data-analysis

August 26, 2025

[396]:
```python
import pandas as pd

def transformToNumber(currency_format):
    # transform $1.230.456,34 to 1230456.34
    currency_format = currency_format.replace(".", "").replace(",", ".").
 ↪replace("$", "")
    return float(currency_format)

def load_dataframe(file_path):
    df = pd.read_csv(file_path, sep=";", encoding="latin1")
    # trim spaces on column names
    df.columns = df.columns.str.strip()
    df = df.dropna()
    df["Costo Contingente"] = df["Costo Contingente"].apply(transformToNumber)
    df["Month"] = df["Fecha Liquidación"].apply(lambda x: x.split("-")[1])
    df["Year"] = df["Fecha Liquidación"].apply(lambda x: x.split("-")[0])
    # Round to 2 decimal places
    df["Cost_per_beneficiary"] = (df["Costo Contingente"] /␣
 ↪df["Beneficiarios"]).round(2)
    return df


data_2025_07 = load_dataframe("dataset/2025-07-pago-del-seguro-de-depositos.
 ↪csv")




# Join two dataframes
data = data_2025_07.copy()

data.head()
```

[396]:
```
            Ruc                                        Razón Social  \
3  9.906220e+11  COOPERATIVA DE AHORRO Y CREDITO \ E.T.G.\" LTD…
4  4.915081e+11  COOPERATIVA DE AHORRO Y CREDITO 10 DE SEPTIEMB…
5  1.891708e+12  COOPERATIVA DE AHORRO Y CREDITO 15 DE DICIEMBR…
6  9.913137e+11   COOPERATIVA DE AHORRO Y CREDITO 19 DE SEPTIEMBRE
```

```
7  1.891723e+12  COOPERATIVA DE AHORRO Y CREDITO 21 DE NOVIEMBR…

  Fecha Liquidación       Sector Segmento   Provincia  Costo Contingente  \
3        2019-01-24  COOP - SFPS        5      GUAYAS           51175.82
4        2019-12-11  COOP - SFPS        5      CARCHI            3042.82
5        2016-05-16  COOP - SFPS        5  TUNGURAHUA           14458.24
6        2018-06-21  COOP - SFPS        5      GUAYAS           72248.46
7        2020-07-01  COOP - SFPS        5  TUNGURAHUA           43302.50

   Beneficiarios Month  Year  Cost_per_beneficiary
3         86.000    01  2019                595.07
4         21.000    12  2019                144.90
5        461.000    05  2016                 31.36
6        110.000    06  2018                656.80
7          1.132    07  2020              38253.09
```

[397]:
```python
# Remove atypical (outlier) values from data using outlier_mask and␣
 ↪outlier_mask_costo
# Define outlier_mask and outlier_mask_costo using IQR method

def get_outlier_mask(series):
        Q1 = series.quantile(0.25)
        Q3 = series.quantile(0.75)
        IQR = Q3 - Q1
        return (series < (Q1 - 1.5 * IQR)) | (series > (Q3 + 1.5 * IQR))

outlier_mask = get_outlier_mask(data["Beneficiarios"])
outlier_mask_costo = get_outlier_mask(data["Costo Contingente"])

# Keep only rows that are not outliers in both columns
clean_data = data[~outlier_mask & ~outlier_mask_costo].copy()

data = clean_data.copy()

clean_data.head()
```

[397]:
```
            Ruc                                       Razón Social  \
3  9.906220e+11  COOPERATIVA DE AHORRO Y CREDITO \ E.T.G.\" LTD…
4  4.915081e+11  COOPERATIVA DE AHORRO Y CREDITO 10 DE SEPTIEMB…
5  1.891708e+12  COOPERATIVA DE AHORRO Y CREDITO 15 DE DICIEMBR…
6  9.913137e+11   COOPERATIVA DE AHORRO Y CREDITO 19 DE SEPTIEMBRE
7  1.891723e+12  COOPERATIVA DE AHORRO Y CREDITO 21 DE NOVIEMBR…

  Fecha Liquidación       Sector Segmento   Provincia  Costo Contingente  \
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4        2019-12-11  COOP - SFPS        5      CARCHI            3042.82
5        2016-05-16  COOP - SFPS        5  TUNGURAHUA           14458.24
```

```
6        2018-06-21  COOP - SFPS        5      GUAYAS           72248.46
7        2020-07-01  COOP - SFPS        5  TUNGURAHUA           43302.50

   Beneficiarios Month  Year  Cost_per_beneficiary
3         86.000    01  2019                595.07
4         21.000    12  2019                144.90
5        461.000    05  2016                 31.36
6        110.000    06  2018                656.80
7          1.132    07  2020              38253.09
```

[398]:
```python
# Costo Beneficiario por Provincia

data_provincia = clean_data.groupby(["Provincia"])["Cost_per_beneficiary"].
 ↪mean().round(2).reset_index()
data_provincia = data_provincia.sort_values("Cost_per_beneficiary",␣
 ↪ascending=False)
```

[399]:
```python
# Media global
costo_promedio_global = data_provincia["Cost_per_beneficiary"].mean().round(2)
costo_promedio_global
```

[399]:
```
np.float64(10271.52)
```

[400]:
```python
from ydata_profiling import ProfileReport

profile = ProfileReport(data, explorative=True)
profile.to_file("reporte.html")
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]

Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]

Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]

Export report to file:   0%|          | 0/1 [00:00<?, ?it/s]
```

[401]:
```python
# create new dataframe where sum of Costo Contingente and beneficiarios by Year
data_yearly = clean_data.groupby(["Year"])["Costo Contingente"].sum().
 ↪reset_index()
data_yearly["Beneficiarios"] = clean_data.groupby(["Year"])["Beneficiarios"].
 ↪sum().values
# Count the number of cooperativas by year
data_yearly["Total_Cooperativas"] = clean_data.groupby(["Year"]).size().values
data_yearly["costo promedio por beneficiario"] = (data_yearly["Costo␣
 ↪Contingente"] / data_yearly["Beneficiarios"] )
data_yearly
```

[401]:
```
   Year  Costo Contingente  Beneficiarios  Total_Cooperativas  \
0  2013          337016.33       1069.000                   5
```

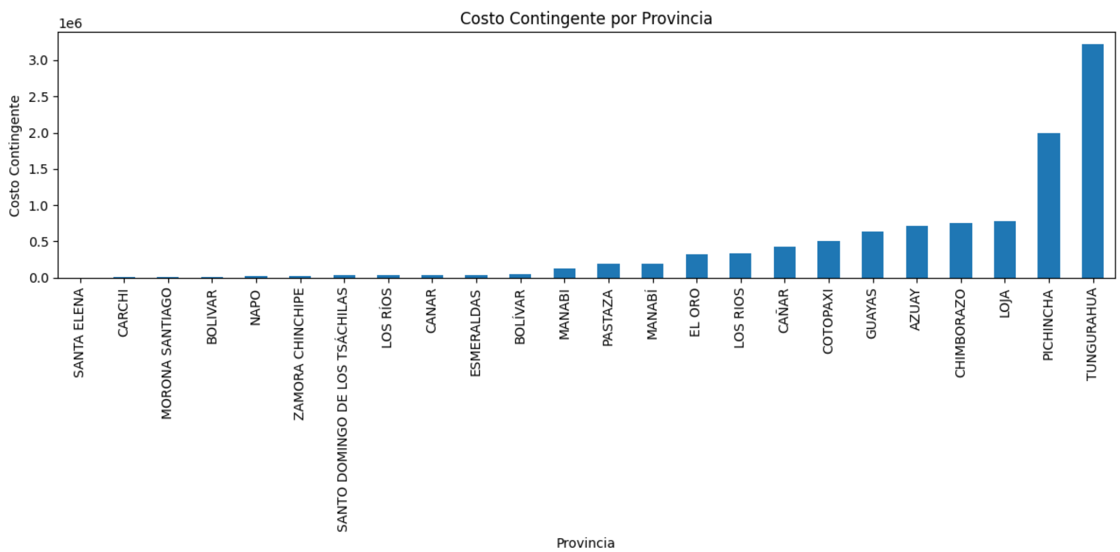
```
1   2014          734924.29       1767.395                    15
2   2015          660262.35       2050.649                    14
3   2016         3205620.96      14620.402                    75
4   2017         1306677.22       2885.474                    21
5   2018         1340108.37       5447.482                    17
6   2019          479529.98       1023.235                     9
7   2020          685205.84       1001.381                    11
8   2021          405069.72       1803.779                    11
9   2022          682070.30       1878.064                     8
10  2023          429194.59        174.228                     4
11  2024          199190.22        703.326                     2

    costo promedio por beneficiario
0                        315.263171
1                        415.823452
2                        321.977262
3                        219.256691
4                        452.846645
5                        246.005103
6                        468.641104
7                        684.260876
8                        224.567267
9                        363.177346
10                      2463.407661
11                       283.211797
```

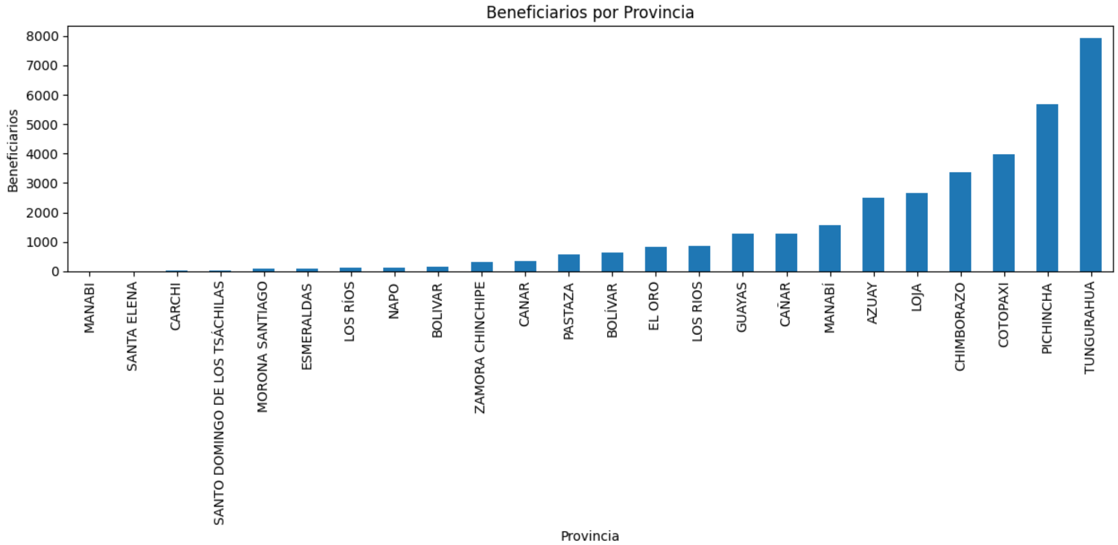
[402]:
```
# Promedio global del costo por beneficiario
avg_global_costo_benef = data_yearly["costo promedio por beneficiario"].mean().
↪round(2)
print("Promedio global del costo por beneficiario:", avg_global_costo_benef)
```

```
Promedio global del costo por beneficiario: 538.2
```

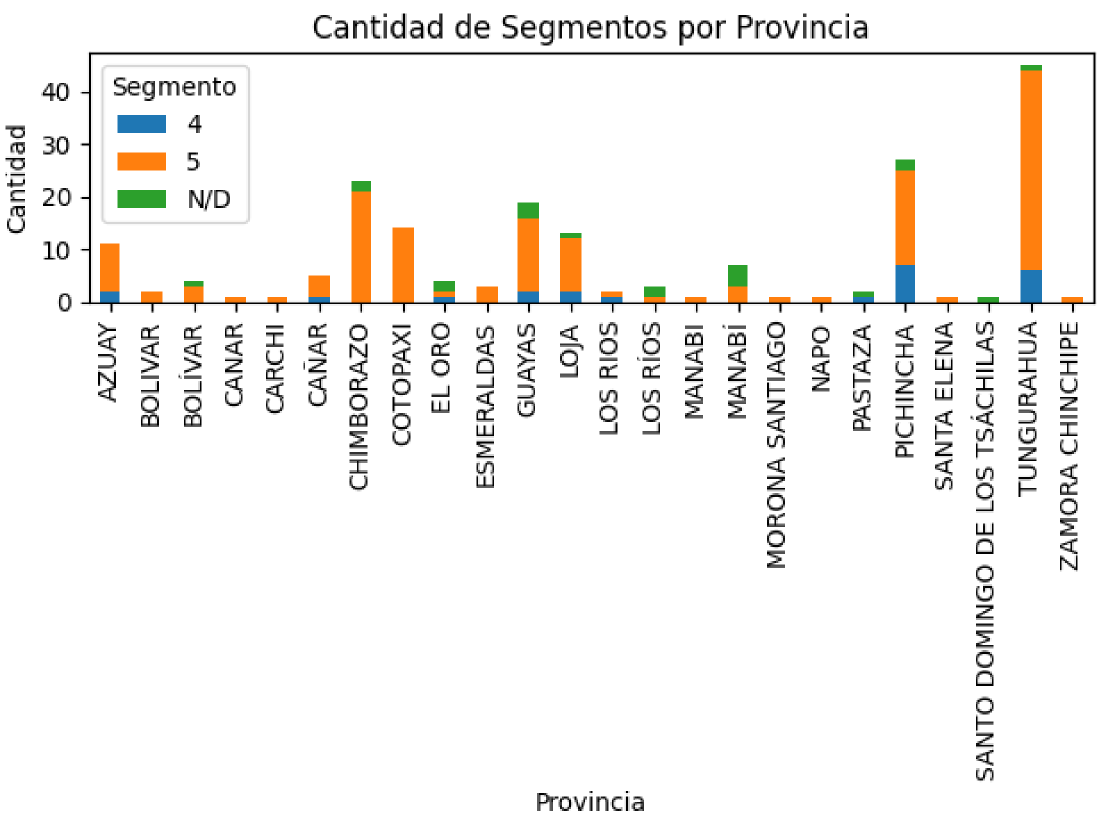
[403]:
```
import matplotlib.pyplot as plt

# Provincia vs Costo Contingente
plt.figure(figsize=(12,6))
data.groupby('Provincia')['Costo Contingente'].sum().sort_values().
↪plot(kind='bar')
plt.title('Costo Contingente por Provincia')
plt.ylabel('Costo Contingente')
plt.xlabel('Provincia')
plt.tight_layout()
plt.show()

# Provincia vs Beneficiarios
plt.figure(figsize=(12,6))
```

```
data.groupby('Provincia')['Beneficiarios'].sum().sort_values().plot(kind='bar')
plt.title('Beneficiarios por Provincia')
plt.ylabel('Beneficiarios')
plt.xlabel('Provincia')
plt.tight_layout()
plt.show()

# Provincia vs Segmento (conteo)
plt.figure(figsize=(12,6))
data.groupby(['Provincia', 'Segmento']).size().unstack().plot(kind='bar',␣
 ↪stacked=True)
plt.title('Cantidad de Segmentos por Provincia')
plt.ylabel('Cantidad')
plt.xlabel('Provincia')
plt.tight_layout()
plt.show()
```



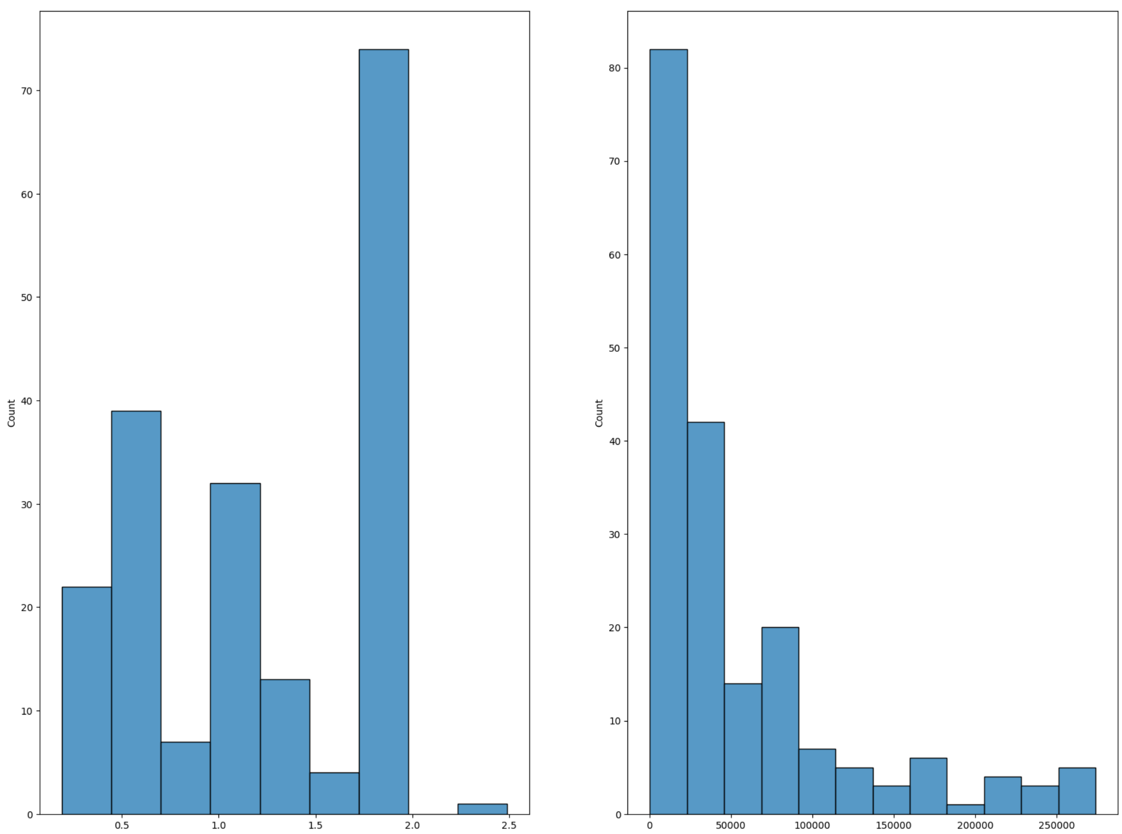


<Figure size 1200x600 with 0 Axes>



[404]:

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


# detección de valores atípicos
numerical_col = data.select_dtypes(include=['int', 'float']).columns
plt.figure
fig, ax = plt.subplots(1,2, figsize=(20,15))

# tenemos 4 valores numéricos.
row, col = 1,2
col_count = 0
for c in range(col):
    if col_count >= len(numerical_col):
        ax[c].text(0.5, 0.5, "no data")
    else:
        sns.histplot(data=data, x=numerical_col[col_count], ax=ax[c])
    col_count += 1

# sns and plt display on notebook
```

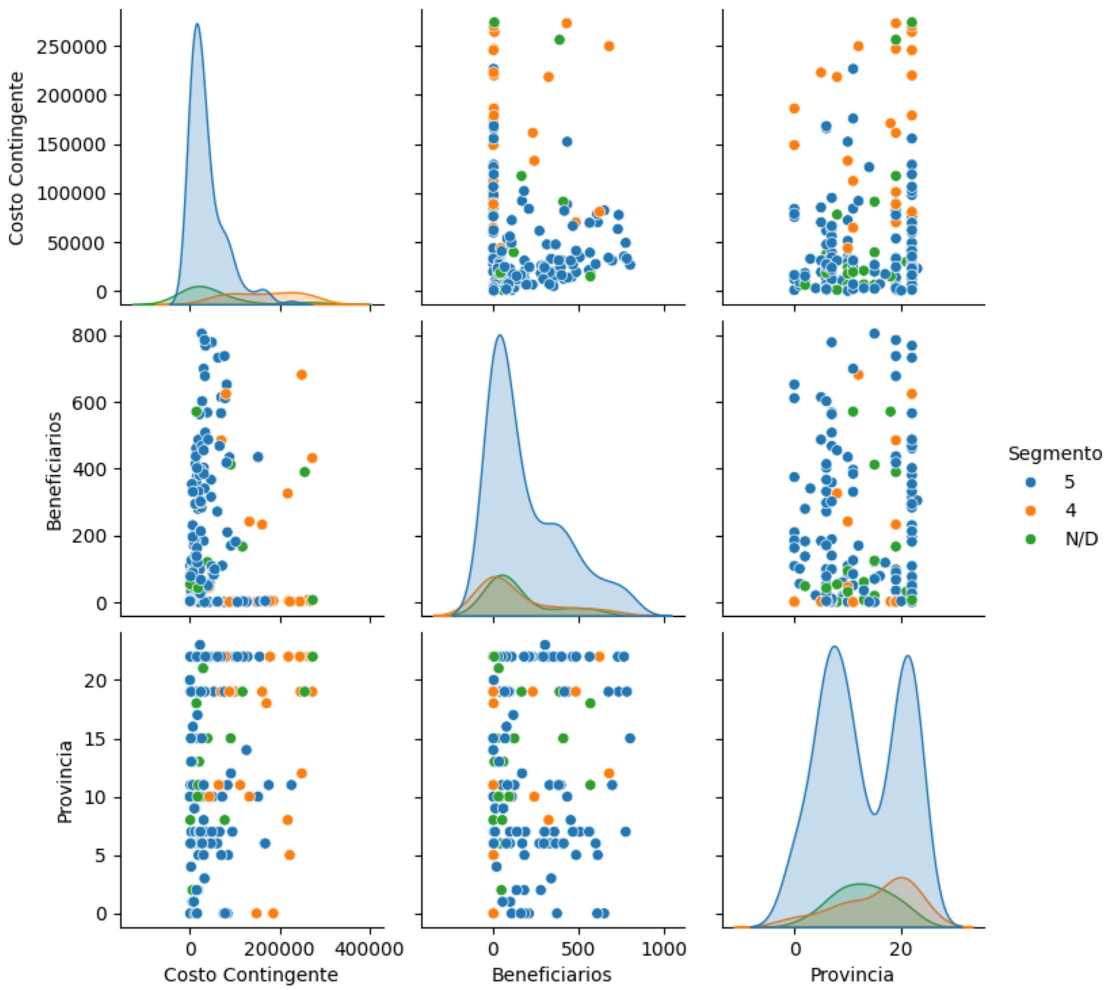


[405]:
```
from sklearn.preprocessing import LabelEncoder

data_kmeans = data.copy()

# Etiquetado de variables categoricas como Provincia use Label Encoder

le = LabelEncoder()
data_kmeans['Provincia'] = le.fit_transform(data_kmeans['Provincia'])
data_kmeans["Cooperativa"] = le.fit_transform(data_kmeans["Razón Social"])

data_kmeans.head()
```

[405]:
```
            Ruc                                        Razón Social  \
3  9.906220e+11  COOPERATIVA DE AHORRO Y CREDITO \ E.T.G.\" LTD…
4  4.915081e+11  COOPERATIVA DE AHORRO Y CREDITO 10 DE SEPTIEMB…
5  1.891708e+12  COOPERATIVA DE AHORRO Y CREDITO 15 DE DICIEMBR…
6  9.913137e+11   COOPERATIVA DE AHORRO Y CREDITO 19 DE SEPTIEMBRE
7  1.891723e+12  COOPERATIVA DE AHORRO Y CREDITO 21 DE NOVIEMBR…

  Fecha Liquidación       Sector Segmento  Provincia  Costo Contingente  \
3        2019-01-24  COOP - SFPS        5         10           51175.82
4        2019-12-11  COOP - SFPS        5          4            3042.82
5        2016-05-16  COOP - SFPS        5         22           14458.24
6        2018-06-21  COOP - SFPS        5         10           72248.46
7        2020-07-01  COOP - SFPS        5         22           43302.50

   Beneficiarios Month  Year  Cost_per_beneficiary  Cooperativa
3         86.000    01  2019                595.07          188
4         21.000    12  2019                144.90            0
5        461.000    05  2016                 31.36            1
6        110.000    06  2018                656.80            2
7          1.132    07  2020              38253.09            3
```

[406]:
```
col = ["Costo Contingente", "Beneficiarios", "Provincia","Segmento"]
sns.pairplot(data=data_kmeans[col], hue="Segmento")
```

[406]: <seaborn.axisgrid.PairGrid at 0x23db5862a20>



[407]:
```python
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import numpy as np

# Seleccionamos las columnas numéricas relevantes
X = data_kmeans[["Costo Contingente", "Beneficiarios", "Provincia",␣
 ↪"Cooperativa"]]

# Escalamos los datos
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Ajustamos KMeans (por ejemplo, 3 clusters)
kmeans = KMeans(n_clusters=3, random_state=42)
data_kmeans['cluster'] = kmeans.fit_predict(X_scaled)
```

```
# Calculamos la distancia de cada punto a su centroide
distances = kmeans.transform(X_scaled)
data_kmeans['distance_to_centroid'] = distances[np.arange(len(X_scaled)),␣
↪data_kmeans['cluster']]

# Definimos anomalías como los puntos más alejados de su centroide (top 5%)
threshold = data_kmeans['distance_to_centroid'].quantile(0.95)
anomalies = data_kmeans[data_kmeans['distance_to_centroid'] > threshold]

print("Número de anomalías detectadas:", len(anomalies))
```

```
Número de anomalías detectadas: 10
```

[408]:
```
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.linear_model import Ridge
from sklearn.metrics import mean_squared_error, r2_score

# Selección de features relevantes (ajustar según disponibilidad real)
features = [
    'Provincia', 'Cooperativa', 'Segmento', "Costo Contingente", "Beneficiarios"
]
target_costo = 'Costo Contingente'
target_benef = 'Beneficiarios'

# Filtrar solo filas con datos completos para las variables seleccionadas
df_model = data_kmeans.dropna(subset=features + [target_costo, target_benef])

X = df_model[features]
y_costo = df_model[target_costo]
y_benef = df_model[target_benef]

# Codificar variables categóricas si es necesario
X = pd.get_dummies(X, drop_first=True)

# Split para entrenamiento y test
X_train, X_test, y_costo_train, y_costo_test = train_test_split(X, y_costo,␣
↪test_size=0.2, random_state=42)
_, _, y_benef_train, y_benef_test = train_test_split(X, y_benef, test_size=0.2,␣
↪random_state=42)

# Modelo 1: Ridge Regression (regularizada)
ridge = Ridge()
ridge.fit(X_train, y_costo_train)
y_costo_pred_ridge = ridge.predict(X_test)

# Modelo 2: Gradient Boosting
```

```
gb = GradientBoostingRegressor(random_state=42)
gb.fit(X_train, y_costo_train)
y_costo_pred_gb = gb.predict(X_test)

# Evaluación
print("Ridge RMSE:", mean_squared_error(y_costo_test, y_costo_pred_ridge))
print("Ridge R2:", r2_score(y_costo_test, y_costo_pred_ridge))
print("GB RMSE:", mean_squared_error(y_costo_test, y_costo_pred_gb))
print("GB R2:", r2_score(y_costo_test, y_costo_pred_gb))

# Repetir para beneficiarios esperados
ridge_b = Ridge()
ridge_b.fit(X_train, y_benef_train)
y_benef_pred_ridge = ridge_b.predict(X_test)

gb_b = GradientBoostingRegressor(random_state=42)
gb_b.fit(X_train, y_benef_train)
y_benef_pred_gb = gb_b.predict(X_test)

print("Beneficiarios Ridge RMSE:", mean_squared_error(y_benef_test,␣
  ↪y_benef_pred_ridge))
print("Beneficiarios Ridge R2:", r2_score(y_benef_test, y_benef_pred_ridge))
print("Beneficiarios GB RMSE:", mean_squared_error(y_benef_test,␣
  ↪y_benef_pred_gb))
print("Beneficiarios GB R2:", r2_score(y_benef_test, y_benef_pred_gb))

# Uso: para nuevas señales de estrés, predecir severidad y beneficiarios␣
  ↪esperados
# Ejemplo:
# new_signals = pd.DataFrame([...]) # con las mismas columnas que 'features'
# new_signals_encoded = pd.get_dummies(new_signals, drop_first=True).
  ↪reindex(columns=X.columns, fill_value=0)
# costo_estimado = gb.predict(new_signals_encoded)
# beneficiarios_estimados = gb_b.predict(new_signals_encoded)
```

```
Ridge RMSE: 1.516057672240708e-14
Ridge R2: 1.0
GB RMSE: 1230327.8647817888
GB R2: 0.9997096626746165
Beneficiarios Ridge RMSE: 1.2406504096181236e-09
Beneficiarios Ridge R2: 0.9999999999999768
Beneficiarios GB RMSE: 12.288123215383305
Beneficiarios GB R2: 0.9997706384217556
```

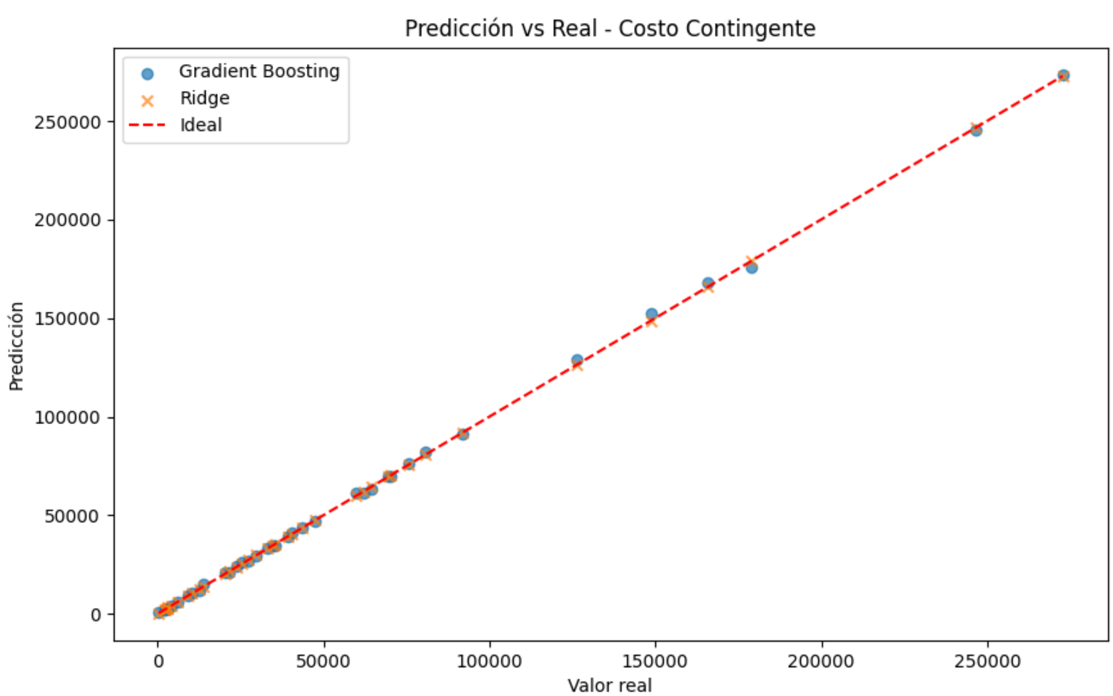
[409]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.linear_model import Ridge
```

```
from sklearn.metrics import mean_squared_error, r2_score

# Selección de features relevantes
features = ['Provincia', 'Segmento', 'Costo Contingente', 'Beneficiarios']
target = 'Costo Contingente'

# Codificar variables categóricas
X = data[features]
X = pd.get_dummies(X, drop_first=True)
y = data[target]

# Split de datos
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Ridge Regression
ridge = Ridge()
ridge.fit(X_train, y_train)
y_pred_ridge = ridge.predict(X_test)

# Gradient Boosting
gb = GradientBoostingRegressor(random_state=42)
gb.fit(X_train, y_train)
y_pred_gb = gb.predict(X_test)

# Evaluación
print("Ridge RMSE:", mean_squared_error(y_test, y_pred_ridge))
print("Ridge R2:", r2_score(y_test, y_pred_ridge))
print("GB RMSE:", mean_squared_error(y_test, y_pred_gb))
print("GB R2:", r2_score(y_test, y_pred_gb))
```

```
Ridge RMSE: 1.9359588676140483e-14
Ridge R2: 1.0
GB RMSE: 1161659.9458001489
GB R2: 0.9997258671844121
```

[410]:
```
import seaborn as sns
from sklearn.metrics import mean_squared_error, r2_score

# Visualización y evaluación del modelo de regresión

import matplotlib.pyplot as plt

# 1. Visualización: Gráfico de dispersión real vs predicho para Costo␣
↪Contingente
plt.figure(figsize=(10,6))
plt.scatter(y_test, y_pred_gb, alpha=0.7, label='Gradient Boosting')
```

```python
plt.scatter(y_test, y_pred_ridge, alpha=0.7, label='Ridge', marker='x')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--',
    label='Ideal')
plt.xlabel('Valor real')
plt.ylabel('Predicción')
plt.title('Predicción vs Real - Costo Contingente')
plt.legend()
plt.show()

# 2. Métricas de desempeño

print("Gradient Boosting RMSE:", mean_squared_error(y_test, y_pred_gb))
print("Gradient Boosting R2:", r2_score(y_test, y_pred_gb))
print("Ridge RMSE:", mean_squared_error(y_test, y_pred_ridge))
print("Ridge R2:", r2_score(y_test, y_pred_ridge))

# 3. Interpretación rápida:
# - RMSE (Root Mean Squared Error) mide el error promedio de predicción (menor
    es mejor).
# - R2 (Coeficiente de determinación) mide qué tan bien el modelo explica la
    variabilidad (más cercano a 1 es mejor).
# - El gráfico muestra qué tan cerca están las predicciones de los valores
    reales (la línea roja es el ideal).
```




```
Gradient Boosting RMSE: 1161659.9458001489
```

```
Gradient Boosting R2: 0.9997258671844121
Ridge RMSE: 1.9359588676140483e-14
Ridge R2: 1.0
```