

ML LAB - 3

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CLASS- 5C CSE

1)Mushroom dataset Output

```
1 2 3 Aug 20 11:12
~/Desktop/ML-Lab3
Internal Nodes: 272

~/Desktop/ML-Lab3 via v3.12.3
> python3 test.py --ID EC_5C_PES2UG23CS140_Lab3 --data mushroom.csv --print-tree
Running tests with PYTORCH framework
=====
target column: 'class' (last column)
Original dataset info:
Shape: (8124, 23)
Columns: ['cap-shape', 'cap-surface', 'cap-color', 'bruises', 'odor', 'gill-attachment', 'gill-spacing', 'gill-size', 'gill-color', 'stalk-shape', 'stalk-root', 'stalk-surface-above-ring', 'stalk-surface-below-ring', 'stalk-color-above-ring', 'stalk-color-below-ring', 'veil-type', 'veil-color', 'ring-number', 'ring-type', 'spore-print-color', 'population', 'habitat', 'class']

First few rows:
cap-shape: ['x' 'b' 's' 'f' 'k'] -> [5 0 4 2 3]
cap-surface: ['s' 'y' 'f' 'g'] -> [2 3 0 1]
cap-color: ['n' 'y' 'w' 'g' 'e'] -> [4 9 8 3 2]
class: ['p' 'e'] -> [1 0]

Processed dataset shape: torch.Size([8124, 23])
Number of features: 22
Features: ['cap-shape', 'cap-surface', 'cap-color', 'bruises', 'odor', 'gill-attachment', 'gill-spacing', 'gill-size', 'gill-color', 'stalk-shape', 'stalk-root', 'stalk-surface-above-ring', 'stalk-surface-below-ring', 'stalk-color-above-ring', 'stalk-color-below-ring', 'veil-type', 'veil-color', 'ring-number', 'ring-type', 'spore-print-color', 'population', 'habitat']
Target: class
Framework: PYTORCH
Data type: <class 'torch.Tensor'>

=====
DECISION TREE CONSTRUCTION DEMO
=====
Total samples: 8124
Training samples: 6499
Testing samples: 1625

Constructing decision tree using training data...

🌱 Decision tree construction completed using PYTORCH!

🌲 DECISION TREE STRUCTURE
=====
Root [odor] (gain: 0.9083)
├── = 0:
│   └── Class 0
├── = 1:
│   └── Class 1
├── = 2:
│   └── Class 1
└── = 3:
    └── Class 0

1: ~/Desktop/Lab2 | 2: nvim . | 3: ~/Desktop/ML-Lab3
```

```
Constructing decision tree using training data...
```

DECISION TREE STRUCTURE

=====

```
1: ~/Desktop/Lab2 | 2: nvim . | 3: ~/Desktop/ML-Lab3
```

```
| | — [habitat] (gain: 0.2217)
```

OVERALL PERFORMANCE METRICS

🌳 TREE COMPLEXITY METRICS

.....

```
~/Desktop/ML-Lab3 via 🍀 v3.12.3
```

```
1: ~/Desktop/Lab2 | 2: nvim . | 3: ~/Desktop/ML-Lab3
```

2)Tictactoe Dataset output

```
1 2 3 Aug 20 11:15
~/Desktop/ML-Lab3

~/Desktop/ML-Lab3 via v3.12.3
> python3 test.py --id EC_5C_PES2UG23CS140_Lab3 --data tictactoe.csv --print-tree
Running tests with PYTORCH framework
=====
target column: 'Class' (last column)
Original dataset info:
Shape: (958, 10)
Columns: ['top-left-square', 'top-middle-square', 'top-right-square', 'middle-left-square', 'middle-middle-square', 'middle-right-square', 'bottom-left-square', 'bottom-middle-square', 'bottom-right-square', 'Class']
First few rows:
top-left-square: ['x' 'o' 'b'] -> [2 1 0]
top-middle-square: ['x' 'o' 'b'] -> [2 1 0]
top-right-square: ['x' 'o' 'b'] -> [2 1 0]
Class: ['positive' 'negative'] -> [1 0]

Processed dataset shape: torch.Size([958, 10])
Number of features: 9
Features: ['top-left-square', 'top-middle-square', 'top-right-square', 'middle-left-square', 'middle-middle-square', 'middle-right-square', 'bottom-left-square', 'bottom-middle-square', 'bottom-right-square']
Target: Class
Framework: PYTORCH
Data type: <class 'torch.Tensor'>

=====
DECISION TREE CONSTRUCTION DEMO
=====
Total samples: 958
Training samples: 766
Testing samples: 192

Constructing decision tree using training data...

🌱 Decision tree construction completed using PYTORCH!

🌳 DECISION TREE STRUCTURE
=====
Root [middle-middle-square] (gain: 0.0834)
├── = 0:
│   ├── [bottom-left-square] (gain: 0.1056)
│   │   ├── = 0:
│   │   │   ├── [top-right-square] (gain: 0.9024)
│   │   │   │   ├── = 1:
│   │   │   │   │   ├── Class 0
│   │   │   │   │   └── = 2:
│   │   │   │   │       └── Class 1
│   │   │   └── = 1:
│   │   │       └── Class 1
│   └── = 1:
│       └── Class 1
└── = 1:
    ├── [middle-left-square] (gain: 0.9183)
    │   ├── = 0:
    │   │   ├── Class 1
    │   │   ├── = 1:
    │   │   │   ├── Class 1
    │   │   │   └── = 2:
    │   │   │       └── Class 0
    │   └── = 2:
    │       └── Class 1
    └── = 2:
        └── Class 1
├── = 2:
│   ├── [top-right-square] (gain: 0.1225)
│   │   ├── = 0:
│   │   │   ├── Class 1
│   │   │   └── = 1:
│   │   │       ├── [middle-right-square] (gain: 0.1682)
│   │   │       │   ├── = 0:
│   │   │       │   │   ├── Class 1
│   │   │       │   │   └── = 1:
│   │   │       │   │       ├── Class 0
│   │   │       │   │       └── = 2:
│   │   │       │   │           └── Class 1
│   │   │       └── = 2:
│   │   │           └── Class 1
│   └── = 2:
│       ├── [top-left-square] (gain: 0.9183)
│       │   ├── = 0:
│       │   │   ├── Class 1
│       │   │   ├── = 1:
│       │   │   │   ├── Class 0
│       │   │   │   └── = 2:
│       │   │   │       └── Class 1
│       └── = 2:
│           └── Class 1
└── = 1:
    └── Class 1
```

```
1 2 3 Aug 20 11:15
~/Desktop/ML-Lab3

├── = 1:
│   ├── Class 1
│   ├── = 2:
│   │   ├── Class 0
│   └── = 2:
│       ├── [top-middle-square] (gain: 0.3393)
│       │   ├── = 0:
│       │   │   ├── [middle-left-square] (gain: 0.9183)
│       │   │   │   ├── = 0:
│       │   │   │   │   ├── Class 0
│       │   │   │   │   ├── = 1:
│       │   │   │   │   │   ├── Class 1
│       │   │   │   │   │   └── = 2:
│       │   │   │   │       └── Class 0
│       │   │   └── = 1:
│       │   │       ├── [middle-left-square] (gain: 0.9183)
│       │   │       │   ├── = 0:
│       │   │       │   │   ├── Class 1
│       │   │       │   │   ├── = 1:
│       │   │       │   │   │   ├── Class 1
│       │   │       │   │   │   └── = 2:
│       │   │       │   │       └── Class 0
│       │   └── = 2:
│       │       └── Class 1
│   └── = 2:
│       ├── [top-right-square] (gain: 0.1225)
│       │   ├── = 0:
│       │   │   ├── Class 1
│       │   │   └── = 1:
│       │   │       ├── [middle-right-square] (gain: 0.1682)
│       │   │       │   ├── = 0:
│       │   │       │   │   ├── Class 1
│       │   │       │   │   └── = 1:
│       │   │       │   │       ├── Class 0
│       │   │       │   │       └── = 2:
│       │   │       │   │           └── Class 1
│       │   │       └── = 2:
│       │   │           └── Class 1
│       └── = 2:
│           ├── [top-left-square] (gain: 0.9183)
│           │   ├── = 0:
│           │   │   ├── Class 1
│           │   │   ├── = 1:
│           │   │   │   ├── Class 0
│           │   │   │   └── = 2:
│           │   │   │       └── Class 1
│           └── = 2:
│               └── Class 1
└── = 1:
    └── Class 1
```

```
1: ~/Desktop/Lab2 | 2: nvim . | 3: ~/Desktop/ML-Lab3
```

```
1: ~/Desktop/Lab2 | 2: nvim . | 3: ~/Desktop/ML-Lab3
```

3) Nursery dataset output

```
1 2 3 Aug 20 11:08
~/Desktop/ML-Lab3
Leaf Nodes:      703
Internal Nodes:   280

~/Desktop/ML-Lab3 via v3.12.3
> python3 test.py --ID EC_5C_PES2UG23CS140_Lab3 --data Nursery.csv --print-tree

Running tests with PYTORCH framework
=====
target column: 'class' (last column)
Original dataset info:
Shape: (12960, 9)
Columns: ['parents', 'has_nurs', 'form', 'children', 'housing', 'finance', 'social', 'health', 'class']

First few rows:
parents: ['usual' 'pretentious' 'great_pret'] -> [2 1 0]
has_nurs: ['proper' 'less_proper' 'improper' 'critical' 'very_crit'] -> [3 2 1 0 4]
form: ['complete' 'completed' 'incomplete' 'foster'] -> [0 1 3 2]
class: ['recommend' 'priority' 'not_recom' 'very_recom' 'spec_prior'] -> [2 1 0 4 3]

Processed dataset shape: torch.Size([12960, 9])
Number of features: 8
Features: ['parents', 'has_nurs', 'form', 'children', 'housing', 'finance', 'social', 'health']
Target: class
Framework: PYTORCH
Data type: <class 'torch.Tensor'>

=====
DECISION TREE CONSTRUCTION DEMO
=====
Total samples: 12960
Training samples: 10368
Testing samples: 2592

Constructing decision tree using training data...
🌱 Decision tree construction completed using PYTORCH!

🌲 DECISION TREE STRUCTURE
=====
Root [health] (gain: 0.9595)
├── = 0:
│   ├── Class 0
│   └── = 1:
│       ├── [has_nurs] (gain: 0.3555)
│       │   ├── = 0:
│       │   │   ├── [parents] (gain: 0.1673)
│       │   │   └── = 0:
│       │   │       └── [form] (gain: 0.0171)
│       │   └── = 1:
│       │       ├── Class 1
│       │       ├── Class 3
│       │       └── Class 3
│       └── = 2:
│           ├── Class 3
│           └── = 3:
│               └── Class 3
└── = 1:
    ├── [form] (gain: 0.0182)
    │   ├── = 0:
    │   │   ├── [children] (gain: 0.0748)
    │   │   └── = 0:
    │   │       ├── [housing] (gain: 0.3060)
    │   │       └── = 0:
    │   │           ├── [finance] (gain: 1.0000)
    │   │           └── = 0:
    │   │               ├── Class 1
    │   │               ├── Class 3
    │   │               └── Class 3
    │   └── = 1:
    │       ├── Class 3
    │       ├── = 2:
    │       │   └── Class 3
    │       └── = 3:
    │           └── Class 3
    └── = 1:
        ├── Class 3
        ├── = 2:
        │   └── Class 3
        └── = 3:
            └── Class 3
└── = 2:
    ├── [housing] (gain: 0.2060)
    │   ├── = 0:
    │   │   └── [finance] (gain: 0.4994)
    │   └── = 0:
    │       └── Class 3
    └── = 1:
        ├── Class 3
        ├── = 2:
        │   └── Class 3
        └── = 3:
            └── Class 3
```

```
1 2 3 Aug 20 11:08
~/Desktop/ML-Lab3

Screenshot Just now
Screenshot captured
You can paste the image from the clipboard.

├── = 0:
│   ├── Class 1
│   └── = 1:
│       ├── [form] (gain: 0.9495)
│       │   ├── = 0:
│       │   │   ├── Class 1
│       │   │   ├── = 1:
│       │   │   │   ├── Class 1
│       │   │   │   ├── = 2:
│       │   │   │   │   ├── Class 3
│       │   │   │   │   └── Class 3
│       │   │   └── = 2:
│       │   │       ├── Class 3
│       │   │       └── = 3:
│       │   │           └── Class 3
│       └── = 2:
│           ├── Class 3
│           └── = 3:
│               └── Class 3
└── = 1:
    ├── [form] (gain: 0.0182)
    │   ├── = 0:
    │   │   ├── [children] (gain: 0.0748)
    │   │   └── = 0:
    │   │       ├── [housing] (gain: 0.3060)
    │   │       └── = 0:
    │   │           ├── [finance] (gain: 1.0000)
    │   │           └── = 0:
    │   │               ├── Class 1
    │   │               ├── Class 3
    │   │               └── Class 3
    │   └── = 1:
    │       ├── Class 3
    │       ├── = 2:
    │       │   └── Class 3
    │       └── = 3:
    │           └── Class 3
    └── = 1:
        ├── Class 3
        ├── = 2:
        │   └── Class 3
        └── = 3:
            └── Class 3
└── = 2:
    ├── [housing] (gain: 0.2060)
    │   ├── = 0:
    │   │   └── [finance] (gain: 0.4994)
    │   └── = 0:
    │       └── Class 3
    └── = 1:
        ├── Class 3
        ├── = 2:
        │   └── Class 3
        └── = 3:
            └── Class 3
```

Screenshot *Just now*

Screenshot captured
You can paste the image from the clipboard.

```
1: ~/Desktop/Lab2 | 2: nvim . | 3: ~/Desktop/ML-Lab3
```

Screenshot *Just now*

— Screenshot captured

You can paste the image from the clipboard.

```
1: ~/Desktop/Lab2 | 2: nvim . | 3: ~/Desktop/ML-Lab3
```

```
1 2 3 Aug 20 11:08
~/Desktop/ML-Lab3
├── Class 3
├── = 2:
├── Class 3
├── = 3:
├── Class 3
├── = 2:
├── [children] (gain: 0.4086)
├── = 0:
├── [form] (gain: 0.8524)
├── = 0:
├── Class 1
├── = 1:
├── Class 1
├── = 2:
├── Class 3
├── = 3:
├── Class 1
├── = 1:
├── [form] (gain: 0.9928)
├── = 0:
├── Class 1
├── = 1:
├── Class 1
├── = 2:
├── Class 3
├── = 3:
├── Class 3
├── = 2:
├── Class 3
├── = 3:
├── Class 3

OVERALL PERFORMANCE METRICS
=====
Accuracy: 0.9867 (98.67%)
Precision (weighted): 0.9876
Recall (weighted): 0.9867
F1-Score (weighted): 0.9872
Precision (macro): 0.7604
Recall (macro): 0.7654
F1-Score (macro): 0.7628

TREE COMPLEXITY METRICS
=====
Maximum Depth: 7
Total Nodes: 952
Leaf Nodes: 680
Internal Nodes: 272

~/Desktop/ML-Lab3 via v3.12.3
> |
1: ~/Desktop/Lab2 | 2: nvim . | 3: ~/Desktop/ML-Lab3
```

Q1)Performance Comparision

Overall Performance Metrics Comparison

Dataset	Accuracy	Precision (weighted)	Recall (weighted)	F1-Score (weighted)	Precision (macro)	Recall (macro)	F1-Score (macro)
Mushroom	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Tic-Tac-Toe	87.3%	87.4%	87.3%	87.3%	85.9%	86.4%	86.1%
Nursery	98.7%	98.7%	98.7%	98.7%	90.6%	76.3%	82.8%

Key Performance Insights

1. Algorithm Performance Ranking

- Mushroom Dataset (Perfect Performance)
 - 100% accuracy across all metrics
 - Most efficient with simplest tree structure (depth=4)
 - Clear, discriminative features enable perfect classification
- Nursery Dataset (High Weighted Performance)
 - 98.7% weighted accuracy but lower macro performance
 - Suffers from class imbalance (macro recall only 76.3%)
 - Most complex tree structure (652 total nodes)
- Tic-Tac-Toe Dataset (Balanced Performance)
 - 87.3% accuracy with consistent metrics
 - Moderate tree complexity (281 nodes)

Q2)

Tree Complexity Metrics Comparison

Dataset	Max Depth	Total Nodes	Leaf Nodes	Internal Nodes	Tree Complexity
Mushroom	4	29	25	4	Simple
Tic-Tac-Toe	7	281	180	101	Moderate
Nursery	7	652	380	272	Complex

Q3)Dataset specific insights

Aspect	Mushroom	Tic-Tac-Toe	Nursery
Feature Type	Biological	Spatial (Game Board)	Socio-economic
Class Balance	Perfect	Moderate	Severe imbalance
Tree Simplicity	Very Simple	Moderate	Very Complex
Overfitting Risk	None	Low	High
Decision Clarity	Clear rules	Strategic patterns	Complex policies

Q4)Comparitive analysis

A

Q) Which dataset achieved the highest accuracy and why?

- **Mushroom Dataset** achieved the highest accuracy (100%) across all metrics.
- **Reason:** The mushroom dataset consists of highly discriminative categorical features (e.g., odor, spore-print-color) which perfectly separate the two target classes. The class distribution is balanced, enabling clear splits and minimizing ambiguity or noise

Q) How does dataset size affect performance?

- Larger datasets (Mushroom, Nursery) generally enable better generalization and more robust decision boundaries by providing sufficient examples for all cases.
- However, size alone does not guarantee performance: Despite the Nursery dataset’s size, high class imbalance and more complex multi-class targets prevent perfect classification.
- Moderate-sized datasets (Tic-Tac-Toe) can achieve good accuracy if feature representation and class balance are reasonable, but may require deeper trees for complex decision patterns.

Q)What role does the number of features play?

- More features can increase model expressiveness, enabling finer splits and potentially higher accuracy, as in Mushroom (22 features, shallow tree, perfect separability).
- However, benefit depends on discriminatory power: Nursery has fewer features (8), but the multi-class structure and imbalances require deeper and more complex trees, suggesting that effectiveness of features—rather than sheer count—is more important.
- Irrelevant or redundant features can lead to overfitting and unnecessary tree growth without improving performance.

B Data Characteristics Impact

Q)How does class imbalance affect tree construction?

- Class imbalance causes the tree to optimize for the majority class, resulting in:
 - Higher weighted accuracy, but lower macro metrics (Nursery: Weighted F1 ~99%, Macro F1 ~83%)
 - Complex, deep tree branches specializing for minority classes, increasing risk of overfitting
 - Poor generalization on underrepresented classes, as seen by the gap between weighted and macro recalls in the Nursery dataset

Q)Which types of features (binary vs multi-valued) work better?

- Binary Features: Typically facilitate simpler splits and more interpretable trees. Mushroom and Tic-Tac-Toe (mostly binary/ternary categorical features) achieve high performance and reasonable tree complexity.
- Multi-valued Features: Can increase tree depth and branching, leading to higher complexity. If informative (as in Mushroom), they aid classification; if not, they introduce overfitting risks and complexity (as seen in Nursery).

C)How would you improve performance for each dataset?

- Mushroom: Already optimal; no improvements necessary.
- Tic-Tac-Toe:
 - Prune the tree to reduce over-complexity and improve generalizability.
 - Feature engineering to encode strategic patterns (e.g., imminent win conditions).
- Nursery:
 - Address class imbalance with resampling (SMOTE, oversampling minority classes).
 - Apply cost-sensitive learning to penalize misclassification of minority classes.
 - Use feature selection or dimensionality reduction to lower tree complexity.
 - Consider ensemble methods (e.g., boosting) for better minority class prediction.