Alaa and Tristan's Epic Analysis of Frequency of Power Outages in Different Regions

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Code

```
In [1]: import pandas as pd
        import numpy as np
        import os

        import plotly.express as px
        import matplotlib.pyplot as plt

        pd.options.plotting.backend = 'plotly'
```

Introduction

In this project, we studied the power outages dataset. Each row of the dataset is a U.S. power outage, each column describes something about that outage. The dataset includes geographical (where did the outages occur) and temporal (when did the outages occur + how long did they last) data, and we connected the two in our analysis.

The dataset has 1534 rows and 55 columns.

We were interested in the 'YEAR','MONTH','CLIMATE.REGION','OUTAGE.DURATION','OUTAGE.START.TIME', 'OUTAGE.START.DATE','CAUSE.CATEGORY', and 'CAUSE.CATEGORY.DETAIL' columns.

We were ultimately interested in how power outage statistics differed by description. Here were some questions we brainstormed:

- how do power outage durations depend on their in-state frequency?
- what is the place with the worst (longest and/or most frequent) power outages?
- when do power outages occur?

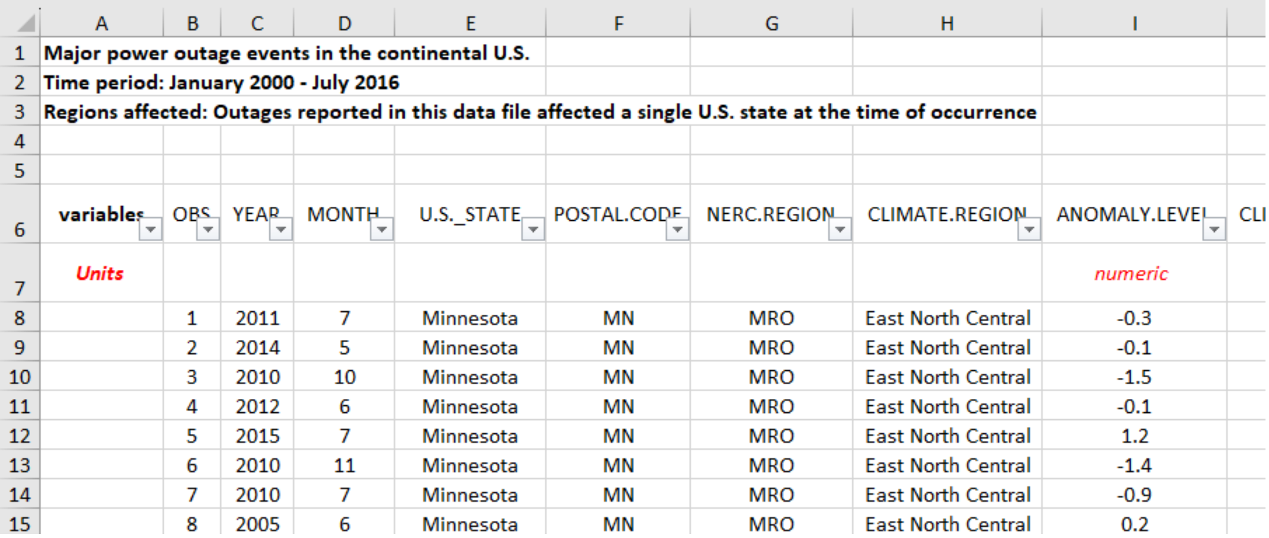
We ultimately landed on the question:

- how do power outages depend on their location?

Cleaning and EDA

We write all in functions to keep processing modular.

This is what the Excel (.xlsx) file initially looks like post download from Purdue:



	A	B	C	D	E	F	G	H	I	
1	**Major power outage events in the continental U.S.**									
2	**Time period: January 2000 - July 2016**									
3	**Regions affected: Outages reported in this data file affected a single U.S. state at the time of occurrence**									
4										
5										
6	**variables**	OBS	YEAR	MONTH	U.S._STATE	POSTAL.CODE	NERC.REGION	CLIMATE.REGION	ANOMALY.LEVEL	CLI
7	*Units*								*numeric*	
8		1	2011	7	Minnesota	MN	MRO	East North Central	-0.3	
9		2	2014	5	Minnesota	MN	MRO	East North Central	-0.1	
10		3	2010	10	Minnesota	MN	MRO	East North Central	-1.5	
11		4	2012	6	Minnesota	MN	MRO	East North Central	-0.1	
12		5	2015	7	Minnesota	MN	MRO	East North Central	1.2	
13		6	2010	11	Minnesota	MN	MRO	East North Central	-1.4	
14		7	2010	7	Minnesota	MN	MRO	East North Central	-0.9	
15		8	2005	6	Minnesota	MN	MRO	East North Central	0.2	

This is not in tidy data format (one row per observation, one column per feature) since there is a header and columns have descriptors below the

In [2]:

```
def get_data():
    """returns data as dataframe"""
    return pd.read_csv('outage_chopped.csv').iloc[1:].reset_index().drop(columns=['OBS','index'])
```

We look at the data and its shape to grow familiarity.

In [3]:

```
df=get_data()
```

In [4]:

```
df.shape
```

Out[4]:

```
(1534, 55)
```

In [5]:

```
with pd.option_context('display.max_rows', None, 'display.max_columns', None):
    display(df.head())
```

	YEAR	MONTH	U.S._STATE	POSTAL.CODE	NERC.REGION	CLIMATE.REGION	ANOMALY.LEVEL	CLIMATE.CATEGORY	OUTAGE.START.DATE	OU
0	2011.0	7.0	Minnesota	MN	MRO	East North Central	-0.3	normal	Friday, July 1, 2011	
1	2014.0	5.0	Minnesota	MN	MRO	East North Central	-0.1	normal	Sunday, May 11, 2014	
2	2010.0	10.0	Minnesota	MN	MRO	East North Central	-1.5	cold	Tuesday, October 26, 2010	
3	2012.0	6.0	Minnesota	MN	MRO	East North Central	-0.1	normal	Tuesday, June 19, 2012	
4	2015.0	7.0	Minnesota	MN	MRO	East North Central	1.2	warm	Saturday, July 18, 2015	

We look at the data types alongside a couple of rows of the data to check that the data types are what they ought to be. The first row contains the data types, the following three rows are a few observations.

In [6]:

```
with pd.option_context('display.max_rows', None, 'display.max_columns', None):  # more options can be specified also
    display(pd.concat([pd.DataFrame(df.dtypes).T,df.iloc[:3]]))
```

	YEAR	MONTH	U.S._STATE	POSTAL.CODE	NERC.REGION	CLIMATE.REGION	ANOMALY.LEVEL	CLIMATE.CATEGORY	OUTAGE.START.DATE	OU
0	float64	float64	object	object	object	object	object	object	object	
0	2011.0	7.0	Minnesota	MN	MRO	East North Central	-0.3	normal	Friday, July 1, 2011	
1	2014.0	5.0	Minnesota	MN	MRO	East North Central	-0.1	normal	Sunday, May 11, 2014	
2	2010.0	10.0	Minnesota	MN	MRO	East North Central	-1.5	cold	Tuesday, October 26, 2010	

We notice that the data types are wrong. Most of the columns are of type object, which is for strings, but the data are supposed to be numeric or dates/timedeltas.

In [7]:

```
pd.concat(
    [
        pd.DataFrame(df.dtypes).reset_index().drop(columns='index').rename(columns={0:'type'}),
        pd.DataFrame(df.shape[1]*['counter']).rename(columns={0:'count'})
    ],
    axis=1
).groupby('type').count()
```

Out[7]:

	count
type	
float64	8
object	47

For example, per the data dictionary, ANOMALY.LEVEL represents the El Niño/La Niña (ONI) index, a numerical climatological measure, but the column is of type object.

Moreover, we notice that some of the float datatypes provided in the original dataset are not supposed to be floats but rather ints. See that the first and second column contain month and year as integer-valued floats. Thus we cannot ignore the eight float64-typed columns as we fix the columnar data types.

We try to fix the data types but run into two issues.

Issue One

We notice columns like OUTAGE.DURATION are integer-valued objects, so we try to cast them to int, but we get this error:

In [8]:

```
try:
    df['OUTAGE.DURATION'].astype(int)
except ValueError as error:
    print(error)
```

```
cannot convert float NaN to integer
```

It appears that int Series cannot contain NaNs.

We try to fix this by ignoring the errors.

In [9]:

```
df['OUTAGE.DURATION'].astype(int,errors='ignore').head(3)
```

Out[9]:

```
0    3060
1       1
2    3000
Name: OUTAGE.DURATION, dtype: object
```

However, we see that the cast failed: the column is still of type object.

We know that the Int32 type is helpful for cases like this, where we want to have an int-valued column that contains NaNs. We try direct conversion but get this error.

In [10]:

```
try:
    df['OUTAGE.DURATION'].astype('Int64') #see here we are using Int64 instead of int
except TypeError as error:
    print(error)
```

```
object cannot be converted to an IntegerDtype
```

We solved this by intermediately casting to float. We deduced this solution by applying two facts

1. Float-like object columns are convertible to the float type without problems
2. NaN-containing float columns are convertible to the Int32 type without problems

and observing

3. Conversion from object to Int32 fails

to perform steps 1 and 2 sequentially instead of 3.

This solution is implemented in the try-except block. It tries to convert to int, and if that fails, it tries the two-step approach.

Issue Two

How do we know which numeric-looking columns are supposed to be floats and which are supposed to be ints? There are over a thousand rows, so we should do this programmatically instead of applying the eye filter. For columns like CUSTOMERS.AFFECTED, we presume this should be an int, as a customer count should be whole number valued, but for columns like DEMAND.LOSS.MW, which measures the difference in the potential and the actual quantity of electricity sold due to outage in megawatts. Whether this measure be integer-valued or float-valued is up to convention. Megawatts are virtually continuously valued, but looking at the table, we see all integers:

In [11]:

```
df['DEMAND.LOSS.MW'].unique()[:10]
```

Out[11]:

```
array([nan, '250', '75', '20', '0', '926', '100', '300', '1', '494'],
      dtype=object)
```

As the logic of convention is forgotten but its' artifacts remain, we should perform programmatic typecasting depending on the contents of the columns instead of the column names.

We can check whether a float or object-typed column of floats is integer-valued by the built-in float type method float.is_integer(). We deploy the integer check on the TOTAL.SALES column, which can be float or integer valued a priori.

In [12]:
```
np.all(
    df['TOTAL.SALES'].astype(float).apply(
        lambda num: num.is_integer() or np.isnan(num)
    )
)
```

Out[12]:
```
True
```

We do this for all numeric-looking columns to infer their types. If the above test returns True, it should be int (or Int32, if it has a NaN); else it should be float.

Issues **One** and **Two** resolved, we can fix the data types.

In [13]:
```
def get_data_with_correct_types():
    """returns data with correct types as dataframe"""
    # data cleaning last 11 columns

    df = get_data()
    # casting as float
    df[['PCT_WATER_INLAND', 'PCT_WATER_TOT', 'PCT_LAND', 'AREAPCT_URBAN', 'POPDEN_RURAL', 'POPDEN_UC', 'POPDEN_URBAN',
        'POPPCT_UC', 'POPPCT_URBAN', \
        'PI.UTIL.OFUSA', 'UTIL.CONTRI', 'PC.REALGSP.CHANGE', 'PC.REALGSP.REL']] = \
        df[['PCT_WATER_INLAND', 'PCT_WATER_TOT', 'PCT_LAND', 'AREAPCT_URBAN', 'POPDEN_RURAL', 'POPDEN_UC',
            'POPDEN_URBAN', 'POPPCT_UC', 'POPPCT_URBAN', \
            'PI.UTIL.OFUSA', 'UTIL.CONTRI', 'PC.REALGSP.CHANGE', 'PC.REALGSP.REL']].astype(float)
    # casting as int
    df[['POPULATION', 'TOTAL.REALGSP', 'UTIL.REALGSP', 'PC.REALGSP.USA']] = \
        df[['POPULATION', 'TOTAL.REALGSP', 'UTIL.REALGSP', 'PC.REALGSP.USA']].astype(int)
    #from front
    #casting as int
    for column in ['YEAR','MONTH','DEMAND.LOSS.MW','CUSTOMERS.AFFECTED',
        'RES.SALES','COM.SALES','IND.SALES','TOTAL.SALES',
        'RES.CUSTOMERS', 'COM.CUSTOMERS', 'IND.CUSTOMERS', 'TOTAL.CUSTOMERS',
        'PC.REALGSP.STATE', 'PC.REALGSP.USA', 'OUTAGE.DURATION']:
        try:
            df[column] = df[column].astype(int)
        except:
            df[column] = df[column].astype(float).astype('Int32')
    #casting as float
    for column in ['ANOMALY.LEVEL','RES.PRICE','COM.PRICE','IND.PRICE','TOTAL.PRICE',
                   'RES.PERCEN', 'COM.PERCEN', 'IND.PERCEN',
                   'RES.CUST.PCT', 'COM.CUST.PCT', 'IND.CUST.PCT',
                   'AREAPCT_UC']:
        df[column] = df[column].astype(float)
    return df
```

In [14]:
```
df=get_data_with_correct_types()
```

We reprint the datatypes with some rows to visually verify our effort. Now all column types appear correct.

In [15]:
```
#(not yet. we still need to do some float conversion and all of the datetime/timedelta conversion).
```

In [16]:
```
with pd.option_context('display.max_rows', None, 'display.max_columns', None):  # more options can be specified also
    display(pd.concat([pd.DataFrame(df.dtypes).T,df.iloc[:3]]))
```

	YEAR	MONTH	U.S._STATE	POSTAL.CODE	NERC.REGION	CLIMATE.REGION	ANOMALY.LEVEL	CLIMATE.CATEGORY	OUTAGE.START.DATE	OU
0	int32	Int32	object	object	object	object	float64	object	object	
0	2011	7	Minnesota	MN	MRO	East North Central	-0.3	normal	Friday, July 1, 2011	
1	2014	5	Minnesota	MN	MRO	East North Central	-0.1	normal	Sunday, May 11, 2014	
2	2010	10	Minnesota	MN	MRO	East North Central	-1.5	cold	Tuesday, October 26, 2010	

We are interested in the columns Year, Month, Climate Region, and Outage Duration as they are the most analyzable.

In [17]:
```
df=df[['YEAR','MONTH','CLIMATE.REGION','OUTAGE.DURATION','OUTAGE.START.TIME','OUTAGE.START.DATE','CAUSE.CATEGORY','CAUSE
```

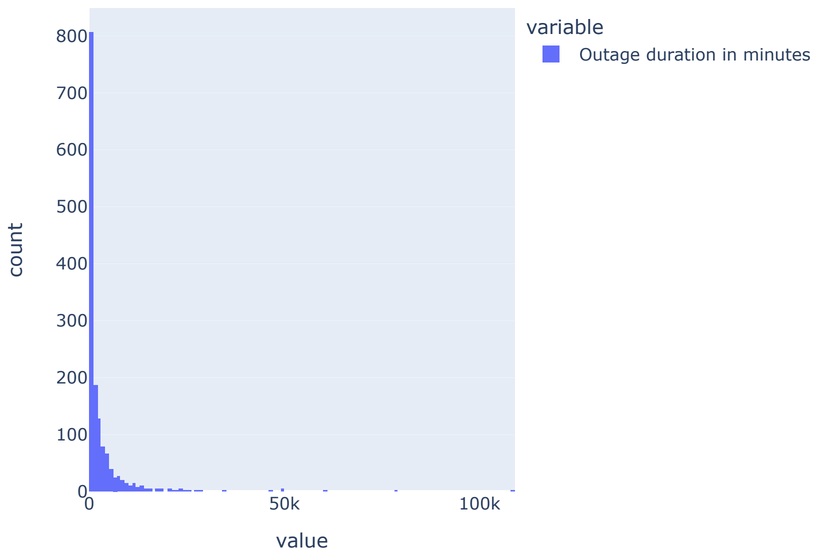
Univariate Analysis

We look at univariate distributions to get a sense of individual column values.

We see that most of the outages are short, but some are very long.

```
In [18]: df[['OUTAGE.DURATION']].rename(columns={'OUTAGE.DURATION':'Outage duration in minutes'}).plot(kind='hist',title='Frequer
```

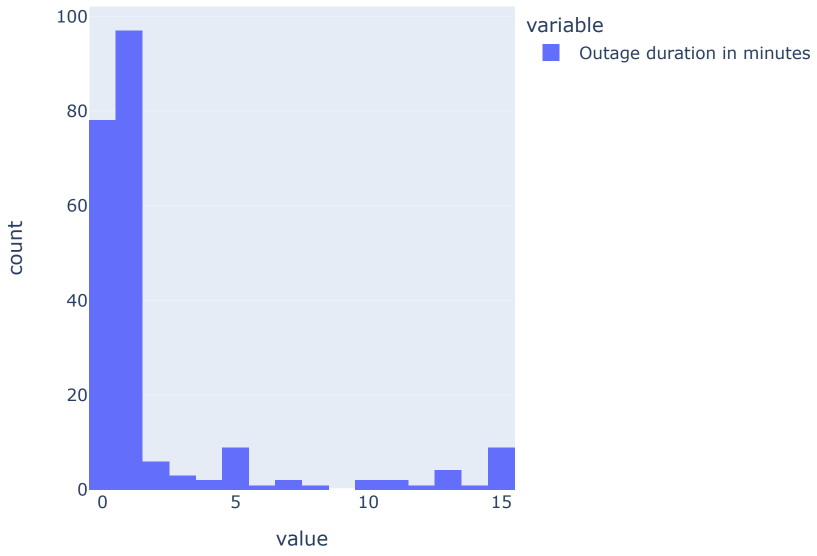
Frequency distribution of outage duration in minutes



What if we look at the shorter outages only? It looks like a huge bulk of the outages last less than two minutes.

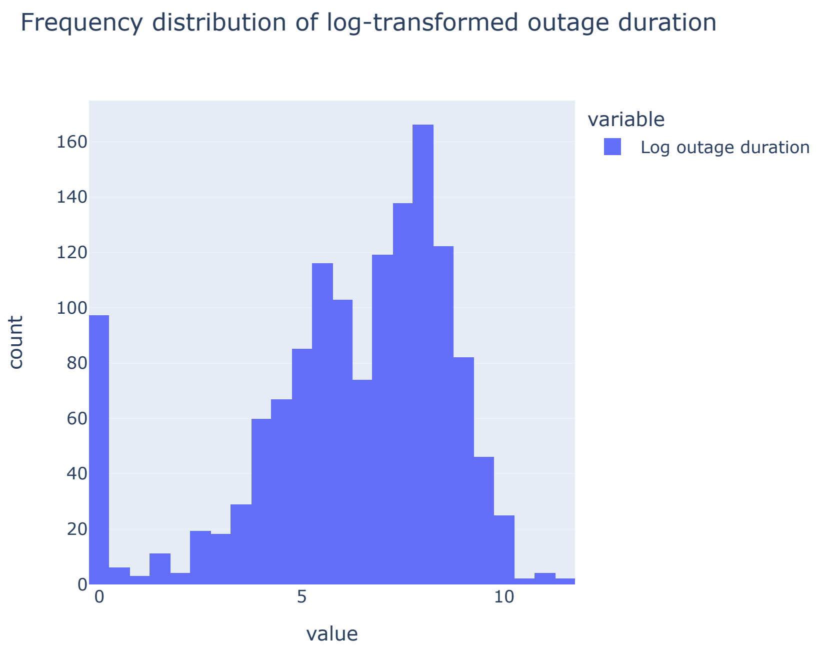
```
In [19]: df[['OUTAGE.DURATION']][df['OUTAGE.DURATION']<=15].rename(columns={'OUTAGE.DURATION':'Outage duration in minutes'}).plot
```

Frequency distribution of the short (<15 minute) outages



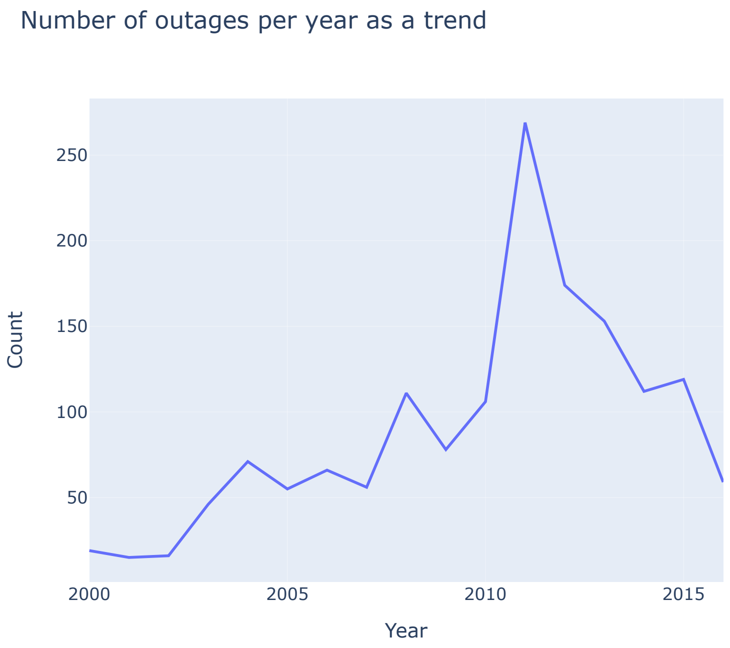
If we log-transform the outage duration, which is meant to give an idea of trend across scales of orders of magnitude, we can see a pattern. It appears to be a point mass at zero added to a bimodal bell, like the sum of two Gaussians with different means, with the lower Gaussian having a wider spread. The point mass at zero is due to the zero and one minute outages.

```
In [20]: non_na_outage_times=df[['OUTAGE.DURATION']][~df['OUTAGE.DURATION'].isna()].reset_index()[['OUTAGE.DURATION']]
         np.log(non_na_outage_times[non_na_outage_times['OUTAGE.DURATION']>0]).rename(columns={'OUTAGE.DURATION':'Log outage dura
```



We can look at how the number of outages per year changed over time. It looks like 2011-2013 have had a lot more power outages than the typical year. We may want to test this visually informed hypothesis statistically with a hypothesis test later on.

```
In [21]: df[['YEAR','MONTH']].groupby('YEAR').count().reset_index().rename(columns={'YEAR':'Year','MONTH':'Count'}).plot(kind='l
```

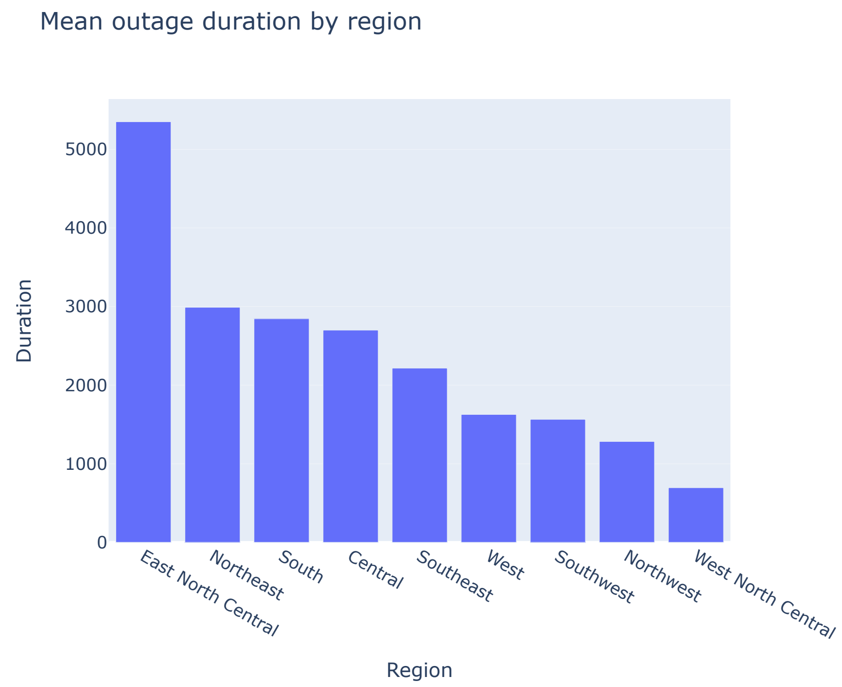


Bivariate analysis

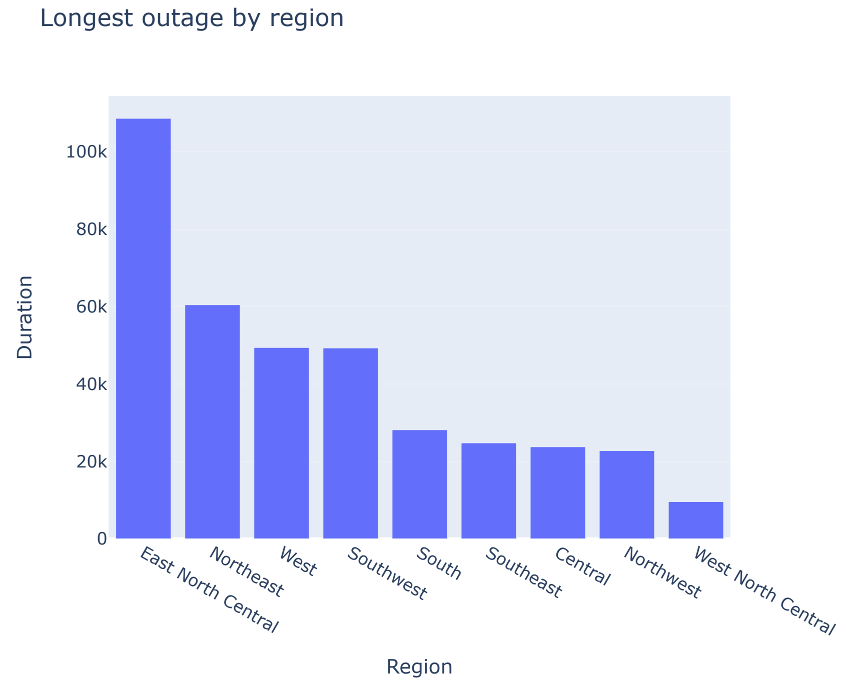
We can also perform some bivariate analysis to understand the associations between variables.

We can visualize outage duration statistics by region to identify patterns between regions and their power outages.

```
In [22]: df[['OUTAGE.DURATION','CLIMATE.REGION']].groupby('CLIMATE.REGION').mean().reset_index().sort_values(by='OUTAGE.DURATION
```

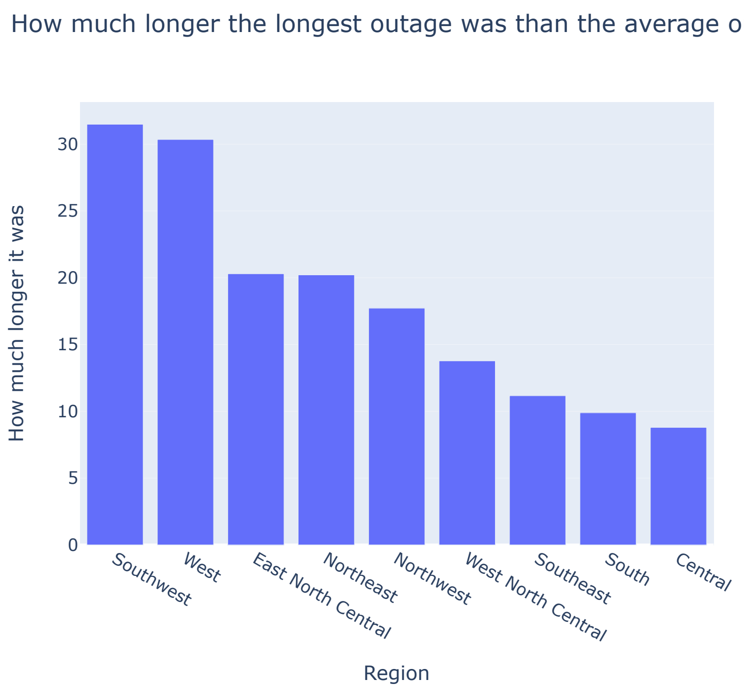

Mean outage duration by region

```
In [23]: df[['OUTAGE.DURATION','CLIMATE.REGION']].groupby('CLIMATE.REGION').max().reset_index().sort_values(by='OUTAGE.DURATION'
```


Longest outage by region

By dividing these two distributions we can identify the relative duration of the longest power outage a region has had compared to their average power outage.

In [24]:
```
(df[['OUTAGE.DURATION','CLIMATE.REGION']].groupby('CLIMATE.REGION').max()/df[['OUTAGE.DURATION','CLIMATE.REGION']].grou
```


How much longer the longest outage was than the average outage

Intereresting Aggregates

Now, we can choose different columns to grouping and pivoting, and examine the aggregate statistics of the data.

First, we combine different columns until we reach a trial that produces a valuable result.

In [25]:
```
d = df.copy()[['YEAR', 'MONTH','CLIMATE.REGION', 'OUTAGE.DURATION']]

region_year_prop = d.groupby(['CLIMATE.REGION','YEAR']).count()[['MONTH']] / d.groupby(['YEAR']).count()[['MONTH']]
region_year_prop
```

Out[25]:

		MONTH
CLIMATE.REGION	**YEAR**	
Central	**2000**	0.210526
	2002	0.062500
	2003	0.130435
	2004	0.070423
	2005	0.090909
...	**...**	...
West North Central	**2009**	0.038462
	2010	0.028302
	2011	0.011152
	2013	0.019608
	2014	0.008929

136 rows × 1 columns

In [26]:

```python
year_region_prop = d.groupby(['YEAR','CLIMATE.REGION']).count()[['MONTH']] / d.groupby(['YEAR']).count()[['MONTH']]
year_region_prop
```

Out[26]:

		MONTH
YEAR	CLIMATE.REGION	
2000	Central	0.210526
	Northeast	0.105263
	South	0.157895
	Southeast	0.315789
	Southwest	0.157895
...	...	...
2016	Northwest	0.237288
	South	0.152542
	Southeast	0.050847
	Southwest	0.118644
	West	0.084746

136 rows × 1 columns

In [27]:

```python
month_prop = (d.groupby('MONTH').count() / d.count())[['YEAR']]
month_prop
```

Out[27]:

	YEAR
MONTH	
1	0.088657
2	0.088657
3	0.065189
4	0.072360
5	0.082790
6	0.127119
7	0.117992
8	0.099739
9	0.061278
10	0.071056
11	0.046936
12	0.072360

In [28]:

```python
print(pd.DataFrame(round(month_prop['YEAR']*100,2).apply(lambda percentage: str(percentage)+'%')).rename(columns={'YEAR
```

```
|   MONTH | Percent of power outages in this month    |
|--------:|:------------------------------------------|
|       1 | 8.87%                                     |
|       2 | 8.87%                                     |
|       3 | 6.52%                                     |
|       4 | 7.24%                                     |
|       5 | 8.28%                                     |
|       6 | 12.71%                                    |
|       7 | 11.8%                                     |
|       8 | 9.97%                                     |
|       9 | 6.13%                                     |
|      10 | 7.11%                                     |
|      11 | 4.69%                                     |
|      12 | 7.24%                                     |
```

In [29]:

```python
year_prop = (d.groupby('YEAR').count() / d.count())[['MONTH']]
year_prop
```

Out[29]:

	MONTH
YEAR	
2000	0.012459
2001	0.009836
2002	0.010492
2003	0.030164
2004	0.046557
2005	0.036066
2006	0.043279
2007	0.036721
2008	0.072787
2009	0.051148
2010	0.069508
2011	0.176393
2012	0.114098
2013	0.100328
2014	0.073443
2015	0.078033
2016	0.038689

In [30]:

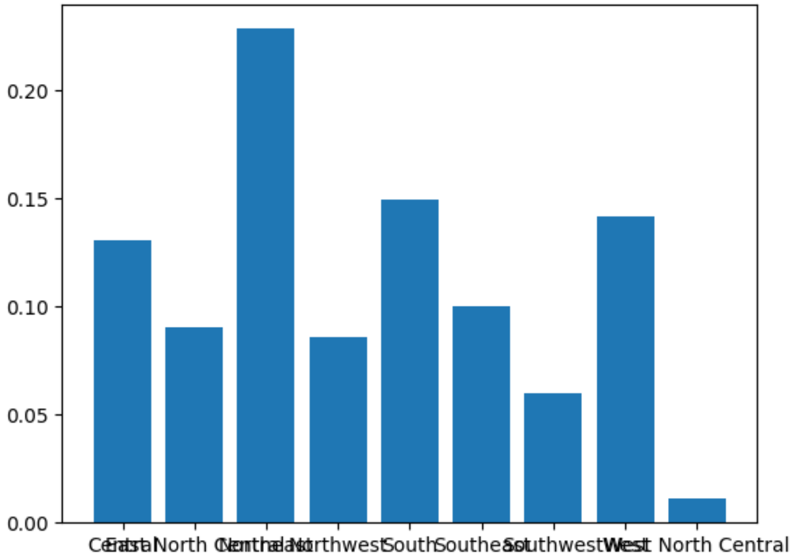
```python
region_prop = (d.groupby('CLIMATE.REGION').count() / d.count())[['YEAR']]
region_prop
```

Out[30]:

	YEAR
CLIMATE.REGION	
Central	0.130378
East North Central	0.089961
Northeast	0.228162
Northwest	0.086050
South	0.149283
Southeast	0.099739
Southwest	0.059974
West	0.141460
West North Central	0.011082

In [31]:

```
region_prop_plot = plt.bar(region_prop.index, region_prop['YEAR'])
region_prop_plot;
```



In [32]:

```
# PIVOT TABLE
region_year_prop_table = region_year_prop.pivot_table(index = 'CLIMATE.REGION', columns = 'YEAR', values = 'MONTH')
region_year_prop_table
```

Out[32]:

YEAR	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
CLIMATE.REGION													
Central	0.210526	NaN	0.0625	0.130435	0.070423	0.090909	0.090909	0.089286	0.216216	0.256410	0.075472	0.148699	0.126437
East North Central	NaN	NaN	0.0625	0.217391	0.070423	0.181818	0.030303	0.160714	0.090090	0.115385	0.122642	0.063197	0.045977
Northeast	0.105263	0.133333	0.1875	0.260870	0.098592	0.109091	0.242424	0.196429	0.189189	0.064103	0.264151	0.308550	0.379310
Northwest	NaN	NaN	NaN	0.043478	0.042254	NaN	0.166667	0.035714	0.018018	0.012821	0.018868	0.137546	0.143678
South	0.157895	0.200000	0.1875	0.065217	0.154930	0.200000	0.151515	0.142857	0.126126	0.243590	0.169811	0.122677	0.132184
Southeast	0.315789	0.066667	0.1250	0.130435	0.366197	0.218182	0.090909	0.035714	0.126126	0.064103	0.066038	0.074349	0.063218
Southwest	0.157895	NaN	0.0625	0.043478	0.042254	0.018182	0.030303	0.017857	0.009009	0.038462	0.018868	0.063197	0.028736
West	0.052632	0.600000	0.3125	0.108696	0.140845	0.181818	0.136364	0.321429	0.207207	0.166667	0.235849	0.066914	0.080460
West North Central	NaN	NaN	NaN	NaN	0.014085	NaN	0.015152	NaN	0.009009	0.038462	0.028302	0.011152	NaN

In [33]:

```
year_region_prop_table = year_region_prop.pivot_table(index = 'YEAR', columns = 'CLIMATE.REGION', values = 'MONTH')
year_region_prop_table
```

Out[33]:

CLIMATE.REGION	Central	East North Central	Northeast	Northwest	South	Southeast	Southwest	West	West North Central
YEAR									
2000	0.210526	NaN	0.105263	NaN	0.157895	0.315789	0.157895	0.052632	NaN
2001	NaN	NaN	0.133333	NaN	0.200000	0.066667	NaN	0.600000	NaN
2002	0.062500	0.062500	0.187500	NaN	0.187500	0.125000	0.062500	0.312500	NaN
2003	0.130435	0.217391	0.260870	0.043478	0.065217	0.130435	0.043478	0.108696	NaN
2004	0.070423	0.070423	0.098592	0.042254	0.154930	0.366197	0.042254	0.140845	0.014085
2005	0.090909	0.181818	0.109091	NaN	0.200000	0.218182	0.018182	0.181818	NaN
2006	0.090909	0.030303	0.242424	0.166667	0.151515	0.090909	0.030303	0.136364	0.015152
2007	0.089286	0.160714	0.196429	0.035714	0.142857	0.035714	0.017857	0.321429	NaN
2008	0.216216	0.090090	0.189189	0.018018	0.126126	0.126126	0.009009	0.207207	0.009009
2009	0.256410	0.115385	0.064103	0.012821	0.243590	0.064103	0.038462	0.166667	0.038462
2010	0.075472	0.122642	0.264151	0.018868	0.169811	0.066038	0.018868	0.235849	0.028302
2011	0.148699	0.063197	0.308550	0.137546	0.122677	0.074349	0.063197	0.066914	0.011152
2012	0.126437	0.045977	0.379310	0.143678	0.132184	0.063218	0.028736	0.080460	NaN
2013	0.104575	0.098039	0.274510	0.065359	0.091503	0.084967	0.143791	0.117647	0.019608
2014	0.169643	0.160714	0.178571	0.062500	0.133929	0.107143	0.107143	0.071429	0.008929
2015	0.117647	0.067227	0.092437	0.134454	0.252101	0.033613	0.084034	0.218487	NaN
2016	0.067797	0.050847	0.237288	0.237288	0.152542	0.050847	0.118644	0.084746	NaN

We see that different regions are impacted by power outages differently. For instance, the Southwest typically has the third shortest outages on average but it once had a power outage 31 times longer than the average, which is the largest such ratio for any region.

Assessment of Missingness

We looked at all of the columns to find a column that is NMAR. We found the column

$$'CAUSE.CATEGORY.DETAIL'$$

to be likely NMAR. We see that 30.7% of the values are missing.

In [34]:

```
str(round(df['CAUSE.CATEGORY.DETAIL'].isna().mean()*100,2))+'%'
```

Out[34]:

```
'30.7%'
```

Though the preceding column, a column highly related in name and meaning, a column which is the categorization of the cause without the detail, is not missing at all.

In [35]:

```
str(df['CAUSE.CATEGORY'].isna().sum())+' missing values'
```

Out[35]:

```
'0 missing values'
```

These two columns are related: the cause.category.detail column is a more detailed version of cause.category. The cause.category column is not missing at all, and the cause.category.detail column is missing a lot. Some of the nonmissing values look like this.

In [36]:

```
for cause_detail in list(df[~df['CAUSE.CATEGORY.DETAIL'].isna()]['CAUSE.CATEGORY.DETAIL'].unique()[:10]):
    print(cause_detail, end=', ')
print('\b\b...')
```

```
vandalism, heavy wind, thunderstorm, winter storm, tornadoes, sabotage, hailstorm, uncontrolled loss, winter, wind sto
rm...
```

We postulate that it takes some effort to source the detailed cause of an outage, in a way that depends on the true details of the cause, thus cause.category.detail is NMAR. We cannot confirm this because we do not have the missing values, but we think that there are missing values for causes that are hard to explain. Not all power outage cause details are equally documentable/explainable, and we think that the harder to document/explain causes are filled in with NAN instead of properly described.

Missingness Dependency

In [37]:

```
x = get_data()[['CLIMATE.REGION','U.S._STATE','NERC.REGION','CAUSE.CATEGORY']]
```

```
In [38]: x['CR_missing'] = x['CLIMATE.REGION'].isna()
         one_dist = (x.pivot_table(index='U.S._STATE', columns='CR_missing', aggfunc='size')
         )

         one_dist.columns = ['CLIMATE.REGION_missing = False', 'CLIMATE.REGION_missing = True']
         one_dist = one_dist / one_dist.sum()
         one_dist[~one_dist['CLIMATE.REGION_missing = True'].isna()]
         one_dist
```

Out[38]:

	CLIMATE.REGION_missing = False	CLIMATE.REGION_missing = True
U.S._STATE		
Alabama	0.003927	NaN
Alaska	NaN	0.166667
Arizona	0.018325	NaN
Arkansas	0.016361	NaN
California	0.137435	NaN
Colorado	0.009817	NaN
Connecticut	0.011780	NaN
Delaware	0.026832	NaN
District of Columbia	0.006545	NaN
Florida	0.029450	NaN
Georgia	0.011126	NaN
Hawaii	NaN	0.833333
Idaho	0.005890	NaN
Illinois	0.030105	NaN
Indiana	0.028141	NaN
Iowa	0.005236	NaN
Kansas	0.005890	NaN
Kentucky	0.008508	NaN
Louisiana	0.026178	NaN
Maine	0.012435	NaN
Maryland	0.037958	NaN
Massachusetts	0.011780	NaN
Michigan	0.062173	NaN
Minnesota	0.009817	NaN
Mississippi	0.002618	NaN
Missouri	0.011126	NaN
Montana	0.001963	NaN
Nebraska	0.002618	NaN
Nevada	0.004581	NaN
New Hampshire	0.009162	NaN
New Jersey	0.022906	NaN
New Mexico	0.005236	NaN
New York	0.046466	NaN
North Carolina	0.026178	NaN
North Dakota	0.001309	NaN
Ohio	0.028141	NaN
Oklahoma	0.015707	NaN
Oregon	0.017016	NaN
Pennsylvania	0.037304	NaN
South Carolina	0.005236	NaN
South Dakota	0.001309	NaN
Tennessee	0.022251	NaN
Texas	0.083115	NaN
Utah	0.026832	NaN
Vermont	0.005890	NaN
Virginia	0.024215	NaN
Washington	0.063482	NaN
West Virginia	0.002618	NaN
Wisconsin	0.013089	NaN
Wyoming	0.003927	NaN

In [39]:

```
n_repetitions = 1000
shuffled = x.copy()

tvds = []

for _ in range(n_repetitions):
    shuffled['U.S._STATE'] =  np.random.permutation(shuffled['U.S._STATE'])

    pivoted = (
        shuffled
        .pivot_table(index='U.S._STATE', columns='CR_missing', aggfunc='size')
        .apply(lambda x: x / x.sum()))

    tvd = pivoted.diff(axis=1).iloc[:, -1].abs().sum() / 2
    tvds.append(tvd)
```

In [40]:

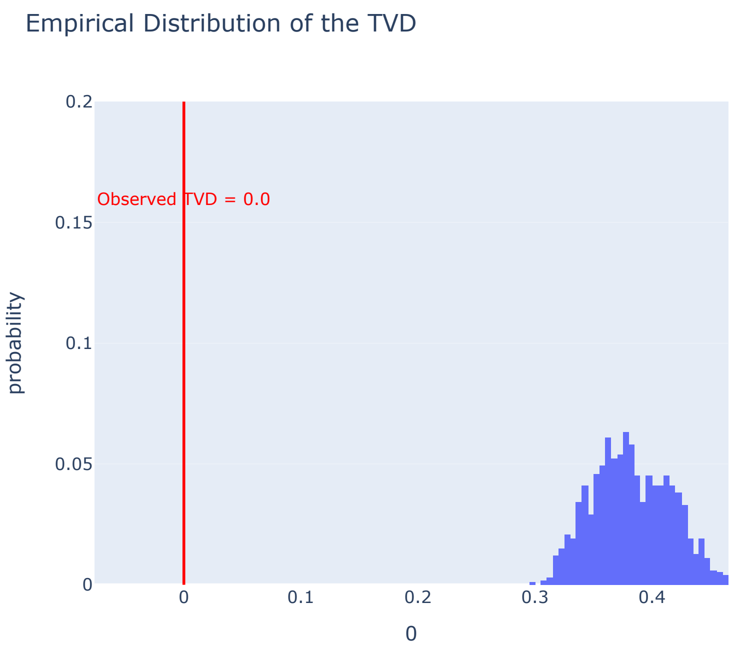
```
observed_tvd = one_dist.diff(axis=1).iloc[:, -1].abs().sum() / 2
observed_tvd
```

Out[40]:

```
0.0
```

In [41]:

```
fig = px.histogram(pd.DataFrame(tvds), x=0, nbins=50, histnorm='probability',
                   title='Empirical Distribution of the TVD')
fig.add_vline(x=observed_tvd, line_color='red')
fig.add_annotation(text=f'<span style="color:red">Observed TVD = {round(observed_tvd, 2)}</span>',
                   x=2.3 * observed_tvd, showarrow=False, y=0.16)
fig.update_layout(yaxis_range=[0, 0.2])
```



In [42]:

```
fig.write_html('missingness-test.html', include_plotlyjs='cdn')
```

In [43]:

```
x
```

Out[43]:

	CLIMATE.REGION	U.S._STATE	NERC.REGION	CAUSE.CATEGORY	CR_missing
0	East North Central	Minnesota	MRO	severe weather	False
1	East North Central	Minnesota	MRO	intentional attack	False
2	East North Central	Minnesota	MRO	severe weather	False
3	East North Central	Minnesota	MRO	severe weather	False
4	East North Central	Minnesota	MRO	severe weather	False
...	...	...	...	...	...
1529	West North Central	North Dakota	MRO	public appeal	False
1530	West North Central	North Dakota	MRO	fuel supply emergency	False
1531	West North Central	South Dakota	RFC	islanding	False
1532	West North Central	South Dakota	MRO	islanding	False
1533	NaN	Alaska	ASCC	equipment failure	True

1534 rows × 5 columns

In [44]:

```
y = x
y['CR_missing'] = y['CLIMATE.REGION'].isna()
two_dist = (y.pivot_table(index='NERC.REGION', columns='CR_missing', aggfunc='size')
)

two_dist.columns = ['CLIMATE.REGION_missing = False', 'CLIMATE.REGION_missing = True']
two_dist = two_dist / two_dist.sum()
two_dist[~two_dist['CLIMATE.REGION_missing = True'].isna()]
two_dist
```

Out[44]:

	CLIMATE.REGION_missing = False	CLIMATE.REGION_missing = True
NERC.REGION		
ASCC	NaN	0.166667
ECAR	0.022251	NaN
FRCC	0.028796	NaN
FRCC, SERC	0.000654	NaN
HECO	NaN	0.500000
HI	NaN	0.166667
MRO	0.030105	NaN
NPCC	0.098168	NaN
PR	NaN	0.166667
RFC	0.274215	NaN
SERC	0.134162	NaN
SPP	0.043848	NaN
TRE	0.072644	NaN
WECC	0.295157	NaN

In [45]:

```
n_repetitions = 500
shuffled = y.copy()

tvds = []

for _ in range(n_repetitions):
    shuffled['NERC.REGION'] =  np.random.permutation(shuffled['NERC.REGION'])

    pivoted = (
        shuffled
        .pivot_table(index='NERC.REGION', columns='CR_missing', aggfunc='size')
        .apply(lambda y: y / y.sum()))

    tvd = pivoted.diff(axis=1).iloc[:, -1].abs().sum() / 2
    tvds.append(tvd)
```

In [46]:

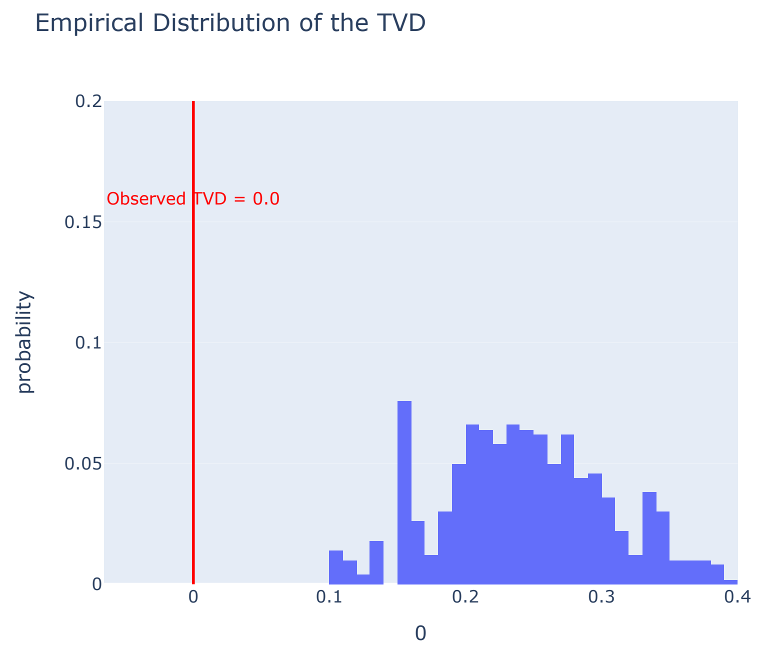
```
observed_tvd = two_dist.diff(axis=1).iloc[:, -1].abs().sum() / 2
observed_tvd
two_dist.diff(axis=1)
```

Out[46]:

	CLIMATE.REGION_missing = False	CLIMATE.REGION_missing = True
NERC.REGION		
ASCC	NaN	NaN
ECAR	NaN	NaN
FRCC	NaN	NaN
FRCC, SERC	NaN	NaN
HECO	NaN	NaN
HI	NaN	NaN
MRO	NaN	NaN
NPCC	NaN	NaN
PR	NaN	NaN
RFC	NaN	NaN
SERC	NaN	NaN
SPP	NaN	NaN
TRE	NaN	NaN
WECC	NaN	NaN

In [47]:

```
fig = px.histogram(pd.DataFrame(tvds), x=0, nbins=50, histnorm='probability',
                   title='Empirical Distribution of the TVD')
fig.add_vline(x=observed_tvd, line_color='red')
fig.add_annotation(text=f'<span style="color:red">Observed TVD = {round(observed_tvd, 2)}</span>',
                   x=2.3 * observed_tvd, showarrow=False, y=0.16)
fig.update_layout(yaxis_range=[0, 0.2])
```



In [ ]:

In [ ]:

In [ ]:

In [48]:
```
z = x
z['CR_missing'] = z['CLIMATE.REGION'].isna()
three_dist = (z.pivot_table(index='CAUSE.CATEGORY', columns='CR_missing', aggfunc='size')
)

three_dist.columns = ['CLIMATE.REGION_missing = False', 'CLIMATE.REGION_missing = True']
three_dist = three_dist / three_dist.sum()
three_dist[~three_dist['CLIMATE.REGION_missing = True'].isna()]
three_dist
```

Out[48]:

	CLIMATE.REGION_missing = False	CLIMATE.REGION_missing = True
CAUSE.CATEGORY		
equipment failure	0.038613	0.166667
fuel supply emergency	0.033377	NaN
intentional attack	0.273560	NaN
islanding	0.030105	NaN
public appeal	0.045157	NaN
severe weather	0.496728	0.666667
system operability disruption	0.082461	0.166667

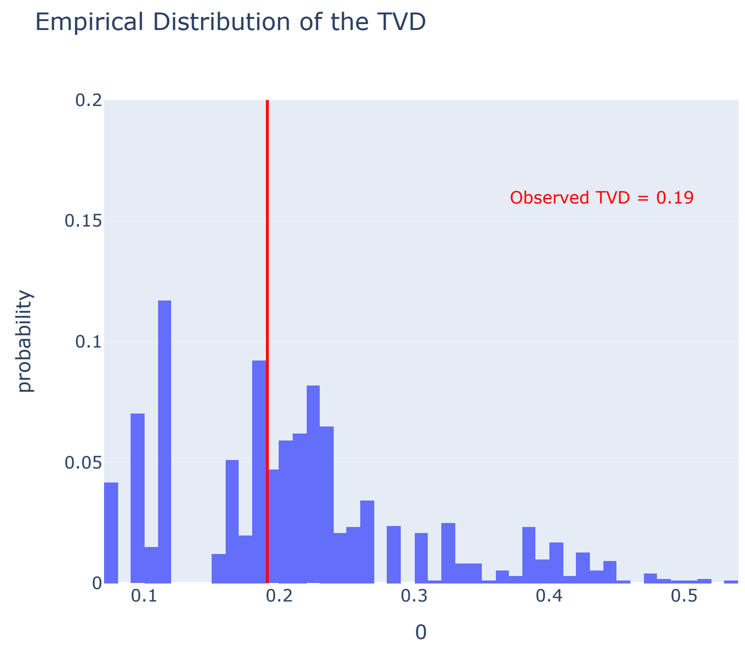
In [49]:
```
n_repetitions = 1000
shuffled = z.copy()

tvds = []

for _ in range(n_repetitions):
    shuffled['CAUSE.CATEGORY'] =  np.random.permutation(shuffled['CAUSE.CATEGORY'])

    pivoted = (
        shuffled
        .pivot_table(index='CAUSE.CATEGORY', columns='CR_missing', aggfunc='size')
        .apply(lambda y: y / y.sum()))

    tvd = pivoted.diff(axis=1).iloc[:, -1].abs().sum() / 2
    tvds.append(tvd)
```

In [50]:
```
observed_tvd = three_dist.diff(axis=1).iloc[:, -1].abs().sum() / 2
observed_tvd
```

Out[50]:
```
0.19109947643979056
```

In [51]:

```
fig = px.histogram(pd.DataFrame(tvds), x=0, nbins=50, histnorm='probability',
                   title='Empirical Distribution of the TVD')
fig.add_vline(x=observed_tvd, line_color='red')
fig.add_annotation(text=f'<span style="color:red">Observed TVD = {round(observed_tvd, 2)}</span>',
                   x=2.3 * observed_tvd, showarrow=False, y=0.16)
fig.update_layout(yaxis_range=[0, 0.2])
```

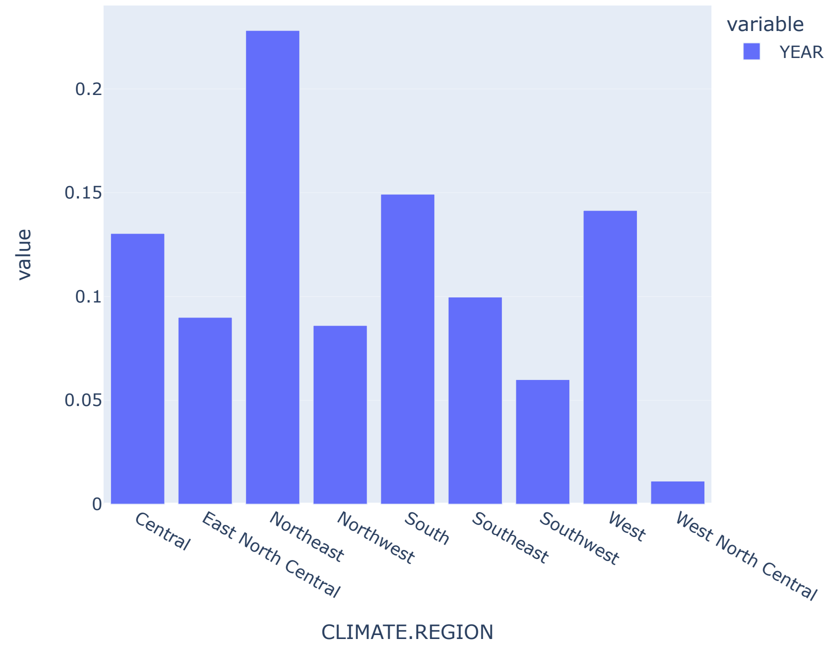


Hypothesis Testing

Let's look at the region outage bar plot again. It gives the proportion of outages observed in each region. It sure looks like different regions have different rates of power outages.

In [52]:

```
region_prop.plot(kind='bar')
```



Is this difference significant or can it be due to chance? We propose a hypothesis test for this claim.

Let $\{p_i : i \in Regions\}$ denote the set of proportion of power outages that occur in each region. That is, p_r for any region r was observed to be equal to the height of its bar. The following table shows the values of p_i for all i.

In [53]:
```
region_prop.reset_index().rename(columns={'CLIMATE.REGION':'Climate region (i)','YEAR':'Proportion (p_i)'})
```

Out[53]:

	Climate region (i)	Proportion (p_i)
0	Central	0.130378
1	East North Central	0.089961
2	Northeast	0.228162
3	Northwest	0.086050
4	South	0.149283
5	Southeast	0.099739
6	Southwest	0.059974
7	West	0.141460
8	West North Central	0.011082

If all regions experience power outages at the same rate then we would expect to see the proportions close to $\frac{1}{\#regions} = \frac{1}{9}$.

So we test

$H_0 : p_i = \frac{1}{9}$ for all i

vs

H_1 : not all of the p_i are $\frac{1}{9}$.

We can let $\alpha = 0.001$.

There were 1534 reported outages.

In [54]:
```
df.shape[0]
```

Out[54]:
```
1534
```

We can simulate a sample from the null distribution by randomly assigning 1534 samples to nine categories uniformly. We can estimate the p_i to be the proportion of outages that land in each region i. The null distribution says that the proportions are all $\frac{1}{9}$, and we can compare these samples from the null distribution to the null distribution by the TVD statistic. We can compute the TVD of the observed region proportions to the null distribution of proportions to get an idea of how extreme our observed proportions were if they truly came from the null distribution.

In [55]:
```
n=df.shape[0]
```

In [56]:
```
def sample_1534_outages():
    return np.random.choice(range(9),size=1534)
```

In [57]:
```
def compute_proportions_in_each_region_of_sample(sample):
    return np.unique(sample,return_counts=True)[1]/1534
```

In [58]:
```
def compute_tvd(proportions):
    return np.abs(proportions - (1/9)).sum()/2
```

In [59]:
```
tvds_of_samples_under_null=[]
```

In [60]:

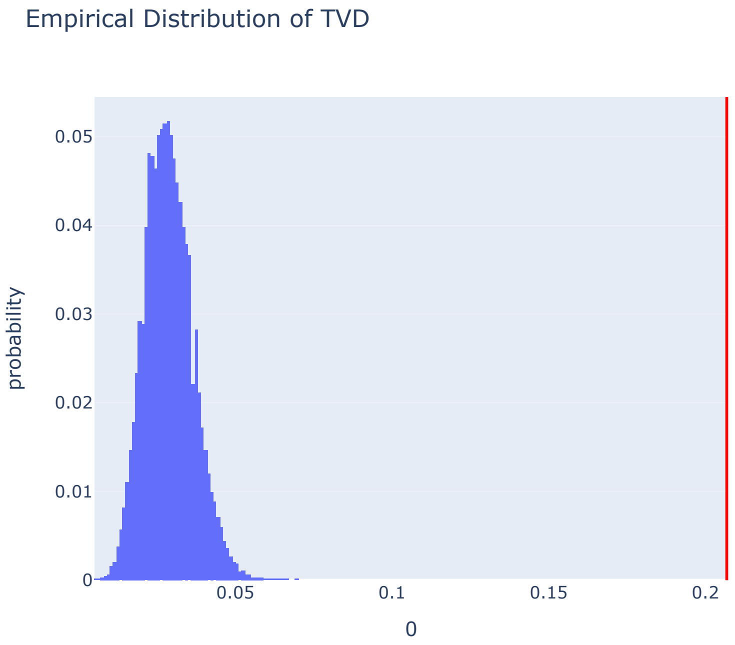
```
num_sims=10**5
for _ in range(num_sims):
    tvds_of_samples_under_null.append(
        compute_tvd(
            compute_proportions_in_each_region_of_sample(
                sample_1534_outages()
            )
        )
    )
```

In [61]:

```
observed_tvd=compute_tvd(np.array(region_prop['YEAR'].to_list()))
```

In [62]:

```
fig = px.histogram(pd.DataFrame(tvds_of_samples_under_null), x=0, nbins=75, histnorm='probability',
                   title='Empirical Distribution of TVD')
fig.add_vline(x=observed_tvd, line_color='red')
```



In [63]:

```
fig.write_html('test-file.html', include_plotlyjs='cdn')
```

The proportion of TVDS computed between the null distribution and its samples to the right (as TVD is unidirectional; bigger is more extreme) of the observed TVD is 0: none of the 100000 sample TVDs came close to the TVD that we saw. Thus since $0 < \alpha = 0.001$ we reject the null hypothesis that all regions get outages with the same rate, and we have evidence that some regions are more prone to power outages than others.