Sustainable Resource Acquisition Path: A Dynamic Model of Embedded Entrepreneurial Network Governance under Uncertainty

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Received: 2 September 2018; Accepted: 31 October 2018; Published: 6 November 2018

Abstract: When dealing with complex entrepreneurial network problems, such as sustainable resource flows, the highly uncertainty in environment that brings cognitive bias in entrepreneurs’ decision-making means which entrepreneurs who are expert in using the entrepreneurial network can acquire sustainable resources by reducing external interference. To answer a link decision problem of the role played by network features in the entrepreneurial process of resource acquisition, we introduce an exploratory model design by the Naïve Bayesian classification with EM (Expectation Maximization) algorithm based on SNA (Social Network Analysis) theory that is focused on filling the missing data of uncertainty, in order to describe the path of entrepreneurial network resources acquisition. An inter-dynamic model has established between network structure and the value of resources to predict linking probabilities. By expectation-maximization method for Naïve Bayesian, the paper concludes with an empirical evaluation to verify the accuracy of resource acquisition prediction, in 201 entrepreneurial companies, and application in uncertain environmental network governance decision-making problem regarding the selection of optimal resource paths for creating a new company. We hope which this work can stimulate a broader research agenda focused on the impact of network structure on entrepreneurs’ decision-making under uncertainty, especially for developing countries where has a new round of entrepreneurial enthusiasm with high uncertainty.

Keywords: entrepreneurial networks; resource acquisition; environmental uncertainty; relational embedding; naïve bayesian classifier

1. Introduction

Considerable academic interest has focused on the entrepreneurial activity—specifically the discovery and exploitation of entrepreneurial network, the role of key resources that are involved in driving the entrepreneurial process, and ultimately, the success of new ventures [1]. However, entrepreneurial activity is a kind of social behavior with high uncertainty [2], and decision makers cannot accurately predict the influence of external environment, therefore the environmental uncertainty becomes the basic feature of entrepreneurship [3], which induces a large number of entrepreneurial research to focus on the impact of the entrepreneurial micro-relationship network and the external macro environment of the enterprise on decision-making behavior [4,5].

From the perspective of resource-based view, mainstream research shows that the process of seeking resources from the external environment can effectively reduce the uncertainty [6,7]. And it shows that only resources that are valuable, difficult to imitate and replace can be the essential factor for new ventures to gain competitive advantage [8,9], namely, the process of acquiring resources by...
enterprises constitutes different entrepreneurial behaviors. So, we can conclude that the ultimate condition for entrepreneurs to achieve value creation is to possess and acquire key resources [10]. However, there are existing new entry defects and resource constraints for start-ups [11]. Besides, faced with limited resources, unlike large and developed companies, ventures that located at early-stage cannot bear the huge cost of developing resources or extensive search for transactional objects, and they can only choose transactional objects based on their social capital or previous relationships [3]. Based on the social network theory, the access to entrepreneurial resources is mainly obtained through the internal and external network relationships [12]. Therefore, how to obtain resources through the network has become a hot topic in current entrepreneurial theory research [11]. Existing research no longer assumes that entrepreneurs are shrewd resource seekers, who can absolutely obtain the demand resources of sustainable development in the relationship network [13]. That is to say, the establishment of entrepreneurial networks is goal-oriented [14] and is the social contact that entrepreneurs consciously build with the long-term goal of corporate sustainable development, but this network construction is bound with uncertainty information and external environment [15]. Since decision-makers have become active planners from passive adoption to establish links, they consider the underlying factors of decision making first. Therefore, the paper builds the theoretical framework by putting uncertainty into the decisive factors of resource acquisition and relationship networks, in order to solve the following two questions: (1) how should the ventures acquire the demand resources at a lower cost? (2) How to rationally and purposefully integrate resources in an external environment under uncertainty?

Although there are many existing literatures discussing the conception of uncertainty in the entrepreneurial network, as well as the importance of using social network to obtain resources [16], it is far from enough to explain entrepreneur’s decision-making problem in an uncertain environment [2,3,5]. On the one hand, the research on environmental uncertainty in enterprise decision-making focuses on the subjective perception of entrepreneurs, or uses uncertainty as a moderator to explore the mechanism of entrepreneurial networks affecting firm performance [15,17]. Few studies have established mathematical models from objective aspects to measure uncertainty. On the other hand, entrepreneurs often face constraints in resource acquisition and utilization efficiency. The literature has regarded entrepreneurial resources as a direct result of network relationships to explore the interaction between entrepreneurial networks and corporate performance [16–18]. However, the construction of the network is not equal to the effective use of resources, which still requires the different ways of network governance, resource integration, and entrepreneurs making strategic decision to obtain the actual value of resources. It can be drawn from most existing research is that entrepreneurial networks are very important for resource acquisition, so increasing their investment in entrepreneurial networks as much as possible is a wise choice for entrepreneurs [19]. But, it is not enough to describe the complete affect path between networks with entrepreneurial decision making.

Based on the above analysis, this paper explores and expands the theory of entrepreneurial networks from three aspects. Firstly, according to the perspective of social network theory, we describe the network structure of new ventures from ties strength, structural equivalence, network size, and heterogeneity. Especially, we put uncertainty as an influence variable rather than a moderator variable into consideration. Secondly, this paper attempts to establish a Naive Bayes based on EM algorithm. The model, through mathematical modeling and assignment calculation, derives the path of entrepreneurial network access to the enterprise’s resources, especially by quantifying the uncertain environment in the entrepreneurial network to predict the resource acquisition probability. Thirdly, based on the datasets of 201 startup companies, the EM-NB algorithm and SVM/KNN classification prediction models are compared. The experimental results show that the prediction performance of the EM-NB algorithm is more accurate than the SVM/KNN classification models in predicting the accuracy of the entrepreneurial resource link, which can achieve an accurate 94.89%. In addition, we assumed a simple situation with the human resources acquisition path of new company, which
explained the basic usage of the model in this paper. The calculation results show that, in addition to considering the prediction probability, entrepreneurs should also combine the value and cost of resources to make entrepreneurial decisions.

Overall, our study contributes to both network theory and entrepreneurship theory by introducing link prediction in social network models that does not only stipulates what kind of network structure will lead to different entrepreneurial decisions [20,21], but rather that networking is entrepreneurial action [22]. Whereas, received networking studies have focused on how entrepreneurs may efficiently reach their goals by targeting desired ties, our model highlights how, under uncertainty, networking increasingly becomes a bridge from entrepreneurial resources to entrepreneur decision. In particular, this requires entrepreneurs to weigh the game between the value of resources and the cost of acquisition. We thus complement and extend current models of using entrepreneurial networking with uncertainty as a critical influence variable, which serves to illuminate a completely new angle on how and why entrepreneurs make governance decision in networking [23]. In doing so, we offer strong theoretical grounding for future research, and present the conceptual framework of the entire article in Figure 1.

![Figure 1. Conceptual Framework.](image)

2. Literature Return and Problem Presentation

2.1. Uncertainty in Entrepreneurial Action

In a nutshell, entrepreneurial action under uncertainty is often the equivalent of “chasing an invisible moving target” [3]. Given the creation of new products, services, businesses, and markets, new internal factors tend to aggravate future uncertainties [5]. Thus, the uncertainty is concept cornerstone of most entrepreneurial theories [2]. From the first theory of the entrepreneur put forth by Richard Cantillon in 1755, in which he defined the entrepreneur as “someone who engages in exchanges for profit; specifically, he or she is someone who exercises business judgment in the face of uncertainty” (quoted in Hebert & Link, 1988: 21), the definition of entrepreneurs basically revolves around the individual who exercises judgment [2], and the decision maker who judges the events that have not occurred. Therefore, how to assess and reduce the uncertainty in entrepreneurial behavior has become the focus of entrepreneurial theory [3,18,24].
Alvarez and Barney used transactions cost and incomplete contracts to explain how firms are organized fail to account for firm creation under conditions of uncertainty [15]. McMullen and Shepherd provided a more complete conceptual model of entrepreneurial action that allows for examination of entrepreneurial action at the individual level of analysis, while remaining consistent with a rich legacy of system-level theories of the entrepreneur [2]. Engel et al. flesh out a dynamic networking process which highlights distinctive elements, such as altruism, pre-commitment, serendipity, and co-creation, can stimulate a broader research agenda focused on the inquiry of networking agency under uncertainty [3]. McKelvie et al. believed that entrepreneurial expertise can reduce the impact of uncertainty on entrepreneurial behavior [5]. Burns et al. believed that the key to seeking resources from stakeholders under uncertainty is to build strong ties and develop strong commitment relationships and mutual recognition [24]. Song et al. found that new ventures respond to a high environmental uncertainty by engaging more in prospector strategy, consequently enhancing the ventures’ performance [4].

Before considering how to reduce the uncertainty in entrepreneurial behavior, we first draw on the theory of “bounded rationality”, which defined the uncertainty as “the inability to accurately predict what is happening in the future”. Actually, in an entrepreneurial context, the risk of uncertainty we describe is the state of asymmetric information between two nodes. An uncertain informational setting, however, is a setting where the decision maker cannot know the complete information, and thus, cannot know the probability of the results of resources acquisition through this information. Relatively conceptualizations of uncertainty can be found within the management, economics, and psychology literature [25,26], but theoretical research focuses on conceptual descriptions, lacking attention to how to quantify and estimate uncertainty. Although most of the literature considers that obtaining sufficient resources can reduce asymmetric information in the entrepreneurial process, whether it is from the perspective of social capital, entrepreneurship, or human resources [27–29], but how to make decision to choose the path of resource acquisition did not get enough attention.

2.2. Entrepreneurial Network and Resource Acquisition

Research on entrepreneurial networks has focused either on network structure or network flows [30]. The structural perspective focuses on who is a part of the network (i.e., which actors), the topology of their relationships, and the entrepreneur’s position in the network [14,31]. This perspective emphasizes how network positions enable the aggregation and combination of resources and is dominated by quantitative methods, such as social network analysis, and typically operationalizes only one type of relationship per study (e.g., investment, patent co-authorship, or strategic alliances). Such structural methods are limited in their ability to capture the diversity of interactions between the various actors and flows that comprise organizational and inter-organizational systems [32], including entrepreneurial networks.

The flow perspective focuses on what types of resources are involved in individual relationships, and on how these diverse resources are put to use, exchanged or transformed [33]. Research using the flow perspective typically focuses on how multiple exchanges occur and interact within a single relationship using qualitative research methods [33,34]. Villanueva et al. suggested that gaining access to external resources depends more on total interdependence than it does on achieving a superior dependence position vis-à-vis the exchange partner [10].

Research on resource acquisition has focused either on organization internal or external. As applied to acquire resource from organization internal, the resource-based view portrays an organization as a bundle of resources and capabilities that are developed over time as the organization interacts with stakeholders [7,9]. While rarely applied, the resource-based view is well suited to study resource acquisition, as it is concerned with “the combination and management of resources and how these resources flow within an organization to lead to more effective processes” [35]. However, resource integration and configuration is a kind of external network behavior actually, entrepreneurial teams using their own complex entrepreneurial networks to identify their needed resources is the
beginning of establishing a startup [8]. Bacq and Eddleston provided the resource-based view of social enterprises that demonstrates how stewardship can be extended beyond the external social mission of an enterprise to the organization’s internal culture to promote scale of social impact [7].

More research focuses on getting access from outside the organization, Granovetter believed that the economic behavior of an individual is embedded in a relevant social structure and that such social structure is an economically institutionalized social network [36]. Hite and Hesterly argued that a strong network of relationships between family and friends is the main resource provider for new businesses [37]. However, at the same time, Zhang underscored the complexity of network use by entrepreneurs, what can help entrepreneurs realize how to capitalize on the value of their social networks while avoiding the dangers of excessive or exclusive reliance [11]. Therefore, while considering the acquisition of resources through the entrepreneurial network, this article also weighs the cost of acquiring resources in order to obtain more reasonable management decisions [38].

Despite the rich conclusions of the current studies, the internal mechanism of resource acquisition path influence on entrepreneurs' decision is insufficiently explained, with regarding the entrepreneurial resources as a direct product of network, but the current research lacks a process perspective to examine the decision-making under uncertainly. Therefore, based on social network theory and resource-based view, this paper combines the resource acquisition path through entrepreneurial networks under uncertainty with entrepreneurial decision-making, and it establishes an econometric model to predict resource link problems in entrepreneurial networks.

2.3. The Link Prediction Problem in Social Network

It is common for online social networks to implement a link prediction technique to automatically suggest acquaintances with a high degree of accuracy [39]. A large number of link prediction techniques have been proposed in the specialized literature [40,41]. For business organizations, such predictions are crucial to many important applications enabled by the growing proliferation of social media, such as social network-based target marketing [42], viral marketing [43], and demand prediction [44]. Then, it brings a question: can these methods be used to predict link problems in entrepreneurial network? And how to apply these methods to predict resource acquisition efficiency within network structure?

Based on the current research, there are two main types of algorithms for link prediction problems, one is the unsupervised algorithm, and the other is the supervised algorithm [20]. In unsupervised algorithms, the simplest type is to calculate the similarity between nodes based on the local extension features [39]. The supervised link prediction algorithm considered link prediction as a 0–1 classification problem [45]. Liben-Nowell et al. proposed an unsupervised learning link prediction algorithm, which became the pioneering work in the field of link analysis [41]. Existing research develops link recommendation methods and it discusses link strength from the perspective of link prediction. Backstrom et al. proposed a supervised random walk algorithm to estimate the ties strength of the social relationship [46]. Hopcroft et al. studied what information in social relationships can be predicted in dynamic networks [47].

At the same time, we find that there is few researches that predict the link between social networks in reality by quantitative model. The reason we conclude are as follows: First, the data of offline entrepreneurial networks is harder to obtain than social network, most of those are missing and incomplete. Second, there are complex environmental uncertainties in real life, which is difficult to capture and measure. To address these research questions, this paper draws on a Naive Bayesian method based EM algorithm proposed by Fang [21,40], which predicts link probabilities in the presence of certainly factors that are generally unobserved. The probability of link establishment directly affects the decision of entrepreneurs to obtain resources, which can lead to different performance and economic benefits of start-ups.
3. Key Factors Underlying Entrepreneurial Decision: Related Theory and Operationalization

First of all, we are thinking about a question—What factors do entrepreneurs usually consider when making entrepreneurial choices? The factors influencing the decision to become self-employed can be classified into several categories. The first category refers to objective individual attributes, demographic characteristics and socioeconomic factors [48]. The second category includes subjective factors that are associated with entrepreneurial activity [49]. Whether subjective or objective factors, the resources that are held by entrepreneurs is the main force driving someone to start the business. We review relevant social network theories that point to several key factors underlying an entrepreneur’s link decision, and then propose ways to operationalize these factors with social network theory.

3.1. Related Theory with Network Structural Feature

Unlike markets or organizations, social networks regard their mutual relations as ties [50]. Strong and weak ties are very important to the resource acquisition and business decision making of entrepreneurs. Specifically, these ties help entrepreneurs obtain information and other resources across social boundaries, promote collaboration among associative members, and facilitate the sharing and transfer of complex knowledge and experience. One of the most famous theories in social network research is “Six Degrees of Separation” [51], which posits that one person can be connected to another through a maximum of six people. This theory shows prevalent “weak ties” in social networks that make people considerably “close” to one another [51]. In The Strength of Weak Ties, the strength of ties among the behavior nodes in social networks positively affects the flow of information and the coordination among organizations [52]. Meanwhile, “weak ties” can reach more members of the society and serve as “bridges” of communication among different social groups; these ties help entrepreneurs to connect with different groups, add diversity to their social networks, and provide enterprises with effective channels for information and resource acquisition [10]. Bratkovic and Antoncic makes a contribution by developing and testing a model of the firm growth that is driven by the entrepreneur’s social capital that considers the entrepreneur’s resource acquisition network ties. In the model, a controversial combination of strong and weak tie arguments is proposed [29].

Strong ties are often expressed as frequent contacts, dialogue and communication, high-quality information delivery, and sharing of experience and knowledge; these ties promote an environment of trust that reduces the cost of breaking promises during the process of development and significantly strengthens resource sharing during the process of cooperation [51]. An increased resourcefulness of entrepreneurs’ networks leads to easier access to resource owners via their existing network route [28]. In this way, start-ups can obtain various forms of external support, such as capital, market, and information, within a short period [53]. Therefore, tie strength helps start-ups to take advantage of fleeting opportunities to improve their performance.

Structural equivalence is the basic structural feature of social networks [54]. This feature suggests that two social entities have identical connections to other entities, occupy the same position in the social structure, and are of different degrees [55]. Structural equivalence is vital to the choices of entrepreneurial teams, that is, structurally equivalent entrepreneurial teams may face a highly intense competition due to their substitutability. Based on the view of power balance in the theory of resource dependence, the structure of the two sides of the entrepreneurial network link does not have the relative dependence on the relative dependence [10], which follows the “power logic” [56]. However, two people with an equivalent structure can take the other as a reference for subjective judgment and may make similar choices without direct communication [54].

Nevertheless, no perfect structure equivalence can be found in social networks. Therefore, the structural equivalence between entrepreneurs is measured by the degree of their structural equivalence. That is, the advantages and disadvantages of power [10]. Structural equivalence is commonly measured by the Euclidean distance.
Based on social capital theory, social network ties enable people to obtain required knowledge, emotional support, and related resources. Increasing the number of network members can promote the resource acquisition of enterprises [57]. Meanwhile, increasing the size and expanding the scale of the network will increase its number of subjects and the richness of its embedded information. Consequently, start-ups become highly capable of identifying potential resource owners by using such information and become likely to obtain the required resources on favorable terms or through cooperation agreements. Start-ups can take advantage of their extensive social ties with various subjects, such as customers, suppliers, competitors, research institutions, and service agencies, to acquire financial capital, key technologies, human capital, and management experience [29].

As a fundamental problem of team composition, network heterogeneity is based on social identity theory [58]. The heterogeneity of an entrepreneurial team can be classified into external plain heterogeneity (e.g., gender, age, race, educational level, and employment experience) and internal deep heterogeneity (e.g., cognition, values, preferences, attitudes, and entrepreneurial commitments) [59]. Supporters of cultural diversity believe that a mosaic of various cultural backgrounds can make team members achieve “complementary advantages” by making full use of their backgrounds, ideas, knowledge, and other aspects of their differences. Diversity can also provide organizations with multiple views and opinions, which in turn, can lead to the formation of broad and creative decision-making programs that ultimately contribute to the shaping of high-quality, effective, and innovative organizational decisions [60].

The heterogeneity of the entrepreneurial team will, to a certain extent, reduce the risk perception of the team. Homogeneous teams can easily reach a consensus on aggressive and risky strategies due to the presence of few barriers to cognition and communication [61]. To develop high-quality and moderate risk decisions in an uncertain environment, managers must seek the cognitive perspectives of their team members to achieve “complementary advantages” and “mutual rectification”, which are often difficult to achieve for homogeneous teams [62]. However, some scholars suggest that a beyond moderate level of team heterogeneity will reduce cohesion and coherence in strategic decision making [63]. There is an inverted U-type relationship between the degree of heterogeneity and the performance of the firm. Thus, the possibility of reaching a consensus is also reduced. Excessive heterogeneity will also affect access to resources and the degree of trust within an entrepreneurial team. Most of the literature supports that there exists a moderate level of moderate heterogeneity in the process.

In addition, more attention must be paid to the utility and value of the resources, therefore, reasonable governance mechanisms must be adopted to effectively manage and control the transactional relationships in networks [64]. Existing literature still cannot explain the “black box” of the transformation process between entrepreneurial activities and final value creation perfectly [38]. Morse, Fowler, and Lawrence believes that the key to acquiring resources is to get the resources they need at the lowest cost [65]. Under the uncertainty environment and bounded rationality, entrepreneurs pursue behavioral constraints in the process of maximizing their own benefits, and the corresponding costs are generated in each process of resource exchange and acquisition. The network is an unstable system. Changes in external conditions will cause major adjustments in the system. The actions of start-ups and individual network participants in the entrepreneurial network depend on the benefits, costs, and systems that they may derive from the network. Entrepreneurial social embedded relationships provide them with access to resources while also limiting their behavior outside the network, so there is a problem of “degree” embedded [66].

Link decisions in a social network may depend on factors beyond ties strength, structural equivalence, network size, and heterogeneity though. Uncertain factors in the entrepreneurial network and the utility of resource should be fully considered in the model construction. Our review of relevant theories thus sheds light on several important factors underlying link prediction: ties strength, structural equivalence, and the network size, heterogeneity, as well as the uncertainty factors. We operationalize each, except uncertainty factors, with entrepreneurial network data.
3.2. Operationalization with Network Structural Feature

Taking \( W = \{w_1, w_2, \ldots, w_n\} \) as a set of social entities. If no social tie is found from \( w_i \) to \( w_j \), then \( x_{ij} = 0 \). The strength of social ties is measured by the frequency of contact among people or groups [50]. The \( x_{ij} \) denotes measurable average frequency of contact between \( w_i \) and \( w_j \). If no ties exist between entities, then \( x_{ij} = 0 \).

\[
F_{ij} = \frac{x_{ij} - x_{\min}}{x_{\max} - x_{\min}}
\]

(1)

where \( x_{\max} \) and \( x_{\min} \) represent the maximum and minimum frequency of contact, respectively. Normalization helps prevent the dependence of \( F_{ij} \) on the unit of measure of \( x_{ij} \) [67].

This paper utilizes competitiveness to measure the structural equivalence of enterprises. The Euclidean distance of the structural equivalence between social entities \( w_i \), and \( w_j \) is denoted as \( y_{ij} \), which is calculated as:

\[
y_{ij} = \sqrt{\sum_{k=1}^{n} (d_{ik} - d_{jk})^2}, i \neq j \neq k.
\]

(2)

If a social tie exists from \( w_i \) to \( w_j \), then \( d_{ij} = 1 \). Otherwise, \( d_{ij} = 1 \). A higher \( d_{ik} \) corresponds to a lower structural equivalence from \( w_i \) to \( w_j \). Therefore, the structural equivalence of entrepreneurs \( w_i \) to \( w_j \) is computed as:

\[
E_{ij} = \frac{y_{\max} - y_{ij}}{y_{\max} - y_{\min}}
\]

(3)

Normalize the structural equivalence, where \( y_{\max} \) and \( y_{\min} \) represent the maximum and the minimum Euclidean distance of the structural equivalence, respectively.

In this paper, \( a_{ij} \) denotes the edge of the relational network for the entrepreneurial team \( w_i \in W \). If no link exists from \( w_i \) to \( w_j \), then \( a_{ij} = 0 \).

\[
D_i = \sum_j a_{ij} = \sum_j a_{ij}
\]

(4)

\[
S_{ij} = \frac{D_i}{\max(D_i, D_j)}
\]

(5)

where \( D_i \) represents the edge number of the node referred to as the degree, which is the network size of the entrepreneurial relationship. We can use \( S_{ij} \) to measure the relative network size of a node.

In this paper, the Jaccard coefficient is chosen as the similar function [68], in which \( r_i, r_j \) measure the attributes of social entities \( w_i \) and \( w_j \), respectively. Thus, a higher \( \text{sim}(r_i, r_j) \) indicates a greater similarity between \( w_i \) and \( w_j \). The heterogeneity of social entities \( w_i \) and \( w_j \) is measured as

\[
\text{sim}(r_i, r_j) = \frac{|r_i \cap r_j|}{|r_i \cup r_j|} \quad \text{and}
\]

\[
H_{ij} = 1 - \text{sim}(r_i, r_j).
\]

(6)

(7)

In order to reasonably assess the value of resources, we introduce real option theory into utility model to discuss the entrepreneurial decision. This process of calculation starts from the perspective of options, and entrepreneurial resources are regarded as hidden assets of enterprises, and their flows can be regarded as multiple transactions. You can think of each network resource acquisition link as an investment decision. As resources are used for a longer period of time, their value is increasing, but at some point, their value is will fall. On the whole, its performance is similar to the normal distribution. The real option rule fully applies this point. Therefore, the resource is regarded as an American call option owned by the enterprise. The feature of American call option which can be executed any day after the expiration of the transaction is more in line with our implementation criteria for value assessment of entrepreneurial. The decision on the construction management of the entrepreneurial
network is based on input and value. In order to determine the value estimate of enterprise resource acquisition decisions [69], in view of the similarity between entrepreneurial resources and financial options, a corresponding real option can be constructed [70]. A financial real power gives investors a right to pay a predetermined execution price for a certain period of time to obtain a specific asset; a company that owns the resource also has such a right to pay a certain amount of money now or in the future. The cost of accessing the resources. The resources obtained from the network are equivalent to the subject matter of financial options. The resource cost is equivalent to the exercise price of the option. The usage time of resources is equivalent to the time from the expiration date of the option. The uncertainty of the potential resource value is equivalent to the size of the risk of the derivative in the option.

Based on the Black-Scholes model, the value of a resource can be defined as:

\[ U_{ij} = S_0 N(d_1) - K e^{-rT} N(d_2) \]  (8)

\[ d_1 = \frac{\ln(S_0/K) + (r + \sigma^2/2)\tau}{\sigma\sqrt{\tau}} \]  (9)

\[ d_2 = \frac{\ln(S_0/K) + (r - \sigma^2/2)\tau}{\sigma\sqrt{\tau}} \]  (10)

where \( U_{ij} \) represents the value of the resource link, \( S_0 \) is the price of a resource at time 0, \( N(x) \) is the cumulative probability distribution function of the standard normal distribution, \( K \) is the expected cash inflow value of the resource, \( \tau \) is the resource life expectancy, \( T \) is the resource’s usage time, \( r \) is the risk-free interest rate, and \( \sigma \) is the resource value fluctuating rate.

However, when considering hidden uncertainty is crucial, which makes it a principal challenge for predicting link probabilities.

4. Model Building

4.1. Construction of the Naive Bayesian Classifier

We use the naive Bayes classifier based on EM algorithm to identify the resource status in existing entrepreneurial networks. The Naive Bayesian algorithm has simple calculations, can effectively deal with the classification problem of mixed index attributes and excellent classification ability [71]. When combined with EM algorithm, it can solve the problem of filling incomplete data and classify unknown data. Prediction [72,73]. As shown in Figure 2, whether a startup establishes a network link should first determine whether there is a resource in the current entrepreneurial network, and then consider whether the cost of establishing the link is too high, and reasonably identify the quality and value of the information and resources to avoid over-embedding of the relationship [66].

![Figure 2. Potential resources of social entities.](image-url)

Let \( W_A \) and \( W_N \) denote a set of entrepreneurial teams with sufficient and limited resources, respectively. Then, \( W_A = \{ w_m \mid w_m \in W, \text{ and, } W_N = \frac{W}{W_A} \} \). The entrepreneurial team \( W_i \) acquires resources by combining the strength of the entrepreneurial network relationship, the institutional
equivalence, and the size and heterogeneity of the network. The set TRAIN, which encompasses the existing data of entrepreneurial teams, is built.

In Figure 3, we can find that the study aims to derive the probability of $w_{ij}$ and $P(A_{ij} = 1|F_{ij}, E_{ij}, S_{ij}, H_{ij}, N_{ij})$, where $A_{ij}$ indicates sufficient access to resources from the existing training set.

Assuming that the actual data of uncertainty factors are available, the classification theory upon which the Bayesian classifier relies uses the Bayesian formula to calculate posterior probability, which refers to the probability for an object to belong to a certain class, through the prior probability of an object. The class with the maximum a posteriori probability is selected as the class to which the object belongs. According to Bayes theorem,

$$P(A_{ij} = 1|F_{ij}, E_{ij}, S_{ij}, H_{ij}, N_{ij}) = \frac{P(A_{ij} = 1)P(F_{ij}, E_{ij}, S_{ij}, H_{ij}, N_{ij}|A_{ij} = 1)}{\sum_{a=0.1} P(A_{ij} = a)P(F_{ij}, E_{ij}, S_{ij}, H_{ij}, N_{ij}|A_{ij} = a)}$$  

(11)

The Naive Bayesian method is based on the strict independence assumption. Tie strength $F_{ij}$, equivalence $E_{ij}$, relative network size $S_{ij}$, and heterogeneity $H_{ij}$ are assumed to be independent of one another. Therefore,

$$P(A_{ij} = 1|F_{ij}, E_{ij}, S_{ij}, H_{ij}, N_{ij}) = \frac{P(A_{ij} = 1)P(F_{ij}|A_{ij} = 1)P(E_{ij}|A_{ij} = 1)P(S_{ij}|A_{ij} = 1)P(H_{ij}|A_{ij} = 1)P(N_{ij}|A_{ij} = 1)}{\sum_{a=0.1} P(A_{ij} = a)P(F_{ij}|A_{ij} = a)P(E_{ij}|A_{ij} = a)P(S_{ij}|A_{ij} = a)P(H_{ij}|A_{ij} = a)P(N_{ij}|A_{ij} = a)}$$  

(12)

This work examines how to obtain $P(F_{ij}|A_{ij} = a)$, where $a = 0.1$. According to the Naive Bayesian learner, $F$ is assumed to be an exponential distribution. In a given resource situation where $a$ is chosen and $P(F_{ij}|A_{ij} = a)$ is the density of $F_{ij}$, a density function $f(x) = \lambda_{F|a}e^{-\lambda_{F|x}}$, $x \geq 0$, where $a = 0.1$, exists and $\lambda_{F|a}$ is a parameter. $P(F_{ij}|A_{ij} = a)$ can be estimated via $f(F_{ij})$. This work estimates $P(E_{ij}|A_{ij} = a)$, $P(S_{ij}|A_{ij} = a)$, $P(H_{ij}|A_{ij} = a)$, and $P(N_{ij}|A_{ij} = a)$ in the same way. A parameter vector $\theta$ is obtained, as follows via TRAIN:

$$\theta = \langle p_1, \lambda_{F[1]}, \lambda_{E[1]}, \lambda_{S[1]}, \lambda_{H[1]}, \lambda_{N[1]}, p_0, \lambda_{F[0]}, \lambda_{E[0]}, \lambda_{S[0]}, \lambda_{H[0]}, \lambda_{N[0]} \rangle,$$

(13)
The first step is to define and learn how to maximize the objective function. We make the maximum likelihood estimation to \( \theta \) with the flag data \((F_{ik}, E_{ik}, S_{ik}, H_{ik}, A_{ik})\) in TRAIN. In this model, \( k = 1, 2, \ldots, n \), where \( n \) is the total number of flag data in TRAIN, \( N_{ik} \) is the uncertainty of the \( k_{th} \) flag data, \( D \) is the complete data, and \( D_{ik} = \langle F_{ik}, E_{ik}, S_{ik}, H_{ik}, N_{ik}, A_{ik} \rangle \), where \( k = 1, 2, \ldots, n \). The likelihood of \( D \) in the given \( \theta \) is marked as \( P(D|\theta) \). We conclude that

\[
P(D|\theta) = \prod_{k=1}^{n} P(D_{ik}|\theta). \tag{14}
\]

The maximum likelihood parameter estimation \( \theta_{ML} \) maximizes \( P(D|\theta) \). We substitute \( \ln[P(D|\theta)] \) for \( P(D|\theta) \), because the former is easily maximized than the latter and its maximum parameter estimation also maximizes that of the latter. Thus,

\[
\theta_{ML} = \arg\max_{\theta} \sum_{k=1}^{n} \ln[P(D_{ik}|\theta)]. \tag{15}
\]

4.2. Estimating Missing Values Using EM Algorithm

To solve the problem of missing values, the Naive Bayesian classifier based on EM algorithm is adopted [74]. The EM algorithm is mainly used to calculate the number or to estimate the maximum likelihood of posterior distribution, which in turn, is used for filling incomplete data [75]. This algorithm initially estimates the missing values and then iteratively performs two basic steps, namely, expectation and maximization [76]. The expectation step defines the expected estimate for the missing value when both the variable and the current parameter estimate are known, while the maximization step maximizes the problem by re-estimating the parameters with the recognition that the estimate of the E-step is correct and that the parameter value has the maximum likelihood with the data completed in the E-step. The likelihood values are not reduced during each iteration, and the final maximum convergence can be ensured [77].

However, no training data are available for calculation. Thus, the estimated value of \( \theta \) cannot be obtained directly by using the same formula. To solve the non-measurability of the potential resource acquisition path by estimating the missing value, the EM algorithm is adopted [77] and is iterated by maximizing the objective function \( Q(\cdot) \).

\[
\theta_{k+1} = \arg\max_{\theta} Q(\theta|\theta_k) \tag{16}
\]

where \( \theta_k \) and \( \theta_{k+1} \) represent the vector of parameter estimation at the \( k \) time(s) and \( k + 1 \) time(s) in the iteration, respectively, and \( Q(\cdot) \) is defined as

\[
Q(\theta|\theta_k) = \sum_{k=1}^{n} \ln[P(D_{ik}, N_{ik}|\theta)]P(N_{ik}|D_{ik}, \theta_k)dN_{ik}, \tag{17}
\]

where \( \ln[P(D_{ik}, N_{ik}|\theta)] \) is the log-likelihood estimation of the complete dataset of the given \( \theta \), while \( P(N_{ik}|D_{ik}, \theta_k) \) is the probability of \( N_{ik} \) with the given \( D_{ik} \) and the prior parameter estimation \( \theta_k \). Equation (16) can be extended: (See Appendix A for the derivation process)

\[
Q(\theta|\theta_k) = \sum_{k=1}^{n} \ln[P(A_{ik}|\theta)] + \sum_{k=1}^{n} \ln[P(E_{ik}|A_{ik}, \theta)] + \sum_{k=1}^{n} \ln[P(H_{ik}|A_{ik}, \theta)] + \sum_{k=1}^{n} \{\ln[P(F_{ik}, N_{ik}|A_{ik}, \theta)] + \ln[P(S_{ik}, N_{ik}|A_{ik}, \theta)] - \ln[P(N_{ik}|A_{ik}, \theta)]\} P(N_{ik}|A_{ik}, \theta_k)d_{H_{ik}} \tag{18}
\]
Calculating the above formula requires the probabilities of $P(A_{ik})$, $P(E_{ik} | A_{ik})$, $P(H_{ik} | A_{ik})$, $P(F_{ik}, N_{ik} | A_{ik})$, $P(S_{ik}, N_{ik} | A_{ik})$, $P(N_{ik} | A_{ik})$, and $A = 0, 1$. First, to obtain the prior probability $P(A_{ik})$, the parameters $P_0 = P(A_{ik} = 0)$ and $P_1 = P(A_{ik} = 1)$ are established. Second, to obtain $P(E_{ik} | A_{ik} = 0, 1)$, this parameter is assumed to follow the exponential distribution. In the Bayesian network, a continuous factor commonly follows the exponential or normal distribution [78]. The density $\lambda_{ik}^2 e^{-\lambda_{ik} x}$ can be used to estimate $P(E_{ik} | A_{ik} = 0)$, and the exponential density $\lambda_{ik}^1 e^{-\lambda_{ik} x}$ can be used to estimate $P(E_{ik} | A_{ik} = 1)$. Therefore, to estimate $P(E_{ik} | A_{ik})$ and $P(H_{ik} | A_{ik})$ effectively, the parameters $\lambda_{ik}^1$ and $\lambda_{ik}^2$ must be estimated.

With a given $A$, $E$, and $N$ are assumed to follow the binary exponential distribution [76], while the density function of the bivariate exponential distribution is computed as

$$f(x, y) = \begin{cases} \lambda x e^{-\lambda x} - \lambda y e^{-\lambda y}, & 0 < x < y \\ \lambda y e^{-\lambda x} - \lambda y e^{-\lambda y}, & 0 < y < x \end{cases}$$

(19)

By substituting the above formula into $P(F_{ik}, N_{ik} | A_{ik})$, we obtain

$$P(F_{ik}, N_{ik} | A_{ik}) = \begin{cases} \lambda_F^A \lambda_N^A e^{-\lambda_F^A F_{ik} - \lambda_N^A N_{ik} - \lambda_F^A F_{ik} - \lambda_N^A N_{ik}} F_{ik} \leq N_{ik} \\ \lambda_F^A \lambda_N^A e^{-\lambda_F^A F_{ik} - \lambda_N^A N_{ik} - \lambda_F^A F_{ik} - \lambda_N^A N_{ik}} N_{ik} \leq F_{ik} \end{cases}$$

(20)

The parameters $\lambda_F^A$, $\lambda_N^A$, $\lambda_F^N$, and $\lambda_N^N$ are estimated using the above formula, while $P(S_{ik}, N_{ik} | A_{ik})$ is calculated the same way and substituted into the bivariate exponential distribution. Therefore, the parameters $\lambda_S^A$, $\lambda_S^N$, $\lambda_S^A$, and $\lambda_S^N$ also need to be estimated.

Finally, in order to estimate $P(N_{ik} | A_{ik})$, with a given $R$, when $N < \min(F_{ik}, S_{ik})$, $N$ follows the exponential distribution with the parameter being $\lambda_N^A$. However, when $N \geq \min(F_{ik}, S_{ik})$, $N$ follows the exponential distribution, with the parameter being $\lambda_N^A$.

$$P(N_{ik} | A_{ik}) = \begin{cases} \lambda_N^A e^{-\lambda_N^A N_{ik}}, & N_{ik} < \min(F_{ik}, S_{ik}) \\ \lambda_N^A e^{-\lambda_N^A N_{ik}}, & N_{ik} \geq \min(F_{ik}, S_{ik}) \end{cases}$$

(21)

This study adopts the theorem provided in the literature [21]. (See Appendix B for the elaboration of the theorem)

**Theorem 1.** In this case, when estimating $\theta_k = < P_0, P_1, A_F^0, A_F^1, A_H^0, A_H^1, A_E^0, A_E^1, A_S^0, A_S^1, A_N^0, A_N^1 >$ with the previously given parameters and the assumed factors $E$, $H$, $F$, $S$, and $N$ in the exponential distribution, a closed optimal solution of $\theta$ exists for maximizing the objective function [21].

The closed-form solution for parameter estimation in Theorem 1 cannot only simplify the operational process of the EM-based algorithm, but it also improves the computational efficiency. The parameter estimation of $\theta = < P_0, P_1, A_F^0, A_F^1, A_H^0, A_H^1, A_E^0, A_E^1, A_S^0, A_S^1, A_N^0, A_N^1 >$ is eventually obtained. The probability density of the latent variable is:

$$f(N_{ik} | \theta) = f(N_{ik} | A_{ik} = 1, \theta) P(A_{ik} = 1 | \theta) + f(N_{ik} | A_{ik} = 0, \theta) P(A_{ik} = 0 | \theta)$$

(22)

Then, calculate the expected value by Monte Carlo method [76] to approximate the probability of $P(A_{ik} = 1 | E_{ik}, H_{ik}, F_{ik}, S_{ik}, N_{ik})$. 
4.3. The Utility-Based Resource Acquisition Decision

After identifying the potential resources in the entrepreneurial network and establishing the acquisition link, it is necessary to play the game between the resource cost and the resource value. First, let us consider a question: Does if a higher risk of uncertainty existed in the path to the resource is equivalent to the resource has a higher return? Generally speaking, entrepreneurs as profit-seeking actors, have more tolerance for high-risk and high-return decisions. They will consider the value that is brought by resources, even if they will undertake more risks. In addition, if the cost of acquiring the resource is higher than the value of the resource itself, even if the probability of establishing the link is extremely high, the enterprise benefit cannot be promoted. From the probability of obtaining the potential resource status A in the previous section, we can find that the enterprise may face the acquisition path of a certain resource in the current entrepreneurial network, or the possibility of one or more acquisition paths, due to direct contact and indirect. The difference in access, the cost of acquiring resources also increases with the complexity and uncertainty of establishing links, leading to differences in the value of a startup’s resources from the network:

\[
U_{ij} = P(A_{ij} = 1 | E_{ij}, H_{ij}, F_{ij}, S_{ij}, N_{ij}) \times V_{ij}, \quad V_{ij} > 0, \quad (23)
\]

According to the probability of obtaining each potential link resource in the entrepreneurial network in the previous section, we can introduce a simple optimization model to get the enterprise’s decision on the resource acquisition behavior in the network:

\[
M_{ij} = \text{MAX}(U_{i1}, U_{i2}, \cdots, U_{ik}, \cdots, U_{in}) \quad (24)
\]

Therefore, we can get how the new enterprise should effectively manage the network relationship to obtain the required resources. The startup enterprise can capture the different information and resources according to the different network characteristics, but the resources are not completely effective, and the enterprise managers are needed. Use a keen eye to identify valuable resources for use in order to achieve steady growth and sustainable economic growth.

5. Empirical Evaluation

In order to understand the mathematical model that is explained in Section 4 and to simplify the complexity of the previous formula, we conducted experiments to evaluate our method using real-world social network data. In this section, we describe the sample and data collection; detail our experimental procedure, and report experimental results.

5.1. Sample and Data Collection

This study combines the research of Lechner et al. [78] and Rosenbusch et al. [79] to define the entrepreneurial enterprise, and collects enterprise data with less than 10 years of establishment and the number of employees of the company is 500 or less as the basis for empirical analysis. The research participants mainly choose the CEO, general manager, or other middle and high managers of the new venture. A research team consisting of 8 students from Chongqing University was organized to distribute and recycle the questionnaire. A total of 334 questionnaires were sent out, and 261 questionnaires were obtained representing an effective response rate of 78.14 percent. Excluding 60 questionnaires that did not correspond the basic requirements, a total of 201 valid questionnaires were obtained, with an effective rate of 60.2%. The start and end dates of the survey are: 21 September 2017, 20 October 2018. The basic conditions of the sample are shown in Table 1.

In addition, two key data source biases were considered in the survey research, one is the non-response bias and the other is the common method variance. In this paper, T-test analysis was performed on the first 30% and the last 30% of the questionnaires that were normally recovered to test the non-response bias. The results showed that the T value was not significant, which indicates that
the problem of non-response bias in this study does not affect the results of the analysis. At the same time, we checked the homology deviation of the data samples by the Harman single factor test. After completing the factor analysis of the entire questionnaire, we found that the first factor explained only 34.364% of the variance without rotation. This indicates that the results of the questionnaire are credible, and subsequent research can be carried out. Refer to the Appendix C for the variable measurement of the questionnaire, and refer to the Appendix D for the reliability of the questionnaire scale.

Table 1. Sample Basic Information (n = 201).

<table>
<thead>
<tr>
<th>Classification</th>
<th>Project</th>
<th>Number of Samples</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year of establishment</td>
<td>Less than 1 year</td>
<td>26</td>
<td>12.94%</td>
</tr>
<tr>
<td></td>
<td>1–2 year</td>
<td>54</td>
<td>26.87%</td>
</tr>
<tr>
<td></td>
<td>3–5 year</td>
<td>55</td>
<td>27.36%</td>
</tr>
<tr>
<td></td>
<td>5–10 year</td>
<td>66</td>
<td>32.83%</td>
</tr>
<tr>
<td>Number of employees</td>
<td>Less than 5 person</td>
<td>21</td>
<td>10.45%</td>
</tr>
<tr>
<td></td>
<td>5–20 person</td>
<td>61</td>
<td>30.35%</td>
</tr>
<tr>
<td></td>
<td>21–50 person</td>
<td>40</td>
<td>19.90%</td>
</tr>
<tr>
<td></td>
<td>51–100 person</td>
<td>34</td>
<td>16.92%</td>
</tr>
<tr>
<td></td>
<td>101–200 person</td>
<td>28</td>
<td>13.93%</td>
</tr>
<tr>
<td></td>
<td>201–500 person</td>
<td>17</td>
<td>8.5%</td>
</tr>
<tr>
<td>Industry</td>
<td>Agricultural and sideline food processing industry</td>
<td>10</td>
<td>4.98%</td>
</tr>
<tr>
<td></td>
<td>Manufacturing</td>
<td>31</td>
<td>15.42%</td>
</tr>
<tr>
<td></td>
<td>Biology and medicine industry</td>
<td>10</td>
<td>4.98%</td>
</tr>
<tr>
<td></td>
<td>Electricity, gas and other related industry</td>
<td>7</td>
<td>3.48%</td>
</tr>
<tr>
<td></td>
<td>Construction industry and real estate industry</td>
<td>19</td>
<td>9.45%</td>
</tr>
<tr>
<td></td>
<td>Transportation, warehousing and postal services</td>
<td>7</td>
<td>3.48%</td>
</tr>
<tr>
<td></td>
<td>Financial industry</td>
<td>19</td>
<td>9.45%</td>
</tr>
<tr>
<td></td>
<td>Wholesale and retail</td>
<td>19</td>
<td>9.45%</td>
</tr>
<tr>
<td></td>
<td>Information transfer</td>
<td>8</td>
<td>3.98%</td>
</tr>
<tr>
<td></td>
<td>Computer service and software industry</td>
<td>19</td>
<td>9.45%</td>
</tr>
<tr>
<td></td>
<td>Accommodation and catering industry</td>
<td>11</td>
<td>5.47%</td>
</tr>
<tr>
<td></td>
<td>Leasing and business services industry</td>
<td>5</td>
<td>2.49%</td>
</tr>
<tr>
<td></td>
<td>others</td>
<td>36</td>
<td>17.91%</td>
</tr>
</tbody>
</table>

5.2. Experimental Design and Results

The experiment in this paper is based on the data of 201 real entrepreneurs. It uses the network scale, relationship strength, structural equivalence, and heterogeneity in social networks to describe a human resource acquisition project the deterministic corresponding attribute value is missing. The experiment in this paper uses a ten-fold cross-validation technique. For each experiment, we divided the data set (201 companies) into ten equal parts, 90% of which were used to be training set, and the remaining 10% was used to be test set [80].

Step 1: We repeat each individual experiment 10 times. The metric used to measure the performance of the predictive model is the average accuracy of the model predictive test data set. We can verify whether these companies have established resource links based on the social network data of the latter 21 startups. That is predictive accuracy. Simultaneously, we compared the accuracy between EM-NB with SVM/KNN.

Figure 4 depicts the performance comparison between the Naive Bayesian classifier based on the EM algorithm and the SVM/KNN method, with the category prediction models built on 201 entrepreneurial data sets. The horizontal axis represents the number of samples of a priori data in Naive Bayes and EM algorithms. It can be seen from Figure 5 that the EM-NB used in this paper has better prediction performance than SVM/KNN in the absence of data sets. Support vector machines (SVM) offers one of the most robust and accurate methods among all well-known algorithms. It has a sound theoretical foundation, requires only a dozen examples for training, and it is insensitive to the number of dimensions [81]. It has been applied to tasks, such as handwritten digit recognition, object recognition, as well as text classification [82]. The KNN method is a stochastic supervised pattern recognition method [83]. It is easy to understand and easy to implement classification technique. Despite its simplicity, it can perform well in many situations [81].
which is \( x_{ij} \), \( i = 1, j = 2, 3, 4, 5, 6 \), \( i \) represents company A, and \( j \) represents other companies that have established resource links with company A. These five resource links exist in different social network dimensions, decision-makers need to make decisions that are based on the current state of the corporate social network and the utility of acquiring resources. According to the evaluation of network structure as the posteriori data, decision-makers of start-ups can construct a Naive Bayes classifier to predict the network connection probability. According to the evaluation of network size, structural equivalence, heterogeneity, uncertainty, the value of resources and utility of obtaining the resource, which as shown in Table 2.

**Figure 4.** The accuracy of different methods.

![Figure 4](image_url)

**Input:**
Samples of enterprises with observed properties, tie strength \( F \), equivalence \( E \), relative network size \( S \), and heterogeneity \( H \), i.e. \( D = \{F_{ij}, E_{ij}, S_{ij}, H_{ij}\} \)

**Initialize:**
stop certiron: \( \varepsilon \)

\( k \leftarrow 0 \)
\( \theta^k \sim Gaussian Distribution \)

**Repeat:**

a) **Estep:**
Calculating \( P (A_{ij}) \), \( P (F_{ij} | A_{ij}) \), \( P (E_{ij} | A_{ij}) \), \( P (H_{ij} | A_{ij}) \), \( P (S_{ij} | A_{ij}) \), \( P (N_{ij} | A_{ij}) \), \( P (X_{ij} | A_{ij}) \) as section 4.2, and acquiring latent variable \( X_{ij} \) by calculating the mean of \( f(\theta^k) \) in formula (12).

b) **Mstep:**
Updating the parameter \( \theta^{k+1} \) by maximizing formula (18) with probability from Estep.

Until \( \|Q(\theta_{k+1}) - Q(\theta_k)\| < \varepsilon \)

**Output:** Completion data set with uncertainty \( D = \{F_{ij}, E_{ij}, S_{ij}, H_{ij}, N_{ij}\} \)

**Split data:**
\( DTrain: p \) percent of \( D \) where \( p \) is from 0.1 to 0.9

**DTest:** the test of \( D \)

**Prediction:**
Calculating posterior probabilities \( P (A_{ij} = \{1\} | F_{ij}, E_{ij}, S_{ij}, H_{ij}, N_{ij}) \) of test enterprises by formula (12) with conditional independence assumption

**Figure 5.** The expectation-maximization method for Naïve Bayesian learning.

Step 2: In order to enable startups to better use our methods in the practice of enterprise development, we assume that there are currently five human resources links in the company A, which is \( x_{1ij} \), \( i = 1, j = 2, 3, 4, 5, 6 \), \( i \) represents company A, and \( j \) represents other companies that have established resource links with company A. These five resource links exist in different social network dimensions, decision-makers need to make decisions that are based on the current state of the corporate social network and the utility of acquiring resources. According to the evaluation of network structure as the posteriori data, decision-makers of start-ups can construct a Naive Bayes classifier to predict the network connection probability \( p_1 \) of obtaining the resource, which as shown in Table 2.
Using the complete data of 201 companies as a priori data to estimate the posterior probability of these five paths. We can see the result from Table 2, where F, S, E, H, N, V, U indicates ties strength, network sizes, structural equivalence, heterogeneity, uncertainty, the value of resources and utility of resources acquisition, and $p_1$ represents the probability of establishing a resource link. By comparing the results of the five resources to get utility, optimization resource acquisition path will be chosen is $x_{1,6}$. We can see that the link probability of $x_{1,3}$ is 91.67%, which is much higher than 74.42% of link $x_{1,6}$. But, when we combine the value and cost into consideration, we find that the utility of link $x_{1,6}$ is higher than that of link $x_{1,3}$. In other words, the decision to build this link to acquire resources is the most effective. The process indicates that, if a company is able to assess current social network dimension metrics, then they can use these factors to estimate the uncertainty of accessing resources, thereby making rationality and thoughtful entrepreneurial decision based on the value of the resource by predicting the probability of establishing a resource link.

In the above, we proved that the method we use had a better prediction rate than the SVM/KNN method in the real data of 201 entrepreneurial social networks, firstly, and as the amount of prior data increased, the accuracy of prediction had a process of decreasing first and then increasing. In our training sets, the prediction probability of the EM-NB algorithm is above 80%, which means that the method we use has quite well predictive performance in practical applications.

Otherwise, we assumed a simple situation with the human resources acquisition path of new company, which explained the basic usage of the model in this paper. The practical application that we focus on is how a startup should choose the most reasonable path among the existing resource links. From Table 2, we can see that venture capital acquisition is not only related to a certain network structure, it is the result of the overall role of the network, and we also need to consider a question, whether it correctly evaluates the cost and value of resource acquisition, if the establishment of a resource acquisition link ultimately does not create corporate performance to promote business development, it is useless.

However, due to the existence of uncertainty, the growth and resource direction of the enterprise may not be completely developed according to the prediction scheme in the future. The calculation result of the EM-NB model is not absolutely assigned, but the link probability of each scheme is predicted to obtain the maximum probability. The path also provides the result of an alternative, which can take other link decisions based on dynamic network changes and future events. The main advantage of the new approach that is presented in this paper is that it provides a broader picture of all the scenarios that may appear in the future and it recommends a link alternative according to the network structure of start-ups.

6. Conclusions

This article began with an examination of the role that uncertainty plays in the entrepreneurship. After establishing the need to consider resource acquisition and entrepreneurial network when examining entrepreneurial action with high uncertainty, this study attempts to reveal the resource acquisition path and network governance decision of the start-up by analyzing the structure of the entrepreneurial network, what can be characterized by tie strength, structural equivalence, network
size, heterogeneity, and uncertainty. In this paper, the estimation of environmental uncertainty is the primary problem to be solved by establishing an empirical model. In the empirical evaluation of this paper, we proved that the method we use had a better prediction rate than the SVM/KNN method in the real data of 201 entrepreneurial social networks firstly. Using our training set, the prediction probability of the EM-NB algorithm is above 80%, which means that the method we use has quite well predictive performance in practical applications. In addition, we assumed a simple situation with the human resources acquisition path of new company, which explained the basic usage of the model.

Understanding what kind of network dimension can effectively reduce the risk of uncertainty and improve the ability to access resources can promote entrepreneurs to build a reasonable network governance mechanism. This paper believed that network characteristics are not solely responsible for resource acquisition, but rather dynamic mechanisms in which multiple dimensions and factors interact. The main answer to this work is: How do startups combine network characteristics to access scarce resources to drive business performance to grow under uncertainty?

Our study has several managerial implications. First of all, based on social network theory and resource theory, we established a method for predicting the probability of an enterprise acquiring resource links. Then, through the EM-NB model and decision-making process, our research prove EM-NB algorithm has good performance in social network link prediction based on the data sets. So it can be used to practical applications with the entrepreneurial network structure with resource acquisition in the presence of uncertainty. In this light, the manager of a start-up making governance decision of entrepreneurial network could purposefully boost linkage likelihood, such that both the planner and stakeholders are benefited. This expands the characteristics of previous research on the entrepreneurial network literature biased qualitative methods.

Secondly, this paper emphasizes that entrepreneurs should focus on the efficiency of resource acquisition rather than over-expanding networks. Fully assessing the current entrepreneurial network can help a manager to reduce the uncertainty and risky in resource acquisition. Changes in the external environment are inevitable, but companies should use such measurement methods to make strategic decisions more carefully to avoid over-embedding of relationships. Firms can use our method to enhance their social network-based target acquiring scarce resources by better governing network structure by reducing uncertainly. For example, in some scenarios like the context of crowdfunding, crowdfunders are typically first-time entrepreneurs. Unlike investors in other entrepreneurial finance settings, they cannot count on investment banks to stimulate demand. The most important route to successful funder sourcing is through their existing social networks, so they can use the model to estimate the probability of acquiring resource from social networks, or to build more effective network links for obtaining funding resources [84].

Last but not least, the assessment of environmental uncertainty that is difficult to measure is the focus of this research. Our findings support and reinforce the motivation of the proposed method, i.e., better predicting link probabilities with a more comprehensive set of key factors underlying resource acquisition decision, including environmental uncertainty factors. We have established a set of practical methods for how international and domestic entrepreneurs can apply the social network dimension to predict the link probability of resource acquisition, and we consider the value and cost of resources to provide decision-making basis for entrepreneurs. All in all, the theoretical model framework for predicting the resource acquisition probability and governance decision-making of enterprises in the entrepreneurial network provides new ideas for entrepreneurs to further strengthen sustainable entrepreneurship.

However, there are still three limitations that need to be considered. First, the network structure is a key variable that determines the acquisition of resources from a theoretical perspective, but many other variables that are involved in the path of resource acquisition should be considered in order to assess the problem from a more comprehensive real-world perspective. Second, since Naive Bayes’ attribute independence hypothesis is difficult to establish in reality, future research should consider how to release the attribute conditional independence hypothesis of naive Bayes classifier. For example,
structural expansion, attribute selection, and local learning are some of the more feasible improvements. Although the computational complexity is increased, these methods can further improve the prediction effect of the model. Third, the most important thing is that real-world relational networks are very complex, and many underlying relationships that cannot be captured may adjust the optimal solution in different ways. In the future research, we hope to dig into the data closer to the network relationship in real life, and more accurately describe the dynamic mechanism of the formation and development of the entrepreneurial network.

Author Contributions: Writing: F.-W.C., M.-X.L.; Providing idea and data: F.-W.C., M.-X.L.; Providing revision advice T.W.

Funding: This research was supported by the National Natural Science Foundation of China (No. 71772019); the Fundamental Research Funds for the Central Universities (No. 106112017CDJXY020002; No. 2018CDXYJG0040).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A  Derivation of Equation (17)

We repeat Equation (17)

\[ Q(\theta | \theta_k) = \sum_{k=1}^{n} \ln[P(D_{ik}, N_{ik} | \theta)]P(N_{ik} | D_{ik}, \theta_k)dN_{ik} \]  

(A1)

\[ P(D_{ik}, H_{ik} | \theta) \] can be expanded to:

\[ P(D_{ik}, H_{ik} | \theta) = P(F_{ik}, E_{ik}, S_{ik}, H_{ik}, N_{ik}, A_{ik} | \theta) \]
\[ = P(F_{ik}, E_{ik}, S_{ik}, H_{ik}, N_{ik} | A_{ik}, \theta)P(A_{ik} | \theta) \]
\[ = P(E_{ik} | A_{ik}, \theta)P(H_{ik} | A_{ik}, \theta)P(F_{ik}, S_{ik}, N_{ik} | A_{ik}, \theta)P(A_{ik} | \theta) \]  

(A2)

\[ P(F_{ik}, S_{ik}, N_{ik} | A_{ik}, \theta)P(A_{ik} | \theta) = P(F_{ik}, S_{ik} | N_{ik}, A_{ik}, \theta)P(N_{ik} | A_{ik}, \theta)P(A_{ik} | \theta) \]
\[ = P(F_{ik} | N_{ik}, A_{ik}, \theta)P(S_{ik} | N_{ik}, A_{ik}, \theta)P(N_{ik} | A_{ik}, \theta)P(A_{ik} | \theta) \]  

(A3)

\[ P(D_{ik}, H_{ik} | \theta) = \frac{P(E_{ik} | A_{ik}, \theta)P(H_{ik} | A_{ik}, \theta)P(F_{ik}, N_{ik} | A_{ik}, \theta)P(S_{ik}, N_{ik} | A_{ik}, \theta)P(A_{ik} | \theta)}{P(N_{ik} | A_{ik}, \theta)} \]  

(A4)

Substituting (A4) into (A1), we can get the formula (18).

Appendix B  Explanation of Theorem 1

In this case, when estimating \( \theta_k \) exists for maximizing the objective function [40].

\[ p_1 = \frac{\sum_{k=1}^{n} A_{ik}}{n} \]  

(A5)

When the value near the zero frequency attribute appears, this probability estimation method produces a biased low estimation probability. More extreme, when a zero-frequency attribute value occurs, it will cause a certain probability value to be 0, which in turn causes the entire amount calculated by
Equation (A5) to be zero. In order to avoid this, this paper uses Laplace estimation to smooth the above probability, where \( n_1 \) is the number of classes. We have:

\[
P_1 = \frac{\sum_{k=1}^{n} A_{ik} + 1}{n + n_1} \tag{A6}
\]

\[
P_0 = 1 - P_1 \tag{A7}
\]

\[
\lambda_{E[1]} = \frac{\sum_{k=1}^{n} A_{ik}}{\sum_{k=1}^{n} A_{ik}} \tag{A8}
\]

\[
\lambda_{E[0]} = \frac{\sum_{k=1}^{n} (1 - A_{ik})}{\sum_{k=1}^{n} (1 - A_{ik})} \tag{A9}
\]

\[
\lambda_{H[1]} = \frac{\sum_{k=1}^{n} A_{ik} \lambda_1}{\sum_{k=1}^{n} A_{ik} \lambda_1} \tag{A10}
\]

\[
\lambda_{H[0]} = \frac{\sum_{k=1}^{n} (1 - A_{ik}) \lambda_0}{\sum_{k=1}^{n} (1 - A_{ik}) \lambda_0} \tag{A11}
\]

\[
\lambda_1 = \frac{\sum_k A_{ik} (2 - I_{ik})}{\sum_k A_{ik} [S_{ik} + \Gamma_2 + I_{ik} \Gamma_3 + (1 - I_{ik}) S_{ik}]} \tag{A12}
\]

\[
\lambda_0 = \frac{\sum_k (1 - A_{ik}) (2 - I_{ik})}{\sum_k (1 - A_{ik}) [S_{ik} + \Gamma_2 + I_{ik} \Gamma_3 + (1 - I_{ik}) S_{ik}]} \tag{A13}
\]

\[
\lambda_1^1 = \frac{\sum_k A_{ik} (1 + I_{ik})}{\sum_k A_{ik} [S_{ik} - \Gamma_2 + I_{ik} \Gamma_3 + I_{ik} S_{ik}]} \tag{A14}
\]

\[
\lambda_0^1 = \frac{\sum_k (1 - A_{ik}) (1 + I_{ik})}{\sum_k (1 - A_{ik}) [S_{ik} - \Gamma_2 + I_{ik} S_{ik}]} \tag{A15}
\]

\[
\lambda_1^2 = \frac{\sum_k A_{ik} (1 + I_{ik})}{\sum_k A_{ik} [F_{ik} + \Gamma_2 + (1 - I_{ik}) \Gamma_3 + I_{ik} F_{ik}]} \tag{A16}
\]

\[
\lambda_0^2 = \frac{\sum_k (1 - A_{ik}) (1 + I_{ik})}{\sum_k (1 - A_{ik}) [F_{ik} + \Gamma_2 + (1 - I_{ik}) \Gamma_3 + I_{ik} F_{ik}]} \tag{A17}
\]

\[
\lambda_1^3 = \frac{\sum_k A_{ik} (1 - I_{ik})}{\sum_k A_{ik} [F_{ik} - \Gamma_2 + (1 - I_{ik}) F_{ik}]} \tag{A18}
\]

\[
\lambda_0^3 = \frac{\sum_k (1 - A_{ik}) (2 - I_{ik})}{\sum_k (1 - A_{ik}) [F_{ik} - \Gamma_2 + (1 - I_{ik}) F_{ik}]} \tag{A19}
\]

\[
\lambda_1^4 = \frac{\sum_k A_{ik} [1 + I_{ik} \Gamma_3 + (1 - I_{ik}) \Gamma_4]}{\sum_k A_{ik} [(N_{ik} + F_{ik}) + \Gamma_2 + I_{ik} (\Gamma_3 + S_{ik}) + (1 - I_{ik}) (\Gamma_4 + F_{ik})]} \tag{A20}
\]

\[
\lambda_0^4 = \frac{\sum_k (1 - A_{ik}) [1 + I_{ik} \Gamma_3 + (1 - I_{ik}) \Gamma_4]}{\sum_k (1 - A_{ik}) [(N_{ik} + F_{ik}) + \Gamma_2 + I_{ik} (\Gamma_3 + S_{ik}) + (1 - I_{ik}) (\Gamma_4 + F_{ik})]} \tag{A21}
\]

\[
\lambda_1^5 = \frac{\sum_k A_{ik} [\Gamma_1 - (F_{ik} + S_{ik}) + I_{ik} S_{ik} (1 - I_{ik}) F_{ik}]}{\sum_k A_{ik} [(N_{ik} + F_{ik}) + \Gamma_2 + I_{ik} (\Gamma_3 + S_{ik}) + (1 - I_{ik}) (\Gamma_4 + F_{ik})]} \tag{A22}
\]

\[
\lambda_0^5 = \frac{\sum_k (1 - A_{ik}) [\Gamma_1 - (F_{ik} + S_{ik}) + I_{ik} S_{ik} (1 - I_{ik}) F_{ik}]}{\sum_k (1 - A_{ik}) [(N_{ik} + F_{ik}) + \Gamma_2 + I_{ik} (\Gamma_3 + S_{ik}) + (1 - I_{ik}) (\Gamma_4 + F_{ik})]} \tag{A23}
\]

where

\[
I_{ik} = \begin{cases} 
1, & F_{ik} > S_{ik} \\
0, & F_{ik} \leq S_{ik} 
\end{cases}
\]
Appendix C Variable Metrics of Questionnaires

This study uses the new employee quantity as the indicator to measure the dimension of the human resource acquiring. We calculate the score reflecting the number of new employees as the value of human resources, which contains five-level Likert scale, and specifically its value “1” to “5” means “very non-conformity” to “very consistent”. Based on the division of social network dimensions, this paper uses a five-level Likert scale to measure the network size (social network size; \( \alpha = 826 \)), the value from “1” to “5” means “rare”, “once a month”, “a few times a month”, “a few times a week” and “every day”. Besides, in order to measure the social network structural equivalence (social network structural equivalence; \( \alpha = 0.907 \)), we made an adjustment on Burt’s measurement scale [87], and obtained the five measurement items, whose value of the scale from “1” to “5” means “very non-conformity” to “very consistent”. Thus, we used a five-level Likert scale adapted from Chatman et al. to measure heterogeneity [89] (social network heterogeneity; \( \alpha = 0.845 \)).

Appendix D Test of Reliability and Validity of Questionnaires

The tests about the scale’s reliability and validity are based on software SPSS 22.0 and AMOS 24.0. The Cronbach’s \( \alpha \) index is only a reference for internal consistency of the scale, and its value is not less than 0.6 indicating that the scale has good reliability. According to Table 2, the \( \alpha \) coefficient is greater than 0.6, and the combined reliability (CR) value of the variable is 0.759 to 0.907, which is obviously above 0.6 such that the reliability of the scale is good (see Table A1 for details). According to the result of model estimation using AMOS 24.0: we estimated the fitting index of all constructs, and the results show that all the measured values are well utilized (see Table A2 for details).
Table A1. Results of reliability & convergence validity analysis.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Variable Item</th>
<th>Factor Load</th>
<th>Cronbach’s α</th>
<th>AVE</th>
<th>CR</th>
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<tbody>
<tr>
<td>Network size</td>
<td>A01</td>
<td>0.549</td>
<td>0.826</td>
<td>0.454321</td>
<td>0.830130672</td>
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<td></td>
<td>A02</td>
<td>0.784</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>A03</td>
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<tr>
<td></td>
<td>A04</td>
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<tr>
<td></td>
<td>A05</td>
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<tr>
<td></td>
<td>A06</td>
<td>0.646</td>
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</tr>
<tr>
<td>Ties strength</td>
<td>B01</td>
<td>0.629</td>
<td>0.907</td>
<td>0.4800928</td>
<td>0.901395106</td>
</tr>
<tr>
<td></td>
<td>B02</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>B03</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>B04</td>
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<tr>
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</tr>
<tr>
<td></td>
<td>B06</td>
<td>0.654</td>
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<td></td>
<td>B07</td>
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<tr>
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<td>B08</td>
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<tr>
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<td></td>
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<td>Structural</td>
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<td>0.758947323</td>
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<td>Heterogeneity</td>
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<td>0.846794735</td>
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<td></td>
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</table>

Table A2. Results of confirmatory factor analysis.

<table>
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<tr>
<th>Variable</th>
<th>(\chi^2/df)</th>
<th>RMSEA</th>
<th>CFI</th>
<th>NFI</th>
<th>RFI</th>
<th>IFI</th>
<th>TLI</th>
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</thead>
<tbody>
<tr>
<td>A</td>
<td>1.443</td>
<td>0.047</td>
<td>0.973</td>
<td>0.921</td>
<td>0.866</td>
<td>0.974</td>
<td>0.955</td>
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<tr>
<td>B</td>
<td>1.891</td>
<td>0.067</td>
<td>0.911</td>
<td>0.833</td>
<td>0.775</td>
<td>0.914</td>
<td>0.879</td>
</tr>
<tr>
<td>C</td>
<td>1.658</td>
<td>0.057</td>
<td>0.985</td>
<td>0.965</td>
<td>0.929</td>
<td>0.986</td>
<td>0.971</td>
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<tr>
<td>D</td>
<td>0.572</td>
<td>0.0</td>
<td>1</td>
<td>0.984</td>
<td>0.968</td>
<td>1.012</td>
<td>1.025</td>
</tr>
</tbody>
</table>

References


52. Granovetter, M. The Strength of Weak Ties. *Am. J. Sociol.* 1973, 78, 1360–1380. [CrossRef]


