

Model-based Exception Mining for Relational Data

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Exception Mining Task

- Identify exceptional individuals whose statistical patterns deviate from the general population
- Can also be used for outlier/ anomaly detection
- Our approach: apply the Exceptional Model Mining framework (EMM) to multi-relational data (Duivesteijn, W.; Feelders, A. J. & Knobbe, A. 2016.)

Highlights

- Leverage: Framework applies to any relational learning method
- Ranking: Provides single score for individual entities
- •Interpretability: Scores can be explained by statistical differences in local feature distributions

Other Approaches

- Association Rules, e.g. Maervoet, J.; Vens, C.; Vanden Berghe, G.; Blockeel, H. & De Causmaecker, P. (2012), 'Outlier Detection in Relational Data: A Case Study in Geographical Information Systems', Expert Systems With Applications **39**(5), 4718--4728.
- Clustering, e.g.

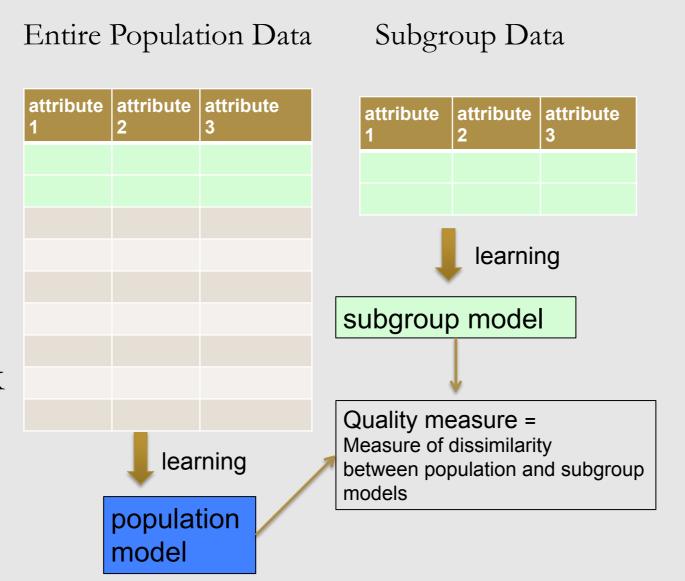
Sun, Y.; Han, J.; Zhao, P.; Yin, Z.; Cheng, H. & Wu, T. (2013), Community Distribution Outlier **Detection in Heterogeneous Information** Networks., in 'ECML/PKDD', pp. 557-573.

Extracting network features, e.g. ODDBALL

Akoglu, L.; Mcglohon, M. & Faloutsos, C. (2010), OddBall: Spotting Anomalies in Weighted Graphs, in 'PAKDD', pp. 410-421.

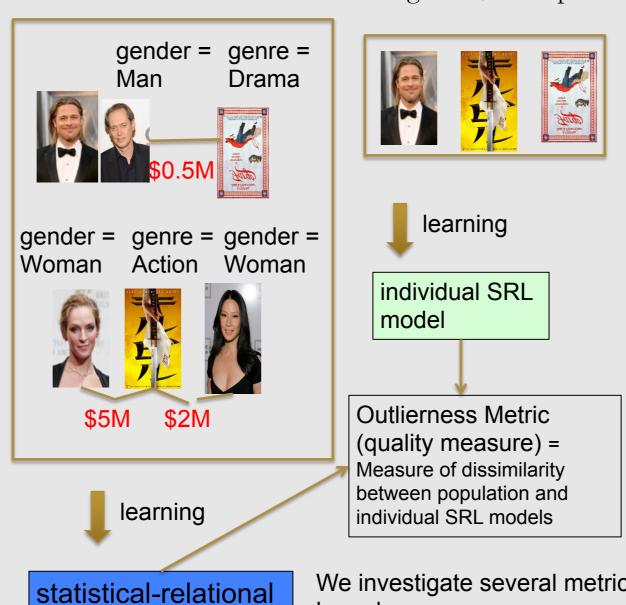
• Propositionalization, e.g. Riahi, F. & Schulte, O. (2016), Propositionalization for Unsupervised Outlier Detection in Multi-Relational Data, in 'FLAIRS', 448-453

EMM for I.I.D. Data



EMM for Relational Data

Entire Observed Network Individual Subnetwork aka "egnoet"/"interpretation"



population model

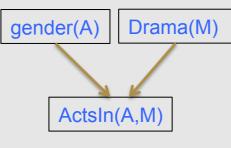
We investigate several metrics based on log-linear likelihood functions

Example

population model B_{p0} for random actor A

individual model B_o for A = Brad Pitt

gender(brad_p)



Gender Drama CP

| L | ActsIn(brad | d_p,M) | |
|---|-------------|--------------|-------------------------|
| | | Drama (M) | CP ActsIr (B.P.,N |

Drama(M)

| (A) | (M) | ActsIn (A,M) |
|-----|-----|-----------------|
| М | Т | 1/2 |
| M | F | 0 |
| W | Т | 0 |
| W | F | 1 |

| Gender (B.P.) | Drama (M) | CP ActsIn (B.P.,M) |
|------------------|--------------|--------------------------|
| M | Т | 0 |
| M | F | 0 |

Outlierness Metrics

- Starting point is KLD between population and individual model
- Promising novel variant ELD= mutual information decomposition + absolute values to avoid cancellations

$$KLD(B_o \parallel B_p) = \sum_{\text{nodes } i \text{ values } k} \sum_{\text{parent-state } j} P_{B_o}(X_i = x_{ik}, Pa(X_i) = pa_j) \times \ln(\frac{P_{B_o}(X_i = x_{ik} \mid Pa(X_i) = pa_j)}{P_{B_p}(X_i = x_{ik} \mid Pa(X_i) = pa_j)})$$

summation over local features

log-difference in empirical conditional probabilities (confidences)

B_p models the population network

B_o models the individual network

Evaluation

AUC for detecting ground-truth outliers (e.g. Goalies injected into set of Strikers)

| Dataset | ELD | KLD |
|-----------------|------|------|
| PL: Strikers | 0.89 | 0.65 |
| PL: Midfielders | 0.66 | 0.55 |
| IMDb: Drama | 0.70 | 0.66 |

Case Studies

For each individual, drill down on the aggregate outlierness score to find

- 1. most unusual feature
- 2. most unusual feature value.

| | | | | | Individual | Group |
|------------|---------|------|-----------------------|------------|-------------|-------------|
| Individual | Group | Rank | Max Node | Max Value | Probability | Probability |
| Edin Dzeko | Striker | | Dribble Efficiency | DE = Low | 0.16 | 0.5 |
| Paul | | | Saves | SM = | | |
| Robinson | Goalie | 2 | Made | Medium | 0.3 | 0.04 |
| Brave | | | Actor | a_quality= | | |
| Heart | Drama | 1 | Quality | 4 | 0.93 | 0.42 |
| Austin | | | Cast | cast_num | | |
| Powers | Comedy | 2 | position | =3 | 0.78 | 0.49 |

Conclusion and Future Work

- •Exceptional Model Mining: New approach for applying SRL models to relational exception mining
- •New log-linear outlierness metric
- •New Model and new metric showed promising results on Soccer and IMDB datasets.
- •Future work:
- 1) explore other SRL models (e.g. Markov Logic Networks) 2) incorporate difference in model structure as well as parameters

Datasets

- •Soccer Data: The Opta dataset released by Manchester City.
- •IMDB Data: From The Internet Movie Database.
- •For synthetic data please see paper

References

Duivesteijn, W.; Feelders, A. J. & Knobbe, A. (2016), 'Exceptional model mining', Data Mining and Knowledge Discovery 30(1), 47--98.

Tutorial on Learning Bayesian Networks for Complex Relational Data, Schulte and Kirkpatrick 2017, https://oschulte.github.io/srl-tutorial-slides/