

Exploiting Temporal Relations of Events for Classification Tasks – Proof of Concept Study with Synthetic Data Sets



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Introduction

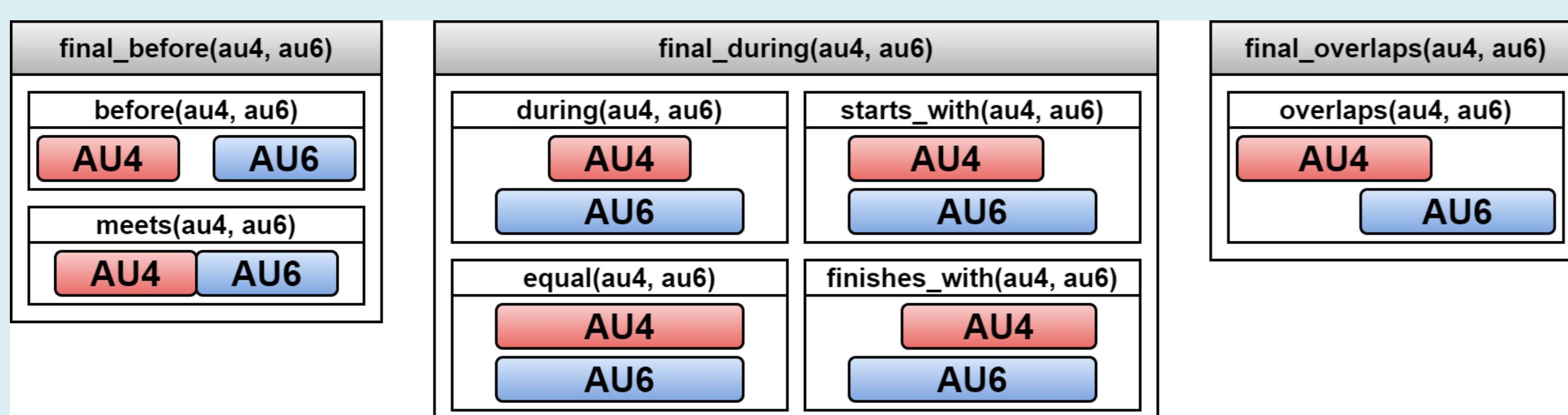
- Facial expressions represented as sets of Action Units (AUs) describing facial muscle movements (Ekman & Friesen 2016) can be indicative of emotions and other internal states like pain (Siebers et al. 2016).
- Representing AU sets as not only points in time but intervals with temporal relations according to the Allen calculus for temporal reasoning (Allen 1981) is expected to increase the diagnostic accuracy (Kunz & Lautenbacher 2014).
- The ILP system Aleph (Srinivasan 2001) is applied to artificial sequences with and without underlying temporal patterns of varying complexity, expecting to recover the original patterns used for the sequence creation.

Applying Aleph to the Sequences

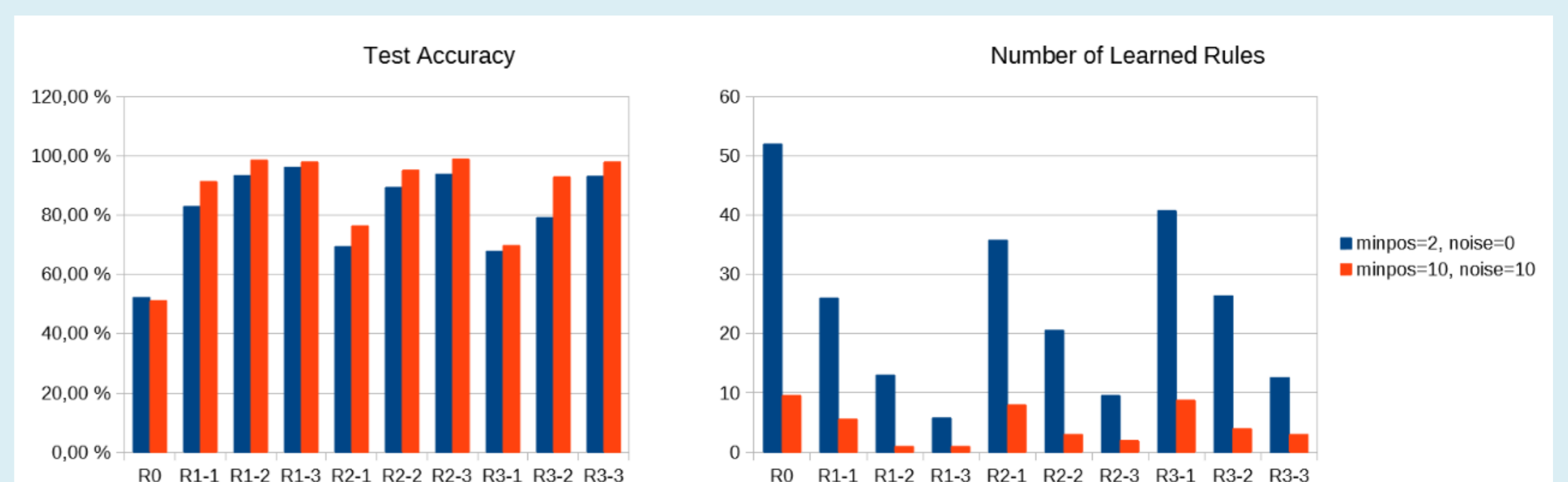
- The output for every rule set is used as input for learning a theory with Aleph, once with the Aleph parameter settings $\text{minpos}=2$, $\text{noise}=0$ and once with $\text{minpos}=10$, $\text{noise}=10$.

Creating Artificial Sequences

- For every artificial sequence, the same 6 AUs are created as intervals with randomly chosen start and end points within given boundaries derived from real-world AU data sets.
- Positive instances of the target class have to satisfy rules that consist of one or more randomly chosen temporal relations between two AUs. The relations from the Allen calculus that are used for sequence creation and as candidate literals for learning with Aleph are simplified as shown in this example:



- The complexity of the underlying rule sets varies from R0 (no rules) to R3-3 (3 rules consisting of 3 relations); for each set except R0, every positive example is created according to one rule out of the set (evenly distributed for multiple rules).
- For each set, 500 sequences are created (200 positive & 200 negative training + 50 positive & 50 negative test examples).



- Data sets without underlying temporal regularities lead to the lowest test accuracy and the highest number of learned rules.
- An increasing complexity (number of relations) of the rules leads to higher accuracy values and fewer learned rules.
- An increasing number of underlying rules corresponds with lower accuracy values and a higher number of learned rules.
- In most cases, higher values for minpos and noise increase the test accuracy while fewer rules are learned.
- Learned rules resemble the original sets used for sequence creation but include noise in order to prevent false positives.
- Allowing a certain number of false positives leads to theories that recover the original rule sets more accurately.

Conclusion

- Aleph seems to be a valid approach for exploiting temporal relations when represented using an interval-based algebra.
- Future work will integrate additional information from use cases dealing with medical diagnoses, like the facial region where an AU occurs, or personal information like age, sex or medical history.

References:

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 Srinivasan, A.: The Aleph manual (2001).