired by the interaction of different preferences in the indicator.

5.3 *Gold* Preference

The selected indicators for this preference were *Gold* and *GoldRate*. They were defined by [den Teuling 2010] as being, respectively: "Amount of gold" and "Amount of gold gained per turn".

We were able to model the *GoldRate* indicator for the two agents as a line. The coefficient of determination of the linear regressions to *Louis XIV* and *Mansa Musa* were, respectively, 98.72% and 96.14%. Besides this, the models coefficient b_1 of each agent is different from zero with a confidence of 99% (we were not able to show b_0 different from zero, what is not a problem since it represents the initial value). These regressions are presented in Table 1 among all other regressions performed in this paper.

This regression indicate us that the amount of gold received each turn grows following a linear function but, apparently the agent preference does not impact in the way it receives gold. This affirmative is valid because even relaxing the confidence of our evaluations we were not able to find intervals that do not overlap. Figure 6 presents a visual evaluation of the regressions done.

Once apparently the amount of gold received each turn is similar, independently of the player preference, the second hypothesis raised is that the amount of gold stored by each agent would be different. Contrary to our expectations we were not able to model gold as a polynomial of degree two (the integral of the growth rate, represented by a linear function). After a more careful analysis we concluded that this was the expected result since accumulated gold may be seen as a waste of resources in the game.

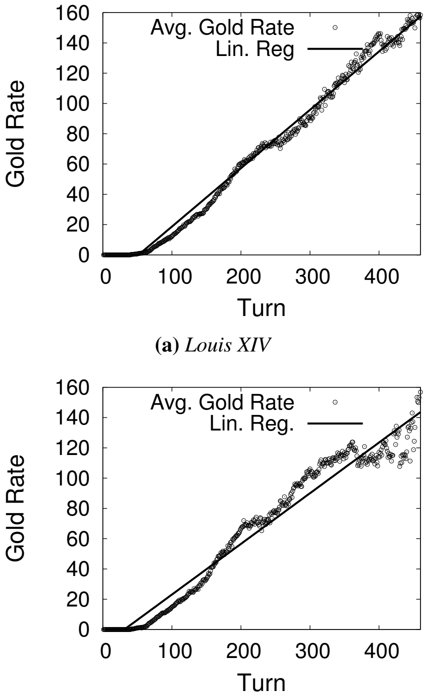
The best characterization we achieved for this indicator was using two different line segments. We believe this is due to the gold importance in the game and the several activities that can be done spending it, like donations to other agents, conversion of it in units upgrades and even receiving it for incapacity to continue constructing some buildings, for example. Figure 7 exemplifies very well this variable behavior.

This division was done aiming that the first regression, for *Louis XIV*, was done in the interval *[1:300]* and for *Mansa Musa* in *[1:340]*. As we can observe in the graph, there is a large variability in this first segment while the second segment is more stable. Despite this analysis we were not able to assure that the regression coefficients are different from zero (the lowest evaluated level of confidence was 90% and is the one presented in Table 6).

Our premise that the indicators *Gold* and *GoldRate* would describe well the agents behavior was partially satisfied since we were able to characterize the *GoldRate* growth but we were not able to do the same for the *Gold* indicator. We believe this difficulty to describe this preference is due to fact that *Gold* is one of the "most common" and important resources in the game, permeating several possibilities, what "degenerates" the *Gold* evolution during the time.

This last preference being analyzed was harder to us to be characterized and we were partially able to model it, since the *GoldRate* describe it but not the *Gold*. The reasons for this is easy to be comprehended after the result analysis: creating a city (which, in this paper, we just related to *Growth* preference) implies in a great loss of gold since the cost of the new cities is higher than its income. The variation observed is explained by this, the cities creation. The great "jump" after the turn 300 can be explained by the "discovery" of mercantilism, besides most of the cities becoming profitable. The similarity of these characteristics with real world are remarkable.

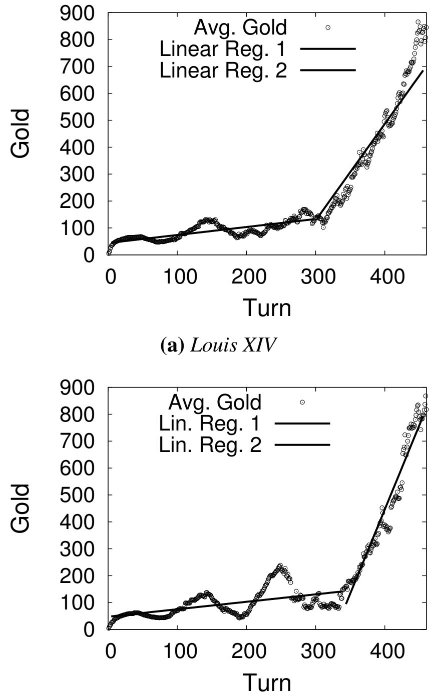
We were unable to distinguish different agents preferences related to *Gold* and we believe this is because gold is an essential resource in the whole game and the preferences are "weaker" when compared to other characteristics not so essential like *Culture* because the agents can obtain this resource from different ways and, for a better player experience, is expected a better balancing of this distribution. During this section we showed the impact of preferences



(a) *Louis XIV*

(b) *Mansa Musa*

Figure 6: *Linear Regression of the GoldRate indicator*



(a) *Louis XIV*

(b) *Mansa Musa*

Figure 7: *Linear Regression of the Gold indicator*

interaction to distinguish and characterize them, this became very evident with this preference.

5.4 Victory and Defeat

Due to our failure distinguishing some preferences with the chosen indicators, mainly the last discussed preference, we decided to evaluate the influence of the game result in the data, *i.e.* we separated the data in two disjoint subsets: those originated from matches that were won and those from lost matches. This decision was motivated by the following question: the analysis of all matches as being in the same group, independently of their result, does not generate noises that distort the real agents behavior? Their separation does not make this data more "stable"?

To answer this question we revisited every generated model recreating them for the two different subsets, *i.e.* each previous model generates two others, using data of victories and defeats. Its intuition is that the game result would impact in the indicators, *e.g.*, an agent that loses cities successively when it loses the game but it conquer them successively when he won the game, maybe because it is extremely offensive at the game end, may have a "stable" behavior when both data are combined but maybe this "stable" behavior is not the best description.

5.4.1 Culture

Another analysis over this preference is useful just to validate the results previously obtained since they were extremely good.

We modeled *Culture* as a polynomial of degree five again and *CultureRate* as a polynomial of degree four. As in the previous modeling our regressions were very good for both sets (R^2 bigger than 98% to all indicators, for both agents) and all obtained coefficients are not zero with a confidence of 99%. The specific information about each regression is in Table 1.

As obtained in the general analysis, the *Hatshepsut* coefficients were higher than those from *Alexander*, who has no interest for it while *Hatshepsut* has. We can conclude that the *Culture* preference was perfectly characterized and distinguished in our work. We do not judge any additional discussion necessary.

5.4.2 Growth

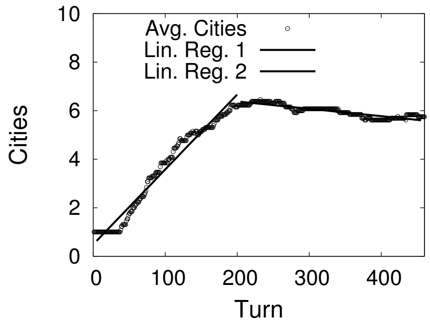
As previously done, we divided all indicators in two periods: an expansionist and a maintenance one. In this preference we were able to observe benefits of the separation between matches that were won or lost. The benefit was a decrease in the data variability and a better understanding of the problem. We were not able to obtain a more distinguishable model for the different agents.

The first evaluated indicator was *Cities*. As in the general evaluation, the expansionist period was easily characterized to *Hatshepsut* and *Alexander* for victory (R^2 equals to 98.01% and 97.91%, respectively) and for defeat (R^2 equals to 96.98% and 96.58%, respectively), with a confidence of 99% that the coefficients are not zero. Is interesting to note that in the subset of matches won, the coefficients overlaps while they do not in the matches lost, with the non-independent coefficient of *Alexander* being higher than the one of *Hatshepsut* with a confidence of 95%.

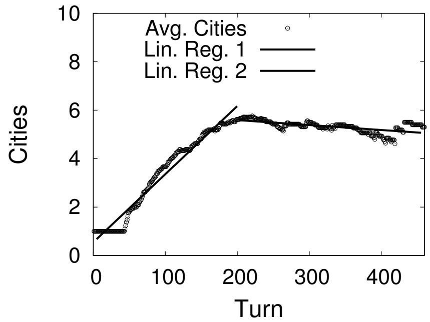
Besides this, when *Hatshepsut* presents a "more" expansionist it increases its victory chances. We believe the statistical difference is achieved only in lost matches because even under adverse situations *Alexander* still aims to expand its borders while *Hatshepsut* does not.

In the stabilization period we were able to better characterize the models of won matches due to the lower data variability (R^2 equals to 95.11% to *Alexander* and 81.79% to *Hatshepsut*). This result corroborates our hypothesis that the game result may influentiate some indicators since we observed a higher variability in the lost matches, probably due to the different types of victory: an agent can lose a game by points, without a single military conflict, or may have its lands devastated by the enemy. The coefficients of determination to *Alexander* and *Hatshepsut* in this situation were, respectively, 79.84% and 39.59%. This difference between then is probably explained by the military preference of the first, not studied here. He is probably better able to defend its lands, even when he loses the game.

Figure 8 presents the number of cities in the lost matches. There is an interesting result here: we have observed that, for the first time, the non-independent coefficients (b_1) were lower than zero, it means that, when an agent loses a game its territory decreases at the ending.

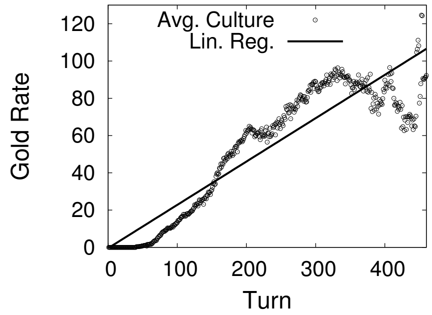


(a) *Alexander (Defeat)*

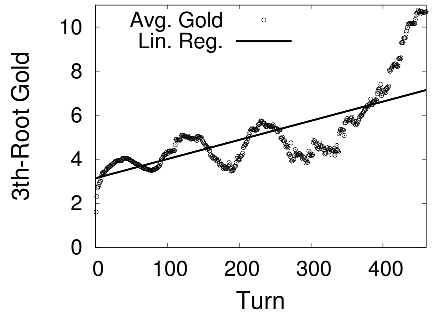


(b) *Hatshepsut (Defeat)*

Figure 8: *Linear Regressions for the Growth preference*



(a) *Mansa Musa (Defeat)*



(b) *Mansa Musa (Defeat)*

Figure 9: *Linear Regressions for the Gold preference*

Once we finished this analysis, by the first time we were able to note the confusion generated by the game result, precisely in the number of cities. The observed variability is big because in some matches, after a specific turn, the cities may continue increasing or start decreasing.

The analysis of the *Land* indicator for victory and defeat is very similar to the general analysis. We were able to characterize well the expansionist period but we were not able to differentiate the coefficients between agents, nor even for matches won or lost. The information about these regressions is in Table 1.

As in the general analysis, the second interval presents a much higher variability. In the set of won matches the coefficient of determination of *Alexander* and *Hatshepsut* was, respectively, 93.65% and 53.95%, with all coefficients different from zero with a confidence of 99%. This difference has already been discussed.

We were able to show in this regression that the growth rate for *Alexander* is bigger than the growth rate of *Hatshepsut*, also with a confidence of 99%. The results for lost matches were extremely variable and any discussion comparing these two agents is meaningless. Despite the variability reduction in the won matches subset we were not able to obtain additional information with this separation.

The last indicator related to this preference that needs to be revisited is *Plots*. The division keeps the excellent characterization of the expansionist period in the victory and defeat subsets and we were still unable to distinguish different agents. The data variability decreased after the division but no additional discussion or analysis is necessary. The results can be seen on Table 1.

5.4.3 Gold

Firstly analyzing the won matches subset, as in the general analysis we were able to obtain very good regressions to the *GoldRate* indicator with an R^2 equals to 98.48% for *Louis XIV* with all coefficients different from zero with a confidence of 99%. We also achieved a R^2 of 97.03% for *Mansa Musa*, with a confidence of 95% that all coefficients are different from zero. Just like the general characterization the coefficients of these regressions overlap. The same occurred in the lost matches subset since we were able to obtain coefficients different from zero with a confidence of 99% and regressions with a R^2 equals to 97.98% to *Alexander* and 84.60% to *Mansa Musa*. Figure 9a presents the regression done for this last case.

The analysis of the defeat situations show us that the higher variability observed in the general data of *Mansa Musa* is explained by the matches lost. Probably this occurs because it loses cities at the end of the game and this implies in a smaller gold rate.

This analysis, despite helping us understand the higher variability in this agent did no allow us to distinguish both and we believe the reasons are the same previously discussed. We present these results in Table 1 with a confidence of 90%, intending to show that this relax is not sufficient to distinguish these coefficients.

We present in Figure 9b the *Gold* graph of *Mansa Musa*, that has a higher variability. This is the unique distribution, among the four analyzed, that we were able to characterize as 2 distinct lines. It was not done because we were looking for functions that were able to characterize both agents. The data variability is evident observing these graphs.

As all other graphs we can observe a high variability of the indicators values and, as previously discussed, probably due to the cities. In the performed analysis we observed, in the won matches subset, that the *Louis XIV* non-independent coefficient (b_1) is higher than the *Mansa Musa* coefficient, that has preference for *Gold*. This relation is inverted on the lost subset matches. Is interesting to note that these results seems counter intuitive since we would expect a higher coefficient in all cases. It does not happen because *Louis XIV* has a high preference for *Culture* and this influences its amount of gold since the *Culture* generates a territorial expansion that implies in a higher number of resources.

After all these analysis is clear that no evaluation form was satisfactory to distinguish the *Gold* preference between the two selected agents. During this section it was clear that, for being a central resource in the game, it suffers impacts from several sources and all these sources distort any analysis. A further study is required for this preference.

5.4.4 Overview

Finishing all these analysis we achieve two different conclusions: first of all, for many analyzed data the separation between matches won and lost generally implies getting half of the models better and the other half worse, that is the most variable part. Despite being able to better characterize the separated models we are not able to distinguish agents preferences that had not been already distinguished by the general data.

We started to believe that the division between matches won and lost is not essential for better agents characterization, mainly because the fusion between both makes implicit the average performance of the agent: if it tends to lose more than win, with the time we would be able to better characterize its losing performance since natural "weights" would raise automatically with the results accumulation. It would be harder to be done with the separated matches. This discussion was valid mainly to show that the game stabilization period is the one that presents higher variability, this result is expected and motivator, forcing us to try to classify the players' preferences as fast as possible.

6 Conclusion

We have presented here an extensive characterization of agents behaviors (inferred with the game states analysis) and the relation between these behaviors and their preferences. This deep analysis showed us peculiar relations in the game as well as an emergent complexity.

While doing our analysis we observed that the difficult to properly characterize a preference is directly proportional to the number of interactions, because some of the game indicators are affected by several preferences. Nevertheless we were able to answer the questions formulated on the first section. After this careful analysis we were able to confirm the hypothesis that the information of partial game states do characterize the different agents preferences since we were able to differ preferences such as *Culture* and *Growth* with game states indicators like *CultureRate* and *Cities*.

The second question presented at the beginning of this paper is very complex to be completely answered since it would demand a scan of all game indicators and the players preferences. Despite this we were able to intuitively present some game state information that characterized some of the agents preferences, showing us cases where exist a direct relation between the indicator slope and the agent preference level. This work has shown that this activity is possible. We believe that the approach we used is applicable in a large number of games where Civilization IV was just a testbed.

A direct benefit of this work is the possibility to implement a *player modeling* system based on *offline review* [Machado et al. 2011] to describe human players over time.

Finally, we also showed that, in most cases, the separation of games based on their result is not beneficial to the characterization for several reasons like the insignificance of the points proportion and a high similarity, in many cases, among the generated subsets and its generator creating a large overhead in the analysis.

Several activities can be done from this point. This work it is just a preliminary study of the agents characteristics. Much more can be done in the *preference modeling* field and we believe that the path started here is very promising. Two immediate works are the comparison between different agents with the same preferences, to confirm the hypothesis that different agents with the same preferences present similar behavior; another work is the characterization of several other preferences that are available in the game, as *Religion* and *Science*.

Another unfinished discussion, that we did not answer in this work is the effect of the initial game turns in the generated models. This question is relevant because the first turns of all agents are very similar since there are not many actions available at the beginning of the game. Previous works [den Teuling 2010], [Spronck and den Teuling 2010] have indirectly shown that the removal of the 100 first turns is beneficial to the agents discrimination, but we believe this is not a simple discussion and it shall be better studied because, by the analysis done in this paper, 100 seems to be a great portion to be removed from the original data.

Since we characterized a pair of agents where the first one had a moderated preference and the other none, is valid to do a deeper characterization of the intermediate preferences, as also confirm that a moderated preference curve lays between the no preference curve and the high preference curve.

Finally, the main goal of this paper is to create models that are able to classify the agents preferences by their behavior in the game and the extrapolation of this model to be applied in human players. As we already said, a similar attempt was presented in [den Teuling 2010] and [Spronck and den Teuling 2010] without success. We believe this presented study is an alternative promising approach to the problem of human classification. As we discussed at the beginning of this work, in our opinion *off line review* [Machado et al. 2011] is a natural approach to the data we have to solve this problem.

Acknowledgments

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Indicator	Agent	Interval	Result	R^2	b_0	b_1	Confidence
GoldRate	Louis XIV	[1:460]	General	98.72%	$-19.7615(\pm 8.1688)$	$0.3853(\pm 0.0307)$	99%
GoldRate	Mansa Musa	[1:460]	General	96.14%	$-11.2732(\pm 20.0013)$	$0.3419(\pm 0.0752)$	99%
Gold	Louis XIV	[1:300]	General	62.39%	$44.0798(\pm 76.3993)$	$0.2969(\pm 0.4400)$	90%
Gold	Mansa Musa	[1:340]	General	31.08%	$47.5944(\pm 295.0593)$	$0.2771(\pm 1.4998)$	90%
Gold	Louis XIV	[301:460]	General	75.33%	$-948.8215(\pm 11127.5812)$	$3.5891(\pm 28.9012)$	90%
Gold	Mansa Musa	[341:460]	General	94.67%	$-2059.4734(\pm 4691.6026)$	$6.2651(\pm 11.6708)$	90%
$\sqrt[4]{CultureRate}$	Alexander	[1:460]	General	98.93%	$1.0939(\pm 0.0035)$	$0.0096(\pm 1 \times 10^{-5})$	99%
$\sqrt[4]{CultureRate}$	Hatshepsut	[1:460]	General	99.11%	$1.3567(\pm 0.0047)$	$0.0101(\pm 2 \times 10^{-5})$	99%
$\sqrt[5]{Culture}$	Alexander	[1:460]	General	99.86%	$1.7772(\pm 0.0019)$	$0.0183(\pm 7 \times 10^{-6})$	99%
$\sqrt[5]{Culture}$	Hatshepsut	[1:460]	General	99.85%	$2.1366(\pm 0.0023)$	$0.0194(\pm 9 \times 10^{-6})$	99%
Cities	Alexander	[1:220]	General	97.17%	$0.49439(\pm 0.0408)$	$0.03143(\pm 0.0003)$	99%
Cities	Hatshepsut	[1:220]	General	96.80%	$0.5561(\pm 0.0411)$	$0.0296(\pm 0.0003)$	99%
Cities	Alexander	[221:460]	General	71.39%	$6.2654(\pm 0.0072)$	$0.0021(\pm 2 \times 10^{-5})$	99%
Cities	Hatshepsut	[221:460]	General	56.02%	$5.9320(\pm 0.0099)$	$0.0018(\pm 2 \times 10^{-5})$	99%
Land	Alexander	[1:200]	General	97.90%	$7.7862(\pm 4.0299)$	$0.4899(\pm 0.0347)$	90%
Land	Hatshepsut	[1:200]	General	93.76%	$16.6760(\pm 13.2991)$	$0.5043(\pm 0.1147)$	90%
Land	Alexander	[201:460]	General	23.90%	$94.9505(\pm 0.8058)$	$0.0078(\pm 0.0015)$	90%
Land	Hatshepsut	[201:460]	General	50.04%	$99.2728(\pm 0.7268)$	$0.0166(\pm 0.0021)$	90%
Plots	Alexander	[1:200]	General	99.15%	$3.6923(\pm 7.0220)$	$0.8176(\pm 0.0606)$	99%
Plots	Hatshepsut	[1:200]	General	98.05%	$12.9458(\pm 19.3722)$	$0.8900(\pm 0.1671)$	99%
Plots	Alexander	[201:460]	General	78.73%	$149.6914(\pm 13.6018)$	$0.1109(\pm 0.0401)$	99%
Plots	Hatshepsut	[201:460]	General	88.22%	$163.7941(\pm 6.0591)$	$0.1053(\pm 0.0178)$	99%
GoldRate	Louis XIV	[1:460]	Victory	98.48%	$-25.3125(\pm 9.2060)$	$0.4694(\pm 0.0346)$	90%
GoldRate	Mansa Musa	[1:460]	Victory	97.03%	$-24.2833(\pm 19.5158)$	$0.4842(\pm 0.0733)$	90%
GoldRate	Louis XIV	[1:460]	Defeat	97.98%	$-11.8778(\pm 4.6118)$	$0.2867(\pm 0.0173)$	90%
GoldRate	Mansa Musa	[1:460]	Defeat	84.60%	$-0.4737(\pm 26.7967)$	$0.2326(\pm 0.1007)$	90%
$\sqrt[3]{Gold}$	Louis XIV	[1:460]	Victory	79.94%	$2.6224(\pm 0.1775)$	$0.0128(\pm 0.0007)$	99%
$\sqrt[3]{Gold}$	Mansa Musa	[1:460]	Victory	72.60%	$3.0379(\pm 0.1408)$	$0.0093(\pm 0.0005)$	99%
$\sqrt[3]{Gold}$	Louis XIV	[1:460]	Defeat	82.35%	$3.1341(\pm 0.0692)$	$0.0087(\pm 0.0003)$	99%
$\sqrt[3]{Gold}$	Mansa Musa	[1:460]	Defeat	60.15%	$2.7212(\pm 0.3289)$	$0.0108(\pm 0.0012)$	99%
$\sqrt[4]{CultureRate}$	Alexander	[1:460]	Victory	99.33%	$1.0614(\pm 0.0029)$	$0.0102(\pm 1 \times 10^{-5})$	99%
$\sqrt[4]{CultureRate}$	Hatshepsut	[1:460]	Victory	98.78%	$1.3165(\pm 0.0065)$	$0.0111(\pm 2 \times 10^{-5})$	99%
$\sqrt[4]{CultureRate}$	Alexander	[1:460]	Defeat	98.95%	$1.0867(\pm 0.0034)$	$0.0086(\pm 1 \times 10^{-5})$	99%
$\sqrt[4]{CultureRate}$	Hatshepsut	[1:460]	Defeat	98.20%	$1.4589(\pm 0.0057)$	$0.0085(\pm 1 \times 10^{-5})$	99%
$\sqrt[5]{Culture}$	Alexander	[1:460]	Victory	99.86%	$1.7152(\pm 0.0022)$	$0.0195(\pm 8 \times 10^{-6})$	99%
$\sqrt[5]{Culture}$	Hatshepsut	[1:460]	Victory	99.87%	$2.0610(\pm 0.0024)$	$0.0210(\pm 8 \times 10^{-6})$	99%
$\sqrt[5]{Culture}$	Alexander	[1:460]	Defeat	99.84%	$1.8082(\pm 0.0019)$	$0.0171(\pm 7 \times 10^{-6})$	99%
$\sqrt[5]{Culture}$	Hatshepsut	[1:460]	Defeat	99.65%	$2.2963(\pm 0.0046)$	$0.0176(\pm 2 \times 10^{-5})$	99%
Cities	Alexander	[1:200]	Victory	98.01%	$0.3077(\pm 0.0188)$	$0.0343(\pm 0.0002)$	90%
Cities	Hatshepsut	[1:200]	Victory	97.91%	$0.3045(\pm 0.0205)$	$0.0350(\pm 0.0002)$	90%
Cities	Alexander	[201:460]	Victory	95.11%	$4.9651(\pm 0.0143)$	$0.0082(\pm 4 \times 10^{-5})$	99%
Cities	Hatshepsut	[201:460]	Victory	81.79%	$6.1602(\pm 0.0202)$	$0.0047(\pm 5 \times 10^{-5})$	99%
Cities	Alexander	[1:200]	Defeat	96.98%	$0.4894(\pm 0.0278)$	$0.0309(\pm 0.0002)$	95%
Cities	Hatshepsut	[1:200]	Defeat	96.58%	$0.5466(\pm 0.0262)$	$0.0281(\pm 0.0002)$	95%
Cities	Alexander	[201:460]	Defeat	79.89%	$6.9878(\pm 0.0072)$	$-0.003(\pm 2 \times 10^{-5})$	95%
Cities	Hatshepsut	[201:460]	Defeat	39.59%	$6.0004(\pm 0.0199)$	$-0.0020(\pm 7 \times 10^{-5})$	95%
Land	Alexander	[1:180]	Victory	98.45%	$5.7677(\pm 3.8054)$	$0.5498(\pm 0.0364)$	95%
Land	Hatshepsut	[1:180]	Victory	96.59%	$11.5814(\pm 10.8481)$	$0.6202(\pm 0.1039)$	95%
Land	Alexander	[181:460]	Victory	93.65%	$89.7060(\pm 0.7846)$	$0.0606(\pm 0.0023)$	95%
Land	Hatshepsut	[181:460]	Victory	53.95%	$111.5217(\pm 1.3284)$	$0.0222(\pm 0.0040)$	95%
Land	Alexander	[1:180]	Defeat	97.96%	$6.7485(\pm 3.3395)$	$0.4475(\pm 0.0320)$	95%
Land	Hatshepsut	[1:180]	Defeat	93.27%	$15.6509(\pm 13.7272)$	$0.4877(\pm 0.1315)$	95%
Land	Alexander	[181:460]	Defeat	74.29%	$85.2093(\pm 0.2312)$	$-0.0145(\pm 0.0009)$	95%
Land	Hatshepsut	[181:460]	Defeat	2.74%	$91.6748(\pm 2.5132)$	$-0.0047(\pm 0.0076)$	95%
Plots	Alexander	[1:250]	Victory	98.43%	$7.9857(\pm 17.0135)$	$0.7904(\pm 0.1175)$	99%
Plots	Hatshepsut	[1:250]	Victory	97.26%	$17.4191(\pm 38.4130)$	$0.8929(\pm 0.2653)$	99%
Plots	Alexander	[251:460]	Victory	96.77%	$0.1694(\pm 0.0104)$	$151.8041(\pm 3.7521)$	99%
Plots	Hatshepsut	[251:460]	Victory	73.78%	$203.3449(\pm 10.4762)$	$0.0866(\pm 0.0290)$	99%
Plots	Alexander	[1:210]	Defeat	99.06%	$7.0925(\pm 6.3405)$	$0.7110(\pm 0.0521)$	99%
Plots	Hatshepsut	[1:180]	Defeat	97.21%	$14.0890(\pm 20.5100)$	$0.8248(\pm 0.1965)$	99%
Plots	Alexander	[211:460]	Defeat	50.76%	$145.9592(\pm 7.0910)$	$0.0424(\pm 0.0207)$	99%
Plots	Hatshepsut	[181:460]	Defeat	42.52%	$152.8303(\pm 11.8983)$	$0.0461(\pm 0.0359)$	99%

Table 1: *Summary table of the linear regressions discussed in this paper, where the adopted model was $y = b_0 + b_1 x$. The column meanings are, respectively: the data collected in the game, the agent who generated the data, the interval (in turns) the data represents, the game result evaluated (victories and defeats, only victories or only defeats), the coefficient of determination (how much of the data is explained by the regression), both coefficients and its confidence intervals and, finally, the confidence used to generate these intervals.*