$softmax_regression_2$

September 10, 2021

```
{\bf Name:}\ {\bf Omar}\ {\bf Khaled}\ {\bf Mahmoud}\ {\bf Safwat}
```

Group: Alex. G3

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

from sklearn import datasets
from sklearn.model_selection import StratifiedShuffleSplit

np.random.seed(42)

[]: iris = datasets.load_iris()
```

[]:	sepal length (cm)	sepal width (cm)	petal length (cm)	<pre>petal width (cm) \</pre>
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

```
target
0 0
1 0
2 0
3 0
4 0
```

1 Mini-Batch GD

2 Softmax Regression

```
[]: class Softmax():
         """Class Implements Softmax Regresson for multinomial classification"""
         def __init__(self):
             self.X_train = None # User input data.
             self.y = None # Target feature
             self.y_ohe = None # Target Variable One-hot encoded
             self.weights = None # weights of model
         def encode_target(self, y):
             """One-hot encode target variable"""
             assert y.ndim == 1, "Target variable should be 1 dimensional"
             y_{ohe} = np.zeros((len(y), y.max() + 1))
             y_{ohe}[np.arange(len(y)), y] = 1
             return y_ohe
         def hypothesis(self, X=None, weights=None, batch_indices=None):
             """Hypothesis function"""
             if X is None:
                 X = self.X
             if weights is None:
                 weights = self.weights
             if batch_indices is None:
                 batch_indices = list(range(len(self.y)))
             score_fun = X[batch_indices, :] @ weights # Score function for each_
      →class, for each sample
             score_exp = np.exp(score_fun)
             # Returns a 2D Numpy array, prediction of each class for each sample
             # Shape: (m, k)
             # m: Number of samples, k: Number of classes
             return(score_exp / np.sum(score_exp, axis=1, keepdims=True))
         def loss(self, h, batch_indices):
             """Cost function"""
             y_ohe = self.y_ohe[batch_indices, :]
             h += 1e-7 # Add tolerance term for the log
             return -np.sum(y_ohe * np.log(h))
         def loss_prime(self, h, batch_indices):
             """Jacobian vector of cost function"""
             y_ohe = self.y_ohe[batch_indices, :]
```

```
X = self.X[batch_indices, :]
       return (X.T @ (h - y_ohe))
   def initialize(self, learn_rate, batch_size):
       Initialize first epoch
       Args:
           learn_rate (float): Learning rate for gradient descent
           guess (int, 2D numpy array): Initial guess for model weights
           batch_size (int): Training set batch size
       11 11 11
       # Initialize quesses
       self.weights_hist = np.random.randn(self.X.shape[1], self.y_ohe.
→shape[1], 1) # Initialize weight vector, account for bias column
       # Initialize history
       self.loss hist = np.empty(shape=(1))
       self.grad_hist = np.empty_like(self.weights_hist)
       self.n_points = batch_size
       self.epoch = 0
       self.learn_rate = learn_rate
   def update_weights_GD(self, idx_1, idx_2, weights):
       Function updates weights along the direction of steepest descent and \Box
\hookrightarrowstores results
       Args:
           idx 1 (int): Start index for the current batch
           idx_2 (int): End index for the current batch (non inclusive)
           weights (2D numpy array): Model weights
       0.00
       # Compute predictions
       self.h_pred = self.hypothesis(batch_indices=self.train_indx[idx_1:__
→idx_2], weights=weights)
       # Compute weights gradient
       grad_new = self.loss_prime(self.h_pred, self.train_indx[idx_1: idx_2])
       self.grad_hist = np.dstack((self.grad_hist, np.atleast_3d(grad_new)))
```

```
# Update Weights
       weights = weights - self.learn_rate * grad_new
       self.weights_hist = np.dstack((self.weights_hist, np.
→atleast_3d(weights)))
   def mini_batch_GD(self, learn_rate=0.01, n_batches=8, max_epochs=1e3,__
⇒seed=None):
        11 11 11
       Optimize weights using Mini_batch Gradient Descent
       Args:
            learn_rate (float, optional): Learning rate for gradient descent
            n_batches (int, optional): Number of batches for mini-batch<sub>□</sub>
\hookrightarrow Gradient descent
            max\_epochs (int, optional): Maximum number of iterations over the \sqcup
\hookrightarrow entire training set
            seed (int, optional): seed the the data shuffeling after before \Box
\rightarrow each epoch
       Returns:
            2d numpy array: Trained model weights
       # Randomly shuffle the dataset's order
       if (seed is not None):
            np.random.seed(seed)
       self.n_batches = n_batches
       np.random.shuffle(self.train_indx)
       self.MAX_EPOCHS = max_epochs
       batch_size = len(self.train_indx) // n_batches
       # Initialize first epoch
       self.initialize(learn_rate, batch_size)
       # Train model using Mini_batches
       while (self.epoch < self.MAX_EPOCHS):</pre>
           for i in range(n_batches):
                idx_1 = i * batch_size
                idx_2 = idx_1 + batch_size
```

```
self.update_weights_GD(idx_1, idx_2, self.weights_hist[:, :,_
→-1])
           # Update Predictions and Loss from last epoch
           self.h_pred = self.hypothesis(batch_indices=self.train_indx[:
→batch_size], weights=self.weights_hist[:, :, -1])
           self.loss_hist = np.append(self.loss_hist, self.loss(self.h_pred,_
⇒self.train_indx[:batch_size]))
           # Increment epoch and shuffle data incides for next epoch
           self.epoch += 1
           np.random.shuffle(self.train_indx)
           # Record minimum loss so far if early stopping is used
           if self.early_stop == True:
               # Check if stop criteria threshold is met
               if (self.epoch - self.best_epoch) > self.early_stop_thresh:
                   self.is_converged = True
                   return self.weights_hist[:, :, -1]
               val_preds = self.hypothesis(batch_indices=self.valid_indx,__
→weights=self.weights_hist[:, :, -1])
               current_loss = self.loss(val_preds, self.valid_indx)
               if self.min_val_loss > current_loss:
                   self.min_val_loss = current_loss
                   self.best_epoch = self.epoch
       return self.weights_hist[:, :, -1]
   def fit(self, X, y, early_stop=False, early_stop_thresh=5, **kwargs):
       """Fit model to training data"""
       # X, and y are 2D Numpy arrays.
       # Add a column of ones for theta O
       self.X = np.hstack((np.ones((len(X), 1)), X))
       self.y = y
       # One-hot encode target variable
       self.y_ohe = self.encode_target(y)
       all_indices = np.array([i for i in range(len(self.X))])
       self.early_stop = early_stop
       # Split the data to validation set to check early stop
       if self.early_stop == True:
```

```
validation_mask = np.array([np.random.choice([0, 1], p=[0.7, 0.3])_u

→for i in range(len(y))], dtype='bool')
           self.valid_indx = all_indices[validation_mask]
           self.train indx = all indices[~validation mask]
           self.min val loss = float("inf")
                                                       # Value of minimum loss
           self.best epoch = 0
                                                       # Epoch with minimum loss
           self.early\_stop\_thresh = early\_stop\_thresh # Maximum number of_{\sqcup}
→epochs to perform without improvement in loss
           self.is_converged = False
       else:
           self.train_indx = all_indices
       self.weights = self.mini_batch_GD(**kwargs)
   def predict(self, X):
       """Returns predictions"""
       X = np.hstack((np.ones((X.shape[0], 1)), X))
       proba = self.hypothesis(X, self.weights, list(range(X.shape[0])))
       return np.argmax(proba, axis=1)
   def predict_proba(self, X):
       """Returns predictions for each class as probabilities"""
       X = np.hstack((np.ones((X.shape[0], 1)), X))
       return self.hypothesis(X, self.weights, list(range(X.shape[0])))
   def accuracy_score(self, X_test, y_test):
       """Returns model accuracy score"""
       return np.sum(self.predict(X_test) == y_test) / len(y_test)
   def show summary(self):
       """Prints a brief summary after stop criteria is reached"""
       print("Solver summary:")
       print("=" * len("Solver summary:"))
       if self.early_stop == True:
           print("Number of epochs: ", self.best_epoch)
           print("Negative Log Likelihood: ", self.loss_hist[self.best_epoch])
           print("Early stop criteria was reached first: ", self.is_converged)
           print("Train accuracy: ", self.accuracy_score(self.X[self.
→train_indx, 1:], self.y[self.train_indx]))
           print("Validation accuracy: ", self.accuracy_score(self.X[self.
→valid_indx, 1:], self.y[self.valid_indx]))
       else:
           print("Number of epochs: ", self.epoch)
           print("Negative Log Likelihood: ", self.loss_hist[-1])
```

3 Train with Mini_batch GD

3.1 Without Early stop

```
[]: # Split dataset into validation and training
    all_indices = np.array([i for i in range(len(X))])
    np.random.shuffle(all_indices)
    validation mask = np.array([np.random.choice([0, 1], p=[0.7, 0.3]) for i in_
     →range(len(y))], dtype='bool')
    train_indx, val_indx = all_indices[~validation_mask],_
     →all_indices[validation_mask]
    X_train, y_train = X[train_indx], y[train_indx]
    X_val, y_val = X[val_indx], y[val_indx]
    softmax = Softmax()
    softmax.fit(X_train, y_train, early_stop=False, learn_rate=0.05)
    softmax.show summary()
    print('Validation accuracy: ', softmax.accuracy_score(X_val, y_val))
    Solver summary:
    =========
    Number of epochs: 1000
    Negative Log Likelihood: 0.5375553478186633
    Train accuracy: 0.9904761904761905
```

3.2 With Early stop

```
[]: softmax = Softmax()
softmax.fit(X, y, early_stop=True, early_stop_thresh=300, learn_rate=0.05)
softmax.show_summary()
```

Validation accuracy: 0.977777777777777

4 Cross Validation

```
[]: class KfoldCV():
       """Class implements k-fold cross validation"""
       def __init__(self, model):
           self.model = model # ML model object
           self.accuracy_scores=None
       def fit(self, X, y, n_folds=3, **kwargs):
         """Train machine learning model using k_folds cross validation"""
         self.accuracy_scores = []
         # Split Dataset
         split = StratifiedShuffleSplit(n_splits=n_folds, test_size=0.2,__
      →random_state=42)
         for train_index, test_index in split.split(X, y):
             X_train, y_train = X[train_index], y[train_index]
             X_test, y_test = X[test_index], y[test_index]
             self.model.fit(X_train, y_train, **kwargs)
             self.accuracy_scores.append(self.model.accuracy_score(X_test, y_test))
       def predict(self, X):
         """Return model predictions for dataset X"""
         return self.model.predict(X)
       def predict_proba(self, X):
         """Return model probability predictions for dataset X"""
         return self.model.predict_proba(X)
       def show_summary(self):
         self.model.show_summary()
      def accuracy_score(self):
         """Returns average accuracy score from CV"""
         return np.mean(self.accuracy_scores)
```

4.1 CV without early stopping

```
[]: softmaxCV = KfoldCV(Softmax())
softmaxCV.fit(X, y, learn_rate=0.05, early_stop=False)
print("Cross Validation accuracy: ", softmaxCV.accuracy_score())
```

Cross Validation accuracy: 0.9111111111111111

4.2 CV with early stopping

Cross Validation accuracy: 0.944444444444443