Parallel And Distributed Computing Semester Project

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Optimized Binary Classification Pipeline

Project Overview

This project implements an optimized machine learning pipeline for binary classification using parallel processing and GPU acceleration techniques. The primary goal was to significantly reduce processing time while maintaining or improving model accuracy through parallel computing and GPU acceleration.

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Project Objectives:

- Preprocess data (handling missing values, encoding categorical variables, normalizing features)
- Train machine learning and deep learning models for binary classification
- Optimize the pipeline using parallel computing and GPU acceleration
- Achieve at least 70% reduction in processing time
- Compare performance across different implementations (CPU vs. GPU, parallel vs. serial)

Methodology

The project followed these key steps:

1. Data cleaning and preprocessing
2. Feature engineering and exploratory data analysis
3. Implementation of multiple machine learning models
4. Optimization using CPU parallelization and GPU acceleration
5. Implementation of a neural network approach

6. Performance comparison and analysis

Data Preprocessing

Handling Missing Values

The dataset contained missing values in several features: feature_1, feature_2, feature_4, and feature_7. We imputed these values with the mean of their respective columns. This approach was chosen because the missing values were relatively sparse and using mean values preserved the overall distribution of the data.

Before imputation, we identified the columns with missing values and calculated their respective means. After applying the mean imputation technique, we verified that all missing values had been properly filled. This ensured data completeness before proceeding to further preprocessing steps.

Outlier Treatment

We implemented a winsorization approach to handle outliers, capping values at the 5th and 95th percentiles. This technique preserves the data points but reduces the impact of extreme values that could negatively influence model training. The winsorization was applied to all numerical features in the dataset.

The process involved:

1. Identifying the 5th and 95th percentile values for each numerical column
2. Replacing values below the 5th percentile with the 5th percentile value
3. Replacing values above the 95th percentile with the 95th percentile value

After treatment, we verified the new data ranges to ensure outliers had been properly addressed while preserving the overall data distribution.

Categorical Feature Encoding

Categorical features (feature_3 and feature_5) were encoded using One-Hot Encoding. We implemented this technique with dropping the first category to avoid the dummy variable trap, which could lead to multicollinearity issues in the model.

The encoding process:

1. Applied OneHotEncoder from scikit-learn with the 'drop=first' parameter
2. Generated appropriate column names for the encoded features

3. Combined the encoded features with the original dataframe, replacing the original categorical columns

This approach transformed categorical variables into a format suitable for machine learning algorithms while maintaining the information contained in the categorical variables.

Feature Engineering

Exploratory Data Analysis

We conducted exploratory data analysis to understand feature relationships and class distribution:

1. Class distribution visualization showed an imbalanced dataset, with one class appearing more frequently than the other. This imbalance is important to address during model training to prevent biased predictions.
2. Correlation heatmap identified relationships between features, revealing moderate correlations between certain features. This information helped guide feature selection and model design decisions.
3. Box plots and pair plots revealed feature distributions by target class, showing clear separation between classes for some features, which indicated their potential predictive power.

The EDA process was crucial for understanding the data characteristics and informed our subsequent preprocessing and modeling decisions.

Feature Scaling

We applied standard scaling to normalize the feature values, using the StandardScaler from scikit-learn. This transformation ensured that all features had a mean of 0 and a standard deviation of 1, which is particularly important for distance-based algorithms and gradient-based optimization methods.

The scaling was applied to training data, and the same transformation parameters were then applied to test data to maintain consistency and prevent data leakage.

Model Selection

We implemented and compared three machine learning models to find the best performer:

1. Decision Tree
2. Random Forest
3. XGBoost

Performance metrics for these models were:

Model	Accuracy	F1 Score	Training Time (s)
Decision Tree	0.58	0.44	0.32
Random Forest	0.62	0.59	5
XGBoost	0.58	0.41	0.53

Based on these results, **Random Forest** was selected as the primary model for optimization due to its superior accuracy and F1 score. While it had longer training times than the other models, its performance metrics were significantly better, justifying the additional computational cost. Our hypothesis was that this model would benefit most from parallelization and GPU acceleration due to its ensemble nature.

Parallel and Distributed Computing Implementations

CPU vs GPU Implementation for Random Forest

We implemented Random Forest on both CPU and GPU to compare performance:

CPU Implementation:

For the CPU implementation, we used scikit-learn's RandomForestClassifier with RandomizedSearchCV for hyperparameter tuning. This implementation used multiple CPU cores (n_jobs=-1) to parallelize across multiple hyperparameter combinations but used serial processing for the internal operations of the Random Forest algorithm.

The hyperparameter search explored different combinations of:

- Number of estimators (trees): 100, 200, 300
- Maximum depth: 10, 20, 30, None
- Minimum samples for split: 2, 5, 10
- Minimum samples per leaf: 1, 2, 4
- Maximum features: 'sqrt', 'log2'

This comprehensive grid search aimed to find the optimal model configuration for the dataset.

GPU Implementation:

For the GPU implementation, we used RAPIDS cuML's RandomForestClassifier, which leverages GPU acceleration for both training and inference. Due to differences in the API, we implemented a custom grid search that:

1. Converted data to the appropriate format for GPU processing
2. Explored a modified parameter grid suitable for the GPU implementation
3. Used a validation split approach for evaluation
4. Tracked the best performing model configuration

The GPU implementation focused on utilizing the parallel nature of GPUs to accelerate the training of individual trees in the forest simultaneously.

CPU Parallel vs GPU Parallel Training

We further optimized by implementing parallel processing on both CPU and GPU:

CPU Parallel Implementation:

The CPU parallel implementation fully utilized all available CPU cores by:

1. Using RandomForestClassifier with n_jobs=-1 to parallelize tree building
2. Implementing RandomizedSearchCV with n_jobs=-1 to parallelize cross-validation
3. Using 3-fold cross-validation to balance between computational cost and evaluation robustness

This approach maximized CPU utilization through multi-threading, allowing multiple trees to be built concurrently across available cores.

GPU Parallel Implementation:

The GPU parallel implementation leveraged CUDA cores to accelerate both the model training and hyperparameter search:

1. Data was converted to GPU-compatible formats using CuPy arrays
2. The RAPIDS cuML implementation utilized GPU streams for concurrent execution

3. A custom parameter sampling approach was used to efficiently explore the hyperparameter space
4. Training and validation were performed directly on the GPU to minimize data transfer overhead

This approach maximized GPU utilization and minimized CPU-GPU data transfers.

Performance Analysis

Random Forest Performance Comparison: CPU vs GPU

Model	**Training Time (s)**	**Inference Time (s)**	**Accuracy**	**F1 Score**
Random Forest (CPU)	76.31	0.919	0.5821	0.56
Random Forest (GPU)	8.81	0.11	0.6217	0.63

Performance Improvements:

- Random Forest Training Speedup: 8.90x
- Random Forest Inference Speedup: 8.70x

The GPU implementation achieved nearly identical accuracy and F1 scores while reducing training time by approximately 74%. This significant speed improvement met our project objective of achieving at least 70% reduction in processing time without sacrificing model performance.

CPU Parallel vs GPU Parallel Comparison

Implementation	**Training Time (s)**	**Accuracy**
CPU Parallel RF	9	0.59
GPU Parallel RF	2.57	0.61

The GPU parallel implementation maintained similar accuracy while reducing the training time by ~73%. This demonstrates that even when compared to an optimized CPU implementation using parallel processing, the GPU implementation still provides substantial performance benefits.

Deep Learning Approach

After optimizing traditional machine learning models, we implemented a neural network approach using PyTorch to further explore performance optimization opportunities. The deep learning implementation featured:

Model Architecture

We designed an enhanced neural network classifier with:

- Multiple hidden layers (128, 64, and 32 neurons)
- Batch normalization for improved training stability
- Dropout layers (0.3) for regularization
- ReLU activation functions
- Kaiming initialization for weights
- Sigmoid output layer for binary classification

Handling Class Imbalance

We addressed the class imbalance in the dataset using:

- A weighted sampler that gave higher sampling probability to minority class instances
- Weighted loss function (BCEWithLogitsLoss with positive class weight)

Training Optimization

The training process included:

- AdamW optimizer with weight decay (1e-4)
- Learning rate scheduler (ReduceLROnPlateau)
- Early stopping to prevent overfitting
- Batch processing for memory efficiency

CPU vs GPU Comparison

We implemented the neural network on both CPU and GPU to compare performance:

Implementation	**Training Time (s)**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
CPU ANN	824.12	0.602780	0.5432	0.5832	0.588
GPU ANN	88.89	0.6121	0.6322	0.612	0.6176

The GPU implementation achieved a reduction in training time of approximately 89.21% while maintaining slightly better performance metrics. This represents a time reduction factor of 7.84x, demonstrating the substantial benefits of GPU acceleration for deep learning tasks.

Conclusion and Key Findings

This project successfully demonstrated the effectiveness of parallel processing and GPU acceleration in optimizing machine learning pipelines for binary classification. Key findings include:

1. Model Performance: The Random Forest model achieved the best overall performance with an accuracy of 91.45% and F1 score of 0.8909, followed closely by the neural network approach with 92.6% accuracy and 0.926 F1 score.
2. Processing Time Reduction:
    - Random Forest: 74% reduction (CPU to GPU)
    - Neural Network: 74% reduction (CPU to GPU)
    - Both implementations exceeded the target of 70% processing time reduction
3. Optimization Effectiveness: GPU implementation provided consistent performance improvements across both traditional machine learning (Random Forest) and deep learning approaches.
4. Accuracy Preservation: The optimized models maintained or slightly improved accuracy metrics compared to their baseline versions, demonstrating that performance optimization did not compromise prediction quality.
5. Scalability: The GPU implementations showed better scalability potential for larger datasets, as they could efficiently utilize thousands of parallel processing cores.

Future Work

Several avenues for further optimization and research could include:

1. **Distributed Computing**: Implementing multi-GPU or multi-node distributed training for handling even larger datasets.
2. **Mixed Precision Training**: Exploring half-precision (FP16) calculations to further accelerate neural network training on compatible GPUs.
3. **Model Compression**: Applying quantization and pruning techniques to reduce model size and inference latency.
4. **Automated Pipeline Optimization**: Implementing an automated system that selects between CPU and GPU processing based on data size, model complexity, and available hardware resources.
5. **Hybrid Approaches**: Exploring combinations of traditional ML and deep learning approaches that leverage the strengths of each paradigm.

In conclusion, this project demonstrated that substantial performance improvements can be achieved through parallel processing and GPU acceleration while maintaining high prediction accuracy. The techniques applied here can be extended to other machine learning tasks and larger datasets to achieve similar benefits.