2.5 Travel Time Analysis

The initial step in our modeling approach involves discerning whether the estimated travel times exhibit variation across different scenarios. This is crucial as it enables ~~us~~ to identify instances where the travel time is influenced by the scenario in question and those where it remains unaffected. A binary outcome is formulated, where “1” indicates a variation in travel time across scenarios and “0” signifies no variation. This differentiation can be modeled using a logistic regression model, considering the binary nature of the outcome. The model can be expressed as:

avoid notation, use verbal description.

$\cancel{glm(differ \sim covariates)}$

where “differ” is the binary outcome and covariates include factors such as season, hour of the day, day of the week, priority, system load. This model will allow ~~us~~ to calculate the probability of observing a variation in travel times across scenarios, given the covariates. For instance, during peak summer seasons or specific hours of the day, the model could reveal a higher probability of variation in travel times across different scenarios, which could be attributed to factors like increased traffic or road closures.

"You" (we are addressing the client)

format / clarity	3/4
accuracy	4/4
completeness	3/4
total	10/12

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add reference & citation

Upon identifying instances where travel times exhibit discernible variation across different scenarios, it becomes imperative to model how these times are dependent on the respective scenarios, contingent upon the presence of such variation. The Linear Mixed Model (LMM), particularly utilizing the lme4::lmer() function in R, emerges as a potent tool for this purpose, adeptly managing both fixed and random effects and thereby navigating through the intrinsic variability embedded within the data. The model can be succinctly expressed as:

aim for a more technical/professional writing style.

word choice?!

$lmer(tt \sim scenario + (1 \mid eventID) + covariates)$

In this model, "tt" denotes the travel time, serving as the response variable we aim to predict or explain; "scenario" acts as a fixed effect, representing the specific ambulance allocation strategy under scrutiny, and is pivotal in quantifying the impact of different deployment strategies on the travel time; "(1 — eventID)" embodies a random effect, which enables each event to possess its distinct baseline travel time, thereby accommodating the unobserved heterogeneity and intrinsic correlations within each event's measurements; and "covariates" encompass additional fixed effects, such as the time of day, season, and system load, providing a mechanism to control and adjust for these variables in the model.

avoid notation

note that inference is focused on the variable 'scenario'. comment on how to use the model's output to compare scenarios.