Playing the Initiative in Real Time Strategy

Abstract

Initiative is a concept which describes certain behaviors in collaborative or competitive play. Due to the broad usage and qualitative nature of the initiative concept, quantitative modeling poses several challenges, not least when it comes to generalization. We propose to decompose initiative into a set of real-valued features. In experiments, we test their utility on a large dataset of recorded games from the domain of Real Time Strategy (RTS). The features are based on a spatio-temporal distribution of actions using Voronoi partitions, time-ranges and definitions of subjects and objects. The ability of these features to predict match outcomes through time is tested using the RandomForest algorithm. Results show empirical support of the initiative concept, and that a Pareto front can be established between the minimization of game-time and the maximization of predictive accuracy. Future work can be directed towards refining and expanding on the model for analytical and/or predictive usecases. For reproducibility, we share data and corresponding results in a public repository.

1. Introduction

Initiative is a well-known concept in system design (Cohen et al. 1998), business and management (MacMillan 1982), international relations (Glaser and Kaufmann 1998), sports psychology (Crognier and Féry 2005) and gameplay (Uiterwijk and Herik 2000). It is usually thought of as something which strives to bring advantage, but there are also differences in definitions, both between research areas and within them. For *competitive* initiative, we can view the term within the *strategic*, *operational* and *tactical* paradigm in war research, where initiative has well-defined and demarcated utilities (Judge 2009). In business and management, *strategic initiative* can be seen as an important step in obtaining advantage over a competitor (MacMillan 1982). In sports psychology, *tactical initiative* has been used to describe the scenario when a tennis or table-tennis player possesses control over where shots are placed (Zhou and Zhang 2022; Crognier and Féry 2005). In research on game-theory and competitive play, Uiterwijk & Herik (Uiterwijk and Herik 2000) propose the following two definitions of initiative:

Definition 1: To make the first move, such as playing as White in the game of Chess.
Definition 2. To control the moves made by the opponent in such a way that it leads to an advantage.

Uiterwijk & Herik’s numerical work is tied to the first definition and turn-based games, and in experiments on two-player k-in-a-row and Domineering, they report a first mover advantage, in terms of win-probability, of 56-75%. This result bears utility within competitive game communities, such as guiding tournament set-ups and how many matches two players need to play against each other to reach a decisive outcome. Furthermore, their work highlights both the need and possibility to test fairness, which is important in fraud-prevention. Kim et al. [] state that “predicting game [outcomes] is a critical issue for … balancing game environments”.

In this paper, the relationship between initiative and advantage is also studied in zero-sum settings and through numerical experimentation. But contrary to Uiterwijk & Herik, we work with Definition 2. One characteristic of Definition 2 is its broader scope. This can be beneficial, due to the opportunity to unify multidisciplinary research on the initiative concept. But the second definition also comes with challenges, most notably due to terms such as “control” and “advantage”. The first definition only requires an observation of the player which makes the first move. The second definition requires a model which evaluates the amount of control a player has over opponent moves.

For our data, we use replays of human player-versus-player (pvp) Real Time Strategy (RTS) matches. In pvp RTS, stationary and non-stationary objects are built and used for the purpose of attaining an advantage over the opponent (adaptation of Schadd et al.’s (Schadd, Bakkes, and Spronck 2007)). The general problem statement is as follows:

Can initiative in competitive RTS be quantified, and can it be statistically linked to advantage and the strength of the players?

Our model of initiative is based on the distribution of Cartesian coordinates and times of actions (Section 3). We investigate statistical links between our initiative model, advantage, in terms of match outcomes, and player strength, in terms of Elo (Albers and Vries 2001) (Section 4.1). We proceed to test the model’s accuracy at predicting match outcomes at different time-intervals using a Machine Learning algorithm (Section 4.2). Due to the multidisciplinary use of the initiative concept, we finally discuss the extent to which our results can be generalized to playground behavior (Section 5).

Contributions:
1. A spatio-temporal model of initiative.
2. Investigation of statistical links between the model, Elo, match times and outcomes.
3. Tests of the model’s descriptive strength through its ability to predict match outcomes in pvp RTS.

We collect our data from the game (‘Age of Empires II Definite Edition’ 1999) (1999) (AoE II). Although AoE II has existed for 24 years, it has persisted as a highly popular title (through series of upgrades), not only within the RTS genre but within the Esports scene as a whole. There are tens-of-thousands of active players, both amateur and professionals, who compete in a “ranked ladder”, where Elo determines the rank of a player. While the generalizable properties of game-data can be debated, it is benefited by a high standard when it comes to quality and accessibility. We use 73770 match replays from 15000 unique players for our analysis, which represent a total of 20000 hours of competitive interactions and 1 million distinguishable actions. For comparison, data collection in domains such as biology and sports is often a painstaking process, and relatable studies there are usually based on just a few dozen or hundred recorded interactions (Crognier and Féry 2005; Newton-Fisher 2017).

2. Related Work

Since our research questions only concerns competitive initiative, we exclude literature on collaborate initiative (see (Cohen et al. 1998) for an example of collaborative initiative). For competitive initiative, there exists a wide variety of studies on initiative-like behavior. Smith & Price (Smith and Price 1973), for example, simulate a scenario where players pick from a set of behaviors, including the “escalation”. Escalation is defined as the introduction of a “dangerous” tactic as opposed to a previous “conventional” one (Smith and Price 1973). Even though Smith &

Price do not use the term “initiative”, there are clear overlaps with Definition 2: Within the context of Definition 2, the “dangerous tactic” can be seen as a way in which to gain control over the opponent, and thereby advantage. In fact, the association between a “dangerous tactic” and control over the opponent is supported widely, for example in Glaser & Kaufman’s (Glaser and Kaufmann 1998) “attacker’s advantage”, Macmillan et al.’s (MacMillan 1982) “punch and counterpunch” planning and Crognier & Fery’s (Crognier and Féry 2005) High Initiative Situation (HIS), where the opponent is placed “on the defensive … reducing his response possibilities”. Essentially, the purpose of player versus player (pvp) initiative is to seize control over the competitive interaction by forcing the opponent to respond to aggression. Another example of ambiguity is with regard to terms such as “tactic” and “strategy”. When reviewing related works below, we use the terms as they occur in the references, rather than replacing them with correct usage (we refer to (Glaser and Kaufmann 1998) for rigorous definitions of these terms).

Since we work with Definition 2, and it requires proportionality between control and advantage, we investigate whether this idea holds support in the literature. Goethe (Goethe 2019) conjectures that advantage, in terms of a win-lose estimate, can be measured through time. Figure 1a is an example, where we see four behaviors, A, B, C, D, and their advantage through time:

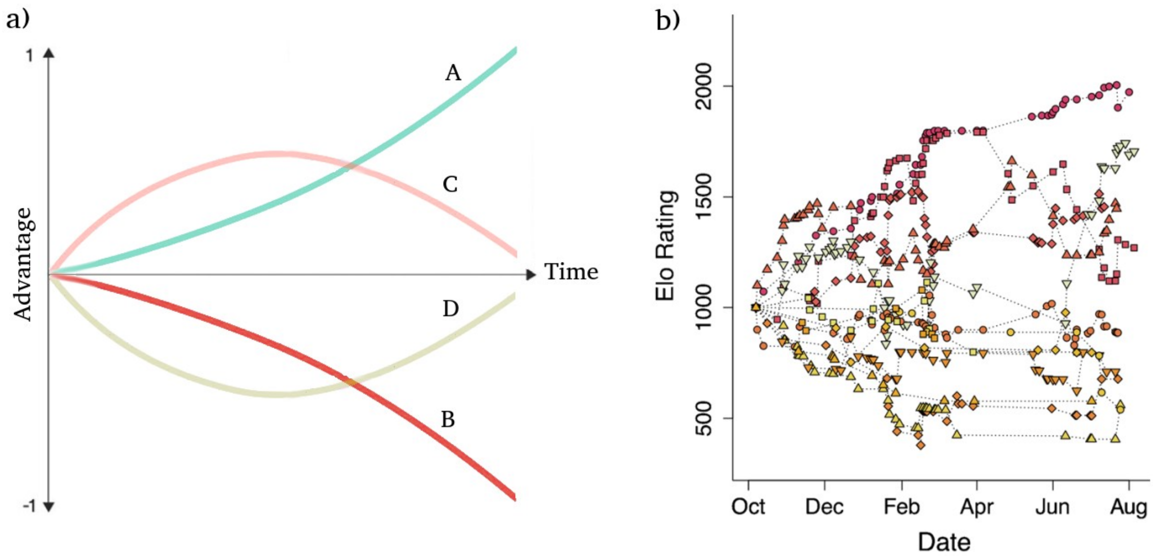


Figure 1. Ways with which to evaluate competitive behavior, in terms of advantage or fitness, through time. a: Change in state-value (advantage) (Goethe (Goethe 2019) with modifications). b: Change in Elo rating [Netwon & Fisher].

Goethe exemplifies Figure 1a for a singular interaction and a time-axis given in seconds and advantage as a player’s ability to act under time pressure. If the length of the time-interval is 2 seconds, option A is better, but if it is halved to 1 second, option C is better. Goethe notes that the curves are theoretical and that the set of features is application-dependent. But given a set of such features, Goethe conjectures that the curves can be modeled as distributions: A/B follow distributions of positive or negative first derivatives, whereas C/D follow distributions of negative or positive second derivatives. The pairs A/B and C/D can also be regarded as advantage through time in zero-sum competition and such curves can be plotted generally as long as there is a model of advantage. In Figure 1b, for example, advantage is given as an Elo rating and a time-axis given in months.

The time axis in Figure 1a can further be discretized, which makes it applicable to turn-based game scenarios and Definition 1 [Uiterwijk & Herik’s], or deviations from it. Zhou & Zhang [] expand on Definition 1 from one to six moves, and find that attacking tactics in the second or fourth strokes in table-tennis rallies are more important than the first one. Crognier et al.'s work on tennis [] fits better within Definition 2: They categorize rallies based on "Initiative Situations" (IS): High (HIS), Moderate (MIS) and Weak (WIS), and find that players in possession of a HIS are particularly successful, partly due to their ability at quickly predicting and thus also preventing effective countermoves.

In the competitive RTS domain, there are several studies which investigate relationships between initiative-type (Definition 2) strategies, advantage and time. RTS strategies can be divided into "rule-based" and "mixed", where the former are human-generated, simpler and more explainable, and the latter computer-generated, complex and less explainable [Marino]. A canonical example of a rule-based strategy is the "rush", which can be regarded as an extreme case of Smith & Price's [] "escalation" tactic (described earlier in this section). The rush can also be regarded as an extreme case of an attempt to seize initiative, and it performs surprisingly well in the µRTS tournament, considering its basic implementation (Ontañón et al. 2018). Silva et al. (Silva et al. 2018) include three rush strategies and three defensive strategies of the same rule-based type, and find that the former perform better than the latter in most experiments. (Čertickỳ, Sarnovskỳ, and Varga 2018) have significantly fewer defensive features in their RTS feature analysis, while including several rush features. Similarly, IGN states that "no one can deny that rush tactics … are some of the most effective" [with regard to the game Starcraft, web.archive], while not mentioning defensive alternatives.

Many studies are neutral with regard to the quality of rule-based strategies. Examples include mixed strategies, such as Strategy Creation via Voting (SCV), Portfolio Greedy Search (PGS) and Stratified Strategy Selection (SSS) (Silva et al. 2018; Marino et al. 2019). Marino et al. (Marino et al. 2019) place these strategies within the framework of a Subset Selection Game (SSG), where an Artificial Intelligence (AI) selects rule-based strategies dynamically, based on information gathered before or during a pvp RTS game. These strategies are designed to mix the best properties of several rule-based strategies, and therefore tend to outperform them in game-simulations and tournaments. The most extreme examples of mixed strategies in RTS come from the domain of Deep Reinforcement Learning (DRL) (Vinyals et al. 2019; Berner et al. 2019), where a large pool of relatively low-level state and action types (e.g. "position", "move" or "attack") are used to evolve powerful strategies. While DRL strategies demonstrate super-human play in advanced RTS scenarios, they are black-box in nature and are particularly weak when it comes to explainability: The only way to explain how a DRL strategy with millions of a parameters works, e.g. with regard to initiative and Definition 2, is by studying its performance. This is certainly valuable (Berner et al. 2019), but explainability and low data requirements are also valuable. Glaser & Kaufman [] reviews the quality of strategies in various scenarios, including high initiative ones with the "attacker's advantage", and point out that the quality of the analysis is closely dependent on the quality of collected data. This can be regarded as a weakness of DRL, since it is specifically dependent not only on high-quality data, but on significant training, tuning and development time on that data as well (Vinyals et al. 2019). A significant portion of the implementational work on the DRL agent by Berner et al. [], for example, is spent tuning it to small changes to the RTS environment(from the game developers), and into mitigating the occurrence of instabilities stemming from the high agent complexity (158 million parameters) and game complexity (starcraft). In summary, we find motivations for both rule-based and mixed strategies in the literature, and implementations of initiative as a balancing act between offence/defence, effectiveness/explainability, generalizability and data accessibility.

We now broaden Figure 1a on both the time x-axis and the y-axis. Newton & Fisher (Newton-Fisher 2017) work with an x-axis given in months and y-axis given in Elo rating. They conduct an experiment where they follow a set of players and record changes in their Elo's based on multiple competitive interactions over months (resulting in trajectories as shown in Figure 1 (right)). While they find that Definition 2-type behavior (control through “intensity of aggression”) is linked with higher Elo, it is perhaps more interesting that their calculations of Elo changes are only partly grounded in definite interactive outcomes. Soft displays of aggression, including threats and charges, are also noted. They also describe an Elo “burn in period”: If no prior information on Elo exists, it requires time and a sufficient amount of data to converge on an accurate rating.

“gain mastery by striking only after the enemy has struck” [Zhou] – does not work in table-tennis.

Data-driven model evaluation

We have now referred to research which attempts to model concepts such as initiative and advantage in competitive play. Below, we discuss how such models can be evaluated numerically. In scenarios where data-availability is low, the evaluation can arguably be carried out on all of the collected data (Newton-Fisher 2017; Crognier and Féry 2005; Zhou and Zhang 2022). When data-availability is high, such as in RTS, the evaluation can be made more robust by carrying it out on previously unseen data. One possibility is to utilize the model within a broader RTS AI agent which attempts to maximize win-rate in a tournament setting [muRTS, AlphaStar]. Another possibility, and which this paper is an example of, is to use the model for analytical purposes and to test statistical links or predictive properties on previously unseen data (Li et al. 2012; Čertický, Sarnovský, and Varga 2018; Kim, Park, and Yang 2019).

Li et al. [] and Kim et al. [] use the RandomForest algorithm to evaluate their RTS models. RandomForest is a Machine Learning algorithm which learns to predict outcomes (binary or float point) by building a set of Decision Trees (Breiman 2001). In the binary prediction case, each Decision Tree has the classification accuracy $E_{X,Y}\{1(Y=\varphi(X))\}$, where X is a dataset, Y are the binary predictor values and $\varphi: X \rightarrow Y$ (Louppe 2014). The results from all the Decision Trees are then used to compute average accuracy:

$$\frac{1}{N}\sum_{x_i,\ y_i \in \Psi} E_{x_i,\ y_i}\{1(y_i=\varphi(x_i))\}$$

Where $x_i,\ y_i$ denote datasets sampled from dataset Ψ. To avoid the problem of overfitting, a common way with which to make the RandomForest classification accuracy robust, is through the cross-validation technique, where the train and test sets are allowed to vary, followed by averaging (Silva et al. 2018). One benefit of the RandomForest algorithm is that it can be used to extract feature importances. These can be estimated based on average reduction in impurities among the Decision Trees (Biau and Scornet 2016).

3. Model

Feature Engineering

Since we strive for as much generalization as possible, it is important that the features in our model are not too closely tied to the specifics of the AoE II environment. Within the AoE II community, a significant proportion of discussions focuses on what we consider non-generalizable features [footnote, blogs and note on that they are mostly used to improve ELO], and we instead focus on high-level features, which, we argue, are more utilizable across research domains. In Section XXX we discuss how the high-level features apply in the AoE II environment. We define these high-level features as follows:

Dataset Ψ: A set of recorded pvp matches $m \in \Psi$, where two players p and p' (the opponent), compete to win. We assume no hidden information (except for one experiment in Section XXX), and henceforth we often mean *either* p or p' in a mirrored sense, when referring to p. A player's Elo is denoted Elo_p. Each match lasts for a time measure $t_{end} \in R^{+¿}¿$. If p wins match m, $w(p, m) = 1$, and $w(p, m) = -1$ otherwise. All the below-listed features are computed on a per-match basis, so for brevity we henceforth often exclude the m symbol, e.g., $w(p) = w(p, m)$.

Advantage: We define advantage as equivalent to $w(p)$. This definition is clearly coarse-grain, as real advantage can vary dynamically as a match unfolds. Modeling advantage dynamically poses its own challenging questions (see Section 2), and one benefit of our definition is simplicity: We argue that the outcome of a match is itself a manifestation of advantage in the general sense that p possesses more advantage over p' in match m if $w(p) = 1$.

Origin locations: For each match, the Cartesian origin location of p is obtained using function $x, y = l(p), x, y \in R^{+¿}¿$.

Actions: During the match, player p carries out a set of actions A_p, $|A_p| > c_1$, where $c_1 \in Z^{+¿}¿$ is used to ensure that there are enough actions in the match (otherwise, the match is removed from Ψ). Each $a \in A_p$ is a tuple containing Cartesian coordinates $l(a) = x, y \in R^{+¿}¿$, time $t(a) \in R^{+¿}¿$, a set of subjects $s(a)$ belonging to p and a set of objects $o(a)$ belonging to p'. The contents and cardinality of these latter two sets depend on the application, but their purpose is to provide a low-level measurement of the level of control that p exerts on p' (we refer to (Comrie 1984) for a linguistic background on subjects, objects and control).

First Escalation: We define action a_0 as follows:

$$a_0 = \underset{a}{\operatorname{argmin}} \left(t(a) \in A_p, \; t(a) \in A'_p \right) \tag{1}$$

s.t.

$$\text{Minimum subjects: } |s(a)| > c_2, \; c_2 \in Z^{+} \tag{2}$$

$$\text{Minimum objects: } |o(a)| > c_3, \; c_3 \in Z^{+} \tag{3}$$

Constraints (2) and (3) are used to help identify the first escalation (Section 2). In some applications, it may be relevant to set a_0 as the first action in the match. A later a_0 is motivated when the application, for example in RTS, includes an initial “build-up” phase where Definition 2 does not apply (it requires competitive interactions between players). We will test and motivate the first escalation further in Section XXX, but the intention of delaying a_0 is to help reduce the amount of irrelevant data used for inference.

Spatial partitioning: For each action $a \in A_p$, we compute , where l_2 denotes the Euclidean norm and which is used to carry out a Voronoi partition: An action is *closer-to-own-origin,* $a \in V_p$, if $r(a) < 1$, $a \in A_p$. An action is *closer-to-opponent-origin,* $a \in V_p^{'}$ if $r(a) > 1,\ a \in A_p$.

Temporal partitioning: $t_0 = t(a_0)$ is the time of the first escalation. We partition the time-range $[t_0,\ t_{end}]$ into K equidistant time-ranges $T\ =\ ([t_0,\ t_1),\ [t_1,\ t_2),\ \ldots\ [t_K - 1,\ t_{end}))$. All actions $a \in A_p$ where $t(a) \geq t_0$, are partitioned into the time-range that they belong to, $T_i \in\ T,\ i \in (1,\ 2, \ldots,\ K)$. Actions in time-range T_i are denoted $A_p,\ V_p,\ V_p^{'} \in T_i$.

Control: Since Definition 2 requires *control*, we define it as the combination of six spatio-temporal features. They are in the range [0, 1] and give the distribution of actions, subjects and objects in spatio-temporal partitions $V_p^{'} \in\ T_i$. Concerning subjects and objects, we use $S(V_p^{'})$ and $O(V_p^{'})$ to denote *all* subjects and objects within $V_p^{'}$. For example:
$S(V_p^{'}) =\ (s(a_i),\ s(a_{i+1}),\ \ldots,\ s(a_N)),\ a_i \in V_p^{'},\ \ i \in 1,\ \ldots,\ N,\ N\ =\ |V_p^{'}|.$ The purpose of the aggregation is to count the frequency of subjects and objects according to how they are spatio-temporally partitioned, giving the following six features (three for p and three for p'):

Actions:
Subjects:
Objects:

where $V_p^{'},\ A_p,\ V_p^{¿},\ A_p^{'} \in T_i,\ i \in (1,\ 2, \ldots,\ K)$. Note that these features exclude explicit use of the *closer-to-own-origin* Voronoi region V_p. They are included implicitly, however, since $A_p = V_p \cup V_p^{'}$, or $A_p^{'} = V_p^{'} \cup V_p^{¿}$. An advantage with excluding V_p is that it halves the number of control features. A disadvantage is that it removes information regarding direct strength proportion of actions, subjects and objects between the players. Rather, we can only infer proportions between the players *with regard to* how much they use features (4, 5, 6) within $V_p^{'}$. On the other hand, this has benefits from a generalization point of view, since it conjectures that direct strength proportions are not a necessary ingredient to model control, but that it instead can be modeled as a purely attention-driven mechanism. In other words, players who devote a significant amount of attention to $V_p^{'}$, regardless of their strength, benefit from a higher amount of control. To test whether this conjecture holds ground, in Section XXX we test the performance of features (4, 5, 6) with and without newly generated features where their denominators are removed. The frequency of subjects and objects in V_p are always excluded, however. The assumption is that Definition 2 requires control in $V_p^{'}$ rather than in V_p, so the exclusion of V_p is certainly motivated. Inclusion of $S(V_p)$ and $O(V_p)$ could still contribute valuable information, however, but we leave this for future work.

Initiative features: While dataset ψ and the features defined above are sufficient for inference and prediction experiments (Section XXX), they do not provide an explicit answer to the question of what initiative *is*. Therefore, we carry out an additional processing step which moves toward an answer to the question. We define the following three *initiative features*:

where $V_p^{'},\ A_p,\ V_p^{¿},\ A_p^{'} \in T_i,\ i \in (1,\ 2,\ldots,\ K)$. From these features it would be possible to hypothesize that player p possesses more initiative than p' if $\Delta_A,\ \Delta_S$ and $\Delta_O\ > 0$. The hypothesis can then be accepted or rejected by a goodness of fit test between the inequality and advantage $w(p)$.

THUNKPAD
Control. A weakness of defining K time-boundaries as ratios against t_end, is that they will have different lengths depending on t_end. An alternative is to define the time-boundaries as constants (e.g. 200s, 400s, …, t_UB) and then use zero-padding for action, subject and object counts between t_end and t_UB. This would be a stronger approach for live-prediction usecases since t_end is unknown and counts |A(p)|, |s(a)|, |o(a)|, a \in A(p) will then be more comparable between matches. It involves more data-processing, however, since the zero-padding has to be replaced with fill values for all matches where t_end < t_UB. Alternatively, matches where t_end << t_UB can be discarded, or focus allocated toward prediction at early stages with t_UB set to a low value. In

Testing the model
We propose to use Machine Learning on dataset ψ to learn a set of inequalities between initiative features $\Delta_A,\ \Delta_S$ and Δ_O. Since these features are based on the six control features (4, 5, 6), we also wish to learn inequalities between those and compare performance. Furthermore, we wish to include other features, such as Elo and modified control features. As prediction model we use the RandomForest algorithm, in the following procedure:

X = ψ \ w(p, m), m, p \in Phi
Y = w(p, m)
model = RandomForestClassifier(X, Y)
accuracy_testset_score= cross_validate(X, Y, model, num_cv=10)

where w(p, m), m, p \in Phi denote the winners, matches and players in dataset Phi, and num_cv the number of cross-validation splits between train and test data

While RandomForest is a black-box algorithm, and thus lacks in explainability, we only utilize it to test the predictive strength of our initiative model, rather than to propose strategies, more akin to the work by Ortanon [], Marino [] on mRTS.

4. Experiments

Data and Constants
We use 73770 RTS match recordings from an official AoE II repository [footnote: aoe2record format DE + gameType=3 , retrieved between September 15 – November 4 2023]. Each match is stored in binary format, and we extend on a public repository [footnote] (henceforth MGZ) to parse all the information needed to construct dataset Phi (Section []). We only use matches where Elo > 900. AoE II players and matches on the repository decrease rapidly as Elo increases beyond ~1200. We were only able to obtain 3167 matches where Elo > 2000 due to recordings only being stored on the repository for a limited amount of time (to obtain more matches one has to download them over several months). The 73770 recordings constitute around 9/10'th of all the recordings we downloaded, where the removed subset could not be parsed by MGZ or processed as described in Section 3. We define origin locations l(p) and l(p') as starting "Town Centers" (TCs), and matches

where there are no starting TCs are discarded. We also discard matches with fewer than 500 actions (constant c1 = 500) or which end in less than 60 seconds. In the remainder of this section, we go into further detail on how actions and other features described in Section 3 apply to the AoE II recordings and their parsing by MGZ (henceforth in this section, we often refer to MGZ instead of AoE II, since we do not obtain information directly from the AoE II engine).

As is usually the case in RTS, an AoE II action starts with the selection of one or several static or movable entities (e.g. buildings and units, respectively). This selection is what we define as the *subject* s(a), a \in Ap. The action continues with the selection of some form of task for the subject. We define the *object* o(a) as tasks in s(a) which include an MGZ “target_id”. In MGZ, the object is never more than a single entity, so |o(a)| \in [0, 1] (0 when there is no target). This definition excludes a significant number of objects, due to the existence of actions which let the AoE II engine designate objects autonomously. These include MGZ action types “patrol”, “garrison” and “de_attack_move”. As far as we are aware, the only way to retrieve these targets/objects is by “re-running” the recording in the AoE II engine (e.g. using Capture Age []). There are also objects which belong to the map environment (AoE II Gaia). The autonomous and environment objects are deemed unessential for our purposes since |O(a)| [CHECK IT], a \in A(p) in AoE II matches is arguably large enough for analysis (note that this is not the case in *all* RTS games). Further, concerning environment objects, our inference model is particularly protected since it excludes them in V(p) (where interactions between p and the map environment, e.g. hunting, can have some meaningful impact on the match outcome).

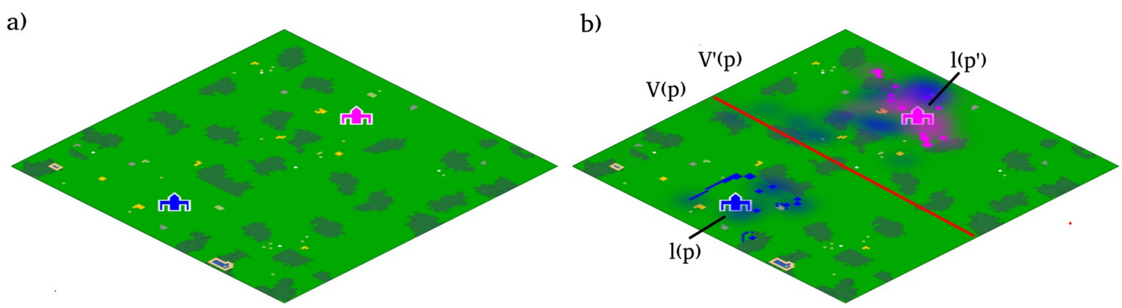


Figure: Example of the AoE II “mini-map” on the “Arabia” map type. Blue is p and pink is p’. (a) shows the map at the start of the match. The house symbols denote the TC’s. (b) shows the situation after 572 seconds into the match, and 183 seconds after the first escalation (T_2 in this case), the distinct polygons are buildings and the shaded regions frequencies of actions (as provided by the “AoE II Insights” analytical service []). p has the initiative.

Concerning the first escalation a_0 (Section 3), we set constants c2 = 2 and c3 = 1 (c3 by default since |o(a)| \in [0, 1] in MGZ). c2 = 2 ensures that a_0 happens after early actions by the AoE II starting “scout” or other single units in V’(p). Common AoE II early rushes (including “Drush”, “Trush” and “TC drop”) are guaranteed to either set a_0 or occur after it with our settings. For the temporal partitioning, we set K = 10, i.e., each match is divided into 10 equidistant time-ranges.

As a final note, we discuss how Definition 2 and our feature processing in Section 3 translates to specific AoE II terminology (as discussed informally by the AoE II community). The AoE II community often refers to “Map-control” and “Boom” as two contrasting strategies (“metas”). The former is spatio-temporally oriented to V’(p) and early initiative, whereas the latter to V(p) and late initiative. The former attempts to control resources around the map in the early stages, followed by consolidation, whereas the latter slowly builds up the “home economy” (“booming”), defense and upgrades, followed by offense (sometimes against an “overextended” opponent). Another popular dichotomy is “forward” versus “defensive” new buildings, particularly in reference to the “castle”, which provide relevant information regarding playstyle (the “Fast Castle” (FC) strategy is another noteworthy case). While our inference is delimited to the offensive V’(p) and V’(p’) regions, we do not see initiative as being necessarily tied to them, nor to map-control, forward buildings, units, ages, technologies etc. Rather, as discussed in previous sections, we measure initiative as real-valued spatio-temporal ratios which can be argued to hold a high degree of generality within and beyond RTS.

RandomForest settings

We use the RandomForestClassifier as described in Section 3 and the Scikit-Learn documentation (Scikit-Learn 2023). We set num_estimators = 200, max_depth = 5. Feature importances.

Experiment Result

We begin by visualizing frequency distributions of t_end, the ratio t_0 / t_end, Elo and initiative features delta …. . Figure 2a shows that the vast majority of matches have a t_end < 5000 seconds, but that there is a long tail (the longest match in our dataset lasted 19610 seconds/5.4 hours). By dividing t_end / K, we get the length of the time-ranges Ti \in T, which we can see are around 250 seconds on average, since we set K = 10. Figure 2b shows that the first escalation occurs around ¼ of the total match time on average, or around 500 seconds. The time of first escalation decreases as Elo increases from 900 to 2000, but it then stops, or even increases slightly. This increase could be due to high-Elo players disfavoring early rush tactics (such as the “Drush” and “Trush”). In order to allow for 2D visualization of initiative, we compute a simple linear combination of our initiative features: delta_a + delta_s + delta_o, normalized to range [-1, 1]. We then visualize the linear combination as frequencies in a Figure 2c.

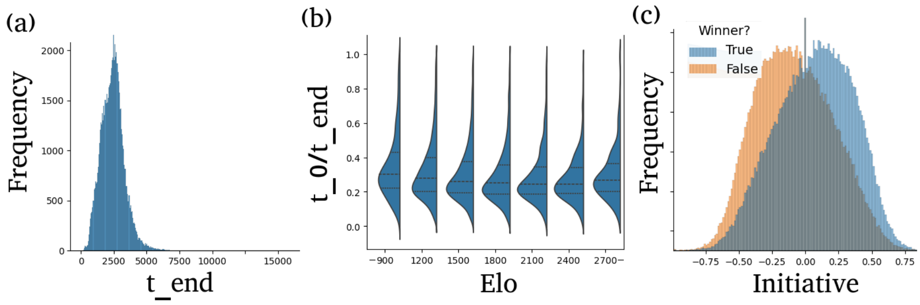


Figure 2. a: Frequency distribution of t_end. b: The time of first escalations (t_0), divided by total time of matches in seconds (t_end). The distributions are normalized according to “area”, meaning that the plot does not show that there are more matches in lower Elo ranges than higher Elo ranges in Phi. c: Frequency distribution of a linear combination of our initiative features .

In Figure 2c and 3a we observe that initiative tends to be lower for losing players and higher for winning players. In Figure 3a we see that difference in initiative between the winner/loser decreases as Elo increases, following a small but significant gradient (p-value < 0.0001). This gradient could be attributed to the above-mentioned complexity of higher-Elo matches, leading to a decrease in the descriptive power of initiative. In Figure 3b we instead plot Elo in terms of its average difference between two players. We find that players with high initiative press it to an advantage in a similar fashion regardless of the Elo of the opponent.

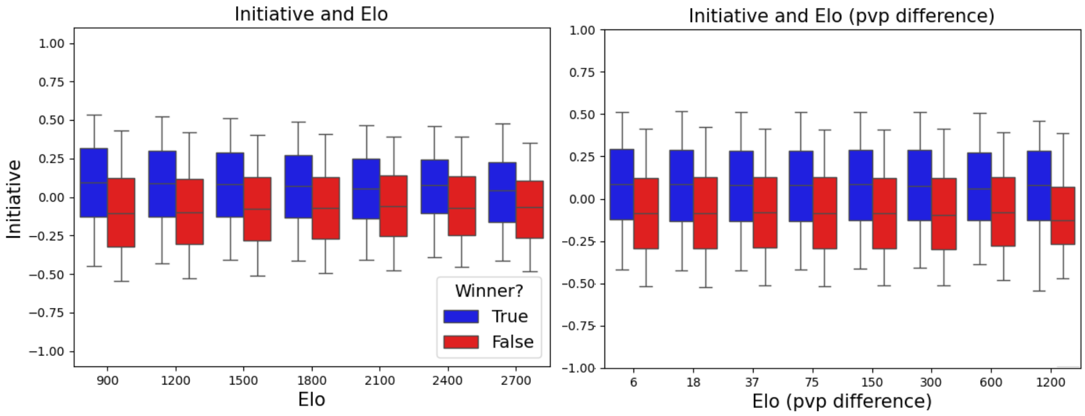


Figure 3. The box edges in b) show the first and third quartiles of the data (Q1, Q3) and the whiskers show (Q1 – 1.5 * IQR, Q3 + 1.5 * IQR), where IQR denotes the Inter Quartile Range. Note that b) includes all the data, and that the differences between winners/losers will decrease if we exclude certain time-ranges T.

When we split the x-axis into 10 time-ranges (K=10), we observe that zero-sum initiative increases or decreases from the time of first escalation according to an exponential trend (Figure XXX). This result fits well within Goethe's A/B distributions in Figure 1a. While many matches deviate from the trend (the shaded areas) mean initiative through time clearly resembles those of A/B type distributions. Note that the winner-loser distributions are separable already at T_1. This implies that information from the first escalation to a short time beyond that point is sufficient to predict the winner within statistical significance. This result also implies that t_0 can be moved further left, i.e., defined as an event earlier than the first escalation (which, as we have shown in Figure 2a, occurs around ¼ into the match). The predictive power

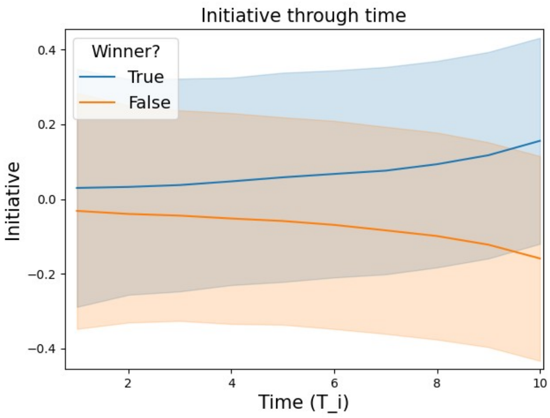
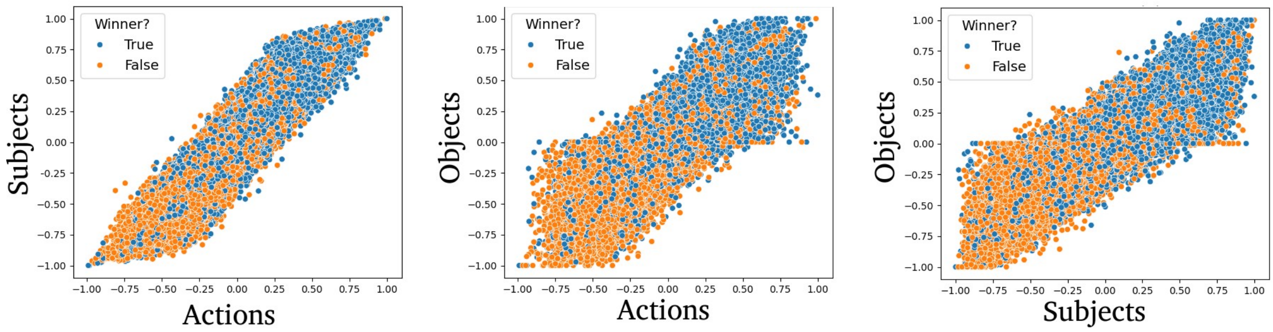


Figure 4. The shaded areas denote data within one standard deviation.

The correlations between delta_A, delta_O and delta_S is plotted in Figure XXX. We note that initiative features delta_A, delta_S and delta_O are correlated linearly, and for future work this can be utilized to normalize the data using techniques such as Principal Component Analysis (PCA).



These initiative features are built on the aggregate of ratios |V'(p)| / |A(p)|, |S(V'(p))| / |S(p)| and |O(V'(p))| / |O(V(p))|, p in P. The features |V'(p)|, |S(V'(p))|, |O(V'(p))| are less general: The counts of actions, subjects and objects are more tied to the AoE II environment compared to the ratios, but they are still highly useful in prediction tasks. Below we see visualize correlation between the subject feature with and without the denominator |S(p)|:

Upper bound of predictive power: The case when ELO difference is > 100.

The result shows that players with higher Elo tend to win games more often when they try to take the tactical initiative. Players with a lower ELO tend to not win games more often when they try to take the tactical initiative. This result is in line with the result by [TENNIS], which proposes that there is a link between ability to utilize a tactical advantage and player skill. Although a direct comparison should not be made, the result bears semblance to the result in the chimpanzee study by Newton-Fisher: Chimpanzees with a high ELO tend to show a higher intensity of aggression.

5. Conclusion

The concept of initiative is used across research disciplines, but there is little consensus regarding how it can be quantitatively measured. In this paper, we propose to decompose initiative into three numerical features, tying initiative to the level of control that a player possesses over an opponent through time. We investigate statistical links between our model and Elo (player strength). We find that our initiative model is agnostic to Elo ratingWe also show that the model can be used to predict match outcomes using the RandomForest algorithm. Our results validate the use of the initiative concept in numerical analysis. Future work can be directed at improving the feature processing and the predictive strength of the model.

Future work. Gated Recurrent Units (GRU). Increasing number of Voronoi regions