

# M156\_Final\_BM

June 9, 2024

## 0.1 Classification on MNIST Dataset

In the question, you are asked to write code for classifying image data using various classifiers. The [MNIST dataset](#) is a database of 70,000 28×28 pixel grayscale images of handwritten single digits.

### A Few Task Reminders:

- Import required libraries.
- Load the data and split into train, validation, and test sets. You can also perform k-fold cross-validation on the train set for better performance estimates and nested cross-validation for hyperparameter tuning.
- Perform any required data pre-processing.
- Train K-NN, Logistic Regression, Decision Trees, and SVM on the data.
- Make predictions, evaluate, and compare the models. Generate confusion matrices and classification reports.
- Summarize your findings and make sure you sufficiently document your code.

Explore the different classifiers listed above and perform hyperparameter tuning as follows:

- For K-NN, explore the effect of varying the number of nearest neighbors
- For Logistic Regression, explore the effect of varying regularization parameter
- For Decision Trees, explore the effect of varying the max depth of the tree
- For SVM, explore the effect of varying the penalty parameter and kernel function

**Note.** It is intentional that this problem assignment extends outside of what we have covered in class (i.e. text data pre-processing) and encourages more independent learning and exploration with ML hands-on experience and applications. I hope you would have fun with these type of questions and that they are not very stressful. Also, feedback is welcomed and encouraged!

```
[4]: # Resources:  
# 1. https://www.openml.org/search?type=data&sort=runs&id=554&status=active  
# 2. https://scikit-learn.org/  
# 3. https://scikit-learn.org/stable/auto\_examples/model\_selection/  
    ↪ plot\_nested\_cross\_validation\_iris.html
```

```
[6]: import numpy as np  
import matplotlib.pyplot as plt  
from sklearn.datasets import fetch_openml  
import seaborn as sns  
import csv
```

```

# Preprocessing
from sklearn.preprocessing import StandardScaler, label_binarize

# Models
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC

# Training and Evaluation
from sklearn.model_selection import train_test_split, RandomizedSearchCV,
    ↳GridSearchCV, KFold, StratifiedKFold, cross_val_score
from sklearn.metrics import confusion_matrix, classification_report,
    ↳precision_recall_fscore_support
from sklearn.metrics import accuracy_score, precision_score, recall_score,
    ↳f1_score, roc_auc_score, log_loss
from sklearn.metrics import roc_curve, auc
from scipy.stats import uniform, randint
from yellowbrick.classifier import ConfusionMatrix, ROCAUC

# Save results
import logging
from joblib import Parallel, delayed
import pickle

```

```

[7]: # Fetch MNIST data (might take some time)
mnist = fetch_openml('mnist_784')

X = mnist.data.astype('float32')
y = mnist.target.astype('int64')

# Normalize the data
X /= 255.0

```

/opt/anaconda3/lib/python3.11/site-packages/sklearn/datasets/\_openml.py:968:  
FutureWarning: The default value of `parser` will change from `liac-arff` to  
`auto` in 1.4. You can set `parser='auto'` to silence this warning. Therefore,  
an `ImportError` will be raised from 1.4 if the dataset is dense and pandas is  
not installed. Note that the pandas parser may return different data types. See  
the Notes Section in fetch\_openml's API doc for details.

```
warn(
```

## 0.2 Split the data into Training, Validation, and Test sets

```
[9]: # MNST is already a balanced dataset, with 60k training, 10k test (source 1)
X_train, X_test = X[:60000], X[60000:]
y_train, y_test = y[:60000], y[60000:]
```

## 0.3 Standardizing the data

```
[11]: # Fit the standardizing parameters (mean, std. dev) for each column of the
      ↪ training data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)

# Utilize the parameters from the training data to standardize the test set
X_test = scaler.transform(X_test)
```

## 0.4 Set Up Pipeline

```
[ ]: # Logging results to a savefile
logging.basicConfig(filename='model_evaluation.log', level=logging.INFO,
      ↪ format='%(asctime)s - %(message)s')

# Logistic Regression model initialize
# TUNE HYPERPARAMETERS HERE
model = LogisticRegression(max_iter=10000)
params = {'C': uniform(0.01, 1)}

# This function takes training data and indices for training and validation
      ↪ splits (made by outer cross validation)
def train_and_evaluate(X_train, y_train, train_idx, val_idx):
    # Create training and validation splits from the outer cv indices
    X_train_outer, X_val_outer = X_train[train_idx], X_train[val_idx]
    y_train_outer, y_val_outer = y_train[train_idx], y_train[val_idx]

    # Inner cross-validation loop for hyperparameter tuning
    inner_cv = KFold(n_splits=5, shuffle=True, random_state=42)
    random_search = RandomizedSearchCV(estimator=model,
      ↪ param_distributions=params, n_iter=10, cv=inner_cv, n_jobs=-1,
      ↪ random_state=42, verbose=2)

    # Find the best hyperparameters for this fold
    random_search.fit(X_train_outer, y_train_outer)
    best_model = random_search.best_estimator_
    best_params = random_search.best_params_

    # Evaluate the model on the validation data for this fold
    y_pred = best_model.predict(X_val_outer)
```

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val_accuracy = accuracy_score(y_val_outer, y_pred)

return best_model, best_params, val_accuracy

# Outer cross-validation loop with 6 splits
# 5 groups used as training -> 50k train, 10k validation on each fold,
↳mimicking the size of holdout data.
outer_cv = KFold(n_splits=6, shuffle=True, random_state=42)

# Logging information
# Deprecated - used when testing multiple models
logging.info("\n=== Training and evaluating Logistic Regression ===")

# Parallelize the outer cross-validation loop for faster processing
results = Parallel(n_jobs=-1)(
    delayed(train_and_evaluate)(X_train, y_train, train_idx, val_idx)
    # Send indexes to split the training data into train/val sets for inner loop
    for train_idx, val_idx in outer_cv.split(X_train)
)

# Initialize arrays for capturing hyper params and evaluation metrics
best_models = []
best_params = []
val_accuracies = []

# Find the best model from each fold
for fold_idx, (best_model, best_param, val_accuracy) in enumerate(results):
    best_models.append(best_model)
    best_params.append(best_param)
    val_accuracies.append(val_accuracy)
    logging.info(f"Fold {fold_idx + 1} - Best Params: {best_param} - Validation_
↳Accuracy: {val_accuracy}")

# Logging information
logging.info("=== Training and validation completed for Logistic Regression_
↳===\n")

# Save the best models and parameters
with open('best_models.pkl', 'wb') as f:
    pickle.dump(best_models, f)
with open('best_params.pkl', 'wb') as f:
    pickle.dump(best_params, f)

# Select the model with the highest validation accuracy
best_model_idx = np.argmax(val_accuracies)
best_model = best_models[best_model_idx]
best_params = best_params[best_model_idx]

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# Logging information
logging.info(f"\nBest Model: Fold {best_model_idx + 1}")
logging.info(f"Best Params: {best_params}")

# Fit the best model on the entire training dataset
best_model.set_params(**best_params)
best_model.fit(X_train, y_train)

# Evaluate the best model on the test set
y_pred = best_model.predict(X_test)
y_pred_proba = best_model.predict_proba(X_test)

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[CV] END ...C=0.7180725777960455; total time= 4.1min
[CV] END ...C=0.7180725777960455; total time= 4.6min

```

```

[ ]: # Calculate metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')
roc_auc = roc_auc_score(y_test, y_pred_proba, multi_class='ovr')
logloss = log_loss(y_test, y_pred_proba)
conf_matrix = confusion_matrix(y_test, y_pred)

# Save metrics
metrics = {
    'accuracy': accuracy,
    'precision': precision,
    'recall': recall,
    'f1': f1,

```

```

        'roc_auc': roc_auc,
        'logloss': logloss,
        'conf_matrix': conf_matrix
    }

    with open('metrics.pkl', 'wb') as f:
        pickle.dump(metrics, f)

    # Print metrics
    print("Accuracy:", accuracy)
    print("Precision:", precision)
    print("Recall:", recall)
    print("F1 Score:", f1)
    print("ROC AUC:", roc_auc)
    print("Log Loss:", logloss)

    # Print classification report
    class_report_test = classification_report(y_test, y_pred)
    print(f"=== Classification Report ===\n{class_report_test}")

    # Save classification report
    with open('classification_report.txt', 'w') as f:
        f.write(class_report_test)

    # One-vs-All ROC Curve
    n_classes = y_pred_proba.shape[1]
    y_test_bin = label_binarize(y_test, classes=np.arange(n_classes))

    plt.figure(figsize=(12, 8))
    for i in range(n_classes):
        fpr, tpr, _ = roc_curve(y_test_bin[:, i], y_pred_proba[:, i])
        roc_auc = auc(fpr, tpr)
        plt.plot(fpr, tpr, label=f'Class {i} (AUC = {roc_auc:.2f})')
    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve')
    plt.legend(loc="lower right")
    plt.tight_layout()
    plt.savefig('roc_curve.png')
    plt.show()
    plt.close()

    # Yellowbrick Confusion Matrix
    cm = ConfusionMatrix(best_model, classes=np.unique(y_test))

```

```
cm.score(X_test, y_test)
cm.poof(outpath="confusion_matrix_yellowbrick.png")
```