outages

May 14, 2021

1 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?

1.0.1 Getting the Data

The data is downloadable here.

A data dictionary is available at this article under *Table 1. Variable descriptions*.

1.0.2 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 or another geospatial plotting library.

1.0.3 Assessment of Missingness

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

1.0.4 Hypothesis Test

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

2 Summary of Findings

2.1 Introduction

The North American Electric Reliability Corporation, hereafter referred to as NERC, is a non-profit, non-governmental organization whose goal is to create and sustain a more reliable and sufficient power grid for the US and Canada. Currently, NERC holds the title of "Electric Reliability Organization" (ERO), which was created by the Energy Policy Act of 2005 and whose role is to enforce compliance with safety and quality standards for the electric industry. Since the Energy Policy Act came into effect in early 2006, I thought a reasonable use of the dataset, hereafter referred to as `outage`, downloaded from the provided link would be to investigate whether there were significant changes in the causes of outages before and after 2006.

Below, the dataset `outage` is imported from an Excel file.

[831]:
```
outage = outage_xlsx_to_df()
outage.head()
```

[831]:
```
   YEAR MONTH U.S._STATE POSTAL.CODE NERC.REGION      CLIMATE.REGION  \
0  2011     7  Minnesota          MN         MRO  East North Central
1  2014     5  Minnesota          MN         MRO  East North Central
2  2010    10  Minnesota          MN         MRO  East North Central
3  2012     6  Minnesota          MN         MRO  East North Central
4  2015     7  Minnesota          MN         MRO  East North Central

  ANOMALY.LEVEL CLIMATE.CATEGORY    OUTAGE.START.DATE OUTAGE.START.TIME  …  \
0          -0.3           normal  2011-07-01 00:00:00          17:00:00  …
1          -0.1           normal  2014-05-11 00:00:00          18:38:00  …
2          -1.5             cold  2010-10-26 00:00:00          20:00:00  …
3          -0.1           normal  2012-06-19 00:00:00          04:30:00  …
4           1.2             warm  2015-07-18 00:00:00          02:00:00  …

  POPPCT_URBAN POPPCT_UC POPDEN_URBAN POPDEN_UC POPDEN_RURAL AREAPCT_URBAN  \
0        73.27     15.28         2279    1700.5         18.2          2.14
1        73.27     15.28         2279    1700.5         18.2          2.14
2        73.27     15.28         2279    1700.5         18.2          2.14
3        73.27     15.28         2279    1700.5         18.2          2.14
4        73.27     15.28         2279    1700.5         18.2          2.14

  AREAPCT_UC PCT_LAND PCT_WATER_TOT PCT_WATER_INLAND
```

```
0         0.6  91.5927       8.40733          5.47874
1         0.6  91.5927       8.40733          5.47874
2         0.6  91.5927       8.40733          5.47874
3         0.6  91.5927       8.40733          5.47874
4         0.6  91.5927       8.40733          5.47874

[5 rows x 55 columns]
```

Further inspection of the dataset reveals that it is in need of cleaning, which is described below.

As can be seen, the `outage` dataset describes characteristics of each outage recorded, of which there were 1534.

2.2 Cleaning and EDA

The primary issue that I found with `outage` is that 705 of the 1534 rows in the column `DEMAND.LOSS.MW`, which describes the amount of peak demand lost during an outage event, are missing. The significance of this missingness is that the classification of what constitutes a major power outage event depends on `DEMAND.LOSS.MW` and `CUSTOMERS.AFFECTED` (which describes how many customers were affected by the outage event) - namely, an outage is said to be "major" if the demand lost is above 300 megawatts or the number of customers affected is above 50,000.

The column `CUSTOMERS.AFFECTED` faces a missingness problem (440 out of 1534) similar to the one faced by `DEMAND.LOSS.MW` described above.

Hence, classification of outages as "major" will be hindered unless some sort of imputation (i.e., filling in missing data with probable data points) is carried out.

A secondary issue was that originally, the year/month/day columns describing when an outage started and when power was restored did not align with the either the duration of the outage (that information is held in the `DURATION` column). Since many more entries in `DURATION` columns than in the `YEAR`, `MONTH`, `DAY`, `OUTAGE.START.TIME`, and `OUTAGE.RESTORATION.TIME` columns were missing, I chose to replace them with entries inferred from the above columns by combining the latter group of columns into `OUTAGE.START.DATETIME` and `OUTAGE.RESTORATION.DATETIME` (in `pd.datetime` format), which is a timestamp.

There was an issue with the type of the data - most of it was stored as an object type, which could not be analyzed easily (eg, a groupby operation would not work with objects as I used groupby). Hence I cleaned `outage` appropriately to convert numeric data stored as objects into data stored as floats.

[832]:
```
outage = combine_times(outage) # fixing columns of time
outage = fix_duration(outage) # enforcing consistency between columns that␣
 ↪describe the same information
outage = fix_types(outage) # fixing the type of data
```

As previously mentioned, let's add a column titled `MAJOR.POWER.OUTAGE`, which will be true if an outage should be classified as major and false otherwise.

```
[833]: mpo = lambda row: row['CUSTOMERS.AFFECTED'] > 50_000 or row['DEMAND.LOSS.MW'] >␣
↪300
outage = outage.assign(**{'MAJOR.POWER.OUTAGE': outage.apply(mpo, axis=1)})
```

One of the first questions I had about `outages` was how missingness in the `DEMAND.LOSS.MW` column might differ by NERC region (the entity responsible for a specific region of NERC's jurisdiction). Below, I aggregate both what the average demand lost per outage (in megawatts) is, per NERC region, and the proportion of outages in which that NERC region reported `DEMAND.LOSS.MW`. As one can see, the latter quantity differs across NERC regions.

```
[835]: loss_by_region = (outage.get(['DEMAND.LOSS.MW', 'NERC.REGION'])
                    .assign(**{'DEMAND.LOSS.MW.NOTNULL': outage['DEMAND.LOSS.MW'].
↪notnull()})
                    .groupby('NERC.REGION').mean())
loss_by_region.head()
```

```
[835]:              DEMAND.LOSS.MW  DEMAND.LOSS.MW.NOTNULL
NERC.REGION
ASCC              35.000000                1.000000
ECAR            1314.483871                0.911765
FRCC             804.450000                0.909091
FRCC, SERC              NaN                0.000000
HECO             466.666667                1.000000
```

One might also wonder how many major power outages happen per year, per cause of outage. That information is displayed below, without `outage` having been given imputed values.

```
[836]: (outage.pivot_table(values='MAJOR.POWER.OUTAGE',
                    index='CAUSE.CATEGORY',
                    columns='YEAR',
                    aggfunc='sum')
                    .fillna(0)
                    .astype(np.int)
)
```

```
[836]: YEAR                          2000.0  2001.0  2002.0  2003.0  2004.0  2005.0  \
CAUSE.CATEGORY
equipment failure                  1       0       0       5       2       2
fuel supply emergency              0       0       0       0       0       0
intentional attack                 0       0       0       0       0       0
islanding                          0       0       0       0       0       0
public appeal                      0       2       0       0       0       0
severe weather                    10       0      12      29      46      39
system operability disruption      3       8       1       6       2       3

YEAR                          2006.0  2007.0  2008.0  2009.0  2010.0  2011.0  \
CAUSE.CATEGORY
```

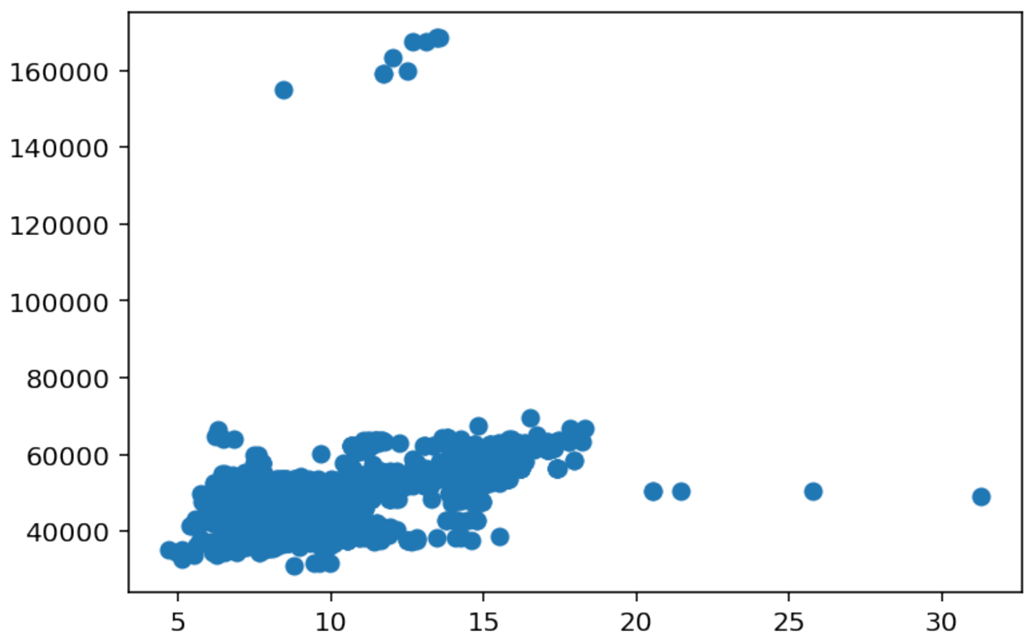
```
equipment failure                    0       2       2       7       1       1
fuel supply emergency                1       0       0       0       0       3
intentional attack                   0       0       0       0       0       1
islanding                            0       0       0       1       0       0
public appeal                        0       0       0       1       0       1
severe weather                      49      36      69      40      60      94
system operability disruption        7       3       9       1       8       7

YEAR                            2012.0  2013.0  2014.0  2015.0  2016.0
CAUSE.CATEGORY
equipment failure                    0       3       0       0       0
fuel supply emergency                2       1       4       1       0
intentional attack                   1       1       0       0       2
islanding                            0       1       0       0       0
public appeal                        0       0       0       1       0
severe weather                      56      42      29      40      11
system operability disruption        1       2       0       6       6
```

Another question might be whether price (cents per kilowatt-hour) of electricity increases as the GSP (gross state product) increases. Although this was not related to my hypothesis, I thought it was an interesting visualization. Below is price, on the x-axis, plotted against GSP, on the y-axis.

[837]:
```
plt.scatter(outage['TOTAL.PRICE'], outage['PC.REALGSP.STATE'])
```

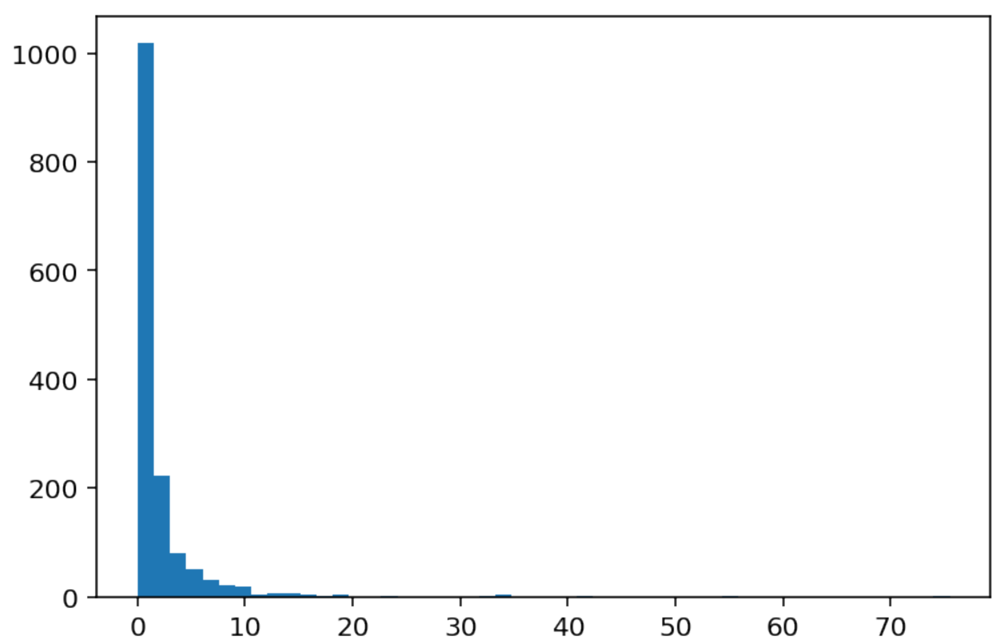
[837]: <matplotlib.collections.PathCollection at 0x7fe77657d400>



As consumers, we should want to expect that outages are resolved as soon as possible. So here is a histogram of how often power is restored. It seems that the vast majority

[930]:
```
float_duration = outage['OUTAGE.DURATION'] / datetime.timedelta(days=1) #␣
↪convert to number of days of outage
plt.hist(float_duration, bins=50)
```

[930]:
```
(array([1.018e+03, 2.230e+02, 7.900e+01, 5.100e+01, 3.000e+01, 2.100e+01,
        1.800e+01, 5.000e+00, 7.000e+00, 6.000e+00, 5.000e+00, 2.000e+00,
        3.000e+00, 0.000e+00, 0.000e+00, 1.000e+00, 0.000e+00, 0.000e+00,
        0.000e+00, 0.000e+00, 0.000e+00, 1.000e+00, 3.000e+00, 0.000e+00,
        0.000e+00, 0.000e+00, 0.000e+00, 1.000e+00, 0.000e+00, 0.000e+00,
        0.000e+00, 0.000e+00, 0.000e+00, 0.000e+00, 0.000e+00, 0.000e+00,
        1.000e+00, 0.000e+00, 0.000e+00, 0.000e+00, 0.000e+00, 0.000e+00,
        0.000e+00, 0.000e+00, 0.000e+00, 0.000e+00, 0.000e+00, 0.000e+00,
        0.000e+00, 1.000e+00]),
 array([ 0.        ,  1.50990278,  3.01980556,  4.52970833,  6.03961111,
         7.54951389,  9.05941667, 10.56931944, 12.07922222, 13.589125  ,
        15.09902778, 16.60893056, 18.11883333, 19.62873611, 21.13863889,
        22.64854167, 24.15844444, 25.66834722, 27.17825   , 28.68815278,
        30.19805556, 31.70795833, 33.21786111, 34.72776389, 36.23766667,
        37.74756944, 39.25747222, 40.767375  , 42.27727778, 43.78718056,
        45.29708333, 46.80698611, 48.31688889, 49.82679167, 51.33669444,
        52.84659722, 54.3565    , 55.86640278, 57.37630556, 58.88620833,
        60.39611111, 61.90601389, 63.41591667, 64.92581944, 66.43572222,
        67.945625  , 69.45552778, 70.96543056, 72.47533333, 73.98523611,
        75.49513889]),
 <BarContainer object of 50 artists>)
```



[929]:
```
outage['OUTAGE.DURATION'].describe()
```

[929]:
```
count                          1476
mean      1 days 19:45:16.585365853
std       4 days 03:03:55.329295850
min                 0 days 00:00:00
25%                 0 days 01:42:15
50%                 0 days 11:41:00
75%                 2 days 00:00:00
max                75 days 11:53:00
Name: OUTAGE.DURATION, dtype: object
```

It seems that 75% of outages are resolved within two days.

2.3 Assessment of Missingness

2.3.1 Addressing potential NMAR in `DEMAND.LOSS.MW` and `CUSTOMERS.AFFECTED`

One issue that may be faced in the classification of outages as major or non-major is that the entries of `DEMAND.LOSS.MW` and in `CUSTOMERS.AFFECTED` may be NMAR, or not missing at random, meaning that the entries in these columns may be missing depending on their value. However, I do not believe that the data in either column is NMAR for the reasons listed below:

`DEMAND.LOSS.MW`: In one case, the data may be NMAR because of intentional underreporting by the member companies of NERC. However, I think the companies responsible for reporting `DEMAND.LOSS.MW` will face high barriers in intentional underreporting of `DEMAND.LOSS.MW` because I surmise that inherently, `DEMAND.LOSS.MW` is not a statistic that is measured explicitly by a sensor - it is a number that is extrapolated from (peak) consumption of electricity or a number measured right before the outage occurred. Since the numbers for electricity consumption are available freely, a company would not find much advantage in concealing `DEMAND.LOSS.MW` entries that could embarass itself because one could find data (provided in a different dataset than `outage`) that could help fill in the missing entries. Also, since `DEMAND.LOSS.MW` may be measured as a statistic taken right before the outage occurred, one could extrapolate from usage statistics taken right before the event what `DEMAND.LOSS.MW` could have been. Hence, the remaining case is that the data is NMAR unintentionally.

The only case in which I think that could happen is that the cause of the outage is so severe that the sensors doing the data collection are burnt out during the event. But the US has not suffered (many) significant power outage events that could case such NMAR-ness to be significant, so I think it is safe to proceed under the assumption that the data is not NMAR.

`CUSTOMERS.AFFECTED`: I think this column is also not NMAR for reasons similar to those above.

With respect to data imputation, I think a reasonable strategy, regardless of whether `DEMAND.LOSS.MW` is NMAR, would be to examine the data in another dataset that contained the electricity consumption statistics for customers of companies in NERC by the hour from 2000 - 2016 (the time range that `outages` spans). I will assume that electricity consumption does not differ "significantly" on a timespan in the appropriate range - e.g., patterns of electricity consumption in the 29th week of the year does not "significantly" differ from the patterns of electricity consumption in the 30th week. Then, when OUTAGE.START.TIME is not null, we can extrapolate from the patterns of electricity consumption of the week prior to the outage what DEMAND.LOSS.MW should be, if DEMAND.LOSS.MW is null. Given the following statistics on the duration of outages:

[498]:
```
outage['OUTAGE.DURATION'].describe()
```

[498]:
```
count                          1476
mean      1 days 19:45:16.585365853
std       4 days 03:03:55.329295850
min                 0 days 00:00:00
25%                 0 days 01:42:15
50%                 0 days 11:41:00
75%                 2 days 00:00:00
max                75 days 11:53:00
Name: OUTAGE.DURATION, dtype: object
```

I think that since most outages are sufficiently short, a dataset on the patterns of electricity consumption could be used to impute the missing values in DEMAND.LOSS.MW, and a similar dataset could be used to impute CUSTOMERS.AFFECTED. However, since I think I should work within the confines of the supplied dataset, I chose not to do so.

Instead, ideally I would employ groupwise **probabilistic** imputation, where the groups are determined by U.S._STATE and YEAR, since I expect outages within the same state and same year to have similar characteristics (the reason being that having fixed a time and place, most of the other characteristics, such as GSP per capita or residential/commercial/industrial character, lose significant effect in predicting missingness). However, because some states will go a year without an outage (thus causing us a loss in data), I choose to impute the missing values of DEMAND.LOSS.MW with just notnull values of that state, allowing YEAR to vary, along with a parameter to be specified.

Testing my guess with the functions ks_missingness_pval and tvd_missinges_pval, which quantify the p-value that the missingness of a given column is dependent on another column, it is found that if U.S._STATE is held fixed, the missingness of DEMAND.LOSS.MW looks more as though it was determined by randomly shuffling null and notnull rows. Because of how computationally expensive running these permutation tests is, I chose to run them on only three states: California, Texas, and Michigan, which I chose because they experienced more outages.

Here are the p-values for California, Texas, and Michigan:

[599]:
```
pvals_compare_filtered.head()
```

[599]:

	California	Texas	Michigan	ALL
CLIMATE.REGION	1.000000	1.000000	1.000000	0.000000
CLIMATE.CATEGORY	0.211060	0.002001	0.014000	0.147949
CAUSE.CATEGORY	0.693848	0.014000	0.042999	0.000000
OUTAGE.DURATION	0.068970	0.009003	0.101013	0.000000
CUSTOMERS.AFFECTED	0.001000	0.000000	0.151978	0.000000

The ALL column is the result of computing similar p-values without holding a state fixed. Per the above, holding a state fixed strongly reduces the likelihood that the missingness of DEMAND.LOSS.MW is dependent on a column (which is a row in the above dataframe). However, note that these are just the first five rows - the other rows are less successful.

However, even after holding a state fixed, there is still considerable variance in `DEMAND.LOSS.MW`, which I surmised to be caused by `CAUSE.CATEGORY`. Here is a quick visualization for five large states of how outages with different `CAUSE.CATEGORY`'s differed with respect to average `DEMAND.LOSS.MW`.

[741]:
```
(outage.pivot_table(values='DEMAND.LOSS.MW',
                    index='CAUSE.CATEGORY',
                    columns='U.S._STATE',
                    aggfunc='mean')
 .fillna(0)
 .astype(int)
 .transpose()
 .loc[['California', 'Texas', 'Michigan', 'Washington', 'New York']]
)
```

[741]:
```
CAUSE.CATEGORY  equipment failure  fuel supply emergency  intentional attack  \
U.S._STATE
California                    375                    635                  31
Texas                         378                   1231                   2
Michigan                      336                      0                   0
Washington                    244                    630                   0
New York                        0                    468                   0

CAUSE.CATEGORY  islanding  public appeal  severe weather  \
U.S._STATE
California            551           8638             412
Texas                   0              0             736
Michigan                0           8881             318
Washington             94            100             430
New York                0             76             336

CAUSE.CATEGORY  system operability disruption
U.S._STATE
California                                335
Texas                                     615
Michigan                                 4197
Washington                                200
New York                                 6975
```

So I additionally held constant the cause of the outage (this is the additional aforementioned parameter), and then used sampled observed data as the imputed data. You might wonder whether there were enough outages from which I could sample data, and there were not - in fact, there were 276 outages that did not have companion outages happening in the same state and were caused by the same cause. So I just dropped them, since those are probably outlier events as opposed to a kind of outage with a consistent pattern behind them. This was kind of unsatisfying, but I still imputed data for 705 - 276 outages, so it was partially successful.

I did the same with `CUSTOMERS.AFFECTED`. If you are curious, here is a groupby for the average number of `CUSTOMERS.AFFECTED` with the same variables as above.

[838]:
```
(outage.pivot_table(values='CUSTOMERS.AFFECTED',
                    index='CAUSE.CATEGORY',
                    columns='U.S._STATE',
                    aggfunc='mean')
 .fillna(0)
 .astype(int)
 .transpose()
 .loc[['California', 'Texas', 'Michigan', 'Washington', 'New York']]
)
```

[838]:
```
CAUSE.CATEGORY  equipment failure  fuel supply emergency  intentional attack  \
U.S._STATE
California                 198608                      0               10660
Texas                       85882                      0                 552
Michigan                        0                      0                   0
Washington                  93300                      0                   0
New York                        0                      0                   0

CAUSE.CATEGORY  islanding  public appeal  severe weather  \
U.S._STATE
California           5039              0          361041
Texas                   0              0          258094
Michigan                0              0          138311
Washington              0           8000          182676
New York                0          18600          165050

CAUSE.CATEGORY  system operability disruption
U.S._STATE
California                             152040
Texas                                  289696
Michigan                               759737
Washington                                  0
New York                              1080998
```

2.4 Find a column that is MCAR

`OUTAGE.DURATION` is **mostly** MCAR with all of the columns I included in my analysis of `outage`, since the result of running `ks_missingness_pval` and `tvd_missingness_pval` on it and on every other column in `outage` resulted in a relatively large p-value (higher than 0.01, the p-value that I will use in my hypothesis test, whose reasons for using I will explain below). Note that not all of them are greater than 0.01 - the ones that are not are:

`TOTAL.PRICE` `TOTAL.SALES`, `PC.REALGSP.USA`, `POPDEN_RURAL`, `OUTAGE.START.DATETIME`, and `OUTAGE.RESTORATION.DATETIME`.

The last two are to be expected - `OUTAGE.DURATION` is formed by their difference, so of course its missingness would be dependent on those two. The others, however, are not as expected - my guess for the reason is that since these columns seem to be population or economic indicators, there are particular regions for which `OUTAGE.DURATION` is not reported. This may be correlated with `NERC.REGION`, but it did not show up in the p-value for `NERC.REGION` because each region is quite large, often spanning multiple states, and so it was not captured.

[918]:
```
pd.Series(randcol_dependencies_tvd).append(pd.Series(randcol_dependencies_ks)).
 ↪head()
```

[918]:
```
U.S._STATE          0.808
NERC.REGION         0.668
CLIMATE.REGION      0.816
CLIMATE.CATEGORY    0.920
CAUSE.CATEGORY      1.000
dtype: float64
```

2.5 Hypothesis Test

I wish to test change in trends of causes of major power outages since 2006, when the Energy Policy Act came into effect. So a natural partition of the data is the set of outages that occurred before 2006 (inclusive) and the set of outages that occurred after 2006 (exclusive).

Null hypothesis: the distribution of causes of major power outages before 2006 is roughly the same as the distribution of causes of major power outages after 2006.

Alternative hypothesis: the distribution of causes of major power outages before 2006 is not the same as the distribution of causes of major power outages after 2006.

The test statistic is the TVD (TVD is defined as halving the absolute difference between the series in question, the difference being taken with the row being fixed), which was chosen because the simulated data will have discrete rows, where each row is a potential cause of an outage, as do the observed data. Since we have distinct groups, no continuous analysis can be done, suggesting that the TVD is an appropriate choice.

Set a significance level of 0.01. It is set to be so low because there is expected to be natural variation between how many outages are caused in different time periods even when the underlying pattern does not change, and if the significance level is too high, then we may mistake noise (natural variation) for a signal.

Now, in order to prepare for the hypothesis test, we impute the values that we can for `DEMAND.LOSS.MW` and for `CUSTOMERS.AFFECTED` and drop the rows that we cannot.

[839]:
```
imputed_outage = imputer(outage, 'DEMAND.LOSS.MW')
imputed_outage = imputer(imputed_outage, 'CUSTOMERS.AFFECTED')
imputed_outage = imputed_outage[imputed_outage['DEMAND.LOSS.MW'].notnull()]
imputed_outage = imputed_outage[imputed_outage['CUSTOMERS.AFFECTED'].notnull()]
```

Let's look at a pivot table of `CAUSE.CATEGORY` vs. `YEAR` as a preliminary inspection of what we should expect - personally, I would have been surprised if there were not a different distribution post-2006 opposed to pre-2006, after having looked at the table below.

```
[841]: mpo_causes = (imputed_outage.pivot_table(values='MAJOR.POWER.OUTAGE',
                                              index='CAUSE.CATEGORY',
                                              columns='YEAR',
                                              aggfunc='sum')
                 .fillna(0)
                 .astype(np.int)
)
mpo_causes
```

```
[841]: YEAR                           2000.0  2001.0  2002.0  2003.0  2004.0  2005.0  \
CAUSE.CATEGORY
equipment failure                   1       0       0       4       2       2
fuel supply emergency               0       0       0       0       0       0
intentional attack                  0       0       0       0       0       0
islanding                           0       0       0       0       0       0
public appeal                       0       0       0       0       0       0
severe weather                      5       0      11      28      45      34
system operability disruption       3       5       1       5       2       3

YEAR                           2006.0  2007.0  2008.0  2009.0  2010.0  2011.0  \
CAUSE.CATEGORY
equipment failure                   0       1       2       4       1       1
fuel supply emergency               0       0       0       0       0       0
intentional attack                  0       0       0       0       0       0
islanding                           0       0       0       0       0       0
public appeal                       0       0       0       0       0       0
severe weather                     40      29      50      30      42      69
system operability disruption       6       2       8       1       2       7

YEAR                           2012.0  2013.0  2014.0  2015.0  2016.0
CAUSE.CATEGORY
equipment failure                   0       3       0       0       0
fuel supply emergency               0       0       2       0       0
intentional attack                  1       1       0       0       2
islanding                           0       1       0       0       0
public appeal                       0       0       0       0       0
severe weather                     34      30      18      28       9
system operability disruption       0       2       0       3       5
```

Because there were more major power outages after 2006 than before 2006 in `imputed_outage`, and because we are wanting proportions of outages that each cause is responsible, let's

1) sum, for each `CAUSE.CATEGORY`, across `YEAR` from 2000 to 2006 and from 2007 to 2016
2) divide that sum by the number of outages caused in those two timeranges to finally obtain the proportions.

These proportions will be interpreted as the probability that a given outage in either timerange was caused by one of the causes in the index of the above pivot table, which I think is reasonable because seven years should be enough time for the long-run average of proportions to have expressed itself - that is, I expect that the Law of Large Numbers will have taken effect, and so these proportions should be roughly correct.

[842]:
```
mpo_causes_before_2006 = mpo_causes.get([2000, 2001, 2002, 2003, 2004, 2005,␣
↪2006])
mpo_causes_after_2006 = mpo_causes.get([2007, 2008, 2009, 2010, 2011, 2012,␣
↪2013, 2014, 2015, 2016])

mpo_props_before_2006 = (mpo_before_2006.sum(axis=1) / mpo_before_2006.sum().
↪sum())
mpo_props_after_2006 = mpo_after_2006.sum(axis=1) / mpo_after_2006.sum().sum()
```

[843]:
```
display(mpo_props_before_2006, mpo_props_after_2006)
```

```
CAUSE.CATEGORY
equipment failure                0.045685
fuel supply emergency            0.000000
intentional attack               0.000000
islanding                        0.000000
public appeal                    0.000000
severe weather                   0.827411
system operability disruption    0.126904
dtype: float64
```

```
CAUSE.CATEGORY
equipment failure                0.030928
fuel supply emergency            0.005155
intentional attack               0.010309
islanding                        0.002577
public appeal                    0.000000
severe weather                   0.873711
system operability disruption    0.077320
dtype: float64
```

Now we can run our hypothesis test. The methodology will be to:

1) take the Total Variation Distance between the above series, in order to measure how different the two series (i.e., the probabilities of pre- and post-2006 causes) are.

2) assume that the distribution of causes of outages occurring after 2006 is the same as the distribution of causes of outages occurring before 2006, so that we can simulate the latter with the former.

3) for each of the 388 major outages occurring after 2006, we assign it a cause with probability given by the distribution of outages occurring before 2006. We do this 100,000 times, and each time, we measure and store the TVD of that simulation.

4) look at the proportion of times the simulation exceeded the observed TVD (the p-value). If the null hypothesis is correct, then we should expect a large p-value, since the observed

distribution of causes of outages after 2006 is supposedly the same as that of outages after 2006. Otherwise, we should get a small p-value.

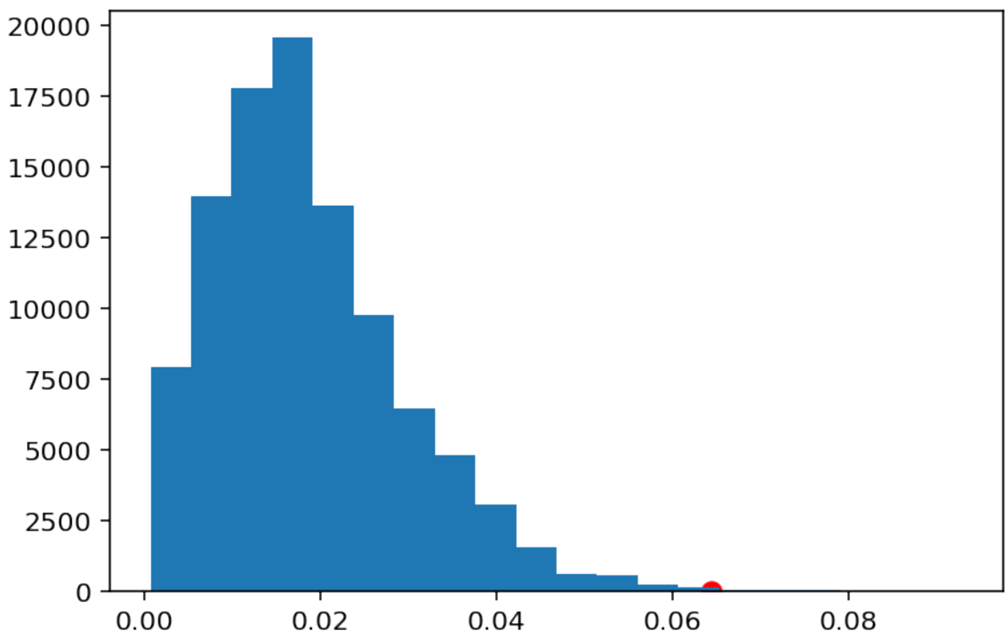
[844]:
```
pval, sim_tvds, obs_tvd = hypothesis_test(100_000)
```

[845]:
```
display(pval, obs_tvd)
```

```
0.00109
```

```
0.06434140980689725
```

[852]:
```
plt.hist(sim_tvds, bins=20)
plt.scatter(obs_tvd, 0, color='red', s=50);
```



As we can see, the observed TVD is an outlier, with simulated values more extreme than it only occurring less than 1% of the time. Our significance level was 0.01, so we reject the null hypothesis - the distribution of causes of outages post-2006 is not the same as the distribution of causes of outages pre-2006.

3 Code

[1]:
```
import matplotlib.pyplot as plt
import numpy as np
import os
import pandas as pd
import seaborn as sns
```

```
%matplotlib inline
%config InlineBackend.figure_format = 'retina'  # Higher resolution figures

import time
import datetime
from scipy.stats import ks_2samp
```

3.0.1 Cleaning and EDA

[117]:
```
def outage_xlsx_to_df():
    outage_raw = pd.read_excel('./outage.xlsx')
    outage_raw.columns = outage_raw.iloc[4]
    outage = outage_raw.drop(range(6), axis=0).reset_index().
 ↪drop(columns=['variables', 'OBS', 'index'])
    outage.columns.name = None
    return outage
```

[898]:
```
def combine_times(outage):
    temp = outage.get(['OUTAGE.START.DATE', 'OUTAGE.START.TIME'])
    outage['OUTAGE.START.DATETIME'] = pd.to_datetime(
        temp['OUTAGE.START.DATE'].dropna().apply(str).apply(lambda x: x.
 ↪split()[0])
        + ' '
        + temp['OUTAGE.START.TIME'].dropna().apply(str))

    temp = outage.get(['OUTAGE.RESTORATION.DATE', 'OUTAGE.RESTORATION.TIME'])
    outage['OUTAGE.RESTORATION.DATETIME'] = pd.to_datetime(
        temp['OUTAGE.RESTORATION.DATE'].dropna().apply(str).apply(lambda x: x.
 ↪split()[0])
        + ' '
        + temp['OUTAGE.RESTORATION.TIME'].dropna().apply(str))
    outage = outage.drop(columns=['RES.PRICE',
                                  'COM.PRICE',
                                  'IND.PRICE',
                                  'RES.SALES',
                                  'COM.SALES',
                                  'IND.SALES',
                                  'RES.PERCEN',
                                  'COM.PERCEN',
                                  'IND.PERCEN',
                                  'RES.CUSTOMERS',
                                  'COM.CUSTOMERS',
                                  'IND.CUSTOMERS',
                                  'OUTAGE.START.DATE',
                                  'OUTAGE.START.TIME',
                                  'OUTAGE.RESTORATION.DATE',
```

```
                                         'OUTAGE.RESTORATION.TIME',
                                         'PC.REALGSP.CHANGE',
                                         #'UTIL.REALGSP',
                                         #'UTIL.CONTRI',
                                         'PI.UTIL.OFUSA',
                                         #'YEAR',
                                         'MONTH',
                                         'POSTAL.CODE',
                                         'ANOMALY.LEVEL',
                                         #'CAUSE.CATEGORY.DETAIL',
                                         'RES.CUST.PCT',
                                         'COM.CUST.PCT',
                                         'IND.CUST.PCT',
                                         'AREAPCT_URBAN',
                                         'AREAPCT_UC',
                                         'PCT_LAND',
                                         'PCT_WATER_TOT',
                                         'PCT_WATER_INLAND'])
    return outage
```

[432]:
```
def fix_duration(outage):
    outage['OUTAGE.DURATION'] = outage['OUTAGE.RESTORATION.DATETIME'] -␣
 ↪outage['OUTAGE.START.DATETIME']
    return outage
```

[901]:
```
def fix_types(outage):
    nan_inserter = lambda x: np.NaN if np.isnan(x) else float(x)
    for obj_col in outage.columns:
        if obj_col not in ['U.S._STATE', 'NERC.REGION', 'CLIMATE.REGION',␣
 ↪'CLIMATE.CATEGORY', 'CAUSE.CATEGORY',
                               'HURRICANE.NAMES', 'OUTAGE.DURATION', 'OUTAGE.START.
 ↪DATETIME',
                               'OUTAGE.RESTORATION.DATETIME', 'CAUSE.CATEGORY.
 ↪DETAIL']:
            outage = outage.assign(**{obj_col: outage[obj_col].
 ↪apply(nan_inserter).astype(float)})
    return outage
```

[902]:
```
outage = outage_xlsx_to_df()
```

[903]:
```
outage = combine_times(outage)
outage = fix_duration(outage)
outage = fix_types(outage)
```

[436]:
```
mpo = lambda row: row['CUSTOMERS.AFFECTED'] > 50_000 or row['DEMAND.LOSS.MW'] >␣
 ↪300
```

```
outage = outage.assign(**{'MAJOR.POWER.OUTAGE': outage.apply(mpo, axis=1)})
```

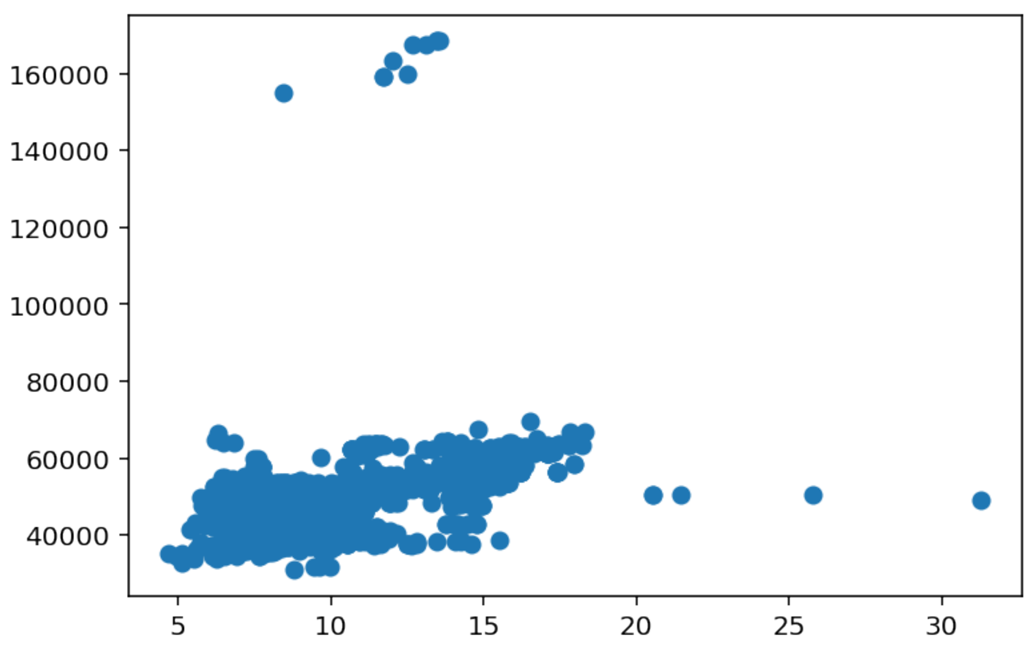
[171]:
```
loss_by_region = (outage.get(['DEMAND.LOSS.MW', 'NERC.REGION'])
                  .assign(**{'DEMAND.LOSS.MW.NOTNULL': outage['DEMAND.LOSS.MW'].
 ↪notnull()})
                  .groupby('NERC.REGION').mean())
loss_by_region
```

[171]:

NERC.REGION	DEMAND.LOSS.MW	PCT_CUSTOMERS_AFFECTED	DEMAND.LOSS.MW.NOTNULL
ASCC	35.000000	0.052181	1.000000
ECAR	1314.483871	0.056895	0.911765
FRCC	804.450000	0.031696	0.909091
FRCC, SERC	NaN	NaN	0.000000
HECO	466.666667	0.273349	1.000000
HI	1060.000000	0.622848	1.000000
MRO	279.500000	0.044697	0.434783
NPCC	930.123288	0.031454	0.486667
PR	220.000000	0.129633	1.000000
RFC	293.153439	0.051329	0.451074
SERC	556.325203	0.032423	0.600000
SPP	159.000000	0.077616	0.358209
TRE	635.620000	0.020607	0.450450
WECC	498.241758	0.020022	0.605322

[239]:
```
plt.scatter(outage['TOTAL.PRICE'], outage['PC.REALGSP.STATE'])
```

[239]: <matplotlib.collections.PathCollection at 0x7fe79051c0d0>



[244]:
```
outage_climate = (outage.get(['NERC.REGION', 'CLIMATE.REGION', 'CLIMATE.
↪CATEGORY', 'OUTAGE.DURATION',
                              'DEMAND.LOSS.MW', 'CUSTOMERS.AFFECTED', 'MAJOR.
↪POWER.OUTAGE'])
                 )
outage_by_region = (outage_climate.groupby('CLIMATE.REGION').mean())
outage_by_category = (outage_climate.groupby('CLIMATE.CATEGORY').mean())
```

[245]:
```
display(outage_by_climate)
display(outage_by_category)
```

CLIMATE.REGION	DEMAND.LOSS.MW	CUSTOMERS.AFFECTED	MAJOR.POWER.OUTAGE
Central	477.481928	126809.872611	0.640000
East North Central	560.405797	138388.932203	0.753623
Northeast	537.410714	121960.011278	0.497143
Northwest	177.896552	81420.000000	0.227273
South	399.086538	183500.774194	0.510917
Southeast	761.532787	180539.538462	0.699346
Southwest	424.555556	39028.911111	0.195652
West	651.456790	194579.893939	0.451613
West North Central	326.000000	47316.000000	0.294118

CLIMATE.CATEGORY	DEMAND.LOSS.MW	CUSTOMERS.AFFECTED	MAJOR.POWER.OUTAGE
cold	391.028000	126840.066869	0.501057
normal	574.796954	153182.834286	0.506720
warm	657.854749	146843.895652	0.545455

3.0.2 Assessment of Missingness

[ ]:
```
# Also, Rhode Island is not in outage['U.S._STATE']
```

[190]:
```
def tvd_missingness_pval(df, m_col, c_col, n_trials, want_hist):
    """
    m_col: column with missing values
    c_col: column being tested for correlations to missing values
    n_trials: number of trials run for permutation test
    """
    n_rows = df.shape[0]
    temp_df = df.get([m_col, c_col])
    temp_df = temp_df.assign(**{'m_col_null': temp_df[m_col].isnull(),
                                'm_col_notnull': temp_df[m_col].notnull()})
    m_by_c_col = temp_df.groupby(c_col).mean().get(['m_col_null',␣
↪'m_col_notnull'])
```

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

    sim_tvds = []
    for _ in range(n_trials):
        temp_df = temp_df.assign(**{'shuffled_m_col': np.random.
↪permutation(temp_df[m_col])})
        temp_df = temp_df.assign(**{'shuffled_m_col_null':␣
↪temp_df['shuffled_m_col'].isnull(),
                                    'shuffled_m_col_notnull':␣
↪temp_df['shuffled_m_col'].notnull()})
        shuffled_m_by_c_col = temp_df.groupby(c_col).mean().
↪get(['shuffled_m_col_null', 'shuffled_m_col_notnull'])
        sim_tvd = shuffled_m_by_c_col.diff(axis=1).iloc[:, -1].abs().sum() / 2
        sim_tvds.append(sim_tvd)

    if want_hist:
        plt.hist(sim_tvds, bins=30)
        print(obs_tvd)

    return np.count_nonzero(np.array(sim_tvds) >= obs_tvd) / n_trials
```

[870]:
```
def ks_missingness_pval(df, m_col, c_col, n_trials, want_hist):
    """
    m_col: column with missing values
    c_col: column being tested for correlations to missing values
    n_trials: number of trials run for permutation test
    """
    temp_df = df.get([m_col, c_col])
    m_col_null = temp_df[temp_df[m_col].isnull()][c_col]
    m_col_notnull = temp_df[temp_df[m_col].notnull()][c_col]
    if (m_col_null.shape[0] != 0 and m_col_notnull.shape[0] != 0):
        obs_ks = ks_2samp(m_col_null, m_col_notnull).statistic
    else:
        obs_ks = 0

    sim_kss = []
    for _ in range(n_trials):
        temp_df = temp_df.assign(**{'shuffled_m_col': np.random.
↪permutation(temp_df[m_col].isnull())})

        shuffled_m_col_null = temp_df.loc[temp_df['shuffled_m_col'], c_col]
        shuffled_m_col_notnull = temp_df.loc[~temp_df['shuffled_m_col'], c_col]

        if (shuffled_m_col_null.shape[0] != 0 and shuffled_m_col_notnull.
↪shape[0] != 0):
```

```
            sim_ks = ks_2samp(shuffled_m_col_null, shuffled_m_col_notnull).
↪statistic
            sim_kss.append(sim_ks)
        else:
            sim_kss.append(0)

    if want_hist:
        plt.hist(sim_kss, bins=30)
        print(obs_ks)

    return np.count_nonzero(np.array(sim_kss) >= obs_ks) / n_trials
```

[ ]:
```
# finding MCAR column
```

[904]:
```
outage.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1534 entries, 0 to 1533
Data columns (total 28 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   YEAR                   1534 non-null   float64
 1   U.S._STATE             1534 non-null   object
 2   NERC.REGION            1534 non-null   object
 3   CLIMATE.REGION         1528 non-null   object
 4   CLIMATE.CATEGORY       1525 non-null   object
 5   CAUSE.CATEGORY         1534 non-null   object
 6   CAUSE.CATEGORY.DETAIL  1063 non-null   object
 7   HURRICANE.NAMES        72 non-null     object
 8   OUTAGE.DURATION        1476 non-null   timedelta64[ns]
 9   DEMAND.LOSS.MW         829 non-null    float64
 10  CUSTOMERS.AFFECTED     1091 non-null   float64
 11  TOTAL.PRICE            1512 non-null   float64
 12  TOTAL.SALES            1512 non-null   float64
 13  TOTAL.CUSTOMERS        1534 non-null   float64
 14  PC.REALGSP.STATE       1534 non-null   float64
 15  PC.REALGSP.USA         1534 non-null   float64
 16  PC.REALGSP.REL         1534 non-null   float64
 17  UTIL.REALGSP           1534 non-null   float64
 18  TOTAL.REALGSP          1534 non-null   float64
 19  UTIL.CONTRI            1534 non-null   float64
 20  POPULATION             1534 non-null   float64
 21  POPPCT_URBAN           1534 non-null   float64
 22  POPPCT_UC              1534 non-null   float64
 23  POPDEN_URBAN           1534 non-null   float64
 24  POPDEN_UC              1524 non-null   float64
 25  POPDEN_RURAL           1524 non-null   float64
```

```
 26  OUTAGE.START.DATETIME        1525 non-null   datetime64[ns]
 27  OUTAGE.RESTORATION.DATETIME  1476 non-null   datetime64[ns]
dtypes: datetime64[ns](2), float64(18), object(7), timedelta64[ns](1)
memory usage: 335.7+ KB
```

[913]:
```
discrete_columns_r = ['U.S._STATE', 'NERC.REGION', 'CLIMATE.REGION', 'CLIMATE.
 ↪CATEGORY','CAUSE.CATEGORY',
                      'CAUSE.CATEGORY.DETAIL', 'HURRICANE.NAMES']
continuous_columns_r = ['DEMAND.LOSS.MW', 'CUSTOMERS.AFFECTED', 'TOTAL.PRICE',␣
 ↪'TOTAL.SALES',
                        'TOTAL.CUSTOMERS', 'PC.REALGSP.STATE', 'PC.REALGSP.
 ↪USA', 'PC.REALGSP.REL',
                        'UTIL.REALGSP', 'TOTAL.REALGSP', 'UTIL.CONTRI',␣
 ↪'POPULATION', 'POPPCT_URBAN', 'POPPCT_UC',
                        'POPDEN_URBAN', 'POPDEN_UC', 'POPDEN_RURAL', 'OUTAGE.
 ↪START.DATETIME',
                        'OUTAGE.RESTORATION.DATETIME']
```

[910]:
```
randcol_dependencies_tvd = {col: tvd_missingness_pval(outage,
                                                     'OUTAGE.DURATION',␣
 ↪col, 250, False)
                                 for col in discrete_columns_r}
```

[911]:
```
display(randcol_dependencies_tvd)
```

```
{'U.S._STATE': 0.808,
 'NERC.REGION': 0.668,
 'CLIMATE.REGION': 0.816,
 'CLIMATE.CATEGORY': 0.92,
 'CAUSE.CATEGORY': 1.0,
 'CAUSE.CATEGORY.DETAIL': 1.0,
 'HURRICANE.NAMES': 0.076}
```

[914]:
```
randcol_dependencies_ks = {col: ks_missingness_pval(outage,
                                                   'OUTAGE.DURATION',␣
 ↪col, 250, False)
                                for col in continuous_columns_r}
```

[915]:
```
display(randcol_dependencies_ks)
```

```
{'DEMAND.LOSS.MW': 0.232,
 'CUSTOMERS.AFFECTED': 0.296,
 'TOTAL.PRICE': 0.0,
 'TOTAL.SALES': 0.008,
 'TOTAL.CUSTOMERS': 0.3,
 'PC.REALGSP.STATE': 0.064,
 'PC.REALGSP.USA': 0.0,
```

```
 'PC.REALGSP.REL': 0.264,
 'UTIL.REALGSP': 0.196,
 'TOTAL.REALGSP': 0.504,
 'UTIL.CONTRI': 0.056,
 'POPULATION': 0.376,
 'POPPCT_URBAN': 0.48,
 'POPPCT_UC': 0.12,
 'POPDEN_URBAN': 0.22,
 'POPDEN_UC': 0.024,
 'POPDEN_RURAL': 0.0,
 'OUTAGE.START.DATETIME': 0.0,
 'OUTAGE.RESTORATION.DATETIME': 0.0}
```

[ ]:
```
# end of finding MCAR
```

[549]:
```
discrete_columns = ['U.S._STATE', 'NERC.REGION', 'CLIMATE.REGION', 'CLIMATE.
 ↪CATEGORY','CAUSE.CATEGORY']
continuous_columns = ['OUTAGE.DURATION', 'CUSTOMERS.AFFECTED', 'TOTAL.PRICE',␣
 ↪'TOTAL.SALES', 'TOTAL.CUSTOMERS',
                      'PC.REALGSP.STATE', 'PC.REALGSP.USA', 'PC.REALGSP.REL',␣
 ↪'UTIL.REALGSP', 'TOTAL.REALGSP',
                      'UTIL.CONTRI', 'POPULATION', 'POPPCT_URBAN', 'POPPCT_UC',␣
 ↪'POPDEN_URBAN', 'POPDEN_UC',
                      'POPDEN_RURAL', 'OUTAGE.START.DATETIME', 'OUTAGE.
 ↪RESTORATION.DATETIME']
```

[862]:
```
demandlossmw_dependencies_tvd = {col: tvd_missingness_pval(outage,
                                                           'DEMAND.LOSS.MW',␣
 ↪col, 200, False)
                                  for col in discrete_columns}
demandlossmw_dependencies_ks = {col: ks_missingness_pval(outage,
                                                         'DEMAND.LOSS.MW', col,␣
 ↪200, False)
                                for col in continuous_columns}
```

[556]:
```
control_for_ca_tvd = {col: tvd_missingness_pval(outage[outage['U.S._STATE'] ==␣
 ↪'California'],
                                                'DEMAND.LOSS.MW', col, 1000,␣
 ↪False)
                      for col in discrete_columns}
control_for_tx_tvd = {col: tvd_missingness_pval(outage[outage['U.S._STATE'] ==␣
 ↪'Texas'],
                                                'DEMAND.LOSS.MW', col, 1000,␣
 ↪False)
                      for col in discrete_columns}
```

```
control_for_mi_tvd = {col: tvd_missingness_pval(outage[outage['U.S._STATE'] ==␣
↪'Michigan'],
                                                'DEMAND.LOSS.MW', col, 1000,␣
↪False)
                      for col in discrete_columns}
```

[558]:
```
control_for_ca_ks = {col: ks_missingness_pval(outage[outage['U.S._STATE'] ==␣
↪'California'],
                                              'DEMAND.LOSS.MW', col, 1000,␣
↪False)
                     for col in continuous_columns}
control_for_tx_ks = {col: ks_missingness_pval(outage[outage['U.S._STATE'] ==␣
↪'Texas'],
                                              'DEMAND.LOSS.MW', col, 1000,␣
↪False)
                     for col in continuous_columns}
control_for_mi_ks = {col: ks_missingness_pval(outage[outage['U.S._STATE'] ==␣
↪'Michigan'],
                                              'DEMAND.LOSS.MW', col, 1000,␣
↪False)
                     for col in continuous_columns}
```

[573]:
```
tvds_states = {}
ds = [control_for_ca_tvd, control_for_tx_tvd, control_for_mi_tvd]
for k in control_for_ca_tvd.keys():
    tvds_states[k] = tuple(d[k] for d in ds)
for k in tvds_states.keys():
    tvds_states[k] = list(tvds_states[k])

kss_states = {}
ds = [control_for_ca_ks, control_for_tx_ks, control_for_mi_ks]
for k in control_for_ca_ks.keys():
    kss_states[k] = tuple(d[k] for d in ds)
for k in kss_states.keys():
    kss_states[k] = list(kss_states[k])
```

[577]:
```
tvds_kss_states = {}
for k in tvds_states.keys():
    tvds_kss_states[k] = tvds_states[k]
for k in kss_states.keys():
    tvds_kss_states[k] = kss_states[k]
```

[598]:
```
demandlossmw_dependencies_all = {}
for k in demandlossmw_dependencies_tvd.keys():
    demandlossmw_dependencies_all[k] = demandlossmw_dependencies_tvd[k]
for k in demandlossmw_dependencies_ks.keys():
```

```
    demandlossmw_dependencies_all[k] = demandlossmw_dependencies_ks[k]

states = pd.DataFrame(data=tvds_kss_states, index=['California', 'Texas',␣
 ↪'Michigan']).transpose()
pvals_all = pd.DataFrame(demandlossmw_dependencies_all, index=['ALL'])
pvals_all = pvals_all.transpose()
pvals_compare = pd.concat([states, pvals_all], axis=1)
pvals_compare_filtered = (pvals_compare.astype(np.float16).drop(index=['NERC.
 ↪REGION', 'U.S._STATE']))
```

[587]:
```
(
    outage.pivot_table(values='DEMAND.LOSS.MW',
                       index='U.S._STATE',
                       columns='YEAR',
                       aggfunc='count')
    .fillna(0).astype(np.int)
    .loc[['California', 'Texas', 'Michigan']]
)
```

[587]:
```
YEAR        2000.0  2001.0  2002.0  2003.0  2004.0  2005.0  2006.0  2007.0  \
U.S._STATE
California       1       7       5       4      10       9       8      12
Texas            2       1       0       3       6       4       8       3
Michigan         0       0       1       8       5       6       2       4

YEAR        2008.0  2009.0  2010.0  2011.0  2012.0  2013.0  2014.0  2015.0  \
U.S._STATE
California      19      10      21      10       6      12       5      15
Texas            4       6       1      12       6       0       0       3
Michigan         3       3       5       9       3       2       0       0

YEAR        2016.0
U.S._STATE
California       4
Texas            1
Michigan         0
```

[736]:
```
def imputer(outage, imp_col):
    """
    uses probabilistic imputation by U.S._STATE (which is never null)
    Strategy: consider the df formed by selecting rows where DEMAND.LOSS.MW is␣
 ↪missing. Fix the state.
    Then find the CAUSE.CATEGORY of the outage (which is never null), and␣
 ↪impute from those values.
    """
    imp_outage = outage.copy()
    states = imp_outage['U.S._STATE'].unique()
```

```
    for state in states:
        outage_state = imp_outage[imp_outage['U.S._STATE'] == state]
        causes = outage_state['CAUSE.CATEGORY'].unique()
        for cause in causes:
            if outage_state.shape[0] != 0:
                imputed = cause_imputer(outage_state, imp_col, cause)
                imp_outage.loc[imputed.index, :] = imputed
            else:
                # since no values here are null
                continue

    return imp_outage
```

[737]:
```
def cause_imputer(outage_state, imp_col, cause):
    outage_state_cause = outage_state[outage_state['CAUSE.CATEGORY'] == cause]
    num_null = outage_state_cause[imp_col].isnull().sum()
    notnull_col = outage_state_cause[imp_col].dropna()
    if notnull_col.shape[0] != 0:
        fill_values = notnull_col.sample(num_null, replace=True)
        fill_values.index = outage_state_cause.loc[outage_state_cause[imp_col].
↪isnull()].index
        imp_outage = outage_state_cause.fillna({imp_col: fill_values.to_dict()})
        return imp_outage
    else:
        # I don't feel comfortable imputing with potentially wildly differing␣
↪values from true, so I'll drop these
        return outage_state
```

[706]:
```
(outage.pivot_table(values='DEMAND.LOSS.MW',
                    index='CAUSE.CATEGORY',
                    columns='U.S._STATE',
                    aggfunc='mean')
 .fillna(0)
 .astype(int)
 .transpose()
 .loc[['California', 'Texas', 'Michigan', 'Washington', 'New York']]
)
```

[706]:
```
CAUSE.CATEGORY  equipment failure  fuel supply emergency  intentional attack  \
U.S._STATE
California                    375                    635                  31
Texas                         378                   1231                   2
Michigan                      336                      0                   0
Washington                    244                    630                   0
New York                        0                    468                   0
```

CAUSE.CATEGORY	islanding	public appeal	severe weather
U.S._STATE			
California	551	8638	412
Texas	0	0	736
Michigan	0	8881	318
Washington	94	100	430
New York	0	76	336

CAUSE.CATEGORY	system operability disruption
U.S._STATE	
California	335
Texas	615
Michigan	4197
Washington	200
New York	6975

[735]:
```
(outage.pivot_table(values='CUSTOMERS.AFFECTED',
                    index='CAUSE.CATEGORY',
                    columns='U.S._STATE',
                    aggfunc='mean')
 .fillna(0)
 .astype(int)
 .transpose()
 .loc[['California', 'Texas', 'Michigan', 'Washington', 'New York']]
)
```

[735]:

CAUSE.CATEGORY	equipment failure	fuel supply emergency	intentional attack
U.S._STATE			
California	198608	0	10660
Texas	85882	0	552
Michigan	0	0	0
Washington	93300	0	0
New York	0	0	0

CAUSE.CATEGORY	islanding	public appeal	severe weather
U.S._STATE			
California	5039	0	361041
Texas	0	0	258094
Michigan	0	0	138311
Washington	0	8000	182676
New York	0	18600	165050

CAUSE.CATEGORY	system operability disruption
U.S._STATE	
California	152040
Texas	289696
Michigan	759737

```
Washington                                  0
New York                              1080998
```

[742]:
```
imputed_outage = imputer(outage, 'DEMAND.LOSS.MW')
imputed_outage = imputer(imputed_outage, 'CUSTOMERS.AFFECTED')
imputed_outage = imputed_outage[imputed_outage['DEMAND.LOSS.MW'].notnull()]
imputed_outage = imputed_outage[imputed_outage['CUSTOMERS.AFFECTED'].notnull()]
```

[778]:
```
mpo_causes = (imputed_outage.pivot_table(values='MAJOR.POWER.OUTAGE',
                                         index='CAUSE.CATEGORY',
                                         columns='YEAR',
                                         aggfunc='sum')
              .fillna(0)
              .astype(np.int)
)
mpo_causes
```

[778]:
```
YEAR                           2000.0  2001.0  2002.0  2003.0  2004.0  2005.0  \
CAUSE.CATEGORY
equipment failure                   1       0       0       4       2       2
fuel supply emergency               0       0       0       0       0       0
intentional attack                  0       0       0       0       0       0
islanding                           0       0       0       0       0       0
public appeal                       0       0       0       0       0       0
severe weather                      5       0      11      28      45      34
system operability disruption       3       5       1       5       2       3

YEAR                           2006.0  2007.0  2008.0  2009.0  2010.0  2011.0  \
CAUSE.CATEGORY
equipment failure                   0       1       2       4       1       1
fuel supply emergency               0       0       0       0       0       0
intentional attack                  0       0       0       0       0       0
islanding                           0       0       0       0       0       0
public appeal                       0       0       0       0       0       0
severe weather                     40      29      50      30      42      69
system operability disruption       6       2       8       1       2       7

YEAR                           2012.0  2013.0  2014.0  2015.0  2016.0
CAUSE.CATEGORY
equipment failure                   0       3       0       0       0
fuel supply emergency               0       0       2       0       0
intentional attack                  1       1       0       0       2
islanding                           0       1       0       0       0
public appeal                       0       0       0       0       0
severe weather                     34      30      18      28       9
system operability disruption       0       2       0       3       5
```

```
[ ]:
```

```
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```

```
[ ]:
```

```
[ ]:
```

3.0.3 Hypothesis Test

```
[ ]: # TODO
     # null hypothesis: distribution of causes before 2006 is the same as the␣
     ↪distribution of causes after 2006
     # alternative hypothesis: they're different
```

```
[781]: mpo_causes_before_2006 = mpo_causes.get([2000, 2001, 2002, 2003, 2004, 2005,␣
       ↪2006])
       mpo_causes_after_2006 = mpo_causes.get([2007, 2008, 2009, 2010, 2011, 2012,␣
       ↪2013, 2014, 2015, 2016])

       mpo_props_before_2006 = (mpo_before_2006.sum(axis=1) / mpo_before_2006.sum().
       ↪sum())
       mpo_props_after_2006 = mpo_after_2006.sum(axis=1) / mpo_after_2006.sum().sum()
```

```
[788]: mpo_before_2006.sum().sum(), mpo_after_2006.sum().sum()
```

```
[788]: (197, 388)
```

```
[818]: def hypothesis_test(n_trials):
           obs_tvd = (mpo_props_before_2006 - mpo_props_after_2006).abs().sum() / 2
           sim_tvds = []
           n_outages_after_2006 = mpo_after_2006.sum().sum()
           for _ in range(n_trials):
               sim_outages = np.random.multinomial(n_outages_after_2006,␣
       ↪mpo_props_before_2006)
               sim_props = sim_outages / sim_outages.sum()
               sim_tvds.append((mpo_props_before_2006 - sim_props).abs().sum() / 2)
           # pval
           return np.count_nonzero(sim_tvds >= obs_tvd) / n_trials, sim_tvds, obs_tvd
```

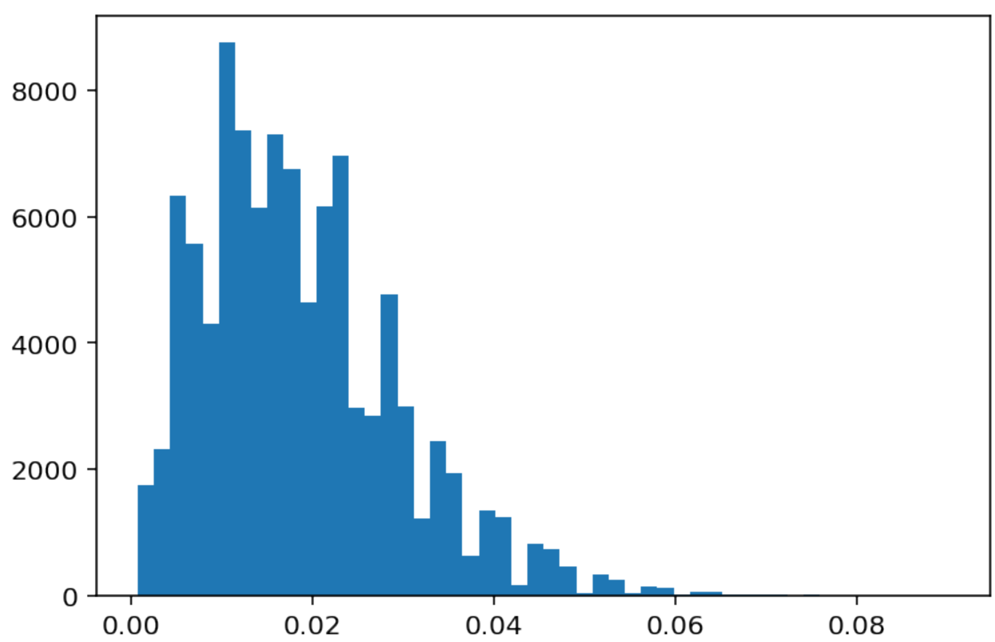
```
[826]: pval, sim_tvds, obs_tvd = hypothesis_test(100_000)
```

```
[827]: pval
```

[827]: 0.00108

[829]:
```
plt.hist(sim_tvds, bins=50)
```

[829]:
```
(array([1.753e+03, 2.311e+03, 6.342e+03, 5.568e+03, 4.295e+03, 8.756e+03,
        7.364e+03, 6.138e+03, 7.311e+03, 6.759e+03, 4.650e+03, 6.157e+03,
        6.962e+03, 2.980e+03, 2.839e+03, 4.760e+03, 3.004e+03, 1.228e+03,
        2.449e+03, 1.941e+03, 6.290e+02, 1.339e+03, 1.244e+03, 1.540e+02,
        8.100e+02, 7.310e+02, 4.560e+02, 2.600e+01, 3.370e+02, 2.460e+02,
        3.000e+01, 1.310e+02, 1.190e+02, 9.000e+00, 5.600e+01, 4.600e+01,
        1.200e+01, 1.700e+01, 1.700e+01, 8.000e+00, 1.000e+00, 9.000e+00,
        2.000e+00, 0.000e+00, 0.000e+00, 2.000e+00, 0.000e+00, 0.000e+00,
        0.000e+00, 2.000e+00]),
 array([0.00070647, 0.0024983 , 0.00429013, 0.00608195, 0.00787378,
        0.0096656 , 0.01145743, 0.01324925, 0.01504108, 0.01683291,
        0.01862473, 0.02041656, 0.02220838, 0.02400021, 0.02579204,
        0.02758386, 0.02937569, 0.03116751, 0.03295934, 0.03475116,
        0.03654299, 0.03833482, 0.04012664, 0.04191847, 0.04371029,
        0.04550212, 0.04729395, 0.04908577, 0.0508776 , 0.05266942,
        0.05446125, 0.05625307, 0.0580449 , 0.05983673, 0.06162855,
        0.06342038, 0.0652122 , 0.06700403, 0.06879586, 0.07058768,
        0.07237951, 0.07417133, 0.07596316, 0.07775498, 0.07954681,
        0.08133864, 0.08313046, 0.08492229, 0.08671411, 0.08850594,
        0.09029777]),
 <BarContainer object of 50 artists>)
```



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