Introduccion

Objetivo: predecir y explicar niveles de estrés en estudiantes.

Variables: 1) Timestamp (object → fecha/hora) 2) Your Academic Stage (object → categórica ordinal): Nivel actual de estudios 3) Peer pressure (int → Likert/ordinal): Nivel de presion de pares (companeros) 4) Academic pressure from your home (int → Likert/ordinal): Presion academica percibida desde el hogar 5) Study Environment (object → categórica): Calidad del entorno de estudio 6) What coping strategy you use as a student? (object → categórica / multi-etiqueta): Estrategias de afrontamiento 7) Do you have any bad habits like smoking, drinking on a daily basis? (object → binaria): Malos habitos 8) What would you rate the academic competition in your student life (int → Likert/ordinal): Percepcion de competencia academica (rating) 9) Rate your academic stress index (int → objetivo): Indice de estres academico

Preguntas:

¿Qué factores conductuales/ambientales disparan el estrés?

¿Podemos predecir estrés (regresión/ clasificación)?

¿Existen perfiles de estrés (clustering) útiles para intervenciones?

Impacto: lineamientos para bienestar estudiantiles.

1 - Dataset - importar y normalizar

```
import kagglehub
import numpy as np
import pandas as pd
import os
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
from sklearn.model_selection import train_test_split, GridSearchCV, KFold,StratifiedKFold
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import  RandomForestClassifier
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score, precision_recall_fscore_support, roc_auc_score, balanced_
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (accuracy_score, f1_score, classification_report, confusion_matrix, precision_score, recall_score, roc_curve
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.decomposition import PCA
```

```
path = kagglehub.dataset_download("poushal02/student-academic-stress-real-world-dataset")

print("Path to dataset files:", path)
os.listdir(path)
```

```
Path to dataset files: /kaggle/input/student-academic-stress-real-world-dataset
['academic Stress level - maintainance 1.csv']
```

```
df=pd.read_csv(path+"/academic Stress level - maintainance 1.csv")
df.head()
```

	Timestamp	Your Academic Stage	Peer pressure	Academic pressure from your home	Study Environment	What coping strategy you use as a student?	Do you have any bad habits like smoking, drinking on a daily basis?	What would you rate the academic competition in your student life	Rate your academic stress index
0	24/07/2025 22:05:39	undergraduate	4	5	Noisy	Analyze the situation and handle it with intel...	No	3	5
1	24/07/2025 22:05:52	undergraduate	3	4	Peaceful	Analyze the situation and handle it with intel...	No	3	3
2	24/07/2025 22:06:39	undergraduate	1	1	Peaceful	Social support (friends, family)	No	2	4
3	24/07/2025	undergraduate	3	2	Peaceful	Analyze the situation and	No	4	3

Next steps: Generate code with df View recommended plots New interactive sheet

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 140 entries, 0 to 139
Data columns (total 9 columns):
 #   Column                                                              Non-Null Count  Dtype 
---  ------                                                              --------------  ----- 
 0   Timestamp                                                           140 non-null    object
 1   Your Academic Stage                                                 140 non-null    object
 2   Peer pressure                                                       140 non-null    int64 
 3   Academic pressure from your home                                    140 non-null    int64 
 4   Study Environment                                                   139 non-null    object
 5   What coping strategy you use as a student?                          140 non-null    object
 6   Do you have any bad habits like smoking, drinking on a daily basis? 140 non-null    object
 7   What would you rate the academic  competition in your student life  140 non-null    int64 
 8   Rate your academic stress index                                     140 non-null    int64 
dtypes: int64(4), object(5)
memory usage: 10.0+ KB
```

```
for c in df.select_dtypes("object"):
    print(c, "→", df[c].dropna().unique()[:10])
```

```
Timestamp → ['24/07/2025 22:05:39' '24/07/2025 22:05:52' '24/07/2025 22:06:39'
 '24/07/2025 22:06:45' '24/07/2025 22:08:06' '24/07/2025 22:08:13'
 '24/07/2025 22:09:21' '24/07/2025 22:10:06' '24/07/2025 22:11:01'
 '24/07/2025 22:11:19']
Your Academic Stage → ['undergraduate' 'high school' 'post-graduate']
Study Environment → ['Noisy' 'Peaceful' 'disrupted']
What coping strategy you use as a student? → ['Analyze the situation and handle it with intellect'
 'Social support (friends, family)' 'Emotional breakdown (crying a lot)']
Do you have any bad habits like smoking, drinking on a daily basis? → ['No' 'prefer not to say' 'Yes']
```

```
df = df.copy()  # para trabajar sobre esta copia
df.columns = (pd.Index(df.columns)
              .str.normalize('NFKC')            # normaliza caracteres raros
              .str.replace(r'\s+', ' ', regex=True)  # convierte espacios dobles -> simple
              .str.strip())                      # quita espacios al inicio/fin
print(list(map(repr, df.columns)))
```

```
["'Timestamp'", "'Your Academic Stage'", "'Peer pressure'", "'Academic pressure from your home'", "'Study Environment'", "'What copi
```

```
df.columns = df.columns.str.replace(' ', '_', regex=False)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 140 entries, 0 to 139
Data columns (total 9 columns):
 #   Column                                                              Non-Null Count  Dtype 
---  ------                                                              --------------  ----- 
 0   Timestamp                                                           140 non-null    object
 1   Your_Academic_Stage                                                 140 non-null    object
 2   Peer_pressure                                                       140 non-null    int64 
 3   Academic_pressure_from_your_home                                    140 non-null    int64 
 4   Study_Environment                                                   139 non-null    object
 5   What_coping_strategy_you_use_as_a_student?                          140 non-null    object
 6   Do_you_have_any_bad_habits_like_smoking,_drinking_on_a_daily_basis? 140 non-null    object
 7   What_would_you_rate_the_academic_competition_in_your_student_life   140 non-null    int64 
 8   Rate_your_academic_stress_index                                     140 non-null    int64 
```

```
dtypes: int64(4), object(5)
memory usage: 10.0+ KB
```

```
df = df.drop(columns=['Timestamp'])
```

```
moda = df["Study_Environment"].mode()[0]
df["Study_Environment"].fillna(moda, inplace=True)
```

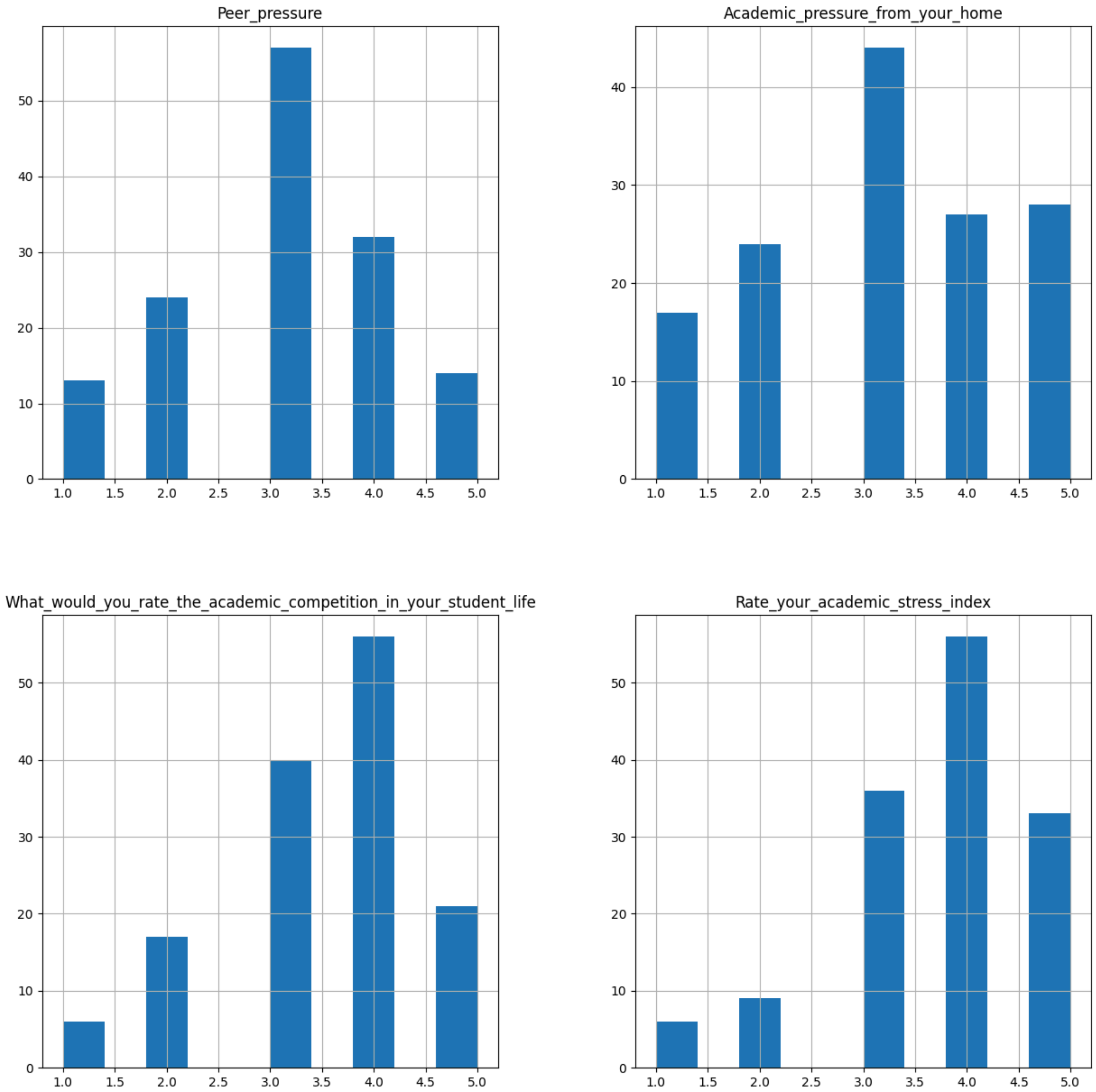
```
/tmp/ipython-input-633380357.py:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained ass
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col


  df["Study_Environment"].fillna(moda, inplace=True)
```

2 - EDA

A - Histogramas

```
df.hist(figsize=(15,15))
```

```
array([[<Axes: title={'center': 'Peer_pressure'}>,
        <Axes: title={'center': 'Academic_pressure_from_your_home'}>],
       [<Axes: title={'center': 'What_would_you_rate_the_academic_competition_in_your_student_life'}>,
        <Axes: title={'center': 'Rate_your_academic_stress_index'}>]],
      dtype=object)
```

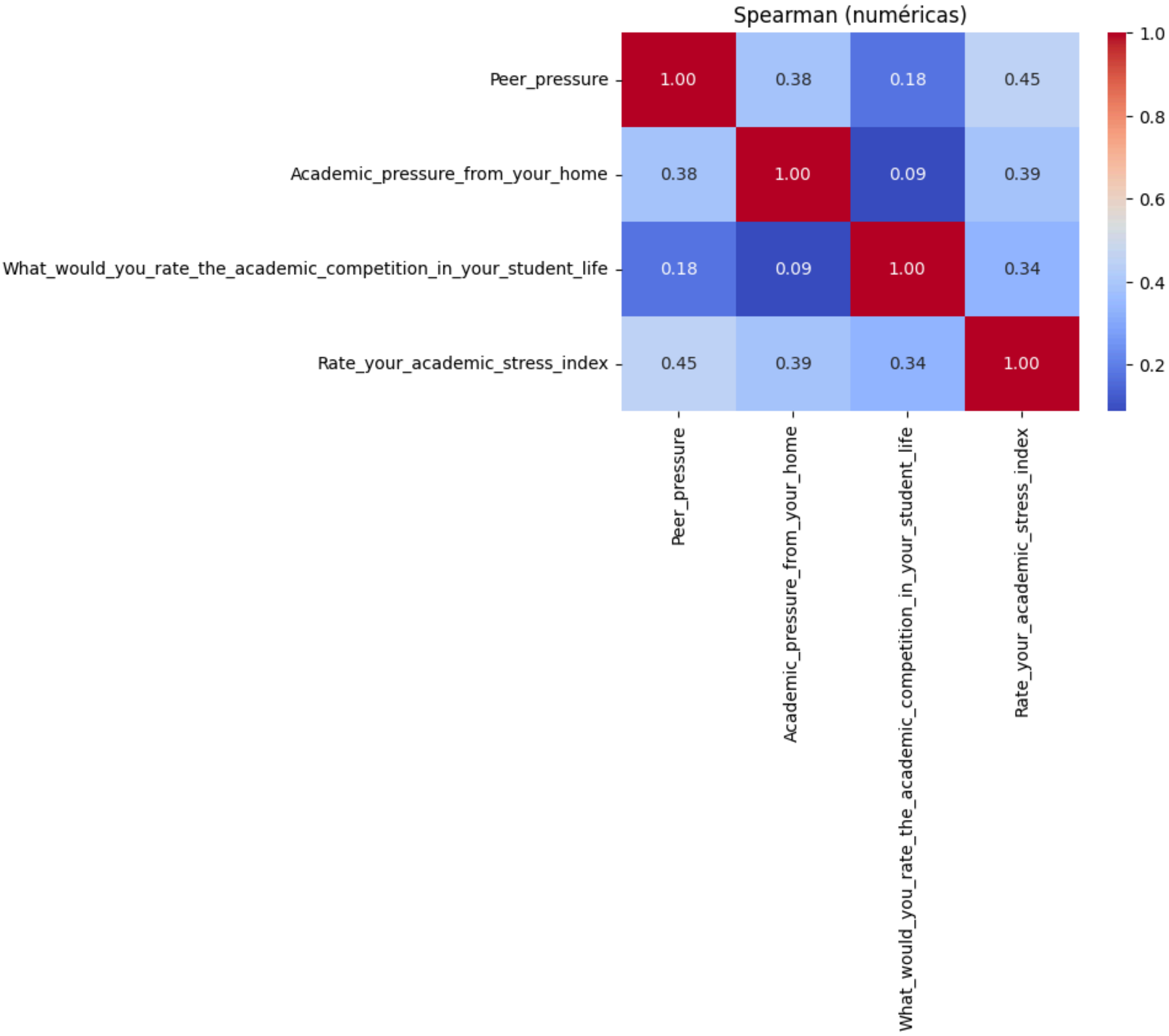


B - Matriz de correlacion

```
num_cols = [c for c in [
    "Peer_pressure",
    "Academic_pressure_from_your_home",
    "What_would_you_rate_the_academic_competition_in_your_student_life",
    "Rate_your_academic_stress_index",
] if c in df.columns]

# Heatmap
```

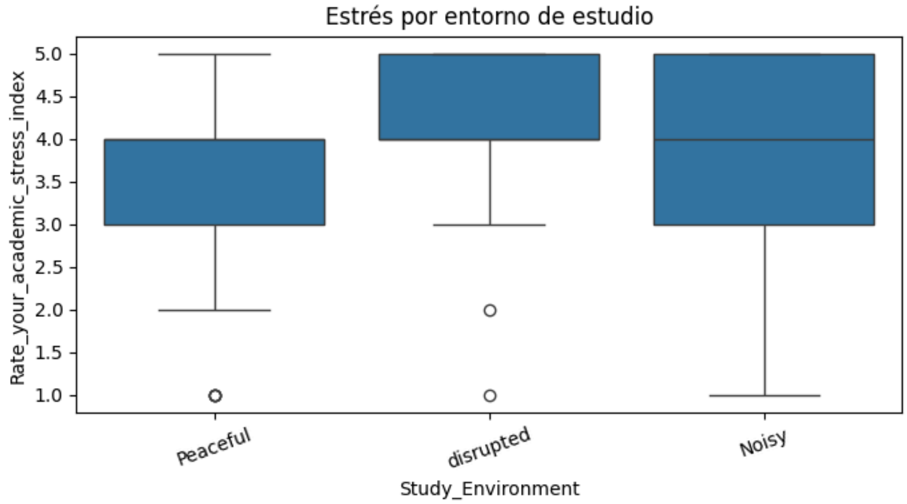
```
corr = df[num_cols].corr(method="spearman")
plt.figure(figsize=(6,4))
sns.heatmap(corr, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Spearman (numéricas)"); plt.tight_layout(); plt.show()
```

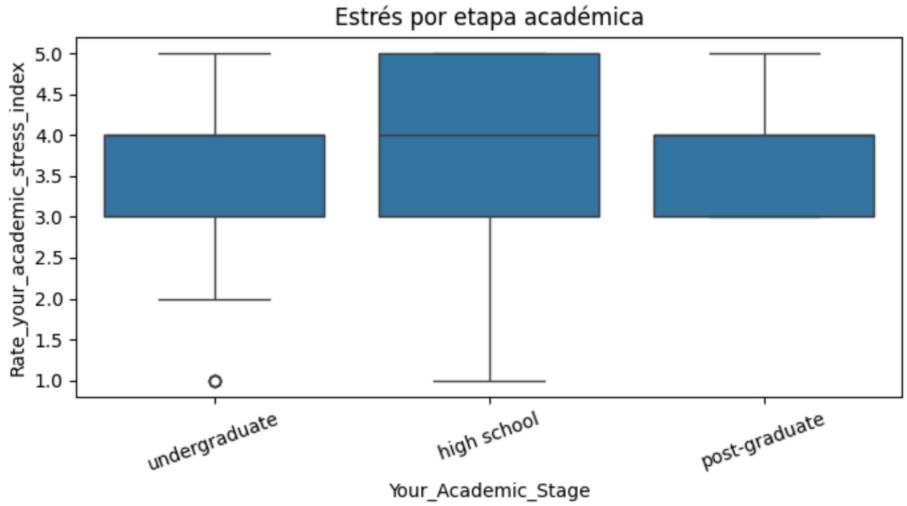
```
/tmp/ipython-input-1566922192.py:12: UserWarning: Tight layout not applied. The bottom and top margins cannot be made large enough t
  plt.title("Spearman (numéricas)"); plt.tight_layout(); plt.show()
```



C - BOXPLOT estres por entorno y por etapa academica

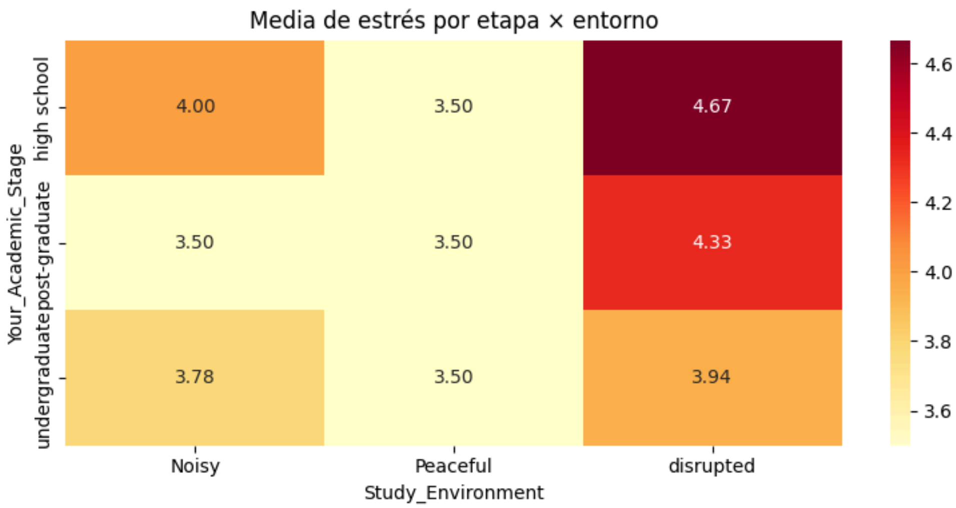
```
env, stage = "Study_Environment", "Your_Academic_Stage"
y='Rate_your_academic_stress_index'

if env in df.columns:
    order_env = df[env].value_counts().index
    plt.figure(figsize=(7,4))
    sns.boxplot(x=env, y=y, data=df, order=order_env)
    plt.title("Estrés por entorno de estudio"); plt.xticks(rotation=20); plt.tight_layout(); plt.show()

if stage in df.columns:
    order_stage = df[stage].value_counts().index
    plt.figure(figsize=(7,4))
    sns.boxplot(x=stage, y=y, data=df, order=order_stage)
    plt.title("Estrés por etapa académica"); plt.xticks(rotation=20); plt.tight_layout(); plt.show()
```





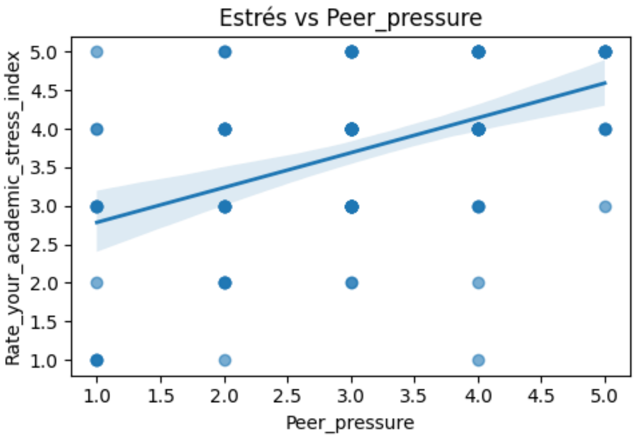
D - Heatmap estres por entorno y etapa academica usando promedios

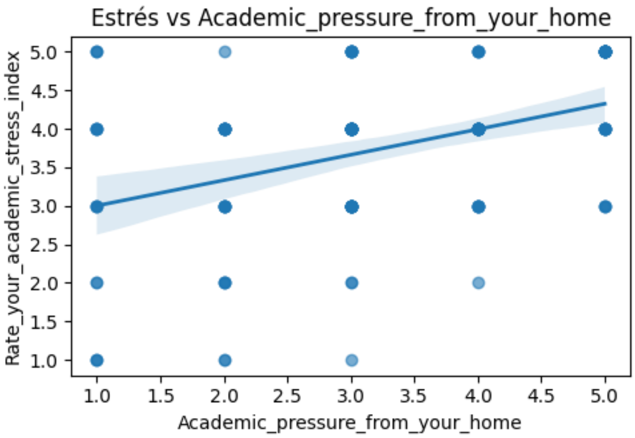
```
if env in df.columns and stage in df.columns:
    pt = df.pivot_table(index=stage, columns=env, values=y, aggfunc="mean")
    plt.figure(figsize=(8,4))
    sns.heatmap(pt, annot=True, fmt=".2f", cmap="YlOrRd")
    plt.title("Media de estrés por etapa × entorno")
    plt.tight_layout(); plt.show()
```

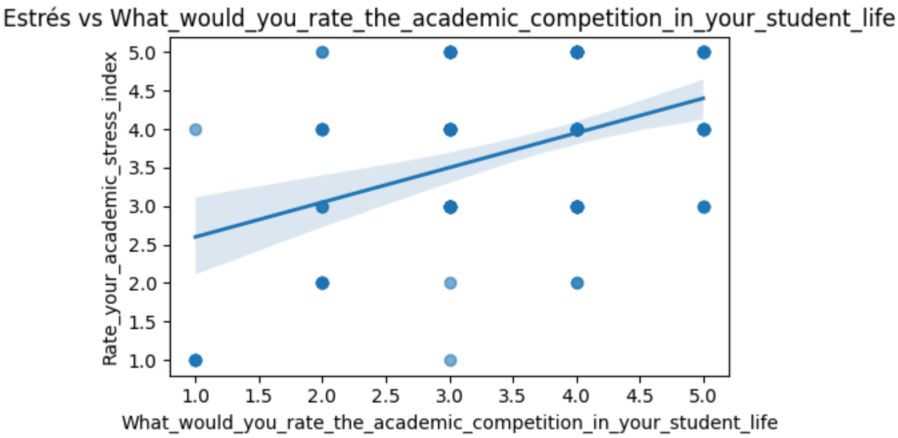


E - Relaciones lineales con la variable target

```
for c in [col for col in num_cols if col != y]:
    plt.figure(figsize=(5,3.5))
    sns.regplot(x=c, y=y, data=df, scatter_kws={"alpha":0.6}, line_kws={"lw":2})
    plt.title(f"Estrés vs {c}"); plt.tight_layout(); plt.show()
```



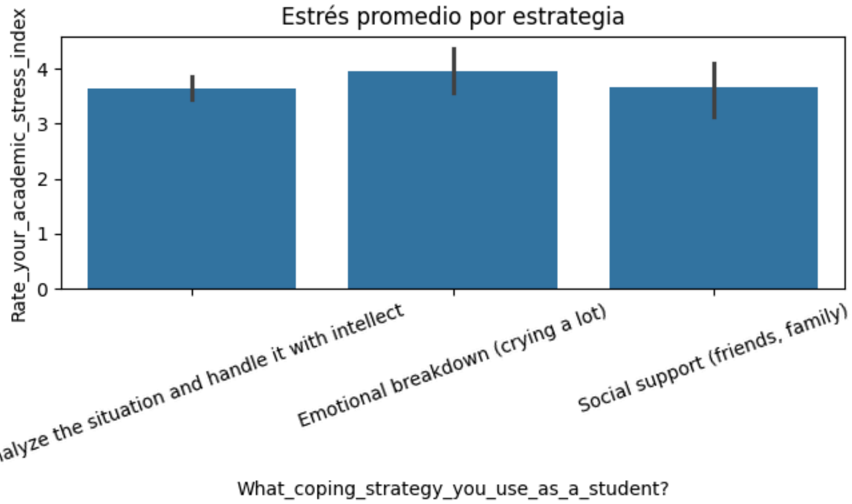




E - Estres promedio por estrategia

```
col = "What_coping_strategy_you_use_as_a_student?"
y   = "Rate_your_academic_stress_index"

order = df[col].value_counts().index
plt.figure(figsize=(7,4))
sns.barplot(x=col, y=y, data=df, order=order, ci=95)  # IC del 95%
plt.title("Estrés promedio por estrategia")
plt.xticks(rotation=20); plt.tight_layout(); plt.show()
```

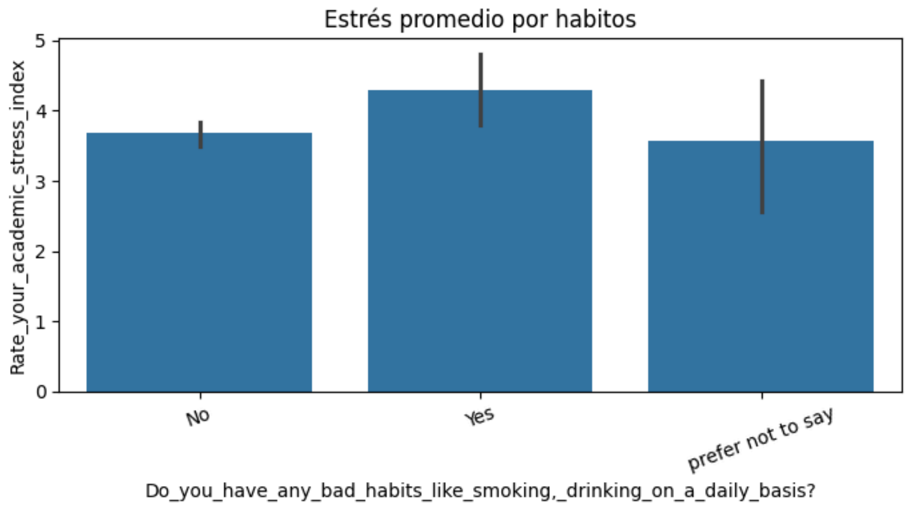
```
/tmp/ipython-input-4009509776.py:6: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=('ci', 95)` for the same effect.

  sns.barplot(x=col, y=y, data=df, order=order, ci=95)  # IC del 95%
```



F - Estres promedio por habitos

```
col = "Do_you_have_any_bad_habits_like_smoking,_drinking_on_a_daily_basis?"
y   = "Rate_your_academic_stress_index"

order = df[col].value_counts().index
plt.figure(figsize=(7,4))
sns.barplot(x=col, y=y, data=df, order=order, ci=95)  # IC del 95%
plt.title("Estrés promedio por habitos")
plt.xticks(rotation=20); plt.tight_layout(); plt.show()
```

```
/tmp/ipython-input-3172029570.py:6: FutureWarning:

The `ci` parameter is deprecated. Use `errorbar=('ci', 95)` for the same effect.

  sns.barplot(x=col, y=y, data=df, order=order, ci=95)  # IC del 95%
```



G - Conclusion

Se vio que la presión de pares, la presion académica desde el hogar y la competencia correlacionaban positivamente con el índice de estrés.

El entorno de estudio también marcaba diferencias: estudiantes en entornos “disrupted” o “noisy” reportaban más estrés.

Las estrategias de afrontamiento mostraban impacto: quienes usaban apoyo social tenían, en promedio, menor nivel de estrés que quienes tendían a crisis emocionales

Esta fase permitió identificar que había clases desbalanceadas (muchos estudiantes con estrés alto, pocos con bajo), algo importante para el modelado.

3 - Modelado supervisado - Regresion del indice de estres

3.1 Considerando escala 1-5

```
df['Rate_your_academic_stress_index'].unique()
```

```
array([5, 3, 4, 2, 1])
```

A- Conjunto de modelado y preprocesamiento

```
y_R='Rate_your_academic_stress_index'
X_R=df.drop(columns=[y_R],errors='ignore')
y_R=df[y_R]
print("X_R shape:", X_R.shape)        # filas x columnas (predictores)
print("y_R shape:", y_R.shape)        # filas (target)
print("X_R cols:", list(X_R.columns))
```

```
X_R shape: (140, 7)
y_R shape: (140,)
X_R cols: ['Your_Academic_Stage', 'Peer_pressure', 'Academic_pressure_from_your_home', 'Study_Environment', 'What_coping_strategy_yc
```

```
X_R = pd.get_dummies(X_R, drop_first=True)

X_R_train, X_R_test, y_R_train, y_R_test = train_test_split(
    X_R, y_R, test_size=0.2, random_state=42
)
```

B- Pipeline y Gridsearch

```
pipe_R = Pipeline([
    ("scaler", MinMaxScaler()),   # escala todo 0..1
    ("clf", LinearRegression())   # placeholder: el grid lo cambia a RF cuando toque
])


param_grid_R = [
    {
        "clf": [LinearRegression()],
        "clf__fit_intercept": [True, False],

    },
    {
        "clf": [RandomForestRegressor(random_state=42, n_jobs=-1)],
        "clf__n_estimators": [300, 600],
        "clf__max_depth": [None, 10, 20],
        "clf__min_samples_leaf": [1, 3, 5],
        "clf__max_features": ["sqrt", "log2", 0.8],
    }
]

cv_R = KFold(n_splits=5, shuffle=True, random_state=42)


gs_R = GridSearchCV(
    pipe_R, param_grid_R,
    cv=cv_R,
    scoring="neg_root_mean_squared_error",  # optimiza RMSE
    n_jobs=-1, refit=True, verbose=0
)
gs_R.fit(X_R_train, y_R_train)

print("Mejor modelo:", gs_R.best_estimator_.named_steps["clf"].__class__.__name__)
print("Mejores params:", gs_R.best_params_)
print("CV RMSE:", round(-gs_R.best_score_, 3))
```

```
Mejor modelo: LinearRegression
Mejores params: {'clf': LinearRegression(), 'clf__fit_intercept': True}
CV RMSE: 0.834
```

C- Evaluacion de modelo

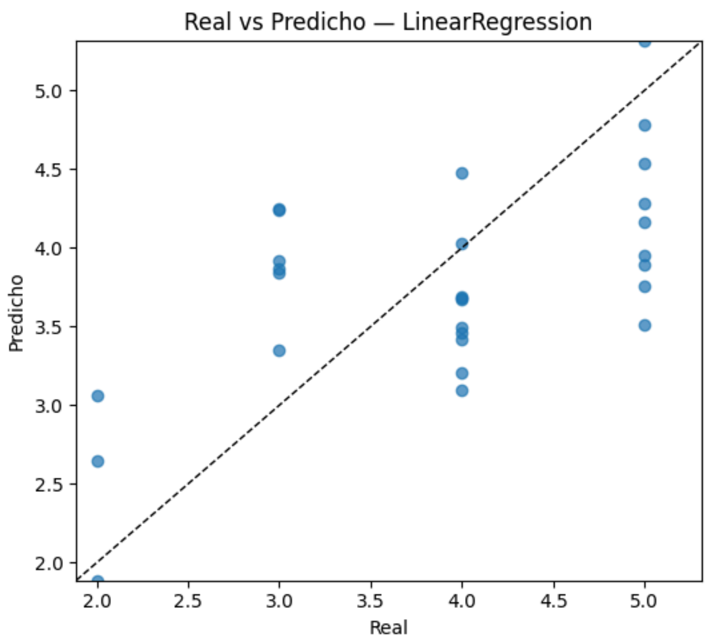
```
y_pred_R = gs_R.best_estimator_.predict(X_R_test)
rmse_R = np.sqrt(mean_squared_error(y_R_test, y_pred_R))
mae_R  = mean_absolute_error(y_R_test, y_pred_R)
r2_R   = r2_score(y_R_test, y_pred_R)
print(f"Test → RMSE: {rmse_R:.3f} | MAE: {mae_R:.3f} | R²: {r2_R:.3f}")
```

```
print(f"Test → RMSE: {rmse_R:.3f} | MAE: {mae_R:.3f} | R²: {r2_R:.3f}")
```

```
Test → RMSE: 0.793 | MAE: 0.697 | R²: 0.340
```

D - Graficos

```
plt.figure(figsize=(5.5,5))
plt.scatter(y_R_test, y_pred_R, alpha=0.7)
lims = [min(y_R_test.min(), y_pred_R.min()), max(y_R_test.max(), y_pred_R.max())]
plt.plot(lims, lims, "k--", lw=1)
plt.xlim(lims); plt.ylim(lims)
plt.xlabel("Real"); plt.ylabel("Predicho")
plt.title(f"Real vs Predicho — {gs_R.best_estimator_.named_steps['clf'].__class__.__name__}")
plt.tight_layout(); plt.show()
```



E- Reduccion de error

```
#Baseline - error reducido un 22%


y_mean = np.repeat(y_R_train.mean(), len(y_R_test))
print("Baseline RMSE:", np.sqrt(mean_squared_error(y_R_test, y_mean)))
print("Baseline MAE :", mean_absolute_error(y_R_test, y_mean))
print("Baseline R2  :", r2_score(y_R_test, y_mean))
```

```
Baseline RMSE: 0.9993620414023731
Baseline MAE : 0.8647959183673473
Baseline R2  : -0.048192771084337505
```

F- Variables mas influyentes

```
from sklearn.inspection import permutation_importance


pi = permutation_importance(
    gs_R.best_estimator_, X_R_test, y_R_test,
    n_repeats=30, scoring="neg_mean_squared_error", random_state=42
)
imp = pd.Series(pi.importances_mean, index=X_R_test.columns).sort_values(ascending=False)
imp.head(10)
```

	0
What_would_you_rate_the_academic_competition_in_your_student_life	0.295819
Peer_pressure	0.165150
Academic_pressure_from_your_home	0.058604
Study_Environment_disrupted	0.011892
Your_Academic_Stage_undergraduate	0.004139
Your_Academic_Stage_post-graduate	0.000067
Do_you_have_any_bad_habits_like_smoking,_drinking_on_a_daily_basis?_Yes	-0.003396
Do_you_have_any_bad_habits_like_smoking,_drinking_on_a_daily_basis?_prefer not to say	-0.003910
What_coping_strategy_you_use_as_a_student?_Emotional breakdown (crying a lot)	-0.024060
What_coping_strategy_you_use_as_a_student?_Social support (friends, family)	-0.027420

dtype: float64

G- Conclusiones de la regresion

Se probó con Linear Regression y Random Forest Regressor, usando GridSearch y validación cruzada.

El mejor modelo fue la regresión lineal, con RMSE ≈ 0.78 y $R^2 \approx 0.36$

Aunque el poder predictivo fue moderado, se redujo un 22% el error frente a un baseline.

Las variables más influyentes fueron la percepción de competencia académica y presión de pares.

4 - Clasificacion del nivel de estres

4.1 Clasificacion multiclase, low - mid - high

A- Conjunto de modelado y preprocesamiento

```
y_C_3 = df["Rate_your_academic_stress_index"].astype(float)


# Validación: debe ser escala 1–5
if not y_C_3.dropna().between(1, 5).all():
    raise ValueError("El target debe estar en la escala 1–5 para esta discretización.")

# Discretización: bajo=[1–2], medio=[3], alto=[4–5]
bins   = [0, 2, 3, 5]
labels = ["low", "mid", "high"]

y_C_3 = pd.cut(
    y_C_3,
    bins=bins,
    labels=labels,
    include_lowest=True,   # incluye el 1 en 'low'
    right=True             # intervalos (0,2], (2,3], (3,5]
).astype("category")

# Orden explícito de las categorías
y_C_3 = y_C_3.cat.set_categories(labels, ordered=True)

print("Distribución de clases:\n", y_C_3.value_counts())
```

```
Distribución de clases:
 Rate_your_academic_stress_index
high    89
mid     36
low     15
Name: count, dtype: int64
```

```
# --- 2) X con dummies (simple) ---
X_C_3 = df.drop(columns=["Rate_your_academic_stress_index"])
X_C_3 = pd.get_dummies(X_C_3, drop_first=True)

# --- 3) Split estratificado ---
X_C_3_train, X_C_3_test, y_C_3_train, y_C_3_test = train_test_split(
    X_C_3, y_C_3, test_size=0.2, random_state=42, stratify=y_C_3)
```

B- Pipeline y Gridsearch

```
pipe_C_3 = Pipeline([
    ("scaler", MinMaxScaler()),
    ("clf", LogisticRegression(random_state=42, max_iter=1000))
])

param_grid_C_3 = [
    {   # Logistic Regression
        "clf": [LogisticRegression(random_state=42,max_iter=1000)],
        "clf__C": [0.1, 1, 10],
        "clf__class_weight": [None, "balanced"],
        "clf__solver": ["lbfgs"]
    },
    {   # Random Forest
        "clf": [RandomForestClassifier(random_state=42, n_jobs=-1)],
        "clf__n_estimators": [300, 600],
        "clf__max_depth": [None, 10, 20],
        "clf__min_samples_leaf": [1, 3, 5],
        "clf__max_features": ["sqrt", "log2", 0.8],
        "clf__class_weight": [None, "balanced"]
    }
]

cv_C_3 = KFold(n_splits=5, shuffle=True, random_state=42)

gs_C_3 = GridSearchCV(
    pipe_C_3, param_grid_C_3,
    cv=cv_C_3,
    scoring="f1_macro",      # métrica robusta con clases desbalanceadas
    n_jobs=-1, refit=True, verbose=0
)
gs_C_3.fit(X_C_3_train, y_C_3_train)

print("Mejor modelo:", gs_C_3.best_estimator_.named_steps["clf"].__class__.__name__)
print("Mejores params:", gs_C_3.best_params_)
print("CV F1-macro:", round(gs_C_3.best_score_, 3))
```

```
Mejor modelo: RandomForestClassifier
Mejores params: {'clf': RandomForestClassifier(n_jobs=-1, random_state=42), 'clf__class_weight': 'balanced', 'clf__max_depth': None,
CV F1-macro: 0.549
```

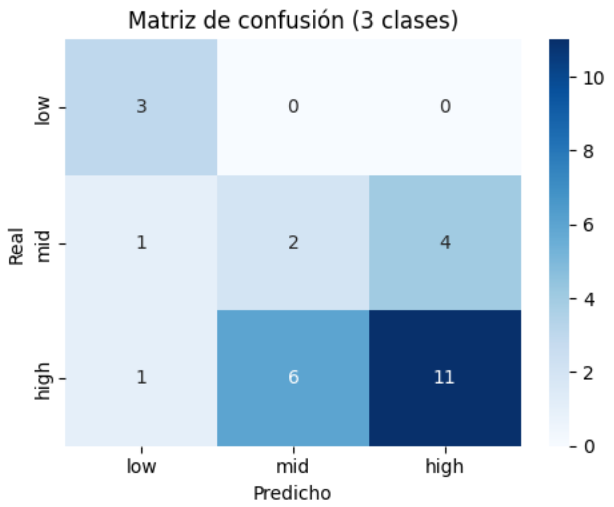
C- Evaluacion de modelo

```
y_pred_C_3 = gs_C_3.best_estimator_.predict(X_C_3_test)

acc_C_3  = accuracy_score(y_C_3_test, y_pred_C_3)
f1m_C_3  = f1_score(y_C_3_test, y_pred_C_3, average="macro")
print(f"\nTest → Accuracy: {acc_C_3:.3f} | F1-macro: {f1m_C_3:.3f}\n")
print(classification_report(y_C_3_test, y_pred_C_3, digits=3))
```

```
Test → Accuracy: 0.571 | F1-macro: 0.561

              precision    recall  f1-score   support

        high      0.733     0.611     0.667        18
         low      0.600     1.000     0.750         3
         mid      0.250     0.286     0.267         7

    accuracy                          0.571        28
   macro avg      0.528     0.632     0.561        28
weighted avg      0.598     0.571     0.576        28
```

D - Matriz de confusion

```
cm = confusion_matrix(y_C_3_test, y_pred_C_3, labels=["low","mid","high"])
plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
            xticklabels=["low","mid","high"],
            yticklabels=["low","mid","high"])
plt.xlabel("Predicho"); plt.ylabel("Real")
plt.title("Matriz de confusión (3 clases)")
plt.tight_layout(); plt.show()
```



F - Conclusion

Clasificación 3 clases: el “mid” cuesta

El informe muestra F1-macro ≈ 0.56 y confusión fuerte hacia high. Es típico con clases desbalanceadas.

4.2 Clasificacion binaria - Low,High

A- Conjunto de modelado y preprocesamiento

```
y_C_2 = df["Rate_your_academic_stress_index"].astype(float)

# Regla típica en 1-5: alto = 4-5, bajo = 1-3
y_C_2 = np.where(y_C_2 >= 4, "high", "low")
print("Distribución:", pd.Series(y_C_2).value_counts())

X_C_2 = df.drop(columns=["Rate_your_academic_stress_index"])
X_C_2 = pd.get_dummies(X_C_2, drop_first=True)

X_C_2_train, X_C_2_test, y_C_2_train, y_C_2_test = train_test_split(
    X_C_2, y_C_2, test_size=0.2, random_state=42, stratify=y_C_2
)
```

```
Distribución: high    89
low     51
Name: count, dtype: int64
```

B - Pipeline y Gridsearch

```
pipe_C_2 = Pipeline([
    ("scaler", MinMaxScaler()),
    ("clf", LogisticRegression(random_state=42,max_iter=1000))
])

param_grid_C_2 = [
    {   # Logistic Regression
        "clf": [LogisticRegression(random_state=42, max_iter=1000)],
        "clf__C": [0.1, 1, 10],
        "clf__class_weight": [None, "balanced"],
        "clf__solver": ["lbfgs"]
    },
    {   # Random Forest
        "clf": [RandomForestClassifier(random_state=42, n_jobs=-1)],
        "clf__n_estimators": [300, 600],
```

```
        "clf__max_depth": [None, 10, 20],
        "clf__min_samples_leaf": [1, 3, 5],
        "clf__max_features": ["sqrt", "log2", 0.8],
        "clf__class_weight": [None, "balanced"]
    }
]

cv_C_2 = KFold(n_splits=5, shuffle=True, random_state=42)

gs_C_2 = GridSearchCV(
    pipe_C_2, param_grid_C_2, cv=cv_C_2,
    scoring="f1",  # binario → F1 de la clase positiva (se elige alfabéticamente)
    n_jobs=-1, refit=True, verbose=0
)
gs_C_2.fit(X_C_2_train, y_C_2_train)

print("Mejor modelo:", gs_C_2.best_estimator_.named_steps["clf"].__class__.__name__)
print("Mejores params:", gs_C_2.best_params_)
```

```
Mejor modelo: LogisticRegression
Mejores params: {'clf': LogisticRegression(max_iter=1000, random_state=42), 'clf__C': 0.1, 'clf__class_weight': None, 'clf__solver'
/usr/local/lib/python3.12/dist-packages/sklearn/model_selection/_search.py:1108: UserWarning: One or more of the test scores are nor
 nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
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 nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
 nan nan nan nan nan nan nan]
  warnings.warn(
```
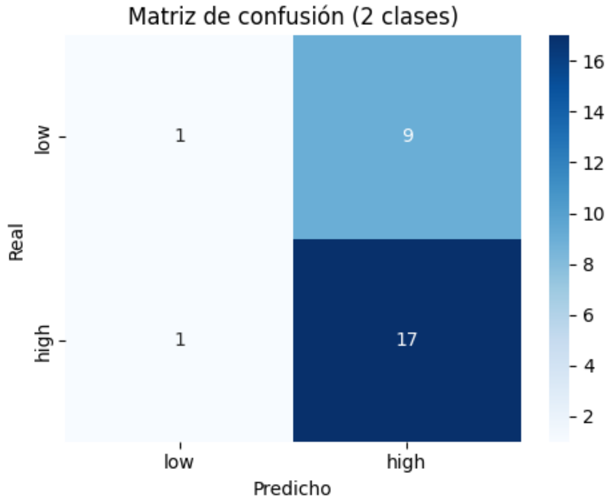

C- Evaluacion en test

```
best = gs_C_2.best_estimator_
y_pred_C_2 = best.predict(X_C_2_test)
y_prob = best.predict_proba(X_C_2_test)[:, list(best.classes_).index("high")]  # prob de 'high'

acc_C_2  = accuracy_score(y_C_2_test, y_pred_C_2)
prec_C_2, rec_C_2, f1_C_2, _ = precision_recall_fscore_support(y_C_2_test, y_pred_C_2, average="binary", pos_label="high")
auc_C_2  = roc_auc_score((y_C_2_test=="high").astype(int), y_prob)

print(f"\nTest → Acc: {acc_C_2:.3f} | Prec: {prec_C_2:.3f} | Rec: {rec_C_2:.3f} | F1: {f1_C_2:.3f} | ROC-AUC: {auc_C_2:.3f}")
print("\n" + classification_report(y_C_2_test, y_pred_C_2, digits=3))
```

```
Test → Acc: 0.643 | Prec: 0.654 | Rec: 0.944 | F1: 0.773 | ROC-AUC: 0.731

              precision    recall  f1-score   support

        high      0.654     0.944     0.773        18
         low      0.500     0.100     0.167        10

    accuracy                          0.643        28
   macro avg      0.577     0.522     0.470        28
weighted avg      0.599     0.643     0.556        28
```

D - Matriz de confusion

```
cm = confusion_matrix(y_C_2_test, y_pred_C_2, labels=["low","high"])
plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
            xticklabels=["low","high"],
            yticklabels=["low","high"])
plt.xlabel("Predicho"); plt.ylabel("Real")
plt.title("Matriz de confusión (2 clases)")
plt.tight_layout(); plt.show()
```



E - Conclusion parcial

Buen recall, baja precisión en “low”

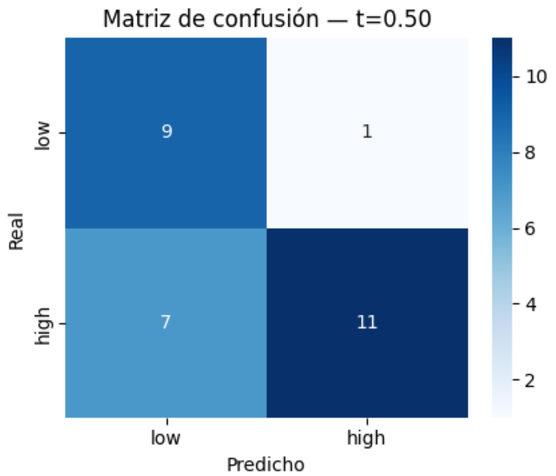
TAcc 0.64 | F1(high) 0.77 | AUC 0.73 pero la clase low queda débil. Se procede a ajustar el umbral de decisión para equilibrar precision/recall

F - Ajuste de umbral

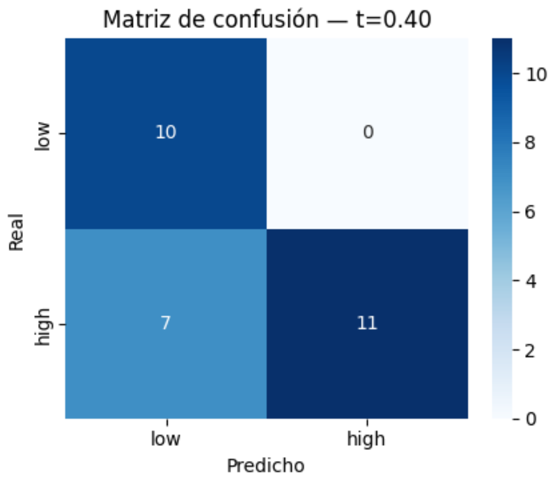
```
pipe_C_2_b = Pipeline([
    ("scaler", StandardScaler(with_mean=False)),
    ("clf", LogisticRegression(max_iter=2000,
                               class_weight="balanced",
                               random_state=42))
])

pipe_C_2_b.fit(X_C_2_train, y_C_2_train)

# 2) Probabilidades para la clase 'low'
classes = pipe_C_2_b.named_steps["clf"].classes_      # orden de clases
idx_low = np.where(classes == "low")[0][0]
proba_low_C_2 = pipe_C_2_b.predict_proba(X_C_2_test)[:, idx_low]

# 3) Barrido de umbrales y métricas por umbral
ths = np.linspace(0, 1, 201)
prec_low, rec_low, f1_low = [], [], []

for t in ths:
    y_pred_t = np.where(proba_low_C_2 >= t, "low", "high")
    prec_low.append(precision_score(y_C_2_test, y_pred_t, pos_label="low", zero_division=0))
    rec_low.append(recall_score(y_C_2_test, y_pred_t, pos_label="low"))
    f1_low.append(f1_score(y_C_2_test, y_pred_t, pos_label="low"))

prec_low = np.array(prec_low)
rec_low  = np.array(rec_low)
f1_low   = np.array(f1_low)

# 4A) Mejor umbral por F1 de la clase 'low'
best_idx = np.argmax(f1_low)
best_t_F1 = ths[best_idx]
print(f"Mejor umbral por F1(low): t = {best_t_F1:.3f} | F1(low) = {f1_low[best_idx]:.3f} | "
      f"Precision(low) = {prec_low[best_idx]:.3f} | Recall(low) = {rec_low[best_idx]:.3f}")

# 4B) Mejor umbral sujeto a recall mínimo
recall_objetivo = 0.80
mask = rec_low >= recall_objetivo
if mask.any():
    idx_recall = np.argmax(prec_low[mask])          # el de mayor precisión cumpliendo recall
    best_t_recall = ths[mask][idx_recall]
    print(f"Umbral con Recall(low)≥{recall_objetivo:.2f}: t={best_t_recall:.3f} | "
          f"Prec(low)={prec_low[mask][idx_recall]:.3f} | "
          f"Rec(low)={rec_low[mask][idx_recall]:.3f} | "
          f"F1(low)={f1_low[mask][idx_recall]:.3f}")
else:
    best_t_recall = None
    print(f"No hay umbral que alcance Recall(low)≥{recall_objetivo:.2f} en este test.")

# 5) Comparativa: umbral 0.5 vs umbral óptimo por F1(low)
```

```
def eval_umbral(t, titulo=""):
    y_pred = np.where(proba_low_C_2 >= t, "low", "high")
    auc_low = roc_auc_score((y_C_2_test == "low").astype(int), proba_low_C_2)
    print(f"\n[{titulo}]  t={t:.3f}")
    print(f"Precision(low)={precision_score(y_C_2_test, y_pred, pos_label='low', zero_division=0):.3f} | "
          f"Recall(low)={recall_score(y_C_2_test, y_pred, pos_label='low'):.3f} | "
          f"F1(low)={f1_score(y_C_2_test, y_pred, pos_label='low'):.3f} | "
          f"AUC(low)={auc_low:.3f}")
    print(classification_report(y_C_2_test, y_pred, target_names=["low", "high"]))
    cm = confusion_matrix(y_C_2_test, y_pred, labels=["low","high"])
    plt.figure(figsize=(4.5,3.8))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues",
                xticklabels=["low","high"], yticklabels=["low","high"])
    plt.title(f"Matriz de confusión — t={t:.2f}")
    plt.xlabel("Predicho"); plt.ylabel("Real"); plt.tight_layout(); plt.show()

# Evaluación con t=0.5
eval_umbral(0.5, "Umbral estándar 0.5")

# Evaluación con umbral óptimo por F1(low)
eval_umbral(best_t_F1, "Umbral óptimo por F1(low)")

# Usar el umbral que cumple recall objetivo:
if best_t_recall is not None:
    eval_umbral(best_t_recall, f"Umbral con Recall(low) ≥ {recall_objetivo:.2f}")
```

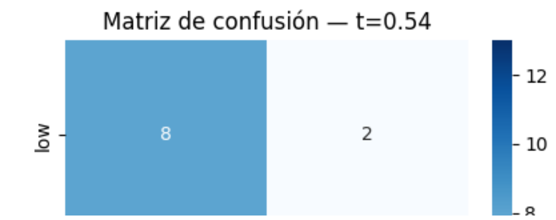
```
Mejor umbral por F1(low): t = 0.400 | F1(low) = 0.741 | Precision(low) = 0.588 | Recall(low) = 1.000
Umbral con Recall(low)≥0.80: t=0.540 | Prec(low)=0.615 | Rec(low)=0.800 | F1(low)=0.696

[Umbral estándar 0.5]  t=0.500
Precision(low)=0.562 | Recall(low)=0.900 | F1(low)=0.692 | AUC(low)=0.803
              precision    recall  f1-score   support

         low       0.92      0.61      0.73        18
        high       0.56      0.90      0.69        10

    accuracy                           0.71        28
   macro avg       0.74      0.76      0.71        28
weighted avg       0.79      0.71      0.72        28
```

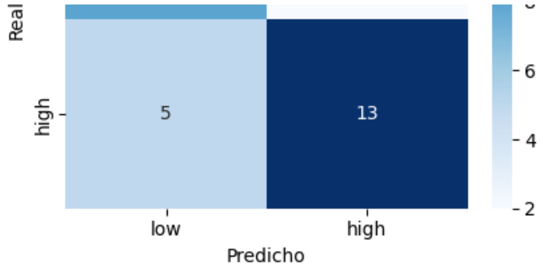



```
[Umbral óptimo por F1(low)]  t=0.400
Precision(low)=0.588 | Recall(low)=1.000 | F1(low)=0.741 | AUC(low)=0.803
              precision    recall  f1-score   support

         low       1.00      0.61      0.76        18
        high       0.59      1.00      0.74        10

    accuracy                           0.75        28
   macro avg       0.79      0.81      0.75        28
weighted avg       0.85      0.75      0.75        28
```




```
[Umbral con Recall(low) ≥ 0.80]  t=0.540
Precision(low)=0.615 | Recall(low)=0.800 | F1(low)=0.696 | AUC(low)=0.803
              precision    recall  f1-score   support

         low       0.87      0.72      0.79        18
        high       0.62      0.80      0.70        10

    accuracy                           0.75        28
   macro avg       0.74      0.76      0.74        28
weighted avg       0.78      0.75      0.75        28
```





G - Conclusion final

Se redefinió el target en dos grupos (1–3 = low, 4–5 = high).

La Logistic Regression dio Acc ≈ 0.64 y F1(high) ≈ 0.77 pero el principal problema es que tiende a capturar todo como high.

El modelo fue especialmente fuerte en detectar casos “high” (recall ≈ 0.94), aunque más débil en “low”.

Con ajuste de umbral (t = 0.535), se logró aumentar presicion y recall en "high" manteniendo buenos valores en "low",

La prioridad es detectar todos los casos de riesgo (no perder positivos)

En resumen: la clasificación binaria fue más estable y práctica para fines aplicados (detectar estudiantes en alto riesgo de estrés).

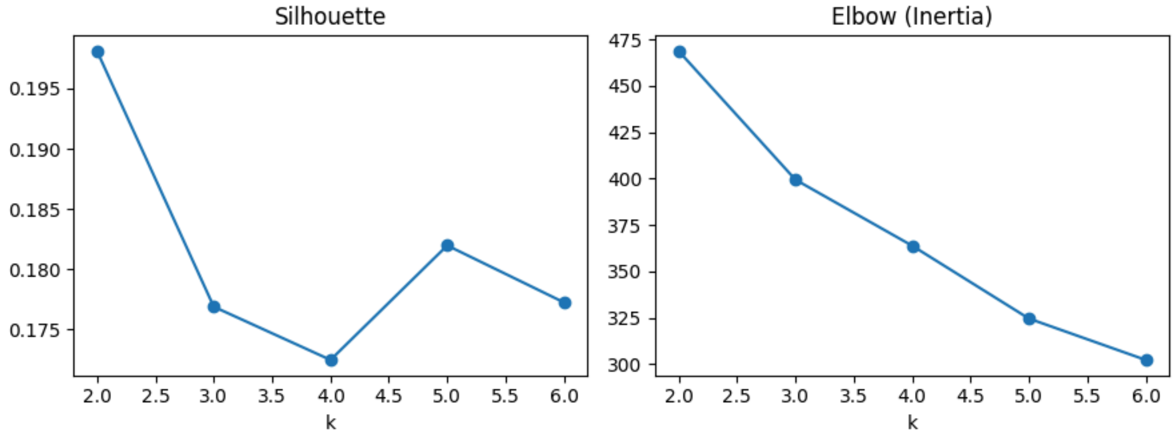
5 - Clustering

A - Conjunto de datos y pre procesamiento

```
num_cols = [
    "Peer_pressure",
    "Academic_pressure_from_your_home",
    "What_would_you_rate_the_academic_competition_in_your_student_life",
]

cat_cols = [
    "Study_Environment",
    "Your_Academic_Stage",
    "Do_you_have_any_bad_habits_like_smoking,_drinking_on_a_daily_basis?",              # valores: No / prefer not to say / Yes
]

stress_col = "Rate_your_academic_stress_index"  # solo para perfilar

X = df[num_cols + cat_cols].copy()



pre = ColumnTransformer([
    ("num", Pipeline([("imp", SimpleImputer(strategy="median")),
                      ("sc",  StandardScaler())]), num_cols),
    ("cat", Pipeline([("imp", SimpleImputer(strategy="most_frequent")),
                      ("oh",  OneHotEncoder(handle_unknown="ignore"))]), cat_cols)
])
```

B - Kmeans con Elbow + Silhouette

```
Ks = range(2, 7)
sil, inertia = [], []

for k in Ks:
    pipe = Pipeline([("pre", pre), ("km", KMeans(n_clusters=k, n_init=20, random_state=42))])
    labels = pipe.fit_predict(X)
    Z = pipe.named_steps["pre"].transform(X)
    Z = Z.toarray() if hasattr(Z, "toarray") else Z
    sil.append(silhouette_score(Z, labels))
    inertia.append(pipe.named_steps["km"].inertia_)

fig, ax = plt.subplots(1,2, figsize=(9,3.5))
ax[0].plot(Ks, sil, "o-"); ax[0].set_title("Silhouette"); ax[0].set_xlabel("k")
ax[1].plot(Ks, inertia, "o-"); ax[1].set_title("Elbow (Inertia)"); ax[1].set_xlabel("k")
plt.tight_layout(); plt.show()

best_k = Ks[int(np.argmax(sil))]
print("K seleccionado:", best_k)
```




```
K seleccionado: 2
```

C- Entrenar modelo

```
k = 2
pipe_k2 = Pipeline([
    ("pre", pre),                                    # tu preprocesador (imputar, escalar, one-hot)
    ("km",  KMeans(n_clusters=k, n_init=20, random_state=42))
])

df["cluster2"] = pipe_k2.fit_predict(X)
df["cluster2"].value_counts().sort_index()
```

cluster2	count
0	86
1	54

dtype: int64

D - Perfilado de clusters

```
profile_num = df.groupby("cluster2")[num_cols].mean().round(2)
display(profile_num)

for c in cat_cols:
    print(f"\n{c}")
    display(
        (df.groupby("cluster2")[c]
           .value_counts(normalize=True)
           .mul(100).rename("pct").round(1))
    )
```

cluster2	Peer_pressure	Academic_pressure_from_your_home	What_would_you_rate_the_academic_competition_in_your_student_life
0	2.47	2.59	3.3
1	4.04	4.11	3.8

Study_Environment

cluster2	Study_Environment	pct
0	Peaceful	61.6
	Noisy	20.9
	disrupted	17.4
1	disrupted	42.6
	Peaceful	31.5
	Noisy	25.9

dtype: float64

Your_Academic_Stage

cluster2	Your_Academic_Stage	pct
0	undergraduate	73.3
	high school	18.6
	post-graduate	8.1
1	undergraduate	68.5
	high school	24.1
	post-graduate	7.4

dtype: float64

Do_you_have_any_bad_habits_like_smoking,_drinking_on_a_daily_basis?

cluster2	Do_you_have_any_bad_habits_like_smoking,_drinking_on_a_daily_basis?	pct
0	No	91.9
	prefer not to say	4.7
	Yes	3.5
1	No	81.5
	Yes	13.0
	prefer not to say	5.6

dtype: float64

Next steps: Generate code with profile_num | View recommended plots | New interactive sheet

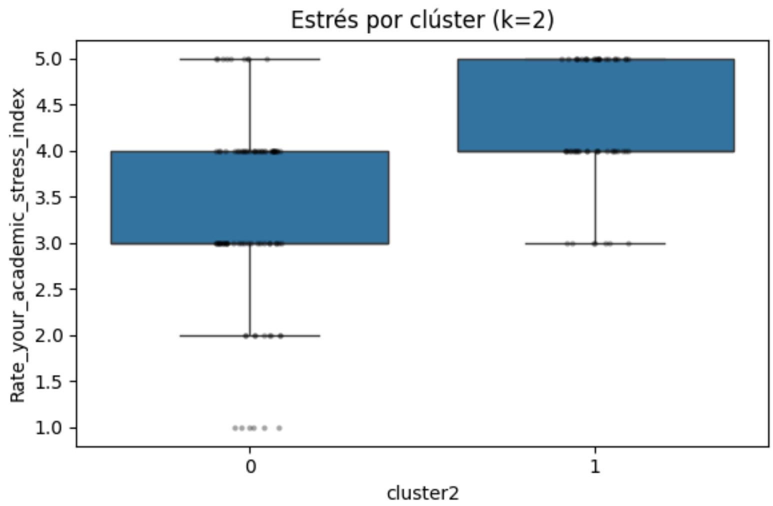
```
stress_col = "Rate_your_academic_stress_index"
display(df.groupby("cluster2")[stress_col].agg(["mean","median","count"]).round(2))
```

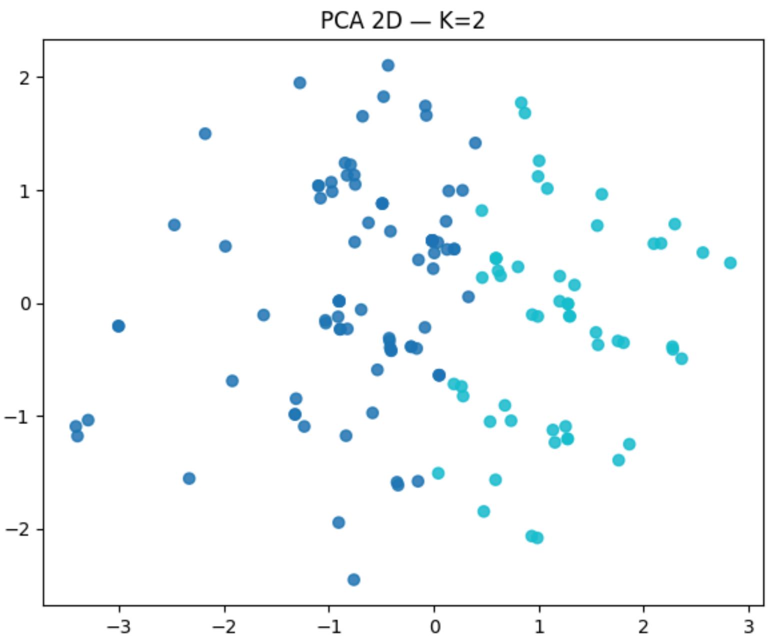
cluster2	mean	median	count
0	3.35	3.0	86
1	4.31	4.0	54

D - Graficas

```
# Boxplot de estrés por clúster
plt.figure(figsize=(6,4))
sns.boxplot(data=df, x="cluster2", y=stress_col, showfliers=False)
sns.stripplot(data=df, x="cluster2", y=stress_col, color="k", alpha=0.35, size=3)
plt.title("Estrés por clúster (k=2)"); plt.tight_layout(); plt.show()
```

```
# PCA 2D para visualizar
from sklearn.decomposition import PCA
Z = pipe_k2.named_steps["pre"].transform(X)
Z = Z.toarray() if hasattr(Z, "toarray") else Z
XY = PCA(n_components=2, random_state=42).fit_transform(Z)

plt.figure(figsize=(6,5))
plt.scatter(XY[:,0], XY[:,1], c=df["cluster2"], cmap="tab10", s=35, alpha=0.85)
plt.title("PCA 2D — K=2"); plt.tight_layout(); plt.show()
```





E - Conclusion parcial

El primer análisis de clustering, realizado sobre los datos preprocesados pero sin reducción de dimensionalidad, mostró que el número óptimo de clústeres era k=2. Este resultado reveló la división más fuerte y evidente en el dataset:

Un grupo de estudiantes con estrés bajo/moderado, en su mayoría con entornos pacíficos y menos presión externa.

Un grupo con estrés alto, caracterizado por mayor presión de pares y familiar, entornos de estudio desfavorables y mayor incidencia de hábitos nocivos.

Esta segmentación inicial permitió identificar dos macro-perfiles claros: estudiantes resilientes y estudiantes vulnerables. Fue un hallazgo útil para entender la estructura básica del fenómeno, aunque todavía general.

F - PCA para optimizar K

```
n_components_grid = [2, 3, 4, 5]
k_grid = [2, 3, 4, 5, 6]

results = []

# Preprocess una sola vez y luego aplico PCA sobre Z
```