Power Outage Data Analysis

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Website Link: (your website link)

In [1]:
```
import pandas as pd
import numpy as np
from pathlib import Path

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

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

In [2]:
```
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, OneHotEncoder, QuantileTra
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import (
    f1_score,
    classification_report,
    confusion_matrix,
    precision_score
)
```

In [3]:
```
import plotly.io as pio
pio.renderers.default = 'browser'
```

Step 1: Introduction

Step 2: Data Cleaning and Exploratory Data Analysis

In [4]:
```
# First step. Data cleaning.
# All of data cleaning stuff

df = pd.read_csv('power_outages.csv')
df = df.set_index('OBS')
# Kept only necessary data
df = df[['YEAR','MONTH','U.S._STATE','POSTAL.CODE', 'NERC.REGION', 'CLIMATE.
   'OUTAGE.START.DATE', 'OUTAGE.START.TIME', 'OUTAGE.RESTORATION.DATE', 'OUT
   'CAUSE.CATEGORY', 'CAUSE.CATEGORY.DETAIL', 'OUTAGE.DURATION', 'CUSTOMERS.
   'POPPCT_URBAN', 'POPDEN_URBAN']]

# Deleted rows with NA's. There were only 9, so it is an insignficant amount
```

```
df = df.dropna(subset=['MONTH', 'CLIMATE.REGION', 'ANOMALY.LEVEL', 'CLIMATE.

# Adjusted data to date time objecst and dropped original
df['OUTAGE.START'] = pd.to_datetime(df['OUTAGE.START.DATE'] + ' ' + df['OUTA
df['OUTAGE.RESTORATION'] = pd.to_datetime(df['OUTAGE.RESTORATION.DATE'] + '
df = df.drop(columns=['OUTAGE.START.DATE', 'OUTAGE.START.TIME', 'OUTAGE.REST

#Fixing columns
df.columns = df.columns.str.lower().str.replace('.', '_', regex=False)
df = df.rename(columns={'u_s__state': 'state'})

# Filling in missing outage_duration and outage_restoration
df['outage_duration'] = (df['outage_restoration'] - df['outage_start']).dt.t
median_durations = df.groupby(['nerc_region', 'cause_category'])['outage_dur
df['outage_duration'] = df['outage_duration'].fillna(median_durations)
# If there are still any NaN values, we can fall back to the overall median
overall_median = df['outage_duration'].median()
df['outage_duration'] = df['outage_duration'].fillna(overall_median)
df.isna().sum()
# Now, for the rows where we imputed the duration, let's also update the res
mask = df['outage_restoration'].isna()
df.loc[mask, 'outage_restoration'] = df.loc[mask, 'outage_start'] + pd.to_ti
# Add a flag to indicate which rows had imputed durations
df['duration_imputed'] = mask

# Let's do the same thing but for customers_efffected
# First, create the flag before filling in values
df['customers_affected_imputed'] = df['customers_affected'].isna()
# Then proceed with filling in the missing values
median_customers = df.groupby(['nerc_region', 'cause_category'])['customers_
df['customers_affected'] = df['customers_affected'].fillna(median_customers)
# If there are remaining missing values we fill in with the overall median
overall_median_customers = df['customers_affected'].median()
df['customers_affected'] = df['customers_affected'].fillna(overall_median_cu

# Fill in cause category. Fill in missing values with original cause_categor
df['cause_detail_missing'] = df['cause_category_detail'].isna()
df['cause_category_detail'] = (df.apply(lambda row: row['cause_category']
                                         if pd.isnull(row['cause_category_det
```

In [5]:
```
# Cleaned data frame
# Example data frame
print(df.head().to_markdown())
```

OBS	year	month	state	postal_code	nerc_region	climate_region	anomaly_level	climate_category	cause_category	cause_category_detail	outage_duration	customers_affected	total_customers	pc_realgsp_state	poppct_urban	popden_urban	outage_start	outage_restoration	duration_imputed	customers_affected_imputed	cause_detail_missing
1	2011	7	Minnesota	MN	MRO	East North Central	-0.3	normal	severe weather	severe weather	3060	70000	2595696	51268	73.27	2279	2011-07-01 17:00:00	2011-07-03 20:00:00	False	False	True
2	2014	5	Minnesota	MN	MRO	East North Central	-0.1	normal	intentional attack	vandalism	1	0	2640737	53499	73.27	2279	2014-05-11 18:38:00	2014-05-11 18:39:00	False	True	False
3	2010	10	Minnesota	MN	MRO	East North Central	-1.5	cold	severe weather	heavy wind	3000	70000	2586905	50447	73.27	2279	2010-10-26 20:00:00	2010-10-28 22:00:00	False	False	False
4	2012	6	Minnesota	MN	MRO	East North Central	-0.1	normal	severe weather	thunderstorm	2550	68200	2606813	51598	73.27	2279	2012-06-19 04:30:00	2012-06-20 23:00:00	False	False	False
5	2015	7	Minnesota	MN	MRO	East North Central	1.2	warm	severe weather	severe weather	1740	250000	2673531	54431	73.27	2279	2015-07-18 02:00:00	2015-07-19 07:00:00	False	False	True

In [6]:

```python
# UNIVARIATE PLOT 1
# Create a Plotly box plot
fig = px.box(
    df,
    x='cause_category',
    y='outage_duration',
    title='Comparison of Outage Durations by Cause',
    labels={
        'cause_category': 'Cause Category',
        'outage_duration': 'Outage Duration (hours)'
    },
    color_discrete_sequence=px.colors.qualitative.Set2
)
```

```
# Update the layout for a clean appearance
fig.update_layout(
    xaxis_title='Cause Category',
    yaxis_title='Outage Duration (hours)',
    title_font_size=16,
    xaxis_tickangle=45,
    xaxis_tickfont=dict(size=12),
    yaxis_tickfont=dict(size=12),
    margin=dict(l=0, r=0, t=50, b=0),
    height=600,
    width=1000
)

# Show the Plotly plot
fig.show()

# Write to HTML
fig.write_html('assets/outage_durations_vs_cause.html', include_plotlyjs='cd
```

In [7]:

```
# BIVARIATE PLOT 1
fig1 = px.scatter(
    df,
    x='outage_duration',
    y='customers_affected',
    color='cause_category',
    title='Customers Affected vs. Outage Duration',
    labels={
        'outage_duration': 'Outage Duration (minutes)',
        'customers_affected': 'Customers Affected'
    },
    color_discrete_sequence=px.colors.qualitative.Set2
)

fig1.update_traces(marker=dict(size=10, line=dict(width=1, color='black')),
fig1.update_layout(
    title_font_size=16,
    xaxis_title='Outage Duration (minutes)',
    yaxis_title='Customers Affected',
    legend_title_text='Cause Category',
    legend=dict(x=1.05, y=1, title_font=dict(size=14), font=dict(size=12)),
    margin=dict(l=0, r=0, t=50, b=0),
    width=1000,
    height=600
)

fig1.show()

fig1.write_html('assets/customers_vs_cause_duration_part1.html', include_plo
```

In [8]:

```
# BIVARIATE PLOT 1 PART 2
df_filtered = df[df['cause_category'] == 'intentional attack'].copy()
fig2 = px.scatter(
    df_filtered,
    x='outage_duration',
```

```
    y='customers_affected',
    title='Customers Affected vs. Outage Duration (Intentional Attack)',
    labels={
        'outage_duration': 'Outage Duration (minutes)',
        'customers_affected': 'Customers Affected'
    },
    color_discrete_sequence=['orange']  #Orange
)

fig2.update_traces(marker=dict(size=10, line=dict(width=1, color='black')),
fig2.update_layout(
    title_font_size=16,
    xaxis_title='Outage Duration (minutes)',
    yaxis_title='Customers Affected',
    margin=dict(l=0, r=0, t=50, b=0),
    width=1000,
    height=600
)

fig2.show()

fig2.write_html('assets/customers_vs_cause_duration_part2.html', include_plo
```

In [9]:

```
# HEATMAP

pivot_table = pd.crosstab(df['nerc_region'], df['cause_category'])

# Convert pivot table (melt) for plotly heatmap
pivot_table_melted = pivot_table.reset_index().melt(id_vars='nerc_region', v

# plotly heatmap
fig3 = px.density_heatmap(
    pivot_table_melted,
    x='cause_category',
    y='nerc_region',
    z='outage_count',
    text_auto=True,  # Show the annotations
    color_continuous_scale='YlOrRd',
    labels={
        'cause_category': 'Cause Category',
        'nerc_region': 'NERC Region',
        'outage_count': 'Number of Outages'
    },
    title='Frequency of Outage Causes by NERC Region'
)

# update style
fig3.update_layout(
    title_font_size=16,
    xaxis_title='Cause Category',
    yaxis_title='NERC Region',
    xaxis_tickangle=45,
    xaxis_tickfont=dict(size=12),
    yaxis_tickfont=dict(size=12),
    coloraxis_colorbar=dict(title='Number of Outages'),
    margin=dict(l=0, r=0, t=50, b=0),
```

```
    width=800,
    height=600
)

fig3.show()

fig3.write_html('assets/causes_vs_NERC_region_heat_map.html', include_plotly
```

In [10]:

```
# ATTACKS PER YEAR

pivot_1 = pd.pivot_table(df, values='outage_duration', index='year', columns
intentional_attacks_by_year = pivot_1['intentional attack']
#print(intentional_attacks_by_year)

markdown_table1 = intentional_attacks_by_year.to_markdown()

# Print the Markdown table
print(markdown_table1)
```

```
|   year |   intentional attack |
|-------:|---------------------:|
|   2000 |                    2 |
|   2001 |                    0 |
|   2002 |                    1 |
|   2003 |                    2 |
|   2004 |                    0 |
|   2005 |                    0 |
|   2006 |                    0 |
|   2007 |                    0 |
|   2008 |                    0 |
|   2009 |                    0 |
|   2010 |                    0 |
|   2011 |                  121 |
|   2012 |                   89 |
|   2013 |                   80 |
|   2014 |                   47 |
|   2015 |                   43 |
|   2016 |                   33 |
```

In [11]:

```
'''Average Outage Duration and Customers Affected by Cause Category and NERC
aggregate_1 = df.groupby(['nerc_region', 'cause_category']).agg({
    'outage_duration': 'mean',
    'customers_affected': 'mean'
}).reset_index()

aggregate_1.sort_values('outage_duration', ascending=False).head(10)
```

Out[11]:

	nerc_region	cause_category	outage_duration	customers_affected
23	RFC	fuel supply emergency	33142.80	0.00
44	TRE	fuel supply emergency	16416.00	56000.00
30	SERC	fuel supply emergency	14805.00	56000.00
...	...	...	...	...
2	ECAR	severe weather	6035.14	166976.21
6	FRCC	public appeal	4320.00	0.00
41	SPP	severe weather	4279.39	173494.11

10 rows × 4 columns

In [12]:
```
'''Frequency of Outage Causes by Year:'''
pivot_1 = pd.pivot_table(df, values='outage_duration', index='year', columns
list(pivot_1['intentional attack'])
pivot_1
```

Out[12]:

cause_category	equipment failure	fuel supply emergency	intentional attack	islanding	public appeal	severe weather	sy opera disru
year							
2000	2	0	2	0	0	10	
2001	1	0	0	0	3	1	
2002	0	0	1	0	0	12	
...	...	...	...	...	...	...	
2014	0	13	47	1	5	45	
2015	0	2	43	9	4	48	
2016	0	3	33	2	0	12	

17 rows × 7 columns

In [13]:
```
'''Average Outage Duration by Month and Cause Category:'''
aggregate_2 = df.groupby(['month', 'cause_category'])['outage_duration'].mea
aggregate_2
```

Out[13]:

cause_category month	equipment failure	fuel supply emergency	intentional attack	islanding	public appeal	severe weather	s ope disr
1.0	618.67	31828.50	286.84	NaN	2681.25	4327.45	
2.0	479.75	12941.11	356.10	359.50	1041.40	3078.62	
3.0	19866.50	17703.60	889.67	51.67	945.50	3321.77	
...	...	...	...	...	...	...	
10.0	NaN	NaN	214.06	13.33	351.00	6289.57	
11.0	503.00	758.00	237.33	129.00	NaN	3035.30	
12.0	838.25	15059.00	598.98	436.00	6293.50	4097.18	

12 rows × 7 columns

In [14]:

```
'''Percentage of Outages by Cause Category for Each NERC Region:'''
cause_by_region = df.groupby(['nerc_region', 'cause_category']).size().unsta
cause_by_region_pct = cause_by_region.div(cause_by_region.sum(axis=1), axis=
cause_by_region_pct
```

Out[14]:

cause_category nerc_region	equipment failure	fuel supply emergency	intentional attack	islanding	public appeal	severe weather	sy opera disru
ECAR	5.88	0.00	2.94	0.00	0.00	82.35	
FRCC	9.30	0.00	4.65	0.00	6.98	60.47	
FRCC, SERC	0.00	0.00	0.00	0.00	0.00	0.00	1
...	...	...	...	...	...	...	
SPP	1.52	1.52	12.12	3.03	24.24	54.55	
TRE	1.80	4.50	8.11	0.00	14.41	55.86	
WECC	6.87	4.43	41.91	7.76	2.66	24.17	

10 rows × 7 columns

Step 3: Assessment of Missingness

In [15]:
```
original_df = pd.read_csv('power_outages.csv')
original_df
original_df = original_df[['YEAR','MONTH','U.S._STATE','POSTAL.CODE', 'NERC.
    'OUTAGE.START.DATE', 'OUTAGE.START.TIME', 'OUTAGE.RESTORATION.DATE', 'OUT
    'CAUSE.CATEGORY', 'CAUSE.CATEGORY.DETAIL', 'OUTAGE.DURATION', 'CUSTOMERS.
    'POPPCT_URBAN', 'POPDEN_URBAN']]
```

In [16]:
```
missingness = original_df.isnull().sum() / len(original_df) * 100
#print(missingness[missingness > 0].sort_values(ascending=False))
original_df['customers_affected_missing'] = original_df['CUSTOMERS.AFFECTED'
original_df['customers_affected_missing']
```

Out[16]:
```
0       0
1       1
2       0
       ..
1531    1
1532    1
1533    0
Name: customers_affected_missing, Length: 1534, dtype: int64
```

In [17]:
```
# permutation test
def permutation_test(df, col1, col2, n_permutations=1000):
    observed_diff = df[df[col2] == 0][col1].mean() - df[df[col2] == 1][col1]

    diffs = []
    for _ in range(n_permutations):
        shuffled = df[col2].sample(frac=1).reset_index(drop=True)
        diff = df[shuffled == 0][col1].mean() - df[shuffled == 1][col1].mean
        diffs.append(diff)

    p_value = (np.abs(np.array(diffs)) >= np.abs(observed_diff)).mean()
    return p_value
```

In [18]:
```
# Test dependency
p_value_duration = permutation_test(original_df, 'OUTAGE.DURATION', 'custome
print(f"P-value for outage_duration: {p_value_duration}")
```

```
P-value for outage_duration: 0.021
```

In [19]:
```
# Test dependency on 'year'
p_value_year = permutation_test(original_df, 'YEAR', 'customers_affected_mis
print(f"P-value for year: {p_value_year}")
```

```
P-value for year: 0.0
```

In [20]:
```
######
#Permutation test 1 visualization

def permutation_test_with_distribution(df, col1, col2, n_permutations=1000):
    observed_diff = df[df[col2] == 0][col1].mean() - df[df[col2] == 1][col1]

    diffs = []
    for _ in range(n_permutations):
        shuffled = df[col2].sample(frac=1).reset_index(drop=True)
        diff = df[shuffled == 0][col1].mean() - df[shuffled == 1][col1].mean
```

```
        diffs.append(diff)

    p_value = (np.abs(np.array(diffs)) >= np.abs(observed_diff)).mean()
    return observed_diff, diffs, p_value

observed_diff, diffs, p_value = permutation_test_with_distribution(original_

fig = go.Figure()

fig.add_trace(go.Histogram(x=diffs, name='Permutation Distribution', opacity

fig.add_trace(go.Scatter(x=[observed_diff, observed_diff], y=[0, 30],
                         mode='lines', name='Observed Difference',
                         line=dict(color='red', width=2, dash='dash')))

fig.update_layout(
    title='Outage Duration vs Customers Affected Missingness',
    xaxis_title='Difference in Means',
    yaxis_title='Frequency',
    title_font_size=18,  # Increase title font size
    margin=dict(l=80, r=80, t=100, b=80),  # Increase margins
    annotations=[
        dict(x=observed_diff, y=25, xref='x', yref='y',
             text=f'observed Diff: {observed_diff:.2f}', showarrow=True,
             font=dict(color='red'), arrowhead=2, ax=50, ay=-40),
        dict(x=0.9, y=0.95, xref='paper', yref='paper',
             text=f'p-value: {p_value:.4f}', showarrow=False,
             font=dict(size=14))
    ],
    autosize=True
)


fig.show()
fig.write_html('assets/permutation_test_outage_duration_vs_missingness_custo
```

In [21]:

```
# Permutation test 2import numpy as np
def permutation_test_with_distribution(df, col1, col2, n_permutations=1000):
    observed_diff = df[df[col2] == 0][col1].mean() - df[df[col2] == 1][col1]

    diffs = []
    for _ in range(n_permutations):
        shuffled = df[col2].sample(frac=1).reset_index(drop=True)
        diff = df[shuffled == 0][col1].mean() - df[shuffled == 1][col1].mean
        diffs.append(diff)

    p_value = (np.abs(np.array(diffs)) >= np.abs(observed_diff)).mean()
    return observed_diff, diffs, p_value

observed_diff, diffs, p_value = permutation_test_with_distribution(original_

fig = go.Figure()

# histogram
fig.add_trace(go.Histogram(x=diffs, name='Permutation Distribution', opacity
```

```
fig.add_trace(go.Scatter(x=[observed_diff, observed_diff], y=[0, 30],
                         mode='lines', name='Observed Difference',
                         line=dict(color='red', width=2, dash='dash')))

# layout
fig.update_layout(
    title='Year vs Customers Affected Missingness',
    xaxis_title='Difference in Mean Year',
    yaxis_title='Frequency',
    title_font_size=18,
    margin=dict(l=80, r=80, t=100, b=80),
    annotations=[
        dict(x=observed_diff, y=25, xref='x', yref='y',
             text=f'Observed Difference: {observed_diff:.2f}', showarrow=Tru
             font=dict(color='red'), arrowhead=2, ax=50, ay=-40),
        dict(x=0.9, y=0.95, xref='paper', yref='paper',
             text=f'p-value: {p_value:.4f}', showarrow=False,
             font=dict(size=14))
    ],
    autosize=True
)

fig.show()

print(f"Observed diff- mean year: {observed_diff:.2f}")
print(f"P-value: {p_value:.4f}")
```

```
Observed diff- mean year: -1.85
P-value: 0.0000
```

In [22]:

```
# MY BOX PLOT
fig = px.box(
    original_df,
    x='customers_affected_missing',
    y='OUTAGE.DURATION',
    title='Outage Duration vs Missingness of Customers Affected',
    labels={
        'customers_affected_missing': 'Customers Affected Missing',
        'OUTAGE.DURATION': 'Outage Duration (minutes)'
    },
    color='customers_affected_missing',
    color_discrete_sequence=['#FF6347', '#4682B4'],
    width=800,
    height=600
)

fig.update_traces(
    boxpoints='outliers',
    opacity=0.9,
    line=dict(width=2),
    marker=dict(size=6, color='black')
)

fig.update_layout(
    yaxis_range=[0, 20000],
    title_font_size=16,
```

```
    xaxis_title='Customers Affected Missing',
    yaxis_title='Outage Duration (minutes)',
    xaxis_tickfont=dict(size=12),
    yaxis_tickfont=dict(size=12),
    showlegend=False,
)

fig.show()
fig.write_html('assets/boxplot_outage_duration_vs_customers_affected.html',
```

Step 4: Hypothesis Testing

In [23]:
```
fig = go.Figure()

# Add histogram of permutation distribution
fig.add_trace(
    go.Histogram(x=diffs, nbinsx=100, name="Permutation Distribution", marke
)

# Add vertical line for observed difference
fig.add_trace(
    go.Scatter(x=[observed_diff, observed_diff],
               y=[0, np.max(np.histogram(diffs, bins=100)[0])],
               mode="lines",
               name=f"Observed Difference: {observed_diff:.2f}",
               line=dict(color="red", width=2, dash="dash"))
)

# Calculate the range for x-axis
max_abs_diff = max(abs(np.min(diffs)), abs(np.max(diffs)), abs(observed_diff
x_range = [-max_abs_diff * 1.1, max_abs_diff * 1.1]

# Update layout
fig.update_layout(
    title_text="Permutation Test: Outage Duration (Severe Weather vs Intenti
    xaxis_title="Difference in Mean Outage Duration (minutes)",
    yaxis_title="Frequency",
    showlegend=True,
    height=600,
    width=1000
)

# Update x-axis
fig.update_xaxes(range=x_range, zeroline=True, zerolinecolor='black', zeroli

# Add annotation for observed difference
fig.add_annotation(
    x=observed_diff,
    y=np.max(np.histogram(diffs, bins=100)[0]) * 0.9,
    text=f"Observed Diff: {observed_diff:.2f}",
    showarrow=True,
    arrowhead=2,
    ax=0,
    ay=-40,
```

```
    bgcolor="yellow",
    bordercolor="black",
    borderwidth=1,
    opacity=0.8
)

fig.show()
fig.write_html('assets/hypothesis_test_graph.html', include_plotlyjs='cdn')
```

Step 5: Framing a Prediction Problem

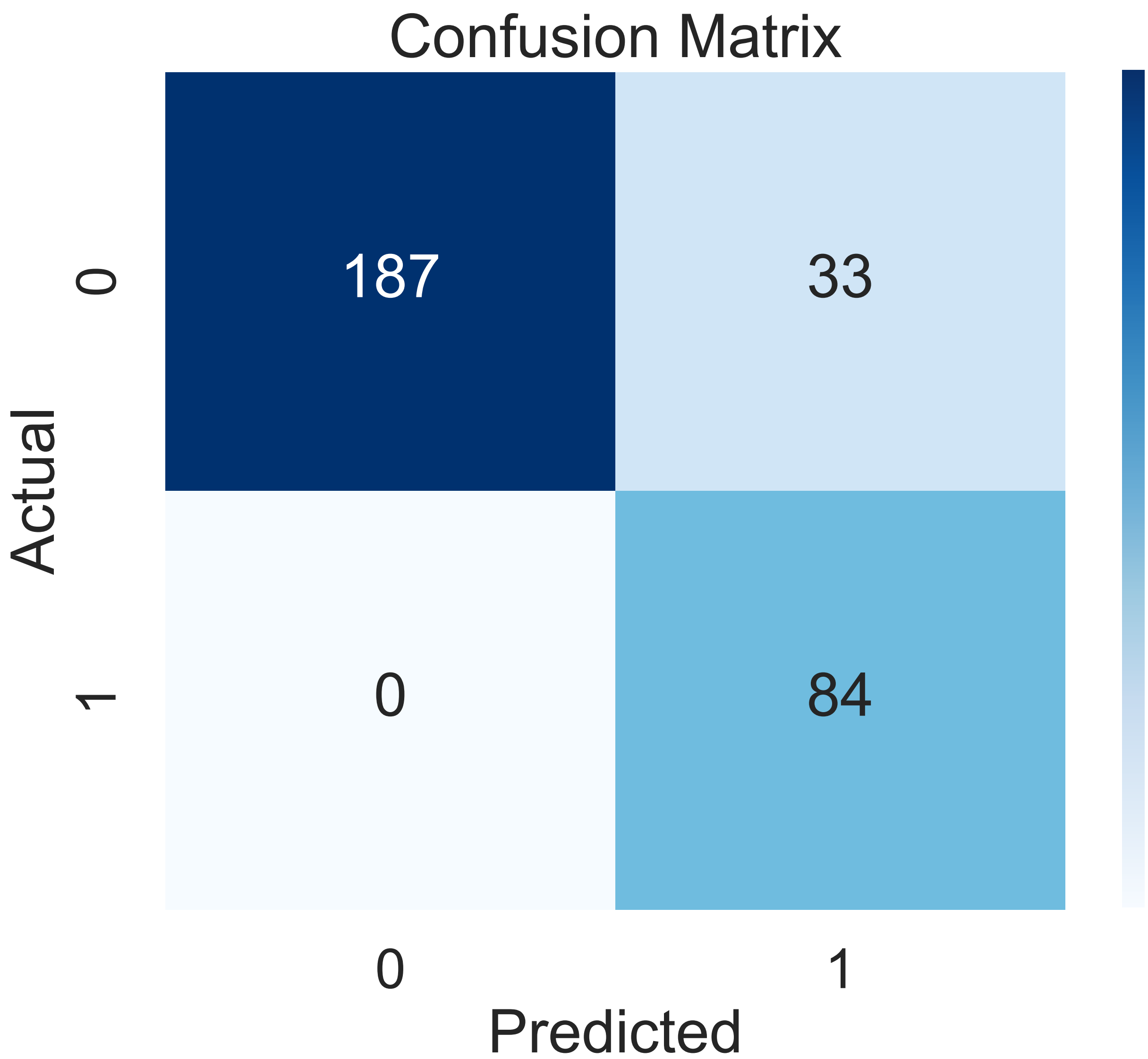
"Predict whether a power outage is caused by an intentional attack based on its characteristics and regional factors."

Step 6: Baseline Model

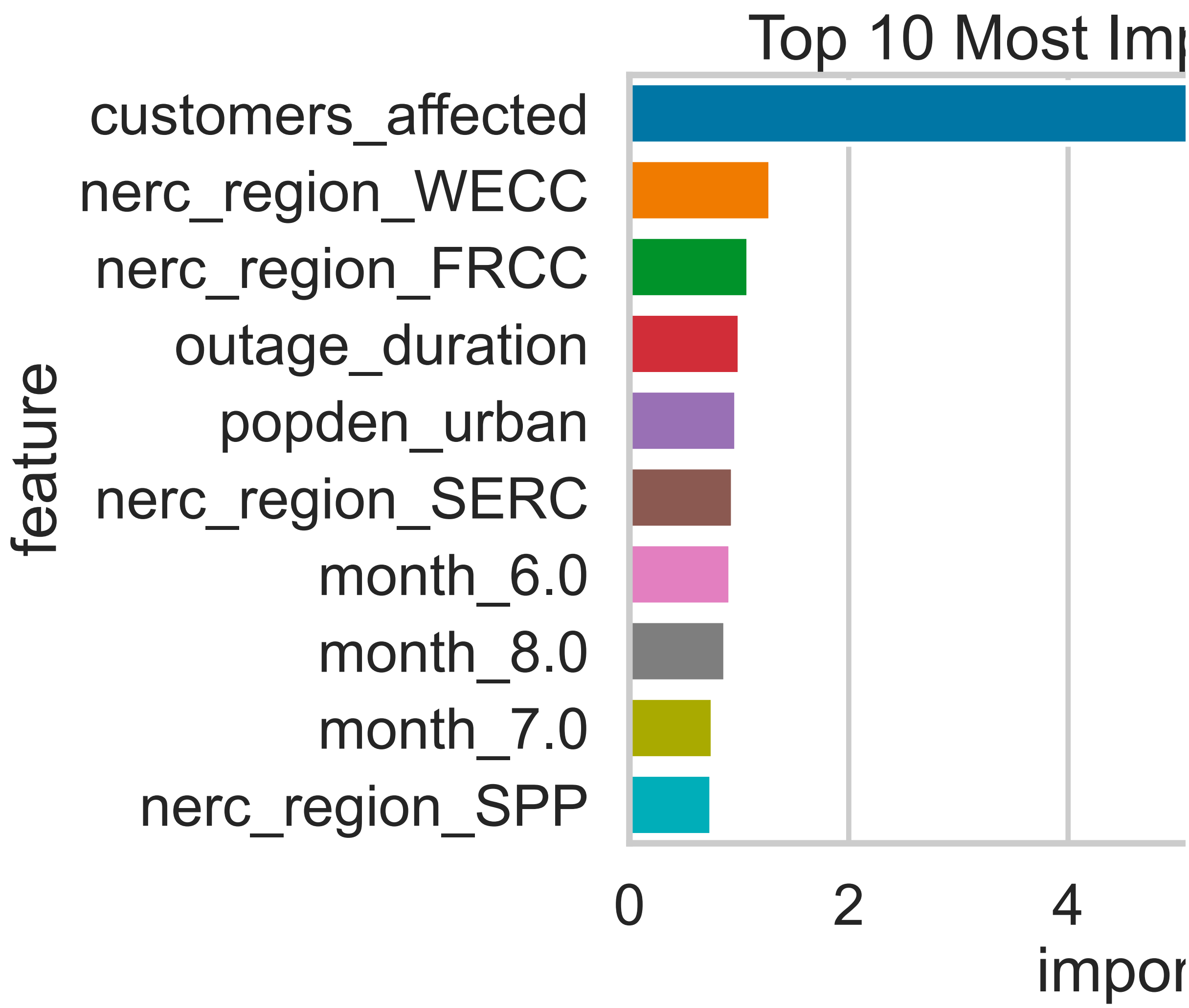
In [24]:
```
df['is_intentional_attack'] = (df['cause_category'] == 'intentional attack')

features = ['nerc_region', 'outage_duration', 'customers_affected', 'month',
            'pc_realgsp_state', 'popden_urban']
X = df[features]
y = df['is_intentional_attack']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ran

numeric_features = ['outage_duration', 'customers_affected', 'pc_realgsp_sta
categorical_features = ['nerc_region', 'month']

preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numeric_features),
        ('cat', OneHotEncoder(drop='first', sparse=False, handle_unknown='ig
    ])

model = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', LogisticRegression(class_weight='balanced'))
])

model.fit(X_train, y_train)

y_pred = model.predict(X_test)

print("Classification Report:")
print(classification_report(y_test, y_pred))
print(f"F1 Score: {f1_score(y_test, y_pred)}")

cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.ylabel('Actual')
```

```
plt.xlabel('Predicted')
plt.show()

feature_names = (numeric_features +
                 model.named_steps['preprocessor']
                 .named_transformers_['cat']
                 .get_feature_names_out(categorical_features).tolist())

coefficients = model.named_steps['classifier'].coef_[0]
feature_importance = pd.DataFrame({'feature': feature_names, 'importance': a
feature_importance = feature_importance.sort_values('importance', ascending=

print("\nTop 10 Most Important Features:")
print(feature_importance.head(10))

plt.figure(figsize=(10, 6))
sns.barplot(x='importance', y='feature', data=feature_importance.head(10))
plt.title('Top 10 Most Important Features')
plt.tight_layout()
plt.show()

class_balance = y.value_counts(normalize=True)
print("\nClass Balance:")
print(class_balance)
```

```
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.85      0.92       220
           1       0.72      1.00      0.84        84

    accuracy                           0.89       304
   macro avg       0.86      0.93      0.88       304
weighted avg       0.92      0.89      0.90       304

F1 Score: 0.835820895522388
```




```
Top 10 Most Important Features:
               feature  importance
1   customers_affected        9.75
12    nerc_region_WECC        1.29
4     nerc_region_FRCC        1.09
..                 ...         ...
19           month_8.0        0.88
18           month_7.0        0.76
10     nerc_region_SPP        0.75

[10 rows x 2 columns]
```




```
Class Balance:
0    0.72
1    0.28
Name: is_intentional_attack, dtype: float64
```

Step 7: Final Model

In [25]:
```
df['is_intentional_attack'] = (df['cause_category'] == 'intentional attack')

df['season'] = pd.to_datetime(df['month'], format='%m').dt.month.map({1: 'Wi
                                                                       4: 'Sp
                                                                       7: 'Su
                                                                       10: 'F

features = ['nerc_region', 'outage_duration', 'customers_affected', 'season'
            'pc_realgsp_state', 'popden_urban']

X = df[features]
y = df['is_intentional_attack']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ran

# preprocessor
numeric_features = ['outage_duration', 'customers_affected', 'pc_realgsp_sta
```

```
categorical_features = ['nerc_region', 'season']

preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), ['customers_affected', 'pc_realgsp_state',
        ('dur', QuantileTransformer(n_quantiles=100, output_distribution='no
        ('cat', OneHotEncoder(drop='first', sparse=False, handle_unknown='ig
    ])

# pipeline
pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', RandomForestClassifier(random_state=42))
])

# hyperparameters
param_grid = {
    'classifier__n_estimators': [50, 100, 200],
    'classifier__max_depth': [None, 10, 20, 30]
}

# GridSearchCV
grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring='f1', n_jobs=
grid_search.fit(X_train, y_train)

# best model
best_model = grid_search.best_estimator_

# predictions
y_pred = best_model.predict(X_test)

# Evaluate
print("Best Parameters:", grid_search.best_params_)
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
print(f"F1 Score: {f1_score(y_test, y_pred)}")

# Compare
baseline_f1 = 0.84  # Replace with your actual baseline F1 score
print(f"\n\nimprovement over baseline: {f1_score(y_test, y_pred) - baseline_
```

```
Best Parameters: {'classifier__max_depth': 10, 'classifier__n_estimators': 5
0}

Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.98      0.97       220
           1       0.94      0.92      0.93        84

    accuracy                           0.96       304
   macro avg       0.95      0.95      0.95       304
weighted avg       0.96      0.96      0.96       304

F1 Score: 0.9277108433734941


improvement over baseline: 0.0877
```

In [26]:
```
# feature names
feature_names = (
    numeric_features +
    best_model.named_steps['preprocessor']
    .named_transformers_['cat']
    .get_feature_names_out(categorical_features).tolist()
)

# feature importances
importances = best_model.named_steps['classifier'].feature_importances_

# dataframe of feature importances
feature_importances = pd.DataFrame({
    'feature': feature_names,
    'importance': importances
}).sort_values('importance', ascending=False)

print("\n\nTop 10 Feature Importances:")
print(feature_importances.head(10))
```

```
Top 10 Feature Importances:
               feature  importance
0      outage_duration    5.51e-01
3         popden_urban    2.05e-01
1   customers_affected    8.48e-02
..                 ...         ...
11      nerc_region_TRE    8.86e-03
10      nerc_region_SPP    7.83e-03
7      nerc_region_NPCC    7.22e-03

[10 rows x 2 columns]
```

Step 8: Fairness Analysis

In [28]:
```
# binary column for WECC
X_test['is_WECC'] = (X_test['nerc_region'] == 'WECC').astype(int)
```

```
# predictions
y_pred = best_model.predict(X_test)

#calculate precision
def get_precision(y_true, y_pred):
    return precision_score(y_true, y_pred, pos_label=1)

# observed difference in precision
wecc_precision = get_precision(y_test[X_test['is_WECC'] == 1], y_pred[X_test
non_wecc_precision = get_precision(y_test[X_test['is_WECC'] == 0], y_pred[X_
observed_diff = wecc_precision - non_wecc_precision

# Permutation test
n_permutations = 1000
diffs = []
for _ in range(n_permutations):
    permuted_wecc = np.random.permutation(X_test['is_WECC'])
    permuted_wecc_precision = get_precision(y_test[permuted_wecc == 1], y_pr
    permuted_non_wecc_precision = get_precision(y_test[permuted_wecc == 0],
    diffs.append(permuted_wecc_precision - permuted_non_wecc_precision)

# Calculate p-value
p_value = np.mean(np.abs(diffs) >= np.abs(observed_diff))

print(f"WECC Precision: {wecc_precision:.4f}")
print(f"Non-WECC Precision: {non_wecc_precision:.4f}")
print(f"Observed difference: {observed_diff:.4f}")
print(f"P-value: {p_value:.4f}")

# histogram
fig = go.Figure()

# histogram of permutation differences
fig.add_trace(go.Histogram(
    x=diffs,
    nbinsx=30,  # Match bins size to original
    marker=dict(color='skyblue', line=dict(color='black', width=1)),
    opacity=0.75
))

# add vertical lines
fig.add_trace(go.Scatter(
    x=[observed_diff, observed_diff],
    y=[0, 50],  # adjust y-values
    mode="lines",
    name=f"Observed Difference: {observed_diff:.4f}",
    line=dict(color="red", dash="dash")
))

fig.add_trace(go.Scatter(
    x=[-observed_diff, -observed_diff],
    y=[0, 50],
    mode="lines",
    line=dict(color="red", dash="dash"),
    showlegend=False
```

```
))

# layout
fig.update_layout(
    title='Distribution of Precision Differences in Permutation Test',
    xaxis_title='Difference in Precision (WECC - Non-WECC)',
    yaxis_title='Frequency',
    width=800,
    height=600,
    showlegend=True
)

# plot
fig.show()
fig.write_html('assets/fairness.html', include_plotlyjs='cdn')
```

```
WECC Precision: 0.9688
Non-WECC Precision: 0.9200
Observed difference: 0.0487
P-value: 0.3720
```

In [ ]:

In [ ]:

In [ ]: