Demystifying Relational Latent Representations

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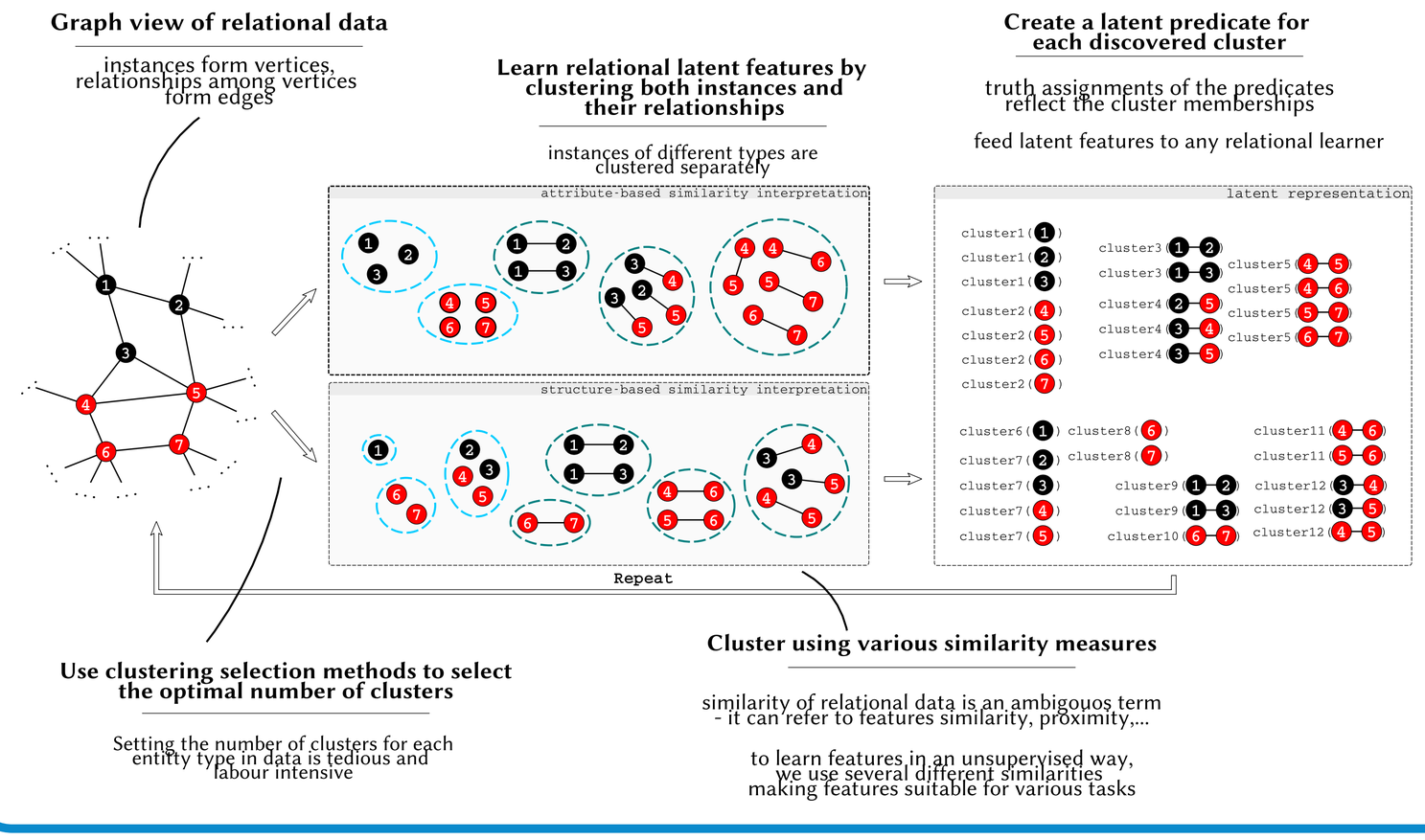
Problem

Bridging advantages of *statistical relational* and *deep learning* started to receive significant attention. Recently, Dumancic & Blockeel introduced CUR^{2}LED - an approach that learns relational latent features by means of clustering and variety of similarity measures, which often increases the performance and reduces complexity of relational learners.

In this work we investigate:

1. *are these features interpretable?*
2. *what makes them effective?*

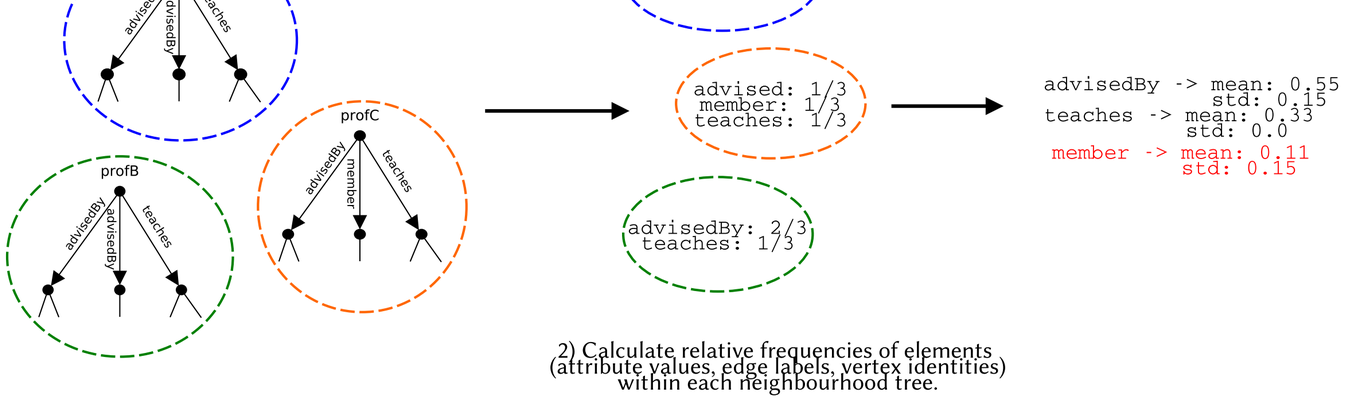
Learning relational latent features



Finding the meaning of latent features

1) Latent features are clusters of neighbourhood trees which represent instances/examples. Edges are treated as ordered sets of neighbourhood trees.

The similarity between neighbourhood trees is defined by similarity, interpretation which defines which constructs can be used in a definition (≈ language bias)



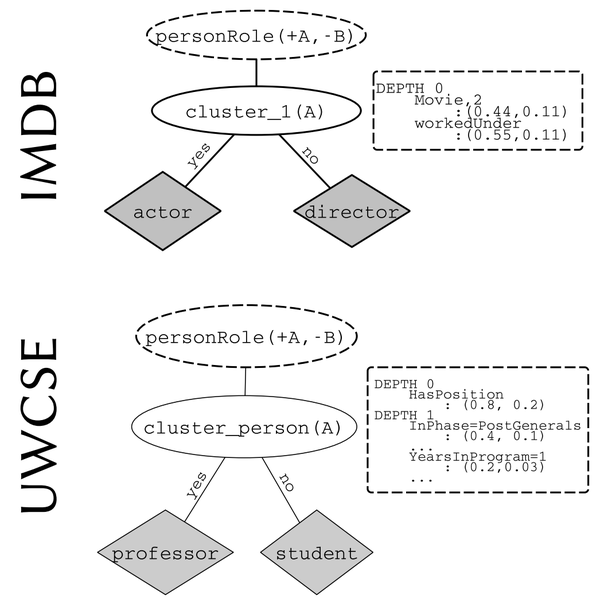
2) Calculate relative frequencies of elements (attribute values, edge labels, vertex identities) within each neighbourhood tree.

3) Summarize the relative frequencies of unique elements across neighbourhood trees in a cluster, with its mean and standard deviation.

Select relevant elements by imposing a bound on the amount of deviation.

Meaning of a latent feature = prototypical neighbourhood tree

Examples



The meaning of latent features cannot be written as a logical formula, but is interpretable

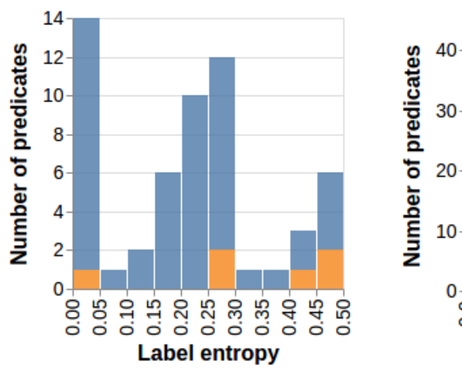
Why are these features effective?

Properties of latent spaces:

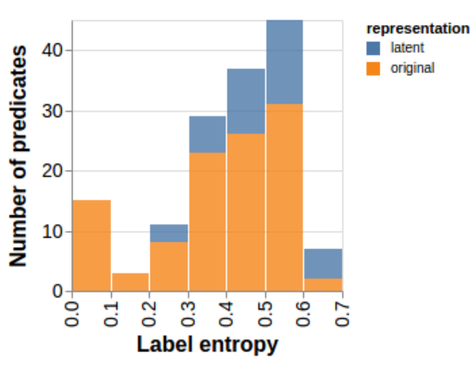
1) label entropy - distribution of labels within predicate's true instantiations

2) sparsity - distribution of labels within true instantiations of predicates

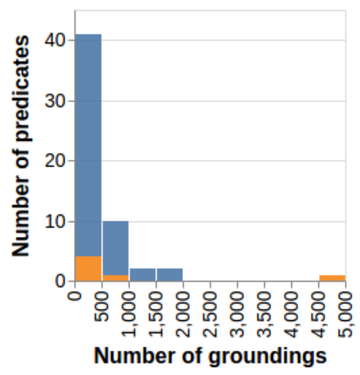
→ both serve as proxy to quantification of learning difficulty



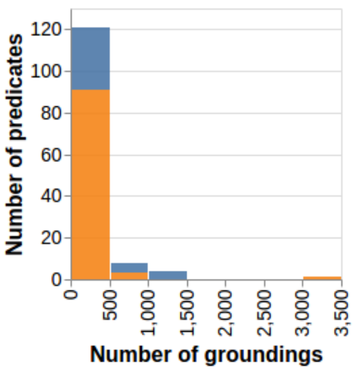
improved results (3) when performance increases, latent representation has many predicates of low label entropy



no improvement



improved results (3) when performance increases, latent representation is sparser than the original one



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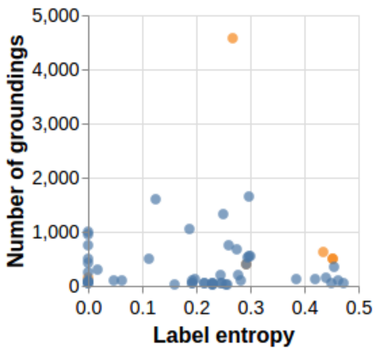
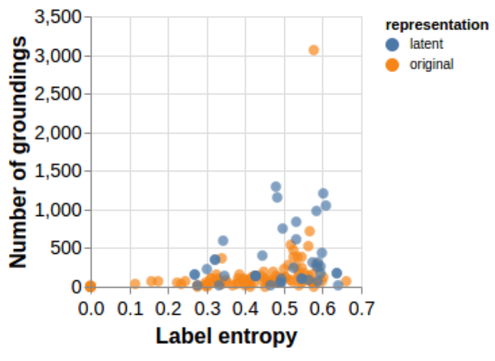
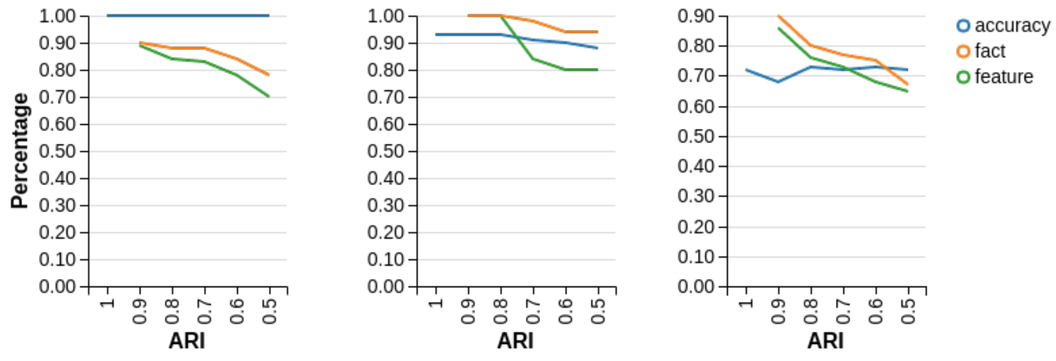


improved results (3)



no improvement

latent features successfully identify local regions in the instance space that match well with the provided labels



checking for overlapping clustering and rejecting them, reduces the number of features and facts up to 30 % without affecting the performance