MAXGBoost: A Fast Novel Heuristic Approach to Adaptive Learning Rates in Gradient Boosted Decision Trees

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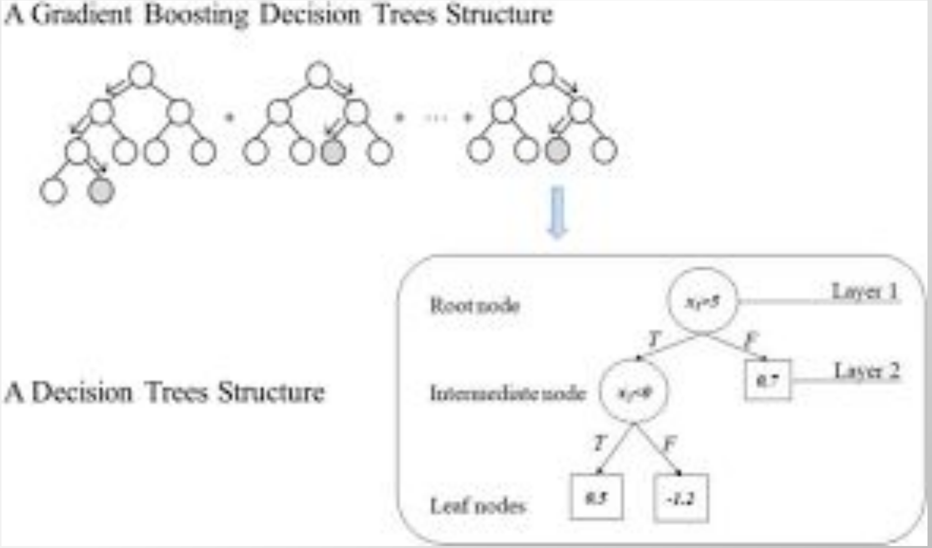
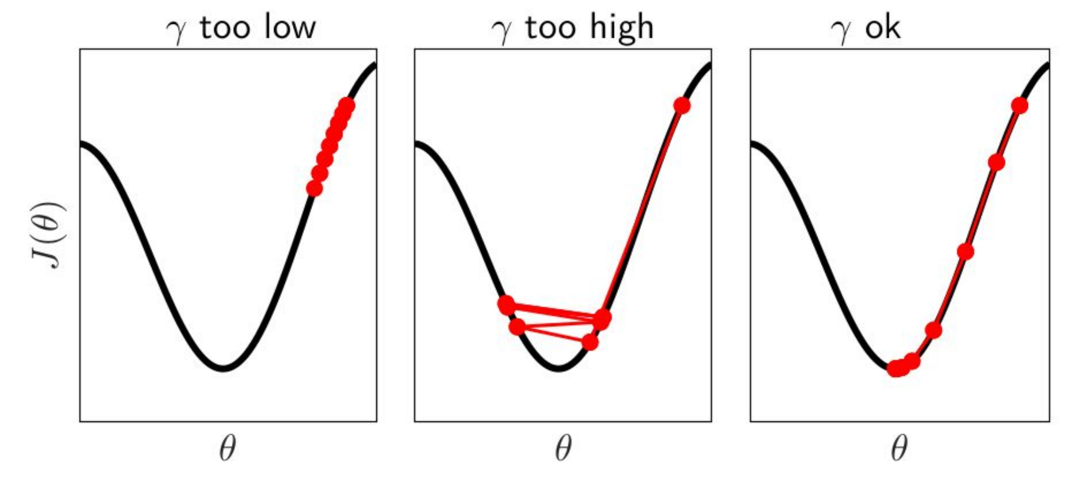
Fundamentals

- GBDTs initialize with a decision tree that's evaluated using a loss function
- The model minimizes loss by moving in the direction of the negative gradient
- This process is similar to neural networks' backpropagation, but creates an ensemble decision tree model



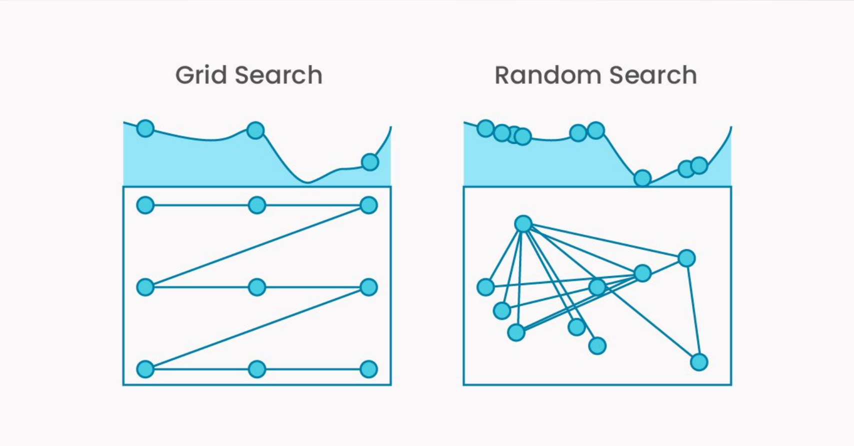
Learning Rate Mechanics

- The algorithm adds new decision trees scaled by a learning rate (η)
- Learning rate determines how far down the loss function the tree will go
- Low η ensures convergence but requires more iterations and computational cost
- High η speeds up convergence but risks overshooting the optimal solution



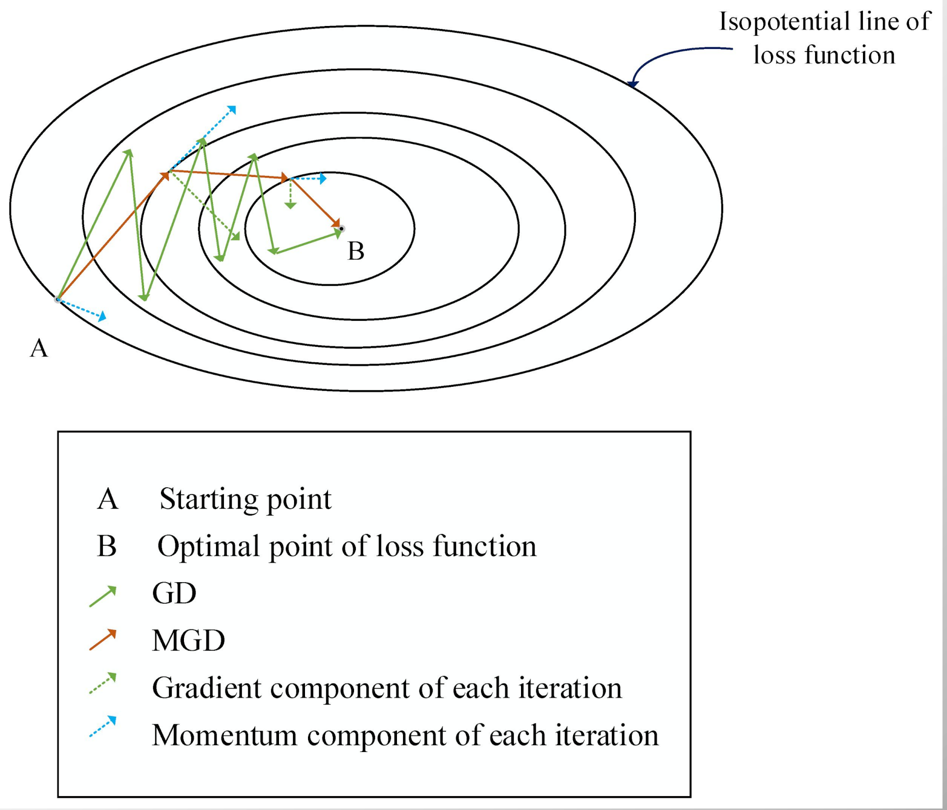
Learning Rate Optimization

- Optimal learning rate depends on both dataset and loss function
- Tuning requires iterative experimentation
- Adaptive strategies help reduce need for extensive hyperparameter searches
- Particularly important for datasets with high sparsity



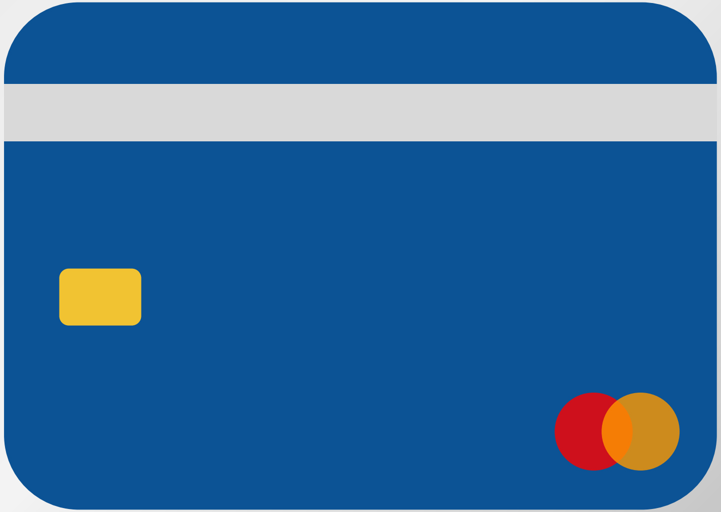
Introduction to MAXGBoost

- Momentum Approximation XGBoost dynamically adjusts learning rate based on loss momentum
- Enables faster convergence
- Reduces need for manual optimization while maintaining high detection accuracy



The Dataset

- Credit Card Fraud Detection
- 284,807 total instances
- 31 total attributes
- Notable Features:
  - Time
  - Amount
  - V1-V38 → Result of PCA
- 492 instances marked as fraud
  - < 0.2% of data
- Dataset already preprocessed



The Algorithm - Traditional Neural Network

$$w_{t+1} = w_t - \eta \nabla L$$

The Algorithm - Neural Network with Momentum

- v = velocity
- β = how influential past velocities are on the new velocity calculated
- Converges faster than with a constant learning rate

$$v_{t+1} = \beta v_t + (1 - \beta)\nabla L$$

$$w_{t+1} = w_t - \eta v_{t+1}$$

The Algorithm - MAXGBoost

- Combines GBDT and momentum-based updates
- Approximates ∇ L
- Using momentum to update the **learning rate**
  - Loss increase = η increase
  - Loss decrease = η decrease

$$v_{t+1} = \beta v_t + (1 - \beta)(L_{t+1} - L_t)$$

$$\eta_{t+1} = \eta_t(1 + v_{t+1})$$

Experiments - Dataset

Splits

- 68%: Training
- 12%: Validation
- 20%: Testing

Analysis

- 5-fold Cross-validation
- Results based on best fold per model

Experiments - Models

Decision Tree	Single Decision Tree
Random Forest	Ensemble Voting Decision Tree Model
Constant η XGBoost	XGBoost with a constant learning rate
Exponential Decay XGBoost	XGBoost with a learning rate multiplied by constant every iteration
MAXGBoost	XGBoost with Momentum Approximation

Experiments - Hyperparameters

Decision Tree	**Max Depth** = 4
Random Forest	**Estimators** = 5
Constant η XGBoost	**Estimators** = 423, **η** = 0.08
Exponential Decay XGBoost	**Estimators** = 423, **x** = 0.9
MAXGBoost	**Estimators** = 423, **Initial η** = 0.89, **β** = 0.99

Results

Model	Accuracy	Precision	Recall	AUC
Decision Tree	0.99946	0.86813	0.80612	0.90296
Random Forest	0.99951	0.77000	0.93902	0.96931
Constant η	0.99977	0.88636	0.96296	0.98139
Exponential decay	0.99979	0.88764	**0.97531**	**0.98757**
MAXGBoost	**0.99980**	**0.93827**	0.92683	0.96337

Discussion - MAXGBoost Strengths

- **Best Precision** in Fraud Detection
  - Exceptional performance in minimizing false positives
  - Effective for high-stakes financial environments
    - Reduces customer friction from false alerts
    - Minimizes operational costs from investigation overhead

Discussion - MAXGBoost Limitations

- Relatively low AUC for Fraud Detection
  - **Rapid** learning rate **decrease** with small loss improvements
  - **Limited exploration of feature space**
  - Over-emphasis on strongly discriminative features
  - Underweighting of subtle fraud patterns

Conclusion

- Decision Tree-based models effective in classifying positive class of fraud **in < 0.2% of data**
  - **Increases the ability for law enforcement** to correctly catch frauds
- MAXGBoost best model comparing accuracy and precision
  - MAXGBoost most effective in **preventing false accusations of fraud** and **increasing customer satisfaction**
- Exponential decay XGBoost most effective in **catching fraudulent cases**, compromising false accusations

Future Work

- **Hybrid Model Development**
  - Combine strengths of EGB and MAXGBoost
  - Create integrated momentum-decay approach
- Feature-specific momentum updates
- Class-aware momentum adjustments

Thanks!

Questions?

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