The Most Livable Areas in New York City

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Abstract

People living in or planning to move into New York City have different standards when considering a place to stay. In many cases, people prefer to live further from their work/school due to their concerns for safety, availability of social services, and financial issues. Our group used the crime data, service call data, and housing data collected from the city government of New York and Airbnb to analyze and rank the most livable areas in 5 boroughs — Bronx, Brooklyn, Manhattan, Queens, and Staten Island — of New York City.

1 Introduction

People living in or planning to move into New York City have different standards when considering a place to stay. In this project, we used big data techniques to investigate the livability of 5 boroughs – Bronx, Brooklyn, Manhattan, Queens, and Staten Island — of New York City, in terms of safety, prices, community ratings, complaints, and social service. Users of our analysis are people who are living or planning to live in New York City. They will benefit from the safety and price information, social services, and traveler's ratings included in our analysis. Our analysis is crucial to provide statistics and visualizations to assist people in making decisions about their housing options and help researchers and policymakers to understand the social and economic structures of each borough of New York City.

2 Related Work

New York Times [1] measured 44 qualities of living in NYC, including safety, service availability, cleanness, and air quality. Each quality is visualized on a map similar to our tableau results. The most favorable neighborhoods were mainly in Manhattan, including the Upper West Side, Lincoln Square, and Manhattan Valley. However, the article only mentioned that these data are collected from the survey, but the data source, data size, and data collection date are not introduced. Therefore, the article cannot be used as ground truth for our analyses, but we can expect some correlations.

3 Goodness

Each of the four datasets only contains objective information collected from either government institution or company and does not contain any predicted or synthesized data. We only considered high-profiled crimes such as shooting, sexual abuse, and physical abuse for the complaint and arrest dataset.

4 Data Sources

4.1 NYPD Historical Crime Complaint Data

The dataset includes all valid felony, misdemeanor, and violation crimes reported to the NYPD from 2006 to

the end of 2019 [2]. The dataset is 2.243GB, containing 7.38M rows and 35 columns. The following table describes the fields that are useful in this project. The description of all fields can be found at NYPD Complaint Incident Level Data Footnotes [3]. We used curl to download the dataset and redirected the output to HDFS. Downloading the dataset takes around 18 minutes. Fig.1 shows a snippet of this dataset.

CMPLNT_N UM	RPT_DT	OFNS_DESC	KEY_ CD	Latitude	Longitude
394506329	12/31/2019	DANGEROUS WEAPONS	118	40.820926797	-73.943324219
968873685	12/29/2019	FORGERY	113	40.8857014060001	-73.861640325
509837549	12/29/2019	MISCELLANEOUS PENAL LAW	578	40.7422811560001	-73.81982408
352454313	12/28/2019	MURDER & NON-NEGL. MANSLAUGHTER	126	40.8753114510001	-73.847545211
248803469	09/05/2008	BURGLARY	101	40.698827283	-73.938819047

Figure 1: Snippet of NYPD Crime Complaints Dataset

4.2 NYPD Historical Arrest Data

The dataset includes every arrest in NYC from 2006 to 2021. Each record represents the arrests in NYC by the NYPD that includes information about the type of crime, the location, and the arrest date [4]. The dataset is 1.13GB, containing 5.15M rows and 19 columns. The description of all fields can be found at NYPD Arrest Incident Level Data Footnotes [5]. We used curl to download the dataset and redirected the output to HDFS. Downloading the dataset takes around 12 minutes. Fig.2 shows a snippet of this dataset.

ARREST_KEY	ARREST_DATE	OFNS_DESC	KEY_CD	Latitude	Longitude
149117452	01/06/2016	RAPE	104	40.648650085000035	-73.95033556299995
199836526	07/16/2019	FELONY ASSAULT	106	40.67549172900004	-73.80092613699998
189476017	11/01/2018	DANGEROUS WEAPONS	118	40.61797007100006	-74.03033045599993
189259155	10/26/2018	SEX CRIMES	233	40.648650085000035	-73.95033556299995
189442667	11/01/2018	FRAUDS	340	40.57758741600002	-73.97633607099993

Figure 2: Snippet of NYPD Arrest Dataset

4.3 Airbnb Listings Dataset

The dataset includes Airbnb listings from 2010 to 2021. The dataset is 1.8GB, containing 500K rows and 89 columns. We used curl to download the dataset and redirected the output to HDFS. Downloading the dataset takes around 20 minutes. Fig. 3 shows a snippet of this dataset.

	Country	City	Name	Summary	Space	Description	Experiences Offered	Neighborhood Overview
1	United States	New York	New York, New York Condo	My place is good for couples, solo a		My place is good for couples, solo a	none	
2	United States	Brooklyn	Beautiful, specious 2 bedroom!	You'll love my place because it is sp	The apartment provides easy and q	You'll love my place because it is sp	none	East New York is an up and comin
3	United States	Brooklyn	Harrigan Luxury Townhouse Suite	My place is close to the airport, publ	This is a three bedroom apartment	My place is close to the airport, publ	none	We are 20 minutes from Manhatts
4	United States	Brooklyn	Feel like you never leave your home	PLEASE READ DESCRIPTION BEFORE	3 Bedrooms home with 2 bath, kitch	PLEASE READ DESCRIPTION BEFORE	none	
5	United States	Brooklyn	New York City Living		PLEASE READ DESCRIPTION BEFORE	PLEASE READ DESCRIPTION BEFORE	none	
6	United States	Brooklyn	Lovely studio 2 min walk to train/ su	2 short blocks from the studio to th		2 short blocks from the studio to th	none	
	United States	Brooklyn	Quiet Sunnyside Getavoy	This 1200 sq. foot space, in quite 81	1200 sq. foot specious with wide Wi	This 1200 sq. foot space, in quite Br	none	This neighborhood is safe, quite a
8	United States	Brooklyn	Front	My place is good for solo adventure	Furnished Bedroom. You share the b	My place is good for solo adventure	none	
9	United States	Brooklyn	Family & Friends in New York City	This large, warm and comfortable 3	This apartment has three bedrooms	This large, warm and comfortable 3	none	The thing that I love most about r
10	United States	Brooklyn	420 friendly Skylight room	I'm near all major transportation an	This room is now all black with strin	I'm near all major transportation an	none	Very friendly and safe neighborho
11	United States	Brooklyn	Nice bunk bed (D)	My place is close to the beach, JFK	My place has a little lamp next to th	My place is close to the beach, JFK	none	Gate way center mall is a walking
12	United States	Brooklyn	Beautiful two bedroom apartment w	This beautiful specious two bedroo	Unique large two bedroom apartme	This beautiful specious two bedroo	none	We are located on a main road in
13	United States	Brooklyn	Cozy Private Bedroom 925 Month	Towels and fresh linens will be provi	This copy, spacious bedroom comes	Towels and fresh linens will be provi	none	The neighborhood offers laundro
14	United States	Brooklyn	Sleep n Go	My place is close to family-friendly a	Since this is a basement unit it only	My place is close to family-friendly a	none	Up and coming area
15	United States	Brooklyn	Brooklyn Beautyll	Enjoy our baby brownstone in beaut	Fully renovated, Luxury apartment	Enjoy our baby brownstone in beaut	none	Real Brooklyn atmosphere. Local :
16	United States	Brooklyn	Zbrs avail. in Bright, Warm Home. 15	My place is close to Euclid av/Pitkin		My place is close to Euclid av/Pitkin	none	
17	United States	Brooklyn	Furnished rooms 20minutes from JPK	Two family house I occupy the seco	Its spacious and feels like a home a	Two family house I occupy the seco	none	Quiet and close proximity to publ
18	United States	Brooklyn	Quest Livings	My place is close to Restaurants and	Duplex setting with 2 full baths	My place is close to Restaurants and	none	
19	United States	Brooklyn	New 4bd room/3 bath w/private roof	This newly built private home offers	This newly built home is a fantastic	This newly built private home offers	none	This a neighborhood in the heart
20	United States	Brooklyn	Clean room 2 block from train	My place is Iterally 2blocks away fro		My place is literally 2blocks away fro	none	
21	United States	Brooklyn	Beautiful bedroom in 3 bedroom sh	Very beautiful and charming little on		Very beautiful and charming little on	none	Neighborhood is nice and vibrant
22	United States	Brooklyn	Feel at home	1 Bedrooms home with bath, kitche	You will be renting the entire home	1 Bedrooms home with bath, kitche	none	My neighbors are very nice and o
23	Canada	Toronto	Luxury 18D Suite in Yorkville	With the Yonge and Bloor subway st		With the Yonge and Bloor subway st	none	The Yorkville Residence in downto
24	United States	Brooklyn	The Experience	This is a family home and we invite	This is a private home SHARED ARA	This is a family home and we invite	none	The location/it's quiet
16	Darland Street	B	Robinson on And Rose Entire Ant other	Across received on the consent the	One because in borotest on the consent	Provint accelerate on the consent for		Law has Resolded and debterhoods

Figure 3: Airbnb Listings Dataset

4.4 311 Social Service Request Dataset

The 311 Social service request data is a dataset that has been updating in real time and has all the requests back from 2010. The dataset was about 15GB and originally contains 41 columns and 28.4M rows. It aggregates all requests from people requesting service from road conditions to any problems with the landlord or any request to the DOF(Department of Finance). With such dataset that contains diverse information we were able to appropriately extract information that relates to the livability of the area. Fig.4 shows a sample view of the processed dataset. Notice there are 7 columns instead of 41 because the dataset was reduced to only contain relevant information such as the complaint type and incident ZIP etc.

Unique ID	Created Date	Closed Date	Complaint Type	Location TYpe	Incident ZIP	City
31952804	11/10/2015 10:45:34 AM	11/16/2015 03:30:18 PM	Maintenance or Facility	Park	10038	NEW YORK
31966864	11/12/2015 11:44:02 AM	11/13/2015 03:49:49 PM	SCRIE	Senior Address	11218	BROOKLYN
32848944	03/07/2016 10:18:16 AM	03/09/2016 03:53:44 PM	SCRIE	Senior Address	10461	BRONX
31970384	11/12/2015 11:47:02 AM	11/13/2015 03:56:10 PM	SCRIE	Senior Address	11218	BROOKLYN
31972398	11/13/2015 11:43:34 PM	11/23/2015 10:16:00 AM	Maintenance or Facility	Park	10002	NEW YORK

Figure 4: 311 Social Service Dataset

5 Design Diagram

We used MapReduce for data profiling and data cleaning. Some members used MapReduce more than once to count the total number of complaints and arrests by zipcode. We used Hive to create a table for a cleaned dataset and visualized with tableau. For complaint dataset and arrest dataset, we consolidated results to measure the total safety.

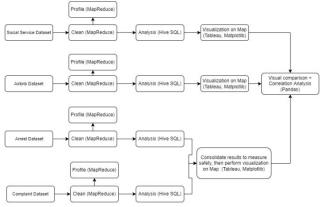


Figure 5: Design Diagram

6 Code Challenges

6.1 Reverse Geocoding

We used the NYPD Crime Complaints and Arrest datasets to investigate the safety condition of neighborhoods in NYC, but the datasets only contained geographic coordinates (latitude, longitude), lacking the human-readable address information. Therefore, we had to convert the geographical coordinates into zip codes. We found a couple of tools, such as Google Geocoding API [6] and GeoPy Python Library [7] that have reverse geocoding functionality, but none of them is entirely freely available in Java. Therefore, we collected geographic coordinates of all the zip codes in NYC from US Census data [8]. For each complaint and arrest data record, we computed the Euclidean distance between its geographic coordinates and the one in the US Census dataset and found the zip code with the closest geographic distance. With Map Reduce, we managed to do it efficiently.

6.2 Evaluation Metrics

Initially, we used crime rate to evaluate the area's safety. However, we realized that the living population of the area might not fully represent the population density, especially when offices and big companies surround the area. Thus, we changed our evaluation metric to absolute count to match better with our expected outcomes from New York Times [1].

6.3 Comparison across Datasets

Comparing results across multiple high-dimensional datasets is a challenging problem. Traditionally, multiview canonical correlation analysis is used to find correlation between multiple datasets [9]. Rather than relying on numerical analyses, we decided to utilize the commonality present in the analyses of our datasets - we mapped the evaluation metrics on to the New York map, divided by zipcodes, and performed side by side comparison.

6.4 Finding the Appropriate Delimiter to Process Data

Finding the appropriate delimiter for the 311 dataset was a challenge there were sentences manually written by the operators under the column "Description" that would contain multiple commas, which was the delimiter of the dataset. Therefore selecting the comma as the delimiter would give back multiple possible tokens. For example, one tokenization of a record even gave back 78 tokens, because the description included a long sequence of commas. Tokenization was utilized such that records only that were completed were to be filtered. However, the "Status" attribute was placed later in the record, so the position of the "Status" column were either 17, 18, or 19 or even further away. To avoid this, we checked the presence of second and third tokens, the opened date and closed date, and confirmed the validity of the dates by checking that the dates matched the definition of the "Status" attribute. Finally, the dataset was filtered by those records.

7 Data Cleaning

7.1 NYPD Historical Crime Complaint Data

GetZipcodeAndCleanMapper.java is the cleaner mapper for this dataset. Input lines were tokenized by comma and handled specially for enclosed strings. Key fields, including complaints id, report date, offense key code, offense description, latitude, and longitude, were extracted and saved to the output. All the other columns were ignored. If any key field was missing in the input line, it would be treated as malformatted and ignored. This cleaner mapper also did reverse geocoding, described in the Code Challenges, to convert geographic coordinates into zip codes. The output of the cleaner mapper was indexed by complaint id, containing values of zip code, report date, offense code, and offense description. Each value is separated by |.

GetZipcodeAndCleanReducer.java is the cleaner reducer for this dataset. It is almost like an identity reducer. The only difference is that it ignored the complaint id and wrote NullWritable as key and the value of mapper as the value.

7.2 NYPD Historical Arrest Data

In the mapper, input lines were tokenized with a special delimiter using a regular expression that handles commas in enclosed strings. Key fields — arrest id, arrest date, offense key code, offense description, latitude, and longitude — were extracted and saved to the output. All the other columns were filtered. If any extracted columns have missing values, they would be treated as malformatted and filtered. To match the timeline of events with other datasets, our group decided to follow the most outdated dataset, which contains the data until 2017. Thus, all the data recorded after 2017 is filtered. The mapper also converts geographic coordinates into zip codes using reverse geocoding. The output of the mapper was indexed by arrest id, containing values of zip code, arrest date, offense code, and offense description. Each value is separated by |.

In the reducer, it simply passes all the values from the mapper and ignores the key.

7.3 Airbnb Listings Dataset

The rows contain a lot of missing data, so after moving the dataset to the HDFS, MapReduce was used to first extract the non-null rows filter by location to extract rows pertaining to the 'city' column (Brooklyn, Staten Island, Queens, New York, and Bronx), then features were selected that seemed most relevant to the problem, namely zip code, property type, price, number of reviews, review ratings, and location ratings. These features were selected based on the intuition that a place is considered more livable when the neighborhood is clean, easily accessible to markets and public transportation, and holds buildings that are relatively more expensive.

7.4 NYC 311 Social Service Request Data

Most of the data in the Social Service Request Data were categorical data. Therefore, I would firstly filter out only resolved requests by checking if both the "Created Date" and "Closed Date" were present in the data, filter our records that are from 2010 and 2017, and aggregate columns that is relevant to the topic of the paper which are "Complaint Types", "Incident ZIP Code", "Longitude" and "Latitude" just in case. These were joined as a string with the "—" as the delimiter. During the filtering process all columns that were not present were excluded. No further processing was done for grouping the "Complaint Type" as Tableau has conveniently provides filter to apply and there were multiple "Complaint Types" that were the still same "Sweeping" complaint but could not be aggregated as within the "Sweeping" category, because it had further classification of "Missing, Inadequate, Inadequate/Missing" categories.

8 Data Profiling

8.1 NYPD Historical Crime Complaint Data

The min, max, average and median number of the the total number of complaints in all zip codes are 6, 111038, 27594, and 24837. Our cleaned dataset contains 71 distinct complaint types. The most frequent one is petit larceny and the least frequent one is kidnapping and related offenses.

8.2 NYPD Historical Arrest Data

The min, max, the average, and the median number of the total number of arrests by all categories of offenses are 1, 1088738, 57903, and 7925. It is interesting to note that there is a vast difference between average counts and median counts. Such difference indicates that some categories have a very high number of counts, and we can notice that the maximum count is over 1 million. The description of the maximum count was 'Dangerous Drugs,' which we did not classify as high-profiled crimes. Thus, the data profiling was helpful for future analysis because we realized it would be better to filter out the low-profiled crimes.

8.3 Airbnb Listings Dataset

The mean and standard deviation for price, number of reviews, overall rating, and location rating are 138.9, 109.828, 13.14, 25.72, 92.789, 58.55, 9.4289, 5.969, respectively. The large standard deviations indicate that the results of the analysis will contain interpretable and comparable results. The total count of listings after data cleaning was 52000.

8.4 311 Social Service Request

For analyzing the livability of the area, the main complaint types were narrowed down to 4 categories: rodent, noise, street condition, and traffic complaint. Rodent was

the only single category and other 3 categories were aggregates of the complaint type. Rodent statistics show 51 requests was maximum number of requests with 1 being the lowest number.

Noise related service requests are composed of commercial noise, house of warship noise, park noise, residential noise. street/sidewalk, noise, vehicle noise, and collection truck noise. The ZIP code area with the most complaints were 10029 with 304 complaints and the second most complaints were 269 from the 10024 area.

For the cleanliness of the streets, we have aggregated complaints that are related to sanitation such as curb condition, dirty conditions, mold, root/sewer/sidewalk condition, sanitation condition, sidewalk condition, street signs that are damaged/dangling/missing, and sweeping that were inadequate/missed or missed-adequate, and urinating in public. The maximum number was 88, minimum was 1.

For traffic requests, we have aggregated the number of complaints such as blocked driveway, derelict bicycle/vehicle/vehicles, for hire vehicle complaint, illegal parking, and taxi complaint that could possibly cause delay in traffic. There was maximum of 311 requests with minimum number of 1 requests related to traffic.

For statistics of the total number of service requests from each ZIP code area, there was minimum of 1, maximum 2658952, a median of 3052 requests and a mean of 69851.255 requests.

9 Results

9.1 NYPD Historical Crime Complaint Data

For each neighborhood in New York City, Fig.14 shows 5 zipcodes that have the lowest number of crime complaints. In Fig.6, we visualized the historical crime complaints for each zipcode in NYC in a Tableau map view.

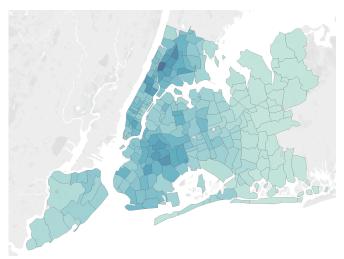


Figure 6: Tableau Map of Complaints in NYC

9.2 NYPD Historical Arrest Data

For each neighborhood in New York City, Fig.15 shows 5 zipcodes that have the lowest number of crime complaints. In Fig.7, we visualized the historical crime complaints for each zipcode in NYC in a Tableau map view.

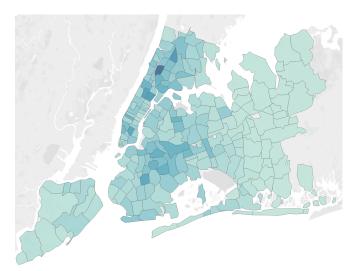


Figure 7: Tableau Map of Arrests in NYC

9.3 Airbnb Listings Data

Based on Fig.8 and Fig.9, wee see that Manhattan has the highest average location ratings, and there is also a positive correlation between price of the listings and location rating.

9.4 311 Social Service Data

For the result compilation, the following visualizations are presented to show which area as more and less requests. In Fig.10, 11, 12, and 13 are presented for each zipcode in NYC in a Tableau map view.

10 Summary

To investigate the most livable areas in NYC, we studied NYPD Crime Complaints Datasets, NYPD Arrest Dataset, NYC Airbnb Listings, and NYC 311 Services Calls Dataset. Based on these datasets, we focused our analysis on safety, location, prices, traveler ratings, noise, rodent, street condition, and traffic. Fig.16 and 17 showed the combination results of our study.

10.1 Future Work

For future improvements, we could combine datasets to further come up with correlations between different variables and present patterns.



Figure 8: Tableau Map of Airbnb Prices in NYC

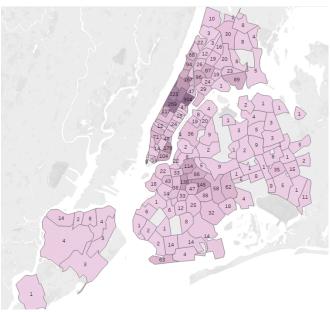


Figure 11: Tableau Map of Noise Requests in NYC



Figure 9: Tableau Map of Location Rating NYC $\,$

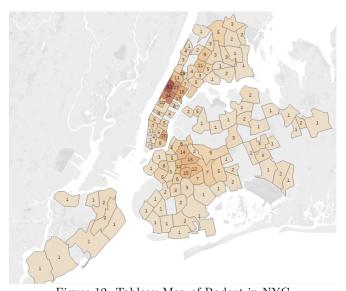


Figure 12: Tableau Map of Rodent in NYC $\,$



Figure 10: Tableau Map of Street Condition Requests in NYC

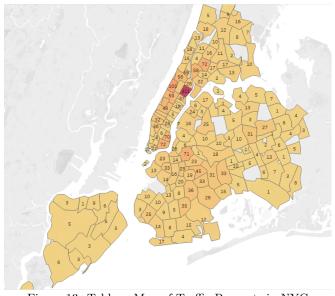


Figure 13: Tableau Map of Traffic Requests in NYC

ZIPCODE	COMPLAINT_COUNT	Neighborhood
10280	9699	Manhattan
10169	11117	Manhattan
10172	12281	Manhattan
10279	12848	Manhattan
10281	13086	Manhattan
10464	9842	Bronx
10471	14261	Bronx
10465	18638	Bronx
10475	22741	Bronx
10469	29302	Bronx
11252	11190	Brooklyn
11242	12992	Brooklyn
11234	20568	Brooklyn
11222	21409	Brooklyn
11241	22803	Brooklyn
11510	6	Queens
11568	42	Queens
11520	43	Queens
11501	219	Queens
11577	326	Queens
10311	10159	Staten Island
10314	10438	Staten Island
10307	11507	Staten Island
10309	11667	Staten Island
10308	13403	Staten Island

Figure 14: Areas with Lowest Number of Complaints in Each Neighborhood

	ZIPCODE	ARREST_COUNT	Neighborhood
5	10006	1981	Manhattan
18	10022	2333	Manhattan
44	10282	2393	Manhattan
40	10075	2432	Manhattan
14	10017	2563	Manhattan
70	10464	1603	Bronx
77	10471	1688	Bronx
71	10465	3102	Bronx
79	10473	4908	Bronx
7 5	10469	6073	Bronx
122	11222	3185	Brooklyn
109	11209	3298	Brooklyn
127	11228	3469	Brooklyn
131	11232	3774	Brooklyn
130	11231	3844	Brooklyn
205	11568	2	Queens
191	11520	4	Queens
210	11577	41	Queens
185	11501	43	Queens
207	11570	65	Queens
56	10314	1046	Staten Island
52	10308	1349	Staten Island
55	10312	1415	Staten Island
51	10307	1458	Staten Island
53	10309	2078	Staten Island

Figure 15: Areas with Lowest Number of Arrests in Each Neighborhood (2010-2016)

Neighborhood	Safety (historic)	Safety (Recent)	Location	Price	Noise	Rodent	Street Condition	Traffic
Upper West Side	***	***	***	***	\$	☆	\$	**
Midtown West	**	**	***	***	***	*	***	*
Chelsea	**	**	**	**	**	****	***	***
West Village	À À	À	*	À	**	**	**	**
Soho	***	***	**	**	***	**	**	**
Tribeca	***	****	☆	***	***	***	***	***
Battery Park	****	****	***	***	****	क्रेक्क्रक	***	***

Figure 16: Ratings of Each Neighborhood in Manhattan (1)

Neighborhood	Safety (Historical)	Safety (Recent)	Location	Price	Noise	Rodent	Street Condition	Traffic
Upper East Side	***	***	****	****	***	***	***	**
Midtown East	***	***	***	***	***	÷	ÀÀ À	***
Murray Hill	***	***	会会	☆☆	***	***		***
Gramercy Flatiron	***	***	会会	☆☆	***	***	☆☆	**
East Village	\$	☆	***	***	***	***	**	\$\$
Financial District	*****	*****	***	****	*****	******	***	****

Figure 17: Ratings of Each Neighborhood in Manhattan (2)

References

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