FinalProject

September 28, 2025

1 Modeling Shark Attack Occurrence: A Supervised Learning Approach

Introduction/Background

Shark attacks are extremely rare events with great consequences for the victims involved. These events have become widely popularized in modern culture and media because of their violent and novel nature. That said, public exposure to these events widely inflated relative to their actual occurrence. Individual risk, as reported by the ISAF is 1 in 11.5 million, but this can vary based on the profile of the individual (e.g. individual's number of visits to the beach, activity while in the water, etc.).

With this in mind, shark attacks are still events that occur with risk that can be modeled. And where risk can be modeled, individuals can assess and make judgements for themselves on how to navigate through the world. This paper will explore various factors associated with shark attack occurrences, and will attempt to quantify the risk involved so that individuals can make judgements for themselves on how to interpret that risk.

The main sources of data for these events is The International Shark Attack File (ISAF). The ISAF is a catalog of all these events and is a widely trusted database on shark attack occurrences globally, curated by researchers at the University of Florida (special acknowledgement and thanks to Dr. Gavin Naylor and Joseph Miguez for this data). To help decrease model complexity and to provide a manageable project scope, only a subset of this data was pulled: specifically, unprovoked attack occurrences on the Atlantic Coast of Florida. The possibility of heterogeneity in pulling a specific dataset such as this, rather than global data is a limitation that will be discussed further in the conclusion of this paper.

Data Citations (also listed in references in bottom of doc):

Florida Museum. (n.d.). International Shark Attack File. Florida Museum of Natural History. Retrieved September 25, 2025, from https://www.floridamuseum.ufl.edu/shark-attacks/

University of West Florida, Haas Center. (n.d.). Tourism indicators. University of West Florida. Retrieved September 25, 2025, from https://uwf.edu/centers/haas-center/explore-the-economy/tourism-indicators/

Problem Statement

The main problem that is being solved by this project is: Given temporal and weather data, can a shark attack occurrence be reliably predicted? This is not to say that the aim of this project is to model individual risk of attack, rather the general occurrence of an attack given the features at hand. This is an important distinction that is necessary to understand when viewing the data and results.

Hypothesis

The two general questions tested in this project are:

1. Can temporal features (i.e. time of day, month of year, and lunar phases) help provide indication of a shark attack occurrence?
2. Can weather features (i.e. barometric pressure, temperature, and the change of these features over time) provide indication of shark attack occurrence?

Regarding temporal features, it is widely known shark attacks occur more often on a seasonal basis. These events happen more often in warmer months due to more beachgoers and shark migratory patterns. Additionally, it is known that more attacks occur during day hours due to the fact that more people visit the beach during the day rather than night. Furthermore, it is also thought that the lunar phases have an effect on shark attack occurrence, due to general lunar illumination. These features and their effect on shark attack occurrence will be tested via the models later mentioned.

Regarding weather features, the interaction that is of interest for this project is barometric pressure, temperature, and the delta and rate of change between these variables over time. As all aquatic life are sensitive to dramatic shifts in their environment, these models will test whether or not these shifts influence shark behavior in a way that has an effect on shark attack occurrence. The causal nature of this affect is not being measured (i.e. whether sharks become more aggressive or whether they flee an area when there are dramatic shifts in these features), rather the overall correlation between these whether events and shark attack occurrences themselves.

2 1. Data Import and Cleansing

In terms of size, the data is 95 columns wide and has 736 rows, some of which have incomplete data.

First importing all the necesary libraries

[1]:
```
import scipy as sp
import scipy.stats as stats
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import copy
import statsmodels.formula.api as smf
import statsmodels.api as sm
import re
import math
from datetime import datetime

#import ephem
```

```python
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression, LinearRegression
from sklearn.metrics import classification_report, roc_auc_score,␣
 ↪average_precision_score, roc_curve, confusion_matrix
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder
from sklearn.pipeline import Pipeline
```

Installing openyxl as the CSV reader was giving me trouble

[2]:
```
!pip install openpyxl
```

```
Collecting openpyxl
  Downloading openpyxl-3.1.3-py2.py3-none-any.whl.metadata (2.5 kB)
Collecting et-xmlfile (from openpyxl)
  Downloading et_xmlfile-1.1.0-py3-none-any.whl.metadata (1.8 kB)
Downloading openpyxl-3.1.3-py2.py3-none-any.whl (251 kB)
                         251.3/251.3 kB
72.9 MB/s eta 0:00:00
Downloading et_xmlfile-1.1.0-py3-none-any.whl (4.7 kB)
Installing collected packages: et-xmlfile, openpyxl
Successfully installed et-xmlfile-1.1.0 openpyxl-3.1.3

[notice] A new release of pip is
available: 23.3.2 -> 24.0
[notice] To update, run:
pip install --upgrade pip
```

One of the main challenges in this project was data sanitization. The ISAF is a near-century old project, with data going back from the 1500s- present. Data drift is an inevitable threat with a project as long-standing as this, and sanitization is a normal part of the modeling process. Why and how values are inputted have changed over time, and the data reflects this. Multiple cleansing and parsing functions were used to create a sanitized output.

The first of these were functions created to parse through the 'time-of-attack' feature, which is one of the most critical to this analysis. As the data varied between written phrases such as "Forenoon" and "Afternoon", the usage of AM/PM, military time, and general ranges such as "2:00- 4:00", a variety of functions were created to parse this information. Additionally, functions were created to "bucket-ize" this time of attack feature and create new features based off of this. This includes the creation of a general time-of-day feature that shows whether the attack occurred in morning, afternoon, evening, or night, which was useful for visualizations.

Additional features were also created from the 'date_at_location' feature to help create more modeling value. The first of these was the creation of general months, and seasons, based on the date. The second was the creation of features related to the lunar phases. Three functions were created to calculate the general lunar phase (new, first quarter, full, last quarter), the general lunar illumination fraction (expressed as a fraction for modeling purposes), and general lunar illumination percentage (expressed as a percentage for visualization purposes).

Another thing to note is that unnecessary columns were dropped (such as body parts involved in the attack) to reduce noise while modeling and to curtail the dataframe. Additionally, all provoked attacks were dropped from the data, as the scope of this project pertains to solely unprovoked instances. As provoked instances vary widely, the risk is that they would have skewed the results of the analysis.

One of the byproducts of this project is a cleaned output of data, as well as a data cleansing pipeline that can both be used for further projects such as this.

In terms of size, the data is 95 columns wide and has 736 rows, some of which have incomplete data.

Reading in the data below

[3]:
```
df = pd.read_excel('data/Atlantic_Coast_Florida_Metadata.xlsx',␣
↪engine='openpyxl')
df_2 = pd.read_excel('data/Air_Traffic_data.xlsx', engine='openpyxl')
```

Inspecting the data to see features available and data quality

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

[4]:
```
                                 authenticity attack_classification  \
0  Confirmed, shark involvement also confirmed     Unprovoked attack
1  Confirmed, shark involvement also confirmed     Unprovoked attack
2  Confirmed, shark involvement also confirmed     Unprovoked attack
3  Confirmed, shark involvement also confirmed     Unprovoked attack
4  Confirmed, shark involvement also confirmed     Unprovoked attack

                                             outcome      continent country  \
0                                          Non-fatal  North America     USA
1  Fatal Attack, body or parts thereof recovered,…  North America     USA
2                                          Non-fatal  North America     USA
3                                          Non-fatal  North America     USA
4                                          Non-fatal  North America     USA

     state              county  \
0  Florida  Palm Beach County
1  Florida     Brevard County
2  Florida       Duval County
3  Florida   St. Johns County
4  Florida   St. Lucie County

                              0-all attacks.locality date_at_location  Year  \
0                                                NaN       1931-09-21  1931
1  Indiatlantic Beach, just across the bridge for…       1934-06-20  1934
2                                            Mayport       1944-05-31  1944
3       Crescent Beach, in front of Sea Haven Condos       1952-06-02  1952
4                           Fort Pierce, South Beach       1957-02-05  1957
```

```
   …                     bone_exposed              body_cavity_exposed  \
0  …                               No  Data insufficient for judgement
1  …  Data insufficient for judgement                               No
2  …  Data insufficient for judgement                               No
3  …                               No                               No
4  …  Data insufficient for judgement                               No

  appendage_loss_to_shark appendage_loss_to_surgery trunk_severed  \
0                      No                        No            No
1                      No                        No            No
2                      No                        No            No
3                      No                        No            No
4                      No                        No            No

  swallowed_whole skeletonized          wounds_other_than_above  \
0              No           No  Data insufficient for judgement
1              No           No  Data insufficient for judgement
2              No           No                               No
3              No           No  Data insufficient for judgement
4              No           No                               No

              provocative_acts  \
0  None known/unprovoked attack
1  None known/unprovoked attack
2  None known/unprovoked attack
3  None known/unprovoked attack
4  None known/unprovoked attack

                               activity_addenda
0                                           NaN
1                                           NaN
2                                           NaN
3                                           NaN
4  Floating on back, no flotation device reported

[5 rows x 95 columns]
```

[5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 736 entries, 0 to 735
Data columns (total 95 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   authenticity                  736 non-null    object
 1   attack_classification         736 non-null    object
```

```
2   outcome                     736 non-null   object
3   continent                   736 non-null   object
4   country                     736 non-null   object
5   state                       736 non-null   object
6   county                      736 non-null   object
7   0-all attacks.locality      728 non-null   object
8   date_at_location            736 non-null   datetime64[ns]
9   Year                        736 non-null   int64
10  victim_activity             736 non-null   object
11  abdomen_stomach             736 non-null   object
12  hands                       736 non-null   object
13  arms                        736 non-null   object
14  feet                        736 non-null   object
15  calf_knee                   736 non-null   object
16  head                        736 non-null   object
17  chest                       736 non-null   object
18  shoulder                    736 non-null   object
19  thigh                       736 non-null   object
20  buttocks                    736 non-null   object
21  genitals                    736 non-null   object
22  waist                       736 non-null   object
23  fingers_toes                736 non-null   object
24  fingers                     736 non-null   object
25  toes                        736 non-null   object
26  back                        736 non-null   object
27  injury_other_than_above     736 non-null   object
28  total_depth                 735 non-null   object
29  depth_of_attack             736 non-null   object
30  relative_depth              622 non-null   object
31  habitat                     736 non-null   object
32  turbidity                   514 non-null   object
33  visibility                  527 non-null   object
34  sunlight_conditions         692 non-null   object
35  gen_weather                 563 non-null   object
36  air_temp                    555 non-null   object
37  water_temp                  736 non-null   object
38  water_clarity               736 non-null   object
39  sea_surf_cond               626 non-null   object
40  locality_Addenda            138 non-null   object
41  time_of_attack              733 non-null   object
42  closest_phase               736 non-null   object
43  waxing_waning               736 non-null   object
44  genus                       736 non-null   object
45  species                     736 non-null   object
46  common_name                 736 non-null   object
47  prior_behavior              671 non-null   object
48  initial_behavior            736 non-null   object
49  subsequent_behavior         736 non-null   object
```

```
 50  final_behavior                 736 non-null    object
 51  form_of_initial_strike         506 non-null    object
 52  strike_direction               736 non-null    object
 53  passes                         736 non-null    object
 54  discrete_strikes               736 non-null    object
 55  discrete_bites                 621 non-null    object
 56  object_of_attack               731 non-null    object
 57  shark_Addenda                  358 non-null    object
 58  no_of_sharks                   701 non-null    object
 59  scuba                          736 non-null    object
 60  face_mask                      736 non-null    object
 61  swim_fins                      736 non-null    object
 62  weapons                        736 non-null    object
 63  life_jacket                    736 non-null    object
 64  dive_bag                       736 non-null    object
 65  wetsuit_drysuit                736 non-null    object
 66  swim_suit                      736 non-null    object
 67  non_swim_clothing              736 non-null    object
 68  hard_hat_suit                  736 non-null    object
 69  gear_clothes_other_than_above  736 non-null    object
 70  degree_type_of_clothing        573 non-null    object
 71  primary_color                  736 non-null    object
 72  secondary_color                736 non-null    object
 73  tertiary_color                 736 non-null    object
 74  gear_clothes_Addenda           333 non-null    object
 75  surfboard_bottom_color         336 non-null    object
 76  surfboard_size                 321 non-null    object
 77  surfboard_number_fins          33 non-null     object
 78  clothing_pattern               578 non-null    object
 79  special_features               580 non-null    object
 80  scrapes_abrasions              736 non-null    object
 81  discontinuous_tooth_marks      736 non-null    object
 82  nonsevere_laceration           736 non-null    object
 83  severe_lacerations             736 non-null    object
 84  significant_tissue_loss        736 non-null    object
 85  bone_exposed                   736 non-null    object
 86  body_cavity_exposed            736 non-null    object
 87  appendage_loss_to_shark        736 non-null    object
 88  appendage_loss_to_surgery      736 non-null    object
 89  trunk_severed                  736 non-null    object
 90  swallowed_whole                736 non-null    object
 91  skeletonized                   736 non-null    object
 92  wounds_other_than_above        736 non-null    object
 93  provocative_acts               708 non-null    object
 94  activity_addenda               231 non-null    object
dtypes: datetime64[ns](1), int64(1), object(93)
memory usage: 546.4+ KB
```

[ ]:

```

```

After doing an inspection of the data, it looks like there are a lot of features that I dont necesarily need for this project. All the data regarding the type of bite, body parts affected, and other miscelaneous information I removed so as to not confound any further analysis I do.

In terms of size, the data is 95 columns wide and has 736 rows, some of which have incomplete data.

[6]:

```
df_clean = df[['attack_classification', 'outcome', 'county',␣
↪'date_at_location', 'Year',
              'time_of_attack','victim_activity', 'sunlight_conditions',␣
↪'gen_weather', 'air_temp', 'water_temp',
              'closest_phase', 'waxing_waning', 'common_name',␣
↪'provocative_acts', 'activity_addenda']].copy()


print(df_clean['time_of_attack'].unique())
print(df_clean['outcome'].unique())
print(df_clean['attack_classification'].unique())
```

```
['Data insufficient for judgement' '09:00'
 'data insufficient for judgement' '10:30' '1530' '11:00' '1700' '15:30'
 '15:00' '12:00' '11:30' 'late afternoon/evening' '1330' '14:30' '13:30'
 '07:00' '1500' '16:00' '16:30' 'afternoon' '14:00' '16:56' '08:55'
 '16:40' '13:50' '10:00' '16:06' '13:00' '11:15' 'morning' '13:15' '17:30'
 '14:45' '14:15' '19:30' '18:00' '09:45' '08:00' '12:30' 'forenoon'
 '17:00' '14:10' '09:15' '19:00' 'night' '18:45' '11:45' '18:30' '12:15'
 '18:20' '16:50' '11:50' '08:30' '16:35' '04:00' '10:55' '17:45' '07:45'
 '18:12' '14:25' '19:35' '09:25' '14:54' '09:10' '13:20' '14:20' '08:45'
 '19:07' '15:50' '07:30' '18:15' '11:06' '13:25' '18:05' '13:45' '11:20'
 '11:36' '10:25' '09:30' '13:43' '17:15' '18:02' '09:35' '11:10' '17:59'
 '20:15' '15:45' '18:40' 'Afternoon' '11:57' '14:55' '17:02' '14:50'
 '17:42' '12:48' '11:00-14:00' '12:46' '10:50' '13:06' '13:14' '16:15'
 '16:20' '14:40' '10:15' '06:45' '10:40' '14:47' '12:05' '15:55' '13:40'
 '19:15' '12:20' '13:23' '13:53' '11:55' '10:07' '14:37' '17:11' '16:14'
 '06:00' '17:25' '11:12' '17:05' '13:55' '14:01' '16:45' nan '14:21'
 '13:21' '12:37' '18:43' '16:12' '11:05' '13:42' '08:10' '18:50' '12:03'
 '15:10' '11:02' '11:40' '10:45' '10:23' '12:45' '13:18' '13:17' '9:50'
 '14:12' '10:48' '08:15' '19:23' '08:14' '11:48' '17:18' '14:27' '14:46'
 '12:53' '15:40' '12:38' '09:50' '14:59' '18:19' '15:38' '15:36' '10:32'
 '15:28' '1000' '2 PM' '5:30 pm' '1930' '1030' '0758' '1036' '1630'
 '12:25' '17:03' '17:20' '10:47' '15:20' '9:00' '7:00' '16:48' '15:57'
 '16:38' '12:23' '10AM' '06:30' '18:36' '13,20' '10:41' '11:14' '15:18'
 '11:25' '16:16' '15:05' '14:06' '9:20' '7:44' '12:11' '9:30' '18:04'
 '15:52']
['Non-fatal'
 'Fatal Attack, body or parts thereof recovered, death considered direct result
```

```
of shark-inflicted wounds'
 'Assumed fatal attack, body not recovered, no personal gear recovered'
 'Assumed fatal attack, body not recovered, personal gear recovered'
 'Fatal, body or parts thereof recovered, not known whether death was a direct
result of shark-inflicted wounds']
['Unprovoked attack' 'Provoked attack' 'No assignment can be made'
 'Air/sea disaster: unprovoked attack']
```

As you can see below, I am cleansing the "Outcome" feature below. I am creating a binary and ternary feature that describes whether the outcome was fatal or non-fatal based on the text entered in this column. This will be useful if I deide to do logistic modeling on the Outcome

Also, I am deleting all rows where the attack classification is a provoked attack. This culls 64 rows from the overall dataset, but this is a necesary action due to the fact that provoked attacks could happen for too many numerous factors. This will protect our data integrity

[7]:
```
#Data Cleansing

df_clean = df_clean[df_clean['attack_classification'] != 'Provoked attack'].
 ↪copy()

#deleting all rows that are provoked attacks

df_clean['outcome'] = df_clean['outcome'].replace({
'Non-fatal': 'non-fatal',
 'Fatal Attack, body or parts thereof recovered, death considered direct result␣
 ↪of shark-inflicted wounds': 'fatal',
 'Assumed fatal attack, body not recovered, no personal gear recovered':␣
 ↪'assumed_fatal',
 'Assumed fatal attack, body not recovered, personal gear recovered':␣
 ↪'assumed_fatal',
 'Fatal, body or parts thereof recovered, not known whether death was a direct␣
 ↪result of shark-inflicted wounds':'fatal'
})

for col in ['attack_classification', 'outcome','county', 'victim_activity',␣
 ↪'sunlight_conditions', 'gen_weather',
            'closest_phase', 'waxing_waning', 'common_name', 'provocative_acts',␣
 ↪'activity_addenda']:
    df_clean[col] = df_clean[col].astype(str).str.strip().str.lower()



df_clean['outcome_binary'] = df_clean['outcome'].map({'fatal': 1,␣
 ↪'assumed_fatal': 1, 'non-fatal': 0})

df_clean['outcome_ternary'] = df_clean['outcome'].map({'fatal': 1,␣
 ↪'assumed_fatal': 2, 'non-fatal': 0})
```

[8]:
```
print(df_clean['outcome'].unique())
```

```
['non-fatal' 'fatal' 'assumed_fatal']
```

Now, I am getting into the temporal data cleansing below. I created a few fucntions that go through the time_of_attack feature and normalize it so it is consistent throughout. I really would like this feature to be used in modelling so I am spending a lot of time and effort cleaning it.

Additionally I am creating a function that bucketizes the data into general day phases (i.e. dawn, day, dusk, night)

[9]:
```
#time_of_attack needs some heavy data cleansing here

def midpoint(h1, h2):
    if h1 is None or h2 is None:
        return None
    return (h1 + ((h2-h1)% 24)/2) % 24

def ampmparse(s: str):
    for fmt in ("%I%p", "%I %p", "%I:%M%p", "%I:%M %p"):
        try:
            t = datetime.strptime(s.strip().upper(), fmt)
            return t.hour + t.minute/60.0
        except ValueError:
            continue
    return None

def hhmmparse(hhmm: str):
    try:
        hh, mm = hhmm.split(":")
        hh, mm = int(hh), int(mm)
        if 0 <=hh <= 23 and 0 <= mm <= 59:
            return hh + mm/60.0
    except Exception:
        pass
    return None

def normalize_time(val):
    if val is None or (isinstance(val, float)and math.isnan(val)):
        return np.nan
    s = str(val).strip()

    sl = s.lower()
    if sl == "data insufficient for judgement":
        return np.nan

    s = s.replace(",", ":")
```

```
    #for the single instance of midpoint range 11:00 - 14:00
    if "-" in s:
        try:
            left, right = s.split("-")
            h1, h2 = hhmmparse(left.strip()), hhmmparse(right.strip())
            return midpoint(h1, h2)
        except Exception:
            return np.nan

    #ampm normalization
    ampm_val = ampmparse(s)
    if ampm_val is not None:
        return ampm_val

    #military time normalization
    if re.fullmatch(r"\d{3,4}", s):
        hh, mm = int(s[:-2]), int(s[-2:])
        if 0<= hh <= 23 and 0<= mm <= 59:
            return hh + mm/60.0

    # HH:MM and H:MM
    if re.fullmatch(r"\d{1,2}:\d{2}", s):
        return hhmmparse(s)


    # HH
    if re.fullmatch(r"\d{1,2}", s):
        hh = int(s)
        if 0<= hh <= 23:
            return float(hh)

    #General phrases
    phrase_map = {"forenoon": 10.0, "morning": 9.0, "afternoon": 15.0, "late␣
↪afternoon/evening" : 18.0, "night": 22.0}
    if sl in phrase_map:
        return phrase_map[sl]

    return np.nan

def time_buck(h):

    if pd.isna(h):
        return "unknown"
    if 5 <= h < 9:
        return "dawn"
    if 9 <= h < 17:
        return "day"
```

```
    if 17<= h < 21:
        return "dusk"
    return "night"
```

Creating my new time of attack features from the functions above

[10]:
```
#data cleansing contd.

df_clean["time_of_attack_hour"] = df_clean["time_of_attack"].
↪apply(normalize_time)

df_clean["time_unknown_flag"] = df_clean["time_of_attack_hour"].isna().
↪astype(int)

df_clean["time_bucket"] = df_clean["time_of_attack_hour"].apply(time_buck)
```

Now, just printing all the unique values to make sure that this worked correctly and to get an idea of what I am working with

[11]:
```
print(df_clean['time_of_attack_hour'].unique())
print(df_clean['time_bucket'].unique())
print(df_clean['time_unknown_flag'].unique())
```

```
[        nan  9.          10.5         15.5         11.          17.
 15.          12.          11.5         18.          14.5         13.5
  7.          16.          16.5         14.          16.93333333  8.91666667
 16.66666667 13.83333333 10.          16.1         13.          11.25
 13.25        17.5         14.75        19.5          9.75         8.
 12.5         14.16666667 19.          22.          18.75        11.75
 18.5         12.25        14.25        18.33333333 16.83333333 11.83333333
  8.5         16.58333333  4.          10.91666667 17.75         7.75
 18.2         14.41666667  9.41666667 14.9          9.16666667 13.33333333
 14.33333333  8.75        19.11666667 15.83333333  7.5         18.25
 11.1         13.41666667 18.08333333 13.75        11.33333333 11.6
 10.41666667  9.5         13.71666667 17.25        18.03333333  9.58333333
 11.16666667 17.98333333 20.25        15.75        18.66666667 14.91666667
 17.03333333 14.83333333 17.7         12.8         12.76666667 10.83333333
 13.1         13.23333333 16.25        16.33333333 14.66666667 10.25
  6.75        10.66666667 14.78333333 12.08333333 15.91666667 13.66666667
 19.25        12.33333333 13.38333333 13.88333333 11.91666667 14.61666667
 17.18333333 16.23333333  6.          17.41666667 11.2         17.08333333
 13.91666667 14.01666667 16.75        14.35        13.35        12.61666667
 18.71666667 16.2         11.08333333 13.7          8.16666667 12.05
 15.16666667 11.03333333 11.66666667 10.75        10.38333333 12.75
 13.3         13.28333333  9.83333333 14.2         10.8          8.25
 19.38333333 18.83333333  8.23333333 11.8         17.3         14.45
 14.76666667 12.88333333 15.66666667 12.63333333 14.98333333 18.31666667
 15.63333333 15.6         15.46666667 10.6         12.41666667 17.05
```

```
 17.33333333 10.78333333 15.33333333 16.8        15.95       16.63333333
 12.38333333  6.5        18.6        10.68333333 11.23333333 15.3
 16.26666667 15.08333333 14.1         9.33333333  7.73333333 12.18333333
 18.06666667 15.86666667]
['unknown' 'day' 'dusk' 'dawn' 'night']
[1 0]
```

Now, I want to work on celaning the date at location feature, deriving the month and general season from that data as well, so I can test my hypothesis on seasonality.

There is some odd air_temp data that seems to be in Farenheight, so I am masking that here as well. This may not be used, but I will cleanse anyways.

[12]:
```
df_clean['date_at_location'] = pd.to_datetime(df_clean['date_at_location'],␣
↪errors = 'coerce')
df_clean['month'] = df_clean['date_at_location'].dt.month
df_clean['season'] = df_clean['month'].map({
 12: 'winter', 1: 'winter', 2: 'winter',
 3: 'spring', 4: 'spring', 5: 'spring',
 6: 'summer', 7:'summer', 8:'summer',
 9:'fall', 10: 'fall', 11: 'fall'})

for col in ['air_temp', 'water_temp']:
    df_clean[col] = pd.to_numeric(df_clean[col], errors = 'coerce')

faren_mask = df_clean['air_temp'] > 60
df_clean.loc[faren_mask, 'air_temp'] = (df_clean.loc[faren_mask, 'air_temp'] -␣
↪32) *(5/9)

hr = df_clean['time_of_attack_hour']


df_clean['hour_sin'] = np.sin(2*np.pi*hr/24)
df_clean['hour_cos'] = np.cos(2*np.pi*hr/24)
```

In the cell below I create functions that derive the moon phase and lunar illumination from the date. This should be more reliable than the given lunar features in the data, and will help me test my hypothesis on lunar phase impacting the occurence of shark attacks

As you can see above, I end up with 4 new features-

lunar_phase: which bucketizes all the occurences into 4 equal bins (new, last_quarter, first_quarter, and full)

lunar_illumination_phase: the 0-1 value of lunar phase

lunar_illumination_frac: 0-1 value that indicates the lunar illumination (0-1 easier for modleing)

lunar_illumination_pct: 0-100 percentage value that indicates the lunar illumination (0-100 easier for visualization)

[13]:
```python
def moon_phase(date):
    if pd.isna(date):
        return None
    last_known_new_moon = pd.Timestamp("2000-01-06")
    syn_month = 29.5305887
    days = (pd.to_datetime(date)- last_known_new_moon).days
    return (days % syn_month)/ syn_month

df_clean["lunar_illumination_phase"]= df_clean["date_at_location"].
 ↪apply(moon_phase)


def illuminationfrac(phase):
    if phase is None:
        return None
    return 0.5* (1-np.cos(2*np.pi*phase))

df_clean["lunar_illumination_frac"] = df_clean["lunar_illumination_phase"].
 ↪apply(illuminationfrac)
df_clean["lunar_illumination_pct"] = df_clean["lunar_illumination_frac"]*100.0



def moon_phase_norm(val):
    if val is None:
        return "unknown"
    if val <0.125 or val >= 0.875:
        return  "new"
    elif val <0.375:
        return "first_quarter"
    elif val<0.625:
        return "full"
    else:
        return "last_quarter"

df_clean["lunar_phase"]= df_clean["lunar_illumination_phase"].
 ↪apply(moon_phase_norm)

print(df_clean['lunar_phase'].value_counts(dropna = False))
print(df_clean['lunar_illumination_pct'].value_counts(dropna = False))
print(df_clean['lunar_illumination_frac'].value_counts(dropna = False))
print(df_clean['lunar_illumination_phase'].value_counts(dropna = False))
```

```
new              183
full             166
last_quarter     163
first_quarter    159
```

```
Name: lunar_phase, dtype: int64
95.828611    4
0.170482     4
12.160051    4
1.573899     4
0.422984     3
            ..
99.692238    1
72.243376    1
97.194988    1
11.465200    1
74.325882    1
Name: lunar_illumination_pct, Length: 599, dtype: int64
0.121601    4
0.015739    4
0.958286    4
0.001705    4
0.004230    3
           ..
0.920522    1
0.058864    1
0.500471    1
0.011702    1
0.408360    1
Name: lunar_illumination_frac, Length: 600, dtype: int64
0.040039    4
0.565472    4
0.979283    3
0.013147    3
0.113381    2
           ..
0.280508    1
0.749577    1
0.756782    1
0.999479    1
0.264208    1
Name: lunar_illumination_phase, Length: 604, dtype: int64
```

Now, I think I am cleansing done for now, so I would like to test and visualize some of the counts and values of the data in the below cells

[14]:
```python
print(df_clean['month'].unique())
#print(df_clean['date_at_location'].unique())
print(df_clean['air_temp'].unique())
print(df_clean['water_temp'].unique())
```

```
[ 9  6  5  2  4  3  7  8  1 10 11 12]
[        nan 24.         26.         29.         28.         30.
 18.         27.         31.         21.         32.         33.
 20.         23.         22.         26.7        28.5        31.1
 25.6        35.         23.8        16.         29.4        32.22
 37.         28.8        25.5        32.2        27.7        33.3
 30.3        36.         28.9        30.5        25.         22.22
 23.89       27.2        19.         24.44       22.77       26.667
 28.3        21.7        31.66666667 31.7        30.6        27.8
 21.4        34.4        33.8        26.1        26.6        32.78
 22.7        29.44       23.9        31.11      ]
[   nan 20.    25.    22.    26.    21.    24.    28.    18.    23.
 29.    27.    17.    31.    32.    30.    33.    19.4   19.    25.6
 29.4   21.6   25.5   26.5   15.6   26.7   23.9   24.44  24.4   20.5
 23.8   22.2   27.8   27.6   21.1   20.6   27.2   26.1   25.56  26.67
 23.3   28.3   21.67  22.7   23.88  27.222 28.9   26.6   27.7   27.78
 27.22  28.33 ]
```

[15]:

```
print(df_clean['outcome'].value_counts(dropna = False))
print(df_clean[['outcome', 'outcome_binary', 'outcome_ternary']].head(10))
print(df_clean['time_bucket'].value_counts(dropna = False))
df_clean[['air_temp', 'water_temp']].describe()
```

```
non-fatal        662
fatal              6
assumed_fatal      3
Name: outcome, dtype: int64
      outcome  outcome_binary  outcome_ternary
0   non-fatal               0                0
1       fatal               1                1
2   non-fatal               0                0
3   non-fatal               0                0
4   non-fatal               0                0
5   non-fatal               0                0
8   non-fatal               0                0
9   non-fatal               0                0
10  non-fatal               0                0
12  non-fatal               0                0
day        444
unknown     97
dusk        95
dawn        33
night        2
Name: time_bucket, dtype: int64
```

[15]:

```
         air_temp  water_temp
count  214.000000  373.000000
```

```
mean    28.201139   25.713812
std      3.888885    3.163131
min     16.000000   15.600000
25%     26.000000   24.000000
50%     29.000000   26.000000
75%     31.000000   28.000000
max     37.000000   33.000000
```

Printing out info and data head below of my newly cleansed data. A couple things that stick out to me is that the hourly time of attack features, as well as the temperature features have a lot of null values. I may have to either ommit those rows, or fill the data synthetically at a later point

[16]:
```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 671 entries, 0 to 735
Data columns (total 29 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   attack_classification    671 non-null    object
 1   outcome                  671 non-null    object
 2   county                   671 non-null    object
 3   date_at_location         671 non-null    datetime64[ns]
 4   Year                     671 non-null    int64
 5   time_of_attack           668 non-null    object
 6   victim_activity          671 non-null    object
 7   sunlight_conditions      671 non-null    object
 8   gen_weather              671 non-null    object
 9   air_temp                 214 non-null    float64
 10  water_temp               373 non-null    float64
 11  closest_phase            671 non-null    object
 12  waxing_waning            671 non-null    object
 13  common_name              671 non-null    object
 14  provocative_acts         671 non-null    object
 15  activity_addenda         671 non-null    object
 16  outcome_binary           671 non-null    int64
 17  outcome_ternary          671 non-null    int64
 18  time_of_attack_hour      574 non-null    float64
 19  time_unknown_flag        671 non-null    int64
 20  time_bucket              671 non-null    object
 21  month                    671 non-null    int64
 22  season                   671 non-null    object
 23  hour_sin                 574 non-null    float64
 24  hour_cos                 574 non-null    float64
 25  lunar_illumination_phase 671 non-null    float64
 26  lunar_illumination_frac  671 non-null    float64
 27  lunar_illumination_pct   671 non-null    float64
 28  lunar_phase              671 non-null    object
```

```
dtypes: datetime64[ns](1), float64(8), int64(5), object(15)
memory usage: 157.3+ KB
```

[17]:
```python
df_clean.head()
```

[17]:
```
  attack_classification    outcome              county date_at_location  Year  \
0     unprovoked attack  non-fatal  palm beach county       1931-09-21  1931
1     unprovoked attack      fatal     brevard county       1934-06-20  1934
2     unprovoked attack  non-fatal       duval county       1944-05-31  1944
3     unprovoked attack  non-fatal    st. johns county       1952-06-02  1952
4     unprovoked attack  non-fatal    st. lucie county       1957-02-05  1957

                  time_of_attack  \
0  Data insufficient for judgement
1                            09:00
2  data insufficient for judgement
3                            10:30
4                             1530

                                    victim_activity  \
0                                          swimming
1                             standing still on bottom
2                      data insufficient for judgement
3                             standing still on bottom
4  floating, little or no motion (includes use of…

             sunlight_conditions                       gen_weather  air_temp  \
0                       daylight                             clear       NaN
1                       daylight  data insufficient for judgement       NaN
2  data insufficient for judgement  data insufficient for judgement       NaN
3                       daylight  data insufficient for judgement       NaN
4                       daylight  data insufficient for judgement       NaN

   …  time_unknown_flag time_bucket month  season  hour_sin  hour_cos  \
0  …                  1     unknown     9    fall       NaN       NaN
1  …                  0         day     6  summer  0.707107 -0.707107
2  …                  1     unknown     5  spring       NaN       NaN
3  …                  0         day     6  summer  0.382683 -0.923880
4  …                  0         day     2  winter -0.793353 -0.608761

   lunar_illumination_phase  lunar_illumination_frac  lunar_illumination_pct  \
0                  0.316535                 0.702989               70.298907
1                  0.281316                 0.597749               59.774941
2                  0.306293                 0.673187               67.318656
3                  0.322267                 0.719313               71.931296
4                  0.194463                 0.329044               32.904399
```

```
   lunar_phase
0  first_quarter
1  first_quarter
2  first_quarter
3  first_quarter
4  first_quarter

[5 rows x 29 columns]
```

[18]:
```
#df_clean.to_csv('df_clean_here', index = False)
```

3 2. EDA and Visualization on Temporal Data

Exploratory data analysis and the creation of visuals is a key step for a project such as this, because it allows one the ability to see what key features they are going to use in modelling and how these features might affect the model. Many visualizations were created to make sense of the data. The visualizations shared below are the most relevant to the modelling that was subsequently done.

Temporal Visualizations

The below visualizations related to count of shark attack occurrences across different measures of time are quite simple in and of themselves, but they do show us a few different things to look out for in the subsequent modeling. The first is that, unsurprisingly, shark attacks for this dataset tend to skew towards daytime hours, specifically in the mid-day to afternoon. The second is that shark attacks for this dataset skew toward late summer, early fall months. The third is that shark attacks for this dataset may have a slight uptick around new moons. All this being said, these visualizations aren't enough to determine whether these imbalances are simply indicative of the dataset itself, or can be used to infer future occurrences. In other words, are these results statistically significant?

3.1 Correlation Heatmap

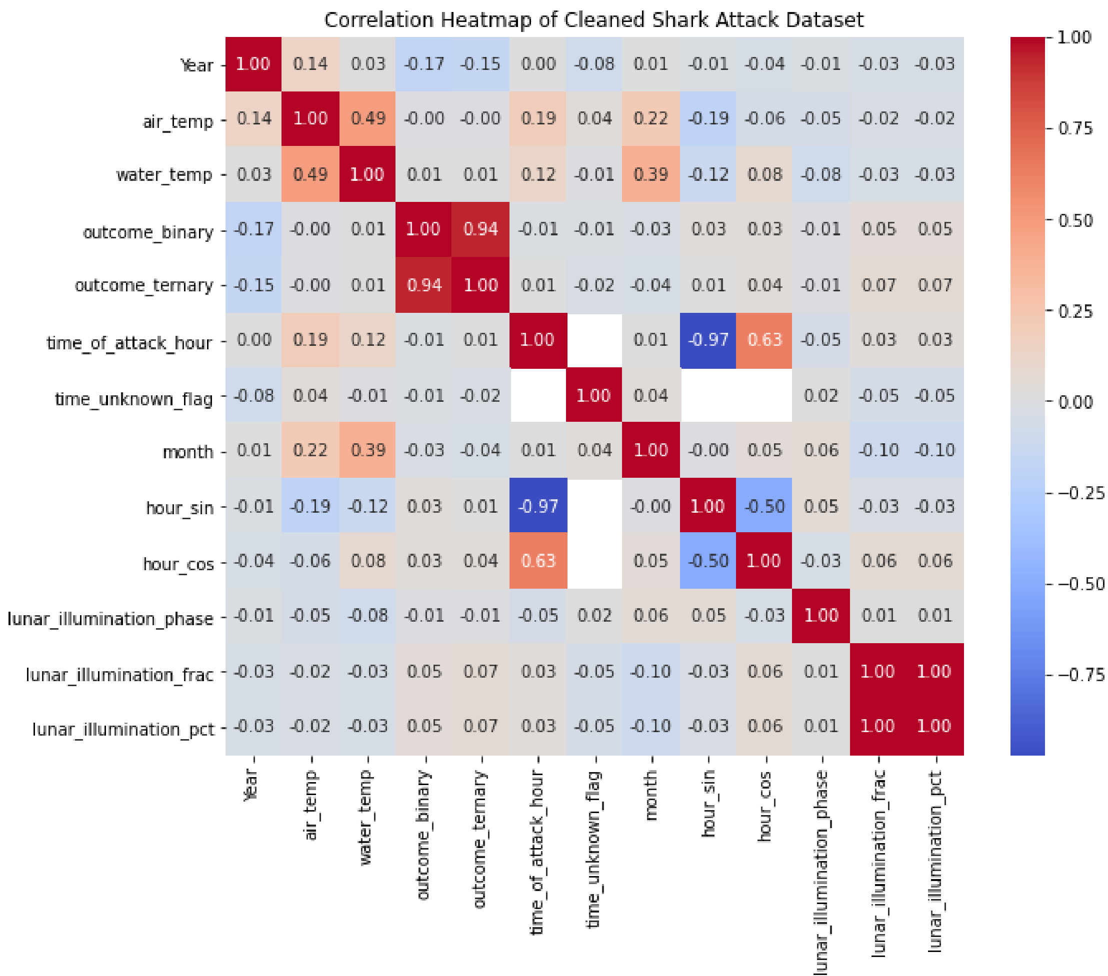
Looking at the features below, there are a few that have some correlation between them. The highest are between some of our feature-engineered values (e.g. hour-sin, hour-cos, and hour), but we can ignore those correlations for now because the engineered features are dependent on what they have been created from.

Some potentially interesting correlations below is water temp and month, as well as air temp and month. This makes sense intuitively as there is a correlation as the air temperature increases in times of the year.

At the moment, this correlation heatmap wont be extremely usefull in identifying model features, due to the fact that synthetic negatives are not created yet. This will be run again after the synthetic negatives are added in.

[19]:
```
plt.figure(figsize=(10, 8))
sns.heatmap(df_clean.select_dtypes(include = ["number"]).corr(),
            annot = True, cmap = "coolwarm", fmt = ".2f", cbar = True)
```

```
plt.title("Correlation Heatmap of Cleaned Shark Attack Dataset")
plt.show()
```



3.2 Hourly Visualizations

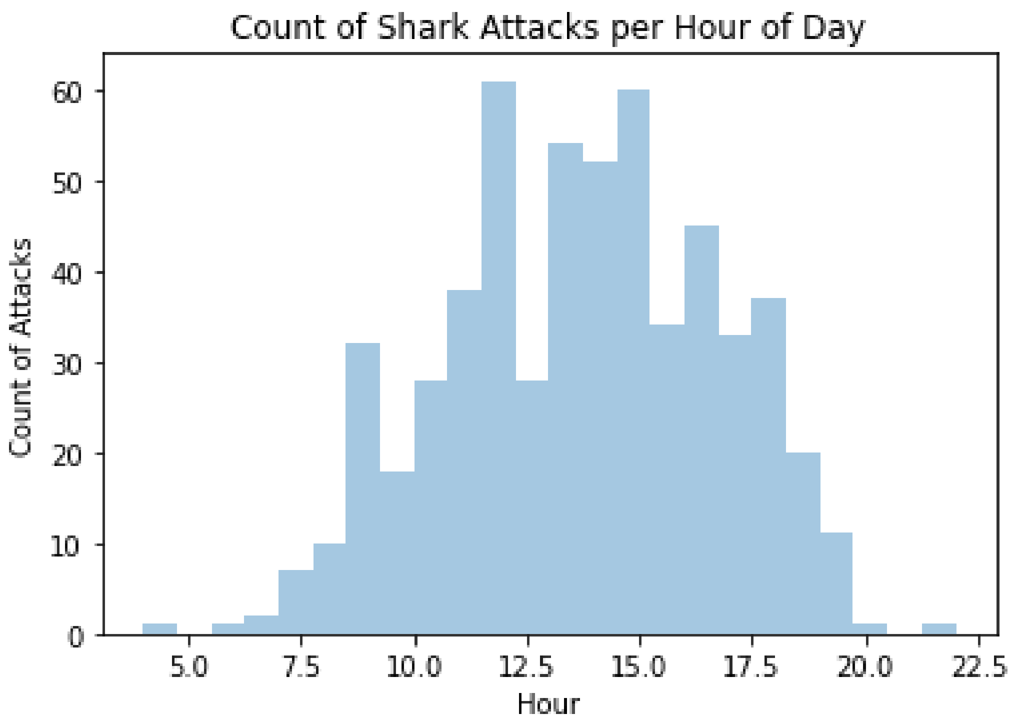
The first thing I want to visualize is the shark attack occurences vs hour of day.

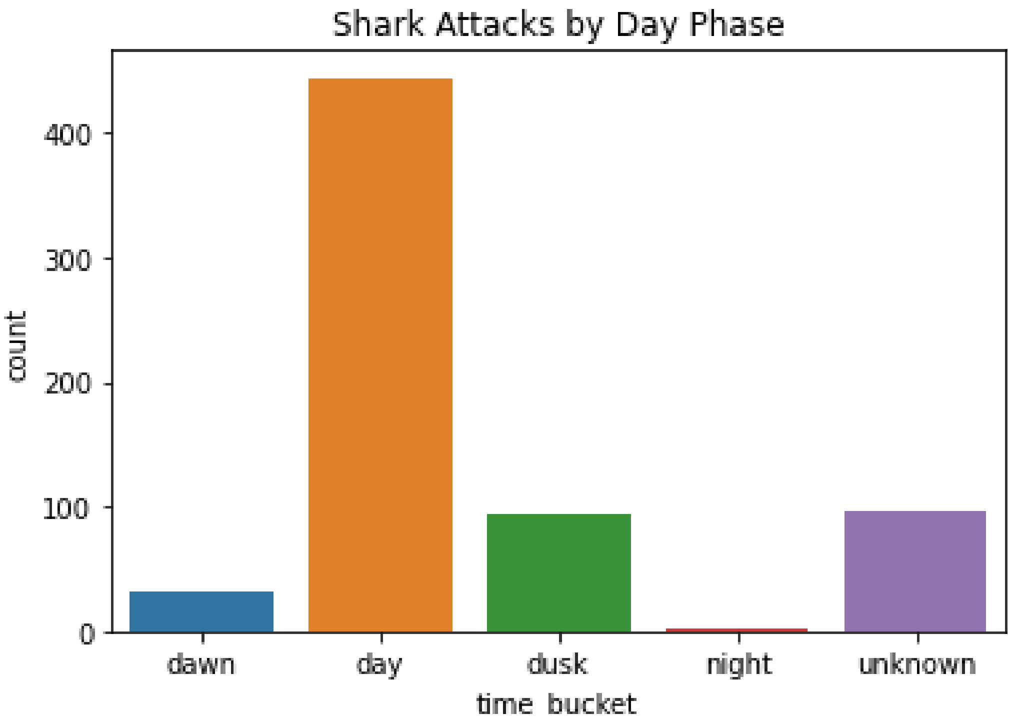
As you can see below, a majority of shark attacks happen towards the daylight hours. This doesnt mean that sharks arent willing to bite people at night-time thought. This more likely due to the fact that beachgoers attend the beach during daylight hours.

[20]:
```
print(sns.__version__)

plt.figure()
sns.distplot(df_clean['time_of_attack_hour'], bins = 24, kde = False)
```

```
plt.xlabel("Hour")
plt.ylabel("Count of Attacks")
plt.title("Count of Shark Attacks per Hour of Day")
plt.show()

plt.figure()
sns.countplot(x = 'time_bucket', data = df_clean, order = ["dawn", "day",␣
↪"dusk", "night", "unknown"])
plt.title("Shark Attacks by Day Phase")
plt.show()
```

0.10.1



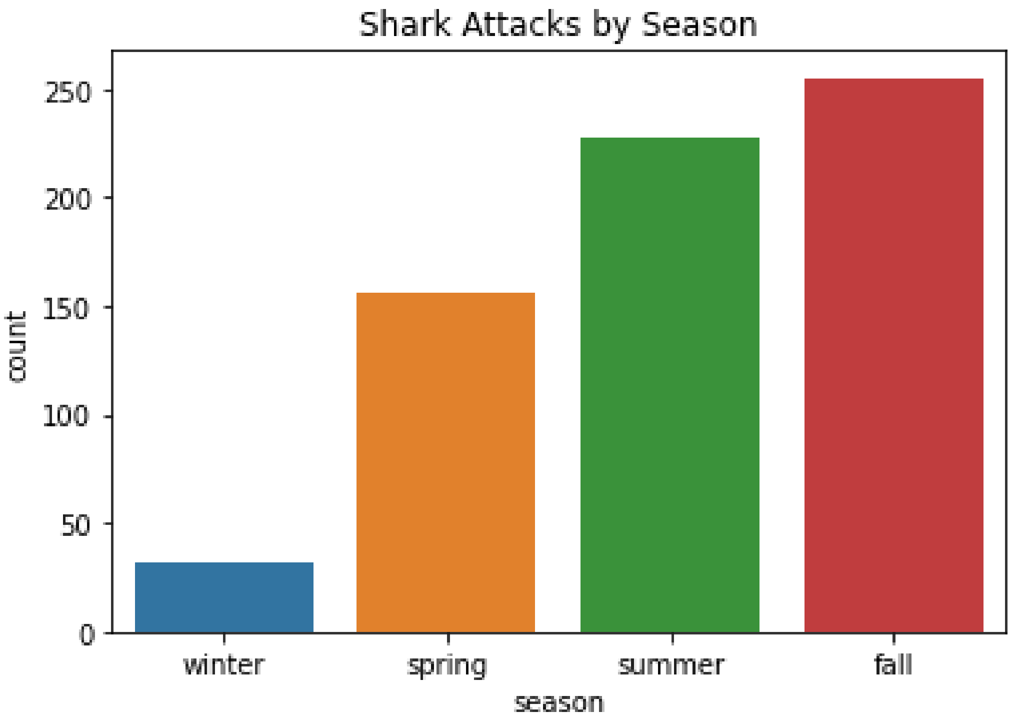


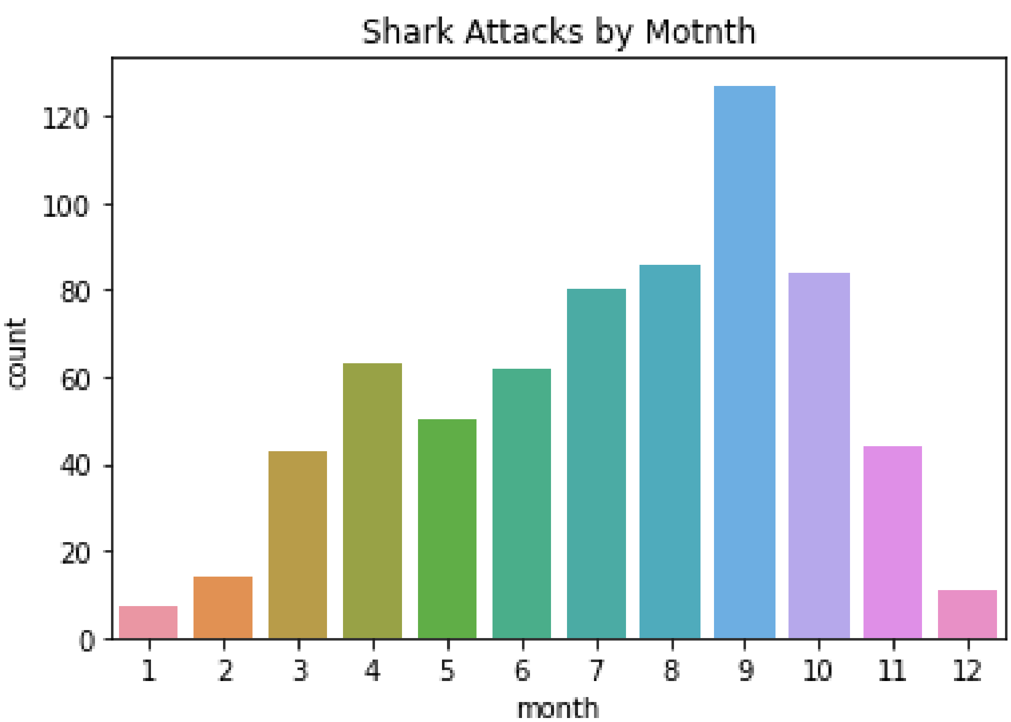
3.3 Monthly/Seasonal Visualizations

Again, visualizing some of the temporal data, but looking at it on a monthly/seasonal basis below.

As you can see, we have a large amount of attacks skewed toward the summer and fall months (months 6-11). Again, this could likely be due to the fact that beachgoers are more likely to visit the beach in the summer and fall months, when temperatures in Florida are more mild, but I would like to inspect this further.

[21]:
```
plt.figure()
sns.countplot(x = 'season', data = df_clean, order = ["winter", "spring",␣
↪"summer", "fall"])
plt.title("Shark Attacks by Season")
plt.show()

plt.figure()
sns.countplot(x = 'month', data = df_clean,)
plt.title("Shark Attacks by Motnth")
plt.show()
```


Shark Attacks by Season
250
200
150
100
50
0
count
winter
spring
summer
fall
season


Shark Attacks by Motnth
120
100
80
60
40
20
0
count
1
2
3
4
5
6
7
8
9
10
11
12
month

3.4 Lunar Phase/Illumination Visualizations

Now, I am looking at the interaction between shark attacks and lunar phase/illumnation percentage.

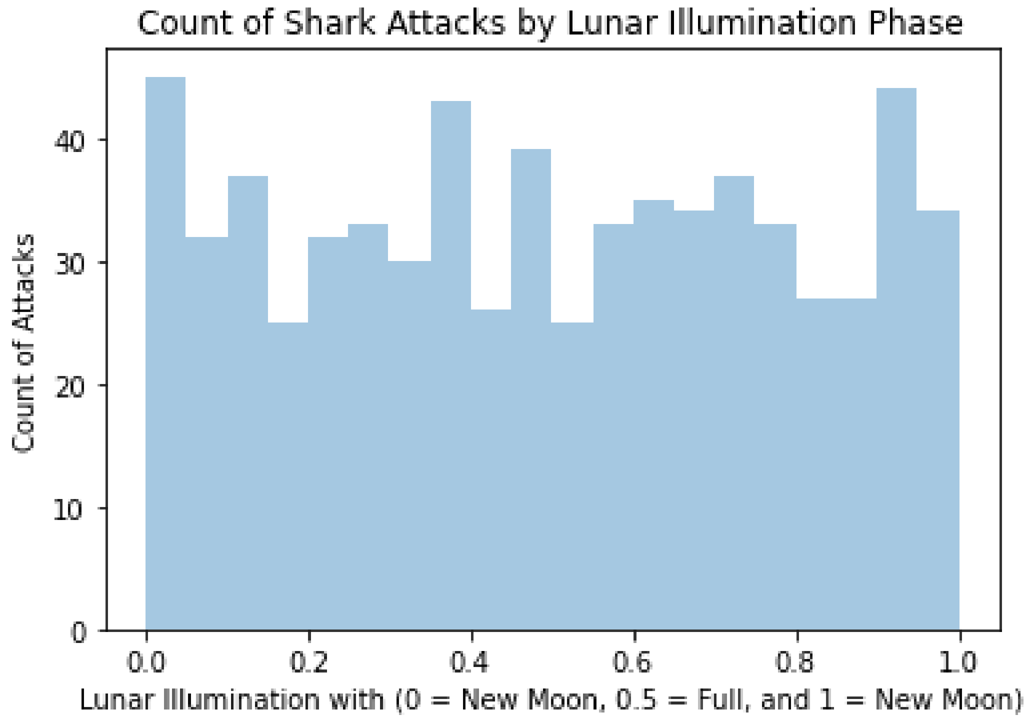
Looking below, you can first see the shark attack occurence plotted with the lunar illumination phase (mapped from 0-1, where 0 is a New moon, 0.5 is full, and 1 is a new moon again). This looks to show a slight skew toward the new moon, but this visualization is not great due to how the feature is set up. The feature is more useful for modleing than visualiing.

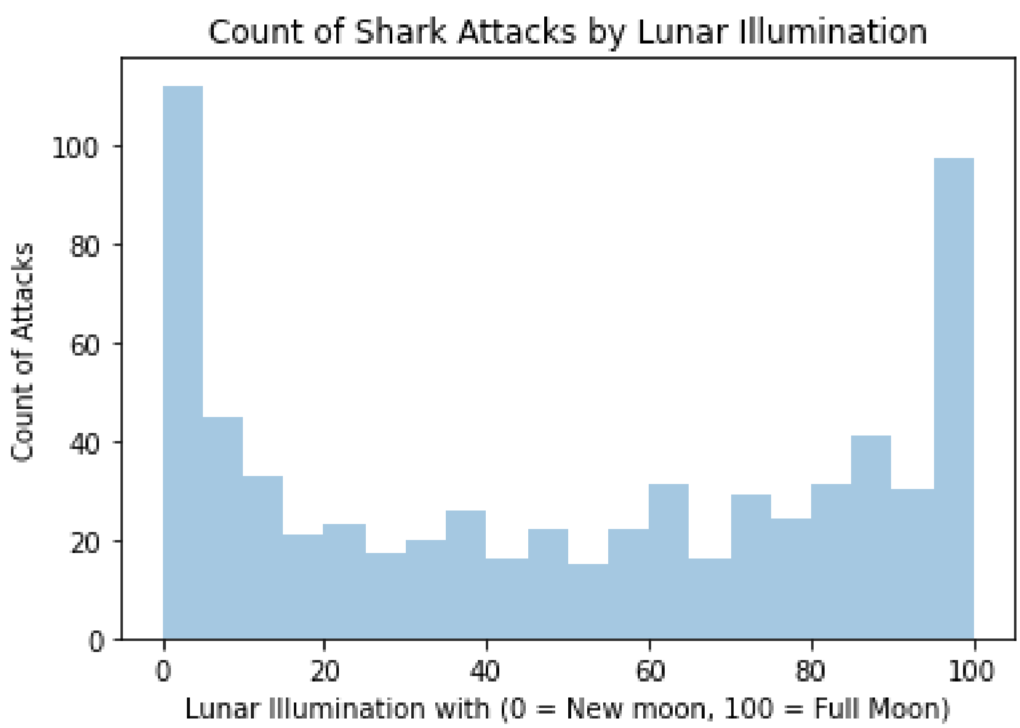
As you can see in the seccond graphic, I mapped the count of attacks by the lunar illumination percentage. This chart is interesting, but it can be decieving, because it looks as though we have a very large skew toward new moons and full moons. While this seems to be the case, the reality is that if you were to also chart the lunar illumination by time, you would see a simmilar breakdown.

So, all that to say, I believe the final visual to be most telling. It shows the shark attack occurences by buketized versions of the lunar phases (first quarter, full, last quarter, and new moon). As you can see in the data, there seems to be a slight skew toward the new moon, but we cannot tell from this visualization alone whether that skew is significant or not. That is what our modeling will be for

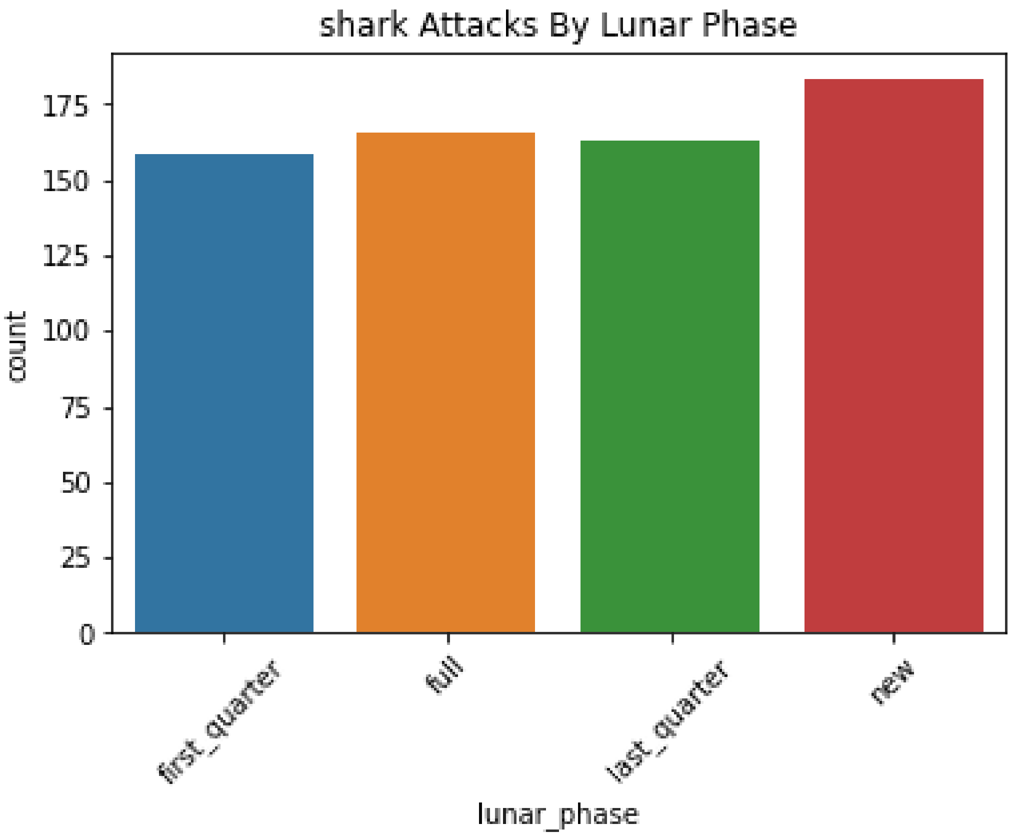
[22]:
```
plt.figure()
sns.distplot(df_clean['lunar_illumination_phase'].dropna(), bins = 20, kde =␣
 ↪False )
plt.xlabel("Lunar Illumination with (0 = New Moon, 0.5 = Full, and 1 = New␣
 ↪Moon)")
plt.ylabel("Count of Attacks")
plt.title("Count of Shark Attacks by Lunar Illumination Phase")
plt.show()


plt.figure()
sns.distplot(df_clean['lunar_illumination_pct'].dropna(), bins = 20, kde =␣
 ↪False)
plt.xlabel("Lunar Illumination with (0 = New moon, 100 = Full Moon)")
plt.ylabel("Count of Attacks")
plt.title("Count of Shark Attacks by Lunar Illumination")
plt.show()

# plt.figure()
# sns.countplot(x = 'closest_phase', data = df_clean, order=␣
 ↪sorted(df_clean['closest_phase'].dropna().unique()))
# plt.xticks(rotation = 45)
# plt.title("shark Attacks By Lunar Phase")


plt.figure()
sns.countplot(x = 'lunar_phase', data = df_clean, order=␣
 ↪sorted(df_clean['lunar_phase'].dropna().unique()))
plt.xticks(rotation = 45)
```

```
plt.title("shark Attacks By Lunar Phase")
```





[22]: Text(0.5, 1.0, 'shark Attacks By Lunar Phase')



3.5 Chi-Squared testing on Lunar Phases

Doing a Chi-square test to see if there is significance in moon phase distribustions

As you can see by the results, the p value is quite high (.259). This means that the shark attacks across the lunar phases are not significant enough to tell me that it is more significant than an even spread.

Although my EDA showed that there was a slight skew toward the new moon, it is not significant enough to filter out the noise.

[23]:
```
phase_counter = df_clean['lunar_phase'].value_counts()
obsv = phase_counter.values

expt = [obsv.sum()/len(obsv)]*len(obsv)

chi2, p_value = stats.chisquare(f_obs = obsv, f_exp = expt)
```

```python
print(obsv)
print(expt)
print(chi2)
print(p_value)
```

```
[183 166 163 159]
[167.75, 167.75, 167.75, 167.75]
1.9955290611028316
0.5733351830119464
```

3.6 Bonus Visualizations: Count of Attacks over time and shark attacks vs temperature

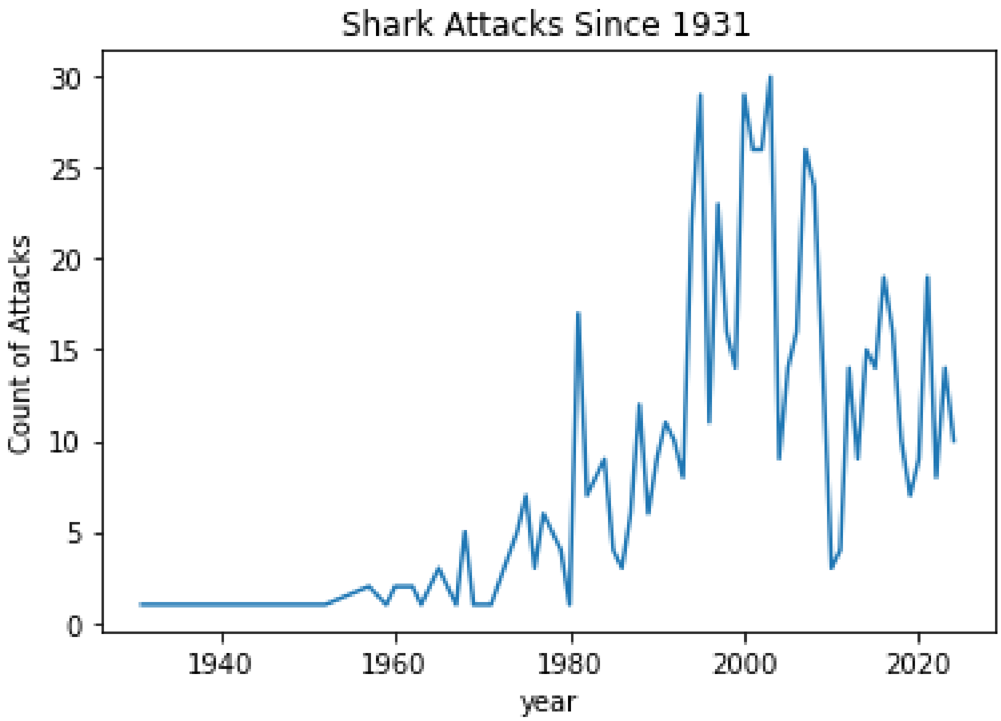
I created a few extra visualizations to see some other interactions that might be intersting to note.

As you can see, the count of shark attacks over time has been increasing. This is a well-known phenomenon and largely attributed to the fact that our global population has grown. More people = more bites. If we were to map this data to the population of Florida, I am sure we would find a similar trend.

Additionally, we have a count of water temperature variance and shark attack occurence. This is an interesting thing to note and something we may come back to later. A skew toward a smaller range of termperatures, but this may just because the majority of Florida seasons involve these temperatures

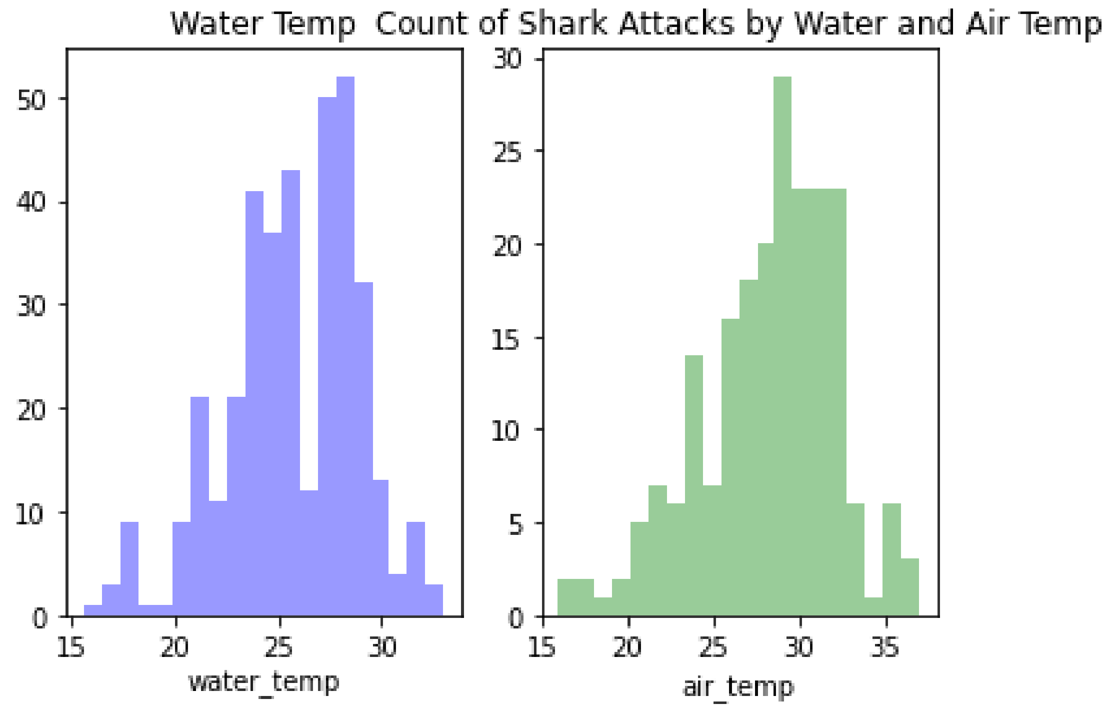
[22]:
```python
plt.figure()
df_clean.groupby('Year').size().plot()
plt.xlabel("year")
plt.ylabel("Count of Attacks")
plt.title("Shark Attacks Since 1931")
```

[22]:
```
Text(0.5, 1.0, 'Shark Attacks Since 1931')
```



[23]:
```
fig = plt.figure()
axes = fig.subplots(1,2)
sns.distplot(df_clean['water_temp'].dropna(), bins = 20, ax = axes[0], color =␣
 ↪"blue", kde = False)
axes[0].set_title("Water Temp")
sns.distplot(df_clean['air_temp'].dropna(), bins = 20, ax = axes[1], color =␣
 ↪"green", kde = False)
axes[1].set_title("Air Temp")
plt.title("Count of Shark Attacks by Water and Air Temp")
plt.show

#Maybe try overlaying month data below air and month temp
```

[23]:
```
<function matplotlib.pyplot.show(*args, **kw)>
```




```
[24]: print(df_clean[['time_bucket', 'time_of_attack_hour', 'month',␣
      ↪'lunar_illumination_frac']].isna().sum())
```

```
time_bucket                 0
time_of_attack_hour        97
month                       0
lunar_illumination_frac     0
dtype: int64
```

3.7 2.5 Bonus: Modeling Shark attack Seasonality via Linear regression

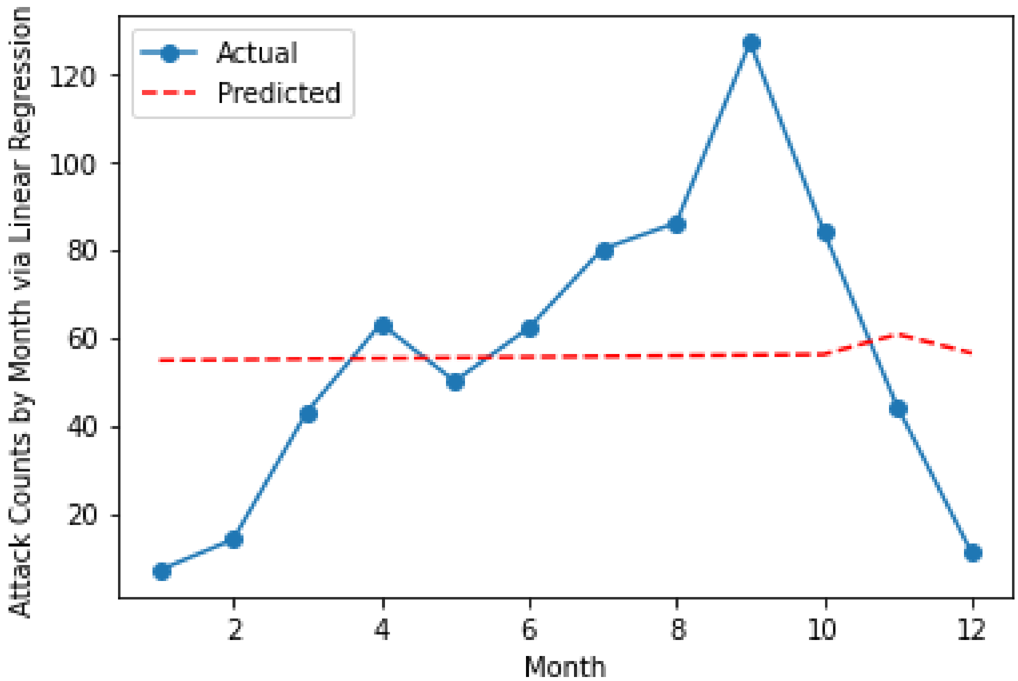
Just out of curiousity, I wanted to create a linear regression model with month predicting shark attack. As you can see below, it is a very deficient model. A single predictor like this is not good enough, and it doesnt fit a linear regression model. I even sin/cos encoded the months to account for a more cyclical action, but this did little to help.

The below model is more of an example of why certain models dont fit certain datasets more than anything else. It shows that the inital thought to use logistic regression for this particular problem is the right one.

```
[25]: monthly_count = df_clean.groupby('month').size().reset_index(name =␣
      ↪'attack_count')

      #monthly_count['month'] = df_clean['month'].copy()
```

```
monthly_count['sin_month'] = np.sin(2*np.pi*monthly_count['month'])
monthly_count['cos_month'] = np.cos(2*np.pi*monthly_count['month'])

X = monthly_count[['sin_month', 'cos_month']]
y = monthly_count['attack_count']

model_linear = LinearRegression()
model_linear.fit(X, y)

print(model_linear.coef_)
print(model_linear.intercept_)

monthly_count['pred'] = model_linear.predict(X)

plt.figure()
plt.plot(monthly_count['month'], monthly_count['attack_count'], 'o-', label␣
 ↪='Actual')
plt.plot(monthly_count['month'], monthly_count['pred'], 'r--', label␣
 ↪='Predicted')

plt.xlabel('Month')
plt.ylabel('Attack Counts by Month via Linear Regression')
plt.legend()
plt.show()

monthly_count.info()
```

```
[-6.17507605e+14  0.00000000e+00]
54.56793138810292
```




```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12 entries, 0 to 11
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   month         12 non-null     int64
 1   attack_count  12 non-null     int64
 2   sin_month     12 non-null     float64
 3   cos_month     12 non-null     float64
 4   pred          12 non-null     float64
dtypes: float64(3), int64(2)
memory usage: 608.0 bytes
```

4 3. Modeling Temporal Data Mapped to Shark Attack Occurences via Logistic Regression

Modeling Approach

Logistic Regression

When approaching how to model this problem, the nature of the what is being modeled was assessed. In this case, the outcome that was to be predicted was binary, whether a shark attack occurred or not based on the predictor at hand. In this case, logistic regression is a clear choice, as the predicted class in this method of supervised learning is a binary case.

Accounting for Non-Shark Attack Occurrences (Negative Events)

After selecting logistic regression as the method of supervised learning to solve this problem, one main issue arose, which is the absence of negative cases. The data involved in this project is confirmed shark attack occurrences, and we do not have confirmed non-occurrences. This seems a silly distinction to make, as this is an obvious thought. There would be no point in recording non-shark attack occurrences, because they happen every day all around the world. The reason it is important is that the model will have to somehow account for these negative events.

To do so, the solution implemented in this particular project was the creation of synthetic negatives. Synthetic negatives allow one to account for all the non-shark attack occurrences. A reasonable question to ask would be: Wouldn't the synthetic negatives just represent the entire date-length of the dataset where attacks didn't occur (e.g. in this case, that would be every non-shark attack month, day, hour since 1931)? Unfortunately, one cannot feed a model this number of negative events, as shark attacks are such rare occurrences, the amount of non-attack occurrences are so large it greatly outweighs the attack occurrences. In this case, an equal length of data is sufficient to remove the model bias that would be had if one were to overwhelm it with negative events.

[39]:
```
df_pos = df_clean[['date_at_location', 'time_of_attack_hour']].copy()
df_pos = df_pos[df_pos['time_of_attack_hour']>= 0]
df_pos['attack_binary'] = 1

df_pos['month'] = df_pos['date_at_location'].dt.month


# df_pos['lunar_illumination_frac'] = df_pos['date_at_location'].
↪apply(moon_phase)
# df_pos['lunar_phase'] = df_pos['date_at_location'].apply(moon_phase_norm)

df_pos['lunar_illumination_phase']= df_pos['date_at_location'].apply(moon_phase)
df_pos['lunar_illumination_frac'] = df_pos['lunar_illumination_phase'].
↪apply(illuminationfrac)
df_pos['lunar_phase']= df_pos['lunar_illumination_phase'].apply(moon_phase_norm)


neg_date_range = pd.date_range(df_clean['date_at_location'].min(),␣
↪df_clean['date_at_location'].max(), freq = 'D')
neg_dates = np.random.choice(neg_date_range, len(df_pos), replace = True)

neg_hours = np.random.randint(0,24, size = len(df_pos))


df_neg = pd.DataFrame({'date_at_location': neg_dates,
                      'time_of_attack_hour': neg_hours,
                     'attack_binary': 0 })

df_neg['month'] = df_neg['date_at_location'].dt.month
```

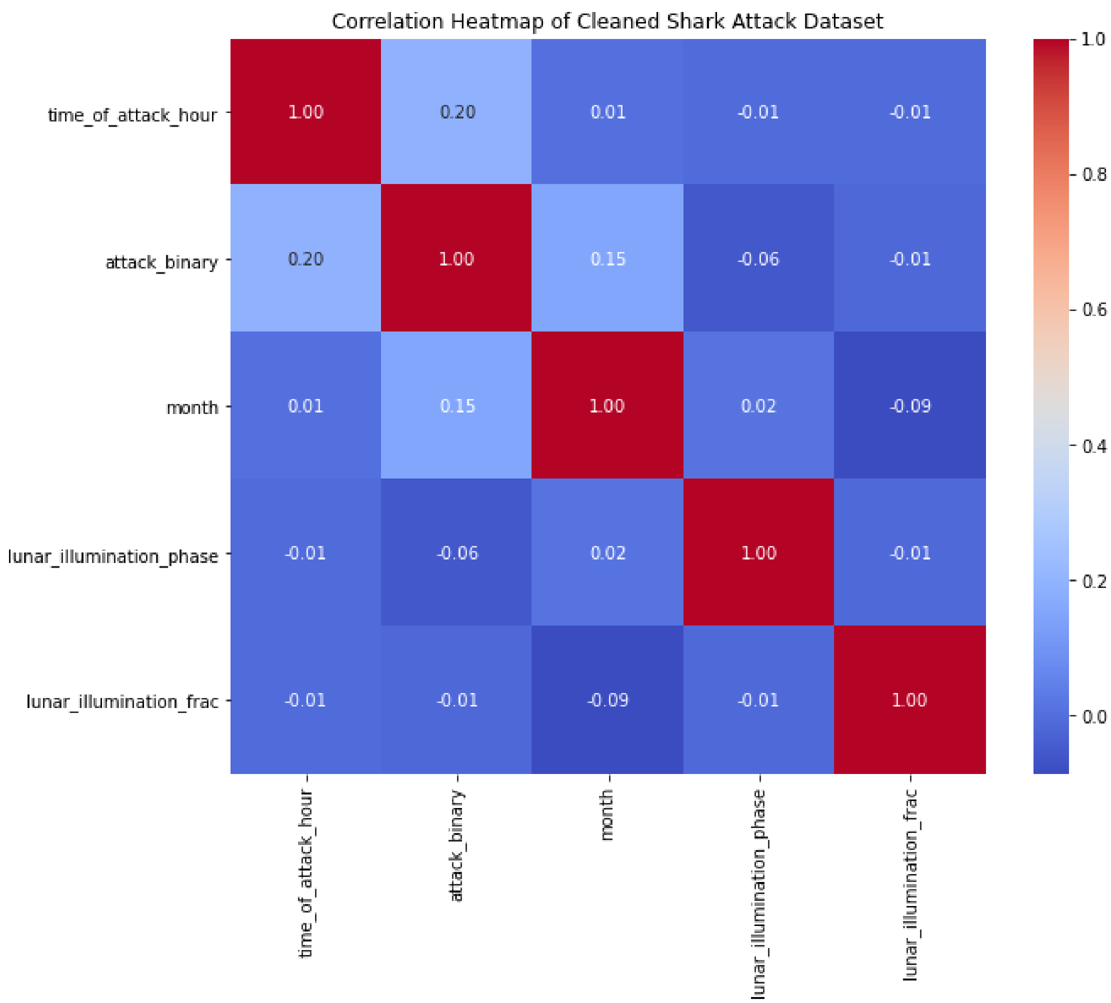
```
# df_neg['lunar_illumination_frac'] = df_neg['date_at_location'].
↪apply(moon_phase)
# df_neg['lunar_phase'] = df_neg['lunar_illumination_frac'].
↪apply(moon_phase_norm)


df_neg['lunar_illumination_phase']= df_neg['date_at_location'].apply(moon_phase)
df_neg['lunar_illumination_frac'] = df_neg['lunar_illumination_phase'].
↪apply(illuminationfrac)
df_neg['lunar_phase']= df_neg['lunar_illumination_phase'].apply(moon_phase_norm)



df_model = pd.concat([df_pos, df_neg], ignore_index = True)

print(df_model.groupby('attack_binary').size())
```

```
attack_binary
0    574
1    574
dtype: int64
```

4.1 Correlation Heatmap for DF_Model

Now it looks like we have some significant results from our correlation heatmap with the synthetic negatives added in. There seems to be a correlation between attack binary (shark attack or not) and month, as well as hour. It should be noted that this is a point-biserial correlation (correlation between linear and binary values), so the correlation may not look as high as it actually is. The models below will prove out whether these are strong indicators or not

[40]:
```
plt.figure(figsize=(10, 8))
sns.heatmap(df_model.select_dtypes(include = ["number"]).corr(),
            annot = True, cmap = "coolwarm", fmt = ".2f", cbar = True)

plt.title("Correlation Heatmap of Model Datafame Shark Attack Data")
plt.show()
```



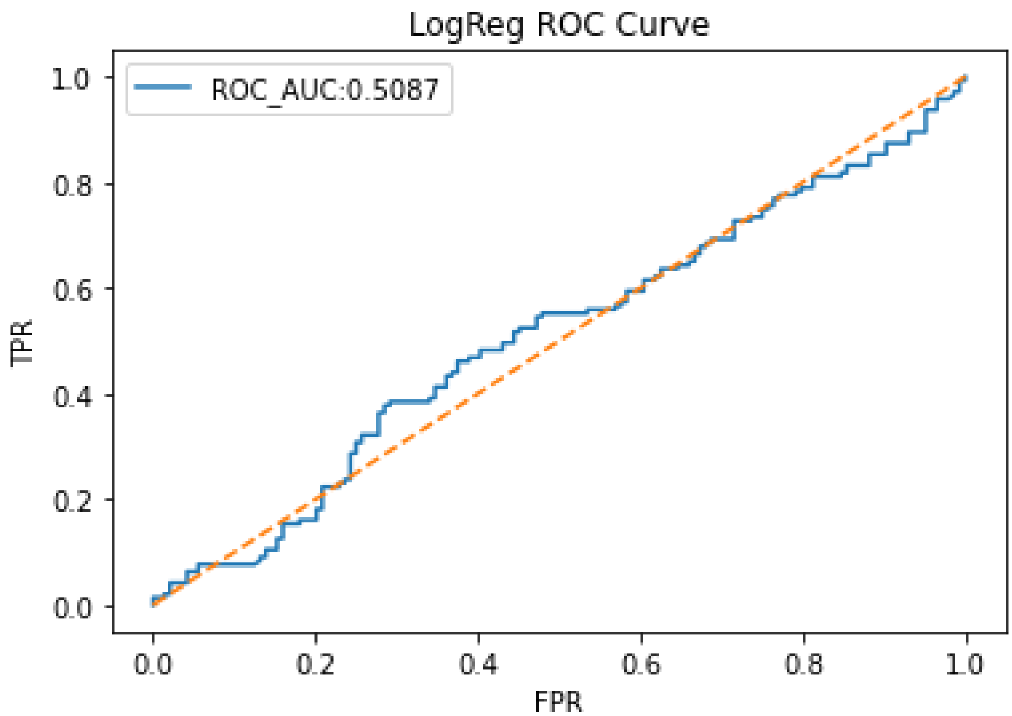
4.2 Logistic Regression: Shark Attack Occurrence ~ Lunar Illumination

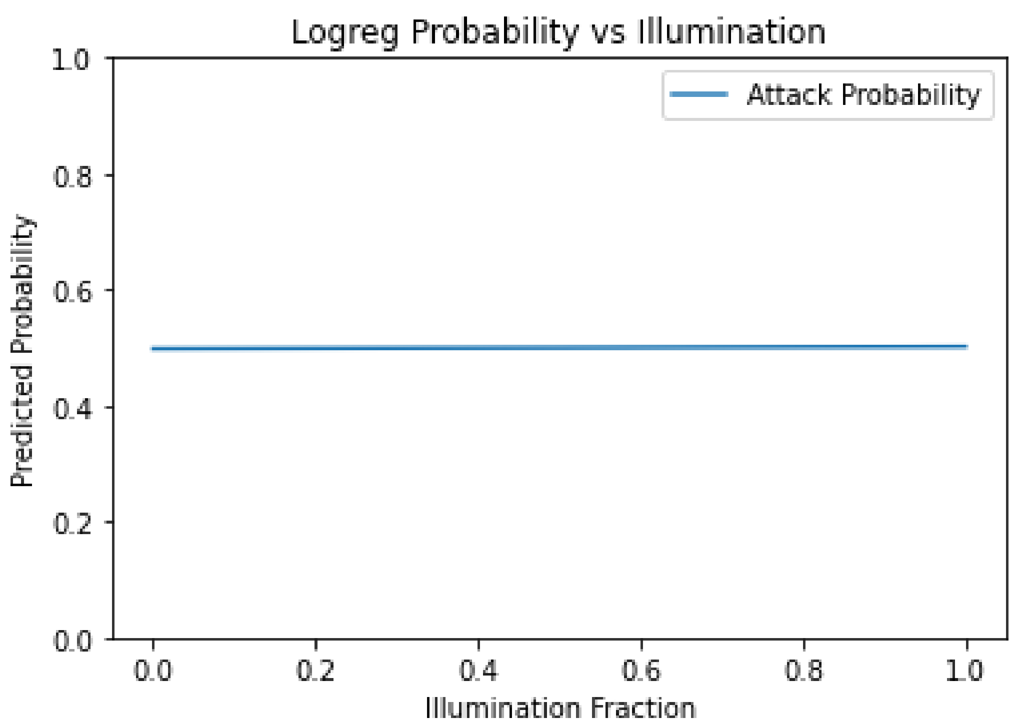
As you can see, the results of our logistic regression below for lunar illumination on the attack ocurrence were not strong. I would not say this is a strong predictor of attack occurence

[74]:
```
X = df_model[['lunar_illumination_frac']]
y = df_model['attack_binary']

X_train, X_test, y_train, y_test = train_test_split(X, y , test_size = 0.25,
 ↪stratify = y, random_state = 42)

model = LogisticRegression(max_iter = 1000, class_weight = 'balanced')
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
```

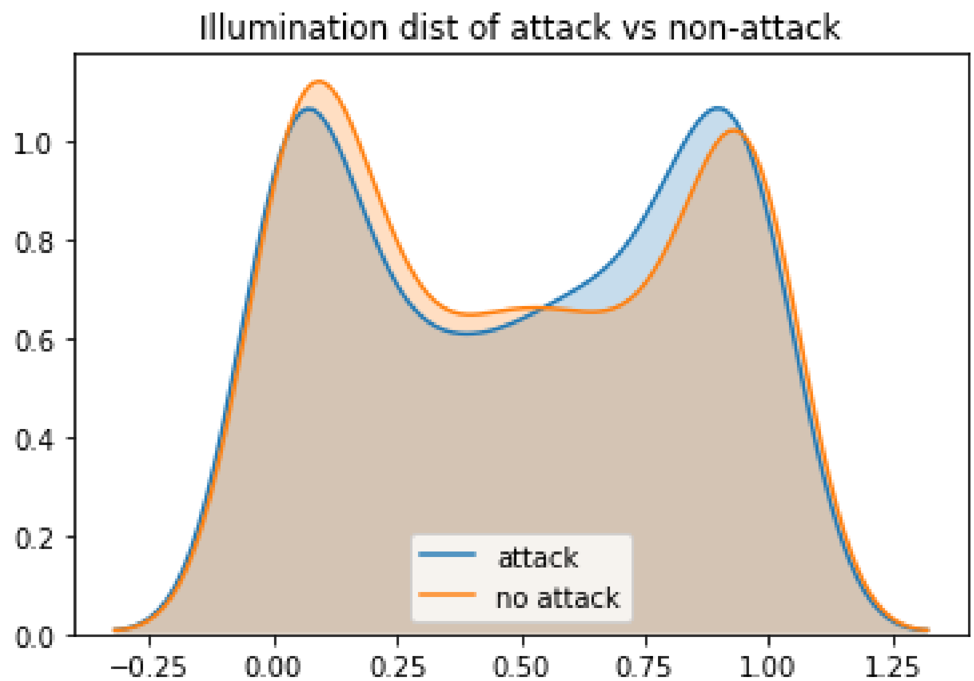
```python
y_prob = model.predict_proba(X_test)[:, 1]

print(classification_report(y_test, y_pred))
print("ROC_AUC:", roc_auc_score(y_test, y_prob))

print("Intercept is ", model.intercept_)
print("Coefficient is ", model.coef_)

fpr, tpr, thresholds = roc_curve(y_test, y_prob)

plt.figure()
plt.plot(fpr, tpr, label = f"ROC_AUC:{roc_auc_score(y_test, y_prob):.4f}")
plt.plot([0,1], [0,1], linestyle = "--")
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('LogReg ROC Curve')
plt.legend()
plt.show()

range_ = np.linspace(0,1,100).reshape(-1,1)
prob = model.predict_proba(range_)[:,1]
plt.xlabel('Illumination Fraction')
plt.ylabel('Predicted Probability')
plt.title('Logreg Probability vs Illumination')
plt.ylim(0,1)
plt.plot(range_, prob, label = 'Attack Probability')
plt.legend()
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.54      0.51      0.52       144
           1       0.53      0.55      0.54       143

    accuracy                           0.53       287
   macro avg       0.53      0.53      0.53       287
weighted avg       0.53      0.53      0.53       287

ROC_AUC: 0.5087412587412588
Intercept is  [-0.00738919]
Coefficient is  [[0.01505197]]
```


LogReg ROC Curve
ROC_AUC:0.5087
TPR
FPR
0.0
0.2
0.4
0.6
0.8
1.0


Logreg Probability vs Illumination
Attack Probability
Predicted Probability
Illumination Fraction
0.0
0.2
0.4
0.6
0.8
1.0

[75]:
```
attack = df_model['attack_binary'] == 1
noattack = df_model['attack_binary'] == 0


sns.kdeplot(data = df_model.loc[attack, 'lunar_illumination_frac'], shade =␣
 ↪True, label = 'attack')
sns.kdeplot(data = df_model.loc[noattack, 'lunar_illumination_frac'], shade =␣
 ↪True, label = 'no attack')
plt.title("Illumination dist of attack vs non-attack")
plt.legend()
plt.show()
```



4.3 Logistic Regression: Shark Attack Occurrence ~ Month of Attack

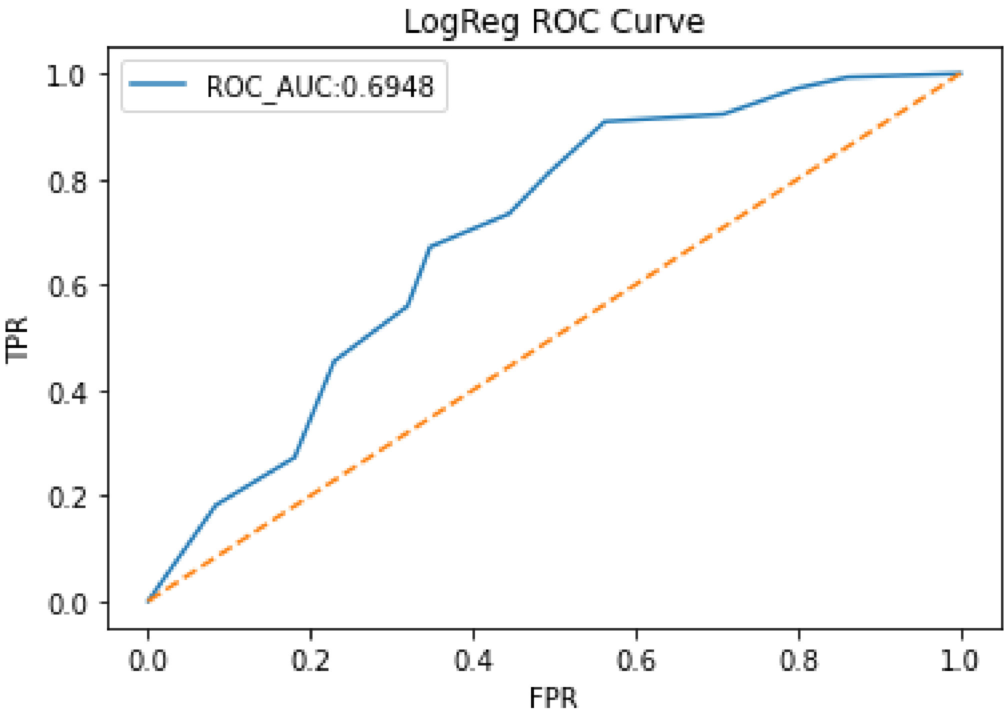
Now looking at the monthly logistic regression model, this is a better indicator than lunar illumination. Looking at the predicted probabilities graph below, one can see that there is a higher predicted probability in the summer/fall months 6-10. You also can see that I had to use sin and cos encoding due to the cylical nature of monthly data

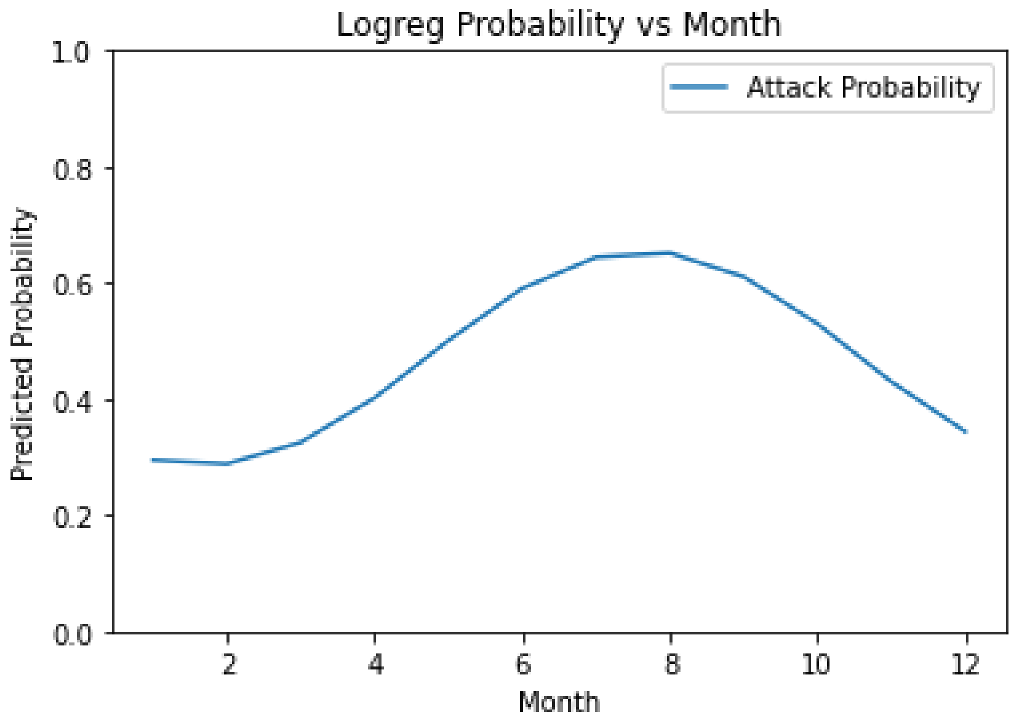
[76]:
```
df_model['month_sin'] = np.sin(2*np.pi*df_model['month']/12)
df_model['month_cos'] = np.cos(2*np.pi*df_model['month']/12)

X = df_model[['month_sin', 'month_cos']]
```

```
y = df_model['attack_binary']

X_train, X_test, y_train, y_test = train_test_split(X, y , test_size = 0.25,␣
 ↪stratify = y, random_state = 42)

model = LogisticRegression(max_iter = 1000, class_weight = 'balanced')
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
y_prob = model.predict_proba(X_test)[:, 1]

print(classification_report(y_test, y_pred))
print("ROC_AUC:", roc_auc_score(y_test, y_prob))

print("Intercept is ", model.intercept_)
print("Coefficient is ", model.coef_)

fpr, tpr, thresholds = roc_curve(y_test, y_prob)

plt.figure()
plt.plot(fpr, tpr, label = f"ROC_AUC:{roc_auc_score(y_test, y_prob):.4f}")
plt.plot([0,1], [0,1], linestyle = "--")
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('LogReg ROC Curve')
plt.legend()
plt.show()

range_ = np.linspace(1,12,12).reshape(-1,1)
month_sin = np.sin(2*np.pi*range_/12)
month_cos = np.cos(2*np.pi*range_/12)
xp = np.c_[month_sin, month_cos]
prob = model.predict_proba(xp)[:,1]
plt.xlabel('Month')
plt.ylabel('Predicted Probability')
plt.title('Logreg Probability vs Month')
plt.ylim(0,1)
plt.plot(range_, prob, label = 'Attack Probability')
plt.legend()
plt.show()
```

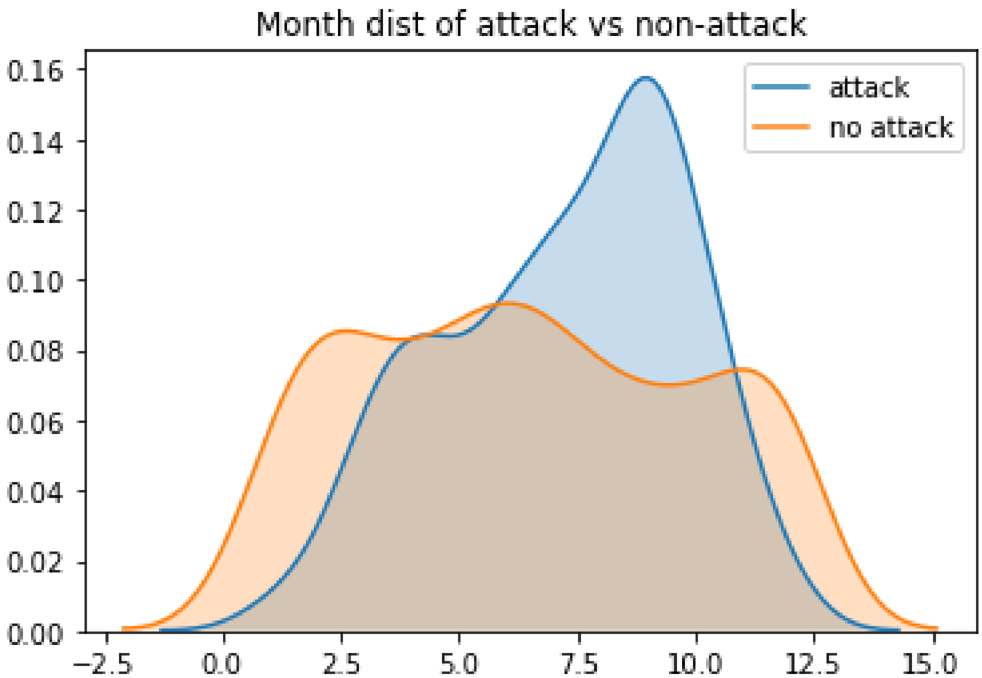
```
              precision    recall  f1-score   support

           0       0.68      0.56      0.61       144
           1       0.62      0.73      0.67       143

    accuracy                           0.64       287
```

```
   macro avg       0.65      0.64      0.64       287
weighted avg       0.65      0.64      0.64       287

ROC_AUC: 0.6947843822843823
Intercept is  [-0.14032613]
Coefficient is  [[-0.59029376 -0.50607677]]
```





[77]:
```
attack = df_model['attack_binary'] == 1
noattack = df_model['attack_binary'] == 0


sns.kdeplot(data = df_model.loc[attack, 'month'], shade = True, label =␣
 ↪'attack')
sns.kdeplot(data = df_model.loc[noattack, 'month'], shade = True, label = 'no␣
 ↪attack')
plt.title("Month dist of attack vs non-attack")
plt.legend()
plt.show()
```



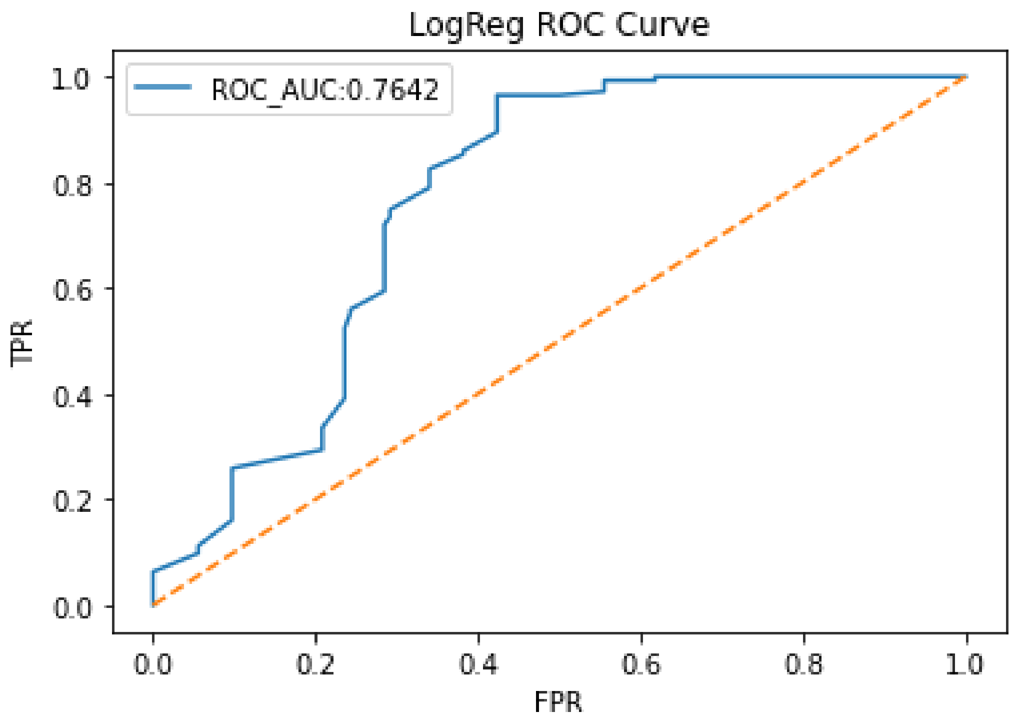
4.4 Logistic Regression: Shark Attack Occurrence ~ Hour of Attack

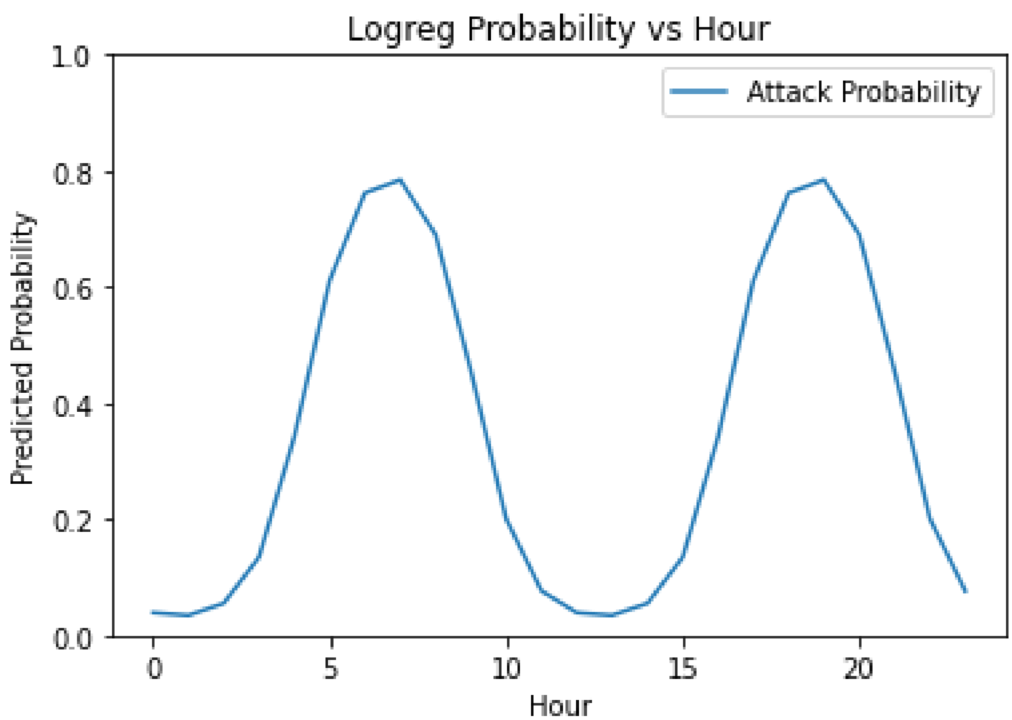
As you can see, the hourly data did yield a high ROC AUC score and seems to be a strong indicator of shark attack occurence. Unfortunately my probability predictions seem a bit innacurate due to the fact that I used sin/cos encoding and we got an assumed two peaks, which is not accurate. This is because sin/cos enforces periodcity. Moving onto the next logistic regression, I decided to bucketize the hours to help with this accuracy.

[78]:
```
df_model['hour_sin'] = np.sin(2*np.pi*df_model['time_of_attack_hour']/24)
df_model['hour_cos'] = np.cos(2*np.pi*df_model['time_of_attack_hour']/24)

X = df_model[['hour_sin', 'hour_cos']]
y = df_model['attack_binary']

X_train, X_test, y_train, y_test = train_test_split(X, y , test_size = 0.25,␣
↪stratify = y, random_state = 42)

model = LogisticRegression(max_iter = 1000, class_weight = 'balanced')
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
y_prob = model.predict_proba(X_test)[:, 1]

print(classification_report(y_test, y_pred))
```

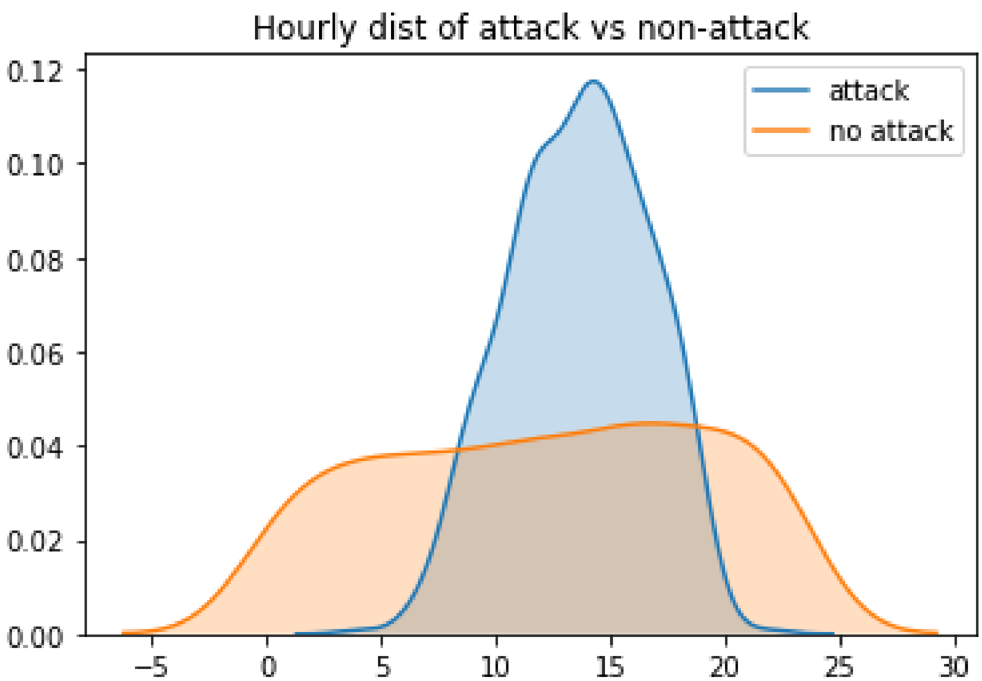
```python
print("ROC_AUC:", roc_auc_score(y_test, y_prob))

print("Intercept is ", model.intercept_)
print("Coefficient is ", model.coef_)

fpr, tpr, thresholds = roc_curve(y_test, y_prob)

plt.figure()
plt.plot(fpr, tpr, label = f"ROC_AUC:{roc_auc_score(y_test, y_prob):.4f}")
plt.plot([0,1], [0,1], linestyle = "--")
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('LogReg ROC Curve')
plt.legend()
plt.show()

range_ = np.arange(0,24)
hour_sin = np.sin(2*np.pi*range_/12)
hour_cos = np.cos(2*np.pi*range_/12)
xp = np.c_[hour_sin, hour_cos]
prob = model.predict_proba(xp)[:,1]
plt.xlabel('Hour')
plt.ylabel('Predicted Probability')
plt.title('Logreg Probability vs Hour')
plt.ylim(0,1)
plt.plot(range_, prob, label = 'Attack Probability')
plt.legend()
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.79      0.66      0.72       144
           1       0.70      0.82      0.76       143

    accuracy                           0.74       287
   macro avg       0.74      0.74      0.74       287
weighted avg       0.75      0.74      0.74       287

ROC_AUC: 0.7642288267288266
Intercept is  [-1.01823709]
Coefficient is  [[-0.84152096 -2.18175898]]
```


LogReg ROC Curve
ROC_AUC:0.7642
TPR
FPR
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0


Logreg Probability vs Hour
Attack Probability
Predicted Probability
Hour
1.0
0.8
0.6
0.4
0.2
0.0
0
5
10
15
20

[79]:
```
attack = df_model['attack_binary'] == 1
noattack = df_model['attack_binary'] == 0


sns.kdeplot(data = df_model.loc[attack, 'time_of_attack_hour'], shade = True,␣
 ↪label = 'attack')
sns.kdeplot(data = df_model.loc[noattack, 'time_of_attack_hour'], shade = True,␣
 ↪label = 'no attack')
plt.title("Hourly dist of attack vs non-attack")
plt.legend()
plt.show()
```



4.5 Logistic Regression: Shark Attack Occurrence ~ Hourly Bucket (Time of Day)

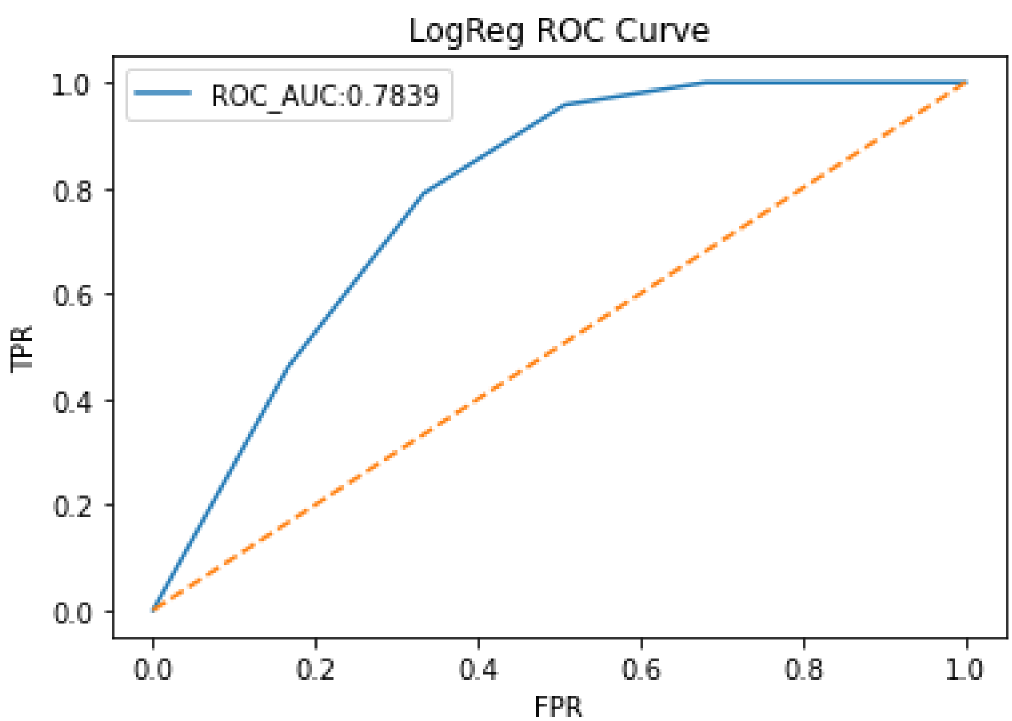
For this model, I bucketed the hours into 5 different categories: Night, morning, mid-day, afternoon, evening, night. As you can see, I split the day categories in to 4 groups evenly, and then had the night as a large bucket by itself that is 2x the size as the other buckets. The reasoning behind this is because there are very few beachgoers in the evening, so it doesnt make sense for it to have the same weight as the other categories.

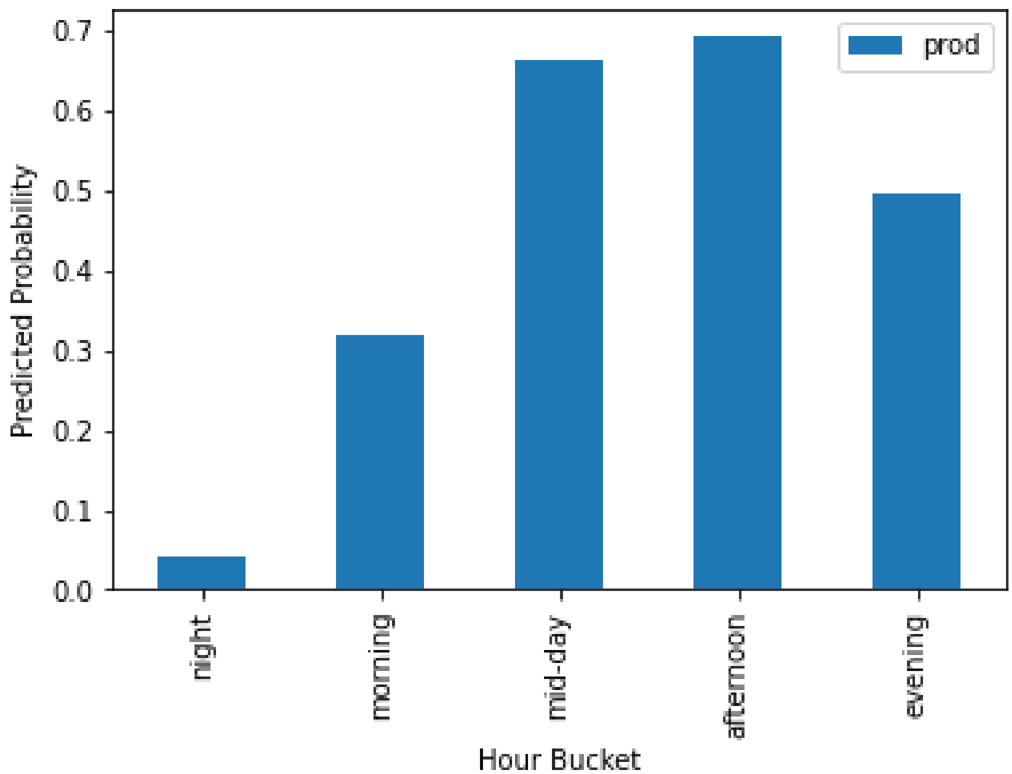
[80]:
```
def new_hour_bucket(hr):
    if 5<= hr <9:
```

```python
        return 'morning'
    if 9<= hr <13:
        return 'mid-day'
    if 13<= hr <17:
        return 'afternoon'
    if 17<= hr <21:
        return 'evening'
    else:
        return 'night'

df_model['hour_bucket'] = df_model['time_of_attack_hour'].apply(new_hour_bucket)


X = pd.get_dummies(df_model[['hour_bucket']], drop_first=True)
y = df_model['attack_binary']

X_train, X_test, y_train, y_test = train_test_split(X, y , test_size = 0.25,␣
 ↪stratify = y, random_state = 42)

model = LogisticRegression(max_iter = 1000, class_weight = 'balanced')
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
y_prob = model.predict_proba(X_test)[:, 1]

print(classification_report(y_test, y_pred))
print("ROC_AUC:", roc_auc_score(y_test, y_prob))

print("Intercept is ", model.intercept_)
print("Coefficient is ", model.coef_)

fpr, tpr, thresholds = roc_curve(y_test, y_prob)

plt.figure()
plt.plot(fpr, tpr, label = f"ROC_AUC:{roc_auc_score(y_test, y_prob):.4f}")
plt.plot([0,1], [0,1], linestyle = "--")
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('LogReg ROC Curve')
plt.legend()
plt.show()


prob = model.predict_proba(X)[:,1]
df_plot = pd.DataFrame({'bucket': df_model['hour_bucket'], 'prod':prob})
df_plot.groupby('bucket').mean().reindex(['night', 'morning', 'mid-day',␣
 ↪'afternoon', 'evening']).plot(kind = 'bar')
```

```
plt.xlabel('Hour Bucket')
plt.ylabel('Predicted Probability')
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.76      0.67      0.71       144
           1       0.70      0.79      0.74       143

    accuracy                           0.73       287
   macro avg       0.73      0.73      0.73       287
weighted avg       0.73      0.73      0.73       287

ROC_AUC: 0.7839452214452214
Intercept is  [0.81176111]
Coefficient is  [[-0.83249805 -0.13858556 -1.56351051 -3.98673338]]
```





4.6 Logistic Regression: Shark Attack Occurrence ~ Lunar Phase

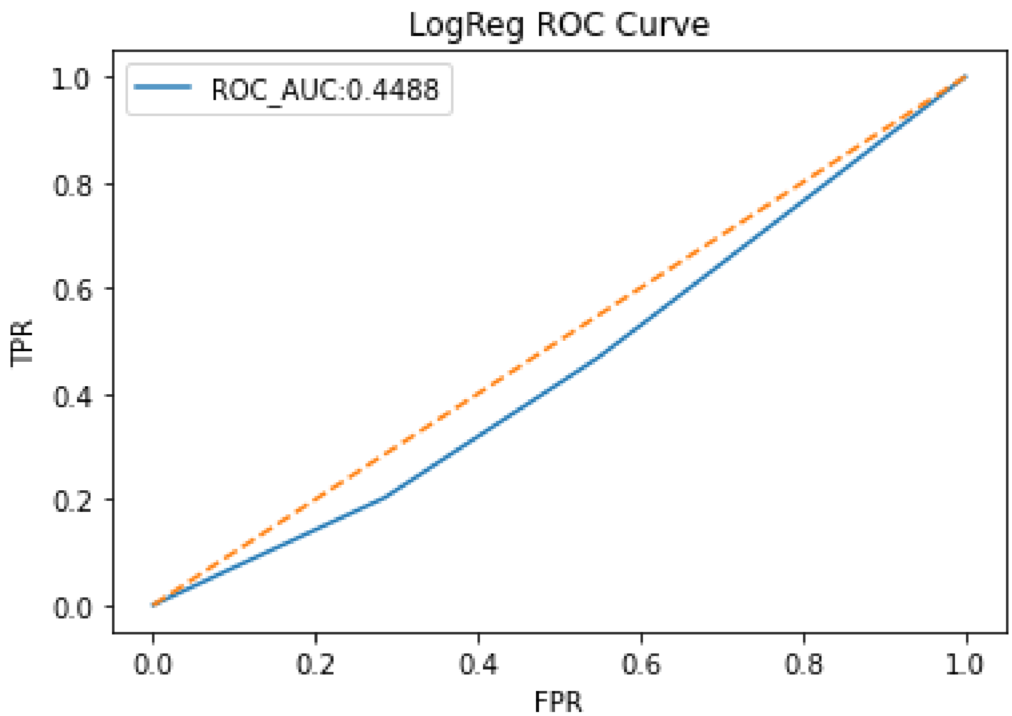
Since I had some success bucketting the hourly data, I am going to try and do the same with the lunar illumination data, and used my already bucketted version of this: the Lunar Phases (First Quarter, Full, Last Quarter, New).

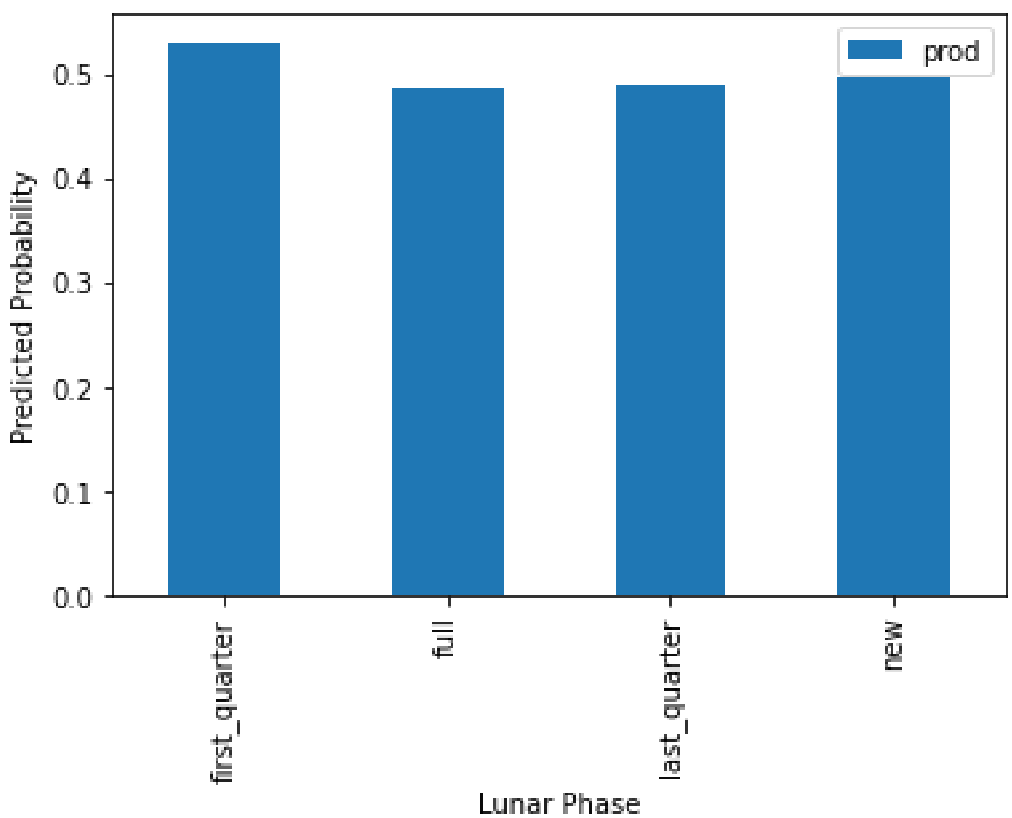
As you can see below, the results were quite insignificant. Although we saw a slight skew toward the New Moon in our EDA, you can see below that the Logistic Regression did not confirm this difference to be significant.

[81]:
```
X = pd.get_dummies(df_model[['lunar_phase']], drop_first=True)
y = df_model['attack_binary']

X_train, X_test, y_train, y_test = train_test_split(X, y , test_size = 0.25,␣
 ↪stratify = y, random_state = 42)

model = LogisticRegression(max_iter = 1000, class_weight = 'balanced')
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
y_prob = model.predict_proba(X_test)[:, 1]
```

```python
print(classification_report(y_test, y_pred))
print("ROC_AUC:", roc_auc_score(y_test, y_prob))

print("Intercept is ", model.intercept_)
print("Coefficient is ", model.coef_)

fpr, tpr, thresholds = roc_curve(y_test, y_prob)

plt.figure()
plt.plot(fpr, tpr, label = f"ROC_AUC:{roc_auc_score(y_test, y_prob):.4f}")
plt.plot([0,1], [0,1], linestyle = "--")
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('LogReg ROC Curve')
plt.legend()
plt.show()


prob = model.predict_proba(X)[:,1]
df_plot = pd.DataFrame({'Lunar Phase': df_model['lunar_phase'], 'prod':prob})
df_plot.groupby('Lunar Phase').mean().reindex(['first_quarter', 'full',␣
↪'last_quarter', 'new']).plot(kind = 'bar')
plt.xlabel('Lunar Phase')
plt.ylabel('Predicted Probability')
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.47      0.72      0.57       144
           1       0.41      0.20      0.27       143

    accuracy                           0.46       287
   macro avg       0.44      0.46      0.42       287
weighted avg       0.44      0.46      0.42       287

ROC_AUC: 0.4487665112665113
Intercept is  [0.12147801]
Coefficient is  [[-0.1751672  -0.16682189 -0.13025515]]
```


LogReg ROC Curve
ROC_AUC:0.4488
TPR
FPR
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0


prod
Predicted Probability
0.5
0.4
0.3
0.2
0.1
0.0
first_quarter
full
last_quarter
new
Lunar Phase

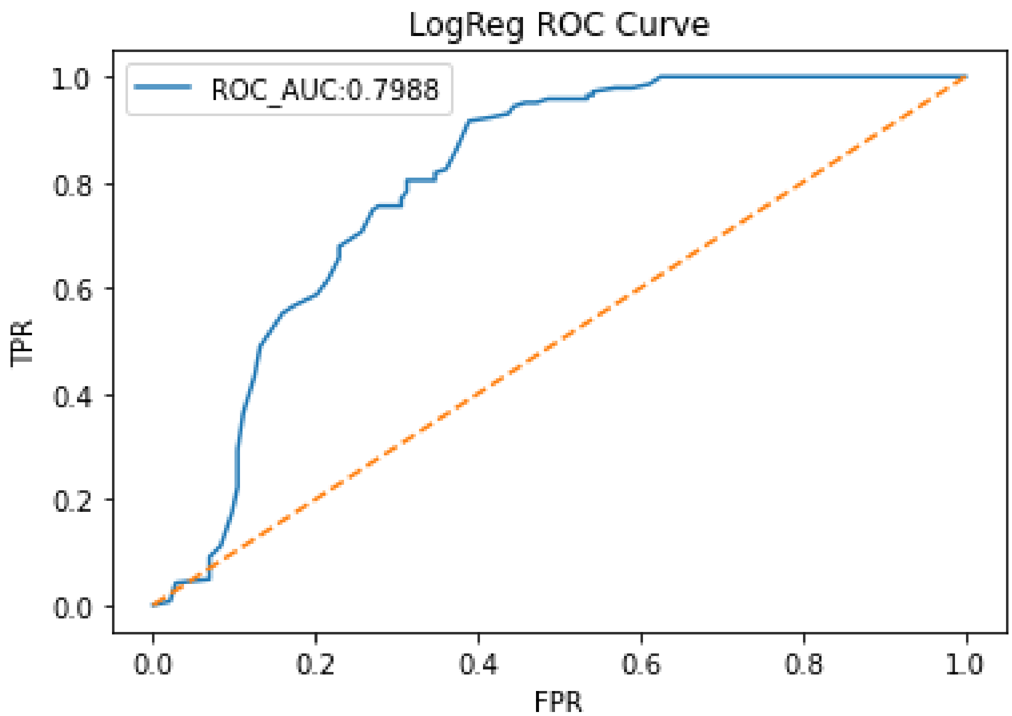
4.7 Logistic Regression: Shark Attack Occurrence ~ Month of Attack + Hourly Bucket (Time of Attack)

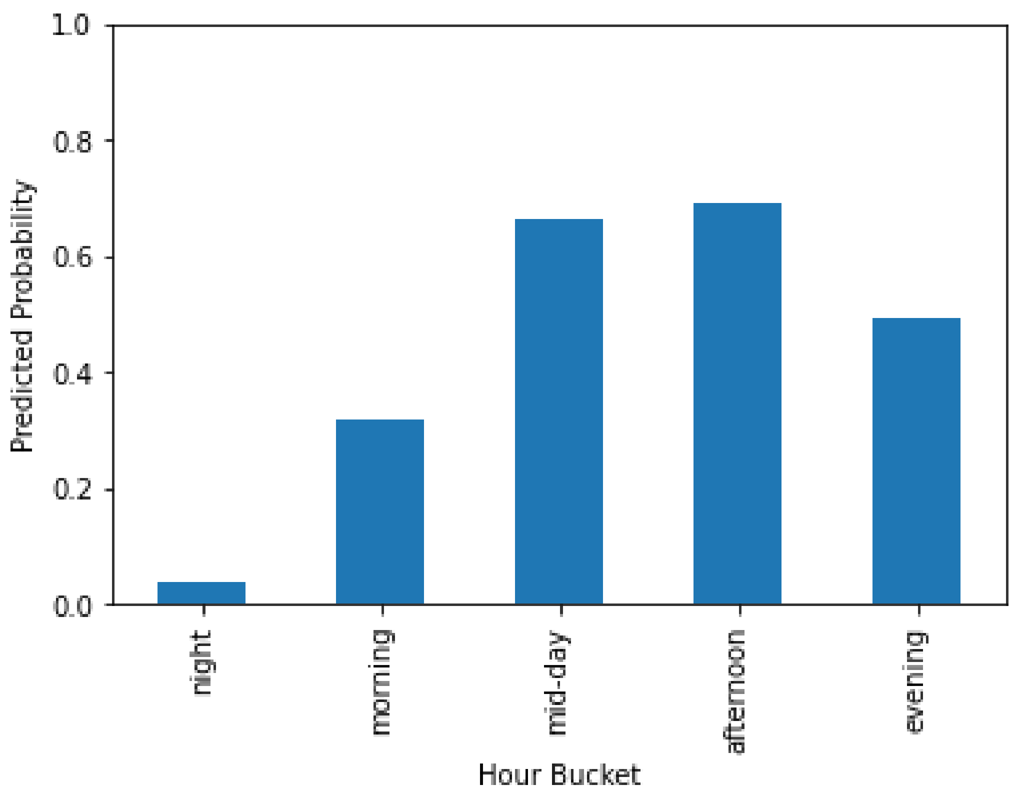
For this final logistic regression model, I wanted to combine Month and the hourly bucket data to see if we could get a significant result. Because those two features alone, showed some promising results, I decided to combine them to see if I could create an enhanced model. The ROC_AUC score was quite significant for this value, so I think this model did yield a significant result, showing both together are strong predictors of an attack occurence. More discussion on this significant result will be had in the Conclusion section

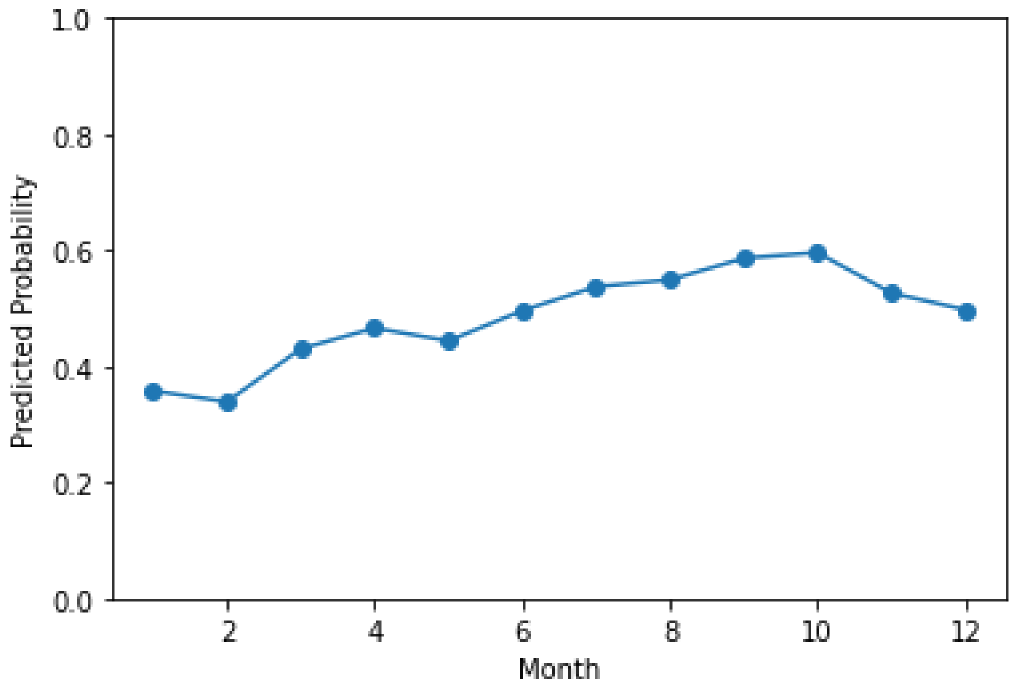
[82]:
```
X = pd.get_dummies(df_model[['month', 'hour_bucket']], drop_first=True)
y = df_model['attack_binary']

X_train, X_test, y_train, y_test = train_test_split(X, y , test_size = 0.25,␣
↪stratify = y, random_state = 42)

model = LogisticRegression(max_iter = 1000, class_weight = 'balanced')
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
y_prob = model.predict_proba(X_test)[:, 1]

print(classification_report(y_test, y_pred))
print("ROC_AUC:", roc_auc_score(y_test, y_prob))

print("Intercept is ", model.intercept_)
print("Coefficient is ", model.coef_)

fpr, tpr, thresholds = roc_curve(y_test, y_prob)

plt.figure()
plt.plot(fpr, tpr, label = f"ROC_AUC:{roc_auc_score(y_test, y_prob):.4f}")
plt.plot([0,1], [0,1], linestyle = "--")
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('LogReg ROC Curve')
plt.legend()
plt.show()


df_model['prob'] =model.predict_proba(X)[:,1]

bucket_ = df_model.groupby('hour_bucket')['prob'].mean()
plt.figure()
```

```python
bucket_.reindex(['night', 'morning', 'mid-day', 'afternoon', 'evening']).
 ↪plot(kind = 'bar')
plt.ylim(0,1)
plt.xlabel('Hour Bucket')
plt.ylabel('Predicted Probability')
plt.show()



month_ = df_model.groupby('month')['prob'].mean()
plt.figure
month_.plot(marker = 'o')
plt.ylim(0,1)
plt.xlabel('Month')
plt.ylabel('Predicted Probability')
plt.show()
```

```
              precision    recall  f1-score   support

           0       0.88      0.61      0.72       144
           1       0.70      0.92      0.79       143

    accuracy                           0.76       287
   macro avg       0.79      0.76      0.76       287
weighted avg       0.79      0.76      0.76       287

ROC_AUC: 0.7988053613053613
Intercept is  [0.25151363]
Coefficient is  [[ 0.08329165 -0.86017853 -0.14383528 -1.60011243 -4.00051617]]
```


LogReg ROC Curve
ROC_AUC:0.7988
1.0
0.8
0.6
0.4
0.2
0.0
TPR
0.0
0.2
0.4
0.6
0.8
1.0
FPR


1.0
0.8
0.6
0.4
0.2
0.0
Predicted Probability
night
morning
mid-day
afternoon
evening
Hour Bucket



5 4. Modeling Pressure and Temperature on Attack Occurence

I got some interesting results with the Temporal data, but now I would like to take the analysis a step further and bring in some weather features, such as pressure and temperature. Below I am pulling in data from meteostat (a weather data library in Python with NOAA station weather data) and merging it in with my original dataframe df_clean

5.1 Meteostat Data Import and Cleansing

[36]:
```
# !pip uninstall -y meteostat
!pip install -q "meteostat==1.6.1"
!pip install "pandas>=1.2,<1.4"
```

```
[notice] A new release of pip is
available: 23.3.2 -> 24.0
[notice] To update, run:
pip install --upgrade pip
Requirement already satisfied: pandas<1.4,>=1.2 in
/opt/conda/lib/python3.7/site-packages (1.3.5)
Requirement already satisfied: python-dateutil>=2.7.3 in
```

```
/opt/conda/lib/python3.7/site-packages (from pandas<1.4,>=1.2) (2.8.1)
Requirement already satisfied: pytz>=2017.3 in /opt/conda/lib/python3.7/site-
packages (from pandas<1.4,>=1.2) (2020.1)
Requirement already satisfied: numpy>=1.17.3 in /opt/conda/lib/python3.7/site-
packages (from pandas<1.4,>=1.2) (1.18.4)
Requirement already satisfied: six>=1.5 in /opt/conda/lib/python3.7/site-
packages (from python-dateutil>=2.7.3->pandas<1.4,>=1.2) (1.14.0)

[notice] A new release of pip is
available: 23.3.2 -> 24.0
[notice] To update, run:
pip install --upgrade pip
```

[37]:
```
from meteostat import Point, Hourly, Stations
```

After importing all data and libraries needed, I am printing all the stations below to see which ones I want to include in my dataset. Ideally I would like bring in all counties that are in df_clean, but because of time and length considerations, I will have to save that for future analysis.

Out of the three counties I see below, I believe my best options are Volusia, Brevard and Duval. All three represent three distinct Atlantic Coast regions in Florida (South, Central, and North Coast), and have a large number of datapoints for me to analyze.

[38]:
```
print(df_clean['county'].value_counts(dropna = False))
```

```
volusia county         322
brevard county         104
palm beach county       66
st. johns county        31
st. lucie county        31
duval county            29
martin county           27
indian river county     19
miami-dade county       14
broward county          13
flagler county           6
nassau county            6
dade county              2
miami-dade               1
Name: county, dtype: int64
```

Here I am printing all the stations that are nearby the county seat of all these counties.

[39]:
```
volusia = Stations().nearby(29.0283, -81.0755)
brevard = Stations().nearby(28.2639, -80.7214)
duval = Stations().nearby(30.3500, -81.6035)

volusia = volusia.inventory('hourly')
brevard = brevard.inventory('hourly')
```

```python
duval = duval.inventory('hourly')

vstations = volusia.fetch(10)
bstations = brevard.fetch(10)
dstations = duval.fetch(10)

print(vstations[[ 'name', 'latitude', 'longitude', 'region']])
print(bstations[['name', 'latitude', 'longitude',  'region']])
print(dstations[[ 'name', 'latitude', 'longitude', 'region']])
```

```
                                                name  latitude  longitude  \
id
KEVB0                     New Smyrna Beach / Isleboro   29.0557   -80.9489
74787          Daytona Beach / Mansfield Mobile Home Park   29.1799   -81.0581
KDED0               Deland / Orangewood Mobile Home Park   29.0670   -81.2837
KOMN0          Ormond Beach / Bear Creek Mobile Home Park   29.3006   -81.1136
KSFB0                        Sanford / Orlando / Midway   28.7767   -81.2355
KXFL0               Palm Coast / Palm Terrace Mobile Manor   29.4674   -81.2063
KTTS0                            Cape Kennedy / Wilson   28.6149   -80.6944
KORL0                            Orlando / Azalea Park   28.5455   -81.3329
KTIX0  Titusville / Manatee Hammock Park Mobile Home …  28.5148  -80.7992
72205                                  Orlando Airport   28.4167   -81.0000

      region
id
KEVB0     FL
74787     FL
KDED0     FL
KOMN0     FL
KSFB0     FL
KXFL0     FL
KTTS0     FL
KORL0     FL
KTIX0     FL
72205     FL
                                                name  latitude  longitude  \
id
74795                     Cocoa / Patrick Air Force Base   28.2333   -80.6000
72204                            Melbourne International   28.1000   -80.6500
74794  Cocoa Beach, Cape Canaveral Air Force Station …  28.4667  -80.5667
KTIX0  Titusville / Manatee Hammock Park Mobile Home …  28.5148  -80.7992
72205                                  Orlando Airport   28.4167   -81.0000
KTTS0                            Cape Kennedy / Wilson   28.6149   -80.6944
YZNBG                     Sebastian Municipal Airport   27.8132   -80.4956
KORL0                            Orlando / Azalea Park   28.5455   -81.3329
KISM0     Orlando / Country Life Family Mobile Home Park   28.2898   -81.4371
74793                                          Gifford   27.6561   -80.4181
```

```
      region
id
74795     FL
72204     FL
74794     FL
KTIX0     FL
72205     FL
KTTS0     FL
YZNBG     FL
KORL0     FL
KISM0     FL
74793     FL
                                                    name  latitude  longitude  \
id
74782          Jacksonville / Hatch Road Mobile Home Park   30.3363   -81.5144
NFUKD                      Jacksonville Naval Air Station   30.2347   -81.6746
KNRB0                                             Mayport   30.3914   -81.4245
KHEG0  Jacksonville / Normandy Estates Mobile Home Co…   30.2778   -81.8059
KNEN0                               Jackson / Mandeville   30.3502   -81.8832
KVQQ0             Jacksonville / Baileys Mobile Home Park   30.2187   -81.8767
KFHB0                     Fernandina Beach / Amelia Island   30.6118   -81.4612
KSGJ0            St Augustine / Kingsley Mobile Home Park   29.9593   -81.3397
K2CB0     Camp Blanding Mil Res(Starke) / Kingsley Beach   29.9669   -81.9832
72206                          Jacksonville International   30.5000   -81.0333

      region
id
74782     FL
NFUKD     FL
KNRB0     FL
KHEG0     FL
KNEN0     FL
KVQQ0     FL
KFHB0     FL
KSGJ0     FL
K2CB0     FL
72206     FL
```

I have chosen the following stations based on their proximity to beaches (where shark attacks happen)

Volusia: KEVB0 New Smyrna Beach / Isleboro 29.0557 -80.9489
Brevard: 74795 Cocoa / Patrick Air Force Base 28.2333 -80.6000
Duval: KNRB0 Mayport 30.3914 -81.4245

[40]:
```
for st_id in ['KEVB0', '74795', 'KNRB0']:
```

```
    data = Hourly(st_id, start = pd.Timestamp("2003-04-08"), end = pd.
↪Timestamp("2003-04-08")).fetch()
    print(st_id)
    print(data.columns)
    print(data[['temp', 'pres', ]].head())
```

```
KEVB0
Index(['temp', 'dwpt', 'rhum', 'prcp', 'snow', 'wdir', 'wspd', 'wpgt', 'pres',
       'tsun', 'coco'],
      dtype='object')
Empty DataFrame
Columns: [temp, pres]
Index: []
74795
Index(['date', 'hour', 'temp', 'dwpt', 'rhum', 'prcp', 'snow', 'wdir', 'wspd',
       'wpgt', 'pres', 'tsun', 'coco'],
      dtype='object')
Empty DataFrame
Columns: [temp, pres]
Index: []
KNRB0
Index(['temp', 'dwpt', 'rhum', 'prcp', 'snow', 'wdir', 'wspd', 'wpgt', 'pres',
       'tsun', 'coco'],
      dtype='object')
            temp    pres
time
2003-04-08  22.8  1017.5
```

Now I am going through and creating a new dataframe that will hold all the hourly meteorological data I want, and then merging it with my shark attack dataset (df_clean).

I should also note here, that I am only taking data from 2001 onward, because the weather data prior to this time can be a bit spotty.

Additionally I am creating 8 new features from the data:

t_detla12- The temperature change from 12 hours past to the time of occurence t_delta24- The temperature change from 24 hours past to the time of occurence p_delta12- The pressure change from 12 hours past to the time of occurence p_delta24- The pressure change from 24 hours past to the time of occurence

t_slope12- The slope of the temperature change from 12 hours past to the time of occurence t_slope24- The slope of the temperature change from 24 hours past to the time of occurence p_slope12- The slope of the pressure change from 12 hours past to the time of occurence p_slope24- The slope of the pressure change from 24 hours past to the time of occurence

I added these features because I was interested to see if not only the pressure and temperature in itself were strong indicators of an attack occurence, but I also wanted to understand if the change in these features could be of significance too.

[41]:
```
county_stat = {'volusia county': 'KEVB0', 'brevard county': '74795', 'duval␣
↪county': 'KNRB0'}

df_a = df_clean[df_clean['county'].str.contains("Volusia|Brevard|Duval", case =␣
↪False)].copy()

df_meteo = []

for county, st_id in county_stat.items():
    subset = df_a[df_a['county'].str.contains(county, case = False)].copy()
    subset = subset[subset['date_at_location']  >= pd.Timestamp("2000-01-01") ]

    if subset.empty:
        continue

    start = subset['date_at_location'].min()
    end = subset['date_at_location'].max()

    meteo = Hourly(st_id, start, end).fetch()
    meteo = meteo.sort_index()

    meteo['t_delta12'] = meteo['temp'].diff(12)
    meteo['t_delta24'] = meteo['temp'].diff(24)
    meteo['p_delta12'] = meteo['pres'].diff(24)
    meteo['p_delta24'] = meteo['pres'].diff(24)

    meteo['t_slope12'] = (meteo['temp'] - meteo['temp'].shift(12))/12
    meteo['t_slope24'] = (meteo['temp'] - meteo['temp'].shift(24))/24
    meteo['p_slope12'] = (meteo['pres'] - meteo['pres'].shift(12))/12
    meteo['p_slope24'] = (meteo['pres'] - meteo['pres'].shift(24))/24

    subset['attack_hour'] = subset['date_at_location'].dt.floor('H')
    meteo_subset = pd.merge(subset, meteo, left_on = 'attack_hour', right_index␣
↪= True, how = 'left')
    meteo_subset['county_match'] = county
    df_meteo.append(meteo_subset)

df_meteo = pd.concat(df_meteo, ignore_index = True)

print(df_meteo[['county_match', 'date_at_location', 'temp', 'pres', 't_delta12',
               't_delta24', 'p_delta12', 'p_delta24']].head(200))
```

```
     county_match date_at_location  temp    pres  t_delta12  t_delta24  \
0    volusia county       2000-06-02   NaN     NaN        NaN        NaN
1    volusia county       2000-06-19   NaN     NaN        NaN        NaN
2    volusia county       2000-07-02   NaN     NaN        NaN        NaN
3    volusia county       2000-07-02   NaN     NaN        NaN        NaN
```

```
4    volusia county       2000-07-04   NaN      NaN         NaN         NaN
..              …                  …    …     …         …         …
195  volusia county       2021-08-14  26.0  1020.0        -3.0        -2.0
196  volusia county       2021-09-05  26.0  1014.0         0.0         0.0
197  volusia county       2021-09-08  27.0  1015.0         1.0         0.0
198  volusia county       2021-09-09  24.0  1013.0        -3.0        -3.0
199  volusia county       2021-09-11  26.0  1016.0         1.0         0.0

     p_delta12  p_delta24
0          NaN        NaN
1          NaN        NaN
2          NaN        NaN
3          NaN        NaN
4          NaN        NaN
..         …         …
195        1.0        1.0
196       -1.0       -1.0
197        1.0        1.0
198       -2.0       -2.0
199        4.0        4.0

[200 rows x 8 columns]
```

Below I am inspecting my final dataframe to see what I have. It looks as though I have a lot of nan values for air temp and pressure. To combat this, I will use bfill and ffill, which will help me backfill (to the nearest hour) any missing weather data.

[42]:
```python
print(len(df_meteo))
print(df_meteo.isna().sum())
#print((df_meteo.isna().mean()*100).round(2))
```

```
284
attack_classification        0
outcome                      0
county                       0
date_at_location             0
Year                         0
time_of_attack               2
victim_activity              0
sunlight_conditions          0
gen_weather                  0
air_temp                   134
water_temp                  99
closest_phase                0
waxing_waning                0
common_name                  0
provocative_acts             0
activity_addenda             0
```

```
outcome_binary                  0
outcome_ternary                 0
time_of_attack_hour            34
time_unknown_flag               0
time_bucket                     0
month                           0
season                          0
hour_sin                       34
hour_cos                       34
lunar_illumination_phase        0
lunar_illumination_frac         0
lunar_illumination_pct          0
lunar_phase                     0
attack_hour                     0
temp                          188
dwpt                          188
rhum                          188
prcp                          234
snow                          284
wdir                          191
wspd                          189
wpgt                          284
pres                          207
tsun                          284
coco                          264
t_delta12                     189
t_delta24                     189
p_delta12                     211
p_delta24                     211
t_slope12                     189
t_slope24                     189
p_slope12                     209
p_slope24                     211
county_match                    0
dtype: int64
```

[43]:

```
df_meteo['p_nan'] = df_meteo['pres'].isna().astype(int)
df_meteo['t_nan'] = df_meteo['temp'].isna().astype(int)

df_meteo2 = df_meteo.groupby('county_match').apply(lambda g: g.ffill().bfill()).
 ↪reset_index(drop = True)
#print(df_meteo2.isna().sum())

df_meteo2['p_nan'] = df_meteo['p_nan'].values
df_meteo2['t_nan'] = df_meteo['t_nan'].values
```

[44]:
```
print(df_meteo2[['temp', 'pres', 't_delta12', 'p_delta12']].describe())
print(df_meteo2['county_match'].value_counts())
```

```
              temp        pres   t_delta12   p_delta12
count   284.000000   284.00000  284.000000  284.000000
mean     25.816549  1015.94507    2.089437   -1.398239
std       2.823145     1.91828    4.898622    1.735280
min      12.000000  1005.00000  -11.000000   -8.200000
25%      24.000000  1016.00000   -1.000000   -2.000000
50%      26.000000  1016.00000    2.000000   -2.000000
75%      29.000000  1016.00000    6.000000   -1.100000
max      29.400000  1022.00000   13.000000   13.200000
volusia county    221
brevard county     45
duval county       18
Name: county_match, dtype: int64
```

5.2 EDA on Pressure and Temperature

Weather Visualizations

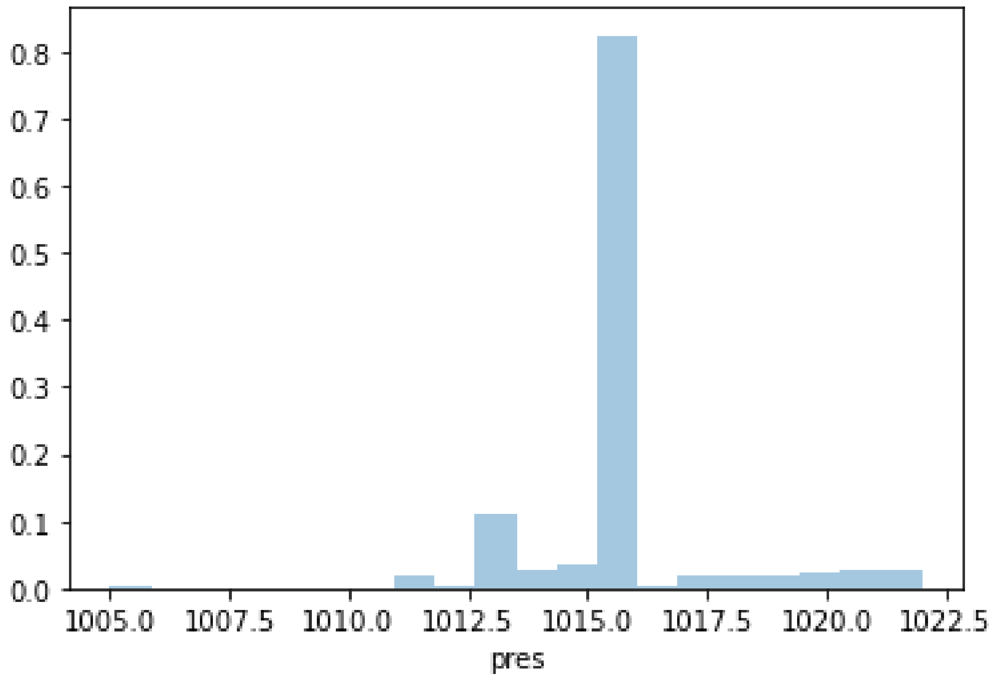
The below visualizations are some significant features that were found to be of note when inspecting the weather data. Data was pulled in from meteostat, which is a python library that contains weather data pulled from NOAA weather stations. With this, a new data byproduct was created, enriching the original shark attack data with meteorological features. A further note regarding this byproduct is that non-attack occurrences were created for comparison to the attack occurrences, but this will be discussed later in this paper.

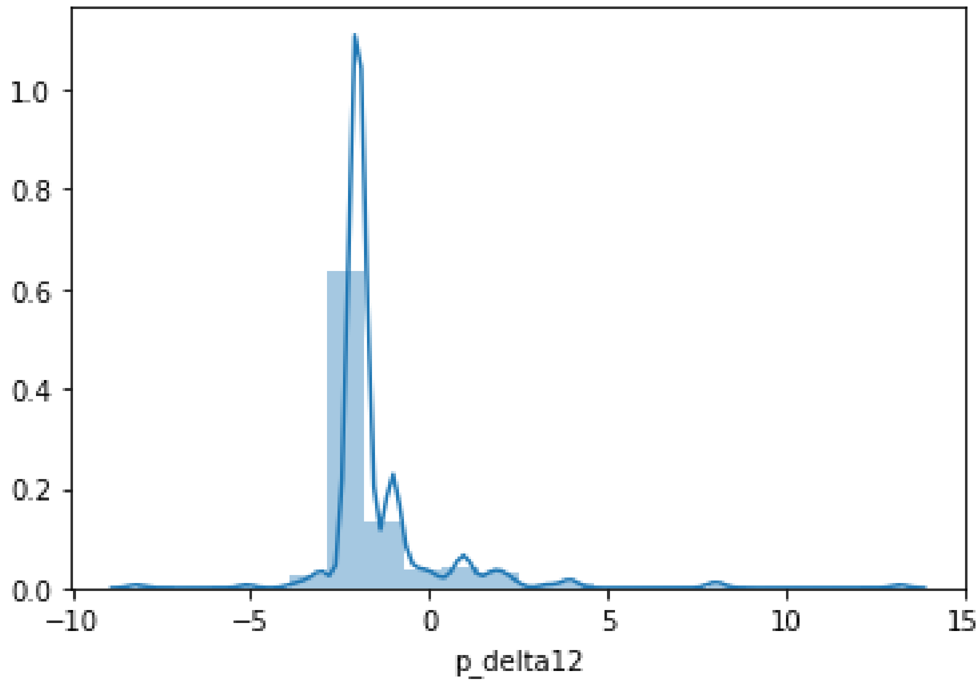
There are some basic box-and-whisker plots that show the distribution of attacks across three different features: temperature, change in pressure, and rate of change (or slope) of pressure. Other features were visualized, but these were the most pertinent to modeling. As one can see by the below visualizations, there is a slight skew toward higher temperature on the attack values vs non-attack values. Additionally, the change in pressure and slope of pressure change give an even slighter skew higher. Moving to the modeling phase, these observations will be tested for their statistical significance.

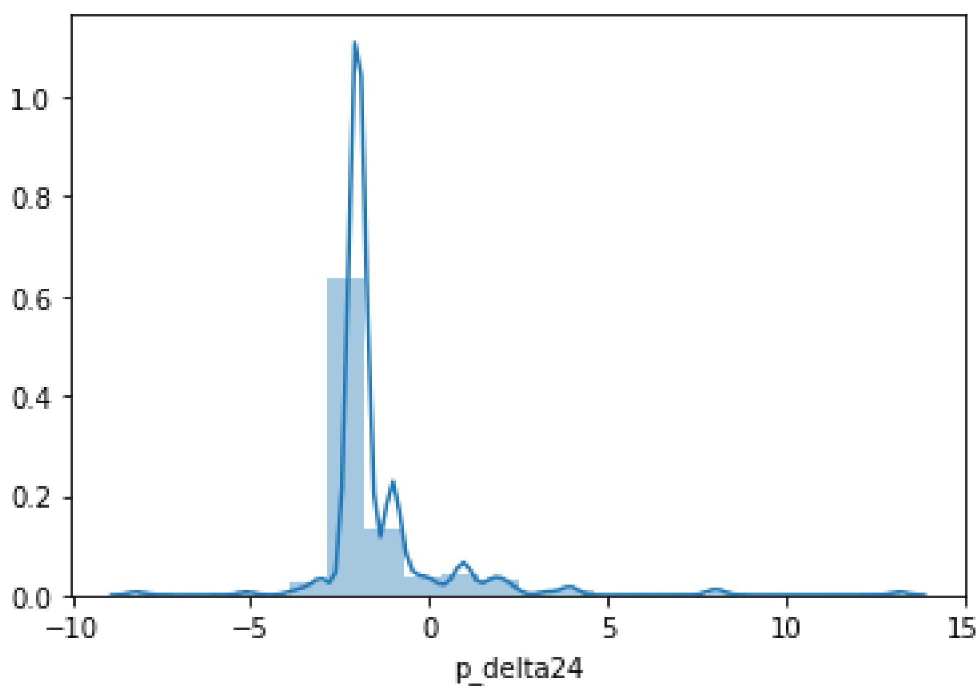
As you can see, just looking at the pressure and time data alone, to identify shark attack occurence, doesnt do much, so I am going to do something similar to what I did before for my Temporal models and create a synthetic negative set that will represent a non-attack occurence.

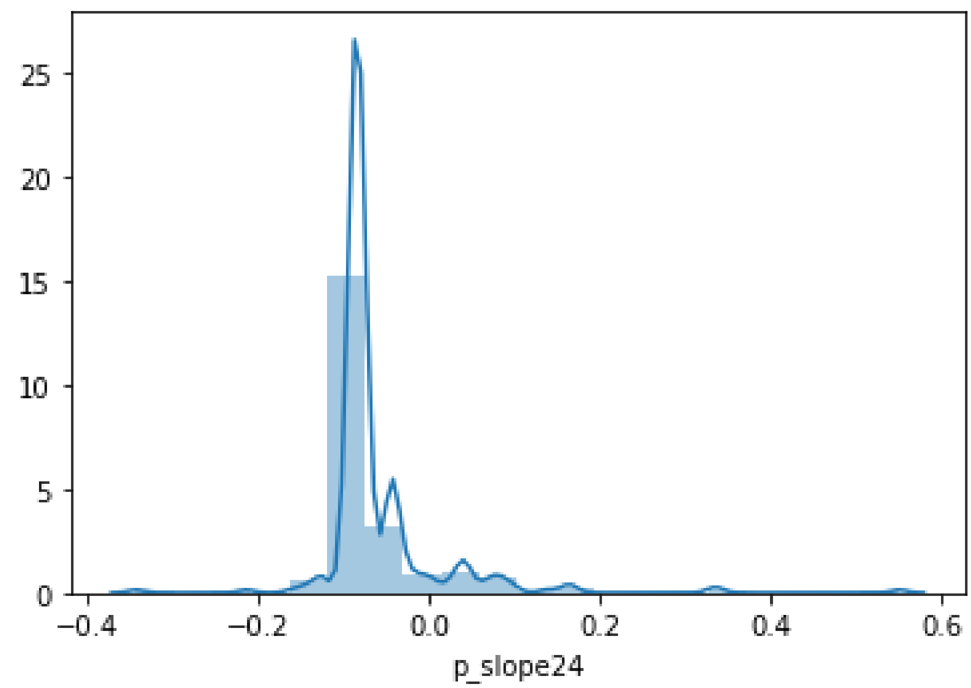
[45]:
```
# sns.distplot(df_meteo2['temp'], bins = 20, kde = True)
# plt.show()

sns.distplot(df_meteo2['pres'], bins = 20, kde = True)
plt.show()

sns.distplot(df_meteo2['p_delta12'], bins = 20, kde = True)
plt.show()
```

```
sns.distplot(df_meteo2['p_delta24'], bins = 20, kde = True)
plt.show()

sns.distplot(df_meteo2['p_slope24'], bins = 20, kde = True)
plt.show()

# sns.distplot(df_meteo2['t_delta12'], bins = 20, kde = True)
# plt.show()
```




1.0
0.8
0.6
0.4
0.2
0.0
−10
−5
0
5
10
15
p_delta12


1.0
0.8
0.6
0.4
0.2
0.0
−10
−5
0
5
10
15
p_delta24



Creating Synthetic Negatives- Weighting Beachgoer Seasonality

To create synthetic negatives the same length as the existing dataset, the simplest approach is to use a random choice function pick non-attack occurrences that are not within the existing dataset. While this is easy to implement, there are some drawbacks to this. For this particular problem, the drawback is that shark attacks only occur when people are present. Furthermore, there are more or less people present at beaches in a) certain times of the year (seasonality) and b) in certain times of the day. If one was to randomly grab days using a random choice function, the randomization would not account for this seasonality and time of day where beachgoers are present.

So, how does one go about normalizing the random choice function to account for beachgoer seasonality? In this instance, data was taken from a publicly accessible dataset created by the University of West Florida in the form of monthly flight inflow data into Florida Coastal airports. Using this data, monthly weights were applied to the randomization to account for the seasonality of beachgoers.

It should be noted, that this weighting is not a perfect representation of when individuals go to the beach, but it does provide a directionally correct indication of beachgoer seasonality. Additionally, although this data is captured on a monthly basis, this particular project did not account for time-of-day (hourly) beach going patterns. This is a note that was created to be implemented in future iterations of this modeling to increase efficacy. Finally, in the case of temporal models, seasonality was not able to be implemented as the synthetic negatives were randomized on an hourly basis to match the dataset. The weather data was specifically where seasonally-adjusted synthetic negatives were implemented. The limitation of the temporal models' synthetic negatives is noted and will fixed for future iterations.

```
[47]: df_2['month'] = pd.to_datetime(df_2['Day of Year']).dt.month

weight_m = df_2.groupby('month')['Airline Passengers'].sum().
 ↪reindex(range(1,13), fill_value =0)
weight_norm = weight_m/weight_m.sum()

print(weight_norm, weight_m)
```

```
month
1     0.060234
2     0.062019
3     0.083680
4     0.086371
5     0.091415
6     0.103811
7     0.104478
8     0.094826
9     0.079498
10    0.087067
11    0.075593
12    0.071008
Name: Airline Passengers, dtype: float64 month
1     3909262
2     4025125
3     5430959
4     5605609
5     5932964
6     6737491
7     6780733
8     6154342
9     5159502
10    5650741
11    4906060
12    4608478
Name: Airline Passengers, dtype: int64
```

After creating my weights above, I now created my synthetic negatives based on those weightings. This allows me to skew the negative occurences (my no-attack values) toward the summer months. Here, after creating these negative occurences, I am joining them to my positive data set. I should note, also, that I am filling the negative occurences with randome weather values from the day I am choosing as well, so that we can compare like features in the positive set.

```
[65]: m= weight_norm.index
w = weight_norm.values

cols = ['date_at_location', 'county_match', 'temp', 'pres', 't_delta12',␣
 ↪'t_delta24', 'p_delta12', 'p_delta24',
        't_slope12', 't_slope24', 'p_slope12', 'p_slope24', 't_nan', 'p_nan']
```

```python
#df_meteo2 = df_meteo2.copy()
df_meteo2['month'] = pd.to_datetime(df_meteo2['date_at_location']).dt.month

df_pos2 = df_meteo2.copy()
df_pos2['attack_binary'] = 1

neg_m = np.random.choice(m, size = len(df_meteo2), p = w)

neg_row = []
for mm in neg_m:
    p = df_meteo2[df_meteo2['month'] == mm]
    if p.empty:
        p = df_meteo2
    r = p.sample(1, replace = True).iloc[0]
    neg_row.append(r[cols + ['month']])

df_neg2 = pd.DataFrame(neg_row).reset_index(drop = True)
df_neg2['attack_binary'] = 0

df_metmodel = pd.concat([df_pos2, df_neg2], ignore_index = True)
print(df_metmodel['attack_binary'].value_counts())
print(df_metmodel.head())
```

```
1    284
0    284
Name: attack_binary, dtype: int64
  attack_classification    outcome           county date_at_location    Year  \
0     unprovoked attack  non-fatal  volusia county       2000-06-02  2000.0
1     unprovoked attack  non-fatal  volusia county       2000-06-19  2000.0
2     unprovoked attack  non-fatal  volusia county       2000-07-02  2000.0
3     unprovoked attack  non-fatal  volusia county       2000-07-02  2000.0
4     unprovoked attack  non-fatal  volusia county       2000-07-04  2000.0

  time_of_attack                  victim_activity sunlight_conditions  \
0          14:55  body surfing, planing on waves            daylight
1          08:30                            wading            daylight
2          17:02        standing still on bottom            daylight
3          14:50        standing still on bottom            daylight
4          18:00                            wading            daylight

                      gen_weather  air_temp  …  p_delta12 p_delta24  \
0                           clear      32.0  …       -2.0      -2.0
1  data insufficient for judgement      32.0  …       -2.0      -2.0
2                      clear/calm      32.0  …       -2.0      -2.0
3  data insufficient for judgement      32.0  …       -2.0      -2.0
4                      clear/calm      32.0  …       -2.0      -2.0
```

```
  t_slope12 t_slope24 p_slope12 p_slope24    county_match  p_nan  t_nan  \
0       0.5       0.0 -0.166667 -0.083333  volusia county      1      1
1       0.5       0.0 -0.166667 -0.083333  volusia county      1      1
2       0.5       0.0 -0.166667 -0.083333  volusia county      1      1
3       0.5       0.0 -0.166667 -0.083333  volusia county      1      1
4       0.5       0.0 -0.166667 -0.083333  volusia county      1      1

   attack_binary
0              1
1              1
2              1
3              1
4              1

[5 rows x 53 columns]
```

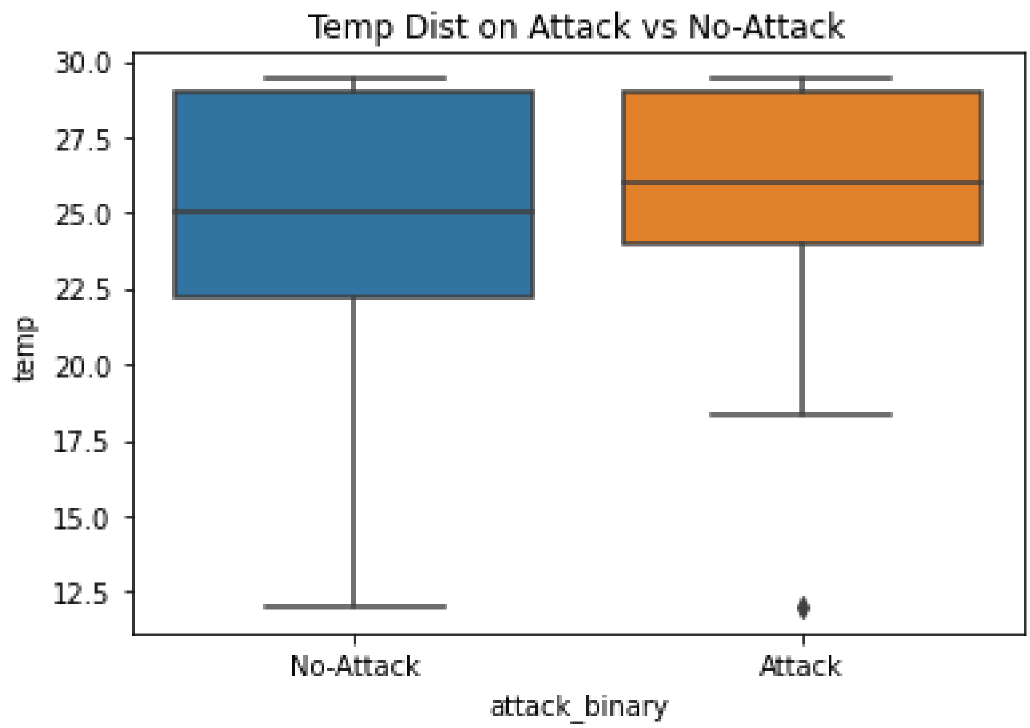
Here I am starting my EDA with the newly added synthetic negatives.

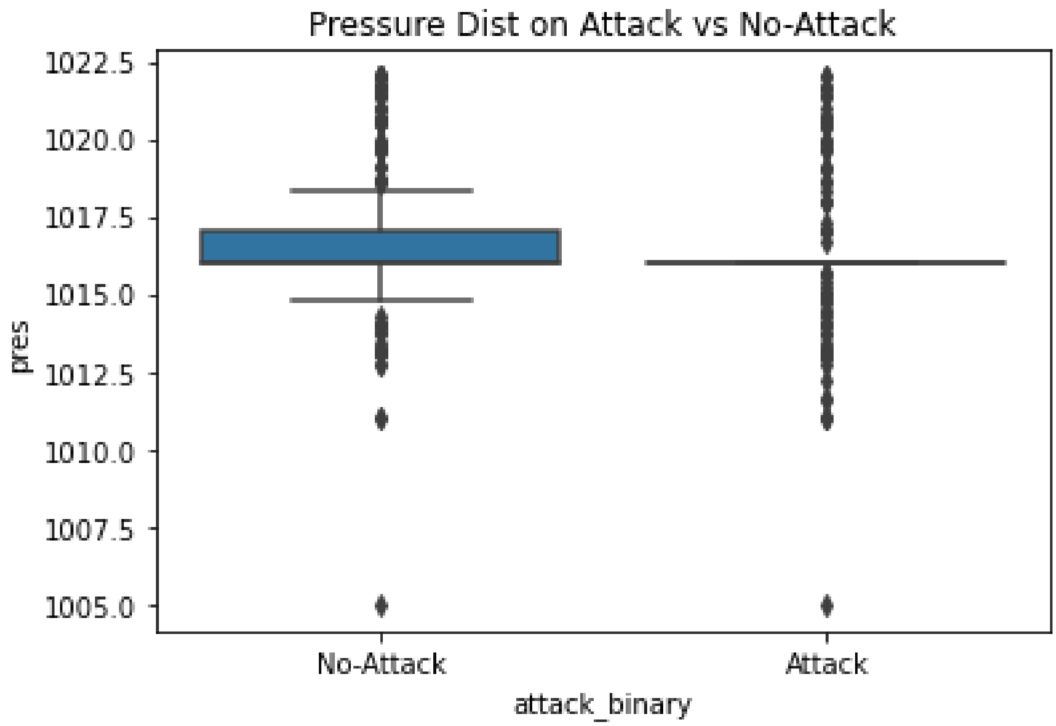
As you can see below, it seems a though there is a slight skew toward higher temperatures for attack occurences, as well as a slight skew toward changes in pressure over a 24 hour span, as well as the slope in the change of pressure over the same 24 hour span.

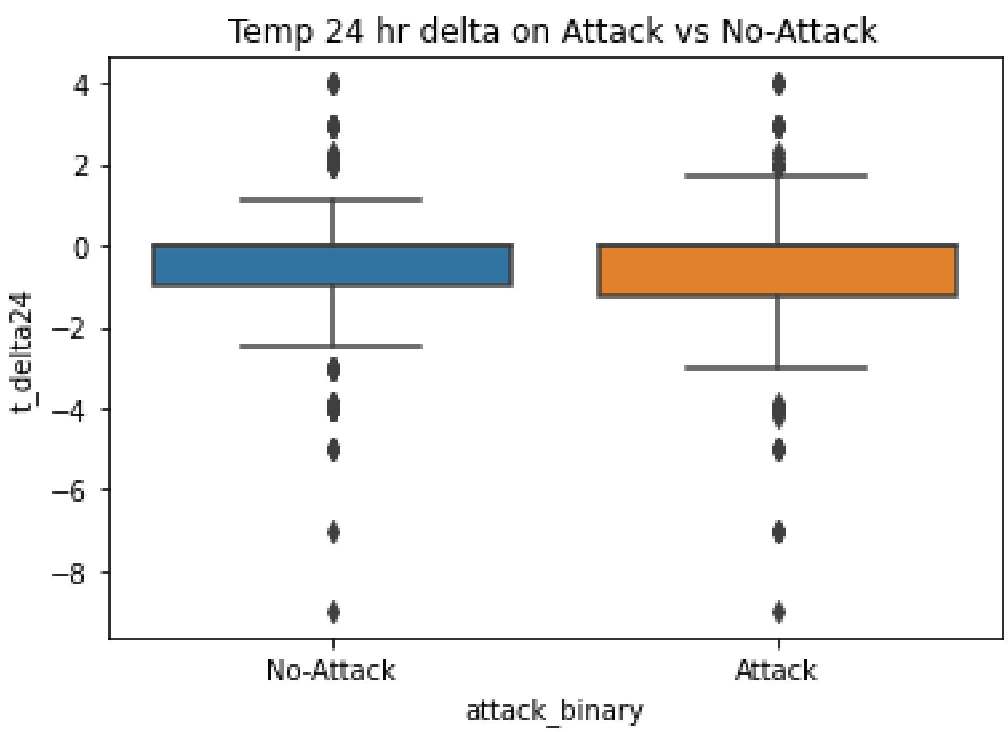
This is an interesting finding to me, and I wonder if we can actually prove that these are strong indicators of an attack vs non-attack in our models. So I will take note of these features for now and include them in my modeling.

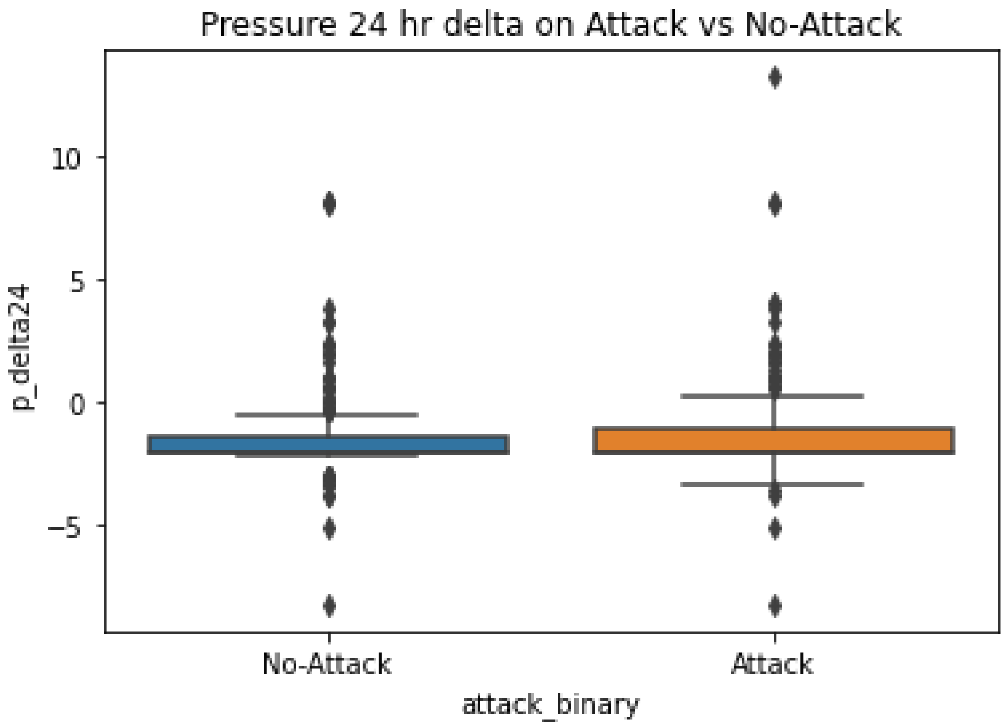
[67]:
```python
plt.figure()
sns.boxplot(x = 'attack_binary', y = 'temp', data = df_metmodel)
plt.xticks([0,1], ['No-Attack', 'Attack'])
plt.title('Temp Dist on Attack vs No-Attack')
plt.show()

plt.figure()
sns.boxplot(x = 'attack_binary', y = 'pres', data = df_metmodel)
plt.xticks([0,1], ['No-Attack', 'Attack'])
plt.title('Pressure Dist on Attack vs No-Attack')
plt.show()

plt.figure()
sns.boxplot(x = 'attack_binary', y = 't_delta24', data = df_metmodel)
plt.xticks([0,1], ['No-Attack', 'Attack'])
plt.title('Temp 24 hr delta on Attack vs No-Attack')
plt.show()

plt.figure()
sns.boxplot(x = 'attack_binary', y = 'p_delta24', data = df_metmodel)
plt.xticks([0,1], ['No-Attack', 'Attack'])
plt.title('Pressure 24 hr delta on Attack vs No-Attack')
```

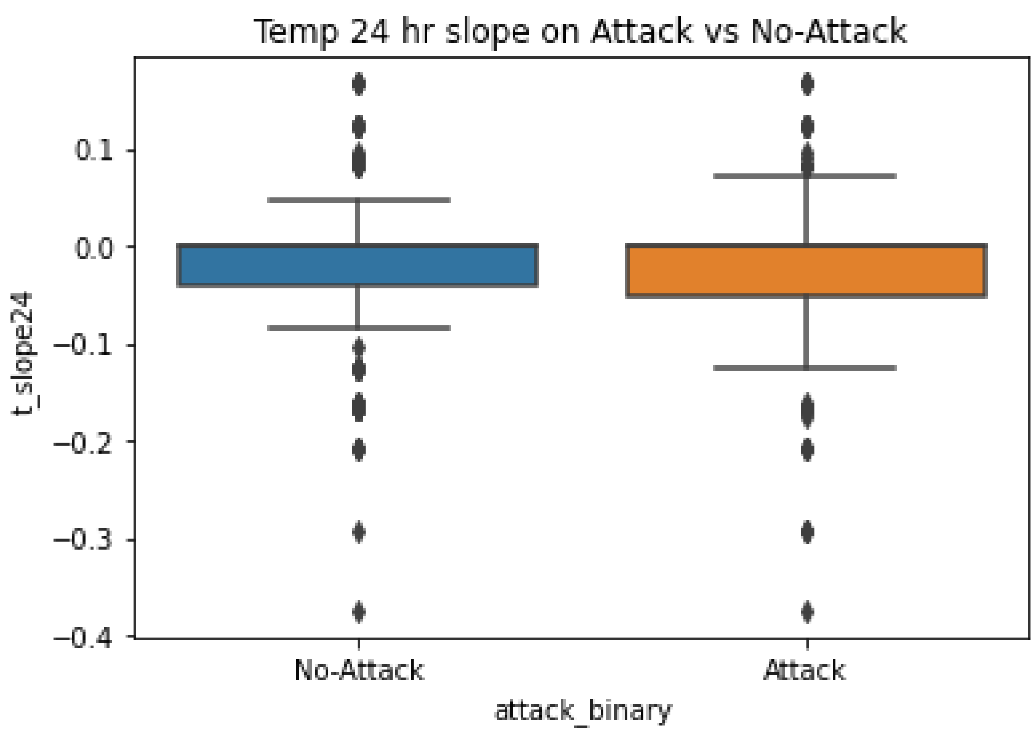
```
plt.show()

plt.figure()
sns.boxplot(x = 'attack_binary', y = 't_slope24', data = df_metmodel)
plt.xticks([0,1], ['No-Attack', 'Attack'])
plt.title('Temp 24 hr slope on Attack vs No-Attack')
plt.show()

plt.figure()
sns.boxplot(x = 'attack_binary', y = 'p_slope24', data = df_metmodel)
plt.xticks([0,1], ['No-Attack', 'Attack'])
plt.title('Pressure 24 hr slope on Attack vs No-Attack')
plt.show()
```

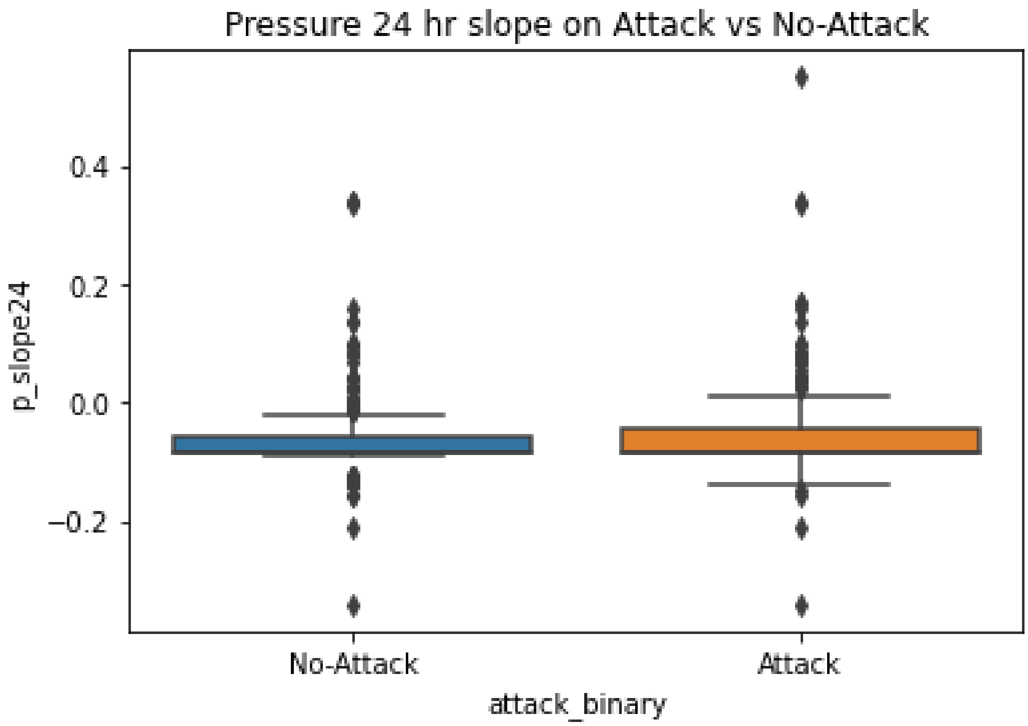



Pressure Dist on Attack vs No-Attack
1022.5
1020.0
1017.5
1015.0
1012.5
1010.0
1007.5
1005.0
pres
No-Attack
Attack
attack_binary


Temp 24 hr delta on Attack vs No-Attack
4
2
0
−2
−4
−6
−8
t_delta24
No-Attack
Attack
attack_binary


Pressure 24 hr delta on Attack vs No-Attack
10
5
0
−5
p_delta24
No-Attack
Attack
attack_binary

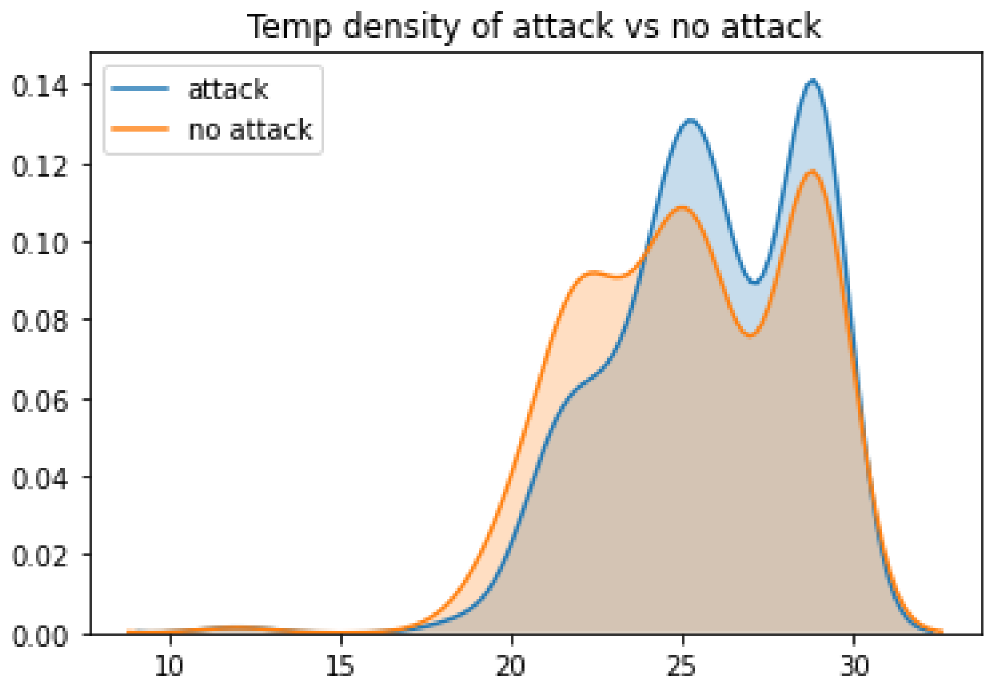

Temp 24 hr slope on Attack vs No-Attack
0.1
0.0
−0.1
−0.2
−0.3
−0.4
t_slope24
No-Attack
Attack
attack_binary

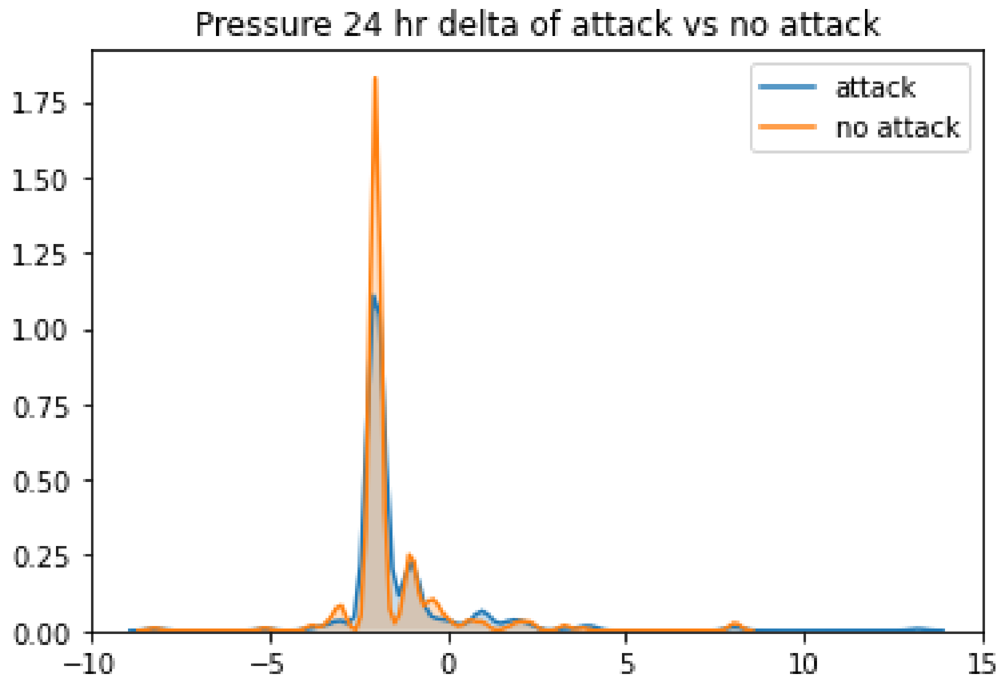


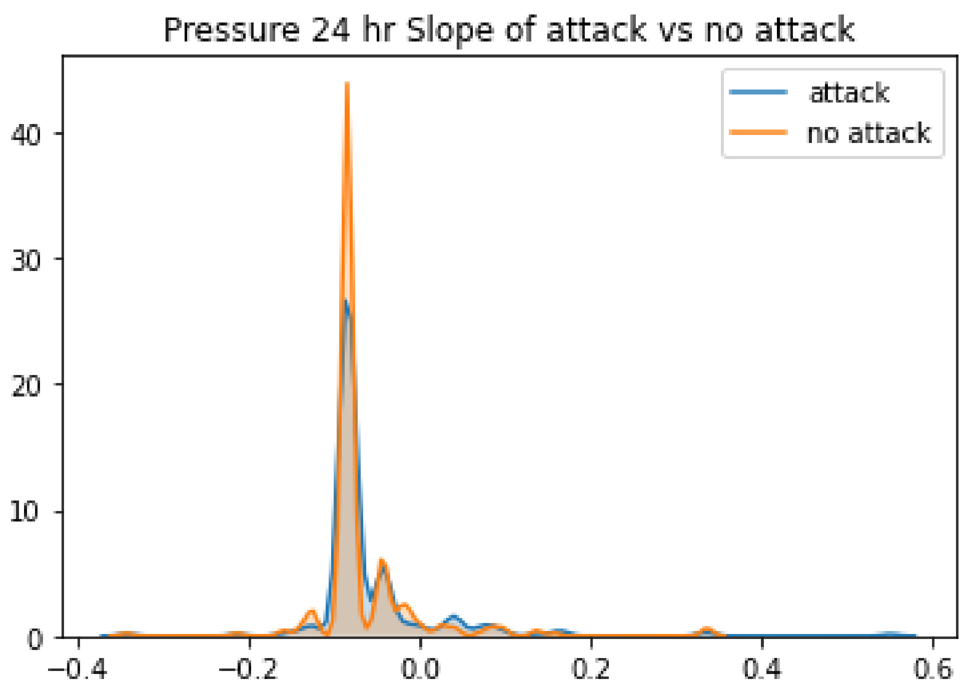
Again, another set of visualizations, this time limited to the three features I have honed in on: temperature, change in pressure over the past 24 hours, as well as the slope of this change. I think we see some variability here between these two features that we can investigate in our models

[68]:
```
plt.figure()
sns.kdeplot(df_metmodel.loc[df_metmodel['attack_binary']==1, 'temp'], label =␣
 ↪'attack', shade = True)
sns.kdeplot(df_metmodel.loc[df_metmodel['attack_binary']==0, 'temp'], label =␣
 ↪'no attack', shade = True)
plt.title('Temp density of attack vs no attack')
plt.legend()
plt.show()

plt.figure()
sns.kdeplot(df_metmodel.loc[df_metmodel['attack_binary']==1, 'p_delta24'],␣
 ↪label = 'attack', shade = True)
sns.kdeplot(df_metmodel.loc[df_metmodel['attack_binary']==0, 'p_delta24'],␣
 ↪label = 'no attack', shade = True)
plt.title('Pressure 24 hr delta of attack vs no attack')
plt.legend()
plt.show()

plt.figure()
```

```
sns.kdeplot(df_metmodel.loc[df_metmodel['attack_binary']==1, 'p_slope24'],␣
 ↪label = 'attack', shade = True)
sns.kdeplot(df_metmodel.loc[df_metmodel['attack_binary']==0, 'p_slope24'],␣
 ↪label = 'no attack', shade = True)
plt.title('Pressure 24 hr Slope of attack vs no attack')
plt.legend()
plt.show()
```




Pressure 24 hr delta of attack vs no attack
attack
no attack
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−10
−5
0
5
10
15


Pressure 24 hr Slope of attack vs no attack
attack
no attack
40
30
20
10
0
−0.4
−0.2
0.0
0.2
0.4
0.6

5.3 Modeling Temperature, 24 Hour Pressure Change, and 24 Hour Pressure Slope

As you can see, my temperature turned out to be a poor indicator. My model really only prediced the outcome based on this feature little more than a coin flip could have. Lets move on to pressure change

[69]:
```
#X_arrary = ['temp', 'p_delta24', 'p_slope24']

X = df_metmodel[['temp']]
y = df_metmodel['attack_binary']


X_train, X_test, y_train, y_test = train_test_split(X, y , test_size = 0.3,␣
↪stratify = y, random_state = 42)

model = LogisticRegression(max_iter = 1000, class_weight = 'balanced')
model.fit(X_train, y_train)

y_pred = model.predict(X_test)


print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(model.coef_)
```

```
              precision    recall  f1-score   support

           0       0.54      0.56      0.55        86
           1       0.54      0.52      0.53        85

    accuracy                           0.54       171
   macro avg       0.54      0.54      0.54       171
weighted avg       0.54      0.54      0.54       171

[[48 38]
 [41 44]]
[[0.07423246]]
```

Pressure change, unfortunately turned out to be a poor indicator as well, again only being slightly better than an coin flip

[70]:
```
X = df_metmodel[['p_delta24']]
y = df_metmodel['attack_binary']


X_train, X_test, y_train, y_test = train_test_split(X, y , test_size = 0.3,␣
↪stratify = y, random_state = 42)
```

```
model = LogisticRegression(max_iter = 1000, class_weight = 'balanced')
model.fit(X_train, y_train)

y_pred = model.predict(X_test)


print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(model.coef_)
```

```
              precision    recall  f1-score   support

           0       0.52      0.77      0.62        86
           1       0.55      0.28      0.37        85

    accuracy                           0.53       171
   macro avg       0.53      0.52      0.50       171
weighted avg       0.53      0.53      0.50       171

[[66 20]
 [61 24]]
[[0.06484879]]
```

As one would expect, the slope (similar to pressure change), preformed poorly as well.

[71]:
```
X = df_metmodel[['p_slope24']]
y = df_metmodel['attack_binary']


X_train, X_test, y_train, y_test = train_test_split(X, y , test_size = 0.3,␣
↪stratify = y, random_state = 42)

model = LogisticRegression(max_iter = 1000, class_weight = 'balanced')
model.fit(X_train, y_train)

y_pred = model.predict(X_test)


print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(model.coef_)
```

```
              precision    recall  f1-score   support

           0       0.52      0.77      0.62        86
           1       0.55      0.28      0.37        85
```

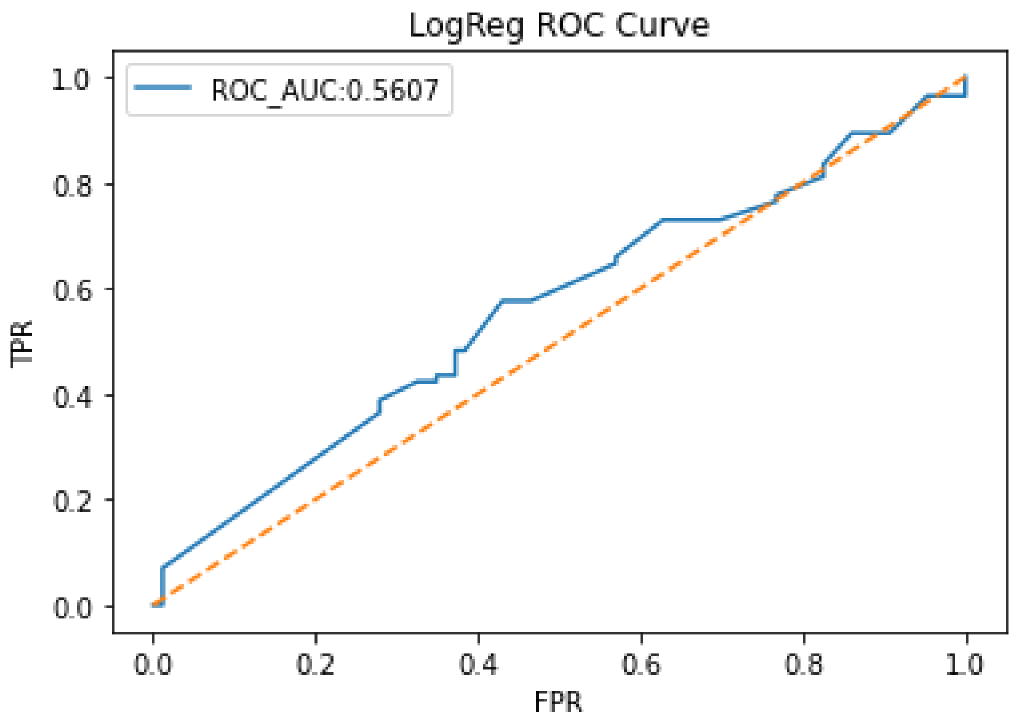
```
    accuracy                           0.53       171
   macro avg       0.53      0.52      0.50       171
weighted avg       0.53      0.53      0.50       171

[[66 20]
 [61 24]]
[[0.51984869]]
```

Finally, lets try combining all three features to see if we can create a stronger model. Unfortunately again, it looks like we are slightly better than a coin flip on this model, so I think we can conclude these features are not strong indicators of shark attack occurence.

[72]:
```
# from sklearn.preprocessing import StandardScaler
# from sklearn.pipeline import make_pipeline

X = df_metmodel[['temp', 'p_delta24', 'p_slope24']]
y = df_metmodel['attack_binary']


X_train, X_test, y_train, y_test = train_test_split(X, y , test_size = 0.3,␣
↪stratify = y, random_state = 42)

model = LogisticRegression(max_iter = 1000, class_weight = 'balanced')
#model = make_pipeline(StandardScaler(), LogisticRegression(max_iter = 1000,␣
↪class_weight = 'balanced'))
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
y_prob = model.predict_proba(X_test)[:, 1]

print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
print(model.coef_)
print(roc_auc_score(y_test, y_prob))

fpr, tpr, thresholds = roc_curve(y_test, y_prob)

plt.figure()
plt.plot(fpr, tpr, label = f"ROC_AUC:{roc_auc_score(y_test, y_prob):.4f}")
plt.plot([0,1], [0,1], linestyle = "--")
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('LogReg ROC Curve')
plt.legend()
plt.show()
```

```
              precision    recall  f1-score   support
```

```
           0       0.55      0.63      0.59        86
           1       0.56      0.48      0.52        85

    accuracy                           0.56       171
   macro avg       0.56      0.56      0.55       171
weighted avg       0.56      0.56      0.55       171

[[54 32]
 [44 41]]
[[0.08335977 0.09148068 0.0038117 ]]
0.5606703146374828
```



6 5. Results, Conclusions, Notes for Further Investigation, and Potential Applications of Findings

Modeling Results

In this project, 10 separate Logistic regression models were created. They are as follows:

1. Shark Attack Occurrence ~ Lunar Illumination,
2. Shark Attack Occurrence ~ Month of Attack,
3. Shark Attack Occurrence ~ Hour of Attack,
4. Shark Attack Occurrence ~ Hourly Bucket (Time of Day),

5. Shark Attack Occurrence ~ Lunar Phase,
6. Shark Attack Occurrence ~ Month of Attack + Hourly Bucket (Time of Day),
7. Shark Attack Occurrence ~ Temperature,
8. Shark Attack Occurrence ~ 24 Hour Pressure Change,
9. Shark Attack Occurrence ~ 24 Hour Pressure Rate of Change,
10. Shark Attack Occurrence ~ Temp + 24 Hour Pressure Change + 24 Hour Pressure Rate of Change

Model Performance Summary and Comparison

Model	Encoding	ROC-AUC	Notes
Shark Attack Occurrence ~ Lunar Illumination	Continuous	~0.50	Weak; nearly random performance.
Shark Attack Occurrence ~ Month of Attack	Cyclical (sin/cos)	~0.69	Not a strong predictor; small seasonal effect visible.
Shark Attack Occurrence ~ Hour of Attack	Cyclical (sin/cos)	~0.76	Moderate strength; improves over month alone.
Shark Attack Occurrence ~ Hourly Bucket (Time of Day)	Categorical	~0.78	Strongest single predictor; captures diurnal patterns well.
Shark Attack Occurrence ~ Lunar Phase	Categorical (New, Full, etc.)	~0.45	Weak; nearly random performance.
Shark Attack Occurrence ~ Month of Attack + Hourly Bucket	One-hot month + Categorical	~0.80	Best performing combined model; strong diurnal + seasonal signal.
Shark Attack Occurrence ~ Temperature	Continuous (°C)	~0.53	Weak; nearly random performance.
Shark Attack Occurrence ~ 24 Hour Pressure Change	Continuous (Δ pressure, hPa)	~0.54	Weak; nearly random performance.
Shark Attack Occurrence ~ 24 Hour Pressure Rate of Change	Continuous (slope, hPa/hr)	~0.54	Weak; nearly random performance.
Shark Attack Occurrence ~ Temp + Pressure Features	Continuous (3 features)	~0.56	Adding multiple meteorological features doesn't improve model.

For the sake of brevity, only two of the most significant results will be listed in this section from both the Temporal and Weather category, but all results are in the above notebook.

For the temporal data "Shark Attack Occurrence ~ Month of Attack + Hourly Bucket (Time of Day)" yielded the most significant results. As you can see by the results, combining these two features yielded a combined ROC AUC score of ~80%. This is a significant outcome, and means this combo model has a strong chance of predicting shark attack occurrence vs non-occurrence.

In the predicted probability charts for the monthly and hourly data in this model, one can see that the distribution of attack probability is similar to the real-world distribution of shark attacks that was seen in the EDA visualizations earlier. This is a robust result, because it shows the model is predicting in a similar fashion to real world outcomes.

Additionally, providing the hourly and monthly distribution of attack vs non-attack below to visually see how the model parsed through positive and negative events in the test and train data:

For the Weather data, "Shark Attack Occurrence ~ Temp + 24 Hour Pressure Change + 24 Hour Pressure Rate of Change" yielded the most significant result. Unfortunately, this model was little better than a coin flip in predicting shark attack occurrences from these three variables stacked, with an ROC AUC score barely over 50%

Discussion of Results

Looking at the results of the modeling done on this dataset, it is easy for one to tell that the temporal indicators provided the results of the highest value. Looking at the overall ROC AUC score of ~80% on the Hourly and Month day combination, this model is provides high efficacy and will accurately predict the occurrence of an attack 76% of the time (accuracy score) when given date-time info. In terms of which model should be iterated upon "Shark Attack Occurrence ~ Month of Attack + Hour of Attack" is the most promising.

Other temporal data features looked promising as well, but may need further refinement. Lunar phases and lunar illumination, which were previously hypothesized to be a potential indicator, but yielded poor results when modelled. This information in itself is useful though in that it tells us that Lunar Phases may have no correlation whatsoever with shark attack occurrences. In this respect, Lunar temporal data requires further investigation.

In regards to the meteorological features- Those that were chosen for modeling (Temperature, 24 Hour Pressure Delta, and 24 Hour Pressure Rate of Change) were extremely poor indicators of shark attack occurrence. There may be further credence to the use of these features as indicators, if modeling is enhanced, but for the time being they lack a significance in the current iteration.

Limitations of Current Model

One notable limitation for the current model is that synthetic negative events for temporal data were completely randomly generated and in future iterations, implementing seasonality and time-of-day into the random choice function would increase model efficacy Additionally time-of-day generation in both random choice functions for temporal and weather data, if beachgoer hourly data is captured would increase model efficacy

Furthermore, lack of expertise in ichthyology and shark research could have caused disregard for potential in other features that could increase the model efficacy. In future iterations, working with the ISAF researchers and gaining first-hand knowledge in shark behavior could help direct additional features to include.

Finally, bias in the geographical nature of data, being that this subset only included Florida Atlantic coast attacks could have very well skewed the results of certain models. Running a global or continent based model could drown out these regional biases. Additionally splitting the data along these regional lines could yield interesting and different results.

Future Applications and Model Iterations

One potential application of a model such as this, when further refined to include additional features to increase overall efficacy, would be the use of a risk indicator of sorts for shark attack occurrence given a specific set of circumstances. Think of a "Smokey the Bear: Wildfire Risk"-type indicator that could provide the generalized risk of a shark attack occurrence. This model could be further refined to add features such as geographical location, tidal and current affects, storm systems in nearby area, species indicators, and so on. With further expert input on the model features to be included, one could more greatly refine to provide individuals with valuable risk information when making decisions about their beach going activities.

7 References

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Special acknowledgement: Dr. Gavin Naylor and Joseph Miguez, Florida Program for Shark Research, for providing ISAF data.

[2]:
```
#df_clean.to_csv('df_clean_here', index = False)
```

[ ]:
```
```