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AN EXPLICIT SOLUTION TO THE PROBLEM OF OPTIMIZING THE ALLOCATIONS OF A BETTOR'S WEALTH WHEN WAGERING ON HORSE RACES

PETER SMOCZYNSKI * ** AND
DAVE TOMKINS,* *** *Thompson Rivers University*

Abstract

An explicit formula for the optimal strategy for betting allocation on horse races is given. The formula for the maximal value of the logarithm of average geometric growth rate is also given. The solution is obtained with the help of KKT theory. Application of the formulas requires the optimal set of horses to bet on to be constructed. For a horse to be included in the set, the expected revenue rate must be greater than the fraction of unallocated wealth. A simple way, without solving any equations, for determining the optimal set of horses is given.

Keywords: Optimal wealth allocation; constrained convex optimization; random processes; Kelly criterion; horse races

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1. Introduction

In the seminal paper [5], Kelly considered repeated betting on horse races. Kelly described the optimal strategy for a single horse and gave an incomplete solution to the problem with many horses; he assumed the track take to be zero. A more general problem was considered in [6] and [3]. In [6] it was proved that, when the number of atoms of the probability distribution is smaller than or equal to the number of degrees of freedom then the problem of finding the optimal solution is reducible to that of solving two systems of equations. It was concluded that it is impossible to find an explicit solution. In [3] several interesting general theorems were proved about the general case; however, explicit solutions were not given. In [2] an elegant algorithm for approximate solutions of the general case was given. In [4], independently of [6], the two systems of equations were introduced and investigated for the problem of horse races with nonzero track take. The method described there produces many candidate solutions. In this paper we use KKT theory to find the optimal solution for horse races with nonzero track take under the condition that the horseplayer cannot borrow money and cannot sell the bets short. We give a complete explicit solution to a problem set by Kelly in [5].

After introducing the problem, we solve it in three steps. Firstly in Section 6 we solve the optimal system, somewhat similarly to the way it was done in [4]. Then in Section 7 we analyze the conditions of solvability and we describe in simple language how to find the unique optimal

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* Postal address: Department of Mathematics and Statistics, Thompson Rivers University, Main Campus, Box 3010, 900 McGill Road, Kamloops, BC, Canada V2C 5N3.
** Email address: psmoczynski@tru.ca
*** Email address: tomkins@tru.ca

solution without solving any equations. In order to do this we reorder the horses according to their expected revenue rates in Section 7. The optimal set, S^{opt}, of horses contains all the horses whose expected revenue rates are bigger than the fraction of the wealth that the horseplayer does not bet, also called the reserve rate.

2. Horse races, track take, and dividends

A total of n horses competes in a horse race repeated infinitely many times. The respective probabilities for each horse to win are the same at each race, π_k for the kth horse, although different horses will be winning in turns. Each time the horseplayer bets an allocation fraction f_k, which is always the same, of his wealth on the kth horse to win. After each race the track management takes some fraction (i.e. the track take, denoted by tt) of the total money bet on all the horses and the dividend fraction, $D = 1 - tt \in (0, 1]$, of the remaining money is divided between those who placed bets on the winning horse, proportionally to their bets. All the other bettors lose their money.

Let $\boldsymbol{b} = [b_1, b_2, \dots, b_n] \in \mathbb{R}^n$ be the vector with components equal to the total sum of money bet on each horse. The total sum to be divided between the bettors and the management of the track establishment is $\sum_m b_m = \sum_{m=1}^{m=n} b_m$. The vector

$$\boldsymbol{\beta} = \frac{\boldsymbol{b}}{\sum_m b_m}$$

satisfies the condition $\sum_m \beta_m = 1$; hence, its components may be interpreted as the belief probabilities that describe the collective belief of the bettors about the respective probabilities of winning for each of the horses. The components of the revenue rates vector are given by

$$r_k = \frac{D}{b_k} \sum_m b_m = \frac{D}{\beta_k} = Q_k + 1, \tag{2.1}$$

and the expected revenues are

$$\mathrm{E}[r_i] = \frac{D\pi_k}{\beta_k} = \pi_i (Q_i + 1). \tag{2.2}$$

Usually the dividend rate is between 0.80 and 0.85, and Q_k represents the odds of horse k (i.e. a profit of Q_k dollars for each \$1 bet, if horse k wins).

3. The objective function and constraints on bets

We consider a horseplayer who has made accurate estimates of the probabilities $\boldsymbol{\pi} = [\pi_1, \pi_2, \dots, \pi_n]$ of each horse winning. We also assume that the horseplayer's bets are small enough as not to alter the estimates $\boldsymbol{\beta}$ of the same probabilities by other players. When the kth horse wins then the horseplayer's wealth grows by a factor of $1 - \sum_m f_m + r_k f_k$, the revenue rate on each dollar bet on the kth horse; see (2.1). The horseplayer's strategy, described by the vector $\boldsymbol{f} = [f_1, f_2, \dots, f_n]$ of allocation fractions bet on horses, constitutes a self-financing strategy if his wealth changes without any further investments after the initial wealth is reserved for betting. After W repetitions of the same race his wealth grows by a factor of

$$\left(\prod_{k=1}^{k=n} \left(1 - \sum_m f_m + \frac{D f_k}{\beta_k} \right)^{w_k / W} \right)^W,$$

where $W = \sum_k W_k$ and w_k is the number of times that the kth horse won. Now,

$$L_w(\boldsymbol{f}) = \sum_k \frac{w_k}{W} \ln\left(1 - \sum_m f_m + \frac{Df_k}{\beta_k}\right)$$

is the average of independent and identically distributed random variables, each taking the value $\ln(1 - \sum_m f_m + Df_k/\beta_k)$ with probability π_k. By the strong law of large numbers, $L_W(\boldsymbol{f})$ converges almost surely to

$$L(\boldsymbol{f}) = \sum_k \pi_k \ln\left(1 - \sum_m f_m + \frac{Df_k}{\beta_k}\right). \tag{3.1}$$

Since $L(\boldsymbol{f}) \le \sum_k \pi_k \ln(1+D/\beta_k)$, under the constraints on $\boldsymbol{f}$ described at the end of Section 3, then

$$\prod_{k=1}^{k=n} \left(1 - \sum_m f_m + \frac{Df_k}{\beta_k}\right)^{w_k/W} = \exp(L_W(\boldsymbol{f}))$$

converges almost surely to $\mathrm{e}^{L(\boldsymbol{f})}$ as e^x is Lipschitz continuous on $(-\infty, \sum_k \pi_k \ln(1 + D/\beta_k)]$. Thus the horseplayer is interested in maximizing the objective function $L(\boldsymbol{f})$. Now,

$$\mathrm{Dom}(L) = \left\{\boldsymbol{f} \in \mathbb{R}^n \;\middle|\; 0 < 1 - \sum_m f_m + \frac{Df_k}{\beta_k} \quad \text{for every } k\right\} \subseteq \mathbb{R}^n$$

is a convex set as an intersection of half-spaces. If any of $\beta_k = 0$ then it is easy to find the optimal strategy: bet a penny on the kth horse and $L(\boldsymbol{f}) = \infty$. The rest of the paper is concerned with the case when all $\beta_k > 0$.

The objective function $L(\boldsymbol{f})$ is of $\mathbb{C}^\infty$ class on its domain and, if all $\pi_k > 0$, then it is strictly concave-downwards as a finite linear combination, with nonnegative coefficients, of strictly concave logarithms. At least one of the revenue rates (2.2) must be bigger than 1, otherwise no bet would be made.

Consequently, $\mathrm{Dom}(L)$ must be unbounded in this direction and $L(\boldsymbol{f})$ must grow to infinity in this direction. Therefore, $L(\boldsymbol{f})$ achieves a unique maximum on every convex bounded subset of $\mathrm{Dom}(L)$ and the maximum is located on the boundary of the subset.

We consider only betting in the North American style, i.e. only backing a horse to win, never laying a horse to lose. The first condition is equivalent to the constraint $\sum_m f_m \le 1$, the second is equivalent to $0 \le f_m$ for all m. Thus we shall look for the maximum value of the objective function (3.1) on the restricted set

$$P = \left\{\boldsymbol{f} \;\middle|\; 0 \le f_m \text{ and } 0 \le 1 - \sum_m f_m\right\} \subseteq \mathrm{Dom}(L(\boldsymbol{f})). \tag{3.2}$$

The restricted domain is convex; hence, there exists exactly one maximum of $L(\boldsymbol{f})$ on P and it is located on the boundary of P.

4. KKT theory

We shall use KKT theory [1] in order to write the system of optimality equations for the point at which L attains its maximum, since it is located at the boundary of P. The maximization problem we consider is of the following form. Find a maximum of a differentiable concave down function $L(\boldsymbol{f})$ on a feasible convex set $\{\phi \mid 0 \leq g_k(\boldsymbol{f})\} \subseteq \mathrm{Dom}(L(\boldsymbol{f}))$, where the functions used in the constraints are also differentiable. In order to write equations for the maximum points, we form the Lagrange function $LL(\boldsymbol{f}, \boldsymbol{\lambda}) = L(\boldsymbol{f}) + \sum_p \lambda_p g_p(\boldsymbol{f})$. KKT theory states that every constrained maximum point of $L(\boldsymbol{f})$ is also an 'unconstrained' maximum point of $LL(\boldsymbol{f}, \boldsymbol{\lambda})$. The list of all the conditions is as follows:

$$\frac{\partial}{\partial f_i} LL(\boldsymbol{f}, \boldsymbol{\lambda}) = \frac{\partial}{\partial f_i} L(\boldsymbol{f}) + \sum_p \lambda_p \frac{\partial}{\partial f_i} g_p(\boldsymbol{f}) = 0, \quad \text{for all } i, \tag{4.1}$$

$$\lambda_p g_p(\boldsymbol{f}) = 0, \tag{4.2}$$

$$0 \leq \lambda_p, \quad \text{for all } p, \tag{4.3}$$

$$\frac{\partial}{\partial \lambda_p} LL(\boldsymbol{f}, \boldsymbol{\lambda}) = g_p(\boldsymbol{f}) \geq 0. \tag{4.4}$$

We now briefly describe the meaning of these requirements. Requirement (4.4) is just repetition of the equations of the constraints imposed on variables f_i, (4.4) is listed here for the sake of symmetry and completeness. Requirement (4.2) states the following: if $0 < g_k(\boldsymbol{f})$ then the additional variables $\boldsymbol{\lambda}$ are all zero. In this case, (4.1) reduces to the simplest requirements for an optimal point: $(\partial/\partial f_i)L(\boldsymbol{f}) = 0$. The additional variables are allowed to be nonzero only if $0 = g_k(\boldsymbol{f})$, that is when the optimal point is on the boundary of the feasible region. Now (4.1) may be interpreted as follows: if the optimal point is on the boundary then the gradient $(\partial/\partial f_i)L(\boldsymbol{f})$ must be a linear combination of the gradients $(\partial/\partial f_i)g_p(\boldsymbol{f})$ of the constraint functions. The essence of this requirement is this: the gradient $(\partial/\partial f_i)L(\boldsymbol{f})$ must be perpendicular to the surface on which $0 = g_k(\boldsymbol{f})$. Intuition says that this is correct, because at an extreme value on the surface $0 = g_k(\boldsymbol{f})$ the derivative of the objective function in any direction tangent to the surface must be zero. But the gradients $(\partial/\partial f_i)g_p(\boldsymbol{f})$ are perpendicular to these tangent directions. At last we explain the meaning of (4.3). The gradients $(\partial/\partial f_i)g_p(\boldsymbol{f})$ are directed towards the interior of the feasible set. Therefore, (4.1) requires that if the optimal point is on the boundary then the objective function wants to grow in the direction perpendicular to the boundary and, by (4.3), towards the exterior of the feasible set.

5. The optimality system

For the problem of maximization of a concave down function (3.1) on the convex set (3.2), the Lagrange function is

$$LL(\boldsymbol{f}, \boldsymbol{\lambda}) = \sum_k \pi_k \ln\left(1 - \sum_m f_m + \frac{D f_k}{\beta_k}\right) + \sum_k f_k \lambda_k + \lambda_0 \left(1 - \sum_k f_k\right).$$

Thus the optimality equations are

$$\frac{\partial}{\partial f_i} LL(\boldsymbol{f}, \boldsymbol{\lambda}) = \frac{\pi_i D/\beta_i}{1 + D f_i/\beta_i - \sum_m f_m} - \sum_k \frac{\pi_k}{1 + D f_k/b_k - \sum_m f_m} + \lambda_i - \lambda_0 = 0, \tag{5.1}$$

$$f_i \lambda_i = 0, \quad \text{for all } i, \tag{5.2}$$

$$\lambda_0 \left(1 - \sum_k f_k\right) = 0, \tag{5.3}$$

$$0 \leq \lambda_i, \quad \text{for all } i, \qquad \text{and} \qquad 0 \leq \lambda_0, \tag{5.4}$$

$$0 \leq f_i, \quad \text{for all } i. \tag{5.5}$$

Equations (5.1) correspond to (4.1), (5.2) and (5.3) to (4.2), (5.4) to (4.3), and (5.5) to (4.4). This system (of equations and inequalities) has got, in the bounded convex set (3.2), a unique solution, since $L(\boldsymbol{f})$ is strictly concave-downwards.

6. Solution to the optimality system

In this section we solve the optimality system (5.1)–(5.5) in the set P given by (3.2). The maxima with $\sum_m f_m = 1$ are lower than the ones found here (the proof is omitted). Hence, we assume in what follows that $0 < 1 - \sum_k f_k$ and then $\lambda_0 = 0$ thanks to (5.3). Using (5.5), the indices $\{1, 2, \ldots, n\}$ may be divided into two groups: the set S of those indices i for which $f_i > 0$ and its complement with $f_j = 0$ for $j \notin S$. So, if $i \in S$ then $\lambda_i = 0$ due to (5.2) and the corresponding equations of the group (5.1) may be written as follows:

$$\frac{D\pi_i}{1 + Df_i/\beta_i - \sum_{m\in S} f_m} = \beta_i\left(\sum_{k\in S} \frac{\pi_k}{1 + Df_k/b_k - \sum_{m\in S} f_m} + \frac{\sum_{k\notin S} \pi_k}{1 - \sum_{m\in S} f_m}\right), \qquad i \in S. \tag{6.1}$$

We sum the part of the equations corresponding to $i \in S$ and we obtain

$$D\sum_{k\in S} \frac{\pi_k}{1 + Df_k/\beta_k - \sum_{m\in S} f_m} = \left(\sum_{k\in S} \frac{\pi_k}{1 + Df_k/b_k - \sum_{m\in S} f_m} + \frac{\sum_{k\notin S} \pi_k}{1 - \sum_{m\in S} f_m}\right)\sum_{k\in S}\beta_k,$$

which we then transform into

$$\sum_{k\in S} \frac{\pi_k}{1 + Df_k/\beta_k - \sum_{m\in S} f_m} = \frac{\sum_{k\notin S} \pi_k}{1 - \sum_{m\in S} f_m}\frac{\sum_{k\in S}\beta_k}{D - \sum_{k\in S}\beta_k}. \tag{6.2}$$

We substitute this into (6.1) and obtain

$$\frac{D\pi_i}{1 + Df_i/\beta_i - \sum_{m\in S} f_m} = \frac{D\beta_i}{D - \sum_{k\in S}\beta_k}\frac{\sum_{k\notin S} \pi_k}{1 - \sum_{m\in S} f_m}, \qquad i \in S,$$

which may be transformed into

$$\beta_i\left(1 - \sum_{m\in S} f_m\right) + Df_i = \pi_i\left(D - \sum_{k\in S}\beta_k\right)\frac{1 - \sum_{m\in S} f_m}{\sum_{k\notin S}\pi_k}, \qquad i \in S. \tag{6.3}$$

We sum these equations given by (6.3) and we transform the obtained equation into

$$1 - \sum_{m\in S} f_m = \frac{D\sum_{k\notin S}\pi_k}{D - \sum_{k\in S}\beta_k}. \tag{6.4}$$

We substitute this into (6.3) and we obtain the following solution after some simplifications:

$$f_i^{\text{opt}} = \pi_i - \beta_i\frac{\sum_{k\notin S}\pi_k}{D - \sum_{k\in S}\beta_k} \quad \text{if } i \in S, \qquad f_j^{\text{opt}} = 0 \quad \text{if } j \notin S. \tag{6.5}$$

When (6.2) and (6.4) are substituted into the remaining equations of the group (5.1), corresponding to $j \notin S$, these then take the following form:

$$\frac{\sum_{k\notin S}\pi_k}{D - \sum_{k\in S}\beta_k}\beta_j = \pi_j + \beta_j\lambda_j\frac{\sum_{k\notin S}\pi_k}{D - \sum_{k\in S}\beta_k}, \qquad j \notin S. \tag{6.6}$$

With the help of (6.5) and (6.6) the inequalities (5.4) and (5.5) may be rewritten as follows:

$$\pi_j(Q_j + 1) = \frac{D\pi_j}{\beta_j} \leq R(S) < \frac{D\pi_i}{\beta_i} = \pi_i(Q_i + 1) \quad \text{for all } i \in S \text{ and all } j \notin S, \tag{6.7}$$

where the right-hand side inequalities of (6.7) are equivalent to $0 < f_i^{\text{opt}}$ and these imply the nontrivial part of (5.5), while the left-hand side inequalities of (6.7) are equivalent to the nontrivial part of (5.4). Here

$$R(S) = 1 - \sum_{m \in S} f_m = \frac{D \sum_{k \notin S} \pi_k}{D - \sum_{k \in S} \beta_k}, \quad \text{if } S \neq \varnothing \text{ and } R(\varnothing) = 1, \tag{6.8}$$

is the reserve rate, that is the fraction of horseplayer's wealth that is not bet on any horse. With the help of (6.5) and (6.8), (3.1) may be rewritten as follows:

$$\ln(G^{\text{opt}}) = L(\boldsymbol{f}^{\text{opt}}) = \sum_{k \in S} \pi_k \ln\left(\frac{D\pi_k}{\beta_k}\right) + \sum_{k \notin S} \pi_k \ln(R(S)). \tag{6.9}$$

7. The optimal set of horses and the optimal allocations

In order to find the solution to the optimality system we need to find an optimal set $S^{\text{opt}} \subseteq \{1, 2, \ldots, n\}$ such that all the inequalities in (6.7) and $0 \leq R(S^{\text{opt}}) = 1 - \sum_{k \in S} f_k \leq 1$ are satisfied. Also, $0 \leq R(S^{\text{opt}}) \leq 1$ is equivalent to $\sum_{k \in S} \beta_k \leq \sum_{k \in S} \pi_k \leq D$; see (6.8). If the only set satisfying these inequalities is $S^{\text{opt}} = \varnothing$, then we should not bet at all. Generally, a set $S \subseteq \{1, 2, \ldots, n\}$ is an optimal set if for every $i \in S$ the expected revenue rate $\mathrm{E}[r_i] > R(S)$ and for every $j \notin S$ the expected revenue rate $\mathrm{E}[r_i] \leq R(S)$. From this it follows that there is always exactly one optimal set of horses, possibly empty (the proofs are omitted). This is the optimal set of horses to bet on.

The optimal set S^{opt} of horses may be obtained with the help of the following algorithm.

1. Calculate expected revenue rates $\mathrm{E}[r_i]$ according to (2.2).

2. Reorder the horses so that the sequence $\mathrm{E}[r_i]$ is nonincreasing.

3. Set $S = \varnothing$, $i = 1$, and $R = 1$.

4. Repeat:

   if $\mathrm{E}[r_i] > R$ then insert the ith horse into the set S and recalculate R according to (6.8),

   else set $S^{\text{opt}} = S$ and stop repetition.

The set S^{opt} produced by this algorithm is the optimal set of horses. When the optimal set of horses is determined then the optimal allocation fractions should be determined from (6.5) and the maximum of the average of the logarithm of the growth rate from (6.9).

This algorithm may be easily implemented in any programming language for use at the racetrack or for online wagering. The next section contains two examples which apply this algorithm.

TABLE 1.

Horse i	Win probability π_i	Belief probability β_i	Expected revenue rate $\mathrm{E}[r_i]$
1	0.003 247	0.025	0.103 9
2	0.003 247	0.037 5	0.069 26
3	0.003 247	0.062 5	0.041 56
4	0.016 23	0.125	0.103 9
5	0.227 3	0.25	0.727 3
6	0.162 3	0.312 5	0.415 6
7	0.584 4	0.187 5	2.494

TABLE 2.

Horse i	S before including horse i, S_i	Reserve rate $R(S_i)$	Expected revenue rate $\mathrm{E}[r_i]$	To bet or not to bet?	Allocation fraction f_i^{opt}
7	$\{\,\}$	1	2.494	yes	0.487 0
5	$\{7\}$	0.542 8	0.727 3	yes	0.097 4
6	$\{7, 5\}$	0.415 6	0.415 6	no	0
1	$\{7, 5, 6\}$	0.415 6	0.103 9	no	0
4	$\{7, 5, 6, 1\}$	0.727 3	0.103 9	no	0
2	–	–	0.069 26	no	0
3	–	–	0.041 56	no	0

8. Examples

In each example the horses are reordered according to the expected revenue rates $\mathrm{E}[r_i]$ (see (2.2)), in decreasing order in the first table. Then in the second table, steps 3 and 4 of the algorithm are summarized.

Example 8.1. The dividend rate is $D = 0.8$, there are seven horses in this race, all the data are in Table 1. Therefore, the order of horses according to the expected revenue rates is $[7, 5, 6, 1, 4, 2, 3]$; hence, if the algorithm is run then it produces the following list of the candidate sets for the optimal betting set:

$$\{\,\},\ \{7\},\ \{7,5\},\ \{7,5,6\},\ \{7,5,6,1\},\ \{7,5,6,1,4\},\ \{7,5,6,1,4,2\},\ \{7,5,6,1,4,2,3\}.$$

Steps 3 and 4 of the algorithm are summarized in Table 2. The optimal set $S^{\mathrm{opt}} = S_5 = \{7, 5\}$ of the horses to bet on consists of all the horses for which the values in the row of the expected revenue rates $\mathrm{E}[r_i]$ are bigger than those in the row of the reserve rates $R(S)$. For horse 6, $\mathrm{E}[r_6] = 0.4156 = R(\{7, 5\})$; hence, this horse and all the other horses with smaller values of $\mathrm{E}[r_i]$ are not included in the optimal set. The logarithm of the maximum possible growth rate is $L(f^{\mathrm{opt}}) = 0.2964$.

Example 8.2. This is the example from [4]. The dividend rate is $D = 0.85$, there are five horses in this race and all the data are in Table 3. Therefore, the order of horses according to the expected revenue rates is $[3, 2, 1, 4, 5]$; hence, the sets of the candidate sets for the optimal betting set are as follows:

$$\{\,\},\ \{3\},\ \{3,2\},\ \{3,2,4\},\ \{3,2,4,1\},\ \{3,2,4,1,5\}.$$

TABLE 3.

Horse i	Win probability π_i	Belief probability β_i	Expected revenue rate $\mathrm{E}[r_i]$
1	0.25	0.17	1.25
2	0.1	0.056 67	1.5
3	0.1	0.034	2.5
4	0.4	0.34	1
5	0.15	0.399 3	0.319 3

TABLE 4.

Horse i	S before including horse i, S_i	Reserve rate $R(S_i)$	Expected revenue rate $\mathrm{E}[r_i]$	To bet or not to bet?	Allocation fraction f_i^{opt}
3	$\{\,\}$	1	2.5	yes	0.147 7
2	$\{3\}$	0.937 5	1.5	yes	0.065 91
4	$\{3, 2\}$	0.895 5	1.25	yes	0.079 55
1	$\{3, 2, 4\}$	0.793 3	1	yes	0.195 5
5	$\{3, 2, 4, 1\}$	0.511 4	0.319 3	no	0

Steps 3 and 4 of the algorithm are summarized in Table 4. The optimal set $S^{\mathrm{opt}} = S_1 = \{3, 2, 4, 1\}$ of the horses to bet on consists of all the horses for which the values in the row of the expected revenue rates $\mathrm{E}[r_i]$ are bigger than those in the row of the reserve rates. The logarithm of the maximum possible growth rate is $L(f^{\mathrm{opt}}) = 0.087\,36$.

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