Estimating Costal Property Values in Florida

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Executive summary

Objective

- Organizational mission: Quantify the financial risk of tidal flooding to address stakeholder concern
- Task for this research: Make the numbers more accurate with market value estimation

Data

- Administrative property records (3 million), transaction records from ATTOM Data Solutions
- Demographic data from census data
- Flooding projections from National Oceanic and Atmospheric Administration (NOAA)

Methodology

- Build seperate models within each city and county
- Regularization models (Ridge, LASSO) as baseline
- Regression trees e.g. random forest and gradient boosting as comparison for trial models

Findings

- Trees work better than baseline
- Random forest algorithm consistently outperformed by gradient boosting
- City-level models have varying performance
- Ability to predict within 10% deviation in some cities

Project roadmap

1. Data preparation
2. Exploratory analysis
3. Seperate modeling: one model for each city/county data
4. Feature selection with individual models
5. Build seperate predictive models for 85 city-level subsamples
6. Functionalities to test and parse out performance metrics for regularized models and regression trees
7. Personalize data filtering parameters
8. Iteration through cities/counties and view corss-validated model performance, map county-level model performance

1. Data preparation

Select features from property records in a real estate broker's database.

```
#Select features to import, subset and save
home_dta <- select(
  home_dta_original,
  attomid,#Matching ID
  deedlastsaleprice,#Transaction price last sale
  situsstatecode,#State code
  situscounty,#County code
  propertyaddresscity,#City code
  ownertypedescription1,#First owner is individual/company?
  ownertypedescription2,#Second owner is individual/company?
  deedlastsaledate,#Date of market sale
  yearbuilt,#Year when built
  propertyusegroup,#Commercial/residential?
  areabuilding,#Living area in sq.feet
  censustract,#Census tract division
  propertylatitude,#Lat of property
  propertylongitude,#Lon of property
  roomsatticflag,#See below
  parkinggarage:communityrecroomflag#A series variable measuring physical attributes of the property, including room
)
```

1. Data preparation

Select features from environmental risk and demographic data set constructed by Porter

```
risk_dta <-
  risk_dta_original %>% select(attomid = ATTOM_ID, #ID
                               dist_coast, #Distance to coast
                               mdkt32, #Flooding probability estimate in next years
                               Totpopbg:near_reading_rates, )#a set of demographic information varying by census tra
```

Get a simple feature of transaction frequence from transaction records

```
trans_dta <-
  trans_dta_original %>% group_by(attomid) %>% summarize(trans_times = n())#Number of transactions
```

```
## Up to here, the data dimension is 3327923 * 203
```

1. Data preparation

- Drop all unary features

```
## Up to here, the data dimension is 3327923 * 91
```

- Drop variables with too many levels, besides those are numerical

```
## [1] "hvacheatingdetail"
## [1] "exterior1code"
## [1] "roofmaterial"
## [1] "roofconstruction"

## Up to here, the data dimension is 3327923 * 87
```

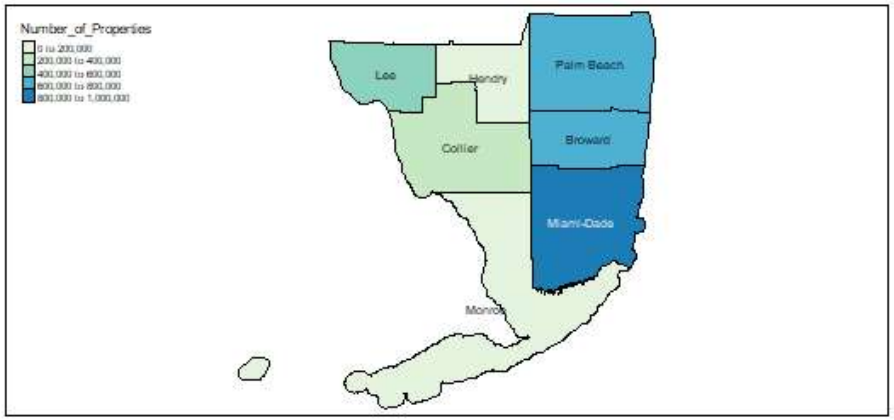
- Recoded characters to factors

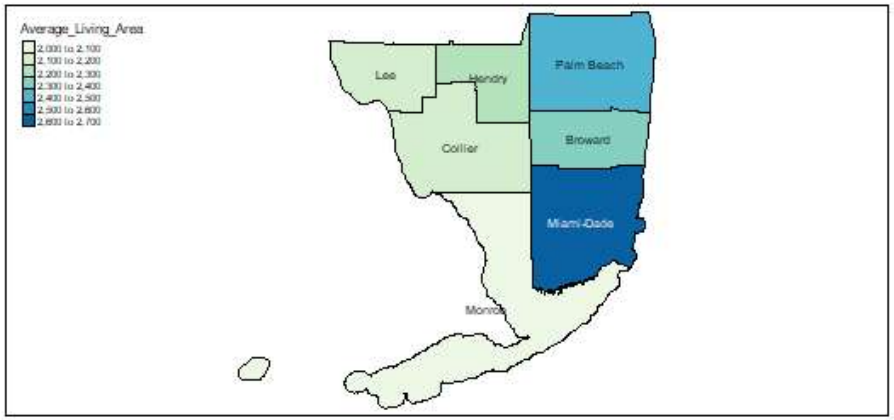
```
## These variables are recoded to factors

## [1] "situsstatecode"
## [1] "situscounty"
## [1] "propertyaddresscity"
## [1] "ownertypedescription1"
## [1] "ownertypedescription2"
## [1] "propertyusegroup"
## [1] "viewdescription"
## [1] "porchcode"
```

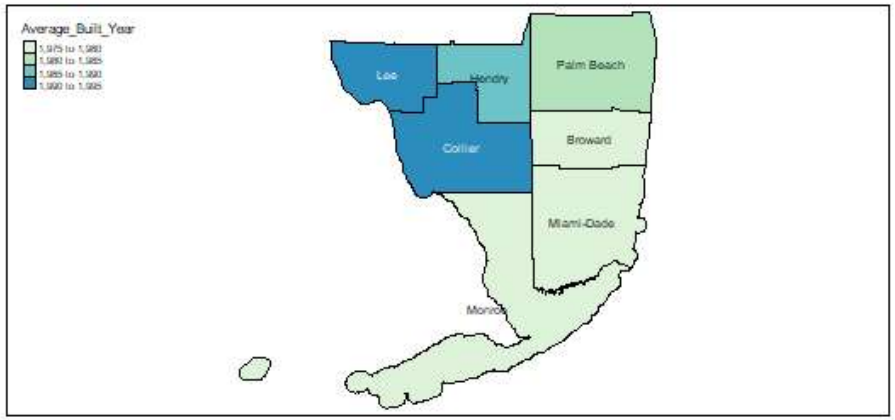
- Hold out cities with sample size too small to go into tree model.

2. Exploratory analysis

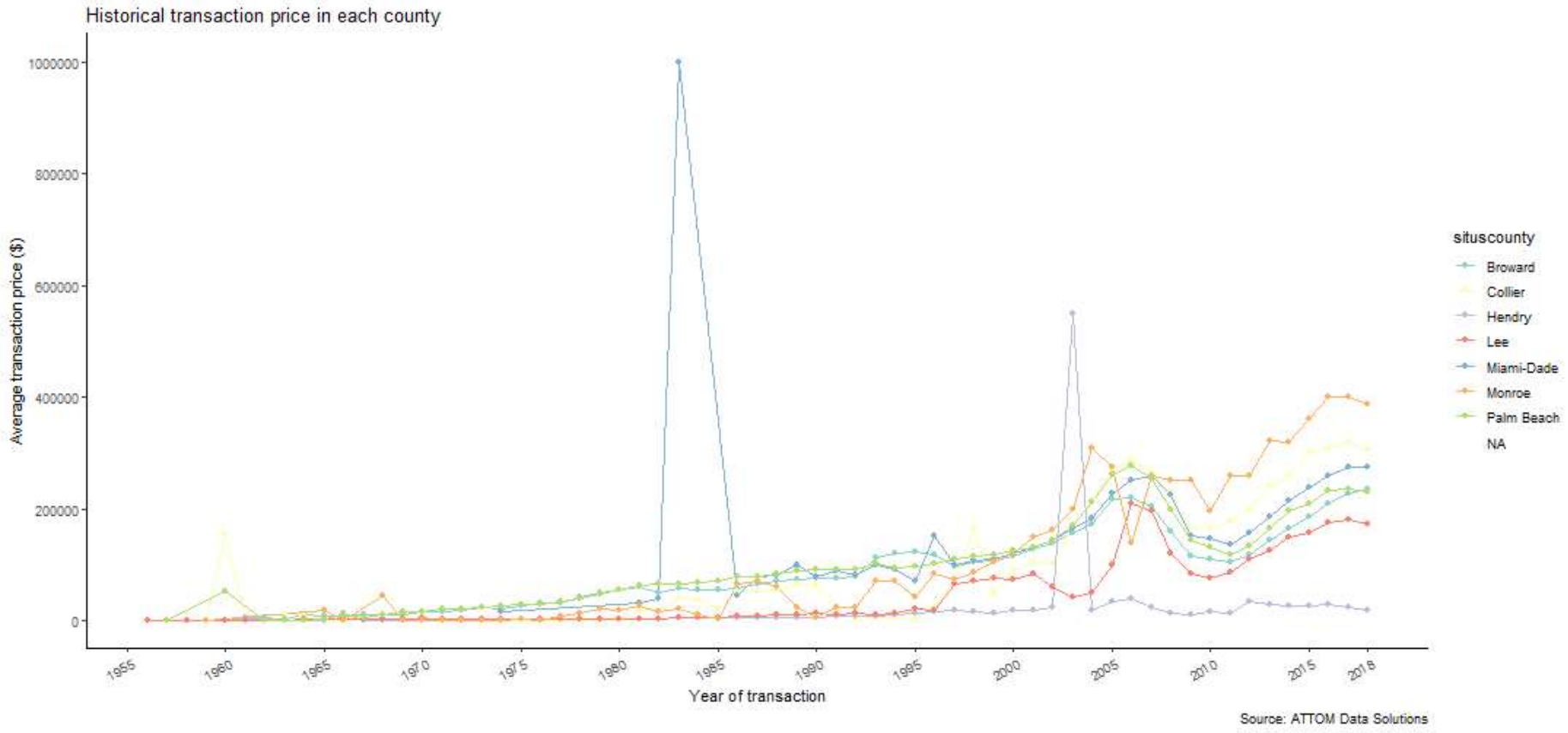
- Summarize a few key variables by county to see the geographical variation







2. Exploratory analysis



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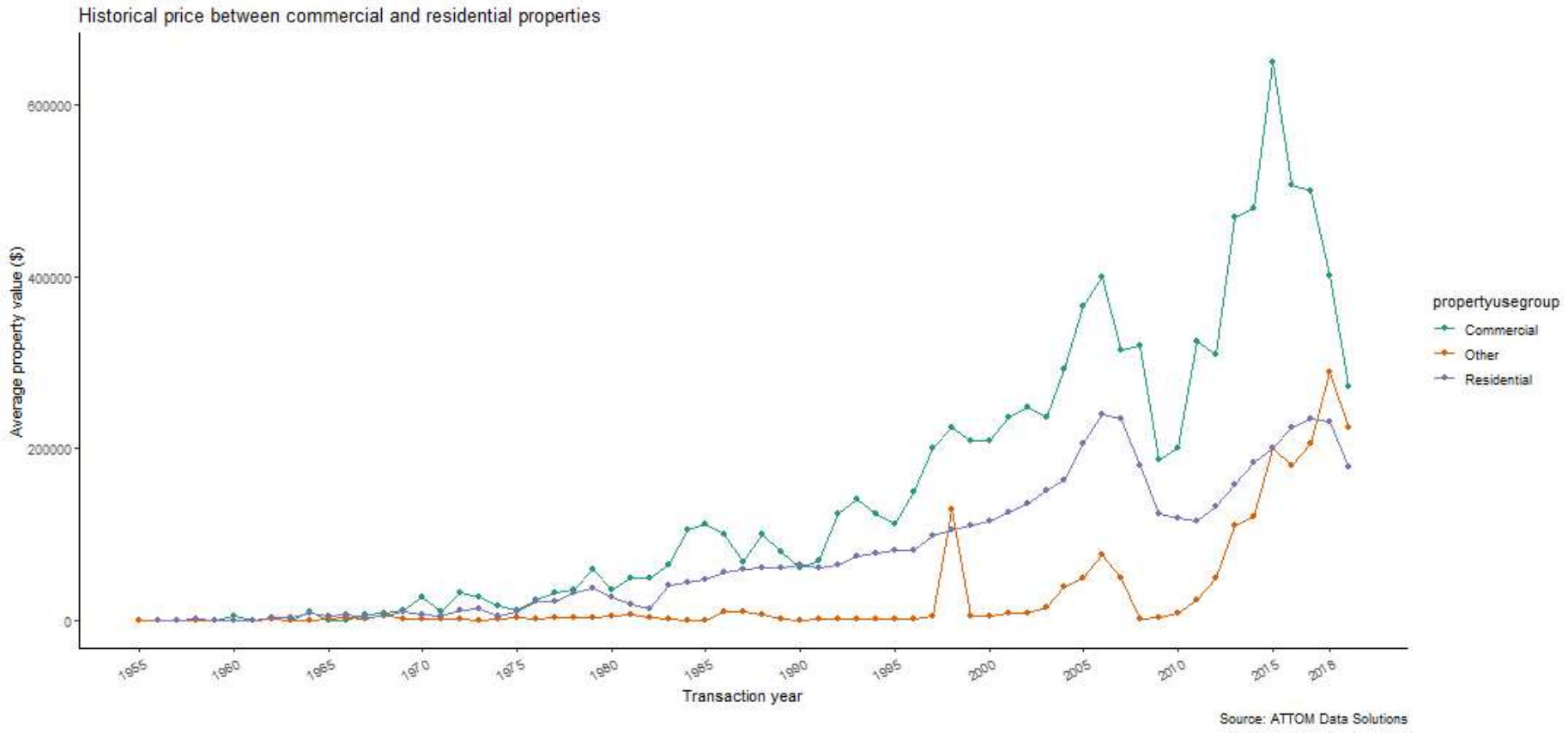

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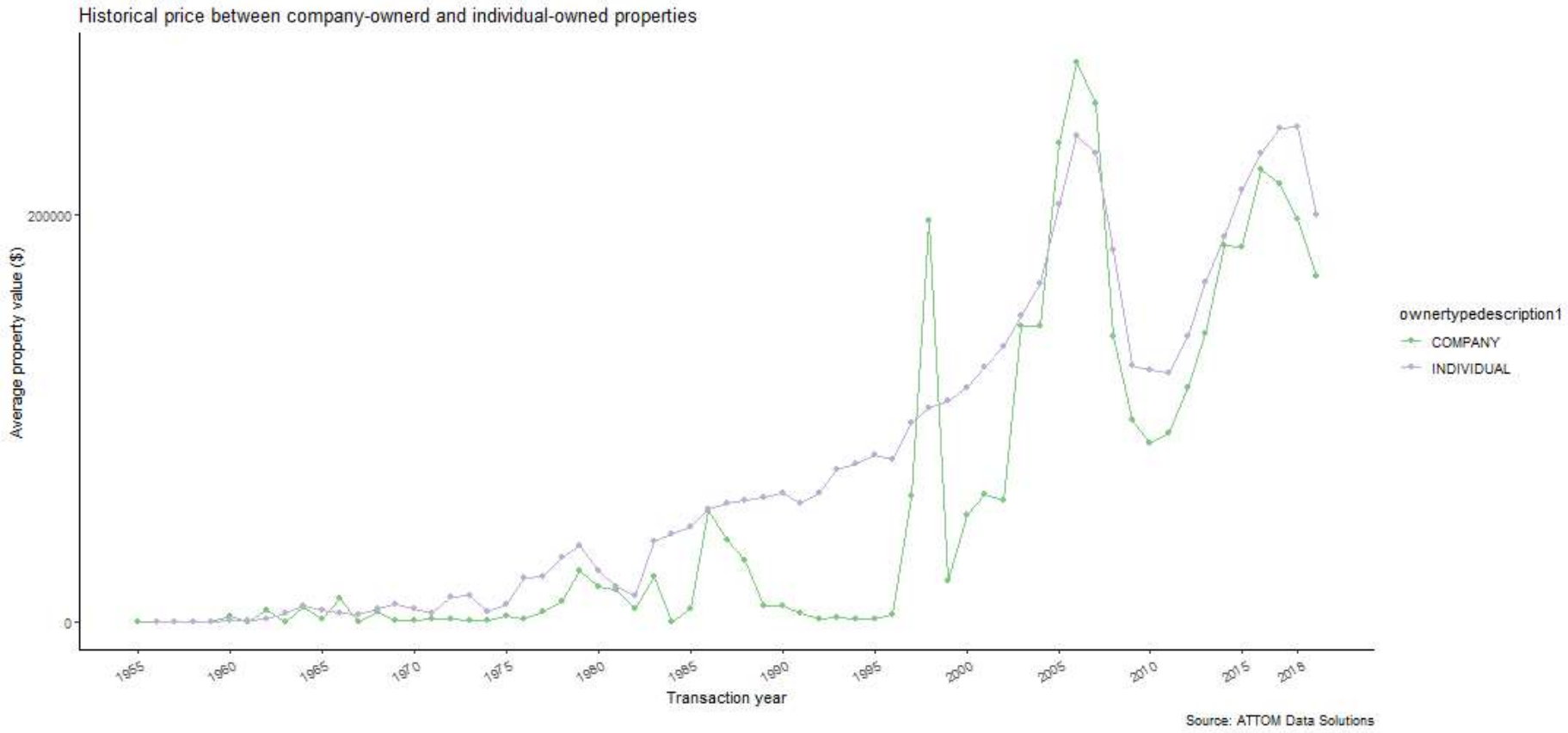

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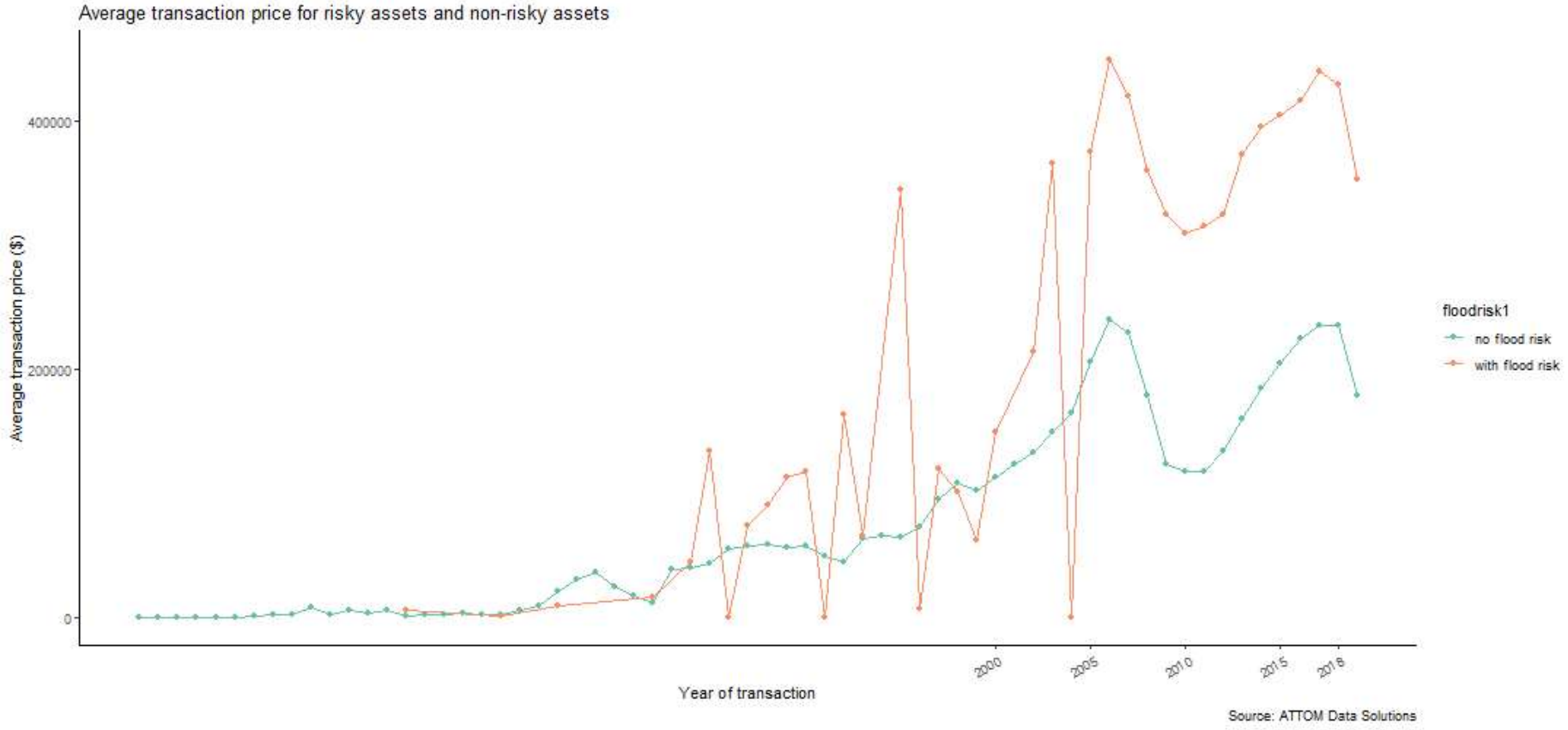

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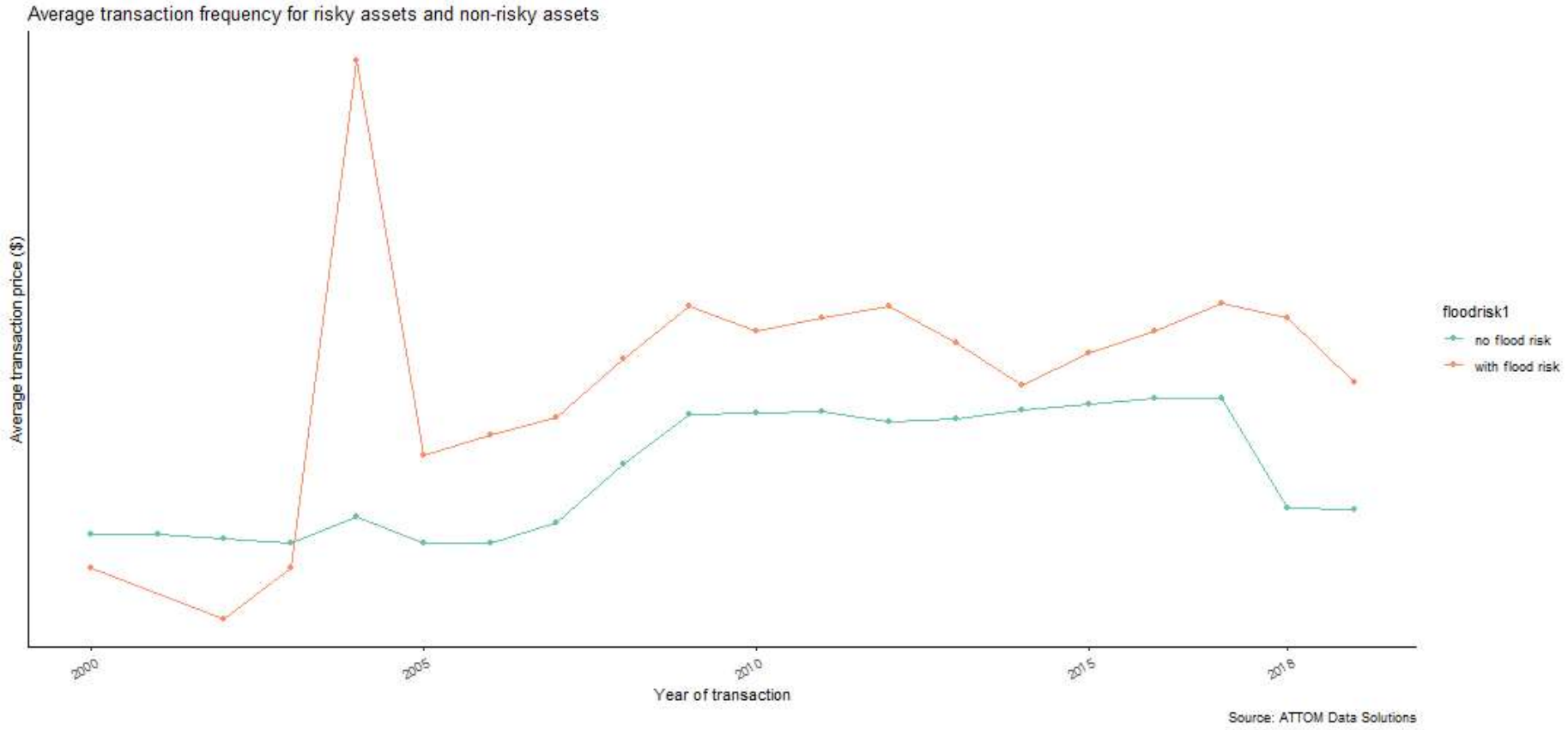

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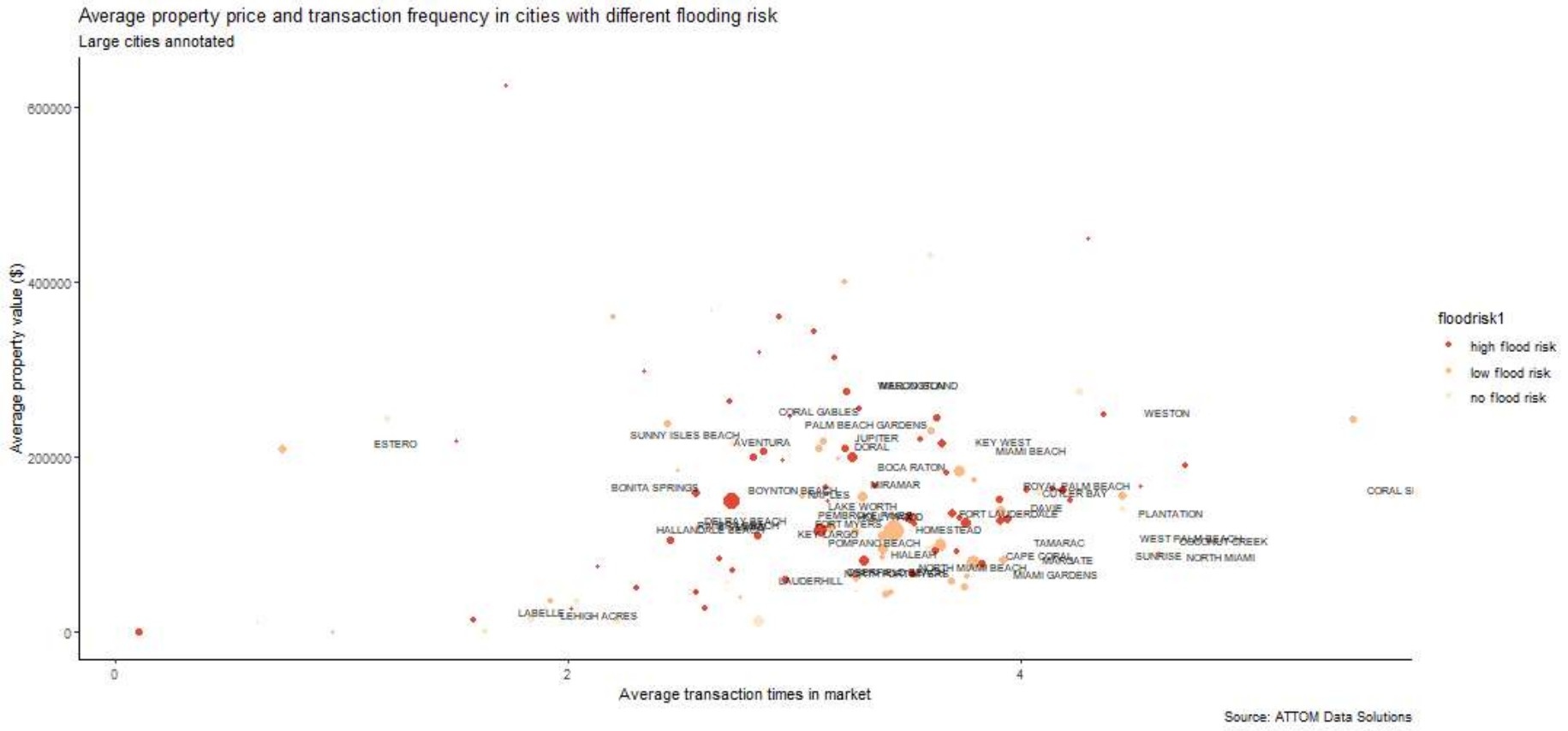

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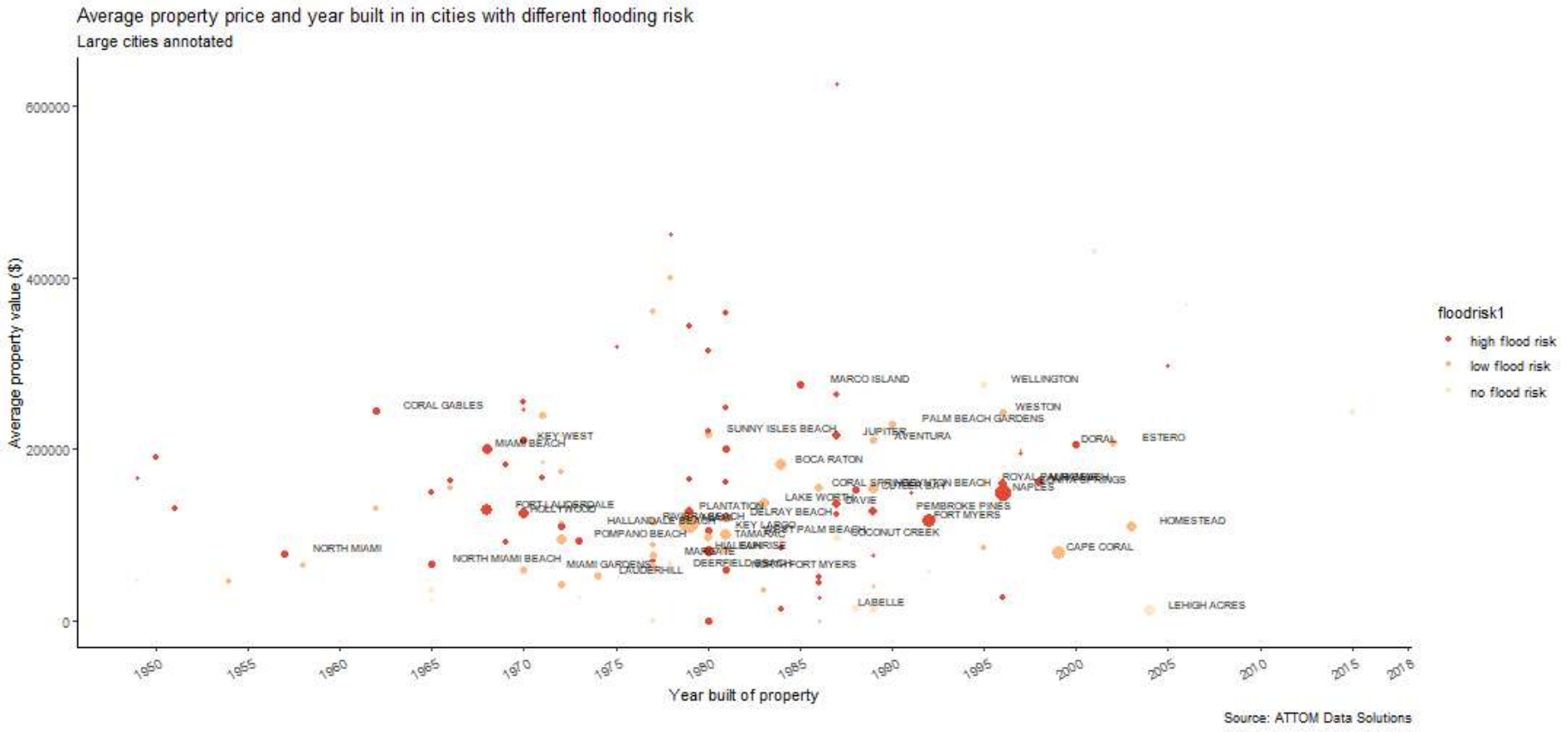


3. Seperate modeling: one model for each city/county data

- For every city/county in South Florida, we fit an individual model to it seperately.
- Inspired by the "submarket" notion (the housing prices between neibourhoods, cities and counties vary a lot)
- Feature structure vary by county
- There are some variables that represent housing attributes that miss in data with different cases between counties.
- The process for county-level modeling is rather straightforward.

4. Feature selection with individual models

- Build function to automatically drop variables that are not important and are missing over 10% values, as we don't wish too many obs are omitted in tree model due to missing value.
- Apply the selection functions built just now to all subsamples
- Divided subsamples by county

```
summary(home_county_cleaned_dta)
```

```
##            Length Class      Mode
## Broward    79     data.frame list
## Collier    72     data.frame list
## Hendry     71     data.frame list
## Lee        79     data.frame list
## Miami-Dade 82     data.frame list
## Monroe     78     data.frame list
## Palm Beach 83     data.frame list
```

4. Feature selection with individual models

- First 5 divided subsamples by city

```
summary(home_city_cleaned_dta)%>%head()
```

```
##                   Length Class      Mode
## ALVA              70     data.frame list
## AVE MARIA         62     data.frame list
## AVENTURA          73     data.frame list
## BAL HARBOUR       68     data.frame list
## BANYAN VILLAGE    15     data.frame list
## BAY HARBOR ISLANDS 69     data.frame list
```

6. Build predictive models for individual subgroups

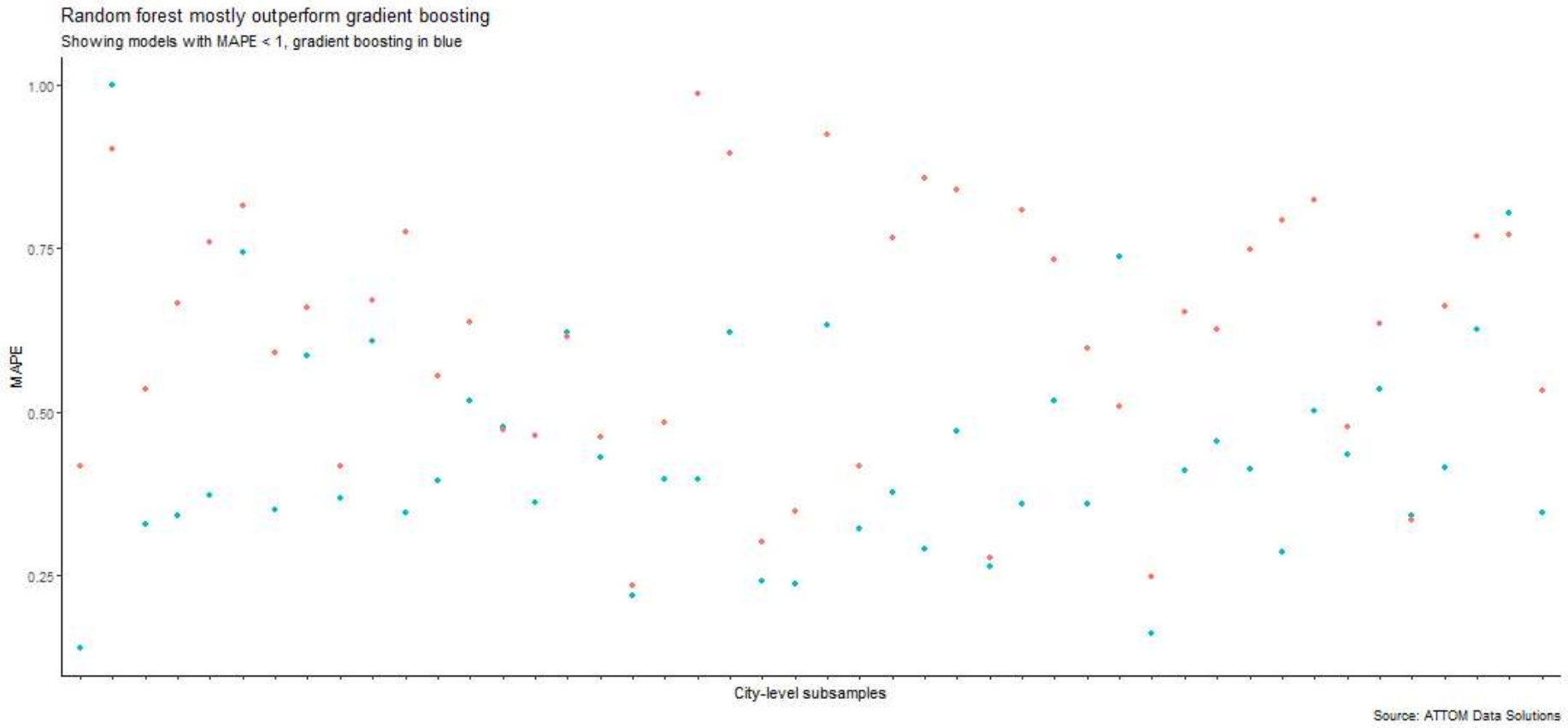
Final Ppreprocessing of individual model before modeling

- Develop functionality for final preprocessing before feeding data into model
- Here we have within each model the control of missing values and division of training/test set
- Therefore, the wragling process was automized and run in each subsample

Modeling functionalities

- Regularization (Ridge and LASSO) as baseline, try also trees
- Random forest deal with data with large variations well
- Gradient boosting is good at learn specific models
- A model comparison with output from random forest and gradient boosting (also Ridge and LASSO)
- The function will parse validated key performance metrics and variables of importance of the models

7 Visualize model performance



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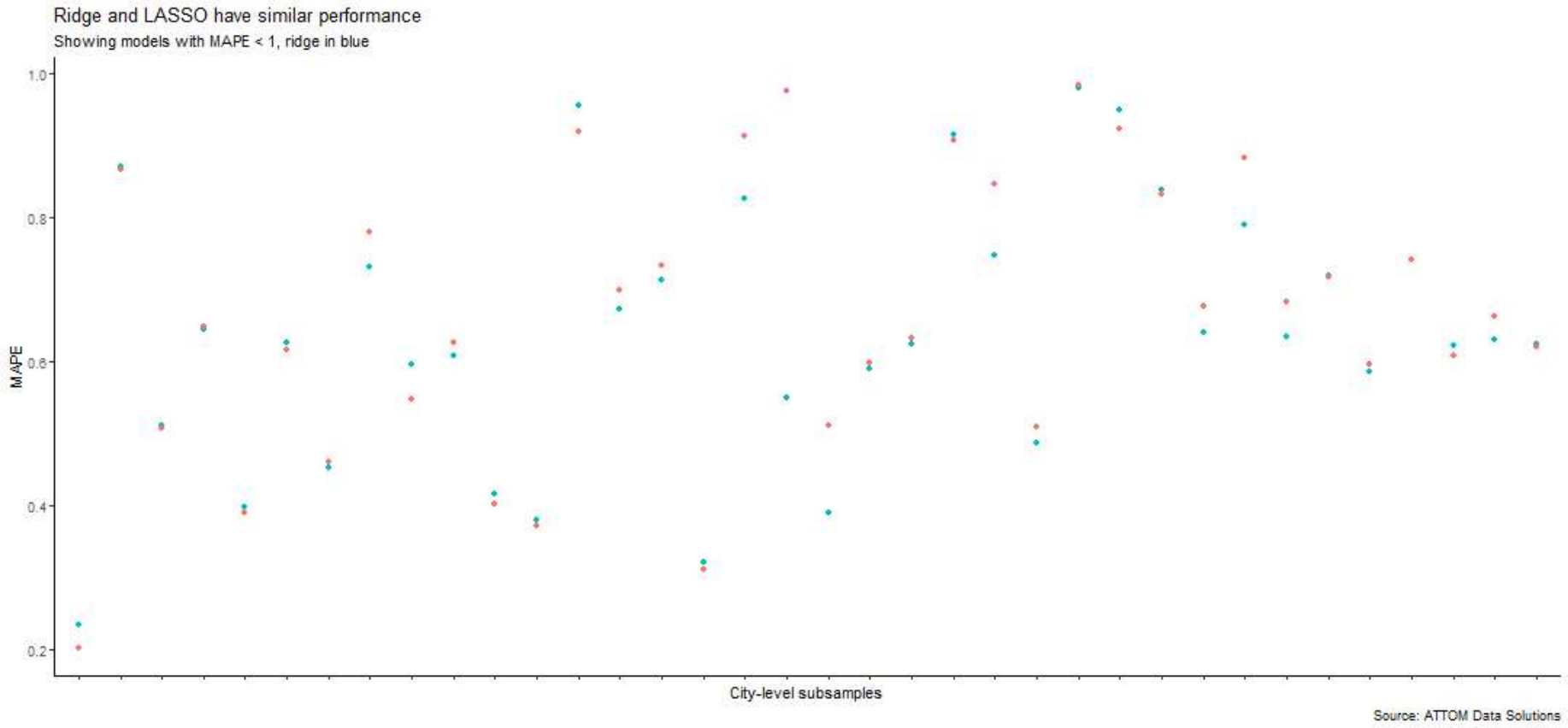

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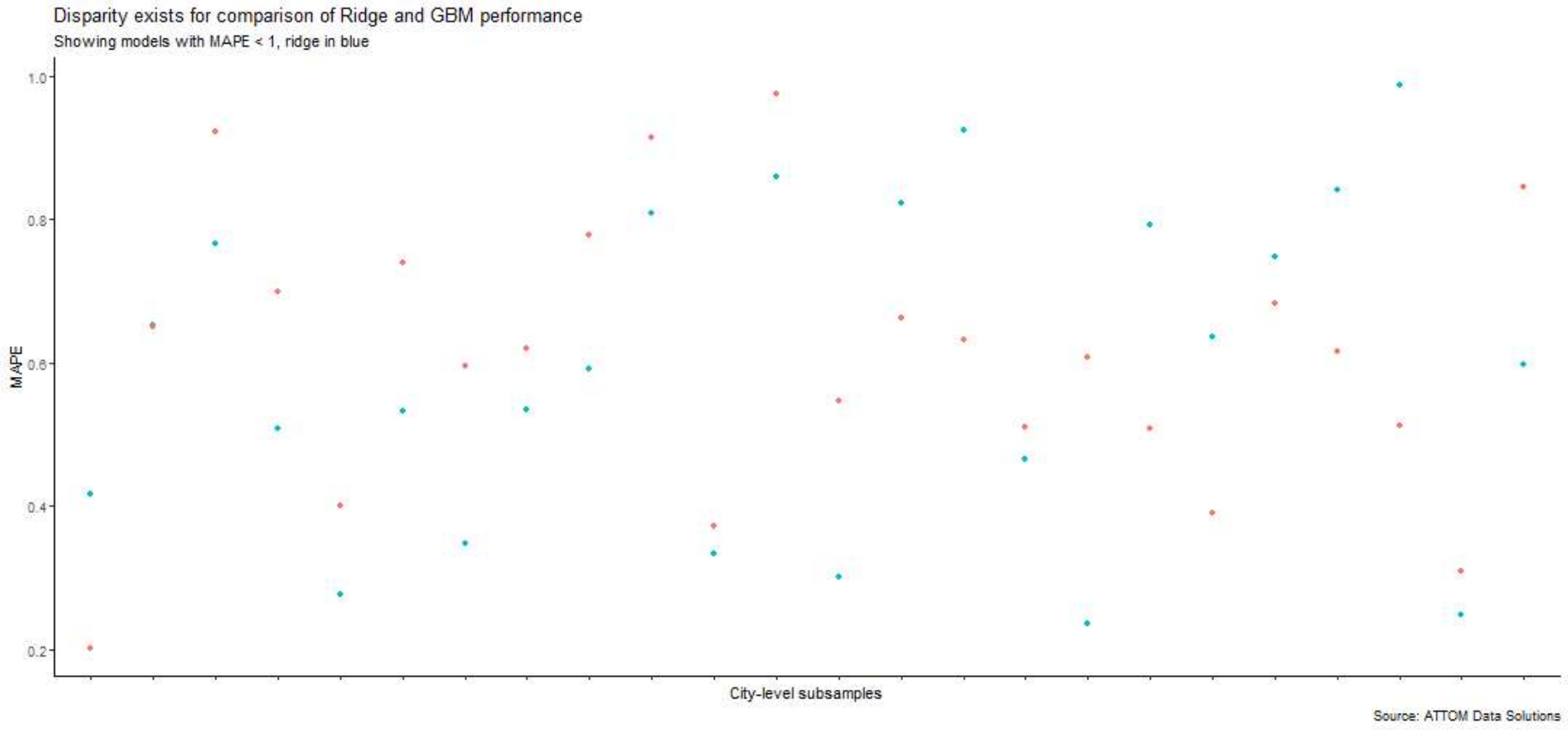

7 Visualize model performance

Show 10 ▼ entries Search:

	subsample	averageprice	floodrisk	rf_MAPE	gb_MAPE	
1	FL_Lee_ALVA	74.597892401553	0.016044061302682	7.63040335953268	10.4672964918621	
2	FL_Collier_AVE MARIA	152.508728179551	0	0.139168804531982	0.417172647871918	0.
3	FL_Miami-Dade_AVENTURA	173.075149838635	0.00141786510026332	7.1957843595276	11.6980898259232	
4	FL_Miami-Dade_BAL HARBOUR	295.389048991354	0.000250878073256397	1.03109217165162	1.04122521856096	
5	FL_Hendry_BANYAN VILLAGE		0	1.53315834349759	1.43580133177156	
6	FL_Miami-Dade_BAY HARBOR ISLANDS	135.947496884088	0.00353982300884956	0.412165184066806	0.748069804780997	0.
7	FL_Palm Beach_BELLE GLADE	26.8028188286809	0	0.853550432457862	1.74058852655098	

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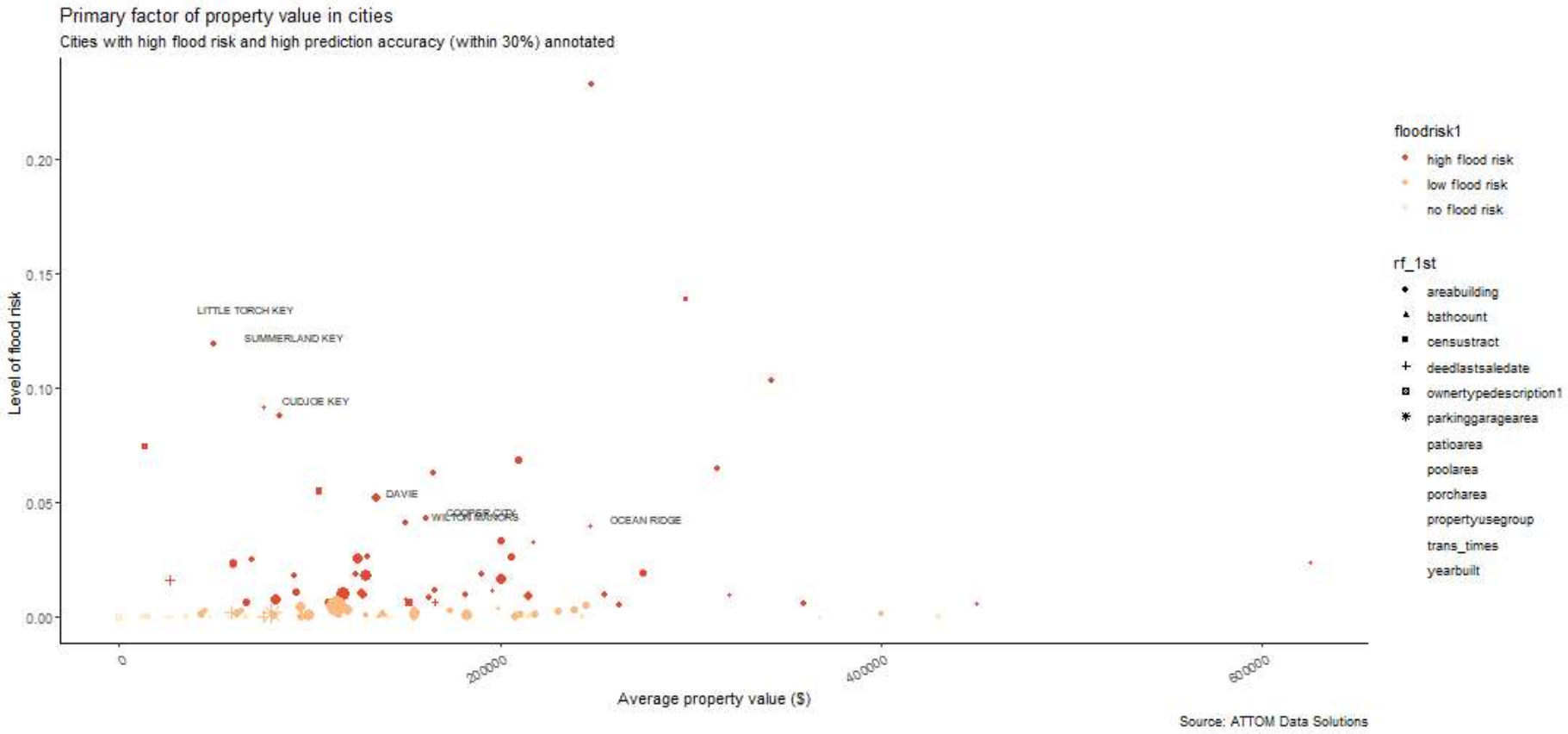
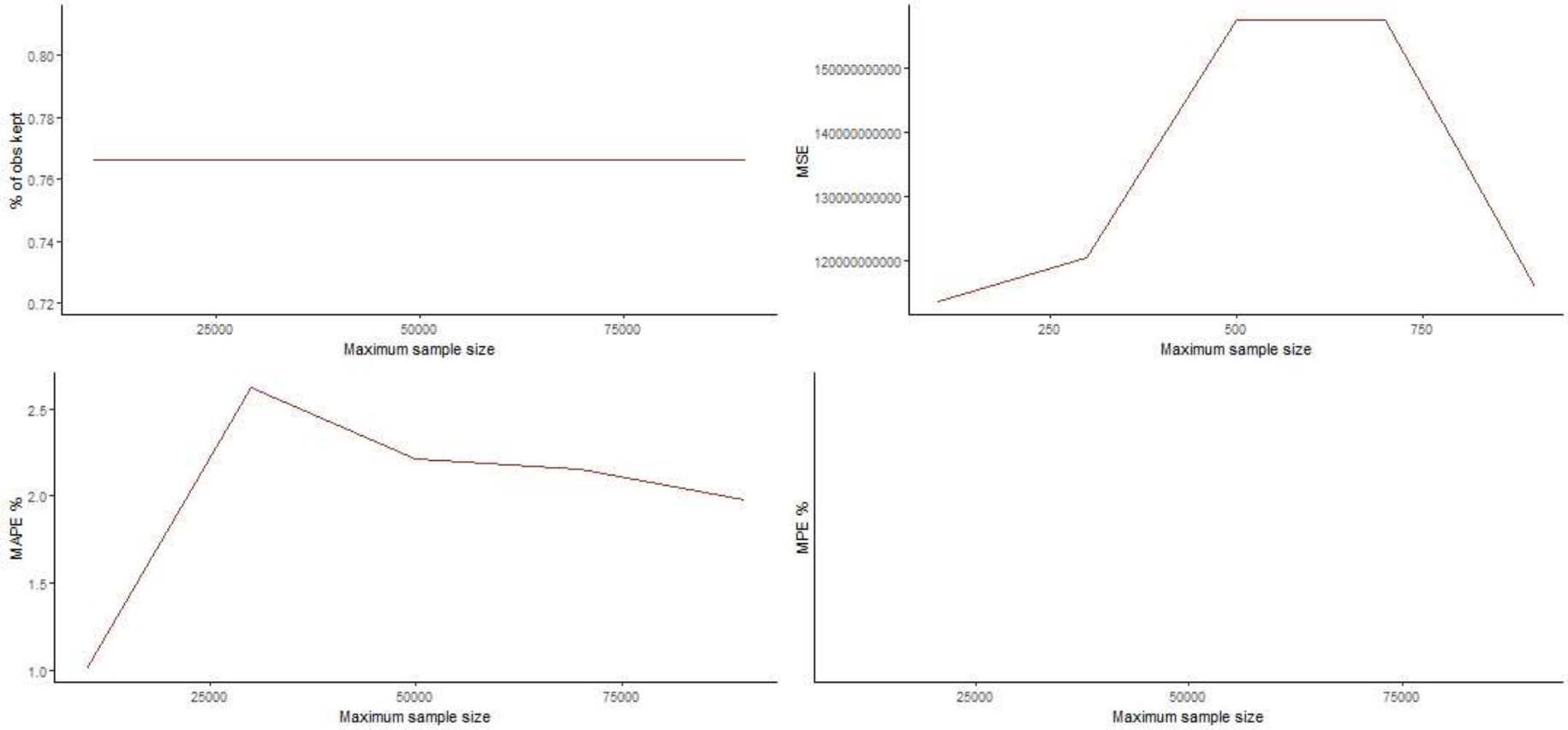
7.5 Visualize model performance



8. Personalize filtering parameters for random forest

- Filtering rule decides whether to include properties with extremely low/high price
- Cruicial to model performance
- Build functionalities to show model performance depending on filtering parameters

8. Personalize filtering parameters for random forest



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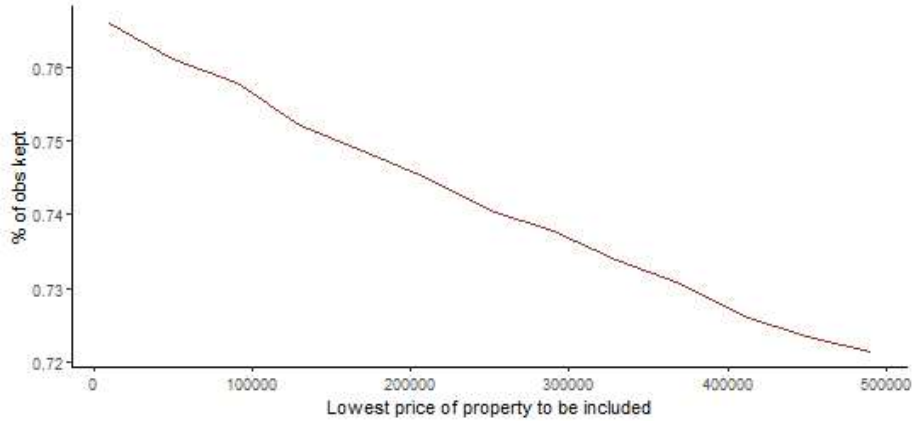

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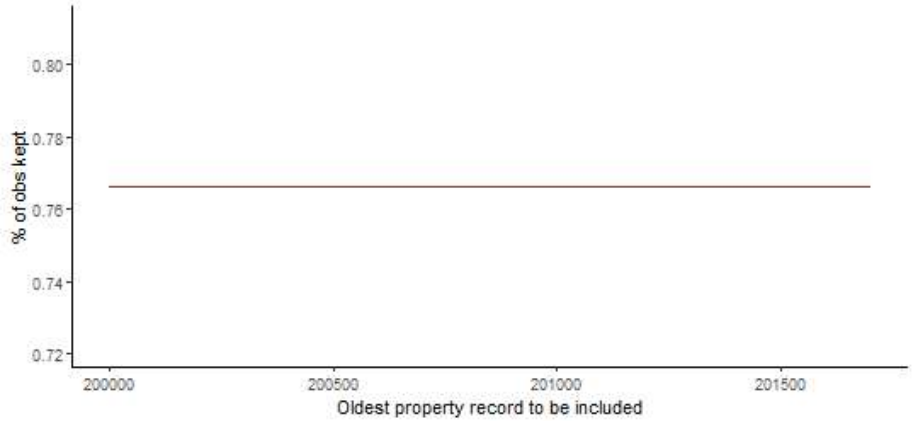

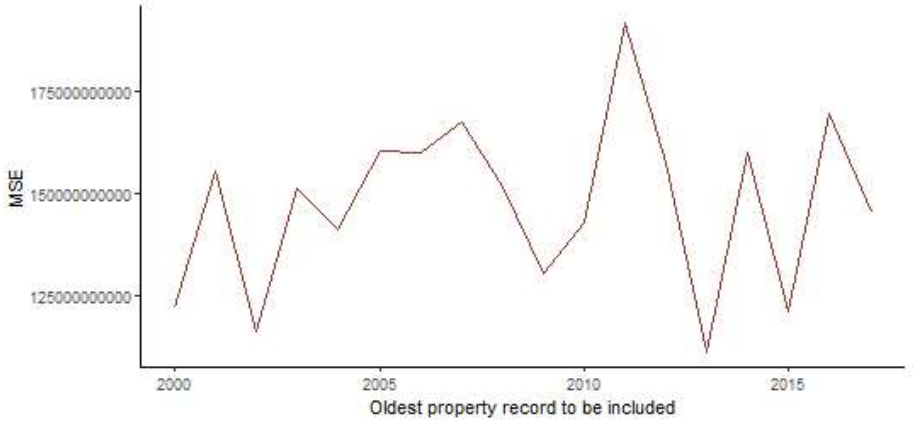

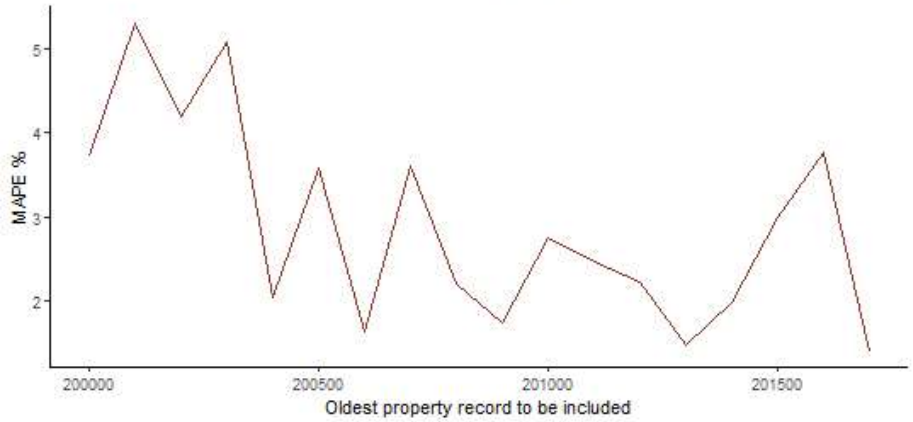

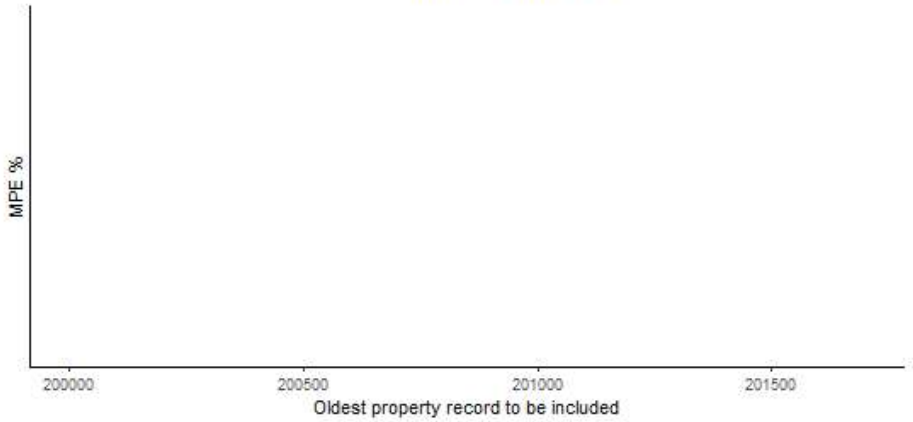

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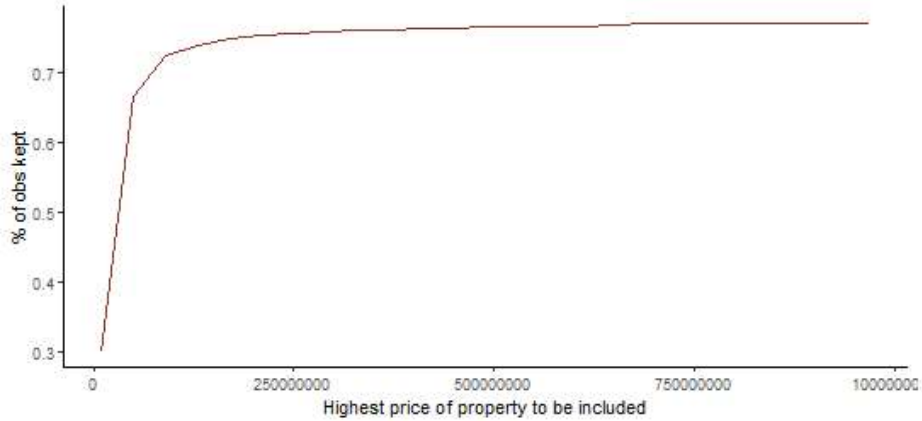

9. Iteration through cities/counties and view corss-validated model performance

- Cities

Show 10 ▼ entries Search:

	subsample	ridge_MPE	ridge_MAPE	LASSO_MPE	LASSO_MAP
..1	FL_Collier_AVE MARIA	0.0203982135201874	0.125724668576108	0.0200407281535674	0.1250528702468
..116	FL_Broward_WESTON	0.0779097395957405	0.208957135411077	0.102455538102122	0.233765815936
..29	FL_Lee_ESTERO	0.00859072147337172	0.285669873444425	0.1243865835056	0.3146799064980
..96	FL_Lee_PUNTA GORDA	0.18024607522673	0.30964530747808	0.187859309819586	0.3216509541667
..2	FL_Miami-Dade_AVENTURA	0.0357523896652135	0.338652338424877	0.0226081928721927	0.3345379769929
..41	FL_Palm Beach_HIGHLAND BEACH	0.112843021869129	0.302315305872082	0.181675875905562	0.3394697685121
..75	FL_Broward_MIRAMAR	0.215140738594086	0.39560114481853	0.166575928827484	0.3798334935117

9. Iteration through cities/counties and view corss-validated model performance

- Counties

Show 10 ▼ entries Search:

	subsample	ridge_MPE	ridge_MAPE	LASSO_MPE	LASSO_MAPE
..1	FL Collier	0.505128671588741	0.799125392180328	0.45493533077685	0.7900587809033
..3	FL Lee	0.658740045381184	0.833696739321913	0.59375836857304	0.80599816818285
.	FL Broward	0.709788388480453	0.899616779825107	0.689732506569334	0.902460244992195
..5	FL Monroe	2.06095987019894	2.26445715482043	1.90690092818672	2.12316217932807
..6	FL Palm Beach	2.33663845125845	2.48427375850428	3.57512033409527	3.76874391506075
..4	FL Miami-Dade	5.6224456642077	6.00813090214987	4.92200213878811	5.26792274384075
..2	FL Hendry	6.82166525108225	7.2131084650709	5.71983329622686	6.19049287168794

Showing 1 to 7 of 7 entries Previous 1 Next

10. Map county-level model performance

We can to see how each county performs on the map.

11. Brief Summary

- Random forest algorithm consistently outperformed by gradient boosting
- City-level models have varying performance and have potential for better model selection
- Ability to predict within 10% deviation in some cities
- Key filtering parameters optimized to improve prediction with reasonable constraint on sample size
- Transaction time and building area is 2 primary factor to determine property value

12. Next step

- Add census tract block medium price as control
- Can try tuning the filtering parameter for each model
- log scale price
- recode zip code to dummy (one-hot recoding)