

CLUSTERING-BASED UNSUPERVISED RELATIONAL REPRESENTATION LEARNING WITH AN EXPLICIT DISTRIBUTED REPRESENTATION



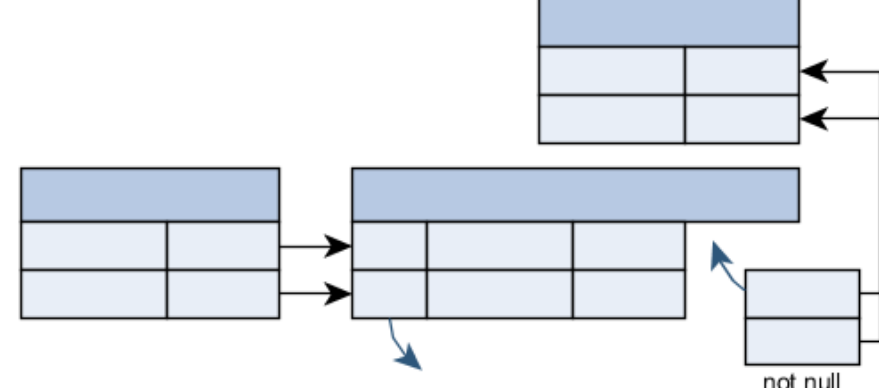
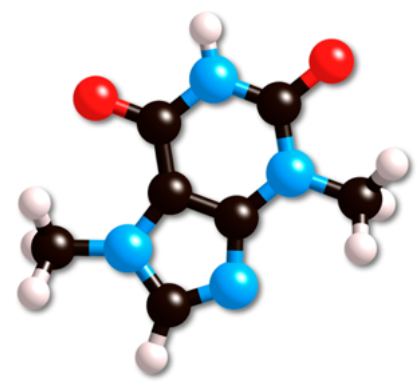
{SEBASTIJAN.DUMANCIC AND HENDRIK.BLOCKEEL }@CS.KULEUVEN.BE

KU LEUVEN

PROBLEM

Deep learning revolutionized machine learning by automatically learning multiple layers of **abstract, re-usable** and **compositional** features for a given task. Despite huge interest, it still heavily focuses on *sensory* data such as images and speech – here we focus on **learning latent features of rich relational data formats** such as *graphs* and *relational databases*!

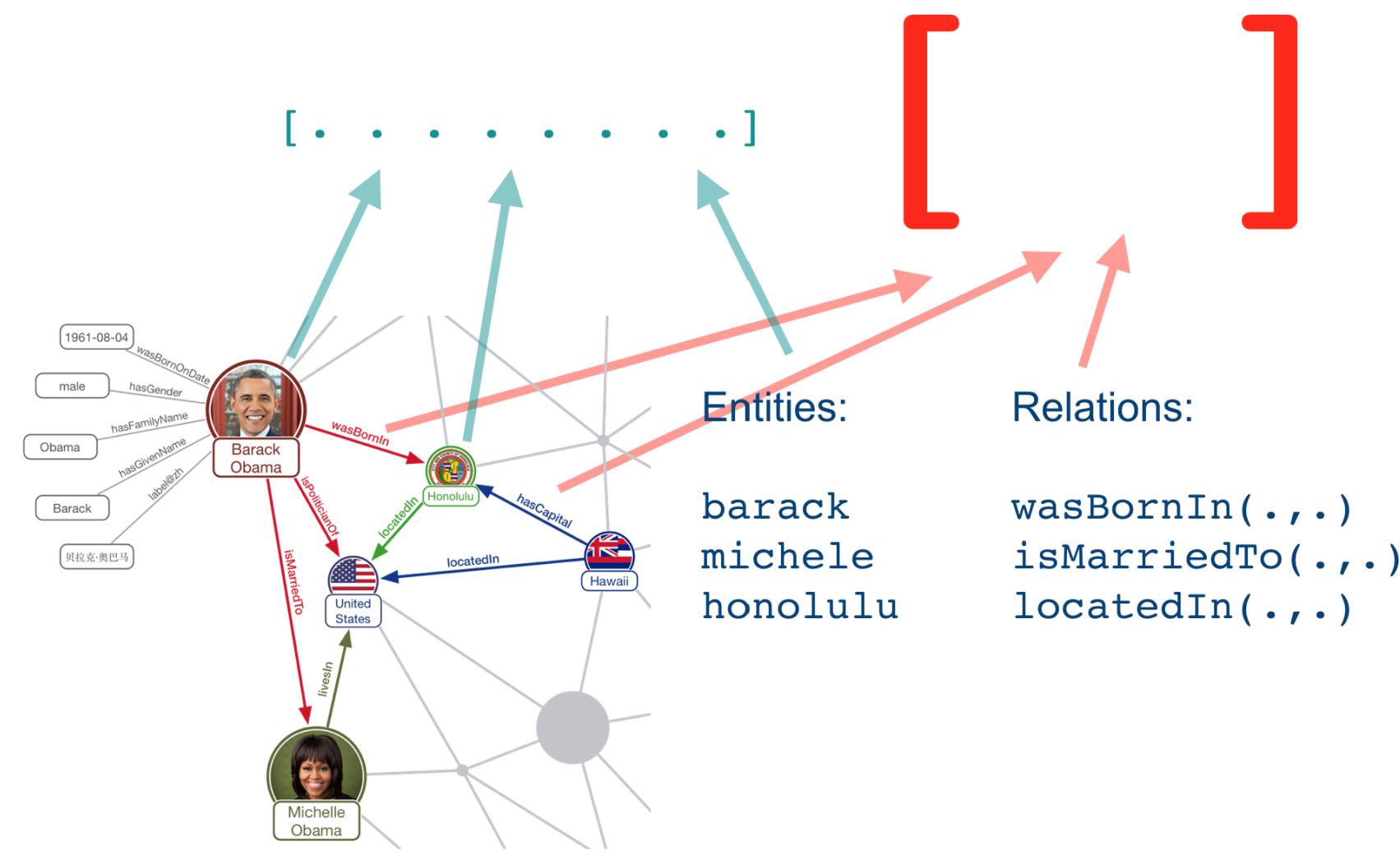
Relational data contains both instances and relationships amongst them



CURRENT STATE OF AFFAIRS

Vectors spaces in knowledge graphs: Replace symbols with vectors, and logic with algebra

Learning representation = learning vector representation on entities, and matrices/functions for relations



A good vector representation is the one that, given a **true** fact `wasBornIn(barack, honolulu)`, results in a high value of the vector-matrix multiplication of the corresponding entities

$$[\text{barack}] \begin{bmatrix} \text{wasBornIn} \end{bmatrix} [\text{honolulu}]^T \approx 1$$

and a *low* value for the *false* example., e.g. `wasBornIn(barack, nairobi)`

Problems: uninterpretable latent features, need big amounts of data, difficult to handle unseen entities, does not integrate in existing relational learners

GOAL

Develop an *relational* representation learning method that is:

- **relational** – considers both instances and their relationships
- **unsupervised** – no labels provided
- **interpretable** – latent features defined in logic
- integrates with existing relational learners

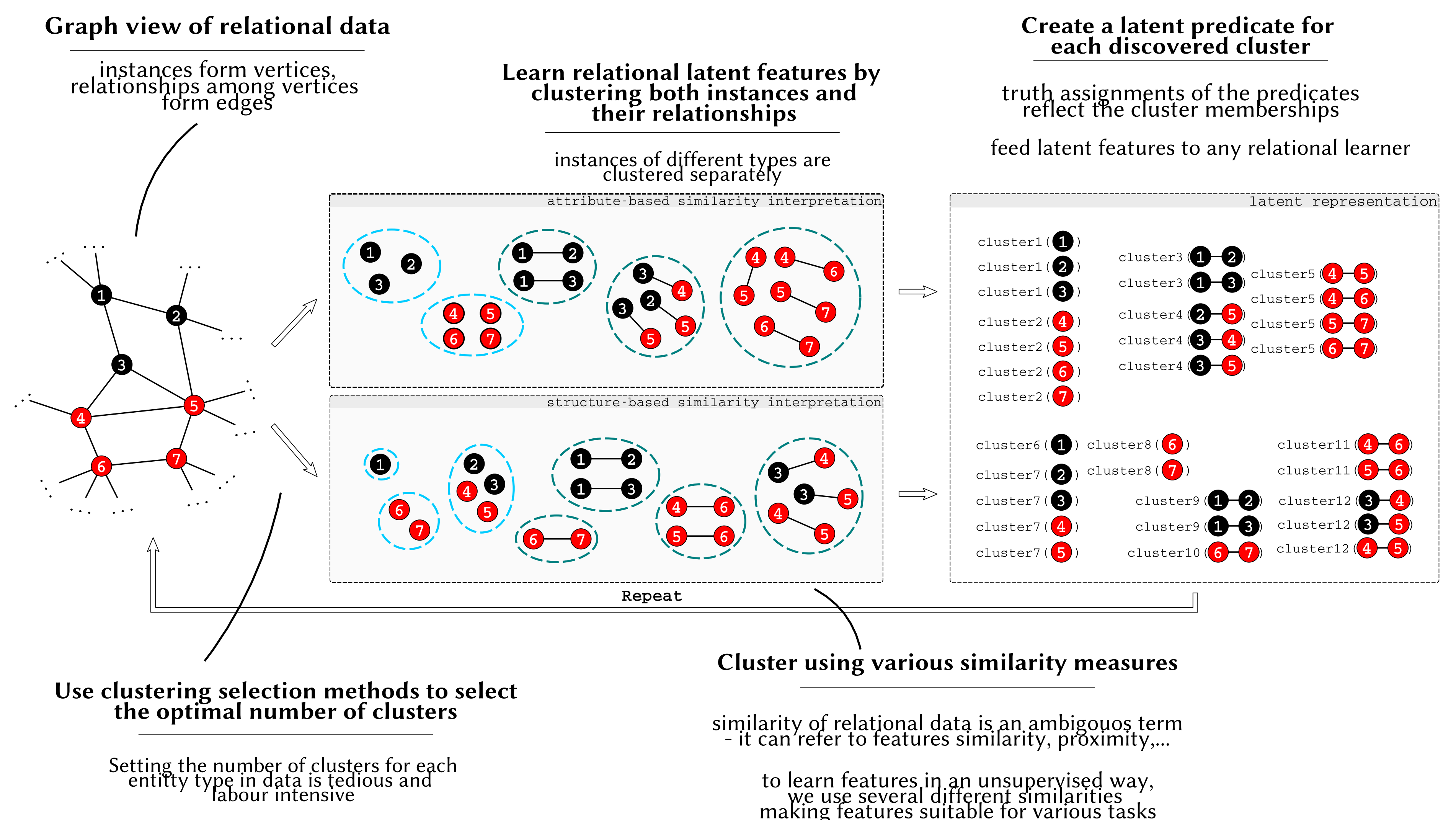
Statistical relational models

```
0.3::stress(X) :- person(X).
0.4::asthma(X) :- smokes(X).
smokes(X) :- stress(X).
smokes(X) :- friend(X,Y).
```

```
person(angelika).
person(joris).
person(jonas).
friend(joris,jonas).
friend(joris,angelika).
```

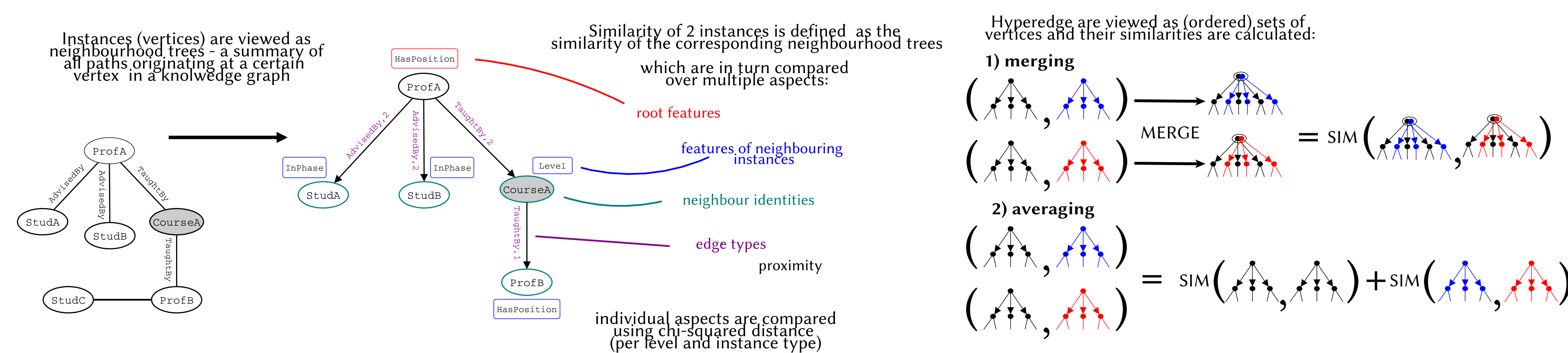
LEARNING RELATIONAL LATENT FEATURES WITH CLUSTERING

The proposed pipeline is inspired by the *k-means feature learning pipeline* [Coates and NG, 2001]

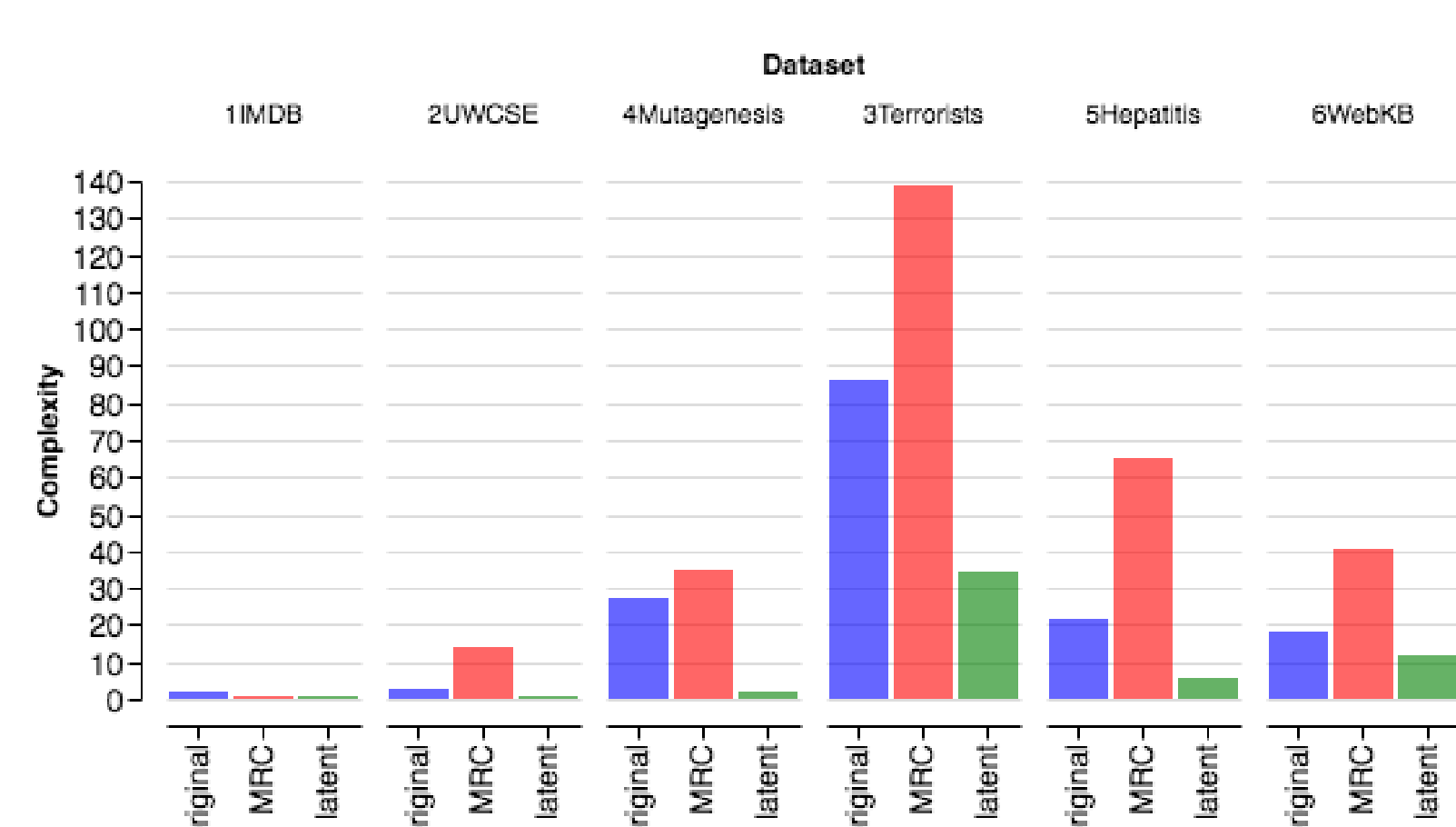


SIMILARITY OF RELATIONAL DATA

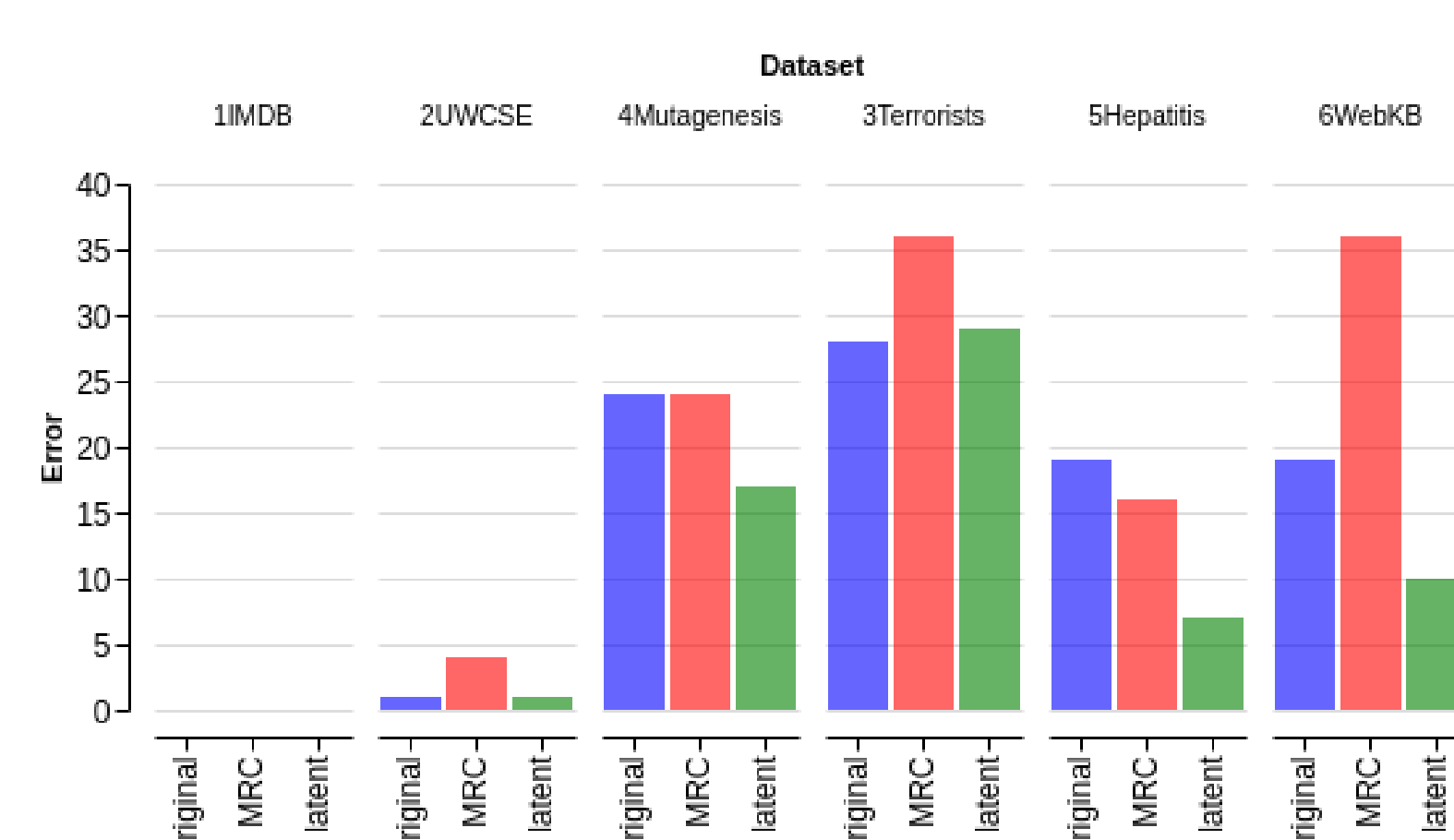
Similarity of instances and their relationships is assessed with ReCeNT [Dumancic & Blockeel, MLJ 2017]



RESULTS



TILDE models learned on latent representations are less complex in terms of the number of nodes in a tree



TILDE models learned on latent representations often perform better (MRC = related approach)

EXPERIMENTS

Question: Does learning from latent spaces benefit relational learners compared to learning in the original space?

- lower model complexity
- improved performance

Setup

- learn features on training set; map test data to learned clusters (cross validation)
- learn relational decision tree TILDE on original and latent representations

REFERENCES

- Coates, A., Lee, H. & Ng, A.: *An analysis of single-layer networks in unsupervised feature learning*, AISTATS 2011
- Dumancic, S., & Blockeel, H.: *An expressive dissimilarity measure for relational clustering using neighbourhood trees*, MLJ, to appear
- Blockeel, H., & De Raedt, L.: *Top-down induction of first-order logical decision trees*, Artif. Intell. 1998
- Kok, S., & Domingos, P.: *Statistical predicate invention*, ICML 2007

CODE:

dtai.cs.kuleuven.be/software/curlcd