EDA

September 15, 2025

1 Importación de librerías

[1]:
```
import numpy as np
import pandas as pd
import scipy.stats as ss
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

2 Importación del dataset

[2]:
```
df = pd.read_csv('../Data/data_raw.csv')
```

3 Análisis exploratorio

3.1 Análisis general

[3]:
```
df.info() # Información general del dataset
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15420 entries, 0 to 15419
Data columns (total 33 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Month                 15420 non-null  object
 1   WeekOfMonth           15420 non-null  int64
 2   DayOfWeek             15420 non-null  object
 3   Make                  15420 non-null  object
 4   AccidentArea          15420 non-null  object
 5   DayOfWeekClaimed      15420 non-null  object
 6   MonthClaimed          15420 non-null  object
 7   WeekOfMonthClaimed    15420 non-null  int64
 8   Sex                   15420 non-null  object
 9   MaritalStatus         15420 non-null  object
 10  Age                   15420 non-null  int64
 11  Fault                 15420 non-null  object
```

```
 12  PolicyType            15420 non-null  object
 13  VehicleCategory       15420 non-null  object
 14  VehiclePrice          15420 non-null  object
 15  FraudFound_P          15420 non-null  int64
 16  PolicyNumber          15420 non-null  int64
 17  RepNumber             15420 non-null  int64
 18  Deductible            15420 non-null  int64
 19  DriverRating          15420 non-null  int64
 20  Days_Policy_Accident  15420 non-null  object
 21  Days_Policy_Claim     15420 non-null  object
 22  PastNumberOfClaims    15420 non-null  object
 23  AgeOfVehicle          15420 non-null  object
 24  AgeOfPolicyHolder     15420 non-null  object
 25  PoliceReportFiled     15420 non-null  object
 26  WitnessPresent        15420 non-null  object
 27  AgentType             15420 non-null  object
 28  NumberOfSuppliments   15420 non-null  object
 29  AddressChange_Claim   15420 non-null  object
 30  NumberOfCars          15420 non-null  object
 31  Year                  15420 non-null  int64
 32  BasePolicy            15420 non-null  object
dtypes: int64(9), object(24)
memory usage: 3.9+ MB
```

[4]:
```
df.head() # Primer vistazo de los primeros 5 registros
```

[4]:

	Month	WeekOfMonth	DayOfWeek	Make	AccidentArea	DayOfWeekClaimed	MonthClaimed	WeekOfMonthClaimed	Sex	MaritalStatus	…	AgeOfVehicle	AgeOfPolicyHolder	PoliceReportFiled	WitnessPresent	AgentType
0	Dec	5	Wednesday	Honda	Urban	Tuesday	Jan	1	Female	Single	…	3 years	26 to 30	No	No	External
1	Jan	3	Wednesday	Honda	Urban	Monday	Jan	4	Male	Single	…	6 years	31 to 35	Yes	No	External
2	Oct	5	Friday	Honda	Urban	Thursday	Nov	2	Male	Married	…	7 years	41 to 50	No	No	External
3	Jun	2	Saturday	Toyota	Rural	Friday	Jul	1	Male	Married	…	more than 7	51 to 65	Yes	No	External
4	Jan	5	Monday	Honda	Urban	Tuesday	Feb	2	Female	Single	…	5 years	31 to 35	No	No	External

```
   NumberOfSuppliments  AddressChange_Claim  NumberOfCars  Year  BasePolicy
0                 none               1 year        3 to 4  1994   Liability
1                 none            no change     1 vehicle  1994   Collision
2                 none            no change     1 vehicle  1994   Collision
3          more than 5            no change     1 vehicle  1994   Liability
4                 none            no change     1 vehicle  1994   Collision

[5 rows x 33 columns]
```

3.2 Descripción de las variables

Variable	Descripción
Month	Mes en el que ocurrió el accidente.
WeekOfMonth	Semana del mes en el que ocurrió el accidente.
DayOfWeek	Día de la semana en el que ocurrió el accidente.
Make	Fabricante del vehículo involucrado en el siniestro.
AccidentArea	Área donde ocurrió el accidente (urbana o rural).
DayOfWeekClaimed	Día de la semana en el que se procesó la reclamación.
MonthClaimed	Mes en el que se procesó la reclamación.
WeekOfMonthClaimed	Semana del mes en la que se procesó la reclamación.
Sex	Género del asegurado.
MaritalStatus	Estado civil del asegurado.
Age	Edad del asegurado.
Fault	Indica si el asegurado tuvo la culpa del accidente.
PolicyType	Tipo de póliza de seguro.
VehicleCategory	Categoría del vehículo.
VehiclePrice	Precio del vehículo.
FraudFound_P	Variable objetivo: indica si se detectó fraude en la reclamación.
PolicyNumber	Identificador único de la póliza de seguro.
RepNumber	Identificador único del representante que gestionó la reclamación.
Deductible	Deducible que debe pagar el asegurado antes de que la aseguradora cubra los costos restantes.
DriverRating	Puntuación del conductor.
Days_Policy_Accident	Días desde la emisión de la póliza hasta el accidente.
Days_Policy_Claim	Días desde la emisión de la póliza hasta la reclamación.
PastNumberOfClaims	Número de reclamaciones anteriores del asegurado.
AgeOfVehicle	Antigüedad del vehículo.
AgeOfPolicyHolder	Edad del asegurado.
PoliceReportFiled	Indica si se presentó un informe policial.
WitnessPresent	Indica si hubo testigos presentes en el accidente.
AgentType	Tipo de agente que gestionó la póliza (interno o externo).
NumberOfSuppliments	Número de documentos o reclamaciones suplementarias relacionadas con el caso.
AddressChange_Claim	Indica si el asegurado cambió de domicilio en el momento de la reclamación.
NumberOfCars	Número de vehículos involucrados en el accidente.
Year	Año en el que se realizó o procesó la reclamación.

Variable	Descripción
BasePolicy	Tipo de póliza base.

3.3 Valores únicos

[5]:
```
# Tabla para visualizar el número de valores únicos de cada variable y cada uno␣
↪de esos valores

resumen_unicos = []

for col in df.columns:
    valores = df[col].value_counts(dropna=False).sort_index()
    resumen_unicos.append({
        "Variable": col,
        "Núm. Valores únicos": df[col].nunique(),
        "Valores": valores.to_dict()
    })

resumen_df = pd.DataFrame(resumen_unicos)
resumen_df
```

[5]:

	Variable	Núm. Valores únicos	\
0	Month	12	
1	WeekOfMonth	5	
2	DayOfWeek	7	
3	Make	19	
4	AccidentArea	2	
5	DayOfWeekClaimed	8	
6	MonthClaimed	13	
7	WeekOfMonthClaimed	5	
8	Sex	2	
9	MaritalStatus	4	
10	Age	66	
11	Fault	2	
12	PolicyType	9	
13	VehicleCategory	3	
14	VehiclePrice	6	
15	FraudFound_P	2	
16	PolicyNumber	15420	
17	RepNumber	16	
18	Deductible	4	
19	DriverRating	4	
20	Days_Policy_Accident	5	
21	Days_Policy_Claim	4	
22	PastNumberOfClaims	4	
23	AgeOfVehicle	8	

24	AgeOfPolicyHolder	9
25	PoliceReportFiled	2
26	WitnessPresent	2
27	AgentType	2
28	NumberOfSuppliments	4
29	AddressChange_Claim	5
30	NumberOfCars	5
31	Year	3
32	BasePolicy	3

	Valores
0	{'Apr': 1280, 'Aug': 1127, 'Dec': 1285, 'Feb':…
1	{1: 3187, 2: 3558, 3: 3640, 4: 3398, 5: 1637}
2	{'Friday': 2445, 'Monday': 2616, 'Saturday': 1…
3	{'Accura': 472, 'BMW': 15, 'Chevrolet': 1681, …
4	{'Rural': 1598, 'Urban': 13822}
5	{'0': 1, 'Friday': 2497, 'Monday': 3757, 'Satu…
6	{'0': 1, 'Apr': 1271, 'Aug': 1126, 'Dec': 1146…
7	{1: 3450, 2: 3720, 3: 3583, 4: 3433, 5: 1234}
8	{'Female': 2420, 'Male': 13000}
9	{'Divorced': 76, 'Married': 10625, 'Single': 4…
10	{0: 320, 16: 9, 17: 6, 18: 48, 19: 32, 20: 28,…
11	{'Policy Holder': 11230, 'Third Party': 4190}
12	{'Sedan - All Perils': 4087, 'Sedan - Collisio…
13	{'Sedan': 9671, 'Sport': 5358, 'Utility': 391}
14	{'20000 to 29000': 8079, '30000 to 39000': 353…
15	{0: 14497, 1: 923}
16	{1: 1, 2: 1, 3: 1, 4: 1, 5: 1, 6: 1, 7: 1, 8: …
17	{1: 987, 2: 956, 3: 949, 4: 912, 5: 987, 6: 94…
18	{300: 8, 400: 14838, 500: 263, 700: 311}
19	{1: 3944, 2: 3801, 3: 3884, 4: 3791}
20	{'1 to 7': 14, '15 to 30': 49, '8 to 15': 55, …
21	{'15 to 30': 56, '8 to 15': 21, 'more than 30'…
22	{'1': 3573, '2 to 4': 5485, 'more than 4': 201…
23	{'2 years': 73, '3 years': 152, '4 years': 229…
24	{'16 to 17': 320, '18 to 20': 15, '21 to 25': …
25	{'No': 14992, 'Yes': 428}
26	{'No': 15333, 'Yes': 87}
27	{'External': 15179, 'Internal': 241}
28	{'1 to 2': 2489, '3 to 5': 2017, 'more than 5'…
29	{'1 year': 170, '2 to 3 years': 291, '4 to 8 y…
30	{'1 vehicle': 14316, '2 vehicles': 709, '3 to …
31	{1994: 6142, 1995: 5195, 1996: 4083}
32	{'All Perils': 4449, 'Collision': 5962, 'Liabi…

3.3.1 Primeras observaciones

Variables categóricas simples

- **AccidentArea** → Convertir a variable booleana (`Urban`=1, `Rural`=0).
- **Sex** → Convertir a booleana (`Male`=1, `Female`=0).
- **Fault** → Convertir a booleana (`Third Party`=1, `Policy Holder`=0).
- **PoliceReportFiled** → Convertir a booleana (`Yes`=1, `No`=0).
- **WitnessPresent** → Convertir a booleana (`Yes`=1, `No`=0).
- **AgentType** → Convertir a booleana (`Internal`=1, `External`=0).

Variables con valores erróneos

- **DayOfWeekClaimed** → 8 valores únicos; el valor `0` es erróneo → eliminar (solo 1 caso).
- **MonthClaimed** → 13 valores únicos; el valor `0` es erróneo → eliminar (solo 1 caso).
- **Age** → Contiene `0` (no válido como edad) → imputar (hay bastantes casos).

Variables redundantes o poco informativas

- **PolicyType** → Parece la combinación de **VehicleCategory** y **BasePolicy**. A analizar su redundancia.
- **Age** y **AgeOfPolicyHolder** → Parecen la misma variable. Como **Age** tiene muchos valores 0, se opta por eliminar esta variable y mantener la segunda.
- **PolicyNumber** → Identificador único, sin valor predictivo.
- **RepNumber** → Identificador único, sin valor predictivo.
- **Year** → Variable temporal que no puede usarse en un entorno real porque no generaliza a años futuro.

Variables con valores en rangos que requieren conversión Para estas variables categóricas con intervalos de valores, reemplazar cada rango por el valor medio y convertir a **float**: - **VehiclePrice** - **Days_Policy_Accident** - **Days_Policy_Claim** - **AgeOfVehicle** - **NumberOfCars** - **PastNumberOfClaims** - **AgeOfPolicyHolder** - **NumberOfSuppliments** - **AddressChange_Claim**

Variables que no tienen clarificación

- **DriverRating** → ¿En qué se basa esa puntuación? Eliminar por falta de información.

Variables categóricas a codificar A continuación, se identifican las variables categóricas que necesitan ser transformadas antes de ser utilizadas en el modelo: - **Month** - **DayOfWeek** - **Make** - **DayOfWeekClaimed** - **MonthClaimed** - **MaritalStatus** - **VehicleCategory** - **BasePolicy** - **AddressChange_Claim**

Problemas de desbalance

- **FraudFound_P** → Variable objetivo muy desbalanceada (~6% casos positivos). Se valora aplicar SMOTE en el modelo.

3.4 Valores atípicos

[6]:
```
# Para variables numéricas:
## Cálculo del coeficiente de asimetría (skewness)

df.select_dtypes(include=np.number).skew()
```

[6]:
```
WeekOfMonth           0.115426
WeekOfMonthClaimed    0.158233
Age                   0.152314
FraudFound_P          3.711164
PolicyNumber          0.000000
RepNumber             0.006628
Deductible            6.078803
DriverRating          0.009283
Year                  0.245689
dtype: float64
```

[7]:
```
# Para variables numéricas:
## Extracción de estadísticas clave: media, desviación estándar (std), mínimo,␣
 ↪máximo, y los percentiles 25%, 50% y 75%

df.describe(include=np.number)
```

[7]:

	WeekOfMonth	WeekOfMonthClaimed	Age	FraudFound_P	\
count	15420.000000	15420.000000	15420.000000	15420.000000	
mean	2.788586	2.693969	39.855707	0.059857	
std	1.287585	1.259115	13.492377	0.237230	
min	1.000000	1.000000	0.000000	0.000000	
25%	2.000000	2.000000	31.000000	0.000000	
50%	3.000000	3.000000	38.000000	0.000000	
75%	4.000000	4.000000	48.000000	0.000000	
max	5.000000	5.000000	80.000000	1.000000	

	PolicyNumber	RepNumber	Deductible	DriverRating	Year
count	15420.000000	15420.000000	15420.000000	15420.000000	15420.000000
mean	7710.500000	8.483268	407.704280	2.487808	1994.866472
std	4451.514911	4.599948	43.950998	1.119453	0.803313
min	1.000000	1.000000	300.000000	1.000000	1994.000000
25%	3855.750000	5.000000	400.000000	1.000000	1994.000000
50%	7710.500000	8.000000	400.000000	2.000000	1995.000000
75%	11565.250000	12.000000	400.000000	3.000000	1996.000000
max	15420.000000	16.000000	700.000000	4.000000	1996.000000

[8]:
```
# Para variables categóricas:
## Extracción de estadísticas clave: top y frecuencia

df.describe(exclude=np.number)
```

[8]:
```
        Month DayOfWeek     Make AccidentArea DayOfWeekClaimed MonthClaimed  \
count   15420     15420    15420        15420             15420        15420
unique     12         7       19            2                 8           13
top       Jan    Monday  Pontiac        Urban            Monday          Jan
freq     1411      2616     3837        13822              3757         1446

          Sex MaritalStatus          Fault         PolicyType  …  \
count   15420         15420          15420              15420  …
unique      2             4              2                  9  …
top      Male       Married  Policy Holder  Sedan - Collision  …
freq    13000         10625          11230               5584  …

       PastNumberOfClaims AgeOfVehicle AgeOfPolicyHolder PoliceReportFiled  \
count               15420        15420             15420             15420
unique                  4            8                 9                 2
top                 2 to 4      7 years          31 to 35                No
freq                 5485         5807              5593             14992

       WitnessPresent AgentType NumberOfSuppliments AddressChange_Claim  \
count           15420     15420               15420              15420
unique              2         2                   4                  5
top                No  External                none          no change
freq            15333     15179                7047              14324

       NumberOfCars BasePolicy
count         15420      15420
unique            5          3
top       1 vehicle  Collision
freq          14316       5962

[4 rows x 24 columns]
```

3.4.1 Observaciones sobre las variables numéricas

1. **Age**
   - Mínimo = 0 → valor inválido.
   - Máximo = 80 → razonable.
   - Media 39.86 → predominan adultos de mediana edad.
2. **FraudFound_P**
   - Media 0.059 → confirma fuerte desbalance (~6% casos positivos).
3. **PolicyNumber**

- Rango 0–15420 → identificador único sin valor predictivo. Se eliminará.

4. **RepNumber**
   - Rango 1–16 → código interno del representante. Se eliminará.
5. **Deductible**
   - Valores entre 300 y 700 esperados, pero predominio claro en 400.
6. **DriverRating**
   - Rango 1–4 → variable ordinal. Se eliminará.
7. **Year**
   - Rango 1994–1996 → dataset solo cubre 3 años.
8. **WeekOfMonth / WeekOfMonthClaimed**
   - Rango 1–5.

   - Medias ~2.7

3.5 Valores faltantes

[9]:
```
# Recuento de valores NaN explícitos

df.isnull().sum()
```

[9]:
```
Month                 0
WeekOfMonth           0
DayOfWeek             0
Make                  0
AccidentArea          0
DayOfWeekClaimed      0
MonthClaimed          0
WeekOfMonthClaimed    0
Sex                   0
MaritalStatus         0
Age                   0
Fault                 0
PolicyType            0
VehicleCategory       0
VehiclePrice          0
FraudFound_P          0
PolicyNumber          0
RepNumber             0
Deductible            0
DriverRating          0
Days_Policy_Accident  0
Days_Policy_Claim     0
PastNumberOfClaims    0
AgeOfVehicle          0
AgeOfPolicyHolder     0
PoliceReportFiled     0
WitnessPresent        0
```

```
AgentType               0
NumberOfSuppliments     0
AddressChange_Claim     0
NumberOfCars            0
Year                    0
BasePolicy              0
dtype: int64
```

Se confirma que no existen valores *missing*.

3.6 Análisis de colinealidad y correlación

3.6.1 Análisis variables numéricas

[10]:
```
# Mapa de calor de correlaciones (heatmap) con degradado de color para␣
↪identificar visualmente relaciones destacadas entre pares de variables

corr = df.select_dtypes(include=np.number).corr()
corr.style.background_gradient(cmap='coolwarm').format(precision=3)
```

[10]:
```
<pandas.io.formats.style.Styler at 0x20610054790>
```

[11]:
```
# Clasificación de correlaciones absolutas respecto a la variable objetivo,␣
↪ordenadas de mayor a menor.

corr = abs(df.select_dtypes(include=np.number).corr())
corr[['FraudFound_P']].sort_values(by = 'FraudFound_P',ascending = False)
```

[11]:
```
                    FraudFound_P
FraudFound_P            1.000000
Age                     0.029741
Year                    0.024760
PolicyNumber            0.020345
Deductible              0.017348
WeekOfMonth             0.011861
RepNumber               0.007551
DriverRating            0.007266
WeekOfMonthClaimed      0.005761
```

Observaciones **Magnitudes muy bajas** - Ninguna variable numérica presenta correlación $>$ 0.03 con **FraudFound_P**. - Esto confirma que no hay una variable numérica aislada que sea un predictor fuerte de fraude. - El poder predictivo probablemente esté en combinaciones de variables y patrones no lineales.

Otras observaciones: - El modelo deberá explotar interacciones y relaciones no lineales, lo que sugiere que algoritmos como árboles de decisión (XGBoost o LightGBM) pueden ser más adecuados que modelos lineales simples.

3.6.2 Análisis variables categóricas

[12]:
```python
# Función V de Cramér
def cramers_v(x, y):
    tab = pd.crosstab(x, y)
    chi2 = ss.chi2_contingency(tab)[0]
    n = tab.values.sum()
    phi2 = chi2 / n
    r, k = tab.shape
    # Corrección por sesgo
    phi2corr = max(0, phi2 - ((k-1)*(r-1))/(n-1))
    rcorr = r - ((r-1)**2)/(n-1)
    kcorr = k - ((k-1)**2)/(n-1)
    denom = min((kcorr-1), (rcorr-1))
    return np.sqrt(phi2corr / denom) if denom > 0 else np.nan

# Selección de categóricas
MAX_CARDINALITY = 50
cat_cols = [
    c for c in df.columns
    if (
        (df[c].dtype == 'object' or str(df[c].dtype) == 'category')
        or (pd.api.types.is_integer_dtype(df[c]) and df[c].nunique() <= 15)
    )
]

# Ajustes varios
target = 'FraudFound_P'
cat_cols = [c for c in cat_cols if c != target]

to_exclude = {'PolicyNumber', 'RepNumber', 'Year', 'DriverRating'}
cat_cols = [c for c in cat_cols if c not in to_exclude]

y = df[target].astype(str)

# Cálculo en bloque
rows = []
for c in cat_cols:
    x = df[c].astype(str)  # tratar NaN como 'nan'
    # (opcional) saltar columnas con cardinalidad desmesurada
    if x.nunique(dropna=False) > MAX_CARDINALITY:
        rows.append({"variable": c, "cardinalidad": x.nunique(), "v_cramer": np.
 ↪nan})
        continue
    v = cramers_v(x, y)
    rows.append({"variable": c, "cardinalidad": x.nunique(), "v_cramer": v})
```

```
cramer_df = (
    pd.DataFrame(rows)
    .sort_values("v_cramer", ascending=False)
    .reset_index(drop=True)
)

cramer_df
```

[12]:

	variable	cardinalidad	v_cramer
0	PolicyType	9	0.166880
1	BasePolicy	3	0.161237
2	VehicleCategory	3	0.136892
3	Fault	2	0.130839
4	AddressChange_Claim	5	0.080827
5	Deductible	4	0.067096
6	VehiclePrice	6	0.063803
7	PastNumberOfClaims	4	0.057230
8	Make	19	0.052072
9	MonthClaimed	13	0.044305
10	AgeOfPolicyHolder	9	0.040269
11	Month	12	0.034914
12	AccidentArea	2	0.032056
13	NumberOfSuppliments	4	0.031336
14	AgeOfVehicle	8	0.031116
15	Sex	2	0.028461
16	Days_Policy_Accident	5	0.022159
17	AgentType	2	0.020341
18	DayOfWeek	7	0.016406
19	PoliceReportFiled	2	0.012863
20	Days_Policy_Claim	4	0.011045
21	WeekOfMonth	5	0.000000
22	DayOfWeekClaimed	8	0.000000
23	MaritalStatus	4	0.000000
24	WitnessPresent	2	0.000000
25	NumberOfCars	5	0.000000
26	WeekOfMonthClaimed	5	0.000000

[13]:
```
# Matriz vacía
redundancy_matrix = pd.DataFrame(index=cat_cols, columns=cat_cols, dtype=float)

# Cálculo
for col1 in cat_cols:
    for col2 in cat_cols:
        if col1 == col2:
            redundancy_matrix.loc[col1, col2] = 1.0
        else:
            redundancy_matrix.loc[col1, col2] = cramers_v(
```

```
                df[col1].astype(str),
                df[col2].astype(str)
            )

redundancy_matrix
```

[13]:

	Month	WeekOfMonth	DayOfWeek	Make
Month	1.000000	0.041288	0.038230	0.000000
WeekOfMonth	0.041288	1.000000	0.015834	0.005024
DayOfWeek	0.038230	0.015834	1.000000	0.000000
Make	0.000000	0.005024	0.000000	1.000000
AccidentArea	0.011199	0.008196	0.024085	0.046078
DayOfWeekClaimed	0.033688	0.009069	0.143995	0.000000
MonthClaimed	0.747048	0.034555	0.011495	0.000000
WeekOfMonthClaimed	0.055586	0.401083	0.000000	0.000000
Sex	0.016662	0.000000	0.019061	0.073264
MaritalStatus	0.000000	0.010735	0.016736	0.067654
Fault	0.009280	0.019905	0.038686	0.046709
PolicyType	0.017798	0.023917	0.029341	0.165184
VehicleCategory	0.018287	0.017377	0.052441	0.192175
VehiclePrice	0.017490	0.000000	0.016892	0.260183
Deductible	0.006343	0.000000	0.017547	0.009295
Days_Policy_Accident	0.000000	0.014556	0.010988	0.018159
Days_Policy_Claim	0.009792	0.007332	0.005856	0.000000
PastNumberOfClaims	0.017109	0.004506	0.015877	0.033761
AgeOfVehicle	0.042221	0.000000	0.013079	0.136873
AgeOfPolicyHolder	0.031756	0.010117	0.021922	0.120186
PoliceReportFiled	0.048222	0.002525	0.012841	0.009755
WitnessPresent	0.000000	0.000000	0.000000	0.000000
AgentType	0.018577	0.000000	0.000000	0.033383
NumberOfSuppliments	0.015619	0.000000	0.005012	0.050781
AddressChange_Claim	0.007780	0.000000	0.000000	0.000000
NumberOfCars	0.059911	0.000000	0.000000	0.027050
BasePolicy	0.027061	0.006613	0.043162	0.114251

	AccidentArea	DayOfWeekClaimed	MonthClaimed
Month	0.011199	0.033688	0.747048
WeekOfMonth	0.008196	0.009069	0.034555
DayOfWeek	0.024085	0.143995	0.011495
Make	0.046078	0.000000	0.000000
AccidentArea	1.000000	0.025763	0.028732
DayOfWeekClaimed	0.025763	1.000000	0.379825
MonthClaimed	0.028732	0.379825	1.000000
WeekOfMonthClaimed	0.008328	0.034784	0.062432
Sex	0.032531	0.000000	0.013365
MaritalStatus	0.000000	0.001638	0.000000
Fault	0.002637	0.018565	0.011617

PolicyType	0.067619	0.027996	0.017422
VehicleCategory	0.063997	0.020026	0.014175
VehiclePrice	0.018663	0.000000	0.024735
Deductible	0.000000	0.004408	0.000000
Days_Policy_Accident	0.000000	0.000000	0.000000
Days_Policy_Claim	0.020319	0.577352	0.577017
PastNumberOfClaims	0.061275	0.003849	0.021527
AgeOfVehicle	0.017491	0.019671	0.050035
AgeOfPolicyHolder	0.019578	0.023098	0.044539
PoliceReportFiled	0.000000	0.010614	0.058189
WitnessPresent	0.025711	0.009409	0.000000
AgentType	0.000000	0.022069	0.026430
NumberOfSuppliments	0.014681	0.000000	0.015780
AddressChange_Claim	0.025268	0.000000	0.000000
NumberOfCars	0.006159	0.003409	0.041025
BasePolicy	0.055858	0.015649	0.032798

	WeekOfMonthClaimed	Sex	MaritalStatus	…	\
Month	0.055586	0.016662	0.000000	…	
WeekOfMonth	0.401083	0.000000	0.010735	…	
DayOfWeek	0.000000	0.019061	0.016736	…	
Make	0.000000	0.073264	0.067654	…	
AccidentArea	0.008328	0.032531	0.000000	…	
DayOfWeekClaimed	0.034784	0.000000	0.001638	…	
MonthClaimed	0.062432	0.013365	0.000000	…	
WeekOfMonthClaimed	1.000000	0.000000	0.005955	…	
Sex	0.000000	1.000000	0.155753	…	
MaritalStatus	0.005955	0.155753	1.000000	…	
Fault	0.000000	0.000000	0.000000	…	
PolicyType	0.013266	0.092137	0.043917	…	
VehicleCategory	0.016659	0.082461	0.044580	…	
VehiclePrice	0.015760	0.146593	0.070636	…	
Deductible	0.000000	0.016676	0.018958	…	
Days_Policy_Accident	0.000000	0.000000	0.019803	…	
Days_Policy_Claim	0.006032	0.000000	0.009557	…	
PastNumberOfClaims	0.015204	0.000000	0.013760	…	
AgeOfVehicle	0.000000	0.212081	0.265808	…	
AgeOfPolicyHolder	0.000000	0.135169	0.304052	…	
PoliceReportFiled	0.023282	0.000000	0.000000	…	
WitnessPresent	0.000000	0.000000	0.012698	…	
AgentType	0.006986	0.008846	0.012194	…	
NumberOfSuppliments	0.009305	0.008177	0.020860	…	
AddressChange_Claim	0.006687	0.000000	0.000000	…	
NumberOfCars	0.000000	0.000000	0.012541	…	
BasePolicy	0.013382	0.068938	0.036605	…	

	PastNumberOfClaims	AgeOfVehicle	AgeOfPolicyHolder	\

Month	0.017109	0.042221	0.031756
WeekOfMonth	0.004506	0.000000	0.010117
DayOfWeek	0.015877	0.013079	0.021922
Make	0.033761	0.136873	0.120186
AccidentArea	0.061275	0.017491	0.019578
DayOfWeekClaimed	0.003849	0.019671	0.023098
MonthClaimed	0.021527	0.050035	0.044539
WeekOfMonthClaimed	0.015204	0.000000	0.000000
Sex	0.000000	0.212081	0.135169
MaritalStatus	0.013760	0.265808	0.304052
Fault	0.126672	0.043507	0.055378
PolicyType	0.231660	0.083601	0.106387
VehicleCategory	0.237430	0.067292	0.075888
VehiclePrice	0.090318	0.192351	0.178653
Deductible	0.000000	0.077220	0.051775
Days_Policy_Accident	0.029486	0.034691	0.018085
Days_Policy_Claim	0.025142	0.034077	0.033518
PastNumberOfClaims	1.000000	0.036825	0.031441
AgeOfVehicle	0.036825	1.000000	0.534242
AgeOfPolicyHolder	0.031441	0.534242	1.000000
PoliceReportFiled	0.002223	0.004303	0.000000
WitnessPresent	0.016320	0.027724	0.013846
AgentType	0.023476	0.013653	0.000000
NumberOfSuppliments	0.065960	0.114915	0.094889
AddressChange_Claim	0.011213	0.013065	0.000000
NumberOfCars	0.012969	0.000000	0.000000
BasePolicy	0.266603	0.095617	0.112224

	PoliceReportFiled	WitnessPresent	AgentType	\
Month	0.048222	0.000000	0.018577	
WeekOfMonth	0.002525	0.000000	0.000000	
DayOfWeek	0.012841	0.000000	0.000000	
Make	0.009755	0.000000	0.033383	
AccidentArea	0.000000	0.025711	0.000000	
DayOfWeekClaimed	0.010614	0.009409	0.022069	
MonthClaimed	0.058189	0.000000	0.026430	
WeekOfMonthClaimed	0.023282	0.000000	0.006986	
Sex	0.000000	0.000000	0.008846	
MaritalStatus	0.000000	0.012698	0.012194	
Fault	0.025564	0.059523	0.000000	
PolicyType	0.041240	0.045639	0.097221	
VehicleCategory	0.038857	0.025268	0.042754	
VehiclePrice	0.000000	0.000000	0.096403	
Deductible	0.000000	0.000000	0.000000	
Days_Policy_Accident	0.017715	0.054121	0.000000	
Days_Policy_Claim	0.007099	0.000000	0.000000	
PastNumberOfClaims	0.002223	0.016320	0.023476	

AgeOfVehicle	0.004303	0.027724	0.013653
AgeOfPolicyHolder	0.000000	0.013846	0.000000
PoliceReportFiled	1.000000	0.195301	0.020126
WitnessPresent	0.195301	1.000000	0.000000
AgentType	0.020126	0.000000	1.000000
NumberOfSuppliments	0.018762	0.006749	0.030873
AddressChange_Claim	0.017343	0.000000	0.021645
NumberOfCars	0.022276	0.000000	0.026340
BasePolicy	0.042135	0.037662	0.082518

	NumberOfSuppliments	AddressChange_Claim	NumberOfCars	\
Month	0.015619	0.007780	0.059911	
WeekOfMonth	0.000000	0.000000	0.000000	
DayOfWeek	0.005012	0.000000	0.000000	
Make	0.050781	0.000000	0.027050	
AccidentArea	0.014681	0.025268	0.006159	
DayOfWeekClaimed	0.000000	0.000000	0.003409	
MonthClaimed	0.015780	0.000000	0.041025	
WeekOfMonthClaimed	0.009305	0.006687	0.000000	
Sex	0.008177	0.000000	0.000000	
MaritalStatus	0.020860	0.000000	0.012541	
Fault	0.025418	0.000000	0.000000	
PolicyType	0.049261	0.035023	0.019327	
VehicleCategory	0.027005	0.000000	0.000000	
VehiclePrice	0.054728	0.000000	0.000000	
Deductible	0.011993	0.534026	0.032926	
Days_Policy_Accident	0.054258	0.009411	0.049161	
Days_Policy_Claim	0.036354	0.000000	0.000000	
PastNumberOfClaims	0.065960	0.011213	0.012969	
AgeOfVehicle	0.114915	0.013065	0.000000	
AgeOfPolicyHolder	0.094889	0.000000	0.000000	
PoliceReportFiled	0.018762	0.017343	0.022276	
WitnessPresent	0.006749	0.000000	0.000000	
AgentType	0.030873	0.021645	0.026340	
NumberOfSuppliments	1.000000	0.000000	0.000000	
AddressChange_Claim	0.000000	1.000000	0.467649	
NumberOfCars	0.000000	0.467649	1.000000	
BasePolicy	0.034918	0.004204	0.000000	

	BasePolicy
Month	0.027061
WeekOfMonth	0.006613
DayOfWeek	0.043162
Make	0.114251
AccidentArea	0.055858
DayOfWeekClaimed	0.015649
MonthClaimed	0.032798

```
WeekOfMonthClaimed      0.013382
Sex                     0.068938
MaritalStatus           0.036605
Fault                   0.206502
PolicyType              0.999805
VehicleCategory         0.680729
VehiclePrice            0.204117
Deductible              0.009129
Days_Policy_Accident    0.024216
Days_Policy_Claim       0.016300
PastNumberOfClaims      0.266603
AgeOfVehicle            0.095617
AgeOfPolicyHolder       0.112224
PoliceReportFiled       0.042135
WitnessPresent          0.037662
AgentType               0.082518
NumberOfSuppliments     0.034918
AddressChange_Claim     0.004204
NumberOfCars            0.000000
BasePolicy              1.000000

[27 rows x 27 columns]
```

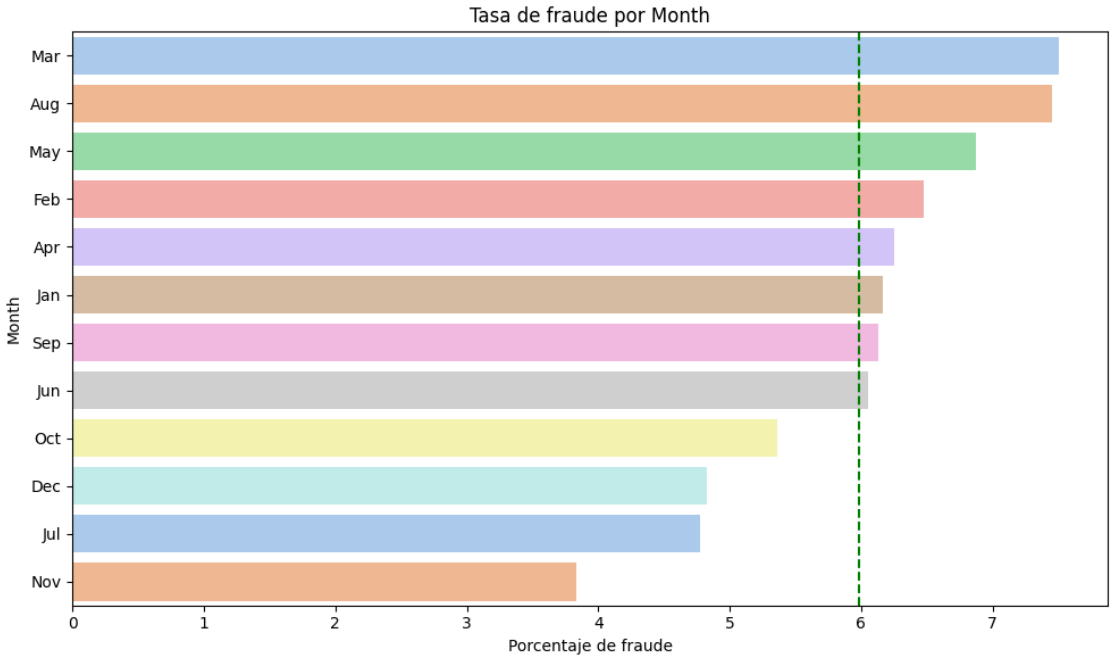
Observaciones **Correlación con la variable objetivo** - Las variables categóricas muestran correlaciones más altas con el fraude.

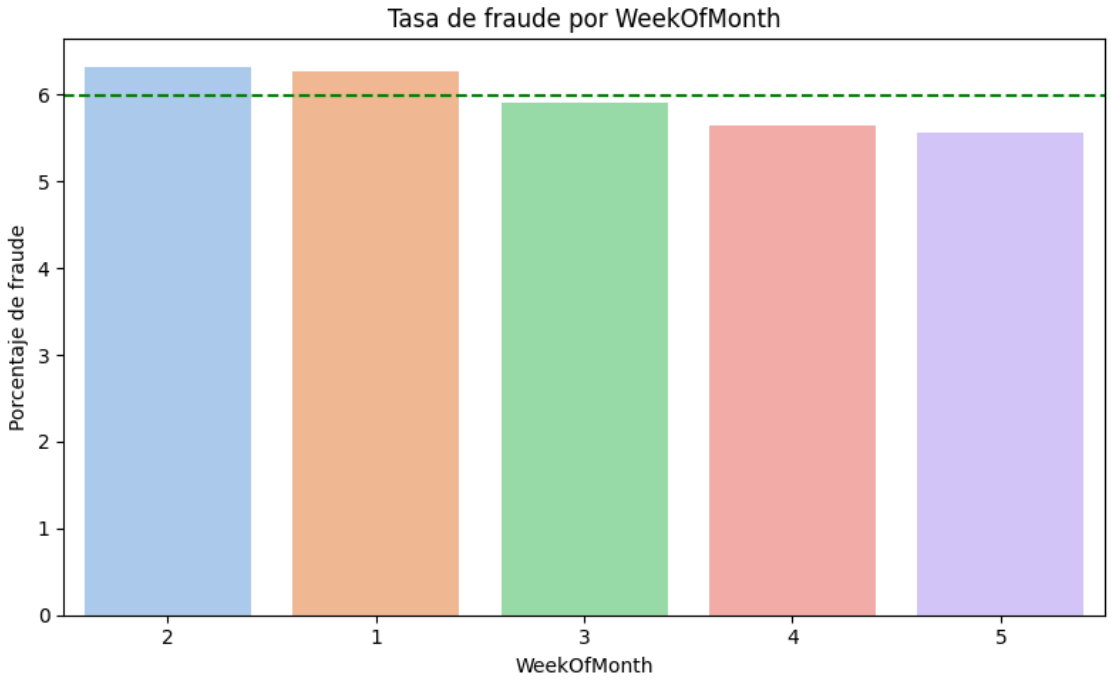
Redundancia entre categóricas relevantes - **PolicyType** **BasePolicy** → V 0.9998 → redundancia casi perfecta. - **PolicyType** **VehicleCategory** → V 0.9998 → redundancia casi perfecta. - Eliminar **PolicyType** para evitar colinealidad extrema.

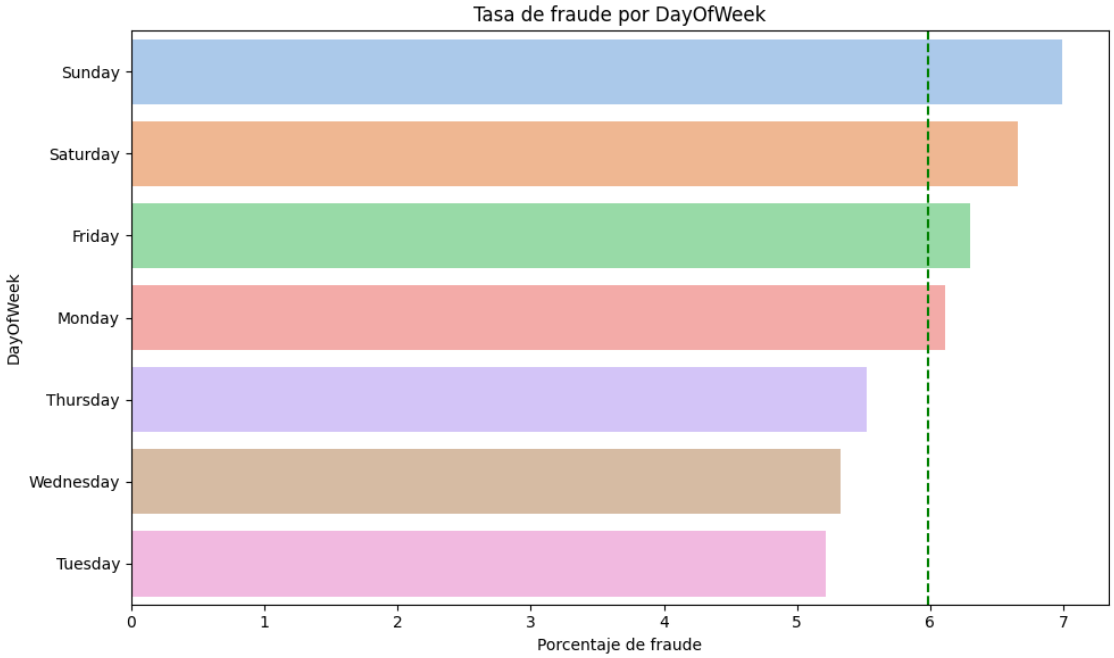
3.7 Descomposición de la variable objetivo por subgrupos predictivos

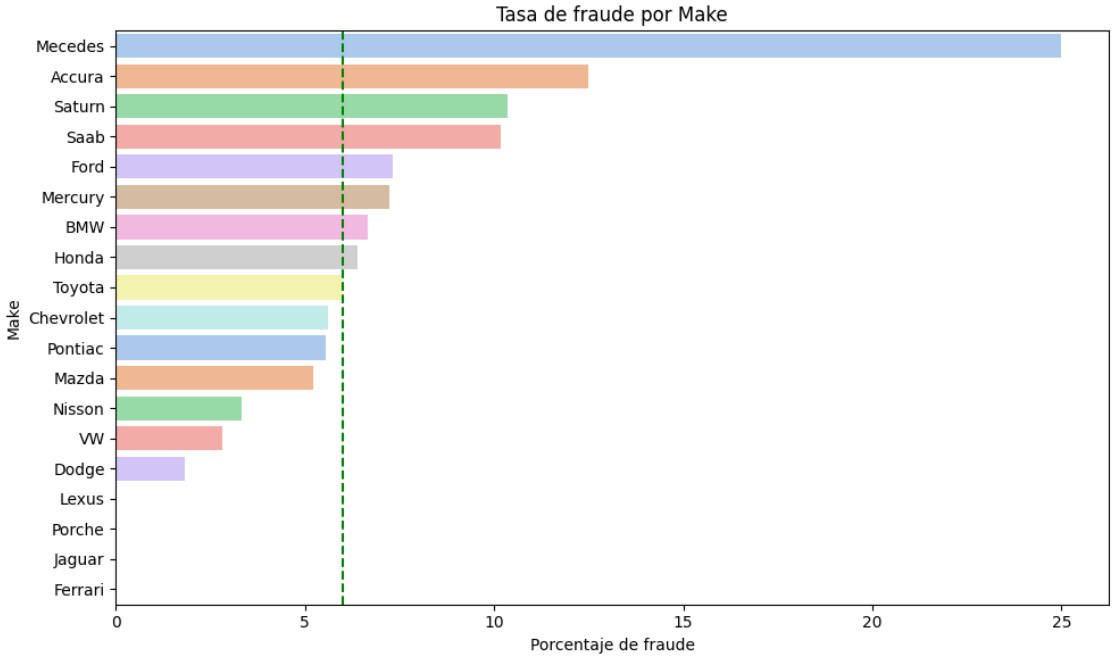
[14]:
```
# Variables a excluir porque se van a eliminar
excluded_cols = ['FraudFound_P', 'PolicyNumber', 'RepNumber', 'PolicyType',␣
 ↪'Age', 'DriverRating', 'Year']
# Variable objetivo
target_col = 'FraudFound_P'

features = [col for col in df.columns if col not in excluded_cols and not col.
 ↪endswith('_binned')]

# Función personalizada que calcula, para cada categoría o intervalo, la tasa␣
 ↪de fraude como el porcentaje de registros etiquetados como fraudulentos
def plot_fraud_rate(df, column, target='FraudFound_P', horizontal=False):
    data = df.groupby(column)[target].agg(['count', 'sum']).reset_index()
    data['percentage'] = 100 * data['sum'] / data['count']
    data = data.sort_values('percentage', ascending=False)
```

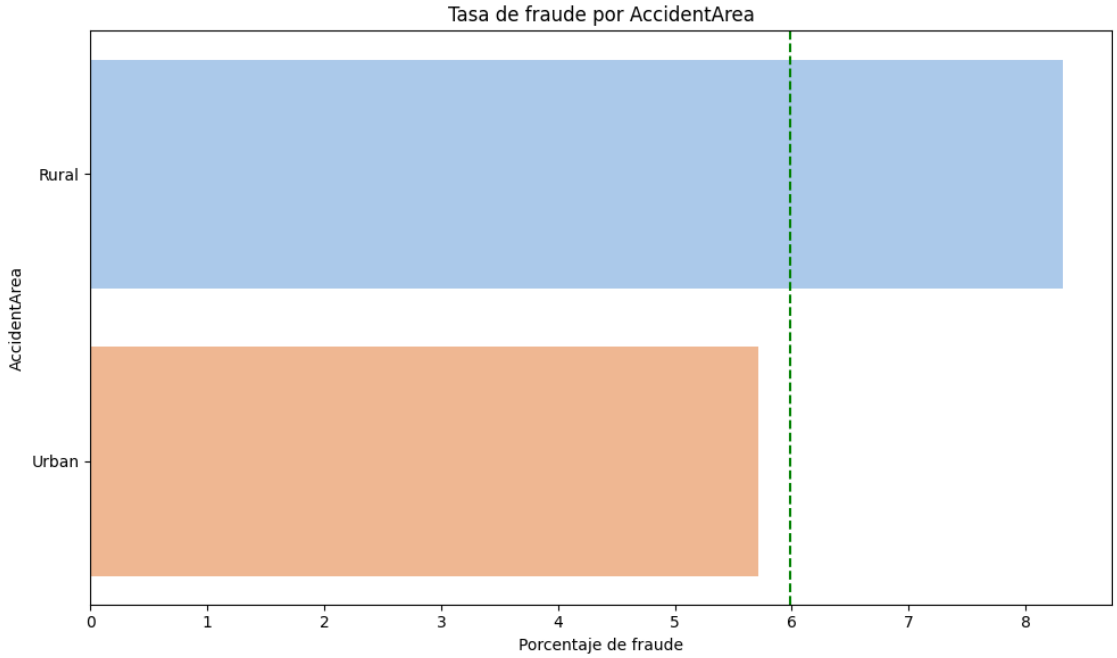
```
    data[column] = data[column].astype(str)

    unique_vals = data[column].nunique()
    palette = sns.color_palette("pastel", n_colors=unique_vals)
    figsize = (10, 6) if horizontal else (8, 5)
    plt.figure(figsize=figsize)
    if horizontal:
        sns.barplot(y=column, x='percentage', data=data, palette=palette)
        plt.axvline(df[target].mean() * 100, color='green', linestyle='--')
        plt.xlabel('Porcentaje de fraude')
        plt.ylabel(column)
    else:
        sns.barplot(x=column, y='percentage', data=data, palette=palette)
        plt.axhline(df[target].mean() * 100, color='green', linestyle='--')
        plt.ylabel('Porcentaje de fraude')
        plt.xlabel(column)

    plt.title(f'Tasa de fraude por {column}', loc='center')
    plt.tight_layout()
    plt.show()

# Para variables numéricas con alta cardinalidad,proceso de discretización por␣
 ↪cuantiles (qcut) en cinco intervalos para facilitar su interpretación y␣
 ↪comparación.
for col in features:
    if df[col].nunique() <= 1:
        continue
    if pd.api.types.is_numeric_dtype(df[col]):
        if df[col].nunique() > 20:
            binned_col = f'{col}_binned'
            df[binned_col] = pd.qcut(df[col], q=5, duplicates='drop')
            plot_fraud_rate(df, binned_col, target=target_col, horizontal=True)
        else:
            plot_fraud_rate(df, col, target=target_col, horizontal=False)
    else:
        plot_fraud_rate(df, col, target=target_col, horizontal=True)
```

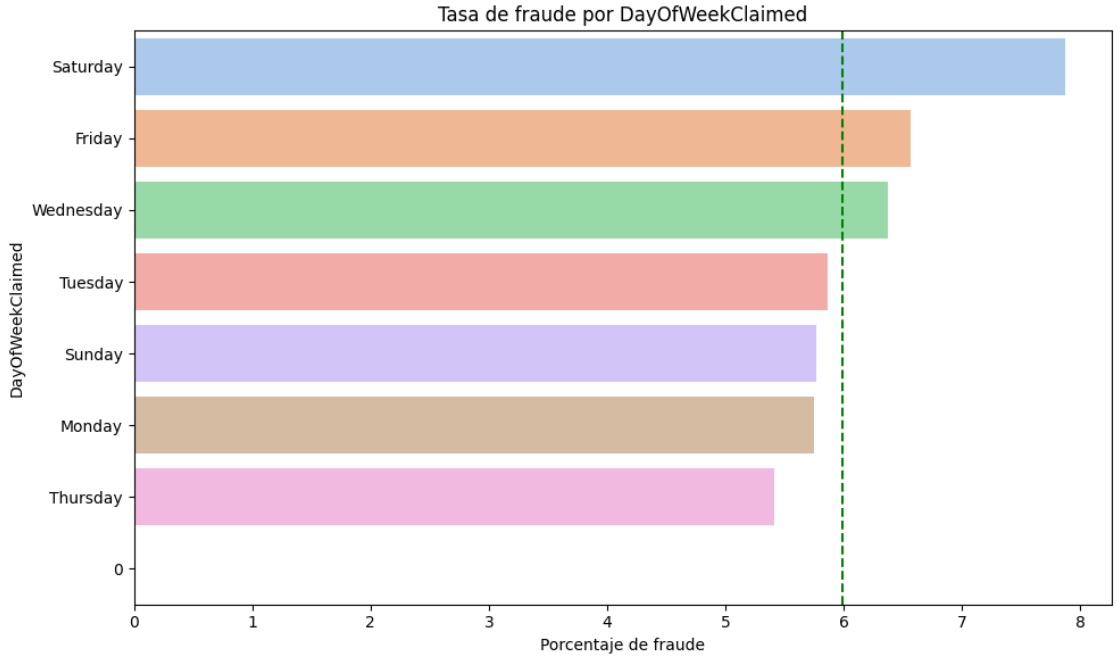

Tasa de fraude por Month
Mar
Aug
May
Feb
Apr
Jan
Sep
Jun
Oct
Dec
Jul
Nov
Month
0
1
2
3
4
5
6
7
Porcentaje de fraude

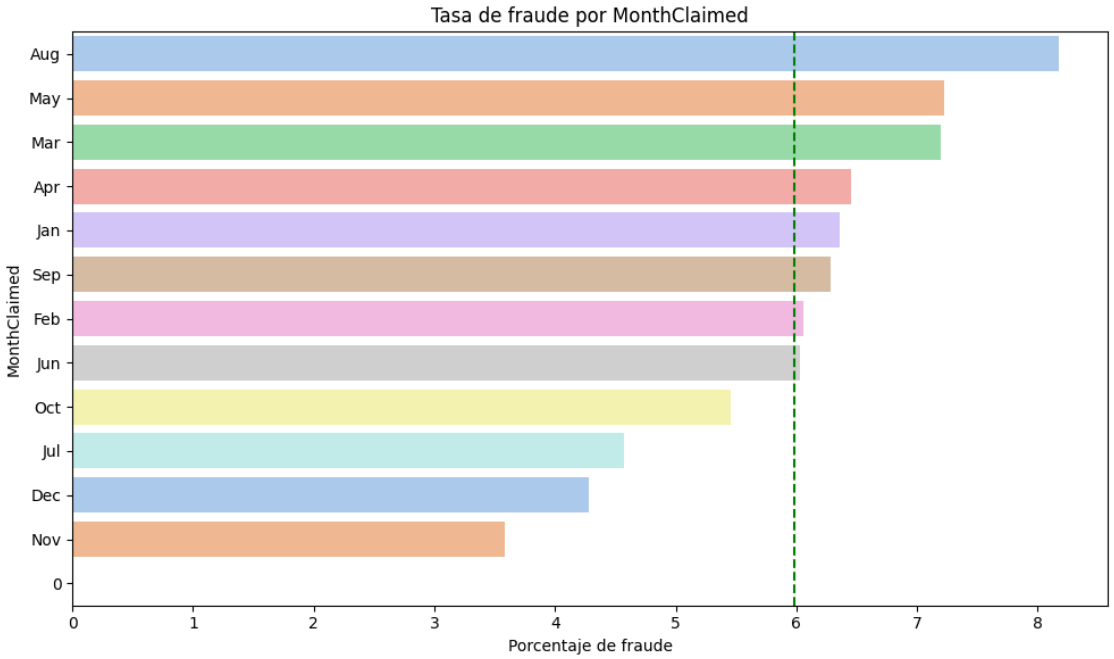

Tasa de fraude por WeekOfMonth
0
1
2
3
4
5
6
Porcentaje de fraude
2
1
3
4
5
WeekOfMonth


Tasa de fraude por DayOfWeek
Sunday
Saturday
Friday
Monday
Thursday
Wednesday
Tuesday
DayOfWeek
0
1
2
3
4
5
6
7
Porcentaje de fraude

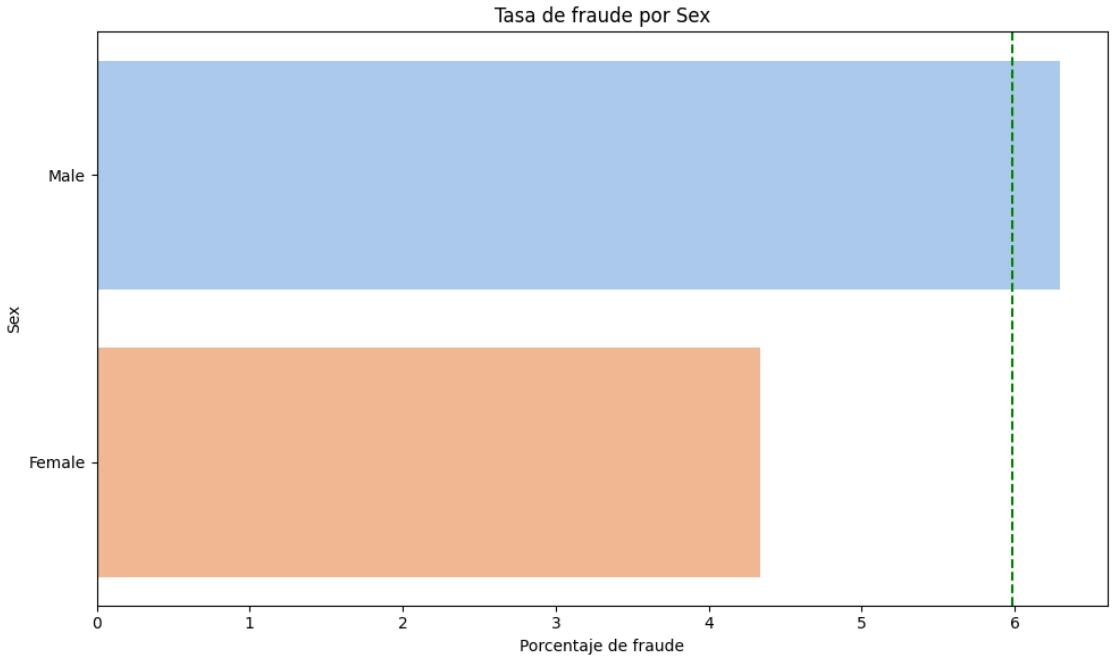

Tasa de fraude por Make
Mecedes
Accura
Saturn
Saab
Ford
Mercury
BMW
Honda
Toyota
Chevrolet
Pontiac
Mazda
Nisson
VW
Dodge
Lexus
Porche
Jaguar
Ferrari
Make
0
5
10
15
20
25
Porcentaje de fraude

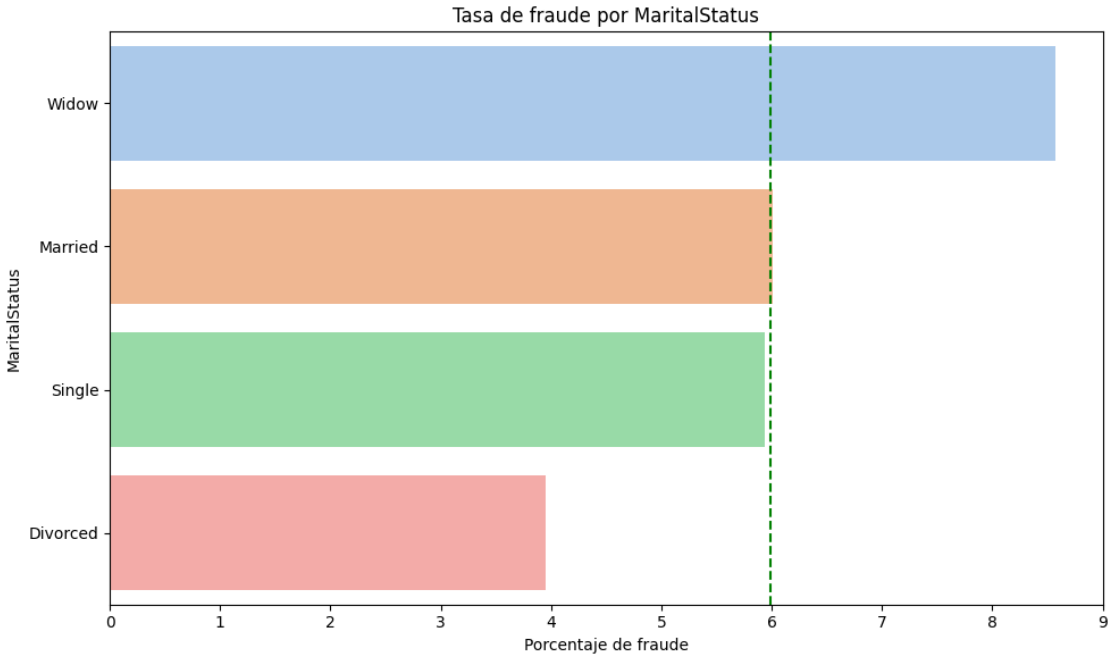

Tasa de fraude por AccidentArea
AccidentArea
Rural
Urban
0
1
2
3
4
5
6
7
8
Porcentaje de fraude

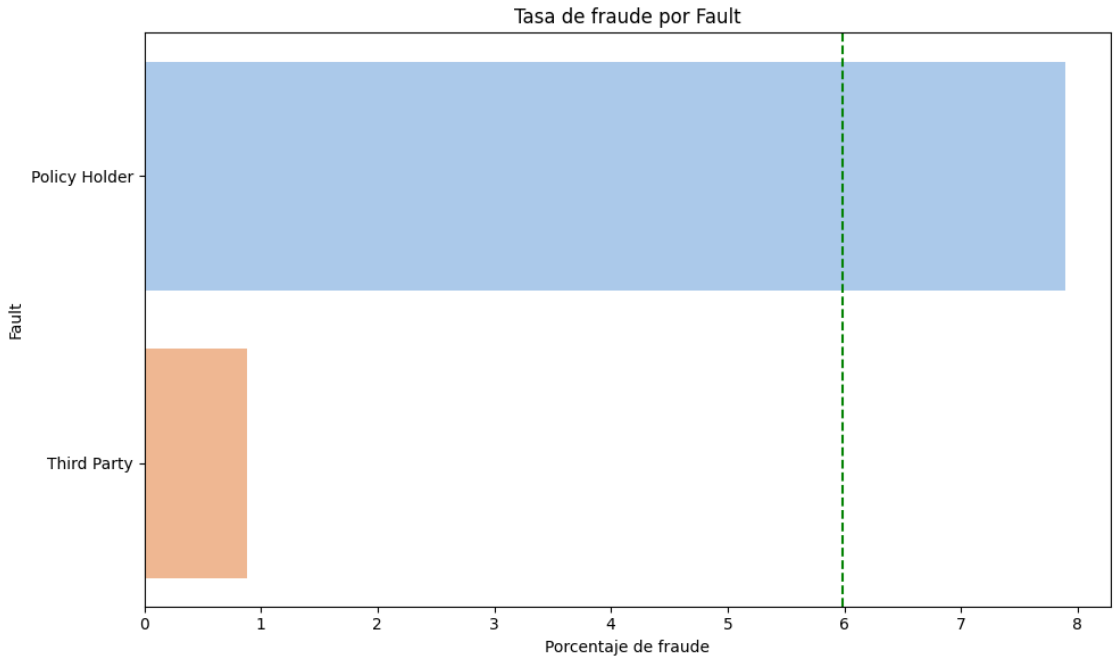

Tasa de fraude por DayOfWeekClaimed
DayOfWeekClaimed
Saturday
Friday
Wednesday
Tuesday
Sunday
Monday
Thursday
0
0
1
2
3
4
5
6
7
8
Porcentaje de fraude

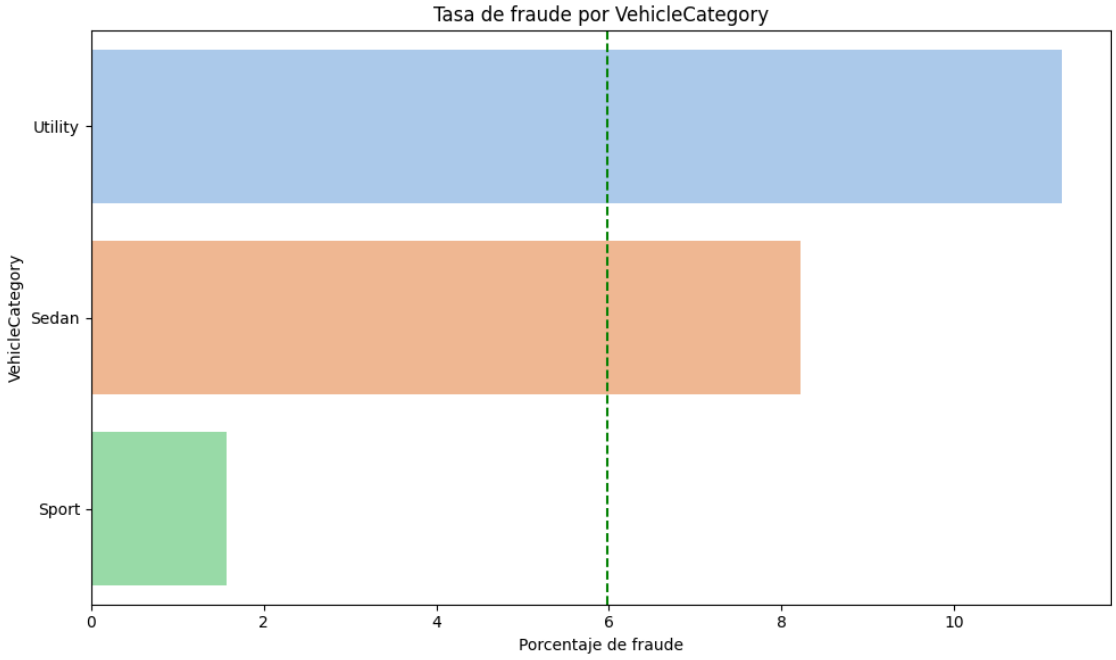

Tasa de fraude por MonthClaimed
Aug
May
Mar
Apr
Jan
Sep
Feb
Jun
Oct
Jul
Dec
Nov
0
MonthClaimed
0
1
2
3
4
5
6
7
8
Porcentaje de fraude

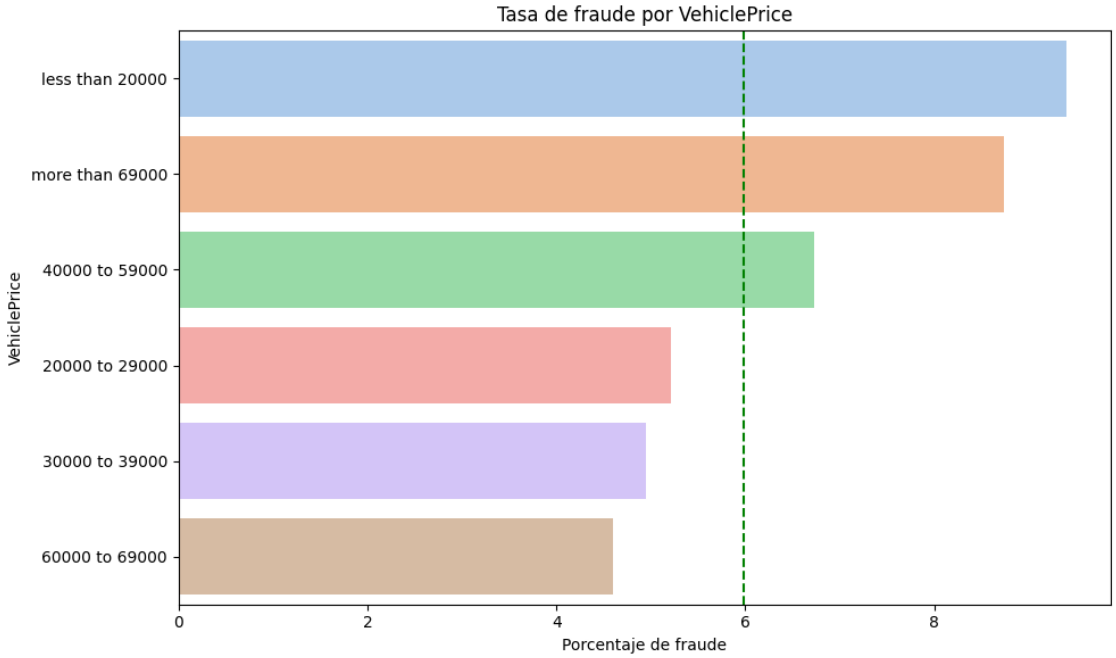

Tasa de fraude por WeekOfMonthClaimed
6
5
4
3
2
1
0
Porcentaje de fraude
1
3
4
2
5
WeekOfMonthClaimed

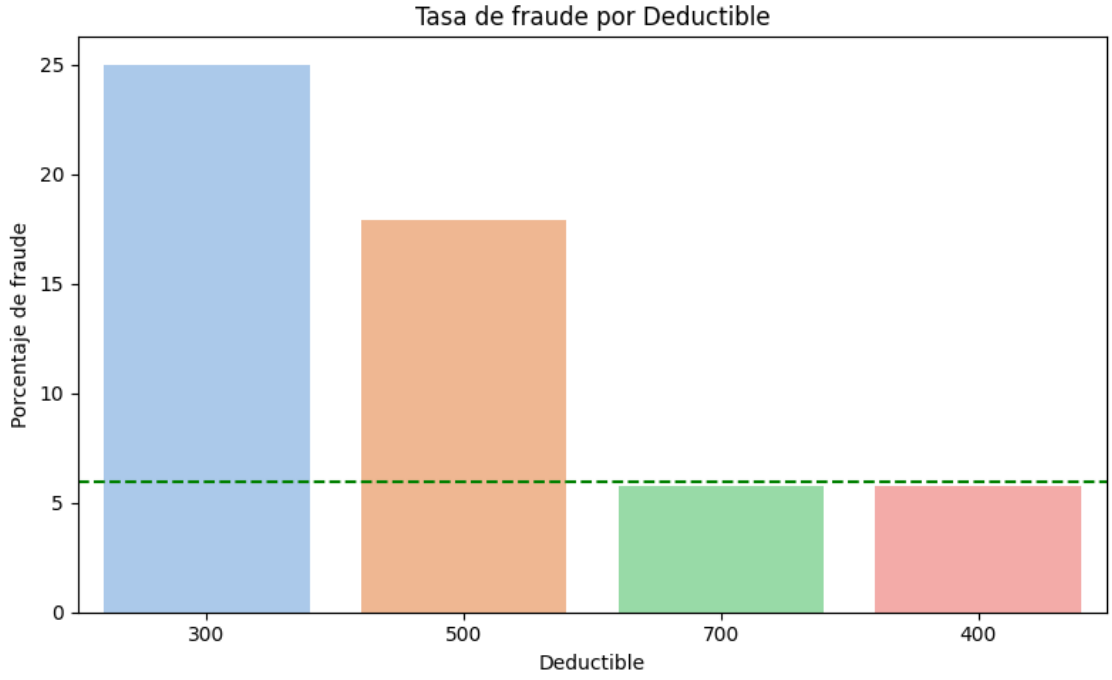

Tasa de fraude por Sex
Male
Female
Sex
0
1
2
3
4
5
6
Porcentaje de fraude

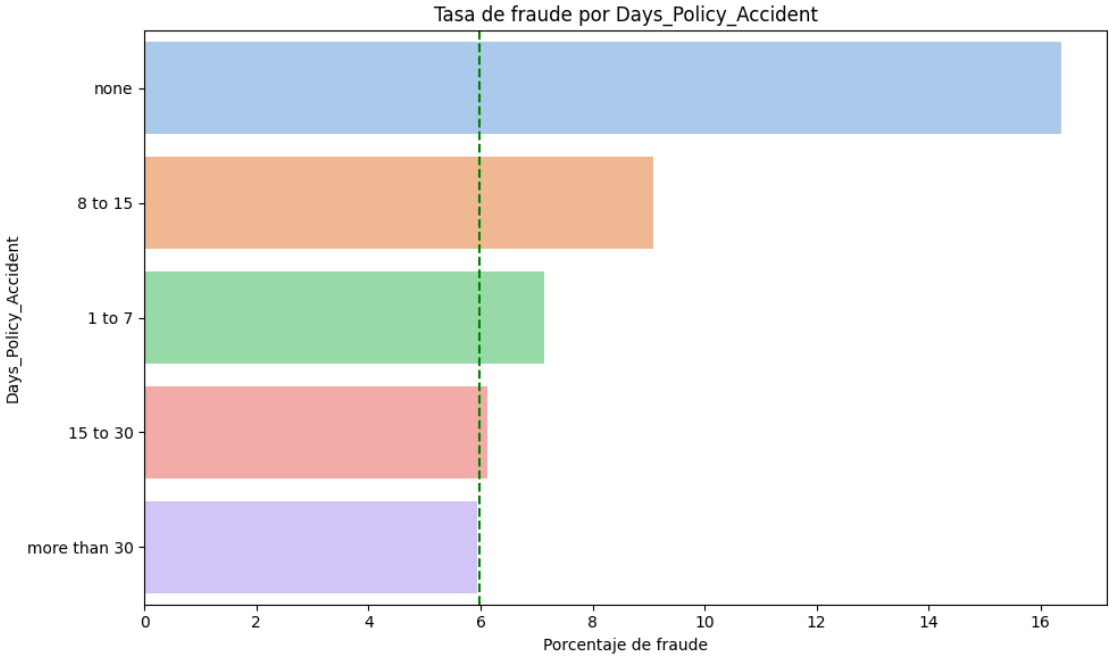

Tasa de fraude por MaritalStatus
Widow
Married
Single
Divorced
MaritalStatus
0
1
2
3
4
5
6
7
8
9
Porcentaje de fraude

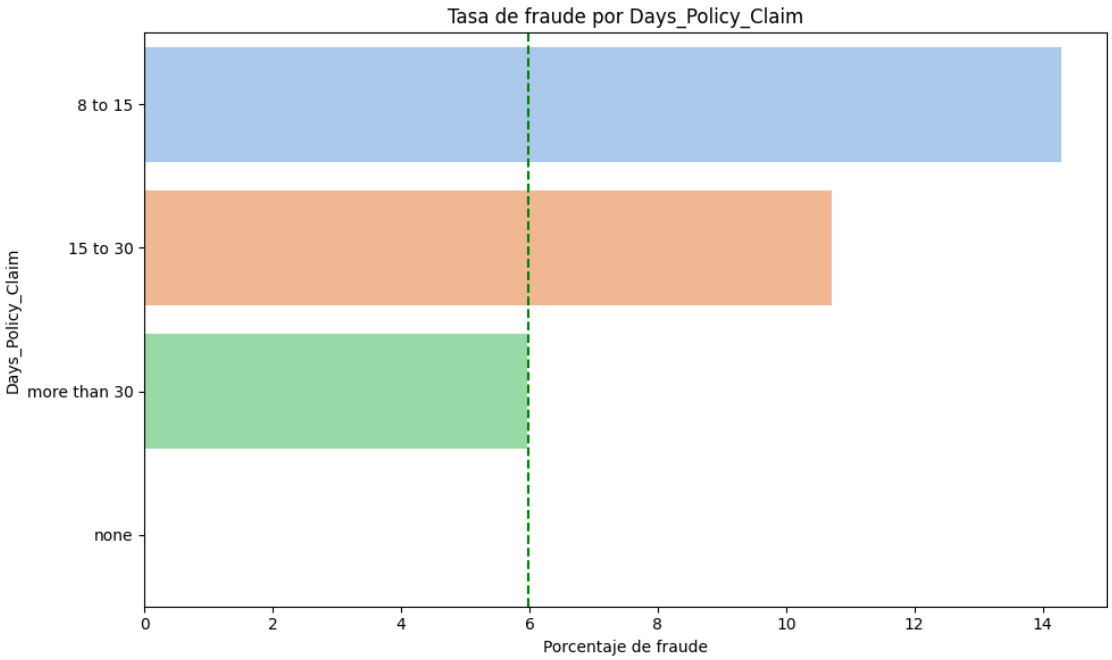

Tasa de fraude por Fault
Policy Holder
Third Party
Fault
0
1
2
3
4
5
6
7
8
Porcentaje de fraude

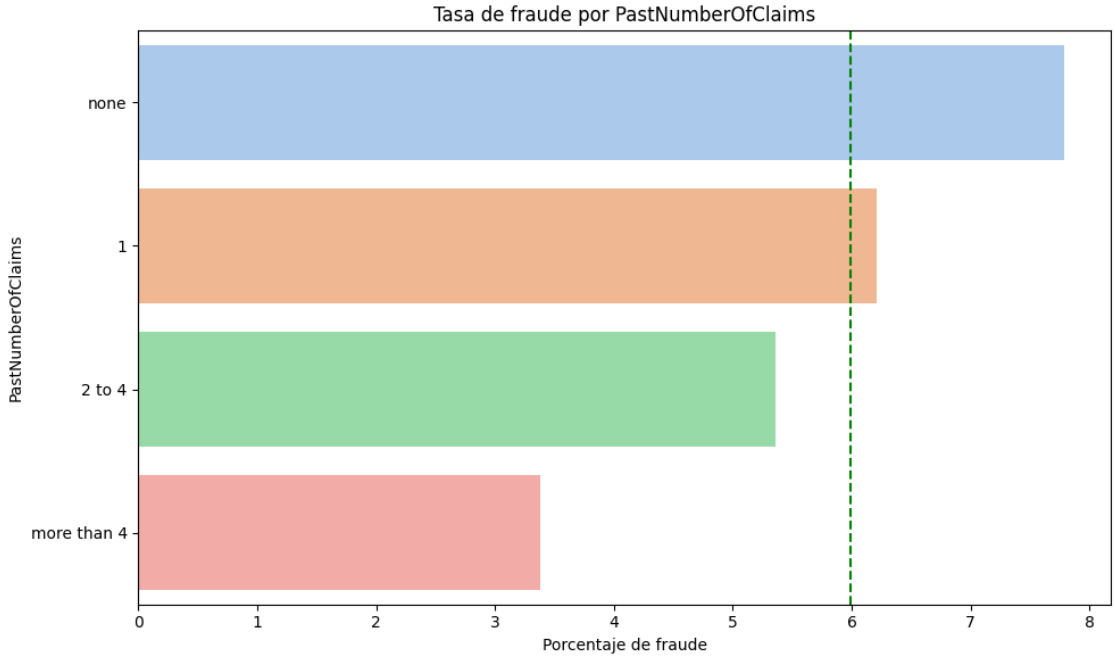

Tasa de fraude por VehicleCategory
Utility
Sedan
Sport
VehicleCategory
0
2
4
6
8
10
Porcentaje de fraude

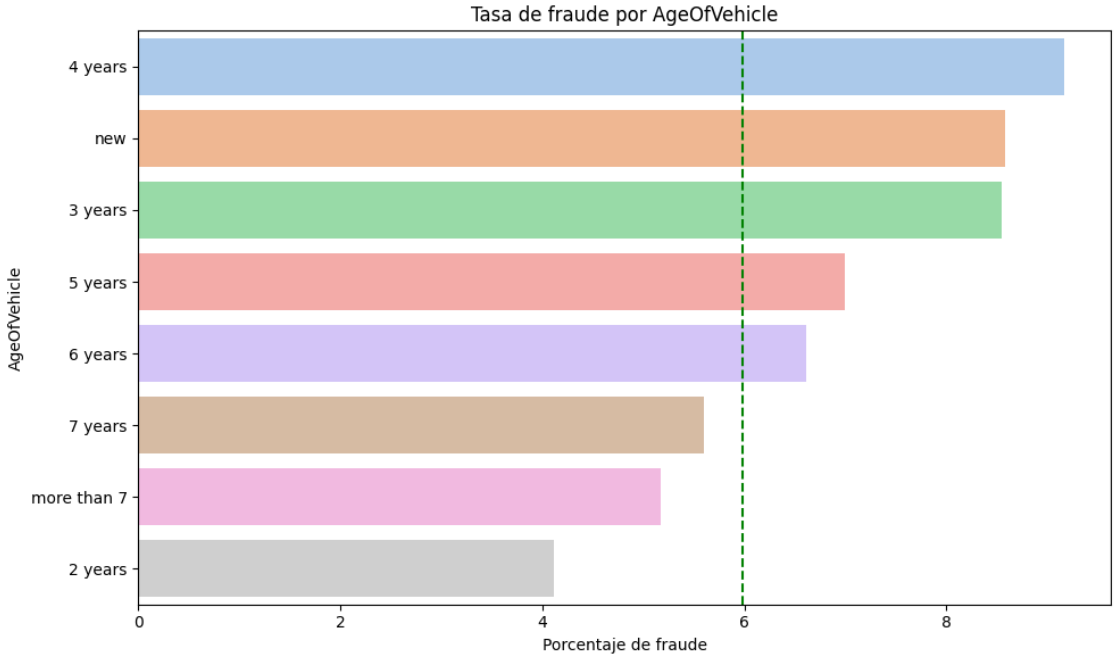

Tasa de fraude por VehiclePrice
less than 20000
more than 69000
40000 to 59000
20000 to 29000
30000 to 39000
60000 to 69000
VehiclePrice
0
2
4
6
8
Porcentaje de fraude

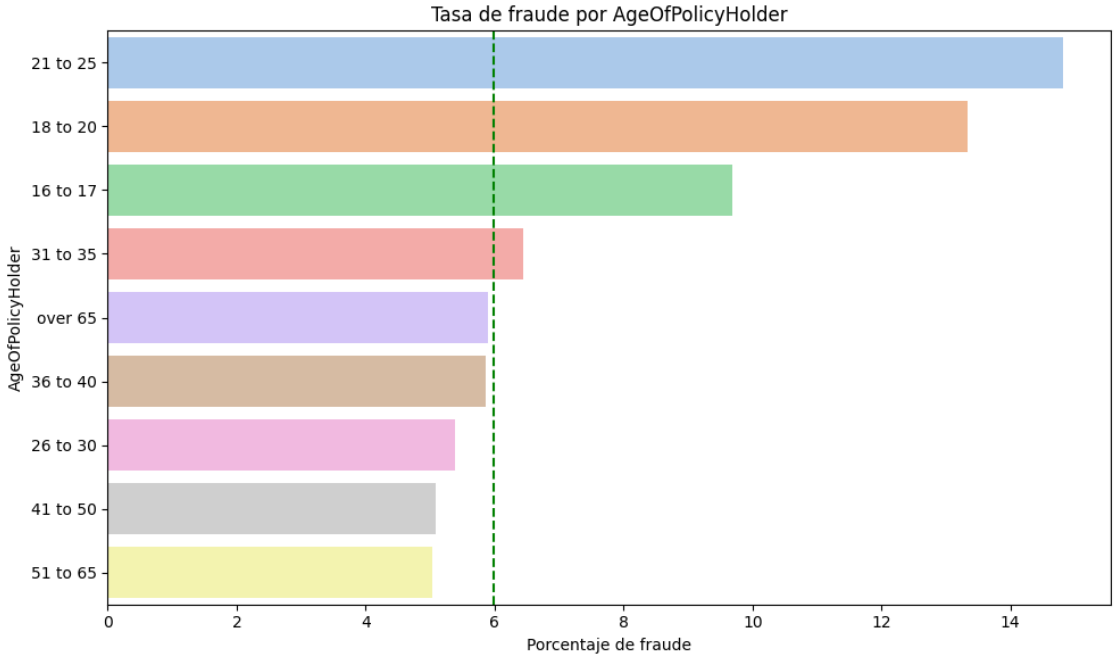

Tasa de fraude por Deductible
25
20
15
10
5
0
Porcentaje de fraude
300
500
700
400
Deductible

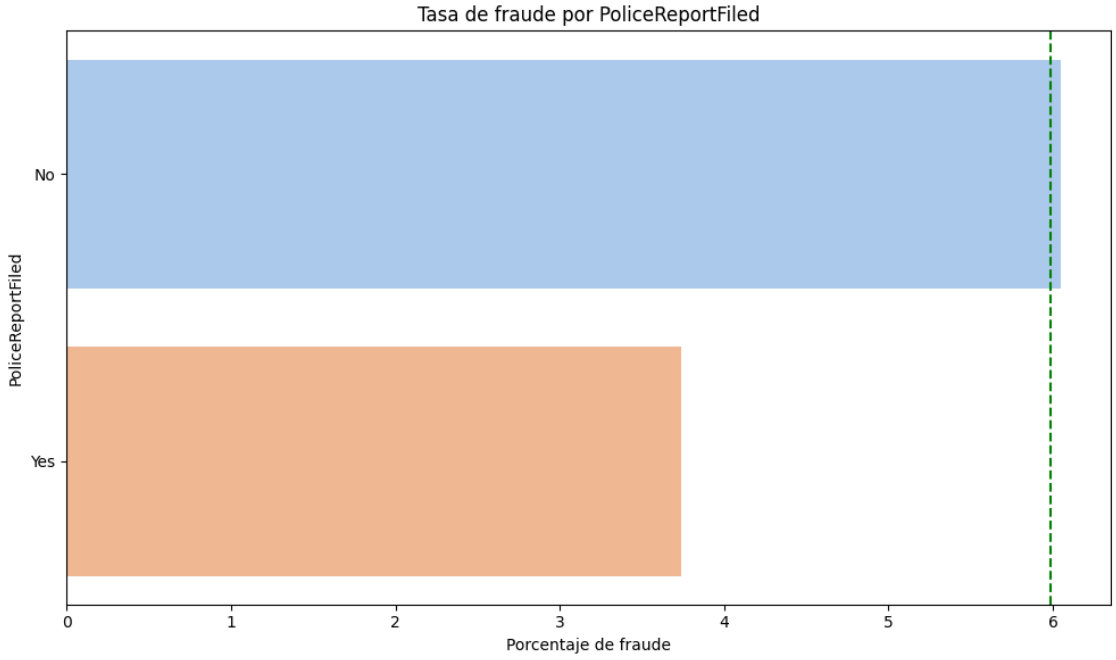

Tasa de fraude por Days_Policy_Accident
Days_Policy_Accident
none
8 to 15
1 to 7
15 to 30
more than 30
0
2
4
6
8
10
12
14
16
Porcentaje de fraude

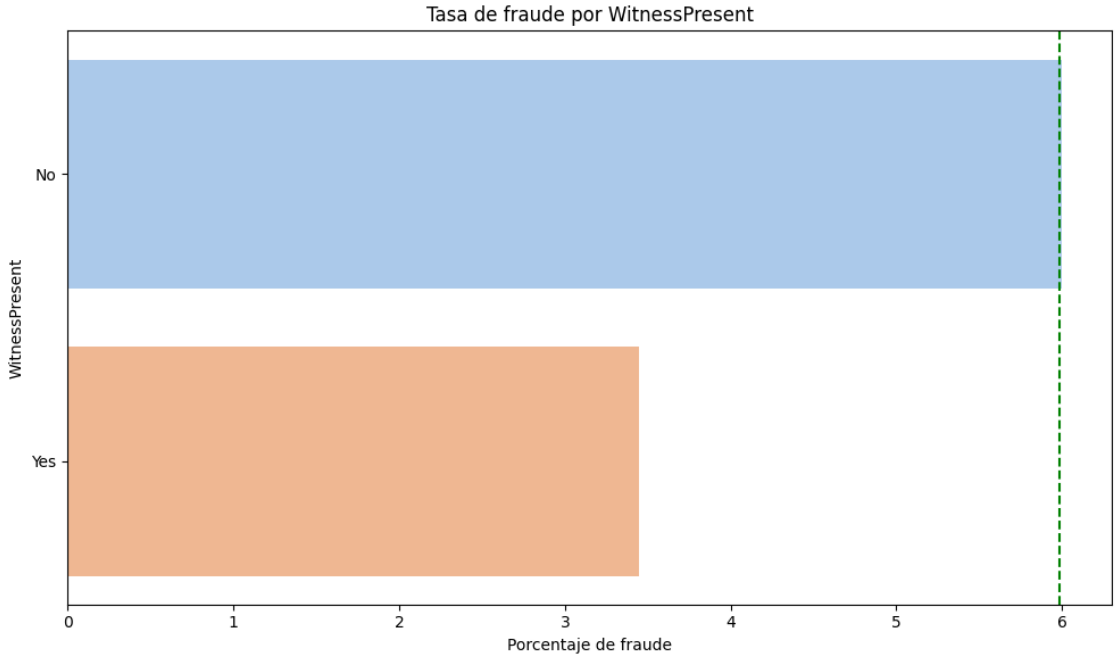

Tasa de fraude por Days_Policy_Claim
Days_Policy_Claim
8 to 15
15 to 30
more than 30
none
0
2
4
6
8
10
12
14
Porcentaje de fraude

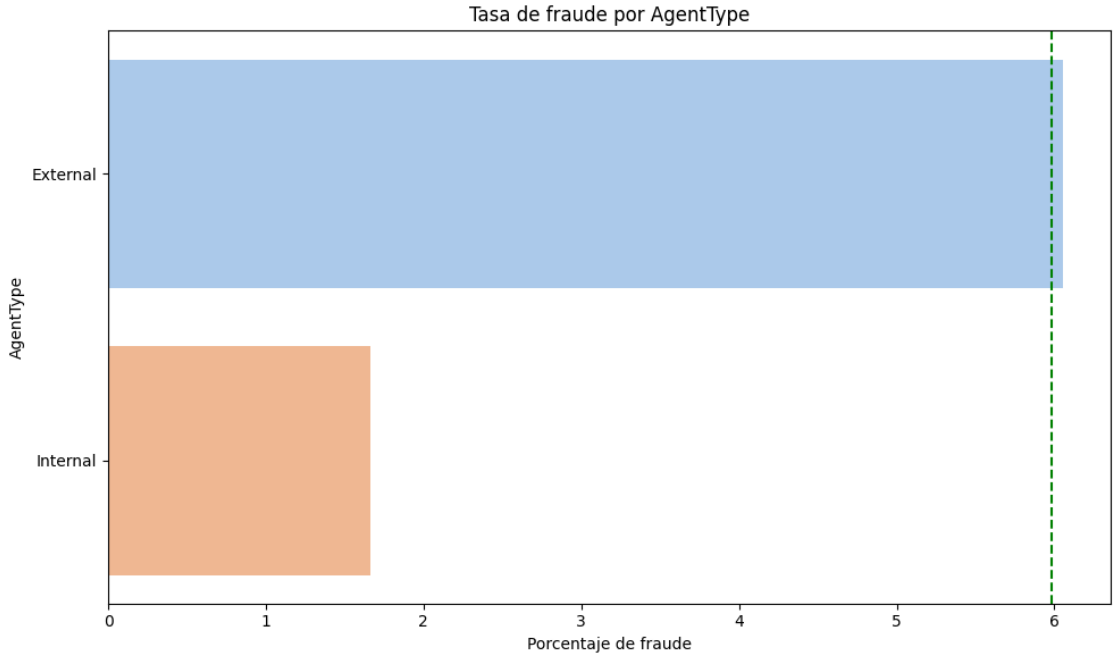

Tasa de fraude por PastNumberOfClaims
PastNumberOfClaims
none
1
2 to 4
more than 4
0
1
2
3
4
5
6
7
8
Porcentaje de fraude

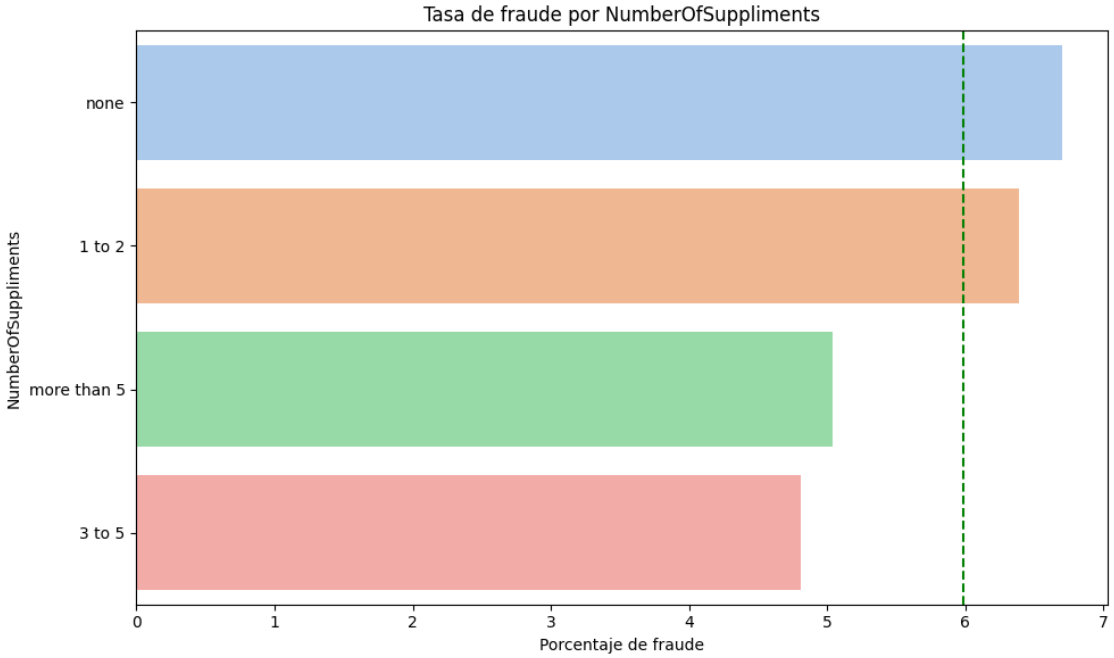

Tasa de fraude por AgeOfVehicle
AgeOfVehicle
4 years
new
3 years
5 years
6 years
7 years
more than 7
2 years
0
2
4
6
8
Porcentaje de fraude

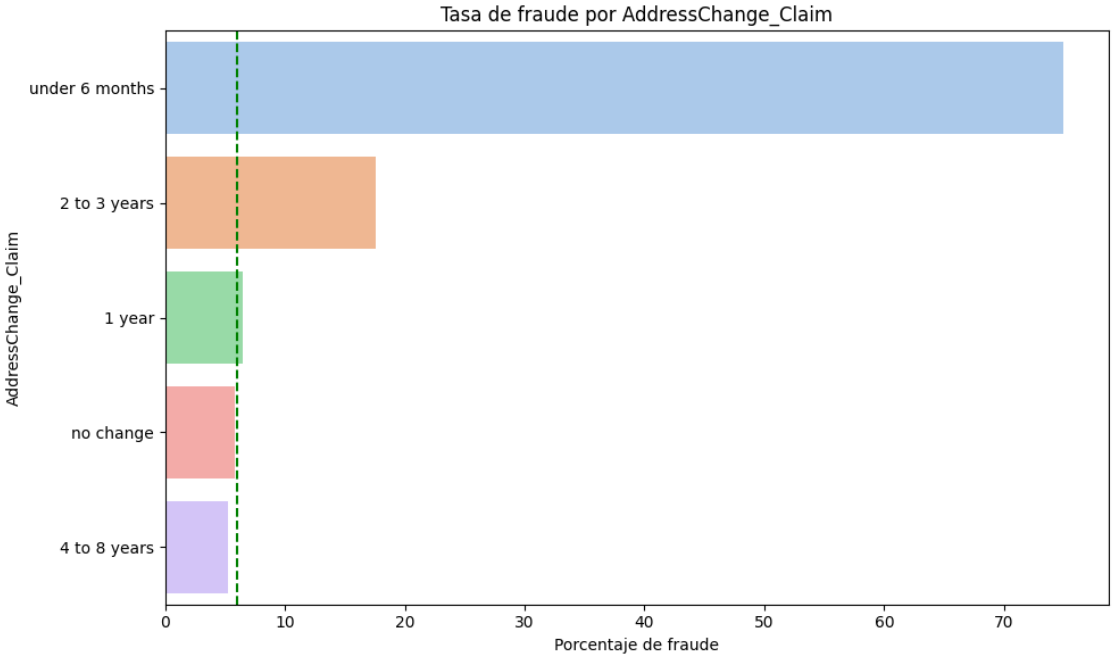

Tasa de fraude por AgeOfPolicyHolder
21 to 25
18 to 20
16 to 17
31 to 35
over 65
36 to 40
26 to 30
41 to 50
51 to 65
AgeOfPolicyHolder
0
2
4
6
8
10
12
14
Porcentaje de fraude

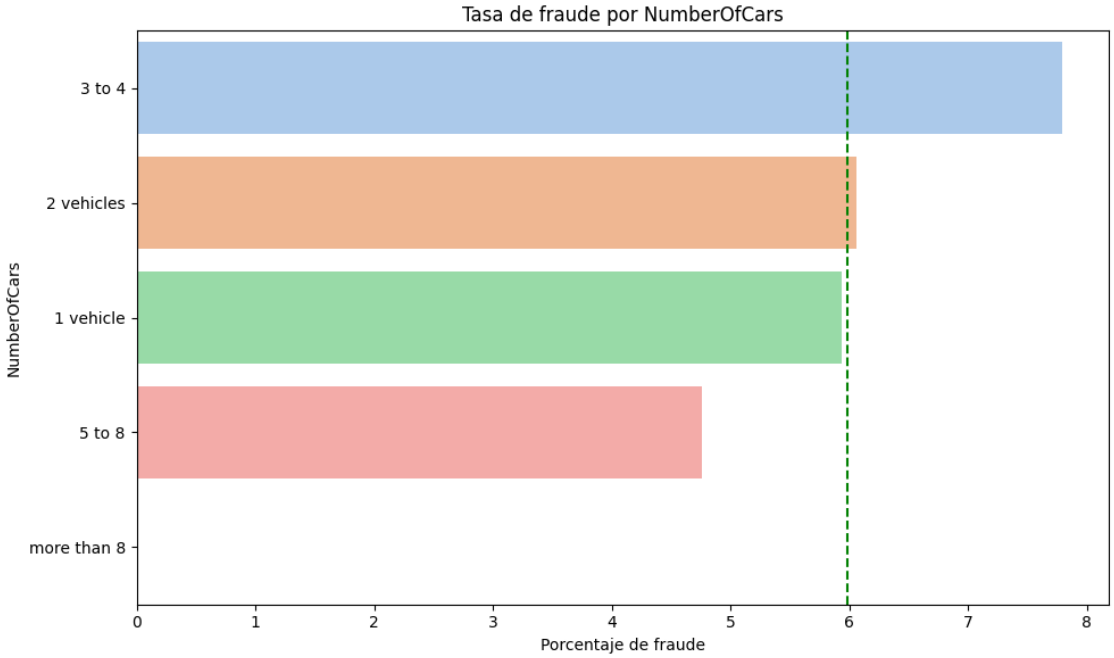

Tasa de fraude por PoliceReportFiled
No
Yes
PoliceReportFiled
0
1
2
3
4
5
6
Porcentaje de fraude

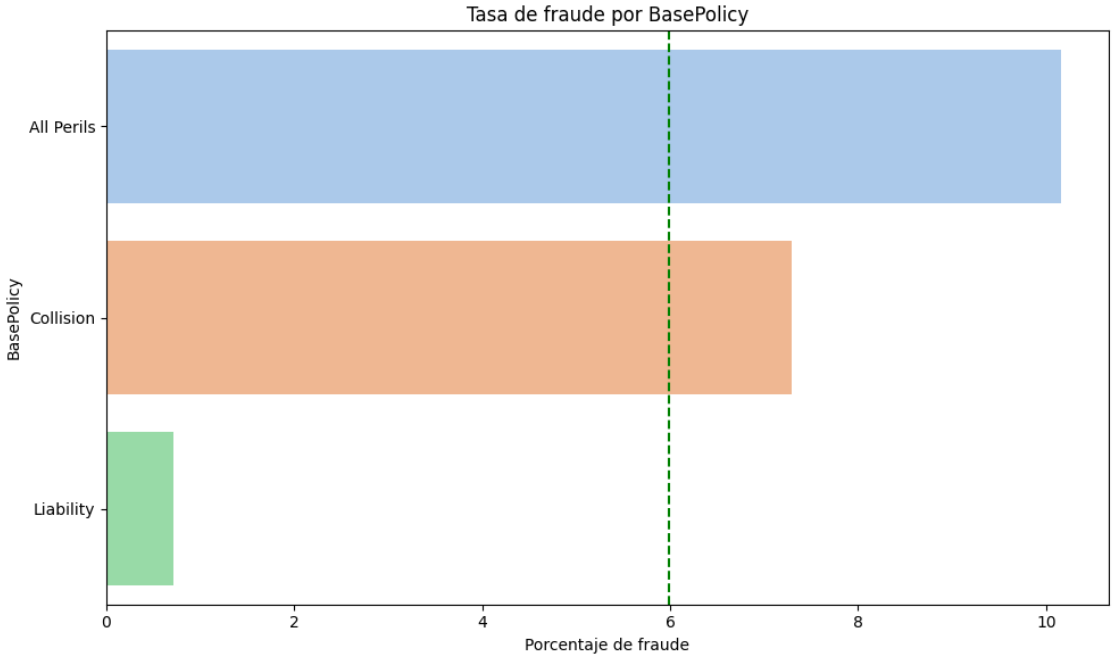

Tasa de fraude por WitnessPresent
WitnessPresent
No
Yes
0
1
2
3
4
5
6
Porcentaje de fraude


Tasa de fraude por AgentType
AgentType
External
Internal
0
1
2
3
4
5
6
Porcentaje de fraude


Tasa de fraude por NumberOfSuppliments
none
1 to 2
more than 5
3 to 5
NumberOfSuppliments
0
1
2
3
4
5
6
7
Porcentaje de fraude


Tasa de fraude por AddressChange_Claim
under 6 months
2 to 3 years
1 year
no change
4 to 8 years
AddressChange_Claim
0
10
20
30
40
50
60
70
Porcentaje de fraude


Tasa de fraude por NumberOfCars
3 to 4
2 vehicles
1 vehicle
5 to 8
more than 8
NumberOfCars
0
1
2
3
4
5
6
7
8
Porcentaje de fraude


Tasa de fraude por BasePolicy
All Perils
Collision
Liability
BasePolicy
0
2
4
6
8
10
Porcentaje de fraude

3.7.1