Taller de Aprendizaje Automático

Clasificación y regresión

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1. Medidas de desempeño
2. Análisis de error
3. Gradiente descendente
4. Curvas de aprendizaje
5. Regularización

Clasificador binario

MNIST dataset

```
y_train_5 = (y_train == 5)
y_test_5 = (y_test == 5)

from sklearn.linear_model import SGDClassifier
sgd_clf = SGDClassifier(random_state=42)
sgd_clf.fit(X_train, y_train_5)

>>> some_digit = X[0]
>>> sgd_clf.predict([some_digit])
array([True])
```

Evaluar desempeño

- accuracy: tasa de acierto

```
>>> from sklearn.model_selection import cross_val_score
>>> cross_val_score(sgd_clf, X_train, y_train_5,
                    cv=3, scoring="accuracy")
array([0.96355, 0.93795, 0.95615])
```

clasificador *tonto*: nunca *5*

```
from sklearn.base import BaseEstimator

class Never5Classifier(BaseEstimator):
        def fit(self, X, y=None):
                pass
        def predict(self, X):
                return np.zeros((len(X), 1),
                                dtype=bool)
```

no sirve para datos desbalanceados!

(solo 10% de los datos son *5*)

```
>>> never_5_clf = Never5Classifier()
>>> cross_val_score(never_5_clf, X_train, y_train_5,
                    cv=3, scoring="accuracy")
array([0.91125, 0.90855, 0.90915])
```

Matriz de confusión

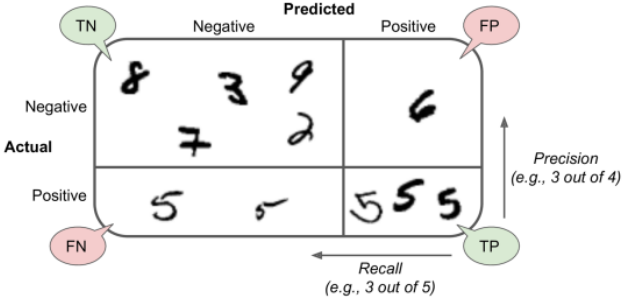
- TP verdaderos positivos
- TN verdaderos negativos
- FP falsos positivos
- FN falsos negativos

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

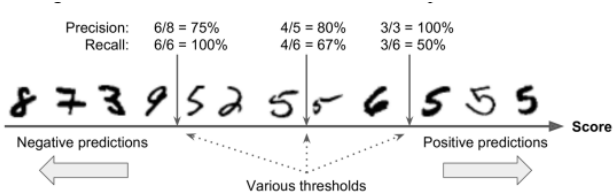
$$\text{F}_1 = 2\,\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

```
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import confusion_matrix

y_train_pred = cross_val_predict(sgd_clf, X_train,
                                 y_train_5, cv=3)

>>> confusion_matrix(y_train_5, y_train_pred)
array([[53057, 1522],
       [ 1325, 4096]])
```

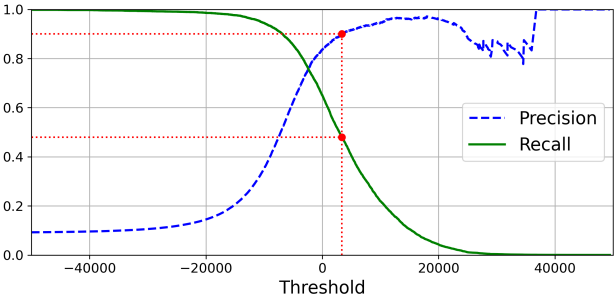


Compromiso Precision–Recall

```
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
>>> precision_score(y_train_5, y_train_pred)
0.7290850836596654
>>> recall_score(y_train_5, y_train_pred)
0.7555801512636044
```

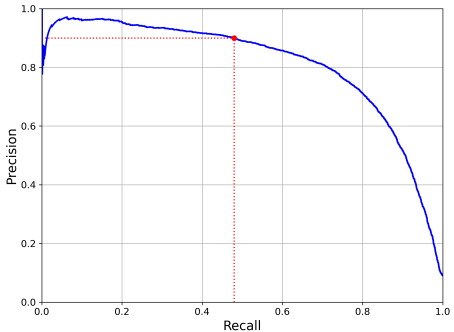



```
>>> y_scores =
    sgd_clf.decision_function([some_digit])
>>> y_scores
array([2412.53175101])
>>> threshold = 0
>>> y_some_digit_pred = (y_scores > threshold)
array([True])
>>> threshold = 8000
>>> y_some_digit_pred = (y_scores > threshold)
array([False])
```



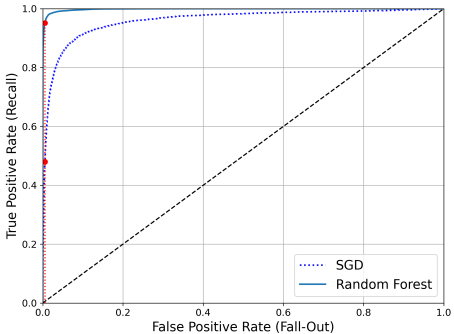
Curva Precision vs Recall

```
y_train_pred_90 = (y_scores >=
     thresholds[np.argmax(precisions >= 0.90)])

>>> precision_score(y_train_5, y_train_pred_90)
0.9000380083618396
>>> recall_score(y_train_5, y_train_pred_90)
0.4368197749492714
```



Curva ROC

```
from sklearn.metrics import roc_curve
fpr, tpr, thresholds = roc_curve(y_train_5, y_scores)

from sklearn.metrics import roc_auc_score
>>> roc_auc_score(y_train_5, y_scores)
0.9611778893101814
```



Clasificación multi clase

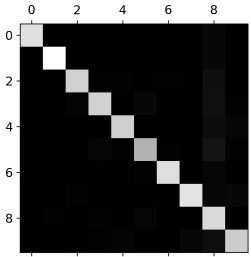
MNIST dataset

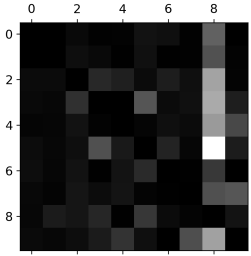
```
from sklearn.linear_model import SGDClassifier
sgd_clf = SGDClassifier(random_state=42)
sgd_clf.fit(X_train, y_train)

>>> some_digit = X[0]
>>> sgd_clf.predict([some_digit])
array([5], dtype=uint8)

>>> cross_val_score(sgd_clf, X_train, y_train,
                    cv=3, scoring="accuracy")
array([0.8489802 , 0.87129356, 0.86988048])

>>> from sklearn.preprocessing import StandardScaler
>>> scaler = StandardScaler()
>>> X_train_scaled = scaler.fit_transform(X_train)
>>> cross_val_score(sgd_clf, X_train_scaled, y_train,
                    cv=3, scoring="accuracy")
array([0.89707059, 0.8960948 , 0.90693604])
```

Análisis de error

```
y_train_pred = cross_val_predict(sgd_clf, X_train_scaled, y_train, cv=3)
conf_mx = confusion_matrix(y_train, y_train_pred)
conf_mx
array([[5577,    0,   22,    5,    8,   43,   36,    6,  225,    1],
       [   0, 6400,   37,   24,    4,   44,    4,    7,  212,   10],
       [  27,   27, 5220,   92,   73,   27,   67,   36,  378,   11],
       [  22,   17,  117, 5227,    2,  203,   27,   40,  403,   73],
       [  12,   14,   41,    9, 5182,   12,   34,   27,  347,  164],
       [  27,   15,   30,  168,   53, 4444,   75,   14,  535,   60],
       [  30,   15,   42,    3,   44,   97, 5552,    3,  131,    1],
       [  21,   10,   51,   30,   49,   12,    3, 5684,  195,  210],
       [  17,   63,   48,   86,    3,  126,   25,   10, 5429,   44],
       [  25,   18,   30,   64,  118,   36,    1,  179,  371, 5107]])
```

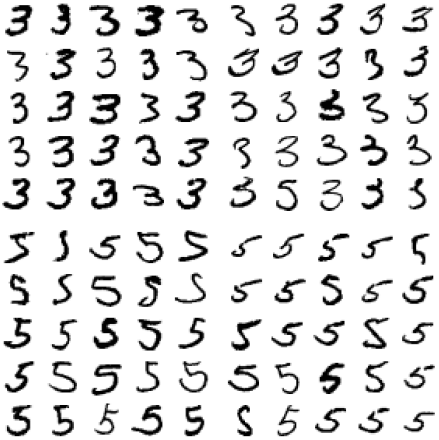
```
row_sums = conf_mx.sum(axis=1, keepdims=True)
norm_conf_mx = conf_mx / row_sums

np.fill_diagonal(norm_conf_mx, 0)
plt.matshow(norm_conf_mx, cmap=plt.cm.gray)
plt.show()
```





Análisis de error

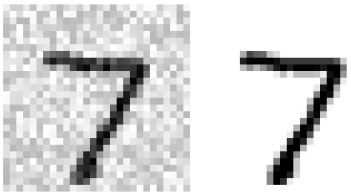
```
cl_a, cl_b = 3, 5
X_aa = X_train[(y_train == cl_a) & (y_train_pred == cl_a)]
X_ab = X_train[(y_train == cl_a) & (y_train_pred == cl_b)]
X_ba = X_train[(y_train == cl_b) & (y_train_pred == cl_a)]
X_bb = X_train[(y_train == cl_b) & (y_train_pred == cl_b)]

plt.figure(figsize=(8,8))
plt.subplot(221); plot_digits(X_aa[:25], images_per_row=5)
plt.subplot(222); plot_digits(X_ab[:25], images_per_row=5)
plt.subplot(223); plot_digits(X_ba[:25], images_per_row=5)
plt.subplot(224); plot_digits(X_bb[:25], images_per_row=5)
plt.show()
```



Ejercicio

En el notebook del capítulo 3 del libro* estudiar en qué consiste:

- clasificación multi etiqueta (mutilabel classification)
- clasificación multi salida (mutioutput classification)

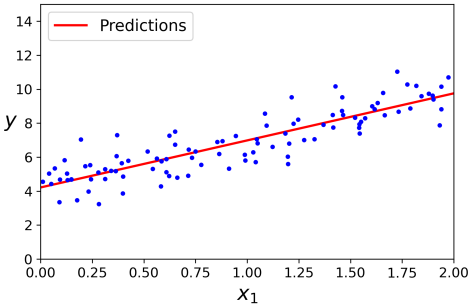


training example

denoised example

*A. Géron, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 3rd Edition*. O'Reilly Media, Inc., 2022

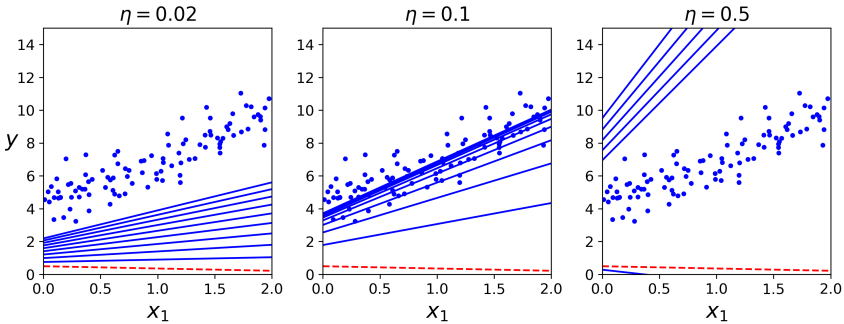
Regresión lineal



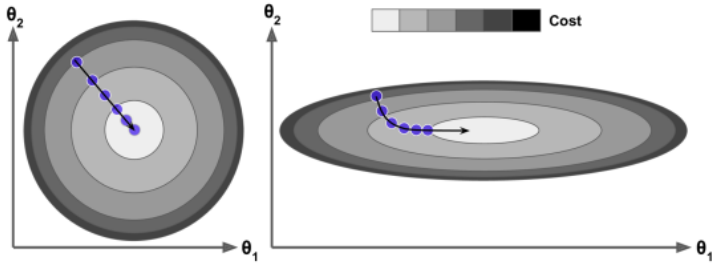

```
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression()
lin_reg.fit(X, y)
```

Gradiente descendente

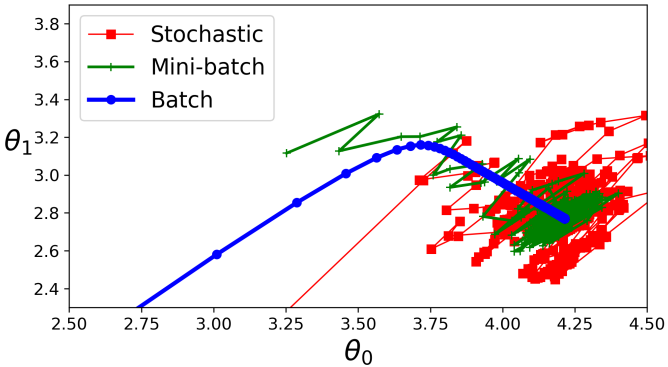
```
from sklearn.linear_model import SGDRegressor

sgd_reg = SGDRegressor(max_iter=1000, tol=1e-3, penalty=None, eta0=0.1, random_state=42)
sgd_reg.fit(X, y.ravel())
```



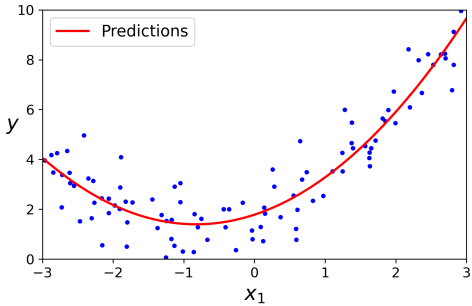
Gradiente descendente



Gradiente descendente

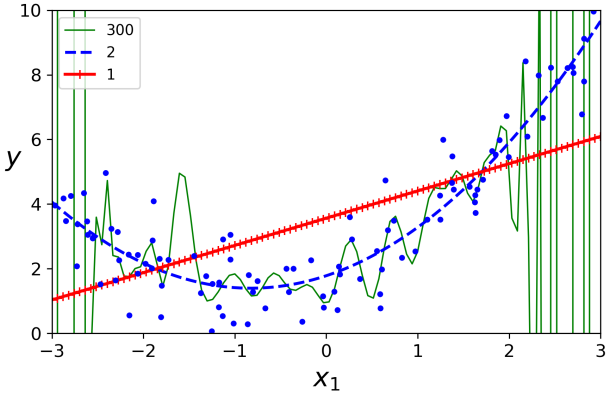


Regresión polinómica



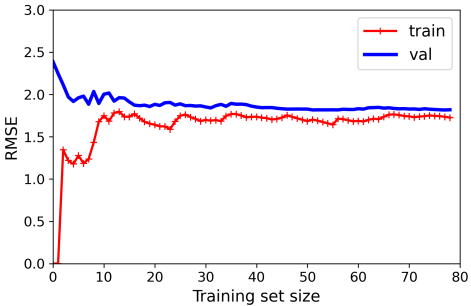

```python
from sklearn.preprocessing import PolynomialFeatures
poly_features = PolynomialFeatures(degree=2,
                                   include_bias=False)
X_poly = poly_features.fit_transform(X)

lin_reg = LinearRegression()
lin_reg.fit(X_poly, y)
```

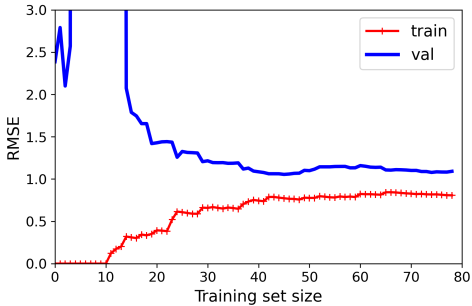
Regresión polinómica



Curvas de aprendizaje

```
from sklearn.pipeline import Pipeline

polynomial_regression = Pipeline([
        ("poly_features", PolynomialFeatures(degree=10, include_bias=False)),
        ("lin_reg", LinearRegression()),
    ])

plot_learning_curves(polynomial_regression, X, y)
```

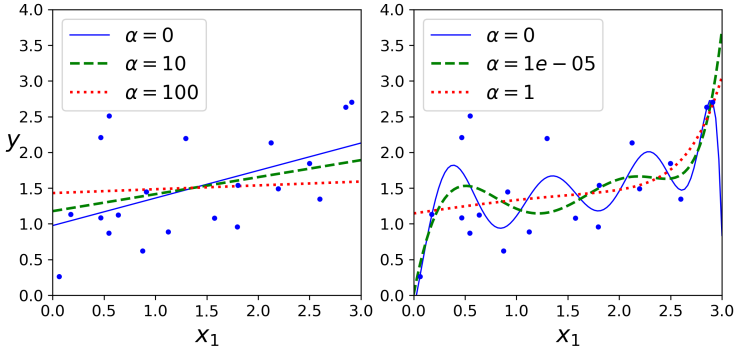




Regresión de Ridge

$$J(\theta) = \mathrm{MSE}(\theta) + \alpha\|\theta\|_2^2$$

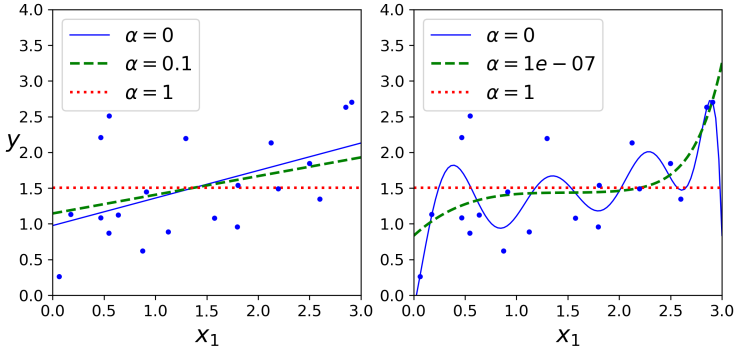
```
sgd_reg = SGDRegressor(penalty="l2")
sgd_reg.fit(X, y.ravel())
```



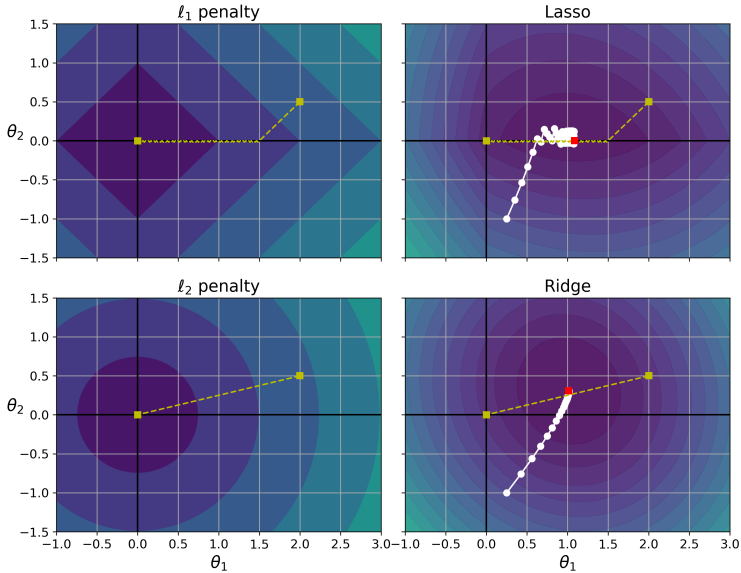
Regresión Lasso

$$J(\theta) = \mathrm{MSE}(\theta) + \alpha\|\theta\|_1$$

```
sgd_reg = SGDRegressor(penalty="l1")
sgd_reg.fit(X, y.ravel())
```



Lasso vs Ridge

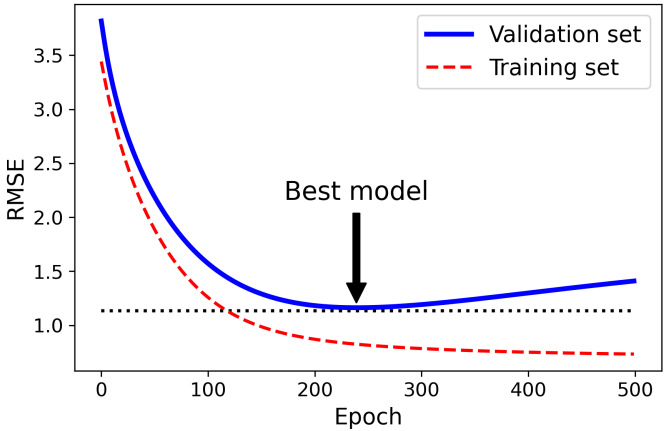


Elastic Net

$$J(\theta) = \mathrm{MSE}(\theta) + r\,\alpha\|\theta\|_1 + (1-r)\,\alpha\|\theta\|_2^2$$

```
from sklearn.linear_model import ElasticNet
elastic_net = ElasticNet(alpha=0.1, l1_ratio=0.5, random_state=42)
elastic_net.fit(X, y)
elastic_net.predict([[1.5]])
```

Early stopping



Referencias


A. Géron, *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 3rd Edition*. O'Reilly Media, Inc., 2022.