intro_aprendizaje_

June 28, 2019

1 INTRODUCCIÓN AL APRENDIZAJE AUTOMÁTICO

1.1 LABORATORIO 1

1.1.1 FERRARO, MARÍA EUGENIA

```
In [4]: import matplotlib.pyplot as plt
        import numpy as np
        import matplotlib as mp

        from matplotlib.colors import ListedColormap
        from sklearn.datasets import load_boston, load_breast_cancer, load_iris
        from sklearn.linear_model import LinearRegression, LogisticRegression, Perceptron, Rid
        from sklearn.metrics import accuracy_score, confusion_matrix, mean_squared_error
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.preprocessing import PolynomialFeatures

        from ml.visualization import plot_confusion_matrix, classifier_boundary

        np.random.seed(1234)  # Setup seed to be more deterministic\n",


        import pandas as pd
        import seaborn as sb


        %matplotlib inline
        import warnings
        warnings.filterwarnings('ignore')
```

2 REGRESION

```
In [29]: def regresion_lineal(xtf,yt,xvf,yv,regularizacion,alpha,feature):
             if regularizacion==False:
                 model = LinearRegression()
                 model.fit(xtf, yt)
             else:
```

```
        model = Ridge(alpha=alpha)
        model.fit(xtf, yt)

    err_train = mean_squared_error(yt, model.predict(xtf))
    err_val = mean_squared_error(yv, model.predict(xvf))

    return [feature,regularizacion,alpha,err_train,err_val,model.coef_,model.intercep


def regresion_polinomial(xtf,yt,xvf,yv,grado_polinomio,regularizacion,alpha,feature):
    poly_features = PolynomialFeatures(grado_polinomio)
    poly_features.fit(xtf)
    X_poly_train = poly_features.transform(xtf)
    X_poly_val = poly_features.transform(xvf)

    if regularizacion==False:
        model = LinearRegression()
        model.fit(X_poly_train, y_train)

    else:
        model = Ridge(alpha=alpha)
        model.fit(X_poly_train, y_train)

    err_train = mean_squared_error(y_train, model.predict(X_poly_train))
    err_val = mean_squared_error(y_val, model.predict(X_poly_val))

    return [feature,grado_polinomio,regularizacion,alpha,err_train,err_val,model.coef_


def modelo(x,coef,x0):
    ymodel = np.zeros(len(x))
    for i in range(len(x)):
        if len(coef)==1:
            ymodel[i] = coef[0]*x[i]
        else:
            for c in range(len(coef)):
                ymodel[i] = ymodel[i] + coef[c]*x[i]**c
    return ymodel+x0


def plot_fit(feature_resultados,tipo,c,lw):
    X_range_start = np.min(np.r_[X_train_feature, X_val_feature])
    X_range_stop = np.max(np.r_[X_train_feature, X_val_feature])
    y_range_start = np.min(np.r_[y_train, y_val])
    y_range_stop = np.max(np.r_[y_train, y_val])

    X_linspace = np.linspace(X_range_start, X_range_stop, 200)
```

```
    # Conjunto de entrenamiento
    plt.scatter(X_train_feature, y_train, facecolor="lightgray", edgecolor="gray", lal
    if tipo=='L':
        for j in range(len(feature_resultados)):
            coef = feature_resultados.Coef.values[j]
            x0 = feature_resultados.Intercept.values[j]
            plt.plot(X_linspace, modelo(X_linspace,coef,x0), color=c, label="modelo",l
    elif tipo=='P':
        grados_= feature_resultados.Degree.unique()
        cc=0
        for g in grados_:
            sub_df = feature_resultados[feature_resultados.Degree==g]
            for j in range(len(sub_df)):
                coef = sub_df.Coef.values[j]
                x0 = sub_df.Intercept.values[j]
                plt.plot(X_linspace, modelo(X_linspace,coef,x0),color=c[cc],label="moc
            cc+=1

    plt.ylim(y_range_start, y_range_stop)

    # Conjunto de validación
    #plt.subplot(1, 2, 2)
    #plt.scatter(X_val_feature, y_val, facecolor=\"dodgerblue\", edgecolor=\"k\", lab
    #plt.plot(X_linspace, model.predict(X_linspace_poly), color=\"tomato\", label=\"m
    #plt.ylim(y_range_start, y_range_stop)
    #plt.title(\"Conjunto de Validación\")

def plot_err(feature_resultados,Err,tipo,c):
    if tipo=='P':
        grados_= feature_resultados.Degree.unique()
        cc=0
        for g in grados_:
            sub_df = feature_resultados[feature_resultados.Degree==g]
            if Err=='T':
                plt.plot(sub_df.Alpha,sub_df.TrainMSE,color=c[cc],label='Grado: '+str
            elif Err=='V':
                plt.plot(sub_df.Alpha,sub_df.ValMSE,color=c[cc],label='Grado: '+str(g)
            cc+=1
        plt.legend(loc='lower right',frameon=False,ncol=3)
    elif tipo=='L':
        if Err=='T':
            plt.plot(feature_resultados.Alpha,feature_resultados.TrainMSE,color=c)
        elif Err=='V':
            plt.plot(feature_resultados.Alpha,feature_resultados.ValMSE,color=c)
    plt.xlabel('alpha')
    plt.ylabel('ECM')

def plot_err_g(feature_resultados,Err,c):
```

```
        if Err=='T':
            plt.plot(feature_resultados.Degree,feature_resultados.TrainMSE,color=c,label=
        elif Err=='V':
            plt.plot(feature_resultados.Degree,feature_resultados.ValMSE,color=c,label='V
        plt.xlabel('Degree')
        plt.ylabel('ECM')
        plt.legend(frameon=False,loc='upper left')
```

In [26]:
```
boston_data = load_boston()
```

In [27]:
```
regresion_lineal_ECM = pd.DataFrame(columns=['Feature','Regularization','Alpha','Trai
regresion_polinomial_ECM = pd.DataFrame(columns=['Feature','Degree','Regularization',


shuff_data = np.random.permutation(506)
shuff_train = shuff_data[:400]
shuff_val = shuff_data[400:]

X_train = boston_data['data'][shuff_train]
X_val = boston_data['data'][shuff_val]

y_train = boston_data['target'][shuff_train]
y_val = boston_data['target'][shuff_val]

feature_map = {feature: idx for idx, feature in enumerate(boston_data['feature_names']

features = boston_data['feature_names']
categorical_features = ['CHAS','RAD','MEDV']
non_categorical_features = set(features)-set(categorical_features)

#alpha = np.arange(0.1, 1.1, 0.1)
grado = np.arange(1,10,1)
alpha = np.arange(1e-5,1e3,10)

cmap = mp.cm.get_cmap('Spectral')
color = []
for i in range(len(grado)):
    color.append(cmap(0.1*i))

for feature in non_categorical_features:
    feature_col = feature_map[feature]
    X_train_feature = X_train[:, feature_col].reshape(-1, 1)
    X_val_feature = X_val[:, feature_col].reshape(-1, 1)

    # regresion lineal
    ## sin regularizacion
    row = regresion_lineal(X_train_feature,y_train,X_val_feature,y_val,False,0,featur
```

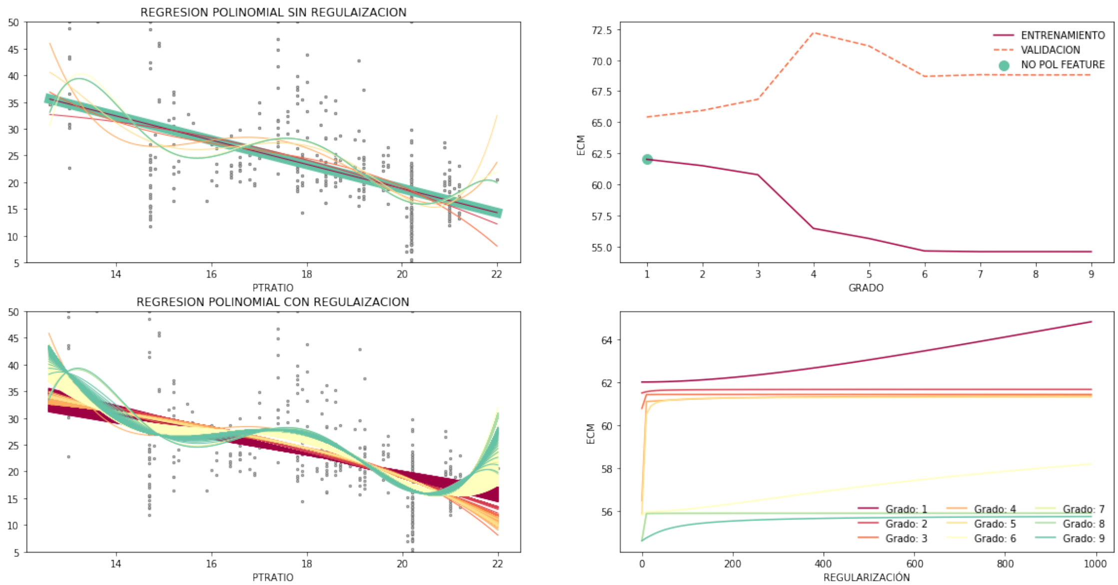
```
    regresion_lineal_ECM = regresion_lineal_ECM.append(pd.Series(row, index=regresion_
    ## con regularizacion
    for i in alpha:
        row = regresion_lineal(X_train_feature,y_train,X_val_feature,y_val,True,i,feat
        regresion_lineal_ECM = regresion_lineal_ECM.append(pd.Series(row, index=regres


    # regresion polinomial
    ## sin regularizacion
    for g in grado:
        row = regresion_polinomial(X_train_feature,y_train,X_val_feature,y_val,g,False
        regresion_polinomial_ECM = regresion_polinomial_ECM.append(pd.Series(row, inde
    ## con regularizacion
        for i in alpha:
            row = regresion_polinomial(X_train_feature,y_train,X_val_feature,y_val,g,T
            regresion_polinomial_ECM = regresion_polinomial_ECM.append(pd.Series(row,
```

A continuación se exponen gráficos de regresón lineal con y sin regularización, de polinomios de distintos grados, para cada una de las variables no categóricas del dataset. A su vez se muestra la evolución del error cuadrático medio del conjunto de entrenamiento y del de validación, en función del grado del polinomio. Por otro lado se muestra, en color verde agua, que los distintos métodos, ya sea polynomial feature o la regresión directa sin pasar por el método anterior, llevan al mismo resultado cuando se trata de ajustar una recta. El punto verde agua representa el error cuando se hace la regresión directa, para un polinomio de grado 1, y la recta verde agua ancha, representa el resultado de dicho método. El resto de las curvas se corresponden con resultados de pasar primero por polynomial features y luego por la regresión.

```
In [31]: diferencias=[]
         for feature in non_categorical_features:
             print(feature)
             feature_col = feature_map[feature]
             X_train_feature = X_train[:, feature_col].reshape(-1, 1)
             X_val_feature = X_val[:, feature_col].reshape(-1, 1)

             plt.figure(figsize=(20,10))

             feature_resultadosl = regresion_lineal_ECM[(regresion_lineal_ECM.Feature==feature)
                                                        (regresion_lineal_ECM.Regularization==F
             punto_err_metodo_lineal = [1,feature_resultadosl.TrainMSE.values[0]]

             #plt.subplot(421)

             feature_resultados = regresion_polinomial_ECM[(regresion_polinomial_ECM.Feature==f
                                                           (regresion_polinomial_ECM.Regulariza
             plt.subplot(221)
             plot_fit(feature_resultadosl,'L',color[-1],lw=10)
             plot_fit(feature_resultados,'P',color,lw=1)
```

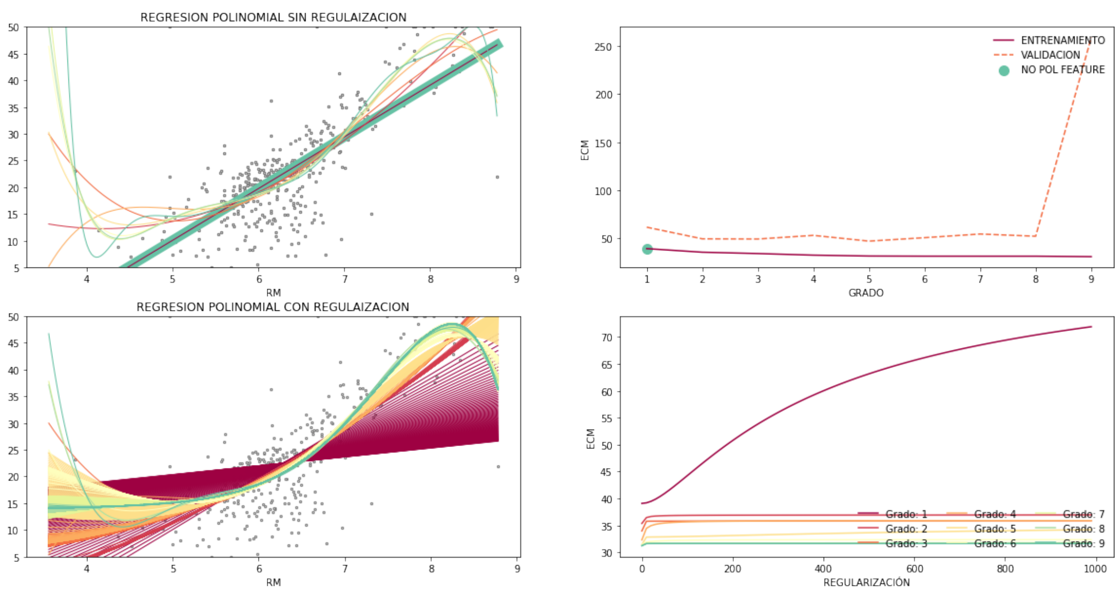
```
    plt.xlabel(feature)
    plt.title('REGRESION POLINOMIAL SIN REGULAIZACION')

    feature_resultados = regresion_polinomial_ECM[(regresion_polinomial_ECM.Alpha==0)&
                                                   (regresion_polinomial_ECM.Feature==

    diferencias.append(punto_err_metodo_lineal[1]-feature_resultados.TrainMSE.values[

    plt.subplot(222)
    plot_err_g(feature_resultados,'T',color[0])
    plot_err_g(feature_resultados,'V',color[2])
    plt.scatter(punto_err_metodo_lineal[0],punto_err_metodo_lineal[1],color=color[-1]
    plt.legend(frameon=False,loc='upper right')
    plt.xlabel('GRADO')


    feature_resultados = regresion_lineal_ECM[(regresion_lineal_ECM.Feature==feature)&
                                              (regresion_lineal_ECM.Regularization==Tr

    #plt.subplot(323)
    #plot_fit(feature_resultados,'L',color[0],lw=1)
    #plt.subplot(324)
    #plot_err(feature_resultados,'L',color[0])

    feature_resultados = regresion_polinomial_ECM[(regresion_polinomial_ECM.Feature==
                                                  (regresion_polinomial_ECM.Regulariza
    plt.subplot(223)
    plot_fit(feature_resultados,'P',color,lw=1)
    plt.xlabel(feature)
    plt.title('REGRESION POLINOMIAL CON REGULAIZACION')
    plt.subplot(224)
    plot_err(feature_resultados,'T','P',color)
    plt.xlabel('REGULARIZACIÓN')
    #plot_err(feature_resultados,'V','P',color)


    plt.show()
```

```
PTRATIO
```



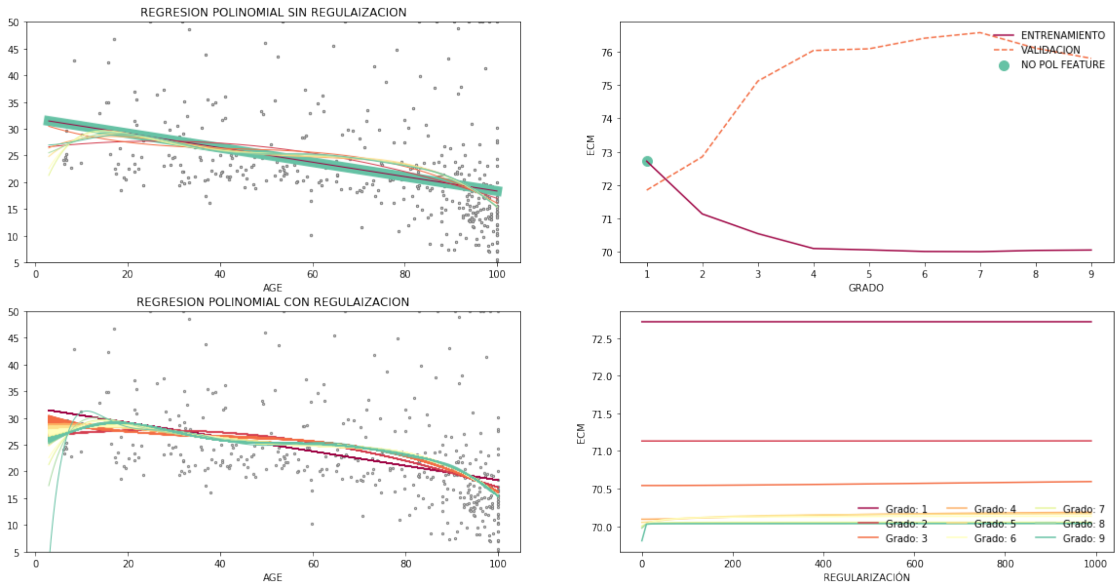
REGRESION POLINOMIAL SIN REGULAIZACION
PTRATIO
ENTRENAMIENTO
VALIDACION
NO POL FEATURE
ECM
GRADO
REGRESION POLINOMIAL CON REGULAIZACION
PTRATIO
ECM
Grado: 1
Grado: 2
Grado: 3
Grado: 4
Grado: 5
Grado: 6
Grado: 7
Grado: 8
Grado: 9
REGULARIZACIÓN

RM

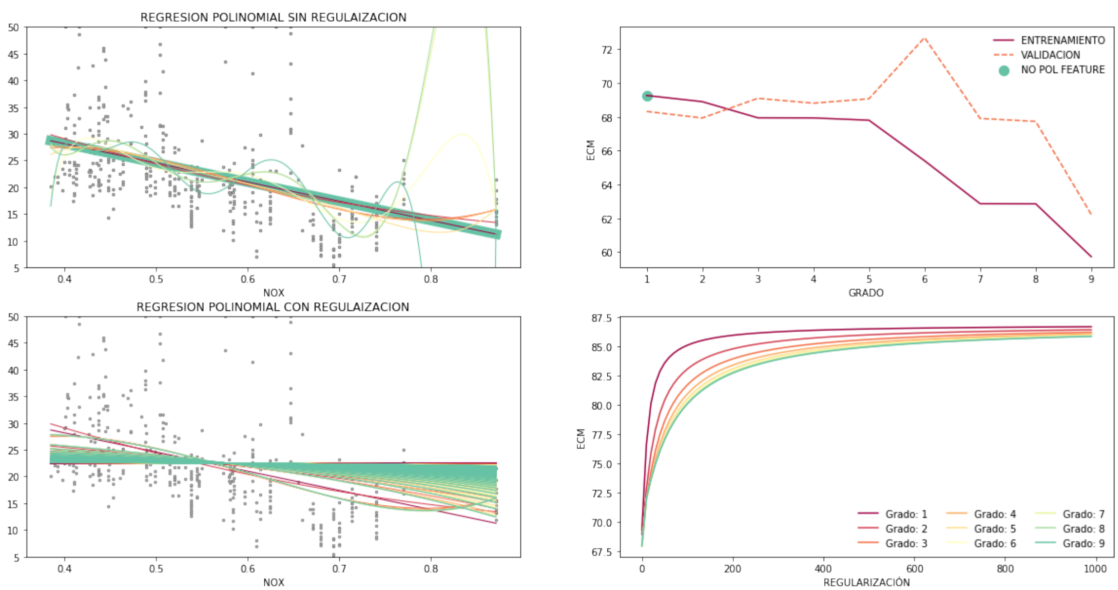


REGRESION POLINOMIAL SIN REGULAIZACION
RM
ENTRENAMIENTO
VALIDACION
NO POL FEATURE
ECM
GRADO
REGRESION POLINOMIAL CON REGULAIZACION
RM
ECM
Grado: 1
Grado: 2
Grado: 3
Grado: 4
Grado: 5
Grado: 6
Grado: 7
Grado: 8
Grado: 9
REGULARIZACIÓN

AGE


REGRESION POLINOMIAL SIN REGULAIZACION
AGE
REGRESION POLINOMIAL CON REGULAIZACION
AGE
ENTRENAMIENTO
VALIDACION
NO POL FEATURE
ECM
GRADO
ECM
REGULARIZACIÓN
Grado: 1
Grado: 2
Grado: 3
Grado: 4
Grado: 5
Grado: 6
Grado: 7
Grado: 8
Grado: 9

NOX


REGRESION POLINOMIAL SIN REGULAIZACION
NOX
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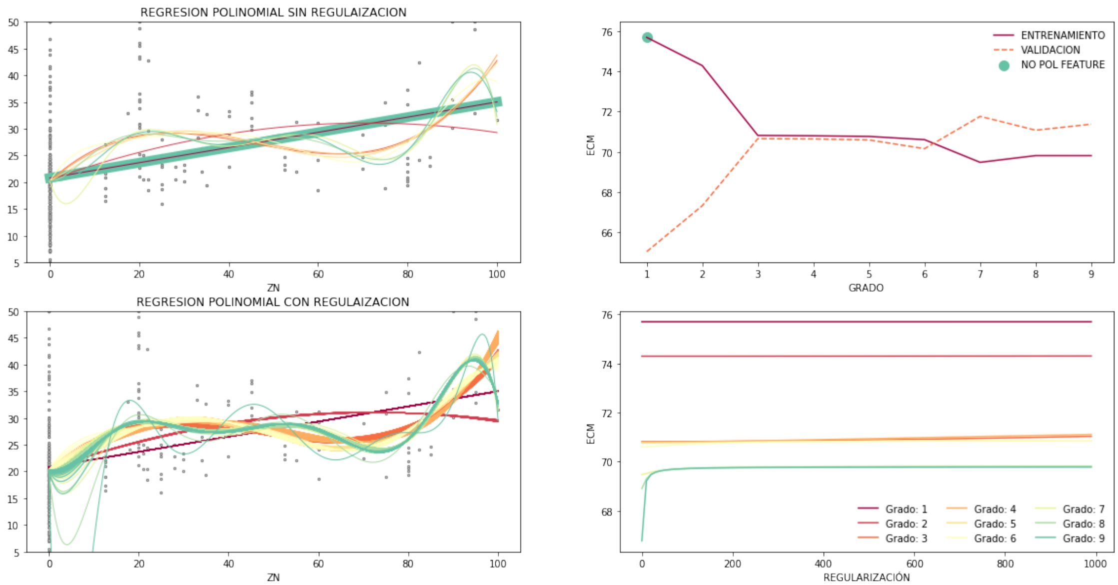
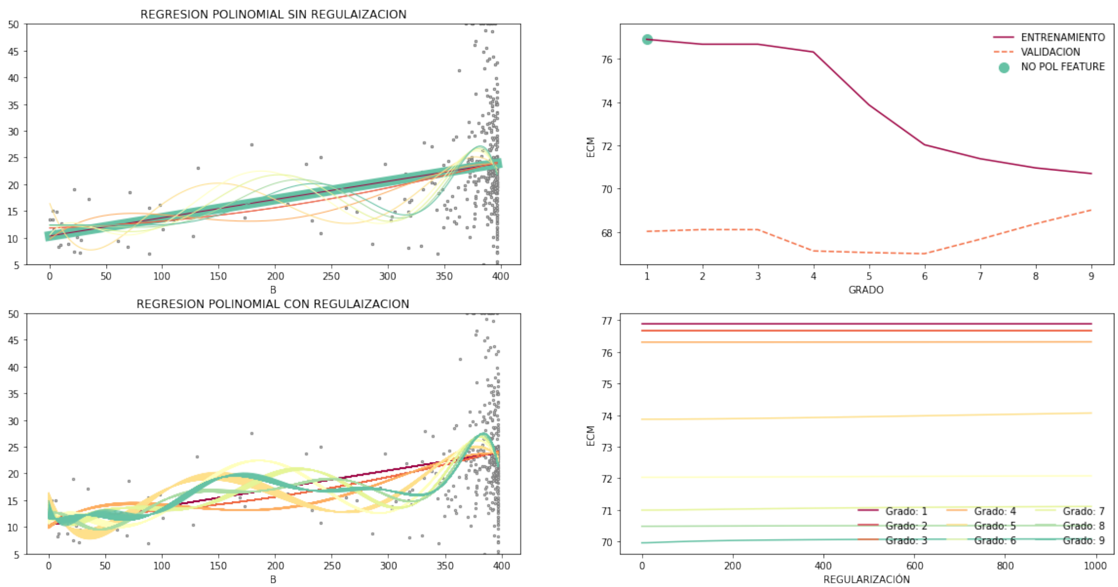
NO POL FEATURE
ECM
GRADO
ECM
REGULARIZACIÓN
Grado: 1
Grado: 2
Grado: 3
Grado: 4
Grado: 5
Grado: 6
Grado: 7
Grado: 8
Grado: 9

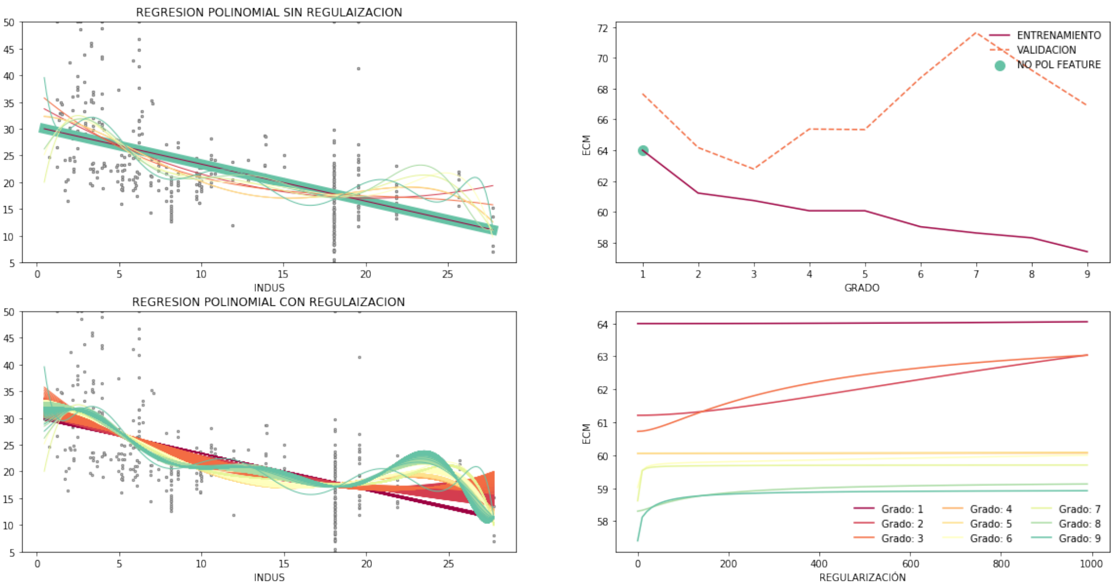
ZN


REGRESION POLINOMIAL SIN REGULAIZACION
ZN
ENTRENAMIENTO
VALIDACION
NO POL FEATURE
ECM
GRADO
REGRESION POLINOMIAL CON REGULAIZACION
ZN
ECM
Grado: 1
Grado: 2
Grado: 3
Grado: 4
Grado: 5
Grado: 6
Grado: 7
Grado: 8
Grado: 9
REGULARIZACIÓN

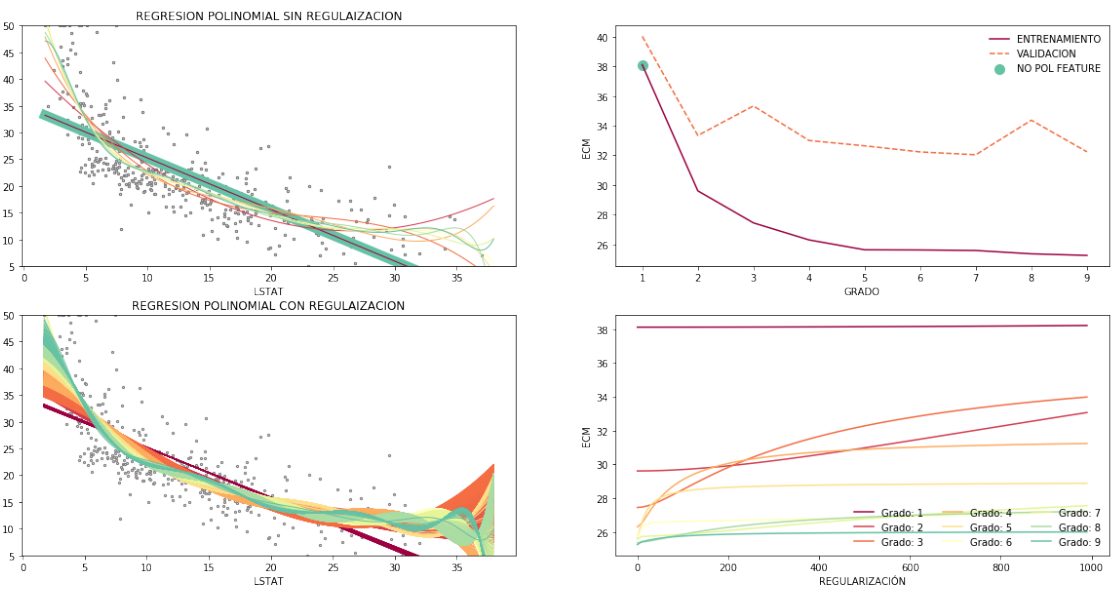
B


REGRESION POLINOMIAL SIN REGULAIZACION
B
ENTRENAMIENTO
VALIDACION
NO POL FEATURE
ECM
GRADO
REGRESION POLINOMIAL CON REGULAIZACION
B
ECM
Grado: 1
Grado: 2
Grado: 3
Grado: 4
Grado: 5
Grado: 6
Grado: 7
Grado: 8
Grado: 9
REGULARIZACIÓN

INDUS


REGRESION POLINOMIAL SIN REGULAIZACION
INDUS
REGRESION POLINOMIAL CON REGULAIZACION
INDUS
ENTRENAMIENTO
VALIDACION
NO POL FEATURE
ECM
GRADO
Grado: 1
Grado: 2
Grado: 3
Grado: 4
Grado: 5
Grado: 6
Grado: 7
Grado: 8
Grado: 9
ECM
REGULARIZACIÓN

LSTAT


REGRESION POLINOMIAL SIN REGULAIZACION
LSTAT
REGRESION POLINOMIAL CON REGULAIZACION
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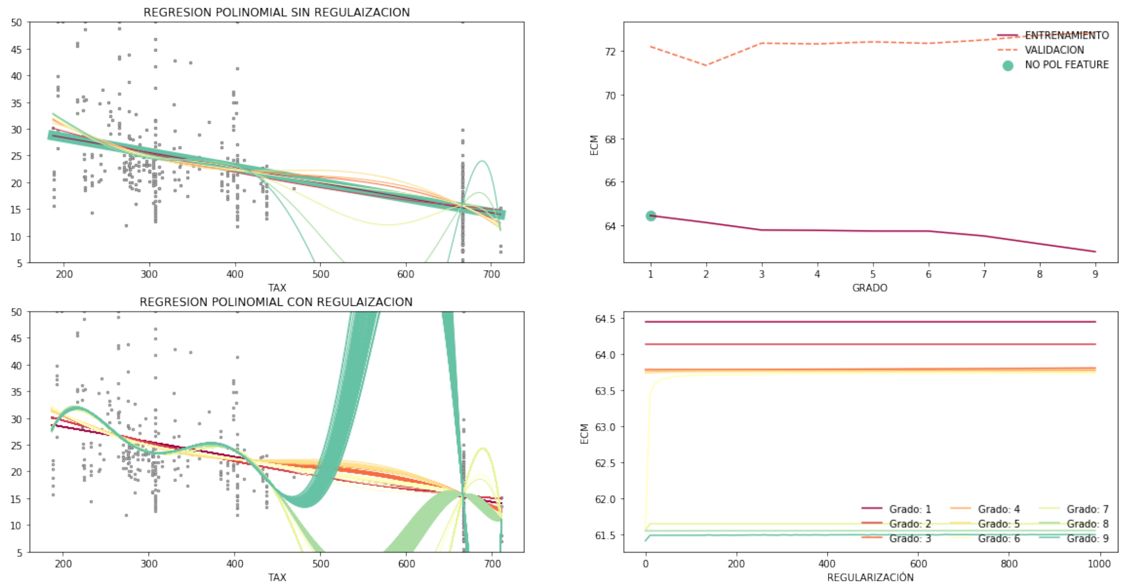
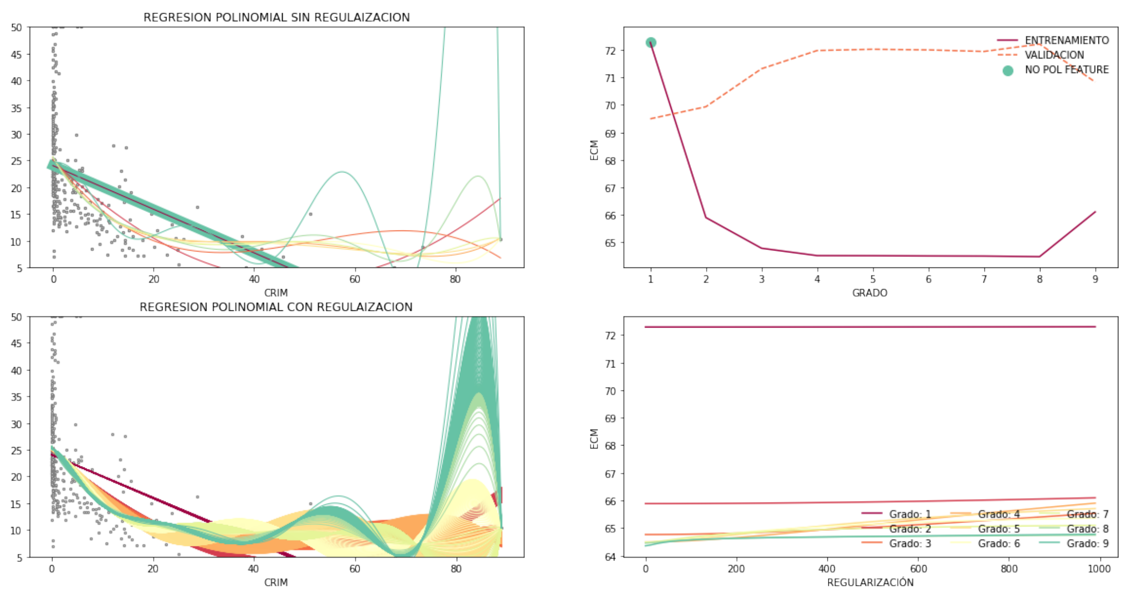
ENTRENAMIENTO
VALIDACION
NO POL FEATURE
ECM
GRADO
Grado: 1
Grado: 2
Grado: 3
Grado: 4
Grado: 5
Grado: 6
Grado: 7
Grado: 8
Grado: 9
ECM
REGULARIZACIÓN

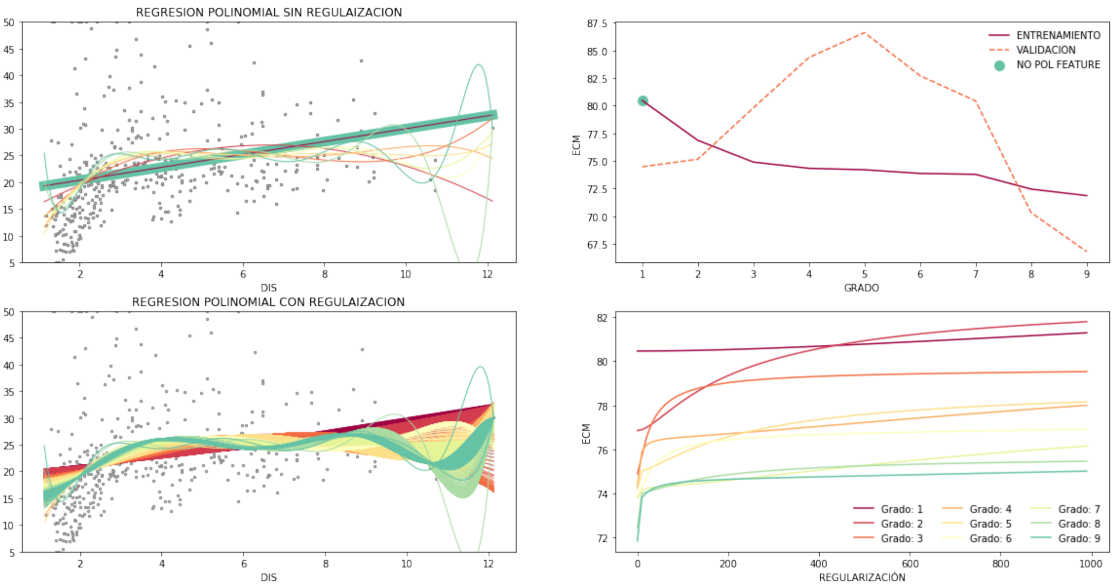
TAX


REGRESION POLINOMIAL SIN REGULAIZACION
TAX
ENTRENAMIENTO
VALIDACION
NO POL FEATURE
ECM
GRADO
REGRESION POLINOMIAL CON REGULAIZACION
TAX
ECM
REGULARIZACIÓN
Grado: 1
Grado: 2
Grado: 3
Grado: 4
Grado: 5
Grado: 6
Grado: 7
Grado: 8
Grado: 9

CRIM


REGRESION POLINOMIAL SIN REGULAIZACION
CRIM
ENTRENAMIENTO
VALIDACION
NO POL FEATURE
ECM
GRADO
REGRESION POLINOMIAL CON REGULAIZACION
CRIM
ECM
REGULARIZACIÓN
Grado: 1
Grado: 2
Grado: 3
Grado: 4
Grado: 5
Grado: 6
Grado: 7
Grado: 8
Grado: 9

DIS



A grandes rasgos se observa: 1. el error por lo general disminuye a medida que aumenta el grado 2. a medida que el grado aumenta, se observa como el overfitting genera grandes amplitudes 3. para grados grandes la regularización no es buena 4. el error en función de la regularización disminuye mientras el grado crece y crece mientras el valor de alpha (lambda en la teoría) crece

3 CLASIFICACION BINARIA

In [25]:
```
breast_cancer_data = load_breast_cancer()
```

In [26]:
```
# Utilizamos aproximadamente 80% de los datos para entrenamiento y 20% para validació
shuff_data = np.random.permutation(569)
shuff_train = shuff_data[:400]
shuff_val = shuff_data[400:]

X_train = breast_cancer_data['data'][shuff_train]
X_val = breast_cancer_data['data'][shuff_val]

y_train = breast_cancer_data['target'][shuff_train]
y_val = breast_cancer_data['target'][shuff_val]


data = pd.DataFrame(breast_cancer_data['data'],columns=breast_cancer_data['feature_nar
data['cancer_label'] = breast_cancer_data['target']
data.describe()
```

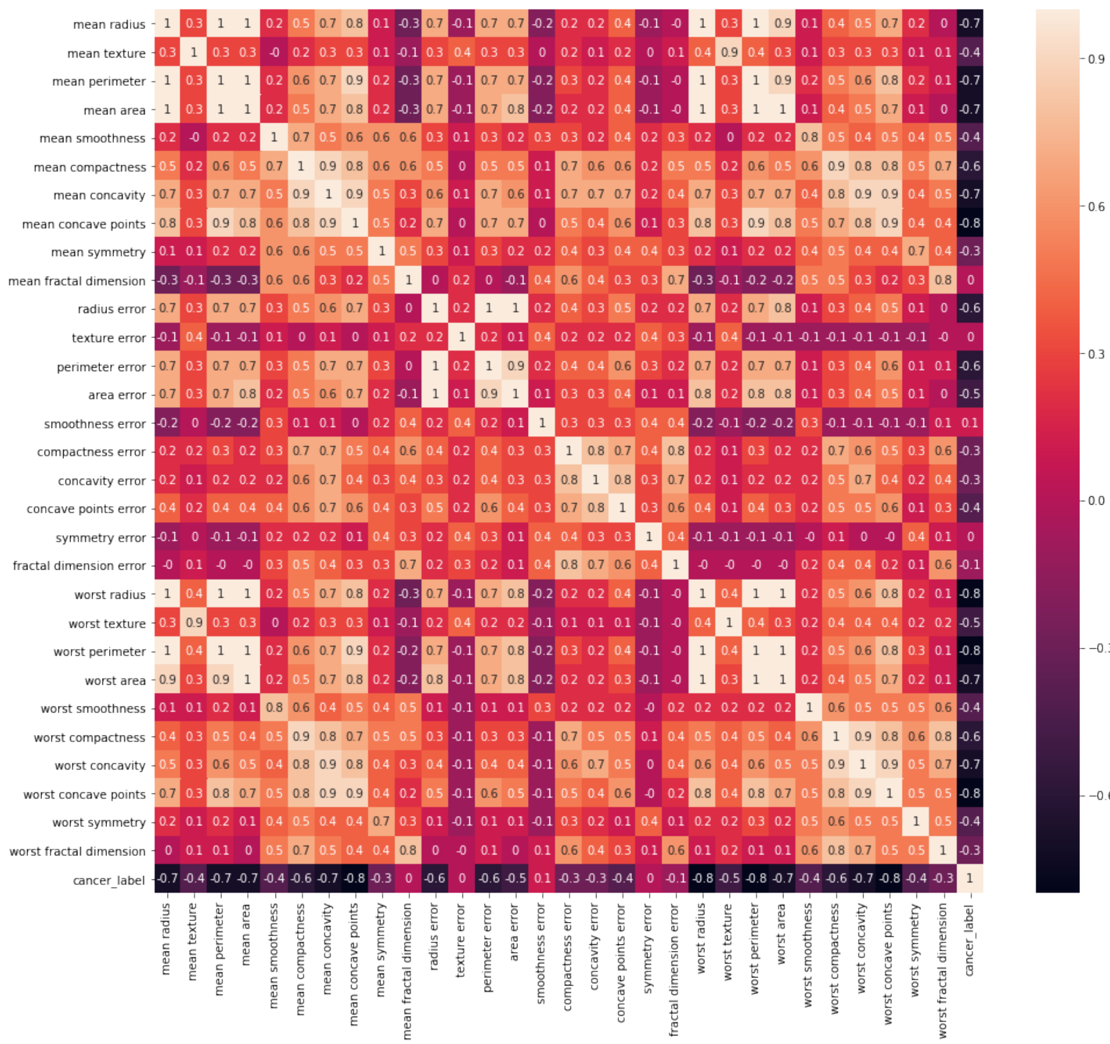
Out[26]:
```
       mean radius  mean texture  mean perimeter    mean area  \
count   569.000000    569.000000      569.000000   569.000000
```

```
mean     14.127292     19.289649       91.969033   654.889104
std       3.524049      4.301036       24.298981   351.914129
min       6.981000      9.710000       43.790000   143.500000
25%      11.700000     16.170000       75.170000   420.300000
50%      13.370000     18.840000       86.240000   551.100000
75%      15.780000     21.800000      104.100000   782.700000
max      28.110000     39.280000      188.500000  2501.000000

       mean smoothness  mean compactness  mean concavity  mean concave points  \
count       569.000000        569.000000      569.000000           569.000000
mean          0.096360          0.104341        0.088799             0.048919
std           0.014064          0.052813        0.079720             0.038803
min           0.052630          0.019380        0.000000             0.000000
25%           0.086370          0.064920        0.029560             0.020310
50%           0.095870          0.092630        0.061540             0.033500
75%           0.105300          0.130400        0.130700             0.074000
max           0.163400          0.345400        0.426800             0.201200

       mean symmetry  mean fractal dimension  ...  worst texture  \
count     569.000000              569.000000  ...     569.000000
mean        0.181162                0.062798  ...      25.677223
std         0.027414                0.007060  ...       6.146258
min         0.106000                0.049960  ...      12.020000
25%         0.161900                0.057700  ...      21.080000
50%         0.179200                0.061540  ...      25.410000
75%         0.195700                0.066120  ...      29.720000
max         0.304000                0.097440  ...      49.540000

       worst perimeter   worst area  worst smoothness  worst compactness  \
count       569.000000   569.000000        569.000000         569.000000
mean        107.261213   880.583128          0.132369           0.254265
std          33.602542   569.356993          0.022832           0.157336
min          50.410000   185.200000          0.071170           0.027290
25%          84.110000   515.300000          0.116600           0.147200
50%          97.660000   686.500000          0.131300           0.211900
75%         125.400000  1084.000000          0.146000           0.339100
max         251.200000  4254.000000          0.222600           1.058000

       worst concavity  worst concave points  worst symmetry  \
count       569.000000            569.000000      569.000000
mean          0.272188              0.114606        0.290076
std           0.208624              0.065732        0.061867
min           0.000000              0.000000        0.156500
25%           0.114500              0.064930        0.250400
50%           0.226700              0.099930        0.282200
75%           0.382900              0.161400        0.317900
max           1.252000              0.291000        0.663800
```

```
       worst fractal dimension  cancer_label
count               569.000000    569.000000
mean                  0.083946      0.627417
std                   0.018061      0.483918
min                   0.055040      0.000000
25%                   0.071460      0.000000
50%                   0.080040      1.000000
75%                   0.092080      1.000000
max                   0.207500      1.000000

[8 rows x 31 columns]
```

In [27]:
```python
correlation_matrix = data.corr().round(1)
fig, ax = plt.subplots(figsize=(16,14))
sb.heatmap(data=correlation_matrix, annot = True)
```

Out[27]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7feb426b54e0>
```



In [28]:
```python
features_original = breast_cancer_data['feature_names']
```

In [34]:
```python
features = []
for f in features_original:
    if 'error' in f: continue
    features.append(f)
```

In [35]:
```python
features
```

Out[35]:
```
['mean radius',
 'mean texture',
 'mean perimeter',
 'mean area',
 'mean smoothness',
 'mean compactness',
 'mean concavity',
 'mean concave points',
 'mean symmetry',
 'mean fractal dimension',
 'worst radius',
 'worst texture',
 'worst perimeter',
 'worst area',
 'worst smoothness',
 'worst compactness',
 'worst concavity',
 'worst concave points',
 'worst symmetry',
 'worst fractal dimension']
```

In [45]:
```python
feature_map = {feature: idx for idx, feature in enumerate(features)}
e4 = 'verdaderos_positivos'
e3 = 'falsos_positivos'
e2 = 'falsos_negativos'
e1 = 'verdaderos_negativos'

penalties = ['None','l1','l2', 'elasticnet']

iterations = [10,100,1000]
alphas = [1e-5,1e-3,1e-1,1e1]
columnas = ['fx','fy','penalty','alpha','iter','ee','ev',e1,e2,e3,e4]
dtCB = pd.DataFrame(columns=columnas)


for fx in features:
    x_feature = fx
```

```
        print('\n\n\n\n******** ',x_feature)
        for fy in list(set(features)-set([fx])):
            print('-',fy)
            y_feature = fy

            x_feature_col = feature_map[x_feature]
            y_feature_col = feature_map[y_feature]
            X_train_feature = X_train[:, [x_feature_col, y_feature_col]]
            X_val_feature = X_val[:, [x_feature_col, y_feature_col]]

            for p in penalties:
                penalty = p
                for a in alphas:
                    alpha = a
                    for it in iterations:
                        max_iter = it

                        model = Perceptron(penalty=penalty, alpha=alpha, max_iter=max_ite
                        model.fit(X_train_feature, y_train)

                        ee=accuracy_score(y_train, model.predict(X_train_feature))
                        ev=accuracy_score(y_val, model.predict(X_val_feature))
                        #print('Exactitud para entrenamiento: %.2f' %  ee)
                        #print('Exactitud para validación: %.2f' % ev)

                        matriz = confusion_matrix(y_train, model.predict(X_train_feature)

                        dtCB = dtCB.append({'fx':fx,'fy':fy,'penalty':penalty,'alpha':alp
                                            'ee':ee,'ev':ev,e1:matriz[0][0],e2:matriz[0][
                                            e3:matriz[1][0],e4:matriz[1][1]},ignore_index
```

```
********  mean radius
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- worst radius
- worst compactness
- worst concavity
- worst perimeter
```

```
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area



******** mean texture
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
- worst perimeter
- mean symmetry
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area



******** mean perimeter
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
- worst perimeter
```

```
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area



******** mean area
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
- worst perimeter
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points



******** mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
- worst perimeter
```

```
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area



********  mean compactness
- mean smoothness
- worst symmetry
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
- worst perimeter
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area



********  mean concavity
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
- worst perimeter
```

```
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area
```

```
********  mean concave points
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
- worst perimeter
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean area
```

```
********  mean symmetry
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
```

- worst perimeter
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area

******** mean fractal dimension
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean radius
- worst radius
- worst compactness
- worst concavity
- worst perimeter
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area

******** worst radius
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst compactness
- worst concavity
- worst perimeter

```
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area



******** worst texture
- mean smoothness
- worst symmetry
- mean compactness
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
- worst perimeter
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area



******** worst perimeter
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
```

```
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area



******** worst area
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
- worst perimeter
- mean symmetry
- mean texture
- worst smoothness
- worst fractal dimension
- mean concave points
- mean area



******** worst smoothness
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
```

- worst perimeter
- mean symmetry
- mean texture
- worst area
- worst fractal dimension
- mean concave points
- mean area

******** worst compactness
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst concavity
- worst perimeter
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area

******** worst concavity
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst perimeter

```
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area



********  worst concave points
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
- worst perimeter
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area



********  worst symmetry
- mean smoothness
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
- worst perimeter
```

```
- mean symmetry
- mean texture
- worst smoothness
- worst area
- worst fractal dimension
- mean concave points
- mean area




********  worst fractal dimension
- mean smoothness
- worst symmetry
- mean compactness
- worst texture
- mean perimeter
- worst concave points
- mean concavity
- mean fractal dimension
- mean radius
- worst radius
- worst compactness
- worst concavity
- worst perimeter
- mean symmetry
- mean texture
- worst smoothness
- worst area
- mean concave points
- mean area
```

In [46]: dtCB

Out[46]:

	fx	fy	penalty	alpha	iter	\
0	mean radius	mean smoothness	None	0.00001	10	
1	mean radius	mean smoothness	None	0.00001	100	
2	mean radius	mean smoothness	None	0.00001	1000	
3	mean radius	mean smoothness	None	0.00100	10	
4	mean radius	mean smoothness	None	0.00100	100	
5	mean radius	mean smoothness	None	0.00100	1000	
6	mean radius	mean smoothness	None	0.10000	10	
7	mean radius	mean smoothness	None	0.10000	100	
8	mean radius	mean smoothness	None	0.10000	1000	
9	mean radius	mean smoothness	None	10.00000	10	
10	mean radius	mean smoothness	None	10.00000	100	
11	mean radius	mean smoothness	None	10.00000	1000	

12	mean radius	mean smoothness	l1	0.00001	10
13	mean radius	mean smoothness	l1	0.00001	100
14	mean radius	mean smoothness	l1	0.00001	1000
15	mean radius	mean smoothness	l1	0.00100	10
16	mean radius	mean smoothness	l1	0.00100	100
17	mean radius	mean smoothness	l1	0.00100	1000
18	mean radius	mean smoothness	l1	0.10000	10
19	mean radius	mean smoothness	l1	0.10000	100
20	mean radius	mean smoothness	l1	0.10000	1000
21	mean radius	mean smoothness	l1	10.00000	10
22	mean radius	mean smoothness	l1	10.00000	100
23	mean radius	mean smoothness	l1	10.00000	1000
24	mean radius	mean smoothness	l2	0.00001	10
25	mean radius	mean smoothness	l2	0.00001	100
26	mean radius	mean smoothness	l2	0.00001	1000
27	mean radius	mean smoothness	l2	0.00100	10
28	mean radius	mean smoothness	l2	0.00100	100
29	mean radius	mean smoothness	l2	0.00100	1000
...	...	...	...	...	...
18210	worst fractal dimension	mean area	l1	0.10000	10
18211	worst fractal dimension	mean area	l1	0.10000	100
18212	worst fractal dimension	mean area	l1	0.10000	1000
18213	worst fractal dimension	mean area	l1	10.00000	10
18214	worst fractal dimension	mean area	l1	10.00000	100
18215	worst fractal dimension	mean area	l1	10.00000	1000
18216	worst fractal dimension	mean area	l2	0.00001	10
18217	worst fractal dimension	mean area	l2	0.00001	100
18218	worst fractal dimension	mean area	l2	0.00001	1000
18219	worst fractal dimension	mean area	l2	0.00100	10
18220	worst fractal dimension	mean area	l2	0.00100	100
18221	worst fractal dimension	mean area	l2	0.00100	1000
18222	worst fractal dimension	mean area	l2	0.10000	10
18223	worst fractal dimension	mean area	l2	0.10000	100
18224	worst fractal dimension	mean area	l2	0.10000	1000
18225	worst fractal dimension	mean area	l2	10.00000	10
18226	worst fractal dimension	mean area	l2	10.00000	100
18227	worst fractal dimension	mean area	l2	10.00000	1000
18228	worst fractal dimension	mean area	elasticnet	0.00001	10
18229	worst fractal dimension	mean area	elasticnet	0.00001	100
18230	worst fractal dimension	mean area	elasticnet	0.00001	1000
18231	worst fractal dimension	mean area	elasticnet	0.00100	10
18232	worst fractal dimension	mean area	elasticnet	0.00100	100
18233	worst fractal dimension	mean area	elasticnet	0.00100	1000
18234	worst fractal dimension	mean area	elasticnet	0.10000	10
18235	worst fractal dimension	mean area	elasticnet	0.10000	100
18236	worst fractal dimension	mean area	elasticnet	0.10000	1000
18237	worst fractal dimension	mean area	elasticnet	10.00000	10
18238	worst fractal dimension	mean area	elasticnet	10.00000	100

```
18239  worst fractal dimension        mean area  elasticnet  10.00000  1000

           ee        ev verdaderos_negativos falsos_negativos  \
0      0.3675  0.390533                  146                0
1      0.7750  0.781065                  138                8
2      0.8350  0.863905                  130               16
3      0.3675  0.390533                  146                0
4      0.7750  0.781065                  138                8
5      0.8350  0.863905                  130               16
6      0.3675  0.390533                  146                0
7      0.7750  0.781065                  138                8
8      0.8350  0.863905                  130               16
9      0.3675  0.390533                  146                0
10     0.7750  0.781065                  138                8
11     0.8350  0.863905                  130               16
12     0.3675  0.390533                  146                0
13     0.7750  0.781065                  138                8
14     0.8350  0.863905                  130               16
15     0.3675  0.390533                  146                0
16     0.7775  0.781065                  138                8
17     0.8775  0.905325                  112               34
18     0.3675  0.390533                  146                0
19     0.7075  0.704142                  142                4
20     0.6975  0.674556                  143                3
21     0.3650  0.390533                  146                0
22     0.3650  0.390533                  146                0
23     0.3650  0.390533                  146                0
24     0.3675  0.390533                  146                0
25     0.7775  0.781065                  138                8
26     0.8550  0.881657                   96               50
27     0.3675  0.390533                  146                0
28     0.7150  0.727811                  140                6
29     0.7125  0.727811                  140                6
...       ...       ...                  ...              ...
18210  0.3650  0.390533                  146                0
18211  0.3650  0.390533                  146                0
18212  0.3650  0.390533                  146                0
18213  0.3650  0.390533                  146                0
18214  0.6375  0.615385                    1              145
18215  0.3650  0.390533                  146                0
18216  0.3650  0.390533                  146                0
18217  0.3650  0.390533                  146                0
18218  0.8525  0.893491                  120               26
18219  0.3650  0.390533                  146                0
18220  0.3650  0.390533                  146                0
18221  0.3650  0.390533                  146                0
18222  0.3650  0.390533                  146                0
18223  0.3650  0.390533                  146                0
```

18224	0.3650	0.390533	146	0
18225	0.3650	0.390533	146	0
18226	0.3650	0.390533	146	0
18227	0.3650	0.390533	146	0
18228	0.3650	0.390533	146	0
18229	0.3650	0.390533	146	0
18230	0.8525	0.893491	120	26
18231	0.3650	0.390533	146	0
18232	0.3650	0.390533	146	0
18233	0.3650	0.390533	146	0
18234	0.3650	0.390533	146	0
18235	0.3650	0.390533	146	0
18236	0.3650	0.390533	146	0
18237	0.3650	0.390533	146	0
18238	0.3650	0.390533	146	0
18239	0.3650	0.390533	146	0

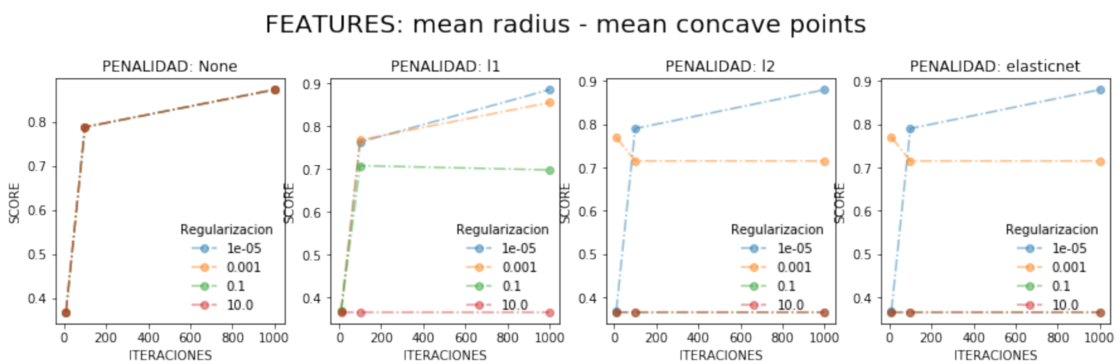
	falsos_positivos	verdaderos_positivos
0	253	1
1	82	172
2	50	204
3	253	1
4	82	172
5	50	204
6	253	1
7	82	172
8	50	204
9	253	1
10	82	172
11	50	204
12	253	1
13	82	172
14	50	204
15	253	1
16	81	173
17	15	239
18	253	1
19	113	141
20	118	136
21	254	0
22	254	0
23	254	0
24	253	1
25	81	173
26	8	246
27	253	1
28	108	146
29	109	145

```
...                 ...                    ...
18210               254                      0
18211               254                      0
18212               254                      0
18213               254                      0
18214                 0                    254
18215               254                      0
18216               254                      0
18217               254                      0
18218                33                    221
18219               254                      0
18220               254                      0
18221               254                      0
18222               254                      0
18223               254                      0
18224               254                      0
18225               254                      0
18226               254                      0
18227               254                      0
18228               254                      0
18229               254                      0
18230                33                    221
18231               254                      0
18232               254                      0
18233               254                      0
18234               254                      0
18235               254                      0
18236               254                      0
18237               254                      0
18238               254                      0
18239               254                      0

[18240 rows x 11 columns]
```

```
In [47]: dtCB.to_csv(r'clasificacion_cancer.csv',index=None,header=True,sep='|')
```

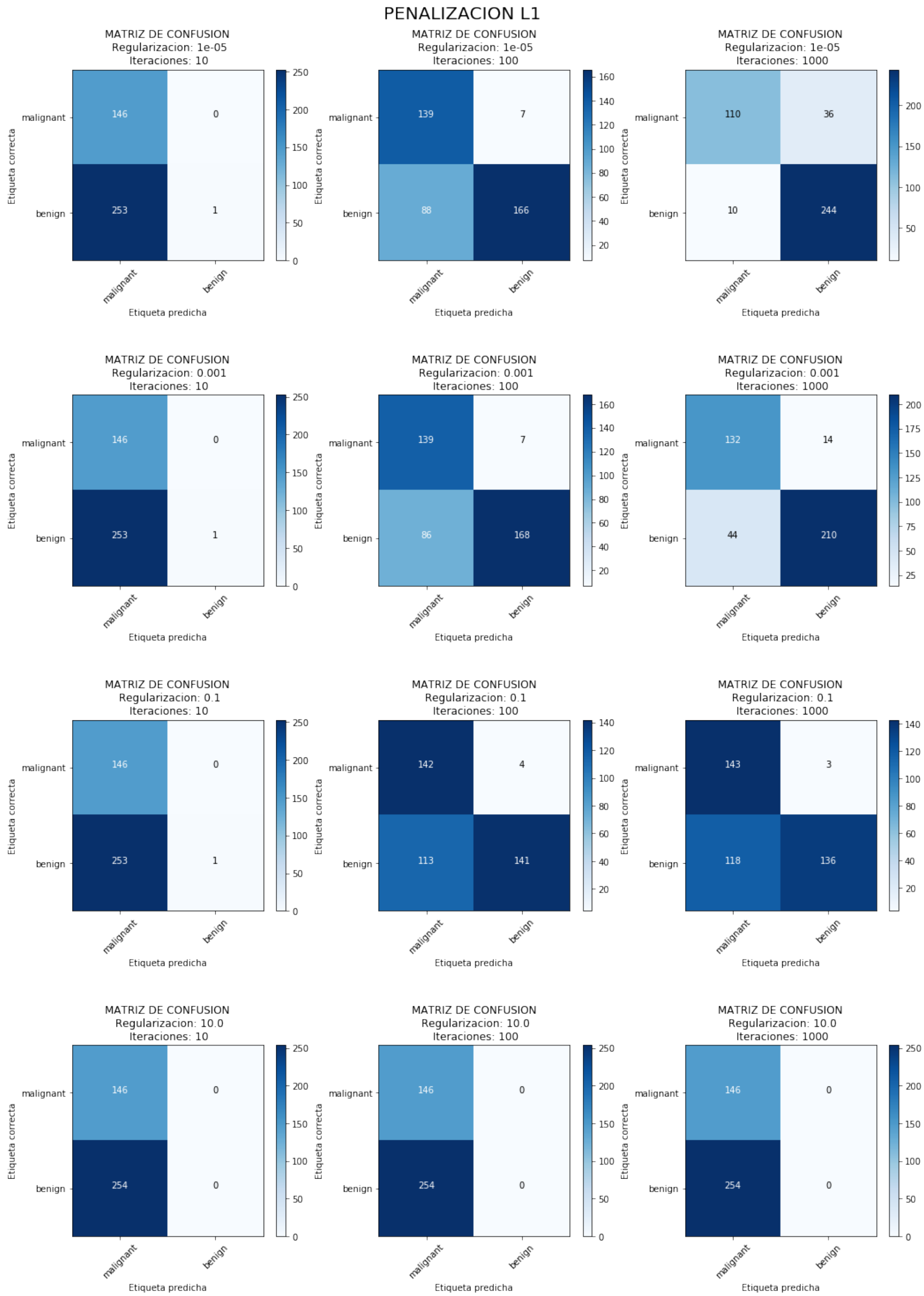
```
In [184]: fig=plt.figure(figsize=(15,4))
          fx = 'mean radius'
          fy = 'mean concave points'

          fig.suptitle('FEATURES: '+fx+' - '+fy , fontsize=20)
          j=1
          ls=['--',':','-.','-']


          for p in penalties:
              plt.subplot(1,4,j)
              sub=dtCB[(dtCB.penalty==p)&(dtCB.fx==fx)&(dtCB.fy==fy)]
```

```
    for a in alphas:
        plt.plot(sub[sub.alpha==a].iter.values,sub[sub.alpha==a].ee.values,label=str
    plt.legend(title='Regularizacion',frameon=False,loc='lower right')
    plt.title('PENALIDAD: ' + p)
    plt.xlabel('ITERACIONES')
    plt.ylabel('SCORE')
    j+=1

plt.subplots_adjust(wspace=0.2, top=0.8)
```



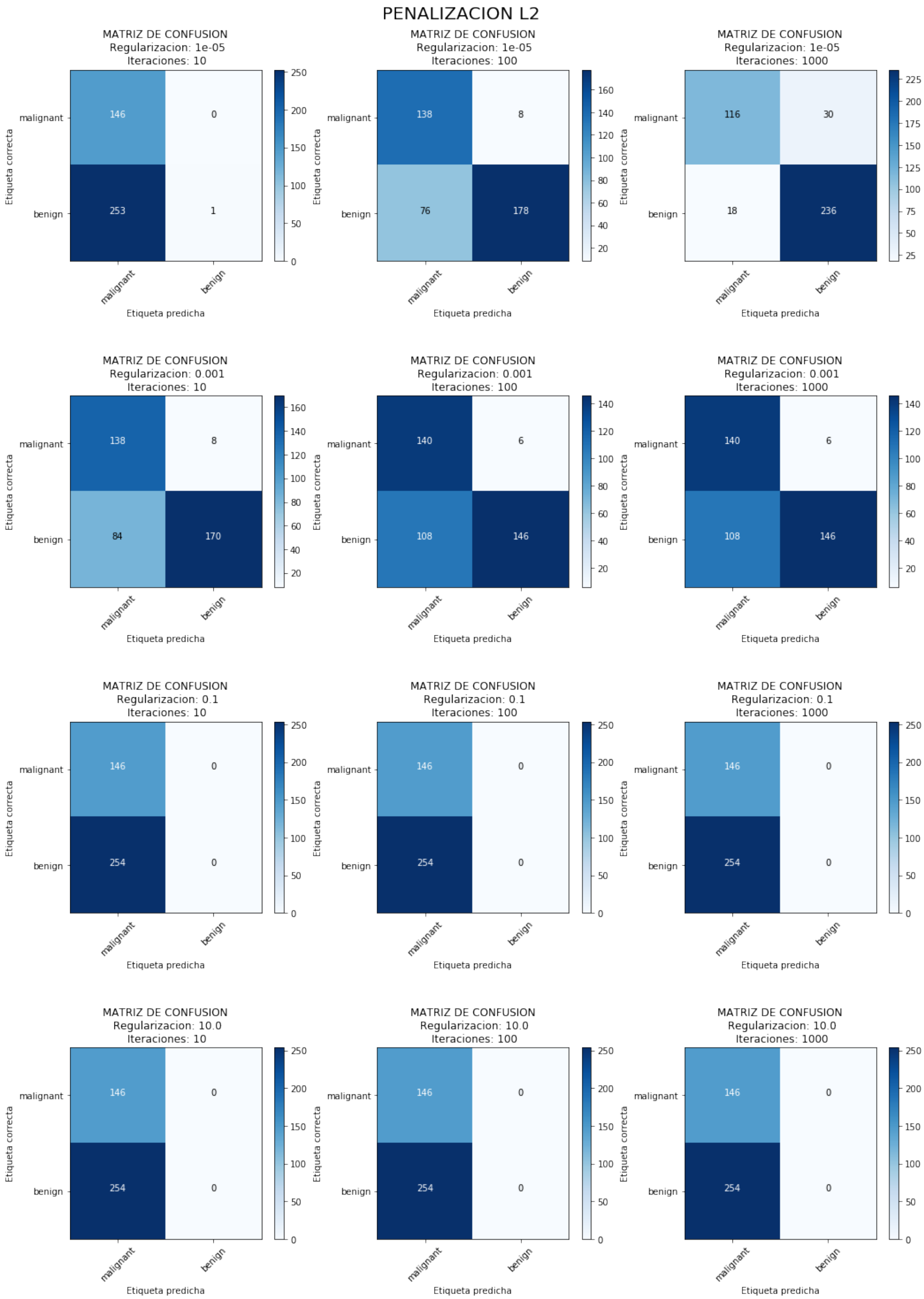
Se puede observar que la penalidad l1, es la única que permite diferenciar los distintos valores que toma el hiperparámetro de regularización para las tres números de iteraciones en estudio., por otro lado se observa que mientras menor es alpha y mayor es el número de iteraciones, la exactidu aumenta, tanto al no considerar penalidad como al tomar la penalidad l1, lo mismo no sucede para la norma al cuadrado o la combinación lineal de ambos tipos (l1,l2)

```
In [185]: sub=dtCB[(dtCB.penalty=='l1')&(dtCB.fx==fx)&(dtCB.fy==fy)]
          fig = plt.figure(figsize=(15,20))
          fig.suptitle('PENALIZACION L1', fontsize=20)
          for i in range(len(sub)):
              plt.subplot(4,3,i+1)
              matriz=np.array([[sub.verdaderos_negativos.values[i],sub.falsos_negativos.values
                  [sub.falsos_positivos.values[i],sub.verdaderos_positivos.values[i]]])
              plot_confusion_matrix(matriz,classes=breast_cancer_data.target_names,
              title='MATRIZ DE CONFUSION\n Regularizacion: '+str(sub.alpha.values[i])+'\n Itera
          plt.subplots_adjust( wspace=0.2, top=0.93, hspace=0.7)
```



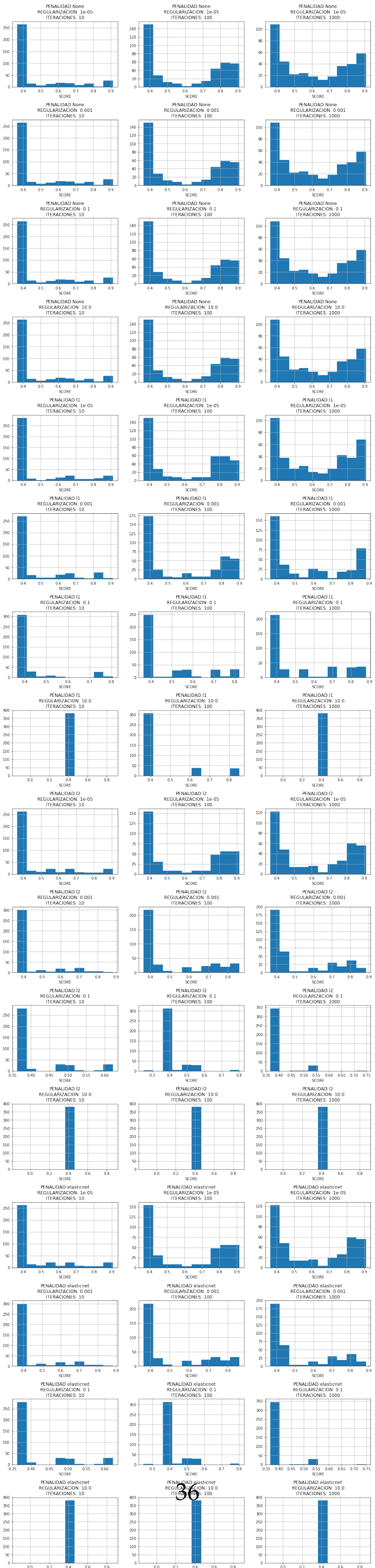
Lo óptimo es minimizar los casos: etiqueta true diagnóstico false, es decir, cancer positivo, diagnóstico o predicción negativa. En el caso de penalidad L1, se puede ver que cuando alpha es muy chico, si bien se observó que la exactitud aumenta, también lo hacen los casos de falsos negativos cuando crece el número de iteraciones, lo cual no es bueno. Lo que se quiere decir, es que el análisis no es trivial y requiere de mucho estudio y de optar por la solución de compromisa más óptima. Tampoco se puede aceptar que el caso de nulidad del número de falsos negativos, pues como se puede ver en la matriz de confusión, tales predicciones conllevan una gran inexactitud, ya que no se predice ningún tumor benigno.

```
In [186]: sub=dtCB[(dtCB.penalty=='l2')&(dtCB.fx==fx)&(dtCB.fy==fy)]
          fig = plt.figure(figsize=(15,20))
          fig.suptitle('PENALIZACION L2', fontsize=20)
          for i in range(len(sub)):
              plt.subplot(4,3,i+1)
              matriz=np.array([[sub.verdaderos_negativos.values[i],sub.falsos_negativos.values
                  [sub.falsos_positivos.values[i],sub.verdaderos_positivos.values[i]]])
              plot_confusion_matrix(matriz,classes=breast_cancer_data.target_names,
              title='MATRIZ DE CONFUSION\n Regularizacion: '+str(sub.alpha.values[i])+'\n Itera
          plt.subplots_adjust( wspace=0.2, top=0.93, hspace=0.7)
```


PENALIZACION L2
MATRIZ DE CONFUSION
Regularizacion: 1e-05
Iteraciones: 10
MATRIZ DE CONFUSION
Regularizacion: 1e-05
Iteraciones: 100
MATRIZ DE CONFUSION
Regularizacion: 1e-05
Iteraciones: 1000
MATRIZ DE CONFUSION
Regularizacion: 0.001
Iteraciones: 10
MATRIZ DE CONFUSION
Regularizacion: 0.001
Iteraciones: 100
MATRIZ DE CONFUSION
Regularizacion: 0.001
Iteraciones: 1000
MATRIZ DE CONFUSION
Regularizacion: 0.1
Iteraciones: 10
MATRIZ DE CONFUSION
Regularizacion: 0.1
Iteraciones: 100
MATRIZ DE CONFUSION
Regularizacion: 0.1
Iteraciones: 1000
MATRIZ DE CONFUSION
Regularizacion: 10.0
Iteraciones: 10
MATRIZ DE CONFUSION
Regularizacion: 10.0
Iteraciones: 100
MATRIZ DE CONFUSION
Regularizacion: 10.0
Iteraciones: 1000
Etiqueta correcta
Etiqueta predicha
malignant
benign

```
In [ ]:
```

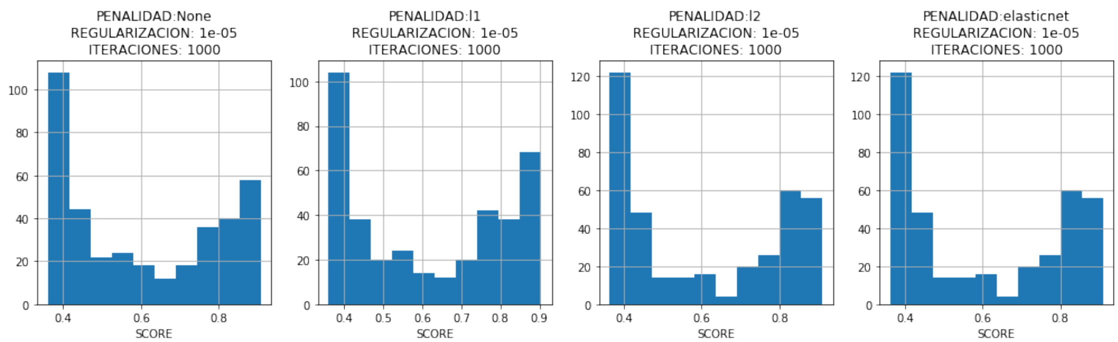
```
In [187]: fig = plt.figure(figsize=(15,20))
          j=1
          for p in penalties:
              for a in alphas:
                  for i in iterations:
                      plt.subplot(16,3,j)
                      dtCB[(dtCB.iter==i)&(dtCB.penalty==p)&(dtCB.alpha==a)].ee.hist()
                      #plt.title('MATRIZ DE CONFUSION\n Regularizacion: '+str(sub.alpha.values
                      plt.title('PENALIDAD:'+str(p)+'\nREGULARIZACION: '+str(a)+'\nITERACIONES
                      plt.xlabel('SCORE')
                      j+=1

          plt.subplots_adjust(left=0.01, wspace=0.2, top=3, hspace=0.5)
```



PENALIDAD None
REGULARIZACION: 1e-05
ITERACIONES: 10
PENALIDAD None
REGULARIZACION: 1e-05
ITERACIONES: 100
PENALIDAD None
REGULARIZACION: 1e-05
ITERACIONES: 1000
PENALIDAD None
REGULARIZACION: 0.001
ITERACIONES: 10
PENALIDAD None
REGULARIZACION: 0.001
ITERACIONES: 100
PENALIDAD None
REGULARIZACION: 0.001
ITERACIONES: 1000
PENALIDAD None
REGULARIZACION: 0.1
ITERACIONES: 10
PENALIDAD None
REGULARIZACION: 0.1
ITERACIONES: 100
PENALIDAD None
REGULARIZACION: 0.1
ITERACIONES: 1000
PENALIDAD None
REGULARIZACION: 10.0
ITERACIONES: 10
PENALIDAD None
REGULARIZACION: 10.0
ITERACIONES: 100
PENALIDAD None
REGULARIZACION: 10.0
ITERACIONES: 1000
PENALIDAD l1
REGULARIZACION: 1e-05
ITERACIONES: 10
PENALIDAD l1
REGULARIZACION: 1e-05
ITERACIONES: 100
PENALIDAD l1
REGULARIZACION: 1e-05
ITERACIONES: 1000
PENALIDAD l1
REGULARIZACION: 0.001
ITERACIONES: 10
PENALIDAD l1
REGULARIZACION: 0.001
ITERACIONES: 100
PENALIDAD l1
REGULARIZACION: 0.001
ITERACIONES: 1000
PENALIDAD l1
REGULARIZACION: 0.1
ITERACIONES: 10
PENALIDAD l1
REGULARIZACION: 0.1
ITERACIONES: 100
PENALIDAD l1
REGULARIZACION: 0.1
ITERACIONES: 1000
PENALIDAD l1
REGULARIZACION: 10.0
ITERACIONES: 10
PENALIDAD l1
REGULARIZACION: 10.0
ITERACIONES: 100
PENALIDAD l1
REGULARIZACION: 10.0
ITERACIONES: 1000
PENALIDAD l2
REGULARIZACION: 1e-05
ITERACIONES: 10
PENALIDAD l2
REGULARIZACION: 1e-05
ITERACIONES: 100
PENALIDAD l2
REGULARIZACION: 1e-05
ITERACIONES: 1000
PENALIDAD l2
REGULARIZACION: 0.001
ITERACIONES: 10
PENALIDAD l2
REGULARIZACION: 0.001
ITERACIONES: 100
PENALIDAD l2
REGULARIZACION: 0.001
ITERACIONES: 1000
PENALIDAD l2
REGULARIZACION: 0.1
ITERACIONES: 10
PENALIDAD l2
REGULARIZACION: 0.1
ITERACIONES: 100
PENALIDAD l2
REGULARIZACION: 0.1
ITERACIONES: 1000
PENALIDAD l2
REGULARIZACION: 10.0
ITERACIONES: 10
PENALIDAD l2
REGULARIZACION: 10.0
ITERACIONES: 100
PENALIDAD l2
REGULARIZACION: 10.0
ITERACIONES: 1000
PENALIDAD elasticnet
REGULARIZACION: 1e-05
ITERACIONES: 10
PENALIDAD elasticnet
REGULARIZACION: 1e-05
ITERACIONES: 100
PENALIDAD elasticnet
REGULARIZACION: 1e-05
ITERACIONES: 1000
PENALIDAD elasticnet
REGULARIZACION: 0.001
ITERACIONES: 10
PENALIDAD elasticnet
REGULARIZACION: 0.001
ITERACIONES: 100
PENALIDAD elasticnet
REGULARIZACION: 0.001
ITERACIONES: 1000
PENALIDAD elasticnet
REGULARIZACION: 0.1
ITERACIONES: 10
PENALIDAD elasticnet
REGULARIZACION: 0.1
ITERACIONES: 100
PENALIDAD elasticnet
REGULARIZACION: 0.1
ITERACIONES: 1000
PENALIDAD elasticnet
REGULARIZACION: 10.0
ITERACIONES: 10
PENALIDAD elasticnet
REGULARIZACION: 10.0
ITERACIONES: 100
PENALIDAD elasticnet
REGULARIZACION: 10.0
ITERACIONES: 1000
SCORE

Los histogramas de exactitud en función de alpha, tipo de penalidad y número de iteraciones muestran: 1. la exactitud tiende a mejorar a partir de 100 iteraciones 2. la penalidad de tipo L1 parece mejor que el resto de las penalidades 3. regularizaciones más chicas implican mayor exactitud

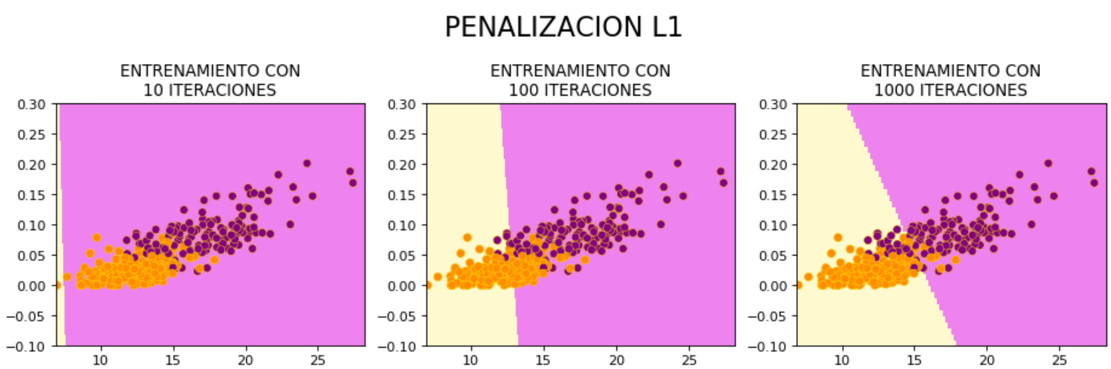
In [188]:
```
fig = plt.figure(figsize=(15,4))
j=1
for p in penalties:
    plt.subplot(1,4,j)
    dtCB[(dtCB.iter==1000)&(dtCB.penalty==p)&(dtCB.alpha==1e-5)].ee.hist()
    #plt.title('MATRIZ DE CONFUSION\n Regularizacion: '+str(sub.alpha.values[i])+'\n
    plt.title('PENALIDAD:'+str(p)+'\nREGULARIZACION: '+str(1e-5)+'\nITERACIONES: '+s
    plt.xlabel('SCORE')
    j+=1

plt.subplots_adjust(left=0.01, wspace=0.2)
```



In [ ]:

In [191]:
```
x_feature = fx
y_feature = fy

x_feature_col = feature_map[x_feature]
y_feature_col = feature_map[y_feature]
X_train_feature = X_train[:, [x_feature_col, y_feature_col]]
X_val_feature = X_val[:, [x_feature_col, y_feature_col]]

penalty = 'l1'
alpha = 1e-5
j=1

fig=plt.figure(figsize=(14, 4), dpi=80, facecolor='w', edgecolor='k')
fig.suptitle('PENALIZACION L1', fontsize=20)
```

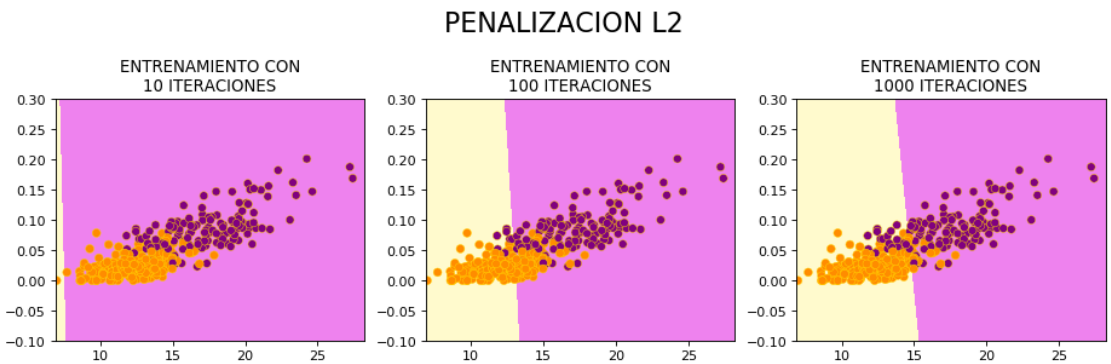
```
for i in iterations:
    max_iter = i
    model = Perceptron(penalty=penalty, alpha=alpha, max_iter=max_iter)
    model.fit(X_train_feature, y_train)

    xx, yy, Z = classifier_boundary(np.r_[X_train_feature, X_val_feature], model)

    cmap_dots = ListedColormap(['purple', 'darkorange'])
    cmap_edge = ListedColormap(['darkviolet', 'gold'])
    cmap_back = ListedColormap(['violet', 'lemonchiffon'])

    # Conjunto de entrenamiento
    plt.subplot(1, 3,j)
    plt.pcolormesh(xx, yy, Z, cmap=cmap_back)
    plt.scatter(X_train_feature[:, 0], X_train_feature[:, 1], c=y_train, cmap=cmap_do
    plt.xlim(xx.min(), xx.max())
    plt.ylim(yy.min(), yy.max())
    plt.title('ENTRENAMIENTO CON\n'+str(i)+' ITERACIONES')

    j+=1
plt.subplots_adjust( top=0.75)
```



Se observa una gran mejora de la caracterización de la frontera a medida que aumenta el número de iteraciones, al menos, dentro de los tres valores, del número iteraciones, considerados

```
In [192]: x_feature = fx
          y_feature = fy

          x_feature_col = feature_map[x_feature]
          y_feature_col = feature_map[y_feature]
          X_train_feature = X_train[:, [x_feature_col, y_feature_col]]
          X_val_feature = X_val[:, [x_feature_col, y_feature_col]]

          penalty = 'l2'
```

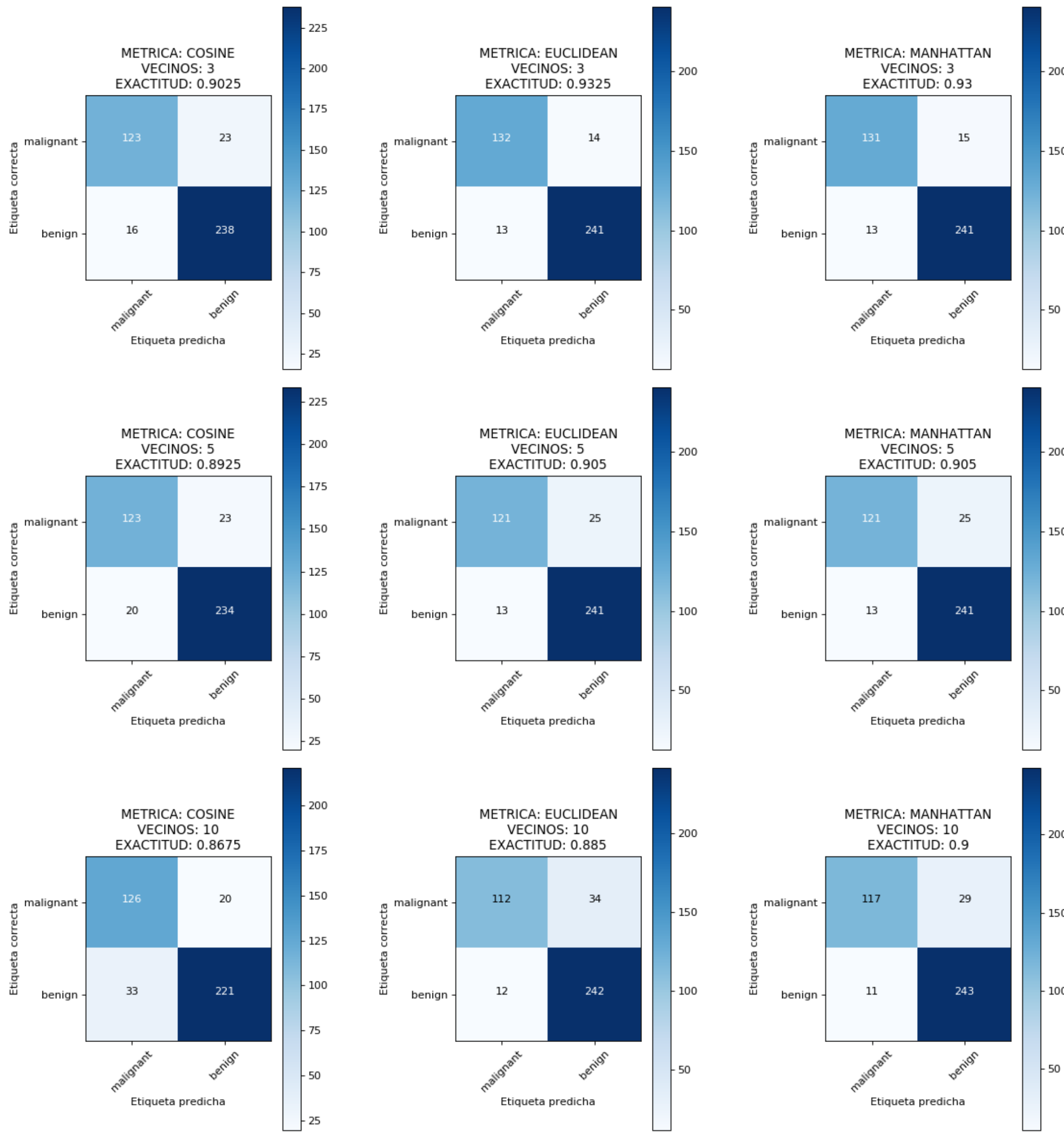
```
alpha = 1e-5
j=1

fig=plt.figure(figsize=(14, 4), dpi=80, facecolor='w', edgecolor='k')
fig.suptitle('PENALIZACION L2', fontsize=20)
for i in iterations:
    max_iter = i
    model = Perceptron(penalty=penalty, alpha=alpha, max_iter=max_iter)
    model.fit(X_train_feature, y_train)

    xx, yy, Z = classifier_boundary(np.r_[X_train_feature, X_val_feature], model)

    cmap_dots = ListedColormap(['purple', 'darkorange'])
    cmap_edge = ListedColormap(['darkviolet', 'gold'])
    cmap_back = ListedColormap(['violet', 'lemonchiffon'])

    # Conjunto de entrenamiento
    plt.subplot(1, 3,j)
    plt.pcolormesh(xx, yy, Z, cmap=cmap_back)
    plt.scatter(X_train_feature[:, 0], X_train_feature[:, 1], c=y_train, cmap=cmap_do
    plt.xlim(xx.min(), xx.max())
    plt.ylim(yy.min(), yy.max())
    plt.title('ENTRENAMIENTO CON\n'+str(i)+' ITERACIONES')

    j+=1
plt.subplots_adjust( top=0.75)
```



4 VECINOS MAS CERCANOS

```
In [209]: neighbors = [3,5,10]
          metricas = ['cosine','euclidean','manhattan']

          plt.figure(figsize=(14,15), dpi= 80, facecolor='w', edgecolor='k')
```

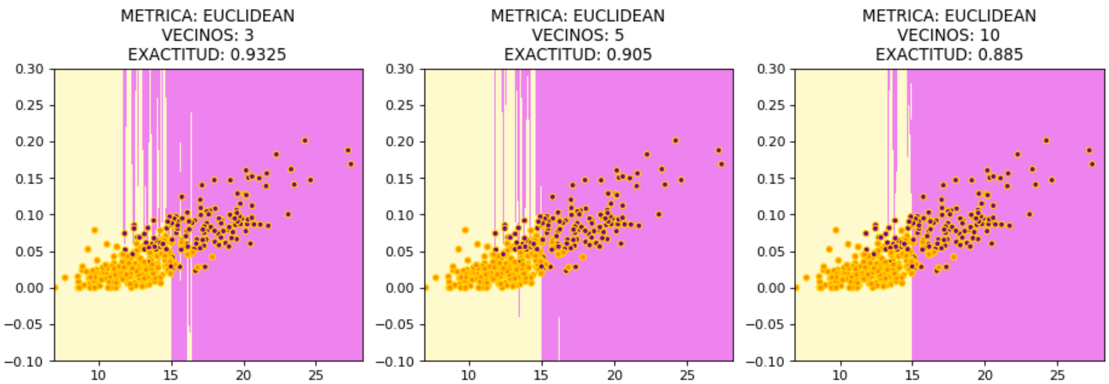
```
j=1
for n in neighbors:
    for m in metricas:
        n_neighbors=n
        metric = m
        model = KNeighborsClassifier(n_neighbors=n_neighbors, metric=metric)
        model.fit(X_train_feature, y_train)

        exactitud = accuracy_score(y_train, model.predict(X_train_feature))

        plt.subplot(3, 3, j)
        plot_confusion_matrix(confusion_matrix(y_train, model.predict(X_train_featur
                      classes=breast_cancer_data.target_names,
                      title='METRICA: '+m.upper()+'\nVECINOS: '+str(n)+'\nEXACTITUD:
        j+=1
plt.subplots_adjust( wspace=0.6)
```



Se observa que para el menor número de vecinos considerado, la métrica euclídea muetsra la mejor exactitud y la menor cantidad de casos falsos negativos, sin embargo, para 10 vecinos es la métrica manhattan la que otorga los mejores predicciones

```
In [215]: plt.figure(figsize=(14,4), dpi= 80, facecolor='w', edgecolor='k')
          j=1
          for n in neighbors:
              for m in metricas:
                  if m!='euclidean':continue
                  n_neighbors=n
                  metric = m
                  model = KNeighborsClassifier(n_neighbors=n_neighbors, metric=metric)
```

```
        model.fit(X_train_feature, y_train)

        exactitud = accuracy_score(y_train, model.predict(X_train_feature))

        plt.subplot(1, 3, j)

        xx, yy, Z = classifier_boundary(np.r_[X_train_feature, X_val_feature], model)
        plt.pcolormesh(xx, yy, Z, cmap=cmap_back)
        plt.scatter(X_train_feature[:, 0], X_train_feature[:, 1], c=y_train, cmap=cma
        plt.xlim(xx.min(), xx.max())
        plt.ylim(yy.min(), yy.max())
        plt.title('METRICA: '+m.upper()+'\nVECINOS: '+str(n)+'\nEXACTITUD: '+str(exac

        j+=1
```



5 CLASIFICACION MULTICLASE

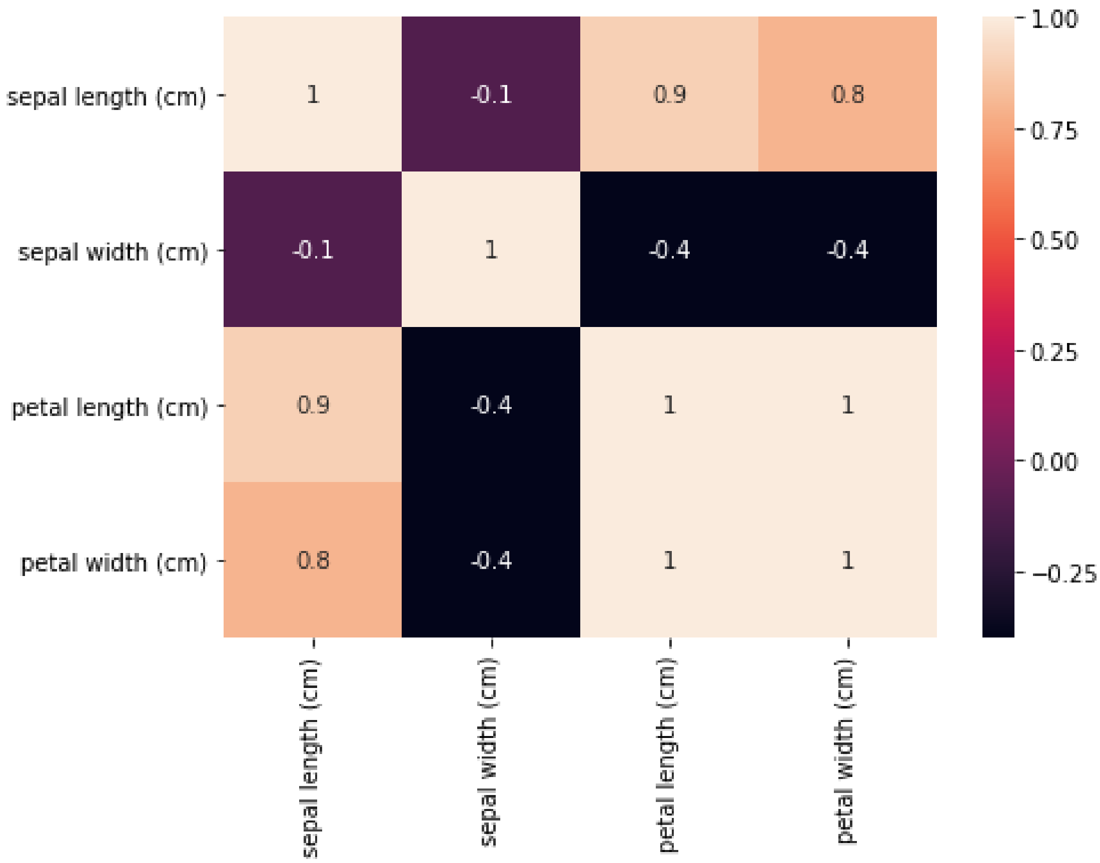
In [2]:
```
iris_data = load_iris()

shuff_data = np.random.permutation(150)
shuff_train = shuff_data[:120]
shuff_val = shuff_data[120:]

X_train = iris_data['data'][shuff_train]
X_val = iris_data['data'][shuff_val]

y_train = iris_data['target'][shuff_train]
y_val = iris_data['target'][shuff_val]

feature_map = {feature: idx for idx, feature in enumerate(iris_data['feature_names'])}

print(iris_data['DESCR'])
```

```
.. _iris_dataset:

Iris plants dataset
--------------------

**Data Set Characteristics:**

    :Number of Instances: 150 (50 in each of three classes)
    :Number of Attributes: 4 numeric, predictive attributes and the class
    :Attribute Information:
        - sepal length in cm
        - sepal width in cm
        - petal length in cm
        - petal width in cm
        - class:
                - Iris-Setosa
                - Iris-Versicolour
                - Iris-Virginica

    :Summary Statistics:

    ============== ==== ==== ======= ===== ====================
                    Min  Max   Mean    SD   Class Correlation
    ============== ==== ==== ======= ===== ====================
    sepal length:   4.3  7.9   5.84   0.83    0.7826
    sepal width:    2.0  4.4   3.05   0.43   -0.4194
    petal length:   1.0  6.9   3.76   1.76    0.9490  (high!)
    petal width:    0.1  2.5   1.20   0.76    0.9565  (high!)
    ============== ==== ==== ======= ===== ====================

    :Missing Attribute Values: None
    :Class Distribution: 33.3% for each of 3 classes.
    :Creator: R.A. Fisher
    :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
    :Date: July, 1988

The famous Iris database, first used by Sir R.A. Fisher. The dataset is taken
from Fisher's paper. Note that it's the same as in R, but not as in the UCI
Machine Learning Repository, which has two wrong data points.

This is perhaps the best known database to be found in the
pattern recognition literature.  Fisher's paper is a classic in the field and
is referenced frequently to this day.  (See Duda & Hart, for example.)  The
data set contains 3 classes of 50 instances each, where each class refers to a
type of iris plant.  One class is linearly separable from the other 2; the
latter are NOT linearly separable from each other.

.. topic:: References
```

```
- Fisher, R.A. "The use of multiple measurements in taxonomic problems"
  Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to
  Mathematical Statistics" (John Wiley, NY, 1950).
- Duda, R.O., & Hart, P.E. (1973) Pattern Classification and Scene Analysis.
  (Q327.D83) John Wiley & Sons.  ISBN 0-471-22361-1.  See page 218.
- Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System
  Structure and Classification Rule for Recognition in Partially Exposed
  Environments".  IEEE Transactions on Pattern Analysis and Machine
  Intelligence, Vol. PAMI-2, No. 1, 67-71.
- Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule".  IEEE Transactions
  on Information Theory, May 1972, 431-433.
- See also: 1988 MLC Proceedings, 54-64.  Cheeseman et al"s AUTOCLASS II
  conceptual clustering system finds 3 classes in the data.
- Many, many more ...
```

In [6]:
```python
data = pd.DataFrame(iris_data['data'],columns=iris_data['feature_names'])
iris_data['iris_label'] = iris_data['target']
correlation_matrix = data.corr().round(1)
fig, ax = plt.subplots(figsize=(7,5))
sb.heatmap(data=correlation_matrix, annot = True)
```

Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5c74dbfb70>



```
In [17]: x_feature = 'petal length (cm)'
         y_features = ['sepal width (cm)','petal width (cm)']
         penalties=['l1','l2']
         alphas=[1e-5,1e1]

         cmap_dots = ListedColormap(['tomato', 'dodgerblue', 'goldenrod'])
         cmap_back = ListedColormap(['lightcoral', 'skyblue', 'palegoldenrod'])


         plt.figure(figsize=(20, 8), dpi= 80, facecolor='w', edgecolor='k')
         j=0
         for yf in y_features:
             y_feature = yf

             x_feature_col = feature_map[x_feature]
             y_feature_col = feature_map[y_feature]
             X_train_feature = X_train[:, [x_feature_col, y_feature_col]]
             X_val_feature = X_val[:, [x_feature_col, y_feature_col]]

             for p in penalties:
                 if p!=penalties[0]:continue
                 penalty = p
                 for a in alphas:
                     if a!= alphas[0]:continue
                     alpha = a
                     model = LogisticRegression(penalty=penalty, C=1./alpha, multi_class='ovr')
                     model.fit(X_train_feature, y_train)
                     exactitud = accuracy_score(y_train, model.predict(X_train_feature))

                     plt.subplot(2, 4, 1+j*4)
                     plot_confusion_matrix(confusion_matrix(y_train, model.predict(X_train_fea
                                           classes=iris_data.target_names,
                                           title='Matriz de confusión')


                     xx, yy, Z = classifier_boundary(np.r_[X_train_feature, X_val_feature], moc


                     plt.subplot(2, 4, 2+j*4)
                     plt.pcolormesh(xx, yy, Z, cmap=cmap_back)
                     plt.scatter(X_train_feature[:, 0], X_train_feature[:, 1], c=y_train, cmap=
                     plt.xlim(xx.min(), xx.max())
                     plt.ylim(yy.min(), yy.max())
                     plt.title("Conjunto de Entrenamiento")
```

```
        n_neighbors = 3 # TODO: Cantidad de vecinos a tener en cuenta
        metric = 'euclidean' # TODO: Medida de distancia. Algunas opciones: cosin



        model = KNeighborsClassifier(n_neighbors=n_neighbors, metric=metric)
        model.fit(X_train_feature, y_train)

        exactitud =accuracy_score(y_train, model.predict(X_train_feature))

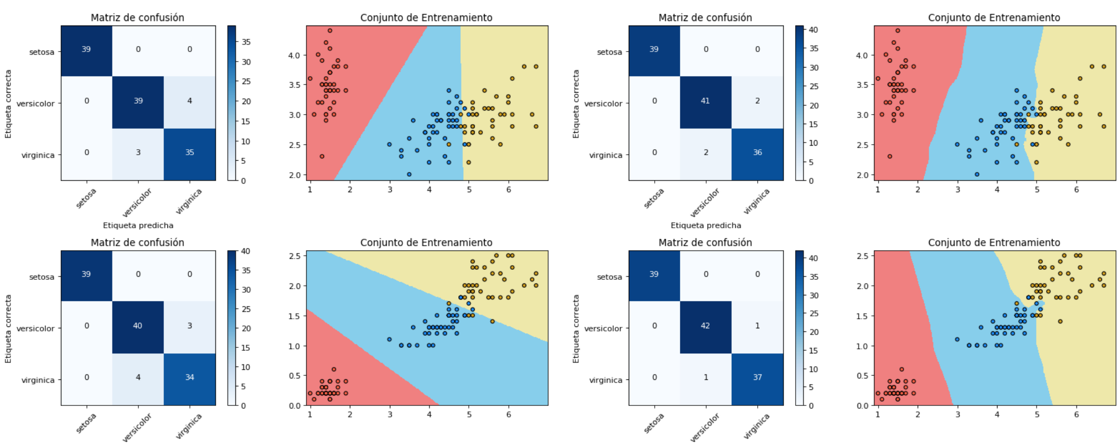

        plt.subplot(2, 4, 3+j*4)
        plot_confusion_matrix(confusion_matrix(y_train, model.predict(X_train_fea
                              classes=iris_data.target_names,
                              title='Matriz de confusión')


        xx, yy, Z = classifier_boundary(np.r_[X_train_feature, X_val_feature], mod

        cmap_dots = ListedColormap(['tomato', 'dodgerblue', 'goldenrod'])
        cmap_back = ListedColormap(['lightcoral', 'skyblue', 'palegoldenrod'])

        plt.subplot(2, 4, 4+j*4)
        plt.pcolormesh(xx, yy, Z, cmap=cmap_back)
        plt.scatter(X_train_feature[:, 0], X_train_feature[:, 1], c=y_train, cmap=
        plt.xlim(xx.min(), xx.max())
        plt.ylim(yy.min(), yy.max())
        plt.title("Conjunto de Entrenamiento")

j+=1
```



In [ ]:

In [24]:
```
x_feature = 'petal length (cm)'
y_features = ['sepal width (cm)','petal width (cm)']
penalties=['l1','l2']
alphas=[1e-5,1e1]

cmap_dots = ListedColormap(['tomato', 'dodgerblue', 'goldenrod'])
cmap_back = ListedColormap(['lightcoral', 'skyblue', 'palegoldenrod'])


plt.figure(figsize=(20, 30), dpi= 80, facecolor='w', edgecolor='k')
fig.suptitle('x_feature: '+x_feature.upper(), fontsize=20)
j=0
for yf in y_features:

    y_feature = yf

    x_feature_col = feature_map[x_feature]
    y_feature_col = feature_map[y_feature]
    X_train_feature = X_train[:, [x_feature_col, y_feature_col]]
    X_val_feature = X_val[:, [x_feature_col, y_feature_col]]

    for p in penalties:
        if p!=penalties[0]:continue
        penalty = p
        for a in alphas:
            if a!= alphas[0]:continue
            alpha = a
            model = LogisticRegression(penalty=penalty, C=1./alpha, multi_class='ovr')
            model.fit(X_train_feature, y_train)

            i=1
            for n in neighbors:
                n_neighbors = n
                metric = 'euclidean'

                model = KNeighborsClassifier(n_neighbors=n_neighbors, metric=metric)
                model.fit(X_train_feature, y_train)

                exactitud = round(accuracy_score(y_train, model.predict(X_train_featu


                plt.subplot(6, 2, i+j*6)
                plot_confusion_matrix(confusion_matrix(y_train, model.predict(X_train_
                                  classes=iris_data.target_names,
                                  title=y_feature.upper()+' MATRIZ DE CONFUSION\nVECI
```

```
            xx, yy, Z = classifier_boundary(np.r_[X_train_feature, X_val_feature]

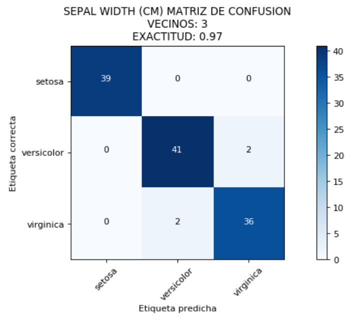
            cmap_dots = ListedColormap(['tomato', 'dodgerblue', 'goldenrod'])
            cmap_back = ListedColormap(['lightcoral', 'skyblue', 'palegoldenrod']

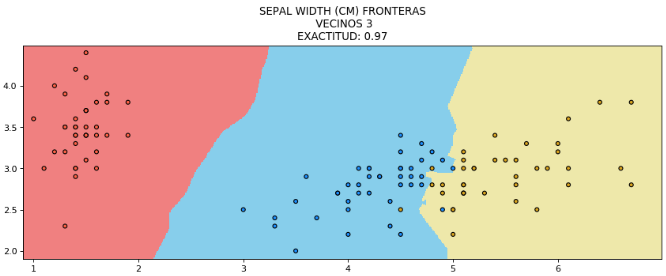
            i+=1

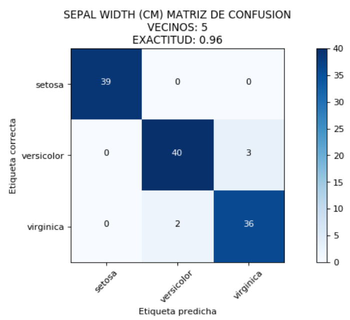
            plt.subplot(6, 2, i+j*6)
            plt.pcolormesh(xx, yy, Z, cmap=cmap_back)
            plt.scatter(X_train_feature[:, 0], X_train_feature[:, 1], c=y_train, c
            plt.xlim(xx.min(), xx.max())
            plt.ylim(yy.min(), yy.max())
            plt.title(y_feature.upper()+' FRONTERAS\n VECINOS '+str(n)+'\nEXACTITU

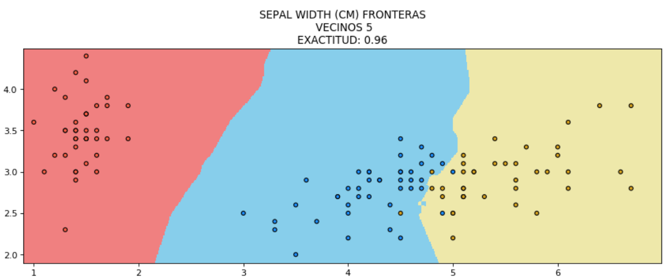
            i+=1

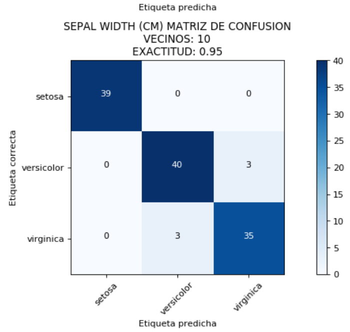
    j+=1
```

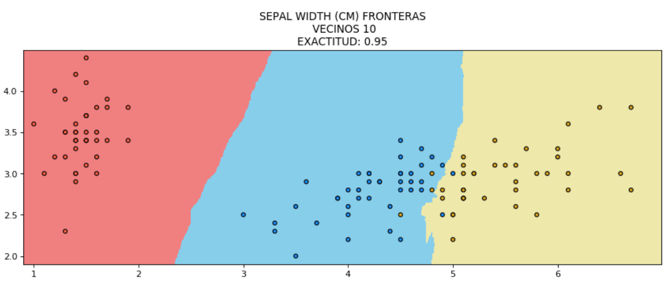

SEPAL WIDTH (CM) MATRIZ DE CONFUSION
VECINOS: 3
EXACTITUD: 0.97
39 0 0
0 41 2
0 2 36
setosa
versicolor
virginica
Etiqueta correcta
Etiqueta predicha

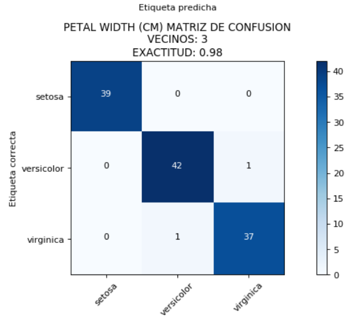

SEPAL WIDTH (CM) FRONTERAS
VECINOS 3
EXACTITUD: 0.97

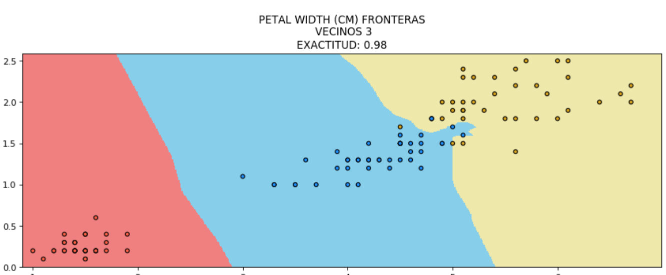

SEPAL WIDTH (CM) MATRIZ DE CONFUSION
VECINOS: 5
EXACTITUD: 0.96
39 0 0
0 40 3
0 2 36
setosa
versicolor
virginica
Etiqueta correcta
Etiqueta predicha

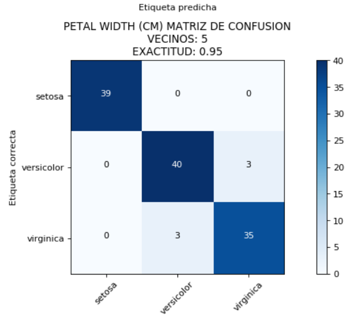

SEPAL WIDTH (CM) FRONTERAS
VECINOS 5
EXACTITUD: 0.96

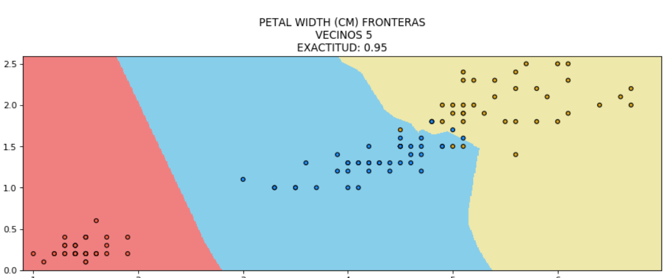

SEPAL WIDTH (CM) MATRIZ DE CONFUSION
VECINOS: 10
EXACTITUD: 0.95
39 0 0
0 40 3
0 3 35
setosa
versicolor
virginica
Etiqueta correcta
Etiqueta predicha

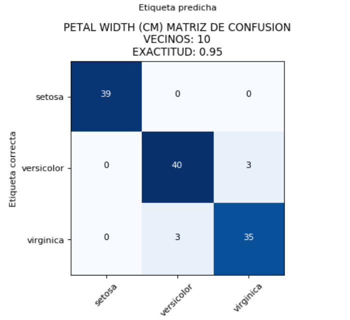

SEPAL WIDTH (CM) FRONTERAS
VECINOS 10
EXACTITUD: 0.95

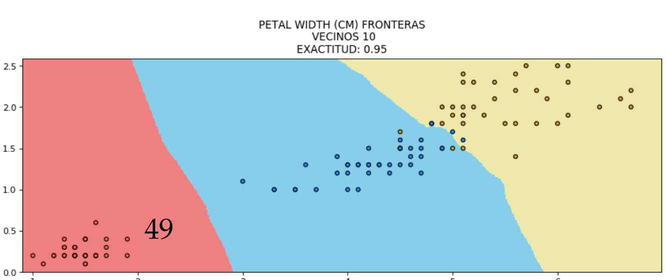

PETAL WIDTH (CM) MATRIZ DE CONFUSION
VECINOS: 3
EXACTITUD: 0.98
39 0 0
0 42 1
0 1 37
setosa
versicolor
virginica
Etiqueta correcta
Etiqueta predicha


PETAL WIDTH (CM) FRONTERAS
VECINOS 3
EXACTITUD: 0.98


PETAL WIDTH (CM) MATRIZ DE CONFUSION
VECINOS: 5
EXACTITUD: 0.95
39 0 0
0 40 3
0 3 35
setosa
versicolor
virginica
Etiqueta correcta
Etiqueta predicha


PETAL WIDTH (CM) FRONTERAS
VECINOS 5
EXACTITUD: 0.95


PETAL WIDTH (CM) MATRIZ DE CONFUSION
VECINOS: 10
EXACTITUD: 0.95
39 0 0
0 40 3
0 3 35
setosa
versicolor
virginica
Etiqueta correcta
Etiqueta predicha


PETAL WIDTH (CM) FRONTERAS
VECINOS 10
EXACTITUD: 0.95

Si bien al considerar menos vecinos, la prediccón es mejor, puede verse que la predicción también depende de los features utilizados. En este caso se escogieron pares de features fuertemente correlacionados y se ve que al variar y_feature entre dos valores, cuando se tienen 3 vecinos, la exactitud varía en 0.01.

```
In [ ]:
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