Clustering

January 8, 2025

1 Title

1.1 Main Objective

1.1.1 Identify Key Drivers of Traffic Safety

- Use dimensionality reduction PCA to identify the features that have the most variance and influence safety indices. ### Monitor Regional Safety Evolution Over Time
- Group data by region ("Entidad") and year ("Año").
- Apply clustering (K-Means and others) to group regions based on safety indices.
  Combine clustering results with temporal data to observe how cluster assignments change over time.

1.2 Dataset Description

This dataset was obtained from the open data page of Gobierno de México since it was sourced as a PDF's it was extracted in the DataExtraction Notebook that can be accessed trough the following link:
* https://github.com/Arniquin/ClusteringTrafficData

Dataset Source: The dataset contains accidents statistics and geographic information per state in Mexico from the year 2018 to 2022.
* https://datos.gob.mx/busca/dataset/estadistica-de-accidentes-de-transito

1.2.1 Dataset Features Description

1. **Entidad**: Administrative region or state.
   Type: Categorical. Example: "Mexico City."
2. **Superficie**: Region's area in square kilometers (km²).
   Type: Numerical. Example: 1256.7.
3. **Habitantes**: Total population.
   Type: Numerical. Example: 123456.
4. **Hombres**: Male population.
   Type: Numerical. Example: 60000.
5. **Mujeres**: Female population.
   Type: Numerical. Example: 63500.

6. **Densidad de población**: Population density (persons/km^2).
   Type: Numerical. Example: 120.5.
7. **Vehículos registrados**: Registered vehicles.
   Type: Numerical. Example: 45678.
8. **Habitantes por vehículo**: Average inhabitants per vehicle.
   Type: Numerical. Example: 3.5.
9. **Índice de motorización**: Vehicles per 1000 inhabitants.
   Type: Numerical. Example: 280.7.
10. **Longitud del camino (km)**: Road length in kilometers (km).
    Type: Numerical. Example: 150.0.
11. **Veh-km (millones)**: Vehicle kilometers traveled (millions).
    Type: Numerical. Example: 45.6.
12. **Accidentes Totales**: Total traffic accidents reported.
    Type: Numerical. Example: 2000.
13. **Accidentes Con muertos**: Traffic accidents with fatalities.
    Type: Numerical. Example: 45.
14. **Accidentes Solo con heridos**: Traffic accidents causing injuries only.
    Type: Numerical. Example: 300.
15. **Accidentes Equivalentes**: Weighted accident count considering severity.
    Type: Numerical. Example: 500.5.
16. **Saldos Muertos**: Total fatalities from traffic accidents.
    Type: Numerical. Example: 100.
17. **Saldos Heridos**: Total injuries from traffic accidents.
    Type: Numerical. Example: 500.
18. **Daños materiales (millones)**: Material damages caused by accidents (millions).
    Type: Numerical. Example: 12.5.
19. **Índices Accidentes por 10 de Veh-km**: Accidents per million vehicle kilometers.
    Type: Numerical. Example: 3.5.
20. **Índices Peligrosidad por 10 de Veh-km**: Danger index per 100,000 vehicle kilometers.
    Type: Numerical. Example: 2.1.
21. **Índices Accidentes mortales por 10 de Veh-km**: Fatal accidents per 100,000 vehicle kilometers.
    Type: Numerical. Example: 0.15.
22. **Índices Muertos por 10 de Veh-km**: Fatalities per 100,000 vehicle kilometers.
    Type: Numerical. Example: 0.25.
23. **Índices Heridos por 10 de Veh-km**: Injuries per 100,000 vehicle kilometers.
    Type: Numerical. Example: 1.8.
24. **Año**: Year of data observation.
    Type: Temporal. Example: 2020.

Necesary libraries installation and importation

[2]:
```
# Installing the necessary libraries
%pip install pandas scikit-learn seaborn matplotlib
```

```
Requirement already satisfied: pandas in c:\users\arnol\desktop\workspace\traffi
cdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages (2.2.3)
Requirement already satisfied: scikit-learn in c:\users\arnol\desktop\workspace\
trafficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages
(1.6.0)
Requirement already satisfied: seaborn in c:\users\arnol\desktop\workspace\traff
icdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages (0.13.2)
Requirement already satisfied: matplotlib in c:\users\arnol\desktop\workspace\tr
afficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages
(3.10.0)
Requirement already satisfied: numpy>=1.26.0 in c:\users\arnol\desktop\workspace
\trafficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages
(from pandas) (2.2.1)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\users\arnol\desktop\
workspace\trafficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-
packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\users\arnol\desktop\workspace\
trafficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages
(from pandas) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in c:\users\arnol\desktop\workspac
e\trafficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages
(from pandas) (2024.2)
Requirement already satisfied: scipy>=1.6.0 in c:\users\arnol\desktop\workspace\
trafficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages
(from scikit-learn) (1.15.0)
Requirement already satisfied: joblib>=1.2.0 in c:\users\arnol\desktop\workspace
\trafficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages
(from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in c:\users\arnol\desktop\wo
rkspace\trafficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-
packages (from scikit-learn) (3.5.0)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\arnol\desktop\worksp
ace\trafficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages
(from matplotlib) (1.3.1)
Requirement already satisfied: cycler>=0.10 in c:\users\arnol\desktop\workspace\
trafficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages
(from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\arnol\desktop\works
pace\trafficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages
(from matplotlib) (4.55.3)
Requirement already satisfied: kiwisolver>=1.3.1 in c:\users\arnol\desktop\works
pace\trafficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages
(from matplotlib) (1.4.8)
Requirement already satisfied: packaging>=20.0 in c:\users\arnol\desktop\workspa
```

```
ce\trafficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages
(from matplotlib) (24.2)
Requirement already satisfied: pillow>=8 in c:\users\arnol\desktop\workspace\tra
fficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages (from
matplotlib) (11.1.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\arnol\desktop\worksp
ace\trafficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages
(from matplotlib) (3.2.1)
Requirement already satisfied: six>=1.5 in c:\users\arnol\desktop\workspace\traf
ficdataanalysisclustering\clusteringtrafficdata\.venv\lib\site-packages (from
python-dateutil>=2.8.2->pandas) (1.17.0)
Note: you may need to restart the kernel to use updated packages.
```

[3]:
```python
import pandas as pd
from sklearn.preprocessing import StandardScaler
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.cluster import KMeans, DBSCAN, AgglomerativeClustering
```

1.2.2 Loading the dataset using pandas read_csv function

[4]:
```python
df = pd.read_csv("./data/accidentes.csv")
df.head()
```

[4]:
```
               Entidad Superficie Habitantes    Hombres    Mujeres  \
0       Aguascalientes      5,625  1,395,794    687,397    708,397
1      Baja California     71,546  3,521,242  1,760,117  1,761,125
2  Baja California Sur     73,943    771,294    392,324    378,970
3             Campeche     57,727    967,319    477,987    489,332
4             Coahuila    151,445  3,132,017  1,562,875  1,569,142

  Densidad de población Vehículos registrados  Habitantes por vehículo  \
0               248.141               611,917                    2.281
1                49.216             1,734,061                    2.031
2                10.431               510,615                    1.511
3                16.757               325,505                    2.972
4                20.681               903,194                    3.468

   Índice de motorización Longitud del camino (km)  …  \
0                   0.438                  392.960  …
1                   0.492                1,854.000  …
2                   0.662                1,331.350  …
3                   0.337                1,287.150  …
4                   0.288                1,955.120  …

  Accidentes Equivalentes Saldos Muertos  Saldos Heridos  \
```

```
0                    836            39            195
1                  1,631           112            241
2                    848            59            149
3                    641            48             80
4                  1,001            75            156

   Daños materiales (millones) Índices Accidentes por 10^6 de Veh-km  \
0                      14.9796                                 0.112
1                      29.7392                                 0.116
2                      11.7975                                 0.084
3                      14.9843                                 0.111
4                      21.1585                                 0.041

   Índices Peligrosidad por 10^5 de Veh-km  \
0                                    0.442
1                                    0.396
2                                    0.361
3                                    0.367
4                                    0.170

   Índices Accidentes mortales por 10^5 de Veh-km  \
0                                           0.002
1                                           0.002
2                                           0.002
3                                           0.002
4                                           0.001

  Índices Muertos por 10^5 de Veh-km  Índices Heridos por 10^5 de Veh-km   Año
0                              0.002                               0.010  2018
1                              0.003                               0.006  2018
2                              0.003                               0.006  2018
3                              0.003                               0.005  2018
4                              0.001                               0.003  2018

[5 rows x 24 columns]
```

[5]:
```
# Creating a copy of the dataset for modification and analysis
df_copy = df.copy()
```

1.3 Data Cleaning

There is no data cleaning needed for this dataset since most of the data inconsitencies where handled during the extraction phase and there are no missing values on this dataset.
The only thing i will do is to convert the data to numeric values since they are Strings because the data was extracted from PDF's.
To do this i will have to replace all of the comas with ' ' to be able to do the conversion from string to numeric.

[6]:
```
# Replaceing the comas with dots before numeric conversion
df_copy = df_copy.replace({',': ''}, regex=True)
```

[7]:
```
# Numeric conversion excluding the column Entidad
exclude_column = 'Entidad'
for col in df_copy.columns:
    if col != exclude_column:
        df_copy[col] = pd.to_numeric(df_copy[col])
```

1.4 Exploratory Data Analysis

[8]:
```
df_copy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 160 entries, 0 to 159
Data columns (total 24 columns):
 #   Column                                         Non-Null Count  Dtype
---  ------                                         --------------  -----
 0   Entidad                                        160 non-null    object
 1   Superficie                                     160 non-null    int64
 2   Habitantes                                     160 non-null    int64
 3   Hombres                                        160 non-null    int64
 4   Mujeres                                        160 non-null    int64
 5   Densidad de población                          160 non-null    float64
 6   Vehículos registrados                          160 non-null    int64
 7   Habitantes por vehículo                        160 non-null    float64
 8   Índice de motorización                         160 non-null    float64
 9   Longitud del camino (km)                       160 non-null    float64
 10  Veh-km (millones)                              160 non-null    float64
 11  Accidentes Totales                             160 non-null    int64
 12  Accidentes Con muertos                         160 non-null    int64
 13  Accidentes Solo con heridos                    160 non-null    int64
 14  Accidentes Equivalentes                        160 non-null    int64
 15  Saldos Muertos                                 160 non-null    int64
 16  Saldos Heridos                                 160 non-null    int64
 17  Daños materiales (millones)                    160 non-null    float64
 18  Índices Accidentes por 10^6 de Veh-km          160 non-null    float64
 19  Índices Peligrosidad por 10^5 de Veh-km        160 non-null    float64
 20  Índices Accidentes mortales por 10^5 de Veh-km 160 non-null    float64
 21  Índices Muertos por 10^5 de Veh-km             160 non-null    float64
 22  Índices Heridos por 10^5 de Veh-km             160 non-null    float64
 23  Año                                            160 non-null    int64
dtypes: float64(11), int64(12), object(1)
memory usage: 30.1+ KB
```

[9]:
```
df_copy.describe()
```

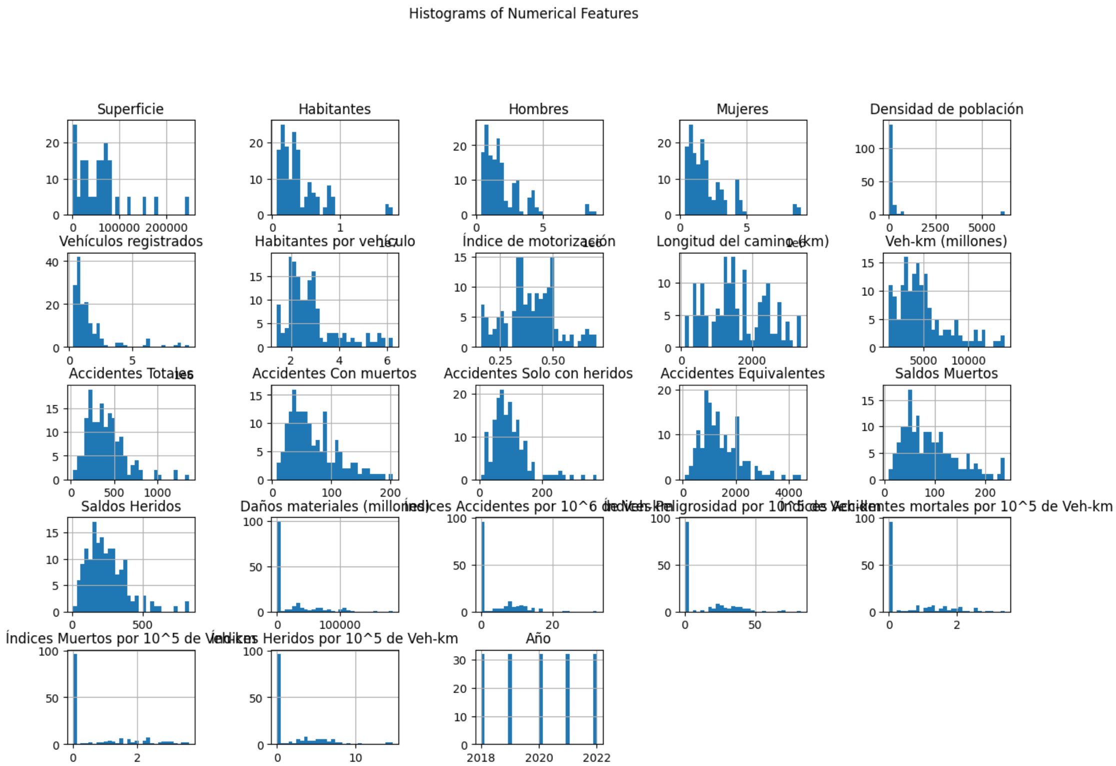
[9]:

```
        Superficie    Habitantes       Hombres       Mujeres  \
count   160.000000  1.600000e+02  1.600000e+02  1.600000e+02
mean   61226.500000  3.969243e+06  1.964661e+06  2.016653e+06
std    53166.230832  3.272130e+06  1.615088e+06  1.671569e+06
min     1484.000000  7.233070e+05  3.606220e+05  3.707690e+05
25%    24143.500000  1.827657e+06  9.076288e+05  9.261395e+05
50%    58197.000000  3.109026e+06  1.559437e+06  1.575788e+06
75%    74311.250000  5.030554e+06  2.548083e+06  2.565437e+06
max   247487.000000  1.777246e+07  9.003038e+06  9.089378e+06

       Densidad de población  Vehículos registrados  Habitantes por vehículo  \
count             160.000000           1.600000e+02               160.000000
mean              309.647544           1.589049e+06                 2.830719
std              1057.829195           1.694634e+06                 1.071586
min                10.431000           3.102990e+05                 1.411000
25%                43.689250           6.628858e+05                 2.092500
50%                66.365500           1.005306e+06                 2.569000
75%               160.611000           1.725183e+06                 3.034000
max              6206.162000           9.421189e+06                 6.241000

       Índice de motorización  Longitud del camino (km)  Veh-km (millones)  \
count              160.000000                160.000000         160.000000
mean                 0.395319               1567.275563        4876.668119
std                  0.122394                833.498482        2855.652149
min                  0.160000                111.600000        1060.784000
25%                  0.329750               1008.650000        3051.545000
50%                  0.389500               1438.720000        4307.519500
75%                  0.477750               2266.075000        5722.105750
max                  0.709000               3363.930000       14140.894000

       …  Accidentes Equivalentes  Saldos Muertos  Saldos Heridos  \
count  …               160.000000      160.000000      160.000000
mean   …              1441.006250       90.487500      246.450000
std    …               780.676682       52.777328      142.993944
min    …                92.000000        9.000000        7.000000
25%    …               878.750000       50.000000      148.750000
50%    …              1270.500000       79.500000      224.000000
75%    …              1912.000000      119.750000      321.250000
max    …              4448.000000      239.000000      825.000000

       Daños materiales (millones)  Índices Accidentes por 10^6 de Veh-km  \
count                   160.000000                             160.000000
mean                  22901.411707                               4.155262
std                   36834.095070                               5.937685
min                       4.562000                               0.027000
25%                      28.270300                               0.071750
50%                      53.535600                               0.114000
```

```
75%                    36339.975000                              8.325000
max                   184258.400000                             32.300000

       Índices Peligrosidad por 10^5 de Veh-km  \
count                               160.000000
mean                                 13.304275
std                                  18.369292
min                                   0.134000
25%                                   0.283750
50%                                   0.403500
75%                                  26.700000
max                                  82.400000

       Índices Accidentes mortales por 10^5 de Veh-km  \
count                                       160.000000
mean                                          0.610962
std                                           0.866557
min                                           0.000600
25%                                           0.001400
50%                                           0.002000
75%                                           1.225000
max                                           3.400000

       Índices Muertos por 10^5 de Veh-km  Índices Heridos por 10^5 de Veh-km  \
count                          160.000000                          160.000000
mean                             0.778069                            2.176519
std                              1.091960                            3.265983
min                              0.000800                            0.002000
25%                              0.002000                            0.005000
50%                              0.003000                            0.007000
75%                              1.500000                            4.300000
max                              3.600000                           14.700000

               Año
count   160.000000
mean   2020.000000
std       1.418654
min    2018.000000
25%    2019.000000
50%    2020.000000
75%    2021.000000
max    2022.000000

[8 rows x 23 columns]
```

[10]:
```
df_copy.hist(bins=30, figsize=(15, 10))
plt.suptitle("Histograms of Numerical Features", y=1.02)
```

```
plt.subplots_adjust(hspace=0.4, wspace=0.6)
```




```
[11]: numeric_columns = df_copy.select_dtypes(include=['float64', 'int64']).
        ↪drop(columns = ['Año'])
      skew_values = numeric_columns.skew()
      print(skew_values)
```

```
Superficie                                  1.658198
Habitantes                                  2.261982
Hombres                                     2.282254
Mujeres                                     2.263493
Densidad de población                       5.272650
Vehículos registrados                       2.812966
Habitantes por vehículo                     1.424870
Índice de motorización                      0.232760
Longitud del camino (km)                    0.224910
Veh-km (millones)                           1.240044
Accidentes Totales                          1.382446
Accidentes Con muertos                      0.965036
Accidentes Solo con heridos                 1.831771
Accidentes Equivalentes                     1.177043
Saldos Muertos                              0.893292
Saldos Heridos                              1.312677
```

```
Daños materiales (millones)                          1.788164
Índices Accidentes por 10^6 de Veh-km                1.582616
Índices Peligrosidad por 10^5 de Veh-km              1.273678
Índices Accidentes mortales por 10^5 de Veh-km       1.158291
Índices Muertos por 10^5 de Veh-km                   1.056544
Índices Heridos por 10^5 de Veh-km                   1.666778
dtype: float64
```

1.5 Feature engineering

Since some absolute values can be misleading when comparing regions with different pipulation sizes i wil be creating some ratios to standardize the data this way allowing fare comparison between regions.
This also helps for identifying trends between regions.
For this reasons i will create a Accidents per capita and a Vehicles per capita features allowing to identify the regions where residents are at a higher risk of being involved in accidents and the level of motorization.

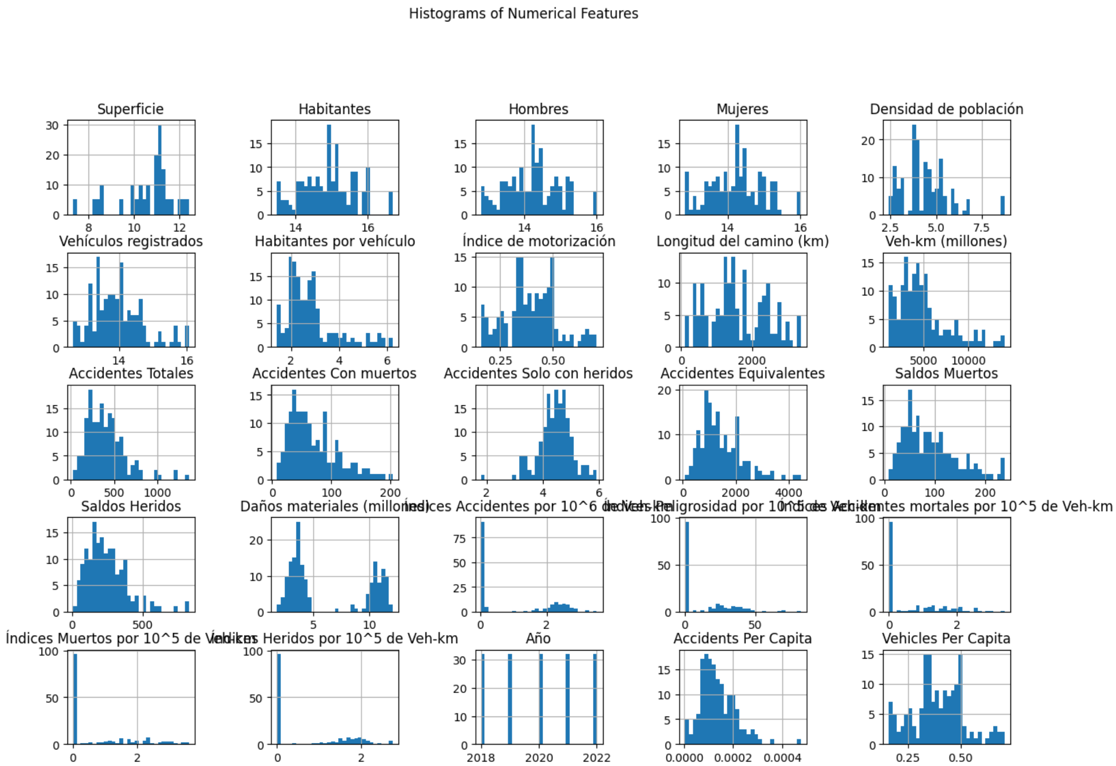
[12]:
```
df_copy['Accidents Per Capita'] = df_copy['Accidentes Totales'] /␣
 ↪df_copy['Habitantes']
df_copy['Vehicles Per Capita'] = df_copy['Vehículos registrados'] /␣
 ↪df_copy['Habitantes']
numeric_columns = df_copy.select_dtypes(include=['float64', 'int64']).
 ↪drop(columns = ['Año'])
df_copy[['Accidents Per Capita', 'Vehicles Per Capita']]
```

[12]:
```
     Accidents Per Capita  Vehicles Per Capita
0                0.000152             0.438401
1                0.000135             0.492457
2                0.000254             0.662024
3                0.000200             0.336502
4                0.000076             0.288375
..                    …                    …
155              0.000218             0.386993
156              0.000288             0.415257
157              0.000138             0.268643
158              0.000129             0.430891
159              0.000192             0.378392

[160 rows x 2 columns]
```

[13]:
```
skew_values = numeric_columns.skew()
high_skew = skew_values[skew_values > 1.5].index
for feature in high_skew:
    df_copy[feature] = np.log1p(df_copy[feature])
```

[14]:
```
df_copy.hist(bins=30, figsize=(15, 10))
plt.suptitle("Histograms of Numerical Features", y=1.02)
```

```
plt.subplots_adjust(hspace=0.4, wspace=0.6)
```



[15]:
```
numeric_columns = df_copy.select_dtypes(include=['float64', 'int64']).
    ↪drop(columns = ['Año'])
skew_values = numeric_columns.skew()
print(skew_values)
```

```
Superficie                                 -1.003703
Habitantes                                  0.107462
Hombres                                     0.119988
Mujeres                                     0.112207
Densidad de población                       1.115272
Vehículos registrados                       0.765874
Habitantes por vehículo                     1.424870
Índice de motorización                      0.232760
Longitud del camino (km)                    0.224910
Veh-km (millones)                           1.240044
Accidentes Totales                          1.382446
Accidentes Con muertos                      0.965036
Accidentes Solo con heridos                -0.643490
Accidentes Equivalentes                     1.177043
Saldos Muertos                              0.893292
Saldos Heridos                              1.312677
```

```
Daños materiales (millones)                        0.416802
Índices Accidentes por 10^6 de Veh-km              0.576693
Índices Peligrosidad por 10^5 de Veh-km            1.273678
Índices Accidentes mortales por 10^5 de Veh-km     1.158291
Índices Muertos por 10^5 de Veh-km                 1.056544
Índices Heridos por 10^5 de Veh-km                 0.684605
Accidents Per Capita                               1.079254
Vehicles Per Capita                                0.233068
dtype: float64
```

Next i will normalize my features to ensure equal weighting in dimensionality reduction and clustering utilizing sklearn's StandardScaler

[16]:
```
scaler = StandardScaler()
numeric_features = df_copy.select_dtypes(include=['float64', 'int64']).columns
df_copy[numeric_features] = scaler.fit_transform(df_copy[numeric_features])
```

[17]:
```
model_df = df_copy.drop(['Entidad', 'Año'], axis=1)  # Drop irrelevant columns
```

[18]:
```
model_df.head()
```

[18]:
```
   Superficie  Habitantes   Hombres   Mujeres  Densidad de población  \
0   -1.624044   -1.073007 -1.091077 -1.066893               0.868053
1    0.543585    0.202218  0.213343  0.183109              -0.386127
2    0.571674   -1.890425 -1.869136 -1.925499              -1.545027
3    0.360648   -1.578342 -1.595141 -1.574693              -1.200137
4    1.182781    0.040792  0.048452  0.024682              -1.043798

   Vehículos registrados  Habitantes por vehículo  Índice de motorización  \
0              -0.833457                -0.514606                0.349815
1               0.560549                -0.748638                0.792398
2              -1.075663                -1.235423                2.185714
3              -1.678216                 0.132257               -0.477979
4              -0.312403                 0.596576               -0.879582

   Longitud del camino (km)  Veh-km (millones)  …  Saldos Muertos  \
0                 -1.413323          -1.047961  …       -0.978624
1                  0.345081          -0.267767  …        0.408889
2                 -0.283943          -0.888524  …       -0.598484
3                 -0.337139          -1.099801  …       -0.807561
4                  0.466782           0.355243  …       -0.294371

   Saldos Heridos  Daños materiales (millones)  \
0       -0.360935                    -0.978268
1       -0.038233                    -0.798093
2       -0.683637                    -1.039425
3       -1.167690                    -0.978187
4       -0.634530                    -0.888237
```

```
   Índices Accidentes por 10^6 de Veh-km  \
0                            -0.770206
1                            -0.767044
2                            -0.792662
3                            -0.770998
4                            -0.828304

   Índices Peligrosidad por 10^5 de Veh-km  \
0                              -0.702404
1                              -0.704916
2                              -0.706827
3                              -0.706499
4                              -0.717258

   Índices Accidentes mortales por 10^5 de Veh-km  \
0                                     -0.704944
1                                     -0.704944
2                                     -0.704944
3                                     -0.704944
4                                     -0.706101

   Índices Muertos por 10^5 de Veh-km  Índices Heridos por 10^5 de Veh-km  \
0                         -0.712943                          -0.771662
1                         -0.712024                          -0.776041
2                         -0.712024                          -0.776041
3                         -0.712024                          -0.777139
4                         -0.713862                          -0.779337

   Accidents Per Capita  Vehicles Per Capita
0              0.215260             0.352974
1             -0.011891             0.795898
2              1.629426             2.185278
3              0.874190            -0.481952
4             -0.830163            -0.876296

[5 rows x 24 columns]
```

Finally for feature engineering i will create a summary statistics of some key features to apply clustering over time.

[19]:
```
region_summary = df_copy.groupby('Entidad').agg({
    'Accidentes Totales': 'sum',
    'Habitantes': 'mean',
    'Vehículos registrados': 'mean',
    'Índices Accidentes por 10^6 de Veh-km': 'mean'
}).reset_index()
```

1.6 Modeling

1.6.1 PCA

[20]:
```
from sklearn.decomposition import PCA

pca = PCA(n_components=0.9)  # Retain 90% of variance
pca_components = pca.fit_transform(model_df)
```

[21]:
```
pca.explained_variance_ratio_
```

[21]:
```
array([0.36975281, 0.24843463, 0.15430659, 0.08817322, 0.07830788])
```

[22]:
```
# Cumulative explained variance
cumulative_variance = np.cumsum(pca.explained_variance_ratio_)
print(cumulative_variance)
```

```
[0.36975281 0.61818744 0.77249402 0.86066725 0.93897513]
```

[23]:
```
pca.components_
```

[23]:
```
array([[ 1.23213182e-01,  2.83314622e-01,  2.84472137e-01,
         2.82715471e-01,  4.60155224e-02,  2.27285926e-01,
         1.02235864e-01, -1.07859362e-01,  2.05273616e-01,
         2.95298560e-01,  2.81542307e-01,  3.01129806e-01,
         2.50060611e-01,  3.09555170e-01,  3.03926902e-01,
         2.87354263e-01,  7.13066541e-02,  1.18612508e-02,
         6.09686908e-03,  8.85330304e-03,  2.00228791e-02,
         1.77409313e-02, -1.32519801e-01, -1.07871494e-01],
       [ 4.48750037e-03, -7.98121369e-02, -7.59784548e-02,
        -8.61017725e-02, -4.92462289e-02, -8.23744939e-02,
         4.65594411e-03, -1.79626327e-02, -2.09365560e-02,
        -4.21587893e-02,  9.95599523e-02,  1.67089857e-02,
         6.08487031e-02,  4.56978993e-02,  1.77947209e-02,
         2.68445108e-02,  3.65754645e-01,  3.91935933e-01,
         3.99884665e-01,  3.93709984e-01,  3.93042775e-01,
         3.96175602e-01,  1.93832728e-01, -1.78592526e-02],
       [-2.66179303e-01,  1.89161828e-01,  1.88826528e-01,
         1.86513738e-01,  3.49144205e-01,  3.52366350e-01,
        -3.39572861e-01,  3.98033335e-01, -2.02151961e-01,
         7.76935210e-02, -6.21434423e-02, -1.84921871e-02,
        -1.48044955e-01, -6.53163657e-02, -3.69177462e-02,
        -8.86114400e-02,  8.65938910e-02,  8.37047952e-02,
         5.41756791e-02,  6.53109720e-02,  5.28968975e-02,
         7.38646492e-02, -1.68116652e-01,  3.97985999e-01],
       [-2.89020585e-01,  1.86032891e-01,  1.82158737e-01,
         1.88742794e-01,  3.64900324e-01, -7.13917235e-03,
         4.44759845e-01, -3.68867796e-01, -1.61383678e-01,
        -4.48776127e-02, -1.04927288e-02, -1.78734520e-01,
```

```
        -1.98295132e-01, -1.30092411e-01, -1.56137153e-01,
        -1.73994176e-01,  6.78979981e-02,  8.07912054e-02,
         3.27391457e-02,  1.58341014e-02,  2.95769494e-02,
         3.83099851e-02, -1.55154611e-01, -3.68900128e-01],
       [ 4.59359595e-01,  1.33199089e-01,  1.34856114e-01,
         1.28894645e-01, -3.39765044e-01,  1.27454409e-01,
         3.03187587e-02,  2.02742256e-02,  3.82440771e-01,
        -1.53439938e-04, -2.35907336e-01, -1.54916994e-01,
        -2.25926984e-01, -1.97972367e-01, -1.34620013e-01,
        -2.06070454e-01,  1.41243284e-01,  8.45353834e-02,
         1.40151448e-02,  4.27419958e-02,  6.87180812e-02,
         9.54734879e-02, -4.28154906e-01,  2.05485906e-02]])
```

[24]:
```python
# Number of components that explain 90% variance
n_components_used = np.argmax(cumulative_variance >= 0.9) + 1
print(f"Number of components used to explain 90% variance: {n_components_used}")
```

```
Number of components used to explain 90% variance: 5
```

[25]:
```python
# Getting the loadings for each principal component and putting them in a␣
↪DataFrame
pca_loadings = pd.DataFrame(pca.components_, columns=model_df.columns)

# Display the loadings for each component
pca_loadings
```

[25]:

	Superficie	Habitantes	Hombres	Mujeres	Densidad de población \
0	0.123213	0.283315	0.284472	0.282715	0.046016
1	0.004488	-0.079812	-0.075978	-0.086102	-0.049246
2	-0.266179	0.189162	0.188827	0.186514	0.349144
3	-0.289021	0.186033	0.182159	0.188743	0.364900
4	0.459360	0.133199	0.134856	0.128895	-0.339765

	Vehículos registrados	Habitantes por vehículo	Índice de motorización \
0	0.227286	0.102236	-0.107859
1	-0.082374	0.004656	-0.017963
2	0.352366	-0.339573	0.398033
3	-0.007139	0.444760	-0.368868
4	0.127454	0.030319	0.020274

	Longitud del camino (km)	Veh-km (millones)	…	Saldos Muertos \
0	0.205274	0.295299	…	0.303927
1	-0.020937	-0.042159	…	0.017795
2	-0.202152	0.077694	…	-0.036918
3	-0.161384	-0.044878	…	-0.156137
4	0.382441	-0.000153	…	-0.134620

Saldos Heridos Daños materiales (millones) \

```
0       0.287354                     0.071307
1       0.026845                     0.365755
2      -0.088611                     0.086594
3      -0.173994                     0.067898
4      -0.206070                     0.141243

   Índices Accidentes por 10^6 de Veh-km  \
0                              0.011861
1                              0.391936
2                              0.083705
3                              0.080791
4                              0.084535

   Índices Peligrosidad por 10^5 de Veh-km  \
0                                0.006097
1                                0.399885
2                                0.054176
3                                0.032739
4                                0.014015

   Índices Accidentes mortales por 10^5 de Veh-km  \
0                                       0.008853
1                                       0.393710
2                                       0.065311
3                                       0.015834
4                                       0.042742

   Índices Muertos por 10^5 de Veh-km  Índices Heridos por 10^5 de Veh-km  \
0                           0.020023                            0.017741
1                           0.393043                            0.396176
2                           0.052897                            0.073865
3                           0.029577                            0.038310
4                           0.068718                            0.095473

   Accidents Per Capita  Vehicles Per Capita
0             -0.132520            -0.107871
1              0.193833            -0.017859
2             -0.168117             0.397986
3             -0.155155            -0.368900
4             -0.428155             0.020549

[5 rows x 24 columns]
```

[26]:
```
# Projecting the data onto the principal components
pca_transformed_data = pca.transform(model_df)

# Convert the transformed data into a DataFrame for easier analysis
```

```
pca_transformed_df = pd.DataFrame(pca_transformed_data, columns=[f'PC{i+1}' for␣
↪i in range(pca_transformed_data.shape[1])])

# Display the first few rows of the transformed data
pca_transformed_df.head()
```

[26]:

```
        PC1       PC2       PC3       PC4       PC5
0 -3.245478 -1.572755  0.278911  0.176296 -1.923056
1  0.503201 -1.764069  0.409409 -1.602399  0.012318
2 -4.296427 -1.132310 -0.332881 -3.800079 -0.438650
3 -4.206019 -1.317774 -2.325177 -0.193951  0.239756
4 -0.365529 -2.028889 -1.722608  0.419264  1.626893
```

[27]:

```
# Define the correct list of safety indices columns
safety_indices_columns = [
    'Índices Accidentes mortales por 10^5 de Veh-km',
    'Índices Muertos por 10^5 de Veh-km',
    'Índices Heridos por 10^5 de Veh-km',
    'Índices Accidentes por 10^6 de Veh-km',
    'Índices Peligrosidad por 10^5 de Veh-km'
]

# Combine the PCA-transformed data with the original model_df (which contains␣
↪the safety indices)
combined_df = pd.concat([model_df[safety_indices_columns], pca_transformed_df],␣
↪axis=1)

# Compute the correlations between the principal components and safety indices
correlations = combined_df.corr().iloc[:len(safety_indices_columns),␣
↪len(safety_indices_columns):]

# Display the correlations
print(correlations)
```

```
                                                     PC1       PC2       PC3  \
Índices Accidentes mortales por 10^5 de Veh-km  0.026373  0.961365  0.125685
Índices Muertos por 10^5 de Veh-km              0.059647  0.959735  0.101795
Índices Heridos por 10^5 de Veh-km              0.052849  0.967385  0.142146
Índices Accidentes por 10^6 de Veh-km           0.035334  0.957033  0.161082
Índices Peligrosidad por 10^5 de Veh-km         0.018162  0.976442  0.104256

                                                     PC4       PC5
Índices Accidentes mortales por 10^5 de Veh-km  0.023034  0.058595
Índices Muertos por 10^5 de Veh-km              0.043026  0.094206
Índices Heridos por 10^5 de Veh-km              0.055730  0.130885
Índices Accidentes por 10^6 de Veh-km           0.117527  0.115890
Índices Peligrosidad por 10^5 de Veh-km         0.047626  0.019213
```

[28]:
```
loadings = pca.components_

# Create a DataFrame with the loadings for better readability
loadings_df = pd.DataFrame(loadings, columns=model_df.columns)

# Get the loadings for PC2 (second principal component)
pc2_loadings = loadings_df.iloc[1].abs()

# Sort the loadings in descending order to find the most important features
sorted_pc2_loadings = pc2_loadings.sort_values(ascending=False)

# Display the top features contributing to PC2
print("Top features contributing to PC2:")
print(sorted_pc2_loadings.head(10))
```

```
Top features contributing to PC2:
Índices Peligrosidad por 10^5 de Veh-km          0.399885
Índices Heridos por 10^5 de Veh-km               0.396176
Índices Accidentes mortales por 10^5 de Veh-km   0.393710
Índices Muertos por 10^5 de Veh-km               0.393043
Índices Accidentes por 10^6 de Veh-km            0.391936
Daños materiales (millones)                      0.365755
Accidents Per Capita                             0.193833
Accidentes Totales                               0.099560
Mujeres                                          0.086102
Vehículos registrados                            0.082374
Name: 1, dtype: float64
```

[29]:
```
# Extract PC2 from the PCA transformed data
pc2_data = pca_transformed_df['PC2']

# Define the safety indices columns
safety_indices_columns = [
    'Índices Accidentes mortales por 10^5 de Veh-km',
    'Índices Muertos por 10^5 de Veh-km',
    'Índices Heridos por 10^5 de Veh-km',
    'Índices Accidentes por 10^6 de Veh-km',
    'Índices Peligrosidad por 10^5 de Veh-km'
]

# Compute the correlation between PC2 and each safety index
correlation_with_pc2 = model_df[safety_indices_columns].apply(lambda x: x.
 ↪corr(pc2_data))

# Display the results
print(correlation_with_pc2)
```

```
Índices Accidentes mortales por 10^5 de Veh-km   0.961365
```

```
Índices Muertos por 10^5 de Veh-km             0.959735
Índices Heridos por 10^5 de Veh-km             0.967385
Índices Accidentes por 10^6 de Veh-km          0.957033
Índices Peligrosidad por 10^5 de Veh-km        0.976442
dtype: float64
```

1.6.2 Clustering

[30]:
```
grouped_data = df_copy.groupby(['Entidad', 'Año']).mean()
safety_data = grouped_data[safety_indices_columns]  # Focus on safety indices
safety_data
```

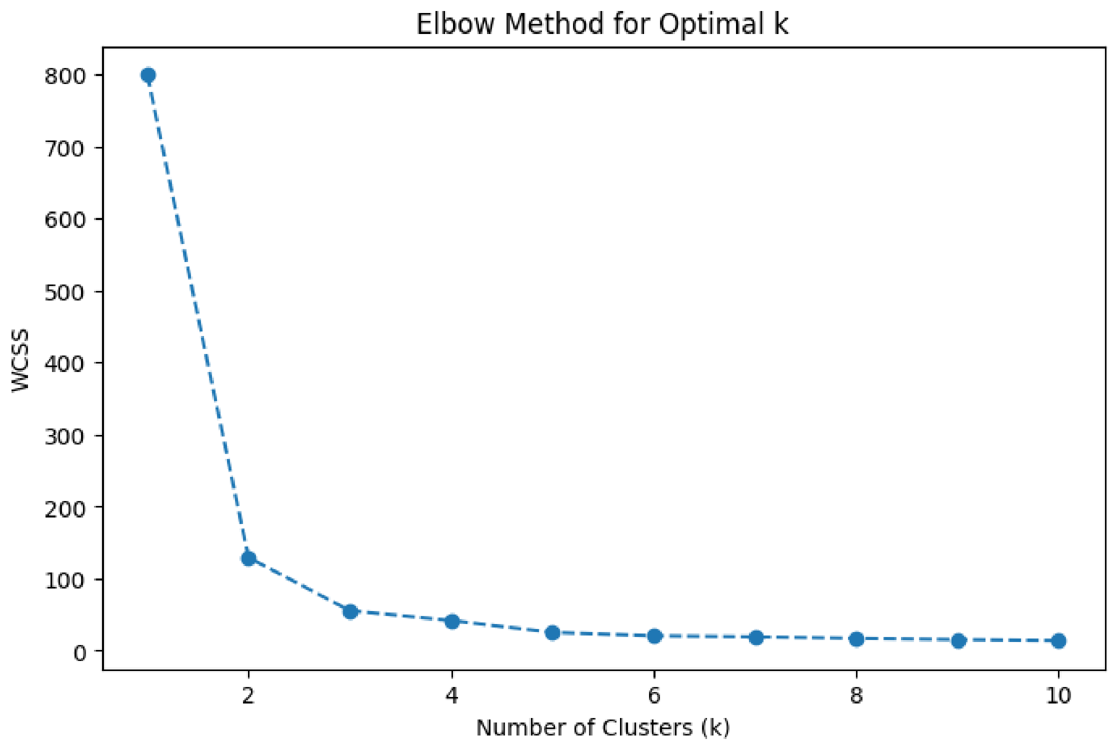
[30]:
```
                          Índices Accidentes mortales por 10^5 de Veh-km  \
Entidad        Año
Aguascalientes -1.414214                                       -0.704944
               -0.707107                                       -0.704944
                0.000000                                       -0.704018
                0.707107                                        2.765588
                1.414214                                        2.418303
…                                                                  …
Zacatecas      -1.414214                                       -0.704944
               -0.707107                                       -0.703786
                0.000000                                       -0.704018
                0.707107                                        2.649827
                1.414214                                        0.566118

                          Índices Muertos por 10^5 de Veh-km  \
Entidad        Año
Aguascalientes -1.414214                           -0.712943
               -0.707107                           -0.712024
                0.000000                           -0.711749
                0.707107                            2.408663
                1.414214                            2.133065
…                                                     …
Zacatecas      -1.414214                           -0.712024
               -0.707107                           -0.712024
                0.000000                           -0.711933
                0.707107                            2.500529
                1.414214                            0.663209

                          Índices Heridos por 10^5 de Veh-km  \
Entidad        Año
Aguascalientes -1.414214                           -0.771662
               -0.707107                           -0.766212
                0.000000                           -0.769260
                0.707107                            2.256376
                1.414214                            2.191225
```

```
…                                                   …
Zacatecas      -1.414214                     -0.770569
               -0.707107                     -0.768388
                0.000000                     -0.772536
                0.707107                      1.922356
                1.414214                      1.441062

                         Índices Accidentes por 10^6 de Veh-km  \
Entidad        Año
Aguascalientes -1.414214                              -0.770206
               -0.707107                              -0.736797
                0.000000                              -0.736035
                0.707107                               1.671629
                1.414214                               1.949346
…                                                           …
Zacatecas      -1.414214                              -0.763893
               -0.707107                              -0.775766
                0.000000                              -0.778160
                0.707107                               1.503133
                1.414214                               1.109400

                         Índices Peligrosidad por 10^5 de Veh-km
Entidad        Año
Aguascalientes -1.414214                                -0.702404
               -0.707107                                -0.691318
                0.000000                                -0.693994
                0.707107                                 2.899536
                1.414214                                 3.079748
…                                                             …
Zacatecas      -1.414214                                -0.699673
               -0.707107                                -0.695578
                0.000000                                -0.700929
                0.707107                                 2.326136
                1.414214                                 0.939052

[160 rows x 5 columns]
```

1.6.3 Kmeans

[31]:
```python
# Finding optimal number of clusters with elbow method
wcss = []
k_values = range(1, 11)
for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(safety_data)
    wcss.append(kmeans.inertia_)
```

[32]:
```
plt.figure(figsize=(8, 5))
plt.plot(k_values, wcss, marker='o', linestyle='--')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('WCSS')
plt.title('Elbow Method for Optimal k')
plt.show()
```



[33]:
```
kmeans = KMeans(n_clusters=3, random_state=42)
kmeans_labels = kmeans.fit_predict(safety_data)
grouped_data['KMeans_Cluster'] = kmeans_labels
```

1.6.4 DBSCAN

[34]:
```
dbscan = DBSCAN(eps=0.5, min_samples=5)
dbscan_labels = dbscan.fit_predict(safety_data)
grouped_data['DBSCAN_Cluster'] = dbscan_labels
```

1.6.5 Agglomerative Clustering

[35]:
```
# Step 4: Apply Agglomerative Clustering
agglo = AgglomerativeClustering(n_clusters=4, linkage='ward')
agglo_labels = agglo.fit_predict(safety_data)
grouped_data['Agglomerative_Cluster'] = agglo_labels
```

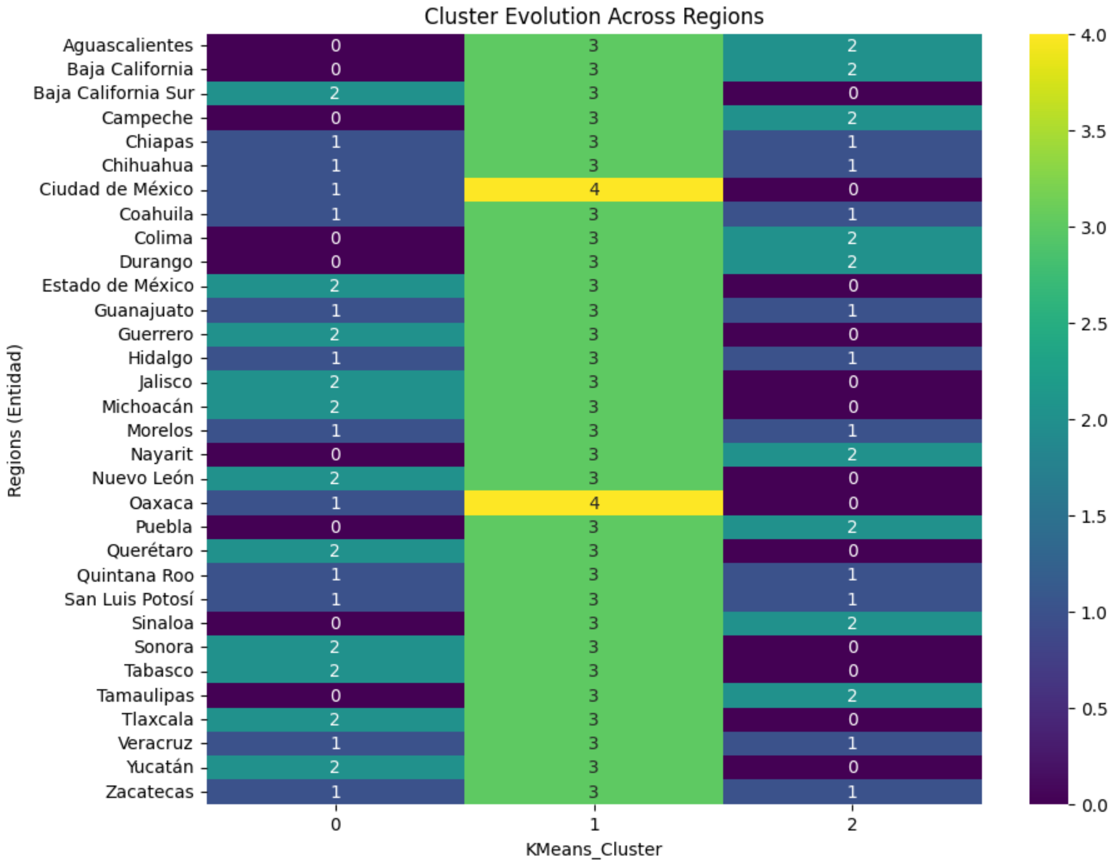
1.6.6 Results

[36]:
```
cluster_evolution = grouped_data.groupby(['Entidad', 'KMeans_Cluster']).size().
 ↪unstack(fill_value=0)
```

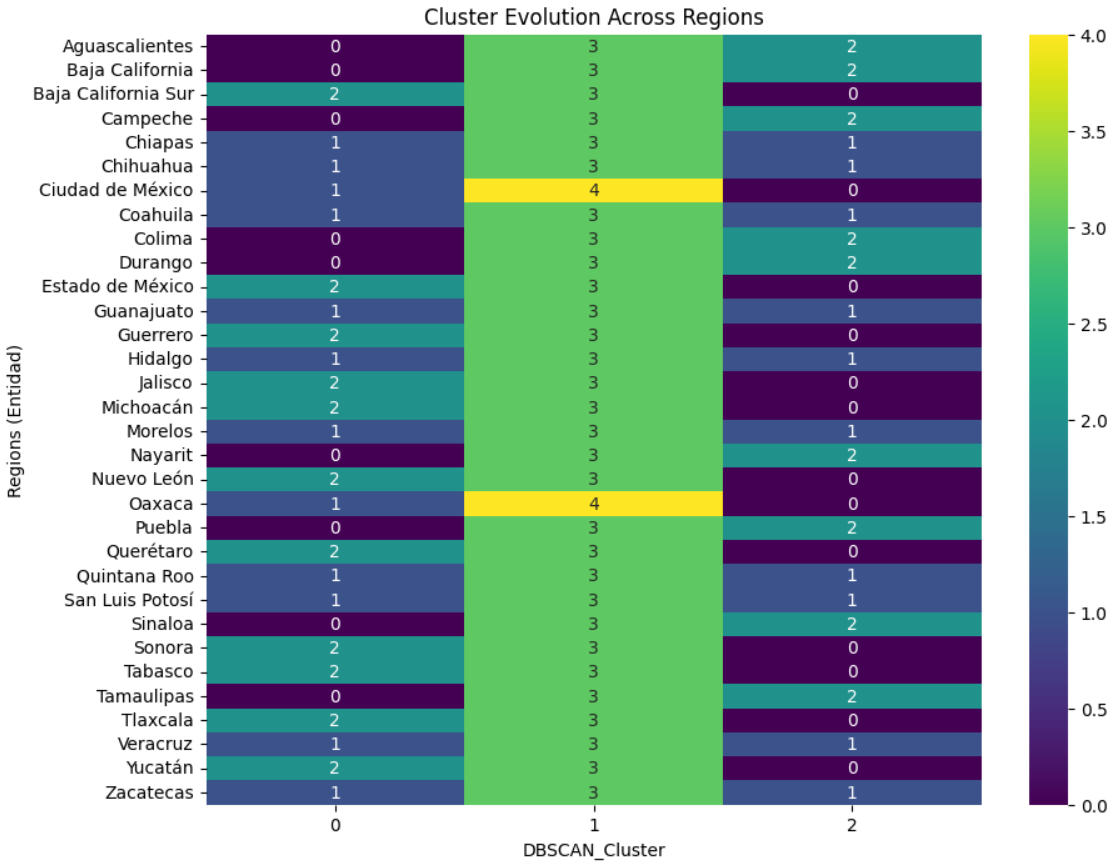
```
KMeans_Cluster       0  1  2
Entidad
Aguascalientes       0  3  2
Baja California      0  3  2
Baja California Sur  2  3  0
Campeche             0  3  2
Chiapas              1  3  1
Chihuahua            1  3  1
Ciudad de México     1  4  0
Coahuila             1  3  1
Colima               0  3  2
Durango              0  3  2
Estado de México     2  3  0
Guanajuato           1  3  1
Guerrero             2  3  0
Hidalgo              1  3  1
Jalisco              2  3  0
Michoacán            2  3  0
Morelos              1  3  1
Nayarit              0  3  2
Nuevo León           2  3  0
Oaxaca               1  4  0
Puebla               0  3  2
Querétaro            2  3  0
Quintana Roo         1  3  1
San Luis Potosí      1  3  1
Sinaloa              0  3  2
Sonora               2  3  0
Tabasco              2  3  0
Tamaulipas           0  3  2
Tlaxcala             2  3  0
Veracruz             1  3  1
Yucatán              2  3  0
Zacatecas            1  3  1
```

[37]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10, 8))
sns.heatmap(cluster_evolution, annot=True, fmt="d", cmap="viridis")
plt.title("Cluster Evolution Across Regions")
plt.xlabel("KMeans_Cluster")
plt.ylabel("Regions (Entidad)")
```

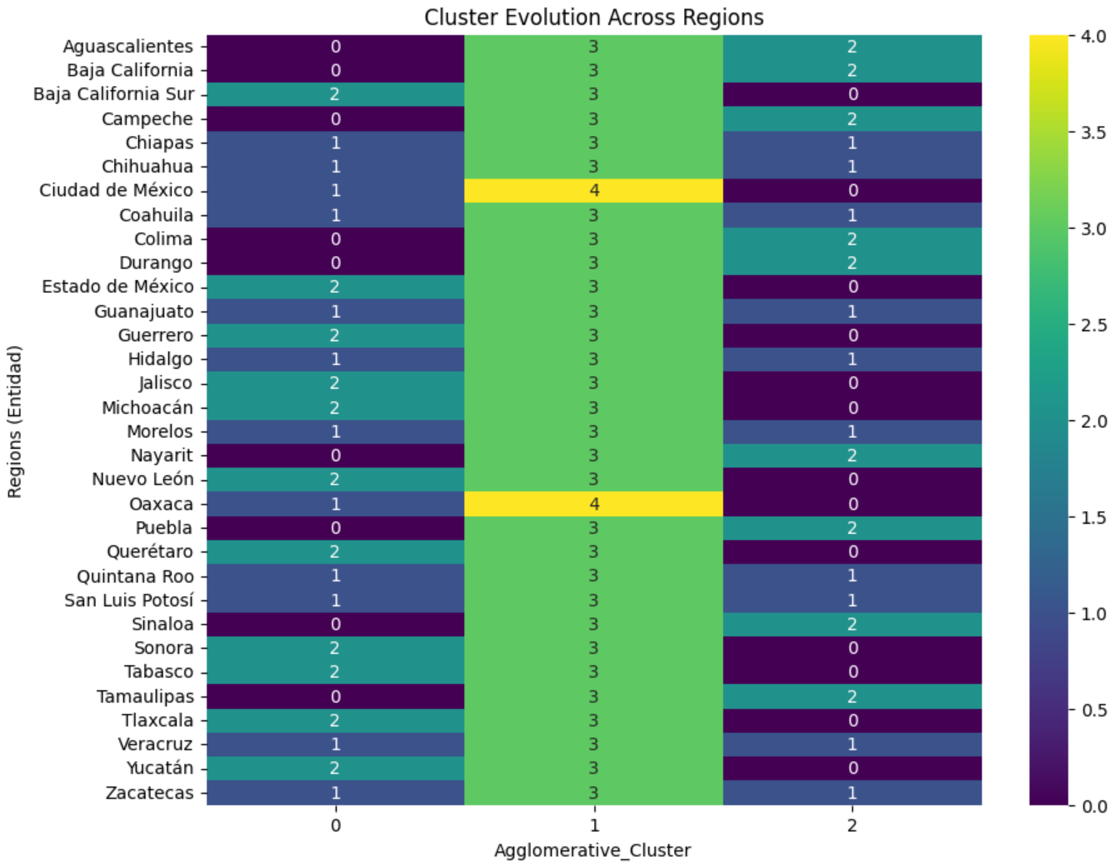
```
plt.show()
```




```
[ ]: cluster_evolution = grouped_data.groupby(['Entidad', 'DBSCAN_Cluster']).size().
     ↪unstack(fill_value=0)

     plt.figure(figsize=(10, 8))
     sns.heatmap(cluster_evolution, annot=True, fmt="d", cmap="viridis")
     plt.title("Cluster Evolution Across Regions")
     plt.xlabel("DBSCAN_Cluster")
     plt.ylabel("Regions (Entidad)")
     plt.show()
```



[39]:
```
cluster_evolution = grouped_data.groupby(['Entidad', 'Agglomerative_Cluster']).
 ↪size().unstack(fill_value=0)
plt.figure(figsize=(10, 8))
sns.heatmap(cluster_evolution, annot=True, fmt="d", cmap="viridis")
plt.title("Cluster Evolution Across Regions")
plt.xlabel("Agglomerative_Cluster")
plt.ylabel("Regions (Entidad)")
plt.show()
```



1.7 Model Recomendation

1.8 Key Findings and Insights

1.9 Next Steps