Applying Link-based Classification to Label Blogs

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Blogs as Multigraphs

- Many interesting new data sources are best modelled as multigraphs, with multiple attributes and link types.
- "Blogs" are an important emerging example of such data:
- Intersect with web, email, chat data, social networks
- React rapidly to major news, defining opinion and identifying articles of interest
- Raise problems of trustworthiness, finding leaders, classifying for expertise and bias

We study labeling problems on these large multigraphs







Learning Labels on Multigraphs



As with all supervised learning, cannot always trust the training data... apparently some people lie about their age

Prior Work on (Multi)graph Learning

- Relational learning: classify objects represented by Relational Database (see work by Getoor et al)
- Typically builds complex models e.g. Relational Markov Networks on relatively small examples (few thousand nodes)
- Our problem is also an instance of semi-supervised learning (input is mix of labelled and unlabeled examples)
- Several works apply matrix decomposition, does not scale well to massive (multi)graphs
- Some work on similar labelling problems on web graph in addition to text (Chakrabarti et al., 1998)

Simple Learning on Graphs

Local: Iterative

Hypothesis: Nodes point to other nodes with similar labels (homophily)



Label is computed from the votes by its neighbors

 Labels are computed iteratively using weighted voting by neighbors

Global: Nearest Neighbor

Hypothesis: Nodes with similar neighborhoods have similar labels (co-citation regularity)



 Label is inferred by searching for similar neighborhoods of labeled nodes

Extend Learning to Multigraphs

Iterative: Pseudo Labels

Hypothesis: Web pages link similar communities of bloggers



 Webpages assigned a pseudo label, based on votes by its neighbors

Nearest Neighbor: Set Similarity

Hypothesis: Distance computation is improved with additional features



 Augment distance with similarity between sets of neighboring web-nodes

Implementation Issues

- Preliminary experiments guided choice of settings:
 - Choice of similarity function for NN classifier: used correlation coefficient between vectors of adjacent labels
 - Smoothed feature vector with triangular kernel because of continuity of ages
 - In multigraph case with additional features, extended by blending with Jacard coefficient of set similarity of features
 - Iterative algorithm allocates label based on majority voting
- Experimented with variety of edge combinations: Friends only, blog only, blog+friends, blog+web

Data Collection Summary

😑 Blogger

400K profiles crawled 50K (12.5%) labeled

41K blog nodes 190K blog links 331K web nodes 997K web links

Median: 4 blog links Median: 3 web links

Most popular weblinks 1. news.google.com 2. picasa.google.com 3. en.wikipedia.org 4. www.flickr.com 5. www.statcounter.com

🕥 L I V E J O U R N A L[®]

300K profiles crawled 124K (41%) labeled

200K blog nodes 404K blog links 289K web nodes 1089K web links

Median: 2 blog links Median: 4 web links

Most popular weblinks 1. maps.google.com 2. www.myspace.com 3. photobucket.com 4. www.youtube.com

5. quizilla.com

Xanga.com

780K profiles crawled 500K (64%) labeled

535K blog nodes 3000K blog links 74K web nodes 895K web links

Median: 5 blog links Median: 2 web links

Most popular weblinks 1. members.msn.com 2. wwp.icq.com 3. edit.yahoo.com 4. www.gottem.net 5. www.crazyarcades.com

≈50GB of data collected

Accuracy on Age Label



- Similar results on age for both methods, some data sets are "easier" than others, due to density and connectivity
- Local algorithm takes few seconds to assign labels, NN takes tens of minutes (due to exhaustive comparisons)

Multigraph Labeling for Age



- Adding web links and using pseudo labels does not significantly change accuracy, but increases coverage
- Assigned age reflects webpage, e.g. bands slipknot (17) vs. Radiohead (28), but also demographics of blog network

Learning Location Labels



 Local algorithm predicts country and continent with high (80%+) accuracy over all data sets, validating hypothesis

Errors come from over-representing common labels:
N. America has high recall, low precision, Africa vice-versa.

Conclusions

- Analyzed performance of simple classifiers for blog data using link and label information only
 - Richness of setting leads to many details: choice of distance, smoothing and voting functions, etc.
 - Links alone still hold a lot of information: 80% accuracy, better than naïve use of standard classifiers
- Simple models are quite limited, do not extend easily
 - Work better for some labels, rely on hypotheses
 - Open to apply and scale richer models (Relational Markov Networks) to blogs
- Need to understand benefit of additional attributes
 - in our expts, extra features did not seem to help

