Tarea1_Aravena_Uribe

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1 Tarea 1 DAML Prueba 2

1.0.1 Joaquín Araena Uribe

1.0.2 2021454110

[87]:
```
#Importamos las librerias

import pandas as pd
import missingno as msno
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import statsmodels.api as sm
import statsmodels.formula.api as smf
import sklearn
import scipy
from scipy.stats import nbinom
from statsmodels.iolib.summary2 import summary_col
import time as time

sns.set_palette("muted")
```

[88]:
```
#Funciones a utilizar

def cardinales(x):
    if x[0] == "N":
        return("N")
    elif x[0] == "S":
        return("S")
    elif x[0] == "E":
        return("E")
    else:
        return("W")
```

1.0.3 Parte 1

Tratamiento de datos

```
[89]: df = pd.read_csv("machine_failure_data.csv") #Leemos el dataframe
df["Failure_today"] = df["Failure_today"].apply(lambda x: 0 if x == "No" else␣
 ↪1) #Modificamos la variable a binaria
#df["Leakage"] = df["Leakage"].apply(lambda x: 0 if x == 0 else 1)

df["Date"] = pd.to_datetime(df["Date"], format="%m/%d/%Y") #Aplicamos arreglo a␣
 ↪las fechas
df = df[~df["Date"].dt.year.isin([2007,2008,2009])]
df["Date"] = df["Date"].dt.date
df["Date"] = df["Date"].astype(str)

df["Fecha"] = pd.to_datetime(df["Date"])
df["Año"] = df["Fecha"].dt.year.apply(str)
df["Mes"] = df["Fecha"].dt.month
#df["Trimestre"] = df["Mes"].apply(lambda x: f"T{((x - 1) // 3) + 1}")
df["Mes"] = df["Mes"].apply(str)

#df["Electricity"] = df["Electricity"].fillna(0)
#df["Evaporation"] = df["Evaporation"].fillna(0)
#df["Electricity_NaN"] = df["Electricity"].isna().astype(int)
#df["Evaporation_NaN"] = df["Evaporation"].isna().astype(int)

df_mask = df[(df["Location"] == 17) | (df["Location"] == 26) | (df["Location"]␣
 ↪== 42)| (df["Location"] == 46)| (df["Location"] == 19)] #Eliminamos años con␣
 ↪pocos datos
df_filtrado = df.drop(df_mask.index)
df = df_filtrado.reset_index(drop=True)

df
```

```
[89]:               Date  Location  Min_Temp  Max_Temp  Leakage  Evaporation  \
0       2010-01-01         3      19.4      31.9      5.0          NaN
1       2010-01-02         3      18.6      29.1     12.4          NaN
2       2010-01-03         3      12.2      29.7      0.0          NaN
3       2010-01-04         3      14.8      32.8      0.0          NaN
4       2010-01-05         3      15.0      35.8      0.0          NaN
…              …        …        …         …        …            …
114562  2017-06-20        14      19.3      33.4      0.0          6.0
114563  2017-06-21        14      21.2      32.6      0.0          7.6
114564  2017-06-22        14      20.7      32.8      0.0          5.6
114565  2017-06-23        14      19.5      31.8      0.0          6.2
114566  2017-06-24        14      20.2      31.7      0.0          5.6

        Electricity Parameter1_Dir  Parameter1_Speed Parameter2_9am  …  \
0               NaN            NNE              39.0             NW  …
1               NaN              W              56.0              S  …
2               NaN              W              30.0            SSW  …
```

```
3                NaN              SW              30.0             ENE  …
4                NaN               W              46.0               E  …
…              …             …               …              …   …
114562          11.0             ENE              35.0              SE  …
114563           8.6               E              37.0              SE  …
114564          11.0               E              33.0               E  …
114565          10.6             ESE              26.0              SE  …
114566          10.7             ENE              30.0             ENE  …

       Parameter5_9am  Parameter5_3pm  Parameter6_9am  Parameter6_3pm  \
0              1012.2          1008.5             NaN             1.0
1              1007.8          1006.2             5.0             NaN
2              1014.4          1012.5             NaN             NaN
3              1017.5          1013.6             NaN             NaN
4              1014.9          1011.5             NaN             NaN
…                 …               …              …              …
114562         1013.9          1010.5             0.0             1.0
114563         1014.6          1011.2             7.0             0.0
114564         1015.3          1011.8             0.0             0.0
114565         1014.9          1010.7             1.0             1.0
114566         1013.9          1009.7             6.0             5.0

        Parameter7_9am  Parameter7_3pm  Failure_today      Fecha   Año  Mes
0                 23.4            30.9              1 2010-01-01  2010    1
1                 20.6            28.0              1 2010-01-02  2010    1
2                 18.0            28.0              0 2010-01-03  2010    1
3                 21.3            30.6              0 2010-01-04  2010    1
4                 23.3            34.9              0 2010-01-05  2010    1
…                  …              …              …         …    …    …
114562            24.5            32.3              0 2017-06-20  2017    6
114563            24.8            32.0              0 2017-06-21  2017    6
114564            24.8            32.1              0 2017-06-22  2017    6
114565            24.8            29.2              0 2017-06-23  2017    6
114566            25.4            31.0              0 2017-06-24  2017    6

[114567 rows x 25 columns]
```

[90]:

```python
#Eliminamos columnas que no vamos a ocupar

df = df.drop(columns=["Electricity", #Muchos NaN

                      "Evaporation", #Muchos NaN
                      "Leakage",
                      "Parameter6_9am",
                      "Parameter6_3pm",
                      "Parameter1_Dir"
                      #"Parameter2_9am",
```

```
                                #"Parameter2_3pm"
                                ]
)

#Eliminamos datos faltantes
df.dropna(inplace=True)
#df["Parameter1_Dir"] = df["Parameter1_Dir"].apply(cardinales)
df["Parameter2_9am"] = df["Parameter2_9am"].apply(cardinales) #Aplicamos␣
 ↪funcion para direcciones cardinales
df["Parameter2_3pm"] = df["Parameter2_3pm"].apply(cardinales)
df = df.reset_index(drop=True)
```

[91]:
```
df #Dataframe limpio
```

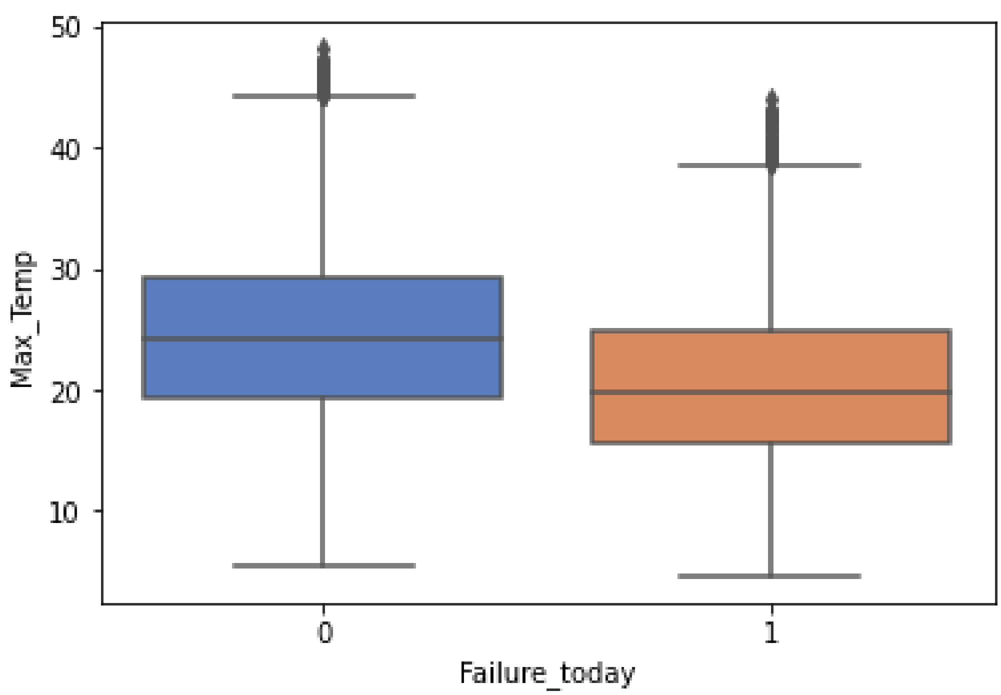
[91]:
```
             Date  Location  Min_Temp  Max_Temp  Parameter1_Speed  \
0      2010-01-01         3      19.4      31.9              39.0
1      2010-01-02         3      18.6      29.1              56.0
2      2010-01-03         3      12.2      29.7              30.0
3      2010-01-04         3      14.8      32.8              30.0
4      2010-01-05         3      15.0      35.8              46.0
…             …         …         …         …                 …
91384  2017-06-20        14      19.3      33.4              35.0
91385  2017-06-21        14      21.2      32.6              37.0
91386  2017-06-22        14      20.7      32.8              33.0
91387  2017-06-23        14      19.5      31.8              26.0
91388  2017-06-24        14      20.2      31.7              30.0

      Parameter2_9am Parameter2_3pm  Parameter3_9am  Parameter3_3pm  \
0                  N              W             9.0             9.0
1                  S              W             6.0            28.0
2                  S              S             9.0            19.0
3                  E              N            11.0             9.0
4                  E              N             4.0            17.0
…                …              …               …               …
91384              S              N             9.0            20.0
91385              S              S            13.0            11.0
91386              E              W            17.0            11.0
91387              S              N             9.0            17.0
91388              E              N            15.0             7.0

       Parameter4_9am  Parameter4_3pm  Parameter5_9am  Parameter5_3pm  \
0                70.0            40.0          1012.2          1008.5
1                88.0            48.0          1007.8          1006.2
2                57.0            32.0          1014.4          1012.5
3                55.0            24.0          1017.5          1013.6
4                46.0            13.0          1014.9          1011.5
…                 …               …               …               …
```

```
91384              63.0             32.0         1013.9          1010.5
91385              56.0             28.0         1014.6          1011.2
91386              46.0             23.0         1015.3          1011.8
91387              62.0             58.0         1014.9          1010.7
91388              73.0             32.0         1013.9          1009.7

       Parameter7_9am  Parameter7_3pm  Failure_today      Fecha   Año  Mes
0                23.4            30.9              1 2010-01-01  2010    1
1                20.6            28.0              1 2010-01-02  2010    1
2                18.0            28.0              0 2010-01-03  2010    1
3                21.3            30.6              0 2010-01-04  2010    1
4                23.3            34.9              0 2010-01-05  2010    1
…                 …              …             …           …     …   ..
91384            24.5            32.3              0 2017-06-20  2017    6
91385            24.8            32.0              0 2017-06-21  2017    6
91386            24.8            32.1              0 2017-06-22  2017    6
91387            24.8            29.2              0 2017-06-23  2017    6
91388            25.4            31.0              0 2017-06-24  2017    6

[91389 rows x 19 columns]
```

Gráficos

[107]:
```
sns.boxplot(df,x="Failure_today",y="Max_Temp")
```

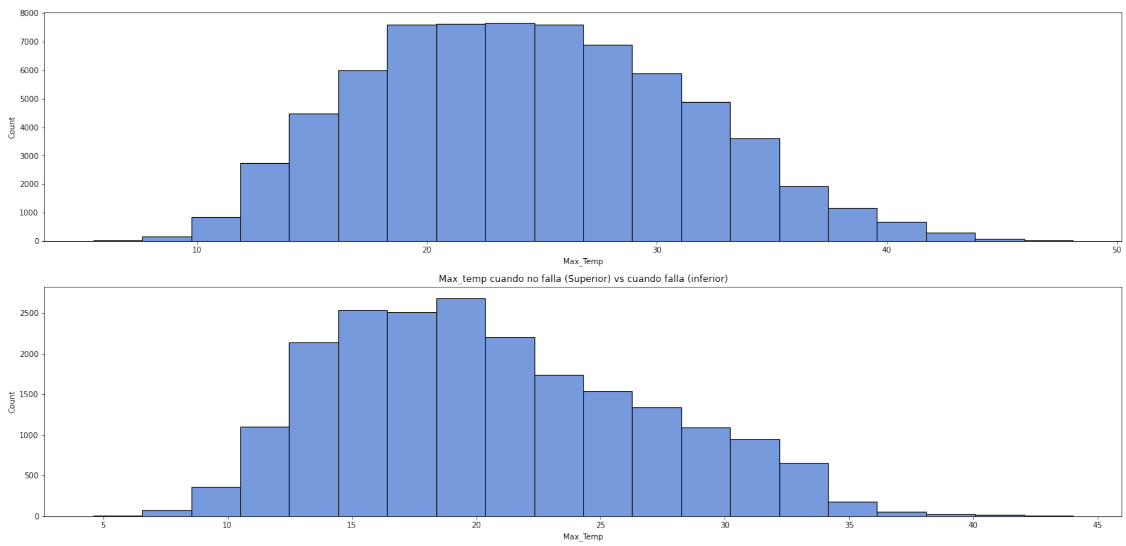
[107]: <Axes: xlabel='Failure_today', ylabel='Max_Temp'>



podemos ver que, cuando la maquina falla, su max_temp está centrada en una menor que cuando no falla

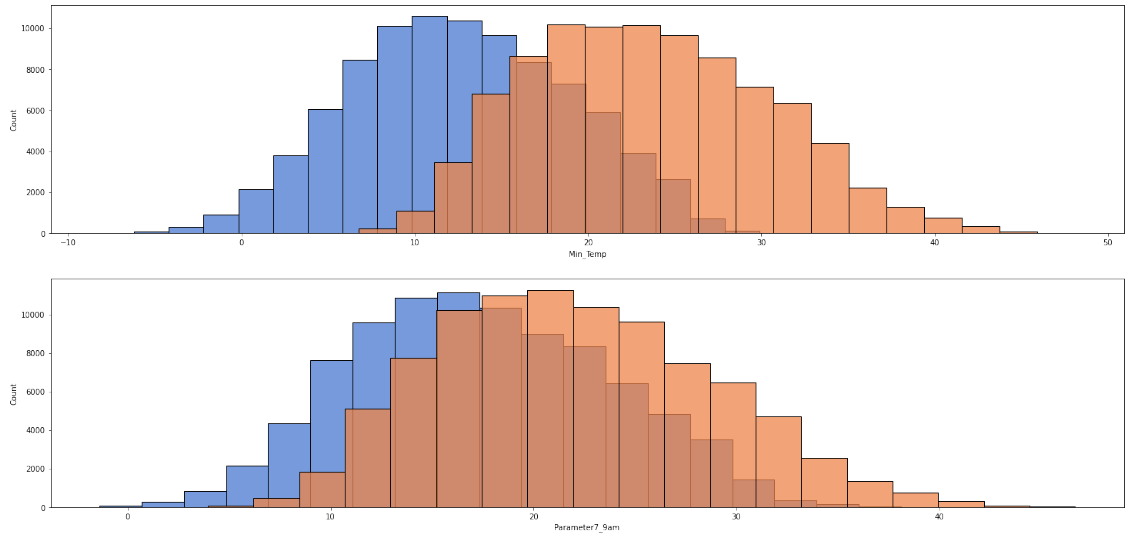
[130]:
```
fig, axes = plt.subplots(2, 1, figsize=(25, 12))
plt.title("Max_temp cuando no falla (Superior) vs cuando falla (inferior)")
sns.histplot(data=df[df["Failure_today"] == 0],x="Max_Temp",bins=20,ax=axes[0])
sns.histplot(data=df[df["Failure_today"] == 1],x="Max_Temp",bins=20,ax=axes[1])
```

[130]:
```
<Axes: title={'center': 'Max_temp cuando no falla (Superior) vs cuando falla
(inferior)'}, xlabel='Max_Temp', ylabel='Count'>
```



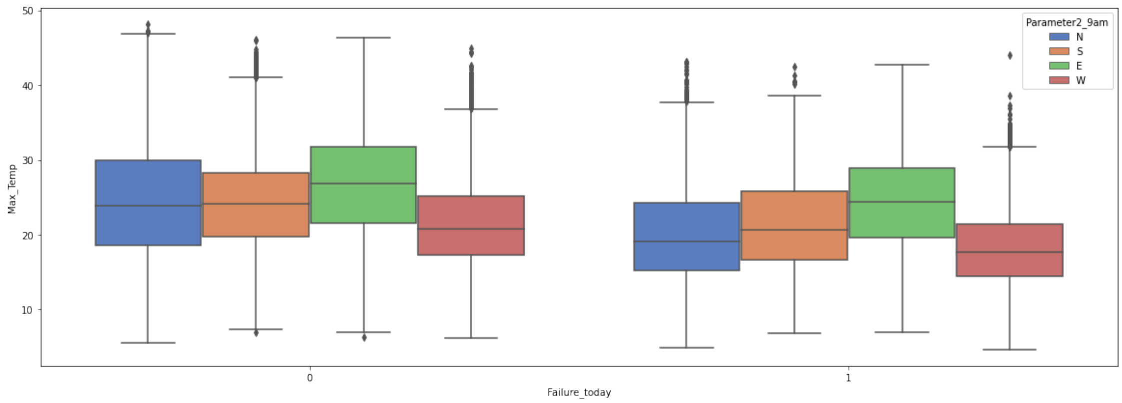
Este histograma nos entrega información diferenciada sobre la temperatura máxima en los casos que el sensor detectó un fallo y en los que no. Si bien se distribuyen de forma similar, podemos ver una leve diferencia en la forma, lo cual corrobora lo visto en el boxplot

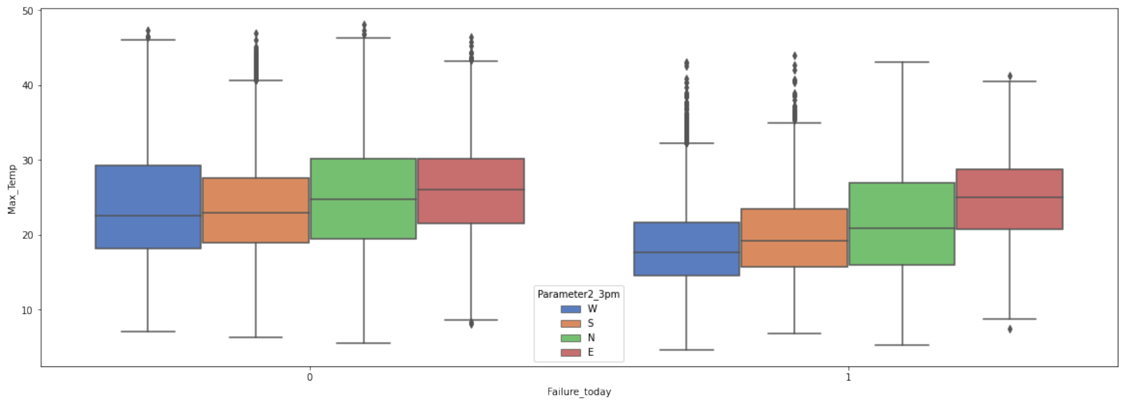
[93]:
```
fig, axes = plt.subplots(2, 1, figsize=(25, 12))
sns.histplot(data=df,x="Min_Temp",bins=20,ax=axes[0])
sns.histplot(data=df,x="Max_Temp",bins=20,ax=axes[0])
sns.histplot(data=df,x="Parameter7_9am",bins=20,ax=axes[1])
sns.histplot(data=df,x="Parameter7_3pm",bins=20,ax=axes[1])
plt.show()
```



Siguiendo con las temperaturas, nos interesa ver la relación de la temperatura maxima con la minima, y podemos notar que tanto en el parametro 7 como en la variable que mide esta se aprecia un comportamiento similar entre las 2 medidas

[94]:
```
fig, axes = plt.subplots(2, 1, figsize=(20, 15))
sns.boxplot(data=df, y="Max_Temp", x="Failure_today",hue="Parameter2_9am",ax=axes[0])
sns.boxplot(data=df, y="Max_Temp", x="Failure_today",hue="Parameter2_3pm",ax=axes[1])
plt.show()
```

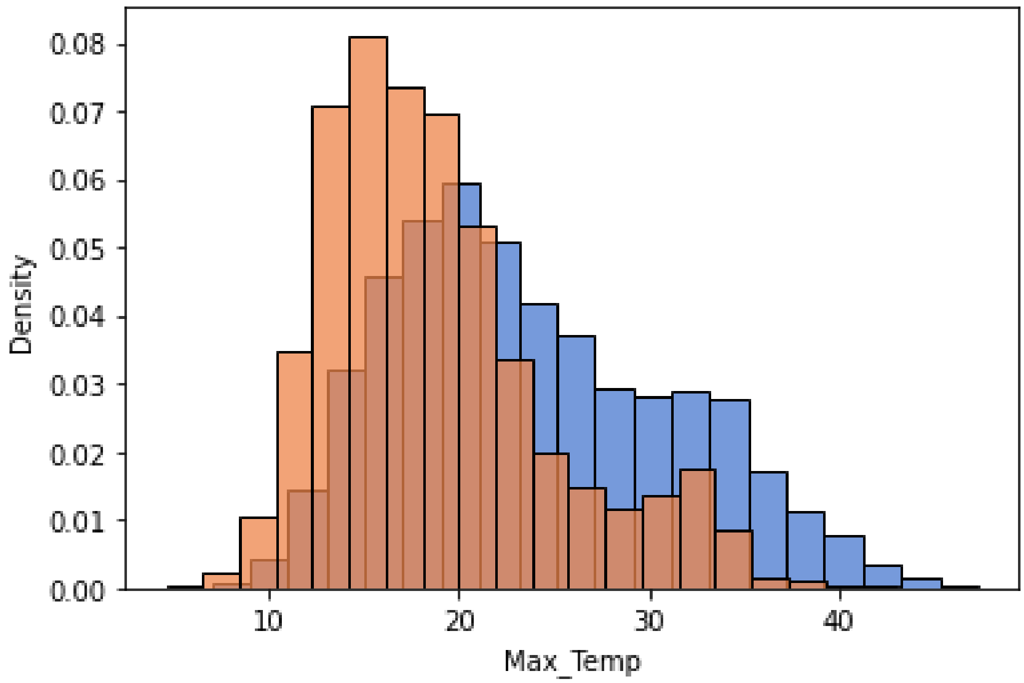




La principal diferencia la podemos encontrar a las 3pm cuando la dirección del viento corre hacia el Oeste. Para interpretar de mejor manera el fenomeno, se hace un histograma

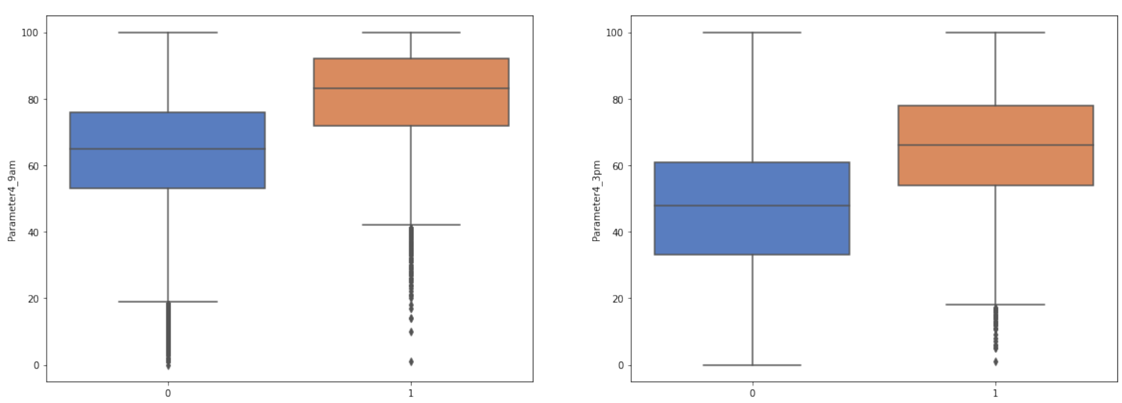
[95]:
```
sns.histplot(data=df[(df["Parameter2_3pm"] == "W") & (df["Failure_today"] == 0)],x="Max_Temp",stat="density",bins=20)
sns.histplot(data=df[(df["Parameter2_3pm"] == "W") & (df["Failure_today"] == 1)],x="Max_Temp",stat="density",bins=20)
```

[95]: <Axes: xlabel='Max_Temp', ylabel='Density'>



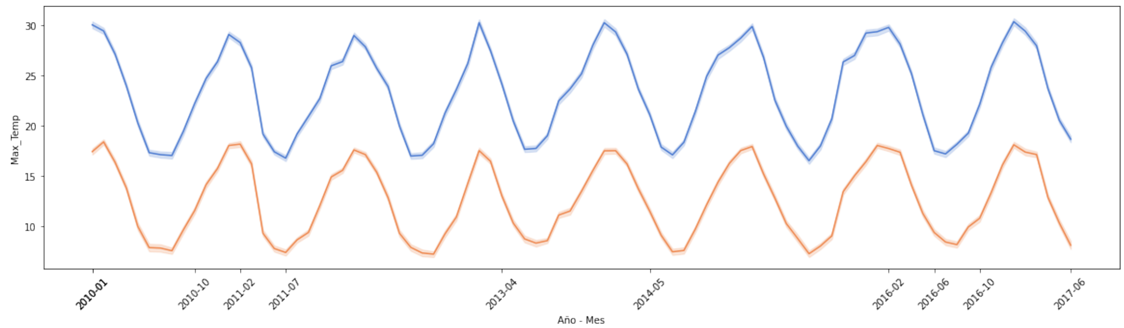
Podemos notar que en proporcion, cuando el viento corre al oeste y la temperatura maxima es mas baja cuando falla. Este comportamiento que identificamos en el boxplot se ve de forma mas clara en el histplot. Si bien, ya sabiamos el hecho de la temperatura, la presencia del viento acrecentua este efecto al parecer.

[96]:
```
fig, axes = plt.subplots(1, 2, figsize=(20, 7))
sns.boxplot(df,x="Failure_today",y="Parameter4_9am",ax=axes[0])
sns.boxplot(df,x="Failure_today",y="Parameter4_3pm",ax=axes[1])
plt.show()
```



Podemos ver que claramente, en ambos horarios, hay una diferencia en el valor centrar y los cuartiles cuando falla y cuando no el sensor. Además, durante la mañana el parametro revela un valor levemente mayor que la tarde

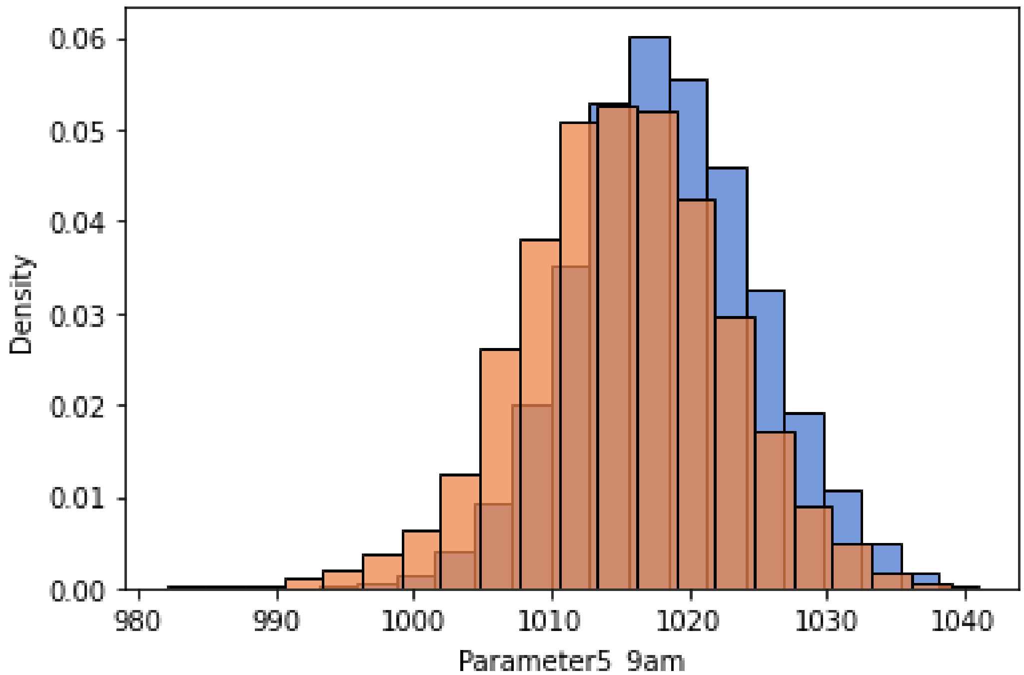
[132]:
```
plt.figure(figsize=(20,5))
sns.lineplot(data=df, x="Año - Mes", y="Max_Temp"); sns.lineplot(data=df,␣
↪x="Año - Mes", y="Min_Temp")
plt.xticks(df["Año - Mes"][::len(df)//10], rotation=45)
plt.show()
```



Podemos notar una clara estacionalidad en la temperatura maxima y minima

[99]:
```
sns.
↪histplot(df[df["Failure_today"]==0],x="Parameter5_9am",stat="density",bins=20)
sns.
↪histplot(df[df["Failure_today"]==1],x="Parameter5_9am",stat="density",bins=20)
```

[99]: <Axes: xlabel='Parameter5_9am', ylabel='Density'>

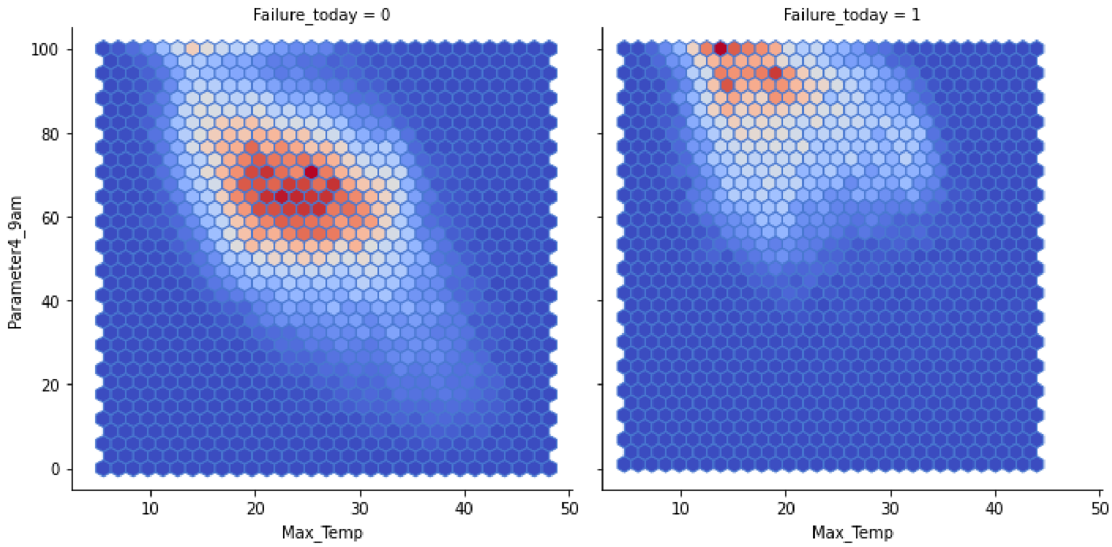


Vemos que hay un leve desplazamiento en el parametro 5 cuando falla el sensor

[100]:
```
g = sns.FacetGrid(df, col="Failure_today", height=5)
g.map_dataframe(plt.hexbin, x="Max_Temp", y="Parameter4_9am", gridsize=30,␣
    ↪cmap="coolwarm")
```

```
C:\Users\joaqu\AppData\Roaming\Python\Python39\site-
packages\seaborn\axisgrid.py:118: UserWarning: The figure layout has changed to
tight
  self._figure.tight_layout(*args, **kwargs)
```

[100]:
```
<seaborn.axisgrid.FacetGrid at 0x21825e85a30>
```



Este grafico que nos muestra la dependencia de 2 variables y su concentración de datos nos evidencia que, si bien no parece haber una relación entre max temp y el parametro 4, vemos que cuando falla estas 2 variables la concentración de la interacción se desplazan bastante en comparación a cuando no, teniendo una temperatura maxima menor pero un valor de parametro 4 mayor.

[101]:
```
df
```

[101]:
```
                Date  Location  Min_Temp  Max_Temp  Parameter1_Speed  \
0         2010-01-01         3      19.4      31.9              39.0
1         2010-01-02         3      18.6      29.1              56.0
2         2010-01-03         3      12.2      29.7              30.0
3         2010-01-04         3      14.8      32.8              30.0
4         2010-01-05         3      15.0      35.8              46.0
…                  …        …         …         …                 …
91384     2017-06-20        14      19.3      33.4              35.0
91385     2017-06-21        14      21.2      32.6              37.0
91386     2017-06-22        14      20.7      32.8              33.0
91387     2017-06-23        14      19.5      31.8              26.0
91388     2017-06-24        14      20.2      31.7              30.0

      Parameter2_9am Parameter2_3pm  Parameter3_9am  Parameter3_3pm  \
0                  N              W             9.0             9.0
1                  S              W             6.0            28.0
2                  S              S             9.0            19.0
3                  E              N            11.0             9.0
4                  E              N             4.0            17.0
…                …              …               …               …
91384              S              N             9.0            20.0
91385              S              S            13.0            11.0
```

```
91386              E              W          17.0            11.0
91387              S              N           9.0            17.0
91388              E              N          15.0             7.0

       Parameter4_9am  Parameter4_3pm  Parameter5_9am  Parameter5_3pm  \
0                70.0            40.0          1012.2          1008.5
1                88.0            48.0          1007.8          1006.2
2                57.0            32.0          1014.4          1012.5
3                55.0            24.0          1017.5          1013.6
4                46.0            13.0          1014.9          1011.5
…                 …              …              …              …
91384            63.0            32.0          1013.9          1010.5
91385            56.0            28.0          1014.6          1011.2
91386            46.0            23.0          1015.3          1011.8
91387            62.0            58.0          1014.9          1010.7
91388            73.0            32.0          1013.9          1009.7

       Parameter7_9am  Parameter7_3pm  Failure_today      Fecha   Año Mes  \
0                23.4            30.9              1 2010-01-01  2010   1
1                20.6            28.0              1 2010-01-02  2010   1
2                18.0            28.0              0 2010-01-03  2010   1
3                21.3            30.6              0 2010-01-04  2010   1
4                23.3            34.9              0 2010-01-05  2010   1
…                 …              …             …          …   …  ..
91384            24.5            32.3              0 2017-06-20  2017   6
91385            24.8            32.0              0 2017-06-21  2017   6
91386            24.8            32.1              0 2017-06-22  2017   6
91387            24.8            29.2              0 2017-06-23  2017   6
91388            25.4            31.0              0 2017-06-24  2017   6

      Año - Mes
0       2010-01
1       2010-01
2       2010-01
3       2010-01
4       2010-01
…         …
91384   2017-06
91385   2017-06
91386   2017-06
91387   2017-06
91388   2017-06

[91389 rows x 20 columns]
```

1.0.4 Parte 2

OLS

[103]:

```
y = df["Failure_today"]
X = df.copy()

X2 = X.copy()
X = pd.get_dummies(X, columns=["Location"], prefix=["Location"],␣
 ↪prefix_sep='__', drop_first=True)
X = X.drop(columns=["Failure_today",
                    "Date",
                    "Año",
                    #"Mes",
                    "Año - Mes",
                    "Fecha"],axis=1)
X = pd.get_dummies(X, columns=["Parameter2_9am",
                               "Parameter2_3pm",
                               "Mes",
                               #"Trimestre"
                               ], prefix_sep='__', drop_first=True)

X=sm.add_constant(X)
model = sm.OLS(y, X)
results = model.fit(cov_type='HC0')
print(results.summary())

#fail - c(location) - 1
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Failure_today   R-squared:                       0.303
Model:                            OLS   Adj. R-squared:                  0.302
Method:                 Least Squares   F-statistic:                     632.4
Date:                jue, 24 abr. 2025   Prob (F-statistic):               0.00
Time:                        20:42:54   Log-Likelihood:                -34482.
No. Observations:               91389   AIC:                         6.910e+04
Df Residuals:                   91322   BIC:                         6.973e+04
Df Model:                          66
Covariance Type:                  HC0
================================================================================
=====
                        coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
const                 8.1858      0.255     32.150      0.000       7.687
8.685
Min_Temp              0.0112      0.001     19.495      0.000       0.010
0.012
Max_Temp             -0.0340      0.001    -29.637      0.000      -0.036
-0.032
```

Parameter1_Speed	0.0055	0.000	34.996	0.000	0.005	0.006
Parameter3_9am	0.0027	0.000	12.944	0.000	0.002	0.003
Parameter3_3pm	-0.0042	0.000	-19.601	0.000	-0.005	-0.004
Parameter4_9am	0.0075	0.000	55.859	0.000	0.007	0.008
Parameter4_3pm	0.0024	0.000	15.119	0.000	0.002	0.003
Parameter5_9am	-0.0401	0.001	-46.347	0.000	-0.042	-0.038
Parameter5_3pm	0.0317	0.001	36.350	0.000	0.030	0.033
Parameter7_9am	-0.0030	0.001	-3.217	0.001	-0.005	-0.001
Parameter7_3pm	0.0279	0.001	21.921	0.000	0.025	0.030
Location__3	-0.0811	0.011	-7.689	0.000	-0.102	-0.060
Location__4	0.1070	0.009	11.403	0.000	0.089	0.125
Location__5	-0.0990	0.011	-9.030	0.000	-0.120	-0.077
Location__6	-0.2364	0.011	-21.411	0.000	-0.258	-0.215
Location__7	-0.1249	0.010	-12.422	0.000	-0.145	-0.105
Location__8	0.0024	0.011	0.218	0.828	-0.019	0.024
Location__9	-0.0604	0.012	-4.977	0.000	-0.084	-0.037
Location__10	-0.0909	0.011	-8.467	0.000	-0.112	-0.070
Location__11	-0.0305	0.009	-3.248	0.001	-0.049	-0.012
Location__12	-0.0405	0.012	-3.515	0.000	-0.063	-0.018
Location__13	-0.1704	0.012	-14.730	0.000	-0.193	-0.148
Location__14	-0.0989	0.012	-8.480	0.000	-0.122	-0.076
Location__15	-0.0719	0.011	-6.463	0.000	-0.094	-0.050
Location__16	-0.1550	0.011	-14.338	0.000	-0.176	-0.134
Location__18	-0.1516	0.013	-11.658	0.000	-0.177	-0.126

Location__20	-0.1727	0.011	-16.381	0.000	-0.193	-0.152
Location__21	-0.1057	0.009	-11.188	0.000	-0.124	-0.087
Location__22	-0.0350	0.010	-3.490	0.000	-0.055	-0.015
Location__23	-0.1038	0.011	-9.515	0.000	-0.125	-0.082
Location__27	-0.1477	0.011	-13.266	0.000	-0.170	-0.126
Location__28	-0.1500	0.011	-13.145	0.000	-0.172	-0.128
Location__29	-0.0891	0.010	-8.919	0.000	-0.109	-0.070
Location__30	-0.0118	0.010	-1.128	0.259	-0.032	0.009
Location__32	-0.0424	0.010	-4.361	0.000	-0.061	-0.023
Location__33	-0.0409	0.010	-4.180	0.000	-0.060	-0.022
Location__34	-0.1339	0.011	-11.753	0.000	-0.156	-0.112
Location__35	-0.0862	0.011	-7.673	0.000	-0.108	-0.064
Location__36	-0.2054	0.011	-18.573	0.000	-0.227	-0.184
Location__38	-0.1007	0.011	-8.934	0.000	-0.123	-0.079
Location__39	-0.0814	0.011	-7.561	0.000	-0.102	-0.060
Location__40	-0.1199	0.011	-10.854	0.000	-0.142	-0.098
Location__41	-0.0684	0.011	-6.317	0.000	-0.090	-0.047
Location__43	-0.0679	0.010	-6.732	0.000	-0.088	-0.048
Location__44	-0.1086	0.011	-9.478	0.000	-0.131	-0.086
Location__45	-0.1610	0.011	-15.168	0.000	-0.182	-0.140
Location__47	-0.0594	0.011	-5.213	0.000	-0.082	-0.037
Location__48	-0.1766	0.011	-16.101	0.000	-0.198	-0.155
Location__49	-0.0908	0.009	-9.750	0.000	-0.109	-0.073
Parameter2_9am__N	-0.0014	0.004	-0.386	0.699	-0.008	0.006

```
Parameter2_9am__S     0.0238      0.004      6.753      0.000       0.017
0.031
Parameter2_9am__W     0.0317      0.005      6.842      0.000       0.023
0.041
Parameter2_3pm__N     0.0024      0.004      0.653      0.514      -0.005
0.010
Parameter2_3pm__S     0.0208      0.004      5.638      0.000       0.014
0.028
Parameter2_3pm__W     0.0293      0.004      6.772      0.000       0.021
0.038
Mes__10               0.0639      0.006     10.548      0.000       0.052
0.076
Mes__11               0.0522      0.006      9.182      0.000       0.041
0.063
Mes__12               0.0301      0.006      5.234      0.000       0.019
0.041
Mes__2               -0.0184      0.006     -3.307      0.001      -0.029
-0.007
Mes__3               -0.0035      0.006     -0.641      0.522      -0.014
0.007
Mes__4                0.0372      0.006      6.182      0.000       0.025
0.049
Mes__5                0.0176      0.007      2.671      0.008       0.005
0.031
Mes__6               -0.0085      0.007     -1.155      0.248      -0.023
0.006
Mes__7                0.0230      0.008      2.976      0.003       0.008
0.038
Mes__8                0.0595      0.007      8.227      0.000       0.045
0.074
Mes__9                0.0734      0.007     11.040      0.000       0.060
0.086
==============================================================================
Omnibus:                     6534.458   Durbin-Watson:                   1.798
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             7967.918
Skew:                           0.718   Prob(JB):                         0.00
Kurtosis:                       2.824   Cond. No.                     2.99e+05
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC0)
[2] The condition number is large, 2.99e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Se puede notar que la mayoria de variables seleccionadas son significativas.

Sobre los sensores, se evidencia que el sensor 4 tiene en promedio un 10% mas de probabilidades de fallar menos que el base, mientras que por el contrario el 6 tiene un 20% menos. Los sensores no significativos como el 30 nos estan indicando que tienen un comportamiento similar al base.

Con estos resultados a simple vista podemos concluir que la ubicacion del sensor afecta en su probabilidad de fallo

Por el lado de los parametros, vemos que el parametro 5 se comporta de formas muy opuestas entre mañana y tarde, aumentando la probabilidad de fallo si aumenta su valor durante la tarde, pero disminuyendo la probabilidad casi en la misma proporcion si el aumento se da en la mañana. Por otro lado, el parametro 4 tiene un comportamiento de aumentar la probabilidad de fallo en ambos periodos, pero mucho mas marcado en las mañanas. Para la temperatura, podemos notar que si aumenta en 1 unidad la temperatura maxima, disminuye en 3% la probabilidad de falla, uno de los impactos mas grandes, lo cual tiene sentido por lo visto en los graficos, que en promedio los sensores cuando fallan tienen una temperatura maxima menor al caso cuando no fallan. El parametro 7 tambien tiene comportamiento opuesto entre mañana y tarde, pero este es atribuible a la temperatura, ya que verificamos con los graficos que representan eso, y con max temp y min temp vimos que tienen efectos opuestos. La diferencia es que, durante la tarde, se comporta muy similar a max_temp, pero durante la mañana si bien tiene el mismo efecto que min_temp de aumentar la probilidad, la magnitud es mucho menor.

Finalmente viendo los efectos por mes, tenemos casos como Febrero, que en comparación con Enero es menos propenso a fallar, por el contrario septiembre aumenta la probabilidad de falla. Esto nos da indicios de estacionalidad en la probabilidad que los sensores detecten una falla.

El caso de la temperatura es interesante, ya que se podria interpretar como si la temperatura tenga relación a la operación de esta maquina, osea que si la temperatura maxima es alta significa que está operando. Es por esto que cuando la temperatura maxima aumenta la probabilidad de fallo baja.

1.0.5 Parte 3

[104]:
```python
X = X.drop(columns=[#"Electricity",
                    #"Evaporation",
                    #"Electricity_NaN",
                    #"Evaporation_NaN"
                    ],axis=1)

model = sm.Probit(y, X)
probit_model = model.fit(cov_type='HC0')
print(probit_model.summary())

mfxp = probit_model.get_margeff()
print(mfxp.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.362559
         Iterations 7
                          Probit Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:                91389
Model:                         Probit   Df Residuals:                    91322
Method:                           MLE   Df Model:                           66
Date:                jue, 24 abr. 2025   Pseudo R-squ.:                  0.3317
```

```
Time:                        20:54:09   Log-Likelihood:                -33134.
converged:                       True   LL-Null:                       -49582.
Covariance Type:                  HC0   LLR p-value:                     0.000
================================================================================
=====
                       coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
const               28.7943      1.122     25.653      0.000      26.594
30.994
Min_Temp             0.0770      0.003     23.695      0.000       0.071
0.083
Max_Temp            -0.1467      0.006    -24.854      0.000      -0.158
-0.135
Parameter1_Speed     0.0207      0.001     29.358      0.000       0.019
0.022
Parameter3_9am       0.0086      0.001      8.765      0.000       0.007
0.011
Parameter3_3pm      -0.0149      0.001    -14.938      0.000      -0.017
-0.013
Parameter4_9am       0.0392      0.001     55.763      0.000       0.038
0.041
Parameter4_3pm       0.0031      0.001      4.452      0.000       0.002
0.004
Parameter5_9am      -0.1416      0.004    -35.427      0.000      -0.149
-0.134
Parameter5_3pm       0.1106      0.004     27.933      0.000       0.103
0.118
Parameter7_9am      -0.0205      0.005     -3.957      0.000      -0.031
-0.010
Parameter7_3pm       0.0693      0.007     10.628      0.000       0.056
0.082
Location__3         -0.3277      0.054     -6.053      0.000      -0.434
-0.222
Location__4          0.2902      0.067      4.353      0.000       0.160
0.421
Location__5         -0.2577      0.053     -4.897      0.000      -0.361
-0.155
Location__6         -1.1510      0.054    -21.320      0.000      -1.257
-1.045
Location__7         -0.5737      0.053    -10.870      0.000      -0.677
-0.470
Location__8          0.3467      0.052      6.706      0.000       0.245
0.448
Location__9          0.1011      0.055      1.848      0.065      -0.006
0.208
Location__10        -0.2989      0.054     -5.570      0.000      -0.404
```

						-0.194
Location__11	-0.1921	0.058	-3.303	0.001	-0.306	-0.078
Location__12	0.0552	0.052	1.068	0.286	-0.046	0.157
Location__13	-0.7918	0.052	-15.128	0.000	-0.894	-0.689
Location__14	-0.0126	0.057	-0.222	0.824	-0.124	0.099
Location__15	-0.0174	0.053	-0.328	0.743	-0.122	0.087
Location__16	-0.5619	0.052	-10.738	0.000	-0.664	-0.459
Location__18	-0.5917	0.059	-10.086	0.000	-0.707	-0.477
Location__20	-0.6839	0.051	-13.369	0.000	-0.784	-0.584
Location__21	-0.6854	0.057	-12.006	0.000	-0.797	-0.574
Location__22	0.0865	0.056	1.536	0.124	-0.024	0.197
Location__23	-0.4711	0.050	-9.377	0.000	-0.570	-0.373
Location__27	-0.4939	0.051	-9.778	0.000	-0.593	-0.395
Location__28	-0.4485	0.050	-9.035	0.000	-0.546	-0.351
Location__29	-0.5793	0.055	-10.507	0.000	-0.687	-0.471
Location__30	0.1328	0.056	2.391	0.017	0.024	0.242
Location__32	-0.0842	0.051	-1.639	0.101	-0.185	0.017
Location__33	-0.0369	0.053	-0.702	0.483	-0.140	0.066
Location__34	-0.5996	0.049	-12.124	0.000	-0.697	-0.503
Location__35	-0.2056	0.054	-3.812	0.000	-0.311	-0.100
Location__36	-0.7599	0.053	-14.433	0.000	-0.863	-0.657
Location__38	-0.2390	0.051	-4.696	0.000	-0.339	-0.139
Location__39	-0.1939	0.052	-3.722	0.000	-0.296	-0.092
Location__40	-0.1336	0.057	-2.355	0.019	-0.245	-0.022
Location__41	-0.2038	0.053	-3.845	0.000	-0.308	

```
-0.100
Location__43          -0.2616      0.055     -4.734      0.000      -0.370
-0.153
Location__44          -0.3981      0.051     -7.829      0.000      -0.498
-0.298
Location__45          -0.6883      0.051    -13.526      0.000      -0.788
-0.589
Location__47          -0.1548      0.053     -2.941      0.003      -0.258
-0.052
Location__48          -0.6166      0.052    -11.923      0.000      -0.718
-0.515
Location__49          -0.7198      0.066    -10.986      0.000      -0.848
-0.591
Parameter2_9am__N     -0.0039      0.020     -0.194      0.846      -0.044
0.036
Parameter2_9am__S      0.1531      0.019      8.092      0.000       0.116
0.190
Parameter2_9am__W      0.1581      0.022      7.223      0.000       0.115
0.201
Parameter2_3pm__N     -0.0102      0.020     -0.514      0.607      -0.049
0.029
Parameter2_3pm__S      0.0429      0.018      2.336      0.019       0.007
0.079
Parameter2_3pm__W      0.0801      0.021      3.725      0.000       0.038
0.122
Mes__10                0.1102      0.032      3.426      0.001       0.047
0.173
Mes__11                0.1697      0.030      5.701      0.000       0.111
0.228
Mes__12                0.1223      0.030      4.038      0.000       0.063
0.182
Mes__2                -0.0592      0.029     -2.040      0.041      -0.116
-0.002
Mes__3                -0.0427      0.027     -1.579      0.114      -0.096
0.010
Mes__4                 0.0361      0.029      1.234      0.217      -0.021
0.094
Mes__5                -0.1006      0.032     -3.180      0.001      -0.163
-0.039
Mes__6                -0.2711      0.035     -7.793      0.000      -0.339
-0.203
Mes__7                -0.1774      0.036     -4.866      0.000      -0.249
-0.106
Mes__8                -0.0117      0.035     -0.329      0.742      -0.081
0.058
Mes__9                 0.1237      0.033      3.713      0.000       0.058
0.189
================================================================================
```

```
=====
       Probit Marginal Effects
=====================================
Dep. Variable:          Failure_today
Method:                          dydx
At:                           overall
================================================================================
=====
                       dy/dx    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
Min_Temp              0.0157      0.001     23.945      0.000       0.014
0.017
Max_Temp             -0.0299      0.001    -25.169      0.000      -0.032
-0.028
Parameter1_Speed      0.0042      0.000     29.902      0.000       0.004
0.004
Parameter3_9am        0.0018      0.000      8.776      0.000       0.001
0.002
Parameter3_3pm       -0.0030      0.000    -15.001      0.000      -0.003
-0.003
Parameter4_9am        0.0080      0.000     60.363      0.000       0.008
0.008
Parameter4_3pm        0.0006      0.000      4.451      0.000       0.000
0.001
Parameter5_9am       -0.0288      0.001    -36.245      0.000      -0.030
-0.027
Parameter5_3pm        0.0225      0.001     28.339      0.000       0.021
0.024
Parameter7_9am       -0.0042      0.001     -3.961      0.000      -0.006
-0.002
Parameter7_3pm        0.0141      0.001     10.646      0.000       0.012
0.017
Location__3          -0.0667      0.011     -6.058      0.000      -0.088
-0.045
Location__4           0.0591      0.014      4.357      0.000       0.033
0.086
Location__5          -0.0525      0.011     -4.896      0.000      -0.074
-0.031
Location__6          -0.2344      0.011    -21.576      0.000      -0.256
-0.213
Location__7          -0.1169      0.011    -10.892      0.000      -0.138
-0.096
Location__8           0.0706      0.011      6.723      0.000       0.050
0.091
Location__9           0.0206      0.011      1.849      0.064      -0.001
0.042
```

Location__10	-0.0609	0.011	-5.573	0.000	-0.082	-0.039
Location__11	-0.0391	0.012	-3.304	0.001	-0.062	-0.016
Location__12	0.0112	0.011	1.068	0.286	-0.009	0.032
Location__13	-0.1613	0.011	-15.192	0.000	-0.182	-0.140
Location__14	-0.0026	0.012	-0.222	0.824	-0.025	0.020
Location__15	-0.0036	0.011	-0.328	0.743	-0.025	0.018
Location__16	-0.1144	0.011	-10.772	0.000	-0.135	-0.094
Location__18	-0.1205	0.012	-10.103	0.000	-0.144	-0.097
Location__20	-0.1393	0.010	-13.407	0.000	-0.160	-0.119
Location__21	-0.1396	0.012	-12.035	0.000	-0.162	-0.117
Location__22	0.0176	0.011	1.537	0.124	-0.005	0.040
Location__23	-0.0960	0.010	-9.390	0.000	-0.116	-0.076
Location__27	-0.1006	0.010	-9.785	0.000	-0.121	-0.080
Location__28	-0.0914	0.010	-9.037	0.000	-0.111	-0.072
Location__29	-0.1180	0.011	-10.535	0.000	-0.140	-0.096
Location__30	0.0270	0.011	2.392	0.017	0.005	0.049
Location__32	-0.0172	0.010	-1.638	0.101	-0.038	0.003
Location__33	-0.0075	0.011	-0.702	0.483	-0.029	0.013
Location__34	-0.1221	0.010	-12.154	0.000	-0.142	-0.102
Location__35	-0.0419	0.011	-3.811	0.000	-0.063	-0.020
Location__36	-0.1548	0.011	-14.499	0.000	-0.176	-0.134
Location__38	-0.0487	0.010	-4.695	0.000	-0.069	-0.028
Location__39	-0.0395	0.011	-3.721	0.000	-0.060	-0.019
Location__40	-0.0272	0.012	-2.353	0.019	-0.050	-0.005

Location__41	-0.0415	0.011	-3.845	0.000	-0.063	-0.020
Location__43	-0.0533	0.011	-4.738	0.000	-0.075	-0.031
Location__44	-0.0811	0.010	-7.835	0.000	-0.101	-0.061
Location__45	-0.1402	0.010	-13.572	0.000	-0.160	-0.120
Location__47	-0.0315	0.011	-2.941	0.003	-0.053	-0.011
Location__48	-0.1256	0.011	-11.936	0.000	-0.146	-0.105
Location__49	-0.1466	0.013	-11.026	0.000	-0.173	-0.121
Parameter2_9am__N	-0.0008	0.004	-0.194	0.846	-0.009	0.007
Parameter2_9am__S	0.0312	0.004	8.095	0.000	0.024	0.039
Parameter2_9am__W	0.0322	0.004	7.223	0.000	0.023	0.041
Parameter2_3pm__N	-0.0021	0.004	-0.514	0.607	-0.010	0.006
Parameter2_3pm__S	0.0087	0.004	2.336	0.020	0.001	0.016
Parameter2_3pm__W	0.0163	0.004	3.725	0.000	0.008	0.025
Mes__10	0.0225	0.007	3.425	0.001	0.010	0.035
Mes__11	0.0346	0.006	5.706	0.000	0.023	0.046
Mes__12	0.0249	0.006	4.040	0.000	0.013	0.037
Mes__2	-0.0121	0.006	-2.039	0.041	-0.024	-0.000
Mes__3	-0.0087	0.006	-1.578	0.114	-0.020	0.002
Mes__4	0.0074	0.006	1.234	0.217	-0.004	0.019
Mes__5	-0.0205	0.006	-3.180	0.001	-0.033	-0.008
Mes__6	-0.0552	0.007	-7.806	0.000	-0.069	-0.041
Mes__7	-0.0361	0.007	-4.870	0.000	-0.051	-0.022
Mes__8	-0.0024	0.007	-0.329	0.742	-0.017	0.012
Mes__9	0.0252	0.007	3.714	0.000	0.012	0.039

```
==============================================================================
=====
```

Para el modelo probit se consiguió un mejor ajuste y resultados muy similares al OLS

Por cada aumento de 1 en la temperatura mínima, la probabilidad de fallo aumenta en 1.57%, mientras que este cambio para la temperatura maxima disminuyedicha probabilidad en 2.99%.

Al igual que en OLS, aumentar la velocidad del viento en 1 unidad aumenta la probabilidad de fallo en un 0.43%, un impacto no tan grande pero significativo. El parametro 5 mantiene su tendencia a aumentar la probabilidad de fallo en las tardes y disminuirlo en las mañanas cuando aumenta en 1 unidad. En general, todo se comporta como en OLS.

Para la dirección del viento, si durante la mañana este se encuentra hacia el sur o el oeste, la probabilidad de fallo aumenta en un 3% en relacion a la ,dirección base que es el este, mientras que durante la tarde no se observan impactos mayores. Cuando el viento corre hacia el norte no nos da significativo, tanto en mañana como en tarde, lo cual nos indica que en ambos casos este se comporta similar a la dirección usada de referencia.

1.0.6 Parte 4

[ ]:
```
model = sm.Logit(y, X)
logit_model = model.fit(cov_type='HC0')
print(logit_model.summary())

mfxl = logit_model.get_margeff()
print(mfxl.summary())

params = logit_model.params
conf = logit_model.conf_int()
conf['Odds Ratio'] = params
conf.columns = ['Odds Ratio', '5%', '95%']
print("Odds Ratios")
print(np.exp(conf).iloc[1:17 , ])
```

```
Optimization terminated successfully.
         Current function value: 0.360972
         Iterations 8
                           Logit Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:                91389
Model:                          Logit   Df Residuals:                    91322
Method:                           MLE   Df Model:                           66
Date:                jue, 24 abr. 2025   Pseudo R-squ.:                  0.3347
Time:                        21:51:25   Log-Likelihood:                -32989.
converged:                       True   LL-Null:                       -49582.
Covariance Type:                  HC0   LLR p-value:                     0.000
==============================================================================
=====
                        coef    std err          z      P>|z|      [0.025
```

```
0.975]
--------------------------------------------------------------------------------
-----
const              49.6439      1.987     24.979      0.000     45.749
53.539
Min_Temp            0.1396      0.006     24.347      0.000      0.128
0.151
Max_Temp           -0.2663      0.011    -25.227      0.000     -0.287
-0.246
Parameter1_Speed    0.0364      0.001     29.157      0.000      0.034
0.039
Parameter3_9am      0.0143      0.002      8.155      0.000      0.011
0.018
Parameter3_3pm     -0.0253      0.002    -14.226      0.000     -0.029
-0.022
Parameter4_9am      0.0717      0.001     57.664      0.000      0.069
0.074
Parameter4_3pm      0.0042      0.001      3.470      0.001      0.002
0.007
Parameter5_9am     -0.2498      0.007    -35.265      0.000     -0.264
-0.236
Parameter5_3pm      0.1962      0.007     28.031      0.000      0.182
0.210
Parameter7_9am     -0.0371      0.009     -4.063      0.000     -0.055
-0.019
Parameter7_3pm      0.1173      0.012     10.187      0.000      0.095
0.140
Location__3        -0.5936      0.095     -6.229      0.000     -0.780
-0.407
Location__4         0.5294      0.118      4.471      0.000      0.297
0.761
Location__5        -0.3818      0.093     -4.089      0.000     -0.565
-0.199
Location__6        -2.0802      0.094    -22.144      0.000     -2.264
-1.896
Location__7        -1.0065      0.093    -10.871      0.000     -1.188
-0.825
Location__8         0.7514      0.091      8.302      0.000      0.574
0.929
Location__9         0.3524      0.095      3.705      0.000      0.166
0.539
Location__10       -0.5106      0.095     -5.354      0.000     -0.697
-0.324
Location__11       -0.3702      0.103     -3.579      0.000     -0.573
-0.167
Location__12        0.2039      0.091      2.250      0.024      0.026
0.382
Location__13       -1.3905      0.092    -15.170      0.000     -1.570
```

						-1.211
Location__14	0.1645	0.099	1.659	0.097	-0.030	0.359
Location__15	0.0921	0.093	0.987	0.324	-0.091	0.275
Location__16	-1.0109	0.093	-10.822	0.000	-1.194	-0.828
Location__18	-1.0165	0.103	-9.874	0.000	-1.218	-0.815
Location__20	-1.1782	0.091	-13.016	0.000	-1.356	-1.001
Location__21	-1.2082	0.101	-12.011	0.000	-1.405	-1.011
Location__22	0.2115	0.102	2.065	0.039	0.011	0.412
Location__23	-0.8147	0.088	-9.233	0.000	-0.988	-0.642
Location__27	-0.8197	0.089	-9.182	0.000	-0.995	-0.645
Location__28	-0.7189	0.087	-8.262	0.000	-0.889	-0.548
Location__29	-1.0446	0.097	-10.753	0.000	-1.235	-0.854
Location__30	0.2596	0.097	2.677	0.007	0.070	0.450
Location__32	-0.0650	0.090	-0.724	0.469	-0.241	0.111
Location__33	0.0136	0.092	0.148	0.882	-0.167	0.194
Location__34	-1.0339	0.087	-11.853	0.000	-1.205	-0.863
Location__35	-0.2804	0.095	-2.946	0.003	-0.467	-0.094
Location__36	-1.3364	0.093	-14.324	0.000	-1.519	-1.154
Location__38	-0.3424	0.090	-3.817	0.000	-0.518	-0.167
Location__39	-0.2860	0.094	-3.058	0.002	-0.469	-0.103
Location__40	-0.0406	0.099	-0.408	0.683	-0.235	0.154
Location__41	-0.3333	0.094	-3.542	0.000	-0.518	-0.149
Location__43	-0.5093	0.098	-5.195	0.000	-0.701	-0.317
Location__44	-0.6783	0.090	-7.560	0.000	-0.854	-0.502
Location__45	-1.2034	0.090	-13.436	0.000	-1.379	

```
-1.028
Location__47        -0.2316      0.092     -2.511      0.012      -0.412
-0.051
Location__48        -1.0316      0.092    -11.189      0.000      -1.212
-0.851
Location__49        -1.3123      0.114    -11.484      0.000      -1.536
-1.088
Parameter2_9am__N   -0.0167      0.036     -0.467      0.641      -0.087
0.053
Parameter2_9am__S    0.2721      0.034      8.090      0.000       0.206
0.338
Parameter2_9am__W    0.2741      0.039      7.072      0.000       0.198
0.350
Parameter2_3pm__N   -0.0219      0.035     -0.625      0.532      -0.091
0.047
Parameter2_3pm__S    0.0494      0.033      1.519      0.129      -0.014
0.113
Parameter2_3pm__W    0.1218      0.038      3.206      0.001       0.047
0.196
Mes__10              0.1663      0.058      2.884      0.004       0.053
0.279
Mes__11              0.3095      0.053      5.802      0.000       0.205
0.414
Mes__12              0.2250      0.055      4.126      0.000       0.118
0.332
Mes__2              -0.0721      0.052     -1.393      0.164      -0.173
0.029
Mes__3              -0.0433      0.048     -0.898      0.369      -0.138
0.051
Mes__4               0.0836      0.052      1.615      0.106      -0.018
0.185
Mes__5              -0.1735      0.056     -3.117      0.002      -0.283
-0.064
Mes__6              -0.4930      0.061     -8.094      0.000      -0.612
-0.374
Mes__7              -0.3309      0.064     -5.179      0.000      -0.456
-0.206
Mes__8              -0.0349      0.062     -0.559      0.576      -0.157
0.087
Mes__9               0.2117      0.059      3.580      0.000       0.096
0.328
================================================================================
=====
        Logit Marginal Effects
=====================================
Dep. Variable:           Failure_today
Method:                           dydx
At:                            overall
```

	dy/dx	std err	z	P>|z|	[0.025	0.975]
Min_Temp	0.0159	0.001	24.595	0.000	0.015	0.017
Max_Temp	-0.0304	0.001	-25.596	0.000	-0.033	-0.028
Parameter1_Speed	0.0042	0.000	29.836	0.000	0.004	0.004
Parameter3_9am	0.0016	0.000	8.164	0.000	0.001	0.002
Parameter3_3pm	-0.0029	0.000	-14.286	0.000	-0.003	-0.002
Parameter4_9am	0.0082	0.000	62.672	0.000	0.008	0.008
Parameter4_3pm	0.0005	0.000	3.471	0.001	0.000	0.001
Parameter5_9am	-0.0285	0.001	-36.277	0.000	-0.030	-0.027
Parameter5_3pm	0.0224	0.001	28.554	0.000	0.021	0.024
Parameter7_9am	-0.0042	0.001	-4.066	0.000	-0.006	-0.002
Parameter7_3pm	0.0134	0.001	10.218	0.000	0.011	0.016
Location__3	-0.0678	0.011	-6.235	0.000	-0.089	-0.046
Location__4	0.0604	0.014	4.474	0.000	0.034	0.087
Location__5	-0.0436	0.011	-4.090	0.000	-0.064	-0.023
Location__6	-0.2375	0.011	-22.425	0.000	-0.258	-0.217
Location__7	-0.1149	0.011	-10.897	0.000	-0.136	-0.094
Location__8	0.0858	0.010	8.322	0.000	0.066	0.106
Location__9	0.0402	0.011	3.708	0.000	0.019	0.061
Location__10	-0.0583	0.011	-5.359	0.000	-0.080	-0.037
Location__11	-0.0423	0.012	-3.580	0.000	-0.065	-0.019
Location__12	0.0233	0.010	2.251	0.024	0.003	0.044

Location__13	-0.1587	0.010	-15.241	0.000	-0.179	-0.138
Location__14	0.0188	0.011	1.660	0.097	-0.003	0.041
Location__15	0.0105	0.011	0.987	0.324	-0.010	0.031
Location__16	-0.1154	0.011	-10.867	0.000	-0.136	-0.095
Location__18	-0.1160	0.012	-9.895	0.000	-0.139	-0.093
Location__20	-0.1345	0.010	-13.065	0.000	-0.155	-0.114
Location__21	-0.1379	0.011	-12.043	0.000	-0.160	-0.115
Location__22	0.0241	0.012	2.065	0.039	0.001	0.047
Location__23	-0.0930	0.010	-9.248	0.000	-0.113	-0.073
Location__27	-0.0936	0.010	-9.197	0.000	-0.114	-0.074
Location__28	-0.0821	0.010	-8.272	0.000	-0.102	-0.063
Location__29	-0.1192	0.011	-10.778	0.000	-0.141	-0.098
Location__30	0.0296	0.011	2.677	0.007	0.008	0.051
Location__32	-0.0074	0.010	-0.724	0.469	-0.028	0.013
Location__33	0.0016	0.010	0.148	0.882	-0.019	0.022
Location__34	-0.1180	0.010	-11.884	0.000	-0.138	-0.099
Location__35	-0.0320	0.011	-2.946	0.003	-0.053	-0.011
Location__36	-0.1526	0.011	-14.404	0.000	-0.173	-0.132
Location__38	-0.0391	0.010	-3.818	0.000	-0.059	-0.019
Location__39	-0.0327	0.011	-3.058	0.002	-0.054	-0.012
Location__40	-0.0046	0.011	-0.408	0.683	-0.027	0.018
Location__41	-0.0380	0.011	-3.543	0.000	-0.059	-0.017
Location__43	-0.0581	0.011	-5.201	0.000	-0.080	-0.036
Location__44	-0.0774	0.010	-7.570	0.000	-0.097	-0.057

```
Location__45          -0.1374      0.010    -13.493      0.000      -0.157
-0.117
Location__47          -0.0264      0.011     -2.511      0.012      -0.047
-0.006
Location__48          -0.1178      0.011    -11.214      0.000      -0.138
-0.097
Location__49          -0.1498      0.013    -11.515      0.000      -0.175
-0.124
Parameter2_9am__N     -0.0019      0.004     -0.467      0.641      -0.010
0.006
Parameter2_9am__S      0.0311      0.004      8.092      0.000       0.024
0.039
Parameter2_9am__W      0.0313      0.004      7.072      0.000       0.023
0.040
Parameter2_3pm__N     -0.0025      0.004     -0.625      0.532      -0.010
0.005
Parameter2_3pm__S      0.0056      0.004      1.519      0.129      -0.002
0.013
Parameter2_3pm__W      0.0139      0.004      3.206      0.001       0.005
0.022
Mes__10                0.0190      0.007      2.884      0.004       0.006
0.032
Mes__11                0.0353      0.006      5.809      0.000       0.023
0.047
Mes__12                0.0257      0.006      4.128      0.000       0.013
0.038
Mes__2                -0.0082      0.006     -1.393      0.164      -0.020
0.003
Mes__3                -0.0049      0.006     -0.898      0.369      -0.016
0.006
Mes__4                 0.0095      0.006      1.616      0.106      -0.002
0.021
Mes__5                -0.0198      0.006     -3.117      0.002      -0.032
-0.007
Mes__6                -0.0563      0.007     -8.099      0.000      -0.070
-0.043
Mes__7                -0.0378      0.007     -5.180      0.000      -0.052
-0.023
Mes__8                -0.0040      0.007     -0.559      0.576      -0.018
0.010
Mes__9                 0.0242      0.007      3.582      0.000       0.011
0.037
================================================================================
=====
Odds Ratios
                  Odds Ratio        5%       95%
Min_Temp            1.136922  1.162757  1.149767
Max_Temp            0.750522  0.782230  0.766212
```

```
Parameter1_Speed    1.034560  1.039639  1.037096
Parameter3_9am      1.010952  1.017945  1.014443
Parameter3_3pm      0.971649  0.978440  0.975039
Parameter4_9am      1.071758  1.076998  1.074375
Parameter4_3pm      1.001831  1.006601  1.004214
Parameter5_9am      0.768225  0.789854  0.778965
Parameter5_3pm      1.200198  1.233586  1.216777
Parameter7_9am      0.946498  0.980985  0.963587
Parameter7_3pm      1.099404  1.150186  1.124509
Location__3         0.458257  0.665793  0.552362
Location__4         1.346212  2.141445  1.697893
Location__5         0.568509  0.819725  0.682658
Location__6         0.103906  0.150163  0.124911
Location__7         0.304839  0.438214  0.365493
```

Para el logit, podemos identificar el mismo comportamiento que los 2 modelos anteriores, teniendo un aumento en la temperatura minima de una unidad un impacto en el 1.59% de probabilidad de fallo y en el max_temp una disminucion de 3%. Un cambio fuerte con respecto al modelo probit se da en la dirección del viento sur durante la tarde, que ahora nos da no significativa, lo que nos indica que se comporta de manera similar a la referencia del este, lo cual no ocurria en el modelo probit.

1.0.7 Parte 5

En los 3 modelos pudimos encontrar resultados bastante similares para la interpretación de las variables, con pequeños cambios en la significancia de algunas de estas, especificamente

Sobre cual modelo recomendaria, de base se descarta OLS al no ser el adecuado para trabajar con una variable dependiente binaria al no estar acotado para [0,1], aunque obviaramos esto es el que posee un R2 mas bajo entre los 3. Fuera de esto, entre logit y probit se comportan de la misma manera, pero al aprecer logit es mas exigente con la significancia. Este comportamiento más conservador puede ser beneficioso y marcar la diferencia a la hora de hacer interpretaciones precisas. Aun asi ambos modelos son extremadamente similares, por lo que no considero que este factor sea clave para elegir uno por sobre el otro de forma tajante.

Sobre la robustez de las variables, la gran mayoria de estas cumplen con esta caracteristica, al ser significativas y tener impactos similares en todos los modelos. Algunas de estas son max_temp y min_temp, parameter1_speed, los parametros5 y algunas locaciones como la 6 y la 4, por otro lado, algunas de las no robustas son el mes 3 al no ser significativo en ningun modelo o el parameter2_3pm_S, al perder su significancia en el modelo logit.

1.0.8 Parte 6

Tratamiento de datos

[109]:
```
X2.drop(columns=["Parameter2_9am",
                 "Parameter2_3pm",
                 #"Location"
                  ], inplace=True)

X2 = X2.groupby(["Año", "Mes","Location"]).agg({
```

```
    **{col: "mean" for col in ['Min_Temp', 'Max_Temp','Parameter1_Speed',
       'Parameter3_9am', 'Parameter3_3pm', 'Parameter4_9am', 'Parameter4_3pm',
       'Parameter5_9am', 'Parameter5_3pm', 'Parameter7_9am', 'Parameter7_3pm']},
        "Failure_today": "sum"
}).reset_index()

X2["Año - Mes"] = X2["Año"].astype(str) + "-" + X2["Mes"].astype(str).str.
 ↪zfill(2)
```

[110]:
```
X2
```

[110]:
```
       Año Mes  Location   Min_Temp   Max_Temp  Parameter1_Speed  \
0     2010   1         1  18.060714  30.917857         37.678571
1     2010   1         3  17.282759  34.420690         43.344828
2     2010   1         4  21.470000  35.153333         45.966667
3     2010   1         5  17.373684  30.884211         42.263158
4     2010   1         6  11.164286  27.246429         47.892857
…      …  ..       …        …          …               …
3306  2017   6        44  10.726316  18.268421         35.421053
3307  2017   6        45   4.345000  14.870000         24.800000
3308  2017   6        47   8.827778  18.661111         37.666667
3309  2017   6        48  11.655556  17.611111         39.833333
3310  2017   6        49   5.952174  18.747826         28.000000

      Parameter3_9am  Parameter3_3pm  Parameter4_9am  Parameter4_3pm  \
0          10.857143       17.821429       43.928571       29.750000
1           9.689655       19.275862       49.724138       21.068966
2          18.700000       19.600000       38.566667       26.300000
3          10.473684       17.684211       69.052632       47.263158
4          20.357143       23.142857       58.107143       36.178571
…               …              …              …              …
3306       11.368421       12.578947       79.526316       66.894737
3307        6.200000        9.500000       97.300000       67.350000
3308       12.833333       18.222222       84.222222       68.888889
3309       15.888889       20.444444       73.111111       69.111111
3310       11.391304       13.391304       66.565217       36.608696

      Parameter5_9am  Parameter5_3pm  Parameter7_9am  Parameter7_3pm  \
0        1014.175000     1012.471429       22.932143       29.017857
1        1012.110345     1009.162069       23.110345       32.755172
2        1008.970000     1005.563333       28.276667       34.110000
3        1013.215789     1010.289474       22.500000       28.942105
4        1013.003571     1011.642857       17.835714       25.039286
…               …              …              …              …
3306     1023.984211     1021.800000       13.394737       17.205263
3307     1028.070000     1025.615000        6.650000       13.735000
3308     1022.788889     1020.844444       13.455556       17.305556
```

```
3309     1026.083333     1024.116667       14.705556       16.650000
3310     1029.586957     1026.939130       10.556522       18.052174

      Failure_today Año - Mes
0                 2   2010-01
1                 3   2010-01
2                 5   2010-01
3                 4   2010-01
4                 4   2010-01
…             …         …
3306              7   2017-06
3307              3   2017-06
3308              6   2017-06
3309              5   2017-06
3310              0   2017-06

[3311 rows x 16 columns]
```

Poisson

[111]:
```python
X3 = X2.copy()

y = X2['Failure_today']
X2=X2.drop(["Año - Mes",
            "Año",
            "Mes",
            #"Location",
            "Failure_today"
            ],
            axis=1)
#X2 = pd.get_dummies(X2, columns=["Año - Mes"], prefix=["Año y mes"],␣
 ↪prefix_sep='__', drop_first=True)
X2 = pd.get_dummies(X2, columns=["Location"], prefix=["Location"],␣
 ↪prefix_sep='__', drop_first=True)

X2=sm.add_constant(X2)
poisson=sm.GLM(y,X2,family=sm.families.Poisson()).fit()
print(poisson.summary())

#0.8101 sin location dummie
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:                 3311
Model:                            GLM   Df Residuals:                     3261
Model Family:                 Poisson   Df Model:                           49
Link Function:                    Log   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -7384.9
```

```
Date:                jue, 24 abr. 2025   Deviance:                     3484.2
Time:                         22:27:31   Pearson chi2:               3.11e+03
No. Iterations:                      5   Pseudo R-squ. (CS):           0.8453
Covariance Type:             nonrobust
================================================================================
====
                     coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
----
const             19.4213      3.349      5.799      0.000      12.857
25.986
Min_Temp           0.0570      0.011      5.151      0.000       0.035
0.079
Max_Temp          -0.0149      0.026     -0.567      0.571      -0.066
0.037
Parameter1_Speed   0.0548      0.003     18.120      0.000       0.049
0.061
Parameter3_9am    -0.0045      0.004     -1.018      0.309      -0.013
0.004
Parameter3_3pm    -0.0633      0.004    -14.686      0.000      -0.072
-0.055
Parameter4_9am     0.0330      0.003     12.000      0.000       0.028
0.038
Parameter4_3pm    -0.0025      0.003     -0.839      0.402      -0.008
0.003
Parameter5_9am    -0.0232      0.020     -1.150      0.250      -0.063
0.016
Parameter5_3pm     0.0040      0.021      0.194      0.846      -0.036
0.044
Parameter7_9am     0.1293      0.016      8.039      0.000       0.098
0.161
Parameter7_3pm    -0.1647      0.030     -5.584      0.000      -0.223
-0.107
Location__3       -0.1381      0.072     -1.920      0.055      -0.279
0.003
Location__4        0.0415      0.091      0.456      0.648      -0.137
0.220
Location__5       -0.3150      0.075     -4.224      0.000      -0.461
-0.169
Location__6       -0.4161      0.082     -5.099      0.000      -0.576
-0.256
Location__7       -0.2279      0.072     -3.149      0.002      -0.370
-0.086
Location__8       -0.1672      0.072     -2.331      0.020      -0.308
-0.027
Location__9       -0.0874      0.079     -1.101      0.271      -0.243
0.068
```

Location__10	-0.1236	0.079	-1.563	0.118	-0.279	0.031
Location__11	-0.0423	0.075	-0.562	0.574	-0.190	0.105
Location__12	-0.0327	0.070	-0.464	0.642	-0.171	0.105
Location__13	-0.4245	0.072	-5.924	0.000	-0.565	-0.284
Location__14	-0.4053	0.083	-4.859	0.000	-0.569	-0.242
Location__15	-0.1759	0.081	-2.167	0.030	-0.335	-0.017
Location__16	-0.5636	0.064	-8.775	0.000	-0.690	-0.438
Location__18	-0.4312	0.079	-5.465	0.000	-0.586	-0.277
Location__20	-0.2788	0.073	-3.832	0.000	-0.421	-0.136
Location__21	-0.1644	0.083	-1.974	0.048	-0.328	-0.001
Location__22	-0.0208	0.087	-0.240	0.810	-0.191	0.149
Location__23	-0.0535	0.070	-0.764	0.445	-0.191	0.084
Location__27	-0.5528	0.066	-8.387	0.000	-0.682	-0.424
Location__28	-0.5379	0.071	-7.625	0.000	-0.676	-0.400
Location__29	-0.1955	0.069	-2.839	0.005	-0.330	-0.061
Location__30	0.0484	0.072	0.669	0.503	-0.093	0.190
Location__32	-0.0619	0.067	-0.931	0.352	-0.192	0.068
Location__33	0.0879	0.072	1.225	0.220	-0.053	0.228
Location__34	-0.2089	0.064	-3.259	0.001	-0.335	-0.083
Location__35	-0.4496	0.074	-6.074	0.000	-0.595	-0.305
Location__36	-0.2506	0.075	-3.340	0.001	-0.398	-0.104
Location__38	-0.2491	0.064	-3.920	0.000	-0.374	-0.125
Location__39	-0.0881	0.069	-1.280	0.201	-0.223	0.047
Location__40	-0.4277	0.087	-4.925	0.000	-0.598	-0.257

```
Location__41         -0.2262      0.072     -3.143      0.002      -0.367
-0.085
Location__43          0.0684      0.073      0.940      0.347      -0.074
0.211
Location__44         -0.5949      0.064     -9.244      0.000      -0.721
-0.469
Location__45         -0.4476      0.065     -6.846      0.000      -0.576
-0.319
Location__47         -0.3397      0.068     -5.016      0.000      -0.472
-0.207
Location__48         -0.7525      0.067    -11.173      0.000      -0.885
-0.620
Location__49         -0.4308      0.095     -4.556      0.000      -0.616
-0.245
================================================================================
====
```

[118]:

```python
pd.set_option('display.float_format', '{:.2f}'.format)
coef=poisson.params
odds_ratios = np.exp(coef)
odds_ratios = 100*(odds_ratios-1)
odds_ratios
```

[118]:

```
const                27200350779.84
Min_Temp                       5.87
Max_Temp                      -1.48
Parameter1_Speed               5.64
Parameter3_9am                -0.45
Parameter3_3pm                -6.13
Parameter4_9am                 3.35
Parameter4_3pm                -0.25
Parameter5_9am                -2.29
Parameter5_3pm                 0.40
Parameter7_9am                13.81
Parameter7_3pm               -15.19
Location__3                  -12.90
Location__4                    4.24
Location__5                  -27.02
Location__6                  -34.04
Location__7                  -20.38
Location__8                  -15.40
Location__9                   -8.37
Location__10                 -11.63
Location__11                  -4.14
Location__12                  -3.21
Location__13                 -34.59
Location__14                 -33.32
```

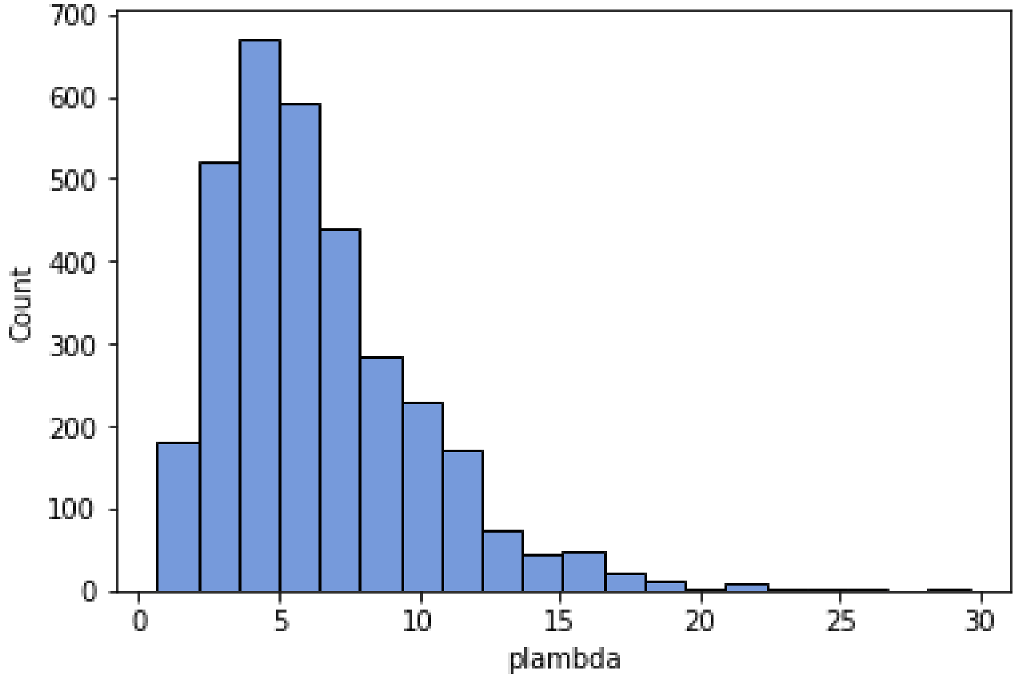
```
Location__15                -16.13
Location__16                -43.09
Location__18                -35.03
Location__20                -24.33
Location__21                -15.16
Location__22                 -2.06
Location__23                 -5.21
Location__27                -42.47
Location__28                -41.60
Location__29                -17.76
Location__30                  4.96
Location__32                 -6.01
Location__33                  9.19
Location__34                -18.85
Location__35                -36.21
Location__36                -22.16
Location__38                -22.05
Location__39                 -8.44
Location__40                -34.80
Location__41                -20.24
Location__43                  7.08
Location__44                -44.84
Location__45                -36.09
Location__47                -28.80
Location__48                -52.88
Location__49                -35.00
dtype: float64
```

Para este modelo evaluaremos la cantidad de fallos del sensor en el mes. Vemos comportamientos similares a los modelos previos, por ejemplo, ante un aumento de 1 unidad en la min_temp, la cantidad de fallos en el sensor durante el mes aumentan en un 5.87% en comparación al caso base. Aquí vemos un comportamiento distinto para los parametros 7, ya que un aumento en 1 unidad en la mañana impacta en un aumento del 13% a la cantidad de fallos, bastante mas que la variable de min_temp. Además, notamos que Max_temp no es significativa, al igual que el parametro 3 en la mañana, los parametros 4, y el 5 en la tarde. Lo que mas incide en la mayoria de casos son la ubicacion de los sensores, los cuales se deben comparar con el sensor base.

1.0.9 Parte 7

[119]:
```
X2['plambda'] = poisson.mu
sns.histplot(data=X2, x="plambda",bins=20)
```

[119]:
```
<Axes: xlabel='plambda', ylabel='Count'>
```



Podemos ver que hay una “cola larga” en la distribucion

[120]:
```
aux=((y-poisson.mu)**2-poisson.mu)/poisson.mu
auxr=sm.OLS(aux,poisson.mu).fit()
print(auxr.summary())
```

```
                                 OLS Regression Results
================================================================================
=======
Dep. Variable:          Failure_today   R-squared (uncentered):
0.001
Model:                            OLS   Adj. R-squared (uncentered):
0.001
Method:                 Least Squares   F-statistic:
3.918
Date:               jue, 24 abr. 2025   Prob (F-statistic):
0.0479
Time:                        23:01:22   Log-Likelihood:
-5717.9
No. Observations:                3311   AIC:
1.144e+04
Df Residuals:                    3310   BIC:
1.144e+04
Df Model:                           1
Covariance Type:            nonrobust
```

```
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
x1            -0.0064      0.003     -1.979      0.048      -0.013   -6.01e-05
==============================================================================
Omnibus:                     2964.467   Durbin-Watson:                   1.815
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           167481.499
Skew:                           4.044   Prob(JB):                         0.00
Kurtosis:                      36.891   Cond. No.                         1.00
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

[123]:

```python
print(f"El alpha estimado es: {np.exp(-0.0064)}")
```

```
El alpha estimado es: 0.993620436379149
```

Al aplicar la estimación de alpha nos da un valor casi igual a 1, lo que confirma que hay sobredispersión, al no ser cercano a 0

[124]:

```python
nbin = smf.negativebinomial("Failure_today ~ Min_Temp + Max_Temp +␣
 ↪Parameter1_Speed + Parameter3_9am + Parameter3_3pm + Parameter4_9am +␣
 ↪Parameter4_3pm + Parameter5_9am + Parameter5_3pm + Parameter7_9am +␣
 ↪Parameter7_3pm + C(Location)", data=X3).fit(alpha=1.24)
print(nbin.summary())
```

```
c:\Users\joaqu\anaconda3\anaconda\lib\site-
packages\statsmodels\base\optimizer.py:17: FutureWarning: Keyword arguments have
been passed to the optimizer that have no effect. The list of allowed keyword
arguments for method bfgs is: gtol, norm, epsilon. The list of unsupported
keyword arguments passed include: alpha. After release 0.14, this will raise.
  warnings.warn(
c:\Users\joaqu\anaconda3\anaconda\lib\site-
packages\statsmodels\discrete\discrete_model.py:2651: RuntimeWarning: divide by
zero encountered in log
  llf = coeff + size*np.log(prob) + endog*np.log(1-prob)
c:\Users\joaqu\anaconda3\anaconda\lib\site-
packages\statsmodels\discrete\discrete_model.py:2651: RuntimeWarning: invalid
value encountered in multiply
  llf = coeff + size*np.log(prob) + endog*np.log(1-prob)
c:\Users\joaqu\anaconda3\anaconda\lib\site-
packages\scipy\optimize\_optimize.py:1292: OptimizeWarning: Maximum number of
iterations has been exceeded.
  res = _minimize_bfgs(f, x0, args, fprime, callback=callback, **opts)

         Current function value: 2.230443
```

```
        Iterations: 35
        Function evaluations: 50
        Gradient evaluations: 50
```

```
c:\Users\joaqu\anaconda3\anaconda\lib\site-
packages\statsmodels\base\model.py:604: ConvergenceWarning: Maximum Likelihood
optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

```
                     NegativeBinomial Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:                 3311
Model:               NegativeBinomial   Df Residuals:                     3261
Method:                           MLE   Df Model:                           49
Date:                jue, 24 abr. 2025   Pseudo R-squ.:                  0.1976
Time:                        23:02:59   Log-Likelihood:                -7385.0
converged:                      False   LL-Null:                       -9203.1
Covariance Type:            nonrobust   LLR p-value:                     0.000
================================================================================
=====
                        coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
Intercept            19.4220      3.352      5.794      0.000      12.852
25.992
C(Location)[T.3]     -0.1373      0.072     -1.907      0.057      -0.278
0.004
C(Location)[T.4]      0.0365      0.091      0.400      0.689      -0.142
0.215
C(Location)[T.5]     -0.3146      0.075     -4.217      0.000      -0.461
-0.168
C(Location)[T.6]     -0.4157      0.082     -5.092      0.000      -0.576
-0.256
C(Location)[T.7]     -0.2258      0.072     -3.119      0.002      -0.368
-0.084
C(Location)[T.8]     -0.1686      0.072     -2.347      0.019      -0.309
-0.028
C(Location)[T.9]     -0.0958      0.080     -1.204      0.229      -0.252
0.060
C(Location)[T.10]    -0.1231      0.079     -1.556      0.120      -0.278
0.032
C(Location)[T.11]    -0.0483      0.075     -0.641      0.522      -0.196
0.099
C(Location)[T.12]    -0.0352      0.070     -0.500      0.617      -0.173
0.103
C(Location)[T.13]    -0.4213      0.072     -5.876      0.000      -0.562
-0.281
C(Location)[T.14]    -0.4101      0.084     -4.889      0.000      -0.574
```

```
-0.246
C(Location)[T.15]    -0.1813      0.081     -2.232      0.026      -0.340
-0.022
C(Location)[T.16]    -0.5630      0.064     -8.760      0.000      -0.689
-0.437
C(Location)[T.18]    -0.4261      0.079     -5.401      0.000      -0.581
-0.271
C(Location)[T.20]    -0.2806      0.073     -3.854      0.000      -0.423
-0.138
C(Location)[T.21]    -0.1715      0.083     -2.055      0.040      -0.335
-0.008
C(Location)[T.22]    -0.0244      0.087     -0.282      0.778      -0.194
0.145
C(Location)[T.23]    -0.0522      0.070     -0.745      0.456      -0.189
0.085
C(Location)[T.27]    -0.5561      0.066     -8.430      0.000      -0.685
-0.427
C(Location)[T.28]    -0.5429      0.071     -7.684      0.000      -0.681
-0.404
C(Location)[T.29]    -0.1945      0.069     -2.824      0.005      -0.329
-0.060
C(Location)[T.30]     0.0494      0.072      0.683      0.495      -0.092
0.191
C(Location)[T.32]    -0.0604      0.067     -0.907      0.365      -0.191
0.070
C(Location)[T.33]     0.0876      0.072      1.220      0.223      -0.053
0.228
C(Location)[T.34]    -0.2036      0.064     -3.175      0.001      -0.329
-0.078
C(Location)[T.35]    -0.4496      0.074     -6.072      0.000      -0.595
-0.304
C(Location)[T.36]    -0.2496      0.075     -3.326      0.001      -0.397
-0.103
C(Location)[T.38]    -0.2533      0.064     -3.983      0.000      -0.378
-0.129
C(Location)[T.39]    -0.0939      0.069     -1.363      0.173      -0.229
0.041
C(Location)[T.40]    -0.4362      0.087     -5.011      0.000      -0.607
-0.266
C(Location)[T.41]    -0.2252      0.072     -3.127      0.002      -0.366
-0.084
C(Location)[T.43]     0.0678      0.073      0.932      0.351      -0.075
0.210
C(Location)[T.44]    -0.5925      0.064     -9.203      0.000      -0.719
-0.466
C(Location)[T.45]    -0.4472      0.065     -6.835      0.000      -0.575
-0.319
C(Location)[T.47]    -0.3370      0.068     -4.972      0.000      -0.470
```

```
-0.204
C(Location)[T.48]     -0.7548      0.067    -11.193      0.000      -0.887
-0.623
C(Location)[T.49]     -0.4377      0.095     -4.623      0.000      -0.623
-0.252
Min_Temp               0.0580      0.011      5.240      0.000       0.036
0.080
Max_Temp              -0.0158      0.026     -0.601      0.548      -0.067
0.036
Parameter1_Speed       0.0546      0.003     17.953      0.000       0.049
0.061
Parameter3_9am        -0.0043      0.004     -0.968      0.333      -0.013
0.004
Parameter3_3pm        -0.0630      0.004    -14.528      0.000      -0.071
-0.054
Parameter4_9am         0.0330      0.003     11.996      0.000       0.028
0.038
Parameter4_3pm        -0.0026      0.003     -0.875      0.382      -0.009
0.003
Parameter5_9am        -0.0207      0.020     -1.029      0.304      -0.060
0.019
Parameter5_3pm         0.0015      0.021      0.075      0.940      -0.039
0.042
Parameter7_9am         0.1291      0.016      8.010      0.000       0.098
0.161
Parameter7_3pm        -0.1644      0.030     -5.569      0.000      -0.222
-0.107
alpha               8.499e-05      0.004      0.023      0.982      -0.007
0.007
================================================================================
=====
```

[125]:
```
np.exp(8.499e-05)
```

[125]: 1.0000849936117524

Y, al correr una binomial sin especificar alpha, nos entrega su estimación de 8.499e-05, que al aplicarle exponencial nos da aproximadamente 1, un valor similar al que estimamos arriba

1.0.10 Parte 8

[126]:
```
negbin=sm.GLM(y,X2,family=sm.families.NegativeBinomial(alpha=np.exp(-0.0064))).
  ↪fit()
print(negbin.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:                 3311
Model:                            GLM   Df Residuals:                     3260
```

```
Model Family:        NegativeBinomial   Df Model:                           50
Link Function:                    Log   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -9225.9
Date:                jue, 24 abr. 2025   Deviance:                       763.67
Time:                        23:04:02   Pearson chi2:                     562.
No. Iterations:                     9   Pseudo R-squ. (CS):             0.2530
Covariance Type:            nonrobust
================================================================================
====
                      coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
----
const              30.7950      9.719      3.169      0.002      11.746
49.844
Min_Temp            0.0615      0.029      2.109      0.035       0.004
0.119
Max_Temp           -0.0362      0.072     -0.501      0.616      -0.178
0.105
Parameter1_Speed    0.1052      0.013      8.208      0.000       0.080
0.130
Parameter3_9am     -0.0099      0.012     -0.814      0.416      -0.034
0.014
Parameter3_3pm     -0.1163      0.015     -7.772      0.000      -0.146
-0.087
Parameter4_9am      0.0502      0.008      6.538      0.000       0.035
0.065
Parameter4_3pm      0.0057      0.009      0.666      0.505      -0.011
0.023
Parameter5_9am     -0.0445      0.056     -0.801      0.423      -0.153
0.064
Parameter5_3pm      0.0126      0.057      0.223      0.824      -0.099
0.124
Parameter7_9am      0.2184      0.043      5.137      0.000       0.135
0.302
Parameter7_3pm     -0.2269      0.081     -2.816      0.005      -0.385
-0.069
Location__3        -0.1146      0.196     -0.584      0.559      -0.499
0.270
Location__4         0.0503      0.219      0.230      0.818      -0.379
0.480
Location__5        -0.5866      0.206     -2.851      0.004      -0.990
-0.183
Location__6        -0.7092      0.240     -2.951      0.003      -1.180
-0.238
Location__7        -0.3248      0.199     -1.636      0.102      -0.714
0.064
Location__8        -0.3303      0.198     -1.670      0.095      -0.718
```

						0.057
Location__9	-0.2285	0.228	-1.003	0.316	-0.675	0.218
Location__10	-0.2262	0.215	-1.051	0.293	-0.648	0.196
Location__11	0.0510	0.189	0.269	0.788	-0.320	0.422
Location__12	-0.1705	0.203	-0.840	0.401	-0.568	0.227
Location__13	-0.7476	0.216	-3.467	0.001	-1.170	-0.325
Location__14	-0.8825	0.237	-3.720	0.000	-1.347	-0.418
Location__15	-0.3656	0.227	-1.614	0.107	-0.810	0.078
Location__16	-0.9798	0.203	-4.824	0.000	-1.378	-0.582
Location__18	-0.7520	0.227	-3.310	0.001	-1.197	-0.307
Location__20	-0.4806	0.211	-2.281	0.023	-0.894	-0.068
Location__21	-0.0657	0.204	-0.322	0.747	-0.466	0.334
Location__22	-0.0252	0.229	-0.110	0.912	-0.474	0.423
Location__23	-0.0857	0.208	-0.413	0.680	-0.493	0.321
Location__27	-0.9601	0.203	-4.730	0.000	-1.358	-0.562
Location__28	-0.9429	0.211	-4.462	0.000	-1.357	-0.529
Location__29	-0.3110	0.190	-1.640	0.101	-0.683	0.061
Location__30	-0.0512	0.200	-0.256	0.798	-0.443	0.341
Location__32	-0.2575	0.180	-1.432	0.152	-0.610	0.095
Location__33	-0.0418	0.198	-0.211	0.833	-0.430	0.346
Location__34	-0.4088	0.194	-2.110	0.035	-0.789	-0.029
Location__35	-0.7355	0.205	-3.580	0.000	-1.138	-0.333
Location__36	-0.5069	0.214	-2.364	0.018	-0.927	-0.087
Location__38	-0.4168	0.187	-2.234	0.025	-0.782	-0.051
Location__39	-0.1747	0.198	-0.881	0.378	-0.563	

```
0.214
Location__40         -0.8546      0.236     -3.626      0.000      -1.317
-0.393
Location__41         -0.3407      0.196     -1.736      0.083      -0.725
0.044
Location__43          0.1603      0.198      0.810      0.418      -0.227
0.548
Location__44         -1.0691      0.204     -5.251      0.000      -1.468
-0.670
Location__45         -0.7551      0.197     -3.842      0.000      -1.140
-0.370
Location__47         -0.6306      0.199     -3.165      0.002      -1.021
-0.240
Location__48         -1.3326      0.219     -6.085      0.000      -1.762
-0.903
Location__49         -0.4038      0.215     -1.882      0.060      -0.825
0.017
plambda              -0.0820      0.019     -4.336      0.000      -0.119
-0.045
================================================================================
====
```

[127]:
```
pd.set_option('display.float_format', '{:.2f}'.format)
coef=negbin.params
odds_ratios = np.exp(coef)
odds_ratios = 100*(odds_ratios-1)
odds_ratios
```

[127]:
```
const                 2366508221587123.00
Min_Temp                             6.35
Max_Temp                            -3.56
Parameter1_Speed                    11.09
Parameter3_9am                      -0.99
Parameter3_3pm                     -10.98
Parameter4_9am                       5.15
Parameter4_3pm                       0.57
Parameter5_9am                      -4.35
Parameter5_3pm                       1.27
Parameter7_9am                      24.41
Parameter7_3pm                     -20.30
Location__3                        -10.83
Location__4                          5.16
Location__5                        -44.38
Location__6                        -50.80
Location__7                        -27.74
Location__8                        -28.13
Location__9                        -20.42
```

```
Location__10                      -20.24
Location__11                        5.23
Location__12                      -15.67
Location__13                      -52.65
Location__14                      -58.63
Location__15                      -30.62
Location__16                      -62.46
Location__18                      -52.86
Location__20                      -38.16
Location__21                       -6.36
Location__22                       -2.49
Location__23                       -8.21
Location__27                      -61.71
Location__28                      -61.05
Location__29                      -26.73
Location__30                       -4.99
Location__32                      -22.70
Location__33                       -4.10
Location__34                      -33.56
Location__35                      -52.07
Location__36                      -39.76
Location__38                      -34.08
Location__39                      -16.03
Location__40                      -57.46
Location__41                      -28.87
Location__43                       17.38
Location__44                      -65.67
Location__45                      -53.00
Location__47                      -46.77
Location__48                      -73.62
Location__49                      -33.22
plambda                            -7.87
dtype: float64
```

Este modelo tiene un ajuste bastante inferior en comparacion al Poisson, pero con efectos muy similares, por ejemplo, si la min_temp aumenta en una unidad, la cantidad de fallos aumentará en un 6%, y en el caso de la velocidad del viento, una unidad impacta en un 11% a la cantidad de fallos en dicho mes. Al igual que en poisson, muchas variables dieron no significativas, y los cambios mas grandes se ven en la ubicacion de los sensores.

1.0.11 Parte 9

Al realizar el test de sobredispersión y obtener los resultados de que si existia, podemos descartar automaticamente el modelo poisson, que si bien nos entregaba un buen ajuste este no era adecuado para el problema. Es asi que, al aplicar el poisson, empeoró bastante, lo cual tiene sentido cuando comparamos con los modelos anteriores (Siendo estudios distintos, hace sentido que tengna un comportamiento similar). Además, si bien un modelo no era adecuado, los coeficientes de ambos se comportan similar con leves diferencias. Las variables robustas fueron min_temp, parameter1_speed, parameter3_3p y parameter4_9am entre otros, pero disminuye la cantidad de robustos en comparación al caso estudiado en 2, 3 y 4