

TORONTO INVESTMENT GUIDE



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introduction

I have found that a problem presented to many budding businessmen and investors is knowing what exactly to invest in. This is a difficulty faced everywhere in the world. For the scope of my model I am going to limit it to the Toronto area, and create a model in which can be used by investments to guide their choices in the area. By giving them an insight into all the prominent neighbourhoods in Toronto using Foursquare API to provide accurate location data. Hence the model will collate the pros and cons of investing in certain neighbourhoods in Toronto based on the types of venues already there and types of business and observing the type of reviews they have received. I feel this model will provide investments a chance to make a good financial decision.

Data

we will be using Foursquare location data and wikipedia First we will need to import the relevant libraries. The Wikipedia http link contained the data about the neighbourhoods in Canada and the foursquare location data contained the venue data. First we used the panda library in order to produce a dataframe. The Data needed to be cleaned and prepared as it had some incomplete data called 'not assigned' and replace it with name of the neighbourhood. And then group the data of the borough and neighborhood and couple that with the geospatial data extracted from the data frame to get:

	PostalCode	Borough	Neighborhood	Latitude	Longitude
0	M1B	Scarborough	Rouge, Malvern	43.806686	-79.194353
1	M1C	Scarborough	Highland Creek, Rouge Hill, Port Union	43.784535	-79.160497
2	M1E	Scarborough	Guildwood, Morningside, West Hill	43.763573	-79.188711
3	M1G	Scarborough	Woburn	43.770992	-79.216917
4	M1H	Scarborough	Cedarbrae	43.773136	-79.239476
5	M1J	Scarborough	Scarborough Village	43.744734	-79.239476
6	M1K	Scarborough	East Birchmount Park, Ionview, Kennedy Park	43.727929	-79.262029
7	M1L	Scarborough	Clairlea, Golden Mile, Oakridge	43.711112	-79.284577
8	M1M	Scarborough	Cliffcrest, Cliffside, Scarborough Village West	43.716316	-79.239476
9	M1N	Scarborough	Birch Cliff, Cliffside West	43.692657	-79.264848
10	M1P	Scarborough	Dorset Park, Scarborough Town Centre, Wexford ...	43.757410	-79.273304

A map of Greater London illustrating bus routes and stops. The map features numerous blue circular icons representing bus stops, distributed across the urban landscape. Red lines indicate specific bus routes, many of which are labeled with numbers such as 400, 401, 409, 427, 46, 73, 7A, 10, 18, 20, 21, 22, 25, 26, 27, 29, 32, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 143, 144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155, 156, 157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169, 170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181, 182, 183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194, 195, 196, 197, 198, 199, 200, 201, 202, 203, 204, 205, 206, 207, 208, 209, 210, 211, 212, 213, 214, 215, 216, 217, 218, 219, 220, 221, 222, 223, 224, 225, 226, 227, 228, 229, 230, 231, 232, 233, 234, 235, 236, 237, 238, 239, 240, 241, 242, 243, 244, 245, 246, 247, 248, 249, 250, 251, 252, 253, 254, 255, 256, 257, 258, 259, 260, 261, 262, 263, 264, 265, 266, 267, 268, 269, 270, 271, 272, 273, 274, 275, 276, 277, 278, 279, 280, 281, 282, 283, 284, 285, 286, 287, 288, 289, 290, 291, 292, 293, 294, 295, 296, 297, 298, 299, 300, 301, 302, 303, 304, 305, 306, 307, 308, 309, 310, 311, 312, 313, 314, 315, 316, 317, 318, 319, 320, 321, 322, 323, 324, 325, 326, 327, 328, 329, 330, 331, 332, 333, 334, 335, 336, 337, 338, 339, 340, 341, 342, 343, 344, 345, 346, 347, 348, 349, 350, 351, 352, 353, 354, 355, 356, 357, 358, 359, 360, 361, 362, 363, 364, 365, 366, 367, 368, 369, 370, 371, 372, 373, 374, 375, 376, 377, 378, 379, 380, 381, 382, 383, 384, 385, 386, 387, 388, 389, 390, 391, 392, 393, 394, 395, 396, 397, 398, 399, 400, 401, 402, 403, 404, 405, 406, 407, 408, 409, 410, 411, 412, 413, 414, 415, 416, 417, 418, 419, 420, 421, 422, 423, 424, 425, 426, 427, 428, 429, 430, 431, 432, 433, 434, 435, 436, 437, 438, 439, 440, 441, 442, 443, 444, 445, 446, 447, 448, 449, 450, 451, 452, 453, 454, 455, 456, 457, 458, 459, 460, 461, 462, 463, 464, 465, 466, 467, 468, 469, 470, 471, 472, 473, 474, 475, 476, 477, 478, 479, 480, 481, 482, 483, 484, 485, 486, 487, 488, 489, 490, 491, 492, 493, 494, 495, 496, 497, 498, 499, 500, 501, 502, 503, 504, 505, 506, 507, 508, 509, 510, 511, 512, 513, 514, 515, 516, 517, 518, 519, 520, 521, 522, 523, 524, 525, 526, 527, 528, 529, 530, 531, 532, 533, 534, 535, 536, 537, 538, 539, 540, 541, 542, 543, 544, 545, 546, 547, 548, 549, 550, 551, 552, 553, 554, 555, 556, 557, 558, 559, 560, 561, 562, 563, 564, 565, 566, 567, 568, 569, 570, 571, 572, 573, 574, 575, 576, 577, 578, 579, 580, 581, 582, 583, 584, 585, 586, 587, 588, 589, 590, 591, 592, 593, 594, 595, 596, 597, 598, 599, 600, 601, 602, 603, 604, 605, 606, 607, 608, 609, 610, 611, 612, 613, 614, 615, 616, 617, 618, 619, 620, 621, 622, 623, 624, 625, 626, 627, 628, 629, 630, 631, 632, 633, 634, 635, 636, 637, 638, 639, 640, 641, 642, 643, 644, 645, 646, 647, 648, 649, 650, 651, 652, 653, 654, 655, 656, 657, 658, 659, 660, 661, 662, 663, 664, 665, 666, 667, 668, 669, 670, 671, 672, 673, 674, 675, 676, 677, 678, 679, 680, 681, 682, 683, 684, 685, 686, 687, 688, 689, 690, 691, 692, 693, 694, 695, 696, 697, 698, 699, 700, 701, 702, 703, 704, 705, 706, 707, 708, 709, 710, 711, 712, 713, 714, 715, 716, 717, 718, 719, 720, 721, 722, 723, 724, 725, 726, 727, 728, 729, 730, 731, 732, 733, 734, 735, 736, 737, 738, 739, 740, 741, 742, 743, 744, 745, 746, 747, 748, 749, 750, 751, 752, 753, 754, 755, 756, 757, 758, 759, 760, 761, 762, 763, 764, 765, 766, 767, 768, 769, 770, 771, 772, 773, 774, 775, 776, 777, 778, 779, 780, 781, 782, 783, 784, 785, 786, 787, 788, 789, 790, 791, 792, 793, 794, 795, 796, 797, 798, 799, 800, 801, 802, 803, 804, 805, 806, 807, 808, 809, 810, 811, 812, 813, 814, 815, 816, 817, 818, 819, 820, 821, 822, 823, 824, 825, 826, 827, 828, 829, 830, 831, 832, 833, 834, 835, 836, 837, 838, 839, 8

Finding out the top 100 venues within 1000 meters of the studio district

```
LIMIT = 100 #
radius = 1000 # radius meters
# create URL
url = 'https://api.foursquare.com/v2/venues/explore?client_id={}&client_secret={}&v={}&ll={},{}&radius={}&limit={}&offset={}'
    CLIENT_ID,
    CLIENT_SECRET,
    VERSION,
    latitude,
    longitude,
    radius,
    LIMIT)
url
```

after receiving the results we converted them into a data frame to show the results.

	name	categories	lat	lng
0	Images Salon & Spa	Spa	43.802283	-79.198565
1	Caribbean Wave	Caribbean Restaurant	43.798558	-79.195777
2	Staples Morningside	Paper / Office Supplies Store	43.800285	-79.196607
3	Wendy's	Fast Food Restaurant	43.802008	-79.198080
4	Wendy's	Fast Food Restaurant	43.807448	-79.199056

methodology

during the course of the project we determined what type of venues were most popular in parts of Canada honing in on the the Toronto boroughs.

Firstly we collected the data and we explained how we did that using jupyter and python in the section above, then we went on the analysis the data and explore the diferent types of venues in the area hence finding out the possible business investment opportunities in the area.

In the final step with the help of k cluster, a machine learning technique will created clusters of the best areas of venues and presented them on a map. The clusters present the basic requirements for investors to use as a starting point to see where they should invest in and one kind of category too. Then they can devote more resources to making a a further on site investigation of the area.

Analysis

Observing the data we can derive further information by making a data frame showing how many venues there are in each neighbourhood.

```
t_venues.groupby('Neighborhood').count()
```

Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Adelaide, King, Richmond	100	100	100	100	100	100
Agincourt	5	5	5	5	5	5
Agincourt North, L'Amoreaux East, Milliken, Steeles East	3	3	3	3	3	3
Albion Gardens, Beaumont Heights, Humbergate, Jamestown, Mount Olive, Silverstone, South Steeles, Thistletown	9	9	9	9	9	9
Alderwood, Long Branch	9	9	9	9	9	9

```
toronto_grouped = toronto_onehot.groupby('Neighborhood').mean().reset_index()
toronto_grouped
```

	Neighborhood	Yoga Studio	Accessories Store	Adult Boutique	Afghan Restaurant	Airport	Airport Food Court	Airport Gate	Airport Lounge	Airport Service	Airport Terminal	Recreation
0	Adelaide, King, Richmond	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.000000	0.0
1	Agincourt	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.000000	0.0
2	Agincourt North, L'Amoreaux East, Milliken, Steeles East	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.000000	0.0
3	Albion Gardens, Beaumont Heights, Humbergate, ...	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.000000	0.0
4	Alderwood, Long Branch	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.000000	0.0

then we can see alphabetically the top 5 venues for every neighborhood.

```
####Adelaide, King, Richmond####
```

```

      venue  freq
0  Coffee Shop  0.06
1      Café    0.05
2      Bar     0.04
3  Thai Restaurant  0.04
4  American Restaurant  0.04
```

```
####Agincourt####
```

```

      venue  freq
0  Clothing Store  0.2
1  Breakfast Spot  0.2
2  Sandwich Place  0.2
3  Chinese Restaurant  0.2
4      Lounge     0.2
```

```
####Agincourt North, L'Amoreaux East, Milliken, Steeles East####
```

```

      venue  freq
0      Park  0.67
1  Playground  0.33
2  Yoga Studio  0.00
3  Miscellaneous Shop  0.00
4  Movie Theater  0.00
```

```
####Albion Gardens, Beaumont Heights, Humburgate, Jamestown, Mount Olive, Silverstone, South Steeles, Thist  
etown####
```

```

venue freq
0 Grocery Store 0.22
1 Pizza Place 0.11
2 Pharmacy 0.11
3 Fast Food Restaurant 0.11
4 Beer Store 0.11
```

```
####Alderwood, Long Branch####
```

```

venue freq
0 Pizza Place 0.22
1 Pharmacy 0.11
2 Gym 0.11
3 Pub 0.11
4 Sandwich Place 0.11
```

```
####Bathurst Manor, Downsview North, Wilson Heights####
```

```

venue freq
0 Coffee Shop 0.11
1 Bridal Shop 0.06
2 Deli / Bodega 0.06
3 Sushi Restaurant 0.06
4 Restaurant 0.06
```

now create a dataframe to show this:

	Neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	Adelaide, King, Richmond	Coffee Shop	Café	Bar	American Restaurant	Thai Restaurant	Steakhouse	Burger Joint	Bakery	Cosmetics Shop	Hotel
1	Agincourt	Chinese Restaurant	Lounge	Breakfast Spot	Clothing Store	Sandwich Place	Women's Store	Discount Store	Dog Run	Doner Restaurant	Donut Shop
2	Agincourt North, L'Amoreaux East, Milliken, St...	Park	Playground	Women's Store	Drugstore	Dim Sum Restaurant	Diner	Discount Store	Dog Run	Doner Restaurant	Donut Shop
3	Albion Gardens, Beaumont Heights, Humburgate, ...	Grocery Store	Sandwich Place	Pharmacy	Pizza Place	Fast Food Restaurant	Coffee Shop	Beer Store	Fried Chicken Joint	Women's Store	Dessert Shop
4	Alderwood, Long Branch	Pizza Place	Pharmacy	Sandwich Place	Pub	Pool	Skating Rink	Gym	Coffee Shop	Colombian Restaurant	Deli / Bodega

results:

From our analysis majority visualised in the data frame above we can see that food relating venues close to the city center. Highest concentration of the them being coffee shops. By using clusters we saw that in the city center the most popular type of venue was 'gardens' but from a business prospective that may not be the best investment so we can look to see the 2nd and 3rd most common venue which was a womens store and dumpling restaurant this is valuable information for a investor, as they can see towards the inner city clothing and food is highly dense, so if they want to find a niche they know what is already common. From the data we can see that as you leave the center of the city center of Toronto we can see that the density of clothing shops decrease as you leave the city center. The purpose of the analysis was put together in order for investors to clearly see the right type of investment to make across Toronto for them to be successful to see where a type of business is already saturated in an area and make them find a niche or already see and trend in a type of business and come in and improve existing services in the area. What ever yields them the highest profits.

Borough	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
Central Toronto	1	Garden	Women's Store	Dumpling Restaurant	Diner	Discount Store	Dog Run	Doner Restaurant	Donut Shop	Drugstore	Eastern European Restaurant

Conclusion

In conclusion by using the foursquare location data we have created data frames to analyse general boroughs in Toronto that meets certain requirements about the preexisting common venues already in the area. Given the finding presented to the potential business investors in Toronto they would also need to take into consideration other factors such as socioeconomic factors of the area , accessibility for example major roads, and local council regulations in which might cause a problem. So in conclusion I believe this study to be a 'first step' in the decision to invest in certain areas in Toronto.