forest_fires

November 9, 2020

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
plt.style.use('ggplot')

from scipy.stats import zscore
```

[2]:
```
# read in forest fires dataset into a pandas dataframe
df = pd.read_csv('forest-fires.csv')

# perform very basic analysis of the metadata (number of points and data types␣
 ↪for each column)
print(df.shape)
print(df.dtypes)
df.describe().T
```

```
(517, 13)
x           int64
y           int64
month      object
day        object
ffmc      float64
dmc       float64
dc        float64
isi       float64
temp      float64
rh          int64
wind      float64
rain      float64
area      float64
dtype: object
```

[2]:

	count	mean	std	min	25%	50%	75%	max
x	517.0	4.669246	2.313778	1.0	3.0	4.00	7.00	9.00
y	517.0	4.299807	1.229900	2.0	4.0	4.00	5.00	9.00
ffmc	517.0	90.644681	5.520111	18.7	90.2	91.60	92.90	96.20

```
dmc   517.0  110.872340   64.046482   1.1   68.6  108.30  142.40   291.30
dc    517.0  547.940039  248.066192   7.9  437.7  664.20  713.90   860.60
isi   517.0    9.021663    4.559477   0.0    6.5    8.40   10.80    56.10
temp  517.0   18.889168    5.806625   2.2   15.5   19.30   22.80    33.30
rh    517.0   44.288201   16.317469  15.0   33.0   42.00   53.00   100.00
wind  517.0    4.017602    1.791653   0.4    2.7    4.00    4.90     9.40
rain  517.0    0.021663    0.295959   0.0    0.0    0.00    0.00     6.40
area  517.0   12.847292   63.655818   0.0    0.0    0.52    6.57  1090.84
```

[3]:
```
# Inspect the first few data points to gain a brief understanding of the data
df.head()
```

[3]:

	x	y	month	day	ffmc	dmc	dc	isi	temp	rh	wind	rain	area
0	7	5	mar	fri	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.0
1	7	4	oct	tue	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.0
2	7	4	oct	sat	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.0
3	8	6	mar	fri	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.0
4	8	6	mar	sun	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.0

[4]:
```
# Find missing values and correct them in the dataset if needed
print(df.isna().sum().sum())
```

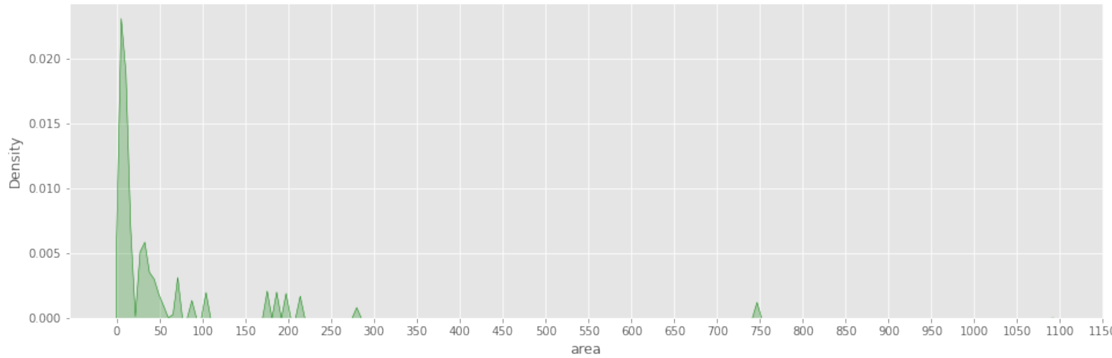
```
0
```

[5]:
```
# Configure plotting library
plt.rcParams['figure.figsize'] = 9,5
```

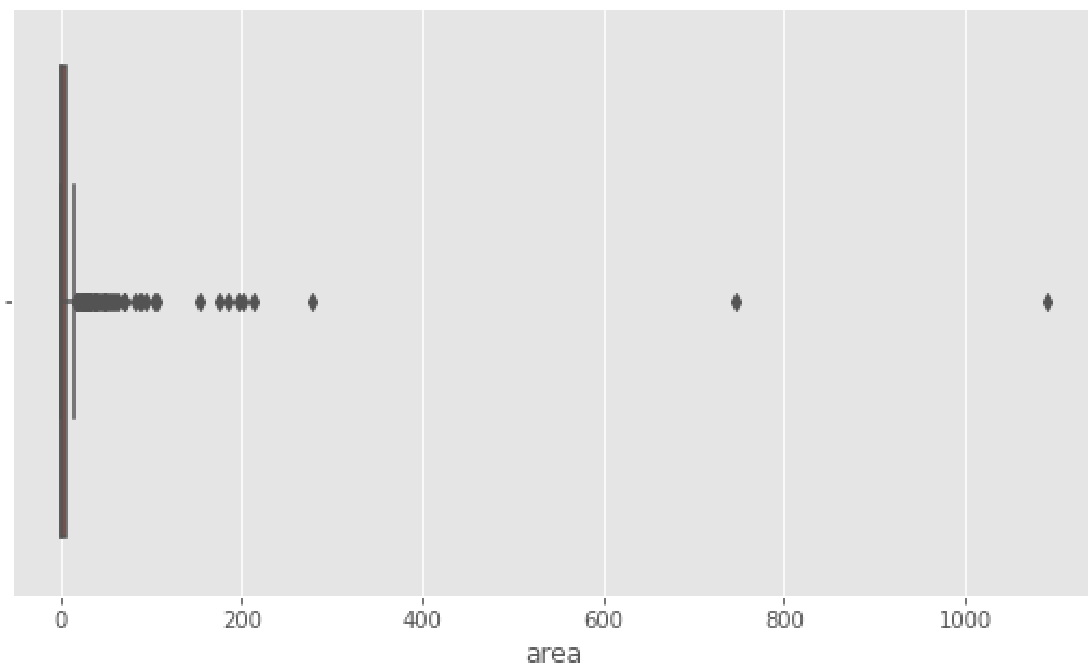
[6]:
```
# Analyze skew and kurtosis values
## Skewness: A measure of how skewed (non-symmetric) the data is relative to␣
↪the midpoint.
print("Area skewness: {}".format(df['area'].skew()))
## Kurtosis: A measure of how heavy the tails are in the data (how many␣
↪outliers there are)
print("Area kurtosis: {}".format(df['area'].kurtosis()))
## The very high skew and kurtosis tell us that this data is very varied and␣
↪has many outliers.
```

```
Area skewness: 12.846933533934868
Area kurtosis: 194.1407210942299
```

[7]:
```
# Plot a Kernel Density Estimate of our data. This is essentially a histogram␣
↪but it provides more useful insights.
plt.figure(figsize=(16,5))
ax = sns.kdeplot(df['area'],bw_adjust=0.02,shade=True,color='g')
plt.xticks([i for i in range(0,1200,50)])
plt.show()
```



[8]:
```
# Plot a boxplot of all the area values to find any outliers
ax = sns.boxplot(x=df['area'])
```



[9]:
```
# Notes:
## The data is very skewed by the outliers.
## We see that most forest fires cover less than 50 hectacres of land.
## The main outliers have been identified below
outliers = df[abs(zscore(df['area'])) >= 3 ]
outliers
```

[9]:

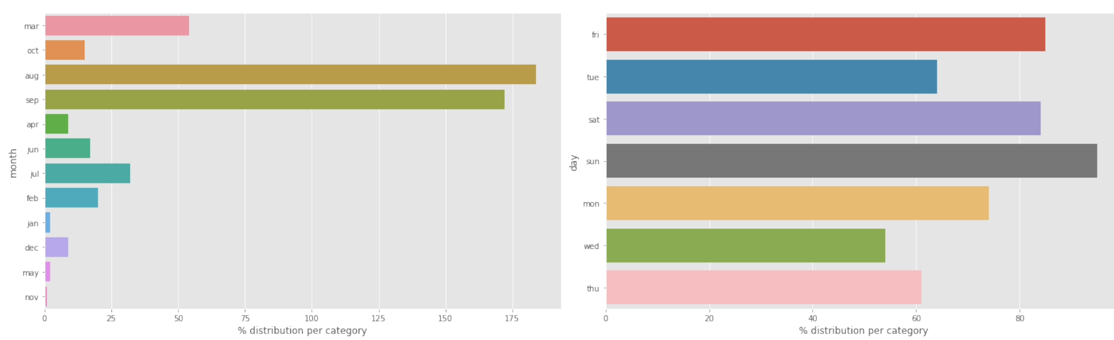
	x	y	month	day	ffmc	dmc	dc	isi	temp	rh	wind	rain	area
237	1	2	sep	tue	91.0	129.5	692.6	7.0	18.8	40	2.2	0.0	212.88
238	6	5	sep	sat	92.5	121.1	674.4	8.6	25.1	27	4.0	0.0	1090.84

```
415  8  6   aug  thu  94.8  222.4  698.6  13.9  27.5  27   4.9   0.0   746.28
479  7  4   jul  mon  89.2  103.9  431.6   6.4  22.6  57   4.9   0.0   278.53
```

[10]:
```
# Create a new dataframe without the area (for which we will later create a␣
↪prediction model)
df_input = df.drop(columns='area')

# Split up the data columns into categorical columns and numerical columns
categorical = df_input.select_dtypes(include='object').columns.tolist()
numerical = df_input.select_dtypes(exclude='object').columns.tolist()

print(categorical)
print(numerical)
```

```
['month', 'day']
['x', 'y', 'ffmc', 'dmc', 'dc', 'isi', 'temp', 'rh', 'wind', 'rain']
```

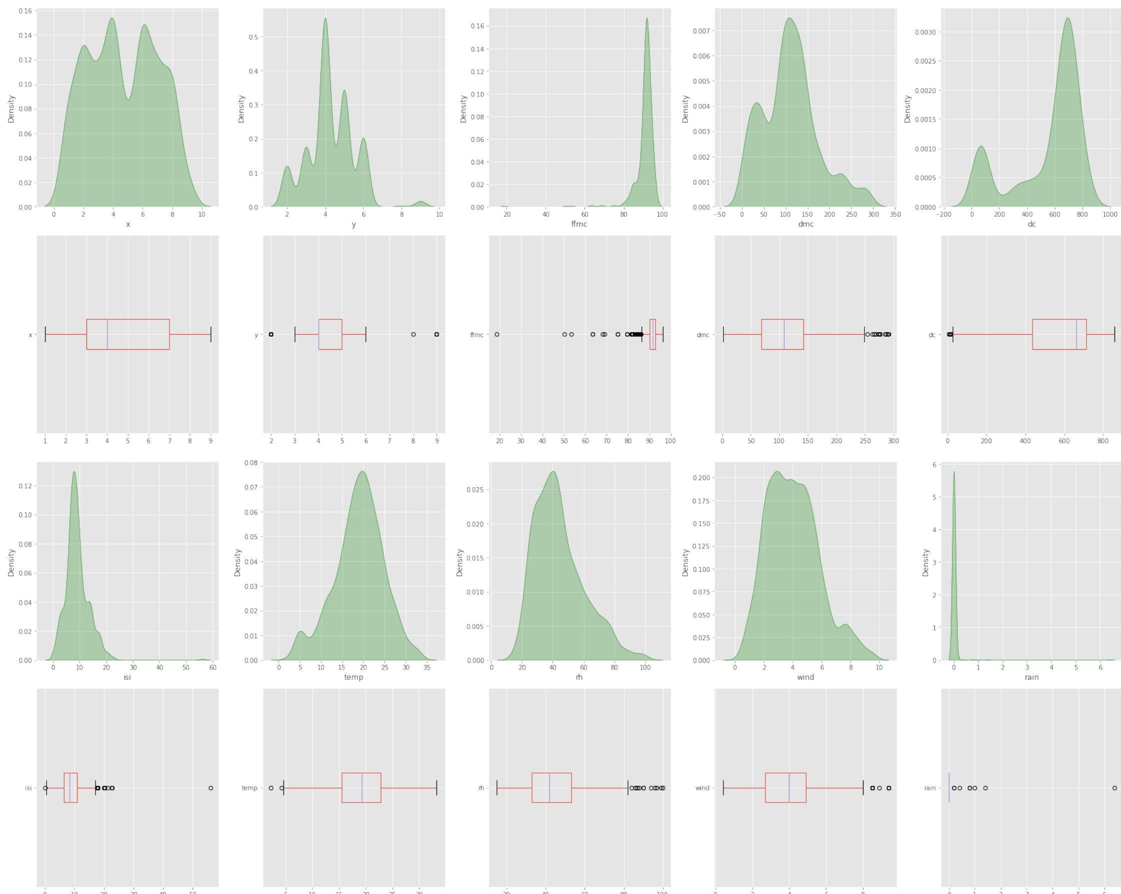
[11]:
```
# Visualize categorical data
plt.figure(figsize=(20,6))
for index, cat_column in enumerate(categorical, start=1):
    plt.subplot(1,2,index)
    sns.countplot(data=df_input,y=cat_column)
    plt.ylabel(cat_column)
    plt.xlabel('% distribution per category')
plt.tight_layout()
plt.show()
```



[12]:
```
# We notice a huge spike in forest fires during August and September.
# Sunday seems to have more fires on avergae, but there seems to be little␣
↪significant difference.
```

[13]:
```
# Visualize numerical data
plt.figure(figsize=(25,20))
for index, num_column in enumerate(numerical, start=1):
    plot_index = index+5 if index > 5 else index
    plt.subplot(4,5,plot_index)
```

```
    sns.kdeplot(data=df[num_column],bw_adjust=0.8,color='g',shade=True)
    plt.subplot(4,5,plot_index+5)
    df[num_column].plot.box(vert=False)
plt.tight_layout()
plt.show()
numerical_data = df[numerical]
pd.DataFrame(data=[numerical_data.skew(),numerical_data.
 ↪kurtosis()],index=['skewness','kurtosis'])
```



[13]:

```
                  x         y       ffmc  ...        rh      wind        rain
skewness   0.036246  0.417296  -6.575606  ...  0.862904  0.571001   19.816344
kurtosis  -1.172331  1.420553  67.066041  ...  0.438183  0.054324  421.295964

[2 rows x 10 columns]
```

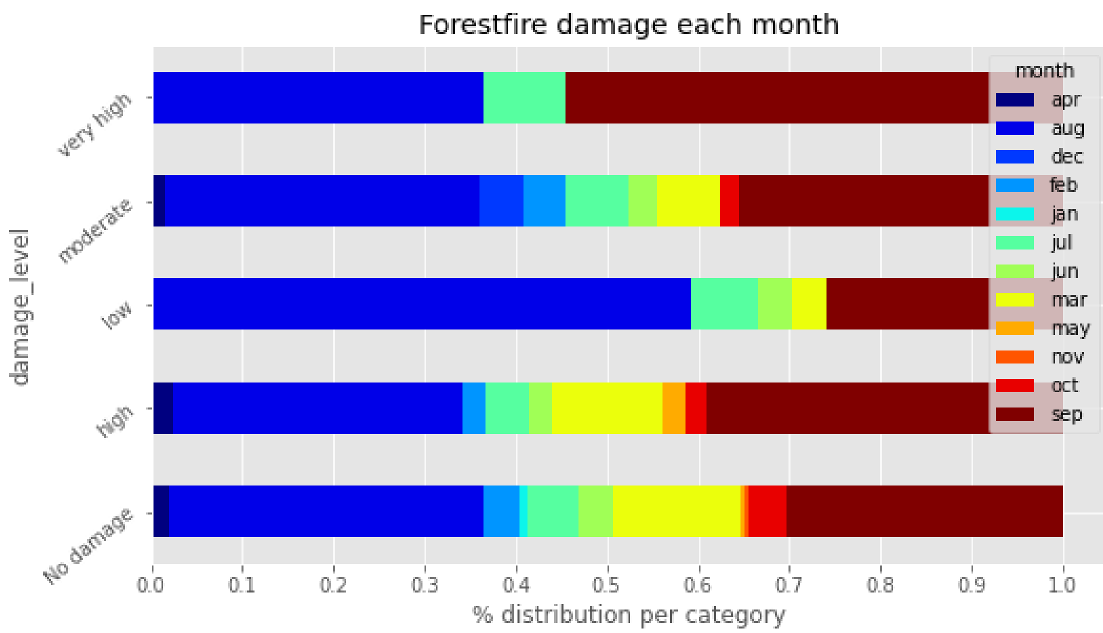
[14]:

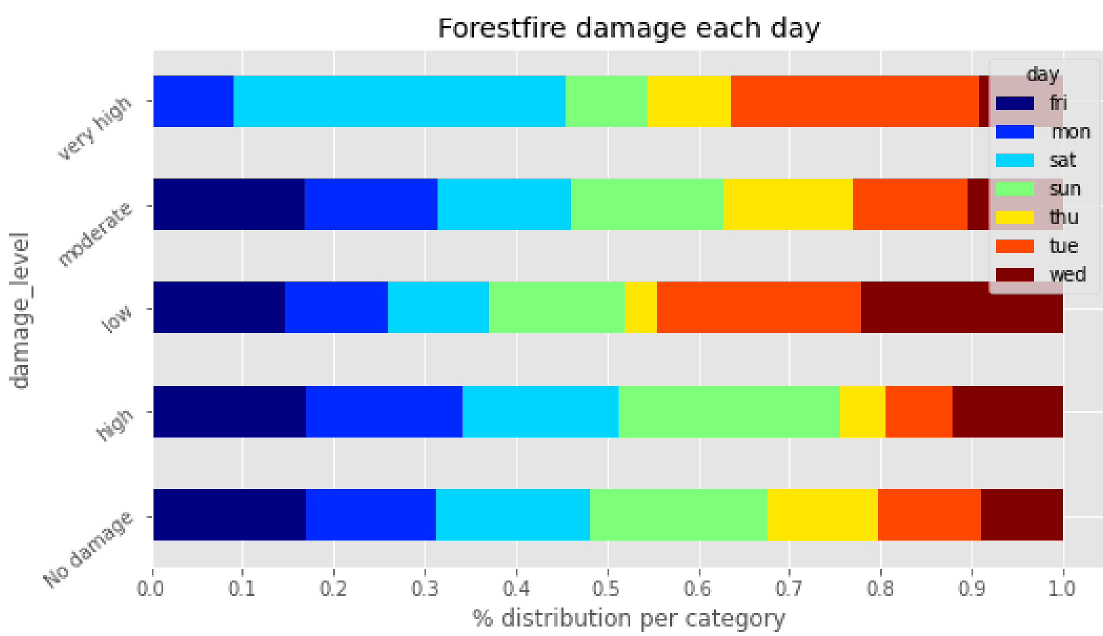
```
# Notes:
## The KDE plots and box plots reveal that there is the most skew and kurtosis␣
 ↪in FFMC, ISI, and rain
## These columns also had the most extreme outliers.
```

[15]:
```python
# Create catergorical representations of the damage from forest fires based on␣
↪area
def damage_level(area):
    if area == 0.0:
        return "No damage"
    elif area <= 1:
        return "low"
    elif area <= 25:
        return "moderate"
    elif area <= 100:
        return "high"
    else:
        return "very high"

df['damage_level'] = df['area'].apply(damage_level)
df.head()
```

[15]:
```
   x  y month  day  ffmc   dmc  ...  temp  rh  wind  rain  area  damage_level
0  7  5   mar  fri  86.2  26.2  ...   8.2  51   6.7   0.0   0.0     No damage
1  7  4   oct  tue  90.6  35.4  ...  18.0  33   0.9   0.0   0.0     No damage
2  7  4   oct  sat  90.6  43.7  ...  14.6  33   1.3   0.0   0.0     No damage
3  8  6   mar  fri  91.7  33.3  ...   8.3  97   4.0   0.2   0.0     No damage
4  8  6   mar  sun  89.3  51.3  ...  11.4  99   1.8   0.0   0.0     No damage

[5 rows x 14 columns]
```

[16]:
```python
# Visualize the damage level with respect to the month and day of the event
for index, category in enumerate(categorical, start=1):
    cross = pd.
↪crosstab(index=df['damage_level'],columns=df[category],normalize='index')
    cross.plot.barh(stacked=True,rot=40,cmap='jet')
    plt.xlabel('% distribution per category')
    plt.xticks(np.arange(0,1.1,0.1))
    plt.title("Forestfire damage each {}".format(category))
plt.show()
```





[17]:
```
# Notes:
## This reveals that although august and september had the most fires, many of them were relatively low damage.
## Furthermore, we can notice that every high damage fire happened within three months: July, August, September.
```

```
## May, April, November, and December had almost no fires, which coincides with␣
 ↪our previous visualization that did't factor in damage done.
## The by day graph provides little valueable insight, since almost every dy␣
 ↪has an even amount of each damage level.
```

[18]:
```
# Visualize the damage level with respect to the numerical columns of the data
plt.figure(figsize=(20,40))
for index, category in enumerate(numerical, start=1):
    plt.subplot(10,1,index)
    if category in ['X','Y']:
        sns.swarmplot(data=df,x=category,y='area',hue='damage_level')
    else:
        sns.scatterplot(data=df,x=category,y='area',hue='damage_level')
plt.show()
```


damage_level
No damage
low
moderate
high
very high
area
x
y
ffmc
dmc
dc
isi
temp
rh
wind
rain