Graph-Based Lexicon Expansion with Sparsity-Inducing Penalties

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Motivation

• FrameNet lexicon (Fillmore et al., 2003)
  – For many words, a set of abstract semantic frames
  – E.g., contribute/V can evoke GIVING or SYMPTOM

• SEMAFOR (Das et al., 2010).
  – Finds: frames evoked + semantic roles

What about the words not in the lexicon or data?
Das and Smith (2011)

• **Graph-based semi-supervised learning** with quadratic penalties (Bengio et al., 2006; Subramanya et al., 2010).
  
  – Frame identification $F_1$ on unknown predicates: $47\% \rightarrow 62\%$
  
  – Frame parsing $F_1$ on unknown predicates: $30\% \rightarrow 44\%$
Das and Smith (2011)

• **Graph-based semi-supervised learning** with quadratic penalties (Bengio et al., 2006; Subramanya et al., 2010).
  
  – Frame identification $F_1$ on unknown predicates:  
    47% → 62% → *(today)* 65%

  – Frame parsing $F_1$ on unknown predicates:  
    30% → 44% → *(today)* 47%

• **Today:** we consider alternatives that target *sparsity*, or each word associating with relatively few frames.
Graph-Based Learning

9264: "similarity"
9265: unknown predicates
9266: unknown predicates
9267: 9268: 9269: 9270: predicates with observed frame distributions
The Case for Sparsity

• Lexical ambiguity is pervasive, but each word’s ambiguity is fairly limited.
• Ruling out possibilities $\rightarrow$ better runtime and memory properties.
Outline

1. A general family of graph-based SSL techniques for learning distributions.
   – Defining the graph
   – Constructing the graph and carrying out inference
   – New: sparse and unnormalized distributions

2. Experiments with frame analysis: favorable comparison to state-of-the-art graph-based learning algorithms
Notation

- $T =$ the set of types (words)
- $L =$ the set of labels (frames)
- Let $q_t(l)$ denote the estimated probability that type $t$ will take label $l$. 
Think of this as a **graphical model** whose random variables take **vector** values.
Factor Graphs
(Kschischang et al., 2001)

• Bipartite graph:
  – Random variable vertices $V$
  – “Factor” vertices $F$

• Distribution over all variables’ values:
  $$\log P \left( \{v\}_{v \in V} \right) = - \log Z + \sum_{f \in F} \log \alpha_f \left( \{v\}_{(v,f) \in E} \right)$$

• Today: finding collectively highest-scoring values (MAP inference) $\equiv$ estimating $q$
  • Log-factors $\equiv$ negated penalties
Notation

- $T =$ the set of types (words)
- $L =$ the set of labels (frames)
- Let $q_t(l)$ denote the estimated probability that type $t$ will take label $l$.
- Let $r_t(l)$ denote the observed relative frequency of type $t$ with label $l$. 
“Each type $t_i$’s value should be close to its empirical distribution $r_i$.”
Empirical Penalties

• “Gaussian” (Zhu et al., 2003): penalty is the squared $L_2$ norm

$$\log \phi_t (q_t, r_t) = -\|q_t - r_t\|_2^2$$

• “Entropic”: penalty is the JS-divergence (cf. Subramanya and Bilmes, 2008, who used KL)

$$\log \phi_t (q_t, r_t) = -\frac{1}{2} \left( D \left( q_t \left\| \frac{q_t + r_t}{2} \right\| \right) + D \left( r_t \left\| \frac{q_t + r_t}{2} \right\| \right) \right)$$
Let’s Get Semi-Supervised
There is no empirical distribution for these new vertices!
Penalties (2 of 3)
Similarity Factors

\[
\log \varphi_{t,t'}(q_t, q_{t'}) = -2 \cdot \mu \cdot \text{sim}(t, t') \cdot \|q_t - q_{t'}\|_2^2
\]

“Gaussian”

\[
\log \varphi_{t,t'}(q_t, q_{t'}) = -2 \cdot \mu \cdot \text{sim}(t, t') \cdot \text{JS}(q_t \parallel q_{t'})
\]

“Entropic”
Constructing the Graph

Conjecture: *contextual* distributional similarity correlates with *lexical* distributional similarity.

- Subramanya et al. (2010); Das and Petrov (2011); Das and Smith (2011)

1. Calculate distributional similarity for each pair.
   - Details in past work; nothing new here.
2. Choose each vertex’s $K$ closest neighbors.
3. Weight each log-factor by the similarity score.
Penalties (3 of 3)
What Might
Unary Penalties/Factors Do?

• Hard factors to enforce nonnegativity, normalization

• Encourage near-uniformity
  – squared distance to uniform (Zhu et al., 2003; Subramanya et al., 2010; Das and Smith, 2011)
  – entropy (Subramanya and Bilmes, 2008)

• Encourage sparsity
  – Main goal of this paper!
Unary Log-Factors

\[ \log \psi_t(q_t) = -\lambda \left\| q_t - \frac{1}{|L|} \right\|_2^2 \]

- Squared distance to uniform:

- Entropy:

\[ \lambda H(q_t) \]

- “Lasso”/L₁ (Tibshirani, 1996):

\[ -\lambda \left\| q_t \right\|_1 \]

- “Elitist Lasso”/squared L₁,₂ (Kowalski and Torrésani, 2009):

\[ -\lambda \left( \left\| q_t \right\|_1 \right)^2 \]
## Models to Compare

<table>
<thead>
<tr>
<th>Model</th>
<th>Empirical and pairwise factors</th>
<th>Unary factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>normalized Gaussian field (Das and Smith, 2011; generalizes Zhu et al., 2003)</td>
<td>Gaussian</td>
<td>squared L(_2) to uniform, normalization</td>
</tr>
<tr>
<td>“measure propagation” (Subramanya and Bilmes, 2008)</td>
<td>Kullback-Leibler</td>
<td>entropy, normalization</td>
</tr>
<tr>
<td>UGF-L(_2)</td>
<td>Gaussian</td>
<td>squared L(_2) to uniform</td>
</tr>
<tr>
<td>UGF-L(_1)</td>
<td>Gaussian</td>
<td>lasso (L(_1))</td>
</tr>
<tr>
<td>UGF-L(_{1,2})</td>
<td>Gaussian</td>
<td>elitist lasso (squared L(_{1,2}))</td>
</tr>
<tr>
<td>UJSF-L(_2)</td>
<td>Jensen-Shannon</td>
<td>squared L(_2) to uniform</td>
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**sparsity-inducing penalties**

**unnormalized distributions**
Where We Are So Far

• “Factor graph” view of semisupervised graph-based learning.
  – Encompasses familiar Gaussian and entropic approaches.
  – Estimating all $q_t$ equates to MAP inference.

Yet to come:
• Inference algorithm for all $q_t$
• Experiments
Inference
In One Slide

• All of these problems are convex.
• Past work relied on specialized iterative methods.
• Lack of normalization constraints makes things simpler!
  – Easy quasi-Newton gradient-based method, L-BFGS-B (with nonnegativity “box” constraints)
  – Non-differentiability at 0 causes no problems (assume “right-continuity”)
  – KL and JS divergence can be generalized to unnormalized measures
Experiment 1

• (see the paper)
Experiment 2: Semantic Frames

- **Types**: word plus POS
- **Labels**: 877 frames from FrameNet
- **Empirical distributions**: 3,256 sentences from FrameNet 1.5 release
- **Graph**: 64,480 vertices (see D&S 2011)
- **Evaluation**: use induced lexicon to constrain frame analysis of unknown predicates on 2,420 sentence test set.
  1. Label words with frames.
  2. ... Then find arguments (semantic roles)
## Frame Identification

<table>
<thead>
<tr>
<th>Model</th>
<th>Unknown predicates, partial match $F_1$</th>
<th>Lexicon size</th>
</tr>
</thead>
<tbody>
<tr>
<td>supervised (Das et al., 2010)</td>
<td>46.62</td>
<td></td>
</tr>
<tr>
<td>normalized Gaussian (Das &amp; Smith, 2011)</td>
<td>62.35</td>
<td>129K</td>
</tr>
<tr>
<td>“measure propagation”</td>
<td>60.07</td>
<td>129K</td>
</tr>
<tr>
<td>UGF-L$_2$</td>
<td>60.81</td>
<td>129K</td>
</tr>
<tr>
<td>UGF-L$_1$</td>
<td>62.85</td>
<td>123K</td>
</tr>
<tr>
<td>UGF-L$_{1,2}$</td>
<td>62.85</td>
<td>129K</td>
</tr>
<tr>
<td>UJSF-L$_2$</td>
<td>62.81</td>
<td>128K</td>
</tr>
<tr>
<td>UJSF-L$_1$</td>
<td>62.43</td>
<td>129K</td>
</tr>
<tr>
<td>UJSF-L$_{1,2}$</td>
<td><strong>65.29</strong></td>
<td><strong>46K</strong></td>
</tr>
</tbody>
</table>
Learned Frames (UJSF-L₁,₂)

• discrepancy/N: SIMILARITY, NON-COMMUTATIVE-STATEMENT, NATURAL-FEATURES
• contribution/N: GIVING, COMMERCE-PAY, COMMITMENT, ASSISTANCE, EARNINGS-AND-LOSSES
• print/V: TEXT-CREATION, STATE-OF-ENTITY, DISPERMAL, CONTACTING, READING
• mislead/V: PREVARICATION, EXPERIENCER-OBJ, MANIPULATE-INTO-DOING, REASSURING, EVIDENCE
• abused/A: (Our models can assign \( q_t = 0 \).)
• maker/N: MANUFACTURING, BUSINESSES, COMMERCE-SCENARIO, SUPPLY, BEING-ACTIVE
• inspire/V: CAUSE-TO-START, SUBJECTIVE-INFLUENCE, OBJECTIVE-INFLUENCE, EXPERIENCER-OBJ, SETTING-FIRE
• failed/A: SUCCESSFUL-ACTION, SUCCESSFULLY-COMMUNICATE-MESSAGE

blue = correct
Frame Parsing (Das, 2012)

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</tr>
</thead>
<tbody>
<tr>
<td>supervised (Das et al., 2010)</td>
<td>29.20</td>
</tr>
<tr>
<td>normalized Gaussian (Das &amp; Smith, 2011)</td>
<td>42.71</td>
</tr>
<tr>
<td>“measure propagation”</td>
<td>41.41</td>
</tr>
<tr>
<td>UGF-L$_2$</td>
<td></td>
</tr>
<tr>
<td>UGF-L$_1$</td>
<td>42.58</td>
</tr>
<tr>
<td>UGF-L$_{1,2}$</td>
<td></td>
</tr>
<tr>
<td>UJSF-L$_2$</td>
<td></td>
</tr>
<tr>
<td>UJSF-L$_1$</td>
<td></td>
</tr>
<tr>
<td>UJSF-L$_{1,2}$</td>
<td><strong>46.75</strong></td>
</tr>
</tbody>
</table>
Example

Discrepancies between North Korean declarations and IAEA inspection findings indicate that North Korea might have reprocessed enough plutonium for one or two nuclear weapons.
Discrepancies between North Korean declarations and IAEA inspection findings indicate that North Korea might have reprocessed enough plutonium for one or two nuclear weapons.
SEMAFOR

http://www.ark.cs.cmu.edu/SEMAFOR

• Current version (2.1) incorporates the expanded lexicon.

• To hear about algorithmic advances in SEMAFOR, see our *SEM talk, 2pm Friday.
Conclusions

• General family of graph-based semi-supervised learning objectives.

• Key technical ideas:
  – Don’t require normalized measures
  – Encourage (local) sparsity
  – Use general optimization methods