

# Information Fusion for Classification of Network Devices

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## Motivation

An important aspect of network monitoring is to keep track of devices connected into the monitored network. For this purpose, various methods of automatic asset discovery and classification are being used. Therefore, deploying multiple methods and combining their results is usually needed — but this is a non-trivial task. We present a two-layer data fusion approach that can effectively fuse multiple heterogeneous and unreliable sources of information about a network device to classify it. The solution is based on a combination of expert-written conditions, machine learning from small amounts of data, and the Dempster-Shafer theory of evidence. Experiments show that our method is on par with the best ML-based methods in classification accuracy but with the advantage of better interpretability and robustness against some types of input data imprecisions that can occur in practice.

## Solution overview



Figure 1: Solution showcase

- Solution showcase on specific use case of the **ADICT project**
  - ADICT is focused on development of new passive monitoring methods
- **Goal:** Fusion of all available device data
- Input:** Attributes from **various classifiers** and monitoring methods
- **Diverse input data:** different types, formats, levels of detail
- Output:** Fused classification for given entity
- Classified aspects: **operating system, device type**

### Key features

- Fusion method **robust against missing inputs**
- Solution **maintains level of detail** of individual sources
- **Configurability;** Open to new data sources
- Leads to significant **improvement in output accuracy** (compared to individual data sources)
- **Interpretable,** explainable

## Information Fusion Model

- **Diverse data sources** require **data normalization**
- **Condition layer** — expert defined **conditions** used to normalize attributes to a **binary vector**.
- **Expert knowledge is not enough;** Determining condition output directly gives bad results - only select relevant attribute values

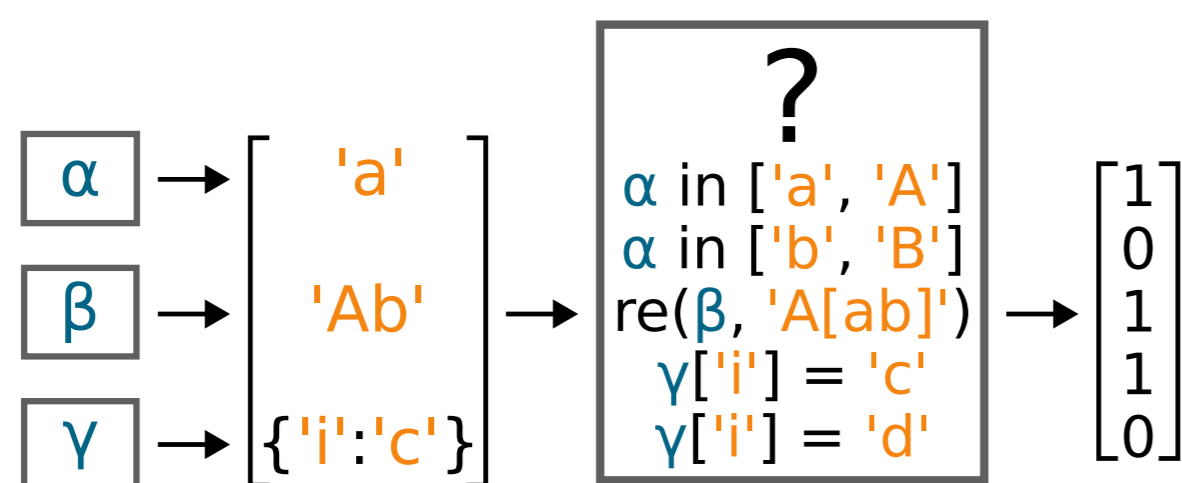


Figure 2: Condition layer transformation. Values from data sources  $\alpha$ ,  $\beta$  and  $\gamma$  are transformed into a vector encoding all relevant information the values contain.

- **Combination layer** — outputs the most probable class
- Any **interpretable classifier** can be used

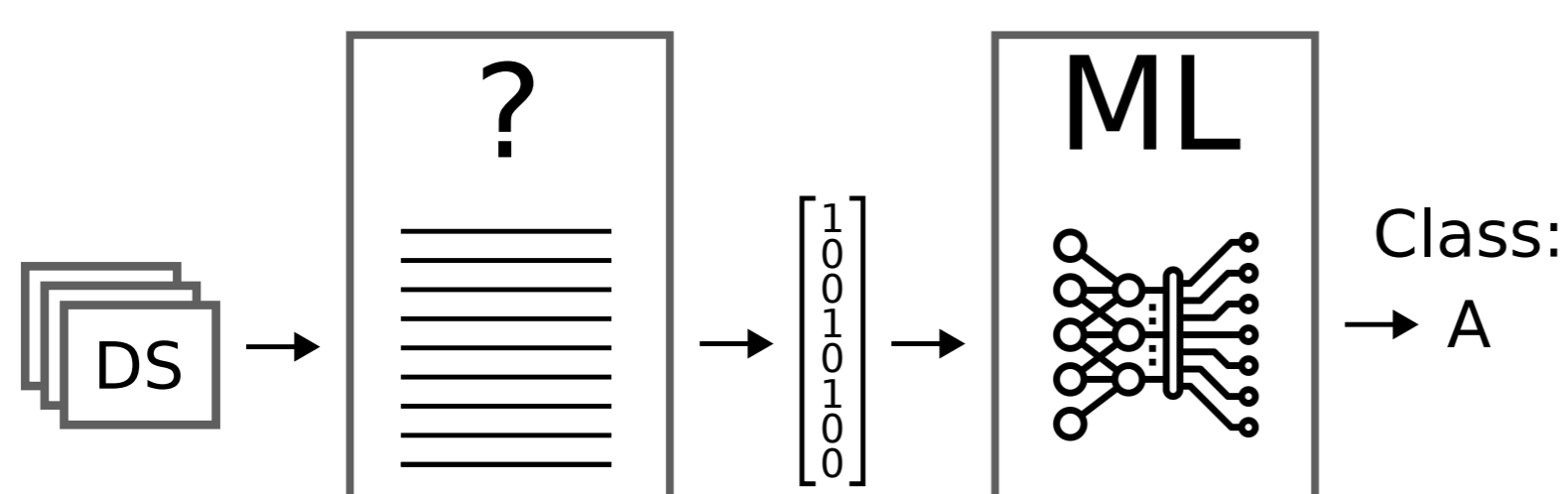


Figure 3: Proposed information fusion model. Values from an arbitrary number of data sources are first transformed by the condition layer. The combination layer determines the output class.

**Tested classifier acronyms:** **ORA:** Oracle, **D-S:** Dempster-Shafer, **DSGD:** Dempster-Shafer Gradient Descent, **AB:** AdaBoost, **WMV:** Weighted Majority Voting, **RF:** Random Forest, **DT:** Decision Tree

## Evaluation

- **Real network dataset:** 5532 samples (classifiable sessions) of 674 unique IP addresses, collected over 93 days
- Tested **various interpretable classifiers**

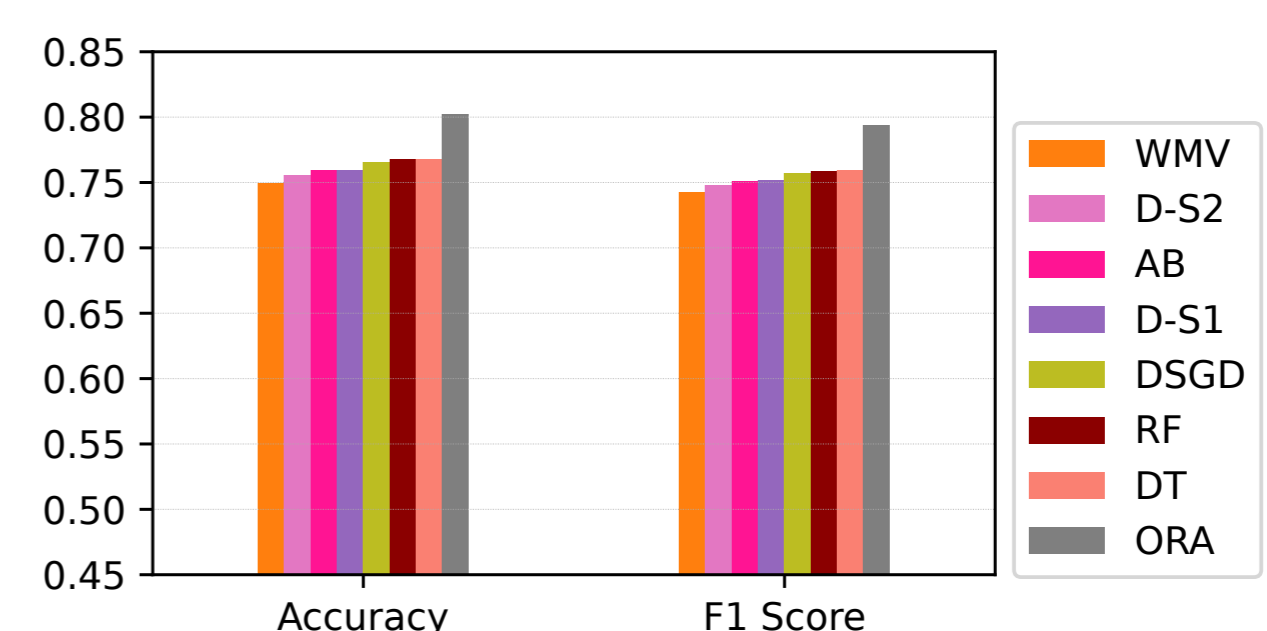


Figure 4: Fusion methods accuracy and F1-Score.

- **Little data source overlap** in real dataset — one possible scenario
- Testing under **different conditions:** series of generated datasets
  - Influence of **number of sources, variability, source faults**

ORA	0.967	0.938	0.920	0.949
D-S1	0.876	0.806	0.799	0.840
DSGD	0.869	0.800	0.783	0.838
D-S2	0.877	0.783	0.761	0.836
AB	0.870	0.793	0.781	0.833
WMV	0.876	0.782	0.762	0.832
RF	0.865	0.782	0.771	0.827
DT	0.821	0.734	0.689	0.776
	Uniform	Variable	Faults	Random

Figure 5: Individual method scores. Averaged over all experiment categories