Table 4.1: Comparison Between Long Training and the Proposed Early Stopping Policy

| Scenario | Metrics(%) | Synethetic Datasets | | | | | |
|---|---|---|---|---|---|---|---|
| | | A.1 | A.2 | A.3 | A.4 | A.5 | A.6 |
| 10k Epoches | Mean TPR | 100 | 100 | 90.2 | 100 | 75.3 | 74.7 |
| | Mean FDR | 0 | 0 | 0 | 42.7 | 38.6 | 42.3 |
| Simple Early Stopping | Mean TPR | ◇ | ◇ | ▼50.7 | ◇ | ▼16.3 | ◇ |
| | Mean FDR | ◇ | ◇ | ◇ | ◇ | ▼20.6 | ▼2.4 |
| | Used Epoch(k) | 1.5 | 1.2 | 1.7 | 5 | 1.9 | 4.2 |

Loss chances to be better

Save Time

Save Time

Individual Settings: **Framework:** *INVASE*; **Hyperparameter:** $\lambda = 0.1$; **Activation**: ReLU.

Notations: ◇ denotes no difference, ▼ indicates a decrease, ▲ signifies an increase.

# Analysis of Performance Influencing Factors in INVASE

# Selection Probabilty Stability-based Early Stopping Policy

❖ Advantages:

- Save unnecessary time
- Aviod performance degradation
- Easy to apply

❖ Drawbacks:

- Still risk of getting sub-optimal explainer
- Need to take efforts to decide appropriate parameters

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Loss chances to be better

Save Time

Save Time

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# Analysis of Performance Influencing Factors in INVASE

## Selection Probabilty Stability-based Early Stopping Policy

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|---|---|---|---|---|---|---|---|
| | | A.1 | A.2 | A.3 | A.4 | A.5 | A.6 |
| 10k Epoches | Mean TPR | 100 | 100 | 90.2 | 100 | 75.3 | 74.7 |
| | Mean FDR | 0 | 0 | 0 | 42.7 | 38.6 | 42.3 |
| Simple Early Stopping | Mean TPR | ◇ | ◇ | ▼50.7 | ◇ | ▼16.3 | ◇ |
| | Mean FDR | ◇ | ◇ | ◇ | ◇ | ▼20.6 | ▼2.4 |
| | Used Epoch(k) | 1.5 | 1.2 | 1.7 | 5 | 1.9 | 4.2 |

Loss chances to be better

Save Time

Save Time

Individual Settings: **Framework:** *INVASE*; **Hyperparameter:** $\lambda = 0.1$; **Activation:** ReLU.
Notations: ◇ denotes no difference, ▼ indicates a decrease, ▲ signifies an increase.

❖ Advantages:

- Save unnecessary time
- Aviod performance degradation
- Easy to apply

❖ Drawbacks:

- Still risk of getting sub-optimal explainer
- Need to take efforts to decide appropriate parameters

# Analysis of Performance Influencing Factors in INVASE

## Post-Training Selection Policy

Table 4.2: Comparison Between Long Training and Post-Training Selection Policy

| Scenario | Metrics(%) | Synethetic Datasets | | | | | |
|---|---|---|---|---|---|---|---|
| | | A.1 | A.2 | A.3 | A.4 | A.5 | A.6 |
| 10k Epoches | Mean TPR | 100 | 100 | 90.2 | 100 | 75.3 | 74.7 |
| | Mean FDR | 0 | 0 | 0 | 42.7 | 38.6 | 42.3 |
| Post-Training Selection Policy | Mean TPR | ◇ | ◇ | ◇ | ◇ | ▼2.4 | ▼3.3 |
| | Mean FDR | ◇ | ◇ | ◇ | ▼3.3 | ▼15.9 | ▼4.7 |

INVASE settings: **Hyperparameter:** $\lambda = 0.1$; **Activation**: ReLU.
Early Stopping Policy settings: $I = 10k$, $m = 100$, $r = 500$, $k = 7$
Notations: ◇ denotes no difference, ▼ indicates a decrease, ▲ signifies an increase.