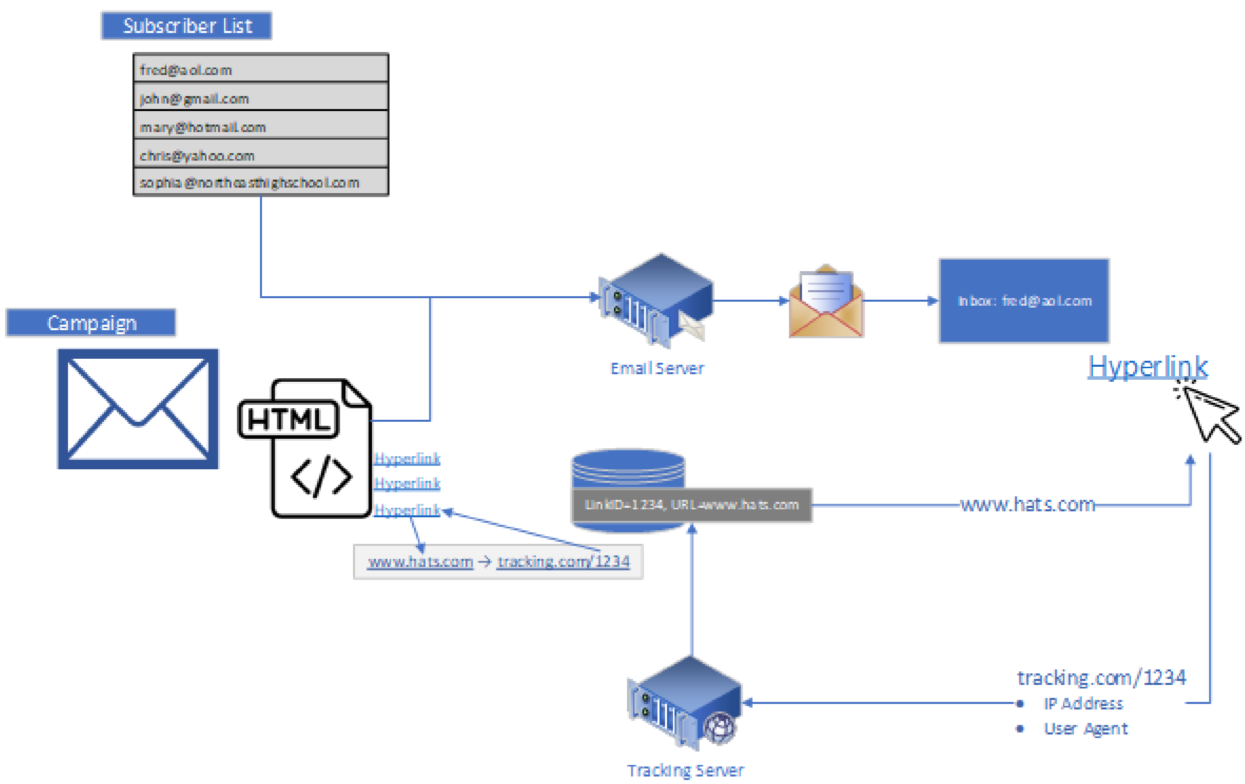
Capstone Project 1: Milestone Report

Background

Email marketing is a form of marketing where emails are sent to a list of subscribers. This form of marketing is often used by e-commerce and brick and mortar merchants as an effective way to increase sales and engage customers. These email campaigns usually include sale items and other offers as a way to increase traffic to their web sites and encourage new orders. Virtually all of these items are links that take the email contact to a specific location on the merchant's web site.

One of the most critical aspects of these email campaigns is the ability to track click activity. The more clicks a campaign receives, the more effect that campaign was. Links with relatively low click rates might indicate the item or product did not present well in the message. New campaigns with decreasing click rates might indicate a lack of interest, poorly written subject lines, or displeasing message layouts.

Click Tracking



•When the contact clicks on a link, they are sent to the tracking server

•The tracking server looks up the original URL form the database

•A redirect to the original URL is sent back to the contact

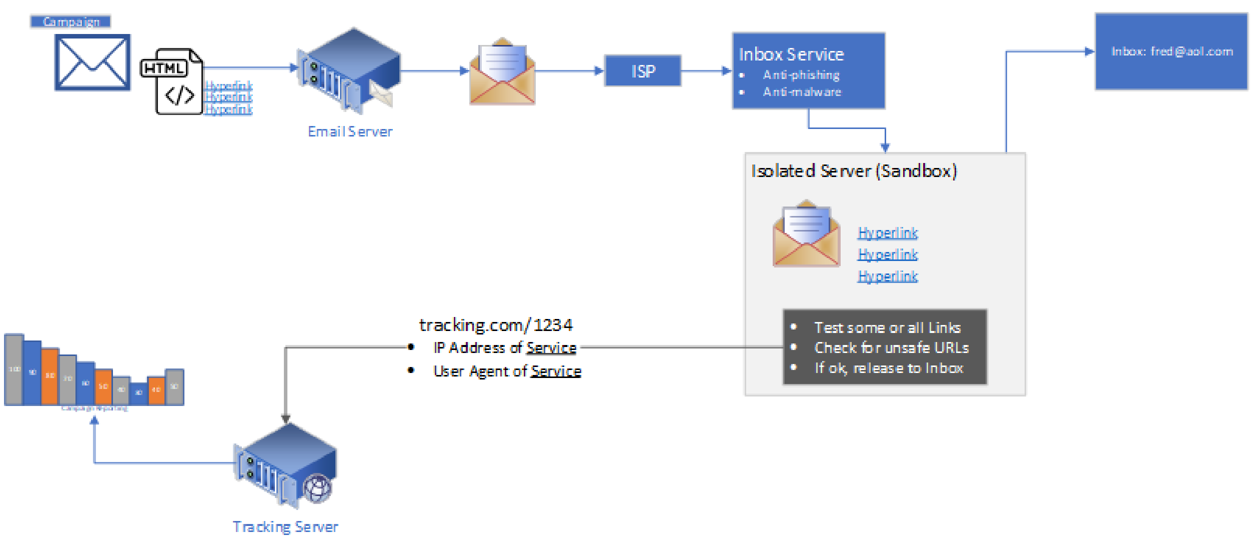
•This automatically sends the contact to the proper URL

Problem

Email has also been an effective medium for malicious activity. Phishing emails are becoming more of a problem each day. These malicious emails are also getting much harder to recognize. This has generated a new industry that offers services to help protect against phishing and malware emails. Typically, these services will receive the email before they go into the contact's inbox. The service will start up a protected sandbox environment and programmatically click on some or all of the links in the email. Based on the response from these clicks, the service will either quarantine the email or pass it along to the contact's inbox.

This type of service is very nascent at this point but growing at a rapid rate. Through manually investigation, many of these services are being used by schools to protect student accounts and computers. Both high schools and colleges are adding this layer of protection, but companies outside of education are also getting onboard with this type of service.

The problem is that the current tracking systems cannot differentiate between organic clicks from the actual contact vs. clicks from these services. Since the bots behind these services usually check every email received, a large percent of the clicks is coming from bots for some campaigns. Though there is no desire to reject these click requests from protective bots, the tracking of these clicks skew the click tracking data. If campaigns are trending up with click rates, they may be from more effective emails or from an increase in bot activity.



Problem Detection

Though bots, both protective and malicious, have plagued email service providers for years, the anti-phishing services have greatly increased the activity. Instead of one or two bot clicks an hour, now up to 40% of a send to 5 million contacts can be from bots. This was first detected not as a bot problem, but as a tracking overload problem. Accounts with large numbers of school aged contacts were the first to show signs. When one of these accounts started a campaign send to a few million contacts, the tracking system would get saturated for a few minutes. In fact, this huge volume of clicks occurred at the start of the send when only 1% or 2% of the subscribers were sent to. Extensive research into these short bursts of click activity using IP and MX lookups revealed the true problem.

The protective services don't want to delay the contact from receiving emails in their inbox. So, the services tend to perform the click analysis as soon as the email is received. Unlike human activity where the clicks would be spread out over a period of time and only a small percent will engage with the campaign, bots respond immediately and respond for every contact that received the message. This along with the common practice for email service providers to send to the most engaged contacts first, makes all the bot activity front loaded in the send stream.

Dataset

The data is proprietary data obtained from employer. The data was obtained via an audit of the raw clickstream. This audit data was stored in a SQL database. Information was then pulled in about the contact including the actual send time and added to the dataset. In addition, information was obtained from IP Lookup data. This IP data includes the CIDR range (blocks of purchased IP Addresses), the owner of the IP block, the geolocation for that owner including their Olson time zone name.

Since the data is proprietary, a large portion of the work was done in SQL. This hidden work included any data cleansing needed, building and populating the look up schema. There were about 6 to 8 lookup tables with fairly complex joins performed to obtain the final result. This was done on a very large dataset with millions of rows, even though only a subset was used in this project.

The resulting dataset was then anonymized including IP Address, CIDR range, email, email domain. The resulting dataset was approved by the security team before it was used in this project.

Subset

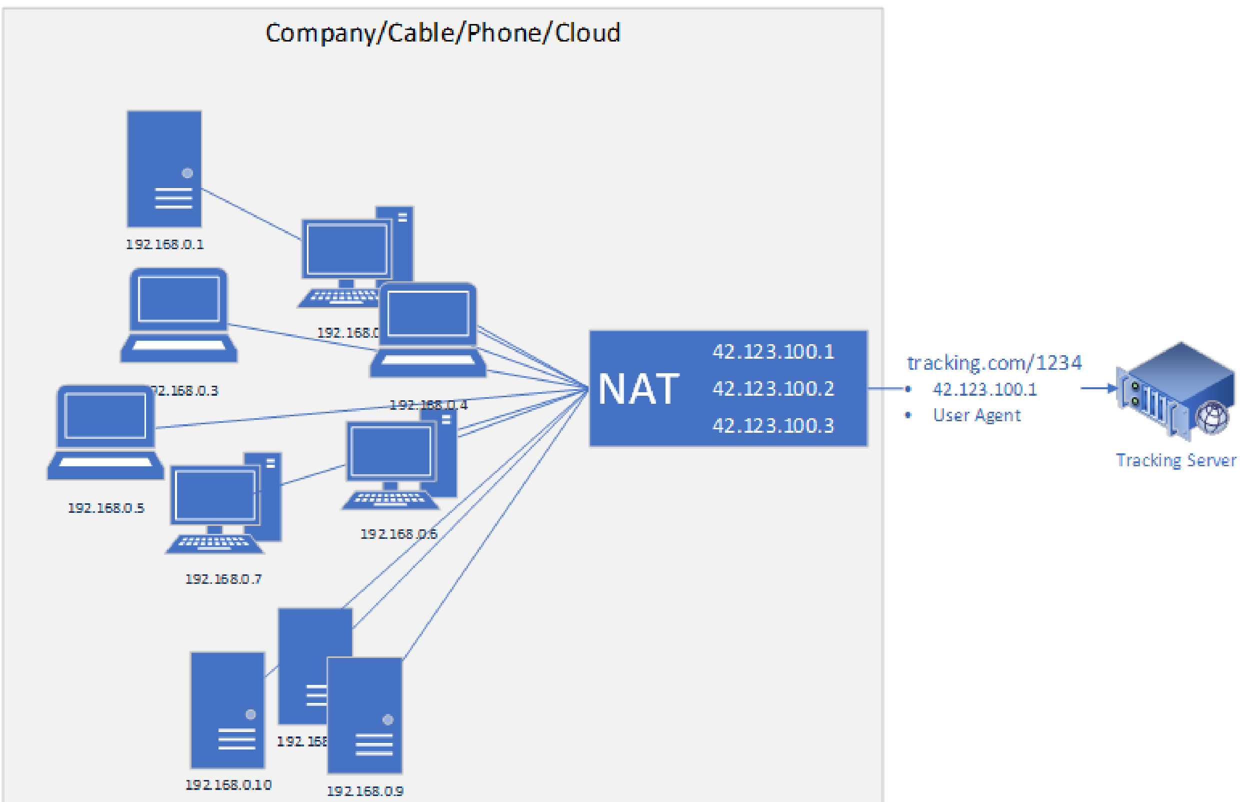
To limit the scope of the project as well as to reduce the row count to a tenable size, only one campaign was obtained. This campaign was chosen from an account with known bot activity. Research on the SQL side showed that more than a dozen campaigns from this account showed very similar click patterns with known bots. One of these campaigns was chosen at random to be used in this project. This gave us over 24 thousand click requests to work from. Note: The full campaign was sent to a few million contacts and the click rate for this campaign was on par for the account and similar to other account's click through rates. The clicks were limited to activity within the first 100 hours after the send.

HTTP Request Background

The way most email service providers (ESP) do click tracking is to rewrite the URL in the composed message. The rewritten URL includes information about the specific send via the

InboxID. This ID lets the EPS lookup who the contact was that received the email along with the campaign and link identifiers. When the contact (or bot) clicks on the link, the EPS receives the request, looks up the original URL from the LinkID and submits a redirect back to the contact. The contact's email click sees the redirect and is then routed to the original URL. The ESP knows who clicked on what link and when the click occurred. This tracking data is stored and used in the reporting system(s).

Along with the click tracking data, the IP and User Agent (info about the browser or email client) is submitted. Historically, when a bot was discovered (usually malicious), the IP and/or User Agent was blacklisted. The redirect was returned as normal, but the tracking data was thrown away. But the anti-phishing services use cloud-based platforms (i.e. AWS) which can offer thousands of IP addresses. Also, if a phishing campaign can detect the anti-phishing bot, it can return a safe URL with the redirect and wait until the organic click comes to present the dangerous link. So, these services find creative ways to hide their existence.



Sessionization

Most email campaigns contain 30 to 100 links. A contact will frequently click on several of these links. Almost always, these multiple clicks occur back-to-back.   One of the ways to judge a contact's behavior is to group all of these back-to-back clicks as a single session. Some sessions only have single click while other sessions may click on 15-20 clicks. The session is usually defined by recurring clicks with no more than 2 minutes between clicks. If there is a larger gap than 2 minutes, a new session is created with the next click request.

Sessions need to have some type of grouping. The same email or InboxID is a good way to do sessions. But since we are looking for bots, we are expecting that the same bot will click on many different messages spanning different emails and InboxIDs. Since the IP and User Agent is our best way to determine the source of the click request, it is logical to build session grouping off of these 2 values. Normally, the same device is being used by a single person, so the IP and UA tend to be unique. But bots will tend to use the same server for many requests. So, we would expect to see the IP/UA session for bots to include many emails and many InboxIDs.

But because of Natting (Network Address Translation), the same public IP can be used for many different computers. Natting is standard practice for most larger companies, ISPs and phone companies. This means that many different computers and/or people will use the same public IP. Since more of the clicks from one of these environments, it will be critical to differentiate these requests from bots.

InboxID	RequestDate	IPAddress	InboxSession	IPSession
123	10:03:01	123.456.1.1	**AAA**	**ZZZ**
123	10:03:01	123.456.1.1	**AAA**	**ZZZ**
456	10:03:02	12.45.8.7	**BBB**	**YYY**
456	10:03:03	45.65.1.4	**BBB**	**XXX**
123	10:03:58	45.65.1.4	**AAA**	**XXX**
789	10:22:22	74.124.5.6	**CCC**	**WWW**
456	10:22:23	74.124.5.6	**DDD**	**WWW**
123	10:22:24	123.456.1.1	**EEE**	**VVV**

InboxSession - Same InboxID without any gaps between requests over 2 mins (IP Address does not matter)

- AAA - Inbox **123** starting at 10:03:01 (3 requests)
- BBB - Inbox **456** starting at 10:03:02 (2 requests)
- CCC - Inbox **789** starting at 10:22:22 (1 request)
- DDD - Inbox **456** starting at 10:22:23 (1 request)
- EEE - Inbox **123** stariting at 10:22:24 (1 request)

IPSession - Same IP Address without any gaps between requests over 2 mins (InboxID does not matter)

- ZZZ - IP **123.456.1.1** starting at 10:03:01 (2 requests)
- YYY - IP **12.45.8.7** starting at 10:03:02 (1 request)
- XXX - IP **45.64.1.4** starting at 10:03:03 (2 request)
- WWW - IP **74.124.5.6** starting at 10:22:23 (2 requests)
- VVV - IP **123.456.1.1** starting at 10:22:24 (1 request)

Goal

Since the data is unlabeled, we need to use unsupervised learning. The final goal is to be able to identify IP address (or CIDR ranges) and User Agents used by bots. This way we can blacklist these IPs and User Agent strings, so our reporting is not skewed by bot activity. The tricky part is to find a way to differentiate bots on cloud services from companies, ISPs and mobile phone systems that use Natting.

Potential Approaches to Implementation in Production

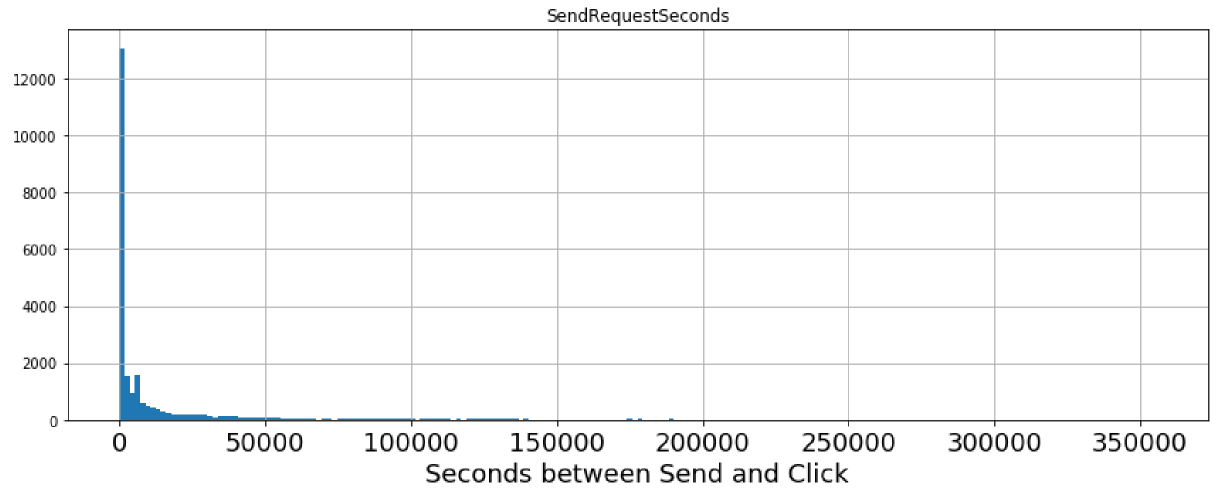
Because we must use unsupervised learning and the fact that these services are so nascent, we can't just move the model to production. So, this leaves us with 2 options. The first is to leverage unsupervised learning along with manual validation to extract thresholds in aggregate features. These thresholds could be updated from time to time and used in a production. For example, if we determine that more than 20 InboxIDs in a single IP/UA session is assumed to be a bot, the click stream could maintain sessions in memory and flag the tracking data as bot when 2 InboxIDs are reached. But this would be difficult since the requests would have to be buffered until the session is. This would be difficult when millions of clicks can come in for a single day.

A second and more simple approach would be to tap into the clickstream data on a weekly/monthly basis. Run the same clustering approach on this audit data and get the unlabeled clustered. Either manual or parameter thresholds could be used to determine likelihood of the cluster as being a bot. Once this is found, any new CIDR range/User Agent combination could be appended to the blacklist.

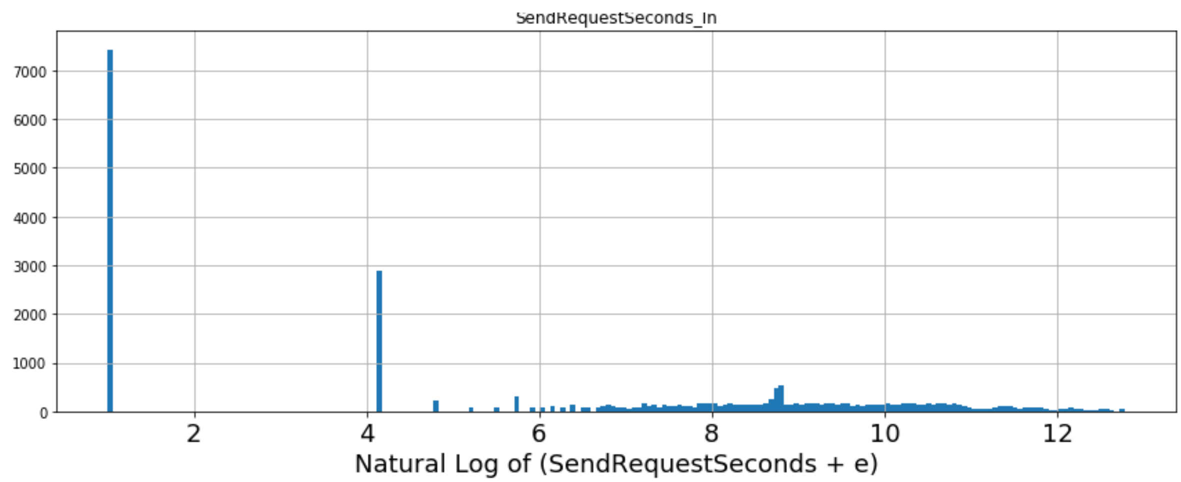
Data Prep

Some of the prep along with the sessionization was moved to a separate Python class in a standalone file (BotDataSet.py). This allows the ability to reuse this class on different datasets. Since the data was mostly prepared in SQL, very little data cleansing had to be done in Python. There were some values in the IP hierarchy that had "unknown" values that have to be changed to nan. 2 calculated columns were added. Both of these columns were based on the time between the actual send date and the time the click request came in. The first column was a direct difference in seconds. But looking at the histogram for this column, it was obvious that this feature followed some sort of an exponential decay PDF. Plotting the histogram with a log y-axis did not flatten this curve that much. A separate notebook was created to see if we could fit this data to a Gamma function via Bayesian inference. This was of limited success, but it did show extreme values for α and β, 0.16 and 207,482 respectively. This says that the time between the send and the click responds tends to be extremely skewed to the left. This is somewhat from the selection of the data with known bot activity reaching 40% of all clicks.

A second calculated column was added to the DataFrame to "tame" this feature down. This feature will be a critical differentiator in our clustering. We did not want to make it completely flat but needed some way to prevent this feature from dominating the model. So, the log of the duration between send and click was used. Euler's number was added to the duration before the natural log was taken since *ln*() approaches $-\infty$ when the value nears zero.



SendRequestSecon_ln =loge(SendRequestSeconds + e)



Sessionization

This was also done in BotDataSet.py. This is a fairly complicated method that required window functionality. Three elements are needed to achieve the proper windowed result:

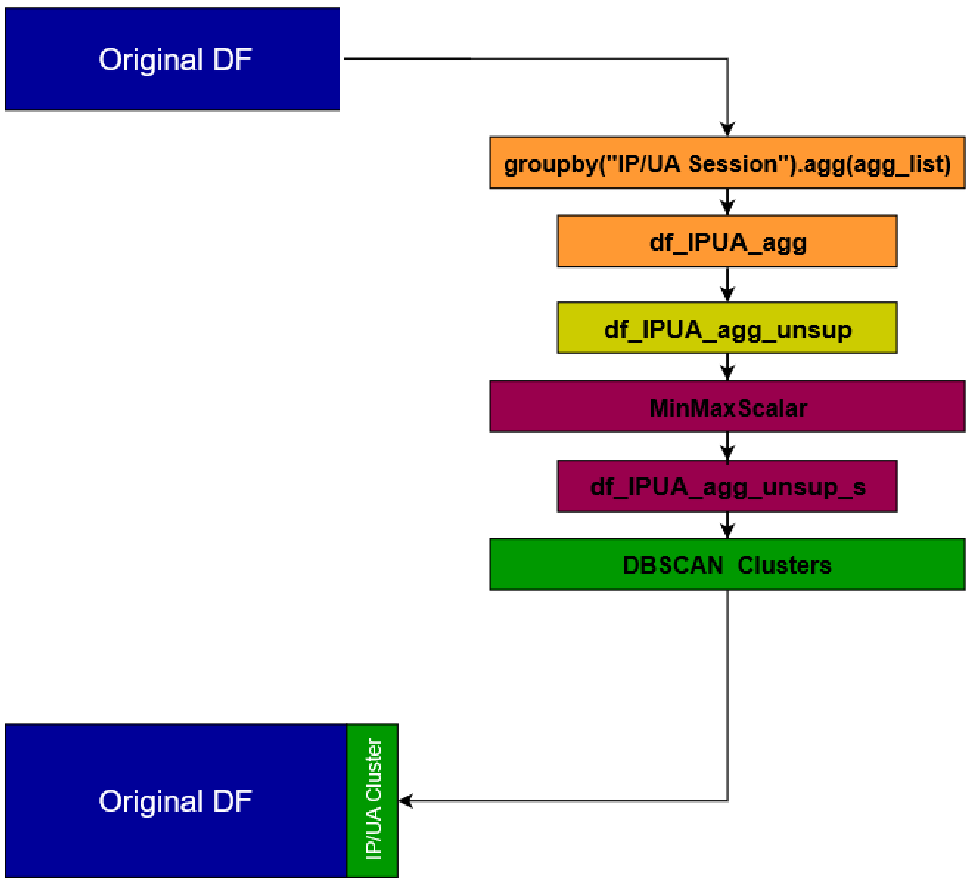
1. Ordering by Click Date
2. Grouping – list of grouping features is passed into the function to allow flexibility
3. Termination of Session – Within the window, the session is closed if the previous Click Date is more than 120 seconds old

Three grouping approaches were built in the notebook. If the first did not show success, the other groupings could be tried. The groups built were

- InboxID
- IP Only
- IP and UA

Since the combination of IP address and User Agent has provided success historically, it was the first tried. Since it proved to be successful, the other grouping approaches did not progress to clustering.

As part of the sessionization, a unique session ID (i.e. "IPUASessionID") is added to the original DataFrame. This session ID is what the aggregation will be based on. It will also allow us to map the aggregate clustering results back to the original df.



Aggregation

Now that we have our data prepped and sessionized, we need to derive features from the group of click events that fall into the session window. Possible aggregates include:

- Count
- Min/Max
- Mean/Variance/Standard Deviation
- Range
- Unique Values

Since the available aggregations would differ based on the grouping approach, a list of aggregations was built for each grouping. For the grouping approached used for this project, the aggregations chosen were:

- RequestCount
- Unique InboxIDs
- Unique Emails
- Unique Email Domains
- Unique Email Root Level Domains
- Unique Link URLs
- MeanSendReqeustSeconds
- SessionDuration

Scaling and Covariance

Each of these aggregate features were rescaled with the SKLearn MinMaxScaller. The correlation matrix was then used to examine the covariance between these aggregate features. Seaborn's pair plotting was also used to examine all the combinations of scatter plots between all features. It was expected that there would be a very high correlation between features like unique emails and unique email domains. But we would not reduce these features unless the clustering was not able to finish in a reasonable time. Through investigation, it was found that the anti-phishing bots are bound to a specific email domain. So even with a Pearson Correlation approaching 1, this could still be a valuable differentiator.

K Means vs. DBSCAN

Looking at the pair plotting, most of the scatter plots showed strong linear morphologies with not obvious distinct clustering. Though K means was tried, DBSCAN was switched to very quickly. After some adjustments to epsilon and min samples, a good result was found with 4 clusters.

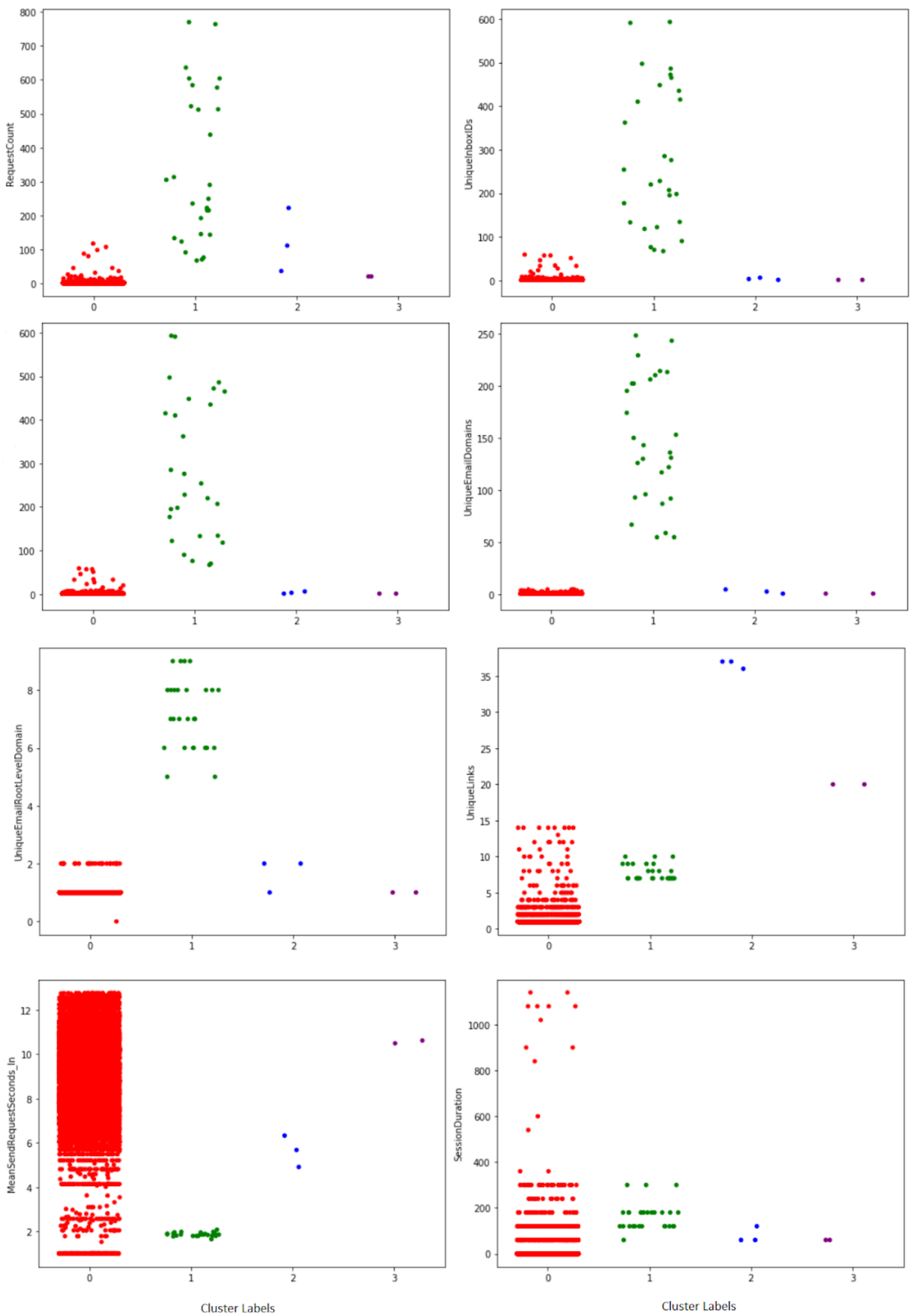
Visualization of Clustering Results

Using both strip plots and pair plotting, it was easy to see the differentiation in feature value ranges between the different clusters. The majority of the data fell into 2 clusters, 0 (red) and 1 (green). For virtually all the aggregate features used, one of the clusters showed a large range of values while the other showed a very compact range.

Feature	Cluster 0 (Red)	Cluster 1 (Green)
Request Count (Click Count)	Small Range	Large Range
Unique InboxIDs	Small Range	Large Range
Unique Emails	Small Range	Large Range

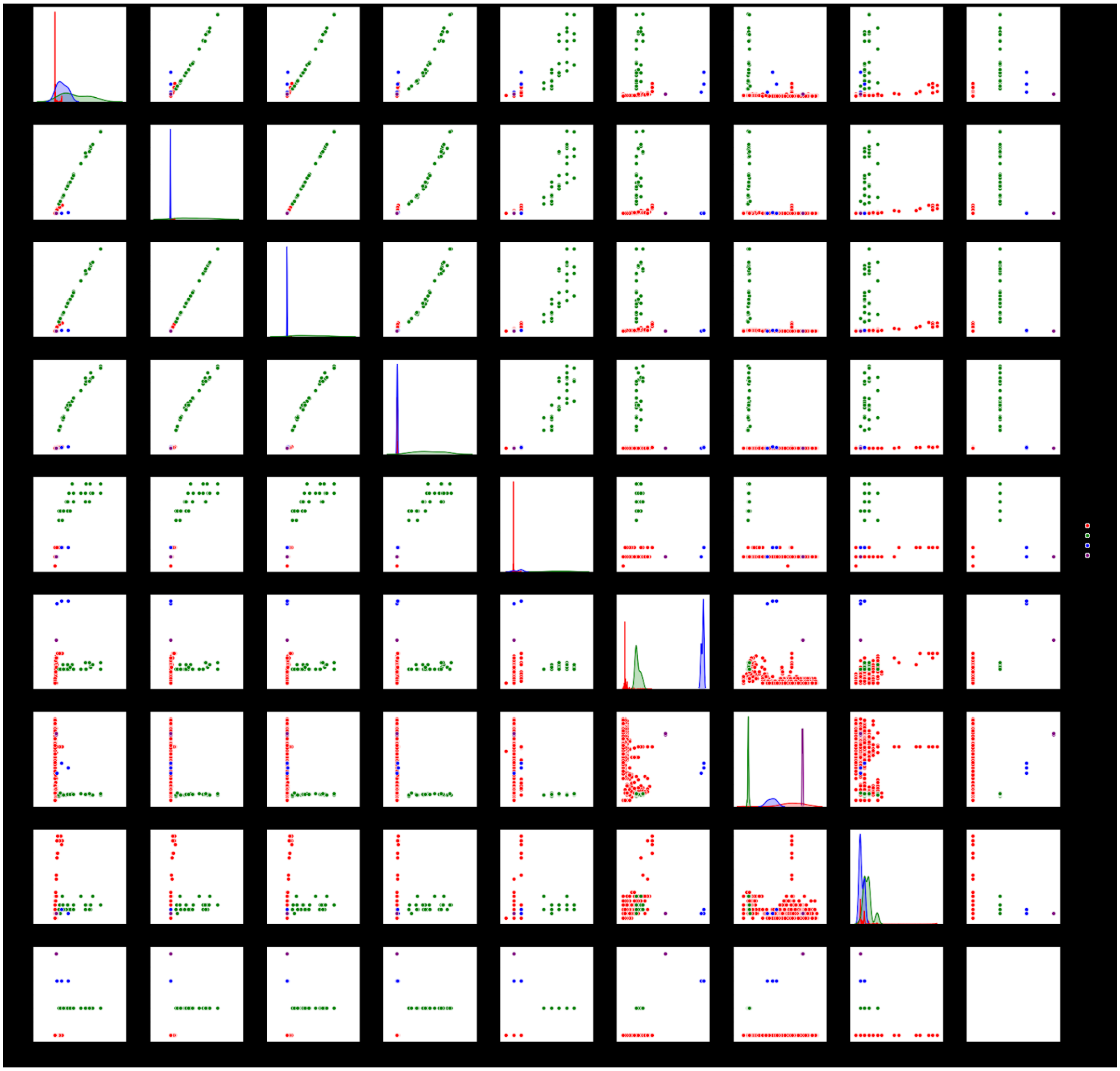
Unique Email Domains	Small Range	Large Range
Unique Root Level Domains	2 values	Medium Range
Unique Links	Medium Range	Small Range
Mean Send to Click Duration	Large Range	Small Range
Session Duration	Large Range	Medium Range

Scatter Plots by Label



Clustering and Pair Plots

The pair plots showed a very nice separation between groups. There were no gaps in some of the scatter plots, but most appear to be logically separated.



Group numbers 2 and 3 did not have large enough numbers so make assumptions about ranges or the scatter plots.

A bar plot of the 4 clusters shows that clusters 0 and 1 held the vast majority of the click requests.

Note: The clustering changes with each run even if the random see is set. So, this reference to the color and number of the clustered is based on the final run.

Merging Aggregate Clustering back into Raw DataFrame

The clustering was based on sessions which were based on grouping requests by IP and User Agent. Each session was given a unique IPUASessionID. This ID allows us to merge the clustering results back into the original DataFrame.

The results of this merge are interesting. If a contact clicks on 5 links at 9:00AM and then 1 click at 2:00PM, that contact would have generated 2 sessions. Since the unsupervised learning was done on the session and not the contact, that contact's 2 sessions might have different cluster labels.

The same can be said for the CIDR range or AS Name (owner of the IP blocks). Some CIDR blocks might have many sessions and these sessions can have different clusters. So, for some CIDR ranges, only one or 2 sessions might have a cluster associated with bot activity, and have many sessions associated with a cluster identified as organic clicks. This will allow us to score IP/UA combinations and CIDR ranges based on how many click requests were in bot clusters. This way, we end up with a majority rules basis for determining if the source IP/CIDR is a bot.

CIDR and AS Name Distributions

It was known that AWS (specifically the Oregon data center) is associated with most of the anti-phishing bots. If we do group by queries with the merge DataFrame, we can see how the AS Name, AS Number and CIDR click request counts match each of the 4 clusters found.

These results were surprisingly good! Clusters 1, 2 and 3 only came from AWS with 1 exception. Cluster 3 had 36 click requests from DigitalOcean, LLC, another cloud provider.

Looking at the AS Number (usually a specific data center), cluster 1 and 2 all came from AWS Oregon and cluster 3 came from AWS Virginia and Digital Ocean. Chances are the Virginia data center hosts a different anti-phishing service than Oregon.

Manual Labeling

The labeled original DataFame was saved and loaded back into the SQL database where the audit data was hosted. Using random samples (~50 for each cluster), clusters 1, 2 and 3 had very strong evidence of bot activity. Whereas cluster 0 looked would be considered organic clicks.

CIDR Reputation

The CIDR reputation is a score that is based on what percentage of the sessions were in bot clusters. There were 13 CIDR ranges that had sessions that had clustered assigned as bots. Some of these CIDR ranges had sessions that were in the organic cluster. This is not unexpected, but of the 13 CIDR ranges, the lowest CIDR reputation score is 90%. The next lowest score was over 97%. Based on these results, chances are the few sessions that did not get placed in a bot cluster were still from a bot source.

ReputationScore = SessionCount(Label > 0)SessionCount(All Labels)

Results

Since we used unsupervised learning, we can't show metrics like accuracy or ROC curves. But we have an advantage here in that these types of bots are in their nascent phase. Because of this, we can fairly accurately identify almost all of the bots simply by identifying the owner of the IP blocks. Any request coming from AWS is almost certain to be a bot. We did see some bot activity from Digital Ocean's data center with manual investigation, but no other data center or ISP was found to be associated with bot activity.

This assumption will not hold for long. If these types of helpful bots become more prevalent, we will need more sophisticated methods to checking accuracy, but for now the data center is probably accurate.

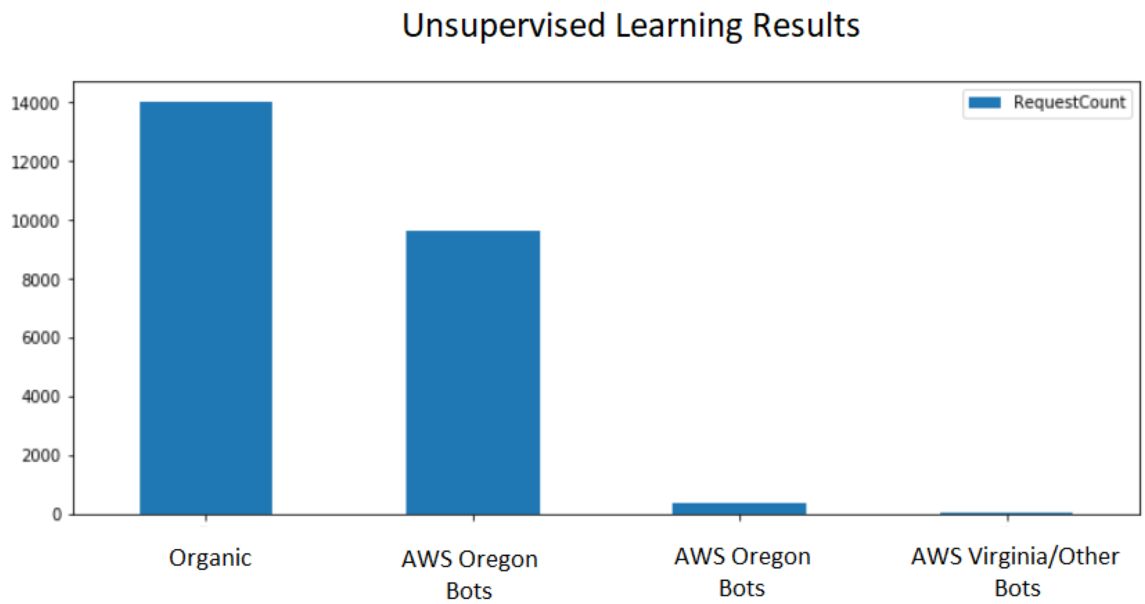
Below is a breakdown of the owner of the IP Address (AS Name) along with the counts for each unsupervised label assigned. Just looking at AWS and assuming all AWS requests are bots, we can get a rough idea of the accuracy we achieved.

Accuracy = 9,608 + 333 + 4011.139 = 89.6%

Chances are the ~10% of the AWS requests that got grouped into the Organic label were underrepresented with only one or two clicks in a session. Running the clustering with larger datasets would probably find more sessions of these CIDR ranges and increase the accuracy.

Owner of IP Address	0 Organic	1 AWS (Oregon)	2 AWS (Oregon)	3 AWS (Virginia)	Total
Amazon.com, Inc.	1158	9608	333	40	11139
Unknown	10562	0	0	0	10562
AT&T Mobility LLC	1118	0	0	0	1118
MCI Communications Services, Inc. Verizon Business	294	0	0	0	294

T-Mobile USA, Inc.	**253**	**0**	**0**	**0**	**253**
Scalair SAS	**217**	**0**	**0**	**0**	**217**
CenturyLink Communications, LLC	**91**	**0**	**0**	**0**	**91**
Google LLC	**86**	**0**	**0**	**0**	**86**
Comcast Cable Communications, LLC	**81**	**0**	**0**	**0**	**81**
DigitalOcean, LLC	**20**	**0**	**36**	**0**	**56**
Level 3 Parent, LLC	**54**	**0**	**0**	**0**	**54**
Windstream Communications LLC	**31**	**0**	**0**	**0**	**31**
TELUS Communications Inc.	**27**	**0**	**0**	**0**	**27**
Shaw Communications Inc.	**16**	**0**	**0**	**0**	**16**
Microsoft Corporation	**12**	**0**	**0**	**0**	**12**
GENESCO INC	**6**	**0**	**0**	**0**	**6**
Johns Hopkins University	**4**	**0**	**0**	**0**	**4**
DoD Network Information Center	**3**	**0**	**0**	**0**	**3**
Sprint	**3**	**0**	**0**	**0**	**3**
Cellco Partnership DBA Verizon Wireless	**3**	**0**	**0**	**0**	**3**
Cogent Communications	**2**	**0**	**0**	**0**	**2**



Future Work

There is still a lot of work that could be done here. Running a larger dataset that spans multiple campaigns and accounts would be a good first step. Since currently the anti-phishing bots seem to be associated with schools, finding subscriber lists whose makeup is from an older population would be important to check. Do these findings still hold up with different contact distributions?

A quick attempt was made with a large dataset but ran into scaling issues with DBSCAN. HDBSCAN was tried once but was dropped due to scope of the project. Larger datasets would be important to capture all the CIDR ranges associated with bot activity. Since this dataset was from a single campaign, chances are not all the available CIDR ranges from AWS were present. A quick analysis from other campaigns from this same account indicated that only about 60% of the CIDR ranges were identified.

A much better approach to using this in production would be the next major effort. Rerunning the clustering on new audit data makes sense, but there is still a lot of subjectivity on assigning clusters as bot sources. For now, we could be just as effective in blacklisting any request from an AWS CIDR, but the landscape is rapidly changing and this assumption could become very inaccurate in a very short period of time.