activities_analysis

August 21, 2024

1 Strava Running Data Analysis: Performance Trends and Influencing Factors

1.1 Foreword

> "Pain is inevitable. Suffering is optional."

A quote from one of the only books I had read about fitness. `"What I Talk About When I Talk About Running"` written by Haruki Murakami. I was curious what was a man like this doing in the fitness section. At that point I hadnt run a single yard more than what was required of me – but by the time I finished reading, I was a changed man.

I slowly built a habit of running from 2016, enjoyed the meditative aspect of it, ran often enough but never really got out of the proverbial shallow end of the pool. Its now 2024 and after many fun years of exploring other sports, I realized my base fitness was lacking. I had decided to pick up running sometime in May, for real this time. Now I've signed up for a half marathon in November, and I want to use what I know about data science to assist me.

1.2 Abstract

In this notebook, we will dive in and analyze running data collected from my ***Strava*** to identify performance trends and influencing factors. The analysis will not only provide insights into overall fitness progression but also inform on the factors that influence running performance as well as the distinct types of runs that are most common.

1.3 Project steps

1. Source data from Strava Export. Download files from Bulk Export on my own profile menu.
2. Load, assess and clean the data for analysis.
3. Create any features that would provide additional insight for analysis.
4. Generate graphs and charts to illustrate insights.
5. Analyze with machine learning.

1.4 Table of Contents

- Machine Learning;
- Conclusion;

[1]:
```
#pandas and plotting
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import matplotlib.dates as mdates
import calendar
from datetime import timedelta
from matplotlib.patches import FancyArrowPatch

# machine learning
from sklearn import preprocessing
from sklearn import metrics
from sklearn.cluster import KMeans
from sklearn.feature_selection import chi2
from sklearn.feature_selection import f_regression
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import SGDClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.model_selection import train_test_split
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler


%config IPCompleter.greedy=True
import warnings
warnings.filterwarnings('ignore')
```

2 Accessing the data

[2]:
```
# Load the data from an export on Strava
original = pd.read_csv('../Data/activities.csv')
print('Dataframe shape:', original.shape)
original.head()
```

```
Dataframe shape: (254, 94)
```

[2]:
```
   Activity ID              Activity Date  Activity Name Activity Type  \
0    676696158   Aug 15, 2016, 9:53:13 AM  Afternoon Run           Run
1    681425706  Aug 19, 2016, 10:11:34 AM    Evening Run           Run
2    683559635  Aug 21, 2016, 10:14:46 AM    Evening Run           Run
```

```
3    689475888  Aug 26, 2016, 10:22:15 AM    Evening Run           Run
4    708051143   Sep 11, 2016, 9:19:10 AM  Afternoon Run           Run

  Activity Description  Elapsed Time  Distance  Max Heart Rate  \
0                  NaN          1414      3.31             NaN
1                  NaN          2062      4.45             NaN
2                  NaN          1903      4.41             NaN
3                  NaN          1920      4.51             NaN
4                  NaN          1922      4.43             NaN

   Relative Effort  Commute  …  Activity Count Total Steps Carbon Saved  \
0              NaN    False  …             NaN         NaN          NaN
1              NaN    False  …             NaN         NaN          NaN
2              NaN    False  …             NaN         NaN          NaN
3              NaN    False  …             NaN         NaN          NaN
4              NaN    False  …             NaN         NaN          NaN

   Pool Length  Training Load  Intensity  Average Grade Adjusted Pace  \
0          NaN            NaN        NaN                          NaN
1          NaN            NaN        NaN                          NaN
2          NaN            NaN        NaN                          NaN
3          NaN            NaN        NaN                          NaN
4          NaN            NaN        NaN                          NaN

   Timer Time  Total Cycles  Media
0         NaN           NaN    NaN
1         NaN           NaN    NaN
2         NaN           NaN    NaN
3         NaN           NaN    NaN
4         NaN           NaN    NaN

[5 rows x 94 columns]
```

2.0.1 First observations:

There are a whopping 94 columns, most of which are either null or dont contribute to the analysis, so lets keep only the relevant columns for research

3 Data cleaning

[3]:
```
original.columns = original.columns.str.lower().str.replace(' ','_') #␣
↪Standardize the column titles
original = original[original['activity_type'] == 'Run'] # Filter to only␣
↪Running values
df = original.copy(deep=True) # Make a copy so that there is always the␣
↪original to reference to
```

[4]:
```
print(df.shape)
df.head()
```

```
(217, 94)
```

[4]:
```
   activity_id              activity_date  activity_name activity_type  \
0    676696158   Aug 15, 2016, 9:53:13 AM  Afternoon Run           Run
1    681425706  Aug 19, 2016, 10:11:34 AM    Evening Run           Run
2    683559635  Aug 21, 2016, 10:14:46 AM    Evening Run           Run
3    689475888  Aug 26, 2016, 10:22:15 AM    Evening Run           Run
4    708051143   Sep 11, 2016, 9:19:10 AM  Afternoon Run           Run

  activity_description  elapsed_time  distance  max_heart_rate  \
0                  NaN          1414      3.31             NaN
1                  NaN          2062      4.45             NaN
2                  NaN          1903      4.41             NaN
3                  NaN          1920      4.51             NaN
4                  NaN          1922      4.43             NaN

   relative_effort  commute  …  activity_count total_steps carbon_saved  \
0              NaN    False  …             NaN         NaN          NaN
1              NaN    False  …             NaN         NaN          NaN
2              NaN    False  …             NaN         NaN          NaN
3              NaN    False  …             NaN         NaN          NaN
4              NaN    False  …             NaN         NaN          NaN

   pool_length  training_load  intensity  average_grade_adjusted_pace  \
0          NaN            NaN        NaN                          NaN
1          NaN            NaN        NaN                          NaN
2          NaN            NaN        NaN                          NaN
3          NaN            NaN        NaN                          NaN
4          NaN            NaN        NaN                          NaN

   timer_time  total_cycles  media
0         NaN           NaN    NaN
1         NaN           NaN    NaN
2         NaN           NaN    NaN
3         NaN           NaN    NaN
4         NaN           NaN    NaN

[5 rows x 94 columns]
```

[5]:
```
def list_nulls(df):
    null_df = [[col, df[col].isnull().sum()] for col in df.columns]
    print('Null Data:', df.isnull().sum().sum())
    print(list(filter(lambda x: x[1]>0, null_df)))

list_nulls(df)
```

```
Null Data: 14355
[['activity_description', 187], ['max_heart_rate', 160], ['relative_effort',
160], ['activity_private_note', 217], ['activity_gear', 168], ['athlete_weight',
92], ['bike_weight', 217], ['average_speed', 90], ['elevation_loss', 100],
['average_positive_grade', 217], ['average_negative_grade', 217],
['max_cadence', 217], ['average_cadence', 217], ['max_heart_rate.1', 170],
['average_heart_rate', 160], ['max_watts', 217], ['average_watts', 217],
['max_temperature', 217], ['average_temperature', 217], ['relative_effort.1',
160], ['total_work', 217], ['number_of_runs', 217], ['uphill_time', 217],
['downhill_time', 217], ['other_time', 217], ['perceived_exertion', 215],
['type', 217], ['start_time', 217], ['weighted_average_power', 217],
['power_count', 217], ['prefer_perceived_exertion', 185],
['perceived_relative_effort', 215], ['total_weight_lifted', 217],
['from_upload', 90], ['grade_adjusted_distance', 62],
['weather_observation_time', 190], ['weather_condition', 190],
['weather_temperature', 190], ['apparent_temperature', 190], ['dewpoint', 190],
['humidity', 190], ['weather_pressure', 190], ['wind_speed', 190], ['wind_gust',
190], ['wind_bearing', 190], ['precipitation_intensity', 190], ['sunrise_time',
190], ['sunset_time', 190], ['moon_phase', 190], ['bike', 217], ['gear', 166],
['precipitation_probability', 190], ['precipitation_type', 191], ['cloud_cover',
190], ['weather_visibility', 190], ['uv_index', 190], ['weather_ozone', 209],
['jump_count', 217], ['total_grit', 217], ['average_flow', 217], ['flagged',
155], ['average_elapsed_speed', 155], ['dirt_distance', 154],
['newly_explored_distance', 217], ['newly_explored_dirt_distance', 217],
['activity_count', 217], ['total_steps', 155], ['carbon_saved', 217],
['pool_length', 217], ['training_load', 217], ['intensity', 217],
['average_grade_adjusted_pace', 176], ['timer_time', 217], ['total_cycles',
217], ['media', 199]]
```

[6]:
```python
columns_keep =␣
 ↪['activity_date','moving_time','distance','max_speed','average_speed','elevation_gain','ele
df = df.loc[:,columns_keep]
print(df.shape)
df.head()
```

```
(217, 14)
```

[6]:

	activity_date	moving_time	distance	max_speed	average_speed	\
0	Aug 15, 2016, 9:53:13 AM	1314.0	3.31	7.2	NaN	
1	Aug 19, 2016, 10:11:34 AM	1802.0	4.45	8.3	NaN	
2	Aug 21, 2016, 10:14:46 AM	1898.0	4.41	5.5	NaN	
3	Aug 26, 2016, 10:22:15 AM	1900.0	4.51	5.7	NaN	
4	Sep 11, 2016, 9:19:10 AM	1913.0	4.43	4.9	NaN	

	elevation_gain	elevation_loss	elevation_low	elevation_high	max_grade	\
0	39.465000	NaN	53.200001	87.599998	16.200001	
1	63.403999	NaN	50.299999	87.300003	40.200001	
2	51.626202	NaN	46.400002	87.699997	16.299999	

```
3      119.328003             NaN      64.000000      137.699997   22.400000
4      130.173996             NaN      64.000000      138.300003   23.500000

   average_grade  max_heart_rate  average_heart_rate  total_steps
0      -0.241473             NaN                 NaN          NaN
1       0.125682             NaN                 NaN          NaN
2      -0.002268             NaN                 NaN          NaN
3       0.026587             NaN                 NaN          NaN
4       0.069921             NaN                 NaN          NaN
```

[7]:
```
df = df.dropna(axis=1,how='all') # Dropping all the rows with completely null␣
 ↪rows
df.shape
```

[7]: (217, 14)

[8]:
```
# Convert 'activity_date' to datetime
df['activity_date'] = pd.to_datetime(df['activity_date'])
```

[9]:
```
df = df.drop(df[(df.distance < 1)].index) # Remove any runs under 1km, most␣
 ↪likely misinputs or warmups
df = df.reset_index(drop=True)
print(df.shape)
df.head()
```

```
(212, 14)
```

[9]:
```
        activity_date  moving_time  distance  max_speed  average_speed  \
0 2016-08-15 09:53:13       1314.0      3.31        7.2            NaN
1 2016-08-19 10:11:34       1802.0      4.45        8.3            NaN
2 2016-08-21 10:14:46       1898.0      4.41        5.5            NaN
3 2016-08-26 10:22:15       1900.0      4.51        5.7            NaN
4 2016-09-11 09:19:10       1913.0      4.43        4.9            NaN

   elevation_gain  elevation_loss  elevation_low  elevation_high  max_grade  \
0       39.465000             NaN      53.200001       87.599998  16.200001
1       63.403999             NaN      50.299999       87.300003  40.200001
2       51.626202             NaN      46.400002       87.699997  16.299999
3      119.328003             NaN      64.000000      137.699997  22.400000
4      130.173996             NaN      64.000000      138.300003  23.500000

   average_grade  max_heart_rate  average_heart_rate  total_steps
0      -0.241473             NaN                 NaN          NaN
1       0.125682             NaN                 NaN          NaN
2      -0.002268             NaN                 NaN          NaN
3       0.026587             NaN                 NaN          NaN
4       0.069921             NaN                 NaN          NaN
```

[10]:
```
# Check for nulls again, consider any imputes or further drops
list_nulls(df)
```

```
Null Data: 665
[['average_speed', 90], ['elevation_loss', 100], ['max_heart_rate', 160],
['average_heart_rate', 160], ['total_steps', 155]]
```

4 Feature engineering

[11]:
```
# Create year and month columns
df['year'] = df['activity_date'].dt.year
df['month'] = df['activity_date'].dt.month

#Convert the speeds into a more familiar metric which is minutes/km
df['moving_time_minutes'] = round(df['moving_time']/60, 2)
df['distance'] = round(df['distance'], 2) # Since its already in km, no need␣
↪for any conversion
df['pace'] = round(df['moving_time_minutes'] / df['distance'],2)
df['max_pace'] = round(1000/df['max_speed'] / 60,2)
df = df.drop(columns=['average_speed','max_speed'])

# Add some useful date & time features
df['week'] = df['activity_date'].dt.to_period('W')
df['start_date'] = df['activity_date'].dt.date
df['start_time'] = df['activity_date'].dt.time
df['week_start_date'] = df.week.apply(lambda r: r.start_time.date())
df['weekday'] = df['activity_date'].apply(lambda x: x.weekday())
df.head()
```

[11]:
```
        activity_date  moving_time  distance  elevation_gain  elevation_loss  \
0 2016-08-15 09:53:13       1314.0      3.31       39.465000             NaN
1 2016-08-19 10:11:34       1802.0      4.45       63.403999             NaN
2 2016-08-21 10:14:46       1898.0      4.41       51.626202             NaN
3 2016-08-26 10:22:15       1900.0      4.51      119.328003             NaN
4 2016-09-11 09:19:10       1913.0      4.43      130.173996             NaN

   elevation_low  elevation_high  max_grade  average_grade  max_heart_rate  \
0      53.200001       87.599998  16.200001      -0.241473             NaN
1      50.299999       87.300003  40.200001       0.125682             NaN
2      46.400002       87.699997  16.299999      -0.002268             NaN
3      64.000000      137.699997  22.400000       0.026587             NaN
4      64.000000      138.300003  23.500000       0.069921             NaN

   …  year  month  moving_time_minutes  pace  max_pace  \
0  …  2016      8                21.90  6.62      2.31
1  …  2016      8                30.03  6.75      2.01
2  …  2016      8                31.63  7.17      3.03
```

```
3  …  2016      8                 31.67  7.02      2.92
4  …  2016      9                 31.88  7.20      3.40

                    week  start_date start_time week_start_date weekday
0  2016-08-15/2016-08-21  2016-08-15   09:53:13      2016-08-15       0
1  2016-08-15/2016-08-21  2016-08-19   10:11:34      2016-08-15       4
2  2016-08-15/2016-08-21  2016-08-21   10:14:46      2016-08-15       6
3  2016-08-22/2016-08-28  2016-08-26   10:22:15      2016-08-22       4
4  2016-09-05/2016-09-11  2016-09-11   09:19:10      2016-09-05       6

[5 rows x 22 columns]
```

4.0.1 –Excess of nulls in the columns Elevation loss, Max Heart Rate, Average Heart Rate and Total Steps–

Besides pace, I suspect the other nulls are due to the fact that majority of my runs were run **before** I bought a fitness tracker watch. Unfortunately, will have to drop them.

But instead of dropping the columns, I will instead ***filter the dataframe*** to the time I started training in 2024, which should have a complete set of data.

[12]:
```
latest_df = df[df.activity_date > '2024-04-01']
list_nulls(latest_df)
print(latest_df.shape)
latest_df.head()
```

```
Null Data: 2
[['max_heart_rate', 1], ['average_heart_rate', 1]]
(43, 22)
```

[12]:
```
          activity_date  moving_time  distance  elevation_gain  \
169 2024-04-23 03:41:19       1005.0      1.36        0.000000
170 2024-04-24 00:04:13       2312.0      4.05      168.199997
171 2024-04-25 01:15:43       1117.0      1.35        0.000000
172 2024-05-01 08:12:56       2280.0      4.07      278.000000
173 2024-04-29 03:30:40       1963.0      2.01        0.000000

     elevation_loss  elevation_low  elevation_high  max_grade  average_grade  \
169        0.000000       0.000000        0.000000   0.000000       0.000000
170      166.199997      36.400002      104.599998  48.522873       0.049375
171        0.000000       0.000000        0.000000   0.000000       0.000000
172      282.799988      72.199997      126.599998  49.813019      -0.117833
173        0.000000       0.000000        0.000000   0.000000       0.000000

     max_heart_rate  …  year  month  moving_time_minutes   pace  max_pace  \
169           186.0  …  2024      4                16.75  12.32      6.01
170           174.0  …  2024      4                38.53   9.51      4.48
171           175.0  …  2024      4                18.62  13.79      5.36
172           174.0  …  2024      5                38.00   9.34      3.95
```

```
173           183.0  …  2024      4              32.72  16.28      6.56

                          week  start_date start_time week_start_date weekday
169  2024-04-22/2024-04-28  2024-04-23   03:41:19      2024-04-22       1
170  2024-04-22/2024-04-28  2024-04-24   00:04:13      2024-04-22       2
171  2024-04-22/2024-04-28  2024-04-25   01:15:43      2024-04-22       3
172  2024-04-29/2024-05-05  2024-05-01   08:12:56      2024-04-29       2
173  2024-04-29/2024-05-05  2024-04-29   03:30:40      2024-04-29       0

[5 rows x 22 columns]
```

[13]:
```
# Impute the remaining missing data with the averages
latest_df['average_heart_rate'] = latest_df['average_heart_rate'].
  ↪fillna(value=latest_df['average_heart_rate'].mean())
latest_df['max_heart_rate'] = latest_df['max_heart_rate'].
  ↪fillna(value=latest_df['max_heart_rate'].mean())
list_nulls(latest_df)
```

```
Null Data: 0
[]
```

[14]:
```
zero_rows = latest_df[(latest_df == 0).any(axis=1)]
print(zero_rows.shape)
zero_rows
```

```
(8, 22)
```

[14]:
```
           activity_date  moving_time  distance  elevation_gain  \
169 2024-04-23 03:41:19       1005.0      1.36             0.0
171 2024-04-25 01:15:43       1117.0      1.35             0.0
173 2024-04-29 03:30:40       1963.0      2.01             0.0
175 2024-05-07 02:21:57       1714.0      3.28             0.0
176 2024-05-08 03:55:46       2147.0      2.09             0.0
184 2024-06-24 22:34:25       2023.0      3.87           200.0
199 2024-07-24 14:49:33       1086.0      2.24             0.0
206 2024-08-05 23:19:57       1254.0      2.18           143.0

     elevation_loss  elevation_low  elevation_high  max_grade  average_grade  \
169        0.000000            0.0        0.000000   0.000000       0.000000
171        0.000000            0.0        0.000000   0.000000       0.000000
173        0.000000            0.0        0.000000   0.000000       0.000000
175        0.000000            0.0        0.000000   0.000000       0.000000
176        0.000000            0.0        0.000000   0.000000       0.000000
184      219.800003           15.6       85.000000  48.284103      -0.517903
199        0.000000            0.0        0.000000   0.000000       0.000000
206      140.000000           16.4       63.200001  48.390980       0.099630

     max_heart_rate  …  year  month  moving_time_minutes   pace  max_pace  \
```

```
169           186.0  …  2024       4                 16.75  12.32       6.01
171           175.0  …  2024       4                 18.62  13.79       5.36
173           183.0  …  2024       4                 32.72  16.28       6.56
175           189.0  …  2024       5                 28.57   8.71       6.46
176           190.0  …  2024       5                 35.78  17.12       6.66
184           168.0  …  2024       6                 33.72   8.71       3.79
199           180.0  …  2024       7                 18.10   8.08       6.35
206           153.0  …  2024       8                 20.90   9.59       4.88

                         week  start_date start_time week_start_date weekday
169  2024-04-22/2024-04-28  2024-04-23   03:41:19      2024-04-22       1
171  2024-04-22/2024-04-28  2024-04-25   01:15:43      2024-04-22       3
173  2024-04-29/2024-05-05  2024-04-29   03:30:40      2024-04-29       0
175  2024-05-06/2024-05-12  2024-05-07   02:21:57      2024-05-06       1
176  2024-05-06/2024-05-12  2024-05-08   03:55:46      2024-05-06       2
184  2024-06-24/2024-06-30  2024-06-24   22:34:25      2024-06-24       0
199  2024-07-22/2024-07-28  2024-07-24   14:49:33      2024-07-22       2
206  2024-08-05/2024-08-11  2024-08-05   23:19:57      2024-08-05       0

[8 rows x 22 columns]
```

4.0.2 –Zero values in many elevation metrics–

With a total of 6 rows containing 0 elevation data, it is worth considering dropping these rows.

Checking on actual strava, I found that these were manual uploads that did not upload properly. Will drop these.

[15]:
```
latest_df = latest_df.drop(zero_rows.index)
latest_df.shape
```

[15]:
```
(35, 22)
```

[16]:
```
latest_df.head()
```

[16]:
```
            activity_date  moving_time  distance  elevation_gain  \
170 2024-04-24 00:04:13       2312.0      4.05      168.199997
172 2024-05-01 08:12:56       2280.0      4.07      278.000000
174 2024-05-04 09:41:57       2359.0      5.01      193.399994
177 2024-05-17 22:25:45       1937.0      3.40      166.400024
178 2024-05-18 23:22:30       8935.0     14.81      992.799927

     elevation_loss  elevation_low  elevation_high  max_grade  average_grade  \
170      166.199997      36.400002      104.599998  48.522873       0.049375
172      282.799988      72.199997      126.599998  49.813019      -0.117833
174      164.600006      -1.600000       37.799999  49.948692       0.570642
177      166.399994     442.399994      481.600006  48.871666       0.047297
178     1008.799988     395.200012      523.000000  49.956367      -0.156001
```

```
     max_heart_rate  …  year  month  moving_time_minutes   pace  max_pace  \
170           174.0  …  2024      4                38.53   9.51      4.48
172           174.0  …  2024      5                38.00   9.34      3.95
174           182.0  …  2024      5                39.32   7.85      1.23
177           166.0  …  2024      5                32.28   9.49      4.27
178           202.0  …  2024      5               148.92  10.06      4.98

                         week  start_date start_time week_start_date weekday
170  2024-04-22/2024-04-28  2024-04-24   00:04:13      2024-04-22       2
172  2024-04-29/2024-05-05  2024-05-01   08:12:56      2024-04-29       2
174  2024-04-29/2024-05-05  2024-05-04   09:41:57      2024-04-29       5
177  2024-05-13/2024-05-19  2024-05-17   22:25:45      2024-05-13       4
178  2024-05-13/2024-05-19  2024-05-18   23:22:30      2024-05-13       5

[5 rows x 22 columns]
```

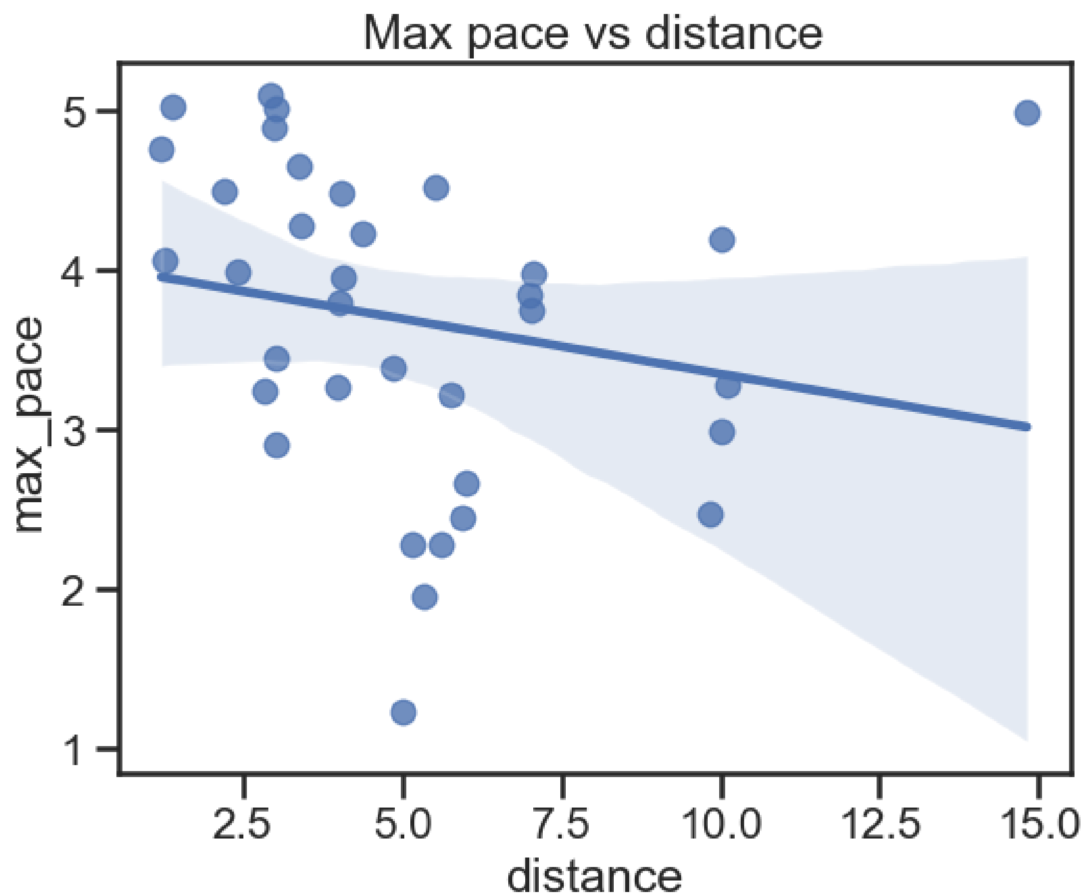
5 Insights

Now we will be exploring some insights using data visualization.

Note: pace is in minutes/km, therefore the *lower* the y-value, the *faster* it is. So `lower=better`.

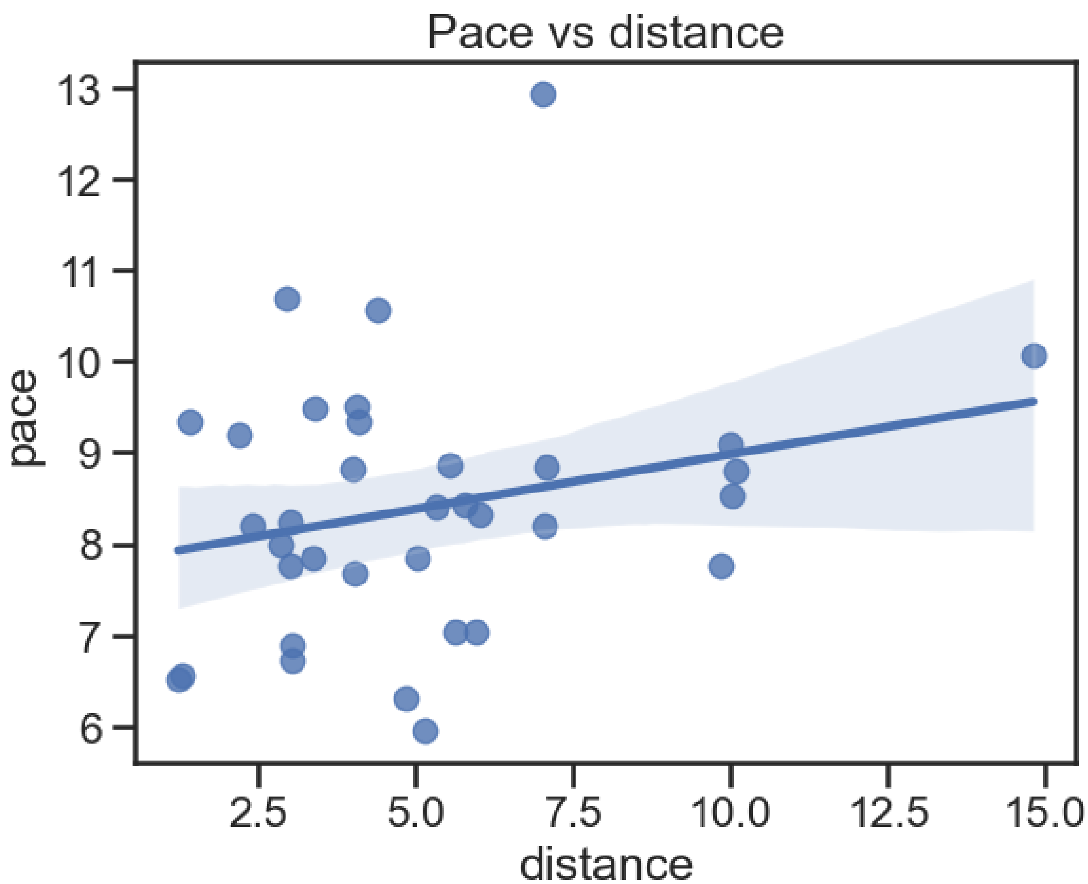
[17]:
```
sns.set(style='ticks',context='talk')
sns.regplot(x='distance',y='max_pace',data=latest_df).set_title('Max pace vs␣
↪distance')
```

[17]:
```
Text(0.5, 1.0, 'Max pace vs distance')
```

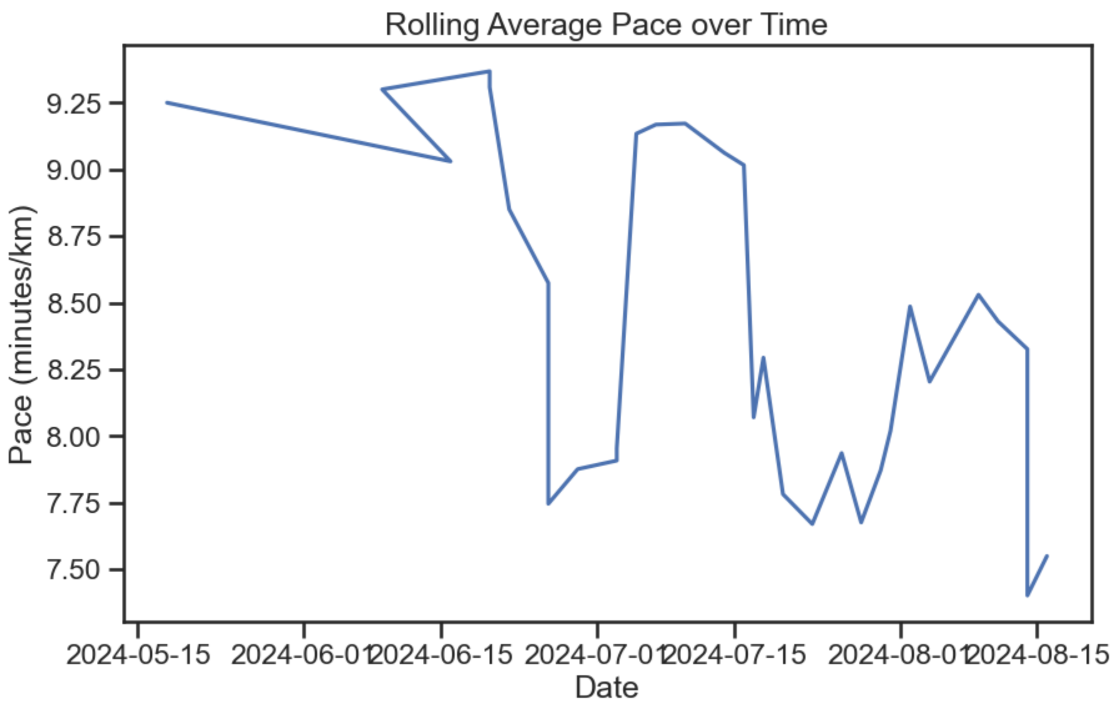


[18]:
```
sns.set(style='ticks',context='talk')
sns.regplot(x='distance',y='pace',data=latest_df).set_title('Pace vs distance')
```

[18]: `Text(0.5, 1.0, 'Pace vs distance')`



[19]:
```
# Calculate rolling average pace to smooth out variations
rolling = latest_df.pace.rolling(window=5).mean()

plt.figure(figsize=(10, 6))
plt.plot(latest_df.start_date, rolling)
plt.title('Rolling Average Pace over Time')
plt.xlabel('Date')
plt.ylabel('Pace (minutes/km)')
plt.show()
```



5.0.1 Rolling Average Insights

The data exhibits a recurring pattern of sharp performance improvements followed by notable pace increases, likely indicative of intense training phases succeeded by recovery periods. Significantly, this cyclical pattern demonstrates a gradual attenuation over time, suggesting:

- Enhanced recovery efficiency
- Improved baseline fitness
- Potential optimization of the training-recovery balance

This trend points towards a maturing and increasingly effective training regimen, where the performance gains more consistently while potentially reducing the physiological stress of intense training phases.

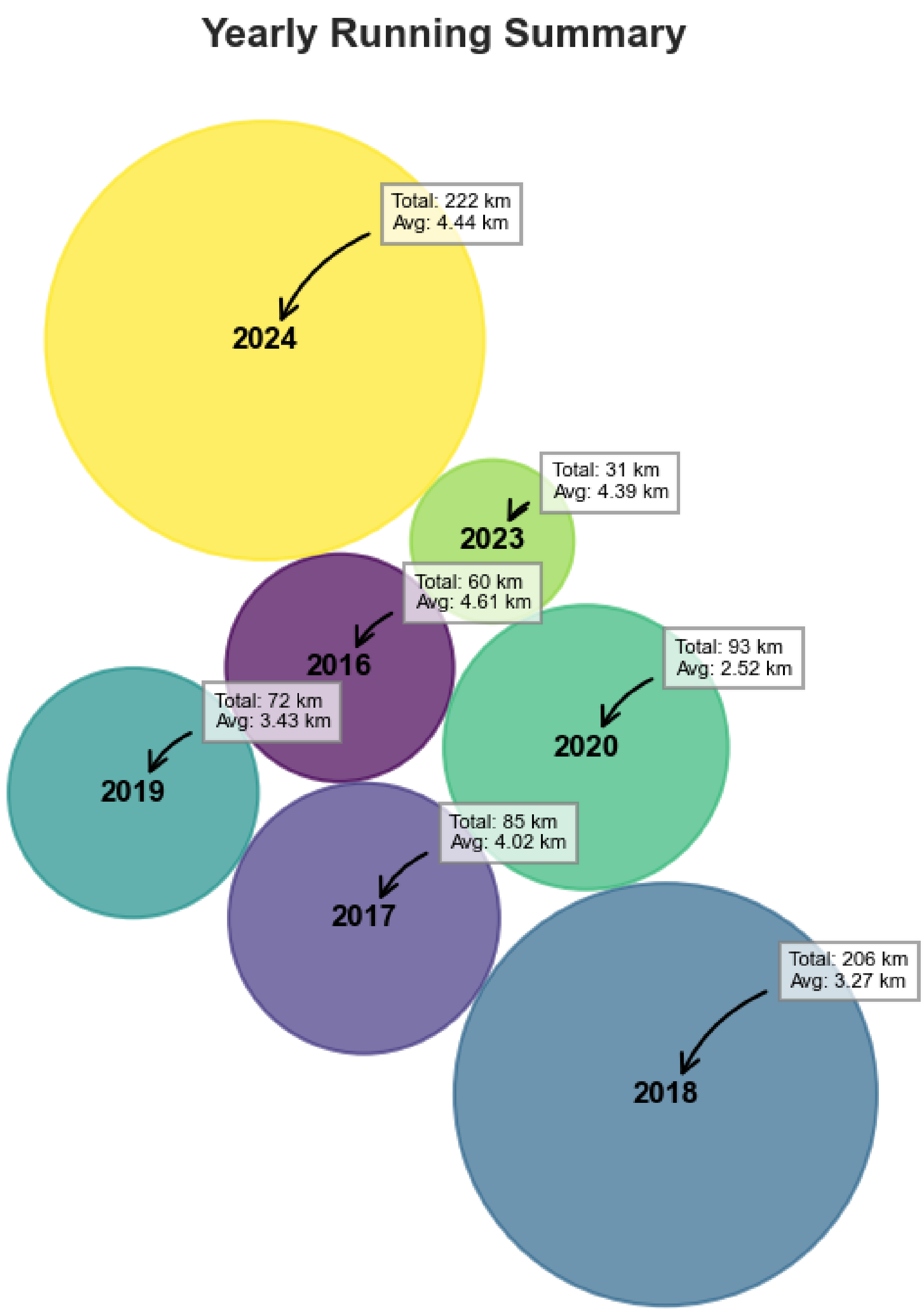
[20]:
```
class BubbleChart:
    def __init__(self, area, bubble_spacing=0):
        area = np.asarray(area)
        r = np.sqrt(area / np.pi)
        self.bubble_spacing = bubble_spacing
        self.bubbles = np.ones((len(area), 4))
        self.bubbles[:, 2] = r
        self.bubbles[:, 3] = area
        self.maxstep = 2 * self.bubbles[:, 2].max() + self.bubble_spacing
        self.step_dist = self.maxstep / 2
        length = np.ceil(np.sqrt(len(self.bubbles)))
```

```
        grid = np.arange(length) * self.maxstep
        gx, gy = np.meshgrid(grid, grid)
        self.bubbles[:, 0] = gx.flatten()[:len(self.bubbles)]
        self.bubbles[:, 1] = gy.flatten()[:len(self.bubbles)]
        self.com = self.center_of_mass()

    def center_of_mass(self):
        return np.average(self.bubbles[:, :2], axis=0, weights=self.bubbles[:,
↪3])

    def center_distance(self, bubble, bubbles):
        return np.hypot(bubble[0] - bubbles[:, 0], bubble[1] - bubbles[:, 1])

    def outline_distance(self, bubble, bubbles):
        center_distance = self.center_distance(bubble, bubbles)
        return center_distance - bubble[2] - bubbles[:, 2] - self.bubble_spacing

    def check_collisions(self, bubble, bubbles):
        distance = self.outline_distance(bubble, bubbles)
        return len(distance[distance < 0])

    def collides_with(self, bubble, bubbles):
        distance = self.outline_distance(bubble, bubbles)
        idx_min = np.argmin(distance)
        return idx_min if type(idx_min) == np.ndarray else [idx_min]

    def collapse(self, n_iterations=50):
        for _i in range(n_iterations):
            moves = 0
            for i in range(len(self.bubbles)):
                rest_bub = np.delete(self.bubbles, i, 0)
                dir_vec = self.com - self.bubbles[i, :2]
                dir_vec = dir_vec / np.sqrt(dir_vec.dot(dir_vec))
                new_point = self.bubbles[i, :2] + dir_vec * self.step_dist
                new_bubble = np.append(new_point, self.bubbles[i, 2:4])
                if not self.check_collisions(new_bubble, rest_bub):
                    self.bubbles[i, :] = new_bubble
                    self.com = self.center_of_mass()
                    moves += 1
                else:
                    for colliding in self.collides_with(new_bubble, rest_bub):
                        dir_vec = rest_bub[colliding, :2] - self.bubbles[i, :2]
                        dir_vec = dir_vec / np.sqrt(dir_vec.dot(dir_vec))
                        orth = np.array([dir_vec[1], -dir_vec[0]])
                        new_point1 = self.bubbles[i, :2] + orth * self.step_dist
                        new_point2 = self.bubbles[i, :2] - orth * self.step_dist
```

```
                        dist1 = self.center_distance(self.com, np.
↪array([new_point1]))
                        dist2 = self.center_distance(self.com, np.
↪array([new_point2]))
                        new_point = new_point1 if dist1 < dist2 else new_point2
                        new_bubble = np.append(new_point, self.bubbles[i, 2:4])
                        if not self.check_collisions(new_bubble, rest_bub):
                            self.bubbles[i, :] = new_bubble
                            self.com = self.center_of_mass()
            if moves / len(self.bubbles) < 0.1:
                self.step_dist = self.step_dist / 2

    def plot(self, ax, data, colors):
        for i, (year, total, avg) in enumerate(data):
            bubble = self.bubbles[i]

            # Create the bubble
            circ = plt.Circle(bubble[:2], bubble[2], color=colors[i], alpha=0.7)
            ax.add_patch(circ)

            # Add year in the center
            ax.text(*bubble[:2], str(year),
                    horizontalalignment='center', verticalalignment='center',
                    color='black', fontname='Arial', fontsize=12,␣
↪fontweight='bold')

            # Add single arrow with both annotations
            self._add_annotations(ax, bubble, total, avg)

    def _add_annotations(self, ax, bubble, total, avg):
        radius = bubble[2]
        angle = 45  # You can adjust this angle as needed

        # Calculate the position for the arrow and text
        arrow_x = bubble[0] + np.cos(np.radians(angle)) * radius * 0.7
        arrow_y = bubble[1] + np.sin(np.radians(angle)) * radius * 0.7

        text_x = arrow_x + np.cos(np.radians(angle)) # * radius * 0.5
        text_y = arrow_y + np.sin(np.radians(angle)) # * radius * 0.5

        # Create the arrow
        ax.annotate('', xy=(bubble[0] + 0.5, bubble[1] + 0.5), xytext=(arrow_x,␣
↪arrow_y),
                    arrowprops=dict(arrowstyle="->",␣
↪connectionstyle="arc3,rad=0.2", color='black'))

        # Add the text annotations
```

```python
        ax.text(text_x, text_y, f"Total: {total:.0f} km\nAvg: {avg:.2f} km",
                horizontalalignment='left', verticalalignment='center',
                color='black', fontname='Arial', fontsize=8,
                bbox=dict(facecolor='white', edgecolor='gray', alpha=0.7,␣
 ↪pad=4))
```

[21]:
```python
# Prepare data for bubble chart
yearly_stats = df.groupby('year').agg({
    'distance': ['sum', 'mean', 'count']
}).reset_index()
yearly_stats.columns = ['year', 'total_distance', 'avg_distance', 'run_count']

# Create bubble chart
bubble_chart = BubbleChart(area=yearly_stats['total_distance'],␣
 ↪bubble_spacing=0.1)
bubble_chart.collapse()

# Set up the plot
fig, ax = plt.subplots(figsize=(8, 8), subplot_kw=dict(aspect="equal"))

# Generate colors
num_years = len(yearly_stats)
colors = plt.cm.viridis(np.linspace(0, 1, num_years))

# Prepare data for plotting
plot_data = list(zip(yearly_stats['year'],
                     yearly_stats['total_distance'],
                     yearly_stats['avg_distance']))

# Plot the bubble chart
bubble_chart.plot(ax, plot_data, colors)

    # Customize the plot
ax.axis("off")
ax.relim()
ax.autoscale_view()
ax.set_title('Yearly Running Summary', fontsize=16, fontweight='bold',␣
 ↪fontname='Arial')

plt.tight_layout()
plt.show()
```



5.0.2 Yearly Running Summary Insights

From 2016 to 2018 there was an obvious gradual increase in volume however, 2019/2020 showed a drastic reduction and completely missing from 2021/2022. This is likely due to **COVID-19**

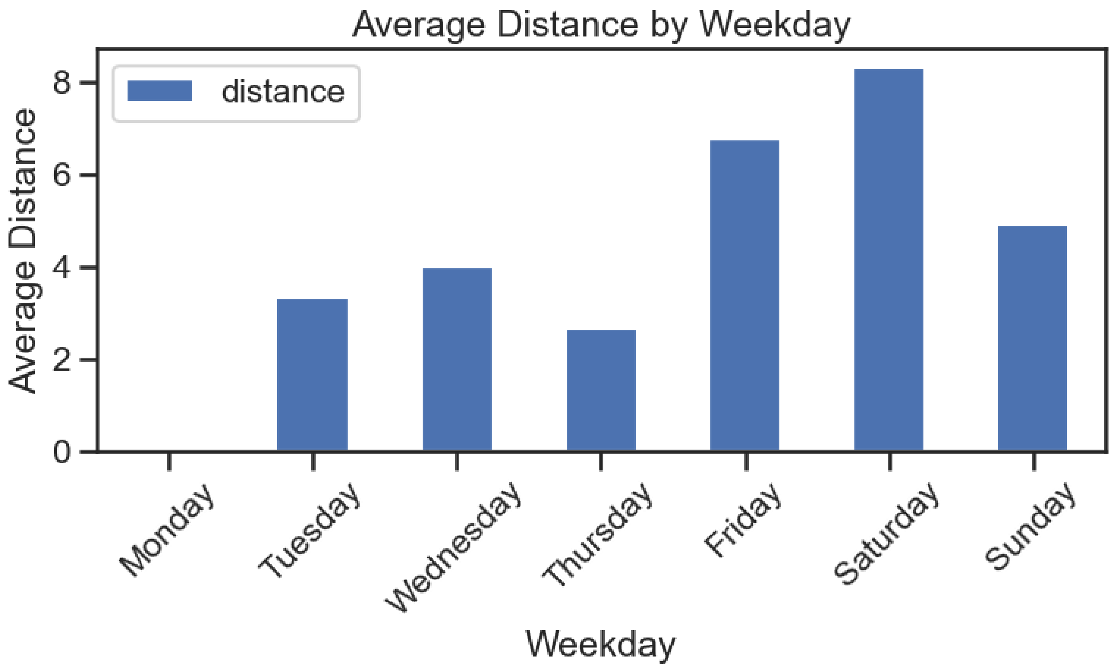
Pandemic and has inadvertedly affected fitness overall.

[22]:
```
latest_df.weekday.value_counts()

# I really have never ran a monday in 8 weeks lol, I can safely say this is␣
↪because Sundays are long run days so naturally
# Mondays are not really an option
```

[22]:
```
weekday
2    11
6     7
4     6
5     5
3     3
1     3
Name: count, dtype: int64
```

[23]:
```
# First, let's create a mapping of weekday numbers to names
weekday_names = {
    0: 'Monday',
    1: 'Tuesday',
    2: 'Wednesday',
    3: 'Thursday',
    4: 'Friday',
    5: 'Saturday',
    6: 'Sunday'
}
```

[24]:
```
# Calculate the mean moving time for each weekday
result = latest_df.groupby('weekday').agg({
    'distance': 'mean'
}).reindex(range(7))  # This ensures all weekdays are included

# Rename the index with weekday names
result.index = result.index.map(weekday_names)

# Plot the results
ax = result.plot(kind='bar', figsize=(8, 5))
plt.title('Average Distance by Weekday')
plt.xlabel('Weekday')
plt.ylabel('Average Distance')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

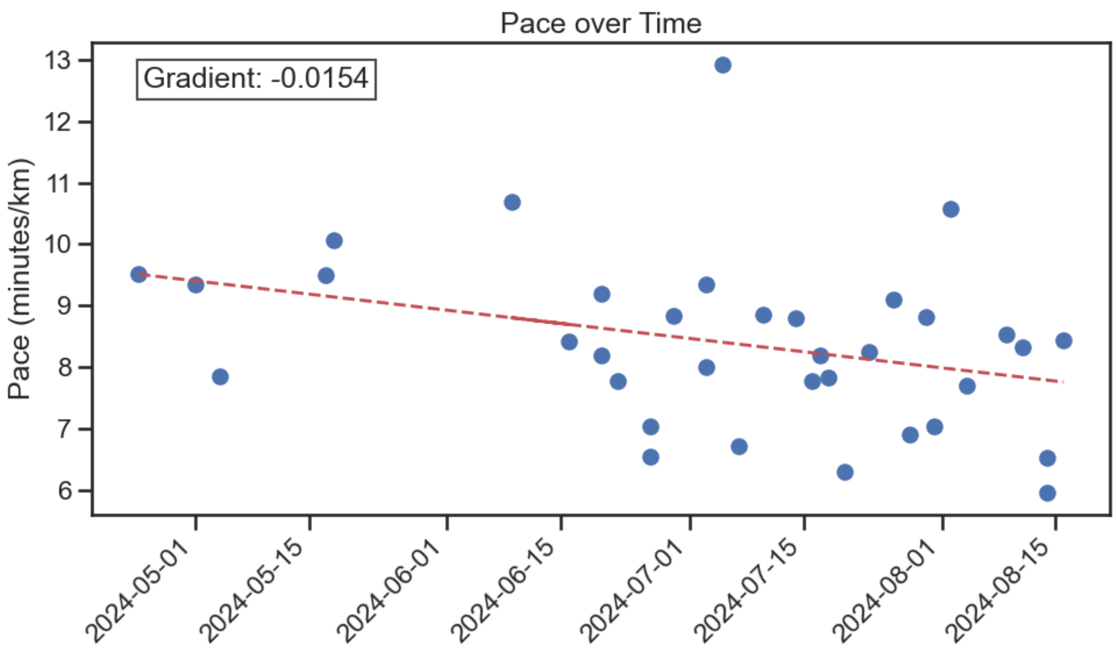


5.0.3 Average Distance by Weekday Insights

Weekends (and fridays) are typically when I have the most freedom to run long distances since the availability for training is greater, whichalso contributes to most of the weekly volume.

[25]:
```
fig = plt.figure(figsize=(10, 6))
ax1 = fig.add_subplot(111)

x = np.asarray(latest_df.start_date)
y = np.asarray(latest_df.pace)

ax1.scatter(x, y)
ax1.set_title('Pace over Time')

x2 = mdates.date2num(x)
z = np.polyfit(x2, y, 1)
p = np.poly1d(z)

# Extract the gradient (slope)
gradient = z[0]

plt.plot(x, p(x2), 'r--', linewidth=2)

# Add gradient text to the plot
ax1.text(0.05, 0.95, f'Gradient: {gradient:.4f}',
```

```
        transform=ax1.transAxes,␣
↪verticalalignment='top',bbox=dict(facecolor='white',edgecolor='black',alpha=0.
↪7))

ax1.set_ylabel('Pace (minutes/km)')
# ax1.legend()

fig.autofmt_xdate(rotation=45)
fig.tight_layout()
plt.show()
```



5.0.4 Pace over Time Insights

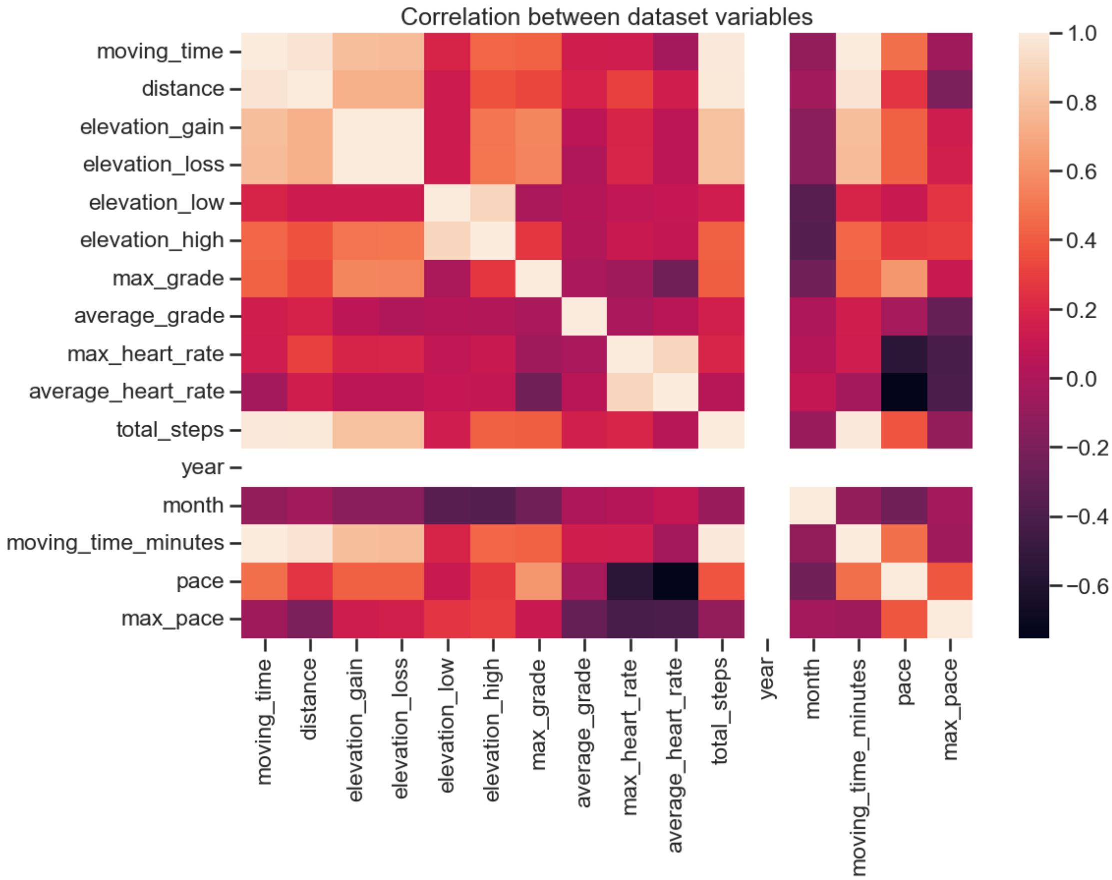
The graph depics a slight overall improvement in speed (lower pace) despite day-to-day variations. In my case, its worth mentioning that this is the result of training and all the effort dedicated to the sport.

6 Feature Selection

This is an important step for the application of machine learning models later. This way we can confirm whether the empirically cited characteristics are really good.

The first way to understand the features and how they interact with the response variable is through the `correlation matrix`.

[26]:
```
numerical_cols = latest_df.select_dtypes(include=['float64','int32'])

corr = numerical_cols.corr()
plt.figure(figsize = (12,8))
sns.heatmap(corr, fmt=".2f");
plt.title('Correlation between dataset variables')
plt.show()
```



6.0.1 Matrix Analysis

From this matrix, it can be defined that the values closest to +1 have a positive correlation and the values closest to -1 have a negative correlation.

To continue with the analyses, the running dataframe will be scrambled so that problems related to bias and dataframe sequence learning are prevented.

[32]:
```
def get_best_rfe_features(X,y, model):
    rfe = RFE(model, step=0.05).fit(X, y)
    selected_features = [i for i, j in zip(X.columns, rfe.support_) if j]
    return selected_features
```

```
runs = numerical_cols.sample(frac=1).reset_index(drop=True)
# list_nulls(runs)

y = runs['pace']
X = runs.drop('pace',axis=1)

encoded_y = preprocessing.LabelEncoder().fit_transform(y)
model = LinearRegression()
linear_feats = get_best_rfe_features(X, encoded_y, model)
linear_feats
```

[32]:
```
['distance',
 'elevation_loss',
 'average_grade',
 'average_heart_rate',
 'month',
 'moving_time_minutes',
 'max_pace']
```

6.0.2 Recursive Feature Elimination

The above code will train the RFE model and recursively elimate features acoording to their lack of importance.

Finally `linear_feats` then are the best variables selected for regression

7 Machine Learning

I will only be using 1 machine learning techniques, among the many available, which is `Clustering`. This is because I have no need for regression to predict when I can easily calculate the pace/distance with the right metrics. It is more important to me what kinds of run im having and the kinds of heart rate I should be aiming for.

7.0.1 Clustering

I will be performing a technique called K-means. This technique will group records of races that are similar. Note that the method is stochastic, so each execution will likely generate different results.

[28]:
```
X = runs.drop('pace',axis=1)
X = pd.get_dummies(X)

model = KMeans(n_clusters=4).fit(X)
clustering_runs = runs.copy()
clustering_runs['Cluster'] = model.labels_
```

[29]:
```
clustering_runs['Cluster'].value_counts()
```

[29]:
```
Cluster
2    16
0    12
1     6
3     1
Name: count, dtype: int64
```

[30]:
```
clustering_runs.groupby('Cluster').mean()
```

[30]:
```
         moving_time   distance  elevation_gain  elevation_loss  \
Cluster
0        1195.166667   2.474167       63.215174       67.928377
1        4947.000000   9.001667      404.646746      403.980249
2        2449.437500   5.008750      177.150003      175.712498
3        8935.000000  14.810000      992.799927     1008.799988

         elevation_low  elevation_high  max_grade  average_grade  \
Cluster
0            42.825000       67.708333  31.144058      -0.246359
1           -16.466667       76.350000  46.251586       0.028638
2            53.287499      103.237501  37.202141       0.035288
3           395.200012      523.000000  49.956367      -0.156001

         max_heart_rate  average_heart_rate   total_steps    year     month  \
Cluster
0            177.333333          162.641992   3004.833333  2024.0  6.750000
1            175.273810          156.252586  11943.000000  2024.0  6.833333
2            182.437500          165.680799   6201.375000  2024.0  6.625000
3            202.000000          181.586426  20382.000000  2024.0  5.000000

         moving_time_minutes       pace  max_pace
Cluster
0                  19.919167   7.996667  4.294167
1                  82.450000   9.328333  3.453333
2                  40.824375   8.238125  3.228750
3                 148.920000  10.060000  4.980000
```

7.1 Cluster Overview

There are 4 distinct clusters, each representing a different type of run or running patern

7.1.1 Clusting Characteristics

Cluster A: ***Moderate*** *Runs* - Average distance: ~5km - Moderate elevation gain - Higher heart rates - Representing typical training runs (also the highest sample among the clusters)

Cluster B: ***Long*** *Runs* - Average distance: ~9km - Higher elevation gain - Lower average heart rate than Moderate Run (likely due to long runs being used for slower, volume jogs) - Endurance building runs

*Cluster C: **Short** Runs* - Average distance: ~2.5km - Lowest elevation gain, flattest ground - Higher pace than the rest - Heart rate roughly matching Cluster 0 even with less distance - Representing speed sessions and/or training sessions

*Cluster D: **Challenging** Long Runs* - Average distance: ~15km - Highest elevation gain - Highest heart rate - Outlier, representing races and trail runs

7.1.2 Interesting Observations:

Run distance The longer runs(Cluster 1) have lower average heart rate than shorter runs (Cluster 2), suggesting better cardiovascular efficiency on longer distances. #### Elevation vs Pace Clusters with higher elevation gain/loss (1 and 3) have slower paces, showing the impact of terrain on speed.

7.1.3 Potential Insights:

Training Variety: A good mix of run types, from short, intense sessions to longer endurance runs. *Heart Rate Zones*: Heart rate varies predictably with run intensity and distance. *Terrain Impact*: There's a clear relationship between elevation changes and pace/effort.

7.2 Calculate the race!

Now to conclude this study, lets predict how long it would take for me to run a 21KM run this November.

Lets try and compare 2 ways of calculating,

1. one by (naively) looking at the gradient of improvement over the past 8 weeks vs
2. one by looking at the rolling average as well as extra weightage on longer runs

7.2.1 –Gradient–

[46]:
```
# Calculate the improvement rate
days = (latest_df.start_date.max() - latest_df.start_date.min()).days
improvement_rate = gradient * days  # Improvement in minutes/km over the entire␣
↪period

# Project future performance
target_pace = 6.0  # 2:06:00 for a half marathon is about 6 min/km
# Get the most recent date
most_recent_date = latest_df['week_start_date'].max()

# Calculate the date two weeks ago
two_weeks_ago = most_recent_date - timedelta(weeks=2)

# Filter the DataFrame for the last two weeks
last_two_weeks_df = latest_df[latest_df['week_start_date'] > two_weeks_ago]

# Get the highest pace from the last two weeks
current_pace = last_two_weeks_df['pace'].mean()
```

```
time_to_target = (current_pace - target_pace) / (-gradient)

def days_to_months_days(total_days):
    average_days_per_month = 30

    # Calculate the number of months
    months = int(total_days // average_days_per_month)

    # Calculate the remaining days
    remaining_days = int(total_days % average_days_per_month)

    return months,remaining_days

months,days = days_to_months_days(time_to_target)


print(f"Current pace: {current_pace:.2f} min/km")
print(f"Improvement rate: {-gradient*365:.2f} min/km per year")
print(f"Estimated days to reach target pace: {time_to_target:.0f}")
print(f"Estimated months and days to reach target pace: {months} months, {days:.
↪0f} days")
```

```
Current pace: 7.55 min/km
Improvement rate: 5.62 min/km per year
Estimated days to reach target pace: 101
Estimated months and days to reach target pace: 3 months, 10 days
```

7.2.2 –Rolling Average–

[45]:
```
def predict_time_to_goal_pace(df, goal_pace, weeks_for_average=4,␣
↪long_run_threshold=10, long_run_weight=1.5):
    # Sort the dataframe by date
    df = df.sort_values('activity_date')

    # Weight long runs more heavily
    weighted_pace = pd.Series(np.where(df['distance'] >= long_run_threshold,
                                       df['pace'] * long_run_weight,
                                       df['pace']))

    # Calculate weighted rolling average
    weighted_rolling_avg = weighted_pace.rolling(window=7*weeks_for_average,␣
↪min_periods=1).mean()

    # Calculate the rate of improvement (pace decrease per day)
    days = (df['activity_date'] - df['activity_date'].min()).dt.days
    improvement_rate = np.polyfit(days, weighted_rolling_avg, 1)[0]
```

```
    # Get the most recent weighted rolling average
    current_weighted_avg = weighted_rolling_avg.iloc[-1]

    # Estimate current half marathon pace (typically 5-10% slower than average␣
 ↪training pace)
    current_hm_pace = current_weighted_avg * 1.07  # Assuming 7% here

    # Calculate time to reach goal pace
    time_to_goal = (current_hm_pace - goal_pace) / (-improvement_rate)

    return current_hm_pace, improvement_rate, time_to_goal

# Example usage
goal_pace = 6.0  # min/km
current_pace, improvement_rate, days_to_goal =␣
 ↪predict_time_to_goal_pace(latest_df, goal_pace)

print(f"Current estimated Half Marathon Pace: {current_pace:.2f} min/km")
print(f"Current improvement rate: {-improvement_rate*365:.4f} min/km per year")
print(f"Estimated days to reach goal pace: {days_to_goal:.0f}")

# Convert days to months and remaining days
months = int(days_to_goal // 30)
remaining_days = int(days_to_goal % 30)
print(f"Estimated time to reach goal pace: {months} months and {remaining_days}␣
 ↪days")
```

```
Current estimated Half Marathon Pace: 9.24 min/km
Current improvement rate: 2.5660 min/km per year
Estimated days to reach goal pace: 460
Estimated time to reach goal pace: 15 months and 10 days
```

8 Conclusion

The comparison of two prediction methods for the upcoming 21KM run in November reveals significantly different outcomes. The **gradient** method, a simpler approach, suggests a current pace of 7.55 min/km and predicts reaching your goal in about 3 months. This method paints an **optimistic picture of rapid improvement**.

In contrast, the **rolling average method**, which factors in longer runs, estimates a slower current pace of 9.24 min/km and projects a longer timeframe of 15 months to reach your goal. This approach likely provides a more realistic prediction, **accounting for the challenges of maintaining pace over longer distances**.

For the November race, it's prudent to base your expectations on the more conservative rolling average estimate while working to exceed it. This balances optimism with realism, setting you up for a potentially satisfying performance without risking disappointment from overly ambitious goals.

Thanks for reading!