Discovering Meta-Paths in Large Heterogeneous Information Network

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Heterogeneous Information Network (HIN) modeled in a directed graph
Introduction

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Meta path [Han VLDB’11]

- A sequence of node class sets connected by edge types

\[ \Pi^{1...n} = C_1 \xrightarrow{e_1} \ldots C_i \xrightarrow{e_i} \ldots C_n \]

- Benefits of Meta Paths
  - Multi-hop relationships instead of direct links
  - Combine multiple relationships
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\( \text{USPresident} \xrightarrow{\text{hasChild}} \text{Person} \xrightarrow{\text{hasChild}^{-1}} \text{USFirstLady} \)
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\[ m_1 : \text{USPresident} \xrightarrow{\text{hasChild}} \text{Person} \xrightarrow{\text{hasChild}^{-1}} \text{USFirstLady}, \]

\[ m_2 : \text{USPresident} \xrightarrow{\text{memberOf}} \text{USPoliticalParty} \xrightarrow{\text{memberOf}^{-1}} \text{USFirstLady}, \]

\[ m_3 : \text{USPresident} \xrightarrow{\text{citizenOf}} \text{Country} \xrightarrow{\text{citizenOf}^{-1}} \text{USFirstLady}. \]
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- Similarity score for a node pair following a single meta-path
  - Path Count (PC) [Han ASONAM’11]
    - Number of the paths following a given meta-path
  - Path Constrained Random Walk (PCRW) [Cohen KDD’11]
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  Aggregate Function $F$ to combine the similarity scores for each single meta path
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Given meta-paths $m_1, m_2, m_3$

$\sigma(s,t|m_1) = 1$
$\sigma(s,t|m_2) = 0.2$
$\sigma(s,t|m_3) = 0.3$
Similarity score for a node pair following a single meta-path

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Similarity score for a node pair following a combination of multiple meta-paths

Aggregate Function $F$ to combine the similarity scores for each single meta path

\[
F = 3 \times \sigma(s,t|m_1) + 2 \times \sigma(s,t|m_2) + \sigma(s,t|m_3)
\]

Given meta-paths $m_1, m_2, m_3$

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$\sigma(s,t|\theta) = 3.7$
Introduction

Applications

- 1. Query by example
  - When user inputs example pairs of similar objects, we could model the user’s preference and find more pairs.

Input:< Barack Obama, Michelle Obama>
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Applications

1. Query by example

When user inputs example pairs of similar objects, we could model the user’s preference and find more pairs.

Input: <Barack Obama, Michelle Obama>

Output: <George Bush, Laura Bush>
<Bill Clinton, Hillary Clinton>
Introduction

Applications

- 2. Link prediction
  - Coauthor prediction (Authors from DB and AI to collaborate)
  - Friendship prediction (Online Social Network)
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Applications

- **2. Link prediction**
  - Coauthor prediction (Authors from DB and AI to collaborate)
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Existing work

- **Designed by experts** [Han VLDB’11]
  - Complex to analyze big data
  - Do not consider user-preference

- **Enumeration within a given length** [Cohen ECML’11]
  - Max length L is large, redundant (Curse of dimension)
    - In Yago, L=3, 135 meta-paths . L=4, 2000 meta-paths
  - L is small, miss some important ones
Problem Definition

Meta Paths Generation

Example node pairs

(B. Obama, M. Obama)
(B. Clinton, H. Clinton)

Knowledge Base

(Yago)

Meta Path Generation

$\Lambda$

Meta-paths

$\Theta$

Similarity Function

$F$

(Linear Function)

Knowledge Base ($Yago$) -> Meta Path Generation

$G$

Meta-paths:

- USPresident $\xrightarrow{\text{hasChild}}$ Person $\xrightarrow{\text{hasChild}}$ USFirstLady,
- USPresident $\xrightarrow{\text{memberOf}}$ USPoliticalParty $\xrightarrow{\text{memberOf}}$ USFirstLady.
Problem Definition

**Meta Paths Generation**

\[ \Lambda \rightarrow \text{Example node pairs} \rightarrow \text{Knowledge Base} \rightarrow G \]

**Contributions**

- Consider the user’s preference: let user input example pairs
- Automatically generate meta paths without a max length: heuristic search instead of enumeration
Two Phase Method

Challenge: Each node has many class labels. The number of candidate meta paths grows exponentially with the length.

First Select Important Meta Path based on Links.

Next Refine the Node types
Generating Meta-Paths

- Phase 1: Link-Only Path Generation
  - **Forward Stagewise Path Generation (FSPG):** iteratively generate the most related meta-path and update the model

Diagram:
- Example Pairs → Converge
- Converge: Y → FINISH
  - Converge: N → Get most related meta-path \( m \) → Model Training
  - Model Training: meta-path \( m \) → Updated model
  - Updated model → An altered LARS model
Generating Meta-Paths

- Phase 1: Link-Only Path Generation
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![Diagram showing the process of generating meta-paths](image)
Generating Meta-Paths

- **GreedyTree**
  - A tree that greedily expands the node which has the largest priority score

- Priority Score: related to the correlation between $m$ and $r$
  - $m$ is the meta path, $r$ is the residual vector which evaluates the gap between the truth and current model

$$\cos(m, r) = \frac{m \cdot r}{\|m\| \times \|r\|}$$

$$S = \frac{\sum_{u \in \mathcal{V}} \sigma(u, v | \Pi) \cdot r(u, \cdot)}{\sqrt{\sum_{u \in \mathcal{V}} \sigma(u, v | \Pi)^2 \times |r|}} \cdot \beta L$$
Generating Meta-Paths

GreedyTree
Generating Meta-Paths
Generating Meta-Paths

GreedyTree

S: Priority Score

<table>
<thead>
<tr>
<th>(u, v)</th>
<th>BPCRW</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1, 1)</td>
<td>1</td>
</tr>
<tr>
<td>(3, 3)</td>
<td>1</td>
</tr>
<tr>
<td>(12, 12)</td>
<td>1</td>
</tr>
<tr>
<td>(14, 14)</td>
<td>1</td>
</tr>
</tbody>
</table>

Node Structure
Generating Meta-Paths

GreedyTree
Generating Meta-Paths

GreedyTree
Generating Meta-Paths

GreedyTree
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GreedyTree
Generating Meta-Paths

GreedyTree
Meta-path Generation

- **Phase 2: Node Class Generation**
  - Why node classes are needed
    - A link only meta path may introduce some unrelated result pairs.
      \[ ? \xrightarrow{\text{liveIn}} ? : \text{is less specific than} \quad \text{Scientist} \xrightarrow{\text{liveIn}} \text{CapitalCity} \]
  - **Solution 1: Lowest Common Ancestor (LCA)**
    - Record the LCA in the node of GreedyTree

![Diagram showing node classes and relationships]
Solution 3: TFOF

\[ \text{score}(\phi) = \frac{tf(\phi)}{\log of(\phi)} \]

- \(tf\) is the frequency of label in positive examples.
- \(of\) is the overall count in KB

\[
\begin{align*}
\text{tf}(\text{USPresident}) &= 2 \\
\text{of}(\text{USPresident}) &= 42 \\
\text{score}(\text{USPresident}) &= 1.23
\end{align*}
\]

- \(of\) can be pre-computed.
Solution 3: TFOF

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- \( tf(\text{USPresident}) = 2 \quad \text{of}(\text{USPresident}) = 42 \)

- \( \text{score}(\text{USPresident}) = 1.23 \)

- \( of \) can be pre-computed
Experiments

- **Dataset**
  - **DBLP (four areas)**
    - (Database, Data Mining, Artificial Intelligence and Information Retrieval).
    - 14376 papers, 14475 authors, 8920 topics, 20 venues.
  - **Yago**
    - A Knowledge Base derived from Wikipedia, WordNet and GeoNames.
    - CORE Facts: 2.1 million nodes, 8 million edges, 125 edge types, 0.36 million node types

- **Link-prediction evaluation**
  - Select \( n \) pairs of certain relationships as example pairs
  - Randomly select another \( m \) pairs to predict the links
Experiments

- Effectiveness

Baseline method: enumerating all meta-paths within a given max length $L$.

- $L$ is small, low recall.
- $L$ is large, low precision.

ROC for link prediction
Case study - Yago citizenOf

- Better than direct link (PCRW 1)
- Better than best PCRW 2
- Better than PCRW 3, 4

5 most relevant meta-paths for citizenOf
Experiments

- **Efficiency**

  - In Yago, 2 orders of magnitude better.
  - In DBLP, the running time is comparable to PCRW 5, but the accuracy is much better.
Conclusion

- We examined a novel problem of meta-paths generation which is highly needed to analyze and query KB.
- We proposed the **FSPG** algorithm, and developed **GreedyTree** to facilitate its execution.
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Thank you!

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Introduction

Applications

- 3. Recommendation
  - Promote Movies for customers
  - Choose representatives to Political or Commercial negotiations
Association Rule mining compared with AMIE

(Luis, WWW’13)

AMIE does not consider the hierarchy of node types. Failed to distinguish Ivy League alumni from the alumni of any other universities.
Experiments

- Class label selection
  - The TFOF method of generating class labels is better for high precision queries.
  - LCA is better than TFOF for higher recall rates.