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Selecting the Best Player Formation for Corner-Kick Situations Based on Bayes' Estimation

Jordan Henrio[1], Thomas Henn[1], Tomoharu Nakashima[1], and Hidehisa Akiyama[2]

[1]Osaka Prefecture University, Osaka, Japan
{jordan.henrio,thomas.henn}@cs.osakafu-u.ac.jp
tomoharu.nakashima@kis.osakafu-u.ac.jp
[2]Fukuoka University, Fukuoka, Japan
akym@fukuoka-u.ac.jp

Abstract. In the domain of RoboCup 2D soccer simulation league, appropriate player positioning against a given opponent team is an important factor of soccer team performance. This work proposes a model which decides the strategy that should be applied regarding a particular opponent team. This task can be realized by applying preliminary a learning phase where the model determines the most effective strategies against clusters of opponent teams. The model determines the best strategies by using sequential Bayes' estimators. As a first trial of the system, the proposed model is used to determine the association of player formations against opponent teams in the particular situation of corner-kick. The implemented model shows satisfying abilities to compare player formations that are similar to each other in terms of performance and determines the right ranking even by running a decent number of simulation games.

Keywords: soccer simulation · strategy selection · Bayes' estimation · earth mover's distance · hierarchical clustering

1 Introduction

One of the essential parts in developing a team in the RoboCup 2D soccer simulation league is to design an effective strategy or method that outperforms opponent teams. Player formation is one of the most important aspects in the strategy design as it gives the guidelines of the decision making during the game. The player formations are generally designed according to a given opponent team. However, this tasks is labourious since the search space can be really large depending on the set-play the formation is associated with. In addition, selecting the best strategy regarding unknown opponents is one of the most challenging task of this league.

On the other hand, it is not necessary to create a specialized player distribution against each of all opponents as it is possible that some of them are similar regarding particular features. By using this fact, it is possible to cluster similar opponents together and then look for the most effective strategy against this group.

This research proposes a model which groups similar opponent teams together during a learning stage and determines the most effective player formation for each cluster by using sequential Bayes' estimations. Then, during a real game the system classify the current opponent among one of the determined clusters and apply the strategy that has been estimated to be the best regarding the resulting classification.

2 Related Work

The task of recognizing the opponent strategy in order to apply an appropriate counter action has been already adressed in previous researches. For example, the works of Visser *et al.*[1] and Drücker *et al.*[2] propose a system for recognizing opponent's formations and then apply a counter formation. This is done by using an artificial neural network that is able to classify data among 16 formation classes and then apply the counter formation especially designed against each class. Classified data are a representation of the field as a grid expressing the formation of the opponent. Riley and Veloso [3] also proposed a method performing opponent classification by using a grid representation of the field. However, the grid is used for displacement and location of objects instead of just observing the structures of formations. Also, they used a decision tree instead of neural networks.

However, this paper focuses on how to select the best player formation regarding a particular cluster rather than the issue of how build clusters. The selection issue is a well know problem in probability, often named as the k-armed bandit problem. This problem has been already addressed in the context of simulated soccer game by Bowling *et al.*[4]. They proposed to apply an algorithm that selects the most effective and available team plans during particular situations. The most effective plan is the one that minimizes the regret which is the amount of additional reward that could have been received by behaving optimally. The work presented in this paper is similar in the sense that we also focus on a method which selects the best choice in a particular situation. However, the situation is considered to be a particular opponent team in a particular event of the game and not a particular state of the environment. Doing so allows us to focus on more precise effectiveness measurement functions.

3 Proposed Model

As a solution, we propose to use a simple model as shown in Fig.1. This system takes a label of cluster of opponent teams' as an input parameter and returns the best strategy to apply. However, it is difficult to estimate the best strategy among the ones we have in hand. For this reason the proposed model consists of two modules, *Learner* and *Selector*.

The *Learner* part works in offline mode. It takes a set of clusters as an input parameter. Clusters are obtained by applying hierarchical clustering on opponent teams' distributions before the *Learner* works. Then, its role is to learn against each cluster, by looking at the set of strategies that we have already developed, which one is the most appropriate. This decision is done by performing statistical analysis on simulated games by using the different strategies as it is explained in Section 5. Once the learner is able to decide which strategy we should apply regarding a particular cluster of opponent teams, it inserts the cluster-strategy pair in a database.

The *Selector* part works in online mode. It takes the resulting classification of the current opponent team as input. Then, by using the estimations done by the learner it can directly return the best strategy to apply.

As a first trial of this system, the proposed model was used to determine which corner-kick formations should be used against particular clusters of opponent teams from JapanOpen competitions. This championship is the RoboCup yearly meeting within Japan.

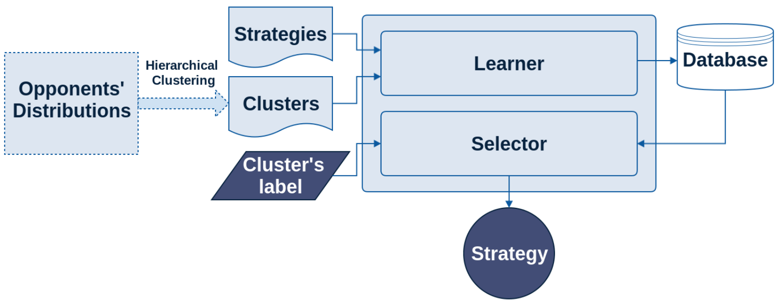


Fig. 1. Proposed model.

4 Opponents Clustering

4.1 Team distributions

At a general level the system groups opponent teams by similarity in the player formation. In order to understand the player formation, the distribution of the players is used. In this paper, offensive corner-kick formations were designed regarding the defensive formation of the opponent. Therefore, this work suggests to build such player distribution representing the defense of the opponent by considering locations of players over the corner-kick area. As a way to represent the opponent player distributions, the system designs a partition of the corner-kick area of the field as shown in Fig.2. This partition is totally arbitrary, but shows how opponent players are spread in this area during their defensive corner-kick situations. Resulting distributions represent the number of players in each

of the 18 blocks in the area of interest (the so-called attacking third). Also, an additional block representing the remaining part of the field is considered. For example, Fig.2 shows eleven opponents in their defensive corner-kick formation. By analyzing this defense player formation, the resulting distribution would be written as the following 19-dimensional integer vector:
$[1, 0, 1, 0, 0, 0, 1, 2, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 2]$.

If we consider a rougher partition of the field, the player distributions would tend to be the same regardless the opponent team. For instance, let us consider the extreme case where the grid is only constitued of one cell. By doing so, any team would be represented by the 1-dimensional integer vector. Conversely, a finer partition would make the player distributions become much more different from each other.

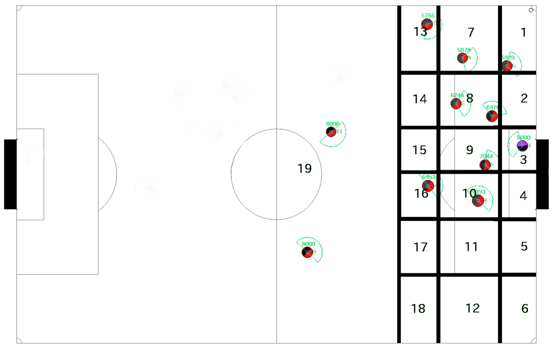


Fig. 2. 19 blocks of the partitioned soccer field.

4.2 Clustering process

Once all opponents' distributions are determined, the degree of similarity between each possible pair is analyzed in order to generate a distance matrix. The distances between distributions are computed by using the Earth Mover's Distance (EMD) [5] method. EMD provides a pseudo metric measure between two probability distributions. It can handle vectors with different dimensionalities and weighted features. The measurement process is expressed as a transportation problem where one distribution is the supplier and the other the customer. The cost between the supplier and customer is related to the distance between features of the two distributions which are computed by using a ground distance such as the euclidean distance. This is an advantage of using EMD since we can evaluate how much two formations of players are different by using a ground distance that makes sense in the case of soccer field. Also, the possibility to consider weighted features could become an advantage in future work since it is possible to give more importance to certain parts of the formations.

It is possible to apply hierarchical clustering on the resulting distance matrix in order to determine clusters of similar opponent teams. This process merges the pairs with the smallest distance together until all the opponents belong to a single cluster. By using a threshold representing the maximum distance accepted between clusters before merging, the user can stop the clustering process and then obtain several clusters rather than a single one.

5 Strategy Selection

5.1 Performance evaluation of player formations

In order to select the most effective strategy from a given set of strategies, the performance evaluation of the player formations with respect to a success metric is required. For example, the probability of success of an attack following a corner-kick as shown in Fig.3, can be used as a performance metric. However, the RoboCup 2D soccer simulation league introduces randomness in the way the players interact with the environment. Each player receives imperfect and noisy information from his virtual sensors. As a result, two soccer games with the exactly same teams can differ significantly. Therefore, evaluating player positioning performance is a challenging task. There is a lot of variance when trying to estimate a success metric. Thus, it is necessary to run a large number of soccer games in order to estimate one player formation's performance with enough precision.

In order to sort each player formation with respect to the others, the difference in means between the probability of successful corner-kick distributions of each player formation's simulation is considered.

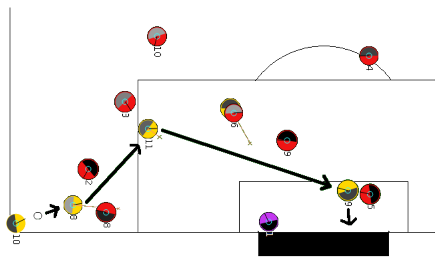


Fig. 3. Example of an actions' chain for a corner-kick which leads to a successful score.

5.2 Sequential Bayes' estimation

Bayes' theorem is stated as in (1):

$$p(\theta|D) = \frac{p(D|\theta)P(\theta)}{p(D)}, \tag{1}$$

where $p(\theta|D)$ is called the posterior, $p(D|\theta)$ is likelihood, $p(\theta)$ the prior and $p(D)$ is the evidence which stands as a normalizing constant. It is calculated as expressed in (2):

$$p(D) = \int p(D|\theta)p(\theta)d\theta, \tag{2}$$

where θ represents the value of the parameter to estimate, in our case that is the probability of the success of an attack following a corner-kick. D corresponds to the new data extracted at the moment of applying the theorem. The purpose of the Bayes' theorem is to update the prior belief $p(\theta)$ we have about the value of θ using new data D. The posterior distribution $p(\theta|D)$ will then correspond to our updated belief in the different possible values of θ.

It is possible to sequentially update the parameters by applying Bayes' theorem each time one or more simulations are over by using the previous posterior as the prior for the next computation of the posteriors.

Obviously, according to the success metric used by the system, the results of one experience (successful corner-kicks observed within one game), the likelihood follows a binomial law as in (3):

$$p(X = k) = C_k^n \theta^k (1-\theta)^{n-k}, \tag{3}$$

where n is the number of total corner-kicks observed during the simulated game, k the number of successful corner-kicks observed and θ the probability of an offensive corner-kick to be successful by using the player formation.

Navarro and Perfors [6] have demonstrated that the posterior distribution of a beta-binomial distribution is also a beta-distribution. Thus, if you consider the probability of getting a successful corner-kick by using a particular formation of players, the posterior distribution after observing k successes over the total n corner-kicks can be expressed as in (4):

$$p(\theta|k,n) \sim B(a+k, n-k+b) \tag{4}$$

where B denotes the beta distribution, a and b are the parameters coming from the prior distribution and θ is the probability of a successful attack following a corner-kick which is the parameter we want to estimate. This fact simplifies computations since it is possible to represent the performance of a player formation by a Beta distribution and then after running a game, construct a new Beta distribution by giving the number of corner-kicks and the number of observed successes.

5.3 Player formations comparisons

A difference distribution is used to determine whether one player formation is better than another or whether additional simulations are required to be sure.

For this purpose, the system begins by computing the Highest Density Interval (HDI) [7] which is the interval that spans most of the mass of the distribution (say 95%) such that every point inside the interval has a higher probability than any point outside the interval.

To compare the performance of two player distributions in the attack case (let us say Distribution 1 and Distribution 2), the probability of success of Distribution 1 and Distribution 2 is considered, defined as p_1 and p_2, respectively. Assume that a posterior distribution for each of those probabilities is obtained. In this case, by calculating all of the possible values of $p_1 - p_2$, it is possible to obtain a distribution of the difference of $p_1 - p_2$. HDI is used instead of the posteriors in order to simplify the computation of this calculation.

Then, there are three possible scenarios as follows. Preliminary, let us define $[u, v] = \{x \in \mathbb{R} | u \leq x \leq v\}$ to be the HDI of the resulting distribution $p_1 - p_2$. The first possible case is when $u \geq 0$, which means $p_1 - p_2 > 0 \Rightarrow p_1 > p_2$. Naturally, the opposite case is also possible, $p_1 - p_2 < 0 \Rightarrow p_1 < p_2$, which happens when $v \leq 0$. Another possible sketch is that $[u, v] = \{x \in \mathbb{R} | w \leq u \leq x \leq v \leq z\}$ where w and z are around 0 which is equivalent to saying that $p_1 = p_2$ for all practical purposes. The $[w, z] = [-0.015, +0.015]$ interval is used in this paper. If the two player formations are deemed equal or when the maximum number of simulations is reached, the player formation with less variance is considered as better than the other.

6 Experiments

6.1 Opponents clustering

First experiments involved 12 teams participating in Japan Open competitions, as well as two versions of Agent2D [8] which does not participate in any competitions, but are used by most of the participants as the starting point of team development. Three clusters were created by the hierarchical clustering. The second cluster is the most populated among the three ones because it represents the teams using a player formation similar (if not the same) to that of Agent2D, which constitutes probably their implementation starting point. On the other hand, the third cluster included only the team Ri-one_B 2015 that is too far to be merged with any other clusters.

6.2 Association learning

In order to experiment the abilities of the learner, we used three corner-kick formations that were already implemented in our team. Additionally, a special script was used. This script runs simulations which only perform corner-kick situations. Generally, 37 corner-kicks are executed during one simulation, but this number can vary from one run to another due to the randomness present in simulations. As first experiment, 10 simulations per strategy were simulated before comparing pairs of player formations and a beta distribution with parameters 2 and 2 (i.e., Beta(2, 2)) was used to represent our prior beliefs.

Table 1. Results summary of the second experiment.

Cluster	Distribution	HDI	Ratio
1	2	[0.203, 0.237]	1.787
2	3	[0.531, 0.571]	2.073
3	1	[0.471, 0.512]	2.179

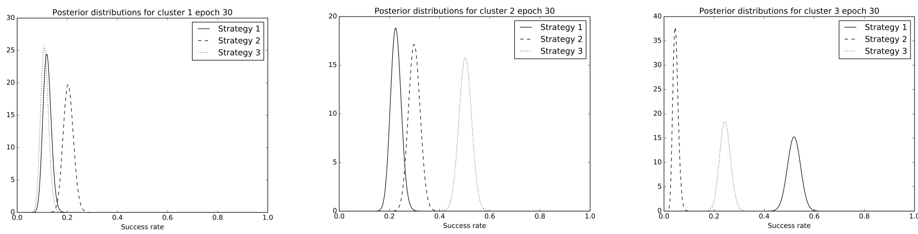
The results of our first experiment are shown in Fig.4, the probability density functions of each player formation against each cluster. It can be seen that each cluster is associated with a different player formation. Excepted the pair (1, 3) for the first cluster (Fig.4a), all pairs can be easily ranked. Then, the most effective player formation can be determined with certainty. However, the HDI of almost all distributions is quite large, thus a precise probability of success cannot be provided.

In order to improve estimations about the player formations' probability of success, a second experiment was conducted and simulations were generated by blocks of 60 games. That is, 60 games for each player formation were conducted every time the performance is compared. Fig.5 shows the resulting probability density functions of the player formation. As expected, curves became finer and tended to be centered to the true probability of their respective player formation. Also, the pairs which were difficult to differentiate after the first experiment, can now be well ordered.

Table 1 provides a summary of the second experience. It shows the final associated player formation for each cluster. Also, it indicates the HDI of the selected player formation. Finally, it gives the ratio of the best player formation's distribution mean over the second best's.

6.3 System validation

The proposed method in this paper estimates the probability of success of offensive player formations against given opponent teams. In other words, the parameter θ of a binomial distribution is estimated. However, it is legitimate to wonder about the correctness of the estimations.



(a) Cluster 1 (b) Cluster 2 (c) Cluster 3

Fig. 4. Posterior distributions for each cluster, by running $M = 10$ simulations

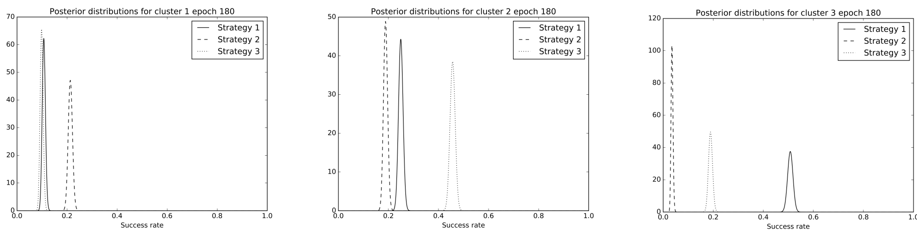
The experiment in this section puts player formations aside and evaluates how well our method can differentiate probability distributions with parameters close together. Additionally, it estimates how many simulations are required to draw trustful conclusions about the ranking of offensive player formations regarding their success probability.

Player formations are substitued by a set of randomly generated parameters θ. Then, a simulation of n offensive corner-kicks by using a particular formation is substitued by n sampling from a binomial distribution parameterized by one of the randomly generated θ values. Notice that the system knows the generated parameters and is able to order them. Afterwards, as in the parameter estimation method, by feeding the Bayesian estimator with the number k of successes over the n samples the system updates prior beliefs about the parameters and tries to estimates the value of the randomly generated parameters. Actually, since the true values are known, it is possible to verify that the system gets back the correct ranking.

Fig.6 shows the results obtained by using $n = 20$ samples per simulation for each distribution. The figure consists of three subplots where the x-axis represents bins of pairs of θs depending on the difference of their respective values. For example, assume $\theta_1 = 0.22$ (22% of chance to get a success) and $\theta_2 = 0.24$. Since the difference between θ_1 and θ_2 is 0.02, this pair is contained in the second bin whose range is from 0.1 to 0.2. The first bin (the one in black) is special, since it represents the interval where parameters are close enough to be considered equal. The number of generated parameters was done in such a way that each bin contains ten pairs of parameters.

The first subplot shows the rate of well ordered pairs in each bin. According to this plot, the system can perfectly rank pairs with a difference greater than 0.04 and this accuracy decreases as the distances between parameters increase. In this subplot the correct ranking inside the first bin is not really important since it contains pairs that are considered to be equal.

The second and third subplots show the number of correctly ranked (respectively uncorreclty ranked) pairs in each bin and the number of sampling steps before drawing conclusion (y-axis). As indicated in the first subplot, the ranking is perfect for any pairs contained in the bin whose range is greater than 0.04.



(a) Cluster 1 (b) Cluster 2 (c) Cluster 3

Fig. 5. Posterior distributions for each cluster, by running $M = 60$ simulations

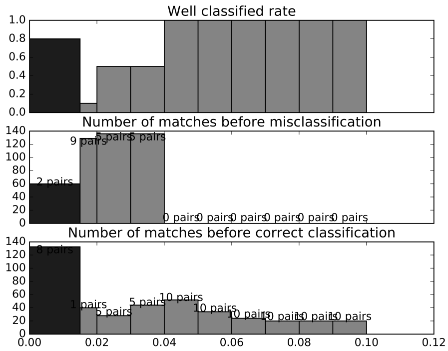


Fig. 6. System's validation by blocks of 20 samples.

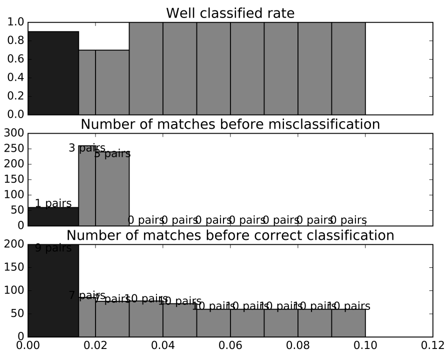


Fig. 7. System's validation by blocks of 60 samples.

Furthermore, at most fifty samples were required to obtain such results and this number decreases as the distances increase. However, the system has difficulties to rank pairs with difference less than 0.04.

Fig.7 shows the performance evaluation by using $n = 60$ samples per simulation for each distribution. Actually, increasing this number improves the accuracy since the system is able to rank prefectly pairs with at least a difference of 0.03 by requiring at most eighty samples. These two experiments show that increasing the number of samples increase the accuracy. On the other hand, since the data that the player receives is biased and because of the rarity of corner-kick event occurence during one single game, a deviation of 4% of success probability between two formations is not so significant. For this reason, in the particular case of selecting the best strategy for offensive corner-kicks, estimating the formations' parameter by running only 20 simulations is enough.

6.4 Cluster validation

It could be also interesting to look at the performance of each player formation in the clusters. While some teams have been considered as similar in terms of defensive player formations, it does not exclude the possibility of disparities among the teams of the same cluster since results of actions are not affected by player positioning only. Proper agents' skills are an equally important factor.

In order to verify the quality of association according to each opponent team, another alternative of the algorithm was applied. This one is nearly the same as the standard version, but rather than trying to estimate the effectiveness of each player formation against the clusters, the system estimates it against every team individually.

Table 2 summarizes the teams whose the most effective strategy is not the same as the one estimated against the cluster which they belong. As a reminder, Cluster 1 counts three teams and Cluster 2 counts ten teams. Regarding the team Ri-one_A 2015 (Cluster 1), Distribution 1 seems to be better than Distribution 2 which is the one associated to its cluster. However, the error seems to be much more serious, according to the team A_TSU_BI-2014 (Cluster 2) since Distribution 2's mean is slightly more than three times better than the selected formation's (Distribution 3) mean. In fact, this association error is not significant during a game against Ri-one_A 2015. On the other hand, performing games against A_TSU_BI-2014 with the wrong strategy would affect the results of games since there is roughly 20% more chance to get a success by using the formation associated to Distribution 2 rather than the one selected (Distribution 3).

Table 2. Difference between expected performances in cluster.

Team	Cluster	Selected (Dist. / HDI)	Best option (Dist. / HDI)	Ratio
Ri-one_A 2015	1	2 / [0.13, 0.16]	1 / [0.23, 0.27]	1.73
A_TSU_BI- 2014	2	3 / [0.07, 0.09]	2 / [0.23, 0.26]	3.28

7 Conclusion

In this research, a system that is able to select the best player formation in corner-kick situations regarding a group of teams was developed. This decision is taken by doing sequential Bayes' estimations from the results of several games. The model does not create effective offensive player formations, but instead indicates the best that we have already in hand.

The results are satisfying since the system is able to rank correctly player formations with at least a difference of 4% of success probability by proceeding only 20 simulations. Furthermore, it is possible to increase the precision of the system by getting more data. However, by doing so the learning time would increase considerably. Additionally, it is quite impossible to feel a difference during one game, since during a true match the number of corner-kicks that happen is very low. This is why such an error rate is acceptable.

On the other hand, there is a possibility of disparities inside the clusters. As explained earlier, if the difference between player formations is only 4% there is actually no real difference in terms of final results of one game due to the rare occurence of corner-kicks executed during a standard game. But if a player formation is not designed to be the best and is actually three times better than the selected one, difference could be observed regarding final results. These disparities are due to the fact that during the clustering process only the positions of opponents are considered and not the defensive skills of the team. Then, another clustering criterion can be considered for better performance.

Finally, while the first trials selected player formations for corner-kicks only it is possible to use it for any situation of the game, at the condition to have a criterion for opponents clustering and a success metric for data observations. Furthermore, it is possible to extend this system in order to build strategies, i.e. sets of player formations that cover any situation, rather than selecting the best player formation according to a particular situation. In this case opponents would not be in only one cluster, but in several clusters, one for each situation. However, such a learning process seems difficult to realize since a very large number of standard games is required, ones which do not simulate only one kind of situation, in order to see enough every kind of situations and hope to obtain good approximations of each player formation.

References

1. Ubbo Visser, Christian Drücker, Sebastian Hübner, Esko Schmidt, and Hans-Georg Weland. Recognizing formations in opponent teams. *RoboCup 2000: Robot Soccer World Cup IV*, pages 391–396, 2001.
2. Christian Drücker, Sebastian Hübner, Esko Schmidt, Ubbo Visser, and Hans-Georg Weland. Virtual Werder. *RoboCup 2000: Robot Soccer World Cup IV*, pages 421–424, 2001.
3. Patrick Riley and Manuela Veloso. On behavior classification in adversarial environments. *Distributed Autonomous Robotic Systems 4*, pages 371–380, 2000.
4. Michael Bowling, Brett Browning, and Manuela Veloso. Plays as effective multiagent plans enabling opponent-adaptive play selection. In *In Proceedings of International Conference on Automated Planning and Scheduling (ICAPS' 04)*, 2004.
5. Rubner Yossi, Tomasi Carlo, and J. Guibas Leonidas. The earth mover's distance as a metric for image retrieval, volume 40. *International Journal of Computer Vision*, pages 99–121, November 2000.
6. Dan Navarro and Amy Perfors. An introduction to the Beta-Binomial model. *COMPSCI 3016: Computational Cognitive Science*, 2012
7. John K. Kruschke. *Doing Bayesian Data Analysis a Tutorial Introduction with R and BUGS*. Academic Press / Elsevier, 2010.
8. Hidehisa Akiyama and Tomoharu Nakashima. Helios base: An open source package for the robocup soccer 2D simulation. *Proc. of RoboCup Symposium 2013*, Total 8 pages, 2013