Tarea1_Lara_Urrutia

May 5, 2025

Tarea 1 Data Analysis And Machine Learning

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- Date: data medida en frecuencia diaria
- Location: ubicacion del medidor
- Min_Temp: temperatura minima observada
- Max_Temp: temperatura maxima observada
- Leakage: Filtracion medida en el area
- Evaporation: Tasa de evaporacion
- Electricity: Consumo electrico KW
- Parameter#: Diferentes sensores de reportando direccion y velocidad de viento en distintos momentos del dia, asi como otras metricas relevantes.
- Failure today: El sensor reporta fallo (o no)

[2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
import statsmodels.formula.api as smf
import sklearn
import scipy
from scipy.stats import nbinom
import seaborn as sns
from statsmodels.iolib.summary2 import summary_col

import warnings
warnings.filterwarnings("ignore")

%matplotlib inline
```

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.

[ ]:
```
df = pd.read_csv('../data/machine_failure_data.csv')
df.head
```

```
[ ]: <bound method NDFrame.head of              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]>
```

[6]:
```
df.describe(include='all')
```

[6]:
```
              Date       Location       Min_Temp       Max_Temp        Leakage  \
count       142193  142193.000000  141556.000000  141871.000000  140787.000000
unique        3436            NaN            NaN            NaN            NaN
top     12/1/2013            NaN            NaN            NaN            NaN
freq            49            NaN            NaN            NaN            NaN
mean           NaN      24.740655      12.186400      23.226784       2.349974
std            NaN      14.237503       6.403283       7.117618       8.465173
min            NaN       1.000000      -8.500000      -4.800000       0.000000
25%            NaN      12.000000       7.600000      17.900000       0.000000
50%            NaN      25.000000      12.000000      22.600000       0.000000
75%            NaN      37.000000      16.800000      28.200000       0.800000
max            NaN      49.000000      33.900000      48.100000     371.000000

         Evaporation   Electricity Parameter1_Dir  Parameter1_Speed  \
count   81350.000000  74377.000000         132863     132923.000000
unique           NaN           NaN             16               NaN
top              NaN           NaN              W               NaN
freq             NaN           NaN           9780               NaN
mean        5.469824      7.624853            NaN         39.984292
std         4.188537      3.781525            NaN         13.588801
min         0.000000      0.000000            NaN          6.000000
25%         2.600000      4.900000            NaN         31.000000
50%         4.800000      8.500000            NaN         39.000000
75%         7.400000     10.600000            NaN         48.000000
```

```
max       145.000000     14.500000            NaN        135.000000

       Parameter2_9am  … Parameter3_3pm  Parameter4_9am  Parameter4_3pm  \
count          132180  …  139563.000000   140419.000000   138583.000000
unique             16  …            NaN             NaN             NaN
top                 N  …            NaN             NaN             NaN
freq            11393  …            NaN             NaN             NaN
mean              NaN  …      18.637576       68.843810       51.482606
std               NaN  …       8.803345       19.051293       20.797772
min               NaN  …       0.000000        0.000000        0.000000
25%               NaN  …      13.000000       57.000000       37.000000
50%               NaN  …      19.000000       70.000000       52.000000
75%               NaN  …      24.000000       83.000000       66.000000
max               NaN  …      87.000000      100.000000      100.000000

        Parameter5_9am  Parameter5_3pm  Parameter6_9am  Parameter6_3pm  \
count    128179.000000   128212.000000    88536.000000    85099.000000
unique             NaN             NaN             NaN             NaN
top                NaN             NaN             NaN             NaN
freq               NaN             NaN             NaN             NaN
mean       1017.653758     1015.258204        4.437189        4.503167
std           7.105476        7.036677        2.887016        2.720633
min         980.500000      977.100000        0.000000        0.000000
25%        1012.900000     1010.400000        1.000000        2.000000
50%        1017.600000     1015.200000        5.000000        5.000000
75%        1022.400000     1020.000000        7.000000        7.000000
max        1041.000000     1039.600000        9.000000        9.000000

        Parameter7_9am  Parameter7_3pm  Failure_today
count    141289.000000   139467.000000         140787
unique             NaN             NaN              2
top                NaN             NaN             No
freq               NaN             NaN         109332
mean         16.987509       21.687235            NaN
std           6.492838        6.937594            NaN
min          -7.200000       -5.400000            NaN
25%          12.300000       16.600000            NaN
50%          16.700000       21.100000            NaN
75%          21.600000       26.400000            NaN
max          40.200000       46.700000            NaN

[11 rows x 22 columns]
```

[7]:
```
df.dtypes
```

[7]:
```
Date                object
Location             int64
```

```
Min_Temp            float64
Max_Temp            float64
Leakage             float64
Evaporation         float64
Electricity         float64
Parameter1_Dir       object
Parameter1_Speed    float64
Parameter2_9am       object
Parameter2_3pm       object
Parameter3_9am      float64
Parameter3_3pm      float64
Parameter4_9am      float64
Parameter4_3pm      float64
Parameter5_9am      float64
Parameter5_3pm      float64
Parameter6_9am      float64
Parameter6_3pm      float64
Parameter7_9am      float64
Parameter7_3pm      float64
Failure_today        object
dtype: object
```

A continuación, se agregan variables categóricas para las direcciones del viento y dummy para Leakage y Failure.

[ ]:
```
VIENTO = list(range(1, 17))
DIRECV = ['SSW','S', 'NNE' ,'WNW', 'N' ,'SE', 'ENE', 'NE' ,'E' ,'SW', 'W',␣
 ↪'WSW', 'NNW', 'ESE','SSE','NW']
df['VIENTO'] = df['Parameter1_Dir'].replace(DIRECV,VIENTO)

df['VIENTO2_9am'] = df['Parameter2_9am'].replace(DIRECV,VIENTO)

df['VIENTO3_2pm'] = df['Parameter2_3pm'].replace(DIRECV,VIENTO)
```

[9]:
```
df['VIENTO'].head
```

[9]:
```
<bound method NDFrame.head of 0         11.0
1          4.0
2         12.0
3          8.0
4         11.0
          ...
142188     9.0
142189     9.0
142190    13.0
142191     5.0
142192     6.0
Name: VIENTO, Length: 142193, dtype: float64>
```

[10]:
```
df['VIENTO2_9am'].head
```

[10]:
```
<bound method NDFrame.head of 0         11.0
1         13.0
2         11.0
3          6.0
4          7.0
          ...
142188    14.0
142189     6.0
142190     6.0
142191     6.0
142192    15.0
Name: VIENTO2_9am, Length: 142193, dtype: float64>
```

[ ]:
```
df['VIENTO3_2pm'].head
```

[64]:
```
df['Failure_today'] = df['Failure_today'].str.strip().str.lower()

df['Failure_today'] = df['Failure_today'].map({'yes': 1, 'no': 0})
```

[12]:
```
df['Failure_today'].head
```

[12]:
```
<bound method NDFrame.head of 0         0.0
1         0.0
2         0.0
3         0.0
4         0.0
          ...
142188    0.0
142189    0.0
142190    0.0
142191    0.0
142192    0.0
Name: Failure_today, Length: 142193, dtype: float64>
```

[13]:
```
df['Failure_today'].value_counts()
```

[13]:
```
Failure_today
0.0    109332
1.0     31455
Name: count, dtype: int64
```

[66]:
```
df['LK'] = df['Leakage'].apply(lambda x: 1 if x > 0 else 0)
print(df['LK'])
```

```
0         1
1         0
```

```
2         0
3         0
4         1
         ..
142188    0
142189    0
142190    0
142191    0
142192    0
Name: LK, Length: 142193, dtype: int64
```

[15]:
```
print(df['LK'].value_counts())
```

```
LK
0    91681
1    50512
Name: count, dtype: int64
```

Se eligen las variables con más de 50 mil NaN y se rellenan con ceros.

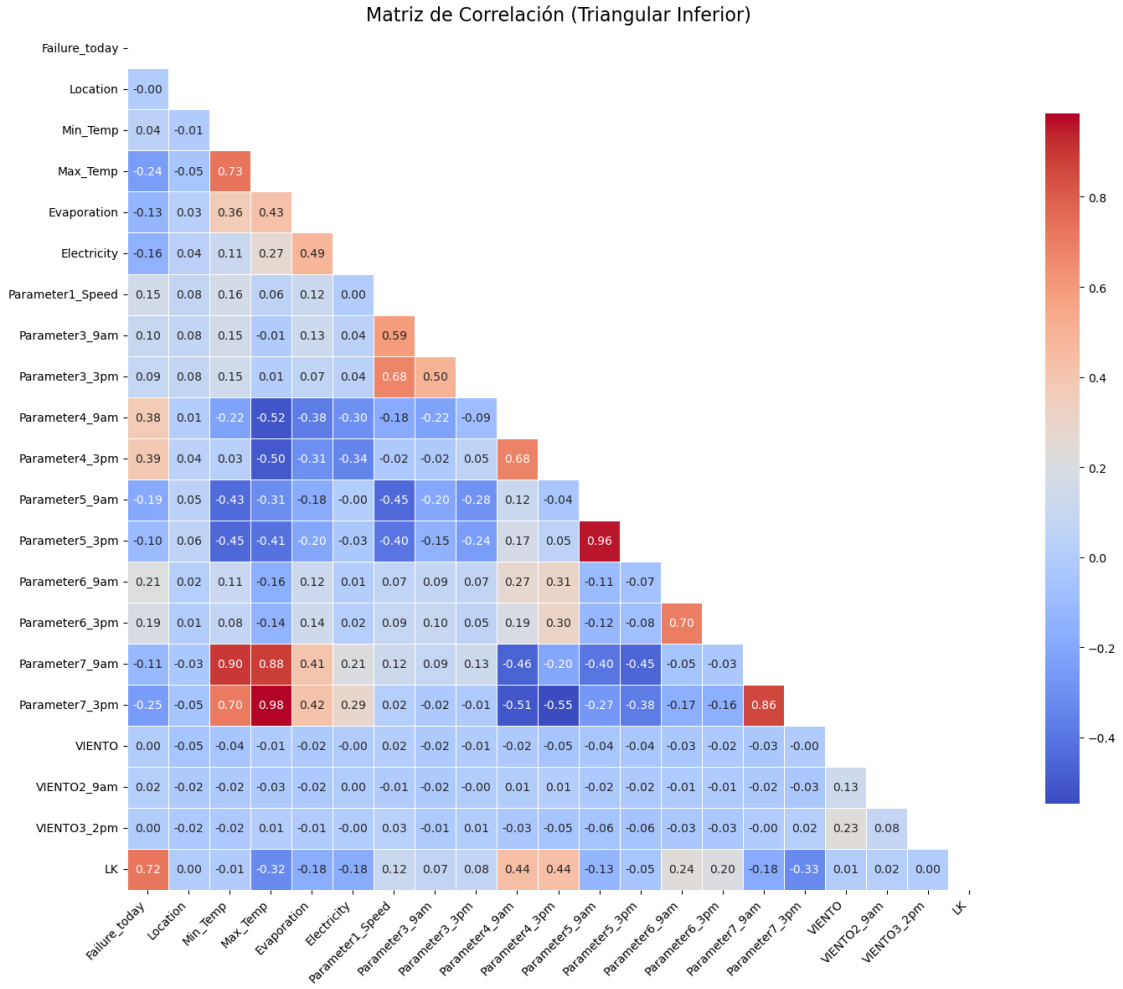
[67]:
```
df['Evaporation'] = df['Evaporation'].fillna(0)
df['Electricity'] = df['Electricity'].fillna(0)
df['Parameter6_9am'] = df['Parameter6_9am'].fillna(0)
df['Parameter6_3pm'] = df['Parameter6_3pm'].fillna(0)
```

Se eliminan filas con NaN en el resto de variables.

[68]:
```
columnas_con_nan = ['Min_Temp', 'Max_Temp', 'Leakage', 'Parameter1_Dir',␣
 ↪'Parameter1_Speed',
                    'Parameter2_9am', 'Parameter2_3pm', 'Parameter3_9am',␣
 ↪'Parameter3_3pm',
                    'Parameter4_9am', 'Parameter4_3pm', 'Parameter5_9am',␣
 ↪'Parameter5_3pm',
                    'Parameter7_9am', 'Parameter7_3pm', 'Failure_today',␣
 ↪'VIENTO', 'VIENTO2_9am', 'VIENTO3_2pm']

df = df.dropna(subset=columnas_con_nan)
```

[69]:
```
parametros = ['Failure_today','Location', 'Min_Temp', 'Max_Temp', 'Evaporation',
       'Electricity', 'Parameter1_Speed', 'Parameter3_9am', 'Parameter3_3pm',␣
 ↪'Parameter4_9am',
       'Parameter4_3pm', 'Parameter5_9am', 'Parameter5_3pm', 'Parameter6_9am',
       'Parameter6_3pm', 'Parameter7_9am', 'Parameter7_3pm',
       'VIENTO', 'VIENTO2_9am', 'VIENTO3_2pm', 'LK']


df_sub = df[parametros]
corr = df_sub.corr(numeric_only=True)
mask = np.triu(np.ones_like(corr, dtype=bool))
```

```
plt.figure(figsize=(15, 12))

sns.heatmap(corr, mask=mask, annot=True, fmt=".2f", cmap='coolwarm',
            square=True, linewidths=0.5, cbar_kws={"shrink": .8})

plt.title('Matriz de Correlación (Triangular Inferior)', fontsize=16)
plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)
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.

R: Se estimó un modelo de probabilidad lineal excluyendo aquellas variables con correlaciones altas, donde la variable dependiente es 'Failure_today', la cual toma valor 1 si es que existe un fallo y 0 en caso que no. De los resultados se obtuvo un R cuadrado de 0.548, es decir, explica el 54.8% de la variabilidad. Según el modelo, la locación, la temperatura máxima, el nivel de evaporación, la electricidad y varios otros se relacionan de manera negativa, es decir, reducen la probabilidad de fallo. Aquellas variables categóricas para las direcciones del viento tienen un valor-p mayor a 0.05, por lo que no son estadísticamente significativas. Finalmente, la variable 'LK' es altamente significativa y tiene un alto impacto en la probabilidad de falla.

[70]:
```
#Regresion excluyendo variables de alta correlacion
y=df['Failure_today']
X=df.drop(['Date', 'Leakage', 'Parameter1_Dir',␣
 ↪'Parameter2_9am','Parameter2_3pm','Failure_today',
           'Parameter7_9am', 'Parameter7_3pm','Parameter5_3pm'], axis=1)
X=sm.add_constant(X)
model = sm.OLS(y, X)
results = model.fit(cov_type='HC0')
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          Failure_today   R-squared:                       0.548
Model:                            OLS   Adj. R-squared:                  0.548
Method:                 Least Squares   F-statistic:                     5448.
Date:                Thu, 24 Apr 2025   Prob (F-statistic):               0.00
Time:                        20:12:45   Log-Likelihood:                -16694.
No. Observations:              112925   AIC:                         3.342e+04
Df Residuals:                  112907   BIC:                         3.360e+04
Df Model:                          17
Covariance Type:                  HC0
==============================================================================
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
const          4.5273      0.172     26.368      0.000       4.191
4.864
Location      -0.0002   5.74e-05     -3.278      0.001      -0.000
-7.57e-05
Min_Temp       0.0055      0.000     19.835      0.000       0.005
0.006
Max_Temp      -0.0043      0.000    -15.401      0.000      -0.005
-0.004
Evaporation   -0.0009      0.000     -4.160      0.000      -0.001
-0.000
Electricity    0.0002      0.000      1.188      0.235      -0.000
0.001
```

```
Parameter1_Speed     0.0022      0.000     21.293      0.000       0.002
0.002
Parameter3_9am       0.0014      0.000     10.853      0.000       0.001
0.002
Parameter3_3pm      -0.0023      0.000    -16.889      0.000      -0.003
-0.002
Parameter4_9am       0.0021   6.74e-05     30.705      0.000       0.002
0.002
Parameter4_3pm    6.755e-05    7.9e-05      0.855      0.392   -8.72e-05
0.000
Parameter5_9am      -0.0046      0.000    -27.773      0.000      -0.005
-0.004
Parameter6_9am      -0.0002      0.000     -0.485      0.628      -0.001
0.001
Parameter6_3pm       0.0011      0.000      2.649      0.008       0.000
0.002
VIENTO            2.943e-05      0.000      0.152      0.879      -0.000
0.000
VIENTO2_9am          0.0001      0.000      0.608      0.543      -0.000
0.000
VIENTO3_2pm      -3.908e-06      0.000     -0.020      0.984      -0.000
0.000
LK                   0.5583      0.003    204.127      0.000       0.553
0.564
==============================================================================
Omnibus:                    11391.614   Durbin-Watson:                   1.903
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            15244.885
Skew:                          -0.849   Prob(JB):                         0.00
Kurtosis:                       3.596   Cond. No.                     1.90e+05
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC0)
[2] The condition number is large, 1.9e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

3. Ejecute un modelo *probit* para responder a la pregunta 2. Seleccione las variables dependientes a incluir en el modelo final e interprete su significado.

R: Se observa que Leakage afecta significativamente a la probabilidad de falla, es decir, un aumento de esta variable aumenta la probabilidad de falla en un 88.01 puntos porcentuales. Como el modelo no convergió correctamente debido a la influencia de esta variable, se optó por excluirla para evaluar los efectos de las demás variables. De este segundo intento, se obtuvo un pseudo R cuadrado moderado de 0.3022 y un LLR p-value de 0.000, lo que indica que el modelo sigue siendo significativo. La mayor parte de las variables aumentaron la magnitud de sus efectos marginales manteniendo el sentido. Por ejemplo, la temperatura máxima y la evaporación disminuyen la probabilidad de falla, donde un aumento de una unidad de esas variables disminuye en 12.08 y 2.83 puntos porcentuales la probabilidad de falla. Por otro lado, la variable VIENTO3_2pm no es estadísticamente significativa, mientras que el resto de variables sí. .

[71]:
```
X = df[['Location', 'Min_Temp', 'Max_Temp', 'Evaporation',
       'Electricity', 'Parameter1_Speed', 'Parameter3_9am', 'Parameter3_3pm',␣
 ↪'Parameter4_9am',
       'Parameter4_3pm', 'Parameter5_9am','Parameter6_9am','Parameter6_3pm',
       'VIENTO', 'VIENTO2_9am', 'VIENTO3_2pm', 'LK']]
y = df['Failure_today']

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

# Efectos marginales
mfx = probit_model.get_margeff()
print(mfx.summary())
```

```
Warning: Maximum number of iterations has been exceeded.
         Current function value: 0.208440
         Iterations: 35
                          Probit Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:               112925
Model:                         Probit   Df Residuals:                   112907
Method:                           MLE   Df Model:                           17
Date:                Thu, 24 Apr 2025   Pseudo R-squ.:                  0.6087
Time:                        20:12:56   Log-Likelihood:                -23538.
converged:                      False   LL-Null:                       -60159.
Covariance Type:                  HC0   LLR p-value:                     0.000
==============================================================================
====
                        coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
----
const                17.4311      1.110     15.698      0.000      15.255
19.607
Location            -0.0005      0.000     -1.117      0.264      -0.001
0.000
Min_Temp             0.0858      0.003     31.901      0.000       0.081
0.091
Max_Temp            -0.0697      0.003    -26.294      0.000      -0.075
-0.065
Evaporation         -0.0144      0.003     -5.402      0.000      -0.020
-0.009
Electricity          0.0105      0.002      5.256      0.000       0.007
0.014
Parameter1_Speed     0.0143      0.001     17.142      0.000       0.013
0.016
Parameter3_9am       0.0072      0.001      6.323      0.000       0.005
```

```
0.009
Parameter3_3pm      -0.0125      0.001    -10.731      0.000      -0.015
-0.010
Parameter4_9am       0.0197      0.001     31.268      0.000       0.018
0.021
Parameter4_3pm      -0.0022      0.001     -3.683      0.000      -0.003
-0.001
Parameter5_9am      -0.0256      0.001    -23.804      0.000      -0.028
-0.023
Parameter6_9am      -0.0127      0.003     -4.113      0.000      -0.019
-0.007
Parameter6_3pm       0.0124      0.003      3.981      0.000       0.006
0.019
VIENTO              -0.0008      0.001     -0.512      0.609      -0.004
0.002
VIENTO2_9am         -0.0002      0.001     -0.107      0.915      -0.003
0.003
VIENTO3_2pm         -0.0003      0.001     -0.221      0.825      -0.003
0.003
LK                   7.4255      0.020    370.262      0.000       7.386
7.465
================================================================================
====

Possibly complete quasi-separation: A fraction 0.64 of observations can be
perfectly predicted. This might indicate that there is complete
quasi-separation. In this case some parameters will not be identified.
       Probit Marginal Effects
=====================================
Dep. Variable:          Failure_today
Method:                          dydx
At:                           overall
================================================================================
====
                       dy/dx    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
----
Location         -6.312e-05   5.65e-05     -1.117      0.264      -0.000
4.77e-05
Min_Temp             0.0102      0.000     33.253      0.000       0.010
0.011
Max_Temp            -0.0083      0.000    -27.050      0.000      -0.009
-0.008
Evaporation         -0.0017      0.000     -5.409      0.000      -0.002
-0.001
Electricity          0.0012      0.000      5.261      0.000       0.001
0.002
```

```
Parameter1_Speed      0.0017   9.76e-05     17.340      0.000       0.002
0.002
Parameter3_9am        0.0009      0.000      6.332      0.000       0.001
0.001
Parameter3_3pm       -0.0015      0.000    -10.780      0.000      -0.002
-0.001
Parameter4_9am        0.0023    7.2e-05     32.351      0.000       0.002
0.002
Parameter4_3pm       -0.0003   7.19e-05     -3.686      0.000      -0.000
-0.000
Parameter5_9am       -0.0030      0.000    -24.287      0.000      -0.003
-0.003
Parameter6_9am       -0.0015      0.000     -4.115      0.000      -0.002
-0.001
Parameter6_3pm        0.0015      0.000      3.983      0.000       0.001
0.002
VIENTO            -9.054e-05      0.000     -0.512      0.609      -0.000
0.000
VIENTO2_9am       -1.826e-05      0.000     -0.107      0.915      -0.000
0.000
VIENTO3_2pm       -3.877e-05      0.000     -0.221      0.825      -0.000
0.000
LK                    0.8801      0.002    449.131      0.000       0.876
0.884
==============================================================================
====
```

Se puede observar que cerca del 63% de los casos si existe filtración, entonces se produce una falla. Este es un caso de cuasi-separación perfecta, por lo que el modelo Probit no converge. Por eso, se realiza un análisis separado sin LK para conocer los efectos de las otras variables.

[24]:
```
pd.crosstab(df['LK'], df['Failure_today'], normalize='index')
```

[24]:
```
Failure_today       0.0       1.0
LK
0              1.000000  0.000000
1              0.367971  0.632029
```

[96]:
```
X = df[['Location', 'Min_Temp', 'Max_Temp', 'Evaporation',
       'Electricity', 'Parameter1_Speed', 'Parameter3_9am', 'Parameter3_3pm',␣
 ↪'Parameter4_9am',
       'Parameter4_3pm', 'Parameter5_9am', 'Parameter6_9am','Parameter6_3pm',
       'VIENTO', 'VIENTO2_9am', 'VIENTO3_2pm']]
y = df['Failure_today']

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

```python
# Efectos marginales
mfx = probit_model.get_margeff()
print(mfx.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.371758
         Iterations 7
                          Probit Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:                112925
Model:                         Probit   Df Residuals:                    112908
Method:                           MLE   Df Model:                            16
Date:                Thu, 24 Apr 2025   Pseudo R-squ.:                  0.3022
Time:                        22:29:48   Log-Likelihood:                -41981.
converged:                       True   LL-Null:                       -60159.
Covariance Type:                 HC0   LLR p-value:                     0.000
==============================================================================
====
                        coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
----
const                30.3564      0.871     34.837      0.000      28.649
32.064
Location            -0.0019      0.000     -5.223      0.000      -0.003
-0.001
Min_Temp             0.1188      0.002     60.827      0.000       0.115
0.123
Max_Temp            -0.1208      0.002    -61.865      0.000      -0.125
-0.117
Evaporation         -0.0283      0.003    -10.310      0.000      -0.034
-0.023
Electricity          0.0153      0.002      9.562      0.000       0.012
0.018
Parameter1_Speed     0.0171      0.001     29.636      0.000       0.016
0.018
Parameter3_9am       0.0077      0.001      9.704      0.000       0.006
0.009
Parameter3_3pm      -0.0137      0.001    -16.962      0.000      -0.015
-0.012
Parameter4_9am       0.0359      0.000     76.251      0.000       0.035
0.037
Parameter4_3pm      -0.0040      0.000     -9.115      0.000      -0.005
-0.003
Parameter5_9am      -0.0324      0.001    -38.468      0.000      -0.034
-0.031
Parameter6_9am      -0.0058      0.002     -2.570      0.010      -0.010
```

```
-0.001
Parameter6_3pm       0.0202      0.002      8.925      0.000       0.016
0.025
VIENTO               0.0037      0.001      3.266      0.001       0.001
0.006
VIENTO2_9am          0.0040      0.001      3.722      0.000       0.002
0.006
VIENTO3_2pm          0.0018      0.001      1.586      0.113      -0.000
0.004
================================================================================
====
       Probit Marginal Effects
=====================================
Dep. Variable:          Failure_today
Method:                          dydx
At:                           overall
================================================================================
====
                       dy/dx    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------------
----
Location            -0.0004   7.45e-05     -5.226      0.000      -0.001
-0.000
Min_Temp             0.0248      0.000     64.768      0.000       0.024
0.026
Max_Temp            -0.0252      0.000    -65.495      0.000      -0.026
-0.024
Evaporation         -0.0059      0.001    -10.372      0.000      -0.007
-0.005
Electricity          0.0032      0.000      9.604      0.000       0.003
0.004
Parameter1_Speed     0.0036      0.000     30.051      0.000       0.003
0.004
Parameter3_9am       0.0016      0.000      9.717      0.000       0.001
0.002
Parameter3_3pm      -0.0029      0.000    -17.034      0.000      -0.003
-0.003
Parameter4_9am       0.0075   8.79e-05     85.118      0.000       0.007
0.008
Parameter4_3pm      -0.0008   9.17e-05     -9.130      0.000      -0.001
-0.001
Parameter5_9am      -0.0068      0.000    -39.111      0.000      -0.007
-0.006
Parameter6_9am      -0.0012      0.000     -2.569      0.010      -0.002
-0.000
Parameter6_3pm       0.0042      0.000      8.934      0.000       0.003
0.005
```

```
VIENTO                0.0008      0.000      3.267      0.001        0.000
0.001
VIENTO2_9am           0.0008      0.000      3.723      0.000        0.000
0.001
VIENTO3_2pm           0.0004      0.000      1.586      0.113    -8.69e-05
0.001
==============================================================================
====
```

De estos resultados se puede observar un mejor ajuste de 0.371569, lo cual es moderado.

4. Ejecute un modelo *logit* para responder a la pregunta 2. Seleccione las variables dependientes a incluir en el modelo final e interprete su significado.

R: Al igual que el modelo Probit, Leakage sigue teniendo un efecto significativo con un efecto marginal de aproximadamente 295 puntos porcentuales. El pseudo R^2 es de 0.6088 y el LLR p-value es de 0.000, lo que indica que el modelo es globalmente significativo. Al excluir 'LK' del modelo, se obtuvo un nuevo pseudo R^2 de 0.3107, y no se detectaron cambios significativos en las magnitudes de los efectos marginales. Se pueden interpretar algunos Odds ratios: cada grado más de temperatura mínima aumenta las probabilidades de falla en un 14.99%, mientras que cada grado más de temperatura máxima reduce las probabilidades en un 22.93% (de la fórmula (Odds - 1)x 100%).

[104]:
```
X1 = df[['Location', 'Min_Temp', 'Max_Temp', 'Evaporation',
       'Electricity', 'Parameter1_Speed', 'Parameter3_9am', 'Parameter3_3pm',␣
 ↪'Parameter4_9am',
       'Parameter4_3pm', 'Parameter5_9am','Parameter6_9am','Parameter6_3pm',
       'VIENTO', 'VIENTO2_9am', 'VIENTO3_2pm', 'LK']]

y = df[['Failure_today']]
model = sm.Logit(y, X1)
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: 0.208418
         Iterations 14
                           Logit Regression Results
==============================================================================
```

```
Dep. Variable:          Failure_today   No. Observations:               112925
Model:                          Logit   Df Residuals:                   112908
Method:                           MLE   Df Model:                           16
Date:                Thu, 24 Apr 2025   Pseudo R-squ.:                  0.6088
Time:                        23:37:43   Log-Likelihood:                -23536.
converged:                       True   LL-Null:                       -60159.
Covariance Type:                 HC0   LLR p-value:                     0.000
==============================================================================
====
                      coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
----
Location           -0.0009      0.001     -1.126      0.260      -0.002
0.001
Min_Temp            0.1427      0.005     31.575      0.000       0.134
0.152
Max_Temp           -0.1165      0.004    -26.234      0.000      -0.125
-0.108
Evaporation        -0.0244      0.005     -5.281      0.000      -0.033
-0.015
Electricity         0.0176      0.003      5.257      0.000       0.011
0.024
Parameter1_Speed    0.0245      0.001     17.174      0.000       0.022
0.027
Parameter3_9am      0.0122      0.002      6.376      0.000       0.008
0.016
Parameter3_3pm     -0.0218      0.002    -11.008      0.000      -0.026
-0.018
Parameter4_9am      0.0324      0.001     30.749      0.000       0.030
0.034
Parameter4_3pm     -0.0038      0.001     -3.713      0.000      -0.006
-0.002
Parameter5_9am     -0.0426      0.002    -23.693      0.000      -0.046
-0.039
Parameter6_9am     -0.0211      0.005     -4.139      0.000      -0.031
-0.011
Parameter6_3pm      0.0204      0.005      3.956      0.000       0.010
0.031
VIENTO             -0.0015      0.002     -0.613      0.540      -0.006
0.003
VIENTO2_9am        -0.0006      0.002     -0.245      0.807      -0.005
0.004
VIENTO3_2pm        -0.0007      0.002     -0.295      0.768      -0.006
0.004
LK                 41.4266      1.862     22.243      0.000      37.776
45.077
==============================================================================
```

```
====

Possibly complete quasi-separation: A fraction 0.64 of observations can be
perfectly predicted. This might indicate that there is complete
quasi-separation. In this case some parameters will not be identified.
        Logit Marginal Effects
=====================================
Dep. Variable:          Failure_today
Method:                          dydx
At:                           overall
==============================================================================
====
                      dy/dx    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
----
Location         -6.351e-05   5.64e-05     -1.126      0.260      -0.000
4.7e-05
Min_Temp             0.0102      0.000     33.261      0.000       0.010
0.011
Max_Temp            -0.0083      0.000    -27.191      0.000      -0.009
-0.008
Evaporation         -0.0017      0.000     -5.289      0.000      -0.002
-0.001
Electricity          0.0013      0.000      5.264      0.000       0.001
0.002
Parameter1_Speed     0.0017      0.000     17.414      0.000       0.002
0.002
Parameter3_9am       0.0009      0.000      6.388      0.000       0.001
0.001
Parameter3_3pm      -0.0016      0.000    -11.074      0.000      -0.002
-0.001
Parameter4_9am       0.0023   7.23e-05     31.993      0.000       0.002
0.002
Parameter4_3pm      -0.0003   7.24e-05     -3.717      0.000      -0.000
-0.000
Parameter5_9am      -0.0030      0.000    -24.265      0.000      -0.003
-0.003
Parameter6_9am      -0.0015      0.000     -4.142      0.000      -0.002
-0.001
Parameter6_3pm       0.0015      0.000      3.959      0.000       0.001
0.002
VIENTO              -0.0001      0.000     -0.613      0.540      -0.000
0.000
VIENTO2_9am      -4.192e-05      0.000     -0.245      0.807      -0.000
0.000
VIENTO3_2pm      -5.185e-05      0.000     -0.295      0.768      -0.000
0.000
```

```
LK                    2.9564      0.130      22.720      0.000        2.701
3.211
==============================================================================
====
Odds Ratios
                     Odds Ratio            5%           95%
Min_Temp           1.143223e+00  1.163659e+00  1.153396e+00
Max_Temp           8.823563e-01  8.978447e-01  8.900668e-01
Evaporation        9.671625e-01  9.848031e-01  9.759429e-01
Electricity        1.011072e+00  1.024396e+00  1.017712e+00
Parameter1_Speed   1.021902e+00  1.027623e+00  1.024758e+00
Parameter3_9am     1.008504e+00  1.016113e+00  1.012301e+00
Parameter3_3pm     9.746836e-01  9.822676e-01  9.784683e-01
Parameter4_9am     1.030793e+00  1.035059e+00  1.032924e+00
Parameter4_3pm     9.942538e-01  9.982207e-01  9.962353e-01
Parameter5_9am     9.549619e-01  9.617105e-01  9.583303e-01
Parameter6_9am     9.694254e-01  9.889678e-01  9.791479e-01
Parameter6_3pm     1.010365e+00  1.031035e+00  1.020648e+00
VIENTO             9.936406e-01  1.003345e+00  9.984809e-01
VIENTO2_9am        9.947254e-01  1.004122e+00  9.994127e-01
VIENTO3_2pm        9.944696e-01  1.004101e+00  9.992737e-01
LK                 2.547009e+16  3.772554e+19  9.802412e+17
```

[105]:
```
X1 = df[['Location', 'Min_Temp', 'Max_Temp', 'Evaporation',
       'Electricity', 'Parameter1_Speed', 'Parameter3_9am', 'Parameter3_3pm',␣
 ↪'Parameter4_9am',
       'Parameter4_3pm', 'Parameter5_9am', 'Parameter5_3pm', 'Parameter6_9am',
       'Parameter6_3pm', 'Parameter7_9am', 'Parameter7_3pm',
       'VIENTO', 'VIENTO2_9am', 'VIENTO3_2pm']]
y = df[['Failure_today']]
model = sm.Logit(y, X1)
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: 0.367194
         Iterations 7
                           Logit Regression Results
```

```
==============================================================================
Dep. Variable:          Failure_today   No. Observations:               112925
Model:                          Logit   Df Residuals:                   112906
Method:                           MLE   Df Model:                           18
Date:                Thu, 24 Apr 2025   Pseudo R-squ.:                  0.3107
Time:                        23:38:52   Log-Likelihood:                -41465.
converged:                       True   LL-Null:                       -60159.
Covariance Type:                  HC0   LLR p-value:                     0.000
==============================================================================
====
                       coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
----
Location            -0.0052      0.001     -8.176      0.000      -0.006
-0.004
Min_Temp             0.1493      0.005     30.401      0.000       0.140
0.159
Max_Temp            -0.2432      0.009    -27.660      0.000      -0.260
-0.226
Evaporation         -0.0614      0.005    -12.698      0.000      -0.071
-0.052
Electricity          0.0277      0.003      9.569      0.000       0.022
0.033
Parameter1_Speed     0.0431      0.001     43.713      0.000       0.041
0.045
Parameter3_9am       0.0061      0.001      4.305      0.000       0.003
0.009
Parameter3_3pm      -0.0286      0.001    -19.380      0.000      -0.032
-0.026
Parameter4_9am       0.0693      0.001     65.052      0.000       0.067
0.071
Parameter4_3pm      -0.0031      0.001     -2.967      0.003      -0.005
-0.001
Parameter5_9am      -0.2166      0.005    -40.988      0.000      -0.227
-0.206
Parameter5_3pm       0.2104      0.005     39.911      0.000       0.200
0.221
Parameter6_9am       0.0014      0.004      0.346      0.729      -0.006
0.009
Parameter6_3pm       0.0386      0.004      9.610      0.000       0.031
0.046
Parameter7_9am       0.0718      0.007      9.837      0.000       0.057
0.086
Parameter7_3pm       0.0631      0.010      6.508      0.000       0.044
0.082
VIENTO               0.0106      0.002      5.386      0.000       0.007
0.014
```

```
VIENTO2_9am          0.0086      0.002      4.542      0.000       0.005
0.012
VIENTO3_2pm          0.0075      0.002      3.826      0.000       0.004
0.011
==============================================================================
====
        Logit Marginal Effects
=====================================
Dep. Variable:          Failure_today
Method:                          dydx
At:                           overall
==============================================================================
====
                       dy/dx    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
----
Location            -0.0006   7.38e-05     -8.186      0.000      -0.001
-0.000
Min_Temp             0.0174      0.001     30.816      0.000       0.016
0.019
Max_Temp            -0.0284      0.001    -28.032      0.000      -0.030
-0.026
Evaporation         -0.0072      0.001    -12.781      0.000      -0.008
-0.006
Electricity          0.0032      0.000      9.603      0.000       0.003
0.004
Parameter1_Speed     0.0050      0.000     45.441      0.000       0.005
0.005
Parameter3_9am       0.0007      0.000      4.306      0.000       0.000
0.001
Parameter3_3pm      -0.0033      0.000    -19.525      0.000      -0.004
-0.003
Parameter4_9am       0.0081      0.000     70.263      0.000       0.008
0.008
Parameter4_3pm      -0.0004      0.000     -2.966      0.003      -0.001
-0.000
Parameter5_9am      -0.0253      0.001    -42.158      0.000      -0.026
-0.024
Parameter5_3pm       0.0246      0.001     40.981      0.000       0.023
0.026
Parameter6_9am       0.0002      0.000      0.346      0.729      -0.001
0.001
Parameter6_3pm       0.0045      0.000      9.622      0.000       0.004
0.005
Parameter7_9am       0.0084      0.001      9.846      0.000       0.007
0.010
Parameter7_3pm       0.0074      0.001      6.518      0.000       0.005
```

```
0.010
VIENTO               0.0012      0.000      5.389      0.000       0.001
0.002
VIENTO2_9am          0.0010      0.000      4.544      0.000       0.001
0.001
VIENTO3_2pm          0.0009      0.000      3.826      0.000       0.000
0.001
================================================================================
====
Odds Ratios
                  Odds Ratio        5%       95%
Min_Temp            1.149880  1.172228  1.161000
Max_Temp            0.770705  0.797732  0.784102
Evaporation         0.931628  0.949441  0.940493
Electricity         1.022295  1.033973  1.028117
Parameter1_Speed    1.041979  1.046010  1.043992
Parameter3_9am      1.003353  1.008982  1.006163
Parameter3_3pm      0.968976  0.974602  0.971785
Parameter4_9am      1.069548  1.074025  1.071784
Parameter4_3pm      0.994902  0.998956  0.996927
Parameter5_9am      0.796986  0.813665  0.805282
Parameter5_3pm      1.221537  1.247048  1.234227
Parameter6_9am      0.993617  1.009191  1.001373
Parameter6_3pm      1.031171  1.047518  1.039312
Parameter7_9am      1.059157  1.089888  1.074413
Parameter7_3pm      1.045048  1.085504  1.065084
VIENTO              1.006773  1.014577  1.010668
```

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 los tres modelos se pudo observar la fuerte influencia que tienen las filtraciones en la probabilidad de fallo en los sensores. MCO no es buen modelo de especificación debido a las variables binarias, sin embargo, permite conocer las correlaciones lineales y las direcciones de influencia. En este contexto, Probit y Logit son modelos más adecuados, ya que determinan los efectos marginales sobre la probabilidad de fallo. Las diferencias identificadas son que en MCO las variables de viento no fueron estadísticamente significativas, mientras que en Probit VIENTO2_9am si lo fué y en Logit se sumó VIENTO como otra variable significativa SOLO al excluir Leakage de los modelos. En este sentido, Logit es más adecuado debido a que tiene más variables significativas que los otros modelos y la naturaleza binaria del análisis.

Variables robustas identificadas son algunas como Min_Temp, Max_Temp, Evaporation, Parameter6_3pm, entre otras, debido a su consistencia en los tres modelos. Esto refuerza su relevancia como predictores del fallo en los sensores.

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.

R: Al agregar la data a nivel mensual, excluyendo las variables categóricas, se obtuvieron un total de 4137 observaciones. El modelo Poisson mostró un pseudo R-cuadrado elevado (0.889) y convergió en solo 5 iteraciones, lo que indica buena estabilidad y ajuste. Se observaron cambios relevantes en la magnitud y dirección de algunos coeficientes respecto a modelos anteriores; por ejemplo, ahora un aumento en la temperatura máxima se asocia a un mayor riesgo de fallas, lo que contrasta con resultados previos. También cambiaron de signo variables como 'Parameter5_3pm' y 'Parameter7_3pm'. Las variables relacionadas con filtraciones, como 'LK' y 'Leakage', se mantienen como factores altamente significativos en la predicción de fallas. En cuanto a los indicadores de datos faltantes, todos resultaron significativos salvo 'I_elect', lo cual es coherente con que la variable 'Electricity' tampoco lo sea. En particular, 'I_param6_9am' mostró una fuerte asociación con menos fallas (coeficiente de -0.3168), mientras que 'I_param6_3pm' se asoció a un mayor número de fallas (coeficiente de 0.3865), lo que sugiere que la presencia o ausencia de datos en estas variables también entrega información importante sobre el comportamiento de los sensores.

[76]:
```
df['Date'] = pd.to_datetime(df['Date'])
df['Month'] = df['Date'].dt.to_period('M')
df['Failure_today'] = df['Failure_today'].astype(int)


df_mes_sensor = df.groupby(['Location', 'Month']).agg({
    'Failure_today': 'sum',
    'Evaporation': 'mean',
    'Electricity': 'mean',
    'Min_Temp': 'mean',
    'Max_Temp': 'mean',
    'Parameter1_Speed': 'mean',
    'Parameter3_9am': 'mean',
    'Parameter3_3pm': 'mean',
    'Parameter4_9am': 'mean',
    'Parameter4_3pm': 'mean',
    'Parameter5_9am': 'mean',
    'Parameter5_3pm': 'mean',
    'Parameter6_9am': 'mean',
    'Parameter6_3pm': 'mean',
    'Parameter7_9am': 'mean',
    'Parameter7_3pm': 'mean',
    'Leakage' : 'mean',
    'LK' : 'mean',
}).reset_index()
```

[77]:
```
df_mes_sensor['I_evap'] = (df_mes_sensor['Evaporation'] == 0).astype(int)
df_mes_sensor['I_elect'] = (df_mes_sensor['Electricity'] == 0).astype(int)
df_mes_sensor['I_param6_9am'] = (df_mes_sensor['Parameter6_9am'] == 0).
 ↪astype(int)
df_mes_sensor['I_param6_3pm'] = (df_mes_sensor['Parameter6_3pm'] == 0).
 ↪astype(int)
```

[79]:
```
df_mes_sensor.head()
```

[79]:

	Location	Month	Failure_today	Evaporation	Electricity	Min_Temp	\
0	1	2008-07	10	2.110000	4.485000	7.000000	
1	1	2008-08	10	1.715789	6.147368	5.936842	
2	1	2008-09	4	4.446154	8.588462	9.461538	
3	1	2008-10	2	5.091667	9.145833	12.383333	
4	1	2008-11	5	6.178571	9.064286	14.210714	

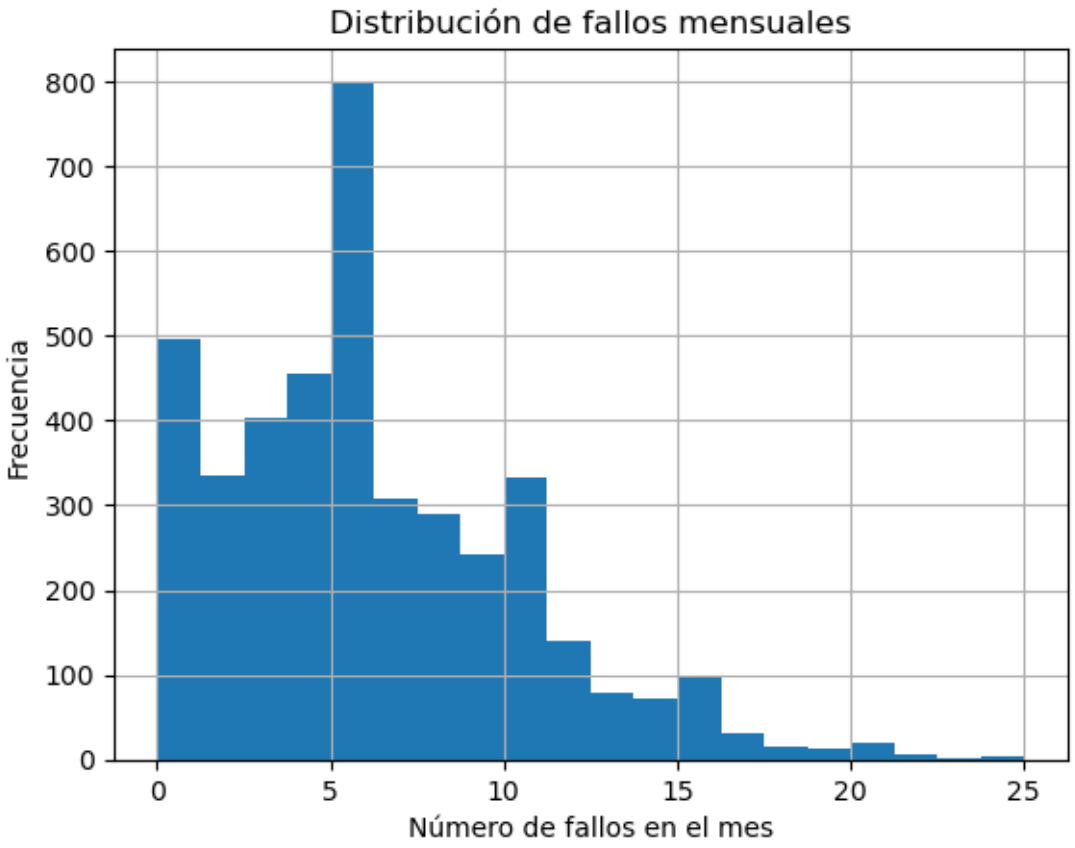
	Max_Temp	Parameter1_Speed	Parameter3_9am	Parameter3_3pm	…	\
0	14.550000	39.450000	11.950000	16.250000	…	
1	14.600000	36.105263	9.315789	15.631579	…	
2	20.234615	39.846154	14.730769	17.807692	…	
3	25.045833	37.291667	11.875000	17.458333	…	
4	24.642857	42.142857	12.607143	18.678571	…	

	Parameter6_9am	Parameter6_3pm	Parameter7_9am	Parameter7_3pm	Leakage	\
0	0.0	0.0	10.795000	13.615000	3.530000	
1	0.0	0.0	9.973684	13.484211	4.242105	
2	0.0	0.0	15.188462	19.211538	0.615385	
3	0.0	0.0	17.933333	23.941667	0.200000	
4	0.0	0.0	18.492857	23.110714	0.492857	

	LK	I_evap	I_elect	I_param6_9am	I_param6_3pm
0	0.700000	0	0	1	1
1	0.631579	0	0	1	1
2	0.346154	0	0	1	1
3	0.166667	0	0	1	1
4	0.321429	0	0	1	1

[5 rows x 24 columns]

[80]:
```
df_mes_sensor['Failure_today'].hist(bins=20)
plt.title("Distribución de fallos mensuales")
plt.xlabel("Número de fallos en el mes")
plt.ylabel("Frecuencia")
plt.show()
```



[81]:
```
parametros = [
    'Min_Temp', 'Max_Temp', 'Evaporation', 'Electricity',
    'Parameter1_Speed', 'Parameter3_9am', 'Parameter3_3pm',
    'Parameter4_9am', 'Parameter4_3pm', 'Parameter5_9am', 'Parameter5_3pm',
    'Parameter6_9am', 'Parameter6_3pm', 'Parameter7_9am', 'Parameter7_3pm',
    'I_evap', 'I_elect', 'I_param6_9am', 'I_param6_3pm','LK','Leakage'
]

formula = 'Failure_today ~  ' + ' + '.join(parametros)
modelo_poisson = smf.glm(formula=formula, data=df_mes_sensor, family=sm.
  ↪families.Poisson()).fit()
print(modelo_poisson.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:                 4137
Model:                            GLM   Df Residuals:                     4115
Model Family:                 Poisson   Df Model:                           21
Link Function:                    Log   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -8676.3
```

```
Date:                Thu, 24 Apr 2025   Deviance:                       3613.3
Time:                        20:20:08   Pearson chi2:                 3.05e+03
No. Iterations:                 5      Pseudo R-squ. (CS):             0.8893
Covariance Type:            nonrobust
==============================================================================
====
                       coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
----
Intercept            6.2671      2.500      2.507      0.012       1.368
11.166
Min_Temp             0.0264      0.007      3.792      0.000       0.013
0.040
Max_Temp             0.0461      0.021      2.156      0.031       0.004
0.088
Evaporation         -0.0334      0.005     -6.341      0.000      -0.044
-0.023
Electricity          0.0108      0.006      1.791      0.073      -0.001
0.023
Parameter1_Speed     0.0151      0.002      6.242      0.000       0.010
0.020
Parameter3_9am      -0.0043      0.003     -1.478      0.139      -0.010
0.001
Parameter3_3pm      -0.0142      0.003     -4.511      0.000      -0.020
-0.008
Parameter4_9am       0.0109      0.002      5.228      0.000       0.007
0.015
Parameter4_3pm      -0.0068      0.002     -2.942      0.003      -0.011
-0.002
Parameter5_9am      -0.0051      0.013     -0.407      0.684      -0.030
0.019
Parameter5_3pm      -0.0006      0.012     -0.048      0.962      -0.025
0.024
Parameter6_9am      -0.0242      0.012     -2.036      0.042      -0.048
-0.001
Parameter6_3pm       0.0636      0.011      5.614      0.000       0.041
0.086
Parameter7_9am       0.0560      0.012      4.753      0.000       0.033
0.079
Parameter7_3pm      -0.1199      0.024     -4.968      0.000      -0.167
-0.073
I_evap              -0.0690      0.033     -2.092      0.036      -0.134
-0.004
I_elect              0.0178      0.048      0.370      0.711      -0.076
0.112
I_param6_9am        -0.3168      0.119     -2.661      0.008      -0.550
-0.083
```

```
I_param6_3pm          0.3865      0.117       3.300       0.001        0.157
0.616
LK                    1.8186      0.055      33.105       0.000        1.711
1.926
Leakage               0.0164      0.002       7.965       0.000        0.012
0.020
==============================================================================
====
```

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

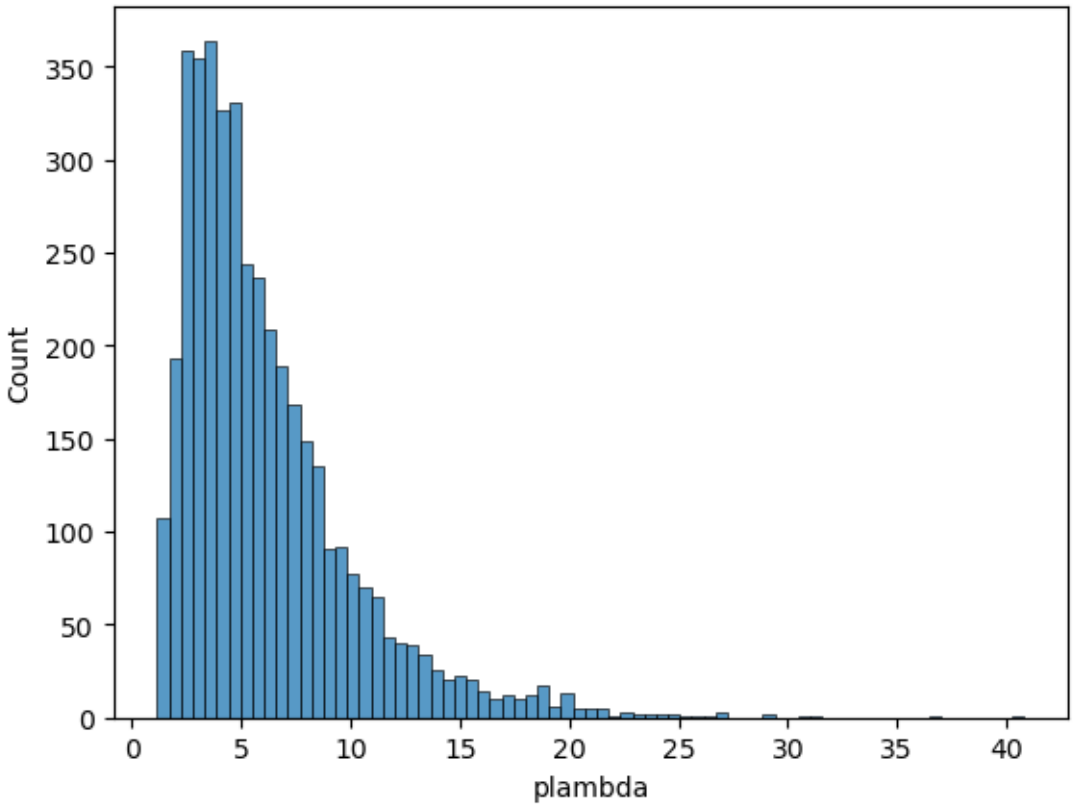
R: El analisis muestra que existe una sobre dispersión de los datos. Esto se observa mejor cuando se compara la media con la varianza, donde la segunda es mucho mayor. Por otro lado, un posible valor óptimo de alpha se obtuvo como 0.9751.

[100]:
```
mean = df_mes_sensor['Failure_today'].mean()
var = df_mes_sensor['Failure_today'].var()
print("Media:", mean)
print("Varianza:", var)
```

```
Media: 6.132221416485375
Varianza: 18.016120620208767
```

[85]:
```
df_mes_sensor['plambda'] = modelo_poisson.mu
sns.histplot(data=df_mes_sensor, x="plambda")
```

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



[101]:
```
y = df_mes_sensor["Failure_today"]
mu = modelo_poisson.mu

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):
0.031
Model:                            OLS   Adj. R-squared (uncentered):
0.030
Method:                 Least Squares   F-statistic:
130.4
Date:                Thu, 24 Apr 2025   Prob (F-statistic):
9.29e-30
Time:                        23:07:28   Log-Likelihood:
-6035.6
No. Observations:                4137   AIC:
```

```
1.207e+04
Df Residuals:                     4136   BIC:
1.208e+04
Df Model:                            1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
x1            -0.0252      0.002    -11.419      0.000      -0.030      -0.021
==============================================================================
Omnibus:                     4199.551   Durbin-Watson:                   1.859
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           454552.246
Skew:                           4.751   Prob(JB):                         0.00
Kurtosis:                      53.465   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.
```

El posible valor óptimo de alpha se calcula como:

[103]:
```
print(np.exp(-0.0252))
```

```
0.9751148695508249
```

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.

R: Se concluye que varias de las variables en el modelo Binomial Negativo son estadísticamente significativas, cumpliendo el criterio de significancia con un valor p inferior a 0.05, como 'Evaporation', 'Parameter1_Speed', entre otros. El modelo explica aproximadamente el 31.18% de la variabilidad en la variable dependiente, que es el número de fallos por sensor observados en un mes. Las variables con mayor incidencia en el número de fallos son las de filtraciones. Por ejemplo, al aumentar LK, la probabilidad de que se presenten más fallos aumenta considerablemente, lo que sugiere una fuerte relación positiva entre esta variable y el número de fallos. Asimismo, al incrementarse la temperatura máxima, también aumenta la probabilidad de que ocurran más fallos en el sistema.

[93]:
```
xx = df_mes_sensor[[
    'Min_Temp', 'Max_Temp', 'Evaporation', 'Electricity',
    'Parameter1_Speed', 'Parameter3_9am', 'Parameter3_3pm',
    'Parameter4_9am', 'Parameter4_3pm', 'Parameter5_9am', 'Parameter5_3pm',
    'Parameter6_9am', 'Parameter6_3pm', 'Parameter7_9am', 'Parameter7_3pm',
    'I_evap', 'I_elect', 'I_param6_9am', 'I_param6_3pm', 'LK', 'Leakage'
]]
```

```
negbin=sm.GLM(y,xx,family=sm.families.NegativeBinomial(alpha=0.9493)).fit()
print(negbin.summary())
```

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:          Failure_today   No. Observations:                 4137
Model:                            GLM   Df Residuals:                     4116
Model Family:        NegativeBinomial   Df Model:                           20
Link Function:                    Log   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -11136.
Date:                Thu, 24 Apr 2025   Deviance:                       950.26
Time:                        21:31:41   Pearson chi2:                     617.
No. Iterations:                    11   Pseudo R-squ. (CS):             0.3118
Covariance Type:            nonrobust
==============================================================================
                     coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------------
Min_Temp             0.0286      0.017      1.688      0.091      -0.005
0.062
Max_Temp             0.1079      0.056      1.940      0.052      -0.001
0.217
Evaporation         -0.0291      0.012     -2.367      0.018      -0.053
-0.005
Electricity          0.0026      0.015      0.175      0.861      -0.026
0.031
Parameter1_Speed     0.0159      0.006      2.636      0.008       0.004
0.028
Parameter3_9am      -0.0040      0.007     -0.548      0.584      -0.018
0.010
Parameter3_3pm      -0.0188      0.008     -2.240      0.025      -0.035
-0.002
Parameter4_9am       0.0189      0.005      3.616      0.000       0.009
0.029
Parameter4_3pm      -0.0208      0.006     -3.308      0.001      -0.033
-0.008
Parameter5_9am      -0.0437      0.033     -1.329      0.184      -0.108
0.021
Parameter5_3pm       0.0443      0.033      1.344      0.179      -0.020
0.109
Parameter6_9am      -0.0194      0.030     -0.642      0.521      -0.078
0.040
Parameter6_3pm       0.0778      0.029      2.670      0.008       0.021
0.135
Parameter7_9am       0.0962      0.030      3.192      0.001       0.037
```

```
0.155
Parameter7_3pm      -0.2240      0.063     -3.581      0.000      -0.347
-0.101
I_evap              -0.0543      0.086     -0.631      0.528      -0.223
0.114
I_elect              0.0081      0.125      0.065      0.948      -0.236
0.252
I_param6_9am        -0.2714      0.319     -0.851      0.395      -0.896
0.353
I_param6_3pm         0.3785      0.314      1.204      0.229      -0.238
0.995
LK                   2.2247      0.158     14.085      0.000       1.915
2.534
Leakage              0.0400      0.007      5.335      0.000       0.025
0.055
==============================================================================
====
```

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: Se pudo observar una clara sobredispersión (varianza > media), por lo que el modelo Poisson no es el más adecuado para estos datos. Es por eso que, en mi opinión, la Binomial Negativa es un modelo más apto, puesto que este permite modelar la sobredispersión de forma explícita. Así, 'Evaporation', 'Parameter1_Speed', 'Parameter4_9am', 'Parameter7_3pm' y 'LK' resultaron ser consistentes en los dos modelos.