Summary of EDA & Key Findings

Objective & Method

- **Guiding Question:** My analysis was driven by the guiding inferential question…
  "After accounting for the *legal reason* for a stop (the confounding variable), what
  other factors (like demographics, time, or location) can statistically explain the
  choice to conduct a search (search_conducted)?"
- **Data Quality, Cleaning, Quick Analysis:**
  - Remove 2,455 ambiguous rows (0.27% of the data) that would have
    introduced errors
  - NaN values were dropped only from essential columns and before their
    specific plots, trying to preserve as much of the data as possible
  - Narrowed down what seems to be good features that would have some
    type of association with search_conducted

    ```
    ['time', 'district', 'subject_age', 'subject_race', 'subject_sex']
    ```

- **The Focus: Controlled Bivariate Analysis**
  - Identified that the target variable, search_conducted, is **highly imbalanced**
    (only 5.78% of data is "True")
  - i.e: comparing raw counts would be misleading, so my analysis focused
    exclusively on **search rates** within a control group
    - analyzed the dataset's largest subgroup: reason_for_stop ==
      "Moving Violation"

Key Findings & Model-Relevant Insights

- **subject_race would seem to be a significant predictor**
  - Even after controlling for "Moving Violations," there are major disparities
    in search rates
  - Search rate for "black" drivers (~12.5%) approx **5 times higher** than for
    "white" drivers (~2.5%) and **8 times higher** than for "asian/pacific islander"
    drivers (~1.7%).
- **subject_age shows a clear association and could also be a good predictor**

- ○ Younger drivers were searched at a higher rate
- ○ **Median age** for searched drivers was ~30 vs. median age for non-searched drivers was ~36
- **district is complex, but can also be a strong predictor**
  - ○ Search rate is not uniform across the city & total amount of stops made isn't associated with search rate (according to previous univariate analysis)
    - ■ District I has the 2nd-highest amount of stops
    - ■ BUT it had one of the lowest search rates (~3%)
  - ○ Suggests search policies or practices may differ significantly by district, independent of stop frequency
- **subject_sex can also be a strong predictor**
  - ○ Within this "Moving Violations" group, "male" drivers were searched at nearly double the rate of "female" drivers (~5% vs. ~2.6%).
- **hour_of_day is NOT a strong predictor**
  - ○ The boxplots (hour_of_day vs. search_conducted) for "True" and "False" search outcomes were nearly identical
  - ○ Suggest time of day is not a significant factor for "Moving Violation" stops

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Takeaways for Model Building & Governance

- **Bias & Governance:** The strong associations w/ subject_race and subject_age highlight a critical area for bias investigation. So, I believe that for any AI governance framework that uses this data should take into account and learn from these disparities.
- **Modeling Recommendation (Imbalance):** The 5.78% imbalance in search_conducted means "accuracy" would be a misleading metric; a model should be evaluated on Recall or F1-Score rather than just accuracy.
- **Limitation & Next Step:** Due to time constraints, my analysis was limited to the "Moving Violation" control group. The immediate next step would be to repeat the bivariate analysis for the "Mechanical Violation" group to see if these current relationships b/w the features and search_conducted persist, which would strengthen (or not) the case for them being strong predictors.