The best place to open a gym in Florida

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1. Introduction

1.1. Background

Florida is the southernmost contiguous state in the United States. With a population of more than 18 million, according to the 2010 census, Florida is the 3rd-most populous (21,312,211 inhabitants) state in USA. Florida's $1.0 trillion economy is the fourth largest in the United States. If it were a country, Florida would be the 16th largest economy in the world. The most part of Florida's population is concentrated in metropolitan areas, the most populous of them are Miami-Fort Lauderdale-West Palm Beach, Tampa-St. Petersburg-Clearwater, Orlando-Kissimmee-Sanford, Jacksonville while there are a large number of smaller municipalities.

Florida is very diverse ethnically and racially. For example Hispanic and Latinos of any race made up 22.5% of the population in 2010.

You can say Florida is very sportive state because Florida has three NFL teams, two MLB teams, two NBA teams, two NHL teams, and one MLS team. According to 2014 State Indicator Report on Physical Activity of National Center for Chronic Disease Prevention and Health Promotion[1] 29.2% of adults in Florida met muscle-strengthening guideline that is close to average value for U.S. According to non-confirmed data the number of health and fitness clubs in USA permanently increases from 2012. So it can be interesting for investors which places in Florida are worse or better for fitness club or gym opening.

1.2. Problem

In this project I'm focusing on determination of the potential of fitness/gym opening in area based on the demographics, tax and some other information about the areas. I consider zip codes as areas.

1.3. Interest

The main interested players are investors of any size who can be choosing the right place for opening the new fitness club or gym. From other hand it can be interested for current owners of fitness clubs chains who may make a decision about reduction of chain. Also it can be useful for some contiguous businesses that is related to fitness industry.

2. Data

2.1. Data sources

In order to solve the problem I use following data sources:
- basic and demographics information about zip codes areas available at https://www.zip-codes.com/state/fl.asp. Unfortunately the demographics based on the Census 2010 and business information is based on the Business Census 2011 but it's most current official information. I also use prediction of current population provided on this website;
- individual income tax statistics in the context of zip code areas for 2016 provided by IRS at https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-2016-zip-code-data-soi;
- information about different venues placement available via Foursquare API

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[1] 2014 State Indicator Report on Physical Activity of National Center for Chronic Disease Prevention and Health Promotion, page 18
(https://www.cdc.gov/physicalactivity/downloads/PA_State_Indicator_Report_2014.pdf)

2.2. Data preparation

I requested information about most popular venues in Florida from Foursquare using consequentially latitude and longitude of all zip codes and then grouped them using zip code got from the address field of the Foursquare records. Because Foursquare API returns information about only 100 most popular venues in the given radius I used 5 different radii from 350 m to 27 km in order to get as more venues as possible. Separately I requested the information about 'Gym' and 'Fitness' using this time zip code as an area identificator. Of course I've got not only gyms, among most popular categories there were: Gym / Fitness, Gym, Martial Arts Dojo, Yoga Studio, Weight Loss Center, College Gym, Gymnastics Gym, Pilates Studio, Gym Pool and even Hotel. Which of these categories to consider as a Gym and which ones not it's a matter of choice. I decided to consider as Gym all categories consisted the word 'Gym' because it includes different kind of gyms and exclude such venues as martial arts dojo, for sure it will also includes pool gym and maybe some other categories that shouldn't be considered as a gym but their quantity is too small, the main splitting will be correct. After that I added all gyms into all venues table and drop duplicates from this table, changing the all categories consisted the word 'Gym' to 'Gym' in advance. So I collected information about more than 57 thousand venues. In this table I merged some similar categories, for example joined all type of restaurants (Mexican, Italian etc.) into one category "Restaurant", the same with joints and museums, combined 'Wine Bar', 'Pub', 'Cocktail Bar', 'Beer Bar' and 'Beer Garden' in 'Bar' category but left 'Juice Bar' in a separate category. Finally, I made one-hot encoding and saved only categories that at least correlated with the number of gyms and counted at least 80 venues. As a result, I had the table with number of venues by 76 categories in each zip code area.

Then venues data were combined with demographics data and taxes data into one table where zip code was an index of rows while different features was the names of columns.
I dropped all rows with missed values: among 1476 rows there was 559 rows with NaN values but most of them was in the rows with Type 'P.O. Box' (491 rows) or 'Unique' (51 rows), these data was unimportant for me because both P.O. Box and Unique type are not the code of any area and exists only for postal purposes. There was also 17 standard zip code areas with missed values but examined it I found out that some of them has no population, some of them has no venues, anyway the data looks strange, maybe incorrect, so I dropped all rows with missed values.

3. Methodology

3.1. Exploratory data analysis

Population density

As you can see on the map there are extreme values of population density in the above mentioned metropolitan areas Miami-Fort Lauderdale-West Palm Beach, Tampa-St. Petersburg-Clearwater, Orlando-Kissimmee-Sanford, Jacksonville. In other regions the density differs not a lot.
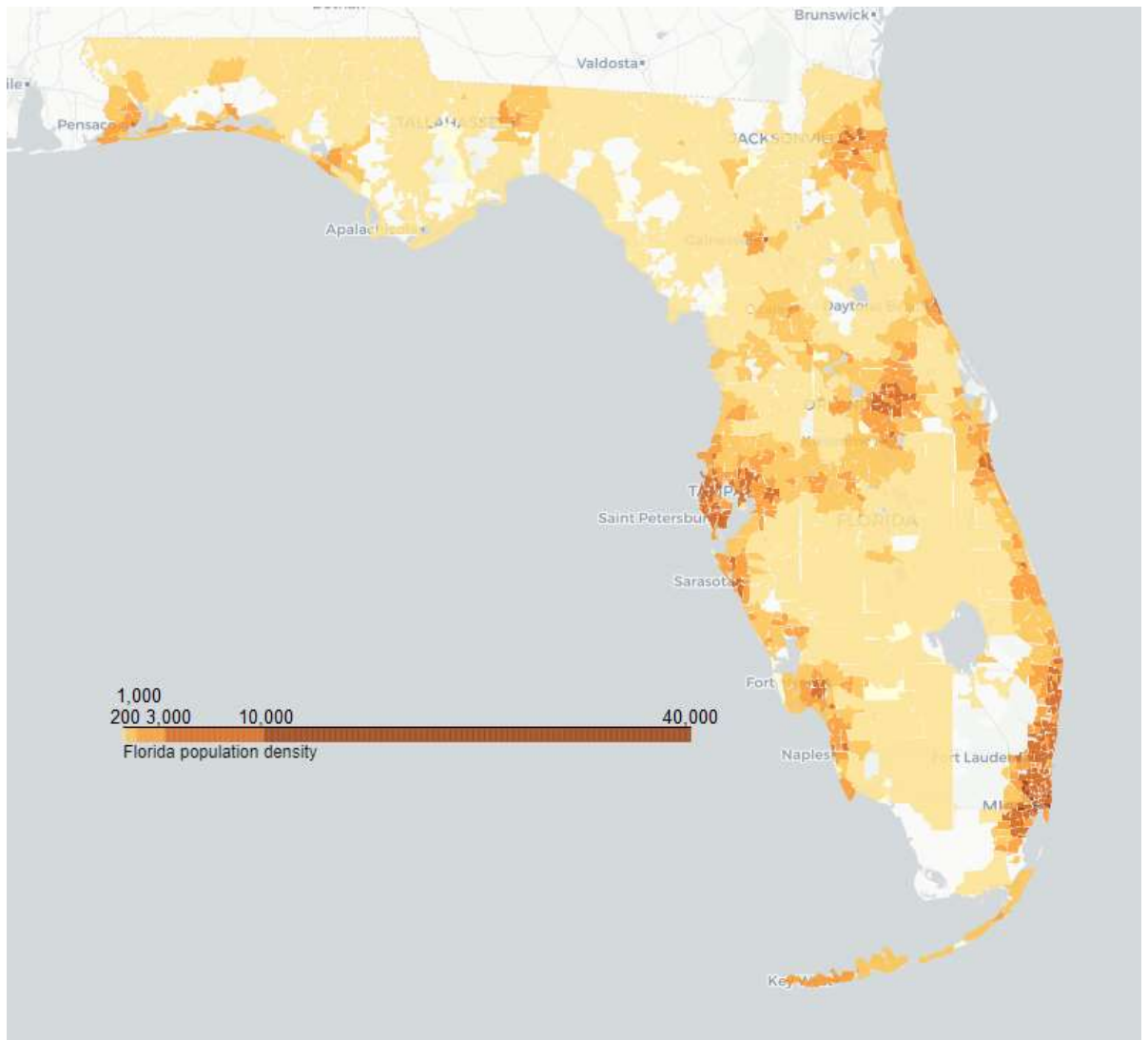
Number of businesses and population

It's not evident but the correlation between number of businesses and number of gyms is much stronger than correlation between population and number of gyms. We can see it on the image above. Among top 5 correlated features there are also Number of Employees and Annual
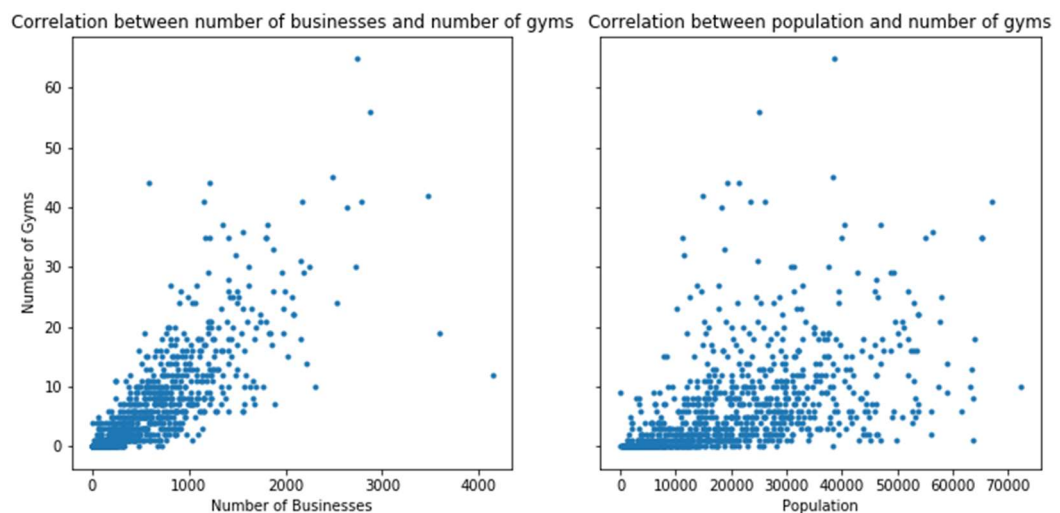
Payroll. It actually means that people prefers to do exercises not near the place of living but near the office or near the shops.

Venues

Among the venue categories most correlated with number of gyms I found Restaurant, Coffee Shop, Bakery, Grocery Store. While the correlation between number of gyms and number of restaurants can be well presented on the image, it's not clear for other 3 categories because the number of venues of these categories differs not a lot.

Demographics

The most correlated with number of gyms demographic groups are Male 25-29 and Female 25-29, next ones are Male 30-34 and Female 30-34 but plots looks are very similar with Total Population plot, so it seemed that just there are strong correlation between demographic groups and total population that is logically sound.

Correlation between number of males of age 25-29 and number of gyms

Correlation between number of males of age 30-34 and number of gyms

Correlation between number of females of age 25-29 and number of gyms

Correlation between number of females of age 30-34 and number of gyms
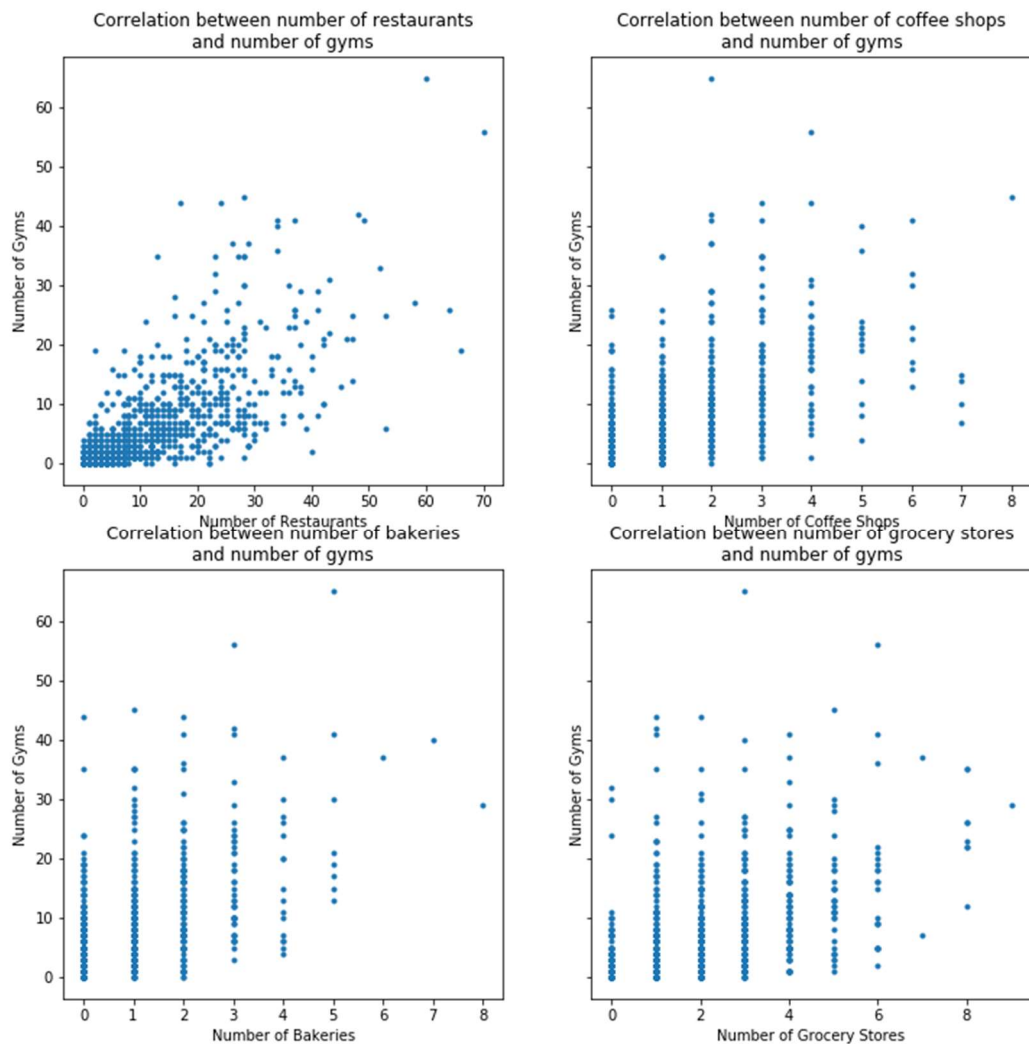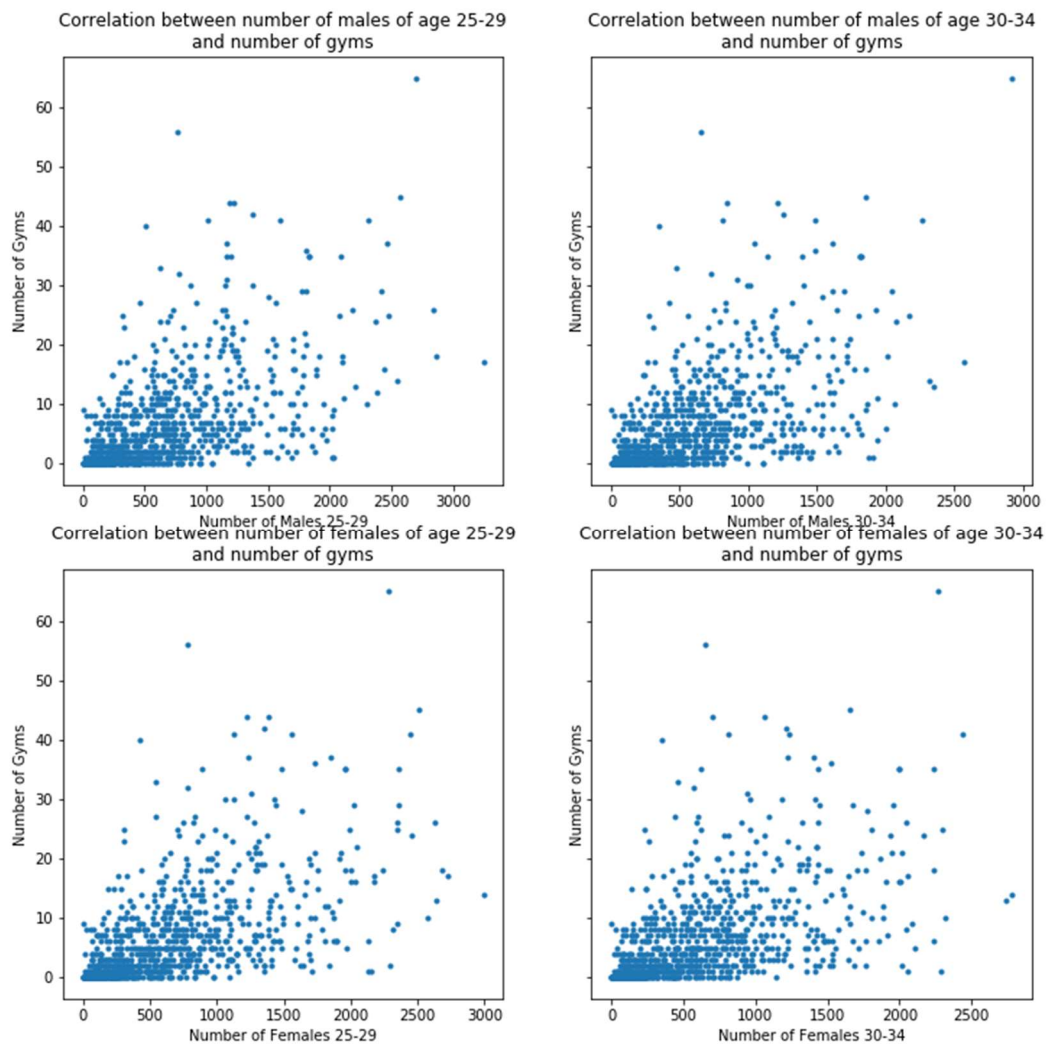
Owner Occupation Share

It's a little unexpectedly but there is a negative correlation between owner occupation share and number of gyms, in other words where owners prefer to live rather than renting housing, the number of gyms is usually less. I can suppose that residents who lives in their own houses and apartments prefer quiet locations where there is no a lot of shops, restaurants and other businesses.

Asian Population Share

Also there is relatively strong correlation between Asian population share and number of gyms, moreover I'm talking about the share but not absolute value, so it cannot be explained by the correlation of the Asian population share and total population. Unfortunately I can't explain it and will use it as is.

Correlation between owner occupation share and number of gyms

Correlation between asian popuation share and number of gyms
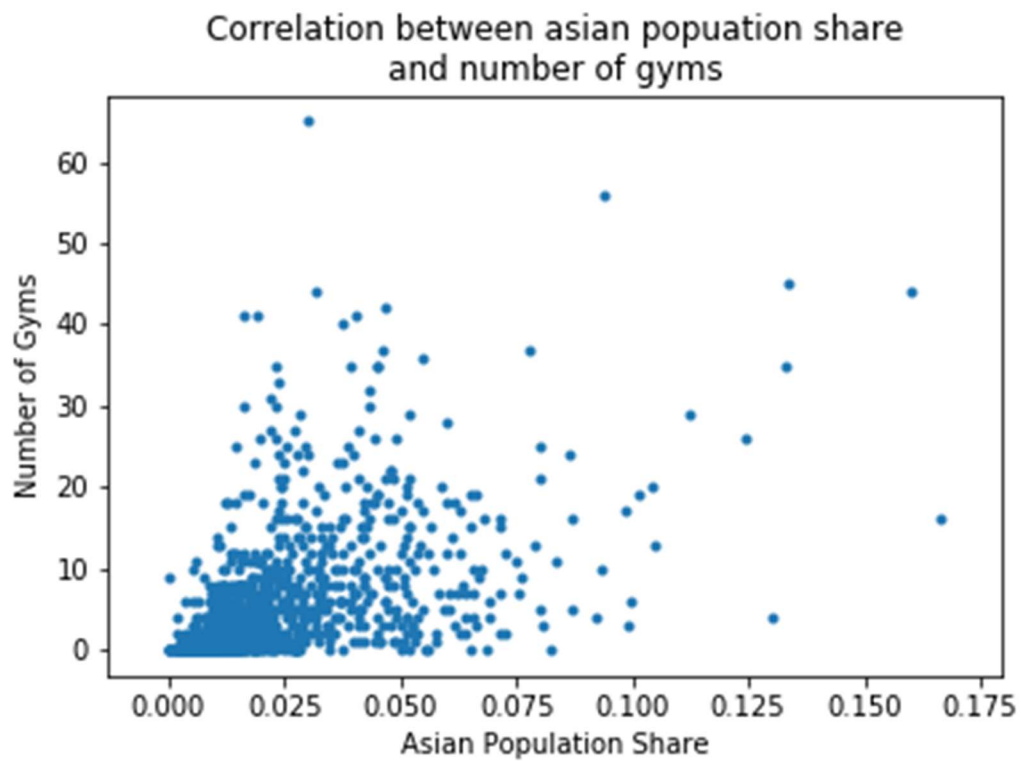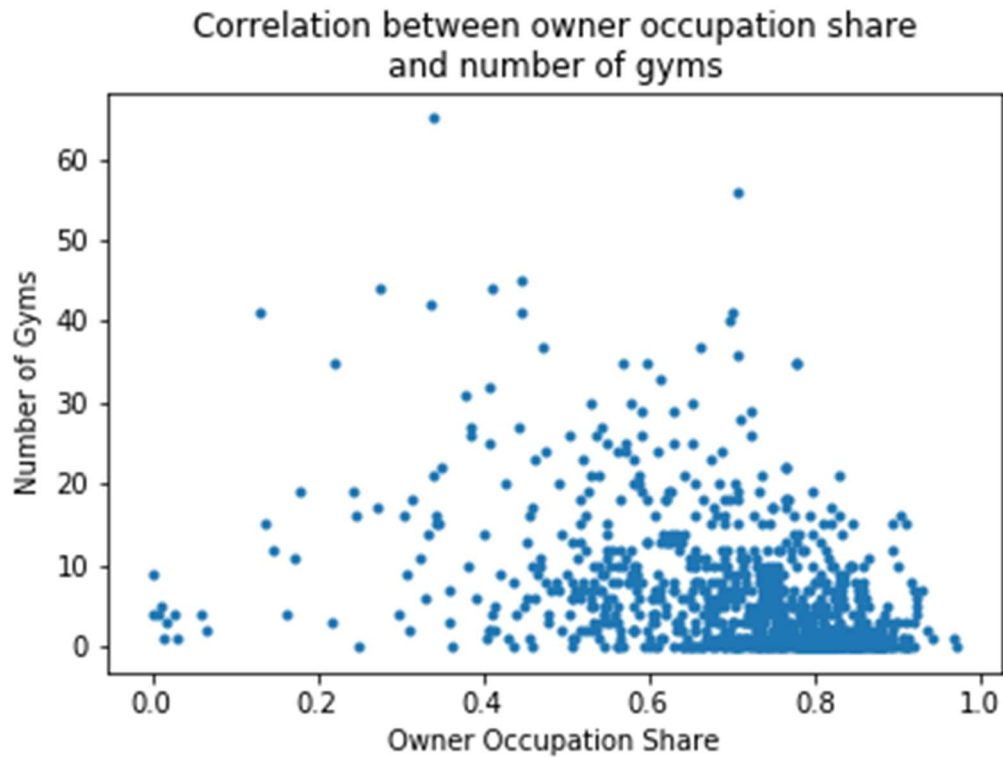
3.2. Research methods

In order to determine the potential of the gym opening in an area I decided firstly to build the model that predicts number of gyms in an area basing on the collected features, and after that just to compare the prediction with real data.

Model

Because the data was very diverse, of different scale and of different nature, a lot of features had high correlation I made a decision to use gradient boosting regressor, the model that is insensitive to such a complexities in the data. I also tried to tune and apply random forest

regressor and even the ensemble of both gradient boosting regressor and random forest regressor but in both cases the error metrics was higher, that's why I continued to use gradient boosting regressor.

Target variable

Although it can look unexpected I used not the number of gyms but logarithm from this number as a target variable. I wanted to consider as an error not the difference between predicted and actual values but ratio of them, so applying logarithm to number of gyms helped me in it because the difference between logarithms is a logarithm of the ratio and logarithm is a monotonically increasing function. But this action made one problem: logarithm from zero is minus infinity. To avoid it I decided to replace all zeros by some float number between 0 and 1, I chose exp(-1).

KFold

In order to split the data to train and test sets and at the same time to have a prediction for every zip code I used KFold technique with 4 folds but to smooth the prediction I applied 5 different splits and averaged the results for each zip code. I chose exactly five splits because with further increasing of the splits number the error metrics doesn't decrease significantly.


Dependence of the mean squared error on the number of splits
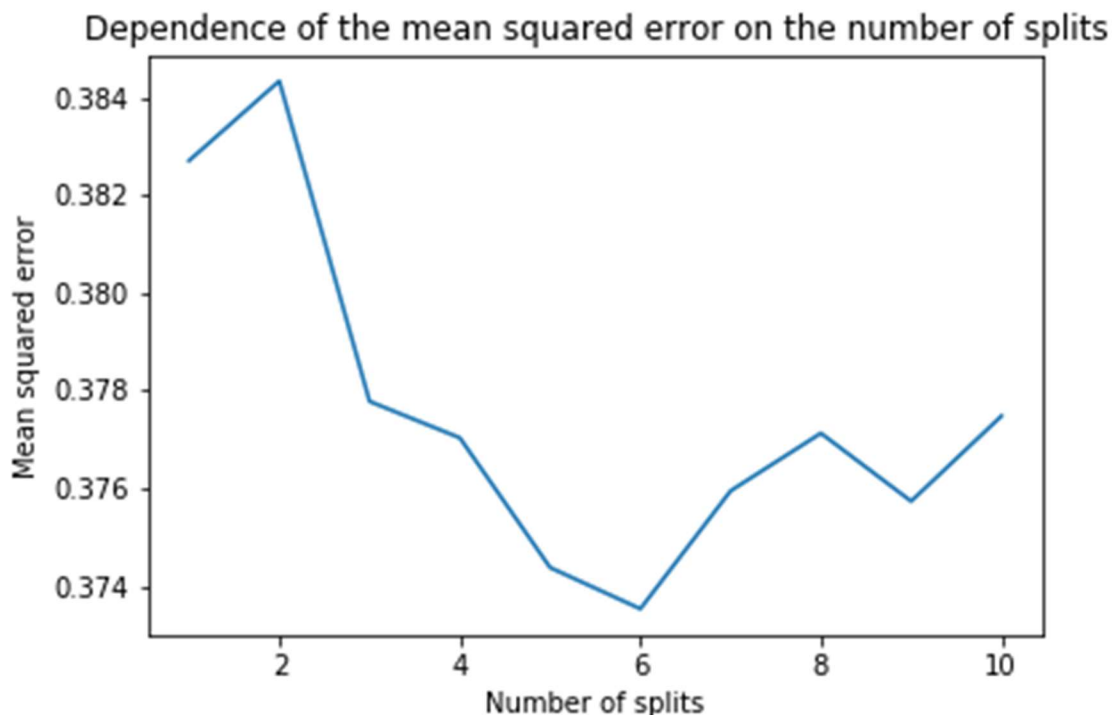
Tuning

I tuned such parameters of the model as learning rate, features fraction, samples fraction and max depth. I made the tuning of the parameters one by one fixing all other parameters and repeating this operation until the result has stopped changing. Finally I've got mean squared error metrics equal to 0.374. So let me explain what does this figure means. It mean that in average the prediction is more than actual value by 84.3% or vice versa the actual value is more than prediction by 84.3%. 84.3% is $0.843 = e^{\sqrt{0.374}} - 1$. It may seem like a big deviation but you have to understand that this difference includes both model error and 'real life error' or in other words, the difference in the development of areas that has appeared accidentally and which I am trying to discover in this study.

Model Prediction

So as a result I've got averaged prediction of number of gyms for every zip code area. Let's look at scatter plots with actual and predicted values. The plot on the left shows the dependence of the target variable and the prediction and the plot on the right shows the dependence of the actual and predicted number of gyms (as I described in "Target variable" section target variable is logarithm from actual number of gyms).
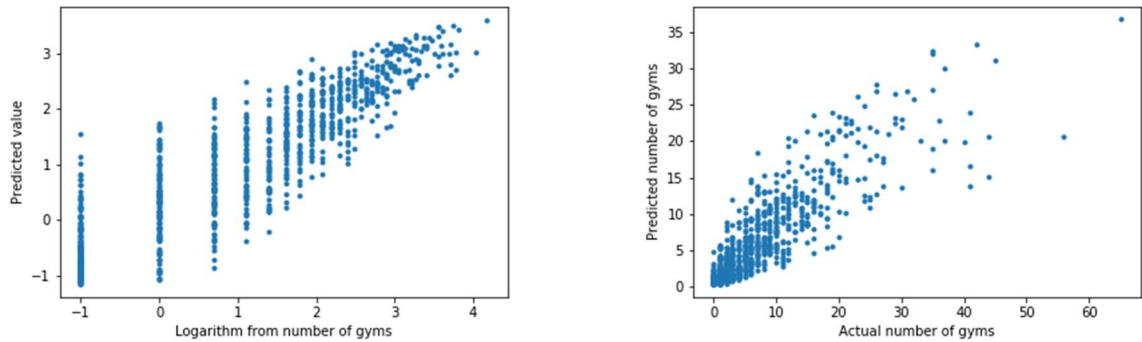
Feature importances

Totally there was 20 models (5 splits x 4 folds) and I averaged feature importances of all 20 models in order to see what features impact on the number of gyms higher. Here is the results:

feature	importance
Number of Businesses	0.187601
Number of Employees	0.087879
Annual Payroll	0.060557
Business Mailboxes	0.054840
Restaurant	0.034511
Asian Population Share	0.034320
Owner Occupation Share	0.020166
Residential Mailboxes	0.020119
Land Area	0.017710
Num_200k_inf[2]	0.016132

So as we can see the main feature is Number of Businesses as I expected based on correlation coefficients. And also here there are Number of Employees, Annual payroll and Business Mailboxes that are very correlated with Number of Businesses. Asian Population Share, Number of Restaurants and Owner Occupation Share is also in top 10 as well as the number of residents with income over 200k USD per year.

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[2] Hereinafter I use this form of label to denote the number of residents who declared annual income in 2016 over 200 thousand USD, the same form will be applied for other income value, for example Num_25k_50k means the number of residents with income from 25 to 50 thousand USD.

Index

After the model was build, fitted and made the prediction I compared predicted values with actual ones. I defined the gym opening potential index as a ratio of the predicted number of gyms and actual number incremented by one. Increment was needed because the new opening would change the ratio and also it lets to avoid the division by zero in the case when actual number of gyms is equal to zero. So I'll discuss the results in the next section but before you start reading it, I advise you to look at the appendix 1 (Top 20 and bottom 20 zip code areas in Florida by opening gym potential index).

4. Results

4.1. Best and worst index values.

In the appendix 1 you can find best and worst zip code areas in Florida to open the gym there. So let's take a closer look at them.

32505

Zip code 32505 is a west part of Pensacola city. According to this work the actual number of gyms is zero while the predicted value based on the features is more than 4.
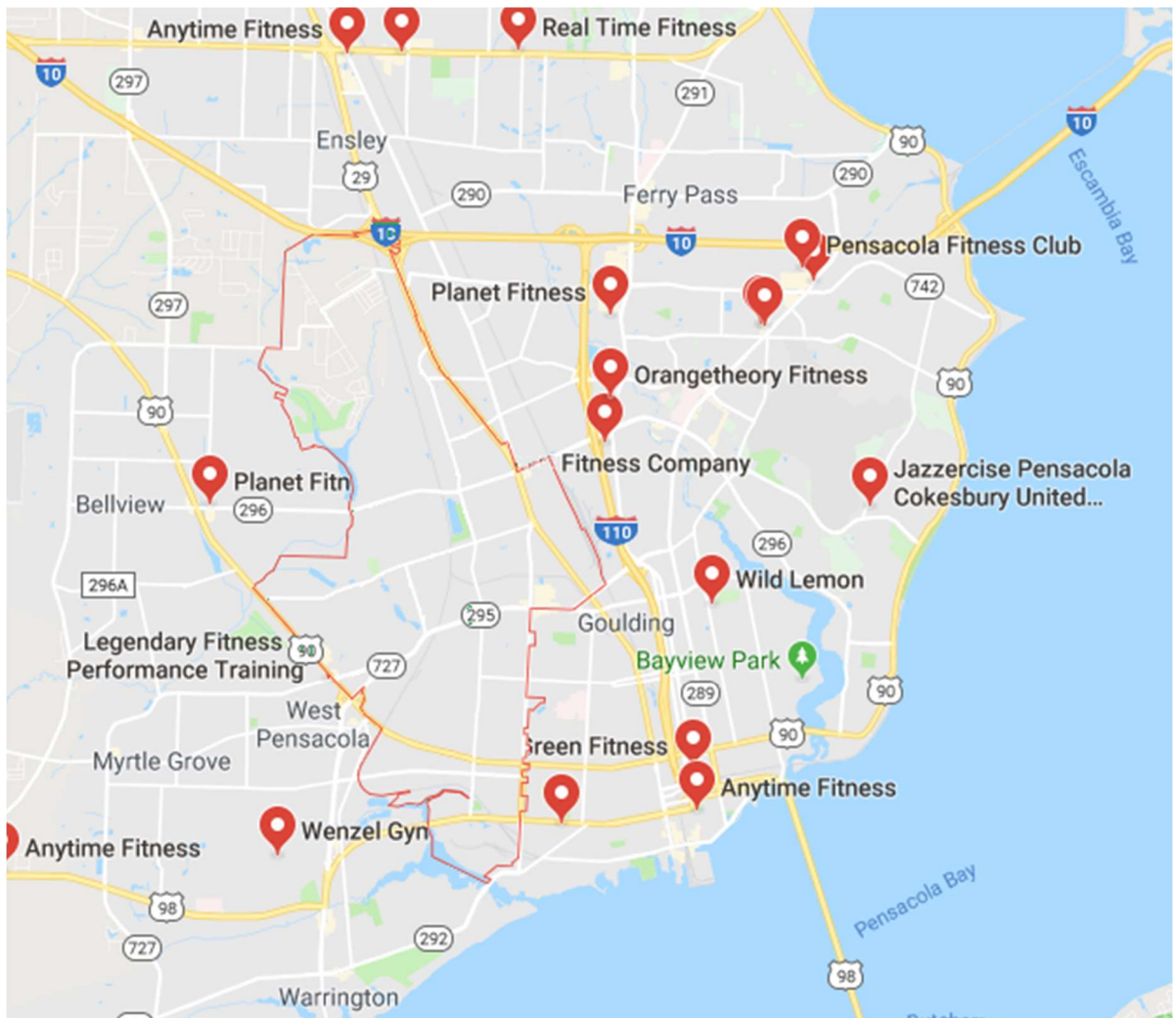
This map was created using Google Mape service. You can see the 32505 area in the centre of this map and fitness clubs around it, they are everywhere but not inside 32505 area. I used Google Maps specifically to show that the choice of application does not affect the result.

And now let's compare zip code area 32505 with 32503 that is nearby.

Zipcode	City	Current Population	Avarage House Value	White Population Share	Black Population Share	Number of Businesses	Male_25_29	Female_25_29	Num_0_25k	Num_25k_50k	Num_50k_75k	Num_75k_100k	Num_100k_200k	Num_200k_inf	Restaurant	Grocery Store	Café	Gym
32505	Pensacola	30559	64200	0.404	0.553	724	957	969	7090	2790	840	380	360	80	8	2	4	0
32503	Pensacola	31850	147500	0.672	0.290	851	1030	1143	6170	3660	1850	1040	1460	610	14	2	2	4

The population and number of businesses are almost the same. There are differences in house value, residents' income and white/black population share. It affected the number of restaurants, but did not affect the number of grocery stores and cafes as well as many other venue categories. So it seems that 0 gyms is really not enough for this area. By the way the predicted number of gyms for 32503 is 8.86, so it's also good place for new fitness clubs.

33323

Zip code 34983 holds the second place in the ranking but here the situation is similar with 32505: 0 gyms at the present and the predicted number 3.13, so I don't want to dwell on it. The third place (zip code 33323) is more interesting because the actual number of gyms is 3 but according to the prediction it's not enough (predicted value is more than 12). It is at the edge of Fort Lauderdale. So I'd like to compare this area with another one, I chose 33314:

Zipcode	City	Current Population	Average House Value	Number of Businesses	Number of Employees	Male_25_29	Female_25_29	Num_0_25k	Num_25k_50k	Num_50k_75k	Num_75k_100k	Num_100k_200k	Num_200k_inf	Restaurant	Grocery Store	Café	Gym
33323	Fort Lauderdale	24455	283800	1141	31564	584	673	3320	2350	1650	1200	1760	470	23	3	2	3
33314	Fort Lauderdale	26824	154700	1073	16934	1025	1073	5390	3290	1490	730	700	190	16	3	1	13

I chose it because the current population and number of businesses is almost the same but as we can see there are significant differences: the house value is much higher in 33323, despite the numbers of businesses are almost equal the numbers of employees differs a lot, also there is a big difference in numbers of residents aged 25 to 29. Most likely it should influence on number of gyms but it doesn't influence on number of restaurants, stores or cafes and the influence cannot be so huge that the actual number of gyms are 3 in 33323 versus 13 in 33314. So I guess zip code 33323 area is also good place to open the gym.

34758

As for worst areas I'd like to check 34758 where there are 5 gyms but predicted value is a little more then one. I found this comparison good:

Zipcode	City	Current Population	Average House Value	White Population Share	Black Population Share	Number of Businesses	Male_25_29	Female_25_29	Num_0_25k	Num_25k_50k	Num_50k_75k	Num_75k_100k	Num_100k_200k	Num_200k_inf	Restaurant	Grocery Store	Café	Gym
34758	Kissimmee	43371	156000	0.588	0.272	203	848	862	9360	5220	1920	750	460	30	1	0	0	5
34743	Kissimmee	40136	150100	0.660	0.157	296	1107	1119	9710	5700	1880	730	420	0	0	0	0	3

4.2. Interesting values

Looking at the scatter plot with dependence of prediction on actual value I've seen some interesting points and would like to discuss them.

32073

In this zip code area there are already 7 gyms but predicted number is more than 18, this point stands out on the scatter plot. So zip code 32073 area is Orange Park, suburb of Jacksonville. Comparison with the area located on the other side of St. Johns River:

Zipcode	City	Current Population	Avarage House Value	White Population	Black Population	Number of Businesses	Male_25_29	Female_25_29	Num_0_25k	Num_25k_50k	Num_50k_75k	Num_75k_100k	Num_100k_200k	Num_200k_inf	Restaurant	Grocery Store	Café	Gym
32073	Orange Park	43934	157600	0.757	0.179	1333	1306	1287	7300	5590	2970	1890	2030	370	35	4	4	7
32223	Jacksonville	26857	243100	0.910	0.057	813	569	548	3540	2620	1820	1370	2380	770	19	6	2	9

From all points of view the quantity of gyms in 32073 area has to be bigger than in 32223 area but actual situation is opposite and this is one more area for investors.

32801

This is almost the center of Orlando. While the actual number of gyms is 19 the predicted one is 24. The index is not very big, just 1.20 but anyway this area has opportunities for gym opening and it is a big city that can give additional advantages.

4.3. Maps

I provide the maps where the zip code areas are colorized according to their gym opening potential index that was calculated in this study in the appendices 2-6. You may find it more convenient to use an interactive map, which is also available. On the maps you can see that areas with high index are in the different parts of Florida.

5. Discussion

I tried to create my research in such a manner that numbers and graphs speak more than any narrative. Nevertheless, I would like to describe once again the most interesting conclusions I came to.

Firstly, in Florida there are enough places with a lack of gyms, there are places where there are no gyms at all, despite the fact that district lives a full life and has a large population. For example, district 32505 with a population of more than 30 thousand, in which the infrastructure is quite developed, but there is not a single gym.

Secondly, the zones of opportunities are not concentrated in one location, but are distributed throughout the state; this can be seen on the map of the state colored according to the index. There are favorable areas both in Fort Lauderdale and near Tampa, in Orlando and Jacksonville and in many other places. For gym chains it can be important if they want to develop their network in relative proximity to the existing clubs or vice versa want to spread their chain as widely as possible. Anyway, a potentially good zone is almost everywhere.

Finally, the potential of opening a gym can be estimated numerically and it can be done in advance. The model that I used predicts the expected number of gyms in the area and comparing it with the number of actually available gyms for each zip code area, I found the potentially most interesting zones. In addition to the already mentioned zone 32505, among the most interesting territories are areas with following zip codes: 34983, 33323, 33331, 33909, 32579, 33486, 33023, 33952, 33460 and 33169. If you are an investor and plan to invest in the opening of the gym, I strongly recommend paying attention to these areas.

6. Conclusion

In this study I determined the potential of fitness/gym opening in areas within Florida based on the demographics, tax and some other information about the areas. Firstly I collect different types of data into one table and then used it to create the model that predicts the number of gyms based on the provided data. After that I calculated the ratio of the predicted value and actual value incremented by one and considered this ratio as a gym opening potential index. This index can be interesting for the investors of any size who is going to operate on the fitness clubs market of Florida. For example, it can be used for choosing the place for new gym.

Future developments

I'd like to suggest some directions for those who want to develop this study:
- you can collect more information about the most impacting venues (restaurants, coffee shops etc.) realizing the same mechanism as I used to collect more data about the gyms;
- you can try to make features engineering and apply some other predictive models, for example, multi-layer perceptron (despite I avoid it in the report I made some attempts but it had no result, so I guess features engineering is possible but requires a very detailed study of the relationship between the features);
- you can define and take into consideration such a feature as a distance from the city center;
- in this study I don't care about the impact of the neighboring areas, so it's good idea to check whether the number of gyms in the neighboring areas impacts on the number of gyms in the area;
- you can use another library for gradient boosting modelling;
- distribution of the actual numbers of gym differs from the distribution of the predictions, so you can try to apply some weights to the sample errors in order to make these distributions to look similar;
- it can be interesting trick to apply the model to data from another state and check what's the error is;
- for further researches I strongly recommend to add crime statistics;
- any financial or operational data from the fitness clubs chain operated in Florida could significantly improve this study.

References:

1. 2014 State Indicator Report on Physical Activity of National Center for Chronic Disease Prevention and Health Promotion (https://www.cdc.gov/physicalactivity/downloads/PA_State_Indicator_Report_2014.pdf)

2. Listing of all zip codes in the state of Florida (https://www.zip-codes.com/state/fl.asp)

3. SOI Tax Stats - Individual Income Tax Statistics - 2016 ZIP Code Data (SOI) (https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-2016-zip-code-data-soi)

4. Foursquare API (https://developer.foursquare.com/)

Acknowledgement:

Appendix 1. Top 20 and bottom 20 zip code areas in Florida by gym opening potential index

zipcode	actual	actual+1	predicted	index	zipcode	actual	actual+1	predicted	index
32505	0	1	4.691647	4.691647	34759	5	6	1.380541	0.230090
34983	0	1	3.130228	3.130228	32628	1	2	0.452278	0.226139
33323	3	4	12.048341	3.012085	33570	6	7	1.566440	0.223777
33331	2	3	8.837829	2.945943	34288	3	4	0.877348	0.219337
33909	1	2	5.705526	2.852763	34758	5	6	1.267979	0.211330
32579	0	1	2.797934	2.797934	34610	2	3	0.627834	0.209278
33486	2	3	8.230125	2.743375	33972	1	2	0.412373	0.206186
33023	1	2	5.459479	2.729739	32744	1	2	0.402322	0.201161
33952	1	2	5.348582	2.674291	32066	1	2	0.402136	0.201068
33460	1	2	5.334014	2.667007	32009	1	2	0.398737	0.199368
33169	2	3	7.637895	2.545965	32347	2	3	0.586604	0.195535
34695	1	2	5.067789	2.533895	32618	1	2	0.383988	0.191994
32653	0	1	2.312939	2.312939	32460	1	2	0.381028	0.190514
32073	7	8	18.354365	2.294296	33538	1	2	0.351891	0.175946
32254	0	1	2.249304	2.249304	32336	1	2	0.351256	0.175628
32920	1	2	4.294061	2.147030	32466	1	2	0.344480	0.172240
32905	2	3	6.368505	2.122835	34289	3	4	0.686268	0.171567
32824	3	4	8.462913	2.115728	34291	2	3	0.495063	0.165021
33612	6	7	14.753063	2.107580	34949	4	5	0.812461	0.162492
34229	0	1	2.104482	2.104482	32577	2	3	0.422276	0.140759

Appendix 2. Map of Florida: gym opening potential index.
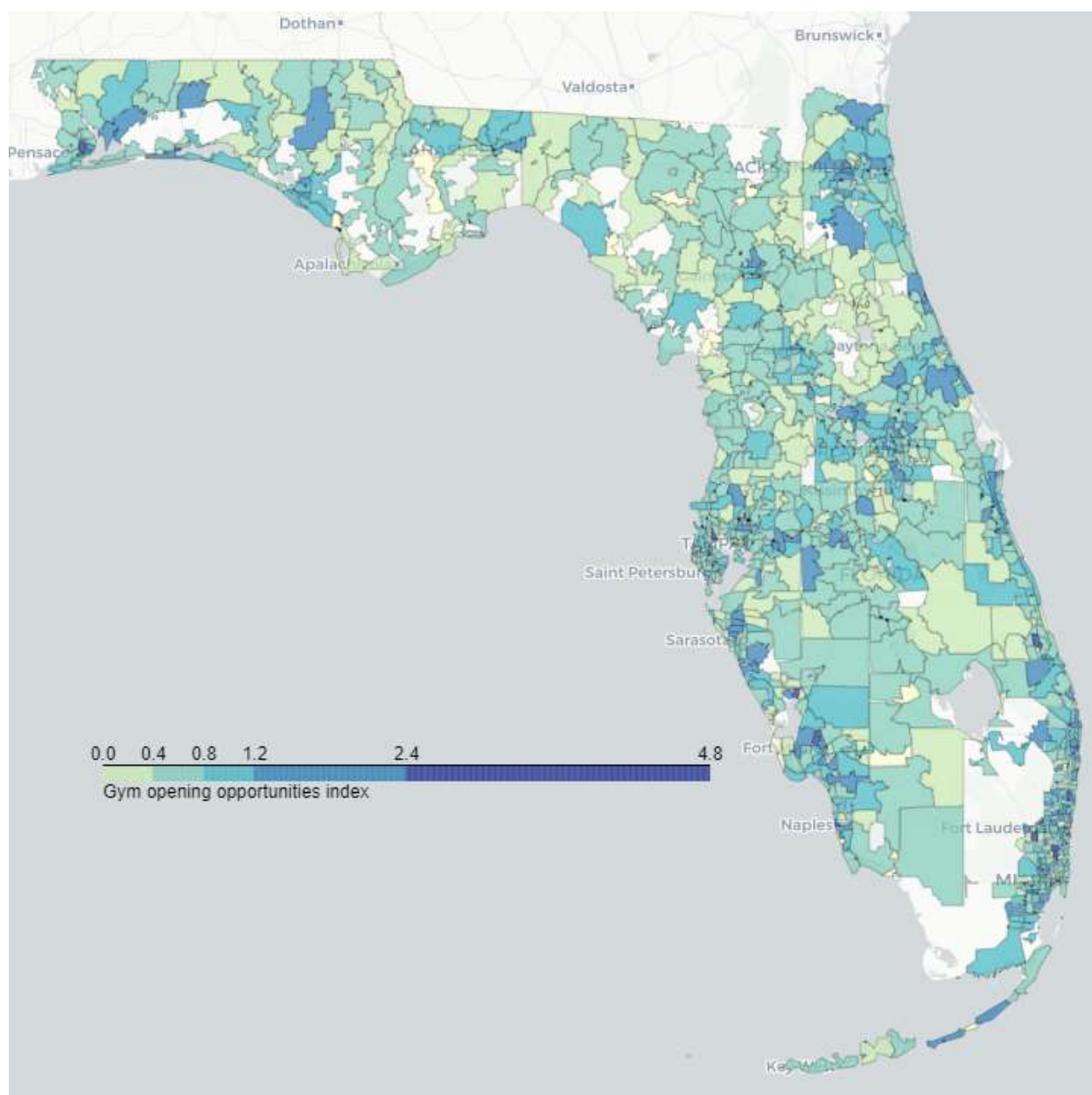
Appendix 3. Map of Miami-Fort Lauderdale-West Palm Beach metropolitan area: gym opening potential index.
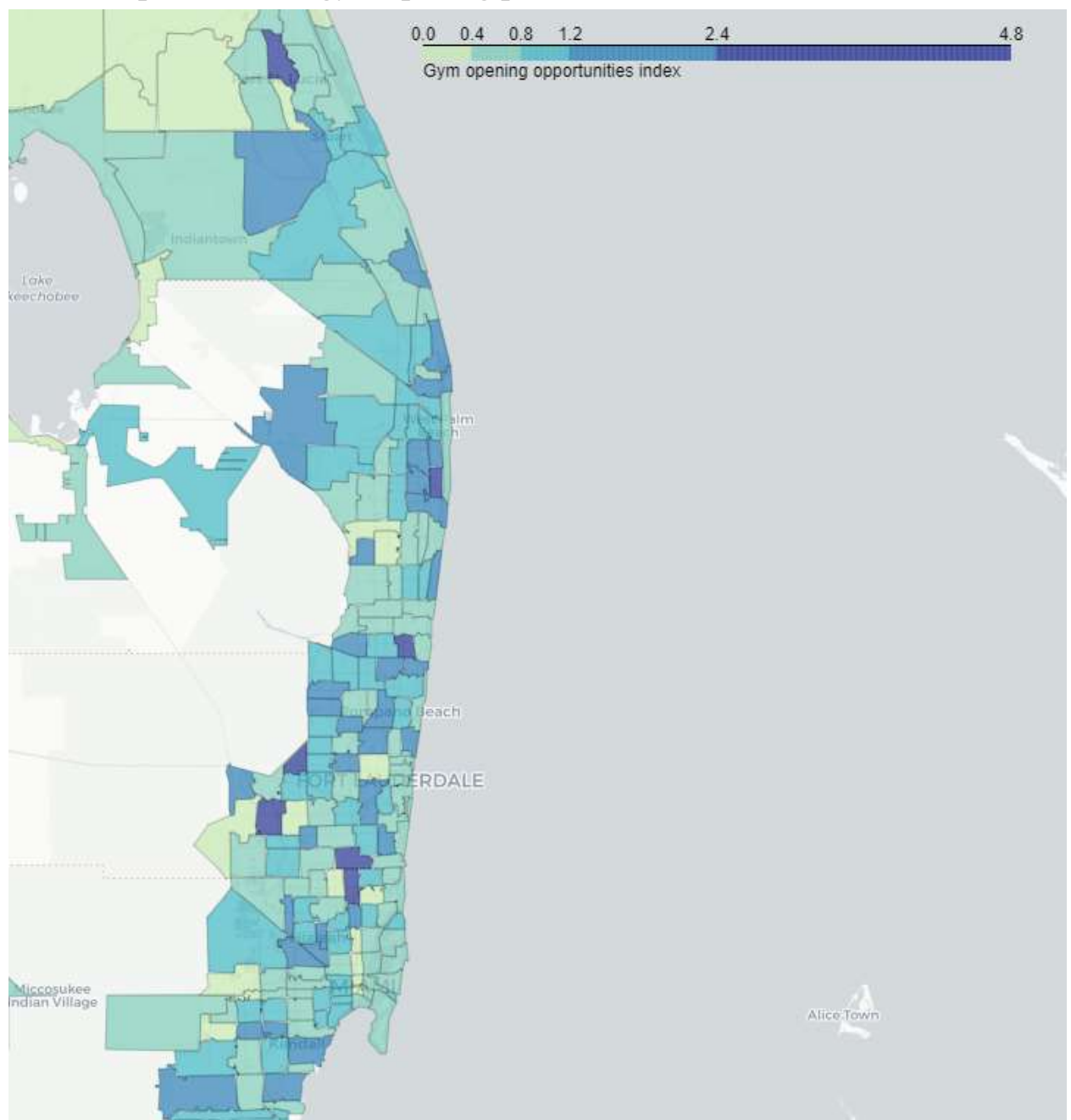
Appendix 4. Map of Tampa-St. Petersburg-Clearwater metropolitan area: gym opening potential index.
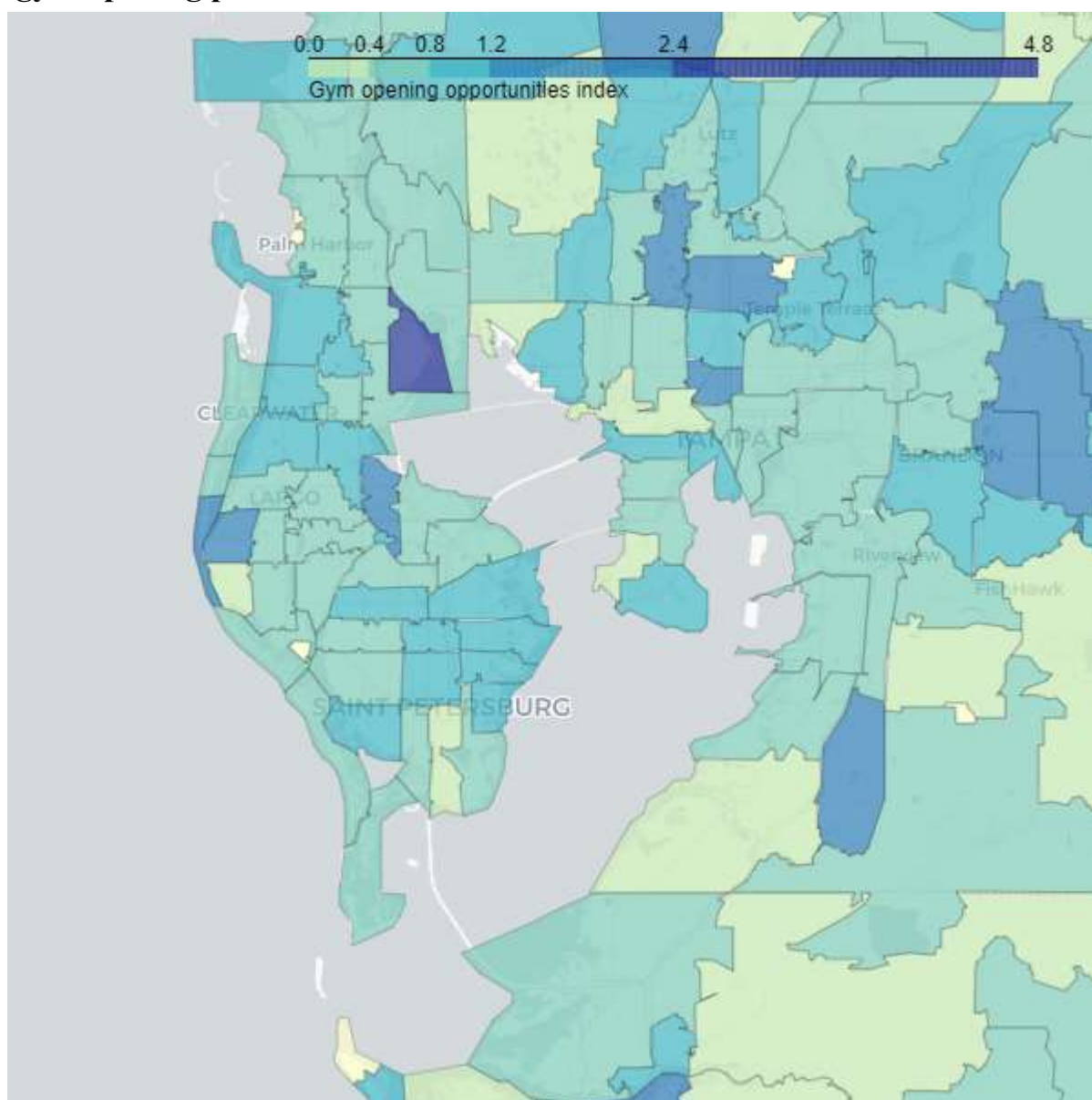
Appendix 5. Map of Orlando-Kissimmee-Sanford metropolitan area: gym opening potential index.
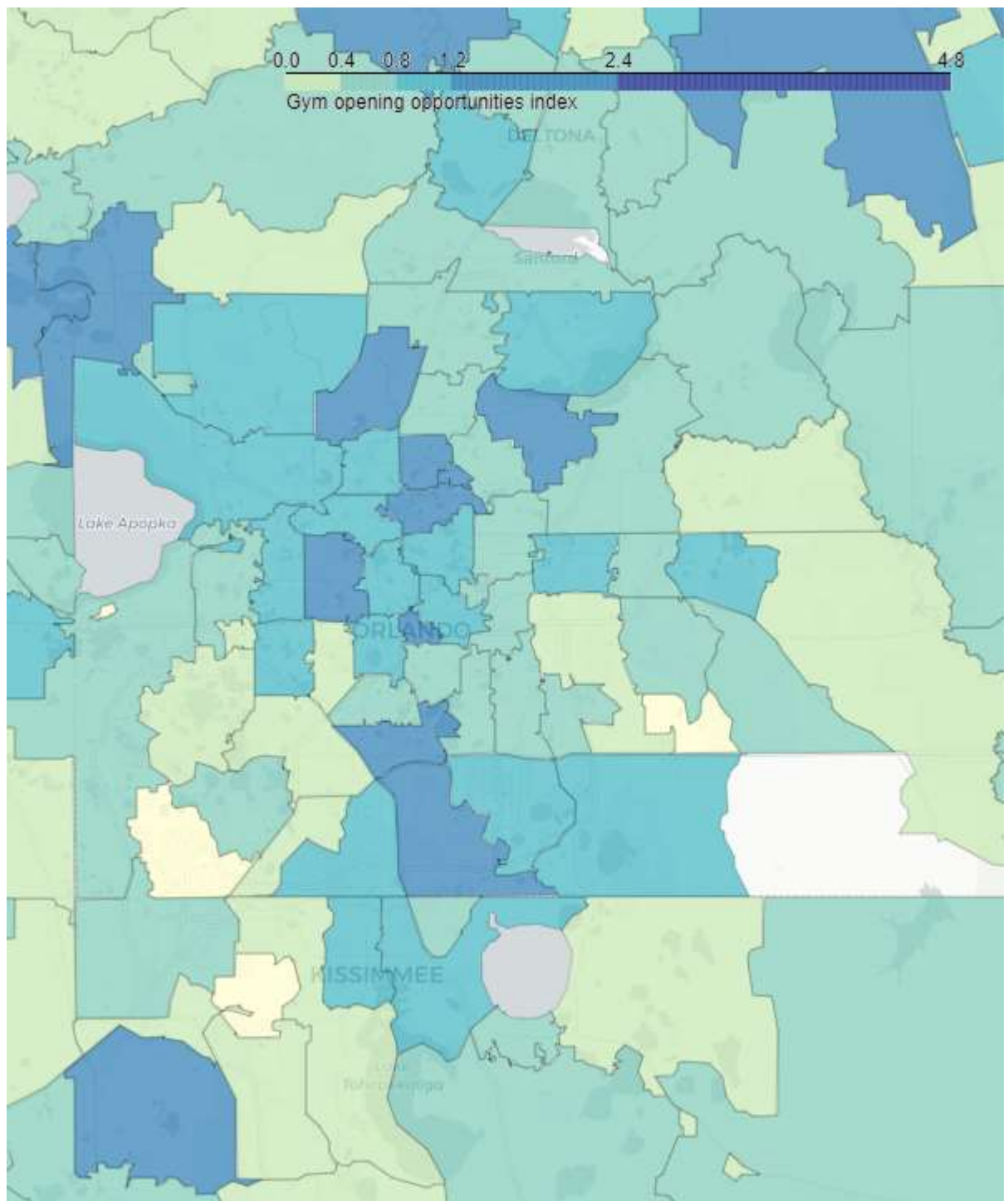
Appendix 6. Map of Jacksonville metropolitan area: gym opening potential index.
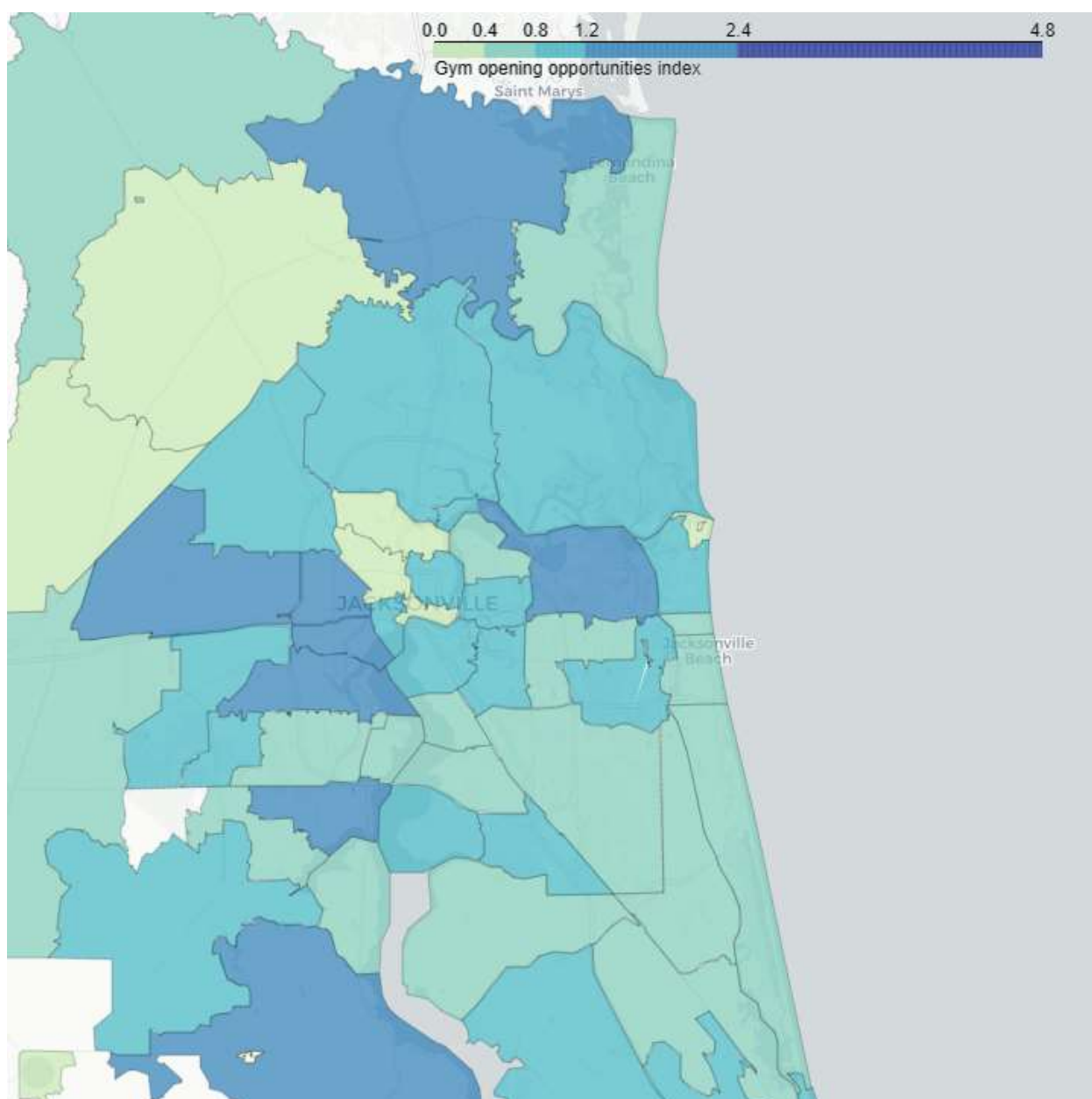
Appendix 7. Gym opening potential index in Florida by zip code areas.

zipcode	actual	actual+1	predicted	index	zipcode	actual	actual+1	predicted	index
32003	13	14	8,626755	0,616197	32124	0	1	0,969998	0,969998
32008	0	1	0,414787	0,414787	32127	5	6	6,224080	1,037347
32009	1	2	0,398737	0,199368	32128	2	3	2,292973	0,764324
32011	2	3	1,118917	0,372972	32129	12	13	3,646829	0,280525
32024	1	2	0,934339	0,467170	32130	0	1	0,420065	0,420065
32025	5	6	2,772099	0,462017	32131	0	1	0,428444	0,428444
32033	0	1	0,435137	0,435137	32132	3	4	1,106623	0,276656
32034	12	13	9,847859	0,757528	32134	0	1	0,398077	0,398077
32038	0	1	0,416433	0,416433	32136	0	1	1,461255	1,461255
32040	0	1	0,586953	0,586953	32137	5	6	9,002759	1,500460
32043	2	3	3,626036	1,208679	32139	0	1	0,358135	0,358135
32044	0	1	0,319019	0,319019	32140	0	1	0,352718	0,352718
32046	1	2	0,867229	0,433614	32141	0	1	1,095567	1,095567
32052	0	1	0,623431	0,623431	32145	0	1	0,369000	0,369000
32053	0	1	0,323379	0,323379	32148	0	1	0,560084	0,560084
32054	0	1	0,672956	0,672956	32159	5	6	5,689241	0,948207
32055	5	6	3,712231	0,618705	32162	1	2	3,980143	1,990071
32058	0	1	0,350885	0,350885	32164	5	6	3,721559	0,620260
32059	0	1	0,340021	0,340021	32168	2	3	4,712554	1,570851
32060	1	2	0,847162	0,423581	32169	1	2	2,684196	1,342098
32063	4	5	1,692924	0,338585	32174	16	17	11,741496	0,690676
32064	2	3	1,341956	0,447319	32176	4	5	2,598503	0,519701
32065	9	10	6,784087	0,678409	32177	8	9	3,483185	0,387021
32066	1	2	0,402136	0,201068	32179	0	1	0,450636	0,450636
32068	5	6	5,106820	0,851137	32180	0	1	0,364026	0,364026
32071	0	1	0,375017	0,375017	32181	0	1	0,343530	0,343530
32073	7	8	18,354365	2,294296	32187	0	1	0,332295	0,332295
32080	9	10	6,380186	0,638019	32189	0	1	0,398643	0,398643
32081	4	5	2,597476	0,519495	32190	0	1	0,364569	0,364569
32082	16	17	11,021973	0,648351	32193	0	1	0,396391	0,396391
32083	0	1	0,398933	0,398933	32195	0	1	0,380034	0,380034
32084	13	14	13,112305	0,936593	32202	15	16	5,977447	0,373590
32086	6	7	5,091857	0,727408	32204	9	10	10,923628	1,092363
32087	0	1	0,430704	0,430704	32205	7	8	9,976250	1,247031
32091	4	5	1,785860	0,357172	32206	1	2	2,308228	1,154114
32092	10	11	9,474387	0,861308	32207	21	22	18,081192	0,821872
32094	0	1	0,348980	0,348980	32208	4	5	1,225007	0,245001
32095	5	6	3,592751	0,598792	32209	2	3	1,180562	0,393521
32096	0	1	0,462093	0,462093	32210	9	10	13,142667	1,314267
32097	1	2	2,483726	1,241863	32211	5	6	5,527377	0,921229
32102	0	1	0,337716	0,337716	32212	4	5	2,246606	0,449321
32110	3	4	0,951984	0,237996	32216	19	20	16,220765	0,811038
32112	1	2	0,493562	0,246781	32217	9	10	7,540673	0,754067
32113	0	1	0,368138	0,368138	32218	16	17	14,928257	0,878133
32114	16	17	10,298807	0,605812	32219	0	1	0,938320	0,938320
32117	3	4	5,037559	1,259390	32220	0	1	1,664429	1,664429
32118	9	10	5,820343	0,582034	32221	2	3	3,183236	1,061079
32119	11	12	4,089467	0,340789	32222	2	3	3,208200	1,069400

zipcode	actual	actual+1	predicted	index	zipcode	actual	actual+1	predicted	index
32223	9	10	8,936752	0,893675	32404	3	4	4,322474	1,080618
32224	18	19	21,466821	1,129833	32405	11	12	12,679173	1,056598
32225	16	17	23,652532	1,391325	32407	10	11	7,436411	0,676037
32226	1	2	2,207428	1,103714	32408	7	8	7,988147	0,998518
32227	4	5	1,313888	0,262778	32409	0	1	0,677597	0,677597
32233	5	6	6,863236	1,143873	32413	8	9	6,071764	0,674640
32234	0	1	0,686959	0,686959	32420	0	1	0,356048	0,356048
32244	10	11	5,943755	0,540341	32421	0	1	0,355661	0,355661
32246	29	30	23,296709	0,776557	32423	0	1	0,365990	0,365990
32250	24	25	19,418070	0,776723	32424	1	2	0,564609	0,282305
32254	0	1	2,249304	2,249304	32425	1	2	0,948566	0,474283
32256	45	46	31,091397	0,675900	32426	0	1	0,414620	0,414620
32257	19	20	15,694798	0,784740	32427	0	1	0,372593	0,372593
32258	13	14	14,507965	1,036283	32428	0	1	1,250565	1,250565
32259	15	16	8,740958	0,546310	32430	0	1	0,459301	0,459301
32266	4	5	2,441883	0,488377	32431	0	1	0,421756	0,421756
32277	4	5	2,917166	0,583433	32433	1	2	0,681910	0,340955
32301	22	23	21,286070	0,925481	32435	0	1	0,854973	0,854973
32303	18	19	17,171178	0,903746	32437	0	1	0,425011	0,425011
32304	12	13	10,011520	0,770117	32438	0	1	0,379156	0,379156
32305	0	1	0,621798	0,621798	32439	4	5	1,225679	0,245136
32308	16	17	16,032528	0,943090	32440	0	1	0,712003	0,712003
32309	5	6	6,201099	1,033516	32442	0	1	0,363766	0,363766
32310	3	4	1,356322	0,339080	32443	0	1	0,464546	0,464546
32311	4	5	1,705754	0,341151	32444	2	3	3,628059	1,209353
32312	8	9	7,829331	0,869926	32445	0	1	0,414339	0,414339
32317	0	1	1,201509	1,201509	32446	5	6	2,141781	0,356964
32320	1	2	0,696047	0,348024	32448	1	2	0,867685	0,433842
32321	0	1	0,416295	0,416295	32449	0	1	0,409756	0,409756
32322	0	1	0,375544	0,375544	32455	0	1	0,417643	0,417643
32324	0	1	0,411684	0,411684	32456	3	4	1,583006	0,395751
32327	2	3	1,138703	0,379568	32459	8	9	8,693354	0,965928
32328	0	1	0,533011	0,533011	32460	1	2	0,381028	0,190514
32331	0	1	0,425799	0,425799	32461	0	1	0,946193	0,946193
32332	0	1	0,390058	0,390058	32462	0	1	0,349995	0,349995
32333	2	3	0,691193	0,230398	32464	0	1	0,375957	0,375957
32336	1	2	0,351256	0,175628	32465	0	1	0,425663	0,425663
32340	1	2	0,841647	0,420824	32466	1	2	0,344480	0,172240
32343	0	1	0,527186	0,527186	32501	4	5	5,059487	1,011897
32344	2	3	0,919036	0,306345	32502	7	8	5,594862	0,699358
32346	0	1	0,445095	0,445095	32503	4	5	8,861295	1,772259
32347	2	3	0,586604	0,195535	32504	14	15	9,065600	0,604373
32348	0	1	0,895460	0,895460	32505	0	1	4,691647	4,691647
32350	0	1	0,340903	0,340903	32506	6	7	5,415118	0,773588
32351	0	1	1,070134	1,070134	32507	6	7	6,043920	0,863417
32352	0	1	0,335235	0,335235	32508	4	5	2,376865	0,475373
32358	0	1	0,426429	0,426429	32514	15	16	9,585991	0,599124
32359	0	1	0,381558	0,381558	32526	9	10	4,801974	0,480197
32401	4	5	6,031994	1,206399	32531	0	1	0,755991	0,755991
32403	1	2	1,823026	0,911513	32533	2	3	1,673190	0,557730

zipcode	actual	actual+1	predicted	index
32534	6	7	3,848895	**0,549842**
32535	0	1	0,412568	**0,412568**
32536	7	8	6,169281	**0,771160**
32539	0	1	2,101762	**2,101762**
32541	14	15	16,553011	**1,103534**
32542	3	4	2,995800	**0,748950**
32544	5	6	2,399553	**0,399925**
32547	12	13	8,385892	**0,645069**
32548	8	9	11,484810	**1,276090**
32550	9	10	10,758215	**1,075822**
32561	7	8	4,246017	**0,530752**
32563	10	11	5,297909	**0,481628**
32564	0	1	0,451792	**0,451792**
32565	1	2	0,486201	**0,243100**
32566	10	11	7,515090	**0,683190**
32567	0	1	0,391003	**0,391003**
32568	0	1	0,437235	**0,437235**
32569	2	3	3,637436	**1,212479**
32570	3	4	4,027475	**1,006869**
32571	5	6	4,595398	**0,765900**
32577	2	3	0,422276	**0,140759**
32578	8	9	8,729526	**0,969947**
32579	0	1	2,797934	**2,797934**
32580	2	3	0,780055	**0,260018**
32583	0	1	1,548270	**1,548270**
32601	16	17	10,806905	**0,635700**
32603	4	5	2,335062	**0,467012**
32605	5	6	10,193365	**1,698894**
32606	9	10	11,168525	**1,116852**
32607	15	16	12,386646	**0,774165**
32608	26	27	27,820370	**1,030384**
32609	4	5	2,822634	**0,564527**
32615	4	5	2,089852	**0,417970**
32617	0	1	0,366135	**0,366135**
32618	1	2	0,383988	**0,191994**
32619	0	1	0,386492	**0,386492**
32621	0	1	0,335106	**0,335106**
32622	0	1	0,381585	**0,381585**
32625	0	1	0,548368	**0,548368**
32626	0	1	0,850916	**0,850916**
32628	1	2	0,452278	**0,226139**
32631	0	1	0,507177	**0,507177**
32640	0	1	0,590183	**0,590183**
32641	0	1	0,490871	**0,490871**
32643	1	2	1,153408	**0,576704**
32648	0	1	0,417456	**0,417456**
32653	0	1	2,312939	**2,312939**
32656	2	3	0,782256	**0,260752**
32666	0	1	0,448145	**0,448145**
32667	0	1	0,397323	**0,397323**

zipcode	actual	actual+1	predicted	index
32668	0	1	0,429764	**0,429764**
32669	4	5	2,699800	**0,539960**
32680	0	1	0,429375	**0,429375**
32686	0	1	0,493784	**0,493784**
32693	1	2	0,747599	**0,373799**
32694	0	1	0,428018	**0,428018**
32696	0	1	1,080674	**1,080674**
32701	7	8	12,829004	**1,603626**
32702	0	1	0,358544	**0,358544**
32703	12	13	11,579787	**0,890753**
32707	11	12	8,817575	**0,734798**
32708	12	13	15,775512	**1,213501**
32709	0	1	0,394058	**0,394058**
32712	6	7	6,639798	**0,948543**
32713	1	2	2,281775	**1,140887**
32714	20	21	21,345555	**1,016455**
32720	5	6	9,270028	**1,545005**
32724	4	5	5,713938	**1,142788**
32725	5	6	2,957174	**0,492862**
32726	5	6	3,942093	**0,657015**
32730	0	1	1,500770	**1,500770**
32732	0	1	0,543305	**0,543305**
32735	0	1	0,593620	**0,593620**
32736	0	1	0,621698	**0,621698**
32738	2	3	1,508260	**0,502753**
32744	1	2	0,402322	**0,201161**
32746	37	38	30,143520	**0,793251**
32750	14	15	9,804924	**0,653662**
32751	8	9	11,856498	**1,317389**
32754	0	1	0,612044	**0,612044**
32757	5	6	7,544779	**1,257463**
32759	0	1	0,359681	**0,359681**
32763	8	9	5,436775	**0,604086**
32764	0	1	0,404464	**0,404464**
32765	36	37	22,867810	**0,618049**
32766	2	3	0,950816	**0,316939**
32767	0	1	0,320109	**0,320109**
32771	21	22	14,374015	**0,653364**
32773	4	5	5,207736	**1,041547**
32776	3	4	1,079243	**0,269811**
32778	1	2	3,850859	**1,925430**
32779	4	5	8,882692	**1,776538**
32780	7	8	5,681971	**0,710246**
32784	1	2	0,706747	**0,353373**
32789	25	26	21,899109	**0,842273**
32792	37	38	20,120255	**0,529480**
32796	2	3	2,245284	**0,748428**
32798	0	1	0,510449	**0,510449**
32801	19	20	24,031596	**1,201580**
32803	21	22	23,283771	**1,058353**

zipcode	actual	actual+1	predicted	index
32804	13	14	13,619674	**0,972834**
32805	3	4	3,341878	**0,835469**
32806	21	22	14,834935	**0,674315**
32807	7	8	5,473986	**0,684248**
32808	2	3	4,013323	**1,337774**
32809	7	8	13,835169	**1,729396**
32810	9	10	10,050484	**1,005048**
32811	18	19	5,291684	**0,278510**
32812	13	14	6,505841	**0,464703**
32814	7	8	3,855837	**0,481980**
32817	12	13	13,841579	**1,064737**
32818	3	4	3,870399	**0,967600**
32819	56	57	20,598199	**0,361372**
32820	0	1	1,053503	**1,053503**
32821	44	45	15,044862	**0,334330**
32822	24	25	11,701655	**0,468066**
32824	3	4	8,462913	**2,115728**
32825	16	17	6,683759	**0,393162**
32826	14	15	9,031891	**0,602126**
32827	7	8	8,073752	**1,009219**
32828	25	26	17,575616	**0,675985**
32829	3	4	1,769619	**0,442405**
32832	4	5	4,898443	**0,979689**
32833	0	1	0,628412	**0,628412**
32835	17	18	16,034654	**0,890814**
32836	16	17	7,819893	**0,459994**
32837	20	21	21,645254	**1,030726**
32839	17	18	10,211733	**0,567319**
32901	8	9	10,247092	**1,138566**
32903	2	3	4,003697	**1,334566**
32904	17	18	14,344348	**0,796908**
32905	2	3	6,368505	**2,122835**
32907	4	5	3,221926	**0,644385**
32908	0	1	0,551031	**0,551031**
32909	1	2	2,245343	**1,122672**
32920	1	2	4,294061	**2,147030**
32922	6	7	3,429753	**0,489965**
32925	1	2	1,781814	**0,890907**
32926	2	3	1,916517	**0,638839**
32927	2	3	1,685333	**0,561778**
32931	6	7	4,697109	**0,671016**
32934	1	2	2,783815	**1,391908**
32935	13	14	11,179748	**0,798553**
32937	7	8	7,735032	**0,966879**
32940	16	17	13,273194	**0,780776**
32948	0	1	0,364218	**0,364218**
32949	0	1	0,441926	**0,441926**
32950	0	1	0,630262	**0,630262**
32951	1	2	1,156144	**0,578072**
32952	2	3	4,038995	**1,346332**

zipcode	actual	actual+1	predicted	index
32953	4	5	5,312086	**1,062417**
32955	12	13	10,505249	**0,808096**
32958	4	5	4,188276	**0,837655**
32960	10	11	12,203667	**1,109424**
32962	2	3	2,053973	**0,684658**
32963	3	4	3,661681	**0,915420**
32966	2	3	3,334120	**1,111373**
32967	2	3	1,745261	**0,581754**
32968	1	2	1,719723	**0,859862**
32976	0	1	0,560158	**0,560158**
33004	9	10	5,677586	**0,567759**
33009	26	27	12,642438	**0,468238**
33010	2	3	4,294076	**1,431359**
33012	10	11	9,325233	**0,847748**
33013	1	2	3,131920	**1,565960**
33014	13	14	12,338923	**0,881352**
33015	13	14	7,445880	**0,531849**
33016	7	8	12,758159	**1,594770**
33018	7	8	4,563936	**0,570492**
33019	11	12	6,069090	**0,505758**
33020	10	11	13,235828	**1,203257**
33021	17	18	21,069770	**1,170543**
33023	1	2	5,459479	**2,729739**
33024	18	19	13,955166	**0,734482**
33025	14	15	10,212556	**0,680837**
33026	6	7	9,417485	**1,345355**
33026	6	7	9,121475	**1,303068**
33027	21	22	22,528561	**1,024026**
33028	6	7	6,208813	**0,886973**
33029	15	16	8,671028	**0,541939**
33030	5	6	4,828775	**0,804796**
33031	0	1	0,862915	**0,862915**
33032	2	3	2,792596	**0,930865**
33033	5	6	4,856188	**0,809365**
33034	1	2	1,602594	**0,801297**
33035	0	1	0,896826	**0,896826**
33036	0	1	1,286916	**1,286916**
33037	6	7	4,641579	**0,663083**
33040	27	28	17,771264	**0,634688**
33042	2	3	0,876612	**0,292204**
33043	0	1	0,766170	**0,766170**
33050	3	4	5,073042	**1,268261**
33054	2	3	1,673753	**0,557918**
33055	1	2	1,405550	**0,702775**
33056	6	7	1,903105	**0,271872**
33060	6	7	6,856413	**0,979488**
33062	18	19	9,471075	**0,498478**
33063	21	22	10,206545	**0,463934**
33064	11	12	12,131186	**1,010932**
33065	12	13	19,388128	**1,491394**

zipcode	actual	actual+1	predicted	index
33066	1	2	1,395307	0,697654
33067	7	8	9,258134	1,157267
33068	1	2	4,150939	2,075470
33069	7	8	10,507195	1,313399
33070	2	3	1,239998	0,413333
33071	12	13	17,222353	1,324796
33073	18	19	17,361551	0,913766
33076	11	12	10,766908	0,897242
33109	0	1	0,810793	0,810793
33122	9	10	5,512245	0,551225
33125	4	5	4,182508	0,836502
33126	14	15	10,764507	0,717634
33127	11	12	4,642935	0,386911
33128	4	5	1,159059	0,231812
33129	8	9	6,450674	0,716742
33130	41	42	13,741009	0,327167
33131	42	43	33,463120	0,778212
33132	35	36	16,006967	0,444638
33133	23	24	19,984881	0,832703
33134	19	20	20,236435	1,011822
33135	3	4	4,718400	1,179600
33136	11	12	3,029378	0,252448
33137	44	45	20,595978	0,457688
33138	14	15	10,778499	0,718567
33139	65	66	36,805290	0,557656
33140	24	25	12,472258	0,498890
33141	14	15	11,962625	0,797508
33142	6	7	3,359936	0,479991
33143	30	31	22,024790	0,710477
33144	6	7	4,771778	0,681683
33145	7	8	8,650317	1,081290
33146	17	18	15,119822	0,839990
33147	1	2	1,727370	0,863685
33149	11	12	5,007305	0,417275
33150	4	5	1,466802	0,293360
33154	7	8	8,582584	1,072823
33155	18	19	13,575868	0,714519
33156	15	16	21,334845	1,333428
33157	10	11	15,499914	1,409083
33158	1	2	1,090751	0,545375
33160	35	36	18,915866	0,525441
33161	6	7	6,223319	0,889046
33162	16	17	4,589913	0,269995
33165	6	7	7,052487	1,007498
33166	12	13	20,395814	1,568909
33167	0	1	0,857185	0,857185
33168	0	1	1,506664	1,506664
33169	2	3	7,637895	2,545965
33170	0	1	0,850417	0,850417
33172	30	31	13,570400	0,437755

zipcode	actual	actual+1	predicted	index
33173	7	8	9,745363	1,218170
33174	6	7	5,305295	0,757899
33175	8	9	8,627460	0,958607
33176	19	20	20,580395	1,029020
33177	5	6	3,848465	0,641411
33178	24	25	24,950826	0,998033
33179	6	7	6,544633	0,934948
33180	30	31	23,089344	0,744818
33181	16	17	11,501799	0,676576
33182	2	3	0,703464	0,234488
33183	3	4	6,225167	1,556292
33184	5	6	2,274177	0,379030
33185	2	3	2,308238	0,769413
33186	41	42	23,953841	0,570330
33187	0	1	1,211432	1,211432
33189	4	5	3,611003	0,722201
33190	0	1	0,863411	0,863411
33193	6	7	2,514772	0,359253
33194	0	1	0,550545	0,550545
33196	8	9	10,129106	1,125456
33301	26	27	21,385602	0,792059
33304	27	28	17,098371	0,610656
33305	10	11	7,647642	0,695240
33306	8	9	4,800435	0,533382
33308	8	9	15,318707	1,702079
33309	10	11	14,458220	1,314384
33311	8	9	3,034783	0,337198
33312	6	7	11,935284	1,705041
33313	2	3	3,757920	1,252640
33314	13	14	12,572504	0,898036
33315	6	7	7,956093	1,136585
33316	23	24	14,649026	0,610376
33317	12	13	9,331094	0,717776
33319	9	10	4,362498	0,436250
33321	7	8	8,407190	1,050899
33322	10	11	8,843763	0,803978
33323	3	4	12,048341	3,012085
33324	29	30	26,577756	0,885925
33325	10	11	10,119469	0,919952
33326	26	27	18,075572	0,669466
33327	1	2	3,730779	1,865390
33328	15	16	9,996709	0,624794
33330	7	8	2,937899	0,367237
33331	2	3	8,837829	2,945943
33332	4	5	1,616388	0,323278
33334	25	26	10,940644	0,420794
33351	12	13	11,352418	0,873263
33401	31	32	26,960633	0,842520
33403	8	9	6,470031	0,718892
33404	4	5	6,300774	1,260155

zipcode	actual	actual+1	predicted	index
33405	2	3	5,282242	**1,760747**
33406	3	4	5,350177	**1,337544**
33407	9	10	8,546645	**0,854664**
33408	8	9	13,074622	**1,452736**
33409	10	11	11,438056	**1,039823**
33410	23	24	21,836755	**0,909865**
33411	35	36	32,549966	**0,904166**
33411	35	36	32,151062	**0,893085**
33412	1	2	1,343179	**0,671590**
33412	1	2	1,278895	**0,639447**
33413	3	4	2,441683	**0,610421**
33414	22	23	22,918540	**0,996458**
33414	22	23	22,561265	**0,980925**
33415	2	3	3,211696	**1,070565**
33417	2	3	3,182671	**1,060890**
33418	14	15	12,821096	**0,854740**
33426	20	21	14,505832	**0,690754**
33428	6	7	9,404591	**1,343513**
33430	0	1	1,057521	**1,057521**
33431	40	41	19,966204	**0,486981**
33432	33	34	20,137324	**0,592274**
33433	15	16	15,668536	**0,979283**
33434	15	16	8,632036	**0,539502**
33435	8	9	5,830329	**0,647814**
33436	9	10	7,953841	**0,795384**
33437	11	12	3,917259	**0,326438**
33438	0	1	0,376777	**0,376777**
33440	3	4	0,941427	**0,235357**
33441	8	9	12,808093	**1,423121**
33442	11	12	15,247381	**1,270615**
33444	10	11	10,351234	**0,941021**
33445	10	11	8,812977	**0,801180**
33446	10	11	5,173017	**0,470274**
33449	3	4	2,101575	**0,525394**
33455	5	6	3,212737	**0,535456**
33458	29	30	22,422734	**0,747424**
33460	1	2	5,334014	**2,667007**
33461	3	4	6,848214	**1,712054**
33462	6	7	8,925103	**1,275015**
33463	7	8	8,404874	**1,050609**
33467	16	17	12,043048	**0,708415**
33469	1	2	3,644612	**1,822306**
33470	1	2	3,982955	**1,991477**
33471	0	1	0,475931	**0,475931**
33472	5	6	2,105627	**0,350938**
33473	0	1	1,263612	**1,263612**
33476	0	1	0,693419	**0,693419**
33477	7	8	4,220711	**0,527589**
33478	2	3	2,128246	**0,709415**
33480	8	9	6,010346	**0,667816**

zipcode	actual	actual+1	predicted	index
33483	7	8	13,022380	**1,627797**
33484	10	11	4,787854	**0,435259**
33486	2	3	8,230125	**2,743375**
33487	17	18	11,015965	**0,611998**
33493	0	1	0,461423	**0,461423**
33496	10	11	7,746526	**0,704230**
33498	6	7	3,021746	**0,431678**
33510	6	7	3,687358	**0,526765**
33511	26	27	26,904850	**0,996476**
33513	1	2	0,731801	**0,365901**
33514	0	1	0,319476	**0,319476**
33523	1	2	0,714346	**0,357173**
33525	4	5	2,083531	**0,416706**
33527	0	1	1,250398	**1,250398**
33534	1	2	1,014790	**0,507395**
33538	1	2	0,351891	**0,175946**
33540	0	1	0,577846	**0,577846**
33541	5	6	2,261758	**0,376960**
33542	4	5	1,741733	**0,348347**
33543	7	8	5,283890	**0,660486**
33544	10	11	7,358095	**0,668918**
33545	0	1	0,861710	**0,861710**
33547	8	9	2,842700	**0,315856**
33548	4	5	3,381570	**0,676314**
33549	5	6	4,810391	**0,801732**
33556	12	13	4,570230	**0,351556**
33558	5	6	5,712375	**0,952062**
33559	7	8	5,057179	**0,632147**
33563	10	11	5,562580	**0,505689**
33565	1	2	1,056486	**0,528243**
33566	1	2	3,529651	**1,764825**
33567	0	1	0,826766	**0,826766**
33569	5	6	3,445164	**0,574194**
33570	6	7	1,566440	**0,223777**
33572	5	6	3,721618	**0,620270**
33573	1	2	2,701762	**1,350881**
33576	2	3	0,692099	**0,230700**
33578	18	19	12,936011	**0,680843**
33579	5	6	1,580398	**0,263400**
33584	6	7	5,298271	**0,756896**
33585	0	1	0,438870	**0,438870**
33592	0	1	0,858941	**0,858941**
33594	3	4	5,165621	**1,291405**
33596	5	6	4,846452	**0,807742**
33597	0	1	0,355031	**0,355031**
33598	0	1	0,744099	**0,744099**
33602	32	33	25,784669	**0,781354**
33603	2	3	4,532389	**1,510796**
33604	3	4	4,503333	**1,125833**
33605	9	10	4,826807	**0,482681**

zipcode	actual	actual+1	predicted	index
33606	23	24	26,122932	1,088456
33607	41	42	16,585724	0,394898
33609	20	21	23,355206	1,112153
33610	6	7	5,105240	0,729320
33611	20	21	15,273076	0,727289
33612	6	7	14,753063	2,107580
33613	16	17	11,577696	0,681041
33614	25	26	11,878243	0,456856
33615	8	9	10,012971	1,112552
33616	4	5	1,657532	0,331506
33617	13	14	12,684910	0,906065
33618	13	14	20,092932	1,435209
33619	10	11	8,067578	0,733416
33621	2	3	2,529508	0,843169
33624	15	16	8,461199	0,528825
33625	7	8	7,035050	0,879381
33626	24	25	14,891631	0,595665
33629	15	16	11,701613	0,731351
33634	18	19	9,307631	0,489875
33635	11	12	3,470163	0,289180
33637	5	6	6,800443	1,133407
33647	35	36	27,113473	0,753152
33701	21	22	20,881102	0,949141
33702	10	11	11,999284	1,090844
33703	3	4	4,450115	1,112529
33704	10	11	8,961700	0,814700
33705	8	9	4,387520	0,487502
33706	8	9	6,649273	0,738808
33707	5	6	5,696483	0,949414
33708	8	9	4,596555	0,510728
33709	5	6	4,030344	0,671724
33710	18	19	13,329626	0,701559
33711	3	4	2,183274	0,545818
33712	11	12	2,774535	0,231211
33713	10	11	11,528849	1,048077
33714	3	4	3,321765	0,830441
33715	1	2	1,180114	0,590057
33716	19	20	12,419733	0,620987
33755	5	6	6,608574	1,101429
33756	9	10	10,643965	1,064396
33759	11	12	8,882552	0,740213
33760	4	5	10,487635	2,097527
33761	12	13	8,170166	0,628474
33762	10	11	8,777981	0,797998
33763	2	3	3,166121	1,055374
33764	8	9	8,116784	0,901865
33765	15	16	11,542534	0,721408
33767	7	8	3,506029	0,438254
33770	10	11	8,224450	0,747677
33771	14	15	8,547771	0,569851

zipcode	actual	actual+1	predicted	index
33772	9	10	6,772732	0,677273
33773	8	9	5,503022	0,611447
33774	2	3	5,258867	1,752956
33776	3	4	1,144590	0,286147
33777	9	10	5,277156	0,527716
33778	2	3	1,783598	0,594533
33781	13	14	11,616799	0,829771
33782	5	6	3,245753	0,540959
33785	0	1	1,871570	1,871570
33786	0	1	0,470559	0,470559
33801	8	9	5,586611	0,620735
33803	18	19	10,785720	0,567669
33805	7	8	3,108309	0,388539
33809	11	12	6,330991	0,527583
33810	2	3	3,198948	1,066316
33811	5	6	3,517492	0,586249
33812	2	3	1,926039	0,642013
33813	15	16	8,447544	0,527971
33815	4	5	1,774352	0,354870
33823	3	4	4,297149	1,074287
33825	1	2	1,503913	0,751956
33827	0	1	0,342066	0,342066
33830	5	6	3,773554	0,628926
33834	0	1	0,601655	0,601655
33837	1	2	2,999580	1,499790
33838	1	2	0,877546	0,438773
33839	0	1	0,595315	0,595315
33841	0	1	0,421550	0,421550
33843	1	2	0,544598	0,272299
33844	3	4	3,168099	0,792025
33849	0	1	0,469092	0,469092
33850	0	1	0,658015	0,658015
33852	2	3	1,393114	0,464371
33853	6	7	2,784128	0,397733
33857	0	1	0,366344	0,366344
33859	2	3	1,304594	0,434865
33860	0	1	1,871614	1,871614
33865	0	1	0,381140	0,381140
33868	0	1	0,492070	0,492070
33870	5	6	4,527564	0,754594
33872	1	2	1,362963	0,681482
33873	1	2	1,060796	0,530398
33875	0	1	0,532611	0,532611
33876	0	1	0,483641	0,483641
33880	4	5	8,014554	1,602911
33881	5	6	4,169322	0,694887
33884	7	8	5,650191	0,706274
33890	0	1	0,413453	0,413453
33896	6	7	2,040893	0,291556
33897	4	5	1,732482	0,346496

zipcode	actual	actual+1	predicted	index
33898	0	1	0,830467	**0,830467**
33901	8	9	13,081496	**1,453500**
33903	1	2	3,799432	**1,899716**
33904	5	6	6,225717	**1,037620**
33905	7	8	5,733009	**0,716626**
33907	20	21	15,982478	**0,761070**
33908	12	13	12,226388	**0,940491**
33909	1	2	5,705526	**2,852763**
33912	6	7	11,849592	**1,692799**
33913	10	11	10,860076	**0,987280**
33914	7	8	6,123807	**0,765476**
33916	7	8	3,117354	**0,389669**
33917	1	2	1,446198	**0,723099**
33919	6	7	9,195120	**1,313589**
33920	1	2	0,539320	**0,269660**
33922	0	1	0,373600	**0,373600**
33928	5	6	8,487763	**1,414627**
33931	2	3	1,767998	**0,589333**
33935	1	2	1,101379	**0,550689**
33936	1	2	1,636036	**0,818018**
33946	1	2	0,489412	**0,244706**
33947	1	2	0,592256	**0,296128**
33948	3	4	5,146892	**1,286723**
33950	8	9	4,974726	**0,552747**
33952	1	2	5,348582	**2,674291**
33953	4	5	1,173823	**0,234765**
33954	3	4	1,852644	**0,463161**
33955	0	1	0,871177	**0,871177**
33956	0	1	0,459850	**0,459850**
33957	1	2	1,941984	**0,970992**
33960	0	1	0,407529	**0,407529**
33966	15	16	8,503291	**0,531456**
33967	3	4	2,969503	**0,742376**
33971	1	2	2,094294	**1,047147**
33972	1	2	0,412373	**0,206186**
33973	0	1	0,624295	**0,624295**
33974	0	1	0,341704	**0,341704**
33976	0	1	0,430712	**0,430712**
33980	6	7	2,382494	**0,340356**
33981	1	2	0,878109	**0,439054**
33982	0	1	0,844394	**0,844394**
33983	1	2	1,378097	**0,689048**
33990	7	8	6,670449	**0,833806**
33991	9	10	4,591399	**0,459140**
33993	0	1	1,448453	**1,448453**
34102	6	7	14,313809	**2,044830**
34103	7	8	9,411837	**1,176480**
34104	11	12	9,348999	**0,779083**
34105	10	11	4,026615	**0,366056**
34108	12	13	7,867511	**0,605193**

zipcode	actual	actual+1	predicted	index
34109	19	20	17,022567	**0,851128**
34110	8	9	9,766341	**1,085149**
34112	2	3	4,494307	**1,498102**
34113	1	2	2,051204	**1,025602**
34114	3	4	1,882674	**0,470668**
34116	3	4	2,948142	**0,737036**
34117	1	2	0,742821	**0,371410**
34119	7	8	8,053553	**1,006694**
34120	2	3	2,733520	**0,911173**
34134	8	9	5,184981	**0,576109**
34135	18	19	8,227078	**0,433004**
34141	0	1	0,440212	**0,440212**
34142	2	3	1,355060	**0,451687**
34145	7	8	5,996954	**0,749619**
34201	6	7	2,892844	**0,413263**
34202	8	9	8,748595	**0,972066**
34203	5	6	10,859423	**1,809904**
34205	8	9	5,773079	**0,641453**
34207	6	7	3,380410	**0,482916**
34208	5	6	7,638584	**1,273097**
34209	12	13	5,052135	**0,388626**
34210	8	9	5,500821	**0,611202**
34211	8	9	2,304642	**0,256071**
34212	3	4	1,567260	**0,391815**
34215	0	1	0,404466	**0,404466**
34217	1	2	1,607788	**0,803894**
34219	3	4	1,512009	**0,378002**
34221	4	5	3,745851	**0,749170**
34222	2	3	2,749980	**0,916660**
34223	3	4	3,065874	**0,766469**
34224	1	2	1,668405	**0,834202**
34228	4	5	1,252356	**0,250471**
34229	0	1	2,104482	**2,104482**
34231	8	9	10,208052	**1,134228**
34232	11	12	9,543902	**0,795325**
34233	13	14	7,491850	**0,535132**
34234	2	3	3,872951	**1,290984**
34235	3	4	1,849494	**0,462373**
34236	25	26	12,251328	**0,471205**
34237	6	7	3,138346	**0,448335**
34238	9	10	5,177255	**0,517725**
34239	8	9	10,277360	**1,141929**
34240	7	8	4,334343	**0,541793**
34241	0	1	1,355447	**1,355447**
34242	3	4	1,472918	**0,368229**
34243	7	8	13,645436	**1,705680**
34251	0	1	0,519942	**0,519942**
34266	2	3	1,956603	**0,652201**
34269	0	1	0,420777	**0,420777**
34275	1	2	2,562513	**1,281257**

zipcode	actual	actual+1	predicted	index	zipcode	actual	actual+1	predicted	index
34285	3	4	4,456963	**1,114241**	34637	3	4	0,946353	**0,236588**
34286	1	2	0,783872	**0,391936**	34638	1	2	3,070432	**1,535216**
34287	3	4	2,934806	**0,733702**	34639	10	11	3,212512	**0,292047**
34288	3	4	0,877348	**0,219337**	34652	5	6	4,575442	**0,762574**
34289	3	4	0,686268	**0,171567**	34653	5	6	2,515320	**0,419220**
34291	2	3	0,495063	**0,165021**	34654	4	5	2,531401	**0,506280**
34292	2	3	2,532684	**0,844228**	34655	14	15	12,570268	**0,838018**
34293	4	5	4,242017	**0,848403**	34667	5	6	4,191063	**0,698511**
34420	1	2	2,358288	**1,179144**	34668	5	6	5,407070	**0,901178**
34428	2	3	0,926919	**0,308973**	34669	1	2	1,207149	**0,603575**
34429	3	4	2,308654	**0,577164**	34677	17	18	9,914937	**0,550830**
34431	0	1	0,458748	**0,458748**	34683	10	11	7,028077	**0,638916**
34432	1	2	0,961796	**0,480898**	34684	20	21	10,313894	**0,491138**
34433	0	1	0,461120	**0,461120**	34685	5	6	4,149678	**0,691613**
34434	1	2	0,569814	**0,284907**	34688	1	2	1,432246	**0,716123**
34436	0	1	0,465812	**0,465812**	34689	12	13	6,084416	**0,468032**
34442	2	3	1,333928	**0,444643**	34690	1	2	1,092364	**0,546182**
34446	1	2	1,245652	**0,622826**	34691	1	2	2,098005	**1,049002**
34448	0	1	0,738058	**0,738058**	34695	1	2	5,067789	**2,533895**
34449	0	1	0,332382	**0,332382**	34698	9	10	10,476498	**1,047650**
34450	1	2	1,505293	**0,752647**	34705	0	1	0,337632	**0,337632**
34452	2	3	0,935904	**0,311968**	34711	18	19	19,778746	**1,040987**
34453	2	3	1,881956	**0,627319**	34714	5	6	1,924593	**0,320766**
34461	2	3	1,748532	**0,582844**	34715	2	3	1,205855	**0,401952**
34465	1	2	1,529652	**0,764826**	34734	2	3	0,720236	**0,240079**
34470	3	4	6,524147	**1,631037**	34736	1	2	1,656235	**0,828117**
34471	13	14	11,542830	**0,824488**	34737	0	1	0,512322	**0,512322**
34472	1	2	1,680202	**0,840101**	34739	0	1	0,445116	**0,445116**
34473	0	1	1,036871	**1,036871**	34741	15	16	17,937809	**1,121113**
34474	11	12	11,758585	**0,979882**	34743	3	4	1,660976	**0,415244**
34475	1	2	2,126965	**1,063482**	34744	6	7	6,982234	**0,997462**
34476	1	2	1,422120	**0,711060**	34746	20	21	6,882082	**0,327718**
34479	1	2	0,789295	**0,394648**	34747	27	28	13,728620	**0,490308**
34480	4	5	2,191692	**0,438338**	34748	8	9	6,820502	**0,757834**
34481	3	4	1,689151	**0,422288**	34753	0	1	0,460565	**0,460565**
34482	1	2	1,400838	**0,700419**	34756	0	1	0,603757	**0,603757**
34484	1	2	0,569397	**0,284698**	34758	5	6	1,267979	**0,211330**
34488	0	1	0,576365	**0,576365**	34759	5	6	1,380541	**0,230090**
34491	1	2	1,555800	**0,777900**	34761	19	20	15,935653	**0,796783**
34498	0	1	0,414156	**0,414156**	34762	0	1	0,413186	**0,413186**
34601	2	3	2,406019	**0,802006**	34769	7	8	3,343033	**0,417879**
34602	0	1	0,645148	**0,645148**	34771	2	3	1,144042	**0,381347**
34604	2	3	1,511440	**0,503813**	34772	2	3	1,366974	**0,455658**
34606	3	4	3,527973	**0,881993**	34773	0	1	0,422758	**0,422758**
34607	3	4	1,215538	**0,303885**	34785	1	2	1,548711	**0,774355**
34608	2	3	1,280581	**0,426860**	34786	19	20	5,502857	**0,275143**
34609	9	10	5,293236	**0,529324**	34787	28	29	21,080083	**0,726899**
34610	2	3	0,627834	**0,209278**	34788	2	3	1,460424	**0,486808**
34613	3	4	2,390473	**0,597618**	34797	0	1	0,452802	**0,452802**
34614	0	1	0,468678	**0,468678**	34945	1	2	0,722173	**0,361087**

zipcode	actual	actual+1	predicted	index
34946	0	1	0,602324	**0,602324**
34947	2	3	0,909906	**0,303302**
34949	4	5	0,812461	**0,162492**
34950	2	3	2,109003	**0,703001**
34951	1	2	1,059396	**0,529698**
34952	10	11	5,738535	**0,521685**
34953	6	7	3,304632	**0,472090**
34956	0	1	0,500774	**0,500774**
34957	7	8	4,945943	**0,618243**
34972	3	4	1,452770	**0,363192**
34974	2	3	1,754940	**0,584980**

zipcode	actual	actual+1	predicted	index
34981	1	2	1,143528	**0,571764**
34982	3	4	2,566043	**0,641511**
34983	0	1	3,130228	**3,130228**
34984	7	8	2,189263	**0,273658**
34986	14	15	7,935571	**0,529038**
34987	3	4	1,557034	**0,389259**
34990	3	4	5,829556	**1,457389**
34994	12	13	10,811510	**0,831655**
34996	2	3	2,989337	**0,996446**
34997	11	12	12,269094	**1,022425**