Power Outages

This project uses major power outage data in the continental U.S. from January 2000 to July 2016. Here, a major power outage is defined as a power outage that impacted at least 50,000 customers or caused an unplanned firm load loss of atleast 300MW. Interesting questions to consider include:

- Where and when do major power outages tend to occur?
- What are the characteristics of major power outages with higher severity? Variables to consider include location, time, climate, land-use characteristics, electricity consumption patterns, economic characteristics, etc. What risk factors may an energy company want to look into when predicting the location and severity of its next major power outage?
- What characteristics are associated with each category of cause?
- How have characteristics of major power outages changed over time? Is there a clear trend?

Getting the Data

The data is downloadable [here (https://engineering.purdue.edu/LASCI/research-data/outages/outagerisks)](https://engineering.purdue.edu/LASCI/research-data/outages/outagerisks).

A data dictionary is available at this [article (https://www.sciencedirect.com/science/article/pii/S2352340918307182)](https://www.sciencedirect.com/science/article/pii/S2352340918307182) under *Table 1. Variable descriptions*.

Cleaning and EDA

- Note that the data is given as an Excel file rather than a CSV. Open the data in Excel or another spreadsheet application and determine which rows and columns of the Excel spreadsheet should be ignored when loading the data in pandas.
- Clean the data.
  - The power outage start date and time is given by `OUTAGE.START.DATE` and `OUTAGE.START.TIME` . It would be preferable if these two columns were combined into one datetime column. Combine `OUTAGE.START.DATE` and `OUTAGE.START.TIME` into a new datetime column called `OUTAGE.START` . Similarly, combine `OUTAGE.RESTORATION.DATE` and `OUTAGE.RESTORATION.TIME` into a new datetime column called `OUTAGE.RESTORATION` .
- Understand the data in ways relevant to your question using univariate and bivariate analysis of the data as well as aggregations.

Hint 1: pandas can load multiple filetypes: `pd.read_csv` *,* `pd.read_excel` *,* `pd.read_html` *,* `pd.read_json` *, etc.*

Hint 2: `pd.to_datetime` *and* `pd.to_timedelta` *will be useful here.*

Tip: To visualize geospatial data, consider [Folium (https://python-visualization.github.io/folium/)](https://python-visualization.github.io/folium/) or another geospatial plotting library.

Assessment of Missingness

- Assess the missingness of a column that is not missing by design.

Hypothesis Test

Find a hypothesis test to perform. You can use the questions at the top of the notebook for inspiration.

Summary of Findings

Introduction

The data used on this project contains information about the major outages that has happened historically in different states in the U.S. between January 2000 and July 2016.

- Major outages is defined by the Department of Energy as those outages that impacted at least 50k customers or caused an unexpected load loss of at least 300 MegaWatts

Apart from major outage data, the dataset contains different characteristics of the states at the time that the outages occured. The datasate contains 55 different variables which can be divided into the following:

- GENERAL INFORMATION (Time of the outage, Geographical information), 5 variables.
- REGIONAL CLIMATE INFORMATION, 3 variables.
- OUTAGE EVENTS INFORMATION (Outage start and end, Cause, Effect of outage), 10 variables.
- REGIONAL ELECTRICITY CONSUMPTION INFORMATION (Price, Consumption, Customers Served), 18 variables.
- REGIONAL ECONOMIC CHARACTERISTICS (Economic output), 8 variables.
- REGIONAL LAND-USE CHARACTERICS (Population, Land Area), 11 variables.

This dataset can be used to analyze the causes of these outages, as well as the effects that these have in different states with varying characteristics and see if there is a pattern. We can also use to spot trends on these major outages.

Cleaning and EDA

To cleaning data I started by combining the data found in the columns OUTAGE.START.DATE and OUTAGE.START.TIME into one single column and I did the same with OUTAGE.RESTORATION.DATE and OUTAGE.RESTORATION.TIME.
After this was done, I dropped the original splitted columns since we don't want repeated data in the dataset.
Then I decided to change the type of the column YEAR to int since float doesn't make sense for a year

value. I thought of performing the same for MONTH but realized that I was not able to since MONTH column contains null values.
Finally, I decided to check the rest of the data types for the rest of the columns and saw that a lot of numerical value columns such as Prices, Sales, Customers, Percentages, were object types, so I decided to convert them all into float type values.

For the univariate anaylisis I decided to create 4 bar charts for different variables and the number of outages per each different value of each variable:

1. State: we can see that California has had significantly more major outages since 2000.
2. Climate Region: we can see that there is usually significantly more major outages in the northeast region of continental U.S.
3. Climate Category: we can see that major outages has happened more in normal weather climates.
4. Cause Category: we can see that the majority of the outages have been caused by severe weather conditions followd by intentional attacks (most likely to the electric infraestructure).

Then I decided to compare the relationship between 2 categorical variables: Climate Region and Cause of the outage.
We can see from the stacked bar chart that the in the majority of the regions most of the major outages have been caused by Severe Weather, these regions being "Central, East North Central, South, Southeast and West".
In the south region there has also been quite a big proportion of outages cuased by public appeal and in the West similar thing happens but is caused by system operability disruption.
Then for the Northwest and the Southwest regions, the majority of the outages have been caused by intentional attacks instead.
And finally we have the West North Central Region where it is affected by severe weather but a bigger proportion have been caused by islanding.

Finally, I decided to group the years and get the mean of the total electricity price for each year. You can kind of see an increase in price since 2000 up until 2007 where it peaked, and then it stabilize between 10 and 11.

Assessment of Missingness

I think that the data in CAUSE.CATEGORY.DETAIL is NMAR. The only other reasonable variable that this one is related to is CAUSE.CATEGORY, but there are no missing values in this one. There is a discrepancy of nearly 500 null values between one and another. So it makes sense that this one is NMAR, maybe at the time were they recorded the data they just didn't know the specific details of what caused the major outage. The missingness of CAUSE.CATEGORY.DETAIL can't be explained by any other observed variable.

Hypothesis Test

Null hypothesis: in the US the distribution of the causes for major outages among the 2 states with most cases outages is the same. The difference between 2 samples is due to chance. (CA, TX)
Alternative hypothesis: in the US the distributions of the causes of major outages of the two states are different.

I performed a permutation test to check if the distributions of the different causes of major outages were similar in the two states with the highest number of these which are California and Texas. Test statistic used is TVD since we are working with categorical variables here.
Using a significance level of 5% we got a p-value of 0, with this result we reject the null hypothesis and conclude that the distributions for the causes of major outages for these 2 states are different.

Ideally I would like to perform more permutation tests comparing each pair of states and see how the distribution of the causes of major outages are related.

Code

In [1]:
```
import matplotlib.pyplot as plt
import numpy as np
import os
import pandas as pd
import seaborn as sns
import re
%matplotlib inline
%config InlineBackend.figure_format = 'retina'  # Higher resolution
figures
```

Cleaning and EDA

In [2]:
```
# Read in the excel file and format it
outages = pd.read_excel('data/outage.xlsx', header=5, usecols='c:BE
').drop(0, axis=0).reset_index(drop=True)
```

In [3]:
```
pd.set_option('display.max_columns', None)
```

In [4]:
```
outages.head()
```

Out[4]:

	YEAR	MONTH	U.S._STATE	POSTAL.CODE	NERC.REGION	CLIMATE.REGION	ANOMA
0	2011.0	7.0	Minnesota	MN	MRO	East North Central	
1	2014.0	5.0	Minnesota	MN	MRO	East North Central	
2	2010.0	10.0	Minnesota	MN	MRO	East North Central	
3	2012.0	6.0	Minnesota	MN	MRO	East North Central	
4	2015.0	7.0	Minnesota	MN	MRO	East North Central	

In [5]:
```
"""
Function that takes in a row with 2 values date and time and combin
es them into on single datetime value.
Meant to be used with apply()
"""
def combine_date_time(row):

    # check that the value is not null
    if not pd.isnull(row.iloc[0]):

        #return the combined datetime object
        return pd.datetime.combine(row.iloc[0], row.iloc[1])

    return np.NaN
```

In [6]:
```
# Combining outages start dates and times into on single datetime v
alue
outage_start = outages[['OUTAGE.START.DATE', 'OUTAGE.START.TIME']]
outages['OUTAGE.START'] = outage_start.apply(combine_date_time, axi
s=1)
```

In [7]:
```
# Combining outages restoration dates and times into on single date
time value
outage_res = outages[['OUTAGE.RESTORATION.DATE', 'OUTAGE.RESTORATIO
N.TIME']]
outages['OUTAGE.RESTORATION'] = outage_res.apply(combine_date_time,
axis=1)
```

In [8]:
```
# drop separate values from the table since we can used the combine
d column
outages.drop(['OUTAGE.RESTORATION.DATE', 'OUTAGE.RESTORATION.TIME',
'OUTAGE.START.DATE', 'OUTAGE.START.TIME'],
                inplace = True, axis=1)
```

In [9]:
```
# convert the year values into type int for readability
outages['YEAR'] = outages['YEAR'].astype(int)
```

In [10]:
```
outages
```

Out[10]:

	YEAR	MONTH	U.S._STATE	POSTAL.CODE	NERC.REGION	CLIMATE.REGION	ANOI
0	2011	7.0	Minnesota	MN	MRO	East North Central	
1	2014	5.0	Minnesota	MN	MRO	East North Central	
2	2010	10.0	Minnesota	MN	MRO	East North Central	
3	2012	6.0	Minnesota	MN	MRO	East North Central	
4	2015	7.0	Minnesota	MN	MRO	East North Central	
...	...	...	...	...	...	...	
1529	2011	12.0	North Dakota	ND	MRO	West North Central	
1530	2006	NaN	North Dakota	ND	MRO	West North Central	
1531	2009	8.0	South Dakota	SD	RFC	West North Central	
1532	2009	8.0	South Dakota	SD	MRO	West North Central	
1533	2000	NaN	Alaska	AK	ASCC	NaN	

1534 rows × 53 columns

In [11]:
```
"""
When checking for the column types we can see that a lot of columns in the range OUTAGE.DURATION
to PCT_WATER_INLAND are object values but they are representing numerical values. So I decided to
convert these columns into float type values.
"""
outages.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1534 entries, 0 to 1533
Data columns (total 53 columns):
YEAR                      1534 non-null int64
MONTH                     1525 non-null float64
U.S._STATE                1534 non-null object
POSTAL.CODE               1534 non-null object
NERC.REGION               1534 non-null object
CLIMATE.REGION            1528 non-null object
ANOMALY.LEVEL             1525 non-null object
CLIMATE.CATEGORY          1525 non-null object
```

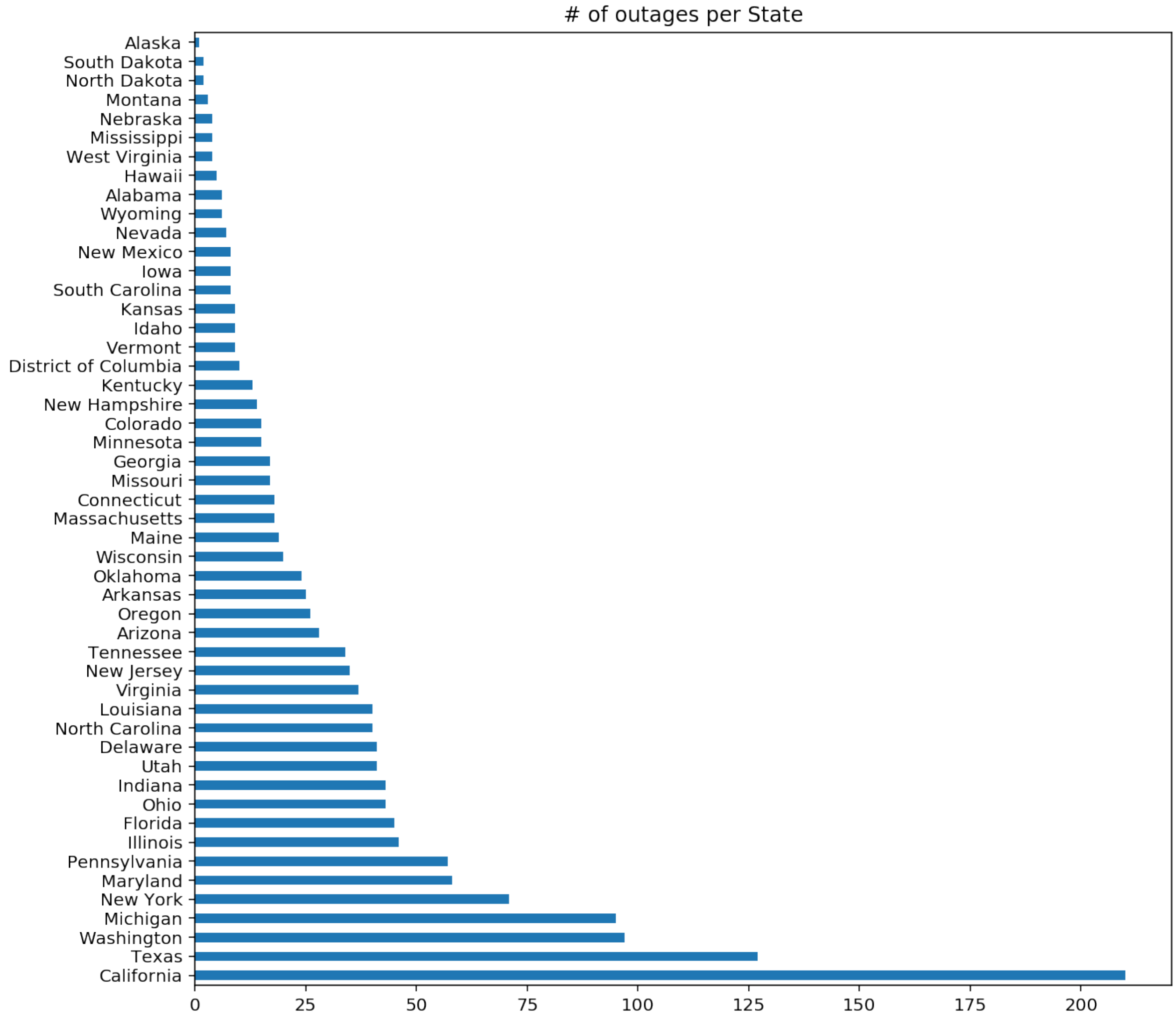
```
CAUSE.CATEGORY          1534 non-null object
CAUSE.CATEGORY.DETAIL   1063 non-null object
HURRICANE.NAMES         72 non-null object
OUTAGE.DURATION         1476 non-null object
DEMAND.LOSS.MW          829 non-null object
CUSTOMERS.AFFECTED      1091 non-null float64
RES.PRICE               1512 non-null object
COM.PRICE               1512 non-null object
IND.PRICE               1512 non-null object
TOTAL.PRICE             1512 non-null object
RES.SALES               1512 non-null object
COM.SALES               1512 non-null object
IND.SALES               1512 non-null object
TOTAL.SALES             1512 non-null object
RES.PERCEN              1512 non-null object
COM.PERCEN              1512 non-null object
IND.PERCEN              1512 non-null object
RES.CUSTOMERS           1534 non-null float64
COM.CUSTOMERS           1534 non-null float64
IND.CUSTOMERS           1534 non-null float64
TOTAL.CUSTOMERS         1534 non-null float64
RES.CUST.PCT            1534 non-null object
COM.CUST.PCT            1534 non-null object
IND.CUST.PCT            1534 non-null object
PC.REALGSP.STATE        1534 non-null object
PC.REALGSP.USA          1534 non-null object
PC.REALGSP.REL          1534 non-null object
PC.REALGSP.CHANGE       1534 non-null object
UTIL.REALGSP            1534 non-null object
TOTAL.REALGSP           1534 non-null object
UTIL.CONTRI             1534 non-null object
PI.UTIL.OFUSA           1534 non-null object
POPULATION              1534 non-null float64
POPPCT_URBAN            1534 non-null object
POPPCT_UC               1534 non-null object
POPDEN_URBAN            1534 non-null object
POPDEN_UC               1524 non-null object
POPDEN_RURAL            1524 non-null object
AREAPCT_URBAN           1534 non-null object
AREAPCT_UC              1534 non-null object
PCT_LAND                1534 non-null object
PCT_WATER_TOT           1534 non-null object
PCT_WATER_INLAND        1534 non-null object
OUTAGE.START            1525 non-null datetime64[ns]
OUTAGE.RESTORATION      1476 non-null datetime64[ns]
dtypes: datetime64[ns](2), float64(7), int64(1), object(43)
memory usage: 635.3+ KB
```

In [12]:
```
# getting range of column names where the numerical values are type
object
columns = outages.columns[11:51]
columns
```

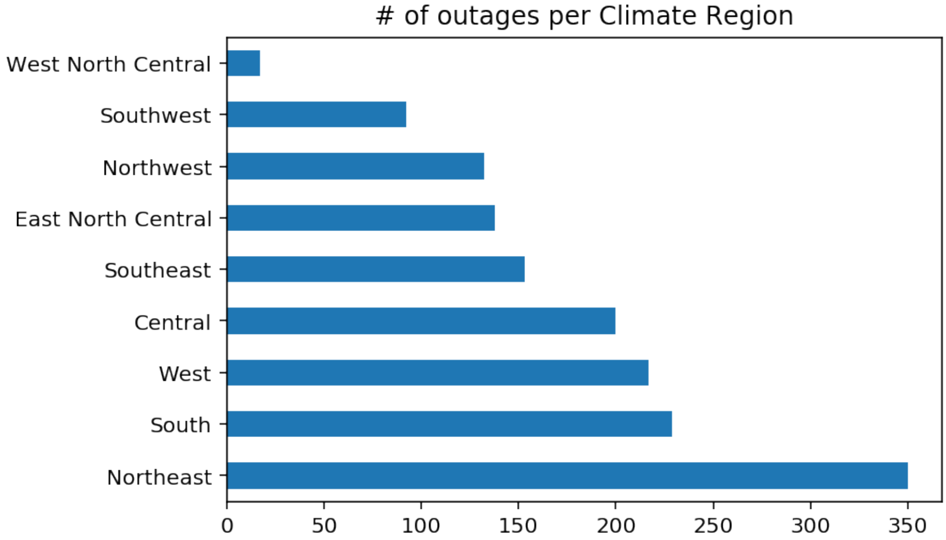
Out[12]:
```
Index(['OUTAGE.DURATION', 'DEMAND.LOSS.MW', 'CUSTOMERS.AFFECTED',
'RES.PRICE',
       'COM.PRICE', 'IND.PRICE', 'TOTAL.PRICE', 'RES.SALES', 'COM.
SALES',
       'IND.SALES', 'TOTAL.SALES', 'RES.PERCEN', 'COM.PERCEN', 'IN
D.PERCEN',
       'RES.CUSTOMERS', 'COM.CUSTOMERS', 'IND.CUSTOMERS', 'TOTAL.C
USTOMERS',
       'RES.CUST.PCT', 'COM.CUST.PCT', 'IND.CUST.PCT', 'PC.REALGSP
.STATE',
       'PC.REALGSP.USA', 'PC.REALGSP.REL', 'PC.REALGSP.CHANGE', 'U
TIL.REALGSP',
       'TOTAL.REALGSP', 'UTIL.CONTRI', 'PI.UTIL.OFUSA', 'POPULATIO
N',
       'POPPCT_URBAN', 'POPPCT_UC', 'POPDEN_URBAN', 'POPDEN_UC',
       'POPDEN_RURAL', 'AREAPCT_URBAN', 'AREAPCT_UC', 'PCT_LAND',
       'PCT_WATER_TOT', 'PCT_WATER_INLAND'],
      dtype='object')
```

In [13]:
```
# changing the type of the previously fetched columns to float type
values
for col in columns:
    outages[col] = outages[col].astype(float)
```

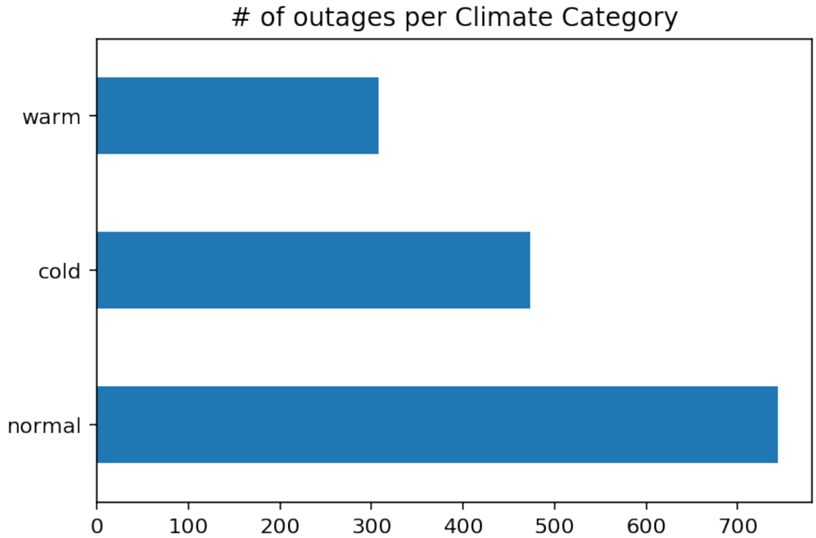
In [14]:
```
"""
Start of the univariate analysis of the number of outages in each S
tate, Climate Region and Category, and Cause
"""
# plotting bar chart for number of outages per state
outages['U.S._STATE'].value_counts().plot(kind='barh', figsize=(10,
10), title='# of outages per State');
```



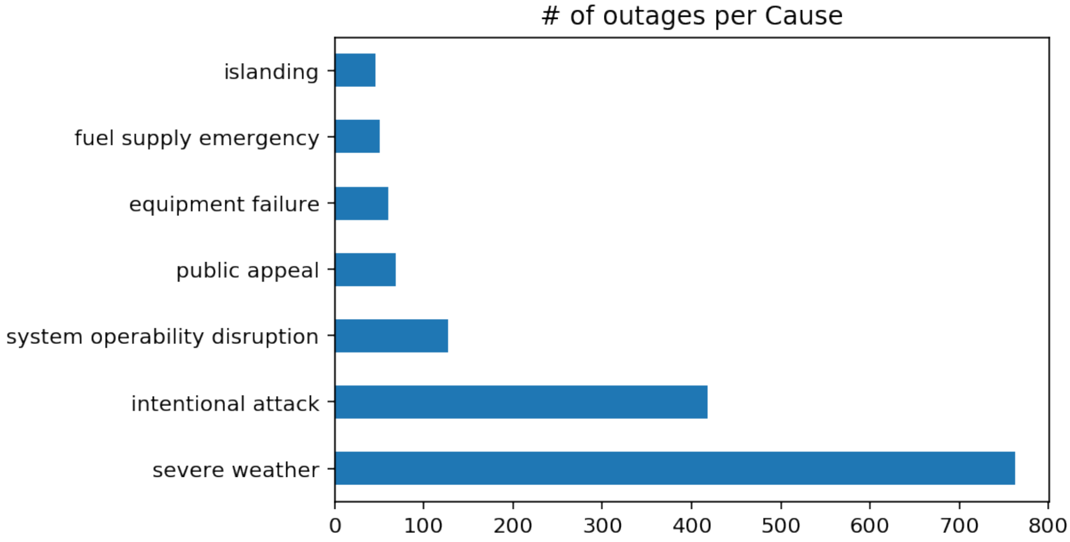
In [15]:
```
# plotting bar chart for number of outages per climate region
outages['CLIMATE.REGION'].value_counts().plot(kind='barh', title='#
of outages per Climate Region');
```



In [16]:
```
# plotting bar chart for number of outages per climate category
outages['CLIMATE.CATEGORY'].value_counts().plot(kind='barh', title=
'# of outages per Climate Category');
```



In [17]:
```
# plotting bar chart for number of outages per cause category
outages['CAUSE.CATEGORY'].value_counts().plot(kind='barh', title='#
of outages per Cause');
```



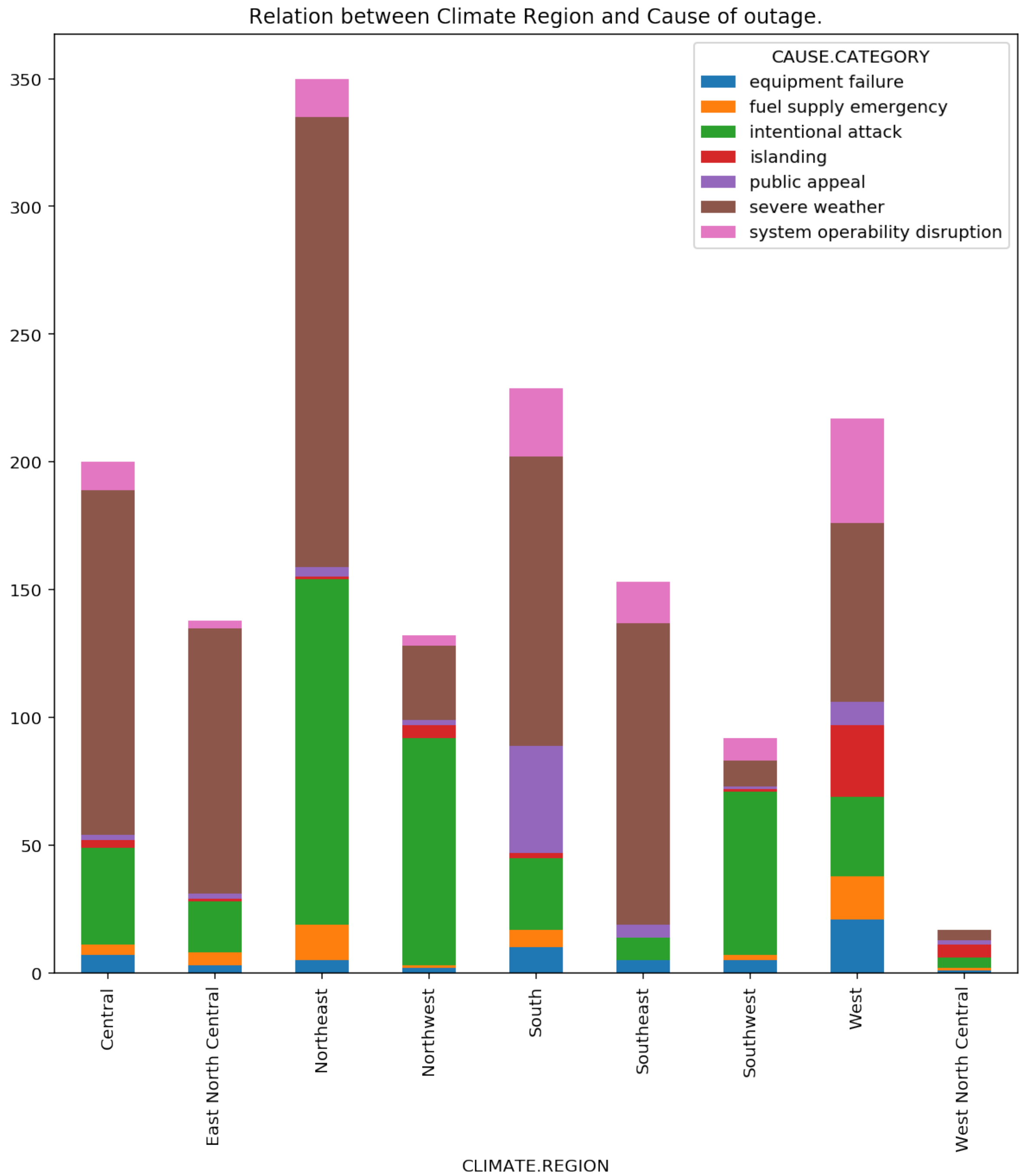
In [18]:
```
"""
Bivariate analysis of the relationship between CAUSE.CATEGORY and C
LIMATE.REGION
"""
# Create the pivot table that counts the occurrence of CAUSE.CATEGO
RY at each CLIMATE.REGION
x = outages.pivot_table(
    index = 'CLIMATE.REGION',
    columns = 'CAUSE.CATEGORY',
    aggfunc = 'size',
    fill_value = 0
)
x
```

Out[18]:

CAUSE.CATEGORY	equipment failure	fuel supply emergency	intentional attack	islanding	public appeal	severe weather	syst operabi disrupt
CLIMATE.REGION							
Central	7	4	38	3	2	135	
East North Central	3	5	20	1	2	104	
Northeast	5	14	135	1	4	176	
Northwest	2	1	89	5	2	29	
South	10	7	28	2	42	113	
Southeast	5	0	9	0	5	118	
Southwest	5	2	64	1	1	10	
West	21	17	31	28	9	70	
West North Central	1	1	4	5	2	4	

In [19]:

```
# plotting the results
x.plot(kind='bar', stacked=True, figsize=(10,10), title='Relation b
etween Climate Region and Cause of outage.');
```

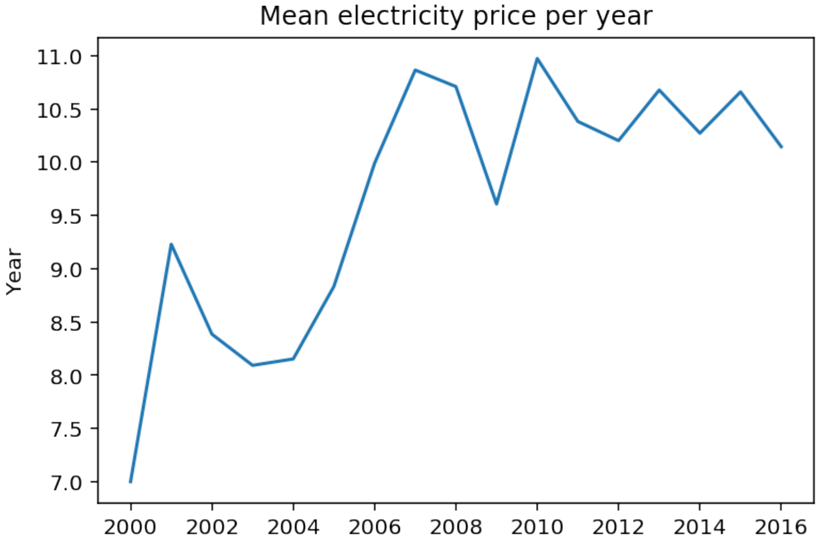

Relation between Climate Region and Cause of outage.
CAUSE.CATEGORY
equipment failure
fuel supply emergency
intentional attack
islanding
public appeal
severe weather
system operability disruption
350
300
250
200
150
100
50
0
Central
East North Central
Northeast
Northwest
South
Southeast
Southwest
West
West North Central
CLIMATE.REGION

In [20]:
```
# group years and get the mean of the total prices of electricity f
or that year
yearly_prices = outages.groupby('YEAR')['TOTAL.PRICE'].mean().to_fr
ame()
yearly_prices
```

Out[20]:

	TOTAL.PRICE
YEAR	
2000	7.000526
2001	9.229333
2002	8.385000
2003	8.091957
2004	8.152113
2005	8.833091
2006	9.988485
2007	10.864464
2008	10.709189
2009	9.606795
2010	10.972736
2011	10.381636
2012	10.201667
2013	10.676993
2014	10.271786
2015	10.659496
2016	10.145000

In [21]:
```
# plot the mean electricity price for each year
plt.plot(yearly_prices.index, yearly_prices['TOTAL.PRICE'])
plt.title('Mean electricity price per year')
plt.ylabel('Mean Electricity price')
plt.ylabel('Year');
```



Assessment of Missingness

In [37]:
```
outages['OUTAGE.DURATION'].isnull().sum()
```

Out[37]: 58

In [ ]:
```

```

Hypothesis Test

In [25]:
```
"""
Null hypothesis: in the US the distribution of the causes for major
outages among the 2 states with most cases
of major outages is the same. The difference between 2 samples is d
ue to chance. (CA, TX)
Alternative hypothesis: in the US the distributions of the causes o
f major outages of the two groups are different.
"""

# getting the rows with California and Texas since they are the sta
tes with highest number of outages.
CA_TX = outages[(outages['POSTAL.CODE'] == 'CA') | (outages['POSTAL
.CODE'] == 'TX')]
CA_TX = CA_TX[['POSTAL.CODE', 'CAUSE.CATEGORY']].reset_index(drop=T
rue) # just getting neccessary columns
CA_TX
```

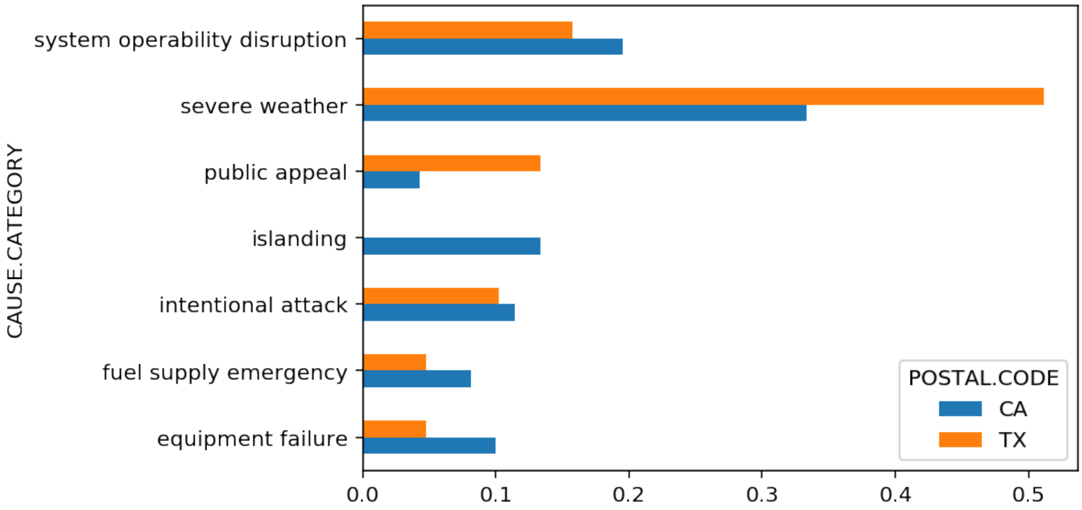
Out[25]:

	POSTAL.CODE	CAUSE.CATEGORY
0	TX	system operability disruption
1	TX	severe weather
2	TX	system operability disruption
3	TX	severe weather
4	TX	intentional attack
...	...	...
332	CA	severe weather
333	CA	fuel supply emergency
334	CA	equipment failure
335	CA	system operability disruption
336	CA	intentional attack

337 rows × 2 columns

In [26]:
```
# get count
count = CA_TX.pivot_table(
            index = 'CAUSE.CATEGORY',
            columns = 'POSTAL.CODE',
            aggfunc = 'size',
            fill_value = 0)
# normalize the values
normalized = count.apply(lambda x: x / x.sum())
```

In [27]:
```
normalized.plot(kind='barh'); # print distribution in bar chart
```



In [28]:
```
"""
Function to calculate the tvd of a given dataframe
"""
def tvd(df):
    # get the count
    count = df.pivot_table(
            index = 'CAUSE.CATEGORY',
            columns = 'POSTAL.CODE',
            aggfunc = 'size',
            fill_value = 0)
    # normalize the values
    normalized = count.apply(lambda x: x / x.sum())
    # return the calculated tvd
    return normalized.diff(axis=1).iloc[:,-1].abs().sum() / 2
```

In [29]:
```
obs_tvd = tvd(CA_TX) # getting the observed tvd
```

In [30]:
```
# simulating values 1000 times
N = 1000
tvds = []
for _ in range(N):
    #shuffle the column representing the state
    shuffled = CA_TX['POSTAL.CODE'].sample(frac=1, replace=False).r
eset_index(drop=True)
    # add shuffled column to the categories
    shuffled_df = CA_TX[['CAUSE.CATEGORY']].assign(**{'POSTAL.CODE'
: shuffled})

    tvds.append(tvd(shuffled_df)) # calculate the tvd and append to
list

tvds = pd.Series(tvds)
```

In [31]:
```
# calculate the p-value
pval = (tvds >= obs_tvd).sum() / N
```

In [32]:
```
# plotting to check results
tvds.plot(kind='hist', title='p-value: %f' % pval)
plt.scatter([obs_tvd], [0], s=50, color='r')
perc = np.percentile(tvds, 95) # 5% significance level
plt.axvline(x=perc, color='y');
```