Spin Cycle to Inferno

How your washing machine could be a firestarter!

London Fire Brigade - White Goods Analysis

This notebook analyses data relating to fires caused by white goods in London.

"The London Fire Brigade attend a number of fires each year where the ignition source of the fire is recorded as 'white goods' (e.g. washing machine, dishwasher, refrigerator). This data sets provides details of such fires by London borough and ward location, and the type of white goods concerned as well as the property type where the fire happened. Where known, the brand and model of the white goods item is included, although this is added as free text so there may be errors it spelling, etc. The data is from January 2009 and is updated annually for each calendar year." (London Datastore)

Dataset

Population figures

Import and clean data

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
# Load data
data = pd.read_excel(r'C:\Users\imoge\AllMLProjects\Data\White goods fires from 2009.xl
```

In [3]:

```
# Check shape
data.shape
```

Out[3]: (5035, 17)

In [4]:

```
# Check head
data.head()
```

Out[4]:

	Year	Month	IncType	ParentPropertyType	NumFireDeaths	NumAllFireInjuries	IncGeo_BoroughCo
0	2009	December	Primary Fire	Offices and call centres	0	0	E090000

	Year	Month	IncType	ParentPropertyType	NumFireDeaths	NumAllFireInjuries	IncGeo_BoroughCo
1	2009	July	Primary Fire	Food and Drink	0	0	E090000
2	2009	December	Primary Fire	House in Multiple Occupation	0	0	E090000
3	2009	April	Primary Fire	Purpose Built Flats/Maisonettes	0	0	E090000
4	2009	May	Primary Fire	Food and Drink	0	0	E090000

In [5]:

```
# Check datatypes and null values
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5035 entries, 0 to 5034
Data columns (total 17 columns):
 #   Column                       Non-Null Count  Dtype 
---  ------                       --------------  ----- 
 0   Year                         5035 non-null   int64 
 1   Month                        5035 non-null   object
 2   IncType                      5035 non-null   object
 3   ParentPropertyType           5035 non-null   object
 4   NumFireDeaths                5035 non-null   int64 
 5   NumAllFireInjuries           5035 non-null   int64 
 6   IncGeo_BoroughCode           5035 non-null   object
 7   IncGeo_BoroughName           5035 non-null   object
 8   IncGeo_WardCode              5033 non-null   object
 9   IncGeo_WardName              5033 non-null   object
 10  IgnitionSourcePower          5035 non-null   object
 11  IgnitionSource               5035 non-null   object
 12  ItemFirstIgnited             5035 non-null   object
 13  LocationFireStarted          5035 non-null   object
 14  ApplianceManufacturer        4462 non-null   object
 15  ApplianceManufacturerOther   590 non-null    object
 16  MainCauseModel               4384 non-null   object
dtypes: int64(3), object(14)
memory usage: 668.8+ KB
```

Assessment of the data and cleaning

We have a lot of missing values in the main cause model columns as well as a few in the appliance manufacturer colums.

In [6]:

```
df = data.copy()
```

In [7]:

```
# Number of nulls for applicance manufacturer
df['ApplianceManufacturer'].isnull().sum()
```

Out[7]: 573

In [8]:
```
# Number of nulls for appliance manufacturer other
df['ApplianceManufacturerOther'].isnull().sum()
```

Out[8]:
```
4445
```

In [9]:
```
# Value counts
df['ApplianceManufacturer'].value_counts()
```

Out[9]:
```
HOTPOINT        842
Other           594
INDESIT         509
BEKO            375
BOSCH           350
               ...
WARWICK           1
ARRON             1
SPEED QUEEN       1
DICON             1
AKAI              1
Name: ApplianceManufacturer, Length: 190, dtype: int64
```

In [10]:
```
# Number of nulls for main cause model
df['MainCauseModel'].isnull().sum()
```

Out[10]:
```
651
```

In [11]:
```
# Value counts for this column
df['MainCauseModel'].value_counts()
```

Out[11]:
```
unknown                 257
Unknown                 149
not known               146
Not known                68
Not Known                59
                       ...
Aquarius extra wd64       1
A146CDW                   1
spin                      1
A Class Frostfree         1
GO482/2-80                1
Name: MainCauseModel, Length: 2984, dtype: int64
```

We will drop the appliance manufacturer other column as there are so many blanks. We will also drop the main cause model as many of the entries although not blank, have 'unknown' as entries.

In [12]:
```
# Drop columns with a lot of missing values
df.drop(columns = ['ApplianceManufacturerOther','MainCauseModel'],axis = 1, inplace = T
```

In [13]:
```
df.head()
```

Out[13]:

	Year	Month	IncType	ParentPropertyType	NumFireDeaths	NumAllFireInjuries	IncGeo_BoroughCo
0	2009	December	Primary Fire	Offices and call centres	0	0	E090000

	Year	Month	IncType	ParentPropertyType	NumFireDeaths	NumAllFireInjuries	IncGeo_BoroughCo
1	2009	July	Primary Fire	Food and Drink	0	0	E090000
2	2009	December	Primary Fire	House in Multiple Occupation	0	0	E090000
3	2009	April	Primary Fire	Purpose Built Flats/Maisonettes	0	0	E090000
4	2009	May	Primary Fire	Food and Drink	0	0	E090000

We also have a couple of missing values in the Geo Ward Code and Geo Ward Name columns

In [14]:
```
df[df['IncGeo_WardCode'].isnull()]
```

Out[14]:

	Year	Month	IncType	ParentPropertyType	NumFireDeaths	NumAllFireInjuries	IncGeo_BoroughCo
4663	2023	June	Primary Fire	Food and Drink	0	0	E09000
4939	2024	July	Primary Fire	Road Vehicle	0	0	E09000

We could drop these but there is some useful information there about the fire type, so we will leave them for now

In [15]:
```
# Check value counts of years
df['Year'].value_counts()
```

Out[15]:
```
2018    360
2012    341
2017    334
2019    331
2010    329
2011    329
2015    323
2013    322
2014    319
2009    305
2021    302
2016    302
2022    286
2020    263
2023    257
2024    237
2025     95
Name: Year, dtype: int64
```

We will drop those relating to 2025 as we only have a few observations so far

In [16]:

```
df = df[df['Year']!=2025]
df.shape
```

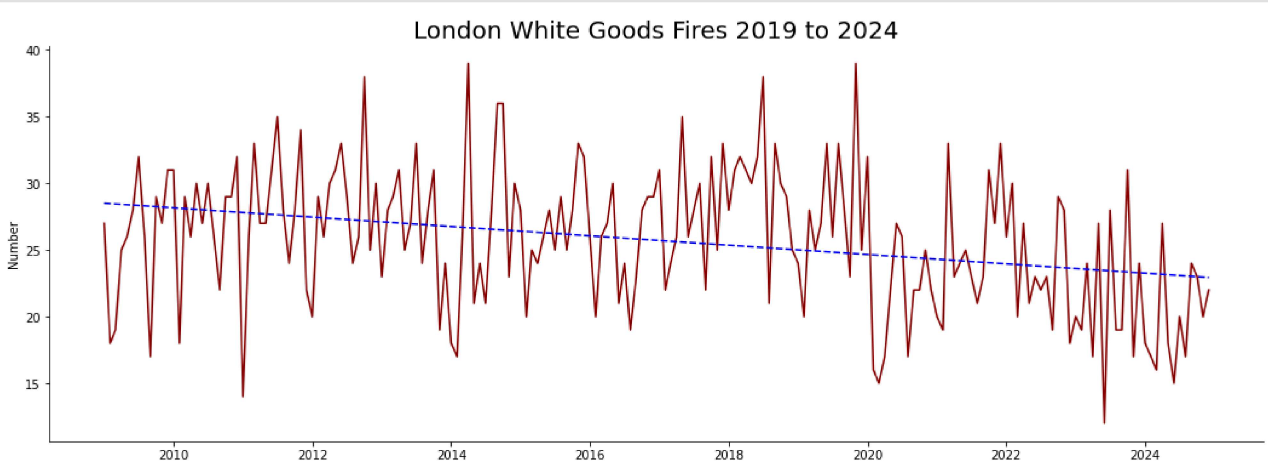
Out[16]: (4940, 15)

Data Analysis

Number of Fires by Month over the Period

In [17]:

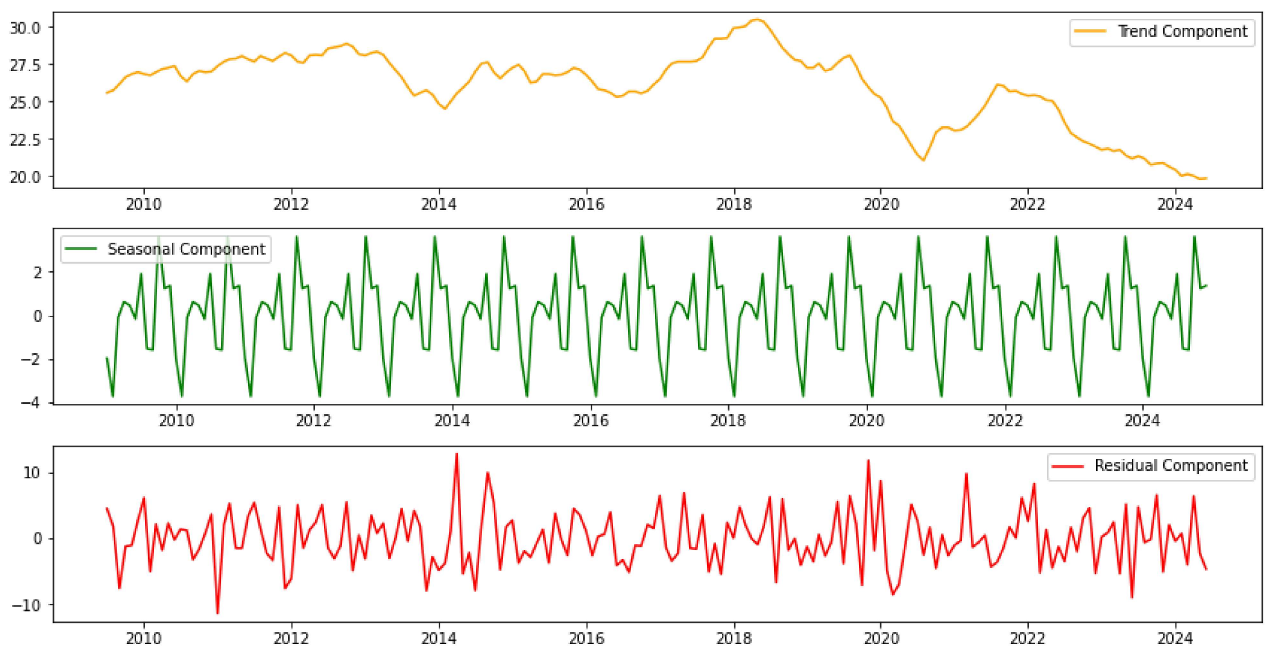
```
# Create a new column of months
df['MonthsNum'] = df['Month']

# Replace the month names with numbers
df['MonthsNum'].replace({'January':1,'February':2,'March':3,'April':4,'May':5,'June':6,
                    'October':10,'November':11,'December':12},inplace = True)

# Create a date column
df['Date'] = pd.to_datetime(df['Year'].astype(str) + '-' + df['MonthsNum'].astype(str))

# Create dataframe of date and number of fires
fires = df.groupby(['Date'],as_index = False)['IncType'].count().set_index('Date')

# Plot the data
fig, ax = plt.subplots(figsize = (18,6))
plt.plot(fires, color = 'darkred')
plt.title("London White Goods Fires 2019 to 2024",fontsize = 20)
plt.ylabel("Number")
ax.spines[['right', 'top']].set_visible(False);

# Add a trendline
import matplotlib.dates as mdates
x = mdates.date2num(fires.index)
y= fires['IncType']
z = np.polyfit(x, y, 1)
p = np.poly1d(z)
#then the plot
plt.plot(x, p(x), "b--");
```



Looking at the plot of fires over time, there is some downward trend, there might be some seasonality also

In [18]:

```python
# Decomposition to split out the components
from statsmodels.tsa.seasonal import seasonal_decompose
series = fires['IncType']
decomposition = seasonal_decompose(series, model='additive', period=12)

# Plot the decomposed components
plt.figure(figsize=(12, 8))

plt.subplot(4, 1, 1)
plt.plot(decomposition.trend, label='Trend Component', color='orange')
plt.legend()

plt.subplot(4, 1, 2)
plt.plot(decomposition.seasonal, label='Seasonal Component', color='green')
plt.legend()

plt.subplot(4, 1, 3)
plt.plot(decomposition.resid, label='Residual Component', color='red')
plt.legend()

plt.tight_layout()
plt.show()
```



Seems that the fires are more common in the autumn and lowest at the start of the year. We will look at this a bit more in following sections

Number of Fires by Year

Which years have the most and least number of reported fires?

In [19]:

```python
# Mean number of fires across the period
df.groupby('Year')['Year'].count().mean()
```

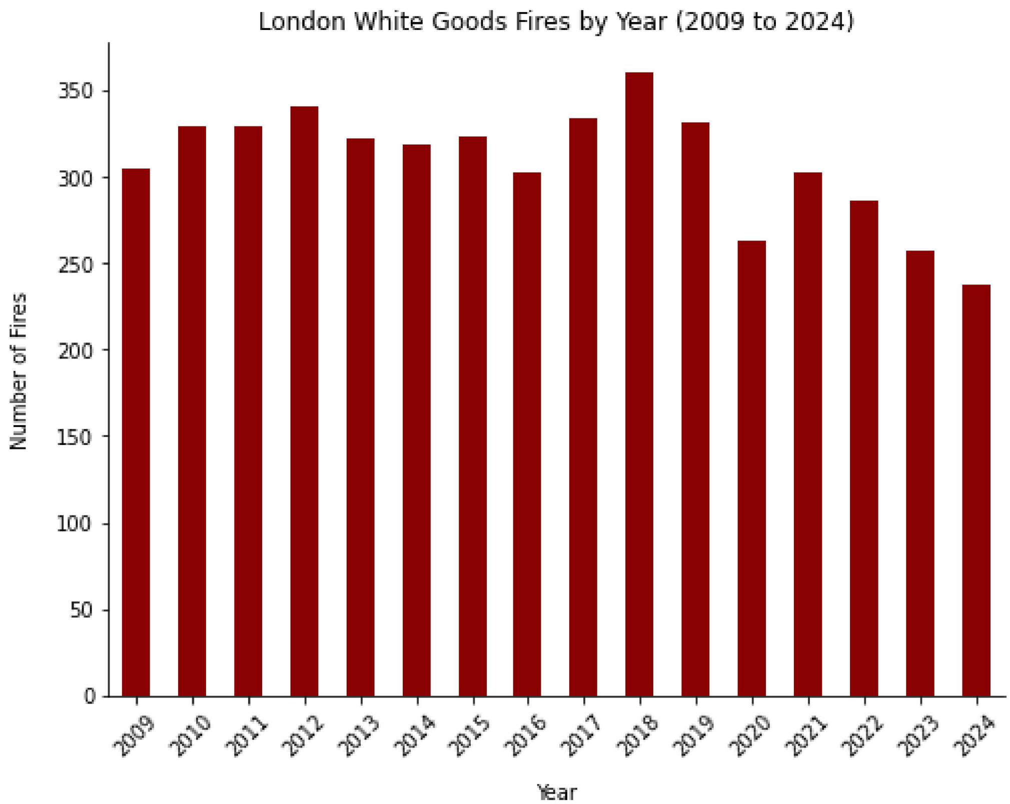
Out[19]: 308.75

In [20]:

```
# Create function for plotting

def plot_func(df,X,Y,kind,t,xlab,ylab):
    fig,ax = plt.subplots(figsize = (8,6))
    df.groupby(X)[Y].count().plot(kind = kind,
                                  title = t,
                                  color = 'darkred')
    ax.spines[['right', 'top']].set_visible(False)
    plt.xlabel(xlab, labelpad = 12)
    plt.ylabel(ylab, labelpad = 12)
    plt.xticks(rotation = 45);
```

In [21]:

```
# Plot fires by year
plot_func(df,'Year',"Year","bar",'London White Goods Fires by Year (2009 to 2024)', "Ye
```



We can see that 2018 had the most white goods fires, with the least in 2024. There appears to be a trend downwards of incidents from 2018 overall. Does this reflect greater public awareness through information after the high number occurring in 2018? What particular issues were relevant to the higher amount of fires in 2018, this could be weather related or other factors at play.

Number of Fires by Month

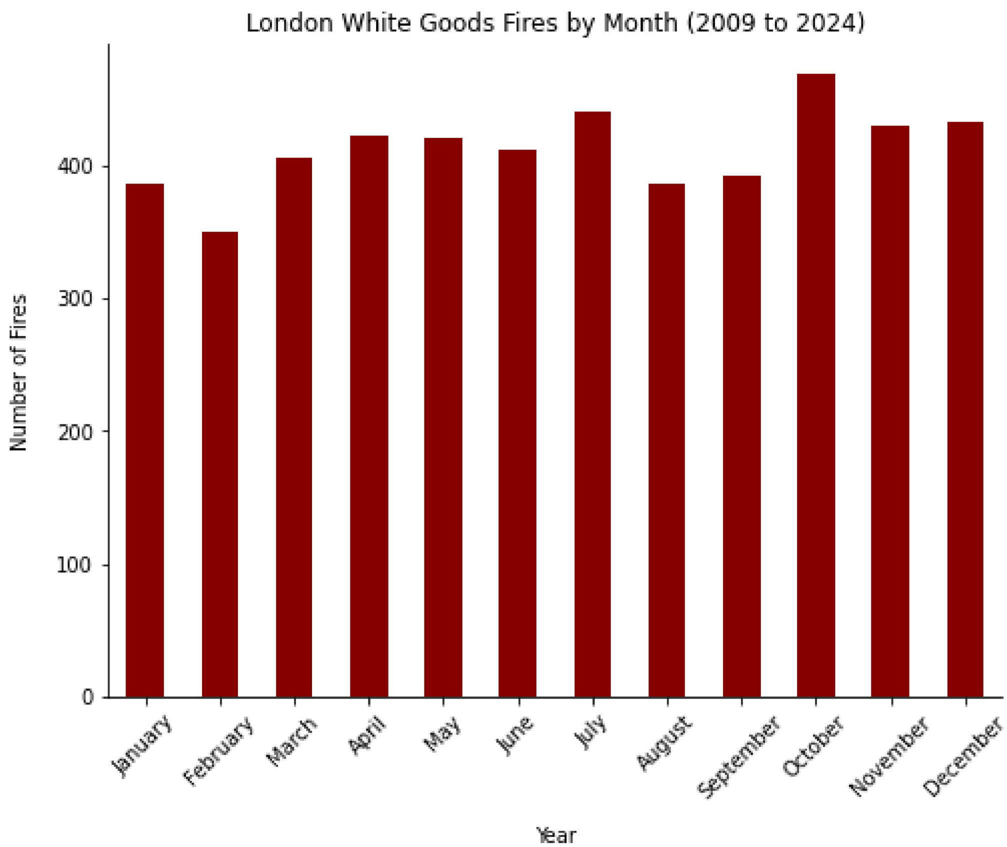
Which months have the most and least reported fires?

In [22]:

```
# Set the months using ordered categoricals to be able to sort them
months = ['January','February','March','April','May','June','July','August','September'
df['MonthName'] = pd.CategoricalIndex(df['Month'], ordered = True, categories = months)
df.groupby('MonthName')['MonthName'].count()
```

Out[22]:
```
MonthName
January      386
February     350
March        405
April        422
May          420
June         412
July         440
August       385
September    391
October      468
November     429
December     432
Name: MonthName, dtype: int64
```

In [23]:
```
# Plot fires by month
plot_func(df,"MonthName","MonthName","bar",'London White Goods Fires by Month (2009 to
```



We can see that the month of October has the highest number of incidents at 468, with the least in February at 348. The previous time series analysis suggested seasonality in the data with more incidents over the autumn. Depending on the type of white good involved, this might reflect increasing use of the equipment into the autumn period as the weather changes, so we will consider this when we analyse the type of white good in a later section. There is also a drop in the early part months of the year. This could be due to the purchase of newer equipment in the sales but also February is a short month.

Number of Fires by Incident Type

In [24]:
```
# Types of fire
df['IncType'].value_counts(normalize = True)
```

```
Out[24]: Primary Fire    0.998178
Late Call       0.001822
Name: IncType, dtype: float64
```

Almost % of the incidents are categorised as a primary fire rather than a late call. Primary fires are more dangerous, late calls are those that are extinguished by the time the event is attended

Number of Fires by Property Type

```
In [25]:
# Fires by property type
df['ParentPropertyType'].value_counts(normalize = True)*100
```

```
Out[25]: Dwelling                                        44.473684
Purpose Built Flats/Maisonettes                 29.251012
Converted Flats/Maisonettes                     11.174089
Non Residential                                  2.955466
Retail                                           2.894737
Food and Drink                                   2.064777
House in Multiple Occupation                     1.639676
Residential Home                                 1.052632
Offices and call centres                         0.910931
Other Residential                                0.829960
Education                                        0.809717
Hospitals and medical care                       0.506073
Outdoor structures                               0.384615
Entertainment and culture                        0.283401
Industrial Manufacturing                         0.141700
Sporting venues                                  0.121457
Road Vehicle                                     0.121457
Warehouses and bulk storage                      0.080972
Transport buildings                              0.080972
Public admin, security and safety                0.080972
Religious                                        0.040486
Public Utilities                                 0.040486
Animal boarding/breeding/kennels (not farm)      0.020243
Industrial Processing                            0.020243
Outdoor equipment and machinery                  0.020243
Name: ParentPropertyType, dtype: float64
```

We can see that the majority of fires are in dwellings, flats and maisonettes. To visualise this a little better we can just take the top five locations

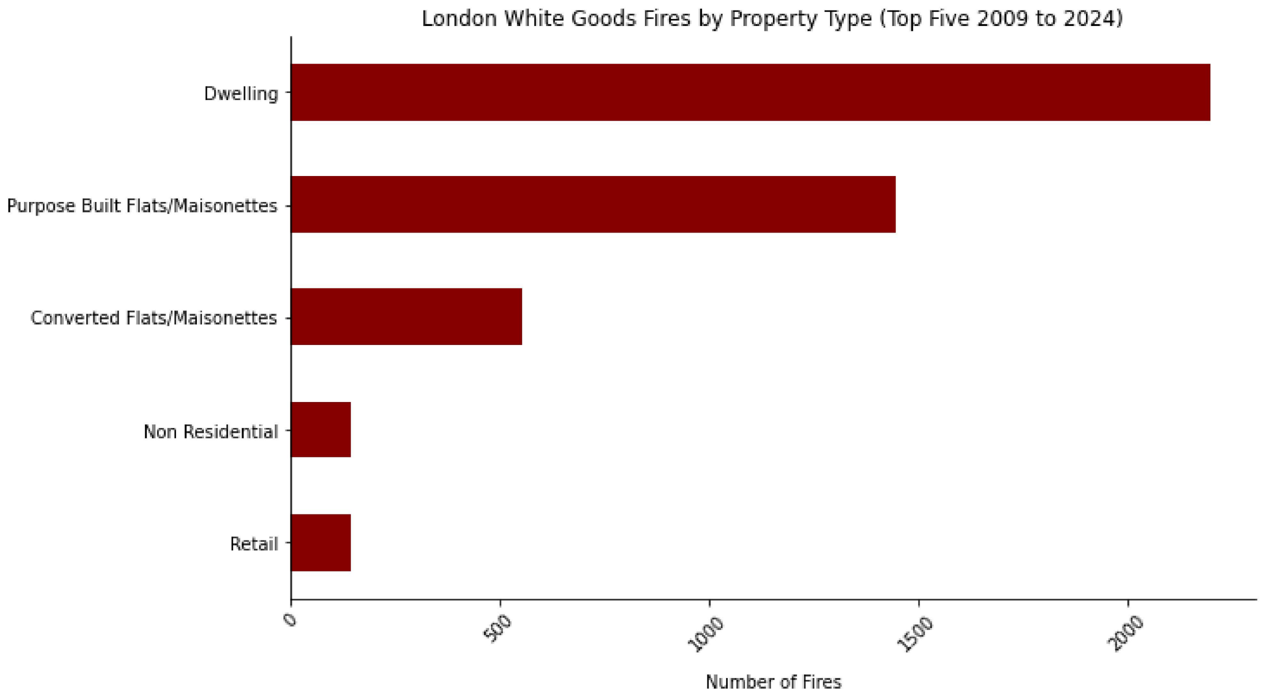
```
In [26]:
# Percentage accounted for by top five
df['ParentPropertyType'].value_counts(normalize = True).head(5).sum()*100
```

```
Out[26]: 90.74898785425101
```

```
In [27]:
# Create function for plotting dataframe with top 5

def plot_func2(df,X,Y,kind,t,xlab,ylab):
    fig,ax = plt.subplots(figsize = (10,6))
    df.groupby(X)[Y].count().sort_values(ascending = False).head(5).plot(kind = kind,
                                    title = t,
                                    color = 'darkred')
    ax.spines[['right', 'top']].set_visible(False)
    plt.xlabel(xlab, labelpad = 12)
    plt.ylabel(ylab, labelpad = 12)
```

```
    plt.xticks(rotation = 45)
    ax.invert_yaxis();
```

In [28]:
```
# Plot by property type
plot_func2(df,"ParentPropertyType","ParentPropertyType","barh",'London White Goods Fire
         "Number of Fires",None)
```



Number of deaths and injuries from Fires

In [29]:
```
# How many deaths and injuries?
print("Deaths:",df['NumFireDeaths'].sum())
print("Injuries",df['NumAllFireInjuries'].sum())
print("Mean Deaths per Year:",df['NumFireDeaths'].sum()/15)
print("Mean Injuries per Year",df['NumAllFireInjuries'].sum()/15)
```

```
Deaths: 85
Injuries 709
Mean Deaths per Year: 5.666666666666667
Mean Injuries per Year 47.266666666666666
```

In [30]:
```
# Number of incidents by number of deaths
df['NumFireDeaths'].value_counts()
```

Out[30]:
```
0     4931
1        6
2        1
6        1
71       1
Name: NumFireDeaths, dtype: int64
```

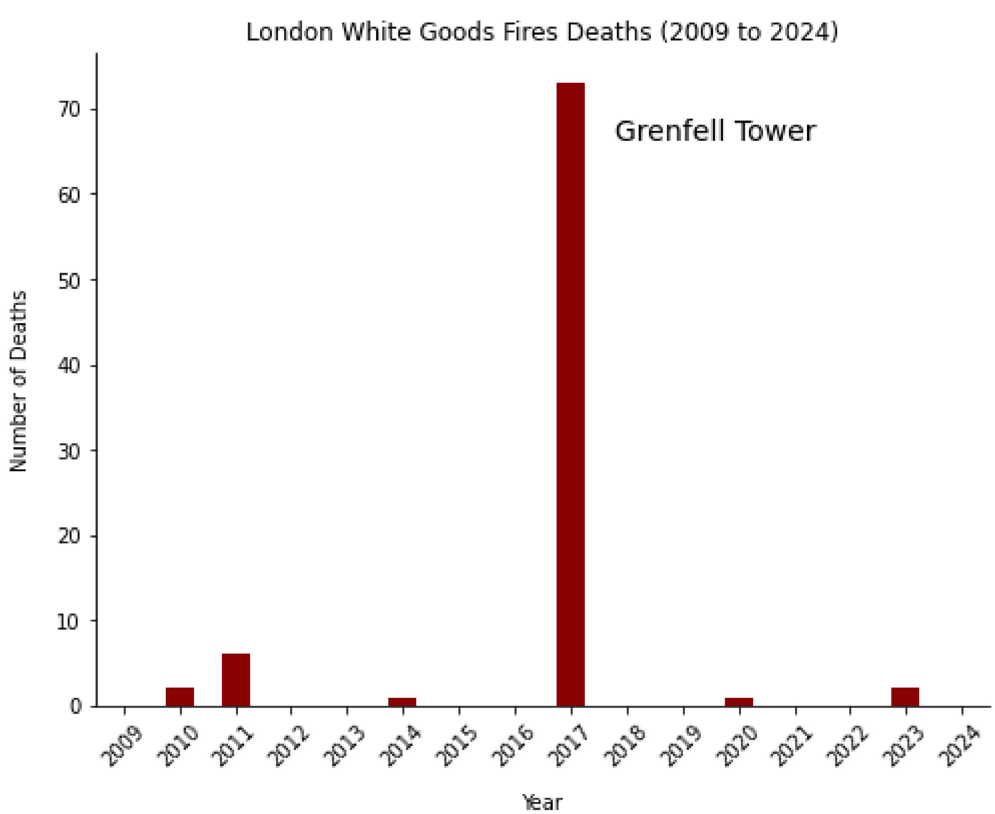
The one incident of 71 deaths relates to Grenfell Tower which was in Kensington and Chelsea

In [31]:
```
# Number of incidents by number of injuries
df['NumAllFireInjuries'].value_counts()
```

Out[31]:
```
0      4604
1       215
2        55
3        29
4        19
5         9
6         4
7         2
109       1
10        1
19        1
Name: NumAllFireInjuries, dtype: int64
```

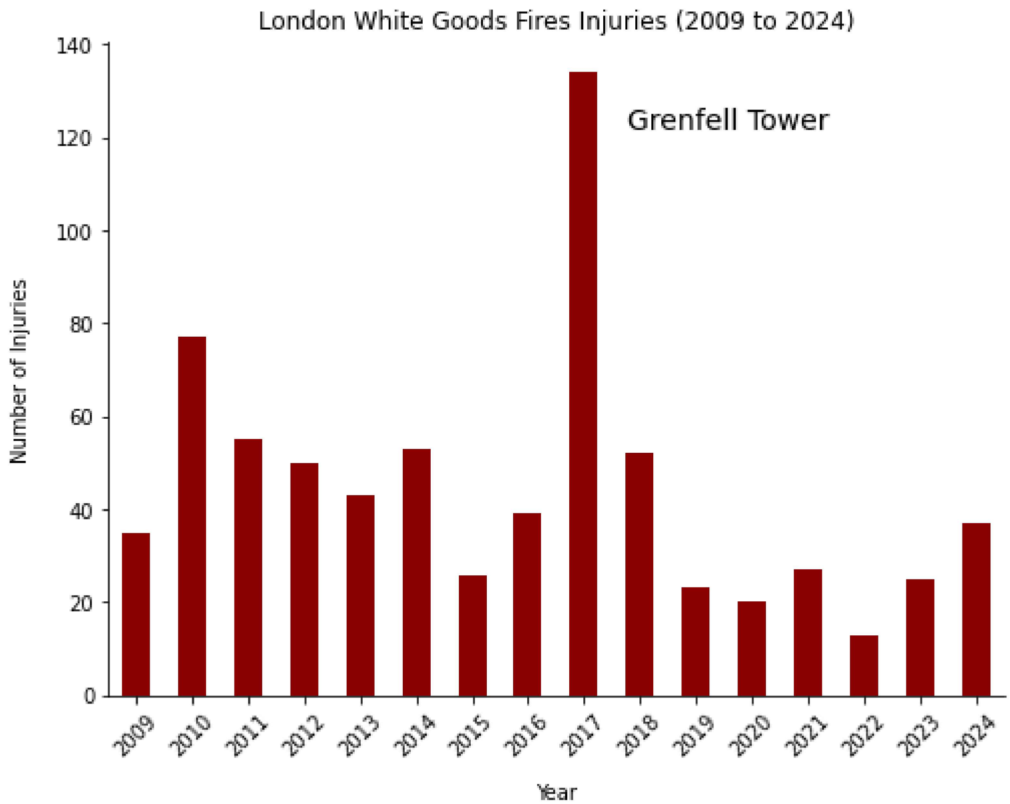
In [32]:
```
# Create function for plotting deaths and injuries

def plot_func3(df,X,Y,kind,t,xlab,ylab):
    fig,ax = plt.subplots(figsize = (8,6))
    df.groupby(X)[Y].sum().plot(kind = kind,
                                    title = t,
                                    color = 'darkred')
    ax.spines[['right', 'top']].set_visible(False)
    plt.xlabel(xlab, labelpad = 12)
    plt.ylabel(ylab, labelpad = 12)
    plt.xticks(rotation = 45)
    ax.text(0.58, 0.9, 'Grenfell Tower',
        fontsize=14,transform=ax.transAxes,
        verticalalignment='top');
```

In [33]:
```
# Plot deaths by year
plot_func3(df,"Year","NumFireDeaths",'bar','London White Goods Fires Deaths (2009 to 20
```



In [34]:

```
# Plot injuries by year
plot_func3(df,"Year",'NumAllFireInjuries','bar','London White Goods Fires Injuries (2009
```



In [35]:

```
df
```

Out[35]:

	Year	Month	IncType	ParentPropertyType	NumFireDeaths	NumAllFireInjuries	IncGeo_Boroug
0	2009	December	Primary Fire	Offices and call centres	0	0	E090
1	2009	July	Primary Fire	Food and Drink	0	0	E090
2	2009	December	Primary Fire	House in Multiple Occupation	0	0	E090
3	2009	April	Primary Fire	Purpose Built Flats/Maisonettes	0	0	E090
4	2009	May	Primary Fire	Food and Drink	0	0	E090
...	...	...	...	...	...	...	
4935	2024	July	Primary Fire	Purpose Built Flats/Maisonettes	0	0	E090
4936	2024	October	Primary Fire	Purpose Built Flats/Maisonettes	0	0	E090
4937	2024	July	Primary Fire	Dwelling	0	0	E090

	Year	Month	IncType	ParentPropertyType	NumFireDeaths	NumAllFireInjuries	IncGeo_Boroug
4938	2024	August	Primary Fire	Retail	0	0	E090
4939	2024	July	Primary Fire	Road Vehicle	0	0	E090

4940 rows × 18 columns

Total of 85 deaths and 707 injuries over the 16 year period which equates to 5 and 47 per year on average
The Grenfell Tower incident stands out as an outlier on the chart, where 71 lives were lost and 109 injuries occurred in June 2017
An electrical fire expert says the blaze probably started from a Hotpoint fridge-freezer in Flat 16 of the tower block. A photo of the small wire connector which is thought to have overheated and started the fire was shown to the inquiry. It was recovered from a small relay compressor compartment at the bottom rear of the fridge-freezer unit.

Source

Fires by IncGeo_BoroughCode

In [36]:
```
# Top Five Locations
df.groupby('IncGeo_BoroughCode')['IncGeo_BoroughCode'].count().sort_values(ascending =
```

Out[36]:
```
IncGeo_BoroughCode
E09000008    260
E09000003    251
E09000028    204
E09000022    200
E09000023    195
E09000009    189
E09000033    188
E09000032    182
E09000006    182
E09000017    170
Name: IncGeo_BoroughCode, dtype: int64
```

In [37]:
```
# Top Five Locations
df.groupby('IncGeo_BoroughName')['IncGeo_BoroughName'].count().sort_values(ascending =
```

Out[37]:
```
IncGeo_BoroughName
BARNET        145
CROYDON       144
LAMBETH       128
SOUTHWARK     125
Croydon       116
WANDSWORTH    112
LEWISHAM      112
BROMLEY       110
EALING        108
```

```
Barnet         106
Name: IncGeo_BoroughName, dtype: int64
```

We have some data cleaning to do with the borough names that are not consistently entered in terms of the free text. For example in the top ten by count of incidents we can see that Barnet and Croydon are shown twice, in upper case and proper case. We could use a reference table but first we will try just setting the case to a consistent case.

In [38]:

```
# Set to title case
df['BoroughName'] = df['IncGeo_BoroughName'].str.title()
```

In [39]:

```
# Check the value counts by borough
df['BoroughName'].value_counts()
```

Out[39]:

```
Croydon                   260
Barnet                    251
Southwark                 204
Lambeth                   200
Lewisham                  195
Ealing                    189
Westminster               188
Bromley                   182
Wandsworth                182
Hillingdon                170
Enfield                   164
Hackney                   162
Brent                     158
Greenwich                 152
Tower Hamlets             148
Waltham Forest            148
Haringey                  144
Hounslow                  142
Bexley                    140
Islington                 139
Newham                    138
Redbridge                 137
Havering                  136
Hammersmith And Fulham    127
Camden                    124
Harrow                    120
Sutton                    118
Kensington And Chelsea    113
Barking And Dagenham      112
Merton                    104
Kingston Upon Thames       89
Richmond Upon Thames       84
City Of London             20
Name: BoroughName, dtype: int64
```

We can see the number of fires by borough and that Croydon, Barnet, Southwark and Lambeth are the top of the table. However, this is a little meaningless without using a base like population to be able to compare properly. We will find some population figures and bring these in to make this comparison

In [58]:

```
pop = pd.read_csv(r'C:\Users\imoge\AllMLProjects\Data\housing-density-borough.csv')
```

In [59]:

```
pop.head()
```

Out[59]:

	Code	Name	Year	Source	Population	Inland_Area _Hectares	Total_Area_Hectares	Population_per_hecta
0	E09000001	City of London	1999	ONS MYE	6581	290.4	314.9	22
1	E09000001	City of London	2000	ONS MYE	7014	290.4	314.9	24
2	E09000001	City of London	2001	ONS MYE	7359	290.4	314.9	25
3	E09000001	City of London	2002	ONS MYE	7280	290.4	314.9	25
4	E09000001	City of London	2003	ONS MYE	7115	290.4	314.9	24

In [60]:

```
# Select data for the year 2021 (last census) and just the columns we want
pop2021 = pop[pop['Year']==2021]
pop2021 = pop2021[['Code','Population']]
pop2021.head()
```

Out[60]:

	Code	Population
22	E09000001	8164
74	E09000002	221495
126	E09000003	411275
178	E09000004	256845
230	E09000005	346437

In [62]:

```
sum(pop2021['Population'])
```

Out[62]: 27894072

Now we need to merge the data with our fire table based on the Borough Code

In [43]:

```
borough_fires = df.groupby(['IncGeo_BoroughCode','BoroughName'],as_index = False)['Year
borough_fires = borough_fires.merge(pop2021, left_on = 'IncGeo_BoroughCode', right_on =
borough_fires.drop(columns = 'Code',axis = 1, inplace = True)
borough_fires.columns = ['Code','BoroughName','Fires','Population']
borough_fires['FiresPer000Pop'] = borough_fires['Fires']/borough_fires['Population']*10
borough_fires.sort_values(by = 'FiresPer000Pop',ascending = False)
```

Out[43]:

	Code	BoroughName	Fires	Population	FiresPer000Pop
0	E09000001	City Of London	20	8164	2.449780
32	E09000033	Westminster	188	262317	0.716690

	Code	BoroughName	Fires	Population	FiresPer000Pop
19	E09000020	Kensington And Chelsea	113	161552	0.699465
12	E09000013	Hammersmith And Fulham	127	195981	0.648022
7	E09000008	Croydon	260	403461	0.644424
27	E09000028	Southwark	204	332679	0.613204
2	E09000003	Barnet	251	411275	0.610297
22	E09000023	Lewisham	195	320574	0.608284
21	E09000022	Lambeth	200	342250	0.584368
18	E09000019	Islington	139	244372	0.568805
11	E09000012	Hackney	162	292023	0.554751
28	E09000029	Sutton	118	213340	0.553108
3	E09000004	Bexley	140	256845	0.545076
31	E09000032	Wandsworth	182	337783	0.538807
5	E09000006	Bromley	182	339466	0.536136
16	E09000017	Hillingdon	170	319467	0.532136
10	E09000011	Greenwich	152	294837	0.515539
15	E09000016	Havering	136	265930	0.511413
8	E09000009	Ealing	189	369685	0.511246
1	E09000002	Barking And Dagenham	112	221495	0.505655
30	E09000031	Waltham Forest	148	292788	0.505485
17	E09000018	Hounslow	142	286947	0.494865
13	E09000014	Haringey	144	291330	0.494285
23	E09000024	Merton	104	214740	0.484307
20	E09000021	Kingston Upon Thames	89	184660	0.481967
6	E09000007	Camden	124	259344	0.478129
9	E09000010	Enfield	164	346635	0.473120
4	E09000005	Brent	158	346437	0.456071
14	E09000015	Harrow	120	263484	0.455436
29	E09000030	Tower Hamlets	148	331620	0.446294
25	E09000026	Redbridge	137	316288	0.433150
26	E09000027	Richmond Upon Thames	84	203312	0.413158
24	E09000025	Newham	138	366943	0.376080

In [66]:

```
borough_fires['Fires100000Pop'] = borough_fires['FiresPer000Pop']*100
borough_fires
```

Out[66]:

	Code	BoroughName	Fires	Population	FiresPer000Pop	Fires100000Pop
0	E09000001	City Of London	20	8164	2.449780	244.977952
1	E09000002	Barking And Dagenham	112	221495	0.505655	50.565476
2	E09000003	Barnet	251	411275	0.610297	61.029725
3	E09000004	Bexley	140	256845	0.545076	54.507582
4	E09000005	Brent	158	346437	0.456071	45.607138
5	E09000006	Bromley	182	339466	0.536136	53.613617
6	E09000007	Camden	124	259344	0.478129	47.812943
7	E09000008	Croydon	260	403461	0.644424	64.442412
8	E09000009	Ealing	189	369685	0.511246	51.124606
9	E09000010	Enfield	164	346635	0.473120	47.312014
10	E09000011	Greenwich	152	294837	0.515539	51.553909
11	E09000012	Hackney	162	292023	0.554751	55.475082
12	E09000013	Hammersmith And Fulham	127	195981	0.648022	64.802200
13	E09000014	Haringey	144	291330	0.494285	49.428483
14	E09000015	Harrow	120	263484	0.455436	45.543562
15	E09000016	Havering	136	265930	0.511413	51.141278
16	E09000017	Hillingdon	170	319467	0.532136	53.213634
17	E09000018	Hounslow	142	286947	0.494865	49.486491
18	E09000019	Islington	139	244372	0.568805	56.880494
19	E09000020	Kensington And Chelsea	113	161552	0.699465	69.946519
20	E09000021	Kingston Upon Thames	89	184660	0.481967	48.196686
21	E09000022	Lambeth	200	342250	0.584368	58.436815
22	E09000023	Lewisham	195	320574	0.608284	60.828389
23	E09000024	Merton	104	214740	0.484307	48.430660
24	E09000025	Newham	138	366943	0.376080	37.608021
25	E09000026	Redbridge	137	316288	0.433150	43.314953
26	E09000027	Richmond Upon Thames	84	203312	0.413158	41.315810
27	E09000028	Southwark	204	332679	0.613204	61.320372
28	E09000029	Sutton	118	213340	0.553108	55.310772
29	E09000030	Tower Hamlets	148	331620	0.446294	44.629395
30	E09000031	Waltham Forest	148	292788	0.505485	50.548520
31	E09000032	Wandsworth	182	337783	0.538807	53.880746
32	E09000033	Westminster	188	262317	0.716690	71.669011

In [68]:

```
# Save out for use in power bi
borough_fires.to_csv('C:/Users/imoge/AllMLProjects/Data/LondonPopFires.csv')
```

When we bring in population data, we can see that the highest number of white goods fires by borough is in the City of London, which has a relatively small population (and large number of commuters for work).
We could look a bit more at this borough to see what types of fires and types of property etc are involved if we wished

Fires by Ignition Source Power and Ignition Source

In [44]:

```
# Source of ignition
df['IgnitionSourcePower'].value_counts(normalize = True)*100
```

Out[44]:

```
Electricity       99.716599
Not applicable     0.101215
Gas - cylinder     0.060729
Other              0.060729
Unknown            0.060729
Name: IgnitionSourcePower, dtype: float64
```

Unsurprisingly, most fires have an electrical source

In [45]:

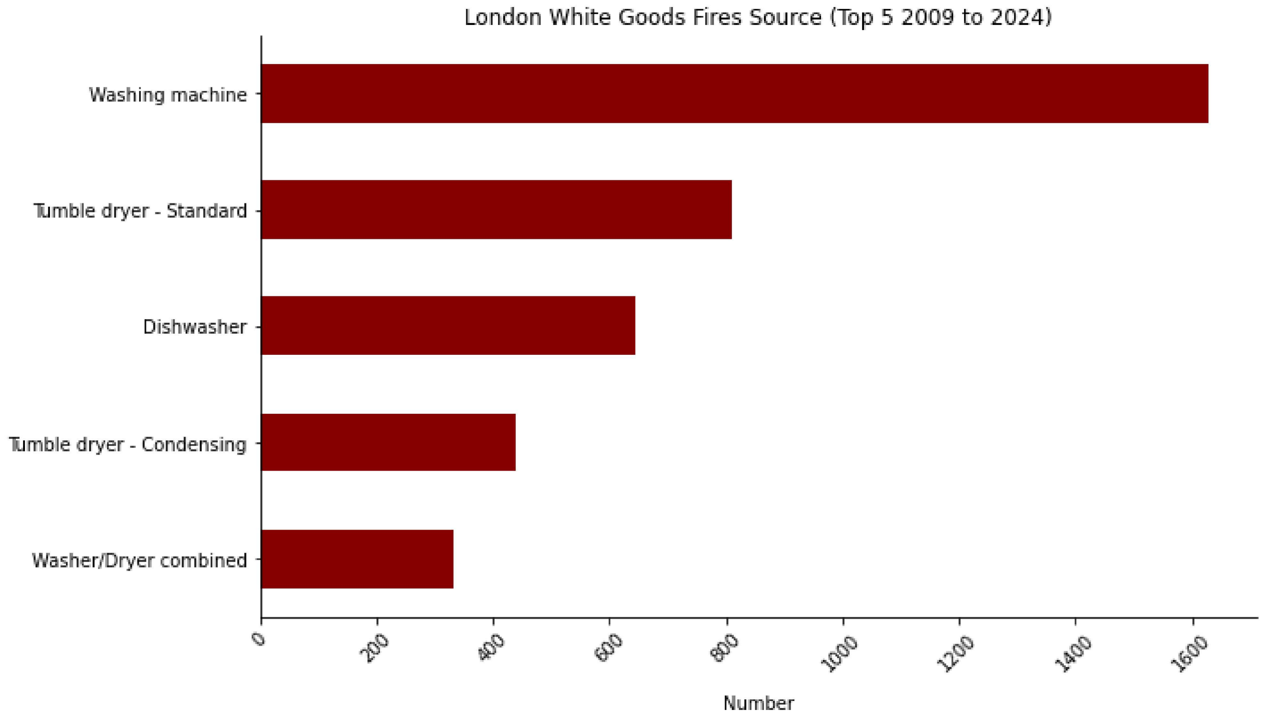
```
# Source of fire
df['IgnitionSource'].value_counts(normalize = True)*100
```

Out[45]:

```
Washing machine                  32.975709
Tumble dryer - Standard          16.396761
Dishwasher                       13.036437
Tumble dryer - Condensing         8.906883
Washer/Dryer combined             6.740891
Fridge/Freezer - Freestanding     5.951417
Fridge/Freezer                    5.202429
Fridge - Freestanding             3.319838
Freezer - Freestanding            3.137652
Spin dryer                        1.801619
Fridge/Freezer - Integrated       0.890688
Fridge - Integrated               0.829960
Freezer - Integrated              0.607287
Tumble dryer - Heat pump          0.202429
Name: IgnitionSource, dtype: float64
```

In [46]:

```
# Plot by fire source
plot_func2(df,"IgnitionSource","IgnitionSource","barh",'London White Goods Fires Source
         "Number",None)
```



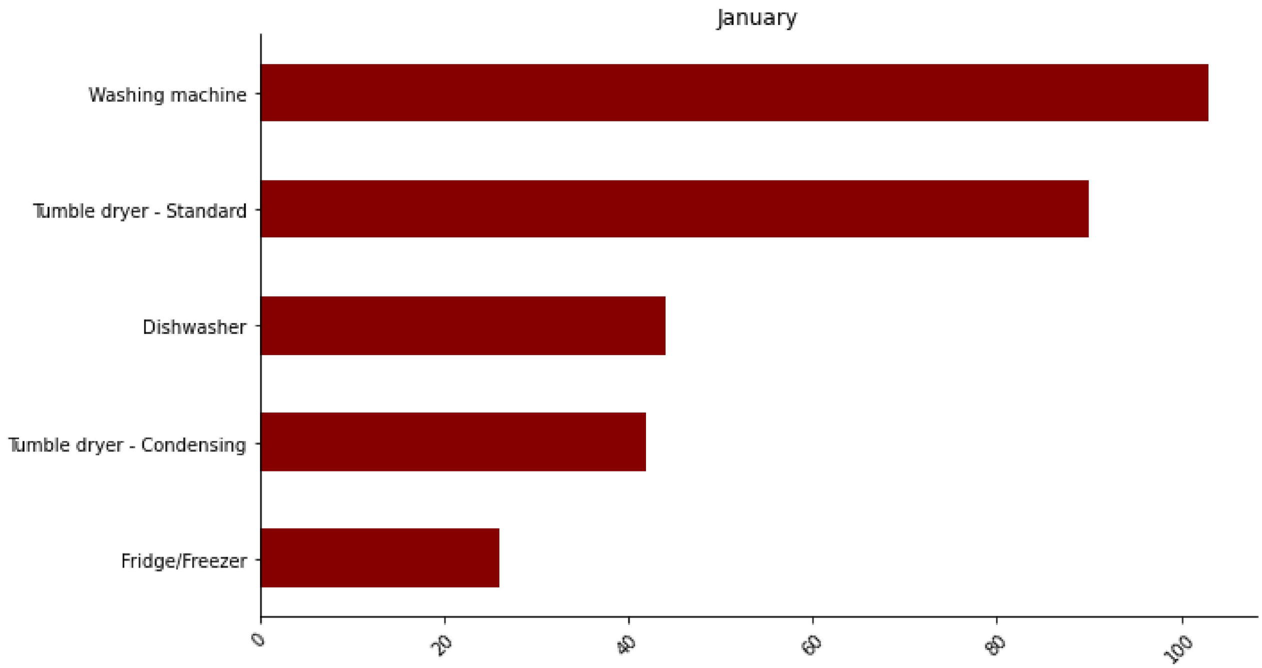
The top appliances involved are washing machines, tumble driers and dishwashers.Reflecting on our earlier findings of an increased number of fires towards the winter, the increased use of tumble driers in wetter weather might lead to increased number of fires. We could look at the type of white good fires by time of year that might provide more insight on this.

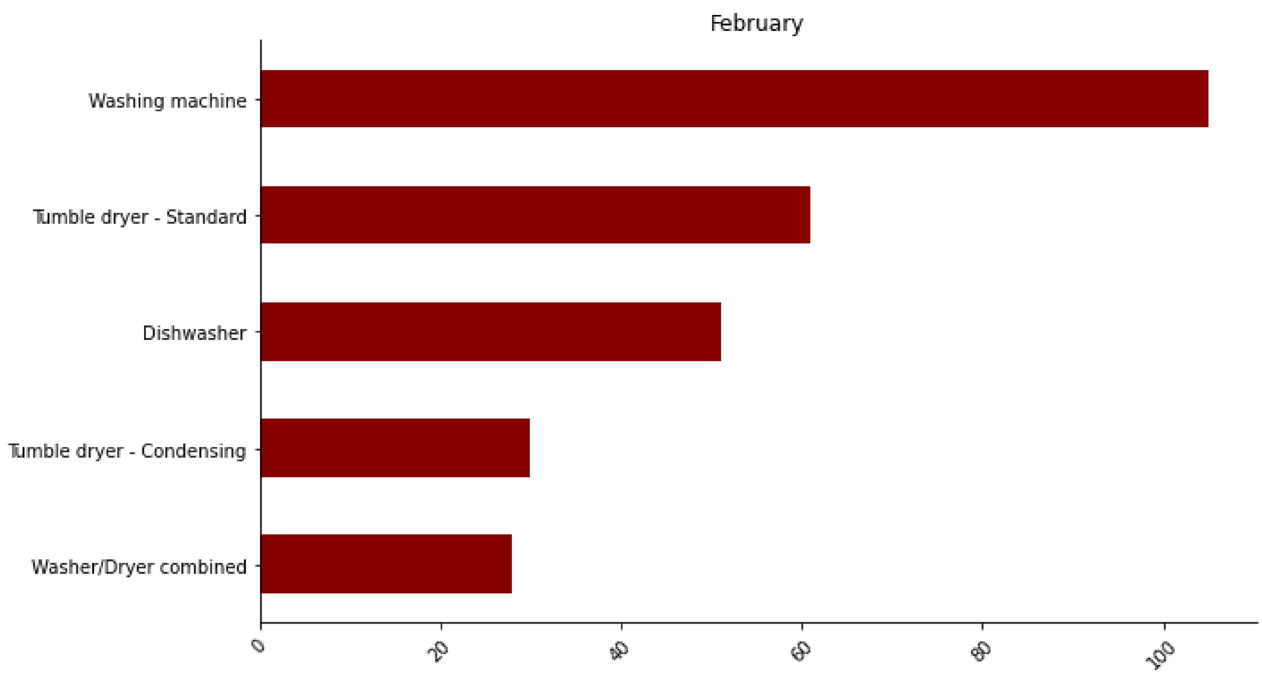
In [47]:

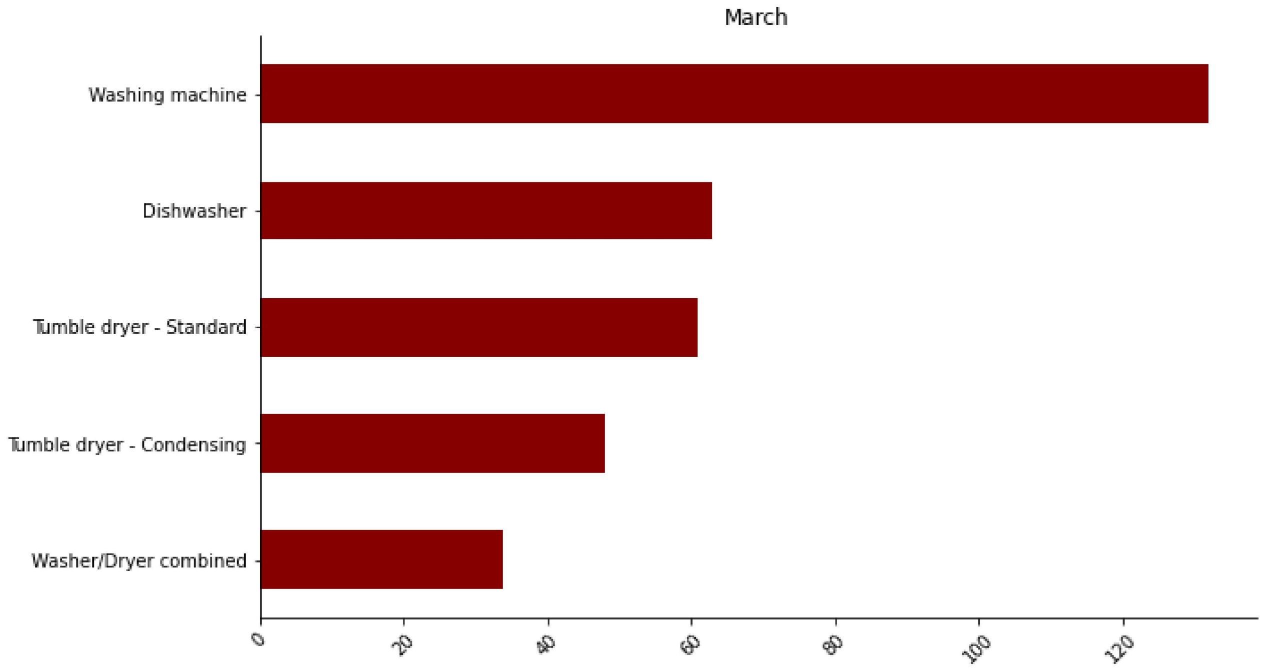
```
# Create list of months and sort in order of months
from calendar import month_name
month_lookup = list(month_name)
months = df['Month'].unique().tolist()
months = sorted(months, key=month_lookup.index)
```

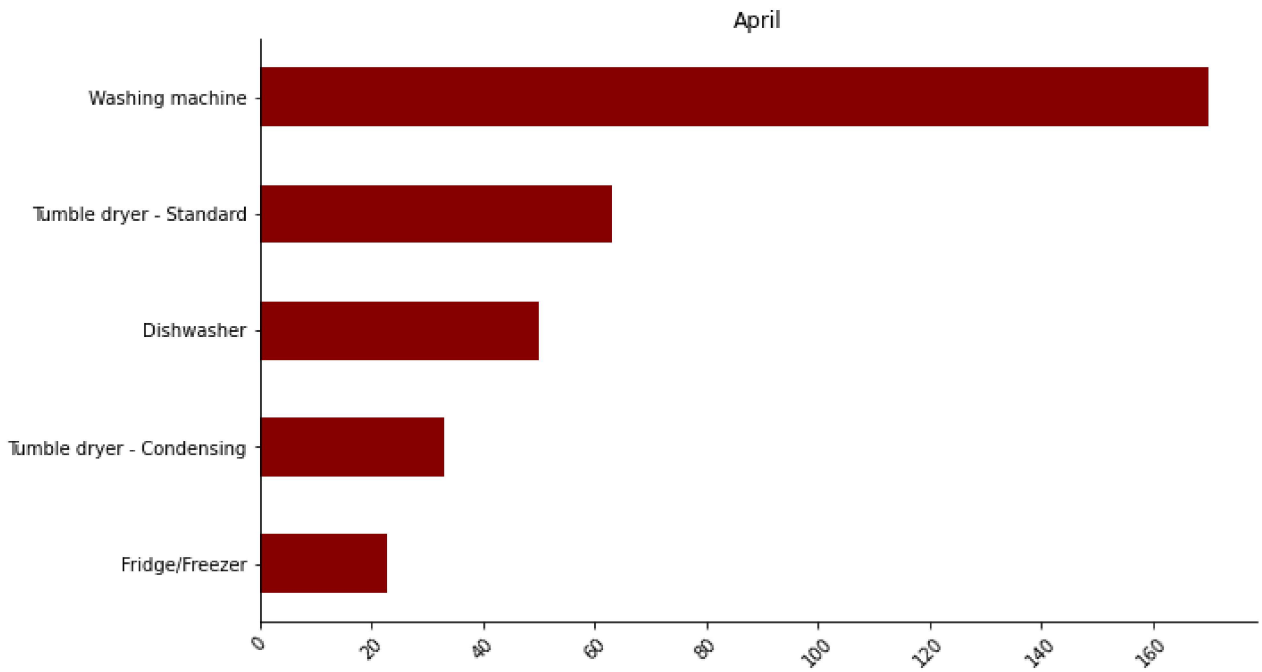
In [48]:

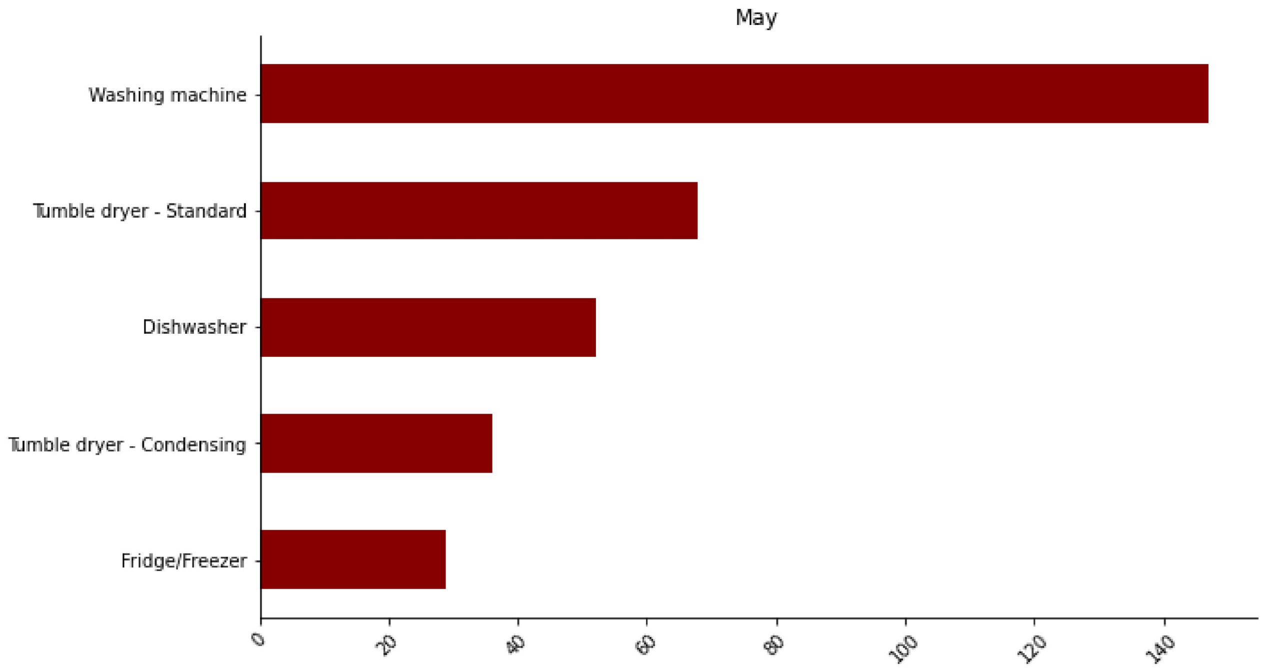
```
# Plot by fire source
for month in months:
    r = df[df['Month'] == month]
    plot_func2(r,"IgnitionSource","IgnitionSource","barh",month,
         None,None)
```

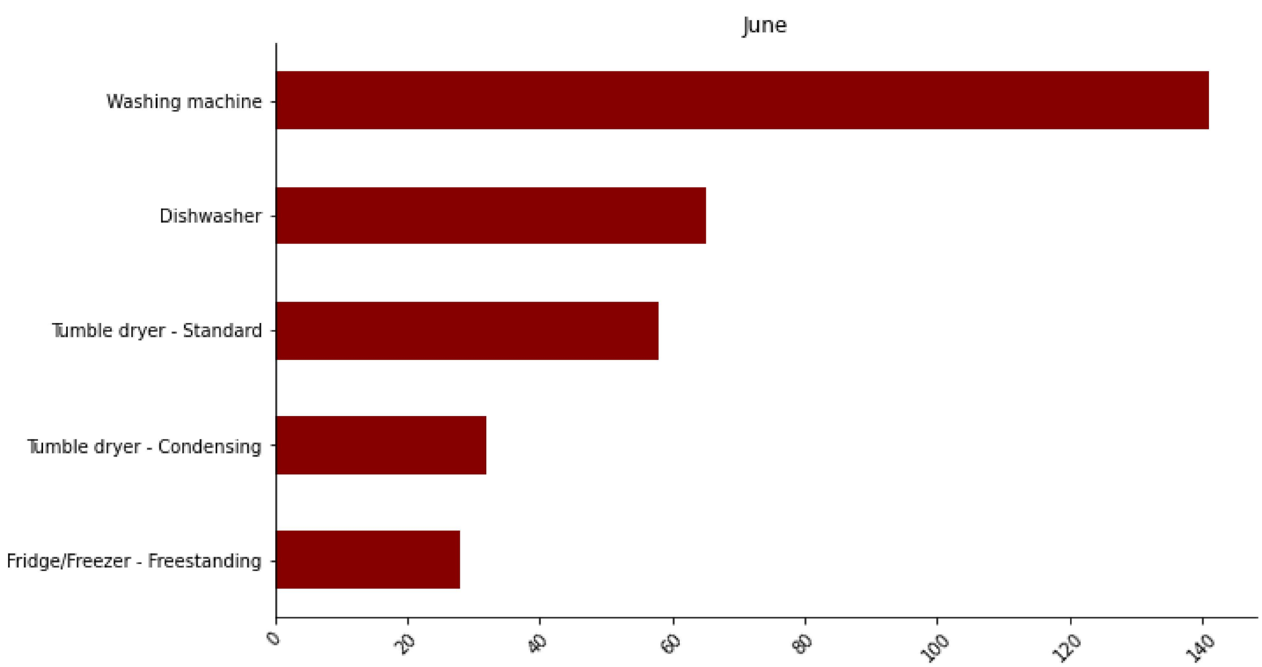

January
Washing machine
Tumble dryer - Standard
Dishwasher
Tumble dryer - Condensing
Fridge/Freezer
0
20
40
60
80
100

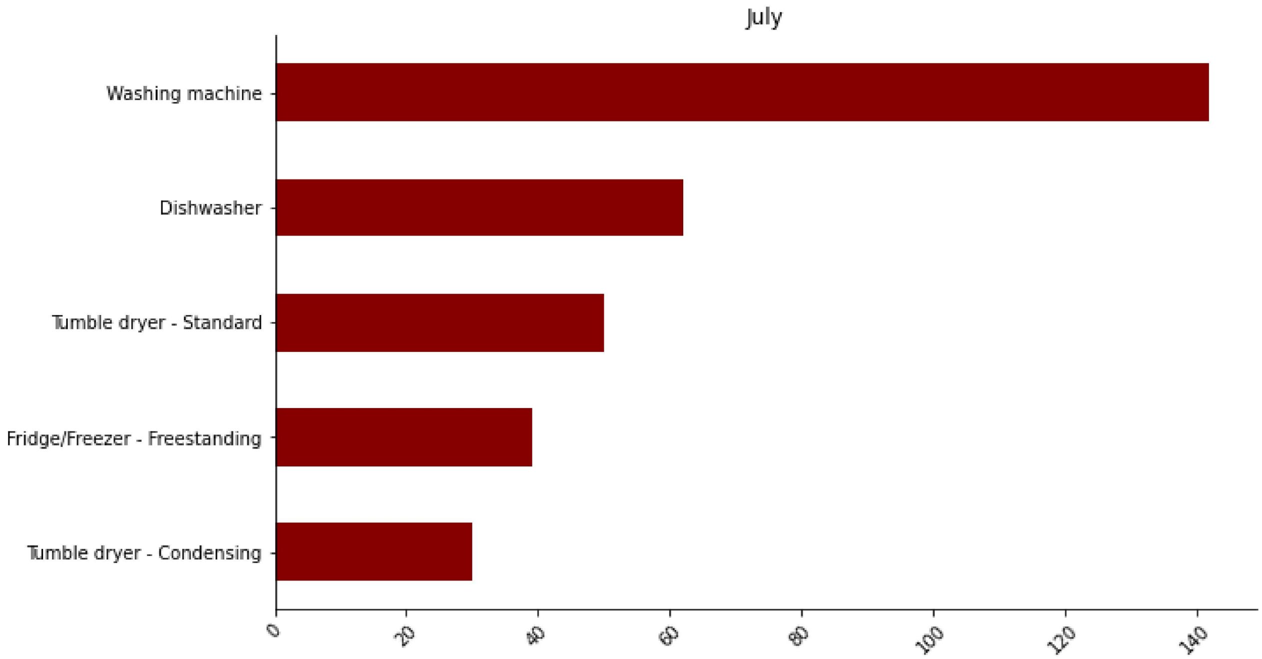

February
Washing machine
Tumble dryer - Standard
Dishwasher
Tumble dryer - Condensing
Washer/Dryer combined
0
20
40
60
80
100

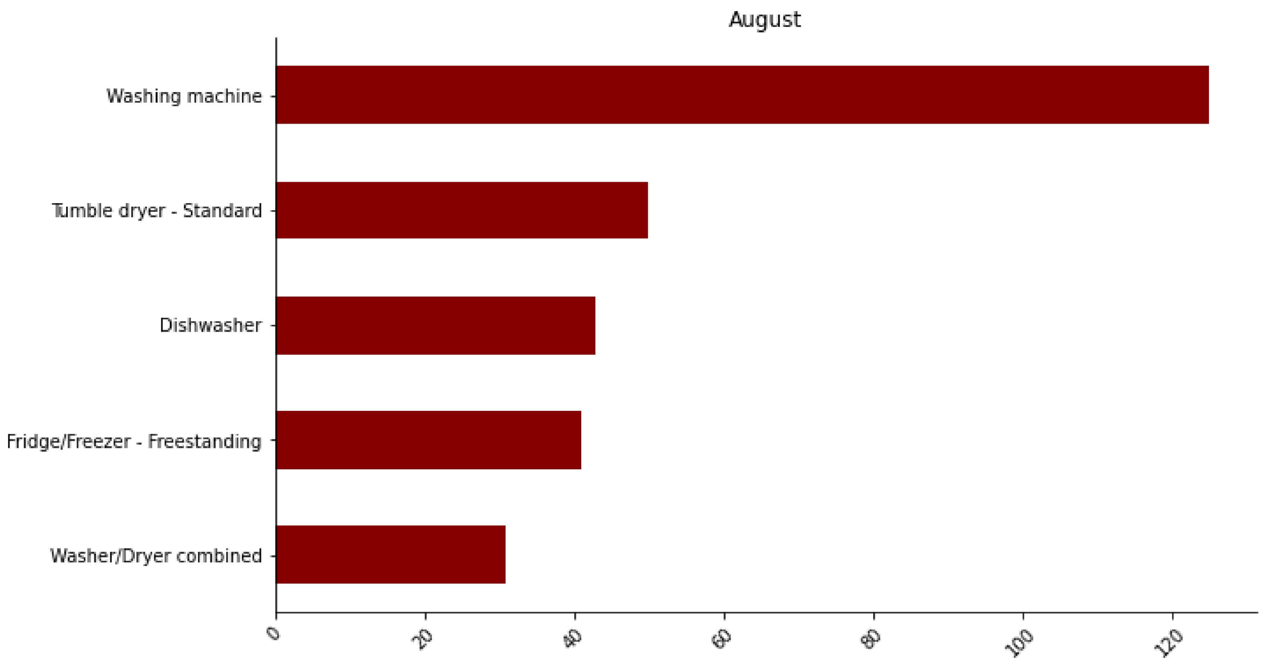

March
Washing machine
Dishwasher
Tumble dryer - Standard
Tumble dryer - Condensing
Washer/Dryer combined
0
20
40
60
80
100
120

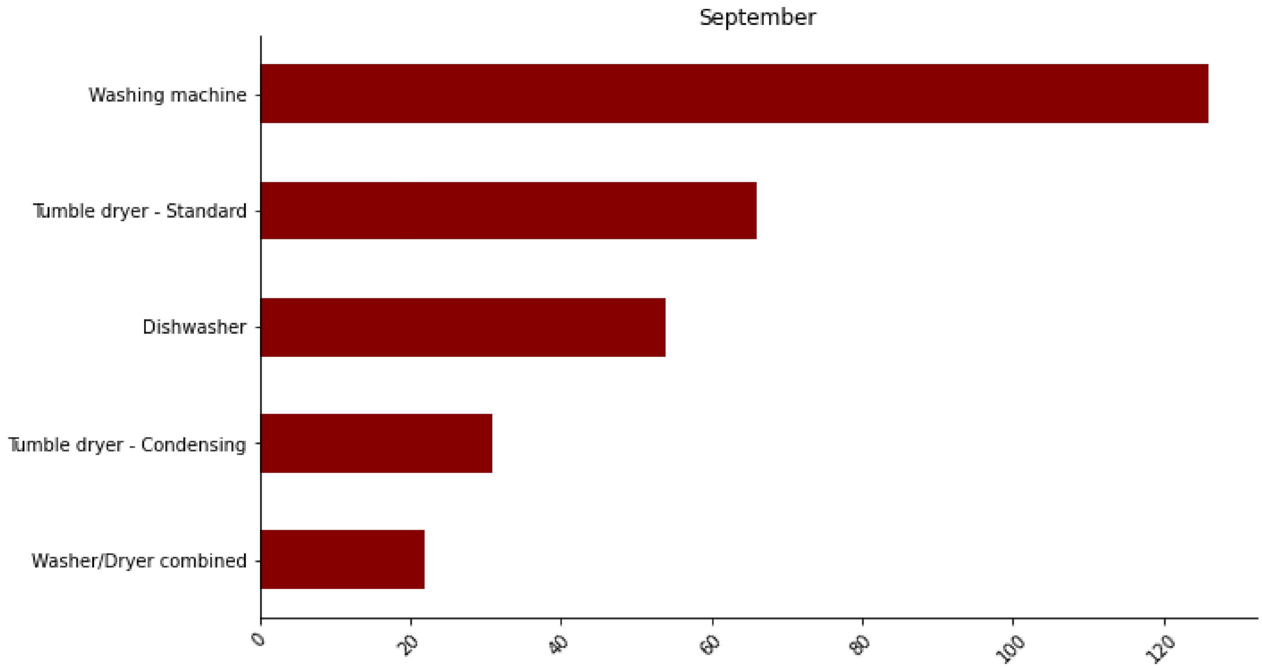

April
Washing machine
Tumble dryer - Standard
Dishwasher
Tumble dryer - Condensing
Fridge/Freezer
0
20
40
60
80
100
120
140
160

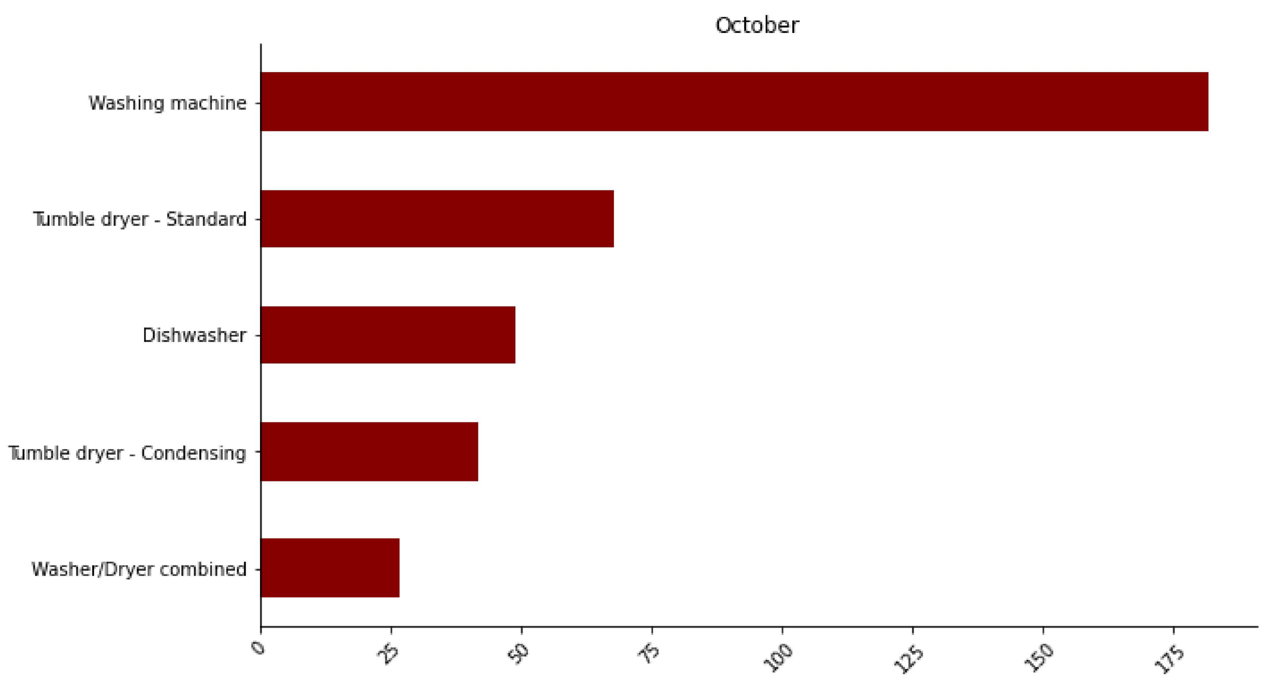

May
Washing machine
Tumble dryer - Standard
Dishwasher
Tumble dryer - Condensing
Fridge/Freezer
0
20
40
60
80
100
120
140

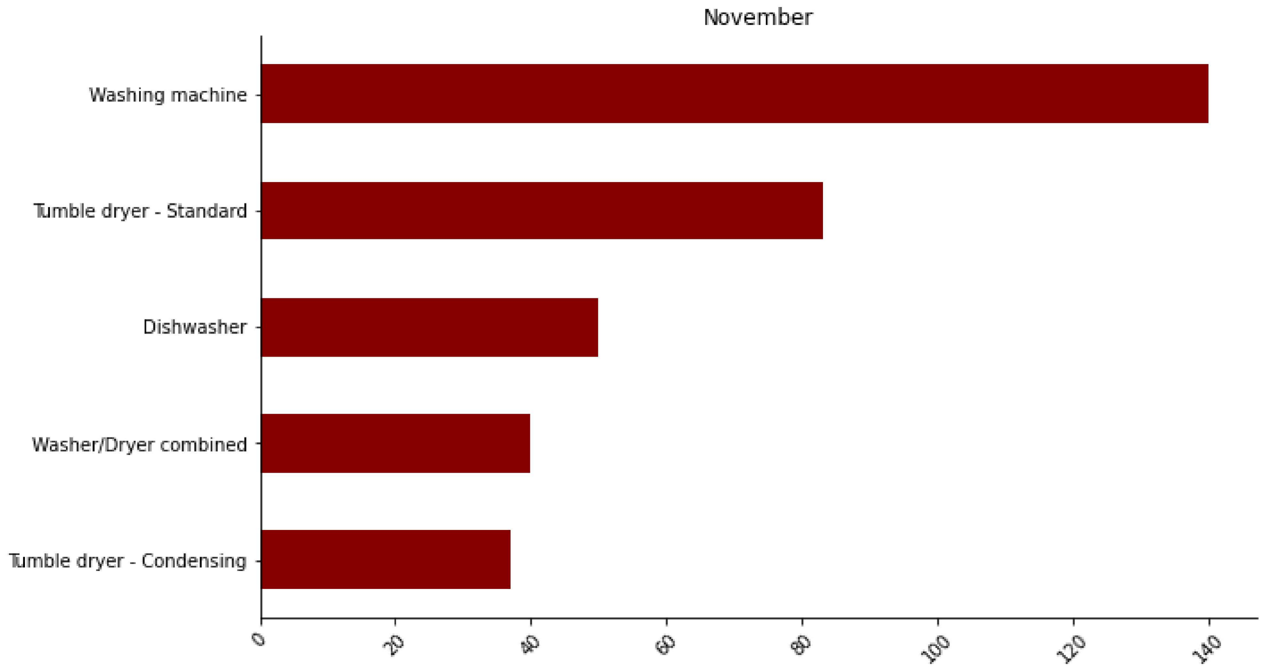

June
Washing machine
Dishwasher
Tumble dryer - Standard
Tumble dryer - Condensing
Fridge/Freezer - Freestanding
0
20
40
60
80
100
120
140

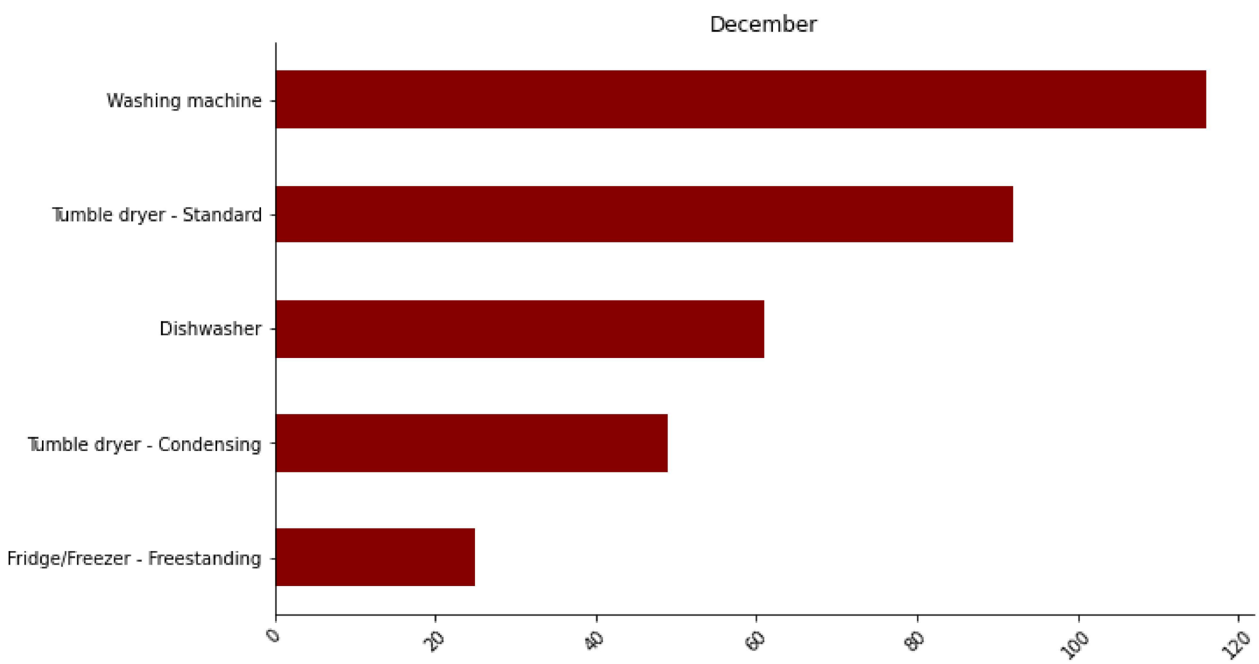

July
Washing machine
Dishwasher
Tumble dryer - Standard
Fridge/Freezer - Freestanding
Tumble dryer - Condensing
0
20
40
60
80
100
120
140


August
Washing machine
Tumble dryer - Standard
Dishwasher
Fridge/Freezer - Freestanding
Washer/Dryer combined
0
20
40
60
80
100
120


September
Washing machine
Tumble dryer - Standard
Dishwasher
Tumble dryer - Condensing
Washer/Dryer combined
0
20
40
60
80
100
120


October
Washing machine
Tumble dryer - Standard
Dishwasher
Tumble dryer - Condensing
Washer/Dryer combined
0
25
50
75
100
125
150
175





We can see that washing machines consistently account for the greatest number of fires followed by tumble driers,with the two categories being similar in the amount of fires for December and January. The exception is June and July where dishwashers take up the number two spot. This likely just reflects the reduced use of tumbledriers over the summer.

Fires by Item First Ignited

In [49]:

```
# Source of fire
df['ItemFirstIgnited'].value_counts(normalize = True)*100
```

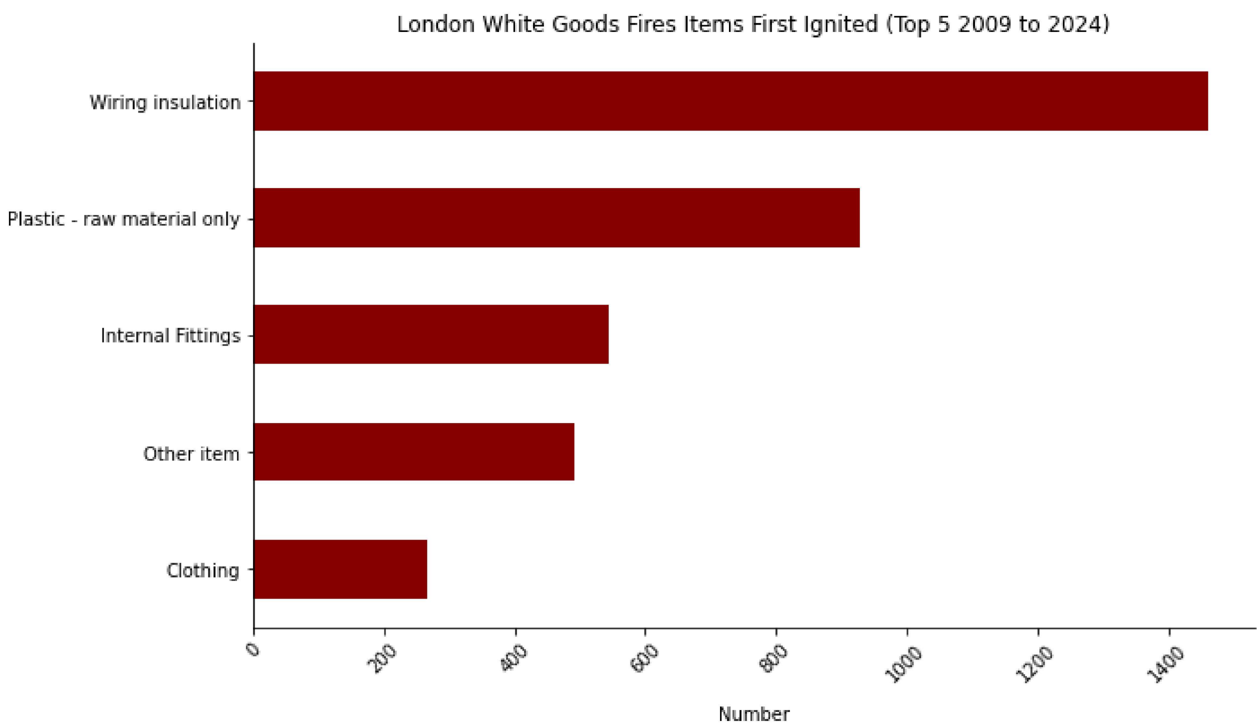
Out[49]:

```
Wiring insulation                                 29.554656
Plastic - raw material only                       18.785425
Internal Fittings                                 10.991903
Other item                                         9.939271
Clothing                                           5.384615
```

```
Not known                                          3.582996
Rubber - raw material only                         3.522267
None                                               3.340081
Printed circuit board                              3.198381
Other textiles                                     2.874494
Capacitor                                          2.834008
Unspecified internal fitting/part of structure     2.044534
Foam - raw material only                           0.931174
Other furniture                                    0.587045
Bedding                                            0.526316
Gases                                              0.323887
Other/Unspecified furnishings                      0.242915
Garden shed                                        0.202429
External fittings                                  0.182186
Other wooden item                                  0.161943
Rubbish/Waste material                             0.141700
Household paper/Cardboard                          0.101215
Floor coverings                                    0.101215
Incontinence Products                              0.080972
Unspecified external fitting/part of structure     0.080972
Petrol/Oil products                                0.060729
Roof                                               0.040486
Upholstered furniture                              0.040486
Other paper product                                0.040486
Paper, cardboard                                   0.020243
Cooking oil or fat                                 0.020243
Paint, varnish, resins, creosote                   0.020243
Other food (not oil or fat)                        0.020243
Bed/mattress                                       0.020243
Name: ItemFirstIgnited, dtype: float64
```

In [50]:

```
# Plot by items
plot_func2(df,"ItemFirstIgnited","ItemFirstIgnited","barh", 'London White Goods Fires I
         "Number",None)
```



Fires by Location

In [51]:

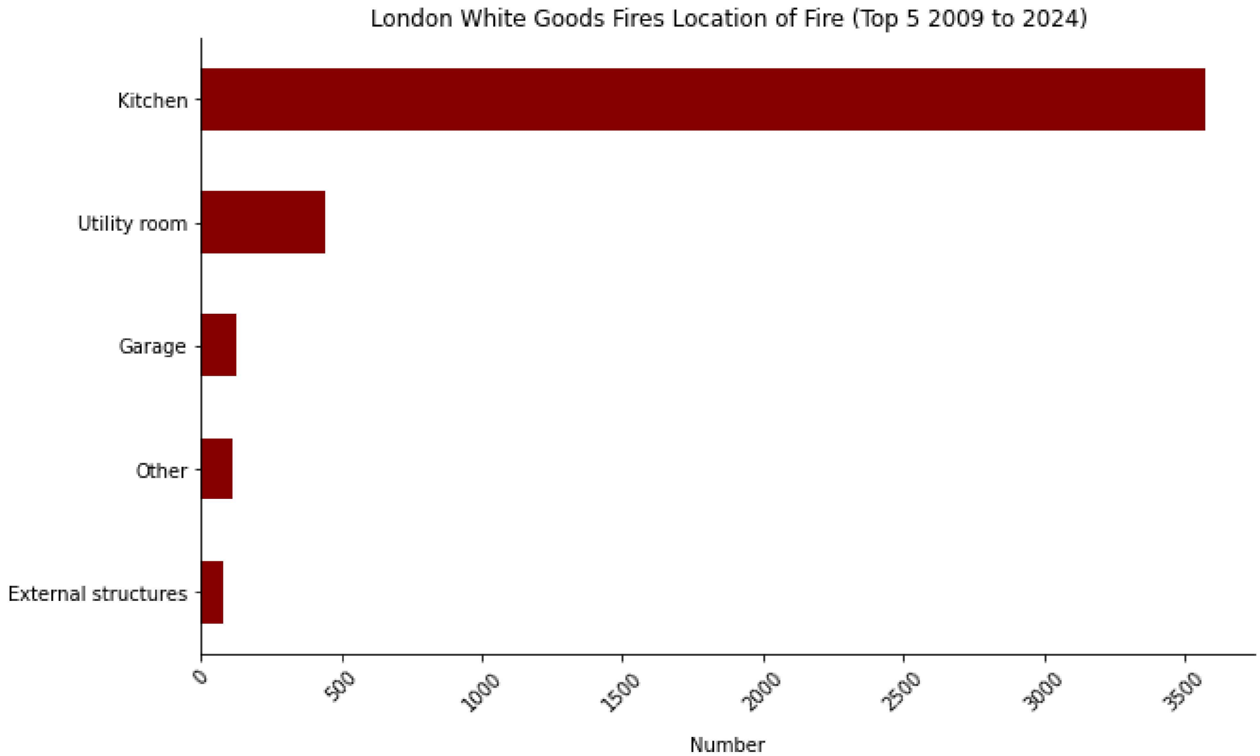
```
# Source of fire
df['LocationFireStarted'].value_counts(normalize = True)*100
```

Out[51]:

```
Kitchen                                    72.348178
Utility room                                8.967611
Garage                                      2.591093
Other                                       2.226721
External structures                         1.619433
Shop floor/Showroom/Display hall            1.619433
Corridor/Hall                               1.153846
Store room                                  1.032389
Laundry room                                1.012146
Living room                                 0.971660
Airing/Drying cupboard                      0.910931
Under stairs (enclosed, storage area)       0.890688
Bedroom                                     0.870445
Conservatory                                0.829960
Bathroom/Toilet                             0.809717
Canteen/Restaurant                          0.384615
Dining room                                 0.303644
Process/Production room                     0.222672
Bedsitting room                             0.202429
Meeting room                                0.161943
Office                                      0.141700
Private balcony                             0.141700
Other inside/Cargo area                     0.101215
Open plan area                              0.101215
Parking garage                              0.080972
Not known                                   0.080972
Communal balcony/Elevated walkway           0.040486
External fittings                           0.040486
Reception area                              0.040486
Barn                                        0.020243
Stairs                                      0.020243
Roof space                                  0.020243
Refuse store/Bin room                       0.020243
Driver/Passenger area                       0.020243
Name: LocationFireStarted, dtype: float64
```

In [52]:

```
# Plot by location
plot_func2(df,"LocationFireStarted","LocationFireStarted","barh",'London White Goods Fi
         "Number",None)
```



Fires by Appliance Manufacturer

In [53]:

```
# Missing values
df['ApplianceManufacturer'].isnull().sum()
```

Out[53]:

```
559
```

In [54]:

```
# Value counts
df['ApplianceManufacturer'].value_counts()
```

Out[54]:

```
HOTPOINT        835
Other           584
INDESIT         497
BEKO            371
BOSCH           345
               ... 
CANDLE            1
WARWICK           1
ARRON             1
SPEED QUEEN       1
AKAI              1
Name: ApplianceManufacturer, Length: 185, dtype: int64
```

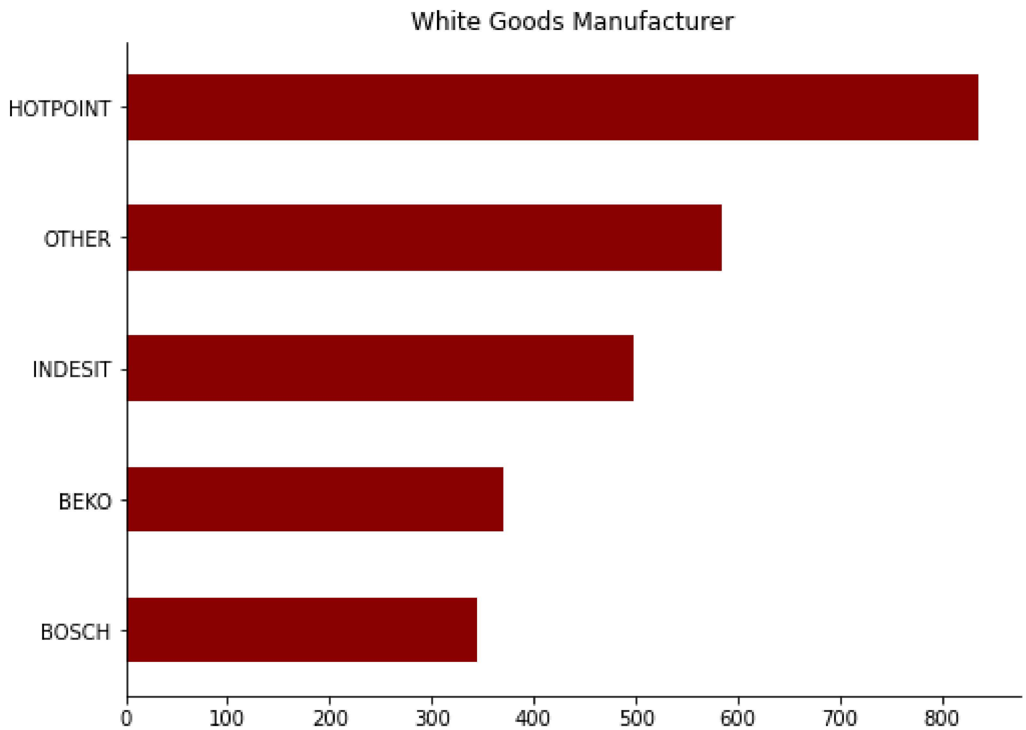
In [55]:

```
# Set the type to upper case
df['ApplianceManufacturer'] = df['ApplianceManufacturer'].str.upper()
```

In [56]:

```
# Select the top five
fig, ax = plt.subplots(figsize = (8,6))
man = df['ApplianceManufacturer'].value_counts().head(5)
man.plot(kind = 'barh',
         color = 'darkred',
        title = "White Goods Manufacturer")
```

```
ax.spines[['right', 'top']].set_visible(False)
ax.invert_yaxis();
```



Findings

- There appears to be a trend downwards of white goods fire incidents from 2018 with 2018 having the most, with the least in 2024.
- October has the highest number of incidents at 468 (average of 29 per year), with the least in February at 348 (average 21 per year).
- There is some seasonality in the data, with more fires in the autumn (particularly October) than in the summer. However, the lowest by month is February which is a short month.
- Washing machines consistently account for the greatest number of fires followed by tumble driers,with the two categories being similar in the total amount of fires for the months of December and January. In June and July dishwashers take up the number two spot. This likely just reflects the reduced use of tumbledriers over the summer.
- Unsurprisingly, most fires started in the kitchen (72%) where white goods are usually located, with a further 8% in utility rooms and the main causes are wiring insulation, plastic and internal fittings issues.
- We are missing over 500 datapoints for the manufacturer of the white good, so we should be careful drawing conclusions. However, from the data we do have, the top brand for problems is Hotpoint. This might not relate to anything in particular wrong with this brand, as it could just be the most popular manufacturer and we do not have any comparison data.
- Almost 85% of fires occur in dwellings, purpose built flats/maisonettes and converted flats and maisonettes. The rest mostly occur in non-residential settings such as retail and food and drink outlets.
- The greatest number of white good fires per head of population occur in the City of London and the least in Newham Borough. The City of London had almost three and a half times more

fires per head than the next borough in the list of Westminster.

- There was a total of 85 deaths and 707 injuries over the 16 year period which equates to 5 deaths and 47 injuries per year on average.
- The Grenfell Tower incident in June 2017 is a significant outlier in the dataset and accounted for 71 lives of the 85 lives lost (83%) and 109 injuries (15%) over the period.

Other questions we might ask

- Are there any other relationships between features, for example does the type of fire, location or item vary between boroughs, over time or month?
- Do white good fires happen more frequently in poorer neighbourhoods, perhaps because they are running older equipment?

In [57]:

```
# Save out file
df.to_csv(r'C:\Users\imoge\AllMLProjects\Data\WhiteGoodsCleaned')
```