To Do:

- Deal with grouping categorical variables.

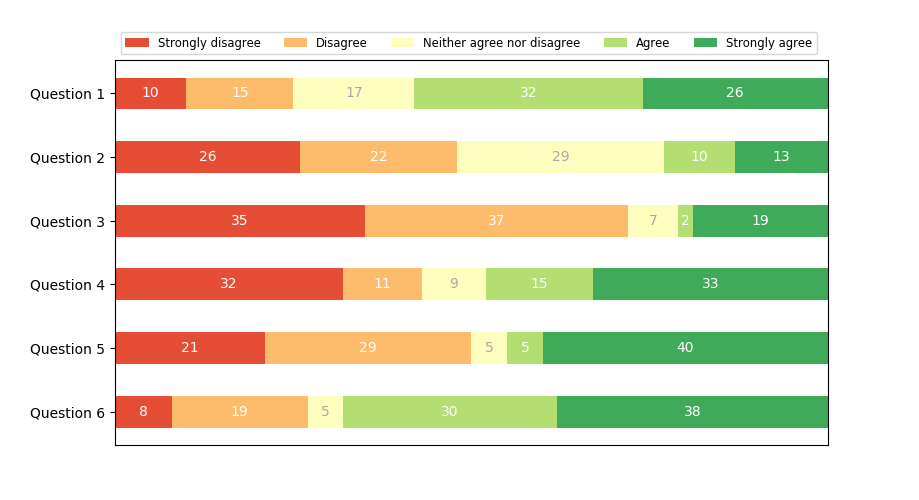
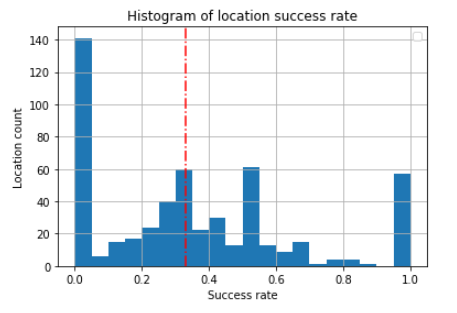
- Decide whether to make groups inside local, departm and stop\_reason.

- The loss function and its relation with classification threshold, precision, and recall.

- GridSearchCV with the appropriate scoring function.

- Dealing with missing values (output -1 and -2 from encoders)

How to decide whether the success rate associated with a given feature’s category is meaningful, i.e., whether this category being present really changes the probability of success?



In the example above we have grouped observations by all the different locations where searches have taken place and plotted the histogram of the success rate. We see that some locations have a success rate higher than average (on the right of the red line) and other locations have a success rate below average. Some locations even have a success rate of 100% and others oh 0%. In order to decide whether the observed success rate is meaningful or is just pure chance, we perform a binomial test with the null hypothesis being.

# Client requirements

## Summary

In this report, *Awkward Problem Solutions™* presents the results of a detailed statistical analysis of the historical data collected by the police department concerning its stop and search for contraband operations. The aim was to evaluate the existence of a bias against people of certain backgrounds in the search decision pattern.

Additionally, we propose a model to predict the risk of contraband based on objective data, in order to fairly decide whether or not to search the car.

## Requirements clarifications

*Awkward Problem Solutions™* has been asked to comply with the following requirements:

1. A minimum 50% success rate for searches (when a car is searched, it should be at least 50% likely that contraband is found)
2. No police sub-department should have a discrepancy bigger than 5% between the search success rate between protected classes (race, ethnicity, gender)
3. The largest possible amount of contraband found, given the constraints above.

The reason for the third requirement is self-evident. If we can increase the percentage of contraband found we also increase the certainty of punishment, producing a stronger deterrent effect which prevents more people from committing contraband crimes. From a specification perspective, this is equivalent to ask for a maximization of the model’s recall score: for a given number of stops the existing contraband is either searched and found (true positives) or not searched and not found (false negative), and we want to find as much contraband as possible (true positives) given its total amount (true positives + false negative). This requirement provides us with a metric or scoring for the evaluation of the classification algorithm, whereas the first two requirements give us constraints that should be complied with.

Regarding the first requirement, it arises from the existence of a cost associated with the searching procedure and a benefit associated with finding contraband. The rationale for this requirement should be the fact that the benefit resulting from finding contraband (let’s call it 2*s*) is valued as twice the cost of searching for it (call it *s*), on average. In this way, since every time a search is made we incur in the cost *s*, searching is ‘cost-effective’ only if the probability of obtaining the expected benefit *2s* by finding contraband and is, at least, 50%. Once we have estimated the probability of finding contraband, this requirement defines the classification threshold to be used by the algorithm[[1]](#footnote-0), i.e. we will predict contraband and clear the search authorization only if we expect contraband to be found with a probability higher than 50%. The definition of the loss function (the cost and benefit associated with each possible decision) is a client’s exclusive responsibility and it is a central part of any classification algorithm, therefore we will stick to this requirement.

the rationale for The client values the success and the search with a cost, the implicit idea in this requirement is that

Loss / benefit

# Dataset analysis

## General analysis

To perform the requested analysis we were provided with a dataset concerning car stops, including whether the car was searched, and if any contraband was found. This dataset comprises records of 2,473,643 car stops between October 2013 and May 2018 and is described by 16 variables. A brief characterization of the dataset is presented below.

* *VehicleSearchedIndicator*: ‘True’/’False’ variable indicating whether the vehicle was searched. We have 76,743 searches in a total of 2.47 million stops, i.e. only about 3,1% of stopped cars are searched.
* *ContrabandIndicator*: ‘True’/’False’ variable indicating whether contraband and/or evidence was discovered. True for 28,341 observations, which amounts to 1.15% of total and 33.25% of searched vehicles.
* *Department Name*: There are 122 police departments in the dataset. The number of traffic stops per department is very dispersed. While the ‘State Department’ accounts for 13% of observations, there are 12 departments with less than 1,000 observations and, between these, 6 departments with less than 100. The average value of traffic stops per department is 20,275 and the 50th percentile is 14,754 stops.
* *InterventionLocationName*: Location of the intervention, 1,500 places reported. Since each police department may perform traffic stops at different places, in this case, the dispersion in the number of traffic stops per local is even larger than above. We have more than 50% of the locations with a single stop reported; 76% locations with 5 or less stops; while for those 75 locations above the 95th percentile the average number of stops is 26,254.
* *InterventionDateTime[[2]](#footnote-1)*: Date and time of the intervention, ranging from October 2013 and May 2018, with a break between April 2015 and September 2015.
* *InterventionReasonCode*: Code for the reason given for stopping the vehicle. Three distinct values: ‘violation’ (88% of the stops, i.e. 2,179,595 observations); ‘equipment’ (10%); ‘investigation’ (2%).
* *StatuteReason*: Reason given for stopping the car. Fifteen distinct classifications. Most frequent are: ‘speed related’ (in 27.5% of stops); ‘defective lights’ (9.2%); ‘registration’ (9.2%); ‘cell phone’ (9.0%); ‘moving violation’ (7.7%); and ‘traffic control signal’ (7.2%). ‘other’/’other error’/missing amount for 8.9%.
* *SearchAuthorizationCode*: Authority to search the vehicle. Three distinct values: ‘Consent’ (35.2% of searches); ‘Inventory’ (20.5%); ‘Other’ (40.0%), which encompasses probable cause, reasonable suspicion, plain view contraband, incident to arrest, drug dog alert or exigent circumstances. Missing values or ‘Not Applicable’ in 4.3% of the searches.
* *ReportingOfficerIdentificationID*: There are 8,593 distinct officers in the dataset.
* *ResidentIndicator*: ‘True’/’False’ variable indicating whether the subject was a resident of the state. In the complete set, 86% of drivers stopped are state residents, whereas considering only the searched vehicles 91% are from state residents.
* *TownResidentIndicator*: ‘True’/’False’ variable indicating whether the subject was a resident of the town. In the complete set, 69% of drivers stopped are town residents, whereas considering only the searched vehicles 60% are from town residents.
* *SubjectAge[[3]](#footnote-2)*: Age of the main occupier of vehicle. Average age is 39 while median is 36.
* *SubjectEthnicityCode*: Officer perception of the ethnicity of subject. Two distinct values: ‘Hispanic’ (13.3% of all subjects, i.e., 328,450) and ‘Middle Eastern’ (1.8% or 45,561 subjects). ‘Not Applicable’ accounts for 85% of observations.
* *SubjectRaceCode*: Officer perception of the race of subject. Four distinct values: ‘White’ (81.6% of subjects), ‘Black’ (15.6%), ‘Asian/Pacific Islander’ (2.0% ) and ‘Indian America/Alaskan Native’ (0.8%). No missing or unknown data, all observations belong to one of the four classifications.
* *SubjectSexCode*: Subject’s gender. Two distinct values: ‘Male’ (63.2% of subjects) and ‘Female’ (36.8%). No missing or unspecified sex.

**Unexpected observations or missing values**

* *ContrabandIndicator*: Expected to be ‘False’ when no search was performed (i.e, *VehicleSearchedIndicator* equal to ‘False’), but there were 2,823 observations with contraband finding without search indication. For training the model these were ignored since we considered only those observations with VehicleSearchedIndicator equal to ‘True’.
* *SearchAuthorizationCode*: Expected to be missing or ‘Not Applicable’ when no search was performed (i.e, *VehicleSearchedIndicator* equal to ‘False’). However, 15,360 of stops without search indication have a valid *SearchAuthorizationCode* classification.
* *TownResidentIndicator*: All state residents were expected to be town residents as well. Nevertheless, 44,904 cases exist (1.82% of the dataset) where town residents are not state residents.
* *SubjectAge*: 1,117 unexpected observations with subject’s age below 16 years old (4.8%). Also no subject older than 99 years old. It is likely that all subjects with more than 100 or more years of age have been classified as being 99 because the number of subjects with this age is 661, while the number of subjects with the age of 98 is 132 and with the age of 97 is 216. Another possible justification for the unexpected ages, is that ages were computed from the date of birth and the year of birth was recorded with only two digits.

## Business questions analysis

The first concern manifested in the briefing was the suspicion that the search decision criterion used by police officers might be biased against people of certain backgrounds. Considering being searched as a sample process from the complete population (in our case, drivers who are pulled over), bias happens if individuals are not equally likely to be selected, particularly if the difference in the probability of being searched arises from belonging to a certain class (race, ethnicity or gender). Under this scenario, certain population classes will be underrepresented or overrepresented in the sample (i.e. in the searches). The plots presented below show us that this effect is indeed happening. For example, ‘Black’ subjects are overrepresented in searches when compared to all traffic stops, since the presence of this race class becomes higher when we consider only searched drivers instead of all drivers. The same occurs with ‘Hispanic’ class and ‘Male’ class.

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Having said that, we must remember that the purpose of a vehicle search is not to draw a random sample from the population, it is to find contraband or crime evidence, and therefore it may be reasonable to accept that the search criterion favours (in other words, biases) certain classes over others (as well as drivers of certain ages or driving during specific hours of the day). In this case the rationale is the following: if we know that the presence of certain characteristics makes contraband or crime evidence more likely to be found (i.e., if these characteristics are correlated with evidence finding), then we may use this information to increase the search success rate. This behavior is even desirable if we want to increase the search success rate, as requested in the first requirement of the briefing.

Now, accepting a bias in the search criterion is justifiable if the evidence shows us that search findings are actually more likely in those classes we have bias against.

We will now focus on the model for contraband detection. First of all, we investigated the predictive power of each variable for contraband detection, in other words, whether or not the probability of finding contraband changes when a given variable changes its value.

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Explain that departments with few stops have more uncertainty about success rate. The same is true for the location (but even worse) and probably carries the same information as the department, that’s why we don’t use location.

## Conclusions and Recommendations

# Modeling

## Model expected outcomes overview

## Model specifications

## Analysis of expected outcomes based on the training set

In-sample-error (ISE) or training error vs. Out-of-sample error (OSE) or testing error

## Alternatives considered

## Known issues and risks

If the training set is a random sample from the population, then the classifier predicted probabilities are expected to be unbiased. However, if we admit the possibility that there was some bias in the drawing for the training set, i.e. if the police search decision was itself biased, then the predicted probabilities will reflect this effect.

Subjects may adapt to the model. For example, if for older people the chance of being searched is low, because the success rate among older people was low on the training set and the model learned that, then people might realize this characteristic of the model and start using it to their advantage.

# Model Deployment

## Deployment specifications

## Known issues and risks

## Dataset technical analysis

# Annexes

## Business questions technical support

## Model technical analysis

1. Notice that the phrasing is not completely clear, as the sentence “a minimum 50% success rate for searches” may be interpreted as a request for an overall success rate of 50%. This interpretation would lead to constraining the precision score of the model to a minimum value of 50%. However, the clarification in parenthesis seems to indicate that the minimum 50% success rate should be ensured in every single search, and not overall. We will follow this interpretation, which brings us to the option of defining a classification threshold of 50%. [↑](#footnote-ref-0)
2. Plots of the monthly evolution of traffic stops and number of searches available in the annexes. [↑](#footnote-ref-1)
3. Histogram of subject’s age available in the annexes. [↑](#footnote-ref-2)