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## **Finding Prospects for Shopping Centers: a machine learning approach**

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### **Abstract**

We have developed an algorithm that predicts which store types are the best prospects to fill vacancies in shopping centers given the combinations of stores already there. The model is able to make predictions with accuracies up to 81.62% for the first prediction, 90.05% for the first two predictions, 93.34% for the first three predictions, 95.52% for the first four predictions, and 96.48% for the first five predictions. The p-values with respect to a naïve strategy of choosing the store types that are simply most frequent are all below 0.0001%. This paper explains how the system was built and some user tests, not all of which were positive. The system can be found at <http://linserv2.cims.nyu.edu:54321>. The code for the project can be found at <https://github.com/jgk99/Store-Prospector>.

### **Introduction**

Other researchers have done work in deciding a suitable shopping mall location, how the stores within a mall should be oriented, and how to decide the rent for a store. But researchers have done limited work in determining the best prospective store types to fill vacancies.

Charles Carter and Marcus Allen, proposed some qualitative principles that could be used to find a good mix of tenants in a mall in their work *Deciding Optimal Tenant Mix in Shopping Centers* [2]. The main point made in their work was that a good center should offer sufficient competition to motivate shoppers to visit but not so much as to reduce individual shop owners' profits significantly.

Sherif A. Fahmy, Bader A. Alablani, and Tamer F. Abdelmaguid [5] designed a facility layout assignment algorithm. Their objective was to maximize flow captured in each location and balance it across all shopping center areas.

Apostolos Arvanitis, Stefanos Giannoulakis and Nicolas Karanikolas [1] approached a similar problem and focused on the location of shopping malls to figure out the stores that should be inside.

The shopping center industry also uses void analyses to help decide which tenants are best for a shopping center. A void analysis looks at the market in the area of the center and determines what is in demand in that area. Then, it provides the user with possible tenants to pursue. Some services that provide these void analyses are Retail Lease Trac, Sites USA, Site Seer, and Tenant Centric.

We believe that our work is the first to use the combinations of stores in shopping centers to determine which store types are the best prospects to fill vacancies.

## **Data**

The data used in the model was the combinations of stores in malls in America. The data was a three column csv file. The first column was the mall the store was in, the second column was the name of the store, and the third column was the type of the store. It looked like this.

**Figure 1**

Mall Number	Store Name	Store Type
1	Bloomingtons	[department_store]
1	Chipotle	[restaurant, fast_food]
2	Verizon	[electronics/cell_store]

There was a total of 619 shopping centers with over 50,000 total stores. Before the data could be used in the machine learning algorithm, it had to be curated. There was some bad data because the store type was sometimes not correct. For example, sometimes it would say “NO RESULTS” or “point\_of\_interest.” This was fixed by using the store names to classify stores. For example, if a store name contained

“restaurant” in it, it was classified as a restaurant. This was done for many other words like “café,” “clothing,” “shoes,” “pub,” “liquor”, etc.

Stores that were not classified had names like “Pineapple’s” and “Superior Alterations,” which clearly were not chains, so we fit them into one broad category: “local”. Future work might consider parsing such stores to determine types (e.g. Pineapple’s might become a restaurant if the website shows menus).

We then formatted the data in preparation for machine learning. The following table presents an extract of the formatted data. In the example, mall 1 has 55 clothing stores, 26 shoe stores, 16 restaurants, and 18 jewelry stores. Mall 2 has 4 clothing stores, 0 shoe stores, 2 restaurants, and 0 jewelry stores. Mall 3 has 34 clothing stores, 16 shoes stores, 66 restaurants, and 14 jewelry stores.

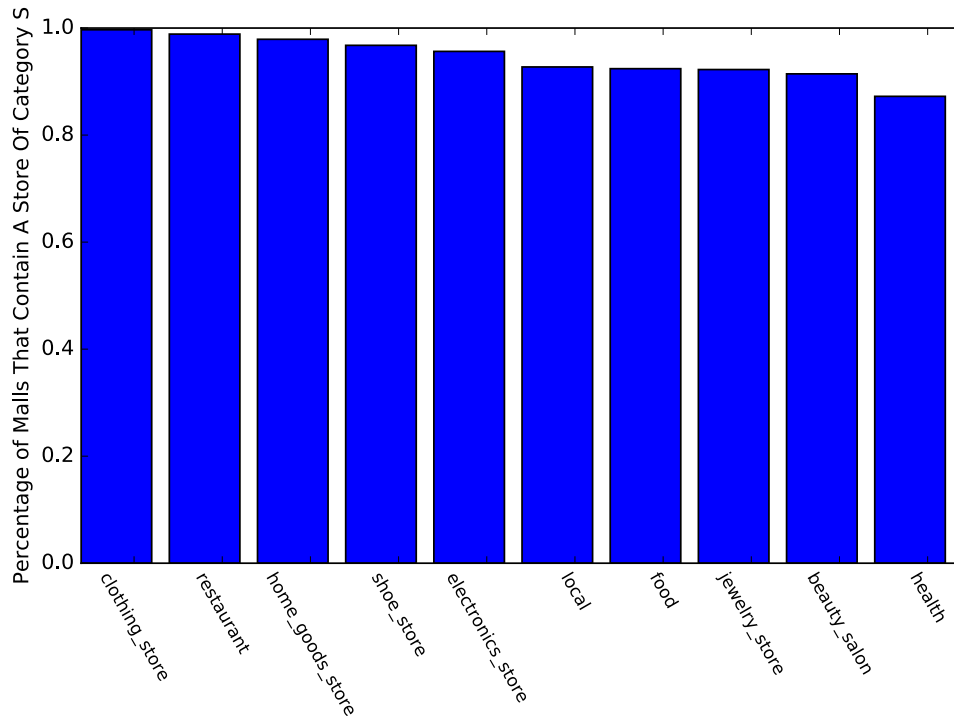
**Figure 2**

mall number	clothing store	shoe store	restaurant	jewelry store	...
1	55	26	16	18	...
2	4	0	2	0	...
3	34	16	6	14	...
....	...	...	...	...	...

Figure 3 shows the percentage of malls that contain a store of a certain category. Figure 3 shows only the top 10.

**Figure 3**

## CATEGORY FREQUENCIES



### Method

To set this up as a machine learning problem, each training case consisted of removing one store from a center and then predicting its type from the remaining stores in the center. This is called a “leave-one-out” test. Scikit Learn’s Random Forest Algorithm was trained on a subset consisting of 500 shopping centers selected by uniform random sampling from the whole set. The model was then tested and scored on the remaining 119 centers using many different accuracy metrics. Two main machine learning variations were tried: in the binary variation, the user would enter which store types were present. In the cardinal variation, the user would enter the number of instances of each existing store type. For both variations, the system would return a predicted store type.

### Results and Analysis

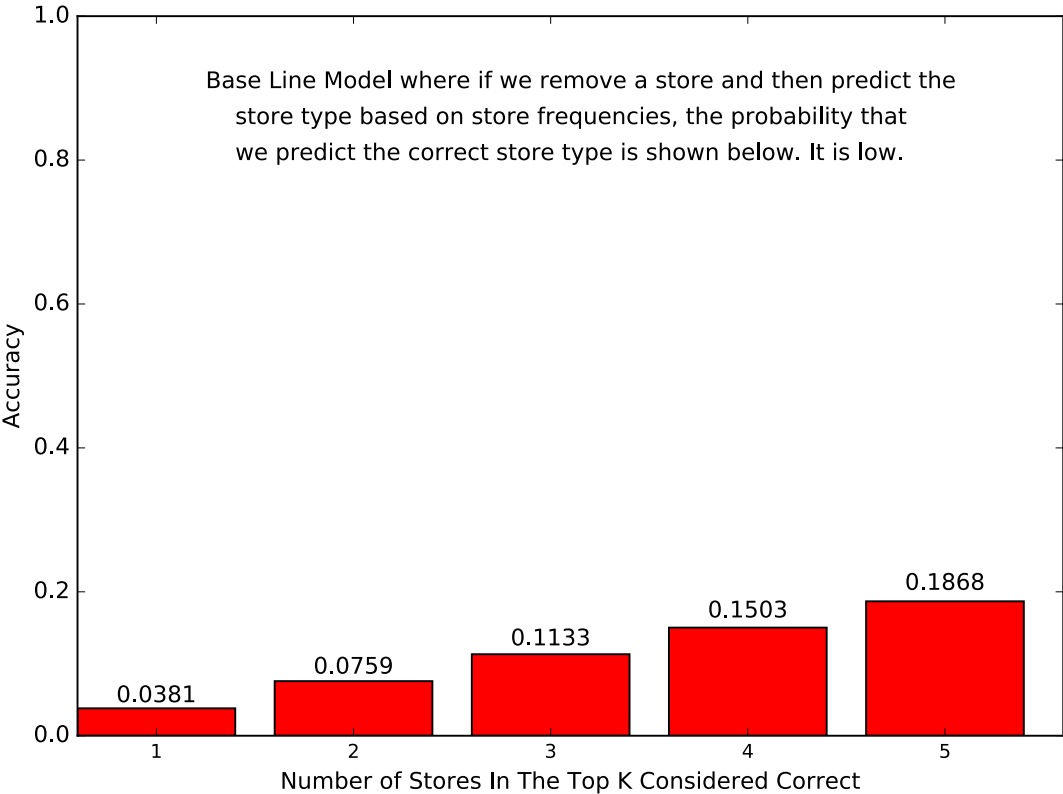
As explained above, shopping centers not used in the training of the model were used as the test set to determine the accuracy of the model.

We first developed a base-line accuracy metric in order to compare the methods. We defined the “base-line accuracy” as the accuracy when predicting the dominant  $k$  stores for all predictions. For each  $k$ , the histogram represents the accuracy if the system simply chose the  $k$  most frequent store types in the training set (e.g. clothing and restaurant for  $k = 2$ ). A machine learning model is valuable if it gives results that are significantly better than this base model.

**Figure 4**

**MODEL ACCURACY USING UNDERLYING FREQUENCIES**

- K=1: *Predict each store is a clothing*
- K=2: *Predict each store is a clothing store or restaurant*
- K=3: *Predict each store is a clothing store, restaurant, or home goods store*
- K=4: *Predict each store is a clothing store, restaurant, home goods store, or shoe store*
- K=5: *Predict each store is a clothing store, restaurant, home goods store, shoe store, or cellphone/electronics*



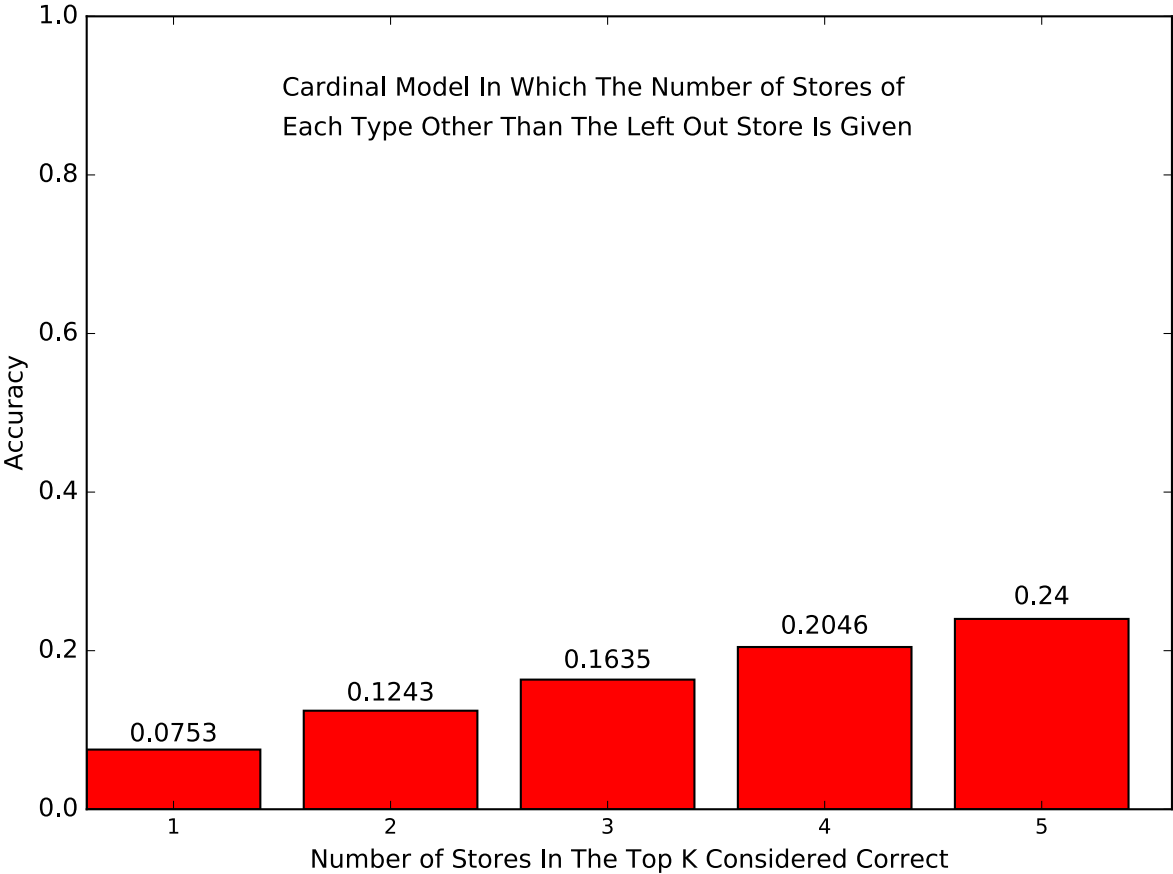
By contrast, figure 5 represents the results of a predictive model (trained on “leave-one-out” data) in which the user inputs the number of each store type in the shopping center. In each test case, one store  $s$  was removed from its category in the shopping center. The remaining stores in the shopping centers were entered. The prediction was said to be accurate if the type of  $s$  was correctly predicted in the top  $k$  predictions and inaccurate otherwise. It was 30.01% to 97.63% more accurate than the baseline predictions in figure 4. Later figures show even better results.

**Figure 5**

**MODEL ACCURACY**

CARDINAL MODEL

Frequency in which one of the top  $k$  predictions was correct after the user enters the number of each store type in a shopping center that has had one store removed.



Here are the p-values for figure 5. These values represent the probability that the model's accuracy is just luck compared to the baseline predictions. In the expression below,  $p$  is the probability of predicting correctly based on the dominant frequencies,  $s$  is the number of successes the model had, and  $t$  is the number of trials that the model was tested on. So the expression asks for the sum of the probabilities that at least  $s$  successes would be obtained from a random model based on dominant frequencies. The values were found in Mathematica [6].

$$\sum_{x=s}^t \binom{t}{x} p^x (1-p)^{t-x}$$

**FIGURE 6: P-Value Chart For Each  $K$  in Cardinal Model**

<b><math>K=1</math></b>	<b><math>K=2</math></b>	<b><math>K=3</math></b>	<b><math>K=4</math></b>	<b><math>K=5</math></b>
$2.42*10^{-22}$	$2.69*10^{-22}$	$9.64*10^{-18}$	$7.53*10^{-18}$	$4.79*10^{-15}$

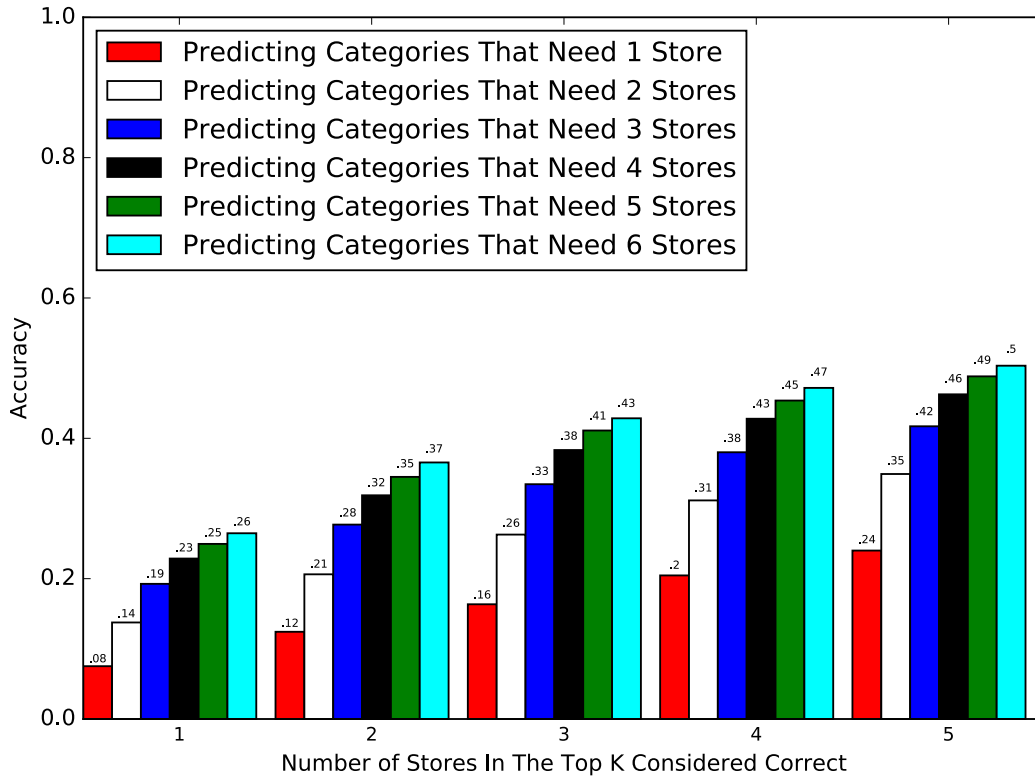
In figure 5, we were predicting the type of one store based on all of the other stores. We called that a “leave-out-one” test. However, we also can consider a test in which we take out several stores of the same type and ask whether that type would be predicted as a good prospect. We found that using this accuracy metric the model's accuracy increased. In figure 7, the horizontal axis represents the  $k$  number of top suggestions considered correct, the different color bars represent the number of stores of a certain type that are removed, and the vertical axis represents the accuracy.

**Figure 7**

**MODEL ACCURACY**

**CARDINAL MODEL**

Frequency in which one of the top  $k$  predictions was correct in predicting which categories needed  $s$  stores



**FIGURE 8: P-Value Chart For Cardinal Model**

Types That Need $N$ Stores	$K=1$	$K=2$	$K=3$	$K=4$	$K=5$
Needs 1 Store	$2.42*10^{-22}$	$2.69*10^{-22}$	$9.64*10^{-18}$	$7.53*10^{-18}$	$4.79*10^{-15}$
Needs 2 Stores	$1.44*10^{-115}$	$1.07*10^{-121}$	$4.52*10^{-120}$	$4.73*10^{-119}$	$2.00*10^{-106}$
Needs 3 Stores	$7.84*10^{-237}$	$1.79*10^{-254}$	$3.71*10^{-239}$	$7.77*10^{-224}$	$1.12*10^{-200}$
Needs 4 Stores	$2.92*10^{-331}$	$2.87*10^{-349}$	$2.57*10^{-338}$	$4.29*10^{-313}$	$1.70*10^{-278}$
Needs 5 Stores	$1.23*10^{-390}$	$1.43*10^{-414}$	$3.27*10^{-401}$	$5.97*10^{-367}$	$2.60*10^{-327}$
Needs 6 Stores	$7.82*10^{-436}$	$1.21*10^{-468}$	$9.31*10^{-443}$	$1.40*10^{-406}$	$5.99*10^{-358}$



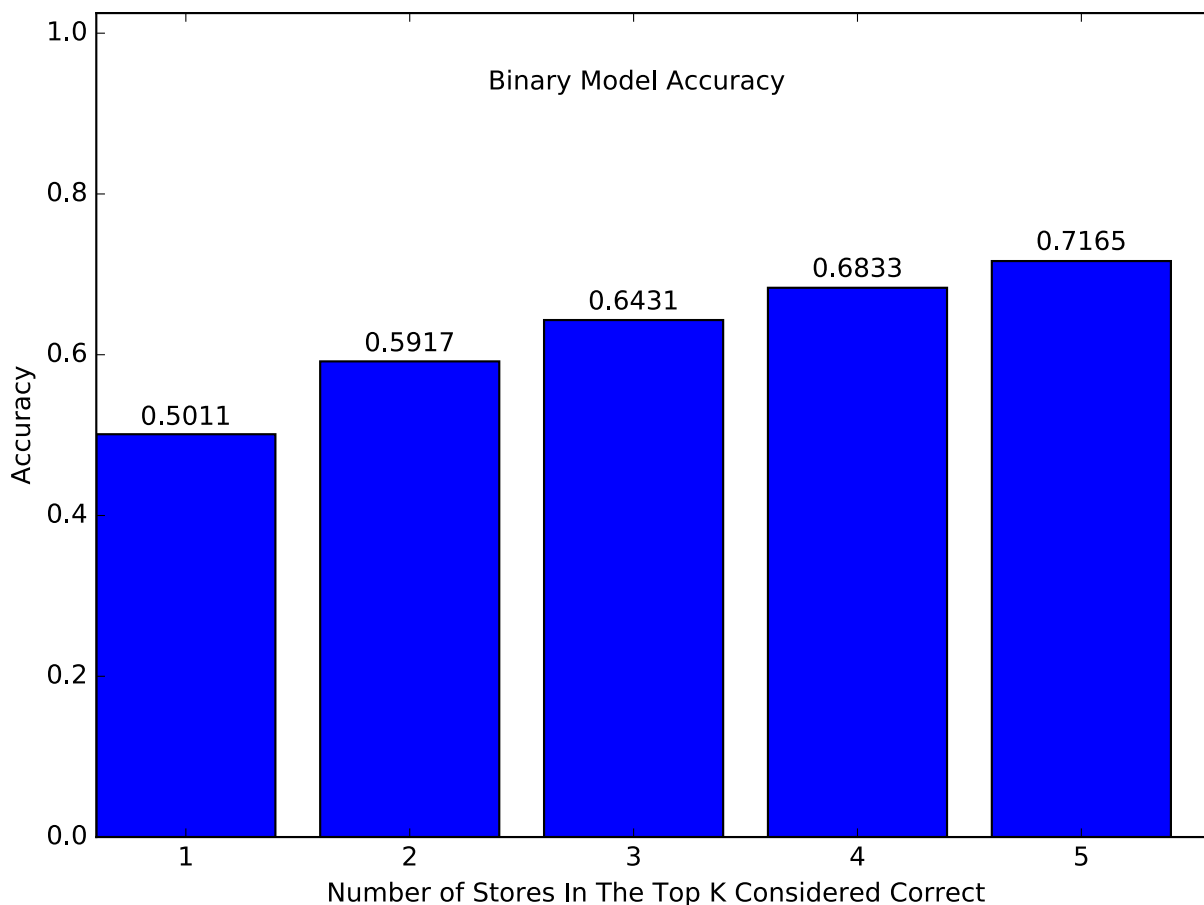
Figure 9 depicts the case in which the user indicates the existence of the store types in the center regardless of the number of stores of that store type. This method is both simple and accurate. When counting the top 5 suggestions as correct, its accuracy is over 70%.

**FIGURE 9**

**MODEL ACCURACY**

BINARY MODEL

Frequency in which one of the top  $k$  predictions was correct



**FIGURE 10: P-Value Chart For Each  $K$  In Binary Model**

$K=1$	$K=2$	$K=3$	$K=4$	$K=5$
$2.18*10^{-1336}$	$6.90*10^{-1272}$	$1.06*10^{-1160}$	$1.23*10^{-1051}$	$2.22*10^{-933}$

## **Website**

The system, Store Prospector, can be found at <http://linserv2.cims.nyu.edu:54321>. It embodies the methods discussed here and was built to be as user friendly as possible. It also contains a store classifier that goes through our data to provide the exact classification of a store.

## **User Experience**

To evaluate the user experience, we consulted Tim Lowe and Eddie Cherry from The Staenberg Group. Tim Lowe is the Vice President of Leasing and Development and has over 30 years of experience in acquisition, development and leasing of regional shopping centers and other retail venues. Eddie Cherry is a Senior Leasing Representative at TSG properties and is responsible for leasing their Midwest Portfolio, which includes Shopping centers throughout Illinois, Missouri, and Oklahoma.

To summarize their feedback, the Store Prospector system is not something they would use. They need systems that go into more depth in the way that their void analysis systems do. They want to learn more than which category they need. They also want to know which specific tenant they should pursue. They also felt that the system would be better if it included features like store square footage and shopping center type. Finally, they thought it would be more valuable if it were based on the entire market in the area rather than on just the single shopping center.

The system was run on 7 of their properties and they provided feedback. Some of the suggestions they felt didn't make sense based on the type of center it was or the square footage available. They also didn't like some of the categories that were part of the dataset in general, partly because the retail market has changed since the data was collected (e.g. electronics stores have encountered great financial difficulties due to online competition). Overall, they felt the system was somewhat helpful, but not specific enough for their needs.

The transcribed version of the conversation/interview/feedback session can be found in the appendix.

## **Conclusion**

We have created the first algorithm (that we know of) that predicts the store types that should be added to malls to fill vacancies. The best model that we created, according to the final accuracy metric predicts its first suggestion with over 81% accuracy and predicts the correct store type in its top 5 choices over 96% of the time.

We have also shown that the combinations of stores in shopping centers is a useful feature to use when predicting the types of stores that should fill vacancies in shopping centers.

One topic for future work is to develop a store classifier. Categorizing the stores was not easy and unfortunately some were called “local” because they could not be classified. A machine learning algorithm to classify stores by scraping websites might be helpful to future researchers.

Another topic for future research would be to investigate other features that could be used with the model. For example, some features that would be helpful would be the wealth of the neighborhood, tenant square footage, and shopping center type.

The main topic for future research is to investigate how this method could be combined with other methods. Because of the lack of specificity, it seems as though the system would perform well when combined with a void analysis system. For example, it could be factored into the market analysis of demand to help figure out the store type to add. Then the void analysis system could work to find possible tenants of the category. This type of hybrid could have lots of potential because the two have different strengths. The void analysis is primarily looking at the market in the area and identifying what is missing from the neighborhood. Mixing it with our method would give it an extra layer of precision. Our method isn't just looking at what is needed in a neighborhood, it is looking at the patterns in shopping centers around the country and predicting based on the combinations of tenants in other shopping centers. Mixing what is needed in the market and a predictor based on hundreds of shopping malls' tenant combinations can take void analyses to the next level.

## **Acknowledgements**

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## **Appendix: Full Conversation/Interview**

Jonathan Kogan: The first suggestion for the grove would be to add an electronics, department, bank, fun\_and\_entertainment, and then candy\_store.

Tim Lowe: Can you read it for me one more time.

Jonathan Kogan: They are electronics, department, bank, fun\_and\_entertainment, and then candy\_store. So what is your opinion on the suggestions? What is your reaction regarding the types and the order of those store types.

Tim Lowe: Let me ask you a question first. Let me get an understanding of how your... What is it using to figure out that an electronics store would be the right store for that property? What is it looking at?

Jonathan Kogan: It's looking at data for 600 malls and the categories of stores in that mall. We use Random Forest machine learning and uses the combinations of stores to best predict the store type to add.

Tim Lowe: So what you've done is you've taken is 600 shopping malls around the U.S. and inputted their tenant mix into their system to create an ideal mix profile and that database is looking for the missing types?

Jonathan Kogan: That's pretty much the general idea.

Tim Lowe: When I looked at it wouldn't let you specify the number of stores in a category.

Jonathan Kogan: We had two models, and we found that the one with only the presence is more accurate. It also does have box for the total number of stores at the bottom.

Tim Lowe: Let me ask you another question, so when you look at 600 shopping centers do you look at anything else to categorize shopping centers.

Jonathan Kogan: No. We have not done that.

Tim Lowe: I would recommend that you do that because my answers will dictate back to this because in our industry... did you look at ICSC (International Council of Shopping Centers) website?

Jonathan Kogan: I looked at a couple of similar things like services that find prospective tenants.

Tim Lowe: Just so you know, Jonathan, there's a lot of different programs that you can purchase that find tenants for shopping malls based on a lot of different things like demographics.

Eddie Cherry: So when you say electronics store is that a 2000 square foot radio shack or a best buy.

Jonathan Kogan: That's the part where it is up to the user. Our system doesn't factor in size. So it could be a Verizon or it could be a best buy...

Tim Lowe: And that's not an electronics in our..., that's cell phones! Let me give you one more suggestion as you look and do something with this. If you got data on 600 shopping centers I highly recommend that you categorize them. There are regional shopping malls, which you find all over, with stuff like Macy's, that entity would be different from something like a power center that is anchored by a Walmart or a big box guy, to something like a neighborhood center. The grove would be a power center. And department stores don't go to power centers. So you really need to know what category each center is. That will refine your data so you would find that department store isn't an option in a power center.

Tim Lowe: I suggest you look at ICSC. Everything is underneath it. It's like a registry. They have a lot of data that may be beneficial. They summarize the industry. To respond to what you asked, we don't really do electronics deals anymore. Radioshack is bankrupt. Bestbuy is... I don't wanna say on the verge of bankruptcy, but they're not doing well...

Eddie Cherry: They also have cell phone stores.

Tim Lowe: That's true.

Eddie Cherry: In your model do you look at what vacancies are currently there and what opportunities there are to build on pads.

Jonathan Kogan: We based it on the stores in the mall. When we train it we don't incorporate how many vacancies are there, but when we use it to predict, it there as an input.

Eddie Cherry: Do you incorporate square footage?

Jonathan Kogan: No.

Eddie Cherry: That seems like a layer that would refine the results. If you had two 1,200 square foot vacancies and it returns a retailer that needs 40,000 square feet it doesn't really help.

Jonathan Kogan: That's something I can definitely look into.

Tim Lowe: So for the Grove your question is does it make sense. So if you're including cell phone stores, we do a lot of cell phone store deals, and that's a category that even if we have, we will do one or two more, and in some places we can even fit 3 or 4 in; department stores aren't an option at the grove; and bank, bank is a service tenant, you just don't see a lot of banks, we look for co-tenancy and what helps us, we do some bank deals, but mostly not.

Eddie Cherry: Traditional banks are moving away from brick and mortar locations cause everything's online, and they are shrinking their portfolios. What you do see is the smaller finance guys like Wells Fargo who are doing small loans and they will take 1,200 feet or so, but the days of depositing your check at a brick and mortar location are going away.

Jonathan Kogan: I understand what you're saying and I'll look into making the fact that cell store is part of electronics store more clear.

Tim Lowe: Maybe even separate the two, cell stores are their own industry now and electronics fall back to Radio shack and Best Buy and those that sell TVs and things like that.

Jonathan Kogan: Ok. So do you want me to go over the suggestions for the other few malls now.

Tim Lowe: Sure.

Jonathan Kogan: So for Chesterfield Commons the system suggested a bakery, pharmacy, bar, candy store, and movie theater.

Tim Lowe: Chesterfield commons is part of a bigger development that is part of 7 other properties so there is already a movie theater down there. Also, we don't do bars and most shopping centers like us don't do bars. When we think of bar we think of somebody that is primarily serving alcohol and most shopping centers restrict tenants who sell more than 50% alcohol. So when we do a bar it's more of a buffalo wild wings where the alcohol is less than 50%.

Eddie Cherry: The other thing is you might want to separate retail and restaurants cause you're getting all these categories of restaurants so obviously there is a food need there so maybe you should make them a sub category of restaurants and then break it down from there and separate it from the retail piece.

Jonathan Kogan: So when it refers to bar it does include restaurants like buffalo wild wings, it's pretty much saying that it would be good to have a bar in it, but it is a pretty flexible definition.

Tim Lowe: The others like pharmacies, we like pharmacies, but there are only really two, CVS or Walgreens and they are really the pharmacies, there's no more local pharmacies anymore. So in some cases they are already in the market and Walmart is in the center and they already have a pharmacy.

Jonathan Kogan: That also could have been a problem with how I entered it because I didn't know the Walmart had a pharmacy when I entered the data myself, so it maybe would have



returned something different had it known. Do you want to hear the suggestions for Union Square in New Castle, Pennsylvania.

Tim Lowe: Sure.

Jonathan Kogan: They are cafe, bar, toy store, bakery, and spa.

Tim Lowe: What do you mean by cafe, Starbucks?

Jonathan Kogan: It could be a coffee shop. It's not so specific so you could interpret it how you would like.

Eddie Cherry: I'm interested that apparel didn't appear because it's in desperate need there.

Jonathan Kogan: I can look into that.

Tim Lowe: What do you consider a toy store? There's not a lot of toy stores anymore.

Eddie Cherry: Well, if he's looking at 600 malls, they have toy stores in pretty much every mall.

Jonathan Kogan: It does encompass regular toy stores, but it also includes stuff like maybe a Game Stop.

Eddie Cherry: I would separate Game Stop and combine it with electronics. People don't consider game stop to be a toy store.

Jonathan Kogan: Kendigg Square had the suggestions: home goods, local store, bar, bakery, toy store. Any thoughts?

Tim Lowe: I know bar pops up a lot and so does bakery. We don't see a lot of bakeries out there. Home goods, I would agree, Home goods is a good category. It's a growing category and there are all different sizes of home goods stores so it would definitely be good.

Eddie Cherry: Again it's missing apparel, it's missing shoes, which are glaring needs there so it's surprising that it didn't pop up.

Jonathan Kogan: Yeah. So you know in Park Plaza clothing and shoe store did pop up as the first suggestions. I'm not sure why they didn't pop up here though. So for Lyndell marketplace, the suggestions were a jewelry store, toy store, bar, gift store, and then a cafe.

Eddie Cherry: Does your system account for medical uses like dental and urgent care?

Jonathan Kogan: Yes. It has the categories: doctor, dentist, and health.

Tim Lowe: Gift store, there's a lot of tenants that fall in that category. Cafe would be a good add there.

Eddie Cherry: You should definitely look at the ICSC website and do a little more research. We are really focused on tenants that are very active now. Maybe like load bare results higher. Nobody's really doing toy stores now, electronics stores are down, gift shops are down. So maybe it would help to take a look at the retailers that are really expanding and factor that in.

Jonathan Kogan: Ok. So now let's go through Park Plaza. Clothing store, shoe store, jewelry store, bakery, and moving company.

Eddie Cherry: Moving Company?

Jonathan Kogan: It's not as common, I don't know. Sometimes it does suggest something that is not as common. It's just based on the combinations so there was probably a mall with a similar combination of stores that had a moving company.

Tim Lowe: We've never done a deal with a moving company and I don't really know what it would be in a center like that. I would probably put that category as... a tenant like that provides no value for a shopping center. It doesn't help co-tenancy. Sometimes we do deals with locals...

Eddie Cherry: Why would a moving company be a store front. Don't people just call them?

Jonathan Kogan: That's one that's in the data set only a few times and it doesn't occur very much. I was surprised that it suggested it too. It is the fifth suggestion, though, so the other 4 suggestions are above it. It was probably because the data had a similar shopping center with a moving company. But would you agree with the clothing store, shoe store, jewelry store type categories for that center.

Tim Lowe: Yes. Clothing would be good. I think we have a shoe store.

Eddie Cherry: No, we tried to do a shoe deal.

Tim Lowe: Yeah, so we've been trying to do a shoe deal so it would be good. Cafés are always good. What were the other ones on that list?

Jonathan Kogan: Clothing store, shoe store, jewelry store, bakery, and moving company.

Tim Lowe: Bakery, I'm not sure. There's really no local bakeries.

Eddie Cherry: I think it's incorporating Panera, McAlister's...

Tim Lowe: So we do do that, Yes.

Jonathan Kogan: So the final mall is Persimmon point. The suggestions are health, bakery, optical store, and book store.

Tim Lowe: Those are pretty good. That location would be good for health users. Bakery if you mean Paneras and tenants like that it would be good. Optical always is good. There's not a lot of optical stores down there, but it's always good. Book store is a dying category, there are very few if any book operators down there.

Jonathan Kogan: Yeah. Book store is one of those less commonly suggested categories.

Eddie Cherry: Yeah. I think that... it's almost like a hit or miss. Some of them are good. To get more value out of this I really think you need to break the shopping centers into categories so you can focus on regional malls and the types of tenants that they bring in, power centers, the types of tenants that go to power centers, and then you get into the smaller neighborhood centers, I thought your category list... I mean moving company would never come in a conversation and I don't think anybody in the industry ever has considered it. So I think your list didn't include some categories and had some categories that probably shouldn't have been on it. I think that if you can try to bring your data more relevant to the model for the center your results might be a little better.

Jonathan Kogan: One thing that was hard, was getting the data. The data from different sources could be expensive and was hard to come by. I could look into other data, but I'm not sure what I'll find that's much better. So overall, is this type of system something that you would consider using when it's more accurate?

Tim Lowe: No. Because the things it doesn't take into account are these tenants could be in the center next door. And the way we typically look at our centers really is ----- . We use something called a void analysis. And what a void analysis does is focus more on who are all the tenants that are already in market and it's specific tenant focused and it'll tell you where the closest one is and where the competition is. So it's basically this, but it dives a lot deeper and gets very very specific. So what it does for example is it tells us how many cell phone stores are already there and where Panera is and all the tenants that we typically look at and it gives us something called a void analysis with those tenants that we typically look at for a center of this caliber that didn't pop up. And it's not only missing from the center, but it's missing from the market. So for us, you know,

telling us that we should put a food store, we always look for food stores, we always look for food stores, we need more than that, we need to know we are missing qsrs or we're missing fast food. We need more specifics. And the void analysis, the companies that sell that product, I don't know what we pay for that, but we pay some kind of monthly amount to be able to use it, but it's much more specific for us as far as putting the list of tenants together that we should be going after. And again remember everybody's going to have a different perspective. We actually are truly leasing shopping centers so for us it's more important to have more information and better data, but somebody might be simplistically looking at a center and trying to find out the missing categories and again I'm not saying that what you've done has no value to anybody, it's just that for us it's not specific enough.

Jonathan Kogan: Ok. I'll take your advice into account and look into what we can do with it. Thank you very much for taking the time to give us some feedback.