Strava Fitness App

Python File Analysis Report

Overview:

In today's fast-paced world, where people are increasingly aware of their health and well-being, fitness tracking apps like **Strava** have become essential tools in everyday life. These platforms not only help individuals stay accountable but also empower them to understand their physical patterns, set goals, and lead healthier lifestyles.

This report focuses on analyzing real-world user data collected from the Strava Fitness App. The goal is to uncover meaningful trends related to users' **physical activity, sleep behavior, calorie expenditure**, and **overall daily movement** across different days of the week.

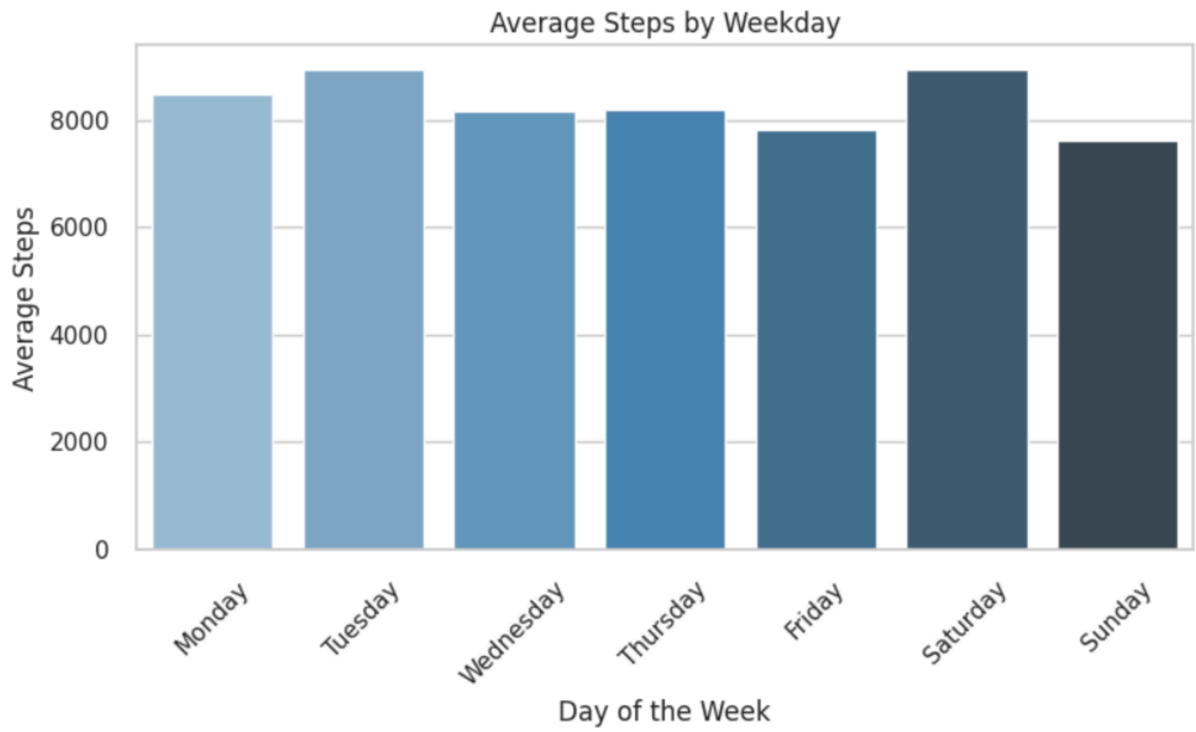
This report provides an exploratory analysis of user fitness behavior using Python-based visualizations. The data is extracted from a merged CSV file that combines multiple aspects such as steps, sleep, calories, weight, heart rate, and activity intensity from Strava fitness trackers. The goal is to reveal patterns and relationships that can help improve health outcomes and fitness engagement.

This Python file includes six key visuals:

1. **Steps Taken Through Weekdays**
2. **Steps vs Calories Burnt**
3. **Active Time Distribution by Type**
4. **Avg. Calories Burnt over time**
5. **Sleep Duration vs. Step count**
6. **Correlation Between Key Metrics**

Each of these visuals is explained in the following sections with actionable insights.

1. **Average Steps Taken Through Weekdays:**



This visual displays the average number of steps users take on each day of the week, helping identify patterns in daily physical activity.

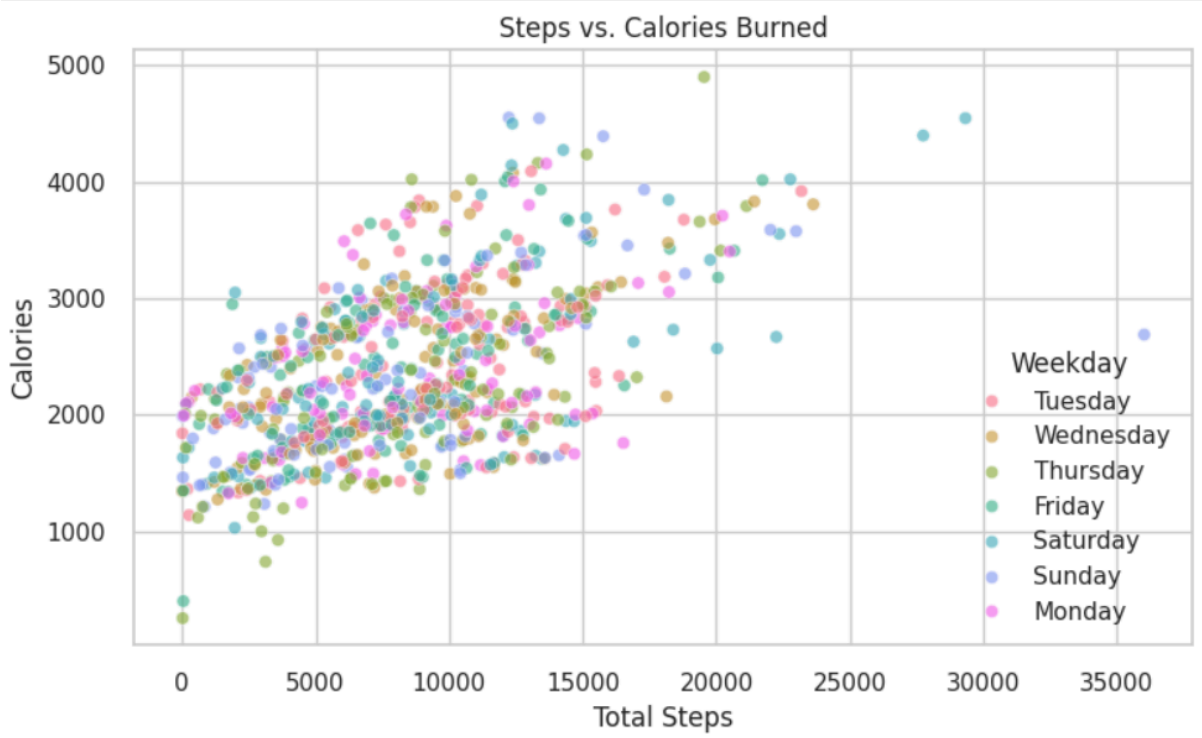
Insights:

- Users tend to be more active on **Tuesdays** and **Saturdays**, possibly due to mid-week workouts or weekend leisure activities.
- **Fridays** and **Sundays** show the lowest average step counts, suggesting users wind down before or after weekends.

Business Impact:

- Promote **step challenges** or **fitness reminders** on low-activity days like Friday and Sunday to balance engagement.
- Use high-performance days to test new features or campaigns, as users are more responsive on active days.

2. Steps vs Calories Burnt



This scatter plot Visualizes the correlation between sleep duration and steps taken the next day.

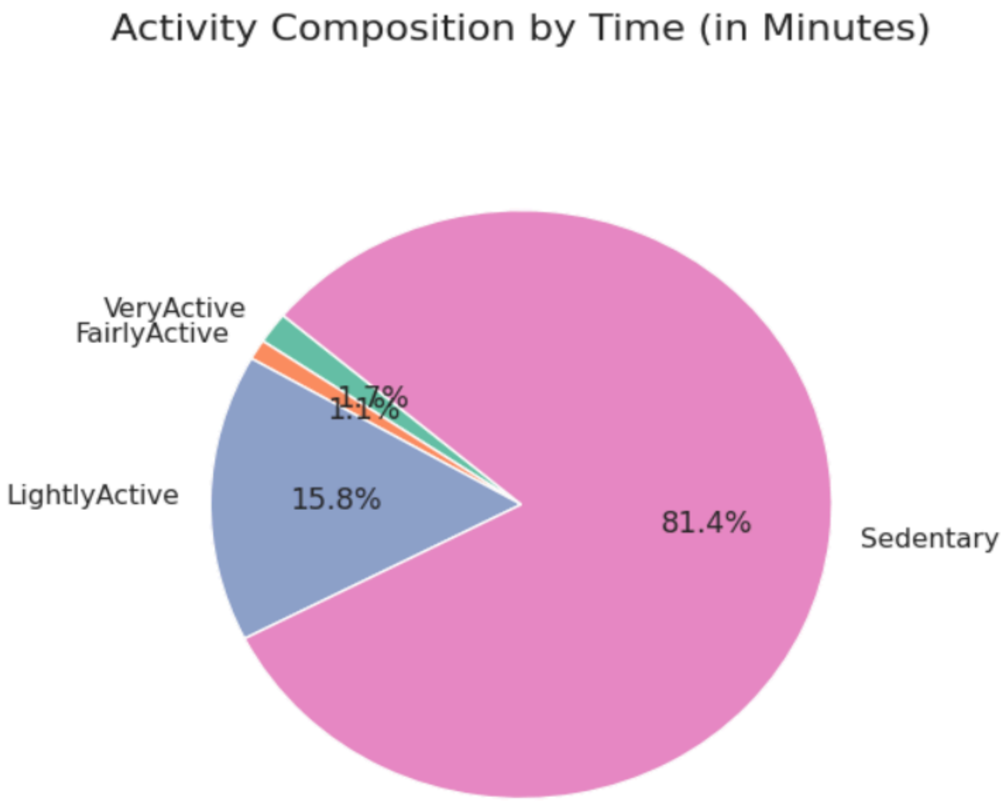
Insights:

- A moderate positive trend shows users with better sleep tend to take more steps, suggesting well-rested users are more active.

Business Impact:

- Educate users about intensity levels and how they affect calorie burn.
- Develop targeted content (videos, notifications) to encourage users to **increase intensity**, not just duration.

3. Active Time Distribution by Type



A pie chart shows the proportion of time spent in Very Active, Fairly Active, Lightly Active, and Sedentary minutes.

Insights:

- The majority of users' active minutes are in the **lightly active** category, such as walking or standing.

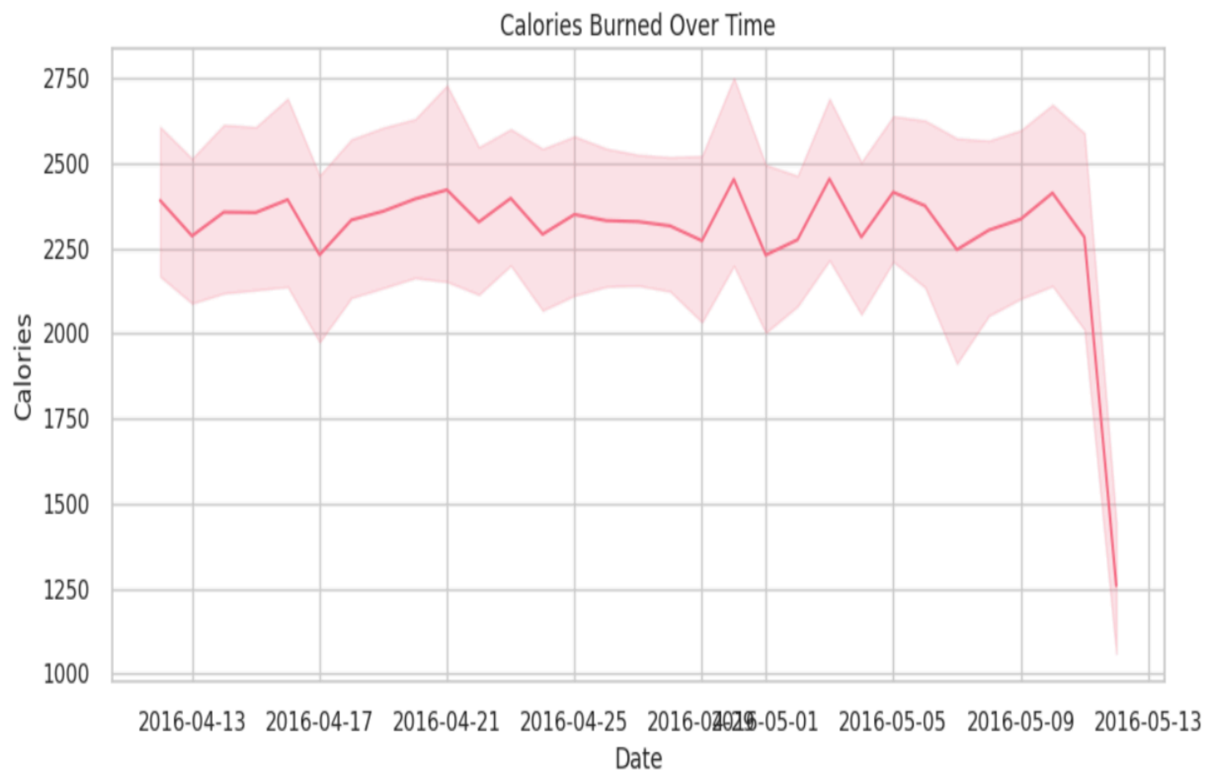
- **Very active minutes** are significantly lower, indicating a lack of high-effort activities like running or intense workouts.

Business Impact:

- Introduce features like "Power Hours" or "HIIT Challenges" to promote more high-intensity activities.

- Segment users based on their intensity levels and offer **personalized recommendations** for more efficient workouts.

4. Average Calories Burnt over time



A matrix or heatmap comparing how much each user burns in calories across different days of the week.

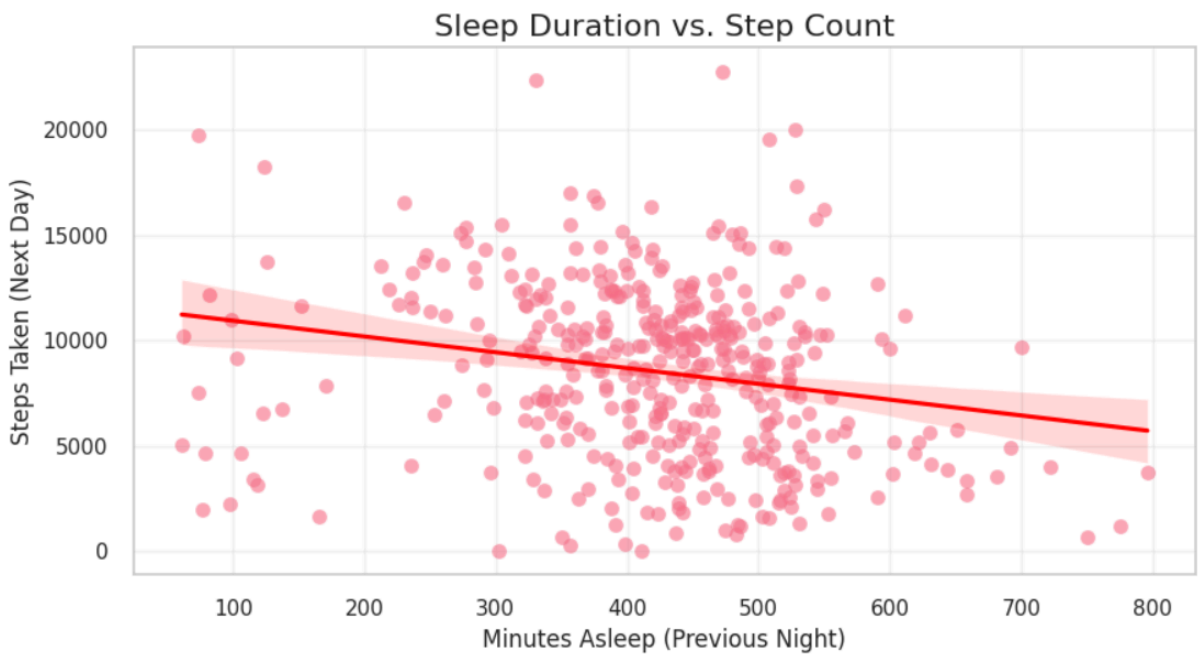
Insights:

- There's a visible performance gap—some users consistently burn high calories, while others show minimal activity.
- Tuesday remains a consistent high-calorie day across many users.

Business Impact:

- Identify **high-performing users** and offer them leadership roles in challenges or communities.
- Create **personalized nudges** for low-engagement users to improve consistency and reduce churn.

5. Sleep Duration vs. Step count



Insights:

- This scatter plot with a regression line indicates a slightly negative correlation between sleep duration and the number of steps taken the following day.
- Contrary to common assumptions, in this dataset, more sleep doesn't directly translate to more physical activity the next day.
- Users with moderate sleep (around 300–500 minutes) show higher variation in steps, while those with long sleep durations (600+ minutes) generally take fewer steps.

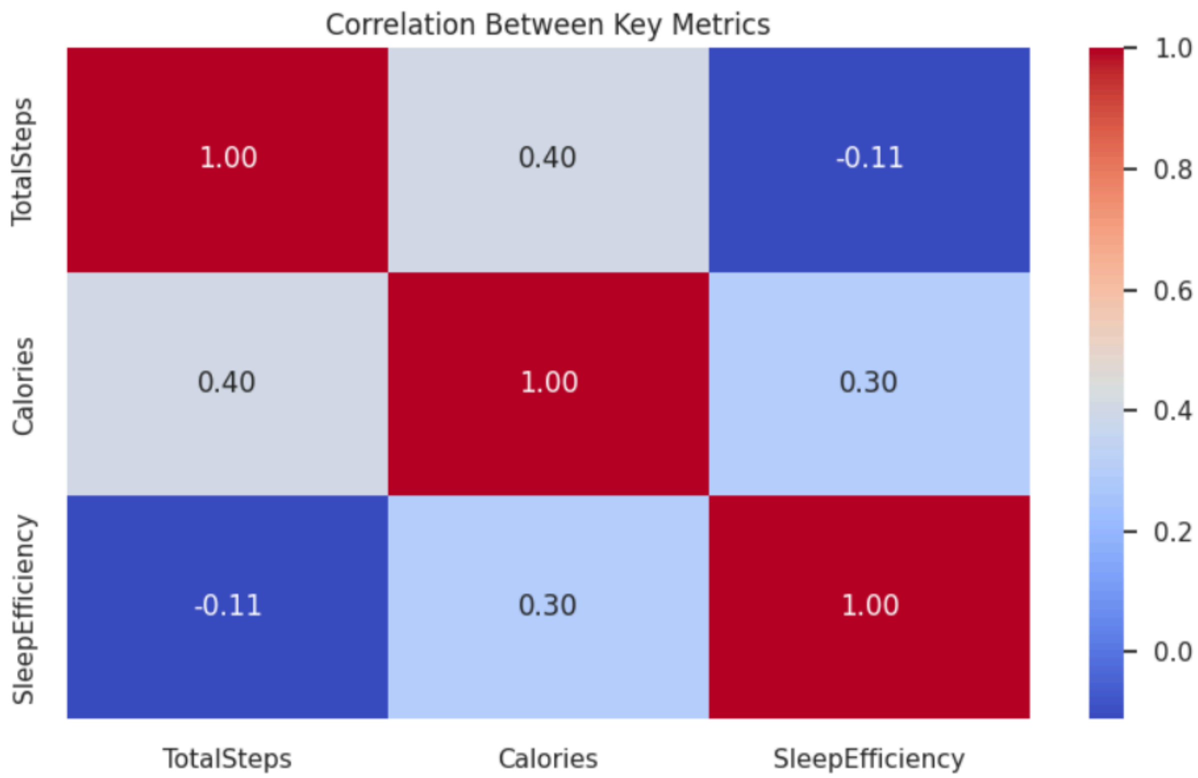
Business Impact:

- Personalized Interventions: Users sleeping excessively might be experiencing fatigue, inactivity, or recovery days. Strava can detect such patterns and provide personalized nudges.
- Health Coaching: Fitness coaches can use this data to strike a balance between adequate sleep and maintaining activity goals, discouraging oversleeping when not required.

- Feature Suggestion: Strava can introduce a “Recovery vs. Performance” badge to help users understand how sleep impacts their physical output.

- Wellness Alert: For users showing a pattern of long sleep and low activity, the app could recommend steps to improve energy levels and maintain a balanced routine.

6. Correlation Between Key Metrics



This chart visualizes the correlation coefficients among three key fitness metrics: total steps, calories, and sleep efficiency. The values range from -1 (strong negative correlation) to +1 (strong positive correlation), indicating how strongly two metrics move together.

Insights:

- **Steps vs Calories** → Moderate positive correlation (**0.40**): Users who walk more tend to burn more calories.

- **Calories vs Sleep Efficiency** → Weak positive correlation (**0.30**): Slight connection between restful sleep and calorie burn.

- **Steps vs Sleep Efficiency** → Weak negative correlation (**-0.11**): More active users do **not** necessarily sleep more efficiently.

Business Impact:

Knowing the relationships between metrics helps the app suggest:

- Whether sleep improvement influences calorie burn.
- If more steps necessarily mean better sleep or just higher energy expenditure.
- Personalized recommendations based on behavior patterns.

Business Solutions

Based on the data-driven insights from visual analysis:

1. **Personalized Recommendations**:
    - Offer personalized workout suggestions based on a user's sleep quality and past step activity.
    - Notify users with consistently low sleep efficiency to reduce activity intensity or adjust bedtime routines.
2. **Balance Recovery with Performance**:
    - Implement in-app prompts encouraging rest for users showing high activity but declining sleep metrics.
    - Introduce a "Recovery Score" feature combining activity and sleep efficiency for optimal fitness planning.
3. **Smart Goal Adjustments**:
    - Adapt step and calorie goals dynamically based on recent sleep trends and performance correlations.
    - Promote weekly reports showing how behaviors interact (e.g., how sleep influences step count).

4. **Segment-Based Coaching**:
    - Classify users into performance/recovery categories using correlation trends to guide AI-based fitness coaching.

Conclusion

The Python visualizations reveal **key interdependencies** among physical activity, calorie expenditure, and sleep behavior. While **steps and calories** are moderately correlated, **sleep metrics** show weaker ties to activity. This highlights the **need for a dual-track strategy**—one that **optimizes both performance and recovery** independently.

In essence, a **balanced approach** to fitness requires:

- **Monitoring not just how much users move**, but **how well they recover**.
- Delivering **custom insights and interventions** that align with individual behavior patterns.

These insights empower the Strava Fitness App to go beyond tracking — and evolve into a **personal wellness coach** that adapts to the user.