Mini-Project 2

MLB Playoff Qualification: A Data Science Perspective

By I. Font

Aim

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Explore the factors influencing playoff qualification in Major League Baseball (MLB) by addressing the following questions:

1. How many games must a team win to qualify for the playoffs?

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Two features created: W_perc and R_diff

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1	0.68	0.96	0.79	80
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32% of the teams predicted as qualifying actually didn't.

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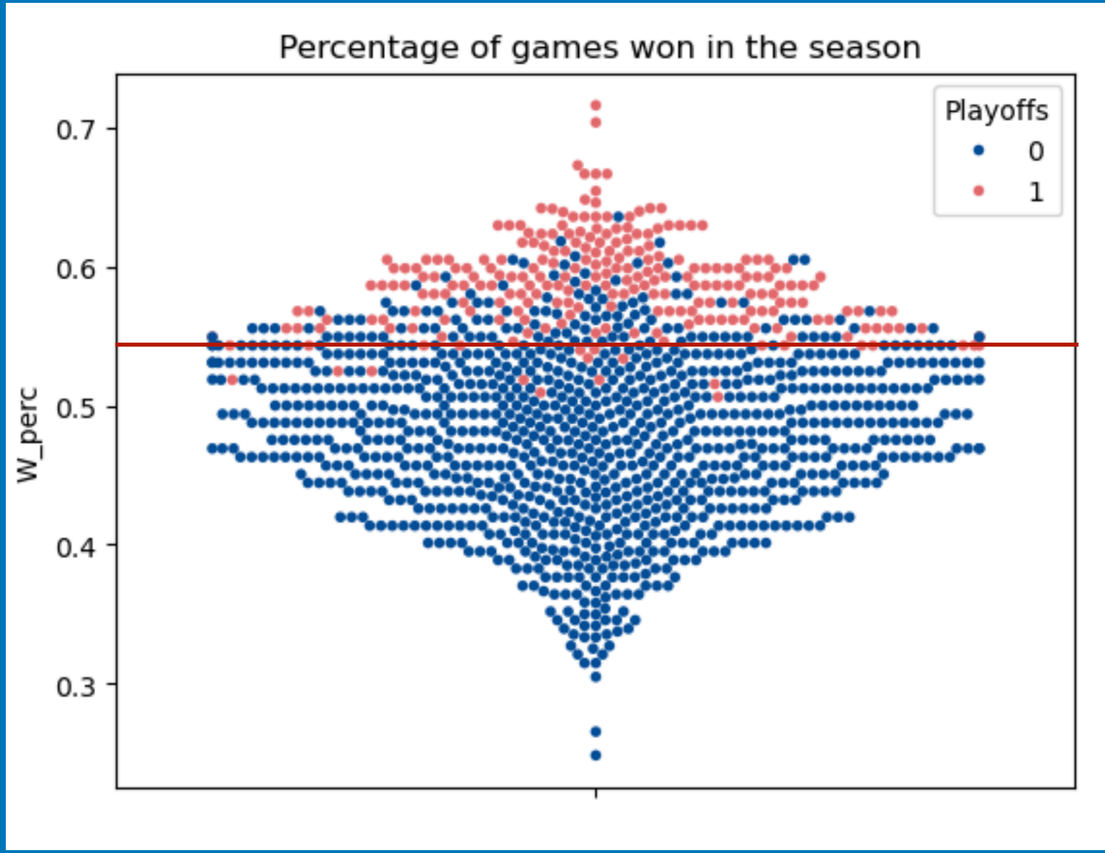

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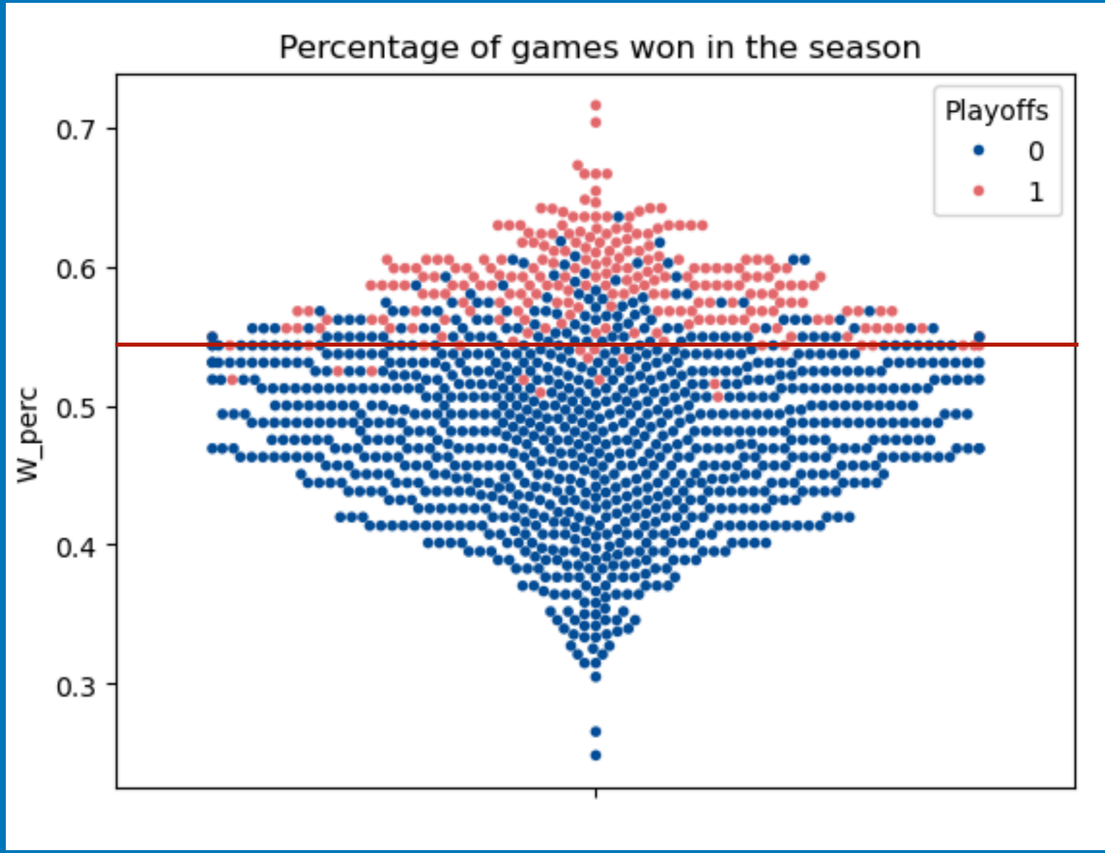

At decision point: W_perc = 0.54, therefore must win 88 out of the 162 games

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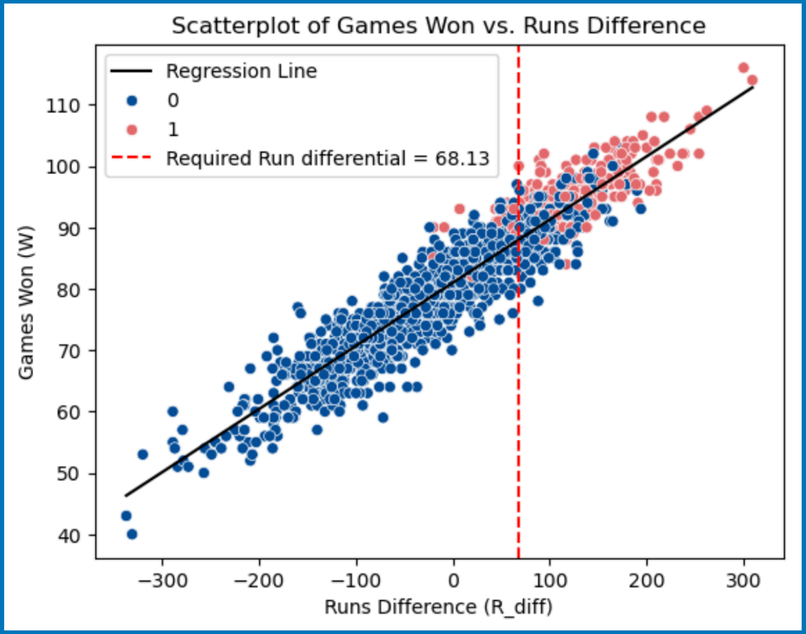

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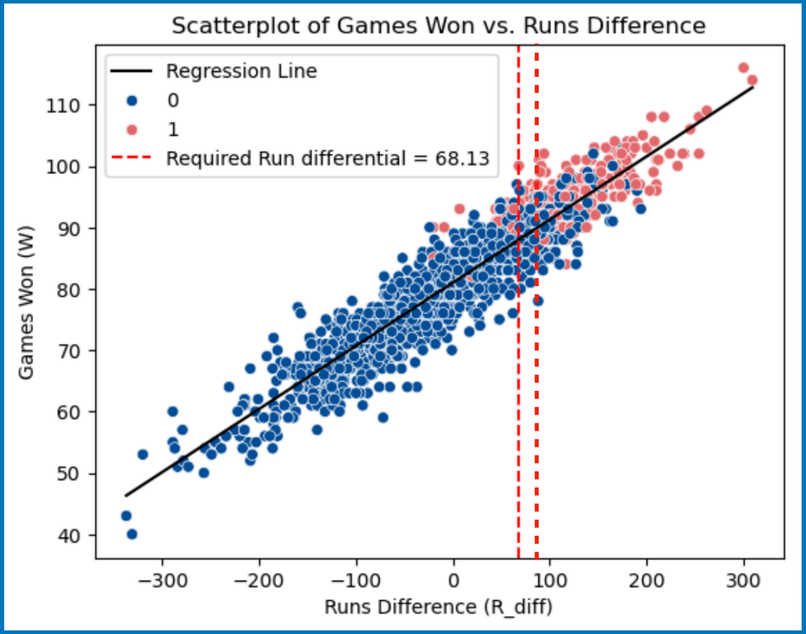

Best closer to 100 !

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Three of the four best features had outliers

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- Enhance dataset quality by collecting more granular data like advanced team metrics and player-level statistics

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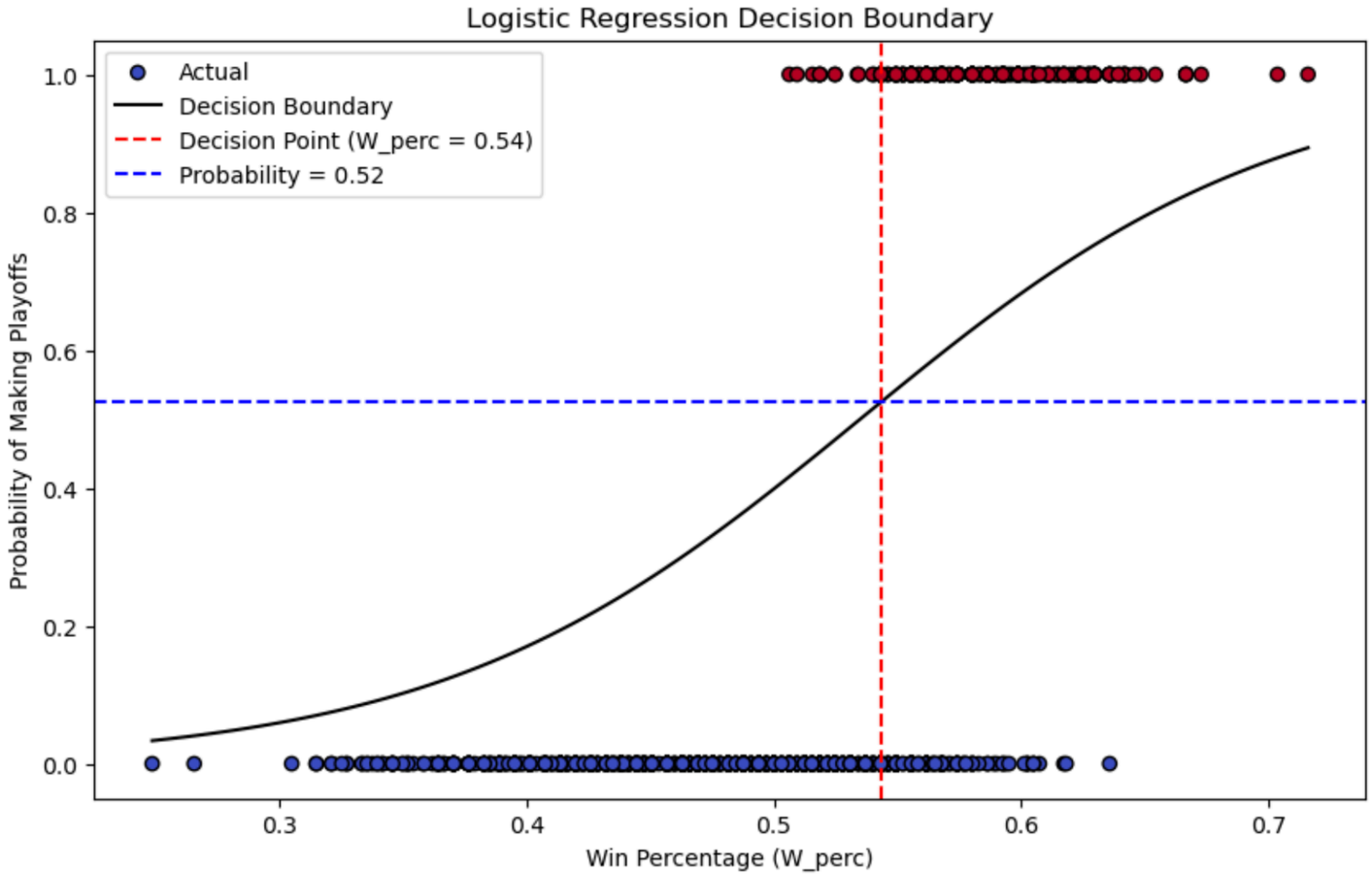
Classification model



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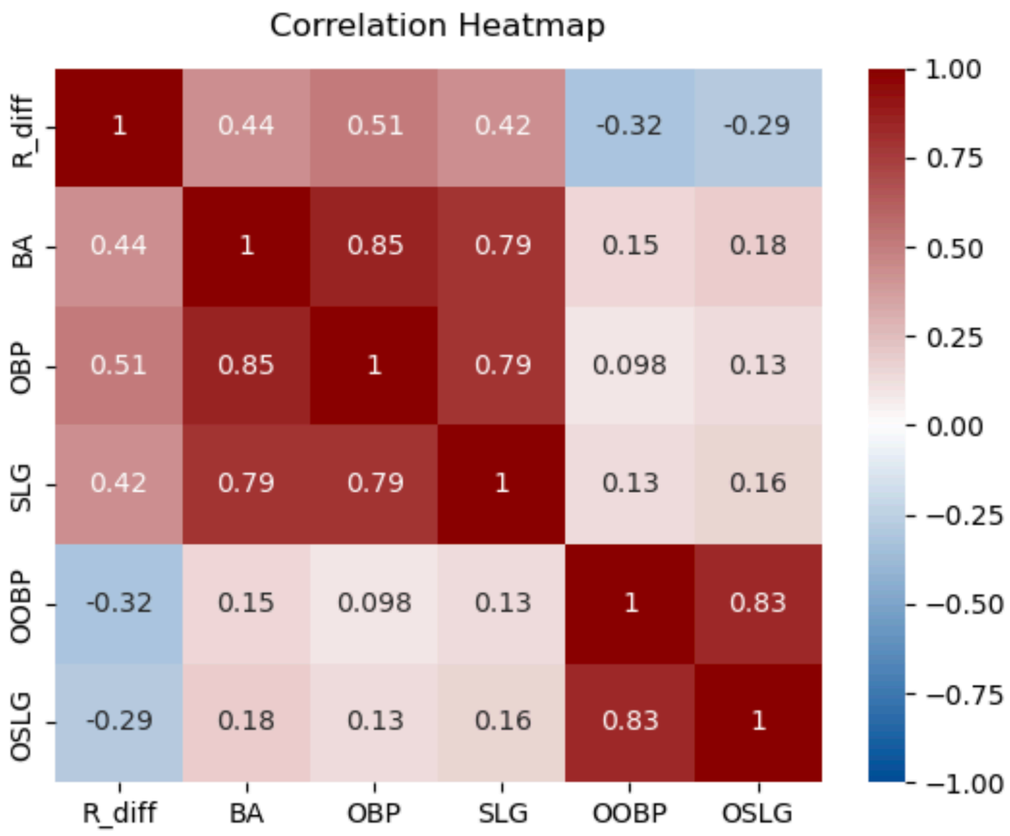

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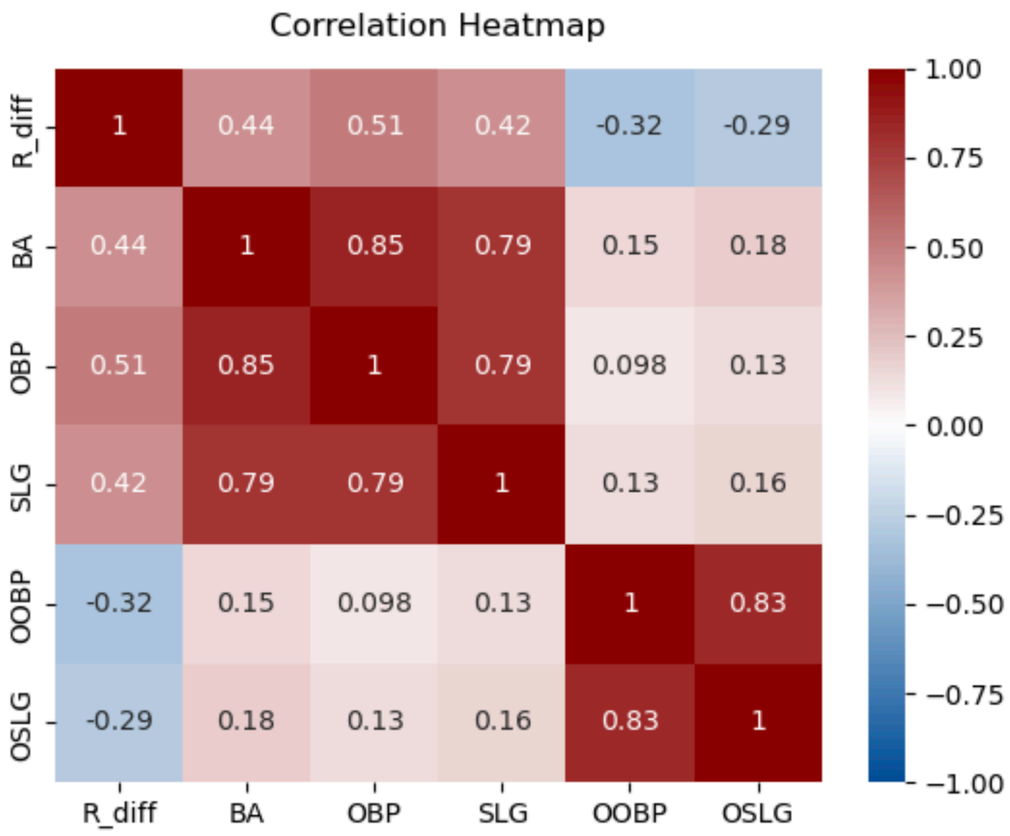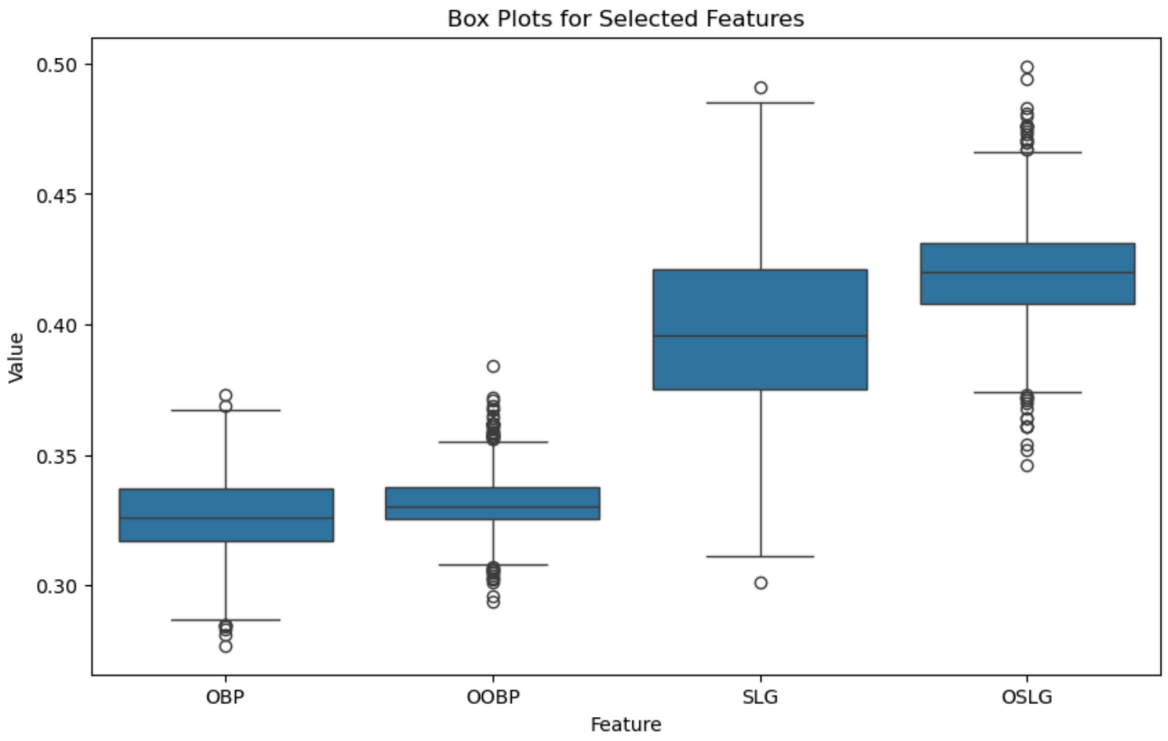
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