Analysis of Rider Performance Across Rider and Stage Classes in a Cycling Manager Game

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1. Introduction

Performance analysis is a central topic in data science, particularly in sports analytics, where outcomes are influenced by multiple interacting factors. In professional cycling, rider performance depends not only on individual abilities but also stage characteristics such as terrain profile. Understanding how rider specialization interacts with stage demands is therefore relevant both for real-world cycling strategy and for simulation-based decision-making systems.

The objective of this report is to analyze rider performance data obtained from a cycling manager game and to investigate whether performance outcomes differ across rider classes and stage classes. Rider performance is measured using points awarded for individual stages of a multi-stage tour.

To address this objective, a structured statistical approach is employed. First, descriptive statistical methods are used to explore performance distributions across rider and stage classes. Subsequently, inferential statistical techniques based on analysis of variance (ANOVA) are applied to formally test for differences in mean performance and potential interaction effects.

The report is organized as follows. Section 2 describes the dataset and its structure. Section 3 formulates the research questions. Section 4 presents the descriptive analysis. Section 5 introduces the inferential statistical methods and reports the results. Finally, Section 6 summarizes and discusses the findings in a broader context.

2. Data Description and Initial Inspection

The dataset used in this analysis originates from a cycling manager game in which professional riders receive points based on their performance in individual stages of a multi-stage tour. The primary purpose of the dataset is to capture rider performance under varying stage conditions.

The dataset consists of **3496 observations and 3 variables**, where each observation represents the performance of a rider in a specific stage. The key variables relevant to this study are:

- **Points:** A metric variable representing the performance score achieved by a rider in a stage.
- **Rider Class:** A nominal categorical variable classifying riders into four categories: All Rounder, Climber, Sprinter, and Unclassified.
- **Stage Class:** A nominal categorical variable indicating the type of stage, namely flat, hilly, or mountain stages.

An initial inspection of the dataset was conducted to assess its structure, data types, and completeness. All variables were found to have appropriate data types corresponding to their measurement scales. A systematic check for missing values revealed that the dataset contains no missing observations, and therefore no imputation or data cleaning procedures were required at this stage.

Furthermore, the distribution of observations across rider classes and stage classes was examined to gain an overview of the data composition. All rider classes and stage classes are sufficiently represented, allowing for meaningful comparative statistical analyses in subsequent sections. This initial inspection confirms that the dataset is well-structured and suitable for descriptive and inferential statistical analysis.

3. Research Questions

The objective of this study is to analyze rider performance in a cycling manager game and to investigate whether performance outcomes differ depending on rider specialization and stage characteristics. Rider performance is measured in terms of points achieved per stage.

Based on the task description and the structure of the dataset, the following research questions are formulated:

- **RQ1:** Is there a difference in performance, measured by points, between the different rider classes?
- **RQ2:** Does rider performance differ across the various stage classes (flat, hilly, and mountain stages)?
- **RQ3:** Does the effect of rider class on performance depend on the stage class?

These research questions aim to assess both the individual effects of rider class and stage class on performance as well as their potential interaction. Addressing these questions provides insight into whether rider specialization leads to systematic performance differences across different stage profiles.

4. Descriptive Analysis

4.1 Scope of the Descriptive Analysis

To address the research questions formulated in Section 3, a descriptive statistical analysis is conducted focusing on rider performance measured by points. The descriptive analysis provides an initial overview of the data and examines performance patterns across rider classes and stage classes prior to inferential statistical testing.

Descriptive statistics are computed for the entire dataset, grouped by rider class, grouped by stage class, and for combinations of rider class and stage class. This structured approach ensures alignment between the descriptive analysis and the research questions.

4.2 Descriptive Measures

Rider performance is summarized using standard descriptive measures appropriate for metric data. For each relevant grouping, the following statistics are reported:

- arithmetic mean as a measure of average performance,
- median as a robust measure of central tendency,
- standard deviation to quantify variability,
- minimum and maximum values to describe the observed range, and
- number of observations to assess group sizes.

These measures provide a comprehensive overview of the distribution of points and facilitate structured comparisons across rider and stage classes.

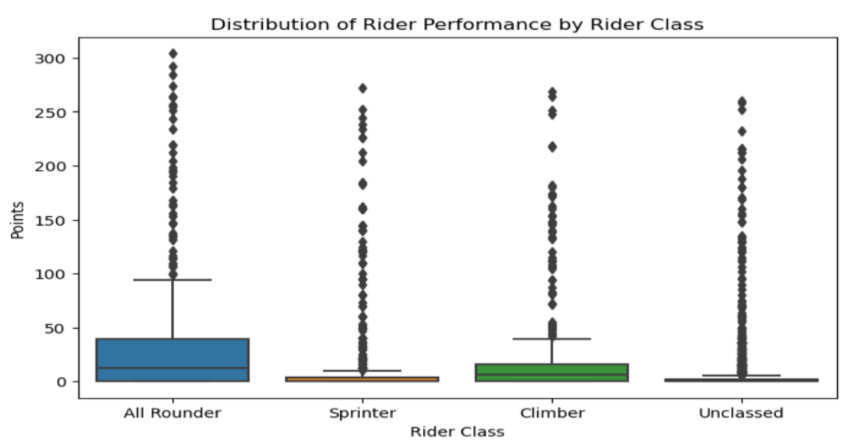
4.3 Descriptive Statistics

An initial summary of the points variable provides an overview of rider performance across all observations. Grouped descriptive statistics indicate differences in central tendency and variability between rider classes as well as between stage classes. The reported means and medians vary across rider types, indicating heterogeneous performance patterns.

Furthermore, descriptive statistics computed for combinations of rider class and stage class illustrate how performance levels differ across stage profiles for different rider types. These combined summaries provide a preliminary indication of potential interaction patterns, which are formally examined in the inferential analysis.

4.4 Descriptive Visualization

To complement the numerical summaries, a statistical graphic is used to visualize the distribution of rider performance. Figure 1 presents boxplots of points grouped by rider class. The boxplots illustrate differences in central tendency, dispersion, and the presence of extreme values across rider classes, providing a clear visual comparison of performance distributions.



(Figure 1: Distribution of rider performance (points) by rider class using boxplots.)

Figure 1 directly addresses Research Question RQ1 by visualizing the distribution of performance scores across rider classes. The boxplots reveal clear differences in central tendency and dispersion between rider classes, suggesting systematic performance differences that are formally examined in the inferential analysis.

5. Inferential Statistical Analysis

5.1 Choice of Statistical Tests

To formally address the research questions, inferential statistical analyses are conducted using analysis of variance (ANOVA). Rider performance is measured on a metric scale, while rider class and stage class are categorical variables with more than two levels. Under these conditions, ANOVA provides an appropriate framework for testing differences in mean performance across groups.

A one-way ANOVA is applied to examine differences in mean performance across rider classes and across stage classes. In addition, a two-way ANOVA including an interaction term is used to investigate whether the effect of rider class on performance depends on the stage class.

ANOVA is preferred over multiple pairwise t-tests because it allows simultaneous comparison of multiple group means while controlling the family-wise error rate.

5.2 Mathematical Formulation of ANOVA

One-Way ANOVA

For a single factor with $k$levels, the one-way ANOVA model is given by:

$$Y_{ij} = \mu + \alpha_i + \varepsilon_{ij},$$

where Y_{ij}denotes the performance score of the j-th observation in group i,
$\mu$is the overall mean,
$\alpha_i$represents the effect of the i-th group, and
$\varepsilon_{ij}$are independent error terms with mean zero and variance σ^2.

The null hypothesis tested is:

$$H_0: \alpha_1 = \alpha_2 = \cdots = \alpha_k = 0,$$

which corresponds to equality of group means.

Two-Way ANOVA with Interaction

To examine the joint effect of rider class and stage class, a two-way ANOVA model with interaction is specified as:

$$Y_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\beta)_{ij} + \varepsilon_{ijk},$$

where $\alpha_i$denotes the effect of rider class,

$\beta_j$denotes the effect of stage class, and

$(\alpha\beta)_{ij}$represents the interaction effect.

The null hypothesis for the interaction term is:

$$H_0: (\alpha\beta)_{ij} = 0 \forall i, j.$$

Test Statistic

In ANOVA, group differences are evaluated using the F-statistic:

$$F = \frac{\text{Mean Square Between Groups}}{\text{Mean Square Within Groups}},$$

which follows an F-distribution under the null hypothesis.

5.3 Assumptions and Inferential Results

The application of ANOVA assumes independence of observations, approximate normality of residuals, and homogeneity of variances across groups. Independence is assumed based on the structure of the dataset, while normality and variance homogeneity are assessed using diagnostic plots and summary statistics. Given the robustness of ANOVA, moderate deviations from these assumptions are considered acceptable.

One-way ANOVA results indicate whether mean performance differs across rider classes and stage classes. In addition, a two-way ANOVA is used to assess whether the effect of rider class on performance depends on stage class. The corresponding F-statistics, degrees of freedom, and

p-values for all tests are reported in Table 1.

Effect	df	F-value	p-value	Decision
Rider Class (one-way)	(3, 3492)	85.51	< 0.001	Reject H_0
Stage Class (one-way)	(2, 3493)	0.24	0.786	Do not reject H_0
Rider Class (two-way)	(3, 3484)	92.82	< 0.001	Reject H_0
Stage Class (two-way)	(2, 3484)	0.28	0.755	Do not reject H_0
Rider × Stage Interaction	(6, 3484)	51.00	< 0.001	Reject H_0

(Table 1: Results of One-Way and Two-Way ANOVA for Rider Performance)

These inferential analyses provide formal statistical evidence regarding performance differences across rider and stage classes, as well as potential interaction effects, and form the basis for interpretation in the subsequent discussion section.

6. Summary and Discussion

This study examined rider performance in a cycling manager game with respect to rider class and stage class. Three research questions were addressed. **RQ1** investigated whether performance differs across rider classes and was answered affirmatively, as significant differences in mean performance were observed. **RQ2** examined whether performance varies across stage classes; no statistically significant differences were found when stage class was considered in isolation. **RQ3** assessed whether the effect of rider class depends on stage class and revealed a significant interaction effect, indicating that rider performance varies across stage profiles depending on rider specialization.

These findings highlight that rider performance cannot be adequately explained by rider characteristics or stage conditions in isolation. Instead, performance outcomes are best understood through their combined effect. From a practical perspective, this emphasizes the importance of aligning rider specialization with stage profiles when modeling performance or planning competitive strategies.

From a practical perspective, these findings are consistent with expectations in multi-stage cycling contexts, where different rider types are suited to different terrain profiles. The results therefore offer insight into how rider characteristics and stage demand jointly shape performance outcomes.

Several limitations should be acknowledged. The data originate from a simulation-based cycling manager game and may not fully reflect real-world professional cycling conditions. Factors such as team strategies, environmental conditions, and rider fatigue are not explicitly modeled. Furthermore, repeated observations of riders across stages may introduce dependencies not fully captured by the applied methods.

Future research could extend this analysis by incorporating additional covariates, longitudinal performance trends, or mixed-effects models to explicitly account for repeated measurements and unobserved heterogeneity. Comparisons with real-world cycling data could further validate the observed patterns.

Overall, this report demonstrates how descriptive and inferential statistical methods can be combined to analyze performance differences in a structured and reproducible manner, emphasizing the importance of considering both rider specialization and stage characteristics in performance analysis.

7. Bibliography

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