Power Outages and Restoration Time

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Website Link: https://keemarice.github.io/PowerOutages/

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import Lasso
from sklearn.preprocessing import StandardScaler, LabelEncoder, FunctionTransformer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
import plotly.graph_objects as go
from sklearn.tree import DecisionTreeRegressor
import plotly.express as px
from sklearn.linear_model import Ridge
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt
import mpld3

pd.options.plotting.backend = 'plotly'

# from lec_utils import * # Feel free to uncomment and use this. It'll make your pl
```

Introduction

In [2]:
```
outageFull = pd.read_csv('outage.csv', usecols = list(range(2, 56)), header = 0, sk
print(outageFull.head())
print(outageFull.columns)
#print nmber of columns
print(outageFull.columns.size)
```

```
     YEAR  MONTH U.S._STATE POSTAL.CODE NERC.REGION      CLIMATE.REGION  \
0     NaN    NaN        NaN         NaN         NaN                 NaN
1  2011.0    7.0  Minnesota          MN         MRO  East North Central
2  2014.0    5.0  Minnesota          MN         MRO  East North Central
3  2010.0   10.0  Minnesota          MN         MRO  East North Central
4  2012.0    6.0  Minnesota          MN         MRO  East North Central

  ANOMALY.LEVEL CLIMATE.CATEGORY                OUTAGE.START.DATE  \
0       numeric              NaN  Day of the week, Month Day, Year
1          -0.3           normal              Friday, July 1, 2011
2          -0.1           normal              Sunday, May 11, 2014
3          -1.5             cold         Tuesday, October 26, 2010
4          -0.1           normal            Tuesday, June 19, 2012

             OUTAGE.START.TIME  ... POPULATION POPPCT_URBAN POPPCT_UC  \
0  Hour:Minute:Second (AM / PM)  ...        NaN            %         %
1                   5:00:00 PM  ...  5348119.0        73.27     15.28
2                   6:38:00 PM  ...  5457125.0        73.27     15.28
3                   8:00:00 PM  ...  5310903.0        73.27     15.28
4                   4:30:00 AM  ...  5380443.0        73.27     15.28

             POPDEN_URBAN                POPDEN_UC             POPDEN_RURAL  \
0  persons per square mile  persons per square mile  persons per square mile
1                     2279                    1700.5                     18.2
2                     2279                    1700.5                     18.2
3                     2279                    1700.5                     18.2
4                     2279                    1700.5                     18.2

  AREAPCT_URBAN  AREAPCT_UC     PCT_LAND PCT_WATER_TOT
0             %           %            %             %
1          2.14         0.6  91.59266587   8.407334131
2          2.14         0.6  91.59266587   8.407334131
3          2.14         0.6  91.59266587   8.407334131
4          2.14         0.6  91.59266587   8.407334131

[5 rows x 54 columns]
Index(['YEAR', 'MONTH', 'U.S._STATE', 'POSTAL.CODE', 'NERC.REGION',
       'CLIMATE.REGION', 'ANOMALY.LEVEL', 'CLIMATE.CATEGORY',
       'OUTAGE.START.DATE', 'OUTAGE.START.TIME', 'OUTAGE.RESTORATION.DATE',
       'OUTAGE.RESTORATION.TIME', 'CAUSE.CATEGORY', 'CAUSE.CATEGORY.DETAIL',
       'HURRICANE.NAMES', 'OUTAGE.DURATION', 'DEMAND.LOSS.MW',
       'CUSTOMERS.AFFECTED', 'RES.PRICE', 'COM.PRICE', 'IND.PRICE',
       'TOTAL.PRICE', 'RES.SALES', 'COM.SALES', 'IND.SALES', 'TOTAL.SALES',
       'RES.PERCEN', 'COM.PERCEN', 'IND.PERCEN', 'RES.CUSTOMERS',
       'COM.CUSTOMERS', 'IND.CUSTOMERS', 'TOTAL.CUSTOMERS', 'RES.CUST.PCT',
       'COM.CUST.PCT', 'IND.CUST.PCT', 'PC.REALGSP.STATE', 'PC.REALGSP.USA',
       'PC.REALGSP.REL', 'PC.REALGSP.CHANGE', 'UTIL.REALGSP', 'TOTAL.REALGSP',
       'UTIL.CONTRI', 'PI.UTIL.OFUSA', 'POPULATION', 'POPPCT_URBAN',
       'POPPCT_UC', 'POPDEN_URBAN', 'POPDEN_UC', 'POPDEN_RURAL',
       'AREAPCT_URBAN', 'AREAPCT_UC', 'PCT_LAND', 'PCT_WATER_TOT'],
      dtype='object')
54
```

Data Cleaning and Exploratory Data Analysis

Cleaning

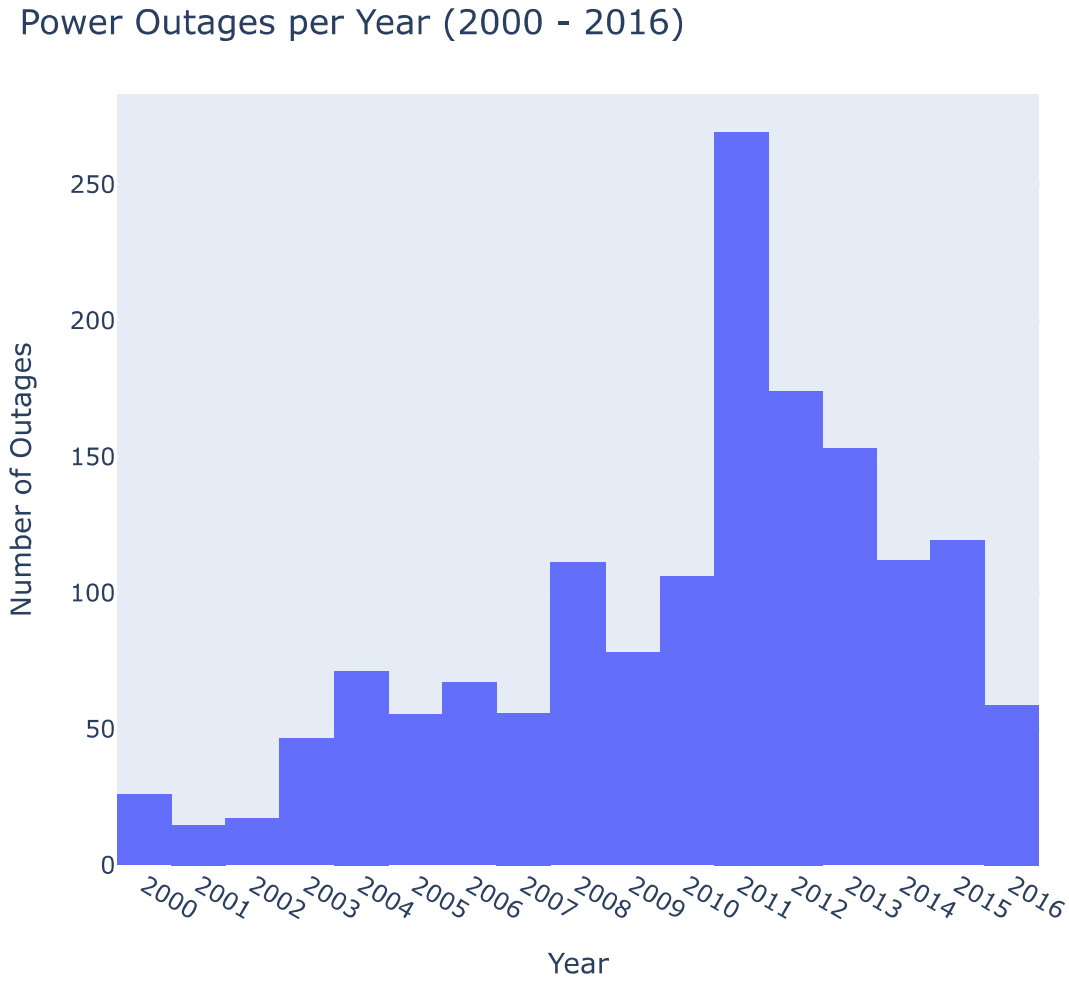
In [3]:
```
outageClean = outageFull[["YEAR", "U.S._STATE", "POSTAL.CODE", "NERC.REGION", "CAUS
outageClean = outageClean.iloc[1:]
outageClean[['YEAR', 'OUTAGE.DURATION']].dropna()
outageClean['YEAR'] = pd.to_numeric(outageClean['YEAR'])
outageClean['OUTAGE.DURATION'] = pd.to_numeric(outageClean['OUTAGE.DURATION'])
outageClean['DEMAND.LOSS.MW'] = pd.to_numeric(outageClean['DEMAND.LOSS.MW'])
outageClean['CUSTOMERS.AFFECTED'] = pd.to_numeric(outageClean['CUSTOMERS.AFFECTED']

outageClean.head()
```

Out[3]:

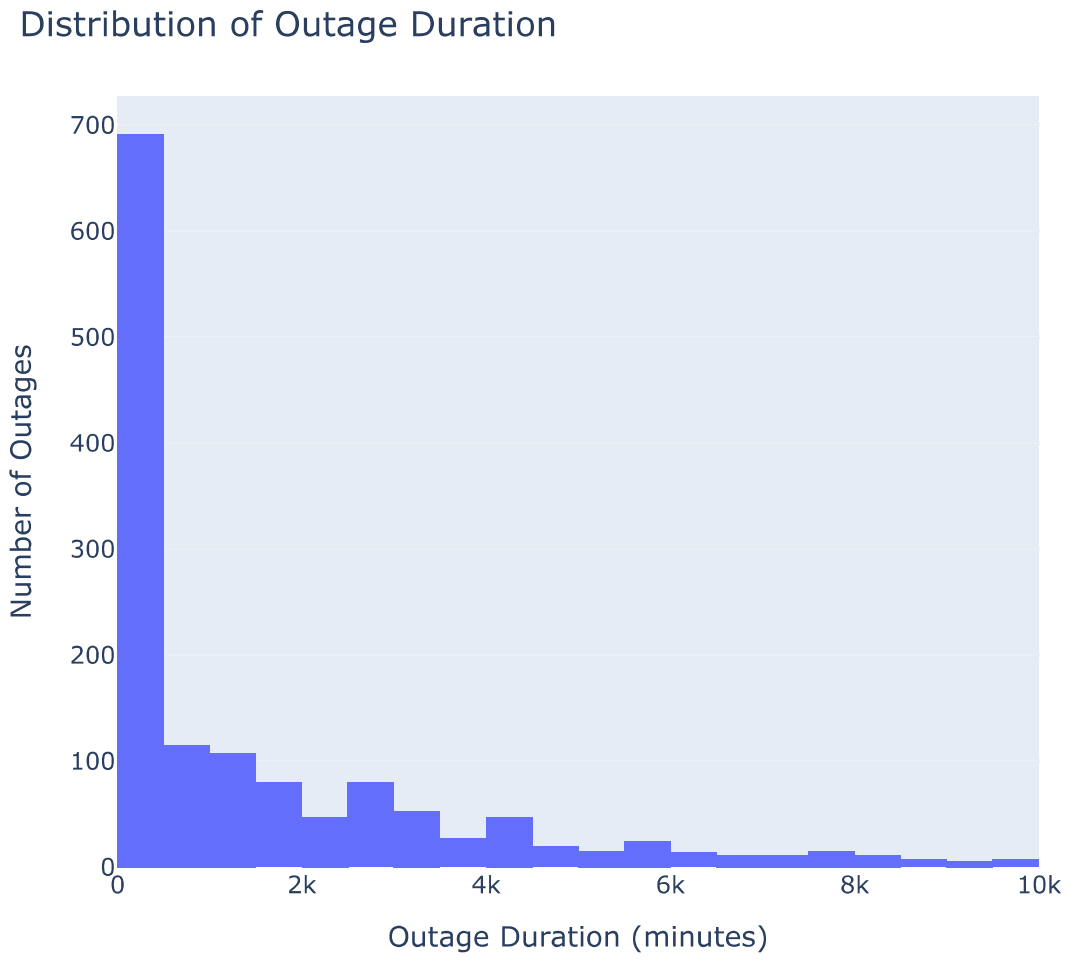
	YEAR	U.S._STATE	POSTAL.CODE	NERC.REGION	CAUSE.CATEGORY	OUTAGE.DURATION
1	2011.0	Minnesota	MN	MRO	severe weather	3060.0
2	2014.0	Minnesota	MN	MRO	intentional attack	1.0
3	2010.0	Minnesota	MN	MRO	severe weather	3000.0
4	2012.0	Minnesota	MN	MRO	severe weather	2550.0
5	2015.0	Minnesota	MN	MRO	severe weather	1740.0

Univariate Analysis

In [4]:
```
fig = px.histogram(outageClean, x = 'YEAR', nbins = 17)
fig.update_layout(title = "Power Outages per Year (2000 - 2016)", xaxis_title = "Ye
fig.update_layout(
   xaxis = dict(
      tickmode = 'linear',
      tick0 = 2000,
      dtick = 1
   )
)
fig.show()
```

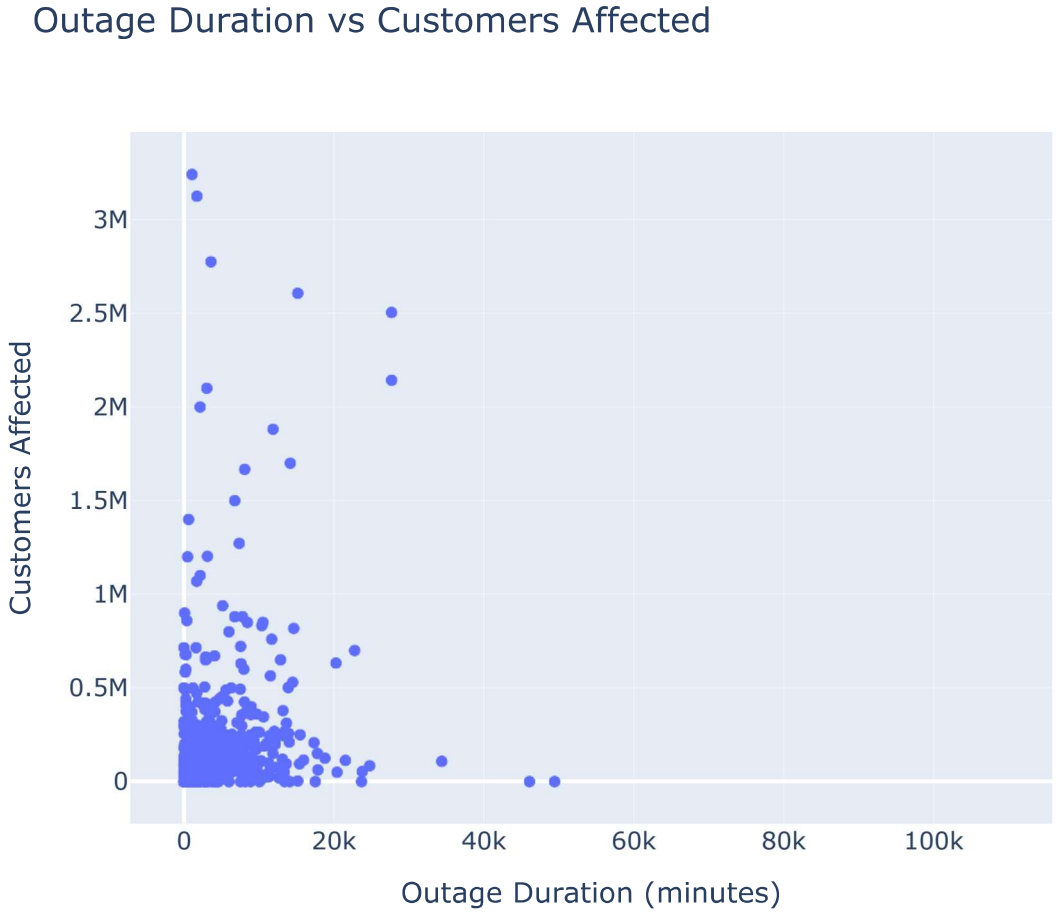


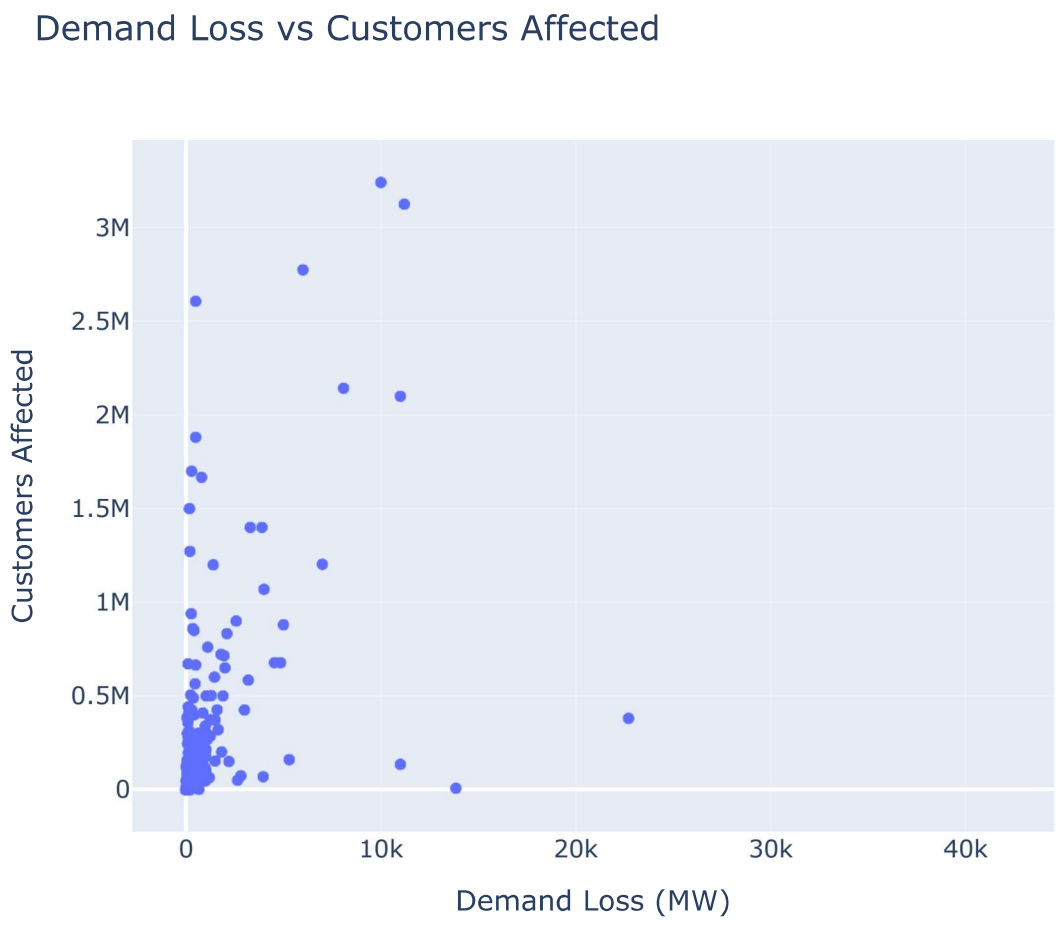
In [5]:
```
small = outageClean[outageClean["OUTAGE.DURATION"] < 10000]

fig = px.histogram(x = small['OUTAGE.DURATION'])
fig.update_layout(title = "Distribution of Outage Duration", xaxis_title = "Outage
fig.show()
```



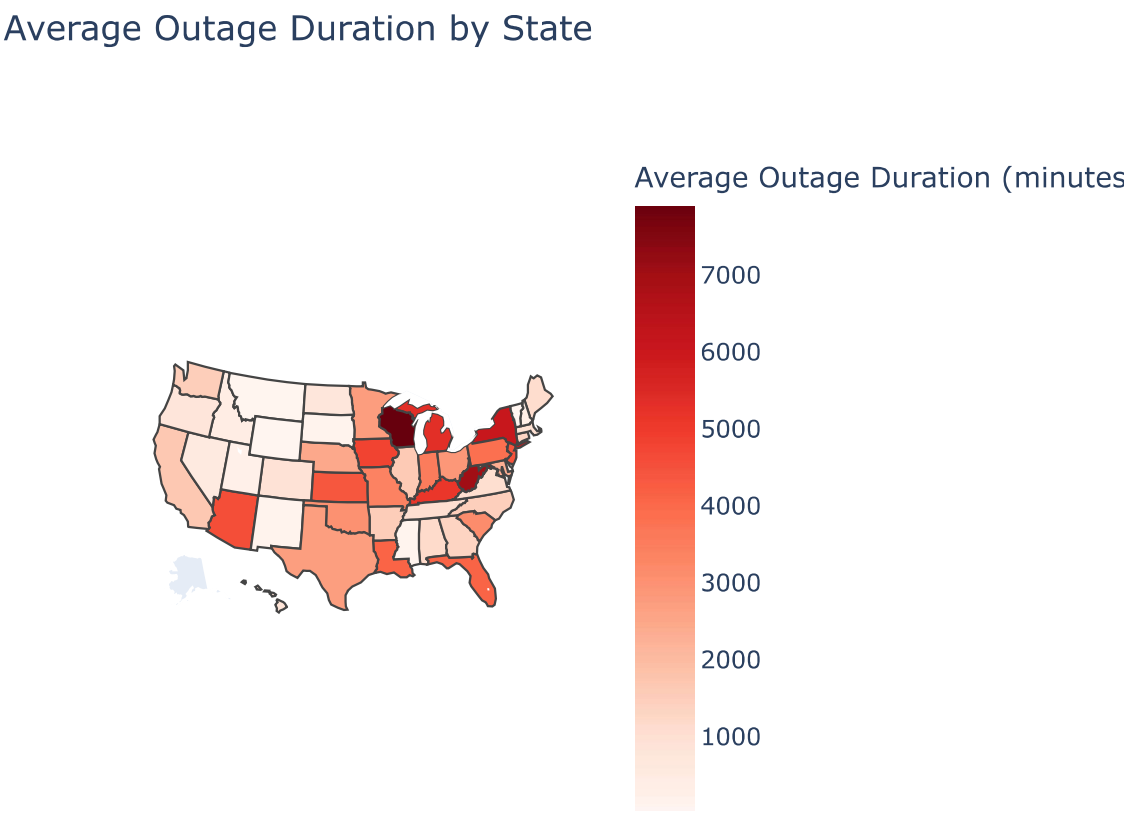
Bivariate Analysis

In [6]:
```
fig = px.scatter(outageClean, x='OUTAGE.DURATION', y='CUSTOMERS.AFFECTED', title='O
fig.update_layout(xaxis_title='Outage Duration (minutes)', yaxis_title='Customers A
fig.show()

fig = px.scatter(outageClean, x='DEMAND.LOSS.MW', y='CUSTOMERS.AFFECTED', title='De
fig.update_layout(xaxis_title='Demand Loss (MW)', yaxis_title='Customers Affected')
fig.show()
```

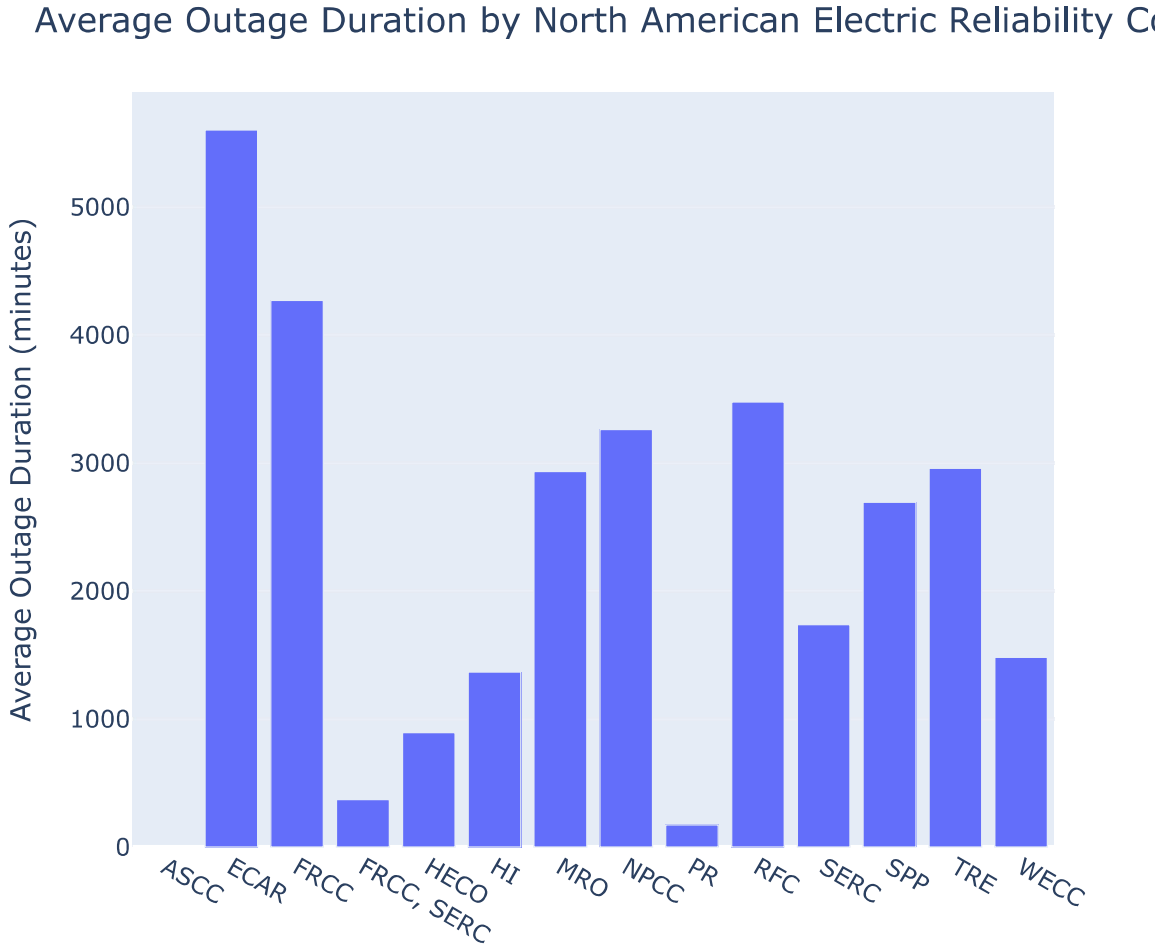

Outage Duration vs Customers Affected
Customers Affected
3M
2.5M
2M
1.5M
1M
0.5M
0
0
20k
40k
60k
80k
100k
Outage Duration (minutes)



In [7]:
```
durationstate = outageClean.groupby("POSTAL.CODE")["OUTAGE.DURATION"].mean().reset_

fig = px.choropleth(
    durationstate,
    locations="POSTAL.CODE",
    locationmode="USA-states",
    color="OUTAGE.DURATION",  # depper red = more customers affected
    scope="usa",
    title="Average Outage Duration by State",
    color_continuous_scale="Reds",
    labels={"OUTAGE.DURATION": "Average Outage Duration (minutes)"},
)
fig.show()
```

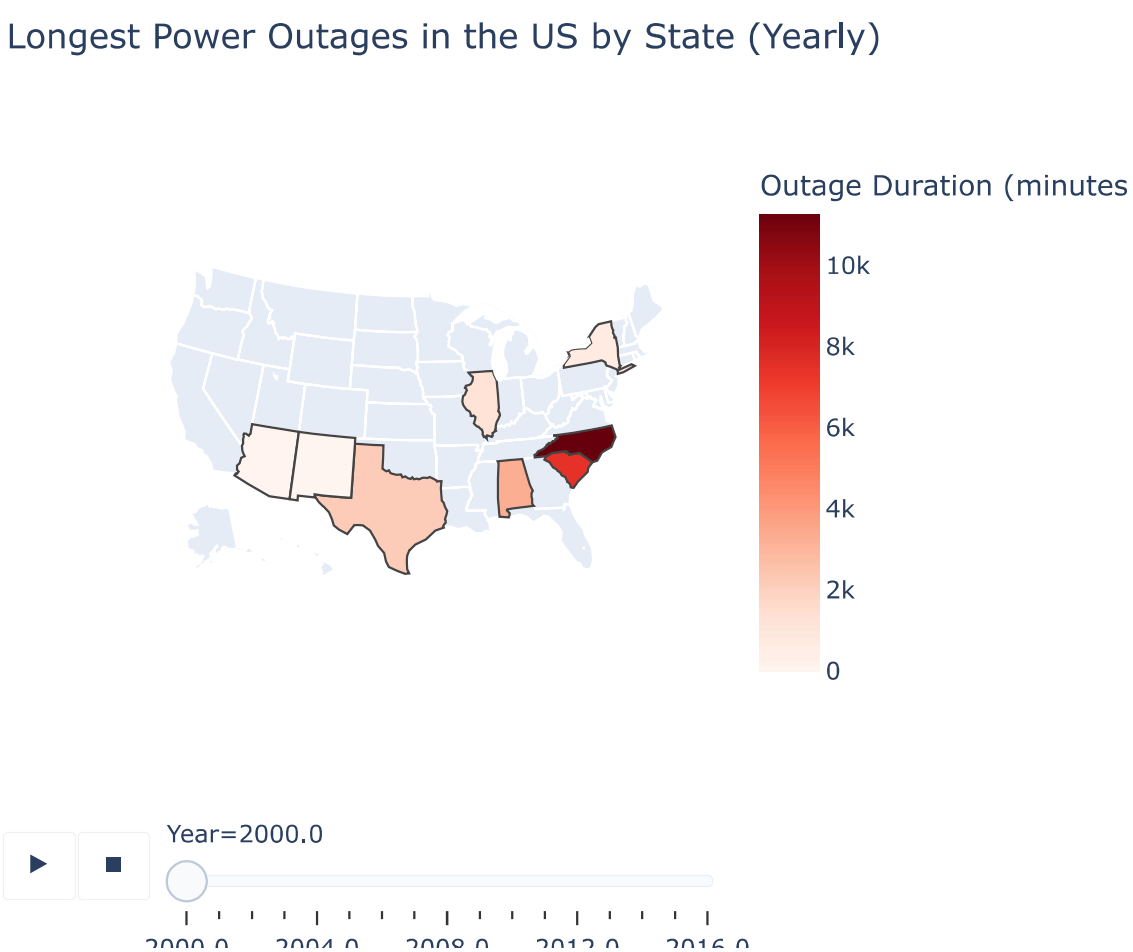


In [8]:
```
durationregion = outageClean.groupby("NERC.REGION")["OUTAGE.DURATION"].mean().reset

fig = px.bar(durationregion, x = 'NERC.REGION', y = 'OUTAGE.DURATION')
fig.update_layout(title = "Average Outage Duration by North American Electric Relia

fig.show()
```



In [9]:
```python
def plot_sorted_longest_outages_by_year(data):

    # drop rows where YEAR is NaN
    data = data.dropna(subset=["YEAR"])
    outage_summary = (
        data.groupby(["POSTAL.CODE", "YEAR"])
        .agg({"OUTAGE.DURATION": "max"})
        .reset_index()
    )

    outage_summary = outage_summary.sort_values(by="YEAR")
    fig = px.choropleth(
        outage_summary,
        locations="POSTAL.CODE",
        locationmode="USA-states",
        color="OUTAGE.DURATION",
        scope="usa",
        animation_frame="YEAR",  # slider for year
        title="Longest Power Outages in the US by State (Yearly)",
        color_continuous_scale="Reds",
        labels={"OUTAGE.DURATION": "Outage Duration (minutes)", "YEAR": "Year"},
    )
```

```
    return fig
plot_sorted_longest_outages_by_year(outageClean).show()
```



Interesting Aggreates

In [10]:
```
outageClean.groupby('YEAR')['OUTAGE.DURATION'].mean().reset_index()
```

Out[10]:

	YEAR	OUTAGE.DURATION
0	2000.0	2843.076923
1	2001.0	1272.071429
2	2002.0	4751.000000
3	2003.0	4652.434783
4	2004.0	4368.788732
5	2005.0	5288.944444
6	2006.0	3329.530303
7	2007.0	2336.666667
8	2008.0	4184.018182
9	2009.0	3660.519481
10	2010.0	2937.528302
11	2011.0	1801.605948
12	2012.0	1877.976879
13	2013.0	1369.164474
14	2014.0	3107.355769
15	2015.0	935.811321
16	2016.0	2225.553191

In [11]:
```
#group by day of the week
outageClean['DATE'] = pd.to_datetime(outageClean['YEAR'], format='%Y')
outageClean['DAY'] = outageClean['DATE'].dt.day_name()
outageClean['DAY'] = pd.Categorical(outageClean['DAY'], categories=['Monday','Tuesd
outageClean.groupby('DAY')['OUTAGE.DURATION'].mean().reset_index()
```

```
/tmp/ipykernel_941/3947489334.py:5: FutureWarning:

The default of observed=False is deprecated and will be changed to True in a future
version of pandas. Pass observed=False to retain current behavior or observed=True t
o adopt the future default and silence this warning.
```

Out[11]:

	DAY	OUTAGE.DURATION
0	Monday	2117.485294
1	Tuesday	2662.568841
2	Wednesday	3581.180000
3	Thursday	2721.417323
4	Friday	2718.816993
5	Saturday	2402.366071
6	Sunday	2278.824268

Framing a Prediction Problem

This prediction problem focuses on building a regression model to predict the outage duration of power outages in the USA, measured in minutes. The response variable, OUTAGE.DURATION, is crucial for utility companies as it reflects the severity and recovery time of an outage.

Baseline Model

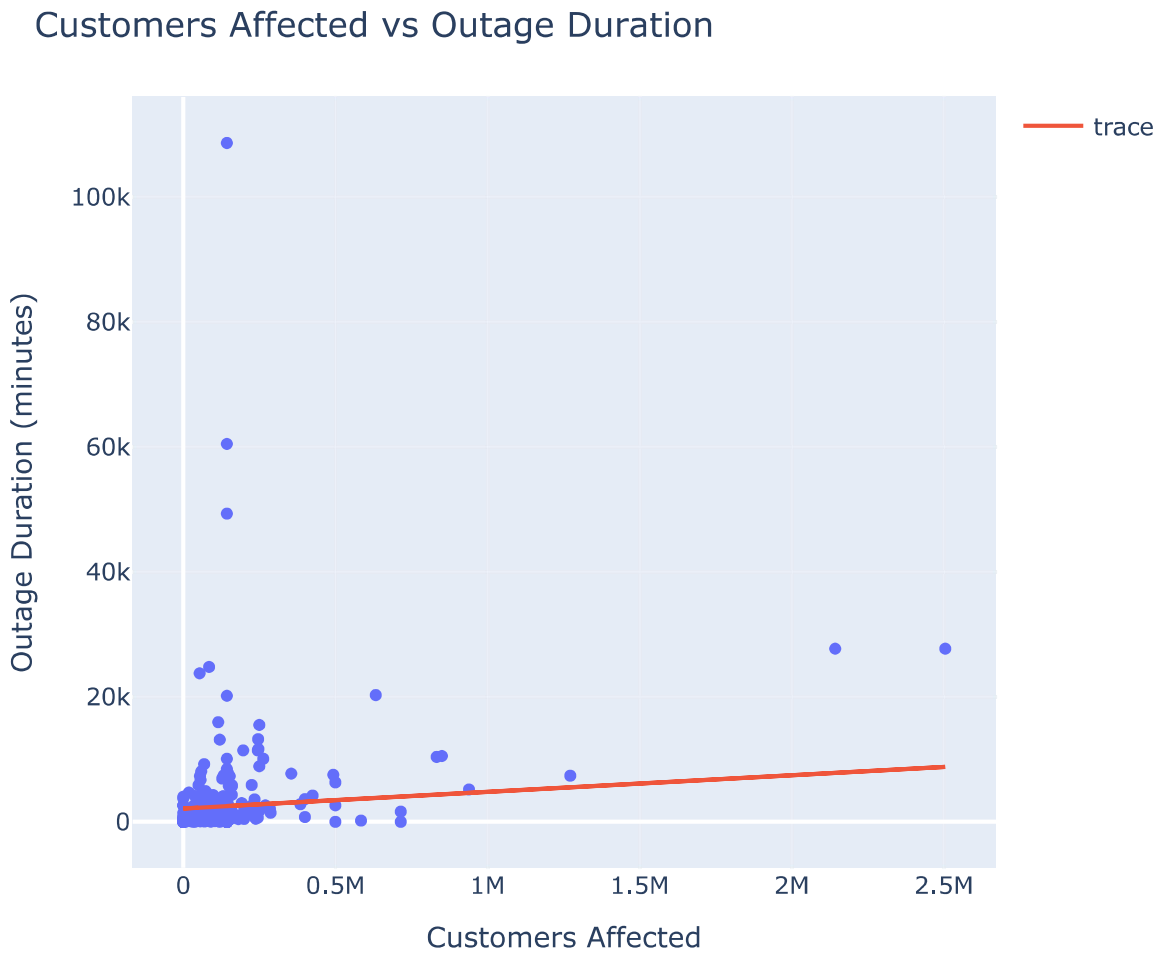
In [12]:
```
numeric_columns = outageClean.select_dtypes(include=['number'])

# Compute the correlation matrix
correlation_matrix = numeric_columns.corr()
correlated_features = correlation_matrix['OUTAGE.DURATION'].drop('OUTAGE.DURATION')

print("Features most positively correlated with OUTAGE.DURATION:")
print(correlated_features[correlated_features > 0].head())

print("\nFeatures most negatively correlated with OUTAGE.DURATION:")
print(correlated_features[correlated_features < 0].head())
```

```
Features most positively correlated with OUTAGE.DURATION:
CUSTOMERS.AFFECTED    0.261916
DEMAND.LOSS.MW        0.026798
Name: OUTAGE.DURATION, dtype: float64

Features most negatively correlated with OUTAGE.DURATION:
YEAR   -0.144047
Name: OUTAGE.DURATION, dtype: float64
```

In [13]:
```
#Linear regression
from sklearn.metrics import mean_squared_error, root_mean_squared_error

X = outageClean[['CUSTOMERS.AFFECTED']]
X = X.fillna(X.mean())
y = outageClean['OUTAGE.DURATION']
```

```
y = y.fillna(y.mean())
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

model = LinearRegression()
model.fit(X_train, y_train)

y_pred = model.predict(X_test)
#print rmse

rmse = root_mean_squared_error(y_test, y_pred)
print(f"Root Mean Squared Error: {rmse}")
fig = px.scatter(x = X_test['CUSTOMERS.AFFECTED'], y = y_test)
fig.add_scatter(x = X_test['CUSTOMERS.AFFECTED'], y = y_pred, mode = 'lines')
fig.update_layout(title = "Customers Affected vs Outage Duration", xaxis_title = "C
fig.show()
```

```
Root Mean Squared Error: 8350.875280739047
```



Final Model

Trying Different Models

In [14]:
```
# Multiple Linear Regression Model
#lets do multiple linear regression, with every column except for the target column
X = outageClean[['CAUSE.CATEGORY', 'NERC.REGION', 'U.S._STATE', 'YEAR', 'CUSTOMERS.
y = outageClean['OUTAGE.DURATION']

X.loc[:, 'YEAR'] = X['YEAR'].fillna(0).astype(int)
X.loc[:, 'CAUSE.CATEGORY'] = X['CAUSE.CATEGORY'].fillna("Missing")
X.loc[:, 'NERC.REGION'] = X['NERC.REGION'].fillna("Missing")
X.loc[:, 'U.S._STATE'] = X['U.S._STATE'].fillna("Missing")
X.loc[:, 'CUSTOMERS.AFFECTED'] = X['CUSTOMERS.AFFECTED'].fillna(X['CUSTOMERS.AFFECT
X.loc[:, 'DEMAND.LOSS.MW'] = X['DEMAND.LOSS.MW'].fillna(X['DEMAND.LOSS.MW'].mean())
y = y.fillna(y.mean())

# Encode categorical columns
label_encoder_cause = LabelEncoder()
label_encoder_nerc = LabelEncoder()
label_encoder_state = LabelEncoder()

X.loc[:, 'U.S._STATE'] = label_encoder_state.fit_transform(X['U.S._STATE'])
X.loc[:, 'CAUSE.CATEGORY'] = label_encoder_cause.fit_transform(X['CAUSE.CATEGORY'])
X.loc[:, 'NERC.REGION'] = label_encoder_nerc.fit_transform(X['NERC.REGION'])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
model = LinearRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
rmse = root_mean_squared_error(y_test, y_pred)
print(f"Root Mean Squared Error: {rmse}")
```

```
Root Mean Squared Error: 4933.434321276498
```

In [15]:
```
# Lasso Model
# Prepare the data
X = outageClean[['CAUSE.CATEGORY', 'NERC.REGION', 'U.S._STATE', 'YEAR', 'CUSTOMERS.
y = outageClean['OUTAGE.DURATION']  # Target variable

# Handle missing values
X.loc[:, 'YEAR'] = X['YEAR'].fillna(0).astype(int)
X.loc[:, 'CAUSE.CATEGORY'] = X['CAUSE.CATEGORY'].fillna("Missing")
X.loc[:, 'NERC.REGION'] = X['NERC.REGION'].fillna("Missing")
X.loc[:, 'U.S._STATE'] = X['U.S._STATE'].fillna("Missing")
X.loc[:, 'CUSTOMERS.AFFECTED'] = X['CUSTOMERS.AFFECTED'].fillna(X['CUSTOMERS.AFFECT
X.loc[:, 'DEMAND.LOSS.MW'] = X['DEMAND.LOSS.MW'].fillna(X['DEMAND.LOSS.MW'].mean())
y = y.fillna(y.mean())

# Label encoding for categorical features
label_encoder_state = LabelEncoder()
label_encoder_cause = LabelEncoder()
label_encoder_nerc = LabelEncoder()

X.loc[:, 'U.S._STATE'] = label_encoder_state.fit_transform(X['U.S._STATE'])
X.loc[:, 'CAUSE.CATEGORY'] = label_encoder_cause.fit_transform(X['CAUSE.CATEGORY'])
X.loc[:, 'NERC.REGION'] = label_encoder_nerc.fit_transform(X['NERC.REGION'])

# Preprocessing pipeline (without Year_Demand_Interaction)
preprocessor = ColumnTransformer(
```

```
    transformers=[
        ('num', Pipeline(steps=[
            ('scaler', StandardScaler())
        ]), ['YEAR', 'CUSTOMERS.AFFECTED', 'DEMAND.LOSS.MW']),
        ('cat', Pipeline(steps=[
            ('log', FunctionTransformer(np.log1p, validate=True)),
            ('scaler', StandardScaler())
        ]), ['CAUSE.CATEGORY', 'NERC.REGION', 'U.S._STATE'])
    ]
)

# Define the pipeline
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('lasso', Lasso())
])

# Hyperparameter tuning
param_grid = {
    'lasso__alpha': [0.001, 0.01, 0.1, 1, 10, 100]
}

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta

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

# Evaluate the model
best_model = grid_search.best_estimator_
y_pred = best_model.predict(X_test)
rmse = root_mean_squared_error(y_test, y_pred)

# Print results
print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"Best Alpha: {grid_search.best_params_['lasso__alpha']}")

# Extract feature importance
lasso_model = best_model.named_steps['lasso']
feature_names = ['YEAR', 'CUSTOMERS.AFFECTED', 'DEMAND.LOSS.MW', 'CAUSE.CATEGORY',
coefficients = pd.DataFrame({
    'Feature': feature_names,
    'Coefficient': lasso_model.coef_
}).sort_values(by='Coefficient', key=abs, ascending=False)

# Display the most influential features
print("Most influential features:")
print(coefficients.head(10))

# Print number of features
print(f"Number of features: {len(feature_names)}")
print(f"Number of non-zero coefficients: {len(coefficients[coefficients['Coefficien
```

```
Root Mean Squared Error (RMSE): 4955.1104505520325
Best Alpha: 100
Most influential features:
              Feature  Coefficient
1  CUSTOMERS.AFFECTED   736.246987
4         NERC.REGION  -496.593846
0                YEAR  -331.945961
5          U.S._STATE   276.073361
2      DEMAND.LOSS.MW   -42.942617
3      CAUSE.CATEGORY     0.000000
Number of features: 6
Number of non-zero coefficients: 5
```

In [16]:

```
# Ridge Model
X = outageClean[['CAUSE.CATEGORY', 'NERC.REGION', 'U.S._STATE', 'YEAR', 'CUSTOMERS.
y = outageClean['OUTAGE.DURATION']

X.loc[:, 'YEAR'] = X['YEAR'].fillna(0).astype(int)
X.loc[:, 'CAUSE.CATEGORY'] = X['CAUSE.CATEGORY'].fillna("Missing")
X.loc[:, 'NERC.REGION'] = X['NERC.REGION'].fillna("Missing")
X.loc[:, 'U.S._STATE'] = X['U.S._STATE'].fillna("Missing")
X.loc[:, 'CUSTOMERS.AFFECTED'] = X['CUSTOMERS.AFFECTED'].fillna(X['CUSTOMERS.AFFECT
X.loc[:, 'DEMAND.LOSS.MW'] = X['DEMAND.LOSS.MW'].fillna(X['DEMAND.LOSS.MW'].mean())
y = y.fillna(y.mean())

label_encoder_state = LabelEncoder()
label_encoder_cause = LabelEncoder()
label_encoder_nerc = LabelEncoder()

X.loc[:, 'U.S._STATE'] = label_encoder_state.fit_transform(X['U.S._STATE'])
X.loc[:, 'CAUSE.CATEGORY'] = label_encoder_cause.fit_transform(X['CAUSE.CATEGORY'])
X.loc[:, 'NERC.REGION'] = label_encoder_nerc.fit_transform(X['NERC.REGION'])

preprocessor = ColumnTransformer(
    transformers=[
        ('num', Pipeline(steps=[
            ('scaler', StandardScaler())
        ]), ['YEAR', 'CUSTOMERS.AFFECTED', 'DEMAND.LOSS.MW']),
        ('cat', Pipeline(steps=[
            ('log', FunctionTransformer(np.log1p, validate=True)),
            ('scaler', StandardScaler())
        ]), ['CAUSE.CATEGORY', 'NERC.REGION', 'U.S._STATE'])
    ]
)

pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('ridge', Ridge())
])

#hyperparameter tuning
param_grid = {
    'ridge__alpha': [0.001, 0.01, 0.1, 1, 10, 100]
}
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring='neg_mean_squared_er
```

```
grid_search.fit(X_train, y_train)
best_model = grid_search.best_estimator_
y_pred = best_model.predict(X_test)
rmse = root_mean_squared_error(y_test, y_pred)

# Print bonanaza
print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"Best Alpha: {grid_search.best_params_['ridge__alpha']}")
ridge_model = best_model.named_steps['ridge']
feature_names = ['YEAR', 'CUSTOMERS.AFFECTED', 'DEMAND.LOSS.MW', 'CAUSE.CATEGORY',
coefficients = pd.DataFrame({
    'Feature': feature_names,
    'Coefficient': ridge_model.coef_
}).sort_values(by='Coefficient', key=abs, ascending=False)

print("Most influential features:")
coefficients.head(10)
print(f"Number of features: {len(feature_names)}")
print(f"Number of non-zero coefficients: {len(coefficients[coefficients['Coefficien
```

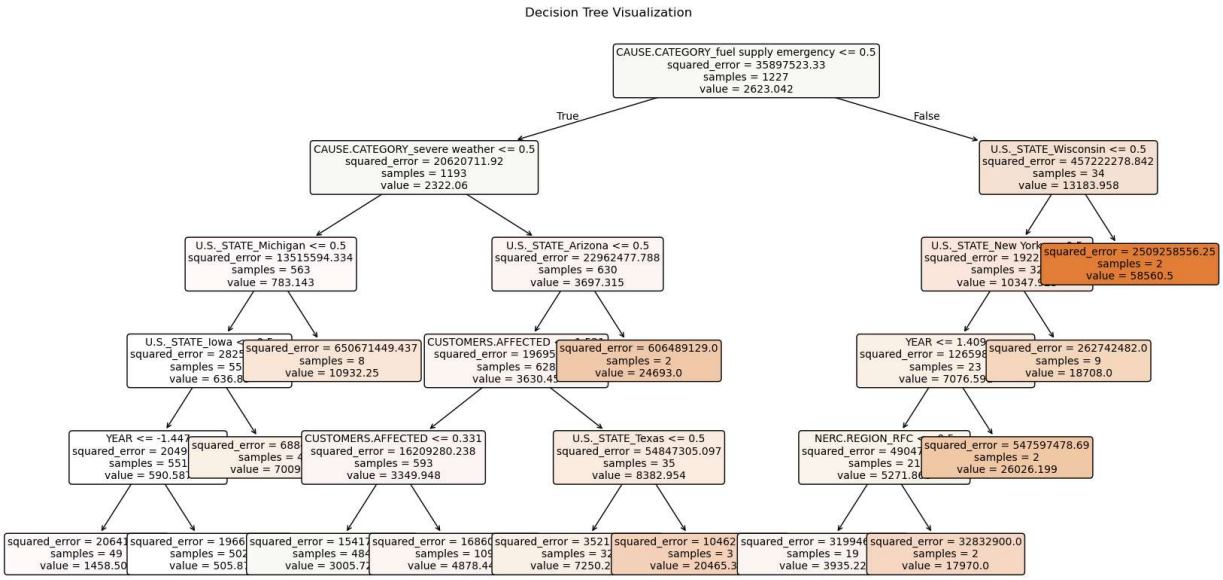
```
Root Mean Squared Error (RMSE): 4948.611435073662
Best Alpha: 100
Most influential features:
Number of features: 6
Number of non-zero coefficients: 6
```

In [17]:

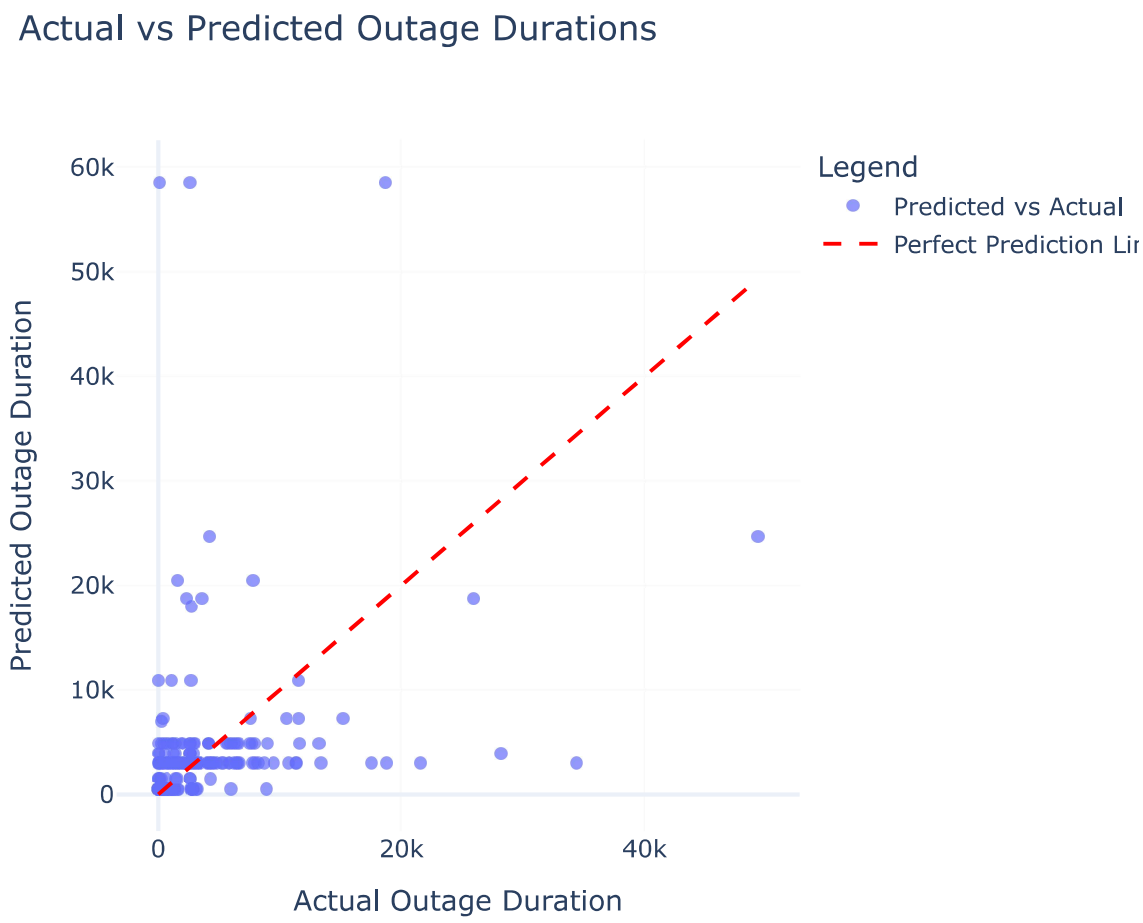
```
# Decision Tree

from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, OneHotEncoder, FunctionTransforme
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import mean_squared_error
import pandas as pd
import numpy as np


X = outageClean[['CAUSE.CATEGORY', 'NERC.REGION', 'U.S._STATE', 'YEAR', 'CUSTOMERS.
y = outageClean['OUTAGE.DURATION'].fillna(outageClean['OUTAGE.DURATION'].mean())
#from error code
X.loc[:, 'YEAR'] = X['YEAR'].fillna(0).astype(int)
X.loc[:, 'CAUSE.CATEGORY'] = X['CAUSE.CATEGORY'].fillna("Missing")
X.loc[:, 'NERC.REGION'] = X['NERC.REGION'].fillna("Missing")
X.loc[:, 'U.S._STATE'] = X['U.S._STATE'].fillna("Missing")
X.loc[:, 'CUSTOMERS.AFFECTED'] = X['CUSTOMERS.AFFECTED'].fillna(0)
X.loc[:, 'DEMAND.LOSS.MW'] = X['DEMAND.LOSS.MW'].fillna(0)

preprocessor = ColumnTransformer(
    transformers=[
        ('num', Pipeline(steps=[
            ('scaler', StandardScaler())
        ]), ['YEAR', 'CUSTOMERS.AFFECTED', 'DEMAND.LOSS.MW']),
        ('cat', OneHotEncoder(handle_unknown='ignore'), ['CAUSE.CATEGORY', 'NERC.RE
    ]
)
```

```
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', DecisionTreeRegressor(random_state=42))
])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
param_grid = {
    'regressor__max_depth': [3, 5, 10, None],
    'regressor__min_samples_split': [2, 5, 10],
    'regressor__min_samples_leaf': [1, 2, 4]
}

grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring='neg_mean_squared_er
grid_search.fit(X_train, y_train)
final_model = grid_search.best_estimator_
y_pred = final_model.predict(X_test)
from sklearn.metrics import root_mean_squared_error
rmse = root_mean_squared_error(y_test, y_pred)
print(f"Root Mean Squared Error (RMSE): {rmse}")
print(f"Best Parameters: {grid_search.best_params_}")


from sklearn.tree import plot_tree
import matplotlib.pyplot as plt
final_tree = final_model.named_steps['regressor']
preprocessor = final_model.named_steps['preprocessor']
categorical_features = preprocessor.transformers_[1][1].get_feature_names_out(['CAU
numeric_features = ['YEAR', 'CUSTOMERS.AFFECTED', 'DEMAND.LOSS.MW']
feature_names = list(numeric_features) + list(categorical_features)
plt.figure(figsize=(20, 10))
plot_tree(
    final_tree,
    feature_names=feature_names,
    filled=True,
    rounded=True,
    fontsize=10
)
plt.title("Decision Tree Visualization")
plt.show()
```

```
Root Mean Squared Error (RMSE): 6913.610292022421
Best Parameters: {'regressor__max_depth': 5, 'regressor__min_samples_leaf': 2, 'regr
essor__min_samples_split': 10}
```



In [18]:
```
# Multiple Regression chosen as the final model
fig = go.Figure()
fig.add_trace(go.Scatter(
    x=y_test,
    y=y_pred,
    mode='markers',
    name='Predicted vs Actual',
    marker=dict(size=6, opacity=0.7)
))

fig.add_trace(go.Scatter(
    x=[y_test.min(), y_test.max()],
    y=[y_test.min(), y_test.max()],
    mode='lines',
    name='Perfect Prediction Line',
    line=dict(color='red', dash='dash')
))
fig.update_layout(
    title='Actual vs Predicted Outage Durations',
    xaxis_title='Actual Outage Duration',
    yaxis_title='Predicted Outage Duration',
    legend=dict(title="Legend"),
    template='plotly_white'
)
fig.show()
```


Actual vs Predicted Outage Durations
Predicted Outage Duration
60k
50k
40k
30k
20k
10k
0
0
20k
40k
Actual Outage Duration
Legend
Predicted vs Actual
Perfect Prediction Lir