Identifying Important Nodes in Heterogeneous Networks

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Abstract

This is a position paper that presents a new approach to identifying important nodes or entities in a complex heterogeneous network. We provide a novel definition of an importance score based on a statistical model: An individual is important to the extent that including an individual explicitly in the model improves the data fit of the model more than it increases the model’s complexity. We apply techniques from statistical-relational learning, a recent field that combines AI and machine learning, to identify statistically important individuals in a scalable manner. We investigate empirically our approach with the OPTA soccer data set for the English premier league.

Introduction

We present a new approach, based on a statistical model, to identifying important individuals in a complex network. Many, if not most, new datasets contain information about networks whose nodes are linked entities. Identifying important individuals in a network is an important task for network analysis. Our new statistical approach is as follows. First, we learn a baseline generic statistical model that describes the dependencies among link types and node features in the network. The generic model refers only to classes of individuals, not to any individual in particular. While adding an individual to the model increases the expressive power of the model, it also increases the number of model parameters and hence the model complexity. A standard statistical model selection score quantifies the trade-off between data fit and model complexity. The importance score of an individual is the improvement in the model selection score that results from introducing the individual into the model. For typical statistical scores (e.g., BIC, AIC), the score improvement can be interpreted in minimum description length terms: whereas adding the individual to the model requires extra bits for specifying the new parameter values, it saves bits by fitting the data more closely. Our model class in this paper is Bayes nets, and the statistical score is the Bayes Information criterion (BIC).

Compared to other approaches for ranking individuals in a network, our statistical approach has several advantages. 1) If the statistical score can be evaluated quickly, as is the case with BIC, computing the score improvement associated with an individual is fast. 2) The importance metric is derived from a general metric of predictive power. Because importance is tied to correlations and probabilistic predictions, the metric provides an explanation of the ranking. 3) Most previous work assumes a homogeneous network with only one type of node and link (e.g., social network, Twitter, web-pages) (Chen et al. 2009). We use models from statistical-relational learning that apply generally to networks with any number of node link types. 4) The statistical score provides a discrete decision as to whether the individual is important or not (score improvement > 0), in addition to ranking. This does not require specifying a k-value for selecting the top-k individuals.

We present a preliminary investigation of our approach on premier league soccer data. Here a player is statistically important to the extent that introducing them into a model increases the quality of predicting their team’s results and other features of teams and matches.

Related Work

In a Bayesian network model, single-table features correspond to nodes (e.g., age, gender). These feature nodes should not be confused with nodes in the data network that represent individuals (e.g., Silva, Chelsea) (Neville and Jensen 2007). For single-table data, there has been much work on selecting, fusing, ranking, and scoring features. The majority of this work applies to explicitly listed features (e.g., column headers) that are shared between independent individuals. Single-table feature selection is different from the problem we address: 1) We describe a method for introducing new features that are not explicitly listed in the data. These new features are of a special type, intuitively “being related to special individual x”. 2) In our definition, the importance of an individual x is based on how much being linked to x explains the features of other individuals. Thus our scoring method is designed to take into account the interdependence of linked individuals that is the defining aspect of relational data.

The task of identifying important individuals was studied in many contexts such as sparse data university environments (Balog et al. 2007) and for bibliographic data and digital libraries (Deng, King, and Lyu 2008)(Zhou et
2. Apply Bayes net learning to (1) input database \( D \)

1. Learn a generic model \( B \) is restricted to the single member database schema; they can also be chosen by the user. For extracting a default set of functor nodes from a relational database \( D \) algorithm (Schulte and Khosravi 2012) takes as input (1) a relational database \( D \) representing a network, (2) a set of functor nodes, and produces a Bayes net for the functor nodes. The learn-and-join algorithm includes a method for extracting a default set of functor nodes from a relational database schema; they can also be chosen by the user.

We use Poole’s Parametrized Bayes nets that are defined as follows. The relational structure contains a list of populations \( \mathcal{P}_1, \ldots, \mathcal{P}_k \), such as player, teams, matches. Population variables such as Player, Team1, Team2, Match are associated with a unique population. A functor is a predicate or function. A functor node is of the form \( f(\sigma_1, \ldots, \sigma_n) \) where each \( \sigma_i \) is a constant or variable of the appropriate population. A Parametrized Bayes net is a Bayes net whose nodes are functor nodes. The state-of-the-art learn-and-join algorithm (Schulte and Khosravi 2012) takes as input (1) a relational database \( D \) representing a network, (2) a set of functor nodes, and produces a Bayes net for the functor nodes. The learn-and-join algorithm includes a method for extracting a default set of functor nodes from a relational database schema; they can also be chosen by the user.

The user chooses a statistical score \( \text{score}(B, D) \) that scores a Parametrized Bayes net \( B \) for a database \( D \). In our experiments, we used the relational Bayes Information Criterion (BIC) (Schulte 2011; Alsanie and Cussens 2012). We evaluate the score improvement due to a target individual \( t \) as follows. Let \( t \) be a constant denoting an individual that instantiates population variable \( X \), with associated population \( \mathcal{P} \). Let \( D_t^+ \) be the database where the population of \( X \) is restricted to the single member \( t \). Let \( D_t^- \) be the database where \( t \) is removed from the population of \( X \).

1. Learn a generic model \( B_D \) for the entire database.
2. Apply Bayes net learning to (1) input database \( D_t^+ \), and (2) the functor nodes that have \( X \) replaced by \( t \). Call the result \( B_t \).
3. The score improvement is given by

\[
\frac{1}{|\mathcal{P}|} \text{score}(B_t, D_t^+) + \frac{|\mathcal{P}|-1}{|\mathcal{P}|} \text{score}(B_D, D_t^-) - \text{score}(B_D, D).
\]

The score improvement formula can be interpreted as follows. Suppose that we randomly select a member \( x \) of the population \( X \). There are two cases: 1) \( x = t \) is the target individual. In that case we use the score for the target’s model \( B_t \) applied to the data describing the target and its links, which is represented by \( D_t^+ \). 2) \( x \neq t \) is different from the target individual. In that case we use the score for the generic model \( B_D \) applied to the data describing the population without \( t \), which is represented by \( D_t^- \). The first case occurs with probability \( 1/|\mathcal{P}| \) and the second with probability \( (|\mathcal{P}|-1)/|\mathcal{P}| \). Therefore the expected score using the individual as well as the generic model is

\[
\frac{1}{|\mathcal{P}|} \text{score}(B_t, D_t^+) + \frac{|\mathcal{P}|-1}{|\mathcal{P}|} \text{score}(B_D, D_t^-).
\]

The score improvement formula compares the score for the two models to the score for using only the generic model for all individuals, which is given by \( \text{score}(B_D, D) \).

Complexity. Typical statistical scores such as BIC can be computed in closed-form given the sufficient statistics. In the case of Bayes nets these are the counts of conjunctive states, which can be described by conjunctive queries. The complexity of evaluating scores is therefore essentially the complexity of computing the frequency of conjunctive queries in a database. Most Bayes net learners follow a score-based approach where candidate models are repeatedly evaluated by applying the score. The cost of applying the score once to evaluate the score improvement is therefore dominated by the cost of learning the Bayes net models. Current state-of-the-art Bayes net learners for relational data scale well to databases with table sizes on the order of \( 10^5 \) (Schulte and Khosravi 2012); extending the scope of scalable relational Bayes net learning is an active research area.

Examples. To build specific models for important players, in the Bayes net of Figure 1(c), we can replace the variable Player by Player = Nasri (b). The database \( D_t^+ \) contains only rows where team = ManchesterCity (MC) and player = Nasri. The database \( D_t^- \) contains the rows for all the other players of MC. Figure (a) illustrates the result of the same procedure for Player = Silva.

To build specific models for important teams, we can replace the variable Team in the generic model of Figure (left) by MC.

Dataset

The dataset in this paper is the Opta data, released by Manchester City. It is a time coded feed that lists all the ball actions within each game by each player from 2011 to 2012. Number of goals, passes, fouls, tackles, saves and blocks and also position assigned to a player in a match are examples of the information associated with each player. The information can be visualized as a heterogeneous network that links players to teams, and teams to matches.
Figure 2: Generic Bayes Net for Teams and the special model for Team = MC (Manchester City). In the generic model, team formation does not predict the result, but in the specific model for Manchester City it does.

Table 2: Data for premier league teams with significant score improvement: Score Improvement, Expected result of the team (as estimated by the specific model), Expected Result Difference from population mean over all teams (0.38).

Table 1: Data for strikers and mid-fielders of Manchester City: Model Score Improvement, Expected percentage of wins when player plays (model estimate) = PWP. Actual Percentage, PWP/Average Time played, salary.

**Scoring Players**

Figure 1 shows special models built for two players of Manchester City (MC). In the generic MC model, scoring the first goal does not predict the result but there is a correlation if Nasri or Silva score it. The length of time played by Silva positively correlates with higher results, but not for Nasri. This illustrates how the Bayes net analysis can find qualitative differences between individuals. We compare the player’s importance score with a simple measure of their value to the team: how the MC average number of wins changes given that they play (WinPercentage). The average number of MC wins is 78%. The BN general population estimates the winning percentage at 70%. The Predicted WinPercentage column shows that this estimate is improved for each player by building a specific model (except for Nasri). The last two columns in Table 1 show that if we divide each player’s WinPercentage by their average time played, there is a strong correlation with salary ($r = 0.813$). The table shows data for the strikers and midfielders for whom we could obtain salary data.

**Scoring Teams**

Table 2 shows that building a specific Bayes net for teams with high importance score allows the model to make more precise predictions for the teams results.

**Discussion.** In general, our method applies to any network that can be represented in a relational database schema. In network terms, the nodes in the Bayes net models in the soccer domain concern correlations among attributes of links and entities. For instance, Figure 1 models a relationship

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**References**


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