WhatPulse Keypress Stats Analyzer

By Kenneth Burchfiel

(I am not affiliated with WhatPulse (https://whatpulse.org) but highly recommend trying out the program, which I've used since September 2008. You can find my online WhatPulse page here: https://whatpulse.org/KBurchfiel)

This script allows you to perform various analyses of your WhatPulse typing stats. It does so by accessing the local WhatPulse database on your computer (along with other copies of databases you might want to include); reading this data into Pandas DataFrames, and then summarizing and graphing that data. The output of the script includes:

1. Rolling average calculations at the 7-, 28-, and 365-day level
2. Percentile and rank calculations
3. Weekly and hourly keypress stats
4. Static (.png) and interactive (.html) keypress charts

By converting this notebook into a Python file and then instructing your computer to run it on an hourly basis, you can also keep track of how much you're typing during your day. Which is sort of nerdy, to be honest. But so is this whole program ;)

I'll first import a number of packages that the program will use:

In [ ]:
```
import time
start_time = time.time() # Allows the program's runtime to be measured
import pandas as pd
import sqlalchemy
import numpy as np
from datetime import date
import statsmodels.api as sm
from scipy.stats import percentileofscore
import plotly.express as px
import kaleido
from IPython.display import Image
import datetime
```

I'll next define the names of folders that will store various outputs, along with default settings to use when converting interactive charts to static .png files:

In [ ]:
```
static_graphs_folder = 'graphs/static/'
interactive_graphs_folder = 'graphs/interactive/'
data_folder = 'data'

default_image_height = 540
default_aspect_ratio = 16 / 9 # Standard HD/UHD aspect ratio
default_image_width = default_image_height * default_aspect_ratio
```

```
default_image_scale = 5 # Creating a smaller graph (e.g. one 540 pixels
# in height) and then scaling it helps keep the text a bit larger.
```

Importing Whatpulse data

In order to analyze my WhatPulse data, I'll first need to import it from my local Whatpulse SQLite database. I'll also import a copy of the Whatpulse SQLite database stored on my old laptop (so that my analysis doesn't have to be limited to my current computer's keypress data.)

You'll of course need to update the following cell with the path(s) to your own WhatPulse database(s).

Note: if you want to run this program on your own, but don't have access to a WhatPulse database, you can still run this program (assuming you've downloaded or cloned it from GitHub). Skip ahead to the line where I read in

In [ ]:
```
database_paths_list = ['C:/Users/kburc/AppData/Local/whatpulse/whatpulse.db',
'C:/Users/kburc/D1V1/Documents/whatpulse_database_backups/a13r2_whatpulse.db',
'G:/My Drive/whatpulse_database_backups/linux_whatpulse.db']
# Note that the first path is to my computer's active database,
# whereas additional paths point towards copies of databases from
# other computers that I have used.
```

The following function analyzes each database's table at either the daily or hourly level.

In [ ]:
```
def generate_keypress_totals(database_path, level = 'daily'):
    '''The level argument can be 'daily', in which case the DataFrame
    returned by the function will show daily keypress totals, or 'hourly',
    which will preserve the hourly keypress totals in the original database.'''
    file_name = database_path.split('/')[-1] # Retrieves the final element
    # of the path (e.g. the file name)
    sqlalchemy_sqlite_engine = sqlalchemy.create_engine(
        'sqlite:///'+database_path)
    # Based on https://docs.sqlalchemy.org/en/13/dialects/sqlite.html#connect-strings
    sqlalchemy_connection = sqlalchemy_sqlite_engine.connect()
    df_keypresses = pd.read_sql("select * from keypresses",
    con = sqlalchemy_sqlite_engine) # Simply reads all of the data from this
    # Capitalizing column names so that less renaming will be necessary
    # when creating graphs:
    df_keypresses.columns = [column.title() for column in df_keypresses.columns]

    # table into a Pandas DataFrame
    df_keypresses = df_keypresses.query("Day != '0000-00-00'").copy() # Removes
    # this blank date value from the database if it happens to be there
    if level == 'daily': # In this case, we'll want to combine hourly keypress
        # totals into a single row for each day
        df_keypresses = df_keypresses.pivot_table(
            index = 'Day', values = 'Count', aggfunc = 'sum')
        df_keypresses.sort_values('Day', inplace = True)
    elif level == 'hourly': # The original data is already displayed
        # at the hourly level, so there's no need for a pivot_table() call.
        df_keypresses.sort_values(['Day', 'Hour'], inplace = True)
    else:
        raise ValueError("Unrecognized level argument passed to function.")
```

```
    df_keypresses.rename(columns={'Count':'Keypresses'},inplace=True)
    return df_keypresses
```

I'll now run generate_keypress_totals in order to create a record of daily keypresses for both my current database and a copy of a past database. (I'll look at hourly keypress totals later on.)

In [ ]:
```
keypress_databases_list = []

for path in database_paths_list: # This loop creates a DataFrame for
    # each WhatPulse database stored in database_paths_list.
    # print("Now loading:",path)
    keypress_databases_list.append(generate_keypress_totals(
        path, level = 'daily'))

# I'll now combine these tables into a single DataFrame.
df_combined_daily_keypresses = pd.concat(
    [keypress_databases_list[i] for i in range(len(keypress_databases_list))])
df_combined_daily_keypresses.sort_index(inplace=True)

# At this point, my copy of df_combined_daily_keypresses has multiple
# entries for days in which I logged keys on multiple operating systems.
# Therefore, the following line groups these entries into a single row
# for each date.
df_combined_daily_keypresses = df_combined_daily_keypresses.reset_index(
).pivot_table(index = 'Day', values = 'Keypresses', aggfunc = 'sum')
df_combined_daily_keypresses.index = pd.to_datetime(
    df_combined_daily_keypresses.index)

df_combined_daily_keypresses.to_csv('data/df_combined_daily_keypresses.csv')
df_combined_daily_keypresses
```

Out[ ]:

	Keypresses
Day	
2020-09-21	19081
2020-09-22	32771
2020-09-23	32065
2020-09-24	34698
2020-09-25	47038
...	...
2023-06-13	23745
2023-06-14	50339
2023-06-15	45835
2023-06-16	40815
2023-06-17	12570

948 rows × 1 columns

The following line rebuilds df_combined_daily_keypresses using a copy of the DataFrame that got exported to a .csv file earlier on. This cell allows allow you to run this script even if you don't have your own WhatPulse database.

In [ ]:
```
df_combined_daily_keypresses = pd.read_csv(
    'data/df_combined_daily_keypresses.csv', index_col='Day')
# The following line makes the index compatible with
# date operations that the following code block will perform.
df_combined_daily_keypresses.index = pd.to_datetime(
df_combined_daily_keypresses.index)
df_combined_daily_keypresses
```

Out[ ]:

Day	Keypresses
2020-09-21	19081
2020-09-22	32771
2020-09-23	32065
2020-09-24	34698
2020-09-25	47038
...	...
2023-06-13	23745
2023-06-14	50339
2023-06-15	45835
2023-06-16	40815
2023-06-17	12570

948 rows × 1 columns

The following code block fills in the DataFrame with missing dates (e.g. dates in which I did not have any keypresses). I want to add in those missing dates so that I can calculate more accurate rolling keypress averages.

In [ ]:
```
first_date = df_combined_daily_keypresses.index[0]
last_date = df_combined_daily_keypresses.index[-1]
full_date_range = pd.date_range(start=first_date, end = last_date)
# https://pandas.pydata.org/docs/reference/api/pandas.date_range.html
df_combined_daily_keypresses = df_combined_daily_keypresses.reindex(
    full_date_range, fill_value=0)
# See https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.reindex.html

df_combined_daily_keypresses.index.name = 'Date'
df_combined_daily_keypresses.reset_index(inplace=True)
```

Now that I have a more complete daily keypress history, I can begin performing analyses on this data. First, I will use the rolling() function within Pandas to calculate 7-, 28-, and 365-day moving

averages. Next, I will use the Series.rank() function twice to (1) calculate the percentile of each keypress and (2) determine each keypress's rank within the entire DataFrame.

In [ ]:
```
df_combined_daily_keypresses['7_day_ma'] = df_combined_daily_keypresses[
    'Keypresses'].rolling(7).mean()
df_combined_daily_keypresses['28_day_ma'] = df_combined_daily_keypresses[
    'Keypresses'].rolling(28).mean()
# I switched from a 30-day MA to a 28-day MA because my average keypresses vary
# significantly by weekday, meaning that a 30-day average would be skewed by
# the number of Saturdays and Sundays present in the data.
df_combined_daily_keypresses['365_day_ma'] = df_combined_daily_keypresses[
    'Keypresses'].rolling(365).mean()

df_combined_daily_keypresses['percentile'] = 100*df_combined_daily_keypresses[
    'Keypresses'].rank(pct=True)
# The pct=True argument generates percentile values for each keypress value.
df_combined_daily_keypresses['rank'] = df_combined_daily_keypresses[
    'Keypresses'].rank(ascending = False)
# Ascending = False instructs the function to assign the lowest number
# (e.g. 1) to the highest value.
# If two dates are tied, the rank may end in a 0.5. That's why these ranks
# appear as floats but not integers.
df_combined_daily_keypresses
```

Out[ ]:

	Date	Keypresses	7_day_ma	28_day_ma	365_day_ma	percentile	rank
0	2020-09-21	19081	NaN	NaN	NaN	40.30	598.0
1	2020-09-22	32771	NaN	NaN	NaN	67.50	326.0
2	2020-09-23	32065	NaN	NaN	NaN	65.90	342.0
3	2020-09-24	34698	NaN	NaN	NaN	70.55	295.5
4	2020-09-25	47038	NaN	NaN	NaN	88.50	116.0
...	...	...	...	...	...	...	...
995	2023-06-13	23745	18202.571429	24115.464286	20799.172603	48.90	512.0
996	2023-06-14	50339	21198.428571	24620.357143	20934.254795	91.80	83.0
997	2023-06-15	45835	23978.000000	25124.642857	21042.520548	87.40	127.0
998	2023-06-16	40815	29523.142857	25422.285714	21048.158904	80.70	194.0
999	2023-06-17	12570	31318.857143	25237.607143	21033.315068	29.10	710.0

1000 rows × 7 columns

Next, I'll add in weekdays using the Series.map() function within Pandas.

In [ ]:
```
weekday_dict = {0:'Monday',1:'Tuesday',2:'Wednesday',3:'Thursday',4:'Friday',
5:'Saturday',6:'Sunday'}
# weekday numbers in Python begin with 0 for Monday and end with 6 for Sunday.
# See https://docs.python.org/3/library/datetime.html#datetime.date.weekday
weekday_dict
```

Out[ ]:
```
{0: 'Monday',
 1: 'Tuesday',
 2: 'Wednesday',
 3: 'Thursday',
 4: 'Friday',
 5: 'Saturday',
 6: 'Sunday'}
```

The following cell adds a 'Weekday' column to the DataFrame by (1) calculating the numerical weekday values for each date in the 'Date' column, then (2) using weekday_dict to map these numerical values to the weekday names.

In [ ]:
```
df_combined_daily_keypresses['Weekday'] = df_combined_daily_keypresses[
    'Date'].dt.weekday.map(weekday_dict)
```

Here are my daily keypress statistics for the last 10 days. Note the presence of the moving average, percentile, rank, and weekday columns.

In [ ]:
```
df_combined_daily_keypresses.tail(10)
```

Out[ ]:

	Date	Keypresses	7_day_ma	28_day_ma	365_day_ma	percentile	rank	Weekday
990	2023-06-08	26378	26142.714286	24598.321429	20701.928767	54.70	454.0	Thursday
991	2023-06-09	1999	21335.428571	23868.785714	20635.723288	13.30	868.0	Friday
992	2023-06-10	0	20283.428571	23562.821429	20623.246575	2.85	972.5	Saturday
993	2023-06-11	14647	18180.142857	24085.928571	20663.087671	32.20	679.0	Sunday
994	2023-06-12	31281	18811.857143	24450.571429	20748.789041	64.20	359.0	Monday
995	2023-06-13	23745	18202.571429	24115.464286	20799.172603	48.90	512.0	Tuesday
996	2023-06-14	50339	21198.428571	24620.357143	20934.254795	91.80	83.0	Wednesday
997	2023-06-15	45835	23978.000000	25124.642857	21042.520548	87.40	127.0	Thursday
998	2023-06-16	40815	29523.142857	25422.285714	21048.158904	80.70	194.0	Friday
999	2023-06-17	12570	31318.857143	25237.607143	21033.315068	29.10	710.0	Saturday

Data Analysis

I'll start my data analysis by calculating some summary statistics. In the output below, 'count' shows the number of days since the earliest entry in my database, rather than the number of

days for which I have keypress data (as the table also includes days without any keypresses).

In [ ]:
```
df_combined_daily_keypresses['Keypresses'].describe()
```

Out[ ]:
```
count     1000.000000
mean     24788.206000
std      17710.280994
min          0.000000
25%       9326.500000
50%      24362.000000
75%      36859.250000
max      90447.000000
Name: Keypresses, dtype: float64
```

Next, I'll calculate my top 50 daily keypress totals. Note that the top-ranked date has a rank of 1 and a percentile of 100.

In [ ]:
```
df_max_keypresses = df_combined_daily_keypresses.sort_values(
    'Keypresses', ascending = False).reset_index(drop=True)
df_max_keypresses.insert(0, 'Rank', df_max_keypresses.index+1)
keypress_difference_list = [
    df_max_keypresses.iloc[i]['Keypresses'] - df_max_keypresses.iloc[i+1][
        'Keypresses'] for i in range(len(df_max_keypresses) -1 )]
# The above list comprehension calculates the difference
# between each row and the row below it. This isn't possible for the final row,
# so I'll instead append a np.Nan to it.)
keypress_difference_list.append(np.NaN)
df_max_keypresses['difference_from_lower_rank'] = keypress_difference_list
df_max_keypresses.head(50)
```

Out[ ]:

	Rank	Date	Keypresses	7_day_ma	28_day_ma	365_day_ma	percentile	rank	Weekday
0	1	2022-12-05	90447	34728.714286	26518.821429	20476.994521	100.0	1.0	Monday
1	2	2021-02-22	77753	47983.000000	41390.857143	NaN	99.9	2.0	Monday
2	3	2020-11-23	76313	50377.571429	39924.107143	NaN	99.8	3.0	Monday
3	4	2020-11-19	75444	47285.571429	37945.892857	NaN	99.7	4.0	Thursday
4	5	2021-11-09	73788	37843.285714	30462.071429	29584.802740	99.6	5.0	Tuesday
5	6	2022-05-03	72910	30511.428571	28489.285714	24401.624658	99.5	6.0	Tuesday
6	7	2021-02-08	70591	30177.428571	34437.357143	NaN	99.4	7.0	Monday
7	8	2021-04-06	68313	40455.857143	40719.178571	NaN	99.3	8.0	Tuesday
8	9	2021-02-15	67930	46174.571429	40268.535714	NaN	99.2	9.0	Monday
9	10	2020-11-30	67533	20747.428571	36843.714286	NaN	99.1	10.0	Monday
10	11	2021-02-17	67505	45946.571429	40801.607143	NaN	99.0	11.0	Wednesday
11	12	2021-10-12	66517	39971.285714	36729.892857	29886.202740	98.9	12.0	Tuesday
12	13	2021-10-14	65935	46708.142857	37694.500000	30001.038356	98.8	13.0	Thursday
13	14	2021-09-23	65907	33891.142857	27215.107143	30006.980822	98.7	14.0	Thursday
14	15	2021-09-27	65464	35955.714286	29346.285714	29877.052055	98.6	15.0	Monday
15	16	2021-01-25	64903	43493.714286	27181.714286	NaN	98.5	16.0	Monday
16	17	2020-10-01	64873	41882.285714	NaN	NaN	98.4	17.0	Thursday
17	18	2023-05-31	64683	26243.000000	21224.750000	20534.572603	98.3	18.0	Wednesday
18	19	2022-08-22	63149	23130.428571	21345.785714	22784.887671	98.2	19.0	Monday
19	20	2021-10-26	62922	30820.000000	37036.107143	29899.287671	98.1	20.0	Tuesday
20	21	2021-04-07	62668	41278.000000	40999.857143	NaN	98.0	21.0	Wednesday

	Rank	Date	Keypresses	7_day_ma	28_day_ma	365_day_ma	percentile	rank	Weekday
21	22	2022-04-26	62596	31803.714286	29291.607143	23983.284932	97.9	22.0	Tuesday
22	23	2021-02-19	62473	47705.571429	41579.714286	NaN	97.8	23.0	Friday
23	24	2022-05-26	62030	21439.571429	20150.964286	23948.786301	97.7	24.0	Thursday
24	25	2020-12-15	61969	44707.000000	35868.785714	NaN	97.6	25.0	Tuesday
25	26	2020-12-03	61437	36799.571429	36592.642857	NaN	97.5	26.0	Thursday
26	27	2022-04-25	61200	28113.428571	28472.321429	23845.347945	97.4	27.0	Monday
27	28	2022-01-21	60953	38414.857143	17726.821429	27924.994521	97.3	28.0	Friday
28	29	2020-10-08	60890	42957.571429	NaN	NaN	97.2	29.0	Thursday
29	30	2021-09-22	60820	31844.285714	25305.500000	29914.263014	97.1	30.0	Wednesday
30	31	2021-03-25	60758	42687.000000	33748.321429	NaN	97.0	31.0	Thursday
31	32	2022-03-23	60708	18780.428571	12933.750000	24456.224658	96.9	32.0	Wednesday
32	33	2020-11-17	60147	42827.000000	36111.750000	NaN	96.8	33.0	Tuesday
33	34	2021-03-30	59733	44573.285714	36193.071429	NaN	96.7	34.0	Tuesday
34	35	2021-10-05	59511	41257.000000	35278.321429	29834.556164	96.6	35.0	Tuesday
35	36	2021-02-01	58958	41228.428571	35547.750000	NaN	96.5	36.0	Monday
36	37	2021-01-22	58872	32598.142857	23012.785714	NaN	96.4	37.0	Friday
37	38	2021-03-24	58764	37907.142857	32834.714286	NaN	96.3	38.0	Wednesday
38	39	2021-12-06	58253	28883.571429	27414.107143	28866.978082	96.2	39.0	Monday
39	40	2022-01-13	58190	24615.000000	10116.392857	27780.265753	96.1	40.0	Thursday
40	41	2021-10-13	58065	43126.857143	37181.785714	29952.904110	96.0	41.0	Wednesday
41	42	2022-10-13	57914	27980.285714	17756.071429	20765.580822	95.9	42.0	Thursday

	Rank	Date	Keypresses	7_day_ma	28_day_ma	365_day_ma	percentile	rank	Weekday
42	43	2020-11-04	57390	28840.285714	33667.428571	NaN	95.8	43.0	Wednesday
43	44	2021-10-11	57380	38970.428571	36170.892857	29777.947945	95.7	44.0	Monday
44	45	2021-12-14	57328	24989.285714	25229.357143	28616.687671	95.6	45.0	Tuesday
45	46	2021-03-31	56913	44308.857143	38024.535714	NaN	95.5	46.0	Wednesday
46	47	2023-04-10	56877	27932.857143	28698.142857	21789.172603	95.4	47.0	Monday
47	48	2021-03-22	56792	37541.857143	31575.607143	NaN	95.3	48.0	Monday
48	49	2020-11-18	56454	44114.285714	36638.392857	NaN	95.2	49.0	Wednesday
49	50	2021-03-09	56342	22351.428571	35691.178571	NaN	95.1	50.0	Tuesday

Next, I'll create a visualization of these 50 dates. I will use Plotly instead of Matplotlib so that I can create both interactive (.html) and static (.png) versions of each chart. The static versions are easier to share, but the interactive versions are easier to analyze, as you can hover over the chart to get more information and zoom in on areas of particular interest.

First, I'll create a function that will make it easier to save .html and .png versions of these charts:

In [ ]:
```
def save_chart(fig, file_name,
interactive_graphs_folder = interactive_graphs_folder,
static_graphs_folder = static_graphs_folder):
    '''Saves a Plotly figure as a .HTML and .PNG file.
    fig: The Plotly figure to save.
    file_name: The filename to use. Don't include the extension.'''
    fig.write_html(
        interactive_graphs_folder+'/'+file_name+'.html')
    # Saving the interactive chart to a .png file:
    fig.write_image(
        static_graphs_folder+'/'+file_name+'.png',
        width = default_image_width, height = default_image_height,
        scale = default_image_scale)
```

In [ ]:
```
# Generating the interactive chart:
fig_max_keypresses = px.bar(df_max_keypresses.head(50),
x = 'Rank', y = 'Keypresses', title = 'Top 50 Daily Keypress Totals',
text = 'Keypresses')

save_chart(fig_max_keypresses, 'top_50_keypresses')
```

Here's a look at the chart:

Note: this and other .html-based charts will probably not display for you within GitHub. In order to view them, you will need to download the files from GitHub (e.g. by cloning them) and view them

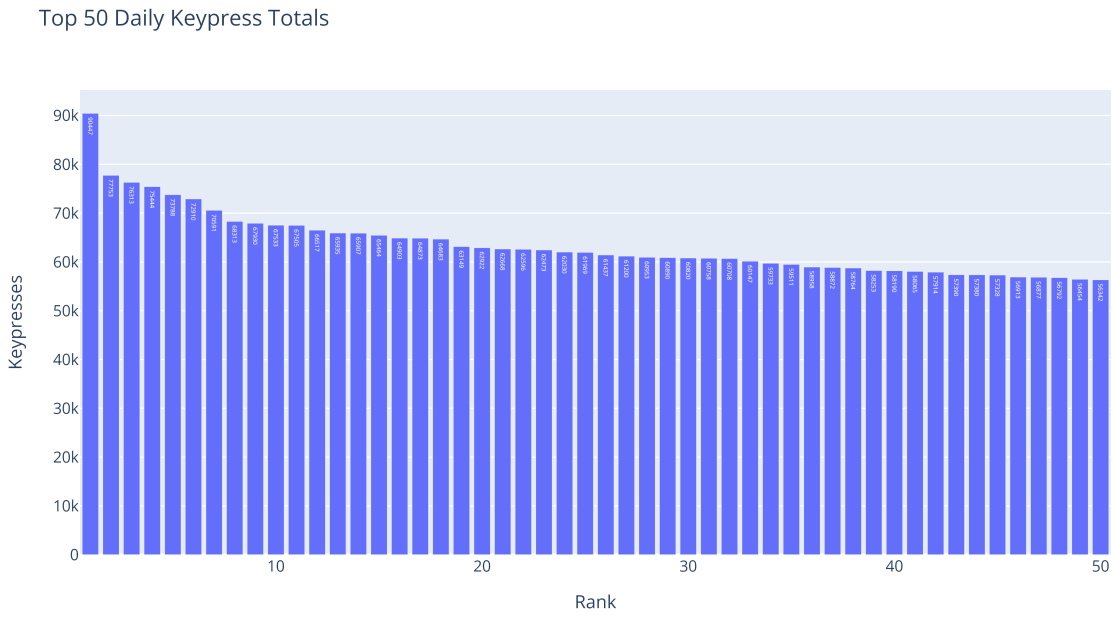
on your computer.

In [ ]:
```
fig_max_keypresses
```

Here's a copy of the static chart in case the .html chart above did not load for you: (I'll also display static versions of later charts as well.)

In [ ]:
```
Image(static_graphs_folder+'top_50_keypresses.png')
```

Out[ ]:



Keypress percentile data:

First, I'll calculate the keypress totals equal to the 90th through 100th percentiles (in 1-percentile increments).

In [ ]:
```
df_combined_daily_keypresses['Keypresses'].describe(
    percentiles=np.linspace(0.9,1,11))[5:-1]
# The first four rows and final row provide additional descriptive statistics,
# so we can get rid of them
# by adding [4:-1] to the end of this line.
# There is probably a more elegant solution that retrieves only percentile
# data, but this option is fairly straightforward.
```

Out[ ]:
```
90%     48630.60
91%     49495.37
92%     50553.12
93%     52561.22
94%     54465.96
95%     56325.85
96%     58070.00
97%     60759.86
98%     62673.08
99%     67505.28
100%    90447.00
Name: Keypresses, dtype: float64
```

Scipy's percentileofscore() function can be used to calculate the percentile corresponding to a specific keypress total. For instance, here's the percentile for a day with only a single keypress: (The percentile may be higher than you'd expect due to the presence of many days with 0 keypresses)

In [ ]:
```
percentileofscore(df_combined_daily_keypresses['Keypresses'], 1)
```

Out[ ]:
```
5.7
```

Next, I'll create a DataFrame showing the keypresses corresponding to every 5th percentile.

In [ ]:
```
df_percentiles = df_combined_daily_keypresses['Keypresses'].describe(
percentiles=np.linspace(0,1,21))[4:-1].reset_index().sort_values(
    'Keypresses', ascending = False).reset_index(drop=True).rename(
        columns={'index':'percentile'})
# Calling reset_index() twice appears inefficient, but it makes it easier
# to sort by a particular value (in this case, keypresses).
keypress_difference_list = [df_percentiles.iloc[
    i, 1] - df_percentiles.iloc[i+1, 1] for i in range(len(df_percentiles) -1 )]
# This list comprehension calculates the difference between each row and
# the row below it. This isn't possible for the final row,
# so we'll instead append a np.Nan to it.)
keypress_difference_list.append(np.NaN)
df_percentiles['difference_from_lower_percentile'] = keypress_difference_list
df_percentiles
```

Out[ ]:

	percentile	Keypresses	difference_from_lower_percentile
0	100%	90447.00	34121.15
1	95%	56325.85	7695.25
2	90%	48630.60	4560.00
3	85%	44070.60	3955.20
4	80%	40115.40	3256.15
5	75%	36859.25	2436.55
6	70%	34422.70	2805.85
7	65%	31616.85	2821.05
8	60%	28795.80	2252.40
9	55%	26543.40	2181.40
10	50%	24362.00	2931.20
11	45%	21430.80	2429.80
12	40%	19001.00	2576.45
13	35%	16424.55	3477.55
14	30%	12947.00	3620.50
15	25%	9326.50	3125.90
16	20%	6200.60	3438.65
17	15%	2761.95	1920.55
18	10%	841.40	841.40
19	5%	0.00	0.00
20	0%	0.00	NaN

The following chart shows the difference in keypresses between the different percentiles on this list.

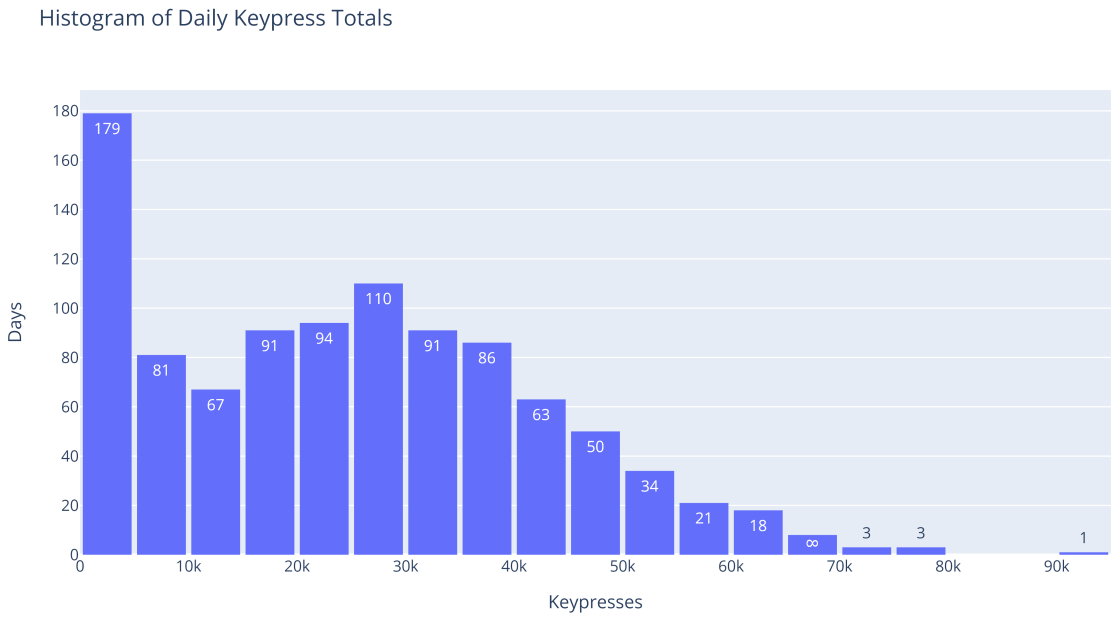
In [ ]:
```
px.bar(df_percentiles, x = 'percentile',
       y = 'difference_from_lower_percentile')
```

And here's a histogram that shows the frequency of different keypress ranges:

In [ ]:
```
fig_keypress_hist = px.histogram(df_combined_daily_keypresses,
x = 'Keypresses', nbins = 40, text_auto = True,
title = 'Histogram of Daily Keypress Totals')
# See https://plotly.com/python/histograms/
fig_keypress_hist.update_layout(bargap=0.1, yaxis_title = 'Days')
# https://plotly.com/python/histograms/
save_chart(fig_keypress_hist, 'daily_keypress_histogram')
fig_keypress_hist
```

In [ ]:
```
Image(static_graphs_folder+'daily_keypress_histogram.png')
```

Out[ ]:



I'll now create a pivot table that shows my average keypresses per weekday:

In [ ]:
```
df_weekday_pivot = df_combined_daily_keypresses.pivot_table(
    index = 'Weekday', values = 'Keypresses', aggfunc = 'mean').sort_values(
    'Weekday', ascending = False).reset_index()
# Adding in a Weekday_Order column so that
# weekdays can be sorted chronologically:
df_weekday_pivot['Weekday_Order'] = df_weekday_pivot['Weekday'].map(
{'Sunday':0,'Monday':1,"Tuesday":2,"Wednesday":3,
"Thursday":4,"Friday":5,"Saturday":6})
df_weekday_pivot
```

Out[ ]:

	Weekday	Keypresses	Weekday_Order
0	Wednesday	30126.776224	3
1	Tuesday	32195.909091	2
2	Thursday	30975.510490	4
3	Sunday	11266.450704	0
4	Saturday	13845.580420	6
5	Monday	31287.454545	1
6	Friday	23725.202797	5

In [ ]:
```
df_weekday_pivot.sort_values('Weekday_Order', inplace = True)
df_weekday_pivot
```

Out[ ]:

	Weekday	Keypresses	Weekday_Order
3	Sunday	11266.450704	0
5	Monday	31287.454545	1
1	Tuesday	32195.909091	2
0	Wednesday	30126.776224	3
2	Thursday	30975.510490	4
6	Friday	23725.202797	5
4	Saturday	13845.580420	6

Graphing my average keypresses per weekday:

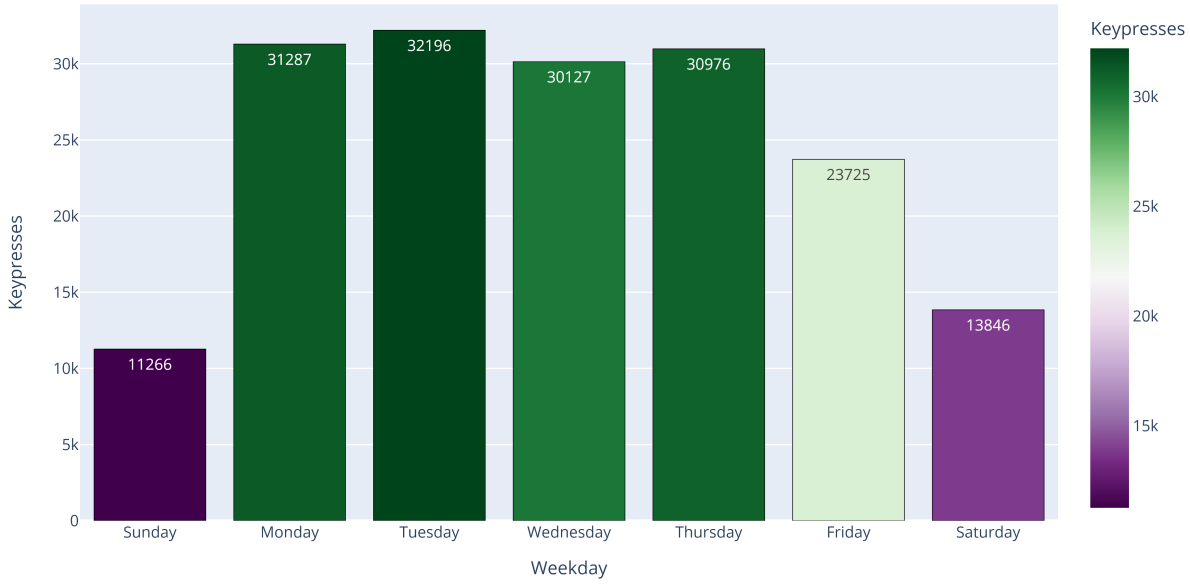
In [ ]:
```
fig_keypresses_by_weekday = px.bar(df_weekday_pivot, x = 'Weekday',
y = 'Keypresses', text_auto = '.0f', color = 'Keypresses',
color_continuous_scale = 'PrGn')
# For text_auto, see:
# https://plotly.com/python-api-reference/generated/plotly.express.bar

# For color scale options and usage,
# visit https://plotly.com/python/builtin-colorscales/
fig_keypresses_by_weekday.update_traces(marker_line_color='rgb(0,0,0)',
                                        marker_line_width=0.5, opacity=1)
fig_keypresses_by_weekday

save_chart(fig_keypresses_by_weekday, file_name = 'keypresses_by_weekday')
```

In [ ]:
```
Image(static_graphs_folder+'keypresses_by_weekday.png')
```

Out[ ]:



Total keypresses since first date in DataFrame:

In [ ]:
```
print("Total keypresess since", str(
df_combined_daily_keypresses.iloc[0]['Date'])+":",'{:,}'.format(
sum(df_combined_daily_keypresses['Keypresses'])))
```

```
Total keypresess since 2020-09-21 00:00:00: 24,788,206
```

Keypresses over the past 50 days:

In [ ]:
```
df_combined_daily_keypresses.tail(50) # Last 50 days
```

Out[ ]:

	Date	Keypresses	7_day_ma	28_day_ma	365_day_ma	percentile	rank	Weekday
950	2023-04-29	86	984.571429	10928.107143	20472.975342	6.60	935.0	Saturday
951	2023-04-30	728	1004.714286	10709.571429	20429.076712	9.70	904.0	Sunday
952	2023-05-01	19015	3704.428571	10657.785714	20459.320548	40.10	600.0	Monday
953	2023-05-02	34457	8225.714286	10572.857143	20446.194521	70.10	300.0	Tuesday
954	2023-05-03	18004	10750.142857	10278.821429	20295.767123	37.70	624.0	Wednesday
955	2023-05-04	37630	16069.000000	10907.857143	20328.997260	76.00	241.0	Thursday
956	2023-05-05	18761	18383.000000	11071.035714	20359.627397	39.40	607.0	Friday
957	2023-05-06	169	18394.857143	10309.500000	20360.090411	7.40	927.0	Saturday
958	2023-05-07	560	18370.857143	9619.500000	20359.041096	9.00	911.0	Sunday
959	2023-05-08	19163	18392.000000	8272.571429	20411.542466	40.40	597.0	Monday
960	2023-05-09	8680	14709.571429	7695.642857	20380.824658	24.30	758.0	Tuesday
961	2023-05-10	11651	13802.000000	7024.892857	20339.323288	27.90	722.0	Wednesday
962	2023-05-11	21576	11508.571429	7114.928571	20352.210959	45.40	547.0	Thursday
963	2023-05-12	22426	12032.142857	7915.857143	20365.186301	46.40	537.0	Friday
964	2023-05-13	8567	13231.857143	8221.464286	20261.473973	24.00	761.0	Saturday
965	2023-05-14	0	13151.857143	8221.464286	20147.783562	2.85	972.5	Sunday
966	2023-05-15	21071	13424.428571	8974.000000	20185.317808	44.20	559.0	Monday
967	2023-05-16	33128	16917.000000	10157.142857	20180.243836	67.80	323.0	Tuesday
968	2023-05-17	36202	20424.285714	11450.071429	20253.912329	73.50	266.0	Wednesday
969	2023-05-18	31715	21872.714286	12581.642857	20339.254795	65.10	350.0	Thursday
970	2023-05-19	32481	23309.142857	13741.678571	20426.805479	67.10	330.0	Friday

	Date	Keypresses	7_day_ma	28_day_ma	365_day_ma	percentile	rank	Weekday
971	2023-05-20	17741	24619.714286	14307.750000	20471.232877	37.20	629.0	Saturday
972	2023-05-21	9439	25968.142857	14623.892857	20486.112329	25.20	749.0	Sunday
973	2023-05-22	28640	27049.428571	15642.571429	20541.139726	59.70	404.0	Monday
974	2023-05-23	34138	27193.714286	16761.500000	20579.046575	69.30	308.0	Tuesday
975	2023-05-24	16854	24429.714286	17351.535714	20552.175342	35.70	644.0	Wednesday
976	2023-05-25	41420	25816.142857	18816.607143	20591.695890	81.70	184.0	Thursday
977	2023-05-26	25947	24882.714286	19651.750000	20492.838356	53.10	470.0	Friday
978	2023-05-27	16401	24691.285714	20234.428571	20441.893151	34.90	652.0	Saturday
979	2023-05-28	0	23342.857143	20208.428571	20404.309589	2.85	972.5	Sunday
980	2023-05-29	1259	19431.285714	19574.285714	20382.767123	11.60	885.0	Monday
981	2023-05-30	33991	19410.285714	19557.642857	20411.580822	68.80	313.0	Tuesday
982	2023-05-31	64683	26243.000000	21224.750000	20534.572603	98.30	18.0	Wednesday
983	2023-06-01	29651	24561.714286	20939.785714	20580.375342	61.50	386.0	Thursday
984	2023-06-02	35650	25947.857143	21542.964286	20603.668493	72.40	277.0	Friday
985	2023-06-03	7364	24656.857143	21799.928571	20558.572603	22.30	778.0	Saturday
986	2023-06-04	29370	28852.571429	22828.857143	20622.049315	61.10	390.0	Sunday
987	2023-06-05	26859	32509.714286	23103.714286	20653.106849	56.10	440.0	Monday
988	2023-06-06	28010	31655.285714	23794.071429	20690.975342	58.40	417.0	Tuesday
989	2023-06-07	29368	26610.285714	24426.821429	20656.701370	61.00	391.0	Wednesday
990	2023-06-08	26378	26142.714286	24598.321429	20701.928767	54.70	454.0	Thursday
991	2023-06-09	1999	21335.428571	23868.785714	20635.723288	13.30	868.0	Friday

	Date	Keypresses	7_day_ma	28_day_ma	365_day_ma	percentile	rank	Weekday
992	2023-06-10	0	20283.428571	23562.821429	20623.246575	2.85	972.5	Saturday
993	2023-06-11	14647	18180.142857	24085.928571	20663.087671	32.20	679.0	Sunday
994	2023-06-12	31281	18811.857143	24450.571429	20748.789041	64.20	359.0	Monday
995	2023-06-13	23745	18202.571429	24115.464286	20799.172603	48.90	512.0	Tuesday
996	2023-06-14	50339	21198.428571	24620.357143	20934.254795	91.80	83.0	Wednesday
997	2023-06-15	45835	23978.000000	25124.642857	21042.520548	87.40	127.0	Thursday
998	2023-06-16	40815	29523.142857	25422.285714	21048.158904	80.70	194.0	Friday
999	2023-06-17	12570	31318.857143	25237.607143	21033.315068	29.10	710.0	Saturday

The following cell outputs various keypress statistics. When this script is run hourly, these statistics (along with other ones) will then appear in the console terminal.

In [ ]:
```
days_with_data = len(df_combined_daily_keypresses)
#  The following column cell shows the ranks immediately above the ranks for the most
keypresses_today = df_combined_daily_keypresses.iloc[-1]['Keypresses']
percentile_today = df_combined_daily_keypresses.iloc[-1]['percentile']
rank_today = df_combined_daily_keypresses.iloc[-1]['rank']
print("Ranks are out of", days_with_data, "days.")
print(f"Today's keypresses: {keypresses_today}")
print(f"Your keypress totals yesterday and 7, 28, and 365 days ago were \
{df_combined_daily_keypresses.iloc[-2]['Keypresses']}, \
{df_combined_daily_keypresses.iloc[-8]['Keypresses']}, \
{df_combined_daily_keypresses.iloc[-29]['Keypresses']}, \
and {df_combined_daily_keypresses.iloc[-366]['Keypresses']}, respectively.")
# If your keypresses today are higher than these values, the moving averages
# associated with those values will increase.
print(f"Today's percentile: {round(percentile_today, 3)}")
print(f"Today's rank: {rank_today} \
(in front of {days_with_data - rank_today} days)")
```

```
Ranks are out of 1000 days.
Today's keypresses: 12570
Your keypress totals yesterday and 7, 28, and 365 days ago were 40815, 0, 17741, and
17988, respectively.
Today's percentile: 29.1
Today's rank: 710.0 (in front of 290.0 days)
```

Days ranked just ahead of today (along with today's rank):

In [ ]:
```
df_days_with_higher_keypresses = df_combined_daily_keypresses.sort_values(
    'rank').query("rank <= @rank_today").tail(11)
keypress_difference_list = [df_days_with_higher_keypresses.iloc[i][
    'Keypresses'] - df_days_with_higher_keypresses.iloc[i+1][
```

```
        'Keypresses'] for i in range(len(df_days_with_higher_keypresses) -1 )]
keypress_difference_list.append(np.NaN)
df_days_with_higher_keypresses[
    'diff_from_following_day'] = keypress_difference_list
df_days_with_higher_keypresses[
    'diff_from_current_day'] = df_days_with_higher_keypresses[
        'Keypresses'] - df_days_with_higher_keypresses.iloc[-1]['Keypresses']
df_days_with_higher_keypresses
```

Out[ ]:

	Date	Keypresses	7_day_ma	28_day_ma	365_day_ma	percentile	rank	Weekday	diff_
851	2023-01-20	12953	17091.571429	17403.571429	20840.136986	30.1	700.0	Friday	
618	2022-06-01	12933	25152.000000	17662.892857	23916.726027	30.0	701.0	Wednesday	
98	2020-12-28	12929	6217.000000	29041.071429	NaN	29.9	702.0	Monday	
173	2021-03-13	12911	38597.142857	35099.107143	NaN	29.8	703.0	Saturday	
693	2022-08-15	12865	16522.857143	22526.535714	22779.410959	29.7	704.0	Monday	
160	2021-02-28	12830	33836.285714	38871.571429	NaN	29.6	705.0	Sunday	
572	2022-04-16	12806	30994.857143	29207.714286	23930.865753	29.5	706.0	Saturday	
214	2021-04-23	12724	31193.857143	35058.035714	NaN	29.4	707.0	Friday	
762	2022-10-23	12601	22229.285714	20244.000000	20422.243836	29.3	708.0	Sunday	
819	2022-12-19	12590	26520.000000	29879.928571	20578.797260	29.2	709.0	Monday	
999	2023-06-17	12570	31318.857143	25237.607143	21033.315068	29.1	710.0	Saturday	

Looking for days with identical non-zero keypress totals:

In [ ]:
```
duplicated_keypress_dates = df_combined_daily_keypresses[
df_combined_daily_keypresses.duplicated(
subset = 'Keypresses', keep = False)].query('Keypresses > 0').sort_values(
'Keypresses', ascending = False)
len(duplicated_keypress_dates)
```

Out[ ]:
```
16
```

In [ ]:
```
duplicated_keypress_dates
```

Out[ ]:

	Date	Keypresses	7_day_ma	28_day_ma	365_day_ma	percentile	rank	Weekday
32	2020-10-23	48908	41125.571429	37996.178571	NaN	90.35	97.5	Friday
183	2021-03-23	48908	36708.000000	32516.464286	NaN	90.35	97.5	Tuesday
3	2020-09-24	34698	NaN	NaN	NaN	70.55	295.5	Thursday
124	2021-01-23	34698	34726.428571	24214.178571	NaN	70.55	295.5	Saturday
318	2021-08-05	32184	29066.857143	29787.500000	NaN	66.35	337.5	Thursday
676	2022-07-29	32184	26384.571429	26299.000000	23180.561644	66.35	337.5	Friday
687	2022-08-09	26905	21784.571429	25372.785714	22972.580822	56.25	438.5	Tuesday
765	2022-10-26	26905	25745.714286	20627.357143	20359.476712	56.25	438.5	Wednesday
55	2020-11-15	26550	36325.285714	35269.428571	NaN	55.15	449.5	Sunday
645	2022-06-28	26550	12407.857143	12670.821429	23373.895890	55.15	449.5	Tuesday
662	2022-07-15	25084	28583.714286	18304.428571	23319.049315	51.45	486.5	Friday
841	2023-01-10	25084	16131.571429	16824.607143	21120.632877	51.45	486.5	Tuesday
321	2021-08-08	6318	30379.714286	30359.035714	NaN	20.35	797.5	Sunday
632	2022-06-15	6318	6218.571429	15957.071429	23702.145205	20.35	797.5	Wednesday
536	2022-03-11	149	10365.285714	15863.214286	25284.586301	7.05	930.5	Friday
538	2022-03-13	149	8908.285714	15542.392857	25160.463014	7.05	930.5	Sunday

In [ ]:
```
df_combined_daily_keypresses
```

Out[ ]:

	Date	Keypresses	7_day_ma	28_day_ma	365_day_ma	percentile	rank	Weekday
0	2020-09-21	19081	NaN	NaN	NaN	40.30	598.0	Monday
1	2020-09-22	32771	NaN	NaN	NaN	67.50	326.0	Tuesday
2	2020-09-23	32065	NaN	NaN	NaN	65.90	342.0	Wednesday
3	2020-09-24	34698	NaN	NaN	NaN	70.55	295.5	Thursday
4	2020-09-25	47038	NaN	NaN	NaN	88.50	116.0	Friday
...	...	...	...	...	...	...	...	...
995	2023-06-13	23745	18202.571429	24115.464286	20799.172603	48.90	512.0	Tuesday
996	2023-06-14	50339	21198.428571	24620.357143	20934.254795	91.80	83.0	Wednesday
997	2023-06-15	45835	23978.000000	25124.642857	21042.520548	87.40	127.0	Thursday
998	2023-06-16	40815	29523.142857	25422.285714	21048.158904	80.70	194.0	Friday
999	2023-06-17	12570	31318.857143	25237.607143	21033.315068	29.10	710.0	Saturday

1000 rows × 8 columns

In [ ]:
```
df_combined_daily_keypresses['Date']
```

Out[ ]:
```
0     2020-09-21
1     2020-09-22
2     2020-09-23
3     2020-09-24
4     2020-09-25
         ...
995   2023-06-13
996   2023-06-14
997   2023-06-15
998   2023-06-16
999   2023-06-17
Name: Date, Length: 1000, dtype: datetime64[ns]
```

Plotting Chronological Keypress Data

Now that we have a DataFrame showing daily keypresses and multiple moving averages, it's time to visualize it! The advantage of creating this chart within Plotly is that, being HTML-based, it is interactive in nature. Thus, you can hover over the lines to view the values corresponding to those lines and zoom in to get a closer look at a particular section of the graph. As before, though, this graph can also be saved as a static image.

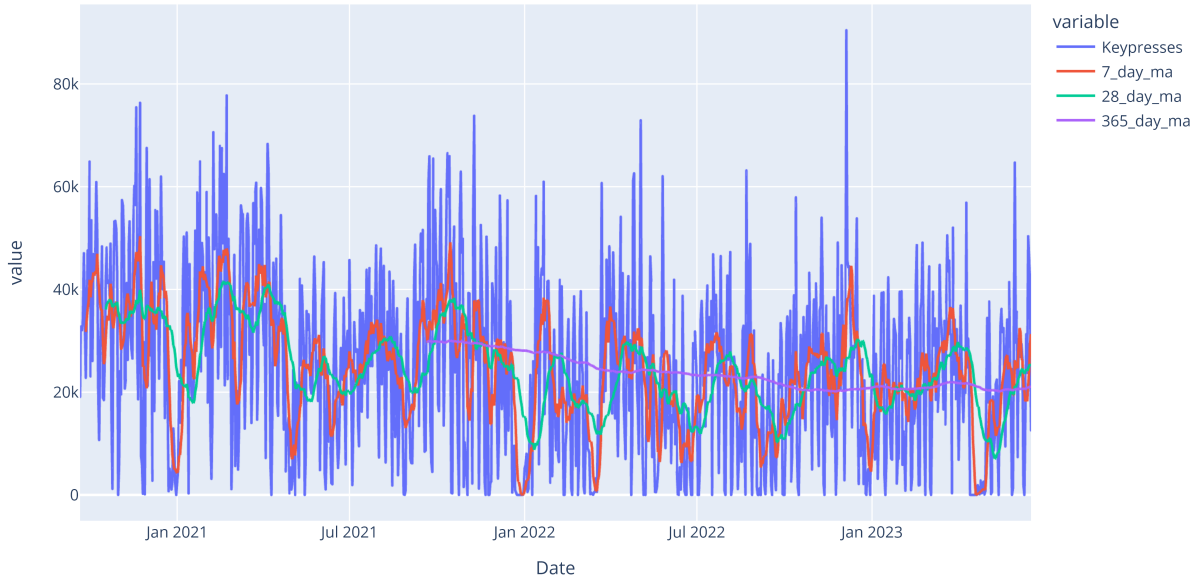
In [ ]:
```
fig_keypresses_line_chart = px.line(df_combined_daily_keypresses, x = 'Date',
y = ['Keypresses', '7_day_ma', '28_day_ma', '365_day_ma'])
# Note that multiple y values can be passed to the line chart.

save_chart(fig_keypresses_line_chart, 'px_daily_keypresses_and_mas')

fig_keypresses_line_chart
```

In [ ]:
```
Image(static_graphs_folder+'px_daily_keypresses_and_mas.png')
```

Out[ ]:



Monthly keypress totals:

In [ ]:
```
df_monthly_keypresses = df_combined_daily_keypresses.copy().set_index(
    'Date').resample('M').sum()['Keypresses'].reset_index()
df_monthly_keypresses['Month'] = df_monthly_keypresses['Date'].dt.to_period('M')
df_monthly_keypresses['Year'] = df_monthly_keypresses['Date'].dt.to_period('Y')
df_monthly_keypresses.drop('Date', axis = 1, inplace = True)
df_monthly_keypresses['Keypresses'] = df_monthly_keypresses.pop('Keypresses')
df_monthly_keypresses
```

Out[ ]:

	Month	Year	Keypresses
0	2020-09	2020	346918
1	2020-10	2020	1140421
2	2020-11	2020	1061614
3	2020-12	2020	823763
4	2021-01	2021	980116
5	2021-02	2021	1088404
6	2021-03	2021	1142850
7	2021-04	2021	833464
8	2021-05	2021	700155
9	2021-06	2021	621894
10	2021-07	2021	881137
11	2021-08	2021	722970
12	2021-09	2021	919571
13	2021-10	2021	1051663
14	2021-11	2021	797115
15	2021-12	2021	515936
16	2022-01	2022	729233
17	2022-02	2022	487910
18	2022-03	2022	552559
19	2022-04	2022	834250
20	2022-05	2022	627263
21	2022-06	2022	412725
22	2022-07	2022	758759
23	2022-08	2022	691636
24	2022-09	2022	330566
25	2022-10	2022	706081
26	2022-11	2022	756509
27	2022-12	2022	720251
28	2023-01	2023	652155
29	2023-02	2023	580208
30	2023-03	2023	892786
31	2023-04	2023	327674
32	2023-05	2023	665769

	Month	Year	Keypresses
33	2023-06	2023	433881

Saving the updated version of this DataFrame to a .csv file:

In [ ]:
```
df_combined_daily_keypresses.to_csv(
    'data/df_combined_daily_keypresses_updated.csv')
```

Hourly keypress stats:

In order to calculate hourly keypress statistics, we'll need to create a new DataFrame that aggregates keypresses by hour instead of by day.

In [ ]:
```
hourly_keypress_db_list = []

for db_path in database_paths_list:
    hourly_keypress_db_list.append(generate_keypress_totals(
        database_path = db_path, level = 'hourly'))

df_hourly_keypresses = pd.concat([
    df for df in hourly_keypress_db_list]).reset_index(drop=True)

# As with my daily keypresess DataFrame, I'll use pivot_table() to group
# multiple rows for the same day and hour into a single row. (These multiple
# rows are the result of my using multiple computers during the same hour.)
df_hourly_keypresses = df_hourly_keypresses.pivot_table(index = [
    'Day', 'Hour'], values = 'Keypresses', aggfunc = 'sum').reset_index().sort_values(

df_hourly_keypresses.to_csv(
    'data/df_combined_hourly_keypresses.csv', index = False)
df_hourly_keypresses
```

Out[ ]:

	Day	Hour	Keypresses
0	2020-09-21	15	278
1	2020-09-21	16	567
2	2020-09-21	17	1218
3	2020-09-21	18	3300
4	2020-09-21	19	3888
...	...	...	...
11394	2023-06-17	12	26
11395	2023-06-17	13	0
11396	2023-06-17	14	4274
11397	2023-06-17	15	0
11398	2023-06-17	16	1748

11399 rows × 3 columns

Recreating the DataFrame from a .csv file so that the following cells can be run by users who don't yet have their own WhatPulse database:

In [ ]:
```
df_hourly_keypresses = pd.read_csv('data/df_combined_hourly_keypresses.csv')
```

In [ ]:
```
df_hourly_keypresses['Day'] = pd.to_datetime(df_hourly_keypresses['Day'])
# Creating a combined day/hour column:
df_hourly_keypresses['Day_and_Hour'] = df_hourly_keypresses[
    'Day'] + pd.to_timedelta(df_hourly_keypresses['Hour'], unit = 'H')
df_hourly_keypresses.set_index('Day_and_Hour', inplace = True)
df_hourly_keypresses
```

Out[ ]:

Day_and_Hour	Day	Hour	Keypresses
2020-09-21 15:00:00	2020-09-21	15	278
2020-09-21 16:00:00	2020-09-21	16	567
2020-09-21 17:00:00	2020-09-21	17	1218
2020-09-21 18:00:00	2020-09-21	18	3300
2020-09-21 19:00:00	2020-09-21	19	3888
...	...	...	...
2023-06-17 12:00:00	2023-06-17	12	26
2023-06-17 13:00:00	2023-06-17	13	0
2023-06-17 14:00:00	2023-06-17	14	4274
2023-06-17 15:00:00	2023-06-17	15	0
2023-06-17 16:00:00	2023-06-17	16	1748

11399 rows × 3 columns

The following cells add in hours with 0 keypresses (of which there are many!). In order to include current/previous hours for the current day in my results, I'll add in keypresses up to the start of the next day (i.e. midnight), then limit the results so that they don't extend beyond the current hour.

Calculating tomorrow's date:

In [ ]:
```
last_date_for_hourly_keypress_log = last_date + datetime.timedelta(days = 1)
last_date_for_hourly_keypress_log
```

Out[ ]:
```
Timestamp('2023-06-18 00:00:00')
```

In [ ]:
```
pd.Timestamp.now()
```

Out[ ]:
```
Timestamp('2023-06-17 16:46:56.400190')
```

Adding hours without keypresses to the DataFrame:

In [ ]:
```
full_hourly_date_range = pd.date_range(start = first_date,
end = last_date_for_hourly_keypress_log, freq = 'H')
df_hourly_keypresses = df_hourly_keypresses.reindex(full_hourly_date_range)
df_hourly_keypresses['Keypresses'].fillna(0, inplace = True)
df_hourly_keypresses['Keypresses'] = df_hourly_keypresses[
    'Keypresses'].astype('int')
# Retrieving date and hour values from the index:
df_hourly_keypresses['Day'] = df_hourly_keypresses.index.date
df_hourly_keypresses['Hour'] = df_hourly_keypresses.index.hour
df_hourly_keypresses
```

Out[ ]:

	Day	Hour	Keypresses
2020-09-21 00:00:00	2020-09-21	0	0
2020-09-21 01:00:00	2020-09-21	1	0
2020-09-21 02:00:00	2020-09-21	2	0
2020-09-21 03:00:00	2020-09-21	3	0
2020-09-21 04:00:00	2020-09-21	4	0
...	...	...	...
2023-06-17 20:00:00	2023-06-17	20	0
2023-06-17 21:00:00	2023-06-17	21	0
2023-06-17 22:00:00	2023-06-17	22	0
2023-06-17 23:00:00	2023-06-17	23	0
2023-06-18 00:00:00	2023-06-18	0	0

24001 rows × 3 columns

Limiting the results to the period leading up to the current hour:

In [ ]:
```
df_hourly_keypresses = df_hourly_keypresses[
    df_hourly_keypresses.index < pd.Timestamp.now()].copy()
df_hourly_keypresses.reset_index(drop=True,inplace=True)
```

Calculating rolling 24-hour keypress totals:

In [ ]:
```
df_hourly_keypresses['keypresses_over_last_24_hours'] = df_hourly_keypresses[
    'Keypresses'].rolling(24).sum()
df_hourly_keypresses
```

Out[ ]:

	Day	Hour	Keypresses	keypresses_over_last_24_hours
0	2020-09-21	0	0	NaN
1	2020-09-21	1	0	NaN
2	2020-09-21	2	0	NaN
3	2020-09-21	3	0	NaN
4	2020-09-21	4	0	NaN
...	...	...	...	...
23988	2023-06-17	12	26	41414.0
23989	2023-06-17	13	0	40460.0
23990	2023-06-17	14	4274	39039.0
23991	2023-06-17	15	0	36194.0
23992	2023-06-17	16	1748	34831.0

23993 rows × 4 columns

Printing out recent hours with keypresses: (This data will also appear on the terminal window when the program is run automatically, which allows you to track your recent productivity.)

In [ ]:
```
print("Keypresses over the last 25 hours (excluding hours \
with 0 keypresses):\n",df_hourly_keypresses.iloc[-25:].query("Keypresses > 0"))
# Hours with 0 keypresses are removed in order to give the console output more
# space to fit on a single line.
```

```
Keypresses over the last 25 hours (excluding hours with 0 keypresses):
                Day  Hour  Keypresses  keypresses_over_last_24_hours
23968  2023-06-16    16        3111                        36370.0
23969  2023-06-16    17        5911                        37877.0
23970  2023-06-16    18        4244                        42121.0
23971  2023-06-16    19        1453                        39374.0
23972  2023-06-16    20        4405                        42592.0
23973  2023-06-16    21        2910                        44398.0
23974  2023-06-16    22        2719                        42621.0
23975  2023-06-16    23         619                        40815.0
23985  2023-06-17     9          16                        40101.0
23986  2023-06-17    10         927                        38011.0
23987  2023-06-17    11        5579                        41388.0
23988  2023-06-17    12          26                        41414.0
23990  2023-06-17    14        4274                        39039.0
23992  2023-06-17    16        1748                        34831.0
```

Keypresses for the last 48 hours (including hours with 0 keypresses, now that they have been added to our table):

In [ ]:
```
df_hourly_keypresses.iloc[-48:]
```

Out[ ]:

	Day	Hour	Keypresses	keypresses_over_last_24_hours
23945	2023-06-15	17	4404	55646.0
23946	2023-06-15	18	0	48818.0
23947	2023-06-15	19	4200	43512.0
23948	2023-06-15	20	1187	44163.0
23949	2023-06-15	21	1104	45267.0
23950	2023-06-15	22	4496	44316.0
23951	2023-06-15	23	2425	45835.0
23952	2023-06-16	0	104	45939.0
23953	2023-06-16	1	0	45939.0
23954	2023-06-16	2	0	45939.0
23955	2023-06-16	3	0	45939.0
23956	2023-06-16	4	0	45939.0
23957	2023-06-16	5	0	45939.0
23958	2023-06-16	6	0	45939.0
23959	2023-06-16	7	0	45939.0
23960	2023-06-16	8	0	45939.0
23961	2023-06-16	9	626	45774.0
23962	2023-06-16	10	3017	46448.0
23963	2023-06-16	11	2202	43874.0
23964	2023-06-16	12	0	39513.0
23965	2023-06-16	13	954	36085.0
23966	2023-06-16	14	5695	38748.0
23967	2023-06-16	15	2845	37453.0
23968	2023-06-16	16	3111	36370.0
23969	2023-06-16	17	5911	37877.0
23970	2023-06-16	18	4244	42121.0
23971	2023-06-16	19	1453	39374.0
23972	2023-06-16	20	4405	42592.0
23973	2023-06-16	21	2910	44398.0
23974	2023-06-16	22	2719	42621.0
23975	2023-06-16	23	619	40815.0
23976	2023-06-17	0	0	40711.0
23977	2023-06-17	1	0	40711.0

	Day	Hour	Keypresses	keypresses_over_last_24_hours
23978	2023-06-17	2	0	40711.0
23979	2023-06-17	3	0	40711.0
23980	2023-06-17	4	0	40711.0
23981	2023-06-17	5	0	40711.0
23982	2023-06-17	6	0	40711.0
23983	2023-06-17	7	0	40711.0
23984	2023-06-17	8	0	40711.0
23985	2023-06-17	9	16	40101.0
23986	2023-06-17	10	927	38011.0
23987	2023-06-17	11	5579	41388.0
23988	2023-06-17	12	26	41414.0
23989	2023-06-17	13	0	40460.0
23990	2023-06-17	14	4274	39039.0
23991	2023-06-17	15	0	36194.0
23992	2023-06-17	16	1748	34831.0

Making sure that all rows with the same day and hour (e.g. from multiple WhatPulse databases) have been merged into the same row:

In [ ]:
```
df_hourly_keypresses[df_hourly_keypresses.duplicated(
    subset = ['Day', 'Hour'], keep = False)]
```

Out[ ]:

Day	Hour	Keypresses	keypresses_over_last_24_hours

Most keypresses typed in a single hour within the entire dataset:

In [ ]:
```
df_hourly_keypresses.sort_values('Keypresses', ascending = False).head(50)
```

Out[ ]:

	Day	Hour	Keypresses	keypresses_over_last_24_hours
19342	2022-12-05	22	17552	83422.0
8650	2021-09-16	10	15446	64271.0
1958	2020-12-11	14	14618	49483.0
13290	2022-03-28	18	13406	44448.0
9442	2021-10-19	10	13345	63492.0
7907	2021-08-16	11	12960	24082.0
3378	2021-02-08	18	12777	53030.0
18190	2022-10-18	22	12173	30179.0
6023	2021-05-29	23	12045	18290.0
6912	2021-07-06	0	11999	26316.0
18062	2022-10-13	14	11698	40281.0
18061	2022-10-13	13	11634	31604.0
13359	2022-03-31	15	11554	50621.0
3210	2021-02-01	18	11331	62572.0
759	2020-10-22	15	11301	48012.0
2663	2021-01-09	23	11300	30575.0
6793	2021-07-01	1	11289	35355.0
8986	2021-09-30	10	11119	66954.0
3548	2021-02-15	20	11113	74179.0
22366	2023-04-10	22	11057	49524.0
10789	2021-12-14	13	11011	35159.0
1119	2020-11-06	15	10981	51438.0
2607	2021-01-07	15	10759	35737.0
21686	2023-03-13	14	10758	37979.0
7223	2021-07-18	23	10732	29008.0
252	2020-10-01	12	10716	48142.0
8985	2021-09-30	9	10702	60848.0
7391	2021-07-25	23	10576	25075.0
19127	2022-11-26	23	10565	49127.0
2629	2021-01-08	13	10517	56691.0
3710	2021-02-22	14	10501	50932.0
10863	2021-12-17	15	10468	31397.0
897	2020-10-28	9	10340	67613.0

	Day	Hour	Keypresses	keypresses_over_last_24_hours
22148	2023-04-01	20	10283	18918.0
14174	2022-05-04	14	10218	62136.0
9441	2021-10-19	9	10176	52756.0
4600	2021-03-31	16	10055	59622.0
10506	2021-12-02	18	10043	46470.0
447	2020-10-09	15	10023	55454.0
4313	2021-03-19	17	10021	48519.0
9658	2021-10-28	10	10013	61658.0
9322	2021-10-14	10	10000	66127.0
108	2020-09-25	12	9953	48047.0
7487	2021-07-29	23	9948	48558.0
10790	2021-12-14	14	9886	42935.0
17807	2022-10-02	23	9872	10006.0
4959	2021-04-15	15	9841	32667.0
3709	2021-02-22	13	9813	40431.0
18068	2022-10-13	20	9788	44976.0
5950	2021-05-26	22	9783	36905.0

Average keypresses by hour:

In [ ]:
```
df_hourly_pivot = df_hourly_keypresses.pivot_table(index = 'Hour',
values = 'Keypresses', aggfunc = ['mean', 'sum']).reset_index()
df_hourly_pivot.columns = df_hourly_pivot.columns.to_flat_index()
# At this point, the columns will read: "(hour, ),      (mean, Keypresses), and
# (sum, Keypresses)". We could convert them to regular columns via a loop,
# but since there are only 3, the simplest solution is to simply rename them
# as follows:
df_hourly_pivot.columns = ['Hour', 'Average Keypresses', 'Keypresses']

# Determining the percentage of total keypresses typed each hour:
total_keypresses = df_hourly_pivot['Keypresses'].sum()
df_hourly_pivot['pct_of_total'] = 100* df_hourly_pivot[
    'Keypresses'] / total_keypresses
df_hourly_pivot


df_hourly_pivot
```

Out[ ]:

	Hour	Average Keypresses	Keypresses	pct_of_total
0	0	999.012000	999012	4.030191
1	1	530.563000	530563	2.140385
2	2	200.571000	200571	0.809139
3	3	69.630000	69630	0.280900
4	4	13.642000	13642	0.055034
5	5	1.632000	1632	0.006584
6	6	0.338000	338	0.001364
7	7	2.765000	2765	0.011154
8	8	153.405000	153405	0.618863
9	9	613.537000	613537	2.475117
10	10	1271.721000	1271721	5.130347
11	11	1584.240000	1584240	6.391104
12	12	1545.269000	1545269	6.233888
13	13	1798.316000	1798316	7.254724
14	14	2147.468000	2147468	8.663265
15	15	2184.511000	2184511	8.812703
16	16	2218.676000	2218676	8.950531
17	17	1714.472472	1712758	6.909568
18	18	1354.026026	1352672	5.456918
19	19	1055.845846	1054790	4.255209
20	20	1033.404404	1032371	4.164767
21	21	1149.985986	1148836	4.634607
22	22	1553.336336	1551783	6.260167
23	23	1601.301301	1599700	6.453472

In [ ]:
```
sum(df_hourly_pivot['pct_of_total'])
# Making sure the percentages were calculated correctly
# (they should add up to 100%)
```

Out[ ]:
```
100.0
```

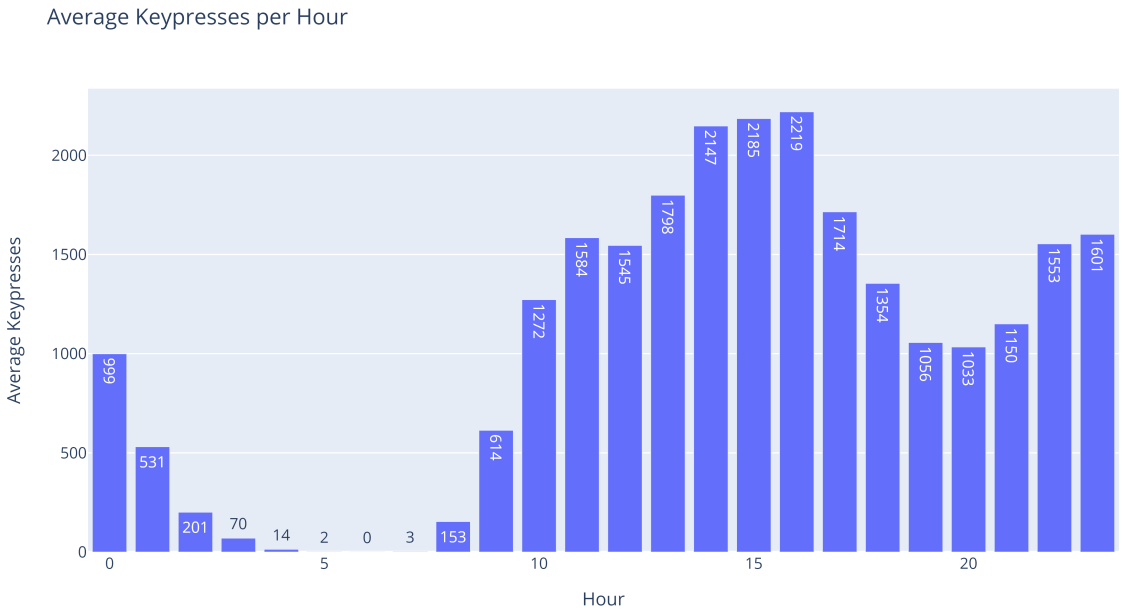
Plotting average keypresses by hour:

Not surprisingly, my hourly keypress averages are highest during the workday and lowest in the middle of the night, although I've been pretty active in the late evening hours also. (More on this below.)

In [ ]:
```
fig_hourly_keypresses = px.bar(df_hourly_pivot, x = 'Hour',
y = 'Average Keypresses', text_auto = '.0f',
title = 'Average Keypresses per Hour')
save_chart(fig_hourly_keypresses, 'average_keypresses_by_hour')
fig_hourly_keypresses
```

In [ ]:
```
Image(static_graphs_folder+'average_keypresses_by_hour.png')
```

Out[ ]:



In [ ]:
```
df_hourly_keypresses['Day'][0]
```

Out[ ]:
```
datetime.date(2020, 9, 21)
```

Saving the updated version of df_hourly_keypresses to a .csv file:

In [ ]:
```
df_hourly_keypresses.to_csv('data/df_combined_hourly_keypresses_updated.csv')
```

Data analysis question: Did marriage change my typing patterns?

I got married in April 2023, and I suspected that my keypress distributions as a married man might skew earlier than they did when I was a bachelor. I decided to investigate this graphically by creating subsets of df_hourly_keypresses that contained pre-marriage and post-marriage datasets, then comparing them via a grouped bar chart.

Setting datetime.date() values that will be used to filter df_hourly_keypresses:

In [ ]:
```
post_mba_work_start_date = datetime.date(2022, 6, 21) # I began my current
# full-time work in June 2022 after finishing my MBA. I chose to limit the
# dataset to this date range so that my results wouldn't be influenced
# by my time as an MBA student (which featured more irregular computer hours).
```

```
last_day_before_marriage = datetime.date(2023, 4, 14)
day_after_honeymoon = datetime.date(2023, 4, 29) # I didn't type much at all
# on my honeymoon, so I excluded this period from my analysis in order not
# to skew the average keypress totals downward.
```

In [ ]:

```
df_hourly_keypresses_pre_marriage = df_hourly_keypresses.query(
"Day > @post_mba_work_start_date & Day <= @last_day_before_marriage"
).pivot_table(index = 'Hour', values = 'Keypresses', aggfunc = 'mean').reset_index()
df_hourly_keypresses_pre_marriage['Period'] = 'Before Marriage'

df_hourly_keypresses_post_marriage = df_hourly_keypresses.query(
    "Day >= @day_after_honeymoon").pivot_table(
        index = 'Hour', values = 'Keypresses', aggfunc = 'mean').reset_index()
df_hourly_keypresses_post_marriage['Period'] = 'After Marriage'

# Combining these two DataFrames together:
df_hourly_keypresses_by_period = pd.concat([df_hourly_keypresses_pre_marriage,
df_hourly_keypresses_post_marriage])

df_hourly_keypresses_by_period
```

Out[ ]:

	Hour	Keypresses	Period
0	0	641.848485	Before Marriage
1	1	296.060606	Before Marriage
2	2	58.700337	Before Marriage
3	3	31.047138	Before Marriage
4	4	0.090909	Before Marriage
5	5	0.000000	Before Marriage
6	6	1.138047	Before Marriage
7	7	4.380471	Before Marriage
8	8	62.777778	Before Marriage
9	9	574.838384	Before Marriage
10	10	1439.505051	Before Marriage
11	11	1632.949495	Before Marriage
12	12	1639.750842	Before Marriage
13	13	1856.245791	Before Marriage
14	14	1962.851852	Before Marriage
15	15	2019.952862	Before Marriage
16	16	1950.003367	Before Marriage
17	17	1412.973064	Before Marriage
18	18	941.222222	Before Marriage
19	19	888.138047	Before Marriage
20	20	873.659933	Before Marriage
21	21	1083.676768	Before Marriage
22	22	1323.804714	Before Marriage
23	23	1364.552189	Before Marriage
0	0	235.180000	After Marriage
1	1	0.000000	After Marriage
2	2	0.000000	After Marriage
3	3	0.000000	After Marriage
4	4	0.000000	After Marriage
5	5	0.000000	After Marriage
6	6	0.000000	After Marriage
7	7	0.660000	After Marriage
8	8	59.520000	After Marriage

	Hour	Keypresses	Period
9	9	689.000000	After Marriage
10	10	1892.540000	After Marriage
11	11	2157.920000	After Marriage
12	12	1735.240000	After Marriage
13	13	1992.300000	After Marriage
14	14	2652.420000	After Marriage
15	15	2248.760000	After Marriage
16	16	1956.040000	After Marriage
17	17	1497.408163	After Marriage
18	18	854.836735	After Marriage
19	19	1122.897959	After Marriage
20	20	775.183673	After Marriage
21	21	766.693878	After Marriage
22	22	933.836735	After Marriage
23	23	569.244898	After Marriage

My daily keypress counts have increased slightly since getting married (at least when the honeymoon isn't taken into account):

In [ ]:
```
df_hourly_keypresses_by_period.pivot_table(
    index = 'Period', values = 'Keypresses', aggfunc = 'sum')
```

Out[ ]:

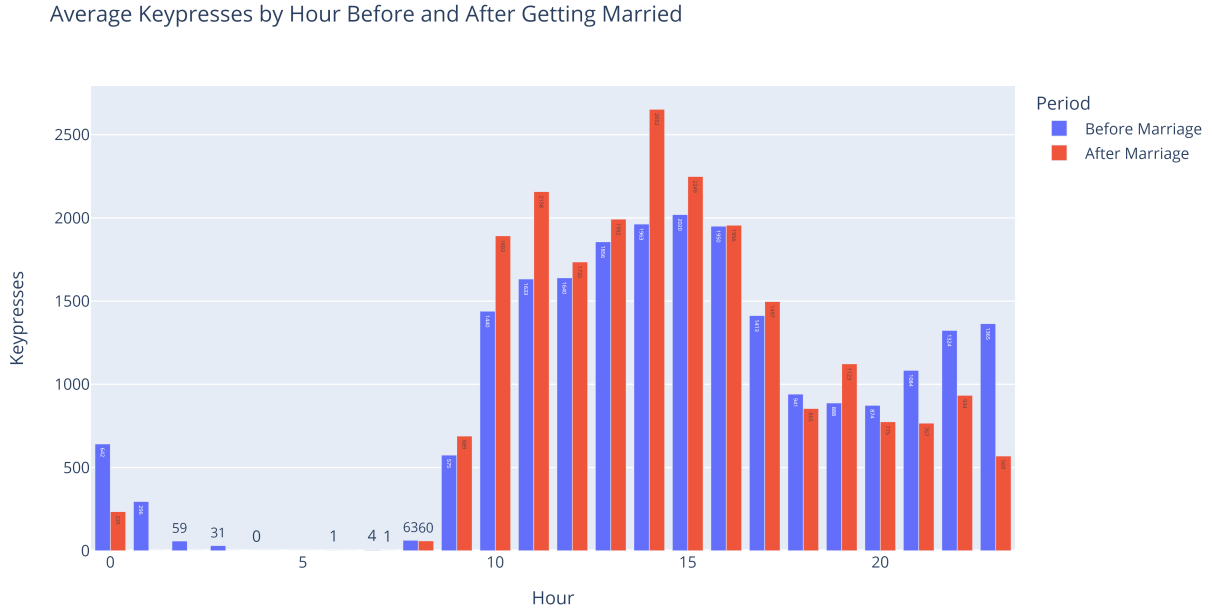
	Keypresses
Period	
After Marriage	22139.682041
Before Marriage	22060.168350

However, as the following chart shows, the hourly distribution of these keypresses has changed significantly. I'm now typing much less late at night and am getting more keypresses in earlier in the day.

In [ ]:
```
fig_keypresses_by_period = px.bar(df_hourly_keypresses_by_period, x = 'Hour',
y = 'Keypresses', color = 'Period', barmode = 'group', text_auto = '.0f',
title = 'Average Keypresses by Hour Before and After Getting Married')
save_chart(fig_keypresses_by_period, 'keypresses_before_and_after_marriage')
# See https://plotly.com/python/bar-charts/
# for the use of the 'color' and 'barmode' arguments.
fig_keypresses_by_period
```

In [ ]:
```
Image(static_graphs_folder+'keypresses_before_and_after_marriage.png')
```

Out[ ]:



In [ ]:
```
end_time = time.time()
run_time = end_time - start_time
run_minutes = run_time // 60
run_seconds = run_time % 60

run_minutes, run_seconds
```

Out[ ]:
```
(0.0, 8.203047275543213)
```

The input() function within the following cell keeps the console window open when running the file in a command prompt. It's not necessary for the Jupyter Notebook, but when I export this notebook as a Python script and then run the script on a scheduled basis, this line gives me time to read the output. See nosklo's response at: https://stackoverflow.com/a/1000968/13097194

In [ ]:
```
print("The program has finished running. Press Enter to exit.") # Lets me know
# that I can now close the program after it has finished running in a console
# window. (I wouldn't want to close it while the
# graphs are in the process of being generated.)
input()
```

```
The program has finished running. Press Enter to exit.
''
```

Out[ ]:

That's it for this program! I hope you enjoy using it to analyze your own WhatPulse keypress statistics.