Multinomial Logistic Regression (Softmax Regression)

```
1 from scipy import optimize
2 from sklearn.linear_model import LogisticRegression
3 from sklearn.model_selection import train_test_split
4 from sklearn.datasets import load_iris
5 from sklearn.preprocessing import OneHotEncoder
6 import matplotlib.pyplot as plt
7 import numpy as np

Load dataset (iris)

• X
```

- o sepal length (cm)
- o sepal width (cm)
- o petal length (cm)
- o petal width (cm)
- y
- Iris-Setosa (0), Iris-Versicolour(1), Iris-Virginica (2)

Split Dataset (using OneHot Encoding)

```
1 y_ohe = OneHotEncoder().fit_transform(y.reshape(-1, 1)).toarray()
2 print(y_ohe)
```

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→ [[1. 0. 0.]
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 1 x_train, x_test, y_train, y_test = train_test_split(x, y_ohe)
 2 y_test, x_train.shape, y_train.shape
(array([[0., 1., 0.], [0., 1., 0.], [1., 0., 0.],
                 [1., 0., 0.],
                [0., 1., 0.],
[1., 0., 0.],
                [0., 0., 1.],
                 [0., 1., 0.],
                [0., 1., 0.],
[0., 1., 0.],
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[1., 0., 0.],
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[1., 0., 0.],
                [1., 0., 0.],
[1., 0., 0.],
                [0., 1., 0.],
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[1., 0., 0.],
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                [0., 0., 1.],
                [0., 1., 0.],
[0., 0., 1.],
                [0., 0., 1.],
                 [1., 0., 0.],
                 [0., 1., 0.]
                [1., 0., 0.]]),
        (112, 4),
        (112, 3))
 1 x1_train = np.hstack([np.ones([x_train.shape[0], 1]), x_train])
 2 \times 1_{test} = np.hstack([np.ones([x_test.shape[0], 1]), x_test])
Learning
```

· loss function

$$\min_{w,b} \sum_{i=0}^{N-1} \sum_{k=0}^{C-1} \left[-y_k \cdot \log \big(\hat{y}_{i,k} \big) \right]$$

```
1 # loss function
2 n_feature = x_train.shape[1]
3 n_class = y_train.shape[1]
4 REG_CONST = 0.01
6 def softmax(z):
      ## IMPLEMENT HERE
      s = np.exp(z) / np.sum(np.exp(z), axis=1).reshape(-1,1)
```

```
9
       return s
10
11 def ce_loss(W, args):
12
       ## IMPLEMENT HERE
13
      train_x, train_y = args
14
      W = W.reshape((n_class, n_feature + 1))
15
      z = (W @ train_x.T).T
16
17
      y_hat = softmax(z)
18
      train\_ce = np.sum(-train\_y * np.log(y\_hat + 1e-10), axis=1)
       train_loss = train_ce.mean() + REG_CONST * np.mean(np.square(W))
19
20
      return train_loss
 1 # optimization
 2 init_w = np.ones(n_class * (n_feature + 1)) * 0.1
 3 result = optimize.minimize(ce_loss, init_w, args=[x1_train, y_train])
```



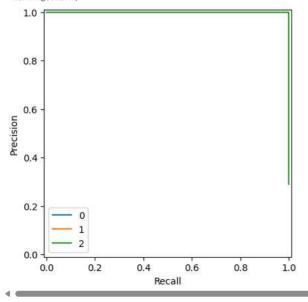
Evaluation

```
1 # Accuracy
2 W = result.x.reshape(n_class, n_feature+1)
3z = (W @ x1_test.T).T
4 y_hat = softmax(z)
5 y_hat = np.argmax(y_hat, axis=1)
6 y_true = np.argmax(y_test, axis=1)
7 \ \text{acc} = (y_hat == y_true).mean()
8 print(f'accuracy: {acc}')
→ accuracy: 0.9736842105263158
1 # PR-Curve
2 from sklearn.metrics import precision_recall_curve, PrecisionRecallDisplay
3 y_hat_sm = softmax(z)
5_, ax = plt.subplots()
6 for i in range(n_class):
      pr, rc, _ = precision_recall_curve(y_true=y_test[:, i], probas_pred=y_hat_sm[:,i])
      disp = PrecisionRecallDisplay(precision=pr, recall=rc)
9
      disp.plot(ax=ax, label=f'{i}')
10 plt.show()
```

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_ranking.py:993: FutureWarning: probas_pred was deprecated in version 1.5 and will be rer warnings.warn(

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