

svm.py

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[ ]: """Support Vector Machine (SVM) model."""

# This source code is modified by Arman Sayan.

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import numpy as np

class SVM:
    def __init__(self, n_class: int, lr: float, epochs: int, reg_const: float):
        """Initialize a new classifier.

        Parameters:
            n_class: the number of classes
            lr: the learning rate
            epochs: the number of epochs to train for
            reg_const: the regularization constant
        """

        self.w = None # Weight matrix of shape (D, C), initialized during
        ↪ training
        self.alpha = lr
        self.epochs = epochs
        self.reg_const = reg_const
        self.n_class = n_class

    def calc_gradient(self, X_train: np.ndarray, y_train: np.ndarray) -> np.
    ↪ ndarray:
        """Calculate gradient of the sum hinge loss.

        Inputs have dimension D, there are C classes, and we operate on
        mini-batches of N examples.

        Parameters:
            X_train: a numpy array of shape (N, D) containing a mini-batch
                    of data
            y_train: a numpy array of shape (N,) containing training labels;
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y[i] = c means that X[i] has label c, where $0 \leq c < C$

Returns:

the gradient with respect to weights w; an array of the same shape as w

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"""
N, D = X_train.shape

# Compute class scores for all samples
scores = X_train @ self.w # Shape (N, C)

# Extract the scores of the correct classes
correct_class_scores = scores[np.arange(N), y_train].reshape(-1, 1)

# Compute the margins for all classes
margins = np.maximum(0, scores - correct_class_scores + 1)

# Zero-out the margins for the correct classes
margins[np.arange(N), y_train] = 0 # Ignore correct class

# Binary indicator: 1 where margin > 0
indicator = (margins > 0).astype(float) # Indicator for incorrect
↪ classes

# For each example, subtract total count of violations from the correct
↪ class column
indicator[np.arange(N), y_train] = -np.sum(indicator, axis=1) # Adjust
↪ correct class

# Compute gradient and add L2 regularization
grad = (X_train.T @ indicator) / N + self.reg_const * self.w # Add
↪ regularization
return grad

def train(self, X_train: np.ndarray, y_train: np.ndarray):
    """Train the classifier.

    Hint: operate on mini-batches of data for SGD.

    Parameters:
        X_train: a numpy array of shape (N, D) containing training data;
                  N examples with D dimensions
        y_train: a numpy array of shape (N,) containing training labels
    """
    N, D = X_train.shape

    # Initialize weights randomly if not already initialized
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        if self.w is None:
            self.w = np.random.randn(D, self.n_class) * 0.01 # Initialize
↪small random weights

        # Perform gradient descent for a number of epochs
        for epoch in range(self.epochs):
            # Compute the gradient of the current loss
            gradient = self.calc_gradient(X_train, y_train)

            # Update weights using the gradient
            self.w -= self.alpha * gradient # Update weights

            # Every 100 epochs, compute and print the average hinge loss
            if epoch % 100 == 0:
                scores = X_train @ self.w # (N, C)
                correct_class_scores = scores[np.arange(N), y_train].
↪reshape(-1, 1) # (N, 1)
                margins = np.maximum(0, scores - correct_class_scores + 1) #
↪(N, C)
                margins[np.arange(N), y_train] = 0 # Zero out correct class
                loss = np.mean(np.sum(margins, axis=1)) # Hinge loss averaged
↪over batch
                print(f"Epoch {epoch}: Loss = {loss:.4f}")

    def predict(self, X_test: np.ndarray) -> np.ndarray:
        """Use the trained weights to predict labels for test data points.

        Parameters:
            X_test: a numpy array of shape (N, D) containing testing data;
                    N examples with D dimensions

        Returns:
            predicted labels for the data in X_test; a 1-dimensional array of
            length N, where each element is an integer giving the predicted
            class.
        """
        # Compute class scores and return the index of the highest score (best
↪class)
        return np.argmax(X_test @ self.w, axis=1)

```