



Property Hunter CA1 – Property Hunter Intelligent Agent

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Team 6

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Project

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1. Executive Summary

There is a business opportunity in providing a more efficient and effective way for potential property buyers to search for, view and make an offer for the property they are interested to purchase. The potential annual revenue is estimated at between \$2.5 Mil and \$5 Mil for the first two years of operation in local market. Three of the six activities in the Property Search and Make Offer process which are more tedious and repetitive can be automated by the solution, leaving only the decision-making task to the buyer.

The solution comprises (1) User Fronting Chat-bot, (2) Property Search Agent, (3) Appointment Scheduling Agent, (4) Market Price Data Retrieval Robot, (5) Image Clustering Model and (6) Current & Future Price Prediction Model. The User Fronting Chat-bot is the conversational user interface that gets request from user to search for a new property and to view selected properties in the list of shortlisted properties. It also answers anticipated user queries about the solution. The Property Search Agent helps user to search for ideal properties from property listing website. It feeds property images into the Image Clustering Model to further down select the properties according to the user's latent needs. The Appointment Scheduling Agent checks user's calendar and arranges with the seller/seller agent the earliest opportunity to view a selected unit. It also passed the details of the selected unit into the Current & Future Price Prediction Model and provide the Estimated Fair Market Value for the user's reference in case the user is keen to make an offer after viewing the unit.

2. Introduction

2.1 Business Opportunity

Buying a property takes a lot of time and effort to search and compare different properties. Not only do buyers need to monitor the market for their preferred choices and watch out for new listings that fit their criteria, buyers also need to research on additional information like market price movement and recent transaction price from the same or nearby projects. Moreover, when a suitable property is found, buyers need to schedule a viewing of the property and make an offer as soon as possible to secure the purchase of the property.

Hence the team sees the opportunity to simplify the buyers' experience and make their life easier through the use of Intelligent Agents, Robotic Process Automation in conjunction with Machine Learning Models to aid their decision-making process and reduce manual effort through automation.

2.2 Proposed Solution

The team proposes an intelligent software agent-based solution consisting of several intelligent software robots working in tandem to provide the below services to the users.

- Property search based on explicit requirements and elicited latent needs
- Automated viewing appointment coordination with seller/seller agent
- Constant search and monitoring of property listing and market price movements

3. Market Research and Business Strategy

3.1 Local Market Size

According to the consolidated private residential property transactions data from the Urban Redevelopment Authority's website, the total private property transaction price in Singapore for year 2018 is around \$50 Billion.

YEAR	Number of Private Property Transactions	Average Transaction Price	Total Transaction Price
2018	22,217	\$2.26 Million	\$50 Billion
2017	27,791	\$1.88 Million	\$52 Billion

3.2 Business Model

This service will be offered free of charge to the potential buyers. The revenue will be generated from the co-broking fee with the seller agent or a small commission from direct sellers, both pegged at 0.1% of the property transacted price.

Based on the local market size and assuming 5% market take up rate in the first year of operation and 10% market take up rate in second year of operation, the forecasted revenue would be \$2.5 Million and \$5 Million respectively for first and second year of operation.

If the business model proves to be successful within the first two year of operation, plans will be made for global expansion.

3.3 Target Customers

The target customer is also the target user of the service. Two categories of users have been identified and they share the common characteristics of being busy professionals and being tech-savvy. They like to search for properties on their own but could not afford the time and their tech-savviness makes them more comfortable to outsource the tasks to an intelligent software agent.

<ul style="list-style-type: none">• Age from 28 to 35, with annually income range from \$ 90,000 to \$ 120,000.• Heavy mobile phone user, some of them are tech-savvy.• Prefer to search and compare constantly, some even have allodoxaphobia.• With limited budget and pay more attention to the furnishment style, facilities, and amenities.	<ul style="list-style-type: none">• Age from 35-50, with annually income from \$ 150,000 to \$240,000.• Second home for investment or renting• Heavy mobile phone user, some of them are tech-savvy.• Pays more attention to details such as location, floor plans, and resale value, etc.
First-Time Buyer	Property Investor

3.4 Potential Partners

Partnership agreements with property listing portals and real estate agencies can be explored to deliver an even more seamless end-to-end process for the potential property buyers.

4. Business Process Overview

The swim lane diagram below shows the high level AS-IS and TO-BE Property Search and Make Offer Process. Three of the six activities in the Property Search and Make Offer process which are more tedious and repetitive are automated by the solution, leaving only the decision making task to the buyer.

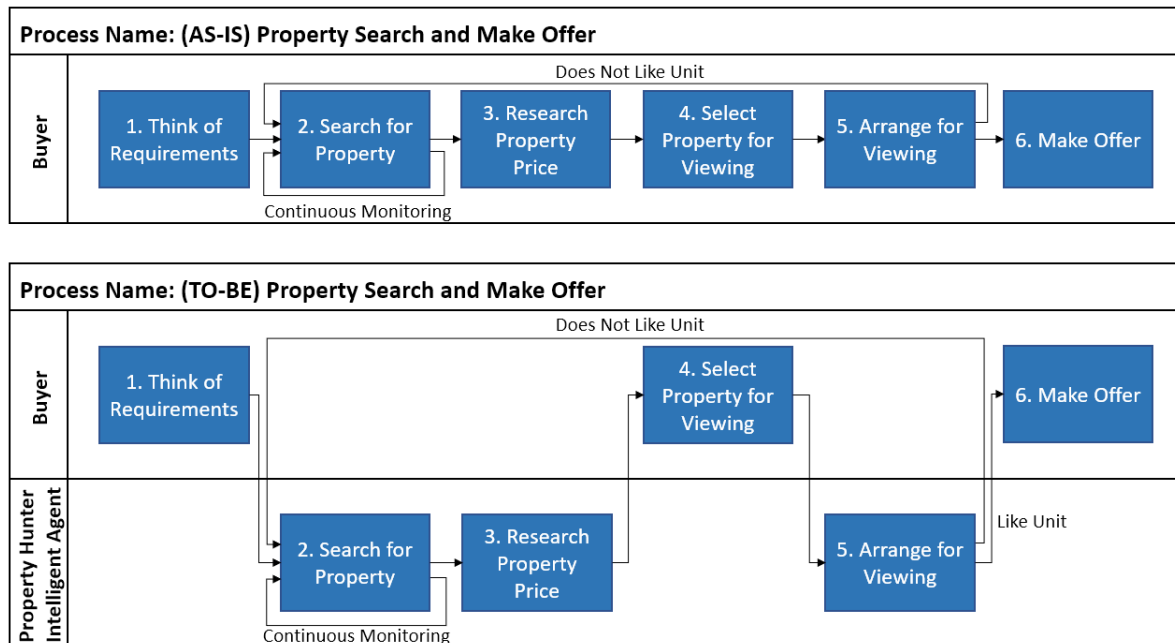


Figure 1: Property Search and Make Offer Process Flow Diagram

5. Solution Overview

The solution comprises (1) User Fronting Chat-bot, (2) Property Search Agent, (3) Appointment Scheduling Agent, (4) Market Price Data Retrieval Robot, (5) Image Clustering Model and (6) Current & Future Price Prediction Model.

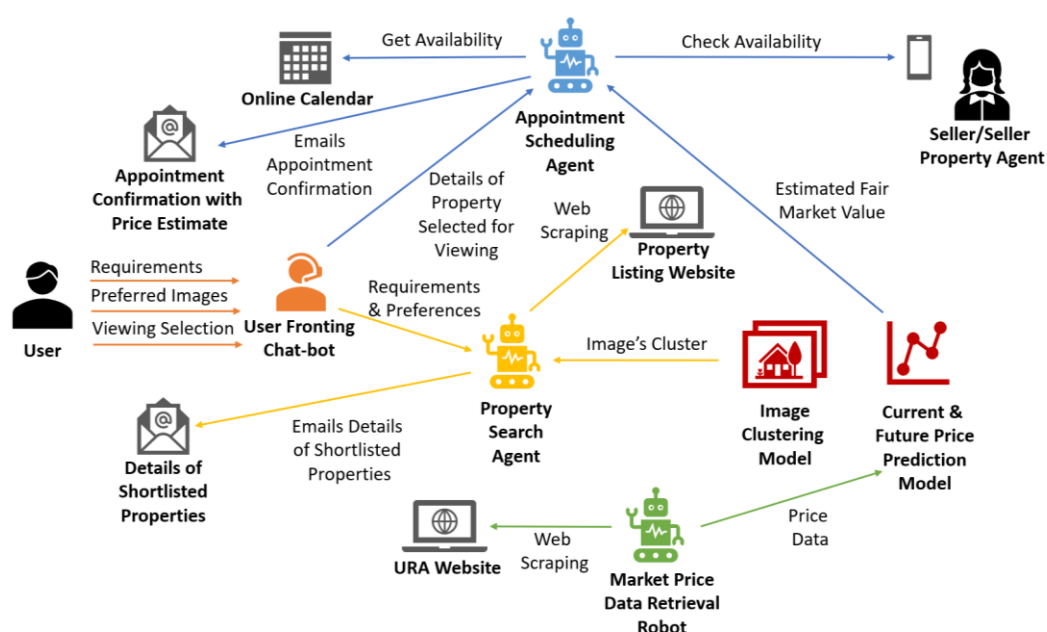


Figure 2: Solution Overview Diagram

The User Fronting Chat-bot gets explicit and latent requirements from the User on what property he is looking for. The Property Search Agent searches the property listing website for suitable properties and runs the image clustering model to further shortlist the properties. The Property Search Agent then sends an email to the User which contains details of shortlisted properties. If the User is interested to view any of the properties, he will inform the User Fronting Chat-bot which will pass the details of the selected property to the Appointment Scheduling Agent. At the same time, the user preference will be updated. The Appointment Scheduling Agent will access the User's online calendar to get his availability and arrange with the Seller/Seller Property Agent on the earliest possible opportunity to view the unit. Once the date and time of the appointment is confirmed, the Appointment Scheduling Agent will run the Current & Future Price Prediction Model to get the estimated fair market value of the property and email it to the user together with the confirmed date and time of the viewing appointment. The Market Price Data Retrieval Robot downloads the past private property transaction price from the URA website as a pre-processing step.

The figure below depicts the high-level system architecture.

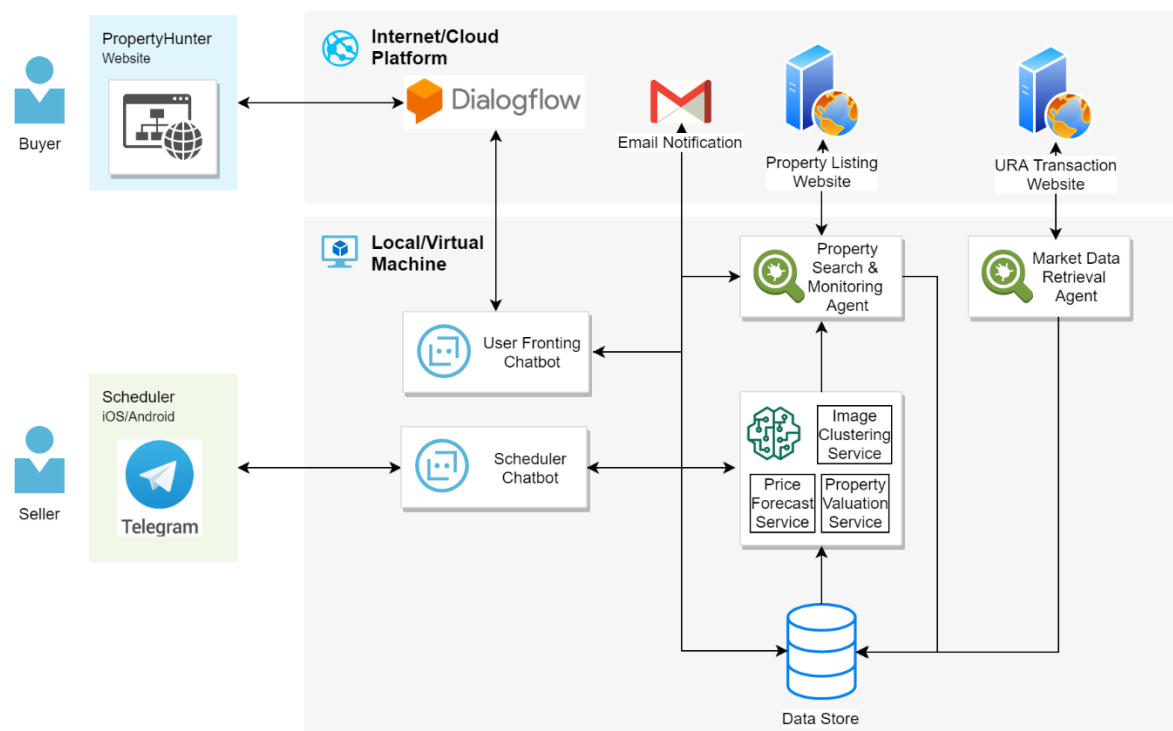


Figure 3: System Architecture Diagram

6. User Fronting Chat-bot

The User Fronting Chat-bot is the conversational user interface that gets request from user to search for a new property and to view selected properties from the list of shortlisted properties. It also answers anticipated user queries about the solution. It was built using Google Dialogflow and has been trained with five first level Intents and a number of follow-on Intents. Two list of Entities for 'location' and 'preference' has been created to help the chat-bot in accurately extracting this information from the user.

Search New Property Intent – User gives basic requirements such as location, floor area, number of bedrooms and budget. User is shown 14 images, 2 images from each of the 7 clusters (explained later

in section 10) and is asked to select 3 of the most preferred images. The user's selection will affect the filtering of the shortlisted properties.

Feedback Interested Property Intent – User provides property ID of property which he is interested to view and is asked to confirm that he wants the system to proceed with automated scheduling of viewing appointment.

Ask Value Proposition Intent – Anticipated user query on what is the value proposition of the solution.

Ask Image Selection Purpose Intent – Anticipated user query on what is the purpose of selecting the 3 images.

Ask Estimated Fair Market Value Intent – Anticipated user query on how the Estimated Fair Market Value is derived.

Location Entity – Locations in the Singapore District Map for Condominiums and Private Apartments (https://www.iproperty.com.sg/resources/District_Guide.aspx).

Preference Entity – Two Character Code for the 14 images for user selection (e.g. A1).

7. Property Search Agent

7.1 Searching for New Property

The Property Search Agent helps user to search for ideal properties from property listing website. The input is the user preference acquired by the User Fronting Chatbot. The output is an email to the user which contains information of the recommended properties.

Chat-bot Input – The user inputs from the Chat-bot contain user's name, email, search location, property size, budget, number of bedrooms, level of floor and the preferred image cluster (furnishing style).

Input Transformation – Some of the user inputs need to be transformed into searchable criteria. Location text is transformed into district number (e.g. River Valley is transformed to D10). Property size and budget is transformed into a range so that the search is more meaningful. A point search on a specific size and budget will likely return zero results.

TagUI Scrapping – Generate search URL links according to the search criteria. From the search result page, scrape URL link of each property and remove advertisements. Access the detail page of each property and scrape detail information of the properties.

Image Classification – From the scraped image file link, download three images for each property. Classify these images into 7 clusters using the image clustering model. According to user's top three preferred furnishing style (cluster number), select the top five properties.

Key Feature Presentation – It was observed that the property key features are unstructured data with different owner highlighting different key features of their property. This resulted in close to 200 unique and sparsely distributed key features which makes it difficult to compare between properties (e.g. two different properties have different set of key features). Our solution overcome this problem by automatically analysing the text data using TF-IDF (term frequency-inverse document frequency) vectorizer and k-means model to present the most representative key features to the user.

Excel Automation – Adjust each column width to display property detail content in a best-fit length. Freeze the first column (property title) to make it easier for smartphone users to view the excel file.

Email Automation – Compile information of shortlisted properties and send this information via email. The email contains PDF documents with images and details for each of the shortlisted properties and an excel file which summarises the details of the shortlisted properties for easy comparison.

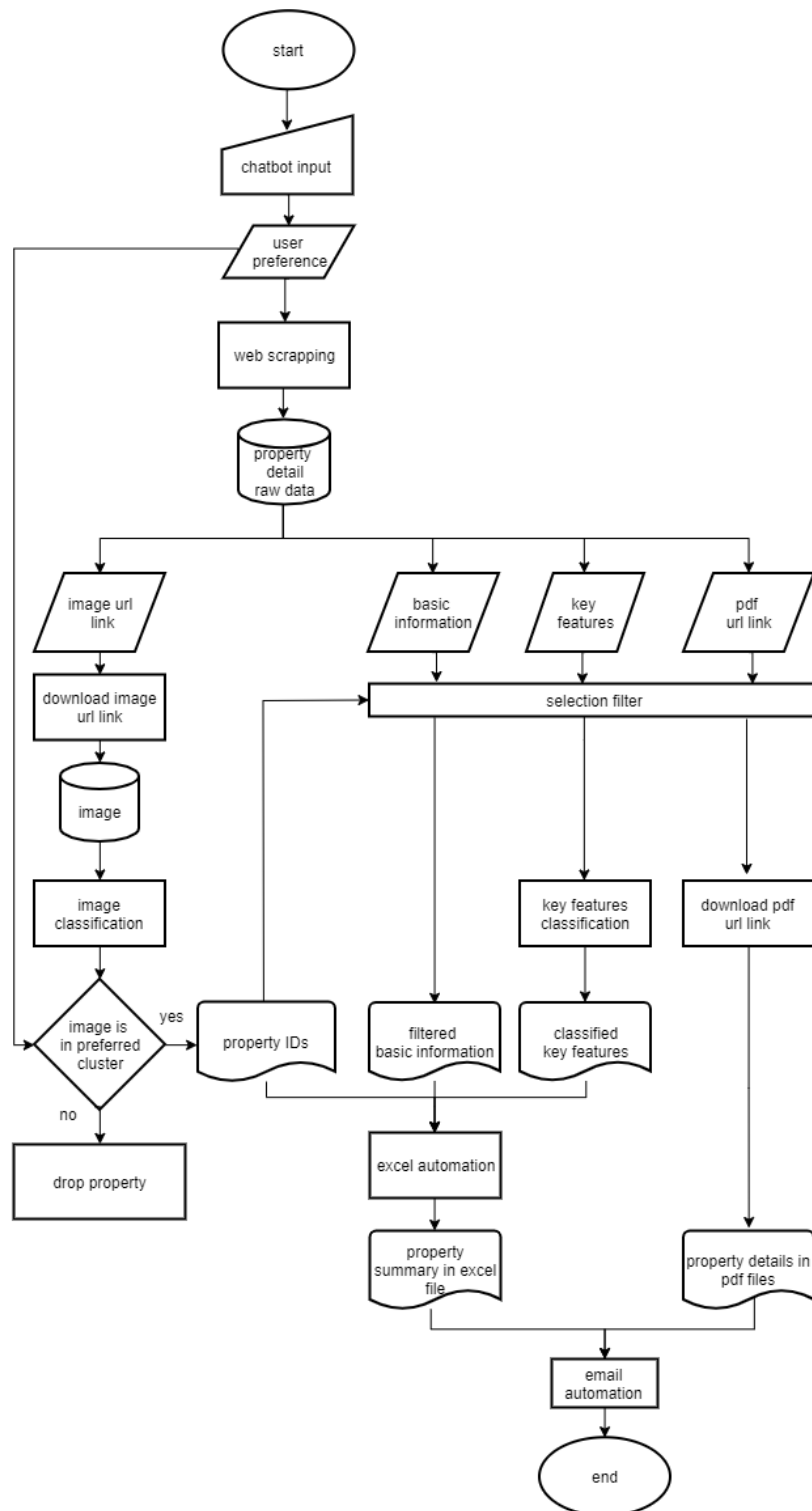


Figure 4: Property Search Data Flow Diagram

7.2 Monitoring of New Listings (for Specific Project)

The Property Search Agent can help the user to monitor for new property listing on specific project of interest. This function can be setup as an hourly batch job to search for new listings and email it to the user. The email format is similar to that of a full search in described in Section 7.1.

8. Appointment Scheduling Agent

For this implementation, the Appointment Scheduling Agent accesses the user's Google Calendar via the Google Calendar API and retrieves all upcoming events for the next 2 weeks. With this information, it tabulates the user's daily availability from 2pm to 9pm (assuming typical viewing hours) giving an hour for viewing and an hour allowance for user to travel to and back from the viewing unit. It then communicates with the Seller/Seller Agent through a scheduler bot on Telegram to arrange for the earliest possible opportunity to view the unit based on the user's availability.

On the seller-side, the seller can converse with a scheduler bot on Telegram to see viewing requests and respond with a time of the seller's convenience. The figure below shows a typical interaction between the seller and the bot. After confirmation to view the viewing request(s), the scheduler bot will prompt a series of available time slots from the potential buyer. The seller can accept or reject the proposed time slots.

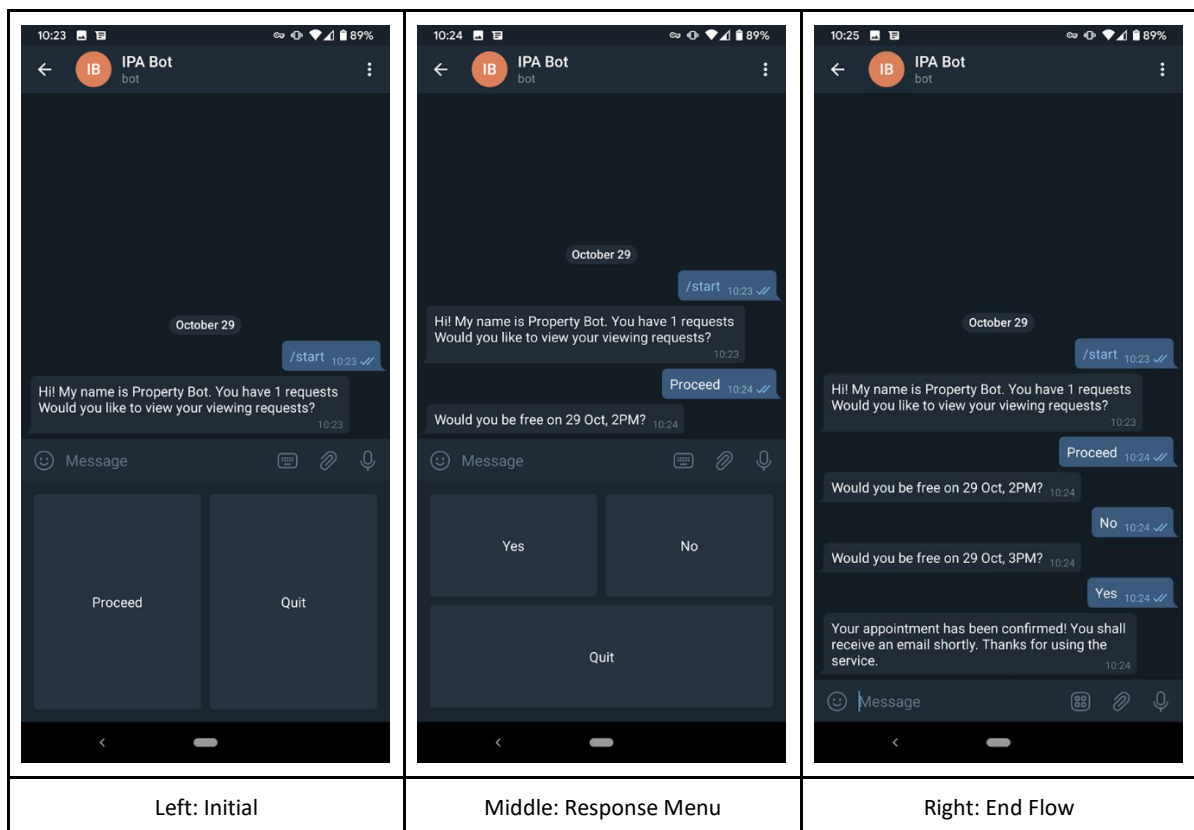


Figure 5: Scheduling Bot on Telegram

After the viewing appointment is confirmed, as a value added service, the Appointment Scheduling Agent runs the Current & Future Price Prediction Model with the property's details such as project name, floor area and low, mid or high floor to get the estimated fair market value of the property. This value can be used as a reference point for the user to make his offer if he likes what he sees. The

confirmed date and time of the viewing appointment together with the estimated fair market value of the property will be emailed to the user.

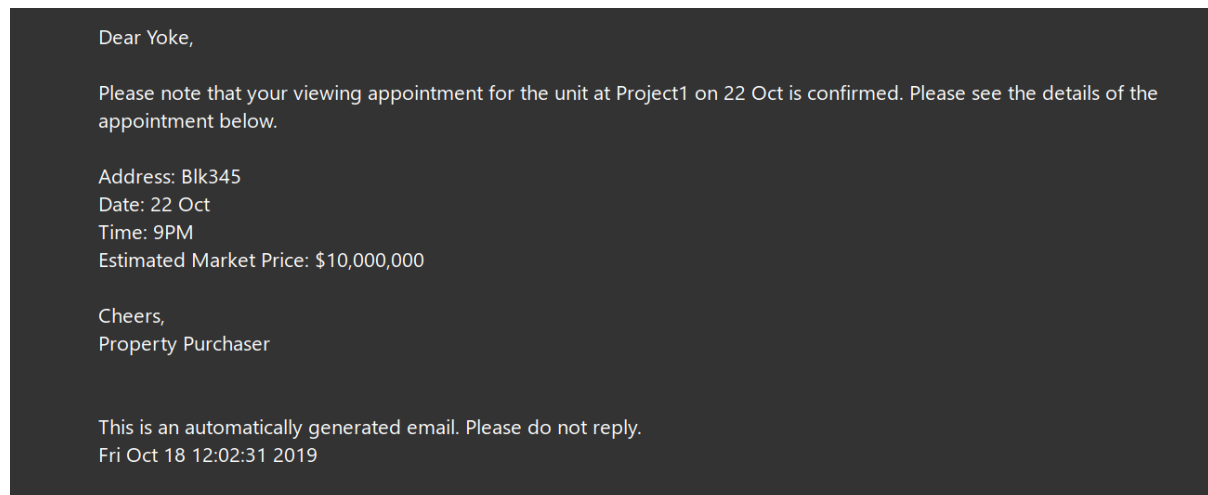


Figure 6: Sample Appointment Confirmation Email

9. Market Price Data Retrieval Robot

The retrieval bot takes the following steps to collect market price data.

1. Launch Chrome Browser
2. Go to URA Private Residential Property Transactions public database website
3. For each time period specified, select New Sale, Sub Sale and Resale categories and select 5 projects
4. Navigate to the next page and click download to save the generated file
5. Repeat Steps 2 to 4 for remaining projects.

All downloaded CSV files are then merged into a single file. The private property price index used to compute the present value of property transactions older than current quarter is updated manually as the index is only created for each quarter and such frequency does not warrant a need for automation.

10. Image Clustering Model

10.1 Auto Encoder-based Dimensionality Reduction

In a typical search system, the user specifies explicit requirements like number of bedrooms, budget and size (in square feet). However, requirements like style and color preferences are not easily captured and are typically viewed and determined by users. Moreover, people might be fuzzy about their preferences and also prefer visual cues to aid their decisions.

Hence the team propose to capture these latent needs by allowing the users to choose pictures of condominiums that they like and such characteristics will be used as additional selection criteria. Clustering will be performed on images of shortlisted properties (shortlist based on explicit requirements) and only properties with images in the user's preferred cluster(s) will be presented to the user. To discover natural clusters in property images, eight thousand over pictures were collected and feature extraction was performed before clustering. Being high-dimensional data, dimensional reduction is first done using autoencoders.

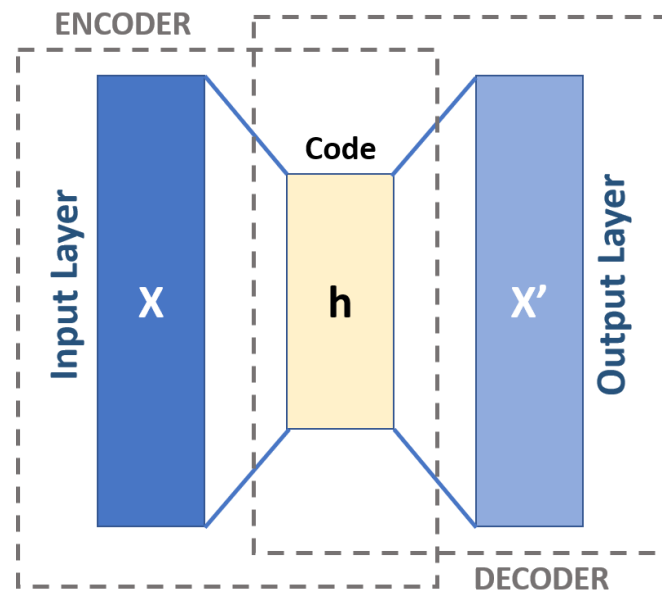


Figure 7: General Autoencoder Architecture

https://en.wikipedia.org/wiki/File:Autoencoder_schema.png

The figure above shows the general autoencoder architecture. A 3-layer feedforward neural-network based auto-encoder is built to reconstruct images from a 'bottleneck' layer that reduced images to 2 features. Images are resized to 64x64 pixels and flattened into 12288 (64x64 pixels, 3 color channels) inputs and fed into the autoencoder.

The detailed model architecture model is shown below.

Model: "sequential_21"

Layer (type)	Output Shape	Param #
=====		
dense_117 (Dense)	(None, 1024)	12583936
dense_118 (Dense)	(None, 512)	524800
dense_119 (Dense)	(None, 256)	131328
bottleneck (Dense)	(None, 2)	514
dense_120 (Dense)	(None, 256)	768
dense_121 (Dense)	(None, 512)	131584
dense_122 (Dense)	(None, 1024)	525312
dense_123 (Dense)	(None, 12288)	12595200
=====		

Total params: 26,493,442

Trainable params: 26,493,442

Non-trainable params: 0

10.2 K-Means Clustering

The bottleneck layer is then extracted for conversion of images to 2 features for K-Means clustering and split into 80% training data and 20% testing data.

Silhouette Analysis is conducted for results between 2 and 10 clusters. It has been determined that a 7-cluster model is the best balance of meeting project requirements, silhouette score and relatively balanced cluster sizes for most of the clusters (with the exception of clusters 2 and 6) as shown below in the figure on the left.

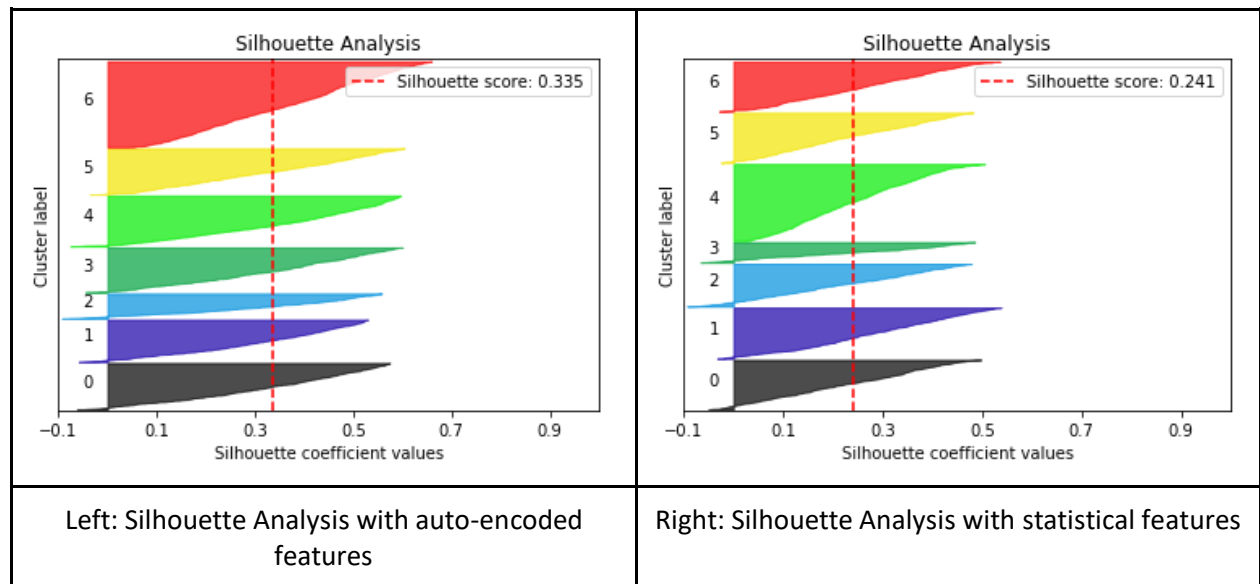


Figure 8: Silhouette Analysis

An alternative clustering model has also been attempted with 6 statistical features extracted i.e. using the mean and standard deviation of Red, Blue and Green channels per image. However, as seen in the image on the right above, for a similar 7-cluster model, the silhouette score is much lower at 0.241 compared to the silhouette score of 0.335 for the 7-cluster model with auto-encoded features and hence the 7-cluster model with auto-encoded features is preferred.

Further to the aforementioned silhouette analysis, visual inspection of the output from the clusters was also performed to ascertain the business relevance. It has been found that the clusters are meaningful in general. For example, cluster 0 generally shows modern design with largely white colors.

A similar visual inspection is done for the remaining clusters and the theme description is shown below.

Cluster	Theme Description
0	white modern
1	dark modern
2	greenery
3	dark blue

4	turquoise or poolside
5	traditional/industrial (wooden)
6	contemporary / 'hotel'

Cluster proportion profiles of the training data set is also validated against the testing data set and it is found to be largely similar and hence determined to be working well.

Cluster	Training Set Proportion	Testing Set Proportion
0	0.136072	0.126892
1	0.123834	0.142026
2	0.073427	0.064028
3	0.131702	0.125728
4	0.148601	0.147846
5	0.135198	0.136205
6	0.251166	0.257276

The encoder model and K-Means model are then packaged with the python pickle library for usage by the Property Search Agent.

11. Current & Future Price Prediction Model

The Current & Future Price Prediction Model was built using the past property transaction price and private property price index data from URA website. The model has two parts, a Regression Model and a Median Price Forecasting Model. The pre-processed past property transaction price data is fed into the Regression Model to get a current price estimate. The current price estimate is multiplied by a weighted prediction multiplier computed by the Median Price Forecasting Model to obtain the Estimated Fair Market Value.

11.1 Data Pre-Processing

Looking at the private property price index for the past 3 years, there is a 15.6% difference between the lowest point in Q2 2017 and the highest point in Q3 2019 and the property price fluctuates from quarter to quarter. To increase the accuracy of the prediction model, the past property transaction price data is adjusted to present value using the simple formula below.

$$\text{Present Price} = \text{Original Price} / \text{Price Index at the time of Transaction} * \text{Current Price Index}$$

For example, if a property is transacted at \$1 Million in August 2017, the adjusted Present Price = \$1,000,000/136.6*152.2 = \$1,114,202.

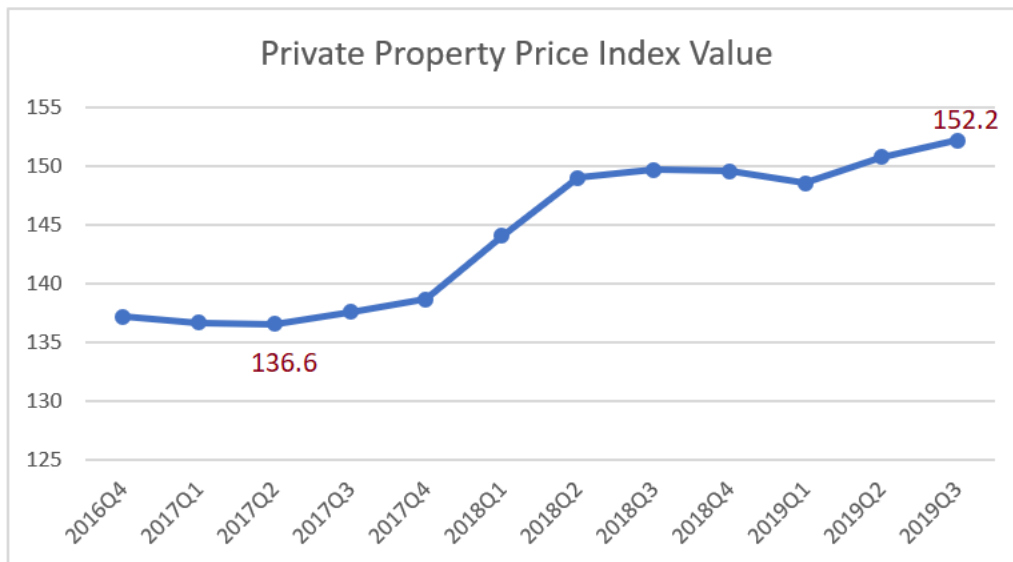


Figure 9: Private Property Price Index

11.2 On-the-Fly Generated Regression Model

The team first set out to build a single regression model for all the private properties in Singapore but quickly realised that a single model will not be accurate as the per square feet price varies widely for properties in different Districts and in some cases projects which are just across the road from each other has a 20% to 30% price difference.

There are over 2000 projects in Singapore and building a single model for each project is not feasible. The team has come up with an approach to generate the Regression Model on-the-fly based on the available data of the property to perform regression on. If the project name is specified and if there exist sufficient data points in the past property transaction data, a regression model will be built using only data points from the specific project. Otherwise, the next best option will be taken to build a regression model using the data points from the district the property of interest is located in.

11.3 Median Price Forecasting Model

To further aid property buyers' decision-making, a representation of the general price movement of the property market is created to estimate next month price. To codify this representation practically, the team set out to build a condominium medium price forecasting model.

Before this, market price data has to be collected. This was accomplished by building a tagui bot to navigate the Urban Redevelopment Authority (URA) of Singapore's Private Residential Property Transactions public database and download information of all projects from September 2016 to September 2019. After which condominium prices are extracted.

After performing exploratory data analysis, it has been found that condominium prices contain a number of outliers as shown in the box plot in the left figure below. Outliers are defined as values that exceed the range of ± 1.5 times the Interquartile Range.

Further breakdown of the outliers show that these outliers are largely highly premium properties in the Core Central Region (CCR) as shown in the bar plot in the right figure below. Example properties come from projects like 8 Saint Thomas, Seven Palms Sentosa Cove and The Sixth Avenue Residences.

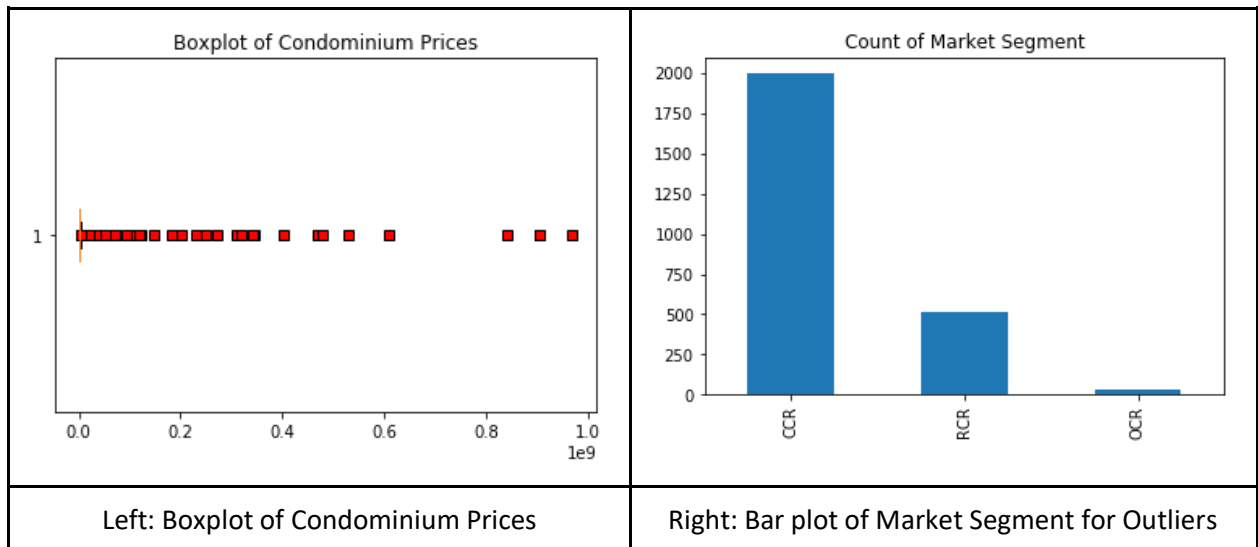


Figure 10: Identifying Outliers

While the outliers are responsible for skewing the market prices, they are nevertheless a fairly common occurrence in the market, occupying 7.7% of the dataset. However, in order to get a good sense of market movement, we need a robust statistic that has good performance for skewed data that is not unduly affected by outliers. Hence the median statistic is chosen to represent the monthly price movement.

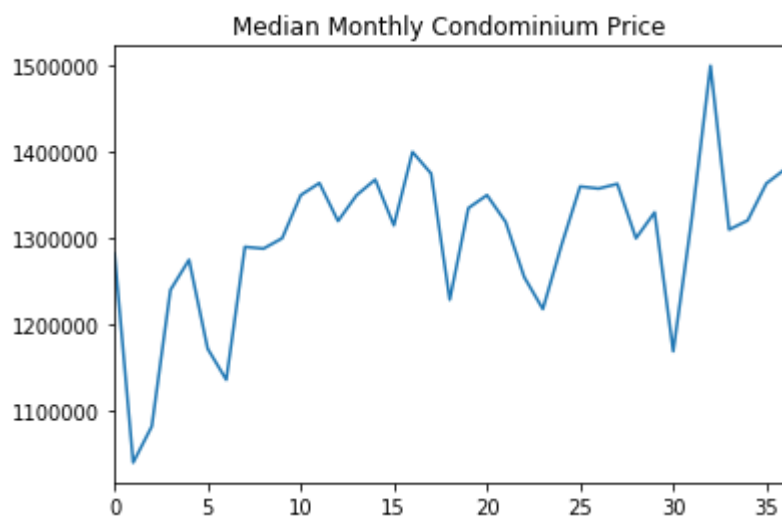


Figure 11: Average Monthly Condominium Prices with outliers removed

The figure above shows the medium monthly condominium price. It is observed that the fluctuations vary differently across time periods, hence a multiplicative forecasting model is fitted using the prophet, an automated forecasting procedure package by Facebook.

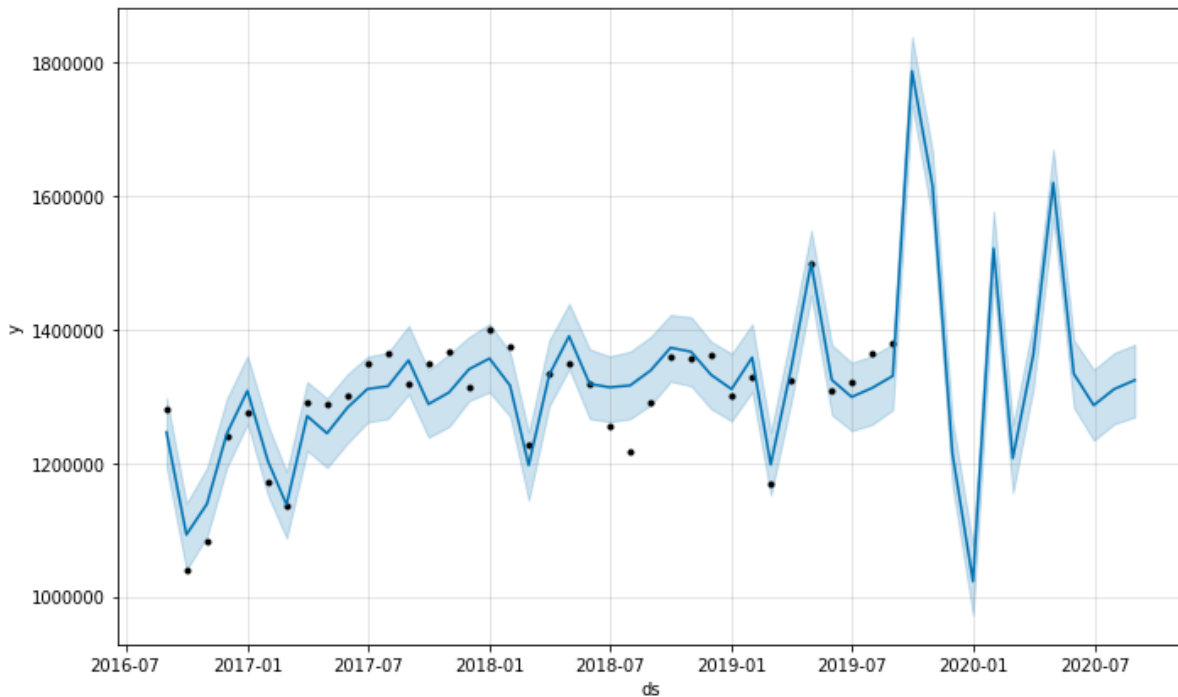


Figure 12: Historical and Forecasted median Condominium Price

The figure above shows that plot of the historical and forecasted median monthly condominium price movement.

A cross-validation procedure is performed with the first 24 months as initial time period. Every month after that, a 3-month forecast is generated, resulting in 9 forecasts being made. The overall cross-validated mean absolute percentage error is 6.14%.

To derive the estimated price movement for next month, a weighted average of the multiplicative terms from the 3-month forecast is taken. This weighted average also serves to take account of the uncertainty in the upcoming forecasted months.

The eventual weighted prediction multiplier of October 2019 is calculated to be 1.155427, which will be applied and returned to the user to present the Estimated Fair Market Value.

12. Conclusion

The team has identified a business opportunity in providing a more efficient and effective way for potential buyers to search for, view and make an offer for the property they are interested to purchase. Initial market research suggested potential revenue of \$2.5 Million to \$5 Million for the first two years of operation.

The team went on to design and implement the Property Hunter Intelligent Agent which consists of various RPA-bots, chat-bot, machine learning models and software agent systems. Through this process, the team has learnt immensely on the application of process automation technologies and how to incorporate machine learning models to provide useful services to the users.

Reference

Facebook, Prophet (2019, October 30). Forecasting at scale: <https://facebook.github.io/prophet/>

Urban Redevelopment Authority, Singapore Government (2019, October 30). Private Residential Property Transactions: <https://www.ur.gov.sg/realEstateIIWeb/transaction/search.action>

Annex A – User Guide

Step 1: Install Anaconda from <https://www.anaconda.org>.

Step 2: Launch Anaconda prompt and enter the following command to create a virtual environment.

conda create --name PHIA python=3.6

Step 3: Enter the following command to activate the newly created environment

Windows: activate PHIA

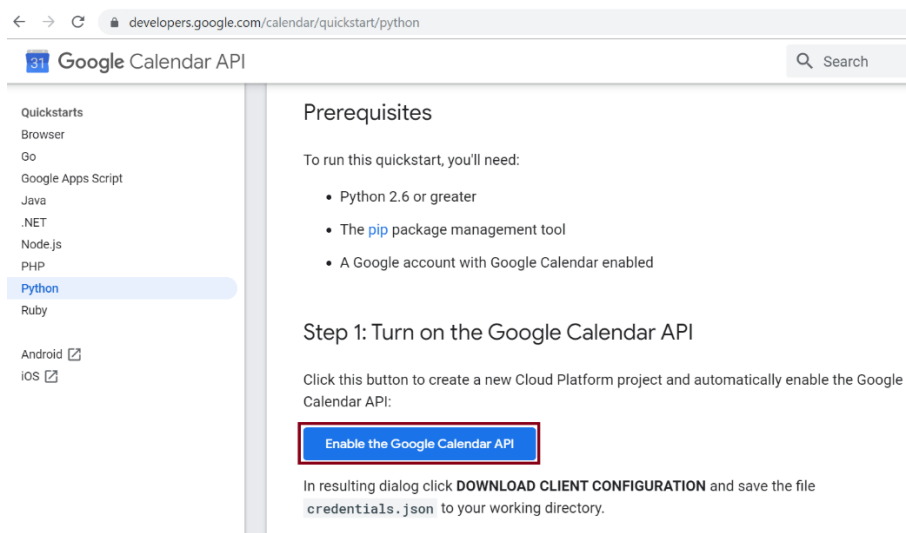
Ubuntu: source activate PHIA

Step 4: Navigate to the PropertyHunterIA folder and enter the following command to install the required packages

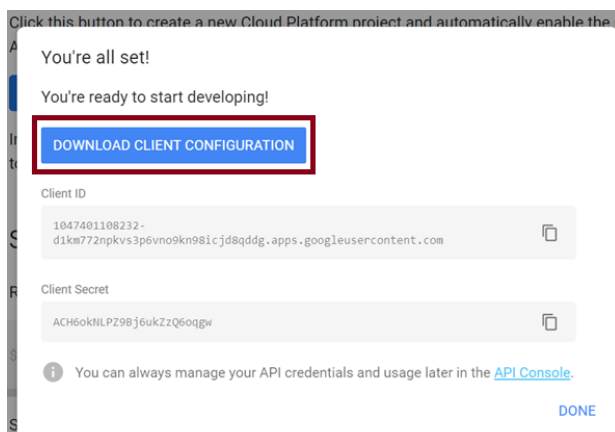
pip install -r requirements.txt

Step 5: Go to <https://developers.google.com/calendar/quickstart/python>

Step 6: Click on Enable the Google Calendar API Button. You need to sign in with a Google Account



Step 7: Click on the Download Client Configuration button to download the credentials.json file. Save the credentials.json file to PropertyHunterIA folder.



Step 8: Download ngrok executable for your respective OS type from www.ngrok.com.

Windows Package link: <https://bin.equinox.io/c/4VmDzA7iaHb/ngrok-stable-windows-amd64.zip>

Linux Package link: <https://bin.equinox.io/c/4VmDzA7iaHb/ngrok-stable-linux-amd64.zip>

Step 9: Unzip and launch ngrok from your home folder and run the below command

Windows: ngrok.exe http 5000

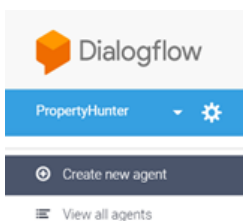
Ubuntu: ./ngrok http 5000

```
ngrok by @inconshreveable
Session Status      online
Session Expires    7 hours, 57 minutes
Update             update available (version 2.3.35, Ctrl-U to update)
Version            2.3.34
Region             United States (us)
Web Interface       http://127.0.0.1:4040
Forwarding          http://a94bcaa5.ngrok.io -> http://localhost:5000
Forwarding          https://a94bcaa5.ngrok.io -> http://localhost:5000

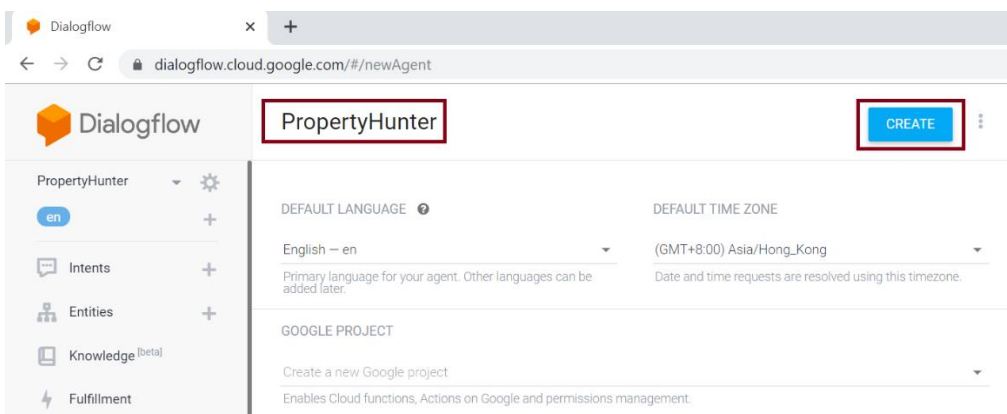
Connections
  ttl  opn  rt1  rt5  p50  p90
    0    0   0.00 0.00 0.00 0.00
```

Step 10: Go to <https://dialogflow.com/> and sign in with Google account. Click on 'Go to console' from the top right.

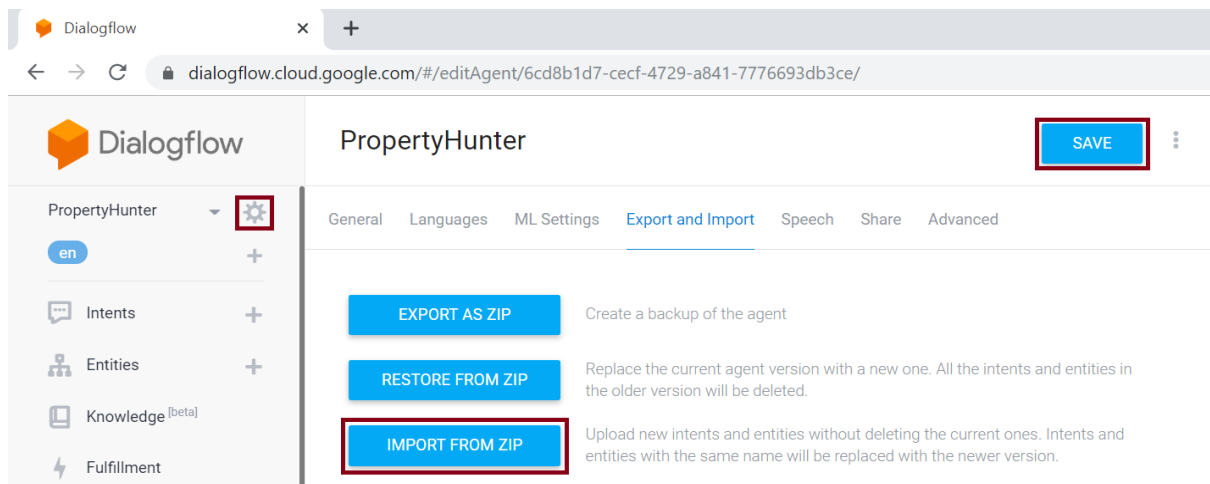
Step 11: Click on the dropdown list on the top left and click 'Create new agent'.



Step 12: Enter a name for the agent and click the 'Create' button.

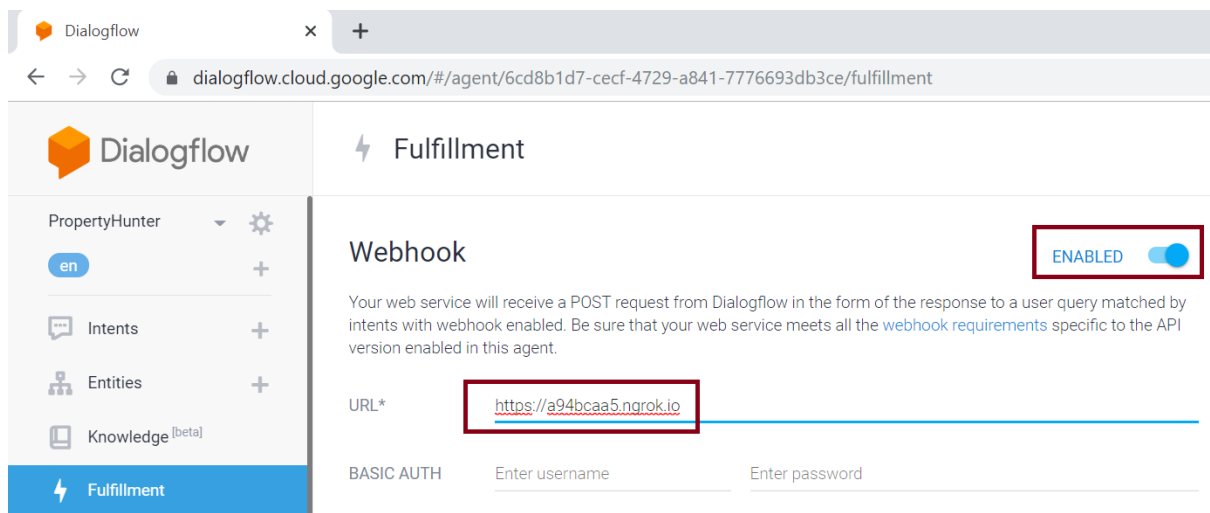


Step 13: Click on the gear icon then click on 'Export and Import' tab. Click on 'IMPORT FROM ZIP' button and select PropertyHunter.zip from the PropertyHunterIA folder and follow on-screen instructions to import



Step 14: Select the imported agent from the top left and click on the 'Fulfillment' tab.

Step 15: Enable the webhook if it is not enabled already. Copy and paste the URL from Step 9.



Step 16: Scroll down and click on the **SAVE** button.

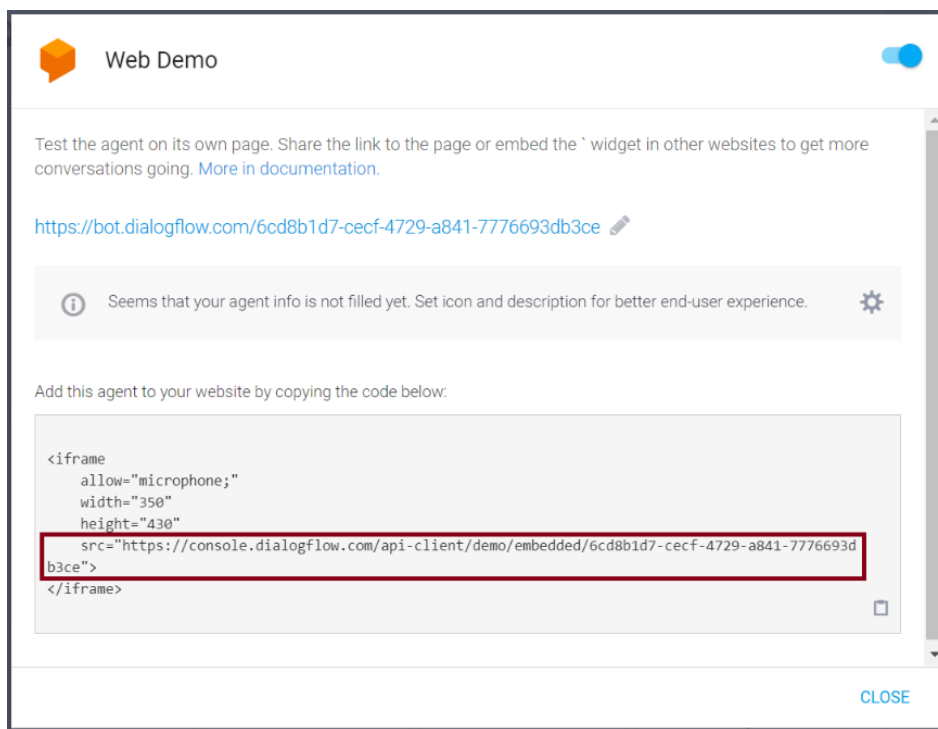
The screenshot shows the Dialogflow Fulfillment Inline Editor. The left sidebar contains navigation options: PropertyHunter, Intents, Entities, Knowledge [beta], Fulfillment (selected), Integrations, Training, Validation [beta], History, Analytics, and Prebuilt Agents. The main area is titled 'Fulfillment' and 'Inline Editor (Powered by Cloud Functions for Firebase)'. It includes a 'DISABLED' toggle switch and a link to 'Docs'. Below this is a code editor showing the 'index.js' file with JavaScript code for handling Dialogflow requests. A red box highlights the 'SAVE' button in the bottom right corner.

```
1 // See https://github.com/dialogflow/dialogflow-fulfillment-nodejs
2 // for Dialogflow fulfillment library docs, samples, and to report issues
3 'use strict';
4
5 const functions = require('firebase-functions');
6 const {WebhookClient} = require('dialogflow-fulfillment');
7 const {Card, Suggestion} = require('dialogflow-fulfillment');
8
9 process.env.DEBUG = 'dialogflow:debug'; // enables lib debugging statements
10
11 exports.dialogflowFirebaseFulfillment = functions.https.onRequest((request, response) => {
12   const agent = new WebhookClient({ request, response });
13   console.log('Dialogflow Request headers: ' + JSON.stringify(request.headers));
14   console.log('Dialogflow Request body: ' + JSON.stringify(request.body));
15
16   // Example fulfillment logic
17   // agent.setResponse([new Card('Example Card'), new Suggestion('Example Suggestion')]);
18   // agent.endResponse();
19
20   return response.status(200).send('Fulfillment response');
21 });
```

Step 17: Click on the 'Integrations' tab and enable Web Demo.

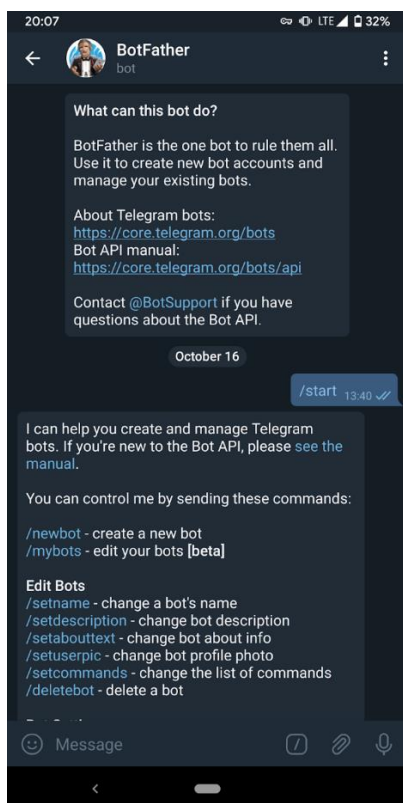
The screenshot shows the Dialogflow Integrations page. The left sidebar is the same as in Step 16, but the 'Integrations' tab is selected. The main area displays various integration options. The 'Google Assistant' integration is shown at the top. Below it, there are four integration cards: 'Web Demo', 'Facebook Messenger', 'Dialogflow Phone Gateway BETA', and 'Slack'. The 'Web Demo' card has a red box around its toggle switch, which is currently turned on.

Step 18: Click on the Web Demo Icon and copy the src string.

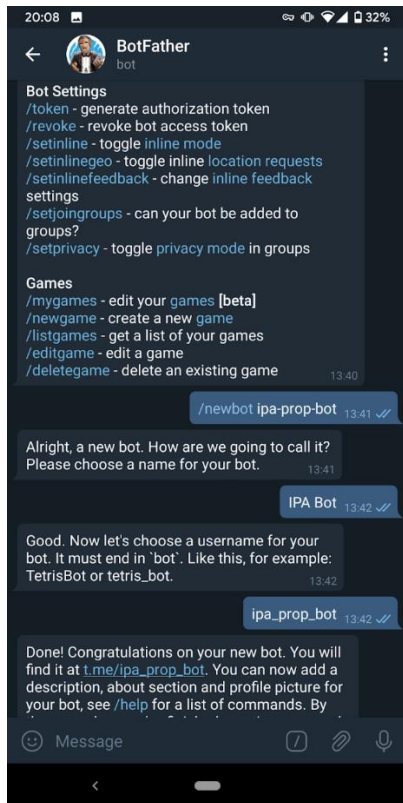


Step 19: Open home.html file in PropertyHunterIA folder using notepad application. Replace the src string copied in Step 19 and save the changes.

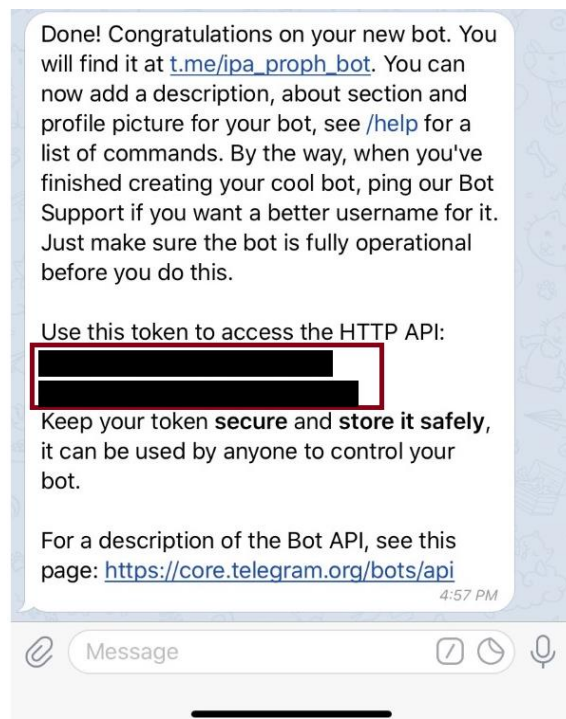
Step 20: Install telegram app on your mobile phone and initiate chat with @BotFather



Step 21: Set up a new bot in telegram by following the prompts from @BotFather. See example below.



Step 22: Open telegram_schedule_bot_v2.py and input the API token in line 15 with the one given by BotFather in the middle of the message (blackout here due to security reason). Save the changes.



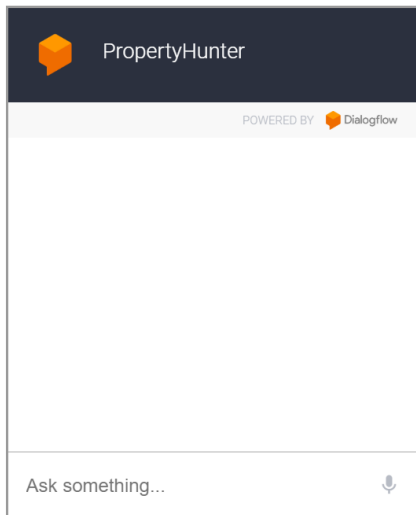
Step 23: Add the bot as a friend in Telegram

Step 24: Go back to the Anaconda prompt (with PHIA activated) and run command: `'python telegram_schedule_bot_v2.py'`

Step 25: Launch another Anaconda prompt, activate PHIA environment, navigate to the PropertyHunterIA folder and run command: `'python BuyerAgent.py'`

Step 26: Open home.html using a web browser (best viewed with 1920 X 1080 display resolution).

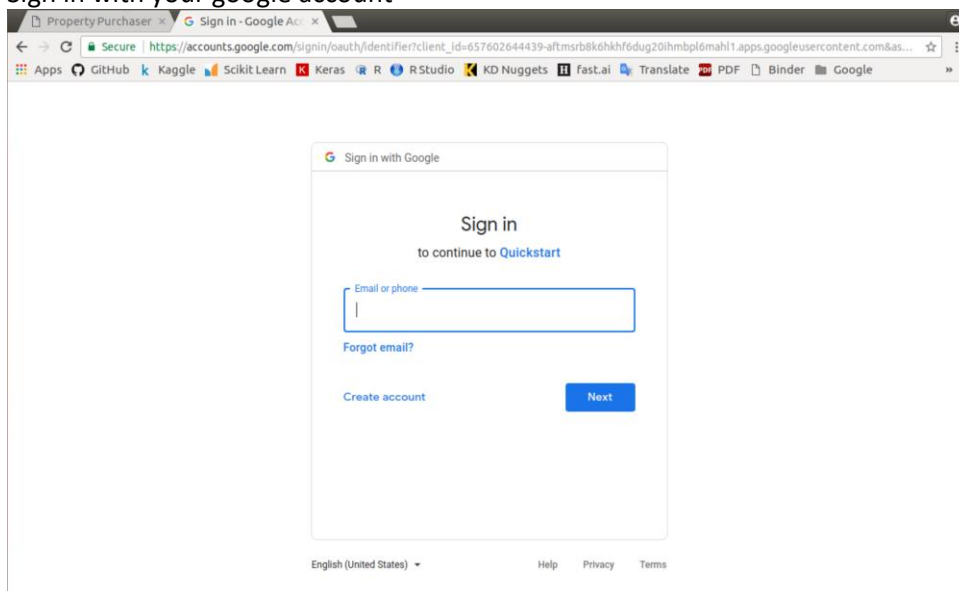
Finding your dream home made easy!



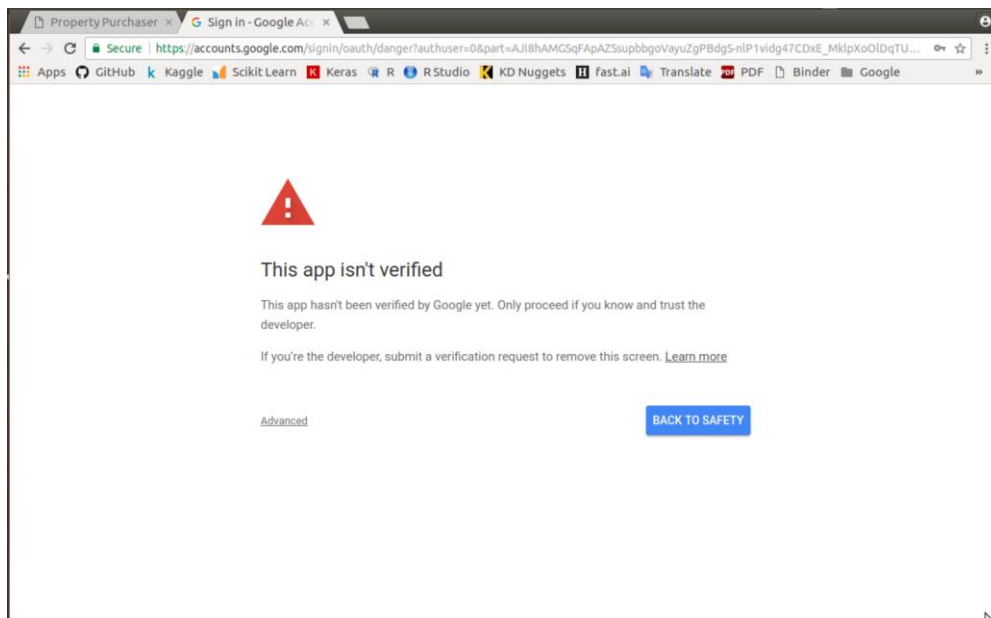
Step 27: Start using the system by typing in 'I am looking for a new house'.

Note: During program execution, you will be prompted to allow access to your Google calendar. If you encountered this scenario, please follow the steps below:

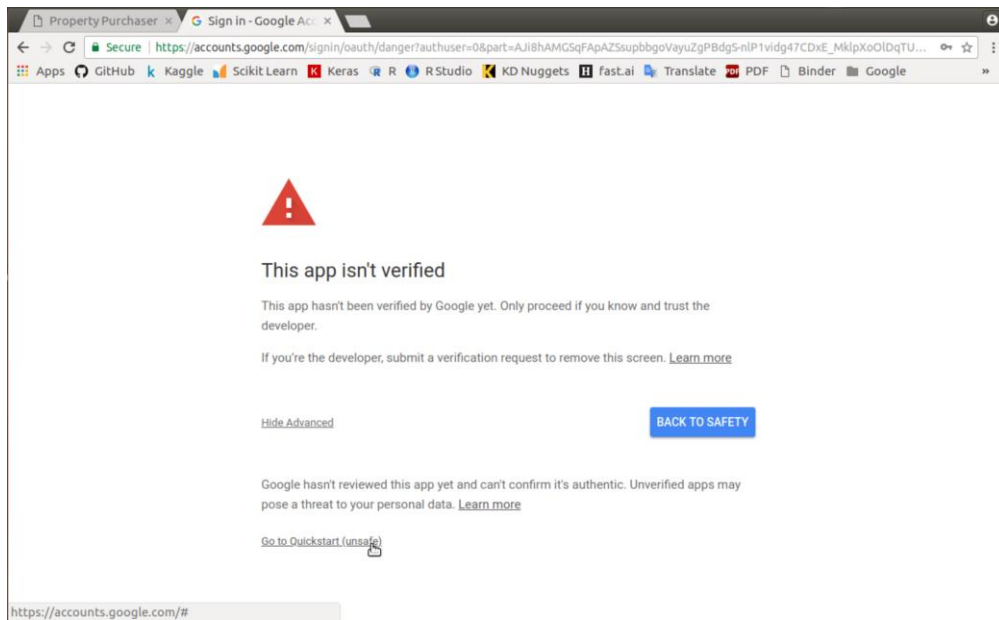
Sign in with your google account



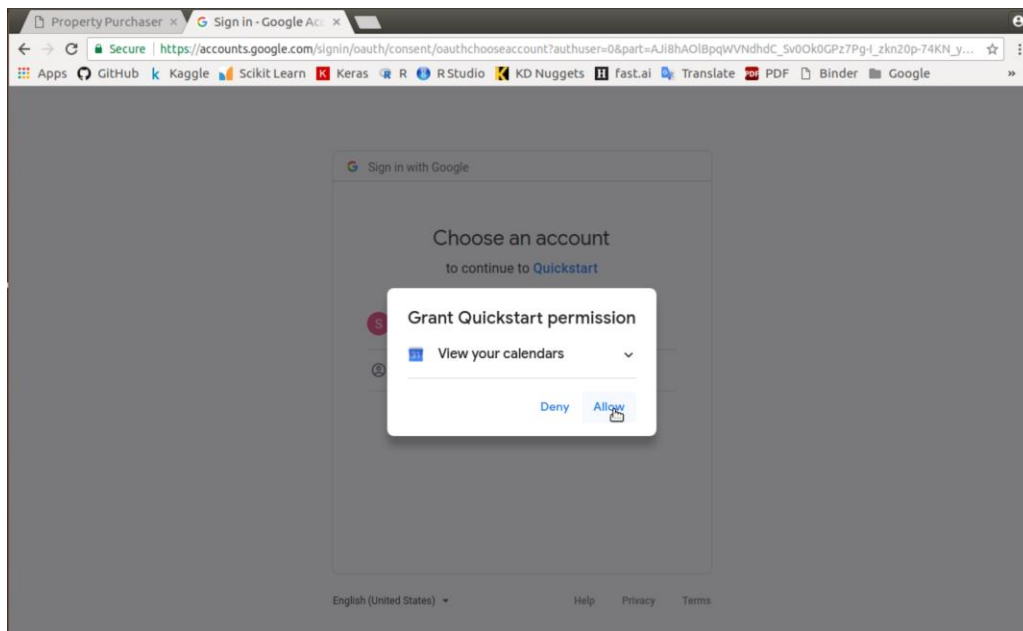
The verification system will mention that the app isn't verified as this is a test app.



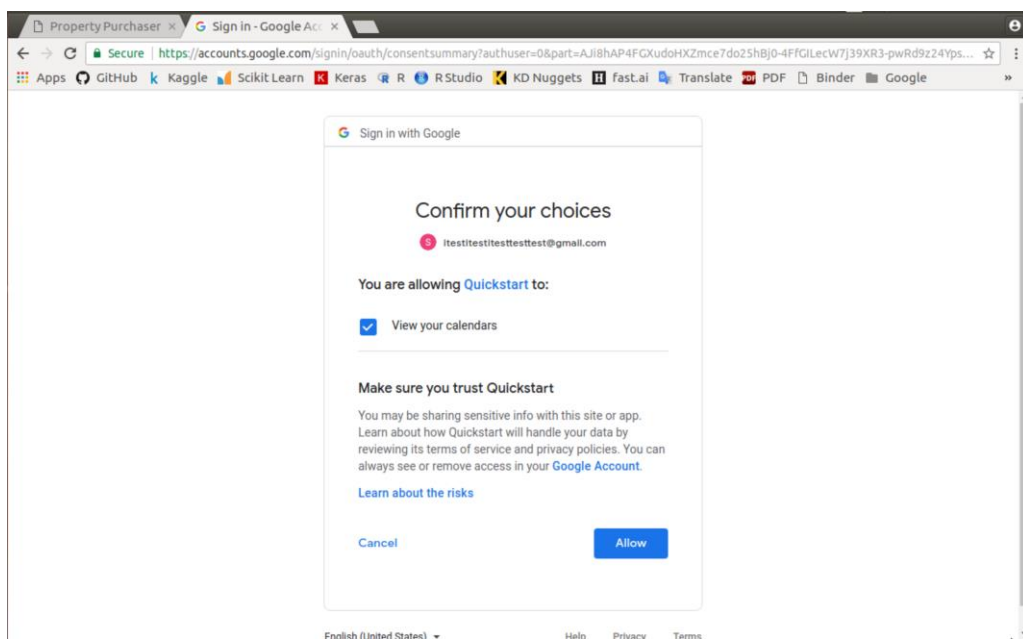
Click on the Advanced link and click on 'Go to Quickstart (unsafe)'



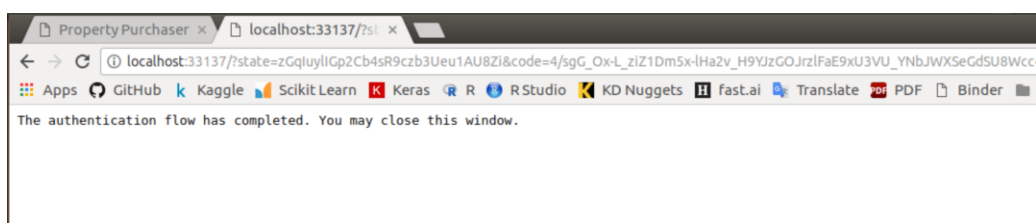
When prompted to grant permission to view calendar, click on the Allow button



On the confirmation screen, click on the Allow button again



Upon successful authentication, you will receive a message like the below and you can proceed to close the browser window/tab



Annex B – MISC Supporting Files

List below are the supporting files used to train the models and to retrieve market data.

In Misc folder:

No.	Filename	Description
1	CA1_Autoencoder_Testing.ipynb	For the testing of models used in the application, including image clustering model and autoencoder model
2	CA1_Autoencoder_Training.ipynb	Demonstrates the training of image clustering and autoencoder models
3	CA1_Forecast_Model_Training_and_Testing.ipynb	Demonstrates the training of forecasting models used to generate multiplier representing market movement

In Misc/market_data_retrieval sub-folder:

No.	Filename	Description
1	rpa_ura_data_v3.py	Demonstrates the collection of market data using RPA (TagUI-Python)
2	merge_ura_data_v2.ipynb	Demonstrates the merging of raw data files and calculation of present value using price index data

Annex C – Test Scenarios

Scenario	Steps and Input Values	Expected Output
Scenario 1: User Search for new property and a few properties were found.	<p>Step 1: Give requirements to Property Hunter Chat-bot</p> <p><i>Input:</i></p> <ul style="list-style-type: none"> • <i>I want to search for a new house</i> • <i>Clementi New Town</i> • <i>2 bedrooms, 800 square feet</i> • <i>Low Floor</i> • <i>1000000</i> • <i>My name is Wang Zilong*, my email address is wzl0917@gmail.com*</i> • <i>A1,B2,A3</i> <p><i>*Please input your own name and email address</i></p>	Appropriate responses from Property Hunter Chat-bot.
	Step 2: Check email after 5 to 10 minutes.	Received email titled Shortlisted Properties with excel and pdf file attachments.
	Step 3: View information in excel file.	Summaried details of shortlisted properties are listed in the excel file. Scroll right to look at key features.
	Step 4: View property details in pdf files.	Property details are listed in pdf files.
	<p>Step 5: Inform Property Hunter Chat-bot on the unit you are interested to view.</p> <p><i>Input:</i></p> <ul style="list-style-type: none"> • <i>I like to view property 21927234</i> • <i>Yes</i> <p><i>* Please use the ID of the property from the email</i></p>	Appropriate responses from Property Hunter Chat-bot.
	Step 6: Scheduler bot check viewing availability with seller/seller agent.	Seller/seller agent respond with availability.

	<i>Input:</i> <ul style="list-style-type: none"> • /start • Proceed • No • Yes 	
	Step 7: Check email after 2 to 3 minutes.	Received email titled Viewing Appointment with appointment details and Fair Esimated Market Value.
Scenario 2: User Search for new property and no matching property is found	Step 1: Give requirements to Property Hunter Chat-bot <i>Input:</i> <ul style="list-style-type: none"> • I want to search for a new house • Clementi • 5 bedrooms, 1800 square feet • Low Floor • 1200000 • My name is Wang Zilong, my email address is wzl0917@gmail.com • A1,B2,A3 <i>*Please input your own name and email address</i>	Appropriate responses from Property Hunter Chat-bot.
	Step 2: Check email after 2 to 3 minutes.	Received email titled No Matching Properties Found with previously given requirements in the email.
Scenario 3: Background monitoring of new property listing (in specific project)	Step 1: At anaconda prompt, run command: " Python PropertyMonitor.py"	Received email titled New Listings with with excel and pdf file attachments.

Annex D – Team Members Individual Reflection

CA1 - Individual Project Report

Your Name:	Alfred Tay Wenjie
Certificate:	Graduate Certificate in Self Learning System

1. Personal contribution to the group project

Ideate and formalize business use case. Perform market research and conceptualize potential business model. Perform AS-IS business process mapping, identify suitable activities for automation and developed the TO-BE business process. Perform overall solution design. Design and implement User Fronting Chat-bot, Appointment Scheduling Agent and Current Price Prediction Model. Perform System Integration and Testing. Report writing on the above portions. Create animated video to illustrate user pain points and to introduce the Property Hunter Intelligent Agent solution. Facilitated project discussions, scoping of work and tracking of project progress.

2. What you have learnt from the project

I have learnt about when and how RPA and IPA can be applied to automate business processes and also how different technologies can be pieced together appropriately to create a seamless experience for the users. Chat-bots provide a means to have real-time interaction with users and is good for getting and clarifying user requirements. Emails automation is good for sending details and appointment confirmations to users for their reference and follow-up at their convenience. I have also learnt that a good approach to build an intelligent agent is to build and test its capabilities modularly and have an architecture that allows the 'mini robots' or 'mini agents' to integrate and cooperate to deliver useful services to the users.

3. How you can apply the knowledge and skills in other situations

Systems similar to the Property Hunter Intelligent Agent can be built for searching, comparing and buying a wide variety of consumer goods (e.g. collector watches, pre-owned cars). Another use case is an Intelligent Nutritionist Agent which tracks nutrition and calories intake and recommends and automates food ordering and restaurant table booking. Besides the aforementioned consumer applications, RPA and IPA can also be applied to a wide range of office automation use cases from decision support to generating consolidated reports. It can be deployed to automatically pull and pre-process data from multiple data sources and feed the pre-processed data into relevant machine learning models to generate insights which allows managers at all levels to make faster and better data driven decisions.

CA1 - Individual Project Report

Your Name:	Wang Zilong
Certificate:	Graduate Certificate in Self Learning System

1. Personal contribution to the group project

- Brainstormed business scenario and implementation techniques.
- Collected 4890 properties data and 8945 image data for exploring and model training.
- Designed multiple features for software agent, Web Scraping RPA: scraped text, image, file data from property portals; Document IPA: analyzed text data and clustered groups with representative features; Excel RPA: compiled Excel file, beautified excel format; Emailing RPA: compiled multiple email responses; Web Monitoring RPA: searched for newly released properties and sent to subscribed user
- Handled multiple exceptions such as restricted redirect page, different web page styles, and missing data.
- System integration: imported intents from chatbot and transformed them into web searching criteria; sorted user preference from image classification outcome.
- System test: test scripts in different environment and solved coding issue.
- Report

2. What you have learnt from the project

- How to address the challenges in business scenarios and organizing process to deliver solutions based on the Developing Minimum Viable Product
- RPA, IPA designing strategy and implementation techniques based on the study of use cases
- Hands-on experience in building software agent including using multiple practical python libraries, system integration, and testing
- Teamwork
- Time management

3. How you can apply the knowledge and skills in other situations

According to what I've learned through the courses and project, more IPA will be implemented in my future work. Starting from receiving Emails from leaders, colleagues or customers, I can deploy an agent to capture content and use text analyzing IPA to classify the senders and subjects. After identifying the type of work, for the routine work, more ad-hoc and rule-based RPA will be implemented, including data input, queries, selection and other cross-platform operations. For those analysis tasks, I will implement regression, classification, visualization analytics IPA in a more complex business scenario.

CA1 - Individual Project Report

Your Name:	Wong Yoke Keong
Certificate:	Graduate Certificate in Self Learning System

1. Personal contribution to the group project

In this project I have contributed to the following activities:

- Implementation and testing of RPA bot to collect URA Private Residential Property Transactions and executing the subsequent data collection and transformations
- Training and cross-validation of next month price movement forecast model using the aforementioned dataset
- Implementation and testing of scheduler agent built on the Telegram Bot API platform
- Exploration, implementation and comparison of image clustering models using statistical feature extraction and auto-encoder dimension reduction approaches where the latter is selected and presented in the application and report
- Implementation of functional interface of image cluster prediction to other modules
- Writing respective portions of project report, user guides, test scenario
- Testing of overall application flow and package/environment setup

2. What you have learnt from the project

The assignment provided me the opportunity to put into practice the Robotic Process Automation (RPA) and Intelligent Process Automation (IPA) concepts learnt in multiple ways.

From a Product perspective, I have gained a better appreciation of the Lean Startup mindset and how the Minimal Viable Product (MVP) plays an important role. Applying this in practice, I worked closely with other team members to research on the local private property market, identify the personas of potential customers and subsequently talked to potential home buyers to understand their pain points and challenges to validate our assumptions. The team also brainstormed to prioritize requirements and implement core features in the first MVP to demonstrate and prove our unique selling proposition.

From an RPA Strategy and Management perspective, I have learnt how to put the Implementation Framework into practice, where we looked at current AS-IS home buying and scheduling processes to identify and map components suitable for RPA/IPA in the TO-BE state, and subsequently developed iterations of the robots and performed testing.

From an RPA tooling perspective, I have become more proficient with the open-source TagUI-Python tool, using it in tandem with other helpful widgets like XPath Helper to build the market data retrieval bot.

From an IPA perspective, I have a greater understanding and appreciation of AI Hybrid Automation system design concepts and applied them to integrate the aforementioned RPA bot with cognitive platforms (Telegram Bot Platform) and custom Machine Learning models. In particular, to model and represent the latent needs of our customers, I drew on the knowledge learnt from the Intelligent Sensing and Sense Making course and experimented with auto-encoders for dimension reduction and image statistical feature extraction and finally compared the performance between these two models using silhouette analysis learnt in the Problem Solving using Pattern Recognition course and selected the optimal approach.

3. How you can apply the knowledge and skills in other situations

In the future, I will be able to use the knowledge and skills learnt to evaluate AS-IS business processes - in particular operational processes - that have the potential to be augmented with RPA and IPA so as to increase productivity and make the lives of users and customers easier.

In addition I will also be able to work with future team members to build a business case along with a minimal viable product, to prove business value and satisfaction of customer requirements and finally, design an appropriate architecture to realize the TO-BE solution and process.

In particular, the experience of integrating various cognitive platforms, machine learning models and software agents will prove very useful when modernizing existing systems.