# Theory and Understanding

At our Formula One racing track, the car racing competition is incredibly intense, with victories often determined by minute differences. As a result, the cars remain extremely close to each other during races, significantly increasing the likelihood of collisions.

In this scenario, we are assuming that Formula One racing does not have a designated road. Instead, we calculate a grey area representing the assumed road using confidence intervals (CIs). The grey area should not be mistaken for the actual road. At a specific moment, April 8th, 10:00 am, there are 11 cars participating in the race, represented by blue dots captured through our GPS camera.

While the GPS system is powerful, its effectiveness is limited in adverse weather conditions and challenging terrains, causing it to miss capturing all cars. Nonetheless, it is crucial to closely monitor the cars as immediate action is necessary if a crash occurs. For instance, if a blue car at the forefront collides with another vehicle, and the respective driver communicates the incident through their microphones, we must have paramedics prepared to attend to the driver promptly. However, providing assistance is only possible when we have precise information about the location of the car.

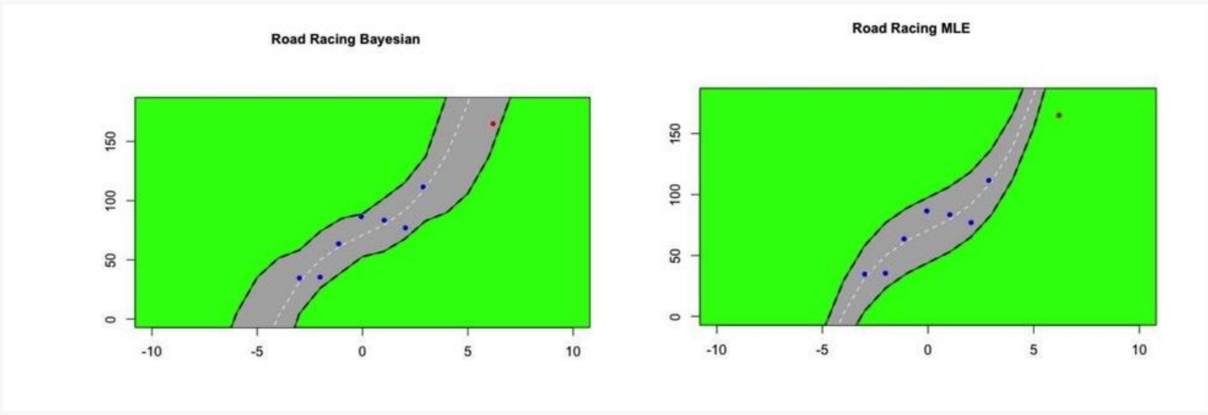
It is important to mention that the paramedics continuously adjust their positions based on the drivers' locations. Therefore, the paramedics' locations are constantly changing to ensure they can quickly respond to any incidents on the race track.

However, due to the limitations of our GPS system, we were unable to capture the image of a red car. Despite this setback, we still require the location of the red car for the reasons mentioned earlier. Therefore, we resort to calculating confidence intervals to determine the possible area where the red car might be located. The purpose of calculating the confidence interval is to gain an understanding of the potential range within which the red car can be found.

Using the frequentist/classical method, we determined confidence intervals with a confidence level of 95%. The grey area represents this confidence interval, while the black lines indicate the upper and lower limits. The white line corresponds to the predicted trajectory, while the blue cars represent observed data. However, the red car is new data that needs to be predicted using this model.
It is essential to note that the boundaries of the road, determined by the confidence interval, play a crucial role in guiding the paramedics' positioning. The paramedics must be stationed within these boundaries to be ready to respond promptly to any incidents that may occur within the predicted area.
The grey area, resembling a road, indicates that based on our method and considering only the ten blue cars' positions, there is a high probability (95 out of 100 random times) that the red car will be located within that grey (road) area. However, it's essential to remember that our red car falls into the remaining 5% where the prediction using the Maximum Likelihood Estimation (MLE) method is not possible.

In the unfortunate event that the red car crashes, we will be aware of the accident as the driver will inform their team. Nevertheless, we won't have the ability to predict the red car's specific path, resulting in our failure to dispatch paramedics promptly to the crash site.

Contrarily, we have Bayesian intervals, which consider both the data (the positions of the blue cars) and the prior distribution, representing the typical driving style of cars in Formula One racing.
With Bayesian intervals, we can predict the location of the red car, even though it may require a larger number of paramedics due to the wider interval. The advantage lies in the ability to make predictions despite the interval's breadth.
Understanding the width of intervals is crucial in this context. A wider interval indicates greater uncertainty in our predictions, which may necessitate more resources, such as additional paramedics, to cover a broader potential area. Conversely, a narrower interval signifies more precise predictions, reducing the need for extensive resource deployment.




Based on the given example, the success rate of Bayesian intervals is 43%, while the success rate of Maximum Likelihood Estimation (MLE) is 26%. Thus, it is evident that Bayesian outperforms MLE in this scenario.