Unsupervised Prediction of Citation Influences

Laura Dietz, Steffen Bickel, Tobias Scheffer
Outline

- Motivation.
  - Filter citation graphs.
  - Predict strength of influence of links.
- Generative models.
  - Copycat model.
  - Citation influence model.
- Experiments.
  - Predictive performance based on labeled data.
- Conclusion & future work.
Read on a New Topic

- Seed publications.
- Add citation vicinity.
- Add cited publications.

- Infer citation strengths.
- Filter edges.
- Filter isolated nodes.

Different reasons for citing:
- Approaches extended by citing paper.
- Baselines / papers tackling the same problem.
- Basic / background literature.
- Related work to be argued against.
- Because everybody cites this.
Read on a New Topic: Filter & Layout
Predict Citation Influence

- Problem:
  - Given citation graph and text for documents.
  - How strong is the influence of a cited publication?
  - No strength labels → unsupervised.

- Idea:
  - LDA like generative model.
  - Capture interactions between publications.
  - Associate words in the publication to citations.
  - If many words are associated to one citation.
  → This citation had a strong influence.
All topics are inherited from cites.
Generative Process: Copycat

1. Document 1
2. Document 2
3. Document 3

- Dirichlet prior \( \alpha_\Theta \)
- Topic mixture of cited pub \( \Theta \)
- Topic for word in cited doc \( \phi_{t'} \)
- Word in cited doc \( W' \)
- Dirichlet prior \( \alpha_\gamma \)
- Strength of citation influences \( \gamma \)
- Cited doc associated with word \( C \)
- Topic for word in citing doc \( \phi_t \)
- Word in citing doc \( W \)

For each token...
For each cited doc...
For each topic...
For each citing doc...
Properties of the Copycat Model

- Tight coupling between:
  - Citing and cited publications.
  - Bibliographically coupled publications.

- Issue: all words have to be associated to a citation.
  - Introduce noise in the shared topic mixture.
  - Influence association process of other citing publications.

- Solution: Model may decide to not associate some words.
Flip unfair coin for word.
If inherit: draw topic from cites (as in copycat).
If innovate: draw from own topic mix.
Collapsed Gibbs Sampler

- Joint distribution for citation influence model:

\[
p(\tilde{w}, \tilde{w}', \tilde{t}, \tilde{t}', \tilde{c}, \tilde{s} | \tilde{\alpha}_\phi, \tilde{\alpha}_\theta, \tilde{\alpha}_\psi, \tilde{\alpha}_\gamma, \tilde{\alpha}_\lambda, \cdot) \\
= \int p(\tilde{w}, \tilde{w}' | \tilde{t}, \tilde{t}', \tilde{\phi}) \cdot p(\tilde{\phi} | \tilde{\alpha}_\phi) \, d\tilde{\phi} \cdot \int p(\tilde{c} | \tilde{\gamma}, L) \cdot p(\tilde{\gamma} | \tilde{\alpha}_\gamma, L) \, d\tilde{\gamma} \\
\cdot \int \int p(\tilde{t}, \tilde{t}' | \tilde{s}, \tilde{c}, \tilde{\theta}, \tilde{\psi}) \cdot p(\tilde{\theta} | \tilde{\alpha}_\theta) \cdot p(\tilde{\psi} | \tilde{\alpha}_\psi) \, d\tilde{\theta} d\tilde{\psi} \cdot \int p(\tilde{s} | \tilde{\lambda}) \cdot p(\tilde{\lambda} | \tilde{\alpha}_\lambda) \, d\tilde{\lambda}
\]

- Derive collapsed Gibbs sampler for both models.
- Convergence monitoring (5 chains). [Brooks & Gelman 98]
Experiments: Predictive Performance

- 26 publications from CiteSeer ’04 data set.
- Labeled by experts on Likert scale: ++, +, -, --.

<table>
<thead>
<tr>
<th>Evaluation sheet</th>
<th>Title</th>
<th>Authors</th>
<th>Abstract</th>
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<tr>
<td>citingPub</td>
<td>112301</td>
<td>Generation of Task-Specific Segmentation Procedures as a Model Selection Task</td>
<td>Tobias Scheffer</td>
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<td>evalAuthor</td>
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<td>Tobias Scheffer</td>
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<td>Tobias Scheffer</td>
<td>Ripple down rule</td>
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<td>An Algorithm for Designing Multiple Gabor Filters for Segmenting Multi-Textured Images</td>
<td>Thomas P.</td>
<td>We present an a</td>
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- Corpus = labeled publications + 1 level of citations (total: 179 docs).
Experiments: Baseline Approaches

- LDA-JS:
  - Similarity of topic mixtures by Jensen Shannon div.
  - $\gamma(c|d) \propto \exp(-D_{JS}(\theta_d \parallel \theta_c))$.

- LDA-post:
  - Use Bayes’ rule / chain rule to convert $p(t|c)$ to $p(c|t)$.
  - $\gamma(c|d) \propto \sum_t p(t|d) p(c|t)$.

- TF-IDF:
  - Cosine TF-IDF similarity.
  - $\gamma(c|d) \propto \cos(\angle(\text{TF-IDF}(d),\text{TF-IDF}(c)))$.

- PageRank:
  - $\gamma(c|d) \propto \text{PageRank}(c)$. (Graph with 3 citation levels).
Experiments: Evaluation Measure

- For each single publication $d$:
  - Citation strength $\gamma_d$ is a decision function.
  - Area under the ROC curve (AUC):
    - ++ vs. +, -, --.
    - ++, + vs. -, --.
    - ++, +, - vs. --.
  - Average AUC values for each $d$.

- Corpus-wide evaluation measure:
  - Mean and std. error for averaged AUCs.
  - Paired-t-tests.
Experiments: Predictive Performance

- Citation influence best method on average.
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- Significantly better than LDA (paired-t-test, $\alpha=5\%$).
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- Unsensitive to number of topics.
Experiments: Predictive Performance

- Citation influence best method on average.
  - Significantly better than LDA (paired-t-test, $\alpha=5\%$).
- Unsensitive to number of topics.
- TF-IDF and PageRank do not work (AUC≈0.5).
Experiments: Convergence

- Citation influence converges faster than copycat.

- Runtime: Citation influence 46 min, copycat 3h.
Narrative Evaluation: Visualization
**Narrative Evaluation: Analyze Abstract**

- Association of words in abstract to cites ($p(w, c|d)$).
- Example: research paper „Latent Dirichlet Allocation“.

<table>
<thead>
<tr>
<th>Cited Title</th>
<th>Associated Words</th>
<th>$\gamma$</th>
</tr>
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<tbody>
<tr>
<td>Probabilistic Latent Semantic Indexing</td>
<td>text(0.04), latent(0.04), modeling(0.02), model(0.02), indexing(0.01), semantic(0.01), document(0.01), collections(0.01)</td>
<td>0.49</td>
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<td>Modelling heterogeneity with and without the Dirichlet process</td>
<td>dirichlet(0.02), mixture(0.02), allocation(0.01), context(0.01), variable(0.0135), bayes(0.01), continuous(0.01), improves(0.01), model(0.01), proportions(0.01)</td>
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<td>Introduction to Variational Methods for Graphical Methods</td>
<td>variational(0.01), inference(0.01), algorithms(0.01), including(0.01), cach(0.01), wc(0.01), via(0.01)</td>
<td>0.22</td>
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Conclusion & Future Work

- Two generative models for link strength prediction.
- Prediction: Citation influence better than LDA.
- Citation influence stable according to number of topics.
- Runtime: Citation influence faster than copycat.
- Useful for filtering citation graphs.

Future work:
- Influence strengths in social networks and web.
- Better authority ranking with link strengths.