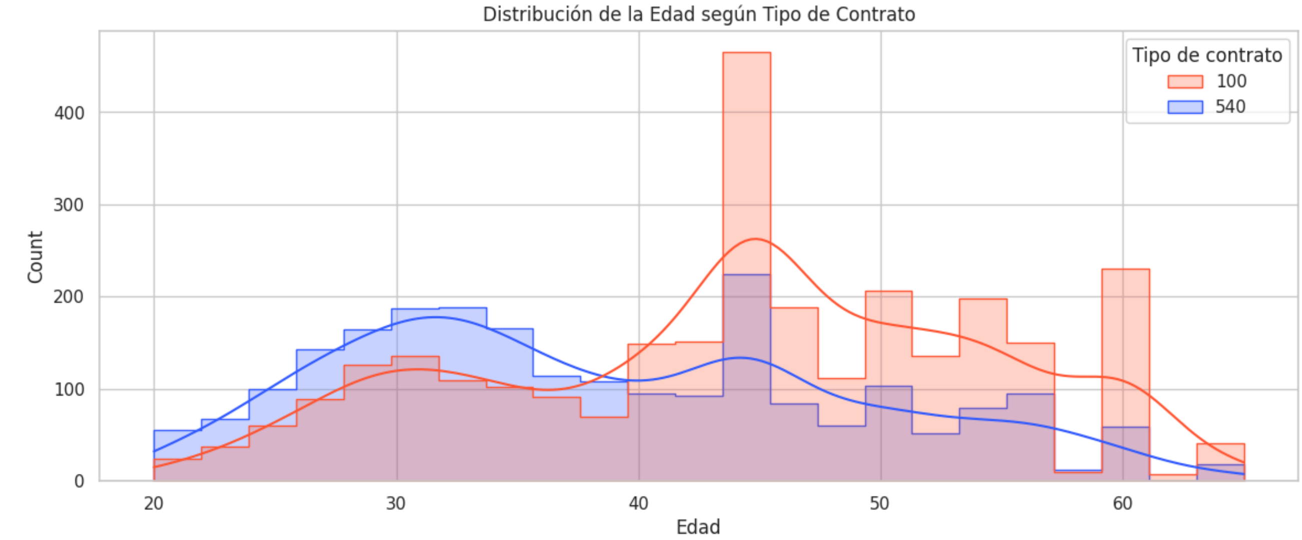
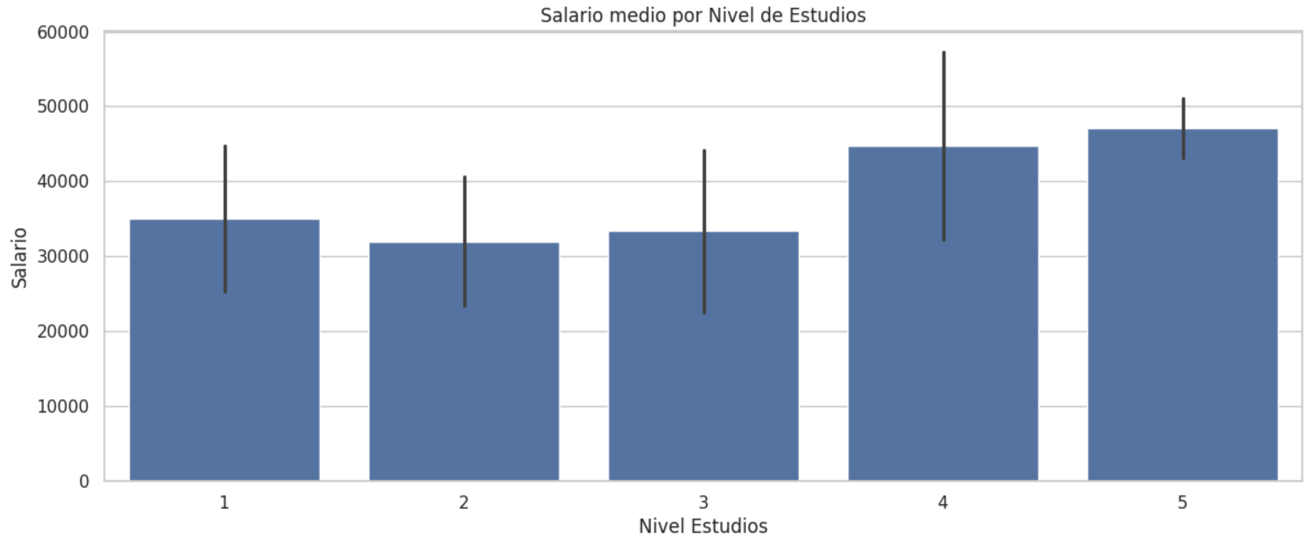
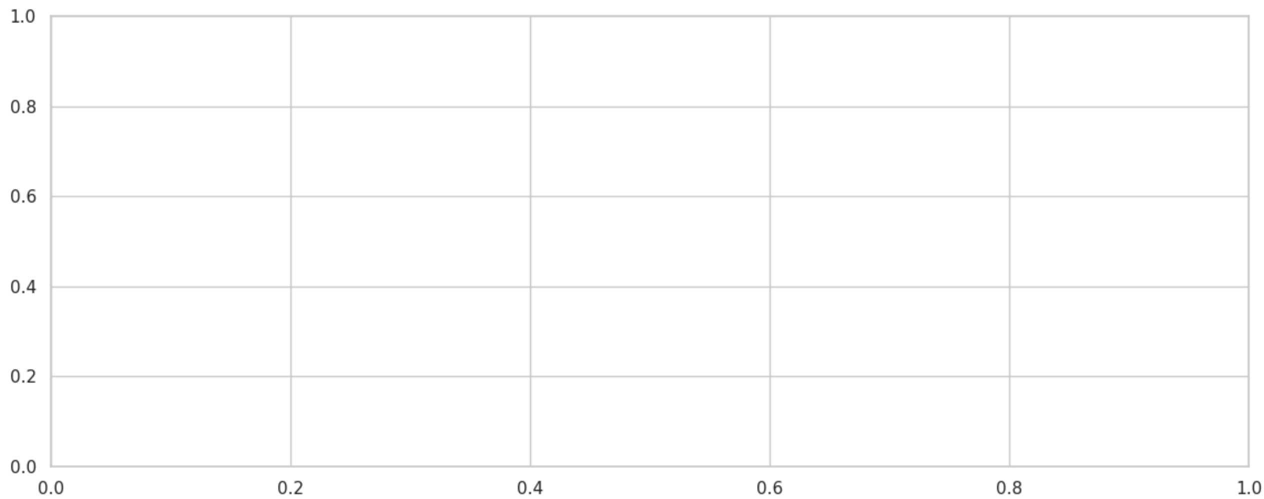
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

file_path = "/content/DatasetFinalNC.xlsx"
df = pd.read_excel(file_path)
```

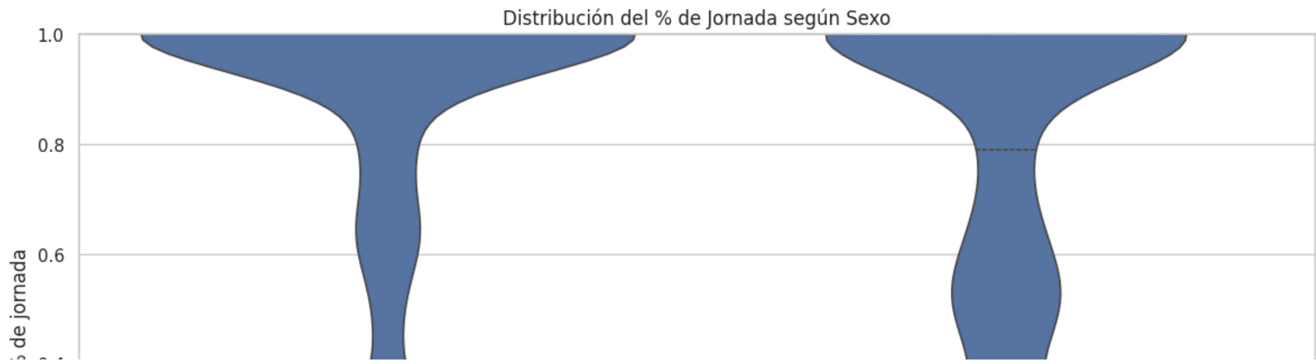
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import pearsonr


file_path = "/content/DatasetFinalNC.xlsx"
df = pd.read_excel(file_path)


sns.set(style="whitegrid")


corr_edad_contrato = pearsonr(df['Edad'], df['Tipo de contrato'])[0]
corr_salario_estudios = pearsonr(df['Salario'], df['Nivel Estudios'])[0]
corr_jornada_sexo = pearsonr(df['% de jornada'], df['Sexo'])[0]


fig, axes = plt.subplots(3, 1, figsize=(14, 18))


palette_contratos = {100: "#FF5733", 540: "#335CFF"}
sns.histplot(
    data=df,
    x='Edad',
    hue='Tipo de contrato',
    kde=True,
    element='step',
    common_norm=False,
    ax=axes[0],
    palette=palette_contratos
)
axes[0].set_title(f'Distribución de la Edad según Tipo de Contrato')


sns.barplot(data=df, x='Nivel Estudios', y='Salario', ci='sd', ax=axes[1])
axes[1].set_title(f'Salario medio por Nivel de Estudios')


plt.figure(figsize=(12, 6))
sns.violinplot(data=df, x='Sexo', y='% de jornada', inner='quartile')
plt.title(f'Distribución del % de Jornada según Sexo')
plt.xlabel('Sexo')
plt.ylabel('% de jornada')
plt.xticks([0, 1], ['Mujer (0)', 'Hombre (1)'])
plt.ylim(0, 1)
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
<ipython-input-3-61dc32990cb0>:36: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same effect.

  sns.barplot(data=df, x='Nivel Estudios', y='Salario', ci='sd', ax=axes[1])
```



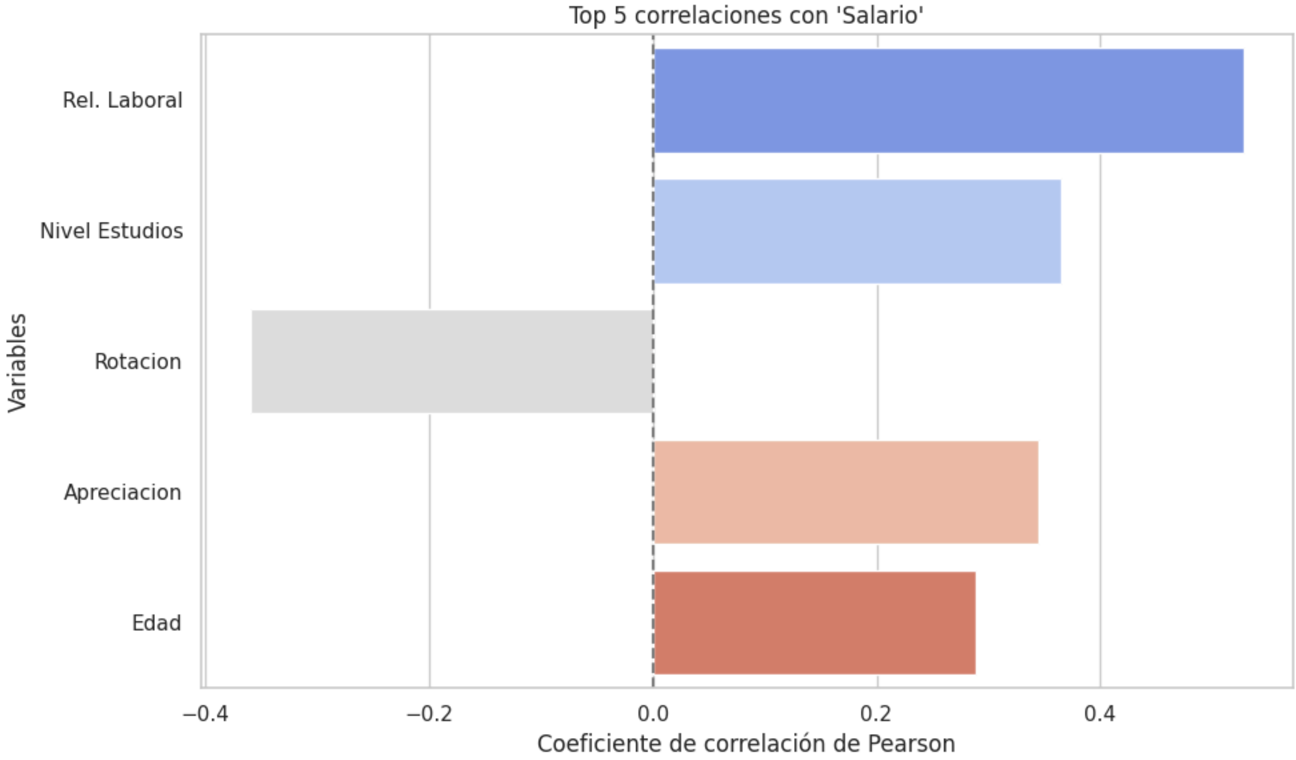






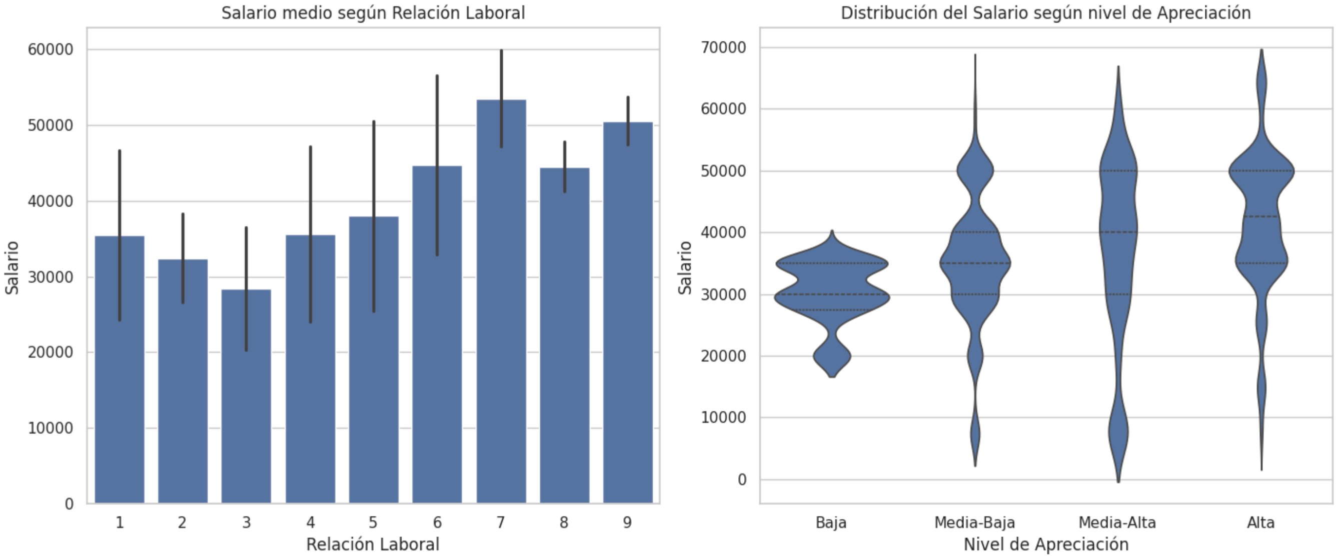

```python
import matplotlib.pyplot as plt
import seaborn as sns

correlation_matrix = df.corr(numeric_only=True)

salario_corr = correlation_matrix["Salario"].drop("Salario").sort_values(key=abs, ascending=False).head(5)


plt.figure(figsize=(10, 6))
sns.barplot(x=salario_corr.values, y=salario_corr.index, palette="coolwarm", orient='h')
plt.title("Top 5 correlaciones con 'Salario'")
plt.xlabel("Coeficiente de correlación de Pearson")
plt.ylabel("Variables")
plt.axvline(0, color='gray', linestyle='--')
plt.tight_layout()
plt.show()
```

```
<ipython-input-4-463359645304>:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `le

  sns.barplot(x=salario_corr.values, y=salario_corr.index, palette="coolwarm", orient='h')
```

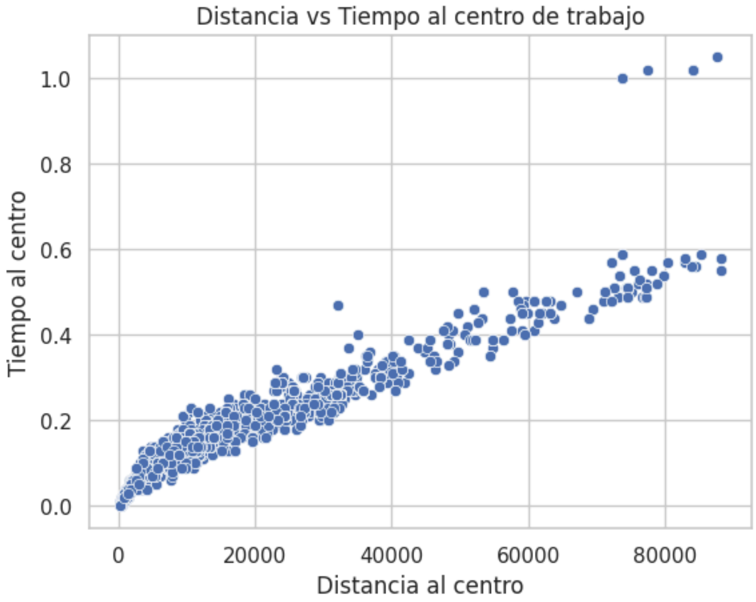


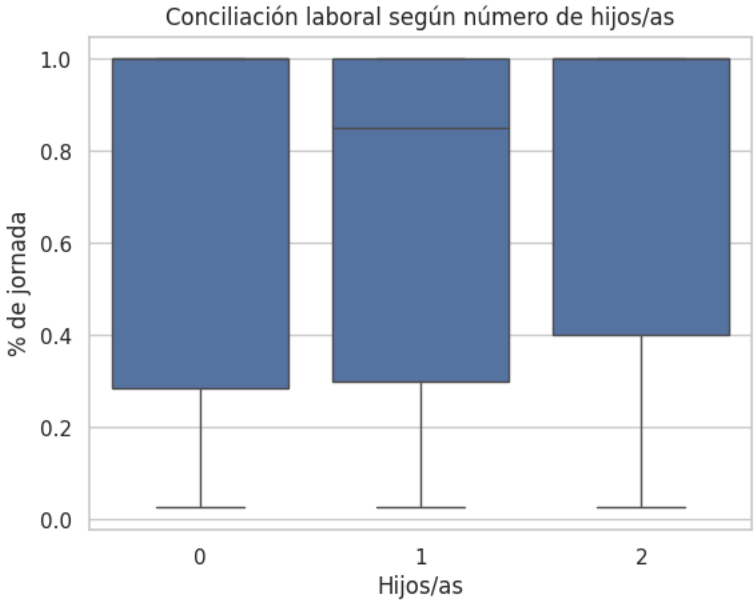

```
df['Apreciacion_bin'] = pd.cut(df['Apreciacion'], bins=[0, 3, 5, 7, 10], labels=['Baja', 'Media-Baja', 'Media-Alta', 'Alta'])

plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
sns.barplot(data=df, x='Rel. Laboral', y='Salario', ci='sd')
plt.title('Salario medio según Relación Laboral')
plt.xlabel('Relación Laboral')
plt.ylabel('Salario')

plt.subplot(1, 2, 2)
sns.violinplot(data=df, x='Apreciacion_bin', y='Salario', inner='quartile')
plt.title('Distribución del Salario según nivel de Apreciación')
plt.xlabel('Nivel de Apreciación')
plt.ylabel('Salario')

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

```
<ipython-input-5-ce016af7e3aa>:6: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar='sd'` for the same effect.

  sns.barplot(data=df, x='Rel. Laboral', y='Salario', ci='sd')
```

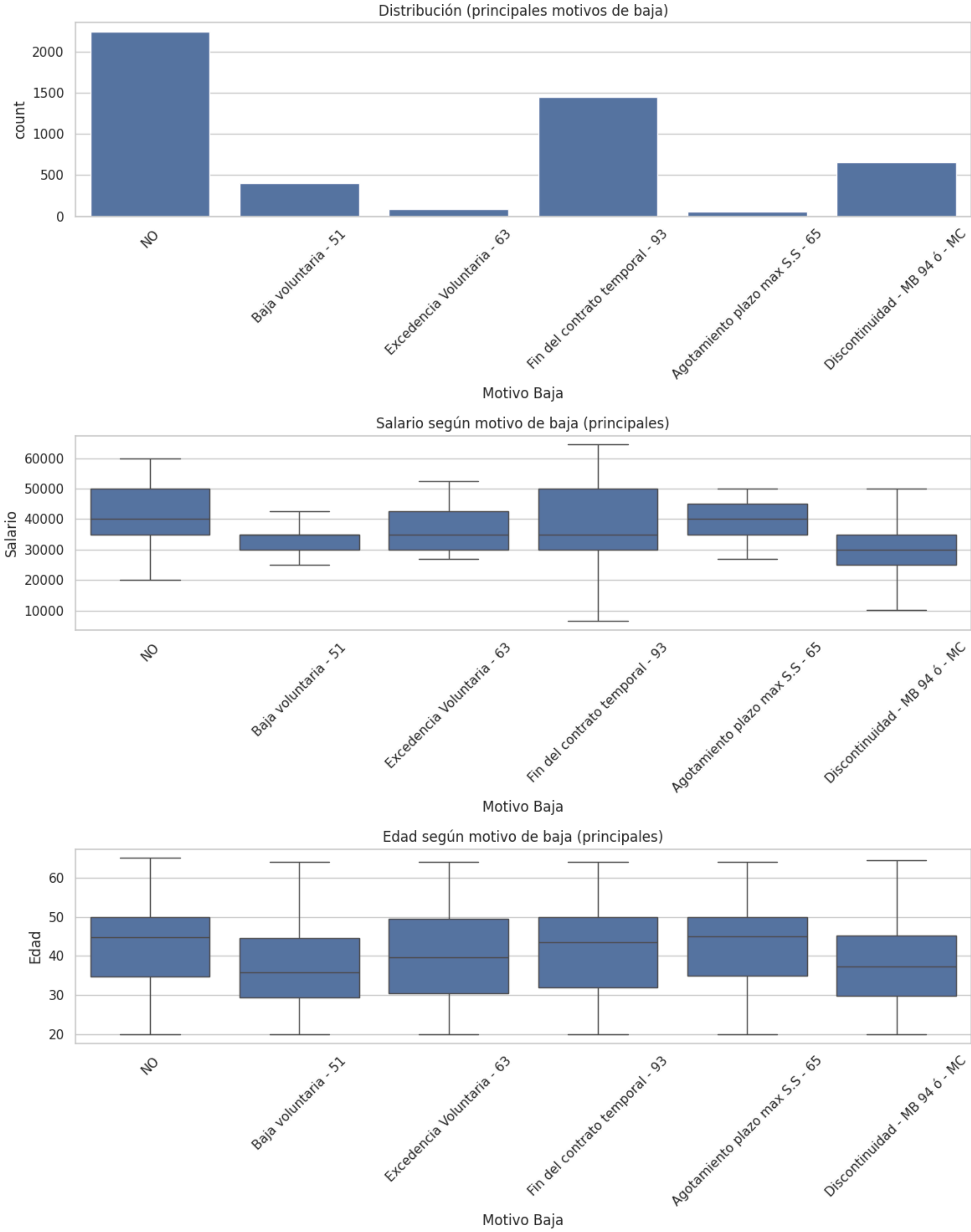



```
sns.scatterplot(data=df, x='Distancia al centro', y='Tiempo al centro')
plt.title('Distancia vs Tiempo al centro de trabajo')
plt.show()

sns.boxplot(x='Hijos/as', y='% de jornada', data=df)
plt.title('Conciliación laboral según número de hijos/as')
plt.show()
```



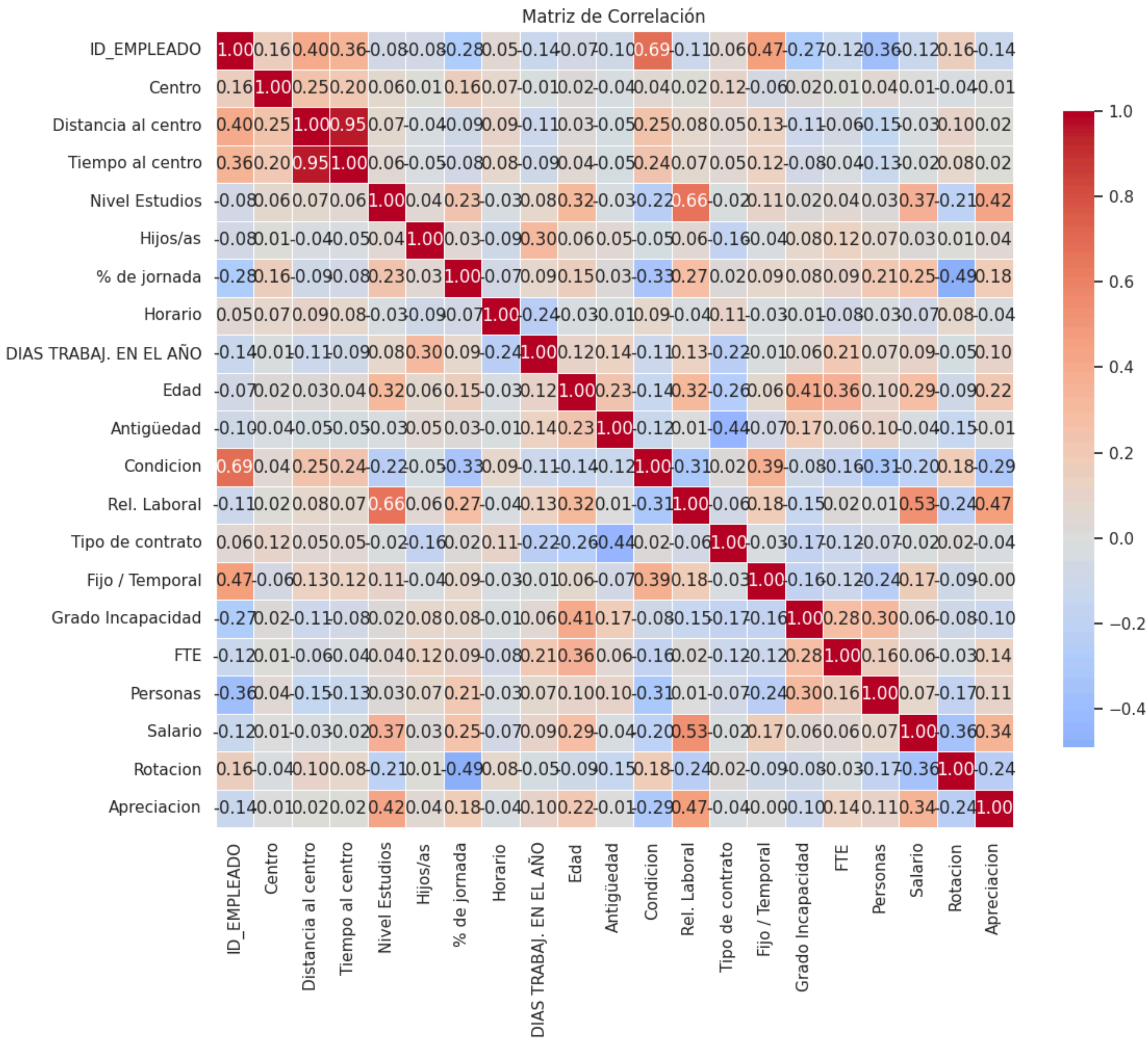



```
top_motivos = df[df['Motivo Baja'] != 'NO']['Motivo Baja'].value_counts().head(5).index.tolist()

motivos_seleccionados = ['NO'] + top_motivos
df_filtrado = df[df['Motivo Baja'].isin(motivos_seleccionados)]

fig, axes = plt.subplots(3, 1, figsize=(12, 15))

sns.countplot(ax=axes[0], data=df_filtrado, x='Motivo Baja')
axes[0].set_title('Distribución (principales motivos de baja)')
axes[0].tick_params(axis='x', rotation=45)

sns.boxplot(ax=axes[1], data=df_filtrado, x='Motivo Baja', y='Salario', showfliers=False)
axes[1].set_title('Salario según motivo de baja (principales)')
axes[1].tick_params(axis='x', rotation=45)

sns.boxplot(ax=axes[2], data=df_filtrado, x='Motivo Baja', y='Edad')
axes[2].set_title('Edad según motivo de baja (principales)')
axes[2].tick_params(axis='x', rotation=45)

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



Análisis de negocio

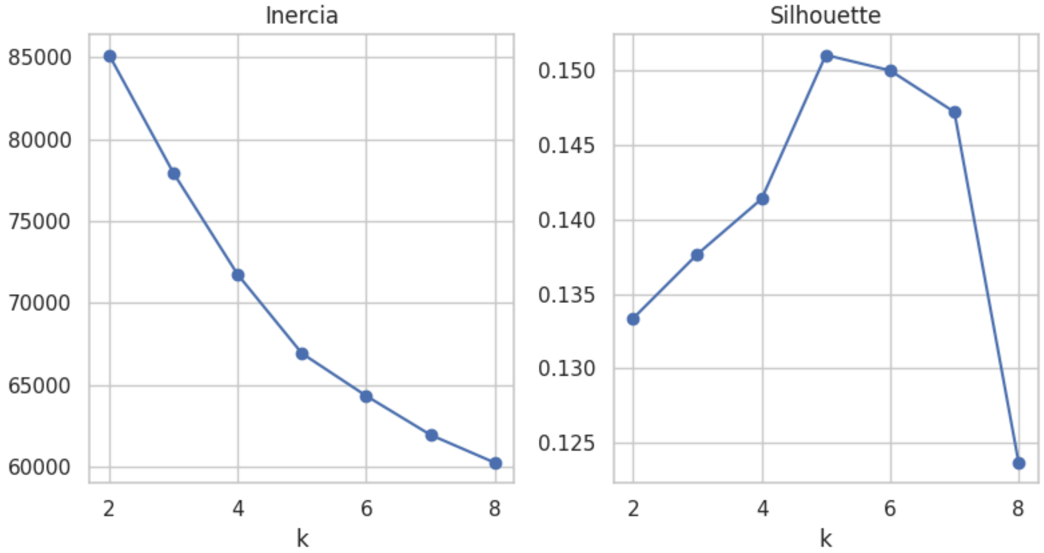
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

file_path = "/content/DatasetFinalNC.xlsx"
df = pd.read_excel(file_path)

corr_matrix = df.corr(numeric_only=True)

abs_corr = corr_matrix.abs()
mask = (abs_corr > 0.2).sum(axis=1) > 1
filtered_corr = corr_matrix.loc[mask, mask]

plt.figure(figsize=(12, 10))
sns.heatmap(filtered_corr, annot=True, fmt=".2f", cmap="coolwarm", center=0,
            square=True, linewidths=0.5, cbar_kws={"shrink": 0.8})
plt.title("Matriz de Correlación")
plt.tight_layout()
plt.show()
```




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

from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
```

```
from sklearn.metrics import (silhouette_score,
                             calinski_harabasz_score,
                             davies_bouldin_score,
                             adjusted_rand_score)

FILE_IN  = "/content/DatasetFinalNC.xlsx"
FILE_OUT = "MasterDataset_k5.xlsx"

df = pd.read_excel(FILE_IN)

feat_cols = [
    "Centro","Sexo","Condicion","Rel. Laboral","Tipo de contrato",
    "Fijo / Temporal","Nivel Estudios","Antigüedad","Edad",
    "Salario","Apreciacion","Distancia al centro",
    "Tiempo al centro","Hijos/as","% de jornada","Horario",
    "Grado Incapacidad","FTE","Personas"
]
X = df[feat_cols].fillna(df[feat_cols].mean())
X_scaled = StandardScaler().fit_transform(X)

ks = range(2, 9)

def dunn_index(X, labels):
    """Devuelve el índice de Dunn (max → mejor)"""
    from scipy.spatial.distance import cdist, pdist
    clusters = [X[labels == k] for k in np.unique(labels)]
    intra_dists = [pdist(c, metric='euclidean').max() if len(c) > 1 else 0
                   for c in clusters]
    max_intra = max(intra_dists)
    inter = np.inf
    for i in range(len(clusters)):
        for j in range(i + 1, len(clusters)):
            dist_ij = cdist(clusters[i], clusters[j], metric='euclidean').min()
            inter = min(inter, dist_ij)
    return inter / max_intra if max_intra > 0 else 0

def gap_statistic(X, refs=10, k_max=10):
    """Calcula Gap Statistic (Tibshirani, 2001) para k = 1 … k_max"""
    from sklearn.cluster import KMeans
    from numpy.random import default_rng
    rng = default_rng(42)
    shape = X.shape
    tops = X.max(axis=0); lows = X.min(axis=0)
    gaps = np.zeros(k_max)
    s_k  = np.zeros(k_max)
    for k in range(1, k_max + 1):
        km = KMeans(n_clusters=k, n_init=10, random_state=42).fit(X)
        orig_disp = np.log(km.inertia_)
        ref_disps = np.zeros(refs)
        for i in range(refs):
            random_ref = rng.uniform(lows, tops, size=shape)
            ref_km = KMeans(n_clusters=k, n_init=3, random_state=42).fit(random_ref)
            ref_disps[i] = np.log(ref_km.inertia_)
        gaps[k-1] = ref_disps.mean() - orig_disp
        s_k[k-1]  = np.sqrt(((ref_disps - ref_disps.mean())**2).sum() / refs) * np.sqrt(1 + 1/refs)
    return gaps, s_k

inertia, silh, ch, dunn, db = [], [], [], [], []
gap, gap_err = gap_statistic(X_scaled, refs=20, k_max=max(ks))

for k in ks:
    km = KMeans(n_clusters=k, n_init=10, random_state=42)
    labels = km.fit_predict(X_scaled)

    inertia.append(km.inertia_)
    silh.append(silhouette_score(X_scaled, labels))
    ch.append(calinski_harabasz_score(X_scaled, labels))
    dunn.append(dunn_index(X_scaled, labels))
    db.append(davies_bouldin_score(X_scaled, labels))

def bootstrap_stability(X, k, n_iter=30, sample_frac=0.8):
    n = X.shape[0]
    labels_master = KMeans(n_clusters=k, n_init=10,
                           random_state=42).fit_predict(X)
    scores = []
    rng = np.random.default_rng(123)
    for _ in range(n_iter):
        idx = rng.choice(n, int(n*sample_frac), replace=False)
        labels_sub = KMeans(n_clusters=k, n_init=10,
                            random_state=42).fit_predict(X[idx])
        scores.append(adjusted_rand_score(labels_master[idx], labels_sub))
    return np.mean(scores)
```

```
stab = [bootstrap_stability(X_scaled, k) for k in ks]

plt.figure(figsize=(12, 8))

plt.subplot(231); plt.plot(ks, inertia, 'o-'); plt.title("Inercia"); plt.xlabel("k")
plt.subplot(232); plt.plot(ks, silh, 'o-');    plt.title("Silhouette"); plt.xlabel("k")

plt.tight_layout(); plt.show()

k_final = 5
km5 = KMeans(n_clusters=k_final, n_init=10, random_state=42)
df["cluster_5"] = km5.fit_predict(X_scaled)

print("\n=== Métricas para k = 5 ===")
print("Silhouette:",       silh[ks.index(5)])
print("Calinski-Harabasz:", ch[ks.index(5)])
print("Dunn:",              dunn[ks.index(5)])
print("Gap:",               gap[4])
print("Estabilidad ARI:",   stab[ks.index(5)])

df.to_excel(FILE_OUT, index=False)
print(f"\nArchivo guardado en: {FILE_OUT}")
```




```
=== Métricas para k = 5 ===
Silhouette: 0.1510636470193829
Calinski-Harabasz: 601.8014978817861
Dunn: 0.03332887161603404
Gap: 0.46081460906701643
Estabilidad ARI: 0.9885181649709127

Archivo guardado en: MasterDataset_k5.xlsx
```

```
import pandas as pd

FILE   = "/content/DatasetFinal.xlsx"
CL_COL = "cluster_5"

df = pd.read_excel(FILE)

counts = df[CL_COL].value_counts().sort_index()
print("\nNº de empleados por cluster:")
print(counts)
```

```
Nº de empleados por cluster:
cluster_5
0    1259
1    1430
2     763
3     652
4    1061
Name: count, dtype: int64
```

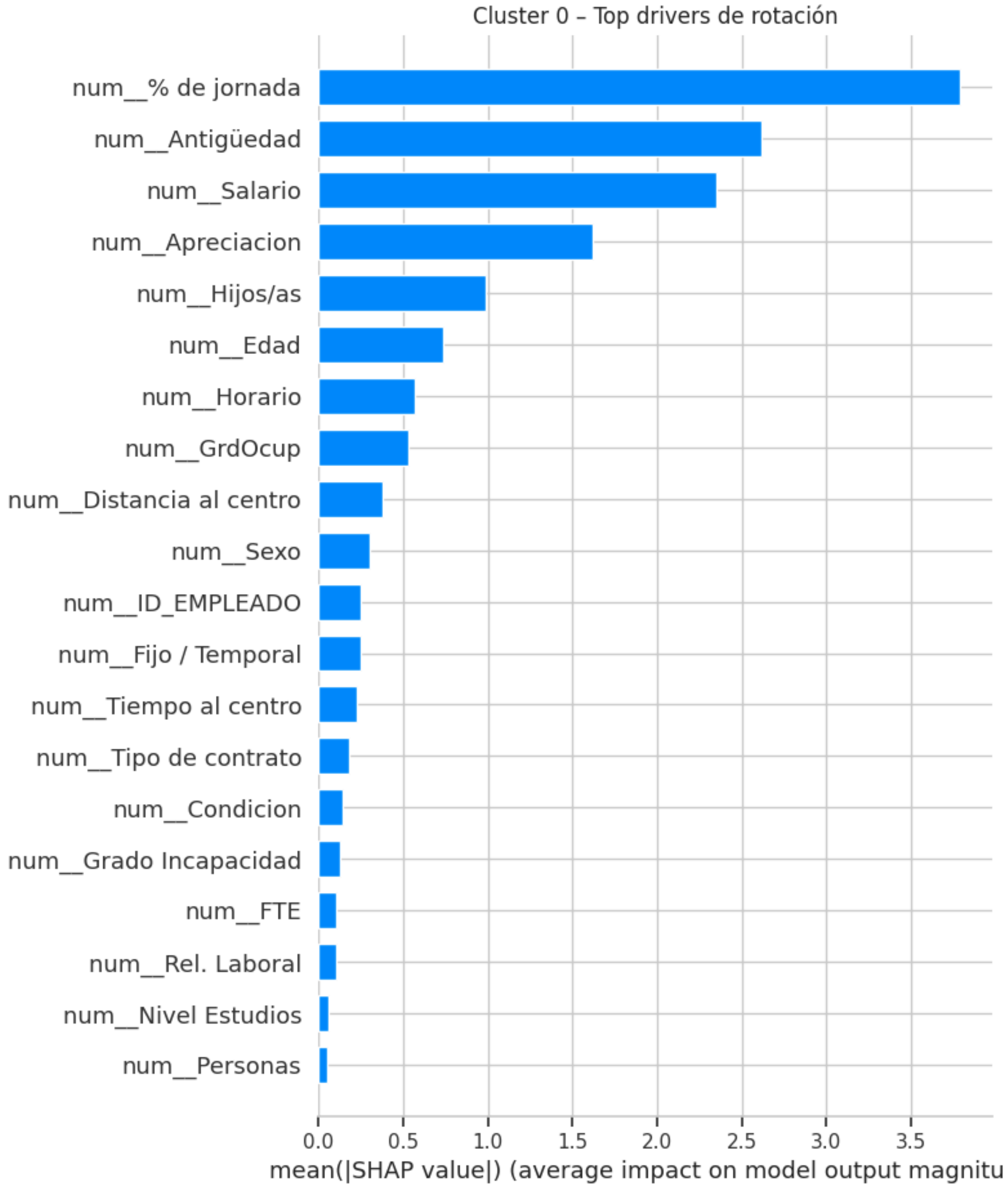
```
# PREGUNTA 1: Perfil detallado de cada cluster
import pandas as pd

FILE_IN  = "/content/DatasetFinal.xlsx"
FILE_OUT = "Cluster_Profile.xlsx"
```

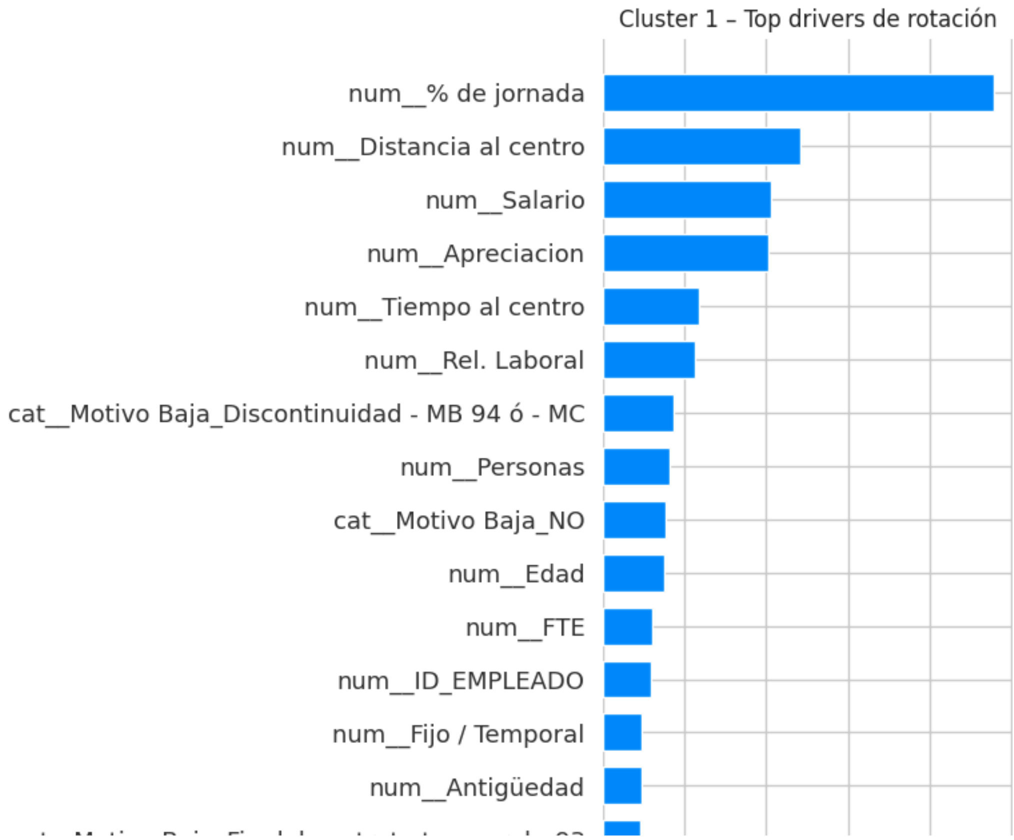
```
df = pd.read_excel(FILE_IN)

cont_cols = ["Salario", "Antigüedad", "Edad", "Apreciacion", "Distancia al centro",
             "Nivel Estudios", "Rel. Laboral", "FTE"]
cat_cols  = ["Fijo / Temporal", "Rotacion"]


cont_stats = (
    df.groupby("cluster_5")[cont_cols]
      .agg(["mean", "median"])
      .round(2)
)


cont_stats.columns = ['_'.join(col) for col in cont_stats.columns]

agg = (
    df.groupby("cluster_5")
      .agg(
         Temporal_rate=("Fijo / Temporal", "mean"),
         Rotacion_rate=("Rotacion", "mean"),
         Num_empleados=("cluster_5", "size")
      )
      .round(3)
)

profile = pd.concat([agg, cont_stats], axis=1).reset_index()

cols_order = ["cluster_5", "Num_empleados",
              "Salario_mean", "Antigüedad_mean", "Edad_mean", "Apreciacion_mean",
              "Distancia al centro_mean", "Nivel Estudios_mean", "Rel. Laboral_mean", "FTE_mean",
              "Temporal_rate", "Rotacion_rate"]

profile = profile[[col for col in cols_order if col in profile.columns]]

print("\n=== Perfil resumido por cluster ===")
print(profile)

profile.to_excel(FILE_OUT, index=False)
print(f"\nTabla exportada a: {FILE_OUT}")
```

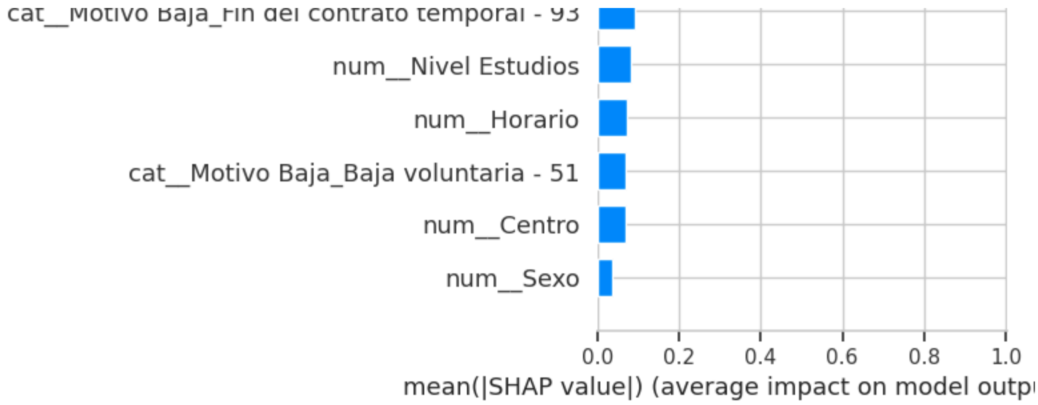
```
=== Perfil resumido por cluster ===
   cluster_5  Num_empleados  Salario_mean  Antigüedad_mean  Edad_mean  \
0          0           1259      38719.39             5.64      49.78
1          1           1430      32606.60             1.24      32.98
2          2            763      45180.21             5.42      42.83
3          3            652      53531.44             4.70      50.46
4          4           1061      26312.44             7.72      37.46

   Apreciacion_mean  Distancia al centro_mean  Nivel Estudios_mean  \
0              5.38                  19426.96                 3.20
1              5.17                  23938.67                 2.82
2              7.82                  20222.55                 3.87
3              7.10                  28683.25                 4.28
4              4.51                  23295.84                 2.34

   Rel. Laboral_mean  FTE_mean  Temporal_rate  Rotacion_rate
0               4.03      0.72          0.192          0.109
1               3.56      0.56          0.302          0.281
2               6.80      0.68          0.020          0.038
3               7.68      0.57          0.890          0.025
4               2.90      0.56          0.287          0.323

Tabla exportada a: Cluster_Profile.xlsx
```

```
# PREGUNTA 2: ¿Qué variables disparan la rotación dentro de cada cluster?

import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
import shap, matplotlib.pyplot as plt

FILE = "/content/DatasetFinal.xlsx"
df = pd.read_excel(FILE)

target = "Rotacion"
```

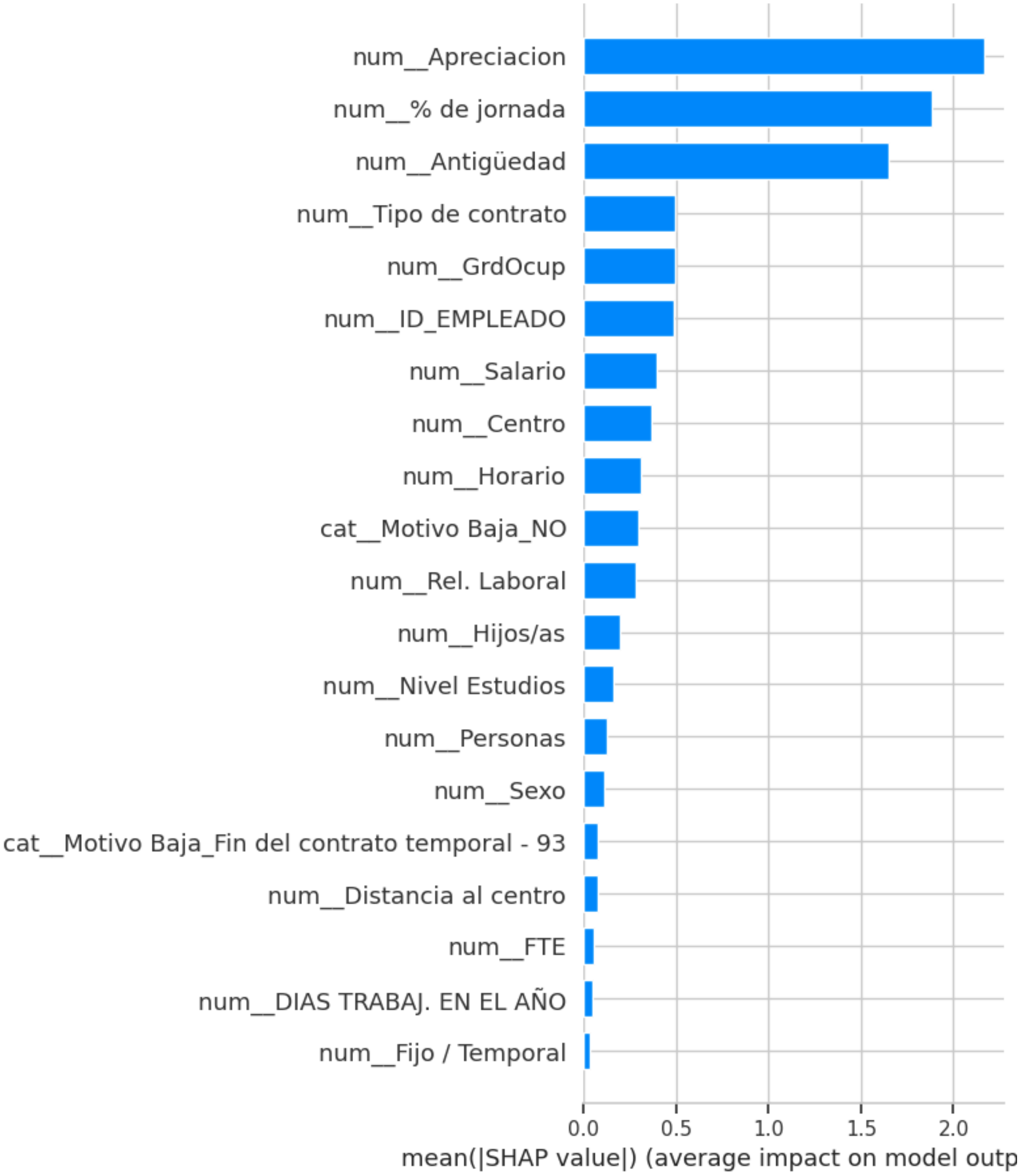
```
num_cols = df.select_dtypes(include="number").columns.tolist()
cat_cols = df.select_dtypes(include="object").columns.tolist()
num_cols.remove(target)

results = []

for cl in sorted(df["cluster_5"].unique()):
    dfi = df[df["cluster_5"] == cl].copy()

    X = dfi[num_cols + cat_cols]
    y = dfi[target]

    numeric_transformer = Pipeline([("scaler", StandardScaler())])
    categorical_transform = OneHotEncoder(handle_unknown="ignore")

    preproc = ColumnTransformer(
        [("num", numeric_transformer, num_cols),
         ("cat", categorical_transform, cat_cols)]
    )

    model = LogisticRegression(max_iter=1000, class_weight="balanced")

    pipe = Pipeline([("prep", preproc),
                     ("clf", model)])

    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size=0.25, random_state=42, stratify=y)

    pipe.fit(X_train, y_train)
    auc = pipe.score(X_test, y_test)
    results.append((cl, auc))

    # --- SHAP: dentro del bucle ---
    explainer = shap.Explainer(pipe["clf"], pipe["prep"].transform(X_train))
    shap_values = explainer(pipe["prep"].transform(X_test))

    feature_names = pipe["prep"].get_feature_names_out()
    X_test_transformed = pipe["prep"].transform(X_test)
    X_test_df = pd.DataFrame(X_test_transformed, columns=feature_names)

    shap.summary_plot(shap_values, features=X_test_df, feature_names=feature_names,
                      show=False, plot_type="bar")
    plt.title(f"Cluster {cl} – Top drivers de rotación")
    plt.tight_layout()
    plt.show()

print("\nAUC/Acc por cluster:", results)
```


Cluster 0 – Top drivers de rotación
num__% de jornada
num__Antigüedad
num__Salario
num__Apreciacion
num__Hijos/as
num__Edad
num__Horario
num__GrdOcup
num__Distancia al centro
num__Sexo
num__ID_EMPLEADO
num__Fijo / Temporal
num__Tiempo al centro
num__Tipo de contrato
num__Condicion
num__Grado Incapacidad
num__FTE
num__Rel. Laboral
num__Nivel Estudios
num__Personas
0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5
mean(|SHAP value|) (average impact on model output magnitu

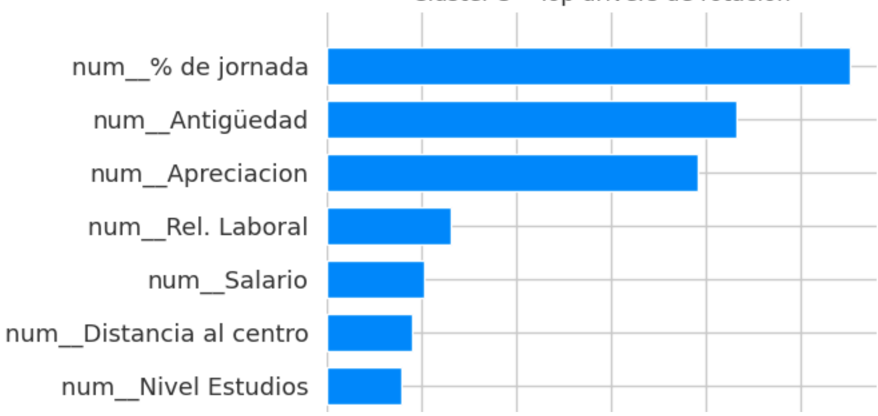

Cluster 1 – Top drivers de rotación
num__% de jornada
num__Distancia al centro
num__Salario
num__Apreciacion
num__Tiempo al centro
num__Rel. Laboral
cat__Motivo Baja_Discontinuidad - MB 94 ó - MC
num__Personas
cat__Motivo Baja_NO
num__Edad
num__FTE
num__ID_EMPLEADO
num__Fijo / Temporal
num__Antigüedad

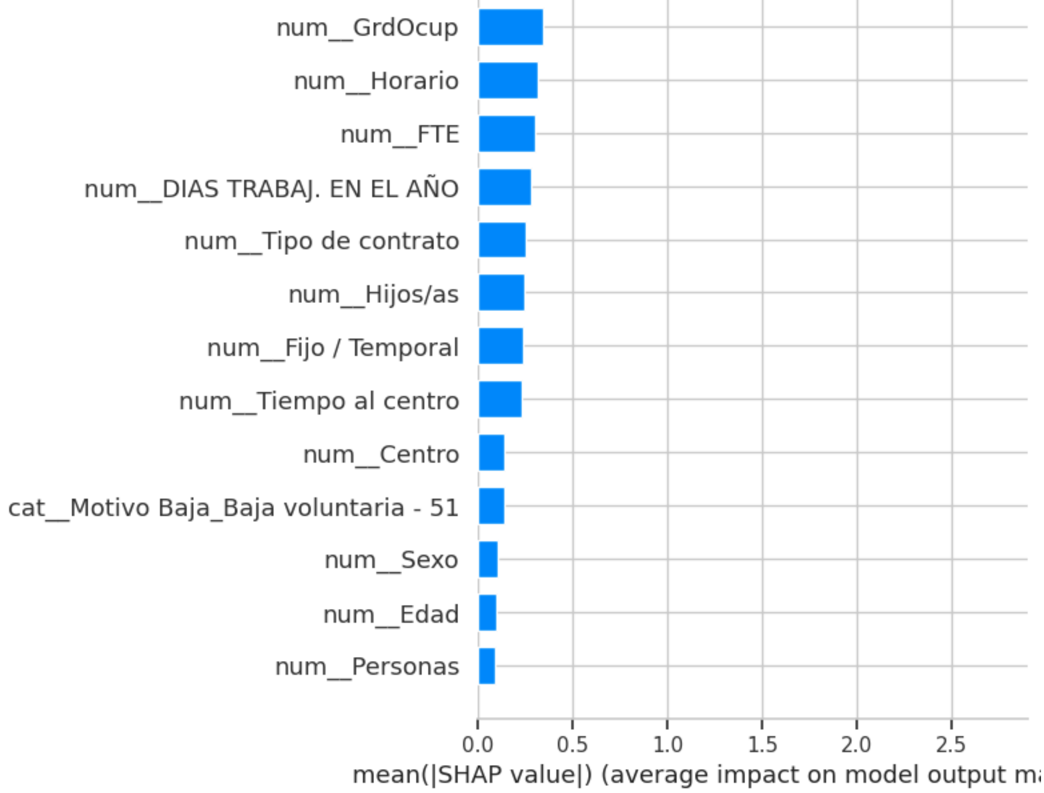


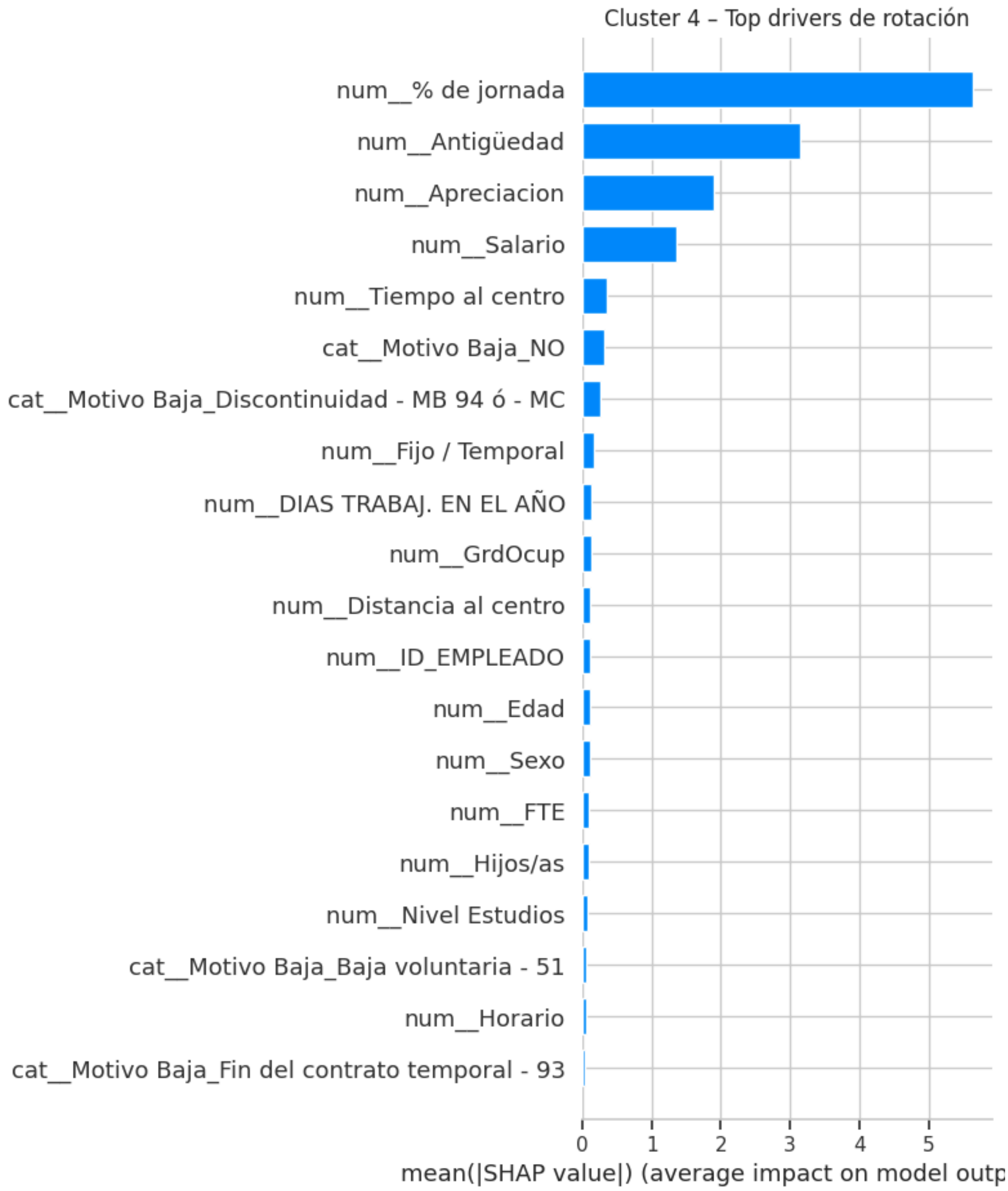
Cluster 2 – Top drivers de rotación



Cluster 3 – Top drivers de rotación





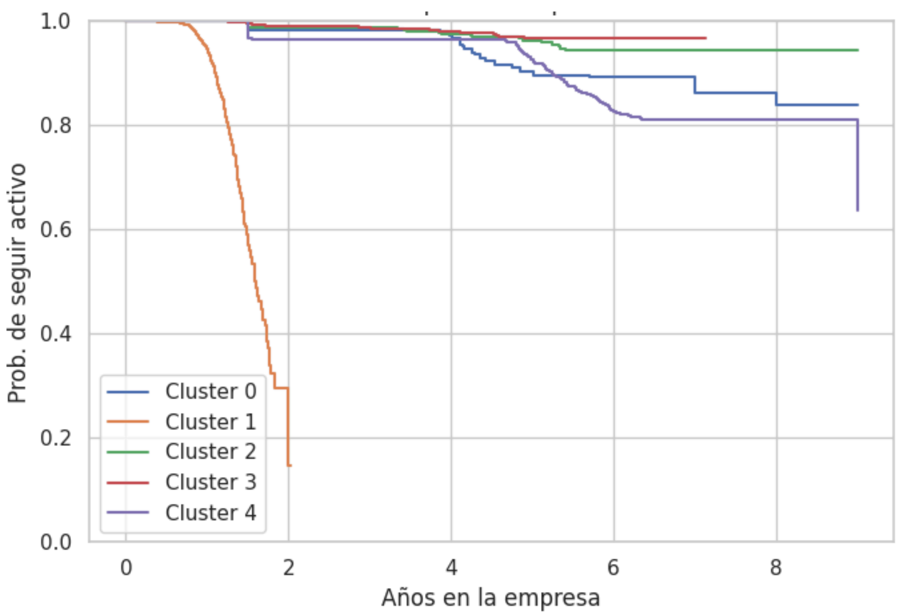



```
AUC/Acc por cluster: [(np.int64(0), 0.9873015873015873), (np.int64(1), 0.7150837988826816), (np.int64(2), 0.9842931937172775), (np_
```

```
!pip install lifelines --quiet
```

```
Preparing metadata (setup.py) ... done
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 349.3/349.3 kB 6.5 MB/s eta 0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 115.7/115.7 kB 8.5 MB/s eta 0:00:00
Building wheel for autograd-gamma (setup.py) ... done
```

```
# PREGUNTA 4: ¿Cómo evoluciona la probabilidad de permanecer en la empresa a lo largo del tiempo y cómo difiere por cluster?

import pandas as pd
import matplotlib.pyplot as plt
from lifelines import KaplanMeierFitter, CoxPHFitter

FILE = "/content/DatasetFinal.xlsx"
df   = pd.read_excel(FILE)

surv_df = df[["Antigüedad", "Rotacion", "cluster_5"]].copy()
surv_df.rename(columns={"Antigüedad": "tenure", "Rotacion": "event"}, inplace=True)

km = KaplanMeierFitter()

plt.figure(figsize=(7,5))
for cl in sorted(surv_df["cluster_5"].unique()):
    mask = surv_df["cluster_5"] == cl
    km.fit(durations=surv_df.loc[mask, "tenure"],
           event_observed=surv_df.loc[mask, "event"],
           label=f"Cluster {cl}")
    km.plot(ci_show=False)

plt.title("Curvas Kaplan-Meier por cluster")
plt.xlabel("Años en la empresa")
plt.ylabel("Prob. de seguir activo")
plt.ylim(0,1); plt.grid(True); plt.tight_layout()
plt.show()

cox_df = pd.get_dummies(surv_df, columns=["cluster_5"], drop_first=True)

cox = CoxPHFitter()
cox.fit(cox_df, duration_col="tenure", event_col="event")
cox.print_summary()
```



model	lifelines.CoxPHFitter
duration col	'tenure'
event col	'event'
baseline estimation	breslow
number of observations	5165
number of events observed	927
partial log-likelihood	-6606.80
time fit was run	2025-05-15 20:48:29 UTC

	coef	exp(coef)	se(coef)	coef lower 95%	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95%	cmp to	z	p	-log2(p)
cluster_5_1	3.78	43.82	0.15	3.48	4.08	32.54	59.01	0.00	24.90	<0.005	452.15
cluster_5_2	-1.20	0.30	0.21	-1.61	-0.80	0.20	0.45	0.00	-5.84	<0.005	27.52
cluster_5_3	-1.19	0.31	0.26	-1.71	-0.67	0.18	0.51	0.00	-4.49	<0.005	17.09
cluster_5_4	0.26	1.30	0.11	0.05	0.48	1.05	1.61	0.00	2.42	0.02	6.03

Concordance	0.79
Partial AIC	13221.61
log-likelihood ratio test	1418.15 on 4 df
-log2(p) of ll-ratio test	1013.51

```
pip install lifelines
```

```
Requirement already satisfied: lifelines in /usr/local/lib/python3.11/dist-packages (0.30.0)
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.11/dist-packages (from lifelines) (2.0.2)
Requirement already satisfied: scipy>=1.7.0 in /usr/local/lib/python3.11/dist-packages (from lifelines) (1.15.3)
Requirement already satisfied: pandas>=2.1 in /usr/local/lib/python3.11/dist-packages (from lifelines) (2.2.2)
Requirement already satisfied: matplotlib>=3.0 in /usr/local/lib/python3.11/dist-packages (from lifelines) (3.10.0)
Requirement already satisfied: autograd>=1.5 in /usr/local/lib/python3.11/dist-packages (from lifelines) (1.8.0)
Requirement already satisfied: autograd-gamma>=0.3 in /usr/local/lib/python3.11/dist-packages (from lifelines) (0.5.0)
Requirement already satisfied: formulaic>=0.2.2 in /usr/local/lib/python3.11/dist-packages (from lifelines) (1.1.1)
Requirement already satisfied: interface-meta>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from formulaic>=0.2.2->lifelines)
Requirement already satisfied: typing-extensions>=4.2.0 in /usr/local/lib/python3.11/dist-packages (from formulaic>=0.2.2->lifelines
Requirement already satisfied: wrapt>=1.0 in /usr/local/lib/python3.11/dist-packages (from formulaic>=0.2.2->lifelines) (1.17.2)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib>=3.0->lifelines) (1.3.2
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib>=3.0->lifelines) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib>=3.0->lifelines) (4.58
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib>=3.0->lifelines) (1.4.
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib>=3.0->lifelines) (24.2)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-packages (from matplotlib>=3.0->lifelines) (11.2.1)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib>=3.0->lifelines) (3.2.3
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (from matplotlib>=3.0->lifelines) (2
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas>=2.1->lifelines) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas>=2.1->lifelines) (2025.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7->matplotlib>=3.0->lif
```

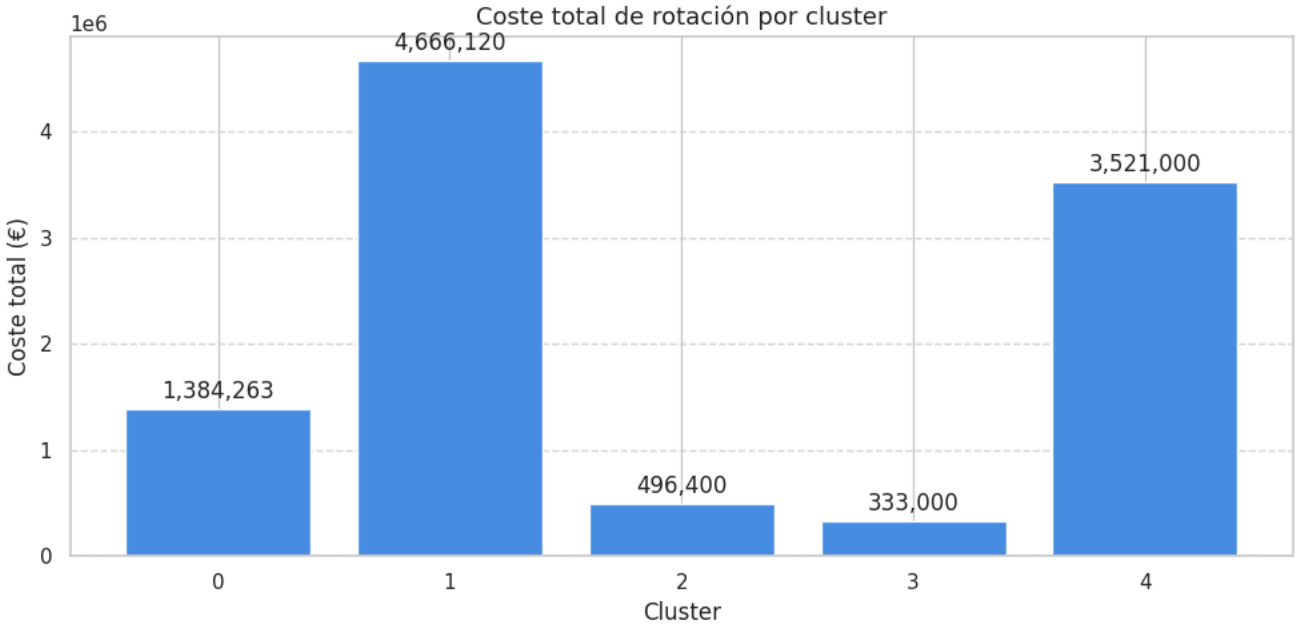
```
import pandas as pd
from lifelines import CoxPHFitter

df = pd.read_excel("/content/DatasetFinal.xlsx")

surv_df = df[["Antigüedad", "Rotacion", "cluster_5"]].copy()
surv_df.rename(columns={"Antigüedad": "tenure", "Rotacion": "event"}, inplace=True)

cox_df_full = pd.get_dummies(surv_df, columns=["cluster_5"], drop_first=True)
cox_full = CoxPHFitter()
cox_full.fit(cox_df_full, duration_col="tenure", event_col="event")
print("AIC parcial del modelo completo:", cox_full.AIC_partial_)

cox_null = CoxPHFitter()
cox_null.fit(surv_df[["tenure", "event"]], duration_col="tenure", event_col="event")
print("AIC parcial del modelo nulo:", cox_null.AIC_partial_)
```

```
AIC parcial del modelo completo: 13221.606254868553
AIC parcial del modelo nulo: 14631.756976704877
```

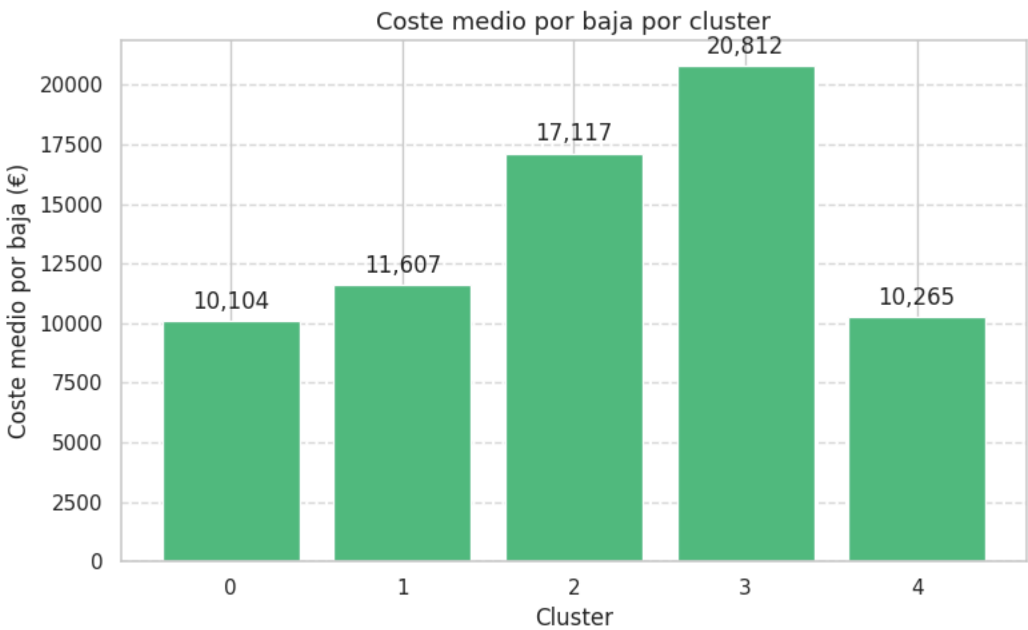
```
# PREGUNTA 5: ¿Cuánto cuesta la rotación en cada cluster y dónde conviene invertir primero?
import pandas as pd

FILE = "/content/DatasetFinal.xlsx"
df = pd.read_excel(FILE)

rotados = df[df["Rotacion"] == 1].copy()

rotados["Coste_baja"] = rotados["Salario"] * 0.4

coste_cluster = rotados.groupby("cluster_5").agg(
    Bajas=("Coste_baja", "size"),
    Coste_total=("Coste_baja", "sum"),
    Coste_medio_por_baja=("Coste_baja", "mean")
).round(0)

coste_cluster = coste_cluster.sort_values("Coste_total", ascending=False)
print(coste_cluster)

coste_cluster.to_excel("Coste_Rotacion_por_Cluster.xlsx")
```

```
           Bajas  Coste_total  Coste_medio_por_baja
cluster_5
1            402    4666120.0               11607.0
4            343    3521000.0               10265.0
0            137    1384263.0               10104.0
2             29     496400.0               17117.0
3             16     333000.0               20812.0
```

```
import matplotlib.pyplot as plt

clusters = ["0", "1", "2", "3", "4"]
costes = [1384263, 4666120, 496400, 333000, 3521000]

plt.figure(figsize=(10, 5))
bars = plt.bar(clusters, costes, color="#4A90E2")

for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval + 50000, f"{int(yval):,}",
             ha='center', va='bottom', fontsize=12)

plt.title("Coste total de rotación por cluster", fontsize=13)
plt.xlabel("Cluster")
plt.ylabel("Coste total (€)")
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.tight_layout()
plt.show()
```



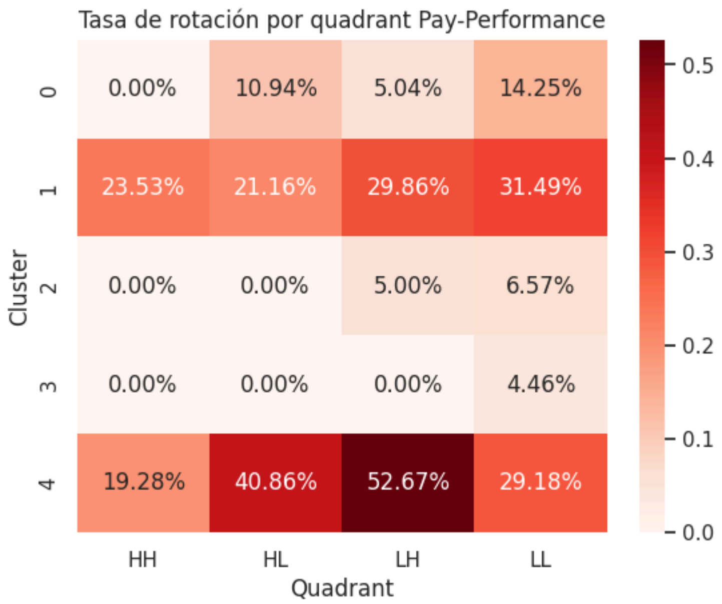

```
import matplotlib.pyplot as plt

clusters = ["0", "1", "2", "3", "4"]
coste_medio = [10104.0, 11607.0, 17117.0, 20812.0, 10265.0]

plt.figure(figsize=(8, 5))
bars = plt.bar(clusters, coste_medio, color="#50B97D")

for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval + 300, f"{int(yval):,}",
             ha='center', va='bottom', fontsize=12)

plt.title("Coste medio por baja por cluster", fontsize=13)
plt.xlabel("Cluster")
plt.ylabel("Coste medio por baja (€)")
plt.grid(axis="y", linestyle="--", alpha=0.7)
plt.tight_layout()
plt.show()
```




```
# PREGUNTA 6: ¿Los empleados con alto desempeño pero salario bajo se marchan más?

import pandas as pd
import numpy as np
from scipy import stats
import seaborn as sns
import matplotlib.pyplot as plt
```

```
FILE = "/content/DatasetFinal.xlsx"
df   = pd.read_excel(FILE)

def label_quadrant(sub):
    q_salary_lo = sub["Salario"].quantile(0.25)
    q_salary_hi = sub["Salario"].quantile(0.75)
    q_perf_hi   = sub["Apreciacion"].quantile(0.75)
    q_perf_lo   = sub["Apreciacion"].quantile(0.25)

    cond_perf_hi = sub["Apreciacion"] >= q_perf_hi
    cond_perf_lo = sub["Apreciacion"] <= q_perf_lo
    cond_sal_hi  = sub["Salario"] >= q_salary_hi
    cond_sal_lo  = sub["Salario"] <= q_salary_lo

    quadrant = np.where( cond_perf_hi & cond_sal_lo, "HL",
               np.where( cond_perf_hi & cond_sal_hi, "HH",
               np.where( cond_perf_lo & cond_sal_hi, "LH","LL")))


    return pd.Series(quadrant, index=sub.index)

df["Quadrant"] = (
    df.groupby("cluster_5", group_keys=False)
      .apply(label_quadrant)
)

tab = (pd.crosstab(index=[df["cluster_5"], df["Quadrant"]],
                   columns=df["Rotacion"],
                   normalize="index")
         .rename(columns={0: "Activo", 1: "Baja"})
         .reset_index())

print(tab.head())

pivot = tab.pivot(index="cluster_5", columns="Quadrant", values="Baja")
sns.heatmap(pivot, annot=True, fmt=".2%", cmap="Reds")
plt.title("Tasa de rotación por quadrant Pay-Performance")
plt.ylabel("Cluster")
plt.show()

chi2, p, dof, exp = stats.chi2_contingency(
        pd.crosstab(df["Quadrant"], df["Rotacion"]))
print(f"χ² global quadrant vs rotación: p = {p:.4f}")
```

```
<ipython-input-21-898783f3c715>:32: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is de
  .apply(label_quadrant)
Rotacion  cluster_5 Quadrant    Activo      Baja
0                 0       HH  1.000000  0.000000
1                 0       HL  0.890566  0.109434
2                 0       LH  0.949640  0.050360
3                 0       LL  0.857546  0.142454
4                 1       HH  0.764706  0.235294
```




```
χ² global quadrant vs rotación: p = 0.0000
```

```
# PREGUNTA 7: ¿Qué ahorro obtendríamos si aplicamos una intervención de RR. HH. y reducimos la rotación?

import pandas as pd
import numpy as np

FILE = "/content/DatasetFinal.xlsx"

COSTE_BAJA = {0: 10104, 1: 11607, 2: 17117, 3: 20812, 4: 10265}

PARAMS = {

    1: dict(
        filtro       = lambda t: (t["Quadrant"] == "HL"),
        convert_pct  = 1.0,
        salary_uplift= 2000,
        bonus        = 0,
        delta_rot    = 0.40
    ),
    4: dict(
        filtro       = lambda t: (t["Quadrant"] == "HL"),
        convert_pct  = 1.0,
        salary_uplift= 2000,
        bonus        = 0,
        delta_rot    = 0.35
    ),
    3: dict(
        filtro       = lambda t: (t["Apreciacion"] >= t["Apreciacion"].quantile(0.70)),
        convert_pct  = 0.0,
        salary_uplift= 0,
        bonus        = 1000,
        delta_rot    = 0.25
    ),
    0: dict(
        filtro       = lambda t: (t["Rotacion"] == 0),
        convert_pct  = 0.0,
        salary_uplift= 0,
        bonus        = 300,
        delta_rot    = 0.30
    ),
    2: dict(
        filtro       = lambda t: (t["Rotacion"] == 0),
        convert_pct  = 0.0,
        salary_uplift= 0,
        bonus        = 0,
        delta_rot    = 0.15
    )
}

df = pd.read_excel(FILE)

if "Quadrant" not in df.columns:
    def label_quadrant(sub):
        q_sal_lo = sub["Salario"].quantile(0.25)
        q_sal_hi = sub["Salario"].quantile(0.75)
        q_perf_hi= sub["Apreciacion"].quantile(0.75)
        q_perf_lo= sub["Apreciacion"].quantile(0.25)
        hi_perf  = sub["Apreciacion"] >= q_perf_hi
        lo_perf  = sub["Apreciacion"] <= q_perf_lo
        hi_sal   = sub["Salario"] >= q_sal_hi
        lo_sal   = sub["Salario"] <= q_sal_lo
        return np.where( hi_perf & lo_sal, "HL",
               np.where( hi_perf & hi_sal, "HH",
               np.where( lo_perf & hi_sal, "LH", "LL")))
    df["Quadrant"] = df.groupby("cluster_5", group_keys=False).apply(label_quadrant)

def simulate(df, cluster, p):
    sub        = df[(df["cluster_5"] == cluster) & (df["Fijo / Temporal"] == 1)]
    eligibles  = sub[p["filtro"](sub)]

    n_conv     = int(len(eligibles) * p["convert_pct"])

    n_bonus    = len(eligibles) if p["bonus"] else 0


    bajas_elig = eligibles["Rotacion"].sum()
    evitadas   = int(bajas_elig * p["delta_rot"])

    ahorro     = evitadas * COSTE_BAJA[cluster]
    coste_conv = n_conv  * p["salary_uplift"]
    coste_bonus= n_bonus * p["bonus"]
    coste_tot  = coste_conv + coste_bonus
    roi        = ahorro / coste_tot if coste_tot else np.nan
```

```
    return {
        "Cluster": cluster,
        "Temporales": len(sub),
        "Eligibles": len(eligibles),
        "Convertidos": n_conv,
        "Ahorro €": round(ahorro),
        "Coste €": round(coste_tot),
        "ROI": round(roi, 2)
    }

resumen = [ simulate(df, cl, PARAMS[cl]) for cl in PARAMS.keys() ]
tabla = pd.DataFrame(resumen)
print(tabla)
tabla.to_excel("ROI_escenarios_segmentados.xlsx", index=False)
```

```
   Cluster  Temporales  Eligibles  Convertidos  Ahorro €  Coste €  ROI
0        1         432          0            0         0        0  NaN
1        4         304          0            0         0        0  NaN
2        3         580        242            0         0   242000  0.0
3        0         242        234            0         0    70200  0.0
4        2          15         15            0         0        0  NaN
<ipython-input-22-517f857bbdcd>:64: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is de
  df["Quadrant"] = df.groupby("cluster_5", group_keys=False).apply(label_quadrant)
```

```
import pandas as pd
import numpy as np

FILE = "/content/DatasetFinal.xlsx"

COSTE_BAJA = {0: 10104, 1: 11607, 2: 17117, 3: 20812, 4: 10265}


PARAMS = {

    1: dict(
        filtro=lambda t: (t["Quadrant"] == "HL") |
                        ((t["Quadrant"] == "HH") &
                         (t["Salario"] < t["Salario"].quantile(0.40))),
        convert_pct=1.0, salary_uplift=1000, bonus=0, delta_rot=0.35
    ),
    4: dict(
        filtro=lambda t: (t["Quadrant"] == "HL") |
                        ((t["Quadrant"] == "HH") &
                         (t["Salario"] < t["Salario"].quantile(0.40))),
        convert_pct=1.0, salary_uplift=1000, bonus=0, delta_rot=0.30
    ),
    3: dict(
        filtro=lambda t: t["Apreciacion"] >= t["Apreciacion"].quantile(0.85),
        convert_pct=0.0, salary_uplift=0, bonus=500, delta_rot=0.25
    ),
    0: dict(
        filtro=lambda t: t["Antigüedad"] < 1,
        convert_pct=0.0, salary_uplift=0, bonus=300, delta_rot=0.40
    ),
    2: dict(
        filtro=lambda t: t["Rotacion"] == 0,
        convert_pct=0.0, salary_uplift=0, bonus=0, delta_rot=0.00
    )
}


df = pd.read_excel(FILE)

if "Quadrant" not in df.columns:
    def quadrant(sub):
        q_sal_lo = sub["Salario"].quantile(0.25)
        q_sal_hi = sub["Salario"].quantile(0.75)
        q_perf_hi= sub["Apreciacion"].quantile(0.75)
        q_perf_lo= sub["Apreciacion"].quantile(0.25)
        hi_perf  = sub["Apreciacion"] >= q_perf_hi
        lo_perf  = sub["Apreciacion"] <= q_perf_lo
        hi_sal   = sub["Salario"] >= q_sal_hi
        lo_sal   = sub["Salario"] <= q_sal_lo
        return np.where( hi_perf & lo_sal, "HL",
               np.where( hi_perf & hi_sal, "HH",
               np.where( lo_perf & hi_sal, "LH", "LL")))
    df["Quadrant"] = df.groupby("cluster_5", group_keys=False).apply(quadrant)

def simulate(df, cluster, p):
```

```
    sub  = df[(df["cluster_5"] == cluster) & (df["Fijo / Temporal"] == 1)].copy()
    elig = sub[p["filtro"](sub)]

    n_conv    = int(len(elig) * p["convert_pct"])
    n_bonus   = len(elig) if p["bonus"] else 0
    bajas_elig= elig["Rotacion"].sum()
    evitadas  = int(bajas_elig * p["delta_rot"])

    ahorro    = evitadas * COSTE_BAJA[cluster]
    coste     = n_conv * p["salary_uplift"] + n_bonus * p["bonus"]
    roi       = round(ahorro / coste, 2) if coste else np.nan

    return dict(Cluster=cluster, Temporales=len(sub), Eligibles=len(elig),
                Convertidos=n_conv, Ahorro=round(ahorro),
                Coste=round(coste), ROI=roi)

tabla = pd.DataFrame([simulate(df, cl, PARAMS[cl]) for cl in PARAMS])
print(tabla)
tabla.to_excel("ROI_escenarios_segmentados_v2.xlsx", index=False)
```

```
   Cluster  Temporales  Eligibles  Convertidos  Ahorro   Coste  ROI
0        1         432          0            0       0       0  NaN
1        4         304          0            0       0       0  NaN
2        3         580        242            0       0  121000  0.0
3        0         242          0            0       0       0  NaN
4        2          15         15            0       0       0  NaN
<ipython-input-24-1efbc42d0794>:53: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is de
  df["Quadrant"] = df.groupby("cluster_5", group_keys=False).apply(quadrant)
```

```
import pandas as pd
import numpy as np

FILE = "/content/DatasetFinal.xlsx"

COSTE_BAJA = {0: 10104, 1: 11607, 2: 17117, 3: 20812, 4: 10265}


PARAMS = {
    1: dict(
        filtro=lambda t: (t["Apreciacion"] >= t["Apreciacion"].quantile(0.70)) &
                         (t["Salario"] <= t["Salario"].quantile(0.40)),
        convert_pct=0.50, salary_uplift=500, bonus=0, delta_rot=0.35
    ),
    4: dict(
        filtro=lambda t: (t["Apreciacion"] >= t["Apreciacion"].quantile(0.70)) &
                         (t["Salario"] <= t["Salario"].quantile(0.40)),
        convert_pct=0.50, salary_uplift=500, bonus=0, delta_rot=0.30
    ),
    3: dict(
        filtro=lambda t: t["Apreciacion"] >= t["Apreciacion"].quantile(0.85),
        convert_pct=0.0, salary_uplift=0, bonus=0, delta_rot=0.00
    ),
    0: dict(
        filtro=lambda t: t["Antigüedad"] < 1,
        convert_pct=0.0, salary_uplift=0, bonus=0, delta_rot=0.00
    ),
    2: dict(
        filtro=lambda t: t["Rotacion"] == 0,
        convert_pct=0.0, salary_uplift=0, bonus=0, delta_rot=0.00
    )
}


df = pd.read_excel(FILE)

if "Quadrant" not in df.columns:
    def quadrant(sub):
        q_sal_lo = sub["Salario"].quantile(0.25)
        q_sal_hi = sub["Salario"].quantile(0.75)
        q_perf_hi = sub["Apreciacion"].quantile(0.75)
        q_perf_lo = sub["Apreciacion"].quantile(0.25)
        hi_perf = sub["Apreciacion"] >= q_perf_hi
        lo_perf = sub["Apreciacion"] <= q_perf_lo
        hi_sal = sub["Salario"] >= q_sal_hi
        lo_sal = sub["Salario"] <= q_sal_lo
        return np.where(hi_perf & lo_sal, "HL",
                        np.where(hi_perf & hi_sal, "HH",
                                 np.where(lo_perf & hi_sal, "LH", "LL")))
    df["Quadrant"] = df.groupby("cluster_5", group_keys=False).apply(quadrant)

def simulate(df, cluster, p):
```

```
    sub = df[(df["cluster_5"] == cluster) & (df["Fijo / Temporal"] == 1)].copy()
    elig = sub[p["filtro"](sub)]

    n_conv = int(len(elig) * p["convert_pct"])
    n_bonus = len(elig) if p["bonus"] else 0
    bajas_elig = elig["Rotacion"].sum()
    evitadas = int(bajas_elig * p["delta_rot"])

    ahorro = evitadas * COSTE_BAJA[cluster]
    coste = n_conv * p["salary_uplift"] + n_bonus * p["bonus"]
    roi = round(ahorro / coste, 2) if coste else np.nan

    return dict(Cluster=cluster, Temporales=len(sub), Eligibles=len(elig),
                Convertidos=n_conv, Ahorro=round(ahorro),
                Coste=round(coste), ROI=roi)


tabla = pd.DataFrame([simulate(df, cl, PARAMS[cl]) for cl in PARAMS])

print(tabla)
tabla.to_excel("ROI_escenarios_segmentados_FINAL.xlsx", index=False)
```

```
   Cluster  Temporales  Eligibles  Convertidos  Ahorro  Coste   ROI
0        1         432        127           63  104463  31500  3.32
1        4         304         91           45   51325  22500  2.28
2        3         580        242            0       0      0   NaN
3        0         242          0            0       0      0   NaN
4        2          15         15            0       0      0   NaN
<ipython-input-25-6e6fbd6d1492>:50: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is de
  df["Quadrant"] = df.groupby("cluster_5", group_keys=False).apply(quadrant)
```

```
import pandas as pd
import numpy as np

FILE = "/content/DatasetFinal.xlsx"
df = pd.read_excel(FILE)

COSTE_BAJA = {0: 10104, 1: 11607, 2: 17117, 3: 20812, 4: 10265}

if "Quadrant" not in df.columns:
    def quadrant(sub):
        q_sal_lo = sub["Salario"].quantile(0.25)
        q_sal_hi = sub["Salario"].quantile(0.75)
        q_perf_hi = sub["Apreciacion"].quantile(0.75)
        q_perf_lo = sub["Apreciacion"].quantile(0.25)
        hi_perf = sub["Apreciacion"] >= q_perf_hi
        lo_perf = sub["Apreciacion"] <= q_perf_lo
        hi_sal = sub["Salario"] >= q_sal_hi
        lo_sal = sub["Salario"] <= q_sal_lo
        return np.where(hi_perf & lo_sal, "HL",
                        np.where(hi_perf & hi_sal, "HH",
                                 np.where(lo_perf & hi_sal, "LH", "LL")))
    df["Quadrant"] = df.groupby("cluster_5", group_keys=False).apply(quadrant)

def simulate_grid(df, cluster, filtro_func, convert_pct_list, uplift_list, delta_rot_list, bonus=0):
    results = []
    sub = df[(df["cluster_5"] == cluster) & (df["Fijo / Temporal"] == 1)].copy()
    elig_total = filtro_func(sub)
    for convert_pct in convert_pct_list:
        for uplift in uplift_list:
            for delta_rot in delta_rot_list:
                elig = sub[elig_total]
                n_conv = int(len(elig) * convert_pct)
                n_bonus = len(elig) if bonus else 0
                bajas_elig = elig["Rotacion"].sum()
                evitadas = int(bajas_elig * delta_rot)
                ahorro = evitadas * COSTE_BAJA[cluster]
                coste = n_conv * uplift + n_bonus * bonus
                roi = round(ahorro / coste, 2) if coste else np.nan
                results.append({
                    "Cluster": cluster,
                    "Convert_pct": convert_pct,
                    "Uplift": uplift,
                    "Delta_rot": delta_rot,
                    "Bonus": bonus,
                    "Eligibles": len(elig),
                    "Convertidos": n_conv,
                    "Ahorro": round(ahorro),
                    "Coste": round(coste),
                    "ROI": roi
                })
```