1. Title
    a. Introduction
    b. Topic - Classifying NYC Restaurant Inspection Grades
2. The question
    a. Clients are senior staff members in the NYC Department of Health and Mental Hygiene
    b. They want to see if restaurant ratings can be predicted
    c. They also have a planned targeted intervention to help improve food safety, and want to see the costs of doing so
3. What is a grade?
    a. Inspections at least once a year, more if a restaurant has a lower grade
    b. Each violation has a predetermined number of points, total points are summed
    c. Been around since 2010, but data online goes back to 2014
    d. Restaurants getting less than an A have the right to an appeal, which is why you'll see "Grade Pending" signs around the city
4. Data
    a. Our data was taken from NYC's OpenData portal and joined with Federal Census Data. This was done to grab local residential income to see effects on restaurant grading.
5. What's in the data
    a. Over 90% of restaurants currently have an "A" rating
    b. 87.2% of historical inspections have resulted in an "A"
    c. NYC publicly shares these high values as evidence of increasing food safety as standards have stayed high
    d. There was too little data to drill into B vs C. So we decided on our classifier predicting "A" vs not "A"
6. Boro Graphs
    a. Full View
        i. Relatively even distribution of A's and not A's across the boros
    b. Zoomed in
        i. Similar for other grades
    c. Note:
        i. **A** = Grade A
        ii. **B** = Grade B
        iii. **C** = Grade C
        iv. **Z** = Grade Pending
        v. **P** = Grade Pending issued on re-opening following mandatory closure
7. Inspections by Cuisine Type
    a. Way more American restaurants in NYC than any other type, with Chinese and Cafes in 2nd and 3rd, respectively.
    b. Grade distribution is also somewhat similar across these

c. Previous research into this field had, before 2014, shown no difference in grade likelihood across types, but I wanted to include in case this effect had changed with a new administration and over a few years.

8. Model Inputs
    a. Features
        i. No need to read the slide
    b. Remind the audience we're modeling "A" ratings vs "Not A"
9. Measurement of Success - CBA
    a. It costs the city about $250 directly for a lower grade due to the 2nd inspection and processing appeals. Not to mention the increased risk of restaurant failure and food sickness by citizens
    b. The Department has recently been designing an intervention for restaurants at risk of receiving lesser healthgrades. They will send literature and an educator to the restaurant to help educate on food safety. This costs the city $100. Therefore, our cost benefit is the equation here - we'll save $150 for any B/C prevented while spending extra on any false positives/negatives
    c. After running multiple types of models, our best results came up with Logistic Regression. This not only has the best interpretability of our models, but also reflected the lowest cost function possible
10. Logistic Regression Cost Effectiveness
    a. Using the equation seen before, we moved our threshold to decide what the model would predict a "not A" at from 0.5 to 0.62 (i.e. raising the bar to predict a "not A"), where our cost function was at its lowest
    b. There, our intervention (on a per try basis) came out to $15.57 when incorporating savings+costs.
11. Our takeaways
    a. By increasing threshold, we increased the number of our false negatives, but overwhelmed this increase by a dramatic decrease in the number of false positives. This led to substantial cost-savings. For an office operating on a limited budget, this can free up resources to target more restaurants citywide, increasing food safety.
    b. Further research should be done into quantifying these effects on small business stability, public health and tourism, as increased restaurant food safety should have ripple effects in many facets of city life.
12. Thank You!