NYC Crime vs Film Permits

Comparison by time and location.

https://data.cityofnewyork.us/Public-Safety/NYPD-Complaint-Data-Current-Year-To-Date-/5uac-w243

https://data.cityofnewyork.us/Social-Services/311-Noise-Complaints/p5f6-bkga

https://www.kaggle.com/dgomonov/new-york-city-airbnb-open-data

https://data.cityofnewyork.us/City-Government/Film-Permits/tg4x-b46p

We are the ACE. Inc, a consulting firm that has been hired by the NYC government to see if there is a relationship between crime data and movie permits. Depending on our findings, the City might want to adjust permit prices and increase promotion in the areas that have more potential for being a movie location but are overlooked due to crime. Knowing which areas have the most certain types of crime might help City officials address the situation in different ways: increase or decrease their presence in the areas at a particular time of day, adjust the number of officers and type of equipment necessary to fight those crimes. Our findings might also be used by many nonprofit organizations that work with local communities in the NYC area to more precisely pinpoint areas where help is most needed to help increase the safety and bring more business to the neighborhoods.

For this project we are focusing on connecting two data sets: "NYPD Complaint Data Current Year To Year", called from now on crime data and "Film Permits" data set. Both sets are obtained from NYC Open Data website. We had a comma issue in our data sets, so we replaced them with forward slashes.

Crime data set has 462 k rows and 35 columns. It contains all crimes in NYC 5 boroughs almost dating back to 1911 - we will focus on one year - 2019.

Columns we think will be the most helpful: name of the borough in which the incident occurred, Exact date of occurrence, Type of offense: felony, misdemeanor, violation. Specific Incident. Suspect's: Age Group, Race, Sex. Victim's: Age Group, Race, Sex. Then location, mainly borough and zip code. Because this data does not have neighborhoods or zip code, these columns have to be added using other data sets. Using "311 Noise Complaint Data Set" zip codes were added first based on longitude and latitude. Then based on yet more more set "NYC Airbnb Open Data", the neighborhoods were added to the set. We also added column names Country and State to populate our location dimension.

The second data set that we were connecting was "FilmPermits". It is featuring all information necessary while obtaining film permits in NYC in the year 2020. Data set had 14 columns: EventID, EventType, StartDateTime, EndDateTime, EnteredOn, EventAgency, ParkingHeld, Borough, Community Board(s), PolicePrecinct, Category, SubcategoryName, Country, ZipCode.

This set also had to be altered; originally all zip codes were listed in one cell because one movie permit was issued for multiple zip codes often closely located. We had to expand the rows by duplicating all information to have each row but splitting the zip code cell into multiple rows. This data set had originally 66k rows but after expanding it has 98k. All the above work, for the crime data set and for the movie set were done in Python in Jupyter notebook using Pandas DataFrame. Some data had to be deleted due to errors or missing critical information, but the amount was minuscule. Here is a link to three files that contains code for this process:

Embellishing crime data by zip codes and neighborhoods:

 $\underline{https://github.com/molinexx/Portfolio/blob/master/crime\%20data\%20merging\%20with\%20zip\%20codes\%20and\%20hoods.ipynb}$

Cleaning crime data:

 $\underline{\text{https://github.com/molinexx/Portfolio/blob/master/crime} \% 20 cleaning \% 20 data \% 20 and \% 20 \% 20 creating \% 20 mini \% 20 csv's.ipynb}$

Expanding film data with copies of rows with single zip codes:

 $\frac{https://github.com/molinexx/Portfolio/blob/master/expand\%20rows\%20using\%20explode()\%20Film\%20Permits\%20Data\%20Set.ipynb}{0Data\%20Set.ipynb}$

Edited Crime Data:

https://drive.google.com/open?id=1iorgj7CryG-wOemavkOs5EeMnWGWG2tF

Edited Film Permit Data:

https://drive.google.com/open?id=1YvYyznLNqlPL9No0AeuQW7JnBAJsViP3

Our KPI's:

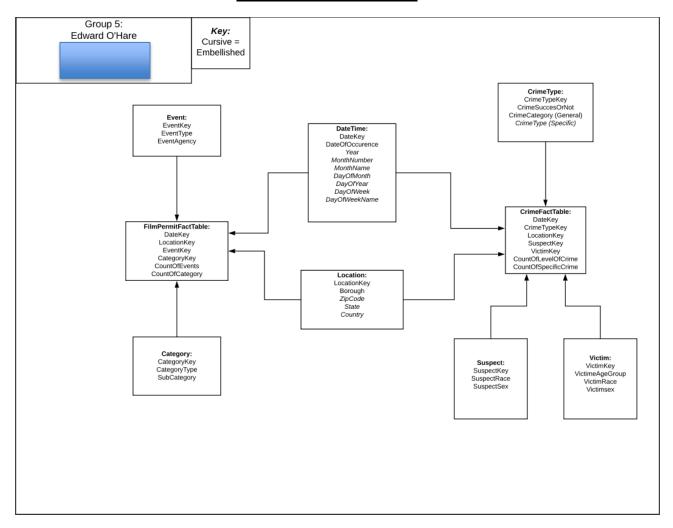
Count Of Events

Count Of Category

Count Of Level Of Crime

Count Of Specific Crime

DIMENSIONAL MODEL



There are two fact tables: Film Permit and Crime. Both are connected by location and date-time dimensions.

Transformations:

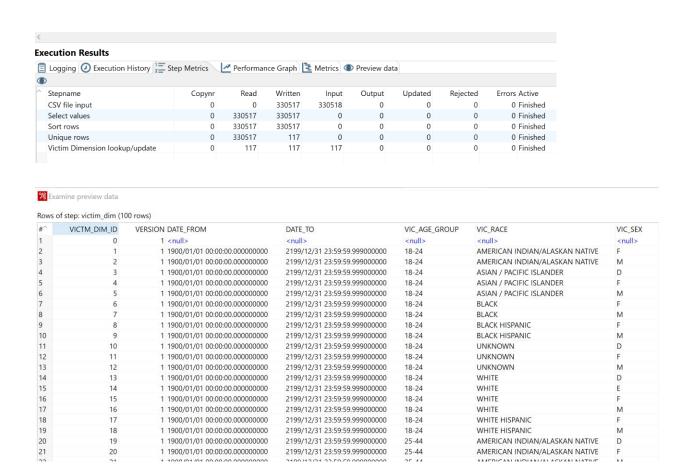
Using the Pentaho Data Integration tool we started creating our data warehouse. This is where we created kettle files for each dimension, and then later on we created the two fact tables.

General Transformation Rules: Take in the data, select correct values for this dimension, sort the data, find the unique rows and then populate the dimension within our database.

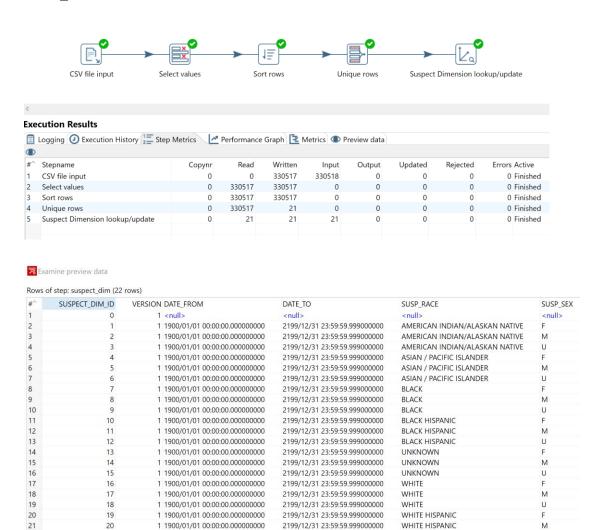
CrimeTable: Suspect, Victim, Crime Type

Victim Transformation: Pulled out the victims race, age group, and sex. Then assigned them a dim_id.





Suspect Transformation: Pulled out the suspects race, age group, and sex. Then assigned them a dim_id.



2199/12/31 23:59:59.999000000

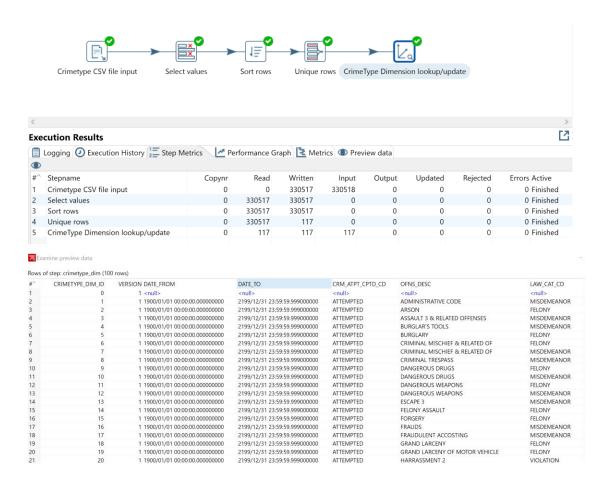
WHITE HISPANIC

1 1900/01/01 00:00:00.0000000000

22

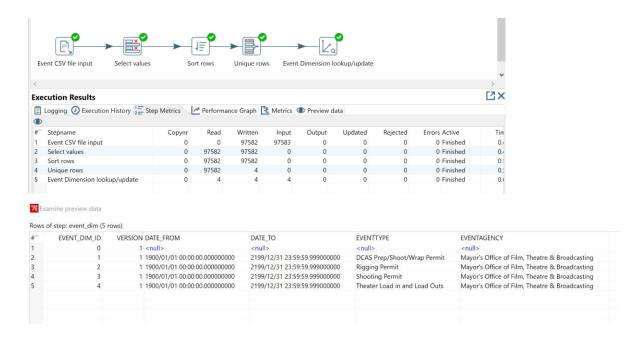
Crime Type Transformation: Pulled out the level of offense, and the exact offense description.

Then assigned it a dim_id.



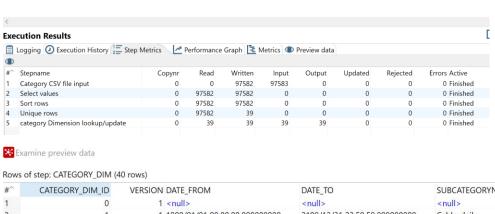
Film permit table: Event, Category

Event Type Transformation: Pulled out the event type and the event agency. Then assigned it a dim_id.



Category Type Transformation: Pulled out the category type and the sub category. Then assigned it a dim_id.

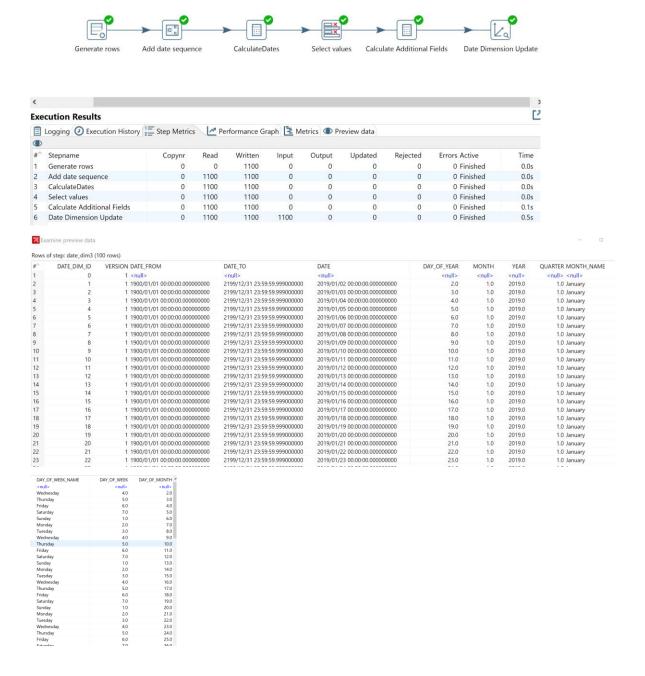




* ^	CATEGORY_DIM_ID	VERSION DATE_FROM	DATE_TO	SUBCATEGORYNAME	CATEGORY
	0	1 <null></null>	<null></null>	<null></null>	<null></null>
2	1	1 1900/01/01 00:00:00.000000000	2199/12/31 23:59:59.999000000	Cable-daily	Television
3	2	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	Cable-episodic	Television
1	3	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	Cable-other	Television
5	4	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	Children	Television
5	5	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	Commercial	Commercial
7	6	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	Commercial	Still Photography
3	7	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	Daytime soap	Television
	8	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	Episodic series	Television
0	9	1 1900/01/01 00:00:00.000000000	2199/12/31 23:59:59.999000000	Feature	Film
1	10	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	Game show	Television
2	11	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	Independent Artist	Music Video
3	12	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	Industrial/Corporate	Commercial
4	13	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	Made for TV/mini-series	Television
5	14	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	Magazine Show	Television
6	15	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	Morning Show	Television
7	16	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	News	Television
8	17	1 1900/01/01 00:00:00.0000000000	2199/12/31 23:59:59.999000000	Not Applicable	Commercial
9	18	1 1900/01/01 00:00:00.000000000	2199/12/31 23:59:59.999000000	Not Applicable	Documentary
20	19	1 1900/01/01 00:00:00.000000000	2199/12/31 23:59:59.999000000	Not Applicable	Film

Date and Location Dimensions

Date Transformation: Created dates for the year 2019, then embellished the date dimension to give an analyst more information to query on, and then assigned it a dim_id. For the embellishment we added: Day of Year, Month, Year, Quarter, Month Name, Day of Week Name, Day of Week, and Day of Month.



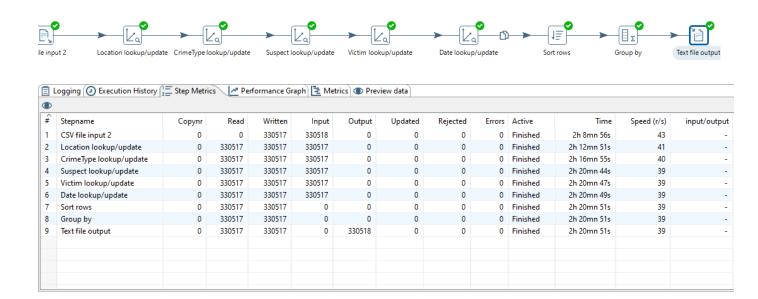
Location Transformation: Had to input the location from our two csv's, select the correct values from each, and then add this to our database. We mainly focused our attention on the borough, as zip code could get a little overwhelming.



Fact Tables:

Crime Fact Table

We took the different dimensions we individually made for the crime data set, put them together, sorted them, and downloaded them to a csv. From that csv file, we uploaded that data directly into the database.





(<u> </u>	.ogging 🕢 Execution Hi	istory 📜 Ste	p Metrics	Performa	nce Graph	Metrics !	Preview da	ıta					
#	Stepname	Copynr	Read	Written	Input	Output	Updated	Rejected	Errors	Active	Time	Speed (r/s)	input/output
1	CSV file input	0	0	330517	330518	0	0	0	0	Finished	49.7s	6,657	-
2	Crime Table output	0	330517	330517	0	330517	0	0	0	Finished	51.5s	6,418	-

4	А	В	С	D	Е	F	G
1	LOCATION_DIM	CRIMETYPE_DIM	SUSPECT_DIM	VICTIM_DIM	DATE_DIM_ID	CountOfLevelOfCrime	CountOfSpecific
2	1	1	1	1	0	4	4
3	1	1	1	1	0	4	4
4	1	1	1	1	0	4	4
5	1	1	1	1	0	4	4
6	1	1	1	1	1	2	2
7	1	1	1	1	1	2	2
8	1	1	1	1	2	3	3
9	1	1	1	1	2	3	3
10	1	1	1	1	2	3	3
11	1	1	1	1	3	1	1
12	1	1	1	1	4	6	6
13	1	1	1	1	4	6	6
14	1	1	1	1	4	6	6
15	1	1	1	1	4	6	6
16	1	1	1	1	4	6	6
17	1	1	1	1	4	6	6
18	1	1	1	1	5	1	1
19	1	1	1	1	6	1	1
20	1	1	1	1	7	3	3

Film Permit Fact Table

We took the different dimensions we individually made for the film permit data set, put them together, sorted them, and downloaded them to a csv. From that csv file, we uploaded that data directly into the database.



Execution Results Logging (2) Execution History 🔚 Step Metrics 🖊 Performance Graph 🔁 Metrics () Preview data • Errors Active Speed (r/s) Stepname Read Written Output Updated Rejected Time input/output Copynr Input CSV file input 2 0 97582 97583 0 0 Finished 36mn 52s 44 Location lookup/update 97582 97582 97582 Finished 41mn 59s 39 Event lookup/update 97582 97582 97582 42mn 3s 39 Finished Category lookup/update 97582 97582 97582 Finished 43mn 33s 37 Date lookup/update 97582 44mn 23s 37 97582 97582 44mn 23s Sort rows 0 Finished 97582 37 Group by 0 97582 0 0 0 0 0 Finished 44mn 23s Text file output 97582 37



Exe	Execution Results													
	Logging 🕢 Execution	History 1 S	tep Metrics	Perfo	rmance Grap	oh 🔁 Metr	ics 💿 Previe	w data						
•														
#	Stepname	Copynr	Read	Written	Input	Output	Updated	Rejected	Errors	Active	Time	Speed (r/s)	input/output	
1	CSV file input	0	0	97582	97583	0	0	0	0	Finished	6.0s	16,237	-	
2	Film Table output	0	97582	97582	0	97582	0	0	0	Finished	6.8s	14,291	-	

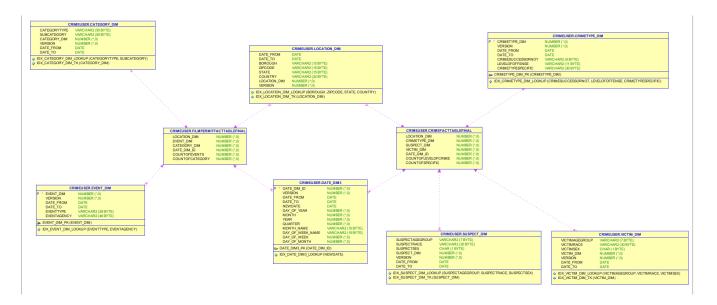
1	Α	В	С	D	Е	F
1	LOCATION_DIM	event_dim	CATEGORY_DIM	DATE_DIM_ID	CountOfEvents	CountOfCategory
2	1	1	1	0	2	2
3	1	1	1	0	2	2
4	1	1	9	0	13	13
5	1	1	9	0	13	13
6	1	1	9	0	13	13
7	1	1	9	0	13	13
8	1	1	9	0	13	13
9	1	1	9	0	13	13
10	1	1	9	0	13	13
11	1	1	9	0	13	13
12	1	1	9	0	13	13
13	1	1	9	0	13	13
14	1	1	9	0	13	13
15	1	1	9	0	13	13
16	1	1	9	0	13	13
17	1	1	9	94	1	1
18	1	1	16	0	3	3
19	1	1	16	0	3	3
20	1	1	16	0	3	3

Data in our Oracle Database:



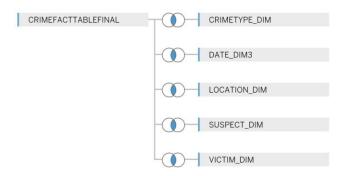
After assembling the tables in Pentaho, we created the link to our oracle database and uploaded them. Oracle server makes our data available for us to work with in SQL Developer using the wallet zip folder. This is where using SQL we created relationships between tables. Below you can see a physical diagram that was created after this step.

Physical diagram: SQL Developer with Foreign Keys



Our Final Technical Schema:

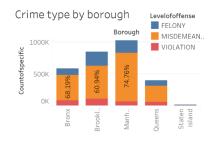
Summarizing, we used Pentaho for creating our dimensions, Oracle database for storing our data, and Tableau for creating our dashboard. We were able to connect Tableau to the Oracle server using your tutorials, where we created a schema for data visualization: for example this is the schema for Crime Fact Table.

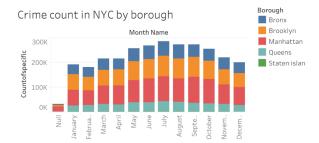


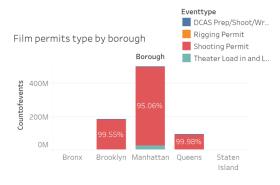
We used KPI such as CountOfEvents, CountOfCategory, CountOfLevelOfCrime, CountOfSpecificCrime to create below dashboard:

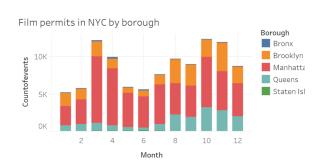


Dashboard:









From our dashboard we can easily compare the amount of crime and film permits by borough and over the year of 2019. May, June, and July are some of the most popular months for crime, but some of the least popular months for film permits. We also can see there is almost no filming done in Staten Island, but there is a very small amount of crime there as well. It may be time for more filming to take place in Staten Island.

Narrative Conclusion:

We think that even though there seems to be some slight evidence that less film permits are equal to more crime, there would have to be a lot more analysis to make any concrete predictions or recommendations. We think adding weather could be an interesting added factor into this analysis. Meaning, on extra hot days is there more crime and less film permits and vice versa?