

数据驱动的推特新闻事件挖掘

Data Driven News Event Mining from Twitter.

报告人：黎谢鹏 指导老师：胡岩峰

目录

一、背景与意义

二、研究内容

三、研究进展

四、研究成果

五、学位论文框架

一、背景与意义

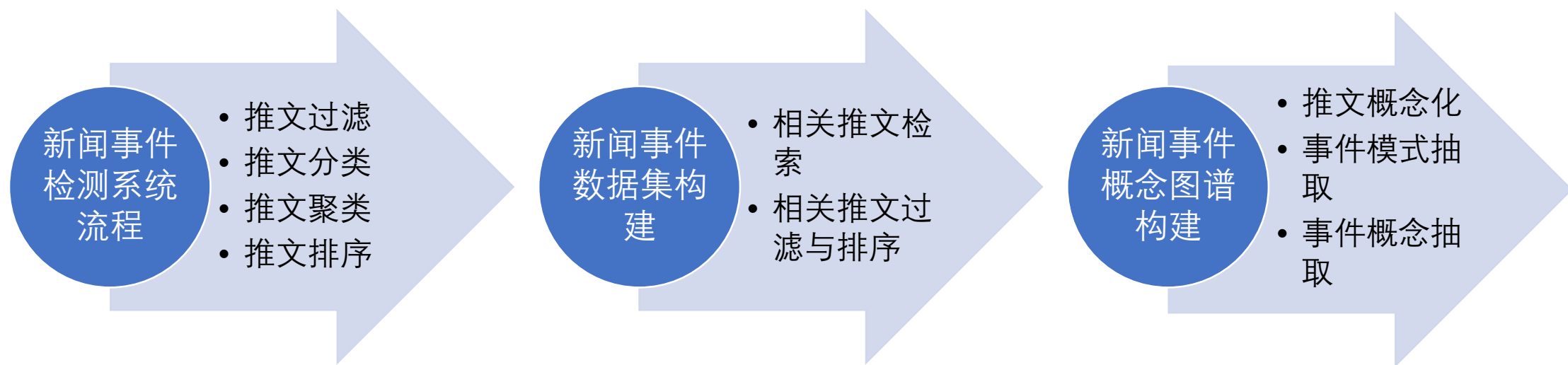
- 社交媒体作为社会传感器为社会科学研究提供了新的数据源。
- 新闻事件挖掘研究可以辅助社会管理者以更高的效率，更全面的信息做出正确的管理决策。

二、研究内容：

- 有监督学习效果好，但数据是瓶颈，构造可用的数据集是关键。
 - 难点：海量，噪音，冗余，多样性
- 知识产生决策，事件概念图谱是利用事件相关知识进行决策辅助的基础。
 - 难点：链接预测时图遍历算法复杂性高

二、研究内容：

新闻事件挖掘任务:



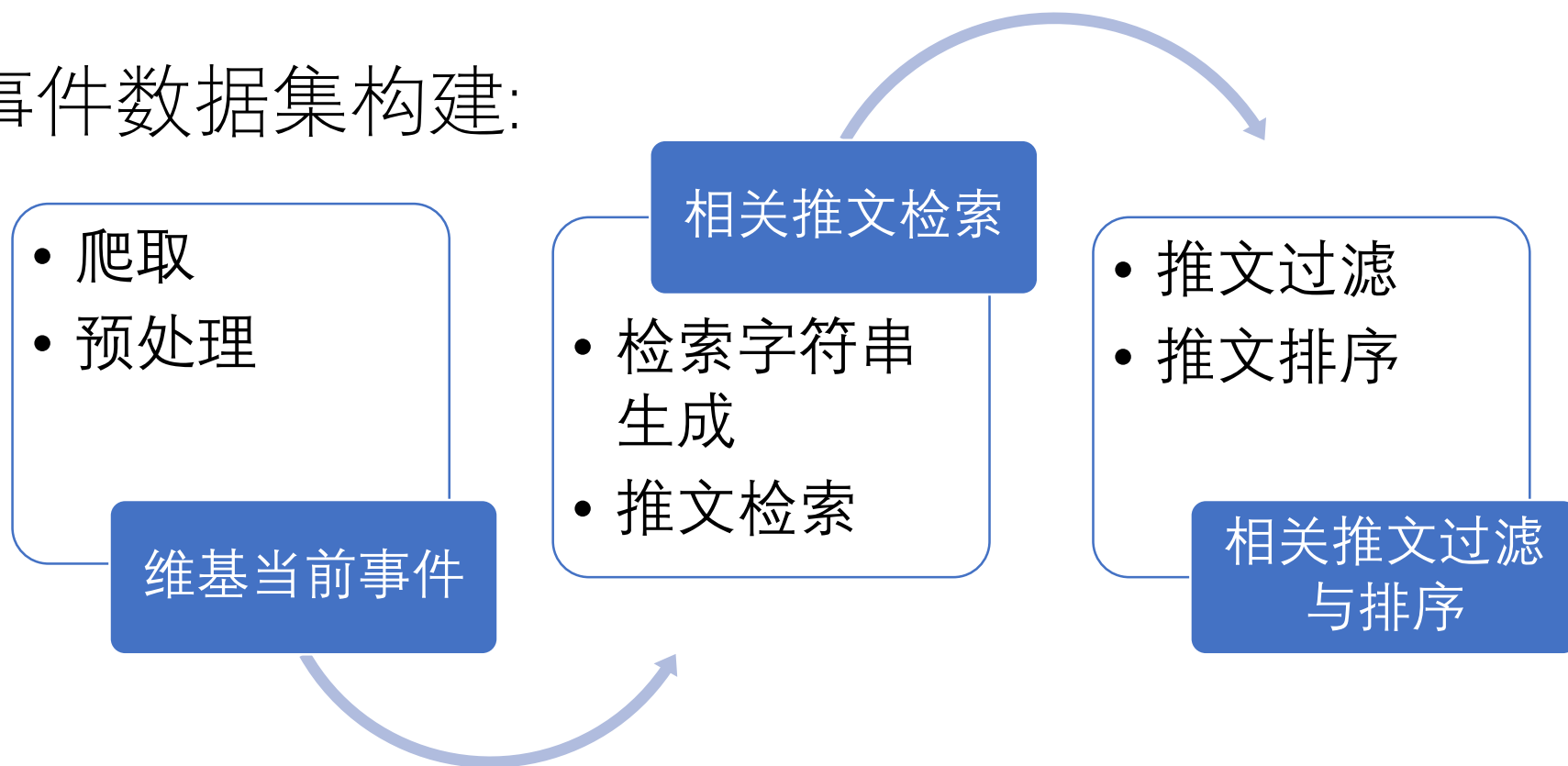
三、研究进展：

新闻事件检测系统流程

- Build a system for event detection in twitter.
- Training a classifier for Tweet classification using char-cnn and word2vec and lexical feature for tweet representation.
- Using K-means for event instance clustering, NER and SRL model for event information extraction.
- Using MMR-submodular based text summarization technology to rank relevant tweets.

三、研究进展：

新闻事件数据集构建：



Wiki current event demo

- An early-morning landslide buries 40 homes and leaves 15 people dead and 114 others missing in Aba Prefecture, Sichuan Province, China. At least 500 rescue workers are on scene, and a 2-km stretch of the river in Mao County is blocked.
- Label: 'disaster and accident'
- 中国四川省阿坝州清晨的滑坡摧毁40所房屋，造成15人死亡和114人失踪。至少有500名救援人员在现场，毛县一条2公里长的河流被封锁。
- 标签：自然灾害与事故

Related Tweets Query Generation

- NER + top_related([V,N]) combination
 - NUM:40 15 114 500
 - LOC: Aba.CITY Prefecture.LOCATION Sichuan.STATE_OR_PROVINCE Province.LOCATION China.COUNTRY Mao.CITY County.LOCATION
 - V: buries leaves missing blocked
 - N: landslide homes people others scene stretch river
 - Related_score(word):=boe_cosine(word,'disaster and accident')
 - Combination : c_4^2
 - Query: Combination;time [-24,+24]

Related Tweets filtering and ranking

- $\text{Related_score} = \text{boe_cosine}(\text{wiki_description}, \text{tweet})$
- Filtering criteria: $(\text{boe_cosine} > 0.75) \ \& \ (10 < \text{num_top_tweets} = 60)$
- Ranking method:
 - MMR(Maximal Marginal Relevance)-submodular
 - Greedy criteria: $F_{\text{mmr}} = \text{graph_cut} - \text{penalty} - \text{contradiction}$
 - Graph_cut: $\lambda * \text{sim}(\text{selected}, \text{unselected})$
 - Penalty: $(1 - \lambda) * \text{sim}(C_s^2)$
 - Contradiction: $\beta * \text{Log}(\text{CrossEntropy}(\text{Label_distribution}(\text{wiki_description}), \text{Label_distribution}(\text{tweet})))$

Related Tweets filtering and ranking

- Demo
 - MMR-submodular based rank:
 - 0.9582722326723183 China : Death toll rises to 15 and over 120 others are missing after a landslide in south-western Sichuan province .
 - 0.9286372801720572 Rescue operation is under way in Sichuan province after more than 40 homes in Xinmo village were engulfed by lan.
 - 0.9461324580032283 More than 120 people are missing after a landslide in Sichuan province in south-western China, 40 homes were destroyed in Xinmo village.
 - 0.9379743462839512 Fifteen people were killed in a landslide in southwest China 's Sichuan Province on Saturday and about 100 were.
 - 0.9365613210034124 Dozens of homes are destroyed and at least 120 people are missing in the wake of a massive landslide in China .

Dataset Usage Demo

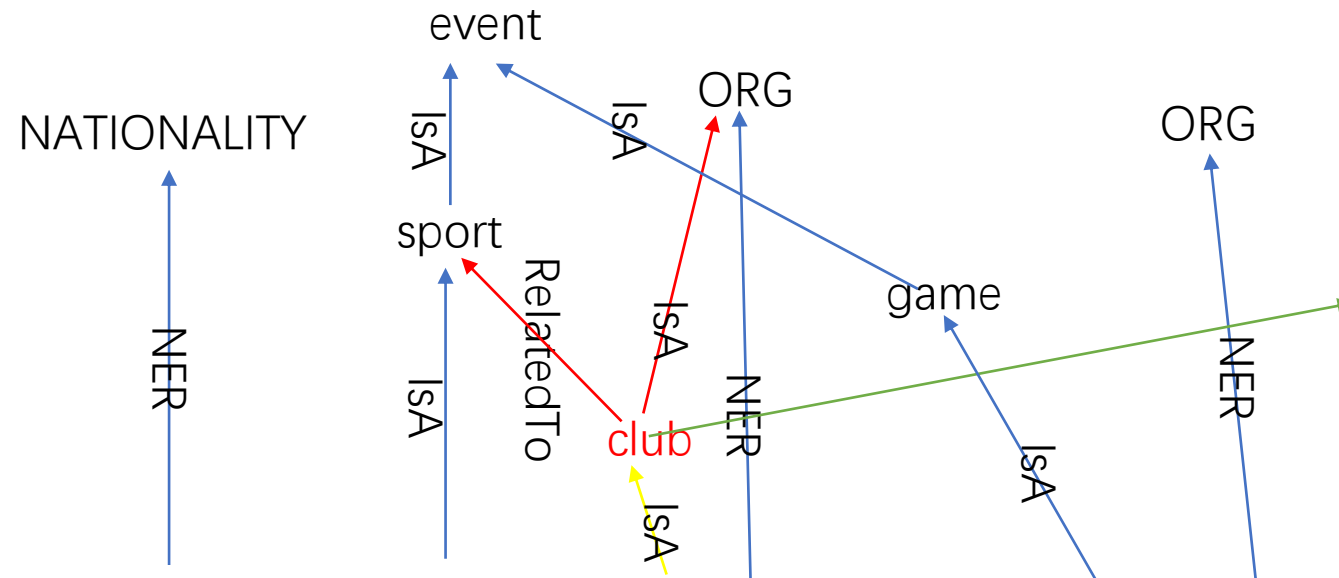
- Top 5: multi-reference news summaration dataset
- Top 15: News Event Concept Graph Building
- Top 30: Classification dataset
- Top 45: Clustering Algorithm testing

三、研究进展：

新闻事件概念图谱构建

- Probase+ConceptNet5：单词或词组表示概念
- Word2vec 候选项高速查询
- HIN（异质信息网络）：
 - $G(V,E)$
 - $\varphi = V \rightarrow A$
 - $\psi = E \rightarrow R$
 - $|A|>1$ or $|R|>1$
 - Meta-path（作为链接预测的特征）： $A_1 \xrightarrow{R_1} A_2 \xrightarrow{R_2} \cdots \xrightarrow{R_l} A_{l+1}$

Simple demo: instance conceptualize



Inference by metapath:

$p = (c) < -[:\text{/r/RelatedTo}] - (a) - [: \text{/r/IsA}] - > (b)$

a: inferred type

b: NER type

c: context concept

- In Spanish football, FC Barcelona win La Liga.

- Concept hierarchy level:

- Level-0: event, entity

```
[predefine]
```

- Level-1: nationality, organization, sport, game, club

[ner & query]

- Level-2: football, win, club

[extract & inference]

- Level-instance: Spanish, FC Barcelona, La Liga

Simple demo: event entity & concept extraction

- Event info:
 - {'event.type':['sport.football','game.win'],
 - 'club.instance': ['FC Barcelona', 'La Liga'],
 - 'football.hasSubEvent':'win',
 - 'event.pattern': 'In [entity.nationality] [event.sport.football],
[entity.organization.club] [event.game.win] [entity.organization.club].'}
 - tweet-based event.pattern-[frequent]->event instance pattern –
 - [frequent]-> event category pattern

Conceptualize the trigger V.&N.

- Rank_score(word)= boe_cosine(word,tweet_categorical_label)
- football,win
- MATCH p=(a)-[:`/r/IsA`:`/r/microsoft/IsA`:`/r/InstanceOf`*1..2]->(b) WHERE a.conceptId IN ['/c/en/football'] AND b.conceptId = "/c/en/event" RETURN extract(x IN nodes(p) | x.conceptId) as nodes,extract(x IN relationships(p) | type(x)) as rels,reduce(prob = 1.0, x IN relationships(p) | prob*x.weight) as probs ORDER BY probs DESC LIMIT 10;

Vector similarity context vs (c)<-[:`/r/RelatedTo`]- (a)




- `wv.most_similar(positive=['win','football','organization'], topn=10, indexer=annoy_index)`
 - `(('football', 0.6417830884456635),`
 - `(('league', 0.6238529682159424), #联赛`
 - `(('win', 0.622621089220047),`
 - `(('team', 0.5995824038982391), #球队`
 - `(('winning', 0.5774330496788025),`
 - `(('teams', 0.5667363405227661), #球队`
 - `(('soccer', 0.5631313323974609), #冠军`
 - `(('championship', 0.5575762391090393),`
 - `(('club', 0.555101752281189), #俱乐部`
 - `(('baseball', 0.5484375953674316))]`

Concept inference by neo4j Cypher query:

- Topk=10
vector_similarity_context=['/c/en/league','/c/en/team','/c/en/championship','/c/en/club']
- MATCH p=(a)-[:`/r/IsA`|:`/r/microsoft/IsA`|:`/r/InstanceOf`*1..1]->(b) WHERE a.conceptId IN {vector_similarity_context} AND b.conceptId = "/c/en/organization" RETURN extract(x IN nodes(p) | x.conceptId) as nodes,extract(x IN relationships(p) | type(x)) as rels,reduce(prob = 1.0, x IN relationships(p) | prob*x.weight) as probs ORDER BY probs DESC LIMIT {topk};
- Add type constraint on vector_similarity_context

Concept inference by neo4j Cypher query:

```
MATCH p=(a)-[:`/r/IsA`|:`/r/microsoft/IsA`|:`/r/InstanceOf`*1..1]->(b) WHERE a.conceptId IN ['/c/en/league','/c/en/team','/c/en/championship','/c/en/club']
AND b.conceptId = "/c/en/organization" RETURN extract(x IN nodes(p) | x.conceptId) as nodes,extract(x IN relationships(p) |
type(x)) as rels,reduce(prob = 1.0, x IN relationships(p) | prob*x.weight ) as probs ORDER BY probs DESC LIMIT 10;
```

H p=(a)-[:`/r/IsA` :`/r/microsoft/IsA` :`/r/InstanceOf`*1..1]->(b) WHERE a.conceptId IN ['/c/en/league','/c/en/team','/c/en/championshi...					
nodes	rels	probs			
["/c/en/club", "/c/en/organization"]	["/r/microsoft/IsA"]	0.012199999764561653			
["/c/en/league", "/c/en/organization"]	["/r/microsoft/IsA"]	0.000399999998989515007			
["/c/en/team", "/c/en/organization"]	["/r/microsoft/IsA"]	0.000399999998989515007			

Level-2 concept relation:

- MATCH p=(a:Concept {conceptId:'/c/en/football'})-[*1..2]->(b:Concept {conceptId:'/c/en/win'}) RETURN extract(x IN nodes(p)|x.conceptId) as nodes,extract(x IN relationships(p)|type(x)) as rels,reduce(prob = 1.0,x IN relationships(p)|prob*x.weight) as probs ORDER BY probs DESC LIMIT 25;

nodes	rels	probs
["/c/en/football", "/c/en/game", "/c/en/win"]	["/r/IsA", "/r/RelatedTo"]	4.463354876537323
["/c/en/football", "/c/en/game", "/c/en/win"]	["/r/RelatedTo", "/r/RelatedTo"]	0.049673997903823874
["/c/en/football", "/c/en/game", "/c/en/win"]	["/r/microsoft/IsA", "/r/RelatedTo"]	0.027612898706710354
["/c/en/football", "/c/en/playing_game", "/c/en/win"]	["/r/microsoft/IsA", "/r/HasSubevent"]	0.0063687002355383715
["/c/en/football", "/c/en/playing_game", "/c/en/win"]	["/r/microsoft/IsA", "/r/Causes"]	0.005200000014156103
["/c/en/football", "/c/en/playing_sport", "/c/en/win"]	["/r/microsoft/IsA", "/r/HasSubevent"]	0.0027000000700354576
["/c/en/football", "/c/en/playing_sport", "/c/en/win"]	["/r/microsoft/IsA", "/r/Causes"]	0.0027000000700354576
["/c/en/football", "/c/en/play_game", "/c/en/win"]	["/r/microsoft/IsA", "/r/MotivatedByGoal"]	0.000399999998989515007
["/c/en/football", "/c/en/play_game", "/c/en/win"]	["/r/microsoft/IsA", "/r/HasSubevent"]	0.00019999999494757503
["/c/en/football", "/c/en/reward", "/c/en/win"]	["/r/microsoft/IsA", "/r/RelatedTo"]	0.0000174999992598896

Level-2 concept relation:

- Constraint on core event relation
 - 同义词-表达多样性 :`/r/FormOf|:`/r/Synonym|:`/r/DerivedFrom`
 - 上下位 :`/r/IsA|:`/r/MannerOf`
 - 因果关系 :`/r/Causes`
 - 目的关系 :`/r/MotivatedByGoal|:`/r/Desires`
 - 包含关系 :`/r/HasSubevent`
 - 条件关系 :`/r/HasPrerequisite|:`/r/Entails`
- Candidate pairs <s,t>:
 - <football,win>
 - <football,club>
 - <win,club>

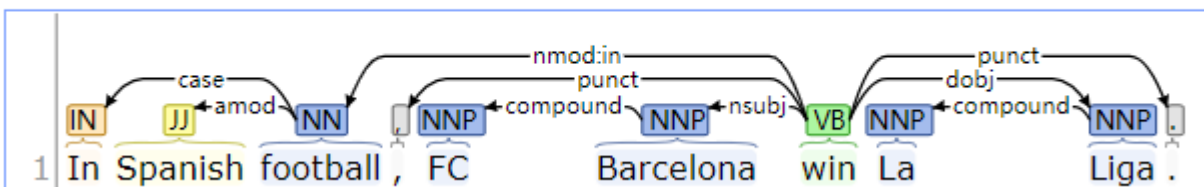
Link prediction in HIN using meta-path feature:

1.fusion of dependencies-graph & concept-graph

Named Entity Recognition:

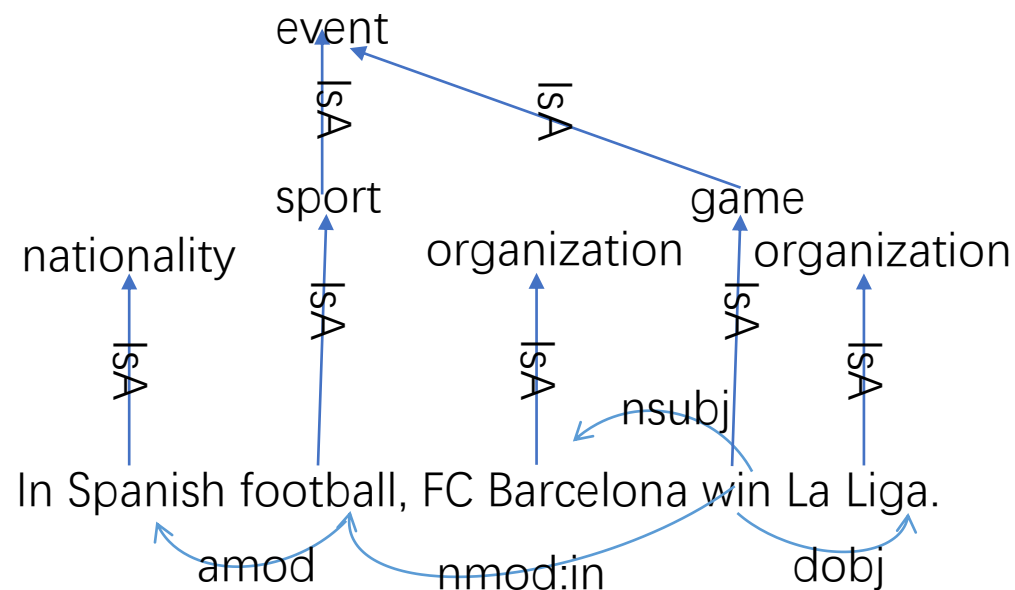
	NATIONALITY		ORGANIZATION		ORGANIZATION	
1	In	Spanish	football	,	FC Barcelona	win La Liga .

Enhanced++ Dependencies:



"nodes"	"rels"	"probs"
["/c/en/football", "/c/en/sport", "/c/en/event"]	["/r/ISA", "/r/microsoft/ISA"]	0.1728000044822693
["/c/en/football", "/c/en/game", "/c/en/event"]	["/r/ISA", "/r/microsoft/ISA"]	0.13930800176915525
["/c/en/football", "/c/en/event"]	["/r/microsoft/ISA"]	0.039000000804662704
["/c/en/football", "/c/en/sport", "/c/en/event"]	["/r/microsoft/ISA", "/r/microsoft/ISA"]	0.013487040774188053

"nodes"	"rels"	"probs"
["/c/en/win", "/c/en/game", "/c/en/event"]	["/r/microsoft/ISA", "/r/microsoft/ISA"]	0.000004560000293478373
["/c/en/win", "/c/en/contest", "/c/en/event"]	["/r/microsoft/ISA", "/r/microsoft/ISA"]	0.000003900000079441811
["/c/en/win", "/c/en/program", "/c/en/event"]	["/r/microsoft/ISA", "/r/microsoft/ISA"]	0.0000011400000733695933



Link prediction in HIN using meta-path feature:

2.auto generate meta-path by random walk

- Random-walk constrain relations and weight
- $\langle s, \dots, _, \dots, t \rangle, r, \text{beam_size}=25$
- MATCH $p=(a:\text{Concept}\{\text{conceptId}:s\})-[*1..1]-(b:\text{Concept}\{\text{conceptId}:_ \})$ RETURN $\text{extract}(x \text{ IN nodes}(p)|x.\text{conceptId})$ as nodes, $\text{extract}(x \text{ IN relationships}(p)|\text{type}(x))$ as rels, $\text{reduce}(\text{prob} = 1.0, x \text{ IN relationships}(p)|\text{prob}*x.\text{weight})$ as probs ORDER BY probs DESC LIMIT 25;

Complex demo : multi-reference dep-tree to dep-graph

- An early-morning landslide buries 40 homes and leaves 15 people dead and 114 others missing in Aba Prefecture, Sichuan Province, China. At least 500 rescue workers are on scene, and a 2-km stretch of the river in Mao County is blocked.
- China : Death toll rises to 15 and over 120 others are missing after a landslide in south-western Sichuan province .
- Rescue operation is under way in Sichuan province after more than 40 homes in Xinmo village were engulfed by lan.
- More than 120 people are missing after a landslide in Sichuan province in south-western China, 40 homes were destroyed in Xinmo village.
- Fifteen people were killed in a landslide in southwest China 's Sichuan Province on Saturday and about 100 were.
- Dozens of homes are destroyed and at least 120 people are missing in the wake of a massive landslide in China .

四、研究成果

- 新闻事件检测系统
- 新闻事件数据集

五、学位论文框架

- 第一章 引言
 - 1.1 研究背景和意义
 - 1.2 国内外研究现状与进展
 - 1.3 本文的研究方法及结构安排
 - 1.4 本文的主要创新点与贡献
- 第二章 基础理论介绍
 - 2.1 引言
 - 2.2 文本表示方法
 - 2.3 基于次模函数的文本摘要方法
 - 2.4 概念图谱与异质信息网络
 - 2.5 本章小结
- 第三章 新闻事件检测系统
 - 3.1 推文表示
 - 3.2 推文过滤与分类
 - 3.3 推文聚类与信息抽取
 - 3.4 本章小结

五、学位论文框架

- 第四章 新闻事件数据集构建
 - 4.1 相关推文检索
 - 4.2 相关推文过滤与排序
 - 4.3 本章小结
- 第五章 新闻事件概念图谱构建
 - 5.1 概念异质信息网络
 - 5.2 推文概念化
 - 5.3 事件模式抽取
 - 5.4 事件概念抽取
 - 5.5 本章小结
- 第六章 总结与展望
 - 6.1 总结
 - 6.2 展望
- 参考文献