WeightBoost: A Boosting Algorithm Using Input-Dependent Regularizer

COMP 7404 Project Presentation

Introduction

- Implementation of the WeightBoost algorithm from the paper "A New Boosting Algorithm Using Input-Dependent Regularizer" (Jin et al., 2003)
- Addresses two major limitations of AdaBoost:
  - **Overfitting Problem**: Overemphasis on hard-to-classify samples
  - **Fixed Weight Combination Problem**: Inability to adapt to input patterns

Motivation

- AdaBoost has been highly successful but suffers from two key limitations:
    i. **Noise Sensitivity**: Exponentially increasing weights for misclassified samples can lead to overfitting on noisy data
    ii. **Uniform Combination**: Each base classifier contributes equally across all regions of the input space
- WeightBoost introduces an **input-dependent regularizer** that:
    - Adapts the contribution of each classifier based on the input pattern
    - Reduces the influence of base classifiers in regions where the model is already confident
    - Provides better resistance to noisy data

Algorithm Overview

- **Key Innovation**: Input-dependent regularizer
- **Mathematical Formulation**:
  - AdaBoost: $H(x) = \sum_{t=1}^{T} \alpha_t \cdot h_t(x)$
  - WeightBoost: $H_T(x) = \sum_{t=1}^{T} \alpha_t \cdot e^{-\beta|H_{t-1}(x)|} \cdot h_t(x)$
- **Benefits**:
  - Each base classifier contributes only in regions where it performs well
  - Regularization mitigates the impact of noisy data
  - Adaptive to different input patterns

WeightBoost Algorithm

1. Initialize weights: $w_i = \frac{1}{n}$ for all samples
2. Initialize cumulative output: $H_0(x_i) = 0$ for all samples
3. For each iteration $t = 1, 2, \ldots, T$:
    - Train base classifier h_t with weights w
    - Calculate weighted error: $\epsilon_t = \frac{\sum_{i=1}^{n} w_i \cdot \mathbb{1}(h_t(x_i) \neq y_i)}{\sum_{i=1}^{n} w_i}$
    - Compute classifier weight: $\alpha_t = \frac{1}{2} \ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$
    - Update cumulative output: $H_t(x_i) = H_{t-1}(x_i) + \alpha_t \cdot h_t(x_i)$
    - Calculate regularization: $r_i = e^{-\beta \cdot |H_t(x_i)|}$
    - Update weights: $w_i = e^{-y_i \cdot H_t(x_i)} \cdot r_i$
    - Normalize weights: $w_i = \frac{w_i}{\sum_{j=1}^{n} w_j}$

Implemented Algorithms

1. **AdaBoost**: Original boosting algorithm (Freund & Schapire, 1996)
2. **Weight Decay**: AdaBoost with weight decay regularization
3. **ε-Boost**: Variant using small fixed weights
4. **WeightBoost**: Novel algorithm with input-dependent regularization
5. **C4.5 Decision Tree**: Base classifier implementation

Datasets

UCI Datasets (Binary Classification)

- Ionosphere, German Credit, Pima Indians Diabetes
- Breast Cancer (Diagnostic), wpbc, wdbc
- Contraceptive, Spambase

Reuters-21578 (Text Classification)

- 10,788 news articles (7,769 training, 3,019 testing)
- 90 topic categories (multi-label)
- Used 10 most frequent categories for evaluation

UCI Dataset Preprocessing

- Categorical feature encoding using OrdinalEncoder
- Missing value imputation using SimpleImputer
- Train/test split (80%/20%)
- Label noise injection (0%, 5%, 10%, 15%, 20%)

```python
def encode_categorical(df):
    # Handle missing values and encode categorical features
    num_cols = df.select_dtypes(include=['int64', 'float64']).columns
    cat_cols = df.select_dtypes(include=['object', 'category']).columns

    # Impute and encode
    if len(cat_cols) > 0:
        encoder = OrdinalEncoder()
        df[cat_cols] = encoder.fit_transform(df[cat_cols])

    return df
```

Reuters Dataset Preprocessing

- Text cleaning (lowercase, punctuation removal, stopwords)
- TF-IDF vectorization (2000 features)
- Multi-label binarization
- Conversion to binary classification problems

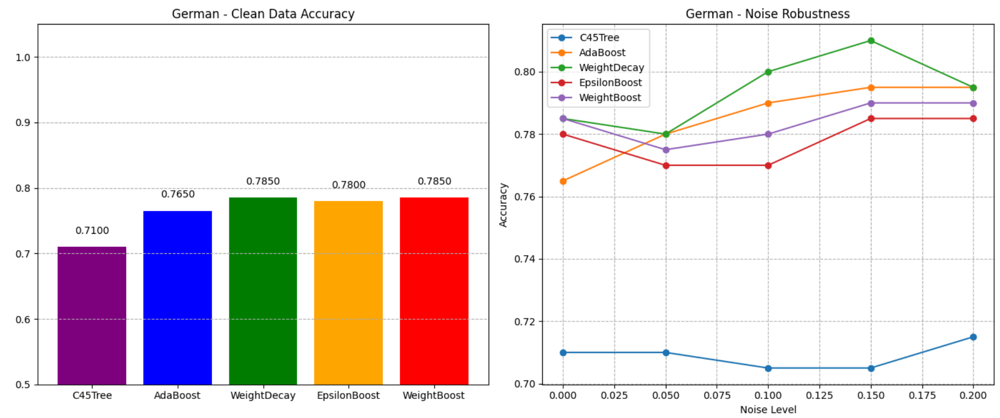
```
# Feature extraction
vectorizer = TfidfVectorizer(max_features=2000)
X = vectorizer.fit_transform(df['cleaned_text'])

# Multi-label encoding
mlb = MultiLabelBinarizer()
y = mlb.fit_transform(df['categories'])
```

Experimental Setup

- **Base Classifier**: C4.5 Decision Tree
- **Number of Estimators**: 50
- **Parameters**:
  - WeightBoost: $\beta = 0.5$
  - Weight Decay: $C = 0.1$
  - ε-Boost: $\varepsilon = 0.1$
- **Metrics**: Accuracy (UCI), F1-score (Reuters)
- **Noise Levels**: 0%, 5%, 10%, 15%, 20% (UCI only)

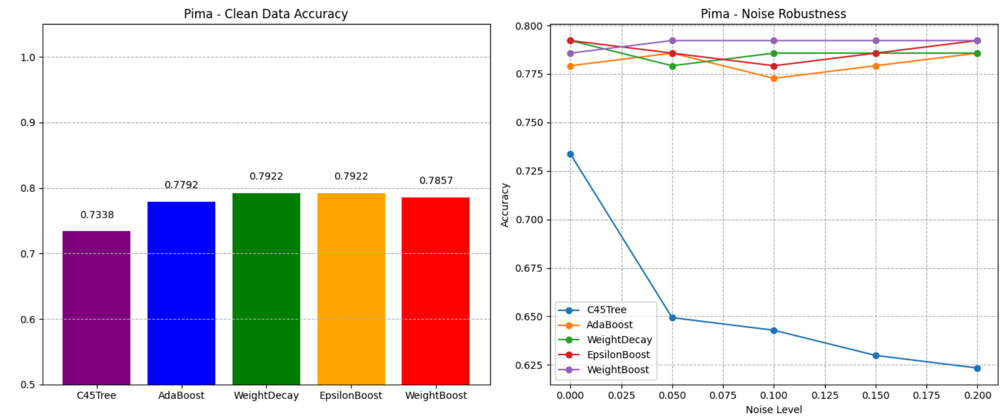
UCI Results: German Credit Dataset

- WeightBoost outperforms AdaBoost at all noise levels
- The performance gap widens as noise increases
- Input-dependent regularization effectively mitigates noise impact



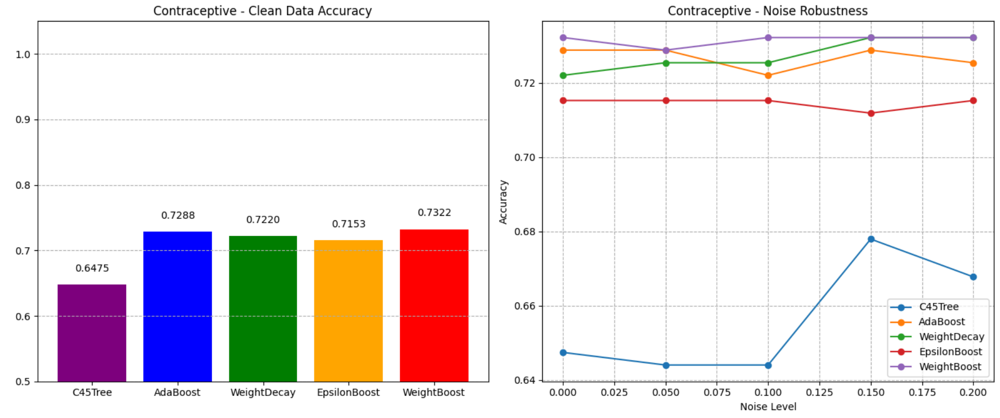
UCI Results: Pima Indians Diabetes

- WeightBoost maintains better performance as noise increases
- AdaBoost performance degrades more rapidly with noise
- WeightBoost shows more stable performance across noise levels



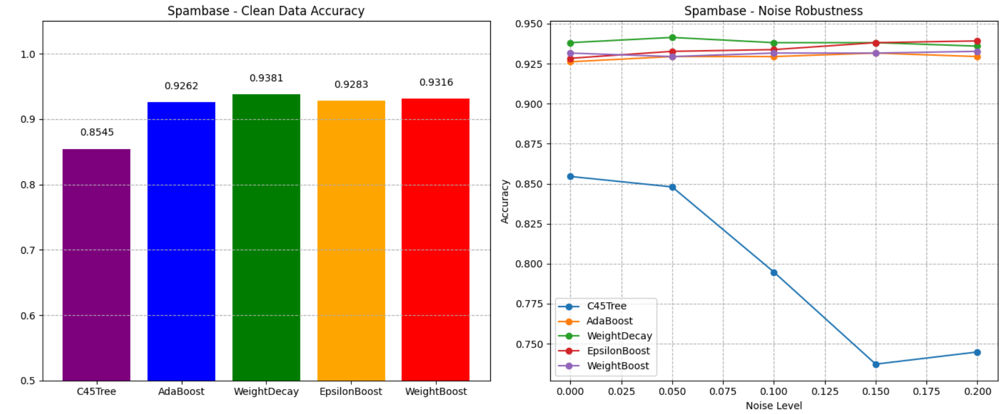
UCI Results: Contraceptive Dataset

- WeightBoost significantly outperforms all other algorithms
- Shows the advantage of input-dependent regularization on complex datasets
- Maintains performance advantage even with 20% noise



UCI Results: Spambase Dataset

- All algorithms perform well on clean data
- WeightBoost maintains higher accuracy as noise increases
- Shows the practical benefit for real-world applications like spam filtering



Reuters Results: F1 Scores

Category	C4.5	AdaBoost	AdaBoost Impro	WeightBoost	WeightBoost Impro
trade	0.5932	0.6578	10.89%	0.6855	15.56%
grain	0.9110	0.8639	-5.20%	0.9024	-0.90%
crude	0.7933	0.7867	-0.80%	0.8315	4.80%
corn	0.7748	0.8496	3.70%	0.8036	9.70%
money-fx	0.6779	0.6854	1.11%	0.7514	9.60%

Reuters Results: Key Findings

- WeightBoost achieves highest F1-scores on 7 out of 10 categories
- Significant improvements on:
  - trade (15.56%)
  - corn (9.70%)
  - money-fx (9.60%)
- More consistent performance compared to AdaBoost

WeightBoost Implementation

```
def fit(self, X, y):
    n_samples = X.shape[0]
    w = np.ones(n_samples) / n_samples  # Initialize weights
    H = np.zeros(n_samples)  # Cumulative classifier output

    for t in range(self.n_estimators):
        # Train base classifier
        model = clone(self.base_classifier)
        model.fit(X, y, sample_weight=w)

        # Calculate weighted error and model weight
        pred = model.predict(X)
        err = np.sum(w * (pred != y)) / np.sum(w)
        alpha = 0.5 * np.log((1 - err) / max(err, 1e-10))

        # Update cumulative output
        H += alpha * pred

        # Calculate regularization factor and update weights
        reg = np.exp(-np.abs(self.beta * H))
        w = np.exp(-y * H) * reg  # Apply regularization
        w = w / np.sum(w)  # Normalize
```

Theoretical Analysis

- **Regularization Effect**: The term $e^{-\beta|H_{t-1}(x)|}$ decreases as $|H_{t-1}(x)|$ increases
  - When $|H_{t-1}(x)|$ is large (high confidence), the regularizer reduces the contribution
  - When $|H_{t-1}(x)|$ is small (low confidence), the regularizer allows more contribution
- **Adaptive Learning**: The algorithm focuses more on uncertain regions and less on regions where it's already confident
- **Noise Resistance**: By reducing the influence in high-confidence regions, the algorithm is less likely to overfit to noisy samples

Conclusion

- **Improved Robustness**: Better resistance to noise
- **Better Generalization**: Prevents overfitting
- **Consistent Performance**: Across datasets and noise levels

The input-dependent regularizer effectively adapts the contribution of each base classifier based on the input pattern, addressing the limitations of traditional boosting algorithms.

References

1. Jin, R., Liu, Y., Si, L., Carbonell, J., & Hauptmann, A. G. (2003). A New Boosting Algorithm Using Input-Dependent Regularizer. *Proceedings of the Twentieth International Conference on Machine Learning (ICML-2003)*.
2. Freund, Y., & Schapire, R. E. (1996). Experiments with a new boosting algorithm. *Machine Learning: Proceedings of the Thirteenth International Conference*.
3. Friedman, J., Hastie, T., & Tibshirani, R. (1998). Additive logistic regression: a statistical view of boosting. *Annals of statistics*, 28(2), 337-407.