Whats the Cause of your Power Outage?

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Website Link: https://k1mittal.github.io/Causes_of_Power_Outages/

In [1]:
```
import pandas as pd
import numpy as np
from pathlib import Path
import scipy
import folium
from folium.plugins import HeatMap
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder, StandardSca
from sklearn.compose import ColumnTransformer
from sklearn.metrics import f1_score, ConfusionMatrixDisplay, confusion_matr
import matplotlib.pyplot as plt

import plotly.express as px
pd.options.plotting.backend = 'plotly'

from dsc80_utils import * # Feel free to uncomment and use this.
```

Step 1: Introduction

Interesting Questions:

- How does the cause of the power outages indicate other factors, for example, does whether related power outages result in more people having no power? Can we predict the cause of power outages?
- Is there a correlation between the time and other factors, do power outages happen in one month specifically? Has the number of power outages decreased over time? Can we predict when the next power outage is using a time series prediction?
- Can we predict the number of people affected by a power outage given certain factors? Are the number of people affected by power outages correlated to other factors?
- Can we predict the duration of power outages given certain factors? How are the duration of power outages correlated to other factors?

Our Choice:

We decided to answer the first bullet point, which is what aspects of power outage are related to each category of cause.

Step 2: Data Cleaning and Exploratory Data Analysis

In [2]:
```
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', 5)
```

In [3]:
```
# Data Init and Cleanin
raw_data = pd.read_excel(Path('./outage.xlsx'))
raw_data.columns = [f'{raw_data.columns[i]}' for i in range(len(raw_data.col
raw_data = raw_data.iloc[1:, 1:].loc[:, ['OBS', 'YEAR', 'MONTH', 'U.S._STATE
```

Below we display the only missing values for outage start dates. Note how there are only 9 entries, and each of these entries also have missing relevant features. Therefore, imputation is not something of interest in this case and we can simply drop these values

In [4]:
```
raw_data = raw_data.dropna(subset = ['OUTAGE.START.DATE', 'OUTAGE.START.TIME

# Concatenates the time and date for both start and end
raw_data['OUTAGE.START'] = pd.to_datetime(
    raw_data['OUTAGE.START.DATE'].astype(str) + ' ' + raw_data['OUTAGE.START
)

raw_data['OUTAGE.END'] = pd.to_datetime(
    raw_data['OUTAGE.RESTORATION.DATE'].astype(str) + ' ' + raw_data['OUTAGE
)
raw_data = raw_data.drop(columns = ['OUTAGE.START.DATE', 'OUTAGE.START.TIME'

raw_data['OUTAGE.START'].isna().sum()
```

```
/var/folders/1m/hjhr1x894h35cktycnd3vr_m0000gn/T/ipykernel_43360/845298299.p
y:4: UserWarning:

Could not infer format, so each element will be parsed individually, falling
back to `dateutil`. To ensure parsing is consistent and as-expected, please
specify a format.

/var/folders/1m/hjhr1x894h35cktycnd3vr_m0000gn/T/ipykernel_43360/845298299.p
y:8: UserWarning:

Could not infer format, so each element will be parsed individually, falling
back to `dateutil`. To ensure parsing is consistent and as-expected, please
specify a format.
```

Out[4]: np.int64(0)

Adding Seasons using Binning

We want to add a column indicating season for our later EDA and tests. Since month is already provided, we can use binning.

In [5]:

```python
# Bins into seasons based on the month of the year
seasons = {'(0, 1]': 'Winter', '(1, 4]': 'Spring', '(4, 7]': 'Summer', '(7,

raw_data['SEASONAL.BINS'] = pd.cut(raw_data['MONTH'], bins = [0, 1, 4, 7, 10
raw_data['SEASONAL.BINS'] = raw_data['SEASONAL.BINS'].astype(str).map(seasor
raw_data
```

Out[5]:

	OBS	YEAR	MONTH	U.S._STATE	NERC.REGION	CLIMATE.REGION	ANOMAI
1	1.0	2011.0	7.0	Minnesota	MRO	East North Central	
2	2.0	2014.0	5.0	Minnesota	MRO	East North Central	
...	...	...	...	...	...	...	
1532	1532.0	2009.0	8.0	South Dakota	RFC	West North Central	
1533	1533.0	2009.0	8.0	South Dakota	MRO	West North Central	

1476 rows × 20 columns

Simple Handling of NaN Values

We will replace all 0 entries for `CUSTOMERS.AFFECTED` and `OUTAGE.DURATION` with `np.nan` for now, because a outage having 0 duration or 0 customers affected implies that it either is missing or was not an "actual" outage

In [6]:
```
# Sets all 0 values for customers affected and outage duration to np.nan for
raw_data.loc[raw_data['CUSTOMERS.AFFECTED'] == 0, 'CUSTOMERS.AFFECTED'] = np
raw_data.loc[raw_data['OUTAGE.DURATION'] == 0, 'OUTAGE.DURATION'] = np.nan
print(raw_data.head().to_markdown(index=False))
```

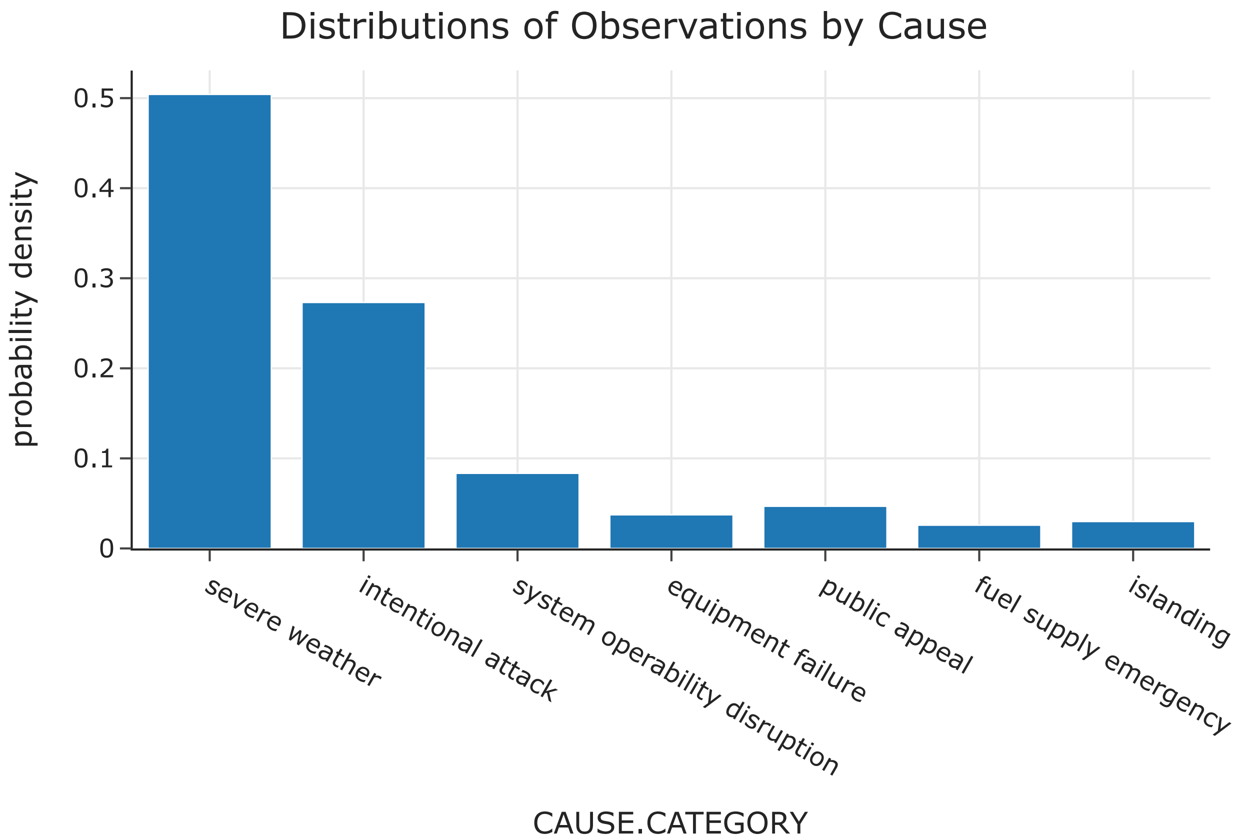
```
|   OBS |   YEAR |   MONTH | U.S._STATE   | NERC.REGION   | CLIMATE.REGION
|   ANOMALY.LEVEL | CAUSE.CATEGORY     | CLIMATE.CATEGORY   | CAUSE.CATEGOR
Y.DETAIL   |   OUTAGE.DURATION |   DEMAND.LOSS.MW |   CUSTOMERS.AFFECTED |
TOTAL.PRICE |   TOTAL.SALES |   TOTAL.CUSTOMERS |   TOTAL.REALGSP | OUTAGE.S
TART         | OUTAGE.END           | SEASONAL.BINS   |
|------:|-------:|--------:|:-------------|:--------------|:----------------
---|----------------:|:-------------------|:-------------------|:-----------
-------------|------------------:|-----------------:|---------------------:|
--------------:|--------------:|------------------:|----------------:|:-----
--------------|:--------------------|:----------------|
|     1 |   2011 |       7 | Minnesota    | MRO           | East North Centr
al |            -0.3 | severe weather     | normal             | nan
|              3060 |              nan |                70000 |          9.2
8 |       6562520 |       2.5957e+06  |         274182 | 2011-07-01 17:00:0
0 | 2011-07-03 20:00:00 | Summer          |
|     2 |   2014 |       5 | Minnesota    | MRO           | East North Centr
al |            -0.1 | intentional attack | normal             | vandalism
|                 1 |              nan |                  nan |          9.2
8 |       5284231 |       2.64074e+06 |         291955 | 2014-05-11 18:38:0
0 | 2014-05-11 18:39:00 | Summer          |
|     3 |   2010 |      10 | Minnesota    | MRO           | East North Centr
al |            -1.5 | severe weather     | cold               | heavy wind
|              3000 |              nan |                70000 |          8.1
5 |       5222116 |       2.5869e+06  |         267895 | 2010-10-26 20:00:0
0 | 2010-10-28 22:00:00 | Fall            |
|     4 |   2012 |       6 | Minnesota    | MRO           | East North Centr
al |            -0.1 | severe weather     | normal             | thunderstor
m              |              2550 |              nan |                68200 |
9.19 |       5787064 |       2.60681e+06 |         277627 | 2012-06-19 04:3
0:00 | 2012-06-20 23:00:00 | Summer          |
|     5 |   2015 |       7 | Minnesota    | MRO           | East North Centr
al |             1.2 | severe weather     | warm               | nan
|              1740 |              250 |               250000 |         10.4
3 |       5970339 |       2.67353e+06 |         292023 | 2015-07-18 02:00:0
0 | 2015-07-19 07:00:00 | Summer          |
```

EDA

Univariate Analysis

We start by displaying the distributions of observations by cause to see how our data is distributed

In [7]:
```
# Displays the probability density histogram of observations by cause
cause_pdf = px.histogram(raw_data, x = 'CAUSE.CATEGORY', title = 'Distributi
cause_pdf.show()
```



Next, we will see the distribution of observations by state. We will use `Folium` as a tool to geospacially visualize this distribution.

In [8]:
```
# Gets the JSON object describing the geospatial data (longitude, latitude,
states_url = f'https://raw.githubusercontent.com/python-visualization/foliur

# Distribution of observation by state
states_data = raw_data['U.S._STATE'].value_counts().reset_index(drop = False
states_data
```

Out[8]:

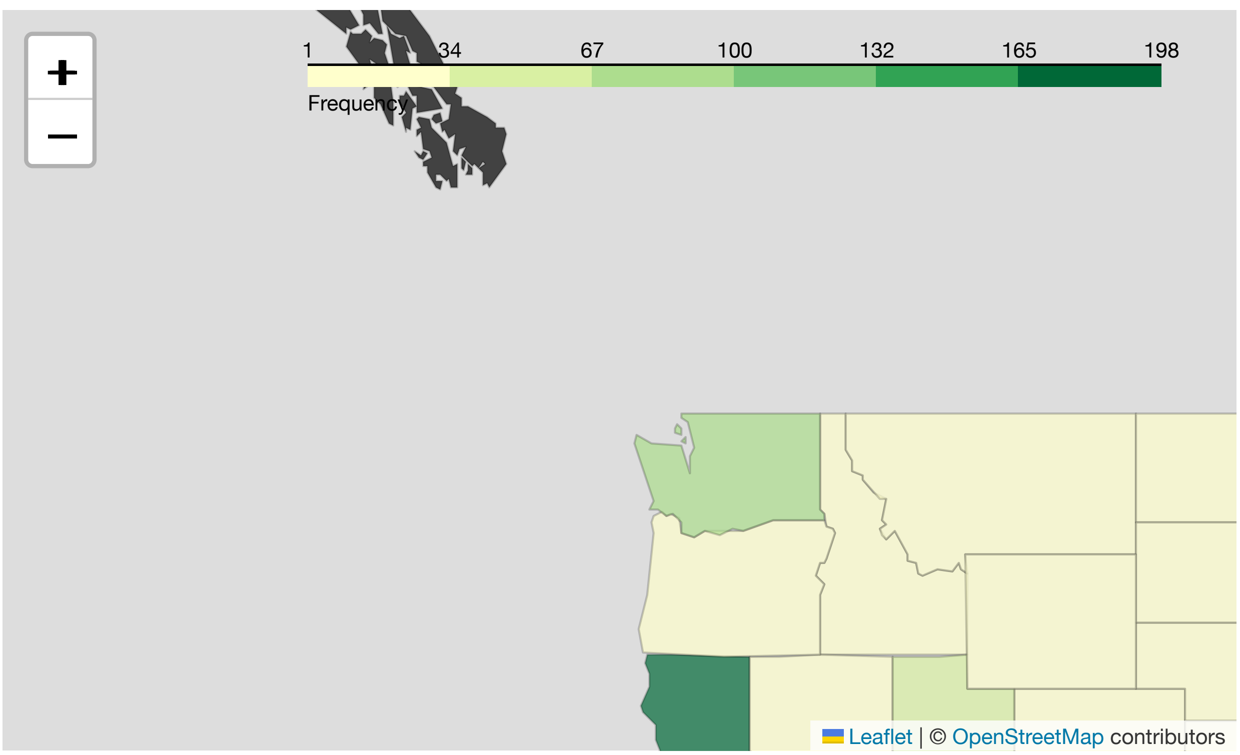
	U.S._STATE	count
0	California	198
1	Texas	122
...	...	...
47	South Dakota	2
48	North Dakota	1

49 rows × 2 columns

In [9]:

```
# Creates a frequency map using Folium
m = folium.Map(location=[37.0902, -95.7129], zoom_start=4) # Centered on the
folium.Choropleth(
    geo_data=states_url,
    name='State Frequency',
    data=states_data,
    columns=['U.S._STATE', 'count'],
    key_on='feature.properties.name',
    fill_color='YlGn',
    fill_opacity=0.7,
    line_opacity=0.2,
    legend_name='Frequency'
).add_to(m)
m
```

Out[9]:



In [10]:
```
raw_data
```

Out[10]:

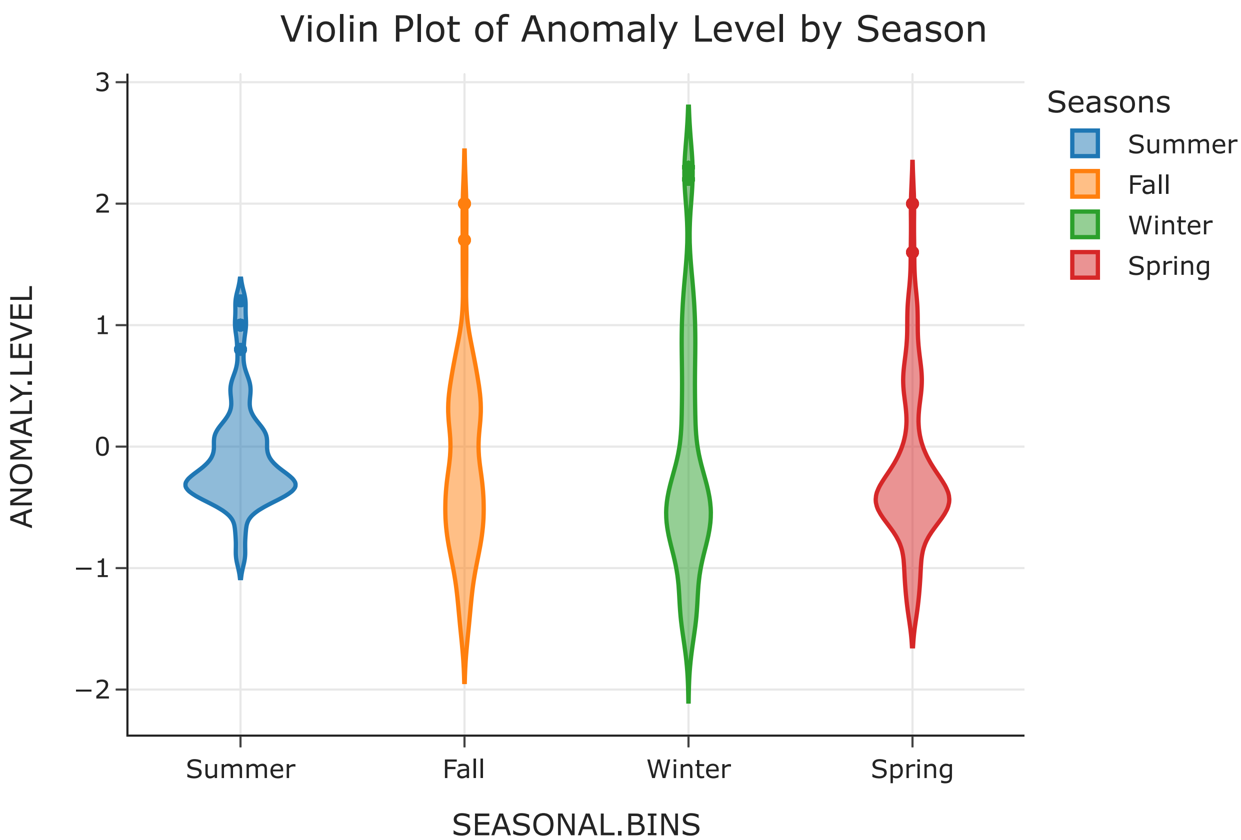
	OBS	YEAR	MONTH	U.S._STATE	NERC.REGION	CLIMATE.REGION	ANOMAI
1	1.0	2011.0	7.0	Minnesota	MRO	East North Central	
2	2.0	2014.0	5.0	Minnesota	MRO	East North Central	
...	...	...	...	...	...	...	
1532	1532.0	2009.0	8.0	South Dakota	RFC	West North Central	
1533	1533.0	2009.0	8.0	South Dakota	MRO	West North Central	

1476 rows × 20 columns

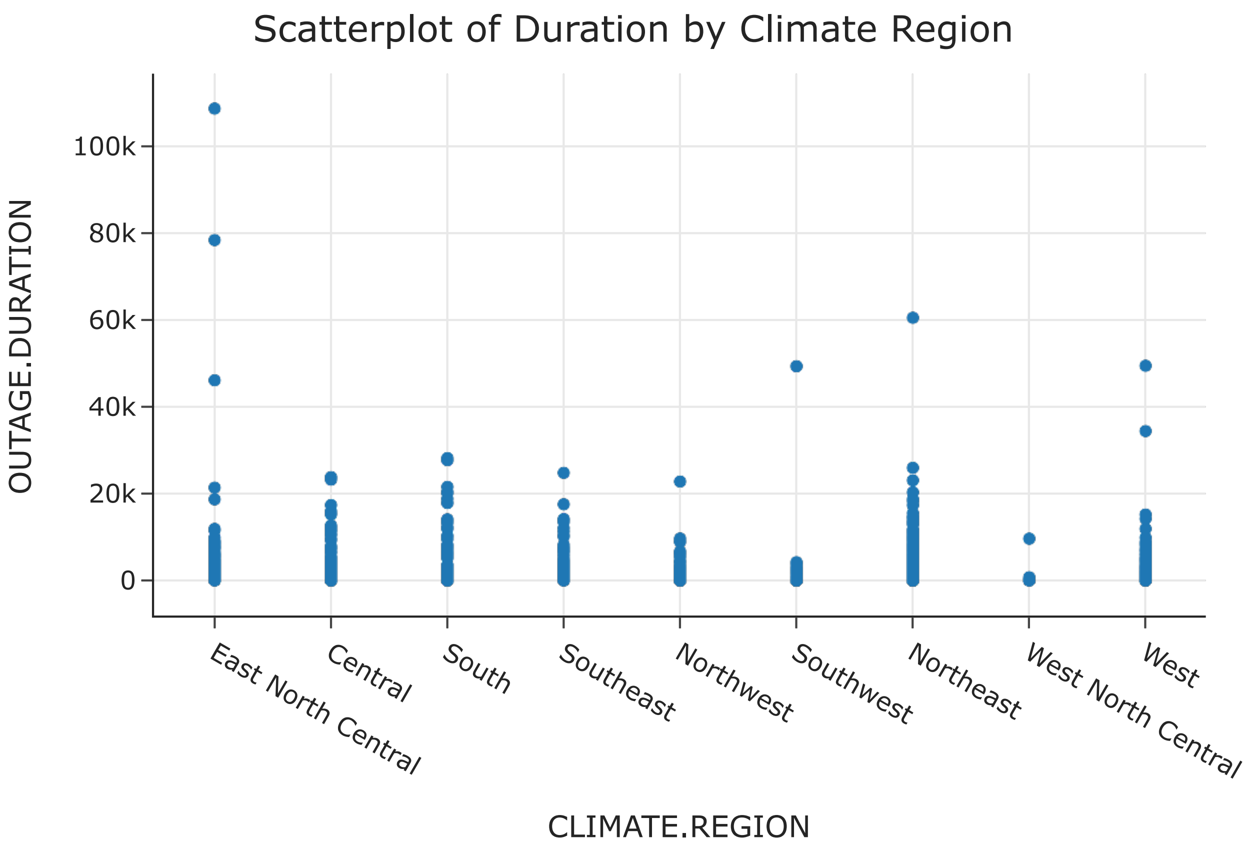
Bivariate Analysis

We start by display a violin plot (summary statistics) by season

In [11]:
```
# Violin plot of anomaly level by season
duration_customers_plt = px.violin(raw_data, x = 'SEASONAL.BINS', y = 'ANOMA
duration_customers_plt.update_layout(legend_title = 'Seasons', title = 'Viol
duration_customers_plt.show()
```



In [12]:
```
# Scatter of duration by climate region
region_duration_plt = px.scatter(raw_data, x = 'CLIMATE.REGION', y = 'OUTAGE
region_duration_plt.update_layout(title = 'Scatterplot of Duration by Climat
```



In [13]:

```
# Pivot table describing the mean of total prices, for each climate region f
price_climate_cause = raw_data.pivot_table(index = 'CAUSE.CATEGORY', columns
price_climate_cause
```

Out[13]:

CLIMATE.REGION	Central	East North Central	Northeast	Northwest	South	Southeast	Southw
CAUSE.CATEGORY							
equipment failure	7.65	7.92	12.35	6.9	8.24	10.15	8
fuel supply emergency	7.44	10.51	16.03	7.29	9.17	NaN	8
...	...	...	...	...	...	...	
severe weather	8.27	9.34	12.45	6.83	8.63	8.36	8
system operability disruption	8.4	8.24	13.71	6.32	8.66	9.11	8

7 rows × 9 columns

Step 3: Assessment of Missingness

Part 3.1: Missingness Mechanism Analysis

If we look at our feature of interest, we can see that approximately 30 percent of values are missing. This is most likely not MCAR and requires more analysis to see if its missingness depends on other features.

In [14]:
```
raw_data[['CAUSE.CATEGORY.DETAIL']]
```

Out[14]:

	CAUSE.CATEGORY.DETAIL
1	NaN
2	vandalism
...	...
1532	NaN
1533	NaN

1476 rows × 1 columns

In [15]:
```
raw_data['CAUSE.CATEGORY.DETAIL'].isna().mean()
```

Out[15]:
```
np.float64(0.3035230352303523)
```

In [16]:
```
raw_data[['CAUSE.CATEGORY.DETAIL', 'CAUSE.CATEGORY']]
```

Out[16]:

	CAUSE.CATEGORY.DETAIL	CAUSE.CATEGORY
1	NaN	severe weather
2	vandalism	intentional attack
...	...	...
1532	NaN	islanding
1533	NaN	islanding

1476 rows × 2 columns

In [17]:
```
''' This cell defines valid, relevant test statistics for permutation and
hypothesis tests.
'''
def tvd(dist1: pd.Series, dist2: pd.Series):
    return (dist1.value_counts(normalize = True) - dist2.value_counts(normal
```

```
def ks(dist1: pd.Series, dist2: pd.Series):
    return scipy.stats.ks_2samp(dist1, dist2).statistic
```

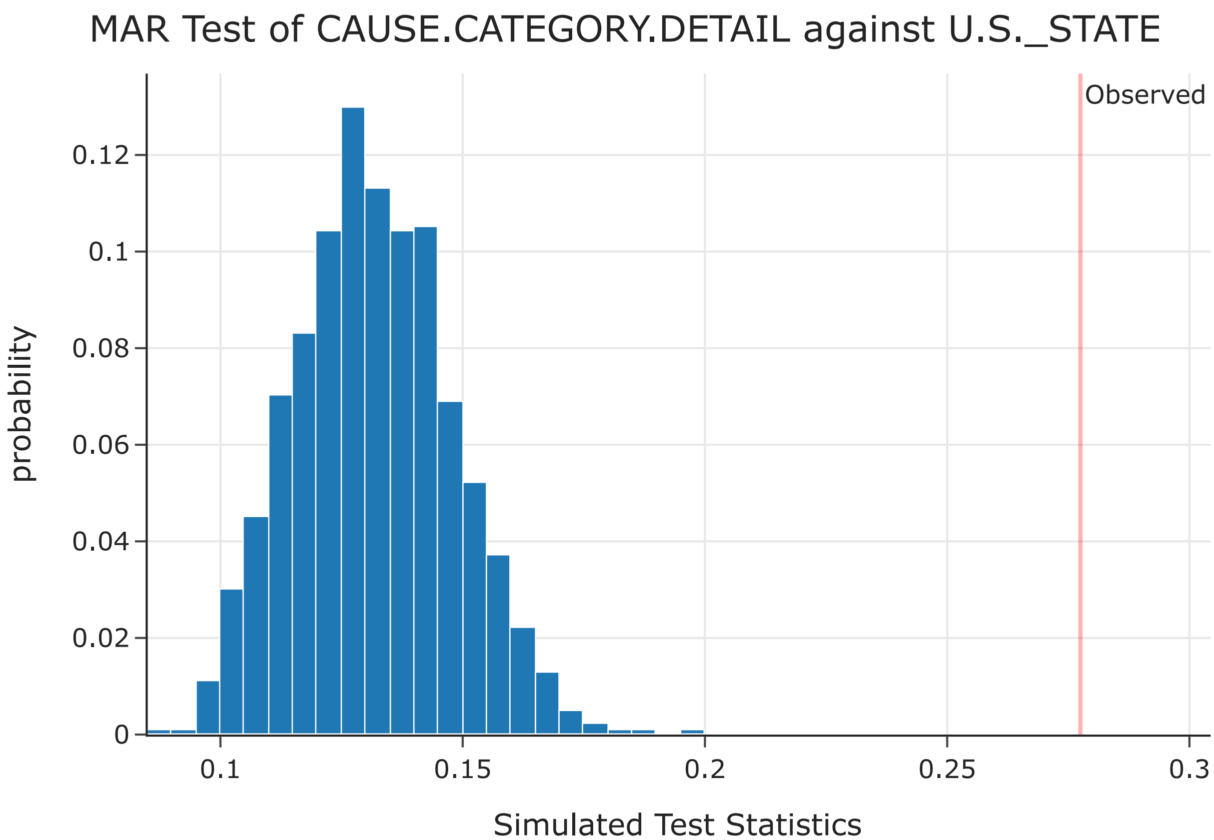
In [18]:
```
''' This function takes in a dataframe, a column with missing values and a
column to analyze the type of missingness mechanism with. It will return
a p-value and an associative True or False indicating if missing_col is MAR
withrespect to col. To conduct the permutation test, it will use the given
test_stat.

The function will also graph the distribution of simulated test statistics
with a line indicating where the observed lies.
'''

def identify_mar(df, missing_col, col, test_stat, N = 1000, alpha = 0.05, di
    missing_dist = df[[col]].assign(is_missing = df[missing_col].isna()).drc
    observed = test_stat(missing_dist[missing_dist['is_missing']][col], miss
    simulations = np.array([])
    for _ in range(N):
        missing_dist['is_missing'] = np.random.permutation(missing_dist['is_
        simulated = test_stat(missing_dist[missing_dist['is_missing']][col],
        simulations = np.append(simulations, simulated)

    simulations = simulations[~np.isnan(simulations)]

    if display:
        fig = px.histogram(x = simulations, title = f'MAR Test of {missing_c
        fig.add_vline(x=observed, line_color='red', line_width=2, annotatior
        fig.show()

    p_value = (simulations > observed).mean()
    return p_value, p_value < alpha
```

H_0: Cause category detail is MAR with respect to U.S. state

H_a: Cause category detail is not MAR with respect to U.S. state

We will perform a permutation test on missing (False or True) and using the TVD as the test statistic, since U.S. state is categorical.

In [19]:
```
p_val, is_mar = identify_mar(raw_data, 'CAUSE.CATEGORY.DETAIL', 'U.S._STATE'
p_val, is_mar
```



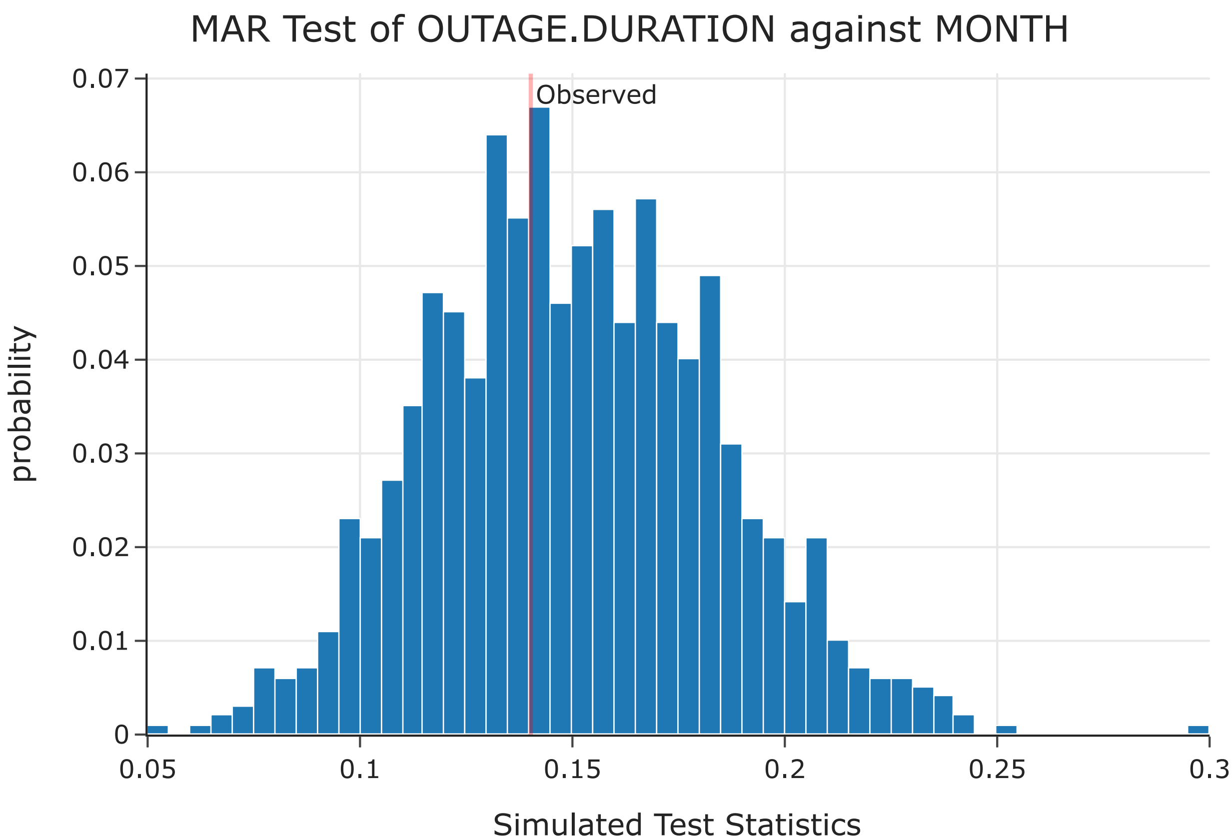
Out[19]:
```
(np.float64(0.0), np.True_)
```

H_0: Outage duration is MAR with respect to month

H_a: Outage duration is not MAR with respect to month

We will perform a permutation test on missing (False or True) and using the TVD as the test statistic, since month is also categorical.

In [20]:
```
p_val2, is_mar2 = identify_mar(raw_data, 'OUTAGE.DURATION', 'MONTH', tvd, 10
p_val2, is_mar2
```



Out[20]:
```
(np.float64(0.603), np.False_)
```

Clearly, there is evidence that the `CAUSE.CATEGORY.DETAIL_` column is **MAR** with respect to `CAUSE.CATEGORY_`. In other words, the missingness for cause category details are *highly* dependent on what the actual cause category is, which makes a lot of sense intuitively.

However, we conclude that `OUTAGE.DURATION` is not **MAR** with respect to `MONTH`, which also makes sense since the month shouldn't tell you the expected duration of an outage.

Step 4: Hypothesis Testing

The first test we conduct is to see whether the proportion of each cause category is relatively reasonable. However, since this will differ widely for each observation, we will analyze its uniformness across *each season*

H_0: The proportion of each cause category is uniformly distributed across each season, for each cause category.

H_a: The proportion of each cause category is not uniformly distributed across each season, for each cause category.

To do this, we will calculate the TVD for each season (for each cause category), and aggregate the TVDs (using an agg function like `mean` or `sum`)

In [21]:
```
''' Calculates the TVD for 2D distributions across each column (axis = 0).
The resulting TVD's will be aggregated (sum or mean) to represent the TVD of
the whole distributions. Assumes the probability distributions are already
calculated and provided.
'''
def tvd_2d(dist1: pd.DataFrame, dist2: pd.DataFrame, aggfunc):
    return (np.sum(np.abs(dist1 - dist2), axis = 0) / 2).agg(aggfunc)
```

First we need to get the empirical distribution of cause category by season.

In [22]:
```
# Creates a pivot table of counts by season and cause category, and normaliz

seasonal_counts = raw_data.pivot_table(values = 'OBS', columns = 'SEASONAL.B

cause_totals = seasonal_counts.sum(axis = 0)
seasonal_totals = seasonal_counts.sum(axis = 1)
expected_proportions = seasonal_totals / seasonal_counts.sum().sum()

observed_dist = seasonal_counts / cause_totals
expected_dist = pd.DataFrame(data = {col: expected_proportions for col in ob
observed_tvd = tvd_2d(expected_dist, observed_dist, 'sum')
observed_dist
```

Out[22]:

SEASONAL.BINS	Fall	Spring	Summer	Winter
CAUSE.CATEGORY				
equipment failure	0.02	0.05	0.05	0.03
fuel supply emergency	0.02	0.04	0.02	0.03
...	...	...	...	...
severe weather	0.57	0.40	0.51	0.53
system operability disruption	0.07	0.11	0.09	0.06

7 rows × 4 columns

In [23]:
```
# Perform a permutation test by recalculating the distribution after permuti

NUM_SIMULATIONS = 1000
sim_season_df = raw_data[['SEASONAL.BINS', 'CAUSE.CATEGORY', 'OBS']]
simulations = []
```

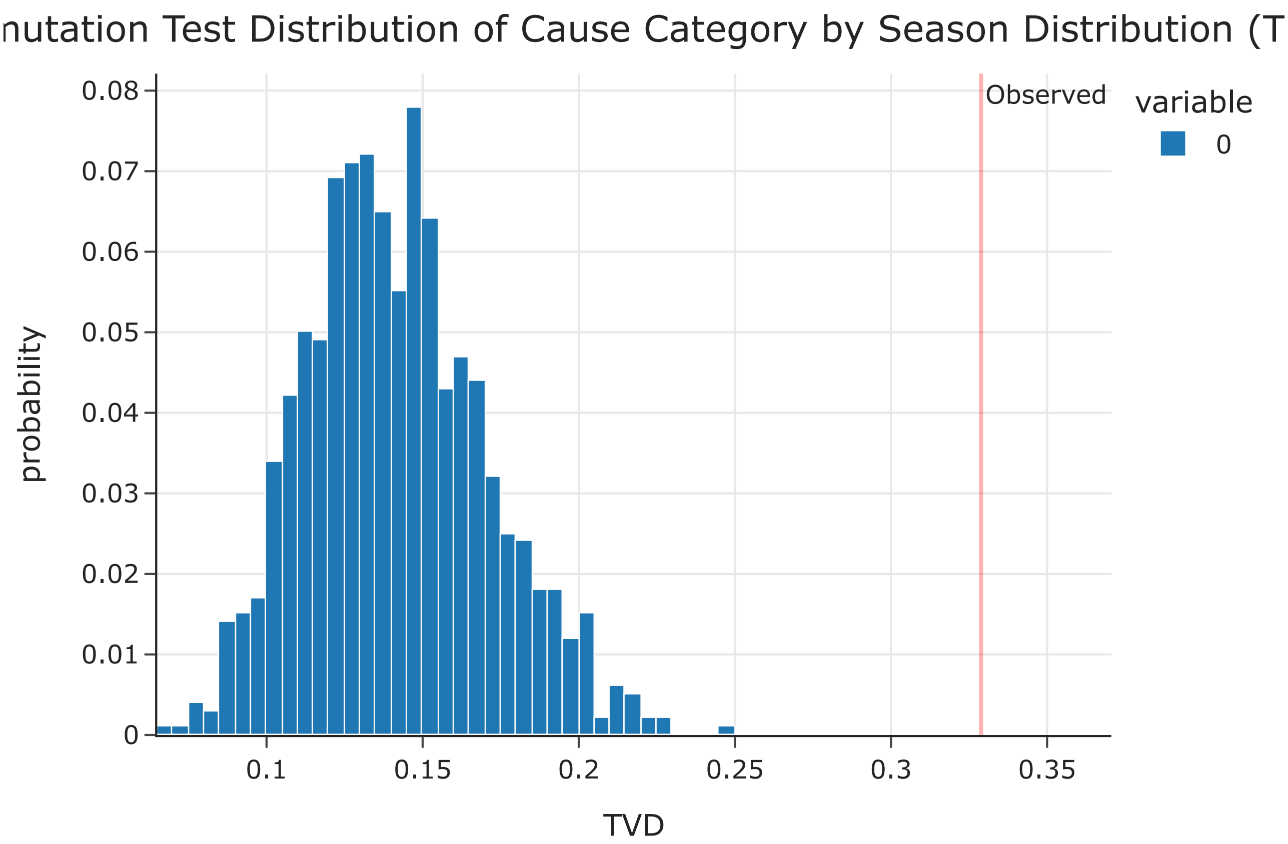
```
for _ in range(NUM_SIMULATIONS):
    sim_season_df['SEASONAL.BINS'] = np.random.permutation(sim_season_df['SE
    sim_counts = sim_season_df.pivot_table(values = 'OBS', columns = 'SEASON

    sim_cause_totals = sim_counts.sum(axis = 0)
    sim_seasonal_totals = sim_counts.sum(axis = 1)
    sim_expected_proportions = sim_seasonal_totals / sim_counts.sum().sum()

    sim_observed_dist = sim_counts / sim_cause_totals
    sim_expected_dist = pd.DataFrame(data = {col: sim_expected_proportions f
    sim_tvd = tvd_2d(sim_expected_dist, sim_observed_dist, 'sum')

    simulations.append(sim_tvd)
simulations[:5]
```

Out[23]:

```
[np.float64(0.08946597819818172),
 np.float64(0.15708773762010508),
 np.float64(0.15930685206943643),
 np.float64(0.12490741781511616),
 np.float64(0.09939371699527222)]
```

In [24]:

```
# Distribution of TVD for the permutation test
fig_hyp1 = px.histogram(simulations, histnorm = 'probability', title = 'Perm
fig_hyp1.add_vline(x=observed_tvd, line_color='red', line_width=2, annotatio
fig_hyp1.update_layout(xaxis_title = 'TVD')
fig_hyp1.show()
```



In [25]:
```
p_val_hyp1 = (observed_tvd < simulations).mean()
p_val_hyp1
```

Out[25]:
```
np.float64(0.0)
```

Therefore, since the p-value << 0.05 we reject the null, and there is evidence to prove that cause categories are not uniformly distributed across each season

Test Number 2

H_0: The distributions of mean affected customers for each state is the same for observations from 2005 and 2006

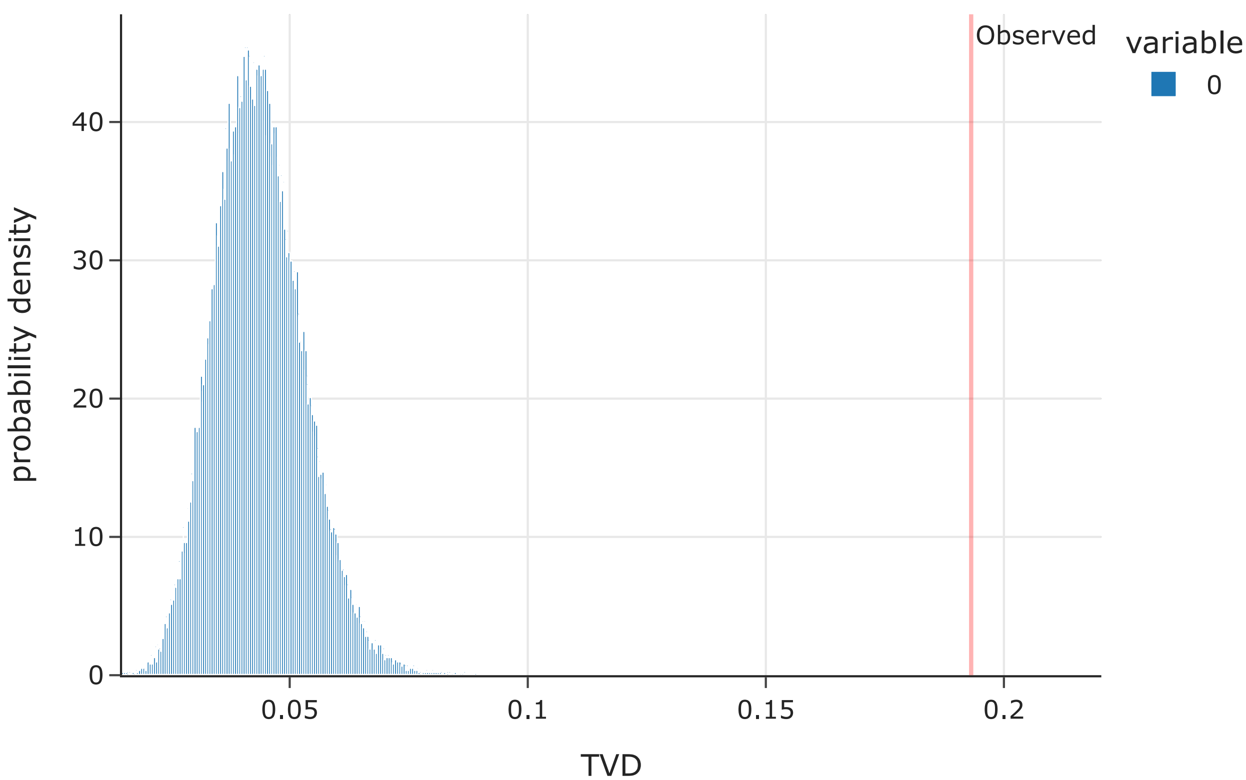
H_a: The distributions of mean affected customers for each state is different for observations from 2005 and 2006

In [26]:
```
raw_data['YEAR'] = raw_data['YEAR'].astype(float)
customers_dist_2005 = raw_data[raw_data['YEAR'] == 2005.0][['U.S._STATE', 'C
customers_dist_2005 /= customers_dist_2005.sum(axis = 0)
customers_dist_2005 = customers_dist_2005['CUSTOMERS.AFFECTED'].dropna()

customers_dist_2006 = raw_data[raw_data['YEAR'] == 2006.0][['U.S._STATE', 'C
```

```
customers_dist_2006 /= customers_dist_2006.sum(axis = 0)
customers_dist_2006 = customers_dist_2006['CUSTOMERS.AFFECTED'].dropna()

observed_tvd_customers = np.abs(customers_dist_2006 - customers_dist_2005).s
observed_tvd_customers
```

Out[26]: np.float64(0.1931225644342009)

In [27]:
```
N_CUSTOMERS = 1000
sim_customers_2006 = np.random.multinomial(N_CUSTOMERS, pvals = customers_di
sim_tvds_customers = np.sum(np.abs(sim_customers_2006 - customers_dist_2005.
hist = px.histogram(sim_tvds_customers, histnorm = 'probability density').ad
hist.update_layout(xaxis_title = 'TVD')
hist.show()
sim_tvds_customers.mean(), sim_tvds_customers.std()
```



Out[27]: (np.float64(0.04379252328222323), np.float64(0.009265433556153432))

In [28]:
```
p_val_hyp2 = (np.array(sim_tvds_customers) >= observed_tvd_customers).mean()
p_val_hyp2
```

Out[28]: np.float64(0.0)

Therefore, we have evidence to reject the null and conclude that that distribution of mean affected customers is different for each state, for years 2005 and 2006

Step 5: Framing a Prediction Problem

We plan to predict the cause column, which represents the general cause of power outages. Since this column contains categorical data, it is a classification problem. We will use features such as the number of people affected, outage duration, demand loss, and climatic conditions to build a predictive model. We aim to uncover patterns that help identify the causes of power outages based on their associated impacts and conditions. This will provide valuable insights for improving outage management and preparedness.

Step 6: Baseline Model

In [29]:
```
# Drop irrelevant columns, and visualize the number of missing values
mdl_data = raw_data.drop(columns = ['CAUSE.CATEGORY.DETAIL', 'OUTAGE.START',
mdl_data.isna().sum(axis = 0).sort_values(ascending=False)
```

Out[29]:
```
DEMAND.LOSS.MW        672
CUSTOMERS.AFFECTED    622
                     ...
TOTAL.CUSTOMERS         0
TOTAL.REALGSP           0
Length: 14, dtype: int64
```

Base model will just simply replace missing values with 0 or drop them, instead of imputing

In [30]:
```
# Fills missing values for demand loss, customers affected and outage durati
mdl_data[['DEMAND.LOSS.MW', 'CUSTOMERS.AFFECTED', 'OUTAGE.DURATION']] = mdl_
mdl_data.dropna(subset = ['TOTAL.PRICE', 'TOTAL.SALES', 'CLIMATE.REGION'], i
```

```
/var/folders/1m/hjhr1x894h35cktycnd3vr_m0000gn/T/ipykernel_43360/4283828493.
py:2: FutureWarning:

Downcasting object dtype arrays on .fillna, .ffill, .bfill is deprecated and
will change in a future version. Call result.infer_objects(copy=False) inste
ad. To opt-in to the future behavior, set `pd.set_option('future.no_silent_d
owncasting', True)`
```

Base model:

1. Data encoding
   A. One-hot encodes US states, climate region and climate category
   B. Ordinal encodes month

   C. Passes the remaining (numerical) columns as is
2. Passes encoded data into a random forest classifier

In [31]:
```
'''
Base model:
1. Data encoding
    1. One-hot encodes US states, climate region and climate category
    2. Ordinal encodes month
    3. Passes the remaining (numerical) columns as is
2. Passes encoded data into a random forest classifier
'''

mdl_base = Pipeline(steps = [
    ('data_encoding', ColumnTransformer(transformers = [
        ('one_hot', OneHotEncoder(handle_unknown = 'ignore'), ['U.S._STATE',
        ('ordinal', OrdinalEncoder(), ['MONTH']),
    ], remainder = 'passthrough')),
    ('random_forest', RandomForestClassifier())
])
```

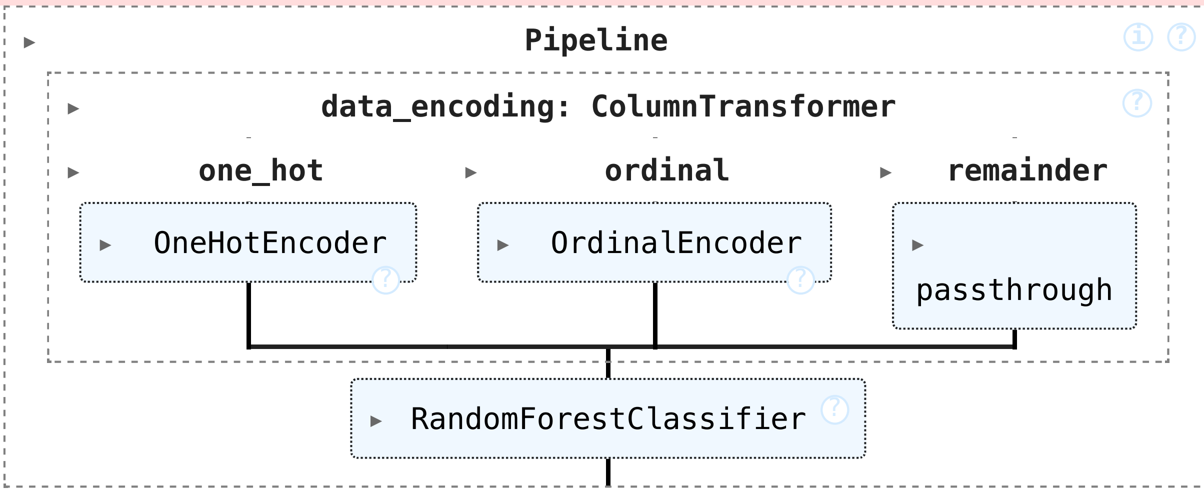
In [32]:
```
# Separates into y and X. Since we are predicting cause category, we use tha

X = mdl_data.drop(columns = ['CAUSE.CATEGORY'])
y = mdl_data['CAUSE.CATEGORY']
X_train, X_test, y_train, y_test = train_test_split(X, y)

mdl_data.isna().sum(axis = 0).sort_values(ascending=False)
```

Out[32]:
```
YEAR                0
MONTH               0
                   ..
TOTAL.CUSTOMERS     0
TOTAL.REALGSP       0
Length: 14, dtype: int64
```

In [33]:
```
mdl_base.fit(X_train, y_train)
```

```
/Users/ketan/miniforge3/envs/dsc80/lib/python3.12/site-packages/sklearn/comp
ose/_column_transformer.py:1623: FutureWarning:


The format of the columns of the 'remainder' transformer in ColumnTransforme
r.transformers_ will change in version 1.7 to match the format of the other
transformers.
At the moment the remainder columns are stored as indices (of type int). Wit
h the same ColumnTransformer configuration, in the future they will be store
d as column names (of type str).
To use the new behavior now and suppress this warning, use ColumnTransforme
r(force_int_remainder_cols=False).
```

Out[33]:



In [34]:
```python
# Indicates that our model is likely overfitting, which makes sense without
mdl_base.score(X_train, y_train)
```

Out[34]: 1.0

In [35]:
```python
# Pretty decent score for R^2 and f1, for the test set
y_base_preds = mdl_base.predict(X_test)
mdl_base.score(X_test, y_test), float(f1_score(y_test, y_base_preds, average
```

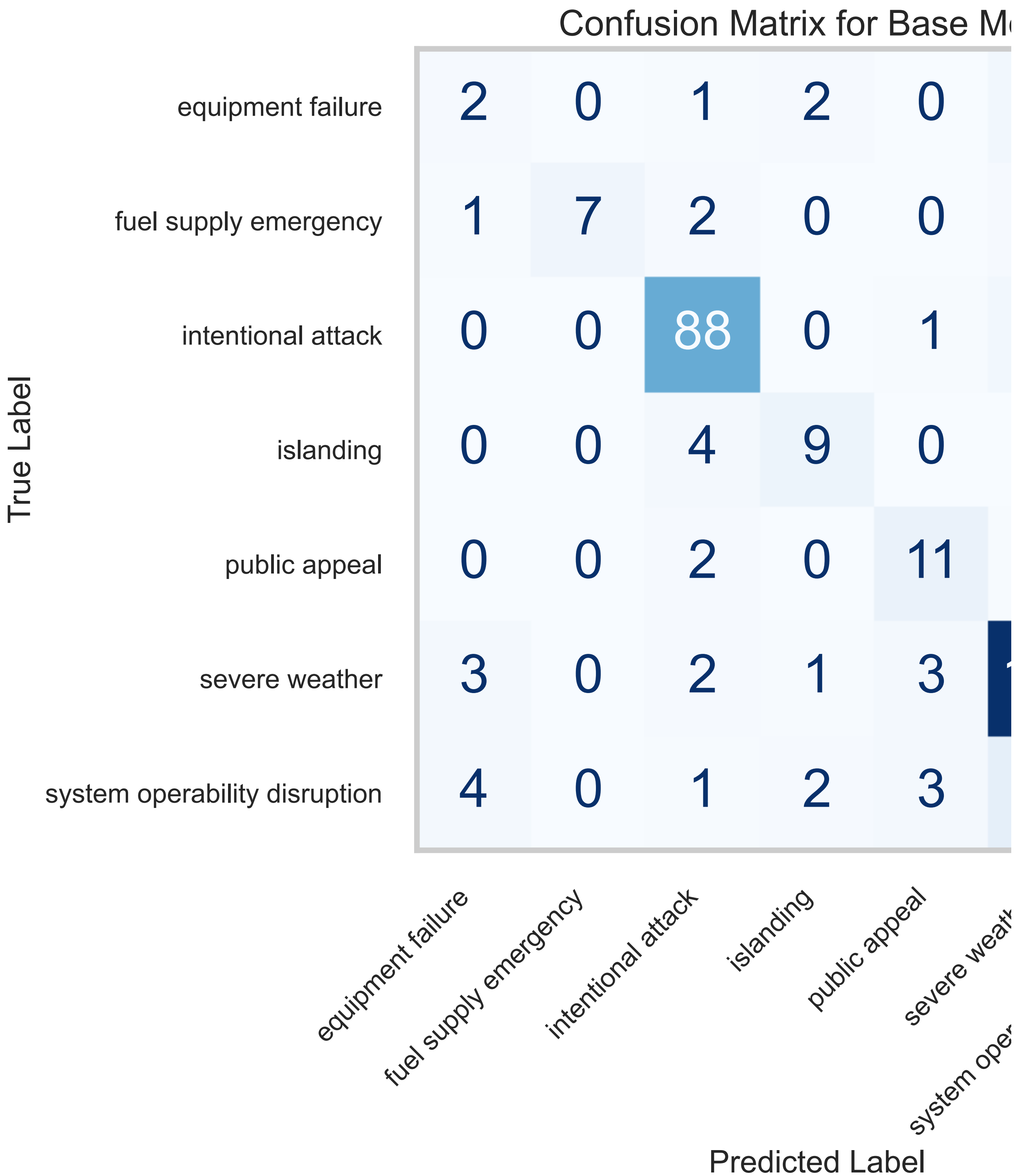
Out[35]: (0.821917808219178, 0.6394880722268838)

In [36]:
```python
# Precision and recall for the test set
from sklearn.metrics import precision_score, recall_score
precision_score(y_test, y_base_preds, average = 'macro'), recall_score(y_tes
```

Out[36]: (np.float64(0.6944759197211223), np.float64(0.6264345159481938))

In [37]:
```python
# Plots the confusion matrix with true label on the Y and predicted on the X
fig, ax = plt.subplots(figsize=(12, 8))
ConfusionMatrixDisplay.from_estimator(
```

```
    mdl_base, X_test, y_test, ax=ax, cmap="Blues", colorbar=True
)

plt.title("Confusion Matrix for Base Model", fontsize=16)
plt.xlabel("Predicted Label", fontsize=14)
plt.ylabel("True Label", fontsize=14)
plt.xticks(fontsize=12, rotation=45, ha="right")

plt.yticks(fontsize=12)
plt.grid(False)

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



Step 7: Final Model

We now define model 2:

1. Data encoding

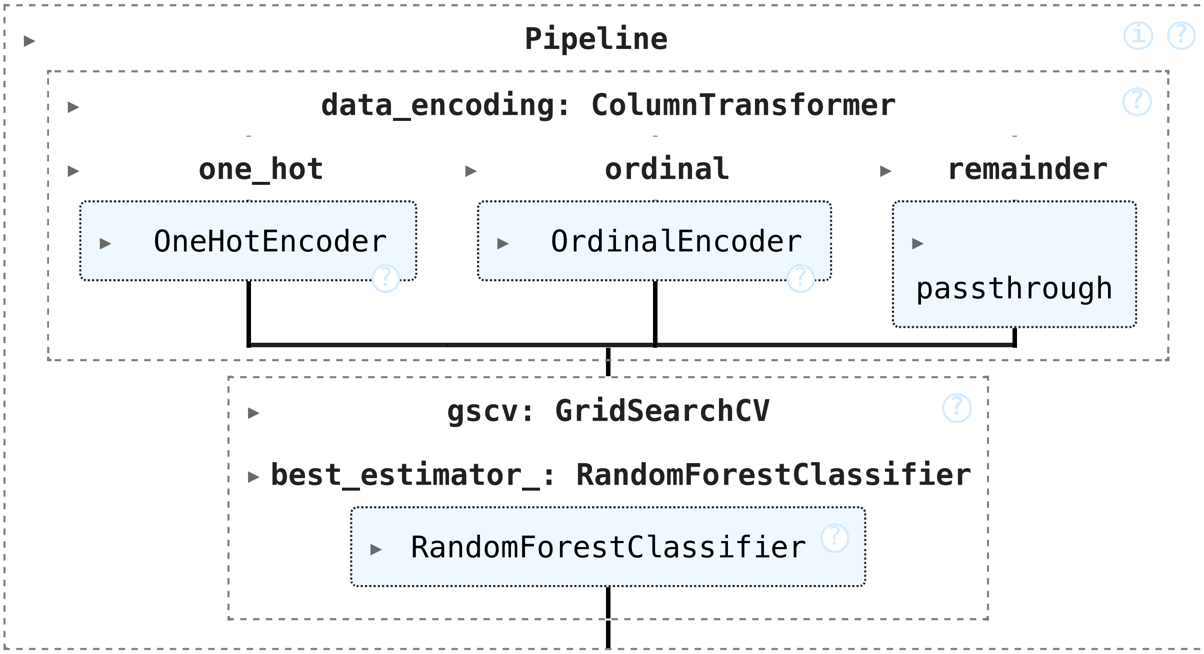
   A. One hot encode US state, climate region and climate category
   B. Ordinal encode month, since it has inherent order to it
   C. Pass rest of (numerical) features through
2. Pass encoded data through random forest classifier
   A. Perform grid search (GridSearchCV) for the random forest criterion, max depth and number of estimators to tune hyperparameters

In [38]:
```
from sklearn.model_selection import GridSearchCV

params_1 = {'criterion': ['gini', 'entropy', 'log_loss'], 'max_depth': np.ar

mdl_1 = Pipeline(steps = [
    ('data_encoding', ColumnTransformer(transformers = [
        ('one_hot', OneHotEncoder(handle_unknown = 'ignore'), ['U.S._STATE',
        ('ordinal', OrdinalEncoder(), ['MONTH']),
    ], remainder = 'passthrough')),
    ('gscv', GridSearchCV(RandomForestClassifier(), param_grid = params_1, c
])
```

In [39]:
```
mdl_1.fit(X_train, y_train)
```

```
/Users/ketan/miniforge3/envs/dsc80/lib/python3.12/site-packages/numpy/ma/cor
e.py:2881: RuntimeWarning:

invalid value encountered in cast

/Users/ketan/miniforge3/envs/dsc80/lib/python3.12/site-packages/sklearn/comp
ose/_column_transformer.py:1623: FutureWarning:


The format of the columns of the 'remainder' transformer in ColumnTransforme
r.transformers_ will change in version 1.7 to match the format of the other
transformers.
At the moment the remainder columns are stored as indices (of type int). Wit
h the same ColumnTransformer configuration, in the future they will be store
d as column names (of type str).
To use the new behavior now and suppress this warning, use ColumnTransforme
r(force_int_remainder_cols=False).
```

Out [39]:



In [40]:
```
# Test R^2 score and f1_score for model 1
y_1_preds = mdl_1.predict(X_test)
mdl_1.score(X_test, y_test), f1_score(y_test, y_1_preds, average = 'macro')
```

Out [40]: (0.821917808219178, np.float64(0.6356607562893146))

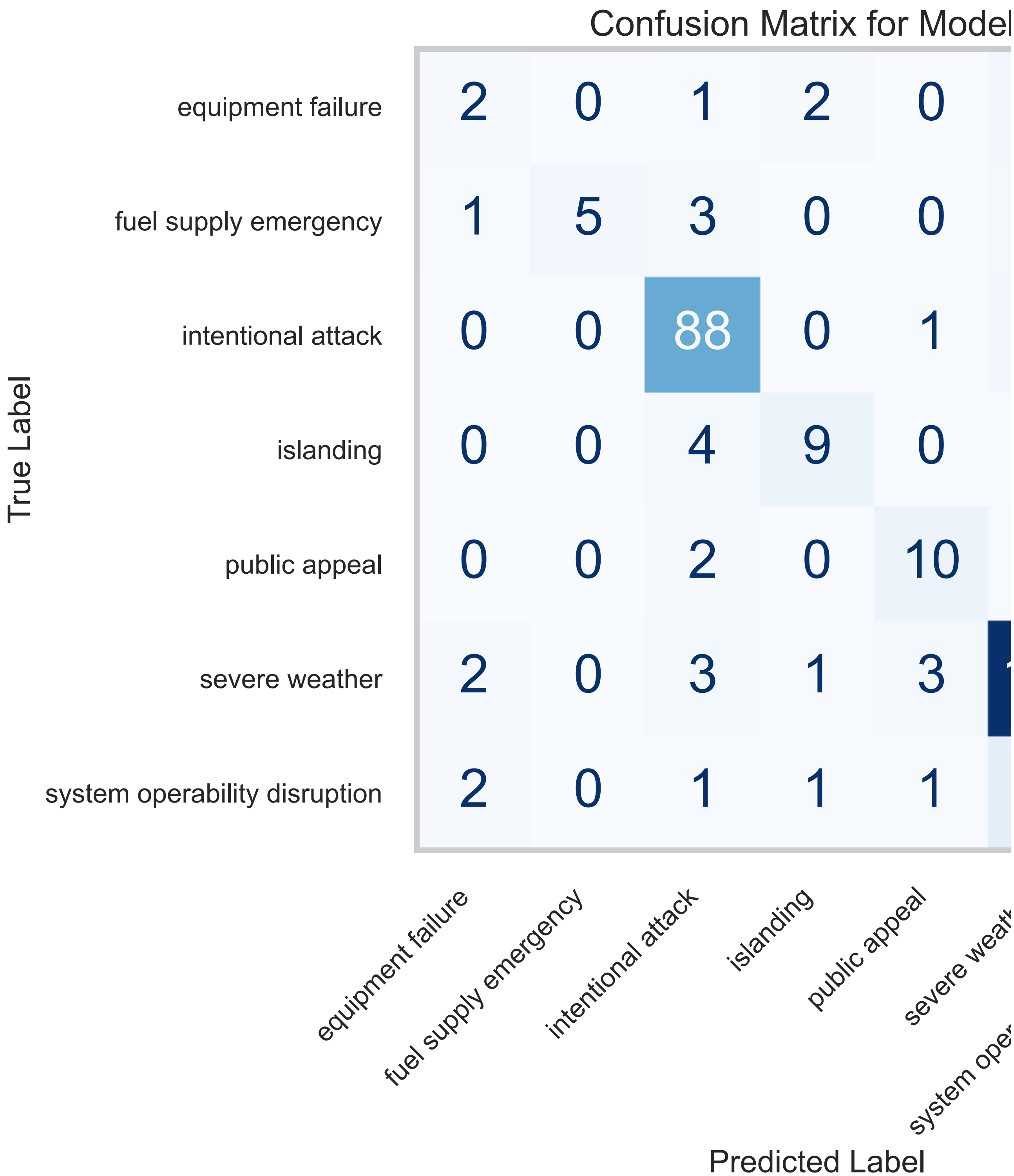
We can see that our model is marginally better than our base, but by a small amount. We can still improve.

In [41]:
```
# Precision and recall for model 1
precision_score(y_test, y_1_preds, average = 'macro'), recall_score(y_test,
```

Out [41]: (np.float64(0.7199547835328463), np.float64(0.6046658084652005))

In [42]:
```
# Display confusion matrix for model 1
fig, ax = plt.subplots(figsize=(12, 8))
ConfusionMatrixDisplay.from_estimator(
    mdl_1, X_test, y_test, ax=ax, cmap="Blues", colorbar=True
)

plt.title("Confusion Matrix for Model 1", fontsize=16)
plt.xlabel("Predicted Label", fontsize=14)
plt.ylabel("True Label", fontsize=14)
plt.xticks(fontsize=12, rotation=45, ha="right")

plt.yticks(fontsize=12)
plt.grid(False)

plt.tight_layout()
```

```
plt.show()
```



Still could use improvement, so we look at the feature space (F) now

In [43]:
```
# Shows the amount of missing values for each feature
mdl_2_data = raw_data.copy().drop(columns = ['OBS', 'CAUSE.CATEGORY.DETAIL',
mdl_2_data.isna().sum(axis = 0).sort_values(ascending = False)
```

Out[43]:
```
DEMAND.LOSS.MW        672
CUSTOMERS.AFFECTED    622
                     ...
TOTAL.CUSTOMERS         0
TOTAL.REALGSP           0
Length: 15, dtype: int64
```

Since we have a lot of missing vaues for customers affected and demand loss, we can perform **MAR** tests on each other column for these two features. Based on our results, we can impute accordingly

In [44]:
```
# For each missing column, go through every other column and perform a MAR t

from collections import defaultdict
num_columns = ['YEAR', 'MONTH', 'ANOMALY.LEVEL', 'OUTAGE.DURATION', 'DEMAND.
missing_cols = ['DEMAND.LOSS.MW', 'CUSTOMERS.AFFECTED']
mar_status = defaultdict(lambda: [])
for missing_col in missing_cols:
    for col in num_columns:
        p_customers, is_mar_customers = identify_mar(mdl_2_data, missing_col
        mar_status[missing_col].append((col, p_customers, is_mar_customers))

mar_status
```

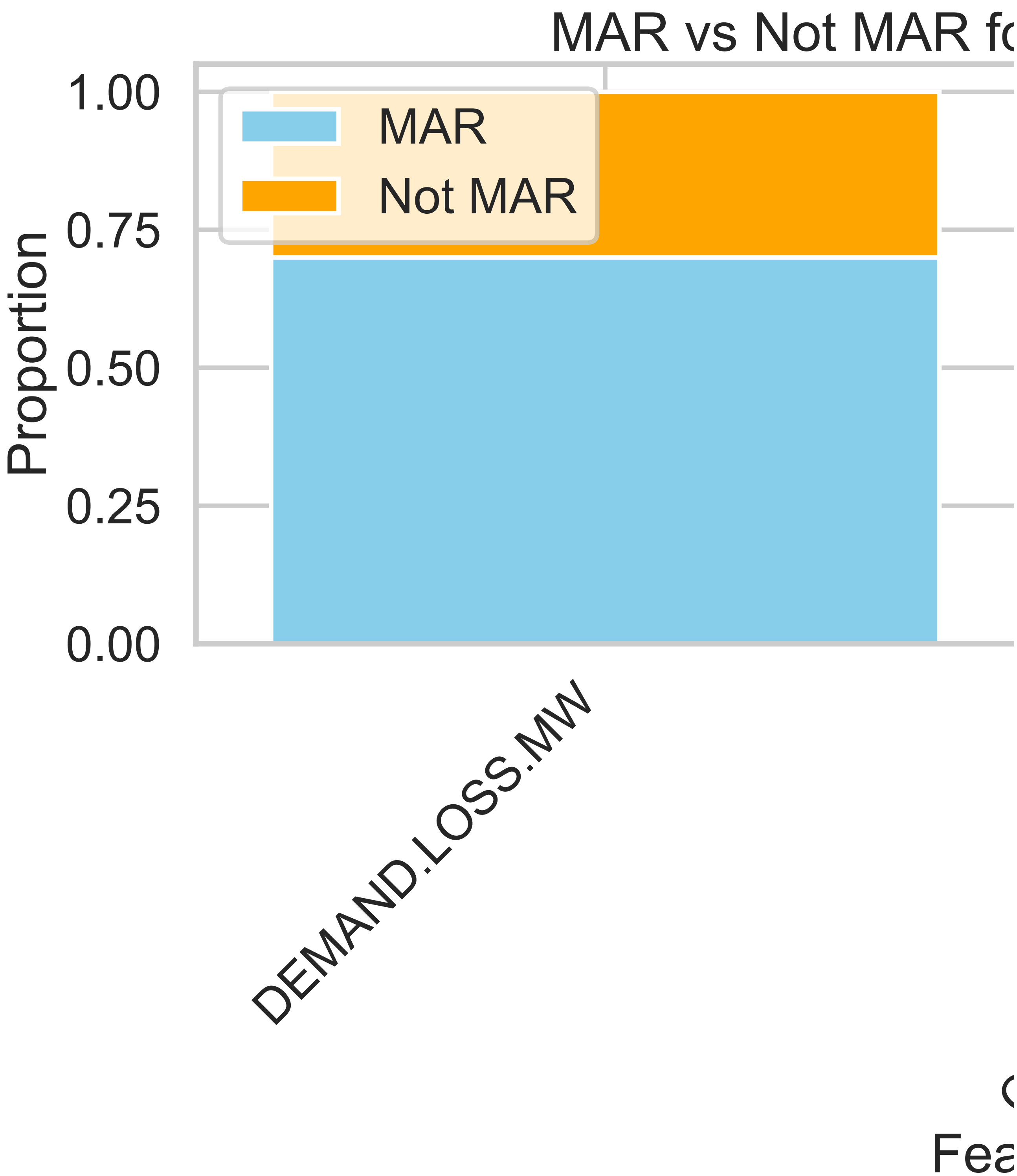
```
/var/folders/1m/hjhr1x894h35cktycnd3vr_m0000gn/T/ipykernel_43360/2091289738.
py:8: SmallSampleWarning:

One or more sample arguments is too small; all returned values will be NaN.
See documentation for sample size requirements.

/var/folders/1m/hjhr1x894h35cktycnd3vr_m0000gn/T/ipykernel_43360/1247589762.
py:27: RuntimeWarning:

Mean of empty slice.

/Users/ketan/miniforge3/envs/dsc80/lib/python3.12/site-packages/numpy/_core/
_methods.py:147: RuntimeWarning:

invalid value encountered in scalar divide

/var/folders/1m/hjhr1x894h35cktycnd3vr_m0000gn/T/ipykernel_43360/2091289738.
py:8: SmallSampleWarning:

One or more sample arguments is too small; all returned values will be NaN.
See documentation for sample size requirements.

/var/folders/1m/hjhr1x894h35cktycnd3vr_m0000gn/T/ipykernel_43360/1247589762.
py:27: RuntimeWarning:

Mean of empty slice.

/Users/ketan/miniforge3/envs/dsc80/lib/python3.12/site-packages/numpy/_core/
_methods.py:147: RuntimeWarning:

invalid value encountered in scalar divide
```

Out[44]:
```
defaultdict(<function __main__.<lambda>()>,
            {'DEMAND.LOSS.MW': [('YEAR', np.float64(0.0), np.True_),
              ('MONTH', np.float64(0.082), np.False_),
              ('ANOMALY.LEVEL', np.float64(0.0), np.True_),
              ('OUTAGE.DURATION', np.float64(0.004), np.True_),
              ('DEMAND.LOSS.MW', np.float64(nan), np.False_),
              ('CUSTOMERS.AFFECTED', np.float64(0.0), np.True_),
              ('TOTAL.PRICE', np.float64(0.011), np.False_),
              ('TOTAL.SALES', np.float64(0.0), np.True_),
              ('TOTAL.CUSTOMERS', np.float64(0.0), np.True_),
              ('TOTAL.REALGSP', np.float64(0.0), np.True_)],
             'CUSTOMERS.AFFECTED': [('YEAR', np.float64(0.0), np.True_),
              ('MONTH', np.float64(0.0), np.True_),
              ('ANOMALY.LEVEL', np.float64(0.0), np.True_),
              ('OUTAGE.DURATION', np.float64(0.0), np.True_),
              ('DEMAND.LOSS.MW', np.float64(0.0), np.True_),
              ('CUSTOMERS.AFFECTED', np.float64(nan), np.False_),
              ('TOTAL.PRICE', np.float64(0.029), np.False_),
              ('TOTAL.SALES', np.float64(0.0), np.True_),
              ('TOTAL.CUSTOMERS', np.float64(0.0), np.True_),
              ('TOTAL.REALGSP', np.float64(0.0), np.True_)]})
```

Now, we want to see how many columns are MAR vs not MAR with respect to the above two missing columns of interest.

In [45]:
```
# This plot displays the proportion of MAR vs not MAR columns for each of th

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd


data = {'Feature': [], 'MAR': [], 'Not MAR': []}

for target_col, features in mar_status.items():
    mar_count = sum([1 for _, _, mar in features if mar])
    not_mar_count = len(features) - mar_count
    total = len(features)

    # Normalize to proportions
    data['Feature'].append(target_col)
    data['MAR'].append(mar_count / total)
    data['Not MAR'].append(not_mar_count / total)


df = pd.DataFrame(data)


fig, ax = plt.subplots(figsize=(12, 8))
```

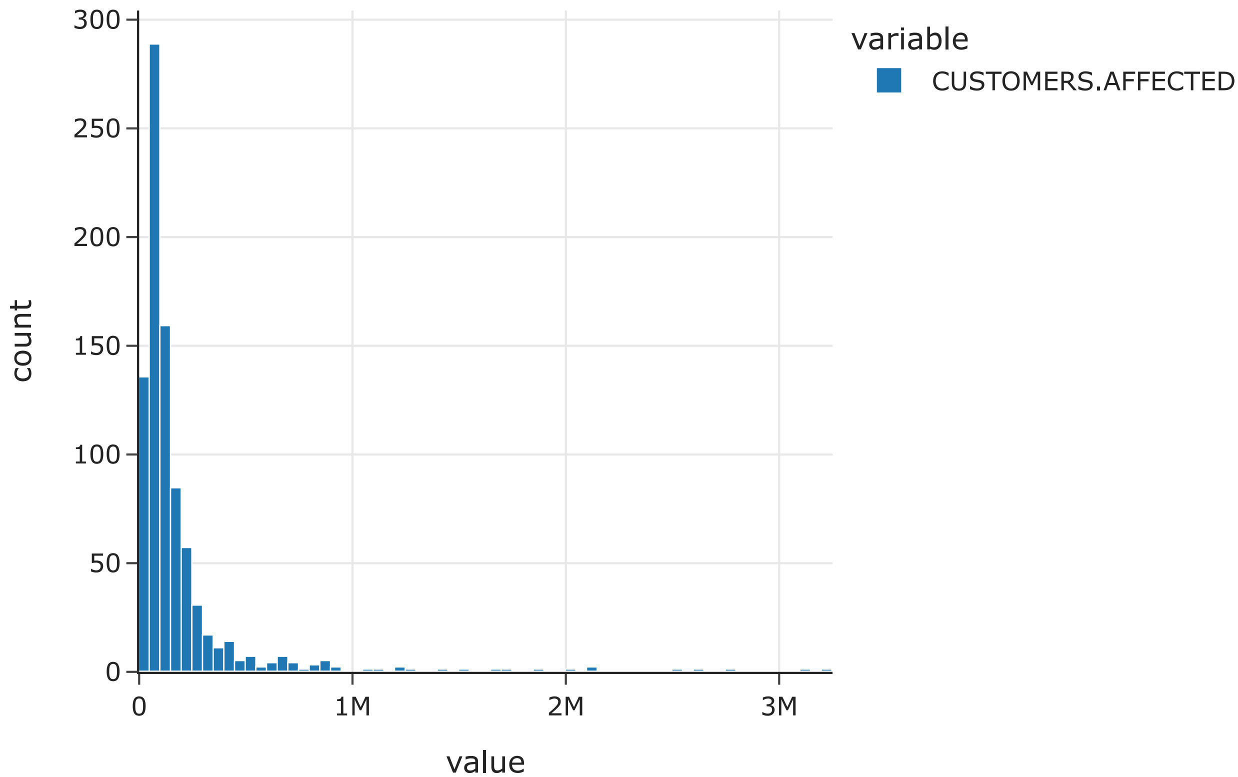
```
ax.bar(df['Feature'], df['MAR'], label='MAR', color='skyblue')
ax.bar(df['Feature'], df['Not MAR'], bottom=df['MAR'], label='Not MAR', colo


ax.set_xlabel('Feature')
ax.set_ylabel('Proportion')
ax.set_title('MAR vs Not MAR for All Other Features')
plt.xticks(rotation=45, ha="right")
ax.legend()


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



Since both `CUSTOMERS.AFFECTED` and `DEMAND.LOSS.MW` are shown to be **MAR** with respect to almost every other feature, we can impute these using techniques like K-Nearest Neighbors or Random Forest Regression

We are also using more features in this model version.

In [46]:
```
px.histogram(mdl_2_data['CUSTOMERS.AFFECTED'])
```



Note how the distribution of customers affected seems relatively normal until outliers stretch the distribution, so we can standardize to account for this difference and hopefully improve our model.

Model 2 (Final Model):

1. Data encoding
   A. One-hot encodes US states, climate region, climate category and NERC region
   B. Ordinal encodes month
   C. Standardizes the customers affected, as this is expected to follow a relatively normal distribution
   D. Passes the remaining (numerical) columns as is
2. Passes encoded data into an iterative imputer
   A. Uses random forest regression to impute missing values based on the provided encoded features. Note that encoding goes before this step, since random forest only works on numerical features (or encoded categorical)|
3. Pass encoded AND imputed data through a random forest classifier
   A. Perform grid search (GridSearchCV) for the random forest criterion, max depth and number of estimators to tune hyperparameters

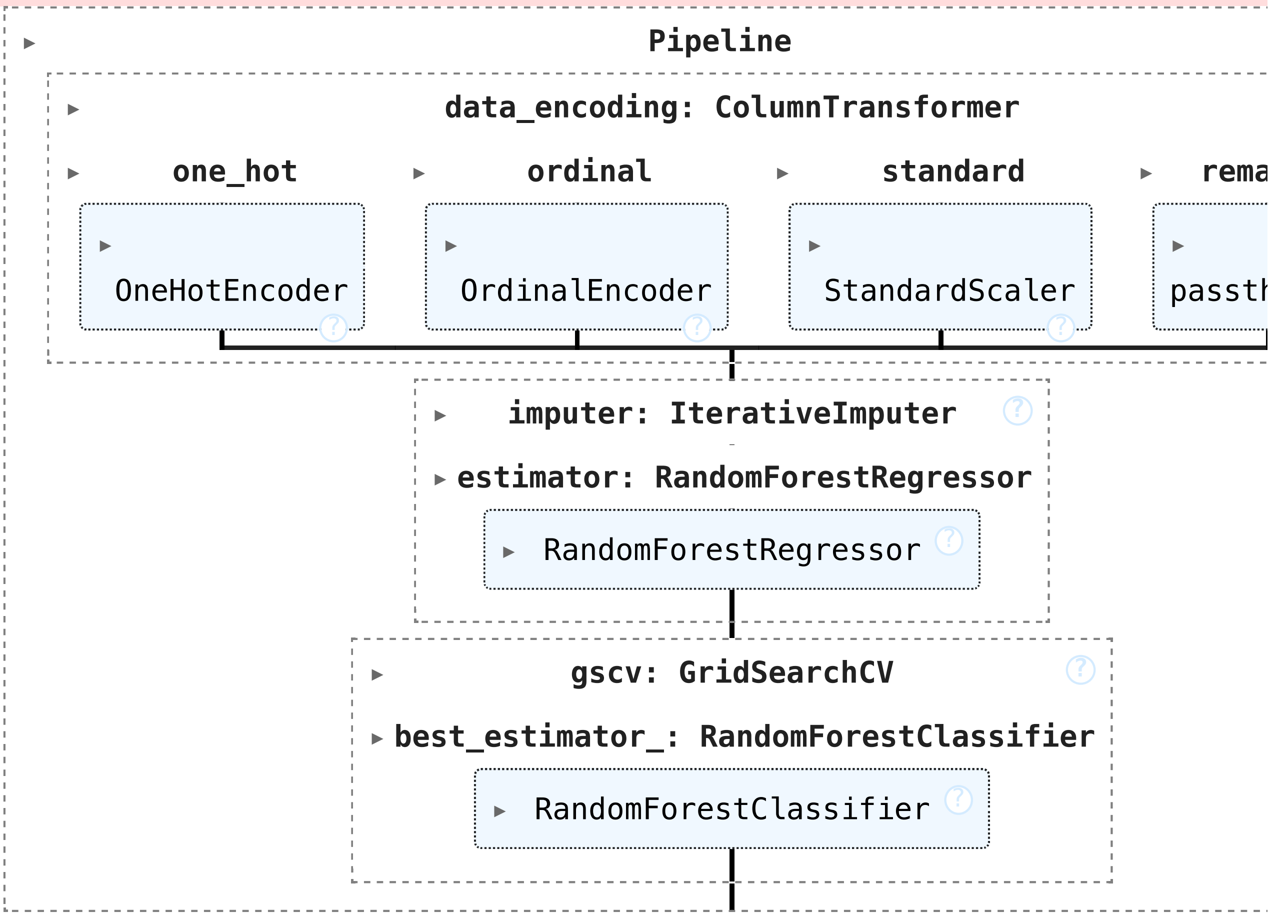
In [58]:
```
'''
Model 2 (Final Model):

1. Data encoding
    1. One-hot encodes US states, climate region, climate category and NERC
    2. Ordinal encodes month
    3. Standardizes the customers affected, as this is expected to follow a
    3. Passes the remaining (numerical) columns as is
2. Passes encoded data into an iterative imputer
    1. Uses random forest regression to impute missing values based on the p
3. Pass encoded AND imputed data through a random forest classifier
    1. Perform grid search (GridSearchCV) for the random forest criterion, m
'''
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder
from sklearn.model_selection import GridSearchCV

params_1 = {
    'criterion': ['entropy'],
    'max_depth': np.arange(5, 25),
    'n_estimators': [5, 10, 20, 50, 100, 200]
}

mdl_2 = Pipeline(steps=[
    ('data_encoding', ColumnTransformer(
        transformers=[
            ('one_hot', OneHotEncoder(handle_unknown='ignore', sparse_output
            ('ordinal', OrdinalEncoder(), ['MONTH']),
            ('standard', StandardScaler(), ['CUSTOMERS.AFFECTED'])
        ], remainder='passthrough')
    ),
    ('imputer', IterativeImputer(
        estimator=RandomForestRegressor(),
        max_iter=10, random_state=0
    )),
    ('gscv', GridSearchCV(RandomForestClassifier(), param_grid=params_1, cv=
])
```

In [59]:
```
# Splits into train and test again since we are using more features this tim
y_2 = mdl_2_data['CAUSE.CATEGORY']
X_2 = mdl_2_data.drop(columns = ['CAUSE.CATEGORY'])
X_2_train, X_2_test, y_2_train, y_2_test = train_test_split(X_2, y_2)
```

In [60]:
```
mdl_2.fit(X_2_train, y_2_train)
```

```
/Users/ketan/miniforge3/envs/dsc80/lib/python3.12/site-packages/sklearn/impu
te/_iterative.py:825: ConvergenceWarning:

[IterativeImputer] Early stopping criterion not reached.

/Users/ketan/miniforge3/envs/dsc80/lib/python3.12/site-packages/sklearn/comp
ose/_column_transformer.py:1623: FutureWarning:


The format of the columns of the 'remainder' transformer in ColumnTransforme
r.transformers_ will change in version 1.7 to match the format of the other
transformers.
At the moment the remainder columns are stored as indices (of type int). Wit
h the same ColumnTransformer configuration, in the future they will be store
d as column names (of type str).
To use the new behavior now and suppress this warning, use ColumnTransforme
r(force_int_remainder_cols=False).
```

Out[60]:



In [61]:

```python
# Train score on this version of the model
mdl_2.score(X_2_train, y_2_train)
```

Out[61]: 1.0

In [ ]:
```
# R^2 test score and f1 score for this model
y_2_preds = mdl_2.predict(X_2_test)
mdl_2.score(X_2_test, y_2_test), f1_score(y_2_test, y_2_preds, average = 'ma
```

This test score is MUCH better! This indicates that this version of our model is the best out of what we developed so far.

In [ ]:
```
# Also has high precision and recall, indicating low bias towards one catego
precision_score(y_2_test, y_2_preds, average = 'macro'), recall_score(y_2_te
```

In [53]:
```
# Visualizes confusion matrix for this model
fig, ax = plt.subplots(figsize=(12, 8))
ConfusionMatrixDisplay.from_estimator(
    mdl_2, X_2_test, y_2_test, ax=ax, cmap="Blues", colorbar=True
)

plt.title("Confusion Matrix for Final Model (Model 2)", fontsize=16)
plt.xlabel("Predicted Label", fontsize=14)
plt.ylabel("True Label", fontsize=14)
plt.xticks(fontsize=12, rotation=45, ha="right")

plt.yticks(fontsize=12)
plt.grid(False)

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

Step 8: Fairness Analysis

We are going to analyze the f1_scores for high vs low electricity consuming outages. This is a relevant feature to analyze since it indicates whether or model is performing fairly for both types of outages, indicating high availability.

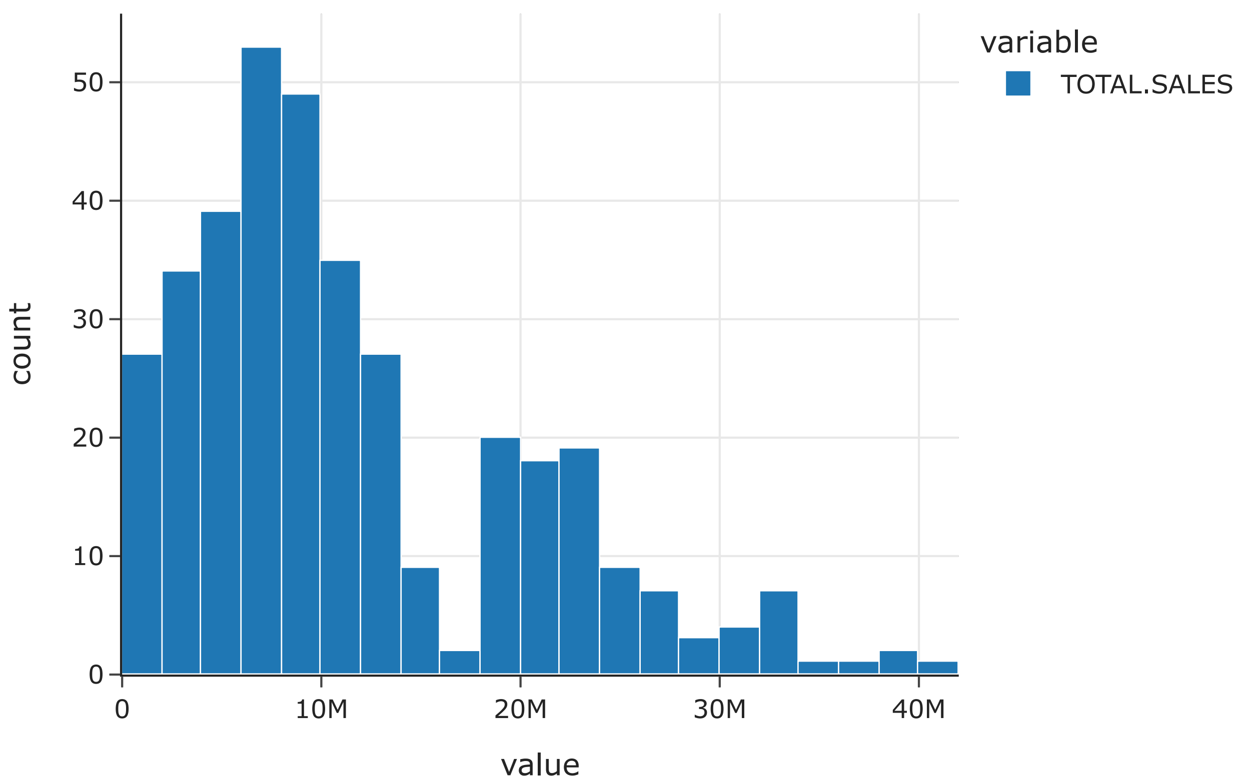
In [54]:
```
# Actual and predicted test values stored in a df
final_mdl_results = pd.DataFrame(data = {'Actual': y_2_test, 'Predicted': y_
final_mdl_results
```

Out[54]:

	Actual	Predicted
181	severe weather	severe weather
86	severe weather	severe weather
...	...	...
878	intentional attack	intentional attack
329	severe weather	severe weather

369 rows × 2 columns

In [55]:
```
total_sales = X_2_test[['TOTAL.SALES']]
px.histogram(total_sales)
```



Based on the above plot, we can choose 18,000,000 as a relevant Binarizer threshold. Values above this will be classified as 1 (high nationwide electricity consumption for the given outage) or 0 (high nationwide electricity consumption for the given outage)

In [56]:
```
bin = Binarizer(threshold = 18_000_000)
final_mdl_results['Group'] = bin.transform(total_sales.fillna(0))
final_mdl_results
```

```
/var/folders/1m/hjhr1x894h35cktycnd3vr_m0000gn/T/ipykernel_43360/2143724488.
py:2: FutureWarning:

Downcasting object dtype arrays on .fillna, .ffill, .bfill is deprecated and
will change in a future version. Call result.infer_objects(copy=False) inste
ad. To opt-in to the future behavior, set `pd.set_option('future.no_silent_d
owncasting', True)`

/Users/ketan/miniforge3/envs/dsc80/lib/python3.12/site-packages/sklearn/bas
e.py:486: UserWarning:

X has feature names, but Binarizer was fitted without feature names
```

Out[56]:

	Actual	Predicted	Group
181	severe weather	severe weather	1
86	severe weather	severe weather	0
...	...	...	...
878	intentional attack	intentional attack	0
329	severe weather	severe weather	0

369 rows × 3 columns

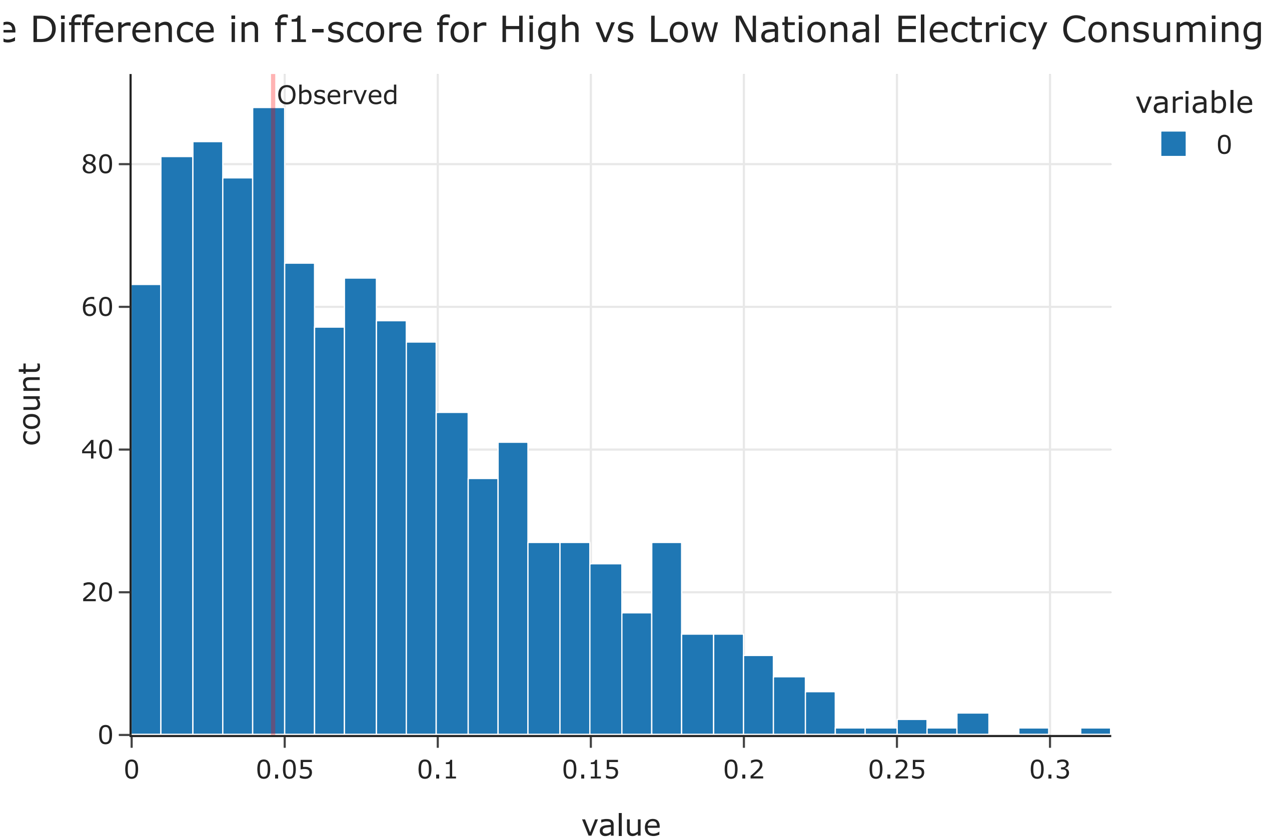
H_0: The model is fair for both high electricity consumption outages and low electricity consumption outages.

H_a: The model is unfair for both high electricity consumption outages and low electricity consumption outages.

We will use the absolute difference in `f1_score` for low outages (group 0) and high outages (group 1). A high test statistic would indicate that our model favors one or the opter (i.e. its predictions are much different for those in group 0 versus those in group 1)

In [57]:
```
# Performs a permutation test, using abs difference in f1_score as the test
obs_fair = abs(f1_score(final_mdl_results[final_mdl_results['Group'] == 0]['

fairness_sim = np.array([])
```

```
for _ in range(1000):
    final_mdl_results['Shuffled'] = np.random.permutation(final_mdl_results[
    sim = abs(f1_score(final_mdl_results[final_mdl_results['Shuffled'] == 0]
    fairness_sim = np.append(fairness_sim, sim)

p_val_fair = (fairness_sim > obs_fair).mean()

fig_fair = px.histogram(fairness_sim, title = 'Absoulte Difference in f1-scc
fig_fair.add_vline(x=obs_fair, line_color='red', line_width=2, annotation_te
fig_fair.show()
p_val_fair
```



Out[57]: np.float64(0.643)

With a p-value of 0.262 >> 0.05, we can conclude that there is significant evidence that our model is fair for both low and high electricity consuming outages.