

San Francisco Rental Slackbot W205 Final Paper

Team Members:

Amy Smessaert Matthew Nelson

Joseph Kunkel

Qing Zhang

Instructor:

Arash Nourian

Introduction

The rental market in San Francisco is one of the fastest-moving in the country. It's also some of the most expensive real estate. Given these conditions, finding a place to live in the city can be especially difficult, and sometimes renters may need to branch out of their original housing parameters to less familiar areas. Our team sought to make this experience easier. We developed a Slackbot that would determine the quality-of-life and propose rental properties in San Francisco based on inputs from a user. We combined available data from DataSF (open source) and Craigslist into a tool that gives users quantitative neighborhood information to evaluate before making a big life decision: where to live.

As motivation for the project, one of the team members had previously gone through the experience of finding an apartment in San Francisco and, months later, stumbled upon this blog: https://www.dataquest.io/blog/apartment-finding-slackbot/. While the blog is a step forward and would have been useful to have during the apartment-finding process, the solution our team implemented is more detailed and precise. The original project was designed to collaborate with others on which Craigslist listings they thought were best, but contributing data was limited to that found in the Craigslist postings.

High-Level Technology Introduction

There were four key considerations that determined the technology we used:

- 1. The rental information needed to be comprehensive, free to access, and up-to-date. For these reasons, we opted to use Craigslist data. There are python packages that provide basic Craigslist scraping capabilities, which we customized to meet our parameters.
- 2. The rental information needed to be easily accessible, and our solution user-friendly. We

decided to use Slack as our communication instrument. Slack has become popular for inter-organizational communication, particularly in the Bay Area. We expect that many users are already familiar with the platform. In addition, Slack provides developer information for application customization.

- 3. We needed to store large diverse sets of data and access them quickly. To accommodate these needs, we decided to implement HDFS on AWS. The key data was cleaned, uploaded and stored in Amazon S3 bucket loading into HDFS via our data load script.
- 4. In order to be useful, our platform needed to rapidly respond to user input with the detailed query response. The bulk of the data was transformed into tables in Hive and queried according to user input with Spark. Implementing Spark via PySpark allowed for seamless integration with our custom framework.

Data Sources

The data sources collected in this project include Craigslist rental listings (https://sfbay.craigslist.org/search/sfc/apa), and raw data and limited descriptive statistics detailing quantitative information about the city and county of San Francisco from Data SF (https://data.sfgov.org), and Vital Signs (https://www.vitalsigns.mtc.ca.gov/).

In our project prototype, we collected available data that described the following quality of life metrics, by zip code or neighborhood name: the number and detail of active businesses, bicycle share locations, bicycle parking, off-street automobile parking, incidents involving the San Francisco police department, incidents involving the San Francisco fire department, local school type and location, and tree coverage. Data detailing available rentals was obtained by a python script that collected listing information from Craigslist.org.

Data Collection & Processing

The data sets used for our project are made available as both JSON or CSV files. We use CSV files in the prototype bot, which necessitates simple data cleaning steps before loading. Hidden return characters were replaced with comma delimiters in bash, correct newlines inserted, and proper names (with extraneous commas) were removed with command line perl regex expressions according to individual needs (ex: > tr -d '\n' <file, > sed -i 's/)"/)"\n/g', > perl -npe 's/^"\w+,\s/"/', etc.)

A	В	C	D	E	F	G	Н	1		J	K	L	М	N	0	P
(37.7830048	-122.48	2299	8)"													
Alvarado Elementary School	SFUSD	0	5 K-5		USD Grades K-5	PS002	5	10	PS		38684786040703	625 DOUGLASS ST, San Francisco, CA 94114	8	6075	SAN FRANCISCO	CA
Aptos Middle School	SFUSD	6	8	8-Jun	USD Grades 6-8	PS003	11	13	B PS		38684786062020	105 APTOS AVE, San Francisco, CA 94127	7	6075	SAN FRANCISCO	CA
Argonne Early Education School	SFUSD	-2	0 PK-TK		USD PreK/TK	PS004	3	5	5 PS		384000981	750 16TH AVE, San Francisco, CA 94118	1	6075	SAN FRANCISCO	CA
Argonne Elementary School	SFUSD	0	5 K-5		USD Grades K-5	PS005	5	10) PS		38684786040737	680 18TH AVE, San Francisco, CA 94121	1	6075	SAN FRANCISCO	CA
Asawa, Ruth Asawa San Francisco School Of The Arts Academy Of Arts And Sciences	SFUSD	9	12	12-Sep	USD Grades 9-12	PS006	14	17	7 PS		38684783830387	.555 PORTOLA DR, SAN FRANCISCO CA, 94131	8	607!		CA (37.745315 6, - 122.44882 7)
Balboa High School	SFUSD	9	12	12-Sep	USD Grades 9-12	PS007	14	17	7 PS		38684783830288	1000 CAYUGA AVE, San Francisco, CA 94112	11	6075	SAN FRANCISCO	CA
Brown, Willie Brown Jr Middle School	SFUSD	6	8	8-Jun	USD Grades 6-8	PS008	11	13	B PS		38684780132241	2055 SILVER AVE, San Francisco, CA 94124	10	6075	SAN FRANCISCO	CA

To avoid similar issues, we recommend manual file review for file-specific data-cleaning solutions. Cleaned data is stored in Amazon S3 to facilitate loading into our EC2 instance.

Our project solution is organized around zip codes. Some DataSF data sets contain address and zip code information, others contain geotag coordinates set in the center of a key building or facility. We use DataSF mapping information

(https://data.sfgov.org/Geographic-Locations-and-Boundaries/Analysis-Neighborhoods/p5b7-5n 3h) and

https://data.sfgov.org/Geographic-Locations-and-Boundaries/San-Francisco-ZIP-Codes/srq6-hmpi) to project geotagged neighborhood information into predefined postal code regions. In the implementation, neighborhoods with irregular, non-rectangular boundaries are transformed into rectangular perimeters that encompass the most distant coordinates to facilitate mapping geotagged coordinates into our zip code framework.

Table construction in Hive

Once our static data was successfully cleaned and loaded into HDFS, we needed to turn it into tables so we could aggregate and query it. We wrote a DDL script to create the tables as the entity relationship diagram shows below. The tables are: Businesses, bike_parking, bike_station, schools, parking, SFPD and trees. Once the DDL script was executed, we performed additional manual checks of each table in Hive in order to ensure there weren't any missed data quality issues. Craigslist data is automatically scraped to a Hive table, so separate quality checks were implemented.

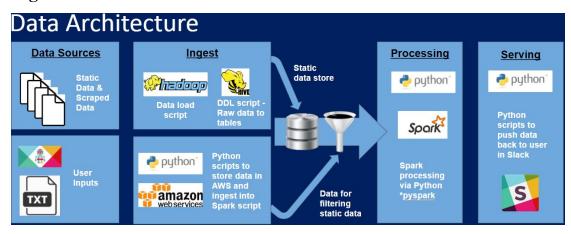
bicycle parking local school information off-street parking availability object id location 1 location 1 year_installed campus_name month_installe ccsf_entity address upper_grade prime_type address location grade range second type street category gar or lo map_labe valet_cap placemen number_of_racks lower_age reg_cap number_of_space: upper_age mc_cap last edited date land use type general type campus_address bicycle share location Active Business supervisor distric county_fips PK station id location id county_name ownership name UID location_1 business_account_numbe site id station_location ownership name FK location_name street_address tree id last edited date city legal_status state species geom source_zipcode address business_start_date crime incidents site order business_end_date PK pd id FK site info location start date incident nun plant_type category business_location description care assistant plant date day of week craigslist_data_tmp date Location id plot_size posted date permit notes pd district geotac x coord resolution y_coord has_image address latitude has_map Ionaitude posting_ic y_coord location name location price pd_id location

Entity Relationship Diagram

There are some instances in the load script and the DDL script where we mention data sets not contained in our prototype. This will be mentioned towards the end of the report in the "Future Roadmap" and "Potential Expansion" sections.

Implementation and Analysis

High Level Architecture



Data Acquisition & Storage

Static data sets from DataSF and Vital Signs were downloaded locally in CSV format. The files Active_Business_Locations.csv, Map_of_Schools.csv, Schools_type.csv, Eviction_Notices.csv, Recreation___Park_Department_Park_Info_Dataset.csv, and Park_and_Open_Space_Map.csv required data cleaning before loading. In this prototype, we were not able to automate the data quality detection and cleaning. Improvements upon this are discussed in "Future Roadmap / Improvements." Cleaned data sets were loaded into Amazon storage in S3. This solution provided a central location for the data sets which assisted in the automation of the load process. Once the clean static data was in S3, a Load Data Lake script was written to create a file structure in HDFS, rename the files and put the respective files into their appropriate locations.

Python scraper code was written to scrape Craigslist data into a Hive table. A custom Slackbot script presents the user with options and asks them to rank their preferences, and stores their responses in a txt file. In order to implement the user interaction, our team needed to generate slack credentials, a unique channel, an APP, and generate an API token. A custom python script runs the app and stores the results of the interaction.

Data Ingest

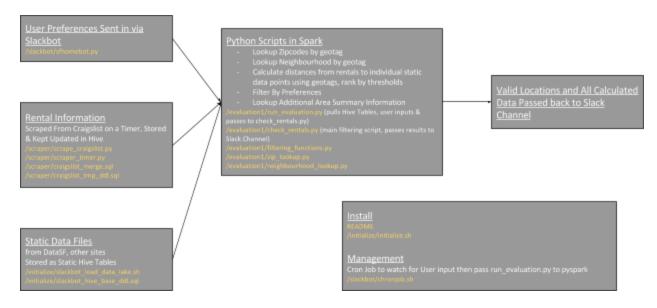
Static data is transformed into Hive tables via DDL scripts. A .txt file from user input via the slackbot is loaded into the EC2 instance, and detected by a cron daemon. Once the .txt file is detected, the Spark analysis is executed and the data processed.

Data Processing and Serving

The PySpark evaluation script is executed, which queries and filters the static datastore using the specific user input recorded in the slackbot .txt file.

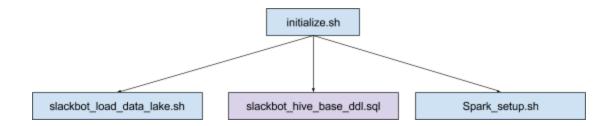
After filtration executes, a Python script aggregates the data and returns the solution to the user via the slack channel (retrieves the token information from the environment, selects, organizes and returns the display).

Implementation



Environment Installation

The README in the repo describes the steps required to instantiate the project slackbot. The project was designed to be replicable on top of a base W205 Spring AWS AMI and utilizes installation scripts as provided throughout the w205 course to properly setup Hadoop, Hive, Postgres and Spark. Within the GitHub repository, the initialize sh script installs many of the necessary packages needed for the slackbot to run.



Initialization Script Details

initialize.sh

- Starts Hadoop, Hive, sets up Spark, enables PATH variables
- Updates Python & PIP 2.6 to 2.7
- Installs required Python packages, python-craigslist and slackclient
- Downloads Static data from shared AWS S3 bin
- Runs slackbot_load_data_lake.sh
- Runs slackbot hive base ddl.sql
- Changes permissions as needed

slackbot load data lake.sh

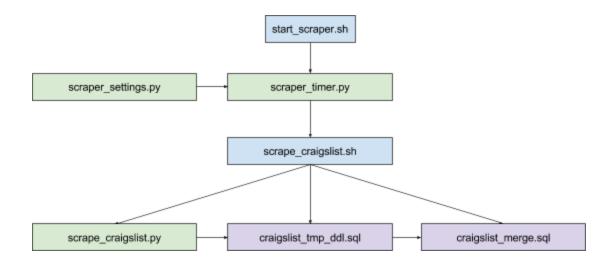
- downloads all Static Data files from S3
- Creates destination directories in Hadoop
- Moves static data files to Hadoop

slackbot hive base ddl.sql

• Creates separate tables in Hive for each static dataset, as outlined in the ER diagram

Craigslist Scraper

The scraper was designed to utilize the functionality of the python-craigslist package, scrape craigslist with predefined settings, save the results as a .csv file, load this .csv file into Hive as a separate table, merge the current scraper results with an existing unique_rentals table in Hive to ensure no duplicates, delete all temporary files, and repeat this process on a timer. Our implementation currently grabs 50 available rentals randomly from the sfc.craigslist site, however a sort_by='newest' flag can be applied in scrape_craigslist.py in order to ensure that the most recent postings are always available to the users query. This would be most effective if the slackbot were left running and the corpus of available rentals grows.



Scraper Script Details

start scraper.sh

- Sets Permissions
- Runs scraper_timer.py

scraper timer.py

• Runs scraper_craigslist.sh once every _ seconds, as defined in scraper_settings.py

scrape craigslist.sh

- Makes directories in Hadoop if they don't exist
- Deletes tmp files from last scraper
- runs scrape craigslist.py
- Copies local tmp file to HDFS
- Runs craigslist tmp ddl.sql
- Runs craigslist_merge.sql

scrape craigslist.py

• Scrapes craigslist (within site='sfbay', area="sfc", category='apa') and saves all scraped

information to a local temporary csv file. Limit of postings per scrape is set to 50.

craigslist tmp ddl.sql

• Creates a table in Hive called craigslist_data_tmp containing the last scrapes rental information

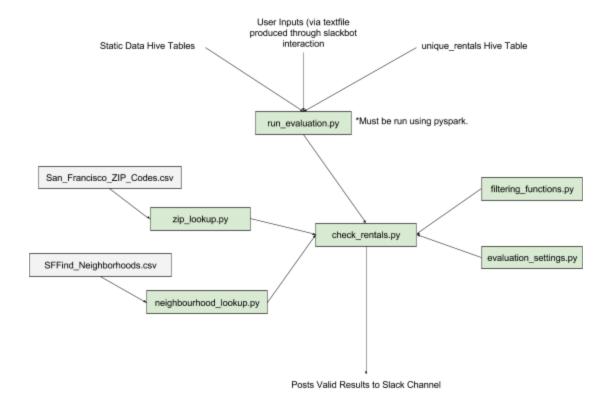
craigslist merge.sql

• Merges craigslist_data_tmp with the unique_rentals table in Hive and saves only unique items

scraper settings.py

• Contains adjustable settings for the Scraper such as timer interval & area

Rental Evaluation



Evaluation Script Details

run evaluation.py

- Opens User inputs from sfhomebot.txt and collects their preferences as variables
- Initiates a Spark Context
- Selects all information from unique_rentals Hive table & converts from a Spark dataframe to a python dictionary
- Queries zipcode, count(parks) from parks Hive table & converts from a Spark dataframe to a python dictionary
- Queries zipcode, count(bars) from businesses Hive table & converts from a Spark dataframe to a python dictionary
- Queries zipcode, count(restaurants) from businesses Hive table & converts from a Spark dataframe to a python dictionary
- Queries zipcode, count(businesses) from businesses Hive table & converts from a Spark dataframe to a python dictionary

- Queries location, geotag from bike_parking Hive table & converts from a Spark dataframe to a python dictionary
- Queries location, geotag from bike_stations Hive table & converts from a Spark dataframe to a python dictionary
- Queries location, geotag from schools Hive table & converts from a Spark dataframe to a python dictionary
- Queries location, geotag from trees Hive table & converts from a Spark dataframe to a python dictionary
- Queries location, geotag from sfpd Hive table & converts from a Spark dataframe to a python dictionary
- Queries location, geotag from parking Hive table & converts from a Spark dataframe to a python dictionary
- Runs check rentals.py and passes in all collected data

check rentals.py

- Runs zip lookup.py if zipcode not present in listing
- Runs neighbourhood_lookup.py if neighbourhood name not present in listing
- Takes each rental and passes it through a number of filters as designed in filtering_functions.py
 - Max Price Filter
 - Min Price Filter
 - Zipcode Based Filters
 - # of Parks in Zipcode
 - # of Fires in Zipcode
 - # of Bars in Zipcode
 - # of Restaurants in Zipcode
 - # of Businesses in Zipcode
 - Distance Based Filters
 - Close to Bike Parking (Yes/No, Distance to)

- Close to Bike Station (Yes/No, Distance to)
- Density Style Filters
 - Density of Schools within certain radius of rental
 - Density of SFPD Events within certain radius of rental
 - Density of Vehicle Parking within certain radius of rental
 - Density of Trees within certain radius of rental
- If rental makes it through all of the filters it is then considered a valid rental and the result is passed to a Slack Channel for the User to View
- Results are formatted for increased readability and include many calculated fields to help facilitate informed decision making

filtering functions.py

- Contains all functions used for filtering the rentals
- Functions used in this evaluation:
 - min_in_zip(zip_eval_dict): counts the maximum and minimum of items in a specific zipcode
 - points2distance(start,end): calculates the distance in km's between one set of lat/longs and another set of lat/longs
 - close_to_bike_parking(geotag, bike_parking_locations): calculates if a rental is close to bike parking & returns Yes/No, closest location name & distance.
 Maximum distance to a bike parking location = 0.5km.
 - close_to_bike_station(geotag, bike_station_locations): calculates if a rental is close to a bike share station & returns Yes/No, closest location name & distance.
 Maximum distance to a bike station = 1km.
 - parking_density(geotag, parking_locations): calculates if a rental is in a high/medium/low density area for parking, separated out by Private and Public lots & returns density and a count of locations for both Private and Public. 1km radius, low density threshold of 100, med density threshold of 500
 - o school_density(geotag, school_locations): calculates if a rental is in a

- high/medium/low density area for schools & returns density and a count of schools. 10km radius, low density threshold of 3, med density threshold of 10
- sfpd_density(geotag, sfpd_locations): calculates if a rental is in a high/medium/low density area for SFPD incident & returns density and a count of incidents. 1km radius, low density threshold of 5000, med density threshold of 10000
- tree_density(geotag, tree_locations): calculates if a rental is in a high/medium/low density area for trees & returns tree density and a count of the trees in the area.
 1km radius, low density threshold of 1000, med density threshold of 10000

evaluation settings.py

• Contains Slack Channel information and pulls in the Slack Token for posting to a channel from the set Environment Variables.

zip_lookup.py

- Imports San_Francisco_ZIP_Codes.csv, takes the given polygon coordinates for each zip code and approximates a square for each given ZIP. This was necessary in order to simplify some very complicated polygons, though it may result in some false-positives when doing the zip lookup.
- Defines functions to check whether a given geotag is located in a calculated zip_box and completes a lookup to determine a zipcode for any given geotag in the San Francisco area.

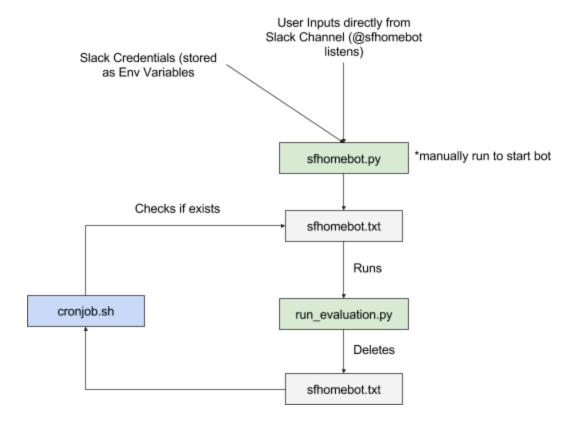
neighbourhood lookup.pv

- Imports SFFind_Neighborhoods.csv, takes the given polygon coordinates for each
 neighbourhood and approximates a square. This was necessary in order to simplify some
 very complicated neighbourhood polygons, though it may result in some false-positives
 when doing the neighbourhood lookup.
- Defines functions to check whether a given geotag is located in a calculated

neighbourhood_box and completes a lookup to determine a neighbourhood name for any given geotag in the San Francisco area.

SlackBot

The slackbot was designed to take input preferences from a user within a Slack channel, and pass this into the above Evaluation code. The implementation of the Bot is highly simplistic and has not been optimized for usability. Only one script had been created to interact with the user, and error handling regarding the user-inputs has not been implemented. The purposes of the SlackBot at this stage of development is simply to show the potential for interaction between a standard user in Slack and the back-end infrastructure / evaluation scripts on the AWS instance. In order to allow the slackbot to automatically begin an evaluation of a user's query, and to reset itself following a successful evaluation, a cron daemon was designed to look for the input .txt file in a specific folder and kick off the evaluation. Following a timer, it would then wipe the .txt file from memory and allow the user to re-submit a query from the top of the slackbot script. The implementation of the cron daemon did not work as intended, and it is recommended to pursue other options for slackbot interaction with our system.



Slackbot Script Details

sfhomebot.py

- Pulls SlackBot credentials from System Env Variables.
- Brings SlackBot online within Slack
- Listens for mentions @botname
- Asks questions of the user according to a specific script
- Parses and saves script replies to sfhomebot.txt

chronjob.sh

- checks if sfhomebot.txt exists
- if so, runs run_evaluation.py in Spark & deletes sfhomebot.txt
- repeats on a timer

Technical Challenges

Collaboration

We faced difficulties sharing the data and credentials. We initially planned to share snapshots of the EBS, but after trying a couple iterations, the snapshot wasn't rendering the loads accurately (unknown cause). Our solution was to use a shared Amazon AWS account with a persistent EBS volume. The credentials and .pem files were shared through different platforms, although we realize that this isn't an ideal solution and isn't the most secure. The overall build of the code for the project occurred within a github repository which ensured that the tables could easily be updated in our working instance simply by pulling the most recent repository and re-running the slackbot_load_data_lake.sh and slackbot_hive_base_ddl.sql scripts. This was executed successfully and team members could then separately work on the data cleaning, Hive DDL statements and main evaluation code separately without conflict.

Data Cleaning

The main issue we encountered was inconsistent formatting in a diverse set of static, open-source data. Data preparation and cleaning required limited, ad-hoc command line formatting changes.

Python version incompatibility

We use the Spring 2016 UCB AMI in our project instance. This AMI includes Python 2.6.6. As is common with code development, it is often easier to get pieces of code to work locally before bringing them into the shared branch. This was the case for our project. The default Python version on our machines is Python 3.5. Our team needed to write a series of scripts to update an AMI from 2.6 to 2.7, so that we could spin up separate instances on-demand.

The SlackClient wasn't compatible with Python 2.6 (update to Python 2.7 solved this incompatibility issue). We implemented a custom bot solution, but have learned of the existence

of a slackbot package that may make integration simpler in the future.

New Technologies

There are a few technologies we did not have prior experience with required we manage steep learning curves:

Slack API. As mentioned above, we could have looked into using a bot package instead of the custom integration. This might have helped with connection/ disconnection from the SlackBot instead of a hard bot reset.

Craigslist Scraper. Due to our limited experience writing custom scrapers, we kept our prototype simple. Future versions might include images, and unstructured text.

Automation. Our team wanted the .txt script from the SlackBot to be automatically ingested into the Spark process. We selected a cron daemon to perform this function, which required significant time and energy investment.

Future Roadmap / Improvements

Our team opted to use technologies described in course exercises. We might have improved implementation by branching out of those technologies. We currently store information in Hive tables and write complex code to aggregate the static data. Had we selected a dynamic storage technology like MongoDB, the aggregation of the data would have been automated.

We opted to keep the user interface simple in our prototype. In order for the user to interact with and respond to our bot, they reference the bot with @sfhomebot in each response. This makes our code move through the question script more easily and also allows the parsing of the .txt script simple. In addition, our code doesn't account for multi-line responses or include error-handling. We might improve upon UI in future implementations.

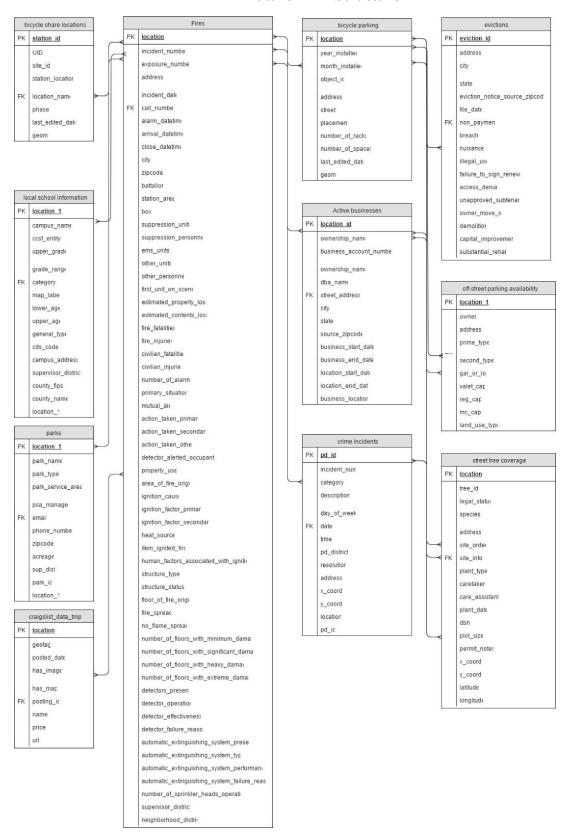
Slackbot disconnect / integration requires manual termination of the session in order to disconnect the SlackBot from the Slack channel. This issue will be solved with the bot package solution.

Our load and DDL scripts account for data that we were ultimately unable to incorporate due to time constraints / complexity issues. The ER diagram on the following page illustrates our intended data offering. With more development time, or a dynamic storage technology, we would have included additional data sets. However, they were not necessary to demonstrate the proof of concept usage of our SlackBot data application.

Potential Expansion

As the figure shows below, there are many other categories of information sources which we could include in an expanded database. These datasets might include local coffee shops, local churches, laundries, public transportations, supermarkets, etc. Providing daily utility information would make the dataset much more valuable to the user. We opted not to include streaming data, but in future iterations could include streaming traffic data, and up-to-minute parking availability. In addition, in our project we limit our focus to San Francisco city and county. We could expand data collection further, to include other areas in the Bay Area. As the open data model is adopted by more municipalities, expand to other metro areas altogether.

Future ERD Structure



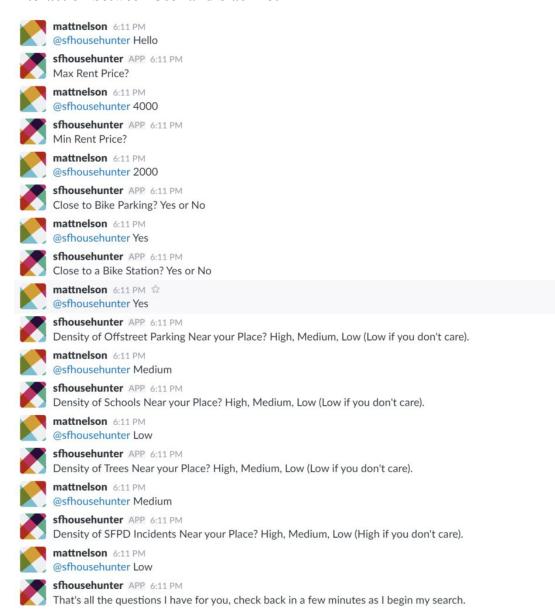
Potential future directions



Example Results

A working implementation of the User Interface and Slackbot Interaction is shown below:

Interaction between User and SlackBot



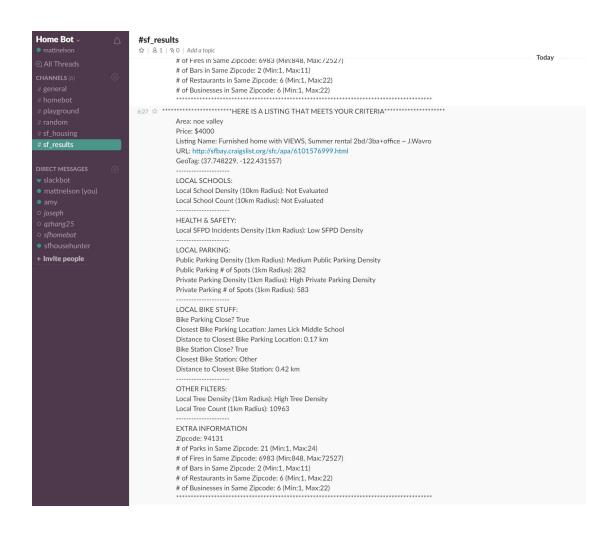
Example of User Output to a .txt file

```
w205@p-172-31-56-108 slackbot]$ ls
pot.py chronjob.sh chrontab.txt print_bot_id.py sfhomebot.py
[w205@ip-172-31-56-108 slackbot]$ ls
pot.py chronjob.sh chrontab.txt print_bot_id.py sfhomebot.py
[w205@ip-172-31-56-108 slackbot]$ cat sfhomebot.txt
[w205@ip-172-31-56-108 slackbot]$ cat sfhomebot.txt
iello
iello
iello
ies
iedium
iew
[w205@ip-172-31-56-108 slackbot]$ |
```

Print statements to the screen while filtering scripts run in PySpark

```
$\text{$\text{$\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitute{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substitue{\substit
```

Responses pushed to Slack Channel



APPENDIX:

Resources

https://sfbay.craigslist.org/search/sfc/apa

https://data.sfgov.org

http://www.vitalsigns.mtc.ca.gov/

https://data.sfgov.org/Geographic-Locations-and-Boundaries/Analysis-Neighborhoods/p5b7-5n3

h

https://data.sfgov.org/Geographic-Locations-and-Boundaries/San-Francisco-ZIP-Codes/srq6-hm

pi

https://www.dataquest.io/blog/apartment-finding-slackbot/

GitHub Repository: Code

Setup System

https://s3.amazonaws.com/ucbdatasciencew205/setup_ucb_complete_plus_postgres.sh