An Analysis on Commercial Real Estate Property Assessment and Property Tax in B.C.

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Summary

Property taxes are the single greatest operating expense for property owners in British Columbia, and mainly depend on two factors: property assessment—published each year in January—and municipal mill rates—published in April. Accurately projecting annual mill rates between January and April and future years' assessment values between May and December would allow businesses and individuals to budget for these expenses. For this purpose, multiple competing models are fitted based on a data set containing assessment values, mill rates, and other property information from 2016 to 2020 of over 200,000 properties. For predicting mill rates early in the year, a random forest regression model is found to be the most accurate. Likewise, another random forest regression model is also the most accurate for predicting future years' assessment values. Both models are incorporated in an interactive Shiny app that provides a straightforward user interface with a property-specific tax assessment.

1 Introduction

For property owners in British Columbia, property taxes are the single greatest operating expense. Mill rates are determined by individual municipalities and depend on a number of factors, including assessment values and municipal budgets. While property assessments are published each year in January, municipal mill rates are not determined until April of the same calendar year, making it difficult for property owners to budget for this large expense. Thus, accurately projecting the annual mill rates between the months of January and April and the next year's assessment values between May and December is a value-add to real estate consulting services. Furthermore, it also assists property owners in financial planning and fund allocation. The objective of this written report is to build accurate statistical predictive models for both future municipal mill rates and property-specific assessment values. This will be done for tax class codes 1 (residential), 5 (light industrial), and 6 (commercial). Guided by the exploratory data analysis in Section 2.2, several modeling techniques are presented in Section 2.3. Mill rate and assessment predictions using these models are available through a straightforward user interface via a Shiny app, which is discussed in the same section. Finally, Section 3 includes some concluding remarks.

2 Statistical analysis

2.1 Data

Han et al. (2020) use the same dataset and offer a thorough description of the data in their analysis. In this report, however, all B.C. municipalities are included in analysis. The variables are summarised in Table 1. Missing mill rate values were imputed by using the average municipality mill rate for the corresponding year and tax class code. This is sensible because mill rates are constant across municipalities, and so a more complex imputation technique is not necessary.

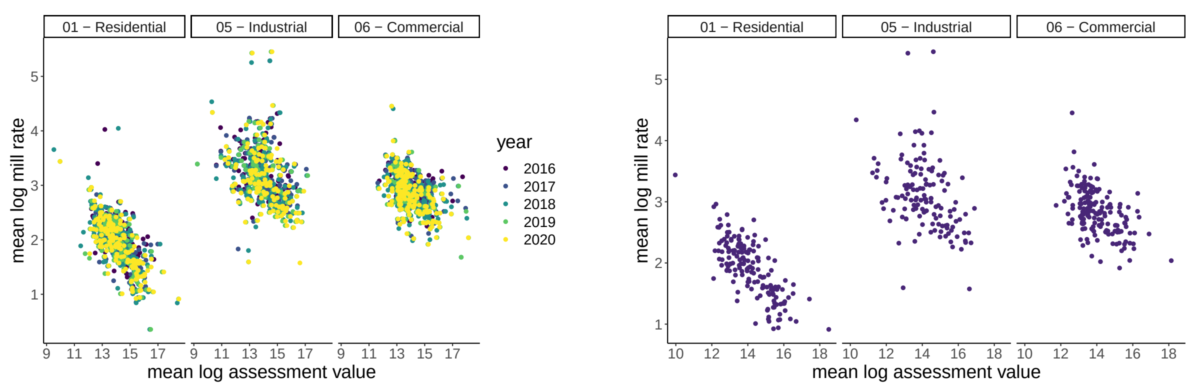
An important feature of the data is that spatial relationships exist within municipalities for assessment values and between municipalities for mill rates. In other words, it is not sensible to assume independence in neither assessment values nor mill rates between different properties because geographical location (and thus proximity) affects these variables. This significantly influences possible model choices as the independence assumption is required for several standard modeling techniques. Furthermore, the data set lacks appropriate spatial information that would allow for geographical variables to be taken into account.

Variable	Type
Mill rate	Continuous
Total assessment	Continuous
Total land assessment	Continuous
Total improvement assessment	Continuous
Tax class code	Categorical. One of 1 (residential), 5 (industrial), 6 (commercial)
Municipality	Categorical
Year	Discrete. Values of 2016, 2017, 2018, and 2019

Table 1: Brief description of the variables included in the data set.

2.2 Exploratory data analysis

The exploratory data analysis (EDA) further investigates aspects of the EDA done by Han et al. (2020). Both assessment values and mill rates have right-skewed distributions, and so they were log-transformed for visualization purposes. A visual inspection of Figure 1a shows that mill rates differ drastically from tax class to tax class, with industrial properties having the highest mill rates. However, neither mill rates nor assessment values seem to vary much over time, which suggests that current values of these variables will be a good indicator of their (short-term) future values. Furthermore, there does not appear to be a clear relationship between assessment values and mill rates when tax class is taken into account—except in the residential tax class, where a slightly negative relationship is present between the logarithms of average municipal assessment values and municipal mill rates. This remains true when only taking into account values from 2020, as can be seen in Figure 1b.



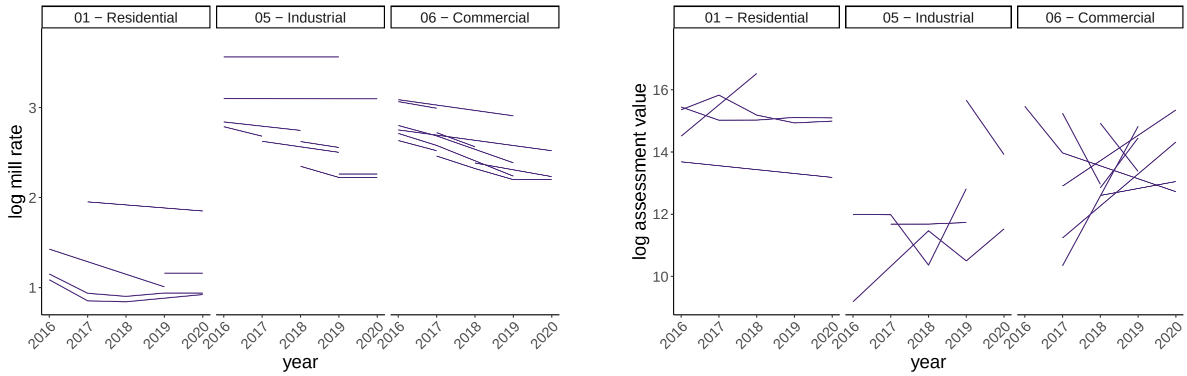
(a) Scatterplot with year in different colors.

(b) Scatterplot only for 2020.

Figure 1: Average log assessment values against log mill rates by municipality across the three different tax classes of interest.

The fact that mill rates remain relatively constant throughout the years is further verified in Figure 2a, where industrial properties are again seen to have the largest mill rates on average. However, Figure 2b suggests that assessment values do not follow this pattern. Municipality plays a role in a property's assessments, something taken into account in the modeling process.

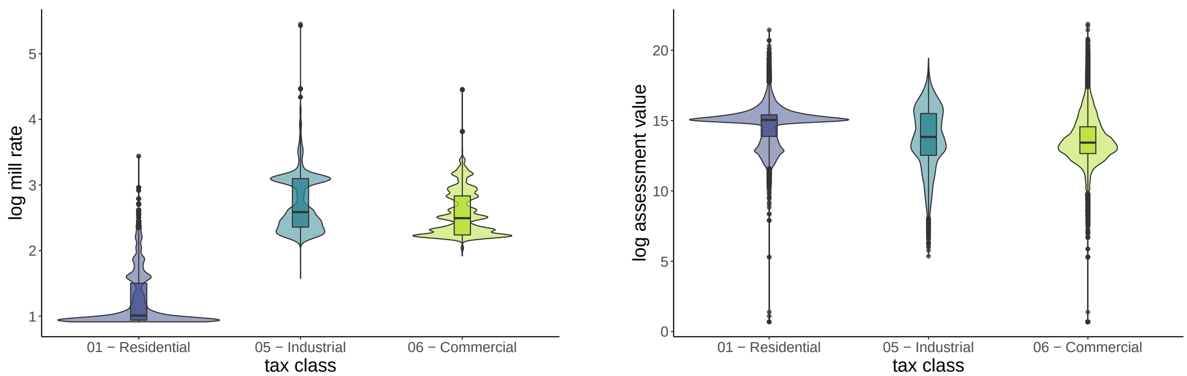
Finally, Figure 3 shows that the distributions of both mill rates and assessment values are indeed right-skewed (the values shown are in logarithmic scale), and further confirms the stark difference in mill rates between the three tax classes. Notably, Figure 3b suggests that this difference is not present in assessment values, which indicates that tax class may not be that relevant for predicting future years' assessment values.



(a) Evolution of (log) mill rates.

(b) Evolution of (log) assessment values.

Figure 2: Evolution of target variables over the years for some randomly-selected properties.



(a) Distribution of (log) mill rates.

(b) Distribution of (log) assessment values.

Figure 3: Violin and boxplots of (log) mill rates and (log) assessment values of individual properties across the three tax classes of interest, taking into account only the year 2020.

2.3 Modeling

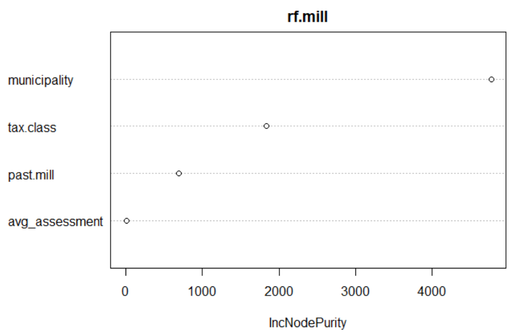
This section describes the models used to predict mill rate and assessment values. Each of the following models were trained on a subset of 75% of the data and tested on the remaining 25%.

2.3.1 Random forest regression

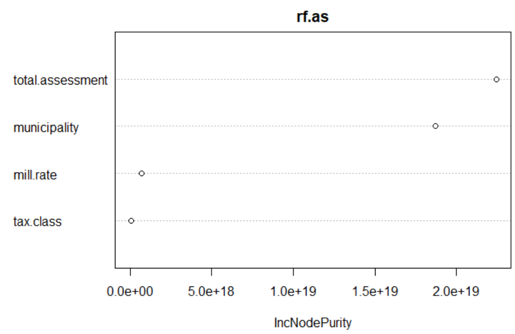
The random forest (RF) algorithm is an ensemble learning method for classification and regression that operates by constructing numerous decision trees and choosing the majority class output (classification) or the average prediction (regression) given by the individual decision trees. Decision trees are trained on different samples (with replacement) of the data, and only a random subset of the covariates is used to define the split at each node, based on a recursive partitioning strategy. RF is preferred over a single decision tree as it overcomes the problem of over-fitting. The following models were constructed using the 'randomForest' package in R (Liaw & Wiener, 2002).

A RF model was fitted to predict mill rate using tax class, municipality, past years' mill rate, and current years' total assessment as independent variables. Another RF model was similarly constructed using next year's assessment value as the dependent variable, and municipality, current years' mill rate, tax class, and current years' total assessment as covariates. The number of trees used for both models was 500, and all 4 predictors were evaluated at each node for splitting. The percent of total variability explained is 96.38 % for the mill rates model and 97.48 % for the assessment values model.

The importance of model covariates is indicated by a higher value of increase node purity (mean decrease accuracy). Municipality was deemed the most important variable in predicting mill rate (see Figure 4a), followed by tax class and past year's mill rate. However, as shown in Figure 4b, current years' assessment value is the most important variable in predicting next years' assessment value, followed by municipality and mill rate.



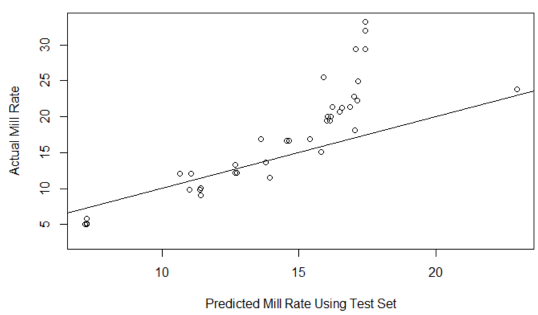
(a) Variable importance plot for mill rates.



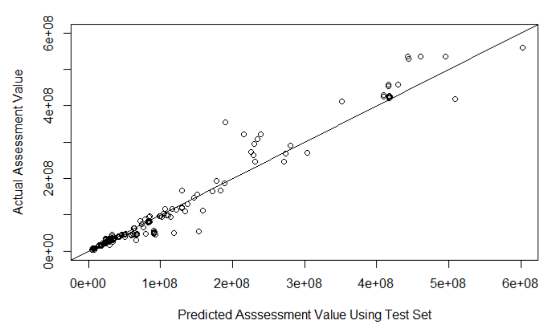
(b) Variable importance plot for assessment values.

Figure 4: Variable importance plot based on increase in node purity for mill rate and total assessment value predictions.

Figure 5 shows the evaluation of the model's performance on a test dataset. The RF model tends to underestimate mill rates, probably due to the greater difficulty of the task. However, RF shows good performance in predicting next year's assessment values.



(a) Performance for mill rates prediction.



(b) Performance for assessment value prediction.

Figure 5: Models' performance on test set.

2.3.2 Mixed effects models and generalized estimating equation

Since the data set contains repeated measurements for both municipalities and properties over the years, it is reasonable to consider a linear mixed effect model (LME) for predicting mill rates and assessment values. Both random slope and random intercept for each municipality are needed based on Figure 2b, which depicts different initial values and rates of change for both assessment values and municipal mill rates. Based on the fixed effects shown in Figure 6b, the direction of change in assessment values fluctuates over time. For example, assessment values increased from 2016 to 2017 but decreased from 2018 to 2020. The median municipal assessment value is positively associated with current mill rate, as is past year's mill rate (Figure 6a). A negative relationship between mill rate and assessment values is observed in Figure 6b, indicating that lower mill rates are associated with higher assessment values.

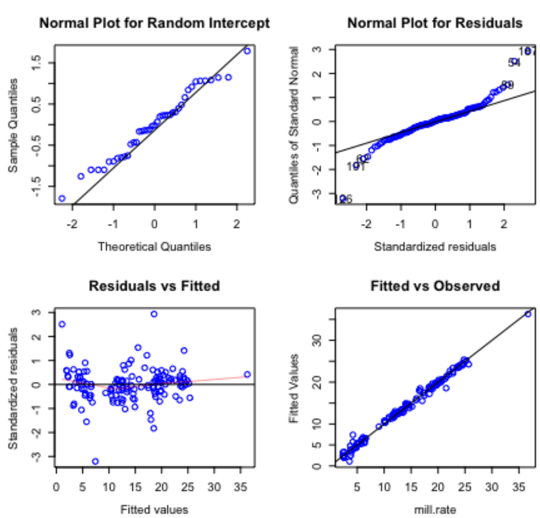
```
Random effects:
 Groups       Name        Variance  Std.Dev. Corr
 municipality (Intercept) 7.023e-01 0.838028
              year        1.868e-06 0.001367 1.00
 Residual                 7.037e-01 0.838889
Number of obs: 141, groups:  municipality, 41

Fixed effects:
                     Estimate Std. Error t value
(Intercept)         1.451e+00  1.101e+00   1.318
as.factor(year)2018 -6.181e-01  2.080e-01  -2.972
as.factor(year)2019 -1.098e+00  2.303e-01  -4.766
as.factor(year)2020 -8.532e-01  2.596e-01  -3.287
tax.class05         1.728e+01  2.774e+00   6.228
tax.class06         1.125e+01  6.965e-01  16.152
avg_assessment      3.583e-07  3.668e-07   0.977
past.mill           2.979e-01  4.012e-02   7.425
```

(a) Summary output for predicting mill rates.

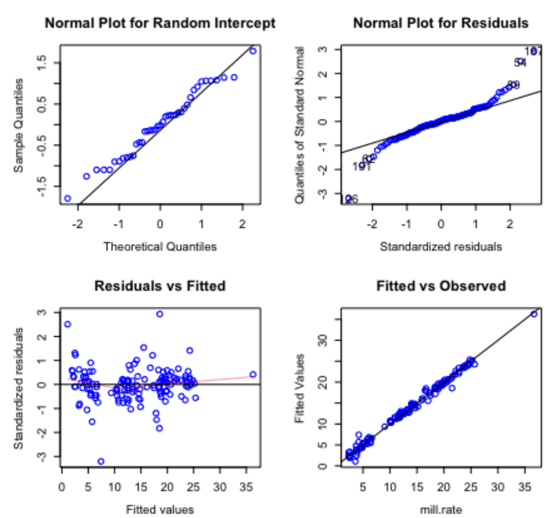
```
Random effects:
 Groups       Name        Variance  Std.Dev. Corr
 municipality (Intercept) 3.832e+15 61900409
              year        1.061e+09    32572 -1.00
 Residual                 3.825e+15 61846281
Number of obs: 753, groups:  municipality, 52

Fixed effects:
                     Estimate Std. Error t value
(Intercept)         -4.150e+06  9.212e+06  -0.450
as.factor(year)2017  7.074e+06  7.467e+06   0.947
as.factor(year)2018  1.229e+07  7.250e+06   1.695
as.factor(year)2019 -1.247e+07  7.304e+06  -1.707
as.factor(year)2020 -4.888e+06  1.152e+07  -0.424
tax.class05          1.006e+07  1.281e+07   0.786
tax.class06          1.308e+07  7.535e+06   1.735
total.assessment     1.028e+00  8.108e-03 126.731
mill.rate           -3.575e+05  4.714e+05  -0.758
```

(b) Summary output for predicting assessment values.

Figure 6: Models summary output.



(a) Diagnostics plots for LME model for mill rate.



(b) Diagnostics plots for LME model for assessment values.

Figure 7: Diagnostics plots.

Unfortunately, the diagnostics plots verifying model assumptions are subpar for both LME models, as can be seen in Figure 7. Residuals are not normally distributed, variance is heterogeneous, and random intercept is non-normal. Thus it does not appear that an analysis using this type of model is appropriate for this data.

2.3.3 Shiny app

A straightforward user interface for making predictions using the RF models for mill rate and assessment values was built by way of a shiny app, which can be found in the GitHub repository (Di-Luvi et al., 2020) or accessed on the web at https://malloryjflynn.shinyapps.io/STAT550_Real_Estate/.

The shiny app calculates predictions of the next years' mill rate or assessment value under the 'Estimate' tab of the main panel. This can be done using either a Property Identifier Code (PIC) or user inputs for municipality, tax class code, and previous year's mill rate (mill rate predictions) or current assessment value (assessment value predictions). To provide the user with a broader view of the trend in mill rate for the municipality selected, a plot of the mill rate for that municipality over the years (2016 - 2020) is visible under the 'Plot' tab of the main panel. When predicting assessment value using a PIC, a plot of the assessment value for that property over time will be displayed alternatively.

3 Conclusions

In this report we built models to predict mill rate and assessment value for properties in British Columbia's municipalities. Random forest was found to be the best fitting model, although it tended to overestimate mill rate predictions. In addition to this, we incorporated the predictive models in a shiny app that allows a user to perform predictions given a set of inputs and to visualize trends in mill rate and assessment value.

The main limitation of our analysis lies in the fact that the models assume independence of the data. However, as was argued in Section 2.1, mill rates and assessment values are highly dependent on spatial information. An attempt to obtain the properties' spatial information was made by transforming the addresses into spatial coordinates using an open source geocoding system provided by the British Columbia Government (see the documentation of Esmukov and Tigas (2018)). However, the open source geocoding system did not recognize some of the addresses in the dataset and provided incorrect coordinates for a large number of properties. Therefore it is recommended that (1) addresses be formatted according to the standards required by the B.C. government, or (2) a private geocoding system that may be able to find addresses using the current format in the data is used. Provided spatial information is available, several model alternatives (e.g. factor models) could be tested to improve prediction accuracy, which take spatial information into account.

References

Di-Luvi, G. C., Flynn, M., Li, S., & Romaniello, V. (2020). *Stat450-550: Real estate consulting project.* Retrieved April 13, 2020, from https://github.com/STAT450-550/RealEstate

Esmukov, K., & Tigas, M. (2018). Geopy 2.0. https://github.com/geopy/geopy

Han, P., Lu, X., Liu, Y., & Wen, Y. (2020). *Stat 450 project: Real estate* (tech. rep.). Department of Statistics, University of British Columbia.

Liaw, A., & Wiener, M. (2002). Classification and regression by randomforest. *R News*, *2*(3), 18–22. https://CRAN.R-project.org/doc/Rnews/

Appendix

A EDA code

```
# preamble ####
library(tidyverse)
library(readr)
library(readxl)
library(ggplot2)
ggplot2::theme_set(theme_classic())
library(viridis)

# data wrangling ####

# data import
columnnames <- readxl::read_xlsx("colnames.xlsx") %>%
  colnames()

real.estate_full <- readr::read_csv("2016 - 2020 Raw.csv",
                                    na = c("", "NA", "NULL", "NULL_1"),
                                    col_names = columnnames,
                                    col_types = "cicccccccccccccdddddiicccddddc")
# data wrangling

# assessments by PIC and year
assessments <- real.estate_full %>%
  dplyr::select(PIC, Year, # relevant variables
                AssessedValueAmt, AssetTypeDesc) %>%
  dplyr::rename(year = Year,
                assessment = AssessedValueAmt,
                assessment.type = AssetTypeDesc) %>%
  dplyr::group_by(PIC, year, assessment.type) %>%
  dplyr::summarise(assessment = sum(assessment)) %>%
  dplyr::ungroup() %>%
  tidyr::spread(assessment.type, assessment) %>%
  dplyr::rename(improvement.assessment = Improvement,
                land.assessment = Land) %>%
  dplyr::select(PIC, year, improvement.assessment, land.assessment) %>%
  dplyr::mutate(total.assessment = improvement.assessment + land.assessment)


re <- real.estate_full %>%
  dplyr::select(PIC, Year, AddressAssessorMunicipalityDesc, # relevant variables
                TaxClassCode, TaxOwingAmountTotalCalculated, TaxClassTaxRate) %>%
  dplyr::rename(year = Year,
                municipality = AddressAssessorMunicipalityDesc, # human-readable names
                tax.class = TaxClassCode,
                tax = TaxOwingAmountTotalCalculated,
                mill.rate = TaxClassTaxRate) %>%
  dplyr::filter(tax.class %in% c("01", "05", "06")) %>%  # relevant values for tax class
  dplyr::distinct() %>%
  dplyr::left_join(assessments, by = c("PIC" = "PIC", "year" = "year")) # add assessment


# data viz ####
# tax classes dictionary
tax.classes <- as_labeller(c(
  `01` = "01 - Residential",
  `05` = "05 - Industrial",
  `06` = "06 - Commercial"
))


# facet scatter plots with year
re %>%
  dplyr::select(-PIC) %>%
  dplyr::filter(!is.na(total.assessment), !is.na(mill.rate)) %>%
  dplyr::group_by(year, municipality, tax.class) %>%
  dplyr::summarise(total.assessment = mean(total.assessment), mill.rate = mean(mill.rate)) %>%
  ggplot(aes(x = log(total.assessment), y = log(mill.rate), color = factor(year))) +
```

```
  geom_point() +
  facet_wrap(.~tax.class, labeller = tax.classes) +
  labs(x = "log assessment value",
       y = "log mill rate",
       color = "year") +
  scale_color_viridis_d() +
  theme(text = element_text(size = 18))
ggsave("RealEstate/src/eda - s550/plots/1. scatter with year.pdf")
ggsave("RealEstate/src/eda - s550/plots/1. scatter with year.png")


# facet scatter plots for 2020 by municipality
re %>%
  dplyr::filter(year == 2020) %>%
  dplyr::select(-PIC, -year) %>%
  dplyr::filter(!is.na(total.assessment), !is.na(mill.rate)) %>%
  dplyr::group_by(municipality, tax.class) %>%
  dplyr::summarise(total.assessment = mean(total.assessment), mill.rate = mean(mill.rate)) %>%
  ggplot(aes(x = log(total.assessment), y = log(mill.rate))) +
  geom_point(color = viridis(20)[3]) +
  facet_wrap(.~tax.class, labeller = tax.classes) +
  labs(x = "log assessment value",
       y = "log mill rate") +
  theme(text = element_text(size = 18))
ggsave("RealEstate/src/eda - s550/plots/2. scatter 2020 by municipality.pdf")
ggsave("RealEstate/src/eda - s550/plots/2. scatter 2020 by municipality.png")



# facet line trends sample of 10
  re %>%
    dplyr::select(-PIC) %>%
    dplyr::filter(!is.na(total.assessment), !is.na(mill.rate)) %>%
    dplyr::group_by(year, tax.class) %>%
    dplyr::sample_n(size = 10) %>%
    dplyr::ungroup() %>%
    dplyr::group_by(year, tax.class, municipality) %>%
    dplyr::summarise(total.assessment = mean(total.assessment), mill.rate = mean(mill.rate)) %>%
    ggplot(aes(x = year, y = log(mill.rate), group = municipality)) +
    geom_line(color = viridis(20)[3]) +
    facet_wrap(.~tax.class, labeller = tax.classes) +
    #scale_color_viridis_d() +
    #theme(legend.position = "none") +
    labs(x = "year",
         y = "log mill rate") +
    theme(text = element_text(size = 18),
          axis.text.x = element_text(angle = 45, hjust = 1))
  ggsave("RealEstate/src/eda - s550/plots/6. mill rate evolution sample.pdf")
  ggsave("RealEstate/src/eda - s550/plots/6. mill rate evolution sample.png")

    # facet line trends sample of 10 assessment
  re %>%
    dplyr::select(-PIC) %>%
    dplyr::filter(!is.na(total.assessment), !is.na(mill.rate)) %>%
    dplyr::group_by(year, tax.class) %>%
    dplyr::sample_n(size = 10) %>%
    dplyr::ungroup() %>%
    dplyr::group_by(year, tax.class, municipality) %>%
    dplyr::summarise(total.assessment = mean(total.assessment), mill.rate = mean(mill.rate)) %>%
    ggplot(aes(x = year, y = log(total.assessment), group = municipality)) +
    geom_line(color = viridis(20)[3]) +
    facet_wrap(.~tax.class, labeller = tax.classes) +
    #scale_color_viridis_d() +
    #theme(legend.position = "none") +
    labs(x = "year",
         y = "log assessment value") +
    theme(text = element_text(size = 18),
          axis.text.x = element_text(angle = 45, hjust = 1))
  ggsave("RealEstate/src/eda - s550/plots/6.1 assessment evolution sample.pdf")
  ggsave("RealEstate/src/eda - s550/plots/6.1 assessment evolution sample.png")
```

```
  # violin plots of mill rates accross tax classes, for 2020
  re %>%
    dplyr::filter(!is.na(total.assessment), !is.na(mill.rate), year == 2020) %>%
    dplyr::group_by(PIC, tax.class) %>%
    dplyr::summarise(total.assessment = mean(total.assessment), mill.rate = mean(mill.rate)) %>%
    ggplot(aes(x = tax.class, y = log(mill.rate), fill = tax.class)) +
    geom_violin(alpha = 0.5, width = 1) +
    geom_boxplot(alpha = 0.75, width = 0.1) +
    labs(x = "tax class",
         y = "log mill rate") +
    #scale_fill_viridis_d(begin=0, end=1) +
    scale_fill_manual(values = c("#3E4A89FF", "#26828EFF","#B4DE2CFF" )) +
    theme(legend.position = "none") +
    scale_x_discrete(labels = c("01 - Residential", "05 - Industrial", "06 - Commercial")) +
    theme(text = element_text(size = 18))
  ggsave("RealEstate/src/eda - s550/plots/7. violin mill rates.pdf")
  ggsave("RealEstate/src/eda - s550/plots/7. violin mill rates.png")


  # violin plots of assessment values accross tax classes, for 2020
  re %>%
    dplyr::filter(!is.na(total.assessment), !is.na(mill.rate), year == 2020) %>%
    dplyr::group_by(PIC, tax.class) %>%
    dplyr::summarise(total.assessment = mean(total.assessment), mill.rate = mean(mill.rate)) %>%
    ggplot(aes(x = tax.class, y = log(total.assessment), fill = tax.class)) +
    geom_violin(alpha = 0.5, width = 1) +
    geom_boxplot(alpha = 0.75, width = 0.1) +
    labs(x = "tax class",
         y = "log assessment value") +
    #scale_fill_viridis_d(begin=0, end=1) +
    scale_fill_manual(values = c("#3E4A89FF", "#26828EFF","#B4DE2CFF" )) +
    theme(legend.position = "none") +
    scale_x_discrete(labels = c("01 - Residential", "05 - Industrial", "06 - Commercial")) +
    theme(text = element_text(size = 18))
  ggsave("RealEstate/src/eda - s550/plots/7.1 violin assessment values.pdf")
  ggsave("RealEstate/src/eda - s550/plots/7.1 violin assessment values.png")
```

Code 1: Code used for the exploratory data analysis.

B Modelling code

```
# preamble

suppressPackageStartupMessages(library(randomForest))
suppressPackageStartupMessages(library(tidyverse))
suppressPackageStartupMessages(library(lme4))
suppressPackageStartupMessages(library(ROCR))
suppressPackageStartupMessages(library(predictmeans))


###########################
# data prep
dat <- readr::read_delim("test_train_data.txt", delim = ",", col_types = "ciccddddddc")
dat$municipality <- as.factor(dat$municipality)
dat$tax.class <- as.factor(dat$tax.class)

factors_tbl = dat %>%
  group_by(municipality) %>%
  count(name="mun_count", sort = TRUE) %>%
  ungroup() %>%
  mutate(perc = mun_count/sum(mun_count),
         cum_perc = cumsum(perc)) %>%
  arrange(desc(mun_count)) %>%
  mutate(rank = row_number(),
         municipality = fct_reorder(municipality, rank)) %>%
  mutate(col_municipality = fct_collapse(municipality, other = levels(municipality)[-c(1:52)])) %>%
  select(municipality, col_municipality)


```

```
med_assessment_by_municipality = dat %>%
  left_join(factors_tbl) %>%
  select(-c(municipality)) %>%
  rename(municipality = col_municipality) %>%
  filter(test.train == "train") %>%
  group_by(municipality, tax.class, year) %>%
  mutate(med_assessment = median(total.assessment, na.rm=TRUE)) %>%
  select(municipality, year, tax.class, med_assessment) %>%
  distinct(municipality, .keep_all = T)

dat_mill <- dat %>%
  left_join(factors_tbl) %>%
  select(-c(municipality)) %>%
  rename(municipality = col_municipality) %>%
  left_join(med_assessment_by_municipality) %>%
  group_by(PIC) %>%
  mutate(next.assess = lead(med_assessment, order_by = year),
         past.mill = lag(mill.rate, order_by = year)) %>%
  arrange(PIC) %>%
  group_by(municipality, year) %>%
  mutate(n.prop = n()) %>%
  arrange(desc(n.prop)) %>%
  distinct(municipality, .keep_all = T) %>%
  select(-c(tax, improvement.assessment, land.assessment, total.assessment))

dat_as <- dat %>%
  left_join(factors_tbl) %>%
  select(-c(municipality)) %>%
  rename(municipality = col_municipality) %>%
  group_by(PIC) %>%
  arrange(year) %>%
  mutate(next.assess = lead(total.assessment, order_by = year),
         past.mill = lag(mill.rate, order_by = year)) %>%
  group_by(municipality) %>%
  top_n(25, wt = total.assessment) %>%
  arrange(municipality)

train_mill <- dat_mill %>%  filter(test.train == "train")
test_mill <- dat_mill %>%  filter(test.train == "test")
train_as <- dat_as %>%  filter(test.train == "train")
test_as <- dat_as %>%  filter(test.train == "test")

####################################
# Random Forest
set.seed(0)

rf.mill <- randomForest(
  mill.rate ~  tax.class + municipality + med_assessment + past.mill, na.action = na.omit, mtry = 4,
  data=train_mill, ntree=500
)

save(rf.mill, file = "rf.mill.rda")

#Evaluate variable importance
importance(rf.mill)
varImpPlot(rf.mill)

rf.as <- randomForest(
  next.assess ~ tax.class + municipality + total.assessment + mill.rate, na.action = na.omit,mtry =
      4,
  data=train_as
)

save(rf.as, file = "rf.as1.rda")
importance(rf.as)
varImpPlot(rf.as)

yhat.bag <- predict(rf.mill,newdata=test_mill)
plot(yhat.bag, test_mill$mill.rate, xlab="Predicted Mill Rate Using Test Set", ylab="Actual Mill Rate
    ")
abline(0,1)

yhat.bag1 <- predict(rf.as,newdata=test_as)
```

```
plot(yhat.bag1, test_as$next.assess, xlab="Predicted Asssessment Value Using Test Set", ylab="Actual Assessment Value", ylim=c(0, 10e8))
abline(0,1)

#################################
# Linear Mixed Effects Model

# both random slope and random intercept
# different rate of change of assessment value and mill rate as well as initial assessment value and mill rate for each municipality

lme.mill <- lmer(mill.rate ~ 1+ (1+year|municipality) + as.factor(year) + tax.class  + avg_assessment + past.mill, data = train_mill)

summary(lme.mill)

lme.as <- lmer(next.assess ~ 1+ (1+year|municipality) + as.factor(year) + tax.class + total.assessment + mill.rate, data = train_as)

summary(lme.as)

# check assumptions of lme

# Homogeneity of Variance
residplot(lme.mill)
residplot(lme.as)
```

Code 2: Code used for the modeling.

C Shiny app code

```

#global.R file

library(shiny)
library(readr)
library(ggplot2)
library(dplyr)
library(DT)
library(tidyr)
library(shinyjs)
library(randomForest)

#PIC used for some testing
# CA-BC-200-001019632060000


# for bookmarking button
enableBookmarking("url")

# read data
dat <- readr::read_delim("test_train_data.txt",
                         delim = ",", col_types = "ciccddddddf")

# creates dataset with only the top 52 municipalities
counts <- dat %>%
  count(municipality, sort = TRUE)

datshort <- dat %>%
  filter(municipality %in% counts$municipality[1:52])


# load dataset used for rf.mill
rfdat <- readRDS("rf_data.rds")

# create dataset used for rf.as
asdat <- readRDS("as_data.rds")

##################################
```

```r
#################################
# ui.R file


# Mallory - STAT 550 2020###
# This is the user interface version of the shiny app

library(shinythemes)
library(png)

ui <- fluidPage(theme = shinytheme("cerulean"), #maybe journal theme?

                # header
                div(id = "headerSection",
                    h2("BC␣Mill␣Rate␣&␣Assessment␣Value␣Predictions"),

                    span(
                      style = "font-size:␣1em",
                      # authors
                      span("Created␣by␣"),
                      a("Gian␣Carlo␣Diluvi,␣Vittorio␣Romaniello,␣Sophia␣Li␣&␣Mallory␣Flynn",
                        href = "https://www.stat.ubc.ca"),
                      HTML("&bull;"),
                      # date
                      span("April␣2020"),
                      HTML("&bull;"),
                      # Shiny app code link
                      span("Code"),
                      a("on␣GitHub",
                        href = "https://github.com/STAT450-550/RealEstate/tree/master/src/shiny_app"),
                    )
                ),
                br(),
                br(),

                # all content goes here, and is hidden initially until the page fully loads
                sidebarLayout(
                  sidebarPanel(
                    # tabsetPanel(
                    #   tabPanel("User Inputs",

                    # Only show the following for assessment predictions:
                    # Use PIC?
                    checkboxInput("picInput", "Use␣PIC?", value = FALSE),
                    selectInput("typeInput", "Estimate␣Type",
                                c("Select", "Assessment␣Value", "Mill␣Rate"),
                                selected = "Select"),

                    # If using PIC:
                    conditionalPanel("input.picInput",
                                     textInput("identInput", "PIC:", placeholder = NULL)),

                    # If PIC is not available:
                    conditionalPanel("!input.picInput",

                                     # for municipality
                                     selectInput("municipalityInput", "Municipality:",
                                                 c("-",sort(unique(datshort$municipality))),
                                                 selected = "-"),

                                     # for Tax Class code
                                     selectInput("taxclassInput", "Tax␣Class␣Code:",
                                                 c("-",sort(unique(dat$tax.class))),
                                                 selected = "-"),

                                     #conditional input for estimate type
                                     conditionalPanel("input.typeInput␣==␣'Assessment␣Value'",
                                                      numericInput("assessmentInput",
                                                                   "Current␣Assessment␣Value:",
                                                                   value = 70000000,
                                                                   min = 4241700,
                                                                   max = 10000000000))
                                     ),
```

```



                     # button to update the data
                     shiny::hr(),
                     actionButton("updateButton", "Update"),



                     # source of data as a footer - Altus Group image not loading
                     br(),
                     br(),
                     p("Generated using data from ",
                       a("the Altus Group Ltd.",
                         href = "https://www.altusgroup.com",
                         target = "_blank")),
                     a(img(src = "altusgroupimg.png", alt = "Altus Group",
                           height = 63, width = 150),
                       href = "https://www.altusgroup.com",
                       target = "_blank"),
                     br(),
                     br(),
                     br(),
                     br(),
                     bookmarkButton()
                     ),


                   # main panel with Estimate tab and plot tab with mill rates
                   # or assessment values over time
                   mainPanel(h4(textOutput("resultsText")),
                             tabsetPanel(
                               tabPanel("Estimate",
                                        br(),
                                        verbatimTextOutput("results")),
                                tabPanel("Plot",
                                         br(),
                                         plotOutput("coolplot"))
                               )
                   )
                 )
                 )


########################################
########################################
# server.R file

# Mallory - STAT 550 2020###
# This is the server file of the shiny app

# fix main title when PIC is checked but empty
# load rdas for each so that estimates can be made
# fix select input to choose only the top 52 categories and other


# in case modified data needs to be accessed
source("helpers.R")

# load models - RF for mill rate predictions and for assessment value predictions
load("rf.mill.rda")
load("rf.as.rda")


# server:
server <- function(input, output, session) {

  filtered <- reactive({

    # Update when following inputs are changed
    input$updateButton

    newdata <- datshort
    d <- NULL
```

```
    #print(dim(dat))

    # Filter data based on the user inputs
    isolate({
          # If using PIC:
          if(input$picInput && input$identInput!=""){
            d <- newdata  %>%
              filter(PIC == input$identInput)
          }


          # If not using PIC, filter by municipality and tax class:
          if(!input$picInput){

            d <- newdata %>%
              filter(tax.class == input$taxclassInput,
                     municipality == input$municipalityInput)
          }

      })

    # return filtered data
    if(dim(d)[1]==0){
      d <- NULL
    }
    d

    })

   ########## PLOTTING TAB ##################
   # Add plots of either mill rate or assessment value over time to plot tab

  # create mill rate plot that reacts to inputs
  millrateplot <- reactive({
    input$updateButton

    data <- filtered()


    isolate({
    if(is.null(data)){
      p <- paste("No corresponding data to plot.")
    }

    # plot mill rates over time for municipality chosen for mill rate predicitons
    if (input$typeInput == 'Mill Rate'){
      p <- ggplot(data, aes(x = year, y = mill.rate)) +
        geom_line(color="#FF3333") +
        geom_point(color="#FF3333") +
        theme_minimal() +
        xlab("Year") +
        ylab("Mill Rate") +
        ggtitle("Municipal Mill Rate Over Time")
    }
    })

    p

  })

  # create assessment plots that react to user inputs
  assessplot <- reactive({
    input$updateButton

    data <- filtered()

    isolate({
      if(is.null(data)){
        p <- paste("No corresponding data to plot.")
        }

    # plot assessment values over time
      if(input$picInput && input$identInput!=""){
        if(input$typeInput == 'Assessment Value') {
```

```
        #print("ggplotting assessment values")
        p <- ggplot(data, aes(x = year, y = total.assessment)) +
          geom_line(color = "#56B4E9") +
          geom_point(color = "#56B4E9") +
          theme_minimal() +
          xlab("Year") +
          ylab("Assessment Value") +
          ggtitle("Assessment Values Over Time")
      }
    }
    else{
      p <- paste("No corresponding data to plot.")
    }
    })

  p

})

# output one of the above plots onto UI
 output$coolplot <- renderPlot({
   if (input$typeInput != 'Select'){
     if(input$typeInput == 'Assessment Value'){
       assessplot()
     }

     else{
       millrateplot()
     }
     }

   else{
     return()
   }
   })


###### ESTIMATE TAB ###################
# give predictions given user inputs for mill rate or assessment value
estimates <- reactive({
  input$updateButton

  isolate({
    if(is.null(filtered())){
      pred <- paste("No data.")
    }

    else{
      # If using PIC:

      # If doing Mill Rate prediciton:
      if(input$typeInput == 'Mill Rate'){
        #print("doing mill rate prediction")

        # extract latest mill rate
        past20 <- filtered() %>%
          filter(year == 2020)

        # if 2020 column is empty, it will break by condition on mean mill rate=0
        meanmillrate <- mean(na.omit(past20$mill.rate))
        print(meanmillrate)

        # put data together in the way rfmill expects as input call it inputdata
        # columns include tax.class, municipality, total.assessment, past.mill
        meanassess <- mean(na.omit(past20$total.assessment))
        print(meanassess)

        pred.data <- cbind(filtered()$tax.class[1],
                           filtered()$municipality[1],
                           meanassess,
                           meanmillrate)
        pred.data <- as.data.frame(pred.data, stringsAsFactors = FALSE)
        colnames(pred.data) <- c('tax.class', 'municipality',
                                 'avg_assessment','past.mill')
```

```


      pred.data$past.mill <- as.numeric(pred.data$past.mill)
      pred.data$avg_assessment <- as.numeric(pred.data$avg_assessment)
      pred.data$municipality <- factor(pred.data$municipality,
                                       levels = levels(rfdat$municipality))
      pred.data$tax.class <- factor(pred.data$tax.class,
                                    levels = levels(rfdat$tax.class))
      print(pred.data)

      # predict next mill rate using random forest
      pred <- round(predict(rf.mill, newdata = pred.data), 2)

      if(meanmillrate==0 || is.na(pred)){
        pred <- paste("No previous mill rate found in data.")
      }

      pred

      }


    # If doing Assessment Value prediction:
    if(input$typeInput == 'Assessment Value'){

      print("doing assessment value prediction")

      # extract latest assessment value
      past20 <- filtered() %>%
        filter(year == 2020)

      # if using PIC and 2020 column is NA for this property's
      # assessment value, it will break
      if(input$picInput){
        print("using PIC")
        if(input$identInput != ""){
          if(!is.na(past20$total.assessment)){
            last.assess <- past20$total.assessment
            }
          else{
            last.assess <- 0
          }
          }
        print(last.assess)
        }

      # if not using PIC, assessment value must come from user input
      else{
        print("not using PIC")
        if(input$assessmentInput != ""){
          last.assess <- input$assessmentInput
          }
        else{
          last.assess <- 0
          }
        print(last.assess)
        }


      # put data together in the way rfmill expects as input call it inputdata
      # columns include tax.class, municipality, total.assessment, and mill.rate
      print(head(filtered()))
      pred.data <- cbind(filtered()$tax.class[1],
                         filtered()$municipality[1],
                         last.assess,
                         past20$mill.rate[1])

      pred.data <- as.data.frame(pred.data, stringsAsFactors = FALSE)
      colnames(pred.data) <- c('tax.class', 'municipality',
                               'total.assessment', 'mill.rate')


      pred.data$mill.rate <- as.numeric(pred.data$mill.rate)
      pred.data$total.assessment <- as.numeric(pred.data$total.assessment)
```

```
          pred.data$municipality <- factor(pred.data$municipality,
                                           levels = levels(asdat$municipality))
          pred.data$tax.class <- factor(pred.data$tax.class,
                                        levels = levels(asdat$tax.class))
          print(pred.data)

          # predict next assessment value using random forest
          pred <- round(predict(rf.as, newdata = pred.data),2)

          if(last.assess==0 || is.na(pred)){
            pred <- paste("Missing required data.")
          }
        }
      }
      })


    pred
    print(pred)

    })

  # create estimates as text for output
  estimatestext <- reactive({
    input$updateButton


    # If using PIC:
    if(input$picInput){
      if(input$identInput!=""){
        if(input$typeInput == 'Mill Rate'){   #need to be changed to extract values
          return(paste("Mill rate prediction for class",
                       filtered()$tax.class[1],
                       "in", filtered()$municipality[1], "- \n",
                       estimates(), sep = " "))  #  RETURN PREDICTION
          }

        if(input$typeInput == 'Assessment Value'){
          return(paste("Predicted next assessment value of property \n", input$identInput,
                       "-", estimates(), sep = " ")) # RETURN PREDICTION
          }

        if(input$typeInput == 'Select'){
          return("Enter prediction type.")
        }
        }

      else{
        return("Please enter PIC.")
      }
      }

    # If not using PIC:
    else{
      if(input$typeInput == 'Mill Rate'){
        return(paste("Mill rate prediction for class", input$taxclassInput,
                     "in", input$municipalityInput, "- \n",
                     estimates(), sep = " ")) # RETURN PREDICTION
        }

      if(input$typeInput == 'Assessment Value'){

        if(!is.null(filtered())){
          md <- asdat %>%
            filter(municipality == input$municipalityInput)

          minm <- min(na.omit(md$total.assessment))
          print(minm)

          maxm <- max(na.omit(md$total.assessment))
          print(maxm)
        }

        if(input$municipalityInput == '-' ||
```

```
            input$taxclassInput == '-'){
          return(paste("Complete␣user␣inputs."))
        }

        return(paste("Predicted␣next␣assessment␣value␣-␣\n",
                     estimates(), "\n␣Valid␣prediction␣range␣for␣this␣municipality␣is",
                     minm, "-", maxm, sep = "␣"))  # RETURN PREDICTION
      }

      if(input$typeInput == 'Select'){
        return("Enter␣prediction␣type.")
      }
      }
    })

    # output the estimates text in the main panel
    output$results <- renderText({
      estimatestext()
    })


  # Titles text for main panel title - describes prediction type or PIC
  # number if applicable
  titles <- reactive({
    input$updateButton

    data <- filtered()

    if(!input$picInput && input$typeInput == 'Select' && input$municipalityInput == '-' &&
       input$taxclassInput == '-'){
      return(paste(""))
    }

    if(is.null(data)){
      return(paste("Could␣not␣find␣matching␣data."))
    }

    else{
      if(input$picInput){
        if(input$identInput!=""){

          if(input$typeInput == 'Assessment␣Value'){
            return(paste("Assessment␣value␣for", input$identInput, sep = "␣")) #ADD PREDICTION HERE
          }

          if(input$typeInput == 'Mill␣Rate'){
            return(paste("Class", filtered()$tax.class[1],
                         "mill␣rate␣for", filtered()$municipality[1], sep = "␣")) #ADD PREDICTION HERE
          }

          if(input$typeInput == 'Select'){
            return(paste("Select␣prediction␣type."))
          }
        }

        else{
          return(paste(""))
        }
      }

      else{
          if(input$typeInput == 'Mill␣Rate'){
            return(paste("Class", input$taxclassInput,
                         "mill␣rate␣for",
                         input$municipalityInput, sep = "␣"))
          }

          else{
            if(input$typeInput == 'Select'){
              return(paste("Select␣prediction␣type."))
            }
            else{
              return(paste("Assessment␣Value␣prediction␣for␣class",
```

```
                            input$taxclassInput, "property \n in",
                            input$municipalityInput, sep = " "))
          }
        }
      }
    }
  })


  output$resultsText <- renderText({
    titles()
  })
}

######################################
#####################################
# helpers.R file
# This file will have helpers for the model and the loading of data for models

# function to modify data for random forest (if needed)

# used to create mill rate data for random forest
# no longer needed for shiny app; included for future use if needed
rfData <- function(data) {

  dat <- data
  dat$municipality <- as.factor(dat$municipality)
  dat$tax.class <- as.factor(dat$tax.class)

  factors_tbl = dat %>%
    group_by(municipality) %>%
    count(name="mun_count", sort = TRUE) %>%
    ungroup() %>%
    mutate(perc = mun_count/sum(mun_count),
           cum_perc = cumsum(perc)) %>%
    arrange(desc(mun_count)) %>%
    mutate(rank = row_number(),
           municipality = fct_reorder(municipality, rank)) %>%
    mutate(col_municipality = fct_collapse(municipality, other = levels(municipality)[-c(1:52)])) %>%
    select(municipality, col_municipality)


  avg_assessment_by_municipality = dat %>%
    left_join(factors_tbl) %>%
    select(-c(municipality)) %>%
    rename(municipality = col_municipality) %>%
    filter(test.train == "train") %>%
    group_by(municipality, tax.class, year) %>%
    mutate(avg_assessment = mean(total.assessment, na.rm=TRUE)) %>%
    select(municipality, year, tax.class, avg_assessment) %>%
    distinct(municipality, .keep_all = T)

  dat_mill <- dat %>%
    left_join(factors_tbl) %>%
    select(-c(municipality)) %>%
    rename(municipality = col_municipality) %>%
    left_join(avg_assessment_by_municipality) %>%
    group_by(PIC) %>%
    mutate(next.assess = lead(avg_assessment, order_by = year),
           past.mill = lag(mill.rate, order_by = year)) %>%
    arrange(PIC) %>%
    group_by(municipality, year) %>%
    mutate(n.prop = n()) %>%
    arrange(desc(n.prop)) %>%
    distinct(municipality, .keep_all = T) %>%
    select(-c(tax, improvement.assessment, land.assessment, total.assessment))

  dat_mill
}

# used to create assessment value data for random forest
# no longer needed for shiny app; included for future use if needed
asData <- function(data) {

```

```
  dat <- data
  dat$municipality <- as.factor(dat$municipality)
  dat$tax.class <- as.factor(dat$tax.class)

  factors_tbl = dat %>%
    group_by(municipality) %>%
    count(name="mun_count", sort = TRUE) %>%
    ungroup() %>%
    mutate(perc = mun_count/sum(mun_count),
           cum_perc = cumsum(perc)) %>%
    arrange(desc(mun_count)) %>%
    mutate(rank = row_number(),
           municipality = fct_reorder(municipality, rank)) %>%
    mutate(col_municipality = fct_collapse(municipality, other = levels(municipality)[-c(1:52)])) %>%
    select(municipality, col_municipality)


  avg_assessment_by_municipality = dat %>%
    left_join(factors_tbl) %>%
    select(-c(municipality)) %>%
    rename(municipality = col_municipality) %>%
    filter(test.train == "train") %>%
    group_by(municipality, tax.class, year) %>%
    mutate(avg_assessment = mean(total.assessment, na.rm=TRUE)) %>%
    select(municipality, year, tax.class, avg_assessment) %>%
    distinct(municipality, .keep_all = T)

  dat_as <- dat %>%
    left_join(factors_tbl) %>%
    select(-c(municipality)) %>%
    rename(municipality = col_municipality) %>%
    group_by(PIC) %>%
    arrange(year) %>%
    mutate(next.assess = lead(total.assessment, order_by = year),
           past.mill = lag(mill.rate, order_by = year)) %>%
    group_by(municipality) %>%
    top_n(25, wt = total.assessment) %>%
    arrange(municipality)

  dat_as
}
```

Code 3: Code used for the Shiny app.