

A Graph-based Semi-Supervised Learning for Question-Answering

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In Proceedings of the 47th Annual Meeting of the ACL and the 4th IJCNLP of the AFNLP,
2009

January 27, 2010

Outline

Objective

The Model

- Feature Extraction

- Graph-based Semi-Supervised Learning

Our case

Some Results

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2. Ranking Question-Answering pairs (score of ranking).

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1. answer contains the fine NER: 1
2. answer contains the coarse NER: 0.5
3. no NER match: 0

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5. Modifier-Match ([X] $\rightarrow$ April 22, 1994)

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5. **Objective**: estimate the true label for the unlabeled data U .

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4. The weight w_{ij} on the edge e_{ij} represent the similarity between x_i and x_j ;

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 - ▶ f is close to the labeled data: $f(x_i) \approx y_i, x_i \in L$;
 - ▶ f is smooth on the graph.

Harmonic Function

1. So the objective function is:

$$\min_{f: f(x) \in \mathbb{R}} \propto \sum_{i=1}^l (y_i - f(x_i))^2 + \sum_{i,j=1}^{l+u} w_{ij} (f(x_i) - f(x_j))^2;$$

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4. Solution: $\begin{cases} f_L = y_L, \\ f_U = -\Delta_{UU}^{-1} \Delta_{UL} y_L. \end{cases}$

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4. Similarity: $w_{ij} = 1 - \sum_{q=1}^d \frac{|x_{iq} - x_{jq}|}{d}$

Year 2007 Question

bus line	time	time	location	location	count
0	1	0	1	0	209
0	1	1	1	0	49
0	1	0	0	0	719
1	1	0	1	0	116
1	0	0	0	0	2770
0	0	0	0	0	5163
1	1	0	0	0	252
1	0	0	1	0	198
0	0	0	1	0	597
0	1	1	0	0	96
1	1	0	1	1	59
1	1	1	0	0	65
0	1	0	1	1	91
1	0	0	1	1	96
0	1	1	1	1	24
0	0	0	1	1	192
1	1	1	1	1	29
1	1	1	1	0	37

Year 2007 Answer

bus line	time	time	location	location	count
1	1	1	1	0	2754
0	0	0	1	1	429
1	1	1	0	0	851
0	0	0	0	0	1186
1	1	1	1	1	2245
0	1	1	0	0	341
0	0	0	1	0	699
1	1	0	1	1	236
1	0	0	1	0	59
0	1	1	1	0	378
0	1	1	1	1	447
1	1	0	1	0	414
0	1	0	1	1	168
0	1	0	0	0	333
1	1	0	0	0	31
0	1	0	1	0	128
1	0	0	0	0	55
1	0	0	1	1	8

Year 2007 – 2009 Question

bus line	time	time	location	location	count
0	1	0	1	0	679
0	1	1	1	0	150
0	1	0	0	0	2718
1	1	0	1	0	411
1	0	0	0	0	11638
0	0	0	0	0	20772
1	1	0	0	0	969
1	0	0	1	0	926
0	0	0	1	0	2877
0	1	1	0	0	278
1	1	0	1	1	237
1	1	1	0	0	173
0	1	0	1	1	273
1	0	0	1	1	392
0	1	1	1	1	94
0	0	0	1	1	831
1	1	1	1	1	83
1	1	1	1	0	120

Year 2007 – 2009 Answer

bus line	time	time	location	location	count
1	1	1	1	0	8848
0	0	0	1	1	1766
1	1	1	0	0	3294
0	0	0	0	0	7007
1	1	1	1	1	8072
0	1	1	0	0	1280
0	0	0	1	0	3740
1	1	0	1	1	1280
1	0	0	1	0	429
0	1	1	1	0	1243
0	1	1	1	1	1573
1	1	0	1	0	1663
0	1	0	1	1	418
0	1	0	0	0	1881
1	1	0	0	0	117
0	1	0	1	0	447
1	0	0	0	0	248
1	0	0	1	1	315

Other results

1. if $Q + A = \{1 \ 1 \ 1 \ 1 \ 1\}$, then we believe that the system answered what user want.
2. 2007 Q-A match: $2446/10762 = 0.2273$
3. 2007 – 2009 Q-A match: $8806/43621 = 0.2019$

Thanks

Q & A

January 27, 2010