

When is your next inspection?

Prediction of restaurant inspections in NYC

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1 Introduction

Food service establishments (FEA's) in New York City receive an unannounced inspection at least once a year by the Health Department to monitor their compliance with food safety regulations. Recorded violations result in a score, which in turn determines the grade issued. A score from 0 to 13 is an A-Grade, 14 to 27 a B-grade, and scores above 27 result in a C-grade.

FEA's that receive an A-grade on their first inspection post it immediately. Restaurants that do not receive an A-Grade on their first inspection can improve their sanitary conditions and are re-inspected. If a restaurant does not receive an A-grade on the re-inspection, it must either post the letter-grade or 'grade pending'. Link

The goal of this project is to use data on these restaurant inspections to predict the duration until the next inspection occurs.

The data set contains information on inspections in New York City carried out by the Department of Health and Hygiene (DOHMH) between 2010 and 2017. It contains the following variables:

- CAMIS: a unique identifier for the restaurant
- DBA: name of (doing business as) the restaurant
- BORO: borough in which the restaurant is located
- BUILDING: building number for the restaurant
- STREET: street name at which the restaurant is located
- ZIPCODE: Zip code as per the (mailing) address of the restaurant
- PHONE: phone number
- CUISINE DESCRIPTION: cuisine of the restaurant
- INSPECTION DATE: date of inspection
- ACTION: action associated with the given inspection
- VIOLATION CODE: violation code associated with the given inspection
- VIOLATION DESCRIPTION: description that corresponds to violation code
- CRITICAL FLAG: indication if violation is critical or not
- SCORE: total score for a particular inspection
- GRADE: grade issued for the given inspection
- GRADE DATE: date when the current grade was issued to the restaurant
- RECORD DATE: The date when the extract was run to produce this data set
- INSPECTION TYPE: The type of inspection. A combination of the program and inspection type

```
df_raw <- read_excel("New_York_City_Restaurants.xlsx",
                      col_types = c(rep("text", 8),
                                    "date",
                                    rep("text", 4),
                                    "numeric",
                                    "text",
                                    rep("date", 2),
                                    "text"))
```

For convenience, we rename the variables.

```
df_raw <- df_raw %>%
  clean_names() %>%
  rename(id = camis, rest_name = dba, cuisine_descr = cuisine_description,
         violation_descr = violation_description)
```

2 Exploratory Data Analysis

We will start the analysis by computing summary statistics for some of the variables in the data set.

2.1 Inspection Date

```
df_raw <- df_raw %>%
  mutate(inspection_date = ymd(inspection_date))
df_raw %>%
  summarise(min = min(inspection_date),
            median = median(inspection_date),
            max = max(inspection_date))

## # A tibble: 1 x 3
##   min      median      max
##   <date>    <date>    <date>
## 1 1900-01-01 2016-08-10 2018-03-19
```

Apparently, there are some observations with an inspection date of “1900-01-01”. Of course, these are faulty values. On closer inspection we see that values for all variables which are related to the inspection at hand are missing.

```
df_raw %>%
  summarise(na_inspectionDate = round((sum(inspection_date == "1900-01-01")/n()), 4))

## # A tibble: 1 x 1
##   na_inspectionDate
##   <dbl>
## 1 0.0031
```

Those observations amount to 0.31 % of all observations. Because it is more convenient, we will exclude them from the subsequent analysis.

```
df_raw <- df_raw %>%
  filter(!inspection_date == "1900-01-01")
```

As we can see now, the remaining observations range from October 2011 to March 2018:

```
df_raw %>%
  summarise(min = min(inspection_date),
            median = median(inspection_date),
            max = max(inspection_date))

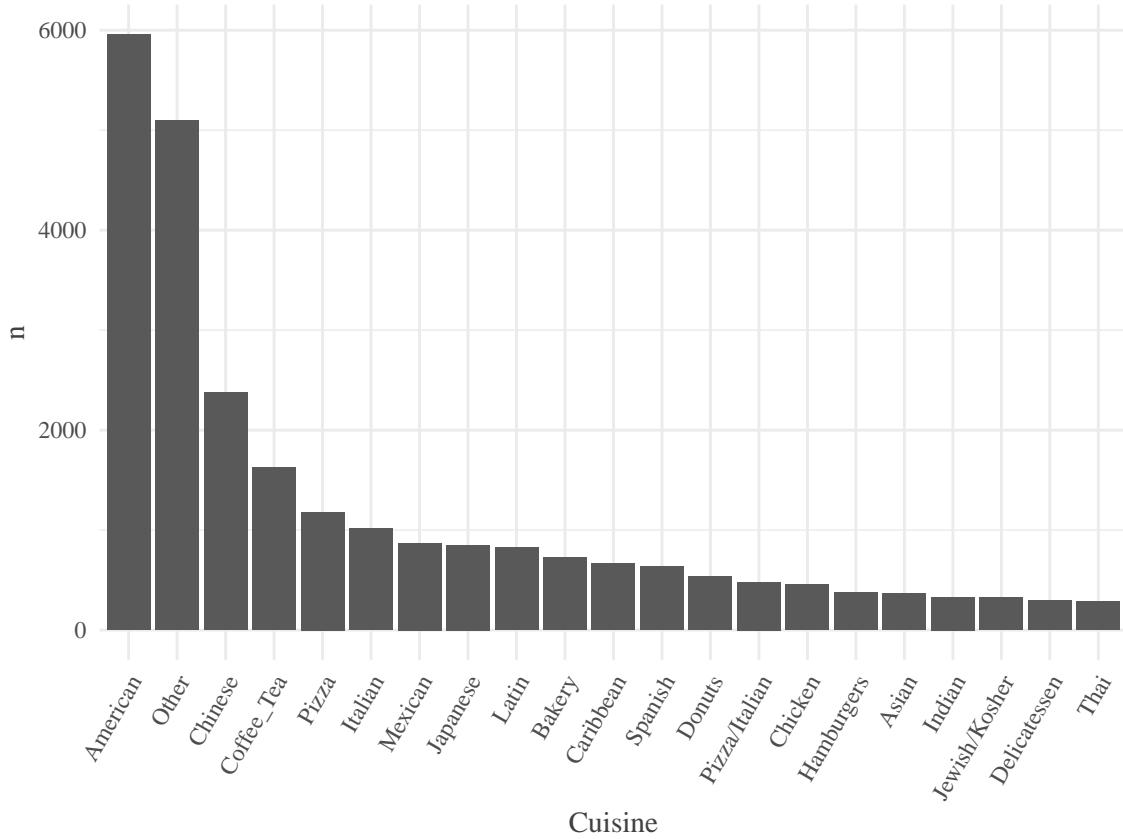
## # A tibble: 1 x 3
##   min      median      max
##   <date>    <date>    <date>
## 1 2011-10-11 2016-08-12 2018-03-19
```

2.2 Cuisine description

```
df_raw <- df_raw %>%
  mutate(cuisine_descr = as_factor(cuisine_descr)) %>%
  # Cuisine_description: Relabel level "CafÃ©/Coffee/Tea" and "Latin (...)"
  # into labels that are more readable:
  mutate(cuisine_descr =
    fct_recode(cuisine_descr,
      Coffee_Tea =
        levels(cuisine_descr) %>%
        str_subset(., "Coffee/Tea"),
      Latin =
        levels(cuisine_descr) %>%
        str_subset(., "Latin")))) %>%
  # only keep the 20 most frequent cuisines
  mutate(cuisine_descr = fct_lump(f = cuisine_descr, n = 20))
```

Let us look at the distribution of ‘cuisine_descr’:

```
df_raw %>%
  group_by(cuisine_descr) %>%
  summarise(n = n_distinct(id)) %>%
  ungroup() %>%
  ggplot(aes(x = reorder(cuisine_descr, -n), y = n)) +
  geom_bar(stat = "identity") +
  xlab("Cuisine") +
  theme_minimal() +
  theme(
    text = element_text(
      family = "serif",
      color = "gray25"
    ),
    axis.text.x = element_text(angle = 60, hjust = 1)
  )
```



The most frequent cuisines are those labelled ‘American’, ‘Other’ and ‘Chinese’.

2.3 Boros

Next, let us take a look at the distribution of ‘Boro’.

```
df_raw <- df_raw %>%
  mutate(boro = na_if(boro, "Missing")) %>%
  mutate(boro = as_factor(boro))
```

```
df_raw %>%
  count(boro)
```

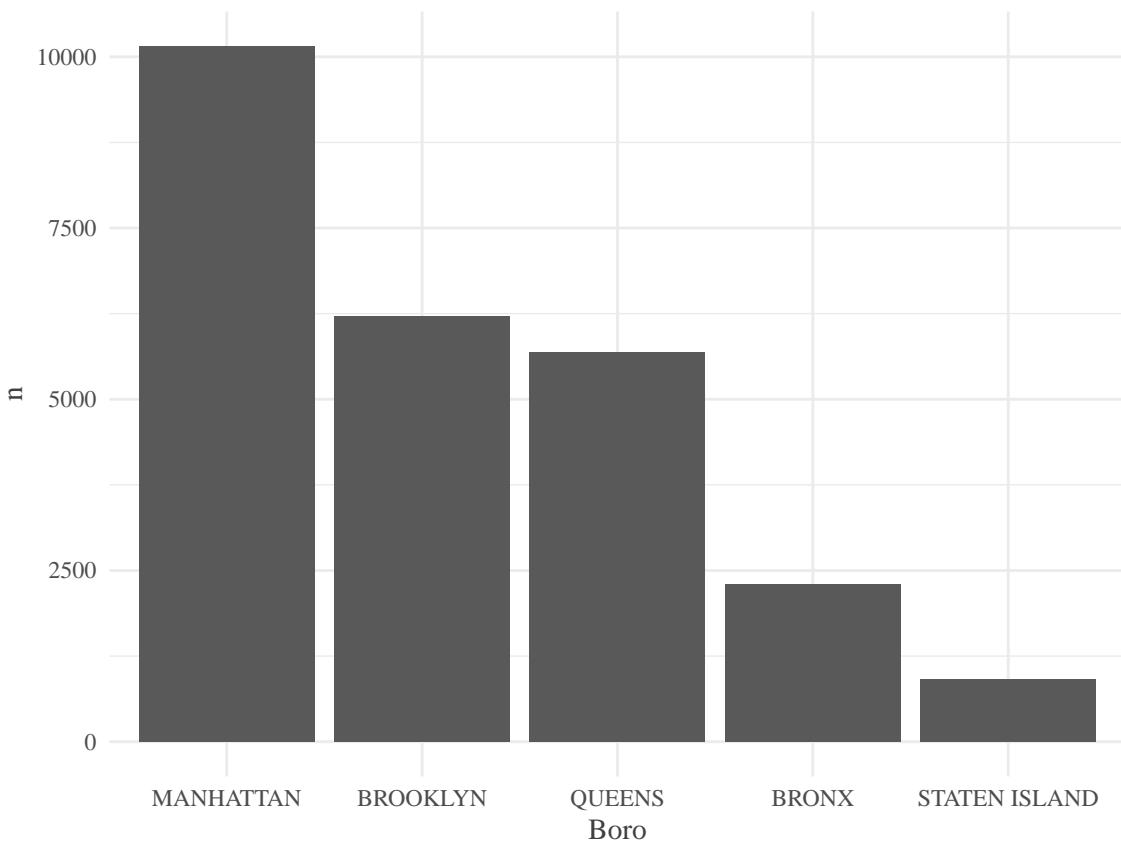
```
## # A tibble: 5 x 2
##   boro          n
##   <fct>     <int>
## 1 MANHATTAN 149821
## 2 BROOKLYN  94772
## 3 QUEENS    85191
## 4 BRONX     33105
## 5 STATEN ISLAND 12900
```

```
df_raw %>%
  group_by(boro) %>%
  summarize(n = n_distinct(id)) %>%
```

```

ggplot(aes(x = reorder(boro, -n), y = n)) +
  geom_bar(stat = "identity") +
  theme(axis.text.x = element_text(angle=60, hjust=1)) +
  xlab("Boro") +
  theme_minimal() +
  theme(
    text = element_text(
      family = "serif",
      color = "gray25"
    )
  )

```



Most of the food service establishments are located in Manhattan, followed by Brooklyn and Queens.

2.4 Actions taken

Next, we look at the variable ‘actions taken’, which describes the action carried out by the DOHMH. The variable takes on the following values:

```

df_raw <- df_raw %>%
  mutate(action = as_factor(action))

df_raw %>%
  distinct(action)

```

```

## # A tibble: 5 x 1
##   action
##   <fct>
## 1 Violations were cited in the following area(s).
## 2 Establishment re-opened by DOHMH
## 3 Establishment Closed by DOHMH.  Violations were cited in the following a~
## 4 No violations were recorded at the time of this inspection.
## 5 Establishment re-closed by DOHMH

```

We rename its levels for convenience:

```

df_raw <- df_raw %>%
  mutate(action = fct_recode(action,
                             "YesViol" = levels(action)[1],
                             "ReOpened" = levels(action)[2],
                             "Closed" = levels(action)[3],
                             "ReClosed" = levels(action)[4],
                             "NoViol" = levels(action)[5]))

df_raw %>%
  pull(action) %>%
  levels

## [1] "YesViol"  "ReOpened" "Closed"    "ReClosed" "NoViol"

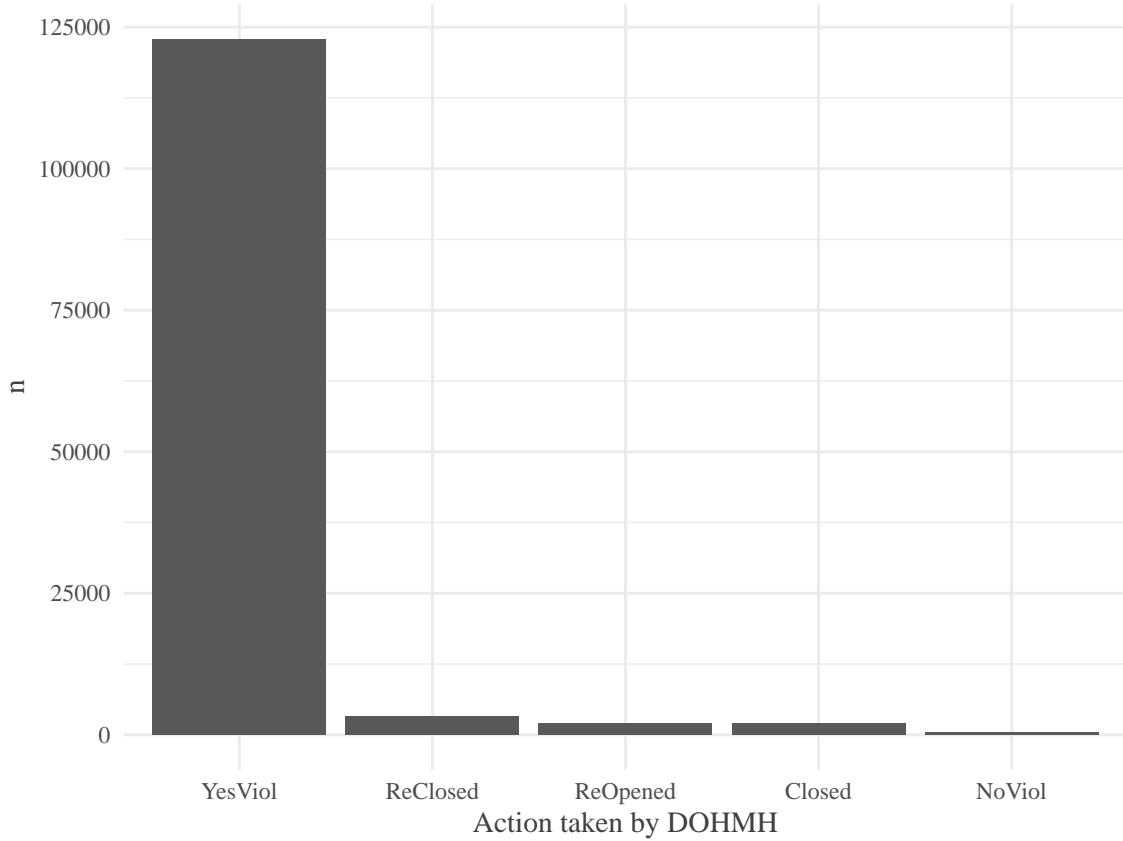
```

Let us have a look at the frequencies of ‘action’.

```

df_raw %>%
  group_by(id, inspection_date) %>%
  summarise(action_taken = first(action)) %>%
  group_by(action_taken) %>%
  summarise(n = n()) %>%
  ggplot(aes(x = reorder(action_taken, -n), y = n)) +
  geom_bar(stat = "identity") +
  xlab("Action taken by DOHMH") +
  theme_minimal() +
  theme(
    text = element_text(
      family = "serif",
      color = "gray25"
    )
  )

```



The most frequent category is ‘YesViol’, i.e., in the majority of inspections there were violations.

2.5 Violation types

Next, we will consider the different types of violations recorded. The most common violation codes are listed below.

```
df_raw %>%
  mutate(violation_code =
    as_factor(violation_code)) %>%
  group_by(violation_code) %>%
  summarise(number = n()) %>%
  mutate(rank = rank(desc(number))) %>%
  filter(rank <= 10) %>%
  arrange(rank)

## # A tibble: 10 x 3
##   violation_code number  rank
##   <fct>        <int> <dbl>
## 1 10F           53154     1
## 2 08A           38706     2
## 3 04L           26768     3
## 4 06C           25521     4
## 5 06D           25215     5
## 6 02G           23866     6
```

```

## 7 10B      21819     7
## 8 02B      19023     8
## 9 04N      18882     9
## 10 04H     8174      10

```

10F (general violation pertaining to non-food contact surfaces) is the most common violation type. followed by 08A (facility not vermin proof), 04L (evidence of mice).

Because some of the violation types occur at low frequencies, we lump them into broader violation groups. Violations are either scored or unscored. Among scored violations, we have to distinguish between so called critical and general violations. Critical violations are deemed more severe than general violations and accordingly, are awarded more points than general violations. We end up with the self-annotated scored categories ‘vermin’, ‘facility’, ‘hygiene’, ‘food protection’, ‘food temperature’, and ‘food source’. Furthermore there are ‘other_scored’ and ‘not_scored’, denoting categories that encompass other scored categories and unscored violations, respectively.

```

# New variable violation_group:
df_raw <-
  df_raw %>%
  mutate(
    violation_group =
      case_when(
        violation_code %in%
          str_c("02", LETTERS[1:10]) ~ "food_temperature",
        violation_code %in%
          c(str_c("03", LETTERS[1:7]),
            str_c("09", LETTERS[1:3])) ~ "food_source",
        violation_code %in%
          str_c("04", LETTERS[1:10]) ~ "food_protection",
        violation_code %in%
          c(str_c("05", LETTERS[1:9]),
            str_c("10", LETTERS[1:10])) ~ "facility",
        violation_code %in%
          str_c("06", LETTERS[1:9]) ~ "hygiene",
        violation_code %in%
          str_c("04", LETTERS[11:15]) ~ "vermin",
        violation_code %in%
          c("07A", "99B") ~ "other_scored",
        !is.na(violation_code) ~ "not_scored"
      )
  )

```

Here is a plot displaying the distribution. We will exclude the category *other_scored* since it contains very few observations.

```

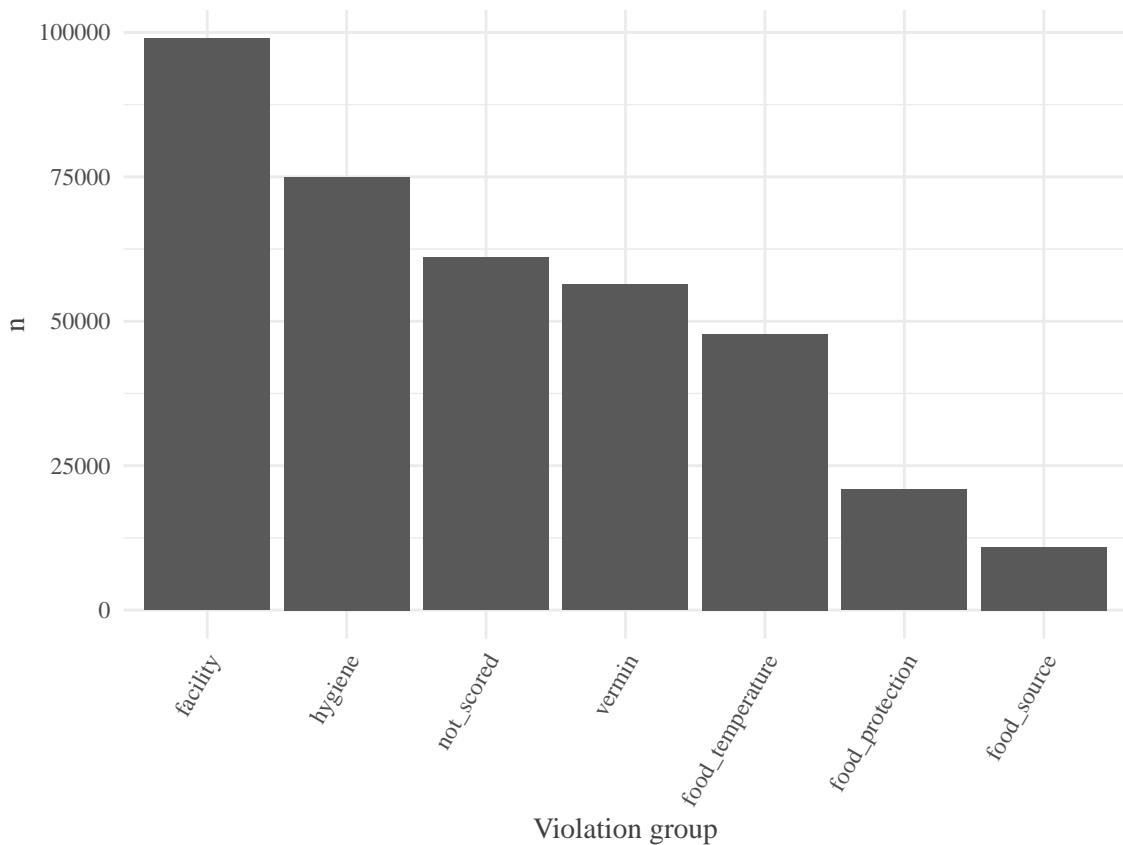
df_raw %>%
  group_by(violation_group) %>%
  filter(!is.na(violation_group),
         violation_group != "other_scored") %>%
  summarize(n = n()) %>%
  ggplot(aes(reorder(violation_group, -n), n)) +
  geom_bar(stat = "identity") +
  xlab("Violation group") +
  theme_minimal() +

```

```

theme(
  text = element_text(
    family = "serif",
    color = "gray25"
  ),
  axis.text.x = element_text(angle = 60, hjust = 1)
)

```



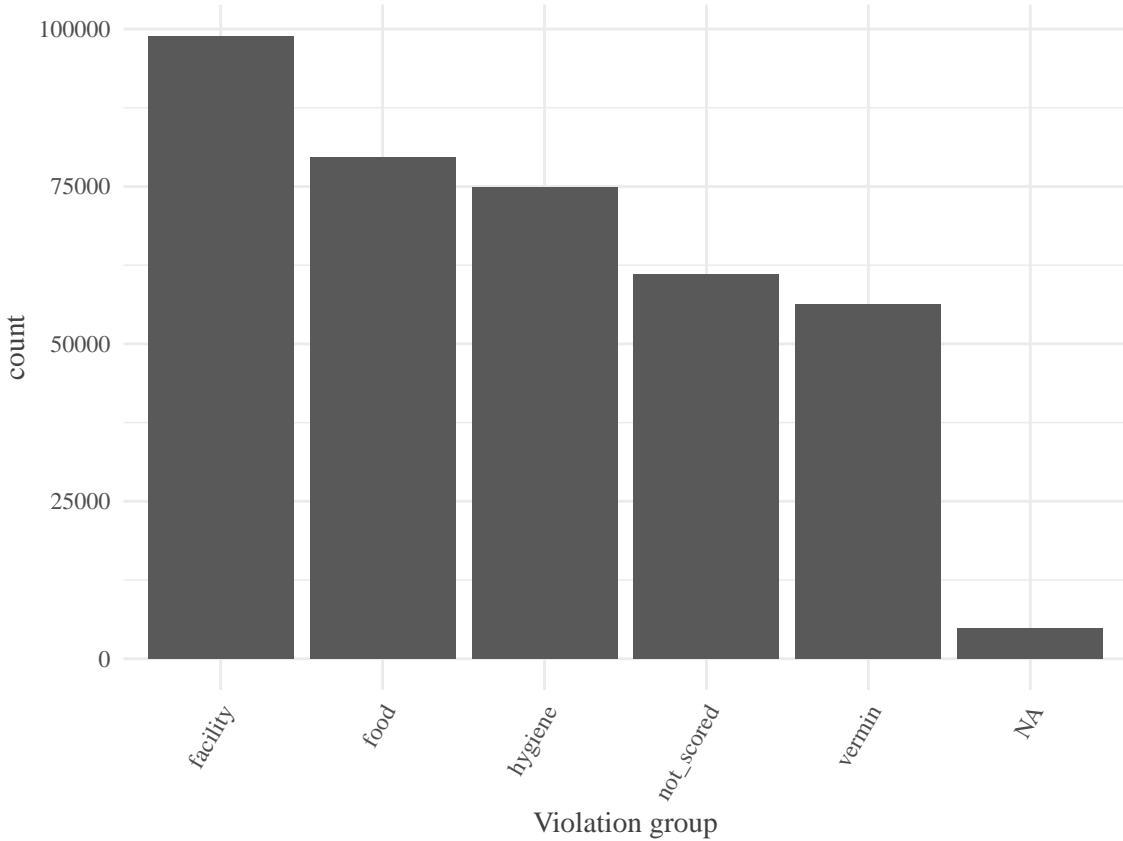
We see that the most frequent category is ‘facility’, followed by ‘hygiene’ and ‘not_scored’. We will lump the *food_**-categories categories *food_protection* and *other_scored* into a category labelled *food*.

```

df_raw <- df_raw %>%
  mutate(violation_group = as_factor(violation_group),
         violation_group = fct_collapse(violation_group,
                                         food = c("food_temperature",
                                                 "food_protection",
                                                 "food_source",
                                                 "other_scored")))

```

Here is a display of the updated *violation_group*:



For later use, we construct indicator variables for the different violation groups.

```
df_raw <- df_raw %>%
  # Create indicator variables for levels of 'violation_group'
  mutate(
    viol_vermin =
      case_when(violation_group == "vermin" ~ 1,
                TRUE ~ 0),
    viol_facility =
      case_when(violation_group == "facility" ~ 1,
                TRUE ~ 0),
    viol_food =
      case_when(violation_group == "food" ~ 1,
                TRUE ~ 0),
    viol_hygiene =
      case_when(violation_group == "hygiene" ~ 1,
                TRUE ~ 0),
    viol_not_scored =
      case_when(violation_group == "not_scored" ~ 1,
                TRUE ~ 0)
  )
```

2.6 Inspection types

The variable inspection type takes on 34 distinct values. Here we show ten of those values.

```

df_raw %>%
  distinct(inspection_type) %>%
  slice(1:10)

## # A tibble: 10 x 1
##   inspection_type
##   <chr>
## 1 Pre-permit (Operational) / Re-inspection
## 2 Administrative Miscellaneous / Initial Inspection
## 3 Pre-permit (Operational) / Initial Inspection
## 4 Cycle Inspection / Re-inspection
## 5 Cycle Inspection / Initial Inspection
## 6 Administrative Miscellaneous / Re-inspection
## 7 Trans Fat / Initial Inspection
## 8 Pre-permit (Operational) / Compliance Inspection
## 9 Cycle Inspection / Reopening Inspection
## 10 Smoke-Free Air Act / Re-inspection

```

As with the violation type, we lump some of these values together. We obtain the following values:

```

df_raw <- df_raw %>%
  separate(
    inspection_type,
    into = c("before_slash", "after_slash"),
    sep = " / ") %>%
  mutate(
    after_slash =
      str_replace_all(after_slash, fixed(" "), fixed("")))) %>%
  mutate(
    inspection_type2 =
      str_replace_all(after_slash, fixed("-i"), fixed("I")),
    inspection_type2 = as_factor(inspection_type2))

```

The variable has the following levels:

```

df_raw %>%
  pull(inspection_type2) %>%
  levels()

## [1] "ReInspection"           "InitialInspection"
## [3] "ComplianceInspection"  "ReopeningInspection"
## [5] "SecondComplianceInspection" "LimitedInspection"

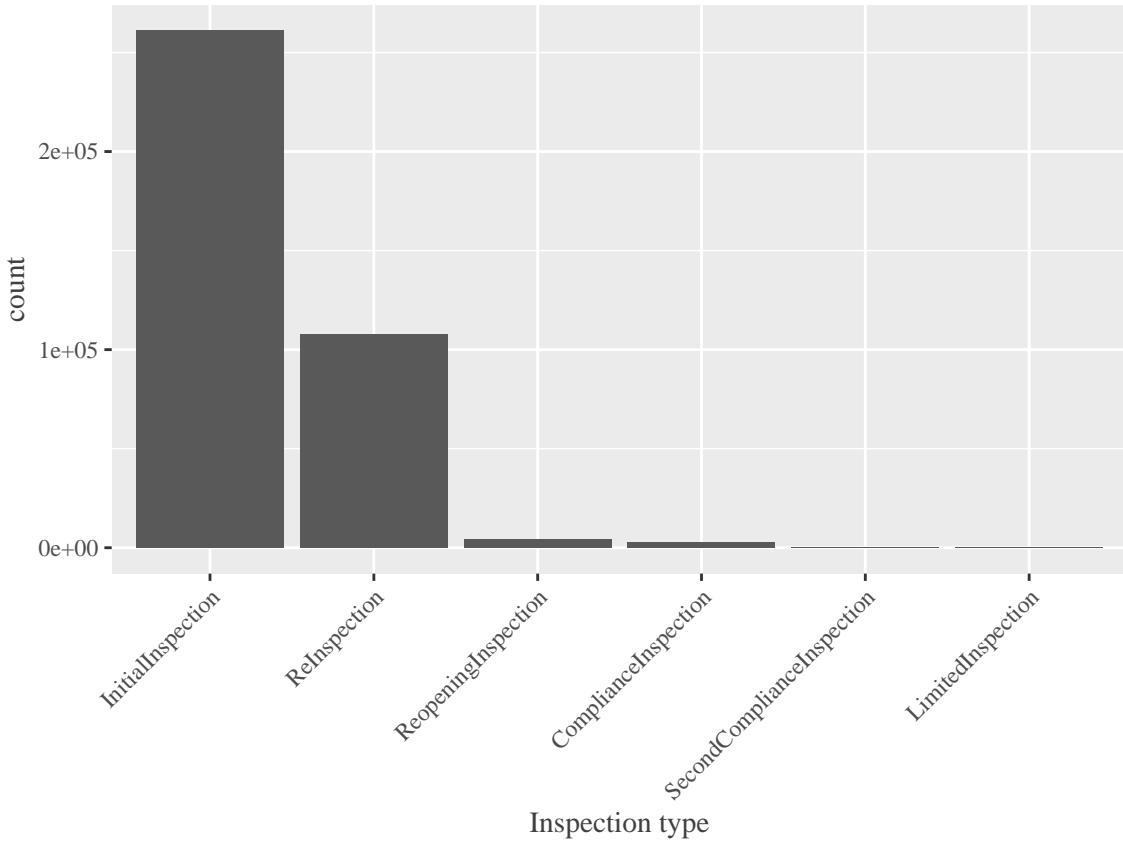
```

Here is a display of the distribution:

```

df_raw %>%
  ggplot(aes(x = fct_infreq(inspection_type2))) +
  geom_bar() +
  xlab("Inspection type") +
  theme(text = element_text(
    family = "serif",
    color = "gray25"),
    axis.text.x = element_text(angle = 45, hjust = 1))

```

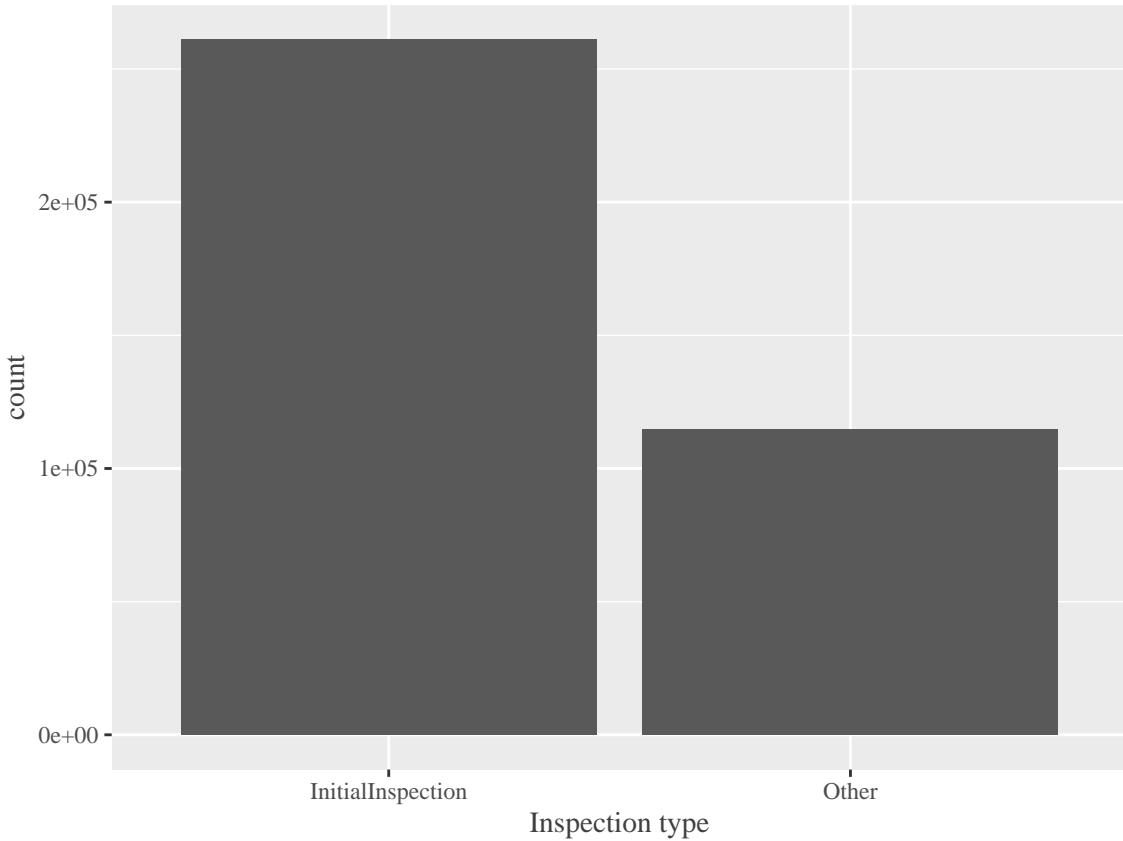


Again, there are categories that are ‘almost empty’. The vast majority of observations are initial and re-inspections: 86306 and 40831, respectively. Hence, we will lump all categories except *Initial Inspection* together:

```
df_raw <- df_raw %>%
  mutate(inspection_type2 = fct_other(inspection_type2,
                                       keep = "InitialInspection"))
```

Let us check what *inspection_type* looks like now:

```
df_raw %>%
  ggplot(aes(x = inspection_type2)) +
  geom_bar() +
  xlab("Inspection type") +
  theme(text = element_text(
    family = "serif",
    color = "gray25"))
)
```



2.7 Grade

Next, we investigate the variable ‘grade’.

```
df_raw %>%
  group_by(grade) %>%
  summarise(n = n()) %>%
  arrange(desc(n))

## # A tibble: 7 x 2
##   grade      n
##   <chr>    <int>
## 1 <NA>     187702
## 2 A        149897
## 3 B        24696
## 4 C        6318
## 5 Z        3510
## 6 Not Yet Graded  1915
## 7 P        1751
```

There is a massive amount of NA’s. We are going to investigate how the number of NAs for ‘grade’ relates to ‘score’ and ‘inspection type.’ More precisely, we know that on initial inspections no grade is issued, if the corresponding score is above 14. It seems plausible that this would lead to a value of NA for ‘grade’.

```

df_raw %>%
  select(inspection_type2, score, grade) %>%
  filter(inspection_type2 == "InitialInspection", score > 14) %>%
  group_by(grade) %>%
  summarise(n = n())

```

```

## # A tibble: 2 x 2
##   grade      n
##   <chr>     <int>
## 1 Not Yet Graded    1548
## 2 <NA>       137410

```

So about 73 % of the missing values for grade are a consequence of a score of 14 or higher. Furthermore, out of the 1915 observations with value ‘Not yet graded’, 1548 are the result of a high score (above 13) in the initial inspection. We will recode these NA’s to “Not Yet Graded” to reduce the number of missing values for ‘grade’.

```

# Recode NA's with inspection type = 'InitialInspection' and 'score' > 14 to "Not Yet Graded":
df_raw <- df_raw %>%
  mutate(grade = case_when(
    is.na(.grade) &
      .$inspection_type2 == "InitialInspection" &
      .$score > 14 ~ "Not Yet Graded",
    TRUE ~ grade
  ))

```

This reduces the number of NA’s to 13 %:

```

df_raw %>%
  summarise(prop_na = round(mean(is.na(grade)), 2),
            n_not_graded = sum(grade == "Not Yet Graded", na.rm = T))

## # A tibble: 1 x 2
##   prop_na n_not_graded
##   <dbl>        <int>
## 1    0.13        139325

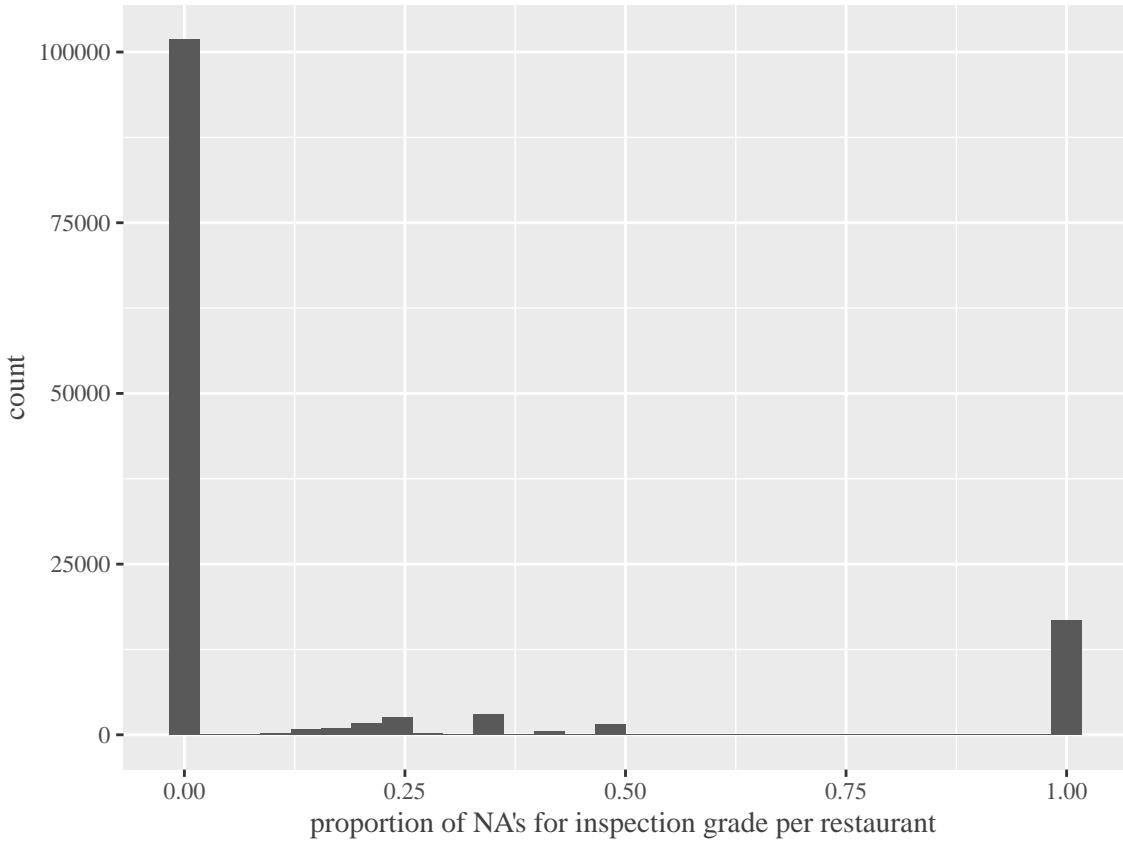
```

Here is the distribution of the proportion of inspections with an NA for grade per restaurant:

```

df_raw %>%
  group_by(id, inspection_date) %>%
  summarise(prop_gradeNA = mean(is.na(grade))) %>%
  ggplot(aes(x = prop_gradeNA)) +
  geom_histogram(bins = 30) +
  xlab("proportion of NA's for inspection grade per restaurant") +
  theme(
    text = element_text(
      family = "serif",
      color = "gray25"
    )
  )

```



It seems that for most restaurants there is no inspection with a missing value for grade. On the other hand, there are some restaurants for whom all values for grade are NA.

```
df_raw %>%
  group_by(id, inspection_date) %>%
  summarise(prop_gradeNA = round(mean(is.na(grade)), 3)) %>%
  ungroup() %>%
  group_by(prop_gradeNA) %>%
  summarise(proportion_of_restaurants = round(n()/nrow(.), 3)) %>%
  arrange(desc(proportion_of_restaurants)) %>%
  slice(1:10)
```

```
## # A tibble: 10 x 2
##   prop_gradeNA proportion_of_restaurants
##       <dbl>                <dbl>
## 1        0                 0.781
## 2        1                 0.128
## 3      0.333               0.024
## 4      0.25                0.02
## 5      0.2                 0.012
## 6      0.5                 0.011
## 7     0.167               0.008
## 8     0.143               0.004
## 9      0.4                 0.003
## 10     0.125              0.002
```

2.8 Score

Let us turn to ‘score’.

```
df_raw %>%
  pull(score) %>%
  summary()

##   Min. 1st Qu. Median    Mean 3rd Qu.    Max.    NA's
## -2.00   11.00  14.00  18.93  24.00 151.00 19514
```

There are 19514 NA’s. So let us look at the proportion of inspections that exhibit an NA for ‘score’.

```
df_raw %>%
  group_by(id, inspection_date) %>%
  summarise(n_na = sum(is.na(score))) %>%
  ungroup() %>%
  summarise(n_na = round(sum(n_na)/n(), 3))

## # A tibble: 1 x 1
##      n_na
##      <dbl>
## 1 0.15
```

15 % of all inspections have a missing value for ‘score’.

We know that there are 61028 observations that refer to violations that are not scored:

```
df_raw %>%
  group_by(violation_group) %>%
  summarise(n = n())
  filter(violation_group == "not_scored")

## # A tibble: 1 x 2
##   violation_group     n
##   <fct>             <int>
## 1 not_scored        61028
```

These observations are expected to have an NA for ‘score’:

```
df_raw %>%
  select(violation_group, score) %>%
  filter(violation_group == "not_scored") %>%
  summarise(n = n(), n_na_score = sum(is.na(score)), prop_na_score = round(n_na_score/n, 2))

## # A tibble: 1 x 3
##       n n_na_score prop_na_score
##   <int>      <int>          <dbl>
## 1 61028      16086         0.26
```

Hence, these 16086 observations account for 82 % of all of the 19514 NA’s for ‘score’. What about the remaining 3428 missing values for ‘score’? Let us consider the relationship with violation group:

```

df_raw %>%
  select(violation_group, score) %>%
  filter(is.na(violation_group)) %>%
  summarise(n = n(), n_na_score = sum(is.na(score)))

## # A tibble: 1 x 2
##       n n_na_score
##   <int>      <int>
## 1     1        3428

```

Hence, the rest of the NA's for score are associated with NA's on 'violation_group'. So let us turn to the NA's for the variable 'violation_group'. One cause for an NA here may be that on a given inspection, there was no violation at all. So what is the number of NA's for violation group among observations that do not exhibit a violation?

```

df_raw %>%
  filter(action == "NoViol") %>%
  summarise(viol_group_NA = sum(is.na(violation_group)))

## # A tibble: 1 x 1
##   viol_group_NA
##       <int>
## 1         1

```

3 Predicting time until the next inspection

Finally, we turn to the question posed in the beginning, namely, whether it is possible to predict the number of days until the next inspection, using the variables described above.

3.1 Split into training and test data

As a first step, we will divide our data set into a training and a test data set, putting 2/3 of the restaurants into the training set.

```

set.seed(1)
train_ids <- sample(unique(df_raw$id), 0.6*length(unique(df_raw$id)))
test_ids <- setdiff(unique(df_raw$id), train_ids)

```

Next, we have to make sure that the distributions of the target feature in training and test data are reasonably similar:

```

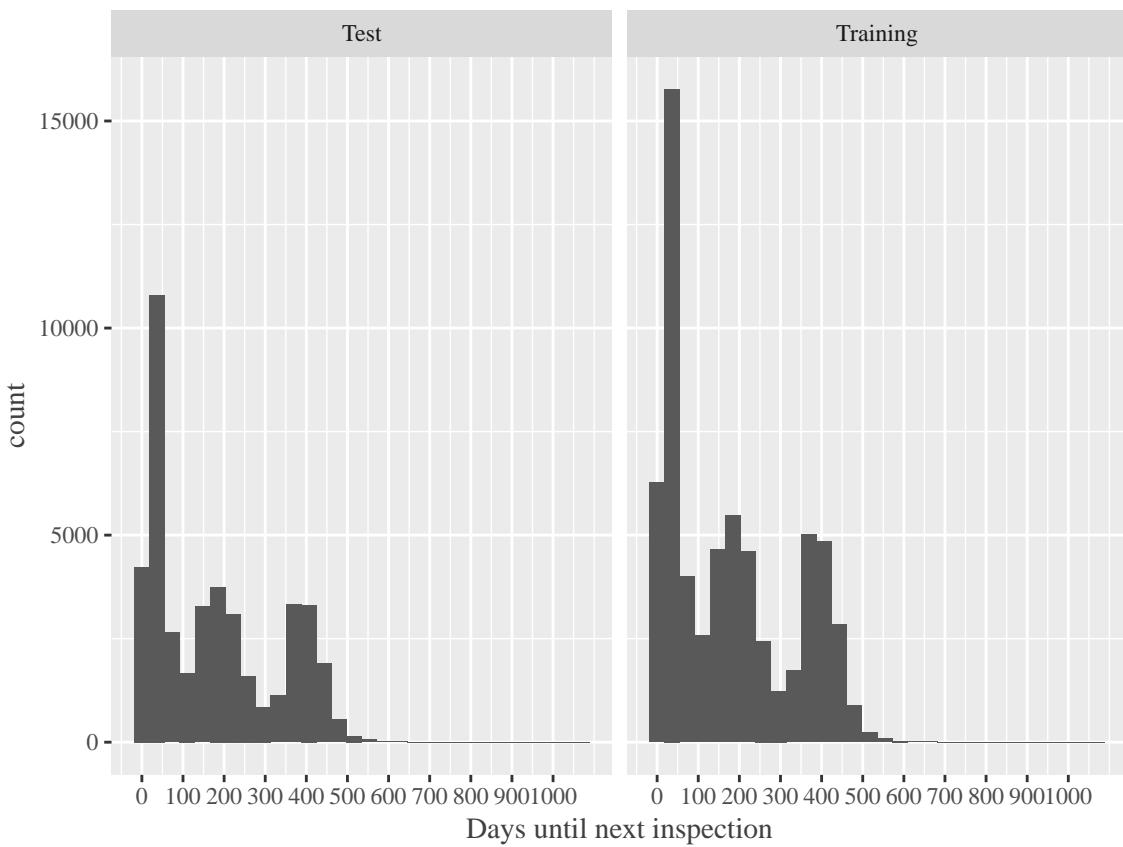
df_raw %>%
  select(id, inspection_date) %>%
  group_by(id, inspection_date) %>%
  arrange(inspection_date) %>%
  summarise() %>%
  mutate(difference = lead(inspection_date) - inspection_date) %>%
  filter(!is.na(difference)) %>%
  mutate(group = ifelse(id %in% train_ids, "Training", "Test")) %>%

```

```

ggplot(aes(as.numeric(difference))) +
  geom_histogram(bins = 30) +
  scale_x_continuous(breaks = seq(0, 1000, by = 100)) +
  xlab("Days until next inspection") +
  facet_grid(. ~ group) +
  theme(
    text = element_text(
      family = "serif",
      color = "gray25"
    )
  )

```



The distribution of the target seems reasonably similar across training and test data.

3.2 Features

Next, we will construct features using the variables in the data set. The result of that construction will be a table, where each row corresponds to an inspection for a given restaurant, containing

- the grade of the inspection (*grade*),
- an indicator whether the row corresponds to an initial inspection(*inspection_type2*),
- the score of the inspection (*score*),
- the cuisine of the restaurant (*cuisine_descr*),
- the number of violations in the different violation_groups (*viol_*), and
- the number of critical flags,

- the number of days until the next inspection (*days_until_next*) which is to be used only in the training data

```

## Create data set with features for inspection type, score, grade and number of violations:

## Make feature set:

make_features_raw <- function ( df ) {

  df %>%
    select ( id, inspection_date, inspection_type2, score,
             grade, cuisine_descr ) %>%
    group_by ( id, inspection_date ) %>%
    arrange ( id, inspection_date ) %>%
    summarise_at ( vars(c("grade", "inspection_type2", "score", "cuisine_descr")),
                  .funs = list(first) ) %>%
    left_join (
      df %>%
        select ( id, inspection_date, starts_with("viol_"), starts_with("critical") ) %>%
        mutate( critical_flag = case_when( critical_flag == "Critical" ~ 1,
                                            TRUE ~ 0 ) ) %>%
        group_by ( id, inspection_date ) %>%
        arrange ( id, inspection_date ) %>%
        summarise_at ( vars(starts_with( "viol" ), starts_with( "critical" ) ),
                      ~ sum( ., na.rm = TRUE ) ),
        by = c ( "id", "inspection_date" ) ) %>%
      ungroup()
    }

# Add target feature

add_target_feature <- function(df) {

  df %>%
    group_by(id) %>%
    arrange(id, inspection_date) %>%
    mutate (
      days_until_next = lead ( inspection_date ) - inspection_date
    ) %>%
    filter(!is.na(days_until_next)) %>%
    ungroup() %>%
    mutate (
      days_until_next_categ =
        case_when (
          between (
            as.numeric ( days_until_next ), 0, 100
            ) ~ "within 3 months",
          between (
            as.numeric ( days_until_next ), 101, 300
            ) ~ "within 3 to 10 months",
          TRUE ~ "in more than 10 months" ),
      days_until_next_categ =
        as_factor ( days_until_next_categ ) ) %>%
}

```

```

ungroup()
}

}
```

As we have seen in the exploration, there are a number of NA's for the features *grade* and *score*. Because the prediction algorithms that we will employ require that there be no missing values, we will impute these values. To impute *score* (*grade*), we will train a regression tree (classification tree) to predict *score* (*grade*) using all the other features on all rows where *score* (*grade*) is not missing.

```

# Impute features

impute_features <- function ( df ) {

  df %>%
    filter(is.na(score)) %>%
    mutate(score =
      predict(df %>%
        filter ( !is.na ( score ) ) %>%
        select (
          score, grade, inspection_type2, cuisine_descr,
          starts_with ( "viol_" ), critical_flag ) %>%
        rpart ( score ~ ., data = ., method = "anova" ), .)
    ) %>%
  bind_rows(df %>% filter(!is.na(score))) %>%
  filter(is.na(grade)) %>%
  mutate(grade =
    predict(df %>%
      filter ( !is.na ( grade ) ) %>%
      select (
        score, grade, inspection_type2, cuisine_descr,
        starts_with ( "viol_" ), critical_flag ) %>%
      rpart ( grade ~ ., data = ., method = "class" ),.,
      type = "class"),
    grade =
    as.character(grade)) %>%
  bind_rows(df %>%
    filter(!is.na(grade)))

}
```

As alluded to above, for the training data we add in *days_until_next*.

```

df_features <- df_raw %>%
  make_features_raw() %>%
  impute_features()

df_train <- df_features %>%
  filter(id %in% train_ids) %>%
  add_target_feature()

df_test <- df_features %>%
  filter(id %in% test_ids)
```

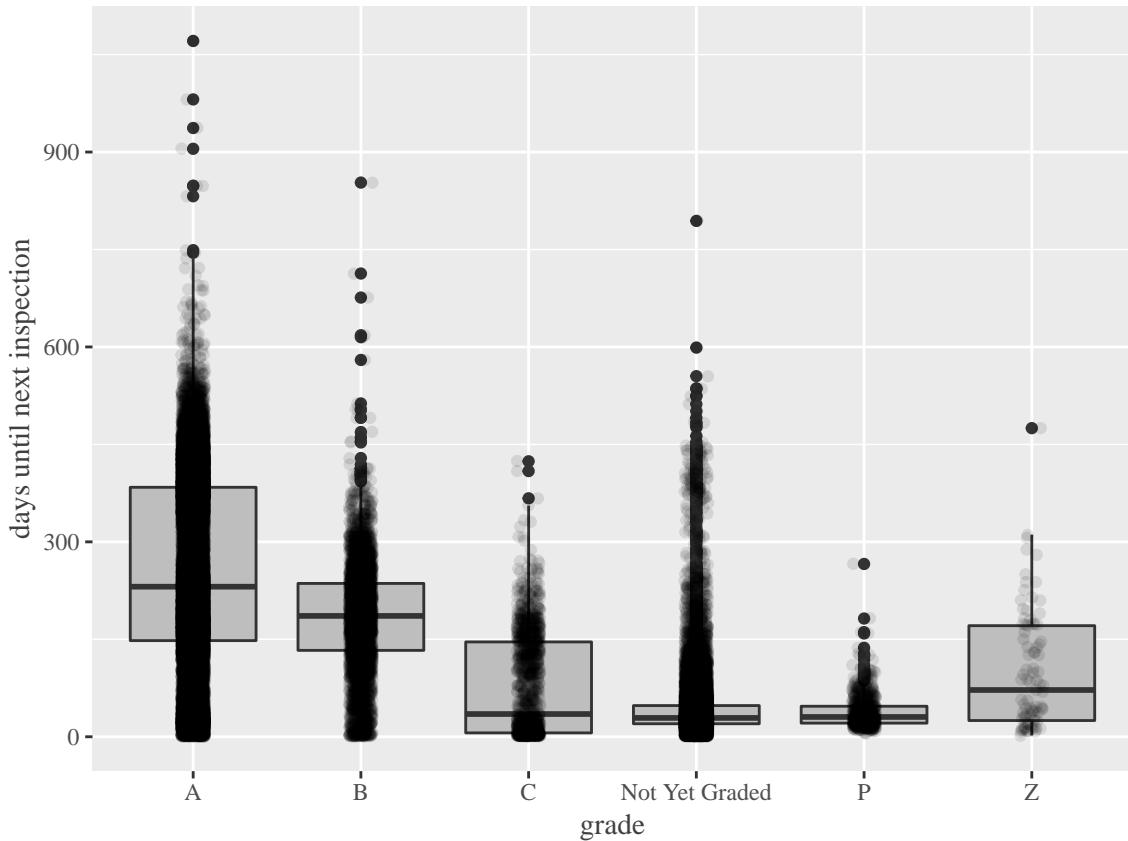
For now, the test data will be removed from the session. Later, we will use it to evaluate the final model.

```
saveRDS(df_test, "df_test.rds")
rm(df_test)
```

3.3 Feature Exploration

Let us first explore a couple of bivariate relationships between the predictors and the target feature. We will begin with the relationship between *grade* and *days until the next inspection*.

```
df_train %>%
  ggplot ( aes ( x = grade, y = as.numeric ( days_until_next ) ) ) +
  geom_boxplot ( fill = "grey" ) +
  geom_jitter(alpha = .1, width = .07) +
  xlab("grade") +
  ylab("days until next inspection") +
  theme(
    text = element_text(
      family = "serif",
      color = "gray25"
    )
  )
)
```



As we can see, the median number of days until the next inspection decreases when moving from A to C. This is not surprising, since a good grade on the initial inspection reduces the likelihood of being subjected to a re-inspection the same inspection cycle.

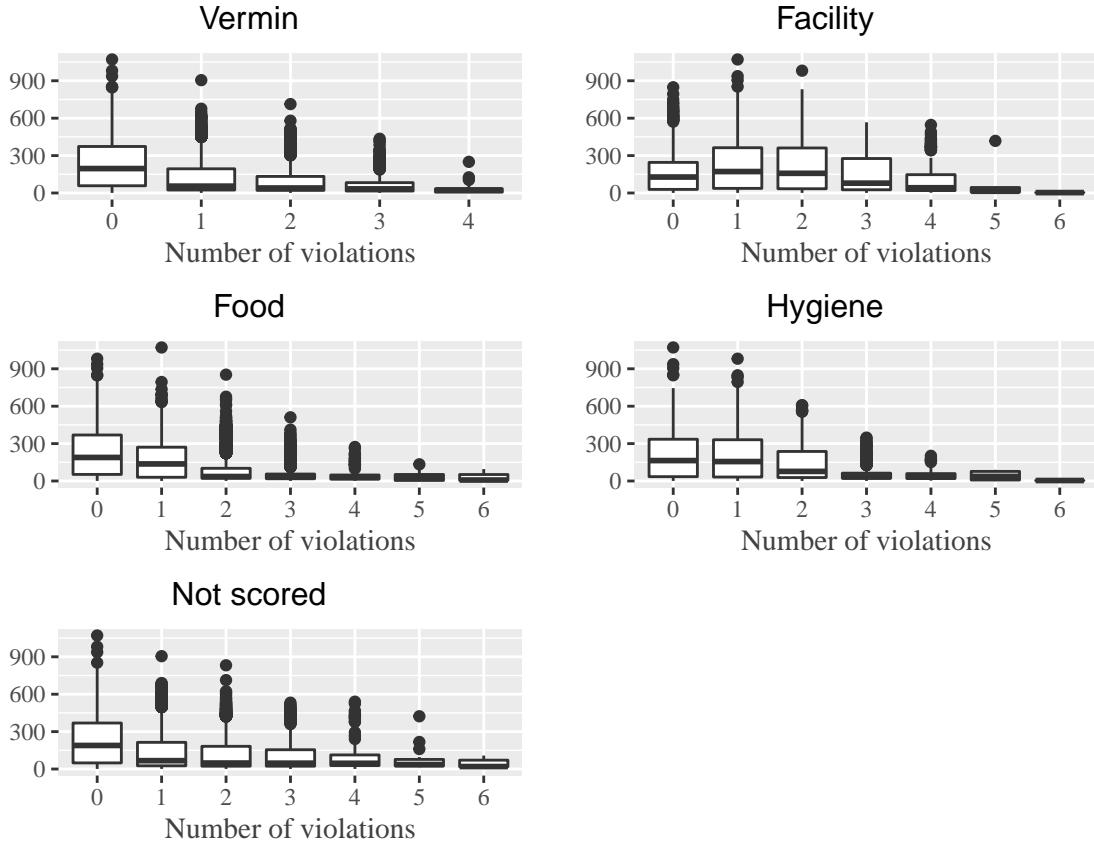
Let us move on to the relationship between violation types and the target feature:

```
# Plotting function
plot_vs_days <- function(z) {

  df_train %>%
    ggplot(aes(x = as.factor(z), y = as.numeric(days_until_next))) +
    geom_boxplot() +
    xlab("Number of violations") +
    ylab("") +
    theme(
      text = element_text(
        family = "serif",
        color = "gray25"
      )
    )
}

# Plot objects
plot_lst <- df_train %>%
  select(starts_with("viol_")) %>%
  map(plot_vs_days)

# Arrange plots in grid
grid.arrange(
  arrangeGrob(plot_lst[[1]], top = "Vermin") ,
  arrangeGrob(plot_lst[[2]], top = "Facility"),
  arrangeGrob(plot_lst[[3]], top = "Food"),
  arrangeGrob(plot_lst[[4]], top = "Hygiene"),
  arrangeGrob(plot_lst[[5]], top = "Not scored"),
  ncol = 2)
```



```
# Remove auxiliary objects
rm(plot_lst)
rm(plot_vs_days)
```

Here also, as expected, the median number of days until the next inspection decreases as the number of violations per inspection increases.

3.4 Linear Regression model

We start with a simple linear regression model, using all features.

```
(lin_reg_model <- df_train %>%
  select(-days_until_next_categ, -id, -inspection_date) %>%
  train(as.numeric(days_until_next) ~ .,
        data = .,
        method = "lm"))
```

```
## Linear Regression
##
## 62767 samples
##    10 predictor
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
```

```

## Summary of sample sizes: 62767, 62767, 62767, 62767, 62767, 62767, ...
## Resampling results:
##
##   RMSE     Rsquared    MAE
##   109.215  0.4772195  79.89552
##
## Tuning parameter 'intercept' was held constant at a value of TRUE

```

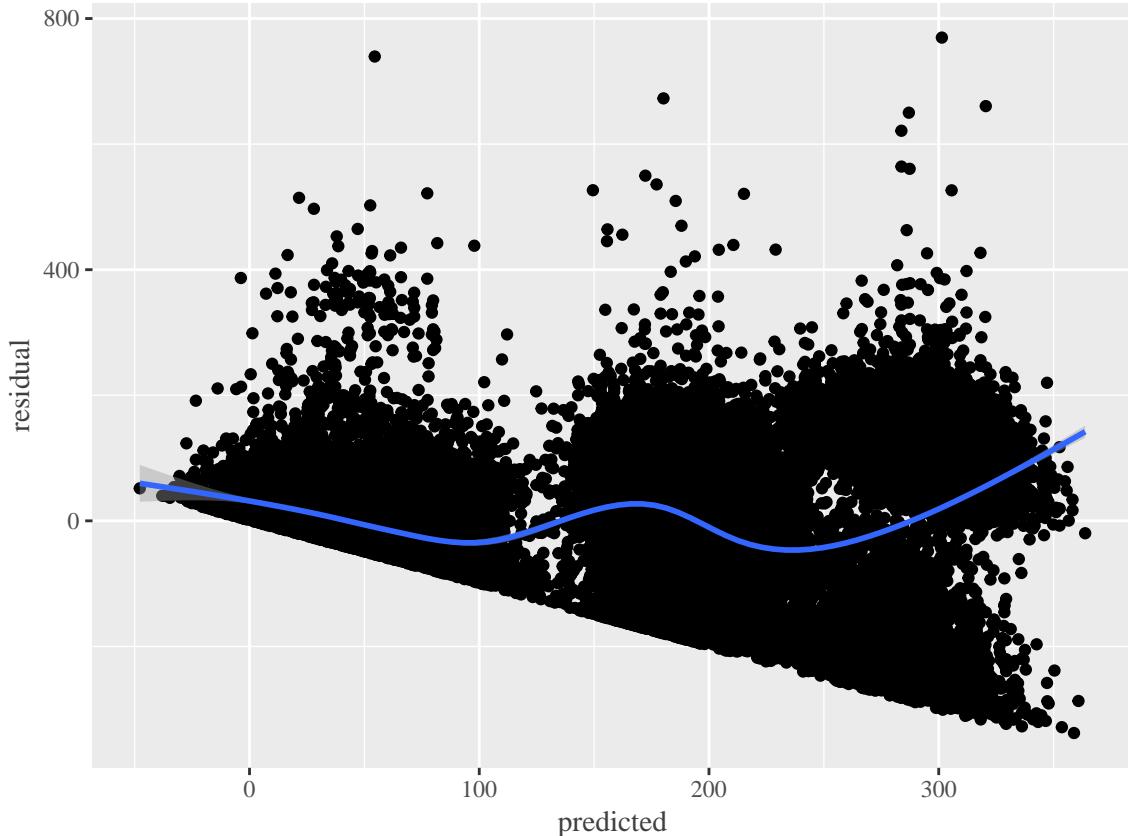
We see that the R squared associated with the model is 0.477, i.e., 47 percent of the variation in the data can be ‘explained’ in terms of the linear regression model. Let us look at the residual plot:

```

df_lin_reg <- data_frame(actual = as.numeric(df_train$days_until_next),
                           predicted = as.numeric(predict(lin_reg_model, df_train)),
                           residual = actual - predicted)

df_lin_reg %>%
  ggplot(aes(x = predicted, y = residual)) +
  geom_point() +
  geom_smooth() +
  theme(
    text = element_text(
      family = "serif",
      color = "gray25"
    )
  )
)

```



There are a few curious things to notice about the plot. First, apparently there is a set of restaurants for which the model predicts a negative duration until the next inspection, which does not make sense. Second, there seems to be some pattern in the residuals. In the presence of nonlinearities, the conclusions drawn from the fit are questionable. At this point, one could investigate how these patterns in the residuals come about. Instead, in the next section, we will fit a nonlinear regression model to the data.

3.5 Regression tree

The linear regression model didn't perform well. The residual plot suggests that a linear model may not be appropriate model. Hence, we will use a more flexible model and fit a regression tree model. First, we set the hyperparameters:

```
# Set hyperparameters for cross-validated classification and regression tree
set.seed(42)
myControl <- trainControl(
  method = "cv",
  number = 10
)
cp.grid <- expand.grid(.cp = (1:10)*0.01)
```

Then we fit the model, employing 10-fold cross validation:

```
set.seed(3333)
(reg_tree_model <-
  df_train %>%
    select(-days_until_next_categ,
           -id,
           -inspection_date) %>%
  train(as.numeric(days_until_next) ~ .,
        data = .,
        method = "rpart",
        trControl = myControl,
        tuneGrid = cp.grid))

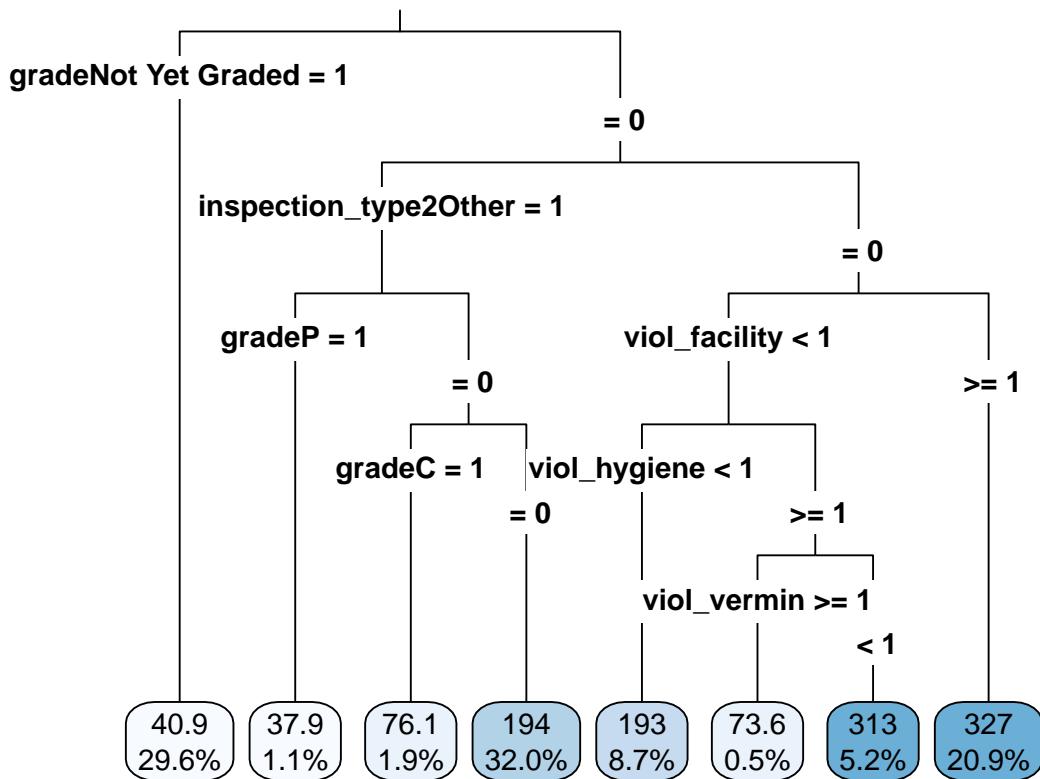
## CART
##
## 62767 samples
##     10 predictor
##
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 56490, 56489, 56491, 56491, 56490, 56492, ...
## Resampling results across tuning parameters:
##
##     cp      RMSE      Rsquared      MAE
##     0.01    105.5183   0.5123524   72.32293
##     0.02    110.5336   0.4648770   77.94083
##     0.03    110.5336   0.4648770   77.94083
##     0.04    113.9228   0.4315671   82.14456
##     0.05    113.9228   0.4315671   82.14456
```

```

##   0.06 113.9228 0.4315671 82.14456
##   0.07 113.9228 0.4315671 82.14456
##   0.08 113.9228 0.4315671 82.14456
##   0.09 122.2085 0.3458682 93.62115
##   0.10 122.2085 0.3458682 93.62115
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was cp = 0.01.

library(rpart.plot)
rpart.plot ( reg_tree_model$finalModel, type = 3, digits = 3, fallen.leaves = TRUE )

```



The model has a slightly higher R squared than the linear regression model. Nevertheless, the fit of the regression to the training data is quite poor.

3.6 Reformulating the problem: Classification

As we have seen, linear regression and regression trees did a poor job of predicting the number of days until the next inspection. So let us try to rephrase the problem. Instead of predicting the number of days, we could give a time interval into which the next inspection will fall. To do that, let's have a look at the distribution of the target feature again.

```

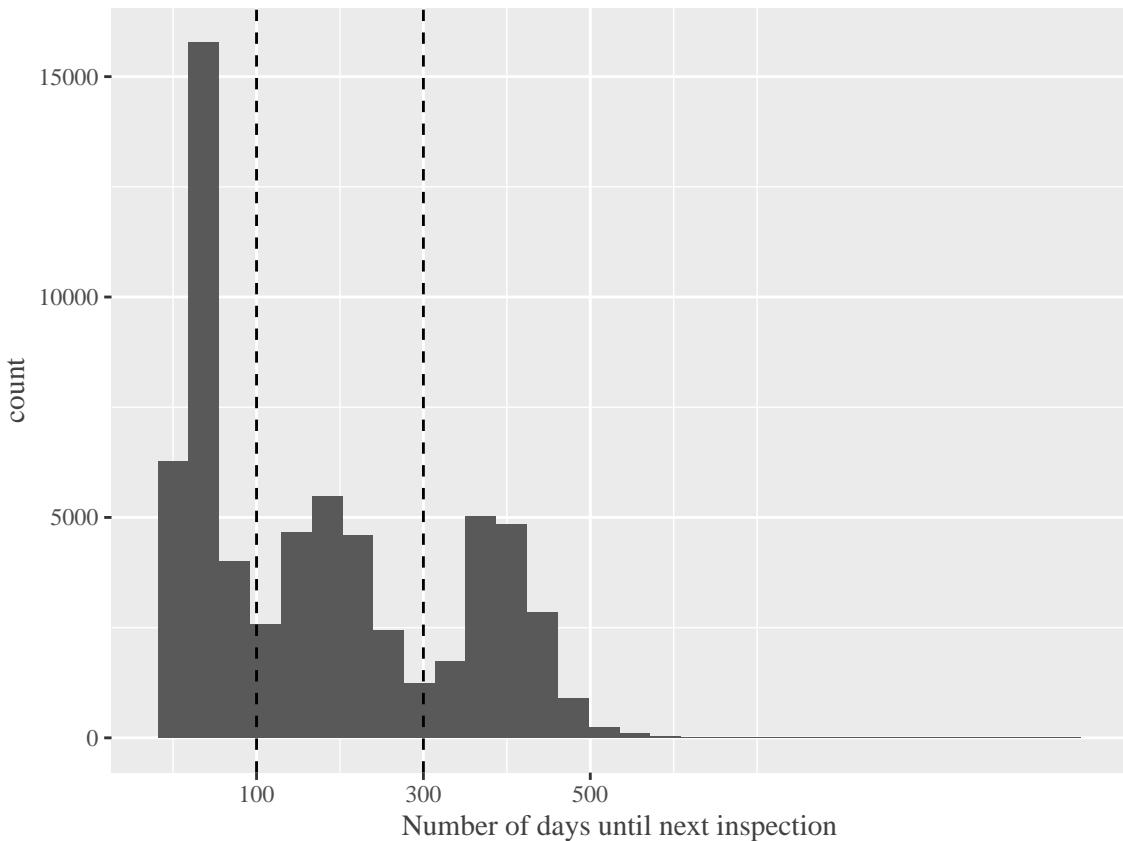
df_train %>%
  ggplot(aes(x = as.numeric(days_until_next))) +
  geom_histogram(bins = 30) +

```

```

geom_vline(xintercept = c(100, 300), linetype = "dashed") +
scale_x_continuous(breaks = c(100, 300, 500)) +
theme(
  text = element_text(
    family = "serif",
    color = "gray25"
  )
) +
xlab("Number of days until next inspection")

```



We can see that there are three humps in the distribution, with borders roughly at 100, 300 and 500, respectively. Hence, we will construct a categorical feature corresponding

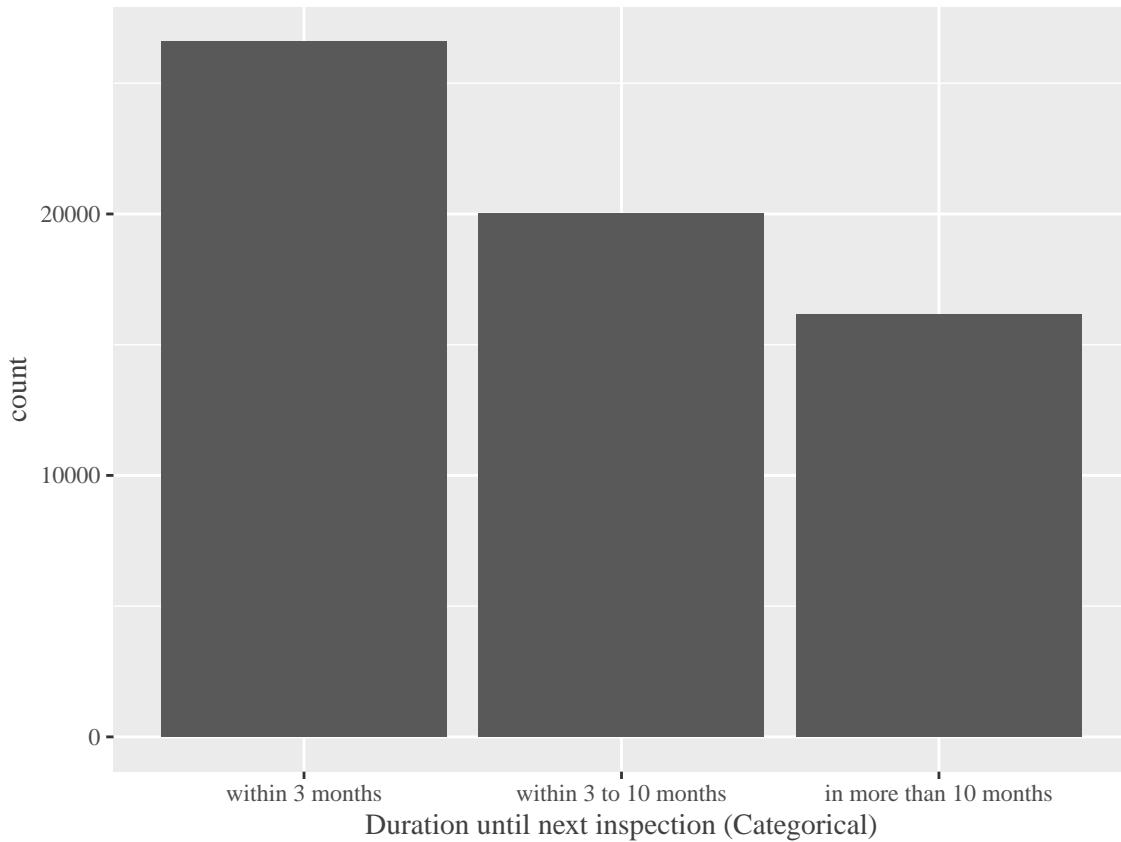
We have already constructed a categorical variable corresponding to those intervals labelled *within 3 months*, *within 10 months* and *in more than 10 months*. The distribution of the new target in the training data looks like this:

```

df_train %>%
ggplot(aes(days_until_next_categ)) +
geom_bar() +
xlab("Duration until next inspection (Categorical)") +
theme(
  text = element_text(
    family = "serif",
    color = "gray25"
)

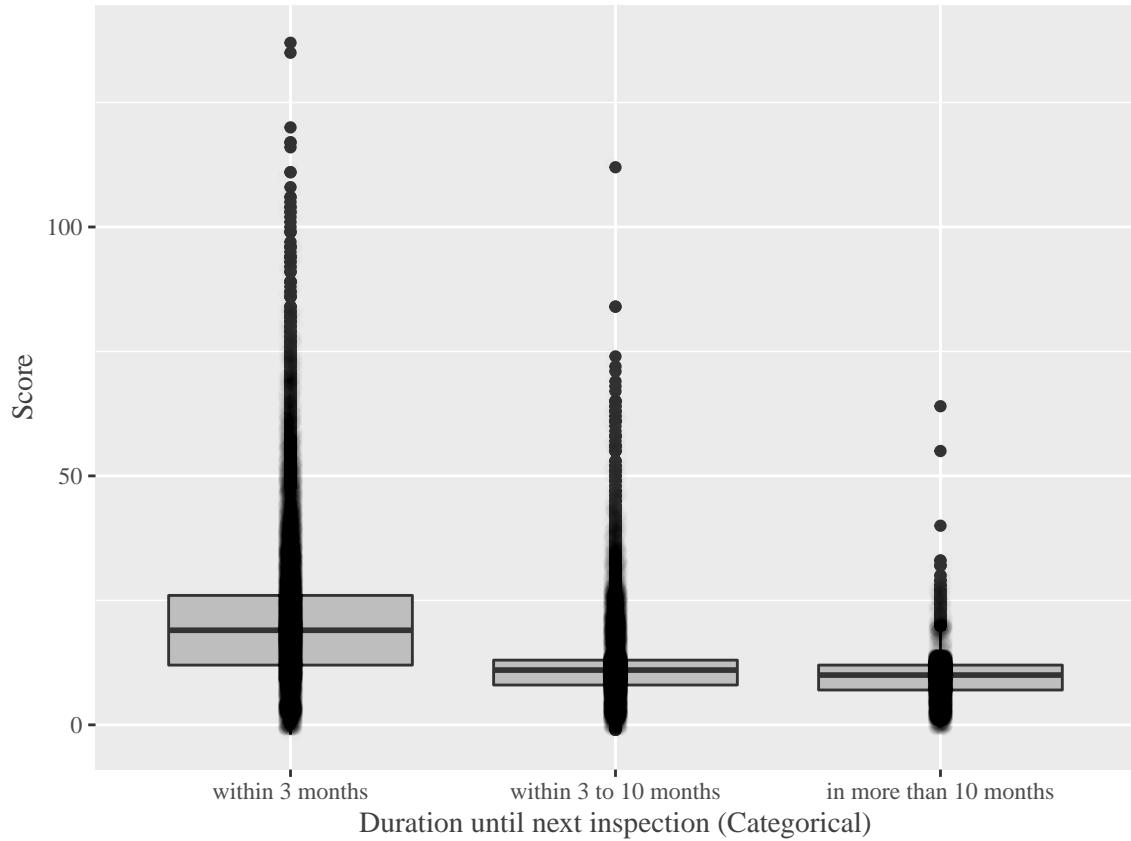
```

```
)
```

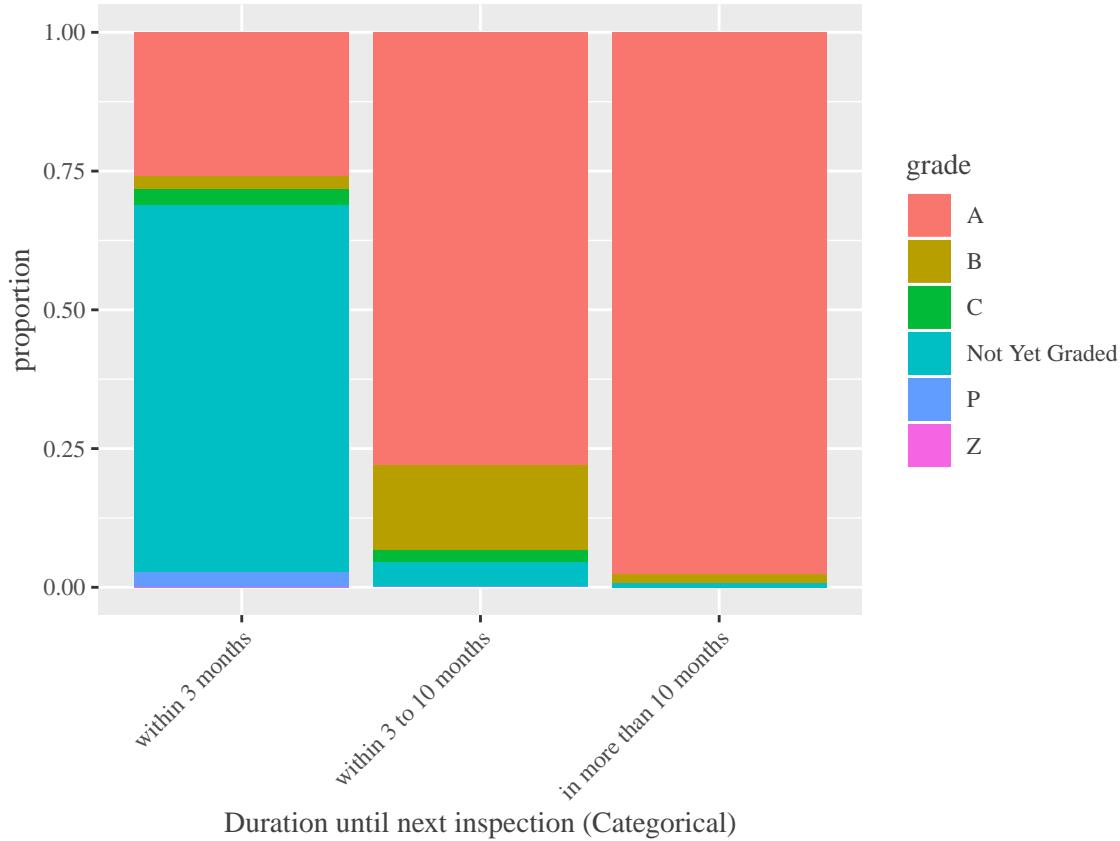


As we can see, for most inspections, the next inspection occurs within the next 2 to 3 months. Let us investigate bivariate relationships between some of the features and the new target:

```
df_train %>%
  ggplot ( aes ( x = days_until_next_categ, y = score ) ) +
  geom_boxplot ( fill = "grey" ) +
  geom_jitter(alpha = .01, width = .02, height = 1) +
  xlab("Duration until next inspection (Categorical)") +
  ylab("Score") +
  theme(
    text = element_text(
      family = "serif",
      color = "gray25"
    )
  )
```



```
df_train %>%
  ggplot ( aes ( x = days_until_next_categ , fill = grade) ) +
  geom_bar ( position = "fill" ) +
  ylab("proportion") +
  xlab("Duration until next inspection (Categorical)") +
  theme(
    text = element_text(
      family = "serif",
      color = "gray25"
    ),
    axis.text.x = element_text(angle = 45, hjust = 1)
  )
```



Not surprisingly, among those inspections for which the next inspection occurs within the next 2 to 3 months, the median score is higher than for the other two categories. Also, the proportion of inspections receiving an ‘A’ is higher among inspections where the duration until the next inspection is longer. This is also something we would expect.

3.6.1 Classification model

Next, we will fit a classification tree to the data, employing 10-fold cross validation:

```
set.seed(3333)
(class_tree_model <- df_train %>% select(-days_until_next, -id, -inspection_date) %>%
  train(days_until_next_categ ~ .,
        data = .,
        method = "rpart",
        trControl = myControl,
        tuneGrid = cp.grid)
)

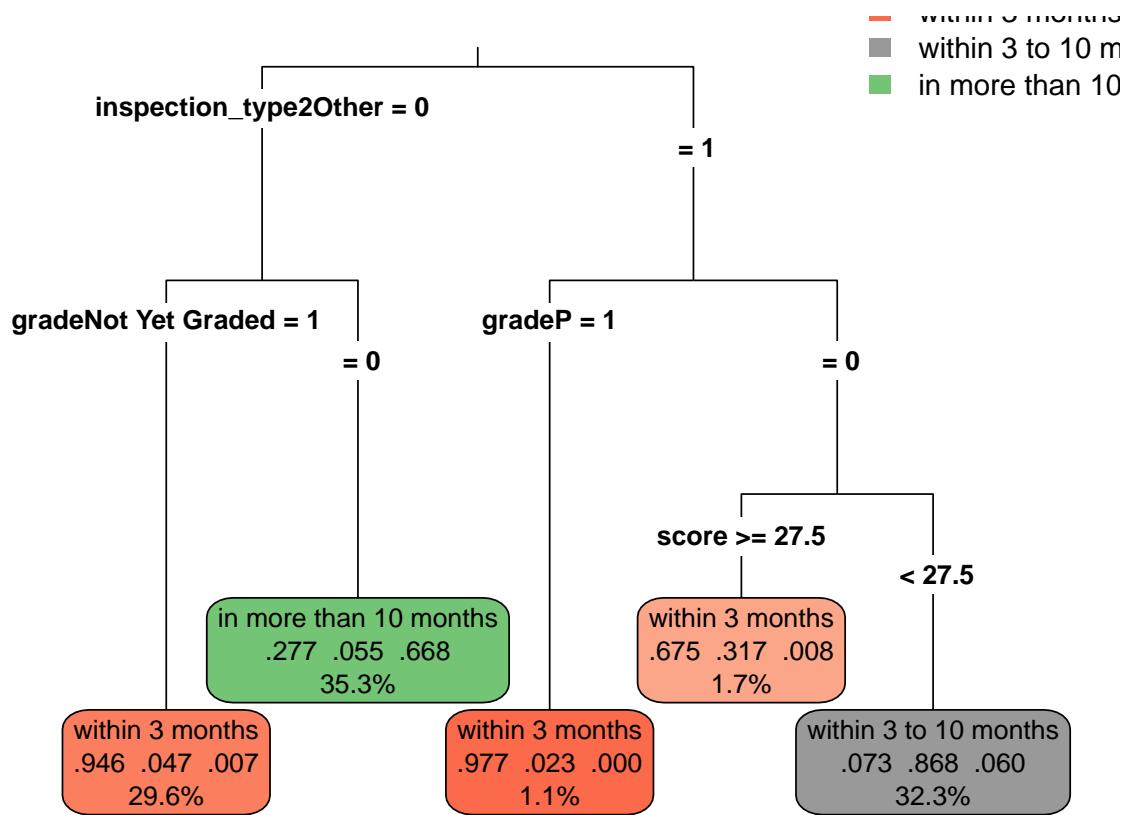
## CART
##
## 62767 samples
##    10 predictor
##      3 classes: 'within 3 months', 'within 3 to 10 months', 'in more than 10 months'
##
## No pre-processing
```

```

## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 56490, 56491, 56491, 56490, 56490, 56490, ...
## Resampling results across tuning parameters:
##
##   cp    Accuracy   Kappa
##   0.01  0.8202559  0.7305833
##   0.02  0.8022048  0.7055560
##   0.03  0.8022048  0.7055560
##   0.04  0.8022048  0.7055560
##   0.05  0.8022048  0.7055560
##   0.06  0.8022048  0.7055560
##   0.07  0.8022048  0.7055560
##   0.08  0.8022048  0.7055560
##   0.09  0.8022048  0.7055560
##   0.10  0.8022048  0.7055560
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was cp = 0.01.

rpart.plot ( class_tree_model$finalModel, type = 3, digits = 3, fallen.leaves = TRUE )

```



Looking at the tree, we see that, once we condition on whether the inspection at hand is initial or not, higher scores are associated with shorter time periods until the next inspection. Furthermore, looking at the left branch of the tree, non-initial inspections that are graded are predicted to be re-inspected within the next 2 to 3 months, provided the recorded score is above 27.

The accuracy of the model is 0.819. Let us look at additional measures of performance:

```

confusionMatrix(data = predict(class_tree_model, df_train),
                 reference = df_train$days_until_next_categ)

## Confusion Matrix and Statistics
##
##                               Reference
## Prediction              within 3 months within 3 to 10 months
##   within 3 months           18989                  1219
##   within 3 to 10 months      1471                  17593
##   in more than 10 months     6138                  1212
##                               Reference
## Prediction              in more than 10 months
##   within 3 months            130
##   within 3 to 10 months       1209
##   in more than 10 months     14806
##
## Overall Statistics
##
## Accuracy : 0.8187
## 95% CI : (0.8157, 0.8217)
## No Information Rate : 0.4238
## P-Value [Acc > NIR] : < 2.2e-16
##
## Kappa : 0.729
## Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                               Class: within 3 months Class: within 3 to 10 months
## Sensitivity                      0.7139                  0.8786
## Specificity                       0.9627                  0.9373
## Pos Pred Value                   0.9337                  0.8678
## Neg Pred Value                   0.8207                  0.9428
## Prevalence                        0.4238                  0.3190
## Detection Rate                   0.3025                  0.2803
## Detection Prevalence             0.3240                  0.3230
## Balanced Accuracy                 0.8383                  0.9079
##                               Class: in more than 10 months
## Sensitivity                      0.9171
## Specificity                       0.8423
## Pos Pred Value                   0.6683
## Neg Pred Value                   0.9670
## Prevalence                        0.2572
## Detection Rate                   0.2359
## Detection Prevalence             0.3530
## Balanced Accuracy                 0.8797

```

For all models, sensitivity and specificity are at least 0.84 for all classes, except for the third class, for which sensitiviy is at 0.71. The model

3.7 Evaluation of final model

Finally we evaluate the final model on the test data:

```

df_test <- readRDS("df_test.rds") %>% add_target_feature()

confusionMatrix(data = predict(class_tree_model, df_test),
                 reference = df_test %>%
                   pull(days_until_next_categ))

## Warning in confusionMatrix.default(data = predict(class_tree_model,
## df_test), : Levels are not in the same order for reference and data.
## Refactoring data to match.

## Confusion Matrix and Statistics
##
##                                     Reference
## Prediction          in more than 10 months within 3 months
##   in more than 10 months             9879        4174
##   within 3 months                  86        12885
##   within 3 to 10 months            743        944
##                                     Reference
## Prediction          within 3 to 10 months
##   in more than 10 months             824
##   within 3 months                  825
##   within 3 to 10 months            12039
##
## Overall Statistics
##
##           Accuracy : 0.8208
##           95% CI : (0.8172, 0.8245)
##   No Information Rate : 0.4246
##   P-Value [Acc > NIR] : < 2.2e-16
##
##           Kappa : 0.7321
##   Mcnemar's Test P-Value : < 2.2e-16
##
## Statistics by Class:
##
##                                     Class: in more than 10 months Class: within 3 months
## Sensitivity                         0.9226        0.7157
## Specificity                          0.8423        0.9627
## Pos Pred Value                      0.6640        0.9340
## Neg Pred Value                      0.9699        0.8211
## Prevalence                           0.2526        0.4246
## Detection Rate                      0.2330        0.3039
## Detection Prevalence                0.3509        0.3254
## Balanced Accuracy                   0.8824        0.8392
##
##                                     Class: within 3 to 10 months
## Sensitivity                         0.8795
## Specificity                          0.9412
## Pos Pred Value                      0.8771
## Neg Pred Value                      0.9425
## Prevalence                           0.3228
## Detection Rate                      0.2839
## Detection Prevalence                0.3237
## Balanced Accuracy                   0.9104

```

Hence, the performance of the model on the test data is similar to the performance on the training data.

4 Conclusion

Our initial goal of predicting the number of days until the next inspection could not be attained. Instead, we rephrased the problem and turned it into a classification problem. The classes are derived from the distribution of the target feature. Then, we fit a classification tree on the training data, using 10-fold cross validation. The model with the lowest cross-validation error also performed well on the test data.

The model can be used by food service establishments to predict a time interval in which the next inspection is likely to fall. Strictly speaking, we failed to deliver on the initial objective of predicting the number of days until the next inspection. But for practical purposes, it may already be useful to have a rough estimate of when to expect the next inspection.

As a next step, we could employ the model in an interactive application that takes the ID of a restaurant and predicts the time interval until the next inspection.