Actividad Semanal – 7 Regresiones y K means

CIENCIA Y ANALITICA DE DATOS
Profesor: María de La Paz Rico

Alumno: Guillermo Alfonso Muñiz Hermosillo - A01793101

ENLACE COLLAB:
https://colab.research.google.com/drive/1XYWc7A6WkHxNMCkBqhdHH_aiYAz2ocqT?usp=sharing

ENLACE GITHUB:
https://github.com/PosgradoMNA/actividades-de-aprendizaje-A01793101-GuillermoMuniz/tree/main/Acitividades%20Semanales/ActividadSemanal7-Regresiones%20y%20K%20means

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COLLAB LINK

GITHUB LINK

In [ ]:
```
import numpy as np
import pandas as pd

from sklearn.model_selection import train_test_split, cross_validate, GridSearc
from sklearn.linear_model import LinearRegression, Ridge, Lasso


from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

import matplotlib.pyplot as plt

import seaborn as sns
sns.set()

import ssl
ssl._create_default_https_context = ssl._create_unverified_context
```

Ejercicio 1. Costo en la industria de manufactura.

In [ ]:
```
df = pd.read_csv('https://raw.githubusercontent.com/marypazrf/bdd/main/Economie
df.sample(10)
```

Out[ ]:

	Number of Units	Manufacturing Cost
982	7.518630	25.169406
610	4.855505	32.989285
83	2.672300	49.030499
913	6.250181	30.838120
814	5.586303	31.731383
346	3.978838	41.817553
766	5.419682	33.692138
11	1.574600	64.552496
691	5.104258	25.245474
418	4.197989	29.317949

Verificando que no existan datos nulos.

In [ ]:
```
df.isna().any()
```

Out[ ]:
```
Number of Units       False
Manufacturing Cost    False
dtype: bool
```

Obteniendo medidas estadisticas

In [ ]:
```
df.describe()
```

Out[ ]:

	Number of Units	Manufacturing Cost
count	1000.000000	1000.000000
mean	4.472799	40.052999
std	1.336241	10.595322
min	1.000000	20.000000
25%	3.594214	32.912036
50%	4.435958	38.345781
75%	5.324780	44.531822
max	10.000000	100.000000

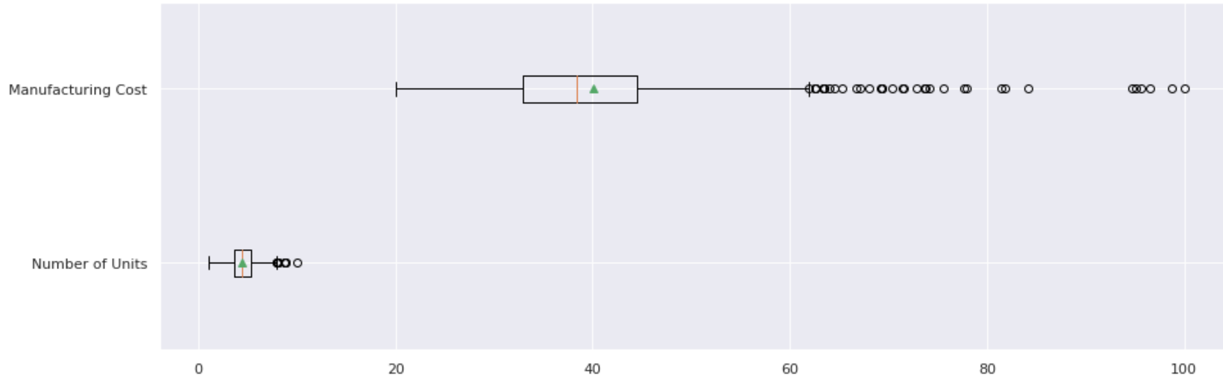
In [ ]:
```
df.columns
```

Out[ ]:
```
Index(['Number of Units', 'Manufacturing Cost'], dtype='object')
```

Para conocer la distribucion de nuestros datos, muestro la siguiente grafica de caja

In [ ]:
```
sns.set(rc={'figure.figsize':(15,5)})
plt.boxplot(df.to_numpy(), labels=df.columns, showmeans=True, vert=False)
```

```
plt.show()
```



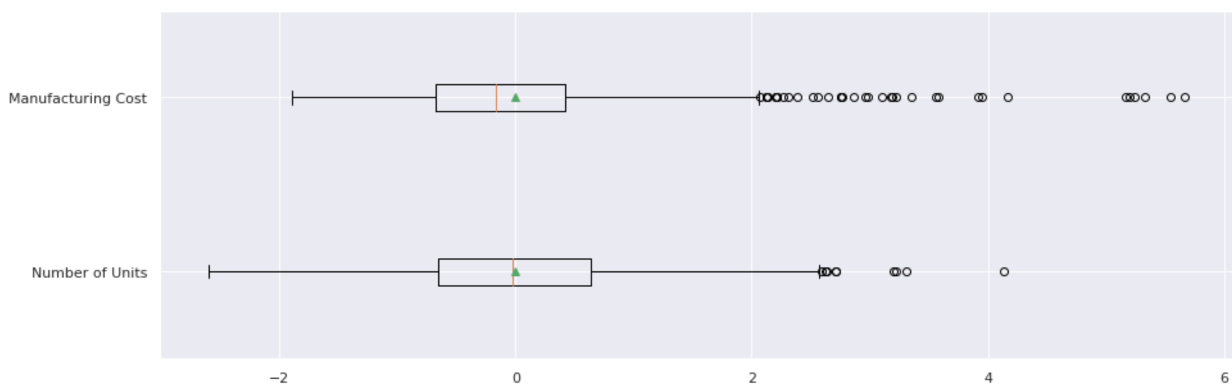
Como podemos ver, Manufactiring cost tiene unos cuantos outliers y su magnitud es un poco mayor al number of units.

In [ ]:
```
scaler = StandardScaler()
dfScaled = pd.DataFrame(scaler.fit_transform(df), columns=df.columns)
dfScaled.head()
```

Out[ ]:

	Number of Units	Manufacturing Cost
0	-2.600231	5.194801
1	-2.460970	5.333204
2	-2.456848	3.173583
3	-2.446910	5.242089
4	-2.376528	5.545221

In [ ]:
```
sns.set(rc={'figure.figsize':(15,5)})
plt.boxplot(dfScaled.to_numpy(), labels=dfScaled.columns, showmeans=True, vert=
plt.show()
```



Divide los datos del costo de manufactura.

Utilizar la función train_test_split.

In [ ]:
```
X = dfScaled[['Number of Units']]
y = dfScaled['Manufacturing Cost']
```

In [ ]:
```
xtrain, xtest, ytrain, ytest =  train_test_split(X, y, test_size=0.2, random_st
```

In [ ]:
```
def graficarPredicciones(x2, ypred):
    plt.scatter(X, y)
    plt.plot(x2, ypred, "r-", linewidth=2, label="Predictions")
    plt.xlabel("$X$", fontsize=18)
    plt.ylabel("$y$", rotation=0, fontsize=18)
    plt.legend(loc="upper left", fontsize=14);
    plt.axis([-3, 6, -4, 7 ]);
```

REGRESION LINEAL

MODELADO

In [ ]:
```
lr = LinearRegression(fit_intercept=True)
lr.fit(xtrain, ytrain)
```

Out[ ]:
```
LinearRegression()
```

La ecuacion generada con el conjunto de entrenamiento es:

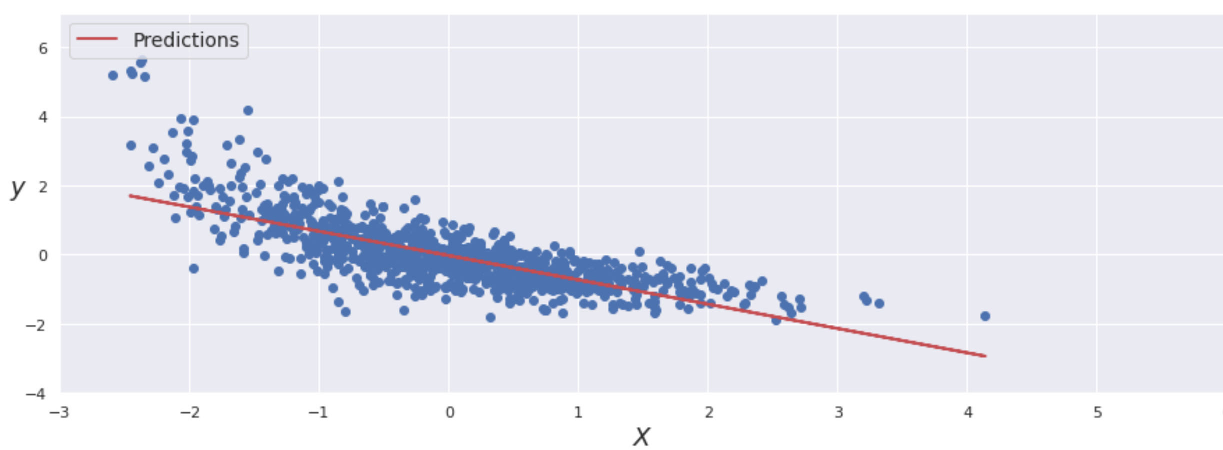
In [ ]:
```
lr.coef_, lr.intercept_
```

Out[ ]:
```
(array([-0.70277861]), -0.028711019387324004)
```

$$\hat{y} = -0.70277X - 0.02871$$

La visualizacion de este modelo generado es:

In [ ]:
```
y_hat = lr.predict(xtrain)

graficarPredicciones(xtrain, y_hat)
```



Sus errores y su r squared son:

In [ ]:
```
from sklearn import metrics
```

```
from sklearn.metrics import r2_score

maes = []
r2s = []
modelos = []
modelos.append('Linear Regression')
maes.append(metrics.mean_absolute_error(ytrain, y_hat))
r2s.append(r2_score(ytrain, y_hat))

print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(ytrain, y_hat)
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(ytrain, y_
print('r2_score',r2_score(ytrain, y_hat))
```

```
Error medio Absoluto (MAE): 0.44487025252822726
Root Mean Squared Error: 0.6125472434542465
r2_score 0.555997358980481
```

REGRESION POLINOMIAL

MODELO

In [ ]:
```
from sklearn.preprocessing import PolynomialFeatures

polyfeat = PolynomialFeatures(degree=3, include_bias=False)
Xpoly = polyfeat.fit_transform(xtrain)
```

In [ ]:
```
lrpoly = LinearRegression(fit_intercept=True)
lrpoly.fit(Xpoly, ytrain)
```

Out[ ]:
```
LinearRegression()
```

La ecuacion generada con el conjunto de entrenamiento es:

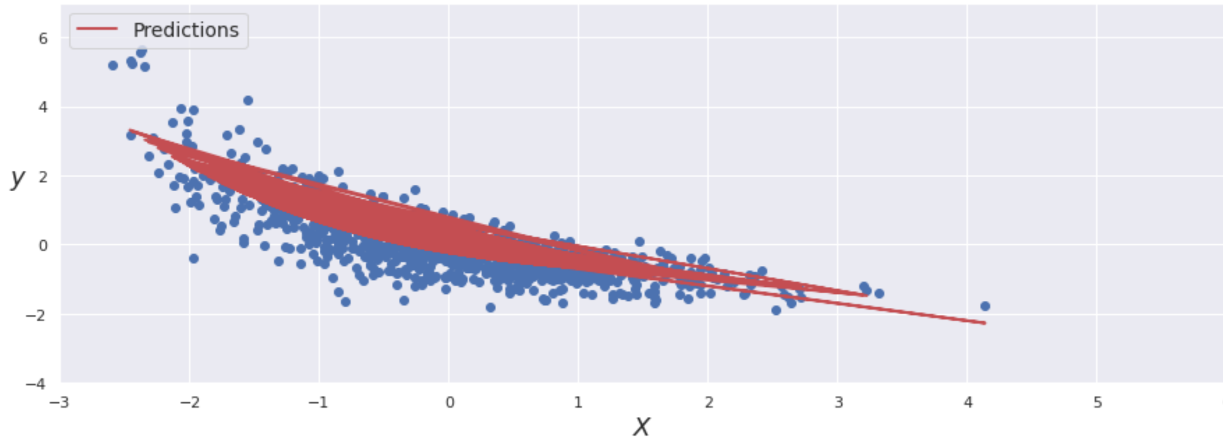
In [ ]:
```
lrpoly.coef_, lrpoly.intercept_
```

Out[ ]:
```
(array([-0.62117566,  0.2198283 , -0.04569872]), -0.2262232795624534)
```

$$\hat{y} = -0.62117X + 0.21982X^2 - 0.04569X^3 - 0.22622$$

La visualizacion de este modelo generado es:

In [ ]:
```
y_hatpoly = lrpoly.predict(Xpoly)
graficarPredicciones(xtrain, y_hatpoly)
```



Sus errores y su r squared son:

In [ ]:
```
modelos.append('Polinomial Regression')
maes.append(metrics.mean_absolute_error(ytrain, y_hatpoly))
r2s.append(r2_score(ytrain, y_hatpoly))

print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(ytrain, y_hatp
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(ytrain, y_
print('r2_score',r2_score(ytrain, y_hatpoly))
```

```
Error medio Absoluto (MAE): 0.41470261009919945
Root Mean Squared Error: 0.5499221716410964
r2_score 0.6421435631309922
```

Realiza la regresión con Ridge y Lasso

MODELOS

In [ ]:
```
RidgeModel = Ridge(alpha = 0.01)
RidgeModel.fit(xtrain, ytrain)

LassoModel = Lasso(alpha = 0.01)
LassoModel.fit(xtrain, ytrain)
```

Out[ ]: `Lasso(alpha=0.01)`

La ecuacion generada por AMBOS MODELOS con el conjunto de entrenamiento es:

In [ ]:
```
RidgeModel.coef_, RidgeModel.intercept_
```

Out[ ]: `(array([-0.70276938]), -0.028711128933458743)`

$$\hat{y} = -0.70276X - 0.02871$$

In [ ]:
```
LassoModel.coef_, LassoModel.intercept_
```

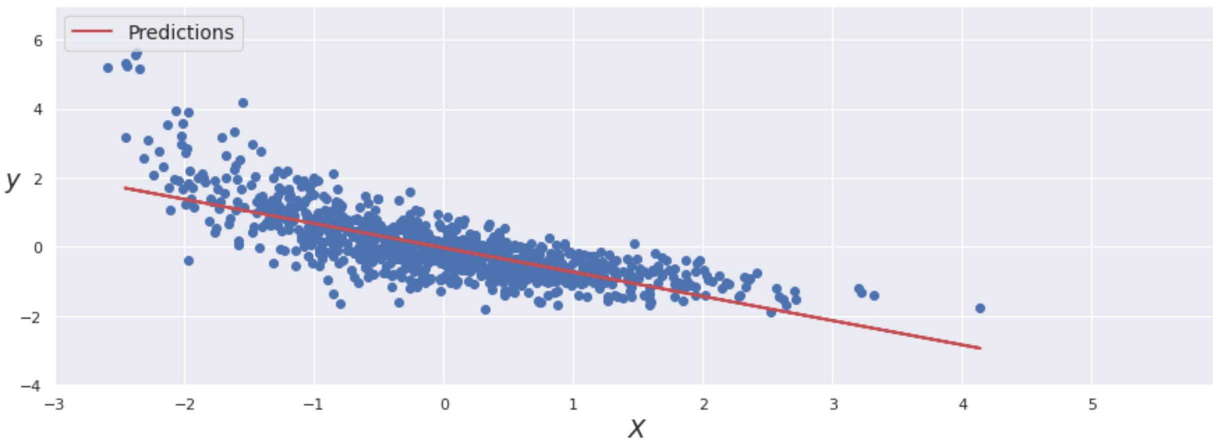
Out[ ]: `(array([-0.69226697]), -0.028835721615773094)`

$$\hat{y} = -0.69226X - 0.02883$$

La visualizacion de este modelo generado es:

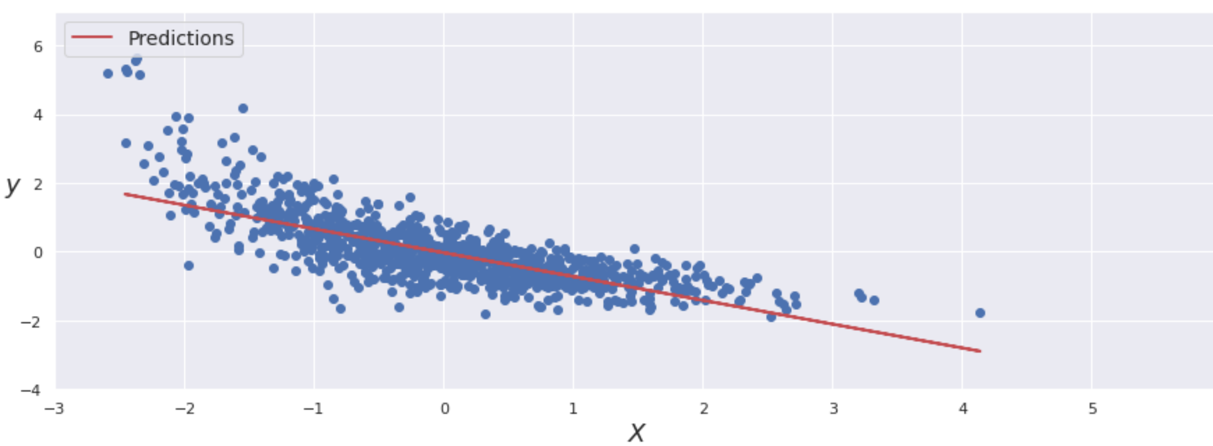
- RIDGE

In [ ]:
```
y_hatRidge = RidgeModel.predict(xtrain)

graficarPredicciones(xtrain, y_hatRidge)
```



- LASSO

In [ ]:
```
y_hatLasso = LassoModel.predict(xtrain)

graficarPredicciones(xtrain, y_hatLasso)
```



Sus errores y su r squared son:

- Ridge

In [ ]:
```
modelos.append('Ridge')
maes.append(metrics.mean_absolute_error(ytrain, y_hatRidge))
r2s.append(r2_score(ytrain, y_hatRidge))
```

```
print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(ytrain, y_hatR
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(ytrain, y_
print('r2_score',r2_score(ytrain, y_hatRidge))
```

```
Error medio Absoluto (MAE): 0.444869731029353
Root Mean Squared Error: 0.6125472435204601
r2_score 0.5559973588844915
```

- Lasso

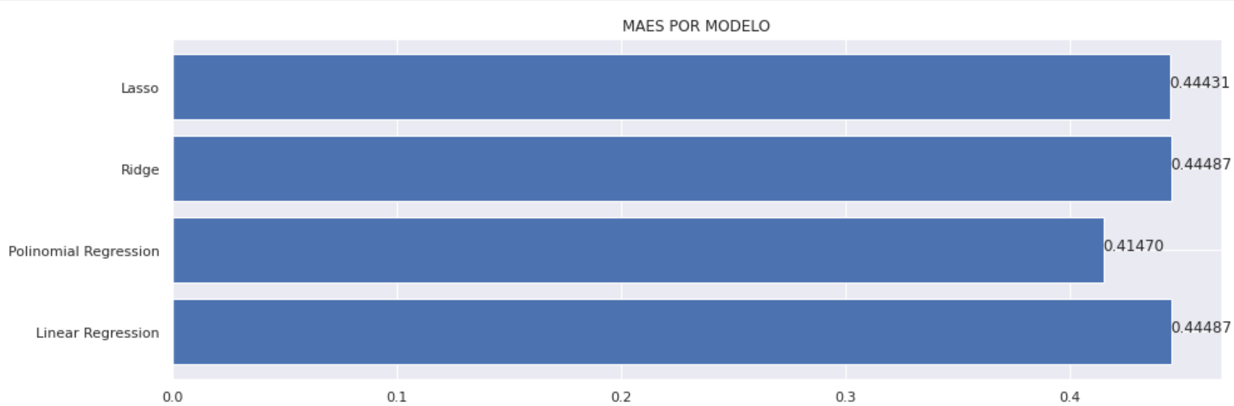
In [ ]:
```
modelos.append('Lasso')
maes.append(metrics.mean_absolute_error(ytrain, y_hatLasso))
r2s.append(r2_score(ytrain, y_hatLasso))

print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(ytrain, y_hatL
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(ytrain, y_
print('r2_score',r2_score(ytrain, y_hatLasso))
```

```
Error medio Absoluto (MAE): 0.4443075550254994
Root Mean Squared Error: 0.6126330401812333
r2_score 0.5558729713790165
```

GRAFICAR MAE y R2

- MAE

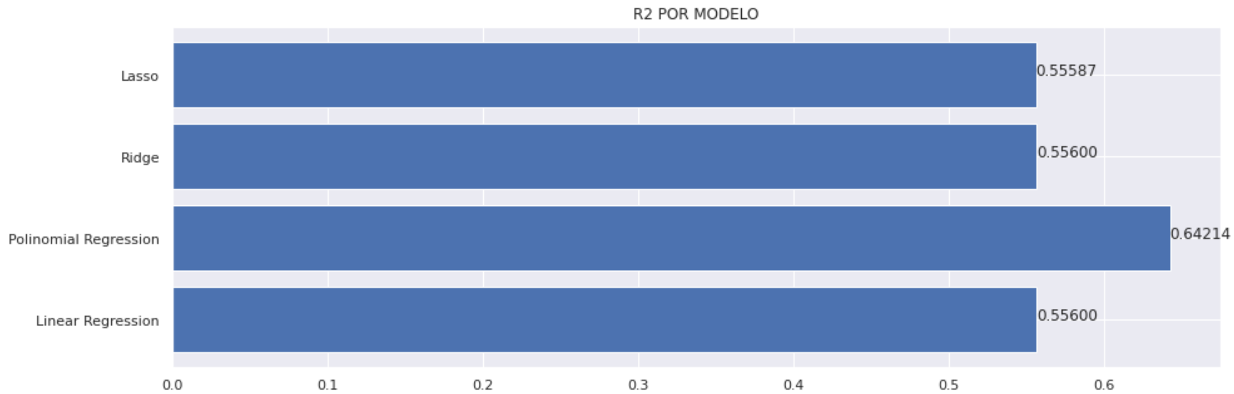
In [ ]:
```
import matplotlib.pyplot as plt

plt.barh(modelos, maes)
plt.title('MAES POR MODELO')
for index, value in enumerate(maes):
    plt.text(value, index,
             str('{:.5f}'.format(value)))

plt.show()
```



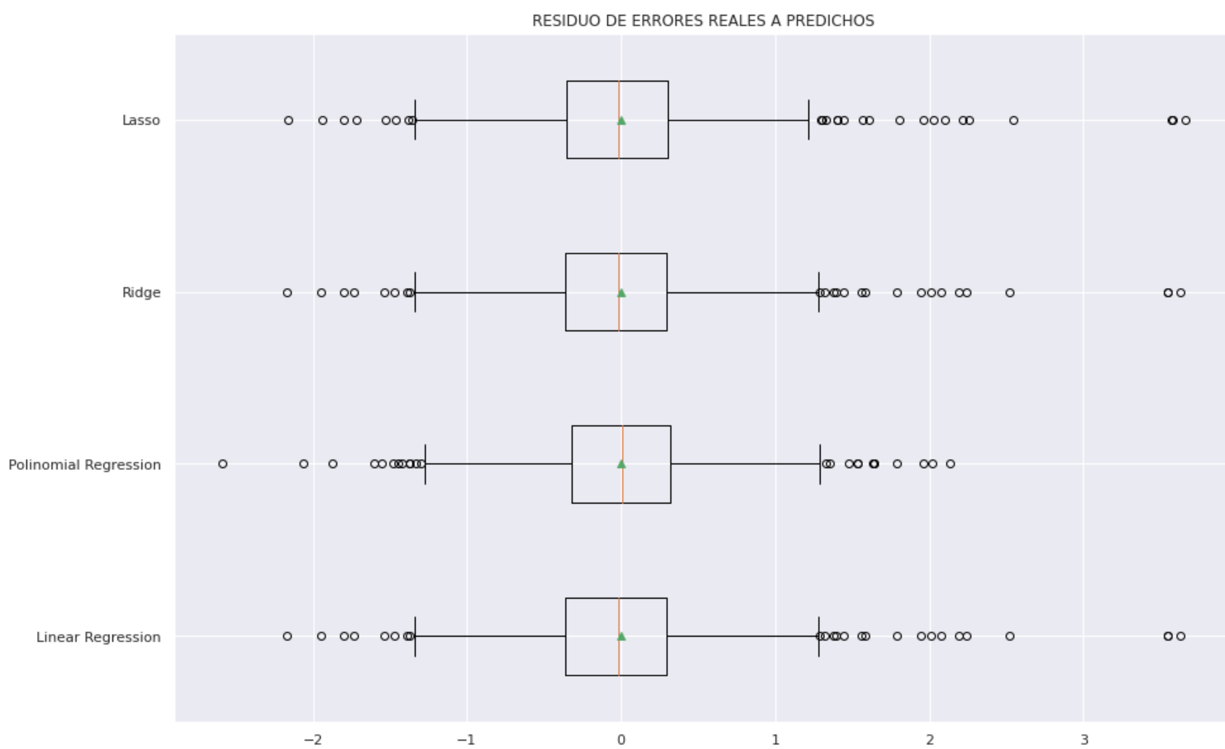
- R SQUARED

In [ ]:
```
plt.barh(modelos, r2s)
plt.title('R2 POR MODELO')
for index, value in enumerate(r2s):
```

```
    plt.text(value, index,
             str('{:.5f}'.format(value)))

plt.show()
```



In [ ]:
```
sns.set(rc={'figure.figsize':(15,10)})
resid = [ytrain-y_hat, ytrain-y_hatpoly, ytrain-y_hatRidge, ytrain-y_hatLasso]
plt.boxplot(resid, labels=modelos, showmeans=True,  vert=False)
plt.title('RESIDUO DE ERRORES REALES A PREDICHOS')
plt.show()
```



Explica tus resultados:

- Que método conviene más a la empresa, ¿por que?

Por el momento el que parece ser mas conveniente a la empresa es la regresion polinomial. Ya que sus predicciones son mas certeras que los otros modelos. Con un error de 0.64 promedio es el que tiene mejor desempeño en el conjunto de validacion.

- ¿Que porcentajes de entrenamiento y evaluación usaste?

Use 80 % del conjunto de datos para entrenamiento y validacion y 20% lo deje destinado a Prueba.

- ¿Que error tienes? ¿es bueno?, ¿cómo lo sabes?

El MAE de 0.414 del modelo polinomial es el mejor. Lo sabemos porque mientras mas cercano sea el MAE a 0, mas preciso sera nuestro modelo. Lo sabemos porque este error es el promedio de los errores absolutos en nuestro conjunto de datos.

Ejercicio 2. Regresión múltiple.

Comenzamos leyendo nuestro conjunto de datos y verificando si existen nulos

In [ ]:
```
dfhouses = pd.read_csv('https://raw.githubusercontent.com/marypazrf/bdd/main/kc
dfhouses.sample(10)
```

Out[ ]:

	id	date	price	bedrooms	bathrooms	sqft_living	sqft_lot
4915	6117500430	20140819T000000	925000.0	5	3.50	4050	13495
21594	5087900040	20141017T000000	350000.0	4	2.75	2500	5995
17931	2979800750	20140911T000000	552000.0	2	1.00	1150	5000
15748	3342103281	20141020T000000	500000.0	4	1.00	1160	20100
8863	1226059161	20141229T000000	562000.0	4	2.75	2560	83200
3357	5742600090	20150425T000000	490000.0	3	1.00	960	5750
9096	4174600331	20140717T000000	384000.0	6	3.00	2320	4502
12004	1965200075	20150316T000000	845000.0	3	1.75	1600	2538
1057	8127700445	20140716T000000	699000.0	3	1.75	1670	5375
815	1421069208	20141223T000000	379000.0	3	3.25	2660	17852

10 rows × 21 columns

In [ ]:
```
dfhouses.isna().any()
```

Out[ ]:
```
id               False
date             False
price            False
bedrooms         False
bathrooms        False
sqft_living      False
sqft_lot         False
floors           False
waterfront       False
view             False
condition        False
grade            False
sqft_above       False
sqft_basement    False
yr_built         False
yr_renovated     False
zipcode          False
lat              False
long             False
sqft_living15    False
sqft_lot15       False
dtype: bool
```

Eliminamos datos no relevantes

In [ ]:
```
dfhouses.drop('id', axis = 1, inplace = True)
dfhouses.drop('date', axis = 1, inplace = True)
dfhouses.drop('zipcode', axis = 1, inplace = True)
dfhouses.drop('lat', axis = 1, inplace = True)
dfhouses.drop('long', axis = 1, inplace = True)
```

Obtenemos las medidas estadisticas

In [ ]:
```
dfhouses.describe()
```

Out[ ]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors
count	2.161300e+04	21613.000000	21613.000000	21613.000000	2.161300e+04	21613.000000
mean	5.400881e+05	3.370842	2.114757	2079.899736	1.510697e+04	1.494309
std	3.671272e+05	0.930062	0.770163	918.440897	4.142051e+04	0.539989
min	7.500000e+04	0.000000	0.000000	290.000000	5.200000e+02	1.000000
25%	3.219500e+05	3.000000	1.750000	1427.000000	5.040000e+03	1.000000
50%	4.500000e+05	3.000000	2.250000	1910.000000	7.618000e+03	1.500000
75%	6.450000e+05	4.000000	2.500000	2550.000000	1.068800e+04	2.000000
max	7.700000e+06	33.000000	8.000000	13540.000000	1.651359e+06	3.500000

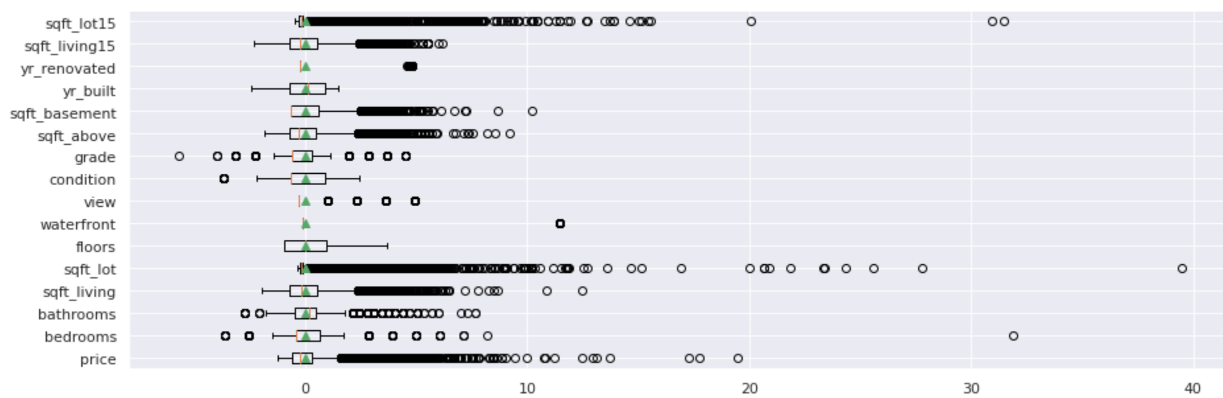
Escalamos nuestro conjunto de datos para tener datos normalizados

In [ ]:
```
dfScaHouse = pd.DataFrame(scaler.fit_transform(dfhouses), columns=dfhouses.colu
dfScaHouse.head()
```

Out[ ]:

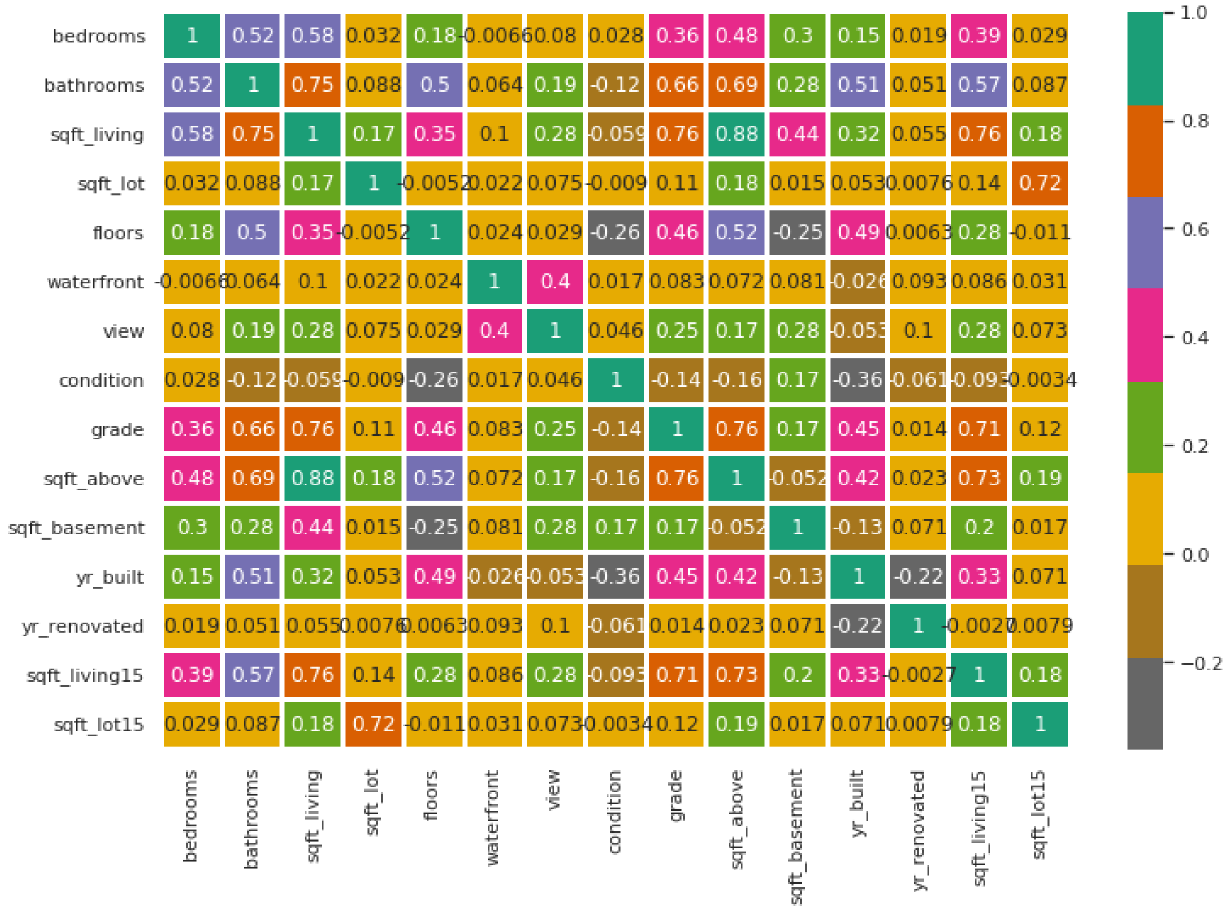
	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view
0	-0.866717	-0.398737	-1.447464	-0.979835	-0.228321	-0.915427	-0.087173	-0.305759
1	-0.005688	-0.398737	0.175607	0.533634	-0.189885	0.936506	-0.087173	-0.305759
2	-0.980849	-1.473959	-1.447464	-1.426254	-0.123298	-0.915427	-0.087173	-0.305759
3	0.174090	0.676485	1.149449	-0.130550	-0.244014	-0.915427	-0.087173	-0.305759
4	-0.081958	-0.398737	-0.149007	-0.435422	-0.169653	-0.915427	-0.087173	-0.305759

In [ ]:
```
sns.set(rc={'figure.figsize':(15,5)})
plt.boxplot(dfScaHouse.to_numpy(), labels=dfScaHouse.columns, showmeans=True, v
plt.show()
```



In [ ]:
```
yhouse = dfScaHouse['price']
Xhouse = dfScaHouse.loc[:, dfScaHouse.columns != 'price']
```

In [ ]:
```
plt.figure(figsize=(12,8))
sns.heatmap(Xhouse.corr(), annot=True, cmap='Dark2_r', linewidths = 2)
plt.show()
```



Divide los datos.

Utiliza la función train_test_split

In [ ]:
```
XtrainH, XtestH, ytrainH, ytestH = train_test_split(Xhouse, yhouse, test_size =

print(f'Numero total de registros en la bdd: {len(Xhouse)}')
print("*****"*10)
print(f'Numero total de registros en el training set: {len(XtrainH)}')
print(f'Tamaño de X_train: {XtrainH.shape}')
print("*****"*10)
print(f'Mumero total de registros en el test dataset: {len(XtestH)}')
print(f'Tamaño del X_test: {XtestH.shape}')
```

```
Numero total de registros en la bdd: 21613
**************************************************
Numero total de registros en el training set: 19451
Tamaño de X_train: (19451, 15)
**************************************************
Mumero total de registros en el test dataset: 2162
Tamaño del X_test: (2162, 15)
```

Regresión Múltiple Lineal

MODELO

In [ ]:
```
lrHouse = LinearRegression()
lrHouse.fit(XtrainH, ytrainH)
```

Out[ ]:
```
LinearRegression()
```

In [ ]:
```
lrHouse.coef_, lrHouse.intercept_
```

Out[ ]:
```
(array([-8.49373282e-02,  8.29572558e-02,  1.34076744e+13,  3.19633535e-04,
         4.71070593e-02,  1.30860436e-01,  8.63454234e-02,  3.66019652e-02,
         3.82672571e-01, -1.20887193e+13, -6.46084260e+12, -2.84053071e-01,
         1.25985923e-02,  5.29822807e-02, -3.90266766e-02]),
 -0.002892357793083432)
```

La visualizacion de este modelo generado es:

In [ ]:
```
y_hatLRHous = lrHouse.predict(XtrainH)
y_hatLRHous
```

Out[ ]:
```
array([ 1.5899611 ,  2.03016508,  1.15105917, ..., -0.50524208,
       -0.23706149, -0.54670679])
```

Sus errores y su r squared son:

In [ ]:
```
maesH = []
r2sH = []
residH = []
maesH.append(metrics.mean_absolute_error(ytrainH, y_hatLRHous))
r2sH.append(r2_score(ytrainH, y_hatLRHous))
residH.append(ytrainH-y_hatLRHous)

print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(ytrainH, y_hat
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(ytrainH, y
print('r2_score',r2_score(ytrainH, y_hatLRHous))
```

```
Error medio Absoluto (MAE): 0.3801957937264814
Root Mean Squared Error: 0.5835971614744226
r2_score 0.6528725163450275
```

REGRESION POLINOMIAL

MODELO

In [ ]:
```
polyfeatH = PolynomialFeatures(degree=8, include_bias=False)
XpolyH = polyfeat.fit_transform(XtrainH)
```

In [ ]:
```
lrpolyH = LinearRegression(fit_intercept=True)
lrpolyH.fit(XpolyH, ytrainH)
```

Out[ ]:
```
LinearRegression()
```

La ecuacion generada con el conjunto de entrenamiento es:

In [ ]:
```
lrpolyH.coef_[0:30], lrpolyH.intercept_
```

Out[ ]:
```
(array([ 2.49310414e+08, -7.49967135e-02, -1.01720819e-01,  6.82339365e-01,
         6.11904319e-02,  1.17439777e-04,  5.04409043e-01, -3.91473610e-01,
        -6.04808889e-02, -2.49721352e-01,  2.66113028e-01, -5.90875831e-01,
        -3.65619600e+01,  1.98318530e-01,  1.79742400e-01, -7.50380009e-03,
         1.25152394e-02, -3.68860364e-03, -1.87834725e-02,  3.78385149e-02,
         2.83822898e+09,  2.51857787e-02,  1.31868571e-03, -3.36515903e-03,
         1.77266449e-03, -1.09218955e-02, -5.33830747e-02,  1.00634433e+00,
        -6.80588931e-03,  6.17225021e-02]), -8.64770484687528)
```

Sus errores y su r squared son:

In [ ]:
```
y_hatPRHous = lrHouse.predict(XtrainH)

maesH.append(metrics.mean_absolute_error(ytrainH, y_hatPRHous))
r2sH.append(r2_score(ytrainH, y_hatPRHous))
residH.append(ytrainH-y_hatPRHous)

print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(ytrainH, y_hat
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(ytrainH, y
print('r2_score',r2_score(ytrainH, y_hatPRHous))
```

```
Error medio Absoluto (MAE): 0.3801957937264814
Root Mean Squared Error: 0.5835971614744226
r2_score 0.6528725163450275
```

Realiza la regresión con Ridge y Lasso

MODELOS

In [ ]:
```
RidgeModelH = Ridge(alpha = 0.10)
RidgeModelH.fit(XtrainH, ytrainH)

LassoModelH = Lasso(alpha = .01)
LassoModelH.fit(XtrainH, ytrainH)
```

Out[ ]:
```
Lasso(alpha=0.01)
```

La ecuacion generada por AMBOS MODELOS con el conjunto de entrenamiento es:

In [ ]:
```
RidgeModelH.coef_, RidgeModelH.intercept_
```

Out[ ]:
```
(array([-0.09677458,  0.08698747,  0.20267555,  0.00193318,  0.04661381,
         0.13024659,  0.08610179,  0.03761732,  0.38258574,  0.16861035,
         0.10511393, -0.28409989,  0.01450908,  0.05415352, -0.04076566]),
 -0.00150914396023756)
```

In [ ]:
```
LassoModelH.coef_, LassoModelH.intercept_
```

Out[ ]:
```
(array([-0.06984475,  0.07145965,  0.38742126, -0.        ,  0.02973128,
         0.12411084,  0.0880468 ,  0.02807131,  0.38116594,  0.        ,
         0.00518928, -0.26357658,  0.010054  ,  0.04219924, -0.0274872 ]),
 -0.0015428850748442054)
```

Sus errores y su r squared son:

- Ridge

In [ ]:
```
y_hatRidgeH = RidgeModelH.predict(XtrainH)

maesH.append(metrics.mean_absolute_error(ytrainH, y_hatRidgeH))
r2sH.append(r2_score(ytrainH, y_hatRidgeH))
residH.append(ytrainH-y_hatRidgeH)

print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(ytrainH, y_hat
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(ytrainH, y
print('r2_score',r2_score(ytrainH, y_hatRidgeH))
```

```
Error medio Absoluto (MAE): 0.3793574029075837
Root Mean Squared Error: 0.5835575262820814
r2_score 0.6529196652973683
```

- Lasso

In [ ]:
```
y_hatLassoH = LassoModelH.predict(XtrainH)

maesH.append(metrics.mean_absolute_error(ytrain, y_hatLasso))
r2sH.append(r2_score(ytrain, y_hatLasso))
residH.append(ytrainH-y_hatLassoH)

print('Error medio Absoluto (MAE):', metrics.mean_absolute_error(ytrain, y_hatL
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(ytrain, y_
print('r2_score',r2_score(ytrain, y_hatLasso))
```

```
Error medio Absoluto (MAE): 0.4443075550254994
Root Mean Squared Error: 0.6126330401812333
r2_score 0.5558729713790165
```

GRAFICAR MAE y R2

- MAE

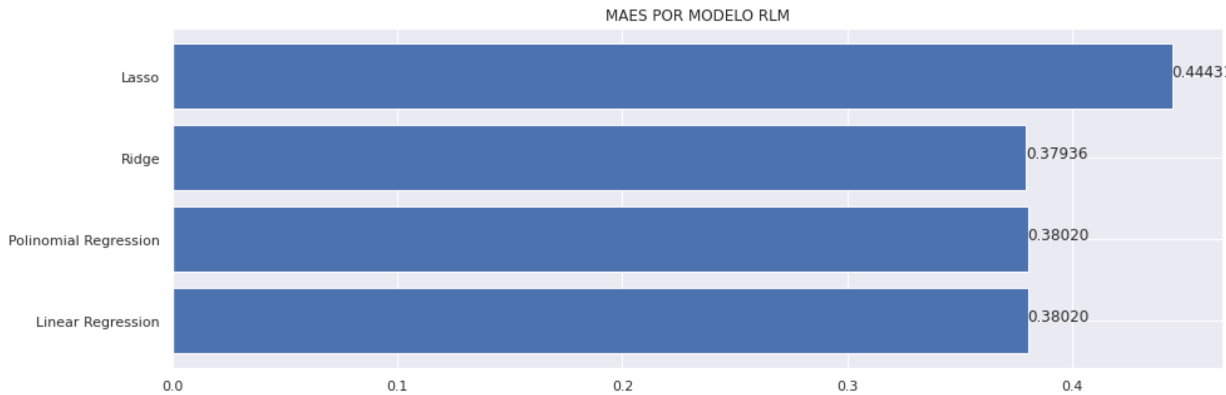
In [ ]:
```
modelos
```

Out[ ]:
```
['Linear Regression', 'Polinomial Regression', 'Ridge', 'Lasso']
```

In [ ]:
```
maesH
```

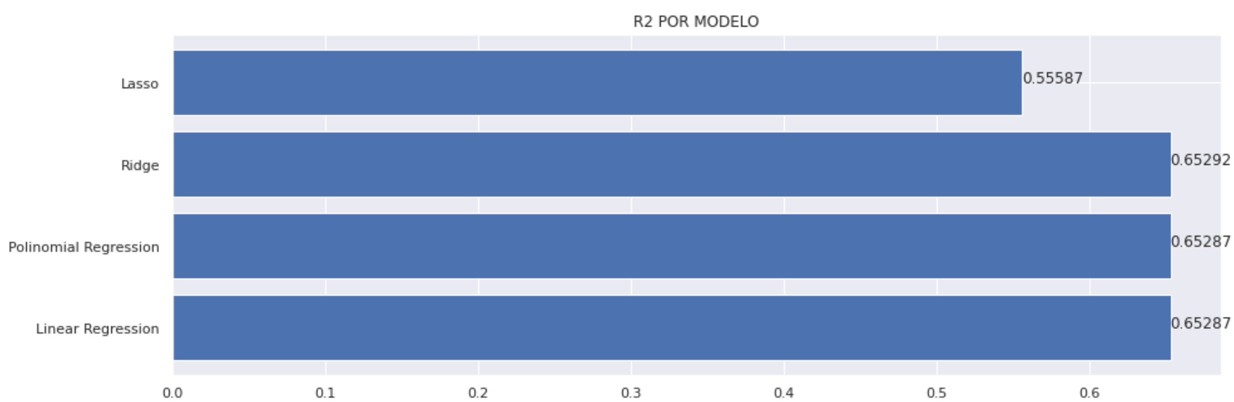
Out[ ]:
```
[0.3801957937264814,
 0.3801957937264814,
 0.3793574029075837,
 0.4443075550254994]
```

In [ ]:
```
plt.barh(modelos, maesH)
plt.title('MAES POR MODELO RLM')
for index, value in enumerate(maesH):
    plt.text(value, index,
             str('{:.5f}'.format(value)))

plt.show()
```

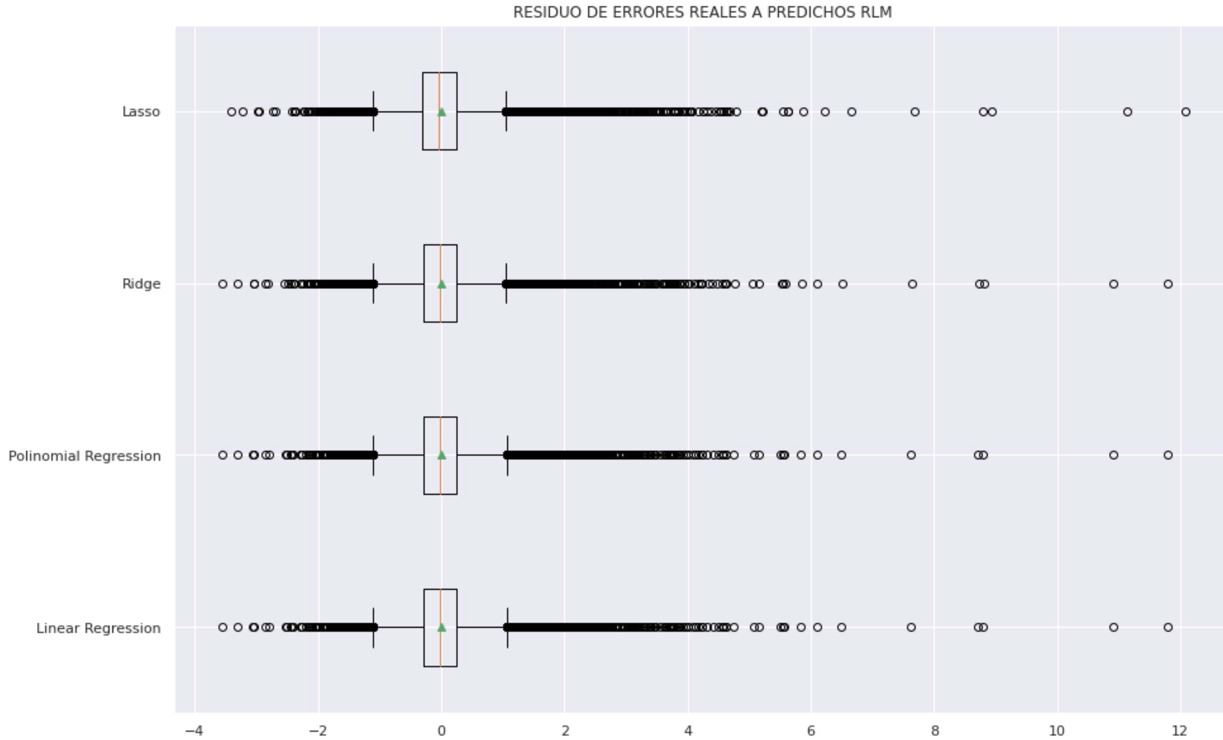


- R SQUARED

In [ ]:
```
plt.barh(modelos, r2sH)
plt.title('R2 POR MODELO')
for index, value in enumerate(r2sH):
    plt.text(value, index,
             str('{:.5f}'.format(value)))

plt.show()
```



In [ ]:
```
sns.set(rc={'figure.figsize':(15,10)})
plt.boxplot(residH, labels=modelos, showmeans=True,  vert=False)
plt.title('RESIDUO DE ERRORES REALES A PREDICHOS RLM')
plt.show()
```



Explica tus resultados:

- Que método conviene más a la empresa, ¿por que?

Por el momento el que parece ser mas conveniente a la empresa es el modelo con correccion Rigge. Ya que sus predicciones son mas certeras que los otros modelos. Con un error de 0.65 promedio y un MAE de 0.35 es el que tiene mejor desempeño en el conjunto de validacion.

- ¿Que porcentajes de entrenamiento y evaluación usaste?

Use 90 % del conjunto de datos para entrenamiento y validacion y 10% lo deje destinado a Prueba.

- ¿Que error tienes? ¿es bueno?, ¿cómo lo sabes?

El MAE de 0.379 del modelo RIDGE es el mejor. Lo sabemos de la misma manera que en el ejercicio 1. Mientras mas cercano sea el MAE a 0, mas preciso sera nuestro modelo. Este error es el promedio de los errores absolutos en nuestro conjunto de datos.

Agrega las conclusiones

Como podemos ver, el modelo de Regresion Lineal Multiple con correccion Ridge y alpha de 0.10 nos entrega un mejor desempeño que cualquier otro modelo que hayamos probado. Si bien es cierto que el R2 deberia de ser un poco mayor por lo que quiza haga falta realizar alguna transformacion adicional para verificar estos valores.

Por el momento para ambos ejercicios podemos deducir que los metodos de regresion nos ayudan a encontrar una funcion para poder predecir nuestra variable de salida.
Necesitamos ser precisos con nuestro preprocesamiento de nuestros datos y encontrar las mejores soluciones posibles.

EJERCICIO 3 - KMEANS

In [ ]:
```
from tqdm import tqdm
!pip install geopandas
import geopandas as gpd

url="https://raw.githubusercontent.com/marypazrf/bdd/main/target-locations.csv'
dfKmeans=pd.read_csv(url)
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-w
heels/public/simple/
Collecting geopandas
  Downloading geopandas-0.10.2-py2.py3-none-any.whl (1.0 MB)
     |████████████████████████████████| 1.0 MB 15.8 MB/s
Collecting pyproj>=2.2.0
  Downloading pyproj-3.2.1-cp37-cp37m-manylinux2010_x86_64.whl (6.3 MB)
     |████████████████████████████████| 6.3 MB 61.9 MB/s
Requirement already satisfied: shapely>=1.6 in /usr/local/lib/python3.7/dist-p
ackages (from geopandas) (1.8.5.post1)
Requirement already satisfied: pandas>=0.25.0 in /usr/local/lib/python3.7/dist
-packages (from geopandas) (1.3.5)
Collecting fiona>=1.8
  Downloading Fiona-1.8.22-cp37-cp37m-manylinux2014_x86_64.whl (16.7 MB)
     |████████████████████████████████| 16.7 MB 69.6 MB/s
Requirement already satisfied: click>=4.0 in /usr/local/lib/python3.7/dist-pac
kages (from fiona>=1.8->geopandas) (7.1.2)
Requirement already satisfied: attrs>=17 in /usr/local/lib/python3.7/dist-pack
ages (from fiona>=1.8->geopandas) (22.1.0)
Collecting munch
  Downloading munch-2.5.0-py2.py3-none-any.whl (10 kB)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-pac
kages (from fiona>=1.8->geopandas) (57.4.0)
Collecting cligj>=0.5
  Downloading cligj-0.7.2-py3-none-any.whl (7.1 kB)
Collecting click-plugins>=1.0
  Downloading click_plugins-1.1.1-py2.py3-none-any.whl (7.5 kB)
Requirement already satisfied: six>=1.7 in /usr/local/lib/python3.7/dist-packa
ges (from fiona>=1.8->geopandas) (1.15.0)
Requirement already satisfied: certifi in /usr/local/lib/python3.7/dist-packag
es (from fiona>=1.8->geopandas) (2022.9.24)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-p
ackages (from pandas>=0.25.0->geopandas) (2022.6)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.7/dist-
packages (from pandas>=0.25.0->geopandas) (1.21.6)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python
3.7/dist-packages (from pandas>=0.25.0->geopandas) (2.8.2)
Installing collected packages: munch, cligj, click-plugins, pyproj, fiona, geo
pandas
Successfully installed click-plugins-1.1.1 cligj-0.7.2 fiona-1.8.22 geopandas-
0.10.2 munch-2.5.0 pyproj-3.2.1
```

In [ ]:

```
dfKmeans.describe()
```

Out[ ]:

	latitude	longitude
count	1839.000000	1839.000000
mean	37.791238	-91.986881
std	5.272299	16.108046
min	19.647855	-159.376962
25%	33.882605	-98.268828
50%	38.955432	-87.746346
75%	41.658341	-80.084833
max	61.577919	-68.742331

In [ ]:

```
dfKmeans.isna().any()
```

Out[ ]:

```
name          False
latitude      False
longitude     False
address       False
phone         False
website       False
dtype: bool
```

In [ ]:

```
latlong=dfKmeans[["latitude","longitude"]]
```

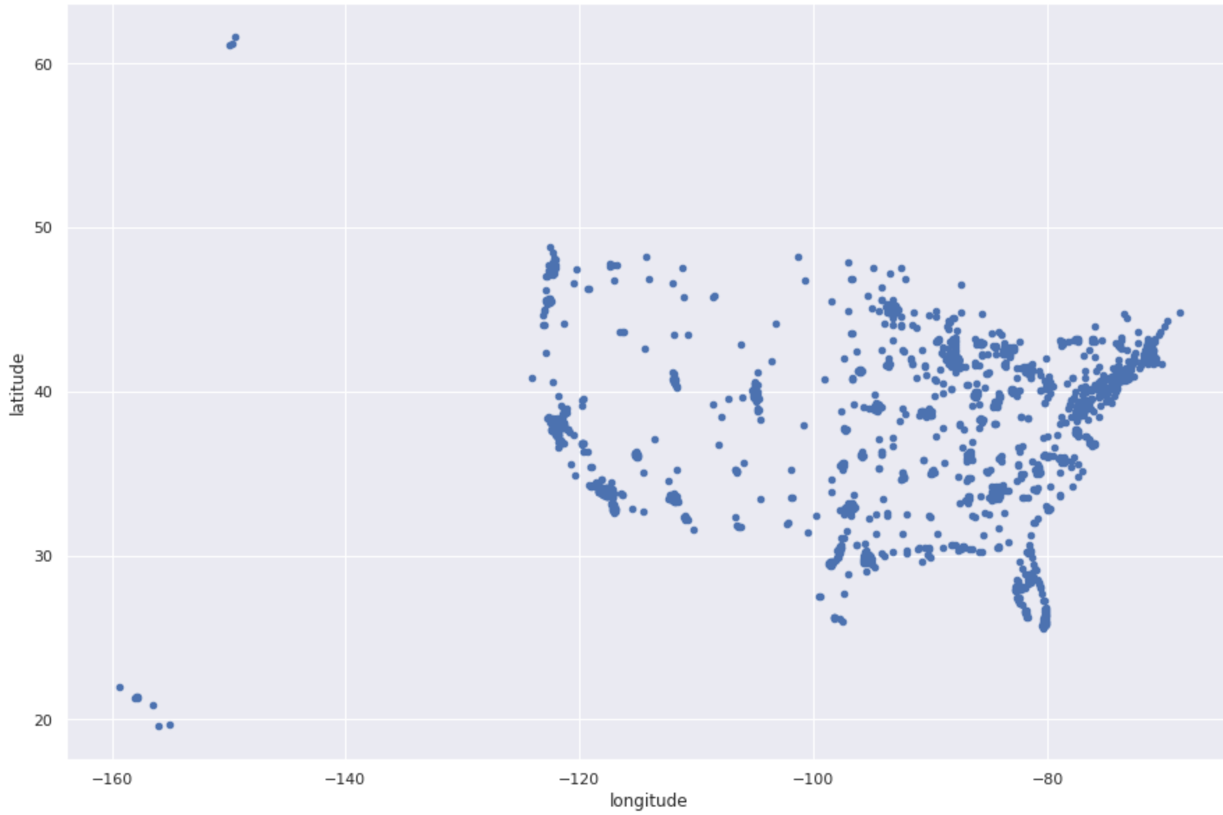
In [ ]:

```
latlong.plot.scatter( "longitude","latitude")
```

```
WARNING:matplotlib.axes._axes:*c* argument looks like a single numeric RGB or
RGBA sequence, which should be avoided as value-mapping will have precedence i
n case its length matches with *x* & *y*.  Please use the *color* keyword-argu
ment or provide a 2-D array with a single row if you intend to specify the sam
e RGB or RGBA value for all points.
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f273c940f90>
```



In [ ]:
```
from shapely.geometry import Point
!pip install qeds
import qeds
qeds.themes.mpl_style();

dfKmeans["Coordinates"] = list(zip(dfKmeans.longitude, dfKmeans.latitude))
dfKmeans["Coordinates"] = dfKmeans["Coordinates"].apply(Point)
dfKmeans.head()
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-w
heels/public/simple/
Collecting qeds
  Downloading qeds-0.7.0.tar.gz (24 kB)
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-package
s (from qeds) (1.3.5)
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-packa
ges (from qeds) (2.23.0)
Collecting quandl
  Downloading Quandl-3.7.0-py2.py3-none-any.whl (26 kB)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages
(from qeds) (1.7.3)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages
(from qeds) (1.21.6)
Collecting quantecon
  Downloading quantecon-0.5.3-py3-none-any.whl (179 kB)
     |████████████████████████████████| 179 kB 19.6 MB/s
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/dist-pac
kages (from qeds) (3.2.2)
Requirement already satisfied: pyarrow in /usr/local/lib/python3.7/dist-packag
es (from qeds) (6.0.1)
Requirement already satisfied: openpyxl in /usr/local/lib/python3.7/dist-packa
ges (from qeds) (3.0.10)
Requirement already satisfied: plotly in /usr/local/lib/python3.7/dist-package
s (from qeds) (5.5.0)
Requirement already satisfied: pandas_datareader in /usr/local/lib/python3.7/d
ist-packages (from qeds) (0.9.0)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.7/dist-p
ackages (from qeds) (1.0.2)
Requirement already satisfied: seaborn in /usr/local/lib/python3.7/dist-packag
es (from qeds) (0.11.2)
Requirement already satisfied: statsmodels in /usr/local/lib/python3.7/dist-pa
ckages (from qeds) (0.12.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-p
ackages (from matplotlib->qeds) (0.11.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /us
r/local/lib/python3.7/dist-packages (from matplotlib->qeds) (3.0.9)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.
7/dist-packages (from matplotlib->qeds) (2.8.2)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/d
ist-packages (from matplotlib->qeds) (1.4.4)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/d
ist-packages (from kiwisolver>=1.0.1->matplotlib->qeds) (4.1.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packa
ges (from python-dateutil>=2.1->matplotlib->qeds) (1.15.0)
Requirement already satisfied: et-xmlfile in /usr/local/lib/python3.7/dist-pac
kages (from openpyxl->qeds) (1.1.0)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-p
ackages (from pandas->qeds) (2022.6)
Requirement already satisfied: lxml in /usr/local/lib/python3.7/dist-packages
(from pandas_datareader->qeds) (4.9.1)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /us
r/local/lib/python3.7/dist-packages (from requests->qeds) (1.24.3)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-p
ackages (from requests->qeds) (2.10)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/d
ist-packages (from requests->qeds) (3.0.4)
```

```
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.7/
dist-packages (from requests->qeds) (2022.9.24)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.7/dis
t-packages (from plotly->qeds) (8.1.0)
Collecting inflection>=0.3.1
  Downloading inflection-0.5.1-py2.py3-none-any.whl (9.5 kB)
Requirement already satisfied: more-itertools in /usr/local/lib/python3.7/dist
-packages (from quandl->qeds) (9.0.0)
Requirement already satisfied: numba in /usr/local/lib/python3.7/dist-packages
(from quantecon->qeds) (0.56.4)
Requirement already satisfied: sympy in /usr/local/lib/python3.7/dist-packages
(from quantecon->qeds) (1.7.1)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-pac
kages (from numba->quantecon->qeds) (57.4.0)
Requirement already satisfied: llvmlite<0.40,>=0.39.0dev0 in /usr/local/lib/py
thon3.7/dist-packages (from numba->quantecon->qeds) (0.39.1)
Requirement already satisfied: importlib-metadata in /usr/local/lib/python3.7/
dist-packages (from numba->quantecon->qeds) (4.13.0)
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-pack
ages (from importlib-metadata->numba->quantecon->qeds) (3.10.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.
7/dist-packages (from scikit-learn->qeds) (3.1.0)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-p
ackages (from scikit-learn->qeds) (1.2.0)
Requirement already satisfied: patsy>=0.5 in /usr/local/lib/python3.7/dist-pac
kages (from statsmodels->qeds) (0.5.3)
Requirement already satisfied: mpmath>=0.19 in /usr/local/lib/python3.7/dist-p
ackages (from sympy->quantecon->qeds) (1.2.1)
Building wheels for collected packages: qeds
  Building wheel for qeds (setup.py) ... done
  Created wheel for qeds: filename=qeds-0.7.0-py3-none-any.whl size=27812 sha2
56=856e99330d68a024ce0a604f5cd1402d7fc9619cf8e4d5fd362db6e4789fce96
  Stored in directory: /root/.cache/pip/wheels/fc/8c/52/0cc036b9730b75850b9845
770780f8d05ed08ff38a67cbaa29
Successfully built qeds
Installing collected packages: inflection, quantecon, quandl, qeds
Successfully installed inflection-0.5.1 qeds-0.7.0 quandl-3.7.0 quantecon-0.5.
3
```

Out[ ]:

	name	latitude	longitude	address	phone	website
0	Alabaster	33.224225	-86.804174	250 S Colonial Dr, Alabaster, AL 35007-4657	205-564-2608	https://www.target.com/sl/alabaster/2276
1	Bessemer	33.334550	-86.989778	4889 Promenade Pkwy, Bessemer, AL 35022-7305	205-565-3760	https://www.target.com/sl/bessemer/2375
2	Daphne	30.602875	-87.895932	1698 US Highway 98, Daphne, AL 36526-4252	251-621-3540	https://www.target.com/sl/daphne/1274
3	Decatur	34.560148	-86.971559	1235 Point Mallard Pkwy SE, Decatur, AL 35601-...	256-898-3036	https://www.target.com/sl/decatur/2084
4	Dothan	31.266061	-85.446422	4601 Montgomery Hwy, Dothan, AL 36303-1522	334-340-1112	https://www.target.com/sl/dothan/1468

In [ ]:

```
gdf = gpd.GeoDataFrame(dfKmeans, geometry="Coordinates")
gdf.head()
```

Out[ ]:

	name	latitude	longitude	address	phone	website
0	Alabaster	33.224225	-86.804174	250 S Colonial Dr, Alabaster, AL 35007-4657	205-564-2608	https://www.target.com/sl/alabaster/2276
1	Bessemer	33.334550	-86.989778	4889 Promenade Pkwy, Bessemer, AL 35022-7305	205-565-3760	https://www.target.com/sl/bessemer/2375
2	Daphne	30.602875	-87.895932	1698 US Highway 98, Daphne, AL 36526-4252	251-621-3540	https://www.target.com/sl/daphne/1274
3	Decatur	34.560148	-86.971559	1235 Point Mallard Pkwy SE, Decatur, AL 35601-...	256-898-3036	https://www.target.com/sl/decatur/2084
4	Dothan	31.266061	-85.446422	4601 Montgomery Hwy, Dothan, AL 36303-1522	334-340-1112	https://www.target.com/sl/dothan/1468

In [ ]:

```
world = gpd.read_file(gpd.datasets.get_path("naturalearth_lowres"))
world = world.set_index("iso_a3")

world.head()
```

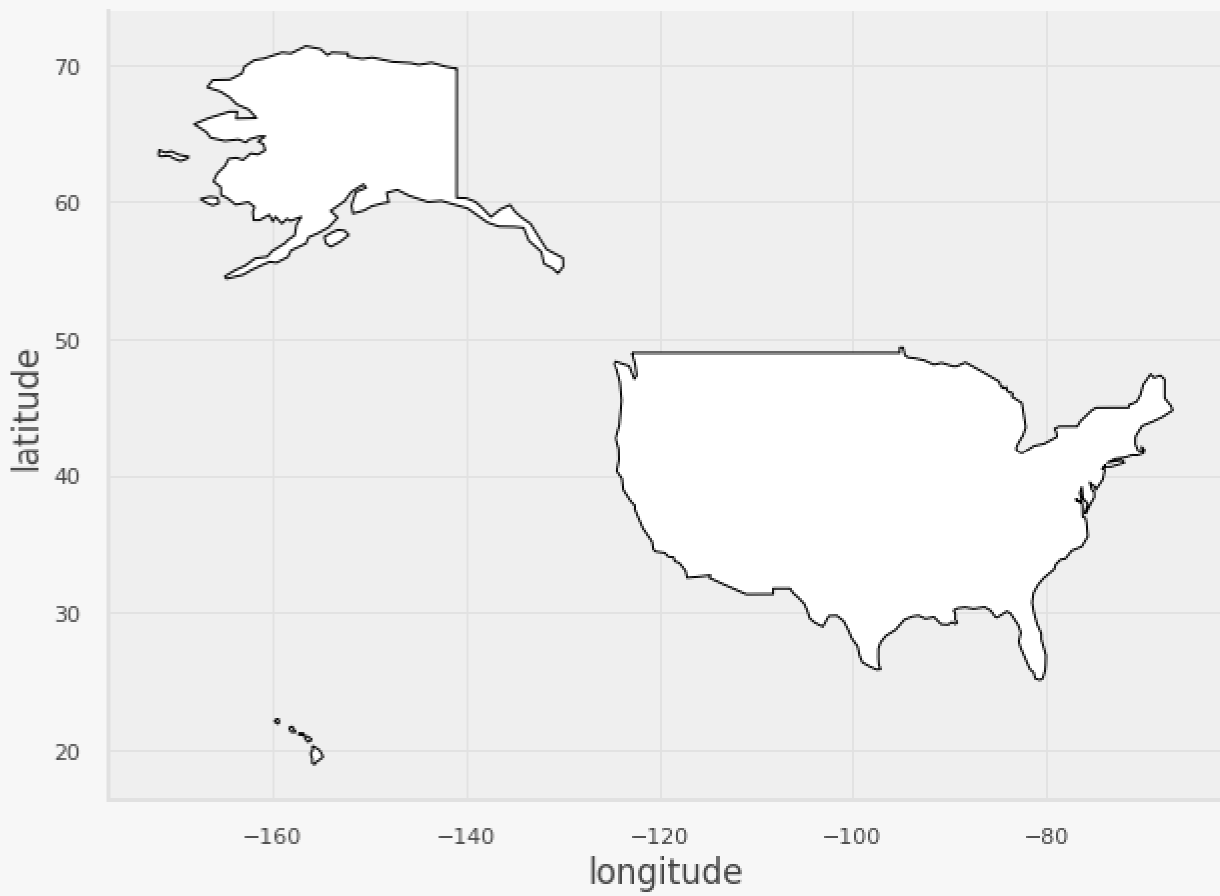
Out[ ]:

iso_a3	pop_est	continent	name	gdp_md_est	geometry
FJI	920938	Oceania	Fiji	8374.0	MULTIPOLYGON (((180.00000 -16.06713, 180.00000...
TZA	53950935	Africa	Tanzania	150600.0	POLYGON ((33.90371 -0.95000, 34.07262 -1.05982...
ESH	603253	Africa	W. Sahara	906.5	POLYGON ((-8.66559 27.65643, -8.66512 27.58948...
CAN	35623680	North America	Canada	1674000.0	MULTIPOLYGON (((-122.84000 49.00000, -122.9742...
USA	326625791	North America	United States of America	18560000.0	MULTIPOLYGON (((-122.84000 49.00000, -120.0000...

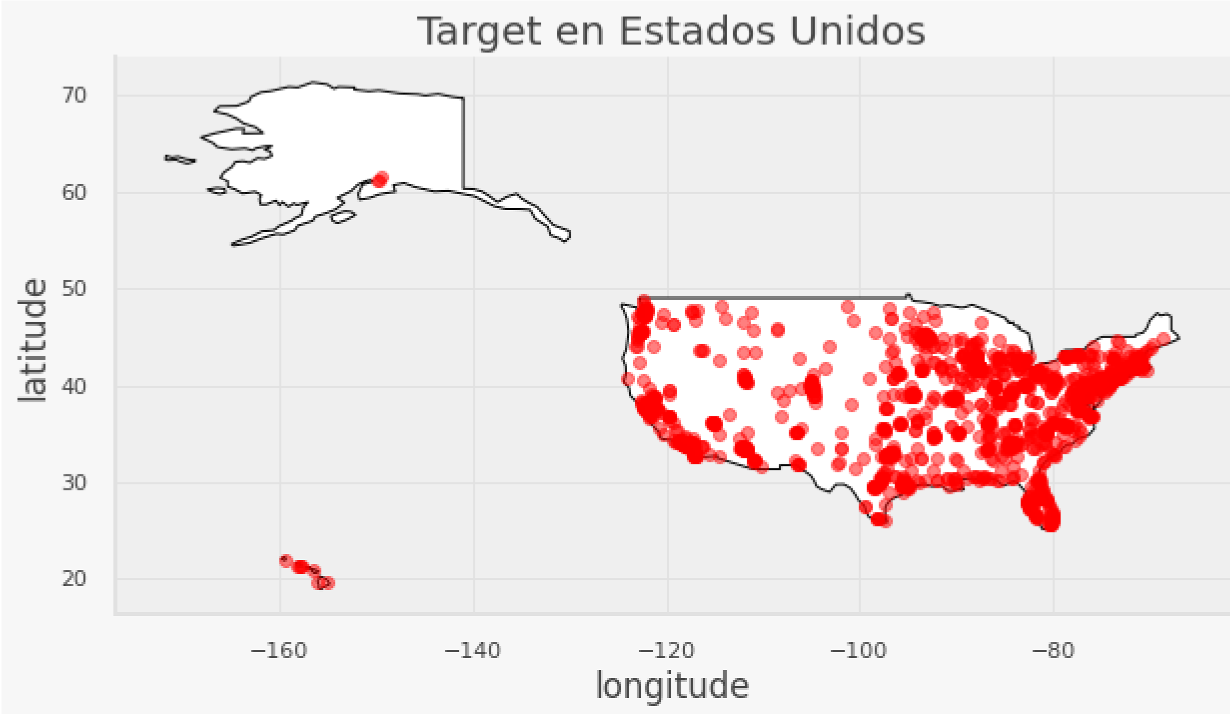
In [ ]:

```
import warnings
warnings.filterwarnings('ignore')

fig, gax = plt.subplots(figsize=(10,10))
# By only plotting rows in which the continent is 'South America' we only plot
```

```
world.query("name == 'United States of America'").plot(ax=gax, edgecolor='black

# By the way, if you haven't read the book 'longitude' by Dava Sobel, you shoul
gax.set_xlabel('longitude')
gax.set_ylabel('latitude')

gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)
```



In [ ]:
```
# Step 3: Plot the cities onto the map
# We mostly use the code from before --- we still want the country borders plot
# add a command to plot the cities
fig, gax = plt.subplots(figsize=(10,10))

# By only plotting rows in which the continent is 'South America' we only plot,
# South America.
world.query("name == 'United States of America'").plot(ax = gax, edgecolor='bla

# This plot the cities. It's the same syntax, but we are plotting from a differ
# I want the cities as pale red dots.
gdf.plot(ax=gax, color='red', alpha = 0.5)

gax.set_xlabel('longitude')
gax.set_ylabel('latitude')
gax.set_title('Target en Estados Unidos')

gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)

plt.show()
```



Convertimos nuestras ubicaciones a un arreglo de Numpy para poder obtener los centros de Kmeans

In [ ]:
```
XKmeans = np.array(latlong.values.tolist())
XKmeans[0:5]
```

Out[ ]:
```
array([[ 33.2242254, -86.8041737],
       [ 33.3345501, -86.9897779],
       [ 30.6028747, -87.8959317],
       [ 34.5601477, -86.9715595],
       [ 31.2660613, -85.4464222]])
```

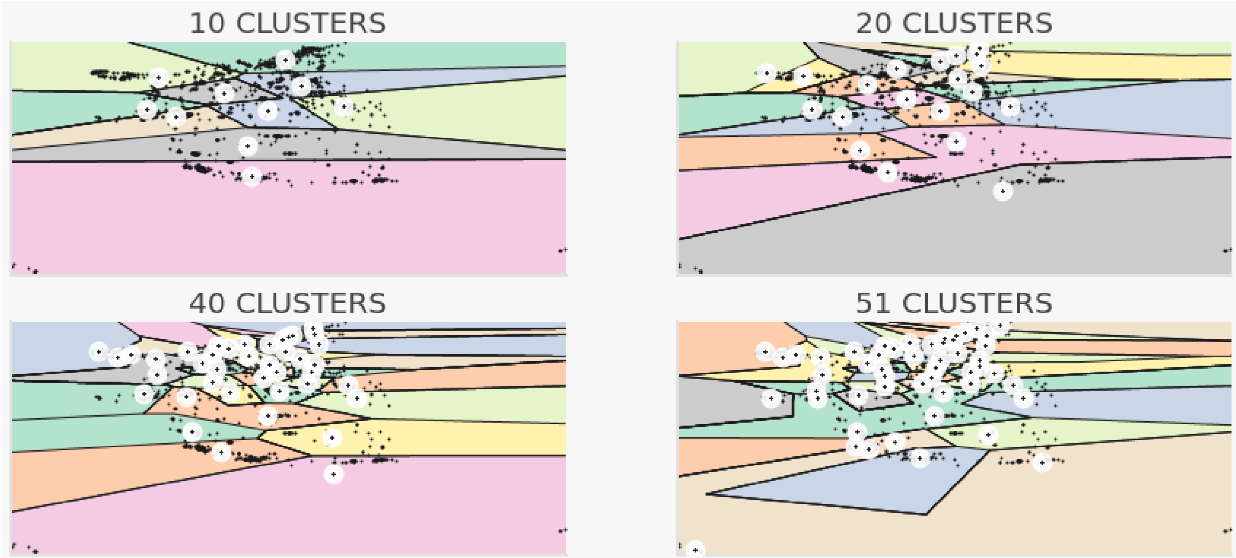
Para encontrar nuestro mejor lugar en el almacen, se necesita encontrar el numero optimo de centroids para poder colocar en esas ubicaciones los almacenes de manera que esten distribuidos especificamente

In [ ]:
```
def plot_data(X):
    plt.plot(X[:, 0], X[:, 1], 'k.', markersize=2)

def plot_centroids(centroids, weights=None, circle_color='w', cross_color='k'):
    if weights is not None:
        centroids = centroids[weights > weights.max() / 10]
    plt.scatter(centroids[:, 0], centroids[:, 1],
                marker='o', s=35, linewidths=8,
                color=circle_color, zorder=10, alpha=0.9)
    plt.scatter(centroids[:, 0], centroids[:, 1],
                marker='x', s=2, linewidths=12,
                color=cross_color, zorder=11, alpha=1)

def plot_decision_boundaries(clusterer, X, resolution=1000, show_centroids=True
                             show_xlabels=True, show_ylabels=True):
    mins = X.min(axis=0) - 0.1
    maxs = X.max(axis=0) + 0.1
```

```
    xx, yy = np.meshgrid(np.linspace(mins[0], maxs[0], resolution),
                         np.linspace(mins[1], maxs[1], resolution))
    Z = clusterer.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)

    plt.contourf(Z, extent=(mins[0], maxs[0], mins[1], maxs[1]),
                cmap="Pastel2")
    plt.contour(Z, extent=(mins[0], maxs[0], mins[1], maxs[1]),
                linewidths=1, colors='k')
    plot_data(X)
    if show_centroids:
        plot_centroids(clusterer.cluster_centers_)

    if show_xlabels:
        plt.xlabel("$x_1$")
    else:
        plt.tick_params(labelbottom=False)
    if show_ylabels:
        plt.ylabel("$x_2$", rotation=0)
    else:
        plt.tick_params(labelleft=False)
```

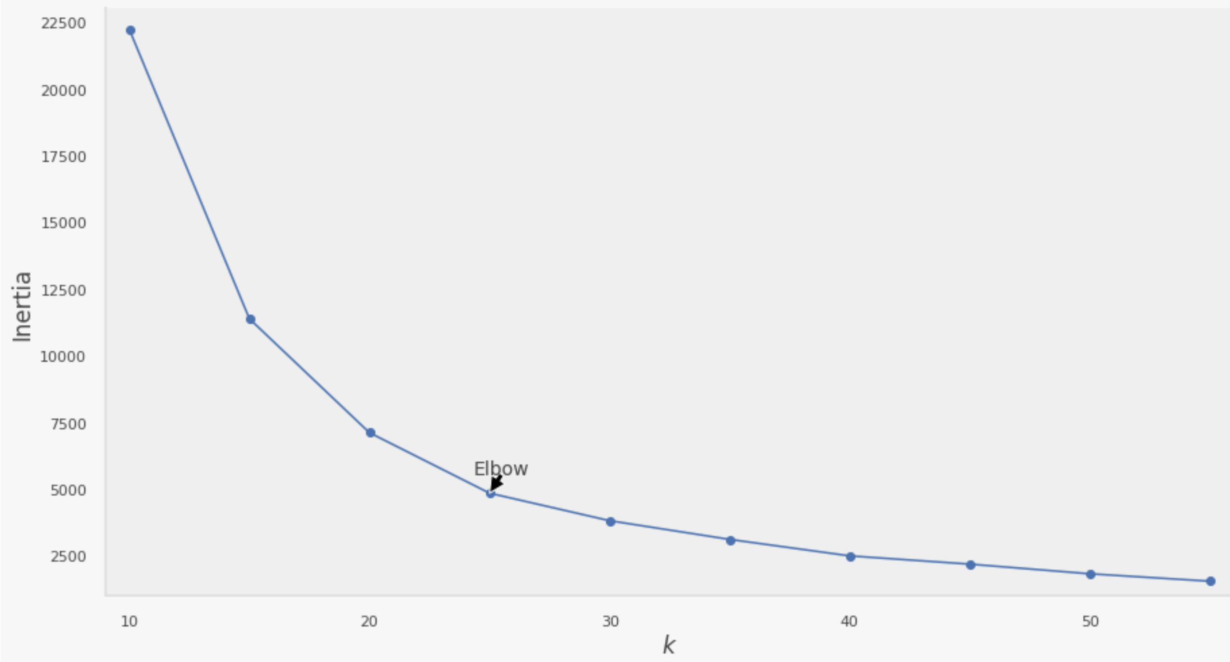
In [ ]:
```
from sklearn.cluster import KMeans

kmeans_iter1 = KMeans(n_clusters=10, init="random", n_init=1, max_iter=10,
                      random_state=5)
kmeans_iter2 = KMeans(n_clusters=20, init="random", n_init=1, max_iter=10,
                      random_state=5)
kmeans_iter3 = KMeans(n_clusters=40, init="random", n_init=1, max_iter=10,
                      random_state=5)
kmeans_iter4 = KMeans(n_clusters=51, init="random", n_init=1, max_iter=10,
                      random_state=5)
kmeans_iter1.fit(XKmeans)
kmeans_iter2.fit(XKmeans)
kmeans_iter3.fit(XKmeans)
kmeans_iter4.fit(XKmeans)

plt.figure(figsize=(15, 10))
plt.subplot(321)
plot_decision_boundaries(kmeans_iter1, XKmeans, show_centroids=False,
                         show_ylabels=False, show_xlabels=False)
plot_centroids(kmeans_iter1.cluster_centers_)
plt.title("10 CLUSTERS")


plt.subplot(322)
plot_decision_boundaries(kmeans_iter2, XKmeans, show_centroids=False,
                         show_ylabels=False, show_xlabels=False)
plot_centroids(kmeans_iter2.cluster_centers_)
plt.title("20 CLUSTERS")



plt.subplot(323)
plot_decision_boundaries(kmeans_iter3, XKmeans, show_centroids=False, show_ylab
plot_centroids(kmeans_iter3.cluster_centers_)
plt.title("40 CLUSTERS")
```

```
plt.subplot(324)
plot_decision_boundaries(kmeans_iter4, XKmeans, show_centroids=False, show_ylab
plot_centroids(kmeans_iter4.cluster_centers_)
plt.title("51 CLUSTERS")

plt.show()
```



In [ ]:

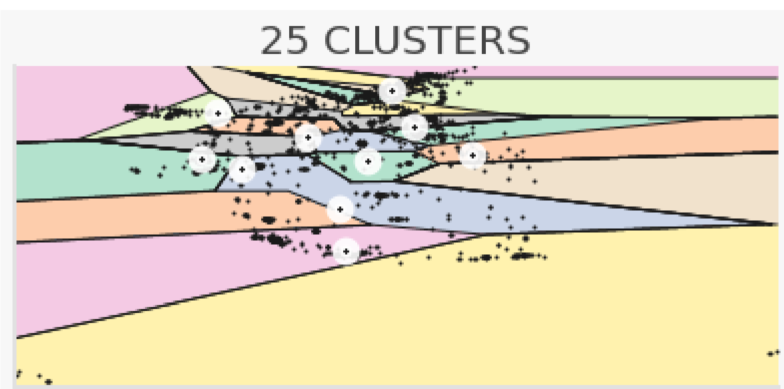
```
kmeans_per_k = [KMeans(n_clusters=k, random_state=42).fit(XKmeans)
                for k in range(10, 60, 5)]
inertias = [model.inertia_ for model in kmeans_per_k]
l = []
for k in kmeans_per_k:
    l.append(k.n_clusters)
plt.figure(figsize=(15, 8))
plt.plot(l, inertias, "bo-")
plt.xlabel("$k$")
plt.ylabel("Inertia")
plt.annotate("", xy=(25, inertias[3]), xytext=(25.5, 5550),
             arrowprops=dict(facecolor='black', shrink=0.001))
plt.text(25.5, 5550, "Elbow", horizontalalignment="center")
plt.axis([9, 56, 1000, 23000])
plt.grid()
plt.show()
```



Por lo visto en las anteriores graficas, tomaremos como 25 el numero de clusters, lo que quiere decir 25 almacenes.

In [ ]:
```
kmeans_final = KMeans(n_clusters=25, init="random", n_init=1, max_iter=30,
                      random_state=5)
kmeans_final.fit(XKmeans)
plt.figure(figsize=(15, 10))
plt.subplot(321)
plot_decision_boundaries(kmeans_final, XKmeans, show_centroids=False,
                         show_ylabels=False, show_xlabels=False)
plot_centroids(kmeans_iter1.cluster_centers_)
plt.title("25 CLUSTERS")
```

Out[ ]: `Text(0.5, 1.0, '25 CLUSTERS')`



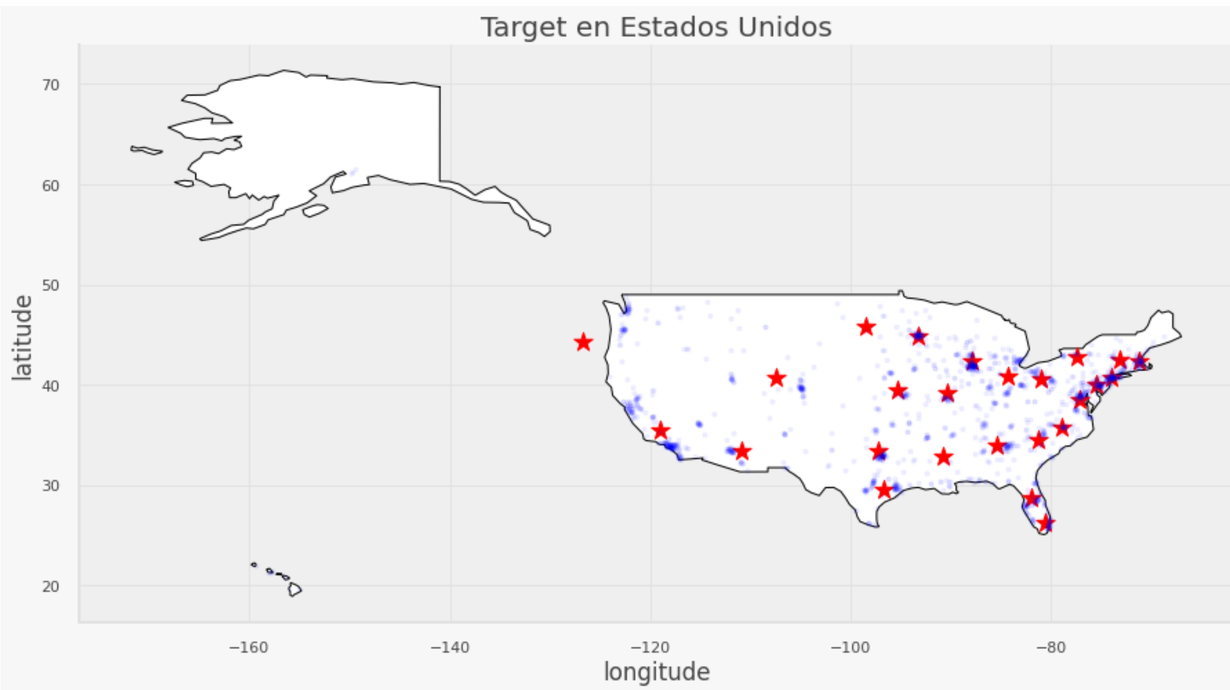
En la grafica anterior, podemos verificar como quedaran los almacenes respecto a las tiendas. A continuacion lo veremos en el mapa

Encuentra las latitudes y longitudes de los almacenes

In [ ]:
```
dfCoordinates = pd.DataFrame(kmeans_final.cluster_centers_, columns=['lat', 'lo
dfCoordinates["Coordinates"] = list(zip(dfCoordinates.long, dfCoordinates.lat))
```

```
dfCoordinates["Coordinates"] = dfCoordinates["Coordinates"].apply(Point)
dfCoordinates = gpd.GeoDataFrame(dfCoordinates, geometry="Coordinates")
```

In [ ]:
```
fig, gax = plt.subplots(figsize=(15,10))


world.query("name == 'United States of America'").plot(ax = gax, edgecolor='bla


dfCoordinates.plot(ax=gax, color='red', marker = "*", markersize = 200)
gdf.plot(ax=gax, color='blue', alpha = 0.05, marker= ".")

gax.set_xlabel('longitude')
gax.set_ylabel('latitude')
gax.set_title('Target en Estados Unidos')

gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)

plt.show()
```



Como podemos observar, existe un punto marcado como almacen fuera de tierra firme, para ese caso necesitariamos ajustar nuestro modelo para tener un rango de coordenadas en las que se pueden construir los almacenes

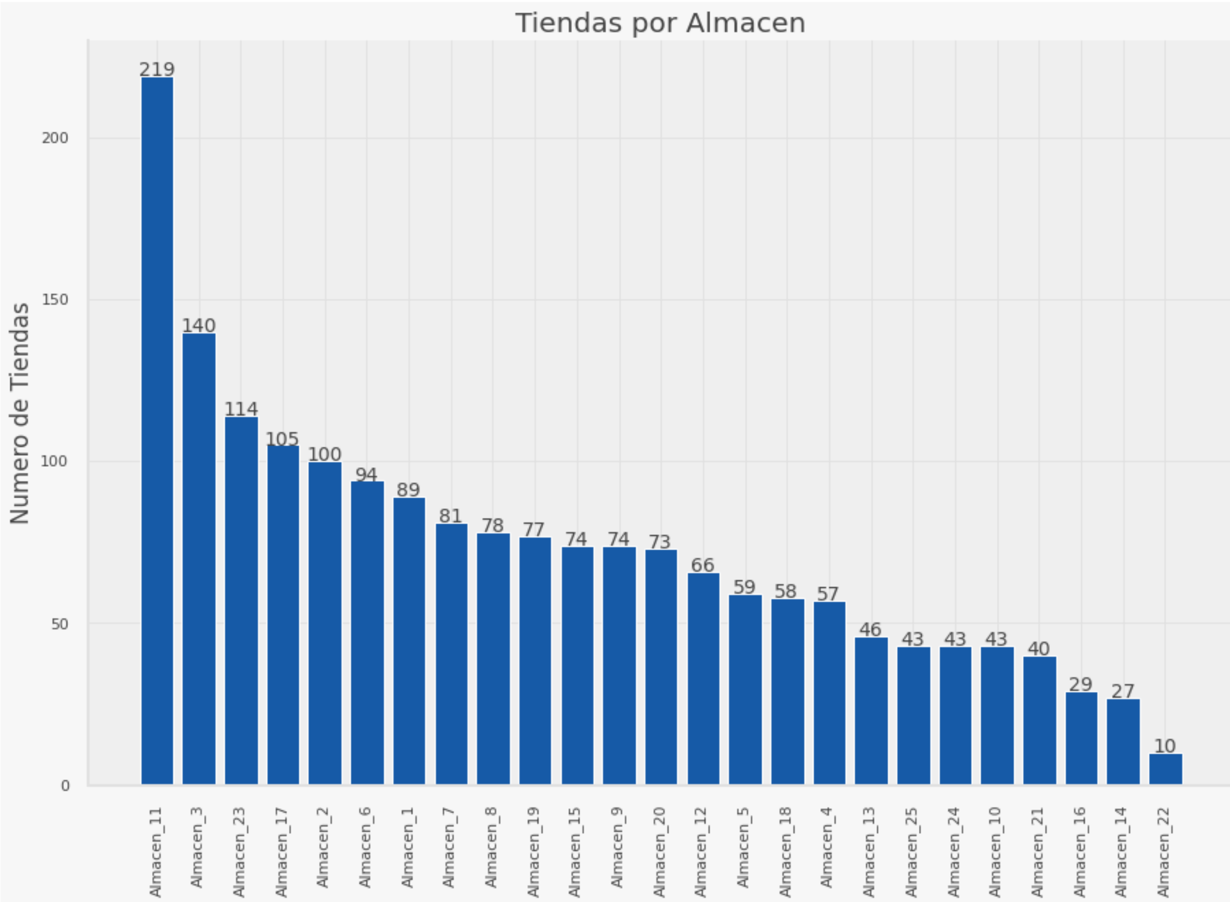
¿a cuantas tiendas va surtir?, ¿sabes a que distancia estará?

In [ ]:
```
columnsKm = np.arange(1, 26, 1)
columnsKm.sort()
distancesKm = pd.DataFrame(kmeans_final.transform(XKmeans).round(2), columns=cc
distancesKm = pd.DataFrame({'Almacen': distancesKm.idxmin(axis=1), 'Distance':
```

In [ ]:
```
yax = distancesKm['Almacen'].value_counts().values
xax = ['Almacen_' + str(x) for x in np.array(distancesKm['Almacen'].value_count
```

```
plt.title('Tiendas por Almacen')
plt.ylabel('Numero de Tiendas')
for i in range(len(xax)):
    plt.text(i, yax[i], yax[i], ha = 'center')
plt.xticks(rotation = 90)
plt.bar(xax, yax)
```

Out[ ]: <BarContainer object of 25 artists>



En el grafico anterior observamos el numero de tiendas a la que cada almacen va a abastecer. En el dataframe podremos observar a que distancia estara.

In [ ]:
```
distancesKm.loc[distancesKm['Almacen'] == 22]
```

Out[ ]:

	Almacen	Distance
931	22	2.06
1275	22	2.50
1276	22	1.94
1277	22	2.51
1278	22	3.70
1481	22	0.36
1482	22	5.00
1483	22	1.68
1484	22	2.87
1485	22	2.92

¿Cómo elegiste el número de almacenes?

El numero de almacenes se eligio al sacar la grafica de Elbow, la cual indica en que numero de clusters la particion en mas empieza a no ser significativa para el promedio de las distancias al centro del grupo.

¿Qué librerías nos pueden ayudar a graficar este tipo de datos?

Las librerias que nos han ayudado en esta practica son todas aquellas de graficos geograficos, matplolib y seaborn. Asi como las librerias para encontrar nuestros modelos optimos y convertir datos.

¿Consideras importante que se grafique en un mapa?, ¿por qué?

Para este caso de K-Mean fue muy importante el graficar en un mapa, ya que pudimos no solo observar la distribucion de las tiendas sino tambien observamos como nuestras predicciones pueden ser erroneas para el caso, como el caso del almacen que no esta en una cordenada con tierra firme. Fue importante poder observar visualmente esta informacion y ayudo a tomar decisiones importantes.

Conclusiones

El metodo de K-means es un metodo de predicciones para datos no etiquetados muy util, ya que para estos casos nos permite conocer, detectar y agrupar nuestros datos para poder realizar las predicciones con un alto grado de precision. En este caso particular al utilizar esta tecnica nos ayudo a identificar el numero y ubicacion de los posibles almacenes algo que definitivamente ayudaria a nuestra empresa a reducir costos y tomar decisiones inteligentes sin depender de datos etiquetados.

K-means me parecio un metodo super interesante ya que el aprendizaje no supervisado me parece que es una parte primordial del aprendizaje automatico y debemos de ser capaces de llevar a cabo estos metodos con precision para poder resolver las necesidades del mundo actual.