

Neighborhood Analysis in the Washington, D.C. Area for the Future Amazon HQ2

Capstone Project - Battle of the Neighborhoods

March 2, 2020

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1 Introduction and Business Problem

On November 13, 2008 Amazon announced their plans to establish a second headquarter office (named HQ2) in the United States, located in New York city and Washington D.C. ([1, 2]). This represents a great opportunity for the greater D.C. area to experience growth and to attract a significant number of both skilled workers and other businesses, which are expected to populate the DMV (D.C., Maryland and Virginia) area.

The National Landing in Arlington County was chosen as the future site of HQ2. This county houses multiple national landmarks (Arlington National Cemetery, the Pentagon), a thriving business economy (with strong presence of both private companies and federal agencies), and along with the neighboring Alexandria routinely top national rankings of best places to live and retire. All these characteristics make it a very desirable area to live and work on.

However, the D.C. metropolitan area already suffers from severe issues that are likely to worsen with the expected heavy affluence of workers. Specifically, this report will look into the housing prices (rent and sales), and the commuting time. This last issue is a major concern in the area, as the D.C. area commute regularly ranks within the national top 5 work commute times (regardless of whether the commute is analyzed in terms of actual time spent commuting, or just the time spent sitting in traffic) ([3, 4]).

For all the reasons above, this document aims to analyze the different regions in the DMV area in order to help understand what is the current situation prior to the arrival of Amazon's HQ2, in order to be able to better plan for the changes that the arrival will trigger, and in this way, allow all the interested stakeholders, from city planners to realtors and small business owners, to identify potential issues and areas to improve.

1.1 Goal

The goal of this analysis will be **to improve the understanding of the DMV area in terms of amenities, commute time, and housing costs**. These are significant aspects that will drive the decision of many of the new workers that will arrive to the area when deciding where to settle down, which will, in turn, affect back to those same issues (amenities, commuting, and housing costs).

It shall be noted that the goal of this analysis is not to perform a prediction on trends or metrics, as the arrival of HQ2 is expected to be significantly disruptive, and therefore using current trends to forecast the future seems not appropriate. Therefore, we will focus this report on the analysis and understanding of the current state of the DMV areas.

1.2 Objectives

In order to achieve the main goal described previously, we will be performing descriptive analyses on the DMV area. Specifically, the following objectives will be targeted:

- *Amenities Similarity*: In order to identify neighborhoods and areas that offer similar amenities to National Landing, we will look for areas that offer similar types and quantities of amenities in the whole DMV area.
- *Commute Time Distribution*: As National Landing sits inside the I-495 Beltway, and is bordered by the Potomac river, the time to commute for new potential workers may be significant. To analyze this, we will study not only the average expected commute time from each neighborhood or area to National Landing, but we will also focus the analysis on finding patterns regarding the distribution of this commute time.
- *Housing Costs*: The study of the costs of renting and purchasing a home in the different areas will also be analyzed, and, as with the commute time analysis, patterns and distributions will be displayed and analyzed.
- *Desirability Distribution*: After individually analysing each of the features previously described, a further study will be performed attempting to combine all these individual aspects in a single metric that tells us how similar in terms of desirability the different areas are.

2 Data

In this chapter we will review the data that will be used for achieving the goals described in Chapter 1. We will look at what type of data is needed (including the formats, ranges, and types), the sources we can use, the understanding of how the data fits into the project, and any preparation that may be needed.

2.1 Data Requirements

In order to achieve the goals of this project, we need several pieces of data:

- **Geographical Description of the Areas to Analyze:** The first piece we will need is the geographical definition of the areas that we will be using for the analysis. These areas should be separate areas (i.e. with no overlapping) that provide full coverage of the areas of District of Columbia, Maryland, and Virginia. Furthermore, we will need to be able to replace each area with a point of reference that can be used to query FourSquare for amenities. Given the large amount of National Parks and water bodies in the area, we will need to be careful to ensure that some areas do not get misrepresented because of the presence of one of these areas (which, for example, would have no amenities nearby if querying from the center of a National Park).
- **Amenities in Each Area:** In order to simplify the analysis, we will be focusing on the top-10 most popular types of amenities in an area, as provided by FourSquare.
- **Commute Times:** The analysis of the commute times will require the availability of the required time to commute from one point to the expected location of HQ2, as it is usually reported by apps like Google Maps, or Waze. Given that this expected commute time may vary significantly from one day of the week to another (e.g. depending on school hours or telecommuting in the area), we will need to consider the average commute time across a number of days and hours, to get a better representation of this metric. In order to simplify the analysis, we will look only at car commute times only, leaving walking, biking, or public transportation for a future extended analysis.
- **Housing Costs:** Finally, we will need to acquire a dataset that provides us with information regarding the cost of renting or buying a home in each of the areas analyzed. This information should be normalized to account for differences in terms of size, number of rooms, etc.

2.2 Data Collection

The main issue in collecting the data for this project may lay in the definition of the areas for the analysis. While D.C. defines neighborhoods, which seem to be a good partition for this type of analysis, it turns out that the definition of those neighborhoods is not clear, and there are overlaps ([5]). For this reason, and in order to have a division that can apply not only to D.C. but also to Maryland and Virginia, we decided to proceed with divisions based on ZIP codes tabulation areas (ZCTA), as defined by the U.S. Census Bureau ([6]). These ZIP code tabulation areas are full-coverage, non-overlapping areas that cover all of the U.S., and we can use the datasets available from the same U.S. Census Bureau to get the coordinates from a representative point of each area. The datasets are provided as Shapefiles, which can be easily converted to CSV files using any GIS application. An example of the resulting CSV can be seen in Figure 2.1. We can see how for each ZIP code (in the ZCAT5CE10 column) we also have the feature called ‘internal point’, for which the latitude and longitude are provided.

FourSquare will provide us with access to the most popular amenities near that representative point for each ZCTA. During the course we have queried the API using the coordinates of a point, so it would seem a good idea to use the internal point provided by the U.S. Census Bureau Shapefile. However, we can prevent the case where a ZCTA falls in a National Park or a similarly deserted area, and query the API using the ZIP code instead, thus helping us overcome

2 Data

one of the main issues of analysing the DMV area. The effectiveness of each of these queries will be evaluated and the one providing the best results will be used. Through the FourSquare API we will obtain a list of popular venues near the point or ZIP code used for the query. An example of the results provided is shown in Figure 2.2. We can see how each venue has an associated venue category. We will use this field to get a distribution of the types of venues and use this distribution to determine which ZCTAs are similar to others.

Expected commute times between points can be obtained through the Bing Distance Matrix API ([7, 8]). Using the provided examples as a base, and automating the calls with Python, we can build our dataset of expected commute times for a range of hours each day between Monday and Saturday (inclusive). A sample of the JSON responses that we can obtain through this service is shown in Figure 2.3. In this example we can see how for a given pair of points the commute time increases in over 8 minutes just by shifting the departure time from 7 am to 8am.

Finally, the housing costs will be obtained from the Zillow Home Value datasets, available at [9]. These datasets can be sorted by ZIP code only if they are provided as time series. Given that we are not interested in forecasting, we will have to filter the time series to process only the last value. The Zillow datasets already provide a single normalized value that accounts for footage and room number, so we will not have to perform any normalization nor create our own metric based on the price. We can see a sample of the dataset in Figure 2.4. We can see how the source file contains the Zillow Index for each month, even though we will only make use of the last column. We can also see how each row represents a ZIP code, which means we can easily link the data to our analysis areas.

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	A	B	C
1	ZCTA5CE10	INTPTLAT10	INTPTLON10
2	43451	41.318301	-83.6174935
3	43452	41.5157923	-82.9809454
4	43456	41.63183	-82.8393923
5	43457	41.2673301	-83.4274872
6	43458	41.5304461	-83.2133648
7	43460	41.6048168	-83.561032
8	43462	41.283785	-83.7228646
9	43463	41.508665	-83.5080344
10	43464	41.4048795	-82.9241092
11	43465	41.5654721	-83.500302
12	43466	41.2953588	-83.5148215
13	43467	41.2432028	-83.483841
14	43468	41.5978668	-83.3414931
15	97824	45.3543012	-117.75647
16	97825	44.3851264	-119.496273
17	97826	45.6642964	-119.2323162
18	97827	45.5754239	-117.8380496
19	97828	45.7165633	-117.2219918
20	97830	44.9666148	-120.1831238
21	97833	44.9288884	-118.0148778
22	97834	44.9722752	-117.1611907
23	97835	45.9100466	-118.786552
24	97836	45.3211522	-119.4746198
25	97837	44.5566606	-118.067106
26	97838	45.853004	-119.2872655
27	97839	45.5912076	-119.5929846
28	97840	44.8560993	-116.9412302
29	97841	45.4651158	-117.9449249
30	97842	45.4235915	-116.6840285
31	97843	45.5023217	-119.9028655
32	97844	45.8841501	-119.5488363
33	97845	44.4018235	-118.9030597
34	97846	45.4626986	-117.0395863
35	97848	44.7221766	-119.5805545
36	97850	45.3035379	-118.1132779
37	97856	44.8152119	-119.1252546
38	97857	45.3592293	-117.52324

Figure 2.1: Sample CSV file from ZCTA Shapefile

2 Data

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Marble Hill	40.876551	-73.91066	Arturo's	40.874412	-73.910271	Pizza Place
1	Marble Hill	40.876551	-73.91066	Bikram Yoga	40.876844	-73.906204	Yoga Studio
2	Marble Hill	40.876551	-73.91066	Tibbett Diner	40.880404	-73.908937	Diner
3	Marble Hill	40.876551	-73.91066	Starbucks	40.877531	-73.905582	Coffee Shop
4	Marble Hill	40.876551	-73.91066	Dunkin'	40.877136	-73.906666	Donut Shop

Figure 2.2: Sample FourSquare Results

```
[16]: url="https://dev.virtualearth.net/REST/v1/Routes/DistanceMatrix?origins=39.144,-77.208&destinations=38.881,-77.113&travelMode=driving&startTime=2020-03-02T07:00:00-05:00&key=
<

[17]: results = requests.get(url).json()
results

[17]: {'authenticationResultCode': 'ValidCredentials',
      'brandLogoUri': 'http://dev.virtualearth.net/Branding/logo_powered_by.png',
      'copyright': 'Copyright © 2020 Microsoft and its suppliers. All rights reserved. This API cannot be accessed and the content and any results may not be used, reproduced or t
in any manner without express written permission from Microsoft Corporation.',
      'resourceSets': [{'estimatedTotal': 1,
                        'resources': [{'__type': 'DistanceMatrix:http://schemas.microsoft.com/search/local/ws/rest/v1',
                                      'destinations': [{'latitude': 38.881, 'longitude': -77.113}],
                                      'errorMessage': 'Request completed.',
                                      'origins': [{'latitude': 39.144, 'longitude': -77.208}],
                                      'results': [{'departureTime': '/Date(1583150400000-0800)/',
                                                  'destinationIndex': 0,
                                                  'originIndex': 0,
                                                  'totalWalkDuration': 0,
                                                  'travelDistance': 40.411,
                                                  'travelDuration': 39.733}]}]},
                        'statusCode': 200,
                        'statusDescription': 'OK',
                        'traceId': '4b6300b0c9184e16b0ebdb60206a8e41|BN000021D4|0.0.0.0|BN00001865, BN00001837'}]

[18]: url="https://dev.virtualearth.net/REST/v1/Routes/DistanceMatrix?origins=39.144,-77.208&destinations=38.881,-77.113&travelMode=driving&startTime=2020-03-02T08:30:00-05:00&key=
<

[19]: results = requests.get(url).json()
results

[19]: {'authenticationResultCode': 'ValidCredentials',
      'brandLogoUri': 'http://dev.virtualearth.net/Branding/logo_powered_by.png',
      'copyright': 'Copyright © 2020 Microsoft and its suppliers. All rights reserved. This API cannot be accessed and the content and any results may not be used, reproduced or t
in any manner without express written permission from Microsoft Corporation.',
      'resourceSets': [{'estimatedTotal': 1,
                        'resources': [{'__type': 'DistanceMatrix:http://schemas.microsoft.com/search/local/ws/rest/v1',
                                      'destinations': [{'latitude': 38.881, 'longitude': -77.113}],
                                      'errorMessage': 'Request completed.',
                                      'origins': [{'latitude': 39.144, 'longitude': -77.208}],
                                      'results': [{'departureTime': '/Date(1583155800000-0800)/',
                                                  'destinationIndex': 0,
                                                  'originIndex': 0,
                                                  'totalWalkDuration': 0,
                                                  'travelDistance': 40.411,
                                                  'travelDuration': 48.3}]}]},
                        'statusCode': 200,
                        'statusDescription': 'OK',
```

Figure 2.3: Sample Commute Time Results

2 Data

	A	B	C	D	E	F	G	JL	JM	JN	JO	JP	JQ	JR	JS	JT	JU	JV	JW	JX	JY	JZ	KA	KB	KC	KD	KE	KF	KG
1	Region	Region	City	State	Metro	County	SizeRat	2018-04	2018-05	2018-06	2018-07	2018-08	2018-09	2018-10	2018-11	2018-12	2019-01	2019-02	2019-03	2019-04	2019-05	2019-06	2019-07	2019-08	2019-09	2019-10	2019-11	2019-12	2020-01
32	66126	20002	Washington DC	Washington District of	31	642927	645306	652601	659182	663825	667974	672325	676955	678672	679491	677840	680823	683020	685948	685454	685010	686268	687180	687794	688027	689493	692341		
46	66133	20009	Washington DC	Washington District of	45	605223	605070	607915	610968	612273	613455	614261	615754	615961	615129	612506	613448	614939	616891	616668	615466	616509	617310	618368	619061	620066	624164		
79	66843	21234	Parkeville	MD	Baltimore	Baltimore	78	208596	209675	210189	211159	212405	213957	214489	215136	215201	215619	216046	215858	215045	214207	213184	213813	213635	213153	212811	212267	211869	211247
81	67732	23464	Virginia Bi	VA	Virginia Bi	Virginia Bi	80	253008	253571	254294	255113	256198	257087	257775	258528	259026	259083	259095	259435	259854	259903	260102	260685	261542	262710	263894	264997	266213	268043
96	67730	23462	Virginia Bi	VA	Virginia Bi	Virginia Bi	95	202131	202629	203217	203956	204675	204813	204982	205161	205681	205785	205937	206211	206625	206762	206982	207323	207967	209112	210216	211363	212421	214049
174	66705	20906	Silver Spring	MD	Washington	Montgomery	173	338028	339386	340395	341976	343193	344430	344414	344152	344855	347138	348564	348936	348596	349280	350236	350314	350461	350606	351629	352576	353012	352670
206	66135	20011	Washington DC	Washington District of	205	626069	628078	633896	639270	642372	645788	648171	653054	656599	659869	659746	663790	667040	671677	673066	673879	676788	679517	683141	685071	687930	691206		
213	67180	22191	Woodbridge	VA	Washington	Prince Will	212	315427	318059	320465	321888	321872	322715	323335	322245	321330	320168	322981	324983	327071	327291	327467	328204	329597	330582	331451	333429	335732	336962
217	67655	23320	Chesapeake	VA	Virginia Bi	Chesapeake	216	244998	245891	246692	247679	248661	249367	250199	251243	252454	253580	254062	254485	254934	255412	255840	256284	256682	257402	257963	259028	259852	258461
219	67010	21740	Hagerstown	MD	Hagerstown	Washington	218	186249	187379	187893	188568	188804	189696	170692	171720	171668	171555	171341	171549	171860	172061	172938	173762	174683	174824	174992	175259	176076	177098
240	66125	20001	Washington DC	Washington District of	239	678644	679934	685238	690355	692660	695056	697439	700720	702217	702102	699968	702561	705592	708499	708038	706932	707957	708200	708219	707237	707269	709018	709018	
246	66785	21117	Owings Mill	MD	Baltimore	Baltimore	245	286218	286866	286851	287405	288300	289481	289903	270513	270425	270965	271657	272127	271753	271977	272804	273249	273226	273178	272836	272934	272658	
276	67222	22304	Alexandria	VA	Washington	Alexandria	275	345772	345571	346123	347583	348493	347862	347945	349278	352179	353591	355221	357379	359555	361172	362383	364124	365516	368551	370551	371777	372099	373285
280	67182	22193	Woodbridge	VA	Washington	Prince Will	279	323977	326567	328838	330455	330819	331814	331944	330388	329171	327989	330648	332565	334509	334690	334917	335358	336329	336948	337870	340156	342328	343401
286	67222	23454	Virginia Bi	VA	Virginia Bi	Virginia Bi	285	289139	289128	289511	290264	291340	291675	292096	292783	293774	293859	293806	294400	294527	294923	295280	295891	296528	297680	298706	299731	300652	302369
295	66242	20147	Ashburn	VA	Washington	Loudoun	294	504136	506847	509000	510771	512527	512597	513480	513052	515614	516623	520317	523864	526496	527335	528479	529801	531109	533641	535582	537921	538109	538701
298	66683	20878	Gaithersburg	MD	Washington	Montgomery	297	544935	545913	546829	547500	547971	548096	547300	546437	546962	550370	551840	551823	549955	549977	550287	550185	550013	549956	550490	550899	550230	548088
302	67787	23666	Hampton	VA	Virginia Bi	Hampton	301	174500	175468	176142	177297	178446	179614	180514	181145	182163	183389	184464	185151	185554	185776	186152	186379	186475	186625	186607	186984	186520	187071
308	67598	22023	Richmond	VA	Richmond	Richmond	307	158415	159102	160232	161900	163551	165403	165361	167375	167699	169179	170200	171317	172044	173246	174258	175200	176200	177098	178021	179398	179222	179748
324	66142	20019	Washington DC	Washington District of	323	311998	315032	320885	327279	332538	336892	340563	344111	347019	349711	351777	356453	360412	363701	364580	365284	366542	368083	370315	373167	376734	380514		
350	67720	23452	Virginia Bi	VA	Virginia Bi	Virginia Bi	349	236991	237401	237539	237991	238273	238139	238084	238130	238731	238832	238944	239214	239737	239879	240343	240946	242142	243813	245558	247344	248673	250571
367	66825	21215	Baltimore	MD	Baltimore	Baltimore	366	126210	127890	129433	130657	132084	134100	136033	137647	137954	138300	138821	138955	139026	138859	139310	139399	139250	138863	137821	137861	138436	139286
373	67719	23451	Virginia Bi	VA	Virginia Bi	Virginia Bi	372	409098	409406	409900	410761	412028	412786	413687	414608	415776	415870	416120	416535	417150	417544	418227	418904	420488	422152	423616	425313	426868	429366
383	66787	21122	Pasadena	MD	Baltimore	Anne Arundel	382	315758	316843	318123	319887	320979	321134	321677	321840	322315	321748	320955	320251	320701	321387	321399	321084	320926	321596	322283	323183	324219	326088
422	66832	21222	Dundalk	MD	Baltimore	Baltimore	421	140609	142091	142421	142638	143034	144228	145010	145905	146062	146418	146786	146591	145749	145200	145131	145605	145781	145400	145068	144626	144571	144392
428	67189	22204	Arlington	VA	Washington	Arlington	427	489635	492302	494938	497733	499441	499444	501864	505373	507058	511071	515541	519280	522014	524122	526074	528897	534829	538079	541613	544268	546960	
435	66679	20874	Germantown	MD	Washington	Montgomery	434	301763	303117	304112	305025	305719	306237	306350	306141	306771	308604	309710	309048	309233	309679	309892	310155	310660	311449	312290	312632	312417	
465	66666	20852	North Bethesda	MD	Washington	Montgomery	464	471143	472530	473365	474197	474572	475177	475000	474413	475252	478320	480041	480137	478870	478960	479584	479679	480026	480157	480774	481336	480959	479489
474	66143	20020	Washington DC	Washington District of	473	328272	330543	334946	338741	341875	346072	350121	354257	357775	361389	364348	369511	373119	377449	378701	380774	381193	384746	386384	388078	389520	391117	392670	
483	66834	21248	Baltimore	MD	Baltimore	Baltimore	482	182587	182674	182550	182634	183062	184160	184707	184419	183261	181954	181892	181037	180422	179596	178939	178494	178076	177184	176254	175000	176388	176872
510	66758	21061	Glen Burn	MD	Baltimore	Anne Arundel	509	249908	250628	251375	252908	254349	254682	255186	255448	256166	255532	256108	256944	257488	257633	257635	258417	259259	259992	260685	261904	263284	
519	67857	23322	Chesapeake	VA	Virginia Bi	Chesapeake	518	343915	345300	346489	347640	348923	349797	350914	352377	354136	355781	356550	357098	357578	358082	358643	359624	360355	361493	362249	362388	362655	363248
568	67723	23455	Virginia Bi	VA	Virginia Bi	Virginia Bi	567	292178	292563	292876	293442	294324	294401	294419	294473	295036	295119	295015	295209	295383	295619	295800	296126	296659	297947	299250	300622	301758	303537
599	66708	20910	Silver Spring	MD	Washington	Montgomery	568	574627	575934	576678	577877	578263	577872	574889	573195	574453	575963	581484	581309	579387	579740	580808	581359	582297	584182	587029	588942	588487	586319
577	67247	22407	Frederick	VA	Washington	Spotsylvania	576	276042	277965	278850	279382	278776	278447	278626	279022	280886	282310	284065	284417	284542	284677	285406	286549	288005	289610	290840	291687	291332	291042
615	66703	20904	Silver Spring	MD	Washington	Montgomery	614	421277	423097	424809	426483	427629	428495	429140	429342	430843	433571	435532	435833	435483	436254	437311	437884	438582	439470	440335	441384	441776	441466

Figure 2.4: Sample Housing Costs Dataset

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