

bikelaneusage_weather

November 17, 2024

1 Introduction: Bike Lane Usage in Vancouver

The city of Vancouver has been actively increasing the number of bike lanes by reducing car lanes on major roads in the last few years to reduce vehicle congestion and enhance cyclist safety. However, the reactions to bike lanes within the city have been mixed. Vancouver is a city that is nicknamed “raincouver” by its residents and like most major cities on west coast of North America, it has been developed around cars. In another words, the population density is low and it is dispersed. Furthermore, due to high housing and rent prices, people have been forced to move further away from the city and are required to commute longer distances and public transit expansion in Vancouver has been minimal. For a city like Vancouver with such conditions is reducing vehicle lanes to increase bike lanes effective? This project aims to explore how weather conditions affect bike lane usage and to build a model to predict bike lane usage based on weather data.

1.1 Executive Summary

Using a Generalized Additive Model (GAM), we aimed to assess the effectiveness of expanding bike lanes in a city known for its high precipitation levels. The analysis revealed that temperature and precipitation significantly impact cycling patterns, with bike usage decreasing notably during rainy and snowy periods. Given that Vancouver experiences rainfall for a considerable portion of the year (40-44% since 2021), this study raises questions about the year-round effectiveness of dedicating vehicle lanes to bike lanes. Additionally, the analysis indicated that higher temperatures drive increased bike usage on Saturdays more than on weekdays, suggesting that bike lanes may be less effective during weekday rush hours. Further investigation into complementary transportation options, such as public transit integration, is recommended to support a balanced approach to urban transportation planning.

1.2 Objectives:

1. Analyze bike lane usage and its relationship with different weather conditions.
2. Develop a predictive modeling for bike lane usage.

1.3 Methodology:

1.3.1 Data Collection:

1. Obtain the bike lane usage data for 2021 and 2022 from the city of Vancouver.
 - <https://vancouver.ca/files/cov/bike-volume-2021-2024.xlsx>
 - According to the City of Vancouver, the bike lane volume is presented as daily two-way totals.

- It is counted at specific location of the bike lane with automated bike counters.
 - Due to possible errors (Sensitivity, Occlusion, Bypass) a constant value correction factor has been applied to the counts by the City of Vancouver.
2. Acquire the weather data for Vancouver in the same periods from Environment Canada.
 - https://climate.weather.gc.ca/climate_data/daily_data_e.html?StationID=51442

1.3.2 Data Preparation:

1. Clean and preprocess the bike lane usage and weather data.
2. Aggregate the bike lane usage data on a daily, monthly, yearly basis to facilitate analysis.
3. Perform necessary transformations to align data for meaningful comparisons.

1.3.3 Exploratory Data Analysis (EDA):

1. Conduct EDA on the bike lane usage and weather data to identify patterns and trends.
2. Analyze the correlation between bike lane usage and rainfall.

1.3.4 Predictive Modeling

1. Develop a model that can be used to predict bike lane usage based on weather data.

1.4 Potential Limitations:

1. Public transit usage data and traffic data in Vancouver is not readily available. It will not be possible to see if vehicle traffic or public transit usage have changed based on weather conditions.
2. Missing data from the automated counters occur within the raw data set due to vandalism or equipment failure. (City of Vancouver)

1.5 Data Preparation

1.5.1 Read in Data Files

```
[46]: # read in bike usage data
import pandas as pd
import altair as alt
import numpy as np
import warnings
from IPython.display import display, Image
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from pygam import LinearGAM, s, f
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
import matplotlib.pyplot as plt

# hide warnings
warnings.filterwarnings('ignore')

excel_file_path = 'data/bike-volume-2021-2024.xlsx'
```

```
sheet_name = 'City of Vancouver Bike Data'
bike_usage = pd.read_excel(excel_file_path, sheet_name=sheet_name,
    ↪engine='openpyxl')
```

```
[47]: bike_usage.head()
```

```
[47]:
```

	Location	Direction \
0	1815 Cornwall - Northside	1815 Cornwall - Northside Cyclist Westbound
1	1815 Cornwall - Northside	1815 Cornwall - Northside Cyclist Eastbound
2	1815 Cornwall - Northside	1815 Cornwall - Northside Cyclist Westbound
3	1815 Cornwall - Northside	1815 Cornwall - Northside Cyclist Eastbound
4	1815 Cornwall - Northside	1815 Cornwall - Northside Cyclist Westbound

	CorrectionFactor	PercentPassing20%	PercentPassing10%	date \
0	1.106145	0.7	0.6	2021-01-01
1	1.106145	0.7	0.6	2021-01-01
2	1.106145	0.7	0.6	2021-01-02
3	1.106145	0.7	0.6	2021-01-02
4	1.106145	0.7	0.6	2021-01-03

	Volume
0	91.810056
1	3.318436
2	57.519553
3	4.424581
4	315.251397

```
[48]: # read in weather data
weather_2021 = pd.read_csv('data/en_climate_daily_BC_1108395_2021_P1D.csv')
weather_2022 = pd.read_csv('data/en_climate_daily_BC_1108395_2022_P1D.csv')
weather_2023 = pd.read_csv('data/en_climate_daily_BC_1108395_2023_P1D.csv')
weather_2024 = pd.read_csv('data/en_climate_daily_BC_1108395_2024_P1D.csv')
```

```
[49]: # combine weather 2021 and 2022
weather = pd.concat([weather_2021, weather_2022, weather_2023, weather_2024],
    ↪axis=0)
weather.head()
```

```
[49]:
```

	Longitude (x)	Latitude (y)	Station Name	Climate ID	Date/Time \
0	-123.18	49.19	VANCOUVER INTL A	1108395	2021-01-01
1	-123.18	49.19	VANCOUVER INTL A	1108395	2021-01-02
2	-123.18	49.19	VANCOUVER INTL A	1108395	2021-01-03
3	-123.18	49.19	VANCOUVER INTL A	1108395	2021-01-04
4	-123.18	49.19	VANCOUVER INTL A	1108395	2021-01-05

	Year	Month	Day	Data Quality	Max Temp (°C)	... Total Snow (cm) \
0	2021	1	1	NaN	10.1	... 0.0

1	2021	1	2	NaN	8.8	...	0.0
2	2021	1	3	NaN	9.3	...	0.0
3	2021	1	4	NaN	7.7	...	0.0
4	2021	1	5	NaN	7.6	...	0.0

	Total Snow Flag	Total Precip (mm)	Total Precip Flag	Snow on Grnd (cm)	\
0	NaN	17.6	NaN	NaN	
1	NaN	12.7	NaN	NaN	
2	NaN	6.4	NaN	NaN	
3	NaN	18.1	NaN	NaN	
4	NaN	29.5	NaN	NaN	

	Snow on Grnd Flag	Dir of Max Gust (10s deg)	Dir of Max Gust Flag	\
0	NaN	9.0	NaN	
1	NaN	15.0	NaN	
2	NaN	14.0	NaN	
3	NaN	10.0	NaN	
4	NaN	11.0	NaN	

	Spd of Max Gust (km/h)	Spd of Max Gust Flag
0	45.0	NaN
1	59.0	NaN
2	41.0	NaN
3	48.0	NaN
4	63.0	NaN

[5 rows x 31 columns]

1.6 Data Cleaning

```
[50]: # clean bike usage data
# filter on year, 2021 and 2022
# missing data. hard to tell difference between if missing or if no one used
# the bike lanes

# check type for date. convert to date
type(bike_usage.date)
bike_usage['date'] = pd.to_datetime(bike_usage['date'])
bike_usage['Year'] = bike_usage['date'].dt.year
```

```
[51]: # only select relevant columns. also has direction per bike lane, we do not
# care about direction
# group by year, by date by bike lane

cols = ['Location', 'date', 'Volume']
bike_usage = bike_usage[cols]
```

```
# group by date, location and sum volume
bike_usage = bike_usage.groupby(['date', 'Location']).sum().reset_index()

# round volume, it is a float currently b/c of the correction factor that has
↳ been applied bike_usage['Volume'] = bike_usage['Volume'].apply(np.ceil)
bike_usage['Volume'] = bike_usage['Volume'].apply(round)
bike_usage.head()
```

```
[51]:      date      Location  Volume
0 2021-01-01  1815 Cornwall - Northside    95
1 2021-01-01  1818 Cornwall - Southside    70
2 2021-01-01      1850 York    164
3 2021-01-01    486 East 37th    83
4 2021-01-01    821 Powell    63
```

1.6.1 Missing Data

- The bike lane data has several gaps, with missing values that the City of Vancouver attributes to factors such as automated counter errors, vandalism, or equipment failure. A correction factor was applied for consistent counter issues. However, most of the missing data points are consecutive and tend to appear either at the start or end of the timeline (where the x-axis represents dates). This pattern could indicate that the bike lane didn't exist at the beginning or was closed towards the end. In one instance—Dunsmuir at Beatty—there is a significant block of missing data in the middle of the timeline, which could potentially be due to construction or other interruptions, though the exact cause is not specified.
- Based on the visualization of the bike lane usage vs date, it seems like there is a clear cyclic pattern for all bikelanes.

Bike Lane Data

```
[52]: # first need to pivot data so that each bike lane is a column
bike_usage_missing = bike_usage.pivot(index='date', columns='Location',
↳ values='Volume').reset_index()
bike_usage_missing.head()
```

```
[52]: Location      date  1815 Cornwall - Northside  1818 Cornwall - Southside  \
0      2021-01-01          95.0          70.0
1      2021-01-02          62.0          43.0
2      2021-01-03         330.0         201.0
3      2021-01-04         161.0         120.0
4      2021-01-05         105.0          89.0

Location  1850 York  486 East 37th  821 Powell  885 Dunsmuir  \
0          164.0          83.0          63.0          158.0
1          123.0          79.0          75.0          166.0
2          572.0         235.0         232.0         386.0
3          387.0         245.0         183.0         646.0
4          401.0         209.0         135.0         564.0
```

Location	Alex Fraser Bridge East	Alex Fraser Bridge West \
0	4.0	4.0
1	4.0	2.0
2	15.0	13.0
3	13.0	11.0
4	8.0	12.0

Location	Burrard at Cornwall - Eastside - Burrard Bridge ... \
0	247.0 ...
1	204.0 ...
2	937.0 ...
3	568.0 ...
4	492.0 ...

Location	Seawall at Creekside Community Centre	Seawall at David Lam Park \
0	302.0	343.0
1	279.0	277.0
2	1539.0	1737.0
3	665.0	659.0
4	399.0	397.0

Location	Seawall at HMCS Discovery	Seawall at Harbour Green Park \
0	179.0	143.0
1	98.0	136.0
2	880.0	686.0
3	186.0	251.0
4	80.0	152.0

Location	Seawall at Lumbermen's Arch	Seawall at Morton Park \
0	NaN	29.0
1	NaN	24.0
2	NaN	40.0
3	NaN	20.0
4	NaN	26.0

Location	Seawall at Second Beach Pool	Stephens at Point Grey \
0	164.0	76.0
1	92.0	43.0
2	891.0	310.0
3	178.0	135.0
4	78.0	108.0

Location	Union at Hawks	Vanness at Brant
0	313.0	0.0
1	299.0	0.0
2	1040.0	0.0

3	979.0	0.0
4	947.0	0.0

[5 rows x 37 columns]

```
[53]: # need to deal with missing data
# find out for each column how many have 0s or nas
zeros_count_perc = ((bike_usage_missing == 0).sum() + bike_usage_missing.isna().
    ↪sum())/len(bike_usage_missing)
print(zeros_count_perc)
```

Location	
date	0.000000
1815 Cornwall - Northside	0.000000
1818 Cornwall - Southside	0.017673
1850 York	0.000000
486 East 37th	0.000000
821 Powell	0.035346
885 Dunsmuir	0.350515
Alex Fraser Bridge East	0.877025
Alex Fraser Bridge West	0.874816
Burrard at Cornwall - Eastside - Burrard Bridge	0.167894
Burrard at Cornwall - Westside - Burrard Bridge	0.206186
Cambie Bridge - Eastside	0.211340
Canada Line Bridge at West Kent	0.253314
Central Valley Greenway at Victoria	0.547865
Comox at Thurlow	0.000000
Dunsmuir Viaduct at Main	0.326951
Dunsmuir at Beatty	0.508100
East 10th at Clark	0.352725
Fleming at East 57th	0.509573
Helmcken at Burrard	0.508100
Hornby at Robson	0.720913
Lions Gate Bridge at Spirit Trail - Eastside	0.276141
Lions Gate Bridge at Spirit Trail - Westside	0.000000
Point Grey at Alma	0.377761
Point Grey at Stephens	0.332842
Point Grey at Volunteer Park	0.597202
Richards at Dunsmuir	0.686303
Seawall at Creekside Community Centre	0.000000
Seawall at David Lam Park	0.000000
Seawall at HMCS Discovery	0.143594
Seawall at Harbour Green Park	0.000000
Seawall at Lumbermen's Arch	0.365243
Seawall at Morton Park	0.970545
Seawall at Second Beach Pool	0.525773
Stephens at Point Grey	0.002209
Union at Hawks	0.051546

Vanness at Brant
dtype: float64

1.000000

```
[54]: # check for consecutive zeros per bike lane
# if consecutive zeros, then we can assume that the bike lane was not used for
↳ specific reasons or it wasn't recorded

def consecutive_zeros(df):
    consecutive_zero_lanes = {}

    for col in df.columns:
        count = 0
        max_count = 0

        for i in range(len(df)):
            if df[col].iloc[i] == 0 or pd.isna(df[col].iloc[i]) or df[col].
↳ iloc[i] == '':
                count += 1
            else:
                max_count = max(count, max_count)
                count = 0

        # for when column ends with 0s
        max_count = max(count, max_count)

        consecutive_zero_lanes[col] = max_count
        # create a dictionary with the bike lane and the number of consecutive
↳ zeros

    result_df = pd.DataFrame(list(consecutive_zero_lanes.items()),
↳ columns=['Lane', 'Max Consecutive Zeros'])

    return result_df

consecutive_zero_lanes = consecutive_zeros(bike_usage_missing)
print(consecutive_zero_lanes)
```

	Lane	Max Consecutive Zeros
0	date	0
1	1815 Cornwall - Northside	0
2	1818 Cornwall - Southside	24
3	1850 York	0
4	486 East 37th	0
5	821 Powell	46
6	885 Dunsmuir	476
7	Alex Fraser Bridge East	1190
8	Alex Fraser Bridge West	1002

9	Burrard at Cornwall - Eastside - Burrard Bridge	186
10	Burrard at Cornwall - Westside - Burrard Bridge	186
11	Cambie Bridge - Eastside	99
12	Canada Line Bridge at West Kent	344
13	Central Valley Greenway at Victoria	337
14	Comox at Thurlow	0
15	Dunsmuir Viaduct at Main	444
16	Dunsmuir at Beatty	447
17	East 10th at Clark	478
18	Fleming at East 57th	398
19	Helmcken at Burrard	361
20	Hornby at Robson	921
21	Lions Gate Bridge at Spirit Trail - Eastside	310
22	Lions Gate Bridge at Spirit Trail - Westside	0
23	Point Grey at Alma	477
24	Point Grey at Stephens	446
25	Point Grey at Volunteer Park	811
26	Richards at Dunsmuir	811
27	Seawall at Creekside Community Centre	0
28	Seawall at David Lam Park	0
29	Seawall at HMCS Discovery	163
30	Seawall at Harbour Green Park	0
31	Seawall at Lumbermen's Arch	463
32	Seawall at Morton Park	1318
33	Seawall at Second Beach Pool	472
34	Stephens at Point Grey	1
35	Union at Hawks	70
36	Vanness at Brant	1358

```
[55]: alt.data_transformers.disable_max_rows()

# Create a line chart with independent y-axis for each facet
chart = alt.Chart(bike_usage).mark_line(point=True).encode(
    x='date:T',
    y='Volume:Q',
    color='Location:N'
).properties(
    width=400,
    height=250
).facet(
    facet='Location:N',
    columns=3 # Number of columns in the grid
).resolve_scale(
    y='independent' # Allow y-axis to be independent for each chart
)

chart
```

```
[55]: alt.FacetChart(...)
```

Removing Outliers/Missing Data

- Remove any zeros that show up consecutively 5 times or more.
- Remove Bike lanes that has significant amount of missing data. (70% or greater)
- Remove outliers
e.g. Richards at Dunsumuir.

Remove Bike lanes with 70% or more data missing

```
[56]: # use zeros_count_perc to determine which bike lanes to drop
# drop bike lanes that have more than 70% zeros

bike_usage_lanes_dropped = bike_usage_missing.
↳ drop(columns=zeros_count_perc[zeros_count_perc > 0.7].index)
bike_usage_lanes_dropped.columns

[56]: Index(['date', '1815 Cornwall - Northside', '1818 Cornwall - Southside',
'1850 York', '486 East 37th', '821 Powell', '885 Dunsmuir',
'Burrard at Cornwall - Eastside - Burrard Bridge',
'Burrard at Cornwall - Westside - Burrard Bridge',
'Cambie Bridge - Eastside', 'Canada Line Bridge at West Kent',
'Central Valley Greenway at Victoria', 'Comox at Thurlow',
'Dunsmuir Viaduct at Main', 'Dunsmuir at Beatty', 'East 10th at Clark',
'Fleming at East 57th', 'Helmcken at Burrard',
'Lions Gate Bridge at Spirit Trail - Eastside',
'Lions Gate Bridge at Spirit Trail - Westside', 'Point Grey at Alma',
'Point Grey at Stephens', 'Point Grey at Volunteer Park',
'Richards at Dunsmuir', 'Seawall at Creekside Community Centre',
'Seawall at David Lam Park', 'Seawall at HMCS Discovery',
'Seawall at Harbour Green Park', 'Seawall at Lumbermen's Arch',
'Seawall at Second Beach Pool', 'Stephens at Point Grey',
'Union at Hawks'],
dtype='object', name='Location')
```

Replace outliers with nan for each bike lane We are removing outliers as there may be event spikes. There are many cycling events in Vancouver and it would distort the data.

```
[57]: # for each bikelane calculate outliers and replace with nan

def replace_outliers(df):
    for col in df.columns:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
```

```

        df[col] = df[col].apply(lambda x: np.nan if x < lower_bound or x >
↪upper_bound else x)

    return df

bike_usage_no_outliers = replace_outliers(bike_usage_lanes_dropped)

```

```

[58]: # pivot bike_usage_no_outliers
bike_usage_no_outliers_check = bike_usage_no_outliers.melt(id_vars='date',
↪var_name='Location', value_name='Volume')

```

Replace consecutive zeros with nan

```

[59]: bike_usage_no_outliers_consecutive_zeros = bike_usage_no_outliers.copy()

for col in bike_usage_no_outliers_consecutive_zeros.columns:
    count = 0
    for i in range(len(bike_usage_no_outliers_consecutive_zeros)):
        if (bike_usage_no_outliers_consecutive_zeros[col].iloc[i] == 0 or
            pd.isna(bike_usage_no_outliers_consecutive_zeros[col].iloc[i]) or
            bike_usage_no_outliers_consecutive_zeros[col].iloc[i] == ''):
            count += 1
        else:
            if count > 3:
                bike_usage_no_outliers_consecutive_zeros[col].iloc[i-count:i] =
↪np.nan
            count = 0

    # Check end of column for remaining sequence
    if count > 3:
        bike_usage_no_outliers_consecutive_zeros[col].
↪iloc[len(bike_usage_no_outliers_consecutive_zeros) - count:] = np.nan

```

Weather Data

- Columns with 70% or more missing data have been removed.
- The following columns 'Longitude (x)', 'Latitude (y)', 'Station Name', 'Dir of Max Gust (10s deg)', 'Dir of Max Gust Flag', 'Spd of Max Gust (km/h)', 'Spd of Max Gust Flag' have also been removed as it will not be used or because it also has high % of missing data.
- Rows with any missing data have also been removed in the rest of the columns.
 - Majority of the rows were future dates for which data does not exist yet.
 - 34 rows of missing data were also removed as they cannot be used in the model.

```

[60]: # missing data for weather
weather.isna().sum()/len(weather)

```

```

[60]: Longitude (x)          0.000000
Latitude (y)              0.000000

```

Station Name	0.000000
Climate ID	0.000000
Date/Time	0.000000
Year	0.000000
Month	0.000000
Day	0.000000
Data Quality	1.000000
Max Temp (°C)	0.069815
Max Temp Flag	0.977413
Min Temp (°C)	0.069815
Min Temp Flag	0.977413
Mean Temp (°C)	0.069815
Mean Temp Flag	0.977413
Heat Deg Days (°C)	0.069815
Heat Deg Days Flag	0.977413
Cool Deg Days (°C)	0.069815
Cool Deg Days Flag	0.977413
Total Rain (mm)	0.052019
Total Rain Flag	0.929500
Total Snow (cm)	0.048597
Total Snow Flag	0.988364
Total Precip (mm)	0.052019
Total Precip Flag	0.924709
Snow on Grnd (cm)	0.963723
Snow on Grnd Flag	0.984942
Dir of Max Gust (10s deg)	0.432580
Dir of Max Gust Flag	0.624230
Spd of Max Gust (km/h)	0.432580
Spd of Max Gust Flag	0.614648

dtype: float64

```
[61]: # select weather columns that will be used
      # drop columns that have more than 70% missing data
```

```
weather = weather.drop(columns=weather.columns[weather.isna().sum()/
↳len(weather) > 0.7])
```

```
[62]: # select columns of interest
weather_dropcols = ['Longitude (x)', 'Latitude (y)', 'Station Name', 'Dir of_
↳Max Gust (10s deg)', 'Dir of Max Gust Flag',
                    'Spd of Max Gust (km/h)', 'Spd of Max Gust Flag'] # we are dropping gust_
↳b/c it's missing a lot of data
```

```
weather = weather.drop(columns=weather_dropcols)
```

```
[63]: # check rows with missing data
weather[weather.isna().any(axis=1)]
```

```
# weather data actually includes future data - data doesn't exist yet.
# drop any rows after 2024-10-24
weather = weather[weather['Date/Time'] <= '2024-10-24']

# check how many rows missing data
weather.isna().sum()
```

```
[63]: Climate ID          0
      Date/Time         0
      Year             0
      Month            0
      Day              0
      Max Temp (°C)     34
      Min Temp (°C)     34
      Mean Temp (°C)    34
      Heat Deg Days (°C) 34
      Cool Deg Days (°C) 34
      Total Rain (mm)    8
      Total Snow (cm)    3
      Total Precip (mm)  8
      dtype: int64
```

```
[64]: # there are very few rows with missing data. we can drop those rows
weather = weather.dropna()
```

1.7 Data Joining

Join bike lane data and weather data. bike_usage_no_outliers_consecutive_zeros, weather

```
[65]: weather['Date/Time'] = pd.to_datetime(weather['Date/Time'])
      # join the data
      bike_weather = pd.merge(bike_usage_no_outliers_consecutive_zeros, weather,
                               ↪how='left',
                               left_on='date', right_on='Date/Time')
      bike_weather.head()
```

```
[65]:
```

	date	1815 Cornwall - Northside	1818 Cornwall - Southside	1850 York \
0	2021-01-01	95.0	70.0	164.0
1	2021-01-02	62.0	43.0	123.0
2	2021-01-03	330.0	201.0	572.0
3	2021-01-04	161.0	120.0	387.0
4	2021-01-05	105.0	89.0	401.0

	486 East 37th	821 Powell	885 Dunsmuir \
0	83.0	63.0	158.0
1	79.0	75.0	166.0
2	235.0	232.0	386.0

3	245.0	183.0	646.0
4	209.0	135.0	564.0

	Burrard at Cornwall - Eastside - Burrard Bridge \
0	247.0
1	204.0
2	937.0
3	568.0
4	492.0

	Burrard at Cornwall - Westside - Burrard Bridge	Cambie Bridge - Eastside \
0	285.0	107.0
1	214.0	139.0
2	1015.0	280.0
3	638.0	342.0
4	513.0	298.0

	...	Month	Day	Max Temp (°C)	Min Temp (°C)	Mean Temp (°C)	\
0	...	1.0	1.0	10.1	6.9	8.5	
1	...	1.0	2.0	8.8	6.9	7.9	
2	...	1.0	3.0	9.3	2.3	5.8	
3	...	1.0	4.0	7.7	3.8	5.8	
4	...	1.0	5.0	7.6	2.8	5.2	

	Heat Deg Days (°C)	Cool Deg Days (°C)	Total Rain (mm)	Total Snow (cm)	\
0	9.5	0.0	17.6	0.0	
1	10.1	0.0	12.7	0.0	
2	12.2	0.0	6.4	0.0	
3	12.2	0.0	18.1	0.0	
4	12.8	0.0	29.5	0.0	

	Total Precip (mm)
0	17.6
1	12.7
2	6.4
3	18.1
4	29.5

[5 rows x 45 columns]

```
[66]: # drop rows with missing Climate ID
bike_weather = bike_weather.dropna(subset=['Climate ID'])
```

```
[67]: # create a list of bikelanes
bikelanes = ['1815 Cornwall - Northside', '1818 Cornwall - Southside',
             '1850 York', '486 East 37th', '821 Powell', '885 Dunsmuir',
             'Burrard at Cornwall - Eastside - Burrard Bridge',
```

```

'Burrard at Cornwall - Westside - Burrard Bridge',
'Cambie Bridge - Eastside', 'Canada Line Bridge at West Kent',
'Central Valley Greenway at Victoria', 'Comox at Thurlow',
'Dunsmuir Viaduct at Main', 'Dunsmuir at Beatty', 'East 10th at Clark',
'Fleming at East 57th', 'Helmcken at Burrard',
'Lions Gate Bridge at Spirit Trail - Eastside',
'Lions Gate Bridge at Spirit Trail - Westside', 'Point Grey at Alma',
'Point Grey at Stephens', 'Point Grey at Volunteer Park',
'Richards at Dunsmuir', 'Seawall at Creekside Community Centre',
'Seawall at David Lam Park', 'Seawall at HMCS Discovery',
'Seawall at Harbour Green Park', 'Seawall at Lumbermen's Arch',
'Seawall at Second Beach Pool', 'Stephens at Point Grey',
'Union at Hawks']
# fix the data so that each row is date + bike lane
id_vars = [col for col in bike_weather.columns.tolist()
            if col not in bikelanes]

bike_weather_melt = pd.melt(bike_weather, id_vars=id_vars,
                            var_name = 'bikelane', value_name='num_usage')

# create a year/month column
bike_weather_melt['year/month'] = bike_weather_melt['Year'].astype(int).
    ↳astype(str) + '/' + bike_weather_melt['Month'].astype(int).astype(str).str.
    ↳zfill(2)
bike_weather_melt['year/month'] = pd.to_datetime(bike_weather_melt['year/
    ↳month'], format='%Y/%m').dt.strftime('%Y/%m')
bike_weather_melt.head()

```

```

[67]:
      date  Climate ID  Date/Time  Year  Month  Day  Max Temp (°C)  \
0 2021-01-01  1108395.0 2021-01-01 2021.0   1.0  1.0          10.1
1 2021-01-02  1108395.0 2021-01-02 2021.0   1.0  2.0           8.8
2 2021-01-03  1108395.0 2021-01-03 2021.0   1.0  3.0           9.3
3 2021-01-04  1108395.0 2021-01-04 2021.0   1.0  4.0           7.7
4 2021-01-05  1108395.0 2021-01-05 2021.0   1.0  5.0           7.6

      Min Temp (°C)  Mean Temp (°C)  Heat Deg Days (°C)  Cool Deg Days (°C)  \
0                6.9              8.5                9.5                0.0
1                6.9              7.9               10.1                0.0
2                2.3              5.8               12.2                0.0
3                3.8              5.8               12.2                0.0
4                2.8              5.2               12.8                0.0

      Total Rain (mm)  Total Snow (cm)  Total Precip (mm)  \
0                17.6                0.0                17.6
1                12.7                0.0                12.7
2                 6.4                0.0                 6.4
3                18.1                0.0                18.1

```

4	29.5	0.0	29.5
---	------	-----	------

	bikelane	num_usage	year/month
0	1815 Cornwall - Northside	95.0	2021/01
1	1815 Cornwall - Northside	62.0	2021/01
2	1815 Cornwall - Northside	330.0	2021/01
3	1815 Cornwall - Northside	161.0	2021/01
4	1815 Cornwall - Northside	105.0	2021/01

1.8 Add Day of Week to data

```
[68]: # add day of week to bike_weather_melt
bike_weather_melt['day_of_week'] = bike_weather_melt['date'].dt.day_name()
```

1.9 Exploratory Data Analysis

1.9.1 Bike lane usage by month per bike lane

- For each bike lane, we can see a spike in users in July and a decline in the fall/winter months through October to April.
- We can also see that the bikelanes along the Seawall are most popular. It makes sense given that it is a tourist attraction and a scenic ride completely separated from cars. However, it's also important to note that the Seawall is not a commuting route. It goes around Stanley Park, English Bay, Yaletown, Granville Island and Kitsilano Beach.

```
[69]: # plot the data
alt.Chart(bike_weather_melt).mark_line().encode(
    x='year/month:T',
    y='mean(num_usage):Q',
    color='bikelane:N'
).properties(
    width=1000,
    height=250
)
```

```
[69]: alt.Chart(...)
```

```
[70]: selection=alt.selection(type="multi", fields=["year/month"])
base = alt.Chart(bike_weather_melt).properties(width=1000, height=250)

bike_usage_by_month = alt.Chart(bike_weather_melt).mark_bar().encode(
    y = "num_usage",
    x = 'year/month',
    color=alt.condition(selection, alt.value("orange"), alt.value("lightgrey"))
).add_selection(selection).properties(height=250, width=500)

usage_per_bike_lane = hist = bike_usage_by_month.mark_bar().encode(
    y = "num_usage",
```



```

    x = "bikelane"
).transform_filter(selection).properties(height=250, width=500)

bike_usage_by_month | usage_per_bike_lane

```

```
[70]: alt.HConcatChart(...)
```

1.9.2 Exploring weather data

- There is precipitation in Vancouver more than 40% of the year. 2024 is not yet done yet and November and December should have more rain.
- The temperature clearly gets lower between September and April.
- There is increase in total precipitation during the same time period.

```

[71]: # per year % of days with rain
weather['Rain Flag'] = weather['Total Precip (mm)'].apply(lambda x: 1 if x > 0
↳ else 0)
rain_days = weather.groupby(['Year']).agg({'Rain Flag': 'mean'}).reset_index()
rain_days

```

```

[71]:   Year  Rain Flag
0  2021    0.444444
1  2022    0.435393
2  2023    0.416901
3  2024    0.393617

```

```

[72]: base = alt.Chart(bike_weather_melt).properties(width=1000, height=250)
min_temp_chart = alt.Chart(bike_weather_melt).mark_line().encode(
    y = 'Min Temp (°C)',
    x = 'date',
    color=alt.condition(selection, alt.value("orange"), alt.value("lightgrey"))
).add_selection(selection).properties(height=250, width=500)

max_temp_chart = alt.Chart(bike_weather_melt).mark_line().encode(
    y = 'Max Temp (°C)',
    x = 'date',
    color=alt.condition(selection, alt.value("orange"), alt.value("lightgrey"))
).add_selection(selection).properties(height=250, width=500)

total_precipt_chart = alt.Chart(bike_weather_melt).mark_line().encode(
    y = 'Total Precip (mm)',
    x = 'date',
    color=alt.condition(selection, alt.value("orange"), alt.value("lightgrey"))
).add_selection(selection).properties(height=250, width=1000)

min_temp_chart | max_temp_chart

```

```
[72]: alt.HConcatChart(...)
```

```
[73]: total_precipt_chart
```

```
[73]: alt.Chart(...)
```

1.9.3 Correlation Matrix

```
[74]: # create a correlation matrix
bike_weather_melt_corr = bike_weather_melt.drop(columns=['date', 'Climate ID',
↳ 'Date/Time', 'Year', 'Month', 'Day', 'bikelane', 'year/month', 'day_of_week',
↳ 'day_of_week'])
# drop where num_usage is na
bike_weather_melt_corr = bike_weather_melt_corr.dropna(subset=['num_usage'])

bike_weather_melt_corr = bike_weather_melt_corr.corr()

# correlation matrix table
bike_weather_melt_corr
```

```
[74]:
```

	Max Temp (°C)	Min Temp (°C)	Mean Temp (°C)	\
Max Temp (°C)	1.000000	0.911261	0.980870	
Min Temp (°C)	0.911261	1.000000	0.973979	
Mean Temp (°C)	0.980870	0.973979	1.000000	
Heat Deg Days (°C)	-0.968943	-0.969570	-0.991397	
Cool Deg Days (°C)	0.533016	0.480760	0.520207	
Total Rain (mm)	-0.182502	-0.025838	-0.112594	
Total Snow (cm)	-0.215686	-0.207602	-0.216970	
Total Precip (mm)	-0.215765	-0.059563	-0.146863	
num_usage	0.497210	0.390844	0.458228	

	Heat Deg Days (°C)	Cool Deg Days (°C)	Total Rain (mm)	\
Max Temp (°C)	-0.968943	0.533016	-0.182502	
Min Temp (°C)	-0.969570	0.480760	-0.025838	
Mean Temp (°C)	-0.991397	0.520207	-0.112594	
Heat Deg Days (°C)	1.000000	-0.403944	0.100725	
Cool Deg Days (°C)	-0.403944	1.000000	-0.129696	
Total Rain (mm)	0.100725	-0.129696	1.000000	
Total Snow (cm)	0.227252	-0.033602	-0.015944	
Total Precip (mm)	0.136816	-0.133707	0.985783	
num_usage	-0.456958	0.220941	-0.270175	

	Total Snow (cm)	Total Precip (mm)	num_usage
Max Temp (°C)	-0.215686	-0.215765	0.497210
Min Temp (°C)	-0.207602	-0.059563	0.390844
Mean Temp (°C)	-0.216970	-0.146863	0.458228
Heat Deg Days (°C)	0.227252	0.136816	-0.456958

Cool Deg Days (°C)	-0.033602	-0.133707	0.220941
Total Rain (mm)	-0.015944	0.985783	-0.270175
Total Snow (cm)	1.000000	0.150580	-0.099076
Total Precip (mm)	0.150580	1.000000	-0.283224
num_usage	-0.099076	-0.283224	1.000000

1.9.4 Scatter plot between weather data and bike lane usage

- The relationship between bike lane usage and total precipitation appears to follow an exponential decay pattern, while there seems to be an exponential relationship between mean temperature and bike lane usage. For Cool Deg Days, it is difficult to determine, what is the relationship between CDD and usage.
- Given strong correlation between some of the independent variables, going to do a PCA.

```
[75]: # Linked views
# Creating a selection:
selection = alt.selection(type="multi", fields=["bikelane"])

# Create a container for our two different views
base = alt.Chart(bike_weather_melt).properties(width=400, height=400)

# Create our scatterplot
tp_bl_scatterplot = base.mark_circle().encode(
    x = 'Total Precip (mm)',
    y = 'num_usage',
    color = alt.condition(selection, "bikelane", alt.value('lightgray'))
).add_selection(selection)

mt_bl_scatterplot = base.mark_circle().encode(
    x = 'Mean Temp (°C)',
    y = 'num_usage',
    color = alt.condition(selection, "bikelane", alt.value('lightgray'))
).add_selection(selection)

ts_bl_scatterplot = base.mark_circle().encode(
    x = 'Total Snow (cm)',
    y = 'num_usage',
    color = alt.condition(selection, "bikelane", alt.value('lightgray'))
).add_selection(selection)

cd_bl_scatterplot = base.mark_circle().encode(
    x = 'Cool Deg Days (°C)',
    y = 'num_usage',
    color = alt.condition(selection, "bikelane", alt.value('lightgray'))
).add_selection(selection)
```

```
tp_bl_scatterplot | mt_bl_scatterplot
```

```
[75]: alt.HConcatChart(...)
```

```
[76]: ts_bl_scatterplot | cd_bl_scatterplot
```

```
[76]: alt.HConcatChart(...)
```

```
[77]: # to get a clear picture, take 5 bike lanes and plot them to see a clearer
      ↪ picture
bike_weather_melt_sample = bike_weather_melt[bike_weather_melt['bikelane'].
      ↪isin(['1815 Cornwall - Northside', '1818 Cornwall - Southside',
            '1850 York', '486 East 37th', '821 Powell'])]

# Create a selection:
selection = alt.selection(type="multi", fields=["bikelane"])

# Create a container for our two different views
base = alt.Chart(bike_weather_melt_sample).properties(width=400, height=400)

# Create our scatterplot
tp_bl_scatterplot = base.mark_circle().encode(
    x = 'Total Precip (mm)',
    y = 'num_usage',
    color = alt.condition(selection, "bikelane", alt.value('lightgray'))
).add_selection(selection)

mt_bl_scatterplot = base.mark_circle().encode(
    x = 'Mean Temp (°C)',
    y = 'num_usage',
    color = alt.condition(selection, "bikelane", alt.value('lightgray'))
).add_selection(selection)

ts_bl_scatterplot = base.mark_circle().encode(
    x = 'Total Snow (cm)',
    y = 'num_usage',
    color = alt.condition(selection, "bikelane", alt.value('lightgray'))
).add_selection(selection)

cd_bl_scatterplot = base.mark_circle().encode(
    x = 'Cool Deg Days (°C)',
    y = 'num_usage',
    color = alt.condition(selection, "bikelane", alt.value('lightgray'))
).add_selection(selection)

tp_bl_scatterplot | mt_bl_scatterplot | ts_bl_scatterplot | cd_bl_scatterplot
```

```
[77]: alt.HConcatChart(...)
```

1.9.5 Bike lane usage based on day of week

Bike lane usage seems to be highest on either Wednesday or Saturday.

```
[78]: # bike lane usage based on day of week per bike lane
# cross tabulate day of week and bike lane usage per bike lane
bike_weather_melt_day_of_week = bike_weather_melt.dropna(subset=['num_usage'])

# get the mean of num_usage per day of week per bike lane
bike_weather_melt_day_of_week = bike_weather_melt_day_of_week.
    ↳groupby(['bikelane', 'day_of_week'])['num_usage'].mean().reset_index()

# sort by day of week
bike_weather_melt_day_of_week['day_of_week'] = pd.
    ↳Categorical(bike_weather_melt_day_of_week['day_of_week'],
    ↳categories=['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',
    ↳'Saturday', 'Sunday'],
                                                    ordered=True)

bike_weather_melt_day_of_week = bike_weather_melt_day_of_week.
    ↳sort_values('day_of_week')

# create a matrix bar chart, get bar chart for each bike lane
alt.Chart(bike_weather_melt_day_of_week).mark_line().encode(
    x='day_of_week',
    y='num_usage',
    color='bikelane'
).properties(
    width=600,
    height=250
)
```

```
[78]: alt.Chart(...)
```

```
[79]: # For each bikelane, find which day has the highest usage
bike_weather_melt_day_of_week_max = bike_weather_melt_day_of_week.
    ↳groupby('bikelane')['num_usage'].idxmax()
bike_weather_melt_day_of_week_max = bike_weather_melt_day_of_week.
    ↳loc[bike_weather_melt_day_of_week_max]

bike_weather_melt_day_of_week_max['day_of_week'].value_counts()
```

```
[79]: day_of_week
Wednesday    15
```

```

Saturday      15
Thursday      1
Monday         0
Tuesday        0
Friday         0
Sunday         0
Name: count, dtype: int64

```

1.10 PCA Dimension Reduction

- The first 4 principal components capture 99% of the variance in the data
- For each of the component, select the variable that is linked closest
 - PC1 - Mean Temp (°C)
 - PC2 - Total Precip (mm)
 - PC 3 - Total Snow (cm)
 - PC 4 - Cool Deg Days (°C)
- Also Day of week will also be added given that it theoretically cannot be correlated with any of the weather data.

```

[80]: features = ['Max Temp (°C)', 'Min Temp (°C)', 'Mean Temp (°C)',
                'Heat Deg Days (°C)', 'Cool Deg Days (°C)',
                'Total Rain (mm)', 'Total Snow (cm)', 'Total Precip (mm)']
X = bike_weather_melt[features]
X_standardized = StandardScaler().fit_transform(X)

# Apply PCA
pca = PCA()
pca.fit(X_standardized)

# Explained variance by each component
explained_variance = pca.explained_variance_ratio_

# Loadings (correlation between original features and principal components)
loadings = pd.DataFrame(pca.components_.T, columns=[f'PC{i+1}' for i in
    range(len(features))], index=features)

# Output results
print("Explained Variance Ratio by each Principal Component:")
print(explained_variance)
print("\nLoadings (Feature Contribution to Each Principal Component):")
print(loadings)

```

Explained Variance Ratio by each Principal Component:

```

[5.40197026e-01 2.41457768e-01 1.23735534e-01 8.50803675e-02
 9.49571261e-03 3.14572363e-05 2.13404242e-06 6.94192592e-34]

```

Loadings (Feature Contribution to Each Principal Component):

```

                PC1      PC2      PC3      PC4      PC5  \

```

Max Temp (°C)	-0.470472	0.034130	0.031069	-0.084855	0.682006
Min Temp (°C)	-0.456402	0.153729	0.015370	-0.144175	-0.723531
Mean Temp (°C)	-0.474784	0.091432	0.024116	-0.115091	0.034045
Heat Deg Days (°C)	0.465092	-0.098867	0.025954	0.258574	-0.042625
Cool Deg Days (°C)	-0.285082	-0.006041	0.339277	0.886281	-0.040322
Total Rain (mm)	0.115791	0.694456	-0.079497	0.075168	0.057777
Total Snow (cm)	0.126290	0.008348	0.933584	-0.316477	0.004883
Total Precip (mm)	0.134146	0.688980	0.067347	0.024591	0.058371

	PC6	PC7	PC8
Max Temp (°C)	0.005108	0.551514	4.648144e-15
Min Temp (°C)	0.004042	0.472788	3.517133e-15
Mean Temp (°C)	-0.003986	-0.471804	-7.270617e-01
Heat Deg Days (°C)	0.004144	0.493861	-6.787108e-01
Cool Deg Days (°C)	-0.000821	-0.075698	1.035999e-01
Total Rain (mm)	0.699270	-0.006081	1.465602e-16
Total Snow (cm)	0.110538	-0.001131	-1.425351e-16
Total Precip (mm)	-0.706206	0.006147	-2.680464e-16

1.11 Model Building

Based on previous analysis we observed the following relationship between bike lane usage and weather data. Given the large differences in bike lane usage depending on the location, the model will be built per bike lane.

- Mean temperature: There appears to be a linear relationship between mean temperature and bike usage
- Total Rain: Bike lane usage shows an exponential decay with increasing rain, suggesting that as rain increases, usage drops off sharply.
- Total Snow: A similar but less pronounced exponential decay relationship is seen with snow-fall, where bike lane usage decreases as snow levels rise, though the effect is not as strong as with precipitation.
- Cool Degree Days: Is a measurement of how hot the temperature is on a given day. The hotter it is, there seems to be a slight increase.
- Day of the Week: Bikelane usage changes based on the day of the week.

$$\text{Bike Usage} = \beta_0 + \beta_1 \cdot e^{\alpha \cdot \text{Mean Temp}} + \beta_2 \cdot e^{-\gamma \cdot \text{Total Rain}} + \beta_3 \cdot e^{-\delta \cdot \text{Total Snow}} + \beta_4 \cdot \text{Cool Deg Days} + \beta_5 \cdot (\text{Cool Deg Days})^2 + \sum_{i=1}^6$$

1.11.1 Summary

1. Model Performance: The models, for the most part, demonstrated reasonably high predictive accuracy across different bike lanes, with varying pseudo R-squared and mean squared error (MSE) values. This suggests that the models effectively capture key drivers of bike lane usage. However, there is a recurring tendency across the models to underestimate high-usage values in certain lanes, indicating that some factors influencing peak usage might be missing from the model.

2. Significant Predictors: Temperature and total precipitation consistently appeared as significant factors across all models. Higher mean temperatures were associated with increased bike usage, as expected, while precipitation (both rain and snow) generally had a dampening effect on usage. This aligns with intuitive patterns, as favorable weather tends to encourage cycling while inclement weather discourages it.
3. Other Predictors: Snow and Cool Degree Days display complex, nonlinear relationships with bike usage, likely benefiting from second, third, or even fourth-degree polynomial terms. Partial dependence plots reveal that bike usage decreases as snow and cooling days increase, but this effect is nonlinear, suggesting threshold levels where bike usage patterns shift significantly. Furthermore, the interaction term between Mean Temperature and Day of the Week indicates a significant positive effect on Saturdays, suggesting that higher temperatures may boost bike usage more on Saturdays than on weekdays.
4. Underestimation of High Usage: Despite the models' overall predictive strength, they often underestimate bike lane usage during high-traffic periods, particularly in certain lanes. This effect was most pronounced in tourist-heavy areas, such as the Seawall and lanes around Kitsilano Beach, as well as the Lions Gate Bridge at Spirit Trail. These lanes likely see elevated usage due to both local and tourist traffic, especially during peak seasons.
5. Model Improvements: Incorporating variables that capture commuting patterns, infrastructure quality, and neighborhood demographics may help explain usage variances in non-tourist lanes. Additionally, including variables that capture time-of-day effects could account for commuter traffic, and further data on lane quality or biking culture could help explain high usage in specific lanes.

```
[81]: # drop all values where num_usage is na
bike_weather_melt = bike_weather_melt.dropna(subset=['num_usage'])
# create interaction term
bike_weather_melt['day_bike_interaction'] = bike_weather_melt['day_of_week'].
↳ astype(str) + "_" + bike_weather_melt['bikelane'].astype(str)

[82]: # create dummy variable for day of week and bikelane
bike_weather_melt['bikelane_original'] = bike_weather_melt['bikelane']
bike_weather_melt_dummies = pd.get_dummies(bike_weather_melt,
↳ columns=['day_of_week', 'bikelane'], drop_first=True)

[83]: # Define features (X) and target (y)
X = bike_weather_melt_dummies[['Mean Temp (°C)', 'Total Rain (mm)', 'Total Snow
↳ (cm)', 'Cool Deg Days (°C)']] +
    [col for col in bike_weather_melt_dummies.columns if 'day_of_week' in
↳ col]]
y = bike_weather_melt_dummies['num_usage']

[84]: # Split the data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳ random_state=42)
```


1.11.2 GAM Results

```
[85]: # Dictionary to store evaluation results
lane_results = {}

# Loop over each bike lane
for lane in bike_weather_melt_dummies['bikelane_original'].unique():
    # Filter data for this specific bike lane
    lane_data = bike_weather_melt_dummies[bike_weather_melt_dummies['bikelane_original'] == lane]

    # Define features and target
    X = lane_data[['Mean Temp (°C)', 'Total Rain (mm)', 'Total Snow (cm)', 'Cool Deg Days (°C)'] +
        [col for col in lane_data.columns if 'day_of_week' in col]
    y = lane_data['num_usage']

    # Create interaction terms between Mean Temp and each day of the week
    for day_col in [col for col in X.columns if 'day_of_week' in col]:
        X[f'MeanTemp_{day_col}'] = X['Mean Temp (°C)'] * X[day_col]

    # Split the data
    X_train, X_test, y_train, y_test = train_test_split(X.to_numpy(), y.to_numpy(), test_size=0.2, random_state=42)

    # Define and fit the model for this lane with the manually added interaction terms
    # Note: Adjust the number of fixed terms (f) to match the number of day_of_week and interaction terms
    gam = LinearGAM(
        s(0) + # Smooth term for Mean Temp
        s(1) + # Smooth term for Total Rain (mm)
        s(2) + # Smooth term for Total Snow
        s(3) + # Smooth term for Cool Deg Days
        f(4) + # Fixed effects for day_of_week_Monday
        f(5) + # Fixed effects for day_of_week_Saturday
        f(6) + # Fixed effects for day_of_week_Sunday
        f(7) + # Fixed effects for day_of_week_Thursday
        f(8) + # Fixed effects for day_of_week_Tuesday
        f(9) + # Fixed effects for day_of_week_Wednesday
        s(10) + # Interaction term MeanTemp_day_of_week_Monday
        s(11) + # Interaction term MeanTemp_day_of_week_Saturday
        s(12) + # Interaction term MeanTemp_day_of_week_Sunday
        s(13) + # Interaction term MeanTemp_day_of_week_Thursday
        s(14) + # Interaction term MeanTemp_day_of_week_Tuesday
        s(15) + # Interaction term MeanTemp_day_of_week_Wednesday
```

```

)

gam.gridsearch(X_train, y_train) # Use gridsearch to find optimal
↪smoothness

# Print summary for each model
print(f"Summary for lane {lane}:")
gam.summary()

# Predict and evaluate
y_pred = gam.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
lane_results[lane] = mse # Store MSE for this lane

# Plot actual vs. predicted for this lane
plt.figure(figsize=(5, 5))
plt.scatter(y_test, y_pred, alpha=0.5, color='blue')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--',
↪linewidth=2)
plt.xlabel("Actual Bike Usage")
plt.ylabel("Predicted Bike Usage")
plt.title(f"Actual vs Predicted Bike Usage for {lane}")
plt.show()

print(f"Mean Squared Error for {lane}: {mse}")

```

```

0% (0 of 11) |                               | Elapsed Time: 0:00:00 ETA:  --:--:--
9% (1 of 11) |##                            | Elapsed Time: 0:00:00 ETA:  0:00:01
18% (2 of 11) |####                         | Elapsed Time: 0:00:00 ETA:  0:00:00
27% (3 of 11) |#####                      | Elapsed Time: 0:00:00 ETA:  0:00:00
36% (4 of 11) |#####                     | Elapsed Time: 0:00:00 ETA:  0:00:00
45% (5 of 11) |#####                    | Elapsed Time: 0:00:00 ETA:  0:00:00
54% (6 of 11) |#####                   | Elapsed Time: 0:00:00 ETA:  0:00:00
63% (7 of 11) |#####                  | Elapsed Time: 0:00:00 ETA:  0:00:00
72% (8 of 11) |#####                 | Elapsed Time: 0:00:00 ETA:  0:00:00
81% (9 of 11) |#####                | Elapsed Time: 0:00:00 ETA:  0:00:00
90% (10 of 11) |#####               | Elapsed Time: 0:00:00 ETA:  0:00:00
100% (11 of 11) |#####              | Elapsed Time: 0:00:00 Time:  0:00:00

```

Summary for lane 1815 Cornwall - Northside:

LinearGAM

```

=====
=====

```

```

Distribution:                               NormalDist Effective DoF:
33.6836
Link Function:                             IdentityLink Log Likelihood:
-11601.8808
Number of Samples:                         1052 AIC:

```

23273.1289

AICc:

23275.5644

GCV:

26072.2562

Scale:

24574.0368

Pseudo R-Squared:

0.7606

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
s(0)		[63.0957]	20	9.9
1.11e-16	***			
s(1)		[63.0957]	20	4.0
1.11e-16	***			
s(2)		[63.0957]	20	2.3
8.56e-01				
s(3)		[63.0957]	20	1.7
4.15e-03	**			
f(4)		[63.0957]	2	0.9
3.58e-01				
f(5)		[63.0957]	2	0.9
2.78e-01				
f(6)		[63.0957]	2	0.9
6.90e-01				
f(7)		[63.0957]	2	0.9
6.80e-01				
f(8)		[63.0957]	2	0.9
7.45e-01				
f(9)		[63.0957]	2	0.8
4.87e-01				
s(10)		[63.0957]	20	2.1
4.05e-01				
s(11)		[63.0957]	20	2.2
1.68e-08	***			
s(12)		[63.0957]	20	2.0
1.31e-01				
s(13)		[63.0957]	20	1.6
9.53e-01				
s(14)		[63.0957]	20	1.6
7.89e-01				
s(15)		[63.0957]	20	1.1
9.61e-01				
intercept			1	0.0

4.53e-01

=====

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

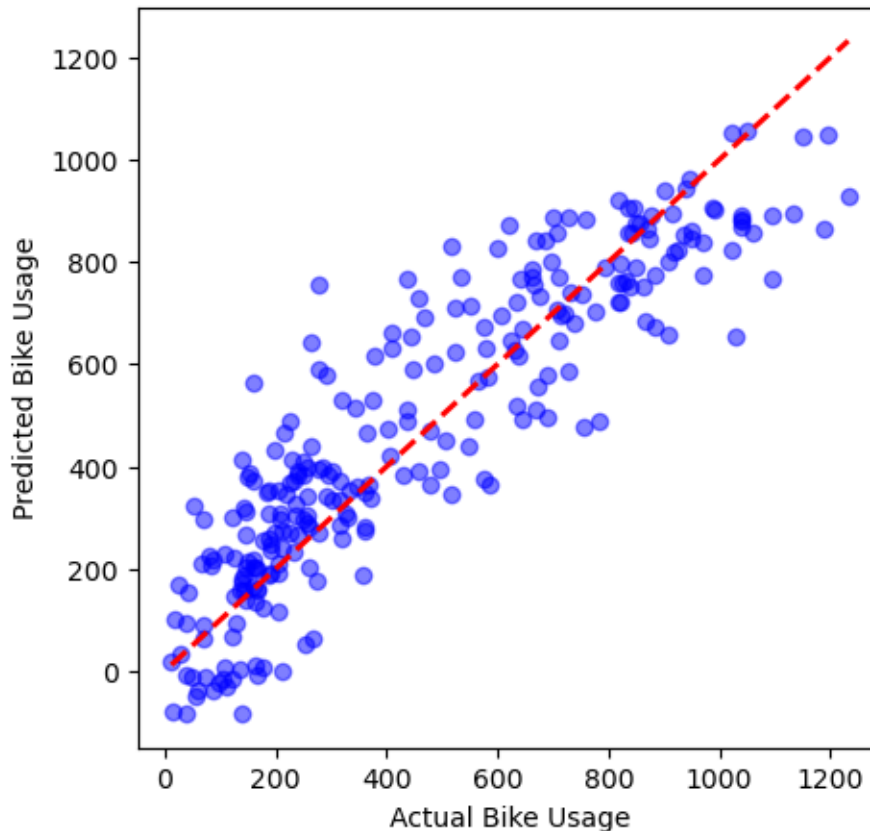
WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for 1815 Cornwall - Northside



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for 1815 Cornwall - Northside: 20062.460673923226

9% (1 of 11) |## Elapsed Time: 0:00:00 ETA: 0:00:00

```

18% (2 of 11) |####| Elapsed Time: 0:00:00 ETA: 0:00:01
27% (3 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) |#####| Elapsed Time: 0:00:00 Time: 0:00:00

```

Summary for lane 1818 Cornwall - Southside:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

34.6524

Link Function: IdentityLink Log Likelihood:

-10796.8646

Number of Samples: 1036 AIC:

21665.0341

AICc:

21667.6493

GCV:

14251.3694

Scale:

13395.9774

Pseudo R-Squared:

0.7742

=====

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
s(0)		[63.0957]	20	9.5
1.11e-16	***			
s(1)		[63.0957]	20	3.9
1.11e-16	***			
s(2)		[63.0957]	20	2.8
9.20e-01				
s(3)		[63.0957]	20	1.6
1.48e-04	***			
f(4)		[63.0957]	2	0.9
7.47e-01				
f(5)		[63.0957]	2	0.9
5.50e-01				
f(6)		[63.0957]	2	0.9

9.59e-01			
f(7)	[63.0957]	2	0.9
5.85e-01			
f(8)	[63.0957]	2	0.9
7.21e-01			
f(9)	[63.0957]	2	0.8
4.44e-01			
s(10)	[63.0957]	20	2.1
6.08e-02	.		
s(11)	[63.0957]	20	2.5
2.57e-06	***		
s(12)	[63.0957]	20	2.0
6.94e-01			
s(13)	[63.0957]	20	2.2
6.81e-01			
s(14)	[63.0957]	20	1.6
6.91e-01			
s(15)	[63.0957]	20	1.1
7.63e-01			
intercept		1	0.0
5.43e-01			

```
=====
=====
```

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

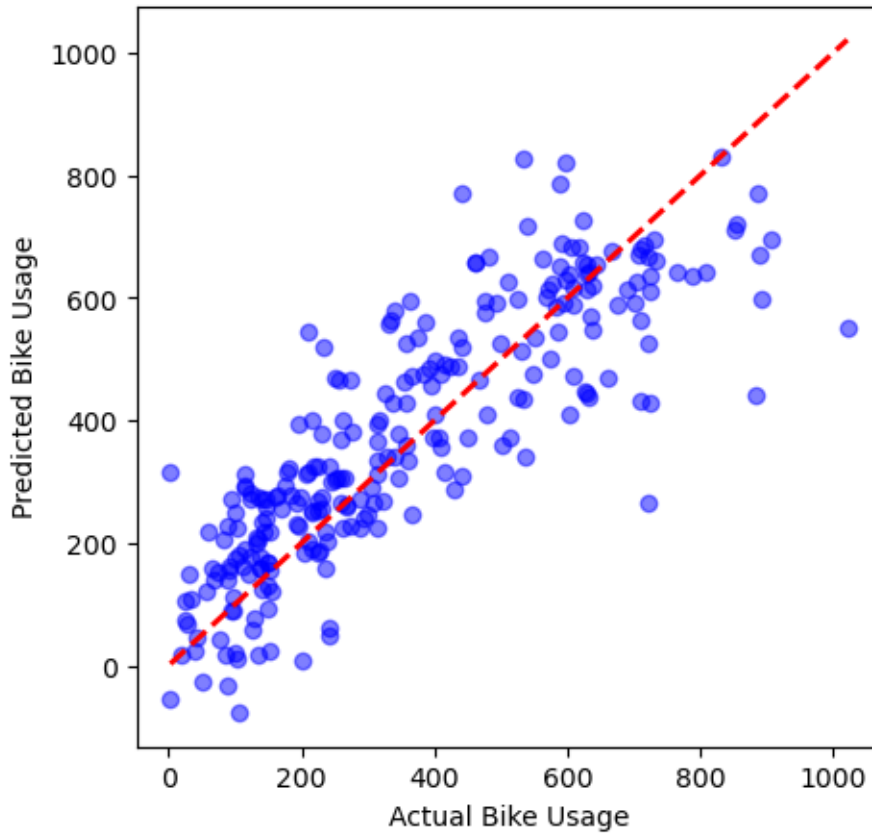
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for 1818 Cornwall - Southside



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for 1818 Cornwall - Southside: 15677.980908007425

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane 1850 York:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

47.7284

Link Function:

IdentityLink Log Likelihood:

-13140.9644

Number of Samples:

1055 AIC:

26379.3857

AICc:

26384.2067

GCV:

111470.3642

Scale:

102431.2969

Pseudo R-Squared:

0.7934

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====		=====	=====	=====
s(0)		[15.8489]	20	11.9
1.11e-16	***			
s(1)		[15.8489]	20	5.3
1.11e-16	***			
s(2)		[15.8489]	20	4.1
7.10e-01				
s(3)		[15.8489]	20	2.3
1.28e-01				
f(4)		[15.8489]	2	0.9
7.03e-01				
f(5)		[15.8489]	2	0.9
9.05e-01				
f(6)		[15.8489]	2	0.9
2.70e-01				
f(7)		[15.8489]	2	0.9
8.74e-01				
f(8)		[15.8489]	2	1.0
7.86e-01				
f(9)		[15.8489]	2	0.9
6.65e-01				
s(10)		[15.8489]	20	4.2
2.89e-01				
s(11)		[15.8489]	20	2.9
3.42e-01				
s(12)		[15.8489]	20	3.0
6.23e-03	**			
s(13)		[15.8489]	20	3.6
4.79e-02	*			
s(14)		[15.8489]	20	2.7

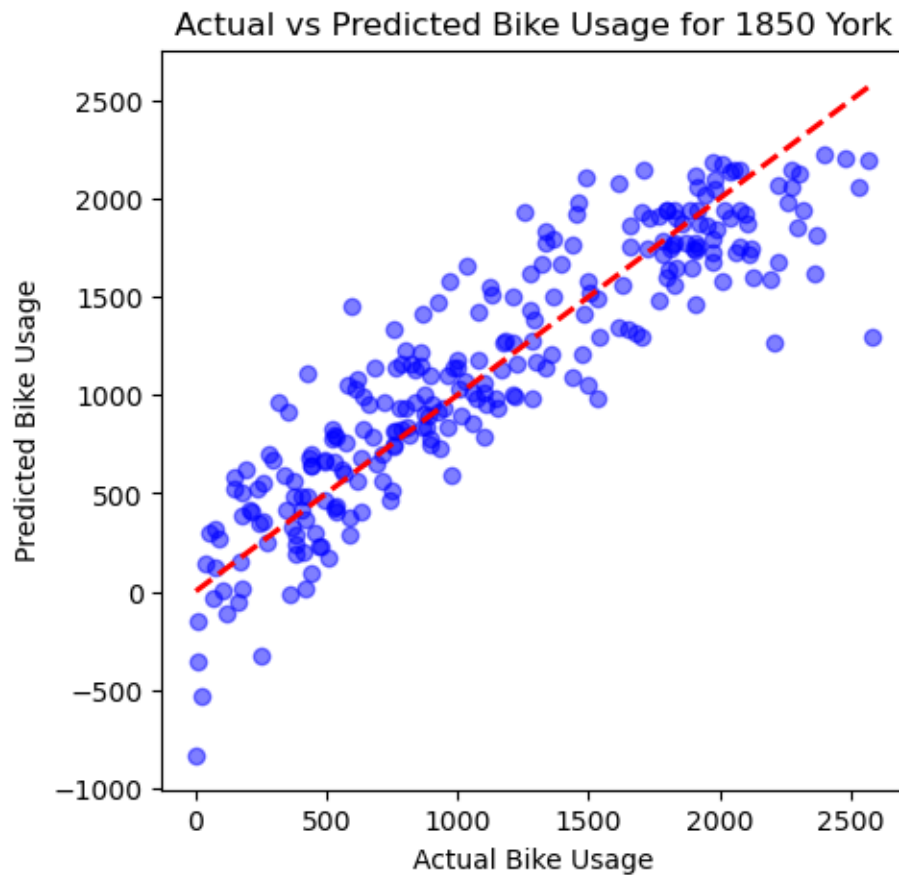

```

7.18e-01
s(15)                [15.8489]                20                2.0
1.69e-02      *
intercept                1                0.0
4.94e-01
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with
known smoothing parameters, but when smoothing parameters have been estimated, the p-values
are typically lower than they should be, meaning that the tests reject the null too readily.



```

0% (0 of 11) |                               | Elapsed Time: 0:00:00 ETA:  --:--:--
Mean Squared Error for 1850 York: 89921.0591823779

 9% (1 of 11) |##                               | Elapsed Time: 0:00:00 ETA:  0:00:00
18% (2 of 11) |####                              | Elapsed Time: 0:00:00 ETA:  0:00:00
27% (3 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
36% (4 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
45% (5 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
54% (6 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
63% (7 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
72% (8 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
81% (9 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
90% (10 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
100% (11 of 11) |#####                             | Elapsed Time: 0:00:00 Time:  0:00:00

```

Summary for lane 486 East 37th:

LinearGAM

```

=====
=====
Distribution:                               NormalDist Effective DoF:
47.7284
Link Function:                             IdentityLink Log Likelihood:
-11122.6107
Number of Samples:                         1055 AIC:
22342.6782
                                           AICc:
22347.4992
                                           GCV:
16454.5209
                                           Scale:
15120.2333
                                           Pseudo R-Squared:
0.7333
=====
=====

```

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
s(0)		[15.8489]	20	11.9
1.11e-16	***			
s(1)		[15.8489]	20	5.3
1.11e-16	***			
s(2)		[15.8489]	20	4.1
3.60e-01				
s(3)		[15.8489]	20	2.3
3.10e-01				
f(4)		[15.8489]	2	0.9

6.05e-01			
f(5)	[15.8489]	2	0.9
9.50e-01			
f(6)	[15.8489]	2	0.9
1.73e-01			
f(7)	[15.8489]	2	0.9
8.23e-01			
f(8)	[15.8489]	2	1.0
7.14e-01			
f(9)	[15.8489]	2	0.9
4.80e-01			
s(10)	[15.8489]	20	4.2
1.83e-01			
s(11)	[15.8489]	20	2.9
7.30e-01			
s(12)	[15.8489]	20	3.0
8.02e-04	***		
s(13)	[15.8489]	20	3.6
9.86e-02	.		
s(14)	[15.8489]	20	2.7
9.61e-01			
s(15)	[15.8489]	20	2.0
6.79e-01			
intercept		1	0.0
3.20e-01			

=====

=====

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

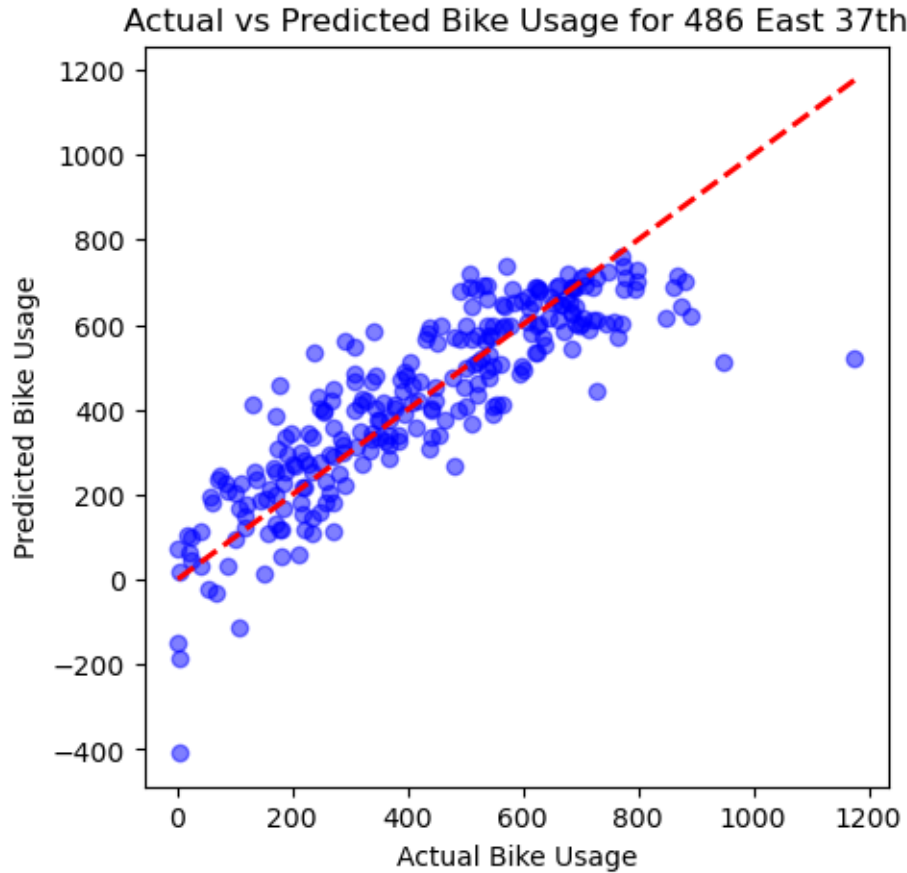
WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for 486 East 37th: 13832.348967938296

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane 821 Powell:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

47.1004

Link Function:

IdentityLink Log Likelihood:

-10200.3451

Number of Samples:

1020 AIC:

20496.8911

AICc:

20501.7562

GCV:

9582.8678

Scale:

8789.7827

Pseudo R-Squared:

0.797

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====		=====	=====	=====
=====				
s(0)		[15.8489]	20	12.1
1.11e-16	***			
s(1)		[15.8489]	20	5.3
1.11e-16	***			
s(2)		[15.8489]	20	3.3
4.81e-01				
s(3)		[15.8489]	20	2.9
4.58e-02	*			
f(4)		[15.8489]	2	0.9
7.55e-01				
f(5)		[15.8489]	2	0.9
7.38e-01				
f(6)		[15.8489]	2	1.0
4.20e-02	*			
f(7)		[15.8489]	2	0.9
4.60e-01				
f(8)		[15.8489]	2	0.9
1.04e-01				
f(9)		[15.8489]	2	0.9
8.38e-01				
s(10)		[15.8489]	20	3.5
3.00e-01				
s(11)		[15.8489]	20	3.3
3.89e-03	**			
s(12)		[15.8489]	20	3.1
9.30e-12	***			
s(13)		[15.8489]	20	3.4
4.50e-01				
s(14)		[15.8489]	20	2.5

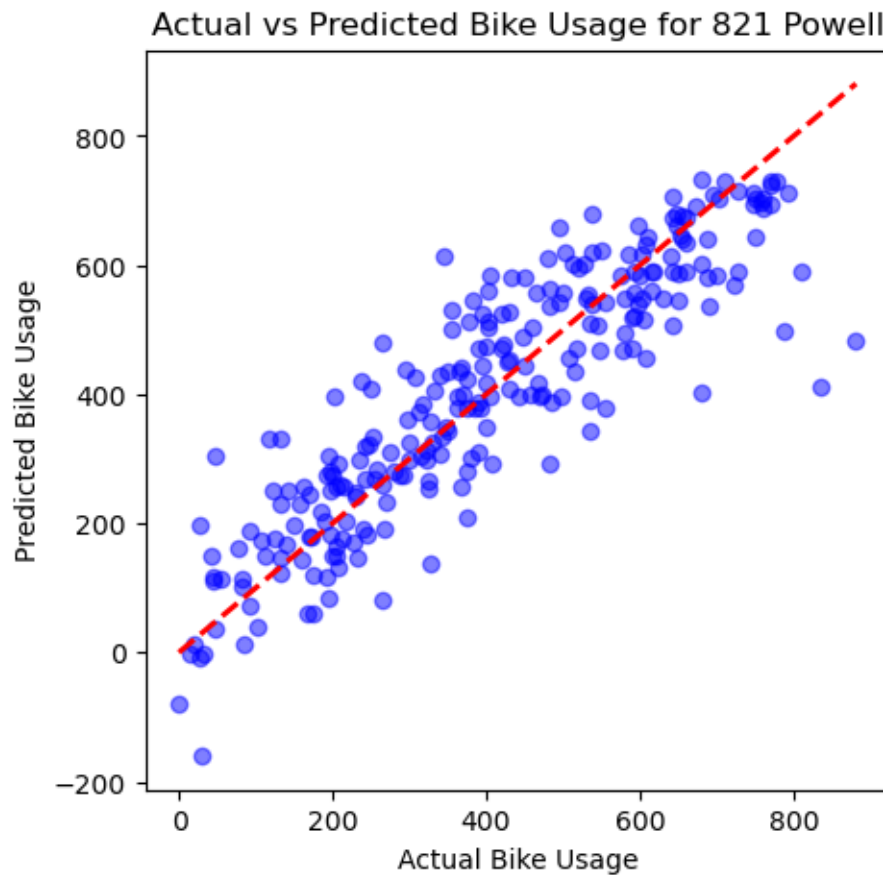
```

6.70e-01
s(15)                [15.8489]                20                2.1
4.94e-02      *
intercept                1                0.0
7.83e-01
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with
known smoothing parameters, but when smoothing parameters have been estimated, the p-values
are typically lower than they should be, meaning that the tests reject the null too readily.



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for 821 Powell: 9458.880769895883

9% (1 of 11) |## Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) |#### Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) |##### Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) |##### Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) |##### Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) |##### Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) |##### Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) |##### Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) |##### Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) |##### Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) |##### Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane 885 Dunsmuir:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

43.6641

Link Function: IdentityLink Log Likelihood:

-7979.5073

Number of Samples: 691 AIC:

16048.3427

AICc:

16054.6636

GCV:

46573.8545

Scale:

41308.2396

Pseudo R-Squared:

0.8654

=====

=====

Feature Function		Lambda	Rank	EDoF
------------------	--	--------	------	------

P > x	Sig. Code			
-------	-----------	--	--	--

=====

=====

s(0)		[15.8489]	20	12.1
1.11e-16	***			
s(1)		[15.8489]	20	5.1
1.11e-16	***			
s(2)		[15.8489]	20	4.2
1.49e-02	*			
s(3)		[15.8489]	20	2.9
4.95e-02	*			
f(4)		[15.8489]	2	0.9

2.16e-01				
f(5)		[15.8489]	2	0.9
8.23e-07	***			
f(6)		[15.8489]	2	0.9
2.15e-06	***			
f(7)		[15.8489]	2	0.9
1.71e-01				
f(8)		[15.8489]	2	0.9
3.93e-02	*			
f(9)		[15.8489]	2	0.9
1.09e-01				
s(10)		[15.8489]	20	2.7
1.22e-01				
s(11)		[15.8489]	20	2.7
6.55e-15	***			
s(12)		[15.8489]	20	2.6
1.11e-16	***			
s(13)		[15.8489]	20	2.4
1.32e-03	**			
s(14)		[15.8489]	20	2.1
3.50e-07	***			
s(15)		[15.8489]	20	1.4
2.41e-04	***			
intercept			1	0.0
2.62e-01				

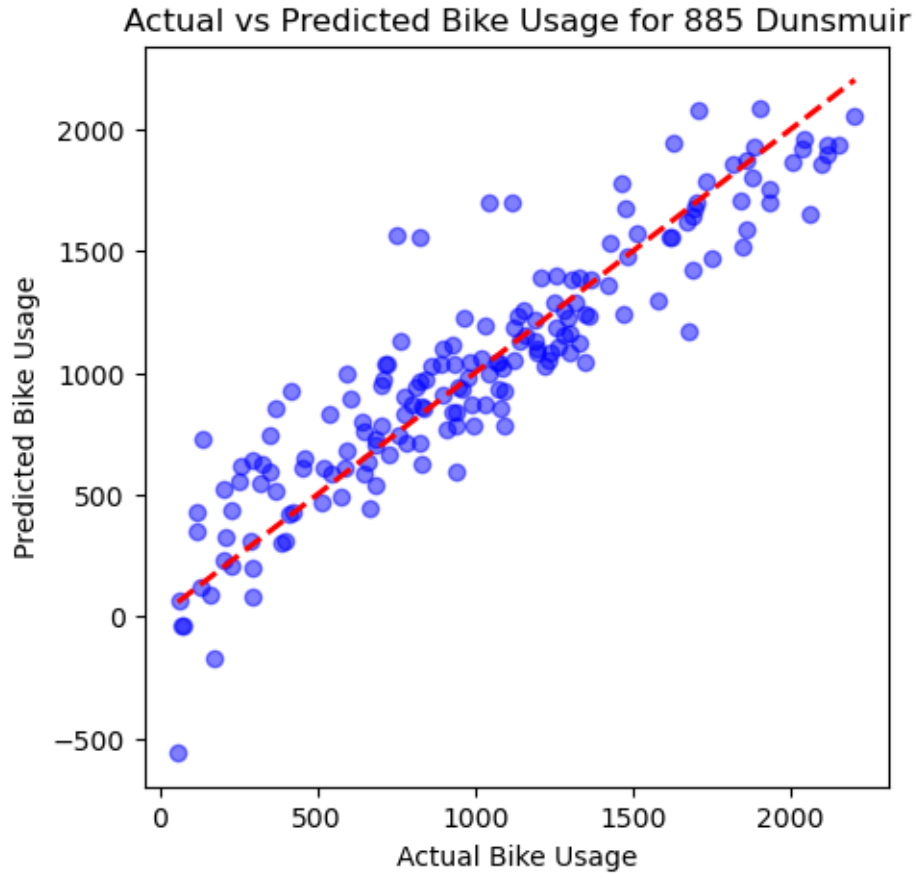
=====

=====

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with
known smoothing parameters, but when smoothing parameters have been estimated, the p-values
are typically lower than they should be, meaning that the tests reject the null too readily.



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for 885 Dunsmuir: 49212.5182340492

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Burrard at Cornwall - Eastside - Burrard Bridge:

LinearGAM

=====

=====

Distribution:

NormalDist Effective DoF:

45.0913

Link Function:

IdentityLink Log Likelihood:

-11671.705

Number of Samples:

881 AIC:

23435.5925

AICc:

23440.7981

GCV:

249065.2322

Scale:

226229.5078

Pseudo R-Squared:

0.8022

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====		=====	=====	=====
s(0)		[15.8489]	20	12.3
1.11e-16	***			
s(1)		[15.8489]	20	5.2
1.11e-16	***			
s(2)		[15.8489]	20	3.1
5.72e-01				
s(3)		[15.8489]	20	3.0
9.57e-04	***			
f(4)		[15.8489]	2	0.9
7.93e-01				
f(5)		[15.8489]	2	0.9
8.65e-01				
f(6)		[15.8489]	2	0.9
4.30e-01				
f(7)		[15.8489]	2	0.9
8.38e-01				
f(8)		[15.8489]	2	0.9
9.61e-01				
f(9)		[15.8489]	2	0.9
2.57e-01				
s(10)		[15.8489]	20	3.4
5.39e-01				
s(11)		[15.8489]	20	3.2
1.48e-04	***			
s(12)		[15.8489]	20	3.1
1.29e-01				
s(13)		[15.8489]	20	2.4
9.12e-01				
s(14)		[15.8489]	20	2.3

```

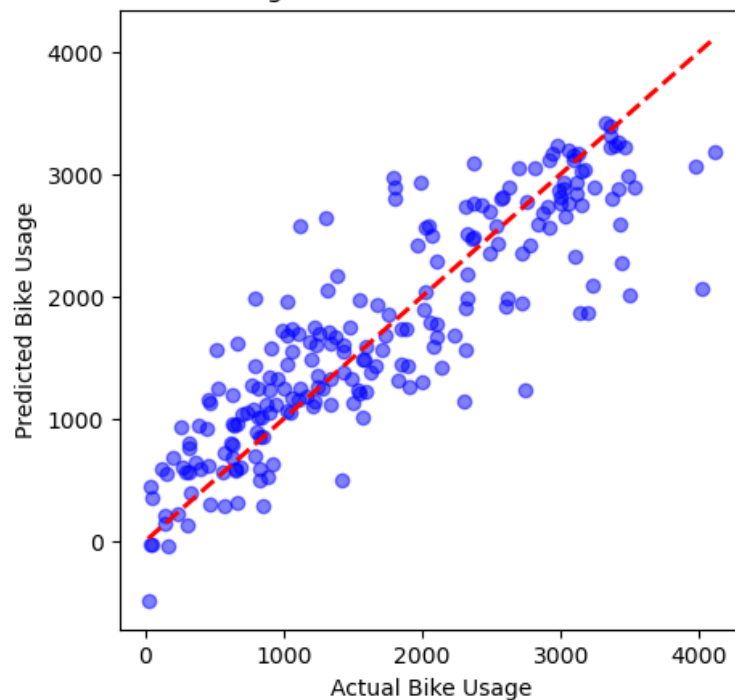
1.23e-01
s(15)                [15.8489]                20                1.6
1.65e-01
intercept            1                0.0
7.29e-01
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with
known smoothing parameters, but when smoothing parameters have been estimated, the p-values
are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Burrard at Cornwall - Eastside - Burrard Bridge



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Burrard at Cornwall - Eastside - Burrard Bridge:
259238.1967909589

```

 9% (1 of 11) |##                               | Elapsed Time: 0:00:00 ETA: 0:00:01
18% (2 of 11) |####                             | Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) |#####                         | Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) |#####                               | Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) |#####                               | Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) |#####                               | Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) |#####                               | Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) |#####                               | Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) |#####                               | Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) |#####                               | Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) |#####                               | Elapsed Time: 0:00:01 Time: 0:00:01

```

Summary for lane Burrard at Cornwall - Westside - Burrard Bridge:

LinearGAM

=====

=====

```

Distribution:                               NormalDist Effective DoF:
45.468
Link Function:                             IdentityLink Log Likelihood:
-11132.6565
Number of Samples:                         840 AIC:
22358.249
                                           AICc:
22363.8153
                                           GCV:
251747.9669
                                           Scale:
227344.5509
                                           Pseudo R-Squared:
0.8183

```

=====

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
s(0)		[15.8489]	20	11.7
1.11e-16	***			
s(1)		[15.8489]	20	5.2
1.11e-16	***			
s(2)		[15.8489]	20	3.6
6.17e-01				
s(3)		[15.8489]	20	2.2
8.24e-04	***			
f(4)		[15.8489]	2	0.9
6.85e-01				
f(5)		[15.8489]	2	0.9
7.90e-01				

f(6)	[15.8489]	2	0.9
2.39e-01			
f(7)	[15.8489]	2	0.9
3.30e-01			
f(8)	[15.8489]	2	0.9
8.30e-01			
f(9)	[15.8489]	2	0.9
2.15e-01			
s(10)	[15.8489]	20	3.3
6.43e-01			
s(11)	[15.8489]	20	3.7
6.37e-03 **			
s(12)	[15.8489]	20	3.1
2.25e-01			
s(13)	[15.8489]	20	2.9
6.87e-01			
s(14)	[15.8489]	20	2.5
5.66e-01			
s(15)	[15.8489]	20	1.8
2.54e-01			
intercept		1	0.0
5.32e-01			

```
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

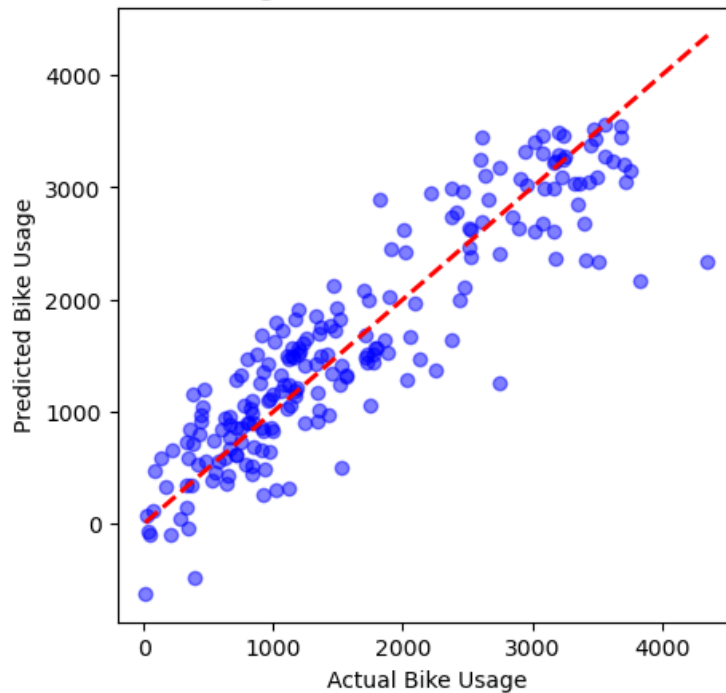
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Burrard at Cornwall - Westside - Burrard Bridge



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Burrard at Cornwall - Westside - Burrard Bridge:
206461.65609922772

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Cambie Bridge - Eastside:

LinearGAM

=====

Distribution: NormalDist Effective DoF:
32.6478

Link Function: IdentityLink Log Likelihood:
-9667.8645

Number of Samples:
19403.0245

838 AIC:

19405.9269

AICc:

43928.3589

GCV:

40858.9184

Scale:

0.695

Pseudo R-Squared:

```
=====
=====
Feature Function      Lambda      Rank      EDoF
P > x      Sig. Code
=====
=====
s(0)                [63.0957]      20      9.4
1.11e-16      ***
s(1)                [63.0957]      20      3.9
1.11e-16      ***
s(2)                [63.0957]      20      2.5
1.54e-01
s(3)                [63.0957]      20      2.0
1.99e-01
f(4)                [63.0957]      2      0.9
9.33e-01
f(5)                [63.0957]      2      0.9
5.63e-04      ***
f(6)                [63.0957]      2      0.9
9.24e-04      ***
f(7)                [63.0957]      2      0.9
8.78e-02      .
f(8)                [63.0957]      2      0.9
1.58e-01
f(9)                [63.0957]      2      0.8
3.80e-01
s(10)               [63.0957]      20      2.1
2.68e-01
s(11)               [63.0957]      20      2.0
2.41e-13      ***
s(12)               [63.0957]      20      2.0
1.11e-16      ***
s(13)               [63.0957]      20      1.4
2.47e-02      *
s(14)               [63.0957]      20      1.3
3.02e-01
s(15)               [63.0957]      20      0.9
1.49e-01
```

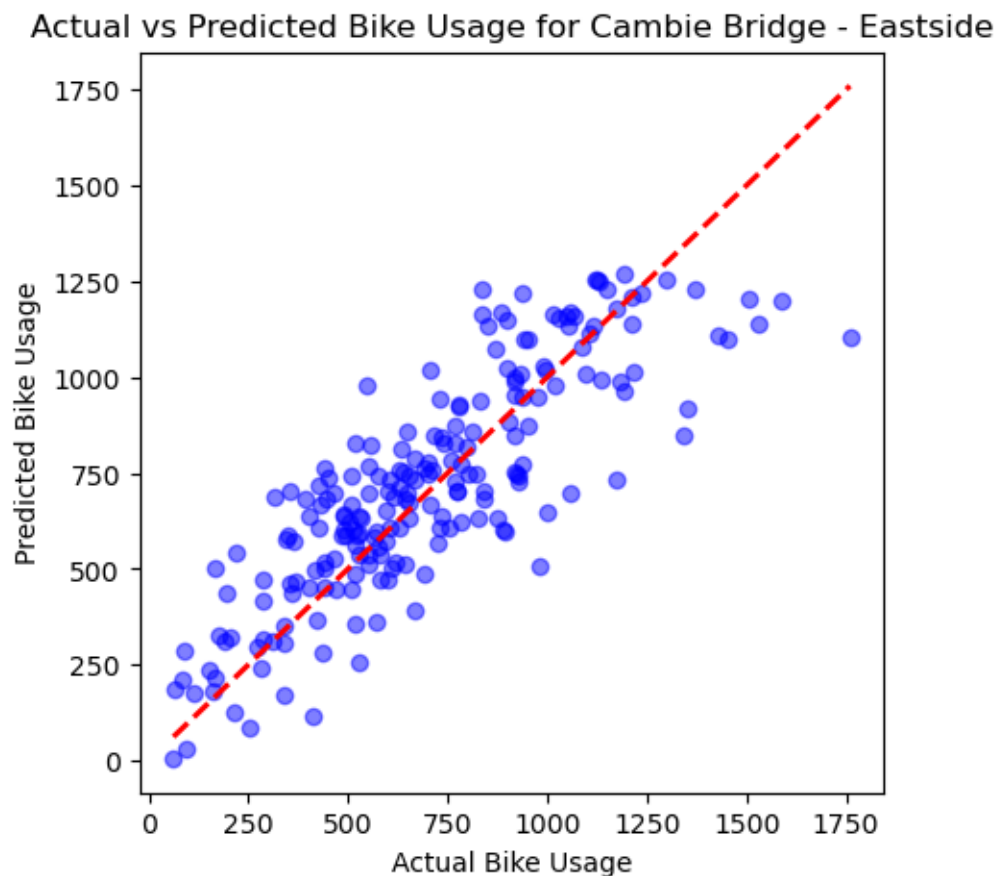
```

intercept                                1          0.0
4.18e-02      *
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem
which can cause p-values to appear significant when they are not.

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known smoothing parameters, but when smoothing parameters have been estimated, the p-values
are typically lower than they should be, meaning that the tests reject the null too readily.



```

0% (0 of 11) |                               | Elapsed Time: 0:00:00 ETA:  --:--:--
Mean Squared Error for Cambie Bridge - Eastside: 33091.23622016974

```



```

 9% (1 of 11) |##                               | Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) |####                             | Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) |#####                           | Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) |#####                         | Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) |#####                       | Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) |#####                     | Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) |#####                   | Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) |#####                 | Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) |#####               | Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) |#####             | Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) |#####           | Elapsed Time: 0:00:00 Time: 0:00:00

```

Summary for lane Canada Line Bridge at West Kent:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

44.3281

Link Function: IdentityLink Log Likelihood:

-9170.7051

Number of Samples: 789 AIC:

18432.0664

AICc:

18437.7215

GCV:

49526.9114

Scale:

44544.8236

Pseudo R-Squared:

0.7696

=====

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
s(0)		[15.8489]	20	12.0
1.11e-16	***			
s(1)		[15.8489]	20	5.1
1.11e-16	***			
s(2)		[15.8489]	20	3.6
9.16e-01				
s(3)		[15.8489]	20	3.0
3.36e-03	**			
f(4)		[15.8489]	2	0.9
8.53e-01				
f(5)		[15.8489]	2	0.9
1.43e-02	*			

f(6)		[15.8489]	2	0.9
4.79e-01				
f(7)		[15.8489]	2	0.9
3.99e-01				
f(8)		[15.8489]	2	0.9
3.73e-01				
f(9)		[15.8489]	2	0.9
2.87e-01				
s(10)		[15.8489]	20	3.1
9.56e-01				
s(11)		[15.8489]	20	2.9
1.33e-13	***			
s(12)		[15.8489]	20	2.8
8.21e-10	***			
s(13)		[15.8489]	20	2.7
3.04e-01				
s(14)		[15.8489]	20	2.2
5.44e-01				
s(15)		[15.8489]	20	1.5
8.35e-01				
intercept			1	0.0
2.43e-02	*			

```
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

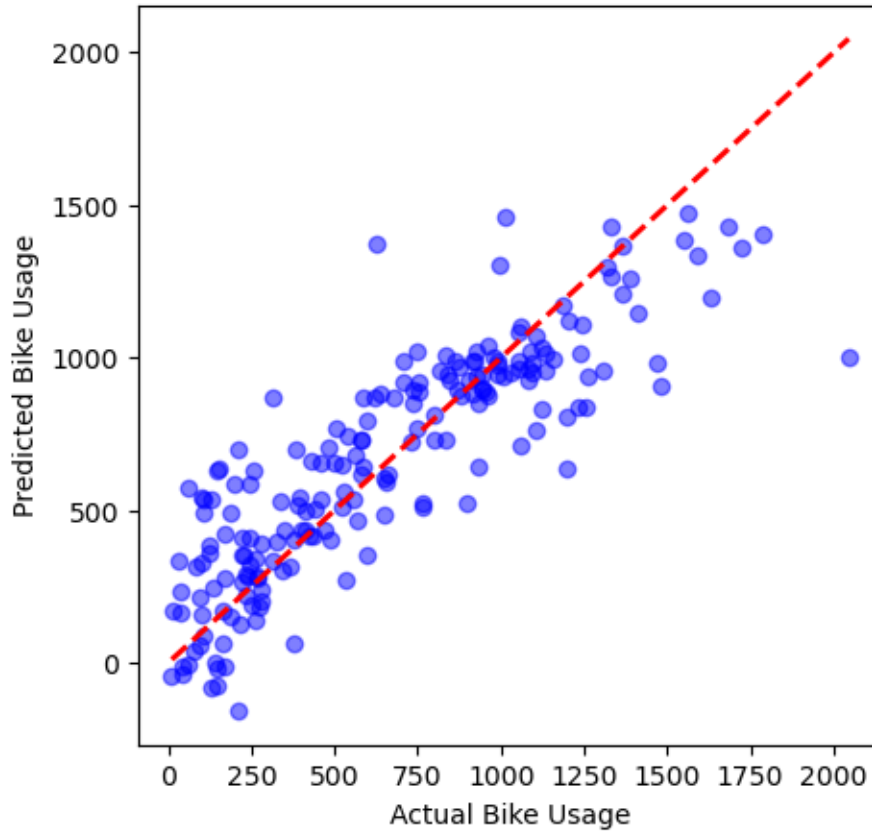
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Canada Line Bridge at West Kent



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Canada Line Bridge at West Kent: 51895.48680391936

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Central Valley Greenway at Victoria:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

21.5354

Link Function:

IdentityLink Log Likelihood:

-6527.4218

Number of Samples:

490 AIC:

13099.9145

AICc:

13102.1886

GCV:

264181.5435

Scale:

243367.594

Pseudo R-Squared:

0.5548

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====		=====	=====	=====
s(0)		[251.1886]	20	6.8
1.11e-16	***			
s(1)		[251.1886]	20	2.7
1.11e-16	***			
s(2)		[251.1886]	20	1.7
8.23e-01				
s(3)		[251.1886]	20	1.1
1.40e-03	**			
f(4)		[251.1886]	2	0.9
9.39e-01				
f(5)		[251.1886]	2	0.8
7.64e-01				
f(6)		[251.1886]	2	0.8
3.55e-01				
f(7)		[251.1886]	2	0.8
7.67e-01				
f(8)		[251.1886]	2	0.8
4.40e-01				
f(9)		[251.1886]	2	0.8
9.27e-01				
s(10)		[251.1886]	20	0.9
8.77e-01				
s(11)		[251.1886]	20	0.9
4.99e-01				
s(12)		[251.1886]	20	0.7
6.03e-02	.			
s(13)		[251.1886]	20	0.8
8.64e-02	.			
s(14)		[251.1886]	20	0.7

```

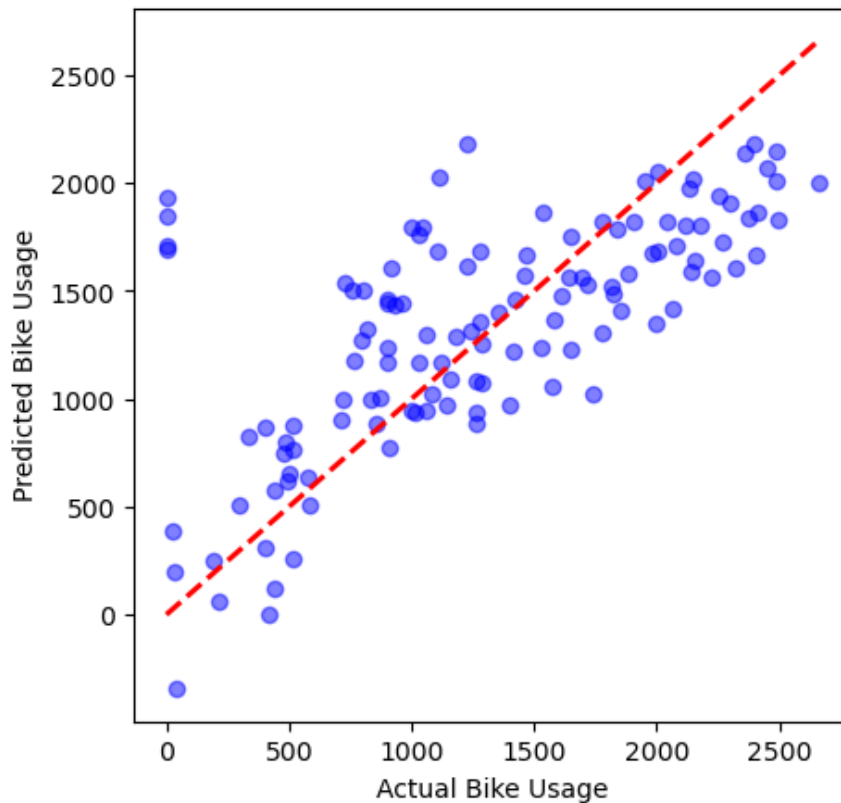
5.12e-01
s(15)                [251.1886]          20          0.4
4.68e-02      *
intercept                1          0.0
4.26e-01
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with
known smoothing parameters, but when smoothing parameters have been estimated, the p-values
are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Central Valley Greenway at Victoria



Mean Squared Error for Central Valley Greenway at Victoria: 260071.06070436985

9% (1 of 11)	##	Elapsed Time: 0:00:00	ETA: 0:00:00
18% (2 of 11)	####	Elapsed Time: 0:00:00	ETA: 0:00:00
27% (3 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
36% (4 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
45% (5 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
54% (6 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
63% (7 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
72% (8 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
81% (9 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
90% (10 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
100% (11 of 11)	#####	Elapsed Time: 0:00:00	Time: 0:00:00

Summary for lane Comox at Thurlow:

LinearGAM

```

=====
Distribution:                      NormalDist Effective DoF:
34.2502
Link Function:                     IdentityLink Log Likelihood:
-10642.8562
Number of Samples:                 1051 AIC:
21356.2127
                                     AICc:
21358.7312
                                     GCV:
10590.2128
                                     Scale:
9970.8646
                                     Pseudo R-Squared:
0.7454
=====

```

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
s(0)		[63.0957]	20	9.7
1.11e-16	***			
s(1)		[63.0957]	20	4.0
1.11e-16	***			
s(2)		[63.0957]	20	2.3
8.72e-04	***			
s(3)		[63.0957]	20	1.4
1.68e-01				
f(4)		[63.0957]	2	0.9
4.39e-01				
f(5)		[63.0957]	2	0.9

7.61e-03	**			
f(6)		[63.0957]	2	0.9
4.83e-01				
f(7)		[63.0957]	2	0.9
1.92e-01				
f(8)		[63.0957]	2	0.9
5.22e-01				
f(9)		[63.0957]	2	0.8
3.52e-01				
s(10)		[63.0957]	20	2.4
1.01e-04	***			
s(11)		[63.0957]	20	2.5
1.17e-06	***			
s(12)		[63.0957]	20	1.9
3.33e-16	***			
s(13)		[63.0957]	20	1.8
2.19e-01				
s(14)		[63.0957]	20	1.7
6.54e-01				
s(15)		[63.0957]	20	1.4
2.38e-01				
intercept			1	0.0
7.99e-02	.			

=====
 Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

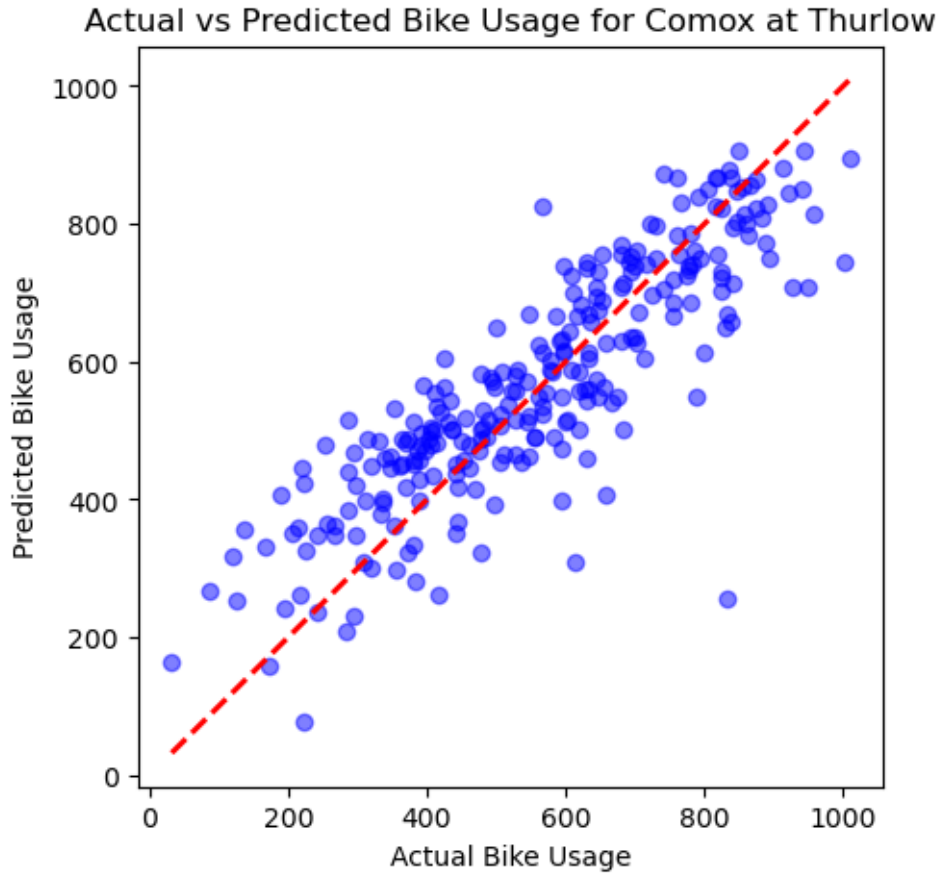
WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.



0% (0 of 11) | | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Comox at Thurlow: 11103.789157697169

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Dunsmuir Viaduct at Main:

LinearGAM

=====

=====

Distribution:

NormalDist Effective DoF:

43.135

Link Function:

IdentityLink Log Likelihood:

-8344.8082

Number of Samples:

716 AIC:

16777.8864

AICc:

16783.8251

GCV:

51529.0302

Scale:

45973.0612

Pseudo R-Squared:

0.854

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
s(0)		[15.8489]	20	12.0
1.11e-16	***			
s(1)		[15.8489]	20	5.1
1.11e-16	***			
s(2)		[15.8489]	20	3.6
9.47e-03	**			
s(3)		[15.8489]	20	2.9
1.14e-01				
f(4)		[15.8489]	2	0.9
3.26e-01				
f(5)		[15.8489]	2	0.9
2.86e-05	***			
f(6)		[15.8489]	2	0.9
1.58e-07	***			
f(7)		[15.8489]	2	0.9
1.60e-01				
f(8)		[15.8489]	2	0.9
2.96e-01				
f(9)		[15.8489]	2	0.9
2.81e-01				
s(10)		[15.8489]	20	3.2
3.28e-01				
s(11)		[15.8489]	20	2.8
1.25e-14	***			
s(12)		[15.8489]	20	2.6
1.11e-16	***			
s(13)		[15.8489]	20	2.3
5.25e-04	***			
s(14)		[15.8489]	20	1.8

```

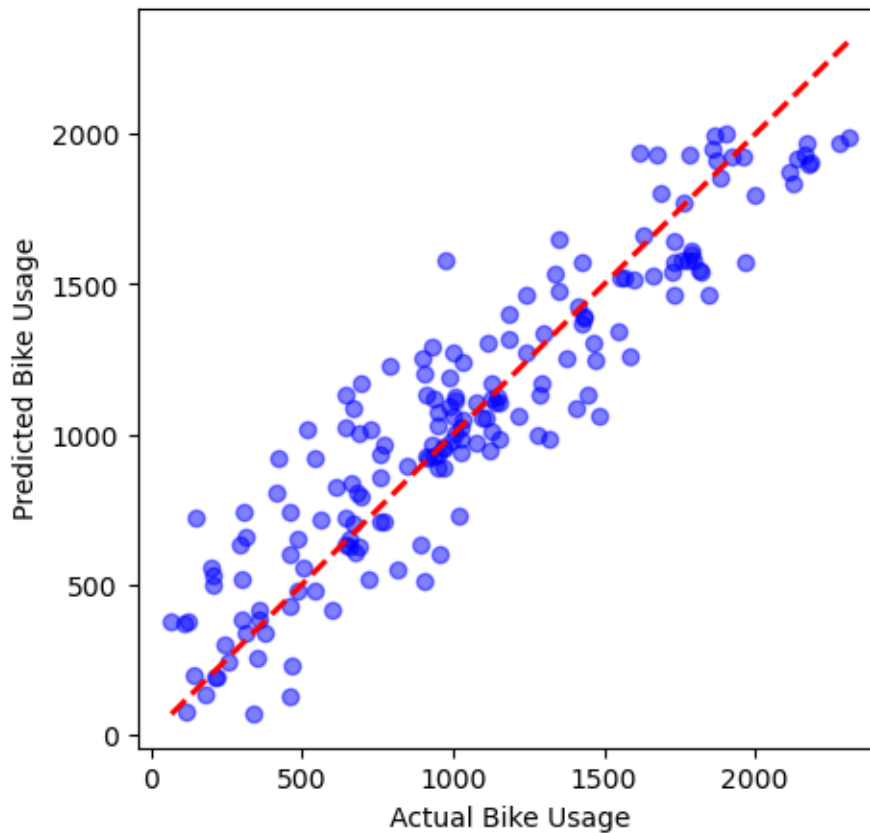
7.19e-07    ***
s(15)                [15.8489]                20                1.4
1.16e-05    ***
intercept                1                0.0
2.69e-01
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with
known smoothing parameters, but when smoothing parameters have been estimated, the p-values
are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Dunsmuir Viaduct at Main



```

0% (0 of 11) |                               | Elapsed Time: 0:00:00 ETA:  --:--:--
Mean Squared Error for Dunsmuir Viaduct at Main: 47750.56948435841

 9% (1 of 11) |##                               | Elapsed Time: 0:00:00 ETA:  0:00:00
18% (2 of 11) |####                              | Elapsed Time: 0:00:00 ETA:  0:00:00
27% (3 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
36% (4 of 11) |#####                            | Elapsed Time: 0:00:00 ETA:  0:00:00
45% (5 of 11) |#####                           | Elapsed Time: 0:00:00 ETA:  0:00:00
54% (6 of 11) |#####                          | Elapsed Time: 0:00:00 ETA:  0:00:00
63% (7 of 11) |#####                         | Elapsed Time: 0:00:00 ETA:  0:00:00
72% (8 of 11) |#####                        | Elapsed Time: 0:00:00 ETA:  0:00:00
81% (9 of 11) |#####                       | Elapsed Time: 0:00:00 ETA:  0:00:00
90% (10 of 11) |#####                      | Elapsed Time: 0:00:00 ETA:  0:00:00
100% (11 of 11) |#####                     | Elapsed Time: 0:00:00 Time:  0:00:00

```

Summary for lane Dunsmuir at Beatty:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

15.5934

Link Function: IdentityLink Log Likelihood:

-6260.0382

Number of Samples: 463 AIC:

12553.2632

AICc:

12554.5741

GCV:

316158.2597

Scale:

297051.4065

Pseudo R-Squared:

0.5877

=====

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====				
=====				
s(0)		[1000.]	20	5.1
1.11e-16	***			
s(1)		[1000.]	20	2.0
1.11e-16	***			
s(2)		[1000.]	20	1.3
9.13e-01				
s(3)		[1000.]	20	1.1
7.72e-01				
f(4)		[1000.]	2	0.7

3.83e-01				
f(5)		[1000.]	2	0.7
3.56e-02	*			
f(6)		[1000.]	2	0.7
1.53e-01				
f(7)		[1000.]	2	0.6
1.43e-01				
f(8)		[1000.]	2	0.6
9.83e-01				
f(9)		[1000.]	2	0.6
3.96e-01				
s(10)		[1000.]	20	0.5
9.75e-01				
s(11)		[1000.]	20	0.4
6.14e-05	***			
s(12)		[1000.]	20	0.4
2.03e-09	***			
s(13)		[1000.]	20	0.3
9.12e-01				
s(14)		[1000.]	20	0.2
9.26e-01				
s(15)		[1000.]	20	0.2
8.63e-01				
intercept			1	0.0
1.36e-01				

=====

=====

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

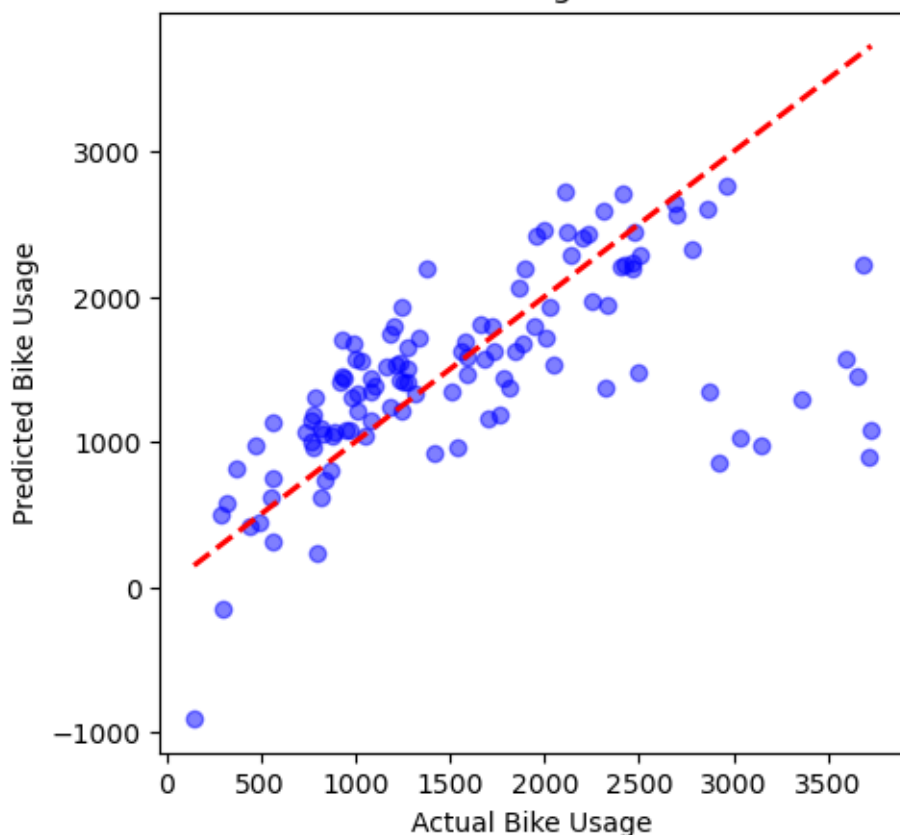
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Dunsmuir at Beatty



0% (0 of 11) | | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Dunsmuir at Beatty: 527109.9577395204

9% (1 of 11)	##	Elapsed Time: 0:00:00	ETA: 0:00:00
18% (2 of 11)	####	Elapsed Time: 0:00:00	ETA: 0:00:00
27% (3 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
36% (4 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
45% (5 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
54% (6 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
63% (7 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
72% (8 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
81% (9 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
90% (10 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
100% (11 of 11)	#####	Elapsed Time: 0:00:00	Time: 0:00:00

Summary for lane East 10th at Clark:

LinearGAM

=====

=====

Distribution:

NormalDist Effective DoF:

22.8937

Link Function:

IdentityLink Log Likelihood:

-9063.1997

Number of Samples:

684 AIC:

18174.1867

AICc:

18175.9916

GCV:

241178.2608

Scale:

226692.8517

Pseudo R-Squared:

0.5362

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====		=====	=====	=====
s(0)		[251.1886]	20	7.1
1.11e-16	***			
s(1)		[251.1886]	20	2.7
1.11e-16	***			
s(2)		[251.1886]	20	1.7
2.48e-01				
s(3)		[251.1886]	20	1.2
9.83e-03	**			
f(4)		[251.1886]	2	0.8
1.98e-01				
f(5)		[251.1886]	2	0.8
2.39e-01				
f(6)		[251.1886]	2	0.8
4.80e-02	*			
f(7)		[251.1886]	2	0.8
3.52e-01				
f(8)		[251.1886]	2	0.8
4.05e-01				
f(9)		[251.1886]	2	0.7
6.72e-01				
s(10)		[251.1886]	20	1.2
5.73e-01				
s(11)		[251.1886]	20	1.2
3.58e-01				
s(12)		[251.1886]	20	1.0
4.89e-02	*			
s(13)		[251.1886]	20	0.9
6.06e-03	**			
s(14)		[251.1886]	20	0.8

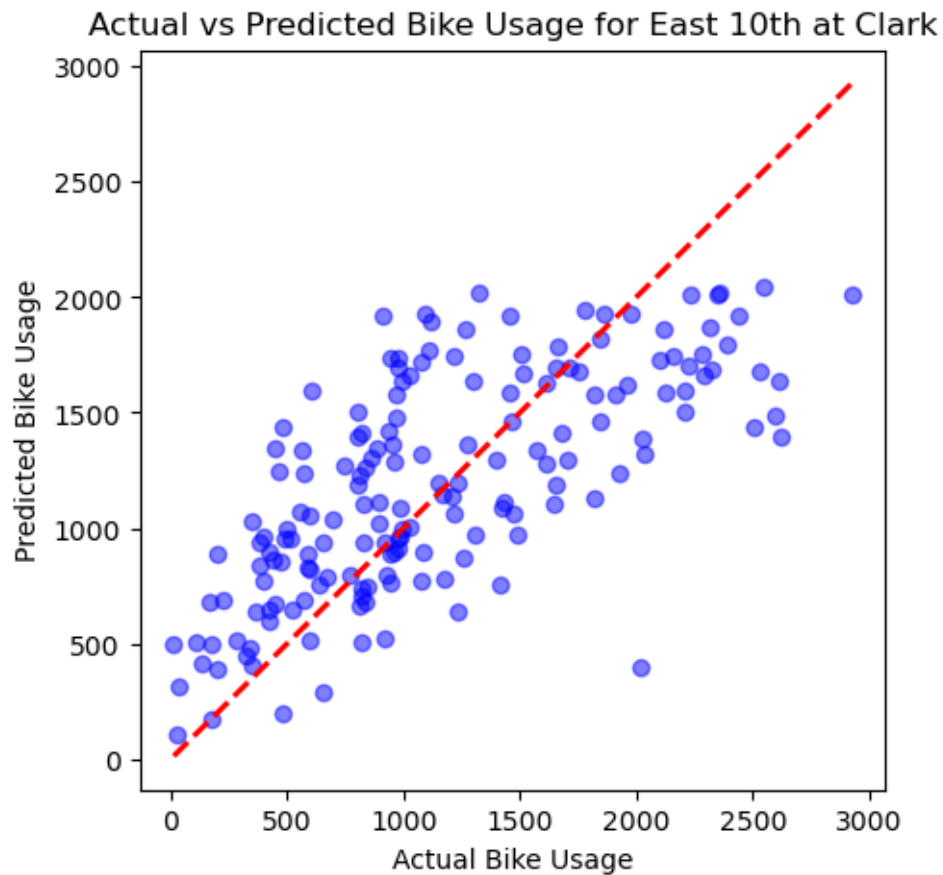
```

1.25e-01
s(15)                [251.1886]          20          0.4
8.24e-01
intercept            1          0.0
3.50e-01
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with
known smoothing parameters, but when smoothing parameters have been estimated, the p-values
are typically lower than they should be, meaning that the tests reject the null too readily.



```

0% (0 of 11) |                               | Elapsed Time: 0:00:00 ETA:  --:--:--
Mean Squared Error for East 10th at Clark: 233144.1929463925

 9% (1 of 11) |##                               | Elapsed Time: 0:00:00 ETA:  0:00:00
18% (2 of 11) |####                              | Elapsed Time: 0:00:00 ETA:  0:00:00
27% (3 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
36% (4 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
45% (5 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
54% (6 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
63% (7 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
72% (8 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
81% (9 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
90% (10 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
100% (11 of 11) |#####                             | Elapsed Time: 0:00:00 Time:  0:00:00

```

Summary for lane Fleming at East 57th:

LinearGAM

```

=====
=====
Distribution:                               NormalDist Effective DoF:
30.3154
Link Function:                             IdentityLink Log Likelihood:
-3593.7329
Number of Samples:                         517 AIC:
7250.0965
                                           AICc:
7254.2722
                                           GCV:
464.9582
                                           Scale:
416.1551
                                           Pseudo R-Squared:
0.8121
=====
=====

```

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
s(0)		[63.0957]	20	9.5
1.11e-16	***			
s(1)		[63.0957]	20	3.6
1.11e-16	***			
s(2)		[63.0957]	20	2.4
2.19e-01				
s(3)		[63.0957]	20	1.9
2.32e-02	*			
f(4)		[63.0957]	2	0.9

4.55e-01				
f(5)		[63.0957]	2	0.9
8.65e-02	.			
f(6)		[63.0957]	2	0.8
2.43e-02	*			
f(7)		[63.0957]	2	0.8
6.75e-01				
f(8)		[63.0957]	2	0.8
4.67e-01				
f(9)		[63.0957]	2	0.8
6.94e-01				
s(10)		[63.0957]	20	2.4
3.09e-01				
s(11)		[63.0957]	20	1.5
2.86e-10	***			
s(12)		[63.0957]	20	1.3
2.62e-13	***			
s(13)		[63.0957]	20	1.1
1.13e-02	*			
s(14)		[63.0957]	20	1.1
2.04e-03	**			
s(15)		[63.0957]	20	0.7
4.51e-02	*			
intercept			1	0.0
1.57e-01				

=====

=====

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

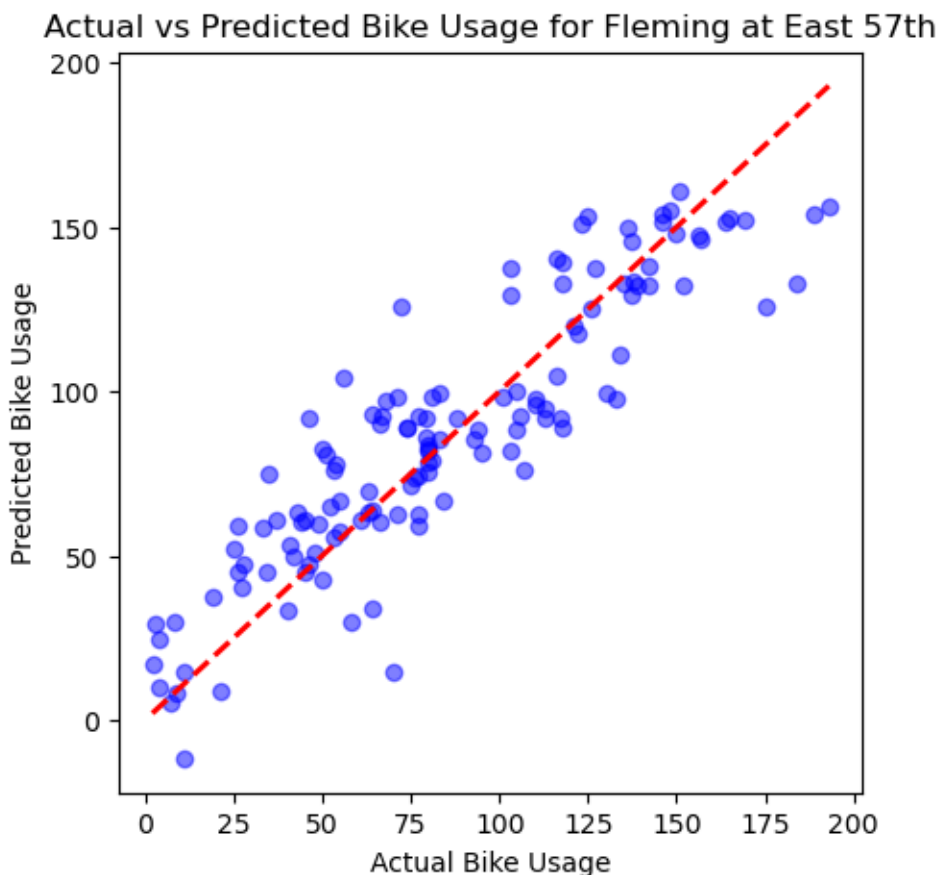
WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Fleming at East 57th: 411.76568013383735

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:01
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Helmcken at Burrard:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

22.1656

Link Function:

IdentityLink Log Likelihood:

-5351.0393

Number of Samples:

520 AIC:

10748.4098

AICc:

10750.6679

GCV:

12720.6548

Scale:

11748.4985

Pseudo R-Squared:

0.8182

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====		=====	=====	=====
s(0)		[251.1886]	20	7.2
1.11e-16	***			
s(1)		[251.1886]	20	2.7
1.11e-16	***			
s(2)		[251.1886]	20	1.4
4.49e-06	***			
s(3)		[251.1886]	20	1.0
9.88e-01				
f(4)		[251.1886]	2	0.8
9.23e-01				
f(5)		[251.1886]	2	0.8
9.52e-03	**			
f(6)		[251.1886]	2	0.8
6.65e-03	**			
f(7)		[251.1886]	2	0.7
4.47e-01				
f(8)		[251.1886]	2	0.8
4.40e-01				
f(9)		[251.1886]	2	0.7
8.18e-01				
s(10)		[251.1886]	20	1.2
4.26e-01				
s(11)		[251.1886]	20	1.2
3.33e-16	***			
s(12)		[251.1886]	20	0.9
1.11e-16	***			
s(13)		[251.1886]	20	0.6
4.18e-01				
s(14)		[251.1886]	20	0.6

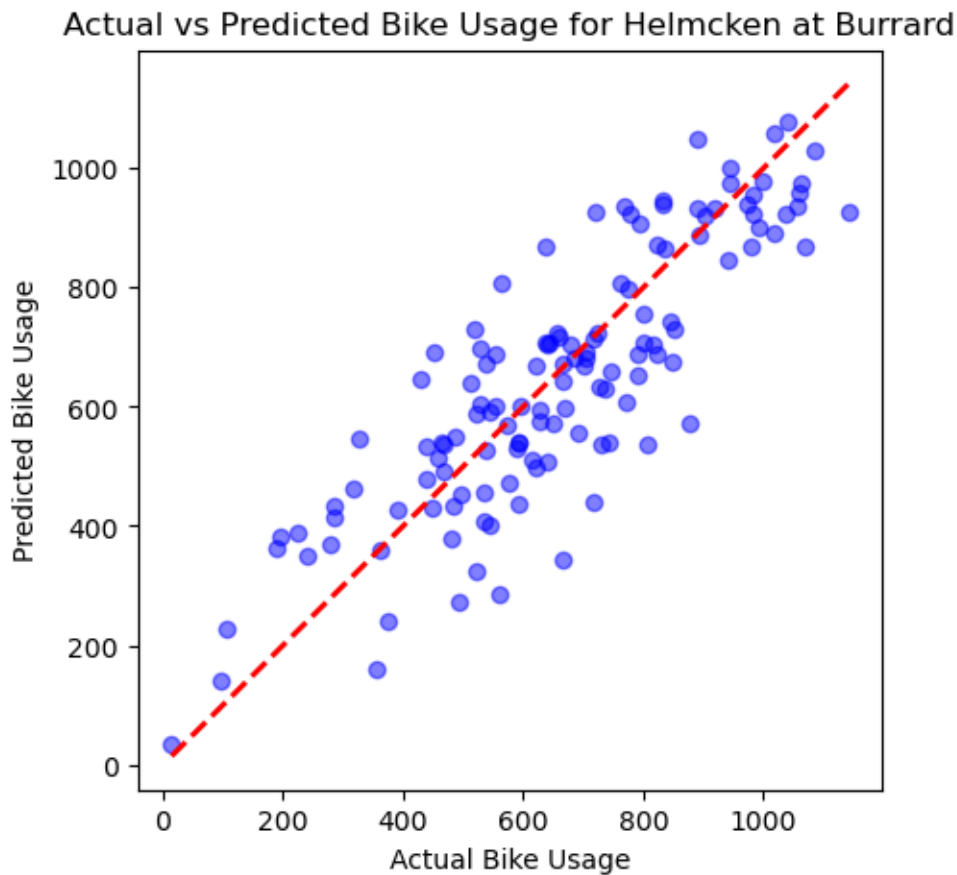
```

1.35e-01
s(15)                [251.1886]          20          0.4
1.86e-01
intercept            1          0.0
4.02e-01
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem
which can cause p-values to appear significant when they are not.

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are typically lower than they should be, meaning that the tests reject the null too readily.



```

0% (0 of 11) |                               | Elapsed Time: 0:00:00 ETA:  --:--:--
Mean Squared Error for Helmcken at Burrard: 15463.1295696251

 9% (1 of 11) |##                               | Elapsed Time: 0:00:00 ETA:  0:00:00
18% (2 of 11) |####                              | Elapsed Time: 0:00:00 ETA:  0:00:00
27% (3 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
36% (4 of 11) |#####                            | Elapsed Time: 0:00:00 ETA:  0:00:00
45% (5 of 11) |#####                           | Elapsed Time: 0:00:00 ETA:  0:00:00
54% (6 of 11) |#####                          | Elapsed Time: 0:00:00 ETA:  0:00:00
63% (7 of 11) |#####                         | Elapsed Time: 0:00:00 ETA:  0:00:00
72% (8 of 11) |#####                        | Elapsed Time: 0:00:00 ETA:  0:00:00
81% (9 of 11) |#####                       | Elapsed Time: 0:00:00 ETA:  0:00:00
90% (10 of 11) |#####                      | Elapsed Time: 0:00:00 ETA:  0:00:00
100% (11 of 11) |#####                     | Elapsed Time: 0:00:00 Time:  0:00:00

```

```

Summary for lane Lions Gate Bridge at Spirit Trail - Eastside:
LinearGAM

```

```

=====
=====
Distribution:                               NormalDist Effective DoF:
32.7391
Link Function:                             IdentityLink Log Likelihood:
-8941.4194
Number of Samples:                         766 AIC:
17950.3168

                                           AICc:
17953.5224

                                           GCV:
50698.153

                                           Scale:
46813.2948

                                           Pseudo R-Squared:
0.757

```

```

=====
=====

```

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====				
=====				
s(0)		[63.0957]	20	9.2
1.11e-16	***			
s(1)		[63.0957]	20	3.8
1.11e-16	***			
s(2)		[63.0957]	20	3.0
9.33e-01				
s(3)		[63.0957]	20	1.7
2.68e-04	***			
f(4)		[63.0957]	2	0.9

4.35e-01			
f(5)	[63.0957]	2	0.9
6.84e-01			
f(6)	[63.0957]	2	0.9
9.63e-01			
f(7)	[63.0957]	2	0.9
8.91e-01			
f(8)	[63.0957]	2	0.9
8.70e-01			
f(9)	[63.0957]	2	0.8
5.63e-01			
s(10)	[63.0957]	20	2.4
7.97e-01			
s(11)	[63.0957]	20	1.8
1.03e-09	***		
s(12)	[63.0957]	20	1.5
8.86e-02	.		
s(13)	[63.0957]	20	1.9
6.84e-01			
s(14)	[63.0957]	20	1.3
6.19e-01			
s(15)	[63.0957]	20	0.9
5.62e-01			
intercept		1	0.0
2.79e-01			

=====

=====

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

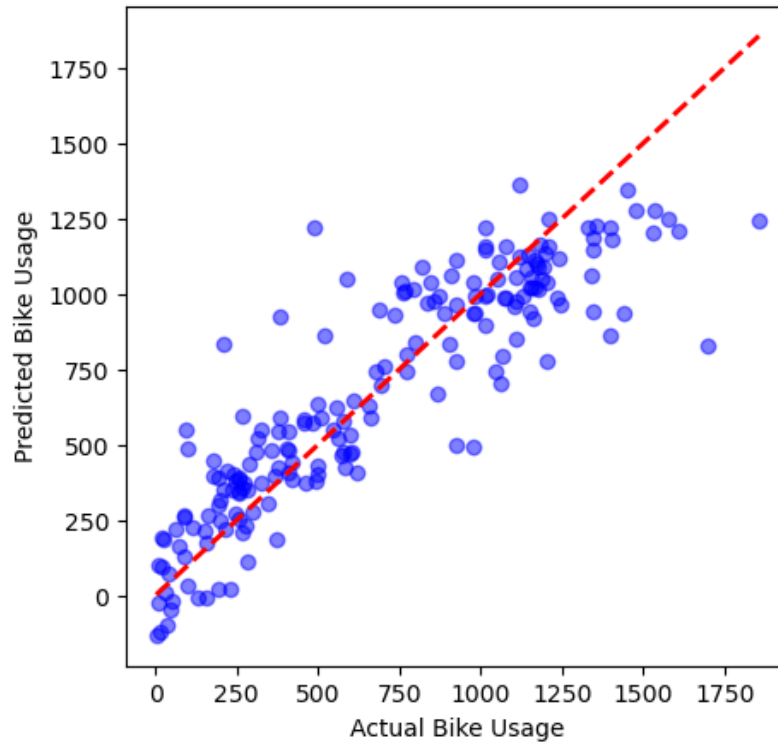
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Lions Gate Bridge at Spirit Trail - Eastside



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Lions Gate Bridge at Spirit Trail - Eastside:
42823.89807446513

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Lions Gate Bridge at Spirit Trail - Westside:
LinearGAM

=====

Distribution: NormalDist Effective DoF:

47.3045

Link Function: IdentityLink Log Likelihood:

-12265.2732

Number of Samples:

1052 AIC:

24627.1553

AICc:

24631.9057

GCV:

50216.064

Scale:

46168.6257

Pseudo R-Squared:

0.7639

=====

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====		=====	=====	=====
=====				
s(0)		[15.8489]	20	12.1
1.11e-16	***			
s(1)		[15.8489]	20	5.3
1.11e-16	***			
s(2)		[15.8489]	20	3.8
7.00e-01				
s(3)		[15.8489]	20	2.4
4.29e-06	***			
f(4)		[15.8489]	2	0.9
6.12e-01				
f(5)		[15.8489]	2	0.9
5.06e-01				
f(6)		[15.8489]	2	0.9
6.77e-01				
f(7)		[15.8489]	2	0.9
8.65e-01				
f(8)		[15.8489]	2	0.9
9.77e-01				
f(9)		[15.8489]	2	0.9
2.50e-01				
s(10)		[15.8489]	20	3.4
8.43e-01				
s(11)		[15.8489]	20	3.5
4.80e-10	***			
s(12)		[15.8489]	20	3.3
2.36e-03	**			
s(13)		[15.8489]	20	3.1
9.33e-01				
s(14)		[15.8489]	20	2.9
8.43e-01				
s(15)		[15.8489]	20	1.9


```

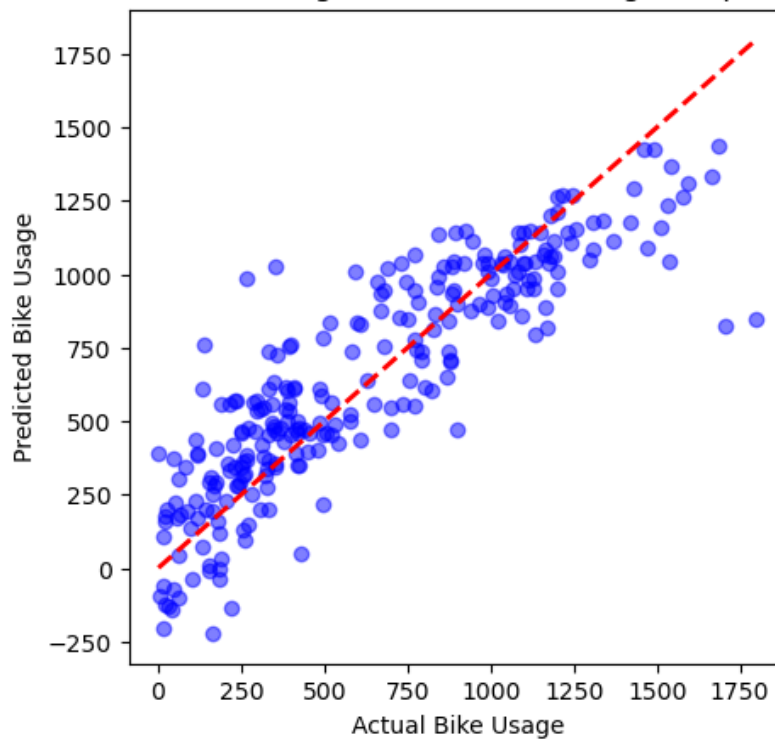
8.54e-01
intercept                                1          0.0
5.03e-01
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem
which can cause p-values to appear significant when they are not.

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known smoothing parameters, but when smoothing parameters have been estimated, the p-values
are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Lions Gate Bridge at Spirit Trail - Westside



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Lions Gate Bridge at Spirit Trail - Westside:
44841.89382542534

9% (1 of 11) |## Elapsed Time: 0:00:00 ETA: 0:00:00

```

18% (2 of 11) |####| Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) |#####| Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) |#####| Elapsed Time: 0:00:00 Time: 0:00:00

```

Summary for lane Point Grey at Alma:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

31.7052

Link Function: IdentityLink Log Likelihood:

-8926.2095

Number of Samples: 652 AIC:

17917.8294

AICc:

17921.3951

GCV:

385667.1028

Scale:

352063.1196

Pseudo R-Squared:

0.7378

=====

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====				
=====				
s(0)		[63.0957]	20	9.5
1.11e-16	***			
s(1)		[63.0957]	20	3.7
1.11e-16	***			
s(2)		[63.0957]	20	2.6
9.88e-01				
s(3)		[63.0957]	20	1.6
1.18e-01				
f(4)		[63.0957]	2	0.8
6.99e-01				
f(5)		[63.0957]	2	0.9
3.28e-01				
f(6)		[63.0957]	2	0.8

4.81e-01			
f(7)	[63.0957]	2	0.8
7.84e-01			
f(8)	[63.0957]	2	0.8
4.80e-01			
f(9)	[63.0957]	2	0.8
3.56e-01			
s(10)	[63.0957]	20	1.9
8.82e-01			
s(11)	[63.0957]	20	2.0
5.34e-07	***		
s(12)	[63.0957]	20	1.7
2.27e-03	**		
s(13)	[63.0957]	20	1.5
7.08e-01			
s(14)	[63.0957]	20	1.4
8.42e-01			
s(15)	[63.0957]	20	0.9
9.75e-01			
intercept		1	0.0
1.53e-02	*		

```
=====
=====
```

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

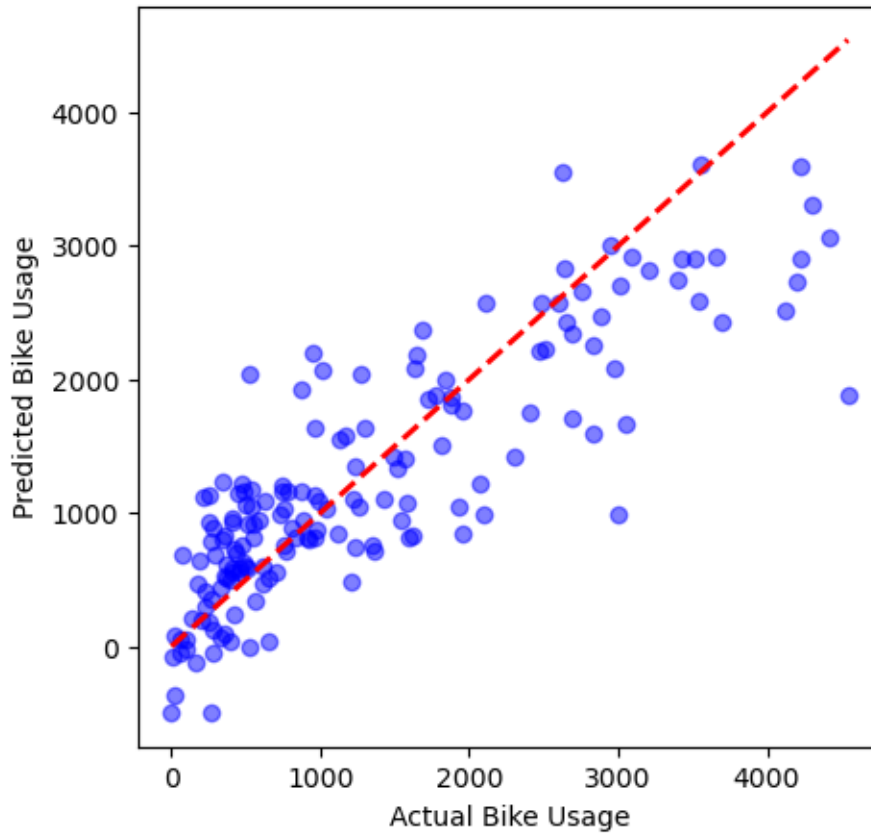
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Point Grey at Alma



0% (0 of 11) | | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Point Grey at Alma: 382277.382368473

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Point Grey at Stephens:

LinearGAM

=====

=====

Distribution:

NormalDist Effective DoF:

31.6203

Link Function:

IdentityLink Log Likelihood:

-8995.0569

Number of Samples:

705 AIC:

18055.3544

AICc:

18058.6215

GCV:

150816.0151

Scale:

138691.0435

Pseudo R-Squared:

0.7026

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====		=====	=====	=====
s(0)		[63.0957]	20	9.5
1.11e-16	***			
s(1)		[63.0957]	20	3.8
1.11e-16	***			
s(2)		[63.0957]	20	2.3
9.75e-01				
s(3)		[63.0957]	20	2.1
1.84e-01				
f(4)		[63.0957]	2	0.8
6.23e-01				
f(5)		[63.0957]	2	0.9
7.62e-02	.			
f(6)		[63.0957]	2	0.9
8.39e-01				
f(7)		[63.0957]	2	0.8
7.95e-01				
f(8)		[63.0957]	2	0.9
4.09e-01				
f(9)		[63.0957]	2	0.8
3.18e-01				
s(10)		[63.0957]	20	1.8
9.14e-01				
s(11)		[63.0957]	20	1.8
1.55e-06	***			
s(12)		[63.0957]	20	1.8
1.40e-02	*			
s(13)		[63.0957]	20	1.3
9.62e-01				
s(14)		[63.0957]	20	1.3

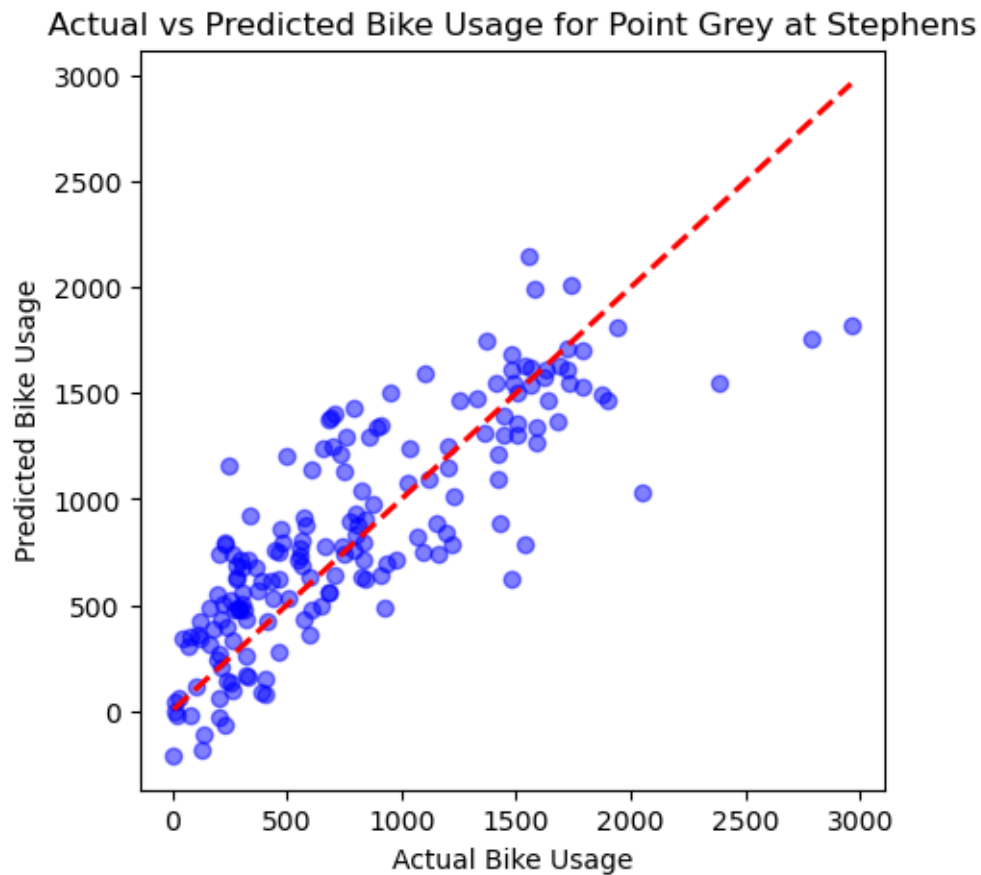
```

5.51e-01
s(15)                [63.0957]                20                0.8
9.19e-01
intercept                1                0.0
1.57e-01
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with
known smoothing parameters, but when smoothing parameters have been estimated, the p-values
are typically lower than they should be, meaning that the tests reject the null too readily.



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Point Grey at Stephens: 116074.8285693996

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Point Grey at Volunteer Park:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

28.8965

Link Function: IdentityLink Log Likelihood:

-6129.2815

Number of Samples: 426 AIC:

12318.3562

AICc:

12323.0319

GCV:

804814.5351

Scale:

707183.8448

Pseudo R-Squared:

0.7048

=====

=====

Feature Function	Lambda	Rank	EDoF
------------------	--------	------	------

P > x	Sig. Code		
-------	-----------	--	--

=====

=====

s(0)	[63.0957]	20	9.1
1.11e-16 ***			
s(1)	[63.0957]	20	3.7
1.11e-16 ***			
s(2)	[63.0957]	20	2.5
9.80e-01			
s(3)	[63.0957]	20	2.2
1.80e-01			
f(4)	[63.0957]	2	0.8

1.02e-01			
f(5)	[63.0957]	2	0.8
3.23e-01			
f(6)	[63.0957]	2	0.8
7.41e-01			
f(7)	[63.0957]	2	0.8
5.87e-01			
f(8)	[63.0957]	2	0.8
9.93e-01			
f(9)	[63.0957]	2	0.8
1.92e-01			
s(10)	[63.0957]	20	1.3
9.02e-01			
s(11)	[63.0957]	20	1.3
2.49e-03	**		
s(12)	[63.0957]	20	1.2
1.93e-03	**		
s(13)	[63.0957]	20	1.3
9.22e-01			
s(14)	[63.0957]	20	0.9
8.74e-01			
s(15)	[63.0957]	20	0.5
5.93e-01			
intercept		1	0.0
3.76e-01			

=====

=====

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

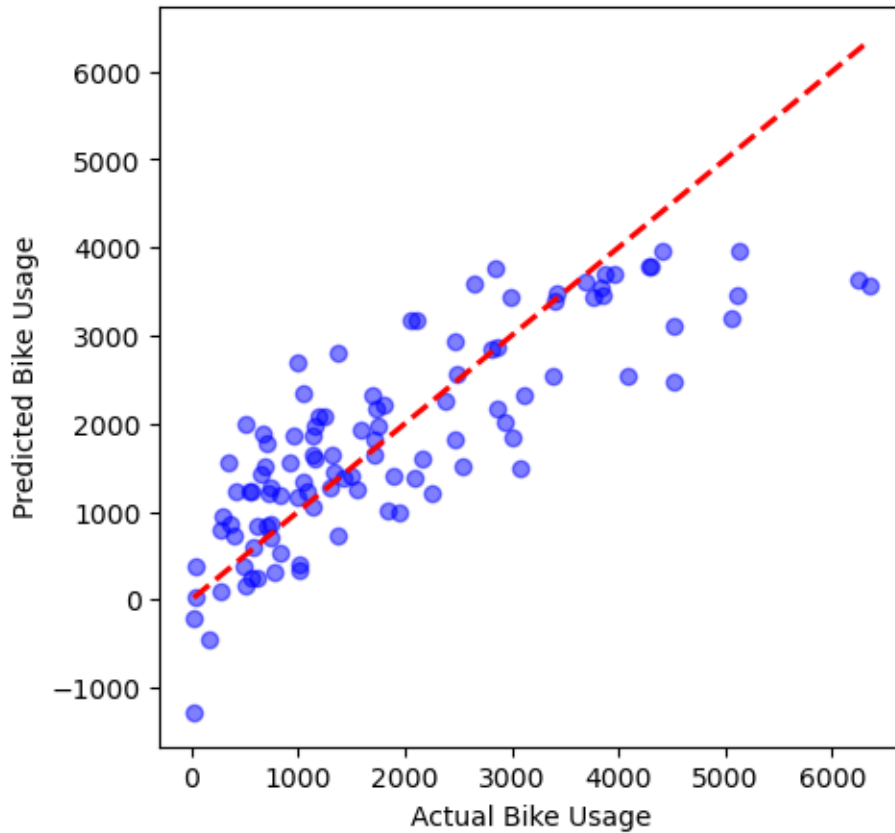
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Point Grey at Volunteer Park



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Point Grey at Volunteer Park: 710180.2043148

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Richards at Dunsmuir:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

20.0228

Link Function:

IdentityLink Log Likelihood:

-2663.5874

Number of Samples:

310 AIC:

5369.2204

AICc:

5372.4358

GCV:

2430.4902

Scale:

2149.6525

Pseudo R-Squared:

0.7454

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====		=====	=====	=====
=====				
s(0)		[251.1886]	20	6.8
1.11e-16	***			
s(1)		[251.1886]	20	2.6
1.11e-16	***			
s(2)		[251.1886]	20	1.7
3.80e-02	*			
s(3)		[251.1886]	20	1.7
1.62e-03	**			
f(4)		[251.1886]	2	0.7
7.82e-01				
f(5)		[251.1886]	2	0.7
6.36e-03	**			
f(6)		[251.1886]	2	0.6
3.22e-02	*			
f(7)		[251.1886]	2	0.7
4.16e-01				
f(8)		[251.1886]	2	0.7
5.16e-01				
f(9)		[251.1886]	2	0.6
1.16e-01				
s(10)		[251.1886]	20	0.6
1.45e-02	*			
s(11)		[251.1886]	20	0.6
1.17e-05	***			
s(12)		[251.1886]	20	0.6
4.67e-10	***			
s(13)		[251.1886]	20	0.6
2.24e-01				
s(14)		[251.1886]	20	0.5

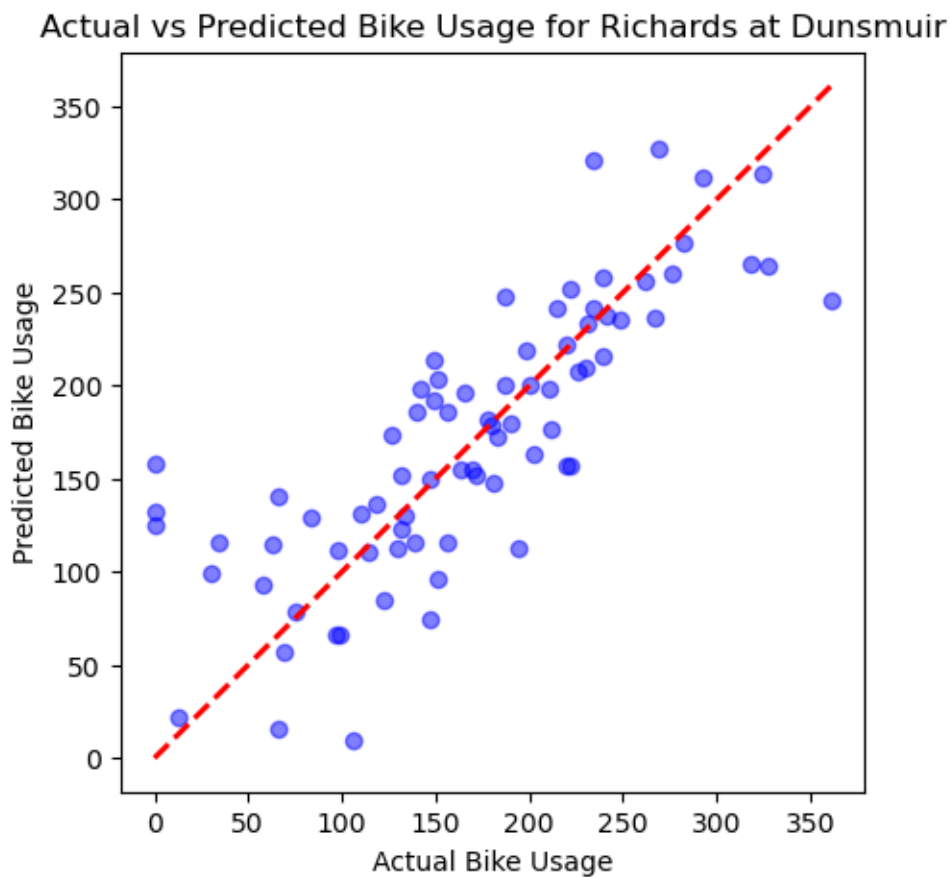
```

3.68e-01
s(15)                [251.1886]          20          0.2
8.14e-01
intercept            1          0.0
9.30e-04      ***
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem
which can cause p-values to appear significant when they are not.

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known smoothing parameters, but when smoothing parameters have been estimated, the p-values
are typically lower than they should be, meaning that the tests reject the null too readily.



```

0% (0 of 11) |                               | Elapsed Time: 0:00:00 ETA:  --:--:--
Mean Squared Error for Richards at Dunsmuir: 2400.0923363636707

 9% (1 of 11) |##                               | Elapsed Time: 0:00:00 ETA:  0:00:00
18% (2 of 11) |####                              | Elapsed Time: 0:00:00 ETA:  0:00:00
27% (3 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
36% (4 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
45% (5 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
54% (6 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
63% (7 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
72% (8 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
81% (9 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
90% (10 of 11) |#####                             | Elapsed Time: 0:00:00 ETA:  0:00:00
100% (11 of 11) |#####                             | Elapsed Time: 0:00:00 Time:  0:00:00

```

```

Summary for lane Seawall at Creekside Community Centre:
LinearGAM

```

```

=====
=====
Distribution:                               NormalDist Effective DoF:
47.3214
Link Function:                             IdentityLink Log Likelihood:
-15010.4901
Number of Samples:                         1052 AIC:
30117.623
                                           AICc:
30122.3768
                                           GCV:
682592.5897
                                           Scale:
627555.7265
                                           Pseudo R-Squared:
0.7463

```

```

=====
=====

```

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====				
=====				
s(0)		[15.8489]	20	12.3
1.11e-16	***			
s(1)		[15.8489]	20	5.3
1.11e-16	***			
s(2)		[15.8489]	20	4.0
9.10e-01				
s(3)		[15.8489]	20	2.4
2.25e-04	***			
f(4)		[15.8489]	2	0.9

5.01e-01			
f(5)	[15.8489]	2	0.9
3.15e-01			
f(6)	[15.8489]	2	0.9
7.79e-01			
f(7)	[15.8489]	2	1.0
7.10e-01			
f(8)	[15.8489]	2	0.9
5.95e-01			
f(9)	[15.8489]	2	0.9
2.08e-01			
s(10)	[15.8489]	20	3.1
3.79e-01			
s(11)	[15.8489]	20	3.3
2.16e-03	**		
s(12)	[15.8489]	20	3.6
2.02e-04	***		
s(13)	[15.8489]	20	3.1
7.90e-01			
s(14)	[15.8489]	20	2.8
6.68e-01			
s(15)	[15.8489]	20	1.9
8.90e-01			
intercept		1	0.0
9.76e-01			

=====

=====

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

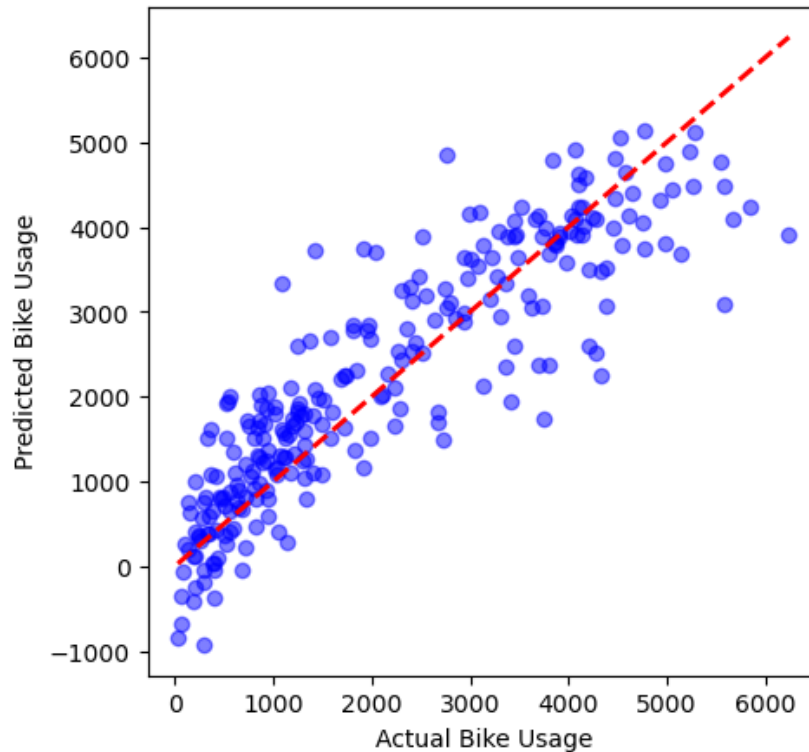
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Seawall at Creekside Community Centre



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Seawall at Creekside Community Centre: 550774.4519403967

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Seawall at David Lam Park:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

47.7284

Link Function: IdentityLink Log Likelihood:

-15428.4941

Number of Samples:

1055 AIC:

30954.445

AICc:

30959.266

GCV:

974609.9454

Scale:

895579.3889

Pseudo R-Squared:

0.7605

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
s(0)		[15.8489]	20	11.9
1.11e-16	***			
s(1)		[15.8489]	20	5.3
1.11e-16	***			
s(2)		[15.8489]	20	4.1
8.42e-01				
s(3)		[15.8489]	20	2.3
3.59e-02	*			
f(4)		[15.8489]	2	0.9
1.37e-01				
f(5)		[15.8489]	2	0.9
2.46e-01				
f(6)		[15.8489]	2	0.9
6.47e-01				
f(7)		[15.8489]	2	0.9
4.06e-01				
f(8)		[15.8489]	2	1.0
2.20e-01				
f(9)		[15.8489]	2	0.9
1.57e-01				
s(10)		[15.8489]	20	4.2
2.27e-02	*			
s(11)		[15.8489]	20	2.9
4.78e-04	***			
s(12)		[15.8489]	20	3.0
6.26e-04	***			
s(13)		[15.8489]	20	3.6
9.16e-01				
s(14)		[15.8489]	20	2.7
6.68e-01				
s(15)		[15.8489]	20	2.0

```

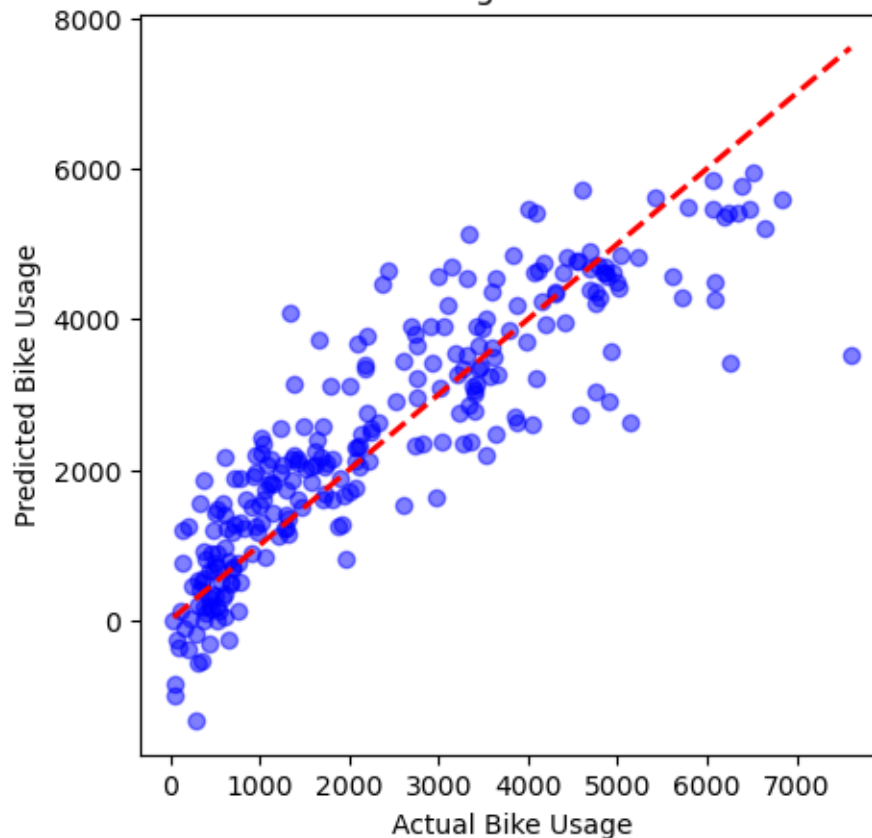
5.33e-01
intercept                1          0.0
8.72e-01
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with known smoothing parameters, but when smoothing parameters have been estimated, the p-values are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Seawall at David Lam Park



0% (0 of 11) |

| Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Seawall at David Lam Park: 746465.8028795036

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Seawall at HMCS Discovery:

LinearGAM

```
=====
=====
Distribution:                      NormalDist Effective DoF:
33.4866
Link Function:                    IdentityLink Log Likelihood:
-12676.0072
Number of Samples:                888 AIC:
25420.9875
                                   AICc:
25423.8586
                                   GCV:
677308.2125
                                   Scale:
631493.8851
                                   Pseudo R-Squared:
0.7704
=====
=====
```

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
s(0)		[63.0957]	20	9.8
1.11e-16	***			
s(1)		[63.0957]	20	3.8
1.11e-16	***			
s(2)		[63.0957]	20	2.4
9.86e-01				
s(3)		[63.0957]	20	1.8
8.73e-04	***			
f(4)		[63.0957]	2	0.9
5.21e-01				
f(5)		[63.0957]	2	0.9

1.34e-01			
f(6)	[63.0957]	2	0.9
5.47e-01			
f(7)	[63.0957]	2	0.9
6.56e-01			
f(8)	[63.0957]	2	0.9
7.62e-01			
f(9)	[63.0957]	2	0.8
1.75e-01			
s(10)	[63.0957]	20	2.2
8.60e-01			
s(11)	[63.0957]	20	2.2
5.54e-09	***		
s(12)	[63.0957]	20	1.7
5.82e-06	***		
s(13)	[63.0957]	20	1.8
8.55e-01			
s(14)	[63.0957]	20	1.5
7.80e-02	.		
s(15)	[63.0957]	20	0.9
1.47e-01			
intercept		1	0.0
7.42e-01			

=====
 Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

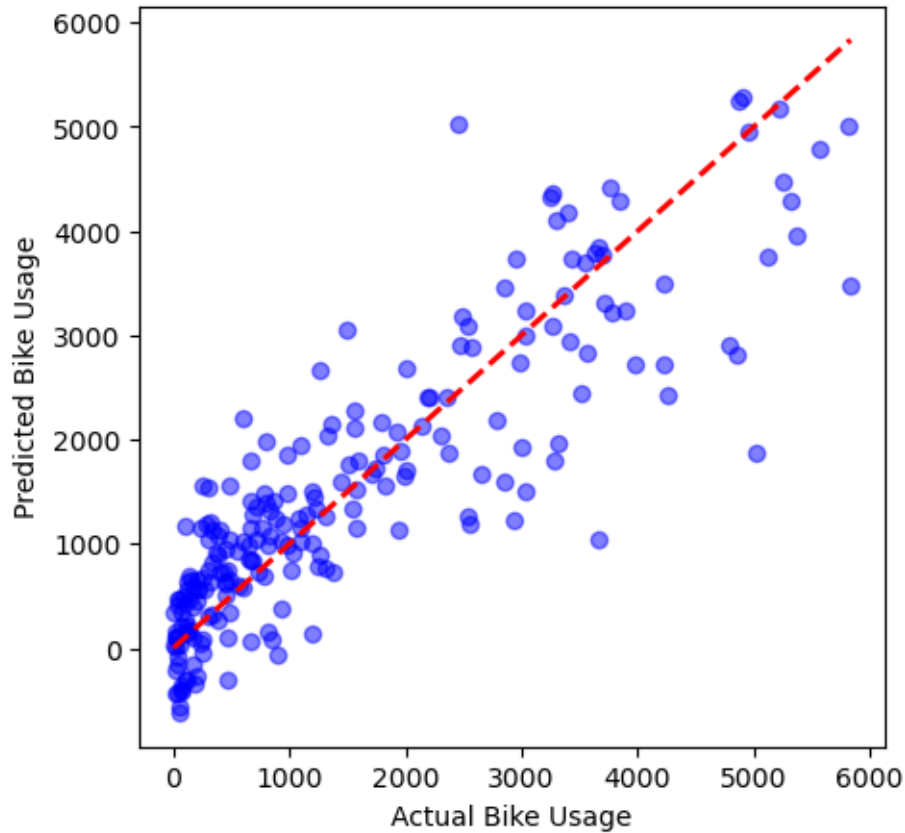
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Seawall at HMCS Discovery



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Seawall at HMCS Discovery: 546480.8785508823

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Seawall at Harbour Green Park:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

47.7284

Link Function:

IdentityLink Log Likelihood:

-13741.5876

Number of Samples:

1055 AIC:

27580.632

AICc:

27585.4529

GCV:

196973.8808

Scale:

181001.3828

Pseudo R-Squared:

0.8324

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====		=====	=====	=====
s(0)		[15.8489]	20	11.9
1.11e-16	***			
s(1)		[15.8489]	20	5.3
1.11e-16	***			
s(2)		[15.8489]	20	4.1
9.63e-01				
s(3)		[15.8489]	20	2.3
1.35e-06	***			
f(4)		[15.8489]	2	0.9
5.54e-01				
f(5)		[15.8489]	2	0.9
2.14e-01				
f(6)		[15.8489]	2	0.9
5.68e-01				
f(7)		[15.8489]	2	0.9
6.56e-01				
f(8)		[15.8489]	2	1.0
3.74e-01				
f(9)		[15.8489]	2	0.9
2.09e-01				
s(10)		[15.8489]	20	4.2
9.34e-04	***			
s(11)		[15.8489]	20	2.9
4.47e-05	***			
s(12)		[15.8489]	20	3.0
5.56e-03	**			
s(13)		[15.8489]	20	3.6
7.59e-01				
s(14)		[15.8489]	20	2.7

```

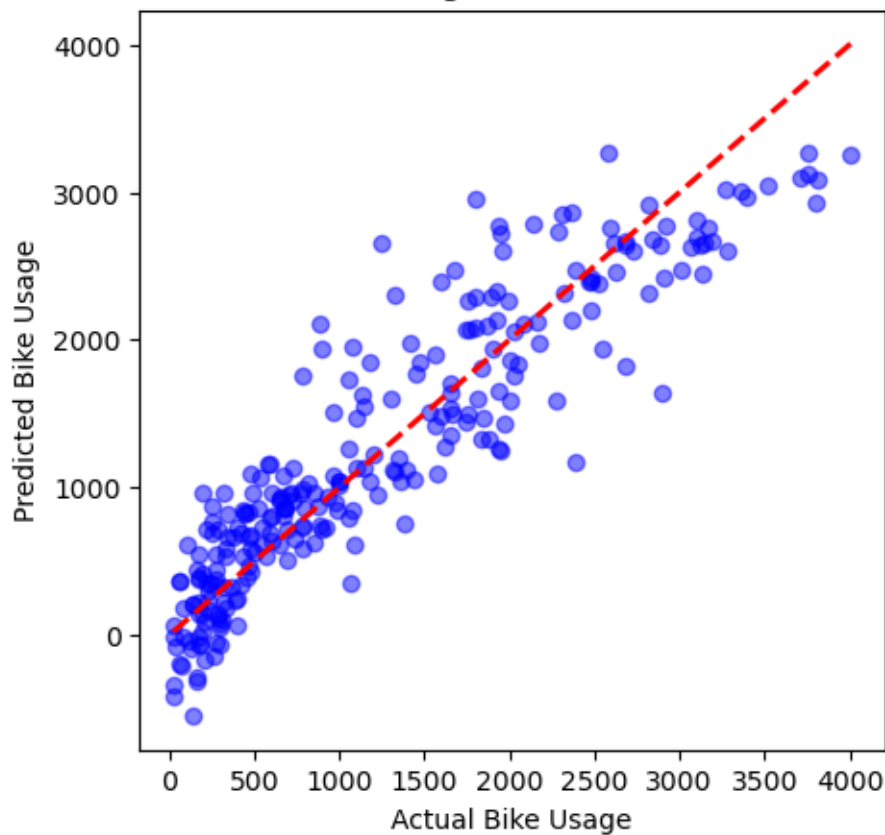
8.73e-01
s(15)                [15.8489]          20          2.0
2.34e-01
intercept            1          0.0
4.42e-01
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with
known smoothing parameters, but when smoothing parameters have been estimated, the p-values
are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Seawall at Harbour Green Park



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Seawall at Harbour Green Park: 166010.83282012853

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Seawall at Lumbermen's Arch:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

22.667

Link Function: IdentityLink Log Likelihood:

-9560.5415

Number of Samples: 667 AIC:

19168.417

AICc:

19170.2348

GCV:

713275.7418

Scale:

669780.9045

Pseudo R-Squared:

0.787

=====

=====

Feature Function	Lambda	Rank	EDoF
------------------	--------	------	------

P > x	Sig. Code		
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=====

=====

s(0)	[251.1886]	20	7.0
1.11e-16 ***			
s(1)	[251.1886]	20	2.6
1.11e-16 ***			
s(2)	[251.1886]	20	1.7
9.90e-01			
s(3)	[251.1886]	20	1.2
1.69e-04 ***			
f(4)	[251.1886]	2	0.8

7.79e-01				
f(5)	[251.1886]	2		0.9
5.83e-01				
f(6)	[251.1886]	2		0.8
3.91e-01				
f(7)	[251.1886]	2		0.8
5.19e-01				
f(8)	[251.1886]	2		0.8
4.81e-01				
f(9)	[251.1886]	2		0.7
5.27e-01				
s(10)	[251.1886]	20		1.2
3.19e-01				
s(11)	[251.1886]	20		1.0
6.14e-12	***			
s(12)	[251.1886]	20		1.0
1.91e-06	***			
s(13)	[251.1886]	20		0.8
3.16e-01				
s(14)	[251.1886]	20		0.9
1.24e-02	*			
s(15)	[251.1886]	20		0.4
5.66e-03	**			
intercept		1		0.0
9.88e-01				

=====

=====

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

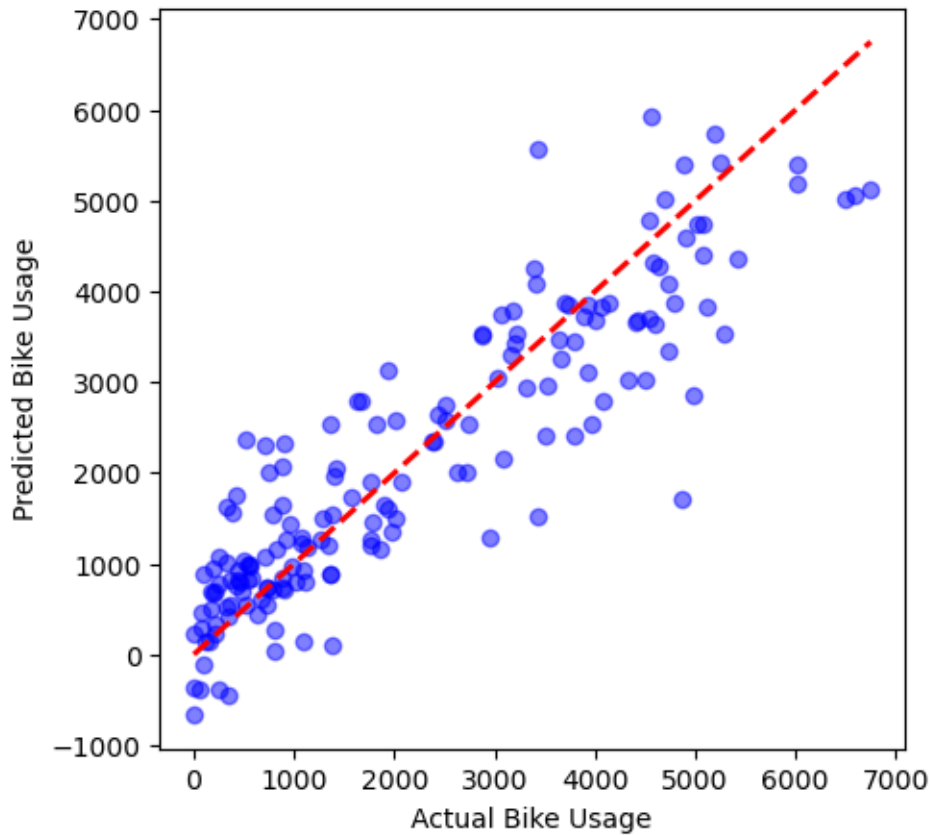
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Seawall at Lumbermen's Arch



0% (0 of 11)	Elapsed Time: 0:00:00 ETA: --:--:--
9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00

Mean Squared Error for Seawall at Lumbermen's Arch: 626890.6850404472

27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Seawall at Second Beach Pool:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

29.9774

Link Function:

IdentityLink Log Likelihood:

-6824.8733

Number of Samples:

467 AIC:

13711.7013

AICc:

13716.2554

GCV:

1001828.5767

Scale:

886778.6805

Pseudo R-Squared:

0.7278

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====		=====	=====	=====
=====				
s(0)		[63.0957]	20	9.4
1.11e-16	***			
s(1)		[63.0957]	20	3.7
1.11e-16	***			
s(2)		[63.0957]	20	3.2
1.00e+00				
s(3)		[63.0957]	20	2.0
2.06e-01				
f(4)		[63.0957]	2	0.8
5.01e-01				
f(5)		[63.0957]	2	0.8
4.29e-01				
f(6)		[63.0957]	2	0.8
2.68e-01				
f(7)		[63.0957]	2	0.8
6.59e-01				
f(8)		[63.0957]	2	0.8
5.79e-01				
f(9)		[63.0957]	2	0.8
2.83e-01				
s(10)		[63.0957]	20	1.4
1.43e-01				
s(11)		[63.0957]	20	1.3
5.76e-04	***			
s(12)		[63.0957]	20	1.1
1.86e-03	**			
s(13)		[63.0957]	20	1.1
2.47e-01				
s(14)		[63.0957]	20	1.2

```

9.50e-03    **
s(15)              [63.0957]          20          0.7
2.03e-03    **
intercept              1          0.0
7.90e-01
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

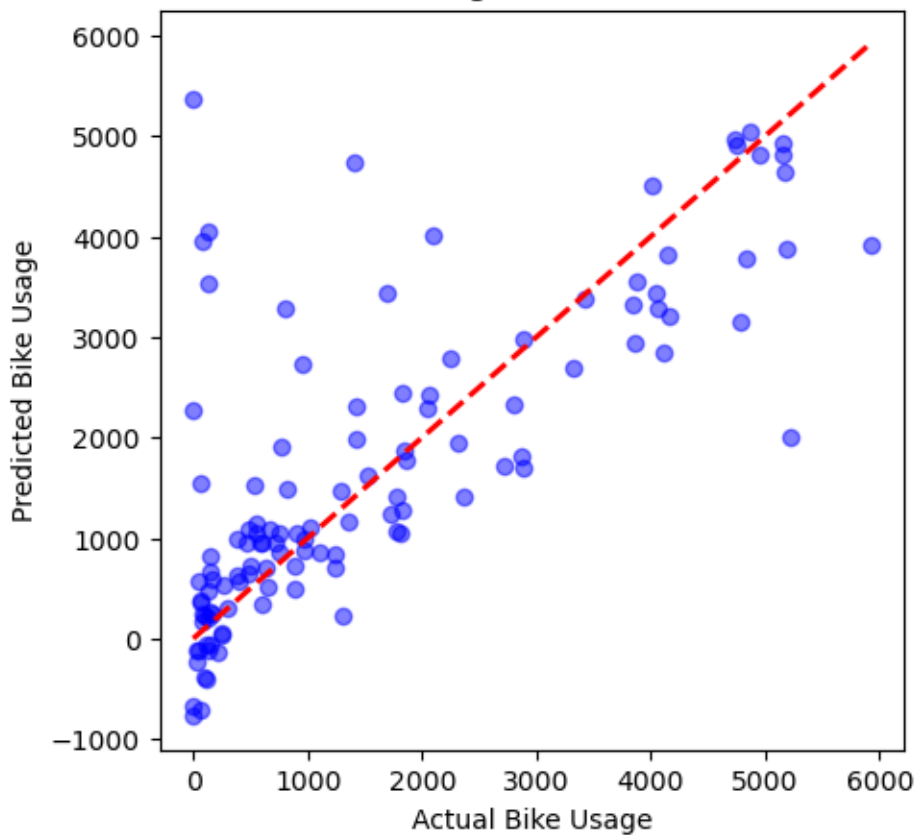
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Seawall at Second Beach Pool



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Seawall at Second Beach Pool: 1292979.5975843756

9% (1 of 11)	##	Elapsed Time: 0:00:00	ETA: 0:00:00
18% (2 of 11)	####	Elapsed Time: 0:00:00	ETA: 0:00:00
27% (3 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
36% (4 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
45% (5 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
54% (6 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
63% (7 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
72% (8 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
81% (9 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
90% (10 of 11)	#####	Elapsed Time: 0:00:00	ETA: 0:00:00
100% (11 of 11)	#####	Elapsed Time: 0:00:01	Time: 0:00:01

Summary for lane Stephens at Point Grey:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

47.5045

Link Function: IdentityLink Log Likelihood:

-12027.1016

Number of Samples: 1054 AIC:

24151.2122

AICc:

24155.9931

GCV:

39190.8267

Scale:

36024.7194

Pseudo R-Squared:

0.7491

=====

=====

Feature Function	Lambda	Rank	EDoF
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P > x	Sig. Code		
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=====

=====

s(0)	[15.8489]	20	12.1
1.11e-16	***		
s(1)	[15.8489]	20	5.3
1.11e-16	***		
s(2)	[15.8489]	20	3.4
9.44e-01			
s(3)	[15.8489]	20	3.0
2.40e-01			
f(4)	[15.8489]	2	0.9

5.91e-01			
f(5)	[15.8489]	2	0.9
3.73e-01			
f(6)	[15.8489]	2	0.9
8.80e-01			
f(7)	[15.8489]	2	1.0
9.78e-01			
f(8)	[15.8489]	2	0.9
9.02e-01			
f(9)	[15.8489]	2	0.9
3.56e-01			
s(10)	[15.8489]	20	4.1
7.64e-01			
s(11)	[15.8489]	20	3.5
3.77e-02	*		
s(12)	[15.8489]	20	2.7
4.31e-01			
s(13)	[15.8489]	20	3.3
6.08e-01			
s(14)	[15.8489]	20	2.6
5.39e-01			
s(15)	[15.8489]	20	1.9
2.12e-01			
intercept		1	0.0
7.76e-02	.		

```
=====
=====
```

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem

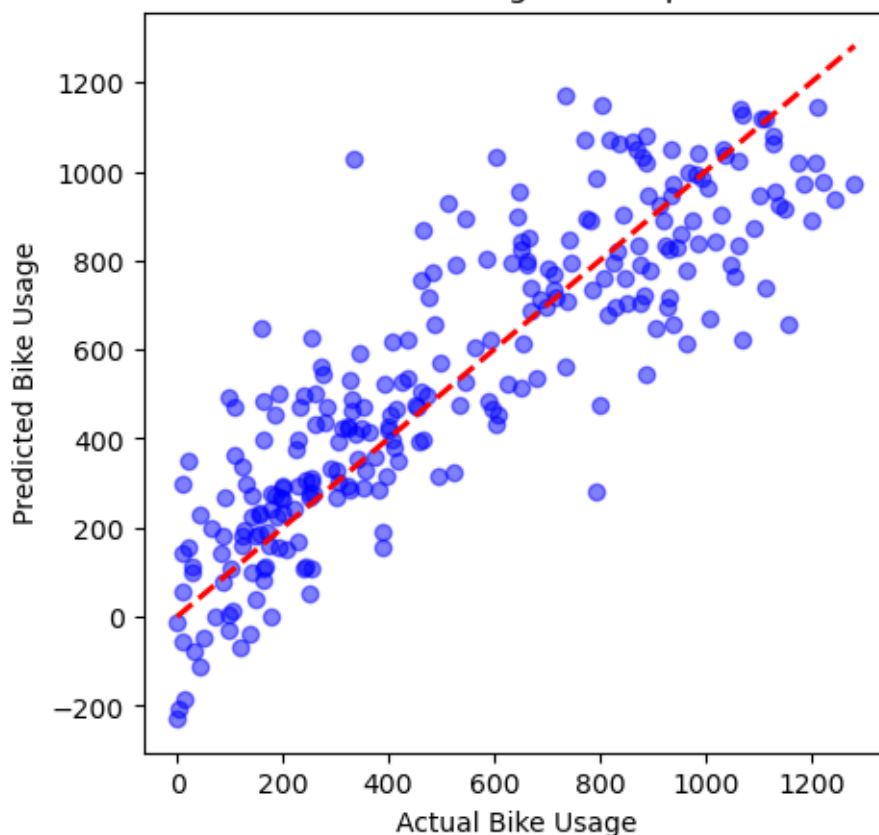
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with

known smoothing parameters, but when smoothing parameters have been estimated, the p-values

are typically lower than they should be, meaning that the tests reject the null too readily.

Actual vs Predicted Bike Usage for Stephens at Point Grey



0% (0 of 11) | Elapsed Time: 0:00:00 ETA: --:--:--

Mean Squared Error for Stephens at Point Grey: 32414.501885912014

9% (1 of 11) ##	Elapsed Time: 0:00:00 ETA: 0:00:00
18% (2 of 11) ####	Elapsed Time: 0:00:00 ETA: 0:00:00
27% (3 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
36% (4 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
45% (5 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
54% (6 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
63% (7 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
72% (8 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
81% (9 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
90% (10 of 11) #####	Elapsed Time: 0:00:00 ETA: 0:00:00
100% (11 of 11) #####	Elapsed Time: 0:00:00 Time: 0:00:00

Summary for lane Union at Hawks:

LinearGAM

=====

=====

Distribution: NormalDist Effective DoF:

46.8961

Link Function:

IdentityLink Log Likelihood:

-13503.368

Number of Samples:

1000 AIC:

27102.5282

AICc:

27107.4529

GCV:

318766.6322

Scale:

291976.2639

Pseudo R-Squared:

0.8024

=====

Feature Function		Lambda	Rank	EDoF
P > x	Sig. Code			
=====		=====	=====	=====
s(0)		[15.8489]	20	12.3
1.11e-16	***			
s(1)		[15.8489]	20	5.2
1.11e-16	***			
s(2)		[15.8489]	20	3.9
2.20e-01				
s(3)		[15.8489]	20	2.8
2.17e-02	*			
f(4)		[15.8489]	2	0.9
7.85e-01				
f(5)		[15.8489]	2	0.9
9.01e-01				
f(6)		[15.8489]	2	0.9
1.65e-02	*			
f(7)		[15.8489]	2	0.9
6.72e-01				
f(8)		[15.8489]	2	0.9
5.65e-01				
f(9)		[15.8489]	2	0.9
8.98e-01				
s(10)		[15.8489]	20	3.2
4.45e-02	*			
s(11)		[15.8489]	20	3.5
1.04e-01				
s(12)		[15.8489]	20	3.3
7.84e-09	***			
s(13)		[15.8489]	20	2.9
8.78e-02	.			
s(14)		[15.8489]	20	2.4

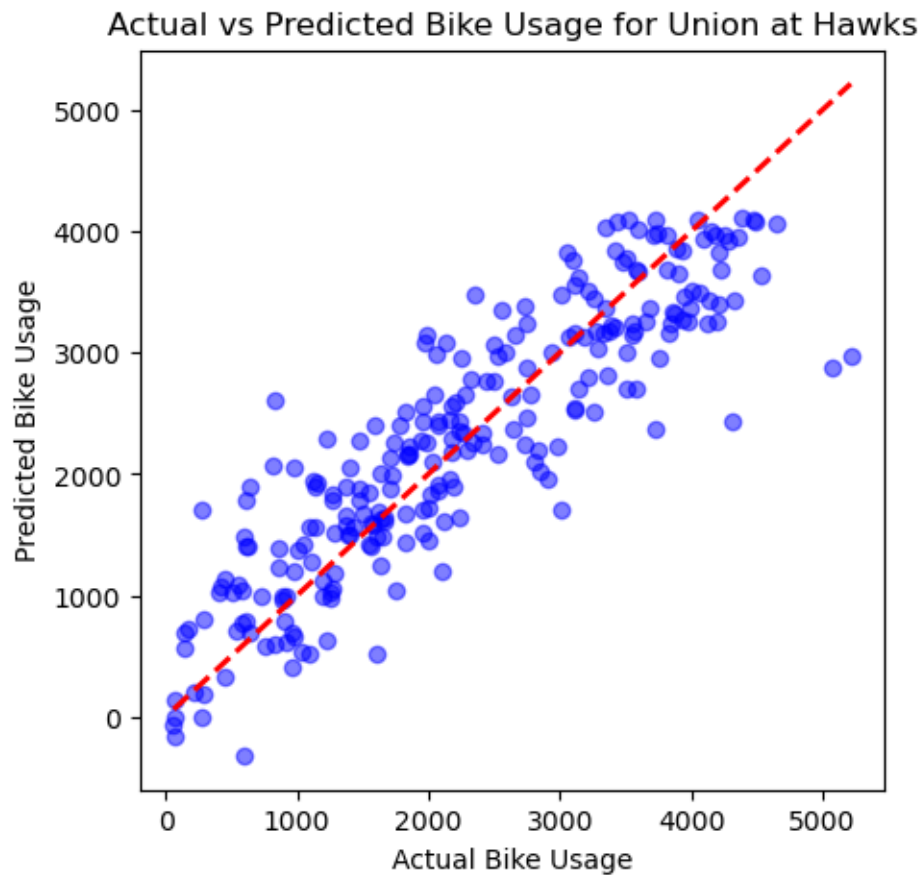
```

4.50e-01
s(15)                [15.8489]                20                1.8
1.88e-02      *
intercept                1                0.0
4.01e-01
=====
=====
Significance codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

WARNING: Fitting splines and a linear function to a feature introduces a model identifiability problem
which can cause p-values to appear significant when they are not.

WARNING: p-values calculated in this manner behave correctly for un-penalized models or models with
known smoothing parameters, but when smoothing parameters have been estimated, the p-values
are typically lower than they should be, meaning that the tests reject the null too readily.



Mean Squared Error for Union at Hawks: 329467.6360162588

1.12 Conclusion

The GAM analysis effectively highlighted the primary drivers of bike usage in Vancouver, revealing that warmer weather promotes cycling, whereas rain and snow significantly decrease it. With rainfall occurring 40-44% of the year, bike lane utilization is highly seasonal, raising questions about the year-round effectiveness of reducing vehicle lanes in favor of bike lanes. Additionally, the analysis suggests that higher temperatures have a more pronounced effect on bike usage on Saturdays compared to weekdays, which may further limit bike lane effectiveness during weekday rush hours. These findings suggest the need for further investigation into complementary transportation modes, such as public transit, and their integration with traffic patterns to develop a more balanced and resilient transportation strategy suited to Vancouver's climate.