Saint Louis University
Department of Health and Clinical Outcome Research

Master of Science in Health Data Science (HDS) Capstone Projects *School of Medicine*

Mental Health Problems in Orange County, California

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HDS 5960 - Capstone Experience

Date of submission: August 11th, 2021

Acknowledgements:

This capstone project was only possible because of the good graces of the Project Manager, ***Mr. Mark Charipar****. I am grateful to have had* ***Mr. Charipar*** *to guide and support me throughout the course of this project.* ***Mr. Charipar*** *did not just teach me about how to bring my data science skills together, he showed me how to solve real life problems and about the many relevant trends in the industry. As well as business skills that I will surely continue to develop throughout my professional career. Most importantly* ***Mr. Charipar*** *taught me that I have an ethical responsibility when handling data and to take personal pride in my technical craftsmanship.*

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1. Abstract

2-1-1 Orange County (211OC) is a local, private, and non-profit organization connected to Orange County, California residents for over twenty-eight years by providing critical social services such as housing, food, education, utilities, and mental health. Mental health problems in Orange County have increased in severity over the past decade, and also suicide rate spiked to a one hundred years high during the COVID-19 pandemic. 2-1-1, Orange County's twenty-four-seven hotline for those struggling with mental health, has seen a profound increase in calls related to mental health during this past year, most likely due to the COVID-19 pandemic.

This paper details the results of an internship with Plan4Co and their stakeholder (211OC) that aimed to forecast the total number of calls related to mental health and to design and develop a high-quality dashboard for the call center using Microsoft BI and Snowflake. An LSTM recurrent neural network was used as a model to create the forecasts and both exploratory and statistical analysis was done during this capstone project. The results show that the number of mental health calls undulate during each week and that the number of forecasted calls for the next thirty days will be increasing by just over one percent (1.38%).

2. Introduction

2.1 Company/Project Overview

Plan4Co is a relatively new data science startup with less than seventy-five contractors. Plan4Co specializes in fulfilling small businesses' data science needs for a competitive price while offering a polished product and a "can-do attitude." It offers comprehensive capabilities and specialized industry knowledge that is important to solving an organization's complex problems. It gives innovative predictive analytics that helps in delivering cost-effective insights through integrated cloud based dashboards and reports.

Orange County is the sixth largest County in California. According to the 2018 indicators report, 8% of the California population lives in Orange County. It has a robust and diverse economy, with a number of household incomes in the upper quartile which have influenced the level of education and thus lowering the rate of crime (Condo et al). However, Orange County's high cost of living is a rising problem that may be strongly correlated to the rise in the quantity of mental health concerns. A mental health survey in Orange County put the interest of adolescents, veterans, and the homeless ("Orange County MHSA Program Analysis"). The findings show that the variance of mental health differs amongst the different demographic groups within the County. The major cause of mental health, according to a survey, was psychological distress ("OC COMMUNITY INDICATORS 2020-2021"). The main intention of the Mental Health Services Act, which was voted for in November of 2004, was to improve mental health services for those individuals that are at the greatest risk. This proposition was also intended to create policies that relied on local agencies to implement new programs. The goal of the capstone project was to make a live forecasting dashboard related to the quantity of mental health calls made to 2-1-1 OC and to help them to make more informed and intelligent decisions.

2.2 Internship experience and learning objectives

From the 24th of May of 2021 to the 15th of August of 2021, the author completed a capstone internship experience with the Data Science and Analytics department of Plan4Co and their stakeholder (2-1-1 Orange County) under the supervision of Mark Charipar (Project Manager and Data Scientist). The internship accounted for two hundred and forty hours, with sixteen hours per week varying depending on other work responsibilities. During the course of the internship, the author enhanced not only his technical skills but also was involved in business activities and solving real world problems.

For this capstone internship experience, the author was required to complete training courses on Microsoft Power BI, Snowflake's SQL database cloud, and the platform SaturnCloud before starting this project. All of this training took one month to complete. After the completion of the training courses, the author began the real world project sponsored by 2-1-1 Orange County. The author interacted with the preceptor on a weekly basis while with the other members of the organization on a daily basis. The author researched the mental health crisis in Orange County which was due to health care services being difficult to access for certain demographics and the lack of overall culture awareness on the effects of social distancing policies on individuals' mental health, as well as the general downturn in the economy. Hours dedicated for completing this project were spent on training courses, conducting literature reviews and gathering background information, uploading the data into a Snowflake, data cleanup and preprocessing, analyzing the data using Microsoft Access and statistical modeling, building a forecasting model using a recurrent neural network LSTM algorithm, designing and developing a live forecasting dashboard, collaborating with Plan4Co team members and 2-1-1 OC employees, and preparing periodic reports and the final capstone internship paper.

2.3 Literature Review

According to the Older Adult Mental Health Resource Guide, older adults have a diverse set of ethnicities and cultures (Dupee). Orange County has inadequate services and programs for adults with mental health. The services provided by the county required community awareness for improving the pre-existing public services and by better meeting the needs of the older adults within the community. The guide provides accessibility, evaluation, counseling, diagnosing, and early prevention has directories which when followed, will ensure older adult mental health concerns are treated effectively.

Orange County, like many other counties, lacks the resource allocations to adequately address the mental health needs of its constituents (“COMMUNITY INDICATORS 2018”). A World Health Organization report from 2016 stated that about 15% of the older adult population suffers from mental issues. From the research, it was evident that adults more advanced in age are more susceptible to concerns relating to mental health. Also, in the Orange County Adult Services Program, depression was indicated as a common diagnosis (Dupee 44).

The current state of mental health is covered within the Orange County MHSA program analysis. It also estimates the prevalence of mental illness and the use of mental services that are homeless. The findings are that the percentage of mental illness prevalence in Orange County among the unsheltered individuals was high (Orange County MHSA Program Analysis). The Mental Health Resource Guide provides the relevant directories to find the required information on a mental issue.

3. Data

3.1 Source of the data

The source for the "Call Reports Dataset" is URL (2-1-1oc). The 2-1-1 Orange County provided the yearly datasets from 2014 to 2021, which contains information about the callers who received assistance from the 2-1-1 support helpline for their concerns, needs, and services. The caller data was contained in excel spreadsheets, which each contained three sheets, NeedsMetAndUnmet, CallReports, and Referrals. Each spreadsheet corresponded to a years worth of caller data and the column names for the CallReports sheets varied from year to year. The customer 2-1-1 OC forwarded the excel spreadsheets directly, because the CRM database they use (iCarol) only allowed them to access their caller data in excel sheet format monthly by request. The details of the datasets are as follows:

<u>Details of the Call Reports Datasets:</u>

Datasets (Call Reports)	Number of variables in each sheet			Number of Observations in each sheet		
	Needs Met and Unmet	Call Reports	Referrals	Needs Met and Unmet	Call Reports	Referrals
Dataset_2014	35	158	20	200404	70759	167015
Dataset_2015	35	158	20	161627	68104	148222
Dataset_2016	35	158	20	164772	69620	153727
Dataset_2017	35	158	20	185584	68344	164587
Dataset_2018	35	158	20	169411	66352	145058
Dataset_2019	35	158	20	169411	66352	145058
Dataset_2020	35	158	20	219181	111927	207138
Dataset_2021	35	158	20	116120	62377	107615

Details of the columns in the Call Reports Datasets: The details of the columns for NeedsMetAndUnmet, CallReports, and Referrals sheets have been shown in Appendix I (See Appendix I).

3.2 Transforming and Data Cleaning with SQL

One of the initial tasks that every data science project requires is preparing, cleaning, and transforming the data for analysis. It is no surprise that approximately 80% of the time spent in this data science project was to extract the insights in the data and to prepare it for analysis. The majority of the data cleansing was done using SQL queries via the cloud platform Snowflake. The author transformed eight years worth of Excel call reports datasets into a Snowflake data cloud warehouse using SQL queries as a standard view. SQL queries were used in the Snowflake tables to select columns, merge, extract, find, remove duplicate rows, add a NumberOfCalls column, and many additional steps to clean the data (i.e., recategorizing outlier data into a predefined 'other' category). This data engineering was extremely necessary in order to analyze the data and to create a model that would produce meaningful output that 2-1-1 OC could use practically.

The author first created the SQL queries that merged the eight datasets into a single dataset and provided the number of unique and NULL values for each column. The majority of the unusable columns that contained an unacceptable level of NULL values were removed from the dataset. After merging the tables using SQL, there were many duplicate rows that had to be removed. This same eventual output likely could have been produced using a more complex SQL query. The project was done while adhering to agile methodologies, so regular updates and progress reports needed to be made to the customer. Several of the columns had the same caller information. The author extracted only those columns that were relevant for the analysis, which is as follows: Date of Call, Taxonomy Code beginning with "R" – this is because the taxonomy codes that begin with 'R' correspond to "Mental Health." The other usable and relevant columns were Gender and Current or Prior Military Experience. The author then transformed the data by using the "Date of Call" column as the index and regrouped the data so that each row contained only one unique date. After cleaning up the data, its size was drastically reduced, now only containing 32,978 rows and 7 columns. The author found that in order to fit the data correctly, selecting only the aforementioned columns was the best possible decision given the customer's request of forecasting the number of mental health calls. Finally, the author exacted an SQL query that shared the cleaned dataset with other Plan4Co team member's Snowflake accounts under the guidance of the preceptor. Figure 1 represents the detailed information of the dataset within the Snowflake database, and figure 2 represents some of the data prior to reindexing the data by "Date Of Call" in the Snowflake Cloud Platform.

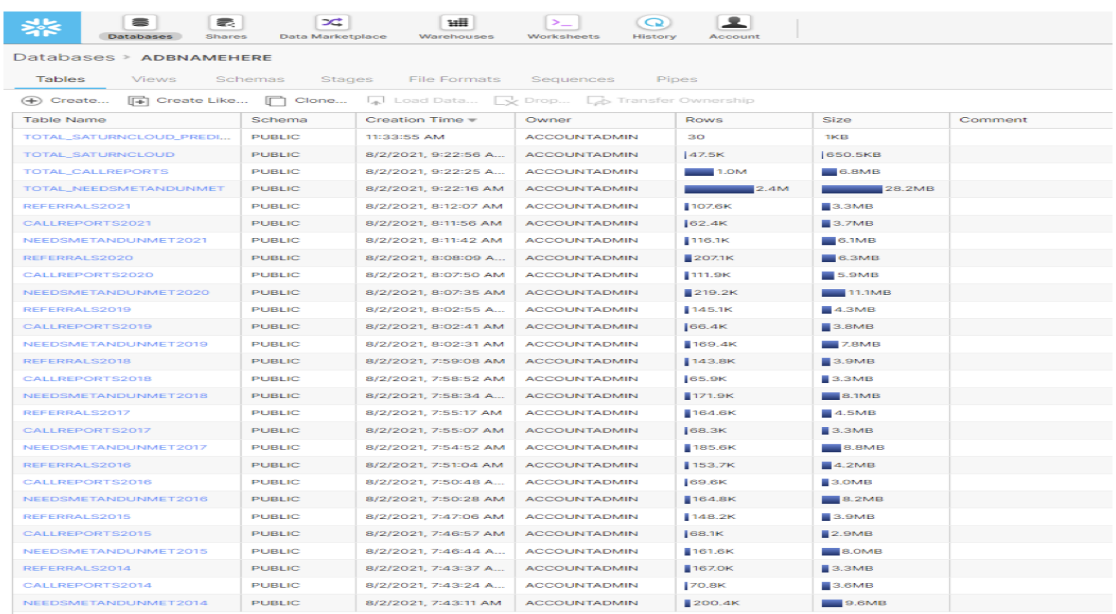


Table Name	Schema	Creation Time	Owner	Rows	Size	Comment
TOTAL_SATURNCLOUD_PREDI...	PUBLIC	11:33:55 AM	ACCOUNTADMIN	30	1KB	
TOTAL_SATURNCLOUD	PUBLIC	8/2/2021, 9:22:56 A...	ACCOUNTADMIN	47.5K	650.5KB	
TOTAL_CALLREPORTS	PUBLIC	8/2/2021, 9:22:25 A...	ACCOUNTADMIN	1.0M	6.8MB	
TOTAL_NEEDSMETANDUNMET	PUBLIC	8/2/2021, 9:22:16 AM	ACCOUNTADMIN	2.4M	28.2MB	
REFERRALS2021	PUBLIC	8/2/2021, 8:12:07 AM	ACCOUNTADMIN	107.6K	3.3MB	
CALLREPORTS2021	PUBLIC	8/2/2021, 8:11:56 AM	ACCOUNTADMIN	62.4K	3.7MB	
NEEDSMETANDUNMET2021	PUBLIC	8/2/2021, 8:11:42 AM	ACCOUNTADMIN	116.1K	6.1MB	
REFERRALS2020	PUBLIC	8/2/2021, 8:08:09 A...	ACCOUNTADMIN	207.1K	6.3MB	
CALLREPORTS2020	PUBLIC	8/2/2021, 8:07:50 AM	ACCOUNTADMIN	111.9K	5.9MB	
NEEDSMETANDUNMET2020	PUBLIC	8/2/2021, 8:07:35 AM	ACCOUNTADMIN	219.2K	11.1MB	
REFERRALS2019	PUBLIC	8/2/2021, 8:02:55 A...	ACCOUNTADMIN	145.1K	4.3MB	
CALLREPORTS2019	PUBLIC	8/2/2021, 8:02:41 AM	ACCOUNTADMIN	66.4K	3.8MB	
NEEDSMETANDUNMET2019	PUBLIC	8/2/2021, 8:02:31 AM	ACCOUNTADMIN	169.4K	7.8MB	
REFERRALS2018	PUBLIC	8/2/2021, 7:59:08 AM	ACCOUNTADMIN	143.8K	3.9MB	
CALLREPORTS2018	PUBLIC	8/2/2021, 7:58:52 AM	ACCOUNTADMIN	65.9K	3.3MB	
NEEDSMETANDUNMET2018	PUBLIC	8/2/2021, 7:58:34 A...	ACCOUNTADMIN	171.9K	8.1MB	
REFERRALS2017	PUBLIC	8/2/2021, 7:55:17 AM	ACCOUNTADMIN	164.6K	4.5MB	
CALLREPORTS2017	PUBLIC	8/2/2021, 7:55:07 AM	ACCOUNTADMIN	68.3K	3.3MB	
NEEDSMETANDUNMET2017	PUBLIC	8/2/2021, 7:54:52 AM	ACCOUNTADMIN	185.6K	8.8MB	
REFERRALS2016	PUBLIC	8/2/2021, 7:51:04 AM	ACCOUNTADMIN	153.7K	4.2MB	
CALLREPORTS2016	PUBLIC	8/2/2021, 7:50:48 A...	ACCOUNTADMIN	69.6K	3.0MB	
NEEDSMETANDUNMET2016	PUBLIC	8/2/2021, 7:50:28 AM	ACCOUNTADMIN	164.8K	8.2MB	
REFERRALS2015	PUBLIC	8/2/2021, 7:47:06 AM	ACCOUNTADMIN	148.2K	3.9MB	
CALLREPORTS2015	PUBLIC	8/2/2021, 7:46:57 AM	ACCOUNTADMIN	68.1K	2.9MB	
NEEDSMETANDUNMET2015	PUBLIC	8/2/2021, 7:46:44 A...	ACCOUNTADMIN	161.6K	8.0MB	
REFERRALS2014	PUBLIC	8/2/2021, 7:43:37 A...	ACCOUNTADMIN	167.0K	3.3MB	
CALLREPORTS2014	PUBLIC	8/2/2021, 7:43:24 A...	ACCOUNTADMIN	70.8K	3.6MB	
NEEDSMETANDUNMET2014	PUBLIC	8/2/2021, 7:43:11 AM	ACCOUNTADMIN	200.4K	9.6MB	

Figure 1: 211OC Dataset's information in Snowflake database

Row	DateOfCall	NumberOfCalls	TaxonomyCode	TaxonomyName	Demographics__Gender__Person_in_Ne	Demographics__Prior_or_Current_U_S__
1	2020-12-31	1	RX-8450.7000	Residential Substance Use Disorder ...	Man	No
2	2020-12-31	3	RF-8380	Talklines/Warmlines	Woman	No
3	2020-12-31	1	RP-5000.1500	Clinical Psychiatric Evaluation	Man	No
4	2020-12-31	1	RX-8500.8000	Sober Living Homes	Woman	No
5	2020-12-31	1	RP-5000.1500	Clinical Psychiatric Evaluation	Woman	No
6	2020-12-30	1	RP-1500.1400-150	Child Abuse Hotlines	Woman	No
7	2020-12-30	1	RP-5000.1500	Clinical Psychiatric Evaluation	Woman	No
8	2020-12-30	4	RF-3300	Individual Counseling	Woman	No

Figure 2: Data visualize in Snowflake Cloud Platform

3.3 Exploratory Data Analysis

Once the data had been cleaned thoroughly, the author conducted some exploratory data analysis in Microsoft Excel and Jupyter Lab to see how the data was distributed and correlated.

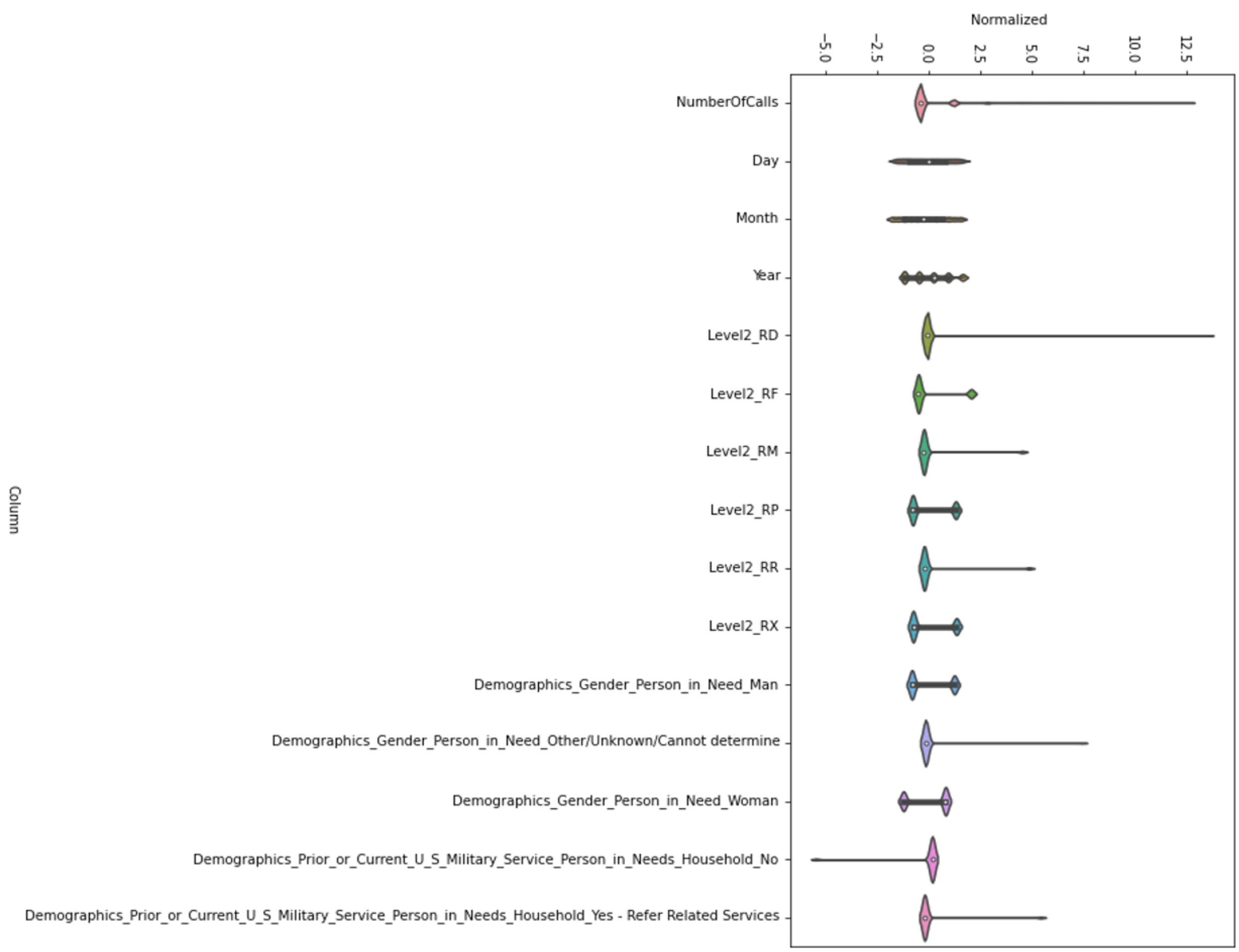


Figure 3: Distribution of Normalized Data

Looking at Appendix II, we can say that the number of mental health calls spiked in 2021 and during October 2014. On the other hand, the number of mental health calls seemed to have the lowest figures from April of 2020 to February of 2021. There were two hundred and two distinct Taxonomy codes, with the highest number of calls being for individual counseling followed by Talklines/Warmlines (See Appendix III). All the level 2 codes started with "R" (calls relating to mental health) seem to have a drastic drop at the end of the "number of calls by date" charts because they were produced by taking the sum of each month and the current month's data had just begun (See Appendix IV). The Plan4Co team found that a very small number of calls referred to the related services. This was because most of these calls were just for counseling. However, the data shows that the largest number of calls were received from females, whereas the largest number of male callers were for related services (See Appendix V & VI). More than 90% of calls were received from individuals who speak English compared to the other languages spoken, such as Spanish, Vietnamese, etc. The largest number of mental health calls with current or prior military history were from males, although more than half of the overall mental health callers are female. (See Appendix VII). This makes sense, as more than 80% of males served in the U.S. military compared to females.

4. Analysis

4.1 Preprocessing

After conducting the exploratory analysis, the author created a python script that connects the data from Snowflake to a Jupyter Lab server in SaturnCloud. After a discussion with the preceptor and analyzing the statistics of the cleaned data, the author decided to do additional preprocessing for a more in depth analysis. In the preprocessing steps, we first renamed some of the variables into the readable format like "Demographics_Gender_Person_in_Need_" to the "Gender" and so on. We dropped the Taxonomy name because the Taxonomy code and the Taxonomy name give the same information. The Taxonomy codes were filtered by their level two codes to reduce the number of unique mental health codes down from two hundred and two. As is usual for machine learning models, the categorical variables had to be transformed using numerical encoding. We transformed the "Militants" categorical variable into a numerical value as well as the "Gender" categorical variable because we are handling a regression problem for time series data using deep learning. We then selected the partition results from rows into groups based on their values in "Date of Calls," sorted in ascending order, and summed them up to get the total number of calls for each column with the Data of Calls being the index with a unique value for each row.

4.2 Methods of analysis

There are different methods available for modeling univariate time series and forecasting their evolution. Some popular time series models that most companies use to develop their business strategies are Naïve, SNaive, Seasonal decomposition (+any model), Exponential smoothing, ARIMA, SARIMA, Dynamic linear models, Prophet, and LSTM. This kind of time series forecasting model can help in many possible applications, such as weather forecasting, stock price forecasting, business planning, resources allocation, and many others. Since our dataset has a large number of observations with long sequences, noisy data, and multiple inputs variables. The author decided to use an LSTM model of deep learning techniques to forecast the mental health calls for this project. Some details about the other methods that can be used for time series forecasting are as follows:

a. Naive, SNaive:

In the Naïve model, a forecast corresponds to the last value, and it is usually referred to as a random walk. The SNaive, on the other hand, is an extension of the Naïve model, and it assumes that the time series has a seasonal component. These models are often used as benchmark models, and they use the last observed values for predicting the future.

b. Exponential smoothing:

Exponential smoothing is similar to the weighted average technique from the observations of the past data and these corresponding weights decrease in an exponential manner as we go backward in time. This is one of the most successful classical forecasting methods.

c. ARIMA, SARIMA:

ARIMA models are the most widely used approaches for time series forecasting. This is a combination of Auto-Regressive models whose forecasts correspond to a linear combination of past values of the variable and the Moving Average model whose forecasts correspond to a linear combination of past forecast errors. SARIMA is an extension of ARIMA, and it adds a linear combination of past seasonal values and/or forecast values.

d. Dynamic linear models:

DLMs are a special case of linear regression models where the parameters are treated as time-varying rather than static. The distribution follows a normal law. It employs the idea that the models correspond to a linear model every time, but regression coefficients change over time.

e. Prophet:

The prophet is an open-source software established by Facebook's Core Data Science team. The model assumes that g (t), s (t), and h (t) correspond respectively to trend, seasonality, and holiday. The Prophet model is inserted in a Bayesian framework, and it allows making a full posterior inference to include model parameter uncertainty in the forecast uncertainty.

4.3 LSTM, an artificial recurrent neural networks model

We used LSTM, an artificial recurrent neural network used in deep learning. We processed sequences of data and got a feedback connection. LSTM is composed of cells that remember values over arbitrary time intervals. The network classifies, processes, and makes predictions based on time series data because there can be lags of unknown duration between important events in a time series. The method was a success because the models were very reliable. Deep learning methods deliver accurate forecasts of past and future data. The trends analysis keeps the data up to date to ensure the method is as accurate as possible.

4.4 Forecast

We used complex linear regression and compared numerous independent variables with another dependent variable to analyze data. We ran a regression analysis on many variables and delivered great accuracy in data analysis after developing a high-quality dashboard to determine the number of future mental health calls. We aimed to identify caller types from the initial calls by dates, taxonomy names, number of calls, and gender.

5. Results

After we analyzed the primary findings from the capstone project, we found that there was an increase in calls during the pandemic period. We compared the variables of calls of the past years and the ones during the COVID-19 period. Mental health was an issue that needed to be solved, as was evident from the alarming rate at which it was growing. The results are accurate because we used the most recent forecast from the interactive visualization. Plan4Co ensures the effectiveness of the project because the practitioners are experts who are capable of explaining and demonstrating the analysis and forecasts that were produced from the reliable model with ease.

6. Discussion

The organization will use results from the analysis to strategize and by developing new theories and conceptual frameworks in the mental health sector. This enables 2-1-1 Orange County to create community level opportunities that will have a positive effect on treating mental illnesses. After analyzing data, other scientists can improve medical research on mental health because the use of large data results in more accurate analysis. If the forecast is accurate, the model will help future projects on mental health and the needs of hospitals. The causes behind mental health can be identified and detected before contributing to overall planning and shaping public policies.

7. Dashboard

The dashboard is a graphical interface that provides key performance indicators that are relevant to this project. It visualizes data and is always linked to regularly updating data sources.

What is it:

A ML pipeline that takes a call centers caller data from an exported excel sheet from a CRM database and uploads it to a SQL database with thirty days of a forecasted number of calls related to mental health and is then synced with a Microsoft Power BI Pro dashboard visualization that can be inserted into any website that can accept an *IFRAME* html tag.

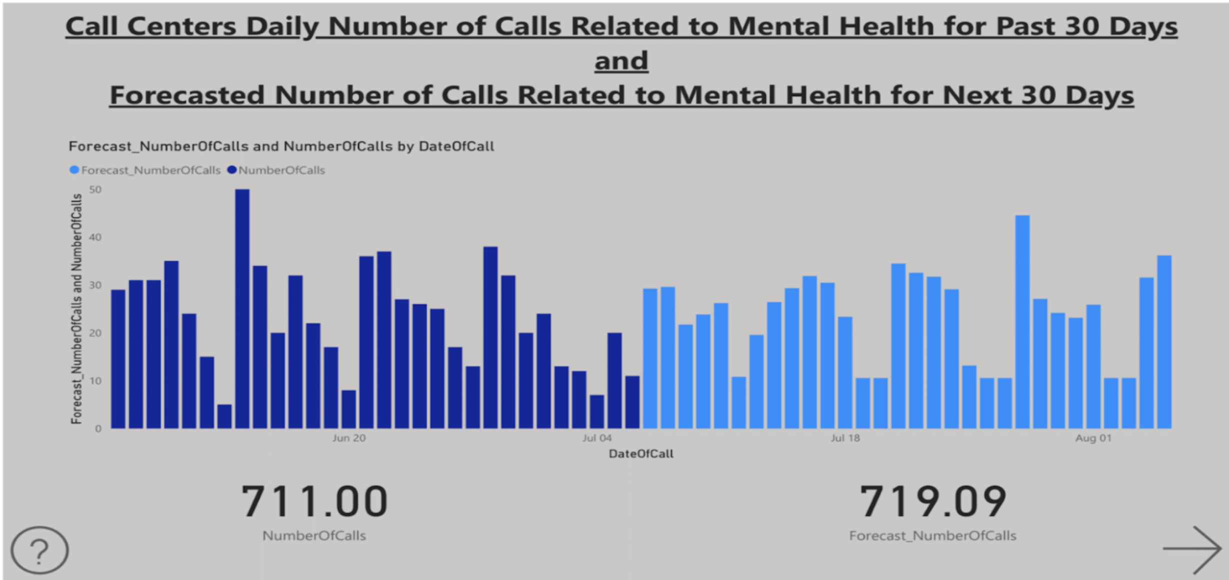


Figure 4: Call Centers Daily Number of Calls Related to Mental Health for Past 30 Days and Forecasted Number of Calls Related to Mental Health for Next 30 Days

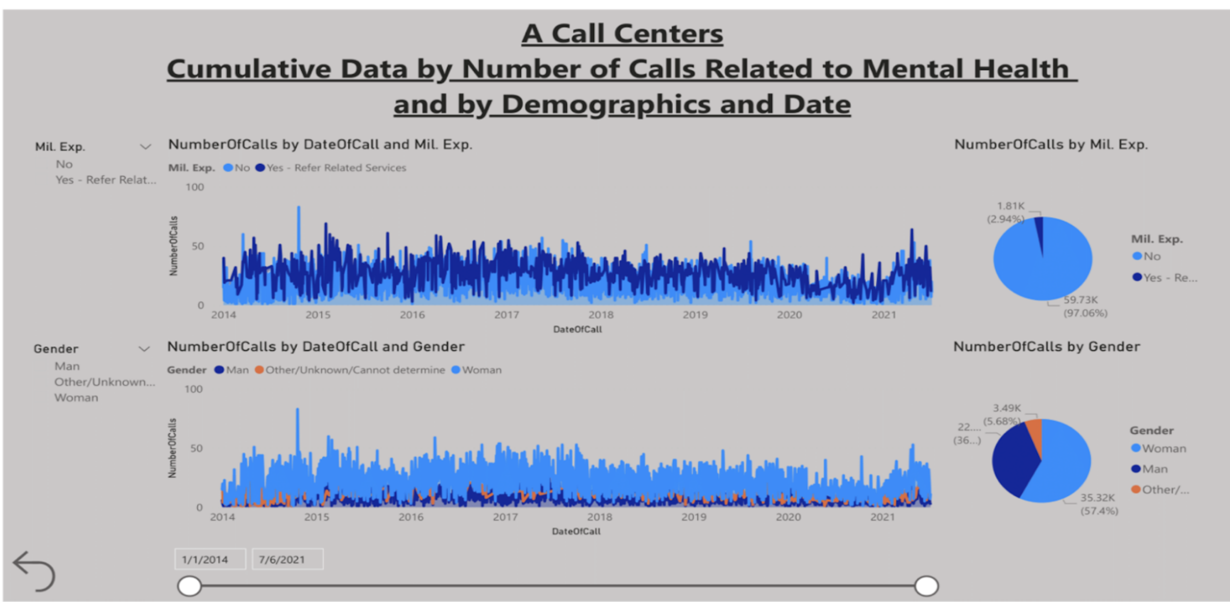


Figure 5: A Call Centers Cumulative Data by Number of Calls Related to Mental Health and by Demographics and Date

8. Reference

a. Codon et al. "OC COMMUNITY INDICATORS 2020-2021." ORANGE COUNTY PROFILE
https://www.ocbc.org/wp-content/uploads/2020/09/2020-Community-Indicators-Report.pdf

b. "COMMUNITY INDICATORS 2018" ORANGE COUNTY PROFILE.
https://www.unitedwayoc.org/wp-content/uploads/2018/07/orange-county-community-indicators-report-2018.pdf

c. Dupee."2020 OC OLDER ADULT MENTAL HEALTH RESOURCE GUIDE". Orange County Mental Health Board, 2020
https://www.211oc.org/images/2020/pdfcorona/2020_Older_Adult_Mental_Health_Resource_Guide.pdf

d. "Orange County MHSA Program Analysis." Needs and Gap Analysis.
http://www.ochealthiertogether.org/content/sites/ochca/Local_Reports/Orange_County_MHSA_Program_Analysis_May_2018.pdf

e. "Time series forecasting" Tensor Flow. Tensor Flow Core.
https://www.tensorflow.org/tutorials/structured_data/time_series

f. "2020-2030 ORANGE COUNTY." Mental Health Services Act.
https://www.ochealthinfo.com/sites/hca/files/import/data/files/116403.pdf

g. '2-1-1oc" https://www.211oc.org/get-help.html.

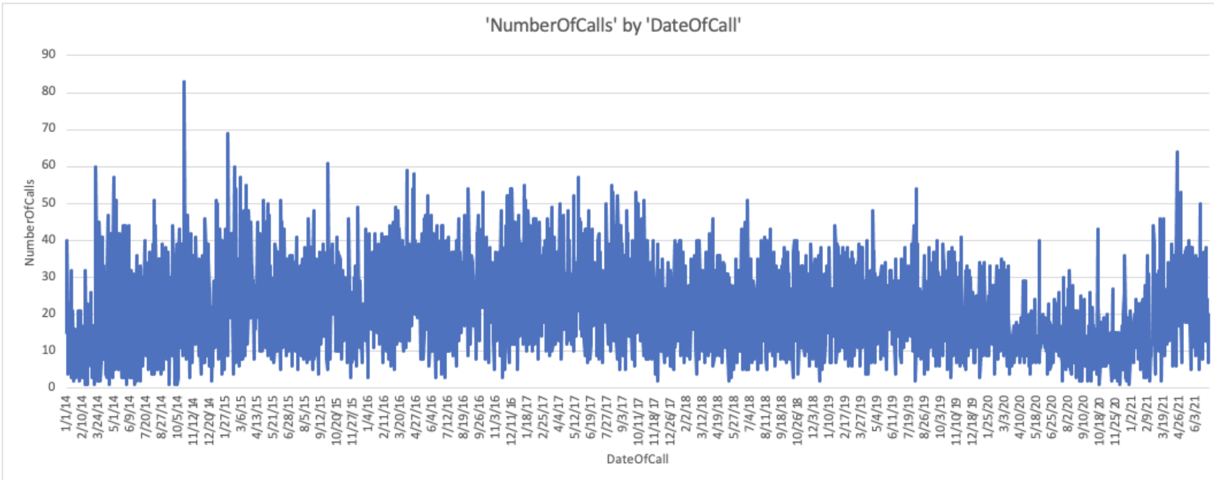
Appendices

Appendix I: Details of the columns in the Call Reports Datasets

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
1	COLUMN_NAME	COUNT_	UNIQUE_'	COUNT_(	COLUMN_NAME	COUNT_C	UNIQUE_'	COUNT_(	COLUMN_NAME	COUNT_OI	UNIQUE_'	COUNT_OF_NULL_VALUES			
2	DateOfCall	47833	>10	0	CallReportNum	66352	>10	0	DateOfCall	47601	>10	0			USABLE
3	CallReportNum	52387	>10	0	ReportVersion	7	2-1-1 Ora	0	CallReportNum	52119	>10	0			USABLE LOCATION
4	ReportVersionNum	6	50980 1!	0	LinkedToCallReportNum	1	-1.0 337	66015	ReportVersionNum	7	50980 1:	0			POSSIBLY USABLE
5	ResourceAgencyNum	3304	>10	16593	CallDateAndTimeStart	59393	>10	0	ResourceNum	3309	>10	0			MAY BE POSSIBLY USABLE
6	AgencyNamePublic	5354	>10	16593	CallDateAndTimeEnd	59014	>10	0	NamePublic	5366	>10	0			NOT USABLE
7	TaxonomyCode	1112	>10	0	CallLength	134	>10	0	CountryName	1	United St	1425			
8	TaxonomyName	1112	>10	0	CallerNum	130	>10	0	StateProvince	36	>10	1489			
9	CountryName	1	United St	1663	CallerName	9943	>10	47	CountyName	132	>10	1447			
10	StateProvince	36	>10	1748	CallerLastName	1922	>10	62905	CityName	343	>10	6827			
11	CountyName	130	>10	1685	PhoneWorkerNum	67	>10	0	PostalCode	468	>10	72741			
12	CityName	336	>10	7984	PhoneWorkerName	58	>10	0	AreaCode	297	>10	801			
13	PostalCode	456	>10	86831	CallerAddress	155	>10	66182	PrefixCode	800	>10	801			
14	AreaCode	297	>10	951	CityName	384	>10	12598	MetOrUnmet	1	Met 145	0			
15	PrefixCode	800	>10	951	CountyName	153	>10	9357	ResourceIDInExternalSystem	1759	>10	66086			
16	NeedWasUnmet	2	False 16	0	StateProvince	39	>10	9358	SiteResourceNum	2098	>10	3242			
17	ReasonIfUnmetOrPar	9	Other	168012	CountryName	1	United St	9335	SiteName	1436	>10	3242			
18	Level1Code	10	B 10046	0	PostalCode	524	>10	37463	ParentResourceNum	1335	>10	2354			
19	Level1Name	10	Basic Nee	0	PhoneNumberFull	37019	>10	430	ParentAgencyName	1331	>10	2354			
20	Level2Code	61	>10	0	PhoneExtension	7	24765	66345	SPA	3	North	8654			
21	Level2Name	61	>10	0	PhoneType	4	Mobile	66332	OC_Unincorporated?	1	Yes 980;	144078			
22	Level3Code	307	>10	0	Narrative	9062	>10	55840							
23	Level3Name	306	>10	11	VolunteerComments	2	currently	66350							
24	Level4Code	728	>10	0	Feedback	4	(No feedl	65185							
25	Level4Name	678	>10	2193	CallersFeedback	1	-has not r	66351							
26	Level5Code	984	>10	0	EnteredByWorkerNum	54	>10	0							
27	Level5Name	861	>10	6169	EnteredByName	46	>10	0							
28	PhoneWorkerNum	56	>10	31549	EnteredOn	66222	>10	0							
29	PhoneWorkerFirstNa	54	>10	31549	Reviewed	2	No 663!	0							
30	PhoneWorkerLastNar	53	>10	31549	FeedbackStatus	4	Not yet	0							
31	AIRSNeedCategory	17	>10	287	FeedbackFromPhoneWorkerNum	7	123374.0	65936							
32	ReportNeedNum	85204	>10	0	FeedbackFromPhoneWorkerName	5	Miguel V	65936							
33	ParentResourceNum	1335	>10	19035	ReferralsMade	31324	>10	14233							
34	ParentAgencyName	1331	>10	19035	OrgNum	1	2287 66	0							
35	SPA	3	North	10036	Application Info - Confirmation Number	568	>10	65770							
36	OC_Unincorporated?	1	Yes 117!	168236	Approved - SAR7 date (6 months)?	23	>10	66322							

Approved - What was the date of approval?	27	>10	66319
Area of Interest - Other Notes:	77	>10	66261
Caller Profile Offer - Email Address	28	>10	66324
Client Information - DOB M/D/YYYY	225	>10	66120
Client Information - Email Address	599	>10	65731
Consent - DOB M/D/YYYY	57	>10	66295
Consent - HMIS Unique ID	92	>10	66225
Follow-up Questions - Service Feedback and N	5	Families I	66347
Secondary Contact Information - Email Addre	6	raquel.re	66346
Secondary Contact Information - Name	22	>10	66329
Secondary Contact Information - Phone	17	>10	66333
Telephony Fields - Contact ID	53538	>10	12814
Telephony Fields - DNIS	5259	>10	12812
Veteran Information (person in need) - DOB M	373	>10	65887
Veteran Information (person in need) - Email	249	>10	66076
Veteran Information (person in need) - Hear a	7	B3	66342
Veteran Information (person in need) - Mobil	682	>10	65482
Veteran Information (person in need) - Refer	33	>10	66241
Application Info - Application	2	Applicati	65770
Application Info - Target Populations	61	>10	65770
Area of Interest - Resources Needed (Check a	83	>10	65479
CalFresh Follow-up Info - Have you heard fro	2	Yes 81; I	66222
CalFresh Follow-up Info - If Yes what is the st	4	N/A - Has	66222
CalFresh Follow-up Info - SSI Household	2	Non-SSI H	66246
CalFresh: - 1. Are you already signed up for Ca	8	Already h	19391
CalFresh: - 2. How many people in your house	11	>10	63105
CalFresh: - 3. Of those people in your home a	2	No- Move	63569
CalFresh: - 4. Is anyone is the household 60 ye	2	No (Conti	63577
CalFresh: - 4.Does anyone in the household re	2	0.0 24; 2	66327
CalFresh: - 4.Does anyone in the household re	9	Yes	64872
CalFresh: - 5. (Subtract answer from question	10	1	65706
CalFresh: - 5. Is the gross household income (I	12	>10	63269
CalFresh: - 6. Is anyone is the household 60 ye	1	No (Conti	66329
CalFresh: - 7. Is the gross household income (I	5	1 person-	66327
CalFresh: - Does anyone in the household rec	4	No	60787
Caller Profile Offer - Start a Profile?	2	Yes start a	66284
Client Information - Do you identify as LGBTQ	1	Not Aske-	66351
Client Information - Gender (Client)	2	Woman	65770
Client Information - Gender (Person in Need)	3	Woman	66231
Client Information - If First Contact - Referral	16	>10	60277
Client Information - If Previously Contacted -	9	First cont	14767
Client Information - If Previously Contacted -	19	>10	14727
Client Information - Is this a DV related call?	6	No	10904
Client Information - Language (Client)	9	English	12265
Client Information - Racial/Ethnicity Identity	1	Not Aske-	66351
Client Information - Relationship to Person in	8	Self	12592
Consent - (NAME) do you agree to give your c	4	Yes	65282
Consent - In order to better serve you do you	4	Yes	65396
Consent - In order to better serve you do you	4	Yes	66231
Contact Type - 4.Does anyone in the househol	3	No 14	66330
Contact Type - Application Type	2	Initial Ap	66093
Contact Type - Contact Category	4	All 2-1-1 (	133
Contact Type - SSI Household	2	Non-SSI H	66093
Contact Type - Type of Contact	14	>10	165
Demographics - "How many people are in you	4	1 person	66314
Demographics - ADDITIONAL QUESTION: D	4	No	65741
Demographics - Age of Person in Need	12	>10	61927
Demographics - Ages of All People in Househ	143	>10	61164
Demographics - Does anyone in the househol	5	No	61963
Demographics - Gender (Person in Need)	6	Woman	12349
Demographics - Household Size (Person in Ne	12	>10	61839
Demographics - Number of Children in House	10	0	61909
Demographics - Prior or Current U.S. Military S	5	No	14615
Demographics - Quarterly Demographic Surve	2	No 296;	34073
Demographics - Veteran - Do you have childre	2	No 136;	66192
Demographics - Veteran - Warm Transfer to	8	Tierney C	66223
Demographics - What is the Race or Ethnicity	12	>10	61818
Denied - What was the reason?	2	Other	66340
Denied - Would you like to appeal?	1	No (offer	66340
Family Status - Do you have any children 18 ye	4	No	65484
Family Status - Marital Status	5	Single	65481
Follow-up Questions - Has the callers situatio	2	No 11;	66337
Follow-up Questions - Reached Referred Age	2	Yes 12; I	66337
Follow-up Questions - Received Needed Assi	5	Other	66337
Follow-up Questions - Unable to Assist - Reas	5	Not appli	66337
Homeless Coordinated Entry System Pre-scre	2	Yes (Skip	47314
Homeless Coordinated Entry System Pre-scre	14	>10	60028
Homeless Coordinated Entry System Pre-scre	4	Individua	59985
Homeless Coordinated Entry System Pre-scre	4	CE prescr	19830
Homeless Coordinated Entry System Pre-scre	2	Yes (trans	65596
Household Size 1 - Gross Annual Household In	10	$24950 or	65524
Household Size 2 - Gross Annual Household In	10	$28500 or	65706
Household Size 3 - Gross Annual Household In	10	$32050 or	65888
Household Size 4 - Gross Annual Household In	10	$35600 or	65980
Household Size 5 - Gross Annual Household In	8	$38450 or	66115
Household Size 6 - Gross Annual Household In	6	$41300 or	66239
Household Size 7 - Gross Annual Household In	5	$44150 or	66311
Household Size 8 - Gross Annual Household In	5	$47000 or	66333
Pending - What else does SSA require?	3	Additiona	66311
Proactive Referrals - Are you interested in ap	5	No	61198
Secondary Contact Information - Relation to V	4	Friend/O	66331
Student CalFresh Questions: - Do any of the fo	2	No- Conti	66349
Student CalFresh Questions: - If you are 21 or	2	No (Conti	66341
Texting - Interested in Texting?	2	No 60;	66284
Veteran Information (person in need) - Branc	7	Army	66058
Veteran Information (person in need) - Branc	1	Army 1;	66351
Veteran Information (person in need) - Comb	3	No	66058
Veteran Information (person in need) - Comm	2	Yes 745;	65487
Veteran Information (person in need) - Conta	6	Self (Vet	65474
Veteran Information (person in need) - Disch	5	Honorabl	66059
Veteran Information (person in need) - Do yo	1	No 1; N	66351
Veteran Information (person in need) - Do yo	5	No	65483
Veteran Information (person in need) - Electr	5	No	65480
Veteran Information (person in need) - Emplo	8	Unemplo	66060
Veteran Information (person in need) - Enroll	4	No	66060
Veteran Information (person in need) - Gende	3	Man	65477
Veteran Information (person in need) - Health	6	Yes - VA I	66059
Veteran Information (person in need) - Highe	9	Some Col	66060
Veteran Information (person in need) - Home	1	Yes 1; N	66351
Veteran Information (person in need) - How c	7	Called/Er	65470
Veteran Information (person in need) - Is the	2	No 765;	65562
Veteran Information (person in need) - Langu	3	English	65470
Veteran Information (person in need) - Milita	5	Discharge	66059
Veteran Information (person in need) - Post 9	2	No 701;	65479
Veteran Information (person in need) - Prefe	5	Mid Day 1	65480
Veteran Information (person in need) - Racial	10	White/Ca	65479
Veteran Information (person in need) - Servic	4	No	66059
Veteran Information (person in need) - Transi	3	No	66059
Veteran Information (person in need) - Type c	6	Veteran	65475
Veteran Information (person in need) - What	13	>10	66059
Warm Transfers - Warm Transfer to:	58	>10	65486
SPA	3	North	14062
OC_Unincorporated?	1	Yes 406;	65946

Appendix II: Number of Calls by Date



Appendix III: Percentage of 'Number of Calls' by Taxonomy Name

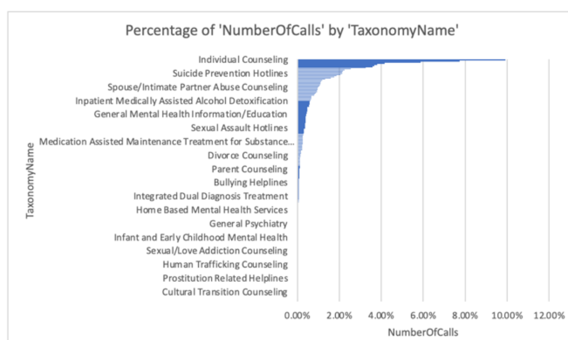
Distinct number of 'TaxonomyCode'

If your data changes, be sure to go back to Analyze Data and ask your question again to get an updated answer.

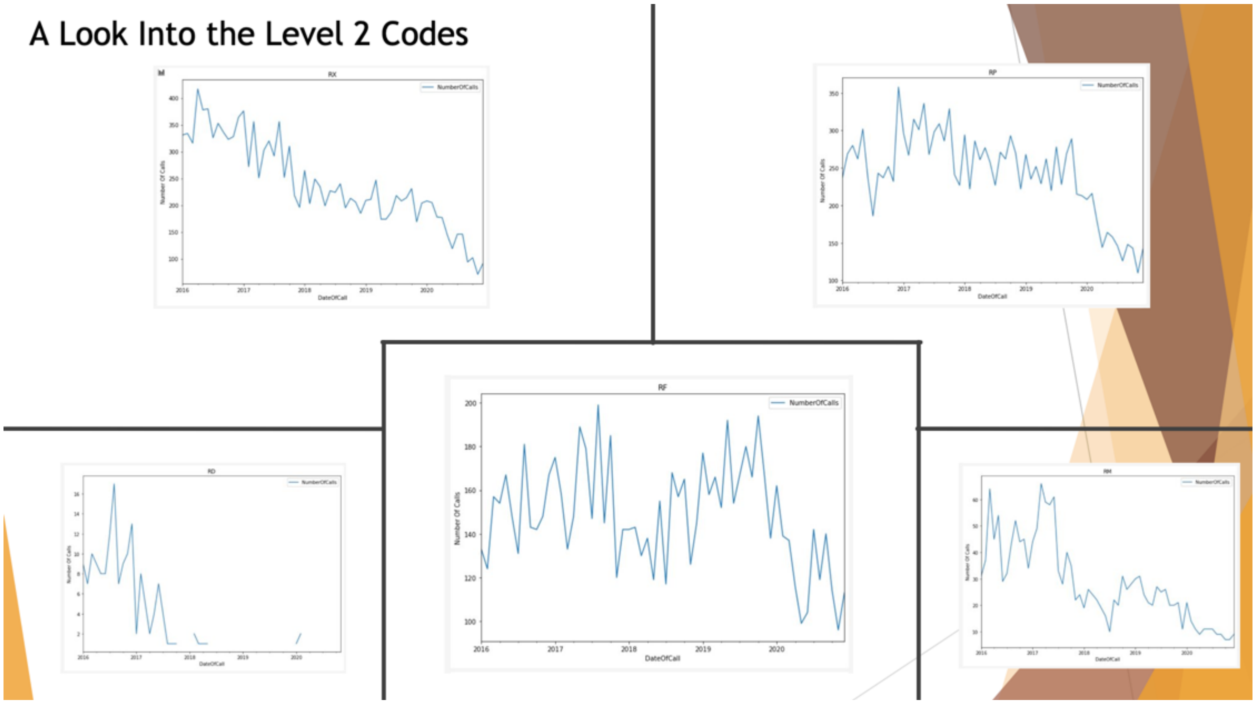
Distinct Count of TaxonomyCode
202

% of total 'NumberOfCalls' by 'TaxonomyName'

Row Labels	Sum of NumberOfCalls
Individual Counseling	9.93%
Talklines/Warmlines	7.75%
Domestic Violence Hotlines	5.87%
Residential Substance Use Disorder Treatment Facilities	4.16%
Detoxification	3.81%
Clinical Psychiatric Evaluation	3.67%
Sober Living Homes	3.60%
Anger Management	3.26%
Family Counseling	2.56%
Psychiatric Mobile Response Teams	2.25%
Inpatient Drug Detoxification	2.16%
Comprehensive Outpatient Substance Use Disorder Treatment	2.15%
Suicide Prevention Hotlines	2.13%
Residential Drug Use Disorder Treatment Facilities	2.06%
Substance Use Disorder Referrals	1.88%
Adolescent/Youth Counseling	1.75%
Psychological Assessment	1.59%
Residential Alcohol Use Disorder Treatment Facilities	1.31%
Conjoint Counseling	1.19%
Psychiatric Day Treatment	1.14%
Psychiatrist Referrals	1.11%
In Person Crisis Intervention	1.09%
Mental Health Drop In Centers	1.06%
Inpatient Mental Health Facilities	1.04%
Spouse/Intimate Partner Abuse Counseling	1.00%
Mental Health Information/Education	0.97%
Child Guidance	0.96%
Inpatient Substance Use Disorder Treatment Facilities	0.95%
Adult Residential Treatment Facilities	0.94%
General Crisis Intervention Hotlines	0.88%
Non-Medically Assisted Alcohol Detoxification	0.82%
Comprehensive Outpatient Drug Use Disorder Treatment	0.81%
Psychiatric Case Management	0.68%

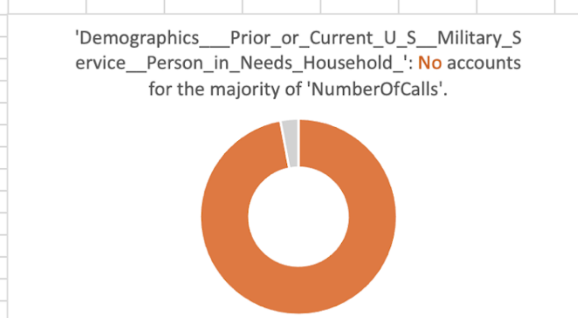


Appendix IV: Number of calls of ‘Level 2 Codes’ by Date



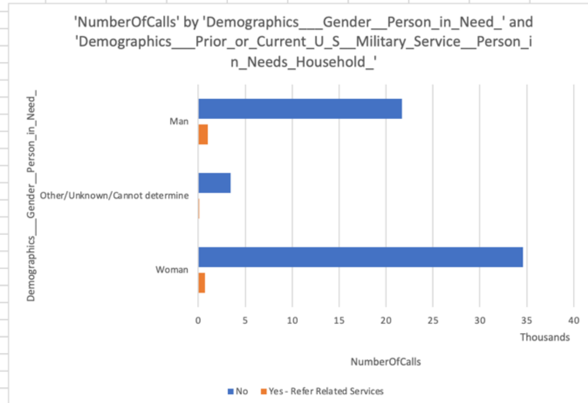
Appendix V: Number of Calls by “Demographics_Prior_or_Current_U_S_Military_Service_Person_in_Needs_Household”

Demographics__Gender__Person_in_Need_	(All)
Row Labels	**Sum of NumberOfCalls**
No	59729
Yes - Refer Related Services	1809
Grand Total	**61538**



Appendix VI: Number of Calls of ‘Demographics_Prior_or_Current_U_S_Military_Service_Person_in_Needs_Household’ by gender

Sum of NumberOfCalls	Column Labels		
Row Labels	No	Yes - Refer Related Services	Grand Total
Man	21702	1020	22722
Other/Unknown/Cannot determine	3410	84	3494
Woman	34617	705	35322
Grand Total	**59729**	**1809**	**61538**



Appendix VII: Mental Health Calls by “Language”, “Gender”, and “With Current or Prior Military History by Gender”