efficiency_correlation_report

November 23, 2024

1 Lap Efficiency Correlation Report

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1.1 Overview

Following our participation in the Formula Sun Grand Prix in July 2024, we present an analysis the factors correlating to our efficiency throughout the race.

1.1.1 Motivation

See Lap Efficiency Correlation DR0.

- Quantitatively investigate which factors affect efficiency at FSGP using:
  - Telemetry data
  - Timing spreadsheet records
  - Weather data
- Purpose: understanding efficiency can help us optimize performance by operating as close as possible to our most efficient conditions

1.1.2 Vocabulary

- Lap Energy
  - The net electrical energy consumed by the motor (accounting for regen) between the lap start and end time recorded in our FSGP Timing Spreadsheet.
- Practical Efficiency
  - The energy per unit distance (J/m) computed as Lap Energy / 5070m, where 5070m is the given length of the NCM Motorsports Park track.
- Real Efficiency
  - The energy per unit distance (J/m) computed as Lap Energy / Distance Travelled where Distance Travelled is obtained as an integral of speed over the lap.

Why motor energy? - LVS & Array Power are largely independent of driving behaviour, so they not relevant to our optimization of speed & driving style.

1.2 Imports

[181]:
```python
from data_tools.query import DBClient
from data_tools.collections import FSGPDayLaps
import datetime
import numpy as np
import pandas as pd

# Plotting
import matplotlib.pyplot as plt
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression

# Open Meteo API
import openmeteo_requests
import requests_cache
from retry_requests import retry

FSGP_TRACK_LEN_M = 5_070

driver_colours = {
    "Alex": "red",
    "Bryan": "orange",
    "Diego": "green",
    "Phoebe": "blue"
}

data_client = DBClient("can_log_prod")
```

```
Creating client with API Token: s4Z9_S6_O09kDzYn1KZcs7LVoCA2cVK9_ObY44vR4xMh-
wYLSWBkypS0S0ZHQgBvEV2A5LgvQ1IKr8byHes2LA==
Creating client with Org: 8a0b66d77a331e96
```

1.3 Load Data

See `correlation_df.py` for querying and derivation of data. Since this querying requires a connection to our UBC Solar Tailnet and takes a few minutes, we have stored our derived data for this analysis in a `lap_data.csv`.

[182]:
```python
df = pd.read_csv("./lap_data.csv")
df.head(10)
```

[182]:
```
   lap_distance_(m)    lap_energy_(J)   lap_energy_(kJ)   energy_regen_(J)  \
0 5422.621217619539 845440.7592498517 845.4407592498517 19444.581794553666
1   5110.3660202388 742762.6773114646 742.7626773114646 24433.210032340416
2 5090.330927985945 622935.3576563572 622.9353576563573  8203.242310369418
3 5171.397775814052 628939.8490316086 628.9398490316086  5167.430689083902
4 5116.421189229325 632982.2708804868 632.9822708804868  1826.344625235744
```

5	5147.460343315915	650760.3479438522	650.7603479438521	2754.9002805427617
6	5269.859661132362	665763.3515050309	665.7633515050309	2868.443348560109
7	5151.753049545288	650773.6780310014	650.7736780310014	6558.633813307358
8	5106.23311301851	627637.1251017407	627.6371251017407	8121.477653482564
9	5152.105992597277	668908.1440541805	668.9081440541805	8188.121412481056

	energy_regen_(kJ)	speed_variance_(mph^2)	motor_power_variance_(W^2)	\
0	19.444581794553663	10.70694366541461	4299372.535592417	
1	24.433210032340416	2.6990476183683114	4754985.389726375	
2	8.203242310369419	1.1828161230215108	1788748.696184072	
3	5.1674306890839015	1.897054651411404	2097404.6645799447	
4	1.826344625235744	1.927264033563438	2787216.020188109	
5	2.7549002805427616	1.7526588702087336	2993137.086520944	
6	2.868443348560109	9.73353496317702	2921007.692465615	
7	6.558633813307358	1.5877723968985706	2751866.8650973705	
8	8.121477653482565	1.341076153409468	2897804.2349360534	
9	8.188121412481056	1.2246257025176737	3412304.448321949	

	motor_current_variance_(A^2)	acceleration_variance_(m^2/s^4)	\
0	285.1222100417652	0.0036770449582751	
1	318.2146439617965	0.0032276091619134	
2	118.54428720581876	0.0017574678779565	
3	140.48855593312013	0.0021367664045727	
4	189.24553497508387	0.0021595044802341	
5	205.29670427715672	0.0023118797050197	
6	200.93325001921963	0.0022854344413118	
7	191.8643217129577	0.0023836313074267	
8	205.41875095603243	0.0023573396019313	
9	246.43155256027887	0.0028051368819056	

	accelerator_variance	…	battery_temp_avg_(C)	pack_current_avg_(A)	\
0	1330.3649889790645	…	29.81666393250792	15.096573856728556	
1	1492.9359629289386	…	30.66600450178685	15.10701511983404	
2	575.6078136218408	…	31.0	10.042580000596228	
3	706.120444204757	…	31.61864392535724	10.421669946462266	
4	893.5734615149352	…	32.0	10.687179977286124	
5	942.051719716663	…	32.21109133825223	11.190643958392863	
6	981.2398394719402	…	33.0	9.809869768138594	
7	890.992443758054	…	32.498827948223926	11.374014286502986	
8	969.8747646775992	…	32.0	11.014714646680018	
9	1195.6621383047614	…	32.0	12.1173889724169	

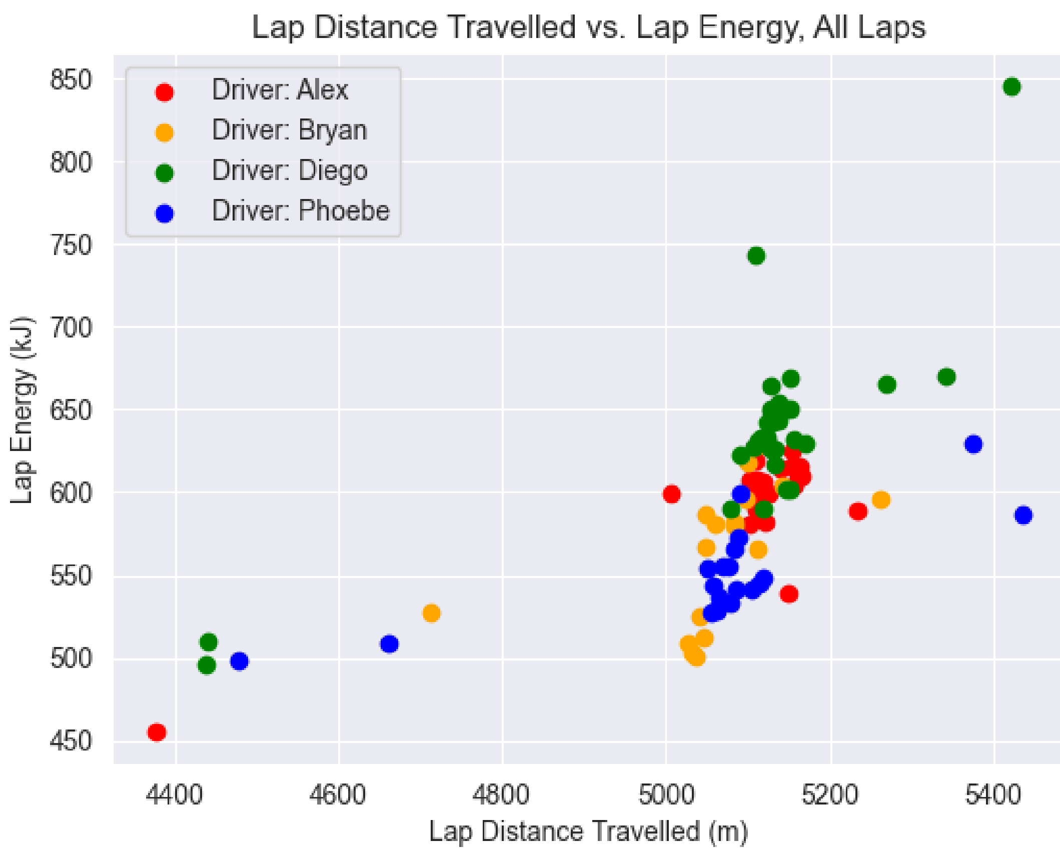
	lap_index	lap_number	lap_end_time	day	driver	\
0	0	1	2024-07-16 15:07:04+00:00	1	Diego	
1	1	2	2024-07-16 15:13:09+00:00	1	Diego	
2	2	3	2024-07-16 15:20:19+00:00	1	Diego	
3	3	4	2024-07-16 15:27:21+00:00	1	Diego	

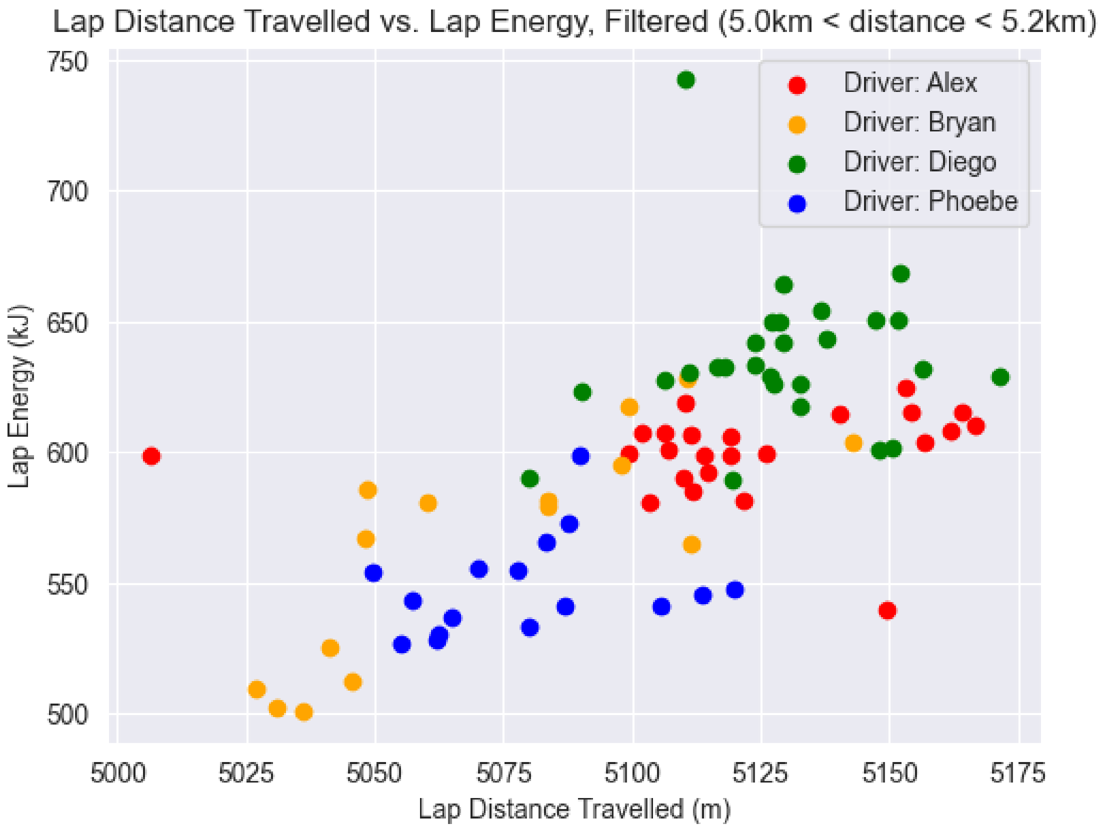
```
4          4          5  2024-07-16 15:33:59+00:00   1   Diego
5          5          6  2024-07-16 15:40:21+00:00   1   Diego
6          6          7  2024-07-16 15:47:45+00:00   1   Diego
7          7          8  2024-07-16 15:54:10+00:00   1   Diego
8          8          9  2024-07-16 16:00:39+00:00   1   Diego
9          9         10  2024-07-16 16:07:05+00:00   1   Diego

  speed_avg_(mph)  efficiency_practical_(J/m)  efficiency_real_(J/m)
0          26.745          166.75360142995103      155.9099788314164
1          31.068           146.5015142626163      145.3443206161496
2          26.372          122.86693444898565     122.37620038248272
3          26.872            124.051252274479     121.61892708642094
4          28.492          124.84857413816307     123.71582547054368
5          29.686          128.35509821377755     126.42357678167994
6          25.541           131.3142705138128      126.3341709866283
7          29.455          128.35772742228824     126.32082162564856
8          29.152          123.79430475379502     122.91587775371224
9          29.378           131.9345451783393      129.8319842439753

[10 rows x 21 columns]
```

Our data contains several outlier laps due to various competition conditions: pitting to switch out a driver or stopping due to an accident on the track, for example. This leads to anomalous data points with energy values that do not reflect car performance. By filtering out values with distances outside the typical range, we can remove such outliers and provide better analysis. Here is a plot of distance vs efficiency (explored in more detail later) to demonstrate the filter.

[183]:
```
distance_filter = np.logical_and(df["lap_distance_(m)"] > 5000,␣
 ↪df["lap_distance_(m)"] < 5200)
filtered_df = df[distance_filter]

for driver, colour in driver_colours.items():
    plt.scatter(df["lap_distance_(m)"][df["driver"] == driver],
                df["lap_energy_(kJ)"][df["driver"] == driver],
                c=colour,
                label=f"Driver: {driver}")
plt.xlabel("Lap Distance Travelled (m)")
plt.ylabel("Lap Energy (kJ)")
plt.legend()
plt.title(f"Lap Distance Travelled vs. Lap Energy, All Laps")
plt.show()

for driver, colour in driver_colours.items():
    combined_filter = np.logical_and(distance_filter, df["driver"] == driver)
    plt.scatter(df["lap_distance_(m)"][combined_filter],
                df["lap_energy_(kJ)"][combined_filter],
                c=colour,
```

```
                label=f"Driver: {driver}")
plt.xlabel("Lap Distance Travelled (m)")
plt.ylabel("Lap Energy (kJ)")
plt.legend()
plt.title(f"Lap Distance Travelled vs. Lap Energy, Filtered (5.0km < distance <
 ↪5.2km)")
plt.show()
```



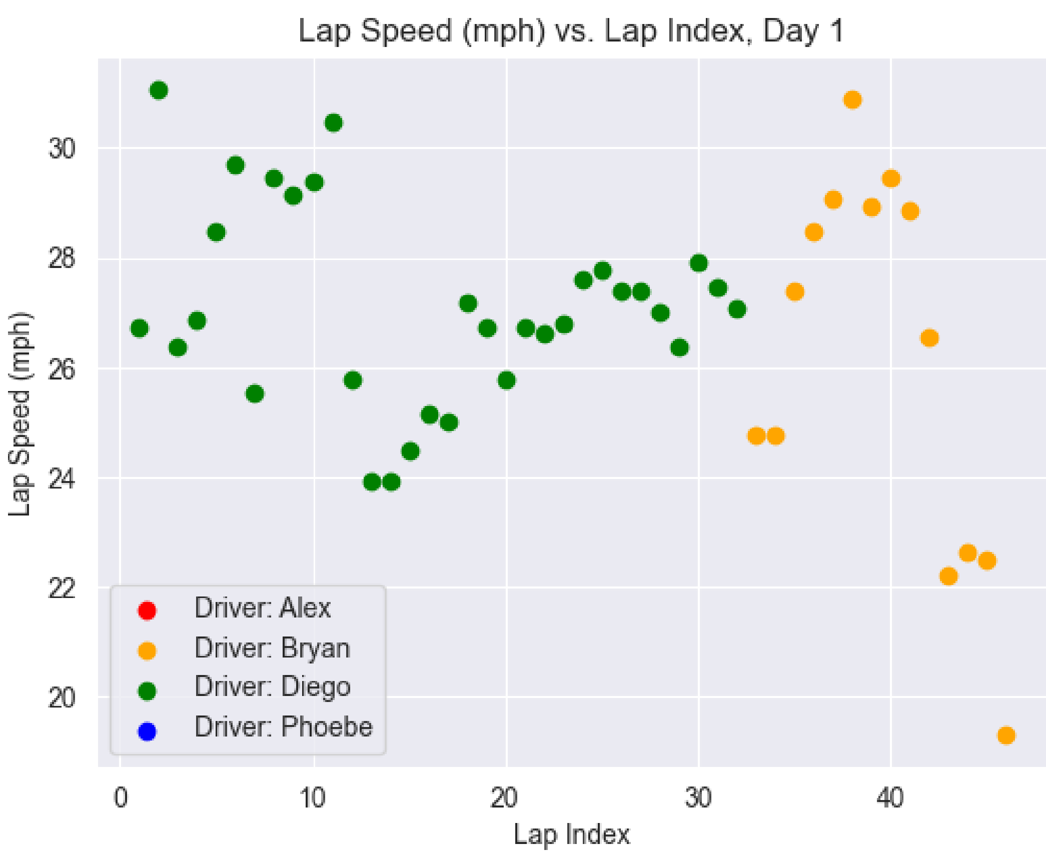


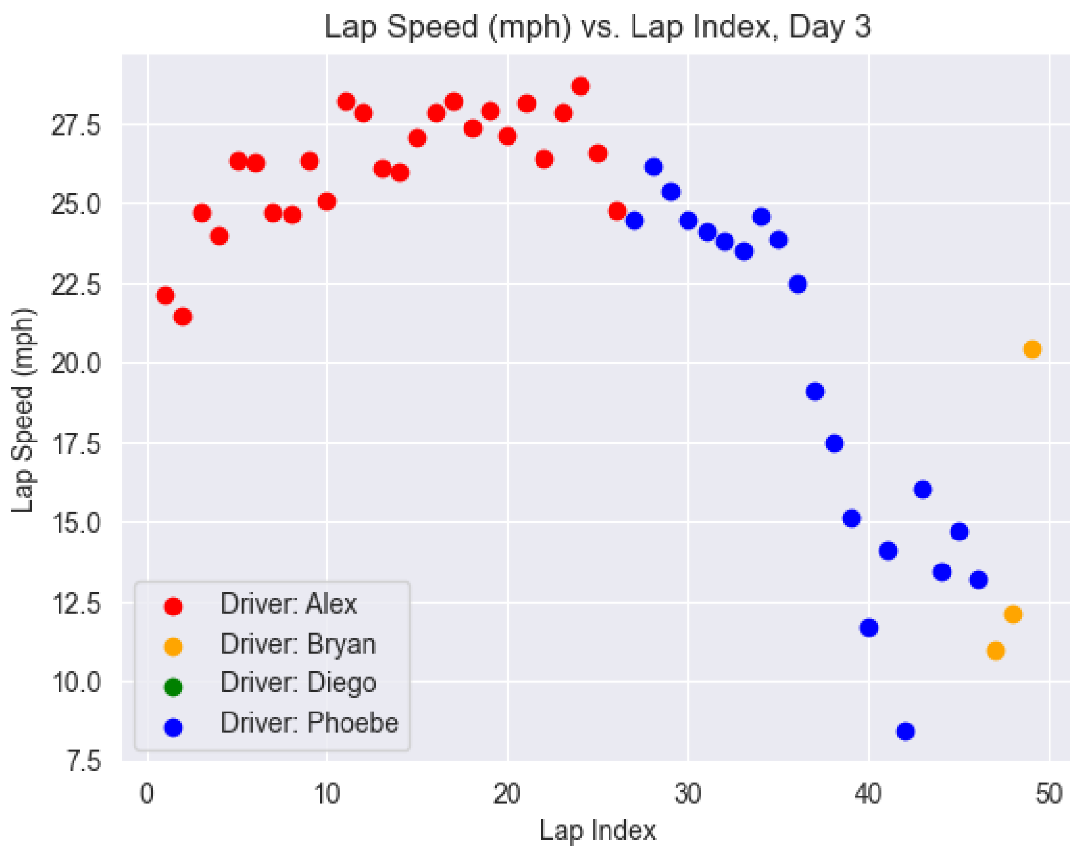
1.4 Context

The plots below show the speeds that we drove at for each lap in FSGP 2024, excluding day 2. We began quickly, aiming to qualify in one day because of concerns of poor weather on day 2. After running out of battery on day 1, we were made aware of the possibility of a provisional qualification which led us to adapt our strategy to instead demonstrate endurance. We drove three slow laps (just enough to qualify Bryan) in heavy rain on day 2 and spent the rest of the day charging as much as possible for day 3. On day 3, we aimed to spend as long as possible on the track, and succeeded in racing all day long. To maintain SoC, we had to dramatically reduce our speed near the end of the day as can be seen with Phoebe's slow laps.

[184]:
```
laps1 = FSGPDayLaps(1)
day_1_laps = laps1.get_lap_count()
day_1_df = df[:day_1_laps]
for driver, colour in driver_colours.items():
    plt.scatter(day_1_df["lap_number"][day_1_df["driver"] == driver],
                day_1_df["speed_avg_(mph)"][day_1_df["driver"] == driver],
                c=colour,
                label=f"Driver: {driver}")
plt.xlabel("Lap Index")
```

```
plt.ylabel("Lap Speed (mph)")
plt.legend(loc="lower left")
plt.title(f"Lap Speed (mph) vs. Lap Index, Day 1")
plt.show()

day_3_df = df[day_1_laps:]
for driver, colour in driver_colours.items():
    plt.scatter(day_3_df["lap_number"][day_3_df["driver"] == driver],
                day_3_df["speed_avg_(mph)"][day_3_df["driver"] == driver],
                c=colour,
                label=f"Driver: {driver}")
plt.xlabel("Lap Index")
plt.ylabel("Lap Speed (mph)")
plt.legend(loc="lower left")
plt.title(f"Lap Speed (mph) vs. Lap Index, Day 3")
plt.show()
```





1.5 Results

The below function simplifies plotting correlation. We then analyze several factors that we believe may have a correlation with lap energy.

[186]:
```
def plot_relationship(df, feature_col, target_col='lap_energy_(kJ)',␣
↪poly_degree=2, color_by_driver=False, show_fit=True):
    """
    Plot the relationship between a feature and the target variable.

    Parameters:
    df (pandas.DataFrame): Input DataFrame
    feature_col (str): Name of the feature column
    target_col (str): Name of the target column
    poly_degree (int): Degree of polynomial fit (default: 2)
    color_by_driver (bool): If True, points will be colored by driver (default:␣
↪False)
    show_fit (bool): If True, shows polynomial fit line (default: True)
    """
    import matplotlib.pyplot as plt
```

```python
import matplotlib.dates as mdates

plt.figure(figsize=(12, 6))

# Convert datetime to numbers for plotting if necessary
if pd.api.types.is_datetime64_any_dtype(df[feature_col]):
    x = mdates.date2num(df[feature_col])
    is_datetime = True
else:
    x = df[feature_col].values
    is_datetime = False

y = df[target_col].values

if color_by_driver and 'driver' in df.columns:
    # Plot points for each driver with their assigned color
    for driver, color in driver_colours.items():
        mask = df['driver'] == driver
        if mask.any():  # Only plot if driver exists in the data
            plt.scatter(df[feature_col][mask], y[mask], alpha=0.5,␣
↪color=color, label=driver)
else:
    # Original single-color scatter plot
    plt.scatter(df[feature_col], y, alpha=0.5)

if show_fit and not is_datetime:  # Only show fit for non-datetime x values
    # Fit polynomial regression
    x_reshape = x.reshape(-1, 1)
    poly_features = PolynomialFeatures(degree=poly_degree)
    x_poly = poly_features.fit_transform(x_reshape)
    model = LinearRegression()
    model.fit(x_poly, y)

    # Sort points for smooth curve
    sort_idx = np.argsort(x.ravel())
    x_sorted = x_reshape[sort_idx]
    y_pred = model.predict(poly_features.transform(x_sorted))

    plt.plot(x_sorted, y_pred, 'r--', label='Polynomial fit')

plt.xlabel(feature_col)
plt.ylabel(target_col)
plt.title(f'Relationship between {feature_col} and {target_col}')

if is_datetime:
    # Format datetime axis
    plt.gcf().autofmt_xdate()
```

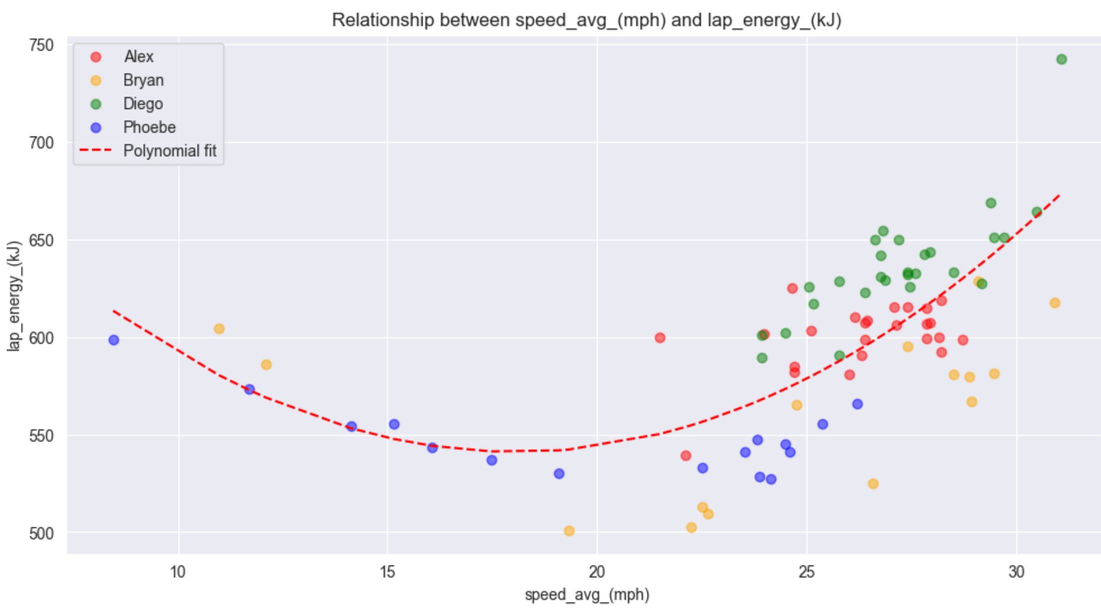
```
    if color_by_driver and 'driver' in df.columns: plt.legend()
    plt.grid(True)
    plt.show()
```

1.6 Speed Factors

1.6.1 Average Speed

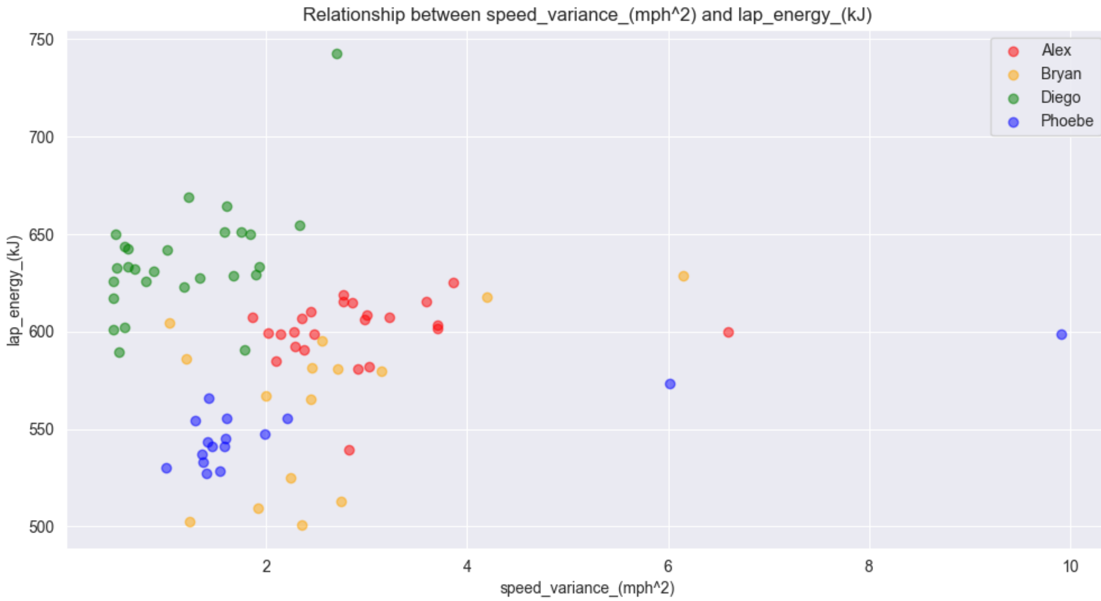
From the average speed plot we see that there seems to be a quadratic relationship between lap energy usage / efficiency and the average speed of a race. The ideal speed to drive that maximized efficiency seems to be around 20 mph. We hypothesize that this optimum exists because aerodynamic drag dominates losses at high speeds ($F_d = C_d A \frac{1}{2} \rho V^2$) and because our motor efficiency is not efficient at low speeds.

[187]:
```
plot_relationship(filtered_df, "speed_avg_(mph)", poly_degree=2,␣
 ↪color_by_driver=True)
```



Below we also have the speed variance per lap. There aren't any clear trends to correlate minimizing speed variance with maximizing efficiency

[188]:
```
plot_relationship(filtered_df, "speed_variance_(mph^2)", show_fit=False,␣
 ↪color_by_driver=True)
```

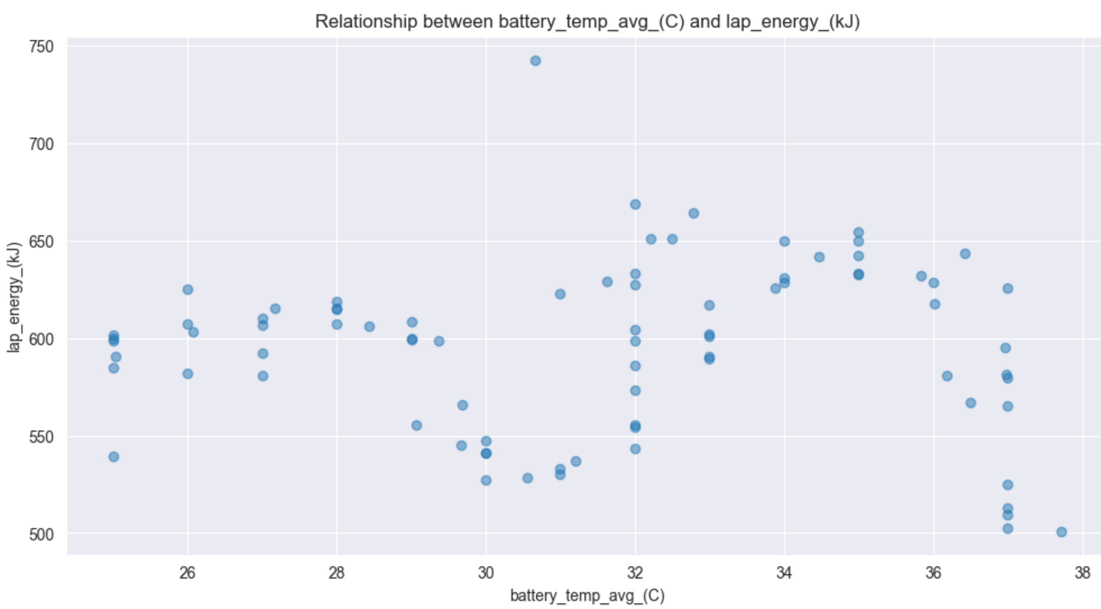


1.7 Battery and Motor

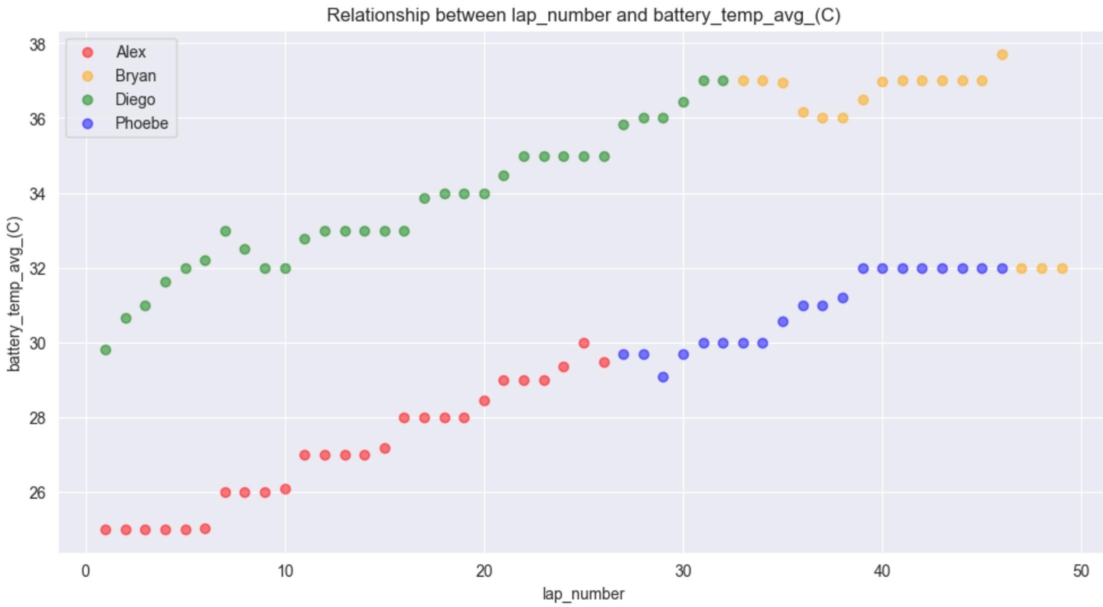
1.7.1 Average Battery Temperature

From the average battery temperature plots, we don't see much of a correlation between it and efficiency but, we do get an idea of how the battery warms throughout a race day.

[189]:
```
plot_relationship(filtered_df, "battery_temp_avg_(C)", show_fit=False)
```

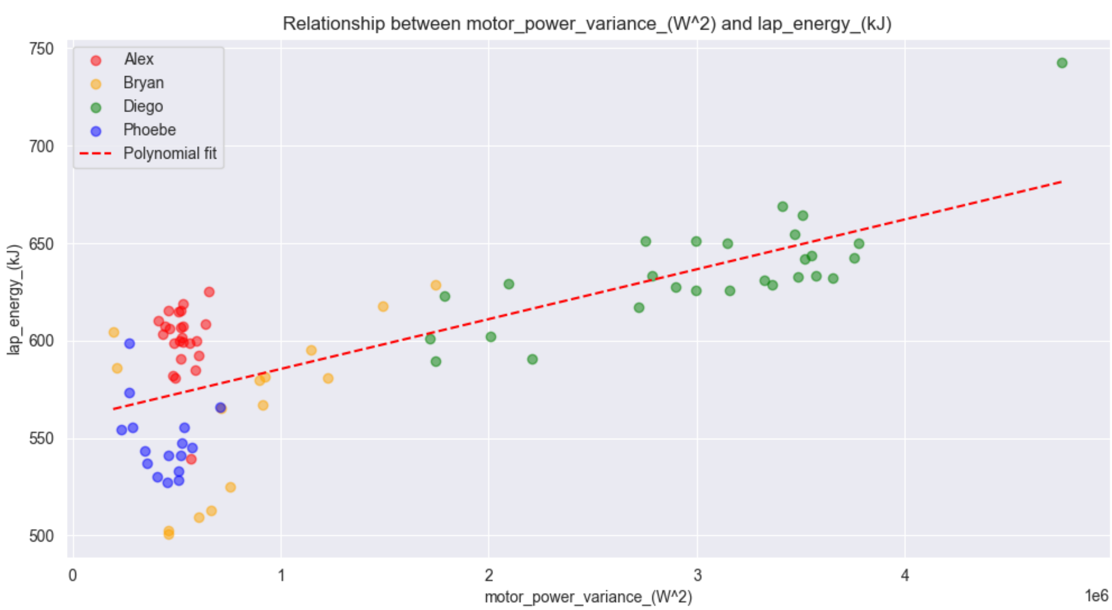


[190]:
```
plot_relationship(df, target_col="battery_temp_avg_(C)",␣
↪feature_col="lap_number", show_fit=False, color_by_driver=True)
```



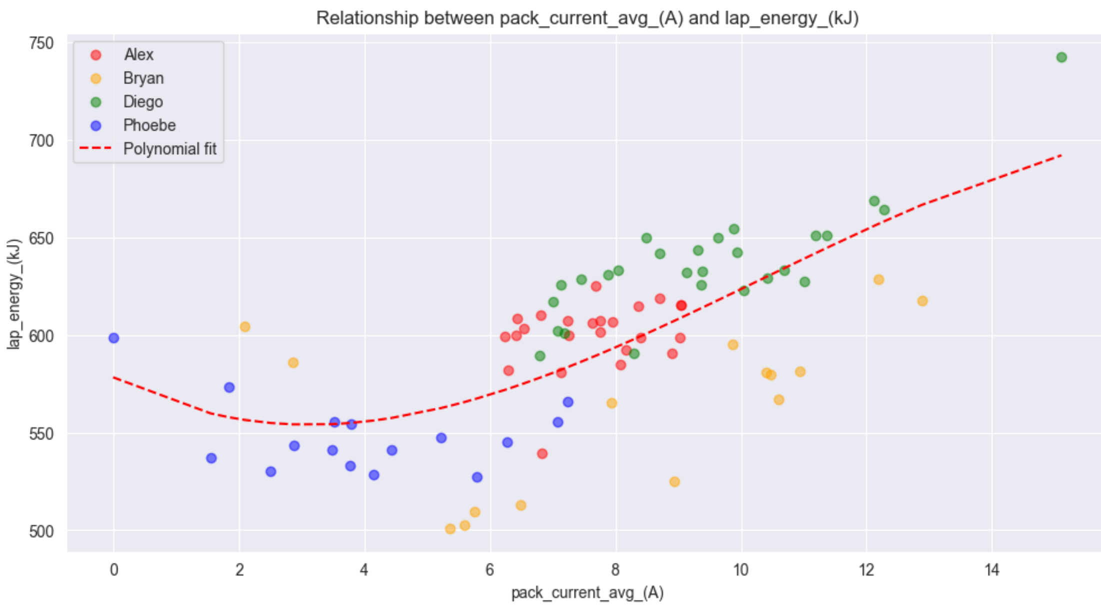
Below are plots to show how our power/current draw from our motor and battery relates to our total energy usage.

[191]:
```
plot_relationship(filtered_df, feature_col="motor_power_variance_(W^2)",␣
↪poly_degree=1, color_by_driver=True)
```



[192]:

```
plot_relationship(filtered_df, "pack_current_avg_(A)", poly_degree=3,␣
↪color_by_driver=True)
```

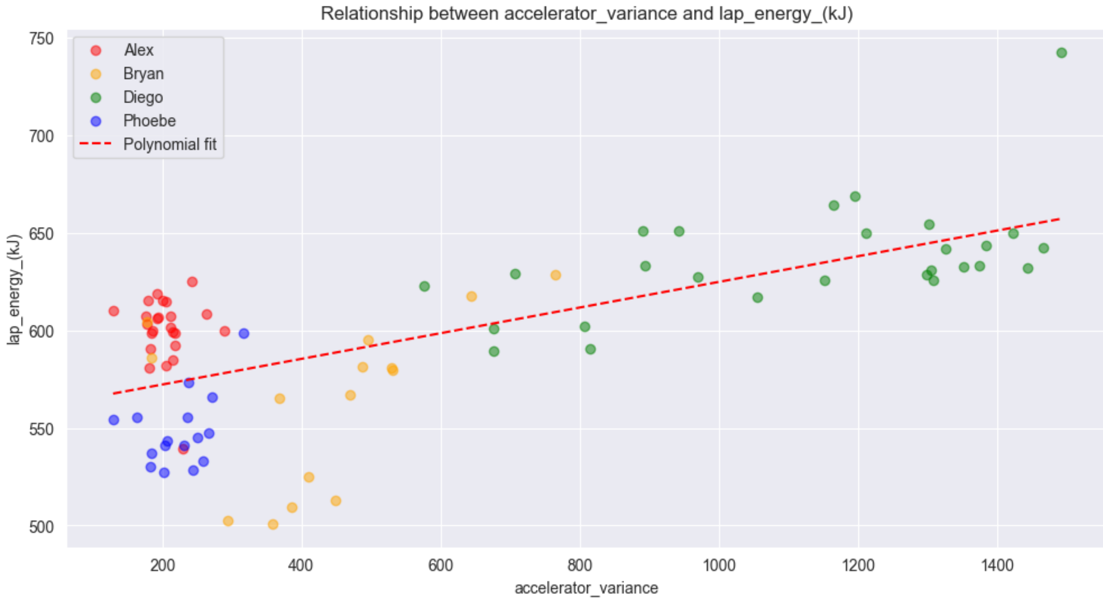


1.8 Accelerator

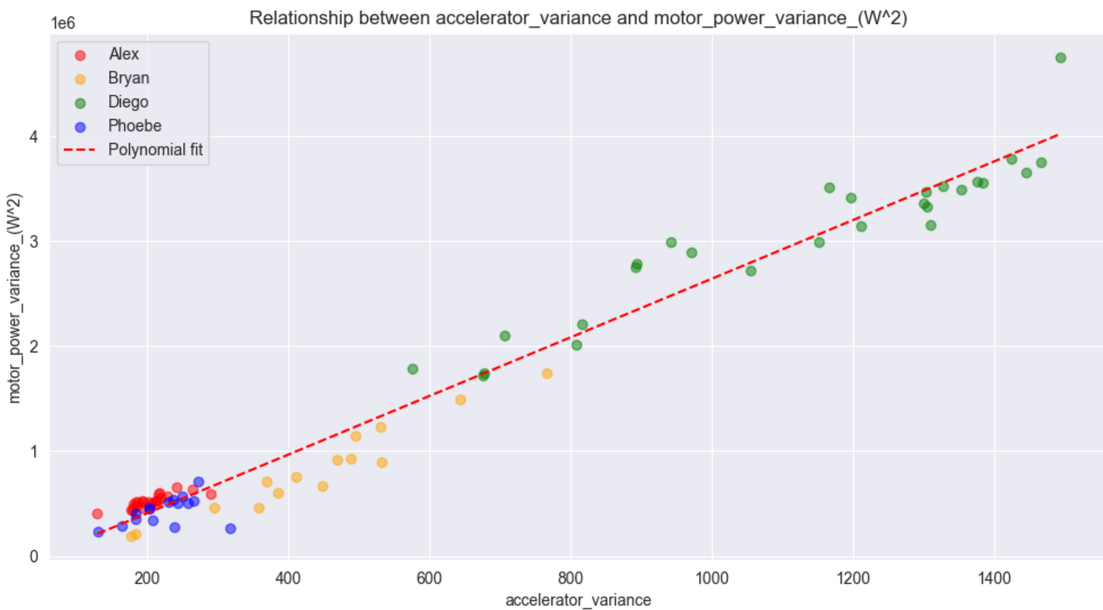
Below are plots that relate how the driver steps on the accelerator with what happens in the rest of the car. Note that we are comparing variance here, which quantifies how chaotic/aggressive the driver is with the accelerator pedal

[193]:

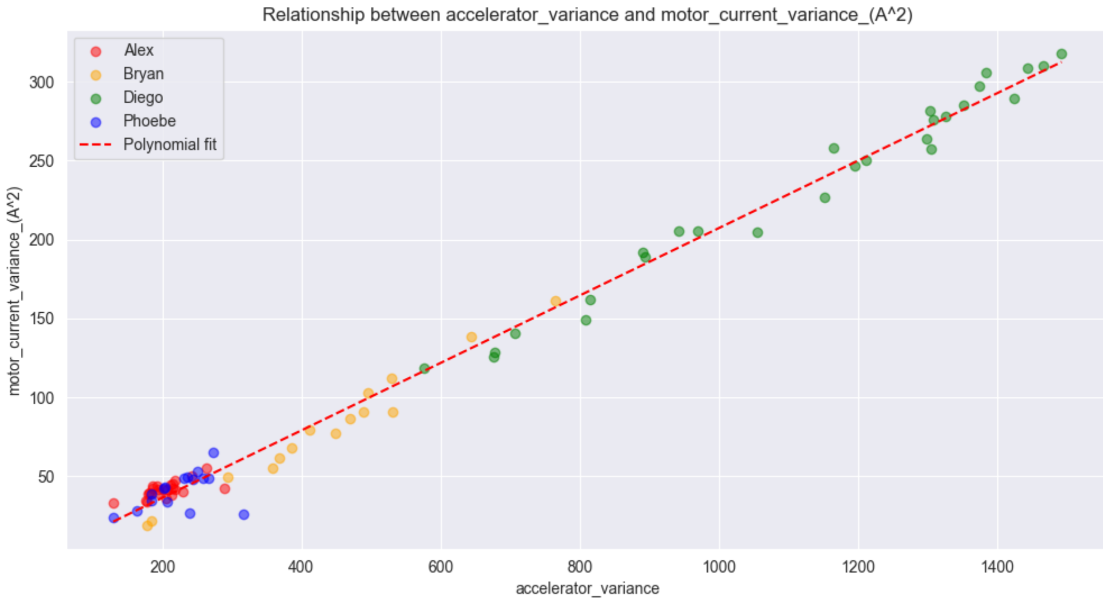
```
plot_relationship(filtered_df, feature_col="accelerator_variance",␣
↪poly_degree=1, color_by_driver=True)
```



[194]:
```
plot_relationship(filtered_df, feature_col="accelerator_variance",␣
↪target_col="motor_power_variance_(W^2)", poly_degree=1, color_by_driver=True)
```



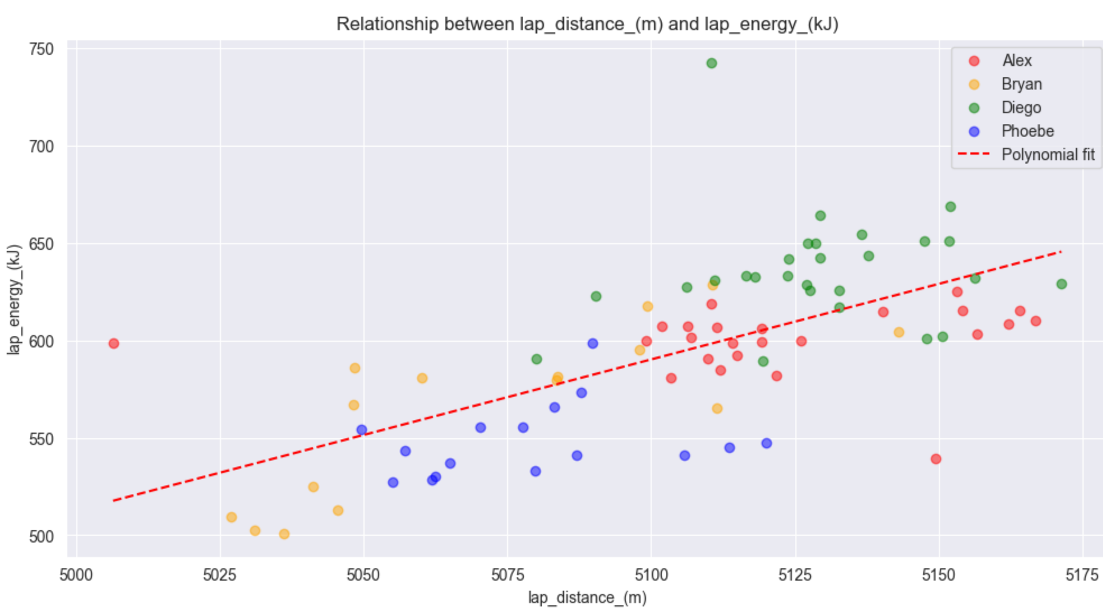
[195]:
```
plot_relationship(filtered_df, feature_col="accelerator_variance",␣
↪target_col="motor_current_variance_(A^2)", poly_degree=1,␣
↪color_by_driver=True)
```



1.9 Distance

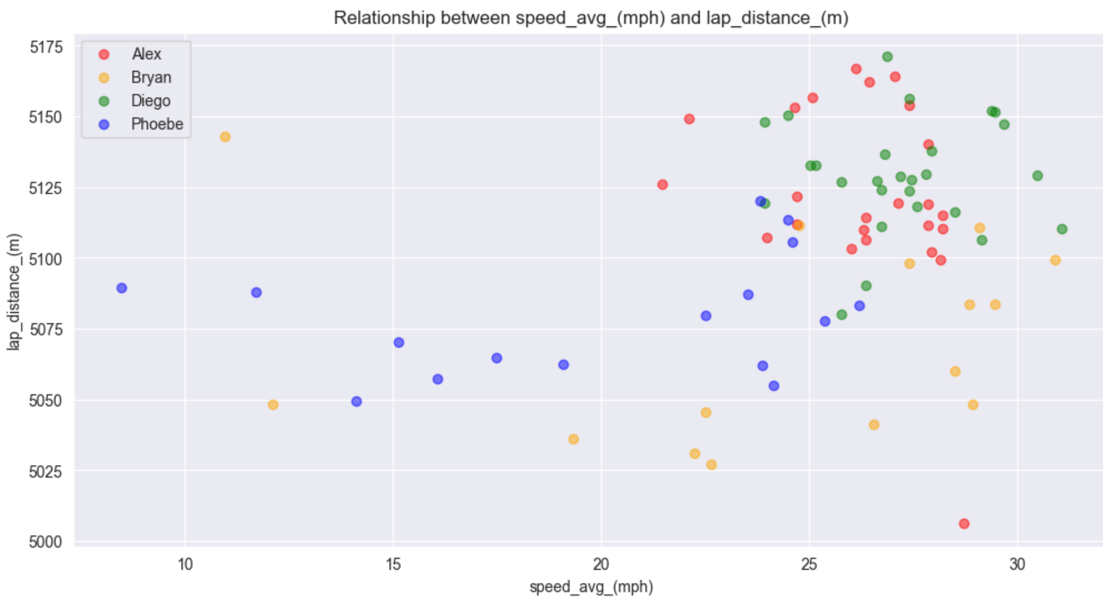
Below is a plot of the actual distance traveled by the car to complete a lap. It suggests a linear trend and intuitive trend that by travelling less of a distance would also reduce energy usage. This suggests that optimizing race lines can be a good strategy. We do see however that lower distance is strongly correlated with slower laps, which is likely because it is easier to take tight corners at lower speed.

[196]:
```
plot_relationship(filtered_df, feature_col="lap_distance_(m)", poly_degree=1,␣
↪color_by_driver=True)
```



To verify the hypothesis that lower speeds makes it easier to take tighter turns and thus reduce lap distance, we can check for a positive correlation between speed and lap distance. We do see a very slight trend, but this is certainly not strong enough to be the cause for the correlation seen above. The ability of a driver to minimize distance and how this is affected by speed also seems to vary person-to-person. For example, Bryan (orange) seemed to be very good at minimizing lap distance when driving at a reduced speed.

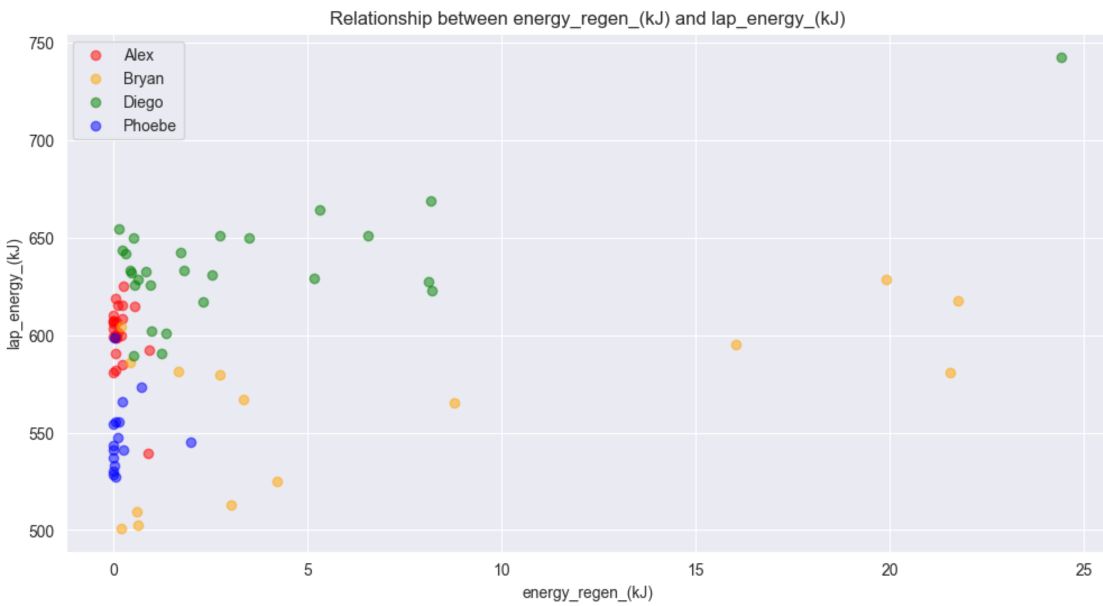
[197]:
```
plot_relationship(filtered_df, feature_col="speed_avg_(mph)",␣
    ↪target_col="lap_distance_(m)", show_fit=False, color_by_driver=True)
```



1.10 Regen

From a regened energy plot alone, we don't see a direct trend with efficiency, but it seems that regen with a specific driver style may optimize efficiency.

[198]:
```
plot_relationship(filtered_df, "energy_regen_(kJ)", show_fit=False,␣
    ↪color_by_driver=True)
```



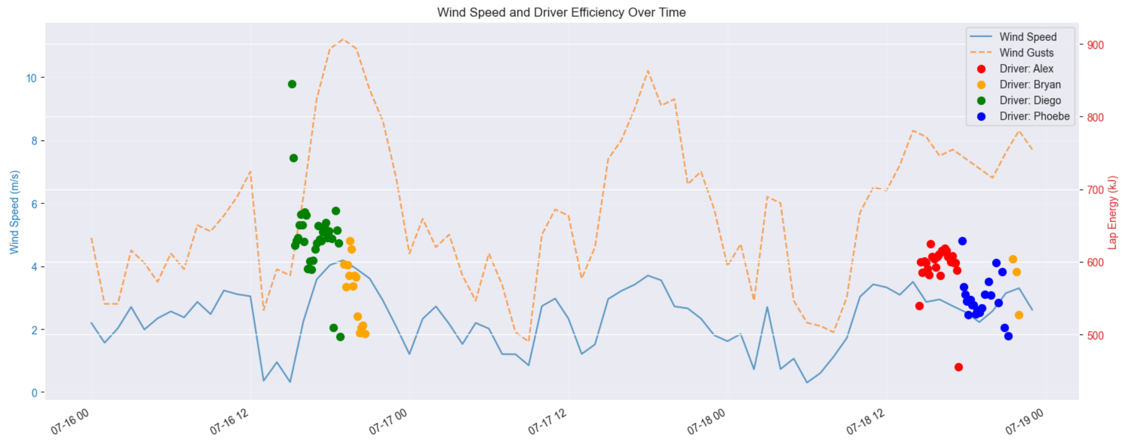
1.11 Wind

Below is a plot of wind speeds throughout the data and lap efficiencies. We hypothesized that high wind speeds would reduce efficiency by increasing aerodynamic drag (even though we might also benefit from tailwinds, the quadratic relationship makes higher wind speeds more punishing). However, the plot below does not show any clear relationship, at least not without decoupling efficiency from the many other more important factors.

[199]:
```
# Setup the Open-Meteo API client with cache and retry on error
cache_session = requests_cache.CachedSession('.cache', expire_after = -1)
retry_session = retry(cache_session, retries = 5, backoff_factor = 0.2)
openmeteo = openmeteo_requests.Client(session = retry_session)

def fetch_wind_data(latitude, longitude, start_date, end_date):
    """
    Fetch hourly wind speed data from Open-Meteo API
    """
    url = "https://archive-api.open-meteo.com/v1/archive"
    params = {
        "latitude": latitude,
        "longitude": longitude,
        "start_date": start_date,
        "end_date": end_date,
        "hourly": ["wind_speed_10m", "wind_gusts_10m"],
        "wind_speed_unit": "ms"  # Using m/s for scientific analysis
    }
```

```
    responses = openmeteo.weather_api(url, params=params)
    response = responses[0]

    # Process hourly data
    hourly = response.Hourly()
    hourly_data = {
        "date": pd.date_range(
            start = pd.to_datetime(hourly.Time(), unit = "s", utc = True),
            end = pd.to_datetime(hourly.TimeEnd(), unit = "s", utc = True),
            freq = pd.Timedelta(seconds = hourly.Interval()),
            inclusive = "left"
        ),
        "wind_speed": hourly.Variables(0).ValuesAsNumpy(),
        "wind_gusts": hourly.Variables(1).ValuesAsNumpy(),
    }

    return pd.DataFrame(data = hourly_data)

def plot_wind_analysis(df, lap_end_times, lap_efficiencies, lap_drivers):
    """
    Create a combined plot of wind data and driver efficiencies using lap end␣
 ↪times.
    """
    fig, ax1 = plt.subplots(figsize=(15, 6))

    # Plot wind data on primary y-axis (left)
    ax1.plot(df['date'], df['wind_speed'], label='Wind Speed', color='tab:
 ↪blue', alpha=0.7)
    ax1.plot(df['date'], df['wind_gusts'], label='Wind Gusts', color='tab:
 ↪orange', linestyle='--', alpha=0.7)
    ax1.set_ylabel('Wind Speed (m/s)', color='tab:blue')
    ax1.tick_params(axis='y', labelcolor='tab:blue')
    ax1.grid(True, alpha=0.3)

    # Set up secondary y-axis for lap efficiencies (right)
    ax2 = ax1.twinx()
    ax2.set_ylabel('Lap Energy (kJ)', color='tab:red')
    ax2.tick_params(axis='y', labelcolor='tab:red')

    # Set y-axis limits to fit lap_efficiencies data range
    if not lap_efficiencies.empty:
        ax2.set_ylim([lap_efficiencies.min() * 0.9, lap_efficiencies.max() * 1.
 ↪1])

    # Plot each driver's efficiencies on secondary y-axis using lap end times
    for driver, color in driver_colours.items():
        mask = np.array(lap_drivers) == driver
```

```python
        if np.any(mask):
            ax2.scatter(
                lap_end_times[mask],
                lap_efficiencies[mask],
                color=color,
                label=f"Driver: {driver}",
                alpha=1,
                s=50  # Increase marker size for visibility
            )

    # Combine legends from both axes
    lines, labels = ax1.get_legend_handles_labels()
    lines2, labels2 = ax2.get_legend_handles_labels()
    ax2.legend(lines + lines2, labels + labels2, loc='upper right')

    # Format x-axis to show dates nicely
    plt.title('Wind Speed and Driver Efficiency Over Time')
    plt.xlabel('Lap End Time')
    plt.gcf().autofmt_xdate()

    plt.tight_layout()
    plt.show()

# lat lon for center of track
latitude = 37.00272354871939
longitude = -86.36671627935802
start_date = "2024-07-16"   # FSGP Day 1
end_date = "2024-07-18"     # FSGP Day 3

wind_df = fetch_wind_data(latitude, longitude, start_date, end_date)
lap_end_timestamps = df["lap_end_time"]
lap_end_times = np.array(
    [datetime.datetime.strptime(ts, "%Y-%m-%d %H:%M:%S%z") for ts in␣
 ↪lap_end_timestamps]

)
plot_wind_analysis(wind_df, lap_end_times, df["lap_energy_(kJ)"],␣
 ↪lap_drivers=df["driver"])
```


Wind Speed and Driver Efficiency Over Time
Wind Speed
Wind Gusts
Driver: Alex
Driver: Bryan
Driver: Diego
Driver: Phoebe
Wind Speed (m/s)
Lap Energy (kJ)
0
2
4
6
8
10
500
600
700
800
900
07-16 00
07-16 12
07-17 00
07-17 12
07-18 00
07-18 12
07-19 00