



Faculty of Computer Science

Data Science

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OSDA Big Homework: Neural FCA

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Dataset

Used dataset: openly available ([1]), with 6 attributes (5 binary and 1 numerical) and 2 target columns, with 120 rows.

The main goal of this dataset is to help predict two diseases of urinary system: an acute inflammations of urinary bladder (or cystitis in medical terms) and an acute nephritis.



Dataset

Dataset attributes and their values:

1. Temperature of patient - int values in the segment [35.5,41.5];
2. Occurrence of nausea - "yes" or "no";
3. Lumbar pain - "yes" or "no";
4. Urine pushing (continuous need for urination) - "yes" or "no";
5. Micturition pains - "yes" or "no";
6. Burning of urethra, itch, swelling of urethra outlet - "yes" or "no".

Our targets for binary classification:

1. Inflammation of urinary bladder (cystitis) - "yes" or "no";
2. Nephritis of renal pelvis origin - "yes" or "no". In this work I will focus only on the prediction of cystitis.



Binarization strategy and prediction quality measure

Binarization strategy. According to [2], let's divide all data in column "Temperature of patient" into 2 groups (answers the question whether the patient has a temperature):

- "no" if temperature $\in [35.5, 37.2]$;
- "yes" if temperature $\in [37.3, 41.5]$.

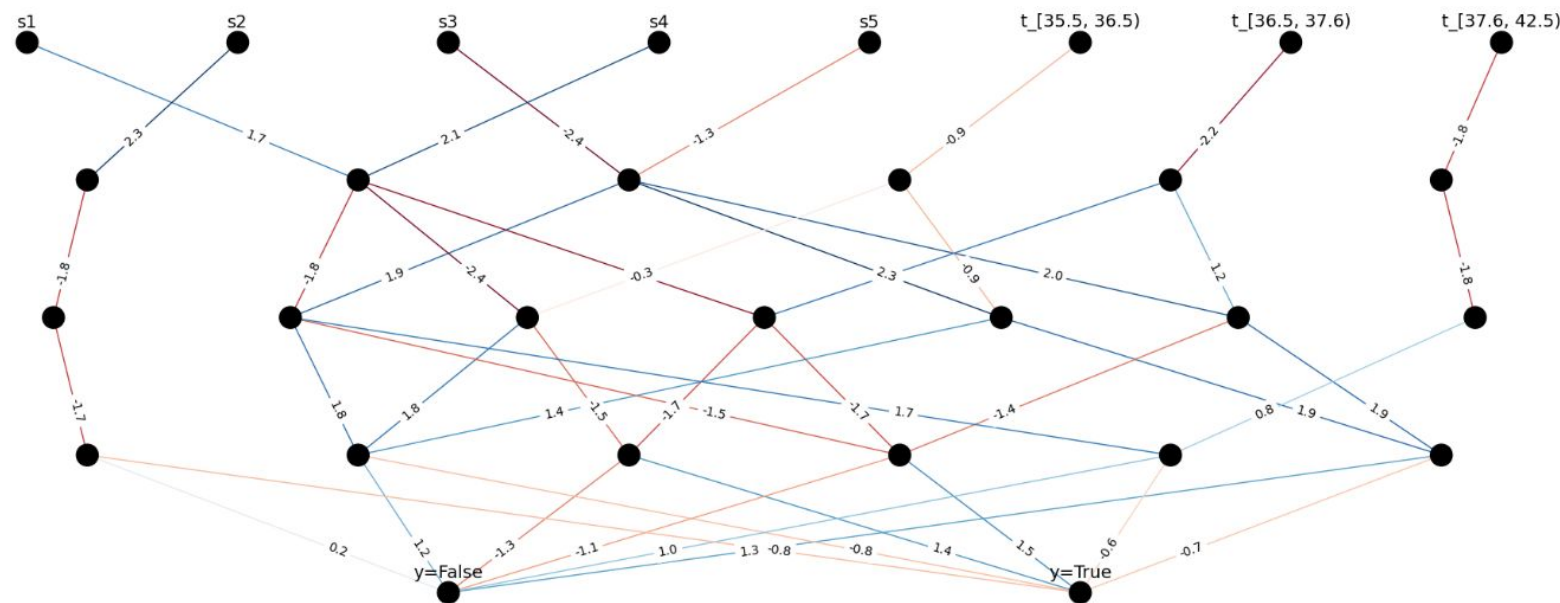
Prediction quality measure. I prefer to use the **F1 score** because it maintains a balance between precision and recall for the classifier and it gives a better measure of the incorrectly classified cases than the accuracy metric.

Another attribute binarization

Based on [3], let's divide "Temperature of patient" into 3 groups: ·

$$t \in [35.5, 36.4]; \cdot t \in [36.5, 37.5]. \cdot t \in [37.6, 41.5].$$

12 best concepts gives F1 score ≈ 0.92 .



Another technique to select best concepts

Initial approach: Selection based on F1-score

- Balances precision and recall
- Suitable for our balanced dataset

Alternative explored: Selection based on Accuracy

- Motivation: To assess impact of metric choice on model performance
- Applied to models 2.1 and 1.3.1

Comparison:

- F1-score selection generally more effective
- Accuracy-based selection showed varied results

Key finding:

- Choice of selection metric significantly influences model performance
- Emphasizes importance of metric selection in concept-based models

Implication:

- Careful consideration needed when choosing concept selection criteria
- May vary depending on specific dataset and problem characteristics

The efficiency of various nonlinaraties to put in the network

Default: ReLU (Rectified Linear Unit)

- Widely used in neural networks
- Helps mitigate vanishing gradient problem

Explored alternatives:

1. Leaky ReLU
 - Addresses "dying ReLU" problem
 - Allows small negative values to pass through
2. Hyperbolic Tangent (tanh)
 - Output range: $[-1, 1]$
 - Can handle negative inputs effectively

Key findings:

- Both Leaky ReLU and tanh showed significant improvements over ReLU
- Models with tanh achieved perfect F1-scores in some configurations
- Leaky ReLU provided more stable performance across different models

Performance comparison:

- ReLU: Mean F1-score up to 0.9311
- Leaky ReLU: Mean F1-score up to 0.9524
- tanh: Mean F1-score up to 1.0 in some cases

Results and Conclusions

Model	Binarization	Epochs	Concept Selection	Concepts	Activation	Mean F1 (Std)
1	Binary	100	F1 score	7	ReLU	0.0 (-)
1.1	Binary	1000	F1 score	7	ReLU	0.92 (-)
1.2	Binary	1000	F1 score	7	ReLU	0.5313 (0.4367)
1.3	Binary	1000	F1 score	7	ReLU	0.7226 (0.3658)
1.3.1	Binary	1000	Accuracy	15	ReLU	0.1257 (0.2514)
2	Triple	1000	F1 score	12	ReLU	0.9311 (0.0673)
2.1	Triple	1000	Accuracy	15	ReLU	0.7641 (0.2988)
2 (LeakyReLU)	Triple	1000	F1 score	12	LeakyReLU	0.9524 (0.0952)
2 (Tanh)	Triple	1000	F1 score	12	Tanh	1.0 (0.0)
2.1 (LeakyReLU)	Triple	1000	Accuracy	15	LeakyReLU	0.9415 (0.0600)
2.1 (Tanh)	Triple	1000	Accuracy	15	Tanh	1.0 (0.0)
Logistic Regression	-	-	-	-	-	1.0 (0.0)
Random Forest	-	-	-	-	-	1.0 (0.0)
XGBoost	-	-	-	-	-	1.0 (0.0)

Table 1: Comparison of model performances



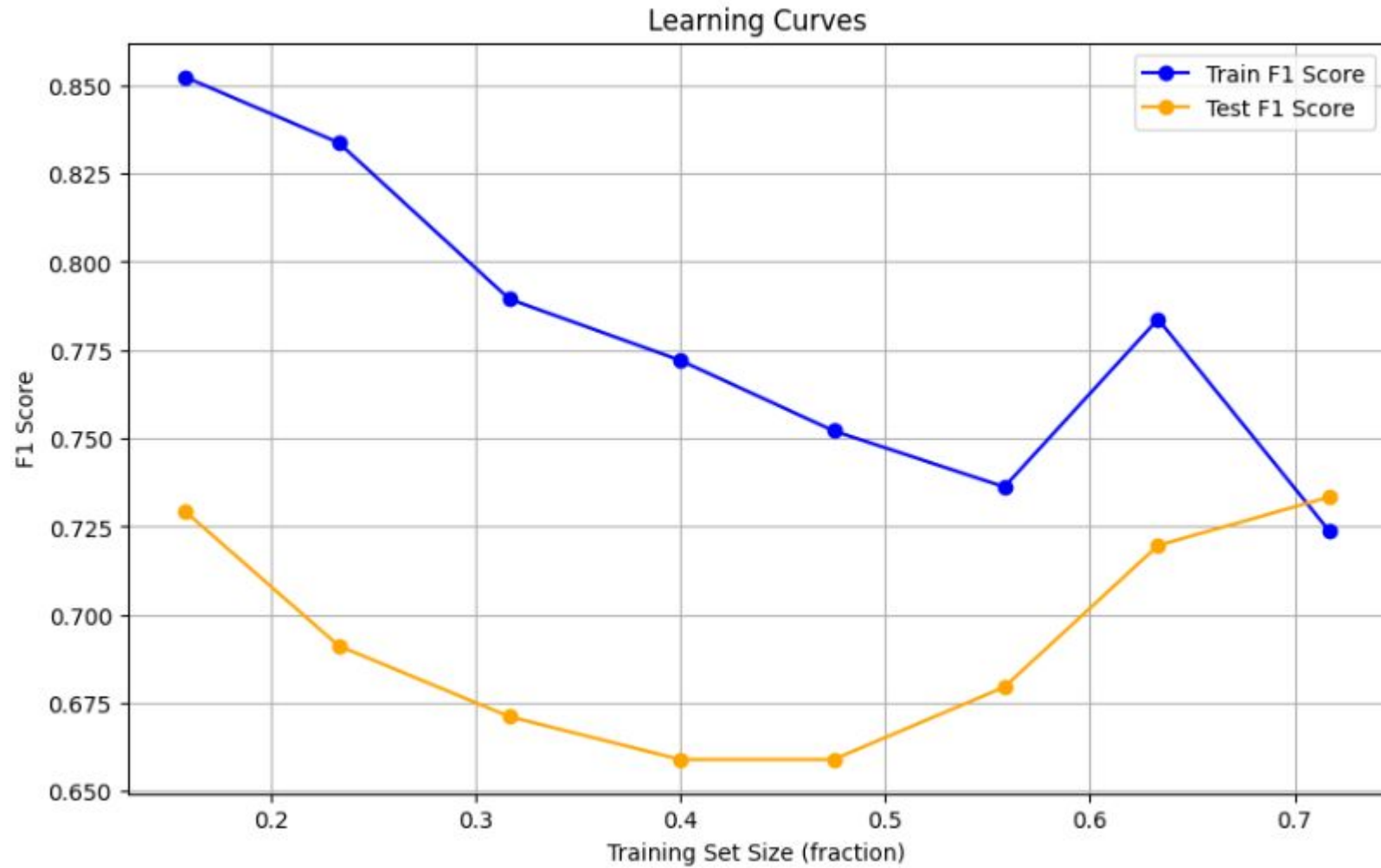
Conclusion

Neural FCA-based models have demonstrated competitiveness compared to classical machine learning methods for the task of classifying acute bladder inflammations. Models with triple temperature binarization and using Leaky ReLU or hyperbolic tangent as activation functions proved particularly effective. However, for practical applications, it's necessary to consider the trade-off between accuracy and training time. Further research could be directed towards optimizing performance, improving interpretability, and testing on larger and more diverse datasets.



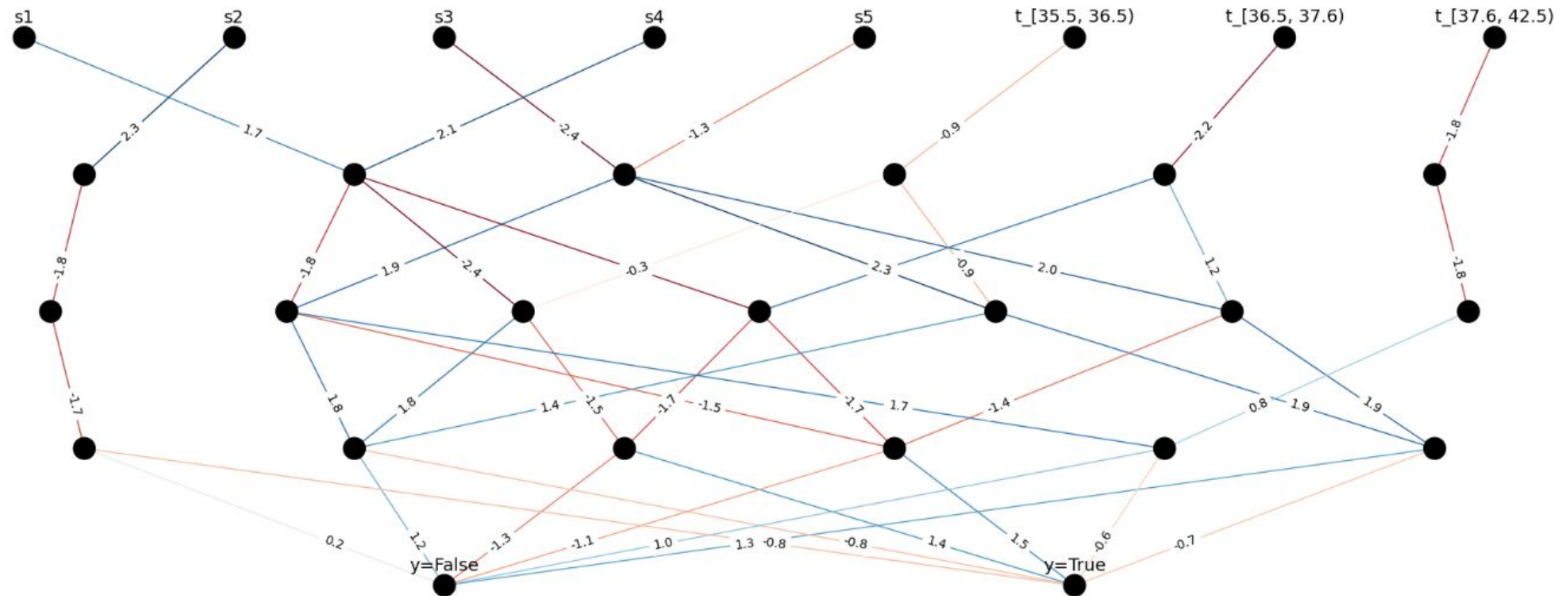
References

- [1] D. Dua and C. Graff. UCI machine learning repository, 2019.
- [2] Il Geneva, B Cuzzo, T Fazili, and W Javaid. Normal body temperature: systematic review. Open Forum Infectious Diseases, 6(4):ofz032, 2019.
- [3] Sanjar Javodov. Neural fca. https://github.com/Sanjar-Javodov/Neural_FCA, 2024.
- [4] Marina Sokolova and Guy Lapalme. A systematic analysis of performance measures for classification tasks. Information processing & management, 45(4):427–437, 2009.
- [5] M Sund-Levander, C Forsberg, and LK Wahren. Body temperature: what is normal? The Lancet, 360(9339):1150, 2002.

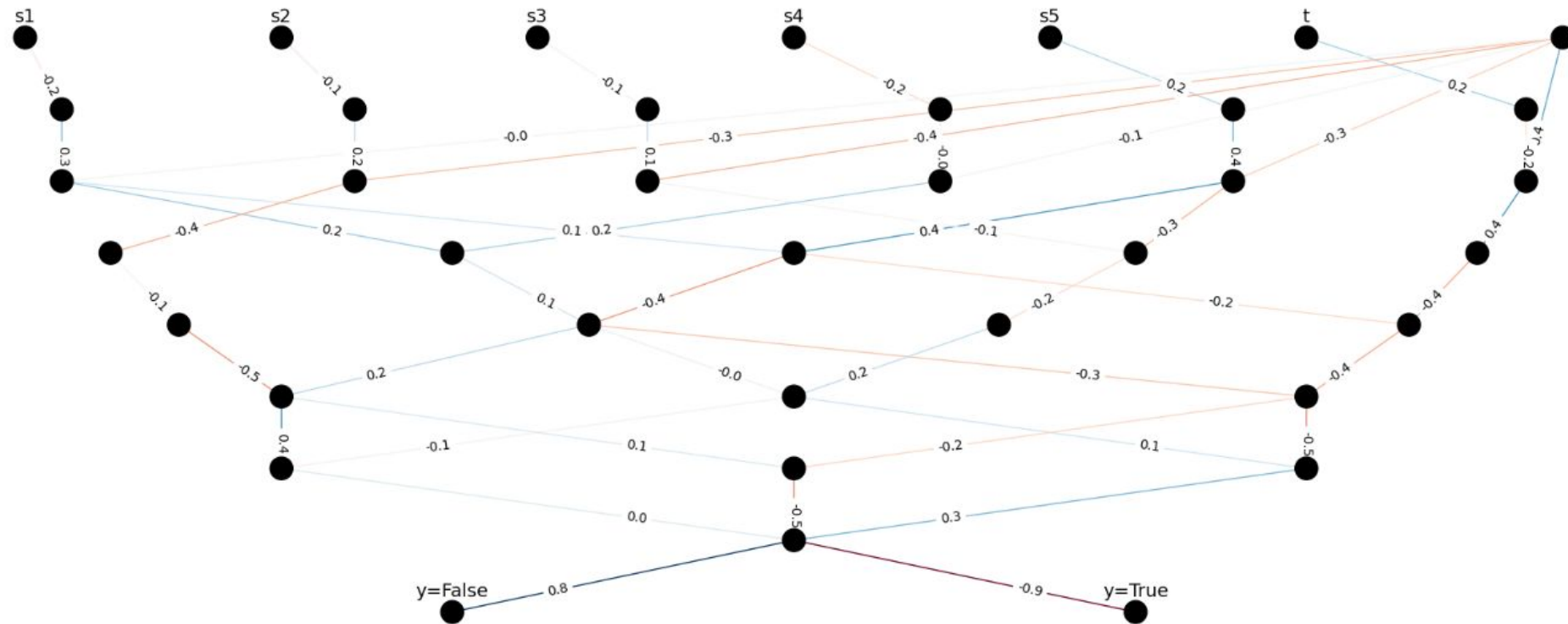




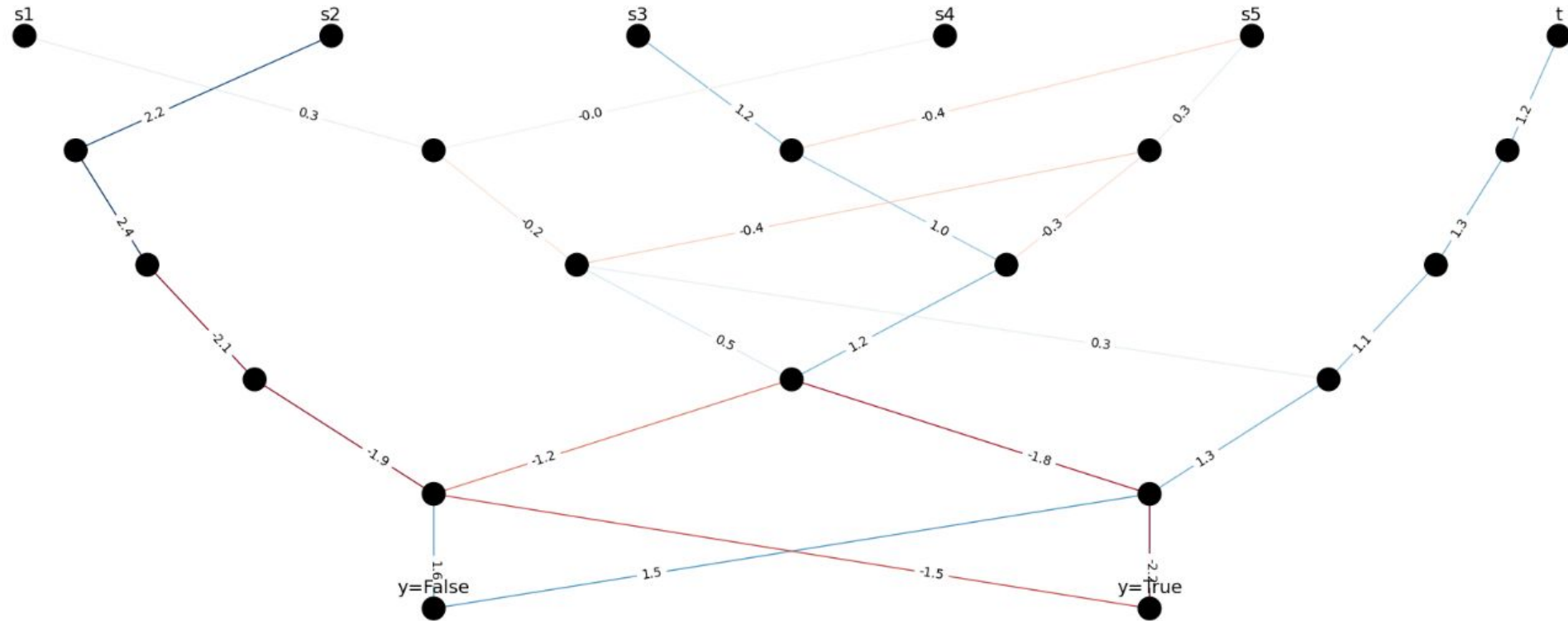
Neural network with fitted edge weights



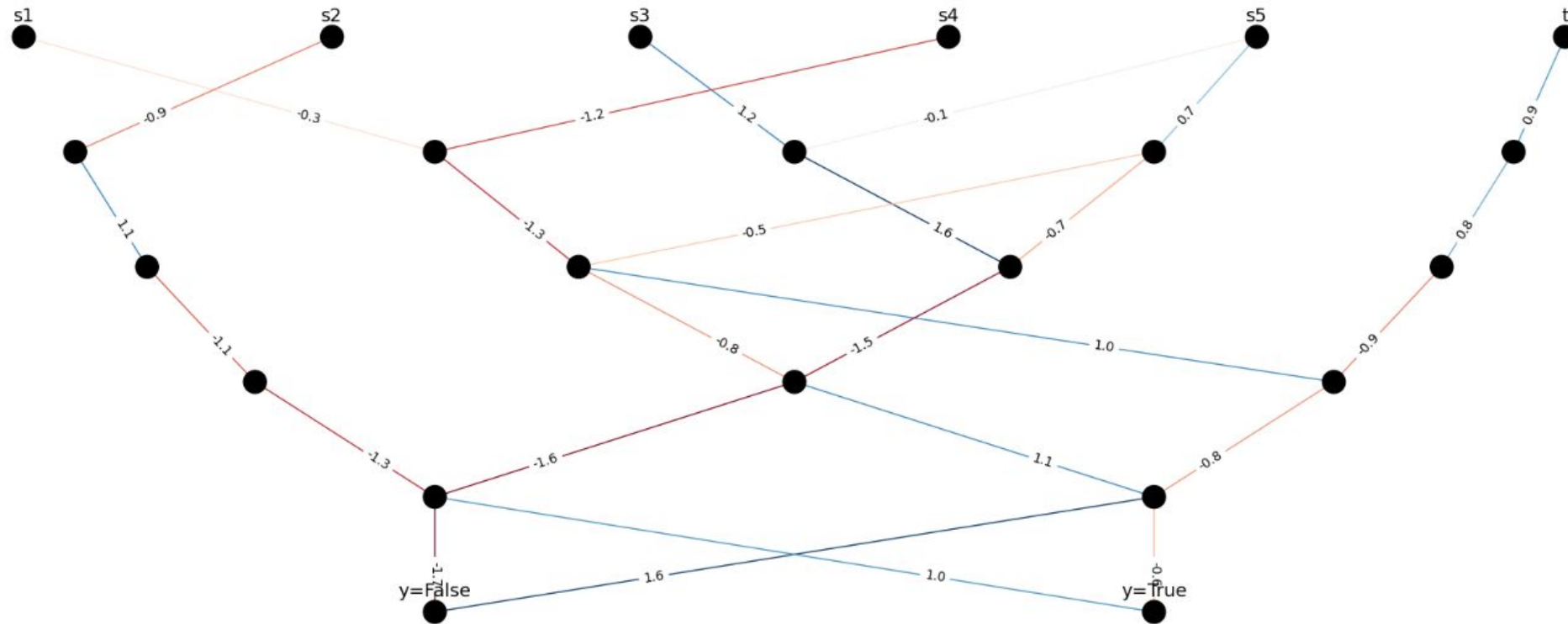
Neural network with fitted edge weights



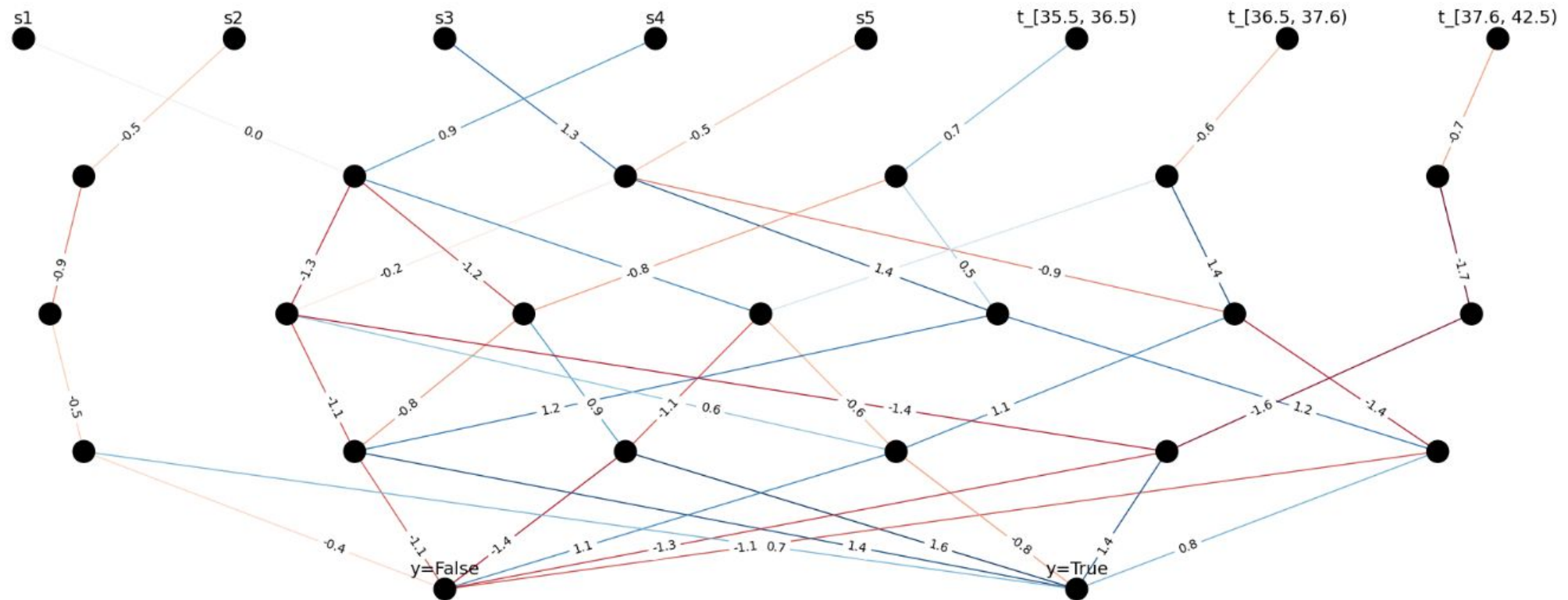
Neural network with fitted edge weights



Neural network with fitted edge weights



Neural network with fitted edge weights





THANKS FOR YOUR ATTENTION!

