# **Fyttlyf Data Science Team Test Solution**

# Part 0: Reading the data

In [1]:

```
# import the needed libraries
import pandas as pd

In [2]:

data_path = 'Fytlyff_DS_Interview.csv'

# read the dataset as a DataFrame
dataset = pd.read_csv(data_path)

dataset.head() # show the first 5 rows from our dataset

Out[2]:
```

Y	ear	Month	MobileWeb_or_Web	Type_of_Customers?	Where_Are_They_comming_from?	Which_Place_in_India?	How_many_Landed_on_our_Page?	How_many_Landed_on_the_our_Pa
0 2	019	Jan	Desktop_Website	Existing_Customer	Came_From_Google	Bangalore	NaN	
1 2	019	Jan	Desktop_Website	Existing_Customer	Came_From_Google	Chennai	NaN	
2 2	019	Jan	Desktop_Website	Existing_Customer	Came_From_Google	Dehradun	NaN	
3 2	019	Jan	Desktop_Website	Existing_Customer	Came_From_Google	Indore	NaN	
4 2	019	Jan	Desktop_Website	Existing_Customer	Came_From_Google	Pune	NaN	
4								Þ

#### Variables and their description for Fyttlyf DS Interview Test

We see that our data has 2160 rows (cases) and 10 columns (features), The columns, their data type and their description are shown in the table below:

Variable	Туре	Description
Year (A)	Numerical (Discrete)	The year when the customer comming
Month (B)	Categorical (Nominal)	The month when the customer comming
MobileWeb_or_Web (C)	Categorical (Nominal)	The service requested by the customer
Type_of_Customers? (D)	Categorical (Nominal)	The customer status
Where_Are_They_comming_from? (E)	Categorical (Nominal)	The company/organization where the customer comming from
Which_Place_in_India? (F)	Categorical (Nominal)	Customer city
How_many_Landed_on_our_Page? (G)	Numerical (Discrete)	Number of our page visits
How_many_Landed_on_the_our_Page_and_clicked_on_a_button? (H)	Numerical (Discrete)	Number of clicks on a button when landing the page
How_many_Landed_on_the_our_Page_and_clicked_on_a_button_and_started_filling_the_Form? (I)	Numerical (Discrete)	Number of clicks on a button when landing the page and filling the form
How_many_Landed_on_the_our_Page_and_clicked_on_a_button_and_started_filling_the_Form_and_Completed_and_submited_the_form? (J)	Numerical (Discrete)	Number of clicks on a button when landing the page and filling the form and completed and submitted the form

# Part 1: Data cleaning

```
In [3]:
```

```
def data_cleaning(dataframe):
    This function will perform the following:
       1. Replace the NA values with Os in the data
       2. In column 'B' replace Jan with 1, feb with 2, march with 3 and so on...
       3. In column 'E' Replace "Came From Google" with "Google" and "Landed on the page Directly" with "Direct traffic"
    Parameters:
       dataframe (dataFrame): The DataFrame of the dataset we used
       df (dataFrame): The cleaned data frame
   df = dataframe.copy(deep=True) # get a copy of the dataframe
    # renaming columns
   df.columns = ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J']
    # get the columns that have NaN values
   null_series = df.isnull().any() # check if there is any missing across each column
   nan_cols = []  # to save the columns that have nan values
   for col, val in null_series.iteritems():
       if val:
```

```
nan cols.append(col)
# replace the nan values with zeros in the dataset
# Note: (by exploring the data we know that the nan values are only in the numerical data)
for nan_col in nan_cols:
   df[nan_col].fillna(0, inplace=True)
# replace months with numbers
months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
nums = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12]
df['B'] = df['B'].replace(months, nums)
# replace "Came_From_Google" with "Google" and "Landed_on_the_page_Directly" with "Direct_traffic"
old vals = ['Came From Google', 'Landed_on_the_page_Directly']
new_vals = ['Google', 'Direct_traffic']
df['E'] = df['E'].replace(old_vals, new_vals)
df.columns = dataframe.columns
# print(dataframe.columns)
return df
```

#### In [4]:

```
# cleaning_data(dataset)
cleaned_data = data_cleaning(dataset)
cleaned_data.head()
```

#### Out[4]:

Year	Month	MobileWeb_or_Web	Type_of_Customers?	Where_Are_They_comming_from?	Which_Place_in_India?	How_many_Landed_on_our_Page?	How_many_Landed_on_the_our_Pa
<b>0</b> 2019	1	Desktop_Website	Existing_Customer	Google	Bangalore	0.0	
1 2019	1	Desktop_Website	Existing_Customer	Google	Chennai	0.0	
2 2019	1	Desktop_Website	Existing_Customer	Google	Dehradun	0.0	
<b>3</b> 2019	1	Desktop_Website	Existing_Customer	Google	Indore	0.0	
4 2019	1	Desktop_Website	Existing_Customer	Google	Pune	0.0	
4							

# **Part 2: Descriptive statistics**

```
In [5]:
```

```
def descriptive_stats(dataframe):
    Generates the summary statistics (Mean, Median, Quartile, standard deviation)
    of all the numerical columns
    Produce a list of all the unique values & data types present in the non-numeric columns
    Parameters:
       dataframe (dataFrame): The cleaned DataFrame of the dataset we used
        summary_stat (dataFrame): A dataframe contains the summary statistics of the numerical data
        unique_vals (list): A list of all the unique values in the categorical data and their data type
    df = dataframe.copy(deep=True)
                                    # get a copy of the dataframe
    # Generate the summary
    summary_stat = df.describe()
    \# get the unique values of the non-numeric columns
    unique vals = []
    for col, val in df.iteritems():
        if col not in summary stat.columns:
           unique_vals.append([col, df[col].unique()])
    return summary_stat, unique_vals
```

## In [6]:

```
summary_statstics, unique_values = descriptive_stats(cleaned_data)
```

#### In [7]:

```
summary_statstics
```

#### Out[7]:

	Year	Month	How_many_Landed_on_our_Page?	How_many_Landed_on_the_our_Page_and_clicked_on_a_button?	How_many_Landed_on_the_our_Page_and_clicked_on_
count	2160.000000	2160.000000	2.160000e+03	2.160000e+03	
mean	2020.000000	6.500000	3.922474e+05	1.792281e+05	
std	0.816686	3.452852	9.555773e+05	3.951562e+05	
min	2019.000000	1.000000	0.000000e+00	0.000000e+00	
25%	2019.000000	3.750000	0.000000e+00	0.000000e+00	
50%	2020.000000	6.500000	1.228350e+04	4.212500e+03	
75%	2021.000000	9.250000	3.816422e+05	1.730452e+05	
max	2021.000000	12.000000	1.127413e+07	4.079301e+06	

# **Part 3: Prescriptive statistics**

1. "Which\_Place\_in\_India?" has the highest "How\_many\_Landed\_on\_the\_our\_Page?"

```
In [9]:
cond_df = cleaned_data.loc[cleaned_data["How_many_Landed_on_our_Page?"] == cleaned_data["How_many_Landed_on_our_Page?"].max()]
cond_df
Out[9]:
```

Year Month MobileWeb\_or\_Web Type\_of\_Customers? Where\_Are\_They\_comming\_from? Which\_Place\_in\_India? How\_many\_Landed\_on\_our\_Page? How\_many\_Landed\_on\_the\_our\_

```
### Pune

| The place | Content | Co
```

The place in India which has the highest number of page visits is Pune

2.
"How\_many\_Landed\_on\_the\_our\_Page\_and\_clicked\_on\_a\_button\_and\_started\_filling\_the\_Form\_and\_Completed\_and\_submited\_the\_foldivided by "How\_many\_Landed\_on\_our\_Page?" is highest for "Which\_Place\_in\_India?"

Before exploring this values, we know that the "How\_many\_Landed\_on \_our\_Page?" column has 0 values which lead to infinty when finding the percentage of "How\_many\_Landed\_on\_the\_our\_Page\_and\_clicked\_on\_a\_button\_and\_started\_filling\_the\_Form\_and\_Completed\_and\_submitted\_the\_form?" from "How\_many\_Landed\_on \_our\_Page?". Thus, we need to fill 0s with more reasonable value, we can use the mean, the median, mode, KNN or MICE methods to handle these missing values

First we will explore filling data with the mean

```
In [12]:
# renaming columns to make it easier while using
cleaned_data.columns = ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J']
```

```
mean_df = cleaned_data.copy(deep=True)
mean = mean_df['G'].mean()

# change 0s with the mean
mean_df['G'].replace(0, mean, inplace=True)

# get the percentage
mean_df['Percentage_submit_landed'] = mean_df['J'] / mean_df['G']

# mean_df.head()

# # get the rows that have the max percentage
high_percent_rows_mean = mean_df.loc[mean_df['Percentage_submit_landed'] == mean_df['Percentage_submit_landed'].max()]
high_percent_mean = high_percent_rows_mean['Percentage_submit_landed'][high_percent_rows_mean.index[0]] * 100

place_mean = high_percent_rows_mean["F"][high_percent_rows_mean.index[0]]

print(f'{place_mean}) has the highest_percentage_of_submitted_forms_which_is {high_percent_mean}')
```

Dehradun has the highest percentage of submitted forms which is 61.8403568548801

#### Second, We will explore filling data with the median

```
In [14]:

median_df = cleaned_data.copy(deep=True)

median = median_df['G'].median()

if median < median_df['J'].max():</pre>
```

```
else:
    # change 0s with the median value
    median_df['G'].replace(0, median, inplace=True)

# get the percentage
    median_df['Percentage_submit_landed'] = median_df['J'] / median_df['G']

# get the rows that have the max percentage
    high_percent_rows_median = median_df.loc[median_df['Percentage_submit_landed'] == median_df['Percentage_submit_landed'].max()]

# high_percent_rows_median
high_percent_median = high_percent_rows_median['Percentage_submit_landed'][high_percent_rows_median.index[0]] * 100
place_median = high_percent_rows_median["F"][high_percent_rows_median.index[0]]

print(f'{place_median} has the highest_percentage_of_submit_def_orms_which_is_{high_percent_median}')
```

This is not reasonable to have submitted forms greater than the number od visits of the page

By exploring filling the null data in "How\_many\_Landed\_on\_our\_Page?" by the median value, we found that there are some cases who submitted the form but doesn't land on the page (number of submissions > number of visits), which is not reasonable in this case. Thus, we cannot handle this with the median value.

#### Third, We will explore filling data with the mode

```
mode_df = cleaned_data.copy(deep=True)
mode = mode_df['G'].mode()

if mode[0] == 0:
    print("The mode for this feature is 0, It's not useful for handling missing values")

else:
    # change 0s with the median value
    mode_df['G'].replace(0, mode, inplace=True)

# get the percentage
    mode_df['Percentage_submit_landed'] = mode_df['J'] / mode_df['G']

# mode_df.head()

# get the rows that have the max percentage
    high_percent_rows_mode = mode_df.loc[mode_df['Percentage_submit_landed'] == mode_df['Percentage_submit_landed'].max()]

# high_percent_rows_mode
high_percent_mode = high_percent_rows_mode('Percentage_submit_landed')[high_percent_rows_mode.index[0]] * 100
```

The mode for this feature is  $\mathbf{0}$ , It's not useful for handling missing values

place\_mode = high\_percent\_rows\_mode["F"][high\_percent\_rows\_mode.index[0]]

print(f'{place mode} has the highest percentage of submitted forms which is {high percent mode}')

#### Fourth, We will explore filling data using KNN imputer

```
In [16]:
from sklearn.impute import KNNImputer
import numpy as np
```

```
In [17]:
knn_df = cleaned_data.copy(deep=True)
imputer = KNNImputer(missing_values=0, n_neighbors=5)  # initiate the imputer
g = np.array(knn_df['G']).reshape(-1, 1)
df_filled = imputer.fit_transform(g)  # Fill the missing values in G
knn_df['G'] = df_filled

# get the percentage
knn_df['Percentage_submit_landed'] = knn_df['J'] / knn_df['G']

# # get the rows that have the max percentage
high_percent_rows_knn = knn_df.loc[knn_df['Percentage_submit_landed'] == knn_df['Percentage_submit_landed'].max()]
high_percent_knn = high_percent_rows_knn['Percentage_submit_landed'][high_percent_rows_knn.index[0]] * 100
place_knn = high_percent_rows_knn["F"][high_percent_rows_knn.index[0]]
print(f'{place_knn}) has the highest percentage of submitted forms which is {high_percent_knn}')
```

Dehradun has the highest percentage of submitted forms which is 61.8403568548801

We notice that the KNN method gives the same result as when using the mean

### **Part 4: Simple Machine learning questions**

```
In [18]:
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_percentage_error
```

```
In [19]:

def create_date_frame(dataframe):
    date_frame = dataframe.copy(deep=True)

    date_frame['Date'] = pd.to_datetime(date_frame.A.astype(str) + '/' + date_frame.B.astype(str) + '/01')
```

```
date_frame['Time'] = np.arange(len(date_frame.index)) # create time dummies for training
return date_frame
```

#### In [20]:

```
df = cleaned_data.copy(deep=True)
df = create_date_frame(cleaned_data)

X = df.loc[:, 'Time'].to_numpy() # x_train
y = df.loc[:, 'J'].to_numpy() # y_train

df.head()
```

#### Out[20]:

	A	В	С	D	E	F	G	Н	1	J	Date	Time
0	2019	1	Desktop_Website	Existing_Customer	Google	Bangalore	0.0	0.0	56892	17178	2019-01-01	0
1	2019	1	Desktop_Website	Existing_Customer	Google	Chennai	0.0	0.0	41460	11916	2019-01-01	1
2	2019	1	Desktop_Website	Existing_Customer	Google	Dehradun	0.0	0.0	55561	19461	2019-01-01	2
3	2019	1	Desktop_Website	Existing_Customer	Google	Indore	0.0	0.0	320923	110667	2019-01-01	3
4	2019	1	Desktop_Website	Existing_Customer	Google	Pune	0.0	0.0	220937	46033	2019-01-01	4

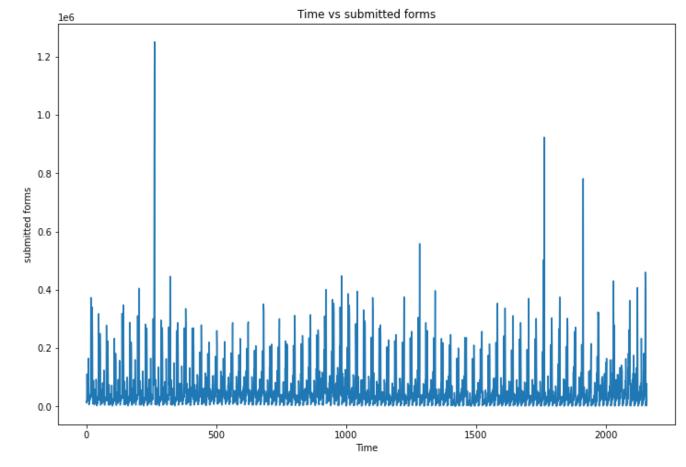
#### In [21]:

```
import matplotlib.pyplot as plt

fig = plt.figure(figsize=(12, 8))

plt.plot(X, y)

# Set the title
plt.title("Time vs submitted forms")
# Set the y-axis label
plt.ylabel('submitted forms')
# Set the x-axis label
plt.xlabel('Time')
plt.show()
```



#### In [23]:

```
def pred_future(X_train, y_train):
    Predicts "How_many_Landed_on_the_our_Page_and_clicked_on_a_button_and_started_filling_the_Form_and_Completed_and_submited_the_
form?"
    for the complete year of 2022
    and generates the overall MAPE of your prediction for the year 2021.
    linear_model = LinearRegression()
    linear_model.fit(X_train.reshape(-1,1), y_train)
    b = linear_model.intercept_
    w = linear_model.coef_
    # predictions for 2022
    x_{test_2022} = np.arange(2160, 2880)
    y_pred_2022 = linear_model.predict(x_test_2022.reshape(-1,1))
    # predictions for 2021
    x test 2021 = X train[1439:]
    y_pred_2021 = linear_model.predict(x_test_2021.reshape(-1,1))
    mape_2021 = mean_absolute_percentage_error(y_train[1439:], y_pred_2021)
    return y pred 2022, mape 2021
y_pred_2022, mape_2021 = pred_future(X, y)
```

print(f'predictions for the complete year 2022:\n {y\_pred\_2022}')
print(f'MAPE of 2021 predictions: {MAPE}')

```
predictions for the complete year 2022:
 [58005.47020183 58004.34496258 58003.21972334 58002.0944841
 58000.96924485 57999.84400561 57998.71876637 57997.59352713
 57996.46828788 57995.34304864 57994.2178094 57993.09257015
 57991.96733091 57990.84209167 57989.71685243 57988.59161318
 57987.46637394 57986.3411347 57985.21589545 57984.09065621
 57982.96541697 57981.84017773 57980.71493848 57979.58969924
               57977.33922075 57976.21398151 57975.08874227
 57973.96350303 57972.83826378 57971.71302454 57970.5877853
 57969.46254605 57968.33730681 57967.21206757 57966.08682833
 57964.96158908 57963.83634984 57962.7111106 57961.58587135
 57960.46063211 57959.33539287 57958.21015363 57957.08491438
 57955.95967514 57954.8344359 57953.70919666 57952.58395741
 57951.45871817 57950.33347893 57949.20823968 57948.08300044
 57946.9577612 57945.83252196 57944.70728271 57943.58204347
 57942.45680423 57941.33156498 57940.20632574 57939.0810865
 57937.95584726 57936.83060801 57935.70536877 57934.58012953
 57933.45489028 57932.32965104 57931.2044118 57930.07917256
 57928.95393331 57927.82869407 57926.70345483 57925.57821558
57924.45297634 57923.3277371 57922.20249786 57921.07725861
 57919.95201937 57918.82678013 57917.70154088 57916.57630164
 57915.4510624 57914.32582316 57913.20058391 57912.07534467
 57910.95010543 57909.82486618 57908.69962694 57907.5743877
 57906.44914846 57905.32390921 57904.19866997 57903.07343073
 57901.94819148 57900.82295224 57899.697713 57898.57247376
57897.44723451 57896.32199527 57895.19675603 57894.07151679
 57892.94627754 57891.8210383 57890.69579906 57889.57055981
 57888.44532057 57887.32008133 57886.19484209 57885.06960284
 57883.9443636 57882.81912436 57881.69388511 57880.56864587
 57879.44340663 57878.31816739 57877.19292814 57876.0676889
 57874.94244966 57873.81721041 57872.69197117 57871.56673193
 57870.44149269 57869.31625344 57868.1910142 57867.06577496
 57865.94053571 57864.81529647 57863.69005723 57862.56481799
 57861.43957874 57860.3143395 57859.18910026 57858.06386101
 57856.93862177 57855.81338253 57854.68814329 57853.56290404
 57852.4376648 57851.31242556 57850.18718631 57849.06194707
 57847.93670783 57846.81146859 57845.68622934 57844.5609901
 57843.43575086 57842.31051161 57841.18527237 57840.06003313
 57838.93479389 57837.80955464 57836.6843154 57835.55907616
 57834.43383692 57833.30859767 57832.18335843 57831.05811919
 57829.93287994 57828.8076407 57827.68240146 57826.55716222
 57825.43192297 57824.30668373 57823.18144449 57822.05620524
 57820.930966 57819.80572676 57818.68048752 57817.55524827
 57816.43000903 57815.30476979 57814.17953054 57813.0542913
57811.92905206 57810.80381282 57809.67857357 57808.55333433
 57807.42809509 57806.30285584 57805.1776166 57804.05237736
 57802.92713812 57801.80189887 57800.67665963 57799.55142039
 57798.42618114 57797.3009419 57796.17570266 57795.05046342
 57793.92522417 57792.79998493 57791.67474569 57790.54950644
 57789.4242672 57788.29902796 57787.17378872 57786.04854947
 57784.92331023 57783.79807099 57782.67283174 57781.5475925
 57780.42235326 57779.29711402 57778.17187477 57777.04663553
 57775.92139629 57774.79615704 57773.6709178 57772.54567856
 57771.42043932 57770.29520007 57769.16996083 57768.04472159
 57766.91948235 57765.7942431 57764.66900386 57763.54376462
 57762.41852537 57761.29328613 57760.16804689 57759.04280765
 57757.9175684 57756.79232916 57755.66708992 57754.54185067
 57753.41661143 57752.29137219 57751.16613295 57750.0408937
 57748.91565446 57747.79041522 57746.66517597 57745.53993673
 57744.41469749 57743.28945825 57742.164219 57741.03897976
 57739.91374052 57738.78850127 57737.66326203 57736.53802279
 57735.41278355 57734.2875443 57733.16230506 57732.03706582
 57730.91182657 57729.78658733 57728.66134809 57727.53610885
 57726.4108696 57725.28563036 57724.16039112 57723.03515187
 57721.90991263 57720.78467339 57719.65943415 57718.5341949
 57717.40895566 57716.28371642 57715.15847717 57714.03323793
 57712.90799869 57711.78275945 57710.6575202 57709.53228096
 57708.40704172 57707.28180248 57706.15656323 57705.03132399
 57703.90608475 57702.7808455 57701.65560626 57700.53036702
57699.40512778 57698.27988853 57697.15464929 57696.02941005
 57694.9041708 57693.77893156 57692.65369232 57691.52845308
 57690.40321383 57689.27797459 57688.15273535 57687.0274961
 57685.90225686 57684.77701762 57683.65177838 57682.52653913
 57681.40129989 57680.27606065 57679.1508214 57678.02558216
 57676.90034292 57675.77510368 57674.64986443 57673.52462519
 57672.39938595 57671.2741467 57670.14890746 57669.02366822
 57667.89842898 57666.77318973 57665.64795049 57664.52271125
 57663.397472
               57662.27223276 57661.14699352 57660.02175428
 57658.89651503 57657.77127579 57656.64603655 57655.5207973
 57654.39555806 57653.27031882 57652.14507958 57651.01984033
57649.89460109 57648.76936185 57647.64412261 57646.51888336
 57645.39364412 57644.26840488 57643.14316563 57642.01792639
 57640.89268715 57639.76744791 57638.64220866 57637.51696942
 57636.39173018 57635.26649093 57634.14125169 57633.01601245
 57631.89077321 57630.76553396 57629.64029472 57628.51505548
 57627.38981623 57626.26457699 57625.13933775 57624.01409851
 57622.88885926 57621.76362002 57620.63838078 57619.51314153
 57618.38790229 57617.26266305 57616.13742381 57615.01218456
57613.88694532 57612.76170608 57611.63646683 57610.51122759
 57609.38598835 57608.26074911 57607.13550986 57606.01027062
 57604.88503138 57603.75979213 57602.63455289 57601.50931365
 57600.38407441 57599.25883516 57598.13359592 57597.00835668
 57595.88311743 57594.75787819 57593.63263895 57592.50739971
57591.38216046 57590.25692122 57589.13168198 57588.00644274
57586.88120349 57585.75596425 57584.63072501 57583.50548576
 57582.38024652 57581.25500728 57580.12976804 57579.00452879
 57577.87928955 57576.75405031 57575.62881106 57574.50357182
57573.37833258 57572.25309334 57571.12785409 57570.00261485
 57560 07737561 57567 75013636 57566 60600710 57565 50165700
```

```
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57478.85823618 57477.73299694 57476.60775769 57475.48251845
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 57460.8544083 57459.72916905 57458.60392981 57457.47869057
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57451.85249435 57450.72725511 57449.60201587 57448.47677662
57447.35153738 57446.22629814 57445.1010589 57443.97581965
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57438.34962344 57437.2243842 57436.09914495 57434.97390571
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 57429.3477095 57428.22247025 57427.09723101 57425.97199177
57424.84675252 57423.72151328 57422.59627404 57421.4710348
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57249.30943064 57248.1841914 57247.05895216 57245.93371291
 57244.80847367 57243.68323443 57242.55799519 57241.43275594
 57240.3075167 57239.18227746 57238.05703821 57236.93179897
 57235.80655973 57234.68132049 57233.55608124 57232.430842
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57226.80464579 57225.67940654 57224.5541673 57223.42892806
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 57217.80273184 57216.6774926 57215.55225336 57214.42701412
 57213.30177487 57212.17653563 57211.05129639 57209.92605714
 57208.8008179 57207.67557866 57206.55033942 57205.42510017
57204.29986093 57203.17462169 57202.04938244 57200.9241432
57199.79890396 57198.67366472 57197.54842547 57196.42318623]
                                         Traceback (most recent call last)
NameError
Input In [23], in <cell line: 27>()
     24 y pred 2022, mape 2021 = pred future(X, y)
     26 print(f'predictions for the complete year 2022:\n {y pred 2022}')
---> 27 print(f'MAPE of 2021 predictions: {MAPE}')
```

J1300.01131301 J1301.13213030 J1300.02009112 J1303.30103100

# **Part 5: Visualization**

NameError: name 'MAPE' is not defined

A line graph for "How\_many\_Landed\_on\_the\_our\_Page\_and\_clicked\_on\_a\_button?" for the different "Which\_Place\_in\_India?" over the months of the year 2019 & 2020.

(Hint: On x axis there should be months for 2019 & 2020 and Y axis should be the "How\_many\_Landed\_on\_the\_our\_Page\_and\_clicked\_on\_a\_button?" and there should different lines depicting different regions of "Which\_Place\_in\_India?")

# In [24]: vis\_df = cleaned\_data.copy(deep=True) months\_2019\_2020 = vis\_df[(vis\_df['A'] == 2019) | (vis\_df['A'] == 2020)] # get 2019 and 2020 from data months\_2019\_2020.head()

Out[24]:

```
A B
                                                           G H
                       C
0 2019 1 Desktop_Website Existing_Customer Google Bangalore 0.0 0.0
                                                                   56892
                                                                           17178
1 2019 1 Desktop_Website Existing_Customer Google
                                                   Chennai 0.0 0.0 41460
                                                                           11916
2 2019 1 Desktop_Website Existing_Customer Google Dehradun 0.0 0.0 55561
                                                                           19461
                                                     Indore 0.0 0.0 320923 110667
3 2019 1 Desktop_Website Existing_Customer Google
4 2019 1 Desktop_Website Existing_Customer Google
                                                      Pune 0.0 0.0 220937
                                                                           46033
```

From the unique values, we know that we have 5 different places in indea: 'Bangalore', 'Chennai', 'Dehradun', 'Indore', 'Pune', do we will make a dataframe for each for ease use

```
In [25]:
```

```
Bangalore = months_2019_2020[months_2019_2020['F'] == 'Bangalore']
Bangalore = create_date_frame(Bangalore)

Chennai = months_2019_2020[months_2019_2020['F'] == 'Chennai']
Chennai = create_date_frame(Chennai)

Dehradun = months_2019_2020[months_2019_2020['F'] == 'Dehradun']
Dehradun = create_date_frame(Dehradun)

Indore = months_2019_2020[months_2019_2020['F'] == 'Indore']
Indore = create_date_frame(Indore)

Pune = months_2019_2020[months_2019_2020['F'] == 'Pune']
Pune = create_date_frame(Pune)
```

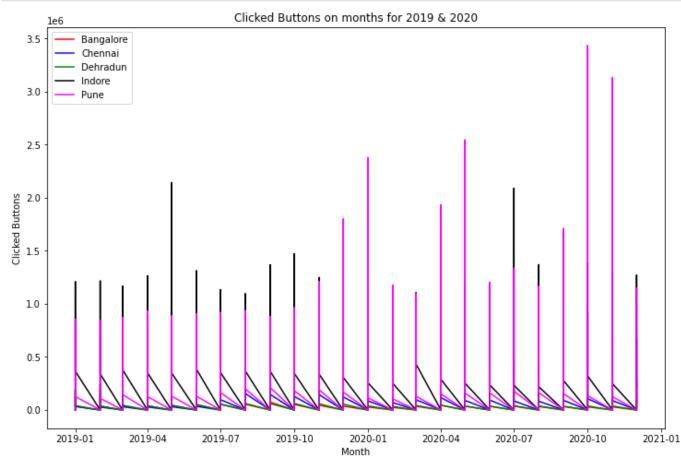
#### In [26]:

```
fig = plt.figure(figsize=(12, 8))

plt.plot(Bangalore['Date'], Bangalore['H'], color='red', label='Bangalore')
plt.plot(Chennai['Date'], Chennai['H'], color='blue', label='Chennai')
plt.plot(Dehradun['Date'], Dehradun['H'], color='green', label='Dehradun')
plt.plot(Indore['Date'], Indore['H'], color='black', label='Indore')
plt.plot(Pune['Date'], Pune['H'], color='magenta', label='Pune')

plt.title('Clicked Buttons on months for 2019 & 2020')
plt.xlabel('Month')
plt.ylabel('Clicked Buttons')

plt.legend()
plt.show()
```



A line graph of the actual and projected number of

"How\_many\_Landed\_on\_the\_our\_Page\_and\_clicked\_on\_a\_button\_and\_started\_filling\_the\_Form\_and\_Completed\_and\_submited\_the\_form?" for the months of the year 2021(Actuals values) & 2022 (Predicted values). (Hint: It should be a line graph)

```
In [27]:
```

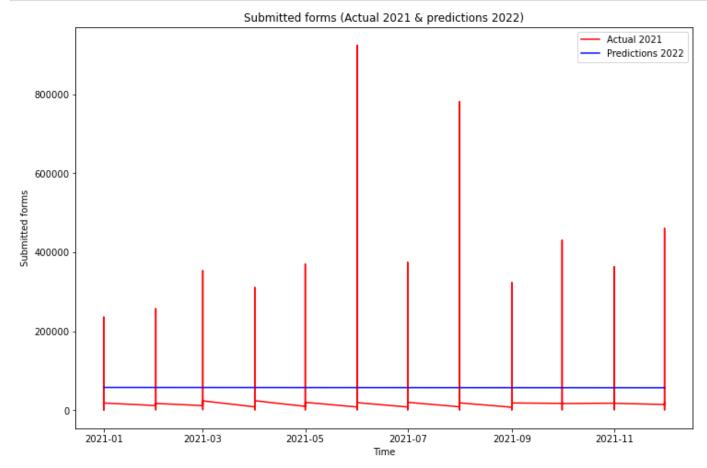
```
fig = plt.figure(figsize=(12, 8))
```

```
actual_2021 = y[1440:]
plt.plot(df.loc[1440:, 'Date'], actual_2021, color='red', label='Actual 2021')

predicted_2022 = y_pred_2022
plt.plot(df.loc[1440:, 'Date'], predicted_2022, color='blue', label='Predictions 2022')

plt.title('Submitted forms (Actual 2021 & predictions 2022)')
plt.xlabel('Time')
plt.ylabel('Submitted forms')

plt.legend()
plt.show()
```



# Part 6: About the previous projects

1. Investigating Netflix Movies and Guest Stars in The Office Project

This project is just for data analysis. In this project, We invistigated Netflix Movies to get insights about the duration of the movies. We appplied EDA on two categories:

- 1. On friend's data: given the average duartions movie during the period from 2011 to 2020.
- 2. On a dataset for Netflix that contains large samples of the movies, tv shows, ...etc. during the period from 1925 to 2021, and of different genres.

We also gained experience in Exploratory Data Analysis, allowing us to manipulate raw data, "Netflix data", and draw conclusions based on the visualizations of the data we created.

GitHub: https://github.com/raniaelhagin/Data-Analysis-Projects-and-Excercises-/tree/main/Investigating Netflix Movies and Guest Stars in The Office

1. Dr.Semmelweis and the Discovery of Handwashing

Also this project was in data analysis. This project is about reanalyzing the data behind one of the most important discoveries of modern medicine, handwashing, and how it was a major cause of childbed fever and by enforcing handwashing, hundreds of lives were saved.

This project have many topics such as Case Studying, Data Manipulation, Data Visualization, Probability and Statistics.

GitHub: <a href="https://github.com/raniaelhagin/Data-Analysis-Projects-and-Excercises-/tree/main/Dr">https://github.com/raniaelhagin/Data-Analysis-Projects-and-Excercises-/tree/main/Dr</a>. Semmelweis and the Discovery of Handwashing

1. Prediction using supervised ML

This project was about using linear regression to predict student scores based on their study hours. I used linear regression using a from scratch approach and in another solution I used Scikit-learn. I explored the data and get the relationship between the features. And this project was in The Sparks Foudation Internship, I also will do more projects with them as soon as possible.

 ${\bf Git Hub:} \ \underline{https://github.com/raniaelhagin/Data-Science-and-Business-analytics-Internship-TSF-GRIP/tree/main/Projects}$ 

# Part 7: Time management

If I get selected in this full-time internship, I will try to manage my time as I have a job in company. Usually I work all the day but if I have a task I will give it more concentration in time, I mean I concentrate in the task all the time I have until I finish my work. I can spend over 10 hours working on a task. always taking notes and define the problem I work on save a lot of time and help me manage my thought. So, taking time at the first for taking notes, define our problem, and have an initial thought about how I will manage and prioritize tasks, and be aware of the deadlines to get the solutions save me a lot of time and organize my work.