

# Impact of the Variation of Horse Racing Odds on the Outcome of Horse Races at the Champ DE Mars

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**Abstract**—Horse Racing is the favourite sports of Mauritians. This can be demonstrated by the presence of huge crowds at the Champ de Mars on racing days. Many people wait for the last moment to bet as they feel that the variation of odds has an influence on the winner of a race at the Champ de Mars. This is the motivation for this research. Thus, in this work, we have used artificial neural networks to predict the winner of a race based on the variation of the odds. The odds were collected at eight different intervals. The training has been done on 232 races and the testing on 27 races. An overall percentage of 7.4% was obtained for the prediction of winners. This shows that the variation in horse racing odds does not have any impact on the outcome of horse races at the Champs de Mars. To our knowledge, this is the first study which studies the relationship between the variation in odds and the rank of horses.

**Keywords**—horse racing; variation in odds; rank; prediction

## I. INTRODUCTION

Horse Racing is one of the most ancient sports in Mauritius. The Mauritius Turf Club (MTC) is the organisation which is responsible for organising horse racing in Mauritius. On top of that, we have the Gambling Regulatory Authority which ensures that things are happening in the proper way and according to the rules and regulations. Horse Racing is the most popular sports in Mauritius. Every racing day, it attracts a huge crowd at the Champs de Mars. The Champ de Mars is found in Port Louis, the capital city of Mauritius. It is a race-track which is well-known for its tricky curves and this is acknowledged by most local and international jockeys. Many top riders from all over the world are fans of the jovial atmosphere that resides at the Champ de Mars during a racing day. The passion of Mauritians for the love of horses and horse racing is often considered as unique in the world by visitors and foreigners. The Maiden Cup, the longest and the most prestigious race in Mauritius, which is run on a Sunday every year, is known

by almost everyone in the country and is undeniably the event which attracts the biggest crowd in Mauritius. In the year 2014, there were 14 stables who were in competition at the Champs de Mars. Due to the well-equipped laboratory of the Mauritius Turf Club, every horse is examined to ensure that no prohibited substances are used on them, so as to allow a fair race and to promote the clean image of the industry [1].

Apart from the classic Maiden Cup, there are several other racing distances on which a stable can enter their horses. In Mauritius, the distances are as follows: 1000m, 1365m, 1400, 1500m, 1600m, 1650m, 1850m, 2200m, 2250m and 2400m. The rating of a horse determines in which race (benchmark) it will run. The rating is a number between 0-100 which is assigned by the MTC to the horse on its arrival in Mauritius. It is based on its performance in its country of origin, its pedigree and the category of races it has run abroad. The odds is perhaps the most important factor which a punter uses to decide on which horse to place his bet. In Mauritius, about a third of favourite hits the post first [1].

In Mauritius, there are many specialised magazines and portals such as the Racetime [1], Défi Sport [2], L'Express Turf [3], Turf Magazine [4], Supertote [5], Totelepep [6], SMSPariaz [7], Turf Maurice [8], RacingMauritius [9], etc., which provides a wealth of information to punters so that they can make their best choices. Most of them also provides betting tips. However, even the best press tipsters had an accuracy of 39.5% for the 2016 racing season [1], which is just slightly higher than the percentage of favourites that won. In this work, our main objective is to use artificial neural networks to predict the winner of horse races. However and contrary to previous approaches which used parameters such as jockey, stable, weight horse is carrying, age of horse, draw, our analysis will be restricted to the variation in odds from the moment the odds are opened until the race is over. The aim is to find out whether it is possible to identify winners by following the trends in the changing odds.

This paper proceeds as follows. In the next section, we provide a brief overview of existing works in the field of horse racing and machine learning. Section III continues with the methodology and description of dataset. The experiments and results are described in Section IV while Section V concludes the paper with a note on future works.

## II. RELATED WORKS

One of the first academic work which investigated the application of neural networks in horse racing was done by Allinson and Merritt in 1991 [10]. The following attributes were used: third last position, second last position, first last position, age of horse, weight, odds, jockey percentage, jockey ranking, trainer percentage, trainer ranking, going and the race value. Out of ten races on which the system was tested, the returns were 40% on average.

In his University thesis, Aaron Bishell (2006) from Massey University, conducted a large number of experiments on horse racing data [11]. Many neural networks were deployed for the prediction task, each time with a different set of data and different parameters. However, in the end, he found that the best results were obtained from the simplest type of neural network. With his generic predictor, he was able to achieve a 66% accuracy for the top 3 positions. Williams and Li (2008) used data collected in 2007 from the Caymans Race Track in Jamaica and the back-propagation neural network to achieve an accuracy of 74% for horses finishing in the top three positions [12]. A similar study was carried out by Davoodi and Khanteymori in 2010 but this time using data collected from the Aqueduct Race Track in New York [13]. They also found that the back-propagation algorithm produced the best accuracy compared to other types of neural networks. They achieved an accuracy of 77%.

In 2010, Nairn carried out an in-depth investigation of the effectiveness of using neural network for predicting winners in horse races [14]. The highest accuracy he achieved for winners only was 14.9%. After performing hundreds of experiments, he found that it was very difficult to predict winners using neural networks as no apparent trends were coming out from these experiments. Pudaruth *et al.* (2015) used artificial neural networks to predict the outcome of horse racing in Mauritius [15]. Testing was done on 16 races only and the success rate was 25%, which is slightly better than what was obtained by Nairn [14]. However, in terms of payout, the system fared better as it was able to identify a few longshots, compared to other systems which are biased towards favourites only.

Pudaruth *et al.* (2013) used the following nine factors: jockey, new horse, odds, three previous rank, draw, type of horse, weight horse is carrying, rating and stable to predict the winner of a race [16]. Each factor was normalised to a value between 0 & 1 and a total was made. The total represents the worth of each horse. The winner is the horse with the highest total. They obtained a prediction accuracy of 58.3% while the best forecast by professional tipsters was at 45%. Testing was performed only on 24 races from the 2010 racing season. Pudaruth *et al.* (2013) were the first researchers to apply fuzzy logic to the field of horse racing [17]. They achieved a prediction accuracy of 41.7%, which is 2.8% higher than the predictions from the best professional tipster for the 2012 racing season [1]. However, the testing was carried out on 3 race meetings only. Jogeah *et al.* (2015) used five input variables to predict the finishing margin of horses using fuzzy logic [18]. They constructed 35 fuzzy rules and tested their algorithm on 26 races from 3 consecutive meetings. The system could only spot 6 (23.1%) winners. However, it was also found that, the winner was among the first three predicted horses in 20 races.

Kempston (2007) used support vector regression to predict the finishing line margin behind the winning horse [19]. Besides the usual attributes like percentage wins by horse/jockey/trainer, weight carried, age of horse and final odds, he also considered the sex of the horse and the medication that was given to the horse. Training and testing was done on a huge dataset of races. However, the accuracy was only about 1% better than a naïve prediction strategy.

The purpose of all the above cited works was to predict the winner of horse races with an accuracy that is better than the market odds or random choice. Horse racing is not a game of chance. Horses are animals that behave in different ways with the environment it is subjected to and consistency of performance can vary to a notable level. A neural network is a tool that can be used in assisting prediction, however, because of the complexity of the domain, hundred percent is not achievable. There are many other important factors that are often neglected by punters. Some examples are: equipment worn by the horse, the pedigree of the horse, changes in weight of the horse since its last race, the preferred distance of the horse, the number of weeks that have elapsed since its last race, the variation in odds, etc. After a thorough review of the literature, we saw that neural networks can be used to increase the accuracy but the results are often misinterpreted and exaggerated. The lack of a common dataset for testing purposes also makes comparison between the different approaches a difficult task. Other machine learning techniques such as decision trees, k-nearest neighbour and naïve bayes must also be investigated.

### III. METHODOLOGY & DESCRIPTION OF DATASET

The odds for this study were obtained from the Mauritius Turf Club [1]. There were 43 meetings for the 2014 racing season. There was an average of 8 to 9 races per meeting which accumulated to a total of 347 races for this season. The odds for each meeting were collected at the same time for each meeting. The odds were taken at the following times:

1. 2 days before at 14:00 hours (Opening Odds)
2. 2 days before at 16:00 hours
3. 1 day before at 10:00 hours

4. 1 day before at 12:00 hours
5. 1 day before at 14:00 hours
6. 1 day before at 16:00 hours
7. On the racing day at 10:00 hours
8. Final odds (Closing Odds)

Eight different odds values are collected for each horse in each race for each meeting. While most normal race meetings are held on Saturdays, classic races are held on Sundays. This is why the day has not been specified above. The odds are stored in an Excel sheet along with the class information, horse number, race number and meeting number. Three different types of classes were used: rank, margin and win/lose.

Table I. 1<sup>st</sup> Race of 1<sup>st</sup> Meeting

| #  | HORSE           | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    |
|----|-----------------|------|------|------|------|------|------|------|------|
| 1  | SAZIWAYO        | 620  | 670  | 700  | 750  | 750  | 750  | 650  | 700  |
| 2  | ALBERT DOCK     | 1600 | 2200 | 2800 | 2200 | 2000 | 2000 | 2000 | 2000 |
| 3  | BONGO BEAT      | 820  | 1200 | 1400 | 1400 | 1400 | 1400 | 1400 | 1500 |
| 4  | TORNADO MAN     | 350  | 400  | 400  | 420  | 400  | 400  | 420  | 400  |
| 5  | KING FAHIEM     | 600  | 720  | 700  | 700  | 650  | 650  | 650  | 800  |
| 6  | AMAPHUPHO       | 820  | 1200 | 1400 | 1400 | 1300 | 1300 | 1200 | 1200 |
| 7  | APPEAL BOARD    | 3000 | 4000 | 5500 | 5000 | 5000 | 5000 | 5000 | 3300 |
| 8  | MESQUE'S WONDER | 1200 | 1300 | 1500 | 1500 | 1400 | 1400 | 1400 | 1200 |
| 9  | LUCKY COLOUR    | 750  | 900  | 650  | 550  | 650  | 650  | 700  | 650  |
| 10 | YOUNG ROYAL     | 750  | 500  | 500  | 550  | 570  | 570  | 600  | 800  |

Since there are large differences between the odds of the favourites and underdogs, all the values are normalised as follows:

$$\% \text{ change} = (\text{New odds} - \text{previous odds}) / \text{previous odds}$$

For example, for the first horse (Saziwayo), the odds has changed from 620 to 670 within an interval of 2 hours. There is a similar trend for the other horses but the amounts are different. Thus, the % change is  $(670-620)/620 = 0.08$ .

Table II. Normalised Data for 1<sup>st</sup> Race of 1<sup>st</sup> Meeting

| #  | 2     | 3     | 4     | 5     | 6    | 7     | 8     |
|----|-------|-------|-------|-------|------|-------|-------|
| 1  | 0.08  | 0.05  | 0.08  | 0.00  | 0.00 | -0.16 | 0.08  |
| 2  | 0.38  | 0.38  | -0.38 | -0.13 | 0.00 | 0.00  | 0.00  |
| 3  | 0.46  | 0.24  | 0.00  | 0.00  | 0.00 | 0.00  | 0.12  |
| 4  | 0.14  | 0.00  | 0.06  | -0.06 | 0.00 | 0.06  | -0.06 |
| 5  | 0.20  | -0.03 | 0.00  | -0.08 | 0.00 | 0.00  | 0.25  |
| 6  | 0.46  | 0.24  | 0.00  | -0.12 | 0.00 | -0.12 | 0.00  |
| 7  | 0.33  | 0.50  | -0.17 | 0.00  | 0.00 | 0.00  | -0.57 |
| 8  | 0.08  | 0.17  | 0.00  | -0.08 | 0.00 | 0.00  | -0.18 |
| 9  | 0.20  | -0.33 | -0.13 | 0.13  | 0.00 | 0.07  | -0.07 |
| 10 | -0.33 | 0.00  | 0.07  | 0.03  | 0.00 | 0.04  | 0.27  |

### IV. EXPERIMENTS, RESULTS AND EVALUATION

Odds for the first 30 meetings (232 races) were used for training. This data was fed to the neural network from the NeuroXL Predictor software [20]. A model was built and saved. The following parameters were used: number of epochs = 10000; initial weight = 0.3; learning rate = 0.3; momentum = 0.6; activation function = zero-based log-sigmoid function. The model was loaded and then applied to all the 27 races from meeting 31, 32 and 33.

The following results were obtained. Only, a total of 2 races were predicted correctly. Another 10 horses out of the 27 actual winners came at the 2<sup>nd</sup> or 3<sup>rd</sup> position and the remaining 15 horses were predicted at other worst positions. A total number of 232 horses participated in these 27 races with an average number of 8.6 horses per race. The average predicted position for all horses for the 27 races was 4.3. Horses which come after the 4<sup>th</sup> position do not earn any stakes money and also cannot be used in any type of bets. Thus, in this case, the neural network has not been able to create any betting advantage for the punters.

Logistic regression, decision trees and support vector machines could not do any better on this dataset. Different classes were used as well. Initially, we used the rank (numeric) as the target, then the margin (numeric) and finally the rank was thresholded to a win/lose (nominal)

attribute. It was the latter which produced the best accuracy. For the 2014 racing season, there was an average of 8.74 horses per race [21]. Random chance alone would have provided a prediction accuracy of 11.4%. Our prediction accuracy of 7.4% is even lower which suggest that the variation in odds does not have any significant influence on the outcome of races at the Champs de Mars race track. However, we believe that additional work is required to confirm this finding. Thus, in the future, we intend to work on a more balanced dataset and to perform more experiments by varying the parameters of the neural network.

## V. CONCLUSION

The main objective of this research was to assess the effect of changes in the odds of horses on the outcome of races. Data for the 2014 racing was collected and analysed. In particular, odds data from 232 races were fed to an artificial neural network for training. The test set consisted of 27 races. It was found that only 2 races were correctly predicted representing an accuracy of 7.4%, which is lower than the number of winners predicted using random-chance. This low accuracy suggests that the variation in odds does not have much impact on the outcome of horse races at the Champs de Mars. However, we believe that further investigations may be necessary to confirm this result. Nevertheless, the outcomes from this study can have applications in other important fields such as finance, medicine, industry, business, management, education and games.

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