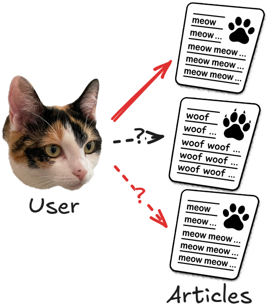
Modeling Behavioral Patterns in News Recommendations Using Fuzzy Neural Networks

Kevin Innerebner, Stephan Bartl, Markus Reiter-Haas, Elisabeth Lex,
Human-Centred Computing

April 28, 2026

Potential of Neuro-Symbolic News Recommendation

- News Recommendation
  - Readers (users) and articles (items)
  - Recommend relevant articles for a reader



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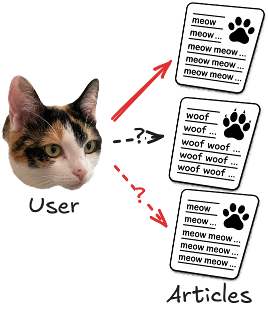

Potential of Neuro-Symbolic News Recommendation

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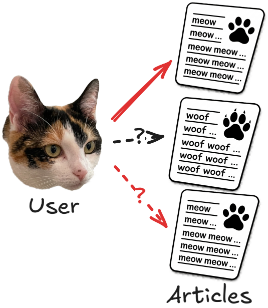
- Reliance on (Deep) Neural Networks
  - Strong predictive accuracy
  - Limited transparency



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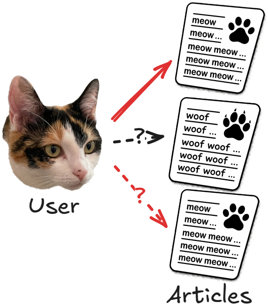
- Editorial gatekeeping in news domain [1]



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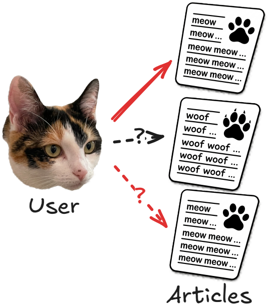

EU Artificial Intelligence Act

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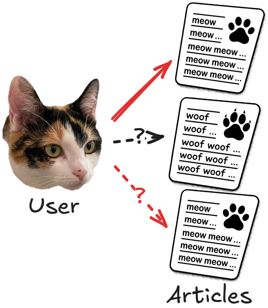
- Potential for neuro-symbolic approaches



EU Artificial Intelligence Act

Fuzzy Logic as a Neuro-Symbolic Foundation

Crisp Logic $\rightarrow$ **Fuzzy Logic**

$$\{0, 1\} \rightarrow [0, 1] \in \mathbb{R}$$

Fuzzy Logic as a Neuro-Symbolic Foundation

Crisp Logic → Fuzzy Logic

$$\{0, 1\} \rightarrow [0, 1] \in \mathbb{R}$$

Product T-norm:

$$a \wedge b \rightarrow a \cdot b$$

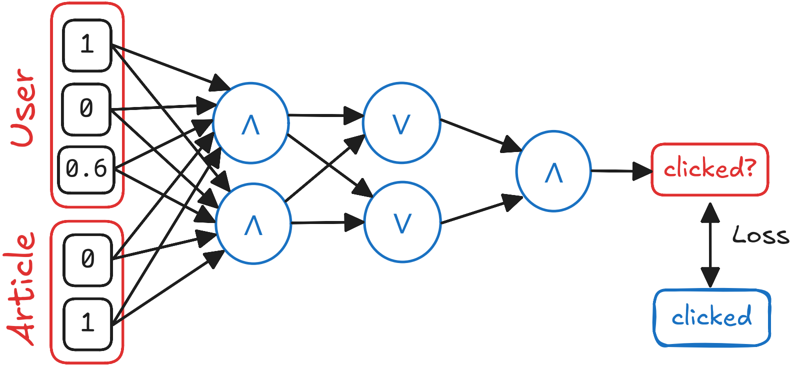
Product T-conorm:

$$a \vee b \rightarrow (a + b) - a \cdot b$$

Negation

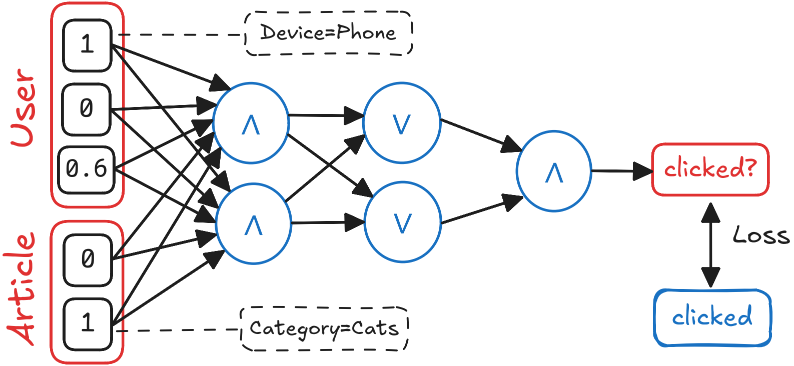
$$\neg a \rightarrow 1 - a$$

Fuzzy Neural Networks Learn Fuzzy Rules



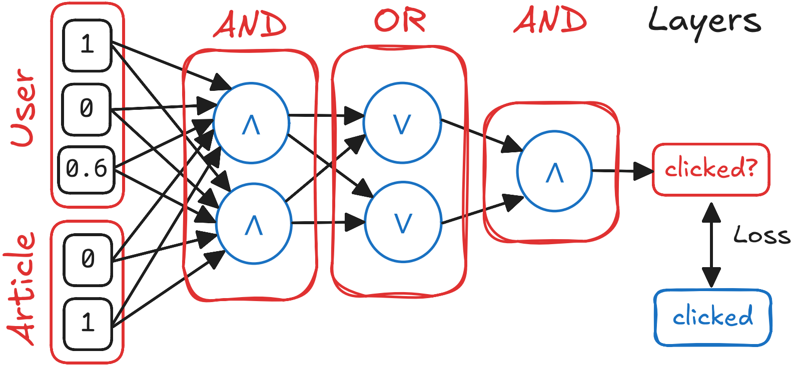
An example of a simple fuzzy neural network.

Fuzzy Neural Networks Learn Fuzzy Rules



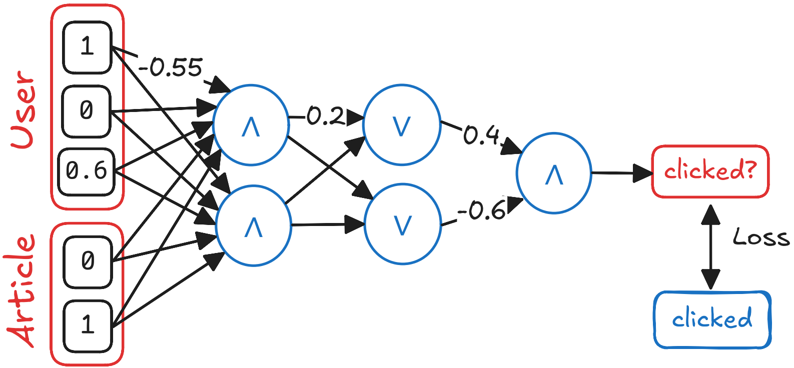
An example of a simple fuzzy neural network with features shown.

Fuzzy Neural Networks Learn Fuzzy Rules



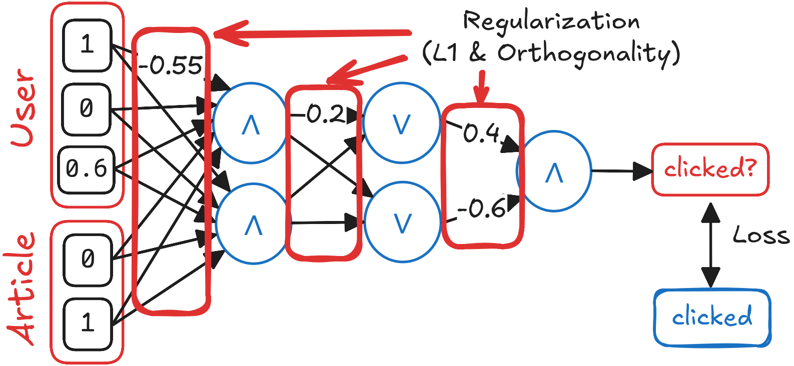
An example of a simple fuzzy neural network with logic layer highlighted.

Fuzzy Neural Networks Learn Fuzzy Rules



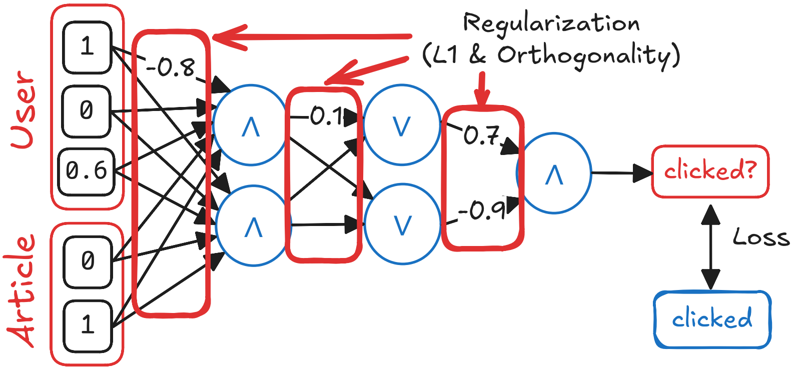
An example of a simple fuzzy neural network with some weights shown, before regularization.

Fuzzy Neural Networks Learn Fuzzy Rules



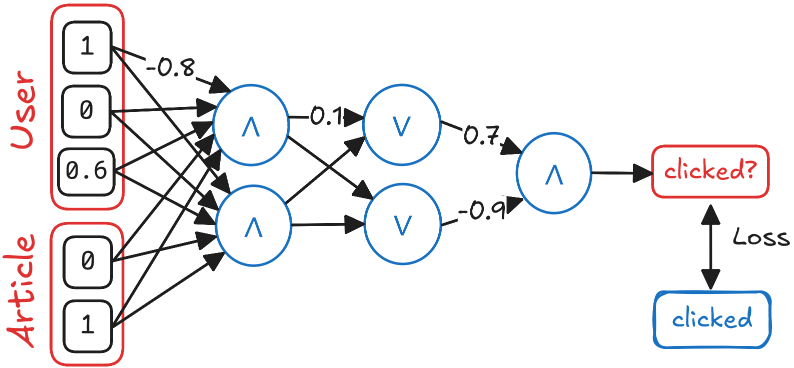
An example of a simple fuzzy neural network with regularization for better interpretability.

Fuzzy Neural Networks Learn Fuzzy Rules



An example of a simple fuzzy neural network with regularization applied.

Fuzzy Neural Networks Learn Fuzzy Rules



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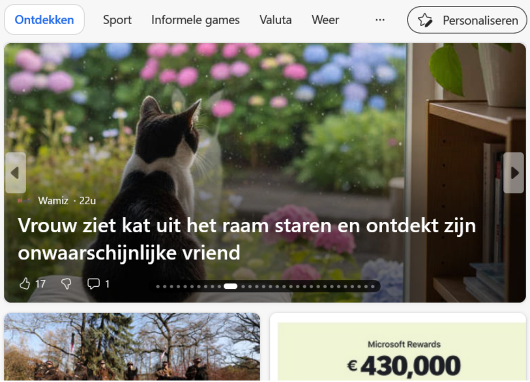
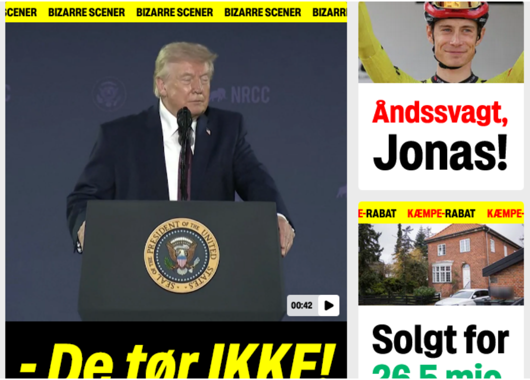
Evaluation on Established Datasets

Microsoft News Dataset (MIND)

Ekstra Bladet Dataset (EB-NeRD)



Microsoft News Website



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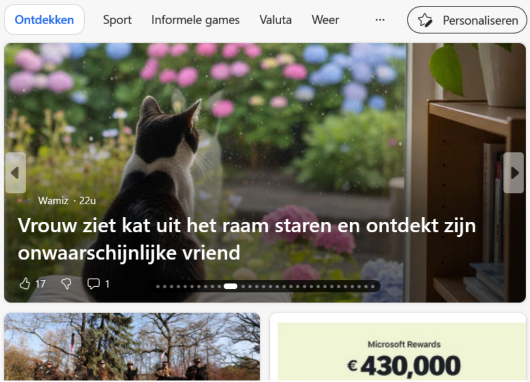

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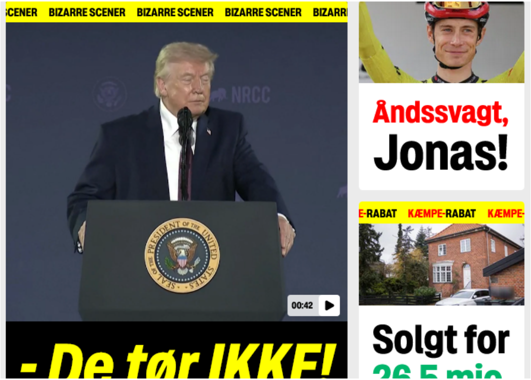

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FNNs Provide Accurate Recommendations (MIND)

Table: Quantitative results (vs. baselines). Best: **Bold**, 2ND Best: Underlined.

Method	MIND Small			
	AUC	MRR	nDCG@5	nDCG@10
Random	.4996	.2184	.2228	.2858
User-KNN	.5004	.2192	.2242	.2864
Item-KNN	.4998	.2183	.2235	.2858
SVD++	.5003	.2197	.2243	.2871
Decision Tree	<u>.5812</u>	<u>.2717</u>	<u>.2963</u>	<u>.3532</u>
NRMS	**.6548**	**.3094**	**.3402**	**.4043**
FNN-or (**ours**)	.5766	.2450	.2716	.3339
FNN-and (**ours**)	.5806	.2485	.2752	.3355

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Random	.5002	.3015	.3211	.4119
User-KNN	.5005	.1681	.1385	.2716
Item-KNN	.5006	.1669	.1381	.2712
SVD++	.5010	.3059	.3382	.4244
Decision Tree	.6039	.3784	.4164	.4840
NRMS	.5548	.3488	.3878	.4648
FNN-or (**ours**)	<u>.6915</u>	**.4582**	<u>.5175</u>	<u>.5662</u>
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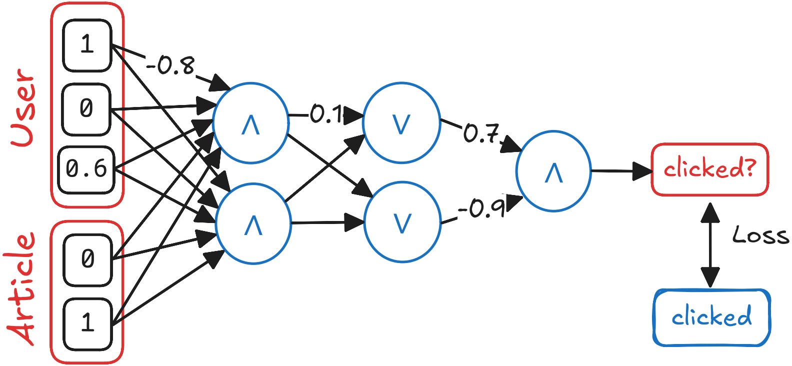
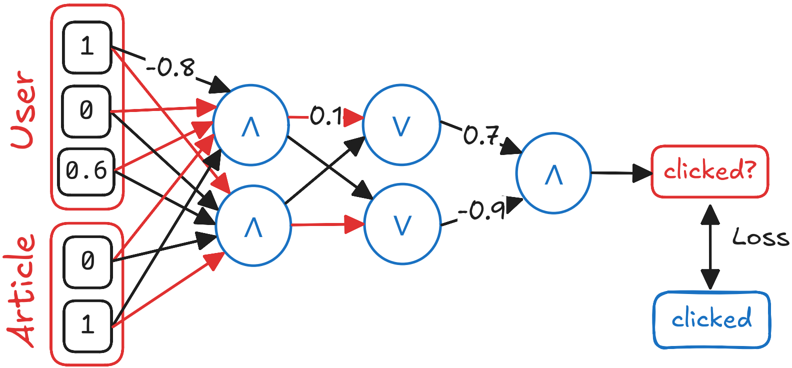
Extracting Crisp Rules from FNN



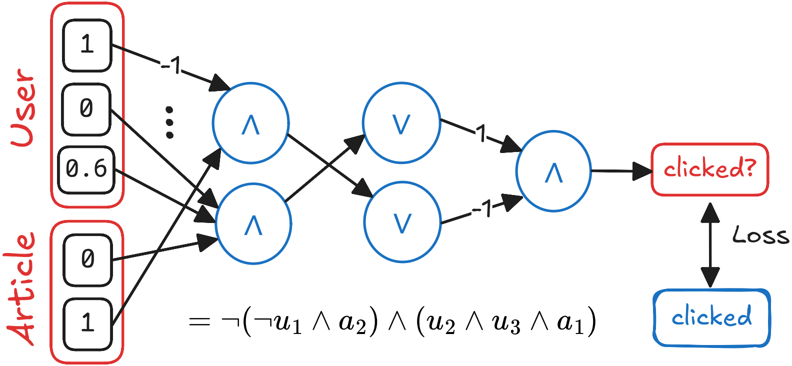
An example of a simple fuzzy neural network with some weights shown, post regularization.

Extracting Crisp Rules from FNN



An example of a simple fuzzy neural network with weak connections in red.

Extracting Crisp Rules from FNN

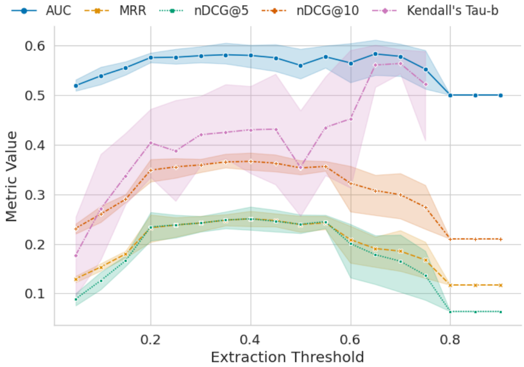


$$= \neg(\neg u_1 \wedge a_2) \wedge (u_2 \wedge u_3 \wedge a_1)$$

An example of a simple fuzzy neural network converted to crisp rules.

Crisp Rules Correspond to Model’s Internal Logic

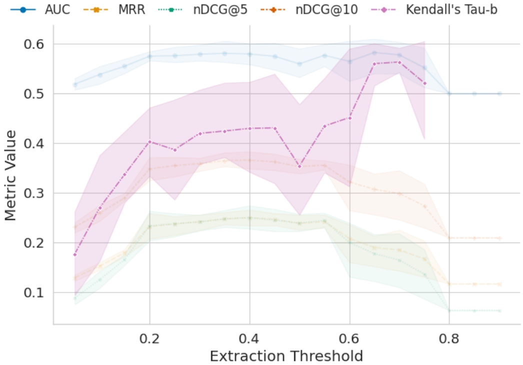
- Crisp rules predict article clicks
- Model has additional fine-grained logic



The alignment and performance of extracted crisp rules

Crisp Rules Correspond to Model's Internal Logic

- Crisp rules predict article clicks
- Model has additional fine-grained logic
- Correlated rule and model ranking



The alignment and performance of extracted crisp rules

FNNs Learn Behavioral Rules

$$C_{\text{nationen}} \lor SC_{\text{german football}} \lor IV_{\text{low}} \lor \neg AA_{30m-1h} \lor \neg AA_{1d<}$$

Rules provide insight:

- Temporal dynamics (e.g., $\neg AA_{30m-1h} \lor \neg AA_{1d<}$)
- Important categories (e.g., $C_{\text{nationen}} \lor SC_{\text{german football}}$)

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Explained by LLM (Le Chat, on 08.01.2026):

“Users are more likely to click on articles that are either:
- About ”Nationen” or German football,
- Rarely recommended (so they feel ”fresh” or unique),
- Or not too new (older than 1 hour) or not too old (younger than 1 day).
This helps editors prioritize content that fits these patterns to boost engagement.”

Takeaways

- Accurate recommendations with behavioral insights

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- Control via regularization and extraction

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- Accurate recommendations with behavioral insights
- Control via regularization and extraction
- Can be complemented with human-defined rules
- Requires decent quality and quantity of features

Thanks for your attention!

Kevin Innerebner

Markus Reiter-Haas

https://aisocietylab.github.io/FNN4NewsRecommendation/

Stephan Bartl

Elisabeth Lex

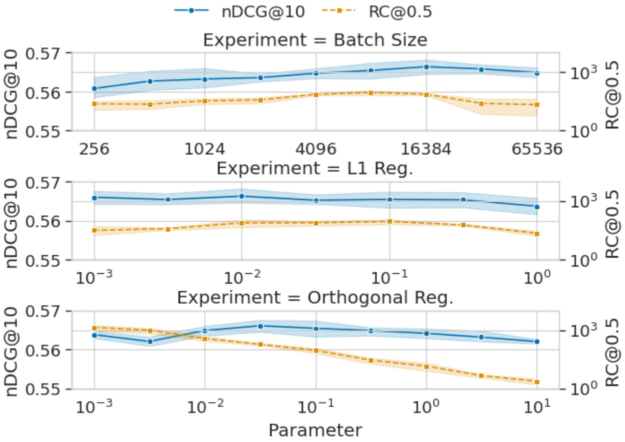
Contact: innerebner@tugraz.at

This research was funded in whole or in part by the Austrian Science Fund (FWF) 10.55776/COE12.

[1] Ragnhild Kristine Olsen, Mona Kristin Solvoll, and Knut-Arne Futsæter. "Gatekeepers as safekeepers—Mapping audiences' attitudes towards news media's editorial oversight functions during the COVID-19 crisis." In: Journalism and Media 3.1 (2022), pp. 182–197.

[2] Markus Schedl, Vito Walter Anelli, and Elisabeth Lex. Technical and Regulatory Perspectives on Information Retrieval and Recommender Systems: Fairness, Transparency, and Privacy. Vol. 50. Springer Nature, 2024.

Regularization Impact on Rule Complexity



Impact of regularization on rule complexity

Ablation Study Shows Robustness

Table: Mean metrics, using different components for our model. The star (*) marks significant ($\alpha = 0.05$) differences (paired Dunn's test w/ Bonferroni correction, w.r.t. FNN-and)

Experiment	AUC	MRR	nDCG@5	nDCG@10	RC@0.5
FNN-and (ours)	**.692**	<u>.457</u>	**.517**	<u>.565</u>	91.2
FNN-or (ours)	.689	.456	.514	.564	13.2
BCE → MSE Loss	<u>.691</u>	**.458**	**.517**	**.566**	33.8
w/o L1 Reg.	<u>.691</u>	.456	<u>.516</u>	.565	40.8
w/o Orthog. Reg.	.687	.453	.512	.562	2475.0
w/o Neg. Sampling	.680	.448	.504	.555	41.0
w/o Article Age	.600*	.374*	.418*	.491*	80.0
Tanh → Sigmoid	.523*	.310*	.343*	.429*	1.0*

FNNs Facilitate Behavioral Insights

Table: Extracted rules from the FNN-and output node.

Rule	Weight	Extracted Crisp Rule
R1	0.95	$C_{\text{side9}} \lor \neg AA_{1d<}$
R2	0.94	$C_{\text{side9}} \lor \neg AA_{30m-1h} \lor \neg AA_{1d<}$
R3	0.93	R2
R4	0.83	$\neg AA_{30m-1h} \lor AA_{2h-1d}$
R5	0.66	R4
R6	0.57	$C_{\text{nationen}} \lor SC_{\text{german football}} \lor IV_{\text{low}} \lor \neg AA_{30m-1h} \lor \neg AA_{1d<}$

AA_{time} . . . Article Age, C_{category} . . . Category, $SC_{\text{subcategory}}$ . . . Sub-Category, IV_{quantile} . . . In-View count

Mapping Features to Fuzzy Logic

$$\{0, 1\} \to [0, 1] \in \mathbb{R}$$

- Fuzzy logic extends crisp logic (i.e., "classical logic")
- Interpretable AND, OR and NOT operations

Product T-Norm

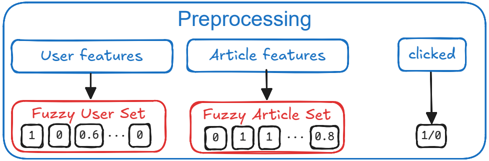
$$\begin{aligned} \mathrm{AND}(a, b) &= a \cdot b \\ \mathrm{OR}(a, b) &= a + b - (a \cdot b) \\ \mathrm{NOT}(a) &= 1 - a \end{aligned}$$

Product T-norm operations for fuzzy logic

Mapping Features to Fuzzy Logic

$$\{0, 1\} \to [0, 1] \in \mathbb{R}$$

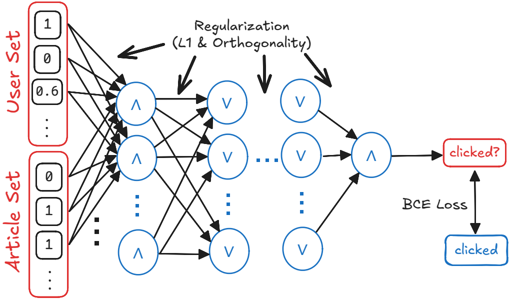
- Fuzzy logic extends crisp logic (i.e., "classical logic")
- Interpretable AND, OR and NOT operations
- How to use non-boolean data?
- Map input features to (fuzzy) atoms
    - Categorical: one-hot encoding
    - Multi-categorical: multi-hot enc.
    - Numerical: quantile binning
    - …



Preprocessing of features

Nested Fuzzy Rules through Logic Layers

- **OR-layers** and **AND-layers**
- Number of layers control nesting



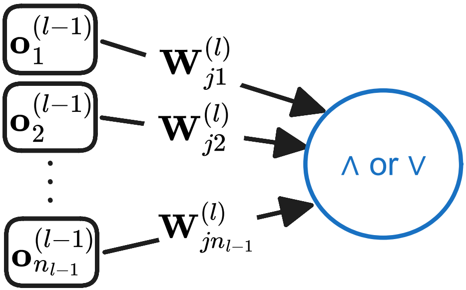
Model Architecture

[a] input=i, layer=l, node=j

Nested Fuzzy Rules through Logic Layers

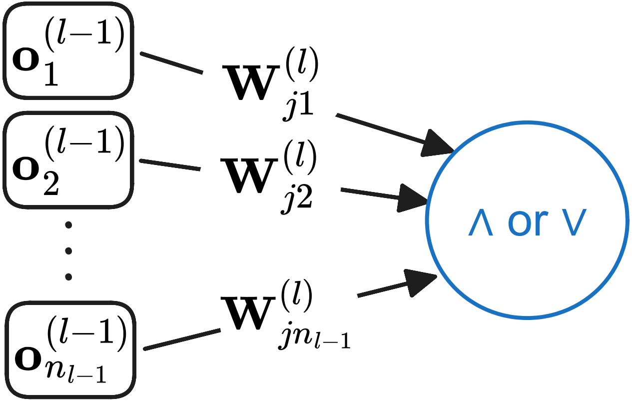
- **OR-layers** and **AND-layers**
- Number of layers control nesting
- Weighting with fuzzy logic[a]:
  - OR-layer: AND($\mathbf{o}'^{(l-1)}_i$, $\mathbf{W}^{(l)}_{ji}$)
  - AND-layer: OR($\mathbf{o}'^{(l-1)}_i$, $1 - \mathbf{W}^{(l)}_{ji}$)
- Negate for neg. weights: $\mathbf{o}'^{(l-1)}_i \coloneqq \text{NOT}(\mathbf{o}^{(l-1)}_i)$

[a] input=i, layer=l, node=j



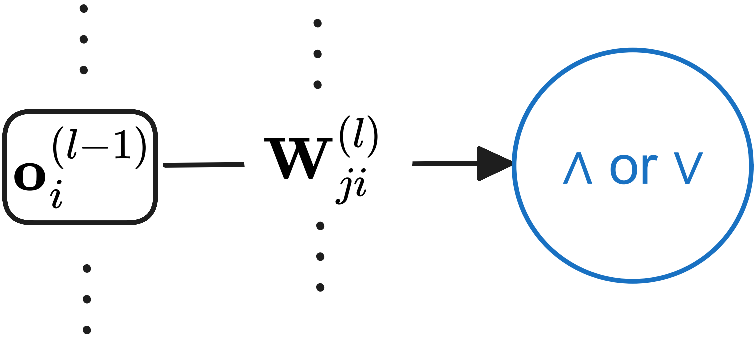
Logical Layer Node

Fuzzy Neural Networks Use Interpretable Logic Nodes



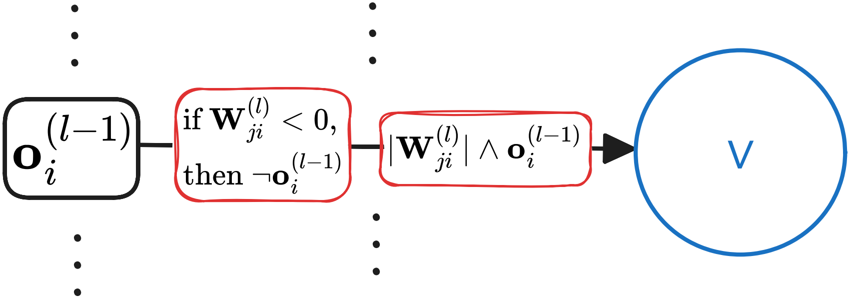
A visualization of a fuzzy logic node with multiple inputs depicted.

Fuzzy Neural Networks Use Interpretable Logic Nodes



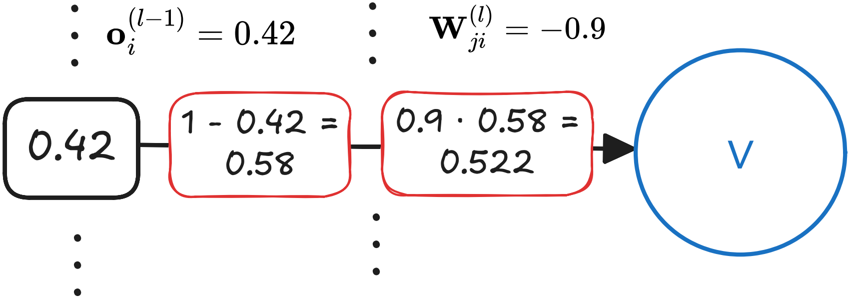
A visualization of a single fuzzy logic node.

Fuzzy Neural Networks Use Interpretable Logic Nodes



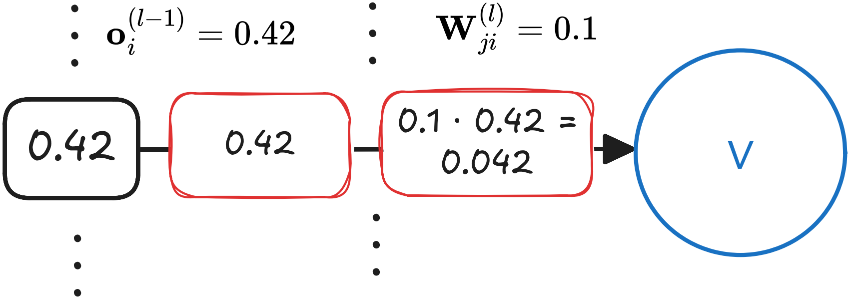
A visualization of a fuzzy OR logic node with the formulas for the weighting computation.

Fuzzy Neural Networks Use Interpretable Logic Nodes



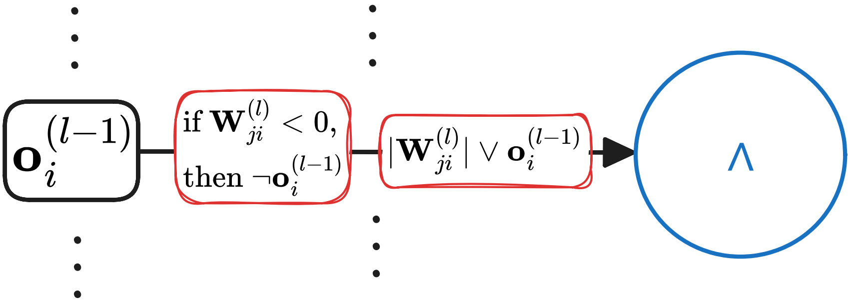
A visualization of a fuzzy OR logic node, weighted by a high negative weight.

Fuzzy Neural Networks Use Interpretable Logic Nodes



A visualization of a fuzzy OR logic node, weighted by a low positive weight.

Fuzzy Neural Networks Use Interpretable Logic Nodes



A visualization of a fuzzy AND logic node.