Tarea1_Santana_Abasolo

April 30, 2025

[ ]:
```python
#Importamos librerias
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.api as sm
import statsmodels.formula.api as smf
```

1. Cargar la base de datos en el ambiente. Identifique los tipos de datos que se encuentran en la base, realice estadisticas descriptivas sobre las variables importantes (Hint: Revisar la distribuciones, datos faltantes, outliers, etc.) y limpie las variables cuando sea necesario

[ ]:
```python
#Leemos y visualizamos la base de datos
df = pd.read_csv("../data/machine_failure_data.csv")
df
```

[ ]:
```
             Date  Location  Min_Temp  Max_Temp  Leakage  Evaporation  \
0       12/1/2008         3      13.4      22.9      0.6          NaN
1       12/2/2008         3       7.4      25.1      0.0          NaN
2       12/3/2008         3      12.9      25.7      0.0          NaN
3       12/4/2008         3       9.2      28.0      0.0          NaN
4       12/5/2008         3      17.5      32.3      1.0          NaN
…             …       …       …        …        …
142188  6/20/2017        42       3.5      21.8      0.0          NaN
142189  6/21/2017        42       2.8      23.4      0.0          NaN
142190  6/22/2017        42       3.6      25.3      0.0          NaN
142191  6/23/2017        42       5.4      26.9      0.0          NaN
142192  6/24/2017        42       7.8      27.0      0.0          NaN

        Electricity Parameter1_Dir  Parameter1_Speed Parameter2_9am  …  \
0               NaN              W              44.0              W  …
1               NaN            WNW              44.0            NNW  …
2               NaN            WSW              46.0              W  …
3               NaN             NE              24.0             SE  …
4               NaN              W              41.0            ENE  …
…             …              …                …             …   …
142188          NaN              E              31.0            ESE  …
142189          NaN              E              31.0             SE  …
```

```
142190          NaN            NNW             22.0              SE  …
142191          NaN              N             37.0              SE  …
142192          NaN             SE             28.0             SSE  …

       Parameter3_3pm  Parameter4_9am  Parameter4_3pm  Parameter5_9am  \
0                24.0            71.0            22.0          1007.7
1                22.0            44.0            25.0          1010.6
2                26.0            38.0            30.0          1007.6
3                 9.0            45.0            16.0          1017.6
4                20.0            82.0            33.0          1010.8
…                 …              …              …              …
142188           13.0            59.0            27.0          1024.7
142189           11.0            51.0            24.0          1024.6
142190            9.0            56.0            21.0          1023.5
142191            9.0            53.0            24.0          1021.0
142192            7.0            51.0            24.0          1019.4

        Parameter5_3pm  Parameter6_9am  Parameter6_3pm  Parameter7_9am  \
0               1007.1             8.0             NaN            16.9
1               1007.8             NaN             NaN            17.2
2               1008.7             NaN             2.0            21.0
3               1012.8             NaN             NaN            18.1
4               1006.0             7.0             8.0            17.8
…                 …              …              …              …
142188          1021.2             NaN             NaN             9.4
142189          1020.3             NaN             NaN            10.1
142190          1019.1             NaN             NaN            10.9
142191          1016.8             NaN             NaN            12.5
142192          1016.5             3.0             2.0            15.1

        Parameter7_3pm  Failure_today
0                 21.8             No
1                 24.3             No
2                 23.2             No
3                 26.5             No
4                 29.7             No
…                 …              …
142188            20.9             No
142189            22.4             No
142190            24.5             No
142191            26.1             No
142192            26.0             No

[142193 rows x 22 columns]
```

[3]:
```
#Visualizamos la información de los datos del df
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 142193 entries, 0 to 142192
Data columns (total 22 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Date              142193 non-null  object
 1   Location          142193 non-null  int64
 2   Min_Temp          141556 non-null  float64
 3   Max_Temp          141871 non-null  float64
 4   Leakage           140787 non-null  float64
 5   Evaporation       81350 non-null   float64
 6   Electricity       74377 non-null   float64
 7   Parameter1_Dir    132863 non-null  object
 8   Parameter1_Speed  132923 non-null  float64
 9   Parameter2_9am    132180 non-null  object
 10  Parameter2_3pm    138415 non-null  object
 11  Parameter3_9am    140845 non-null  float64
 12  Parameter3_3pm    139563 non-null  float64
 13  Parameter4_9am    140419 non-null  float64
 14  Parameter4_3pm    138583 non-null  float64
 15  Parameter5_9am    128179 non-null  float64
 16  Parameter5_3pm    128212 non-null  float64
 17  Parameter6_9am    88536 non-null   float64
 18  Parameter6_3pm    85099 non-null   float64
 19  Parameter7_9am    141289 non-null  float64
 20  Parameter7_3pm    139467 non-null  float64
 21  Failure_today     140787 non-null  object
dtypes: float64(16), int64(1), object(5)
memory usage: 23.9+ MB
```

Parameter6_9am tiene 88536 datos y Parameter6_3pm 85099, aproximadamente 51 000 datos menos en comparación a las demás variables por lo tanto los eliminamos directamente. Eliminamos asi mismo a Evaporation y Electricity. En el caso de Leakage resulta ser un estimador perfecto para el modelo, por lo que también lo eliminamos.

[4]:
```
#Eliminamos las columnas y volvemos a visualizar los datos del df
df=df.drop(columns=["Parameter6_9am","Parameter6_3pm"])
df=df.drop(columns=["Evaporation","Electricity"])
df=df.drop(columns=["Leakage"])
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 142193 entries, 0 to 142192
Data columns (total 17 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Date              142193 non-null  object
 1   Location          142193 non-null  int64
 2   Min_Temp          141556 non-null  float64
```

```
 3   Max_Temp          141871 non-null  float64
 4   Parameter1_Dir    132863 non-null  object
 5   Parameter1_Speed  132923 non-null  float64
 6   Parameter2_9am    132180 non-null  object
 7   Parameter2_3pm    138415 non-null  object
 8   Parameter3_9am    140845 non-null  float64
 9   Parameter3_3pm    139563 non-null  float64
 10  Parameter4_9am    140419 non-null  float64
 11  Parameter4_3pm    138583 non-null  float64
 12  Parameter5_9am    128179 non-null  float64
 13  Parameter5_3pm    128212 non-null  float64
 14  Parameter7_9am    141289 non-null  float64
 15  Parameter7_3pm    139467 non-null  float64
 16  Failure_today     140787 non-null  object
dtypes: float64(11), int64(1), object(5)
memory usage: 18.4+ MB
```

[5]:
```
df.describe(include='all')
```

[5]:
```
             Date       Location       Min_Temp       Max_Temp Parameter1_Dir  \
count      142193  142193.000000  141556.000000  141871.000000         132863
unique       3436            NaN            NaN            NaN             16
top     6/23/2017            NaN            NaN            NaN              W
freq           49            NaN            NaN            NaN           9780
mean          NaN      24.740655      12.186400      23.226784            NaN
std           NaN      14.237503       6.403283       7.117618            NaN
min           NaN       1.000000      -8.500000      -4.800000            NaN
25%           NaN      12.000000       7.600000      17.900000            NaN
50%           NaN      25.000000      12.000000      22.600000            NaN
75%           NaN      37.000000      16.800000      28.200000            NaN
max           NaN      49.000000      33.900000      48.100000            NaN

        Parameter1_Speed Parameter2_9am Parameter2_3pm  Parameter3_9am  \
count      132923.000000         132180         138415   140845.000000
unique               NaN             16             16             NaN
top                  NaN              N             SE             NaN
freq                 NaN          11393          10663             NaN
mean           39.984292            NaN            NaN       14.001988
std            13.588801            NaN            NaN        8.893337
min             6.000000            NaN            NaN        0.000000
25%            31.000000            NaN            NaN        7.000000
50%            39.000000            NaN            NaN       13.000000
75%            48.000000            NaN            NaN       19.000000
max           135.000000            NaN            NaN      130.000000

        Parameter3_3pm  Parameter4_9am  Parameter4_3pm  Parameter5_9am  \
count    139563.000000   140419.000000   138583.000000   128179.000000
```

```
unique          NaN          NaN          NaN           NaN
top             NaN          NaN          NaN           NaN
freq            NaN          NaN          NaN           NaN
mean      18.637576    68.843810    51.482606   1017.653758
std        8.803345    19.051293    20.797772      7.105476
min        0.000000     0.000000     0.000000    980.500000
25%       13.000000    57.000000    37.000000   1012.900000
50%       19.000000    70.000000    52.000000   1017.600000
75%       24.000000    83.000000    66.000000   1022.400000
max       87.000000   100.000000   100.000000   1041.000000

        Parameter5_3pm  Parameter7_9am  Parameter7_3pm Failure_today
count    128212.000000   141289.000000   139467.000000        140787
unique             NaN             NaN             NaN             2
top                NaN             NaN             NaN            No
freq               NaN             NaN             NaN        109332
mean       1015.258204       16.987509       21.687235           NaN
std           7.036677        6.492838        6.937594           NaN
min         977.100000       -7.200000       -5.400000           NaN
25%        1010.400000       12.300000       16.600000           NaN
50%        1015.200000       16.700000       21.100000           NaN
75%        1020.000000       21.600000       26.400000           NaN
max        1039.600000       40.200000       46.700000           NaN
```

[6]:

```
#Aqui pasamos de las 16 direcciones de viento a angulos y posteriormente a 4␣
 ↪grupos (N, E, S y O)
direccion_a_angulo = {
    'N': 0,
    'NNE': 22.5,
    'NE': 45,
    'ENE': 67.5,
    'E': 90,
    'ESE': 112.5,
    'SE': 135,
    'SSE': 157.5,
    'S': 180,
    'SSW': 202.5,
    'SW': 225,
    'WSW': 247.5,
    'W': 270,
    'WNW': 292.5,
    'NW': 315,
    'NNW': 337.5
}

# Mapear a ángulos
df['Parameter1_Dir_angle'] = df['Parameter1_Dir'].map(direccion_a_angulo)
```

```python
df['Parameter2_9am_angle'] = df['Parameter2_9am'].map(direccion_a_angulo)
df['Parameter2_3pm_angle'] = df['Parameter2_3pm'].map(direccion_a_angulo)

df['Parameter1_Dir_angle'] = df['Parameter1_Dir_angle'].fillna(0)
df['Parameter2_9am_angle'] = df['Parameter2_9am_angle'].fillna(0)
df['Parameter2_3pm_angle'] = df['Parameter2_3pm_angle'].fillna(0)

def agrupar_direccion(angle):
    if (angle >= 315 or angle < 45):
        return 'N'
    elif (angle >= 45 and angle < 135):
        return 'E'
    elif (angle >= 135 and angle < 225):
        return 'S'
    elif (angle >= 225 and angle < 315):
        return 'W'
    else:
        return 'Desconocido'

columnas_angulos = ['Parameter1_Dir_angle', 'Parameter2_9am_angle',␣
 ↪'Parameter2_3pm_angle']

# Aplicar la funcion a cada columna que termina en _angle y creamos _region
for col in columnas_angulos:
    nueva_col = col.replace('_angle', '_region')
    df[nueva_col] = df[col].apply(agrupar_direccion)

df=df.
 ↪drop(columns=["Parameter1_Dir","Parameter2_9am","Parameter2_3pm",'Parameter1_Dir_angle',␣
 ↪'Parameter2_9am_angle', 'Parameter2_3pm_angle'])
df
```

[6]:

```
             Date  Location  Min_Temp  Max_Temp  Parameter1_Speed  \
0       12/1/2008         3      13.4      22.9              44.0
1       12/2/2008         3       7.4      25.1              44.0
2       12/3/2008         3      12.9      25.7              46.0
3       12/4/2008         3       9.2      28.0              24.0
4       12/5/2008         3      17.5      32.3              41.0
…             …         …         …         …                 …
142188  6/20/2017        42       3.5      21.8              31.0
142189  6/21/2017        42       2.8      23.4              31.0
142190  6/22/2017        42       3.6      25.3              22.0
142191  6/23/2017        42       5.4      26.9              37.0
142192  6/24/2017        42       7.8      27.0              28.0

        Parameter3_9am  Parameter3_3pm  Parameter4_9am  Parameter4_3pm  \
0                 20.0            24.0            71.0            22.0
```

```
1                 4.0            22.0            44.0            25.0
2                19.0            26.0            38.0            30.0
3                11.0             9.0            45.0            16.0
4                 7.0            20.0            82.0            33.0
…                 …             …             …             …
142188           15.0            13.0            59.0            27.0
142189           13.0            11.0            51.0            24.0
142190           13.0             9.0            56.0            21.0
142191            9.0             9.0            53.0            24.0
142192           13.0             7.0            51.0            24.0

        Parameter5_9am  Parameter5_3pm  Parameter7_9am  Parameter7_3pm  \
0               1007.7          1007.1            16.9            21.8
1               1010.6          1007.8            17.2            24.3
2               1007.6          1008.7            21.0            23.2
3               1017.6          1012.8            18.1            26.5
4               1010.8          1006.0            17.8            29.7
…                 …             …             …             …
142188          1024.7          1021.2             9.4            20.9
142189          1024.6          1020.3            10.1            22.4
142190          1023.5          1019.1            10.9            24.5
142191          1021.0          1016.8            12.5            26.1
142192          1019.4          1016.5            15.1            26.0

       Failure_today Parameter1_Dir_region Parameter2_9am_region  \
0                 No                     W                     W
1                 No                     W                     N
2                 No                     W                     W
3                 No                     E                     S
4                 No                     W                     E
…               …                   …                   …
142188            No                     E                     E
142189            No                     E                     S
142190            No                     N                     S
142191            No                     N                     S
142192            No                     S                     S

       Parameter2_3pm_region
0                          W
1                          W
2                          W
3                          E
4                          N
…                       …
142188                     E
142189                     E
142190                     N
```

```
142191                       W
142192                       N

[142193 rows x 17 columns]
```

[7]:

```python
#Transformamos la fecha a formato "datetime" y agrupamos las fechas en 4␣
↪estaciones
df['Date'] = pd.to_datetime(df['Date'], format='%m/%d/%Y')

def obtener_estacion(fecha):
    mes = fecha.month
    if mes in [12, 1, 2]:
        return 'invierno'
    elif mes in [3, 4, 5]:
        return 'primavera'
    elif mes in [6, 7, 8]:
        return 'verano'
    else:
        return 'otoño'


df['estacion'] = df['Date'].apply(obtener_estacion)
df
```

[7]:

```
             Date  Location  Min_Temp  Max_Temp  Parameter1_Speed  \
0      2008-12-01         3      13.4      22.9              44.0
1      2008-12-02         3       7.4      25.1              44.0
2      2008-12-03         3      12.9      25.7              46.0
3      2008-12-04         3       9.2      28.0              24.0
4      2008-12-05         3      17.5      32.3              41.0
…             …       …       …       …                 …
142188 2017-06-20        42       3.5      21.8              31.0
142189 2017-06-21        42       2.8      23.4              31.0
142190 2017-06-22        42       3.6      25.3              22.0
142191 2017-06-23        42       5.4      26.9              37.0
142192 2017-06-24        42       7.8      27.0              28.0

        Parameter3_9am  Parameter3_3pm  Parameter4_9am  Parameter4_3pm  \
0                 20.0            24.0            71.0            22.0
1                  4.0            22.0            44.0            25.0
2                 19.0            26.0            38.0            30.0
3                 11.0             9.0            45.0            16.0
4                  7.0            20.0            82.0            33.0
…                …              …              …              …
142188            15.0            13.0            59.0            27.0
142189            13.0            11.0            51.0            24.0
142190            13.0             9.0            56.0            21.0
```

```
142191             9.0             9.0            53.0            24.0
142192            13.0             7.0            51.0            24.0

        Parameter5_9am  Parameter5_3pm  Parameter7_9am  Parameter7_3pm  \
0               1007.7          1007.1            16.9            21.8
1               1010.6          1007.8            17.2            24.3
2               1007.6          1008.7            21.0            23.2
3               1017.6          1012.8            18.1            26.5
4               1010.8          1006.0            17.8            29.7
…                  …             …             …             …
142188          1024.7          1021.2             9.4            20.9
142189          1024.6          1020.3            10.1            22.4
142190          1023.5          1019.1            10.9            24.5
142191          1021.0          1016.8            12.5            26.1
142192          1019.4          1016.5            15.1            26.0

       Failure_today Parameter1_Dir_region Parameter2_9am_region  \
0                 No                     W                     W
1                 No                     W                     N
2                 No                     W                     W
3                 No                     E                     S
4                 No                     W                     E
…                …                   …                   …
142188            No                     E                     E
142189            No                     E                     S
142190            No                     N                     S
142191            No                     N                     S
142192            No                     S                     S

       Parameter2_3pm_region  estacion
0                          W  invierno
1                          W  invierno
2                          W  invierno
3                          E  invierno
4                          N  invierno
…                       …       …
142188                     E    verano
142189                     E    verano
142190                     N    verano
142191                     W    verano
142192                     N    verano

[142193 rows x 18 columns]
```

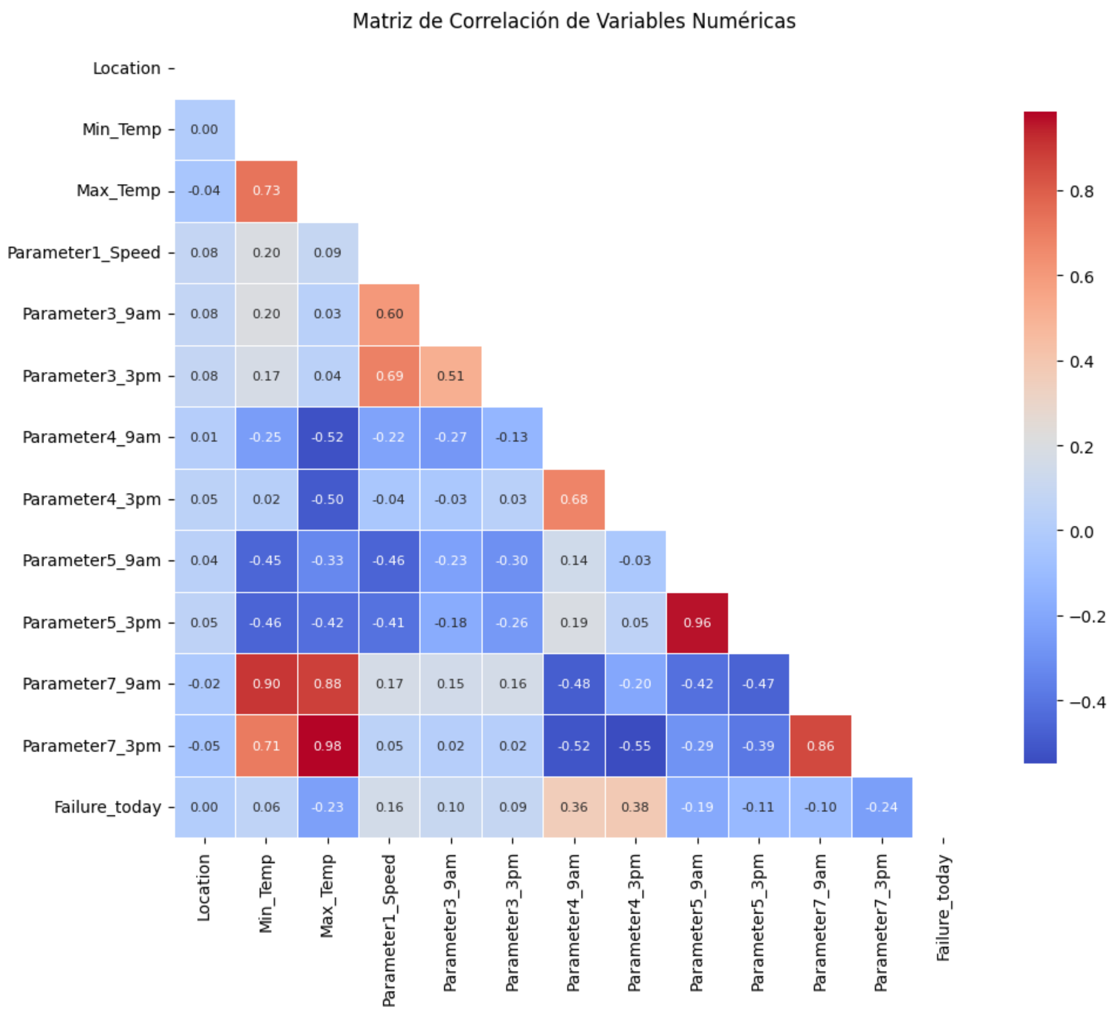
[8]:
```
#Asignamos valores binarios a la variable de fallos y borramos las filas con␣
↪datos NaN.
df['Failure_today'] = df['Failure_today'].map({'Yes': 1, 'No': 0})
```

```
df.dropna(inplace=True)
df.describe()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 119590 entries, 0 to 142192
Data columns (total 18 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   Date                   119590 non-null  datetime64[ns]
 1   Location               119590 non-null  int64
 2   Min_Temp               119590 non-null  float64
 3   Max_Temp               119590 non-null  float64
 4   Parameter1_Speed       119590 non-null  float64
 5   Parameter3_9am         119590 non-null  float64
 6   Parameter3_3pm         119590 non-null  float64
 7   Parameter4_9am         119590 non-null  float64
 8   Parameter4_3pm         119590 non-null  float64
 9   Parameter5_9am         119590 non-null  float64
 10  Parameter5_3pm         119590 non-null  float64
 11  Parameter7_9am         119590 non-null  float64
 12  Parameter7_3pm         119590 non-null  float64
 13  Failure_today          119590 non-null  float64
 14  Parameter1_Dir_region  119590 non-null  object
 15  Parameter2_9am_region  119590 non-null  object
 16  Parameter2_3pm_region  119590 non-null  object
 17  estacion               119590 non-null  object
dtypes: datetime64[ns](1), float64(12), int64(1), object(4)
memory usage: 17.3+ MB
```

[9]:

```
#Creamos heatmap para observar correlaciones entre variables.
numeric_df = df.select_dtypes(include=['float64', 'int64'])
corr = numeric_df.corr()

mask = np.triu(np.ones_like(corr, dtype=bool))
f, ax = plt.subplots(figsize=(11, 9))
cmap = sns.diverging_palette(230, 20, as_cmap=True)

sns.heatmap(
    corr, annot=True, mask=mask, fmt=".2f", cmap='coolwarm', square=True,␣
 ↪linewidths=0.5, annot_kws={'size': 8}, cbar_kws={"shrink": .8})
plt.title('Matriz de Correlación de Variables Numéricas')
plt.show()
```

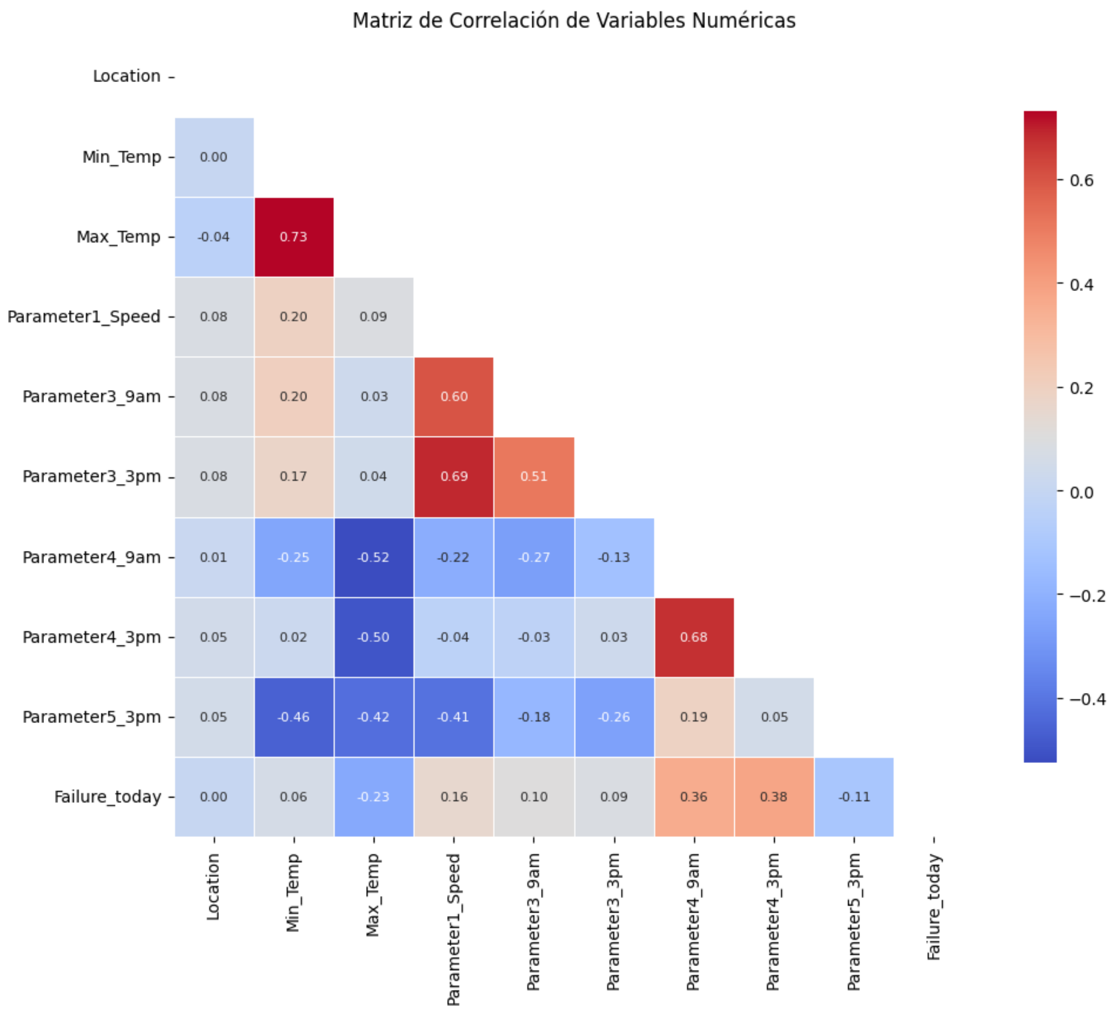


Alta correlacion entre Parameter7_9am y Min_Temp, Parameter7_3pm y Max_temp, Parameter5_3pm y Parameter5_9am. Estas dos primeras puede que también representen temperaturas y por eso presenten tal correlación. Eliminamos algunas para evitar correlación en el modelo.

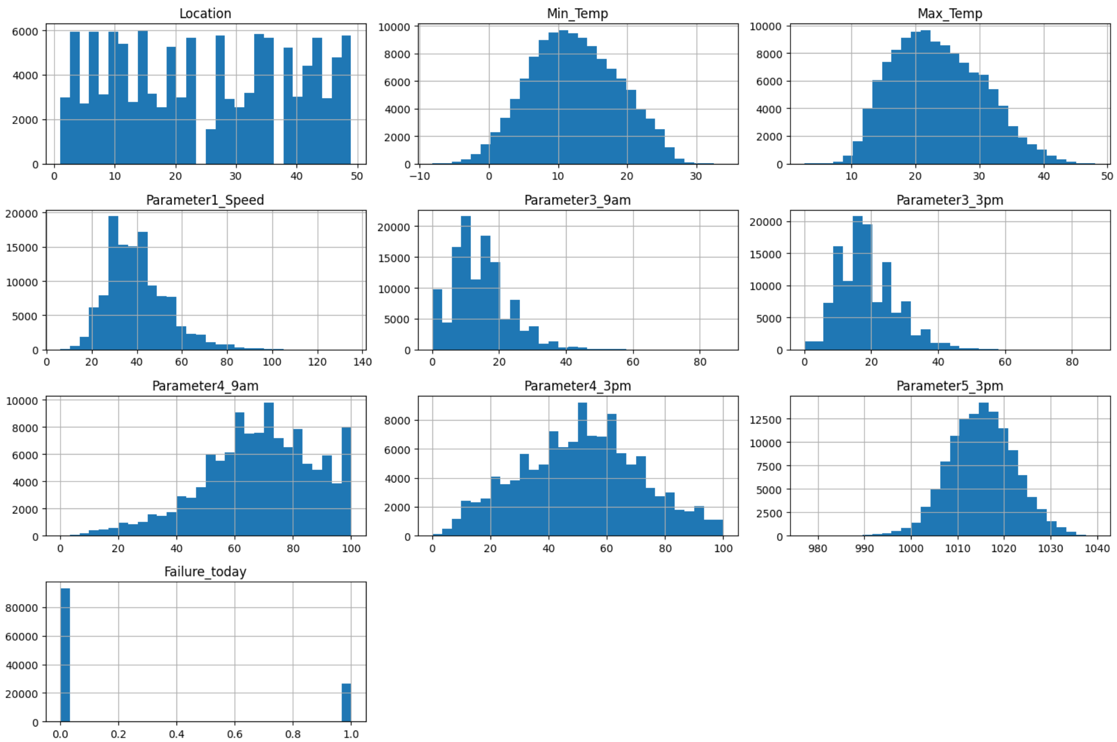
[10]:
```
df=df.drop(columns=["Parameter7_9am", "Parameter7_3pm","Parameter5_9am"])
```

[11]:
```
#Volvemos a crear el heatmap para observar después del cambio
numeric_df = df.select_dtypes(include=['float64', 'int64'])
corr = numeric_df.corr()

mask = np.triu(np.ones_like(corr, dtype=bool))
f, ax = plt.subplots(figsize=(11, 9))
cmap = sns.diverging_palette(230, 20, as_cmap=True)

sns.heatmap(
```

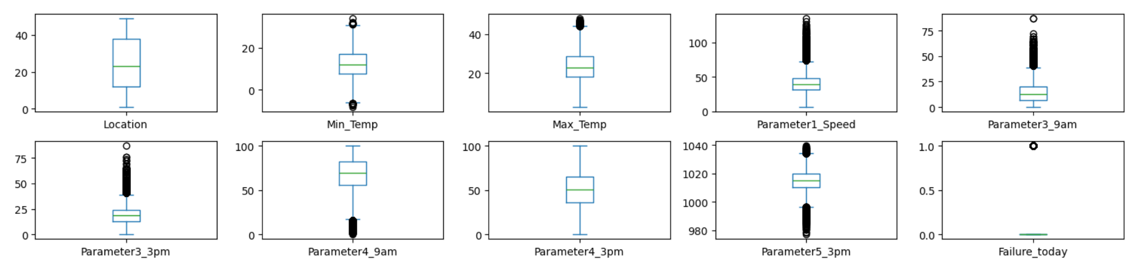
```
    corr, annot=True, mask=mask, fmt=".2f", cmap='coolwarm', square=True,␣
 ↪linewidths=0.5, annot_kws={'size': 8}, cbar_kws={"shrink": .8})
plt.title('Matriz de Correlación de Variables Numéricas')
plt.show()
```



[12]:
```
#Creamos gráficos de barra para observar las distriuciones de nuestras variables
df.select_dtypes(include=['float64', 'int64']).hist(bins=30, figsize=(15, 10))
plt.tight_layout()
plt.show()
```



[13]:
```
#Hacemos lo mismo pero con graficos de caja para observar datos extremos
df.select_dtypes(include=['float64', 'int64']).plot(kind='box', subplots=True, layout=(6, 5), figsize=(15, 10), sharex=False, sharey=False)
plt.tight_layout()
plt.show()
```



2. Ejecute un modelo de probabilidad lineal (MCO) que permita explicar la probabilidad #de que un dia se reporte fallo medido por sensor, a partir de las informacion disponible. #Seleccione las variables dependientes a incluir en el modelo final e interprete su significado

[14]:
```
#Transformamos a dummies todas las variables categoricas que utilizaremos en los modelos (Direcciones de viento, location, estacion) en un dataframe nuevo.
```

```python
df_model = df.drop(columns=["Date"])

#Para direcciones de viento
cols_region = [col for col in df_model.columns if col.endswith('_region')]
df_dummies_region = pd.get_dummies(df_model[cols_region], prefix=cols_region,␣
↪drop_first=True)
df_model = pd.concat([df_model, df_dummies_region], axis=1)
df_model.drop(columns=cols_region, inplace=True)

#Para location
df_model = pd.get_dummies(df_model, columns=['Location'], drop_first=True)

#Para estacion
df_model = pd.get_dummies(df_model, columns=['estacion'], drop_first=True)

#Convertir booleanos a enteros
df_model = df_model.astype({col: int for col in df_model.
↪select_dtypes(include='bool').columns})

df_model
```

[14]:

```
        Min_Temp  Max_Temp  Parameter1_Speed  Parameter3_9am  Parameter3_3pm  \
0           13.4      22.9              44.0            20.0            24.0
1            7.4      25.1              44.0             4.0            22.0
2           12.9      25.7              46.0            19.0            26.0
3            9.2      28.0              24.0            11.0             9.0
4           17.5      32.3              41.0             7.0            20.0
…              …         …                 …               …               …
142188       3.5      21.8              31.0            15.0            13.0
142189       2.8      23.4              31.0            13.0            11.0
142190       3.6      25.3              22.0            13.0             9.0
142191       5.4      26.9              37.0             9.0             9.0
142192       7.8      27.0              28.0            13.0             7.0

        Parameter4_9am  Parameter4_3pm  Parameter5_3pm  Failure_today  \
0                 71.0            22.0          1007.1            0.0
1                 44.0            25.0          1007.8            0.0
2                 38.0            30.0          1008.7            0.0
3                 45.0            16.0          1012.8            0.0
4                 82.0            33.0          1006.0            0.0
…                    …               …               …              …
142188            59.0            27.0          1021.2            0.0
142189            51.0            24.0          1020.3            0.0
142190            56.0            21.0          1019.1            0.0
142191            53.0            24.0          1016.8            0.0
142192            51.0            24.0          1016.5            0.0
```

```
        Parameter1_Dir_region_N  …  Location_43  Location_44  Location_45  \
0                             0  …            0            0            0
1                             0  …            0            0            0
2                             0  …            0            0            0
3                             0  …            0            0            0
4                             0  …            0            0            0
…                           …  …          …          …          …
142188                        0  …            0            0            0
142189                        0  …            0            0            0
142190                        1  …            0            0            0
142191                        1  …            0            0            0
142192                        0  …            0            0            0

        Location_46  Location_47  Location_48  Location_49  estacion_otoño  \
0                 0            0            0            0               0
1                 0            0            0            0               0
2                 0            0            0            0               0
3                 0            0            0            0               0
4                 0            0            0            0               0
…               …          …          …          …             …
142188            0            0            0            0               0
142189            0            0            0            0               0
142190            0            0            0            0               0
142191            0            0            0            0               0
142192            0            0            0            0               0

        estacion_primavera  estacion_verano
0                        0                0
1                        0                0
2                        0                0
3                        0                0
4                        0                0
…                      …              …
142188                   0                1
142189                   0                1
142190                   0                1
142191                   0                1
142192                   0                1

[119590 rows x 64 columns]
```

[15]:

```
#Definimos nuestro X en base al df creado anteriormente y dropeamos la variable␣
↪a predecir
X = df_model.drop(columns=["Failure_today"])  # Variables explicativas
X = sm.add_constant(X)

y = df_model['Failure_today']                 # Variable dependiente
```

```python
modelo = sm.OLS(y, X).fit()
print(modelo.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Failure_today   R-squared:                       0.281
Model:                            OLS   Adj. R-squared:                  0.281
Method:                 Least Squares   F-statistic:                     741.1
Date:                Fri, 25 Apr 2025   Prob (F-statistic):               0.00
Time:                        12:57:55   Log-Likelihood:                -44784.
No. Observations:              119590   AIC:                         8.970e+04
Df Residuals:                  119526   BIC:                         9.032e+04
Df Model:                          63
Covariance Type:            nonrobust
================================================================================
===========
                              coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----------
const                       6.2809      0.207     30.324      0.000       5.875
6.687
Min_Temp                    0.0190      0.000     47.418      0.000       0.018
0.020
Max_Temp                   -0.0191      0.000    -47.073      0.000      -0.020
-0.018
Parameter1_Speed            0.0055      0.000     43.040      0.000       0.005
0.006
Parameter3_9am              0.0031      0.000     18.543      0.000       0.003
0.003
Parameter3_3pm             -0.0040      0.000    -22.639      0.000      -0.004
-0.004
Parameter4_9am              0.0077   8.89e-05     86.186      0.000       0.007
0.008
Parameter4_3pm              0.0008   9.84e-05      7.668      0.000       0.001
0.001
Parameter5_3pm             -0.0065      0.000    -32.376      0.000      -0.007
-0.006
Parameter1_Dir_region_N    -0.0043      0.004     -1.119      0.263      -0.012
0.003
Parameter1_Dir_region_S     0.0108      0.004      3.011      0.003       0.004
0.018
Parameter1_Dir_region_W     0.0193      0.004      4.959      0.000       0.012
0.027
Parameter2_9am_region_N    -0.0093      0.003     -2.818      0.005      -0.016
-0.003
Parameter2_9am_region_S     0.0151      0.003      4.448      0.000       0.008
```

						0.022
Parameter2_9am_region_W	0.0617	0.004	16.540	0.000	0.054	0.069
Parameter2_3pm_region_N	0.0078	0.004	2.069	0.039	0.000	0.015
Parameter2_3pm_region_S	0.0416	0.004	11.817	0.000	0.035	0.048
Parameter2_3pm_region_W	0.0555	0.004	14.238	0.000	0.048	0.063
Location_3	-0.0586	0.009	-6.304	0.000	-0.077	-0.040
Location_4	0.1079	0.009	11.379	0.000	0.089	0.126
Location_5	-0.0981	0.010	-10.187	0.000	-0.117	-0.079
Location_6	-0.1816	0.010	-18.754	0.000	-0.201	-0.163
Location_7	-0.0887	0.009	-9.487	0.000	-0.107	-0.070
Location_8	-0.0114	0.009	-1.211	0.226	-0.030	0.007
Location_9	-0.0537	0.010	-5.385	0.000	-0.073	-0.034
Location_10	-0.0689	0.009	-7.288	0.000	-0.087	-0.050
Location_11	-0.0249	0.009	-2.662	0.008	-0.043	-0.007
Location_12	-0.0331	0.010	-3.369	0.001	-0.052	-0.014
Location_13	-0.1076	0.010	-11.173	0.000	-0.126	-0.089
Location_14	-0.1001	0.010	-10.255	0.000	-0.119	-0.081
Location_15	-0.0778	0.010	-8.009	0.000	-0.097	-0.059
Location_16	-0.1280	0.009	-13.730	0.000	-0.146	-0.110
Location_17	-0.0675	0.015	-4.401	0.000	-0.098	-0.037
Location_18	-0.1070	0.011	-9.961	0.000	-0.128	-0.086
Location_19	-0.1093	0.010	-10.920	0.000	-0.129	-0.090
Location_20	-0.1485	0.009	-15.695	0.000	-0.167	-0.130
Location_21	-0.0822	0.009	-8.847	0.000	-0.100	-0.064
Location_22	-0.0506	0.010	-5.286	0.000	-0.069	

						-0.032
Location_23	-0.0695	0.009	-7.353	0.000	-0.088	-0.051
Location_26	-0.1480	0.011	-13.158	0.000	-0.170	-0.126
Location_27	-0.1569	0.010	-16.484	0.000	-0.176	-0.138
Location_28	-0.1539	0.010	-16.182	0.000	-0.173	-0.135
Location_29	-0.0714	0.009	-7.664	0.000	-0.090	-0.053
Location_30	-0.0119	0.010	-1.223	0.221	-0.031	0.007
Location_32	-0.0168	0.009	-1.857	0.063	-0.035	0.001
Location_33	-0.0215	0.009	-2.311	0.021	-0.040	-0.003
Location_34	-0.0912	0.009	-9.640	0.000	-0.110	-0.073
Location_35	-0.0861	0.009	-9.075	0.000	-0.105	-0.067
Location_36	-0.1753	0.010	-18.142	0.000	-0.194	-0.156
Location_38	-0.1109	0.010	-11.012	0.000	-0.131	-0.091
Location_39	-0.0905	0.009	-9.576	0.000	-0.109	-0.072
Location_40	-0.1033	0.010	-10.456	0.000	-0.123	-0.084
Location_41	-0.0544	0.009	-5.780	0.000	-0.073	-0.036
Location_42	0.0747	0.012	6.484	0.000	0.052	0.097
Location_43	-0.0514	0.009	-5.498	0.000	-0.070	-0.033
Location_44	-0.0899	0.010	-9.426	0.000	-0.109	-0.071
Location_45	-0.1332	0.009	-14.295	0.000	-0.151	-0.115
Location_46	-0.0574	0.010	-5.663	0.000	-0.077	-0.038
Location_47	-0.0375	0.010	-3.866	0.000	-0.056	-0.018
Location_48	-0.1797	0.009	-19.017	0.000	-0.198	-0.161
Location_49	-0.0894	0.009	-9.496	0.000	-0.108	-0.071
estacion_otoño	0.0299	0.003	8.824	0.000	0.023	

```
0.037
estacion_primavera          -0.0151      0.003     -4.625      0.000      -0.022
-0.009
estacion_verano             -0.0175      0.004     -4.011      0.000      -0.026
-0.009
==============================================================================
Omnibus:                     9821.479   Durbin-Watson:                   1.795
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            12305.241
Skew:                           0.779   Prob(JB):                         0.00
Kurtosis:                       2.801   Cond. No.                     2.08e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.08e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

R: De acuerdo a los resultados obtenidos del modelo, el aumento de la temperatura minima se asocia con un incremento en la probabilidad de fallo, por el lado contrario una mayor temperatura maxima en el proceso disminuye la probabilidad. También se observa que a mayores velocidades en el Parameter1_Speed también aumenta la probailidad. En cuanto a los parametros, el "Parameter4_9am" es el mas significativo de estos. En cuanto a las "Location" podemos observar que la mayoria de estas representan una disminución en la probabilidad de fallo a excepción de "Location_4" y "Location_42", esto puede corresponder a que en dichas localizaciones se hace mal uso de la máquina. En las variables de estacion podemos observar que las estaciones de primavera y verano tienden a disminiur la probabilidad de fallo, al contrario de otoño la cual lo aumenta.

3. Ejecute un modelo probit para responder a la pregunta 2.

[16]:
```python
#Utilizamos la mismas variables dependientes e independientes que usamos en el modelo anterior.
modelo = sm.Probit(y, X)
probit = modelo.fit(cov_type="HC0")
print(probit.summary())

mfx= probit.get_margeff()
print(mfx.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.356680
         Iterations 7
                          Probit Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:               119590
Model:                         Probit   Df Residuals:                   119526
Method:                           MLE   Df Model:                           63
Date:                Fri, 25 Apr 2025   Pseudo R-squ.:                  0.3248
Time:                        12:57:57   Log-Likelihood:                -42655.
```

```
converged:                       True   LL-Null:                       -63172.
Covariance Type:                  HC0   LLR p-value:                     0.000
================================================================================
===========
                              coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-----------
const                      21.4906      0.951     22.591      0.000      19.626
23.355
Min_Temp                    0.1097      0.002     53.764      0.000       0.106
0.114
Max_Temp                   -0.1299      0.002    -55.838      0.000      -0.134
-0.125
Parameter1_Speed            0.0211      0.001     35.320      0.000       0.020
0.022
Parameter3_9am              0.0119      0.001     14.330      0.000       0.010
0.014
Parameter3_3pm             -0.0135      0.001    -15.865      0.000      -0.015
-0.012
Parameter4_9am              0.0419      0.001     82.859      0.000       0.041
0.043
Parameter4_3pm             -0.0027      0.000     -5.963      0.000      -0.004
-0.002
Parameter5_3pm             -0.0239      0.001    -26.095      0.000      -0.026
-0.022
Parameter1_Dir_region_N    -0.0444      0.020     -2.264      0.024      -0.083
-0.006
Parameter1_Dir_region_S     0.0307      0.018      1.735      0.083      -0.004
0.065
Parameter1_Dir_region_W     0.0887      0.019      4.554      0.000       0.051
0.127
Parameter2_9am_region_N    -0.0085      0.017     -0.494      0.621      -0.042
0.025
Parameter2_9am_region_S     0.1290      0.017      7.565      0.000       0.096
0.162
Parameter2_9am_region_W     0.2710      0.018     15.124      0.000       0.236
0.306
Parameter2_3pm_region_N    -0.0139      0.019     -0.721      0.471      -0.052
0.024
Parameter2_3pm_region_S     0.1310      0.017      7.552      0.000       0.097
0.165
Parameter2_3pm_region_W     0.1588      0.020      8.007      0.000       0.120
0.198
Location_3                 -0.1956      0.046     -4.253      0.000      -0.286
-0.105
Location_4                  0.2484      0.061      4.044      0.000       0.128
0.369
```

Location_5	-0.2381	0.046	-5.210	0.000	-0.328	-0.149
Location_6	-0.9238	0.047	-19.488	0.000	-1.017	-0.831
Location_7	-0.3808	0.046	-8.267	0.000	-0.471	-0.291
Location_8	0.3170	0.044	7.258	0.000	0.231	0.403
Location_9	0.0628	0.045	1.400	0.162	-0.025	0.151
Location_10	-0.1535	0.046	-3.351	0.001	-0.243	-0.064
Location_11	-0.1270	0.053	-2.416	0.016	-0.230	-0.024
Location_12	0.0671	0.045	1.492	0.136	-0.021	0.155
Location_13	-0.5069	0.044	-11.522	0.000	-0.593	-0.421
Location_14	-0.0776	0.047	-1.668	0.095	-0.169	0.014
Location_15	-0.0631	0.045	-1.399	0.162	-0.151	0.025
Location_16	-0.3587	0.045	-8.054	0.000	-0.446	-0.271
Location_17	0.0277	0.079	0.350	0.726	-0.127	0.183
Location_18	-0.3442	0.049	-6.981	0.000	-0.441	-0.248
Location_19	-0.2927	0.047	-6.281	0.000	-0.384	-0.201
Location_20	-0.5514	0.045	-12.193	0.000	-0.640	-0.463
Location_21	-0.5649	0.051	-11.114	0.000	-0.664	-0.465
Location_22	-0.0144	0.051	-0.282	0.778	-0.114	0.086
Location_23	-0.3140	0.044	-7.204	0.000	-0.399	-0.229
Location_26	-0.7974	0.058	-13.641	0.000	-0.912	-0.683
Location_27	-0.5230	0.044	-11.838	0.000	-0.610	-0.436
Location_28	-0.5060	0.043	-11.833	0.000	-0.590	-0.422
Location_29	-0.4938	0.049	-10.054	0.000	-0.590	-0.398
Location_30	0.1161	0.049	2.364	0.018	0.020	0.212

```
Location_32                  0.0874      0.043      2.025      0.043       0.003
0.172
Location_33                  0.0961      0.046      2.108      0.035       0.007
0.185
Location_34                 -0.4255      0.043     -9.915      0.000      -0.510
-0.341
Location_35                 -0.2180      0.045     -4.820      0.000      -0.307
-0.129
Location_36                 -0.6216      0.046    -13.486      0.000      -0.712
-0.531
Location_38                 -0.2526      0.046     -5.522      0.000      -0.342
-0.163
Location_39                 -0.2139      0.045     -4.707      0.000      -0.303
-0.125
Location_40                 -0.1297      0.047     -2.764      0.006      -0.222
-0.038
Location_41                 -0.0849      0.045     -1.871      0.061      -0.174
0.004
Location_42                  0.2088      0.077      2.698      0.007       0.057
0.361
Location_43                 -0.1769      0.049     -3.632      0.000      -0.272
-0.081
Location_44                 -0.2959      0.043     -6.860      0.000      -0.380
-0.211
Location_45                 -0.5283      0.044    -12.006      0.000      -0.615
-0.442
Location_46                 -0.0289      0.047     -0.611      0.541      -0.121
0.064
Location_47                 -0.0459      0.045     -1.028      0.304      -0.134
0.042
Location_48                 -0.6068      0.045    -13.571      0.000      -0.694
-0.519
Location_49                 -0.7232      0.060    -12.119      0.000      -0.840
-0.606
estacion_otoño               0.0477      0.017      2.727      0.006       0.013
0.082
estacion_primavera          -0.1530      0.016     -9.545      0.000      -0.184
-0.122
estacion_verano             -0.2773      0.022    -12.865      0.000      -0.319
-0.235
================================================================================
===========
       Probit Marginal Effects
=====================================
Dep. Variable:          Failure_today
Method:                          dydx
At:                           overall
================================================================================
```

```
===========
                             dy/dx    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-----------
Min_Temp                    0.0220      0.000     55.585      0.000       0.021
0.023
Max_Temp                   -0.0260      0.000    -59.057      0.000      -0.027
-0.025
Parameter1_Speed            0.0042      0.000     36.045      0.000       0.004
0.004
Parameter3_9am              0.0024      0.000     14.378      0.000       0.002
0.003
Parameter3_3pm             -0.0027      0.000    -15.925      0.000      -0.003
-0.002
Parameter4_9am              0.0084   8.78e-05     95.524      0.000       0.008
0.009
Parameter4_3pm             -0.0005   9.14e-05     -5.971      0.000      -0.001
-0.000
Parameter5_3pm             -0.0048      0.000    -26.346      0.000      -0.005
-0.004
Parameter1_Dir_region_N    -0.0089      0.004     -2.265      0.024      -0.017
-0.001
Parameter1_Dir_region_S     0.0062      0.004      1.735      0.083      -0.001
0.013
Parameter1_Dir_region_W     0.0178      0.004      4.552      0.000       0.010
0.025
Parameter2_9am_region_N    -0.0017      0.003     -0.494      0.621      -0.008
0.005
Parameter2_9am_region_S     0.0258      0.003      7.568      0.000       0.019
0.033
Parameter2_9am_region_W     0.0543      0.004     15.162      0.000       0.047
0.061
Parameter2_3pm_region_N    -0.0028      0.004     -0.721      0.471      -0.010
0.005
Parameter2_3pm_region_S     0.0262      0.003      7.558      0.000       0.019
0.033
Parameter2_3pm_region_W     0.0318      0.004      8.012      0.000       0.024
0.040
Location_3                 -0.0392      0.009     -4.257      0.000      -0.057
-0.021
Location_4                  0.0497      0.012      4.044      0.000       0.026
0.074
Location_5                 -0.0477      0.009     -5.213      0.000      -0.066
-0.030
Location_6                 -0.1849      0.009    -19.697      0.000      -0.203
-0.167
Location_7                 -0.0762      0.009     -8.284      0.000      -0.094
```

						-0.058
Location_8	0.0635	0.009	7.265	0.000	0.046	0.081
Location_9	0.0126	0.009	1.400	0.162	-0.005	0.030
Location_10	-0.0307	0.009	-3.353	0.001	-0.049	-0.013
Location_11	-0.0254	0.011	-2.418	0.016	-0.046	-0.005
Location_12	0.0134	0.009	1.492	0.136	-0.004	0.031
Location_13	-0.1015	0.009	-11.561	0.000	-0.119	-0.084
Location_14	-0.0155	0.009	-1.668	0.095	-0.034	0.003
Location_15	-0.0126	0.009	-1.399	0.162	-0.030	0.005
Location_16	-0.0718	0.009	-8.074	0.000	-0.089	-0.054
Location_17	0.0055	0.016	0.350	0.726	-0.025	0.037
Location_18	-0.0689	0.010	-6.991	0.000	-0.088	-0.050
Location_19	-0.0586	0.009	-6.289	0.000	-0.077	-0.040
Location_20	-0.1104	0.009	-12.239	0.000	-0.128	-0.093
Location_21	-0.1131	0.010	-11.147	0.000	-0.133	-0.093
Location_22	-0.0029	0.010	-0.282	0.778	-0.023	0.017
Location_23	-0.0629	0.009	-7.216	0.000	-0.080	-0.046
Location_26	-0.1596	0.012	-13.697	0.000	-0.182	-0.137
Location_27	-0.1047	0.009	-11.869	0.000	-0.122	-0.087
Location_28	-0.1013	0.009	-11.864	0.000	-0.118	-0.085
Location_29	-0.0989	0.010	-10.091	0.000	-0.118	-0.080
Location_30	0.0232	0.010	2.364	0.018	0.004	0.042
Location_32	0.0175	0.009	2.025	0.043	0.001	0.034
Location_33	0.0192	0.009	2.109	0.035	0.001	0.037
Location_34	-0.0852	0.009	-9.941	0.000	-0.102	

```
-0.068
Location_35                -0.0436      0.009     -4.823      0.000      -0.061
-0.026
Location_36                -0.1244      0.009    -13.555      0.000      -0.142
-0.106
Location_38                -0.0506      0.009     -5.526      0.000      -0.069
-0.033
Location_39                -0.0428      0.009     -4.709      0.000      -0.061
-0.025
Location_40                -0.0260      0.009     -2.763      0.006      -0.044
-0.008
Location_41                -0.0170      0.009     -1.872      0.061      -0.035
0.001
Location_42                 0.0418      0.015      2.698      0.007       0.011
0.072
Location_43                -0.0354      0.010     -3.635      0.000      -0.054
-0.016
Location_44                -0.0592      0.009     -6.868      0.000      -0.076
-0.042
Location_45                -0.1058      0.009    -12.054      0.000      -0.123
-0.089
Location_46                -0.0058      0.009     -0.611      0.541      -0.024
0.013
Location_47                -0.0092      0.009     -1.028      0.304      -0.027
0.008
Location_48                -0.1215      0.009    -13.616      0.000      -0.139
-0.104
Location_49                -0.1448      0.012    -12.178      0.000      -0.168
-0.121
estacion_otoño              0.0096      0.004      2.727      0.006       0.003
0.016
estacion_primavera         -0.0306      0.003     -9.548      0.000      -0.037
-0.024
estacion_verano            -0.0555      0.004    -12.898      0.000      -0.064
-0.047
================================================================================
===========
```

R: Interpretamos similarmente a la pregunta anterior, en base a estos resultados las temperaturas mínimas y máximas se comportan de la misma forma que en el modelo (MCO), Min_Temp tiene dy/dx = 0.0220 y Max_Temp tiene dy/dx = -0.0260. En cuanto a las velocidades del viento "Parameter1_Speed" se comporta igual que antes, indicando un aumento de probabilidad cuando este aumenta (dy/dx = 0.0042). En el caso de las estaciones tampoco cambia el comportamiento. En cuanto a las "Location" se observan cambios con respecto al modelo anterior, indicando que algunas location ahora aumentan la probabilidad de fallo cuando antes indicaban que no.

[17]:
```python
modelo_logit = sm.Logit(y, X).fit(disp=False)
print(modelo_logit.summary())
```

```python
mfx= modelo_logit.get_margeff()
print(mfx.summary())
```

```
                           Logit Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:               119590
Model:                          Logit   Df Residuals:                   119526
Method:                           MLE   Df Model:                           63
Date:                Fri, 25 Apr 2025   Pseudo R-squ.:                  0.3272
Time:                        12:58:06   Log-Likelihood:                -42502.
converged:                       True   LL-Null:                       -63172.
Covariance Type:            nonrobust   LLR p-value:                     0.000
================================================================================
===========
                           coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-----------
const                   36.9592      1.666     22.187      0.000      33.694
40.224
Min_Temp                 0.1967      0.004     52.421      0.000       0.189
0.204
Max_Temp                -0.2396      0.004    -59.421      0.000      -0.248
-0.232
Parameter1_Speed         0.0371      0.001     35.677      0.000       0.035
0.039
Parameter3_9am           0.0203      0.001     13.876      0.000       0.017
0.023
Parameter3_3pm          -0.0227      0.001    -15.237      0.000      -0.026
-0.020
Parameter4_9am           0.0761      0.001     86.470      0.000       0.074
0.078
Parameter4_3pm          -0.0058      0.001     -7.258      0.000      -0.007
-0.004
Parameter5_3pm          -0.0412      0.002    -25.622      0.000      -0.044
-0.038
Parameter1_Dir_region_N -0.0955      0.036     -2.688      0.007      -0.165
-0.026
Parameter1_Dir_region_S  0.0347      0.032      1.079      0.281      -0.028
0.098
Parameter1_Dir_region_W  0.1410      0.035      4.056      0.000       0.073
0.209
Parameter2_9am_region_N -0.0212      0.031     -0.682      0.495      -0.082
0.040
Parameter2_9am_region_S  0.2253      0.031      7.204      0.000       0.164
0.287
Parameter2_9am_region_W  0.4770      0.032     14.752      0.000       0.414
```

						0.540
Parameter2_3pm_region_N	-0.0327	0.035	-0.941	0.347	-0.101	0.035
Parameter2_3pm_region_S	0.2192	0.031	7.021	0.000	0.158	0.280
Parameter2_3pm_region_W	0.2618	0.035	7.493	0.000	0.193	0.330
Location_3	-0.4099	0.082	-4.977	0.000	-0.571	-0.248
Location_4	0.3676	0.112	3.294	0.001	0.149	0.586
Location_5	-0.4069	0.083	-4.888	0.000	-0.570	-0.244
Location_6	-1.7276	0.083	-20.868	0.000	-1.890	-1.565
Location_7	-0.7195	0.084	-8.607	0.000	-0.883	-0.556
Location_8	0.6299	0.080	7.907	0.000	0.474	0.786
Location_9	0.2190	0.082	2.668	0.008	0.058	0.380
Location_10	-0.3012	0.083	-3.629	0.000	-0.464	-0.139
Location_11	-0.3160	0.094	-3.375	0.001	-0.499	-0.133
Location_12	0.1613	0.081	1.981	0.048	0.002	0.321
Location_13	-0.9266	0.079	-11.752	0.000	-1.081	-0.772
Location_14	-0.0201	0.084	-0.239	0.811	-0.185	0.144
Location_15	-0.0402	0.082	-0.488	0.625	-0.201	0.121
Location_16	-0.6818	0.078	-8.686	0.000	-0.836	-0.528
Location_17	0.1855	0.143	1.294	0.196	-0.096	0.467
Location_18	-0.6223	0.089	-6.992	0.000	-0.797	-0.448
Location_19	-0.5307	0.082	-6.479	0.000	-0.691	-0.370
Location_20	-1.0022	0.080	-12.472	0.000	-1.160	-0.845
Location_21	-1.0492	0.092	-11.358	0.000	-1.230	-0.868
Location_22	-0.0334	0.093	-0.358	0.720	-0.216	0.149
Location_23	-0.5814	0.078	-7.435	0.000	-0.735	

						-0.428
Location_26	-1.4462	0.104	-13.849	0.000	-1.651	-1.241
Location_27	-0.9191	0.079	-11.673	0.000	-1.073	-0.765
Location_28	-0.8777	0.077	-11.470	0.000	-1.028	-0.728
Location_29	-0.9575	0.086	-11.113	0.000	-1.126	-0.789
Location_30	0.2137	0.089	2.409	0.016	0.040	0.388
Location_32	0.1934	0.080	2.416	0.016	0.037	0.350
Location_33	0.1964	0.085	2.324	0.020	0.031	0.362
Location_34	-0.7737	0.076	-10.183	0.000	-0.923	-0.625
Location_35	-0.3658	0.083	-4.417	0.000	-0.528	-0.203
Location_36	-1.1410	0.082	-13.978	0.000	-1.301	-0.981
Location_38	-0.4240	0.082	-5.171	0.000	-0.585	-0.263
Location_39	-0.3786	0.080	-4.719	0.000	-0.536	-0.221
Location_40	-0.1056	0.088	-1.207	0.228	-0.277	0.066
Location_41	-0.1758	0.082	-2.137	0.033	-0.337	-0.015
Location_42	0.3162	0.142	2.224	0.026	0.037	0.595
Location_43	-0.3984	0.086	-4.623	0.000	-0.567	-0.230
Location_44	-0.5270	0.077	-6.841	0.000	-0.678	-0.376
Location_45	-0.9763	0.079	-12.426	0.000	-1.130	-0.822
Location_46	-0.0443	0.084	-0.528	0.597	-0.208	0.120
Location_47	-0.0836	0.080	-1.048	0.295	-0.240	0.073
Location_48	-1.0698	0.079	-13.492	0.000	-1.225	-0.914
Location_49	-1.3775	0.106	-13.019	0.000	-1.585	-1.170
estacion_otoño	0.0667	0.030	2.211	0.027	0.008	0.126
estacion_primavera	-0.2541	0.028	-9.047	0.000	-0.309	

```
-0.199
estacion_verano            -0.4959      0.038    -13.218      0.000      -0.569
-0.422
================================================================================
===========
        Logit Marginal Effects
=====================================
Dep. Variable:          Failure_today
Method:                          dydx
At:                           overall
================================================================================
===========
                              dy/dx    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-----------
Min_Temp                     0.0221      0.000     54.507      0.000       0.021
0.023
Max_Temp                    -0.0269      0.000    -62.449      0.000      -0.028
-0.026
Parameter1_Speed             0.0042      0.000     36.480      0.000       0.004
0.004
Parameter3_9am               0.0023      0.000     13.925      0.000       0.002
0.003
Parameter3_3pm              -0.0026      0.000    -15.305      0.000      -0.003
-0.002
Parameter4_9am               0.0086   8.72e-05     98.095      0.000       0.008
0.009
Parameter4_3pm              -0.0007   8.98e-05     -7.262      0.000      -0.001
-0.000
Parameter5_3pm              -0.0046      0.000    -25.913      0.000      -0.005
-0.004
Parameter1_Dir_region_N     -0.0107      0.004     -2.688      0.007      -0.019
-0.003
Parameter1_Dir_region_S      0.0039      0.004      1.079      0.281      -0.003
0.011
Parameter1_Dir_region_W      0.0158      0.004      4.057      0.000       0.008
0.024
Parameter2_9am_region_N     -0.0024      0.003     -0.682      0.495      -0.009
0.004
Parameter2_9am_region_S      0.0253      0.004      7.208      0.000       0.018
0.032
Parameter2_9am_region_W      0.0536      0.004     14.799      0.000       0.047
0.061
Parameter2_3pm_region_N     -0.0037      0.004     -0.941      0.347      -0.011
0.004
Parameter2_3pm_region_S      0.0246      0.004      7.028      0.000       0.018
0.031
```

Parameter2_3pm_region_W	0.0294	0.004	7.501	0.000	0.022	0.037
Location_3	-0.0461	0.009	-4.978	0.000	-0.064	-0.028
Location_4	0.0413	0.013	3.295	0.001	0.017	0.066
Location_5	-0.0457	0.009	-4.890	0.000	-0.064	-0.027
Location_6	-0.1941	0.009	-21.013	0.000	-0.212	-0.176
Location_7	-0.0809	0.009	-8.617	0.000	-0.099	-0.062
Location_8	0.0708	0.009	7.911	0.000	0.053	0.088
Location_9	0.0246	0.009	2.668	0.008	0.007	0.043
Location_10	-0.0338	0.009	-3.630	0.000	-0.052	-0.016
Location_11	-0.0355	0.011	-3.376	0.001	-0.056	-0.015
Location_12	0.0181	0.009	1.981	0.048	0.000	0.036
Location_13	-0.1041	0.009	-11.778	0.000	-0.121	-0.087
Location_14	-0.0023	0.009	-0.239	0.811	-0.021	0.016
Location_15	-0.0045	0.009	-0.488	0.625	-0.023	0.014
Location_16	-0.0766	0.009	-8.698	0.000	-0.094	-0.059
Location_17	0.0208	0.016	1.294	0.196	-0.011	0.052
Location_18	-0.0699	0.010	-6.999	0.000	-0.090	-0.050
Location_19	-0.0596	0.009	-6.485	0.000	-0.078	-0.042
Location_20	-0.1126	0.009	-12.506	0.000	-0.130	-0.095
Location_21	-0.1179	0.010	-11.381	0.000	-0.138	-0.098
Location_22	-0.0038	0.010	-0.358	0.720	-0.024	0.017
Location_23	-0.0653	0.009	-7.442	0.000	-0.083	-0.048
Location_26	-0.1625	0.012	-13.893	0.000	-0.185	-0.140
Location_27	-0.1033	0.009	-11.701	0.000	-0.121	-0.086

```
Location_28                    -0.0986      0.009    -11.499      0.000      -0.115
-0.082
Location_29                    -0.1076      0.010    -11.133      0.000      -0.127
-0.089
Location_30                     0.0240      0.010      2.409      0.016       0.004
0.044
Location_32                     0.0217      0.009      2.416      0.016       0.004
0.039
Location_33                     0.0221      0.009      2.324      0.020       0.003
0.041
Location_34                    -0.0869      0.009    -10.201      0.000      -0.104
-0.070
Location_35                    -0.0411      0.009     -4.419      0.000      -0.059
-0.023
Location_36                    -0.1282      0.009    -14.027      0.000      -0.146
-0.110
Location_38                    -0.0476      0.009     -5.175      0.000      -0.066
-0.030
Location_39                    -0.0425      0.009     -4.721      0.000      -0.060
-0.025
Location_40                    -0.0119      0.010     -1.207      0.228      -0.031
0.007
Location_41                    -0.0198      0.009     -2.137      0.033      -0.038
-0.002
Location_42                     0.0355      0.016      2.224      0.026       0.004
0.067
Location_43                    -0.0448      0.010     -4.625      0.000      -0.064
-0.026
Location_44                    -0.0592      0.009     -6.847      0.000      -0.076
-0.042
Location_45                    -0.1097      0.009    -12.459      0.000      -0.127
-0.092
Location_46                    -0.0050      0.009     -0.528      0.597      -0.023
0.013
Location_47                    -0.0094      0.009     -1.048      0.295      -0.027
0.008
Location_48                    -0.1202      0.009    -13.536      0.000      -0.138
-0.103
Location_49                    -0.1548      0.012    -13.051      0.000      -0.178
-0.132
estacion_otoño                  0.0075      0.003      2.211      0.027       0.001
0.014
estacion_primavera             -0.0286      0.003     -9.057      0.000      -0.035
-0.022
estacion_verano                -0.0557      0.004    -13.249      0.000      -0.064
-0.047
===============================================================================
===========
```

R: En este caso los resultados del modelo logit obtenemos comportamientos muy similares a los obtenidos en el modelo probit. Las temperaturas se comportan de la misma manera pero con unas leve diferencia en su magnitud. El parametro de velocidad "Parameter1_Speed" se comporta de igual forma hasta en su magnitud (dy/dx = 0.0042). En cuanto a las location tampoco se observan mayores diferencias, asda asdasdsa. Las estaciones se comportan de igual manera.

5. Comente los resultados obtenidos en 2, 3 y 4. ¿Cuáles y por qué existen las diferencias entre los resultados?. En su opinión, ¿Cuál sería el más adecuado para responder la pregunta de investgación y por qué? ¿Qué variables resultaron ser robustas a la especificación?

R: De acuerdo a los resultados obtenidos en los 3 modelos, podemos observar que las variables a estudiar se comportan generalmente de igual forma, en el sentido de si aumentan o disminuyen la probabilidad de que ocurra un fallo. Una diferencia entre los modelos ocurre entre el modelo OLS y los modelos Probit y Logit con respecto a la variable de "Location", según el modelo OLS casi todas las "Location" indicaban una disminución en la probabilidad de fallo, pero tanto en el modelo Probit como Logit se observa que varias de estas invierten sus comportamientos. En mi opinión de acuerdo a que modelo es más adecuado para nuestro caso de estudio, el modelo OLS (MCO) no es adecuado dado que no se ajusta bien a la variable binaria a predecir (Failure_Today), en cambio los modelos Probit y Logit ya que están diseñados para manejar variables dependientes binarias. En los dos modelos se obtuvo resultados bastante similares en cuanto a sus valores de R y en cuanto a sus coeficientes marginales por lo que entre elegir uno u otro no hay mayor diferencia, sin embargo el modelo Probit puede ser más adecuado para nuestros datos dado que no tenemos tantos datos extremos.

6. Agregue la data a nivel mensual, usando la data promedio de las variables (ignorando aquellas categoricas, como la direccion del viento). En particular, genere una variable que cuente la cantidad de fallos observados en un mes, utilice un valor de 0 si en ese mes no se reporto fallos en ningun dia. Use un modelo Poisson para explicar el numero de fallas por mes. Seleccione las variables dependientes a incluir en el modelo final e interprete su significado.

[18]:
```
#Creamos un nuevo df para el modelo poisson y excluimos las variables␣
↪categoricas
df_poisson = df.copy()

df_poisson = df_poisson.select_dtypes(exclude=['object', 'category'])

df_poisson
```

[18]:
```
              Date  Location  Min_Temp  Max_Temp  Parameter1_Speed  \
0       2008-12-01         3      13.4      22.9              44.0
1       2008-12-02         3       7.4      25.1              44.0
2       2008-12-03         3      12.9      25.7              46.0
3       2008-12-04         3       9.2      28.0              24.0
4       2008-12-05         3      17.5      32.3              41.0
…              …         …         …         …                 …
142188  2017-06-20        42       3.5      21.8              31.0
142189  2017-06-21        42       2.8      23.4              31.0
142190  2017-06-22        42       3.6      25.3              22.0
142191  2017-06-23        42       5.4      26.9              37.0
```

```
142192 2017-06-24        42       7.8      27.0              28.0

        Parameter3_9am  Parameter3_3pm  Parameter4_9am  Parameter4_3pm  \
0                 20.0            24.0            71.0            22.0
1                  4.0            22.0            44.0            25.0
2                 19.0            26.0            38.0            30.0
3                 11.0             9.0            45.0            16.0
4                  7.0            20.0            82.0            33.0
…                  …              …              …              …
142188            15.0            13.0            59.0            27.0
142189            13.0            11.0            51.0            24.0
142190            13.0             9.0            56.0            21.0
142191             9.0             9.0            53.0            24.0
142192            13.0             7.0            51.0            24.0

        Parameter5_3pm  Failure_today
0               1007.1            0.0
1               1007.8            0.0
2               1008.7            0.0
3               1012.8            0.0
4               1006.0            0.0
…                  …             …
142188          1021.2            0.0
142189          1020.3            0.0
142190          1019.1            0.0
142191          1016.8            0.0
142192          1016.5            0.0

[119590 rows x 11 columns]
```

[19]:
```
df_poisson=df_poisson[df_poisson["Date"].dt.year>2008] #Consideramos desde el␣
↪año 2009 en adelante porque faltan algunos location
df_poisson["Mes"] = df_poisson["Date"].dt.to_period("M")

df_poisson
```

```
C:\Users\Nacho\AppData\Local\Temp\ipykernel_6444\1462064157.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_poisson["Mes"] = df_poisson["Date"].dt.to_period("M")
```

[19]:
```
              Date  Location  Min_Temp  Max_Temp  Parameter1_Speed  \
30      2009-01-01         3      11.3      26.5              56.0
31      2009-01-02         3       9.6      23.9              41.0
```

```
32      2009-01-03         3      10.5      28.8              26.0
33      2009-01-04         3      12.3      34.6              37.0
34      2009-01-05         3      12.9      35.8              41.0
…           …        …       …       …              …
142188  2017-06-20        42       3.5      21.8              31.0
142189  2017-06-21        42       2.8      23.4              31.0
142190  2017-06-22        42       3.6      25.3              22.0
142191  2017-06-23        42       5.4      26.9              37.0
142192  2017-06-24        42       7.8      27.0              28.0

        Parameter3_9am  Parameter3_3pm  Parameter4_9am  Parameter4_3pm  \
30                19.0            31.0            46.0            26.0
31                19.0            11.0            44.0            22.0
32                11.0             7.0            43.0            22.0
33                 6.0            17.0            41.0            12.0
34                 6.0            26.0            41.0             9.0
…                  …              …              …              …
142188            15.0            13.0            59.0            27.0
142189            13.0            11.0            51.0            24.0
142190            13.0             9.0            56.0            21.0
142191             9.0             9.0            53.0            24.0
142192            13.0             7.0            51.0            24.0

        Parameter5_3pm  Failure_today      Mes
30              1003.2            0.0  2009-01
31              1013.1            0.0  2009-01
32              1014.8            0.0  2009-01
33              1010.3            0.0  2009-01
34              1009.2            0.0  2009-01
…                  …            …       …
142188          1021.2            0.0  2017-06
142189          1020.3            0.0  2017-06
142190          1019.1            0.0  2017-06
142191          1016.8            0.0  2017-06
142192          1016.5            0.0  2017-06

[117793 rows x 12 columns]
```

[20]:
```
promedios = df_poisson.groupby(["Mes", "Location"]).agg({"Min_Temp": "mean",
 "Max_Temp":"mean","Parameter1_Speed":"mean","Parameter3_9am": "mean",
 "Parameter3_3pm":"mean","Parameter4_9am":"mean","Parameter4_3pm":
 ↪"mean","Parameter5_3pm":"mean",
 "Failure_today":"sum"}).reset_index()
promedios
```

[20]:
```
          Mes  Location   Min_Temp   Max_Temp  Parameter1_Speed  \
0     2009-01         1  17.975862  31.868966         39.965517
```

```
1     2009-01         3  16.312903  34.658065          42.677419
2     2009-01         4  22.422581  36.058065          51.258065
3     2009-01         5  16.250000  32.733333          41.300000
4     2009-01         6  10.617241  28.548276          48.620690
…       …       …        …        …                …
4071  2017-06        45   4.424000  14.744000          24.040000
4072  2017-06        46  10.100000  18.356000          34.120000
4073  2017-06        47   8.736000  18.616000          34.000000
4074  2017-06        48  11.788889  17.816667          37.166667
4075  2017-06        49   5.800000  18.754167          27.666667

      Parameter3_9am  Parameter3_3pm  Parameter4_9am  Parameter4_3pm  \
0          10.448276       17.931034       38.689655       23.827586
1          11.935484       18.548387       41.903226       17.870968
2          18.516129       25.032258       37.096774       24.516129
3           7.300000       17.466667       65.466667       35.933333
4          20.172414       22.241379       50.586207       24.379310
…                …              …              …              …
4071        4.960000        9.280000       97.840000       67.760000
4072       16.440000       16.440000       87.200000       70.880000
4073        9.520000       16.320000       88.520000       67.280000
4074       14.666667       19.000000       72.166667       68.666667
4075       11.375000       12.833333       66.041667       35.875000

      Parameter5_3pm  Failure_today
0        1012.324138            0.0
1        1009.770968            1.0
2        1004.732258            3.0
3        1012.353333            3.0
4        1011.451724            0.0
…                …            …
4071     1026.476000            3.0
4072     1023.492000           13.0
4073     1022.168000            9.0
4074     1024.283333            4.0
4075     1027.033333            0.0

[4076 rows x 11 columns]
```

[21]:
```
poisson= smf.poisson("Failure_today ~ C(Location) + Min_Temp + Max_Temp +␣
↪Parameter1_Speed + Parameter3_9am + Parameter3_3pm + Parameter4_9am +␣
↪Parameter4_3pm + Parameter5_3pm",
                     data=promedios).fit()

print(poisson.summary())
```

```
Optimization terminated successfully.
         Current function value: 2.227737
```

```
        Iterations 8
                          Poisson Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:                 4076
Model:                        Poisson   Df Residuals:                     4024
Method:                           MLE   Df Model:                           51
Date:                Fri, 25 Apr 2025   Pseudo R-squ.:                  0.3207
Time:                        12:58:15   Log-Likelihood:                -9080.3
converged:                       True   LL-Null:                       -13366.
Covariance Type:            nonrobust   LLR p-value:                     0.000
================================================================================
=====
                       coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
Intercept           21.1181      2.908      7.262      0.000      15.418
26.818
C(Location)[T.3]     0.0610      0.066      0.931      0.352      -0.067
0.189
C(Location)[T.4]     0.0868      0.082      1.063      0.288      -0.073
0.247
C(Location)[T.5]    -0.1696      0.068     -2.497      0.013      -0.303
-0.036
C(Location)[T.6]    -0.3748      0.074     -5.056      0.000      -0.520
-0.229
C(Location)[T.7]    -0.1099      0.067     -1.650      0.099      -0.240
0.021
C(Location)[T.8]    -0.0205      0.060     -0.342      0.732      -0.138
0.097
C(Location)[T.9]    -0.0363      0.063     -0.572      0.567      -0.161
0.088
C(Location)[T.10]   -0.0183      0.073     -0.250      0.802      -0.162
0.125
C(Location)[T.11]   -0.0322      0.070     -0.459      0.646      -0.169
0.105
C(Location)[T.12]    0.0211      0.063      0.337      0.736      -0.101
0.144
C(Location)[T.13]   -0.2443      0.066     -3.712      0.000      -0.373
-0.115
C(Location)[T.14]   -0.3463      0.064     -5.405      0.000      -0.472
-0.221
C(Location)[T.15]   -0.0981      0.069     -1.420      0.156      -0.233
0.037
C(Location)[T.16]   -0.6157      0.059    -10.487      0.000      -0.731
-0.501
C(Location)[T.17]   -0.5770      0.111     -5.203      0.000      -0.794
-0.360
```

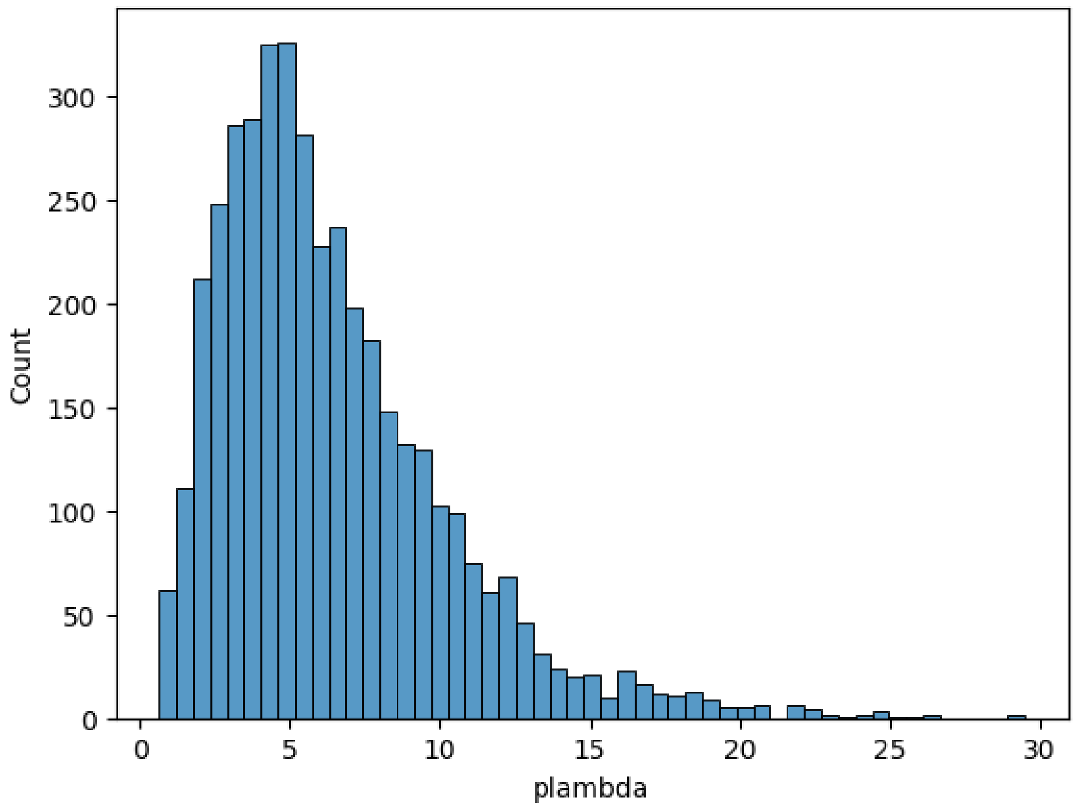
C(Location)[T.18]	-0.3062	0.071	-4.326	0.000	-0.445	-0.167
C(Location)[T.19]	-0.3500	0.064	-5.433	0.000	-0.476	-0.224
C(Location)[T.20]	-0.2537	0.067	-3.807	0.000	-0.384	-0.123
C(Location)[T.21]	-0.1130	0.076	-1.482	0.138	-0.262	0.036
C(Location)[T.22]	-0.0414	0.077	-0.535	0.593	-0.193	0.110
C(Location)[T.23]	0.0094	0.064	0.146	0.884	-0.117	0.135
C(Location)[T.26]	-0.2527	0.086	-2.925	0.003	-0.422	-0.083
C(Location)[T.27]	-0.6315	0.060	-10.511	0.000	-0.749	-0.514
C(Location)[T.28]	-0.5966	0.064	-9.377	0.000	-0.721	-0.472
C(Location)[T.29]	-0.1018	0.063	-1.608	0.108	-0.226	0.022
C(Location)[T.30]	-0.0240	0.069	-0.350	0.726	-0.158	0.110
C(Location)[T.32]	0.1022	0.060	1.702	0.089	-0.016	0.220
C(Location)[T.33]	0.1806	0.065	2.787	0.005	0.054	0.308
C(Location)[T.34]	-0.2429	0.059	-4.087	0.000	-0.359	-0.126
C(Location)[T.35]	-0.1752	0.067	-2.605	0.009	-0.307	-0.043
C(Location)[T.36]	-0.2039	0.070	-2.927	0.003	-0.340	-0.067
C(Location)[T.38]	-0.2886	0.060	-4.818	0.000	-0.406	-0.171
C(Location)[T.39]	-0.1318	0.062	-2.135	0.033	-0.253	-0.011
C(Location)[T.40]	-0.3602	0.070	-5.150	0.000	-0.497	-0.223
C(Location)[T.41]	0.0161	0.067	0.240	0.811	-0.115	0.147
C(Location)[T.42]	-0.0881	0.107	-0.820	0.412	-0.298	0.122
C(Location)[T.43]	0.0915	0.067	1.373	0.170	-0.039	0.222
C(Location)[T.44]	-0.4687	0.058	-8.018	0.000	-0.583	-0.354
C(Location)[T.45]	-0.3892	0.060	-6.480	0.000	-0.507	-0.271

```
C(Location)[T.46]    -0.0503      0.067     -0.750      0.453     -0.182
0.081
C(Location)[T.47]    -0.0746      0.060     -1.234      0.217     -0.193
0.044
C(Location)[T.48]    -0.8283      0.061    -13.490      0.000     -0.949
-0.708
C(Location)[T.49]    -0.4593      0.088     -5.235      0.000     -0.631
-0.287
Min_Temp              0.1073      0.008     13.493      0.000      0.092
0.123
Max_Temp             -0.1054      0.008    -13.352      0.000     -0.121
-0.090
Parameter1_Speed      0.0571      0.003     21.382      0.000      0.052
0.062
Parameter3_9am       -0.0098      0.004     -2.572      0.010     -0.017
-0.002
Parameter3_3pm       -0.0582      0.004    -16.280      0.000     -0.065
-0.051
Parameter4_9am        0.0162      0.002      9.600      0.000      0.013
0.019
Parameter4_3pm        0.0164      0.002      8.205      0.000      0.012
0.020
Parameter5_3pm       -0.0208      0.003     -7.438      0.000     -0.026
-0.015
================================================================================
=====
```

R: Para responder esta pregunta agrupamos la data a nivel mensual y por "Location". Se estimo el promedio mensual de los datos para cada "Location", se eliminaron las variables categoricas y se generó un conteo de los fallos por mes en cada "Location" para luego poder aplicarla en el modelo Poisson. En cuanto a los resultados del modelo se obtienen comportamientos similares a los modelos ajustados anteriormente, las variables de temperaturas se comportan de la misma forma, al igual que la de velocidad de viento. En el caso de las "Location" se observa que la mayoria entregan coeficientes negativos, como en el caso de "Location_48" que tiene un coeficiente negativo fuerte (=-0.8283). Se infiere que la ubicación geografica es significativa en cuantos fallos se promedian en el mes.

[22]:
```
promedios['plambda'] = poisson.predict()
sns.histplot(data=promedios, x="plambda")
```

[22]:
```
<Axes: xlabel='plambda', ylabel='Count'>
```



7. Determine sobre dispersion en la data y posible valor optimo de alpha para un modelo Binomial Negativa.

[23]:
```
#Utilizamos una formula para calcular la sobredispersión y usamos un mu␣
↪predecido
mu = poisson.predict()
y = promedios["Failure_today"]
aux = ((y - mu)**2 - mu) / mu
auxr = sm.OLS(aux, 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:
5.239
Date:                Fri, 25 Apr 2025   Prob (F-statistic):
```

```
0.0221
Time:                        12:58:15   Log-Likelihood:
-7162.4
No. Observations:                4076   AIC:
1.433e+04
Df Residuals:                    4075   BIC:
1.433e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
x1            -0.0067      0.003     -2.289      0.022      -0.013      -0.001
==============================================================================
Omnibus:                     3528.464   Durbin-Watson:                   1.822
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           153178.109
Skew:                           3.948   Prob(JB):                         0.00
Kurtosis:                      31.975   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.
```

R: A pesar de obtener un alpha negativo, obtuvimos que es distinto de 0, por lo que concluimos que el modelo Poisson no es adecuado y que existe sobredispersión.

8. Usando la informacion anterior, ejecute un modelo Binomial Negativa para responder a la pregunta 6. Seleccione las variables dependientes a incluir en el modelo final e interprete su significado

[24]:
```
binomial_negativa = smf.glm(
    formula="Failure_today ~ C(Location) + Min_Temp + Max_Temp +␣
 ↪Parameter1_Speed + Parameter3_9am + Parameter3_3pm + Parameter4_9am +␣
 ↪Parameter4_3pm + Parameter5_3pm",
      data=promedios,
      family=sm.families.NegativeBinomial()
).fit()
print(binomial_negativa.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:                 4076
Model:                            GLM   Df Residuals:                     4024
Model Family:        NegativeBinomial   Df Model:                           51
Link Function:                    Log   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -11277.
```

```
Date:                Fri, 25 Apr 2025   Deviance:                    1069.9
Time:                        12:58:15   Pearson chi2:                  748.
No. Iterations:                     9   Pseudo R-squ. (CS):          0.2767
Covariance Type:            nonrobust
================================================================================
=====
                       coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
Intercept           22.7994      8.317      2.741      0.006       6.498
39.101
C(Location)[T.3]     0.1330      0.179      0.744      0.457      -0.218
0.484
C(Location)[T.4]     0.0414      0.182      0.227      0.820      -0.316
0.399
C(Location)[T.5]    -0.1932      0.183     -1.054      0.292      -0.553
0.166
C(Location)[T.6]    -0.3812      0.212     -1.801      0.072      -0.796
0.034
C(Location)[T.7]    -0.0561      0.181     -0.310      0.757      -0.411
0.299
C(Location)[T.8]    -0.1003      0.166     -0.604      0.546      -0.425
0.225
C(Location)[T.9]    -0.2221      0.185     -1.202      0.229      -0.584
0.140
C(Location)[T.10]    0.0398      0.196      0.203      0.839      -0.344
0.423
C(Location)[T.11]    0.0274      0.173      0.158      0.874      -0.311
0.366
C(Location)[T.12]   -0.0735      0.181     -0.406      0.685      -0.429
0.281
C(Location)[T.13]   -0.2849      0.193     -1.474      0.140      -0.664
0.094
C(Location)[T.14]   -0.7159      0.183     -3.920      0.000      -1.074
-0.358
C(Location)[T.15]   -0.2505      0.194     -1.291      0.197      -0.631
0.130
C(Location)[T.16]   -0.6486      0.167     -3.888      0.000      -0.976
-0.322
C(Location)[T.17]   -0.9800      0.285     -3.442      0.001      -1.538
-0.422
C(Location)[T.18]   -0.3504      0.198     -1.772      0.076      -0.738
0.037
C(Location)[T.19]   -0.3749      0.181     -2.076      0.038      -0.729
-0.021
C(Location)[T.20]   -0.2376      0.188     -1.264      0.206      -0.606
0.131
```

C(Location)[T.21]	-0.0061	0.186	-0.033	0.974	-0.370	0.358
C(Location)[T.22]	-0.0033	0.195	-0.017	0.986	-0.385	0.378
C(Location)[T.23]	0.0245	0.191	0.128	0.898	-0.350	0.399
C(Location)[T.26]	-0.2113	0.227	-0.929	0.353	-0.657	0.234
C(Location)[T.27]	-0.7723	0.171	-4.506	0.000	-1.108	-0.436
C(Location)[T.28]	-0.7806	0.185	-4.230	0.000	-1.142	-0.419
C(Location)[T.29]	-0.0426	0.173	-0.246	0.806	-0.383	0.297
C(Location)[T.30]	-0.0846	0.182	-0.464	0.643	-0.442	0.273
C(Location)[T.32]	-0.0147	0.165	-0.089	0.929	-0.338	0.308
C(Location)[T.33]	0.0672	0.179	0.376	0.707	-0.283	0.417
C(Location)[T.34]	-0.3618	0.178	-2.028	0.043	-0.712	-0.012
C(Location)[T.35]	-0.1803	0.182	-0.993	0.321	-0.536	0.176
C(Location)[T.36]	-0.2398	0.193	-1.243	0.214	-0.618	0.138
C(Location)[T.38]	-0.3479	0.172	-2.021	0.043	-0.685	-0.010
C(Location)[T.39]	-0.1861	0.177	-1.054	0.292	-0.532	0.160
C(Location)[T.40]	-0.6407	0.188	-3.400	0.001	-1.010	-0.271
C(Location)[T.41]	0.0678	0.180	0.376	0.707	-0.286	0.421
C(Location)[T.42]	-0.1455	0.227	-0.642	0.521	-0.590	0.299
C(Location)[T.43]	0.1766	0.180	0.984	0.325	-0.175	0.528
C(Location)[T.44]	-0.6051	0.174	-3.486	0.000	-0.945	-0.265
C(Location)[T.45]	-0.3826	0.172	-2.229	0.026	-0.719	-0.046
C(Location)[T.46]	-0.0652	0.185	-0.352	0.725	-0.429	0.298
C(Location)[T.47]	-0.1997	0.179	-1.116	0.264	-0.550	0.151
C(Location)[T.48]	-0.9981	0.172	-5.791	0.000	-1.336	-0.660

```
C(Location)[T.49]    -0.4051      0.193     -2.100      0.036      -0.783
-0.027
Min_Temp              0.1130      0.021      5.393      0.000       0.072
0.154
Max_Temp             -0.1058      0.021     -4.996      0.000      -0.147
-0.064
Parameter1_Speed      0.0646      0.008      8.433      0.000       0.050
0.080
Parameter3_9am       -0.0075      0.010     -0.734      0.463      -0.028
0.013
Parameter3_3pm       -0.0657      0.010     -6.671      0.000      -0.085
-0.046
Parameter4_9am        0.0158      0.004      3.532      0.000       0.007
0.025
Parameter4_3pm        0.0235      0.006      4.259      0.000       0.013
0.034
Parameter5_3pm       -0.0230      0.008     -2.875      0.004      -0.039
-0.007
==============================================================================
=====

c:\Users\Nacho\AppData\Local\Programs\Python\Python313\Lib\site-
packages\statsmodels\genmod\families\family.py:1367: ValueWarning: Negative
binomial dispersion parameter alpha not set. Using default value alpha=1.0.
  warnings.warn("Negative binomial dispersion parameter alpha not "
```

R: De acuerdo a los resultados obtenidos en el modelo binomial negativo obtuvimos un menor ajuste de R cuadrado en comparación al modelo Poisson, lo que no es lo esperado dado que al determinar que existia una sobredispersión se esperaria que el modelo binomial negativo se ajustara mejor a los datos. Sin embargo por el lado de los coeficientes se comportan de la misma forma que los coeficientes obtenidos en poisson.

9. Comente los resultados obtenidos en 6, 7 y 8. ¿Cuáles y por qué existen las diferencias entre los resultados?. En su opinión, ¿Cuál sería el más adecuado para responder la pregunta de investgación y por qué? ¿Qué variables resultaron ser robustas a la especificación?

R: En los resultados se obtuvo para el modelo Poisson un Pseudo R cuadrado = 0.3207, en el modelo Binomial Negativo un Pseudo R-squ = 0.2767 y en la pregunta 7 se determinó un alfa negativo (distinto de 0) y significativo ($P>|t| = 0.022$). De acuerdo a los resultados obtenidos es más adecuado el modelo Poisson para responder la pregunta de investigación, dado que reduce en mayor cantidad la incertidumbre a un modelo sin predictores (32.07% > 27.67%). Sin embargo esto no corresponde a lo esperado, como mencioné en la respuesta de la pregunta 8, se esperaría que al confirmar sobredispersión, el modelo de binomial negativa redujera en mayor cantidad la incertidumbre en comparación a Poisson. Por otro lado variables robustas a la especificación a lo largo de los modelos fueron “Min_Temp”, “Max_Temp”, “Parameter1_Speed”, algunas “Location” como “Location_48” que mantuvo constantemnte una relación negativa con respecto a los fallos, tambien las variables estacionales mantuvieron sus comportamientos.