WeightBoost: A Boosting Algorithm Using Input-Dependent Regularizer

COMP 7404 Project Presentation

LI MINGYANG	3036371613
YE HAO	3036371821

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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: $w_i = \frac{w_i}{\sum_{j=1}^{n} w_j}$

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
```

Compared Implemented Algorithms

Following this paper, we implemented 4 algrithms for the comparison experiments part: C4.5 Decision Tree, Adaboost, Weight Decay and epsilon boost.

1. C4.5 Decision Tree

- **Base Classifier**: Extension of ID3 algorithm with improvements
- **Split Criterion**: Uses gain ratio instead of information gain
  - $\mathrm{GainRatio}(S, A) = \frac{\mathrm{Gain}(S,A)}{\mathrm{SplitInfo}(S,A)}$
- **Features**:
  - Handles both continuous and discrete attributes
  - Deals with missing values
  - Implements pruning using pessimistic error estimation
  - Converts trees to rules for improved interpretability

2. AdaBoost (Adaptive Boosting)

- **Original Algorithm**: Developed by Freund & Schapire (1996)
- **Key Idea**: Iteratively train weak learners with adjusted sample weights
- **Weight Update**: $w_i = w_i \cdot e^{-\alpha_t \cdot y_i \cdot h_t(x_i)}$
- **Final Classifier**: $H(x) = \text{sign}\left(\sum_{t=1}^{T} \alpha_t \cdot h_t(x)\right)$
- **Strengths**: Simple, effective, and theoretically sound
- **Limitations**: Sensitive to noisy data and outliers

3. Weight Decay

- **Variant of AdaBoost**: Adds regularization to mitigate overfitting
- **Key Innovation**: Introduces a regularization term to control the growth of weights
- **Weight Update**: $w_i = e^{-y_i \cdot H_t(x_i) - C \cdot \zeta_i}$
- **Regularization**: $\zeta_i = H_t(x_i)^2$ is a cumulative weight (slack variable)
- **Parameter C**: Controls the strength of the regularization (default: 0.1)
- **Benefit**: Helps prevent overfitting by penalizing large margins

4. ε-Boost (Epsilon Boost)

- **Simplified Variant**: Uses small fixed weights for base classifiers
- **Key Difference**: Uses a constant α (epsilon) instead of adaptive weights
- **Weight Calculation**: $\alpha_t = \epsilon$ (fixed small constant)
- **Parameter ε**: Typically set to a small value (default: 0.1)
- **Advantage**: Slower convergence but can lead to better generalization
- **Application**: Often used in gradient boosting frameworks
- **Trade-off**: Sacrifices rapid convergence for improved regularization

Datasets

1. UCI Datasets

The UCI Machine Learning Repository provides widely-used public datasets for classification and regression tasks. Eight datasets were selected for binary classification:

Dataset	Samples	Features	Description
Ionosphere	351	34	Radar signal classification data
German Credit	1000	20	Credit risk assessment
Pima Indians Diabetes	768	8	Diabetes diagnosis prediction
Breast Cancer	286	9	Tumor malignancy classification

Dataset	Samples	Features	Description
wpbc	198	30	Breast cancer recurrence prediction
wdbc	569	30	Breast cancer diagnostic data
Contraceptive	1473	10	Contraceptive method choice prediction
Spambase	4601	58	Email spam classification

Datasets

2. Reuters-21578 Dataset

- **Description**: Classic multi-label text classification dataset containing Reuters news articles
- **Size**: 10,788 news articles (7,769 training, 3,019 testing)
- **Classes**: 90 topic categories (multi-label)
- **Structure**: Each article contains:
  - Document ID (with train/test designation)
  - Categories (one or more topic labels)
  - Raw text content

2. Reuters-21578 Dataset

- **Characteristics**:
    - Imbalanced class distribution
    - Multiple labels per document
    - Varying text lengths and complexity

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%)

```
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
```

Datasets

Reuters Dataset Preprocessing

- **Text Cleaning**:
  - Lowercase conversion
  - Punctuation removal
  - Stopword filtering using NLTK
  - Word stemming with Porter Stemmer

Reuters Dataset Preprocessing

- **Feature Extraction**:
  - TF-IDF vectorization (2,000 features)
  - Multi-label binarization for categories
- **Handling Imbalance**:
  - Focus on 10 most frequent categories for evaluation
  - Conversion to binary classification problems

Reuters Dataset Preprocessing

Data Cleaning

- **Text Normalization**:
  - Lowercase conversion
  - Punctuation removal using regex: `re.sub(r"[^\w\s]", "", text)`
  - Tokenization into words
- **Noise Reduction**:
  - Stopword removal using NLTK's English stopwords
  - Word stemming with Porter Stemmer to reduce inflected words
  - Rejoining tokens into cleaned text

Feature Extraction

- **Vectorization**:
  - TF-IDF representation with 2,000 most important features
  - `TfidfVectorizer(max_features=2000)` from scikit-learn
- **Multi-label Encoding**:
  - Categories transformed to binary indicator matrix
  - `MultiLabelBinarizer()` used for one-hot encoding of labels
  - Results in a sparse matrix of shape (n_samples, 90)

Data Splitting

- **Train/Test Division**:
  - Uses document IDs to determine split:
    - `training/XXXX`: Training set (7,769 articles)
    - `test/XXXX`: Test set (3,019 articles)
  - No cross-validation needed as split is predefined

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: Classification Errors

Collection Name	C4.5	AdaBoost	WeightDecay	ϵ-Boost	WeightBoost
Ionosphere	**7.04%**	9.86%	8.45%	8.45%	**7.04%**
German	29.00%	23.50%	**21.50%**	22.00%	**21.50%**
Pima Indians Diabetes	26.62%	22.08%	**20.78%**	**20.78%**	21.43%
Breast Cancer Diagnostic	5.40%	4.50%	3.70%	**3.20%**	3.30%
wpbc	25.00%	35.00%	32.50%	**20.00%**	22.50%
wdbc	3.51%	3.51%	5.26%	4.39%	**2.63%**
Contraceptive	35.25%	27.12%	27.80%	28.47%	**26.78%**
Spambase	14.55%	7.38%	**6.19%**	7.17%	6.84%

- The results show `WeightBoost` has the lowest error rate on four datasets and the second lowest on the other four.

UCI with Noise Results: Classification Errors

Dataset	10% Noise			20% Noise		
	C4.5	AdaBoost	WeightBoost	C4.5	AdaBoost	WeightBoost
Ionosphere	12.68%	**9.86%**	**9.86%**	26.76%	11.27%	**8.45%**
German	29.50%	23.00%	**22.50%**	29.00%	23.50%	**22.00%**
Pima	28.57%	**20.78%**	21.43%	35.06%	**20.78%**	21.43%
BreastCancer	3.57%	**0.00%**	**0.00%**	3.57%	**0.00%**	**0.00%**
wpbc	27.50%	32.50%	**20.00%**	22.50%	**20.00%**	22.50%
wdbc	6.14%	3.51%	**2.63%**	7.89%	**3.51%**	**3.51%**
Contraceptive	34.92%	28.47%	**27.46%**	36.27%	27.46%	**27.12%**
Spambase	18.68%	**6.51%**	6.84%	41.59%	**6.62%**	7.06%

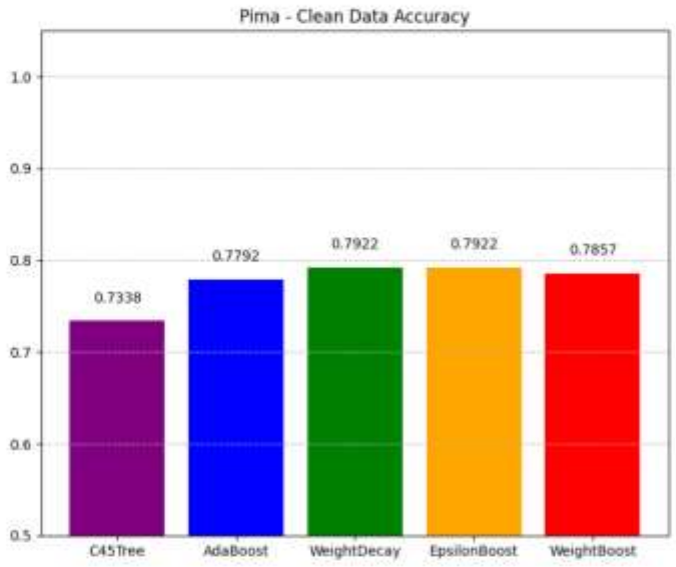
UCI with Noise Results: Classification Errors (cont'd)

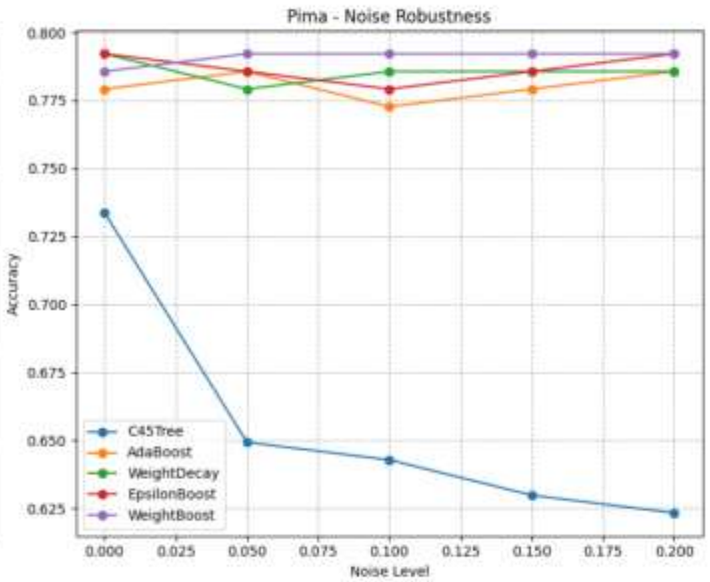
Dataset	30% Noise		
	C4.5	AdaBoost	WeightBoost
Ionosphere	38.03%	12.68%	**8.45%**
German	29.50%	25.00%	**23.00%**
Pima	37.01%	**20.78%**	**20.78%**
BreastCancer	7.14%	**0.00%**	**0.00%**
wpbc	**22.50%**	**22.50%**	27.50%
wdbc	35.96%	3.51%	**2.63%**
Contraceptive	32.88%	27.12%	**26.78%**
Spambase	41.69%	**6.62%**	7.06%

- Experimental results demonstrate that `WeightBoost` is the most noise-resistant model.

UCI Results: Pima Indians Diabetes

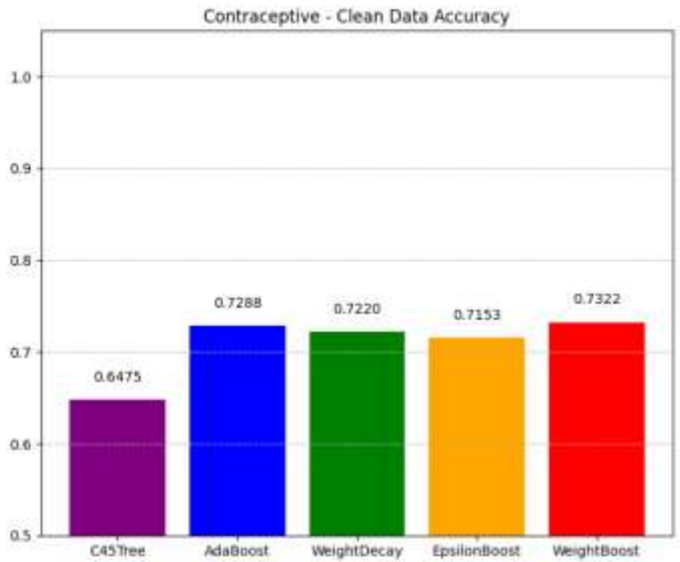
- WeightBoost maintains better performance as noise increases
- AdaBoost performance degrades more rapidly with noise
- WeightBoost shows more stable performance across noise levels

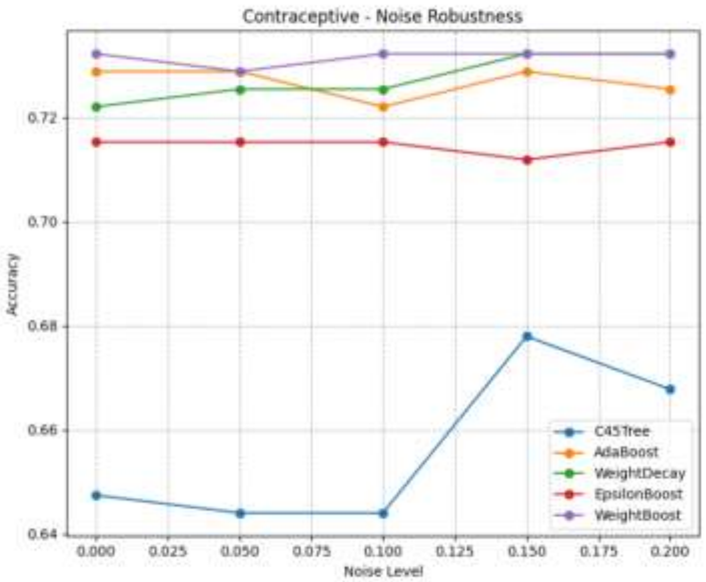




UCI Results: Contraceptive Dataset

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





Reuters Results: F1 Scores

Category	C4.5_F1	AdaBoost_F1	AdaBoost_Impro	WeightBoost_F1	WeightBoost_Impro
trade	0.5932	0.6578	10.89%	0.6855	15.56%
grain	0.911	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%
ship	0.7229	0.7791	7.80%	0.7135	-1.30%

Reuters Results: F1 Scores (cont'd)

Category	C4.5_F1	AdaBoost_F1	AdaBoost_Impro	WeightBoost_F1	WeightBoost_Impro
wheat	0.8194	0.831	1.40%	0.8552	4.40%
acq	0.8703	0.8772	0.80%	0.8924	2.50%
interest	0.6824	0.6853	0.40%	0.7064	3.50%
money-fx	0.6779	0.6854	1.11%	0.7514	9.60%
earn	0.9571	0.9566	-0.10%	0.9572	1.04%

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

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

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