

Corporate Leaders Analytics and Network System (CLANS): Constructing and Mining Social Networks among Corporations and Business Elites in China

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- 1 Introduction
- 2 CLANS System
- 3 Website Illustration

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2 CLANS System

3 Website Illustration

Background

- Social networks are essential for business.



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- In US, social networks among firms benefit the debt financing, firm performance, and corporate governance¹²³.

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- Especially, relationship plays a crucial role in Chinese business model.
- To the best of our knowledge, few studies focus on the social network of corporations and elites in China

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 - Construct a business social network and formulate similarity relations among individuals and corporations

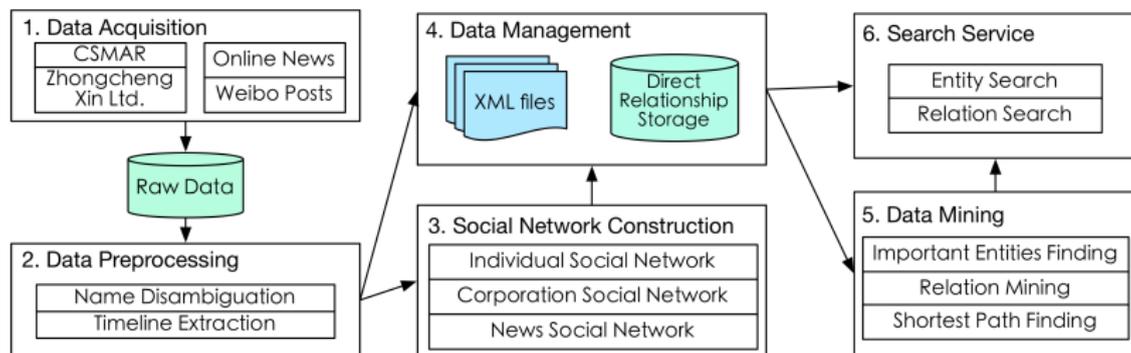
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- Main contributions
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 - Construct a business social network and formulate similarity relations among individuals and corporations
 - Conduct data mining to discover more implicit information

1 Introduction

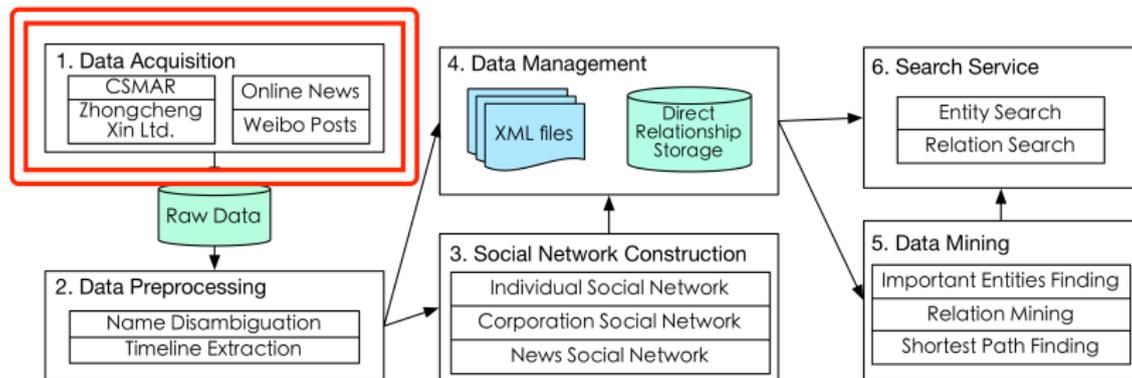
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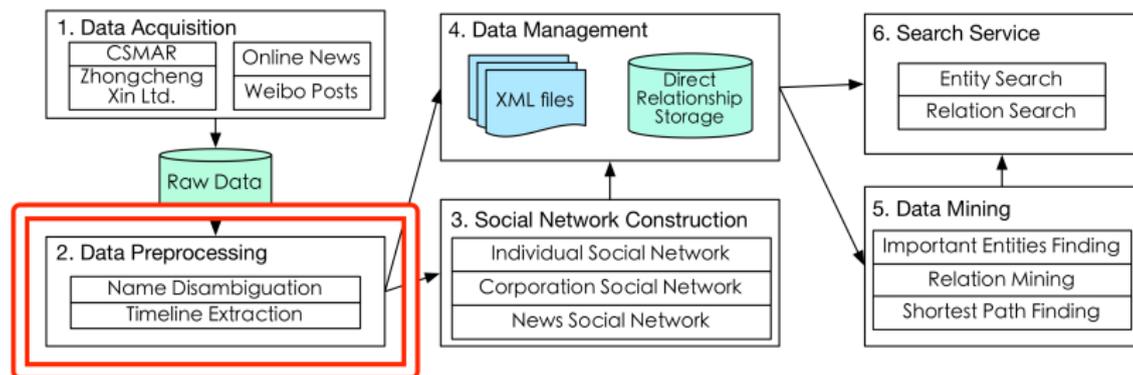
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Sources	People	Company
Online news	16,374,279	1,126,299
Sina Weibo	19,445,929	2,367,619

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- Result
 - Identify 87,458 individual entities in CSMAR and find the common 46,130 people in two datasets

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 - Third round, apply the Latent Semantic Allocation to the labeled result from the second round, map all the documents to vectors in the lower dimensional latent semantic space, calculate document similarities, set the threshold and label the rest.

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- Result

- Select random sample of 1000 posts and news, Weibo posts is 98% and online news is 86% by precision rate.

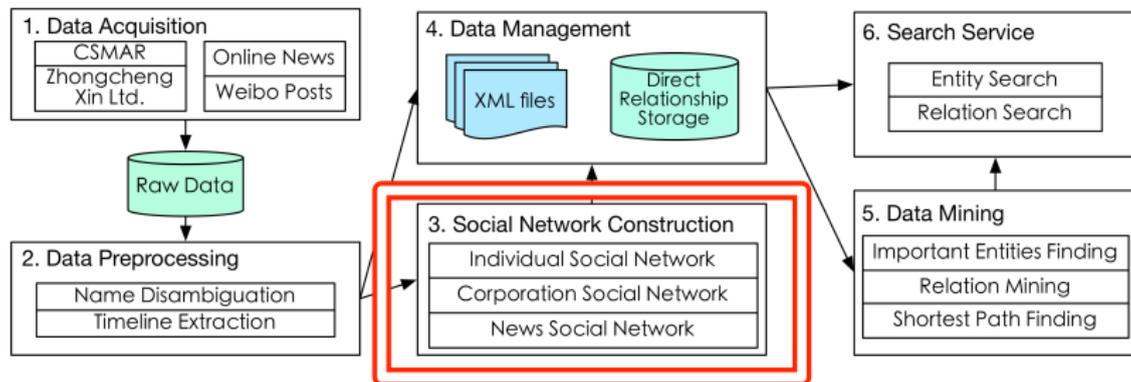
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- Result
 - 95.1% precision rate for education timeline, 83.1% for working timeline.

System Overview



Social Network Construction

Alumni Social Network

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 - The weight of farthest relationship is 0.1 (with different major, different degree and no intersection school time)

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- Let colleague relationship denoted as a combination of value relation and close relation.

- The colleague weight between person p_i and p_j is defined as

$$\omega_{p_i, p_j} = \sum_{t \in L(p_i, p_j)} \frac{PS_{t, p_i} + PS_{t, p_j}}{2}, \quad (1)$$

where $L(p_i, p_j)$ denotes a collection of the intersection years that person p_i and p_j used to work with each other, and PS_{t, p_i} denotes the position rank of person p_i in the year t . At the end, all the weights are normalized, which is also applied in the following weight calculation.

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where $\omega_{i,j}^{al}$ is a weight for alumni relationship, $\omega_{i,j}^{co}$ for colleague relationship; α and β denotes the corresponding percentage.

Social Network Construction

Corporation Social Network

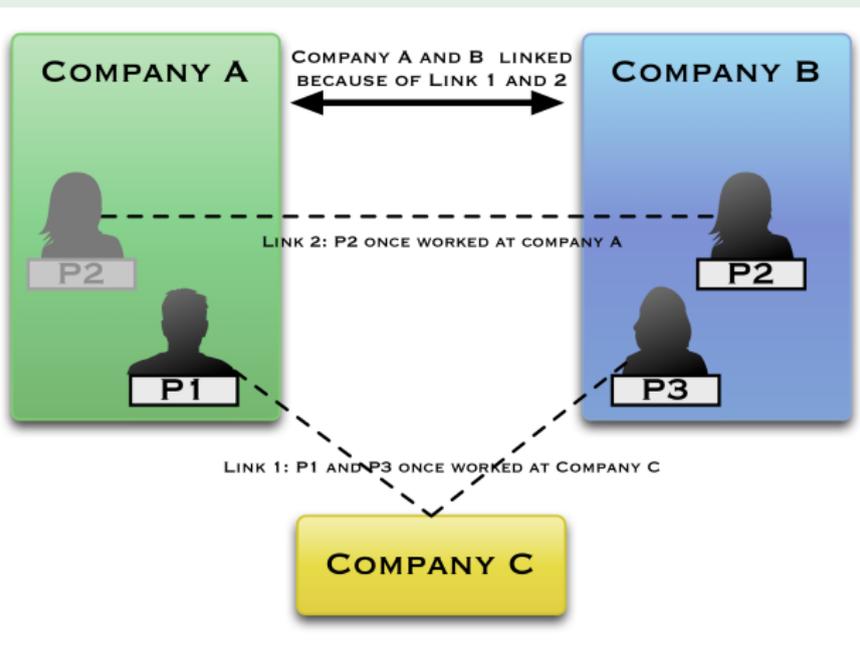
Definition

We define the corporation social network as an directed graph $\hat{G}(\hat{V}, \hat{E})$. In $\hat{G}(\hat{V}, \hat{E})$, every vertex (corporation) has feature set $P_i = \{p_i^1, p_i^2, \dots, p_i^n\}$ and every direct edge (relationship) has weighted value $W_{i,j} = (\omega_{i,j}^{gp}, \omega_{i,j}^{nk})$. n is the size of the set (total number of staffs); $\omega_{i,j}^{gp}$ is a weight for group membership, $\omega_{i,j}^{nk}$ for network relationship.

Social Network Construction

Corporation Social Network

Example



Individual Social Network Construction

Corporation Social Network

- $\omega_{i,j}^{gp}$, $\omega_{i,j}^{nk}$ are defined as follows:

$$\omega_{i,j}^{gp} = \sum_{p_i^k \in P_i \cap P_j} PS_{p_i^k} * \omega_{p_i^k}^{gp}, \quad (3)$$

$$\omega_{i,j}^{nk} = \sum_{(p_i^k, p_j^r) \in L_2(P_i, P_j)} PS_{p_i^k} * \omega_{p_i^k, p_j^r}^{nk}. \quad (4)$$

$PS_{p_i^k}$ denotes the position rank of person p_i^k in corporation i ; $\omega_{p_i^k}^{gp}$ is a weight for p_i^k connecting P_i with P_j ; $L_2(P_i, P_j)$ denotes a collection of connections between $(P_i - P_i \cap P_j)$ and $(P_j - P_i \cap P_j)$; $\omega_{p_i^k, p_j^r}^{nk}$ denotes a weight between p_i^k and p_j^r calculated in the previous equation.

- Corporation weight from corporation i to j is defined as

$$W_{i,j} = \alpha \omega_{i,j}^{gp} + \beta \omega_{i,j}^{nk}$$

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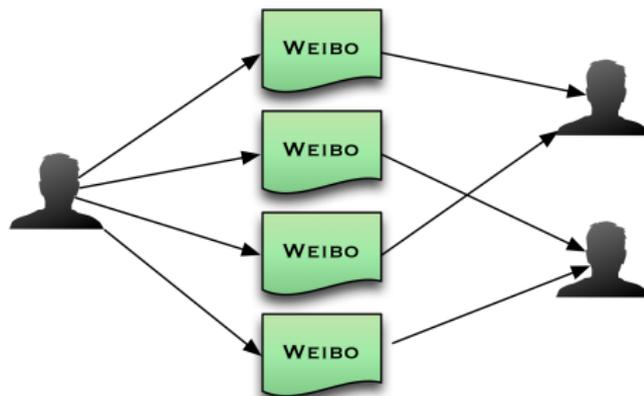
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 - If two individuals or corporations are mentioned in the same posts or news, we consider they have a link.

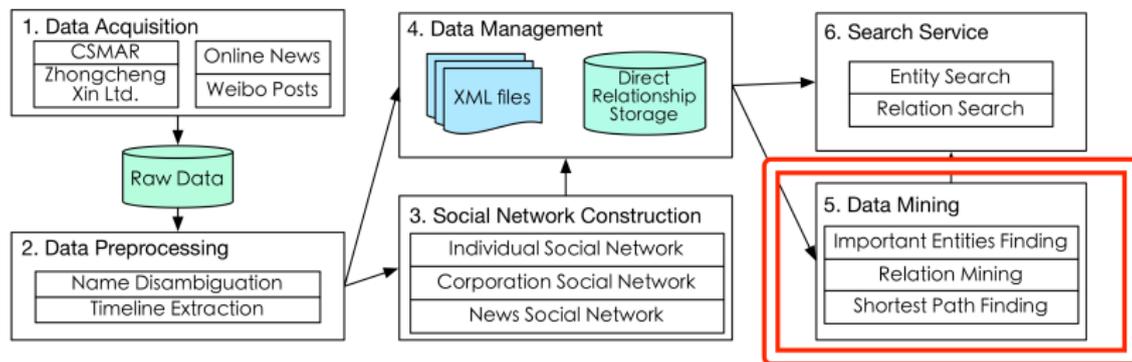
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- For corporation social network
 - Use PageRank algorithm

- Relation Mining
 - Aim to find out important people's link between two corporations' link

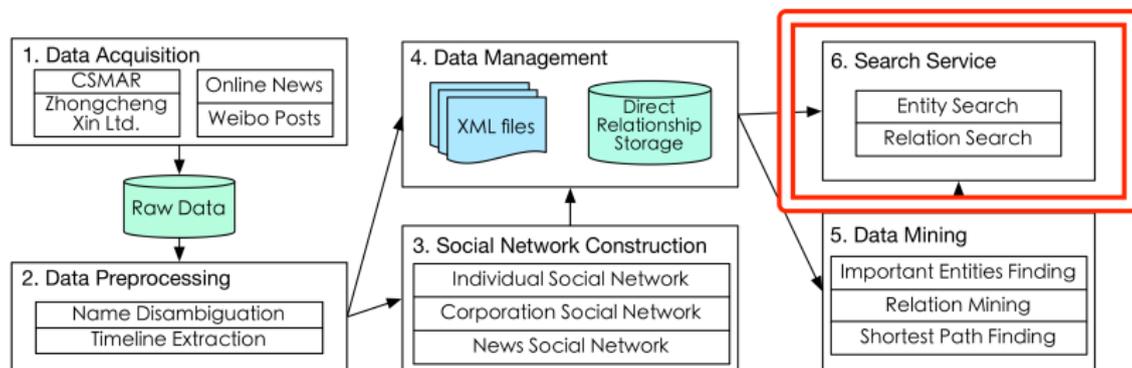
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 - Given any two keywords, the system returns shortest path between them and the corresponding intermediate nodes and link information.

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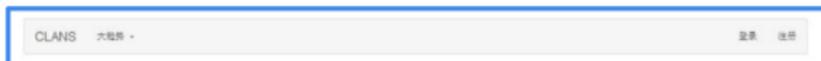
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Website Illustration

Homepage

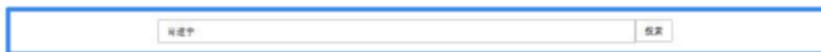
Header



CLANS

Corporate Leaders Analytics and Network System

Search Function



Hot News



Footer



Website Illustration

Person Page

The screenshot shows a web browser window displaying a profile page for a person named 肖遂宁 (Xiao Suining) on the CLANS platform. The page is organized into several sections:

- 1. Basic Information:** A form-like layout with fields for Name (肖遂宁), Gender (男), Birth Date (1949-03-00), Education (大专), and Current Position (执行董事, 深圳发展银行股份有限公司).
- 2. Timeline:** A horizontal timeline showing the person's career path, with a focus on their role as 执行董事 (Executive Director) at 深圳发展银行股份有限公司 (Shenzhen Development Bank Co., Ltd.) from 2010 to 2018.
- 3. Recent News:** A list of news items, including articles about fund investments and bank management.
- 4. Positive News:** A list of news items, including articles about fund investments and bank management.
- 5. Negative News:** A list of news items, including articles about bank management and industry trends.

1. Basic Information

2. Timeline

3. Recent News

4. Positive News

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Website Illustration

Person Page

The image displays six numbered screenshots of a person's website profile, each illustrating a different social network feature:

- 6. Alumni Social Network:** A single green circular node.
- 7. Colleague Social Network:** A central green node connected to five surrounding blue nodes.
- 8. Integrated Individual Social Network:** A complex network graph with a central green node, several blue nodes, and many orange nodes.
- 9. Shortest Path with Another Person:** A path of four nodes: green, blue, black, and purple.
- 10. News Social Network:** A central blue node connected to five surrounding green nodes.
- 11. Comments:** A list of comments with user avatars and text.

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Company Page



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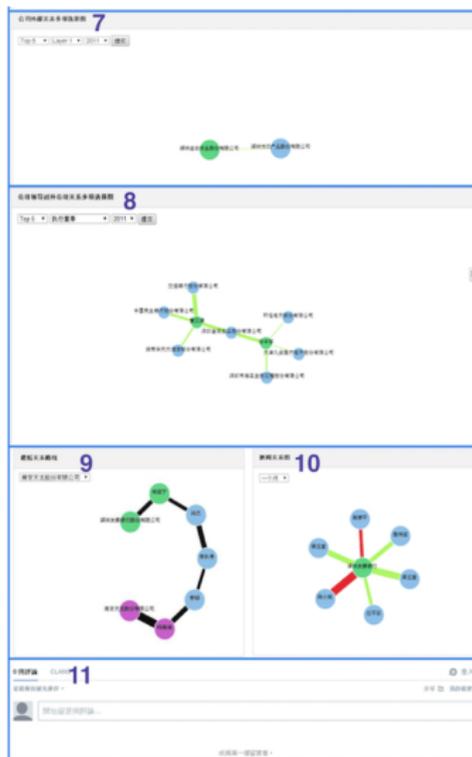
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6. Stock Value Trend

Website Illustration

Company Page



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8. Corporate
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Q&A