# 01\_assignment\_perceptron\_robertson

#### February 18, 2025

# **Assignment 1: Perceptron**

CPSC 381/581: Machine Learning

Yale University

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#### Prerequisites:

1. Enable Google Colaboratory as an app on your Google Drive account

2. Create a new Google Colab notebook, this will also create a "Colab Notebooks" directory under "MyDrive" i.e.

## /content/drive/MyDrive/Colab Notebooks

3. Create the following directory structure in your Google Drive

/content/drive/MyDrive/Colab Notebooks/CPSC 381-581: Machine Learning/Assignments

4. Move the 01\_assignment\_perceptron\_multiclass.ipynb into

/content/drive/MyDrive/Colab Notebooks/CPSC 381-581: Machine Learning/Assignments so that its absolute path is

/content/drive/MyDrive/Colab Notebooks/CPSC 381-581: Machine Learning/Assignments/01\_assignment

In this assignment, you will implement both binary and multiclass perceptron classifiers from scratch. You will test your implementations on the digits dataset from scikit-learn. The assignment is divided into three main parts:

- 1. Implementing a binary perceptron for digit classification (0 vs 1)
- 2. Implementing a multiclass perceptron for full digits classification (0-9)
- 3. Comparing your implementations with scikit-learn's Perceptron

### **Submission**:

- 1. Implement all TODOs in the code blocks below.
- 2. Report your validation and testing scores. For full credit, your testing scores should be higher than 0.9.

#### BinaryPerceptron:

Best model test accuracy: 0.9861

```
Scikit-learn Perceptron test accuracy: 1.0000
     MultiClassPerceptron:
     Best model test accuracy: 0.9611
     Scikit-learn Perceptron test accuracy: 0.9361
       3. List any collaborators.
     Collaborators: N/A
[26]: import numpy as np
      import sklearn.datasets as skdata
      from sklearn.linear_model import Perceptron
      import sklearn.metrics as skmetrics
      from sklearn.model_selection import train_test_split
      import warnings, time
      import matplotlib.pyplot as plt
      warnings.filterwarnings(action='ignore')
      np.random.seed(42)
[27]: class BinaryPerceptron:
          Implementation of Binary Perceptron
          111
          def __init__(self):
              self.__weights = None
          def __update(self, x, y):
              Update weights for misclassified examples
              Arq(s):
                  x : numpy.ndarray
                      Feature vector of shape d x 1
                  y:int
                      Label/target (-1 or 1)
               111
              # DONE: Implement weight update rule for binary perceptron
              # NOTE: x = (d+1, 1) column vector with bias, so select first column
       \rightarrow for (d+1,) array
              self._weights[:, 0] += y * x
          def fit(self, x, y, max_iter=100):
```

Fit the binary perceptron to training data

```
Arq(s):
           x : numpy.ndarray
               Features of shape d x N
           y : numpy.ndarray
               Labels/targets of shape (1 \ x \ N) or (N \ x \ 1)
           max iter : int
               Maximum number of iterations
       111
      n_features, n_samples = x.shape
       # DONE: Initialize weights (including a bias term, w0) as zeros vector
\rightarrow with shape d+1 x 1
      self.__weights = np.zeros((n_features + 1, 1))
       # DONE: Append artificial coordinate (x0) to the data
       # NOTE: This makes the shape d+1 \ x \ 1 since bias isn't separate
      x = np.concatenate((np.ones((1, n_samples)), x), axis=0)
       # DONE: Implement training loop
      for _ in range(max_iter):
          n_updates = 0
           # Process each sample
          for n in range(n_samples):
               # DONE: Calculate prediction
               binary_prediction = np.sign(self.__weights.T @ x[:, n])
               # print(binary_prediction, y[n]) # shape (1,1) but single value
               # DONE: Update weights if misclassified
               if binary_prediction != y[n]:
                   self._update(x[:, n], y[n])
                   # print(self.__weights)
                   n_updates += 1
           # DONE: Break if no updates were made, e.g., check for convergence
           if n updates == 0:
               break
  def predict(self, x):
      Make predictions
      Arq(s):
           x : numpy.ndarray
```

```
Features of shape d x N
       Returns:
           numpy.ndarray : Predicted labels (-1 or 1) of 1 x N
      n_features, n_samples = x.shape
       # DONE: Append artificial coordinate (x0) to the data
      x = np.concatenate((np.ones((1, n_samples)), x), axis=0)
       # DONE: Implement prediction logic
       \# NOTE: Was having a lot of trouble getting shapes to match (see notes \sqcup
→above) so ended up doing .flatten() to deal with scalar
      binary_prediction = np.sign(self._weights.T @ x).flatten()
      return binary_prediction
  def score(self, x, y):
      Calculate prediction accuracy
      Arg(s):
           x : numpy.ndarray
              Features of shape d x N
           y : numpy.ndarray
               Labels/targets of shape (1 \times N) or (N \times 1)
       Returns:
          float: Accuracy score
       # DONE: Implement accuracy calculation
      binary_predictions = self.predict(x)
      binary_accuracy = np.mean(binary_predictions == y.flatten())
      return binary_accuracy
```

```
Update weights for misclassified examples
S
        Arg(s):
            x : numpy.ndarray
                Feature vector of shape d x 1
            y:int
                Label/target (-1 or 1)
            y_hat : int
                Predicted label (-1 or 1)
        # DONE: Implement weight update rule for multiclass case
        self.__weights[:, y] += x
        self.__weights[:, y_hat] -= x
    def fit(self, x, y, max_iter=100):
        Fit the multiclass perceptron to training data
        Arq(s):
            x : numpy.ndarray
                Feature vector of shape d x N
            y : numpy.ndarray
                Label/target (-1 or 1) of shape (1 \times N) or (N \times 1)
            max\_iter : int
                Maximum number of iterations
        111
        # Flattening y for 1D everywhere
        y = y.flatten()
        n_features, n_samples = x.shape
        # DONE: Get number of classes from unique values in y
        self.__n_classes = np.unique(y).size
        # DONE: Initialize weights matrix of zeros with shape d+1 \ x \ C
        self._weights = np.zeros((n_features + 1, self._n_classes))
        # DONE: Append artificial coordinate (x0) to the data such that it is _{f \sqcup}
 \hookrightarrow d+1 \times N
        x = np.concatenate((np.ones((1, n_samples)), x), axis=0)
        # DONE: Implement training loop
        for _ in range(max_iter):
            n_updates = 0
```

```
# Process each sample
        for n in range(n_samples):
             # DONE: Calculate scores and make prediction for each class
            scores = self.__weights.T @ x[:, n]
            y_hat = np.argmax(scores)
            # Update if prediction is wrong
            if y_hat != y[n]:
                self._update(x[:, n], y[n], y_hat)
                n updates += 1
        # DONE: Break if no updates were made, e.g., check for convergence
        if n_updates == 0:
            break
def predict(self, x):
    Make predictions on new data
    Arg(s):
        x : numpy.ndarray
            Features of shape d \times N
    Returns:
        numpy.ndarray : Predicted class labels
    n_features, n_samples = x.shape
    # DONE: Append artificial coordinate (x0) to the data
    x = np.concatenate((np.ones((1, n_samples)), x), axis=0)
    # DONE: Implement prediction logic for multiclass case
    scores = self.__weights.T @ x
    multi_prediction = np.argmax(scores, axis=0).flatten()
    return multi_prediction
def score(self, x, y):
    Calculate prediction accuracy
    Arg(s):
        x : numpy.ndarray
            Features of shape d x N
        y : numpy.ndarray
```

```
Label/target (-1 or 1) of shape (1 x N) or (N x 1)

Returns:
    float : Accuracy score
'''

# DONE: Implement accuracy calculation
multi_predictions = self.predict(x)
multi_accuracy = np.mean(multi_predictions == y.flatten())

return multi_accuracy
```

```
[29]: def prepare binary_digits_data(digits_zero=0, digits_one=1):
          Prepare binary classification dataset from digits
          Args:
              digits_zero : int
                  First digit to classify
              digits_one : int
                  Second digit to classify
          Returns:
              tuple: (X_train, y_train, X_val, y_val, X_test, y_test)
                  X_train : N x d
                  y train : N x 1
                  X_{val} : M x d
                  y_val : M x 1
                  X_{test} : P x d
                  y_test : P x 1
          ,,,
          # Load digits dataset using sklearn.datasets
          digits = skdata.load_digits()
          # Select only the two specified digits
          mask = np.isin(digits.target, [digits_zero, digits_one])
          X = digits.data[mask]
          y = digits.target[mask]
          # Convert labels to -1/1
          y = np.where(y == digits_zero, -1, 1)
          # Split into train (60%), validation (20%), and test (20%) sets using \Box
       \rightarrow random\_state=42
          X_temp, X_test, y_temp, y_test = train_test_split(X, y, test_size=0.2,__
       →random_state=42)
```

```
X_train, X_val, y_train, y_val = train_test_split(X_temp, y_temp,_
       →test_size=0.25, random_state=42)
          # Had to change a little to get it to work with the rest of the code (X.T_{\sqcup}
       \hookrightarrow instead of X)
          return X_train.T, np.expand_dims(y_train, axis=-1), X_val.T, np.
       →expand_dims(y_val, axis=-1), X_test.T, np.expand_dims(y_test, axis=-1)
[30]: def prepare_multiclass_digits_data():
          Prepare multiclass classification dataset from digits
          Returns:
              tuple: (X_train, y_train, X_val, y_val, X_test, y_test)
                  X train : N x d
                  y_train : N x 1
                  X_{val} : M x d
                  y_val : M x 1
                  X_test : P x d
                  y_test : P x 1
          111
          # Load digits dataset using sklearn.datasets
          digits = skdata.load_digits()
          X, y = digits.data, digits.target
          # Split into train (60%), validation (20%), and test (20%) sets with
       ⇔random state=42
          X_temp, X_test, y_temp, y_test = train_test_split(X, y, test_size=0.2,__
       →random_state=42)
          X_train, X_val, y_train, y_val = train_test_split(X_temp, y_temp,_
       →test_size=0.25, random_state=42)
          # NOTE: Had to change a little to get it to work with the rest of the code
       \hookrightarrow (X.T instead of X so shape is (d, N))
          return X_train.T, np.expand_dims(y_train, axis=-1), X_val.T, np.
       expand_dims(y_val, axis=-1), X_test.T, np.expand_dims(y_test, axis=-1)
 []: # Binary classification experiment
      print("Binary Classification Experiment (0 vs 1)")
      print("-" * 50)
      labels = [0, 1]
      # Load and prepare binary data (0 vs 1)
      X_train, y_train, X_val, y_val, X_test, y_test = prepare_binary_digits_data(0,_u
```

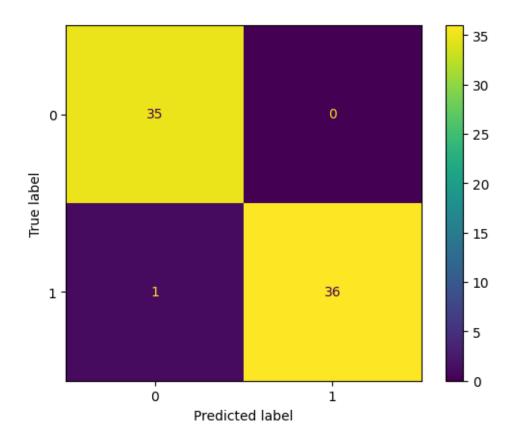
**→**1)

```
# Try different max iter values
max_iters = [10, 50, 100]
best_val_score = 0
best_model = None
for max_iter in max_iters:
    # DONE: Initialize and train binary perceptron
    model = BinaryPerceptron()
    model.fit(X_train, y_train)
    # DONE: Calculate validation score
    val_score = model.score(X_val, y_val)
    print("Max iterations: {}, Validation accuracy: {:.4f}".format(max_iter,__
 ⇔val_score))
    # DONE: Update best_model if current model performs better
    if val score > best val score:
        best_val_score = val_score
        best model = model
# DONE: Test best model on test set
test_score = best_model.score(X_test, y_test)
print("\nBest model test accuracy: {:.4f}".format(test_score))
# DONE: Create a confusion matrix using skmetrics.confusion_matrix on the test_{\sqcup}
 \hookrightarrowset
# NOTE: Flattening since y_test is (P, 1)
binary_conf_matrix = skmetrics.confusion_matrix(y_test.flatten(), best_model.
 →predict(X_test))
# Show confusion matrix
binary_conf_matrix_plot = skmetrics.ConfusionMatrixDisplay(
    confusion_matrix=binary_conf_matrix,
    display_labels=labels
binary_conf_matrix_plot.plot()
plt.show()
time.sleep(1)
# DONE: Compare with scikit-learn implementation by training with max iter=10,1
→and random_state=42 and testing on the test set
# NOTE: Had to transpose X train and X test / flatten y train and y test to qet_{\sqcup}
→ the shapes to match
sk_model = Perceptron(max_iter=10, random_state=42)
sk_model.fit(X_train.T, y_train.flatten())
```

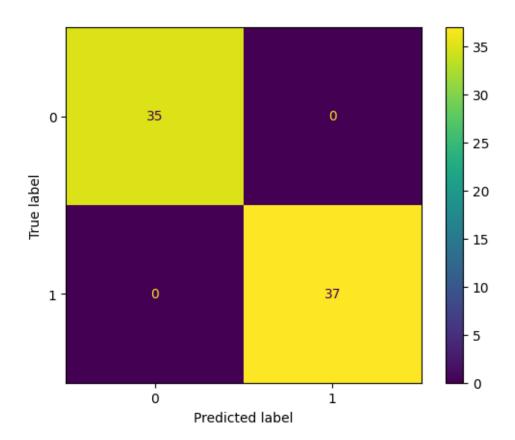
```
sk_score = sk_model.score(X_test.T, y_test.flatten())
print("Scikit-learn Perceptron test accuracy: {:.4f}".format(sk_score))
# DONE: Create a confusion matrix using skmetrics.confusion matrix for scikit⊔
 ⇔model on the test set
sk binary conf matrix = skmetrics.confusion matrix(y test.flatten(), sk model.
 →predict(X_test.T))
sk_binary_conf_matrix_plot = skmetrics.ConfusionMatrixDisplay(
   confusion_matrix=sk_binary_conf_matrix,
   display_labels=labels
sk_binary_conf_matrix_plot.plot()
plt.show()
time.sleep(1)
print("\nMulticlass Classification Experiment (0-9)")
print("-" * 50)
labels = [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
# Load and prepare multiclass data
X_train, y_train, X_val, y_val, X_test, y_test =
 prepare_multiclass_digits_data()
# Try different max_iter values
max_iters = [10, 50, 100]
best_val_score = 0
best_model = None
for max_iter in max_iters:
   # DONE: Initialize and train multiclass perceptron
   model = MulticlassPerceptron()
   model.fit(X_train, y_train)
   # DONE: Calculate validation score
   val_score = model.score(X_val, y_val)
   →val score))
   # DONE: Update best_model if current model performs better
   if val_score > best_val_score:
       best_val_score = val_score
       best_model = model
# DONE: Test best model on test set
```

```
test_score = best_model.score(X_test, y_test)
print("\nBest model test accuracy: {:.4f}".format(test_score))
# DONE: Create a confusion matrix using skmetrics.confusion matrix for your
 ⇔model on the test set
multi conf matrix = skmetrics.confusion matrix(y test.flatten(), best model.
 →predict(X_test))
multi_conf_matrix_plot = skmetrics.ConfusionMatrixDisplay(
    confusion_matrix=multi_conf_matrix,
    display_labels=labels
)
multi conf matrix plot.plot()
plt.show()
time.sleep(1)
# DONE: Compare with scikit-learn implementation by training with max_iter=10_{\sqcup}
 →and random_state=42 and testing on the test set
# NOTE: Had to transpose X_test and X_train / flatten y_train and y_test to get \bot
 → the shapes to match to match sk docs
sk model = Perceptron(max iter=10, random state=42)
sk model.fit(X train.T, y train.flatten())
sk_score = sk_model.score(X_test.T, y_test.flatten())
print("Scikit-learn Perceptron test accuracy: {:.4f}".format(sk_score))
# DONE: Create a confusion matrix using skmetrics.confusion_matrix for youru
 ⇔model on the test set
sk_multi_conf_matrix = skmetrics.confusion_matrix(y_test.flatten(), sk_model.
 →predict(X_test.T))
# Show confusion matrix
sk_multi_conf_matrix_plot = skmetrics.ConfusionMatrixDisplay(
    confusion_matrix=sk_multi_conf_matrix,
    display_labels=labels
sk_multi_conf_matrix_plot.plot()
plt.show()
time.sleep(1)
Binary Classification Experiment (0 vs 1)
Max iterations: 10, Validation accuracy: 1.0000
Max iterations: 50, Validation accuracy: 1.0000
Max iterations: 100, Validation accuracy: 1.0000
```

Best model test accuracy: 0.9861



Scikit-learn Perceptron test accuracy: 1.0000

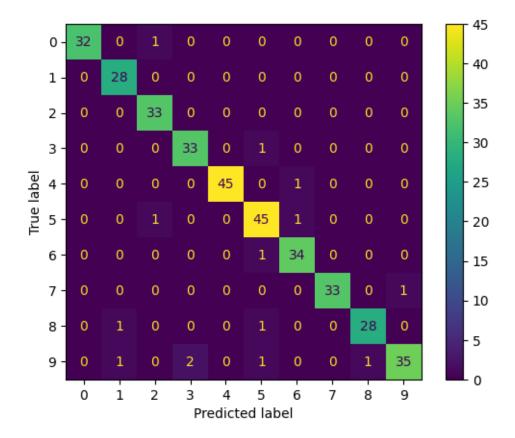


# Multiclass Classification Experiment (0-9)

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Max iterations: 10, Validation accuracy: 0.9583 Max iterations: 50, Validation accuracy: 0.9583 Max iterations: 100, Validation accuracy: 0.9583

Best model test accuracy: 0.9611



Scikit-learn Perceptron test accuracy: 0.9361

